

THE SPEED OF A BIASED WALK ON A GALTON-WATSON TREE WITHOUT LEAVES IS MONOTONIC FOR LOW VALUES OF BIAS

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Abstract

We show that for $\lambda \in [0, m_1/(1 + \sqrt{1 - 1/m_1})]$, the biased random walk's speed on a Galton–Watson tree without leaves is strictly decreasing, where $m_1 \ge 2$. Our result extends the monotonic interval of the speed on a Galton–Watson tree.

Keywords: Galton-Watson tree; biased random walk; speed; monotonicity

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1. Introduction

In this paper, we investigate the properties of biased random walks denoted as RW_{λ} on Galton–Watson trees \mathbb{T} . We focus our attention on the following inquiry: Is the speed of RW_{λ} monotonic non-increasing as a function of its bias λ when the Galton–Watson tree has no leaves?

Let \mathbb{T} denote a Galton–Watson tree with the root e, v represent the offspring distribution with $m = \mathbb{E}(v) > 1$. Denote the associated probability space as (Ω, \mathbb{P}) . Note that \mathbb{T} is supercritical and the extinction probability $q = \mathbb{P}[\mathbb{T} \text{ is finite}] < 1$. Let v(x) denote the number of children of a vertex $x \in \mathbb{T}$. For any $x \in \mathbb{T} \setminus \{e\}$, let x_* be the parent of x, which refers to the neighbor of x that lies on a geodesic path from x to e. We write xi, $1 \le i \le v(x)$, as the children of x.

For any $\lambda \ge 0$, a λ -biased random walk RW_{λ} , $(X_n)_{n=0}^{\infty}$, on the Galton–Watson tree \mathbb{T} is defined as follows. The transition probability from x to an adjacent vertex y is

$$p(x, y) = \begin{cases} \frac{1}{\nu(x)} & \text{if } x = e, \\ \frac{\lambda}{\lambda + \nu(x)} & \text{if } y = x_*, \ x \neq e, \\ \frac{1}{\lambda + \nu(x)} & \text{otherwise.} \end{cases}$$

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 $(X_n)_{n=0}^{\infty}$ is a reversible Markov chain for $\lambda > 0$. Let \mathbf{P}_x be the quenched probability of RW_{λ} starting at x and \mathbb{P}_x the annealed probability obtained by the semi-direct product $\mathbb{P}_x = \mathbb{P} \times \mathbf{P}_x$. Denote the respectively associated expectations by \mathbf{E}_x and \mathbb{E}_x . A motivation for the introduction of RW_{λ} on trees is its ability to obtain almost uniform samples from the set of self-avoiding walks of a given length on a lattice [6]. For further insights into the motivations for biased random walks on graphs, see the existing surveys [3, 12].

On a general tree, [8] showed that there exists a critical parameter λ_c for RW_{λ} , where λ_c is equal to the exponential of the Hausdorff dimension of the tree boundary. It was found that RW_{λ} exhibits transient behavior for $\lambda < \lambda_c$ and recurrent behavior for $\lambda > \lambda_c$. It was also proved that, for almost every Galton–Watson tree conditioned on non-extinction, RW_{λ} is transient for $0 \le \lambda < m$. In [9], it was shown that, conditional on non-extinction, RW_m is null recurrent, while RW_{λ} is positive recurrent for $\lambda > m$.

Let |x| be the graph distance between x and e for any vertex $x \in \mathbb{T}$. Note that |x| is also the generation of x. Fix $X_0 = e$. The speed ℓ_{λ} of RW_{λ} is defined as the almost sure limit, if it exists, of the ratio $|X_n|/n$ as $n \to \infty$. In this paper, the dependence of ℓ_{λ} with respect to the environment will often be omitted. A transient RW_{λ} may exhibit zero speed when an excessive amount of time is allocated to the leaves. In [11], it was proved that, conditional on non-extinction, ℓ_{λ} exists almost surely and ℓ_{λ} is deterministic and positive if and only if $\lambda \in (\mathbb{E}(vq^{\nu-1}), m)$. From [10], $\ell_1 = \mathbb{E}((v-1)/(v+1))$. An expression for ℓ_{λ} , shown in (1), was specified in [2], though an artificial parent to e was added there. For related results, see [7].

The following problem was raised in [11] (see also [12]), and was called the Lyons–Pemantle–Peres monotonicity problem in [4].

Problem 1. ([11].) Assume $\mathbb{P}(\nu = 0) = 0$, namely that the Galton–Watson tree \mathbb{T} has no leaf, meaning that the extinction probability q = 0. Is the speed ℓ_{λ} of RW_{λ} on \mathbb{T} monotonic non-increasing in $\lambda \in [0, m)$?

