6.047/6.878 - Computational Biology: Genomes, Networks, Evolution

## Lecture 18 Molecular Evolution and Phylogenetics



Patrick Winston's 6.034
Somewhere, something went wrong...

## Challenges in Computational Biology

(4) Genome Assembly

(8) Gene expression analysis

(9) Cluster discovery 10 Gibbs sampling
(11) Protein network analysis

(12) Metabolic modelling
(13) Emerging network properties


## Concepts of Darwinian Evolution



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## Concepts of Darwinian Evolution



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Charles Darwin 1859. Origin of Species [one and only illustration]: "descent with modification"

Taken from Yuri Wolf, Lecture Slides, Feb. 2014

## Tree of Life


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## Goals for today: Phylogenetics

- Basics of phylogeny: Introduction and definitions
- Characters, traits, nodes, branches, lineages, topology, lengths
- Gene trees, species trees, cladograms, chronograms, phylograms

1. From alignments to distances: Modeling sequence evolution

- Turning pairwise sequence alignment data into pairwise distances
- Probabilistic models of divergence: Jukes Cantor/Kimura/hierarchy

2. From distances to trees: Tree-building algorithms

- Tree types: Ultrametric, Additive, General Distances
- Algorithms: UPGMA, Neighbor Joining, guarantees and limitations
- Optimality: Least-squared error, minimum evolution (require search)

3. From alignments to trees: Alignment scoring given a tree

- Parsimony: greedy (union/intersection) vs. DP (summing cost)
- ML/MAP (includes back-mutations, lengths): peeling algorithm (DP)

4. Tree of Life in Genomic Era

- The prokaryotic problem (no real taxa and HGT)
- Interpreting the forest of life


# Introduction: Basics and Definitions 

Characters, traits, gene/species trees

## Common Phylogenetic Tree Terminology



## Extinctions part of life

Phylogenetic tree showing archosaurs, dinosaurs, birds, etc. through geologic time removed due to copyright restrictions.

## Phylogenetics

General Problem:
Infer complete ancestry of a set of 'objects' based on knowledge of their 'traits'
'Objects' can be: Species, Genes, Cell types, Diseases,
Cancers, Languages, Faiths,
Cars, Architectural Styles
'Traits' can be: Morphological, molecular, gene expression, TF binding, motifs, words...

Historical record varies: Fossils, imprints, timing of geological events, 'living fossils', sequencing of extinct species, paintings, stories.

Today: Phylogenies using only extant species data
$\rightarrow$ gene trees (paralog / ortholog / homolog trees)

## Inferring Phylogenies: Traits and Characters

## Trees can be inferred by several criteria:

- Traditional traits: Morphology data

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- Modern traits: Molecular data



## From physiological traits to DNA characters

- Traditional phylogenetics
- Building species trees
- Small number of traits
- Hoofs, nails, teeth, horns
- Well-behaved traits, each arose once
- Parsimony principle, Occam's razor
- Modern phylogenetics
- Building gene trees and species trees
- Very large number of traits
- Every DNA base and every protein residue
- Frequently ill-behaved traits
- Back-mutations are frequent (convergent evolution)
- Small number of letters, arise many times independently


## Three types of trees



Topology only

Chronogram


Topology +
Divergence times

Phylogram


Topology +
Divergence times + Divergence rates

## Inferring a tree from nucleotides/peptides



## Two basic approaches for phylogenetic inference

Distance based


Character based


Sequence alignment


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## 1. From alignments to distances

## Modeling evolutionary rates


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## Measuring evolutionary rates

- Nucleotide divergence
- Uniform rate. Overall percent identity.
- Transitions and transversions
- Two-parameter model. A-G, C-T more frequent.
- Synonymous and non-synonymous substitutions
- $\mathrm{Ka} / \mathrm{Ks}$ rates. Amino-acid changing substitutions

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | AGA |  |  |  |  |  |  |  |  | UUA |  |  |  |  | AGC |  |  |  |  |  |
|  | AGG |  |  |  |  |  |  |  |  | UUG |  |  |  |  | AGU |  |  |  |  |  |
| GCA | CGA |  |  |  |  |  | GGA |  |  | CUA |  |  |  | CCA | UCA | ACA |  |  | GUA |  |
| GCC | CGC |  |  |  |  |  | GGC |  | AUA | CUC |  |  |  | CCC | UCC | ACC |  |  | GUC | UAA |
| GCG | CGG | GAC | AAC | UGC | GAA | CAA | GGG | CAC | AUC | CUG | AAA |  | UUC | CCG | UCG | ACG |  | UAC | GUG | UAG |
| GCU | CGU | GAU | AAU | UGU | GAG | CAG | GGU | CAU | AUU | CUU | AAG | AUG | บUU | CCU | UCU | ACU | UGG | UAU | GUU | UGA |
| Ala | Arg | Asp | Asn | Cys | Glu | G1n | G1y | His | 11 e | Leu | Lys | Met | Phe | Pro | Ser | Thr | Trp | Tyr | Val | stop |
| A | R | D | N | C | E | 0 | G | H | I | L | K | M | F | P | 5 | T | W | Y | V |  |

