

# ON RANDOM MINIMUM LENGTH SPANNING TREES

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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  $H$ ,

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

(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  $\lambda$  loops and  $v$  non-loops then  $H_n$  has  $\mu = \binom{n}{2} \lambda + n^2 v$  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  $\varepsilon > 0$  there exists  $c$ ,  $0 < c < 1$  such that

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

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  $\mu$  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  $\Pi$

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

This follows from

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

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  $l(u_i) \leq l(u_{i+1})$ ,  $i = 1, 2, \dots, \mu-1$  where  $l(u)$  is the length of edge  $u$ .

A minimum length tree may be constructed using the Greedy Algorithm of Kruskal [4]. Let  $F_0 = \varnothing$ ,  $F_1 = \{u_1\}$ ,  $F_2, \dots, F_{hn-1}$  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

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

and thus

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

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

**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  $\Gamma_{t_r}, \Gamma_{t_r+1}, \dots, h_{t_{r+1}-1}$  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

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

We must therefore estimate  $E(\sum_{m=1}^{\mu} \kappa_m)$ . It will be easier to work with  $H_{n,p}$  and so let  $\kappa_p$  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.**

$$\int_0^1 E(\kappa_p) dp = \int_0^1 \sum_{m=0}^{\mu} \binom{\mu}{m} p^m (1-p)^{\mu-m} E(\kappa_m) dp = \sum_{m=0}^{\mu} E(\kappa_m) \binom{\mu}{m} \frac{m!(\mu-m)!}{(\mu+1)!}. \quad \blacksquare$$

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

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

where

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

(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  $\tau_p$  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

$$\begin{aligned} E(\tau_p) &= \sum_{s=1}^{n^{1/2}} \sum_{T \in \mathcal{T}_s(H_n)} p^{s-1} (1-p)^{rns - \alpha(T)} = \\ &= (1 + o(n^{-1/4})) \sum_{s=1}^{n^{1/2}} |\mathcal{T}_s(H_n)| p^{s-1} e^{-rns p}. \end{aligned}$$

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  $T' \in \mathcal{T}_s(H_n)$  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  $T \in \mathcal{T}_s(K_s)$

$$(11) \quad hn \prod_{k=1}^{s-1} r(n-k) \leq \sum_{T' \in \mathcal{T}_s(H_n)} |\mathcal{F}(T, T')| \leq hn \prod_{k=2}^{s-1} rn.$$

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

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

and then from (9)

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

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  $s! \geq (s/e)^s$

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

This implies, from (12), that

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

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

$$(14) \quad E(\sigma_p) \leq \sum_{s=1}^{n^{1/3}} \sum_{T \in \mathcal{T}_s(H_n)} p^{s-1} (1-p)^{rns-a(T)} \sum_{k=1}^{r\binom{s}{2}-s+1} \binom{r\binom{s}{2}}{k} p^k (1-p)^{-k} = \\ = E(\tau_p) \times o(n^{-1/4}).$$

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

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

where

$$u(k, l) = \binom{n}{k} \binom{n}{l} (1-p)^{k(n-l)+l(n-k)} \leq \\ \leq n^{k+l-4(k+l)+(8kl/n)} \leq \\ \leq n^{-(3-2(k+l)/n)(k+l)}.$$

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

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

#### 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  $0 < \varepsilon < 2h/r$

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

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

**Lemma 6.** *Let  $t_1, t_2, \dots, t_{m-1}$  be as in (5) and  $0 < \varepsilon < 1$  be fixed. Then for  $n$  sufficiently large*

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

**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  $X^{(i)}$  denote  $(X_1, X_2, \dots, X_i)$ . Suppose that the random variable  $Z$  is determined by  $X^{(N)}$ . For each  $i=1, 2, \dots, N$  let

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

Here  $E(Z|X^{(0)})$  means just  $E(Z)$ . The following inequality is a special case of a martingale inequality due to Azuma (see e.g. Stout [6]). For any  $u \geq 0$

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

To apply (18) we take  $N = \lceil \mu/n^{3/4} \rceil$  and let  $X_i = u_i$ , the  $i^{\text{th}}$  shortest edge of  $H_n$ . Let  $Z = \sum_{m=1}^N \kappa_m$ . It is not difficult to see that for  $\delta_i$  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  $X_k = Y_l$ ,  $X_l = Y_k$  and  $X_i = Y_i$  otherwise.

