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## SPEECH UNDERSTANDING SYSTEMS

# Summary of Results of the Five-Year Research Effort at Carnegie-Mellon University 

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## PREFACE

This report is an augmented version of a report originally issued in September of 1976, during the demonstration at the end of the five-year speech effort. The first section reports on the various speech understanding systems developed at CMU during the five year period and highlights their individual contributions. Section II contains a brief description of several techniques and knowledge sources that contributed to the success of the final systems. Section III gives detailed performance results of the Harpy and Hearsay-II systems. Results include the performance of the systems not only for the 1000 word task but for several simpler tasks. Section IV contains reprints of papers presented at various conferences since September 1976. Section $V$ contains a list of publications of the CMU speech group.
The CMU Speech Group gratefully acknowledges the following contributions which have been instrumental to the successful conclusion of the five-year speech understanding systems research effort at Carnegie-Mellon University:

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# I. MULTI-SYSTEM APPROACH TO SPEECH UNDERSTANDING* <br> Raj Reddy 

## INTRODUCTION

In 1971, a group of scientists recommended the initiation of a five-year research program towards the demonstration of a large-vocabulary connected speech understanding system (Newell et al., 1971). Instead of setting vague objectives, the group proposed a set of specific performance goals (see Fig. 1.1 of Newell et al., 1971). The system was required to accept connected speech from many speakers based on a 1000 word vocabulary task-oriented grammar, within a constrained task. The system was expected to perform with less than 107 , semantic errors, using about 300 million instructions per second of speech (MIPSS)** and to be operational within a five year period. The proposed research was a highly ambitious undertaking, given the almost total lack of experience with connected speech systems at that time.

The Harpy and Hearsay-II systems developed at Carnegie-Mellon University had the best overall performance at the end of the five year period. Figure 1 illustrates the performance of the Harpy system relatise to the original specifications. It not only satisfies the original goals, but excerds some of the stated objectives. It recognizes speech from male and female speakers using a 1011-word-vocabulary document retrieval task. Semantic error is 5 ', and response is an order of magnitude faster than expected. The Hearsay-II system achieves similar accuracy and runs about 2 to 20 times slower than Harpy.

Of the many factors that led to the final successful demonstration of these systems, perhaps the most important was th. systems development methodology that evolved. Faced with prospects of develoning systems with a large number of unknowns, we opted to develop several intermediate "throw-away" systems rather than work towards a single carefully designid ultimate system. Many dimensions of these intermediate systems were deliberately finessed or ignored so as to gain deeper understanding of some aspect of the overall system. The purpose of this paper is to

GOAL (Nov. 1971)
Accept connected speech from many cooperative speakers in a quiet room using a good microphone with slight tuning/speaker accepting 1000 words using an artificial syntax in a constraining task yielding < 102 semantic error requiring approx. 300 MIPSS**

$$
\begin{aligned}
& \text { HARPY (Nov. 1976) } \\
& \text { Yes } \\
& 5 \text { ( } 3 \text { male, } 2 \text { female) } \\
& \text { yes } \\
& \text { computer terminal room } \\
& \text { close-talking microphone } \\
& \text { 20- } 30 \text { sentences/talker } \\
& 1011 \text { word vocabulary } \\
& \text { ave. branching factor }=33 \\
& \text { document retrieval } \\
& 5 / \\
& \text { requiring } 28 \text { MIPSS } \\
& \text { using } 256 \mathrm{k} \text { of } 36 \text { bit words } \\
& \text { costing } \$ 5 \text { per sentence processed }
\end{aligned}
$$

Figure 1. Harpy performance compared to desired goais.

[^0]```
Task characteristics
    speakers; number, male/female, dialect
    vocabulary and syntax
    response desired
Signal gathering environment
    room noise level
    transducer characteristics
Signal transformations
    digitization speed and accuracy
    special-purpose hardware required
    parametric representation
Signai-to-symbol transformation
    segmentation?
    level transformation occurs
    label selection technique
    amount of training required
Matching and searching
    relaxation: breadth-first
    blackboard: best-first, island driven
    productions: best-first
    Locus: beam search
Knowledge source representation
    networks
    procedures
    frames
    productions
System organization
    levels of representation
    single processor / multi-processor
```

Figure 2. Design choices for speech understanding systems.
illustrate the incremental understanding of the solution space provided by the various intermediate systems developed at CMU.

Figure 2 illustrates the large number of design decisions which confront a speech understanding system designer*. For each of these 10 to 15 design decisions, we have 3 to 10 feasible alternative choices. Thus the solution space for speech systems seems to contain $10^{6}$ to $10^{8}$ possible system designs. Given the interactions between design choices, it is not possible to evaluate each design choice in isolation outside the framework of the total system.

* Further discussion of many of these design choices can be found in Reddy (1976).


Figure 3. CMU Speech Understanding Systems Genealogy

## SYSTEMS

Figure 3 shows the genealogy of the peech understanding systems developed at CMU. In this section we will briefly outline the interesting aspects of each of these systems and discuss their contributions towards the development of speech understanding systems technology. More complete descriptions of these systems can be found in the references listed at the end.

## The Hearsay-I System (Erman, Fennell, Lowerre, Neely, and Reddy)* <br> Hearsay-1 (Reddy, Erman and Neely 1973; Reddy, Erman, Fennell and Neely 1973), the first speech understanding system developed at Carnegie-Mellion University, was demonstrated in June of 1972. This system was one of the first connected speech understanding systems to use task dependent knowledge to achieve reduction of the search space. Recognition uses a best-first scarch strategy.

## Model

Hearsay-l was the first system to utilize independent, cooperating knowledge sources and the concept of a global data base, or "blackboard", through which all knowledge sources communicate. Knowledge sources consist of the acoustic-phonetic, syntactic, and semantic modules. Each module operates in the "hypothesize-and-test" mode. Synchronous activation of the modules leads to a best-first search strategy. Several other systems have used this strategy (Forgie 1974). This system was one of the first to use syntactically derived word diagrams and trigrams, as anti-productions (Neely 1973), to predict forward and backward from "islands of reliability". Task dependent knowledge, such as a board position in the chess task, is used by the semantic module (Neely 1973) to reject nieaningless partial parses early in the recognition process. The acoustic-phonetic module uses amplitude and zero-crossing parameters to obtain a multilevel segmentation into syllable-size and phoneme-size units (Erman, 1974).

## Performance

Over a wide range of tasks, the averafe sentence error rate was 697 with a a word error rate of 457. Speed varied betwe en 3 and 15 MIPSS over 162 utterances containing 578 words. Hearsay-I yields much higher accuracies on tasks with which it is carefully trained. For the chess task, for instance, average sentence and word error rates were 21 and 7 percent, respectively, with an average speed of 2 MIPSS.

## Discussion

Hearsay-I, as a successful connected-:peech understanding system, served to clarify the nature and necessary interaction of several sources of knowledge. Its flexibility provided a means for testing and evaluating competing theories, allowing the better theories to be chosen as a basis for later systems. In retrospect, we believe this system organization would have been adequate for the ARPA specifications given present acoustic-phonetic knowledge.

* The principle contributors towards the development of each of these systems are listed within parentheses.


## The Dragon System (Baker)

Baker formulated the recognition process as a dynamic programming problem. The Dragon recognition system (Baker, 1975), based on this model was first demonstrated in April of 1974. The systen was motivated by a desire to use a general abstract model to represent knoviledge sources. The model, that of a probabilistic function of a Markov process, is flexible and leads to features which allow it to function despite high error rates. Recognition accuracy was greater with Dragon than with Hearsay-I, but the system ran significantly slower.

## Model

Dragon was the first system to demonstrate the use of a Markov model and dynamic programming in a connected speech understanding system. It included several interesting features, such as delayed decisions and integrated representation, and is based on a general theoretical framework. The general framework allows acousticphonetic, syntactic, and semantic knowledge to be embodied in a finite-state network. Each path through this precomplied network represents an allowed pronunciation of a syntactically acceptable sentence. Recognition proceeds left-to-right through the network, searching all possible paths in parallef to determine the globally optimal path (i.e., the path which best matches the spoken utterance). Acoustic inputs are peak-topeak amplitudes and zero-crossings from overtapping, one-third octave filters, sampled every centi-second.

## Performance

Recognition accuracy was greater with Dragon than that obtained with HearsayI, but at a cost of speed, Dragon being approximately 5 to 10 times slower. Over a wide variety of tasks, the average sentence crror rate was 517 . Speed ranged from 14 to 50 MIPSS. The computation is essentially linear with the number of states in the Markov network. Performance was later improved by Lowerre (Lowerre, 1976).

## Discussion

Dragon, with more accurate performaice than Hearsay-I, served to stimulate further research into factors that led to its improved performance. Many of the ideas motivating its design were important in the development of subsequent connectedspeech understanding systems. Although later systems do not use the Markov Model and do not guarantee finding the globally optımal path, the concepts of integrated representation of knowledge sources and delayed decisions proved to be very valuable.

## The Harpy System (Lowerre and Reddy)

The Harpy system (Lowerre 1976) was the first connected speech system to satisfy the original specifications given in the Newell report and was first demonstrated in September of 1976. System design was motivated by an investigation of the important design choices contributing to the success of the Dragon and Hearsay-1 systems. The result was a combination of the "best" features of these two systems with additional heuristics to give high speed and accuracy.

## Model

The Harpy system uses the locus model of search. The locus model of search, a very successful search technique in speech understanding research, is a graphsearching technique in which all except a beam of near-miss alternatives around the
best path are pruned from the search tree at each segmental decision point, thus containing the exponential growth without requiring backtracking. This technique was instrumental in making Harpy the most successful connected speech understanding system to date. Harpy represents syntactic, lexical, and juncture knowledge in a unified network as in Dragon, but without the a-priori transition probabilities. Phonetic classification is accomplished by a set if speaker-dependent acoustic-phonetic templates based on LPC parameters which represent the acoustic realizations of the phones in the lexical portion of the network.

## Performance

The system was tested on several different tasks with different vocabularies and branching factors. On the 1011-word task using the AIX05 grammar (see Appendix III-C), the system word error rate was 37. and the semantic error rate was $5 \%$ (see fig. 1). The system was also tested with connected digits recognition attaining a 27 word error rate. Using speaker-independent templates, error rate increases to 77 over 20 speaker including 10 new speakers. Using telephone input increases the error rate to 77 to 117 depending on the noise characteristics of the telephone system.

## Discussion

- Backtracking and redundant computation have always been problematic in AI systems. The Harpy system eliminates these in an elegant way, using the beam search technique. By compiling knowledge ahead of time, Harpy achieves a level of efficiency that is unattainable by systems that dynamically interpret their knowledge. This permits Harpy to consider many more alternatives and deal with error and uncertainty in a graceful manner.


## The Hearsay-II System (Erman, Hayes-Foth, Lesser, and Reddy)

Hearsay-Il has been the major researich effort of the CMU speech group over the last three years. During this period, solutions were devised to many difficult conceptual problems that arose during the implementation of Hearsay-1 and other earlier efforts. The result represents not onl, an inleresting system design for speech understanding but also an experiment in the area of knowledge-based systems architecture. Attempts are being made by other Al groups to use this type of architecture in image processing and other knowledge-intensive systems.

Hearsay-II is similar to Hearsay-1 in that it is based on the hypothesize-and-test paradigm, using cooperating independent knowledge sources communicating through a global data structure (blackboard). It differs in the sense that many of the limitations and shortcomings of Hearsay-I are resolved in Hearsay-II.

Hearsay-ll differs from the Harpy systion in that it views knowledge sources as different and independent and thus cannot always be integrated into a single representation. Further, it has as a design yoal the ability to recognize, understand, and respond even in situations where sentences cannot be guaranteed to agree with some predefined, restricted language model $a$ as is the case with the Harpy system.

## Model

The main features of the Hearsay-II sy:tem structure are: 1) the representation of knowledge as self-activating, asynchronous, parallel processes, 2) the representation of the partial analysis in a generalized three-dimensional network; the dimensions being level of representation (e.f., parametric, segmental, syllabic, lexical, syntactic), time, and alternatives, with contextual and structural support connections explicitly specified, 3) a modular structure for incorporating new knowledge into the system at any level, and 4) a system structure suitable for execution on a parallel processing system.

## Performance

The present system has been tested using about 100 utterances of the training data for the 1011 -word vocabulary task. For a grammar with simple syntax (AIX05, the same one used by Harpy), the sentence error rate is about $16 \%$ (semantic error 167). For a grammar with more complex syntax (AlX15, see appendic III-C), the sentence error rate is about 427 , (semantic ertor 267 ). The syslem runs about 2 to 20 times slower than Harpy.

## Discussion

Hearsay-1I represents an important anci continuing development in the pursuit of large-vocabulary speech understanding systems. The system is designed to respond in a semantically correct way even when the information is fuzzy and only partial recognition is achieved. Independent knowledge sources are easily written and added to Hearsay-II; knowledge sources may al:o be removed in order to test their effectiveness. The Hearsay-II system architecture offers great potential for exploiting parallelism to decrease recognition times and is capable of application to other knowledge-intensive AI problems dealing with errorful domains. Many more years of intensive research would be necessary in order to evaluate the full potential of this system.

## The Locust System (Bisiani, Greer, Lowerre, and Reddy)

Present knowledge representation ancl search used in Harpy tend to require much memory and are not easily extendable to very large languages (vocabularies of over 10,000 words and more complex syntax). But we do not view this as an insurmountable limitation. Modified knowledse representation designed for use with secondary memories and specialized pagir.? should overcome this difficulty. In addition, it appears larger-vocabulary speech understanding systems can be implemented on mini-computers without significant degradation in performance. Locust is designed to demonstrate the feasibility of these ideas.

## Model

The model is essentially the same $\therefore$ : the Harpy system except, given the limitations of storage capacity of main memory, the knowledge representation has to be reorganized significantly. The network is assumed to be larger than main memory, stored on secondary memory, and retrieved u'mp, a specialized paging mechanism. The choice of the file structure representation and clustering of the states into pages of uniform size are the main technical problems associated with the development of this system.

## Discussion

A paging system for the 1011 word ncabulary is currently operational on a PDP-11/40E and has speed and accuracy perinrmance comparable to Harpy on a PDP10 (KA1O). Simulation of various paging modils is currently in progress. As memories with decreased access times become availatlo, this class of systems is expected to perform as accurately and nearly as fast as sistems requiring no secondary memory.

## Parallel Systems (Feiler, Fennell, Lesser, McCracken, and Oleinick)

Response time for the present systerr: is usually greater than real-time, with indications that larger vocabularies and more complex syntax will require more time for search. One method of achieving greater sped is to use parallel processing. Several systems designed and developed at CMU e\%ploit multi-processor hardware such as C. mmp and Cm *.

## Models

Several systems are currently under development as part of multi-processor research projects which attempt to explore potential parallelism of Hearsay and Harpylike systems. Fennell and Lesser (1977) stucied the expected performance of parallel Hearsay systems and issues of algorithm decomposition. McCracken (1977) is studying a production system implementation of the H:arsay model. Oleinick (1977) and Feiler (1977) are studying parallel decompositions of the Harpy algorithm. Several of these studies are not yet complete, but preliminary performance results are very encouraging. Oleinick has demonstrated a version of Harpy that runs faster than realtime on C.mmp for several tasks.

## Discussion

The main contribution of these system studies (when completed) will be to show the degree of parallelism which can reasonably be expected in complex speech understanding tasks. Attempts to produre reliable and cost-effective speech understanding systems would require extensive studies in this direction.

## DISCUSSION

In the previous section we have briefly outlined the structure and contributions of various speech systems developed at CMII. In retrospect, it is clear that the slow rate of progress in this field is directly attributable to the large combinatorial space of design decisions involved. Thus, one might reasonably ask whether the human research strategy in solving this and other cimilar problems can benefit from search reduction heuristics that are commonly used in Al programs. Indeed, as we look around, it is not uncommon to find research paradigms analogous to depth-first exploration, breadth-first with shallow cut-olf, backtracking, "jumping-to-conclusions", thrashing, and so on.

Our own research has been dominated by two such paradigms. First is a variant of best-first search: find the weakest link (and thus the potential for most improvement) in the system and attempt to improve it. Second is a variant of the beam search: when several alternative approaches look promising, we use limited parallel search with feed-forward. The systems shown in Figure 3 are examples of this type of system iteration and multi-systemis approach.

Many system design decisions require an operational total systems framework to conduct experiments. However, it is not necessary to have a single system that permits all possible variations of system designs. Given enough working components, with well-designed interfaces, one can construct new system variants without excessive effort.

The success of the speech understanding research effort is all the more interesting because it is one of the few examples in AI research of a five year prediction that was in fact realized on time and within budget. It is also one of the few examples in AI where adding additional knowledge can be shown to lead to system speed-up as well as improved accuracy.

We note in conclusion that speech undistanding research, in spite of the many superficial differences, raises many of the same issues that are central to other areas of AI. Faced with the problem of reasoning in the presence of error and uncertainty, we generate and search alternatives which have associated with them a likelihood value representing the degree of uncertaints. Faced with the problem of finding the most plausible symbolic description of the utterance in a large combinatorial space, we use techniques similar to those used in least-cost graph searching methods in problem
solving. Given the problems of acquisition and representation of knowledge, and control of search, techniques used in speech are similar to most other knowledge intensive systems. The main difference is that given human performance the criteria for success, in terms of accuracy and response time, far exceed the performance requirements of other AI tasks except perhaps vision.

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# II. KNOWLEDGE SOURCES AND TECHNIQUES 

## The Zapdash Parameters, Feature Extraction, Segmentation, and Labeling for Speech Understanding Systems (Goldberg, Reddy, and Gill)

## Introduction

In spite of early success with very simple parametric representations of speech (see Reddy 1966 and Erman 1974), recent emphasis has been on highly accurate but computationally expensive parameter extraction techniques such as LPC spectral analysis, formant tracking, etc. We feel that simpler, more efficient methods must first be applied to reduce the amount of input data before more expensive analysis is performed. The uniform application of LPC analysis to all the input produces accurate but very redundant results, and at high cost. (see Goldberg 1975)

Our approach involves two levels of parameter extraction and analysis. The first level produces an accurate segmentation with strong clues as to manner of articulation and phonetic identity of the segments. For this purpose, we have developed the ZAPDASH parameters, described below. They provide a highly efficient basis for an accurate, robust segmenter and broad classifier. After the phonetic elements are isolated, a uniform LPC labeling stage is applied only where it is needed to further refine the segment identification. Preliminary evaluations show significant computational savings is possible with no sacrifice of segmentation or labeling accuracy.

## The ZAPDASH Parametric Representation

As digital processing of speech becomes commonplace, it becomes desirable to have a parametric representation of speech which is simple, fast, accurate, and directly obtainable from the PCM representation of speech. The ZAPDASH representation of speech (Zerocrossings And Peaks of Differenced And Smootㅂ waveforms) is of this nature. An important means of reducing computational cost in much of the low level processing of speech is to reduce the quantity of data in the input representation to the minimum necessary for accurate analysis of the phonetic content of the speech signal. Our past experience shows that very simple measures of activity in the low and the high frequency bands (approximately: $<1 \mathrm{kHz}$. and $>1 \mathrm{kHz}$.) would suffice for all but the fine labeling stage. Peak-to-peak amplitudes and zero-crossing counts provide simple measures of the amount of activity within each particular band. In ZAPDASH, the PCM data is used to generate a differenced waveform and a down-sampled, smoothed waveform (for 10 KHz sampling rate, the smoothing FIR filter coefficients were -1012444210-1, used every 4th point). Peak-to-peak distances and number of zero-crossings are calculated each 10 ms , resulting in 4008 -bit parameters per second of speech. ZAPDASH can be calculated in 15 to 20 computer instructions per sample and, therefore, can be extracted in less than a $1 / 3$ real time on minicomputers with 2 micro-sec. instruction time. A simple parametric representation like ZAPDASH appears to provide sufficient information for accurate phone segmentation, thus sharply reducing the amount of more detailed spectral analysis required by many other methods. The resulting four parametric measurements (Smoothed Peak-to-peak, Smoothed Zero-crossing, Differenced Peak-to-peak, and Differenced Zero-crossing) are sufficient to detect, with reasonable accuracy, a set of 10 features, described below, which are quite useful for both segmentation and initial broad labeling. The ZAPDASH parameters are used by the first stage segmenter to make decisions on manner of articulation. The resulting segmentation and broad classification is accurate yet inexpensive. Further refinement of the segment labels using spectral analysis is then much more economical.

## Segmentation and Broad Classification

The first stage of the program contains an hierarchical, feature-extraction based segmenter and classifier. A number of features relating to manner of articulation are extracted. Silence, voicing, frication, front-back placement, high-low placement, consonant-like, flap-like, aspiration-like, nasal, and sibilant decisions are made using the ZAPDASH parameters. In the processing of an utterance, a set of segments is chosen, with broad classification, for the entire utterance. These identify regions of the signal such as SIL-silence, SON-sonorant, UFR-unvoiced fricative, VBK-back vowel, etc. Further sub-segmentation and/or reclassification is conditional upon segment class type, context, and feature values. There are 59 classes currently used internally, although many overlap one another in the acoustic space.

## Modified LPC Labeling

At the second stage, where no further refinement is possible using the ZAPDASH information, a fine labeler is applied at the mid-points of all segments. The original PCM signal is compared against stored templates by a modified LPC distance metric. Itakura's minimum prediction residual metric (Itakura 1975) is used to compare the segment mid-point to a set of speaker-specific trained templates. The segment class is used to provide a sub-set of the approximately 100 templates, or a set of a priori weights to be added to the metric values for all templates. In this way, the manner-of-articulation and the contextual information provided by the earlier feature extraction improve the labeling.

## Results

The highly efficient segmentation procedures in the first level segmenter and the limitation upon the need for LPC analysis provide a factor of 5 speedup over the uniform procedures used by HARPY and Hearsay-II. Preliminary tests with this program indicate that results for HARPY using this parameterization will be just as accurate and will be computed faster than the results obtained with the more redundant parameterization it now uses. Present performance of ZAPDASH can be summarized as follows: Segmentation -- less than $20 \%$ extra segments, less than $2 \%$ missed segments, and boundary placement within an average of 10 ms . of the manually defined location. Labeling (broad classes) -- 90\% correct, (finer labeling) -- correct template in first place 50\% of the time, in the first five places $75 \%$ of the time. A more detailed evaluation will be available shortly.

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## A Syllable Based Word Hypothesizer for Hearsay-II (Smith)

## Problem and Motivation

A central problem for speech understanding systems is efficiently and accurately determining what words are implied at the lexical level by the data at lower levels. One solution to the problem is to map each word hypothesized by syntactic and semantic information to the lower level representation, then match and rate the word.

But as speech systems permit larger vocabularies and languages with less restricted syntax and semantics, they must depend more on bottom-up methods to limit the search space of possible word sequences. The effectiveness of a hypothesizer can be measured by the percent of the correct words and the number of competing words it hypothesizes. One method of bottom up word hypothesization is to go directly from the phone sequences found for the utterance to word hypotheses as in the BBN HWIM speech system (Klovstad, 1976). The solution used in Hearsay-II uses an intermediate level of syllables between the words and phone segments.

## Solution

- The word hypothesizer uses equivalence classes of syllables (called Syltypes) to support word hypotheses (Smith, 1976). These Syltypes were defined so that syllables which were likely to be given similar segments and labels by the speech system would have the same Syltype. No attempt is made by the word hypothesizer to distinguish between words which have the same sequence of Syltypes. The word verifier later makes this distinction as it rates the words.

The Syltypes we now use are defined by a sequence of states corresponding to phoneme equivalence classes. A Markov probability model relates the state sequence of a Syltype to the segment labels hypothesised by the segmenter and labeler. A word may be hypothesised by the following sequence of events: For each syllable nucleus in the utterance (defined by a heuristic using segment labels and an amplitude function), the most likely Syltype state sequences are found by searching the segments from the nucleus out to adjacent nuclei, or perhaps the utterance boundaries. For each Syltype hypothesized with a "good" rating the set of words containing syllables mapping to the Syltype, are retrieved using an inverted lexicon. A multi-syllabic word in the set is rejected if it matches poorly with adjacent Syltype hypotheses. The word verifier is then called to rate each word. Those with a poor rating are rejected.

## Results

Since the word hypothesizer's ratings for words are used only to determine whether to reject the word or to verifier the word, it is used as a filter for the word verifier. The performance relevant to this task is the percentage of the spoken words correctly hypothesized and the fraction of the vocabulary hypothesized per spoken word. The results from twenty test sentences indicate that, for a 1011 word vocabulary, 677 of the correct words are hypothesized when 80 words are hypothesized per spoken word ( 87 , of the vocabulary). Of course these numbers can be varied by changing thresholds. If the speech system can function with only $57 \%$ of the correct words hypothesized bottom-up, then only 51 words need to be hypothesized per spoken word (5\% of the vocabulary). Similarly, higher accuracy can be obtained with a greater number of competing word hypotheses.

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## Wizard: A Word Verifier for Hearsay-II (McKeown)

## Problem and Motivation

A key problem for speech understanding systems is the verification of word hypotheses generated by various knowledge sources in the system. The verifier must assign a likelihood score which is commensurate with the match between the
underlying acoustic data and the phonetic description of the word. The goodness of a score may be only temporally significant; the scores should rank order competitive words in any time area such that the correct word is high in the ordering. In addition to this acceptance criteria, it is also necessary for the verifier to reject absolutely a large percentage of the hypothesized words, without rejecting a significant number of correct words, in order to constrain the combinatorics at higher levels.

## Solution

In HEARSAY II, words may be generated bottom-up by the word hypothesizer (POMOW) or predicted top-down by the syntax and semantics module (SASS). Each uses a very different strategy for verification since bottom-up hypothesis have a known approximate begin/end time while top-down hypotheses use a verified word to predict words to the left or right, and thus only one time is known.

The word verifier, WIZARD, uses a general Markov model for speech recognition (BAKER, 1975 ; LOWERRE,1976). The acoustic information is a segmentation of the utterance where each segment is represented as a vector of phoneme probabilities. Each word in the lexicon is represented by a statically defined network which embodies alternate pronunciations of the word. This model finds the optimal path through the word network and assigns as the word score a normalized sum of all the log-probabilities for states (phonemes) on that path. Networks do not take into account word junctures but do handle internal phoneme junctures. Thus WIZARD attempts to verify words as if they exist in isolation.

Wizard handles bottom-up words in the following manner: The predicted begin/end times are mapped into their respective begin/end segments: bseg/eseg. All paths which begin at bseg $-1 / \mathrm{bseg} / \mathrm{beg}+1$ and end at eseg-1/eseg/eseg +1 are explored in parallel. Each of the nine possible optimal mappings is examined and the best of these is chosen as the mapping of the word network over the segmented acoustic data. This possible time shifting allows the verifier to recover from incorrect times due to differences in representation of the acoustic data between knowledge sources. As a result, the verifier may change times on word hypotheses as well as rate them.

Words which are hypothesized top-down pose a different problem in terms of verification, since only the begin or end time is known. In this mode it is necessary for WIZARD to predict the missing time as well as to return a rating. A major problem is bounding the number of segments considered in a prediction. Currently several heuristics are employed. Since all states on the optimal path must be mapped to at least one segment, the lower bound on the number of segments is the minimal number of network transitions (mintran). An upper bound was experimentally determined to be $4 * m i n t r a n$, thus on the average no more than 4 segments are mapped into any one state. This number is a function of the segmentation, which tends to over-segment, and the network descriptions, which allow reduced spellings. The POMOW word hypothesizer generates an upper bound based on the expected number of vowel nuclei in the word and their position relative to the beginning of the prediction. The smaller of these upper bounds is used. WIZARD iteratively maps each of the segments from the given begin segment to the upper bound. It considers those mappings which fall between the lower and upper bounds and picks the best after appropriate normalization. The time of the best end segment is returned along with the rating.

## Results and Conclusions

The results summarized in Table I are for five data sets, containing 100 utterances, in which 332 correct words were hypothesized bottom-up by POMOW. In addition, 13053 incorrect words were generated. The vocabulary size for POMOW and WIZARD was approximately 550 words. WIZARD rated each of the words using begin/end times generated bottom-up. Each verification took, on the average, 100 ms of CPU time on a DEC PDP-10 (KA). For each rating threshold ( 15,10 ) the number of correct and incorrect words that were accepted or rejected is tabulated. From this
data the number of words hypothesized per word position and the percent of the vocabulary hypothesized per word position can be calculated. These numbers give a vocabulary independent measure of performance, allowing comparisons between various system configurations. An average rank order of the correct word is provided which measures, at each threshold, the number of words in each word position that must be examined in order to include the correct word. The range of rank orders between the data sets ( 20 utterances/set) is also indicated.
thble I

| THR 15 | * HYPED BY POMOH | ACCEPTED | REJECTED | 5.6 RRNK ORDER |
| :---: | :---: | :---: | :---: | :---: |
| CORRECT | 332 | 326 (98\%) | 6 ( $2 \%$ ) | (3.6-7.1) |
| INCORRECT | 13853 | 18426 (88\%) | 2627 (28\%) |  |
| TOTAL | 13385 | 18752 (88\%) | 2633 (28\%) |  |
| \#/WORD POS | 48 (8\%) | 32 ( 6\%) | 8 ( 2\%) |  |
| THR 18 | * HYPED BY POMOH | ACCEPTED | Rejected | 4.5 RANK ORDER |
| CORRECT | 332 | 312 (94\%) | 28 ( 6\%) | (3.4-5.6) |
| INCORRECT | 13853 | 6462 (49\%) | 6591 (51\%) |  |
| TOTAL | 13385 | 6774 (51\%) | 6611 (49\%) |  |
| \#/WORD POS | 40 (8\%) | 28 (4\%) | 20 (4\%) |  |

Sample results of verification in the prediction mode are presented in Table II. In this mode it is important that the best rating for the predicted word comes from a mapping that closely approximates the actual time in which the word appears. If this is not the case there is the danger that a correct word, which is highly rated, will be hypothesized with times which will disrupt the recognition of word sequences by top end knowledge sources. Small errors in the determination of the missing time can propagate time errors which may cause whole words to be missed. Table II summarizes the results of an experiment to predict begin/end times of 529 words where both times were actually known. The distance, in segments, is calculated from the known word bound and its predicted word bound. The table also shows the distribution of distances for the best mapping. Given that the average segment duration is 3.2 cs , a distance of 2 would correspond to a range of predicted bounds 6.5 cs about the actual bound. Each prediction takes, on the average, 180 ms of CPU time.

TABLE II
beSt ranked predicted word boundary

| DIST | FREQ | $\%$ | CUM $\%$ |
| :---: | ---: | ---: | :---: |
| 8 | 125 | $24 \%$ | $24 \%$ |
| 1 | 289 | $48 \%$ | $64 \%$ |
| 2 | 183 | $19 \%$ | $83 \%$ |
| 3 | 41 | $8 \%$ | $91 \%$ |
| 4 | 20 | $4 \%$ | $95 \%$ |
| 5 | 17 | $3 \%$ | $98 \%$ |
| 6 | 7 | $1 \%$ | $99 \%$ |
| 7 | 4 | $1 \%$ | $180 \%$ |
| 8 | 2 | $8 \%$ |  |
| 9 | 1 | $8 \%$ |  |
| 18 | 8 |  |  |

Areas of further research involve dynamic generation of multiple word networks
using static networks and word juncture rules, alternate score normalization schemes, and improvement in the effectiveness of bounding predictions using vowel nuclei.

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## Word Pair Adjacency Acceptance Procedure in Hearsay-II (Robert Cronk)

## Introduction

In the Hearsay-II speech understanding system, several knowledge sources attempt to construct sequences of words from the word candidates hypothesized on the blackboard. Pairs of words which are approximately time-contiguous and syntactically adjacent (may be paired in the grammar) are considered for extending word sequences. To avoid the combinatorial explosion which occurs in a grammar with a large branching factor, a procedure is required which will constrain the number of word pairs to those which have a high probability of being the correct ones.

Such a procedure must be computationally inexpensive, since it must make decisions on hundreds of pairs of hypothesized words. It must rely upon knowledge of word junctures and upon the information contained in the segmental transcription of the spoken utterance. And it must reject as many incorrect pairs (word pairs not actually spoken) as possible, without rejecting any of the correct pairs.

This paper describes the word pair adjacency acceptance procedure (JUNCT) developed for Hearsay-II, the knowledge it uses, and the current results.

## Description

Input to the JUNCT procedure is a pair of word hypotheses. If it determines that the words are adjacent, based upon the times associated with the hypotheses, the juncture rules contained in the procedure, and the blackboard segmental description of the spoken utterance the pair is accepted as a valid sequence; otherwise it is rejected.

Word junctures which JUNCT must use to make its decisions fall within three distinct cases:
(1) Time-contiguous hypotheses: Words which are time contiguous in the blackboard are immediately accepted by JUNCT as a possible sequence. No further tests for adjacency are performed.
(2) Overlapping hypotheses: When two words overlap in time, juncture rules are applied in the context of the blackboard segmental transcription of the utterance to determine if such a juncture is allowable for the word pair.
(3) Separated hypotheses: When the words are separated by some interval of time, rules are applied, as in the overlap case, to determine whether the pair can be accepted as a valid sequence in the utterance.

The juncture rules used by JUNCT are of two types: (1) allowable overlaps of word end-phoneme and begin-phoneme, and (2) tests for disatlowed segments within the word juncture. A bit matrix of allowable overlaps is precompiled into the procedure, and is indexed by the end-phoneme and begin-phoneme of the word pair. Any overlap juncture involving phonemes which are not allowed to share segments is rejected by JUNCT. In the separation case, as in allowed overlaps, the blackboard segmental description of the spoken utterance is examined in the context of the endphoneme and begin-phoneme of the word pair to determine if any disallowed segments are present in the juncture gap. If such segments are found, the word pair is rejected. Only when a word pair passes all rule tests which apply in the segmental context of its juncture is it accepted as a valid sequence.

## Current Results

Stand-alone performance evaluation runs were made over 60 utterances using words generated from files produced by the Hearsay-II word hypothesizer. Syntactically adjacent pairs of words whose ratings were 40 and above (on a scale from 0 to 100) and whose times (left-word end time and right-word begin time) were within a 200 millisecond interval were considered. All of the words used for testing the procedure were hypothesized "bottom-up" in Hearsay-II; no predictions were used in the evaluation runs. The following table summarizes the performance of the JUNCT procedure.

|  | CORRECT <br> WORD PAIRS | INCORRECT <br> WORD PAIRS | TOTAL |
| :--- | :---: | :---: | :--- |
| ACCEPTED | 188 (957) | 2891 (417) | 3079 (427) |
| REJECTED | $5(5 \%)$ | $4224(597)$ | $4233(587)$ |
| TOTAL | 197 | 7115 | 7312 |

It is expected that, as lower-level sources of knowledge provide more accurate times for word hypotheses, the rutes for acceptance of valid word pairs may be tightened, further increasing the speed and performance of Hearsay-II.

## Syntactic Processing in Hearsay-II (Hayes-Roth, Erman, Fox, and Mostow)

The basic tasks facing the three syntactic knowledge sources in Hearsay-II are: to parse syntactically acceptable sequences of words; to predict words that can be (syntactically) adjacent to the ends of a word sequence; and to construct larger sequences when predicted words are verified. The chief obstacle is finding all possible syntactic structures that can produce a given sequence of words. Of the traditional parsing mechanisms, only bottom-up Kay-type parsers have addressed the problem of building phrase-structure trees which are not necessarily anchored at the start (or end) of a sentence. But these methods are still inadequate for parsing in the current environment because of their requirement that all constituents of a phrase be present in order for a phrase to be recognized. In Hearsay-II, a general method for such partial parsing of incomplete phrase structures has been developed and is used to parse grammatical word sequences, to predict extensions, and to join up to three sequences of words together in a new syntactic structure.

The details of the method are now briefly described. To minimize redundant computing, the syntactic (context-free) grammar is converted to an equivalent template normal form grammar in which all sequential productions have binary derivations (e.g., $A \rightarrow B C D$ is replaced by $A \rightarrow B X$ and $X \rightarrow C D$ ). Thus, frequently occurring grammatical subsequences are replaced by a common higher-order non-terminal
thereby minimizing recomputation of common subexpressions (Hayes-Roth and Mostow, 1975).

The word-sequence hypothesizer, WOSEQ, generates the initial word sequences that are partial-parsed. Given a word sequence wl ... wn, the RECOGNIZE parser knowledge source works in a conventional bottom-up manner, with the exception that any words or phrases (non-terminals) that are required by a grammar rule to precede (follow) a constituent at the first (last) position of the sequence are pseudorecognized; that is, if the word sequence w1 ... wn can be derived from the productions $S \rightarrow A T, T \rightarrow w 1 V, V \rightarrow U X, U \rightarrow \ldots w n, A \rightarrow w 0$, and $X \rightarrow w(n+1)$, then the non-terminals $A$ and $X$ will be pseudo-recognized and the sequence $w 1 \ldots$ wn will be parsed as an instance of $S$, with closest left-missing constituent $A$ and closest right-missing constituent $X$. Bottom-up parsing continues until all of the words in the input sequence are subsumed by each highest-order phrase or until no further rewrites are possible. The highest-order phrases constructed that derive the entire word sequence are referred to as spanning phrases. Because parsing is discontinued on spanning phrases, the partial-parse technique essentially identifies minimal (lowest-order) parses of each sequence. Each distinct parse of a sequence specifies a spanning phrase and the pseudo-recognized closest missing constituents. There may, of course, be several distinct parses of any word sequence. If no parse of a sequence is found, it is rejected. Whenever a sequence hypothesized by the word-sequence hypothesizer is rejected, that knowledge source wakes up, decomposes the rejected sequence into maximal subsequences, and then hypothesizes any sufficiently rated new word sequences.

Given a spanning parse of a sequence w1 ... wn with closest left and rightmissing constituents $A$ and $X$, the words that can be adjacent to <wl or wn> are all rightmost derivatives of $A$ or leftmost derivatives of $X$. If a spanning phrase has no closest left-missing (right-missing) constituent, the possible adjacent words are found by "going up-and-over": the rightmost (leftmost) derivatives are computed for each constituent that can be directly adjacent to this left-complete (right-complete) phrase in some higher-level spanning phrase. Predictions of words are made by the PREDICT knowledge source whenever the extension of a previously parsed word sequence is scheduled and executed. Predictions may be made to both sides or to only one side depending on the relative and absolute numbers of grammatically possible words on the two sides. In any case, if none of the predicted words on one side is verified, the word-sequence hypothesis, although syntactically valid, is deactivated. No further processing of that sequence can occur unless it is retrieved by another sequence extension colliding with it on the side that failed the extension effort. Such a salutary collision results in the reactivation of the sequence.

When predicted words are verified, the CONCAT knowledge source may extend the parse by concatenating the verified words to the predicting word reference. Given the sequence $\langle w 1 \ldots$ wn> and verified preceding predicted words al, a2, ..., ak and verified succeeding predicted words $\mathrm{b} 1, \mathrm{~b} 2, \ldots, \mathrm{bm}$, an attempt is made to partialparse all sequences <ai w1 ... wn bj> as well as all sequences <x $1 \times 2$... xp ai w1 ... wn bj y1 y2 ... yq> where <x1 x2 ... xp ai> (<bj yl y1 ... yq>) is a previously parsed sequence of words on the blackboard that is time-adjacent to and precedes (succeeds) <w1 ... wn>. All successfully parsed sequences generate phrasal hypotheses. Thus, in addition to simply extending sequences a-word-at-a-time in each direction, finding a predicted word as the terminus of an existing adjacent sequence can trigger the concatenation of three sequences at once.

## Conclusion

Because the words that are hypothesized from other knowledge sources form arbitrary sequences that usually do not completely satisfy constituent structures of phrase rewriting rules, a general mechanism for partial-parsing is needed. The current implementation generates minimal spanning phrases and retains at most one closest
missing constituent on each side of each phrase. Partial-parsing times average about 50 msec on the KL10 for a 1000 word vocabulary with a. 15 branching-factor grammar. Extensions of sequences are quickly computed by running down the right or left sons of the binary sequence nodes of the closest missing constituents. Three adjacent sequences are syntactically concatenated by partial-parsing the concatenated word sequences. The current implementation provides an efficient solution to essential problems of syntactic processing. In addition, the three related knowledge sources decompose this processing into natural components with a grain-size that is attractive for focusing and control.

## References

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## Focus and Control in Hearsay-II (Hayes-Roth and Lesser)

The Hearsay-II speech understanding system currently comprises 13 knowledge sources (KSs), 11 of which are data-directed. Each data-directed KS is invoked whenever new or modified blackboard data configurations matching patterns of interest are found. Monitoring for potentially relevant data changes is performed in two steps: changes in hypotheses or links at particular levels are collected in change sets specific to each KS; procedures called preconditions then closely examine each accumulated change and its blackboard context to determine if the exact pattern of interest is present. Once such a pattern is detected, the relevant KS is invoked (scheduled) to operate upon it. The basic control problem is to execute first those preconditions and KSs that are most likely to lead to successful recognition of the utterance. The two chief subgoals are: (1) to find the best interpretation as quickly as possible and (2) to reduce the number of incorrect hypotheses that are generated and tested. In fact, if too many incorrect hypotheses are examined, working storage capacity of the system may be exceeded, thus precluding eventual correct recognition of the utterance.

The current approach to the control problem follows closely the design of the focus of attention mechanism described in detail in Hayes-Roth and Lesser (1976). The basic concepts of that paper are quickly reviewed here: (1) The Competition Principle: the best of several alternatives should be performed first; (2) The Validity Principle: more processing should be given to KSs operating on more valid data; (3) The Significance Principle: more processing should be given to KSs whose expected results are more significant; (4) The Efficiency Principle: more processing should be given to KSs that perform most reliably and inexpensively; (5) The Goal Satisfaction Principle: more processing should be given to KSs whose responses are most likely to satisfy processing goals.

The degree to which a precondition or KS satisfies these principles is reflected by its desirability, an increasing function of its validity, duration, level of analysis, importance, concordance with control thresholds (goals), (relative and absolute) expected superiority over the best competing alternative in the same time area, and the time elapsed since an improved degree of recognition was achieved (stagnation) in that time area. While the desirability of a KS instantiation awaiting execution is determined directly from only one data pattern and the declarative control knowledge about the direction (on the blackboard) and relative effectiveness of its actions, the desirability of a precondition is taken to be the maximum of such values over all hypotheses in its change set.

Using this general scheme, we have implemented one particular control strategy by setting particular processing goals on the blackboard. Initially the
segmenter/labeller is executed and is forced to run to completion. This insures that bottom-up syllable hypothesization will have the benefit of complete segmental contexts. The syllable hypothesizer is executed in turn, and for a similar reason is also forced to run to completion. At this point the syllable-to-word KS responds to new syllables and generates all potentially plausible words. The strategy module then establishes thresholds governing which of these words is hypothesized. It attempts to have several highly rated words hypothesized in each area of the utterance. After this processing is completed, the word-sequence hypothesizer examines all words in parallel and identifies promising connected sequences of time-adjacent syntactically possible pairs of words (seeds). The best of these in each time are then hypothesized. From this point on, a complex sequence of data-directed preconditions and KSs is invoked, scheduled, and executed to control syntactic parsing, hypothesization of plausible words to extend syntactic sequences, concatenation of verified words or phrases with adjacent phrases, and the generation of further seeds wher the system is stagnating. Whenever any new complete parse is found, a special KS is invoked to determine which remaining hypotheses and KS instantiations are insufficiently attractive to preserve. These are either rejected or deleted. Processing then continues until a quiescence occurs reflecting that the remaining alternatives are insufficiently credible to continue. If a sufficiently plausible sentence has been recognized, the stopping condition KS decides to terminate the analysis; or if no complete sentence has been formed, an attempt is made to interpret the best partial sequences by the syntax and semantics knowledge source.

## Conclusion

Each precondition and KS is regarded as a [condition $\rightarrow$ action] schema, with known inputs (blackboard hypotheses and links), a known direction of action (bottomup, top-down, or same-level and forwards, backwards, or same-time), known reliability and efficiency, and therefore, a known expected result. By comparing the expected results of all scheduled activities to the current state of recognition and desired areas of activity, the best pending instantiation can be execued first. As a result of tuning the various weighting factors, we seem to have achieved a desirable balance of breadth- and depth-first search (in a global sense) with effective suppression of suboptimal (in a local sense) activities. Further, by separating expensive searches into two or more successive steps (e.g., change sets and preconditions do gross filtering and only subsequent KSs do fine, expensive processing; or, before expensive syntactic searches are performed, inexpensive searches are made for plausible sequences of syntactic word pairs), it appears that we have achieved some efficiency in the overall organization and control of the search process.

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## Policies for Rating Hypotheses, Halting, and Selecting a Solution in HearsayII (Hayes-Roth, Lesser, Mostow, and Erman)

## Purpose of hypothesis validity ratings

The rating policy module (RPOL) in Hearsay-II provides a uniform basis for comparing the plausibility of different hypotheses. The hypotheses may be competing alternative interpretations of the same portion of the utterance at some level of the blackboard, in which case the hypothesis whose validity rating is higher is considered
more likely to be the correct interpretation. However, the hypotheses may describe different portions of the utterance, or provide representations at different levels of the blackboard. Having a uniform rating policy means that such hypotheses may nonetheless be meaningfully compared on the basis of their validity ratings. This information is used in three ways by Hearsay-Il:
(1) to focus attention in promising directions by considering higher-rated (more likely correct) hypotheses before lower-rated hypotheses. This is implemented by making the priority of a scheduled action an increasing function of the validity ratings of the hypotheses which are being acted upon (Hayes-Roth and Lesser, 1976). Also, certain types of actions are not even scheduled on hypotheses which fail minimum plausibility tests specified by knowledge source modules. These tests use validity ratings as a measure of plausibility.
(2) to select the most likely correct interpretation of the utterance if there is more than one phrasal hypothesis spanning the utterance. The highest-rated such hypothesis is then the chosen interpretation.
(3) to prune the search once a solution (i.e., an utterance-spanning phrasal hypothesis) has been found. This is done by restricting further processing to those actions which are capable of leading to a better (higher-rated) solution.

Computation of hypothesis validity ratings
Hypotheses in Hearsay-II represent interpretations of the speech signal at various levels of representation: segmental (lowest level), syllabic, lexical, wordsequential, and phrasal (highest level). An hypothesis may be either conjunctive, representing a logical product, or temporal sequence, of lower level hypotheses or disjunctive, representing a logical summation of lower level alternative hypotheses. The degree to which each lower level hypothesis supports the upper hypothesis is indicated by an implication between -100 (maximally disconfirming) and +100 (maximally confirming). This number is attached to a link in the blackboard from the lower to the upper hypothesis.

The validity rating VLD(H) of an hypothesis H is a measure of the extent to which that hypothesis is supported, ultimately, from the acoustic data. The lowest level hypotheses are rated by the bottom-end processor. The rating of a higher level hypothesis $H$ is computed from the validities of the hypotheses which support $H$ directly from below, and is stored on the blackboard as part of $H$. The validity rating of H need only be recomputed when the validity or implication of its support changes, or when $H$ receives new support. In such cases, RPOL immediately propagates resultant validity changes up through the blackboard. Storing the ratings on the blackboard avoids the expense of recomputing them recursively whenever they are used.

The validity rating $V L D(H)$ of a disjunctive hypothesis $H$ supported by $n$ lower level hypotheses $H 1, \ldots, H n$ via respective links $L 1, \ldots, L n$ is given by

## Max VLD(Hi) IMPLICATION(Li)/100, ( $1 \leq i \leq n$ ).

Similarly, the validity rating of a coniunctive hypothesis at the word level or below is given by

$$
(1+(n-1) / 10) *(\text { Sum VLD }(H i) * \operatorname{IMPLICATION(Li}) / 100),(1 \leq i \leq n) .
$$

The weighting factor $(1+(n-1) / 10)$ reflects the increased plausibility of an hypothesis which has many conjunctive supports.

Above the word level, a somewhat different function is used to rate conjunctive hypotheses. The validity $\operatorname{VLD}(\mathrm{H})$ of a phrasal or word sequence hypothesis H is given by the duration-weighted average validity of its $n$ underlying words Wi , where duration is measured in number of syllables. I.e.,

$$
\operatorname{VLD}(H)=\left(\text { Sum } \operatorname{VLD}\left(W_{i}\right) * \text { length }\left(W_{i}\right)\right) / \text { Sum length }\left(W_{i}\right),(1 \leq i \leq n),
$$

where length $\left(\mathrm{Wi}_{\mathrm{i}}\right)=$ length (in syllables) of the word hypothesis Wi. This formula is based on the empirical observation that the longer a word $W$ i, the greater the correlation between its correctness and the correctness of H .

## Halting conditions and heuristic pruning

A phrasal hypothesis can be thought of as a subpath through a flow graph whose arcs are word hypotheses, and whose source and sink are respectively the beginning and end of the utterance. A solution (utterance-spanning phrase) then corresponds to a complete path through the graph. The validity rating of a subpath (hypothesis) is given by the average arc (word hypothesis) validity along the subpath, weighted by arc (word) length measured in syllables.

There is a qualitative difference between the task of searching for a solution (complete path) and the task of deciding when to stop searching and accept the current best solution. The former task can efficiently be done best-first, i.e., by extending the most promising path at each step in the search. In contrast, the latter task inherently involves searching all possible paths in order to guarantee that no path is better than the best one found so far. Once a path has been found, the goal of processing should be to enable such a guarantee to be made as quickly as possible. In order to accelerate the attainment of this goal, two heuristics for pruning the search are used.

The first heuristic consists of rejecting every word, word sequence, and phrase hypothesis which, due to its low rating, cannot be extended into a better solution than the best already found. This heuristic can be thought of as a form of alpha-beta pruning, simplified for the case of a one-player game. Rejecting a subpath (hypothesis) amounts to abandoning certain nodes in the search tree which correspond to extensions of that subpath. In operation, an hypothesis is rejected if, when it is extended into an utterance-spanning path using the highest-rated word hypotheses currently on the blackboard, the resulting (not necessarily syntactically legal) path is rated lower than the best existing solution. Further processing on rejected hypotheses is cancelled. This operationalization is imperfect in that it ignores the possibility of "missing arcs," i.e., words which may subsequently be predicted by the syntax module (added as arcs in the graph) and be rated high enough to invalidate previous decisions to reject earlier hypotheses.

The second heuristic is based on the observation that, if a better solution than the current best solution exists, it must be possible to construct it by extending some existing subpath (hypothesis) which is rated higher than the subpath of the existing solution spanning the same time interval. (Once again, the missing arc problem is ignored.) All hypotheses (subpaths) which do not have this property are deactivated, i.e., incapacitated as active stimuli. Any scheduled inferential action based on a stimulus set of hypotheses is cancelled if all the hypotheses in the set are deactivated. This heuristic can be thought of as another form of alpha-beta pruning, modified to allow sharing of common subtrees in the search tree. Deactivating a subpath (hypothesis) amounts to deferring expansion of certain search tree nodes which correspond to extensions of that subpath.

The observed effect of these two heuristics is to cancel a large amount of scheduled processing once a solution is found, and to focus attention on those activities which are capable of leading to a better solution. When no such activities are left to pursue, RPOL halts processing, selects the highest-rated solution, and passes it to the semantics module to be interpreted.

## Solutions and partial solutions

RPOL also halts processing when Hearsay-II exceeds predefined limits on size or execution time. In this case, RPOL chooses the highest-rated utterance-spanning phrasal hypothesis as its solution. If no such hypothesis has been generated, RPOL tries to extract a maximum of information from the blackboard by selecting the best partial parses (phrasal hypotheses) and pa:sing them to the semantics module for further interpretation (Hayes-Roth, Fox, Gill, and Mostow, 1976). Here, the "best" phrase hypothesis $H$ at time $t$ is considered to be the hypothesis whose time interval includes $t$ and which has the highest information content, defined by VLD $(H) *$ length $(H)$. RPOL finds the best hypothesis at each time $t$ (measured in syllables from the beginning of the utterance), and passes the (typically small) set of such hypotheses to the semantics module. Thus even when Hearsay-Il fails to find a complete solution, the best partial solution (set of partial interpretations) is found, and this information is used in determining the system's response to the utterance (Hayes-Roth, Gill, and Mostow, 1976).

## Conclusions

The task of rating hypotheses in Hearsay-II is handled by the system policy module RPOL. The role of knowledge source modules in this task is limited to linking together hypotheses and specifying the implications with which lower hypotheses support upper hypotheses. Thus the effects of hypothesis rating changes due to new information are automatically propagated throughout the blackboard without requiring the help of the knowledge source modules. The centralized implementation of rating computation and propagation has made it easy to experiment with different rating formulas. It has also simplified the task of developing new knowledge source modules.

The uniform rating scheme employed permits the meaningful comparison of the plausibility of any two hypotheses. Validity ratings are used by Hearsay-II to focus processing, to prune the search, and to select the best solution or partial solution. In addition, hypothesis validity ratings are used by the knowledge source modules for plausibility tests which must be satisfied in order for various inferencing rules to be applied. Thus validity ratings help to guide processing in a best-first direction until a solution is found, and to validate it quickly thereafter as the best possible solution.

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Semantics and Pragmatics in Hearsay-II (Hayes-Roth, Fox, Gill, and Mostow)
A speech understanding system differs from a recognition system in two principal ways. First, an understanding system verifies that the sentences it hears are meaningful and plausible. This requires use of semantic knowledge. Second, the understanding system expects particular types of communication to occur in specific discourse contexts and interprets the sentences it recognizes accordingly. Such expectation and contextual interpretation requires pragmatic knowledge. The purpose of semantics and pragmatics knowledge sources is to convert this knowledge about meanings, intentions, and communication conventions into effective action. The most significant type of action is one that constrains the recognition process, a search for a plausible parse of the spoken utterance. The second most important type of action is to hypothesize what was intended, when what was said cannot fully be recognized. The last type of effective action needed is to interpret (deduce the intention) of a successfully parsed utterance.

The complexity of artificial spoken languages may be constrained by restricting either the way ideas are expressed (syntax) or the number of ideas that can be expressed (semantics). Our approach, in the news retrieval and computer science abstract retrieval tasks, has been to develop one comprehensive semantic grammar (average branching factor 50) used for interpretation of recognized word sequences and to vary systematically the syntactic con, traint of the languages used for speech recognition per se (branching factors 5, 15, 25). Regardless of the particular syntax used for recognition, the same general semantic grammar is used for semantic analysis. This grammar is a template grammar like those developed for Parry by Colby, with distinct templates for each unique type of semantic form (Colby, 1974; Hayes-Roth and Mostow, 1975). Semantic interpretation is accomplished by extracting from the (parse) tree of instantiated templates the particular words or expressions filling the various functional "slots."

Partially recognized sentences are also easily interpreted in this framework. When the attempt to recognize a complete sentence has failed, the best (longest and most highly rated) syntactic word sequences in each time area of the utterance are passed to semantic analysis. All templates fully or partially satisfied by word sequences are instantiated. The most fully matched semantic pattern is then chosen as the interpretation of the utterance. Thus, the recognized sequence "Newell or Simon" would be interpreted effectively as if "List all abstracts by Newell or Simon from any journal from any date" had been recognized.

The capacity to provide semantic constraint during recognition is determined primarily by the reliability of predictions regarding what the speaker is likely to say. We have implemented a discourse knowledge source including a conversation model that prompts the speaker with questions, provides information about using the system and the organization of the data base, and predicts the (semantic and syntactic) type of utterance next expected. Earlier versions of the syntax and semantics knowledge source biased recognition actions in favor of predicted communication forms. However, both because any valid sentence is permitted at any time and because the system is usually employed for isolated sentence understanding, no direct semantic bias is currently used. The basic scheme for such bias is, however, conceptually simple: given an expected type of utterance (a highest-level semantic template), recursively compute the expected lower-order subtemplates and, ultimately, the words and phrases that would instantiate the expected meaning templates. During recognition, priority is given to actions based on expected forms, at the expense of delayed processing of unexpected word sequences.

## Conclusions

We have identified three types of actions to be performed by semantics and pragmatics knowledge sources: (1) bias recognition in favor of expected forms; (2) interpret semantically plausible, partial sequences; and (3) correctly interpret the intention of the speaker when a sentence is fully recognized. These actions are effected in Hearsay-II by combining semantic template grammars with a conversational model that anticipates the speaker's general intention and can enumerate its manner of expression. The realization of such actions, at least in restricted domains of discourse, can now be considered a well-understood technology.

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## Discourse Analysis and Task Performance in Hearsay-II (Hayes-Roth, Gill, and Mostow)

The discourse analysis module (DISCO) in Hearsay-II uses knowledge about the state of the conversation to interpret the speaker's intention and to direct the appropriate actions within the task program. Usually, the intention of the speaker is to establish a general area of interest, to retrieve articles by keyword expression, to further qualify a keyword expression, to print selected articles, or to request certain information about the retrieved articles, such as title, date, author, author's affiliation, or publisher. The speaker can also ask for help or complain about the system's response.

The state of discourse is represented by the contents of several semantic registers, one of which points to a node in a finite state automaton discourse model. (See Figure 1.) Each node in the model corresponds to a general sentence pattern or template (Hayes-Roth, Fox, Gill, and Mostow, 1976). (See Figure 2.) Other registers hold the current menu (general area of interest), the most recent keyword expression, the article most recently referred to, the most recently retrieved articles, and the subset of retrieved articles which satisfy further qualifications specified by the speaker. The finite state model is used to interpret yes-or-no responses and partially-recognized utterances, and to make predictions about what the speaker is likely to say next. All possible transitions between nodes in the model are permitted; the arcs in the model indicate the transitions which are considered likely.

Figure 3 shows a sample interaction between DISCO and a speaker. Utterances enclosed in square brackets denote recognized spoken utterances. In the example shown, the first utterance

## [ WE'RE INTERESTED IN LEARNING ]

is recognized by the semantics module as an instance of the \$SELECTION template, and the semantic feature SLEARNING (indicated area of interest, or menu) is extracted. This semantic interpretation of the utterance is passed to DISCO, which records the indicated area of interest, LEARNING, in the MENU register, and sets the NODE register to point at the $\$$ SELECTION node in the finite state model. DISCO then predicts that the next utterance will be an instance of the SREQUEST template and will concern the area of LEARNING. These predictions can be used to bias subsequent processing to favor recognition of keywords in the LEARNING menu and function words characteristic of a \$REQUEST (Hayes-Roth, Fox, Gill, and Mostow, 1976). Such predictions can also be used to respond gracefully in the case of a partially-recognized utterance (Hayes-Roth, Lesser, Mostow, and Erman, 1976). In the example, if the speaker's second utterance

## [ WERE ANY ARTICLES ON LEARNING WRITTEN IN MAY 1974]

were not fully recognized, DISCO would assume that the speaker had REQUESTed some articles about LEARNING and could ask him to repeat the request. If the utterance fragment "LEARNING WRITTEN IN MAY 1974" were recognized and interpreted by the semantics module, DISCO could retrieve articles on learning dated May, 1974.


Figure 1: Semantic registers and finite state discourse model. labels $Y$ and $N$ indicate $Y E S$ and NO responses; 0 indicates empty retrieval set.

SSELECTION [ WERE INTERESTEO IN LEARNING ]
Specifies a menu. DISCO responds by printing keywords and phrases from the menu.
SREQUEST [ WERE: ANY ARTICLES ON IEARNING WRITTEN IN MAY 1974 ]
Specifies a set of articles. DISCO retrieves the articies and asks for further directions.
SPRUNE:LIST [ WHCH OF THESE MENTION ROBOTS ]
Further specifics a set of articies. DISCO removes articles from the currently retrieved set which don't satisfy the new restrictions.

SGETINFO [ WHO WROTE THESE ]
Requests information about the retrieved articles. DISCO prints the requested information.

## SLISTITHEM [ PLEASE LIST THEM ]

Requests oulput of a set of articles. DISCO prints all the articles in the currently retrieved set.

## SLIST!IT [ PRINT IT ]

Requests output of a single article. DISCO prints the article most recently referred to.
SSTOPIIISTING [ STOP LISTING PLEASE ]
Requests cessation of output. DISCO aborts the current output operation.

## SMAKE!FILE [ MAKE A FILE OF THI:SE PIECES ]

Requests file output. DISCO creates a file containing the retrieved articles.
SCONTENTSMAENU [ WHAT ARE THE KEYWORDS FOR LEARNING ]
Reguests the contents of a menu. DISCO lists the keywords and phrases of the menu.
SHELP [ WHAT CAN I ASK ]
Requests assistance or information about the system. DISCO attempts to fulfill the request.
SGRIPE [ WHIY ARE YOU SO SLOW ]
Complaint. DISCO responds with a pacifying message.
The following three nodes represent responses to yes-or-no questions asked by DISCO.
SWANT SEF:
DISCO has printed the tille of an article and asked, "Do you want to see this article?"

## SWANTMKRE:

DISCO has printed some of the arlicles in the currently retrieved set and asked,
"Do you want to see another of these articles?"
SNOREONHKNIJ
DISCO has exhausted the currently retrieved set and asked, "Do you want to ask more about
<current menu>?" where <current menu> is the most recent area of interest.

Figure 2. Templates corresponding to nodes in the finite state model. Instances of templates are shown in square brackets.
Text describes the intention of each utterance template and DISCO's response to it.

OK, WHAT SUBJ:CT DO YOU WANT TO ASK ABOUT?
[ WE'RE INTERF:STEO IN LEARNING]
THE KEYWORO PHiASES WHICH I KNOW ABOUT ARE:
LEARNING
HYPOTHESIS FORTIATION
CELL ASSEMBLY THEORY
BRAIN THEORY
CAUSAL REASONNMG
COMAMON SENGE. TH:ORY FORMATION
COWOEPTUMI INFERE:NCE
CYBERN:TICS
GRanthatical Inference
NEUTRAI. NI:TWORF:S
PERCEPTRONS
RULE ACOUISITION CAPABBLItIES
ABSTRACTION
ACQUEITION OF KNOVLLEOGE
OK, ASK ME ABOLIT LFARNING
[ WEERE ANY ARTICIES ON LEARNING WRITTEN IN MAY 1974]
TH:RE: ART: 2 STORIES
THE FIRST ONE IS:
T!TIE:
OESIGN OF AN INTLRACTIVE ENVIROHAENT TO STUDY THE BEHAVIOR OF SEVERAL ROBOTS WHICH CAN L.EARIN, PLAN THEIR ACTIONG, AND COEXIST

DO YOU WANT TO SEE THS ARTICLE?
[ WHO WROTE THESE]
DESICN OF AN IMTERACTIVE ENVIROHMENT TO STUOY TH: BEHAVIOR OF SEVERAL. robots vilhch can learn, plain their actiong, and coexist NICHOLAS V. FIMmer
próleinfan. l.eariving in woridg of roeots LAURENT Siklossy

Figure 3. Sample interaction between DISCO and speaker. Spoken ullerances are enclesed in square brackets.
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## PARALLEL PROCESSING IN SPEECH UNDERSTANDING SYSTEMS

## Parallelism in Artificial Intelligence Problem-solving (Lesser and Fennell)

## Background

Many artificial intelligence problem-solving tasks require large amounts of processing power because of the size of the search space that needs to be examined during the course of problem solution. This is especially true for tasks that involve the interpretation of real-world perceptual data which is generally very noisy (i.e., speech and image understanding systems). For example, a speech-understanding system capable of reliably understanding connected speech involving a large vocabutary is likely to require from 10 to 100 million instructions per second of computing power, if the recognition is to be performed in real time. Recent trends in technology suggest that raw computing power of this magnitude can be economically obfained through a closely-coupled network of asynchronous "simple" processors. The major problem with using a network multiprocessor is in specifying the various problem-solving algorithms in such a way as to exhibit a structure appropriate for exploiting the available parallelism.

This restructuring of an artifiicial intelligence task for parallel processing may not be as difficult as might be expected. The basic problem-solving paradigm that is used to resolve ambiguities resulting from the error in input data and the imprecise and errorful nature of knowledge sources implicitly involve parallel activity. This parallel activity arises because many weakly supported alternative hypotheses must be "simultaneously" evaluated in order to locate a consistent hypothesis which is a solution to the problem. These problem-solving techniques are implemented through sophisticated control structures that (1) permit the selective searching (usually heuristic) of a large part of the state-space of possibilities and (2) allow the combining of multiple, diverse sources of knowledge (e.g., in the speech domain, acoustics, syntax, semantics, prosodics) so as to cooperate in resolving ambiguity [Reddy 76, Woods 74, and Lesser 75A]. The state-space searching in existing systems is implemented through backtracking control structures; these are basically sequential implementations of non-deterministic control structures. Thus, a large potential for parallelism arises from implementing these non-deterministic control structures in a parallel manner, i.e., searching different parts of the state space in parallel. In addition, if these diverse knowledge sources (KS's) can be made independent, there exists the potential for a proportional speed-up in the recognition process by executing them in parallel. Finally, there is the possibility of decomposing each knowledge source into separate parallel processes.

## Summary of Current Research

In order to test the ease and effectiveness with which an artificial intelligence task could be structured for and executed on a multiprocessor, an organization for a knowledge-based artificial intelligence problem-solving system was developed which takes maximum advantage of any separability of the processing or date components available within that organization. Knowledge sources are intended to be largely
independent and capable of adynchronous execution in the form of knowledge source processes. Overall system control is distributed and primarily data-directed, being based on events occurring in a globally shared data base. Such a problem-solving organization is believed to be particularly amenable to implementation in the hardware environment of a network of closely-coupled asynchronous processors which share a common memory. The Hearsay II speech-understanding system (HSII) [Lesser 75, Fennell 77, Erman 75], which has been developed using the techniques for system organization described above, has provided a context for evaluating the multiprocessing aspects of this system architecture.

Based on multiprocess simulations and implementation of these systems on the C.mmp multiprocessor, the following results were obtained [Fennell 75]:

1. There does exist extensive paratlelism in the speech understanding task (e.g., given a small configuration of knowledge sources, between 4-14 processors could be effectively utilized).
2. The overheads involved in supporting the multiprocessing and synchronization primitives are quite high (e.g., over 100\%).
3. The locking structures had to ve very carefully tailored to the particular set of knowledge sources; otherwise, the effective paralletism would be significantly degraded.

In trying to understand the implications of the last two results, some tentative observations were made. The first and somewhat surprising observation was that the basic self-correcting nature of the information flow in the HSII system, which comes from knowledge source cooperation through a hypothesize-and-test paradigm, may obviate the need for most uses of explicit synchronization techniques to maintain data integrity. To elaborate on this point, one knowledge source can correct the mistake of another knowledge source whether the error arises from a mistake in the theory behind the knowledge source or from incorrect synchronization (i.e., working on partially invalid data). Another example of this self-correcting type of computation structure is the relaxation method (iterative refinement) used to solve partial differential equations. This type of computational structure, when put on asynchronous multiprocessors, can be decomposed so as to avoid a lot of explicit synchronization at the expense of more cycles for convergence. This type of decomposition is accomplished by not requiring each point to be calculated based on the most up-to-date values of its neighboring points. The iterative refinement nature of computation will correct (within a certain range) for this lack of synchronization. It is felt the feed-forward/feed-backward data-directed problem-solving paradigm of HSIl has similar properties. The other observation was that a drastic decrease in the cost of certain types of synchronization primitives could be accomplished if their implementation is tailored to their (statistical) usage.

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## The HSII/C.mmp System (Lesser, Buchalter, McCracken, Robertson, and Suslick)

The HSII/C.mmp system has been developed to test whether an asynchronous multiprocess architecture such as C.mmp ( 16 PDP- 11 processors sharing a common memory) can be effectively applied to speed up the higher level processing of a speech understanding system. Extensive simulation studies were done on a PDP-10 using a multiprocess version of Hearsay-II to test the feasibility of the idea before embarking on the actual implementation (Fennell and Lesser 1977).

A prototype version of this system written in L*, a system building language developed by Newell et al. 1970-71, was constructed and running in February of 1976. In addition, an algebraic-language interpreter, SL*, was constructed for executing knowledge sources written in an Algol dialect. However, the knowledge source modules were very primitive, and no substantial results were obtained except the measurement of the overhead of certain Hearsay-II primitives. As a result of these measurements, a reimplementation was begun in order to significantly speed up the system (especially those system primitives which deal with synchronization operations), and to make it possible to run large knowledge source modules in the small address space environment that the PDP-11 provides. This reimplementation is now almost complete, with preliminary results indicating a speed-up of approximately 10 over the original version. In addition, a translator has been developed which takes most PDP-10 statements written in SAIL and translates them into equivalent SL* statements. Thus, it should be possible in the next few months to run, without major code conversion, the knowledge source modules of the PDP-10 Hearsay-II system on the HSII/C.mmp system.

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## A Parallel Production System for Speech Understanding (McCracken)

The question addressed by this thesis (McCracken 1977) is whether or not a production system architecture ${ }^{1}$ can remedy some of the chronic problems of knowledge representation and system organi ation in large knowledge-based artificial intelligence systems, particularly speech understanding systems. Of particular interest is the problem of exploiting parallel machine architectures to obtain near real-time response. To explore this question, a production system version of the Hearsay-Il speech understanding system, called HSP, for HearSay Production system, is being implemented on C.mmp, the CMU multi-mini-processor. A large fraction of the HearsayII speech knowledge has been translated into productions for HSP, specifically: POMOW (word recognizer), POSSE-WOMOS (word verifier) and SASS (syntax and semantics) ${ }^{2}$.

Expected results come under two main categories: comparisons between the way knowledge is encoded in HSP versus Hcarsay-11, and comparisons in the use of parallelism. The major differences between the HSP and Hearsay-II architectures are: (1) the basic knowledge unit in HSP, a production, is considerably smaller than a Hearsay-Il Knowledge Source ; (2) HSP encodes knowledge in a more formal and simple, but less expressive, language than Hearsay-II; (3) HSP totally segregates condition from action (i.e., read from write), while Hearsay-ll allows a mixture; and (4) there is virtually no use of local working meniory in HSP (only a single shared working memory), whereas Hearsay-II knowledge sources make use of rather large local data contexts in addition to the shared Blackboard. It is expected that these architectural differences will yield an improvement for HSP in effective parallelism, in clarity of knowledge, in ease of augmentation, and in other problem areas, such as handling of error, directionality control, and performance analysis.

1. A production system encodes all long-term knowledge as simple condition-action rules which operate from a shared working memory. For entry into the subject see: R. Davis and J. King, An Overview of Production Systems, Computer Science Department, Stanford University, Oct. 1975.
2. POSSE, WOMOS, and the version of SASS used are from an earlier version of Hearsay-II used in the Spring of 1972.

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## III. PERFORMANCE MEASUREMENT

In this section we present the detailed performance results obtained for the Harpy and Hearsay-II systems in September of 1976. Since then both systems have been improved; future papers will provide results of improved performance. The purpose of this section is to provide a record of system performance as measured on September 8, 1976.

In addition to the performance of the systems on the 1011-word tasks, this section also contains results of experiments on connected digit recognition, effect of telephone on accuracy, effect of multiple speakers (using speaker independent templates) on accuracy, and effects of branching factor and vocabulary size on the performance of the Harpy system.

## Performance of the Harpy and Hearsay-II Systems

Figure 1 gives the performance of the Harpy system on the 1011-word AI abstract retrieval task. The vocabulary used in this task and the phone dictionary associated with the vocabulary is given in Appendix III-B.

Given the vocabulary and protocols taken of humans interacting with a mock system, Hayes-Roth generated a set of typical sentences that are likely to be useful in the abstract retrieval task. No attempt was made to restrict these to any specific grammar. However, care was taken to see that each word in the vocabulary occured at least once in these sentences. These sentences (a total of 496) served two purposes: 1) as a set of training sentences (spoken by Lee Erman), and 2) for the tesign of a family of languages with varying branching factors that accept at least the iraining sentences and possibly many more.

Goodman designed many such languages. Two extreme examples are a language where any word (of the 1011) could follow any other word, permitting many nonsense sentences, and another in which only the 496 training sentences were legal. Of the several languages chosen for the experimentation, three specific ones--AIX05, AIX15, and AIXF--are given in Appendix III-C (an earlier version of AIXF was developed by Hayes-Roth).

The grammar that allowed Harpy to reach the performance goals of the ARPA program was AIXO5, with a static branching factor of 9.53 and an average dynamic fanout of 33.4. The others were too large to fit within the memory of the PDP-10 system. However, it was possible to study the performance of AIX15 and AIXF using variants which used smalier vocabularies, created by eliminating some of the proper nouns.

The training sets for the other four speakers (two male and two female) consisted of a small subset of the original training sentences. These were used to generate speaker-dependent phone templates for each of the speakers (see the paper by Lowerre in Section IV on speaker adaptation).

A completely new set of 100 test sentences was created by Hayes-Roth which were not part of the training set. These are given in Appendix IIl-A. Erman recorded all the 100 test sentences and the other four speakers recorded a subset of twenty one sentences each. These sentences were used only for testing the performance. of the system; the system was not tuned in any way in response to errors in this set.

The Harpy system achieved an aggregate $91 \%$ sentence accuracy and $95 \%$ semantic accuracy over all the 5 speakers and required 27.9 million instructions per second of speech processed (Fig. 1). Hearsay-II (Fig. 3) was tested on only twenty two sentences.for lack of time and achieved $91 \%$ semantic accuracy and required about 85 mipss. Figures 2 and 4 give the performance of the two systems on test sentences recorded live in the classroom on September 8. The 'Harpy system recognized four of
the five sentences recorded by two male and one female speaker correctly. The Hearsay-II system recognized three of the five. These sentences were generated by the observers who were given copies of the grammar; the sentences were in no way preselected. The classroom environment was somewhat more noisy than the terminal room environment normally used to collect training data.

