Detecting outliers in heterochronous phylogenetic trees

Richard Neher

(Dated: August 11, 2023)

Misdating of sequences, or sequences with many sequencing errors, commonly distort time scaled phylogenetic trees. A common tactic to spot such sequences is to plot the root-to-tip distance as a function of time, reroot to optimize the correlation between them, and exclude tips that are far from the regression line. This is what augur, treetime, and TempEst currently do.

The problem with this approach is that it is not very sensitive since it ignores phylogenetic relationships among the tips. A sequence dated a year too early might still fall into the distribution of root-to-tip distances of that date, but is a clear outlier when compared directly to its neighbors in the tree.

To spot such outliers sensitively, we model the distribution in time for samples of a particular genotype i as

$$P(t|\tau_i, \sigma) = e^{-\frac{(t-\tau_i)^2}{2\sigma^2}}/\sqrt{2\pi\sigma^2} \tag{1}$$

Here τ_i is the time when most samples of this genotype are around, σ is the width of this distribution, which could correspond to the growth and decline of a variant or clade. Different genotypes are phylogenetically related and the molecular clock constrains how the τ_i change along the tree. For simplicity, we will models this as a Gaussian as well. Referring to the parent of i as p_i, we have for the full log-LH

$$\mathcal{L} = \sum_i \left(\frac{(\mu(\tau_i - \tau_{p_i}) - d_i)^2}{2(d_i+1)} + \sum_{\alpha \in s_i} \frac{(t_\alpha - \tau_i)^2}{2\sigma^2} \right) \tag{2}$$

where d_i is the number of mutations between i and p_i. We want to optimize this with respect to the genotype timings τ_i. Diffentiating with respect to τ_k, we have

$$\partial_{\tau_k}\mathcal{L} = \mu\frac{(\mu(\tau_k - \tau_{p_k}) - d_k)}{d_k+1} + \sum_{\alpha \in s_k} \frac{(\tau_k - t_\alpha)}{\sigma^2} - \sum_{c\in k} \mu\frac{(\mu(\tau_c - \tau_k) - d_c)}{d_c+1} = 0 \tag{3}$$

This is a sparse linear system that can be readily solved for τ_k. This could also be solved analytically in a forward backward fashion. It will be useful to define the average time $\bar{t}_i$ and the number of observations of genotype i as n_i to simplify the above to

$$\partial_{\tau_k}\mathcal{L} = \mu\frac{(\mu(\tau_k - \tau_{p_k}) - d_k)}{d_k+1} + n_k\frac{(\tau_k - \bar{t}_k)}{\sigma^2} - \mu\sum_{c\in k} \frac{(\mu(\tau_c - \tau_k) - d_c)}{d_c+1} = 0 \tag{4}$$

The resulting times can then be plugged into $\mathcal{L}$ and we can optimize σ and maybe μ. Once those are optimized, we can compare each nodes sampling time to its distribution. If we did the forward-backward distributions, we could also look at the leave-on-out signal.

Forward-backward solution

For a terminal node k, the optimal position given the position of the parent τ_{p_k} is

$$\tau_k = \left(\frac{n_k}{\sigma^2} + \frac{\mu^2}{d_k+1}\right)^{-1}\left(\frac{n_k\bar{t}_k}{\sigma^2} + \mu\frac{\mu\tau_{p_k} + d_k}{d_k+1}\right) = a + b\tau_{p_k}. \tag{5}$$

This expression weighs the evidence of the node being placed close to the average samples against the position of and the mutations relative to the parent. A similar calculation can be done for internal nodes where we have additional contributions from the children where we plug in the expression for their optimal position given the parent.

$$\mu\frac{(\mu(\tau_k - \tau_{p_k}) - d_k)}{d_k+1} + n_k\frac{(\tau_k - \bar{t}_k)}{\sigma^2} - \mu\sum_{c\in k} \frac{(\mu(a_c + b_c\tau_k - \tau_k) - d_c)}{d_c+1} = 0 \tag{6}$$

Collecting all terms proportional to τ_k, we find

$$\tau_k \left(\frac{n_k}{\sigma^2} + \frac{\mu^2}{d_k + 1} + \mu^2 \sum_{c \in k} \frac{1 - b_c}{d_c + 1} \right) = \frac{n_k \bar{t}_k}{\sigma^2} + \mu \frac{\mu \tau_{p_k} + d_k}{d_k + 1} + \mu \sum_{c \in k} \frac{\mu a_c - d_c}{d_c + 1} \tag{7}$$

Which can again be solved for τ_k and is a linear function of τ_{p_k}.

$$\tau_k = \left(\frac{n_k}{\sigma^2} + \frac{\mu^2}{d_k + 1} + \mu^2 \sum_{c \in k} \frac{1 - b_c}{d_c + 1} \right)^{-1} \left(\frac{n_k \bar{t}_k}{\sigma^2} + \mu \frac{\mu \tau_{p_k} + d_k}{d_k + 1} + \mu \sum_{c \in k} \frac{\mu a_c - d_c}{d_c + 1} \right) = a + b \tau_{p_k} \tag{8}$$

At the root, the term from the parent is absent and their is no conditioning on τ_{p_k} anymore

$$\tau_k = \left(\frac{n_k}{\sigma^2} + \mu^2 \sum_{c \in k} \frac{1 - b_c}{d_c + 1} \right)^{-1} \left(\frac{n_k \bar{t}_k}{\sigma^2} + \mu \sum_{c \in k} \frac{\mu a_c - d_c}{d_c + 1} \right) = a + b \tau_{p_k} \tag{9}$$

Once all the root τ is known, all other τ_k can be calculated in one backward pass.

The optimal timings can be calculated in linear time, along with the cost-function. This cost-function can then be optimized for σ and μ.