Thus

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

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

$$(20) \quad \Pr(Z' \neq \mu - N) = 0(n^2 e^{-n^{1/4}})$$

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  $u = \frac{1}{2} \varepsilon n^2$  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  $\mu$  independent uniform  $[0, 1]$  random variables. Let  $1 \leq t_1 < t_2 < \dots < t_{hn-1} \leq \mu$  and  $T = \sum_{k=1}^{hn-1} t_k$ . Then for any fixed  $0 < \varepsilon < 1$

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

**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  $Z_i = \frac{Y_i}{Y_{\mu+1}}$ ,



$i=1, 2, \dots, \mu$  are distributed as  $u_i$ ,  $i=1, 2, \dots, \mu$  where  $Y_i = X_1 + X_2 + \dots + X_i$ . It suffices therefore to prove (22) with  $u_{t_k}$  replaced by  $Z_{t_k}$ . Note now that

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

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

$$\begin{aligned} P(S \equiv (1+\varepsilon)T) &= P(e^{\lambda S - \lambda(1+\varepsilon)T} \equiv 1) \leq \\ &\leq E(e^{\lambda S - \lambda(1+\varepsilon)T}) \\ &= \prod_{j=1}^{\mu+1} \frac{e^{-\lambda(1+\varepsilon)a_j}}{1 - \lambda a_j} \quad \text{if } 0 < \lambda < \min \{1/a_j\} \\ &\leq \prod_{j=1}^{\mu+1} e^{-\varepsilon \lambda a_j + \frac{2}{3}(\lambda a_j)^2} \quad \text{if } 0 < \lambda < \frac{1}{3} \min \{1/a_j\} \end{aligned}$$

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

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

Similarly, for any  $\lambda > 0$ ,

$$(24) \quad P(S \leq (1-\varepsilon)T) = P(e^{-\lambda S + \lambda(1-\varepsilon)T} \equiv 1) \leq e^{-\frac{\varepsilon^2 T}{2hn}}$$

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

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

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

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

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

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

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

Then

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

Now Lemma 6 gives

$$P(B_n) \leq P\left(|T - (h/r)(\mu+1)\zeta(3)| \geq (\varepsilon hr/4) \binom{n}{2}\right) \leq \exp(-\varepsilon^2 n^{1/4}/65rh).$$

Furthermore,

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

where

$$\tilde{\varepsilon} = (\varepsilon/2)/((h/r)\zeta(3) + \varepsilon/2)$$

and

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

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  $\varepsilon > 0$ . For  $e \in E(H)$  let

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

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

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

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

$$P\left(\sum_{e \in T} D_e^{-1} X_e h_e(X_e) < -\varepsilon \sum_{e \in T} X_e\right) \leq e^{-nv/3}$$

for some  $v' = v'(\varepsilon) > 0$ .

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  $\varepsilon > 0$ .

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

and

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

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

$$\begin{aligned} (29a) \quad P(L(H'_n) \geq ((1+\varepsilon)/(1-\varepsilon))(h/D)\zeta(3)) &\leq \\ &\leq e^{-nv'/6} + P(L(H_n) \geq (1+\varepsilon)(h/D)\zeta(3)) \end{aligned}$$

and

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

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  $D'_e$ ,  $0 < D'_e < D_e$  for  $e \in E(H)$  such that  $\sum_{v \in e} D'_e = D'$  for  $v \in V(H)$ . A similar approximation from above may be obtained by the reader.

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

$$\sum_{v \in e} x_e = (1-\varepsilon)D$$

$$1/N \leq x_e \leq [(1-\varepsilon)ND_e]/N$$

is non-empty, since it contains the point  $x_e = (1 - \varepsilon)D_e$ ,  $e \in E(H)$ . 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  $\hat{H}$  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  $L(H_k)$  and  $L(\hat{H}_n)$  have the same distribution, and we have already shown the required result for  $L(\hat{H}_n)$ .

### References

- [1] B. BOLLOBÁS and I. SIMON, On the expected behaviour of disjoint set union algorithms, *Proceedings of the Seventeenth Annual ACM Symposium on Theory of Computing*, (1985) 224—231.
- [2] W. FELLER, *An Introduction to Probability Theory, Volume 1*, John Wiley and Sons (1966).
- [3] A. M. FRIEZE, On the value of a random minimum spanning tree problem, *Discrete Applied Mathematics*, **10** (1985) 47—56.
- [4] C. J. H. McDIARMID, On the greedy algorithm with random costs, *Mathematical Programming*, **36** (1986) 245—255.
- [5] M. J. STEELE, On Frieze's  $\zeta(3)$  limit for lengths of minimal spanning trees, *Discrete Applied Mathematics*, **18** (1987) 99—103.
- [6] W. F. STOUT, *Almost Sure Convergence*, Academic Press, 1974.

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