

Multi-gene phylogenies (phylogenomics)

Large evolutionary-scale (deep) phylogenetic analyses

Laura Eme

Assistant Prof.

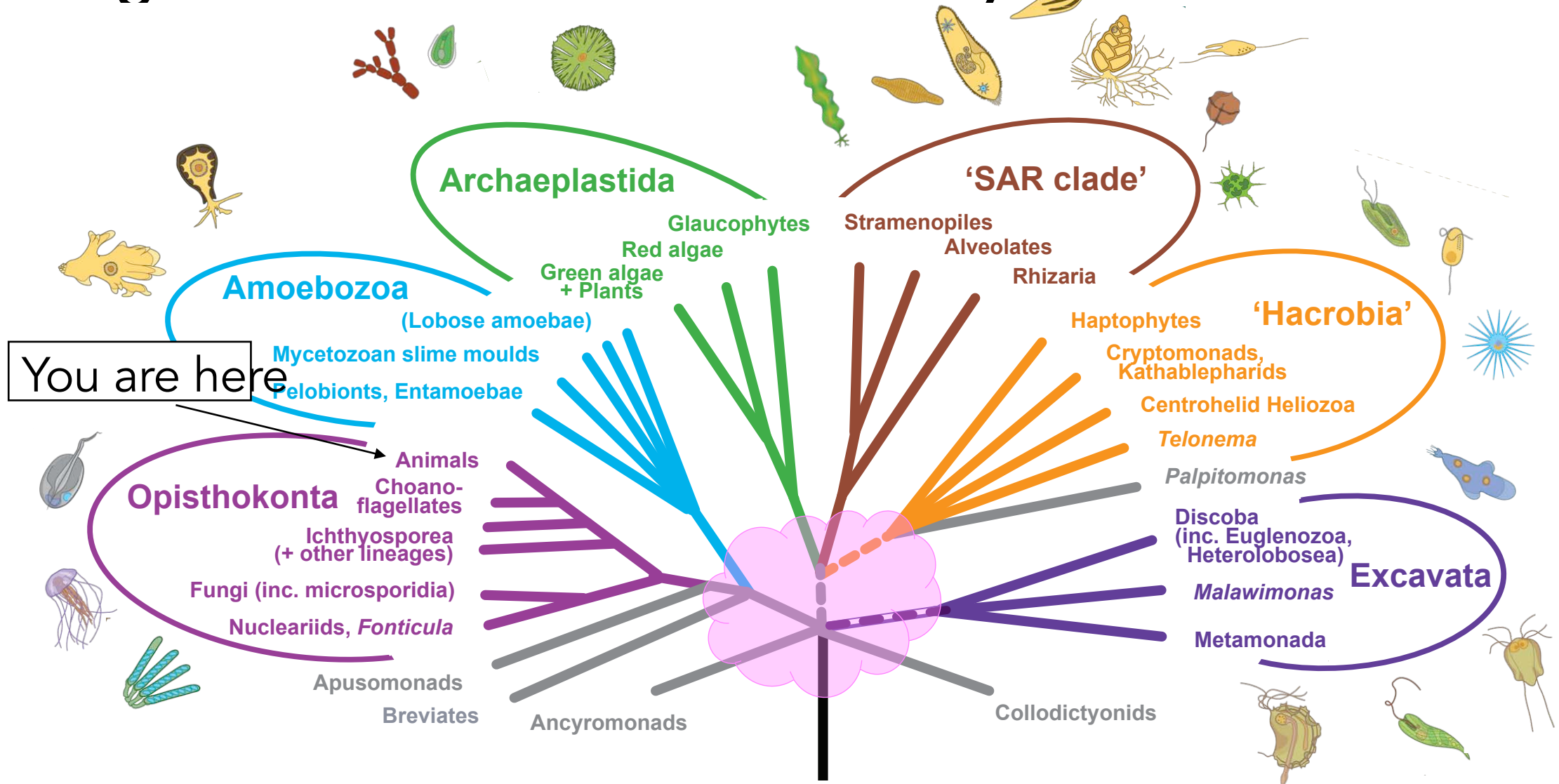
Paris-Sud University

<http://emelaura.com>

Disclaimer

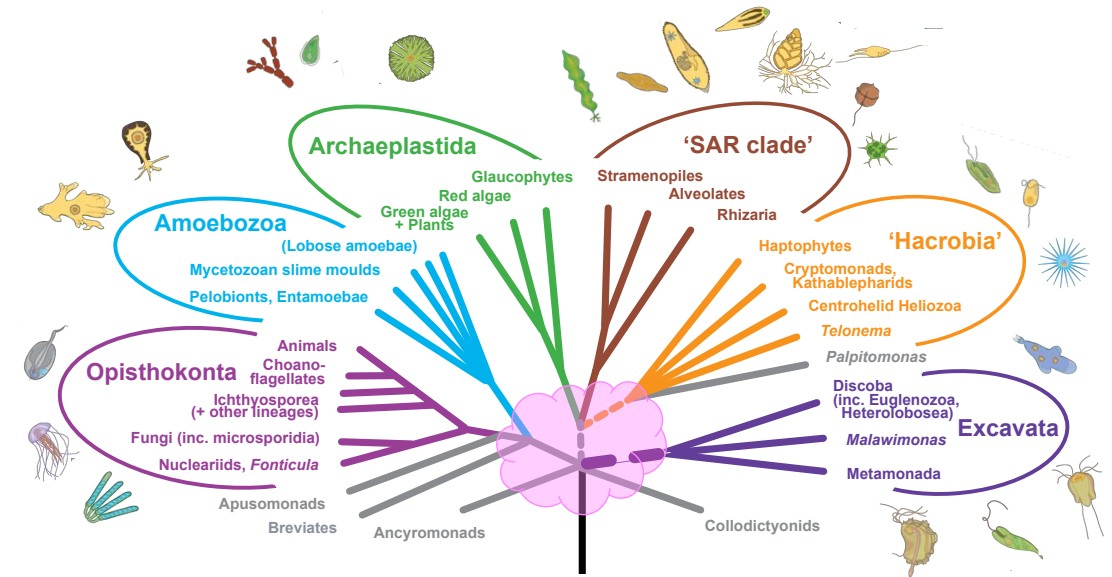
What I do and how, and how that can hopefully apply
to your questions

Origin and evolution of eukaryotes



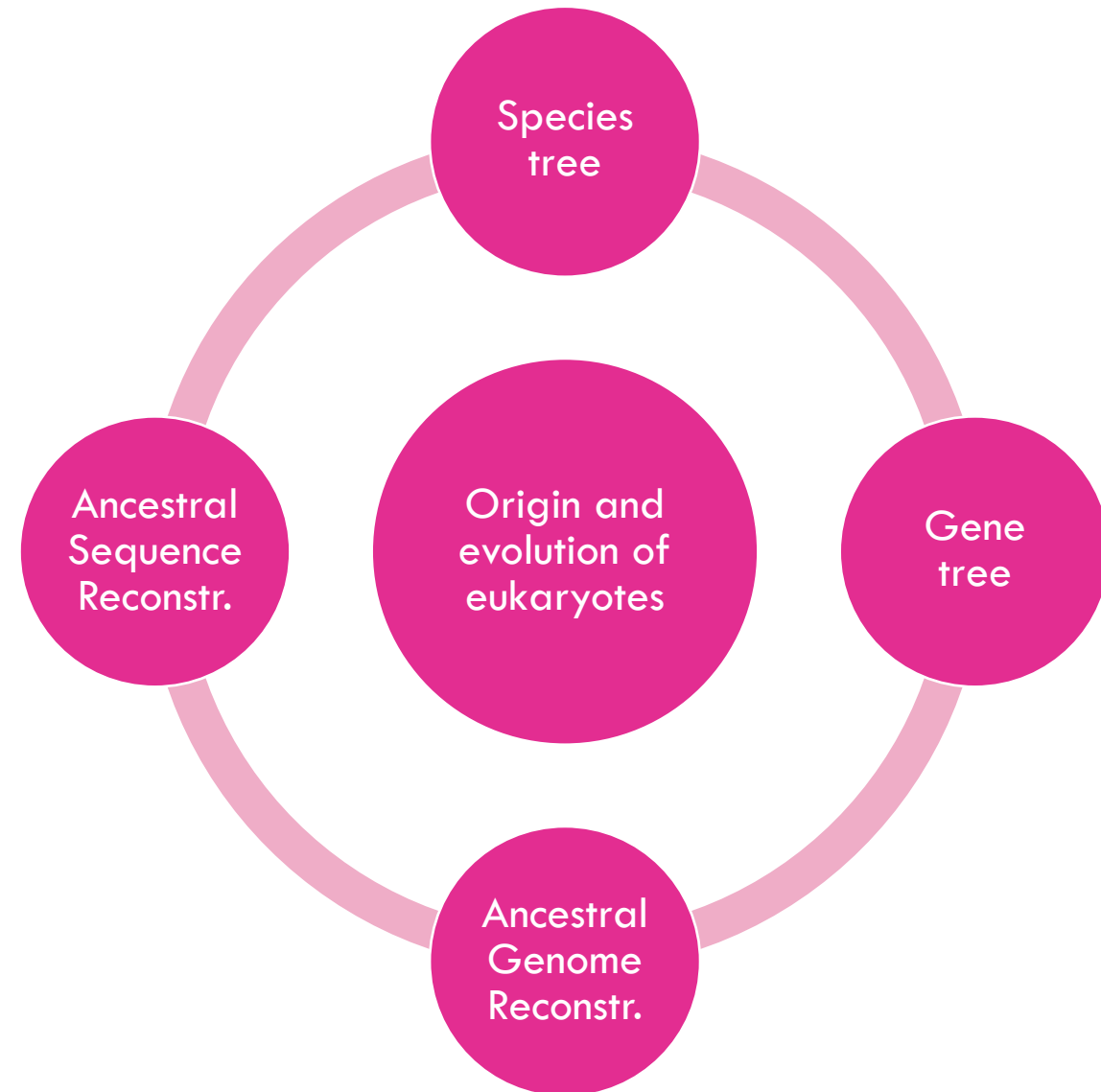
Origin and evolution of eukaryotes

- Tree of eukaryotes (deep relationships between major groups)
 - Origin of eukaryotes (i.e., their placement within the tree of life)
 - Origin and evolution of specific eukaryotic genes/systems (e.g., endomembrane system)
 - Evolution of gene content along the species tree (origin of major clades)
 - Impact of LGT on genome evolution
- ➔ Large evolutionary scale questions



