

LINEARIZING GEOMETRIC PROGRAMS

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Abstract

A geometric program concerns minimizing a function subject to constraint functions, all functions being of posynomial form. In this paper the posynomial functions are condensed to monomial form by use of the inequality reducing a weighted arithmetic mean to a weighted geometric mean. The geometric mean is a monomial and by a logarithmic transformation it becomes a linear function. This observation shows that the condensed program is equivalent to a linear program. Moreover by suitable choice of the weights it is found that the minimum of the condensed program is the same as the minimum of the original programs. This fact together with the duality theorem of linear programming proves that the maximum of the dual geometric program is equal to the minimum of the primal geometric program. With this result as a basis a new approach to the duality properties of geometric programs is carried through. In particular it is shown that a ¹¹ duality gapⁿ cannot occur in geometric programming.

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LINEARIZING GEOMETRIC PROGRAMS

1. Introduction

It was shown by Federowicz that by a simple transformation of variables a linear program can be expressed as a geometric program [1, p.265]. In this paper a converse question is treated. It is shown that a geometric program can define an associated family of linear programs. This linearization can be of use both analytically and computationally.

The linearization is achieved by use of the inequality reducing an arithmetic mean to a geometric mean. This operation performed on the polynomial functions defining the geometric program condenses them to monomial functions. But by the Federowicz transformation a monomial geometric program is equivalent to a linear program.

Linearization is employed in this paper as a theoretical tool. It enables the duality theory of linear programming to prove part of the duality theory of geometric programming. In this way it is shown that if the minimization of a primal geometric program yields a finite value then maximization of the dual program is feasible and yields the same value. This result is termed Theorem 4a.

To obtain a complete duality theory it is necessary to show that, conversely, if the maximization of the dual program yields a finite value, then the minimization of the primal program is feasible and yields the same value. This is termed Theorem 4b. The proof of Theorem 4b is given by a reduction ^{ft} ad absurdum¹¹ making essential use of Theorem 4a.

The duality theorems proved here are essentially equivalent to those proved previously [1,2]. However, the old proof and this new proof shed light on different facets of the problem.

It will be apparent from Section 4 to follow that the condensation method used to linearize geometric programs suggests various computational applications. However, these questions will not be pursued.

The proofs to follow depend on elementary inequalities and the duality theorem of linear programming. Otherwise the paper is self contained.

2. Definition of posynomial geometric programs.

The primal geometric program is denoted by the letter A and is stated as follows.

Primal Program A. Seek the minimum value of a function $g_0(t)$ subject to the constraints

$$(1) \quad t_1 > 0, t_2 > 0, \dots, t_m > 0$$

and

$$(2) \quad g_1(t) \leq 1, g_2(t) \leq 1, \dots, g_p(t) \leq 1.$$

Here

$$(3) \quad g_k(t) = \sum_{i=m_k}^{n_k} c_i t_1^{a_{i1}} t_2^{a_{i2}} \dots t_m^{a_{im}}, \quad k = 0, 1, \dots, p$$

where $n_p = n$ and

$$m_0 = 1, \quad m_1 = n_0 + 1, \quad m_2 = n_1 + 1, \quad \dots, \quad m_p = n_{p-1} + 1.$$

The exponents a_{ij} are arbitrary real constants, but the coefficients c_i are positive constants.

The functions $g_k(t)$ are termed posynomials. If there is a point t which satisfies the constraints (1) and (2) then program A is said to be consistent. If A is consistent let

$$(4) \quad M_A = \inf g_0(t)$$

for points t which satisfy the constraints. Then M_A is termed the infimum of A. Program A is said to have a finite infimum if $M_A > 0$.

Associated with the preceding minimization program is a maximization program termed a dual geometric program. The dual program is denoted by the letter B and is stated as follows.

Dual program B. Seek the maximum value of a product function

$$(5) \quad v(\beta) = \sum_{i=1}^n c_i \beta_i \prod_{k=1}^p \lambda_k$$

where

$$(6) \quad A_{\beta} = \sum_{i=m_k}^{i=n_k} \beta_i$$

with $n_p = n$ and

$$r_{\lambda} = 1, \quad m_1 = n+1, \quad m_0 = n-i+1, \quad \dots, \quad m_p = n-p+1.$$

The factors c_i are assumed to be positive constants and the vector variable $\beta = (\beta_1, \dots, \beta_n)$ is subject to the linear constraints;

$$(7) \quad \beta_1 \geq 0, \quad \beta_2 \geq 0, \quad \dots, \quad \beta_n \geq 0, \quad (\text{positivity})$$

$$(8) \quad \sum_{i=1}^n \beta_i = 1, \quad (\text{normality})$$

and

$$(9) \quad \sum_{i=1}^n \beta_i a_{ij} = 0, \quad j = 1, 2, \dots, m. \quad (\text{orthogonality})$$

Here the coefficients a_{ij} are real constants.

