

































By forward search,  $\pi(s, v) = \pi^f(s, v) + \sum_{u \in V} r^f(s, u) \pi(u, v)$ , it follows that  $\sum_{u \in V} r^f(s, u) \pi(u, v) \leq \pi(s, v)$ , and thus

$$\begin{aligned} E[X_i^2] &\leq 2r_{sum}^f (r_{max}^b)^2 \sum_{v \in V} \left( \frac{d_{in}(v)}{\pi(s, v)} \cdot \pi(s, v) \right) \\ &= 2r_{sum}^f (r_{max}^b)^2 \sum_{v \in V} d_{in}(v) = 2r_{sum}^f (r_{max}^b)^2 \cdot m. \end{aligned}$$

Therefore, we have  $E[Y] \leq 2mr_{sum}^f (r_{max}^b)^2$ . Let  $z = \frac{8(r_{sum}^f)^2 \log n}{n_r}$ , since each  $X_i^2 \leq (r_{sum}^f)^2$ , by Chernoff inequality, the probability that  $Y \leq 2E[Y] + z \leq 4mr_{sum}^f (r_{max}^b)^2 + \frac{8(r_{sum}^f)^2 \log n}{n_r}$  is at most

$$\begin{aligned} &\exp\left(-n_r (E[Y] + z)^2 / (r_{sum}^f)^2 \cdot \left(\frac{8}{3}E[Y] + \frac{2}{3}z\right)\right) \\ &\leq \exp\left(-\frac{3}{8}n_r \cdot (E[Y] + z) / (r_{sum}^f)^2\right) \leq \exp\left(-\frac{3n_r \log n}{n_r}\right) \leq \frac{1}{n^3}, \end{aligned}$$

and the lemma follows.  $\square$

PROOF OF LEMMA 4.8. By Lemma 4.7, we need to show that if at some iteration, the number of random walks  $n_r = \frac{cmr_{sum}^f (r_{max}^b)^2}{gap_\rho^2} \log n$  for constant  $c$ , we have  $\beta(s, t) \leq gap_\rho/4$  for any  $t \in C$ . Recall that

$$\beta(s, t) = \sqrt{\frac{2\bar{\sigma}^2(s, t) \ln(3n^3 \log^2 n_r)}{n_r} + \frac{3r_{sum}^f \ln(3n^3 \log^2 n_r)}{n_r}}. \quad (3)$$

By the assumption that  $r_{max}^b \geq \sqrt{\frac{gap_\rho}{m}}$ , we have

$$n_r \geq \frac{cmr_{sum}^f (r_{max}^b)^2}{gap_\rho^2} \log n \geq \frac{cmr_{sum}^f \cdot \frac{gap_\rho}{m}}{gap_\rho^2} \log n \geq \frac{cr_{sum}^f \log n}{gap_\rho},$$

and thus we can bound the the second term of equation (3) as

$$\frac{6r_{sum}^f \ln(3n^3 \log^2 n_r)}{n_r} \leq gap_\rho \frac{6 \log(3n^3 \log^2 n_r)}{c \log n} \leq gap_\rho/8. \quad (4)$$

For  $c$  sufficiently large. The last inequality is due to  $n \geq \log \frac{m}{gap_\rho}$ .

To bound the first term of equation (3), we observe that by Lemma 4.1, the empirical variance  $\bar{\sigma}^2(s, t) \leq 2mr_{sum}^f (r_{max}^b)^2 + \frac{8(r_{sum}^f)^2 \log n}{n_r}$  with probability at least  $1 - 1/n^3$ . If  $2mr_{sum}^f (r_{max}^b)^2 \leq \frac{8(r_{sum}^f)^2 \log n}{n_r}$ , we have  $\bar{\sigma}^2(s, t) \leq \frac{16(r_{sum}^f)^2 \log n}{n_r}$  and the first term of equation (3) can be bounded by

$$\sqrt{\frac{2\bar{\sigma}^2(s, t) \ln(3n^3 \log^2 n_r)}{n_r}} \leq \sqrt{\frac{16(r_{sum}^f)^2 \log n}{n_r} \ln(3n^3 \log^2 n_r)} \leq \frac{1}{8} gap_\rho.$$

