# Neighbor Joining with Subtree Weights 

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## Phylogeny

Phylogenetic trees illustrate the evolutionary relations among groups of organisms.


## Why we care?

- We can analyze changes that have occurred in evolution of different species.
- Phylogenetic relations among different species help predict which species might have similar functions.
- We can predict changes occurring in rapid changing species, such as HIV virus.


## Input Data for Phylogeny

- Numerical data
- Distance between different species. Each branch length represents evolutional time along an edge of the tree.
We can derive distances from DNA sequences.
- Discrete characters
- Each character has finite number of states e.g. DNA $=\{A, T, C, G\}$.


## Distance Based Methods

We reconstruct phylogenetic trees with distance based methods.

Input: Pair-wise distances from $n$ many species.
Output: An unrooted edge weighted binary tree with $n$ leaves.
Distance based methods operate two steps:

1. Compute pair-wise distance between every pair of taxa.
2. With all pair-wise distances, compute tree topology and all branch length.

## Distance Matrix

A distance matrix for a tree $T$ is a matrix $M$ whose entry $M_{i j}$ stands for the mutation distance between $i$ and $j$.


## Distance Matrix

|  | 1 | 2 | 3 | 4 | 5 | 6 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 0 | 6 | 8 | 9 | 12 | 11 |
| 2 | 6 | 0 | 6 | 7 | 10 | 9 |
| 3 | 8 | 6 | 0 | 3 | 6 | 5 |
| 4 | 9 | 7 | 3 | 0 | 5 | 4 |
| 5 | 12 | 10 | 6 | 5 | 0 | 5 |
| 6 | 11 | 9 | 5 | 4 | 5 | 0 |

Table 1: Distance matrix $M$ for the example.
Let $D(i j)$ be a pairwise distance between $i$ and $j$.

## Definitions

Def. A distance matrix $M$ is a metric iff $M$ satisfies:

- Symmetric: $M_{i j}=M_{j i}$ and $M_{i i}=0$.
- Triangle Inequality: $M_{i k}+M_{j k} \geq M_{i j}$.

Def. $M$ is an additive metric iff there exists a tree $T$ s.t.

- Every edge has a positive weight and every leaf is labeled by a distinct species in the given set.
- For every pair of $i, j, M_{i j}=$ the sum of the edge weights along the path from $i$ to $j$.

Also we call such $T$ an additive tree.

If we want to reconstruct an additive tree $T$ from an additive metric $M$, we can do in polynomial time on $n$.

## Problem:

- A distance matrix $M$ obtained from an alignment of DNA sequences is a non-additive metric.
- If $M$ is not additive, finding the nearest additive metric $\bar{M}$ is NP-hard (by Farach, Kannan, and Warnow).

We are interested in estimating the additive tree $T$ of $\bar{M}$ in polynomial time.

## Neighbor Joining Method

Def. We call a pair of two distinct leaves $\{i, j\}$ a cherry if there is exactly one intermediate node on the unique path between $i$ and $j$.

Thm. [Saitou-Nei and Studier-Keppler]
$\{i, j\}$ is a cherry if $A_{i j}=D(i j)-\left(r_{i}+r_{j}\right) /(n-2)$, where $r_{i}:=\sum_{k=1}^{n} D(i k)$, is minimal.

Neighbor Joining Method:
Idea. Initialize a star-like tree. Then find a cherry $\{i, j\}$ and computing branch length from the interior node $x$ to $i$ and from $x$ to $j$. Repeat this process recursively until we find all cherries.

## Neighbor Joining Method




## Advantages and Disadvantages

The most popular and widely used distance based method for reconstructing a phylogenetic tree.

## Advantages:

- Fast (the time complexity of this algorithm is $O\left(n^{3}\right)$ ).
- Permits lineages with largely different branch lengths.


## Disadvantages:

- Sequence information is reduced.
- Gives only one possible tree.


## Neighbor Joining with Subtree Weights

- Extended the Neighbor Joining method with the weights of $m$-leaf subtrees.
- Increasing $2 \leq m \leq \frac{n+1}{2}$, reconstructed tree from our method gets closer to the additive tree of the nearest additive matric.
- If $m=3$, the time complexity of our new method is $O\left(n^{3}\right)$, which is the same as the Neighbor Joining with pairwise distances and a tree reconstructed by our method is more accurate than the one with pairwise distances.

