

ON RANDOM MINIMUM LENGTH SPANNING TREES

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Abstract

We extend and strengthen the result that, in the complete graph K_n with independent random edge-lengths uniformly distributed on $[0,1]$, the expected length of the minimum spanning tree tends to $\zeta(3)$ as $n \rightarrow \infty$. In particular, if K_n is replaced by the complete bipartite graph $K_{n,n}$ then there is a corresponding limit of $2\zeta(3)$.

§1 Introduction

Suppose that we are given a complete graph K_n on n vertices together with lengths on the edges which are independent identically distributed non-negative random variables. Suppose that their common distribution function F satisfies $F(0) = 0$, F is differentiable from the right at zero and $D = F'_+(0) > 0$. Let X denote a random variable with this distribution.

Let L_n denote the (random) length of the minimum spanning tree in this graph. Frieze [3] proved the following:

Theorem 1

(a) If $E(X) < \infty$ then $\lim_{n \rightarrow \infty} E(L_n) = \zeta(3)/D$, where

$$\zeta(3) = \sum_{k=1}^{\infty} k^{-3} = 1.202\dots$$

(b) If $E(X^2) < \infty$ then $\lim_{n \rightarrow \infty} \text{Var}(L_n) = 0$, and so in particular $L_n \rightarrow \zeta(3)/D$ in probability. □

Recently, Steele [5] has shown that the convergence in probability above holds without assumptions on moments.

In this paper we generalise Theorem 1 to graphs other than K_n . We shall also simplify the proofs and sharpen the results.

Let H be a fixed connected multigraph, with vertex set $V(H) = \{v_1, v_2, \dots, v_h\}$. Corresponding to each edge e of H let F_e be a distribution function of a non-negative random variable such that $F_e(0) = 0$ and F_e has a right derivative D_e at 0. We assume that there exists $D > 0$ such that for each vertex v of H ,

$$\sum_{e \in V} D_e = D.$$

(Observe that loops contribute once to this sum.)

For each $n = 1, 2, \dots$ let H_n be a (loopless) graph obtained as follows. Replace each vertex v_i of H by a set V_i of n new vertices, so that $|V(H_n)| = nh$. Now join two distinct vertices of H_n by the same number of edges as join the corresponding vertices of H . Thus if H has λ loops and ν non-loops then H_n has $\mu = \binom{n}{2}\lambda + n^2\nu$ edges.

Let the edges of H_n have independent lengths, where the length of an edge e is distributed according to the distribution for the edge of H from which e arose. Let us extend our notation so that the length of $e \in E(H_n)$ has distribution function F_e as well.

For any connected graph G with non-negative edge-lengths let $L(G)$ denote the length of a minimum spanning tree in G .

Theorem 2

As $n \rightarrow \infty$, $L(H_n) \rightarrow (h/D)\zeta(3)$ a.s.

□

This result follows (by a Borel-Cantelli lemma) from

Lemma 0

For any $\epsilon > 0$ there exists c , $0 < c < 1$ such that

$$P(|L(H_n) - (h/D)\zeta(3)| > \epsilon) < c^{n^{1/4}}.$$

Theorem 1 follows from the case where H has a single vertex and a

single loop, so that $H_n = K_n$. Some other interesting cases are the following, where for simplicity we make each edge length uniform on $[0,1]$.

$$(1) \quad L((K_r)_n) \rightarrow \frac{r}{r-1} \zeta(3) \quad \text{a.s.}$$

(Here $(K_r)_n$ is the complete multipartite graph with r blocks each of size n .) In particular $L(K_{n,n}) \rightarrow 2 \zeta(3)$ (see [4]).

$$(2) \quad L((C_k)_n) \rightarrow \frac{k}{2} \zeta(3) \quad \text{a.s.}$$

(Here C_k is a cycle with k vertices.)

$$(3) \quad L((Q_k)_n) \rightarrow \frac{2^k}{k} \zeta(3) \quad \text{a.s.}$$

(Here Q_k is the k -cube.)