- $\mathrm{N}_{\text {actual mutations }}>\mathrm{N}_{\text {observed substitutions }}$
- Some fraction of "conserved" positions mutated twice



## ‘Evolving’ a nucleotide under random model

- At time step 0, start with letter A
- At time step 1:
- Remain A with probability 0.7
- Change to C,G,T with prob. 0.1 each
- At time step 2:
- In state A with probability 0.52
- Remain A with probability 0.7 * 0.7
- Go back to A from C,G,T with $0.1^{*} 0.1$ each

- In states C,G,T with prob. 0.16 each

|  | $\mathrm{t}=1$ | $\mathrm{t}=2$ | $\mathrm{t}=3$ | $\mathrm{t}=4$ | $\mathrm{t}=5$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| A | 1 | 0.7 | 0.52 | 0.412 | 0.3472 |
| C | 0 | 0.1 | 0.16 | 0.196 | 0.2176 |
| G | 0 | 0.1 | 0.16 | 0.196 | 0.2176 |
| T | 0 | 0.1 | 0.16 | 0.196 | 0.2176 |

## Modeling Nucleotide Evolution

During infinitesimal time $\Delta t$, there is not enough time for two substitutions to happen on the same nucleotide

So we can estimate $P(x \mid y, \Delta t)$, for $x, y \in\{A, C, G, T\}$

Then let
$S(\Delta t)=\quad\left(\begin{array}{lll}P(A \mid A, \Delta t) & \ldots & \mathrm{P}(\mathrm{A} \mid \mathrm{T}, \Delta \mathrm{t}) \\ \ldots & \ldots \\ \mathrm{P}(\mathrm{T} \mid \mathrm{A}, \Delta \mathrm{t}) & \ldots \ldots & \mathrm{P}(\mathrm{T} \mid \mathrm{T}, \Delta \mathrm{t})\end{array}\right)$

## Modeling Nucleotide Evolution

Reasonable assumption: multiplicative (implying a stationary Markov process)
$S\left(t+t^{\prime}\right)=S(t) S\left(t^{\prime}\right)$

That is, $P\left(x \mid y, t+t^{\prime}\right)=\Sigma_{z} P(x \mid z, t) P\left(z \mid y, t^{\prime}\right)$

Jukes-Cantor: constant rate of evolution

For short time $\varepsilon, S(\varepsilon)=\left(\begin{array}{llll}1-3 \alpha \varepsilon & \alpha \varepsilon & \alpha \varepsilon & \alpha \varepsilon \\ \alpha \varepsilon & 1-3 \alpha \varepsilon & \alpha \varepsilon & \alpha \varepsilon \\ \alpha \varepsilon & \alpha \varepsilon & 1-3 \alpha \varepsilon & \alpha \varepsilon \\ \alpha \varepsilon & \alpha \varepsilon & \alpha \varepsilon & 1-3 \alpha \varepsilon\end{array}\right)$

## Modeling Nucleotide Evolution

## Jukes-Cantor:

For longer times,
$S(t)=\left(\begin{array}{llll}r(t) & s(t) & s(t) & s(t) \\ s(t) & r(t) & s(t) & s(t) \\ s(t) & s(t) & r(t) & s(t) \\ s(t) & s(t) & s(t) & r(t)\end{array}\right)$

Where we can derive:

$$
\begin{aligned}
& r(t)=1 / 4\left(1+3 e^{-4 \alpha t}\right) \\
& s(t)=1 / 4\left(1-e^{-4 \alpha t}\right)
\end{aligned}
$$

Geometric asymptote to $1 / 4$


## Modeling Nucleotide Evolution

## Kimura:

Transitions: A/G, C/T
Transversions: A/T, A/C, G/T, C/G

Transitions (rate $\alpha$ ) are much more likely than transversions (rate $\beta$ )

$S(t)=$|  |
| :---: |
| $A$ |
| $G$ |
| $C$ |
| $T$ |\(\left(\begin{array}{llll}A \& G \& C \& T <br>

r(t) \& s(t) \& u(t) \& u(t) <br>
s(t) \& r(t) \& u(t) \& u(t) <br>
u(t) \& u(t) \& r(t) \& s(t) <br>
u(t) \& u(t) \& s(t) \& r(t)\end{array}\right)\)