In evaluating the product function $v(\beta)$ it is to be understood that $x^+ = x^- = 1$ for $x = 0$. This will make $v(\beta)$ continuous over its domain of definition. Program B is said to be consistent if there is a point β which satisfies the constraints (7), (8), and (9). If program B is consistent let

$$(10) \quad M_B = \sup v(\beta)$$

for points β which satisfy the constraints. Then M_B is termed the supremum of B. If $M_B < \infty$ then program B is said to have a finite supremum.

3. The geometric inequality.

The inequality stated in the following lemma is termed a geometric inequality.

Lemma 1. If $u_i > 0$ and $\delta_i \geq 0$ for $i = 1, \dots, N$ then

$$(1) \quad \left(\sum_{i=1}^N u_i \right)^\lambda \geq \pi \left(\frac{u_i}{\delta_i} \right)^{\delta_i} \lambda^\lambda$$

where

$$(2a) \quad \lambda = \sum_{i=1}^N \delta_i \quad \text{and}$$

$$(2b) \quad (u_i/\delta_i)^{\delta_i} = 1 \quad \text{if} \quad \delta_i = 0.$$

Moreover the inequality becomes an equality if, and only if,

$$(3) \quad \delta_j \sum_{i=1}^N u_i = u_j \sum_{i=1}^N \delta_i, \quad j = 1, 2, \dots, N.$$

Proof: We consider three exclusive cases: (a) all δ_i are positive, (b) some but not all δ_i are positive, and (c) all δ_i are zero.

In the case (a) let "weights" ϵ_i be defined as

$$(4) \quad \epsilon_i = \delta_i/\lambda \quad \text{and} \quad U_i = u_i/\delta_i.$$

Then the classical inequality stating that the weighted arithmetic mean of U_1, U_2, \dots, U_N is not less than the weighted geometric mean can be written as follows

$$(5) \quad \sum_{i=1}^N \epsilon_i U_i \geq \pi \prod_{i=1}^N U_i^{\epsilon_i}.$$

Substituting relations (4) into (5) is seen to prove inequality (1). Moreover for positive weights ϵ_i it is known that (5) is an equality if and only if

$$(6) \quad U_1 = U_2 = \dots = U_N.$$

Clearly this is equivalent to (3). This proves Lemma 1 in case (a).

In case (b) it is seen that if $\delta_j = 0$ then $(u_j/\delta_j)^{\delta_j} = 1$ so the right side of relation (1) does not depend on u_j . However the left side increases with u_j . This fact together with the proof of case (a) shows that (1) is a strict inequality in case (b). Moreover (3) is not satisfied for $i = j$. Thus relation (1) and (3) both hold in case (b)*

In case (c) it follows that (1) becomes the equality $1 = 1$ and (3) becomes $0 = 0$. This proves case (c). Since the three cases are exhaustive the proof of Lemma 1 is complete.

The following result is termed ^t the main lemma¹¹ of geometric programming. It is a consequence of repeated application of the geometric inequality of Lemma 1.

Theorem 1. If t satisfies the constraints of primal program A and δ satisfies the constraints of its dual program B then

$$(7) \quad g_0(t) \wedge g_-(t) \stackrel{P}{=} \text{Tr}[g_+(t)]^k \wedge v(\delta).$$

Moreover, under the same conditions $g^+(t) = v(\delta)$ if, and only if,

$$(8) \quad g_0(t)\delta_i = u_i(t) \quad i = 1, \dots, n_0 \quad \text{and}$$

$$(9) \quad \delta_{\pm} = A_k u_{\pm}(t) \quad i = m_k, \dots, n_k.$$

Here $k = 1, \dots, p$ and

$$(10) \quad u_i(t) = t_1^{a_{i1}} \dots t_m^{a_{im}}.$$

Proof. Then for $k = 0, 1, \dots, p$

$$(11) \quad g_k = \sum_{m_k}^{n_k} u_i$$

and by virtue of the geometric lemma

$$(12) \quad (g_k)^{\lambda_k} \geq \pi_{m_k}^{n_k} \left(\frac{u_i}{\delta_i}\right)^{\delta_i} \lambda_k^{\lambda_k} \quad k = 0, 1, \dots, p.$$

Here $\lambda_0 = 1$ and $m_0 = 1$. Multiplying these $p + 1$ inequalities together gives

$$g_0 \pi_1^p g_k^{\lambda_k} \geq \pi_1^n \left(\frac{u_i}{\delta_i}\right)^{\delta_i} \pi_1^p \lambda_k^{\lambda_k}.$$

Then by the definition of the dual function $v(\delta)$

$$(13) \quad g_0 \pi_1^p g_k^{\lambda_k} \geq v(\delta) t_1^{D_1} t_2^{D_2} \dots t_m^{D_m}$$

where

$$(14) \quad D_j = \sum_1^n \delta_i a_{ij} \quad j = 1, \dots, m.$$

Since δ_i satisfies the orthogonality condition it follows that

$D_j = 0$. Thus

$$(15) \quad g_0 \pi_1^p g_k^{\lambda_k} \geq v(\delta).$$

But t satisfies the constraints of A so

$$(16) \quad g_k \leq 1 \quad k = 1, \dots, p.$$

Thus (15) and (16) together prove inequality (1).