It was conjectured in [11, 12] that Problem 1 should have a positive answer. If we consider general trees, monotonicity does not hold. Moreover, we should notice that speed might not exist on general trees. For instance, on a binary tree with pipes (a binary tree to every vertex of which is joined a unary tree), which is a multi-type Galton–Watson tree, the speed is $(2-\lambda)(\lambda-1)/(\lambda^2+3\lambda-2)$ for $1 \le \lambda \le 2$ [12]. For any $0 < \lambda_1 < \lambda_2$, by the repeated filtering method we can produce a tree such that the speed of RW_{λ_1} is less than that of RW_{λ_2} [12]. Notice that these examples are not Galton–Watson trees and show the complexity of Problem 1. Therefore, the monotonicity of ℓ_{λ} would represent a highly significant and fundamental characteristic of Galton–Watson trees.

The Lyons-Pemantle-Peres monotonicity problem for Galton-Watson trees without leaves was proven to have a positive solution for $\lambda \le m_1/1160$ in [4], where $m_1 = \min\{k \ge 1: P[\nu = k] > 0\}$ is the minimal degree of the Galton-Watson tree. This result was improved in [1] to $\lambda \le \frac{1}{2}$ by a completely different approach. In [5], the Einstein relation was obtained for RW_{λ} on Galton-Watson trees, which implies that Problem 1 holds in a neighborhood of m. These slow advances indicate that Problem 1 is rather difficult. For more information on RW_{λ} on \mathbb{T} , see [3, 12] and references therein. For the monotonicity of the speed of biased random walks on groups, see [14, 15].

The main result of our study is presented as follows.

Theorem 1. The speed ℓ_{λ} of RW_{λ} on a Galton–Watson tree \mathbb{T} without leaves is strictly decreasing in $\lambda \in [0, m_1/(1+\sqrt{1-1/m_1})]$ when $m_1 \geq 2$.

2. Proof of Theorem 1

Inspired by [1], based on some new observations, we prove Theorem 1. Let \mathbb{T}_* be the tree obtained from \mathbb{T} by adding an artificial parent e_* to the root e. For any vertex $x \in \mathbb{T}_*$, let $\tau_x = \min\{n \geq 0, X_n = x\}$, where $\min \emptyset = \infty$ and $(X_n)_{n=0}^{\infty}$ is a λ -biased random walk on \mathbb{T}_* . For $x \neq e_*$, let $\beta(x) := \beta(x, \lambda) = \mathbf{P}_x(\tau_{x_*} = \infty)$ be the quenched probability of never reaching the parent x_* of x when starting from x. Since \mathbb{T} has no leaf and $\lambda < m$, we have $\beta(x) > 0$ due to transience. Let $(\beta_i)_{i\geq 0}$ be generic independent and identically distributed random variables distributed under \mathbb{P} as $\beta(e)$, and independent of ν .

The following expression for ℓ_{λ} was given in [2]:

$$\ell_{\lambda} = \frac{\mathbb{E}\left((\nu - \lambda)\beta_0 / \left(\lambda - 1 + \sum_{i=0}^{\nu} \beta_i\right)\right)}{\mathbb{E}\left((\nu + \lambda)\beta_0 / \left(\lambda - 1 + \sum_{i=0}^{\nu} \beta_i\right)\right)}, \quad \lambda < m.$$
 (1)

Notice that (1) holds trivially when $\lambda = 0$. In this context, it is important to note that RW_{λ} on \mathbb{T}_{*} and RW_{λ} on \mathbb{T} have a slight difference, but due to $\lambda < m$ and transience these two biased random walks have the same speed when starting at e. Indeed, we have the following result.

Lemma 1. For $\lambda < m$, RW_{λ} on \mathbb{T}_* and RW_{λ} on \mathbb{T} have the same speed when starting at e.

Proof. Since the random walk on $RW_{\lambda}(X_n)_{n=0}^{\infty}$ on \mathbb{T}_* is transience, the edge ee_* (ee_* denotes the edge that connects the vertices e and e_*) can be visited only a finite number of times. We can define $K = \sup\{n, X_n \notin \{e, e_*\}\}$, where K is finite. And $RW_{\lambda}(X_n)_{n=K+1}^{\infty}$ is a biased random walk on \mathbb{T} . This implies the lemma.

