APPENDIX TO Non-bifurcating phylogenetic tree inference via the adaptive LASSO

7.1. Lemmas. Here we perform further theoretical development to establish the main theorems. We remind the reader that we will continue to assume Assumptions 2.1 and 2.2. The following lemma allows gives a lower bound on the fraction of sites with state assignments in a given set. It will prove useful to obtain an upper bound on the likelihood.

**Lemma 7.1.** For any non-empty set A of single-site state assignments to the leaves, we define

$$k_A = |\{i : \mathbf{Y}^i \in A\}|$$

There exist  $c_3 > 0, c_4(\delta, n) > 0$  such that for all k, we have

$$\frac{k_A}{k} \ge c_3 - \frac{c_4}{\sqrt{k}} \qquad \forall A \neq \emptyset$$

with probability at least  $1 - \delta$ .

Proof of Lemma 7.1. Since the tree distance between any pairs of leaves of the true tree is strictly positive, there exists  $c_3 > 0$  such that  $P_{q^*}(\psi) \ge c_3$  for all state assignments  $\psi$ .

Using Hoeffding's inequality, for any state assignment  $\psi$ , we have

$$\mathbb{P}\left[\left|\frac{k_{\{\psi\}}}{k} - P_{q^*}(\psi)\right| \ge t\right] \le 2e^{-2kt^2}.$$

We deduce that

$$\mathbb{P}\left[\exists \psi \text{ such that } \left|\frac{k_{\{\psi\}}}{k} - P_{q^*}(\psi)\right| \ge t\right] \le 2e^{-2kt^2} \cdot 4^N.$$

For any given  $\delta > 0$ , by choosing

$$c_4(\delta, N) = \sqrt{\frac{\log(1/\delta) + (2N+1)\log 2}{2}}$$

and  $t = c_4(\delta, N)/\sqrt{k}$  we have

$$\left|\frac{k_{\{\psi\}}}{k} - P_{q^*}(\psi)\right| \le \frac{c_4(\delta, N)}{\sqrt{k}} \qquad \forall \psi$$

with probability at least  $1 - \delta$ . This proves the Lemma.

**Lemma 7.2** (Generalization bound). There exists a constant  $C(\delta, n, Q, \eta, g_0, \mu) > 0$  such that for any  $k \geq 3$ ,  $\delta > 0$ , we have:

$$\left|\frac{1}{k}\ell_k(q) - \phi(q)\right| \le C\left(\frac{\log k}{k}\right)^{1/2} \qquad \forall q \in \mathcal{T}(\mu)$$

with probability greater than  $1 - \delta$ .

*Proof.* Note that for  $q \in \mathcal{T}(\mu)$ ,  $0 \ge \log P_q(\psi) \ge -\mu$  for all state assignments  $\psi$ . By Hoeffding's inequality,

$$\mathbb{P}\left[\left|\frac{1}{k}\ell_k(q) - \phi(q)\right| \ge y/2\right] \le 2\exp\left(-\frac{y^2k}{2\mu^2}\right).$$

For each  $q \in \mathcal{T}(\mu)$ , k > 0, and y > 0, define the events

$$A(q,k,y) = \left\{ \left| \frac{1}{k} \ell_k(q) - \phi(q) \right| > y/2 \right\}$$

and

$$B(q,k,y) = \left\{ \exists q' \in \mathcal{T}(\mu) \text{ such that } \|q'-q\|_2 \le \frac{y}{4c_2} \text{ and } \left|\frac{1}{k}\ell_k(q) - \phi(q)\right| > y \right\}$$

then  $B(q, k, y) \subset A(q, k, y)$  by the triangle inequality, (3.3), and (3.4). Let

$$y = \sqrt{\frac{C\log k}{k}}$$

Since  $\mathcal{T}(\mu)$  is a subset of  $\mathbb{R}^{2N-3}$ , there exist  $C_{2N-3} \geq 1$  and a finite set  $\mathcal{H} \subset \mathcal{T}(\mu)$ such that

