

# Monotonicity for $\lambda \leq 1/2$

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The speed  $\ell_\lambda$  of the  $\lambda$ -biased random walk on a Galton–Watson tree is given by

$$(0.1) \quad \ell_\lambda = \mathbb{E} \left[ \frac{(\nu - \lambda)\beta_0}{\lambda - 1 + \sum_{i=0}^{\nu} \beta_i} \right] / \mathbb{E} \left[ \frac{(\nu + \lambda)\beta_0}{\lambda - 1 + \sum_{i=0}^{\nu} \beta_i} \right].$$

The  $(\beta_i, i \geq 0)$  are i.i.d copies of the conductance  $\beta$ , and  $\nu$  is independent of the  $\beta$ 's and is the offspring distribution associated to the Galton-Watson tree.

## 1 The derivative of $\beta$ when $\lambda < 1$

In this section, we write  $\beta_\lambda$  to make the dependency in  $\lambda$  explicit. One way to construct  $\beta_\lambda$  is the following: For  $n \geq 1$ , define  $\beta_{\lambda,n}(x) = 1$  if  $|x| = n$ . Then, for any vertex  $|x| < n$ , define

$$(1.1) \quad \beta_{\lambda,n}(x) := \frac{\sum_{i=1}^{\nu(x)} \beta_{\lambda,n}(xi)}{\lambda + \sum_{i=1}^{\nu(x)} \beta_{\lambda,n}(xi)}.$$

Here,  $xi$  is the  $i$ -th child of  $x$  and  $\nu(x)$  is the number of children of  $x$ . Then,  $\beta_\lambda(e)$  ( $e$  being the root) is the almost sure limit of  $\beta_{\lambda,n}(e)$  as  $n \rightarrow \infty$ . It is easy to check that  $\lambda \rightarrow \beta_{\lambda,n}(x)$  has a continuous derivative for any  $n$  and  $|x| \leq n$ . Write

$$A_n(x) := \frac{\lambda}{(\lambda + \sum_{i=1}^{\nu(x)} \beta_{\lambda,n}(xi))^2}$$
$$B_n(x) := \frac{\sum_{i=1}^{\nu(x)} \beta_{\lambda,n}(xi)}{(\lambda + \sum_{i=1}^{\nu(x)} \beta_{\lambda,n}(xi))^2}.$$

Using the fact that  $\beta_\lambda \geq 1 - \lambda$ , we check that

$$(1.2) \quad A_n(x) \leq \frac{\lambda}{\lambda + \sum_{i=1}^{\nu(x)} \beta_{\lambda,n}(xi)}$$

$$(1.3) \quad B_n(x) \leq \beta_{\lambda,n}(x).$$

Derivating (1.1) yields that for any  $|x| < n$ ,

$$-\beta'_{\lambda,n}(x) = A_n(x) \sum_{i=1}^{\nu(x)} -\beta'_{\lambda,n}(xi) + B_n(x)$$

where  $\beta'_{\lambda,n}(x)$  is the derivative in  $\lambda$  of  $\lambda \rightarrow \beta_{\lambda,n}(x)$ . We get that

$$(1.4) \quad -\beta'_{\lambda,n}(e) = \sum_{k=0}^{n-1} \sum_{|x|=k} B_n(x) \prod_{i=0}^{k-1} A_n(x_i)$$

where  $x_i$  is the ancestor at generation  $i$  of  $x$ . Similarly, in view of (1.1), we have that for any  $k \in [0, n-1]$ ,

$$\beta_{\lambda,n}(e) = \sum_{|x|=k} \beta_{\lambda,n}(x) \prod_{i=0}^{k-1} \frac{1}{\lambda + \sum_{j=1}^{\nu(x_i)} \beta_{\lambda,n}(x_{ij})}$$

( $x_{ij}$  is the  $j$ -th child of the ancestor  $x_i$ ). From (1.2) and (1.3), we deduce that for any  $k \in [0, n-1]$ ,

$$(1.5) \quad \sum_{|x|=k} B_n(x) \prod_{i=0}^{k-1} A_n(x_i) \leq \sum_{|x|=k} \beta_{\lambda,n}(x) \prod_{i=0}^{k-1} \frac{\lambda}{\lambda + \sum_{j=1}^{\nu(x_i)} \beta_{\lambda,n}(x_{ij})} = \lambda^k \beta_{\lambda,n}(e).$$

Let us go back to (1.4). Observe that, for each vertex  $x$ ,  $A_n(x)$  and  $B_n(x)$  converge as  $n \rightarrow \infty$ , this uniformly in  $\lambda \in (0, 1 - \varepsilon)$  (for this notice that  $\beta_{\lambda,n}(x) - \beta_{\lambda}(x)$  is less than the probability that the random walk starting at level  $n$  touches the vertex  $x$ , then use coupling with a 1-d biased random walk). We deduce by dominated convergence (see (1.5)) that  $\beta'_{\lambda,n}(e)$  converges uniformly in  $\lambda \in (0, 1 - \varepsilon)$  as  $n \rightarrow \infty$  to some limit, say  $F_{\lambda}$ . In particular  $\lambda \rightarrow F_{\lambda}$  is continuous on  $(0, 1 - \varepsilon)$ . Moreover, summing (1.5) over  $k \in [0, n-1]$ , we have that

$$|\beta'_{\lambda,n}(e)| \leq \frac{\beta_{\lambda,n}(e)}{1 - \lambda}.$$

By dominated convergence  $\int_0^{\lambda} \beta'_{s,n}(e) ds$  converges to  $\int_0^{\lambda} F_s ds$  which is also  $\beta_{\lambda}(e) - 1$ . Hence  $\beta_{\lambda}(e)$  is differentiable for  $\lambda \in (0, 1)$  and

$$(1.6) \quad |\beta'_{\lambda}(e)| \leq \frac{\beta_{\lambda}(e)}{1 - \lambda}.$$