Now suppose that the condition (8) of Theorem 1 holds. Then

(12) is an equality for $k = 0$ because condition (8) of Theorem 1 is the same as condition (3) of Lemma 1 when $\lambda_0 = 1$.

If condition (9) of Theorem 1 holds and $A_k = 0$ then (12) is an equality because then condition (9) implies condition (3) of Lemma 1. If $A_k \neq 0$ then sum (9) and obtain

$$(17) \quad \sum_{m_k}^{n_k} \delta_i = \lambda_k \sum_{m_k}^{n_k} u_i$$

This shows that $g_k = 1$ and consequently (3) and (9) are equivalent.

Thus (12) is seen to be an equality also in the case $A_k \neq 0$.

Since (12) is an equality for $k = 0, 1, \dots, p$ it follows that (15) is an equality. However if $A_k = 0$ then $g_k = 1$ and if $A_k \neq 0$ we have seen that $g_k = 1$. Thus $g_k = 1$ for $k = 1, \dots, p$ and this together with the equality (15) give $g_0 = v$. This proves the second part of Theorem 1.

To prove the third part of Theorem 1 suppose that $g_0 = v$. Then (15) and (16) show that actually $g_k = 1$ for $k = 1, \dots, p$. Moreover all the inequalities (12) must be equalities. Then relation (3) of Lemma 1 holds and since $g_k = 1$ for $k = 1, \dots, p$ it follows that (3) implies (9). Since $A_0 = 1$ it follows that (3) implies (8). Thus it has been shown that if $g_0 = v$ then (8) and (9) hold and the proof of Theorem 1 is complete.

~~Corollary 1. Suppose that $S(v^*) < 1$ for some value of k and for some point t^* satisfying the primal constraints. Then the inequality~~

$$(18) \quad v(6) \leq c$$

for some positive constant c implies that

$$(19) \quad A_k \leq \log[g_0(t^*)c^{-1}] / \log[g_k(t^*)]^{-1}$$

for any θ satisfying the dual constraint and (18).

Proof It is a direct consequence of inequality (7) that

$$(20) \quad g_0(t^*) \leq [g_k(t^*)]^k \geq v(\theta)$$

This is equivalent to (19).

Corollary 2. If $g(t) = v(\theta)$ where t satisfies the primal constraints and θ satisfies the dual constraints then

$$(21) \quad M = \begin{matrix} n & A. \\ \text{Tr} & \end{matrix} \theta = \begin{matrix} P \setminus n & A. \\ \text{Tr} & \end{matrix} A^{-k} V C^{-1}$$

for any A satisfying the dual constraints.

Proof; The equations (8) and (9) are raised to the powers A^k and multiplied. This gives

$$(22) \quad \begin{matrix} A^k & n & A. \\ g_0 & \text{Tr} & \end{matrix} \theta = \begin{matrix} A & n & A. \\ \text{Tr} & & \end{matrix} A^k \begin{matrix} n & A. \\ \text{Tr} & \end{matrix} u^x$$

where $A_0 = \sum_{i=1}^n \theta_i$. But $g_0(t) = M_A$, $A_0 = 1$, and

$$(23) \quad \begin{matrix} n & A_i \\ \text{Tr} & \end{matrix} u_i^x = \begin{matrix} n & A_i \\ \text{Tr} & \end{matrix} c_i^x$$

Thus (22) and (23) prove (21).

Relation (21) is due to Clarence Zener. It can be used to derive the "maximizing equations" [1, p.88]. The maximizing equations are of prime importance for computational work.

Corollary 3. If program A and program B are both consistent then

$$(24) \quad M_A > 0$$

Proof; This follows directly from (7).

4. Condensed Programs.

Proof for duality theorems to follow is based on the notion of a condensed program. A condensed program is equivalent to a linear program. It is denoted by \bar{A} and defined as follows.

Primal Program \bar{A} . Given program A and a set of non-negative weights $\epsilon_1, \dots, \epsilon_n$ such that

$$(1) \quad \sum_{m_k}^{n_k} \epsilon_i = 1 \quad k = 0, 1, \dots, p.$$

Then the condensed program is obtained by replacing $g_k(t)$ by

$$(2) \quad \bar{g}_k(t) = \pi_{m_k}^{n_k} \left(\frac{u_i}{\epsilon_i} \right)^{\epsilon_i}$$

where the u_i are the terms of g_k . Thus

$$(3) \quad \bar{g}_k(t) = \bar{c}_k t_1^{\bar{a}_{k1}} \dots t_m^{\bar{a}_{km}},$$

$$(4) \quad \bar{c}_k = \pi_{m_k}^{n_k} \left(\frac{c_i}{\epsilon_i} \right)^{\epsilon_i},$$

$$(5) \quad \bar{a}_{kj} = \sum_{m_k}^{n_k} \epsilon_i a_{ij} \quad k = 0, 1, \dots, p.$$

Note that it is a direct consequence of the geometric inequality that

$$(6) \quad g_k(t) \geq \bar{g}_k(t).$$

Thus if program A is consistent so also is program \bar{A} and $M_A \geq M_{\bar{A}}$.