Where

$$
\begin{aligned}
& s(t)=1 / 4\left(1-e^{-4 \beta t}\right) \\
& u(t)=1 / 4\left(1+e^{-4 \beta t}-e^{-2(\alpha+\beta) t}\right) \\
& r(t)=1-2 s(t)-u(t)
\end{aligned}
$$

Distance between two sequences
Given (well-aligned portion of) sequences $x^{i}, x^{j}$,

Define

$$
\mathrm{d}_{\mathrm{ij}}=\text { distance between the two sequences }
$$

One possible definition:

$$
\mathrm{d}_{\mathrm{ij}}=\text { fraction } f \text { of sites } u \text { where } x^{\mathrm{i}}[u] \neq x^{j}[u]
$$

Better model (Jukes-Cantor):

$$
d_{i j}=-3 / 4 \log (1-4 f / 3)
$$

$$
\begin{aligned}
& r(t)=1 / 4\left(1+3 e^{-4 \alpha t}\right) \\
& s(t)=1 / 4\left(1-e^{-4 a t}\right)
\end{aligned}
$$

$$
\text { Observed } \left.F=\left[\begin{array}{llllll}
0.1 & 0.2, & 0.3 & 0.4, & 0.5, & 0.6
\end{array} 0.7\right]\right)
$$

Actual $\quad D=[0.11,0.23,0.38,0.57,0.82,1.21,2.03]$

Many nucleotide models have been developed
Varying levels of complexity (parameters)

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4. Tree of Life in Genomic Era

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## 2. Distance-based tree-building algorithms

## Mapping a distance matrix to a tree


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## Distance matrix $\Leftrightarrow$ Phylogenetic tree

|  | Hum | Mou | Rat | Dog | Cat |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Human | 0 | 4 | 5 | 7 | 6 |
| Mouse | h.y.m | 0 | 3 | 8 | 5 |
| Rat | h.y.r | m.r | 0 | 9 | 7 |
| Dog | h.z.x.d | m.y.z.x.d | r.y.z.x.d | 0 | 2 |
| Cat | h.z.x.C | m.y.z.x.c | r.y.z.x.c | d.c | 0 |
| Tree implies Map distances $\mathrm{D}_{\mathrm{ij}}$ a distance matrix to a tree $M_{i j}$ $\min \sum_{i \mathrm{ij}}\left(\mathrm{D}_{\mathrm{ij}}-\mathrm{M}_{\mathrm{ij}}\right)^{2}$ |  |  |  |  |  |

Goal:
Minimize discrepancy between observed distances and tree-based distances

## Ultrametric distances \& 3 Point Condition

- For all points i, j, k
- two distances are equal and third is smaller

$$
\begin{aligned}
& d(i, j)<=d(i, k)=d(j, k) \\
& a+a<=a+b=a+b
\end{aligned}
$$


where $\mathrm{a}<=\mathrm{b}$

- Result:
- All paths from leaves are equidistant to the root
- Rooted tree with uniform rates of evolution


## Ultrametric trees

## A B C <br> A 066 <br> A 033 <br> B 302 <br> B $6 \quad 0 \quad 4$ <br> C 320 <br> C 640

For now imagine that these are just the number of substitutions between pairs:

## Symmetric 0-diagonal matrix of divergence times

A:
GCCCAACTA
B :
GTTTCCCTC

## Ultrametric Trees

- Given a symmetric $\mathrm{n} \times \mathrm{n} 0$-diagonal matrix D , an ultrametric tree T for that matrix is one in which:
- There are $n$ leaves, one for each row (column) of $D$
- Each internal node is labeled by a time in D and has exactly two children
- Along any path from the root to a leaf, the (divergence) times at the internal nodes strictly decrease
- For any two leaves $i, j$ of $T$, the LCA of $i, j$ is labeled with time $D(i, j)$

|  | A | B | C |
| :---: | :---: | :---: | :---: |
| A | 0 | 3 | 3 |
| B | 3 | 0 | 2 |
| C | 3 | 2 | 0 |



## Ultrametric Matrix Construction

|  | A | B | C | D | E |  | A | B | C | D | E |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| A | 0 | 5 | 2 | 5 | 7 | A | 0 | 5 | 2 | 5 | 7 |
| B | 5 | 0 | 5 | 3 | 7 | B | 5 | 0 | 4 | 3 | 7 |
| C | 2 | 5 | 0 | 5 | 7 | $C$ | 2 | 4 | 0 | 5 | 7 |
| D | 5 | 3 | 5 | 0 | 7 | D | 5 | 3 | 5 | 0 | 7 |
| E | 7 | 7 | 7 | 7 | 0 | E | 7 | 7 | 7 | 7 | 0 |

- Algorithms exist for "ultrametrifying" matrices.


