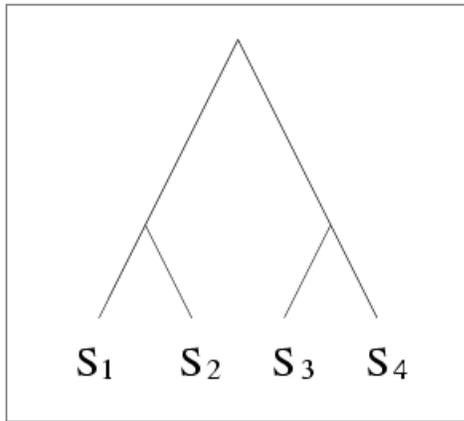


Distance-based phylogeny estimation

CS 598 AGB

Distance-based Methods

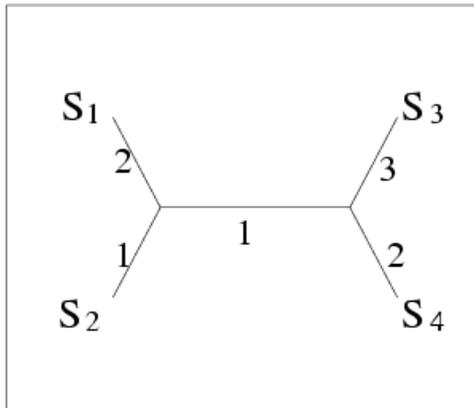


TRUE TREE

S₁ ACAATTAGAAC
S₂ ACCCTTAGAAC
S₃ ACCATTCCAAC
S₄ ACCAGACCAAC

DNA SEQUENCES

STATISTICAL
ESTIMATION
OF PAIRWISE
DISTANCES



INFERRED TREE

METHODS
SUCH AS
NEIGHBOR
JOINING

	S ₁	S ₂	S ₃	S ₄
S ₁	0	3	6	5
S ₂		0	5	4
S ₃			0	5
S ₄				0

DISTANCE MATRIX

Today's Class

- Phylogeny as statistical estimation problem
- Stochastic models of evolution
- Distance-based estimation
- Statistical consistency of distance-based methods

Note overlap with material from January 21, 2016

Simplest model of binary character evolution: **Cavender-Farris**

- For each edge **e**, there is a probability **p(e)** of the property “changing state” (going from 0 to 1, or vice-versa), with $0 < p(e) < 0.5$ (to ensure that CF trees are identifiable).
- Every position evolves under the same process, independently of the others.

CF tree estimation

- Instead of directly estimating the tree, we try to estimate the process itself.
- For example, we try to estimate the probability that two leaves will have different states for a random character.

Cavender-Farris pattern probabilities

- Let x and y denote nodes in the tree, and p_{xy} denote the probability that x and y exhibit different states.
- In other words,

$$p_{xy} = \Pr[(x=0 \ \& \ y=1) \ \text{OR} \ (x=1 \ \& \ y=0)]$$

Cavender-Farris pattern probabilities

- Theorem: Let p_i be the substitution probability for edge e_i , and let x and y be connected by path $e_1e_2e_3\dots e_k$. Then
$$1-2p_{xy} = (1-2p_1)(1-2p_2)\dots(1-2p_k)$$
- Proof: by induction on k .

And then take logarithms

- The theorem gave us:

$$1-2p_{xy} = (1-2p_1)(1-2p_2)\dots(1-2p_k)$$

- If we take logarithms, we obtain

$$\ln(1-2p_{xy}) = \ln(1-2p_1) + \ln(1-2p_2) + \dots + \ln(1-2p_k)$$

- Since $0 < p_i < 0.5$, $0 < 1-2p_i < 1$, and $\ln(1-2p_i) < 0$.
- Multiply by -1 to get positive numbers.