For the reader's convenience, we provide a more detailed proof as follows. For $RW_{\lambda}(X_n)_{n=0}^{\infty}$ on \mathbb{T}_* with $X_0 = e$, define the following regenerative times [16]:

- $\tau_0 = 0$, $\sigma_0 = \inf\{n > \tau_0 : X_n \notin \{e, e_*\}\};$
- $\tau_1 = \inf\{n > \sigma_0 : X_n = e\}, \ \sigma_1 = \inf\{n > \tau_1 : X_n \notin \{e, e_*\}\}\$ when $\tau_1 < \infty$;
- for any $i \ge 1$, $\tau_{i+1} = \inf\{n \ge \sigma_i : X_n = e\}$, $\sigma_{i+1} = \inf\{n \ge \tau_{i+1} : X_n \notin \{e, e_*\}\}$ when $\tau_{i+1} < \infty$.

Since RW_{λ} $(X_n)_{n=0}^{\infty}$ is transient, there exists a unique \hat{i} such that $\tau_i < \infty$ and $\tau_{i+1} = \infty$. Define a random walk $(Y_n)_{n=0}^{\infty}$ as follows:

$$(Y_n)_{n=0}^{\infty} = (X_{\tau_0}, \underbrace{X_{\sigma_0}, \ldots, X_{\tau_1}}_{, x_{\sigma_i}}, \underbrace{X_{\sigma_1}, \ldots, X_{\tau_2}}_{, \ldots, x_{\tau_2}}, \ldots, \underbrace{X_{\sigma_{i-1}}, \ldots, X_{\tau_i}}_{, x_{\sigma_i}}, X_{\sigma_i}, X_{\sigma_{i-1}}, \ldots).$$

It is evident that the sequence $(Y_n)_{n=0}^{\infty}$ is just an RW_{λ} on \mathbb{T} starting at e. It is known that, almost surely, both $\lim_{n\to\infty} (|Y_n|/n)$ and $\lim_{n\to\infty} (|X_n|/n)$ exist and are deterministic. By construction, there exists a random function $s(\cdot)$ on non-negative integers such that, almost surely, $Y_n = X_{s(n)}, n \ge 1$, and $\lim_{k\to\infty} (s(k)/k) = 1$. Therefore, almost surely,

$$\lim_{n\to\infty}\frac{|Y_n|}{n}=\lim_{n\to\infty}\frac{|X_{s(n)}|}{n}=\lim_{n\to\infty}\frac{|X_{s(n)}|}{s(n)}=\lim_{n\to\infty}\frac{|X_n|}{n}.$$

This implies the lemma.

For any $n \ge 1$, let $\beta_n(x) := \beta_{n,\lambda}(x)$ denote the probability of hitting level n before x_* when $|x| \le n$. Recall that, for a given vertex x, x^i is its ith child and v(x) is the number of its children.

Then $\beta_n(x) = 1$ if |x| = n and, for |x| < n,

$$\beta_n(x) = \frac{\sum_{i=1}^{\nu(x)} \beta_n(xi)}{\lambda + \sum_{i=1}^{\nu(x)} \beta_n(xi)}.$$

Fix $\lambda \in [0, m)$, and consider the derivative of $\beta_n(x)$ at λ ; we have

$$\lim_{\lambda_{1} \to \lambda} \frac{\beta_{n,\lambda_{1}}(x) - \beta_{n,\lambda}(x)}{\lambda_{1} - \lambda} \\
= \left(\frac{\sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi)}{\lambda_{1} + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi)} - \frac{\sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)}{\lambda + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)}\right) / (\lambda_{1} - \lambda) \\
= \lim_{\lambda \to \lambda_{1}} \frac{\left(\lambda + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)\right) \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi) - \left(\lambda_{1} + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi)\right) \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)}{\left(\lambda_{1} + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi)\right) \left(\lambda + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)\right)} / (\lambda_{1} - \lambda) \\
= \lim_{\lambda \to \lambda_{1}} \frac{\lambda \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi) - \lambda_{1} \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)}{\left(\lambda_{1} + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi)\right) \left(\lambda + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)\right)} / (\lambda_{1} - \lambda) \\
= \lim_{\lambda \to \lambda_{1}} \frac{\lambda \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi) - \lambda_{1} \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)}{\left(\lambda_{1} + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi)\right) \left(\lambda + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)\right)} / (\lambda_{1} - \lambda) \\
= \lim_{\lambda \to \lambda_{1}} \frac{\lambda \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi) - \lambda_{1} \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)}{\left(\lambda_{1} + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi)\right) \left(\lambda + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)\right)} / (\lambda_{1} - \lambda) \\
= \lim_{\lambda \to \lambda_{1}} \frac{\lambda \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi) - \lambda_{1} \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)}{\left(\lambda_{1} + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi)\right) \left(\lambda + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)\right)} / (\lambda_{1} - \lambda) \\
= \lim_{\lambda \to \lambda_{1}} \frac{\lambda \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi) - \lambda_{1} \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)}{\left(\lambda_{1} + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi)\right) \left(\lambda + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)\right)} / (\lambda_{1} - \lambda) \\
= \lim_{\lambda \to \lambda_{1}} \frac{\lambda \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi) - \lambda_{1} \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)}{\left(\lambda_{1} + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi)\right) \left(\lambda + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)\right)} / (\lambda_{1} - \lambda) \\
= \lim_{\lambda \to \lambda_{1}} \frac{\lambda \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi) - \lambda_{1} \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)}{\left(\lambda_{1} + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)\right)} / (\lambda_{1} - \lambda) \\
= \lim_{\lambda \to \lambda_{1}} \frac{\lambda \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi)}{\left(\lambda_{1} + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda}(xi)\right)} / (\lambda_{1} - \lambda) \\
= \lim_{\lambda \to \lambda_{1}} \frac{\lambda \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi)}{\left(\lambda_{1} + \sum_{i=1}^{\nu(x)} \beta_{n,\lambda_{1}}(xi)\right)} / (\lambda_{1} - \lambda)$$