## Minimum Spanning Tree (MST)



- There is a unique path between any two vertices in a spanning tree
- Adding an edge to a spanning tree creates a cycle
- Any edge on that cycle can be removed and we'll still have a spanning tree
- MST is found using Prim's Algorithm (graph traversal)


## The "Ultrametrification" Algorithm

Given $\mathrm{n} \times \mathrm{n}$ symmetric 0-diagonal matrix D that is not ultrametric
1.Construct a completely connected graph with n vertices, one per row of $A$. The edge weight from vertex $i$ to vertex $j$ is $D(i, j)$.
2.Find a minimum spanning tree (MST) of this graph. 3.Build a new matrix $D^{\prime}$ such that $D^{\prime}(i, j)$ is the largest weight on the unique path from $i$ to $j$ in the MST.

## Distances: (b) Additive distances

- All distances satisfy the four-point condition
- Any quartet can be labeled $\mathrm{i}, \mathrm{j}, \mathrm{k}, \mathrm{I}$ such that:
- $d(i, j)+d(k, l)<=d(i, k)+d(j, l)=d(i, l)+d(j, k)$
- $(a+b)+(c+d)<=(a-C)+(b-\square)+d)=(a-d)+(b-c)$

- Result:
- All pairwise distances obtained by traversing a tree


## Distances: (c) General distances

- In practice, a distance matrix is neither ultrametric nor additive
- Noise
- Measured distances are not exact
- Evolutionary model is not exact
- Fluctuations
- Regions used to measure distances not representative of the species tree
- Gene replacement (gene conversion), lateral transfer
- Varying rates of mutation can lead to discrepancies
- In the general case, tree-building algorithms must handle noisy distance matrices
- Such a tree can be obtained by
- Enumeration and scoring of all trees (too expensive)
- Neighbor-Joining (typically gives a good tree)
- UPGMA (typically gives a poor tree)


## Algorithms: (a) UPGMA (aka Hierarchical Clustering)

(Unweighted Pair Group Method with Arithmetic mean)

## Initialization:

Assign each $x_{i}$ into its own cluster $C_{i}$ Define one leaf per sequence, height 0

## Iteration:

Find two clusters $C_{i}, C_{j}$ s.t. $d_{i j}$ is min Let $\mathrm{C}_{\mathrm{k}}=\mathrm{C}_{\mathrm{i}} \cup \mathrm{C}_{\mathrm{j}}$
Define node connecting $\mathrm{C}_{\mathrm{i}}, \mathrm{C}_{\mathrm{j}}$, \& place it at height $\mathrm{d}_{\mathrm{ij}} / 2$
Delete $\mathrm{C}_{\mathrm{i}}, \mathrm{C}_{\mathrm{j}}$

## Termination:

When two clusters i, j remain, place root at height $\mathrm{d}_{\mathrm{ij}} / 2$


## Ultrametric Distances \& UPGMA



UPGMA is guaranteed to build the correct tree if distance is ultrametric

## Proof:

1. The tree topology is unique, given that the tree is binary
2. UPGMA constructs a tree obeying the pairwise distances

## Weakness of UPGMA

Molecular clock assumption: implies time is constant for all species

However, certain species (e.g., mouse, rat) evolve much faster

Example where UPGMA messes up:


UPGMA


## Algorithms: (b) Neighbor-Joining

- Guaranteed to produce the correct tree if distance is additive
- May produce a good tree even when distance is not additive

Step 1: Finding neighboring leaves
Define
$D_{i j}=d_{i j}-\left(r_{i}+r_{j}\right)$
Where



Claim: The above "magic trick" ensures that $D_{i j}$ is minimal $\underline{i f f} i, j$ are neighbors Proof: Beyond the scope of this lecture (Durbin book, p. 189)

## Algorithm: Neighbor-joining

## Initialization:

Define $T$ to be the set of leaf nodes, one per sequence
Let $\mathrm{L}=\mathrm{T}$

