Eliminating Subjectivity, Quantifying Uncertainty, and using Machine Learning for Phylogenetic Inference

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 - 2. Heidelberg Institute for Theoretical Studies
 - 3. Institute of Theoretical Informatics, Karlsruhe Institute of Technology

www.biocomp.gr (Crete lab)

www.exelixis-lab.org (Heidelberg lab)

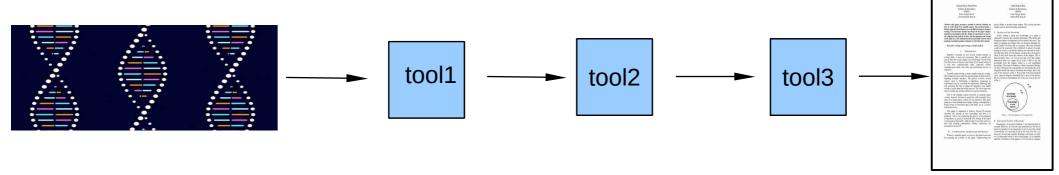
Group Setup

- Computational Molecular Evolution group Heidelberg Institute for Theoretical Studies
 - 5 PhD students + 1 staff Scientist
 - www.exelixis-lab.org
- Biodiversity Computing Group Institute of Computer Science,
 Foundation for Research and Technology Hellas (Crete)
 - 3 PhD Students + 3 PostDocs
 - www.biocomp.gr
 - EU ERA chair program
- Ancient DNA lab Institute of Biology and Biotechnology, Foundation for Research and Technology Hellas (Crete)
 - https://ancient-dna.gr/index.php/en/
 - 2 PostDocs + 1 lab technician + 1 archaeologist

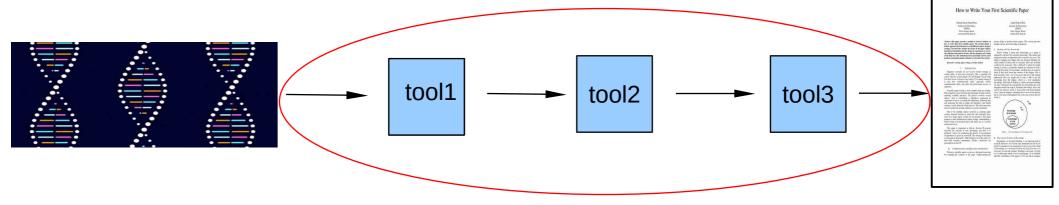




Bioinformatics

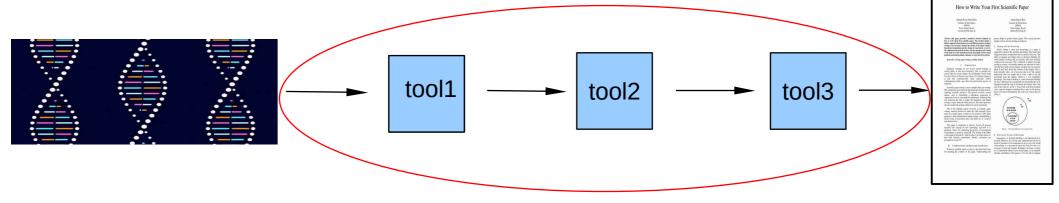


Bioinformatics

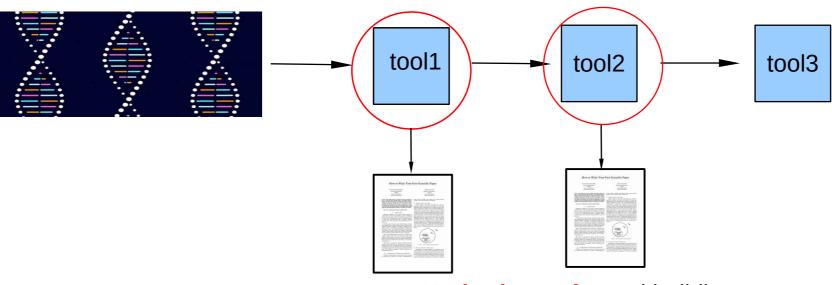


Data-centric: pipeline building

Bioinformatics



Data-centric: pipeline building



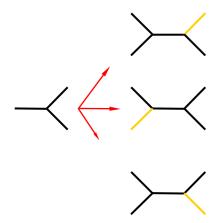
Method-centric: tool building

Outline

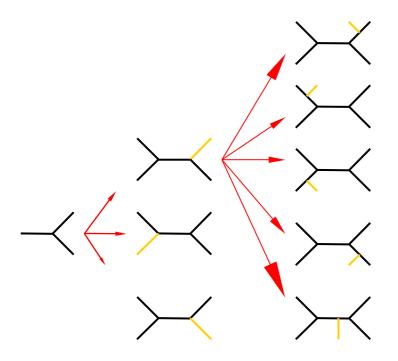
- Introduction to Phylogenetic Inference
- Sources of Uncertainty
- Phylogenetic Difficulty
- Using Phylogenetic Difficulty
- Bootstrap Prediction
- Other Stuff we work on



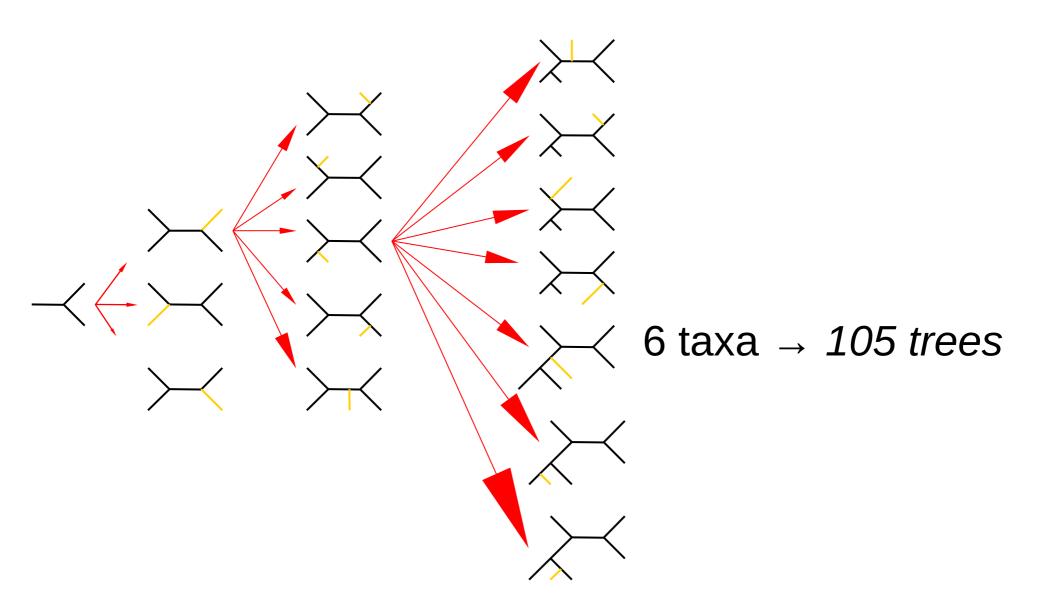
 $3 taxa \rightarrow 1$ tree



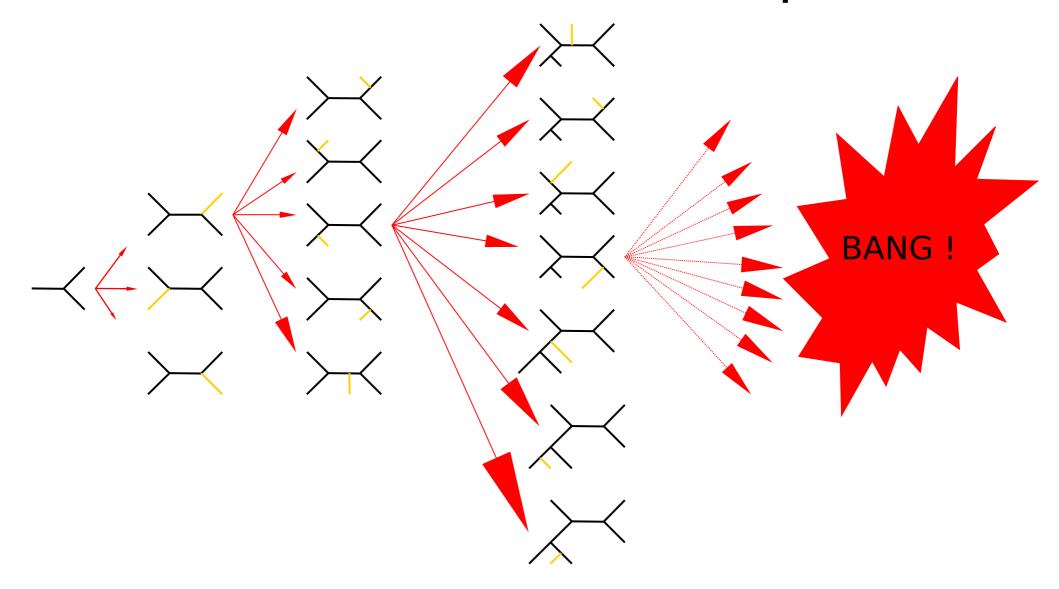
4 taxa → 3 trees



 $5 taxa \rightarrow 15 trees$



The number of trees explodes!



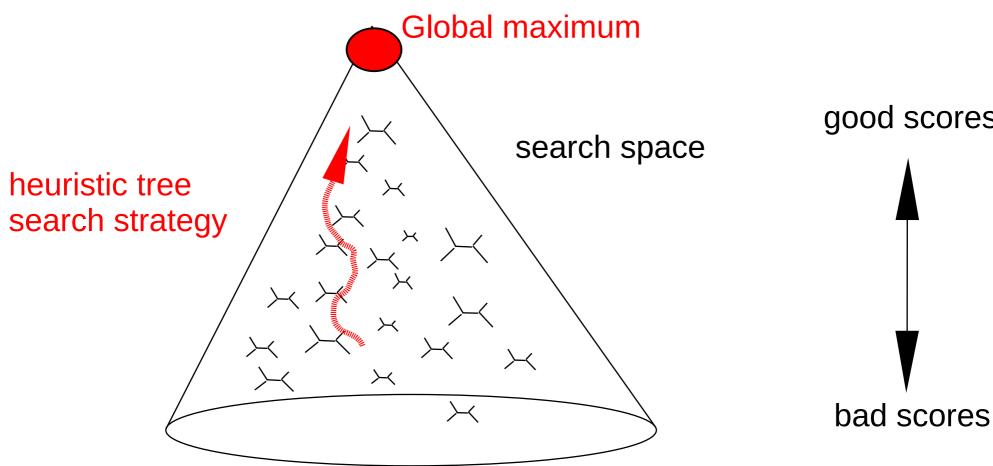
possible trees with 2000 taxa

stamatak@exelixis:~/Desktop/GIT/TreeCounter\$./treeCounter -n 2000

GNU GPL tree number calculator released June 2011 by Alexandros Stamatakis

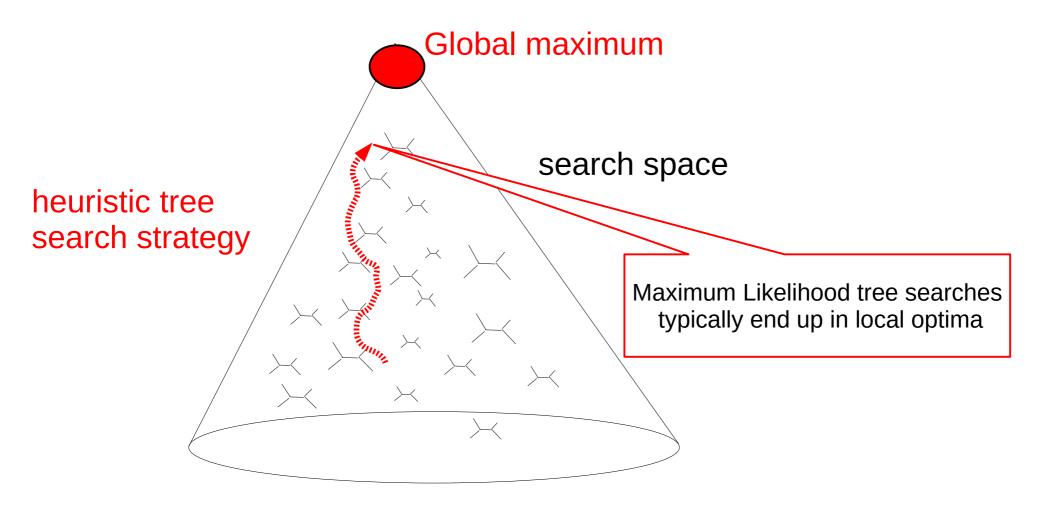
Number of unrooted binary trees for 2000 taxa: 30049638174211656151632910065681814981377232074237013089504954043012636525258308210827685996688247000464352 350341796875