```
TASK
    Recognition of Al information retrieval task
    - Vocabulary size: 1011
        Branching factor: 9.53
        Average fanout: 33.4
DATA
    Number of speakers: 5
        3 male
    2 female
    Training set for speaker L.E
        4 9 6 ~ s e n t e n c e s ~
        4 0 4 9 \text { words}
    24.7 minutes of speech
    Training set for speakers DS KP BH CW
        256 sentences
        1444 words
        10.1 minutes of speech
        Test set for al! speakers
        184 sentences
        1138 words
        6.5 minutes of speech
PERFORMANCE ON THE TEST DATA
    97% word accuracy
    91% sentence accuracy
    95% semantic accuracy
    27.9 Mipss
```

Figure 1. Harpy results for the Al retrieval task test data.


Figure 2. Harpy results for the live demonstration, 8 September 1976.

```
TASK Recognition of AI information retrieval task
    Vocabulary size: 1811
    Branching factor: }9.5
    Average fanout: 33.4
DATA Number of speakers: 1 male speaker
    Training set for word hypothesizer
        6 8 \text { sentences}
        340 words
        2.2 minutes of speech
        Training set for word verifier
    7 4 7 \text { sentences}
    4 0 4 9 \text { words}
    24.7 minutes of speech
    Test set for all speakers
        22 sentences
        154 words
        1.0 minute of speech
PERFORMANCE ON THE TEST DATA
    86% word accuracy
    73% sentence accuracy
    91% semantic accuracy
    85.0 Mipss
```

Figure 3. Hearsay-II results for the Al retrieval task test data.