In a similar manner a partially condensed program can be defined when at least two terms are condensed into a single term by the geometric inequality. Condensed and partially condensed programs suggest approximation procedures for computation

but these questions are not treated.

The posynomials of program \bar{A} have only one term so the dual program \bar{B} can be expressed in the following form.

Dual Program \bar{B} . The maximum of a product function

$$(7) \quad \bar{v}(A) = \prod_{k=0}^p (C_k)^{x_k}$$

is sought where A_0, A_1, \dots, A_p are subject to the constraints

$$(8) \quad A_k \geq 0 \quad k = 0, 1, \dots, p$$

$$(9) \quad x_0 = 1$$

$$(10) \quad \sum_{k=0}^p A_k \bar{a}_{kj} = 0 \quad j = 1, \dots, m$$

It will now be shown that \bar{A} and \bar{B} are equivalent to linear programs.

Make the following one to one transformation:

$$(11) \quad z_j = \log t_j \quad j = 1, \dots, m$$

$$(12) \quad G_k = \log \bar{g}_k \quad k = 0, 1, \dots, p$$

$$(13) \quad C_k = \log \bar{c}_k \quad k = 0, 1, \dots, p$$

$$(14) \quad v = \log \bar{v}$$

Then program \bar{A} becomes equivalent to the following linear program.

Program \bar{A}_L . Seek the minimum of the linear function

$$(15) \quad G_0 = \sum_{j=1}^m \bar{a}_{0j} z_j + C_0$$

subject to the constraints

$$(16) \quad G_k = \sum_{j=1}^m \bar{a}_{kj} z_j + C_k \leq 0 \quad k = 1, 2, \dots, p$$

Under the transformation, program \bar{B} also becomes equivalent to a linear program.

Program \bar{B}_L . Seek the maximum of the linear function

$$(17) \quad v = c_0 + \sum_1^p \lambda_k c_k$$

subject to the constraints

$$(18) \quad \lambda_k \geq 0 \quad k = 1, \dots, p$$

$$(19) \quad \bar{a}_{0j} + \sum_1^p \lambda_k \bar{a}_{kj} = 0 \quad j = 1, \dots, m.$$

It is clear that \bar{A}_L and \bar{B}_L are a pair of dual linear programs.

Lemma 2. Suppose condensed program \bar{A} is consistent. Then $M_{\bar{A}} > 0$ if and only if the weights ϵ_i satisfy the relations

$$(20a) \quad \epsilon_i \sum_{m_k}^{n_k} \delta'_j = \delta'_i \quad m_k \leq i \leq n_k$$

for $k = 0, 1, \dots, p$ and for some δ' satisfying the constraints of program B. Moreover δ' can be chosen so as to also satisfy

$$(20b) \quad M_{\bar{A}} = v(\delta').$$

Proof. Suppose first that program \bar{A} has the infimum $M_{\bar{A}} > 0$. It follows by the transformations (11), (12) and (13) that program \bar{A}_L has the infimum $\log M_{\bar{A}}$. Then by the duality theorem of linear programming it follows that there is a point λ' where the program \bar{B}_L has the maximum value $\log M_{\bar{A}}$. Thus by the transformation (14) program \bar{B} has the maximum value $M_{\bar{A}}$. Thus λ' satisfies the constraints of program \bar{B} and

$$(21) \quad M_{\bar{A}} = \pi \prod_{k=0}^p (\bar{c}_k)^{\lambda'_k}.$$

Now substitute in (21) the expression (4) for \bar{c}_k obtaining

$$(22) \quad M_A^* = \sum_{k=0}^p IT \left[\sum_{i=1}^{n_k} \frac{c_i}{m_k} \right] \cdot \sum_{i=1}^{n_k} \frac{A_{ik}}{m_k} \delta_i^t = IT \left(\sum_{i=1}^{n_k} \frac{f_i}{m_k} \right) \delta_i^t$$

where δ_i^t is defined as

$$(23) \quad \delta_i^t = e_i^t \quad \text{for } m_k \leq i \leq n_k.$$

Summing these relations gives

$$\langle 24 \rangle \quad \delta_i^t = \lambda_k.$$

Multiplying relation (5) by A_k^i and summing gives

$$\sum_{k=0}^p \lambda_k \sum_{i=1}^{n_k} A_{ik} = \sum_{i=1}^{n_k} \delta_i^t \sum_{k=0}^p A_{ik} = \sum_{i=1}^{n_k} \delta_i^t \cdot \dots$$