Problem Complexity

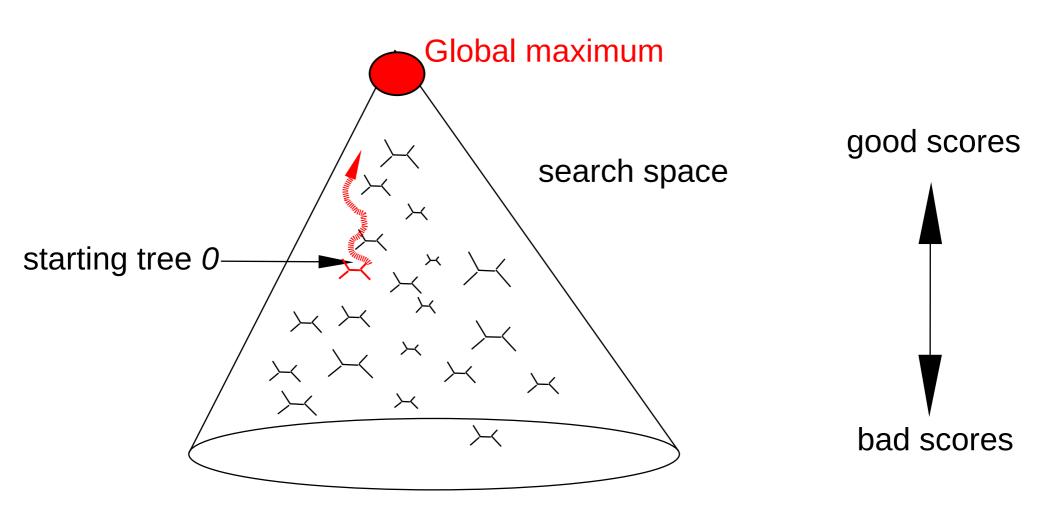


good scores

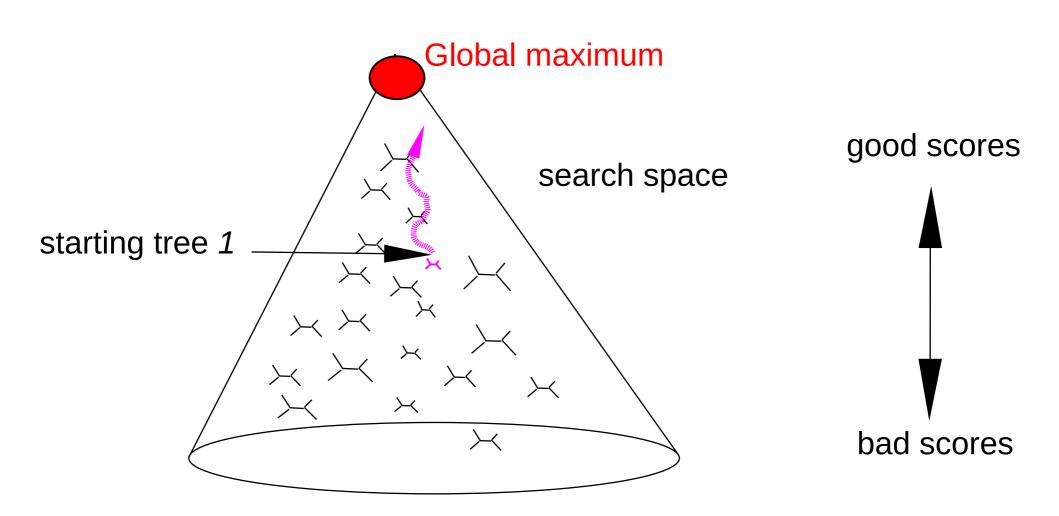
Problem Complexity



Starting Trees



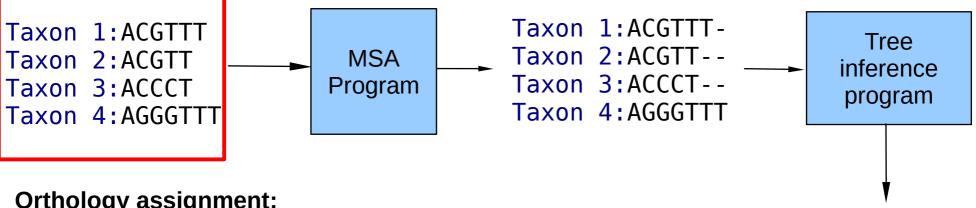
Starting Trees



Outline

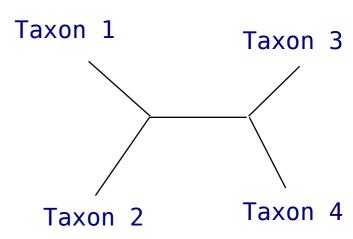
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Tree Inference Pipeline

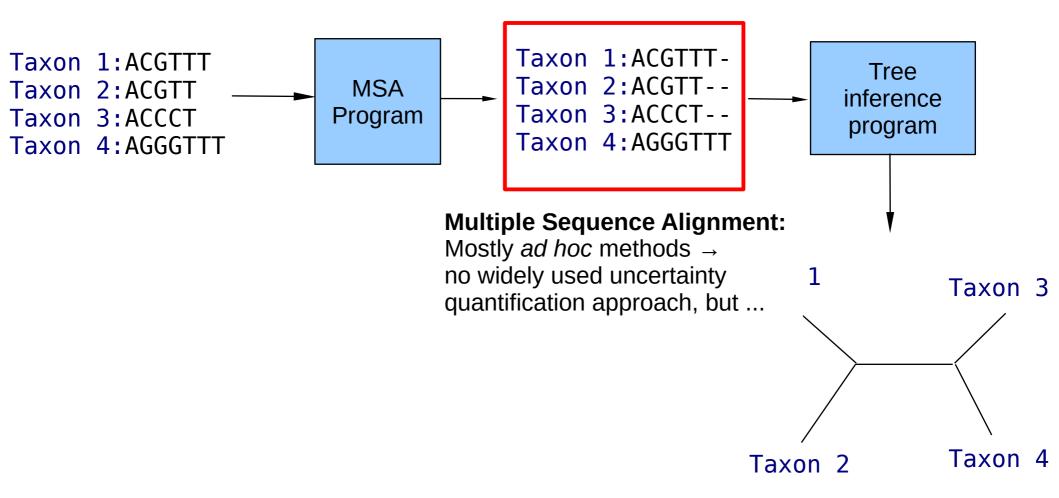


Orthology assignment:

Mostly "dirty" ad hoc methods → no widely used uncertainty quantification approach



Tree Inference Pipeline



Muscle5

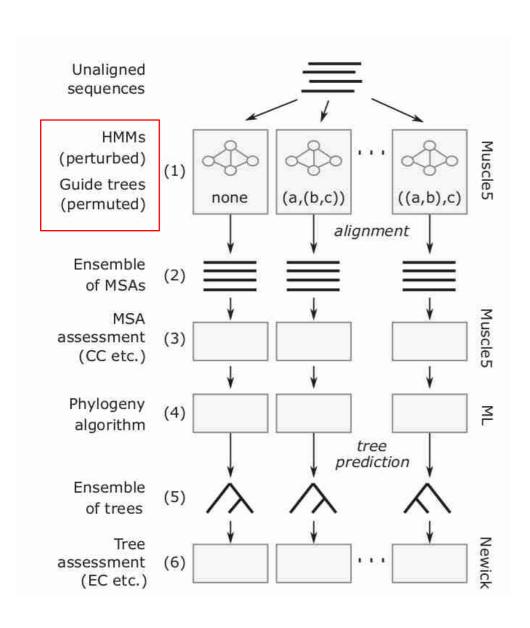
Article Open Access | Published: 15 November 2022

Muscle5: High-accuracy alignment ensembles enable unbiased assessments of sequence homology and phylogeny

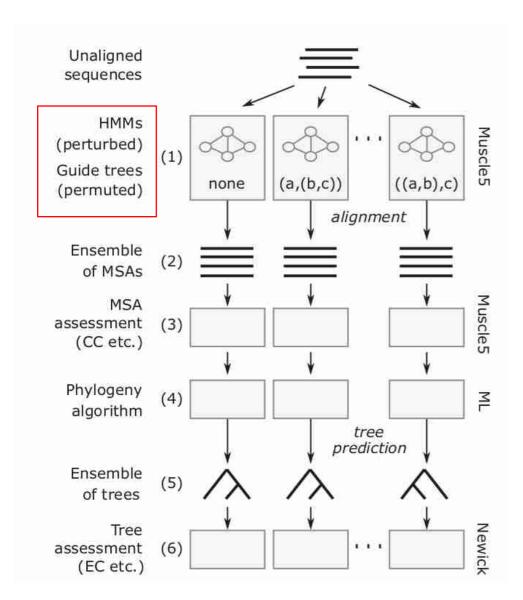
Robert C. Edgar

Nature Communications 13, Article number: 6968 (2022) | Cite this article

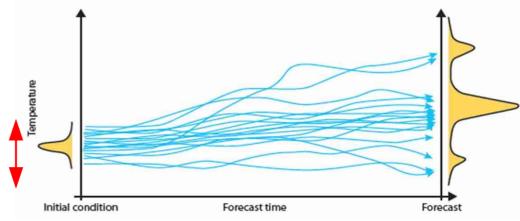
Muscle5



Muscle5

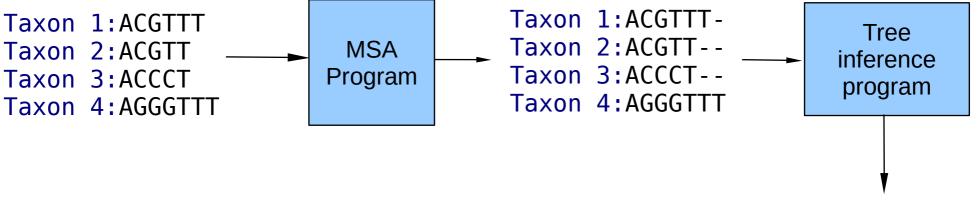


Temperature Ensemble Forecast



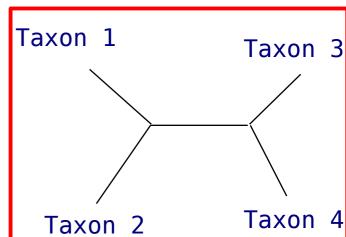
perturb starting conditions

Tree Inference Pipeline

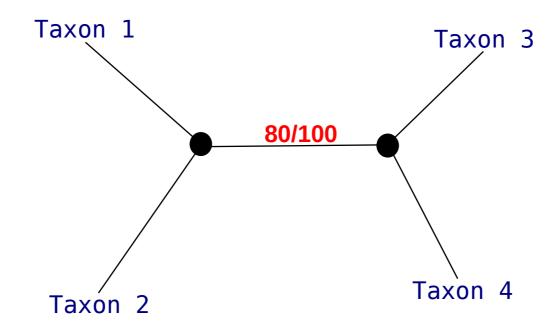


Phylogenetic Inference:

A long history of explicit uncertainty models Bootstrap Methods for Maximum Likelihood Posterior Probabilities for Bayesian Inference using MCMC



A Tree with Support Values



Sources of Uncertainty thus far

- 1 Orthology Assignment
- 2 Multiple Sequence Alignment
- 3 Tree Inference
- 4 BUT

Software Issues

- Bugs & Software Quality
- Numerical Instability
- Reproducibility (2 versus 4 cores)
- We re-designed & optimized numerous tools the Next Generation (NG) tools series
 - RAxML-NG
 - ModelTest-NG
 - EPA-NG
 - Lagrange-NG

Sources of Uncertainty

- 1 Orthology Assignment
- 2 Multiple Sequence Alignment
- 3 Tree Inference
- 4 Software issues
- 5 BUT

Propagating Uncertainty

Assume

- 10 alternative orthology assignments
- 10 x 10 alternative MSAs
- 10 x 10 x 10 alternative trees
 - → exponential explosion with increasing pipeline length
 - → targeted approach to explore parameter space in pipelines needed

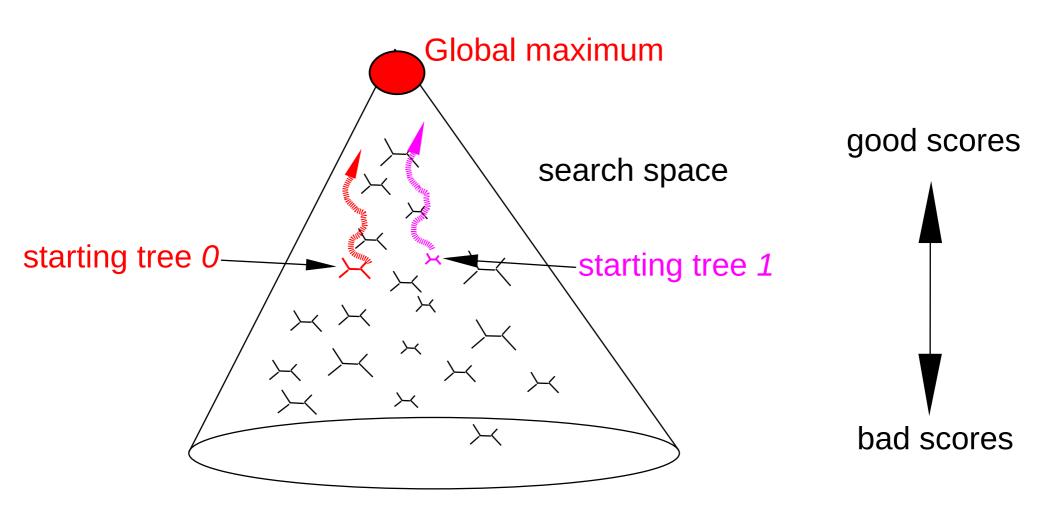
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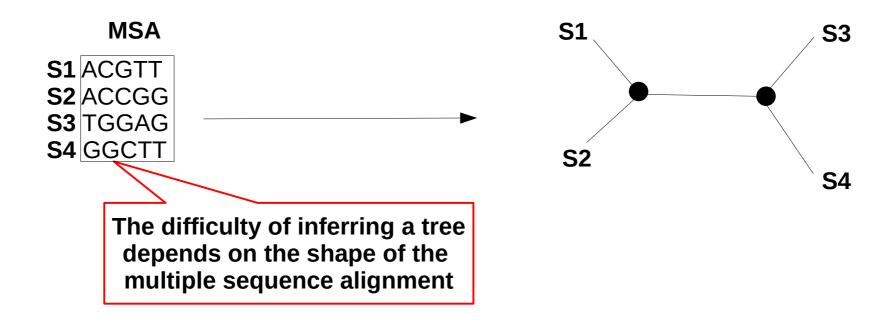
Disclaimer

- I never wanted to do machine learning
- Somebody must keep working on algorithms,
 HPC, hardware architectures, C++
- Current generation of CS students
 - "I want to do something with data science and/or machine learning"

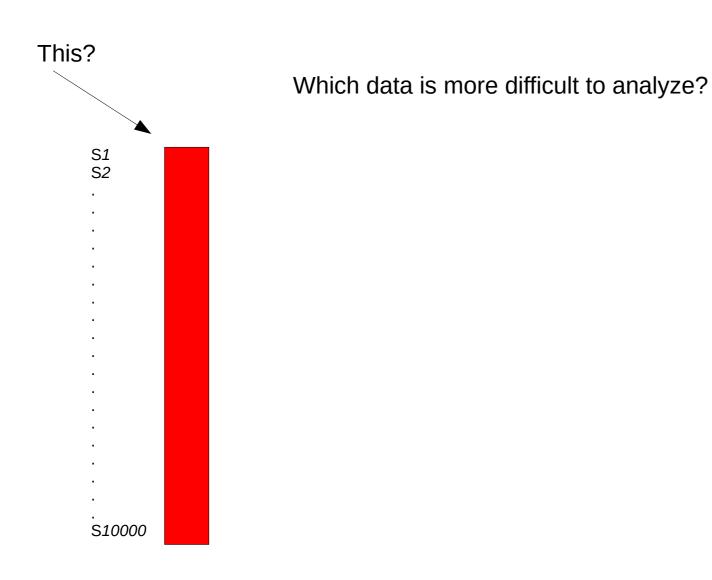
Can we predict how difficult a phylogenetic analysis will be?



Phylogenetic Inference

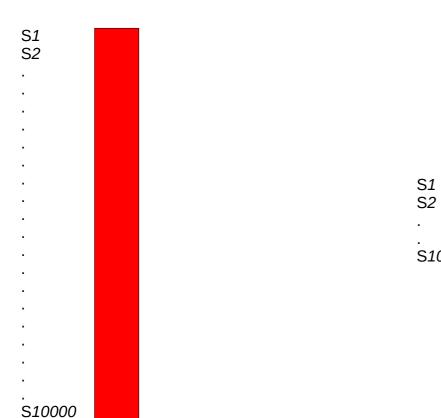


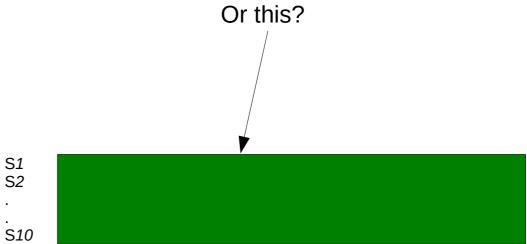
Dataset Shapes



Dataset Shapes

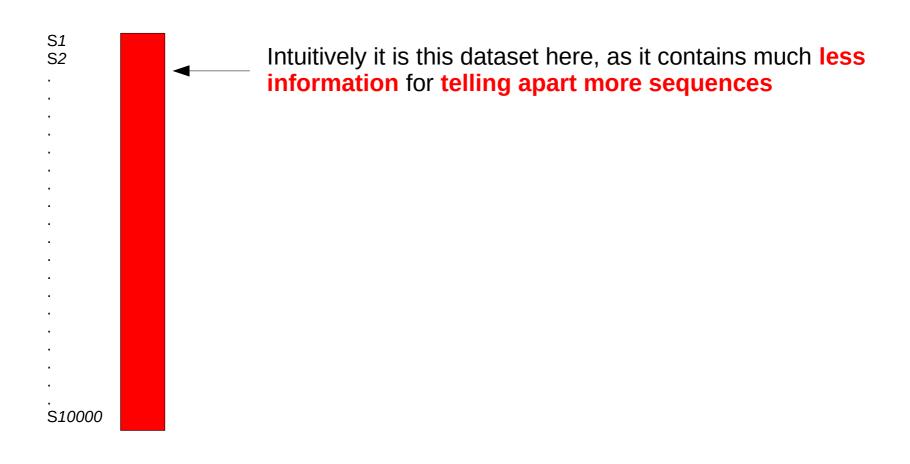
Which data is more difficult to analyze?



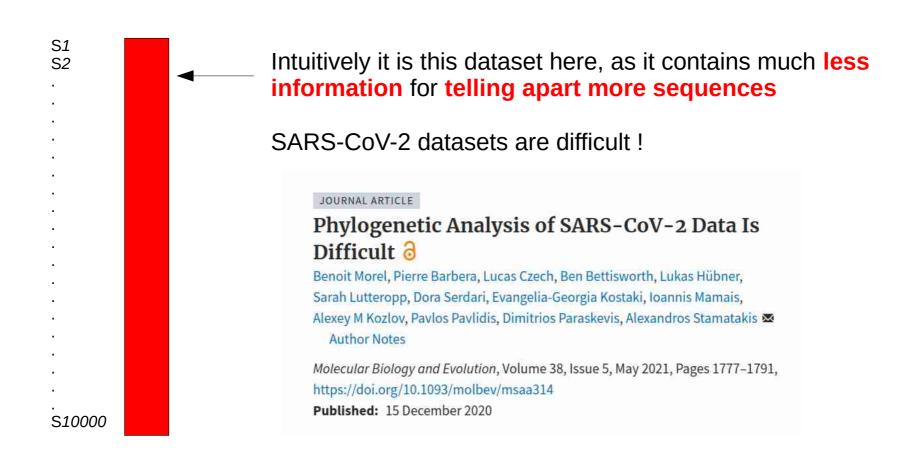


Few sequences, long sequence length

Dataset Shapes



Dataset Shapes



SARS-CoV-2

- Assembled 4 distinct datasets
- Per dataset
 - → executed 100 independent tree searches
- We use likelihood models
 - → determine trees that are not statistically significantly different from each other in sets of 100 trees

Results SARS-CoV-2

 For all 4 datasets about 70 out of 100 trees are not significantly different from each other with respect to their likelihood scores

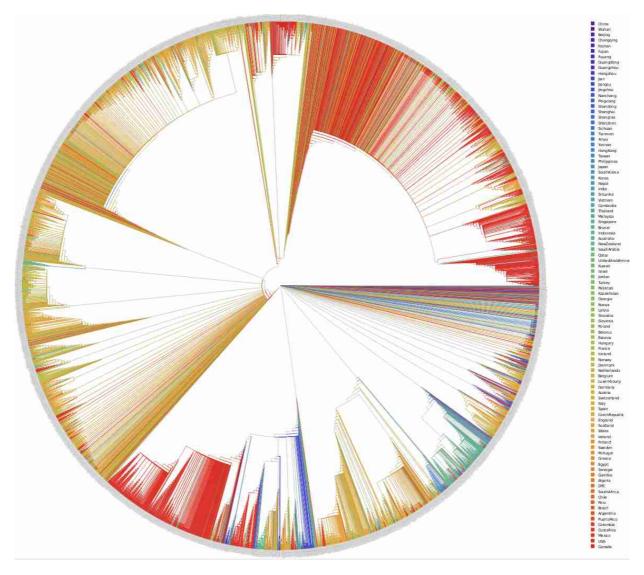
Results SARS-CoV-2

- For all 4 datasets about 70 out of 100 trees are not significantly different from each other with respect to their likelihood scores
- But, their pair-wise topological differences amount to about 70%!

Results SARS-CoV-2

- For all 4 datasets about 70 out of 100 trees are not significantly different from each other with respect to their likelihood scores
- But, their pair-wise topological differences amount to about 70%!
 - → extremely weak signal
 - → don't draw conclusions from a single tree!
 - → summarize the trees via summary statistics!

Summarized Trees



SARS-CoV-2 consensus tree colored by country

Difficulty of an MSA

This is **hand-wavy** → can we quantify & predict this?