Origin and evolution of eukaryotes

- Tree of eukaryotes (deep relationships between major groups)
 - Origin of eukaryotes (i.e., their placement within the tree of life)
 - Origin and evolution of specific eukaryotic genes/systems (e.g., endomembrane system)
 - Evolution of gene content along the species tree (origin of major clades)
 - Impact of LGT on genome evolution
- ➔ Large evolutionary scale questions



1 - Protein models of evolution

Empirical models, GTR model, Mixture models

1.1 Empirical models

Code degeneracy

Glu-Gly-Ser-Ser-Trp-Leu-Leu-Leu-Gly-Ser

Glu-Gly-Ser-Ser-Tyr-Leu-Leu-Ile-Gly-Ser

Asp-Gly-Ser-Ala-Trp-Leu-Leu-Leu-Gly-Ser

Asp-Gly-Ser-Ala-Tyr-Leu-Leu-Ala-Gly-Ser

GAA-GGA-AGC-TCC-TGG-TTA-CTC-CTG-GGA-TCC

GAG-GGT-TCC-AGC-TAT-CTA-TTA-ATT-GGT-AGC

GAC-GGC-AGT-GCA-TGG-TTG-CTT-TTG-GGC-AGT

GAT-GGG-TCA-GCT-TAC-CTC-CTG-GCC-GGG-TCA

Protein sequence evolves slower than nucleotide

Code degeneracy

- Base composition bias can lead to large difference in codon usage
- Comparing protein sequences can reduce the compositional bias problem

Evolutionary models for amino acid changes

Typically

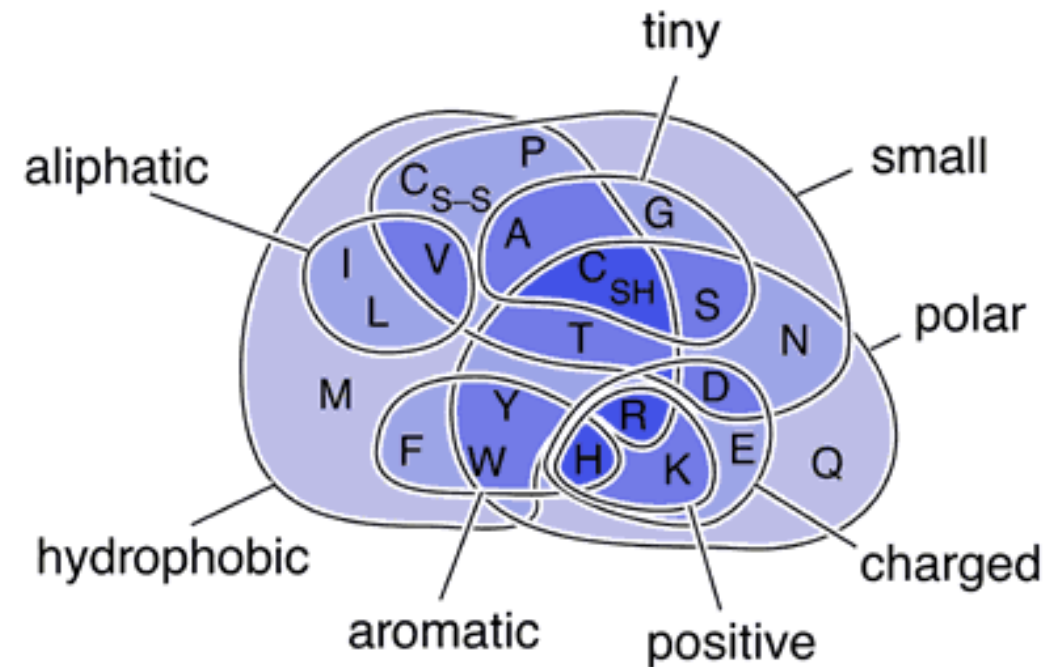
- A 20x20 rate matrix
- Assumes stationarity and reversibility

Amino acid physico-chemical properties

- AA can be categorized according to their physicochemical properties
- Major factor in protein folding (secondary, tertiary, quaternary structure)
- Key to protein functions (e.g., catalytic sites)

➔ Major influence in pattern of amino acid mutations

Some amino acid changes are more commonly fixed than others



Empirical models: amino acid substitution matrices based on observed substitutions

Summarise the substitution patterns from a large number of existing alignments ('average' models)

Empirical models: amino acid substitution matrices based on observed substitutions

Summarise the substitution patterns from a large number of existing alignments ('average' models)



Raw data: observed changes in pairwise comparisons

```
seq.1  AIDESLIIASIATATI
        |*||*||*||*||*||
seq.2  AGDEALILASAATSTI
```

seq.1 AIDESLIIASIATATI

|*||*||*||*||*||

seq.2 AGEERALILASAATSTI

	A	S	T	G	I	L	E	D
Raw matrix	A 3							
Symmetrical	S 2 1							
	T 0 0 1							
	G 0 0 0 0							
	I 1 0 0 1 2							
	L 0 0 0 0 1 1							
	E 0 0 0 0 0 0 1							
	D 0 0 0 0 0 0 1 0							

seq.1 AIDE**S**LIIASIAT**A**TI
 |*||*||*||*||*||
 seq.2 AGE**E**ALILASAAT**S**TI

	A	S	T	G	I	L	E	D
Raw matrix	A 3							
Symmetrical	S 2	1						
	T 0	0	1					
	G 0	0	0	0				
	I 1	0	0	1	2			
	L 0	0	0	0	1	1		
	E 0	0	0	0	0	0	1	
	D 0	0	0	0	0	0	1	0

seq.1 AIDE**S**LIIASIAT**A**TI
 |*||*||*||*||*||
 seq.2 AGE**E**ALILASAAT**S**TI

	A	S	T	G	I	L	E	D
Raw matrix	A 3							
Symmetrical	S 2 1							
	T 0 0 1							
	G 0 0 0 0							
	I 1 0 0 1 2							
	L 0 0 0 0 1 1							
	E 0 0 0 0 0 0 1							
	D 0 0 0 0 0 0 1 0							

➔ The larger the dataset, the better the estimates

Amino acid exchange matrices

$$\begin{pmatrix} - & s_{1,2} & s_{1,3} & \dots & s_{1,20} \\ s_{1,2} & - & s_{2,3} & \dots & s_{2,20} \\ s_{1,3} & s_{2,3} & - & \dots & s_{3,20} \\ \dots & \dots & \dots & \dots & \dots \\ s_{1,20} & s_{2,20} & s_{3,20} & \dots & - \end{pmatrix}$$

$$X \operatorname{diag}(\pi_1, \dots, \pi_{20}) = Q \text{ matrix}$$

Q Rate matrix

s_{ij} Exchangeabilities of amino acid pairs ij

$s_{ij} = s_{ji}$ Time reversibility (usually)

π_i Stationarity of amino acid frequencies
(typically the observed proportion of residues in the dataset)

Empirical models

- Summarise the substitution patterns from a large number of existing alignments ('average' models)
- Different substitution matrices come from:
 - Selection of specific proteins
 - Globular proteins, membrane proteins?
 - Mitochondrial proteins?
 - Range of sequence similarities used
 - Counting methods
 - On a tree
 - Pairwise comparison from an alignment

Empirical models

Dayhoff (Dayhoff et al., 1978): Nuclear encoded genes (~ 100 proteins) → PAM matrices

JTT (Jones et al., 1992): 59,190 point mutations from 16,300 proteins from membrane spanning segments

Closely related sequence pairs ($>85\%$ identity):

- 1) count the number of amino acid changes of each type per pair
- 2) rescale these by the sequence divergence for the analyzed pair
- 3) Average over all sequence pairs

Limitation: for less similar sequences, no linearity between observed and real substitution rate (hidden substitutions)

Empirical models

Dayhoff (Dayhoff et al., 1978): Nuclear encoded genes, ~100 proteins → PAM matrices

JTT (Jones et al., 1992): 59,190 point mutations from 16,300 proteins from membrane spanning segments

WAG (Whelan and Goldman, 2001): General matrix

LG (Le and Gascuel, 2008): General matrix

The WAG matrix

- Globular protein sequences
 - 3,905 sequences from 182 protein families
- Produced a phylogenetic trees for every family and used maximum likelihood to estimate the relative rate values in the rate matrix (i.e., maximizes the overall lnL over 182 different trees)
- Better fit of the model with most data (significant improvement of the tree lnL when compared to PAM or JTT matrices)
- Can be used for (more) distant homologues

Further improvements: the LG matrix

- Used the same phylogenetic approach as WAG
- Further refine the method by adding the variability of evolutionary rates across sites when estimating the matrix and increase the number of sequences used
- Better fit of the model with most data (significant improvement of the tree InL when compared to WAG and other matrices)

Empirical models

Dayhoff (Dayhoff et al., 1978): Nuclear encoded genes, ~100 proteins → PAM matrices

JTT (Jones et al., 1992): 59,190 point mutations from 16,300 proteins from membrane spanning segments

WAG (Whelan and Goldman, 2001): General matrix

LG (Le and Gascuel, 2008): General matrix

Mtrev24 (Adachi and Hasegawa, 1996) : Mitochondrial (vertebrates)

Mtmam (Yang et al., 1998): Mitochondrial (mammals)

mtART (Abascal et al., 2007): Mitochondrial (Arthropoda)

CpRev (Adachi et al., 2000): Chloroplast

VT (Müller and Vingron, 2000): General matrix

RtRev (Dimmic et al., 2002): Retrovirus

DayhoffDCMUT (Kosiol and Goldman, 2005): Revised Dayhoff matrix

(and more...)