## Iteration:

Pick $\mathrm{i}, \mathrm{j}$ s.t. $\mathrm{D}_{\mathrm{ij}}$ is minimal
Define a new node $k$, and set $d_{k m}=1 / 2\left(d_{i m}+d_{j m}-d_{i j}\right)$ for all $m \in L$
Add k to T , with edges of lengths $\mathrm{d}_{\mathrm{ik}}=1 / 2\left(\mathrm{~d}_{\mathrm{ij}}+\mathrm{r}_{\mathrm{i}}-\mathrm{r}_{\mathrm{j}}\right)$
Remove i, j from L;
Add k to L

## Termination:

When $L$ consists of two nodes, $i, j$, and the edge between them of length $\mathrm{d}_{\mathrm{ij}}$

## Algorithms: (c) Distance-fitting algoriths

- With distance-based algorithms, we can also aim to directly minimize discrepancy between original distance matrix and tree-based distance matrix

COMPUTATIONAL METHOD Optimality criterion Clustering algorithm

|  | PARSIMONY <br> MAXIMUM LIKELIHOOD |  |
| :---: | :---: | :---: |
|  | MINIMUM EVOLUTION <br> LEAST SQUARES | UPGMA <br> NEIGHBOR-JOINING |

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| Rat | h.y.r | m.r | 0 | 9 | 7 |
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| Cat | h.z.x.c | m.y.z.x.c | r.y.z.x.c | d.c | 0 |
| Tree implies a distance matrix $M_{i j}$ |  |  |  |  |  |

Goal:
Minimize discrepancy between observed distances and tree-based distances.

## Aside: Alternative to Molecular clock?

Divergence between orthologous sequences is proportional to time separating the species.

Different genes evolve at specific, roughly constant rates.

## Zuckerkandl \& Pauling 1962




Courtesy of Yuri Wolf; slide in the public domain. Taken from Yuri Wolf, Lecture Slides, Feb. 2014

## Molecular Clock

Under MC all individual gene trees are ultrametric (up to a sampling error) and identical to the species tree up to a scaling factor (evolution rate).

Are these really ultrametric?


Courtesy of Yuri Wolf; slide in the public domain.

## Molecular Clock

Most of the real phylogenetic trees are far from being ultrametric.
Molecular clock is substantially overdispersed.

observed


Courtesy of Yuri Wolf; slide in the public domain.
Taken from Yuri Wolf, Lecture Slides, Feb. 2014

## Relaxed Molecular Clock

Relaxed molecular clock models allows for rate variation.
Rates are sampled from prior distributions with limited variance, independently or in autocorrelated manner.

Genes are either analyzed individually, or as concatenated alignments (implying evolution as a single unit).


Courtesy of Yuri Wolf; slide in the public domain.

## Universal Pacemaker

Universal Pacemaker model assumes that evolutionary time runs at different pace in each lineage.

Under the UPM, species trees are intrinsically non-ultrametric.


Courtesy of Yuri Wolf; slide in the public domain.
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## Pacemaker vs Clock

Both overdispersed MC and UPM models predict that individual gene trees would deviate from ultrametricity.

Under MC these deviations are expected to be uncorrelated.
Under UPM these deviations are expected to be correlated, so there exists a non-ultrametric pacemaker tree that can significantly reduce variance of observed rates.

A testable hypothesis!

2,300 trees of 100 prokaryotic species;
7,000 trees of 6 Drosophila species
1,000 trees of 9 yeast species
5,700 trees of 8 mammalian species

## Pacemaker vs Clock

2,300 trees of 100 prokaryotic species;
7,000 trees of 6 Drosophila species
1,000 trees of 9 yeast species
5,700 trees of 8 mammalian species
All show an overwhelming support to UPM model.

## Snir 2012; work in progress at NCBI (NIH)

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4. Tree of Life in Genomic Era

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## 3. Character-based tree-scoring algorithms 3a: Parsimony (set-based) 3b: Parsimony (Dyn. Prog.) 3c: Maximum Likelihood


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## Basic algorithms of phylogenetic methods

## Distance based



Sequence alignment
Pair-wise distance matrix
Output tree

## Character based

Sequence alignment


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## Character-based phylogenetic inference

- Really about tree scoring techniques, not tree finding techniques
- Couple them with tree proposal and update and you have an algorithm (part 4 of the lecture)
- Two approaches exist, all use same architecture:
- Minimize events: Parsimony (union/intersection)
- Probabilistic: Max Likelihood / MAP


## Parsimony scoring (a): Union and intersection

Given a tree, and an alignment column
Label internal nodes to minimize the number of required substitutions

## Initialization:

Set cost $C=0 ; k=2 N-1$

## Iteration:

If $k$ is a leaf, set $R_{k}=\left\{x^{k}[u]\right\}$
If $k$ is not a leaf,
Let $i, j$ be the daughter nodes;
Set $R_{k}=R_{i} \cap R_{j}$ if intersection is nonempty