Difficulty Prediction

JOURNAL ARTICLE

From Easy to Hopeless—Predicting the Difficulty of Phylogenetic Analyses 8

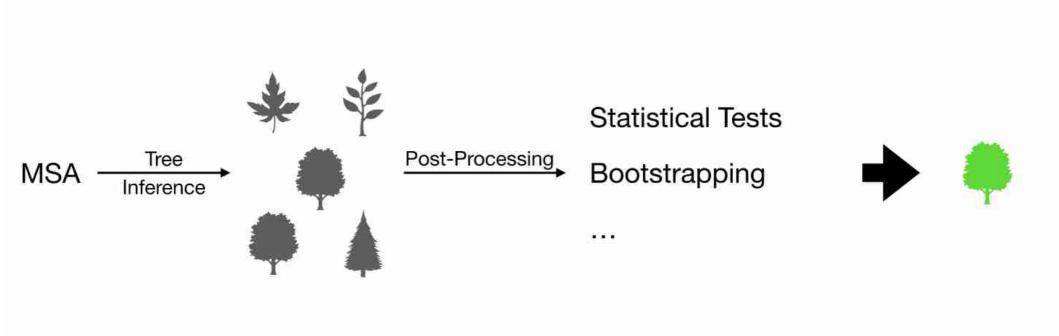
Julia Haag █, Dimitri Höhler, Ben Bettisworth, Alexandros Stamatakis

Molecular Biology and Evolution, Volume 39, Issue 12, December 2022, msac254,

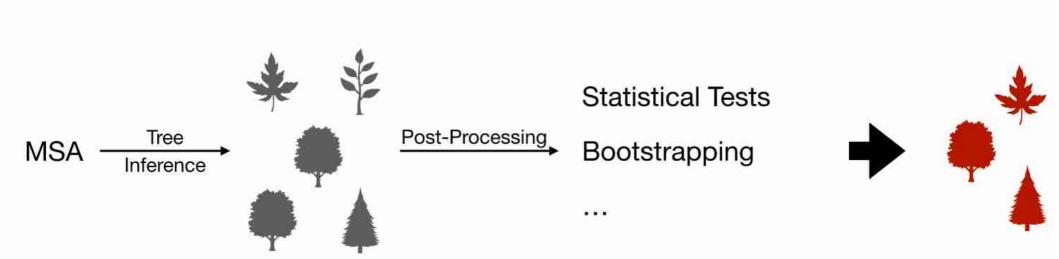
https://doi.org/10.1093/molbev/msac254

Published: 17 November 2022

Easy



Difficult



SARS-CoV-2

What does Difficulty mean?

Difficulty = ruggedness of the tree space

Easy

- Few highly similar tree topologies
- Single likelihood peak

Difficult

- Highly distinct topologies, statistically indistinguishable
- Multiple likelihood peaks

Predicting Difficulty with Pythia

- Pythia = Boosted Tree Regressor
- Supervised Regression Task
 - Predict difficulty between 0 (easy) and 1 (difficult)
 - Ground truth difficulty as training target based on 100 distinct Maximum Likelihood tree inferences
- Initially trained on 4K empirical MSAs
 - Mean absolute error: 2.5%

Pythia developments

- New release (May 19, 2023)
 - Trained on 12K datasets
 - 11,108 DNA MSAs
 - 979 Protein MSAs
 - 460 Morphological MSAs
 - Two new features
 - Improved accuracy
 - Mean absolute error: 0.07 (previously 0.09)
 - Mean absolute percentage error: 1.7% (previously 2.5%)

SARS-CoV-2 data

The predicted difficulty for MSA examples/covid.fasta is: 0.84. FEATURES: num_taxa: 4869 JOURNAL ARTICLE Phylogenetic Analysis of SARS-CoV-2 Data Is num_sites: 28361 Difficult 8 Benoit Morel, Pierre Barbera, Lucas Czech, Ben Bettisworth, Lukas Hübner, [...] Sarah Lutteropp, Dora Serdari, Evangelia-Georgia Kostaki, Ioannis Mamais, Alexey M Kozlov, Pavlos Pavlidis, Dimitrios Paraskevis, Alexandros Stamatakis 🗷 num_sites/num_taxa: 5.82 Author Notes Molecular Biology and Evolution, Volume 38, Issue 5, May 2021, Pages 1777-1791, [...] https://doi.org/10.1093/molbev/msaa314 Published: 15 December 2020 avg_rfdist_parsimony: 0.79 proportion_unique_topos_parsimony: 1.0 Feature computation runtime: 1830.182 seconds [...]

PYTHIA Features

Table 1. Importance of the Subset of Features we use to Train Pythia.

Feature	Impurity Importance
% Unique topologies parsimony trees	42.9%
RF-distance parsimony trees	33.2%
Entropy	17.0%
Patterns-over-taxa	13.6%
% Gaps	2.5%
Bollback	2.3%
Sites-over-taxa	1.5%
% Invariant	0.6%

Parsimony = 76%

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Using Pythia as End-User

- Prior to tree inference
 - → determine analysis & post-analysis setup
 - → adjust/modify MSA
 - → explore data filtering & assembly strategies
 - → adjust user/reviewer expectations about data

Simulation Study Using Pythia as Developer





New Results

A Follow this preprint

A representative Performance Assessment of Maximum Likelihood based Phylogenetic Inference Tools

Dimitri Höhler, Julia Haag, O Alexey M. Kozlov, Alexandros Stamatakis doi: https://doi.org/10.1101/2022.10.31.514545

This article is a preprint and has not been certified by peer review [what does this mean?].

ML Score as Function of Difficulty

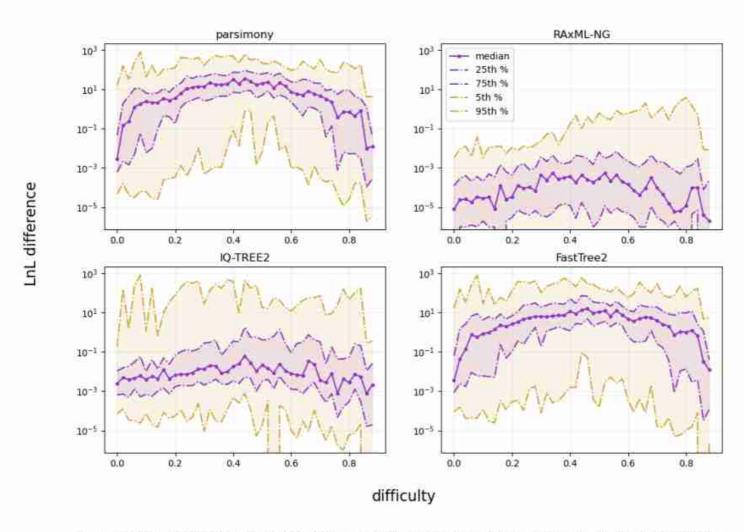


Fig. 3. Absolute log-likelihood (LnL) score differences (log scale) from the best-known ML tree on TreeBASE data.

Adaptive RAxML-NG

JOURNAL ARTICLE

Adaptive RAxML-NG: Accelerating Phylogenetic Inference under Maximum Likelihood using Dataset Difficulty 8

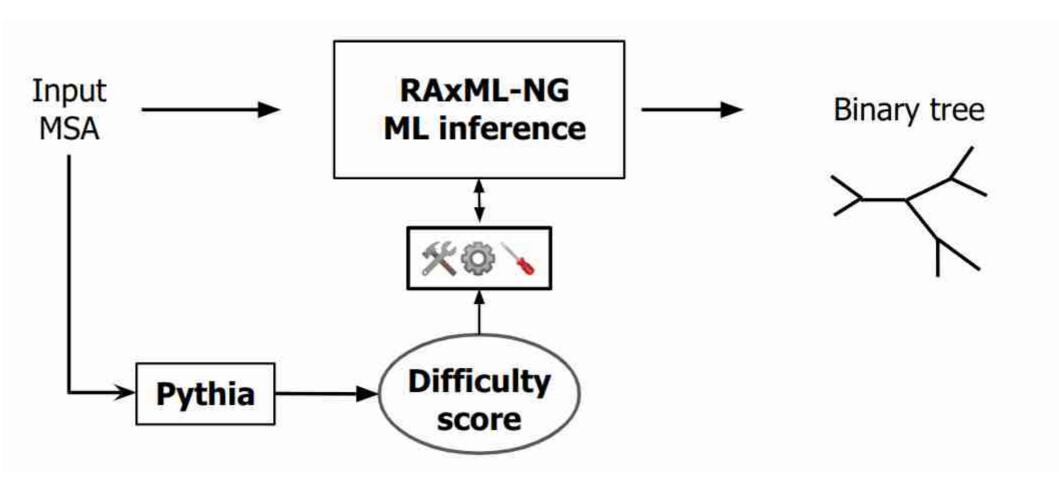
Anastasis Togkousidis M. Oleksiy M Kozlov, Julia Haag, Dimitri Höhler,
Alexandros Stamatakis Author Notes

Molecular Biology and Evolution, Volume 40, Issue 10, October 2023, msad227,

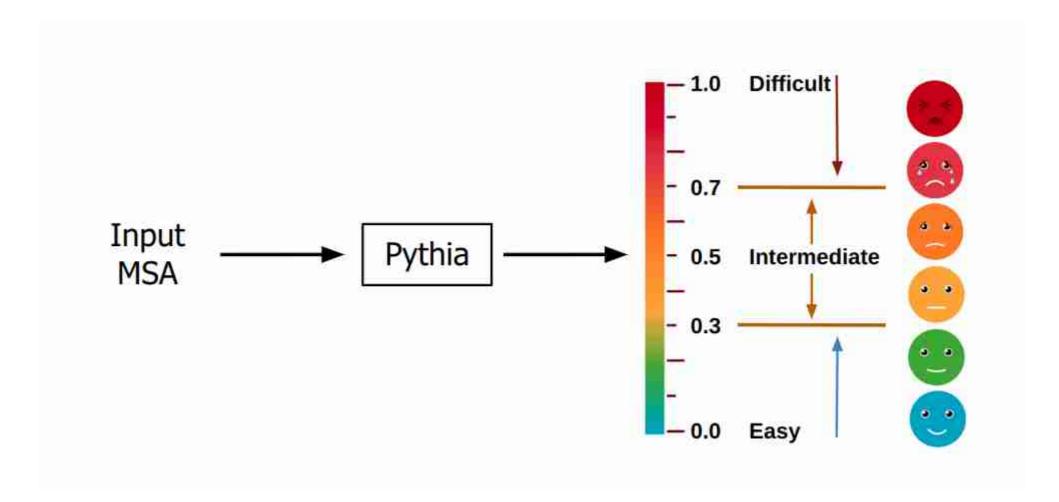
https://doi.org/10.1093/molbev/msad227

Published: 06 October 2023 Article history ▼

Adaptive RAxML-NG



Pythia



Adaptive RAXML-NG Heuristics

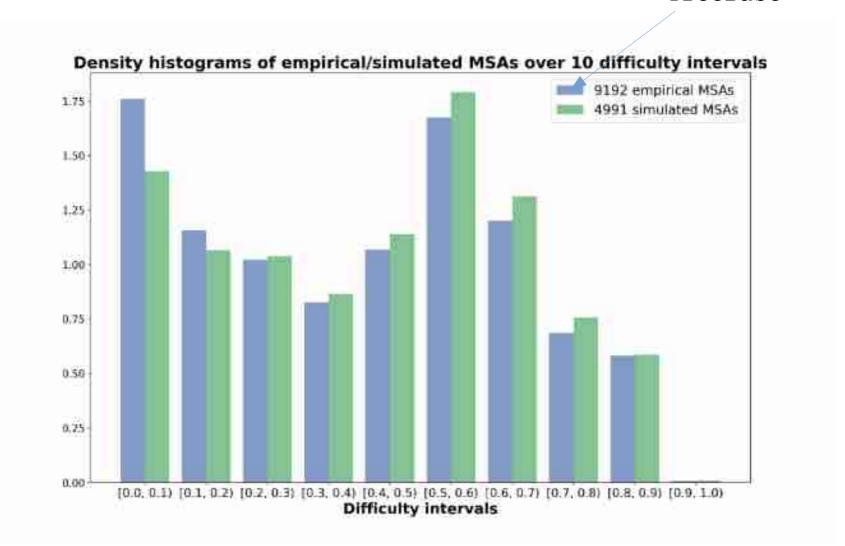
- As a function of PYTHIA difficulty modify
 - 1) number of independent ML tree searches
 - 2) thoroughness of the searches