We shall prove lemma 0 (and thus Theorem 2) in three stages (sections 3,4,5 below), but first we have:

§2. Notation and Preliminaries

We use two models of random subgraph of H_n .

For $1 \leq m \leq \mu$ $H_{n,m}$ has the same vertex set as H_n and for its edge set a random m -edge subset of $E(H_n)$.

For $0 \leq p \leq 1$ $H_{n,p}$ has the same vertex set as H_n and each of the μ edges of H_n are independently included with probability p and excluded with probability $1 - p$.

We have need of the following simple relation between $H_{n,m}$ and $H_{n,p}$ where $p = \frac{m}{\mu}$: for any property Π

$$(4) \quad P(H_{n,m} \in \Pi) \leq 2\sqrt{\mu} P(H_{n,p} \in \Pi).$$

This follows from

$$P(H_{n,p} \in \Pi) = \sum_{m'=0}^{\mu} P(H_{n,p} \in \Pi \mid |E(H_{n,p})| = m') P(|E(H_{n,p})| = m')$$

and the fact that (i) $H_{n,p}$ conditional on $|E(H_{n,p})| = m'$ is distributed as $H_{n,m'}$, and (ii) $|E(H_{n,p})|$ has the binomial distribution $B(\mu, p)$.

§3. Expected value for uniform [0,1] case

Our approach to proving theorem 2 is similar to that of [3] but uses martingale inequalities in place of the Chebycheff inequality. We first discuss the case where edge lengths are uniform on [0,1] and H is r -regular (with loops counting once towards the degree of a node).

Suppose that the edges $E(H_n) = \{u_1, u_2, \dots, u_\mu\}$ are numbered so that $\ell(u_i) \leq \ell(u_{i+1})$, $i = 1, 2, \dots, \mu-1$ where $\ell(u)$ is the length of edge u .

A minimum length tree may be constructed using the Greedy Algorithm of Kruskal [4]. Let $F_0 = \phi$, $F_1 = \{u_1\}$, F_2, \dots, F_{hn-1} be the sequence of edge sets of the successive forests produced. Here $|F_i| = i$ and F_{hn-1} is the set of edges in a minimum spanning tree.

Next define $t_i = \max\{j: u_j \in F_i\}$. Then

$$(5) \quad L(H_n) = \sum_{i=1}^{hn-1} u_{t_i},$$

and thus

$$(6) \quad E(L(H_n)) = \frac{1}{\mu+1} E\left(\sum_{i=1}^{hn-1} t_i\right).$$

The subgraph Γ_m of H_n induced by $U_m = \{u_1, u_2, \dots, u_m\}$ is distributed as $H_{n,m}$. Let κ_m denote the number of connected components of Γ_m .

Lemma 1

$$\sum_{i=1}^{hn-1} t_i = \sum_{m=1}^{\mu} \kappa_m + hn - \mu - 1.$$

Proof

$$\sum_{m=1}^{\mu} \kappa_m = \sum_{r=1}^{hn-1} (hn-r)(t_{r+1}-t_r)$$

where $t_{hn} = \mu+1$. This is because $\Gamma_{t_r}, \Gamma_{t_r+1}, \dots, \Gamma_{t_{r+1}-1}$ all have $hn-r$ components. Thus

$$\sum_{m=1}^{\mu} \kappa_m = -(hn-1)t_1 + t_2 + t_3 + \dots + t_{hn-1} + t_{hn},$$

and the result follows on noting that $t_1 = 1$ and $t_{hn} = \mu + 1$.

□

It follows from (6) and the above lemma that

$$(7) \quad E(L(H_n)) = \frac{1}{\mu+1} (E\left(\sum_{m=1}^{\mu} \kappa_m\right) + hn) - 1.$$

We must therefore estimate $E(\sum_{m=1}^{\mu} \kappa_m)$. It will be easier to work with $H_{n,p}$ and so let κ_p denote the (random) number of components in $H_{n,p}$. The following simplification is from Bollobás and Simon [1].