We can deduce that each $\beta_n(x)$ has a continuous derivative in λ when $|x| \le n$. Also, $\beta_n(e) \downarrow \beta(e)$ as $n \uparrow \infty$, almost surely. To continue, we need Lemmas 2 and 3. For any natural number d, let \mathbb{T}_{d+1} denote the (d+1)-regular tree.

Let \mathbf{P}_x represent the probability measure of RW_λ starting at x on \mathbb{T}_{d+1} with a fixed root e, and τ_{x_*} denote the hitting time of x_* .

Lemma 2. For any $\lambda \geq 0$ and any vertex $x \in \mathbb{T}_{d+1} \setminus \{e\}$ with parent x_* ,

$$\mathbf{P}_{x}(\tau_{x_{*}}=\infty)=1-\frac{\lambda\wedge d}{d}.$$

Proof. We can project the biased random walk on \mathbb{Z} as the tree is regular.

Let us analyze the meaning of $\beta(e)$ within the framework of electric networks. Consider any weighted graph (say, an electric network) G = (V(G), E(G)) with a non-negative edge weight function c (here the weights are called conductances). Suppose $a \in V(G)$ and $Z \subseteq V(G)$. Write $\mathbf{P}_a^{G,c}(a \to Z) = \mathbf{P}_a^{G,c}(\tau_Z < \tau_a^+)$, where $\tau_Z = \inf\{n \ge 0 : X_n \in Z\}$, $\tau_a^+ = \inf\{n \ge 1 : X_n = a\}$, $(X_n)_{n \ge 0}$ is the random walk associated with electric network G, and $\mathbf{P}_a^{G,c}$ is the law of $(X_n)_{n \ge 0}$ starting at a. Let $\pi(x) = \sum_{y \in V(G): y \sim x} c(\{x, y\})$ for all $x \in V(G)$, where $y \sim x$ means y is adjacent to x. Then $\pi(\cdot)$ is a stationary measure of $(X_n)_{n \ge 0}$. Call

$$\mathcal{C}_G(a \leftrightarrow Z) := \mathcal{C}_{G,c}(a \leftrightarrow Z) = \pi(a) \mathbf{P}_a^{G,c}(a \to Z)$$

the effective conductance between a and Z. Note that $\mathbb{P}_a^{G,c}(a \to \infty) = \mathbb{P}_a\{X_i \neq a \text{ for } i \ge 1\}$. Then call

$$C_G(a \leftrightarrow \infty) := C_{G,c}(a \leftrightarrow \infty) = \pi(a)\mathbf{P}_a^{G,c}(a \to \infty)$$

the effective conductance from a to ∞ in G.

To emphasize the concentration on \mathbb{T}_* , denote $\beta(e) = \beta(e, \lambda)$ by $\beta_{\mathbb{T}_*}(e, \lambda)$. When $\lambda > 0$, on \mathbb{T}_* endow any edge $\{x, y\}$ where $x, y \neq e_*$ with a weight $\lambda^{-|x| \wedge |y| - 1}$, and the edge $\{e_*, e\}$ with weight 1; denote this weight function by c_0 . Then, for $\lambda > 0$, the RW_{λ} on \mathbb{T}_* is the random walk associated with the weighted graph (electric network) \mathbb{T}_* ;

$$\beta_{\mathbb{T}_*}(e,\lambda) = \mathbf{P}_{e_*}^{\mathbb{T}_*,c_0}(e_* \to \infty) = \mathcal{C}_{\mathbb{T}_*,c_0}(e_* \leftrightarrow \infty).$$