```
RESULTS OF live SENTENCES: hearsay-II
UTT 1: UTT="I RM INTERESTED IN ENGLISH"
        REC="I RM INTERESTED IN ENGLISH"
UTT 2: UTT="ARE RNY PRPERS ABOUT SEMANTIC NETWORKS"
    REC= "RRE ANY PAPERS ABOUT A SEMRNTIC NETWORK"
UTT 3: UTT="DOES SEMANTIC NETS GET MENTIONED ANYWHERE"
    TIMEOUT - 2 best partial parses are:
        IDO SIMULTANEOUS ACIIONS........]
        [....DESIGN AND SYNTAX MENTIONED ANYWHERE]
UTT 4: UTT="HOH MANY ARTICLES ON CHESS AND LEARNING ARE THERE"
    timeout
UTT 5: UTT="WE'RE INTERESTED IN HEARSAY"
    REC="WE'RE INTERESTED IN HEARSAY"
```

40\% SENTENCE RCCURACY
60\% SEMANTIC ACCURACY

Figure 4. Hearsay-11 results for the live demonstration, 8 September 1976.

## Gonnected Digit Recognition using Symbolic Representation of Pronunciation Variability (Goodman, Lowerre, Reddy, and Scelza)

Most connected speech recognition systems, such as Harpy and Hearsay-II, use some form of symbolic representation to represent alternative pronunciations of the vocabulary, whereas most isolated word recognition systems use word templates. In an attempt to compare relative performance of systems that use symbolic representations of words, the Harpy system was run on four tasks requiring the recognition of random sequences of digits. Recording was in a computer terminal room environment (approximately 60 dBA ) with speakers recording one session per day in order to include as much intra-speaker variability as possible. Both male and female speakers were used.

## 3-Digits Task

This task was selected as a typical numerical data input task. Sentences are connected sequences of three digits, such as "zero three eight". Each of ten speakers spoke thirty training sentences and 100 test sentences over a period of three weeks. Using speaker-specific phoneme templates, the word error rate over all ten speakers was about 27.

## 7-Digits Task

This task, sometimes refered to as the "telephone number task", consists of connected seven digit sequences such as "seven three nine six one seven three". This task was selected as a benchmark. Error rate for the single speaker was $1 \%$.

## Telephone Input Task

Sentences are three digit connected sequences, as in the 3 -digits task. Recordings were taken over telephone line: in order to determine the effects of restricted frequency response, distortion, envelope delay, etc. The error rate under these conditions was 77.

## Speaker Independent Task

This task is similar to the 3 -digits task. However, recognition is performed using speaker-independent phoneme templates computed from the training data for all speakers. The word error rate was about $7 \%$ on test data of 1200 random three-digit sequences from twenty speakers, including ten new speakers.

A summary of the results for these tasks is shown in the accompanying tables. The total test data are 2700 sentences, representing more than an hour of recorded speech. While this is already a large amount of data, a more extensive and thorough study is to be initiated.

| TASK | 3-Digit | 7-Digit | Telephone | SpeakerIndependent |
| :---: | :---: | :---: | :---: | :---: |
| Vocabulary Size | 10 | 10 | 10 | 10 |
| Branching Factor | 18 | 10 | 10 | 18 |
| No. of Speakers | 10 | 1 | 4 | 20 |
| Male | 7 | 1 | 3 | 14 |
| Female | 3 |  | 1 | 6 |
| Training Set |  |  |  |  |
| No. of Sentences | 388 | 30 | 128 | 300 |
| No. of Words | 988 | 210 | 360 | 900 |
| Mins. of Speech | 7.5 | 1.4 | 3.1 | 7.6 |
| Words/minute | 120 | 150 | 116 | 118 |
| Test Set |  |  |  |  |
| No. of Sentences | 1080 | 108 | 408 | 1200 |
| No. of Words | 3888 | 780 | 1208 | 3680 |
| Mins. of Speech | 25.1 | 4.8 | 10.3 | 33.8 |
| Words/minute | 128 | 146 | 117 | 189 |
| Performance on Test Data 93 |  |  |  |  |
| \%Word Accuracy | 98 | 99 | 93 | 93 |
| \%Sent.Accuracy | 96 | 96 | 82 | 83 |
| Mipss | 3.5 | 3.5 | 3.5 | 3.5 |

## Effects of Branching Factor and Vocabulary Size on Performance (Goodman, Lowerre, and Reddy)

## Analysis

Analysis of the languages of a given set of recognition tasks permits the comparison of the relative difficulties of the tasks. We have developed notions of equivalent vocabulary size, branching factor, effective branching factor, search space size, and search space reduction (Goodman 1976). All of these are useful as relative comparison measure.

## Design

A family of languages having varying characteristics is required in order to be able to compare language measures with actual performance data. Such a family has been generated for the AI abstract retrieval task by interactive grammatical inference. There are four subfamilies for each of the (approx.) vocabulary sizes $250,500,750$, and 1000 words. Several grammars representing differing branching factors exist within each subfamily. With the 250 word grammar, for instance, the available branching factors are $1.23,3.87,4.6,8.2,8.8,11.9,33.3$, and 39.5.

## Results

The relationships between accuracy and speed versus branching factor and vocabulary size are summarized in the accompanying tables. As expected, there is positive correlation in all cases. In the case of speed versus branching factor, the relationship is almost linear. A more comprehensive study of measures for grammatical complexity and their predictive abilities is necessary before any significance can be attached to these preliminary results.

Table l. Effects of branching factor on error rates of the Harpy system within the 250 word family of grammars.

| GRAMMAR |  | STATIC |  |
| :---: | :---: | :---: | :---: |
|  |  | BRANCHING | ERROR |
|  | MIPSS | FACTOR | RATE |
| AIS06 | 6.63 | 4.6 | $0 \%$ |
| AIS10 | 9.36 | 8.2 | 4\% |
| AIS15 | 13.65 | 11.9 | 6\% |
| AIS30 | 44.72 | 33.3 | 16\% |
| AIS48 | 59.15 | 39.5 | 16\% |

Table II. Speed versus vocabulary size for Harpy when branching factor is held constant (approx. 10).

BRANCHING

| GRAMMAR | MIPSS |  | FACTOR |  |
| :--- | :---: | :---: | :---: | :---: |
| AIS10 | 9.36 | 8.2 |  | 250 |
| AIM12 | 16.77 | 18.5 | 500 |  |
| AIXB5 | 26.80 | 9.5 | 1800 |  |

## References

R. G. Goodman (1976). "Analysis of languages for mán-machine voice communication," Ph.D. dissertation., Comp. Sci. Dept., Stanford Univ., Tech. Rept. Comp. Sci. Dept., C-MU, Pittsburgh, Pa.

## APPENDICES for Section III

Appendix III-A lists the 100 test sentences used by the Harpy and Hearsay-II systems, along with characteristics measuring their complexity relative to several grammars.

Appendix III-B is the phonetic dictionary for the 1011 words used in the AI retrieval language.

Appendix III-C contains the complete definition of three of the grammars (AIXF, AIX15, and AIX05) used in testing the systems. These grammars have become standards for future development and testing. AIXF was not used to test Harpy because the network was too large to be generated.

## Appendix III-A. Characteristics of the AI Retrieval Task sentences

Below is a description of the test sentences used for the Harpy and Hearsay-II systems. The September Hearsay-II results used 22 of the sentences randomly selected from the 100. The entire set of 100 was used for the 100 single-speaker test sentences for Harpy, and 21 of them were used for the other four speakers tested on Harpy.

## CMU Test Sentences

The branching factors previously given for the languages used by the CMU speech understanding systems (HARPY and Hearsay-II) are "static" branching factors (SBF) (as derived by Gary Goodman and described in his recent thesis). Intuitively, they can be thought of as being derived by doing a Monte Carlo probing of a network describing all acceptable word sequences and taking the average of the number of words possible following any legal initial sequence. Other groups have generated somewhat similar numbers.

What we present here is a characterization of the lexical fanout allowed by our grammars for the particular test sentences. The notion is to calculate the average fanout for each sentence-initial sequence of words (i.e., going left-to-right).

The method used here is the following: For any sequence of words, denote by Word Branches (WB) the number of words that may legally follow that sequence in the given language. Consider a sentence of length N-1 words to have N WB's -- each is calculated from the initial sequence of $i$ words, $i=0,1 \ldots . N$. (I.e., the first $W B$ for any sentence is always the same -- the number of legal first words.) Then, for any sentence or collection of sentences, the Average Fanout (AF) is the arithmetic mean of the WB's of the sentence(s).

The languages used (all defined using the same 1011-word vocabulary) are called AIX05, AIX15, and AIXF. The first two have static branching factors of 10 and 28 , respectively. This summary is over 100 test sentences containing a total of 683 words.

| AF |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| AIX05 | AIX15 | AIXF | sents | words/sent |
| 33.4 | 46.5 | 68.0 | 108 | 6.83 (average over all) |
| 17.3 | 26.0 | 33.4 | 2 | 3 |
| 31.3 | 45.4 | 84.8 | 10 | 4 |
| 36.1 | 58.7 | 73.8 | 11 | 5 |
| 29.7 | 41.5 | 60.3 | 21 | 6 |
| 33.6 | 47.8 | 78.2 | 24 | 7 |
| 37.2 | 51.1 | 70.3 | 15 | 8 |
| 30.1 | 48.5 | 63.0 | 9 | 9 |
| 42.3 | 61.5 | 70.8 | 3 | 10 |
| 42.8 | 57.9 | 76.3 | 3 | 11 |
| 21.2 | 29.9 | 53.4 | 2 | 12 |

The 100 sentences, presented with fanouts according to the AIX05 language.
[ 66 DO 6 ANY 6 OF 3 THESE 3 MENTION 192 PSYCHOLOGY 3 words=6 $A F=39.857$
[ 66 WHICH 21 COGNITIVE 1 PSYCHOLOGY 2 CONTAINED 192 WINOGRAD'S 1 ARTICLE 1 words=6 $A F=40.5 \%$
[ 66 WHAT 26 TOPICS 1 ARE 1 RELATED 1 TO 192 SEMANTIC 2 NETWORKS 3. words $=7 \quad A F=36.508$
[ 66 DOES 196 PATTERN 3 DIRECTED 1 FUNCTION 1 INVOCATION 3 GET 2 DISCUSSED 1 ANYWHERE 1 words=8 $A F=30.444$
[ 66 WHICH 21 TITLES 1 CONTAIN 1 THE 1 PHRASE 192 TIME 2 COMPLEXITY 3 words=7 AF $=35.875$
[ G6 DOES 196 THAT 1 ARTICLE 1 MENTION 192. TIME 2 OR 1 SPACE 1 BOUNDS 3 words=8 $\quad$ AF $=51.444$
[ 66 WHICH 21 OF 2 THEM 1 DISCUSSES 192 EVALUATION 1 FUNCTIONS 3 words $=6 \quad A F=40.857$
[ 66 ARE 292 THERE 2 ANY 5 ABSTRACTS 1 WHICH 1 REFER 1 TO 192 PAPERS 1 BY 96 NEWELL 3 words $=18 \quad \mathrm{AF}=60.000$
[ 66 WHERE 5 IS 192 PREDICATE 1 CALCIGUS 3 MENTIONED 1 words=5 $A F=44.667$
[ 66 WHAT 26 ARE 3 SOME 1 OF 1 THE 1 AREAS 1 OF 192 ARTIFICIAL 1 INTELLIGENCE 3 words=9 AF:=29.588
[ 66 WHAT 26 WAS 1 ITS 1 TITLE 1 words $=4 \mathrm{AF}=19.000$
[ 66 WHO 5 WAS 2 THE 1 AUTHOR 1 words $=4 \mathrm{AF}=15.000$
[ 66 WHERE 5 DOES 1 HE 1 WORK 1 words $=4 A F=14.800$
[ 66 WHAT 26 IS 4 HER 1 AFFILIATION 1 words $=4$ AF $=19.680$
[ 66 WHAT 26 ADDRESS 1 IS 1 GIVEN 1 FOR 1 THE 1 AUTHORS 1 words=7 $\mathrm{AF}=12.258$
[ 66 HOW 4 MANY 8 REFERENCES 1 ARE 1 GIVEN 1 words $=5$ AF $=13.500$
[ EG PLEASE 4 LIST 1 THE 1 AUTHORS 1 words $=4 \mathrm{AF}=14.600$
[ 66 PLEASE 4 MAKE 1 ME 1 A 1 FILE 1 OF 1 THOSE 1 words $=7$ AF $=9.500$
[ 66 CAN 2 I 1 HAVE 1 THESE 1 ABSTRACTS 1 LISTED 1 words $=6$ AF $=10.429$
[ G6 ARE 292 ANY 6 ARTICLES 2 ABOUT 192 STRUCTURED 1 PATTERN 1 RECOGNITION 3 words $=7 \quad \mathrm{AF}=70.375$
[ 66 DO 6 ANY 6 OF 3 THE 1 ABSTRACTS 1 MENTION 192 LEARNING 3 words=7 AF $=34.750$
[ 66 HOW 4 MANY 8 OF 1 THESE 1 ALSO I DISCUSS 192 ABSTRACTION 3 wor $d s=7 \quad A F=34.500$
[ 66 WHICH 21 PAPERS 7 ON 192 LANGIJASE 6 UNDERSTANDING 4 ARE 1 ABOUT 192 ENGLISH 3 words=8 AF=54.667
[ 66 DO 6 ANY 6 PAPERS 5 ON 192 AUTOMATIC 7 PROGRAMMING 3 EXIST 1 words $=7 \quad A F=35.750$
[ 66 WHAT 26 ABOUT 288 PROGRAM 1 VERIFICATION 3 words $=4$ AF $=76.880$
[ 66 I 2 AM 2 INTERESTED 1 IN 192 ARTIFICIAL 1 INTELLIGENCE 3 words $=6 \quad A F=38.143$
[ 66 THE 3 AREA 211 AM 1 INTERESTED 1 IN 1 IS 192 UNDERSTANDING 3 words $=8 \quad A F=30.008$
[ 66 DON' $T 1$ GET 1 ME 1 ANY 1 ARTICLES 1 WHICH 1 MENTION 192 GAME 2 PLAYING 3 words $=9$ AF $=26.900$
[ 66 I 2 AM 2 ONLY 1 INTERESTED 1 IN 1 PAPERS 1 ON 192 CHESS 4
words=8 AF=30.008
[ 66 LET'S 1 RESTRICT 1 OUR 1 ATTENTION 1 TO 1 PAPERS 1 SINCE 1 NINETEEN 1 SEVENTY 1 FOUR 1 words $=10$ AF=6.909
[ 66 DO 6 ANY 6 PAPERS 5 THIS 1 YEAR 1 CITE 96 ROSENFELD 3 words=7 $A F=23.008$
[ 66 ARE 292 COMPUTER 7 NETWORKS 4 M.NTIONED 2 ANYWHERE 1 words=5 $A F=62.000$
[ 66 ARE 292 ANY 6 ARTICLES 2 ABOUT 192 GRAIN 1 OF 1 COMPUTATION 3 words $=7 \quad A F=70.375$
[ 66 ARE 292 ANY 6 ARTICLES 2 BY 96 ROSENFELD 3 words=5 AF=77.500
[ 66 ARE 292 ANY 6 BY 96 FEIGENBAUM 3 AND 96 FELDMAN 1 words $=6$ $A F=80.000$
[ 66 ARE 292 THERE 2 ANY 5 ABSTRACTS 1 WHICH 1 REFER 1 TO 192 PAPERS 1 BY 96 HOLLAND 3 words $=10 \quad A F=60.080$
[ 66 ARE 292 THERE 2 ANY 5 NEW 2 PAPERS 1 ON 192 PROGRAM 1 VERIFICATION 3 words $=8 \quad A F=62.667$
[ 66 DO 6 ANY 6 OF 3 THESE 3 ALSO 2 MENTION 192 PLANNER-LIKE 1 LANGUAGES 3 words=8 $\mathrm{AF}=31.333$
[ 66 DOES 196 PROBLEM 1 SOLVING 3 GET 2 MENTIONED 1 ANYWHERE 1 words=6 $\quad A F=38.571$
[ 66 WHICH 21 PAPERS 7 CITE 96 NEWELI 3 AND 96 SIMON 1 words=6 $A F=41.429$
[ 66 ANY 1 ABSTRACTS 1 REFERRING 1 TO 192 AI 4 OR 191 ARTIFICIAL 1 INTELLIGENCE 1 words=8 $\mathrm{AF}=50.889$
[ 66 ARE 292 ASSOCIATIVE 2 MEMORIES 4 DISCUSSED 1 IN 1 RECENT 1 JOURNALS 1 words $=7 \quad A F=46.080$
[- 66 ARE 292 LEARNING 4 AND 191 NEURAL 1 NETWORKS 2 MENTIONED 2 ANYWHERE 1 words $=7 \mathrm{AF}=69.875$
[ 66 IID 99 REDOY 5 PRESENT 2 A 1 PAPER 1 AT 2 IJCAI 1 words=7 $A F=22.125$
[ 66 DIDN' T 1 THAT 1 PAPER 1 QUOTE 95 DREYFUS 3 words $=5$ AF $=28.000$
( 66 DOES 196 PICTURE 1 RECOGNITION 3 GET 2 MENTIONED 1 ANYWHERE 1 words $=6 \quad \mathrm{AF}=38.571$
〔 66 GET 1 ME 2 EVERYTHING 1 ON 192 DYNAMIC 3 CLUSTERING 3 words=6 $A F=38.286$
[ 66 GENERATE 1 A 1 COPY 1 OF 1 THOSE 1 mords=5 AF $=11.833$
[ EG GIVE $2 . \mathrm{ME} 4$ THE 1 DATE 1 OF 1 THAT 1 ABSTRACT 1 words=7. $A F=9.625$
[ 66 HOW 4 CAN 111 USE 1 THE 1 SYSTEM 1 EFFICIENTLY 1 words=7 $A F=9.500$
[ 6612 AM 2 INTERESTED 1 IN 192 LEARNING 3 words 5 AF $=44.333$
[ G6 I'D 1 LIKE 1 TO 2 SEE 1 THE 1 MENUS 1 words=6 AF $=10.429$
[ 66 SELECT 1 FROM 1 ARTICLES 1 ON 192 GAME 2 PLAYING 3 words=6 $A F=38.000$
[ 66 WHAT 26 ADDRESSES 1 ARE 1 GIVEN 1 FOR 1 THE 1 AUTHORS 1 words=7 $A F=12.258$
[ 66 WHAT 26 PAPERS 1 ON 192 PREFERENTIAL 1 SEMANTICS 3 ARE 1 THERE 1 words=7 AF $=36.375$
[ 66 WHEN 3 WAS 194 A 28 SEMANTIC 1 NETWORK 3 LAST 2 REFERRED 1 TO 1 words $=8 \quad A F=32.333$
[ 66 WHICH 21 PAPERS 7 CITE 96 FELDMAN 3 words $=4$ AF $=38.600$
[ GG WHO 5 HAS 1 WRITTEN 1 ABOUT 192 AUTOMATIC 7 PROGRAMMING 3 words $=6 \quad A F=39.286$
[ 66 WHO 5 WAS 2 QUOTED 1 IN 1 THAT 1 ARTICLE 1 words $=6$ AF $=11.000$
[ 66 WHICH 21 IS 1 THE 1 OLDEST 1 words=4 $A F=18.000$
[ 66 ARE 292 ANY 6 NEW 1 BOOKS 1 BY 76 TERRY 1 WINOGRAD 3 words 7 $A F=58.25 B$
[ 66 CAN 211 HAVE 1 THESE 1 ABSTRACTS 1 LISTED 1 words=6 AF=10.429
[ 66 DID 99 CARL 1 HEWITT 5 PRESENT 2 A 1 PAPER 1 AT 2 THE 1 IFIP 1 MEETINGS 1 IN 1 SEPTEMBER 1 words=12 $\mathrm{AF}=14.880$
[ 66 DID 99 ANY 4 ACL 1 PAPERS 1 CITE 96 RICK 1 HAYES-ROTH 3 wordse 7 $A F=33.875$
[ 66 DO 6 ANY 6 OF 3 THOSE 1 PAPERS 1 MENTION 192 AXIOMATIC 1 SEMANTICS 3 words=8 $A F=31.000$
[ 66 DURING 1 WHAT 1 MONTHS 1 WERE 1 THEY 1 PUBLISHED 1 words=6 $A F=10.286$
[ 66 HOW 4 MANY 8 RECENT 1 ISSUES 1 CONCERN 192 INVARIANCE 1 FOR 1 PROBLEM 1 SOLVING 3 words $=9 \quad A F=27.800$
[ 66 HOW 4 MANY 8 SUMMARIES 1 DISCUSS 192 KNOWLEDGE 2 BASED 1 SYSTEMS 3 words $=7 \quad \mathrm{AF}=34.625$
[ 66 HAVE 97 ANY 2 NEW 1 PAPERS 1 BY 96 LEE 1 ERMAN 3 APPEARED 1 words $=8 \quad A F=29.778$
〔 G6 I'D 1 LIKE 1 TO 2 KNOW 1 THE 1 PUBLISHERS 1 OF 1 THAT 1 STORY 1 words $=9 \quad A F=7.60 D$
[ 66 IS 290 HUMAN 3 BEHAVIOR 5 OR 191 HUMAN 3 MEMORY 3 DISCUSSED 2 IN 1 A 1 RECENT 1 SUMMARY 1 words $=11$ AF=47. 250
[ 66 LIST 2 THE 2 ABSTRACTS 1 BY 96 HERB 1 SIMON 3 words $=6$ AF $=24.429$
[ 66 WAS 290 ALLEN 2 NEWELL 3 CITED 2 IN 1 THAT 1 SUMMARY 1 words $=7$ $A F=45.750$
[ G6 WHAT 26 ABOUT 288 ALLEN 2 COLLINS 3 words $=4 \mathrm{AF}=77.000$
[ 66 WHERE 5 DID 1 THAT 1 ARTICLE 1 APPEAR 1 words=5 AF $=12.500$
[ 66 WHO 5 HAS 1 WRITTEN 1 ABOUT 192 LANGUAGE 6 COMPREHENSION 3 AND 191 LANGUAGE 6 DESIGN 1 words=9 $A F=47.200$
[ 66 QUIT 1 LISTING 1 PLEASE 1 words=3 AF=17.250
[ 66 WEREN' T 1 SOME 1 ARTICLES 1 PUBLISHED 1 ON 192 GOAL 1 SEEKING 1 COMPONENTS 3 words $=8$ AF $=23.667$
[ 66 WHAT 26 SORTS 1 OF 192 LANGUAGE 6 PRIMITIVES 3 ARE 1 WRITTEN 1 UP 1 words=8 $A F=33.000$
[ 66 HASN' T 192 A 21 CURRENT 1 REPORT 1 ON 192 PRODUCTION 1 SYSTEMS 3 BEEN 1 RELEASED 1 words $=9$ AF $=47.900$
[ GG ARE 292 THERE 2 ANY 5 ISSUES 1 ABOUT 192 COOPERAT]NG 1 SOURCES 1 OF 1 KNOWLEDGE 3 words $=9 \quad A F=56.400$
[ 66 DID 99 VIC 1 LESSER 5 PRESENT 2 PAPERS 1 AT 2 IFIP 1 words=7 $A F=22.125$
[ 66 DID 99 ANYONE 1 PUBLISH 1 ABOUT 192 LARGE 1 DATA 1 BASES 3 IN 1 COMMUNICATIONS 1 OF 1 THE 1 ACM 1 words $=12 \mathrm{AF}=28.385$
[ 66 DO 6 ANY 6 AUTHORS 1 DESCRIBE 192 DRAGON 3 words $=5$ AF $=45.667$
[ 66 DOES 196 HE 1 WORK 1 AT 1 CMU 1 mords $=5$ AF $=44.333$
[ 66 DO 6 ANY 6 RECENT 4 ACM 1 CONFERENCES 1 CONSIDER 192 SEMANTIC 2 NETS 3 OR 191 SEMANTIC 2 NETWORKS 1 words $=11$ AF $=39.583$
[ 66006 RESPONSES 1 EVER 1 COME 1 .FASTER•1 words=5 AF=12.667
[ 66 HAS 96 LEE 1 ERMAN 4 BEEN 1 REFERENCED 1 IN 1 ANY 1 OF 1 THOSE 1 words $=9 \quad A F=17.388$
[ 66 HAS 96 ALLEN 2 NEWELL 4 PUBLISHED 2 ANYTHING 1 RECENTLY 1 words $=6 \quad \mathrm{AF}=24.571$
[ 66 HAVE 97 ANY 2 NEW 1 PAPERS 1 BY 95 TERRY 1 WINUGRAD 3 APPEARED 1 words=8 AF $=29.778$
1 66 HOW 4 BIG 1 IS 1 THE 1 DATA 1 BASE 1 words $=6$ AF $=18.714$
[ 66 HOW 4 MANY 8 OF 1 THESE 1 ALSO 1 DISCUSS 192 DYNAMIC 3 BINDING 3 words $=8 \quad A F=31$. 000
[ 66 HOW 4 MANY 8 RECENT 1 ISSUES 1 CONCERN 192 DISPLAY 1 TERMINALS 3 words=7 AF=34.500
[ 66 KILL 1 THE 1 LISTING 1 words $=3$ AF $=17.258$
[ 66 PLEASE 4 MAKE 1 ME 1 A 1 FILE 1 OF 1 THOSE 1 words= $A F=9.500$
[ 66 WHAT 26 IS 4 HIS 1 AFFILIATION 1 words $=4$ AF $=19.600$
[ 66 WHICH 21 OF 2 THESE 5 CITES 96 PERRY 1 THORNDYKE 3 words $=6$ $\mathrm{AF}=27.714$
[ 66 WHICH 21 PAPERS 7 ON 192 DESIGN 6 IN 1 THE 1 ARTS 4 ALSO 2 DISCUSS 192 DESIGN 5 AUTOMATION 3 words $=11$ AF $=41.667$
[ 66 WHO 5 WAS 2 QUOTED 1 IN 1 THAT 1 ARTICLE 1 words $=6$ AF $=11.000$
[ G6 WHICH 21 PAPERS 7 WERE 1 WRITTEN 2 AT 1 NRL 1 OR 1 AT 1 SMC 1 words $=9 \quad A F=10.280$

## Appendix III-B. Al Retrieval Language Dictionary

| A | (-,0) (AX!, UHA!, EHA! EYL EYC! EYR) |
| :---: | :---: |
| ABOUT | (-,0) (AH2,AX,EH3,0) (\& (-,0),-\{4\}) (B,0) (AWL,0) AWC! (AWR,0) ( $+(-, 0),-(4\})(T, 0), D X)$ |
| ABSTRACT | (-,0) AE3 ( $\leftarrow(-, 0),-)$ S (,- 0 ) (DR (R,0), T R) AE2! ( $\leftarrow(-, 0),-\{4\}$ ) (T,0), DX) |
| ABSTRACTION | $(-, 0)$ AE3 ( $-(-, 0),-) S(-, 0)$ (DR (R,0), T R) AE2! $\leftarrow(-, 0),-)$ SH IH5 N |
| ABSTRACTS | $(-, 0)$ AE3 $(+(-, 0),-)$ S (-,0) (DR (R,0), T R) AE2! ( $+(-, 0),-) \mathrm{S}(\mathrm{HH}, 0)$ |
| ACL | (-,0) (EYL,0) EYC (EYR,0) S IV (EH EL,EL2) |
| ACM | (-,0) (EVL,0) EYC! (EYR,0) S IV AH2 M |
| ACQUISITION | $(-, 0)$ AE5 ( $-(-, 0),-)$ WH IH! ( $\mathrm{\{ }$ \{ 4$\},(\mathrm{Z}, 0) \mathrm{S}$ ) IH2 SH IH5 N |
| ACTIONS | $(-, 0)$ AE5 (- (-,0),-) SH! IH5 N ( $Z\{4\},(Z, 0)$ S) |
| ACTIVE | $(-, 0)$ AE $\leftarrow(-,-0),-)$ T! IH $V(F, 0)$ |
| ACYCLIC | $(-, 0)$ (EYL, O) EYC (EYR,0) S IH3! ( $-(-, 0),-\{4\}$ ) (K,0) L UH2 ( $-(-, 0),-\{4\})(\mathrm{K}, 0)$ |
| ADAPTATION | $(-, 0)$ AE4 ( $\leftarrow(-, 0),-$ D) ( $\mathrm{D}, 0)$ AE5 ( $\leftarrow(-, 0),-)$ T (EYL,0) EYC! (EYR,0) SH IH5 N |
| ADAPTIVE | $(-, 0)($ IX,UH) $(\leftarrow-(-, 0),-)(D, 0)$ AE $(\leftarrow(-, 0),-)$ T IX V (F,O) |
| ADDITION | $(-, 0)$ IH3 ( $(\leftarrow(-, 0),-)(\mathrm{D}, 0), \mathrm{DX})$ IH3! SH IH5 N |
| ADDRESS | $(-, 0)((A E, I X), U H)(\leftarrow(-, 0),-)$ DR R EH2! S (HH,O) |
| ADDRESSES | $(-, 0)((A E, I X), \mathrm{UH})(\leftarrow(-, 0),-)$ DR R EH2! S IH4 (Z\{4\},(Z,0) S) |
| ADVISING | $(-, 0)(\mathrm{IX}, \mathrm{UH})(\leftarrow(-, 0),-)(\mathrm{D}, 0) \vee(A Y L, 0)$ AYC! (AYR,0) (Z\{4\},(Z,0) S) (IH3,IY) NX |
| AESTHETICS | $(-, 0)$ AX S TH EH ( $-(-, 0),-)$ † IH ( $-(-, 0),-)$ S (HH,0) |
| AFFILIATION | $(-, 0)(E H 3, A H)$ F (IH,O) EL. IY (EYL,0) EVCl (EYR,O) SH IH5 N |
| AFFILIATIONS | (-,0) AX (-,0) F EH2 L IV2 (EYL,0) EVC! (EYR,0) SH IH5 N (Z\{4\}, (Z,0) S) |
| AFTER | $(-, 0)$ AE! F ( $(+(-, 0),-)$ T,DX) ER |
| AI | (-,0) (EYL,0) EYC! (EYR,0) (AYL,0) AYC (AYR,0) |
| ALGEBRAIC | $(-, 0)$ AE3 EL $(\leftarrow(-, 0),-) S H_{4}, 8 ; \mathrm{IH}(\leftarrow-(-, 0),-\{4\})(\mathrm{B}, 0) \mathrm{R}$ (EYL,0) EYC (EYR,0) IH2 ( $\left.\leftarrow(-, 0),-\{4\}\right)(\mathrm{K}, 0)$ |
| Al. GOL | $(-, 0)$ AE4 EL ( $\sim(-, 0),-)(\mathrm{G}, 0)$ OW3 EL3 |
| ALGORITHM | $(-, 0)$ AE EL $(\leftarrow(-, 0),-)(\mathrm{G}, 0)(\mathrm{AA}, \mathrm{OW}) \mathrm{R}!\mathrm{IH}$ (TH,OH) ( $\mathrm{IH}, \mathrm{IX}, \mathrm{O}$ ) M |
| ALGORITHMIC | $(-, 0)$ AE EL $(\leftarrow(-, 0),-)(G, 0)(A A, O W)$ R! IH (TH,OH) M IH ( $\leftarrow(-, 0),-\{4\})(\mathrm{K}, 0)$ |
| ALL | $(-, 0)$ OWA! EL |
| ALL-OR-NONE | $(-, 0)$ OW4! EL (,- 0 ) (AA4,0) ER2! 7,14$\}(-, 0) \mathrm{N}$ UH ( $\mathrm{N}, \mathrm{DX}$ ) |
| ALLEN | (-,0) AE! EL3 (1H6 N,EN) |
| ALSO | (-,0) (AO,OW4) EL S (IH6 (OW2,0),OW) |
| ALWAYS | (-,0) AO EL W (EYL, 0 ) EYC! (EYR,0) ( $Z\{4\},(Z, 0)$ S) |
| AM | $(-, 0)$ ( $E$ EH2!,AE3!) M, EM ${ }^{\text {) }}$ |
| AMONG | $(-, 0)(I X!A X!)$ M UH2 NX |
| AN | $(-, 0)$ AE5 ( $E N, N$ ) |
| ANALOGY | $(-, 0)$ AE5 (N,EN) AE4! (EL,L) OW4 (ヶ (-,0),-) SHf, 8) IY |
| ANALVSIS | $(-, 0)$ UH4 N AE EL3! (UH2\{2,6\}, IH6,0) S IH6 S (HH,0) |
| ANALYZER | $(-, 0)$ AE5 N EL2 (AVL,0) AYC! (AYR,0) ( $Z\{4\},(\mathrm{Z}, 0) \mathrm{S}$ ) ER2 |
| AND | $(-, 0)$ AE5 $\{5,10\} N(\leftarrow(-, 0),-, 0)(D, 0)$ |
| ANN | $(-, 0)$ AE4! ( $\mathrm{N}, \mathrm{DX}$ ) |
| ANOTHER | $(-, 0)$ AH N AA2! (DH, TH) (ER,AA2) |
| ANSWER | $(-, 0)$ AE5! N S ER |
| ANSWERING | (-,0) AEA N S! (R,ER) IH5 NX |
| ANTHONY | $(-, 0)$ AEA (N, - ) ( $-(-, 0),-, 0)$ TH IH4! N IY |
| ANY | (-,0) (EH3,EH) (N\{2\},DX) IY! (IY3,0) |
| ANYONE | $(-, 0)(E H 3, E H)$ ( $\mathrm{N}\{2\}, \mathrm{DX}$ ) IY! (IY3,0) (-,0) W AH ( $\mathrm{N}, \mathrm{DX}$ ) |
| ANYTHING | (-,O) (EH3,EH) ( $\mathrm{N}\{2\}, \mathrm{DX}$ ) IY ${ }^{\text {I }}$ TH (IH3, IY) NX |
| ANYWHERE | (-,0) (EH3,EH) ( N [2 2 , DX) IV! (-,0) W (EH3,0) ER |
| APPEAR | (-,0) ( $A H 3, \mathrm{UH2})(\leftarrow(-, 0),-)(\mathrm{P}, \mathrm{PH})$ IY2! ERI, 18; |
| APPEARED | $(-, 0)($ AH3, UH2) ( $\leftarrow(-, 0),-)(\mathrm{P}, \mathrm{PH}) \mathrm{IY} 2!$ ER\{,18\} ( $\leftarrow(-, 0),-)(\mathrm{D}, \mathrm{DH}, 0)$ |
| APPLICATION | $(-, 0)$ AE3 ( $-(-, 0),-)$ (P L,PL (L,0)) IH6 ( $-(-, 0),-)(\mathrm{K}, 0)$ (EYL,0) EYC! (EYR,0) SH IH5 N |
| APPRENTICE | $(-, 0)$ EH3 ( $\leftarrow(-, 0),-)$ (PR,PR (R,0)) EH2! $\mathrm{N}(\leftarrow(-, 0),-, 0)$ T IH4 S (HH,0) |
| APPROACH | $(-, 0)$ UH\{2\} ( $\leftarrow(-, 0),-)$ (P R,PR (R,0)) OW 2 ! ( $\leftarrow(-, 0),-)$ SH\{, 8$\}$ |
| APRIL | (-,0) (EYL, 0 ) EYC! (EYR,0) ( $\leftarrow(-, 0),-)(P \mathrm{R}, \mathrm{PR}(\mathrm{R}, 0)$ ) (IH EL,EL2) |
| ARBIB | $(-, 0)$ AA R $\leftarrow \leftarrow(-, 0),-\{4\})(B, 0)$ IY $(\leftarrow(-, 0),-)(B, 0)$ |
| ARE | (-,0) (AA3! 1 \} (ER2,ER), ER2!) |
| AREA | $(-, 0)$ IH2! ER IY2 UH |


| AREAS | (-,0) JH2! ER IV2 UH ( $2143,(\mathrm{Z}, 0) \mathrm{S}$ ) |
| :---: | :---: |
| ARE.N'T | $(-, 0)$ (AA3! (ER2, ER , , ER2!) < $(\leftarrow(-, 0),-\{4\})(T, 0), D K)$ |
| ARPA | $(-, 0)$ AA! (ER,ER? ) ( $\leftarrow(-, 0),-) \mathrm{P}(1] \mathrm{JH}$ |
| ART |  |
| ARTICLE |  |
| ARTICLES |  |
| ARTIFICIAL. | $(-, 0)$ (AA3 (ER, $)$, ER2) ( $(+(-, 0),-)$ T, DX) IH7! ( -0 ) F IH3 SH EL |
| ARTS | $(-, 0)$ AA 3 ( $E R, 0)(1-(-, 0),-) \mathrm{S}\left(\mathrm{HH}_{1}\right)$ ) |
| ASIMOV | (-,0) AE: ( $Z\{4$, |
| ASK' | $(-, 0)$ AE $3!S-(k, 0)$ |
| ASSEMMin. ${ }^{\text {P }}$ | $(-, 0)$ UHA $S$ EHA $\mathrm{N}^{\prime}(\ldots-(-, 0),-\{4\})(B, 0)$ L IY |
| Assehtions | $(-, 0)$ Alf S ER' Sif lif $\mathrm{N}(\mathrm{Z}\{4,4,(Z, 0)$ S $)$ |
| ASSIMILATION | (-,0) IHG S IH M EL3 (t.YL,0) EYC (EYR,0) SH IH5 N |
| ASSSCCIATION | ( $\ldots, 0$ ) UHA S OW 3 ( $5, S \mathrm{~S}$ ) IY AE! SH ( $\mathrm{AX}, \mathrm{IX}, \mathrm{IH5}$ ) ( $\mathrm{N}, \mathrm{DX}$ ) |
| ASSOCIATIVE. | $(-, 0)$ UHA! S OW3 ( $\mathrm{S}, \mathrm{SH}$ ) IY IH7 ( $(6)(-, 0),-)$ T, DX $)$ IH3 $V(F, 0)$ |
| AT | $(-, 0)(A E \cap!, \wedge[2!)(<+(-, 0),-\{4\})(T, 0), D X)$ |
| ATIENTION | $(-, 0)$ (1H2, (UH) ( $-(-, 0),-$ ) T EH2? N SHI IHS N |
| AUGMENTED | $(-, 0)$ A $(\leftarrow-(-, 0),-)$ M EH $N((+\sim(-, 0),-, 0)$ T, DX $)$ IH3 $(\leftarrow(-, 0),-)(0,0)$ |
| Alliust | $(-, 0) \mathrm{AO}(\leftarrow-(-, 0),-)(6,0)$ iH3! S - 14$)(\mathrm{T}, 0)$ |
| AUTHOR | $(-, 0)$ AO! $(-, 0)$ TH ER |
| AUTHORS |  |
| AUTOMATED | $(-, 0)$ AO ( $(-(-, 0\rangle,-)$ T, DX) EH3 M (EYL,0) EYC (EYR, 0 ) ( $\leftarrow(-, 0),-)$ T,OX) IH3 ( $\leftarrow(-, 0),-)(0,0)$ |
| AlITOMATIC | $(-, 0)$ AO ( $(-(-, 0),-)$ T,DX) EH3 M AE! ( $(+(-, 0),-) T, O X)$ IH3 $(\leftarrow(-, 0),-\{4\})(\mathrm{K}, 0)$ |
| AUTOMATION | $(-, 0)$ AA ( $(\leftarrow(-, 0),-)$ T,DK) OW2! M (EYL, 0 ) EYC ( E YR, 0 ) SH IH5 N |
| AVAILABLE: |  |
| AWARD | $(-, 0)$ UW2 W! JWA ER ( $(-(-, 0),-)(0,0)$, DK) |
| AXIOMATIC | $(-, 0)$ AE $(+(-, 0),-)$ S IY UH M AE ( $(\leftarrow)(-, 0),-)$ T, DK $)$ IH3 $(\leftarrow(-, 0),-)(K, 0)$ |
| Axioms | $(-, 0)$ AE ( $\leftarrow(-, 0),-)$ S IYI UH M ( $2\{4\},(Z, 0)$ S) |
| AZRIEL | (-,0) AES ( $2\{4\}, 1$, (1) S) 3 H (ER,R) EL'2 |
| BACKGAMAMON |  |
| BANERJ | $(\sim(-, 0),-\{4\})(8,0)$ IHT N ER! ( $-(-, 0),-)$ SH\{, ; IV |
| BANK |  |
| BARROW | ( $\leftarrow(-, 0),-\{4)(B, 0)$ EH 3 (ER, ) OW |
| BASE |  |
| BASEBALL |  |
| BASES |  |
| BASES |  |
| bates |  |
| BAY | ( $\leftarrow(-, 0),-\{4 ;)\left(F_{1}, 0\right\rangle($ F.YL, 0$\rangle$ EYC! (EYR, 0 ) |
| BEE:N | $(6-(-, 0),-143)\langle 8,0\rangle$ )H2! ( $\mathrm{N}, \mathrm{DX}$ ) |
| BEFORE. |  |
| BEHAVIOR | $(+(-, 0),-\{A\})(B, 0)$ IV $(H H, H H 22,0\rangle$ (EYL, 0 ) EYC! (EYR, 0 ) $\vee$ Y ER3 |
| bselilef | $\left(\leftarrow(-, 0),-A_{i}^{\prime}\right)(B, 0)(H, I Y) L$ IY! F $\left(H H_{1}, 0\right)$ |
| BERKELEY |  |
| BERL.INEK | $\left(\sim(-, 0),-1 A^{\prime}\right)(B, 0)$ ER? L U UHA $N(E H, 0)$ ER |
| BE:RNARO | $(+(-, 0),-(A) \quad(B, 0)(A A A, O)$ ER2 N AA3 F.R $\langle+(-, 0),-)(0,0)$ |
| BERT | $(\leftarrow(-, 0),-\{A\})(B, 0)$ ERP? $(<-(-, 0),-\{A\})(T, O), D K)$ |
| BETWE:TV |  |
| ${ }^{\text {B }} 16$ | $(\leftarrow(-, 0),-\{A, 0)(\mathbb{B}, 0\rangle(2 H 1,1 X!)(-(-, O),-)(G, O)$ |
| BILL |  |
| BINDING | $(-(-, 0),-(A))(B, 0)(A Y L,(1) A Y C(A Y R, 0) N(6-(-, 0),-, D)(0,0)(1 H 3, I Y) N X$ |
|  |  |
| BIOMP:İCMN: |  |
| [3LIDSDE | $(\ldots(-, 0),-\{A\})(f\}, 0)$ L All ? ! ( $-(-, 0),-)$ S OW |
| Block | $(\leftarrow(-, 0),-i A j)(B, 0) \backslash A O!(-(-, 0),-i A\})(K, 0)$ |
| BOBROW | $(\leftarrow(-, 0),-14)$ ) ( $B, 0)($ AWL, 0 ) AWC! (AWR,0) ( $-(-, 0),-\{4\})(B, 0)$ R OW |
| BONNIE | ( $1-(-, 0),-i A l)(B, 0)$ AA! $N$ IY |
| BOOK | $(\leftarrow(-, 0),-\{4\})(B, 0) \cup W(\{4\})(\leftarrow(-, 0),-\{4\})(K, 0)$ |


| BOOKS | $(\leftarrow(-, 0),-\{4\})\langle B, 0\rangle$ UW! 44$\}(\leftarrow-(-, 0),-) S(H H, 0)$ |
| :---: | :---: |
| BOUNDS | $(\leftarrow(-, 0),-\{4\})(B, 0)$ (AWL, 0$)$ AWC! (AWR, 0 ) $N(\leftarrow(-, 0),-) \mathrm{S}(\mathrm{HH}, 0)$ |
| BRAJN | $(\leftarrow(-, 0),-\{4\})(B, 0) R$ (EYL, 0$\rangle$ EYC (EYR, 0 ) ( $\mathrm{N}, \mathrm{DX}$ ) |
| BRUCE | ( $-(-, 0),-\{4\})(B, 0) \mathrm{R}$ LWW3! $\mathrm{S}(\mathrm{HH}, 0\rangle$ |
| BUCHANAN | $(\leftarrow(-, 0),-\{4\})(B, 0)$ Y IV2! $\leftarrow \sim(-, 0),-)(K, 0)$ AES N UHA ( $N, D X$ ) |
| BUSINESS | $(\leftarrow(-, 0),-\{4\}\rangle(8,0)$ IH $(Z \backslash 4\},(Z, 0) S)(N$ IX,EN $)$ S (HH,0) |
| BUT | ( $\leftarrow(-, 0\rangle,-\{4\})(B, 0)$ UH! ( $(+(-, 0),-\{4\})(T, 0\rangle, D X)$ |
| BY | $(\leqslant(-, 0),-\{4 ;)(B, 0\rangle$ (AYL, 0$)$ AYCl (AYR, 0 ) |
| CACM | (-,0) S IV (EYL,0) EYC! (EYR,0) S IV AH2 M |
| CAI | (-,0) S IY (EYL, 0 ) EYC (EYR,0) (AYL, O) AYCl (AYR,0) |
| CALCULISS | ( $-(-, 0),-)(K, 0)$ AES! ELA ( $-(-, 0),-)(\mathrm{K}, 0)$ IH3 L IHG S ( $\mathrm{HH}, \mathrm{O}$ ) |
| CAN | $(\leftarrow(-, 0),-)(K, G)(A E \cap 1,143!)(N, D X)$ |
| CAPABILITIES |  |
| $(\leftarrow(-, 0)$, |  |
| CAR | $(\leftarrow(-, 0),-)(K, 0)$ AA! (E.R2\{, 12, 0) ER |
| CARL. | ( $\leftarrow(-, 0),-)(K, 0)$ AA3! ER2 EL3 |
| CARTOGRAPHY | $(\leftarrow(-, 0),-)(K, 0)$ AA3! ER ( $-(-, 0),-)$ T AO ( $-(-, 0),-)(\mathrm{G}, 0)$ ER F IY |
| CASE | $(\leftarrow(-, 0),-)(K, 0)(F . Y L, 0)$ EYC! (EYR,O) S ( $H \%, 0)$ |
| CALISAL | $(-(-, 0),-)(K, 0)$ AO! ( $2\{4\},(7,0)$ S) UH2 EL |
| CEASE | $(-, 0) S[Y!S(H H, 0)$ |
| C.E.I. | (-, O) S (E, H, AA 3) El 2 ! |
| CHARNIAK | $(\leftarrow(-, 0),-)$ SH $(, R$; ER N IY! AE5 $(\leftarrow(-, 0),-\{4\})(K, 0)$ |
| CHECKER | ( $-(-, 0),-) S H\{10] E H!(\leftarrow(-, 0),-)(K, 0)$ ER |
| CHICKING | $(-(-, 0),-) \mathrm{SH}$ EH $(1-(-, 0),-)(\mathrm{K}, 0)(1 \mathrm{~N}, \mathrm{IV}) \mathrm{NX}$ |
| CHESS |  |
| Choose. | $(\leftarrow(-, 0),-) \mathrm{SH}(1 \mathrm{H} 2,0)$ UH! (Z[4), (Z,0) S) |
| CHRISTOPMER | ( $-(-, 0),-)(\mathrm{K}, 0) \mathrm{R}$ IH? S S - T IH (,- 0 ) F ER2 |
| CHUCK | $(\leftarrow(-, 0),-)$ SH\{,10\} AA3! $(\leftarrow-(-, 0),-\{4\})(K, 0)$ |
| CIRCLE | $(-, 0\rangle$ S ( $\mathrm{H}, \mathrm{IX}, \mathrm{O}) \mathrm{ER}(\mathrm{L}(-, 0),-)(\mathrm{K}, 0\rangle \mathrm{EL}$ |
| CIRCUIT | $(-, 0)$ S (IH,0) ER ( $-(-, 0),-)(\mathrm{K}, \mathrm{O})$ UH! ( $(-\langle-, 0),-\{4\})(T, 0), \mathrm{DX})$ |
| CIRCUITS | $(-, 0)$ S ER $(1 .(-, 0),-)(K, 0)$ IX ( $+(-, 0),-) \mathrm{S}(\mathrm{HH}, 0)$ |
| CITE | $(-, 0) S(A Y L, 0)$ AYC! (AYR, 0 ) ( $6-(-, 0),-\{4\})(\mathbb{T}, 0), 0 \times$ ) |
| CITED | $(-, 0)$ S (AYL, 0) AYC! (AYR,0) ( $-(-, 0),-)$ T, DX $)$ IH3 ( $-(-, 0),-)(0,0)$ |
| cites | $(-, 0)$ S (AYL, 0 ) AYC! (AYR,0) (- (-,0),-) S (HH,0) |
| CLIMBING | ( $-(-, 0),-)(K, 0) \perp(A Y L, 0)$ AYC! (AYR,O) M IHS NX |
| CLUSTERING | $(\leftarrow(-, 0),-)(K, 0)$ L UH2! 5 - T ER ( H ( $3, \mathrm{IY}$ ) NK |
| CMII | $(-, 0)$ S IY EH2 M! Y \{ $\mathrm{IH} 4, \mathrm{Q}$ ) UW2 |
| CODE | $(1-(-, 0),-)(K, 0)$ OWW! ( $-(-, 0),-)(0,0)$ |
| CODING | $(\leftarrow(-, 0),-)(K, 0)(1) \cup!(\leftarrow(-, 0),-)(0,0 X)(\mathrm{H} 3, \mathrm{IY}) \times \mathrm{NX}$ |
| COGNITION | $(\leftarrow(-, 0),-)(\mathbb{K} 0)$ AA3 $(\leftarrow(-, 0),-)(G, 0)$ N IH3! SH IHS N |
| COGNITIVE | $(\leftarrow(-, 0),-)(K, 0)$ AA3! ( $\leftarrow-(-, 0),-, 0)$ N,DX) IH4 ( $(\leftarrow(-, 0),-)$ T, DX $)$ IH4 V (F,0) |
| COLBY | ( \& (-, 0),-) (K,0) OW'3! E.L. $3(+(-, 0),-(4\})(B, 0)$ IY |
| COLES | $(\sim(-, 0),-)(K, 0)$ OW EL ( $Z\{4\}, 17,0)$ S $)$ |
| COLLINS | $(\leftarrow(-, 0),-)\langle\mathrm{K}, 0)$ AO EL3 UH2 $\mathrm{N}(\mathrm{Z}\{4\},(\mathrm{Z}, 0) \mathrm{S})$ |
| COM作. | $(\leftarrow(-, 0),-)$ (K,0) AA5! M |
| COMPEIVIS | ( $-(-, 0),-)(K, 0)$ AA M EH2! $\mathrm{N}(\ldots-(-, 0),-) \mathrm{S}(\mathrm{HH}, 0)$ |
| COMMITTEE |  |
| COM1MON | $(-(-, 0),-)\left(K_{1}(1)\right.$ AA M AX $(N, D X)$ |
| COMMIUNICATION |  |
| COMAMUNICATIONS $(\leftarrow(-, 0),-)(k, 1)$ AH M UW N IH ( $\leftarrow(-, 0),-)(K, 0\rangle$ (EYL, 0 ) EYC! (EYR,0) SH IH5 N ( $2\{4\},(2,0)$ S) |  |
| COMPI.I. K | $(\leftarrow(-, 0),-)(K, 0)$ AA M ( $-(-, 0),-, 0)$ (PL,PLL (L,0) ) EH ( $\leftarrow(-, 0),-) \mathrm{S}(\mathrm{HH}, \mathrm{O})$ |
| COMPITEITY |  |
| COMPONENTS | $(\leftarrow(-, 0),-)(K, 0)$ AX M $\leftarrow(-,-0),-, 0)$ P OW N AX $N\{\leftarrow(-, 0),-) S(H H, 0)$ |
|  |  |
| COMPUTATION | $(-(-, 0),-)\left(K_{1}(0)\right.$ AA! M ( $\left.-(-, 0),-0\right)$ P $1133(1-(-, 0),-)$ T (EYL, 0 ) EVC (EYR, 0 ) SH IH5 N |
|  |  |
| COMPISTER |  |
| COMPIJTERS |  |


| COMPITILS |  |
| :---: | :---: |
| CONCEPTUAL | $(\leftarrow(-, 0),-)(K, 0) A X N S E H(+(-, 0),-)$ SH\{,10\} UW EL. |
| CONCERN | $(\leftarrow(-, 0),-)(K, 0)(1 / 7, I H 3)$ N S ER! ( $\mathrm{N}, \mathrm{OX}$ ) |
| CONCERNED | $\left.(\leftarrow)(-, 0)_{-}\right)(K, 0)(1 \% 7,1 H 3) N$ S ER! N $(--(-, 0),-)(0,0)$ |
| concerning | ( $-(-, 0),-$ ) (K,0) ( $1 H 7,1 H 3) N$ S ER! N IH5 NX |
| CONCURRENT | $(\leftarrow-(-, 0),-)(K, 0)$ IH5 $N(1-(-, 0),-)$ K! ER EH2 $N((+-\{-, 0),-\{4\})(T, 0), D X)$ |
| CONFERELICE | ( $+(-, 0),-)(K, 0)$ AA! $N(-, 0)$ F ER IHG S S (HH,0) |
| CONFERELICES | ( $-(-, 0),-)(K, 0)$ AA! $N(\ldots, 0)$ F ER IHG N S IH4 S ( $\mathrm{HH}, 0)$ |
| CONFINE | $(1-(-, 0),-)(K, 0)(H 17,1 H 3) N F!(A Y L, O)$ AYC (AYR, 0 ) (N,DX) |
| CONSIDER | $(\leftarrow(-, 0),-)(K, 0)$ IH3 N S IH3! ( $¢$ ( $(-, 0),-)(0,0), 0 \mathrm{O})$ ER |
| CONSIDERED |  |
| CONSTRAINT |  |
| CONSTRUCTING |  |
| CONSTRUCTION |  |
| CONSULTANT | $(\leftarrow-(-, 0),-)(K, 0) 147!N S A O E L(\leftarrow(-, 0),-)$ T IHG $N(\leftarrow(-, 0),-)(0, T)$ |
| CONSULTATION | $(\leftarrow(-, 0),-)(K, 0)$ AA N S EL3 $\uparrow(-(-0),-)$ T (EYL, 0$)$ EYC (EYR,0) SH IH5 N |
| CONSULTATIONS |  |
| CONTAIN |  |
| CONTAINED |  |
| CONTAINS |  |
| CONTEXT |  |
| CONTIMUOUS | $(-(-, 0),-)(K, 0)$ IHS! N (1- (-, () ),-) T IH3 N Y UH2 AHIS (1HH,0) |
| CONTROL |  |
| controllen | $(\leftarrow(-, 0\rangle,-)(K, 0)\langle 1 才\rangle, H 3) \times(1-(-, 0),-)\langle T, S H\{10\})$ R OW $(E 1,0)\langle\leftarrow(-, 0),-)(0,0)$ |
| CONVENTICN |  |
| CORVENIICANG |  |
| COOPl:RATHG |  |
| COOPERAIION |  |
| COPY | $(-(-, 0),-)(K, 0)$ AA! ( $-(\ldots, 0),-)$ P IV |
| COPYIHG |  |
| conrtcinness |  |
| could | ( $-(-, 0),-)(\mathbb{K}, 0)$ (fH! ( $-(-, 0),-)(0,0)$ |
| CURRRENT |  |
| CURVFIS | $(1-(\cdots, 0),-)(k, 0)$ UliA! CR (F,V) < $-(-, 0),-)(0,0)$ |
| CVEBERNETICS |  |
| creouc |  |
| DANNY | $((-)-, 0\rangle,-)(0,0), D \mathrm{D})$ AEA! N IY |
| DATA |  |
| date |  |
| DATES |  |
| DAVE | $((-)(-0),-)(0,0), D X)(E Y L, O)$ EYCI (EYR, 0 ) $\vee(F, 0)$ |
| DAVID ( |  |
| debate |  |
| DECEMAER |  |
| DECISION | $((\leftarrow)(-, 0),-)\langle(0,0)$, DX $)$ IH2 S IH $(\leftarrow(-, 0),-)$ SHIHSN |
| DEDUCTION ( |  |
| DEOUCTIVE ( |  |
| DEMAND ( | $($ ( $\leftarrow(-, 0\rangle,-)(0,0), D \mathrm{C})$ IH! M AEA $\mathrm{N}(\leftarrow(-, 0),-)(0,0)$ |
| DENOTATIONAL ( |  |
| DEPTH ! | $((\leftarrow)(-, 0\rangle,-)(0,0), D X)$ EHA $(\ldots-(-, 0),-)$ TH (HH,O) |
| DERIVATION ( | $(¢ \leftarrow(-, 0),-)(0,0\rangle, D X)$ IH, ER (IH,0) $\vee$ (EYL,O) EYC (EYR, 0 ) SH! IH5 N |
| DESCRIBE ( | $((\leftarrow)(-, 0),-)(0,0), D X)$ IH4! S - (K,WH, (0) R (AYL, 0 ) AYC (AYR, 0 ) B |
| DESCRIPTION ( | $((+-(-, 0),-)(0,0)$, DX $)$ IHAS S ( $\mathrm{K},(0)$ R IH2 $(t-(-, 0),-)$ SH IHS N |
| DESCRIPTIONS ( | $((\leftarrow)(-, 0),-)(0,0)$, DX) IX S - (K,0) R IH ( $-(-, 0),-)$ SH IH5 N ( $\mathrm{Z}\{4\}(\mathrm{Z}, 0) \mathrm{S}$ ) |
| DESIGN ( |  |
| DESIRE (C | $((\leftarrow)(-, 0),-)(0,0), D X)(\$ H, I Y)(Z\{4),(Z, 0)$ S) (AYL, 0 ) AYC! (AYR, 0 ) ER |
| DETECTION ( | $((\sim-(-, 0),-)(0,0), D X)(1), I Y)(+-(-, 0),-)$ T FH! $(\leftarrow(-, 0),-) S H$ IHS N |
| DEVICES ( |  |




| EXPLAPATION |  |
| :---: | :---: |
| EXPRESSIONS | $(-, 0)$ ]H3 ( $1-(-, 0),-)$ S - \{P R,PR (R, 0$\rangle)$ EH3! SH (IH5 N,EN) (Z $(4),(\mathrm{Z}, 0) \mathrm{S})$ |
| FABLES |  |
| FACES | (-, ()) F (EYL,0) EYC! (EYR,0) S IHA ( $2\{4\},(Z, 0)$ S) |
| FACTS | $(-, 0)$ F AE! ( $\sim(-, 0),-) S(\mathrm{HH}, 0)$ |
| FAILIMAN | $(-, 0)$ F AO EL? M UHA ( $\mathrm{N}, \mathrm{D}$ ( $)$ |
| FAIRY | (-,0) F EH! (ER,R) IY |
| FASTER | (-,0) F AE3! S - T ER |
| FEATIIRT-DRI | EN(-,0) F IV ( $-(-, 0),-)$ SHf, 10) ER! ( $\leftarrow(-, 0),-)$ DR R IH $V(($ IH,IX) N $)$, EN $)$ |
| FEBRUARY | $(-, 0)$ F EH3! ( $-(-, 0),-(A)$ ) ( $B, 0)(R, Y)$ (UW (W,0),0) AA (ER,R) IY |
| FEDERAL | $(-, 0)$ F EH! ( $(-(-, 0),-)$ D, DX $)$ ER2 EL3 |
| FEIGEENGAIM | $(-, 0)$ F (AYL,0) AYC (AYR,0) (- $(-, 0),-)(G, 0)$ IH5 $N\left(-(-, 0)_{1}-0\right)(B, 0)$ (AWL,0) AWC! (AWR,0) M |
| FEICMAN | $(-, 0)$ F EH2! EL $(\leftarrow(-, 0),-)$ M IHG (N,DX) |
| FICTION | $(-, 0)$ F JH2 ( $+(-, 0),-)$ SH! IHS N |
| FIFTEEN | $(-, 0)$ F Ill 2 ! $\mathrm{F}(6,-(-, 0),-) \mathrm{T}, \mathrm{DX})$ IY ( $\mathrm{N}, \mathrm{DX}$ ) |
| FJFTY | $(-, 0)$ F IH2! F ( $(-(-, 0),-)$ T, DX $)$ IY |
| FIKES | $(-, 0)$ F (AYL, 0 ) AYCi ( $\mathrm{AYR}, \mathrm{O}$ ) (- (-,0),-) S (HH,0) |
| FILE | (-,0) F (AYL,0) AYC! (AYR,0) EL3 |
| FINISH | (-,0) F IH3! N [H5 SH $(\mathrm{HH}, \mathrm{O})$ |
| FINISHED | $(-, 0\rangle$ F IH3! N IH5 SH - $\{4\}$ ( 7,0$\rangle$ |
| FIRST | (-,0) F (AA3 ER,ER? ) S! - [A? (T,0) |
| FIVE | $(-, 0)$ F (AVL,O) AYC! (AYR, O) ( $V, F$ ) |
| FOR | $(-, 0)$ F ( $A, 4,0)$ ER! |
| FORESTS | (-,0) F AA2 ER! IH S - S (HH,0) |
| FORMAL | $(-, 0)$ F ANA! ER? $(\mathbb{1},(1)$ EL? |
| FORMATION | $(-, 0)$ F AAA ER M (EYL, O) EYC! (EYR, 0 ) SH IH5 N |
| FORTY | $(-, 0)$ F AAA! (ER,ERY? ) ( 6 - (-,0),-) T, DX $)$ IY |
| FOUR | $(-, 0)$ F AAA! ER |
| FOURTEEN | $(-, 0)$ F AAB! ER ( $(-)(-, 0),-)$ T, DX ) IV ( $\mathrm{N}, \mathrm{OX}$ ) |
| FRAME | (-,0) F R (E.YL,O) EYC! (EYR,0) M |
| FRAMES | $(-, 0) F R(E Y L, 0)$ EYC (EYR, 0 ) M ( $Z\{4\},(Z, 0) \mathrm{S})$ |
| FROM | $(-, 0)$ F R All! $M$ |
| FLJ | (,- 0 ) F UW2! |
| FUNCTION | (-,0) F AN! NX $(+\{-, 0),-, 0)$ SH IHS N |
| FUNCTIONS | (-,0) F AA! N: $(+(-, 0),-0)$ SH IHS $N(Z, 4\},(Z, 0)$ S) |
| FIJZZY | (,- 0 ) F UH2! ( $Z(4\},(Z, 0)$ S) IY |
|  | ( $-(-, 0),-)(G, 0)$ (E.YL,O) EYC! (EYR,0) M |
| GAMPES | $(\leftarrow(-, 0\rangle,-)\langle G, 0)\langle$ (EYL, 0$\rangle$ EVC! (EYR,0) M ( $Z\{4\},(\mathrm{Z}, 0\rangle \mathrm{S})$ |
| GARY | $(\leftarrow(-, 0),-)(6,0)$ AER! ER IY2 |
| gaschinig | $(\leftarrow(-, 0),-)(6,0)$ AES SH N IH3 $(\leftarrow(-, 0),-\{4\})\langle K, 0\rangle$ |
| GENERAL | $(\leftarrow(-, 0),-)$ SH\{,10) EH? N [R2! EL3 3 |
| GENERATE | $(\leftarrow(-, 0\rangle,-)$ SH, 10] EH2 N ER (EYL, 0$\rangle$ EYC! (EYR, 0 ) ( $¢ \leftarrow(-, 0),-\{4\})(T, 0), \mathrm{DX})$ |
| GENERATION | $(\leftarrow(-, 0),-)$ SH\{, 10$\}$ Ill 45 N ER (EYL, O) EYC! (EYR, 0 ) SH IHS N |
| geometrle: |  |
| ge.orge | $(\leftarrow(-, 0),-)$ SH, 10! LIWA ER! ( $\leftarrow(-, 0),-)$ SH $\left.H_{1}, 10\right\}$ |
| GET |  |
| GIPG |  |
| gIVE | $(\leftarrow(-, 0),-)(G, 0)$ iH2! (F,V (F,O) |
| GIVEN | $(\sim(-, 0),-)(G, 0)$ IH3! $\vee \cup \cup 1 / n(N, 1) X)$ |
| GM | ( $-(-, 0),-$ ) SH4, 10: IY! F.H2 M |
| 60 |  |
| GO-mokU | ( $(-(-, 0),-)(G, 0)$ OW M 1 )W! ( $-(-, 0),-)(K, 0)$ UW |
| GOAL | (r. $(-, 0),-)\langle(6,0)$ OWI El |
| GOALS |  |
| GRAIN | ( $-(-,-0),-)(6,0)$ R (EVL,O) EVC! (EYR,O) ( $N, D X$ ) |
| GRAMIMARS | $(\leftarrow(-, 0),-)(6,0)$ R AESS M ER! ( $Z\{4\},(2,0) \mathrm{S}$ ) |
| GRAMMATICAL | $(r-(-, 0),-)(G, 0)$ ER M AE! ( $(\leftarrow(-, 0),-)$ T, OX) IH8 $\langle\sim(-, 0),-\{4\})(K, 0)$ EL |
| GRAPH | $(\leftarrow(-, 0),-)(G, 0)$ R AE3! $\mathcal{F}(H H, 0)$ |


| GRAPHICS |  |
| :---: | :---: |
| Havizurg | $(-, 0)(H H, 0)$ AA! M ( $-(-, 0),-, B)(B, 0)$ ER2 $\ll(-, 0),-)(G, 0)$ |
| HAN'S | $(-, 0)(H H, 0)$ AA! $N(-, 0)$ S ( $\mathrm{HH}, 0)$ |
| HAPPEN | $(-, 0)(H H, 0)$ AE! ( $\leftarrow(-, 0),-)$ P EH2 ( $\mathrm{N}, \mathrm{DX}$ ) |
| HARRY | $(-, 0)$ ( $\mathrm{HH} 2, \mathrm{HH}$ ) AE2! (ER,R) IYZ |
| HAS | (-,0) (HH,HH2,0\} AEA! ( $Z\{4\},(\mathrm{Z}, 0) \mathrm{S})$ |
| HASNT | $(-, 0\rangle(H H, H H 2,0\rangle$ AE! (Z, 4$\},(\mathrm{Z}, 0) \mathrm{S})$ JH6 $\mathrm{N}(1+(-, 0),-\{4\})(T, 0), D \mathrm{C})$ |
| HAVE | $(-, 0)(H H, H M 2,0\rangle(A E!, A E S!) \vee(F, 0\rangle$ |
| HAVEV'T |  |
| HAYESS-ROTH |  |
| HE | $(-, 0)(H H, H H 2,0)$ IY! |
| HEARSAY | $(-, 0)(H H, H H 2,0)$ IY2 ER (,- 0 ) S (EYL,0) EYC! (EYR,0) |
| HET.O | $(-, 0)(H H, 0)$ AA3! Flia ( $-(-, 0),-)(P, 0)$ |
| HEWDRIX |  |
| HE: |  |
| HERIS | $(-, 0)(H B, 0)$ ER! ( $\leftarrow(-, 0),-\left\{A^{3}\right)(B, 0)$ |
| HE:REERT | $(-, 0)(H H, 0)$ ER P! ( $1-(-, 0),-\{4\})(8,0)$ ER ( $1+(-, 0),-\{4\})(T, 0), D \times\}$ |
| hillerostatic | $(-, 0)\langle H H, 0\rangle$ EH $(+(-, 0),-)$ DR R OW S - T AE ( $(-(-, 0),-)$ T, DX $)$ IH3 $(\leftarrow(-, 0),-)(K, 0)$ |
| HeUlisistic |  |
| HEWSIT | $(-, 0\rangle(H H, H H 2,0)$ Y UW IIAA $\left(\leftarrow(-, 0)_{1}\right)(\mathrm{T}, 0)$ |
| HILARY | (-,0) (HH1,HH2,0) EL, 3 ER! IV2 |
| H1LL. | $(-, 0)($ HH, HH2,0) AH3! EL, |
| HIS | $(-, 0)(\mathrm{HH}, 0) \mathrm{H} 3 \mathrm{l}$ ( $\mathrm{Z}: 4,1,(\mathrm{Z}, 0) \mathrm{S}$ ) |
| HISTORY | (-,0) (HH,0) ]H3! S - DR ER IY |
| HOLLALD | $(-, 0)($ HH, 0 ) AA! EL.3 EN $(-(-, 0), \ldots, 0\rangle\langle 0,0)$ |
| How | $(-, 0)(H H, H H 2,0)$ (AWL., ()) AWCl (AWR,0) |
| mught | $(-, 0)$ (HH,HH2,0) 1 H 2 UH? |
| HIJMAN |  |
| HUNDRED | $(-, 0)(H H, 0)$ (AA5!,An2!) $N(1-(-, 0),-)(0 R, 0,0)$ ER $(+-(-, 0),-)(0,0)$ |
| HUNGRY | $(-, 0)$ (HH,0) UH2! NX ( $-(-, 0),-)(G, 0)$ R IY3 |
| HUNT | $(-, 0)(H H, 0)$ UH2! $N((\leftarrow)(-, 0),-\{4\})(T, 0), D X)$ |
| HVPOTHESIS |  |
| I | $(-, 0)(A Y L, 0)$ AYCl (AYR, 0 ) |
| I'D | $(-, 0\rangle\langle A Y L, 0)$ AYC! (AYR. 0$\rangle\langle\leftarrow(-, 0),-)\langle 0,0\rangle$ |
| 1'M | (-,0) (AYL,0) AYC! (AYR,AYY,0) M |
| IEEE: | $(-, 0)(A Y L, 0)$ AYC (AYR, 0 ) ( $\leftarrow(-, 0),-)$ T,DX) R IH! ( $\leftarrow(-, 0),-) P(E L, A X E L) ~ I Y$ |
| IFIP | $(-, 0)(A Y L, 0)$ AYC! (AYR,0) F IH2 ( $-(-, 0),-)(P, 0)$ |
| IJCAI |  |

IJCAI
$(-, 0)$ (AYL,O) AYC (AYR, (0) ( $-(-, 0),-)$ SH $(, 10)$ (EYL,O) EYC! (EYR,0) S IY (EYL,O) EYC (EYR,0) (AYL,O) AYC (AYR,O)
ILLINOIS $\quad(-, 0)$ IHZ ELS UHA N (OYL,O) OYC! (OYR,O)
ILAGE $\quad(-, 0)$ EH2 M! IH $3(+(-, 0),-)$ SH\{, ;

IMPRDVING $\quad(-, 0)$ IH3 M $\leftarrow(-, 0), \ldots, 0)$ P! R $(I H, 0)$ UW! $\vee(1 H 3, I Y) N K$
IN
$(-, 0)(1 \mathrm{HH}, \mathrm{J}(\mathrm{S}, \mathrm{IX})(\mathrm{N}, \mathrm{DX})$
INDUCTIVE (-,0) IHA $\mathrm{N}(\leftarrow(-, 0),-, \mathrm{D})\langle\mathrm{D}, 0)$ AA3 $(\leftarrow(-, 0),-)$ T IH2 $\vee(\mathrm{F}, 0\rangle$
INDUSTRIAL $\quad(-, 0)$ IH4 $\mathrm{N}(\leftarrow(-, 0\},-, \mathrm{D})(\mathrm{D}, 0)$ AA2! $\mathrm{S}-\mathrm{DR}(\mathrm{R}, 0)$ IH2 EL3
INEXACT
INFFRELICE.
$(-, 0)$ IH5 N IH3! $(-(-, 0),-)(Z\{4\},(Z, 0)$ S) AE $(\{-(-, 0),-\{4\})(T, 0), 0 X)$
(-, (0) JH3 NF! R HKG N S (Hill,o)

INFEREWTINL (-,0) IH3 NF ER?! EH2 NSHEL
INFORMATION (-,0) IH3 N F ERZ M (E:YL,O) EVC (EYR,O) SH! IHS N
INHERITAKCE
$(-, 0)$ IH3 N (HH1,HH2,0) [H3 ER! IH2 ( $1-(-, 0),-)$ T IH4 N S $\langle H H, 0\rangle$
INSARE:
institure
intelligence
INTELIIGENT
INTENSITY
(,- 0 ) IH3 N S (E.YL, 0) EVC! (EYR,0) (N,DK)
$(-, 0)$ IH3 N S - T IHA ( $-(-, 0),-)$ T UW3! $(<+(-, 0),-\{4\})(T, 0), D X)$
(-, © ) $1113 \mathrm{~N}\left((\leftarrow(-, 0),-)\right.$ T,DX) EH EL $1 H G^{\prime}(-(-, 0),-)$ SH IH3 N S $(H H, O)$
$(-, 0)$ )H3 $N((\leftarrow(-, 0),-)$ T,DX) EH EL IH6! ( $-(-, 0),-)$ SH IH3 $N(\leftarrow(-, 0),-)(0, T)$
INTENTIONS $\quad(-, 0)$ IH5 $N(\leftarrow(-, 0),-)$ T EHTR NSHIHS $N(Z\{4 ;,(Z, 0\rangle S)$


| learning | (-, ©) L2 ER! N 1 H7 NX |
| :---: | :---: |
| lectures |  |
| LEE. | $(-, 0)$ L IY! |
| LFNAT |  |
| LEONARD | $(-, 0)$ L AA2 EN ${ }^{\text {P }}$ ( ( $\left.\left.-(-, 0),-\right)(0,0), D X\right)$ |
| LES | $(-, 0)$ L UHA! 5 ( HH,0) $^{(1-0)}$ |
| Lessea | $(-, 0)$ L AHIS ER2. |
| LET | $(-, 0)$ L AH2! ( $(6)(-, 0),-\{9 ;)(T, 0), D \mathrm{C})$ |
| LET'S | $(-, 0)\llcorner$ AH2! ( $\leftarrow(-, 0),-)$ S $(H H, 0)$ |
| LEXICOMETRY | $(-, 0)$ L EH ( $-(-, 0),-)$ S IH2! ( $\leftarrow(-, 0),-)(\mathrm{K}, 0)$ AA M UHA ( $\leftarrow(-, 0),-)$ DR R IY2 |
| LIGHT | $(-, 0)$ L (AYL, 0$)$ AYC! (AYR,0) ( $<-(-, 0),-\{4\})(T, 0), D \mathrm{C})$ |
| LIKE | $(-, 0) \mathrm{L}$ (AYL, 0 ) AYC! (AYR,0) ( $-(-, 0),-\{4\})(\mathrm{K}, 0)$ |
| LIMIT | $(-, 0)$ L IH M UH4! ( $(-$ (-, 0), -\{4\}) (T, 0), DX) |
| LIMITED | $(-, 0)$ L IH M UHA! ( $(-4-0),-)(T, 0,0), \mathrm{DX})$ IH4 $(\leftarrow(-, 0),-)(0, D)$ |
| LINDA | $(-, 0)$ L IHG $\mathrm{N}!(6-(-, 0),-, \mathrm{D}\rangle(\mathrm{D}, 0) \mathrm{UH} 4$ |
| LINE | $(-, 0) \mathrm{L}$ (AYL, O) AYC! (AYR, 0 ) (N,DX) |
| LINEAR | $(-, 0) \mathrm{L}$ IH3' N IY ER |
| LINGUISTICS | (-,0) L. IH3 NX $4+(-, 0),-)$ WH IH S - T IH3 ( $-(-, 0),-) \mathrm{S}(\mathrm{HH}, 0)$ |
| L.ISP | (-, (1) L LHG! S - (P,0) |
| LIST | $(-, 0)$ L IHGI ( $2(4,3,3,0) \mathrm{S})(-(T, 0), 0)$ |
| LISTED | $(-, 0)$ L IHGI $5-\mathrm{T}(\mathrm{IX}, \mathrm{IHS})(\mathrm{L}(-, 0),-)(0, \mathrm{DH}, 0)$ |
| LISTING | (-,0) 1 UH4 S - T! (IH3, WV) NX |
| LOCATION |  |
| L.OCATIONS |  |
| logic |  |
| logical |  |
| long | $(-, 0)$ L2 OWA! NX |
| LOSING |  |
| low | $(-, 0)$ L OW |
| MACHINE | ( - , 0) M IH5 SH! IV (N, (0X) |
| MACHINES | (-,0) M JHf SH! IY N ( $2: 4,(2,0)$ S) |
| MACRO) | $(-, 0) \mathrm{M}$ Afs $(\leftarrow-(-, 0),-)(k, 0) \mathrm{R}$ DW |
| MADEIINE | $(-, 0)$ M AE! ( $(+-(-, 0),-)(0,0), D X)$ AH EL IHO (N,DX) |
| MAGSAZINES |  |
| MAKE |  |
| MANAGEMENT |  |
| maimpulating |  |
| MANIPULATORS |  |
| MANNA | $(-, 0)$ M AA! N NA |
| mantra | $(-, 0) \mathrm{M}$ ^() N! $\{\leftarrow(-, 0),-)$ DR R IH2 |
| MANV |  |
| MAPPPING | $(-, 0) \mathrm{MAES}(\leftarrow(-, 0),-) \mathrm{P}(1 \mathrm{H} 3, \mathrm{IV})$ NX |
| MARCH | (-.0) M AA! R ( $-(\ldots, 0),-)$ SH ( $H \mathrm{H}, 0$ ) |
| market |  |
| MARR | $(-, 0)$ M AA! ER2 |
| MARSLAND | $(-, 0) \mathrm{M}$ AO ER ( $Z\{4,4,(2,0)$ S) L UH4! $N(\leqslant(-, 0),-, 0\rangle\langle 0,0)$ |
| martelli | (-,0) M ER2' ( ¢ (-, 0) ,-) T ELS İ\% |
| MARVIN | $(-, 0)$ M AA R ! V IH ( $N,($ OX $)$ |
| MARY | (-,0) M AE2! ER IY2 |
| MASINTER | (-,0) M UHA S EH?! N (<- (-,0),-) T, OX ) ER |
| MASSACHUSETTS |  |
| matching | $(-, 0) \mathrm{MAFS5}(-(-0),-)$ SH, 10) 1H5 NX |
| MAY | (-,0) $M$ (EYL, (0) EYC EYR! |
| mecartiv | (-,0) M AAS (- (-,0),-) (K,0) AA3! ER2 TH IY |
| MCCORDULK |  |
| MCOERHOTTT | $(-, 0) \mathrm{M}$ IH3 $(\leftarrow(-, 0),-)$ DR ER M EH4 $(\leftarrow(-, 0),-)(\mathrm{T}, 0)$ |
| ME. | $(-, 0) \mathrm{M}$ IY! |
| MEANJIS | $(-, 0)$ M IV N! (1H3,IV) NX |



| NEWEY | $(-, 0) N(1) H A, 0\rangle$ UW! IV |
| :---: | :---: |
| NEWSLETTER | $(-, 0)$ N IH5! (UW 3,0$\rangle(7!4\},(2,0)$ S $)$ L EH2 ( $(-(-, 0),-)$ T, DX ) ER |
| NEXT | $(-, 0)$ N Elll ( $\leftarrow(-, 0),-) \mathrm{S}-(\mathrm{T}, 0)$ |
| NHH | $(-, 0)$ EN ( $A Y L, 0)$ AYC! (AYR,0) (EYL, 0 ) EYC (EYR,0) (- (-,0),-) SH (HH,0) |
| NJLS | (,- 0$)$ N IH3! EL ( $Z\{4\},(7,0) 5$ ) |
| NHSSSON | $(-, 0) N$ IV EL3! $(-, 0)$ S UHO ( $\mathrm{N}, \mathrm{D} \mathrm{X})$ |
| NINE | $(-, 0) N(A Y L, 0) A Y C ~(A Y R, 0) ~ N!$ |
| NJweleen | $(-, 0) N(A Y L, 0)$ AYC (AYR, 0 ) $\mathrm{N}(1-(-, 0),-)$ T,DX) IY! ( $\mathrm{N}, \mathrm{DX}$ ) |
| NJNETY | $(-, 0) \times(A Y L, 0)$ AYC (AYR,0) $N((-2-, 0),-)$ T,DX) IY! |
| NO | $(-, 0)$ N OW4! |
| NOMINATING | $(-, 0)$ N AA M UH N (EYL, 0 ) EYC! (EYR,0) ( $(+(-, 0),-) \mathrm{T}, \mathrm{OX})(\mathrm{IH} 3, \mathrm{IV}) \mathrm{NX}$ |
| NOMINATION | $(-, 0) N$ AA M UH N (EYL,0) EYC! (EYR,0) SH IH5 N |
| NOMINEES | $(-, 0) N$ AA M LUH! $N$ IY ( $2 ; A ;,(Z, 0)$ S) |
| NON-INDEPENDEWT |  |
| NONDETERTMINIS |  |
| $(-, 0) N$ A |  |
| NORI | $(-, 0) N$ A A 4 ER2 IY |
| NORIMAN | $(-, 0)$ N OW4! ER2 M UH ( $N$, DX) |
| NOT |  |
| NOTES | $(-, 0) \mathrm{N}$ OW! $(\leftarrow(-, 0),-$ ) S ( $\mathrm{HH}, 0,0$ |
| NOVEMBIER | $(-, 0) \mathrm{N}$ OW! $\vee$ EH3 M ( $-(-, 0),-\{4\})(B, 0)$ (ER, A $1+3$ ) |
| NRL | (-,0) (F.H N,EN) AA3 ERR! EH EL |
| OB.JECT |  |
| OB.ISC.TS |  |
| october | $(-, 0)$ AA2 ( $(+-(-, 0),-) \mathrm{T}, \mathrm{DX})$ OW! ( $-(-, 0),-\{4\})(\mathrm{B}, 0) \mathrm{ER}$ |
| OF | $(-, 0)(\mathrm{JH}, \mathrm{JHK} 2) \mathrm{V}$ ! |
| OHLANDER | $(-, 0)$ OW El. 2 ! AE4 $\mathrm{N}(\mathrm{l}-(-, 0),-) \mathrm{D}, \mathrm{DX}) \mathrm{ER}$ |
| OK | $(-, 0)$ OW ( $-(-, 0),-$ ( $K, 0$ ) (EYL, 0 ) EYC! (EYR,0) |
| OLDEST | $(-, 0)$ OW! El. ( $(\leftarrow(-, 0),-)(0,0), D \mathrm{C})$ IHGS -\{4\} (T,0) |
| ON | $(-, 0)$ AA2! ( $\mathrm{N}, \mathrm{DX}$ ) |
| ON-LINE | (-,0) AA N L. 2 (AYL, O) AYC! (AYR,0) ( $\mathrm{N}, \mathrm{DX}$ ) |
| ONE | (-,0) W AAA! (N, DK) |
| ONES | (-, (1) W AA! N ( 2 [4;, 7,0$)$ S) |
| ONLY | $(-, 0)$ OWA! N2 L2 IY |
| ONTOGENY |  |
| OPERATIDNAL |  |
| OPrimal | $(-, 0)$ AA ( $(-(-, 0),-)$ T, DX') IHG M P F. 2 ? |
| OPTIMIEES |  |
| OR | (-,0) (OW'3,AAA, (1) \{R?! 5,14$\}$ |
| ORDER | $(-, 0)$ UWA ER! ( $(1-(-, 0),-)$ D, DX $)$ ER |
| ORDERS | $(-, 0)$ UW4 ER! ( $\left(1-\langle-, 0)_{,-}\right.$) D,DX) ER ( $Z_{4}(4,(Z, 0)$ S) |
| ORCANJZATION | $(-, 0)$ AAA ER ( $-(-, 0),-)(6,0)$ IH3 N IH6 ( 2,4$\},(2,0)$ S) (EYL,0) EYC! (EYR,0) SH IH5 N |
| ORIENTED | $(-, 0)$ UWA ER2! IY EH2 $\mathrm{N}($ ( $1-(-, 0),-)$ T, OX $)$ IHA $(+(-, 0),-)(0,0)$ |
| OUR |  |
| OURSEEVES |  |
| OVERI.AYS | (-,0) OW V ER L (EYL, ) EYC (EYR,0) ( $2\{4\},(\mathrm{Z}, 0) \mathrm{S})$ |
| PACKET |  |
| PAIR | (- ( $-0,0$,-) P EH: ER |
| PARMELA |  |
| PAPER | $(\leftarrow(-, 0),-) P(E Y L, O)$ EYC! (EYR, 0 ) ( $-(-, 0),-)(P, 0)$ ER2 |
| PAPERS | ( $-(-, 0),-) P(E Y L, 0\rangle$ EYC! (EYR, 0 ) ( $-(-, 0),-)(P, 0\rangle$ ER ( $Z\{4\},(Z, 0)$ S) |
| PAPERT | $(\leftarrow(-, 0),-)$ P AE3! ( $-(-, 0),-)(P, 0\rangle$ ER $(\leftarrow(-, 0),-)(T, 0)$ |
| parallel.isin |  |
| PARANOIA | ( $-(-, 0),-)(P, 0)$ ER LUH N (OYL, O) OVC! (OYR,0) IH2 |
| PARAPHRASE | ( $\leftarrow(-, 0),--)$ P AE2 ER (AX,0) F R (EYL,0) EVC! (EYR,0) ( $Z\{4\},(2,0) \mathrm{S})$ |
| PARRY | $(\leftarrow(-, 0),-)$ P AE2 ER! JV2 |
| PARTIAL | (* (-,0),-) P AR3 ER SHi, 10 ] IH EL |


| PASCAL | (- (-, 0) , - ) P AEA! S - (K, (1) AE. EL3 |
| :---: | :---: |
| PAT | $(\leftarrow(-, 0),-) P$ PE! ( $(+(-, 0),-\{4\})(T, 0), 0 \mathrm{X})$ |
| PATHFINDER |  |
| PATtERN | $(\leftarrow(-, 0),-) P$ AES! ( $D X,((4+(-, 0),-) \mathrm{T}, \mathrm{DK})$ ) $\mathrm{ER}(\mathrm{N},() \mathrm{X})$ |
| PEARL. | $(\sim(-, 0),-)\langle P, 0\rangle$ ER2! Fl.? |
| PrRCEPTION | ( $-(-, 0),-)(P, 0)$ E.R S EHA! ( $\leftarrow(-, 0),-)$ SH\{, 10$\}$ LH5 N |
| PERCEPTRONS | $(\leftarrow(-, 0),-)(P, 0)$ ER S EHT ( $\leftarrow(-, 0),-)$ OR R AA $N(Z\{4),(Z, 0) S)$ |
| PERFORMAILCE | ( $-(-, 0),-)(P, 0)$ ER? $F$ AAA! ERT M UH N S (HH,0) |
| PERRY | ( $-(-, 0\rangle,-)$ P E.H3 ER! IY |
| PETER | $(\leftarrow(-, 0),-) P$ IV! $((+-(-, 0),-) T, D X)(E, H 3,0)$ ER |
| PHOTOGRAMME |  |
| Phrase |  |
| PHRASES | (-,0) F R (EYL, O) EYC $(E Y R, 0)(Z\{4\},(Z, 0)$ S) IH4 $(Z, 4\},(Z, 0)$ S) |
| Phiysicians |  |
| PIC:TURE: | $(\leftarrow(-, 0),-)$ P ill $3(\ldots(-, 0),-)$ SH\{, 10) ER |
| Plece: | $\left.(1-(-, 0))_{2}\right)$ P IY!S $(\mathrm{HH}, 0)$ |
| PINGLE | $(-(-, 0),-) P(1143,1 Y) N$ N ( $-(-, 0),-)(6,0) \mathrm{EL} 2$ ! |
| PLANES |  |
| PLANSER-LIKE |  |
| Plakiving | $(\leftarrow(-, 0),-)(P \mathrm{~L}, \mathrm{Pl}(\mathbb{L}, 0)$ ) AE5! ( $\mathrm{DX}, \mathrm{N}$ ) (1/(3,IY) NX |
| PLANS |  |
| Playing |  |
| Plense |  |
| POKE\% | $(\leftarrow(-, 0),-)$ P OW $(1-(-, 0),-)(K, 0) \in \mathbb{R}$ |
| POLYHEDRA | $(\leftarrow(-, 0),-)$ P AO [L. L'H IV SH:, 10 ) ER3 IH? |
| PREDICATE |  |
| PREETERENTIAL |  |
| PRESELIT |  |
| PRICE |  |
| Pruce's |  |
| PRIA,1]TJVES |  |
| PRINT |  |
| PRINTED |  |
| PRINTHGG |  |
| Probleld | $(+(-, 0),-)(P R, P R(R, 0)$ AO $\leftarrow(-, 0),-\{4!)(B, 0)$ EL! M |
| PROBLIEMS |  |
| Proceioukna | $(\leftarrow(-, 0),-)(P, 0)[R 2$ S IY ( $\leftarrow(-, 0),-)$ SH!, 10) ER2! EL. |
| Proceloures | $(\leftarrow(-, 0),-) P(R A X!, E R) S$ IV ( $-(-, 0),-)$ SHi, 10; ER (Z $\{4 ;,(Z, 0)$ S $)$ |
| Procileming | $(\leftarrow(-, 0),-) P(R A X!, E R) \subseteq$ IV $(6-(-, 0),-)(0,0), D X)$ IH!S NX |
| Frocelinincos |  |
| Procressics |  |
| Prockesing | $(\leftarrow(-, 0),-)\langle P R, P R$ (R,0) AAIS IH6S S (Hi3,IY) NX: |
| Produce |  |
| PRODUCF: 0 |  |
| PRODUCTION |  |
| ProDlletivity ( |  |
| PROSRAM |  |
| PROSRAMMING |  |
| PROGRAMS |  |
| Procirss | $(\leftarrow\{-, 0),-\rangle\langle P \mathrm{R}, \mathrm{PR}(22), 0\rangle)$ AO! (- (-,0) ,-) (G,0) R EHA S (HH,0) |
| Proor | ( $-(-, 0),-$ ) (PR,PR (R,0!) UWU! F ( $\mathrm{H} 1 \mathrm{O}, 0$ ) |
| proors |  |
| Prorderes |  |
| PROTOCOL | $(-(-, 0),-)\left(P R, P R(R, 0)\right.$ OW $((1-(-, 0),-) T, O X) O W^{\prime}(-(-, 0),-)(K, 0)$ AO EL |
| Protocols |  |
| PROVER ( | $(\leftarrow(-, 0),-)(P \mathrm{R}, \mathrm{PR}(\mathrm{R}, 09)$ LW2! $\vee$ ER2 |
| PROVING ( | $(\sim(-, 0),-)(P R, P R$ RR,0) UW! $\vee$ H 145 NX |
| PSYCHOLOGY | $(-, 0)$ S (AYL,O) AYC! (AYR,O) ( $-(-, 0),-)(\mathrm{K}, 0) \mathrm{AO}(\mathrm{L}, \mathrm{EL} 3) \mathrm{UH}$ ( $-(-0),-) \mathrm{SH}$ IY |


| PUBLISH | $(\leftarrow(-, 0),-)(P, 0\rangle\langle 1 J H 2, A C)(\leftarrow(-, 0\rangle,-\{4\})(8,0)$ L IHA! SH $(H H, 0)$ |
| :---: | :---: |
| PUBLISHED | $(\leftarrow(-, 0),-)(\mathrm{P}, 0\rangle\langle 1 \mathrm{JHz}, \mathrm{AO})(\leftarrow<-, 0\rangle,-\{4\}\rangle(\mathrm{B}, 0) \mathrm{L} \mathrm{IH} 4!\mathrm{SH}-(\mathrm{D}, 0\rangle$ |
| PUBLISHER | $\left.(\leftarrow(-, 0))_{-}\right)\{P, 0\rangle(13 H 2, \Lambda 0)\{\leftarrow(-, 0),-\{4\})(B, 0)$ L IH2! SH ER |
| PUBLISHERS | $(\leftarrow(-, 0),-)(P, 0)(1 J H 2, A O)(\leftarrow(-, 0),-\{4\})(8,0)$ L IH2! SH ER (Z\{4; ( 2,0$) \mathrm{S})$ |
| PIJRPOSE |  |
| PUTNAM | $(\leftarrow(-, 0),-)$ P AA! $(\leftarrow(-, 0),-)$ N UHA M |
| QUERIES | $(\leftarrow(-, 0),-)$ WH IV3 (ER (R,0),R) IY2! ( $Z(4\},(2,0)$ S) |
| QUESTION | ( $-(-, 0)_{,-}$) W/H EH3! S (-,0) SH IH5 N |
| OUIT | ( $¢(-, 0),-)$ WHIH! ( $(1 .(-, 0),-\{4!)(T, 0), \mathrm{DX})$ |
| OUSOTE | $(\leftarrow(-, 0),-)$ WH OW! ( $(6-(-, 0),-\{4\})(T, 0), \mathrm{DX})$ |
| OLJOTEO | ( $\leftarrow(-, 0),-)$ WH OW! ( $(\leftarrow(-, 0),-)$ T, DX $)$ IX ( $\leftarrow(-, 0),-)(0,0)$ |
| RADIO | $(-, 0)$ R (EYL, 0 ) EYC! (EYR,0) ( $(\leftarrow(-, 0),-) 0,0 X)$ IY OW |
| RAJ | $(-, 0)$ R AOI ZH |
| RALSTON | (-, (1) R AO [L2! S-T JH (N, ()X |
| Raswali | $(-, 0)$ R AA! N AAZ ( $\mathrm{N}, \mathrm{DX}$ ) |
| RAPItaE: | $(-, 0)$ R AEA F IV2 EL. 3 |
| RAYMSTPO | $(-, 0) \mathrm{R}(\mathrm{FYL}, 0) \mathrm{EYC}$ (EYR, 0 ) M IJH N( $(-(-, 0),-)(0,0)$ |
| RLAL. WCRLD | $(-, 0)$ R IV2 EL $(-, 0)$ W ER2 EL ( $\leftarrow(-, 0),-)(0,0)$ |
| RIASONING | $(-, 0)$ R IV! ( 2 ( 4 ; ( 2,0 ) S) ( $1 \mathrm{H} 6,0) \mathrm{N}$ ( $1 \mathrm{H} 3, \mathrm{IV}$ ) NX |
| RECENT |  |
| RECENTLY | (-,0) R IV2! S (JHGN,EN) ( $1+(-, 0),-\{4\}$ ) (T,0), DX $) 1$. IY |
| Rec:Ognliton | $(-, 0)$ R EH3! ( $-(-, 0),-)(\mathbb{K}, 0)$ IX ( $-(-, 0),-) \mathrm{N}$ IH3 SH IH5 N |
| RE:CDY | (-,0) $\mathrm{R}_{6}^{\prime}, 151$ EH2! ( $(6$ (-,0),-) (0,0),DX) IY |
| REDLICTION | $(-, 0)$ R IY2 ( $(+(-, 0),-)$ D, DX $)$ AAR! ( $\leftarrow(-, 0),-)$ SH IH5 N |
| RE:ED | $(-, 0)$ R IY (... $(\ldots, 0),-)(\mathrm{D}, 0)$ |
| RESE: ${ }^{\text {d }}$ | $(-, 0)(\mathrm{R}, 0)$ IY 2 ! (,- 0$\rangle$ F ER |
| REFEREMCE |  |
| Refermiced | $(-, 0)$ R EH3! (,- 0$\rangle$ F ER N S - 4 ( $;(1,0)$ |
| Reetrelices |  |
| REFERMPD | $(-, 0)$ R IY2! ( $\ldots, 0)$ F ER ( $1-(\ldots, 0),-)(0,0)$ |
| REFERRING | $(-, 0)$ R IY ${ }^{\text {! }}(\cdot, 0) \mathrm{F}$ ER (IH3,IY,0) NX |
| REGARDING | $(-, 0)$ R IY2! ( $1 .(-, 0),-)(6,0)$ AA2 ER (DX,0) IHS NX |
| REGION |  |
| REGULARLY | $(-, 0)$ R EH! ( $-(-, 0),-)(\mathrm{G}, 0)(\mathrm{Y}, 0)$ UW (EL,L) ER L IY |
| REITER |  |
| REIATE | (-,0) R (IH3,IY2) L (EYL,0) EYC EVR! ( $+(-, 0),-(4\})(T, 0), 0 \mathrm{C})$ |
| RELATED | $(-, 0) R(1 H 3, I Y 2)$ L ( F YL, O) EYC EYR! ( $(\leftarrow(-, 0),-)$ T, DX $)($ IH3,IX $)(\leftarrow(-, 0),-)(\mathrm{D}, \mathrm{DH}, 0)$ |
| RELATES | (-,0) R ( $1 \mathrm{H} 3, \mathrm{IV} 2)$.L ( E YL, 0 ) EYC EYR! ( $-(-, 0),-) \mathrm{S}(\mathrm{HH}, 0)$ |
| REI.ATIONAL | (-,0) R IY L (EYL, O) EVCl (EYR,0) SH N EL |
| RELEASED | (-,0) R ( $1133, \mathrm{YY} 2$ ) L IV! S -\{4; ( 7,0$\rangle$ |
| REPORT | $(-, 0)$ R $1113(\leftarrow(-, 0),-)$ P An4! E.R $\langle(6-(-0),-\{4\}\}(T, 0)$, DK $)$ |
| REpORTER |  |
| REPCRTERS |  |
| REPDRTS | (-,0) R (1H3,IY2) (+ (-,0),-) P OW! (R,ER2) ( - (-,0),-)S (HH,0) |
| REPRRESENTATION |  |
| REPMRESELVTHG |  |
| REoquesi | $(-, 0) \mathrm{R}$ ( $1 \mathrm{H} 3, \mathrm{IY} 3).(+(-, 0),-)(\mathrm{K}, 0)$ OW AES -\{4\} (T,0) |
| RESERRCH | (,- 0 ) R IV S ER! ( $-(-, 0),-)$ SH(, 10 ; |
| RESODUTION |  |
| rescolmee | (-,0) R IV S UWA! ER S (HH,0) |
| RESPDNses | $(-, 0) \mathrm{R}(143, \mathrm{IV} 2) \mathrm{S}-(\mathrm{P}, 0\rangle$ AA! NS (-,IX) ( 214$\},(\mathrm{Z}, 0) \mathrm{S})$ |
| RISTRJC: |  |
| RE:MRIEVAL |  |
| RETRJEVE |  |
| REVIEVS |  |
| RHOMBERG | $(-, 0)$ R AA M $(\leftarrow-(-, 0),-\{4\})(B, 0)$ ER2 $(\leftarrow-(-, 0),-)(6,0)$ |
| RICH | (-,0) R $\left.1+13^{\prime}(\leftarrow-(-, 0),-) S H_{4}, 10\right\}$ |
| RICHARO | $(-, 0) \mathrm{R} 1 \mathrm{H} 2$ ! $\leftarrow(-, 0),-) \mathrm{SH}\{, 10 \mathrm{E}$ ER $(+(-, 0),-)(0,0)$ |


| RICK | $(-, 0\rangle$ R It 4 ( $\leftarrow(-, 0),-\left\{A_{j}^{\prime}\right)(K, 0)$ |
| :---: | :---: |
| RIEGER | $(-, 0)$ R IY2! ( $-(-, 0\rangle,-, 0\rangle\langle G, 0\rangle$ ER |
| RIESBECK | (-,0) R IY S - <B,0) EHA $\langle+(-, 0),-\{4\}$ ( $\mathrm{K}, 0\rangle$ |
| RISEMAN | $(-, 0)$ R (AYL, 0 ) AYC! (AYR, 0$\rangle$ ( $Z\{4\},(Z, 0)$ S) M EH2 ( $N, D X$ ) |
| ROBERT | $(-, 0)$ R AO! $(\leftarrow-(-0),-\{4\}\rangle(B, 0)$ ER ( $(-(-, 0),-\{4\})(T, 0), D X)$ |
| ROBOT | $(-, 0)$ R OW $\{⿺ 𠃊(-, 0),-\{4\})(A, 0\rangle$ AO! ( $(6-(-, 0),-\{4\})(T, 0), D \times)$ |
| ROBOTIC | $(-, 0)$ R OW $\left(\leftarrow-(-, 0),-\left\{\begin{array}{l}\text { ¢ }\end{array}\right)(8,0)\right.$ AO! ( $(-(-, 0),-)$ T,OX) IH3 $(-(-, 0),-\{4\})(K, 0)$ |
| ROBOTICS |  |
| ROBOTS | $(-, 0)$ R OW $(\leftarrow(-, 0),-\{4\rangle$ ( $B, 0)$ AA $(\leftarrow(-, 0),-) \mathrm{S}(\mathrm{HH}, 0)$ |
| ROCHESTER | $(-, 0) \mathrm{R}$ AN! $\left.(\leftarrow \sim(-0),-) S H_{1}, 10\right\}$ EH4 S - DR ER |
| ROGER | $(-, 0)$ R AOM ( $+(-, 0),-)$ SH(, 10] ER |
| RON | $(-, 0)$ R AA! ( $\mathrm{N}, \mathrm{OX}$ ) |
| ROSENFELD |  |
| RUJBIN | $(-, 0)$ R UW' $(\leftarrow \sim-, 0),-\{4\})(B, 0)$ IH ( $\mathrm{N}, \mathrm{DX}$ ) |
| RIII.E. | $(-, 0)$ R UWW 2 ¢ FL |
| Rthes | (-,0) R UWW4! EI. ( $2: 4 ;$, ( 7,0$)$ S) |
| RUMEILIART | (-, 0) R AA M EL2 (HH, 0 ) AA3 ER (+ (-, 0),-) ( $T, 0$ ) |
| RIJTGERS | $(-, 0) \mathrm{R}$ AA5 ( $(-(-, 0),-)(6,0)$ ER! ( $2(4 ;,(7,0)$ S) |
| RVCHINER | $(-, 0) \mathrm{R}$ IH ( $-(-, 0),-) \mathrm{N}$ [R |
| S-L-gRAPHS | $(-, 0)$ EHI? S AH2, EL! ( $-(-, 0),-)(6,0)$ R AE F S (Hill, 0 ) |
| SACFRMOII |  |
| SANMMEY | $(-, 0)$ S ALS M EMA ( $1-(-, 0),-)(T, 0)$ |
| SANDICWALL | $(-, 0)$ S AEA $N(\ldots(-, 0),-)(0,0)$ W EL2 |
| satisfacticn | $(-, 0) \subseteq$ AC $\langle T, D X)$ IX S F AE $(\leftarrow(-, 0),-)$ SH IHLS N |
| SAY | $(-, 0) S(E . Y L, 0)$ EYC (EYR,0) |
| SCENE | $(-, 0)$ S IY' ( $N$, DX) |
| SCHARK' | $(-, 0)$ SH AES! ND: $(-(-, 0),-0)(\mathrm{k}, 0$ ) |
| SCIENCE | $(-, 0)$ S (AYL, O) AYC! (AYR,0) IH5 N S $\langle$ HH,0) |
| SCOTT | $(-, 0) S-(K, 0)$ AAЗ! ( $(-(-, 0)--44\})(T, 0), D X)$ |
| SEARCH | $(-, 0)$ S ER ( $1-(-, 0),-$ ) Sil ( $\mathrm{HH}, 0\rangle$ |
| SEEE | (-,0) S IYI |
| SEFK | $(-, 0) S(\mathrm{Y} \backslash, \mathrm{IX}$ ) $\langle<-(-, 0),-\{4\}\rangle(\mathrm{K}, 0)$ |
| SEEKING |  |
| SEGMENTATION | $(-, 0)$ S EH? ( $-(-, 0),-)(\mathrm{G}, 0) \mathrm{M}$ UHA! $N(5-(-, 0),-)$ T (f.VL, 0 ) EYC (EYR,0) SH IH5 N |
| SElecit | $(-, 0) S(A X, I X)$ L EH! ( $(\ldots-(-, 0),-\{4\})(T, 0), D X)$ |
| SELİER | $(-, 0)$ S EH EL2! ( - (,- 00 ),-) S ER |
| SEMANTIC |  |
| SEFMANTICS | $(-, 0\rangle$ S IHG! M AES N ( $<-(-, 0),-)$ T, DX) IH3 < - (-, O),-) S (HH,0) |
| SENSE | (-,0) S EH N S ( $\mathrm{HH}, \mathrm{O}$ ) |
| SEMTENCE | (-,0) S (EH? ( $-(-, 0),-)$ EN. (EH2 N,EN) ( $-(-, 0),-, 0)$ T EH2 N) S! (HH,0) |
| SENTENCES |  |
| SEpTEMAER | $(-, 0)$ S EH! $\leqslant(-, 0),-)$ T EH M $(\sim(-, 0),-\{4\})(8,0)$ ER |
| SERIAL. | ( - , 0) S JH? ER IY2' AH EL. |
| SESSION | (-,0) S (Ait?, F.H) $(-, 0)$ SH! IHS N |
| SESSIONS | $(-, 0) S(A H 2, E H)(-, 0)$ SHI IHS $N(Z, 4),(Z, 0)$ S $)$ |
| SEVEIV | (,- 0 O S AH\% V! UHA ( $N$, DX ) |
| SEVEWTEEN | $(-, 0) S(A H 2, E H\rangle$ V! ( $(1 H 5, E H 2)$ N,EN) ( $(+(-, 0),-) T, O X)$ IV (N,DX) |
| SEVENTY |  |
| SEVERAL | (-,0) S EH2 VIR EL. |
| SEYMOUR | (-,0) S IV MI DW ER2. |
| SHAPE | $(-, 0)$ SH (EYL, O) EYC! (EYR, 0 ) ( - (-,0),-) (P,0) |
| SHAW | $(-, 0) \mathrm{SH}$ AOM |
| SHE: | $(-, 0) \mathrm{SH}$ IV! |
| SHDOTANG | (-, O) SH WW3 ( $(\mathrm{c}(-, 0), 0\rangle$ T, DX) ( $\mathrm{HH} 3, \mathrm{IY}$ ) NX |
| Shortliffe |  |
| SHOLIS | $(-, 0)$ SHf ( 143,0 ) (HHA! ( $(1-(-, 0),-\rangle(0,0), 0 \times$ ) |
| SHOW | $(-, 0\rangle$ SH AAS ! (OW, 0 ) |
| SIGART |  |


| SIklossy | $(-, 0) S$ IH2 $(\ldots-(-, 0),-)\left(\mathrm{K}_{1}, 0\right)$ L AAZ! S IY |
| :---: | :---: |
| SIMON | $(-, 0)$ S (AYL, 0 ) AYC! ( $A Y \mathrm{R}, 0) \mathrm{M}$ ( $\mathrm{UH} 2,1 \mathrm{lH} 3)(\mathrm{N}, \mathrm{DX}$ ) |
| SIMMI.ATION | $(-, 0)$ S IH3 M Y \{HH! L (EYL, O) EVC! (EVR,0) SH (IH5 N, EN) |
| SIMULTTANEOUS | $(-, 0) \mathrm{S}$ ( $\mathrm{AYL}, 0$ ) AYC! (AYR, 0 ) M EL3 ( $\leftarrow(-, 0),-)$ T (EYL, 0 ) EYC (EYR,0) N IY IH3 S (HH,0) |
| SIMULTANEOUSL |  |
| SINCE |  |
| SIX | $(-, 0)$ S IH3! ( $\leftarrow(-, 0),-) \mathrm{S}(\mathrm{HH}, 0)$ |
| SIXTEEN | $(-, 0)$ S IHI $(-(-, 0),-)$ S - T IY ( $\mathrm{N}, \mathrm{DX}$ ) |
| SIXTY | $(-, 0)$ S IK! $(\sim \sim-(, 0),-)$ S - T IY |
| SIZE | $(-, 0) \mathrm{S!}(\mathrm{AYL}, 0) \mathrm{AYC}(A Y R, 0)(Z\{4\},(2,0) \mathrm{S})$ |
| SLAGLE | $(-, 0)$ S L (EYL, 0 ) EYC (EYR,0) ( $\leftarrow(-, 0),-)(\mathrm{G}, 0) \mathrm{EL}$ |
| SLOW | (-,0) 5 L OW! |
| SMC | $(-, 0)$ EHA S EH2! MS IY |
| SMITH | $(-, 0)$ S M 1H3! TH ( $\mathrm{HH}, 0$ ) |
| SNARING | (-,0) S N (EYL,0) EYC! (EYR,0) ER (IH3,IY) NX |
| SO | $(-, 0)$ S OW's! |
| SOBEL |  |
| SOFTWARE | $(-, 0)$ S AO! F $(-, 0)(T, 0)$ W ER? |
| SOLOWAY | $(-, 0)$ S AO [L. 3 UW2 W (LYL., 0 ) EVC! (EYR,0) |
| SOLUTIONS | (-,0) S OW L.! IJW SH IHf N ( $\mathrm{Z}\{4\},(\mathrm{Z}, 0) \mathrm{S}$ ) |
| SOLVING | $(-, 0)$ S AA! El.? V IHS $N X$ |
| SOME. | $(-, 0)$ S AA! M |
| SOMETHING | $(-, 0)$ S AA! M THI (IM3, IV) NX |
| SOMEWHERE: | (-,0) S AA! M W E:H3 ER |
| SORT | $(-, 0)$ S UWA! ER ( $(6-(-, 0),-\{A\})(T, 0), D \mathrm{X})$ |
| SORTS | $(-, 0\rangle$ S UWA! ER (n (,- 0 ),-) S ( $\mathrm{HH}, \mathrm{O}^{(1)}$ |
| sources | $(-, 0)$ S UWA ER S ILA! ( $2\{4\},(7,0)$ S |
| Spact: |  |
| spanning |  |
| Speech | (-,0) S - ( $P, 0$ ) IY! ( $-(-, 0),-)$ SH (HH,0) |
| SPl:E) | $(-, 0) S-(P, 0)$ IY! (r-(,- 0 ),-) (0,0) |
| Sproull | $(-, 0) \mathrm{S}-(\mathrm{P} R, \mathrm{PR}(\mathrm{R}, 01) \mathrm{A} \cap \mathrm{EL} 3$ |
| SRI | $(-, 0)$ EHA S AAZ ER2. (AYL, 0 ) AYC! (AYR,0) |
| STANTORD | $(-, 0)$ S - T $A E S$ N F ER ( $6 .(-, 0),-)(0,0)$ |
| State | $(-, 0\rangle S-T(E Y L, 0\rangle$ EVC! (EYR,0) ( $(+(-, 0),-\{4\})(T, 0), 0 \times$ ) |
| STEREO | $(-, 0)$ S - T JH3! ER IY2 OW |
| Steve | $(-, 0) \mathrm{S}-\mathrm{T}$ IY! $\vee(\mathrm{F}, 0)$ |
| stochastic | $(-, 0)$ S - T IH3 ( $-(-, 0),-)(\mathrm{K}, 0)$ AE4! S - T IH3 $(\ldots-(-, 0),-\{4\})(\mathrm{K}, 0)$ |
| stock | $(-, 0) S-T \wedge 01(\leftarrow(-, 0),-\{4\})(\mathrm{K}, 0)$ |
| Stop | $(-, 0) S-T$ AA! $(\sim-(, 0),-)(P, 0)$ |
| Stornge | $(-, 0)$ S - T IJW4! FR JH2 (- (-, 0),-,0) ( $\mathrm{ZH}(\mathrm{SH}, 0), \mathrm{SH}$ ) |
| Stores | $(-, 0) S-T(A A A, 10) ~ E R!~(-(-, 0),-)(0,0)$ |
| STORIES | $(-, 0) S$ - T ( $A A A, A O)$ ER ${ }^{\prime}$ IV ( $2\{4\},(Z, 0) 5$ ) |
| STORY | $(-, 0) S$ - T ACIER IY |
| STRUCTURE |  |
| Structured |  |
| STRUCTURES |  |
| STUDIES | $(-, 0\rangle$ S - T UHA! ( $(\leftarrow(-, 0),-)$ D,OX) IY ( $Z: 4\},(Z, 0)$ S) |
| SUBJECT | $(-, 0\rangle$ S AAI $\leftarrow(-, 0\rangle,-)$ SH IH3 ( $(6-(-, 0),-\{4\})(T, 0), \mathrm{DK})$ |
| SUBine:TS | $(-, 0)$ S AA $\left.{ }^{( } \leftarrow(-, 0),-\right)$ SH IH3 ( $\left.-(-, 0),-\right)$ S (HH,0) |
| SUBPROELEMS |  |
| SUBSELECT | $(-, 0)$ S AAt $(\leftarrow(-, 0),-\{4\})(B, 0) S$ AX EL. EH $(1+(-, 0),-\{4\})(T, 0), \mathrm{DK})$ |
| SUBSYSTEM | $(-, 0)$ S LH? ( $+(-, 0),-\{4\})(B, 0)$ S IH4! S - T (HHO M,EM) |
| SUMF. ${ }^{\text {S }}$ | $(-, 0)$ S UH2! M EH2 ( $\leftarrow(-, 0),-)$ S $\langle\mathrm{HH}, 0)$ |
| SUMMARIES | $(-, 0)$ S UHA! Hf R IV2 ( $2(4),(2,0) \mathrm{S}$ ) |
| SUMMARY | $(-, 0)$ S UH4! WS R IY2 |
| SUNG |  |
| SUNSHINE | $(-, 0)$ S UH2 N SH ( $A Y L, 0$ ) AYC! (AYR,O) ( $\mathrm{N}, \mathrm{DX}$ ) |


| SURE | (,- 0 ) SHER! |
| :---: | :---: |
| Surnotes | $(-, 0)$ S ( $\mathrm{H}_{4}$, $)$ ER N OW'! OW ( $-(-, 0),-$ ) S (HH,O) |
| SURVEY |  |
| SURVEYS | $(-, 0) S E R V(E Y L, 0\rangle$ EYC! (EYR, 0$\rangle(7,4\},(Z, 0) S$ ) |
| SUSSEX | $(-, 0)$ S UH2! S IM3 ( $1-(-, 0)$,-) S |
| SUZUKI | $(-, 0)$ S IHA ( $2\{4\},(\mathrm{T}, 0)$ S UW3! ( $-(-, 0),-)(\mathrm{K}, 0)$ IY |
| SYKES | $(-, 0) S(A Y L .0\rangle$ AYC! (AYR, O) (- (-,0),-) S $\langle H H, 0\rangle$ |
| SYMEDL | $(-, 0) S$ IHS M! $(-1-0),-, B)(B, 0)$ EL? |
| SYNCHRONIZATIO |  |
| SYNTACTIC | $(-, 0) S$ IH3 $\mathrm{N}(\mathrm{r}(-, 0),-)$ T AE ( $-(-, 0),-)$ T IH3 K |
| SYNTAX |  |
| SYNTHESIS | $(-, 0)$ S IHS N TH IHG! S IHA S ( $\mathrm{HH}, 0)$ |
| SVNTHESIZER | $(-, 0) 51 H 5 N$ TH IHGS (AYL,0) AYC! (AYR,0) ( $Z: 4\},(\mathrm{Z}, 0)$ S) ER |
| SYSTEM |  |
| SYSTEMS | (-,0) S IH41 5 - T IH6 M ( $\mathrm{Z}_{1} / 4 ., \mathrm{Z},(0) \mathrm{S}$ ) |
| TAKE |  |
| tales | $((\leftarrow)(-, 0),-)$ Y, DK') (AE, EYL EYC EYR) L ( $2\{4 ;$; $\mathrm{Z}, \mathrm{O}$ ) S) |
| TASK | ( ( $-(-, 0),-)$ T, DK ${ }^{\prime}$ AES $-(K, 0)$ |
| TECH-II | ( ( $\leftarrow(-, 0)$,-) T, DX ) EH! ( $\leftarrow(-, 0),-)$ T (JH2,0) LIW |
| TECHNICAL |  |
| TECHNJQUES |  |
| TECHNOLOGY |  |
| TED | $((\leftarrow)(-,(1),-) \mathrm{T}, \mathrm{DX}) \mathrm{EH}!(+\cdot(-, 0),-)(0,0)$ |
| TElfolotical |  |
| TELL | $((\leftarrow)(-,(1),-)$ T,DX) (AAB, (1) El |
| TEMPORAL |  |
| TEN |  |
| TERSIINAL | ( $\leftarrow(-, 0),-)$ DR ER2 M! ( $1455,14+2) \mathrm{N}$ EL? |
| TERMINALS |  |
| TER M NATE |  |
| TERMINATION | ( $(\sim(-, 0),-)$ T, $0 \times$ ) ER M IHS $\mathrm{N}(\mathbb{C V L}, 0)$ EVC! (EYR,0) SH IHS N |
| TERRY |  |
| TEXT |  |
| texture | $((,-(-, 0),-)$ T, DX $)$ EH $(\ldots,-\cdots, 0),-) S(-, 0) S H, 11\}$ ER |
| THANK |  |
| Thaskes |  |
| THAT |  |
|  |  |
| THE: |  |
| THEIR | (-, O) ( $\mathrm{OH}, \mathrm{OH}$ ) AH2! ER |
| THEM | (-,0) ( DH H,TH) EHO1 M |
| THEOREM |  |
| THEORY ( | (-,0) (DH,TH) IH2' (ER.R. IY\% |
| THERE |  |
| THESE: |  |
| THEY | $(-, 0)$ OH (EYL, 0 ) EYC! (EYR,0) |
| THIRTEEN | $(-, 0)$ TH JHI R ( $(6 \ldots(-, 0),-)$ T, DX $)$ JY ( $\mathrm{N}, \mathrm{DK}$ ) |
| THIRTY | (-, (0) TH IH\# R ( ( $-(-, 01),-) \mathrm{T}, \mathrm{DX}$ ) IV |
| THIS | (-,0) (DH,TH) IKOI 5 ( $\mathrm{HH}, \mathrm{O}$ ) |
| THOMAS | ( ( - (-, O) ,-) T, DKO) AA M IHG S (HH,O) |
| THORNDYKE |  |
| ThOSE |  |
| THOUGHT | $(-, 0)$ TH AOP ( 6 ( $\langle-, 0\rangle,-\{4 ;)(T, 0\}, D \times$ ) |
| THREE | (-,0) TH R IV: |
| THROUGH | (-,0) TH R UW! |
| TIL. |  |
| TINGE ( | $((\leftarrow)(-, 0),-)$ T, DX) (AYL,O) AYC! (AYR, 0 ) M |
| TIMFS ( | $((\leftarrow\langle-, 0),-)$ T, DX $)\langle A Y L, 0\rangle$ AYC (AYR,0) M! ( $2\{4\},(Z, 0) S$ ) |



个个个T个T个T个TTTT个个个 （，0）W（EYL，0）EYC（EYR，0）$\vee$ FAORM $(Z\{4 ;,(Z, 0) S)$ W）WAA！（Z： 4$\} ;(Z, 0)$ S）IHG N $((+-(-, 0),-\{4\})(T, 0), 0 X)$
 $-, 0) \vee$ IH2！$(\in(-, 0),-)(Z H(S H, 0), S H)$ UW2 EL
$(-, 0) \vee$ Alf Bi．Y $1 H 5 \mathrm{M}(Z: 4 ;,(Z, 0) S)$




$$
\begin{align*}
& (, 0) Y \text { UWS! (ZiA } A_{i},(Z, 0) \text { S) (HM,IY) NX } \\
& (-0) Y \text { UW EHI! SEHS AA2 ER? }
\end{align*}
$$

$$
\begin{aligned}
& (-, 0) \text { AA2! }(\leftarrow-(-, 0),-)(P, 0) \\
& (-, 0) \text { IHG! } \mathrm{S}(H H, 0) \\
& (-, 0) \text { Y UW! }(Z \mid 4 ;, 17.0) \mathrm{S})
\end{aligned}
$$

$$
\begin{aligned}
& (-, 0) \text { Y } 1 H 4 \text { N! EHA3 } \vee E R 2 S E L(Z\{4\},(Z, 0) S
\end{aligned}
$$

$(-, 0)$ Y UW E．HA！$S(H H, 0)$
$(-, 0)$ Y UWA！ER

$$
\begin{aligned}
& (\leftarrow)-(-, O),-) \quad 1, D C)(A Y L, 0) \\
& (-, 0) \text { Y UW E.HA! } S(H H, 0)
\end{aligned}
$$




|  |  |
| :---: | :---: |
| $(-, 0\rangle,-) T, D X)(A Y L, 0\rangle A Y C!(A Y R, 0\rangle((+(-, 0),-) T, 0 X)\langle A H 3,0\rangle$ EL（ $Z\{4\},(Z, 0) S)$ |  |
|  |  |
| $(-, 0),-) \mathrm{T}, \mathrm{OX})$ AA $($（ $-(-, 0),-)(\mathrm{P}, 0\}$ IH3 $(-(-, 0),-\{4\})(\mathrm{K}, 0)$ |  |
| $(-, 0),-)$ T，DX）A（）（ $-(\ldots, 0),-)(P, 0)$ IH3！（ $-(-, 0),-) \mathrm{S}(\mathrm{HH}, 0)$ |  |
|  |  |
|  |  |
| $(-0),-)(S H\{, B ; 0 R)(R, 0)$ AEQ！NS AE（ $-(-, 0),-)$ SH\｛， 8$\}$ IHS $N(Z\{4\},(Z, 0) S)$ |  |
| $(-, 0),-)($ SH： $8: D R)(R, 0)$ AEQ！N S F ER2 |  |
|  |  |
|  |  |
|  |  |
|  |  |
| （－，0），－）（SH $\{, 8\}, 0 \mathrm{R})(\mathrm{R}, 0) \mathrm{AA}$ ！（ $+(-, 0),-\{4\})(B, 0), B) \mathrm{EL}$ |  |
| ，，0），－）（ SHL， $8_{1}^{\prime}, \mathrm{DR}$ ）（R，0）（AYL， 0 ）AYC（AYR，0） |  |
| （－，0），－）T，DX）UW！（（－（－，0），－）T，DX）ER |  |
| $(-, 0),-)$ T，DX）UWW3！（ $(6)(-, 0),-)$ T，DX）AA4 ER IY2 EL3 |  |
| $(-, 0),-) T, D X)$ UW！（ $(+(-, 0),-)$ T，DX）ER（IH3，IY）NX |  |
| $(-, 07,-)$ T，DX）IY！$\vee$ IY2 |  |
| （－，（1），－）T，DX ）OW AAS EL V（F，0） |  |
| $(-, 0),-)$ T，DX）OW EHS $N(1+(-, 0),-)$ T，DX，0）IY |  |
|  |  |

## Appendix III-C-1. AI Retrieval Language Grammar: AIXF