Set $R_{k}=R_{i} \cup R j$, and $C+=1$, if intersection is empty

## Termination:

Minimal cost of tree for column $u,=c\{A\}$


## Parsimony traceback to find ancestral nucleotides

## Traceback:

1. Choose an arbitrary nucleotide from $\mathrm{R}_{2 \mathrm{~N}-1}$ for the root
2. Having chosen nucleotide $r$ for parent $k$, If $r \in R_{i}$ choose $r$ for daughter $i$
Else, choose arbitrary nucleotide from $\mathrm{R}_{\mathrm{i}}$

Easy to see that this traceback produces some assignment of cost $C$

Accessible to traceback


Still optimal, but not found by traceback


Parsimony Scoring (b): Dynamic programming

|  | M | R | B 1 | H | B 2 | D | B 3 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| A | 0 | 1 | 1 | 0 | 1 | 1 | 2 |
| C | 1 | 1 | 2 | 1 | 3 | 1 | 4 |
| G | 1 | 0 | 1 | 1 | 2 | 0 | 2 |
| T | 1 | 1 | 2 | 1 | 3 | 1 | 4 |

- Each cell (N,C) represents the $\min$ cost of the subtree rooted at N , if the label at N is C .
- Update table by walking up the tree from the leaves to the root, remembering max choices.
- Traceback from root to leaves to construct a min cost assignment


Mouse Rat Human Dog

## Goals for today: Phylogenetics

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1. From alignments to distances: Modeling sequence evolution

- Turning pairwise sequence alignment data into pairwise distances
- Probabilistic models of divergence: Jukes Cantor/Kimura/hierarchy

2. From distances to trees: Tree-building algorithms

- Tree types: Ultrametric, Additive, General Distances
- Algorithms: UPGMA, Neighbor Joining, guarantees and limitations
- Optimality: Least-squared error, minimum evolution (require search)

3. From alignments to trees: Alignment scoring given a tree

- Parsimony: greedy (union/intersection) vs. DP (summing cost)
- ML/MAP (includes back-mutations, lengths): peeling algorithm (DP)

4. Tree of Life in Genomic Era

- The prokaryotic problem (no real taxa and HGT)
- Interpreting the forest of life


## Scoring (c) Maximum Likelihood \& Max-a-Posteriori

Input: Sequence alignment
Output: tree with maximum likelihood / max a posteriori prob.
Search: Heuristic search for max likelihood tree.

## Maximum Likelihood (ML) $\mathrm{B}^{\wedge}, \mathrm{T}^{\wedge}=\operatorname{argmax}_{\mathrm{B}, \mathrm{T}} \mathrm{P}(\mathrm{D} \mid \mathrm{B}, \mathrm{T})$

$D=$ seq. alignment data
$B=$ branch lengths
T = topology

$$
\begin{aligned}
& \text { Maximum a Posteriori (MAP) } \\
& \begin{aligned}
\mathrm{B}^{\wedge}, \mathrm{T}^{\wedge} & =\operatorname{argmax}_{B, T} P(B, T \mid D) \\
& =\operatorname{argmax}_{B, T} P(B, T, D) / P(D) \\
& =\operatorname{argmax}_{B, T} P(B, T, D) \\
& =\operatorname{argmax}_{B, T} P(D \mid B, T) P(B, T)
\end{aligned}
\end{aligned}
$$

likelihood
$P(D \mid B, T)$ is the likelihood of data given model
$\rightarrow$ Use seq evolution model: JC,K2P,HKY.
Compute recursively using DP
$P(B, T)$ is a prior on trees/branch lengths
$\rightarrow$ Use Yule process, Birth-Death process to model

‘Peeling' algorithm for $P(D \mid B, T)$ term

1. Assume sites $\mathbf{j}$ evolve independently.
$\rightarrow$ Treat each column of the alignment in isolation
2. Assume branch independence, conditioned on parent
$\rightarrow$ Expand total joint probability into prod of $P\left(x_{i} \mid x_{\text {parent }}, \mathrm{t}_{\mathrm{i}}\right)$
$\rightarrow$ Only $\mathrm{P}\left(\mathrm{x}_{2 n-1}\right)$ remains, root prior, background nucl. freq.
3. We know how to compute $\mathbf{P}\left(\mathbf{x}_{\mathbf{i}} \mid \mathbf{x}_{\text {parent }(\mathbf{i})}, \mathbf{t}_{\mathbf{i}}\right)$ for fixed pair
$\rightarrow$ Defined by our sequence model (JC, K2P, HKY, etc)
$\rightarrow$ Easily calculate for any given assignment of internal nodes
4. As internal node values are not known $\rightarrow$ marginalize
$\rightarrow$ Sum over all possible values of all internal/root nodes
$\rightarrow$ Let $x_{n+1}, \ldots, x_{2 n-1}$ represent seqs of $n-1$ internal nodes