It follows from (24) and (25) together with (8), (9) and (10)

that δ_i^t satisfies the constraints of program B, moreover

(23) and (24) prove (20a). Substituting (23) in (22) gives

$$(26) \quad M_A^* = \sum_{k=0}^p \frac{n_k}{m_k} \left(\frac{c_1 A_k}{m_k} \right) \delta_i^t.$$

This may be written in the form

$$(27) \quad M_A^* = \sum_{i=1}^{n_k} \frac{c_i}{m_k} \delta_i^t \sum_{k=0}^p \frac{A_{ik}}{m_k}.$$

The right side is the dual function $v(\delta^t)$. This proves (20b).

Next suppose δ^t is given to satisfy the constraints of

program B. Let A_k be defined by (24). If $A_k = 0$ let e_i^t

be defined by (23). If $A_k = 0$ let e_i^t be arbitrary. Then

relations (20a) are satisfied. Clearly (8) and (9) hold and

(25) proves (10) so A satisfies the constraints of B. Since

B and A are both consistent Corollary 3 gives $M_A^* > 0$. Q. E. D.

5. Superconsistent programs.

Program A is defined to be superconsistent if

$$(1) \quad g_k(t^*) < 1 \quad k = 1, 2, \dots, p$$

for at least one point t^* .

Theorem 2. Suppose program A is superconsistent and has a minimum $M_A > 0$ at a point t' . Then in the condensed program \bar{A} let the weights be chosen for $m_k \leq i \leq n_k$ as

$$(2a) \quad \epsilon_i = u_i(t') / \sum_{m_k}^{n_k} u_i(t') \quad k = 0, 1, \dots, p.$$

Then program \bar{A} also has a minimum at t' . Moreover $M_{\bar{A}} = M_A$.

Proof. It follows from (2a) and the definition of \bar{g}_k that

$$(2b) \quad \bar{g}_k(t') = g_k(t').$$

Suppose that, contrary to the statement of the theorem, there is a point t^0 such that

$$(3) \quad \bar{g}_0(t^0) < M_A, \quad \bar{g}_k(t^0) \leq 1, \quad k = 1, \dots, p.$$

Also since program A is superconsistent there is a point t^* such that

$$(4) \quad 1 > g_k(t^*) \geq \bar{g}_k(t^*), \quad k = 1, \dots, p.$$

Let $\alpha > 0$, $\beta > 0$, and $\alpha + \beta = 1$. Then let

$$(5) \quad t'' = (t^0)^\alpha (t^*)^\beta.$$

Since \bar{g}_k has only one term

$$(6) \quad \bar{g}_k(t'') = [\bar{g}_k(t^0)]^\alpha [\bar{g}_k(t^*)]^\beta.$$

It follows from (3), (4) and (6) that if p is sufficiently small

$$(7) \quad i_0(t'') < M_A, \quad i_k(t'') < 1, \quad k = 1, \dots, p$$

Next choose h_j so that

$$(8) \quad t_3 = t_3 e^{h_j D}$$

Then define t_j in terms of s as

$$(8) \quad t_j = t_j e^{s I_k} \quad 0 < s < 1.$$

Thus

$$(9) \quad \log g_k(t) = \log g_k(t_j) + s I_k h_j.$$

Since $g_0(f) = M^A$ and $g_0(t'') < M^A$ this shows that

$$(10) \quad 2^A \wedge O D^{h_j} < 0^*$$

Likewise if $\bar{g}_k(t') = 1$ then $\bar{g}_k(t'') < 1$ and

$$(11) \quad 1 \wedge \bar{a}_{h_j} < 0.$$

Now note that

$$(12) \quad \frac{dg_k}{ds} = \sum_{m=1}^{n_k} u_i \sum_{l=1}^m a_{il} h_i$$

Set $s = 0$ and employ the definition of p_i and \bar{a}_{ij} to obtain

$$(13) \quad \frac{L}{g_k} \frac{d\phi_i}{ds} = A_{i0} \cdot 2? a_{ij} h_j = \sum_{j=1}^3 \bar{a}_{ij} h_j.$$

It now follows that if $k = 0$ or if $g_k(f) = 1$ then

$$(14) \quad \bar{d}_i < 0.$$

Hence if (14) holds and s is small and positive

$$(15) \quad g_k(t) < g_k(f) \cdot$$

Consequently

$$(16) \quad g_0(t) < M_A \text{ and}$$

$$(17) \quad g_k(t) < 1 \cdot$$

But if $g_k(t) < 1$ then (17) also holds if s is small and positive. Thus (17) holds for $k = 1, \dots, p$. Thus (16) and (17) give a contradiction showing that the assumed relation (3) is false. This proves $M_A = M^*$.