Lemma 3. Assume the Galton–Watson tree \mathbb{T} has no leaf. Then, almost surely,

$$1 - \frac{\lambda \wedge m_1}{m_1} \le \beta_{\mathbb{T}_*}(e, \lambda) \le 1 - \frac{\lambda}{m_2}, \quad \lambda \in [0, m),$$

where $m_2 = \sup\{k \ge 1 : P[v = k] > 0\}.$

Proof. When $m_2 = \infty$, $\beta(e) \le 1 - \lambda/m_2$ holds trivially. Clearly, the lemma holds true when $\lambda = 0$, so we assume $m_2 < \infty$ (namely ν takes finitely many values) and $0 < \lambda < m$. In a natural way, we can embed an m_1 -ary tree \mathbb{H}^1 into \mathbb{T} and also embed \mathbb{T} into an m_2 -ary tree \mathbb{H}^2 such that the roots of \mathbb{H}^1 and \mathbb{H}^2 are the root e of \mathbb{T} . Similarly to \mathbb{T}_* , let each \mathbb{H}^i_* be obtained from \mathbb{H}^i by adding the artificial parent e_* of e to \mathbb{H}^i .

Like the electric network (\mathbb{T}_*, c_0) , we endow each \mathbb{H}^i_* with a weight function c_i , and view c_0 and c_1 as functions on the set of edges of \mathbb{H}^2_* by letting $c_0(\{x, y\}) = 0$ ($c_1(\{x, y\}) = 0$) when $\{x, y\}$ is not an edge of \mathbb{T}_* (\mathbb{H}^1_*). Then $c_1(\{x, y\}) \le c_0(\{x, y\}) \le c_2(\{x, y\})$ for any edge $\{x, y\}$ of \mathbb{H}^2_* .

Notice that

$$\beta_{\mathbb{T}_{*}}(e,\lambda) = \mathbf{P}_{e_{*}}^{\mathbb{T}_{*},c_{0}}(e_{*} \to \infty) = \mathbf{P}_{e_{*}}^{\mathbb{H}_{*}^{2},c_{0}}(e_{*} \to \infty) = \mathcal{C}_{\mathbb{H}_{*}^{2},c_{0}}(e_{*} \leftrightarrow \infty),$$

$$\beta_{\mathbb{H}_{*}^{i}}(e,\lambda) = \mathbf{P}_{e_{*}}^{\mathbb{H}_{*}^{i},c_{i}}(e_{*} \to \infty) = \mathbf{P}_{e_{*}}^{\mathbb{H}_{*}^{2},c_{i}}(e_{*} \to \infty) = \mathcal{C}_{\mathbb{H}_{*}^{2},c_{i}}(e_{*} \leftrightarrow \infty), \quad i = 1, 2.$$

Recall Rayleigh's monotonicity principle from [13, Section 2.4]: Let G be an infinite connected graph with two non-negative edge weight functions c and c' such that $c \le c'$ everywhere. Then, for any vertex a of G, $\mathcal{C}_{G,c'}(a \leftrightarrow \infty) \le \mathcal{C}_{G,c'}(a \leftrightarrow \infty)$.

Therefore, we have $\mathcal{C}_{\mathbb{H}^2_*,c_1}(e_*\leftrightarrow\infty)\leq \mathcal{C}_{\mathbb{H}^2_*,c_0}(e_*\leftrightarrow\infty)\leq \mathcal{C}_{\mathbb{H}^2_*,c_2}(e_*\leftrightarrow\infty)$. In other words, $\beta_{\mathbb{H}^1_*}(e,\lambda)\leq \beta_{\mathbb{T}_*}(e,\lambda)\leq \beta_{\mathbb{H}^2_*}(e,\lambda)$. Hence, by Lemma 2, we obtain that

$$1 - \frac{\lambda \wedge m_1}{m_1} \le \beta_{\mathbb{T}_*}(e, \lambda) \le 1 - \frac{\lambda}{m_2}.$$

The lemma holds.

Put

$$A_n(x) = \frac{\lambda}{\left(\lambda + \sum_{i=1}^{\nu(x)} \beta_n(xi)\right)^2}, \qquad B_n(x) = \frac{\sum_{i=1}^{\nu(x)} \beta_n(xi)}{\left(\lambda + \sum_{i=1}^{\nu(x)} \beta_n(xi)\right)^2}.$$

Now we are in a position to prove the following lemma on the derivative of $\beta(e, \lambda)$.

