

A. Technical Material

Theorem 4. *For any ϵ , there exists an n such that $L_{\min}(T^n) < \epsilon$, and any algorithm must sample at least $(32\Delta L_{\min})^{-1}$ observations in order to reconstruct the edge set of T^n with probability at least $7/8$.*

Let P_a denote the distribution when T_n^a is the underlying network. Let P_b denote the distribution when T_n^b is the underlying network. We show that $\mathbf{d}_{\text{KL}}(P_a \parallel P_b) \leq 4\Delta L_{\min}$ where $p_{(u,v)} = q_u = \Delta$. Theorem 4 then follows by Pinsker's inequality. Specifically, consider any algorithm A that samples fewer than m times, and let \mathcal{E} be the event that the algorithm determines that the edge (z_0, a) exists. Pinsker's inequality implies that $|P_a(\mathcal{E}) - P_b(\mathcal{E})| \leq \sqrt{2m\Delta L_{\min}}$. Thus, so long as $m < \frac{1}{32\Delta L_{\min}}$, either $P_a(\mathcal{E}) < 1/2$ or $P_b(\mathcal{E}) \geq 1/4$. Ultimately this implies that the algorithm A must incorrectly reconstruct the network with probability at least $1/8$.

For a collection of vertices $U \subset V$, let $I(U) \in \{0, 1\}^{|U|}$ be a random vector indicating whether each u is infected. In other words $I(U)_u = \mathbf{1}[u \in A]$. For a distribution P over random variables X, Y , we use the notation $P(X)$ to denote the marginal distribution on X and $P(X \mid Y)$ to denote the conditional distribution on X , given Y . The key lemmas for establishing the lower bound are the following.

Lemma 6. $\mathbf{d}_{\text{KL}}(P_a \parallel P_b) \leq 4p^2(1-q)^2 P_a(z_0 \notin A) \leq 4p^2(1-q)^3(1-pq)^n$

Proof. Let $Z = \{a, b, z_0, z_1\}$.

$$\begin{aligned} \mathbf{d}_{\text{KL}}(P_a \parallel P_b) &= \mathbf{d}_{\text{KL}}(P_a(I(Z)) \parallel P_b(I(Z))) \\ &\quad + \mathbf{d}_{\text{KL}}(P_a((S, A) \mid I(Z)) \parallel P_b((S, A) \mid I(Z))) \\ &= \mathbf{d}_{\text{KL}}(P_a(I(Z)) \parallel P_b(I(Z))) + 0 \\ &= \mathbf{d}_{\text{KL}}(P_a(I(z_0, z_1)) \parallel P_b(I(z_0, z_1))) \\ &\quad + \mathbf{d}_{\text{KL}}(P_a(I(a, b) \mid I(z_0, z_1)) \parallel P_b(I(a, b) \mid I(z_0, z_1))) \\ &= \mathbf{d}_{\text{KL}}(P_a(I(a, b) \mid I(z_0, z_1)) \parallel P_b(I(a, b) \mid I(z_0, z_1))) \end{aligned}$$

Where the above equalities follow by application of the chain rule of relative entropy; observing that (S, A) is equally distributed under P_a and P_b , given Z ; chain rule; and the observation that the marginal distribution on $I(z_0, z_1)$ is identical under both P_a and P_b .

Conditioned on $I(z_0, z_1) = (0, 0)$ (both z_0 and z_1 are uninfected), the distribution on $I(a, b)$ is identical under both P_a and P_b . This is also true when $I(z_0, z_1) = (1, 1)$. Therefore:

$$\begin{aligned} \mathbf{d}_{\text{KL}}(P_a \parallel P_b) &= \sum_{x \in \{0, 1\} \times \{0, 1\}} P_a(I(z_0, z_1) = x) \\ &\quad \mathbf{d}_{\text{KL}}(P_a(I(a, b) \mid I(z_0, z_1) = x) \parallel P_b(I(a, b) \mid I(z_0, z_1) = x)) \\ &= P_a(I(z_0, z_1) = (0, 1)) \mathbf{d}_{\text{KL}}(P_a(I(a, b) \mid I(z_0, z_1) = (0, 1)) \\ &\quad \parallel P_b(I(a, b) \mid I(z_0, z_1) = (0, 1))) \\ &\quad + P_a(I(z_0, z_1) = (1, 0)) \mathbf{d}_{\text{KL}}(P_a(I(a, b) \mid I(z_0, z_1) = (1, 0)) \\ &\quad \parallel P_b(I(a, b) \mid I(z_0, z_1) = (1, 0))) \end{aligned}$$

