

Challenge and novel approaches for multiple sequence alignment and phylogenetic estimation

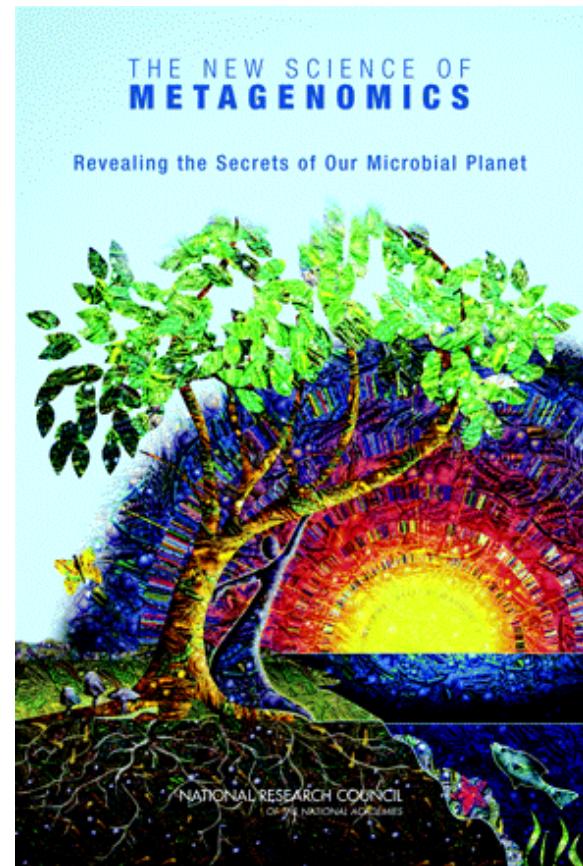
Tandy Warnow

Department of Computer Science
The University of Texas at Austin

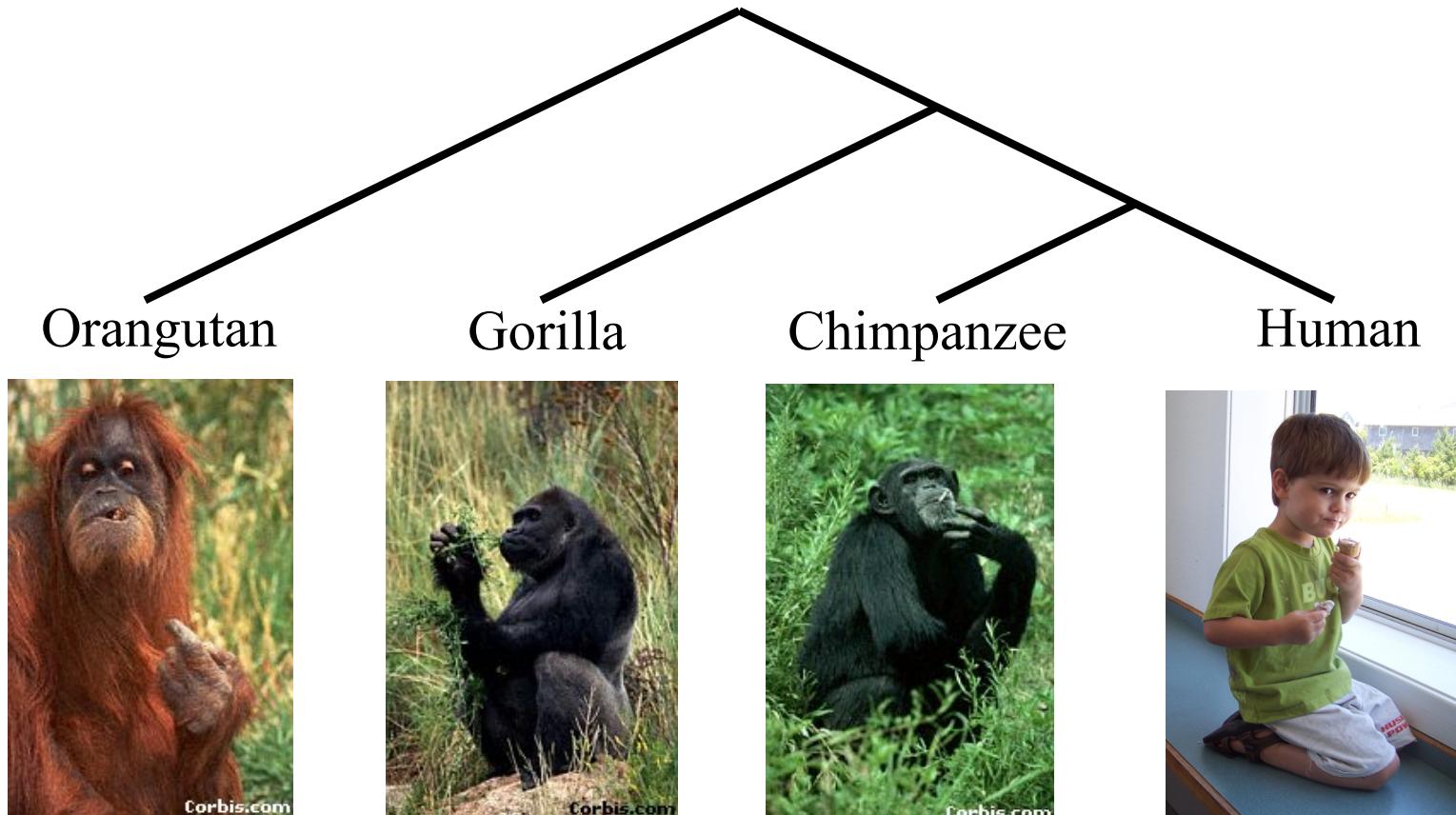
Computational Phylogenetics and Metagenomics



Courtesy of the Tree of Life project



Phylogeny (evolutionary tree)



*From the Tree of the Life Website,
University of Arizona*

How did life evolve on earth?

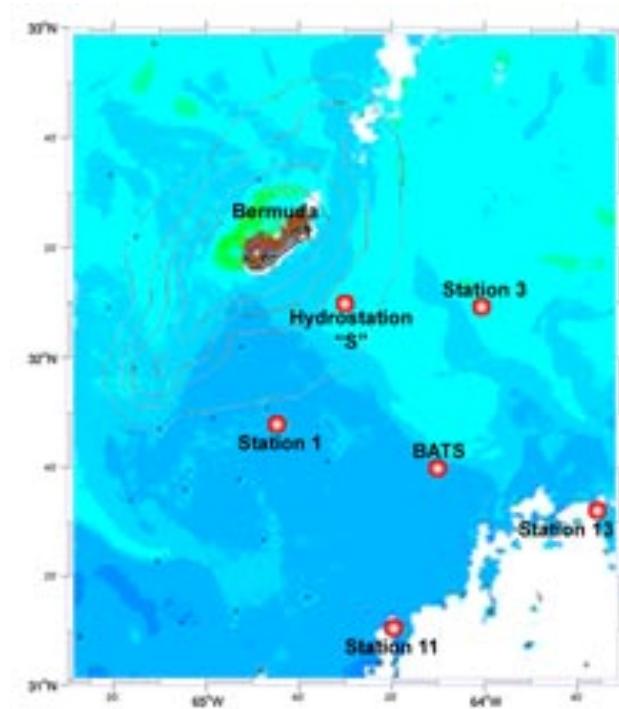


Courtesy of the Tree of Life project

Metagenomics:

Venter et al., Exploring the Sargasso Sea:

Scientists Discover One Million New Genes in Ocean Microbes



Major Challenges

- **Phylogenetic analyses:** standard methods have *poor accuracy* on even moderately large datasets, and the most accurate methods are enormously *computationally intensive* (weeks or months, high memory requirements)
- **Metagenomic** analyses: methods for species classification of short reads have *poor sensitivity*. Efficient high throughput is necessary (millions of reads).

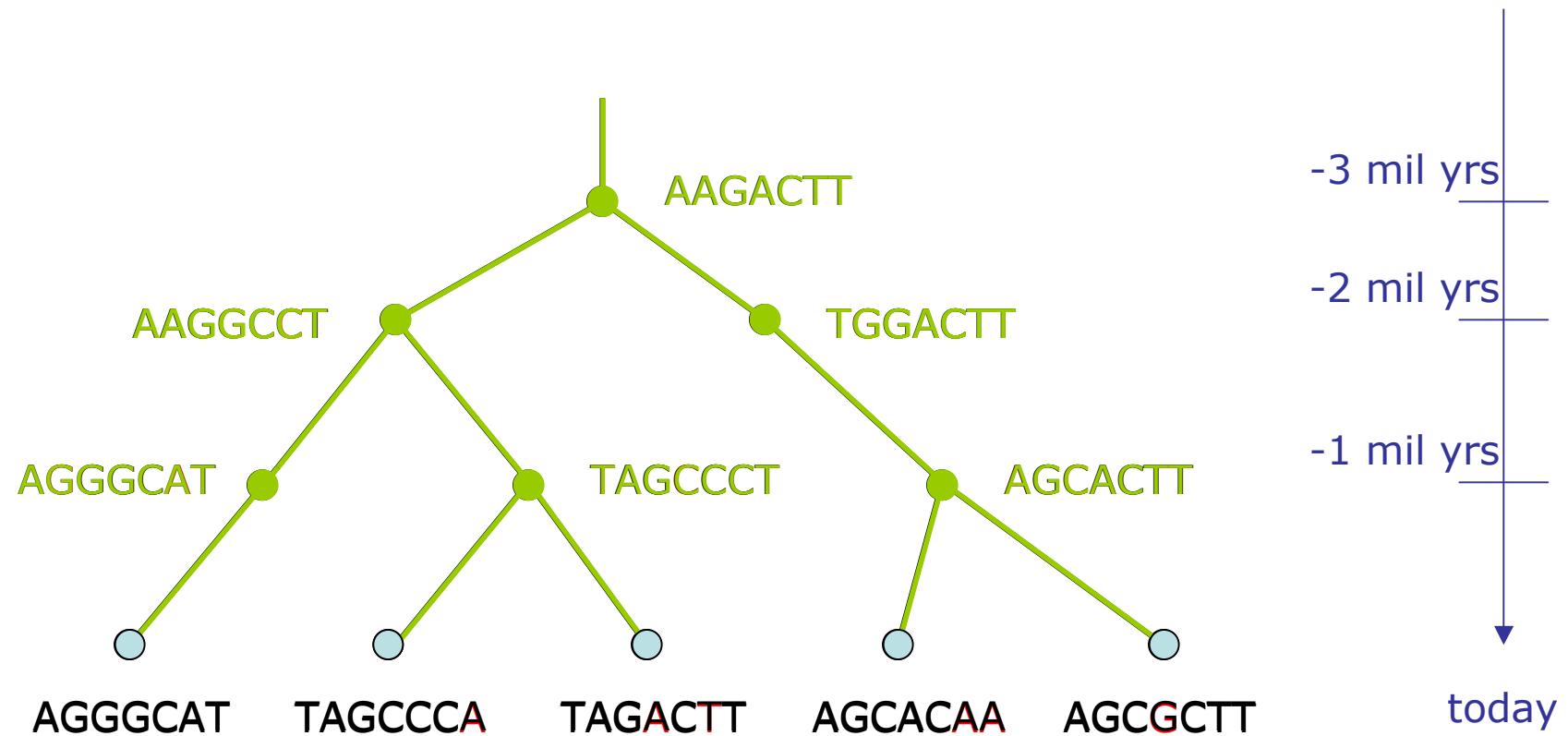
Phylogenetic “boosters” (meta-methods)

Goal: improve accuracy, speed, robustness, or theoretical guarantees of base methods

Examples:

- [DCM-boosting for distance-based methods \(1999\)](#)
- DCM-boosting for heuristics for NP-hard problems (1999)
- [SATé-boosting for alignment methods \(2009\)](#)
- SuperFine-boosting for supertree methods (2011)
- DACTAL-boosting: almost alignment-free phylogeny estimation methods (2011)
- SEPP-boosting for phylogenetic placement of short sequences (2012)
- TIPP-boosting for metagenomic taxon identification (2013)

DNA Sequence Evolution





The **true** multiple alignment

- Reflects historical substitution, insertion, and deletion events
- Defined using transitive closure of pairwise alignments computed on edges of the true tree

U

V

W

X

Y

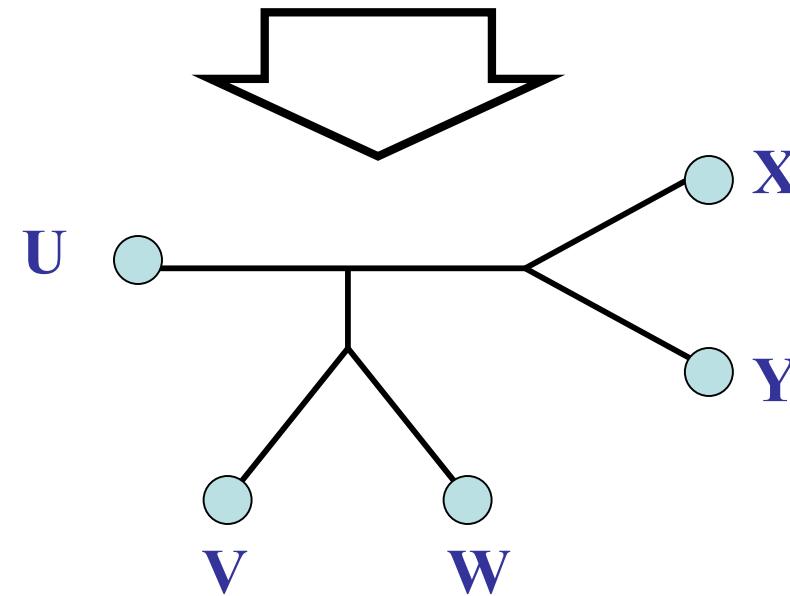
AGGGCATGA

AGAT

TAGACTT

TGCACAA

TGCGCTT



Input: unaligned sequences

S1 = AGGCTATCACCTGACCTCCA

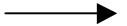
S2 = TAGCTATCACGACCGC

S3 = TAGCTGACCGC

S4 = TCACGACCGACA

Phase 1: Multiple Sequence Alignment

S1 = AGGCTATCACCTGACCTCCA
S2 = TAGCTATCACGACCGC
S3 = TAGCTGACCGC
S4 = TCACGACCGACA



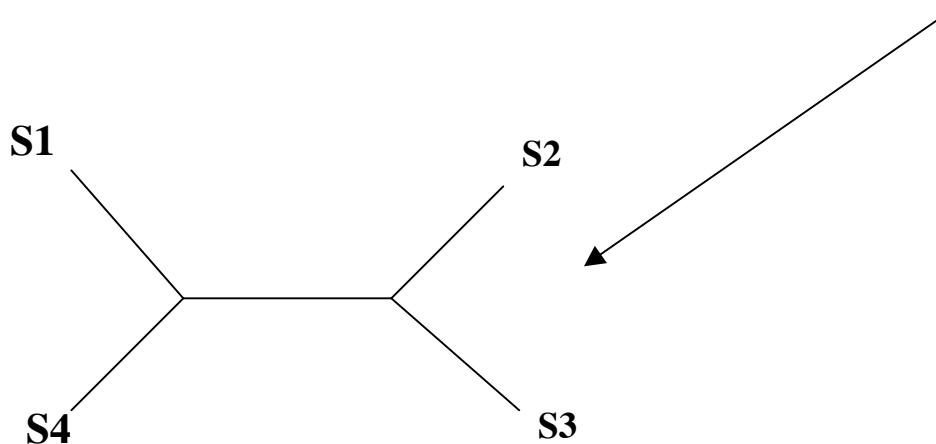
S1 = -AGGCTATCACCTGACCTCCA
S2 = TAG-CTATCAC--GACCGC--
S3 = TAG-CT-----GACCGC--
S4 = -----TCAC--GACCGACA