Note: If $m=2$, then our method is the Neighbor Joining method with pairwise distances.

## Notations and Definitions

Notation. Let $[n]$ denote the set $\{1,2, \ldots, n\}$ and $\binom{[n]}{m}$ denote the set of all $m$-element subsets of $[n]$.

Def. A m-dissimilarity map is a function $D:\binom{[n]}{m} \rightarrow \mathbb{R}_{\geq 0}$.
In the context of phylogenetic trees, the map $D\left(i_{1}, i_{2}, \ldots, i_{m}\right)$ may measure the weight of a subtree that spans the leaves $i_{1}, i_{2}, \ldots, i_{m}$.

Denote $D\left(i_{1} i_{2} \ldots i_{m}\right):=D\left(i_{1}, i_{2}, \ldots, i_{m}\right)$.

## Weights of Subtrees in $T$


$D(i j k l)$ is the total branch length of the subtree in green. Also $D\left(x_{1} x_{2}\right)$ is the total branch length of the subtree in pink and it is also a pairwise distance between $x_{1}$ and $x_{2}$.

Thm. [Levy, Pachter, Y.] Let $D_{m}$ be an $m$-dissimilarity map on $n$ leaves, $D_{m}:\binom{[n]}{m} \rightarrow \mathbb{R}_{\geq 0}$, and define

$$
S(i j):=\sum_{X \in\binom{[n-i-j]}{m-2}} D_{m}(i j X) .
$$

If the weights $D_{m}$ correspond to $m$-subtree weights of a tree $T$ then $S(i j)$ is a tree metric.

Furthermore, if $T^{\prime}$ is the additive tree corresponding to this tree metric then $T^{\prime}$ and $T$ have the same tree topology and there is an invertible linear map between their edge weights.

Note. This means that if we reconstruct $T^{\prime}$, then we can reconstruct $T$.

## Computing edge weights on $T$

Lemma 1. [Levy, Pachter, Y.] If $e$ is an internal edge of $T$ (equivalently $T^{\prime}$ ), then

$$
w_{T^{\prime}}(e)=\frac{1}{2}\left[\binom{\left|L_{1}(e)\right|-2}{m-2}+\binom{\left|L_{2}(e)\right|-2}{m-2}\right] w_{T}(e)
$$

where $L_{1}(e)$ and $L_{2}(e)$ are the two leaf sets of $T-e$.

For an edge $e \in E(T)$ and a leaf $i, L_{i}(e)$ denotes the set of leaves in $T-e$ that are in the same connected component as $i$.

$$
\text { If } i=3 \text {, then } L_{3}(e)=\{3,4,5,6\}
$$



Lemma 2. [Levy, Pachter, Y.] Denote the edges adjacent to the leaves by $e_{1}, \ldots, e_{n}$.

Let $\left.C_{i}=\sum_{e \in \operatorname{int}(E(T))}\binom{n-2}{m-2}-\binom{\left|L_{i}(e)\right|-2}{m-2}\right) w_{T}(e)$. Then

$$
\left(\begin{array}{c}
w_{T}\left(e_{1}\right) \\
\vdots \\
w_{T}\left(e_{n}\right)
\end{array}\right)=A^{-1}\left(\begin{array}{l}
2 w_{T^{\prime}}\left(e_{1}\right)-C_{1} \\
\vdots \\
2 w_{T^{\prime}}\left(e_{n}\right)-C_{n}
\end{array}\right),
$$

where $A^{-1}=\frac{1}{2\binom{n-2}{m-2}}\left(\mathbf{I}-\frac{m-2}{(m-1)(n-2)} \mathbf{J}\right)$.

## Neighbor Joining with Subtree Weights

Input: $n$ many DNA sequences.
Output: A phylogenetic tree $T$ with $n$ leaves.

1. Compute all $m$-subtree weights via the maximum likelihood.
2. Compute $S(i j)$ for each pair of leaves $i$ and $j$.
3. Apply Neighbor Joining method with a tree metric $S(i j)$ and obtain additive tree $T^{\prime}$.
4. Using Lemma 1, obtain a weight of each internal edge of $T$.
5. Using Lemma 2, obtain a weight of each leaf edge of $T$.