Summary

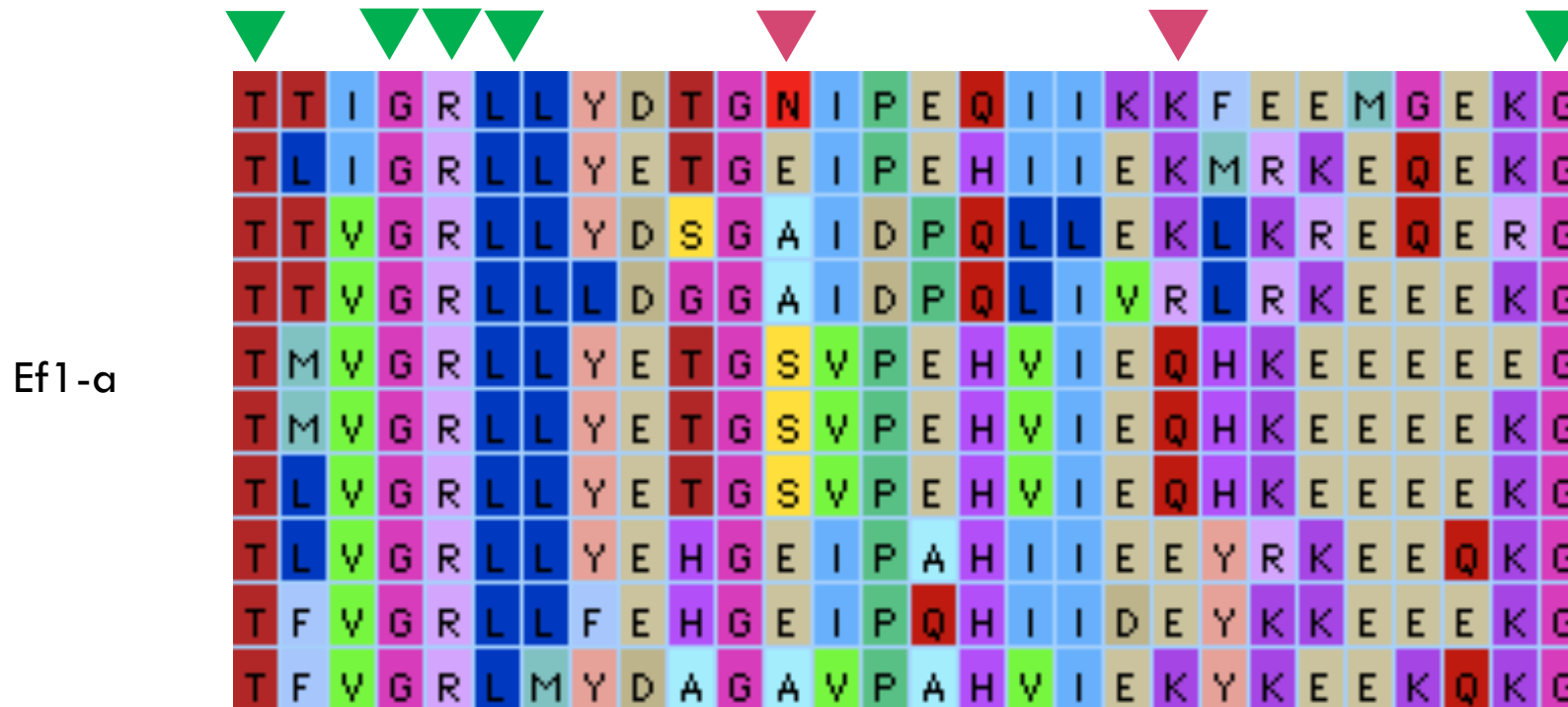
- Many amino acid rate matrices exist
- One should make a rational choice (as much as possible):
 - How was the rate matrix produced?
 - What are the structural features of the sequences that you are analyzing? Globular/membrane protein? Overall level of sequence identity of the compared sequences? Specific compositional bias (mitochondrial proteins matrix: mtREV24; Transmembrane domains: PHAT)?
 - ModelTest, ModelFinder (IQtree), ProtTest... to compare models

Correcting for equilibrium frequencies

- Empirical matrices are obtained by averaging the observed changes and amino acid frequencies between numerous proteins and are used for your specific dataset
- With recent software, you can correct the π_i values based on the observed frequencies in your data (“+F” option). E.g. LG+G+F

Rate heterogeneity parameter

- Not all sites “evolve” at the same speed depending on how it impacts function



Rate heterogeneity parameter

- Discretized Gamma distribution (+G)
 - Default is usually 4 categories but can be set to be more (but more computationally intensive)

Rate heterogeneity parameter

- Discretized Gamma distribution (+G)
 - Default is usually 4 categories but can be set to be more (but more computationally intensive)
- FreeRate model (+R)
 - Does not follow a parametric distribution
 - Not all categories will have the same number of sites
 - More realistic but more computationally intensive
 - Typically fits data better than the +G model and is recommended for analysis of large data sets

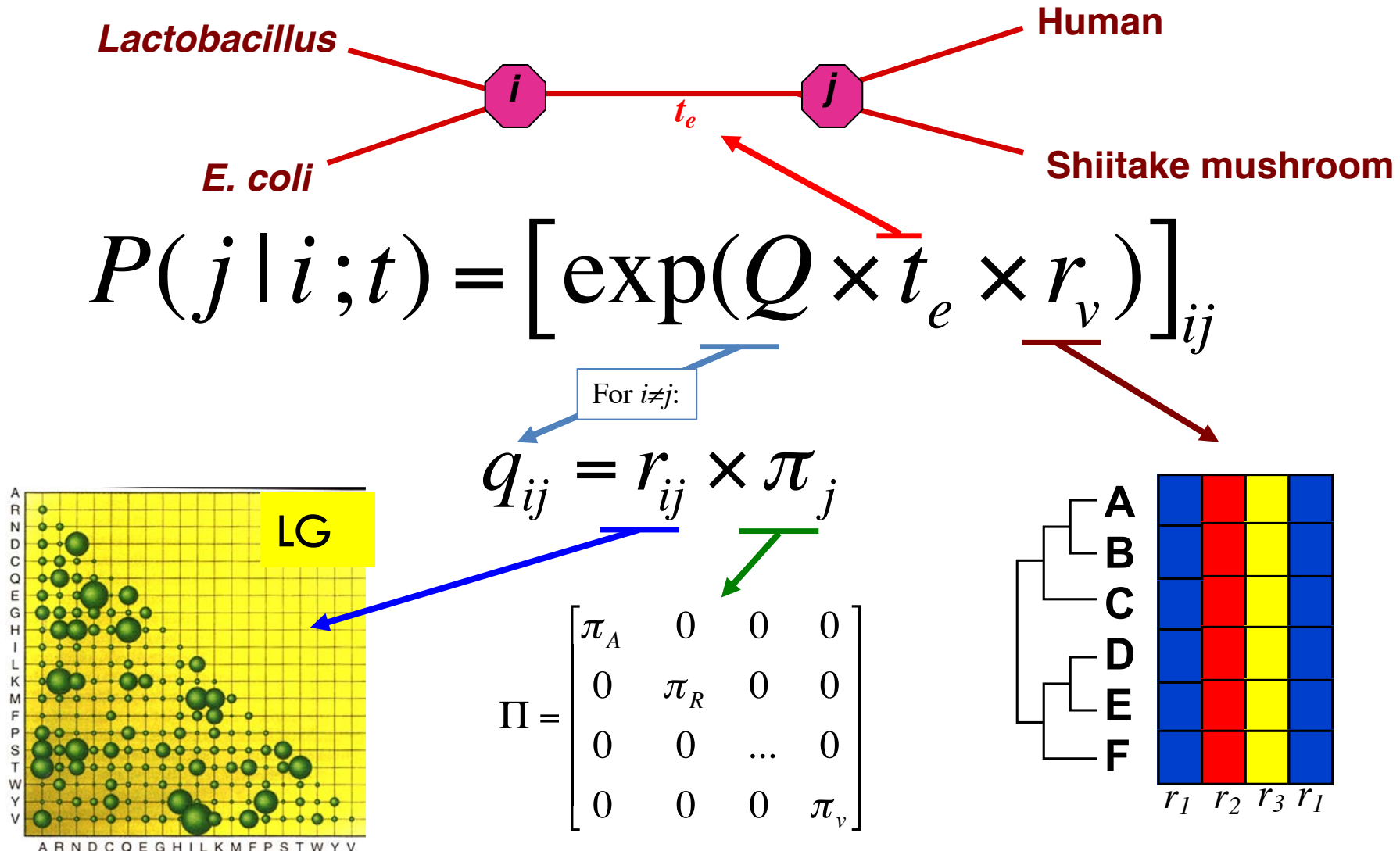
1.2 Fully parameterized time-reversible model

GTR (General time reversible)