Lemma 2

$$\frac{1}{\mu+1} E(\sum_{m=1}^{\mu} \kappa_m) = \int_0^1 E(\kappa_p) dp.$$

Proof

$$\begin{aligned} \int_0^1 E(\kappa_p) dp &= \int_0^1 \sum_{m=0}^{\mu} \binom{\mu}{m} p^m (1-p)^{\mu-m} E(\kappa_m) dp \\ &= \sum_{m=0}^{\mu} E(\kappa_m) \binom{\mu}{m} \frac{m!(\mu-m)!}{(\mu+1)!} \end{aligned}$$

□

Thus to compute $E(L(H_n))$ we need an accurate estimate of $E(\kappa_p)$.

Lemma 3

If $p \leq 4 \log n/n$ then

$$(8) \quad E(\kappa_p) = \ln \phi(rnp) + o(n^{3/4})$$

where

$$\phi(a) = \sum_{s=1}^{\infty} \frac{s^{s-2}}{s!} a^{s-1} e^{-as}.$$

(The 'little o' notation in (8) is intended to imply uniformity over relevant p .)

Proof

As we shall see, the most important components from our point of view are small isolated trees. Let therefore τ_p denote the number of components in $H_{n,p}$ which are trees of order $n^{1/3}$ or less. Let $\mathcal{T}_s(G)$ denote the set of s -vertex subtrees of a graph G . For $T \in \mathcal{T}_s(H_n)$ we find

$$P(T \text{ is a component of } H_{n,p}) = p^{s-1}(1-p)^{rns-\alpha(T)}$$

where, rather crudely,

$$0 \leq \alpha(T) \leq r \binom{s}{2} + r.$$

Hence

$$\begin{aligned} E(\tau_p) &= \sum_{s=1}^{n^{1/3}} \sum_{T \in \mathcal{T}_s(H_n)} p^{s-1}(1-p)^{rns-\alpha(T)} \\ (9) \quad &= (1 + o(n^{-1/4})) \sum_{s=1}^{n^{1/3}} |\mathcal{T}_s(H_n)| p^{s-1} e^{-rns p}. \end{aligned}$$

We must now estimate $|\mathcal{T}_s(H_n)|$.

For each tree T in $\mathcal{T}_s(K_s)$ and each tree T' in $\mathcal{T}_s(H_n)$ let $\mathcal{F}(T, T')$ be the set of bijections f between $E(T)$ and $E(T')$ that correspond to bijections between $V(T)$ and $V(T')$.

Now if $T' \in \mathcal{T}(H_n)$ then

$$\sum_{T \in \mathcal{T}_s(K_s)} |\mathcal{F}(T, T')| = s!$$

since each bijection between $\{1, \dots, s\}$ and $V(T')$ contributes exactly one to the sum on the left hand side. Hence

$$(10) \quad |\mathcal{T}_s(H_n)| = \frac{1}{s!} \sum_{T \in \mathcal{T}_s(K_s)} \sum_{T' \in \mathcal{T}_s(H_n)} |\mathcal{F}(T, T')|.$$

We shall show that for each $T \in \mathcal{T}_s(K_s)$

$$(11) \quad \ln \prod_{k=1}^{s-1} r(n-k) \leq \sum_{T' \in \mathcal{T}_s(H_n)} |\mathcal{F}(T, T')| \leq \ln \prod_{k=1}^{s-1} rn.$$

Using (11) in (10) and $|\mathcal{T}_s(K_s)| = s^{s-2}$ yields

$$|\mathcal{T}_s(H_n)| = (1 + o(n^{-1/4})) \frac{s^{s-2}}{s!} \ln r^{s-1} n^s,$$

and then from (9)

$$(12) \quad E(\tau_p) = (1 + o(n^{-1/4})) \ln \sum_{s=1}^{n^{1/3}} \frac{s^{s-2}}{s!} (nrp)^{s-1} e^{-mp}.$$

To prove (11) note that when $s = 1$ it is correct (if we interpret $\prod_{k=1}^0$ as 1). Assume that it is true for some $s \geq 1$: we shall show that it is

true for $s + 1$. Consider a tree T in $\mathcal{T}_{s+1}(K_{s+1})$ and assume without loss of generality that $s + 1$ is a leaf of T , with incident edge e . Then having fixed a bijection f on the tree $T - (s+1)$ in $\mathcal{T}_s(K_s)$ there are between $r(n-s)$ and rn choices for the image of e . This completes our proof of (11) and thus of (12).

