

Consistency, Long Branch Attraction, Robustness to Model Violations, ...

Of the 3 methods of tree construction we have learned about --

MP, distance methods ML -- which is best?

...

For sure, one wants a statistical estimator to be **CONSISTENT**

(informally: if your data is perfectly in accord with the model

[or method], the method X reconstructs the true tree.)

For the formal definition, suppose you have chosen a ^{specific} model with parameters $M_0 = (T, N)$ N = numerical parameters and your data consists of site pattern frequencies computed from n independent trials of the experiment. i.e. n sites were generated under M_0 independently.

for notational ease

Focusing only on the tree (easy extension to (T, N)),

then let \hat{T}_n denote the estimator from your method based on a sample of size n . Suppose $\epsilon > 0$ is arbitrary. Then if

$$\lim_{n \rightarrow \infty} \text{Prob} \left(\underbrace{\| \hat{T}_n - T \|}_{\text{measurement of how close } \hat{T}_n \text{ is to the true value } T} < \epsilon \right) = \underline{\hspace{2cm}}$$

↑
probabilistic quantification of when \hat{T}_n will be within ϵ of T

↑
let the sample size go to ∞

then \hat{T}_n is a CONSISTENT ESTIMATOR of $T = (T, N)$

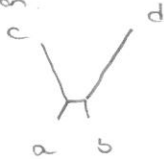
Formalization of a very basic requirement for inference.

If \hat{T}_{method} is not consistent, in practice no amount of data collection will help you to estimate T with "method."

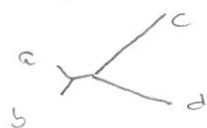
Which methods are consistent?

⋮

Parsimony and Long Branch Attraction.

We know that a metric tree  can be hard to infer since a, b are the closest, i.e. their DNA sequences should look the

most similar, but a, c are sister. Indeed, NJ was introduced to address this issue. We might expect parsimony to struggle for such trees. For such a tree, a "method" might infer



a tree in which the long branches are attracted.
 \equiv Long Branch Attraction

This phenomenon (LBA) extends to larger trees $n > 4$ and can throw off inference if too remote an outgroup is contained in data. Another way to view this is taxa c, d are essentially independent if those terminal branch lengths are long enough.

We will show that parsimony (MP) can be inconsistent

under a "2-state JC" model called the Cavender-Farris-Neyman CFN model. "Gelsenstein Zone"

Method:

Details: Parsimony on a 4-taxon tree

Model: Explained below CFN 2-state model

Data: Pattern frequencies

xxyy

xyxy

xyyx

↑

↑

↑

 n_1 n_2 n_3

Counts from data

(Order reversed in book)

3-trees to choose from

 $T_1: ab|cd$

$$ps(T_1) = n_1 + 2n_2 + 2n_3 = 2n - n_1$$

 $T_2: ac|bd$

$$ps(T_2) = 2n_1 + n_2 + 2n_3 = 2n - n_2$$

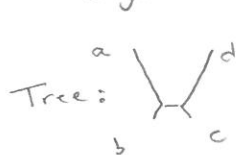
 $T_3: ad|bc$

$$ps(T_3) = 2n_1 + 2n_2 + n_3 = 2n - n_3$$

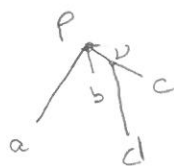
Where $n = \#$ of informative sitesParsimony Criterion: Choose T_i with n_i largest (so $2n - n_i$ smallest)

End data analysis.

Begin: Generate sequences assuming the CFN model



root →



Book: Here root at a

2-states

Root Distribution is $p_r = (0.5, 0.5)$

2 Markov matrices one for short edges, one for long edges

$$M_{\text{long}} = \begin{pmatrix} 1-q & q \\ q & 1-q \end{pmatrix}$$

$$M_{\text{short}} = \begin{pmatrix} 1-p & p \\ p & 1-p \end{pmatrix}$$

 $p, q \in (0, 0.5)$

With this model

4.

$$xxyy \quad p_1 = (1-q)^2 p (1-p)^2 + 2q(1-q)p(1-p)^2 + q^2 p^3$$

$$xyxy \quad p_2 = (1-q)^2 p^2 (1-p) + 2q(1-q)p^2(1-p) + q^2(1-p)^3$$

$$xyyx \quad p_3 = (1-q)^2 p^3 + 2q(1-q)p(1-p)^2 + q^2 p(1-p)^2$$

↑
Work (including HW)

(1)

If MP were to choose the true tree T_1 , then since

$$\lim_{n \rightarrow \infty} \frac{n_i}{n} = p_i$$

it must be that $p_1 > p_2, p_3$