$$\mathcal{T}(\mu) \subset \bigcup_{q \in \mathcal{H}} V(q, \epsilon)$$
 and  $|\mathcal{H}| \le C_{2N-3}/\epsilon^{2N-3}$ 

where  $\epsilon = y/(4c_2)$ ,  $V(q,\epsilon)$  denotes the open ball centered at q with radius  $\epsilon$ , and  $|\mathcal{H}|$  denotes the cardinality of  $\mathcal{H}$ . By a simple union bound, we have

$$\mathbb{P}\left[\exists q \in \mathcal{H} : \left|\frac{1}{k}\ell_k(q) - \phi(q)\right| > y/2\right] \le 2\exp\left(-\frac{y^2k}{2\mu^2}\right)C_{2N-3}/\epsilon^{2N-3}.$$

Using the fact that  $B(q, k, y) \subset A(q, k, y)$  for all  $q \in \mathcal{H}$ , we deduce

$$\mathbb{P}\left[\exists q \in \mathcal{T}(\mu) : \left|\frac{1}{k}\ell_k(q) - \phi(q)\right| > y\right] \le 2\exp\left(-\frac{y^2k}{2\mu^2}\right)C_{2N-3}/\epsilon^{2N-3}.$$

To complete the proof, we need to chose C in such a way that

$$C_{2N-3}\left(\frac{4\sqrt{k}g_0c_2}{\sqrt{C\log k}}\right)^{2N-3} \times 2\exp\left(-\frac{C\log k}{2\mu^2}\right) \leq \delta.$$

Since  $k \geq 3$  and  $C \geq 1$ , the inequality is valid if

$$C_{2N-3} \left(4g_0 c_2\right)^{2N-3} \times 2k^{\frac{2N-3}{2} - \frac{C}{2\mu^2}} \leq \delta$$

and can be obtained if

$$\frac{2N-3}{2} - \frac{C}{2\mu^2} < 0, \quad \text{ and } \quad C_{2N-3} \left(4g_0c_2\right)^{2N-3} \times 2 \cdot 3^{\frac{2N-3}{2} - \frac{C}{2\mu^2}} \leq \delta.$$

In other words, we need to choose C such that

$$C \ge 2\mu^2 \left( \log(1/\delta) + \log C_{2N-3} + (2N-3)\log(4\sqrt{3}g_0c_2) \right).$$

This completes the proof.

## 7.2. Proofs of main theorems.

Proof of Theorem 3.10. By definition of the estimator, we have

$$-\frac{1}{k}\ell_k(q^{k,R_k}) + \lambda_k R_k(q^{k,R_k}) \le -\frac{1}{k}\ell_k(q^*) + \lambda_k R_k(q^*)$$

which is equivalent to  $U_k(q^{k,R_k}) \leq \lambda_k R_k(q^*) - \lambda_k R_k(q^{k,R_k})$ . We have  $q^{k,R_k} \in \mathcal{T}(\mu)$  with probability at least  $1 - 2\delta$  from Lemma 3.9 for k sufficiently large. Therefore by Lemma 3.6,

$$\mathbb{E}[U_k(q^{k,R_k})] \le \frac{1}{k} \quad \text{or} \quad \frac{1}{2} \mathbb{E}[U_k(q^{k,R_k})] \le U_k(q^{k,R_k}) + \frac{C\log k}{k^{2/\beta}},$$

 $\mathbf{2}$ 

with probability at least  $1 - 3\delta$ . The second case implies that

$$\begin{aligned} \frac{c_1^{\beta}}{2} \| q^{k,R_k} - q^* \|_2^{\beta} &\leq \frac{1}{2} \mathbb{E}[U_k(q^{k,R_k})] \\ &\leq \lambda_k R_k(q^*) - \lambda_k R_k(q^{k,R_k}) + \frac{C\log k}{k^{2/\beta}} \leq \frac{C\log k}{k^{2/\beta}} + \lambda_k R_k(q^*) \end{aligned}$$

while for the first case, we have

$$\frac{c_1^{\beta}}{2} \| q^{k,R_k} - q^* \|_2^{\beta} \le \mathbb{E}[U_k(q^{k,R_k})] \le \frac{1}{k} \le \frac{C\log k}{k^{2/\beta}} + \lambda_k R_k(q^*)$$

since  $\beta \geq 2$  and  $C \geq 1$ . This demonstrates (3.7).