Test Data & Setup

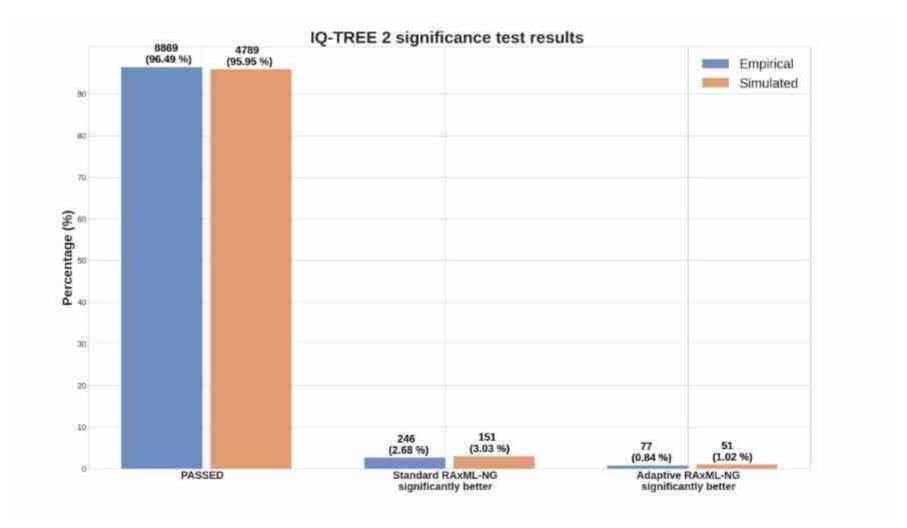
- 9192 empirical MSAs from TreeBase
- 4991 simulated MSAs

Difficulty Score Distribution

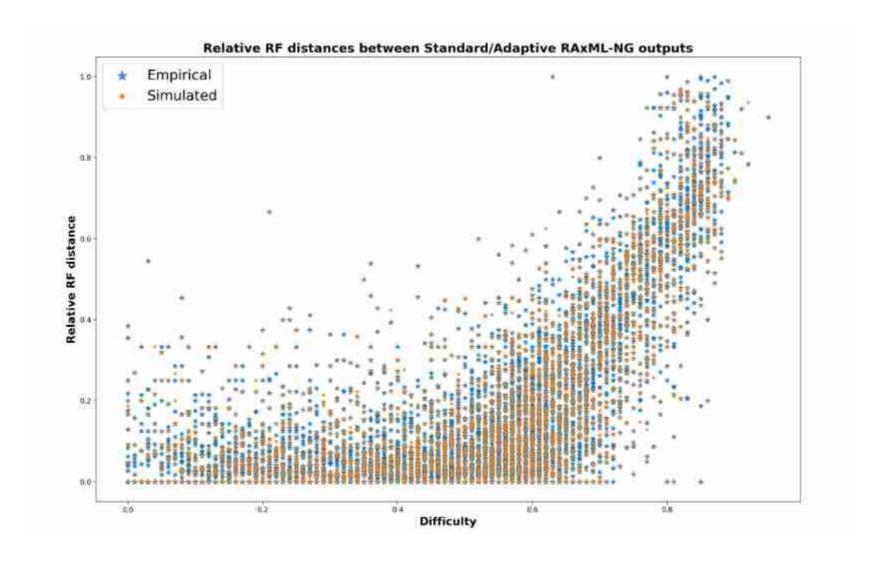
TreeBase

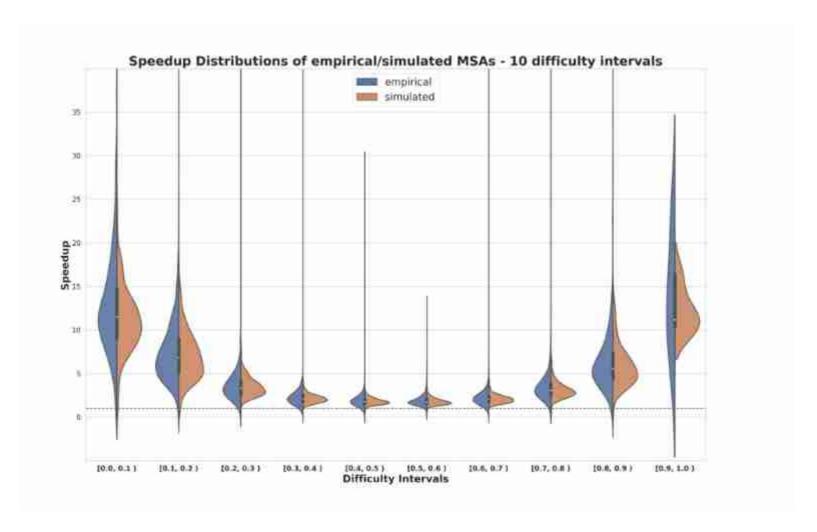


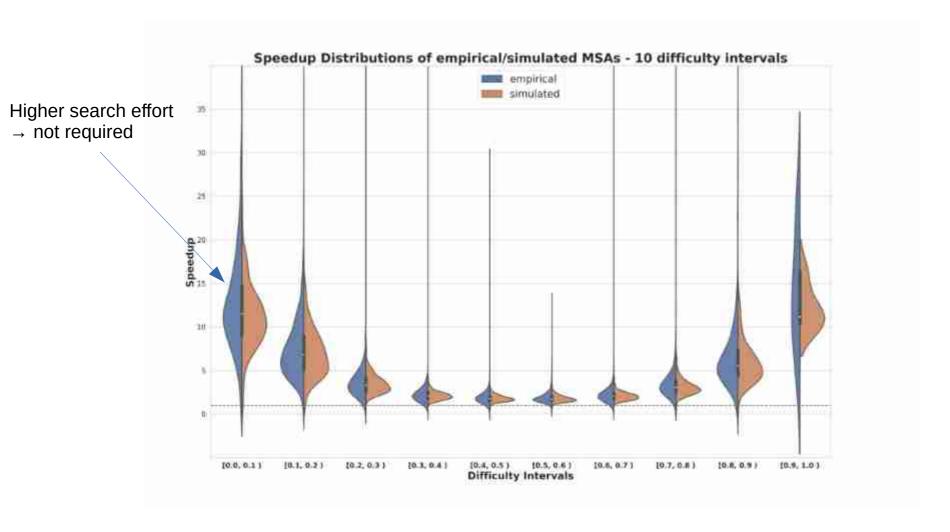
Significance Tests

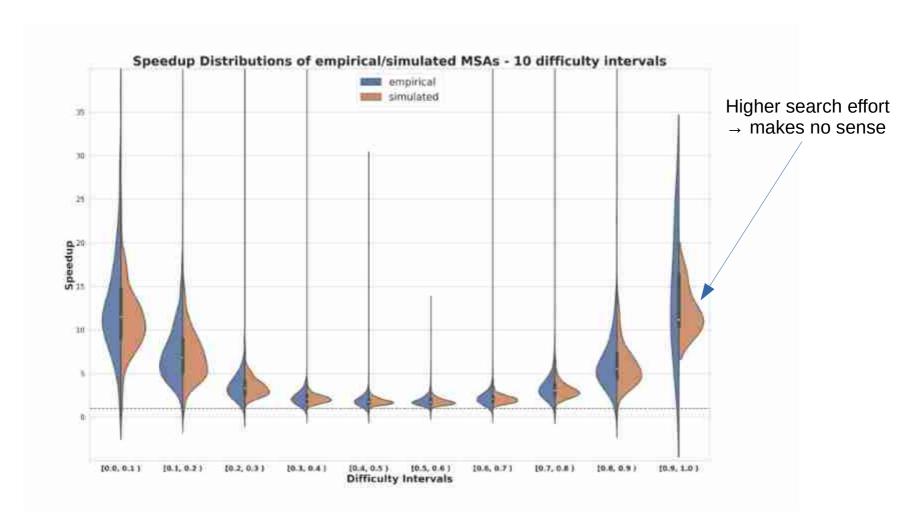


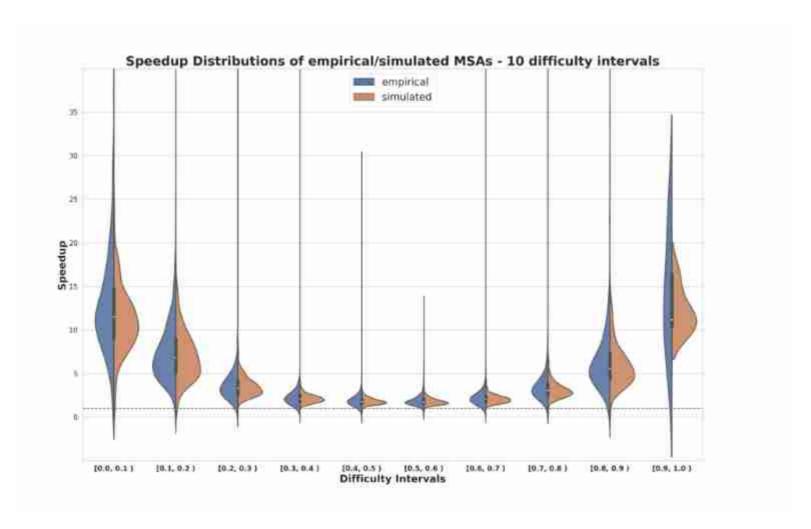
Distances between trees











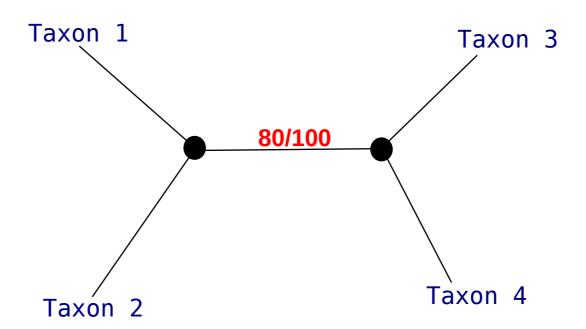
Overall accumulated speedup over all difficulties approx. 3 on empirical data

Outline

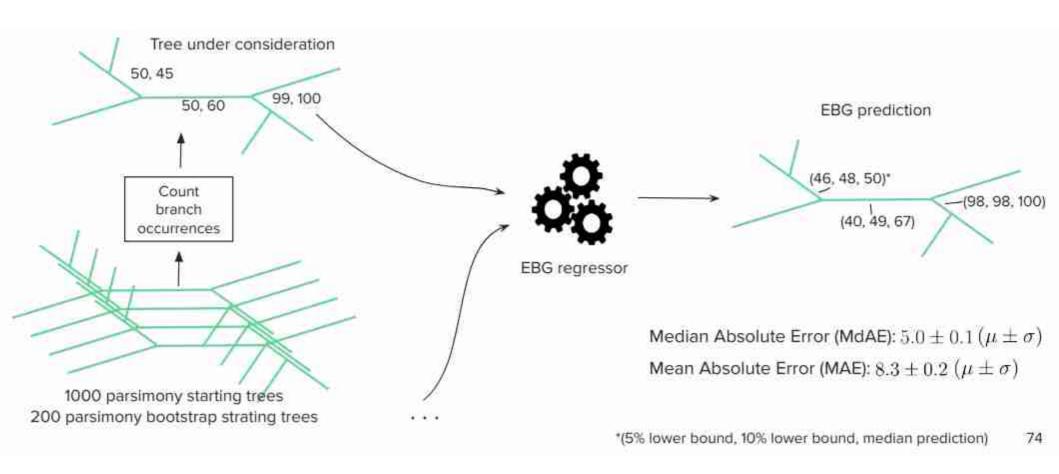
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Accelerated Bootstrapping

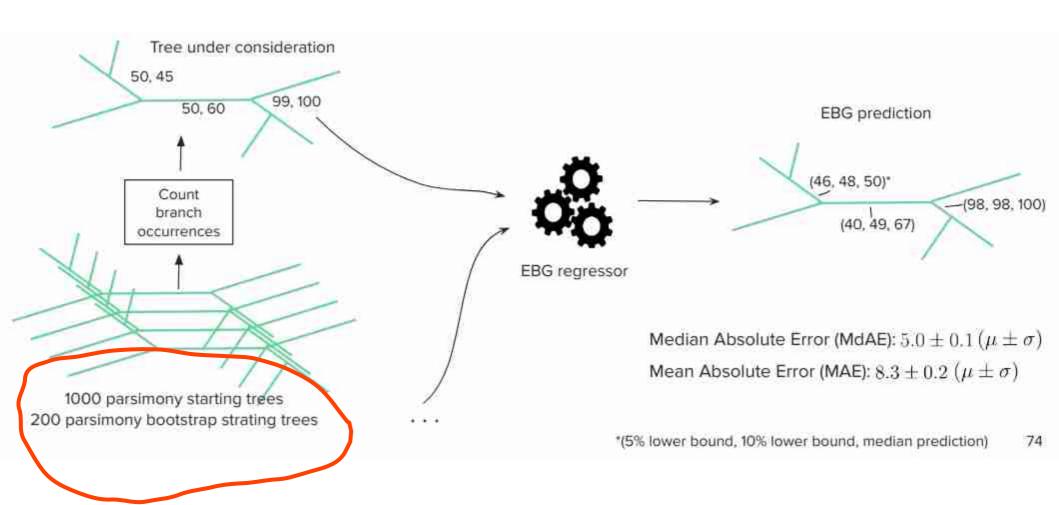
- Bootstrapping is compute-intensive
 - → Can we predict Bootstrap Support Values via Machine Learning?