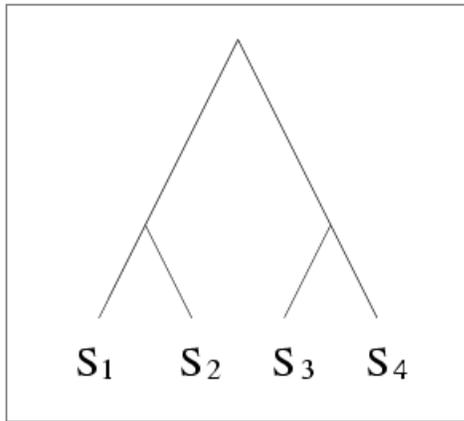
Additive Distance Matrix

- Consider $D_{xy} = -\ln(1-2p_{xy})$
- Let $w(e_i) = -\ln(1-2p_i)$. Note that $w(e_i) > 0$.
- We have shown $D_{xy} = w(e_1) + w(e_2) + \dots + w(e_k)$, where e_1, e_2, \dots, e_k is the path in the true tree between leaves x and y .

In other words, the distance matrix D is **additive on the true tree T** . Furthermore, given D we can reconstruct the tree T and its edge weights.

We write this as $D \rightarrow (T, w)$.

Distance-based Methods

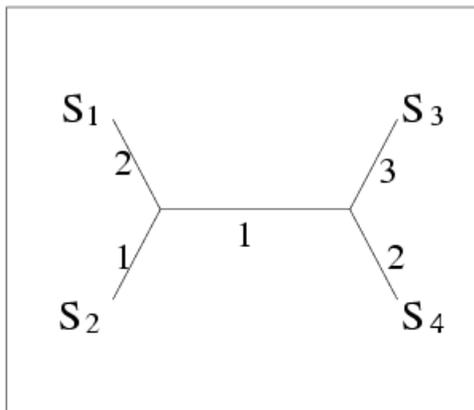


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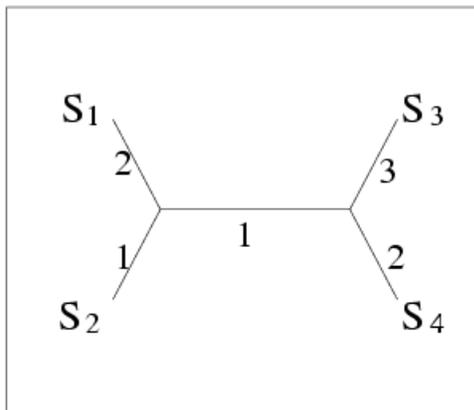
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DISTANCE MATRIX

Additive distance matrix



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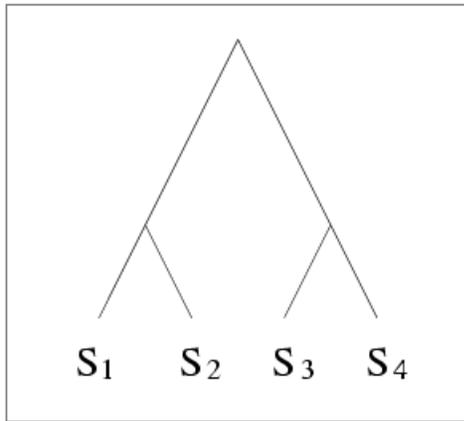
DISTANCE MATRIX

What now?

- The matrix D defined by $D_{ij} = -\ln(1-2p_{ij})$ is additive, and if we have the matrix, we can compute the true tree in polynomial time.
- But we don't know these p_{ij} values.
- Question: can we estimate p_{ij} in a statistically consistent manner?

Recall how to estimate the probability of a head...

Distance-based Methods

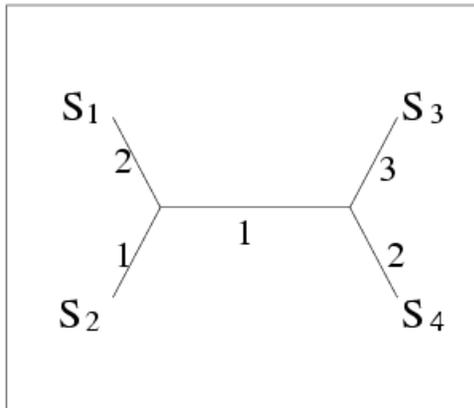


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DISTANCE MATRIX

Estimating CF distances

Consider H_{ij}/k , where k is the number of characters, and H_{ij} is the Hamming distance between sequences s_i and s_j .