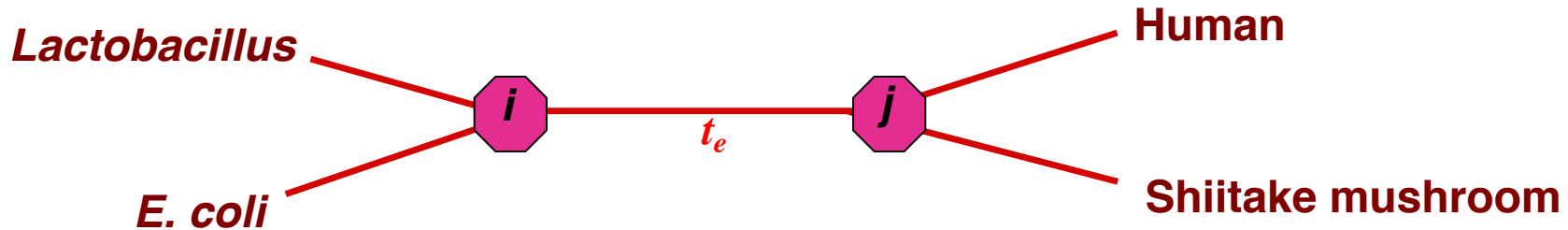
- One can generate a dataset-specific model
 - All parameters of the Q matrix are estimated from your data (exchangeabilities and equilibrium frequencies)
 - GTR20: General time reversible model for amino-acids: 189 rate parameters!
- *WARNING* Parameter-rich: parameter estimates might not be reliable if made on short alignments (not enough phylogenetic information)

1.3 Mixture models

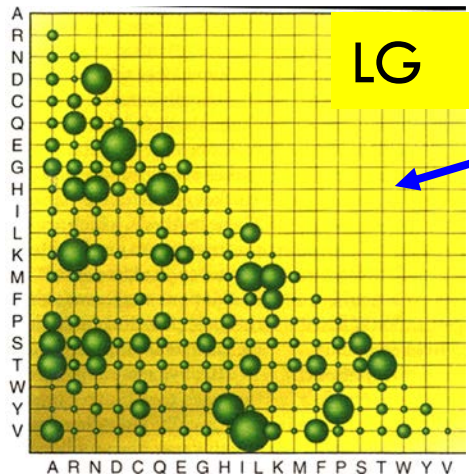
Your model is giving you the probability of going from amino acid i to j at site x , evolving at rate r_v on branch t_e



Your model is giving you the probability of going from amino acid i to j at site x , evolving at rate r_v on branch t_e



$$P(j|i;t) = \left[\exp(Q \times t_e \times r_v) \right]_{ij}$$



For $i \neq j$:

$$q_{ij} = r_{ij} \times \pi_j$$

$$\Pi = \begin{bmatrix} \pi_A & 0 & 0 & 0 \\ 0 & \pi_R & 0 & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \pi_v \end{bmatrix}$$

Assumptions

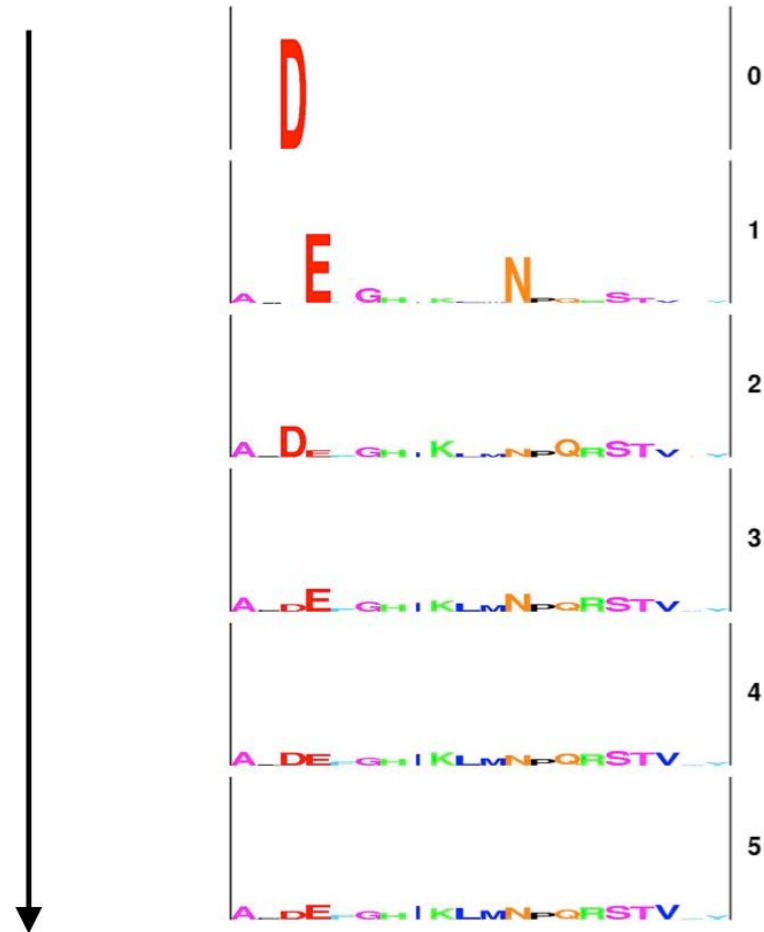
- different sites in protein and organisms all evolve according to the same general 'rules'
- i.e. rate matrices (R 's) and frequencies (Π 's) are the 'same' for all sites and branches

The problem...

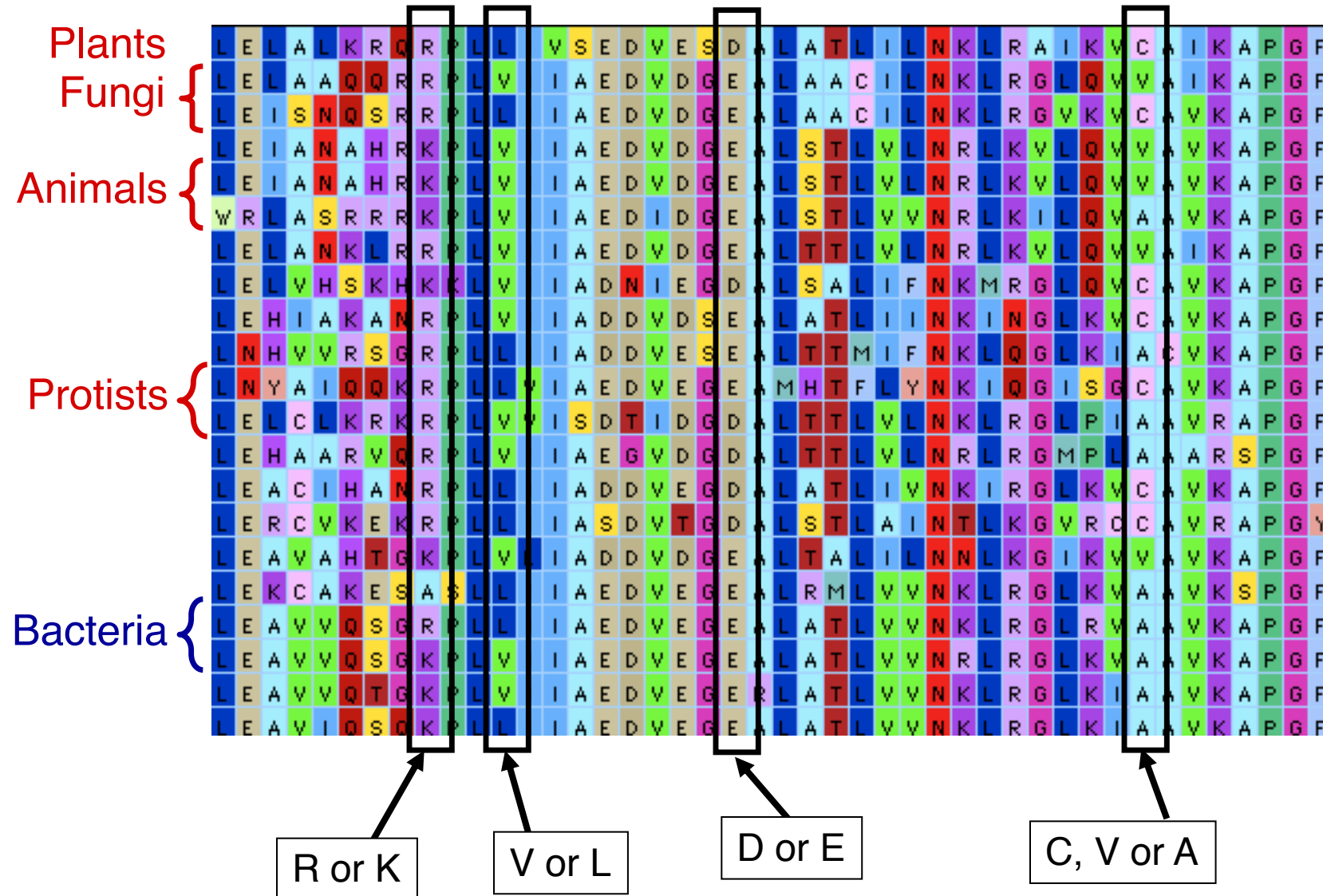
- Such models are a dramatic over-simplification of what is really going on
 - Average over sites, average over different organisms, average across protein families
- Sites in proteins can change function over time
 - sites under negative selection ↔ neutral ↔ positive selection
- Every amino acid site in a protein has a unique structural/functional context
 - Hydrophobicity, polarity, charge, size, functional group, etc.
 - Different sites have different exchangeabilities
 - Different frequencies of AAs occur at different sites

Starting at a D with a site homogeneous matrix (LG+F)