We observe that since $s! \geq (s/e)^s$

$$\frac{s^{s-2}}{s!} p^{s-1} e^{-rns} \leq \frac{e}{s^2} (rn e^{1-rnp})^{s-1}$$

$$\leq \frac{e}{s^2}.$$

This implies, from (12), that

$$(13) \quad E(\tau_p) = \ln \phi(rnp) + o(n^{3/4}).$$

We now look at $\sigma_p =$ the number of non-tree components of $H_{n,p}$ of order at most $n^{1/3}$. As each such component consists of a tree $T \in \mathcal{T}_s(H_n)$ plus some k extra edges, we deduce that

$$(14) \quad E(\sigma_p) \leq \sum_{s=1}^{n^{1/3}} \sum_{T \in \mathcal{T}_s(H_n)} p^{s-1} (1-p)^{rns-\alpha(T)} \sum_{k=1}^{r\binom{s}{2}-s+1} \binom{\binom{s}{2}}{k} p^k (1-p)^{-k}$$

$$= E(\tau_p) \times o(n^{-1/4}).$$

As $H_{n,p}$ contains at most $n^{2/3}$ components of size exceeding $n^{1/3}$, the lemma follows from (13) and (14).

□

For $p \geq 4 \log n/n$ we use the following.

Lemma 4

(a) If $p = 4 \log n/n$ then

$$P(H_{n,p} \text{ is not connected}) = O(n^{-3}).$$

(b) If $p = n^{-3/4}$ then

$$P(H_{n,p} \text{ is not connected}) = O(ne^{-n^{1/4}}).$$

Proof

(a) If $H_{n,p}$ is not connected then either

(i) $h = 1$

or

(ii) there is a pair of distinct adjacent vertices v_i, v_j in H such that the subgraph of $H_{n,p}$ induced by $V_i \cup V_j$ is not connected.

In case (i) $H_{n,p}$ is the standard model $G_{n,p}$ and in case (ii) the subgraph K induced by $V_i \cup V_j$ contains a random bipartite graph. For brevity we deal with case (ii) and leave case (i) to the reader. Both cases are straightforward.

If K is not connected then there exist $S \subseteq V_i, T \subseteq V_j$ such that $1 \leq |S| + |T| \leq n$ and no edge of $H_{n,p}$ joins $S \cup T$ to $V_i \cup V_j - S \cup T$.

Hence

$$P(\text{ii}) \leq \binom{h}{2} \sum_{\substack{k, \ell=0 \\ 1 \leq k+\ell \leq n}}^n u(k, \ell)$$

where

$$u(k, \ell) = \binom{n}{k} \binom{n}{\ell} (1-p)^{k(n-\ell)+\ell(n-k)}$$

$$\leq n^{k+\ell - 4(k+\ell) + \frac{8k\ell}{n}}$$

$$\leq n^{-(3 - 2(k+\ell)/n)(k+\ell)}.$$

Part (a) now follows easily, and part (b) may be proved in a similar manner.

□

We can now obtain the limiting value for $E(L(H_n))$ in the special case under consideration.