Theorem: as k increases, $H_{ij}/k \rightarrow p_{ij}$

Estimating CF distances

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Theorem: as k increases, $H_{ij}/k \rightarrow p_{ij}$

And therefore as k increases,

$$d_{ij} = -\ln(1-2H_{ij}/k) \rightarrow -\ln(1-2p_{ij}) = D_{ij}$$

Estimating CF distances

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And therefore as k increases,

$$d_{ij} = -\ln(1-2H_{ij}/k) \rightarrow -\ln(1-2p_{ij}) = D_{ij}$$

Therefore, the matrix d of estimated distances converges to the matrix D of model distances, which is additive on the true tree T .

Distance-based CF tree estimation

- Step 1: Compute Hamming distances
- Step 2: Correct the Hamming distances, using the CF distance calculation
- Step 3: Use distance-based method (neighbor joining, naïve quartet method, etc.)

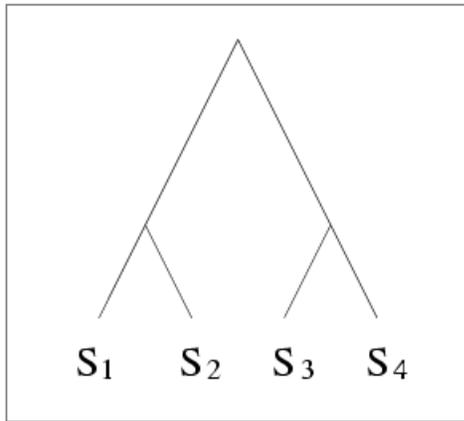
In this scenario, the only thing we are trying to estimate is the tree T , and not necessarily the lengths of the edges.

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Distance-based Methods

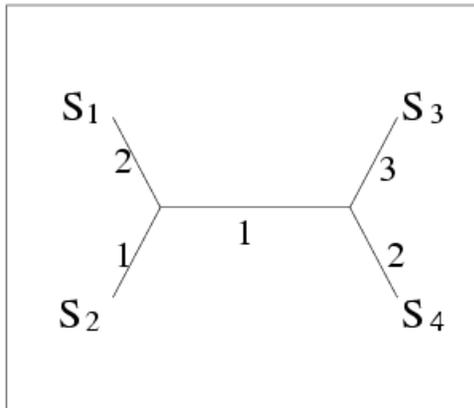


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DISTANCE MATRIX

Statistical consistency

To prove that a method M for estimating CF model tree topologies is statistically consistent, we need to show that

for all model CF trees (T,w) and for all $\varepsilon > 0$, there is some sequence length L such that $\Pr[M(S)=T] > 1-\varepsilon$, given sequences S of length L generated on (T,w) .

Statistical consistency

- In other words, it's not enough to show that the method M returns T given additive distance matrix for T .

Statistical consistency of distance-based methods

- Let D be defined by $D_{ij} = -\ln(1 - 2p_{ij})$. Recall that D is additive on T , and that $d_{ij} \rightarrow D_{ij}$ for all i, j , (specifically, d converges to D in probability).
- Suppose there exists $\delta > 0$ such that
 $M(d) = M(D) = T$ whenever $\max_{ij} |d_{ij} - D_{ij}| < \delta$
- Then we will have a proof of statistical consistency for M !

This is called “error tolerance”

Four Point Method

- Input: Given 4x4 dissimilarity matrix A and four leaves i, j, k, l
- Output: a tree on i, j, k, l
- Step 1: Compute the three pairwise sums,
- Step 2: Return quartet tree $ij|kl$ if
$$A_{ij} + A_{kl} < \min\{A_{ik} + A_{jl}, A_{il} + A_{jk}\}$$

Error tolerance for FPM

Theorem: Suppose $D \rightarrow (T, w)$ where T is the true tree, and $\max_{ij} |d_{ij} - D_{ij}| < f/2$ where $f = \min_e w(e)$. Then the Four Point Method will return the correct tree on any four leaves in T .

Error tolerance for FPM

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Proof: Let i, j, k, l be any four leaves and suppose $ij|kl$ is the true tree in T .

Error tolerance for FPM

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Proof: Let i, j, k, l be any four leaves and suppose $ij|kl$ is the true tree in T .

Hence $D_{ij} + D_{kl} \leq \min\{D_{ik} + D_{jl}, D_{il} + D_{jk}\} - 2f$.

Error tolerance for FPM

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Suppose $\max_{ij} |d_{ij} - D_{ij}| < f/2$ where $f = \min_e w(e)$.