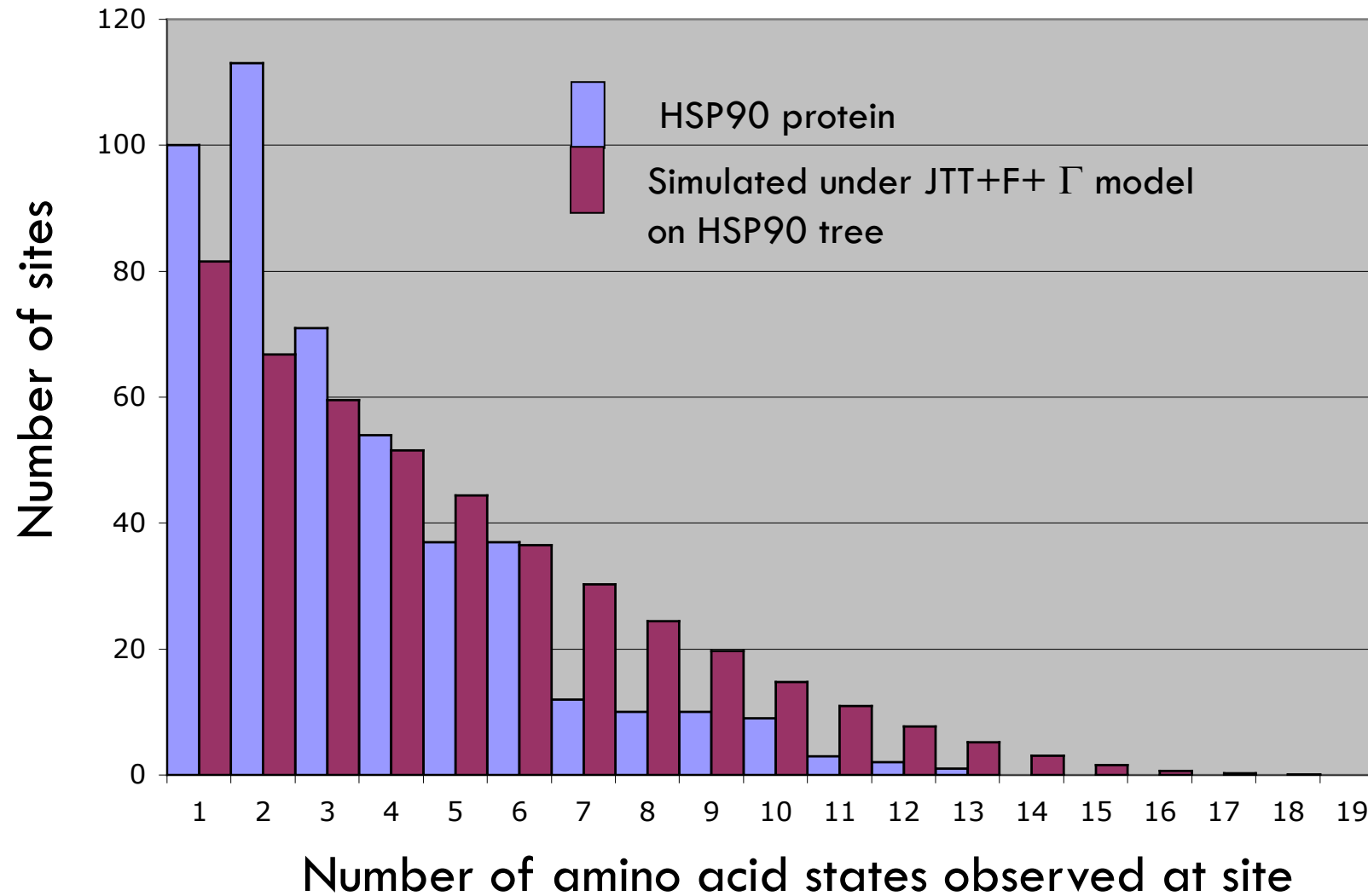
substitutions



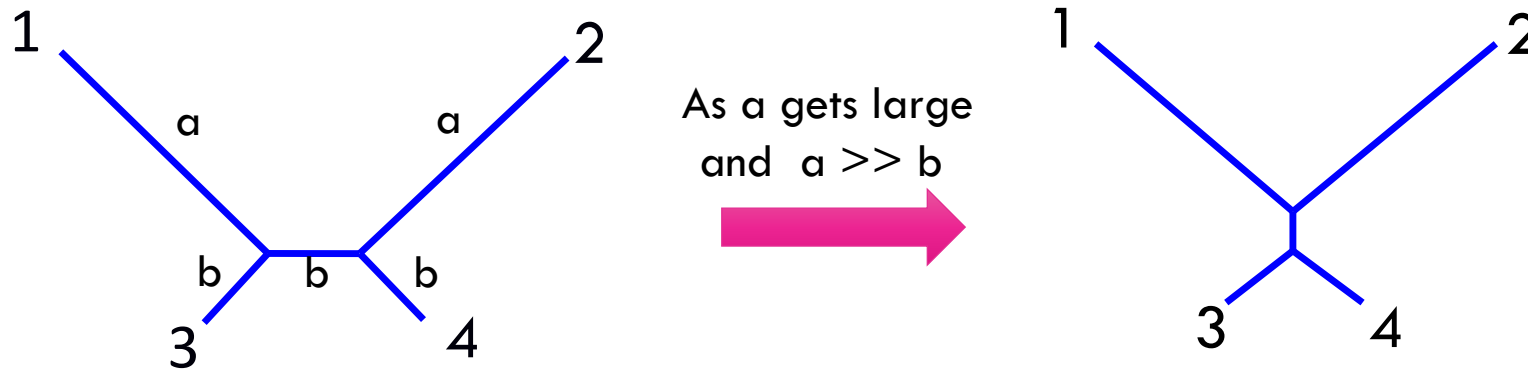
Evolution of chaperonin 60 over ~1.5 billion years



Distribution of the number of different amino acids at aligned sites



So what happens to phylogenetic estimation when you ignore site-heterogeneity?



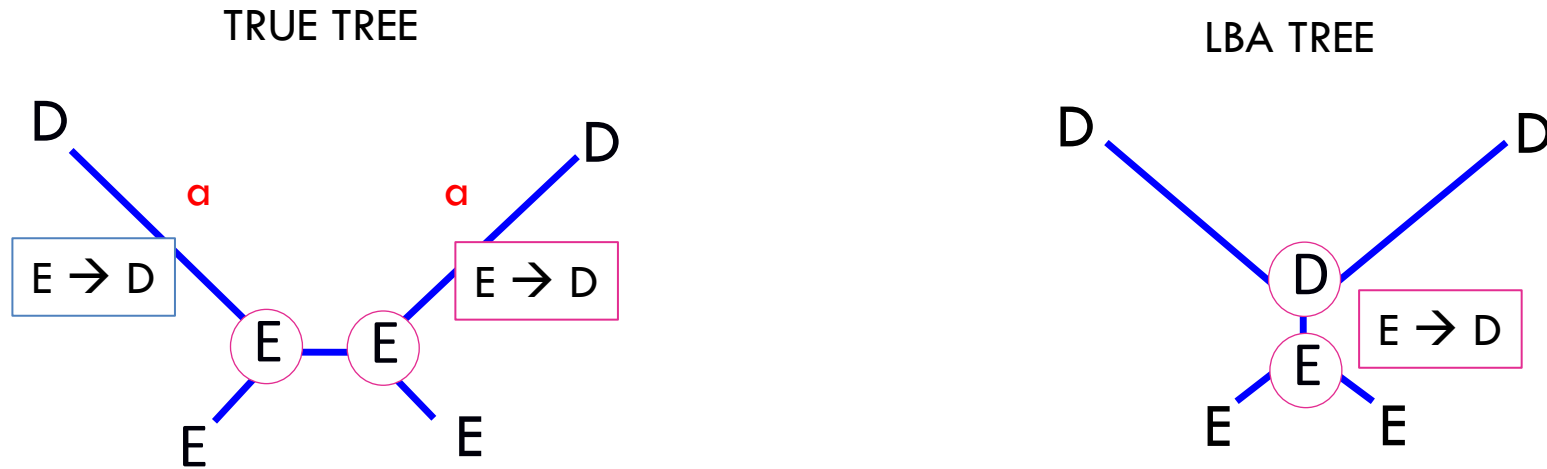
Long branch attraction

Susko et al. (2004) *Mol. Biol. Evol.* 21:1629

Lartillot and Philippe (2007) *BMC Evol. Biol. Suppl* 1, S4.

Wang et al. (2008) *BMC Evol. Biol.* 8:331

Why long branch attraction (LBA)?