## 1. Site evolution over single branch Remember: Jukes-Cantor (JC)

JC is a Continuous-Time Markov Chain (CTMC)

- Defines instantaneous rates of transition between states (bases)



## Discrete MC version

- Given time t, we define a discrete MC with transition matrix is $\mathrm{S}(\mathrm{t})$, also called a substitution probability matrix.
- Gives the probability of seeing base a given initial base $b$ after duration time $t$.

$$
P(a \mid b, t)=S(t)=\left(\begin{array}{cccc}
r_{t} & s_{t} & s_{t} & s_{t} \\
s_{t} & r_{t} & s_{t} & s_{t} \\
s_{t} & s_{t} & r_{t} & s_{t} \\
s_{t} & s_{t} & s_{t} & r_{t}
\end{array}\right) \quad \begin{aligned}
& r_{t}=\frac{1}{4}\left(1+3 e^{-4 \alpha t}\right) \\
& s_{t}=\frac{1}{4}\left(1-e^{-4 \alpha t}\right)
\end{aligned}
$$

Use JC to define single site evolution:

## 2. Sequence evolution over single branch

- Assume site independence

$$
-P\left(x_{i} \mid x_{k}, t_{i j}\right)=\Pi_{j} P\left(b=x_{i j} \mid a=x_{k j}, t_{i}\right)
$$

Use product to define sequence evolution:

$$
t_{x_{i}=\text { "CAAGTC" }}^{x_{k}=" A A A C T G "} P\left(x_{i} \mid x_{k}, t_{i}\right)
$$

## 3. Sequence evolution over entire tree

- Assume branch independence
$-P\left(x_{1}, \ldots x_{n}, \ldots, x_{2 n-1} \mid T, t\right)=P\left(x_{2 n-1}\right) \Pi_{i} P\left(x_{i} \mid x_{\text {parent }}(i), t_{i}\right)$
- Assume prior on root sequence, e.g.
$-P\left(x_{2 n-1}\right)=P\left(x_{2 n-1, j}\right)=(1 / 4)^{\wedge} m$ for sequence length $m$
Use product and prior to define sequence evolution over tree:



## 4. Integrate (marginalize) over hidden ancestral seqs!

- Notice, all sequences are needed, both internal nodes and leaves
- $P\left(x_{1}, \ldots x_{n}, \ldots, x_{2 n-1} \mid T, t\right)$
- But, only leaves are given: $x_{1}, \ldots x_{n}$
- Therefore, need to marginalize (sum) over unknowns: $x_{n+1}, \ldots, x_{2 n-1}$
- This looks expensive!
$-P\left(x_{1}, \ldots x_{n} \mid T, t\right)=\sum_{x_{n+1}, \ldots,} \sum_{x_{2 n-1}} P\left(x_{1}, \ldots x_{n}, \ldots, x_{2 n-1} \mid T, t\right)$
- Don't worry, dynamic programming can do it efficiently.



## Basic trick to efficient marginalization



## Peeling algorithm

- $L(i, j, \mathrm{a})$ is the DP table.

$$
P\left(x_{1}, \ldots, x_{n} \mid T, t\right)=\prod_{j} \sum_{a} L_{2 n-1, j, a} P(a)
$$

- Each entry contains the probability of seeing the leaf data below node $i$, given that node $i$ has base a at site $j$.
- The leaves of the table are initialized $L_{i, j, a}=\{$ based on the observed sequence. Entries populated in post-order traversal.
$L_{i, j, a}= \begin{cases}1 & \text { if } x_{i, j}=a, i \leq n \\ 0 & \text { if } x_{i, j} \neq a, i \leq n \\ \sum_{b, c} P\left(b \mid a, t_{l e f t}\right)(i) L_{l e f t(i), j, b} & \text { if } i>n \\ P\left(c \mid a, t_{\text {right }(i)}\right) L_{\text {righ }}(i),,, c\end{cases}$