The last inequality is due to inequality (4). On the other hand, if

$2mr_{sum}^f (r_{max}^b)^2 \geq \frac{8(r_{sum}^f)^2 \log n}{n_r}$ , we have  $\bar{\sigma}^2(s, t) \leq 4mr_{sum}^f (r_{max}^b)^2$ , and thus

$$\sqrt{\frac{2\bar{\sigma}^2(s, t) \ln(3n^3 \log^2 n_r)}{n_r}} \leq \sqrt{\frac{8mr_{sum}^f (r_{max}^b)^2 \ln(3n^3 \log^2 n_r)}{n_r}}$$

$$= \sqrt{\frac{8mr_{sum}^f (r_{max}^b)^2 \ln(3n^3 \log^2 n_r)}{\frac{cmr_{sum}^f (r_{max}^b)^2}{gap_\rho^2} \log n}} \leq gap_\rho \sqrt{\frac{24 \log n \log n_r}{c \log n}} \leq \frac{gap_\rho}{8}$$

for  $c$  sufficiently large. Thus we have  $\beta(s, t) \leq gap_\rho/4$  for  $c$  sufficiently large, and the Lemma follows.  $\square$

## C.8 Proof of Theorem 4.9 and Theorem 4.10

PROOF. Recall that at the  $i$ -th iteration, we have  $r_{max}^f = \frac{1}{2^i m}$  and  $r_{max}^b = 1/2^i \sqrt{m}$  and walk number  $n_r = c2^i n \log n / |C|$ . The total query cost is  $cost(forward) + cost(backward) + cost(walk)$ , which can be bounded by

$$O\left(\frac{1}{r_{max}^f}\right) + O\left(\frac{\sqrt{m}}{r_{max}^b}\right) + n_r |C| = O\left(2^i m + c2^i n \log n\right). \quad (5)$$

For worst-case graph, if we can prove that TopPPR stops before iteration when  $2^i = 1/\sqrt{gap_\rho}$ , then the total query cost is bounded

by  $O\left(\frac{m+n \log n}{\sqrt{gap_\rho}}\right)$  and Theorem 4.9 follows. More precisely, we have  $r_{max}^f = \sqrt{gap_\rho}/m$ ,  $r_{max}^b = \sqrt{gap_\rho}/m$ . By Lemma 4.8 and  $r_{max}^b = \sqrt{gap_\rho}/m$ , we have  $n_r \geq \frac{c2^i n \log n}{|C|} \geq \frac{cn \log n}{\sqrt{gap_\rho} \cdot |C|} \geq \frac{c \log n}{\sqrt{gap_\rho}}$ . The last inequality uses the fact that  $|C| \leq n$ . Therefore, we have  $r_{max}^f (r_{max}^b)^2 = \frac{(\sqrt{gap_\rho})^3}{m^2}$  and  $n_r \geq \frac{c \log n}{\sqrt{gap_\rho}} \geq \frac{cm^2 (\sqrt{gap_\rho})^3}{m^2} \log n \geq \frac{cmr_{sum}^f (r_{max}^b)^2}{gap_\rho^2} \log n$ . This proves that the

number of walks  $n_r = \Omega\left(\frac{cmr_{sum}^f (r_{max}^b)^2}{gap_\rho^2} \log n\right)$ , and by Lemma 4.7, the algorithm stops at this iteration.

Similarly, for power law graph, we can prove that TopPPR stops before iteration when  $2^i = \frac{1}{\sqrt{gap_\rho}} \cdot \frac{k^{\frac{1}{4}}}{n^{\frac{1}{4}}}$ , under Assumption 1. Thus Theorem 4.10 follows from equation 5.  $\square$

## C.9 Proof of Lemma 5.1

PROOF. We define two types of random walks. A non-stop random walk from  $s$  is a traversal of  $G$  that starts from  $s$  and, at each step, proceeds to a randomly selected out-neighbor of the current node. An  $(1 - \alpha)$ -walk is a random walk in which at each step the random walk proceeds to the next node with probability  $1 - \alpha$  and terminates with probability  $\alpha$ .

Let  $p_i(s, t)$  denote the probability that a non-stop random walk from  $s$  visits  $t$  in the  $i$  step. We have  $\pi(s, t) = \sum_{i=0}^{\infty} \alpha(1 - \alpha)^i p_i(s, t)$ . To see this, note that  $\alpha(1 - \alpha)^i p_i(s, t)$  is the probability that a  $(1 - \alpha)$ -walk starts at  $s$  and terminates at  $t$  using  $i$  steps. Summing  $i$  over 0 to  $\infty$  and the equation follows. For  $(\sqrt{1 - \alpha})$ -walk, recall that  $(\sqrt{1 - \alpha})^i p_i(s, t)$  is the probability that the  $\sqrt{1 - \alpha}$ -walk visits  $t$  at the  $i$ -th step, and  $(\sqrt{1 - \alpha})^i$  is the value added to  $\hat{\pi}(s, t)$ , we have

$$E[\hat{\pi}(s, t)] = \sum_{i=0}^{\infty} \alpha(\sqrt{1 - \alpha})^i \cdot (\sqrt{1 - \alpha})^i p_i(s, t) = \pi(s, t),$$

and the Lemma follows.  $\square$