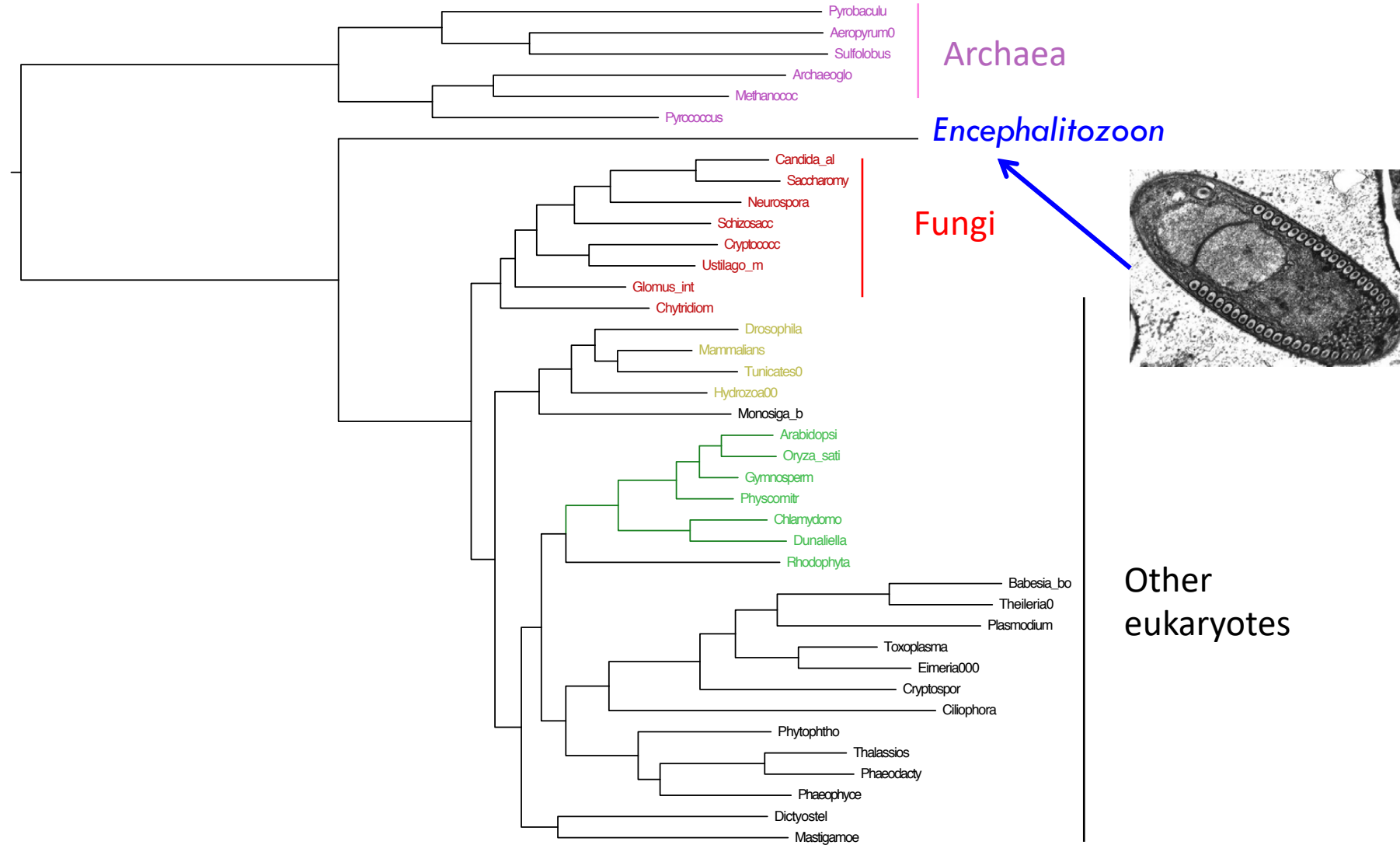
Under site homogeneous model (LG+F+G), the probability of converging on the same state: i.e. $E \rightarrow D$ twice is pretty low:

- if branch-length α is really long, then $P(\text{convergence})_{\text{LG}} \approx \pi_D^2 = (0.057)^2 = 0.0032$

Under a site-specific model where you can only be D or E (with equal frequency of 0.5):

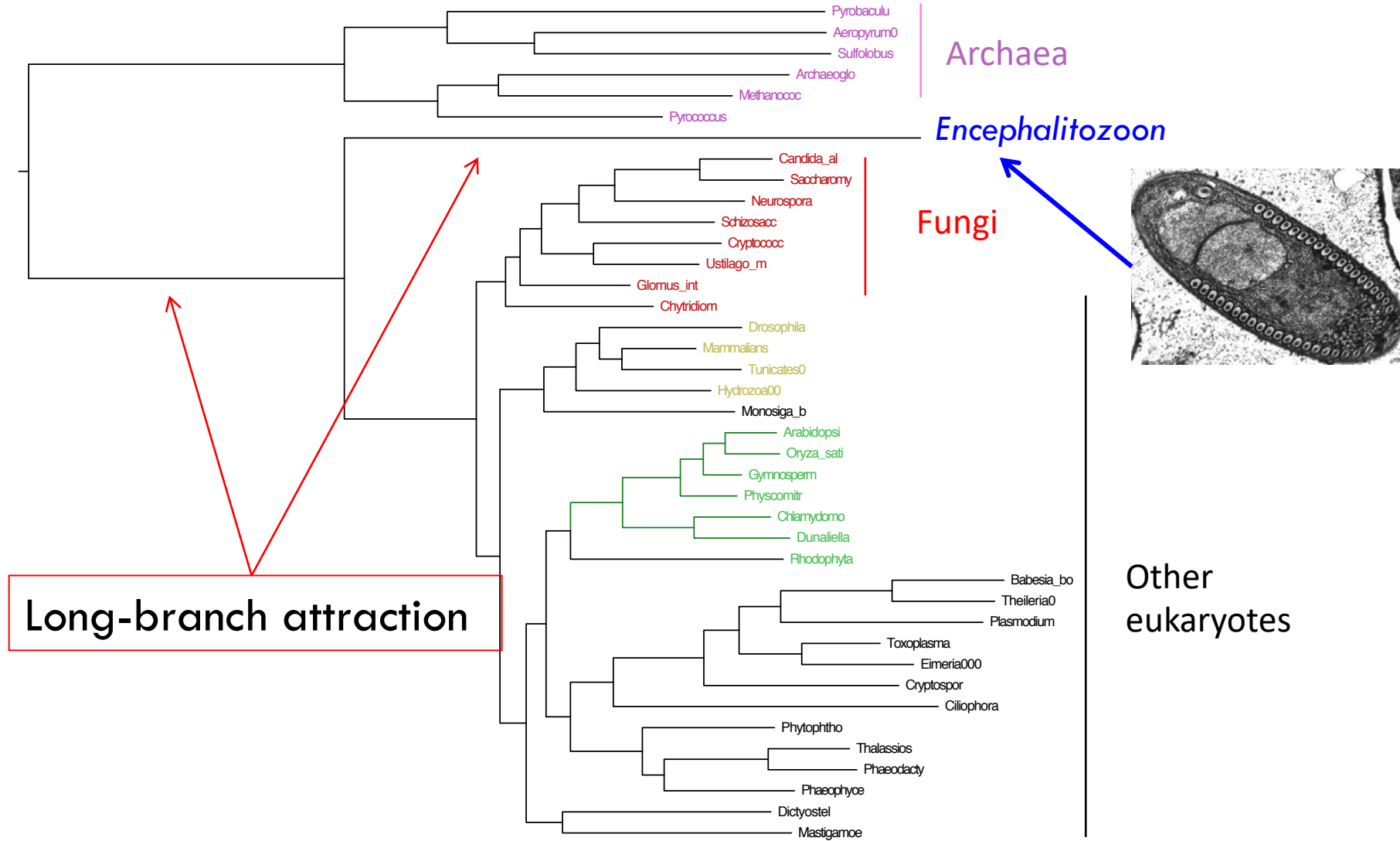
- $P(\text{convergence})_{\text{ss}} \approx \pi_D^2 = (0.5)^2 = 0.25$

ML tree based on site-homogeneous LG+F+ Γ model



40 sequences, 133 genes, 24291 aa

ML tree based on site-homogeneous LG+F+ Γ model

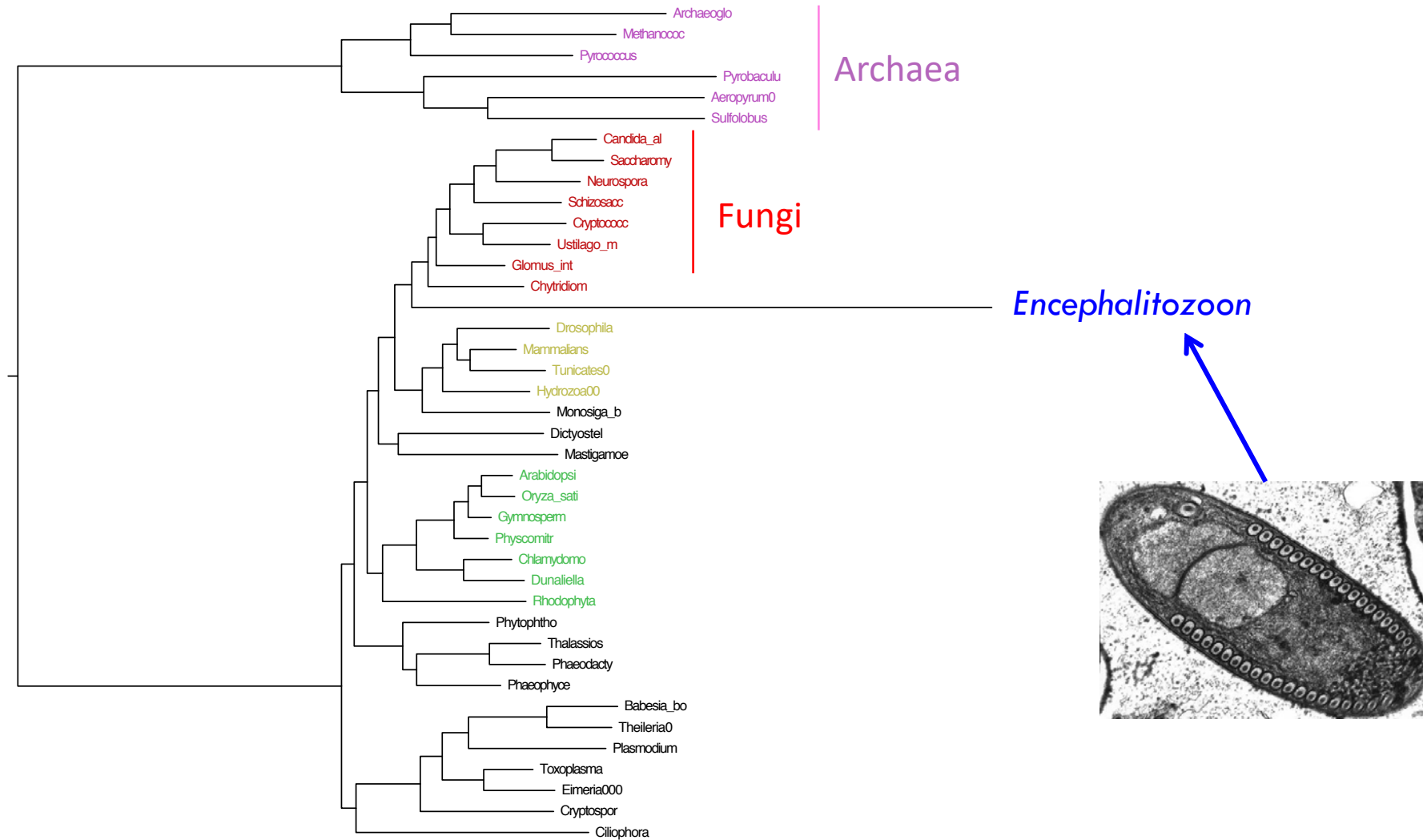


40 sequences, 133 genes, 24291 aa

0.2 subs/site

'MA tree' = LBA tree

ML tree based on site-heterogeneous LG+C20+F+ Γ model



0.4 subs/site

‘MF tree’ = true tree

Mixture models

- Standard protein substitution models: single Q matrix
- Mixture models: combine several amino-acid replacement matrices
- Same principle as rate heterogeneity gamma distribution
 - For each site, its likelihood is the **sum of its weighted likelihood under each Q matrix** that is are part of the mixture model