Lemma 5

If H is r -regular and edge-lengths are independent and all uniform on $[0,1]$ then

$$\lim_{n \rightarrow \infty} E(L(H_n)) = (h/r)\zeta(3).$$

Proof

It follows from (7) and Lemma 2 that

$$E(L(H_n)) = \int_0^1 (E(\kappa_p) - 1) dp + \frac{hn}{\mu+1}.$$

Now if $p_0 = 4 \log n/n$ then by Lemma 3,

$$\begin{aligned} \int_0^{p_0} E(\kappa_p) dp &= hn \sum_{s=1}^{\infty} \frac{s^{s-2}}{s!} \int_0^{p_0} (rnp)^{s-1} e^{-rnp s} dp + o(n^{3/4} p_0) \\ &= (h/r) \sum_{s=1}^{\infty} \frac{s^{s-2}}{s!} \int_0^{4r \log n} x^{s-1} e^{-sx} dx + o(\log n/n^{1/4}) \\ &= (h/r) \zeta(3) + o(\log n/n^{1/4}). \end{aligned}$$

To see the last equation above note that

$$\int_{\omega}^{\infty} x^{s-1} e^{-sx} dx = O(e^{-\omega/2}) \quad \text{if } \omega = \omega(n) \rightarrow \infty$$

and

$$\int_0^{\infty} x^{s-1} e^{-sx} dx = (s-1)!/s^s.$$

It follows from Lemma 4(a) that for $p \geq p_0$, $E(\kappa_p) = 1 + O(n^{-2})$ and so

$$\int_{p_0}^1 (E(\kappa_p) - 1) dp = O(n^{-2}). \quad \text{Hence}$$

$$(15) \quad E(L(H_n)) = (h/r) \zeta(3) + o(\log n/n^{1/4}).$$

□

§4. Probability inequality for uniform [0,1] case

Our aim next is to prove that there is a constant $A = A(r, h) > 0$ such

that for any $0 < \epsilon < 2h/r$

$$(16) \quad P(|L(H_n) - (h/r)\zeta(3)| \geq \epsilon) \leq e^{-A\epsilon^2 n^{1/4}}$$

for n sufficiently large. We do this in two stages.

Lemma 6

Let $t_1, t_2, \dots, t_{hn-1}$ be as in (5) and $0 < \epsilon < 1$ be fixed. Then for n sufficiently large

$$P\left(\left|\sum_{i=1}^{hn-1} t_i - (h/r)(\mu+1)\zeta(3)\right| \geq \epsilon n^2\right) \leq e^{-\epsilon^2 n^{1/4}/r^3 h^3}.$$

Proof

We prove this using a martingale inequality. Let X_1, X_2, \dots, X_N be random variables, and for each $i = 1, \dots, N$ let $\underline{X}^{(i)}$ denote (X_1, X_2, \dots, X_i) . Suppose that the random variable Z is determined by $\underline{X}^{(N)}$. For each $i = 1, 2, \dots, N$ let

$$(17) \quad \delta_i = \sup |E(Z|\underline{X}^{(i-1)}) - E(Z|\underline{X}^{(i)})|.$$

Here $E(Z|\underline{X}^{(0)})$ means just $E(Z)$. The following inequality is a special case of a martingale inequality due to Azuma. For any $u \geq 0$

$$(18) \quad \Pr(|Z - E(Z)| \geq u) \leq 2 \exp\{-u^2/2 \sum_{i=1}^m \delta_i^2\}.$$

To apply (18) we take $N = \lceil \mu/n^{3/4} \rceil$ and let $X_i = u_i$, the i^{th} shortest edge of H_n . Let $Z = \sum_{m=1}^N \kappa_m$. It is not difficult to see that for δ_i as defined by (17) we have $\delta_i \leq N - i + 1$. This follows from the fact (in an obvious notation) that $|\kappa_m(X^{(N)}) - \kappa_m(Y^{(N)})| \leq 1$ if there exists k such that $X_i = Y_i$ for $i \neq k$ or there exist k, ℓ such that $X_k = Y_\ell$, $X_\ell = Y_k$ and $X_i = Y_i$ otherwise.

