## Neighbor Joining with Subtree Weights

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The software package MJOIN will be available at http://bio.math.berkeley.edu/mjoin/

## Introduction

- The Neighbor-Joining algorithm is a recursive procedure to reconstruct a phylogenetic tree using a transformation of pairwise distances between leaves for identifying cherries in the tree.
- Pachter and Speyer showed that we can recover an $n$-leaf tree from the weights of $m$-leaf subtrees if $n \geq 2 m-1$ [PS04
- We generalized the cherry picking criterion with estimates of the weights of $m$-leaf subtrees
- We showed that a reconstructed tree from such weights is more accurate than one using pairwise distances.
- This leads to an improved neighbor-joining algorithm whose total running time is still polynomial in the number of taxa


## Neighbor Joining with Pairwise Distances

Theorem. (the cherry picking criterion) [SN87, SK88]
Suppose $D(i j)$ is a pairwise distance between taxa $i$ and $j$. Then, $\{i, j\}$ 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.

Idea. Initialize a star-like tree and find a cherry. Then we compute branch length from the interior node to each leaf. Repeat this process recursively until we find all cherries.



Figure 1: The traditional Neighbor Joining with pairwise distances.

## Neighbor Joining with Subtree Weights

Notation. Let $[n]$ denote the set $\{1,2, \ldots, n\}$ and $\binom{[n]}{m}$ denote the set of all $m$-element subsets of $[n]$.
Definition. A $m$-dissimilarity map is a function $D:\binom{[n]}{m} \rightarrow \mathbb{R}_{\geq 0}$. In terms of
phylogeny, this corresponds to the weights of $m$-subtree weights of a tree $T$.
Theorem. Let $D_{m}$ be be an $m$-dissimilarity map on $n$ leaves, $D_{m}:\binom{(n)}{m} \rightarrow \mathbb{R} \geq 0$ correspond to the weights of $m$-subtree weights of a tree $T$ and we define

$$
S(i j):=\sum_{X \in\left(\begin{array}{l}
(n) \mid i(i, j) \\
m-2 \\
)
\end{array}\right.} D_{m}(i j X) .
$$

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.

## Algorithm. (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 $j$.
2. Apply Neighbor Joining method with a tree metric $S(i j)$ and obtain additive tree $T^{\prime}$.
3. Using a linear mapping, obtain a weight of each internal edge and each leaf edge of $T$.

## Cherry Picking Theorem

Theorem. 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 $Q_{D}(a b)$ is a minimal element of the matrix
then $\{a, b\}$ is a cherry in the tree $T$
Note. The theorem by Saitou-Nei and Studier-Keppler is a corollary from Cherry
Picking Theorem.

## Time Complexity

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

$$
m=3 .
$$

## Computational Results

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


T1


T2

Figure 2: Modeled from Strimmer and von Haeseler

The number represents a percentage which we got the same tree topology. $l$ is the length of sequences.

| 1 | $\mathrm{a} / \mathrm{b} \quad \mathrm{m}=2 \mathrm{~m}=3 \mathrm{~m}=4$ fastDNAml |
| :--- | :--- |


| 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 |
| :--- | :--- | :--- | :--- | :--- | | $0.02 / 0.19$ | 87.6 | 88.6 | 96.2 | 88 |
| :--- | :--- | :--- | :--- | :--- | :--- | | $0.03 / 0.42$ | 33.4 | 35 | 52.4 | 33.6 |
| :--- | :--- | :--- | :--- | :--- |

The table above represents success rates for the model $T_{1}$. We compared our method with fastDNAm1 [HO94]

| l | $\mathrm{a} / \mathrm{b}$ |  | $\mathrm{m}=2$ |  | $\mathrm{~m}=3$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{~m}=4$ | 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 |

The table above represents success rates for the model $T_{2}$. We compared our method with fastDNAml [HO94]

## References

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