If the additional assumption (3.6) is satisfied, we also have

$$\|q^{k,R_k} - q^*\|_2^{\beta} \le \frac{C'\log k}{k^{2/\beta}} + C_3\lambda_k\|q^{k,R_k} - q^*\|_2.$$

Using Lemma 3.7 with

$$\nu = 1/\beta, \qquad x = \|q^{k,R_k} - q^*\|_2^{\beta}, \qquad a = C_3 \lambda_k \qquad \text{and} \qquad b = \frac{C' \log k}{k^{2/\beta}},$$

we obtain

$$x \le C_1 a^{1/(1-\nu)} + C_2 b_2$$

which implies

$$\|q^{k,R_k} - q^*\|_2^{\beta} \le C'(\delta,C_3) \left(\frac{\log k}{k^{2/\beta}} + \lambda_k^{\beta/(\beta-1)}\right).$$

This completes the proof.

*Proof of Theorem* 3.11. We first note that by Theorem 3.10, the estimator  $q^{k,R_k}$  is consistent, which guarantees  $\lim_{k\to\infty} q^{k,R_k} = q^*$  almost surely. Thus

$$\lim_{k \to \infty} S_k(q^*) = \lim_{k \to \infty} \sum_{q_i^* \neq 0} (q_i^*)^{1-\gamma} < \infty.$$

The hypotheses of this theorem imply that  $\lambda_k \to 0$  and thus by Theorem 3.10, we also deduce that  $q^{k,S_k}$  is also a consistent estimator. This validates (i).

To establish topological consistency under (ii), we divide the proof into two steps. As the first step, we prove that  $\lim_k \mathbb{P}(\mathcal{A}(q^*) \subset \mathcal{A}(q^{k,S_k})) = 1$ . If  $q_{i_0}^* = 0$  for some  $i_0$ , then from Theorem 3.10, we have

$$q_{i_0}^{k,R_k} \leq C'(\delta) \left(\frac{\log k}{k^{2/\beta}} + \lambda_k^{\beta/(\beta-1)}\right)^{1/\beta} \qquad \forall k$$

with probability at least  $1 - \delta$ . By the definition of  $w_{k,i_0}$ , we have

$$\lim_{k \to \infty} \alpha_k w_{k,i_0} \geq \lim_{k \to \infty} \alpha_k (C'(\delta))^{-\gamma} \left( \frac{\log k}{k^{2/\beta}} + \lambda_k^{\beta/(\beta-1)} \right)^{-\gamma/\beta}$$
$$= (C'(\delta))^{-\gamma} \lim_{k \to \infty} \left( \frac{\log k}{\alpha_k^{\beta/\gamma} k^{2/\beta}} + \alpha_k^{-\beta/\gamma} \lambda_k^{\beta/(\beta-1)} \right)^{-\gamma/\beta}$$

which goes to infinity since by the hypotheses of the Theorem

$$\alpha_k^{\beta/\gamma} \succ \frac{\log k}{k^{2/\beta}}$$
 and  $\alpha_k^{\beta/\gamma} \succ \lambda_k^{\beta/(\beta-1)}$ 

Since  $\delta > 0$  is arbitrary, we deduce that  $\lim_{k\to\infty} \alpha_k w_{k,i_0} = \infty$  with probability one.