Thus

$$(19) \quad P(|Z - E(Z)| \geq u) \leq 2e^{-3u^2/N(N+1)(2N+1)} \quad \text{for } u \geq 0.$$

Now let $Z' = \sum_{m=N+1}^{\mu} \kappa_m$. It follows from (4) and Lemma 4(b) that

$$(20) \quad P(Z' \neq \mu - N) = O(n^2 e^{-n^{1/4}})$$

and so

$$(21) \quad E(Z') = \mu - N + o(1).$$

Now (7), (15) and (21) imply that

$$E(Z) = (h/r)(\mu+1)\zeta(3) + O(n^{7/4} \log n).$$

We can then use (19) with $u = \frac{1}{2} \epsilon n^2$ together with Lemma 1, (20) and $\mu \leq \frac{1}{2} r h n^2$ to obtain the Lemma.

□

We must now show that sums of order statistics of a large number of

independent uniform $[0,1]$ random variables usually behave as expected.

Lemma 7

Let u_i , $i = 1, 2, \dots, \mu$ denote the order statistics of μ independent uniform $[0,1]$ random variables. Let $1 \leq t_1 < t_2 < \dots < t_{hn-1} \leq \mu$ and

$$T = \sum_{k=1}^{hn-1} t_k. \quad \text{Then for any fixed } 0 < \epsilon < 1$$

$$(22) \quad P\left(\left|\sum_{k=1}^{hn-1} u_{t_k} - \frac{T}{\mu+1}\right| > \frac{\epsilon T}{\mu+1}\right) \leq e^{-\frac{\epsilon^2 T}{16hn}}.$$

Proof

It is well known (see for example Feller [2]) that if $X_1, X_2, \dots, X_{\mu+1}$ are independent exponential random variables with mean 1 then the variables

$$Z_i = \frac{Y_i}{Y_{\mu+1}}, \quad i = 1, 2, \dots, \mu \quad \text{are distributed as } u_i, \quad i = 1, 2, \dots, \mu \quad \text{where}$$

$$Y_i = X_1 + X_2 + \dots + X_i. \quad \text{It suffices therefore to prove (22) with } u_{t_k} \text{ replaced by}$$

$$Z_{t_k}. \quad \text{Note now that}$$

$$S = \sum_{k=1}^{hn-1} Y_{t_k} = \sum_{j=1}^{\mu+1} a_j X_j$$

where $a_j = |\{k: t_k \geq j\}|$, and that $T = \sum_{j=1}^{\mu+1} a_j$. Now for $\lambda > 0$

$$P(S \geq (1+\epsilon)T) = P(e^{\lambda S - \lambda(1+\epsilon)T} \geq 1)$$

$$\leq E(e^{\lambda S - \lambda(1+\epsilon)T})$$

$$\begin{aligned}
&= \prod_{j=1}^{\mu+1} \frac{e^{-\lambda(1+\epsilon)a_j}}{1 - \lambda a_j} && \text{if } 0 < \lambda < \min\{1/a_j\} \\
&\leq \prod_{j=1}^{\mu+1} e^{-\epsilon\lambda a_j + \frac{2}{3}(\lambda a_j)^2} && \text{if } 0 < \lambda < \frac{1}{3} \min\{1/a_j\}
\end{aligned}$$

and on taking $\lambda = \frac{\epsilon}{3hn}$

$$\begin{aligned}
&\leq \prod_{j=1}^{\mu+1} e^{-\frac{\epsilon^2 a_j}{3hn} (1 - \frac{2}{9} \frac{a_j}{hn})} \\
(23) \quad &\leq e^{-\frac{7\epsilon^2}{27} \frac{T}{hn}} && \text{as } a_j \leq hn.
\end{aligned}$$

Similarly, for any $\lambda > 0$,

$$\begin{aligned}
&P(S \leq (1-\epsilon)T) = P(e^{-\lambda S + \lambda(1-\epsilon)T} \geq 1) \\
(24) \quad &\leq e^{-\frac{\epsilon^2 T}{2hn}}
\end{aligned}$$

on taking $\lambda = \frac{\epsilon}{hn}$.