```
<SUTTERANCE>: - [ <SSENTENCE 1> )
<SA>:= THE
    A
    AN
<$ACQUIRE,:- HAVE
    SEE:
    KINOW
    GET
<$AFFILIATION>:= <ACDRCSS/S>
    <AFFILIATION/S>
<ADDRESS/S>:= ADORESSTS
    ADORESS
<AFFILIATION/S>:= AFFILIATIONS
        AFFILIATION
<$Al>:= AI
        ARTIFICIAL intEllIGENCE
<SALSO.- = ALSO
    in AOEITION
<$ALSOWAEWTIONTOPICS> = -GMFLYION> <STOPICS>
        <SMELGTION> <STOPICS> <EALSO>
        <SALSO> :STMEIVTIGN> <STOPICS:
<SMFINTION> = CITE
        REF:IN TO
        <SBE> SRF1>
        <DISCIJGS/S>
        CONCERN
        CONTAIN THE PHRASE
        DESCRIBE
        RELATE TO
        <SHAVE> <SMFINTIONEDGHAVE>
        CONSIDER
        <MFNTION/S>
<STOPICS:* - -STOPIC.
        <STOPIC> <ECONSUNCTION> <STOPIC>
<SALWIAYS>.. ALVIAYS
        USIJAlly
        RE.genarly
<SANY!UODATEQUECES>- <GPJECFSS\
        <SSOMETHHNG;
        <SSOM隹< <SPIECESS>
<SPJECFSS> = <STORY/S>
        <ARTICLE/S>
        <BOOK/S>
        <PAPCR/S:
        <ABSTHACITS,
        <PROCHLIDING/S>
        <RTMORT/S>
        <ISSUF/S>
        <JOUJNNAL/S>
        NOTES
        <RI:VIEW/S>
        <VOLUME/S>
        PIECE:
        <SURVEY/S>
        <SUMMARY/S;
        TECHNICAL PAPERS
```

```
<$PIECES1 2;= <STORY/S 2>
        <ARTICLE/S ?>
        <BOOK/S 2>
        <PAPER/S 2>
        <ABSTRACT/S 2>
        <PROCEEEDING/S 2>
        <REPORT/S 2>
        <ISSUE/S 2>
        <JOURNAL/S 2>
        NOTES
        <REVIEW/S 2>
        <VOLUME/S 2>
        PIECE
        <SURVEY/S 2>
        <SUMMMARY/S 2>
        TECHNICAL PAPERS
<SSOMETHING>:* ANYTHING
        SOMETHING
        EVERYTHING
<SSOMF!>:: <SA>
    <$5OME>
<SANYIPIECFS>: <SPIECFS>
    <SSOMF!MECESS
    <SSOME1> OF THE <SPIECES>
    <SSOMEIHING; <SRECENT>
<SPIECFS>* <SPIECFS1>
    <SDATE> <SPIECES1>
    <$PIECES1> <SWHEN!DATE>
    <SPIESH:SI> <SWRITTENI> <SWHENIDATE>
    <SRTCENT> <SPIECES1>
<SSOME!PIECFS>:* <SSOMEIHING>
    <SA> <SPIECFS>
    <SSOMF1> <STHAT!PIECEA>
    <SSOMF1> <$PIECES>
<SSOMP: >>= AlL
    MANY'
    AN'
    ANY MORE
    MORE
    SOMf
    ANOTHER
    SOM位 MORE
<$RECENT>:= LATEST
    RECENT
    NEW
    CURREIVT
<$AN\!SOURCE!PIECES,:= -SSOURCE!PIECES:
    <SSOME!> <SSOURCEIPIECES.
    <SSOMEI> <$RECENT> <SSOURCEIPIECESARECENT>
    <SSOMFF> <$PIECES> <$FROM> <$SOURCE>
    <SRECENT> <SSOURCE!PIECESTRECENT>
    <SPIECES> <SFROM> <SSOURCE>
<$SOURCE!PIECES:- -SCONFE:RFHCE>
    <SSOURCE> <&PJECES1 2>
    <PRCCFEDING/S> <SFROM> <SA> <SCONFERENCE>
    <$CONFEREHCE: < PPIECES1 2>
    <$PJECES> <SFROM> <$SOURCE>
<SSOURCE!PIECESERECENT>- < <SONFFRENCE>
```

```
            <SSOURCE> <SPIECFS12;
            <PRCCIIDING/S> <SFROM> <SA> <SCONFERENCE>
            <SCONFERTHCL> <SPIECESI 2>
<SARTICLEMTILE>: HIJMAN PROBLLIM SOLVING
            THOUGHT ANO LINGUAGE
<SASK>:- ASK
            REOUEST
            dEmand
            SAY
<$AUTHORS>:= <SAUTHORSI>
            <SAUTHORS1> <SCONJUNCTION> <SAUTHORS1>
<$AUTHORS 1> = RF.DDY
                            DREYFUS
                            ANN RIJBIN
                            ANTHONY MARTELLI
                            BERNASOD MALITZER
                            BERT RAPHAEL
                            BONNIE NASH-WEGBER
                            CHRISTOPMER RIESBECK
                            CHLCK RJEGER
                            DAVE RUMFIHIRT
                            DAVID MARR
                            david michie
                            DICK SEITZER
                            DONALD NORIMAN
                            DOUG, IENAT
                            DREW NISDERMOTT
                            EARL. HUNT
                            EARI SACFRMOTI
                            ED RISEMAN
                            ELIIOT SOLOWAY
                            ERJK SANDIWALL.
                            fugENE: CHARNIAK
                            gaRY HENiDRJX
                            GEORSE: ERNGT
                            HERIBIRT BIOCK
                            HJLARY PISTNAIH
                            Hjgh NACiEl.
                            IRV SOBEE.
                            JACK wINKLK
                            JACK MOSTOW
                            J^wu:S SLAGLE
                            JEAN SNN(SM: 
                            JEFEREY HID.WaN
                            Jorin gaschmig
                            JOHN MG:CARTHY
                            JOHN NEWCOOMEN
                            JOSEPR WEIZENBAUM
                            JIJDEA PEARL
KARL PINGLE
kEITH PrICE
KEN RALSTON
KING SUNG FU
LAURENT SIKLOSSY
LINDA MASINTER
LES EARNESI
MADELINE BATES
MARY NEWBORN
```

```
MARY SHINW
MIKE RVC:HMMFR
MITC.mfl. NIEWEY
NORI SUITHKI
PAMM:IA MCCORDUCK
PAT WINSTON
PERRY lHORNDYKE:
PETER KUGEL
RANAI: BAN:RJI
RAYMOHD SPROULL
RICH FIKES
RICH SMMTH
RICHARO MIICHALSKI
RICHARD WALDINGER
ROBERT REITER
ROGER SCHANK
RON OHLMIDER
SCOTT FARLMAN
SEYIMOUR PAPERT
STEVE REED
STEVE COLES
STEVE ZUCKER
TED SHORTLIFFE
THOMAS MARSLAND
THOMASS SYKES
VIC LESSF.l
WAlLY RHCMBERg
w(yODY BLFDDSOE
YORJCK WILKS
ZOHAR MANNA
SIMON
NEWE:l
WCOODS
HOLIAND
ROSENFEL.(D
FEIGEINBAUM
Ff:(DMAN
NILSSON
UHH
WINOGRAD
MINSG'V
Allen COLliNS
AllEN NEWELL
AZRIEL ROSENFEL.()
BILL W(OODS
BRUCE BUCHANAN
C.ARL HEWITT
DANNV BOBROW
ED) FEIGENGAUMM
GiPG
HANS DERTINER
HARRY GARRDW
HERR\SIMODN
ISSAC ASIMOV
Jf.RRY f&l.GMANN
JOHN HOLLAND
KEN COLBY
LEE. ERMAN
```

```
    IEONARD IHR
    MARVIN MINSNY
    MICHAEL ARB1E3
    NJLS NILSSON
    RAJ REIDY
    RIC:K HAYES-ROTH
    TERRY UINOGRAD
<$CONIINNCTION>:* ANO
    NOT
    OR
    BUT FOT
    AN(D)NOT
    OR NOT
<SAUTHIORSIIIAIE> - <AUTHOR/S> AND <DATE/S>
    <DATE/S> ANO <AUTHOR/S>
<AUTHIOR,'S>:: AUTHORS
    ALITHOR
<DATE/S>:= DATES
    DATE
<SBE>:=<SBE1>
    <SHAVE> BEEL/
<$BE]>= <SBE[PR[S]>
    <SBE{PAST]>
<SHAVE: E HAVE
    H,NS
<HAPPEN/S>: HAPPEN
<SBE!>>- <SBE>
    <SBE1> NOT
    ISNT
    ARENT
    WASN'Y
    WEREN'T
<SBE!TOPICSWFIITIONED>* <SHAVE!> <STOPICS> BEEN <SMEMTIONED[PP]> <SSOMEWHERE>
        <,BF!: <$TOPLCS: <&MFIWTIONED{PP]>
    <SHAVE!> &$TOHICS, BEEH <{MFITIONED{PP]>
    <:;DOI> <STOFICS> GET <SMENTIGNED[PP]> <SSOMEWHERE;
    <5DOl> <$TORICS. GEY <$MELVTICNLD[PP]>
<SHAVEO, <SHAVE>
    HAVEIN'T
    <SHAVE> NOT
    HASNET
<SMEIVTGGN[D[PP]> - <SCITED>
    DISCUSSED
    MEWHIGNED
    CONSIDEREID
    <SWKIITEN> ABOUT
<$SOM&VRIFHIS:% IN <SANYPIECES>
    SOMEWHFUL:
    ANTWIHF:KI:
    AT ALL
<$SOMEVSHERE: Z-:- IN <SANUPIECES>
    SOM隹WIHERE
    AN'NVHELE:
    A`` ALL
<SDO!> = <SDO>
    <SDON'T>
<SBE[PR[G]>:= IS
    ARE
```

```
<SBE[PAST]>:= WAS
    WERE.
<$BE[THERE]>>:* <$BF!>
        <SDO!> <SHFNRSAY> HAVE
        <SBEITHERES
<SHEARSAY>:- YOU
    THE DATA BANK
    THE DATA BASE
    HEARSAY
    THE: SYSTEM
<SBE!THERE:>: <SBE!> THIRE:
    <SHAVE!> THERE: BEEN
<SBF[THEPL:IANYIPIECFS>:= <SBE[THYRH]> <SANYIPIECES>
        DO YOU HAPPEN TO HAVE <SANY!PIECES>
        <SHOW!laAN\!PIECES?> ARE THERE
<SHOW!NAN'!PIECRS%>: <SHOW!NAN'>
        <SHOWUSAN'> <SPIECES>
<$CHESS:>. CHESS
        GAINt: PI.A'ING
<SCHOOSK>:. GEY
        CHOOSt:
        SElem:
        SUBSELIC;
        RETRIEVE
<SCITE>:= <CITE./S>
    REFEMENCE
    QuOTE
    REPRR 1O
    <SHAVE> <SCITEO>
<CITE/S>:= CITES
    CITE
<CITED> = CITEO
    OUOTED
    REFERE:LCED
    REFERRED TO
<SCOMMAND:>: TRY TO GET <SWHAT>
<SWHAT> - <SWHAT2>
    <SWHAT2> <SCONJUNC.TION> <SWHAT1>
<SCONFERELICE3>:: <SA> <SCONFERLICE,
    <SCONFERELCFS
<SCONFFRELNCE.* <SCONFFRF:ICE.1>
    <SCONFFRE:NCE1> <SCONFERENCE2>
<SCONFERRELCE.l>:- IJCAI
    ACM
    IEE:
    IFIP
<SCONFEHH:HCCR>: <MEEMNG/S>
        <CONF:MEHCE/S>
        <SCSSION/S>
        <CONVENTIGN/G>
<MEEYING/G>:= MEFHINGS
        MEETING
<CONFERH:NCE/S>- CONFEHENCES
        CONFERENCE
<SESSHON/S>. SESSIONS
        SESSION
<CONVENTION/S>:= CONVENTIONS
        CONVENTION
```

```
    <$CONTAIN>:= <CONTAIN/S>
        CONTAINE:)
    <CONTAIN/S>:: CONTAINS
        CONTAIN
    <$CONTENTSIMEINH>:= <SIMMMF, THE <SKEYWORDS>
        <SWHAT!WHICH> <SKEYWORDS> <$RELATE!TO> <SSUPERIMENU>
        <SWHAT!WHICH> <SMFNISMENU> <SRELATEITO> <SSUPERIWEINU>
        <SWHATIWHICH> <S.KFYWOROS> <SMAY> <SI> USE FOR RETRIEVAL
        <SWHATIBE> THE. <दूKEYWORDS>
    <SGIMME::- - SIWANNA,
        <SIEBMME:- CSACOUIRE;
        <SWOULD> <SHEARSAY> RETRIEVE
        <SWOULD> <SIHTARSAY> <SLIST>
        <SIIST,
        <SWOAILD> <SHEARSAY> <SGIVE> <SME.>
        <SGIVE> <SME,
        <SGIVE.>
        <SIIST> FOR <SME:,
        <SIWANNA; TO -SACQUIRE,
        TRY IOGET
    <SK'EYWOROSS:- KLY <WORD/S>
        KEY <PHRASE/S>
        RETRIEVAL <KEY/S>
<SWHATMV/HICH> - WIHAT
        WHICH
<SREIATEGO)>=<REIATL/S> TO
        <$[BE> RELNTED 10
<SSUPER!W|IN!B;:-SAl>
        GAMI: PLAVING
        LEARNING
        JNFERLTSCE
        SEMMNTIC HETWORKS
        COMPISTATIONAL LINGUISTICS
        UNOERSTANOING
        ndapIATION
        INTERACTIVE DESIGN
        DESIGN
        AUTOMATIC PROGRAMBMING
        HYPOTHESSIS FORIMNTION
        DEDUCTIVE RETRIEVAL
        GEOMETRIC: MODELING
        INTERACTIVE KNOWLEDOE SYSTEMS
        COGNITIVE SCIEIVE
        COGNITION
        AUTOMATION
        DATA STRUSCIURES
        FORIAAI. SEMANTICS
        lafiglage lindergtanding
<SMFINIMMEINJ>: <TOPIC/S>
        TORIC <MENIJ/S>
        <MFINIJ/S>
        <SIJB.ICCT/S>
        <ARLA/S>
<SMAY:. CAN
    COUID
    Shoulo
    MIIST
    MAY
```

```
<SI>:*: I
WE
<$WHAT!BE>:= <$WHAT!W/HICH> <$BE>
    WHAT'S
<SDATE>:- <SDATE.>
    THE LAST <SNIJMBER> <STIMES,>
        <$DATE.> <$CONJUINCTION> <$DATEI>
        <SDATE. > <$THRDUGH> <SDRTEI>
<SDATE1>:- <SVFAR>
        <SMONTH;
        THE: <MONTH/S> OF <SMONTH>
        <SMONTH> <SYEAR.
<SNUJMII:R>:- <&IIJNDREDS>
        <SNIJMMS:R1>
        <SHIUNJIREDS> <$NUMBERI>
<STIMES:-: WONTHS
        ISSUES
        VOLUIMES
        YEARS
        TMMES
<STHRDUGH\>:E TO
        THROUGH
        TILL
<$YEAR:>:= NINETEEN <$NUMBER1>
<SMONTH> = MAY
        JANUSARY
        FEBIRUARY
        MARCH
        APRIL
        JUNE
        JULY
        Aljgust
        SEPTEMIBER
        OCTOBER
        NOVEMMER
        DECEMBER
<MONTH/S>:= MONTHS
        MONTH
<SDESIRE:>* <SWANT>
        WOULD LIKE
        DESIRE
<SWANT>:- DESIRE
    SEE.K
    WANT
    WISH
<SDIGITS>: ONE
    TWO
    THR!:E
    FOUR
    FIVE
    SIX
    SEVEN
    EICHT
    NINE
<SDO>:= DO
    DOES
    DID
<SDON'T>:= DON'T
```

```
        DIONT
        DOESN'T
        <SDO> NOT
<SOOSOM1!>>: <SDO!> <SSOME!>
<SFILE>>-FILE
        COPY
<$FINISHEO)>= <$FINISHED1>
        ALL <SFINISHED1>
<SFINISHED1>-- THROUGH
        DONE
        FINISHED
<$FROM>:= IN
        OF
        FROM
        AMONG
<$GETIAFFILIATION>:= WHERE: <SDO> <$THEY> WORK
        <SDO!> <STHEV> WORK < SWHERE:>
        <SWHAT!BE> <STHEIR> <SAFFILIATION>
        WHAT <ADDRESS/S> <$BE> GIVEN FOR <SITSIAUTHOR>
<STHEY >:= THEY
        HE
        SHE
<SWHERE:>. -SWHERE1>
        <SWHERF.1> <SCONJUNCTION> <SWHERE1>
<STHFIR>.-THEIR
        HIS
        HER
<SITSIAUTHOR;:: <SITS> <AUTHIOR/S>
    THE: <AUITHOR/S> <SOFITHATIPIECE.>
<SGETIAUTHOR>:- <SPROVIDE> <SITSIAUTHOR>
    WHO
    WHO WROTE <STHATIPIECE>
    WHO) <\deltaBF;> < $ITSVAUTHOR>
<$PROVIDE>: <$GIMMMF:>
        <SWHATIBE>
<STHATMIECH> = <STHESL;
        <$THATIPIECE.2>
<SGEVIAUTHOR!DAIE>: <SPRDVIDE> <SITSIAUTHORIDATE>
<SITSIAUTHORDDATE: - <SITS> <SALIHDRSINATE>
    THLL <SAUTHORS!DAIE> <SOF!THNT!PIECE>
<SGETIDAIE> = <$PROVIDE> <$ITSIDATE>
        <$WIAEN> <SWHATTWHICH,> <MONTH/S> <$DE[PAST]> <$THAT!PIECE> <SWRITTEN1>
        WHEN <SBF;> <STHATIPIECE> <SWRITTENI>
<SITSUAIE>:= <$ITS> <DATE/S>
        THE <DATE/S> <SOFIHOTIPIECE>
<SWHEN.>= <SFROM>
        SINCE
        AFTER
        BEFORE
        DURING
<$WRITTEN1>:= PUBLISHED
    PRINTEO
    WRITEEN
    WRITTEN UP
    ISSUED
    REIEASED
    PRCDUCED
<$WRITTENI 2>:- PUBLISHED
```

```
    PRINTED
    WRITTEN
    WRITTEN UP
    ISSUED
    RC.IEASED
    PRODUCED
<SGET!NNO>:- <SGETIAFFILIATION>
    <SGET:AUTHOR.
    <sgEIIAUTHOR!DATE>
    <SGET!DAIE>
    <SGETNEWEST>
    <SGEMMITLE>
    <SET!MTLE!HEWEST>
    <SGEMMITE!OLDEST>
    <SGEY!PUBLISHER>
    <SGET!REFFHENCES.
    <SGET!OLDEST>
<SGETINEWEST>: < SPROVIDE> THE <SNEWEST>
<$GET!YITLE>:= <$PROVIDE> <$ITS!TITLE>
    WHICH <ONE/S>
<SGETITITLE!NEWEST>: = SGETIITILE> OF THE <SNEWEST>
<SGET!IITLEMLDEST>:= <SGETITITLE> OF THE <SOLDEST>
<$GET!PUBLISHER>::= <SPROVIDE> <$ITS!PUBLISHER>
        <SBE> <STHATIPIECE> PUBLISHED <SIN> <$SOURCE2>
        WHERE DID <STHATIPIECE. APPEAR
<SGET!REFERENCES::- <SPROVIDE> <SITSIREFERENCES>
    WHO <{[B[{PAST]> <$CITED> <$IN> <$THAT!PIECE>
    <$DO'> <$THAT!PIECE> <$CITE> <$SOURCE2>
    <SHOW!MANN'; REFERF.HCES <$WERE:THERE!INTHAT!PIECE>
<SGET!OLDEST>: < SPROVIDE> THE. <SOLDEST>
<$NEWEST>:* < SNEWEST1>
    <SNEWEST1> ONES
    <SNEWESTI> <SNIJMBER>
    <SNEWEST1> <SNIMBER> <$PIECES1>
    <SNFWESTI> <$FROM> <STHAT!PIECE>
    <SNEWEST1> <SPIECES1 2>
<SOLDEST>:- -SOLDEST1>
    <SOLDESTI> ONES
    <SOLDEST > <SNIJMBER>
    <SOLDESTI> <SFROM> <STHATIPIECE>
<$ITS!PUBLISHER>:: <$ITS> <PUBLISHER/S>
        THH: <PUBLISHEK/S> <$OF!THAT!PIECE>
<SIN>:= IN
    BY
<SSOURCE2>: <SCONFERENCES>
    <SSOLIRCE>
    <SA> <SSOURCE>
    <SA> <SRECENT> <SSOURCE>
<SITS!RLHEMENCES>- <SITS> <REFGIRENCE/S>
    THE: <REFE:REIICE/S> <SFROM> <$THAT!PIECE>
    <SAN\!PIECES> <SCITED> <SIN> <STHAT!PIECE>
<SHOW!WMN''>:= <$WHATIWHICH>
        HOW MANY
<SWERE!TH:HEINTHHTTPIECE> = <SBETTHERE>
        <SBE> GIVEN
        <SBE[THERE:]> <SFROM> <STHAT!PIECE>
<SITSTTITLE>: < <ITS> <TITLE/S>
        THE <TITLE/S> < SOFITHNTIPIECE>
```