Under P_a , conditioned on $I(z_0, z_1) = (0, 1)$, the vertex a is infected with probability q , while the vertex b is infected

independently with probability $q + (1-q)p$. While under P_b , conditioned on $I(z_0, z_1) = (0, 1)$, the vertex a is infected with probability $q + (1-q)p$, while b is independently infected with probability q . Thus, $\mathbf{d}_{\text{KL}}(P_a(I(a, b) \mid I(z_0, z_1) = (0, 1)) \parallel P_b(I(a, b) \mid I(z_0, z_1) = (0, 1))) \leq 2((1-q)p)^2$, where $((1-q)p)^2$ upper-bounds the KL-divergence between two Bernoullis whose parameters differ by $(1-q)p$.

A similar argument when $I(a, b) = (1, 0)$ lets us conclude that:

$$\begin{aligned} \mathbf{d}_{\text{KL}}(P_a \parallel P_b) &\leq 2P_a(I(z_0, z_1) = (0, 1))((1-q)p)^2 \\ &\quad + 2P_a(I(z_0, z_1) = (1, 0))((1-q)p)^2 \\ &\leq 2P_a(z_0 \notin A)((1-q)p)^2 + 2P_a(z_1 \notin S)((1-q)p)^2 \\ &= 4P_a(z_0 \notin A)((1-q)p)^2 \end{aligned}$$

Let \mathcal{E} be the event that (1) $z_0 \notin S$ (2) for each edge $(x_i^{(0)}, z_0)$ either $x_i^{(0)} \notin S$ or $(x_i^{(0)}, z_0)$ was inactive, and (3) either $a \notin S$ or (a, z_0) was inactive. $z_0 \notin A$ implies \mathcal{E} . Therefore:

$$\begin{aligned} \mathbf{d}_{\text{KL}}(P_a \parallel P_b) &\leq 4P_a(z_0 \notin A)((1-q)p)^2 \\ &\leq 4P_a(\mathcal{E})(1-q)^2 p^2 \\ &\leq 4(1-q)^3 p^2 ((1-q) + q(1-p))^n \\ &= 4(1-q)^3 p^2 (1-pq)^n \end{aligned}$$

□

Lemma 7. *For the tree T_a^n , $p(1-p)(1-q)^2(1-pq)^n \leq L_{\min} \leq (1-pq)^{n-1}$.*

Proof. Recall from Section 4.1 that $\phi(u, v)$ is the probability that the path $u-v$ is active, and $\psi(u, v)$ is the probability that there are no active tributaries for $u-v$.

Appealing to Lemma 3, we see that for any edge $(u, v) \in T_a^n$, $L(v \mid u) = \phi(u, v)\psi(u, v) = p\psi(u, v)$. For the upper bound, consider the edge (z_0, a) . $L_{\min} \leq L(z_0 \mid a) = \phi(z_0, a)\psi(z_0, a) \leq \psi(z_0, a) \leq [1-q + q(1-p)]^{n-1} = (1-pq)^{n-1}$. The final inequality follows from the fact that z_0-a having no infecting tributaries for z_0-a implies that, for each $x_i^{(0)}$, either $x_i^{(0)}$ was not seeded or it was seeded, but the edge $(x_i^{(0)}, z_0)$ was not active.

For the lower bound, note that $\psi(\cdot, \cdot)$ is minimized for the edge (z_0, z) . Let \mathcal{E} be the event that none of the edges $(x_i^{(0)}, z_0)$, (a, z_0) are infecting tributaries for z_0-z , $z_0, z \notin S$, and the edge (z, z_1) is inactive. \mathcal{E} implies that there are no infecting tributaries for z_0, z . Therefore $\psi(z_0, z) \geq P_a(\mathcal{E}) = (1-pq)^n(1-q)^2(1-p)$, and therefore $L_{\min} = p\psi(z_0, z) \geq p(1-p)(1-q)^2(1-pq)^n$. □

Let $p = q = \Delta$ in the previous construction. Combining the previous Lemmas, we can conclude that $\mathbf{d}_{\text{KL}}(P_a \parallel P_b) \leq 4\Delta L_{\min}$ and this finishes the proof.