Now for any branch length vector q, we define f(q) as the vector obtained from q by setting the  $i_0$  component of q to 0. By definition of the estimator  $q^{k,S_k}$ , we have

$$-\frac{1}{k}\ell_k(q^{k,S_k}) + \alpha_k \sum_i w_{k,i} q_i^{k,S_k} \le -\frac{1}{k}\ell_k(f(q^{k,S_k})) + \alpha_k \sum_i w_{k,i}[f(q^{k,S_k})]_i$$

or equivalently

$$\alpha_k w_{k,i_0} q_{i_0}^{k,S_k} \le \frac{1}{k} \ell_k(q^{k,S_k}) - \frac{1}{k} \ell_k(f(q^{k,S_k})).$$

Lemma 3.8 establishes that there exist,  $\mu^* > 0$  and a neighborhood V of  $q^*$  in  $\mathcal{T}$  such that  $V \subset \mathcal{T}(\mu^*)$ . Since the estimator  $q^{k,S_k}$  is consistent and  $q_{i_0}^* = 0$ , we can assume that both  $q^{k,S_k}$  and  $f(q^{k,S_k})$  belong to  $\mathcal{T}(\mu^*)$  with k large enough. Thus, from Lemma 3.5, we have

$$\left|\frac{1}{k}\ell_k(q^{k,S_k}) - \frac{1}{k}\ell_k(f(q^{k,S_k}))\right| \le c_2 \|q^{k,S_k} - f(q^{k,S_k})\|_2 = c_2 q_{i_0}^{k,S_k}$$

If  $q_{i_0}^{k,S_k} > 0$ , we deduce that  $\alpha_k w_{k,i_0}$  is bounded from above by  $c_2$ , which is a contradiction. This implies that  $q_{i_0}^{k,S_k} = 0$ , and we conclude that

$$\lim_{k} \mathbb{P}(\mathcal{A}(q^*) \subset \mathcal{A}(q^{k,S_k})) = 1.$$

As the second step, we prove that  $\lim_k \mathbb{P}(\mathcal{A}(q^{k,S_k}) \subset \mathcal{A}(q^*)) = 1$ . Indeed, the consistency of  $q^{k,S_k}$  guarantees that

$$\lim_{k \to \infty} q^{k, S_k} = q^*$$

almost surely. Therefore, if  $q_{i_0}^* > 0$  for some  $i_0$ , then  $q_{i_0}^{k,S_k} > 0$  for k large enough. In other words, we have  $\lim_k \mathbb{P}(\mathcal{A}(q^{k,S_k}) \subset \mathcal{A}(q^*)) = 1$ .

Combing step 1 and step 2, we deduce that the adaptive estimator is topologically consistent.  $\hfill \Box$ 

*Proof of Lemma* 3.12. Since  $q^{k,S_k}$  is topologically consistent and  $q^{k,R_k}$  is consistent, we have

$$\mathcal{A}(q^{k,S_k}) = \mathcal{A}(q^*)$$
 and  $q_i^{k,R_k} \ge q_i^*/2$   $\forall i \notin \mathcal{A}(q^*)$ 

with probability one for sufficiently large k. Defining  $b = \min_{i \notin \mathcal{A}(q^*)} q_i^*$ , we have

$$|S_k(q^{k,S_k}) - S_k(q^*)| = \left|\sum_{q_i^* \neq 0} w_{k,i}(q_i^{k,S_k} - q_i^*)\right| \le \sqrt{2N - 3} \, (b/2)^{-\gamma} \, \|q^{k,S_k} - q^*\|_2$$

via Cauchy-Schwarz which completes the proof.

Proof of Theorem 3.13. We note that for the LASSO estimator,  $R_k^{[0]}(q^*) = \sum_i q_i^*$  is uniformly bounded from above. Hence, the LASSO estimator is consistent. We can then use this as the base case to prove, by induction, that adaptive LASSO and the multiple-step LASSO are consistent via Theorem 3.11 (part (i)). Moreover,  $R_k^{[0]}$  is uniformly Lipschitz and satisfies (3.6), so using part (ii) of Theorem 3.11, we deduce that adaptive LASSO (i.e., the estimator with penalty function  $R_k^{[1]}$ ) is topologically consistent.