## Complexity

Lemma. [Levy, Pachter, Y.] If $m \geq 3$, the time complexity of this algorithm is $O\left(n^{m}\right)$, where $n$ is the number of leaves of $T$ and if $m=2$, then the time complexity of this algorithm is $O\left(n^{3}\right)$.

Sketch of Proof: If $m \geq 3$, the computation of $S(i j)$ is $O\left(n^{m}\right)$ (both steps are trivially parallelizable). The subsequent neighbor-joining is $O\left(n^{3}\right)$ and edge weight reconstruction is $O\left(n^{2}\right)$. If $m=2$, then the subsequent neighbor-joining is $O\left(n^{3}\right)$ which is greater than computing $S(i j)$. So, the time complexity is $O\left(n^{3}\right)$.

Note: The running time complexity of the algorithm is $O\left(n^{3}\right)$ for both $m=2$ and $m=3$.

## Cherry Picking Theorem

Thm. [Levy, Pachter, Y.] Let $T$ be a tree with $n$ leaves and no nodes of degree 2 and let $m$ be an integer satisfying $2 \leq m \leq n-2$. Let $D:\binom{[n]}{m} \rightarrow \mathbb{R}_{\geq 0}$ be the $m$-dissimilarity map corresponding to the weights of the subtrees of size $m$ in $T$. If $Q_{D}(i j)$ is a minimal element of the matrix

$$
Q_{D}(i j)=\left(\frac{n-2}{m-1}\right) \sum_{X \in\binom{[n-i-j]}{m-2}} D(i j X)-\sum_{X \in\binom{n-i]}{m-1}} D(i X)-\sum_{X \in\binom{[n-j]}{m-1}} D(j X)
$$

then $\{i, j\}$ is a cherry in the tree $T$.
Note. The theorem by Saitou-Nei and Studier-Keppler is a corollary from Cherry Picking Theorem.

## Simulation Results

## Consider two tree models...

Modeled from Strimmer and von Haeseler.


T1


T2

We generate 500 replications with the Jukes-Cantor model via a software evolver from PAML package.

The number represents a percentage which we got the same tree topology.

| I | $\mathrm{a} / \mathrm{b}$ | $\mathrm{m}=2$ | $\mathrm{~m}=3$ | $\mathrm{~m}=4$ | fastDNAmI |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 500 | $0.01 / 0.07$ | 68.2 | 76.8 | 80.4 | 74.8 |
|  | $0.02 / 0.19$ | 54.2 | 61.2 | 73.6 | 55.6 |
|  | $0.03 / 0.42$ | 10.4 | 12.6 | 23.8 | 12.6 |
| 1000 | $0.01 / 0.07$ | 94.2 | 96 | 97.4 | 96.6 |
|  | $0.02 / 0.19$ | 87.6 | 88.6 | 96.2 | 88 |
|  | $0.03 / 0.42$ | 33.4 | 35 | 52.4 | 33.6 |

Table 2: Success Rates for the model $T_{1}$.

| I | $\mathrm{a} / \mathrm{b}$ | $\mathrm{m}=2$ | $\mathrm{~m}=3$ | $\mathrm{~m}=4$ | fastDNAml |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 500 | $0.01 / 0.07$ | 84.4 | 86 | 85.6 | 88.4 |
|  | $0.02 / 0.19$ | 68.2 | 72 | 73.2 | 88.4 |
|  | $0.03 / 0.42$ | 18.2 | 29.2 | 36.2 | 87.4 |
| 1000 | $0.01 / 0.07$ | 95.6 | 97.8 | 97.4 | 99.4 |
|  | $0.02 / 0.19$ | 88.4 | 89.6 | 93.4 | 99.8 |
|  | $0.03 / 0.42$ | 40 | 48.2 | 57.6 | 96.6 |

Table 3: Success Rates for the model $T_{2}$.

## Questions??

## Paper and Software

The paper will be available soon at Arxiv

Software package Shinrin will be available soon.

Download at http://bio.math.berkeley.edu/mjoin/

## Thank you...