We may argue as above with each $a_j = 1$ (or otherwise) to obtain

$$(25) \quad P(|Y_{\mu+1} - (\mu+1)| \geq \epsilon(\mu+1)) \leq e^{-\frac{\epsilon^2}{4} \mu}.$$

The result follows from (23), (24) and (25) after replacing ϵ by $\epsilon/2$ throughout the proof.

□

We can now readily establish (16). Let $T = \sum_{i=1}^{hn-1} t_i$, and let

$$A_n = \{ |L(H_n) - (h/r)\zeta(3)| \geq \epsilon \},$$

$$B_n = \{ |T/(\mu+1) - (h/r)\zeta(3)| \geq \epsilon/2 \}.$$

Then

$$P(A_n) \leq P(B_n) + P(A_n | \bar{B}_n).$$

Now Lemma 6 gives

$$\begin{aligned} P(B_n) &\leq P(|T - (h/r)(\mu+1)\zeta(3)| \geq (\epsilon hr/4) \binom{n}{2}) \\ &\leq \exp(-\epsilon^2 n^{1/4}/65rh). \end{aligned}$$

Furthermore,

$$\begin{aligned} P(A_n | \bar{B}_n) &\leq P(|L(H_n) - T/(\mu+1)| \geq \epsilon/2 | \bar{B}_n) \\ &\leq \exp(-\tilde{\epsilon}^2 \tilde{T}/16hn) \qquad \text{by Lemma 7,} \end{aligned}$$

where $\tilde{\epsilon} = (\epsilon/2)/((h/r)\zeta(3) + \epsilon/2)$ and

$$\tilde{T} = ((h/r)\zeta(3) - \epsilon/2)(\mu+1).$$

The inequality (16) now follows.

§5. General case

We will now use the inequality (16) to complete the proof of lemma 0 and thus of Theorem 2 in the general case. We shall assume that $D_e > 0$ for each edge e in $E(H)$. Any edges e with $D_e = 0$ would cause only minor irritation.

We will first use the approach of Steele [5] to relate a random edge-length X_e with distribution function F_e to one which is uniform in $[0, D_e^{-1}]$. Let A_e denote the set of atoms of F_e and define Y_e by

$$Y_e = \begin{cases} D_e^{-1} F_e(X_e) & X_e \notin A_e \\ D_e^{-1} (F_e(X_e^-) + U_e (F_e(X_e) - F_e(X_e^-))) & X_e \in A_e. \end{cases}$$

where U_e is a uniform $[0,1]$ random variable (and we make a suitable assumption of independence)..

Observe that Y_e is uniform on $[0, D_e^{-1}]$ and $X_e > X_{e'}$ implies $Y_e \geq Y_{e'}$. It follows that there is always a tree T which is simultaneously of minimum length for edge-lengths $\{X_e\}$ and $\{Y_e\}$.

Our hypotheses for the F_e , $e \in E(H)$ show that we may write $F_e(x) = D_e x + x g_e(x)$ and $F_e(x^-) = D_e x + x h_e(x)$ where g_e and h_e go to zero as $x \rightarrow 0$. We then have

$$(27) \quad \sum_{e \in T} D_e^{-1} X_e h_e(X_e) \leq \sum_{e \in T} Y_e - \sum_{e \in T} X_e \leq \sum_{e \in T} D_e^{-1} X_e g_e(X_e).$$

Our immediate task is to bound the probability that either of the outside terms of (27) is significant. Let $g_e^*(x) = \sup\{g_e(y) : 0 \leq y \leq x\}$ for $e \in E(H)$. Now fix $\epsilon > 0$. For $e \in E(H)$ let

$$\lambda_e = \lambda_e(\epsilon) = \sup\{\lambda : g_e^*(\lambda) \leq \epsilon D_e\}.$$

Let

$$\mu = \min\{\lambda_e : e \in E(H)\}$$

and

$$v = \min\{P(X_e < \mu) : e \in E(H)\},$$

and note that $\mu > 0$, $v > 0$.