## 2 The derivative of the speed

By symmetry, we can rewrite (0.1) as

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

Beware that we are back to the old notation where the dependency in  $\lambda$  is hidden. We write  $\beta'$  for the derivative in  $\lambda$  of  $\beta$ . We compute that  $f'(\lambda)$  is

$$-\mathbb{E} \left[ \frac{1}{\nu + 1} \frac{\sum_{i=0}^{\nu} \beta_i}{\lambda - 1 + \sum_{i=0}^{\nu} \beta_i} \right] - \mathbb{E} \left[ \frac{\nu - \lambda}{\nu + 1} \frac{\sum_{i=0}^{\nu} (\beta_i + (1 - \lambda)\beta'_i)}{(\lambda - 1 + \sum_{i=0}^{\nu} \beta_i)^2} \right]$$

and  $g'(\lambda)$  is

$$\mathbb{E} \left[ \frac{1}{\nu + 1} \frac{\sum_{i=0}^{\nu} \beta_i}{\lambda - 1 + \sum_{i=0}^{\nu} \beta_i} \right] - \mathbb{E} \left[ \frac{\nu + \lambda}{\nu + 1} \frac{\sum_{i=0}^{\nu} (\beta_i + (1 - \lambda)\beta'_i)}{(\lambda - 1 + \sum_{i=0}^{\nu} \beta_i)^2} \right].$$

We have  $\ell'_\lambda = \frac{f'(\lambda)g(\lambda) - f(\lambda)g'(\lambda)}{g(\lambda)^2}$ . We find that  $\ell'_\lambda \leq 0$  is equivalent with

$$(2.1) \quad \mathbb{E} \left[ \frac{\nu}{\nu + 1} \frac{\sum_{i=0}^{\nu} \beta_i}{\lambda - 1 + \sum_{i=0}^{\nu} \beta_i} \right] \mathbb{E} \left[ \frac{1}{\nu + 1} \frac{\sum_{i=0}^{\nu} (\beta_i + (1 - \lambda)\beta'_i)}{(\lambda - 1 + \sum_{i=0}^{\nu} \beta_i)^2} \right]$$

$$(2.2) \quad - \mathbb{E} \left[ \frac{1}{\nu + 1} \frac{\sum_{i=0}^{\nu} \beta_i}{\lambda - 1 + \sum_{i=0}^{\nu} \beta_i} \right] \mathbb{E} \left[ \frac{\nu}{\nu + 1} \frac{\sum_{i=0}^{\nu} (\beta_i + (1 - \lambda)\beta'_i)}{(\lambda - 1 + \sum_{i=0}^{\nu} \beta_i)^2} \right]$$

$$(2.3) \quad \leq \frac{1}{\lambda} \mathbb{E} \left[ \frac{\nu}{\nu + 1} \frac{\sum_{i=0}^{\nu} \beta_i}{\lambda - 1 + \sum_{i=0}^{\nu} \beta_i} \right] \mathbb{E} \left[ \frac{1}{\nu + 1} \frac{\sum_{i=0}^{\nu} \beta_i}{\lambda - 1 + \sum_{i=0}^{\nu} \beta_i} \right]$$

We know that  $\beta + (1 - \lambda)\beta' \geq 0$  by (1.6). Hence the expectations in (2.2) are positive. Since  $\beta' \leq 0$ , (2.1) is less than (taking  $\lambda < 1$ )

$$\begin{aligned} & \mathbb{E} \left[ \frac{\nu}{\nu + 1} \frac{\sum_{i=0}^{\nu} \beta_i}{\lambda - 1 + \sum_{i=0}^{\nu} \beta_i} \right] \mathbb{E} \left[ \frac{1}{\nu + 1} \frac{\sum_{i=0}^{\nu} \beta_i}{(\lambda - 1 + \sum_{i=0}^{\nu} \beta_i)^2} \right] \\ & \leq \frac{1}{1 - \lambda} \mathbb{E} \left[ \frac{\nu}{\nu + 1} \frac{\sum_{i=0}^{\nu} \beta_i}{\lambda - 1 + \sum_{i=0}^{\nu} \beta_i} \right] \mathbb{E} \left[ \frac{1}{\nu + 1} \frac{\sum_{i=0}^{\nu} \beta_i}{\lambda - 1 + \sum_{i=0}^{\nu} \beta_i} \right] \end{aligned}$$

which is less than (2.3) if  $\lambda \leq 1/2$ .