Phase 2: Construct tree

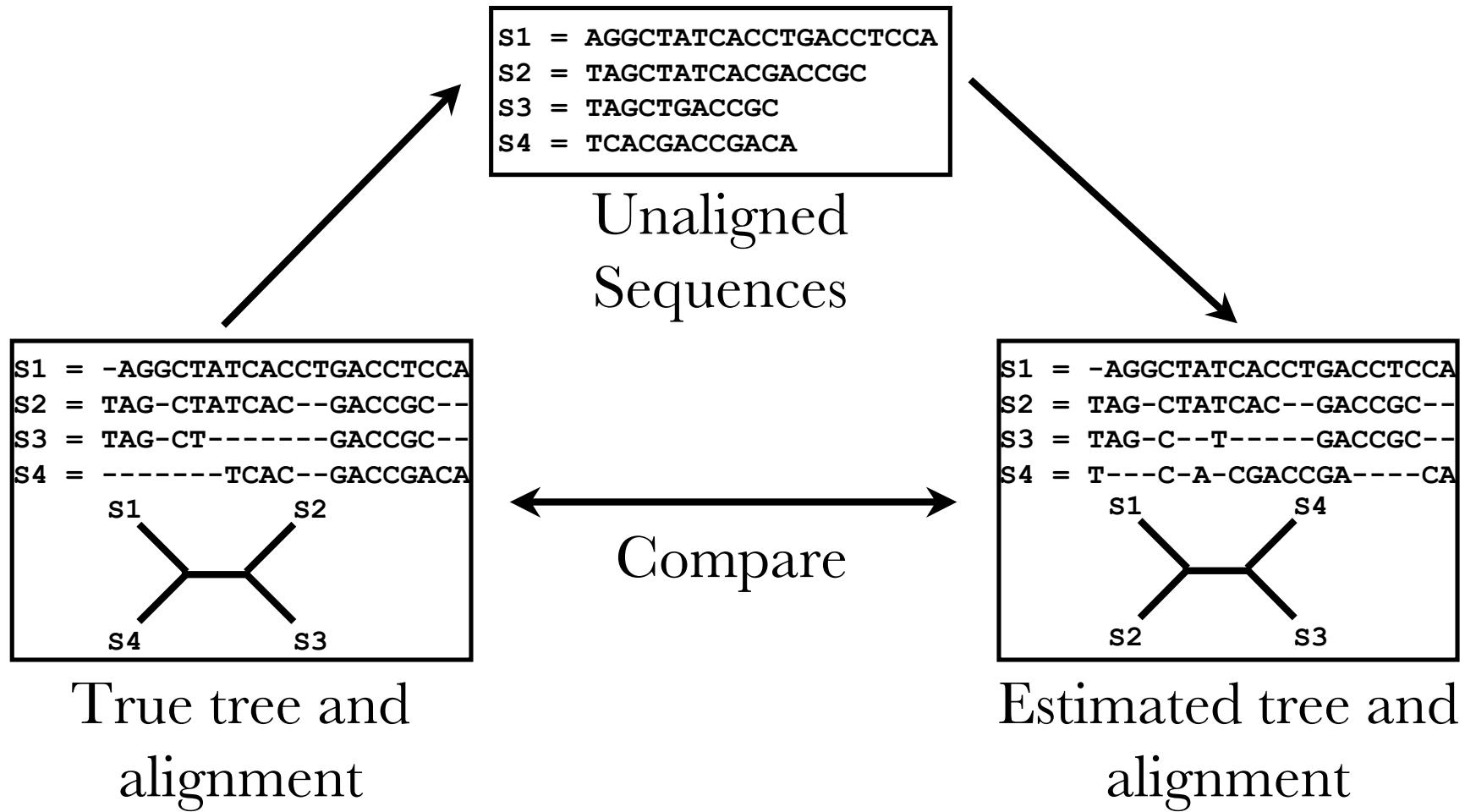
S1 = AGGCTATCACCTGACCTCCA
S2 = TAGCTATCACGACCGC
S3 = TAGCTGACCGC
S4 = TCACGACCGACA



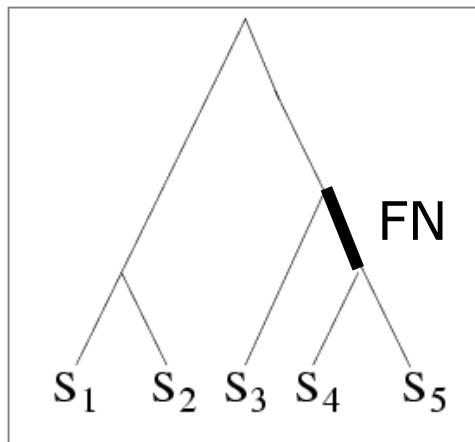
S1 = -AGGCTATCACCTGACCTCCA
S2 = TAG-CTATCAC--GACCGC--
S3 = TAG-CT-----GACCGC--
S4 = -----TCAC--GACCGACA



Simulation Studies



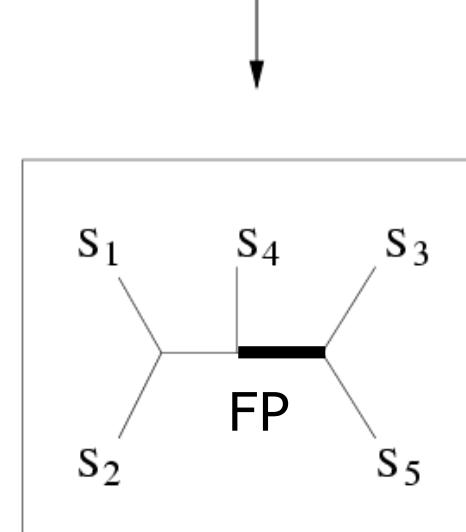
Quantifying Error



TRUE TREE

S_1	ACAATTAGAAC
S_2	ACCCTTAGAAC
S_3	ACCATTCCAAC
S_4	ACCAGACCAAC
S_5	ACCAGACCGGA

DNA SEQUENCES



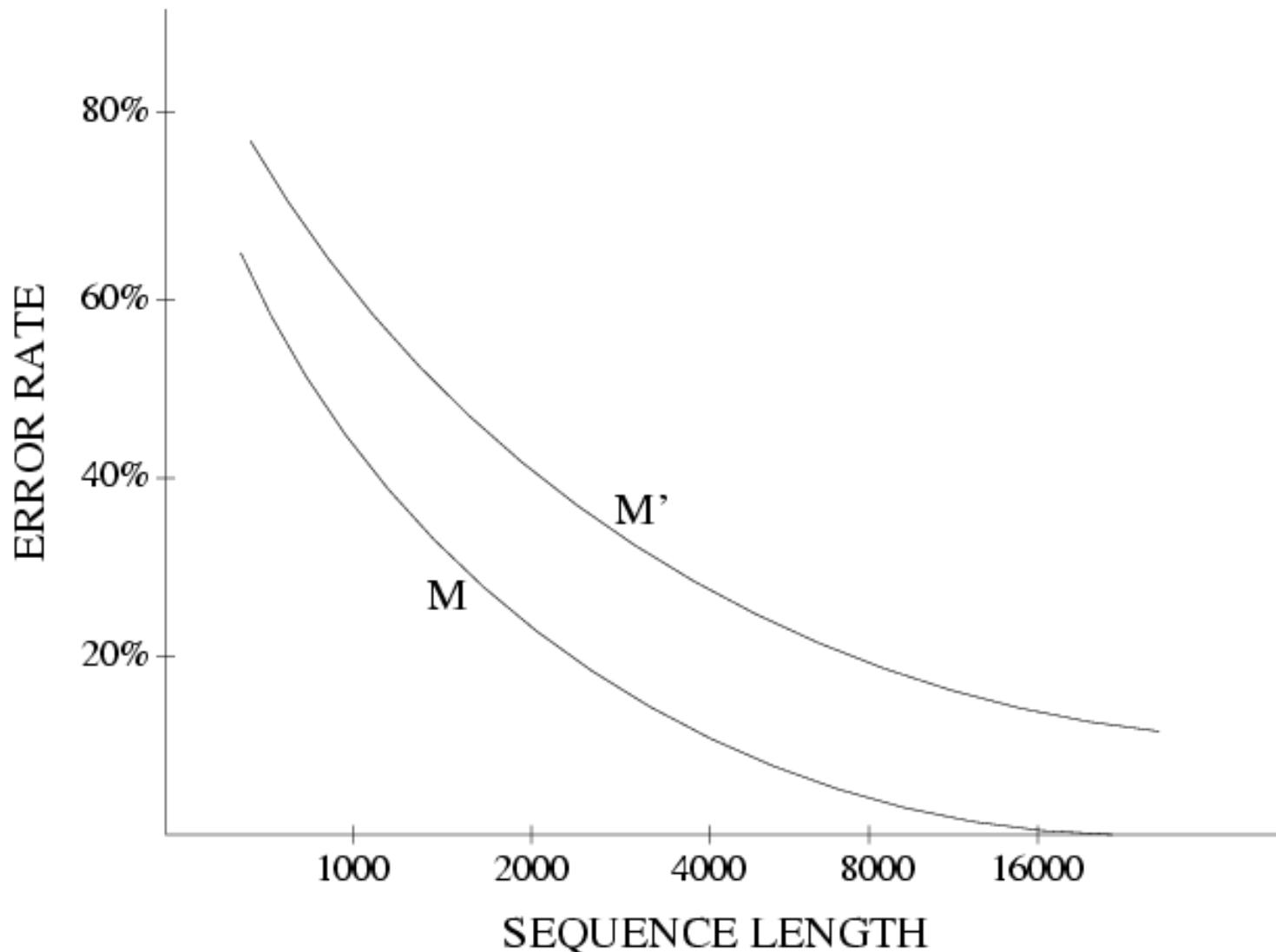
FN: false negative
(missing edge)

FP: false positive
(incorrect edge)

50% error rate

INFERRRED TREE

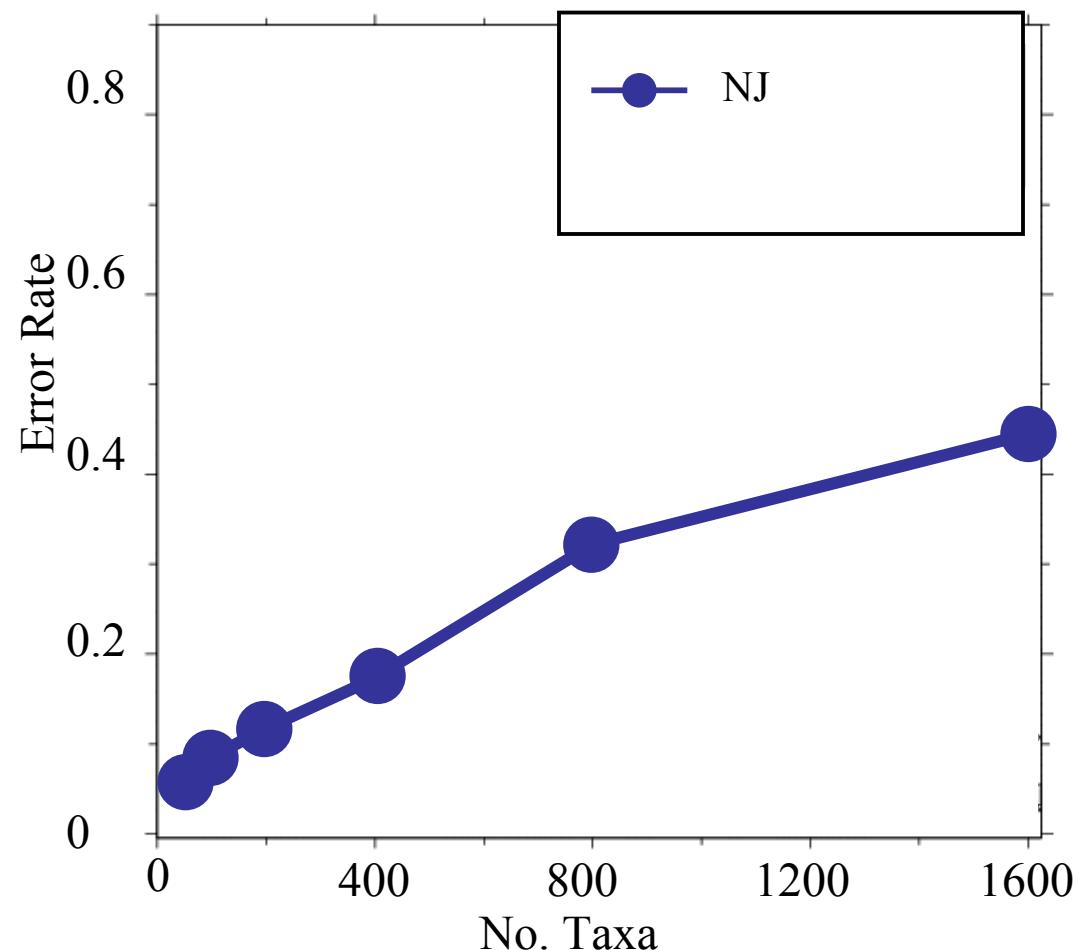
Statistical consistency and convergence rates



Part I: “Fast-Converging Methods”