Error tolerance for FPM

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Then $d_{ij} + d_{kl} < \min\{d_{ik} + d_{jl}, d_{il} + d_{jk}\}$.

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Suppose $\max_{ij} |d_{ij} - D_{ij}| < f/2$ where $f = \min_e w(e)$.

Then $d_{ij} + d_{kl} < \min\{d_{ik} + d_{jl}, d_{il} + d_{jk}\}$.

Hence, the FPM will return $ij|kl$ given matrix d .

Naïve Quartet Method

- Compute the tree on each quartet using the four-point condition
- Merge them into a tree on the entire set if they are compatible using the **All**

Quartets Method:

- Find a sibling pair A,B
- Recurse on $S-\{A\}$
- If $S-\{A\}$ has a tree T, insert A into T by making A a sibling to B, and return the tree

Error tolerance for NQM

- Suppose every pairwise distance is estimated well enough (within $f/2$, for f the minimum length of any edge).
- Then the Four Point Method returns the correct tree on every quartet.
- And so all quartet trees are compatible, and NQM returns the true tree.

In other words:

- The NQM method is statistically consistent methods for estimating Cavender-Farris trees!
- Plus it is polynomial time!

DNA substitution models

- Every edge has a substitution probability
- The model also allows 4x4 substitution matrices on the edges:
 - Simplest model: Jukes-Cantor (JC) assumes that all substitutions are equiprobable
 - General Time Reversible (GTR) Model: one 4x4 substitution matrix for all edges
 - General Markov (GM) model: different 4x4 matrices allowed on each edge

Jukes-Cantor DNA model

- Character states are A,C,T,G (nucleotides).
- All substitutions have equal probability.
- On each edge e , there is a value $p(e)$ indicating the probability of change from one nucleotide to another on the edge, with $0 < p(e) < 0.75$ (to ensure that JC trees are identifiable).
- The state (nucleotide) at the root is random (all nucleotides occur with equal probability).
- All the positions in the sequence evolve identically and independently.

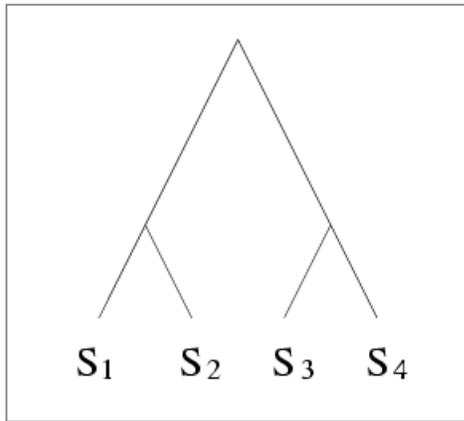
Jukes-Cantor distances

- $D_{ij} = -3/4 \ln(1 - 4/3 H(i,j)/k)$ where k is the sequence length
- These distances converge to an additive matrix, just like with Cavender-Farris distances
- Hence, the NQM is statistically consistent under the JC model.

The NQM is statistically consistent under other models

- Note that the proof that the NQM is statistically consistent depends on $d_{ij} \rightarrow D_{ij}$ (i.e., we can estimate the model distances in a statistically consistent manner).
- This property is true for these other stochastic models of evolution (but not for arbitrary models).

Distance-based Methods

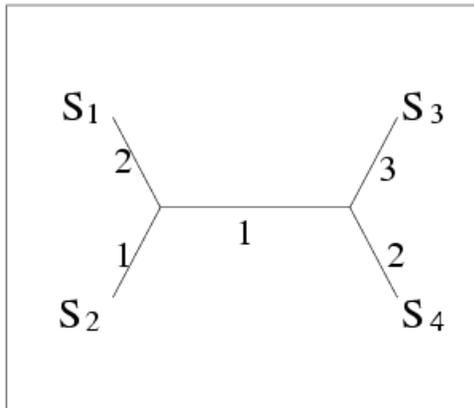


TRUE TREE

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DISTANCE MATRIX

Other distance-based methods

- Neighbor Joining (Saitou and Nei):
 - Kevin Atteson proved NJ has error tolerance of $f/2$
- 3-approximation to L-infinity nearest tree (Agarwala et al.)
 - Easy to see has error tolerance of $f/8$
 - Exact algorithm has error tolerance of $f/4$
- FastME, BioNJ, Weighbor, NINJA, FastTree, and many others (most statistically consistent but not analyzed for error tolerance)
- UPGMA – not consistent