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We will prove that the multiple-step LASSOs are topologically consistent by induction. Assume that  $q^{k,R_k^{[m]}}$  is topologically consistent, and that  $q^{k,R_k^{[m-1]}}$  is consistent. From Lemma 3.12, we deduce that there exists C > 0 independent of k such that

(7.1) 
$$\left| R_k^{[m]} \left( q^{k, R_k^{[m]}} \right) - R_k^{[m]} (q^*) \right| \le C \left\| q^{k, R_k^{[m]}} - q^* \right\|_2 \quad \forall k.$$

This enables us to use part (ii) of Theorem 3.11 to conclude that  $q^{k, R_k^{[m+1]}}$  is topologically consistent. This inductive argument proves part (i) of the Theorem. We can now use (7.1) and Theorem 3.10 to derive the convergence rate of the estimators.

## 7.3. Technical proofs.

**Lemma 2.3.** If the penalty  $R_k$  is continuous on  $\mathcal{T}$ , then for  $\lambda > 0$  and observed sequences  $\mathbf{Y}^k$ , there exists a  $q \in \mathcal{T}$  minimizing

$$Z_{\lambda,\mathbf{Y}^k}(q) = -\frac{1}{k}\ell_k(q) + \lambda R_k(q).$$

Proof of Lemma 2.3. Let  $\{q^n\}$  be a sequence such that

$$Z_{\lambda,\mathbf{Y}^k}(q^n) \to \nu := \inf_q Z_{\lambda,\mathbf{Y}^k}(q).$$

We note that since  $\ell_k(q^*) \neq -\infty$  and  $R_k$  is continuous on the compact set  $\mathcal{T}$ ,  $\nu$  is finite. Since  $\mathcal{T}$  is compact, we deduce that a subsequence  $\{q^m\}$  converges to some  $q^0 \in \mathcal{T}$ . Since the log likelihood (defined on  $\mathcal{T}$  with values in the extended real line  $[-\infty, 0]$ ) and the penalty  $R_k$  are continuous, we deduce that  $q^0$  is a minimizer of  $Z_{\lambda, \mathbf{Y}^k}$ .

**Lemma 3.5.** For any  $\mu > 0$ , there exists a constant  $c_2(N, Q, \eta, g_0, \mu) > 0$  such that

(3.3) 
$$\left|\frac{1}{k}\ell_k(q) - \frac{1}{k}\ell_k(q')\right| \le c_2 ||q - q'||_2$$

and

(3.4) 
$$|\phi(q) - \phi(q')| \le c_2 ||q - q'||_2$$

for all  $q, q' \in \mathcal{T}(\mu)$ .

*Proof of Lemma* 3.5. Using the same arguments as in the proof of Lemma 4.2 of Dinh et al. (2018), we have

$$\left|\frac{\partial P_q(\psi)}{\partial q_i}\right| \le \varsigma 4^n$$

for any state assignment  $\psi$  where  $\varsigma$  is the element of largest magnitude in the rate matrix Q. By the Mean Value Theorem, we have

$$|\log P_q(\psi) - \log P_{q'}(\psi)| \le c_2 \sqrt{2N - 3} ||q - q'||_2 \quad \forall q, q', \psi$$

where  $c_2 := \varsigma 4^n / e^{-\mu}$ , and  $\|\cdot\|_2$  is the  $\ell_2$ -distance in  $\mathbb{R}^{2N-3}$ . This implies both (3.3) and (3.4).

**Lemma 3.6.** Let  $G_k$  be the set of all branch length vectors  $q \in \mathcal{T}(\mu)$  such that  $\mathbb{E}[U_k(q)] \geq 1/k$ . Let  $\beta \geq 2$  be the constant in Lemma 3.3. For any  $\delta > 0$  and previously specified variables there exists  $C(\delta, N, Q, \eta, g_0, \mu, \beta) \geq 1$  (independent of k) such that for any  $k \geq 3$ , we have:

$$U_k(q) \ge \frac{1}{2} \mathbb{E}[U_k(q)] - \frac{C \log k}{k^{2/\beta}} \qquad \forall q \in G_k$$

with probability greater than  $1 - \delta$ .