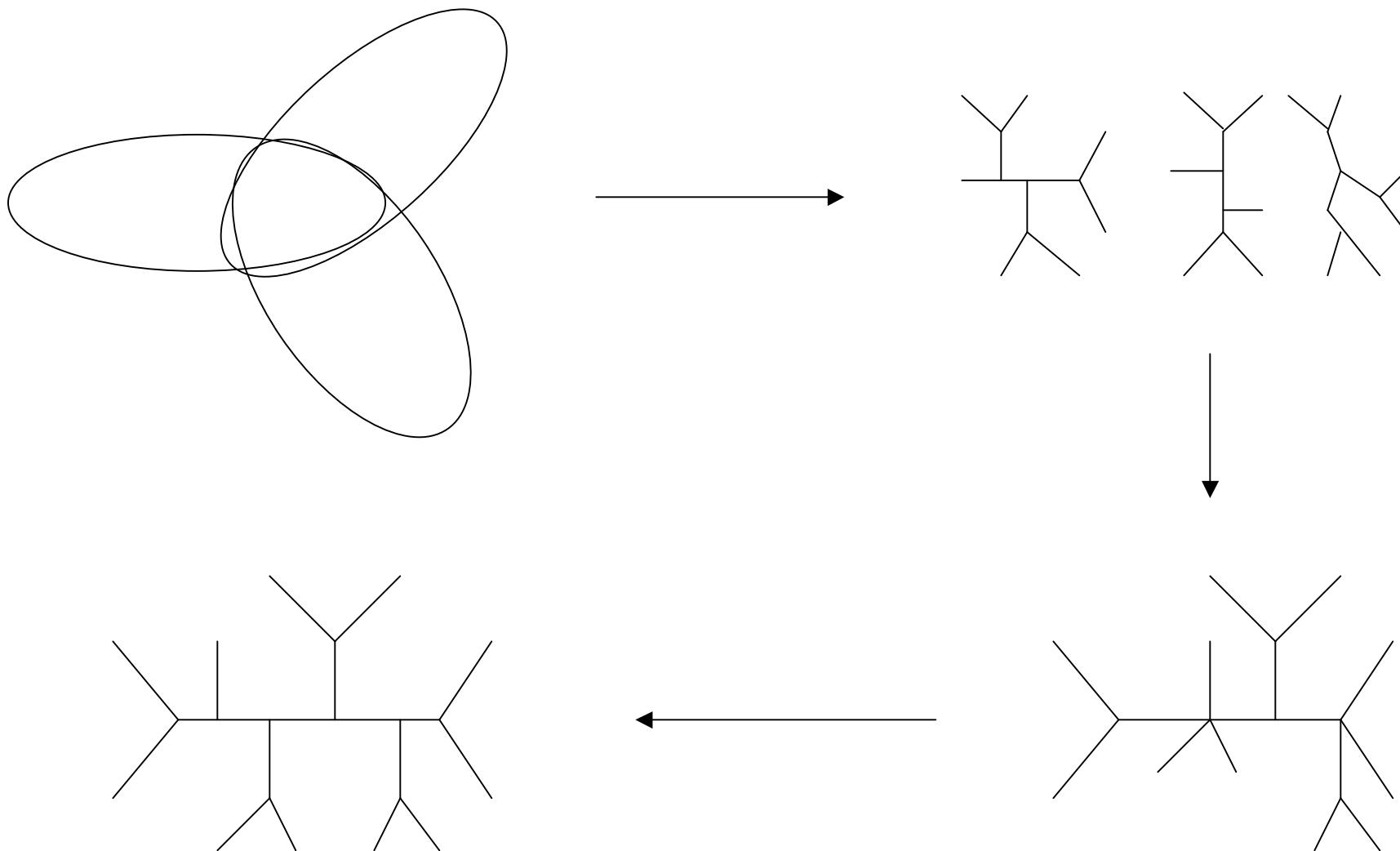
- Basic question: how much data does a phylogeny estimation method need to produce the true tree with high probability?

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



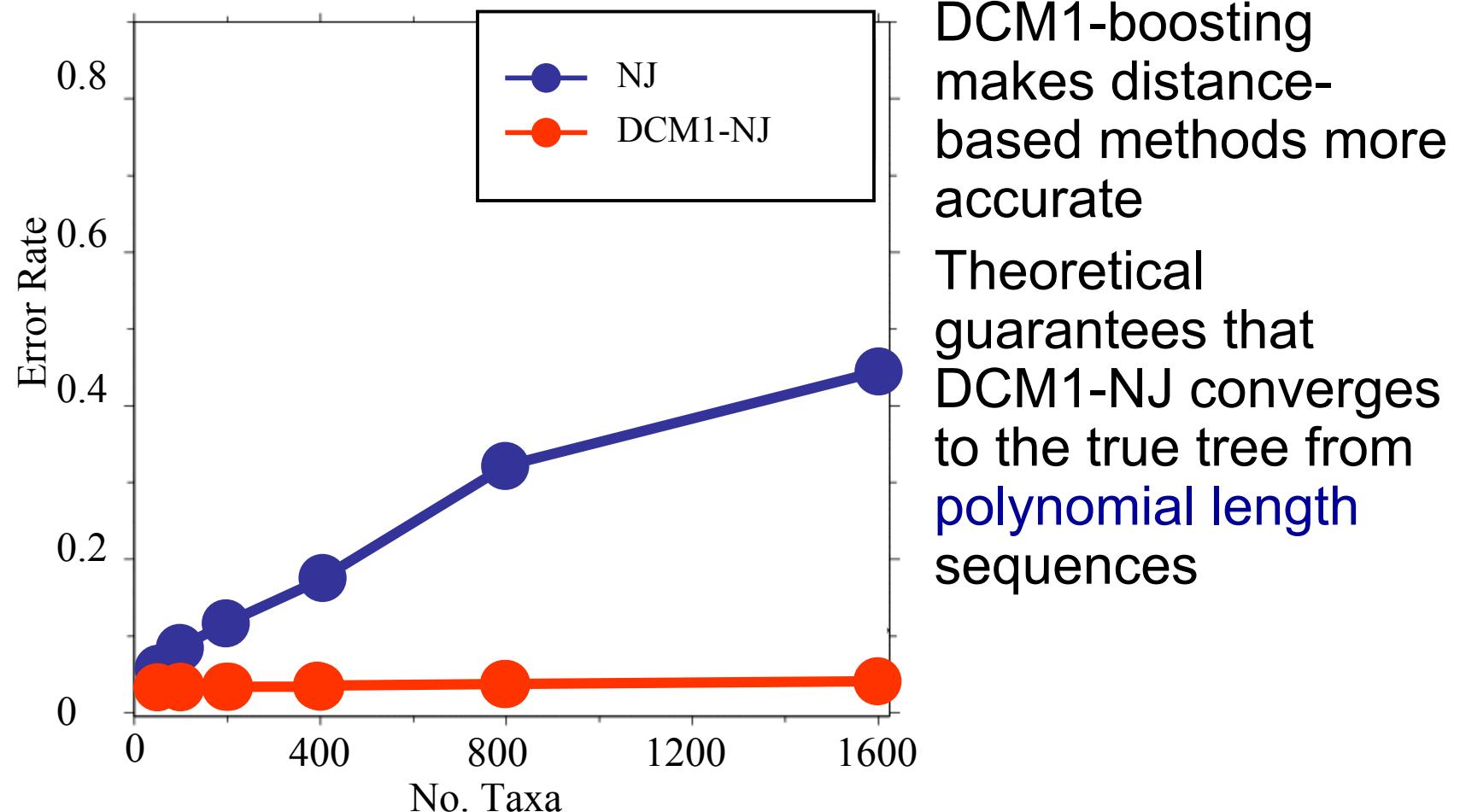
Theorem (Atteson):
Exponential
sequence length
requirement for
Neighbor Joining!

Disk-Covering Methods (DCMs) (starting in 1998)



DCM1-boosting distance-based methods

[Nakhleh et al. ISMB 2001]



Part II: SATé

Simultaneous Alignment and Tree Estimation

Liu, Nelesen, Raghavan, Linder, and Warnow,
Science, 19 June 2009, pp. 1561-1564.

Liu et al., Systematic Biology 2012

Public software distribution (open source)
through the Mark Holder's group at the
University of Kansas

Two-phase estimation

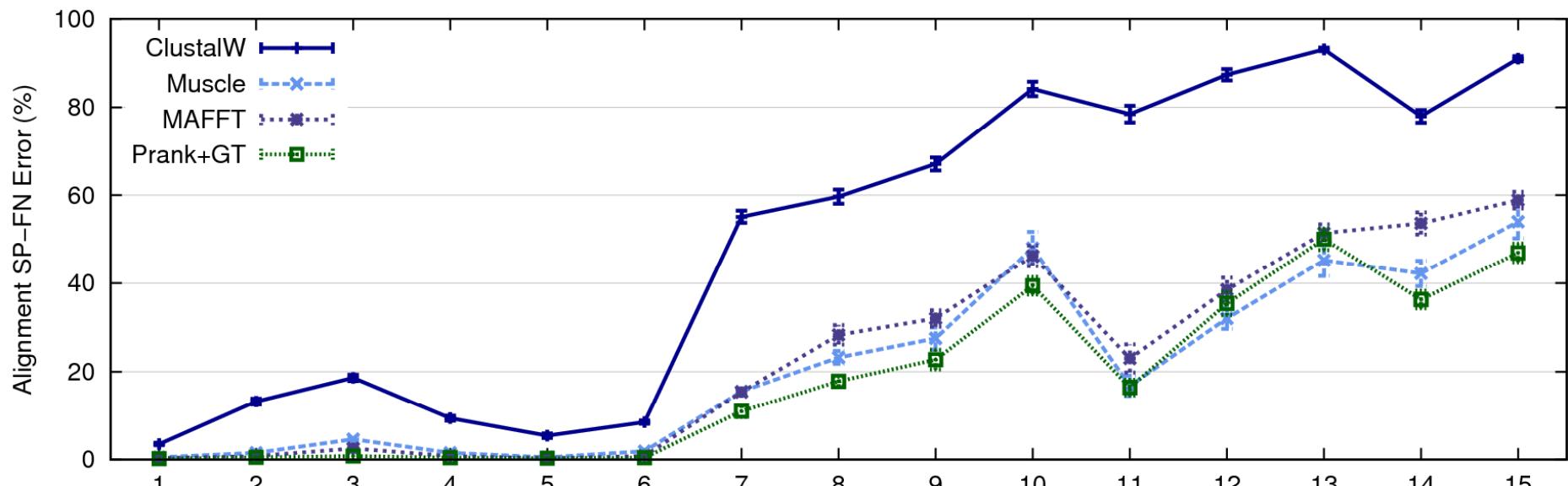
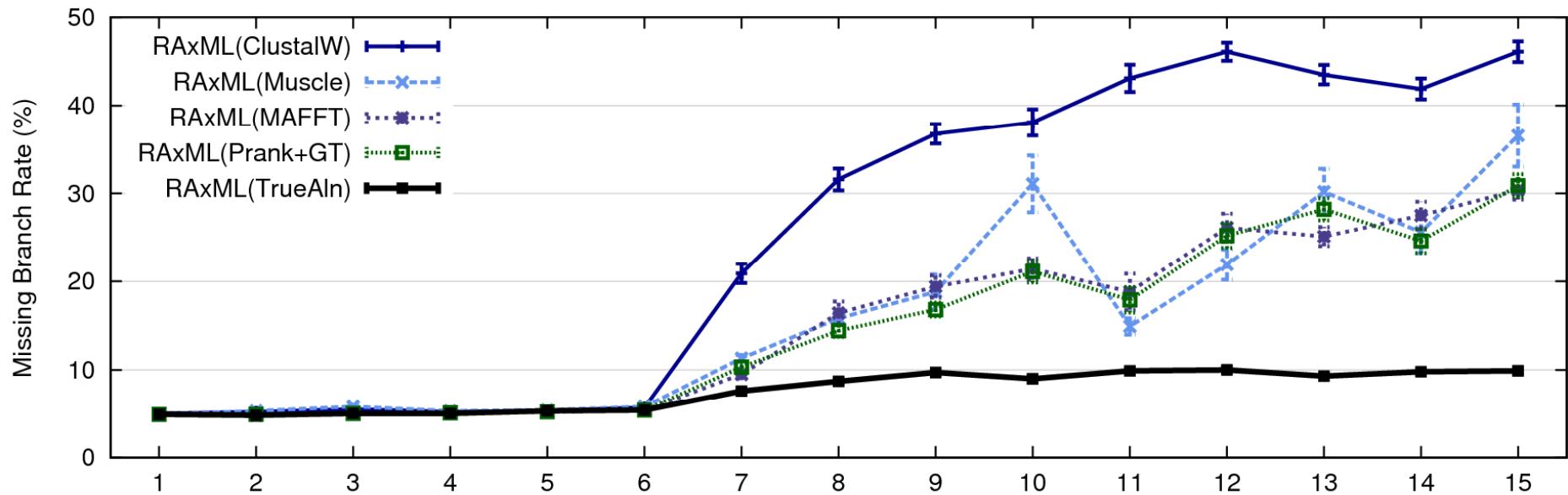
Alignment methods

- Clustal
- POY (and POY*)
- Probcons (and Probtree)
- Probalign
- MAFFT
- Muscle
- Di-align
- T-Coffee
- Prank (PNAS 2005, Science 2008)
- Opal (ISMB and Bioinf. 2007)
- FSA (*PLoS Comp. Bio.* 2009)
- Infernal (*Bioinf.* 2009)
- Etc.

Phylogeny methods

- Bayesian MCMC
- Maximum parsimony
- **Maximum likelihood**
- Neighbor joining
- FastME
- UPGMA
- Quartet puzzling
- Etc.

RAxML: heuristic for large-scale ML optimization



1000 taxon models, ordered by difficulty (Liu et al., 2009)

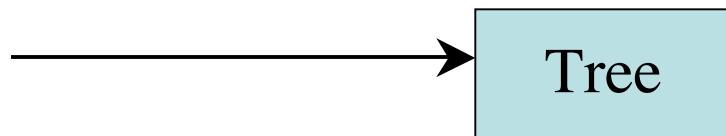
Problems

- Large datasets with high rates of evolution are hard to align accurately, and phylogeny estimation methods produce poor trees when alignments are poor.
- Many phylogeny estimation methods have poor accuracy on large datasets (even if given correct alignments)
- *Potentially useful genes are often discarded* if they are difficult to align.