UPGMA

While $|S| > 2$:

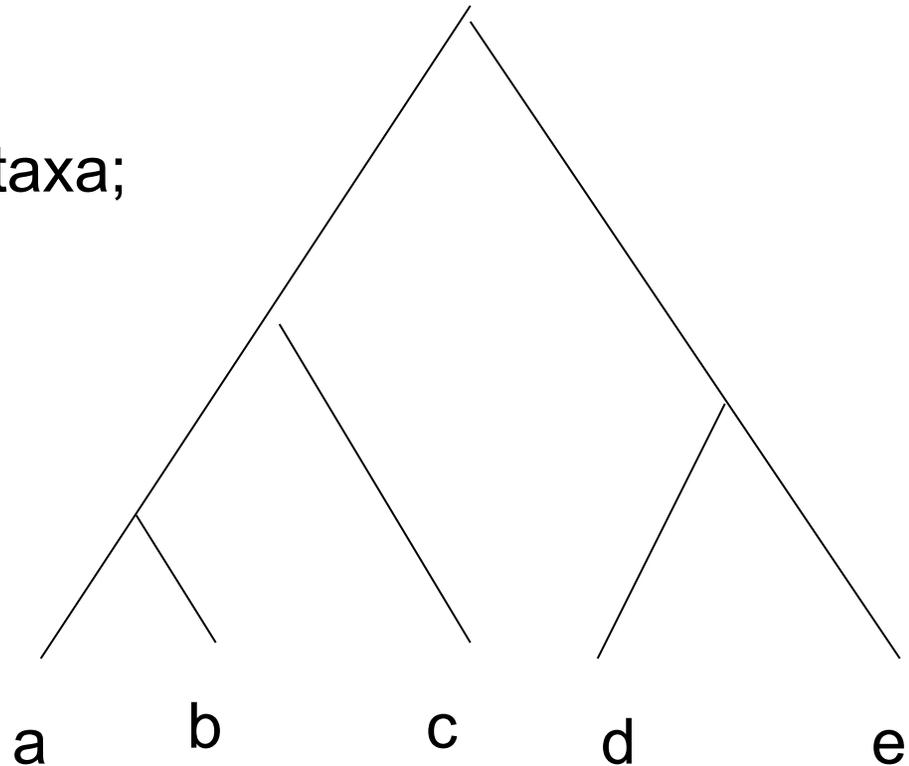
find pair x, y of closest taxa;