Theorem 3. Suppose program A is superconsistent and has an infimum $M_A > 0$. Then the dual program B is consistent and has a maximum M_B at a point 6^f . Moreover $M_B = M_A$ &

Proof: First suppose program A has a minimum point $t^1_{\#}$. Hence $g(t^1) = M_A > 0$. Then Theorem 2 gives that $M_B = M_A$. Thus according to Lemma 2 there is a 6^f such that

$$(18) \quad g_0(t^f) = M_B = v(6^f).$$

This together with inequality (7) of Theorem 1 shows that $v(6^f) = M_A$. Hence Theorem 3 is true if program A has a minimum.

If program A does not have a minimum point consider a modified program A_n in which the following $2m$ additional constraints are imposed:

$$(19) \quad g_{p+j}(t) = ht_j \leq 1 \quad j = 1, \dots, m,$$

$$(20) \quad g_{p+n+j}(t) = ht_j^1 \leq 1 \quad j = 1, \dots, m.$$

Then if h is a sufficiently small positive number it is clear that A_n also is superconsistent. Moreover the additional constraints insure that the set of consistent points is compact. Consequently program A_n has a minimum point t^{1*} and by what has just been proved

$$(21) \quad g_0(t^n) \leq v_h(6^n)$$

for a point 6^n satisfying the constraints of program B_n .

The dual function is

$$(22) \quad v_1(6) = v(6) \quad \text{IT} \quad h^x$$

The constraints of B_n are

$$(23) \quad 6_i \geq 0 \quad i = 1, \dots, n+2m$$

$$(24) \quad F_1 \circ 6_+ = 1$$

$$(25) \quad \sum_i a_{ij} 6_{n+j} - 6_{n+m} = 0 \quad j = 1, 2, \dots, m$$

Now let $h \rightarrow 0$ then $g_0(t^n) \rightarrow M_A$. Then because of (21) we have $v_1(6^n) \rightarrow M_A > 0$. Since program A_n has a superconsistent point t^* it follows that Corollary 1 applies to each of the functions g_k so there is a constant $d > 1$ such that as $h \rightarrow 0$

$$(26) \quad A_k \geq d \quad k = 1, 2, \dots, p+2m$$

Also $A_0 = 1$ so as $h \rightarrow 0$

$$(27) \quad 6_i \geq d \quad i = 1, 2, \dots, n+2m$$

For $k > p$ we see that $g_k(t^*) = ht^* \rightarrow 0$ as $h \rightarrow 0$. Thus it follows from Corollary 1 that

$$(28) \quad \delta_i'' \rightarrow 0 \quad \text{for } i = n+1, \dots, n+2m.$$

By virtue of relation (27) the points δ_i'' are confined to a compact region. Thus as $h \rightarrow 0$ there is at least one limit point δ_i' . Since $\delta_i' = 0$ for $i > n$ it is seen from (23), (24) and (25) that δ_i' satisfies the constraints of program B. Also if $h < 1$

$$(29) \quad v_h(\delta'') \leq v(\delta'').$$

Taking the limit of this relation gives

$$(30) \quad M_A \leq v(\delta')$$

but Theorem 1 shows that $M_A \geq v(\delta')$. This is seen to complete the proof of Theorem 3.

6. Subconsistent programs.

In Theorem 4 to follow the condition of consistency is replaced by a weaker condition termed subconsistency. Program A is termed subconsistent if the program A^θ defined by the functions

$$(1) \quad g_k^\theta(t) = \theta g_k(t) \quad k = 0, 1, \dots, p$$

is consistent for any constant θ in the range $0 < \theta < 1$. Thus suppose program A is subconsistent and let M_{A^θ} be the infimum of program A^θ . Note that M_{A^θ} is an increasing function of θ so as $\theta \rightarrow 1$ let the subinfimum be defined as

$$(2) \quad m_A = \lim_{\theta \rightarrow 1} M_{A^\theta}$$

with the understanding that m_A can be $+\infty$ when the right side is unbounded. Finite m_A means $0 < m_A < \infty$.

Theorem 4a. If program A is subconsistent and has a finite subinfimum m_A then program B is consistent and has a finite supremum. Moreover $m_A = M_B$.

Proof. Clearly the programs A^θ are all superconsistent. Moreover if θ is close to 1 then $M_{A^\theta} > 0$. Thus by Theorem 3 we have

$$(3) \quad M_{A^\theta} = M_{B^\theta} = v_\theta(\delta^\theta).$$

Where v_θ is the dual function for B^θ . Clearly

$$(4) \quad v_\theta(\delta^\theta) = v(\delta^\theta) \theta^{\sum_{i=1}^n \delta_i^\theta} \leq v(\delta^\theta).$$

If δ^θ satisfies the constraints of B^θ it also satisfies the constraints of B so (3) and (4) give

$$(5) \quad m_A^p \leq v(6) \leq M_B.$$

Allowing θ to approach zero give

$$(6) \quad m_A \leq M_B.$$

On the other hand if θ satisfies the constraints of program B it follows from Theorem 1 that

$$(7) \quad m_A^0 \wedge v(6) e^{\frac{TL}{L} \theta}.$$

Allowing θ to approach zero with θ fixed gives

$$(8) \quad \inf_A v(6).$$

Taking the supremum of the right side gives

$$(9) \quad m_A \wedge M_B.$$

Then (6) and (9) together prove Theorem 4a.