These issues seriously impact large-scale phylogeny estimation (and Tree of Life projects)

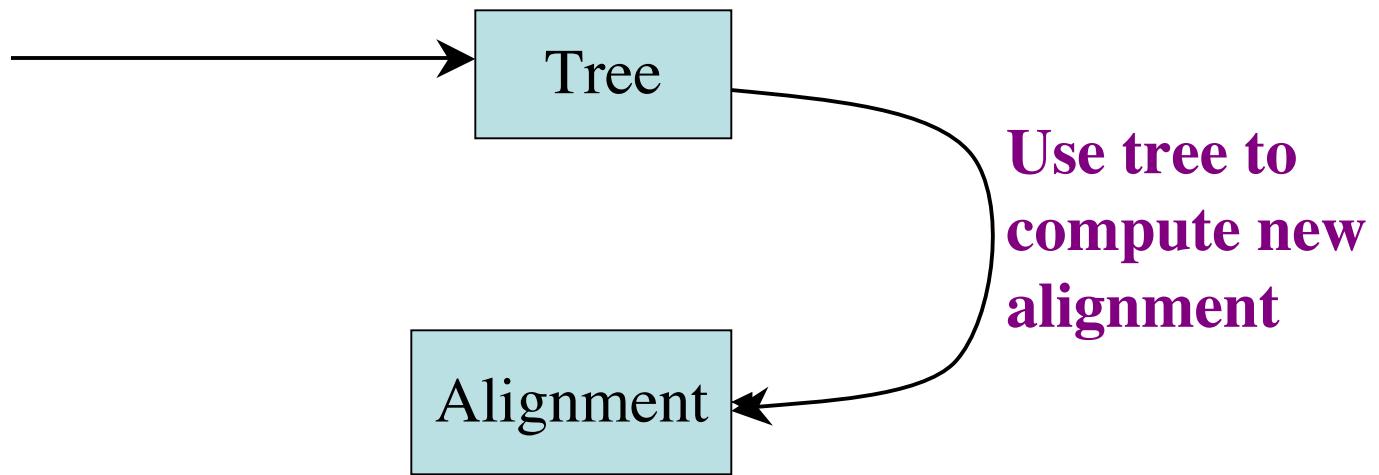
SATé Algorithm

Obtain initial alignment
and estimated ML tree



SATé Algorithm

Obtain initial alignment
and estimated ML tree

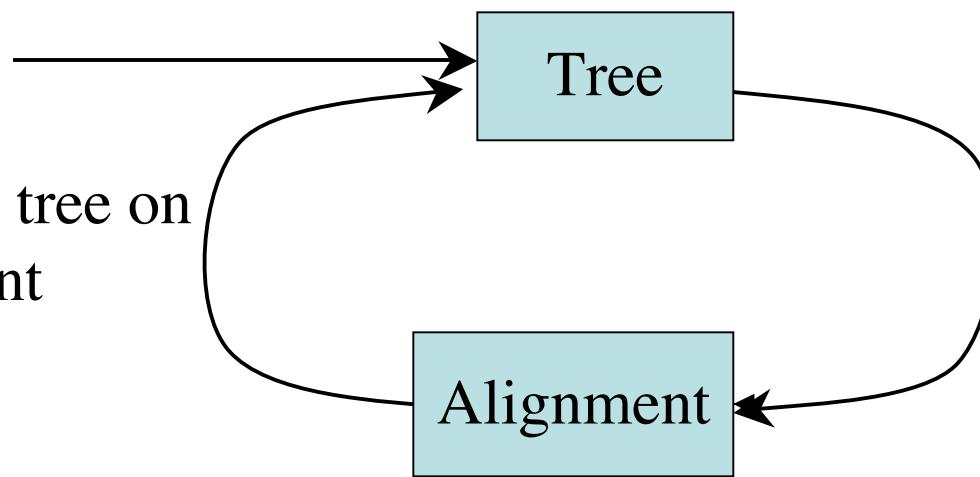


SATé Algorithm

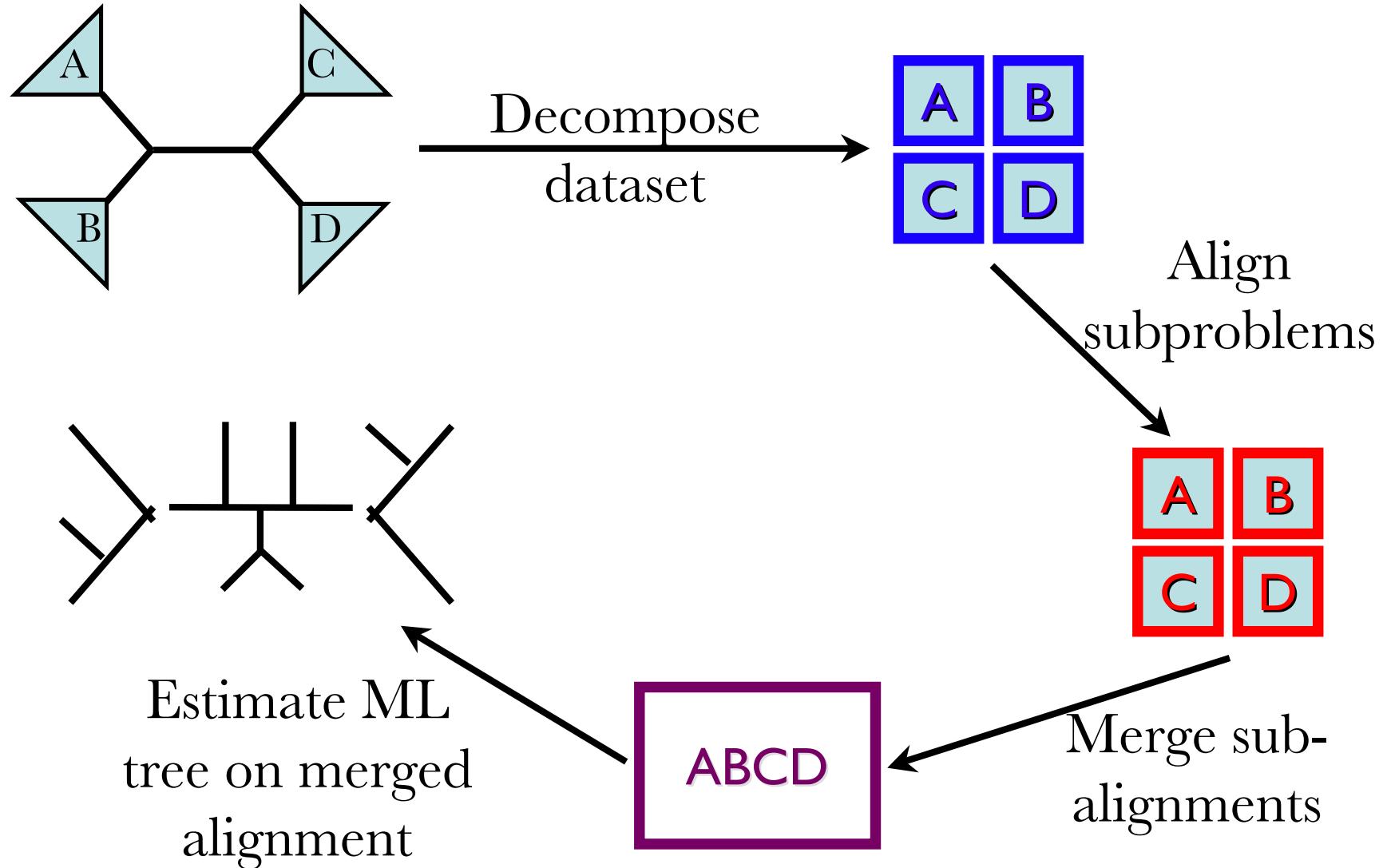
Obtain initial alignment
and estimated ML tree

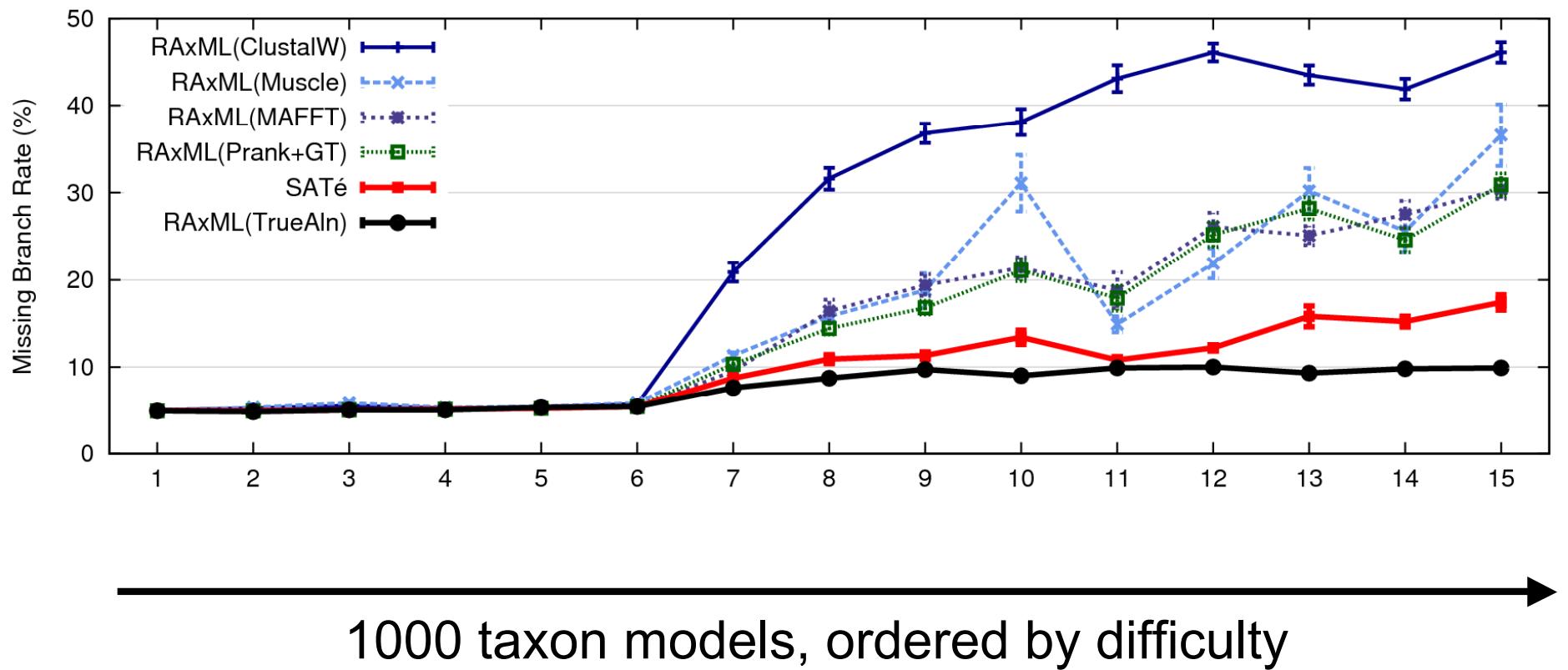
Estimate ML tree on
new alignment

Use tree to
compute new
alignment

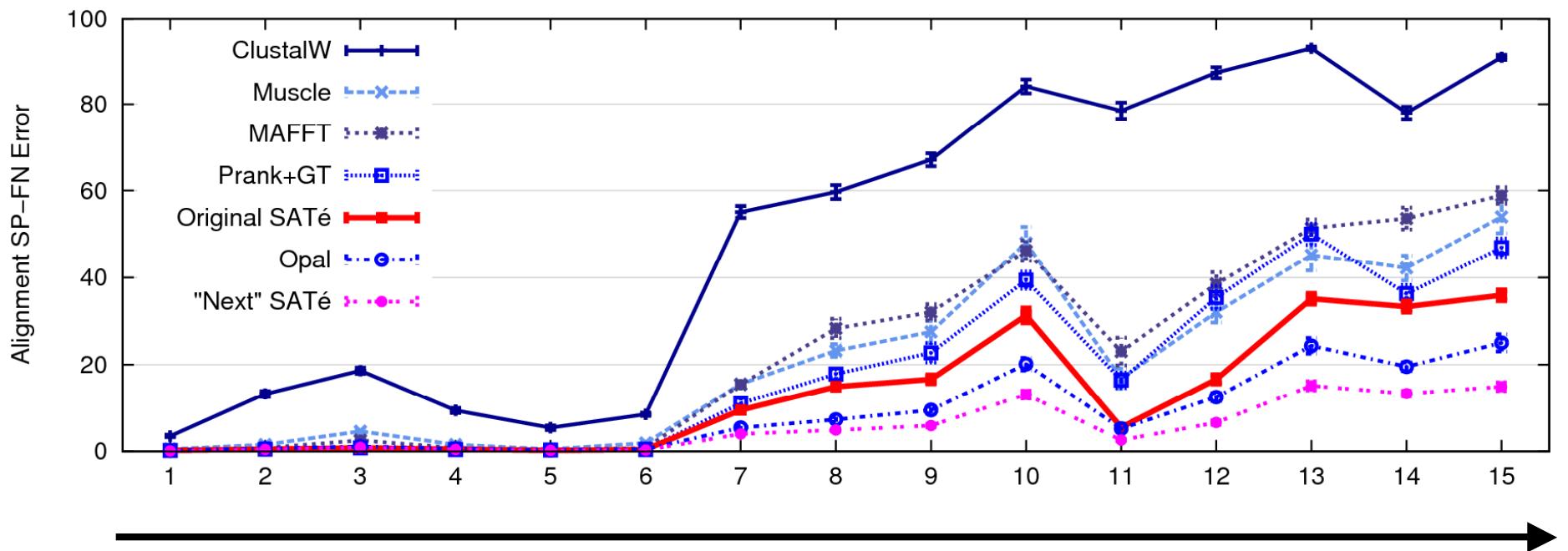
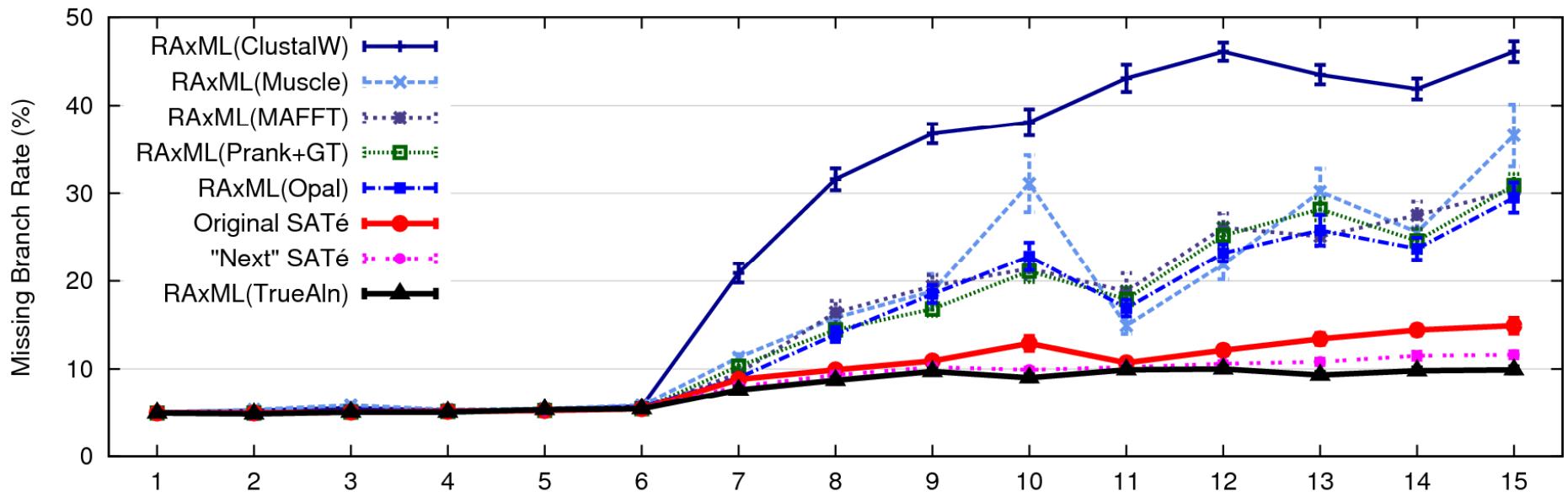