Mixture models: terminology warning

- Different kinds of mixture models!
- Rate-category gamma distribution is a mixture model
- **Usually people refer to mixture of amino-acid replacement matrices**
- Mixtures can be apply to any part of the model (e.g., branch lengths)

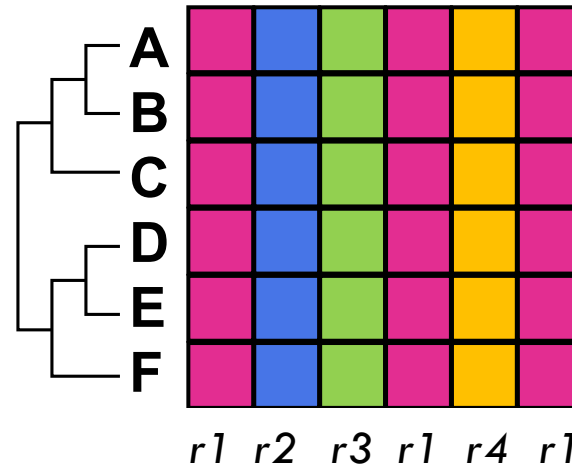
LG4M and LG4X mixture models

“the variability of evolutionary rates corresponds to one of the most apparent heterogeneity factors among sites, and **there is no reason to assume that the substitution patterns remain identical regardless of the evolutionary rate**” Le, Dang, Gascuel 2012

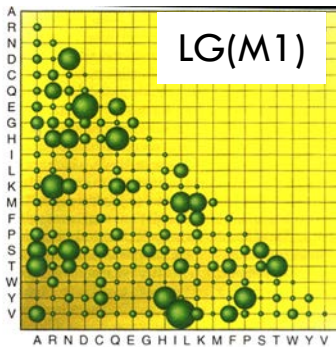
Standard LG+gamma model: only the global rate differs from one category to another

LG4M and LG4X mixture models

LG4M: each gamma rate category gets its own Q matrix (i.e., each of the 4 gamma-distributed rate category gets its own amino acid equilibrium distributions and exchangeabilities)

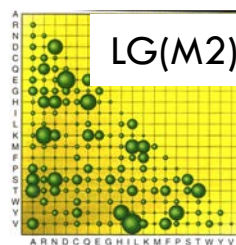


25%



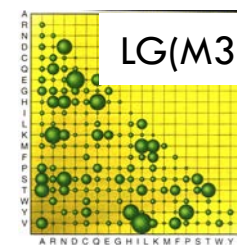
$$\Pi = \begin{bmatrix} \pi_A & 0 & 0 & 0 \\ 0 & \pi_R & 0 & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \pi_v \end{bmatrix}$$

25%



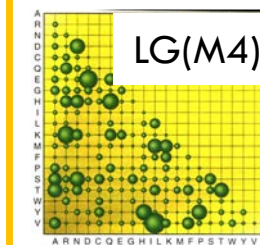
$$\Pi = \begin{bmatrix} \pi_A & 0 & 0 & 0 \\ 0 & \pi_R & 0 & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \pi_v \end{bmatrix}$$

25%



$$\Pi = \begin{bmatrix} \pi_A & 0 & 0 & 0 \\ 0 & \pi_R & 0 & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \pi_v \end{bmatrix}$$

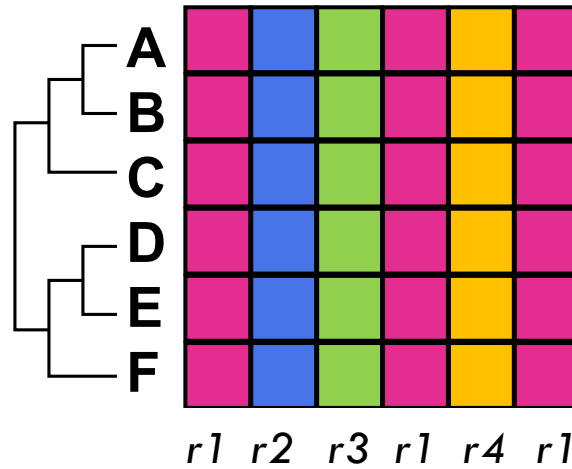
25%



$$\Pi = \begin{bmatrix} \pi_A & 0 & 0 & 0 \\ 0 & \pi_R & 0 & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \pi_v \end{bmatrix}$$

LG4M and LG4X

LG4X: each rate category gets its own Q matrix BUT rates and weights are left out of the gamma distribution assumption

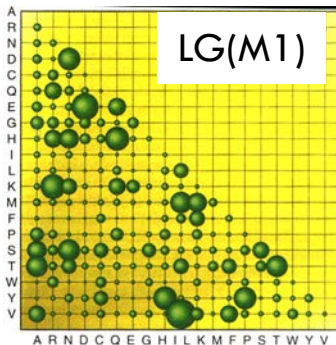


50%

15%

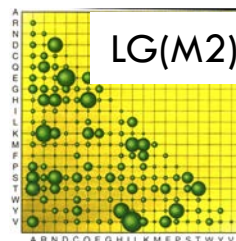
30%

5%



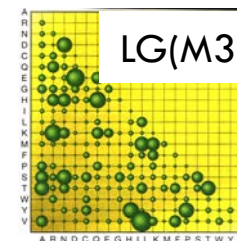
LG(M1)

$$\Pi = \begin{bmatrix} \pi_A & 0 & 0 & 0 \\ 0 & \pi_R & 0 & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \pi_v \end{bmatrix}$$



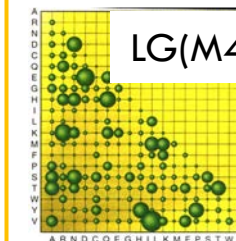
LG(M2)

$$\Pi = \begin{bmatrix} \pi_A & 0 & 0 & 0 \\ 0 & \pi_R & 0 & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \pi_v \end{bmatrix}$$



LG(M3)

$$\Pi = \begin{bmatrix} \pi_A & 0 & 0 & 0 \\ 0 & \pi_R & 0 & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \pi_v \end{bmatrix}$$



LG(M4)

$$\Pi = \begin{bmatrix} \pi_A & 0 & 0 & 0 \\ 0 & \pi_R & 0 & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \pi_v \end{bmatrix}$$

Mixture models based on site exposure (buried or exposed) or secondary structure

Site evolution is highly heterogeneous and depends on many factors: genetic code; solvent exposure; secondary and tertiary structure; protein function; etc.

Mixture models based on site exposure (buried or exposed) or secondary structure

Site evolution is highly heterogeneous and depends on many factors: genetic code; solvent exposure; secondary and tertiary structure; protein function; etc.

EX2 : Two-matrix model for exposed/buried AA sites

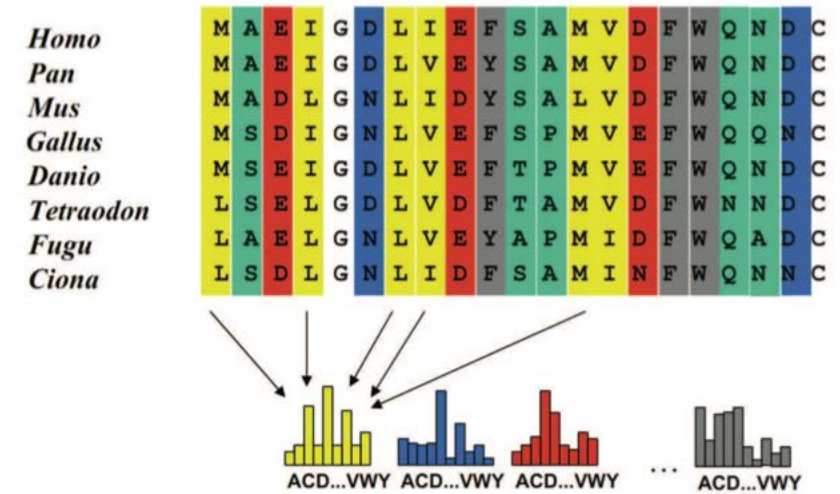
*based on their
relative accessibility
to solvent*



EX3 : Three-matrix model for highly exposed/intermediate/buried AA sites

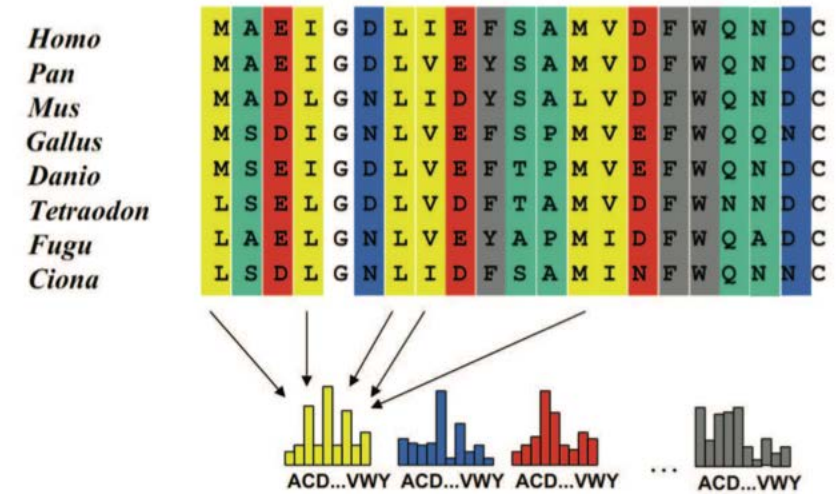
EHO : Three-matrix model for extended/helix/other sites

The CAT model



- Bayesian framework only
- Free number of profiles in the mixture model (estimated during the Bayesian procedure). “Infinite mixture model”
- Each profile corresponds in practice to a *biochemical profile*: only a small number of AA are highly probably, while the frequency of all others will be ~ 0 .