delete x

Recurse on $S - \{x\}$

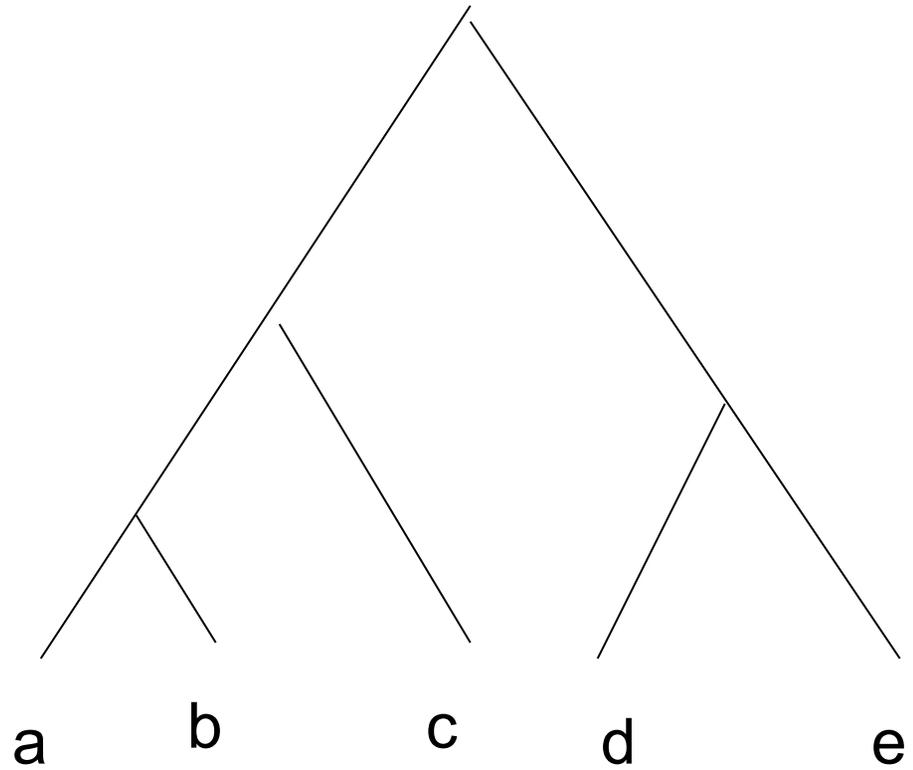
Insert y as sibling to x

Return tree



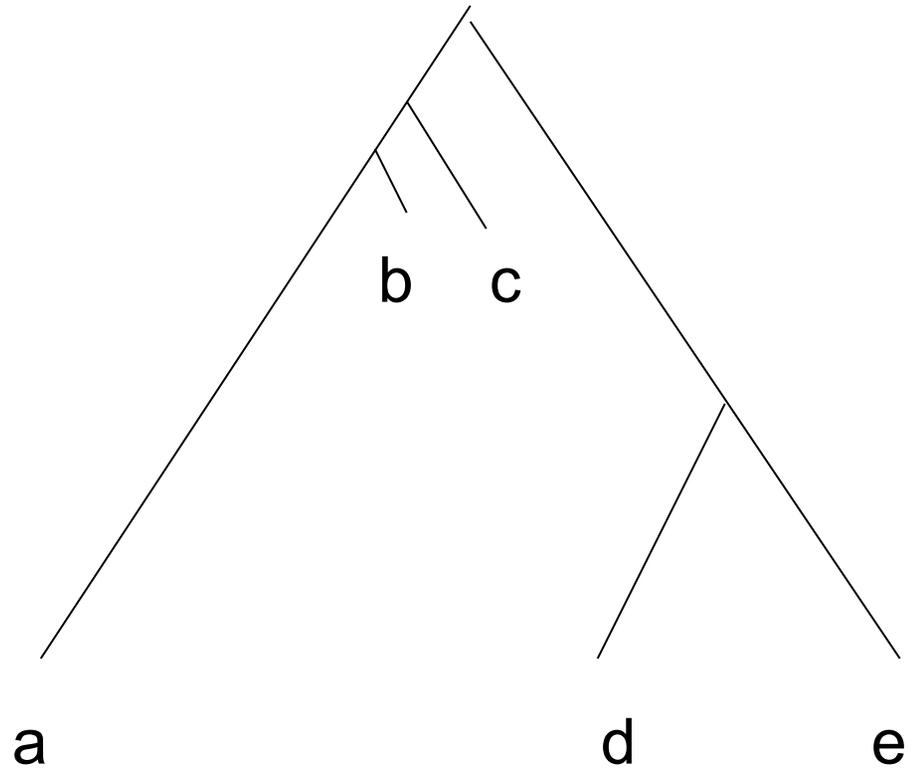
UPGMA

Works when
evolution is
“clocklike”



UPGMA

Fails to produce true tree if evolution deviates too much from a clock!



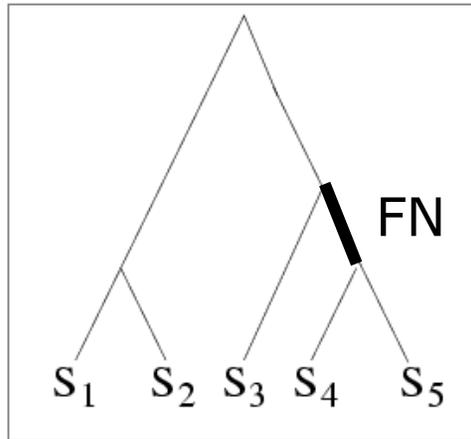
Summary (so far)

- Distance-based phylogeny estimation is popular because it is computationally fast.
- Many distance-based methods are statistically consistent under standard stochastic models. The proofs require
 - (a) that an additive distance matrix for the true tree can be estimated in a statistically consistent manner, and
 - (b) the method M return the true tree T given an additive matrix for (T,w) , for any positive edge weighting w , and
 - (c) the method M has error tolerance.
- The ability to estimate additive distances for the true tree depends on the stochastic model, and does not apply to all models.
- The ability to compute the tree T from a noisy distance matrix depends on the method M , and does not apply to all methods.