## Use DP to compute argmax $P(D \mid B, T)$ efficiently



## Initialization and Termination

|  | Root | Internal Nodes |  |  |  |  |  |  |  | Leaves |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 2n-1 | ... | ... | ... | i | J | k | ... | n+1 | n | ... | 3 | 2 | 1 |
| A |  |  |  |  |  |  |  |  |  | 0 | 0 | 1 | 0 | 0 |
| C |  |  |  |  |  |  |  |  |  | 1 | 0 | 0 | 0 | 1 |
| G |  |  |  |  |  |  |  |  |  | 0 | 0 | 0 | 0 | 0 |
| T |  |  |  |  |  |  |  |  |  | 0 | 1 | 0 | 1 | 0 |

- Characters at the leaves are already known - Their likelihood is 1 or 0 , indicating the known char
- Fill in internal node likelihood vectors iteratively
- Once we reach the root, multiply by the base freqs
- Maximization over Topologies and Lengths
$\rightarrow$ Numerical: gradient descent, Newton's method


## Advantages/disadvantages of ML/MAP methods

- Advantages:
- Inherently statistical and evolutionary model-based.
- Usually the most 'consistent' of the methods available.
- Used for both character and rate analyses
- Can be used to infer the sequences of the extinct ancestors.
- Account for branch-length effects in unbalanced trees.
- Nucleotide or amino acid sequences, other types of data.
- Disadvantages:
- Not as intuitive as parsimony (e.g. may choose more events if they're more likely in our probabilistic model)
- Computationally intense (limits num taxa, sequence length).
- Like parsimony, can be fooled by high levels of homoplasy.
- Violations of model assumptions can lead to incorrect trees.


## Tree reliabilit: Bootstianoing

## 1. Re-sample alignments:

- Randomly sample alignment columns with replacement
- Create many alignments of equal size.

2. Build a phylogenetic tree for each sample
3. Repeat (1) and (2) many times - 1000s of times
4. Output summary tree

- Tree constructed most frequently
- Consensus tree (even if not most freq)
- Other options

5. Report observation frequency of each branch

- Each branch is a binary split


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4. Tree of Life in Genomic Era

4 - The prokaryotic problem (no real taxa and HGT)

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## Tree of Life in Genomic Era

Genomic era - growing frustration with discrepancies between the trees reconstructed for individual genes and heroic efforts to overcome the noise. Role of horizontal gene transfer in the evolution of prokaryotic genomes is established.

Major lines of approach:

- gene repertoire and gene order
- distribution of distances between orthologs
- concatenated alignments of "non-transferable" gene cores
- consensus trees and supertrees


Ciccarelli 2006. Towards automatic reconstruction of a highly resolved tree of life. Science 311, 1283-1287 [Figure 2]

## Tree of Life, Rejected

Troubled times - "uprooting" of TOL for prokaryotes.

- horizontal gene transfer is rampant; no gene is exempt
- histories of individual genes are non-coherent with each other
- vertical signal is completely lost (or never existed at all)
- there are no species (or other taxa) in prokaryotes
- a consistent signal we observe is created by biases in HGT


Doolittle 2000. Uprooting the tree of life. Sci. Am. 282, 90-95 [modified]
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## Forest of Life - Methods

Source data and basic analysis methods:

- 100 hand-picked microbial genomes (41 archaea and 59 bacteria) representing a "fair" sample of prokaryote diversity (as known in 2008)
- clusters of orthologous genes (NCBI COGs and EMBL EggNOGs)
- multiple protein sequence alignments $\rightarrow$ index orthologs $\rightarrow$ ML phylogenetic trees
- 6901 trees cover 4-100 species; of them 102 cover $90-100$ species (Nearly Universal Trees)
- direct tree comparison (distances between trees)
- quartet decomposition; analysis of quartet spectra
- simulation evolutionary models


## Forest of Life - Analysis



NUTs are much closer to each other than expected by chance


NUTs don't form clusters (random scatter around center)


NUTs form a tightly connected network when clustered by similarity


NUTs are connected to the rest of the forest
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## Forest of Life - Analysis

"Tree-like" vs "Net-like" components of the trees (how many quartets agree/disagree with the consensus tree).

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NUTs are dominated by tree-like descent

Overall the forest of life is dominated by network-like relationships (HGT)

## Forest of Life - Analysis

Simulated example of 16 trees for 10 organisms:


No two trees are the same; each contains 2 random deviations from the consensus tree. Common statistical trend is visible.

## Module V: Evolution/phylogeny/populations

- Phylogenetics / Phylogenomics
- Phylogenetics: Evolutionary models, Tree building, Phylo inference
- Phylogenomics: gene/species trees, reconciliation, coalescent, pops
- Population genomics:
- Learning population history from genetic data
- Assembling and getting information on genomes
- Recitation about suffix arrays used in genome mapping and assembly
- Next Pset due on Nov $1^{\text {st }}$
- Don't wait until the last week to start it!

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