Lemma 4. For a Galton–Watson tree \mathbb{T} without leaves, $\beta(e) = \beta(e, \lambda)$ almost surely has a continuous derivative $\beta'(e) = \beta'(e, \lambda)$ in $\lambda \in [0, m_1)$, with

$$0 < -\beta'(e, \lambda) \le \frac{\beta(e, \lambda)}{m_1 - \lambda}, \quad \lambda \in [0, m_1).$$

Proof. Differentiating (1) for $\lambda < m$ yields $-\beta'_n(x, \lambda) = A_n(x) \sum_{i=1}^{\nu(x)} -\beta'_n(xi, \lambda) + B_n(x)$, where $\beta'_n(x, \lambda)$ is the derivative in λ . Then

$$-\beta'_n(e,\lambda) = \sum_{k=0}^{n-1} \sum_{|x|=k} B_n(x) \prod_{i=0}^{k-1} A_n(x_i), \quad \lambda < m,$$
 (2)

where x_i is the ancestor at generation i of x. And, for any $k \in [0, n-1]$,

$$\beta_n(e,\lambda) = \sum_{|x|=k} \beta_n(x,\lambda) \prod_{i=0}^{k-1} \frac{1}{\lambda + \sum_{i=1}^{\nu(x_i)} \beta_n(x_i j,\lambda)}, \quad \lambda < m.$$

Here, $x_i j$ is the jth child of the ancestor x_i .

Clearly, $\beta_n(x, \lambda)$ is non-increasing in n. By Lemma 3, $\lambda + \sum_{i=1}^{\nu(x)} \beta_n(xi, \lambda) \ge m_1$, $\lambda < m$. Hence, for $\lambda < m$,

$$A_n(x) \le \frac{1}{m_1} \frac{\lambda}{\lambda + \sum_{i=1}^{\nu(x)} \beta_n(xi, \lambda)}, \qquad B_n(x) \le \frac{1}{m_1} \beta_n(x, \lambda).$$

For $\lambda < m$,

$$\sum_{|x|=k} B_n(x) \prod_{i=0}^{k-1} A_n(x_i) \le \frac{1}{m_1^{k+1}} \sum_{|x|=k} \beta_n(x,\lambda) \prod_{i=0}^{k-1} \frac{\lambda}{\lambda + \sum_{i=1}^{\nu(x_i)} \beta_n(x_i j,\lambda)} = \frac{\lambda^k}{m_1^k} \frac{1}{m_1} \beta_n(e,\lambda). \quad (3)$$

By (2) and (3), almost surely,

$$0 \le -\beta'_n(e, \lambda) \le \frac{\beta_n(e, \lambda)}{m_1 - \lambda} \le \frac{1}{m_1 - \lambda}, \quad \lambda < m_1.$$

From this, given any small enough $\varepsilon > 0$, we see that, almost surely, as a sequence of functions on $[0, m_1 - \varepsilon]$ $\{(\beta_n(e, \lambda) : \lambda \in [0, m_1 - \varepsilon])\}_{n \ge 1}$ is equi-continuous. Combining this with $\beta_n(e, \lambda) \downarrow \beta(e, \lambda)$ as $n \uparrow \infty$ for all $\lambda \in [0, m)$ almost surely, by the Ascoli–Arzelà theorem, $\{\beta_n(e, \lambda) : \lambda \in [0, m_1 - \varepsilon]\}_{n \ge 1}$ converges uniformly to $(\beta(e, \lambda) : \lambda \in [0, m_1 - \varepsilon])$ almost surely.

Note that, for any vertex $x \in \mathbb{T}$, $(\{(\beta_n(x,\lambda): 0 \le \lambda < m)\}_{n\ge 1}, (\beta(x,\lambda): 0 \le \lambda < m))$ has the same distribution as $(\{(\beta_n(e,\lambda): 0 \le \lambda < m)\}_{n\ge 1}, (\beta(e,\lambda): 0 \le \lambda < m))$. We obtain that, almost surely, for any vertex $x \in \mathbb{T}$, $\{\beta_n(x,\lambda): \lambda \in [0,m_1-\varepsilon]\}_{n\ge 1}$ converges uniformly to $(\beta(x,\lambda): \lambda \in [0,m_1-\varepsilon])$. Hence, by the definitions of $A_n(x)$ and $B_n(x)$, we have that, almost surely, for any vertex x, $A_n(x)$ and $B_n(x)$ converge uniformly in $\lambda \in [0,m_1-\varepsilon]$ to some continuous functions A(x) and B(x) respectively.

Notice (2) and (3). By the dominated convergence theorem, we see that, almost surely, $(\beta'_n(x,\lambda):\lambda\in[0,m_1-\varepsilon])$ converges uniformly to some continuous function $(F_\lambda:\lambda\in[0,m_1-\varepsilon])$. By the dominated convergence theorem again, almost surely, $\int_0^\lambda \beta'_n(e,s)\,\mathrm{d}s$ converges to $\int_0^\lambda F_s\,\mathrm{d}s$, which is also $\beta(e,\lambda)-1$ for all $\lambda\leq m_1-\varepsilon$.