Other statistically consistent methods

- Maximum Likelihood
- Bayesian MCMC methods
- Absolute fast converging methods, such as the Dyadic Closure Method (Erdos et al., 1997) and DCM_{NJ} (Warnow et al. 2001).

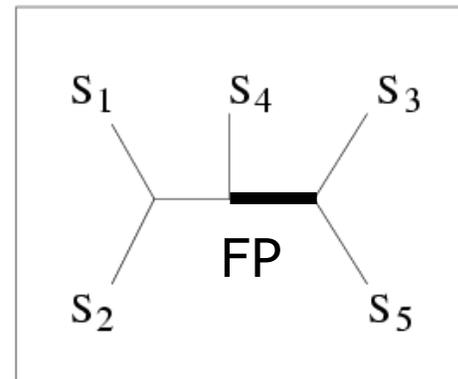
Quantifying Error



TRUE TREE

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S ₅	ACCAGACCGGA

DNA SEQUENCES

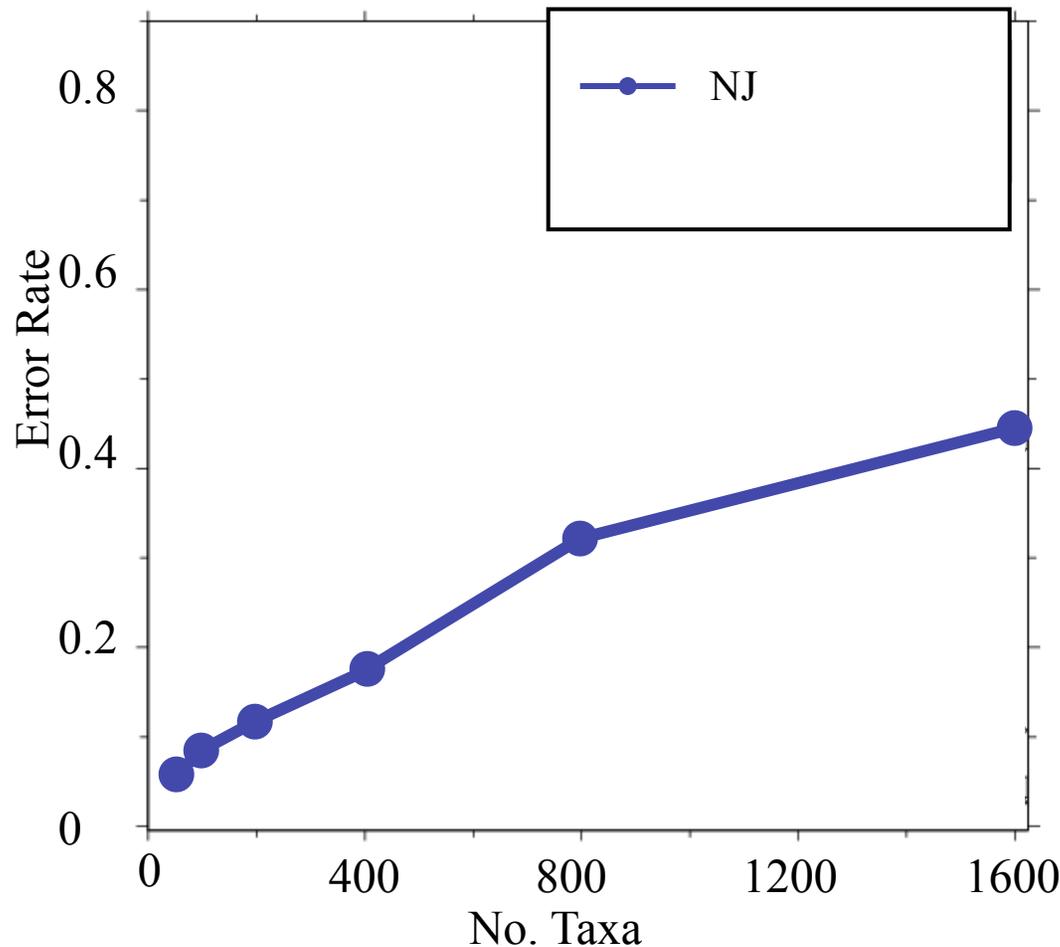


INFERRED TREE

FN: false negative
(missing edge)
FP: false positive
(incorrect edge)