```
<ONE/S>:= ONE
    ONES
<SIWANNA>:* <SI'D> LIKE
        <ST> <SDESIRE.>
<SLEMMNIS:- I.ET <SMF.>
        L[T'S
        <SMAY> <SI>
<$WOULD;:% WOLLD
    CAN
    COULD
<SLIST>:- L.IST
    PRINT
    TRANSMIT
    WRITE
<SGIVE>:* <SGIVEl>
        GET FOR
        TELL
<$MF>:% MH:
    US
<SGIVE1>:= GET
        GIVE.
        SHOW
<$GRIPE>: <SBS:> <$MINRSAV> <SALWAVS> <SSLOW>
    HAVEN'T YOU FINISHED
    WHY <SBE> <SHIARSAY> SO SLOW
    DO RESPONSES EVER GOMF: FASTER
    HOW SMMAY, <SI> <SIMPROVE!HS>
    DO ALL QUERIES TAKE THIS LONG
    HOW LONG DOES IT TAKE
    WHEN WILL <SHEARSAY> HAVE THE ANSWER
    DOES IT ALV/AYS TAKE THIS LONG TO ANSWER <SME>
    WHAT -SMAY> <SI> DO TO <SIMPROVE!HS>
<SSLOW,: SO SLOW
    SLOW
    THIS SLOW
<$IMPROVEHS>\: HEL.P
    SPEED <SHFRRSAY> UP
    HELP < GHFARSAY>
    USE. <SHEARSAY > EFFICIENTLY
<SHEIP:M:* HEL.P
    HOW HIG IS THE. DATA BASE
    <SWIHAT!SORTSIOF> <RTTRIEVAL/S> CAN <SHEARSAY> DO
    TELI. <SIME: WIHAT TODO
    <SWHATWHHCH> < SME:NHMPHIJ> <SMAY> <SI> <SSEEK;
    <SWIHATGORTSIOF> RETRIEVAL <KEY/S> <SMAY> <SI> <SSEEK>
    <SWHATIGORTSIOF> <SPIECES1> <SBE!PREG)> AVAILABLE'
    <SWHATISORTS!OF> <SMENIIMMENIJ> <SBE> STORED
    WHAT IS KNOWN <SRT;, EVERY <SPIECESI>
    WHAT DO < SI> HAVE TO DO
    CANY(HS HELW
    <SWHATISORTSIOF> <SMENUMMENU> <SBEITHERE>
    CAN Y(OH HEL.P <SMF.>
    HELP <$MF:
    <SPROVIDE> <$A> <$MFNIIMEIIJ>
    <SWHATIIS> <SSOME> <SMFIWIMMFINJ> <SFROM> <SAL>
    <SWHAT!WHICH> FACTS ARES STORED>
    <SWHATIIS> THE SIZE OF <SHEARSAY>
    WHAT <SMAY> <SI> <$ASK>
```

```
    WHAT CAN <SHEARSAY> DO
<SWHATISORTS!OF>:= <SWHAT!WHICH> <$SORTS> OF
<RETRIEVAL/S>:- RETRIEVAL
<$SEEK>:n REQUEST
    CHOOSE
    SEEK
<KEY/S>:F KEYS
    KEY
<SRF>:- <SRR:1>
    <$WHICH> <&MENTION>
<SWHATIIS>: WHAT'S
        WHAT <SBE[PR[S]>
<SSOMF.>: <SSOMEI>
        <SSOM作1> OF THE
<SHOW!\AANVINLTHIORS:: <SHOW!|ANW'> <AUTHOR/S>
    <SOOISON隹!> <AUTHOR/S:
```



```
        <SDE:><SSOME!OFTHIV,*
```



```
        <SHOWM|AN'> OF <STHATIPECES>
<SSOM隹(OFITHIMS: = <STHATIPIECE>
        <SSOMP1> OF <STHATIPIECEA>
<$THAT!PIECE:3>:= <STHATIPIECE2>
        <$THET\
<SHOW!WMN゙T!TIECES> = <SHOW!MANM!PIECES?.
        <SODI> <SANV!PIECES>
<SHOW!ANHN'GOURCE!PIECES>* <SDD\> <SANVISOURCE!PIECES>
        <SHOW!|ATW\IPIECES. <SFRCM>> <SSOURCE2>
        <SWHAT!WHICH> <$SOURCE>
        <$HOWIIWNY'> <'SOURCEIPIECES>
<SSOURCE> = <SAI> JOURIVAL
    ASSOCINTION FOR COMPUTATIONAL LINGUISTICS
    COGNITIVE PSYCHOLOGY
    ACL
    Al TEXt
    ARPA SURNOTES
    SIGART NEWSLETTER
    COMI.AINICATIONS DF THE ACM
    CACM
    COMPIJTING -SURVEY/S.
    COM位JTING REVIEV/S
    INFORMATION ANI CONTROL.
    IEEf: <TRANGACTICN/S>
    IJCA] <PRCCEEIDINS/S>
    IFIP <FROCEEOING/S>
    IGIJRNAL OF THE AC:M
<SHUNDREDS> = <SNIJMBFR1> HUNURED
    A HuNORED
<SNIJMBIRRI>:< <SDIGITS>
    <SNIMMBI:R2>
    <STEENS>
<SI!BE>** <SIM>
    <SI'VE> BEE:N
<SI'M>: - | AHM
        I'M
        WE'RL:
        WE ARL:
<SI'VE>:=1 HAVE
```

```
        WE'VE
        WE HAVE
    <$I'D>: < <$I> WOULD
        I'D
        WE'D
    <SITS>:= THE
        THEIR
        ITS
    <$OF!THATIPIECE>:= OF <STHATIPIECE>
        FROM <STHATIPIECE>
    <PUBLISHER/S:`:- PUBLISHERS
        PUBLISHER
    <REFEIRFHCE/S>:* REFERFINCE
        REFEA:LCES
<TITLE/S>:- TITLES
        TITLE
    <WORD/S>:= WORDS
        Wosed
    <PHRASE/S> - PIIRASES
        PHRASE
<SLAST>: LAST
    MOST RECENTLY
<SIEARNINS>:* LEARNUNO
    GRAMsMATICAL INFEREHCE
    NEIJRAL NETWOORKS
    ABSTKACIMGN
    OYNAINIC CLUSTERING
    CELL ASSEMMIS.Y THIORY
<SLIST!THEM>:- THE: <SNEWEST>
    <STHF!NEXT>
    <SGINMME.< <STHLHNFXT>
    <SMAY> <SI> HAVE <STHATIFIECE> <SLISTEO>
    <SITST. THE <SNFWFST>
    <SIIST> <STHNTHPIECE>
<$THE|H:XT>:= THE: NEXT
    THE NEXT <SNIJMBEER.
    THE FIRGT
    UP TO <SNUMABER,
    BETWEEN <SINIMMER. AND < SNUMBER> OF THEM
    <SNIJMBER.- MORE
    THE FIRST <SNUMBER,
<SLISTED>:= LISTED
    PRINTEO
    WRITTEN
<SLISTHNG>:, LISTING
    PRINTING
    TRANSMITTING
    WRITING
<SNAAKE>: COPY
    WRITE
    MAKE
    produce
    GENERATE
<SMAKEADHLE>: <SMAKE> <SMF:= A <SFHE>
    <SWAKEAITILE> OF THE <SNEWCST>
    <SMAKE> A <SFIIE>
<SMAKE!FILE>* <SINAKEAFILE>
    <SMAKEIA!FILE> <$FROM> <STHAT!PIECE>
```

```
<$RE1>= REI.ATED TO
    ABOUT
    REGARDING
    ON
    REFERRING TO
    DISCUSSING
    CONCERNJNG
    MEINTIONING
<DISCUSS/S>:= DISCUSSES
    DISCUSS
<SMENTIONND>:: -SBE> <SRE>
    <SMEIVTIONEDOHAVE>
<$ME.NTIONED&HAVE>:* <SMF.NTICNED[PP]>
    RELATED TO
    CONCERNED
<MFINTION/S>:- MF.NTIONS
    MFINTION
<SWRITTEN>:- <SWRITTEN1>
    <SRI:CENTLY> <SWRITTENI>
    <SWRITTEN1> <SRFCFNTLY>
<SWRITTEN 2;** <SWRITTEN1 2>
    <SRECENTLY 2> <SWRITTEN1 2>
    <SWRITTEN1 2> <SRECENTLY 2>
<TOPIC/S>: TOPICS
    TOPIC
<MF:NI/S/S>= MFWUS
    MF.NTI
<SUBJECT/S:%= SUBJECTS
    subjec%
<AREA/S;>: AREAS
    AREA
<$MY>::- OUR
<$NEGSTATEMFNT>:- <SI> <SUNWANT> TO <SACQUIRE> <SWHAT>
    <SDONT> <$GIVE> <$ME> <$WHAT>
<SINNWANT>:= WOULD NOT LIKE
    <SDON'T> <SWANT>
<SNEWEST1>== LAST
    NEWEST
    <SLAST> <SWRITTEN>
    LATEST
    MOST RECENT
<$NO>:= NO
<SNUMBER2>::= <STENS>
    <STENS> <$DIGITS>
<STEENS>:= NINETEEN
        TEN
        ELEVEN
        TWEIVE
        THIRTEEN
        FOURTEEN
        FIFTEEL
        SIXTEEN
        SEVt:NTEEN
        EIGHTEEN
<STENS>:- TWENTY
        THIRTY
        FORTY
        FIFTY
```

```
    SIXTY
    SEVFWTY
    EIGHTY
    NinETY
<$OLDEST >>:= OLDEST
    FIRST
    EARLIEST
    FIRST < SWRITTEN>
<SOURSFIVES>:= <RETRIEVAL/S>
    <SMY> ATTENTION
    MYSELF
    OURSE:LVES
    ALL <RETRIEVNL/S>
<SWHENDDAYE>:= THIS YEAR
    LAST YEAR
    SINCE LAST YEAR
    <SWHEN> SSDATE>
<STORY/S:%: STORIES
    STORY
<ARTICLE/S>:* ARTICLES
    ARTICLE
<BCOK/S>: BOOKS
    BOOK
<PAPER/S:- PAPERS
    papek
<ABSTRACT/S>. ABSTRACTS
    ABSTRAC!
<PROCELDING/S> = PROCEFDINGS
    PROCEEDANG
<REPPORT/S>- REPPDRTS
    REPORT
<ISSUE/S>: ISSUES
    1SSUE.
<JOIJRNAL/S> = JOLJRNALS
    JOURNAL
<RI:V/EW//S> = RCVIEV/S
<VOLUJME/S>:= VOLUMES
<SURVEY/S>:= SURVEYS
    SUR\EYY
<SUMMARY/S>:= SUMMARIES
    SUMNARRY
<STORY/S 2>= STORIES
    STORY
<ARTICLEKS 2>:= ARTICLES
    ARTICLE
<BOOK/S 2>:= BOOKS
    BOOK
<PAPER/S Z>= PAPERS
    PAPERR
<ABSTRACT1/S 2>:= ABSTRACTS
    ABSTRACT
<PROCELDING/S 2>"= PROCEEDINGS
    PROCEEDING
<REPORT/S 2>:= REPORTS
    REPORT
<ISSUE/S 2>-ISSUES
    ISSUE
<JOLRNAL/S 2>: JOURNALS
```

JOURNAL
<REVIEW/S 2>: REVIEWS <VOLUME./S ? >:- VOLUMES <SURVEY/S 2>:- SURVEYS SURVEY
<SUMMARY/S 2>:- SUMMARIES
SUMMARY
<\$POLITENESS>: : PLEASE
THANKS
THANK YOU
<SPRUNEIDATE>:= <SIEMME: < $\$$ RESSTRICI> < SOURSELVES> TO <SANYIPIECES>

<SI'M> INTERESTEL IN <SANY!HODATE!PIECES> <\$WRITTEN1> <SWHENIDATE>
<SCHOOSE> < $\$$ FROM > < $\$ A N Y!$ NODATE!PIECES> < SWHEN!DATE>
<SRESTRXIT>: CONFINE
RESTRICT
LIMIT
<SPRUNEIIIST>: = <SPRUNEIIRTE>
<SPRUNE!IIGT!TOPIC.
<SPRUNELISTIAUTHOR,
<SPRUNEILISTITITLE>
<SPRUNEIIITICITATION>
<SPRLINE!IISTIDATE,
<SPRUNE I 1ST!SOURCE>
<SPRUNEIIST!SOURCEIDATE, <SPRISNEIIISTIWHERETURRITTEN>

<SI'Ki: ONLY INTERESTEO IN <SWHAT>
<SBE> < STHATIPIECE> [SRE:TOPICS](SRE:TOPICS)


 <SHOWMAANVIDE, CSWRITTENHY> <SAUTHORS> <SBE > < SSOME: BY < SAUTHORS;
<SPRIJNLIIISTITITLE> - <SWHATWHHICH> <TITLE/S> <SMENTION> <STOPICS>
<SPRUNLHISTICITATION> = <SDO'> < SSOMFIWFIHIM, <SCITE> <SAUTHORS>
<SBE! \ll SAUTHORS: < $\delta C I T E D><$ SIN \llSTHATIPJECE>
<SHOWMSAW'WF!THETA> CSCITE> <SAUTHORS,
<SBF: > < \& AUTHORS > < SCITEU> <SIN> <SSOME!OF!THEM> <SHAVE! < \&AUTHHRS > BEEIS <SCITED> <SIN> <SSOME!UFITHEM> <SBF: > < SAIJTHORS > <SCITED> <SIN> <SSOMFIOFIHHLM
<SPRIJNEII!STIDAPE>- [SIB:PAST](SIB:PAST) <SSOMFI> <SWRITTENI > <SWHENDATE> <SI> DEWMNN < SANV WODATEQUECES> < SWHENIDATE>
 <SBF'> <SSOMFKFMHEMS <SFROM> <SSOURCE2> <SBE! \ll SSOMEMF!lHEM> < SFROM> < SANY!SOURCE!PIECES>
<SPRUNEIIISTGCUKCEIDATE>: < SBE1> <SSOMEMFITHEM> <SFROM> <SANYISOURCE!PIECES> < $\$$ WHENIDATE>
 <SHOWIMANV'ITE: < SWRITTEN> < $\$ W H E R E>$
<SWRITTENIBY = BY
<SWRITTEN 2>BY
<\$RECENTLY'>: RECENTLY
Intely
IN RECENT SSTIMES:
IN RECENT <SPIECESS.>
<\$RECENTLY 2>:= RECENTLY
LATELY
IN RECENT < STIMES:

IN RECENT <SPIECFS1 2>
<\$RFITOPICS>:- <SRF: \ll TOPICS> < $\$ W H E N I D A T E>~$
<SRE: < STOPICS.
<SWHENIDATE> <SREITOPICS.
<\$QUERY - - $\$$ QUERY $>$
<SOUERY1: <SRECENTLY 2>
<SQUERY 1. .- < SOUERVIAITHOR,
<SCUUERYIAITTIORIATIPLACE>
<SQUERY!AUIHORIIDATE>
<SOILERYIAUTHORITOPIC>
<SOUEAY!TOPIC>
<SQUERYICITATION>
[SOUERYMWHFRE:CONTERINCE](SOUERYMWHFRE:CONTERINCE) <SQUERYIDATE> <SOUERYIDATEMFIARTICLEITILE: <SQUERY!LASTIGYAUTHORS <SOUERYINEWESTIOPIC. <SOUERY!REFERELCEDPIECE> <SOUERYISOLIRCE> <SQUERYISOURCEIUTHOR. <SQUERYISOURCECCITATION> <SOUERYISOURCEVDATE <SOUERVISOURCEMEFRERELCED. <SQUERYISOURCEITOPIC> <SQUERYITITLEGOURCE> SSQUERY!TOPICIORIE, <SQUERYIAUTHOR > : = SBELTHEREJIANYIPIECES> <SWRITTEN!AY> <SAUTHORS> DID <SNUTHORS: <SWRITE> <SANY!NODATE!PIECES> <\$RECENTLY> DID < $\$$ AUTHORS > < SWRITE> < SANV!PIECES> WHAT <SHAVE> <SAUTHORS > < SWRITTEN>
 <SHOW!MAMN!!?IECES\%. <SBE.> <SWRITTEN!BY> <SAUTHORS> WHAT ABOUT <SALTHORS, <SHOWUSANUITECES\%> <SHAVE> <SAUTHORS. <SWRITTEN> <SHAVE> CSAUTHORS: <SWRITTEN 2> <SANYIPIECES.
 <SHAVFI> < SAIVYIPIECES > <SWRITTENHY> <SAUTHORS > ARPEARED <SHAVE!- SSANYIPIECES P BFEN CSWRITTENHY> <SAUTHORS.
< SWRITE: WRITE PUBIISH
<SOUERYIALTHORIATIPIACE. - <SHOWIASAVY: <AUTHOR/S > WORK <SWHERE,
<SQUERYIAITTHORIDATE > - DID < SAUTHORS > < SWRITE > <SAINYMODATE! IPIECES > < SWHENIDATE> <SHAVT> -SALTHORS < SWWRITEN > <SWHENIDATE,


<SQUERYIAUTHORTTOPIC> - WHO WROTE < SANVIHODATEYIECES>
<SOUERYIOPIC: <SWRITTENAY> <SAUTHORS>
<SHOWHWAMMETHDRS: <SMEHTION> <STOPICS> <SOUERYIAITHOR: < SRE!TOPICS>

<SQUERYITOPIC> - <SBETOPICSIMEIVIONED> WHAT ALSOUT ©STOPICS.
[SBE:](SBE:) <SANY'PIECES> <SWRITTEN> <SREITOPICS <SBF[PAST]> <STOPICS> WRITTEN LSP <SRECENTLY>
 WHEN <S[BE[PAST]> <STOPICS. LAST <SMENTIONED> <SSOMFIPIECES> <SRE!TOPICS. <SHOW!MAN'!PIECES> < \$MEIVTIGN> < STOPICS.

```
    <SWHATISORTSIOF> <STOPICS> <SBE> <SWRITTEN>
    WHEN <$BE1> <STOPICS> <&LAST> <SMFINTIONED[PP]>
    <$HOW!MANWIPIECES> <SREITOPICS. <$ALSOMMENTIONIOPICS>
    WHERF: <IBETTOPICSMMEIYIONED>
    <SBE!TOPICS!ME:NTIONED> <SSOMEWHERF: 2>
    <SBETTOPICS!MFINIIONED> <SSOMFWHFRFF 2> <SRECENTLY>
    <SHAVE!> <$ANYYJECE.S> <SRF!TOPICS. BEEN <SWRITTEN>
    <SBE[THERE:]ANYIPIECES> < SRFITOPICS>
    <SBFITOPICSMMENTICNED> <SIN> <SANVINIECES>
    <SHAVEL> <SANYIPIECES> APPEARFD <SWHICH> <SMFNTION> <STOPICS>
    <SHOW!MAN\!PIECES'?> <ERITOPICS> <SBE> THCRE:
    <SHOW!MANNTIECES%> -SREMOPICS> <SRE> <SWRITTEN>
    <\deltaDO!> < SANYTPIECFS; <&RI:TOPICS. EXIST
<SQUERYICITATION> = <SHOWU|NN'IPSECES> <SCITE> <SAUTHORS>
    <SBE> <$AIJTHORS> <SMINTIONED[PP]> <$SOMFWHERL:%
    <SW/HAT!WH)CH> < S.PJEC.ES1> <SWRITTENEYY <SAUTHORS> <SBE> <SCITED>
    <SBR[THHERI]IANY!PIECES> <SWWICH> <SMFNTION> <SANV!PIECES> <SWRITTENIBY> <SAUTHORS>
    <SBE!!> < SAUTHORS; <SCITEO> <SIN> <SANYMODATE!PIECES> <$WRITTENI> <SWHENIDATE>
    <SHAVE; <SAN\!PIECES> <SClTEO> <SALTHORS,
    <SHAVE; < $AUTHORS> BEE:H < CCITED> <SIN> <$ANV!PIECES>
<SWHICH>:WHO
    WHIC:H
    THAT
```



```
    <SBE[THERE]> <SSOMF!> <CONFERENCE/S> <$WHERE:
```



```
    <SWIHATIWHICH> < 今BE!> THE <SNEWESH> <SWRITTENIBY> <SAUTHORS>
    <SBETTHELE, <&AW`QODATEDIECES, < SWHENDATE>
    <SGIMMME: <SANVNODATETPIECFSS <SWRITTENI> <SWHENIDATE>
<$QUERYMATE!OFIARTICLETITLE> - WIHEN WAS <SARTICLETTITLE> <SWRITTENI>
<SOUERYILASTBYIAUTHOR: = WHEN WAS THE LAST <SPIECFSI> <SWRITTENBY> <SAUTHORS> <SWRITTENI>
<SQUERYONEWESTITOPIC>= -SPROVIDE> THE <$NEWEST> <SRE!TOPICS,
```



```
<SQUERYISOURCE>:= <SBE[THEREJANYIPIECESS <SFROM> <SSOURCE2>
        <SDOSOMEI, & SONFERELICE> PUBLISH PROCEEOINGS
<SQUERYISOURCEIAUTHOR;: < SHOWMMAW'SOURCE!PIECES: CONTAINED <$ANYIPIECES> <SWRITTEN!GY> <$AUTHORS>
        <SHOWIISNW'ISOURCEEPIECES: <SCONTAIN> WINOGRAD'S ARTICLE
        DID <SAUTHORS> PRESELIT <SNMVYODATE!NJECES> AT <SCONFERENCES>
        DID < SAUTHORS, PRESELT &GAM'!HODATEPIECES: AT <SCONFERENCE3> <SWHENIDATE>
<SQUERYISOURCEICITATION>: <SHOWMMM\\GOURCE!PIECFS. <$CITE> <SAUTHORS:
<SQUERYISCURCE!OATE>* DID <SSOURCE2> PUBLISH <$SOMETHING> <SWHENIDATE>
        <SBE!THERE:, <SANV'SOURCEIPIECFS. <SWHEN!DATE>
<SOUERYISCURCEIREF:IRENCCO>..SSIMMSF: TSANYISOURCEMJECES> <SCITED> BY <$AUTHORS>
<SQUERYISCLIRCEITOFIC>:* <SGIN作\ <SANYIPIECES> <&FROM> <$SOURCE2> <$REITOPICS>
    DID ANYONF. PUBLISH <$REITOPICSS IN <SSOURCE2>
    <SHOW!MANN'GOLJRCEIPIECES> <SMENTION> <STOPICS>
        <SBFITOPICSIMENTIONED. IN <SSOLRCE?>
<SOUERVITITLKKOIJRCE>- &WHATBE> THE: <TITLL/S> <SFROM> <$SOURCE2>
        <SPROVIDE; <SITSMITLE> <SFROM> <SSOURCE!PIECES.
<SQUERYTDOPICOOATE>* <SHOW!MAIN'> <SPIECES1> <SWHENIDATE> <SMENTIONED> <STOPICS>
<RELATE/S;., RELATE
    RE:ATES
<SRROUISIT> - <SCOMMAND>
        <SNFGSTATEMENT.
        <SOUERY,
        <SSTATEMEINT>
```



```
        TELL <SME> <SRIOMOPICS>
```

```
<SSELCTHON> = <WWHATIS> <SSOMF'> <SMENJPMENU> <SFROM> <SSUPERIMENL\
        <SHGE> INTERESTED SN ©SSUPERMNERJ>
        <SWHATIWHICHY <SMFINIMMHU> <SBE[PRES]> RELATEO TO <SWHATIMENLS
        <SIBE> ONL.Y INTERE.STELD IN <SPIECESI> <SRE; <SWHATIMENU>
        THE: <SMEFNDMNHWIJ> <SI'M: INTERESTED IN <SBE[PRES]> <SWHAT!MENU>
        <SJWM JNTERESTED JN <SWHATMARLD>
        <SCHOOSE; <SFRDNA: <SWHATIMENU>
    <SWHAT!M:NU:= <SSUPERUMENLS
```



```
        <SWHATIMINUJ> <SCONJLINCTION> <SWHATIMENL\
<SSC.MNNTICNNETS> = <SUNDERSTANDING>
    SEMANTIC HETWORKS
    A SEMMNTIC HETWORK
    SE.tinNTIC NETS
<SUNDERSTANOING; . HEARSAY
    LAMGUAGE INi!ERSTANDING
    Natural language.
    ENGLISH
    NATURAL LANGUAGE LNDERSTANOING
    SPIECH UNDERGTANDING
    SYINTAX
<SSE/VTENCE>* - SCONTENTSIME:NU>
        < SGETINFO>
        SETRIPI:
        <SHILA:
        <SIISTMHEM,
        <SMAKE!ILLE>
        <SNO>
        <SPRISNEMIST>
        <SREOLITSi>
        <sSEliCMION>
        <SVES>
        <SSTOPLIISTING>
< SYES> = YES
        OK
        SURE
<$STOPMISTING>= <$1'M, < SFINIGHEO>
    NO Move
    <SIVE- <SFINISHED>
    <SSTOP; <SLIGTING>
    <SSTOP, THE -SLISTHIG>
<SSEIVTENCE1>"= <SSFINTENCE>
        <SPOLITENESS: <SSENTENCE,
        <SSENTENCE, <SPOLITENESS.
<STHATIPIECEA> = <STHAT> <SPIECES1>
        <STHFT,4.
<SSORTS> = <SORT/S>
    <KIND/S>
    <TYFE/S>
    <VARIETY/S>
<SORT/S:`: SORTS
    SORT
<KIND/S>: KINDS
    KIND
<TYPF/SS:: TYPFS
<VARIETY/S>:= VARIETY
<TRANSACTICN/S>.E TRANSACTIONS
    TRANSACTICN
```

```
<$STOP;:= STOP
    CEASE
    terminate
    KHLL
    FINISH
    QUIT
<STHAT>:= THIS
    THAT
    THESE
    THOSE
<$THESf:>:- IT
    <STHAT>
    THEY
    E^CH
<$THAT!PIECE2>>= <STHAT> <$PIECES1>
    <STHAT> <ONE/S>
<STHEMS_- <STHAT>
    THENA
<STIMESGFMCE>: THME
    SPACE.
    TIKPE. <SCONJUNCTION> SPACE.
    SPACF. <SCONJUNCTION> TIME
<$TOPIC>: <SAI>
    PROBLITA SOLVING
    GIPS
    <SCHESS:
    <SIFARNING;
    INFERINCE
    <SEPMAWTICINETS,
    CYEBCRMETICS
    COMPIJTATIONAL LINGUISIICS
    PSYC:HDLOGY
    CONTROL
    ADAPIATION
    INTERACTIVE DESIGN
    DESIGN
    AlJOMATIC PROGRAMMMING
    HYPOTHESIS FORMATION
    dEDUCTIVE RETRIEVAL
    GEOMEIRIC MODELING
    INTERAS:TIVE KNOWLEOGE SYSTEMS
    KNOWLEDGE SYSTEMS
    COGNITIVE SCIENCE
    COGNITION
    ALITOMATION
    DATA STRLCCTURES
    FORMAL SEMANTICS
    A TASK ORIENTED dialogle
    THE TECH-JI CHESS PROGRAM
    SYNTHESIS OF LINE DRAWINGS
    TELEOLOLICAL REASONING
    TEMPDDRAL SCENE ANALYSIS
    TEXTURE: ANALVSIS
    A THALiMATLIRGIST
    SHAPE TOPOLOEY
    THREE DIWENSIONAL MODELS
    A TUTOR OR TUTORING ON TV
    THE WEAK LOGIC OF PROGRAMS
```

[^1]```
ANALYSIS OF CONTEXT
CONTEXT
ANALYSIS OF SENTENCES
ASSIMILATION OF NEW INFORMATION
AUGMENFTED TRANSITION NETWORXS
AIJTOMATED DEDUCTION
DEDLICTION
AlfOMATIC CODING
AlITOINTIC COMPISTATION
AlJTOMATIC, PROGGRAMS SVNTHESIS FROM EXAMPLE PROBLEMS
AlITOMATIC PROGRRIG WRITING
AlIOMATIC PROOR OF CORRECTNESS
AlITOMATIC THEOREM PROVING
axicmatjC SEMANTICS
BAC:KGQAMMKZM
BEI.EEF SYSTEMS
BINIINGS
BIOMFDTCONE
BRAIN THEORY
BUSINFSS PROBLEM SOLVING
CARTOGRAPHY
CASE SYSTEMS
CAUSAL REASONJNG
CHECKING PROOFS
CHESS PLAYING PROGRAIBS
CIRCUIT ADr,MVS1S
COGNITIVE ROBOTIC SVSTEMS
COMHNON SENYSE
COMAMSN SFISSE THEORY FORMATION
COMPLEK WAVEFORMS
COMPIJTER ART
COMPIIER BASED CONSULTATIONS
COMPIJTER CONTROLLED MANIPULATORS
COMPISTER GRAPHICS
COMBISTER MUSIC
COMIISTER VISION
CONCFPTUAL DESCRIPTIONS
CONCEPTUNL INFEHENCE
CONCEPTIAAL OVERIAVS
constraint satigfncticin
CONSTRIECTILG PROGRANS FROM EXAMPLES
CONSTRUCIION OF PROGRAMS
CONTHNUOUS PROCESSR.S
COOPI:RAIIIG SOURCES OF KNOWLLDGE
COFVING l.IST STRUCTURES
CURVED CHMmCTS
DATA BASLSGOR INTERACTIVE OESIGN
DECISION THEORY
THE: DEDUCHIVE PATHANDER
DENOTATIONAL SEMANTICS
DEPTH PERCEPTION
DEPIVATION PIANG
DESIGN ALIOMATLON
DESIGN IN THE ARIS
DETECTICN OF LIGHT SOURCES
DISPLAY YERKINALS
DRAGON
DRIVING A CAR
```

DYNAMIC BINDING
DVNAIMIC PROGRAMMING
ELECTRONIC CIRCUITS
ELECTRONICS
THE ENVIRONIMIIT
EXPERT SYSTEMS
EXPLANATION CAPABILITIES
FABLES OR FAIRY TALES
FEATURE-DRIVEN SVSTEMS
THE: FEDERAL JUDICIAL SYSTEM
FIRST ORDER LOGIC
FRAMES
FRAMES ANG THE ENVIRONMENT
FIJZZY KNOWLIDGE
FUZZY PROEILI:I SOLVING
A GAh1: MODEL.
general purpose models GENFRATION OF NATIIRAL LANGUAGE
GO OR GO-MOKU
GOAL SETEKING COMPONFWTS
GRAPH INTERPRETABLI: GAMIS
HEYERISSTATJC THEORY
HEUJRISTIC PROGRAMMING
H:URISTIC TECHINIQUES
HJMAN BEIAAVIOR
HUMAN MEMGRY
HIJMAN VISION
IMPRDVING PROGRAISS
INDUGTIVE ASSEHTIONS
INDUSTRIAL APPLICATION
INEXACT RLPRESEINTATION
INFEREHCES
INFERELTIAL QUESTION ANSWERING
INFORIANTION PROCESSING UNIVERSALS
INHERITANCE OF PROFERTIES
INTELIIGENT MACHINES
INTENTIONS
INTERACTIVE PROGRAM SYNTHESIS
INTERPRETIVE SEMANTICS
INTOHATION
INVARIANCE FOR PROBLEM SOLVING
INVESTMEIVT ANMIVGIS
ITERATION
KNOWLCDGE BASED SYSTEMS
Lavibida cal cuilus
language design
LANGUAGE FRIMATIVES
large data bases
THE BAY ARE:A CIRCIF:
Thi BERKELIV ORBATE
THE DREYFUS DEBATE
THE: HISTORY OR AI
THE HUNGRY MMOKEY
THI: INSANE: HELRISTIC
AXIOMS FOR GO
COMPIJTER BASEG CONSULTANT
JMAGE INTENSITY UNDERSTANDING
trouble shooting

```
    LANOLAGE COMPRE:GENGION
    <STIM㑑PMCi%> EOUNDS
    PERCEPTRONS
    COMPISTER NETWORKS
    GRAPH MATCHING
    ASSOCINTIVE <MENHORY/S,
    UNIFORM PROOF PROCEDURES
    PL_NNER-LIKE LANGUAGES
    hill Climibing
    <STIMESPACF: COMPLEKITY
    EVALUATION FIJNCTIONS
    PROGRRAM VE:RIFICATION
    FRAME THEORY
    PREDICRTE CALCUUUS
    GRAIN OF COMPlitATION
    PATTERN FintCHING
    RECOGNITION DEVICES
    PATTERN RICOCINTION
    STRIECTURED PATTERN RECOGNITION
    PATTERN DIRECTED FIUNCTION INVOCATION
    RESOLUTICN THEOREM PROVING
    ME.dicial CONSUITATION
    VISUAL COMMIINICATION
    A PARTIA! EVALIIATOR
    thE I.anguage pasical
    photogramMiYHy
    picYure recoginition
    VISUAL Pl.ANES IN THE RECOGNITION OF POLYHEDRA
    pREFI:H:NTINL SEMANTICS
    thil gamm: dF poxEk
    PROCEDDJKAL EVENSS
    pruce'S 'LITORIAL.
    pRODUCTIVITY TECHNOLOGY
    A RLGION ANALYSIS SUBSSYTEM
    RE.PRESELHIHG RFAL-WORLI KNOWLEDGE IN RELATIONAL PRODUCTION SYSTEMS
    ROBOTICS COOPIRATION ANU RESOURCE LIMITEO PROCESSES
    USTNG S-L-GRAPHS
    RIULE. AC:QliSITION CAPABILITIES
    scene segmeniation
    SERIAL PAITERN ACRLISITION
    THIL SIX SEVF.N &IGHT NINE GAME:
    SNARING DR^GOHS
    SE.WTENCE MF.ANHIG IN CONTEXT
    SOFTWARE INTERRUPTS
    SEVEHML GOALS SIMIUITANEOUSLY
    SHAPE GRAbmMARS
    SIMILLTANEOUS ACTIONS
    STATE DESCRIPTION MODELS
    STOCHASTIC MODELING
    A STERL:O PMIR OF VIEWS
    storage reduciIon
    SYNTACTIC METHODS
    SYNCHRONIZATION OF CONCURRENT PRCCESSES
    AI LECTURES
    THE. COHAPISTERS AND THOUGHT AWARD
\angleMFMOEY/S,: MFMORY
    MFMMPRIES
<$WHAT2>:- <$ANY!PJECFS. <SRE!TOPICS>
```

<\$WHATI>- \ll RE!TOPICS.
<SWHAT2>
[SWHERI:1](SWHERI:1): AT \&SWORKPLACE> IN \&SWORKPLACE? WITH SUMEXX
<SWORKPLACE>:- CMI)
THE GM RESEARCH LABS
THE INSTITUTE FOR SEMANTIC AND COGNITIVE STUDIES
MASSACHUSETTS
NRL
NIH
ROCHESTER
RUTGERS
SMC
SRI
STANFORD
SUSSEX
WATSON RESEARCH
Hulnois
HAWBURG
EDINEURGH
<SWORKPLACER. - THE SUNSHINE STATE
THE US.
THE USSR

## Appendix III-C-2. Al Retrieval Language Grammar: AIX15

```
<SENT>: [ <SS> ]
<SS>::* <SANY'FAFERS> <EABOLITTOPIC>
    <SARL:THERE:> &ANYJOUNNALS> < $ABOLUTTOPIC>
    <$ARETHHRE: <§ANVPAPERS> <§ABOUTTOPIC>
    <SARE THERE: < SANVPAPERS. IN < SJOURNAL>
    <SARETHENE: <SANVYPAPERS> SINCE <SDATE>
    <SARETHLRE: <&ANVPAPERS. THAT MENTION THE <SDATESOFTHE.CONFERENCE>
    <SARETHE:H!; ESANYPAPERS: WHICH <$CIFEAUTHOR,
    <$ARETHINE:> <SPAPERS. < $AGOLIT.TOPIC>
    <SARE> < SANV'JOLKNALS> <$ASOUTTOPIC> BUT NOT < STOPICS>
    <SARE> <SANVPAPERS> <SABOLTTOPIC>
    <SARE> <$ANY'PAPERS> <SABOUTTOPIC> <$ALSOABOLTTTOPIC>
    <SARE> <SANY'PAPERS> <SBYAUTHOR;
    <SARE> <SANH'PAPERS> FROM < SACONFERELLCE>
    <SARE> <SANYYAPERS> FROM <SUOURNAL>
    <$ARE> <SANY'NAPE&S, FROM <$THE CONFERL:NCERS> IN THE MONTH OF <$DATE>
    <SARE> <SAUTHORTS> CITED BY <SANYPAPERS.
    <$AHE> <$AUTHOROS> CITED IN :SANYPAPERS.
    <$ARE> <$TOPICS> <$NENTIGNED> ANYWHERE
    <SARE, <STOPICS. <SMENTIONEO> IN <SAPAPER.
    <SARE> <$TOPICSS> <SMEINTIONED> IN <SJOURNALPS>
    <SARE, ANY :SBYAWYHOR,
    <SARE> YOU <SALWAYS> <$THIS SLOW>
    <SDODDID> <SANYCONFEIRFINCE\S, <SMENTION TOFIC.
    <SDOIDID> <SANY CONFEREIFCE%S, PUBLISH <$JOURNAL7S>
    <$DO'DID> <\ANY'.JOURNALS> < SMFNTIONTOPIC>
    <SDOIDID> <SAN' PAPERS> <SAISOLTTOPIC- <$ALSO WFINTIONTOFIC>
    <SDOIDID> <SANY FAPERS> < SAFOLT TOPIC> <$NFIVTIONTOPIC>
    <SDOIDID> <SAWY PAFERS> <SABOLITTOPIC> EXIST
    <SDOIDID> <SANY PAPERS> < SASSOMENTION TORIC>
    <SDOIWID> <SAN'PAPERSS <SCITE AUTHOR;
    <SDOHDID> <SANVFAPERS> <SMINTIONTOPIC,
    <SDONID> <SANYPAPERS, &SNINTIONTOPIC, BUT NOT <STOPICS,
    <SDOPDID> <SANY'PAPE:RS> <S.THIS YEAR; <SCITE AUTHOR,
```



```
    <SDODIO> <SALTHORIS; PRESENT <SAPAPER: AT <STHECONFENENCEIS> IN <SDATE>
    <SDODDID> <SAUTHORTS> PRFSLLIF :SPAPERS> AT <STHECONFERENCEFS>
    <SDOLOIO> <SAUTHIOR`S> FUB!.JSH <SADAPER>
    <SDOIOJO> < SAUTIIORTS> WRITE <SAPAPER.
    <SDOUOIO> <SAUTYIORTS, WRITE <SA PAPER, <SLATELY>
    <EDOIDIU> <SAUTHOR?S> WRIIE. <SAPAPER> <$THIS.YEAR>
    <SDOUIO> <STHI AUJTHORS> <SMINTIONTOPIC>
    <SDODDO> <STHI: JOUNRIAL>PUELISH ANYTHINGIN <SDATE> OR <SDATE>
    <$DOLDIO> <STHF,FAPER> <SCOTE NUTHOR>
    <SDODID> ALL OULRIES TAKF. THIS LONG
    <SDODIO> ANYONF. PUBLISH <SAGOUT TOPIC> IN <$THEJOURNAL>
    <$ODOID> RESPDNSZS EVER COME. FASTER
    <SDD THEV WC\RK; AT <SWRORKPLACE;
    <SDOESUDOSN'T> <STHF.FAPER> <SMENTIONTOPIC,
    <$DOES!ODESN'l> < THEPAPER. REEERRFICE <SA JOURNAL>
    <$DOES!DIESN'I> <STOPICS> <$CEYME: <SMENTIONED> ANIWHERE.
    <SDOES'DOESN'T> IT <SALWAYS> TAKE THIS LONG TO ANSWER ME
    <SDONTGETMF.> < SANY'PASERSS <SABOLT.TOPIC>
    <$GETN隹: <SAJOURNAL> REFEIRELCED <SBY.AUTHOR>
    <$GETMES < SAPAPER: AFTER <$DNTE>
    <SGETME, <$ANYPAPERS. <$ABOUTTOPIC>
```

```
<SGETMS: < SANY PAPFRRS> <EABOUTTOPIC> BUT NOT <$TOPICS>
<SGETME> < SANY PAPERS> < SASOUTTOPIC> FROM <SDATE> TILL <SDATE>
<SGET.ME: <SANN'PAPERS> <SEYAAITHOR>
<SGETME: <SPAPERS> PRINTEOUN <$TIME!PTHOOD>
<SCETMM:> <SOUANTITY> <SPAPERS; <SABOUTTOPIC>
<SGETMR:> <SOUANTITY> MORE PLEASE
<SGETMES FVERYIHING <SAISDUTTOPIC>
<SGEYMGI: SOME REVIEV/S <SAESOUTTOPIC>
<SGETMES SOMETHINL <SABOUTTOPIG>
<SGELML:> SOMFITHNG FROM - SNOIRNAL> <SABOUTTOPIC>
<SGETMA: THI <SANDORINUTHORIOATETITLE > FROM <STHE JOURNAL>
<SGETME; THLE <SANDORINUTHORDATEITITLE> OF <STHE.PAPER>
<STETMEP THE <SANDOORINUTHORIDATEITITLE> OF EACH
<SGETME: THE MFNLSS
<SHOWMMNN'FASE:RS> <SALSO MELVIONTOPIC>
<SHOW MANYPAPERS> <SMEITINNTOPIC>
<SHOWMANN'PAPERS.- STHIS.YEAR> <SMFNTIONTOPIC>
<SHOWMAN'PAPERS> <SWERE> <SBYAUTHOR.
<SHOWWAMY'FAPERS> <SWERE> <SBYAUTHOR> AND NOT <SAUTHOR%S>
<SHOWMANTPAPERSS <SWERE> <$WRITMENIPUBLISHED> FROM <$DATE> TO <SDATE>
<SHOW MANNTPAPERS> FROM <SDATE> THROUGH <SDATE> <SMENTIONED.TOPIC>
<SHOWMMNTPAPERSS HAVE <SAUTHORZS. <SIWRITTENIPUBLISHEO> SINCE <$DATE>
<SHOW MAN'> -SJOURNALTS> &SMENTIONTOFIC>
<SHOWMMNN'> REFEREHCES <'JARE. GIVEN
<SISTHLRE: rSACONFEMELICL> IN <SGEOPLACE>
<SISTHIRE: <$N.OUURNAL: FROM <SDATE> OR <SDATE>
<SISTHERE; SIAPAPER. &ABOUYTOPIC;
<SIS THEME:, MIYYTHING NEW <SAEOUTTOPIC>
<SIS> <$ALITHOR%S> BUT NOT <SAUTHOR2S> CITED IN <SANY PAPERS:
<SIS> <SAUTHORIS> CITED BY <SANY FAPERS. ISSUED IN <STIMEIPERIOD>
<SIS> <SAUTHOR%S> CITED BY <STHESEFAPERS.
<SIS> <SALTHOR2S. CITED IN <SANY'PAPERS.
<SIS> <SALTHOR%S: CITED IN <STHF.PAPER.
<SIS> <STOPICS:- <AMFNIICNED>
<SIS> <STORICS. < RMELNTICINED> <SIATELY>
<SIS> <STOPICS: <SMFNTIONCD> AIN'WHER:
<SIS> <STOPICS> -SMEWHONED> IN SAPAPER,
<SIS> <STOPICS> <EMENTIONED> SOMEWHFH:
<SIS> <STOPICS, <SMENTIONED> SOMFWHERI: <SLATELY>
<SIS> IT &SWRIITENIPUSLISIEDD, BY <STHEASGOCIATION.FORCOMPUTATIONALLINGUISTICS>
<@1S> IT <SWVITTENPPISSLISHEO)>BY <$THE JOURNAL;
<SIS> THAT < SALSOUTTOPIC>
<SK|L>
<scluANTJi/>
<SOIJANTHIV> PLINGE
<SWERE:INTERLSGLDIN> <SJOURWALOS> AFTER <SDATE>
<SWE'RE INTEKLGBLDIN> <SPAPERS> <SAGOUT TOPIC>
```



```
<SWEPE WTGR(STEOIN> <SPAPERS. 1SSIJED SINCE <SDATE>
<SWEREINIERUSIEDIN> <SPAPERS> SINCE <SDATE>
<SWERL:IWTERESTEOIN> <STOPICS>
<SWERE, SLAN'PAPERS: SSBVAUTHIOR,
<SWERE> &ANNPAOERS\ -SWRITENPPJBLISHEO\ <SABOUTTOPIC>
<SWERE: CSANY PAPERS> -SWRITTENPUBGLISHEO> IN <SGEOPLACE> OR IN <SGEOPLACE>
<SWERE> AN'Y :SWRITTENIPIJBLISHED> AFTER <SDATE>
<SWHAT ABOUT> <$AUTHOR%S,
<SWHAT ARE> SOMNE DF THE AREAS OF <STOPICS.
<SWHATARE> THE < SANDLORIAUTHORIDATETTITLE> OF THE RECENT <SJOURNAL>
```

```
<SWHAT ARE, THE KEY PHRASES
<SWHAT ARE, THEIR AFFILIATIONS
<SWHATHAS> <SAUTHORZS> <SWRITTENIPUBLISHED> <SLATELV>
<SWHATIS> <SHFRPHSS AFFILIATION
<SWHATIS> KNOWN AGOUT EVERY ARTICIE
<SWHATIS> THE <SANDOORINUTHORDDATE!TITLE> OF <SQUANTITY>
<SWHATIS> THE &SANDIORIAUTHORIDATEITITLE> OF <STHEPAPER>
<$WHATIS> THE {SANDORIAUTGORDDATE!TITLE> OF THAT PIECE
<$WHATIS> THE SIZE OF THE DATA BANK
<SWHENWAS> <SHIJMAN.PROBLIMGOIVIIG` <SWRITTENIPUBLISHEO>
<SWHENWASS> <STHEPAPER> <SWRITTEN:PUBLISHED>
<SWHENWAS> <STOPICS. <S.MFLNTIONLD>
<SWHENWAS: II <SWRITTENPISBLISHED>
<SWHENWAS> THIE LAST PAPER <§IYYAUTHOR> <SWRITTENIPUBLISHED>
<SWHE:REIS: < STOPICS> < EMENTIENED>
<SWHICHAUTHORS: WORK AT <SGEOPLACE; OR AT <SGEOPLACE>
<SWHICHAUTHORG; WORK AT <SWCDKPLACE, OR AT <SWORKPLACE,>
<SWIHCHAUJTHORG; WORK WITHI <SWORKPLACE> OR AT <SGEOPLACE>
<SWHICHOHTHHSST> &AGSOUTOPIC> <SALSOMFNTIONTOPIC>
<SWHICHOFTHHSF:S CSABOUHTOPIC; <SMFINTONTOPIC,
<SWHINCHOFTHESI< <$ABOUTTOPIC> <SWERE> <SWRITTENPPUBLISHED> <SLATELY>
<SWHICHOH 1HIS:S\: +SARES SBY AUTHOR>
<SWHICHOFTHHSS>> +SBY AUTHOR> <SARE> REFERENCED
<SWHICHOH THFSTB SGOITE AUTHOR>
<SWHICHOHYYHSL; CSCONTAINED> STHEPAPER> <SEYAUTHOR>
<SWHICHOH THEST; +SCONTAINED> <STOPICS>
<SWHICHOFTHESLS <SMEIWTIONTOPIC>
<SWHICHOF THISF.> &MENTLONEDTOPIC,
<SWHICHOFTHESL; -SWERF, <SBY AUTHOR>
<SWHICHOF THESI; &SWERE> <SBY AUTHOR> SINCE LAST YEAR
<SWHICHOHTHFSI\ <SWERE, <SWRITTEN!PIBLISHED> AT <SWORKPLACE> OR AT <SWORKPLACE>
<SWHICHOFTHILSL` APPEAREO) <SIATELY> IN <STHE JOURNAL>
<SWHICHOHTHHSGL: GITES <SAUTHOR"S>
<SWHICHOF THFSF; NENIIONS <STOPICS.
<SWHICHOF THESf: REFIR TO THESE
<SWHICHOF THESL:; WAS <SBYAUTHOR>
CAN I HAVE <STHESE.PAPERS> LISTED
CAN YOU HELP ME
CHOOSE AMONG - SJOURNAL:S: BEFORE <SDATE>
DURING WHNT MONTHS -SWERF, THEY <$WRITTEN!PIJBLISHED>
GENERATE A COFY OF THOSE
HAS <SAUTHOR%S: <\hat{WRITTENPIJBLISHED> <SANYYAPERS, <STHIS.YEAR>}
HAS <$AUTHOR%S:> <SWRITTENIPIJBLISHED> ANYTHING <$LATELY>
HAS <SAUTHOROS; BEEH REFIMEICE[D IN <SNAVPAPERS:
HASNT <SAPAPER> <SABOLTT TOFIG> BEEN REILASED
HASNT <STOPICS. EBEEN CONSIDERED IN < JOURNAL>
HAVE <SANYPAPERS> <SBY AUITHOR, APP!:ARED
HAVE <SANY'PASLRS: APPEARFOC < SABOLTTOPIC;
HAVE <SAUTHORSS\ & SWRITTENPIDBLISHED> <STHIS YEAR>
HAVEN'T VOU FINISHED
HC.P
HOW GIG IS THE DATA GASE
HOW CAN I LSF THE SYSTEM EFFICICNTLY
HOW LONG -SDOESITYAKE,
I'O LJKE TO KNOW THIE <SANOIORIAUTHOR!DATETTITLE> OF <STHE.PAPER.
LIST <SOIJANTITY> HUNDRED
LIST BETWEEN <SOIJANTITY> ANI) <SOUANTITY> OF THEM
LIST THE <SPAPERS: <$BYAUIHOR>
```

```
NO MORE PIEASE.
NO THANNS
OK
PLENGE HELPMME
PLEAGE LIST <STHEALTHORS,
PLEASE MAKE NE ^ FILE OF THOSE
PRINT <SQUANTITY>
PRODUCE A COFY OF <SQUANTITY> <SPAPERS>
SELCCT FROM <SPAPERS:` <SABOUT TOPIC>
SHOW NMF <SQUANTITY>
SHOW ME: ITS <SANDDORIAUTHORIDATEITITLE>
SUBSELECT TROA - STOPICS.
SURE THARKS
TELL KIF: <SWIAAT TODO>
TELL MF. THE <SANDDORIALTHORDATE!TITLE> OF <SQUANTITY>
THANK VOIS <SWLTHC; DONE
TRANSMIT &SOLANTITV>
WHAT <SABOUSTOPIC:
WHAT <ECANIDOD TO SPERD VOUIUP
WHAT <SDOIHAVETODD>
WHAT <SIS. ITS <SANODRIAUTHORDATETITLE>
WHAT &GOHINNALFS: DLIRING <SDATE> ANO <SOATE> <SMENTLONTOFIC>
WHAT &SPAPERS: CEMENILGNTOPIC,
WIHAT <ESORTOF SUMMMARY: IS AVAlLABLE
WHAT ADOREGG, IS GIVEN TOR < STHE AlTHORS,
WIHAT ADDRESSGS ARL GIVEIV TOR -STHE:AUTHORS,
WHAT CAN ETHE SYSTEMDO.
WHAT CONFIHR:ICI WAS AT <SWORKPLACE> OR AT <SGEOPLACE>
WHAT COONICRIICI WAS AT <SWORKPLACE> OR AT <SWORKPLACE>
What FACTE < SARG` STORED
WHAT KlY WORD RFIATES TO <STORICS.
WIHAT KEY WOROS SHOULD I USEFDOR <STOPICS>
WIGAT kIND OF MMNUSS <SARETHERE:
WHAT KINISS OF SUBJECTS <SARE> STORED
WHAT MISST I ASG
WHAT SHOLIDI I ASK
WHAT SHOLIID I SAV
WHAT SORTS OF <STOPICS. <SARE. <SMENTIONED>
What subjl:TT GAN I REQUGG
WHAT TOPIC MELIIS CAIV I CHOOSE
WHAT TOPICS &SARF, RFIATEO IO <STOPICS>
WHAT TYPES OF &RETRIEVAL CANGFARSAYDO,
WHFN WILL YOH Have THE AgSWER
WHFRE - SARE: STOPICS> SSMITTICNED>
WHERE: &DO THEY WORN,
WIHERE DID -STHE PAPER. APPPGR
WHICH <SAITEXT> \SCONTAINED> STOPICS.
WHICH AUTHORS < SMENTIONTOPIC,
WHICH CONFEREHCES WERE: AT <SGEOPLACE> OR AT <SGEOPLACE>
WHICH IS <SQUANTITY>
WHICH NOTES < SABOLTTOPIC> <SALSO MEINTIONTORIC>
WHICH ONES
WHHCH SORT OF <SRFTRIEVAL KEYS> CAN I SEEK'
WHICH TITLES <OMAFNTIONTORIC>
WHICH WAS THE L.AST ARTICLE <SBY.AITHOR>
WHO
WHO HAS <SWRITTENIPIIBLISHED> <SABOLTTTOPIC>
WHO WAS QUOTED IN <STHEPPAPER.
```