Since ε is arbitrary, $\beta(e, \lambda)$ is almost surely differentiable in $\lambda \in [0, m_1)$. Further, almost surely,

$$0 \le -\beta'(e, \lambda) \le \frac{\beta(e)}{m_1 - \lambda}, \quad \lambda \in [0, m_1).$$

By checking (2) and the definitions of $A_n(x)$ and $B_n(x)$, when taking limits we indeed have, almost surely,

$$0 < -\beta'(e, \lambda) \le \frac{\beta(e)}{m_1 - \lambda}, \quad \lambda \in [0, m_1).$$

By symmetry, we have

$$\ell_{\lambda} = \mathbb{E}\left(\frac{\nu - \lambda}{\nu + 1} \frac{\sum_{i=0}^{\nu} \beta_i}{\lambda - 1 + \sum_{i=0}^{\nu} \beta_i}\right) / \mathbb{E}\left(\frac{\nu + \lambda}{\nu + 1} \frac{\sum_{i=0}^{\nu} \beta_i}{\lambda - 1 + \sum_{i=0}^{\nu} \beta_i}\right).$$

By Lemma 4, each β_i has a derivative in $\lambda \in [0, m_1)$, and so does ℓ_{λ} . Write each β_i' and ℓ_{λ}' for the derivatives in $\lambda \in [0, m_1)$ of β_i and ℓ_{λ} respectively. Then, by straightforward calculus [1], for $\lambda \in [0, m_1)$, $\ell_{\lambda}' < 0$ is equivalent to

$$\mathbb{E}\left(\frac{\nu}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right) \mathbb{E}\left(\frac{1}{\nu+1} \frac{\sum_{i=0}^{\nu} (\beta_{i}+(1-\lambda)\beta_{i}')}{\left(\lambda-1+\sum_{i=0}^{\nu} \beta_{i}\right)^{2}}\right) \\
-\mathbb{E}\left(\frac{1}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right) \mathbb{E}\left(\frac{\nu}{\nu+1} \frac{\sum_{i=0}^{\nu} (\beta_{i}+(1-\lambda)\beta_{i}')}{\left(\lambda-1+\sum_{i=0}^{\nu} \beta_{i}\right)^{2}}\right) \\
< \frac{1}{\lambda} \mathbb{E}\left(\frac{\nu}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right) \mathbb{E}\left(\frac{1}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right). \tag{4}$$

Lemma 5. For a Galton–Watson tree \mathbb{T} without leaves, when $m_1 \ge 2$ (4) is true for $\lambda \in [0, m_1/(1+\sqrt{1-1/m_1})]$.

Proof. Note that, by Lemma 4,

$$0 < -\beta_i'(\lambda) \le \frac{\beta_i(\lambda)}{m_1 - \lambda}, \ \lambda < m_1, \quad i \ge 0.$$

By Lemma 3,

$$\lambda - 1 + \sum_{i=0}^{\nu} \beta_i \ge \lambda - 1 + \left(1 - \frac{\lambda}{m_1}\right) \times (m_1 + 1) = m_1 - \frac{\lambda}{m_1} > m_1 - 1, \quad \lambda < m_1. \quad (5)$$

Then, for any $\lambda < 1$, $0 \le \beta_i(\lambda) + (1 - \lambda)\beta_i'(\lambda) < \beta_i(\lambda)$ and

$$\mathbb{E}\left(\frac{1}{\nu+1}\frac{\sum_{i=0}^{\nu}\beta_{i}}{\lambda-1+\sum_{i=0}^{\nu}\beta_{i}}\right)\mathbb{E}\left(\frac{\nu}{\nu+1}\frac{\sum_{i=0}^{\nu}(\beta_{i}+(1-\lambda)\beta_{i}')}{\left(\lambda-1+\sum_{i=0}^{\nu}\beta_{i}\right)^{2}}\right)\geq0.$$

When $\lambda < 1$.

$$\mathbb{E}\left(\frac{\nu}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right) \mathbb{E}\left(\frac{1}{\nu+1} \frac{\sum_{i=0}^{\nu} (\beta_{i}+(1-\lambda)\beta_{i}')}{\left(\lambda-1+\sum_{i=0}^{\nu} \beta_{i}\right)^{2}}\right) < \frac{1}{m_{1}-\lambda/m_{1}} \mathbb{E}\left(\frac{\nu}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right) \mathbb{E}\left(\frac{1}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right).$$