EBG: Educated Bootstrap Guesser work in progress

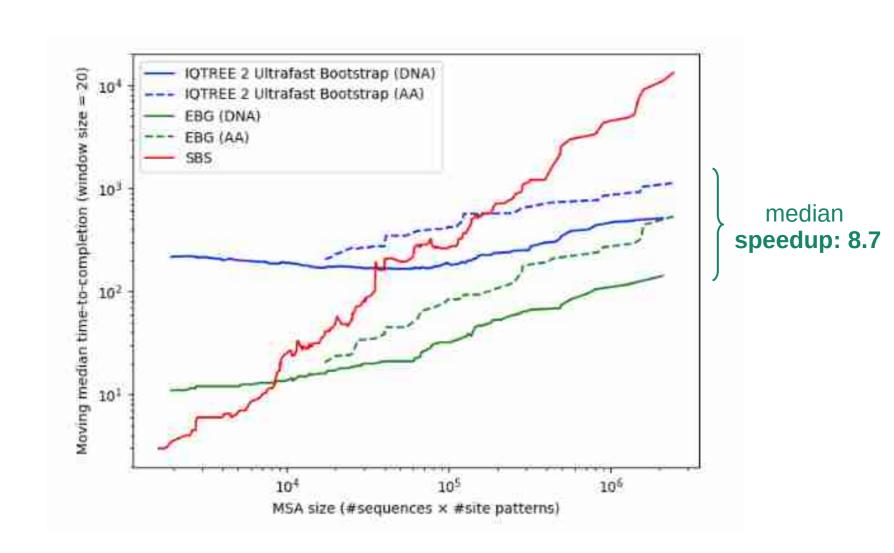


EBG: Educated Bootstrap Guesser

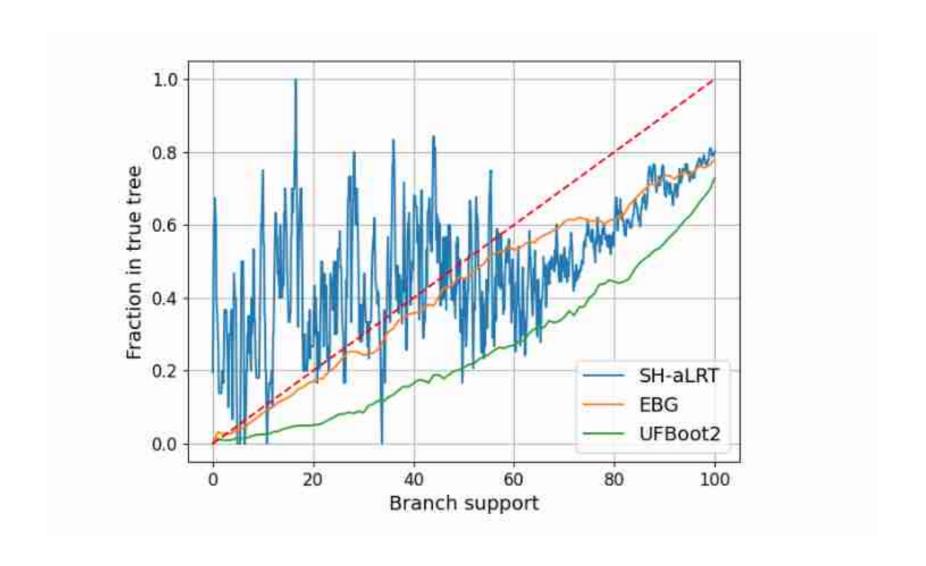


Parsimony again!

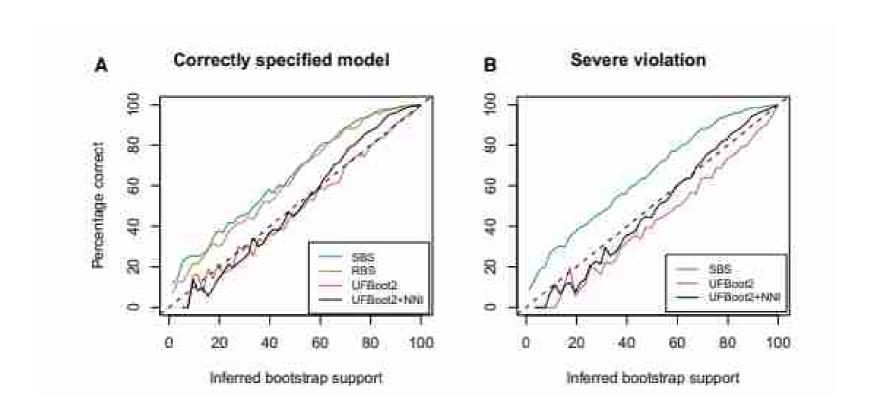
Run-times



Accuracy – Simulated Data

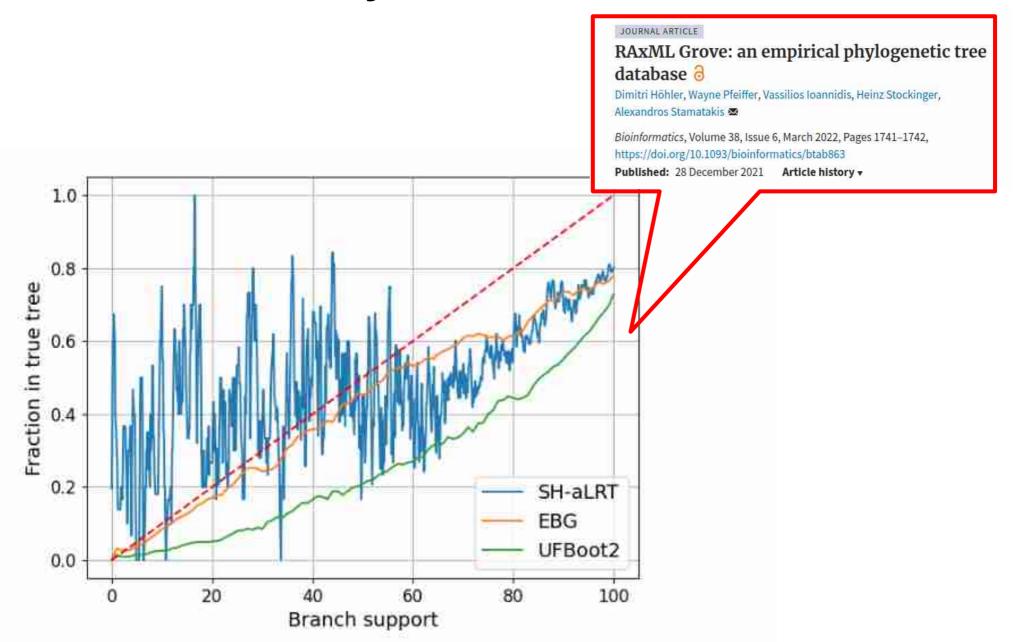


But ...



Accuracy on simulated data from UFBoot2 paper

Accuracy – Simulated Data



Empirical Data

- EBG support value correlations with Standard Bootstrap Supports
- 220 unseen empirical MSAs from TreeBase

22999_3	1.0	0.017	
23036_0	0.94	0.0	
23279_0	0.96	0.0	
23282.0	0.95	0.0	
23436.0	0.82	0.0	
23535_1	0.84	0.0	
23593_0	0.95	0.0	
23768_0	0.89	0.0	
23884_0	0.93	0.0	
25031_0	0.8	0.0	
25084.2	0.9	0.0	
25181_0	0.94	0.0	
25256.20	0.93	0.002	
25256_23	1.0	0.0	
25284_1	0.9	0.0	
25341_1	0.92	0.0	
25554.1	0.92	0.0	
25635_1	0.83	0.0	
25818_4	0.94	0.0	
25829_8	0.87	0.0	
26085_4	0.95	0.0	
26188_0	0.85	0.0	
26212.1	0.91	0.0	
26551_4	0.95	0.0	
26628_4	0.97	0.0	
26669_46	0.96	0.0	
26988_12	0.79	0.0	
26988_8	0.97	0.0	
27016_1	0.94	0.0	
27176_0	0.93	0.0	
27689_0	0.91	0.0	
28112_0	0.85	0.0	
28258.0	0.98	0.0	
28360.17	0.98	0.0	
28360_18	0.96	0.0	
28360_2	0.95	0.0	
28360_30	0.95	0.0	
28360_8	0.96	0.0	
362_1	0.89	0.0	
684_1	0.96	0.0	
688_1	0.95	0.0	
9936_1	0.97	0.0	
9972.0	0.96	0.0	

19060_0	0.96	0.0		
19447_0	0.91	0:0		
19466_3	0.92	0.0		
19509_1	0.99	0.0		
19579_0	0.91	0.0		
19740_5	0.82	0.0		
9782_3	0.78	0.0		
19797_0	0.95	0.0		
19889_1	0.89	0.0		
9925_0	0.96	0.0		
19925.6	0.95	0.0		
20079.4	0.94	0.0		
20196_18	0.96	0.0		
20196_19	0.96	0.0		
20239_0	0.93	0.0		
20239_3	0.95	0.0		
20250_1	0.87	0.0		
20736_0	0.94	0.0		
20944_1	0.79	0.0		
21191_0	0.83	0.0		
21303_0	0.92	0.0		
2180_2	0.95	0.0		
21817.6	0.87	0.0		
2191.2	0.94	0.0		
21973_9	0.98	0.0		
22052_0	0.93	0.0		
22091_1	0.78	0.0		
2217_0	0.93	0.0		
22200_0	0.91	0.0		
2224_0	0.92	0.0		
22408_11	0.97	0.0		
22429_0	0.9	0.0		
22442.11	0.92	0.0		
22442_6	0.85	0.002		
22475_0	0.9	0.0		
2248_0	0.96	0.0		
2250_0	0.91	0.0		
22552_1	0.91	0.0		
2256.1	0.98	0.0		
22751_1	0.95	0.0		
22798_0	0.85	0.0		
22805:0	0.93	0.0		
22941_0	0.92	0.0		

16009_1	0.89	0.0
6105_0	0.88	0.0
16141_1	0.78	0.041
16190_2	0.94	0.0
16269_0	0.92	0.0
16313.11	0.94	0.0
16453.0	1.0	1.0
16629_0	0.88	0.0
16632_2	0.96	0.0
16637.2	0.97	0.0
16675.0	0.88	0.0
16737_0	0.84	0.0
16748_0	0.84	0.0
16785_1	0.9	0.0
16855.2	0.97	0.0
17014_0	0.9	0.0
17168_0	0.95	0.0
17390_1	0.92	0.0
17443_0	0.92	0.0
17594_11	0.93	0.0
17594_13	0.95	0.0
17666.0	0.89	0.0
17723_0	0.94	0.0
17749_1	0.9	0.0
17761_0	0.91	0.0
17774.4	0.97	0.0
17791_0	0.85	0.0
17814.0	0.93	0.0
17878.9	0.85	0.0
17885_1	0.96	0.0
17896_31	0.92	0.0
18077.0	0.94	0.0
18131_0	0.84	0.0
18218.1	0.96	0.0
18258.2	0.92	0.0
18438_0	0.75	0.003
18448_0	0.89	0.0
18465_0	0.94	0.0
18638.0	0.87	0.0
18638.1	0.92	0.0
18654_0	0.95	0.0
18850.2	0.62	0.574
18883.0	0.92	0.0

Feature Importance

Parsimony: 85%

Feature	Importance in $\%$		
PBS	82.2		
PS	3.1		
Normalized branch length	2.0		
# child inner branches	1.7		
Skewness PBS	1.5		

PBS = **P**arsimony **B**ootstrap **S**upport from *200* parsimony bootstraps PS = **P**arsimony **S**upport from *1000* parsimony starting trees

Feature Importance

A Renaissance of parsimony as predictor for likelihood?