WHO WAS THE ALITHOR
WHO WERE: <STHE AUTHORS> OF <STHEPAPER: WHO WROTE <SPAPERS> < SAGOUTTTOPIC> <STHIS.YEAR> WHO WROTE IT
WHY IS THIE SYSTEM - STHISSLOW>
WOULD YOU LIST <SOLANTITY>
WRITE A FILE OF THOSE.
YES PLEASE

```
<$RETRIEVAL CANIIF.ARSAY DO>* <$RITRIEVAL CAN.HEARSAY> DO
<SDOESITTAKE>:r DOES IT TAKE
<SDATES UFTHE\ONFFRELCES:- DATES OF <STHE.CONFERENCERS>
<SWHAT.TODO>:* WHAT TO DO
<SCANIDO>:- CAN I DO
<STHESYSTEMOD>:- THE SYSTEM DDO
<SDOILHAVETODO>: DO I HAVE TO DO
<STHE:AUJTHORG>:- THE: AlITHORS
    ANY AUTHORS
<$KILL>:= <CEASE.PRINTING>
    PLEASE <CEASEPRINTING>
    <CEASEPRINTING> PLENSE
<CEASE.PRINTING>:= <CEASE> <PRINTING>
<CEASE>:= CEASE
    STOP
    TERMINATE
    FINISH
    QUIT
    KILL THE
<PRINTING>:* PRINTING
    LISTING
    TRANSMITTING
```

```
<SHOW.MAN'>: HOW MANY
<$HOW MANV'PAPERS>:- HOW MANY <SPAPERS,
    HOW MANY OF THESE
<SARE.THEIIF:%: <AREIWERE> THERE
        <SDOUDID > YOU HAVE
        <SDO!DID> YOU HAPPEN TO HAVE
<AREIWIERE,:- <SARE>
    <SWERE;
<SWERF.>. WIERF.
    WEREN'T
    WERE NOT
<SDOIDID> - DO
    DON'T
    DID
    DIDN'T
<SDOESDOOESN'l>>:= DOES
    DOESN'T
<SGETME:* <GETIGIVE> ME
    <GET!GIVE>
    TRY TO GET
    TRY TO GEY MF.
    COULO Y(YU REYRIEVE
    <IWWE> <DEMANDIVANT>
    <IWE, <DEMANDNVANT> TO <SEE!GEY>
    <I'DUWEOD> LIKE TO <SEEIGIG>
<GETGIVE>:-GET
    GIVE
<IUNE>* I
    WE
<DEMANIDWANT> - DEMANO
    DESIRE
    WISH
    WANT
<I'D!WEOP - I'D
    We:
<SEGIGET>- SEE
    GET
<SOON'TGETME> - OON'T <$GETME>
<SWHERE: 15:= WHERE 1S
<SIS>:. IS
    ISN'T
    WAS
    WASN'T
<$ARE:- ARE
    ARI: NOT
    ARI:NY
<SISTHERI:>: <SIS> THERE
<SHER!HS>> HER
    HJS
<SWHATHAS>:= WHAT <HAS!HAVE>
<HAS!HAVE>= HAS
    HAVE
<SWHENWAS >: WHEN WAS
    WHEN WERE
```

```
<SDOTHEYWGOK'; <DOTHEY> WORK
<DOTHEY>:= <SDODDD> THEY
    <SDOESIDOESN'T> <HEISHE;
<HEISHI:?:* HE
    SHE
<SWE'RE INTERESHEDIN>: <SWE'RE, <INTERESTEDIN>
    <SWE'RE; ONLY sINTERESTEDIN>
    THE ARE:A <SWE'RE> <INTERESTEDIN> IS
    THE ONLY AREA <SWERE, <INTERESTEDIN> IS
    <LET'S> <RESTRICT> <OURSELVES> TO
<SWE'RE:= - WE'RE
    WE'VE BEEN
    WE HAVE BEEN
    <I'M:
|I'M:- = I'MA
    I AM
<INTERFSTEDIN> - INTERESTEID IN
<LET'S> - LET'S
    LET <USMMF:
<US!MF.:: US
    MF
<RESIRICT>- REGIRICY
    CONFINE
    LIMIT
<OURSEIVES>* OURSEEVES
    OUR ATIENTION
    MYSELF
<SWHAT ABOLST> E WHAT ABOUT
<$WHATARE>:: WHAT AR:
<SWHATIS>: WHAT IS
    WHAT'S
<SWIHICHAUTHORS:, WHICH AUIHORS
```



```
    WHICH PAPEH
    WHICH <SPAPERS:
    WHHCH <SJOURNAL;
    WHICH <SJOUJRNAL.%S>
<THESE!IHIMA:= YHESE
    THEM
```

```
<SWORKPLACE>:-CMIS
    NIH
    NRL
    RUTGERS
    SMS:
    SRI
    STANFORD
    SUMEX
    THE GM REs[ARCH LABS
    THIF. INSTITUTE FOR SEMANTIC AND COGNITIVE STUDIES
    WATSON REStARCH
<SGEOFLACE: FGIINHLRGH
    HANM(3)RG
    ILIINOIS
    MASSACHIJSETTS
    ROCHESIEK
    sussix
    THIL SUNSHINE STATE
    THE: US.
    THE USSR
<SLATELV> = IATELY
    RECENTLY
    IN RECENT TIM隹S
<SWRITTEN&PJSULSHED> - WRITTEN
    PUBLISIED
    PRODUCEO
<&ALWAYS>:= ALWAYS
    RE:GULARL.Y
    usunlly
<STHISSLOW> = TTHISGO. SLOW
<THISIGO.:= THIS
    SO
<$CONTAINED>:= CONTAINED
    CONTAINS
<SSORTOF SUMMMARY> = SORT OF SUMMARY
    SORTS OF SUMMARIES
```

```
<SALSOCITE AITHOR:% = ALSO <SCITE AUTHOR,
    <SCITEAUTHOR: <INADDITION>
<$CITE AUTHOR>:- <CITE > <SAUTHORIS>
    REFER TO <SPAPFRS> BY <$AUTHOR%S>
<CITE>:= CITE
    QUOTE
    REFE|t:ICE
    DISCUSS
<INADDITION>: IN ADDITION
    Also
    SImill.tane(ousiy
<$ALSOIGYAUITHOR>:= ALSO<SBY AUTFOR>
    <SBY AUITHOR: SINADDITION>
<SBYAUHHOR:= -WRLTTENBY> <SAUTHOROS>
<WRITTENBY> = BY
```

        WRITTEN BY
    ```
<SDATE;: <YEAR;
    <MNNTH> <YEAR;
    <MONTH> OF <YEAR:,
    <MONTH> OF <STHIS.YEAR>
    <MONTH>
<YEAR:*-<CENTURY> <SNIMBIER1-99,
    <CENTURY> MUNDRED <SNIJMBLR1-99>
    <CENTUPY> HUNDRED
<CENTURY:> = NINEYEEN
    EIGHTEEN
    SEVENGEEN
    SIXTEEN
<MONTH; = JANUUARY
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    BRUCE BUCHANAN:
    CARE. HEWITT
    CHRISTOPMER RIESBECK
    CHUCK RIEG:G
    DANINY BOESROW
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    DAVID MARR
    DAVID MICHIE
    DICK SEL.TZER
    DONALD NORMAN
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    EllidT SOloway
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    FEGGENHAUMM
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    george monst
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    JACK MOSTOW
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    JEFGid:Y Imelmats
    JHRRY flmban
    JOHNN GASCHNIG
    JOHN HOLLAND
    JOHN MCCARTHY
    JOHN NEWCOMER
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SHAPE TOPOLOGY
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SPEECH LINDERSTANDING
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THE: BAY art:A CJRCL.E
THE: berkElev DIIBale
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THE: DEDUCTIVE PATHFINDER
THE: DRLYFIJS DEBAIE
THLE ENVIRCDNWIWT
THE. FEDERAL JHDICIAL SYSTEM
THE GAIAI: OF POKEK
THE HISTORY OR AI
THLL HUNGPY MONK!:Y
thE INGANE: hEuRISTIC
THE LANGUAGE PASCAL
THE l.OCATION OF OBJEC'TS IN MAGAZINES
THE LOGICAL REIDLIGTION OF LISP DATA BASES
THE META-SYMBOLIC SIMULATION OF MULTIPROCESS SOFTWARE
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THE ONTOGENY OF NON-INDEPERDENT SUBPROBLEMS
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THE PERFCRMANICE OF PATTERN MATCHING RULES
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THE STOCK MARKET
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THE TECH-II CHESS PROGRAIM
THE WENK LOGIC OF PROGRAMS
THREE: DIMERSIONAL MODELS
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TINAE DR SPACE BOUNDS
TROUBLE SHOOTING
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UNDERSTANDING
UNIFORM PROOF PROCEDURES
USING S-L-GRAPHS
VISlual COnimilinication
VIGUAL PLANES IN THE RECOGNITION OF POLYHEDRA

## Appendix III-C-3. AI Retrieval Language Grammar: AIX05

<SENT > : [ < SS> ]
<SS>: = ANY ABSTPACTS REFTRRING TO <STOPICS> ARE <SAUTHOR/S> CITED BY AN' OF THOSE ARE < SAUTHOR/S: CITED IN ANV RFGENT PAPERS ARE < STOPICS> DISCUSSED IN RECENT JOURNALS
ARE < STOPICS> MEINTIONED ANYWHERE
ARE STOPJCS. MENTIONED IN AN ABSTRACT
ARE ANI ARTICIES ABOLT <STOPICS,
ARE ANY ARTICLES BY <SAUTHOR/S>
ARE: ANY BY -SAUTHORR/S>
ARE ANY NEW BOOKS BY <SAUTHOR/S:
ARE ANY OF THF. PAPERS ON <STOHICS: ALSO ABOUT <STOPICS>
ARE ANY OF THESL BY <SAUTHOR/S>
ARE ANY OF THESE FROM AN ACM SESSION
ARE ANY OF THESE. FROM THE ITIP SESSIUNS IN THE MONTH OF JUNE
ARE ANY PAPERS ABOUT <STOPICS.
ARE ANY RECENT ISSUES AROLIT <STOPICS. BUT NOT <STOPICS:
ARE NOT SOME: DF THESE FROM COMPIJTHG SURVEYS
ARE THIERE ANV 么BSTRACTS WHICH REFER TO <STOPICS>
ARE THERI: ANY ABSTRACTY WHCH REFER TO PAPERS BY <SAUTHOR/S>
ARE: THEHI: ANY ARTICLES ABOUT <STOPICS>
ARE THERE: ANY ISSUES ABOLIT <STOPICS:
ARE THIERS ANY NEW ISSLIES CONCERNING <STOPICS>
ARE: THERE: ANY NEW PAPERS ON <STOPICS.
ARE THIER: ANV PAPERS THAT MENTION <STOPICS>
are thepe: any recent articles in cacm
ARE THERE ANY RESERT BCOKS ABOUT <STOPICS
ARE THERE: SOME PABERS ON CSTOPLCS.
ARE: YOUJ AI WAYS THIS SLOW
are: yeus peghlarly this slow
ARE YKMU USUALLY SO SIOW
ARL:NT THR!: ARY ABSTRACYS SINCE NINETEEN SEVENTY FIVE
CAN I HAVE THEST ABSIKACIS LISTED
CAN YOUHEIP ME
CEASE PRINTJNG
CHOOSE AMONG VOIURAES BEFORE NINETEEN SIXTY
COLLO YOU RETRIEVE SOMETHING FROM <SINFORMATION+AND+CONTROL> DISCUSSING <\$TOPICS>
DII) <SNUTHOR/S> PRESILIT A PADER AT IJCAI

DID - SAUTHOR/S: PREGIVT A FAfP:R AI THE IFIP MEETINGS IN SEPTEMBER
DIO <SNUTHOR/S: PRESE:ITT PAPERS AT IFIP
DID <SAUTHOR/S P PRESELIT PAPERS AT IJCAI
DIO <SAUTHOR/S: PUBLISH A PAEFR
DID <SAUTHOR/S> WRITE A BOOK.
DIO <SAUTHOR/S. WRITE A BOOK RECENTLY
DID ©SAUTHOR/S, WRITE A PAPER THIS YEAR
DID ANY' $\because$ AI JOURNAL > PAPERS CIFE <SAUTHOR/S>
DIO ANV ACL PAPERS CITE < SAUTHOR/S:
DIO ANY IEEL COIVENTICNS PUBLISH PROCEEDINGS
DID AN' OF THOSE. PAPERS CITE <SALTHOR/S>
DID RNTONE PUBLISH ABOLT -STOPICS. IN COMMUNICATIONS OF THE ACM
DIO THE SIGART NEWSLETTER PUBLISH ANYTHING IN OCTOBER OR NOVEMBER
DIDN'T THAT PAPER OUOTE <SALTHOR/S>
DO ALL QUEMES TAKE THIS LONG
DO ANV ARTICLES DN SSTOPICS: WV ADDITION CONSIDER \&STOPICS.
DO ANY ARTICLES ON <STOPICS. MENTION <STOPICS:
DO ANY ARTICLES REFER TO <STOPICS,

DO ANY AUTHORS DESCRINE: STOPICS
DO ANV NEW ARTICLIS NEENTIGN STOPICS.
DO ANY OF THE AESTRACTS BTHTLON <STOPICS.
DO ANV OF THESE: ALSO DISCUSS < STOPICS.
DO ANV OF THESL: ALSO MENTICN <STOPICS,
DO ANV OF THESL. CITE <SAUYHOR/S>
DO ANV OF THESG: MENTION <ETOPJCS,
DO AN' OF THOSF PAPE:RS MEETION <STOFICS:
DO ANT PAPEKLS ALIDUT <STOPICS: AISO CONSIDER <STOPICS>
DO ANV PAFIOSS CITE <SAUTHOR/S>
DO AN PAPERS DISCUSS -STOPICS.
DO ANY PAPERS DISCUSS -STOPICS. BUT NOT <STOPICS•
DO ANY PAPERS DN <STOPICSS EXIST
DO ANI PAPEES THIS VEAR CITE <SAUTHOR/S,
DO AN' RECENT ACM CONFEMACES COHSIDER <STOPICS.
DO ANV RECENT BOORS CITE \& SAUTHOR/S:
DO ANI RFCFENT BCOKS MENTION <STOPICS,
DO AN' RECEENT JOURNAIS DJGCLSS <STOPICS:
DO ANV REEENT SUMMARIFS DISCUSS <STOPICS.
DO MANY ABSTRACTS DISCUSS <EAUTHOR/S>
DO MAN' ABSTRACT'S DISCUSS -STOPICS:
DO RESPDNSIUS EVER COME FASTER
DO THIY WOAK AT THE GM RESTARCH LABS
DO YOU HAPPENTO HAVE ANY REGENT PAPERS ON STOPICS>
DO YOU HAVE AN' ARTICLES DN KSTOPICS.
DO YOU HAVE ANY NEW PADERS DN <STOFICS:
DO YOU HAVE ANY RECENT PAPERS ON <STOPICS>
DO YOU HAVE ANY SUAMARIES ABDUT -STOPICS.
DO YOU HAVE NEW PApERS ON <STOPICS,
DOES <STOPICS. (ifY DISCUSSED AINYWHERE
DOES < STOPICS: GFT AFEITIONED ANYWHERE
DOES HE WORK AT CMM
DOES IT ALWAYS TAKE THIS LONG TO ANSWER ME
DOES SHE WORK AT THE INSTITUTE FOR SEWANTIC AMD COGNITIVE STUDIES
DOES THAT ARTICLX MELTION <STOPICS.
DOESiNT THIS PADER RTTIMELICE AN IEEE TRANSACTION
DON'T GET ME ANY ARTICIES WHICH MEIVIION <STOPICS>
DURING WIAT MOMTHS WIPE THEY PUBLISHED
FINISIT FRINTINS
GeNERATE A COPY OF THOSE
GEY ME ANY GOOKC: WHITTEN BY -SAUTHOR/S>
GEI ME. EVERYHINLS ON STOFICS.
GIVE: ME: ANY ABSTRACIS ITTNTLONING <STOPICS> BUT NOT <STOPICS>
GIVE MF. ANY ARTICLES ABOUT < STOPICS,
GIVE MF. ANY PAPERS ON <STOPICS> FROM JUNE TILL AUGUST
GIVE ME: DNE MORE PLEASE
GIVE ME SOMETHING MFNTIONING GTOPICS.
give me the date or that abshbact
give the altrior and daie or each