Since $\lambda < 1$ and $m_1 \ge 2$, $m_1 - \lambda/m_1 > \lambda$ and we obtain that, when $\lambda < 1$,

$$\mathbb{E}\left(\frac{\nu}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right) \mathbb{E}\left(\frac{1}{\nu+1} \frac{\sum_{i=0}^{\nu} (\beta_{i}+(1-\lambda)\beta_{i}')}{(\lambda-1+\sum_{i=0}^{\nu} \beta_{i})^{2}}\right) \\
-\mathbb{E}\left(\frac{1}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right) \mathbb{E}\left(\frac{\nu}{\nu+1} \frac{\sum_{i=0}^{\nu} (\beta_{i}+(1-\lambda)\beta_{i}')}{(\lambda-1+\sum_{i=0}^{\nu} \beta_{i})^{2}}\right) \\
< \frac{1}{\lambda} \mathbb{E}\left(\frac{\nu}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right) \mathbb{E}\left(\frac{1}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right);$$

namely, (4) holds.

When $\lambda = 1$, (4) becomes

$$\mathbb{E}\left(\frac{\nu}{\nu+1}\right)\mathbb{E}\left(\frac{1}{\nu+1}\frac{1}{\sum_{i=0}^{\nu}\beta_{i}}\right) - \mathbb{E}\left(\frac{1}{\nu+1}\right)\mathbb{E}\left(\frac{\nu}{\nu+1}\frac{1}{\sum_{i=0}^{\nu}\beta_{i}}\right) < \mathbb{E}\left(\frac{\nu}{\nu+1}\right)\mathbb{E}\left(\frac{1}{\nu+1}\right),$$

while, by Lemma 3, $\sum_{i=0}^{\nu} \beta_i(1) \ge m_1 - 1/m_1 > 1$, which implies the above inequality. When $m_1 > \lambda > 1$,

$$\beta_i + (1 - \lambda)\beta_i' \le \frac{m_1 - 1}{m_1 - \lambda}\beta_i.$$

Combining this with (5), we obtain, for $1 < \lambda < m_1$,

$$\mathbb{E}\left(\frac{\nu}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right) \mathbb{E}\left(\frac{1}{\nu+1} \frac{\sum_{i=0}^{\nu} (\beta_{i}+(1-\lambda)\beta_{i}')}{\left(\lambda-1+\sum_{i=0}^{\nu} \beta_{i}\right)^{2}}\right) \\
\leq \frac{(m_{1}-1)/(m_{1}-\lambda)}{m_{1}-\lambda/m_{1}} \mathbb{E}\left(\frac{\nu}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right) \mathbb{E}\left(\frac{1}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right).$$

When

$$\frac{(m_1-1)/(m_1-\lambda)}{m_1-\lambda/m_1} \le \frac{1}{\lambda}$$

and $1 < \lambda < m_1$, namely $\lambda \in (1, m_1/(1 + \sqrt{1 - 1/m_1})]$, we have

$$\mathbb{E}\left(\frac{\nu}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right) \mathbb{E}\left(\frac{1}{\nu+1} \frac{\sum_{i=0}^{\nu} (\beta_{i}+(1-\lambda)\beta_{i}')}{\left(\lambda-1+\sum_{i=0}^{\nu} \beta_{i}\right)^{2}}\right) \\
\leq \frac{1}{\lambda} \mathbb{E}\left(\frac{\nu}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right) \mathbb{E}\left(\frac{1}{\nu+1} \frac{\sum_{i=0}^{\nu} \beta_{i}}{\lambda-1+\sum_{i=0}^{\nu} \beta_{i}}\right). \quad (6)$$

Note when $1 < \lambda < m_1, \sum_{i=0}^{\nu} (\beta_i + (1 - \lambda)\beta_i') > \sum_{i=0}^{\nu} \beta_i > 0$ and

$$\mathbb{E}\left(\frac{1}{\nu+1}\frac{\sum_{i=0}^{\nu}\beta_{i}}{\lambda-1+\sum_{i=0}^{\nu}\beta_{i}}\right)\mathbb{E}\left(\frac{\nu}{\nu+1}\frac{\sum_{i=0}^{\nu}(\beta_{i}+(1-\lambda)\beta_{i}')}{\left(\lambda-1+\sum_{i=0}^{\nu}\beta_{i}\right)^{2}}\right)>0.$$

Therefore, combining with (6), we see that for $\lambda \in (1, m_1/(1 + \sqrt{1 - 1/m_1})]$, (4) holds. We have thus finished proving Theorem 1.

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There were no competing interests to declare which arose during the preparation or publication process of this article.

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