Re-aligning on a tree



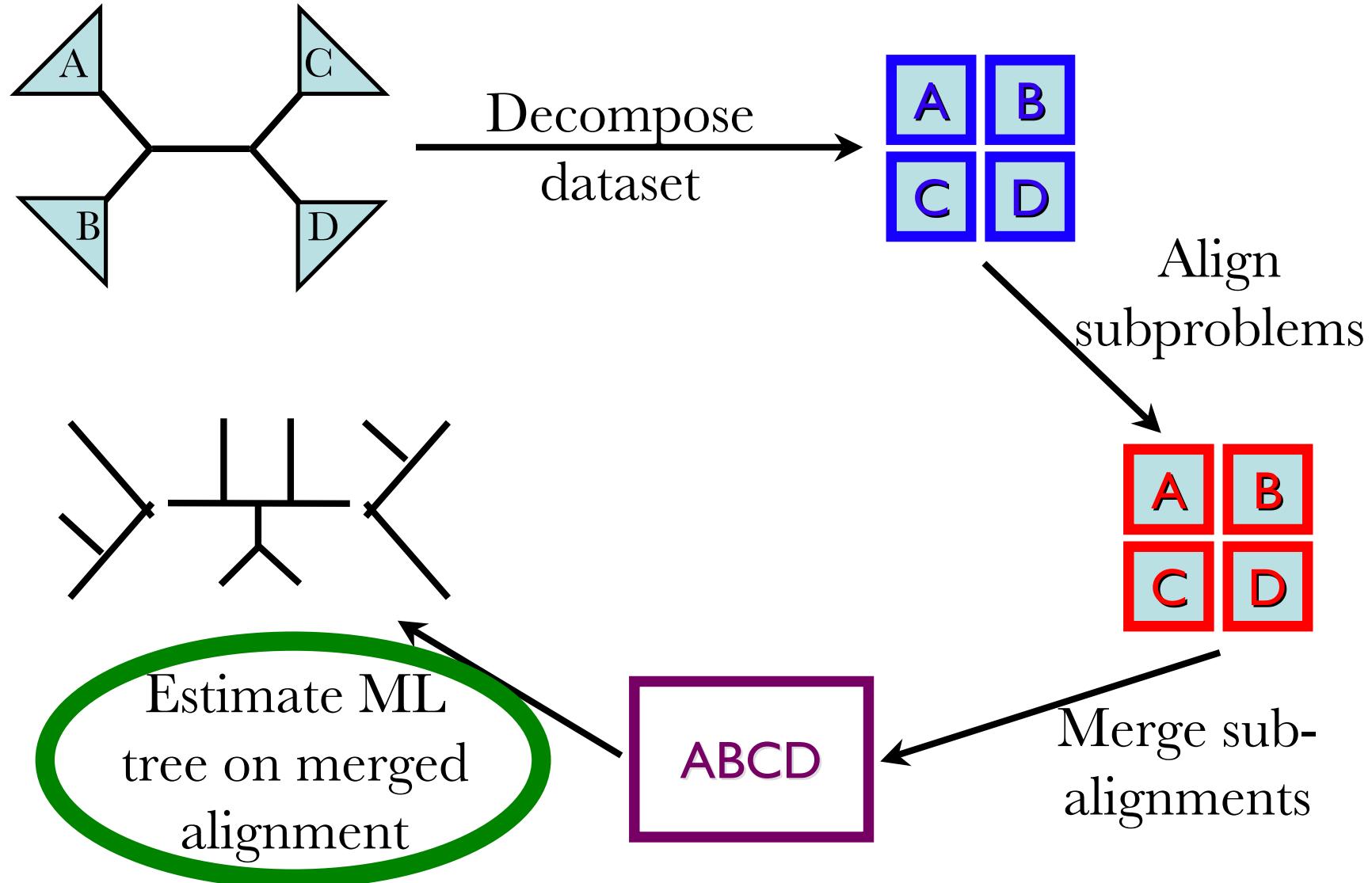


24 hour SATé analysis, on desktop machines
(Similar improvements for biological datasets)



1000 taxon models ranked by difficulty

Limitations

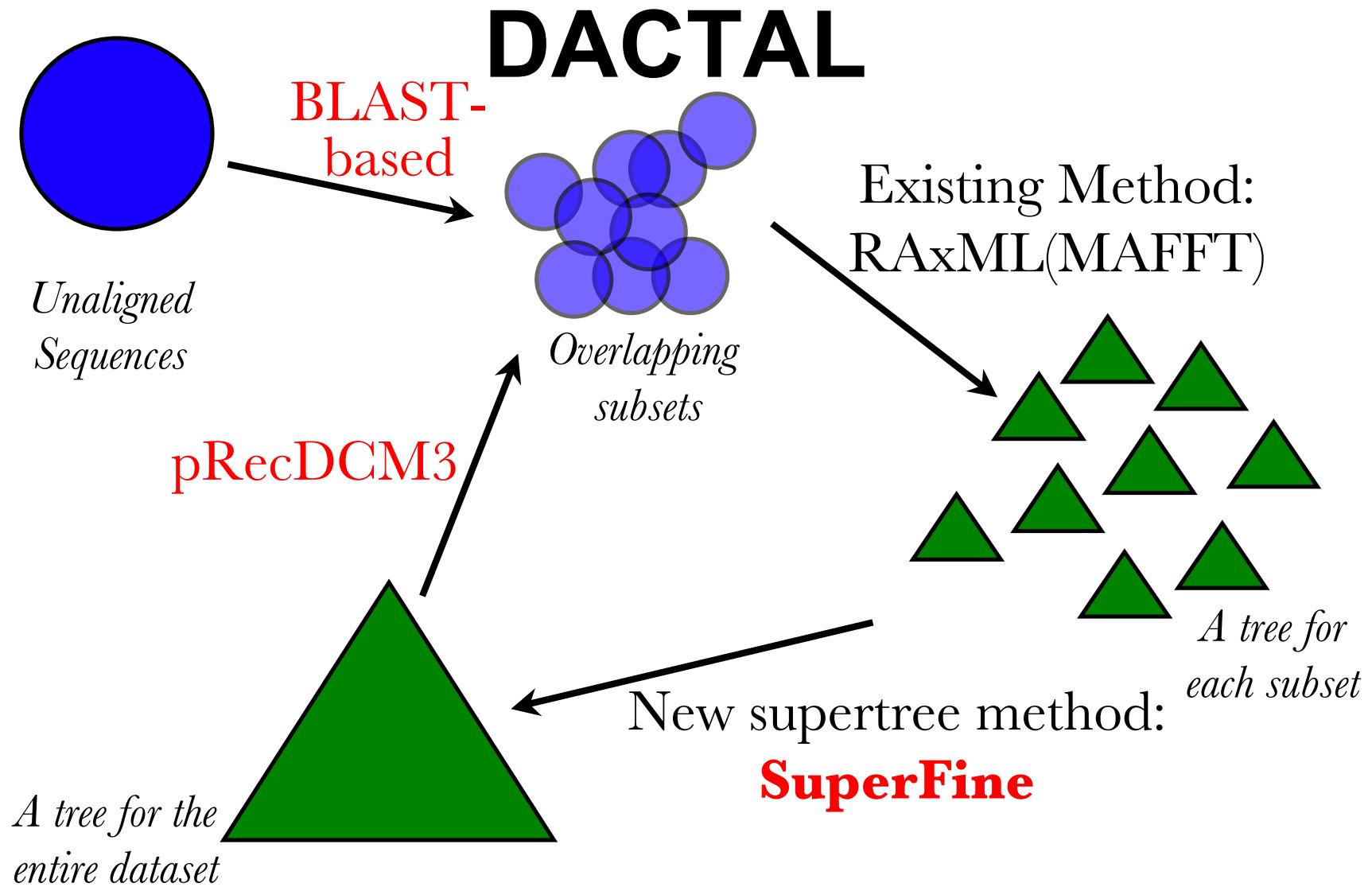


Part III: DACTAL

(Divide-And-Conquer Trees (Almost) without alignments)

- Input: set S of unaligned sequences
- Output: tree on S (but no alignment)

Nelesen, Liu, Wang, Linder, and Warnow,
ISMB 2012 and Bioinformatics 2012



Average of 3 Largest CRW Datasets

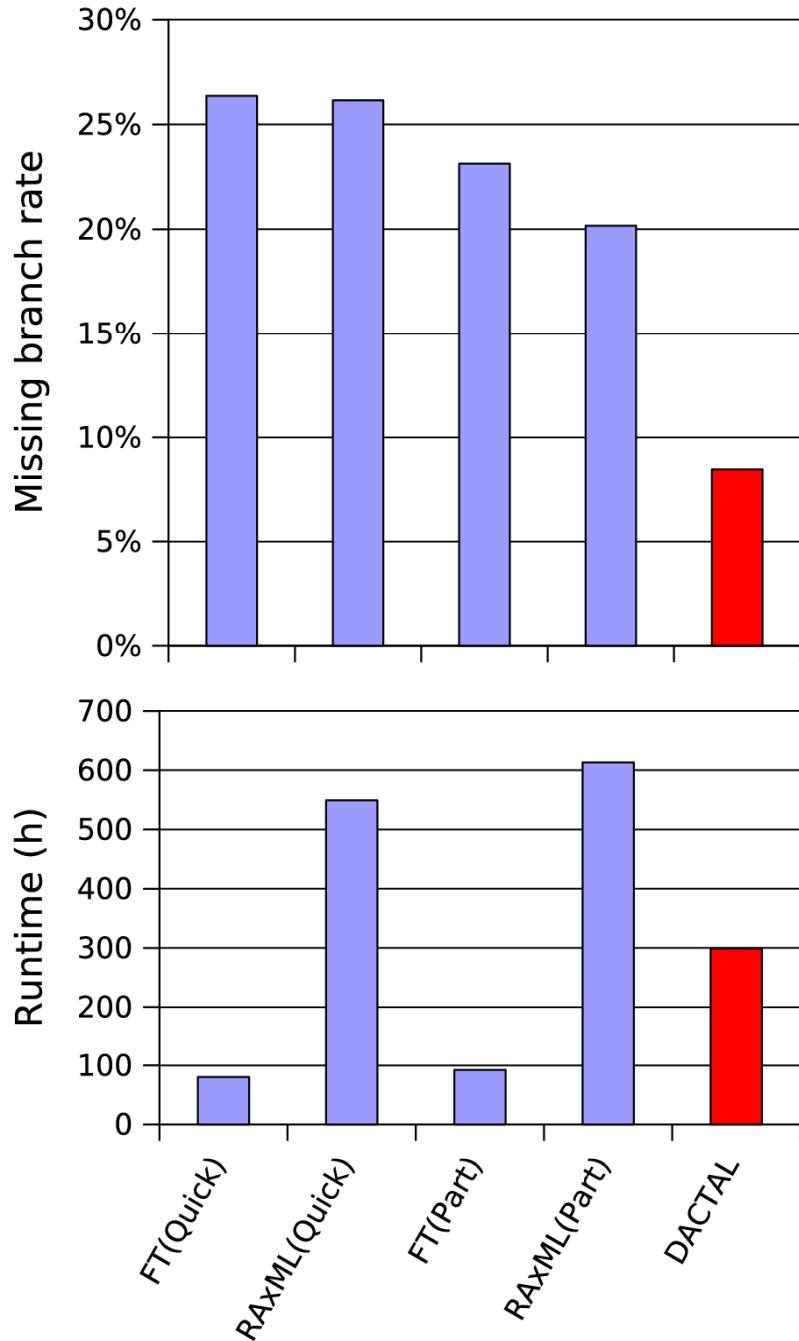
CRW: Comparative RNA database,
Three 16S datasets with **6,323** to **27,643** sequences

Reference alignments based on secondary structure

Reference trees are 75% RAxML bootstrap trees

DACTAL (shown in red) run for 5 iterations starting from FT(Part)

FastTree (FT) and RAxML are ML methods



Part III: SEPP

- SEPP: SATé-enabled Phylogenetic Placement, by Mirarab, Nguyen, and Warnow
- Pacific Symposium on Biocomputing, 2012 (special session on the Human Microbiome)

Phylogenetic Placement

Input: **Backbone** alignment and tree on full-length sequences, and a set of **query** sequences (short fragments)

Output: Placement of query sequences on backbone tree

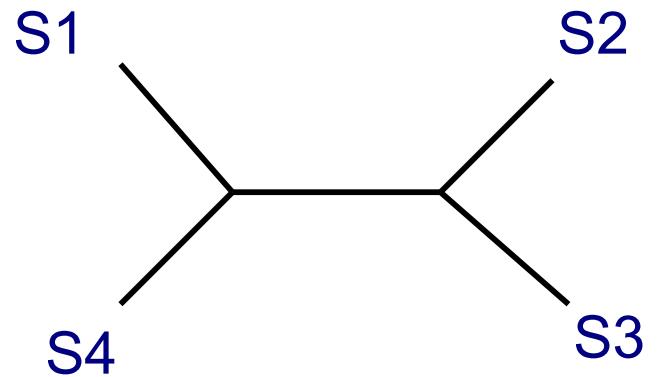
Phylogenetic placement can be used for taxon identification, but it has general applications for phylogenetic analyses of NGS data.