Parsimony: 85%

Feature	$Importance\ in\ \%$		
PBS	82.2		
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PBS = **P**arsimony **B**ootstrap **S**upport from *200* parsimony bootstraps PS = **P**arsimony **S**upport from *1000* parsimony starting trees

Outline

- Introduction to Phylogenetic Inference
- Sources of Uncertainty
- Phylogenetic Difficulty
- Using Phylogenetic Difficulty
- Bootstrap Prediction
- Other Stuff we work on

Simulated Data Suck!

JOURNAL ARTICLE

Simulations of Sequence Evolution: How (Un)realistic They Are and Why 8

Johanna Trost, Julia Haag ∰, Dimitri Höhler, Laurent Jacob, Alexandros Stamatakis, Bastien Boussau Author Notes

Molecular Biology and Evolution, Volume 41, Issue 1, January 2024, msad277, https://doi.org/10.1093/molbev/msad277

Published: 20 December 2023 Article history ▼

We can distinguish between empirical and simulated MSAs with high accuracy using two distinct and independently developed machine learning based classification approaches!

Pandora Work in Progress

Estimating
Dimensionality
Reduction
Stability of
Genotype Data
via Bootstrapping

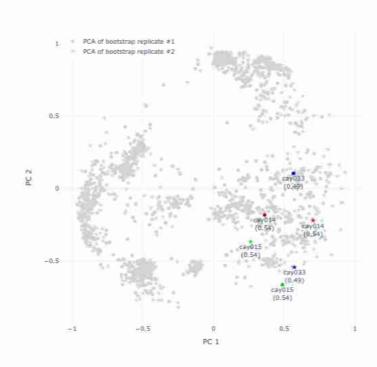
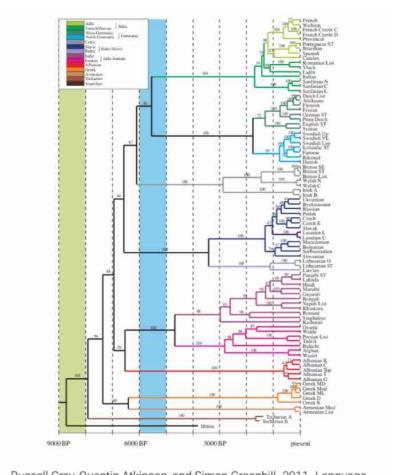


Figure 6: The three Çayönü individuals with the lowest PSVs plotted for two randomly selected bootstrap PCA results. The gray dots indicate the projections of one bootstrap, the gray stars indicate the projections of the second bootstrap. The highlighted individuals indicate the respective projection of the three Çayönü individuals in both PCAs.

Language Evolution Eliminating Subjectivity



Russell Gray, Quentin Atkinson, and Simon Greenhill. 2011. Language Evolution and Human History, pages 269–288

Cognate Data

- A cognate dataset
 - relies on a list of concepts
 - provides a word for each concept in each language
 - selects every-day words describing the concepts precisely (A)
 - Is represented by a binary character matrix (B) for the tree inference with RAXML-NG

	big		big_1	big_2	big_3
English	big, great	E	1	1	0
German	groß	G	0	1	0
Dutch	groot	D	0	1	0
Norwegian	stor	Ν	0	0	1
Swedish	stor	S	0	0	1
	(A)	,		(B)	

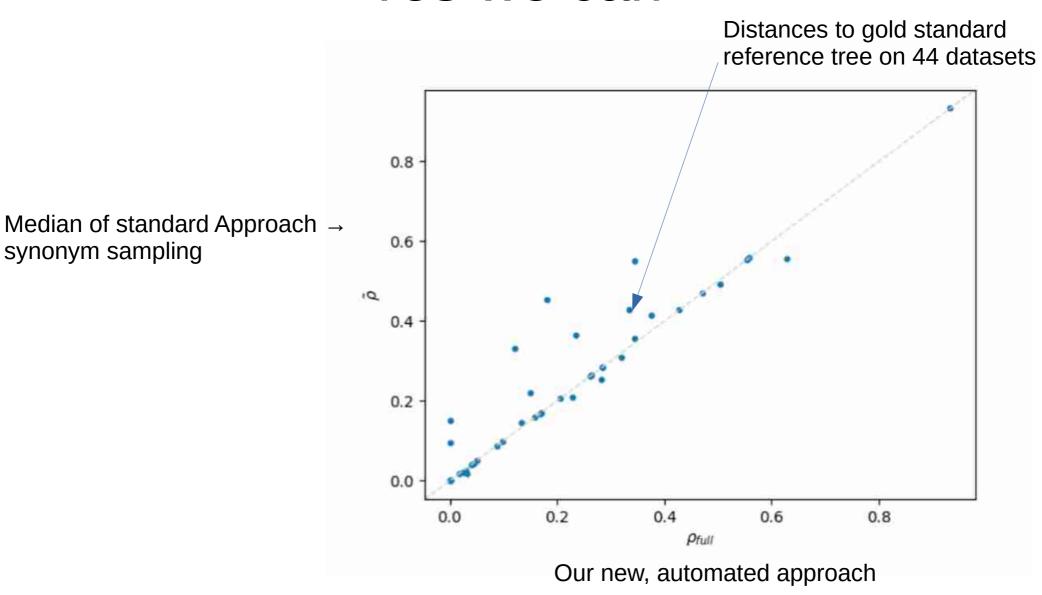
Synonyms

- Synonyms
 - distinct words describing the same concept
 - e.g. "töten" and "umbringen" both describe the concept "to kill" in German
- Traditional recommendation in linguistics:
 Select one (most frequent) synonym only →
 work intensive & subjective choice

Synonyms

- Synonyms
 - distinct words describing the same concept
 - e.g. "töten" and "umbringen" both describe the concept "to kill" in German
- Traditional recommendation in linguistics: Select one (most frequent) synonym only → work intensive & subjective choice
- Can we somehow include all synonyms without any subjective choice?
- Can phylogenetic likelihood models naturally accommodate all synonyms?

Yes we can



Yes we can

synonym sampling

Distances to gold standard reference tree on 44 datasets 0.8 Median of standard Approach → 0.6 Ď 0.4 0.2 0.0 0.2 0.4 0.6 0.0 0.8 Pfull Our new, automated approach

Energy Efficiency

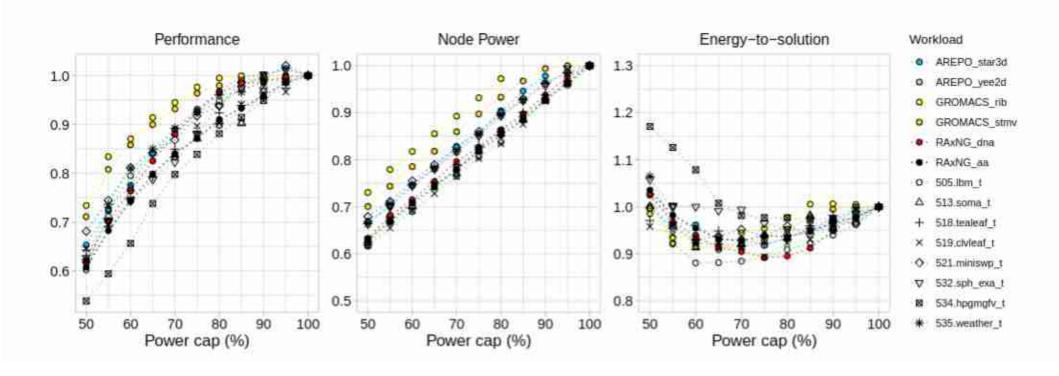
EcoFreq: compute with cheaper, cleaner energy via carbon-aware power scaling

Oleksiy M. Kozlov 1500 and Alexandros Stamatakis 2,1,3

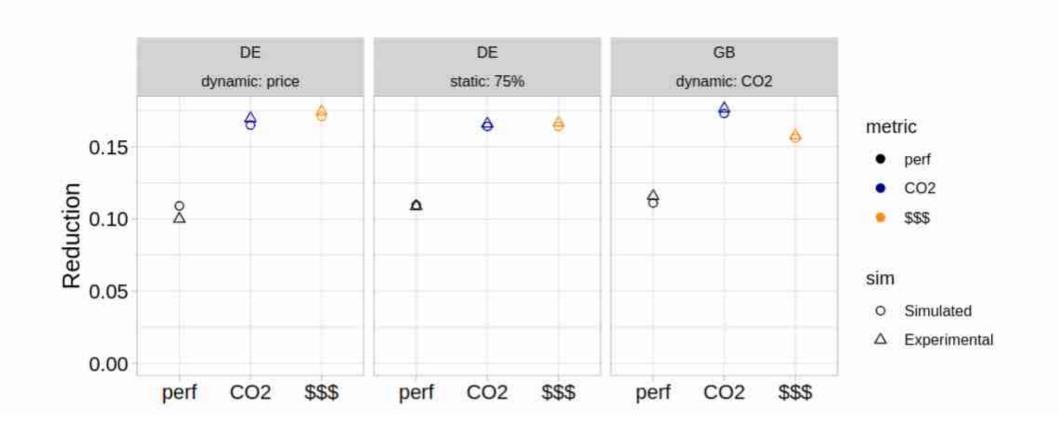
¹Computational Molecular Evolution group, HITS gGmbH, Heidelberg, Germany
²Institute of Computer Science, Foundation for Research and Technology Hellas, Heraklion, Greece
³Institute of Theoretical Informatics, Karlsruhe Institute of Technology, Karlsruhe, Germany