Proof of Lemma 3.6. The difference of average likelihoods  $U_k(q)$  is bounded by Lemma 3.5 and the boundedness assumption on  $\mathcal{T}$ , thus by Hoeffding's inequality

$$\mathbb{P}\left[U_k(q) - \mathbb{E}\left[U_k(q)\right] \le -y\right] \le \exp\left(-\frac{2y^2k}{c_2^2 \|q - q^*\|^2}\right)$$

By choosing  $y = \frac{1}{2}\mathbb{E}[U_k(q)] + t/2$ , we have  $y^2 \ge t\mathbb{E}[U_k(q)]$ . For any  $q \in G_k$ , we deduce using (3.5) (and the fact that  $\beta \ge 2$ ) that

$$\mathbb{P}\left[U_k(q) \le \frac{1}{2}\mathbb{E}\left[U_k(q)\right] - t/2\right] \le \exp\left(-\frac{2c_1^2 t k \mathbb{E}[U_k(q)]}{c_2^2 \mathbb{E}[U_k(q)]^{2/\beta}}\right) \le \exp\left(-\frac{2c_1^2 t k^{2/\beta}}{c_2^2}\right).$$

For each  $q \in G_k$ , define the events

$$A(q,k,t) = \left\{ U_k(q) - \frac{1}{2} \mathbb{E}\left[ U_k(q) \right] \le -t/2 \right\}$$

and

$$B(q,k,t) = \left\{ \exists q' \in G_k \text{ such that } \|q' - q\|_2 \le \frac{t}{4c_2} \text{ and } U_k(q') - \frac{1}{2}\mathbb{E}\left[U_k(q')\right] \le -t \right\}$$

then  $B(q, k, t) \subset A(q, k, t)$  by the triangle inequality, (3.3), and (3.4). Let

$$t = \frac{C\log k}{k^{2/\beta}}$$

To obtain a union bound and complete the proof, we need to chose C in such a way that

$$C_{2N-3} \left(\frac{4k^{2/\beta}g_0 c_2}{C\log k}\right)^{2N-3} \times 2\exp\left(-\frac{2c_1^2 C\log k}{c_2^2}\right) \leq \delta$$

where  $C_{2N-3}$  is defined as in the proof of Lemma 7.2. This can be done by choosing

$$C \ge \frac{4\beta c_2^2}{9c_1^2} \left( \log(1/\delta) + \log C_{2N-3} + (2N-3)\log(4 \cdot 3^{2/\beta}g_0c_2) \right).$$

**Lemma 3.8.** There exist  $\mu^* > 0$  and an open neighborhood V of  $q^*$  in  $\mathcal{T}$  such that  $V \subset \mathcal{T}(\mu^*)$ .

Proof of Lemma 3.8. Let

$$\mu^* = -2\min_{\psi} \log P_{q^*}(\psi)$$

then we have  $\log P_{q^*}(\psi) > -\mu^*$  for all state assignments  $\psi$ .

For a fixed value of  $\psi$ , log  $P_q(\psi)$  is a continuous function of q around  $q^*$ . Hence, there exists an neighborhood  $V_{\psi}$  of  $q^*$  such that  $V_{\psi}$  is open in  $\mathcal{T}$  and log  $P_q(\psi) > -\mu^*$ . Let  $V = \bigcap_{\psi} V_{\psi}$ . Because the set of all possible labels  $\psi$  of the leaves is finite, V is open in  $\mathcal{T}$  and

$$\log P_q(\psi) > -\mu^* \qquad \forall \psi, \forall q \in V.$$

In other words, we have  $V \subset \mathcal{T}(\mu^*)$ .

**Lemma 3.9.** If the sequence  $\{\lambda_k R_k(q^*)\}$  is bounded, then for any  $\delta > 0$ , there exist  $\mu(\delta) > 0$  and  $K(\delta) > 0$  such that for all  $k \ge K$ ,  $q^{k,R_k} \in \mathcal{T}(\mu)$  with probability at least  $1 - 2\delta$ .