Phylogenetic Placement

- Align each query sequence to backbone alignment
- Place each query sequence into backbone tree, using extended alignment

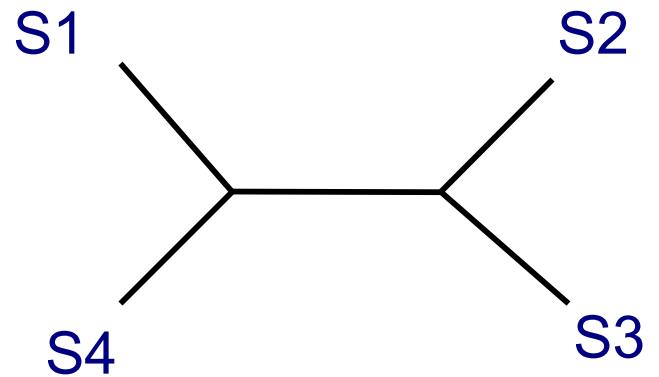
Align Sequence

S1 = -AGGCTATCACCTGACCTCCA-AA
S2 = TAG-CTATCAC--GACCGC--GCA
S3 = TAG-CT-----GACCGC--GCT
S4 = TAC----TCAC--GACCGACAGCT
Q1 = TAAAAAC



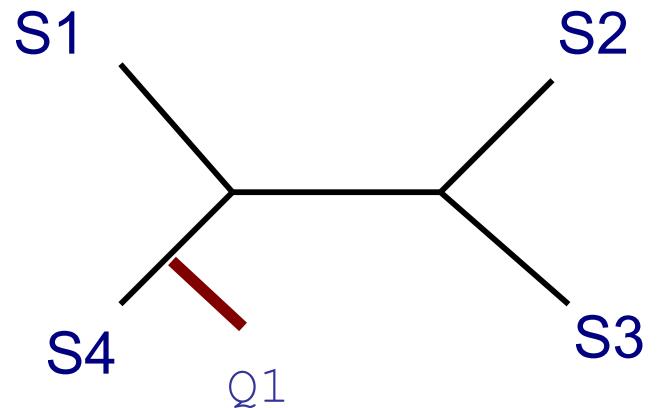
Align Sequence

S1 = -AGGCTATCACCTGACCTCCA-AA
S2 = TAG-CTATCAC--GACCGC--GCA
S3 = TAG-CT-----GACCGC--GCT
S4 = TAC----TCAC--GACCGACAGCT
Q1 = -----T-A--AAAC-----



Place Sequence

S1 = -AGGCTATCACCTGACCTCCA-AA
S2 = TAG-CTATCAC--GACCGC--GCA
S3 = TAG-CT-----GACCGC--GCT
S4 = TAC----TCAC--GACCGACAGCT
Q1 = -----T-A--AAAC-----

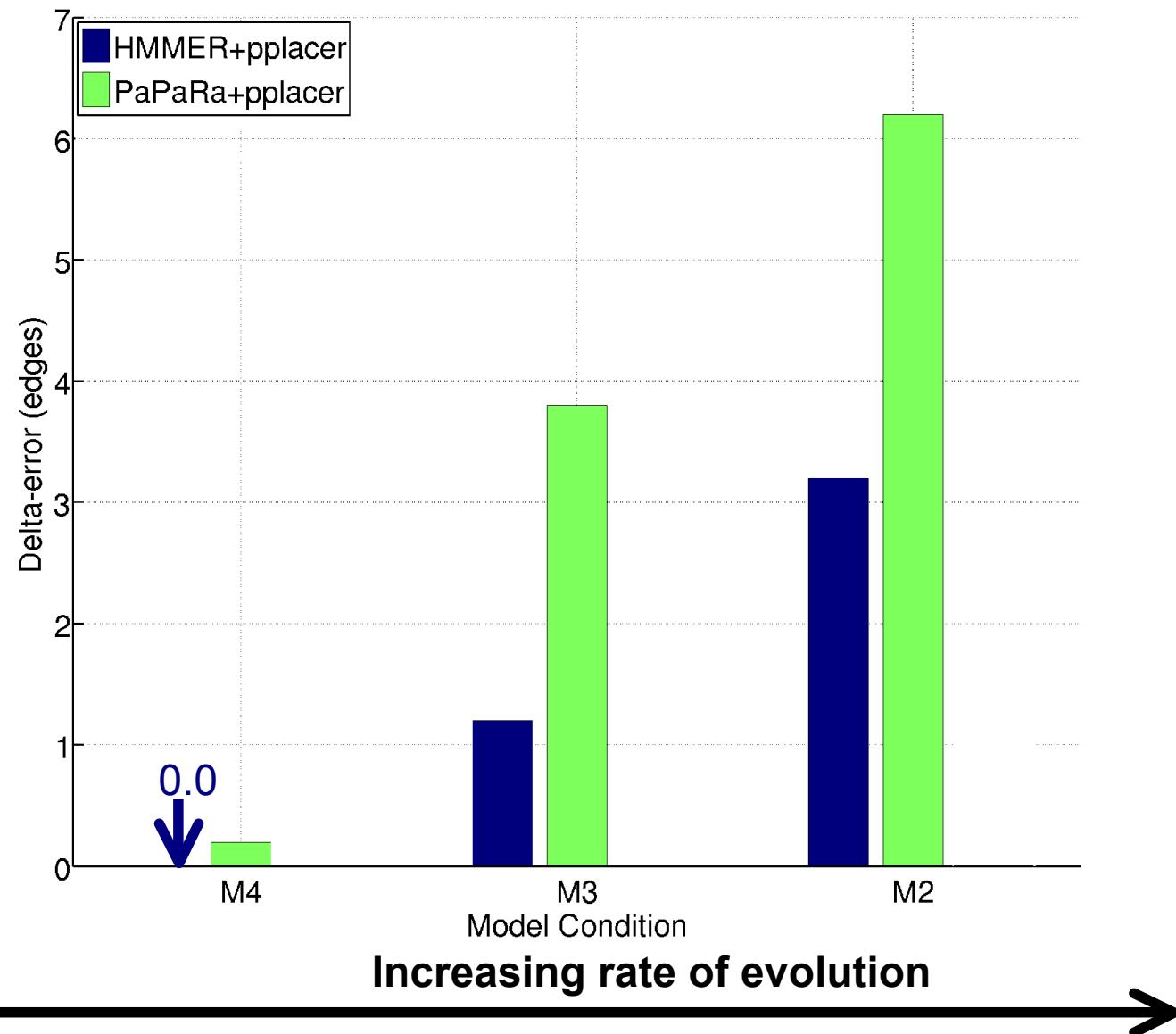


Phylogenetic Placement

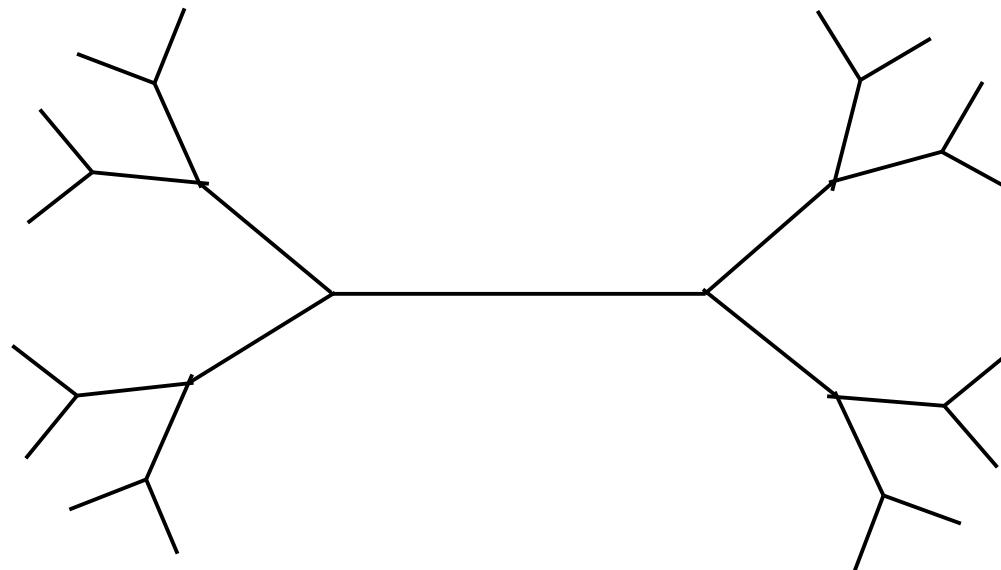
- Align each query sequence to backbone alignment
 - **HMMALIGN** (Eddy, Bioinformatics 1998)
 - **PaPaRa** (Berger and Stamatakis, Bioinformatics 2011)
- Place each query sequence into backbone tree
 - **Pplacer** (Matsen et al., BMC Bioinformatics, 2011)
 - **EPA** (Berger and Stamatakis, Systematic Biology 2011)

Note: pplacer and EPA use maximum likelihood

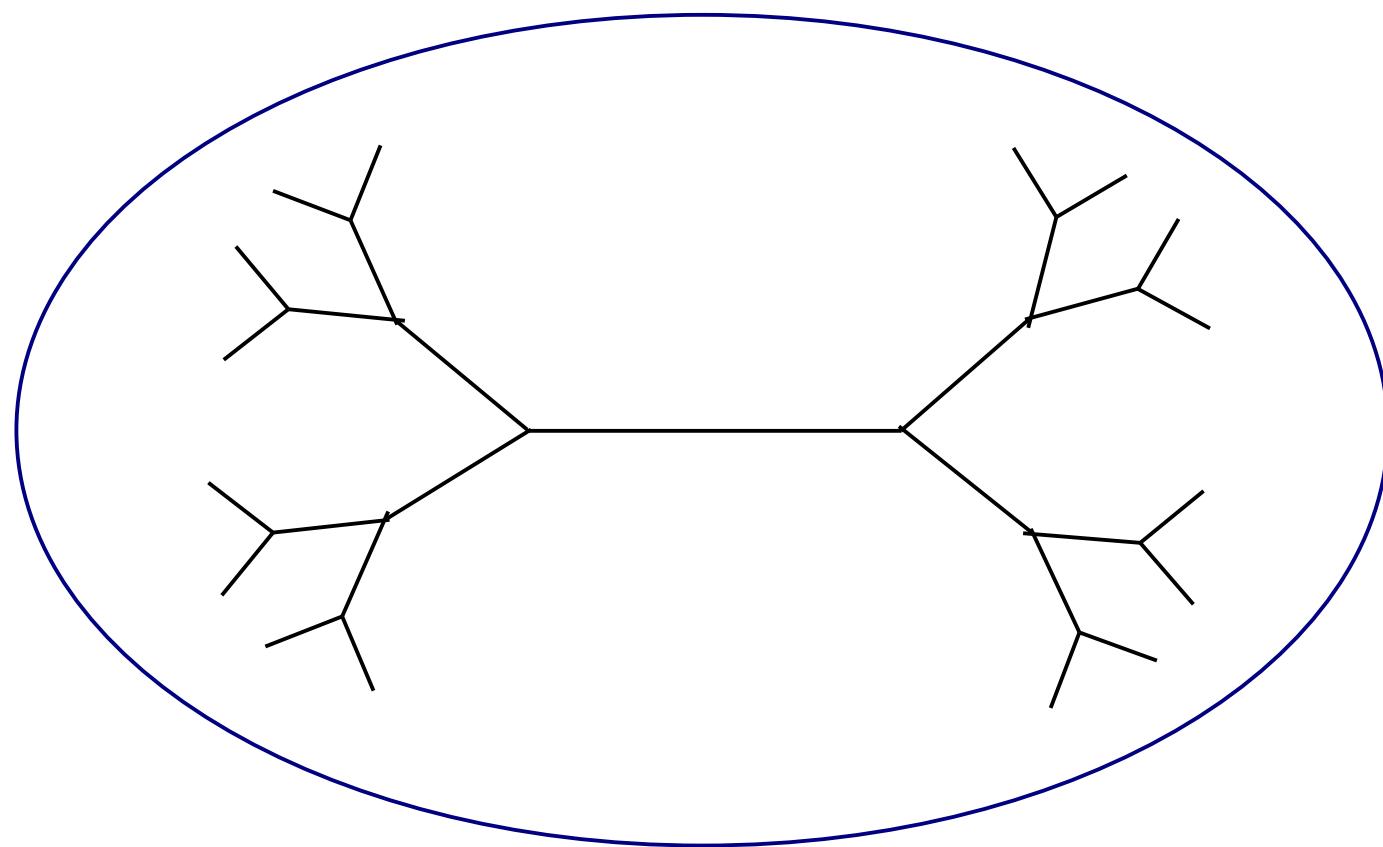
HMMER vs. PaPaRa



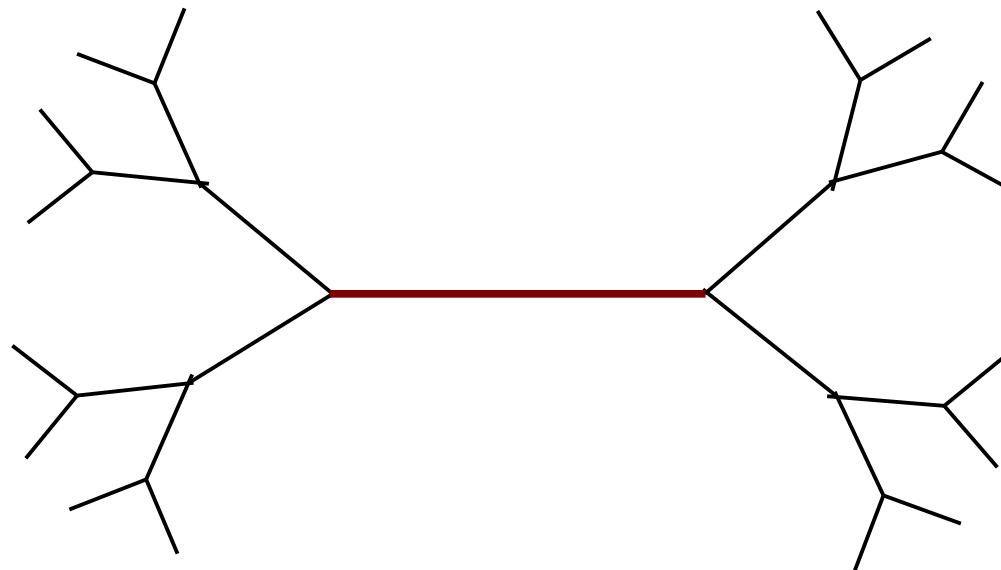
Insights from SATé



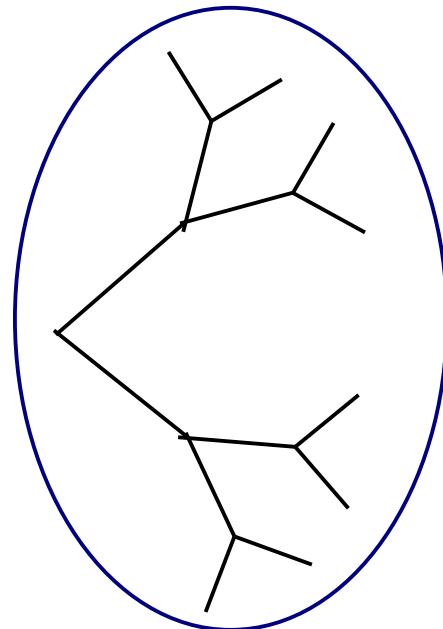
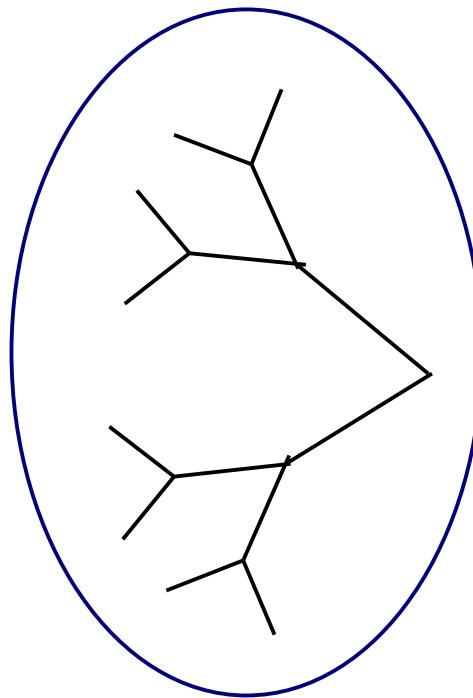
Insights from SATé