Theorem 4b. If program B is consistent and has a finite supremum M_B then program A is subconsistent and has a finite subinfimum in A . Moreover $m_A = M_B$.

Proof. If program A is not subconsistent then it follows that there is an integer $q \leq p$ such that the set of inequalities

$$(10) \quad g^1, \dots, g_{q-1} \leq 1$$

is subconsistent but the constraints (10) imply that there is a constant D such that

$$(11) \quad g_q > D > 1.$$

Thus let the program A^q be the minimization of g_q subject to the constraints (10). Then the dual program B^q is the

maximizing of the dual function

$$(12) \quad W(\Delta) = \prod_{i=1}^{n_q} \left(\frac{c_i}{\Delta_i} \right)^{\Delta_i} \Lambda_1^{\Lambda_1} \dots \Lambda_q^{\Lambda_q}$$

where $\Lambda_1 = \sum_{m_1}^{n_1} \Delta_i$ etc. The constraints are

$$(13) \quad \sum_{m_1}^{n_q} \Delta_i a_{ij} = 0 \quad j = 1, \dots, m$$

$$(14) \quad \Delta_i \geq 0 \quad \text{and} \quad \Lambda_q = 1.$$

Then by virtue of Theorem 4a it is possible to choose Δ so that

$$(15) \quad W(\Delta) > D.$$

Let N be a positive integer then it follows from the definition of W that

$$(16) \quad W(N\Delta) = [W(\Delta)]^N$$

Let $\Delta_i = 0$ for $i < m_1$ and for $i > n_q$ then it is seen that

$$(17) \quad \delta_i^{(N)} = \delta_i + N\Delta_i$$

satisfies the constraints of dual program B if δ_i does.

Clearly

$$(18) \quad \frac{v(\delta + N\Delta)}{v(\delta)} = \frac{W(\delta + N\Delta)}{W(\delta)} \quad \text{and}$$

$$(19) \quad W(\delta + N\Delta) = [W(\Delta + \delta/N)]^N.$$

By continuity of the function W it follows that there is an N_0 such that for $N > N_0$

$$(20) \quad W(\Delta + \delta/N) > D.$$

This inequality together with identities (18) and (19) give

$$(21) \quad v(6 + NA) \leq \frac{v(6)}{w(\delta)} D^N .$$

Hence v is unbounded as $N \rightarrow \infty$. This contradiction proves that program A is subconsistent.

Program A is superconsistent and program B is consistent. Thus by Theorem 1

$$(22) \quad M_A \wedge M_B > 0 .$$

Then by Theorem 3

$$(23) \quad M_A = v(6^0) \sum_{x=0}^n \delta^x$$

where 6^0 is a maximizing vector for B. Since $0 < 1$ the equality (23) gives the inequality

$$(24) \quad M_A \leq v(6^0) \leq J .$$

This shows that M_A has a finite limit as $\theta \rightarrow 1$. In other words A has a finite subinfimum. Theorem 4b then follows directly from Theorem 4a.

7. The question of a duality gap.

It is easy to construct examples of primal programs which are subconsistent but which are not consistent. On the other hand if program A is consistent it is also subconsistent and clearly

$$(1) \quad m_A \leq M_A.$$

It is worth noting that there are examples in programming theory where the relation corresponding to (1) can be a strict inequality [3], [4]. This has been termed a ^M duality gap¹¹. That a duality gap can never appear in geometric programming is now to be shown.

Theorem 5. If program A is consistent then the infimum M_A and the subinfimum m_A are equal.

Proof. If A is consistent then relation (1) holds. As a consequence the subinfimum can not be infinite. Then by the definition of the subinfimum there must exist a sequence of points $t = T(r)$ such that as $r = 1, 2, \dots, \infty$.

$$(2) \quad g_{\mathbf{i}}(T) = t n_{\mathbf{i}},$$

$$(3) \quad \limsup g_{\mathbf{i}}^{-1}(T) \leq 1 \quad k = 1, \dots, p.$$

Since the terms $u_{\mathbf{i}}(T)$ are uniformly bounded it may be supposed that they have limits $e_{\mathbf{i}}$ for a suitable subsequence. Then the following lemma applies.