HAS \& SALTHORRS, PUBIISHEO ANY PAPERS THIS YEAR
HAS < SAUTHOR/S: PUBLISHED AN'THING RECENTLY
HASN'T SSTOPICS. BELF CONSIDEREO IN COMPUTING REVIEWS
HASN'Y A CURRI:NT REPDRT ON CETOPICS. BEEN RELEAGED
HAVE <SAUTHOR/S: PUBLISHED THIS YEAR
HAVE ANY ARTICLES APPEAREO WHICH MENTION <STOPICS>
HAVE ANY NEW PAPERSS BY <SALTHOR/S P APPEAREO
HAVEN'Y YOU FINISHED

```
HEI.I
HOW BIG IS THE DATA BASE
HOW CAN I USE THE SYSTEM EFFICIENTLY
HOW LONG DOES IT TAKE
HOW MANY ABSTRACTS ARE THERE ON <STOPICS>
HOW MANY ABSTRACTS REFE:I TO <STOPICS.
HOW MANY ARTICLES DJSCUSS <STOPICS>
HOW MANY ARTICLES ON <STOPICS. ARF THERE
HOW MANY' ARTICLES WERF. WRITTEN BY <$AUTHOR/S> AND NOT <$AUTHOR/S>
HOW MANH BOOKS DISCUSS -STOPICS>
HOW MANY BOOK!S WERE PRODUCED FROM MARCH TO DECEMBER
HOW NANY BOOKS WERR: W'KITTEN BY <SAUTHIOR/S>
HOW MANY OF THESL. AISO DISCUSS < STOPICS.
HOW MANV PAPERS ARE: AlOLIT <STOPICS.
HOW MANY PAPERS CONSIDER < STOPICS> SIMULTANEOUSLY
HOW MANY PAPERS DISCUSS <STOPICS>
HOW MANY PAPERS FROM APRUL THROUGH AUGUST CONCERNED <STOPICS>
HOW MAAUY PAPERS HAVL: <SAUTHOR/S> WRITTEN SINCE JANUARY
HOW MANY PAPERS REFTH TO <STOPICS>
HOW MANY PAPEES THIS VEAR DISCUSS <STOPICS>
HOW MANY PAP(RSG WERI: WK)TTEN BY <SAUTHOR/S>
HOW MANY RECEENT ISSUES CONCERN <STOPICS>
HOW MANY REFERFHCESS ARE GIVEN
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I AM INTERESTED IN <STOPICS>
I AM DNIV INTERESGESI IN PAPERS ON <STOPICS>
1 DEIMNND ANOTHER ARIICLE AFTER AUGUST NINETEEN THIRTEEN
I'D LIKE TO KNOW THE PUBLISHERS OF THAT STORY
I'D LIKE TO SEE THE NFENUS
IS <$AUTHOR/S> BUT NOT <SAUT&IOR/S> CITED IN SOME OF THOSE ARTICLES
IS <$AUTHOR/S> CITED BY THOSE ABSIRACIS
IS <SAUTHOR/S. CITED IN ANN' OF THESE
IS <$TOPICS: DISCUSSED ANYWHERE
IS <STOPICS> DISCUSSED IN A RECENT SUMMARY
IS <STOPICS. MENTIONED
IS <STOPICS. MEWTIONED ANYWHERE
IS < $TOPICS: MENTIONED IN NIN ABSTRACT
IS <STOPICS: REITRRED TO
IS <STOPICS: REIERRRED TO ANYWHERE
IS THAT ABOUT -STOFICS.
IS THERE A RECENT ARTICLE ABODLT <STOPICS.
IS THERE: A RECENT PAPER ABOUT <STOPICS,
IS THERE: A RECENT PAPER MFNTIONING <$TOPICS>
IS THERK: AN AR)IC(E: AROUT <STOPICS,
IS THERF: AN IFIF CONVENTION ISSUE. FROM MAY OR JUNE
IS THERE: ANYTHING NEW REGARDINT <STOPICS:
1SN"T <STOPICS. MENTIONED IN AN ABSTRACT
ISN'T THEME: AN ARTICLE: ABOLT <STOPICS.
KILL. THE LISTING
LE.Y MF I.TMIT MYSEIF TO RIPDORS ISSUED SINCE NINETEEN FIFTEEN
LEI US CONFINE OURSGIUES TO JUIRNALS AFTER FEBRUARY NINETEEN FIFTY
LEI'S RESTRICT OUR ATTENIICN TO PAPFRS SINCE NINETEEN SEVENTY FOUR
LIST BEFWECN TW/ELVE AN() TWEHTY OF THEM
LIST THIS. ABSTRACT'S BY <SALTHIOR/S>
LIST THE NEXT FOURTEEN MIJNDRED
NO MORE PLEASE
NO THANKS
OK
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    PLEASE HELP ME
    PLINSE LIST THE AlITHORS
    plense make mf a file of those
    plenge terminate traivomitilig
    PRINT THE NEXT ONE
    PRODUCE A COPY OF THE NEWEST EIGHTY ARTICLES
    QUIT LISTING PLIAGE
    SELECT FRCM AIRTICLES DN <STOPICS.
    SHOW ME. ITS PUBLISHER
    SHOW ME THE LATEST EIEVEN
    STOP TRAN'SMITTING PIEASE
    SUBSELEC'I FROM <STOPICS>
    SURE THALIKS
    TELL N隹 THE TITLES DF thE EARLIESt TEN
    TELL MF: WHAT TODO
    THANK YOU I'M DOHE.
    THE AREA I ATA INTERESIEDIN IS <STOPICS.
    THE: AREA I'IA INTERESTEDIN IS <STOPICS.
    THE. FIRETT TWO
    THE. I. ATEST SIXTEEN PLINSE
    TRANSMIT THIE. NEXT EIGHTEEN
    tRY TO GEY SURVEYS PRINTED IN THE l.AST EIGHTY MONTHS
    WAS <SAUTHOR/S> CITED BY ANV' REPDRTS ISSLIED IN THE LAST NINETY YEARS
    WAS <SALITHOR/S: CITEDIN THAT SUMMMARY
    WAS <STOPICS> MENHICNED SOR,1FWIEERE: IN RECENT TIMES
    WAS <$TOPICSS WRIITEN LIP RCCENTLY
    WAS IT PIJBLISHEO (IY <STHF.4SSOCIATJON+FOR+COMPUTATIONAL+LINGUISTICS>
    WAS IT PIJBLISHED [3Y THI: jolirhal OF the ACM
    WAS THERE: A COHFERENCE IN THE USSR
    WASN'Y <SOPlCSO MENTlONED RTCENTLY
    WASN'Y &SOFICS, REFLIRRE:D IO SOMEWIUERE
    WE: DLSIRE A PROCHEDING (F THE ACM MEETING REFEHELCED BV <$AUTHOR/S>
    W: WANT SOMF RLVIEWS CONCERNING <STOPICS>
    WE WISH TO GEY THE LATEST FORTY ARTICLES ON <STOPICS>
    WEO LIKE TO SEF THE TITLES FROM PROCEEDINGS OF THE ACM CONFERENCE
    WEPR: INTERESTED IN & STOPICS.
    WERE: ITEEESTEO IN ARTICLSS PUBLISHEO IN THE LAST THIRTY YEARS
    WEVE BEEN INTERESTED IN eSTOPICS,
    WERE: AINY OF THESE ARIJCLES WRITTEN BY <SNUTHOR/S>
    WERE ANM' (%F THiG&: PLiblISHED IN THE SUNSHINE STATE OR IN THE U.S
    WERE: ANY OF THFS: WRITTENBY &SAUTHOR/S>
    WERE: ANY puEdished a tek June nineteen sixty five
    WERE: THERE: ANY ARTICLES ABOLIT < STOPICS.
    WERENT SOMA ARIICLES PUBLISHED ON <STOPICS,
    WHAT ABOLST -SALTHOR/S:
    WHAT ABOUT -STOPICS.
    WKAT ADDRESS IS GIVEN FOR THE AUITHORS
    WHAT ADDRESECSSAPE GINEN FOR THE AUTHORS
    WHAT ARE SOR价.DF THE ARLAS OF <$TOPICS.
    WHAT ARE THE KEY PHRASES
    What are the titles of the recent arpa surnotes
    what are their nimlliations
    WHAT GOOKS MENTION <STOPICS:
    WHAT GAN I dO TO SPEED vOL UP
    WHAT CAN THE SYSTEMDO
    WHAT CONFERLNCE WAS AT RUTGERS OR AT SRI
    WHAT CONFERE:NCE. WAS AT WATSON RESEARCH OR AT ILLINOIS
What dO I havE TO dO
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WHAT FACTS ARE STORED
WHAT HRS < SAUTHOR/S, WRITIEN LATELY
WHAT HAS < SAUTHOR/S: WRITTEN RECENTLY
WHAT HAVE <$AlJTHOR/S> WRITTEN LATELY
WHAT IS HER AIFILIATION
WHAT IS HIS AFFILIATION
WHAT IS KNOWN ABOLIT EVERY ARTICLE
WHAT IS THIE SIZE OF THE DATA baNK
WHAT IS the title of that paper
WHAT IS THIE TITLE OF THE EARTIEST ONE
WHAT IS THI: TITLE OF THE MOST RICENT ONE
WHAT IGSUES DURING JANUARY AND JLLY CONCERN <STOPICS>
WHAT KLY WORDD REIATES TO <STOPICS>
WHAT KIY WORDS SHOULD I LSSE FOR <STOPICS>
WHAT K'IND OF MEINJS ARE: THERE:
WHAT KINDS OF SIJBJICTSS ARE STORED
WHAT MIIST I ASTK
WHAT PAPERS DN <STOPICS, ARE THERE
WHAT SHOLILD I ASK
WHAT SHOllLD I SAY
WHAT SORT OF SUMMARRY IS AVAILABLE
WHAT SORTS OF <STOPICS. ARF. WRITTEN UP
WHAT SUbJECT C:AN I RFQUEST
WHAT TOPIC MENUS CAN I CHOOSE
WHAT TOPICS ARE: RELATEO TO <STOPICS.
WHAT TVPES OF <SRCTRIEVAL+CAN+HEARSAY> DO
WHAT WAS ITS TITLE
WHOT'S THE PLEBLISHER OF THAT PIECE
WHEN WAS <SHUMAN+PROBLELG,SOLVIN'G> WRITTEN
WIHEN WAS <STOPICS: LAST MENTIONED
WHEN WAS <STOFICS. LAST RETEMMED TO
WHEN WAS IT PUBLISHEI)
WHEN WAS THAT BOOK WRITTEN
WHEN WAS that paper published
WHENW WAS THE LAST PAPER BY <SAUTHOR/S> PUBLISHED
WHEN WERE <STOPICS. LAST RETFERRED TO
WHEN WILL YCOU HAVE THE ANSWER
WHFRE: ARE: < $TOPICS: REFERRED TO
WHFRE: DID THAT ARTICLE. APPERR
WHERE: DO THEY WORK
WHHERE DOES HE WORK
WHERE IS < STOFICS. MENTIGNED
WHICH < SAl,7EXT> CONTAINED < STOPICS.
WHICH <SCOGNITIVLFPSYCHOLOGY> CONTAINED <STOPICS>
WHIC:H <SCOONNTIVF.PSYCHOLOGY> CONTAINS <STOPICS>
WHICH AlSSYRACYSG CONCEPN STOPICS,
WHHCH AESTRAC:Y'SRFERTO STOPICS.
W(H)CH ARIICGSS CONCEPN \STOPICS:
WHICH ARTICLES HAVE CONCERNED <STOPICS>
WHHCH ARTICUSSDN <STOPICS> ALSO CONCERN <STOPICS>
WHCH ARIICESS REFEH TO THESE
WHHCFI AUTHORS WORK AT HANUIURG OR AT EDINBURGH
WHHCH AlITHORS WORK AT NHH OR AT STANFORD
WHICH AUTHIORS WORK WITH SUMEX OR AT SUSSEX
WHICH BOOKS ON <STOPIC:S, WERE PUBLISHED RECENTLY
WHICH BOOKS WIRE: WRITTEN EY <SAUTHOR/S> SINCE LAST YEAR
WHICH COMPITIHG SURVEY ARTICLES RELATE TO <$TOPICS>
WHICH COMPIJTIHG SURVEYS CONTAINED THE ARTICLE BY <SALTHOR/S>
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[^3]```
<SINFORMATION+AND+CONTROL>:- INFORIMATION AND CONTROL
<SCOGNITIVE+PSYCHOLOGY> - COGNITIVE PSYGHOLOGY
<STHF.WORLD+COMPIITER+CHESS.CONFERFINCE>:- THE WORLD COMPUTER CHESS CONFERENCE
<SAI+JOURINAL; : - AI JOURNAL
<SAI+TEXT>:- AI TEXT
<$THF.4SSGCIATION+FOR+COMPIJTATIONAL+LINGUISTICS::- THE ASSOCIATION FOR COMPUTATIONAL LINGUISTICS
<SRETRJEVAL.CAN+HEARSAY>:- RETRIEVAL CAN HEARSAY
<SHIJMAN+PROBLEIM+SOIVIHG>:: HHMAN PROBLEM SOLVING
<$RI:TRIEVAL+KEVS> = RE:TRIEVAL KEYS
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<$AUTHOR/S,:: <AUTHOR>
    <AUTHOR> <ANDOR 1> <AUTHOR>
<ANDIOR 1>:= AND
    OR
<AUTHOR::= AlL[H COLLINS
        ALLEH NEWELL
        ANN RUBIN
        ANTHONY MARTELLI
        AZRIEL ROSENFELD
        BE.RNARD MELTZER
        BERT RAPHAEL
        BILL WOODS
        BONNIE NASH-WEBBER
        BRUCE BUCHANAN
        CARL. HEWITI
        CHRISTOPHEN RIESBECK
        CHUCK RIEGER
        DANNY BOESROW
        DAVE RUMFIHART
        DAVID MARR
        DAVID MICHIE
    DICK SELTZER
    DONALD NORMAN
    DOUG L.ENAT
    DREW MCIFERMOTT
    DREYFUS
    EARI. HUNT
    EARI. SACFFRDOII
    ED FEIGENBAIIM
    ED RISEMANN
    ELIIOT SOLOWAY
    ERIK SANIDLWALL
    EUGENE CHARNIAK
    FELGiENHAUM
    FEl.(IMAN
    GARY HENDRIX
    GEORGE ERNST
    GIPS
    HAN'S BERIINER
    HARRY BARROW
    HERT? SIMON
    HERPEERT BLOCK
    HILARY PUTNAIM
    hollano
    HUGH NAGEL
    IRV SOREL
    ISSAC Asimov
    JACK ISINKER
    JACK' MOSTOW
    jabues Slagle
    JEAN SNOWM&:T
    JF.FFRIEY IN.LIMAN
    JERIRY FESOLIAN
    JOHNV GASCHNIG
    joHN hOLLAND
    JOHN MCCARTHY
    JOHN NEWCOMER
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.JOSEPH WEITEINBAUM
JUDEA PEARI
KARL PINGLE
KEITH PRICE
KEN COLBY
KEN RALSTON
KING SIJNG FU
LAURENT SIKLOSSV
LEE ERMAN
LEONARO) IIHR
LES EARNEST
LINDN NIASINTER
MADELINE BATES
MARVIN MINSKY
MARY NEWFORN
MARY SHINW
MICHNEL ARBIB
MIKE RYC:HENER
MING:Y
MITCHEIL NEWEY
NEWELL
NILS NJLSSON
NILSSON
NORI SUSIIKI
PAMMFIG MCCORDLJCK
PAT IVINSTON
PERRY THORNDVKF
pever kIGEEL
RAJ RE.DDY
RANAIN BANKR!!!
RAYMMSNOD SPROULL
RI:DINY
RICH FIKES
RJCH SMITH
RICHIARO MICHALSKI
RICHAFLO WIALDINGER
RICK' HAYES.ROTH
ROBLRT RLItER
ROGER SCHANK
RON OHIMNDER
ROSE/RFELD
SCOTT FABTMMA'
SEYMOUR PAPERT
SIMMON
STEVE: COLES
STEVE REED
STEVE ZUCKER
TED SHORTLIFTE
TERRY WINOGRAD
THOMAS MARSLAND
THOMAS SYKES
UHRR
vIC LESsin
WALIV RHOMBERG
WOODS
WODDY BUEDSOE
YORICK WILKS
ZOHAR MANNA
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<STOPICS>: <ANDIORTTOPICS>
    WINOGRAD'S ARTICLE.
<ANIDORITOPICS.: <TOPIC>
        <TOPIC> <ANDIOR 2> <TOPIC,
<ANIDOR 2>-ANI)
    OR
<TOPIC>: A CAI MONITOR
        A COMMMON SINSE ALGORITHM
        A GARAF MODEL.
        A lOSING MKOVE:
        A MIM.rlLEVt.l URGNNIZATION
        A PAC;KE: BASED APPROACH TO NETWORK COMMIJNICATION
        A PARIIAR EVALUATOR
        A PROGRAIM SYNTHESIZER FOR NETWORK PROTOCOLS
        A PROLIRAMGINGG APPRENTICE
        A PROOH ChICKKER FOR PROTOCOL TERKINATION EXPRESSIONS
        A RADIO INTERVIEV/ ON SCIELICE FICTION
        A REGION ANALVGOS SUBSYSTEM
        A GTEREO PAIR OF VIEWS
        A TASK OREENTED DIALOGUE
        A THAUSMATLIRGIST
        A THEOREM PROVER PLANNING FOR PROGRESS
        A TIW&F DOHANIN {NALVZER
        A tutOR OR tlitoring ON IV
        A TV REPCRTER
        ABSTRACIICN
        ACQLISITION OF KNOWLEDGE
        ACTIVE KNOWIEOGE
        ACYCLIC ISOMF.RS
        ADAPTATION
        ADAPTIVE PRODUCTIUN SYSTEMS
        ADVISING PHYSICINNS
        AI
        AI lectures;
        AlgeibRaiC REDliction
    AlfiOL
    Al GORITHMIC mesmmerics
    All-OR NONE SOLUTIONS
    AN ADAPITIVE. NATIIRAL LANGUAGE SYSTEM
    AN ASSClWIm.Y ROROT
    AN AKICMATIC SYSTEM
    ANALOGY IN PROBLCHM SOLVING
    ANALYSIS OF CONTEXT
    ANAIYSIS OF GENTENCES
    artificial intelllgence
    ASSIMMLATION OF NEW INFORIMATION
    ASSOCINTIVE MEMGIRIES
    ASSVCIATIVF MEMORY
    AUgMENTEO TRANGITION NETWORKS
    Alitomated dedlcition
    AllOMANTIC CODING
    AlHOMATIC COMFIJTATION
    AUTOMATIC MANTRA GLNERATION
    AUTOMATIC PRDGRAM SYNTHESIS FROM EXAMPLE PROBLEMS
    AUTOMANTIC PROCGRAMS WRITING
    AUTOMNTIC PROGRAMMIMING
    AUTOMNTIC PRCOT OF CORRECTNESS
    AUTOMANTIC THEOREM PROVING
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ALJTOMATION
AXIGMATIC SEMANTICS
AXIOMS FOR GO
BACK[AMMMNON
BELIEF SYSTEMS
BINDINGS
BIOMEDICINE:
BRAJN THE.ORY
BUSINESS PROBLEM SOLVING
CARTOGRAPHY
CASE SYSTEMS
CAUISAL REASONING
CF.L. ASSEMIII.Y THEORY
CHECKING PROOFS
CHESS
CHESS: PLAYING PROGRAMS
CIRCUIT ANALYSIS
COGNITION
COGNITIVI: ROBOTIC SYSTEMS
COGNITIVE SCIElicE
COMMKON SLINSE
COMMIMM SEITSE THIORY FORMATION
COMPIIK WAVEFORMS
COMPUJTATIONAL LINGUISTICS
COMPISTER AR:
COMFIJTER BASEO CONSULTANT
COMPIJTER BASE:D CONSULTATIONS
COMPUTER CONTROLLED MANIPULATORS
COMPISTER GRAPHICS
COMPISTER MUSIC
COMPUJTER NETWORKS
COMPISTER VISION
CONCEPTUAL DESCRIPTIONS
CONCEPTUNL INFFREFCE
CONCEPTUAL OVERLAYS
CONSTRAINT SATISFACTICN
CONSTRUCTING PROGRAIMS FROM EXAMPLES
CONSIRUCTION OF PROGRAIMS
CONTEXT
CONTINUOUS PROCESSES
CONTROL
CODPERATHGG SOISRCES OF KNOWLEDGE
COPYJNG LIST STRIJCTURES
CURVE.I) OE.NE:TS
CYBEIRNCTICS
CYCi.lC
DATA BASES
DATA BASES FOR INTERACTIVE DESIGN
DATA STRUCTURES
DECISION THEORY
DEDUCTION
DEDLCTIVE RETRIEVAL
dEINOTATIONAL GF:mANTICS
DE.pTH PERCEPTION
DERIVATION PLANS
DESIGN
DESIGN AUTOMATION
DESIGN IN THE ARIS
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DETECTION OF LIGHT SOURCES
DISPLAY TERWINALS
DRAGON
DRIVING A CAR
DYNAMIC BINDING
DYNAMIC CLUSTERING
DYNAIMIC PROGRRMMING
EIECTRONIC CIRCUITS
ElfcTRONICS
ENGLIGH
EVALUATION FUNCTIONS
EXPERT SVGTERSS
explanation capabilities
FABLFS DR FAIRY TALES
FEATUIL.- IRIVEN SVSTEMS
FIRST ORDER LOGIC
FORIMAL SEMINNTICS
FRAMFE. THEORY
FRAMES
FRAMES ANI THF ENVIRONMIWT
FUZZY kNOWLCDGE
FILZZY PROBILEA SOLVING
GAME OF POKEK
GAM借 PIAYIKG
GENERAL PIJRPOSE MODELS
GENEFATIGN OF NATIIRAL LANGUAGE
GEOA隹TBC: MODELING
GO OR GO-MCXES
GOAL SEET)NG (OMMONENTS
GRAIN OF COMPIITATION
GRAMSMATICAL INFERI:NCE
gRAPH NNERPMETABLE: GAMES
GRAPH MATCHING
heargay
HETEROSTATIC THEORY
HEURISTIC PROGRAMMING
HEURISTIC TECHNIQUES
HLL CLIMMBING
hujman belhavior
HUMAN MEFSHPY
HUMANN VISION
HYPOTHESIS FORMATION
MIAGE INTENSITY UNDERSTANDING
HF雉\VINGG PROGRAIMS
INDUCTIVE ASSERTIONS
INDUSTRIAL APPLICATION
INEXACT REPRESEIVTATION
INFEREMCE:
INFERFNCES
INFF.RE:IGIAL QUESTION ANSWERING
INFORMAATION TROCESSING UNIVERSALS
mHERITANCE OF proferties
INTELLIGENT MACHINES
INTENTIONS
INTEN'ACTIVE DESIGN
INTERACTIVE KNOWLEDGE SYSTEMS
INTERACTIVE PROGRAM SYNTHESIS
INTERPRETIVE SEMANTICS
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INTOHATION
INVARIANCE FOR PROBLEIA SOLVING
INVARIANCES JN THE PERCEPTION OF FACES
INVESTMENT ANALVSIS
ITERAIION
KNOWLEOGE BASED SVSTEMS
KNOWLE:DGE SYSTEMS
labmida calculus
LANGUAGE COMPREMENSION
language design
laNGUAGE PARAPHRASE
lANGUAGE PAGCAL
LANGUAGE PRIMITIVE.S
LANGUAGE UNDERSTANDING
large data bases
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## IV. COLLECTED PAPERS

A collection of papers, all of which appoared in the Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing, Hartford, Connecticut, May 9-11, 1977, with the exception of the last paper, "A halting condition and related pruning heuristic for combinatorial search", which is an unpublished working paper.

## A FUNCTIONAL DESCRIPTION OF THE HEARSAY-II SPEECH UNDERSTANDING SYSTEM

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#### Abstract

A description of the September, 1976, version of the Hearsay-ll system is given at the knowledge-source level, indicating the actions of each knowledge-source and their interactions.


## INTRCDUCTICN

The Hearsay-II system has been described elsewhere in terms of its system organization, including the model which has driven that design [Letis75, ErMu75, FePa76]. Also, the individual knowledge sources (KSs) have been separately reporled on in detail. In this paper, a description of the September, 1976, version of the system is given in terms of the functions and interactions of the KS. ${ }^{2}$ This does not include a description of how this configuration is realized within the general Hearsay model and Hearsay-ll system, nor does it include many details of the inner workings of the KSs, or comparisons of Hearsay-Il with any other systems.

The task for the system is to answer questions about and retrieve documents from a coliection of computer science abstracts (in the area of artificial inteiligence). Example sentences are:
"Which abstracts refer to theory of computation?"
"List those articles."
"What has Minsky writien since nineteen seventy-four?" The vocabulary contains 1011 words (in which each extended form of a root, e.s., the plural of a noun, is counted separately, if it appears). The grammar which defines the legal sentences is context free and includes recursion. The style of the grammar is such that there are many more non-terminals than in conventional syntactic grammars; the information contained in the greater number of nodes provides semantic and pragmatic constrant within the grammatical structure. For example, in place of "Noun' in a conventional grammar, this grammar inclucles such non-terminais as 'Topic', 'Author', 'Year', 'Publisher', etc.

The grammar ailows each word, on the average, to be followed by seventeen other words of the vocabulary. The

[^4]standard deviation of this measure is very high (about 51), since some words can be followed by many others (up to 300 in several cases). For the sentences used for performance testing, the average length is seven words and the average number of words that can follow any initial portion of the sentence is thirty-four.

The Septentber, 1976, configuration of the system recognizes about 807. of its test utterances (run blind) word-for-word correctly, with about 907 of the utterances being interpreted semantically correct.

## SIGNAL ACOUISITION, PARAMETER EXTRACTIOM, SECMENTATION, and LABFLLING

An inpuł utterance is spoken into a medium-quaity Electro-Voice RE-51 close-speaking headset microphone in a farily norsy environment ( $>65 \mathrm{db}$ ). The audio signal is lowpassed filtered and 9 -bil sampled at 10 KHz . Ail subsequent processing, as well as controlling the A/D converter, is digital and is done on a time-shared FDP- 10 computer. Four parameters (called "ZAPOASH") are derived by simple algorithms operating directly on the sampled signal [GoZa77]. These parameters are extracted in real-time and are initially used to detect the beginning and end of the utterance.

The ZAPDASH parameters are next used by the SEC knowledge-source as the basis for an acoustic segmentation and classification of the utferance. This segmentation is accomplished by an iterative refinement lechnique: First, silence is separated from non-silence; then, the non-silence is broken down into the sonorant and non-sonorant regions, etc. Eventually, five classes of segments are produced: silence, sonorant peak, sonorant non-peak, fricative, and flap. Associated with each classified segment is its duration, absoiute amplitude, and amphitude relative to its neighboring segments (i.e., local peak, local value, or plateau). The segments are contiguous and non-overlapping, with one class designation for each.

Finally, the SEG KS does a finer labelling of each segment. The labets are allophoric-like; there are currently 98 of them. Each of the 98 labeis is defined by a vector of autocorrelation coefficients [itMi75]. These iemplates are generated from speaker-dependent training data that have been hand-labelled. The result of the labelling process, which matches the central portion of each segment against each of the teniplates using the Itakura metric, is a vector of 98 numbers; the ith number is an estimate of the (negative log) probability that the segment represents an occurrence of the $i$ 'th allonhone in the labet set.

## WORD SPOTTIivG

The initial generation of words, boltom-up, 15 accomplished by a three-step process.

First, using the labelled segments as input, the POM knowledge source [SmWo76] generates hypotheses for likely syilable classes. This 15 done by first identifying syilable nuclei and then "parsing" outward from each nucleus. The syllable-class parsing is driven by a probabilistic "grammar" of "syllable-class -> segment" productions; the rules and their probabilities are learned by an oiflune program which is trained on inand-labelled utterances. (The current training, which is speaker-dependent, is over 60 utterances containing about 360 word tokens.) For each nucleus position, several competing syllable-class hypotheses are generated -- typically three to eight.

The syllable classes are used to hypothesize words. Each of the 1011 words in the vocabulary is specified by a pronunciation oescription. For word hypothesization purposes, an inverted form of the dictonary is hept, in which there is associated with each syllabie-class ait the words which have some pronunciation containing that syllable-ciass. The MOW KS [SmWo76] looks up eacin hypotriesized syllable ciass and generates word candidates from aniong those words containing that syllable-ciass. For each word that is multi-syliabic, all of the syllables in one of the pronunciations must maten above a threshold. Typically, 50 words of the 1011 -word vocabulary are generated at each syllable nucleus position.

Finally, the generated word candidates are rated and their begin- and end-times adjusted by the wIZARD knowledge source [McW077]. For each word in the vocabulary, WIZARD has a network which describes the possible pronunciations. This rating is calculated by finding the path through the network which best matches the labeiled segments, using the distances associated with each label for each segment; the rating is then based on the difference between this best path and the segment labels. ${ }^{3}$

The result of the word processing so far is a set of words. Each word includes a begin-time, an end-ime, and a confidence rating. A policy KS , cailed wORD-CTi f'word control'), selects a subset of these words, based on thear times and ratings, to be hypothesized; it is these selected word hypotheses that form much of the base for the "top-end" processing that now begins. Fypucally, these selected hypotheses include about $75 \%$ of the words actuatly spoken (i.e., "correct" word hypotheses) and with each correct hypothesis having a rating which ranks to the average about three, as combared to the five to twenty-five or so hypotheses which compete with it (i.e., which significantly overlap it in time). The non-selected words are retaned internally by WORD-CTL for possible later hypothesization.

3 WIZARD is, in effect, a miniature version of the HARPY speech recognition system [Lorta76], except that it has one network for each word, rather than one network with all words and all sentences.

## TOP-END PROCESSING

## Word-Island Generation

The WOSEQ knowledge source [LeSe77] has the job of generating, from the word hypotheses generated bottom-up, a small set (about three to ten) of word sequence hypotheses. Each of these sequences, or islands, can be used as the basis for expansion into larger islands, hopefully culminating in an hypothesis that spans the entire utterance. Multi-word istands are used rather than single-word islands because of the relatwely poor relabinty of ratings of single words as well as the lmited syntactic constraint supplied by single words.

WOSEQ uses two kinds of knowledge to generate multiword islands:

A table derived from the grammar indicates for every orderea pair of words in the vocabulary (1011× 1011) whether that parr can occur in that order in some sentence of the defined ianguage. This binary table (which contans about $1.7 \%$ " 1 "'s) thus defines "language-adjacency".

Acoustic-phonetic knowledge, embodied in the JUNCT KS, is appied to pars of word hypotheses and is used to decide if that pair might be considered to be tine-adjacent in the utterance. JUNKT uses the dictionary pronunciations and examines the segments at their functire (eap or overlap) in making its decision.

WOSEQ takes the highest-rated single words and generates multi-word sequences by expanding them with other hypothesized words that are both time- and languageadjacent. This expansion is controlled by heuristics based on the number and ratings of competing word hypotheses. The best of these words sequences (which occasionally includes singie words) are hypothesized.

The top-end processing is started by the creation of these word-sequence hypotheses. Subsequently, WOSEQ may generate additional hypotheses if the recognition process seems rot to be makng progress based on those already nypothesized. These additional hypotheses may include shorter, decomposed versions of some of the original ones.

## Word-Sequence Parring

Because the syntactic constraints used in the generation of the word sequences are only pair-wise, a sequence longer than two words may not be syntactically acceptabie. A component of the SASS [HaSy77, HaLin77] knowledge source can parse a word sequence of arbitrary length, using the full constraints given by the language. This parsing does not require that the word sequence form a complete non-terminal in the grammar nor that the sequence be sentence-initial or sentence-final, only that the words occur contiguously somewhere in some sentence of the language. If a sequence hypothesis does not parse, the hypothests is marked as "rejecled". Otrerwise, a phrase hypothesis is created. Associated with the phrase hypothesis is the wora sequence of which it is composed, as well as information about the way for ways) the woras parsea.

## Word Predictions from Phrases

Another component of the SASS knowledge source can, for any phrase hypothesis, generate predictions of all words which can immediately precede and all which can immediately follow the phrase in the language. in doing the computation to generate these predictions, this KS uses the parsing information attached to the phrase hypothesis by the parsing component.

## Word Verificalion

An attempt is made to verify the existence of or reject each such preaicted word, in the context of its predicting phrase. If verified, a confidence rating for the word must also be generated. First, if the word has been hypothesized previously and passes the test for lime-adjacency (by the JUNKT KS), It is marked as verified and the word hypothesis is associated with the prediction. (Note that a single word may thus become associated with several diflerent phrases.) Second, a search is made of the internal store of WORD-CTL to see if the candidate can be matched oy a prevousiy generated candidate which had not been hypolhesized. Again, JUNCT makes a juggment about tine-adjacency. Finally, WIZARD compares its word-pronunctation network to the segments in an attempt to verify the prediction.

For eaci of these different wieds of verification, the approximate begin-time (end-time) of the word being preacted to the right dieft) of the phrase 15 taxen to be the end-time (begin-time) of the phrase. The end-time (begin-time) of the predicted word is not known and, in lact, one requirement of the verfication step is to generate an approximate end-time (begin-time) for the verified word. In gene:al, several different "versions" of the word may be generated which differ primarily in there end-limes; since no context to the right (left) of the predicted word s given, several different estimates of the end (beginning) of the word may be plausible based solely on the segmental intormation.

## W'ord-Phrase Concatenation

For each verified word and its predicting phrase, a new and longer phrase may be generated. This process, accomphished by a component of SASS sinviar to the WordSequence recognition component, invclues parsing the words of the origmat phrase augmented by the newly ver:tied word. The extended phrase is then hypothesized and inciudes a rating based on the ratings of the words that compose it.

## Complete Sentences and Haiting Criteria

Two unique "word" hypotheses are generated before the first and after the last segment of the utterance io denote begin and end of utterance, respectively. These same "words" are included in the syntactic specification of the language and appear as the ilrst and last terminals of every complete sentence. Thus, any verified phrase that includes trese as its extreme constituents is a compicte sentence and spans the entire utterance. Such a sertence becomes a candidate for selection as the system's recogntion result.

In general, the control and rating strategies do not
guarantee that the first such compicte spanning hypothesis found will have the highest rating of all possible spanning sentence hypotneses that might be found if the search were aliowed to continue, so the system does not just stop with the first one generated. However, the characteristirs of such an hypothesis are used to prune from further consideration other partial hypotheses which, because of their low ratings, are unlikely to be extenciaivie into spanning hypotheses with ratings higher than the best already-discovered spanning sentence. This heuristic pruning procedure is based on the form of the ratings function (i.e., how the rating of the phrase is derived from its constituent words). The pruning procedure constiers each partial prrase and uses the ratings of other word hypotheses in the time areas not covered by the phrase to determine if the phrase might be extendable to a phrase rated higher than the spanning hypothesis; if not, the partial phrase is pruned. This pruning process and the rating and halting policies are discussed in [HaPo77].

The recognition processing finally halts in one of two ways: First, there may be no more partial hypotheses left to consider for predicting and extencing. Because of the combinatorics of the grammar and the likelihood of finding some preciction that is rated at ieast above the absolute rejection threstiold, this form of termination happens when the pruning, procedure has been effective and has eliminated alt compctitors. Second, the expenditure of a prectefined amount of comouting resourtes (time or space) also halts the recozmion procesis; tro actuat trosnolds used are set accorong to tren dast feriviriance of the system on similar sentences fie, of the given length and over the same vocabuiary and Eriammar)

Once the recognotion process is haited, a selection of one or more phrase hypotheses is made to represent the result it at least one spanning sentence hypothesis was found, the highest-rated such rypothesis is chasen; otherwise, a seiection of several of the highest-rated of the partial phrase hypotheses is maje, biasing the setection to the tongest ones which tend to overup (in time) the ienst.

## Altention Focuseng

The top-end processing operations include (a) wordisiand generatior, (b) word sequencs parsing, (c) word prearction from crirases, (a) word verfication, and (e) wordphrase concatenation of these, (b), (c), and (d) are the most trequently peramicu. in general, there are a number of these actions wating to be performed at varous places in the utterance. The se ection at each poini in the proressing of whicls of these actions to perform is a probiem of combinatoric controi, since the eyection of each act:on will, in generat, generate more such actions to be done.

To handle this problem, the Hearsay-ll system has a statistically-hased scheduier [HaFo77] which calcuiates a priority ior each action ame seiects, at each time, the watting action with the hignesi prority. The priority calculation atternpts to estimate the usefuress of the action in fulfolling the overal syoien geal of recognizing the utterance. The calculation is based on riformation specified when the action is trgaered. For exaniple. the word verifier is triggered whenever words are predicted from a phrase hypothesis; the information passed to the scheower in order to help salculate the priority of thas mistant aiton of the werifier includes such
things as the time and rating of the predicting phrase and the number of words predicted. In addition to the action-specific information, the scheduler keeps track of the overall state of the system in terms of the kinds and quality of hypotheses in each time area.

## INTERPRETATION and RESPOINSE

The SEMANT knowledge-source [HaDi77] accepts the word sequence(s) result of the recognition process and generates an interpretation in an unambiguous format for interaction with the data base that the speaker is querying. For example, the spoxen sentence
"What has Minsky written since 1974?"
is represented in this format as
Type: EREQUEST
Subtype: SQUERY!AUTHOR!DATE
[Date: >1974; Author: "MINSKY"]
The interpretation is constructed by actions associated with "semanticaily interesting" non-ierminats in the parse tree(s) of the recognized sequence(s). If recognition results in two or more partial sequences, SEMANT constructs a consistent interpretation based on all of the partial sentences, taking into account for each partial sentence its rating, temporal position, and consistency (or competitiveness) as compared to the other partial sentences.

The DISCO knowledge-source [HaDi77] accepts the formatted interpretation of SEMANT and produces a response to the speaker. This response is often the display of a selected portion of the queried data base. In order to retain a coherent interpretation atross sentences, DISCO has a finitestate model of the discourse which is updated with each interaction.

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# selection of woro islanos <br> IN <br> THE HEARSAY-II SPEECH UNDERSTANCING SYSTEM 

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#### Abstract

In Hearsay-11, a word recognizer hypathesizes words bottom-up from acoustic data. Usuaily many comoeting words are hypothesized for each time interval of speech, with the correct word rarely top-ranked. Due to the unreliable ratings of words and the lumited syntactic constraint supplied by single words, the use of single-word islands would cause the recognition system to explore many blind alleys before abandoning an incorrect island. In addition, the multiplicity of words makes the parsing of ail possible word sequences extremely time-consuming. The Hearsay-It island selection strategy uses (1) knowtedge of what word adjacencies are allowed by the grammar, (2) analysis of acoustic data at the junctures between word hypotheses, and (3) heuristics based on the number of competing word hypotheses, fo form multi-word istands which the syntax-ievel knowleage source first checks for gramnatically and then attempls to extend to form a complete recognition.


## INTRODUCTICN

Conventional strategies for controlling the search in a continuous speech understanding system fall into two major categories: left-to-right (HARPY [Lowerre, 1976\}, Hearsay-1 [Reddy, 1973]) and isiand-driven (SRI [Paxion, 1975], SPCHILS [Woods, 1975], Hearsay-ll [Lesser, 1975]) strategies. In the left-toright strategy, as the nante implies, the search always begins at the start of the utterance and continues to extend in a left-to-right manner each partially hypothesized phrase that appears placsible. In contrast, the island-diven stratezy, before beginning the process of phrase hypothesization and extension, first performs a scan of the entire citterance in an attempt to spot likely words [Smith 1976, Klovstad 1976j. The best words found in this phase are chosen as the initial phrasai hypotheses for the second phase of the searcn. in this second phase, a partial phrase chosen for further extensions can be extended by prediction of grammatically legal word extensions on either the left or right or in both directions, depending, for instance, on the constraints given by the

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grammar about which direction has fewer extensions (see Hayes-Roth and Lesser 1976, Paxion and Robinson 1975, and Woods 1975 for a discussion of techniques for choosing the next hypothesis to extend); this strategy allows the phrasal hypothesis to be concatenated with existing partial phrases to construct new, eniarged hypotheses.

The advantages of the lett-to-rignt strategy over the more soohisticated +sland-driven strategy are mainly in the area of eificiency: (1) the computationally expensive wordspotting phase is bypassed and (2) the application of grammatical knowledze and the overhead for controlling the search is much less expensive. The major disadvantage of the left-to-right scheme is that the beginning of the utterance may not contain very good acoustic data and thus lead to initial word predictions that are very poor; in this case, it may be very difficult or impossible (if the correct word was not hypothesized) to recognize the utterance. The major advantage of isfand-driven strategy is its robustness; there may be hypothesized more than one correct initial island, and thus there exists more than one sequence of steps to acheve the correct recognition. In addition, the island-driven strategy would seem to have a higher probability of starting the search with an intial island that is valid because of its word-spotling phase. However, this word-spotting search may not in practice produce results as valid as would be expected because words are predicted based only on acoustic constraints; netther grammatic nor co-articulation constratnts are used except at the beginning and end of the utterance. Another advantage of the istand-driven strategy is that it can use variations in the branching factor of the grammar at different points in the utterance to reduce the space needed to be searched.

The major disadvantage of both of these search strategies is that they are particularly senstive to major rating "errors" on single words--cases where a valid word is rated lower than an invalid word in the same time area. If the correct word in the starting area is very poorly rated, a best-first search from the higher-rated alternatives will develop a very large search space, and backtracking ail the way to the initial incorrect decision will be very expensive and unlikely.

Two means of overcoming this shortcoming exist. First, in the limited-breadth-first search, the $N$ top rated words in an area are used to begin searches, and as long as one of these is correct, recognition is not preckuded. The second alternative is to identify multi-word sequences of word hypotheses that are most probably correct as the

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starting islands in an island-driven strategy. in comparison with single-word islands or left-to-right single-wiord starting hypotheses, multi-word sequences are more reliable for iwo reasons: under certain generaily applicable conditions, the credibility of a sequence hypothesis exeeeds that of a single word hypothesis and, secondly, the resiabllity of a validity rating for a sequence is greater than that of a single word hypothesis.

To substantiate this conjecture, consider the foltowing average rank order statistics for initial istands based on the three different approaches. These data were collected over 34 training utterances, with each island generation strategy applied to all utterances. The average sentence length was 5.5 words. The left-to-right and the single-word islanddriven strategies have the same ranx order statistic which is 2.6 (i.e., there are on the average 1.6 islands with ratings better than the correct one). It is interesting to note that in none of the 34 utterances did the left-to-right strategy not hypothesize the correct word in the initial utterance position; the average number of words hypothesized for the initial position was eleven words. The average rank order statistic for the multi-word island strategy, it one utterance is eliminated in which the rank orcer is 30 , is 2.0 ; the average length of the best correct multi-word island is 2.3 words, where the average number of correct words hypothesized bottom-up is 3.0;

## A MULTI-LEVEL ISLAND DRIVEN STRATEGY

The strategy found to be most effective in the Hearsay-ll system (as applied to a 1000-word votabulary with an average word fanout of 33) is to select multi-word sequences of word hypotheses as starting islands for syntax-level processing. This strategy introduces a new level of hypothesis, the word sequence, between the conventional lexical and phrase levels. A word-sequence hypothesis is a concatenation of one or more word hypotheses. In contrast with a phrasal hypothesis, a wordsequence hypothesis is created berore the syntax-level knowledge source begins its work, and may not be grammatical (i.e., it may represent a sequence of words which does not appear in any sentence in the language defined by the grammar).

The decision to create word-sequence hypotheses arose from the realization that the combinatorial spate of all possible sequences of word hypotheses, generaied as a result of the word-spotting scan, can be reduced snarply by applying a computationally inexpensive filter to the data. This filter is based on simple kinds of grammatical and coarticulation knowledge about whish word pars are possible. The grammatical constraints are specified through a square bit matrix, whose order is the size of the vocabulary; each entry ( $i, j$ ) in the matrix indicates whether word $j$ can follow word $i$ in the grammar. If two words can follow each other, they are called "language-adjacent". The co-articulation constraints are specified through another square matrix, whose order is the size of the number of phonemes. Each entry ( $i, j$ ) in the matrix indicates what tyee of acoustic segments are allowed in the juncture between two words, the first word ending with the phoneme 1 and the second word beginning with phoneme $j$. The appendix contains a more detailed description of how the co-articulation constraints are implemented. If two words pass these co-
articulation constraints, they are said to be "time-adjacent". A word-sequence hypothesis always consists of word hypotheses which are pair-wise language-adjacent and time-adjacent.

Consider a pair of word hypotheses that are language - and time-adjacent. If there is a third hypothesis that is language- and time-adjacent, either to the lelt of the first word of the parr or to the right of the second, it can be concatenated onto the pair to torm a three word hypothesis. This action of extending could be repeated lefiward and rightward) untit there were no more possible extensions. If there were many alternative extensions at each point, this process would result in the creation of a larger numoer of partially similar word sequences. However, it is ciear that a sequence of more than two words may not de granimatical, since language-adjacency is defined only between successive two word pairs. The determination of the grammaticality of a sequence by the syntax-jevel knowledge source is a relatively expensive operation (between. 1 and 1 seconds on a PDP-10 KA10); thus, there is a bias against creating word sequences which have a high probability of being incorrect.

The factors which are of interest in deciding whether a word sequence is good are the length of the sequence, the ratings of its individual word hypotheses, and the numiser of other word hypolheses competing (overtapping in time) with each of them. The best starting island is the longest one which has a very high probabifily of being correct, with correctness taking precedence over length; correctness is a function of both individual word validity rating and the lack of simitar alternative sequences. These considerations led to the following algorithm for sequence creation:
(1) The 30 highest-rated word hypotheses anywhere in the utterance are chosen as initial one word sequences. Those with ratings less than some cutoff are discarded uniess doing so wculd leave less than five, in which case the five top words are kept.
(2) Each initial sequence is assigned a compcting sequence count (CSC) of 1.
(3) For each current sequence, the sets of alt word hypotheses left-(right) language- and time-adjacent to the beginning (ending) words of the sequence are founa. If the current sequence has CSC $=N$, and $R$ pight-adjacent words are found, then a rignt extension would have CSC=ivsR.
(4) Only those extensions whose average word ratings exceed a cutoff procortional to the square root of litR are formed. The direction chosen for extenstion is a function of CSC count for the direction and the validity of the highest word that remans to be extended in the specific direction.
(5) Steps 3 and 4 are redeated in a recursive manner untii no more extensions can be formed.

All sequences that are generated as a result of this process which are subsequences of another sequence are discarded.

This algorithm produces a large number of potential word sequences, usualiy between 10 and 100 . The cost of validiating them all for grammaticality is expensive. Thus,
another level of fittering is performed, based on a rating attached to each word sequence. The rating of a sequence is an increasing function of these quantities: (1) the duration-weighted average word rating, AVGRATE, computed by summing the product (word's rating) (number of syllables it contains) over all words in the sequence and then dividing by the number of syllables in the sequence; (2) the duration, OUR, computed as the percent of the utterance's syllables contained in the sequence; (3) the numiber of words in the sequence, NWOROS. The rating function is

RATE = AVGRATE + 0.1 = NWORDS * AVGRATE + 0.5 * DUR
The highest rated word sequence plus word sequences whose rating is some epsition away from the highest are chosen as candidates for further evaluation. in addition, another criteria is employed to choose sequences for further evaluation: if at all possible, there should be at least one word sequence for each area of utterance; the time areas nol covered by the highest rated wordsequences are the areas that are attempted to be covered by lesser rated word-sequences. Word sequences not chosen by this filtering are not distarded but rather are held in abeyance until either processing later on stagnates, or an existing word sequence candidate has been found to be ungrammatical or cannot be successfully extended; in these cases, these poorer-rated sequences are hypothesized for consideration by the rest of the system. This process of word sequence generation for the 34 utterances results in an average of 8.1 initial candidates, with an average of 6.6 more candidates being generated during the run.

The basic result of this algorithm is the identification of sequences of time-adjacent and language-adjacent words whose credibility is high. Although a iarge proportion of these sequences may not be grammatical, very few highestrated sequences are ever incorrcct (unless no successive correct word pairs are hypothesizeal. Furthermore, the computation of CSC biases against forming long sequences except where the chance occurrence of a language-adjacent pair is small; thus, in only ten percent of utterances does a highly-rated incorrect sequence contain a correct subsequence of lenglh greater than one which does not occur in a longer correct sequence. In such a case, if the granmaticality of the incorrect long sequence is refecled by the syutax knowledge source, a decomposition of the sequence into two maximal subsequences oczurs; these decompositions will be hypothesized subsecuentily if rated sufficiently high. This is a form of backtracking and, therefore, is subject to the same weaknesses as other backtracking search algorithms. In this case, however, the probabifity of a false initial island has been greatly reduced. As a result, the chance of a totally truitiess search is correspondingly reduced.

The effectiveness, in terms of both total system error $r$ ate and amount of search oerformed, of this multi-word island approach over both the leit-to-right and single-word island-driven strategies is indicated by following statistics; the overall error rate for the three strategres is $677,47 \%$ and 547 , respectively. in the ten sentences that were recognized coriectly by all three strategles, the average number of pirases hypothesized are 47,68 and 68 , respectively.

## COMCLUSIQN

The multi-word sequence generation procedure is a ke: knowledge sources in Hearsay-II. By exploting the redundancy of the language to identify plaustile word sequences and, incidentally, increasing the probability that a valid starting island hypothesis will be more highiy rated than an incorrect one, this source of knowledge provides very reliable and useful knowledge to direct the overali search. In our opinion, this knowledge source is a paradigmatic exampic of the effective use of redundancy and statistical sampling to acheve a reduction of uncertainty in problems characterized by fuzzy and partial information.

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## APPENDIX

This appendix describes the word pair adjacency acceptance procedure (JUNCT) developed for Hearsay-il, the knowledge it uses, and the current results. Such a procedure must be computationally inexpensive, making decisions on hundreds of pairs of hypothesized words. It must rely udon knowledge of word junctures and upon the information contained in the segmental transcription of the spoken utterance. And it must reject as many incorrect pairs (word pairs not actually spoken) as possible, without rejecting any of the corroct pairs.

As input, JUNCT receives a pair of word hypotheses. If it determines, based upon the times associaled with the hypotheses, the juncture rutes contaned in the procedure, and the segmental description of the spoken utterance, that the words are adjacent, the pair is accepted as a valid sequence; otherwise it is rejected.

The word junctures upon which JUNCT mus! make its decisions fall within three distinct cases: (1) Time-contiguous hypotheses: Words which are lime contiguous are immediately accepled by JUNiCT as a possible sequence; no further tests for adjacency are performed. (2) Querlapping hypotheses: When two words overlad in time, juncture rules are applied in the context of the segmental interpretation of the utterance to determine if such a juncture is allowable for the word pair. (3) Separated hypotheses: When the words are separated by some interval of time, rules are applied, as in the overlap case, to determine whether the pair can be accepted as a valid sequence in the utterance.

The juncture rules used by JUNXCT are of two types: (1) allowable overlaps of word end- and begin-phonemes, and (2) tests for disallowed segments within the word juncture. A bit matrix of aliowable overiaps is precompiled into the procedure, and is indexed by the end- and begin-phonemes of the word pair. Any overlap juncture involving phonemes which are not allowed to share segments is rejected by JUNCT. In the separation case, as in allowed overiaps, the
segmental description of the spoken utterance is examined in the context of the end- and begin-phonemes of the word pair to deternine if any difallowed segments are present in the juncture. If such segments are found, the word pair is rejected. Only when a word pair passes all rule tests which apply in the segmental context of its juncture is it accepted as a valid sequence.

Examples of allowable phoneme overlaps are the following:
(1) Allow words to share a flap-like segment if one of the juncture phonemes is a stop. (2) Allow nasal-like segment overlaps in nasai-stop phoneme junctures. (3) In a fricative-stop phoneme juncturs, alfow sharing of aspirations, fricatives, silences, and tlap-like segments.

Examples of non-allowed segments in a juncture are the following: (1) Do not allow a vowel segment in any functure (overlap or separation), unless it is a vowed-vowel phoreme juncture. (2) Do not allow a fricative segment in any nonfricative juncture.

## Current Results

Stand-alone pertormance evaluation runs were made over 60 utterances using words generated from files produced by the Hearsay-Il word hypothesizer. Syntactically adjacent pairs of words whose ratings were 40 and above (on a scale from 0 to 100) and whose times (lefl-word end time and right-word begin time) were within a 200 milisecond interval were considered. All of the words used for testing the procedure were hypothesized "bottom-up" in Hearsay-ll; no grammatically based prodictions were used in the evaluation runs. Table 1 summarizes the performance of the JUMCT procedure.

It is expected that, as lower-level sources of knowledge provide more accurate times for word hypotheses, the rules for acceptance of valid word pairs may be tigitened, further increasing the speed and performance of Hearsay-ll.

|  | CORRECT <br> WORD PA RSS | NCORRECT <br> WORD PAIRS | TOTAL |
| :---: | :---: | :---: | :---: |
| ACCEPTED | $185(95.4 \%)$ | $2891(41 \hat{x})$ | $3079(42 \%)$ |
| REJECTED | $5(2.5 \hat{6})$ | $4224(59 \%)$ | $4233(58 \%)$ |
| TOTAL | 197 | 7115 | 7312 |

Table 1. JUNCT performance (60 utterances)

# Word Verification in the HEARSAY II Speech Understanding System 

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## ABSTRACT

A key problem for speech understanding systems is the verification of word hypotheses gererated by various knowledge sources in the system. In this paper we will discuss the general problem of word verificalion in speech understanding systems. A description of our matching algorithm for word verification which is oased on that used in the HARPY system, a general connected speech recognition system (towerre, 1976), is given. An example of the verification of a word hypothesis using this algorithm is prosented. Problems which arose in aoplying this technimue to verification of individual words in a connected speech understanding system and their solutions are discursed. A performance analysis of the verifier in ternis of accuracy and speed is given and directions for future work are indicated.

## INTRODUCTION

Word verification is the evaluation of word hypotheses in speech understanding or recognition systems. The aim of this evaluation is to decide which hypotheses aro worthy of further processing by other earts of the system. This evaluation is generally performed by measuring how closely a given word matches its predefmed representation. The representation and the match of the acoustic signal may be performed at various representaticnal levols such as the parametric, phonelic and syllabic. Since errors are introduced and propagated as information is encoded from the parametric to the syllabic level, accurate matching becomes increasingly difficult at each successive level of abstraction. However the computation time for matching decreases since there are tewer maticn elements each containing more information.

Words may be hypothesized from many diverse sources of knowledge not solely based upon acouslic evidence. If 57 to 87 of the vocabutary is hypathesized for each word position in the utterance (the current HEARSAY bottom-up performance), the verifier must distinguish between 50 to 80 competing word candidates in a 1000 word vocabuiary. Even with significant improvements in word hypothesization (ie. decreasing the eflective vocabulary hypothesized to .57. per word position), as we move to systems with large vocabutaries ( $\sim 100,000$ words see Smith 1977) the number of potentral verifiable words remains quite large.

The verifier must assign a likelinood score which is commensurate with the match between the undertying acoustic data and the phonetic description of the word. The goodness of a score may be only temporaty significant so The scores should rank order the competitive words in any time area such that the correct word is high in the ordering.

Besides this acceptance criteria, it is also necessary for the verifier to reject absolutely a large percentage of the hypothesized words, without rejecting significant numbers of correct words, in order to constrain the combinatoric explosion of hypotheses at higher levels.

## THE HEARSAY ENVIRONAENT

Word verification is performed within HEARSAY If in the following environment. Word candidates may be supplied from a bottom-up word hypothesizer (PCMOW) based on acoustic information or from a top-down syntax and semantics knowledge source (SASS) based on syntactic information and constraints proviocd by the grammar. PONOW (Smith 1976) provides word hypotheses which have reasonable underlying acoustic support over a definile portion of the utterance. The times supplied are used to guide verification but do nol preclude change. SASS (Hayes-Roth 1977) provides words which can be characterized as being syntactically plausible in a particular time area of the utterance. No pruning is performed according to the credibility of the underlying acoustic information. Since these words are aiways hypothesized based on a previously verified word or from the boundaries of the utterance, only one time is known. This requires that the verifier must not onty rate the hypothesis, but must also predict the missing time. In addition, since words may be predicted to the left or right of a verified word, the verifier must have the ability to match words in both directions.

HEARSAY operates under the hypothesize-and-test paradigm to produce many competing hypotheses which overtap in time. Each word hypothesis must be verfied and assigned a rating before is can be used by other sources of knowledge. Each of these verified hypotheses can in turn be used as seeds to generate new sels of syntactically plausible words. A measure of the tan-out from each word s the effective branching factor of the hEAFSAY II grammar (Goodman 1976) which is is between 5 and 15 . Thus regardless of the scoring performance, a verifier must be computationally efficient in order to be useful in this typo of system.

## VERIFICATION MODEL

WIZARD can be decomposed into three major parls: word networks, a segmentation of the utterance, and a control structure which implements the matching alforithm. First, each word in the lexicon is represented by a statically defined network which embodies alternate pronunciations of the word. Each node in the word network represents a phone and arcs indicate successor/predecessor relationships between phones.

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Figure 1 gives an example of the network for the word ABSTRACT. These networks are stored as a static data structure in a packed formal. The uniform representation of words by a single network which embodies all speech dependent knoxledge gives severai advantages over other approaches. First, the generation of proper network descriptions can be handled on a case by case basis without the need of a generai theory for all. This also eliminates the need for speciai case solutions when the generat theory fais or is tound incomplete. Tools are atso available to generate word descriptions and tune the acoustic-phonetic templates (Lowerre, 1976).

The acoustic information is a segmentation of the utterance where each segment is represented as a vector of phone probabilities. WILARD benefits from the use of the same templates and segmentation as the HARPY system (Lowerre, 1976). As in HARPY the phone probabilttes are distance measures between each sesment and acousticphonetic templates in the phonetic cictionary. This vaiue is a scaled log likelihood measure (since the probabihties do not sum to 1) and is used direclly in computing the word match score over the given segments. WIZARD uses approximately 90 templates to cover all phonetic variations in its 1024 word vocabulary.

The last component is the dynamic matching algorithm. Although there is no speech dependent knowledge embodied in this module, several heuristics are employed to find optimal starting points and to choose the best final segment. These heuristics are discussed in the following section on implementation issues.

Figure 3 illustrates the matching of the word ABSTRACT to ten segments of an utterance. The malch score for any phone $I$ in the Tth segment can be caiculated from the following:
$M_{1, T}=M_{1 n}\left(M_{3, T-1}\right)+P_{1, T}$
Where $M_{J, T-1}$ is be best match score in the previous segment for phone $]$ where

## $J=1$ or

$J$ precedes I in the network
and $P_{i, T}$ is the acoustic match score of phone I in segment $T$

Figure 2 gives the phone probabilitics for each phene in the network in each of the segments over which the match is performed

Those scores in Figure 3 marked with $*$ indicate the best path through the mapping. The begin time of each segment is given, along with the segment number, on the top of the figure. The left side is labeled with each phore in the network. Entries in the table of ou indicate that a prone mapping to that segment is not allowed. The tinal mapping is given at the botlom of the figure. The final match score of 40 is the score of the best phone which transitions into the final state 1 plus the acoustic match probavility of $]$ which is defined to be zero. This represents the score of the best path through the network. This score would be normalized (by the number of sergments mapped -i) :o A and would receive a HEARSAY score of 90 out of a possidie $: 00$. Other paths can be found by tracing back from the other four possible ending phones: - (48) - (46), DX (66), and (46).

## IMPLEMENTATION ISSUES

Initially several problems arose while integrating this knowledge source into HEARSAY ii. The following is a discussion of the problems addressed during the implementation of the verifier. First, sunce we were cealing with single words and attempting to verity them as if iney existed in isolation, many of the constraints provided by word juncture rules and syntactic knowiedge were unavailable for use. In light of the power that these constraints give to similiar systems \{́Lowerre 1976) wouid verification be tractable?

Words could be hypothesized bottom-us with incorrect times. This meant that procedures had to be employed to search the segmentation for the local best
starting and endine, point around the given points. Words predicted top-down always had a missing time, and procedures for predicting these limes accurately had to be developed. Problems in the generation of end and begin times of words which share vowels often cause valid word pairs to be rejected by higher level knowledge sources.

The conversion of internal match scores to HilARSAY Il ratings while mantaining consistency of the ratings proved to be a major concern when it was noticed that the average internal ratings for words varied considerably depending on where in the utterance the words occurred. The notion of rank order of the word with respect to its compotitors rather than absolute scorc proved to be unimplementable in practice. While useful in static tests outside of the systern as a measure of performance, a rank order scheme which assumed all competitors in a parlicular time area were avallable to be rated at the same time, or remembered at some later fime, proved intractable.

It has been noticed by other researchers that short function words such as on, the, of, to, in, tend to be hyputhesized at many places in the utterance, with good ratings and are nost often taise alarms. Our experience was much the same and we chose to attemot to hande this problem direcliy rather than pass it on to the higher level knowledze sources.

## solutions

Several modes of verification are supported within WIZARD. Each represents a partial solution to one or more of the problems oullined. Non-pad mode uses no heuristics to determine the boundaries of the match. The predicted begin/end times are mapoed directly into their respective segments and verification is performed across those segments. It takes approximately 60 miliseconds of CP time on a PCP-KAIO to perform matcong in this mode.

Pad mode was added to handie the probtem that bottom-up times may be incorrect. This mode is currently used to verify all bottom-up hypothesis. in this mode the begin/end times are mapped into segmants as in non-pad mode. Then a ons segment uncertanty is allowed during the matching. Thus if $B$ is the begin sesmont, $E$ is the eno segment, segments $B-1 / B / B+1$ are allowable starting points for the match and $E-1 / E, E+1$ are the ailowable ending points. The nine paths between the boundary segments are evaluated in parallet by moaifying the boundary conditions in the matching atoorithm. As a result WIZARD must backtrack from each of the final end segments in order to find the correct begin segment associated with the path. Thus is necessary so that the begin time of the segment can be returned as the begin time of the word and to octernine the path length (number of phones on the path) for scoring. This mode takes about 100 milliseconds of CPU time on the POP-YA10 and is about 3.5 times faster than exploring each of the nine paths in non-pad mode.

As we have mentioned before it is necessary 10 perform verification wiere only one of the word times is known Two prectetion modes are implemented in WIZARD, one where the end time is unknown (rigint) and the other predicis a missing tersin time (left). As in pad mode a one segment window is evaluated around the given starting segment. Then each cuccessive segment is malched and the match scorc is compulea as if the match were ending in that segment. The scores are ordered and the score for the best path is returned along with the missing time. Several heuristics are used to prune the number of end segments actually looked at 35 possible end states. This is the most computationally expensive of the verification modes takint about 160 miliseconds per verification on a PDP-kA10 processor.

Several experments were performed to deternune the best way to normarze the match scores. The techncue employed was to ver:fy approximately 10000 bottomiup word hypotheses from 60 ylterances, normatire the scores and caiculate the average rank order of the correct words. The rank order gives the number of incorrect words that
were rated as high as, or higher than, the correct word. This ordering is a measure of how many words per word position nust be considered by the lop level knowledge sources in order to have confidence that the correct word is present, assuming it has been hypothesized. Normalizing the scores by the time duration of the word antolified the problem of function words receiving unusually good scores. More complex normalizalions based on non-linear time scaling were also rejected. Segmental normatizations employing penalties for mapping the same phone into many successive segments proved 10 be too time consuming in light of the benefil derived. Currently, predict mode scores are normalized by the number of sesments in the match path $N$ witile the other modes are normaiized by $N-1$. These normalizations are computationally simple and emballistments tried to date have not performed significantly better

The conversion of internal WIZARO scores to HEARSAY il hypothesis ratings was accomplished by conducting a statistical analysis of correct/incorrect word ratings over approximately 50000 verifications. By knowing the distribution of correct and incorrect words over each of the internal score values (dynamic range of 64), a corresponding distribution of HEARSAY scores was calculated. The HEARSAY score distribution allows tor the absolute rejection of verified words. This threshold was sel so as to reject no correct words. Scores above that threshold were distributed so as to capitalized on the distributions of the correcl words. Several tradeofis are possible here. If one requires that no potential correct words be rejected then WIZARO was able to reject 127 to 197. of the incorrect words hypothesized. On the other hand if it were possible for the system to perform with a small number of the correct words being rejected, a higher percentage of incorrect words could ive rejected. Allowing a 67. rejection rate of correct words approximately 517 of the incorrect words can be eliminated from consideration by the higher level knowledge sources.

To aid in compentating for the apparent temporal difference in word scores, the acoustic match probabilities generated by the segmenter were normalized such that the score of the best phone in a segment had the absolute eest match score. This alteviated the probiem and improved the reliability of the normalized malch score while leaving the rank order statistics unchanged.

## RESULTS

The results summarized in Figure 4 are for five data sels, containing 100 utterances, in which 332 correct words were hypothesized bottom-up by PONOW. In addition, 13053 incorrect words were generated. The vocabulary size for POMOV and WIZARD was approximalely 550 words. WIZARD rated each of the words using pad mode verification. For each rating threshold $(15,10)$ the number of correct and incorrect words that were accepted or rejected is tabulated. From this data the number of words hypothesized per word position, and the percent of the vocabulary per word position, can be calculated. These numbers give a vocabulary independent measure of performance, allowing comparisons belween various system configurations. An average rank order of the correct word is provided which measures, at each threshold, the number of words in each word position that must be examined in order to include the correct word. The range of rank orders between the data sets ( 20 utterances $/ \mathrm{set}$ ) is also noted.

## DISCUSSION

The major direction of this work is the application of the HARPY network representations to the verification of single words in a connected soeecn understanding system. This includes the modifications to allow the various verification modes dictated oy the HEARSAY il system strategies. We teel that WILARD makes an important contribution to the overalt pertormance of HEARSAY il and forms a groundwork upon which more sophisticaled verifiers can be developed.

Several problems with the current word verification system can not be solved within the existing framework. Future work is required in the following areas. New schemes for normatization of scores have been proposed to improve the performance in seomentations having many very short transition segments. These segments in general have poor ratings and offen degrade the composite word scoro.

Although we felt that the matching algorithm was computationally efficient when first implemented, as system strategies evolved it was found that a significant portion of recognition time was being spent in verification. A sizable increase in speed can be obtained by coding certain of the inner loops in assembly language. Other impiementation oriented optimizations may be neecied.

A most useful addition to WIZARO would be the ability to verify sequences of words by oynamic generation of multiple word networks. These networks would embociv the appropriate word juncture rules and would allow WIZARD to rate phrasal hypotheses diecetly rather than having other knowledge sources calculate a compasite scorc from the individual word scores. Along these lines, perhaps as a first step, it is necessary to handle word juncture problems which cannot be stalically encoded in the singie word networks themselves. These juncture problems are a major cause of incorrect times on word hypotheses.

It will be necessary to augment this word verification system with a component to perform more direct signal matching. The purpose of this addition is to disambiguate competing words which have goon WIZARD scores in the same time area. We propose 10 extract word templates at the parameiric level and perform matching using Itakura's method (Itakura, 1975). The philosophy here is to store templates for a small number of poientially difficuit words rather than synthesize the templates by a rule-based system. This time consuming matching would be performed when indicated by higher sources of knowledige.

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Figure 1


FIGURE 2

| TIME | 93 | 99 | 108 | 112 | 118 | 123 | 128 | 136 | 145 | 148 | 150 |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| SEC | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 38 |  |
| 1 * | * | * | $\cdots$ | * | * | $\cdots$ | * | * | $\cdots$ | $\cdots$ | - |  |
| - | * | $\cdots$ | $\cdots$ | $\cdots$ | ${ }^{*}$ | $\cdots$ | * | - | $\cdots$ | $\cdots$ | $\cdots$ | 4 |
| - | 27 | 56 | 68 | 86 | 118 | $\$ 36$ | 172 | 214 | 238 | 238 | 252 | - |
| AE3 * | * 2 | 4 | 39 | 73 | 196 | 123 | 146 | 152 | 158 | 181 | 193 | $\omega$ |
| * | $\cdots$ | 12 | * 3 | 38 | 65 | 91 | 125 | 153 | 163 | 150 | 188 | $\omega$ |
| - $\quad$ | $\cdots$ | 31 | 14 | 19 | 45 | 71 | 107 | 149 | 173 | 158 | 172 | - |
| S | * | $\cdots$ | 57 | * 3 | *21 | 63 | 99 | 141 | 183 | 188 | 178 |  |
| - | * | $\cdots$ | $\cdots$ | 73 | 29 | 47 | 83 | 125 | 149 | 149 | 163 |  |
| OR | * | $\cdots$ | * | 86 | 27 | *21 | 57 | 98 | 138 | 144 | 158 | $\cdots$ |
| $R$ | $\omega$ | $\cdots$ | $\cdots$ | $\pm$ | 98 | 48 | -28 | 45 | 52 | 88 | 121 |  |
| $T$ | $\cdots$ | * | $\cdots$ | 63 | 16 | 37 | 73 | 115 | 146 | 157 | 257 | - |
| AE2 | $\cdots$ | $\cdots$ | $\cdots$ | $\cdots$ | 119 | 43 | 31 | * 32 | *32 | 61 | 98 | $\cdots$ |
| - | $*$ | 4 | $\cdots$ | $\cdots$ | $\cdots$ | 145 | 77 | 59 | 43 | 34 | 54 | $\oplus$ |
| - | * | $\cdots$ | $\cdots$ | - | $\cdots$ | $\cdots$ | 181 | 119 | 83 | 43 | 48 | - |
| - | * | $\cdots$ | $\cdots$ | $\cdots$ | $\omega$ | 145 | 79 | 73 | 56 | . 32 | 45 | - |
| $1 *$ | - | $\cdots$ | - | $\cdots$ | * | * | 181 | 119 | 98 | 54 | +40 | $\cdots$ |
| DX | $\cdots$ | * | - | $\cdots$ | $\cdots$ | 133 | 62 | 48 | 35 | 59 | 86 | $\cdots$ |
| - | $\cdots$ | $\cdots$ | * | $\cdots$ | $\cdots$ | 145 | 79 | 73 | 56 | 32 | 46 | - |
| 1 | AE3 | AE3 | * | 5 | $s$ | Of | ค | AE2 | AE2 | - | 7 | \$ |

FIGURE 3

| THR | 15 | - HYPEO | 0 by potidil |  | CPPTEO | REJECTEO | 5.6 Mank OROEA$(3.8-7.1)$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | cornect |  | 332 | 326 | (98\%) | 6 ( 2\%) |  |
|  | INCORRTC.T | 13853 |  | 18426 | (80\%) | 2627 (28\%) |  |
|  | TOTAL | 13385 |  | 10752 | (80\%) | 2633 (28x) |  |
|  | A/NOAD PDS |  | 48 (8\%) | 32 | ( 6\%) | 8 ( 2x) |  |
| TMA | 10 | - MYPED | BY POLIOL |  | EPTEO | REJECTED | 4.5 RAMK ORDEA |
|  | CORRECT |  | 332 | 312 | (947) | 20 (67) | (3.4-5.9) |
|  | INCOAAECY |  | 13853 | 6452 | (49\%) | 6591 (512) |  |
|  | TOTAL |  | 13385 | 6774 | (512) | 6611 (49x) |  |
|  | SHORD PDS |  | 40 (8z) |  | ( 4x) | 20 (4x) |  |

FIGURE 4

# The d' Model of Signal Detection Applied to Speech Segmentation 

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Abstract The statistical measure, d', from Signal Detection Theory, [Swe64] has been shown to parametrize the "detectability" of signal over noise in a wide variely of perceplual stituations. Its usefulness is extended to the problem of quantifying error rates for segmentation of continuous speech. It has often been impossible to accurately compare different machine techniques for segmentation since errors occur as either missing or extra segment boundaries whose rates are related by internal decision thresholds. The basc $d$ model is shown 10 accurately ( $>95 \%$ confidence) describe the missing versus extra segment trade-off found in at least one, non-trivial, speech segmentation program. [Gol75]

Introduction The last few years of computer speech recognition research have produced, among other things, a number of techniques for machine segmentation of the speech signal into phonetic (or acoustic) units. [e.g. Dix 75 , Bak 75, Goi75] The difficulties involved in evaluating and comparing the performance of segmenters seem to occur in two areas. First, one must acquire a definition of the "correct" segments for some large set of data. This is usually done by hand, although some automatic techniques are available." Since the production of "correct" segmentations and their comparison with macmine segmentations (e.g. What amount of mis-alignment, etc. should one allow?) involve a number of linguistic as well as recognition system-specific issues, we will not deal further with these problems here.

However, a second problem is that segmentation errors occur in two types: missed boundaries (segments) and extra boundaries (segments). There is clearly a tradeoff between these two types of error, but we have rot understood it well enough in a quantitative sense to compare different segmenters for even the same segmenter "funed" to a different point of the $M / E$ tradeoff). What was needed was a model of this trade-off which yielded a single, comparable measure of segmentation efficacy for any set of data with errors marked missing or extra. Sucls a model is provided by Signal Detection Theory. We wilt show that the theory agrees quite well with the results of a set of segmentation triais run to explore the $M / E$ trade-off.
*The Harpy speech recognition system [Low76] can be forced to the correct words. This produces a "best" fit of the system's acoustic and phonological knowiedge to the signal. When a very line graned fit is made (average acoustic segment duration, 30 ms .), the resuiting phonetic segments are very close to those produced by humans.

Signal Detection Theory The theory of Signal Detection, as formulated by Tanner, Swels, and Green, [Tan64, Lic64] is primarily applied to detection trials which may be considered similar to the segmentation process. A detection trial presents a stimulus, which may be composed of noise or of notse and some known signal, and requires a decision to be made about the presence of the signal. This is not untike the decision process resulting in the placement of a segment boundary based upon local information only. It is assumed that the a priori likehinoods and costs of varibus errors are known to a decision process which senses and possibly transforms the stimulus into some internal signal space before it yields a decision on the presence of the signal. The detector's sensory data is considered, in this model, to be reduced to a single decision oarameter. An optimai one, according to decision theory, is the ratio of the probabilities of two hypotheses -- that the input stimulus was signal plus noise or that it was norse alone. A simple threshold on this single parameter may be placed to optimize the expected costs given a priori likelihoods, costs of misses, false alarms, etc. Figure 1 represents such a nypothetical internal decision parameter, L .


Figure 1: Signal Detection Model
Very simply stated, the model assumes a single decision parameter, $L$, which may be any sensory measurement one wishes. The distribution of $L$ values for the two types of stimull, signal-plus-noise and nose-atone, are assumed to be normal (with equal variance in the simplest version of the model). Their means differ by $d$ ' limes the etandard deviation. Rates of "hut" and "false
alarm" -- Pr\{accept|signal\} and Pr\{accept|noise\} respectively -- are sufficient to determine the least $d^{\prime}$ for which an optimal decision process can display the observed rates. When the hit and faise alarm rates are plotted against one another for a number of sets of trials where the detector's acceptance threshold has been altered, a response operator characteristic (ROC) curve is obtained (see figure 2).


Figure 2: Typical ROC Plot
The theory states that the curve is totally determined by $d$. When the axes of the ROC curve are transformed by the inverse function of the Normal distribution function, the curve is approximately a straight line with stope $-s i g m a(n o i s e) /$ sigma(signal) and $x$ intercept $=d^{\prime}$. [Egā̄4]

This theory has been most often applied to defection trials to provide estimates of the detectability of the signal as it appears in a human perceiver's internal sensory signal space. The estimate of $d$ provided by the signal detection model may then be compared with well known properties of visual or auditory signals to provide a bound on the efficacy of the perceiver's iransduction process -the sensory channel. While the main thrust of its application is not relevant here, the signal detection model and the dimensionless measure $d^{\prime}$ can be used as a normalized measure of segment boundary defection that is relatively unaffected by adjustments in the proportion of missing versus extra segment errors. Furthermore, the d' value, once estimated, may be used to predict the entire response-operator characteristic.

Segmentation The results reported here are, for the most part, obtained from a segmentation program written for a comparison study of parametric representations [Gol75] and used for a while as the initial signal-to-symbol stage of the Hearsay II speech understanding system. [Erm74] A short description of the segmenter is therefore called for.

The signal amplitude, and measures of signal and of amplitude change,** (each measured over both 10 and 30

[^5]ms. intervals), are input. Speech is separated from silence and from near-silence, and flaps are detecled by their amplitude contours. Then the measures of change are inspected for significant peaks (possible boundaries). The union of all such detections is processed by a correction routine to merge multiple boundaries caused by the same underlying phonetic change. The program has two advantages for this study. First, the input parametric representation is easily changed, and second, the internal, segment detection process is easily tuned along the $M / E$ trade-off.

Results from this program were compared with a "correcled" hand segmentation. That is, the machine segmentation was compared to a phonemic-level human segmentation for discovering missing segments, and to a finer-grained phonetic-level segmentation for discovering extra segment errors.

Results The first experiment validates the Signal Detection model assumption of two (nearly) normal distributions in a signal, hypothetical decision variabie. A set of 40 sentences with 1093 phonemes and 1541 phonetic segments was segmented seven times. Internal thresholds were varied to produce segmentations performing over a wide range of the $M / E$ trade-off. The resultant error rates are plotted on a normal-normal grid in Figure 3. A least-squares regression fit a line with slope $=1.00$ (Noise standard deviation / Signal standard deviation), and $x$-intercepta 2.25 (d' -- the separation of the means of the two cistributions).


Figure 3: The M/E Trade-off
The line is the ROC of the segmenter with this particular parametric representation, "correct" segment definitions, etc. for all M/E. trade-off tuning.

A second experiment, run with different input parameters, gives a measure of confidence in the d' estimates. When the 40 sentence were divided into 10 groups, and estimates of d' made for each group, the $95 \%$ confidence interval in $d^{\prime}$ was found to be +-0.14 (i.e. the estimate from 4 sentences fits the d' computed from all 40 within the confidence interval). Since this interval is considerably smailer than the differences found between segmentation programs, or between input parametric
representations, we teel such comparisons are meaningful using d'. For example, tour representation of the signat were tested [Gol75] yelding d' values from 1.29 to 2.38 . Furthermore, published results of two other segmenters [Bak75, Dik75] allowed estimates of d' to be made of 2.26 and 2.73. The ordering of all these segmentation runs agrees very well with our intuitions about the programs, as well as with the (somewhat sparse) results of speech recognition use of them.

Conclusions We believe that the model provided by Signal Detection Theory, and particularly the d parameter of that model, offer a higtily suitabic and attractive measure of segmentation efficacy, and a means of better understanding the $M / E$ trade-off. Different segmenters, conforming to needs of different speech recognition systems, can be quantifatively compared, and their performance under different "tuning" of the $M / E$ trade-of" can be predicted.

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# an application of connected speech TO THE CARTOGRAPHY TASK 

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## ABSTRACT

This paper summarizes initial development of a system for visual and verbal data acquisition in the cartography task. Visual input and output is provided by agraphics tablet in conjunction with a graphic display termmal. Verbal input consists of sequences of commands and map feature descriptors which are recognized by the Harpy speech recognition system. An important and interesting aspect of this research involves the design and analysis of vocabularies and grammars for tasks of this nature.

## INTRODUCTION

The cartography task is an interesting application in man-machine communication combining several forms of input. It is a practical task, used dail', by map makers, and has a well defined protocol. In this lask features are selected and traced from a map and further described by a sequence of descriptor phrases. The graphical input is obtained using an $x-y$ coordinate input device, such as a graphics tablet. In currently used cartography systems, the textual descriptions are entered via keyboard. This paper describes the VICS system, a cartography system in which conrected speech input replaces keyboard input. VICS stands for Voice input Cartography System.

This project was undertaken because it represented a practical and useful apptication for speech input of sufficient size to be interesting, but small enough to be feasible. An important aspect of the research is the pursuit of a methodology for language design for man-machine volce communication. Interaction with the user is sufficiently ffexible to allow the investigation of several different methods of language structure, from little or no constraint to highly constrained sequences. Further, since a smoothly interacting system with adequate response would have immediate application, there is great potential for study of the many problems associated with man-machine systems.