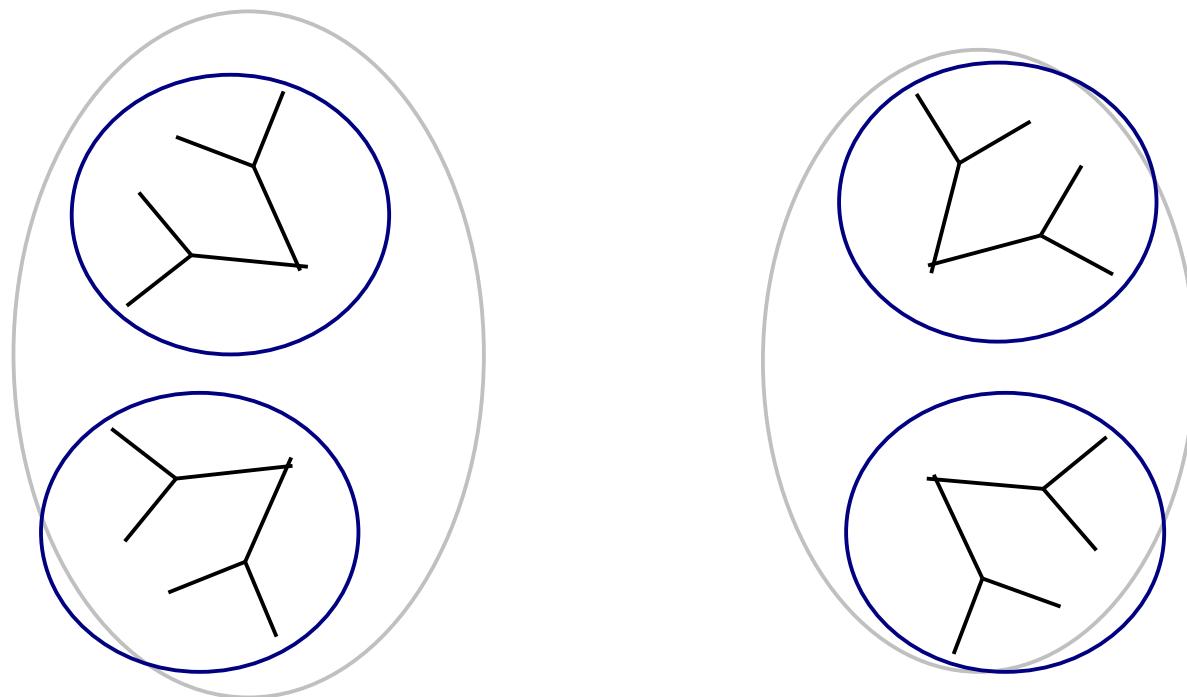
Insights from SATé



Insights from SATé



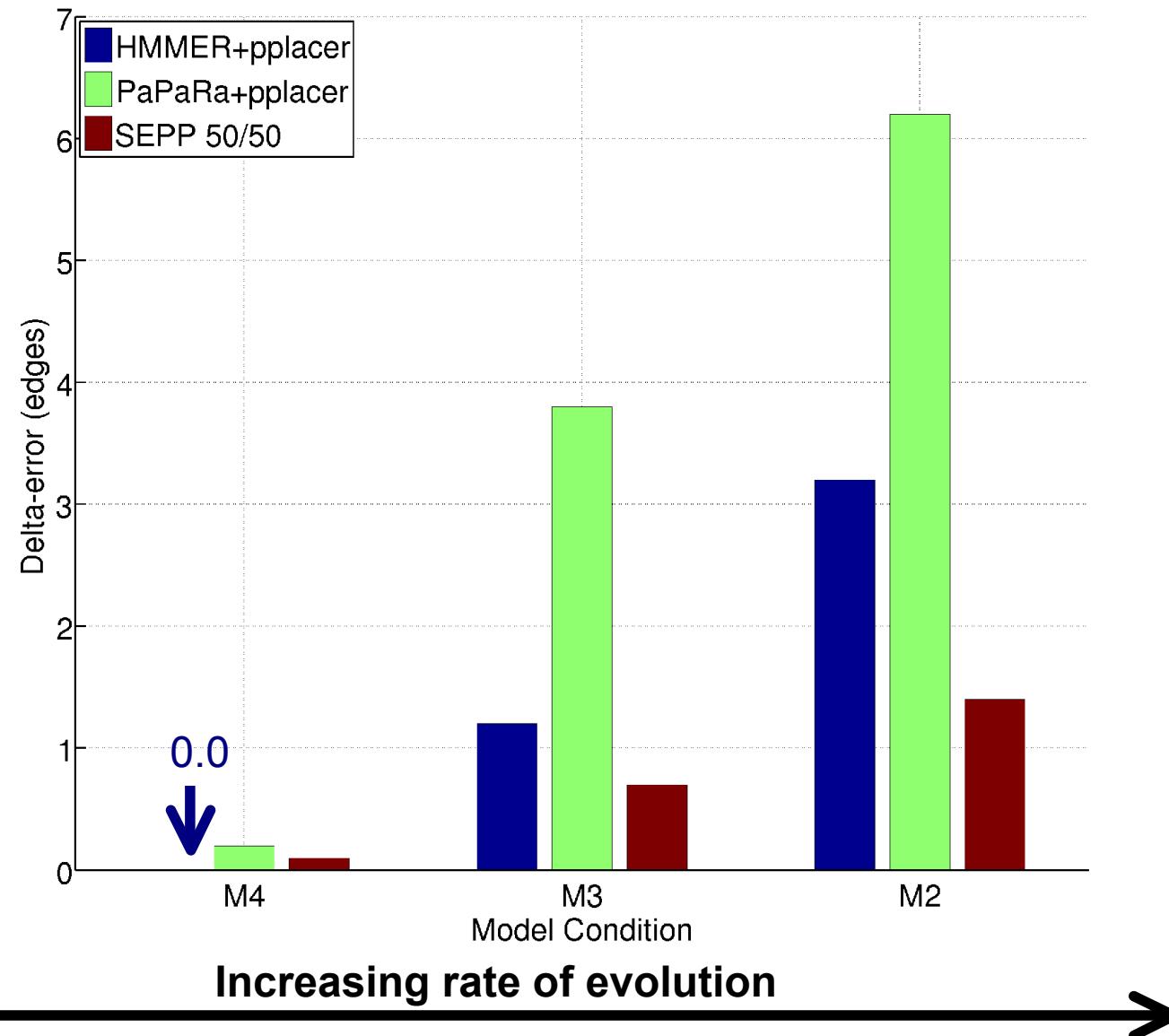
Insights from SATé



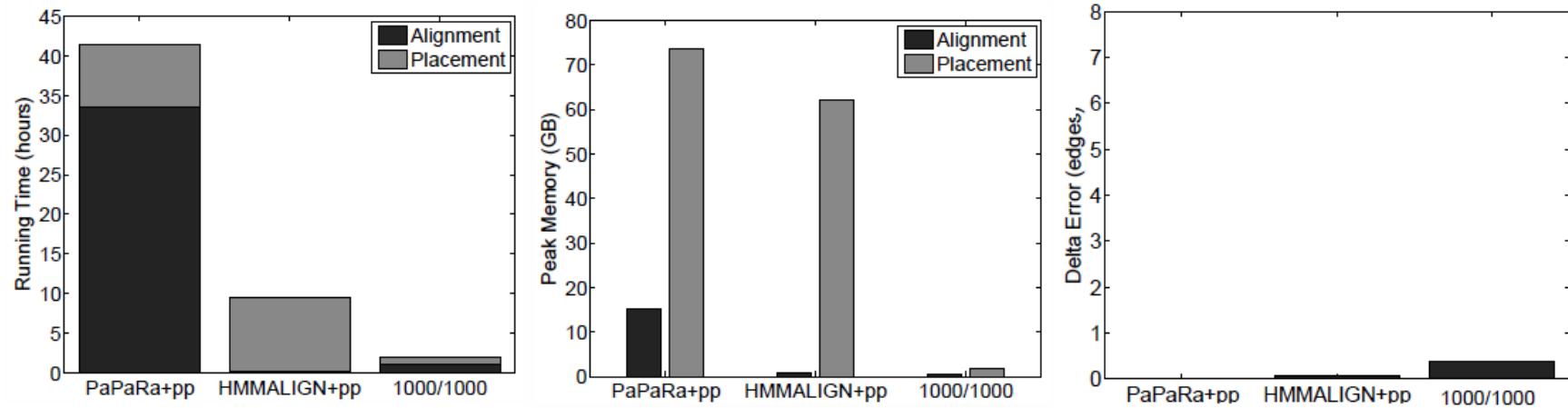
SEPP Parameter Exploration

- Alignment subset size and placement subset size impact the accuracy, running time, and memory of SEPP
- 10% rule (subset sizes 10% of backbone) had best overall performance

SEPP (10%-rule) on simulated data

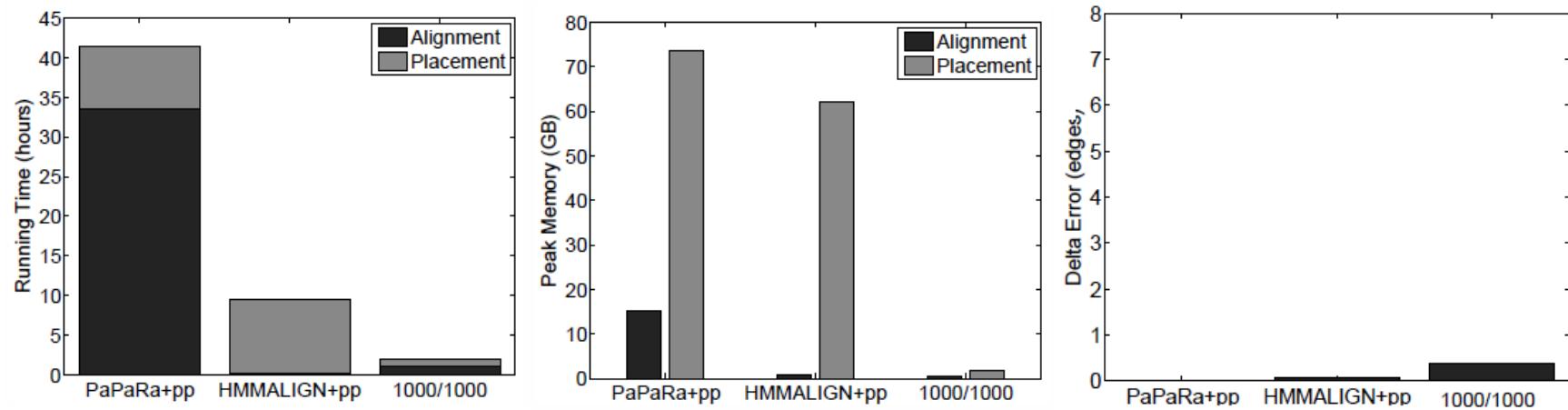


SEPP (10%) on Biological Data



16S.B.ALL dataset, 13k curated backbone tree, 13k total fragments

SEPP (10%) on Biological Data



16S.B.ALL dataset, 13k curated backbone tree, 13k total fragments

For 1 million fragments:

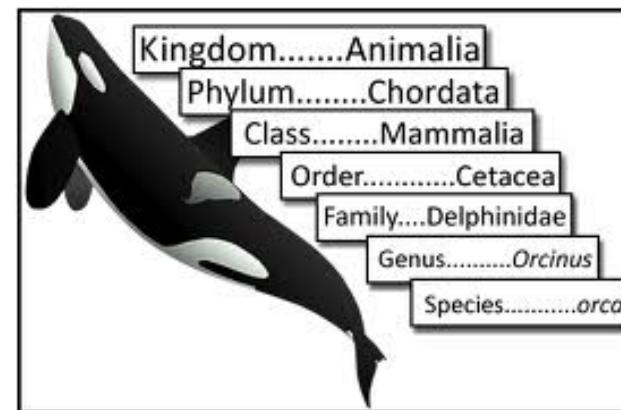
PaPaRa+pp: ~133 days

HMMALIGN+pp: ~30 days

SEPP 1000/1000: ~6 days

Part IV: Taxon Identification

Objective: classify short reads in a metagenomic sample



Metagenomic data analysis

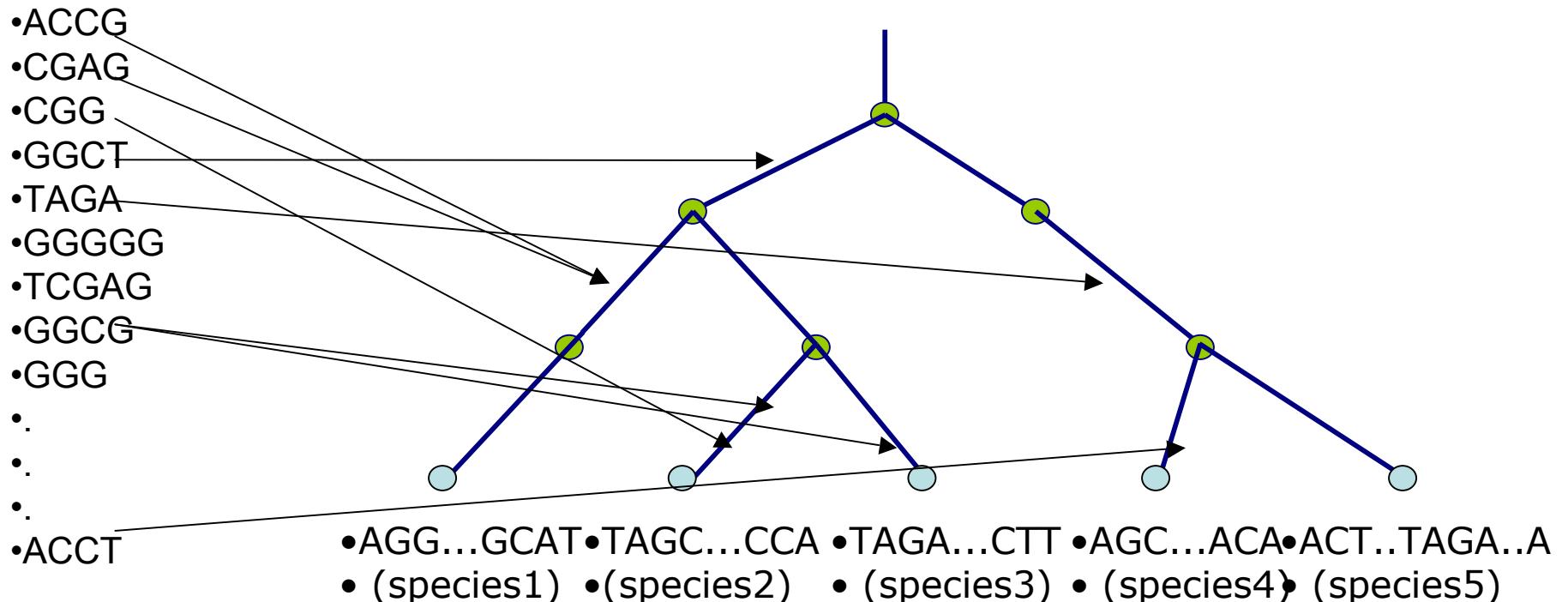
NGS data produce fragmentary sequence data
Metagenomic analyses include unknown species