50% error rate

Neighbor joining has poor performance on large diameter trees *[Nakhleh et al. ISMB 2001]*



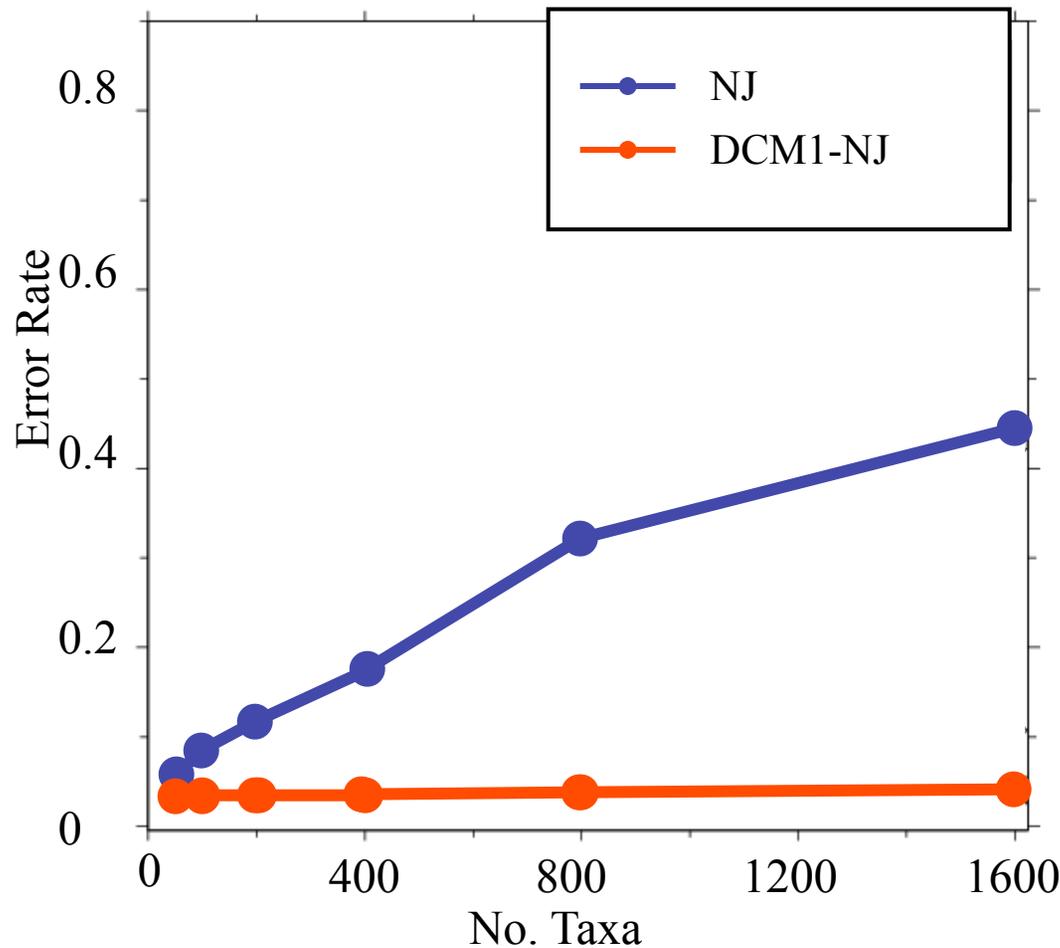
Simulation study

based upon fixed edge lengths, K2P model of evolution, sequence lengths fixed to 1000 nucleotides.

Error rates reflect proportion of incorrect edges in inferred trees.

DCM1-boosting distance-based methods

[Nakhleh et al. ISMB 2001]



Theorem
(Warnow et al.,
SODA 2001):
DCM1-NJ
converges to the
true tree from
polynomial length
sequences

Advanced material

- Absolute Fast Converging Methods
- Will be covered at the end of the course