Lemma 3. Suppose the terms $u^{\mathbf{i}}$ have limits $e_{\mathbf{i}}$ as t runs through a sequence $t = T(r)$. Then there is another sequence $t = T'(r)$ such that as $r \rightarrow \infty$

$$(4) \quad u_{\mathbf{i}}(T') = e_{\mathbf{i}} \quad \text{if} \quad e_{\mathbf{i}} > 0,$$

(5) $u_i(T^1) = 0$ if $e_i = 0$.

Proof. Linear functions $U_i(Z)$ are defined by

(6) $u_i = \log\left(\frac{u_i}{c_i}\right) = \sum_j x_j$

where $Z_j = \log T_j$. Thus

(7) $U_i(Z) - E_i = \log(e_i/c_i)$ if $e_i > 0$

(8) $U_i(Z) = -\infty$ if $e_i = 0$.

Let N be the set of functions U_1, \dots, U_n . Let P be the subset corresponding to (7) and let Q be the subset corresponding to (8). Let p be a maximal linearly independent subset of P . Let q be a maximal subset of Q such that $M = p \cup q$ is linearly independent. Thus assigning values of U_j in the set M determines all U_i in the set N . Moreover for certain b_i

(9) $U_i = \sum_j b_j U_j$ U_i in P

(10) $U_i = \sum_j b_j U_j$ U_i in Q

Let $U_j^1 = E_j$ in p , $U_j^1 = U_j(Z)$ in q . Then (9) shows that

(11) $U_i^1 = E_i$ in P .

Also (7), (8), (9) and (10) show that $U_i^1 - E_i$ is bounded.

Thus

(12) $u_i \in [-\infty, \infty)$ in Q .

However the U variables are dependent on the Z variables so there is a sequence Z^1 such that $U_i^1 = U_i(Z^1)$ in N . Then by taking $T^1 = \exp(Z^1)$ it is seen that (11) and (12) prove (4) and (5).

Lemma 4. Let $G(t)$ be a posynomial and let $t'_j > 0$ and $t^*_j > 0$.

Let

$$(13) \quad t''_j = (t'_j)^\alpha (t^*_j)^\beta \quad j = 1, \dots, m$$

where α and β are positive constants such that $\alpha + \beta = 1$ then

$$(14) \quad G(t'') \leq [G(t')]^\alpha [G(t^*)]^\beta .$$

Proof. Clearly

$$(15) \quad G(t'') = \Sigma [u_i(t')]^\alpha [u_i(t^*)]^\beta .$$

Then apply Holder's inequality with the standard terminology

$1/p + 1/q = 1$. Take $p = 1/\alpha$ and $q = 1/\beta$ and the proof of (14) follows.

Returning to the proof of Theorem 5 let the sequence T define a new sequence T' as in Lemma 3. Then given an $\epsilon > 0$ there exists an r_0 such that

$$(16) \quad g_0(T') < m_A + \epsilon/2, \quad r \geq r_0 .$$

Let t^* be a point which satisfies the constraints of program A and let $T'' = (T')^\alpha (t^*)^\beta$. Then by use of Lemma 4

$$(17) \quad g_0(T'') \leq [g_0(T')]^\alpha [g_0(t^*)]^\beta .$$

It is clear therefore, that if β is sufficiently small

$$(18) \quad g_0(T'') \leq m_A + \epsilon, \quad r \geq r_0 .$$

Next consider the constraint function g_k . First suppose g_k contains no term u_i for which $e_i = 0$ then by Lemma 4

$$(19) \quad g_k(T'') \leq [g_k(T')]^\alpha [g_k(t^*)]^\beta \leq 1 .$$

If g_k contains terms for which $e_i = 0$ let

$$(20) \quad G_k(t) = g_k(t) - (\text{terms for which } e_i = 0).$$

Then by Lemma 4

$$(21) \quad G_k(T'') \leq [G_k(T')]^\alpha [G_k(t^*)]^\beta.$$

But $G_k(T') \leq 1$ and $g_k(t^*) \leq 1$. But since some terms of g_k have been deleted $G_k(t^*) < 1$. Hence there exists a constant $h > 0$ such that

$$(22) \quad G_k(T'') \leq 1 - h.$$

But $g_k(T'') - G_k(T'') \rightarrow 0$ as $r \rightarrow \infty$. Thus there is an r_k such that

$$(23) \quad g_k(T'') < 1 \quad \text{for } r \geq r_k.$$

Let $R = \max r_k$ for $k = 0, 1, \dots, p$. Then (19) and (23) show that T'' satisfies the constraints if $r \geq R$. Moreover (18) holds and since ϵ is arbitrary it follows that

$$(24) \quad M_A \leq m_A.$$

Of course this implies $M_A = m_A$ and the proof is complete.

Theorem 6. If program A is consistent and has a finite infimum M_A then program B is consistent and has a finite infimum M_B . Moreover $M_A = M_B$.

Proof. This is a direct corollary of Theorem 4a and Theorem 5.

It is now seen that Theorems 4 and 6 form a rather complete duality theory for geometric programming.

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