Then

$$\begin{aligned} & P\left(\sum_{e \in T} D_e^{-1} X_e g_e(X_e) > \epsilon \sum_{e \in T} X_e\right) \\ & \leq P(X_e \geq \mu \text{ for some } e \in E(H)) \\ & \leq P(H_{n,v} \text{ is not connected}). \end{aligned}$$

But this last quantity is at most $e^{-nv/3}$ (for n sufficiently large) by an argument similar to that of Lemma 4. An analogous argument yields

$$P\left(\sum_{e \in T} D_e^{-1} X_e h_e(X_e) < -\epsilon \sum_{e \in T} X_e\right) \leq e^{-nv'/3}$$

for some $\nu' = \nu'(\epsilon) > 0$.

Thus if $L(H'_n)$ denotes the length of a minimum spanning tree when the length X'_e of edge $e \in E(H)$ is uniform in $[0, D_e^{-1}]$ then we can write, for small fixed $\epsilon > 0$,

$$\begin{aligned} (28a) \quad P(L(H_n) \geq (1+\epsilon)^2 (h/D)\zeta(3)) \\ \leq e^{-nv/3} + P(L(H'_n) \geq (1+\epsilon)(h/D)\zeta(3)) \end{aligned}$$

and

$$\begin{aligned} (28b) \quad P(L(H_n) \leq (1-\epsilon)^2 (h/D)\zeta(3)) \\ \leq e^{-nv'/3} + P(L(H'_n) \leq (1-\epsilon)(h/D)\zeta(3)). \end{aligned}$$

These results reduce the general case of the theorem to the case of uniform edge-lengths. Thus in particular the inequality (16) holds also when all edge lengths have the negative exponential distribution with mean 1.

However, the above argument works also in the other direction; and we have

$$\begin{aligned}
(29a) \quad & P(L(H'_n) \geq ((1+\epsilon)/(1-\epsilon))(h/D)\zeta(3)) \\
& \leq e^{-nv'/3} + P(L(H_n) \geq (1+\epsilon)(h/D)\zeta(3))
\end{aligned}$$

and

$$\begin{aligned}
(29b) \quad & P(L(H'_n) < ((1-\epsilon)/(1+\epsilon))(h/D)\zeta(3)) \\
& \leq e^{-nv/3} + P(L(H_n) < (1-\epsilon)(h/D)\zeta(3)).
\end{aligned}$$

Thus the case of uniform edge-lengths reduces to the case of (negative) exponential edge-lengths.

Now we are almost home. We wish to show that lemma 0 holds when the edge-lengths have exponential distributions.

Let us check first that we may take each D_e rational. Let D' be rational, $0 < D' < D$. We shall show that there exist rational D'_e , $0 < D'_e \leq D_e$ for $e \in E(H)$ such that $\sum_{e \in \mathcal{E}v} D'_e = D'$ for $v \in V(H)$. A similar approximation from above may be obtained by the reader.

Suppose then that $0 < \epsilon < 1$ and $D' = (1-\epsilon)D$ is rational. Write $D' = M/N$ where M and N are positive integers such that both $\epsilon ND_e \geq 1$ and $(1-\epsilon)ND_e \geq 1$ for each $e \in E(H)$. Observe next that the polyhedron

$$\begin{aligned}
& \sum_{e \in \mathcal{E}v} x_e = (1-\epsilon)D \\
& 1/N \leq x_e \leq [(1-\epsilon)ND_e]/N
\end{aligned}$$

is non-empty, since it contains the point $x_e = (1-\epsilon)D_e$, $e \in E(H)$. But the



polyhedron is rational, and so it contains a rational point, as required.

Finally then we wish to show that lemma 0 holds when each edge e of H has exponential distribution with rational parameter $\lambda_e = D_e = P_e/Q$. Consider the graph \tilde{H} obtained from H by replacing each edge e by P_e parallel copies, each with edge-length exponentially distributed with parameter $1/Q$ (mean Q). Then $L(H_n)$ and $L(\hat{H}_n)$ have the same distribution, and we have already shown the required result for $L(\hat{H}_n)$.

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