[^6]In order to combine voice and graphical input in a practical system, one needs 1) a speech recognition system capable of recognizing utterances from a language as complex as required by the task, 2) a graphic system sufficiently llexible to allow graphical input and visual feedback as necessary for the task, and 3) some method of interfacing them so the system behaves in a way which appears as natural as possible to the user. Two systems designed at Carnegie-Mellon University provide the necessary tools. The Harpy speech recognition system [Lowerre, 1976 and 1977] recognizes live voice input with the ability to apply grammatical constraints. The SPACS graphic system [Greer, 1976], originally built as a stand alone interactive graphics editor, uses a tabiet input device in conjunction with a graphics display terminat. Its capabilities include free-hand line drawing and the ability to create tables, flow charts, logic diagrams, and other schematic diagrams. The interfacing problem is solved by the use of a task module in the Harpy system.

Other systems for speech input are available. The isolated word recognition system developed by Threshold Technology [Martin, 1975) and the Bell Labs connected speech system [Sambur and Rabiner, 1976] are accurate systems, but at present lack the desired fiexibility in structuring the grammar. Other successful systems, such as Hearsay-il [Erman et.al., 1976 and Lesser et.al., 1975], HWIM [Woods, 1976], and the IBM system [Jelinek, et.al., 1975 and Eahl, et.al., 1976], have much more elaborate control structures and were designed for larger tasks. The overhead involved in these systems is considered unacceptable for tasks such as this one.

## THE HARPY COHHHCTID SPEECH RECOGINTION SYSTEM

In the Harpy system the recognition process consists of searching for the best path through a precompiled nelwork, given the acoustic evidence present in the utterance. The search scheme uses heuristics to reduce the number of paths considered, resulting in only a tew "best" paths being searched in parallet. The recognized utterance

The authors wish to acknowledge Raj Reddy for assisting in the overall design of the system, Bruce Lowerre for creating dictionaries and designing the task module intertace, ard Ken Greer for making the necessary changes to the graphics editor.

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is then turned over to a task module, a prograin whose purpose is to respond to the user in a way appropriate to the task. The simplest task module would simply type the recognized utterance on some output device such as a CRT, In more complicated cases, such as the Al abstract retrieval task, the task module would extract the intent (meaning) of the utterance, consult its data base, and supply an appropriate response, eg. "There are 17 articles on that topic".

The recognition process in Harpy uses a precompied network which integrates syntactic, lexical, and word juncture knowiedge. Syntactic knowledge is specified by a context-tree grammar defining the input language. Lexical information is embodied in a symbolic phonetic dictionary containing pronunciations and alternate pronunciations for each word in the task language. Word juncture phenomena are characterized by a set of a priort juncture rules giving alternate pronunciations of word beginnings and endings based on the context of adjacent words. All these sources of knowledge serve as inputs to a program which compiles a network representing all possibie pronunciations of all possible input utterances.

The acoustic evidence used to determine the best path in the network is obtained by segtaenting the input and extracting LPC parameters for each segment. These LPC parameters are matched with phone templates to produce a metric between the segments and the symisois (phones) associated with network states. This metric is in the form of the probability that the segment is an instance of the symbol. Probabilities are learned from exemplars taken as Iraining data.

Creating a new task for Harpy consists of defining the language, training the phone templates, and specifying the task module. To define the language one first specifies the grammar for the input language and then obtains from it a list of all the words used in the language. For each of these words a description of its allowed pronunciations is entered into the dietionary. These deseriptions are in terms of a standard set of phones.

## THE VICS SYSTEM

The task module coordinates verbal and graphicat input and controls discourse with the user. Figure i shows a user at the graphics display interacting with the VICS system. Verbal mput is a sequence of words or phrases which may be commands for the task mociule or descriptions of the map feature. Graphic input is via a graphics tablet $x$ $y$ sensor. There are two graphic input nodes: point mode and trace mode. The user enters point mode by saying "point" or "point mode". In this moce the user defines one position on the map corresponding to the location of an feature such as a well, pond, or water tank. For more complicaled and larger features, such as lakes, islands, shorelines, and harbors, trace mode is entered. in this mode the $x-y$ sensor position is continuously montored giving a graphical description consisting of a set of lines. In both modes the graphical description is dispiayed on a CRT for visual verification. Figure 2 shows how the graphics display appears after the user has traced an intermuttent siream. At this point the user describes the feature verbally according to the vocabulary and gramnatical structure. The
 with the VICS system.


Figure 2. Graphics Display after tracing an intermittent siream.


Figure 3. Graphics display after verbaliy describing tre intermittent stream.
display after verbally describing the stream is shown in figure 3. Figure 4 shows the display after another tracedescribe cycle describing an adjacent pond. After the description is complete the user may reject or accept it using voice commands. If accepted, the description is stored for future use.


Figure 4. Graphics display after description of both stream and pond.

The vorabulary for the VICS system consists of task module commands and words or phrases for describing the map feature. These plrases are fanuliar content phrases used by map makers and are contained in a document produced jointly by the Department of Commerce and the Department of Defense [U.S. Dept. of Commerce, 1975] Sone examples from this document are shown in figure 5. We have chosen, in cooperation with RADC, 691 phrases from this document. A 77 phrase subset, used in the descriplion of features in the class drainage, has been chosen for test purposes. The first few lines of the task dietionary are shown in figure 6.

The choice of grammar is dictated both by the nature of the task, eg. the description of map features, and by the desired user interactions, eg. user commands. A factor relating to user satisfaction is grammatical constraint. A grammar with high constraint implies, in general, fewer recognition errors and thereforo greater satisfaction. Caro must be taken, however, to not constrain the grammar so much that interaction becomes unnatural for the user.

There are several ways of imposing grammatical structure on the phrases which make up the verbal description. We are currently experimenting with two methods, which represent the extremes of constraint. The first method is unstruclured where any phrase may be followed by any phrase, i.e. not consiraint. This gives the user complete freedom to describe the map feature in the most naturai way. Since there are other methods which allow the naturalness but also have some constraint, this mode is used for the investigation of what accuracies are attainabie in the worst case. If accuracy is adequate in this case, then it will be more than adequate in situations with greater constraint. The second method is complete constraint, or free-like, where each description is represented by a path from the root of a tree to the one of its leaves. In this method menues representing all possible choices at a node of the tree are shown to the user. After one of these possible utterances is spoken and recognized, the system uses the recognized phrase to move to the appropriate new node and presents the next menu according to the choices at the new node. The first menu (top or root node) presented to the user is shown in figure


Figure 5. Examples from cartography feature charts.

| above |  |
| :---: | :---: |
| ACCLP ${ }^{\text {d }}$ | $(-, 0)$ AE! ( $-(-, \theta),-) \mathrm{SEH}(-(-, \theta),-)(\mathrm{P}, \theta)$ |
| ALOS | ( $E Y L, 0$ ) EYC1 (EYR, $\theta$ ) ( $(-(-, \theta),-1$ |
| BEC | $(+(-, \theta),-)(8, \theta)$ EH! ( $-(-, 0),-)(0, \theta)$ |
| BELOH | $(-(-, \theta),-)$ ( $(8, \theta)$ ( $1 \mathrm{HJ}, \mathrm{iY}$ ), B$) \mathrm{L!}$ OH |
| BOC | $(\sim(-, 0),-)(6,8)$ AS! ( $-(-, 8),-)(6,8)$ |
| CANAL | (- $(-, 0),-) \mathrm{K}$ IHS N! AE EL |
| constal | (- $(-, \theta),-1$ K OH! S - T (AH2,0) EL |
| culture | (a) $(-, 0),-1 \times$ KH! EL ( $-(-, 0),-1)$ SH ER |
| Ooudie |  |
| DRAIN |  |

Figure 6. Example showing dictionary format for the carlography task.

## Roads

Populated Places
Railroads
Culture
Boundaries
Relief
Drainage
Coastal/Hydro
Vegetation
Navigational Aids
Ports/Harbors
Marine Dangers
Figure 7. First menu presented to the user after tracing map feature..
7. This menu describes the major classification of the feature being described. Each menu contains "restart" and "backup" as possible verbal commands. Restart means go back to the root node of the grammar tree and start the current description again. Backup means move back to the previous node of the tree. This command be used when a error was encountered. As the description is entered verbally, the recognized phrases are placed on the display, near the graphical description, for verification. The final menu contains "ok", "accept", "backup", and "restart" as possible inputs.

Neither of these methods for grammatical structure is viewed as being entirely appropriate to the task. Another method which we intend to investigate is an unordered Ireelike scheme where each description is a path thru a tree structure, but phrases can be entered in any order and the user need supply only enough of the path to make it unique. A variation allows teatures to have certain default attributes, eg. "river" implies "natural". The default would be used to construct the unique description unless some other counteracting choice, such as "man-made" were mentioned.

The VICS system was first demonstrated in Seplember 1976 after less than a man-month of effort. Recent emphasis has been on investigation of various language studies. While no extensive accuracy studies have been made, it appears that 987. accuracies are attainable with moderate grammatical constraint.

## DISCUSSION

The research reported represents initial progress toward the development of a system combining visual and verbal data acquisition for the carlography task. We have shown that a new task can be conslructed in a relatively short time. The system is still in its infancy and many interesting research problems remain in vocabulary analysis and design, language analysis and design [Goodman, 1976], effects of language structure and user discourse, interactive techniques, and the investigation of recognition characteristics under various vocabulary and grammatical complexities. We look forward to pursuing these areas of research.

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# Dynamic Speaker Adaptation in the Harpy Speech Recognition System 

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#### Abstract

The Harpy speech recognition system works optimally when it "knows" the speaker, i.e. when it has learned the speaker dependent characteristics (speaker dependent parameters) of the speaker. There are three methods of learning these parameters. One way is to generate them from a set of training data which covers all the altophones that occur in the task language. A second method is to use "speaker independent" paramelers with a resulting reduction in accuracy performance. Since it is inconvenient for a "new" speaker to say a set of training data before using the system and the low accuracy with speaker independent parameters is unacceptable, a third method has been devised to allow the system to dynamically fearn the speaker dependent parameters while using the system. The new speaker starts with a set of speaker independent parameters. These parameters are then altered after correct recognition (which can be forced if necessary) to match the spoken utterance.


## INTRODUCTION

This paper presents a method by which the Harpy is able to adapt to non-familiar speakers. The first section gives a short description of the Harpy system, its data structures, and its current performance. The following sections discuss the speaker variability issue and several approaches that have been taken towards its solution. These approaches include speaker specific tuning, speaker independent tuning, and dynamic speaker adaptation. The last section discusses how these averaging techniques can also be used in isolated word recognition systems.

## THE HARPY SYSTEM

The Harpy system is the first system to be demonstrated with a vocabulary of over 1000 words. The sysiem was demonstrated at the completion of the five year Advanced Research Projects Agency (ARPA) speech research project in September, 1976. It had a sentence accuracy, across five speakers (both male and female), of 917 and ran in about 30 MIPSS (a MIPSS is mitlions of machine instructions executed per second of speech). Since that time, improvements have been made in the speed of the system. The current system runs in less than 7 MPSS. The system is a recognition system rather than an understanding system since it uses no
semantic knowledge about the task in decoding the utterance. However, there are several other sources of knowledge in the system such as syntactic, lexical, word juncture phenomena, speaker characteristics, and intrinsic phoneme durations (see Lowerre, 1976 for complete details).

In the Harpy system, the syntactic, lexical, and word juncture knowledge are combined together into one integral network representation similar to that of the Dragon system (Baker, 1975). The syntactic knowledge is specified by a context free set of production rules for the task language. A dictionary is used to represent the lexical knowtedge. The dictionary contains symbolic phone spellings and specifies alternate pronunciations of the words in the task language. Word juncture rules are also included in the network to account for inter-word phonetic phenomena. The network consists of a set of states and inter-state pointers. Each state has associated with it phonetic, lexical, and duration information. The pointers indicate what states may follow any given state. Two special states in the network, the initial state and the final state, indicate the starting point and ending point for all utterances respectively. The network is, therefore, a complete (and pre-compiled) representation of all possible pronunciations of atl possible utterances in the task language. This network is used to guide the recognition process.

The recognition process of the Harpy system is based on the Locus model of search. The Locus model rejects all but a narrow beam of paths around the most likely path through the network. These "best" paths are searched in parallel with one pass through the speech data and theretore does not require backtracking.

The foltowing is a short description of the recognition process: The utterance is digitized at 10 KHz . This continuous signal is segmented into consecutive acoustically simitar sound units (based on distance measures of the data) and autocorrelation values and tinear predictor coding (LPC) coefficients are extracted for each segment. The segments are then mapped to the network states based on the probability of match (distance match) of the LPC data and the expected phones of each state. The matching of the LPC's and the network states is accomplished by use of phone templates. The templates contain the idealized parameters for each phone that occurs in the network states and they may be ether speaker specific or speaker independent. The metric used for this matching is Itakura's minimum prediction residual error (see Itakura, 1975).

The mapping schense used is a modified graph search in which heuristics are used to reduce the number of paths that are checked. The result is that only a few "best" paths are searched in parallel during the recognition processes thus greatly reducing the computational overhead.

Results The current system achieves a sentence accuracy of 90.07 and a word accuracy of 94.37 , on a 1011 word task and runs in 6.8 MIPSS .

## SPEAKER ADAPTATION IN THE HARPY SYSTEM

Speaker variability Speaker variability generally occurs in three forms, dialectic, contextual, and acoustic. Dialectic variability involves changes in the pronunciation of words among speakers. Contextual variability involves changes in word pronunciation do to the context of the words. Acoustic variability results from vocal tract changes among speakers. Either or all types of variability can occur when changing speakers. The Harpy system attempts to recognize these different variabilities and to separate the effects made by each. Dialectic variability is an effect across a broad group of speakers and the variability is encoded into the lexicon. Many dialects can be encoded into the lexicon or different lexicons can be used for different dialects. The current Harpy system uses the "mid-western American" dialect of English. The contextual variability is handled in the word juncture phenomena rules and, to a lesser extent, in the lexicon itself. The acoustic variability is a speaker dependent phenomenon and can be separated from the other types of variability.

Approach to speaker variability Many proposals and attempts have been made, from such groups as SDC, BBN, Lincoln Labs, etc., as to how to handle the speaker variability problem, These proposals include such ideas as vowel formant normalizations as an attempt to deternine speaker independent characteristics of the speech signal. The Harpy system handies speaker variability by the use of phone templates to capture the vocal tract characteristics. We achieve this by identifying all the unique sounds that occur in the task language (called phones). It is important to realize that these phones may or may not bear a resemblance to what may be usually thought of as a phonetic sound in the English language. For example, there are usually several occurrences of one vowel (allophones) in our set of phones each of which has a unique name. Also, there could be a single phone which represents what is usually thought of as a combination of phones (e.g. the phone "WH" represents the characteristics of the aspiration sound when pair "K W" that occures together as in the word "queen"). Each of the phones used in the Harpy system represents one unique phonetic sound.

Phonetic knowledge in the Harpy system The Harpy system uses a phonetic dictionary (along with word juncture rules) to represent the lexicon of the task language. The spelifings in the dictionary are strings of phones (along with a special syntax) which are used to represent primary and alternate pronunciations of the words in the lexicon. The phonetic dictionary is a representation of the actual realizations of the task language words rather than a pronunciation dictionary. A set of speaker dependent phone templates (one per phone) is used to match the symbolic lexicon to the actual acoustic signal. The phones of the lexicon represent
all the unique phonetic sounds that occur in the task language. Since the lexicon contains symbolic spellings which are speaker independent and there is a one to one mapping of the templates to the phones, the acoustic speaker variability can be handled effectively by using a unique set of templates for each speaker. The templates model speaker dependent vocal characteristics. For example, the dictionary spelling for "CONCERN" is " $(\leftarrow(-, 0),-)$ ( $\mathrm{K}, \mathrm{O}$ ) (IH7,IH3) N S ER (N,OK)". Optional paths are enclosed within parenthesis and are separated by commas (the " 0 " represents the null option). The spelling is interpreted as either a voice bar ("ட") followed by an optional silence ("-") or just a silence, followed by an optional " $k$ ", followed by either a "IH7" or "IH3", followed by an "N", foliowed by a " S ", followed by an "ER", followed by either an " $N$ " or "DX". See Mckeown, 1977, for an example network.

Averaging of template exemplars The success of the speaker dependent phonetic templates depends of the ability to average many exemplars of each phone together to generate each template. This averaging enables the automatic cancelation of errors (provided they are small). Since the template is an average, there is no need to find the single "ideal" exemplar that best fits all occurrences of the phone. The averaged template will usually match all exemplars of the phone in the training data to a high degree of accuracy. If a match of an exemplar in the training data is too far from the average template, then this indicates a missing phone.

The metric used by the Harpy system is Itakura's minimum prediction residual error of the LPC data. A method was needed to average samples together that could be used for generating the templates for this metric. The method we use is to sum the autocorrelation data of the samples that are used in generating the template. The justification of this is that the LPC's are independent of the number of autocorrolation samples that are used to generate them. The obvious danger is that non-similar sounds may be averaged resulting is a poor spectrum. This is a real probiem and is handied by a semi-automatic procedure for generation of the phones, templates, lexicon, and word juncture rules described below.

Speaker specific tuning The phones, templates, lexicon, and word juncture rules are generated from a set of training data that contains occurrences (and hopetully all contexts) of all the words in the lexicon. A semi-automatic iterative procedure is used to generate (or more precisely, update) these knowledge sources. There is a "chicken-egg" problem with this iterative procedure in that the data sources must already exist in order to update them. The generation of the initial knowledge sources is a tedious manual bootstrapping procedure. The training data must be carefully hand labeled (both al the word level and the phone level) and initial guesses are made about what phones, word spellings, juncture rules, etc. are needed. This manual effort is the main botlle-neck for developing larger vocabulary systems. Automatic methods must be developed before larger systems can be atlempted.

The following is the semi-automatic procedure used to update the data sources: The Harpy system is run in a forced recogntion mode with a previously generated set of tenplates (which can be from some other speaker) to produce a parsing of the phones to the acoustic data. This
forced recognition can be done either by using a unique network for each utterance (which represents only the one utterance) or by considering only paths in a large network that represent each single utterance. The parsings generated from the forced recognition runs are used to locate the autocorrelation data for the averaging of the templates. After the averaging is completed, a new set of templates is generated and used to again run the training cycle. This cycle is run several times until the templates converge. If the templates do not converge, then this indicates an error in either the lexicon or word juncture rules or a missing phone which must be manually analyzed and corrected.

Speaker independent tuning The speaker dependent templates are an averaging of many phone exemplars for each template. Since there is a unique set of templates for each speaker, they capture the individual vocal tract characteristics. This idea of capturing vocal tract characteristics by the use of templates can be extended to multiple speakers. When a number of these speaker dependent sets of templates are generated, another set of templates can be generated from all of them by a similar averaging technique. This set of templates, since they are an averaging of several speakers, will be speaker independent. The performance with speaker independent templates will of course be lower than with the speaker dependent templates. For example, one experiment done with connected digits gave the following result: Ten speakers (including males and females) were used to produce ten speaker dependent sets of templates. The average word accuracy for all ten speakers (when tested on the speaker dependent templates with a total of 1000 three word utterances) was $98 \%$. These ten template sets were then used to generate a set of speaker independent templates. These same ten speakers plus ten new speakers were then tested with the system. The word accuracy for all 20 speakers (on 1200 utterances) was 937 . An interesting observation is that there was no significant difference between the accuracies of the ten speakers whose templates were used to generate the speaker independent set and the ten new speakers.

Dynamic speaker adaptation The high error rate (77) with the speaker independent templates makes this alternative to the handling of acoustic variability unacceplable. Further, the training cycle mentioned earlier to generate the speaker dependent templates is inconvenient do to the large amount of training data needed and is computationally expensive. A third scheme was devised which allows a new user the immediate use of the system but also allows for the speaker dependent vocal characteristics. This is the dynamic tuning of the speaker templates. A new speaker to the system starts with the set of speaker independent tempiates. The system will, upon all correct recognitions, automatically average the autocorrelation data with the corresponding templates and update the tempiate parameters. The first occurrence of a phone spoken by the speaker will replace the speaker independent template. Further occurrences of the same phone will add to the average of the template. This will result in the phone template being altered quickly for the first occurrences of a phone and a gradual fine tuning of the template by additional occurrences of the phone. In this method, the system quickly adapts itself to the speaker's acoustic characteristics. If the system makes an error in recognition, one can either speak the same
utterance again with the hope that it will be recognized correctly the second time or the system can be rerun on the same utterance and forced to recognize the utterance. To force a recognition, the appropriate switch is set and the correct utterance is typed to the system. The system will then only consider paths in its network which represent the spoken utterance.

The error rate when first starting is, of course, 77. but quickly drops off towards the 27 error rate of the speaker dependent templates. The time needed for the updating of the templates is zero during the actual recognition but requires up to one times real time after recognition depending on the number of templates that are updated. Therefore, the overhead of doing the dynamic speaker adaptation is minimal.

## OISCUSSION

Summary In this paper we have considered several sources of variability in the connected speech signsl, i.e. dialectic, contextual, and speaker dependent variability, and described how the Harpy system attempts to cope with all these sources of variability. The dialectic and contextual variability are encoded into the lexicon and word juncture rules. The speaker dependent sources of variability are handled by averaging phone paramelers (i.e., the autocorrelation coefficients, not the LPC's) from among several exemplars of a given phone by the same speaker (for speaker specific templates) or from many speakers (for speaker independent templates). In the case of dynamic adaplation, a set of speaker independent templates are used initially and the system automatically alters the templates during use to adapt to the specific speaker.

It appears straight forward to adopt the above techniques for isolated word recognition systems also. Given several training samples of the same word, one can align the speech signal by dynamic programming techniques and average the autocorrelation coetficients as in the connected speech case. Since this averaging would be independent of word representation used, i.e. whether one uses segmentation and phone templates to represent words or the conventional brute force word templates, one can still use the above averaging technique to generate betier templates.

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# USE OF SEGMENTATION AND LAGELING IN ANALYSIS-SYNTHESIS OF SPEECH 

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#### Abstract

We have been attempling to produce further bandwidth reduction in LPC based analysis-synthesis techniques by using the segmentation and labeling algorithms used in the Harpy and Hearsay-11 systems. Preliminary results indicate that a factor of 3 to 5 further reduction in bandwidth might be possible using segmentation and labeling in conjunction with LPC vocoders.


## INTRODUCTION

An important application of speech analysis-synthesis is digital voice transmission. Real-time transmission at low bandwidths can only be achieved through efficient analysis and encoding techniques. While present analysis methods, based on signal processing techniques, have been used successfully to obtain bandwidth reductions of over an order of magnitude, further inprovement is possible if higher level properties of speech are also taken into account. In this paper, we demonstrate how segmentation and tabeling, two techniques commonly used in connected speech recognition, can be applied to vocoder systems as a means of improving coding efficiency.

In the remaining sections, we describo segmentation and labeling techniques, and their use in vocoder systems. Results from three different vocoder simulations based on these techniques are presented and evaiuated. We then consider some of the practical aspects of real-time speech transmission using these methods. Finally, the advantages and disadivantages of high level speech processing as applied to vocoders are discussed.

APPROACH
Our goal in this sludy was to evaluaie the usefulness of segmentation and labeling as techniques for improving vocoder coding efficiency. To accomphish this, two vocoder simulations using each of these tectniques separately, and a vocoder simulation which combined the techniques, were run. The resuits were compared with those obtained using conventional parameter encoding methods, and evaluated in terms of bandwidth reduction and quality of synthetic speech.

Of the several techniques for speech analysis that exist, this paper considers only those based on the autocorrelation method of linear prediction. A complete vocoder simulation based on this technique has already been developed by Markel and Gray[Markel and Gray, 1974] Since a detailed aiscussion can be found in this referonce, we consider only those aspects relevant to the banawidth problem here.

Analysis parameters in autocorrelation based linear prediction systems consist of pitch period, a voiced/unvoiced decision, ampitude information, and parcor coefficients. These parameters are generally encoded into a minimal bit representation and transmitted at a constant frame rale. The system on which our comparisons are based uses a trame rate of 100 frames $/ \mathrm{sec}$, where each frame consists of 200 speech samples. A total of 64 bits are allocated to the 14 parcor parameters, which are quantized as described in [Markel and Gray, 1974] Pitch period and the voiced/unvoiced decision are encoded together in 6 bits, and the amplitude is coded into 5 bits.

SEGMENT-CODER
Classically, information concerning the vocal tract shape is transmitted in the form of parcor parameters once per analysis frame. Speech, however, can be segmented into events, for the duration of which, vocal tract shape may be considered approximately constant. Cases where this is not true, such as glides and diphthongs, may be approximated by a series of shorter segments. Therefore, it should be passible, without significant degradation in synthetic speech quality, to transmit parcor parameters once per segment, rather than once per trame. Since segment duration is relatively long compared with analysis trame length, a savings in the number of bits needed to encode the analysis parameters should resuft. A vocoder simulation based on this hypothesis was developed.

Segmentation is preformed using algorithms developed for the Hearsay speech recognition system[Goldberg and Reddy, 1976) Three stages are involved in the overali process: daramelrization, segmentation, and classification. The first step in parametrization is to generate smoothed and differenced wavetorms trom the sampled speech. Next, peak to peak amplitudes and zero crossing counts are extracted from each waveform once per centisecond of speech. Segmentation is based on these parameters.

Segment boundarias are determined by successive subdivision of the waveform. First, silences and unvoiced fricatives are detected by a throsholding technique. Next, the remaining segments are divided where significant dips in the smoothed peak to peak parameter occur. A region growing techniaue is then applied to further subdivide the segments. Finally, the resulting segments may opionally be classified in terms of manner of articulation. Decision rules based on the averaged parameter values for each segment are used for this purpose.

Operation of the vocoder is reiatively straightforward. Speech is segmented as it enters the system. When a segment boundary occurs, parcor parameters for that segment are calculated. By definition, all trames within a segment shou!d have similar spectral properties, however


Figure 1. Spectral mismatch resulting from interpolation of parcor coefficients at segment boundaries.
this is not always the case. Near segment boundaries, the vocal tract is changing, and cannot be assumed to have constant resonances. To eliminate possible errors due to these changes, the parcor coefficients are computed at the segment midpoint. Once calculated, these coefficients, along with the segment duration, are transmitted. Pitch and amplitude are then extracted from each frame in the segment, encoded, and transmitted. Thus, with this scheme, pitch and amplitude are still transmitted at the constant rate of once per frame, but parcor coefficients are transmitted at the rate of once per segment, which is not necessarily constant.

Except at its boundaries, the same set of parcor coefficients is used to synthesize speech for each frame within a segment. Near boundaries variation in the parcor coefficients due to vocial tract changes must be taken into account. Good results have been obtained using simple linear interpolation. For most segments it is adequate to interpolate over 5 centiseconds, from 2 centiseconds before the segment boundary, to 2 centiseconds after. For shorter sogments, indicating rapid changes in the spectral structure, interpolation is done from the segment midpoint.

The effects of parcor coefficient interpolation are illustrated in Figure 1. This figure shows the spectral onvolopes for a transition from one segment to the next. The darker curve represents the conventional synthatic speech, the lighter represents the speech synthesized from interpolated parcor cocfficients. Note that although the peak amplitude and shape differ slightly, the peak locations are nearly identical.

Figure 3 shows a digital spectrogram for the utterance "The area I'm intercsted in is understanding," synthesized with the Segment-coder. For comparison purposes, a digital spectrogran of the utterance synthesized with conventional methods is shown in Figure 2. As can be seen, the spectrograns resenble each other closely. in informal listening tests, the synthetic speech generated with parcor parameters transmitted only once per segment was nearly indistinguishable from that generated with parcor parameters transmitled every frame.

The degree of improvement in coding efficiency will vary from systen to system, depending on frame rate, and the precision to which each of the paramelers are encoded. For the system described earlier, a total of $(6+5+64) \times 100-7500$ bits $/ \mathrm{sec}$ are required to encode the analysis parameters. Using segmentation, pitch period and amplitude information are still transmitted for each frame,
but parcor coefficients are transmitted only once per segment. Another parameter, the segment duration, must also be transmitted with each segment. Allocation of 4 bits for this parameter allows for segment lengths up to 16 centiseconds. Segments exceeding this length are rarely encountered, and can easily be split into multiple segments. On average, the segmentation algorithm produces 15 segments per second of speech. Thus, the total bit rate needed for this scheme is $(6+5) \times 100+(4+64) \times 15=2120$ $\mathrm{bits} / \mathrm{sec}$. This represents improvement by a factor of about 3.5 over the conventional method.

Reductions of this order have been obtained in conventional vocoders by using reduced frame rate. Rather than transmitting one frame per centisecond, these vocoders might transmit one frame every 3 centiseconds, indiscriminately ignoring data between trames. This has a smoothing effect which results in the loss of short events that may be perceptualiy significant. Thus, the overalt quality of the synthetic speech should be lower than that oistained with the segmentation scheme.

LABEL-CODER
A second technique makes use of an assumption that all speech, regardless of its complexity, can be torned by combinations of a small number of basic sounds. The VORTRAX speech synthesizer is an example of one such system based on this assumption. Associated with each sound is unique formation of the vocal tract, and associated with each vocal tract formation is a set of parcor coefficients. If speech at each analysis frame can be identified and classified as one of these sounds, then it would only be necessary 10 transmit a label identifying the sound, rather that the entire set of parcor parameters. Since the number of sounds is small, significantly fewer that 64 bits are needed to encode the label, and an improvement in coding efficiency would result.

Prior to the development of vocoder simulation, the properties of each sound must be determined and represented in a format usable by the system. A procedure to accomplish this was developed for use with the Harpy system[Lowerre, 1976]. Segments from soveral utterances, spoken by a particular speaker, are identitied and grouped according to their sound class. Autocorrelation coefticients for each segment are computed and averaged over all segments in the same class. For each averaged autocorrelation sequence, hereafter reterred to as a template, linear prediction coefficients, parcor cosfficients,


Figure 2. Digital spectrogram of synthetic speech for the utterance "The area I'm interested in is understanding," generated using conventional signal encoding techniques.


Figure 3. Spactrogram of the synthetic speech generated by the Segment-coder.


Figure 4. Spectrogram of the synthetic speech generated by the Label-coder.


Figure 5. Spectrogram of the synthetic speech generated by the Segment-label-coder.


Figure 6. Spectral mismatch resulting from replacing parcor coefficients by a single phone label.
and b-coefficients[Itakura, 1975] are compuled. This information is made available to both the transmitter and receiver portions of the vocoder.

The task of the vocoder, then, is to determine, for each analysis frame, which template best matches the speech signal. The LPC matching technique developed by Itakura[ltakura, 1975] has been used for this purpose. A distance metric is applied between each frame and all templates. The best template, in terms of minimum distance, is selected. A label identifying this tempiate, along with pitch and amplitude information is transmitted. At the receiver, a simple table lookup, using the label as an index, is preformed to determine the parcor parameters of each frame. From this point on, synthesis proceeds normally.

Figure 6 shows the spectral mismatch between original spectra and the labels assigned to them. The darker curve corresponds to the original speech, the lighter to speech synthesized with the labeling method. The curves illustrate typical spectral errors that occur with the labeling method.

Displayed in Figure 4 is a digital spectrogram of the test utterance, synthesized with the Label-coder. This may be compared with the spectrogram of the conventional synthetic speech in Figure 2. Although the synthetic speech was intelligible, there was considerable distortion. We believe that this can be eliminated by changes in the template generation and matching algorithms.

Again, the bandwidth reduction afforded by this technique depends on how accurately the parameters are quantized, but in this case it is independent of frame rate. As before, we base our comparison on the system described earlier. For this system a total of $6+5+64=75$ bits/frame are needed to encode the speech. For the system with labeling, a label, along with the encoded pitch and amplitude, is transmitted for each frame. To uniquely identify each of the 96 templates used in this simulation, 7 bits were allocated for the label. Thus, with labeling, only $6+5+7=18$ bits are needed to encode each frame. This represents a bandwidth reduction by a factor of 4 .

## SEGMENT-LABEL-CODER

Clearly, if only one set of parcor coefficients is necessary to encode the spectral structure of each segment, and if each spectral structure can be identified by a label, then it should be possible to transmit only one label per segment. Examination of the analysis parameters trom the labeling system reveals that this is indeed the case. Most
frames within a segment werc found to be labeled with the same label. Those that were not, were labeled with an acoustically similar label. Once again, a vocoder simulation to test the hypothesis was developed.

The separate use of segmentation and labeling has already been discussed. This system is merely a combination of the two previous ones. After segmentation, the labeling algorithm is applied at the midpoint of each segment. The label which best characterizes the spectral properties of that segment, and the segment duration are encoded for transmission. Of course, pitch and amplitude information are still transmitted for every frame. Received labels are first used deternine the parcor parameters associated with each segment, which in turn are used to synthesize speech for ail frames within that segment. Interpolation at segment boundaries is carried out as previously described

The spectrogram for speech synthesized by this system is shown in Figure 5. Note its similarity to the spectrogram for speech synthesized by the labeling system. This is to be expected, since it was aiready determined that segmentation causes no significant degradation. The differences between this and the other spectrograms are due to degradation introduced by labeling.

Again, we calculate coding efficiency by comparison with the conventional system. With this encoding scheme, a total of 6 bits for pitch, and 5 bits for amplitude are transmitted every frame. An additional 4 bits for segment duration, and 7 bits to identify the template are transmitted for each segment. Using a frame rate of 100 frames $/ \mathrm{sec}$, and an average of 15 segments per second of speech, a data rate of $(6+5) \times 100+(4+7) \times 15=1265$ bits/second is obtained. This is approximately 5.9 times smaller than the 7500 bits $/ \mathrm{sec}$ of the conventional system.

## DISCUSSION

We have shown that segmentation and labeling can be used as a means of reducing bandwidth in speech analysissynthesis systems. Since the primary application of such systems is secure voice communications, it is appropriate to mention some of the practical aspects of a vocoder based on these techniques.

A problem arises when the vocoder is converted to real-time operation. Since analysis parameters for each segment are not transm+tted until the entire segment has been spoken, it is cossibie for the synthesizer to complete synthesis of one segment before it receives parameters for
the next. If this happens, a pause in the synthesizer output will occur. To avoid these pauses it is necessary define a maximum segment duration, and delay the synthesis by this amount. We have already indicated that 16 centiseconds is a reasonable thoice for maximum segment duration. If the synthesizer lags the transmitter by this amount, plus an additional 2 centiseconds to allow for interpolation, continuous synthetic speeth can be guaranteed. In practice, this is not a serious drawback. Delays of this magnitude are secondary in nature to those normally encountered in satellite based transmission systems.

From the discussion of labeling it should be clear that both transmitter and receiver must access to the same set of tempiates. Since the templates vary from speaker to speaker, it is impractical to make them a permanent part of the system. Rather, at the beginning of a conversation, templates for each speaker could be loaded into the corresponding transmitter and transmitted to the connecting receiver. Another possibility would be to use a single set of templates which has been averaged over many speakers. However, lower quality synthesis can be expected with this method.

In addition to the obvious reduction in bit rate, there are other advantages to the use of these techniques. At first, the additional processing needed to segment and classify speech would seem to result in slower vocoder operation, however this is not the case. Once the segments are known, the time consuming autocorrctation analysis need be preformed only once per segment. Thus, overall vocoder operation is actually faster. Furthermore, since gross segment classifications are obtained during the segmentation process, specialized processing, depending on the segment class can be preformed. For example, silences can be dismissed with no processing, and low coefficient LPC analysis can be preformed for fricatives. This should result in a more accurate synthesis.

The main point should be clear: through the use of specialized knowledge of the nature of speech, and higher level signal-to-symbol transformation techniques, incrementally better vocoders can be oblained. We have demonstrated two steps in this progression. The first was the transition from systems based solely on spectral analysis, to a system that combined knowledge of segments with spectral analysis. The next step was the use of labeling in addition to segmentation to give even further bandwidth reduction. As speech recognition systems evolve, better and better encodings will become practical. Eventually, it should be possible to transmit syllable sized units.

Finally, improvement in coding efficiency is obtained at the expense of generality. As more specialized knowledge of speech and language is used, the variely of sounds that can be transmitted is reduced. At the lowest level is the system that transmits sampled speech directly. With this system, arbitrary sounds can be represented accurately. The step to conventional vocoders limits those sounds which can be transmitted to speech. Greater restrictions occur as the vocoder becomes more and more language oriented.

## CONCLUSIONS

We have presented two techniques, based on algorithms developed for the Hearsay and Harpy speech recognition systems, which use knowledge about speech phenomena, to yield reductions in vocoder bandwidth. While the degree of improvemant varies from system to system,
typical reduction factors ranging from 3 to 4 can be expected from each method. Furthermore, improvements by a factor of 5 or more can be realized if the tectiniques are combined.

Use of segmentation caused no noticeable degradation in the synthetic speech quality. With labeling, considerable degradation occured, however it is felt that this can be eliminated with better templates.

Some of the practical aspects of vocoder implementation based on these techniques, along with the advantages and disadvantages to the use of speciaiized knowledge, were discussed. On the basis of arguments presented then, we believe that speech analysis-synthesis using segmentation and labeling is worthy of further research.

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# A HAlTING CONDITION AND RELATED PRUNING HEURISTIC FOR COMBINATORIAL SEARCH 

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#### Abstract

Many combinatorlal search problems can be viewed within the "Chinese restaurant menu selection paradlgm" of "choose one from Column $A$, one from Column $B$, ...." A solution to such a problem consists of a set of selections which are mutually consistent according to some set of constraints. The overall value of a solution is a composite function of the value of each individual selection. The goal of the search is to find the best (highest-rated) solution. Examples of such search problems occur in the domains of speech understanding, vision, and medical diagnosis.


This paper describes a search-pruning heurlstic and halting condition which are conservative in that they will not miss the best solution by pruning tiout of the search or by terminating the search before it is found. The method explolts information about alreadyfound solutions in order to prune the search and decide when to terminate it. An implementation of the halting condition and pruning heuristic within the Hearsay-ll speech understanding system is described and evaluated, and the conditions governing its applicabllity and performance are discussed.

## INTRODUCTION: SOME EXAMPLES

A frequently-occurring problem in Al involves finding the best combination of choices for a set of interdependent multiple-choice decisions. The possible combinations form a combinatorial search space. Each decision corresponds to a data element which can be labelled (explained, interpreted) In several alternatlve ways, some of which may be preferable to (more approprlate than) others. Legal solutions (combinations of labels) must satisfy certain domalnspecific consistency constraints governing the interdependencles between the varlous elements to be labelled.

One example of combinatorial search occurs in the domain of speech understanding. A spoken utterance can be viewed as a set of contlguous pofnts in time. The combinatorial search task of a speech understanding system is to label each time interval with the word apparently spoken during that interval. Several labels may appear plausible due to the uncertalnty of the speech signal and the word recognition process [7]. A solution consists of a transcription of the utterance, i.e., a sequence of word labels, which is syntactically and semantlcally consistent. The credibility (probability of correctness) of such a solution depends on the overall goodness of fit between the labels and their time intervals.

Another example comes from the domain of vision. The contour detection

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problem can be described as follows: glven a scene represented by an array of pixel gray levels, label each pixel with a vector corresponding to the apparent intensity gradient at that point in the image [9]. A consistent interpretation of the scene assigns parallel gradients to contiguous plxels on a contour and null gradients to plxels in the interior of a region. The accuracy of an Interpretation depends on the overall degree to which the labels match the visual data they attempt to describe.

A third example can be found in the domaln of medical diagnosis. Here the data elements to be explained are the pattent's symptoms. A diagnosis provides consistent explanations for all the symptoms. The plausibllity of a dagnosis depends on the overall plausibility with which the individual symptoms are accounted for [1].

## PROPERTIES OF COMBINATORIAL SEARCH

Let us now examine these search problems in order to discover common propertles which can be exploited in designing halting conditions and pruning heuristics. in each example, the set of data elements (points in time, pixels, symptoms) to be explained or labelled is known at the beginning of the search. (Actually, this assumption does not hold ror systems like MYCIN which collect data during the course of the search. However, as we shall see, it is sufficient for the set of elements to be determined anytime before the first solution is found.)

A partial solution consists of consistent explanations for a subset of the elements. Combinatorial search algorithms typlcally extend and combine such partial solutions. In fact, each step in the search can be characterized as examining a collection of partial solutions $I_{1}, \ldots, I_{k}$, and then possibly creating a new partial solution $I$. We can use rating information about partial solutions in order to decide when to halt the search once some solution has been found. For example, suppose we examine the ratings of all existing partial soluttons and conclude that none of them can be extended into a complete solution rated higher than the best one found so far. Under this condition, it is safe to halt the search; the best solution found is the best one possible. This condition is the destred conservative halting condition.

A simllar technique can be used to prune the search. If a partial solution cannot possibly be extrapolated into a complete solution superior to the best existing one, it can be rejected -- i.e., all efforts to extend it or comblne it with other partial solutions can safely be abandoned. This pruning heuristic is conservative but also rather weak. A more powerful heuristic depends on certaln propertles of the function used for rating solutions. Let us consider this function in more detall.

## THE RATING FUNCTION

A complete solution consistently explains all the elements ${ }^{1}$ and is rated according to how well each element is explained. i.e., If the rating function $R(I, S)$ measures how well the interpretation 1 explains the elements of the set $S$, then $R(1, S)=f(R(1, e) \mid e$ in $S\}$, where $R(I, e)$ measures how well 1 explains the element e. $R(I, S)$ is assumed to be an increasing function of the terms $R(I, e)$. The interpretation is a set of labels for the elements of s, l.e., for alle in $S$ l:e $\rightarrow l_{1}(e)$. The rating $R(l, e)$ may be context-sensitive, f.e, depend on how other elements besides $e$ are labelled (e.g., its neighbors, if $e$ is a plxel). A considerable

[^7]simplification is possible if $R(i, e)$ is context-free, l.e., $R\left(l_{1} e\right)=R\left(I_{1}(e), e\right)$, where $l_{l}(e)$ is the label assigned by 1 to $e$, and $R(1, e)$ measures the goodness of fit between the label 1 and the element e. In this case, $R(I, S)=f\left\{R\left(l_{1}(e), e\right) \mid e \operatorname{in} S\right\}$. If. $f$ is a simple averaging function, then $R(I, S)=$ Average $\left\{R\left(l_{I}(e), e\right) \mid e\right.$ in $\left.S\right\}$.

The best solution I maximizes $R(I, S)$ subject to the consistency constraints. Note that the function $R$ may produce higher values if applled to inconsistent interpretations (non-solutions). For example, the interpretation imaxie -> Imax(e), where imax (e) is the highest-rated label for $e$, will in general maximize $R(I, S)$ but is not in general consistent.

## A HALTING CONDITION AND PRUNING HEURISTIC

We can now prectsely define our halting condition and pruning heuristic in terms of the rating function $R$. Let $S^{\prime}$ be a subset of the element set $S$, and let $I^{\prime}$ be a partial solution which explains $\mathrm{S}^{\prime}$. Let I be the highest-rated solution found so far during the search.

I' can be extended into a complete (not necessarily consistent!) interpretation $I^{\prime \prime}$ by assigning $\operatorname{lmax}(e)$ to every $e$ in $S-S^{\prime}$. $\mathrm{I}^{\prime \prime}$ is the highest-rated possible complete extrapolation of $I^{\prime}$. Thus if $R\left(I^{\prime \prime}, S\right) \leq R(1, S)$, $I^{\prime}$ cannot be extended Into a solution better than $I$, and it is safe to reject $l^{\prime}$ and all its potential extensions. Unfortunately, this condition is too strong and is not often satisfled. A more powerful (but still conservative) pruning heuristic is made possible by assuming that $R$ is context-free in the sense defined earlier.

## a more powerful pruning heuristic

Suppose that $R$ is context-free and that a solution I has been found. If a better solution is possible, there must exist a partial solution $I^{\prime}$ which is locally superior to 1 . I' is locally supertor to $I$ over domaln $S^{\prime}$ if $R\left(I^{\prime}, S^{\prime}\right)>R\left(I, S^{\prime}\right)$. Intultively, $I^{\prime}$ explalns some subset $\mathbf{S}^{\prime}$ better than 1 does. If no such $I^{\prime}$ exists, then 1 is the best solution, and it is safe to halt the search.

This reasoning requires some justification. We consider all individual element labels to be one-element partial solutions, and assume that they are avallable to the search aigorlthm as such. If some potential complete solution l" is better than l, then there must exist at least one element $e \ln S$ such that $R\left(I^{\prime \prime}, e\right)=R\left(I_{I^{\prime \prime}}(e), e\right)>R\left(I_{1}(e), e\right)=R(I, e)$. (Otherwise $R\left(I^{\prime \prime}, S\right) \leq R(I, S)$.) This one-element partial solution can be extended step by step into $I^{\prime \prime}$ so that the partial solution I' at each step is locally superior to $I$. We assume that such a sequence of partial solutions can be found by the search algorithm. This is a strong assumption. Many sequences of partlal solutions may lead by stepwlse extension and comblnation to the same solution, but not all will malntaln local superiority at each step, and not all may be realizable by the search algorthm being used.

With this caveat, we now observe a happy property of context-free rating functions: once a solution has been found, only partlal solutions which are locally superior to it need be considered. All others may be deactivated, i.e., ignored except for combination with active partial solutions.

We can now express a powerful conservative pruning condition: A proposed search operation based on partial solutions $I_{1}, \ldots, I_{k}$ may safely be cancelled if
(1) Any of the $I_{1}$ has been rejected, or
(2) All of the $I_{1}$ have been deactivated.

The halting condition is trivial: halt when all pending search operations have been cancelled.

## UNDERLYING ASSUMPTIONS

Let us now re-examine some of the assumptions on which this method is based, and the motivations for making them.
(1) The rating function is context-free. Otherwise the local superiority criterion is not valid.
(2) The labels lmax(e) are known at the beglnning of the search, and exist as one-point partal solutions. Otherwise correct but low-rated partial solutions might be erroneously rejected. Actually, in order to avold erroneous rejection, it is only necessary to know an upper bound function $R \max (e) \geq R(l, e)$ for alle $\ln S$. The lighter this upper bound, the more partlal solutions can be rejected. The Rmax function used by the HWIM speech understanding system is defined by the score of the best phonetic label for each segment [8]. Since this score is based on the best posslble word match for each segment rather than on the best actual word match, it provides a poor (over-optimistic) upper bound on the actual word ratings, and produces mediocre results. The Rmax function used in Hearsay-II is defined by the score of the highest-rated hypothesized word at each point in the utterance, and produces good results.
(3) If a potentlal solution $l^{\prime \prime}$ is better than an existing solution I , the search algorithm must be capable of building $\mathrm{l}^{\prime \prime}$ in such a way that each partlal solution $\mathrm{I}^{\prime}$ in the derivation sequence $1 s$ locally superior to $I$. Otherwlse the derlvation of $I^{\prime \prime}$ might require operating on a set of deactlvated partial solutions and be blocked by the deactivation pruning heurlstic.

## EXAMPLE FROM HEARSAY-II

The Hearsay-Il speech understanding system [2] segments a spoken utterance into syllable-length time intervals. These are the elements. The labels for each element are taken from a 1,000 -word vocabulary. A complete solution is a grammatical transcription spanning the utterance. A partial solution is a grammatical phrase spanning part of the utterance. The rating function is a slmple average of label fit goodness. A (partial) solution I covers a time Interval [first!syl:last!syl]. Its rating is its average word rating welghted by the number of syllables in each word. L.e., $R(I,[f i r s t ' s y l: l a s t!s y l])=$ Average $\left\{R\left(W_{l}(\right.\right.$ syl $\left.\left.\left.) \mid A(s y l)\right)\right)\right\}$, where first!syl $\leq$ syl $\leq$ last!syl, $A(s y l)$ represents the acoustic data in the interval syl, $W_{I}(s y l)$ is the word label assigned by $I$ to syl, and $R(W \mid A)$ measures how closely the word $W$ matches the acoustic data $A . R(W \mid A)$ is computed by the word verifier [6].

In Hearsay-1I, partlal solutions are explicitly represented as hypotheses on a global data structure called a blachboard. Search operations are proposed by varlous knowledge sources which monltor the data on the blackboard. The operations relevant to the discussion at hand are [5]
(1) Recognition: given a sequence of words, parse it and record it as a partial solution if it is grammatical.
(2) Prediction: given a recognized phrase, propose words which can grammatically precede or follow it. Predtctions which are rated above a specifled threshold by the word-verlfier are recorded on the blackboard as one-word hypotheses. Thus prediction
dynamically assigns extra labels to elements, and could potentlally violate our earller assumption that Rmax (e) is known before the rejection pruning heurlstic is applied. This is not a problem in practice, however, since most label assignment (word recognition) is done at the beginning of the search or before the first complete solution is found, and predicted words are seldom rated higher than the best previously-recognized words.
(3) Concatenation: glven two temporally adjacent phrases (or a phrase and a word predicted next to it and subsequently verlfied), concatenate them and record the result as a partial solution if it is grammatical.

These search operations are performed in order of thelr prloritles, which are assigned by a central focus-of-attention module [3]. The focus module tries to order the search in a best-first manner, and succeeds about $50 \%$ of the tlme on the corpus tested for this paper. This figure seems to increase as the constraints on grammatical consistency are Increased, i.e., as the branching factor of the language is reduced. For a best-first search, the best halting pollcy is to terminate the search as soon as a solution is found. Note that the rejection and deactivation pruning heuristics are inapplicable if this policy is used, since these heuristics do not become applicable untll some solution is found.

## EVALUATION

The deactivation and rejection heuristics were evaluated on a corpus of 34 utterances drawn from a 262 -word vocabulary. Utterance length ranges from 3 to 9 words, with an average of 6 . The fanout (number of grammatical word successors in each word position) averages 27 for the corpus.

Each utterance was processed in 5 modes. Mode $N$ uses nether heuristic; mode $R$ uses rejection; mode D uses deactlvation; and mode B uses both. In mode F, the system accepts the first solution it finds and immediately halts. The results of the experiment are shown in Table 1.

The simple accept-the-first-solution pollcy used in mode $F$ is fastest, but at a considerable cost in accuracy, since it falls for those runs (about $50 \%$ ) In which the highestrated solution is not the first one found. A more conservative policy finds these solutions at the cost of extra search in those runs where the best solution is found first. The correct choice of policy (simple versus conservative) depends on a tradeoff between effictency and accuracy. Since accuracy is very important in speech understanding, the conservative policy is preferred despite its extra cost.

The heuristics can be evaluated according to two criterta. First, how fast is the best solution found once the first solution is found? As Table 1 shows, deactivation is about twice as powerful as rejection in speeding up this phase of the search. The combination of heuristics is only slightly more effective than using deactivation alone.
Mode: $\quad \mathrm{N}$
R
D
B
F

Average number of search operations (Hearsay-li knowledge source and precondition executions) to find first solution: ${ }^{1}$
$153157 \quad 145 \quad 152 \quad 152$

Average number of (percent) extra search operations to find the best solution once the first solution has been found:

| 71 | 58 | 30 | 26 | 0 |
| :---: | :---: | :---: | :---: | :---: |
| $46 \%$ | $37 \%$ | $2.1 \%$ | $17 \%$ | $0 \%$ |
| In this phase of the search relative to mode $N:$ |  |  |  |  |


| 1 | 1.2 | 2.4 | 2.7 | Infinity |
| :--- | :--- | :--- | :--- | :--- |

Average total number of search operatlons to find best solution:

| 223 | 215 | 175 | 178 | 152 |
| :--- | :--- | :--- | :--- | :--- |

Average number of (percent) extra search operations to satisfy halting condition ${ }^{2}$ once the best solution has been found (excluding runs in which time or space is exhausted): ${ }^{3}$

| 241 | 153 | 89 | 52 | 0 |
| :--- | :--- | :--- | :--- | :--- |
| $108 \%$ | $71 \%$ | $51 \%$ | $29 \%$ | $0 \%$ |

Average total number of search operations untll halting condition is satisfied:

| 286 | 282 | 253 | 226 | 152 |
| :--- | :--- | :--- | :--- | :--- |

Number (percent) of utterances in which halting condition is satisfied before system exceeds predefined limits on time (800 search operations) or space (193K):

| 4 | 17 | 32 | 32 | 34 |
| :--- | :--- | :--- | :--- | :--- |
| $12 \%$ | $50 \%$ | $94 \%$ | $94 \%$ | $100 \%$ |

Table 1. Results of experimental evaluation of prining heuristics.

[^8]Second, how fast is the halting condition sattsfied once the best solution is found? An ideal pollcy would halt as soon as the best solution was found. The deviation of an actual policy from this ideal can be measured by its "halting overhead," i.e., the amount of extra search performed after the best solution is found. When neither heuristic is used, the halting condition is satisfied in only $12 \%$ of the runs (time or space bounds are exceeded in the others) and the halting overhead in those runs is $108 \%$. The rejection heuristic succeeds in satisfying the haliting condition in $50 \%$ of the runs, with an overhead of $71 \%$. Deactivation leads to halting in $94 \%$ of the runs, with $51 \%$ overhead. The combination of both heuristics also causes halting in $94 \%$ of the runs, but reduces overhead to only $29 \%$.

These results can be summarized as follows:
(1) Deactlvation is about twice as powerful as rejection in accelerating the search for the best solution once the first solution has been found. This difference in empirical performance substantiates the intuitive notion that the conditions for deactivating a partial solution are substantlally easler to satisfy than the conditions for rejecting it. The combined heuristlics speed up this phase of the search by a significant factor (2.7).
(2) The combined heurtstics succeed most ( $94 \%$ ) of the time in satisfylng the halting condition, at a reasonable cost $(29 \%)$ compared to the time it takes to find the best solution. The large variance in this cost and the fallure to satisfy the halting condition in the other $6 \%$ of the runs suggest that other techniques are needed to further streamline the search without ellminating the best solution.

## DISCUSSION OF APPLICABILITY

What propertles of Hearsay-II make this method applicable?
(1) Most of the word labelling is performed before the first solution is found and the heuristics are applied. Seldom is a new word subsequently hypothesized with a rating higher than all the other words in its time interval. Thus the necessary information (the Rmax function) is determined before the heuristics are applied. Exceptions do not automatically cause erroneous rejection, since the Rmax function generally provides a safety margin by overestimating the rating of the best possible solution.
(2) A solution must account for the whole time Interval of the utterance, i.e., for every element (syllable). This facilitates the comparison of extrapolated potentlal solutions with already-found solutions.
(3) The rating function for evaluating solutions is context-free. This facllitates the local comparison of partial solutions with complete solutions.

The context-free property is somewhat counter-intultive since the consistency criteria are in general context-sensitive, l.e., the admissibility of a label depends on the labels assigned to other elements. The rating function might be expected to rate solutions (consistent interpretations) higher than inconsistent explanations, but a context-free rating function does not have thls intultively satisfying tratt. Our approach separates two propertles of a solution:
(1) satisfaction of consistency constraints.
(2) goodness of fit between labels and data.

Consistency is considered to be an all-or-none property and is guaranteed by the form of the search. Relative goodness of fit is assumed to be local, rather than context-sensitive. When this assumption approximates the truth, it becomes possible to apply the powerful deactivation heuristic.

## CONCLUSIONS

Conservative pruning heuristics for comblnatorial search have been presented. They operate by ellminating branches of the search which cannot lead to solutions better than those found already. In this respect, they can be thought of as alpha-beta pruning heurlstics in a one-player game. The pruning heuristics and associated halting condition have been implemented in Hearsay-ll and shown to be effective in the realworld problem domain of speech understanding.

When the object of a search is to find the best solution (not Just any solution), there is an important tradeoff between speed and accuracy. The simplest halting policy accepts the first solution found. This policy is correct if the search is always best-first; the closer the search is to best-first, the more attractive such a simple pollcy becomes. More sophisticated policies increase accuracy at the expense of prolonging the search so as to guarantee that the best solution is not missed.

In a nearly-best-first search, the discovery of a solution changes the purpose of the search from one of finding the best possible solution to one verifying that there is no better solution than the one found. This change of purpose should be reflected in the searchguiding pollcles.

The approach described exploits certaln assumptions about the search.
(1) The search space can be represented by a set of elements (data) each of which can be labelled in several ways. A solution labels all the elements and satisfies specified conslstency constralnts.
(2) A rating function evaluates how well a given label fits a given element. An upper bound on the best label rating for each element should be determined by the time the first solution is found. The tighter the bound, the better the performance of the pruning heuristics.
(3) The rating of a solution should be a function of the ratings of its individual labels. It should be possible to compute an upper bound on the rating of the best possible extrapolation of a given partial solution. The tighter the bound, the better the performance.
(4) The better the found solution relatlve to the best (generally inconsistent) Interpretation Imax (which assigns each element its highest-ranked label), the more pruning can be done. The stronger the conslstency constralnts, the lower a solution will tend to be rated compared to Imax, and the worse the performance.

Many search problems (e.g., speech and tmage understanding, medical diagnosis) appear to fit the paradigm of "choose one from Column $A$, one from Column $B_{1}$ " i.e., given alternative cholces for a set of declsion points, find the best-rated consistent set of cholces. When efficlent best-first search algorlthms are infeasible, some mechanism is needed for deciding when to halt the search and accept the best solution found so far. Such a mechantsm should terminate the search as soon as possible without lgnoring better solutions. This paper has shown how such a mechanism can explolt information about already-found solutions to accelerate the search conservatively, i.e., without ignoring better solutions.

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Er76He Erman, L. D., Hayes-Roth, F., Lesser, V. R. and Reddy, D. R. The Hearsay-II speech understanding system. 92nd Meeting Acous. Soc. Amer., San Diego, CA, Nov., 1976. For abstract see JASA, Vol 60, Suppl. No. 1, S11.

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Gi76Pa Gill, G. and Reddy, D. R. Parametric representation of speech. 92nd Meeting Acous. Soc. Amer., San Diego, CA, Nov., 1976. For abstract see JASA, Vol 60, Suppl. No. 1, S11.
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Ha76Fo Hayes-Roth, F. and Lesser, V. R. Focus of attention in a distributed-logic speech understanding system. Proc. 1976 IEEE Inter. Conf. on ASSP, Philadelphia, PA, Apr., 1976, 416-420. Also appeared in CM76W4. See . Ha77Fo for a more up-to-date description.
Ha 76 Hy Hayes-Roth, F., Erman, L. D. and Lesser, V. R. Hypothesis validity ratings in the Hearsay-11 speech understanding system. In CM76W4.
Ha 760 r Hayes-Roth, F. and Mostow, D. J. Organization and control of syntactic, semantic, inferential, and world knowledge for language understanding. Proc. 1976 Inter. Conf. on Comp. Linguistics, Ottawa, Canada, 1976.
Ha76Sy Hayes-Roth, F. and Mostow, D. J. Syntax and semantics in a distributed speech understanding system. Proc. 1976 IEEE Inter. Conf. on ASSP, Philadelphia, PA, Apr., 1976, 421-424. Also appeared in CM76W4.
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Lo76Pe Lowerre, B. T. and Reddy, D. R. The Harpy speech recognition system: performance with large vocabularies. 92nd Meeting Acous. Soc. Amer., San Diego, CA, Nov., 1976. For abstract see JASA, Vol 60, Suppl. No. 1, S10.
Lo76Th Lowerre, B. T. The Harpy speech recognition system. Tech. Report, CMUCSD, 1976. Ph.D. Dissertation.

Re76Sp Reddy, D. R. Speech recognition by machine: A review. Proc. of the IEEE 64 (Apr. 1976) 501-531. Invited paper.
Sh76Ph Shockey, L. and Adam, C. The phonelic component of the Hearsay-II speech understanding system. In CM76W4.
Sm76Wo Smith, A. R. Word hypothesization in the Hearsay-II speech system. Proc. 1976 IEEE Inter. Conf. on ASSP, Philadelphia, PA, Apr., 1976, 549-552. Also. appeared in CM76W4.
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Gi75Se Goldberg, H. G. Segmentation and labeling of speech: a comparative performance evaluation. Tech. Report, CMUCSD, Dec., 1975. Ph.D. Dissertation.
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Re74Co Reddy, D. R. Computer as a research tool in speech understanding research. Fed. of Am. Soc. for Exp. Biology 33 (Dec. 1974) 2347-2351.

Re74Kn Reddy, D. R. and Newell, A. Knowledge and its representation in a speech understanding system. In Knowledge and Cognition. (Gregg, L. W., Ed.) Lawrence Erlbaum, Washington, D.C., 1974.
Ri74In Rich, E. Inference and use of simple predictive grammars. Proc. 1974 IEEE Symp. Speech Recognition, Pittsburgh, PA, Apr., 1974, 242. Also appeared in Er74Co and CM74W3.
Sh74Qu Shockey, L. and Reddy, D. R. Quantitative analyses of speech perception: results from transcription of connected speech from unfamiliar laguages. Speech Communication Seminar, Storkholm, Sweden, Aug.; 1974.
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Sh74Tr Shockey, L. and Reddy, D. R. Transcription of unfamiliar language material. 87th Meeting Acous. Soc. Amer., New York, NY, Apr., 1974. For abstract see JASA, Vol. 55, Suppl. 1, S88.

Bk73Ma Baker, J. K. Machine-aided labeling of connected speech. In CM73W2.
Bm73Ne Baker, J. M. A new time-domain analysis of human speech. In CM73W2.
Br73Ja Brooks, R., Erman, L. D. and Neely, R. Jabberwocky: a semi-automated system for the transcription of verbal protocols. Behavioral Research Methods and Instrumentation (May 1973).
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Er73Re Erman, L. D., Lowerre, B. T. and Reddy, D. R. Representation and use of acoustic-phonetic knowledge in the Hearsay-I system. 86th Meeting Acous. Soc. Amer., Los Angeles, CA, Nov., 1973, 49. (Abstract only)
Er73Rw Erman, L. D. and Reddy, D. R. Report of a workshop on machine segmentation and labeling of connected speech. 86th Meeting Acous. Soc. Amer., Los Angeles, CA, Nov., 1973, 51. (Abstract only)
Er73Sy Erman, L. D., Fennell, R. D., Lesser, V. R. and Reddy, D. R. System organizations for speech understanding: implications of network and multiprocessor computer architectures for Al. Proc. IJCAI-73, Stanford, CA, 1973, 194-199. Also appeared in CM73W2 and IEEE Trans. Computers, C-25, No. 4, April, 1976, 414-421. Early motivation for the Hearsay-II multi-process structure.
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Nw73Sp Newelt, A., Barnett, J., Forgie, J., Green, C., Klatt, D., Licklider, J. C. R., Munson, J., Reddy, R. and Woods, W. Speech Understanding Systems: Final Report of a Study Group. North-Holland, 1973. Originally appeared in 1971. This seminal work set the goals and orientation for the ARPA SUR effort.
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Re73He Reddy, D. R., Erman, L. D., Fennell, R. D., Lowerre, B. T. and Neely, R. B. The Hearsay speech understanding system. 86th Meeting Acous. Soc. Amer., Los Angeles, CA, Nov., 1973, 49. (Abstra t only)
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Re73Hx Reddy, D. R., Erman, L. D., Fennell, R. D. and Neely, R. B. The Hearsay(-I) speech understanding system: an example of the recognition process. Proc. IJCAI-73, Stanford, CA, 1973, 185-193. Also appeared in CM73W2 and IEEE Trans. Computers, C-25, No. 4, April 1976, 422-431.
Re73Mo Reddy, D. R., Erman, L. D. and Neely, R. B. A model and a system for machine recognition of speech. IEEE Trans. on Audio and Electroacoustics AU-21 (June 1973) 229-238. Also appeared in CM73W2. First report on Hearsay-1.

Re73Ph Reddy, D. R. Phonemic and morphemic variability in connected speech. 86th Meeting Acous. Soc. Amer., Los Angeles, CA, Nov., 1973. For abstract see JASA 55, 411.
Re73So Reddy, D. R. Some numerical problems in artificial intelligence: implications for complexity and machine architecture. In Complexity of Sequential and Parallel Numerical Algorithms. (Traub, J. F., Ed.) Academic Press, 1973.

CM72W1 CMU Computer Science Speech Group. Working papers in speech recognition. I. Tech. Report, CMUCSD, 1972. Includes Er71Im, NE71Sp, Re70Sp, Re70Cm, $\mathrm{Re} 71 \mathrm{Sp}, \mathrm{Re} 71 \mathrm{Sm}$ and Re72Me.
Re72Me Reddy, D. R., Erman, L. D. and Neely, R. B. A mechanistic model of speech perception. Proc. 1972 IEEE Conf. Speech Communication and Processing, Newton, MA, Apr., 1972, 334-337. Also appeared in CM72W1. (abstract only)
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Er71Im Erman, L. D. and Reddy, D. R. Implications of telephone input for automatic speech recognition. Proc. 7 th Inter. Congress on Acoustics, Vol. 3. Budapest, Hungary, 1971, 85-88. Also appeared in CM72W1. Experiments with the Vicens-Reddy system.
Ne71Sp Neely, R. B. and Reddy, D. R. Speech recognition in the presence of noise. Proc. 7th Inter. Congress on Acoustics, Vol. 3. Budapest, Hungary, 1971, 177180. Also appeared in CM72W1. Experiments with the Vicens-Reddy system.

Re $715 m$ Reddy, D. R., Bell, C. G. and Wulf, W. A. Speech recognition in a multiprocessor environment. Proc. 1971 IEEE Conf. on Automatic Control, Miami, Florida, 1971. Also appeared in CM72W1.

Re715p Reddy, D. R. Speech recognition: prospects for the seventies. Proc. IFIP 1971, Ljubljana, Yugoslavia, 1971, I.5-1.13. Also appeared in CM72W1. Invited paper.

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Re 70 Cm Reddy, D. R., Erman, L. D. and Neely, R. B. The CMU speech recognition project. Proc. 1970 IEEE System Sciences and Cybernetics Conf., Pittsburgh, PA, 1970. Also appeared in CM72W1.
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(The following earlier papers were done at Stanford and are included here for reference.)

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Re69Se Reddy, D. R. Segment-synchronization problem in speech recognition. J. Acous. Soc. Amer. 46 (July 1969) 89. (Abstract only)
Re69Us Reddy, D. R. On the use of environmental, syntactic, and probabilistic constraints in vision and speech. Tech. Report, Stanford University, AI Memo 78, Stanford, CA, 1969.
Vi69As Vicens, P. J. Aspects of speech recognition by computer. Tech. Report, Stanford University, AI Memo 85, Stanford, CA, 1969. Ph.D. Dissertation. The "Vicens-Reddy" system.
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Mc68Co McCarthy, J., Earnest, L., Reddy, D. R. and Vicens, P. J. A computer with hands, eyes and ears. Proc. FJCC, 1968, 329-337.
Re68Cn Reddy, D. R. Consonantal clusters and connected speech recognition. Proc. 6th Inter. Congress on Acoustics, Tokyo, Japan, 1968, 57-60.
Re68Co Reddy, D. R. On computer transcription of phonemic symbols. J. Acous. Soc. Amer. 44 (Feb. 1968) 638-639.
Re68Ph Reddy, D. R. and Robinson, A. E. Phoneme to grapheme translation of English. IEEE Trans. Audio and Electroacoustics 16 (Feb. 1968) 240-246.
Re68Pr Reddy, D. R. and Vicens, P. J. A procedure for segmentation of connected speech. J. Audio Engr. Soc. 16 (Apr. 1968) 404-412.
Vi68Pr Vicens, P. Preprocessing for speech analysis. Tech. Report, Stanford University, AI Memo 71, Stanford, CA, 1968.

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Re67Ph Reddy, D. R. Phoneme grouping for speech recognition. J. Acous. Soc. Amer. 41 (May 1967) 1295-1300.
Re67Pi Reddy, D. R. Pitch period determination of speech sounds. Comm. ACM 10 (June 1967) 343-348.
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Re66Ap Reddy, D. R. An approach to computer speech recognition by direct analysis of the speech wave. Tech. Report, Stanford University, AI Memo 43, Stanford, CA, 1966. Ph.D. Dissertation.
Re66Se Reddy, D. R. Segmentation of speech sounds. J. Acous. Soc. Amer. 40 (Aug. 1966) 307-312.
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Re64Ex Reddy, D. R. Experiments on automatic speech recognition by a digital computer. Tech. Report, Stanford University, AI Memo 26, Stanford, CA, 1964.

Abbreviations:
ASSP -- Acoustics, Speech and Signal Processing.
CMUCSD -- Department of Computer Science, Carnegie-Mellon University, Pittsburgh, PA, 15213. (412) 621-2600 x. 141.
IJCAI -- International Joint Conferences on Artificial Intelligence.
JASA -- Journal of the Acoustical Society of America.


[^0]:    ** Paper to appear in Carnegie-Mellon Comout:r Science Research Review, 1977.
    ** The actual specifications stated "a few limes reai-time" on a 100 MIPS instructions per second) machine.

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[^4]:    1 This work was supported by the Defense Advanced Researcin Projects Agency (F44620-73-C-0074) and is monitored by the Air Force Office of Scientific Research.
    2 Henceforth, all descriptions are uncerstood to apply to the September, 1976, system.

[^5]:    **Signal change is typically a paltern recognition match score.

[^6]:    This work was supported in part by the Defense Advanced Pesearch Projects Agency (F44620-73-C0074) and is monitored oy the Air Force Office of Scientific Research.

[^7]:    1 This condition could be relaxed by allowing complete solutions to label some elements "IGNORED." The rating function would then have to reflect the relative significance of explaining or ignoring a given element, so as to allow meaningful comparison between solutions accounting for different subsets of the element set.

[^8]:    1 Ideally these numbers should be equal, since the heuristics are not applied until the first solution is found. The variation in these figures is caused by some randomness in the Hearsay-II scheduler in choosing between equally promising search operations.

    2 The halting condition is satisfied when no more search operations are pending, or when all the pending operations are considered unpromising by the system.

    3 Speedup ratios between different modes are not meaningful here since the set of excluded utterances varies from mode to mode.