https://github.com/amkozlov/eco-freq

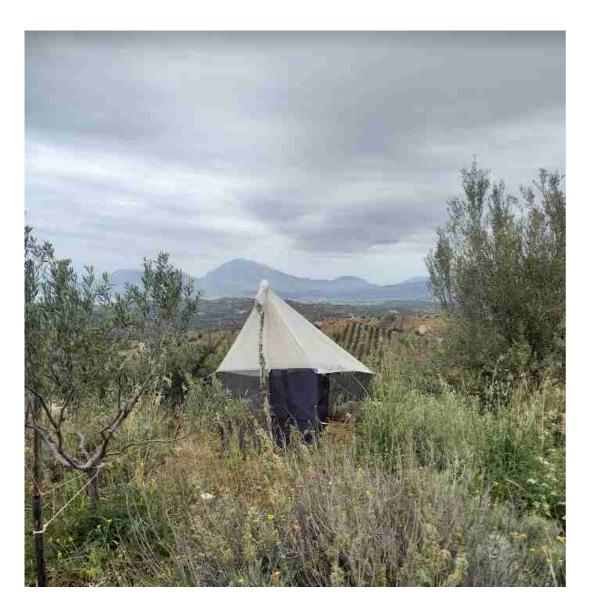
EcoFreq



EcoFreq

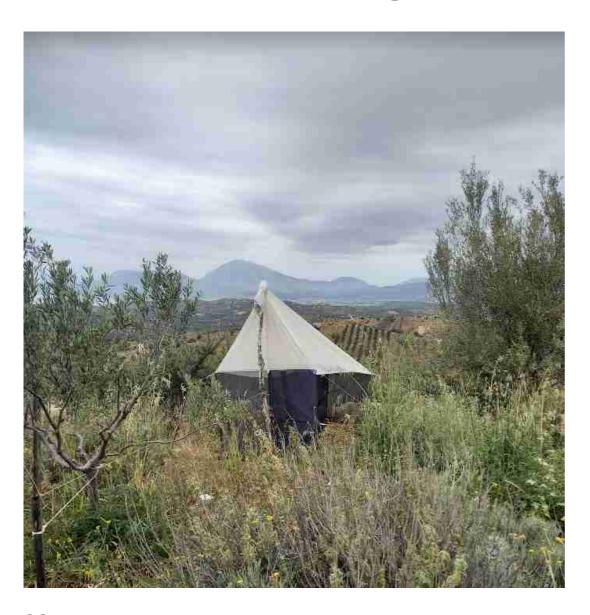


Biological Field Work





Biological Field Work



Work on designing improved insect barcode analysis pipelines



Gene Tree Species Tree Reconciliation

- There are other phenomena that complicate evolution
 - Gene loss
 - Gene transfer
 - Gene duplication
 - → gene tree ≠ species tree
- Infer & correct trees under a joint likelihood model comprising the phylogenetic likelihood and a reconciliation likelihood model

GeneRax

 First full and efficient Maximum Likelihood implementation to infer gene family trees using a given rooted species tree under a joint phylogenetic & reconciliation likelihood model

GeneRax: A Tool for Species-Tree-Aware Maximum Likelihood-Based Gene Family Tree Inference under Gene Duplication, Transfer, and Loss &

Benoit Morel 록, Alexey M Kozlov, Alexandros Stamatakis, Gergely J Szöllősi

Molecular Biology and Evolution, Volume 37, Issue 9, September 2020, Pages 2763–2774, https://doi.org/10.1093/molbev/msaa141

Published: 05 June 2020

SpeciesRax

 Goal: Simultaneously infer the gene family trees and the species tree under a joint phylogenetic/reconciliation likelihood model

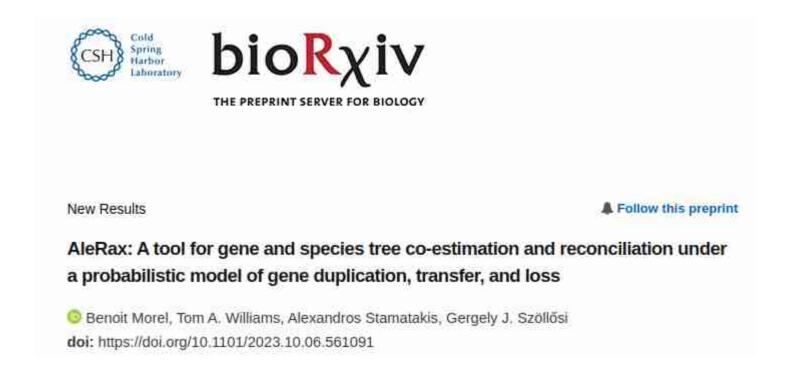
Species Rax: A Tool for Maximum Likelihood
Species Tree Inference from Gene Family Trees
under Duplication, Transfer, and Loss ∂
Benoit Morel ☒, Paul Schade, Sarah Lutteropp, Tom A Williams, Gergely J Szöllősi,
Alexandros Stamatakis

Molecular Biology and Evolution, Volume 39, Issue 2, February 2022, msab365,
https://doi.org/10.1093/molbev/msab365

Published: 11 January 2022

AleRax

- Uses concept of amalgamated likelihoods → requires posterior per-gene tree set as input :-(
- https://github.com/BenoitMorel/AleRax



Software Quality Assessment

 SoftWipe tool for automatic scientific software quality assessment (C and C++)

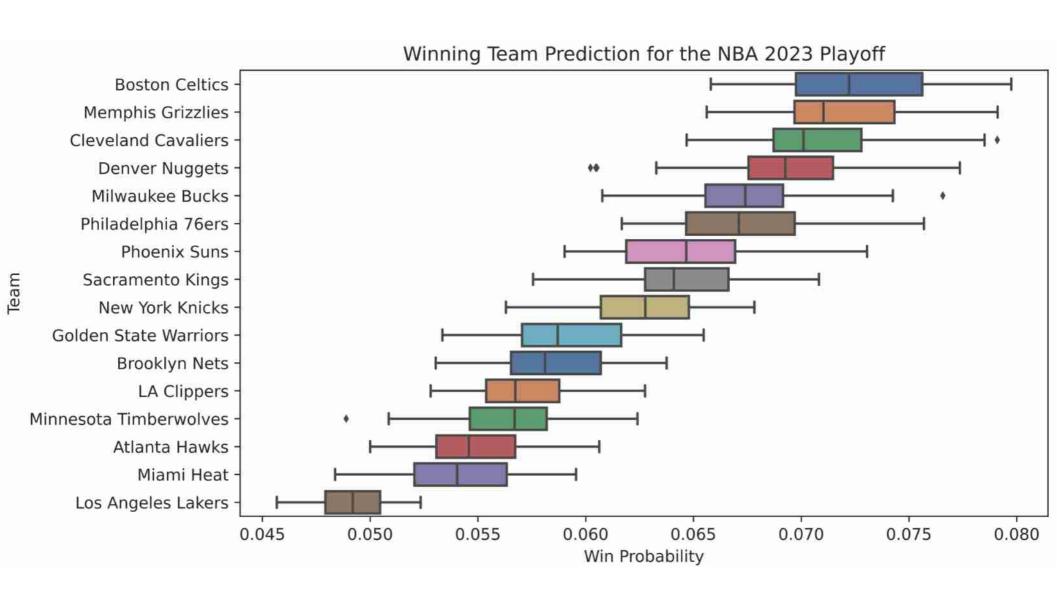
```
The SoftWipe tool and benchmark for assessing coding standards adherence of scientific software

Adrian Zapletal, Dimitri Höhler, Carsten Sinz & Alexandros Stamatakis 

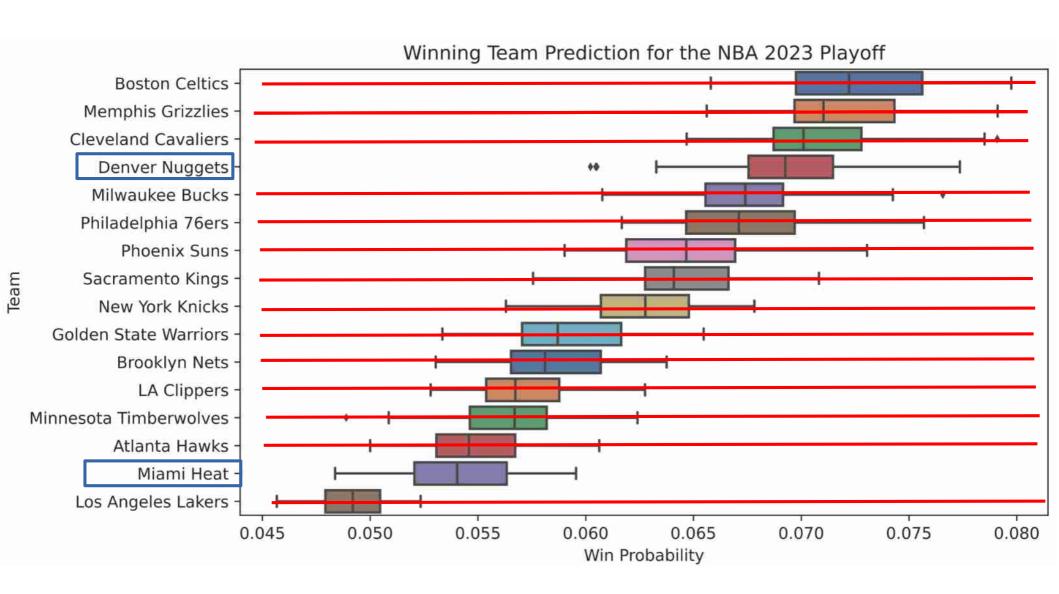
Scientific Reports 11, Article number: 10015 (2021) | Cite this article

4270 Accesses | 1 Citations | 115 Altmetric | Metrics
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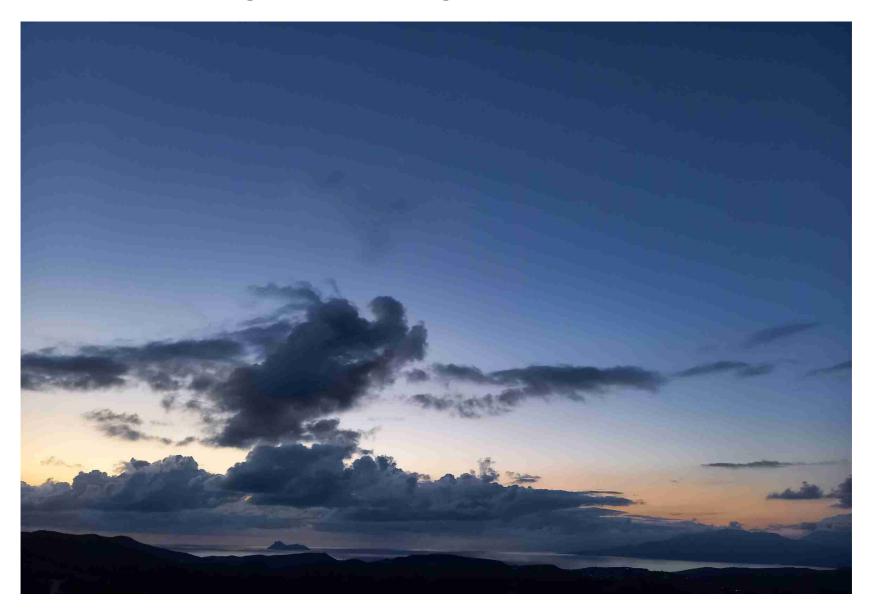
Tournament Prediction



Tournament Prediction



Thank you for your attention



Listaros village, Crete

Definition of Difficulty

MSA
$$\frac{\text{Tree Inference}}{(\text{RAxML-NG})}$$
 $\frac{N_{\text{all}} = 100}{N_{\text{pl}}}$ $\frac{\text{Statistical Tests}}{(\text{IQ-Tree})}$ $\frac{N_{\text{pl}}}{N_{\text{pl}}}$ plausible trees $\frac{RF_{\text{pl}}}{N_{\text{pl}}}$ $\frac{RF_{\text{pl}}}{N_{\text{pl}}}$ difficulty(MSA) = $\frac{1}{5} \cdot \left[RF_{\text{all}} + \frac{N_{\text{all}}^*}{N_{\text{all}}} + RF_{\text{pl}} + \frac{N_{\text{pl}}^*}{N_{\text{pl}}} + \left(1 - \frac{N_{\text{pl}}}{N_{\text{all}}} \right) \right]$

Prediction Features

- Eight Features
 - 4 MSA attributes
 - Sites-over-taxa
 - patterns-over-taxa
 - % gaps
 - % invariant sites
 - 2 MSA information metrics
 - Shannon entropy
 - Bollback multinomial test statistic
 - 2 Parsimony-tree-based features
 - Infer 100 parsimony trees
 - → average RF-Distance
 - → % unique topologies