Proof of Lemma 3.9. We first assume that  $\mu > \mu^*$ , where  $\mu^*$  is defined in Lemma 3.8. Thus, we have  $q^* \in \mathcal{T}(\mu^*) \subset \mathcal{T}(\mu)$ . By definition, we have

$$-\frac{1}{k}\ell_k(q^{k,R_k}) + \lambda_k R_k(q^{k,R_k}) \le -\frac{1}{k}\ell_k(q^*) + \lambda_k R_k(q^*)$$

which implies via Lemma 7.2 that

(7.2) 
$$\phi(q^*) - C(\delta) \frac{\log k}{\sqrt{k}} + \lambda_k R_k(q^{k,R_k}) - \lambda_k R_k(q^*) \le \frac{1}{k} \ell_k(q^{k,R_k})$$

with probability at least  $1 - \delta$ .

Let  $c_3$  and  $c_4(\delta, N)$  be as in Lemma 7.1, and assume that k is large enough such that

(7.3) 
$$c_3 - c_4(\delta, N) \frac{\log k}{\sqrt{k}} > 0.$$

Denoting the upper bound of  $\{\lambda_k R_k(q^*)\}$  by U, we define

$$\mu = \max\left\{-2\left(c_3 - c_4(\delta, N)\frac{\log k}{\sqrt{k}}\right)^{-1}\left(\phi(q^*) - C(\delta)\frac{\log k}{\sqrt{k}} - U\right), \mu^*\right\}.$$

If we assume that  $q^{k,R_k} \notin \mathcal{T}(\mu)$ , then the set  $I = \{\psi : \log P_{q^{k,R_k}}(\psi) \leq -\mu\}$  is non-empty. Using Lemma 7.1, we have

(7.4) 
$$\frac{1}{k}\ell_k(q^{k,R_k}) \le \frac{1}{k} \sum_{Y_i \in I} \log P_{q^{k,R_k}}(Y_i) \le -\mu \cdot \frac{k_I}{k} \le -\mu \cdot \left(c_3 - c_4(\delta) \frac{\log k}{\sqrt{k}}\right)$$

with probability at least  $1 - \delta$ .

Combining equations (7.2) and (7.4), and using the fact that  $\{\lambda_k R_k(q^*)\}$  is bounded by U, we obtain

$$\phi(q^*) - C(\delta) \frac{\log k}{\sqrt{k}} - U \le -\mu \cdot \left(c_3 - c_4(\delta, N) \frac{\log k}{\sqrt{k}}\right).$$

This contradicts the choice of  $\mu$  for k large enough such that (7.3) holds.

We deduce that  $q^{k,R_k} \in \mathcal{T}(\mu)$  with probability at least  $1 - 2\delta$ .

7.4. More experimental results. Here we present additional experimental results for the case of  $\gamma > 1$ .

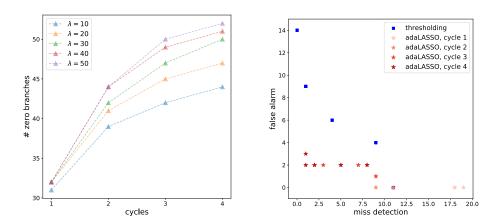


FIGURE S1. Topological consistency comparison of different phylogenetic LASSO procedures on simulation 2.  $\gamma = 1.01$ .

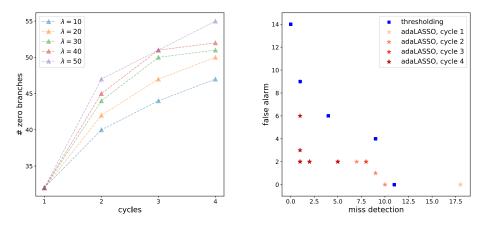


FIGURE S2. Topological consistency comparison of different phylogenetic LASSO procedures on simulation 2.  $\gamma=1.1.$ 

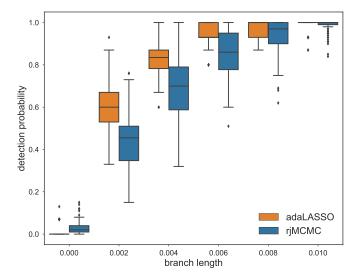


FIGURE S3. Box plot showing performance of multistep adaptive phylogenetic LASSO and rjMCMC at detecting short branches.  $\gamma=1.1$