Taxon identification: given short sequences, identify the species for each fragment

Applications: Human Microbiome
Issues: accuracy and speed

TIPP: Taxon Identification by Phylogenetic Placement

- Fragmentary Unknown Reads:
 - (60-200 bp long)
- Known Full length Sequences,
 - and an alignment and a tree
- (500-10,000 bp long)



TIPP: Taxon Identification using Phylogenetic Placement - Version 1

Given a set Q of query sequences for some gene, a taxonomy T , and a set of full-length sequences for the gene,

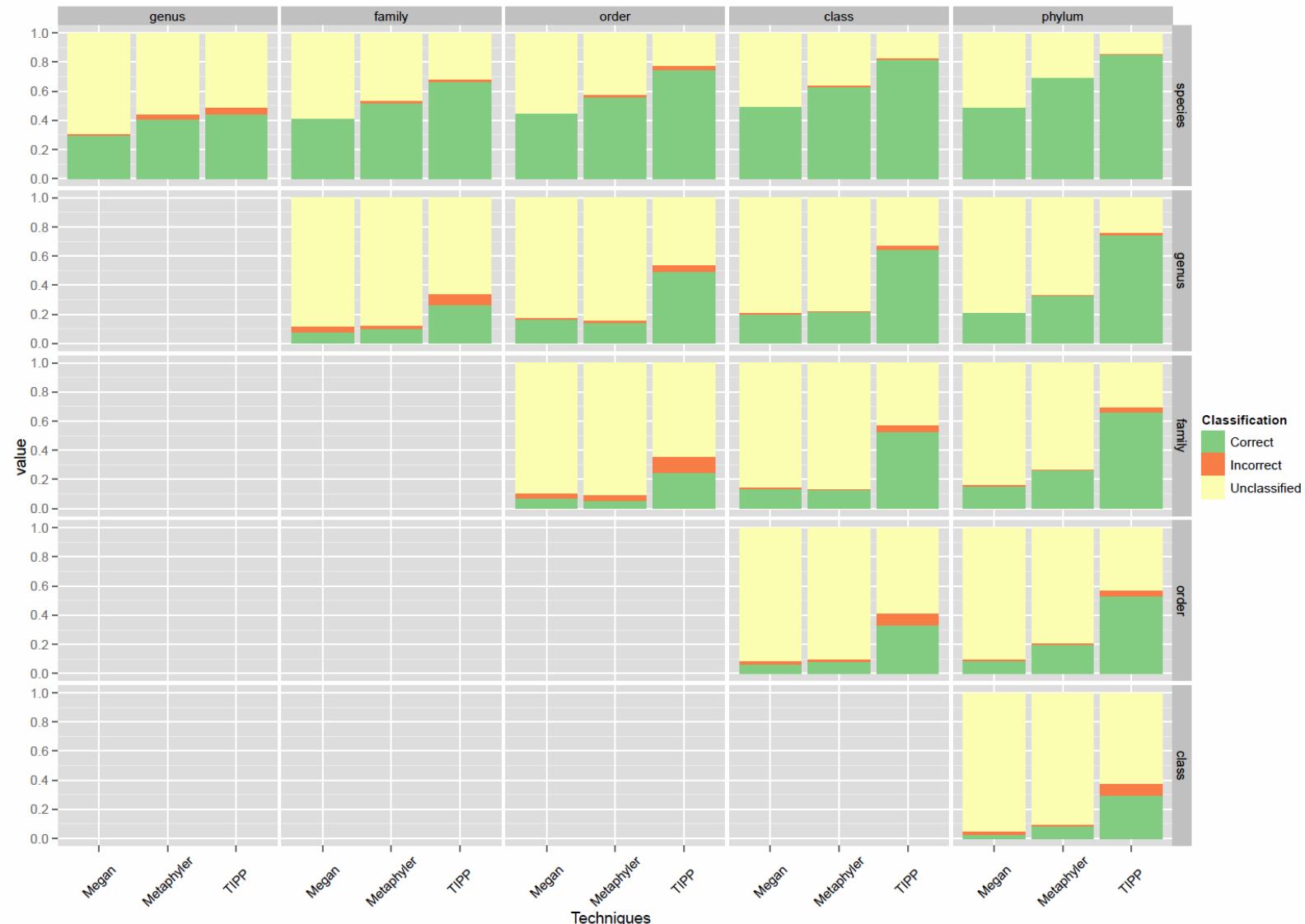
- Compute reference alignment and tree on the full-length sequences, using SATé
- Use SEPP to place each query sequence into the taxonomy (alignment subsets computed on the reference alignment/tree, then inserted into taxonomy T)

TIPP version 2- considering uncertainty

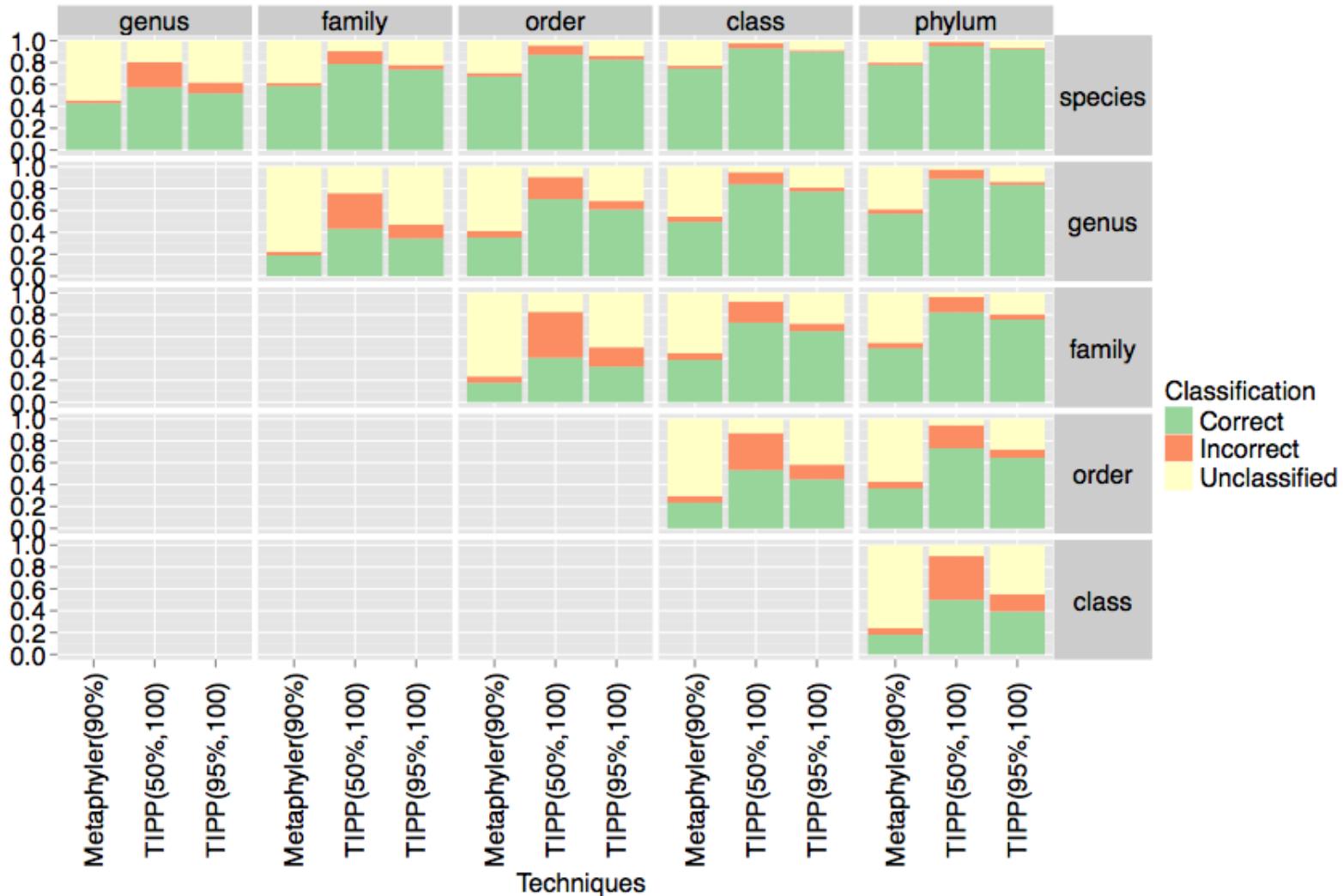
TIPP version 1 too aggressive (over-classification)

TIPP version 2 dramatically reduces false positive rate with small reduction in true positive rate, by considering uncertainty, using statistical techniques.

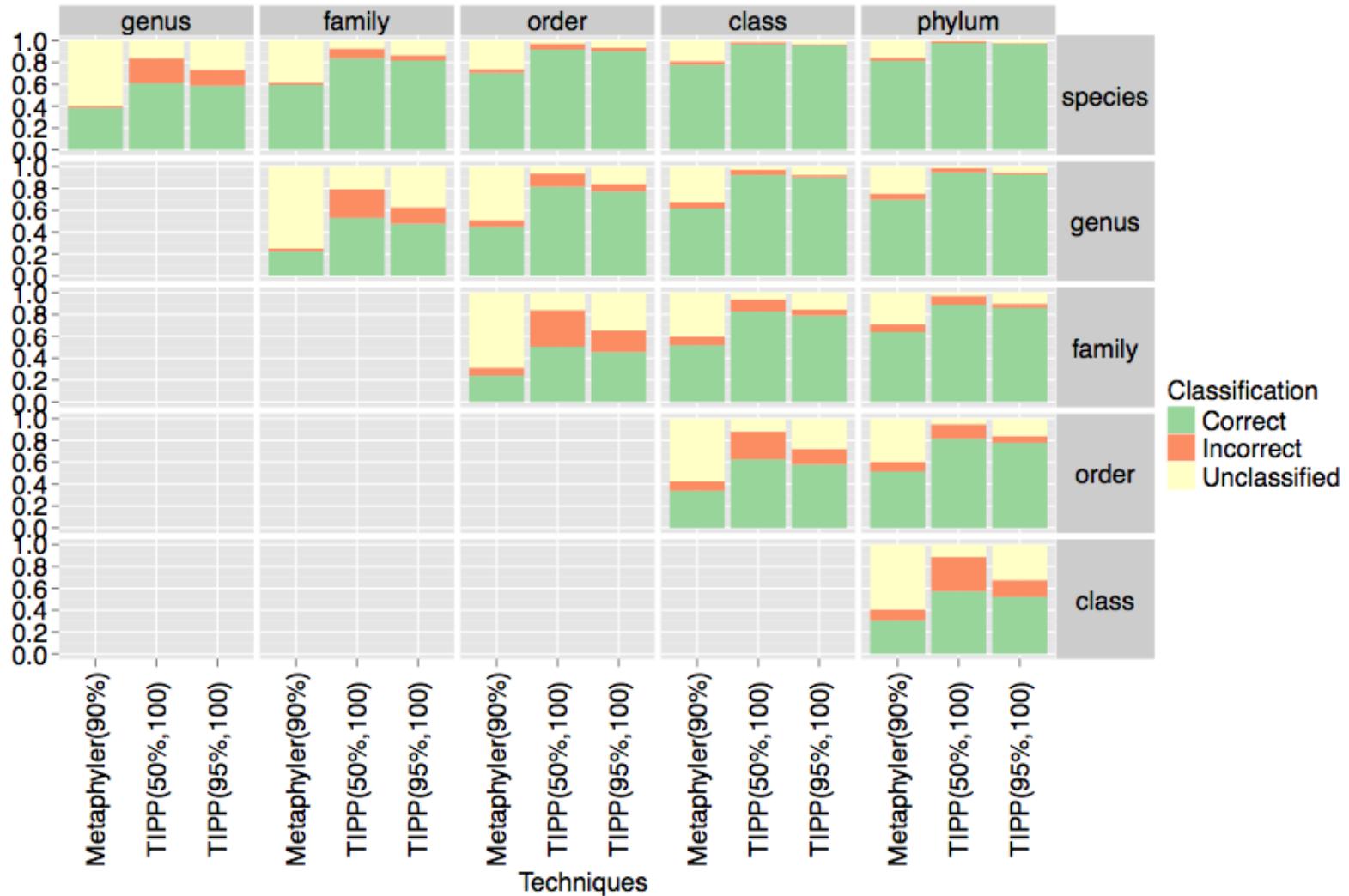
60bp error-free reads on rpsB marker gene



Results on 30 marker genes, leave-one-out experiment with Illumina errors



Results on 30 marker genes, leave-one-out experiment with 454 errors



Five “Boosters”

- DCM: distance-based tree estimation
- SATé: co-estimation of alignments and trees
- DACTAL: large trees without full alignments
- SEPP: phylogenetic placement of short reads
- TIPP: taxon identification of fragmentary data

Algorithmic strategies: divide-and-conquer and iteration to improve the accuracy and scalability of a *base method*

General Observations - Part I

- Relative performance of methods can change dramatically with dataset size
- Statistical inference methods often do not scale well

Observations - Part II

- Meta-methods can improve accuracy and even speed
- Hidden Markov Models (HMMs) can be improved by making a set of HMMs instead of a single HMM
- Algorithmic parameters let you explore sensitivity/specificity
- Parallelism is easily exploited

Overall message

- When data are difficult to analyze, develop better methods - don't throw out the data.
- BIGDATA problems in biology are an opportunity for computer scientists to have a big impact!

Discussion points

- Applicability to other machine learning problems? Classification and clustering problems, in particular?
- Space issues can arise if multiple solutions are maintained.
- Enabling plug-ins?
- How to enable parameter exploration? Statistically sound parameter selection?

Acknowledgments

- Guggenheim Foundation Fellowship, Microsoft Research New England, National Science Foundation: Assembling the Tree of Life (ATOL), ITR, and IGERT grants, and David Bruton Jr. Professorship
- Collaborators:
 - DCM-NJ: Bernard Moret and Katherine St. John
 - SATé: Kevin Liu, Serita Nelesen, Sindhu Raghavan, and Randy Linder (and also Mark Holder at Kansas for public distribution)
 - DACTAL: Serita Nelesen, Kevin Liu, Li-San Wang, and Randy Linder
 - SEPP: Siavash Mirarab and Nam Nguyen
 - TIPP: Siavash Mirarab, Nam Nguyen, Mihai Pop, and Bo Liu