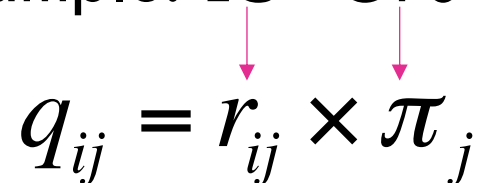
The CAT model



- CAT-Poisson: very simple amino-acid replacement process (R matrix). Each time a substitution event occurs, a new amino-acid is chosen at random, according to the probabilities defined by the profile (*Poisson* or *proportional* amino-acid replacement process). Eg., any AA has the same probability to mutate to a Valine.
- CAT-GTR: GTR exchangeability matrix with 189 parameters!

C10, C20, ..., C60 mixture models

- 10, 20, 30, 40, 50, 60-profile mixture models are approximations of the CAT model for ML
- 10 (20, 30...) different pre-computed (empirical) Q matrices that correspond to 10 (20, 30...) most-common types of biochemical profiles in proteins
- By default, assume Poisson AA replacement but can be combined with empirically estimated exchangeabilities, such as from the LG matrix.
For example: LG+C10

$$q_{ij} = r_{ij} \times \pi_j$$


Problem with mixture models

- As the number of sites and proteins increases the computational cost becomes prohibitive
 - For an ML analysis of 104 taxa and ~90,000 sites (350 proteins concatenated) LG+C60+F+G model takes >350 GB of RAM and ~3 weeks on 12 cores to estimate **the ML tree** using IQTREE v. 1.5
 - **5.5 years to do true bootstrap analysis**
 - Phylobayes-MPI using CAT+GTR takes weeks to get only ‘thousands’ of MCMC generations in the same time
 - Multiple chains almost never converge on the same posterior distribution of trees
- ➔ PMSF (Posterior Mean Site Frequency) approximation

PMSF (Posterior Mean Site Frequency) model

Implemented in IQtree

- 1) Reconstruct an ML tree under a 'reasonably good' model = guide tree
- 2) Using the guide tree, estimate, **for each site x**, the posterior probability of each amino-acid class c (e.g.: C1, C2, ..., C60)

Posterior probability of 'class c' at site x

$$P(c|x) = \frac{w_c \times P(x|c)}{\sum_c w_c \times P(x|c)}$$

- 3) For each site x, estimate the **posterior mean frequency of each amino acid j**

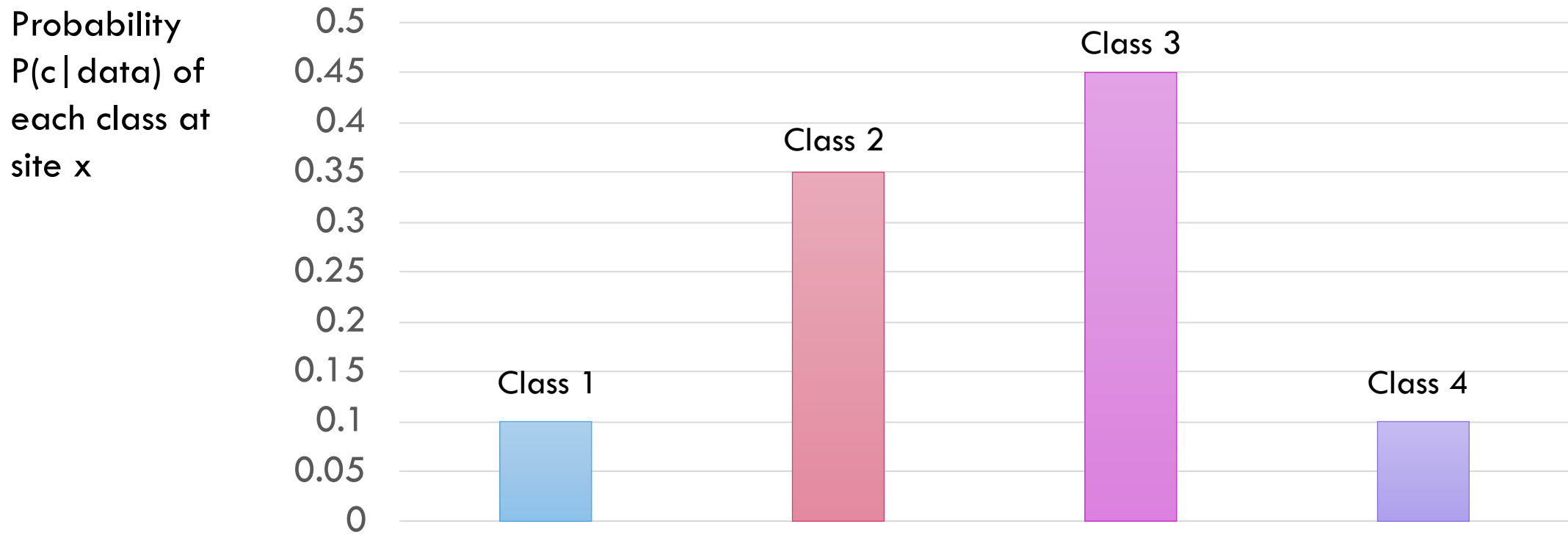
Posterior mean frequency of amino acid j at site x over all c classes ($f_{j,x}$)

$$f_{j,x} = \sum_c f_{j,c} \times P(c|x)$$

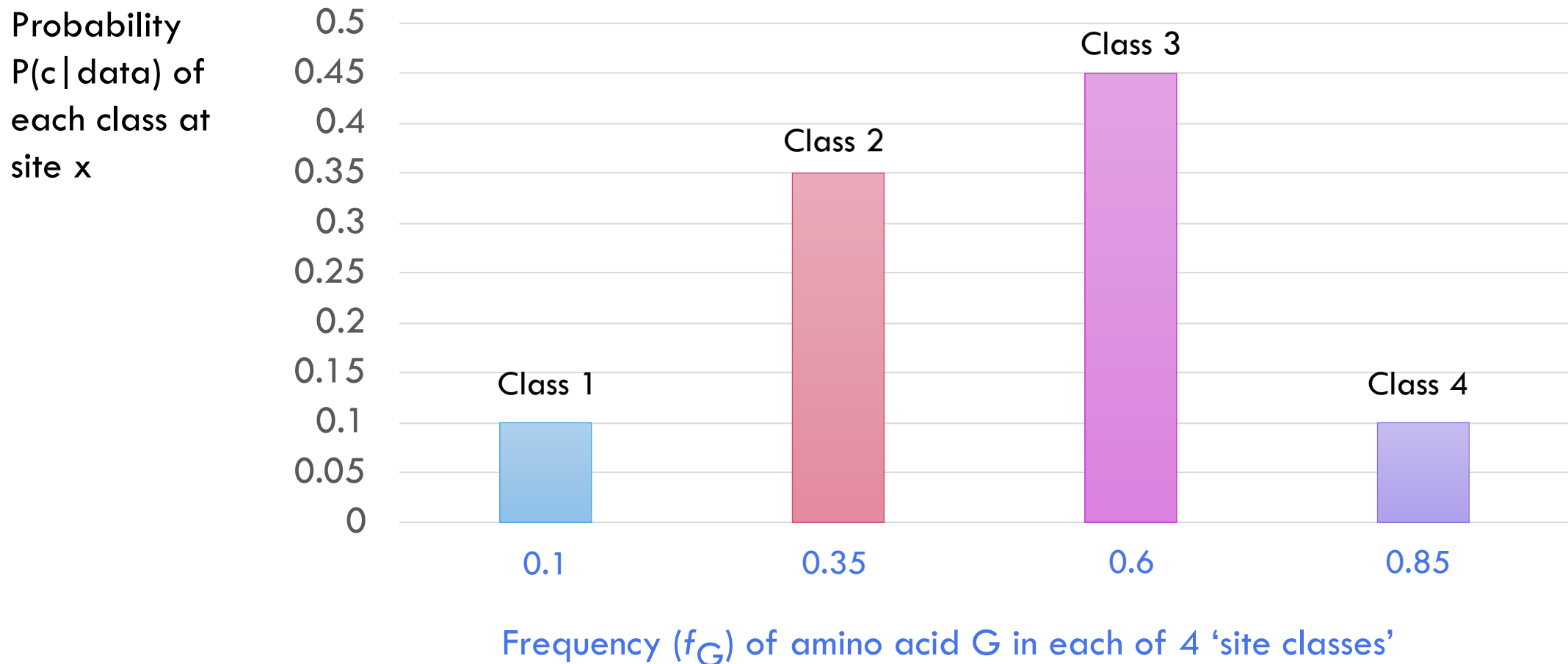
Freq of AA j for class c Prob of class c at site x

Sum over all classes

E.g.: Posterior mean site frequency for 'G' at a given site x , with a 4 class mixture model



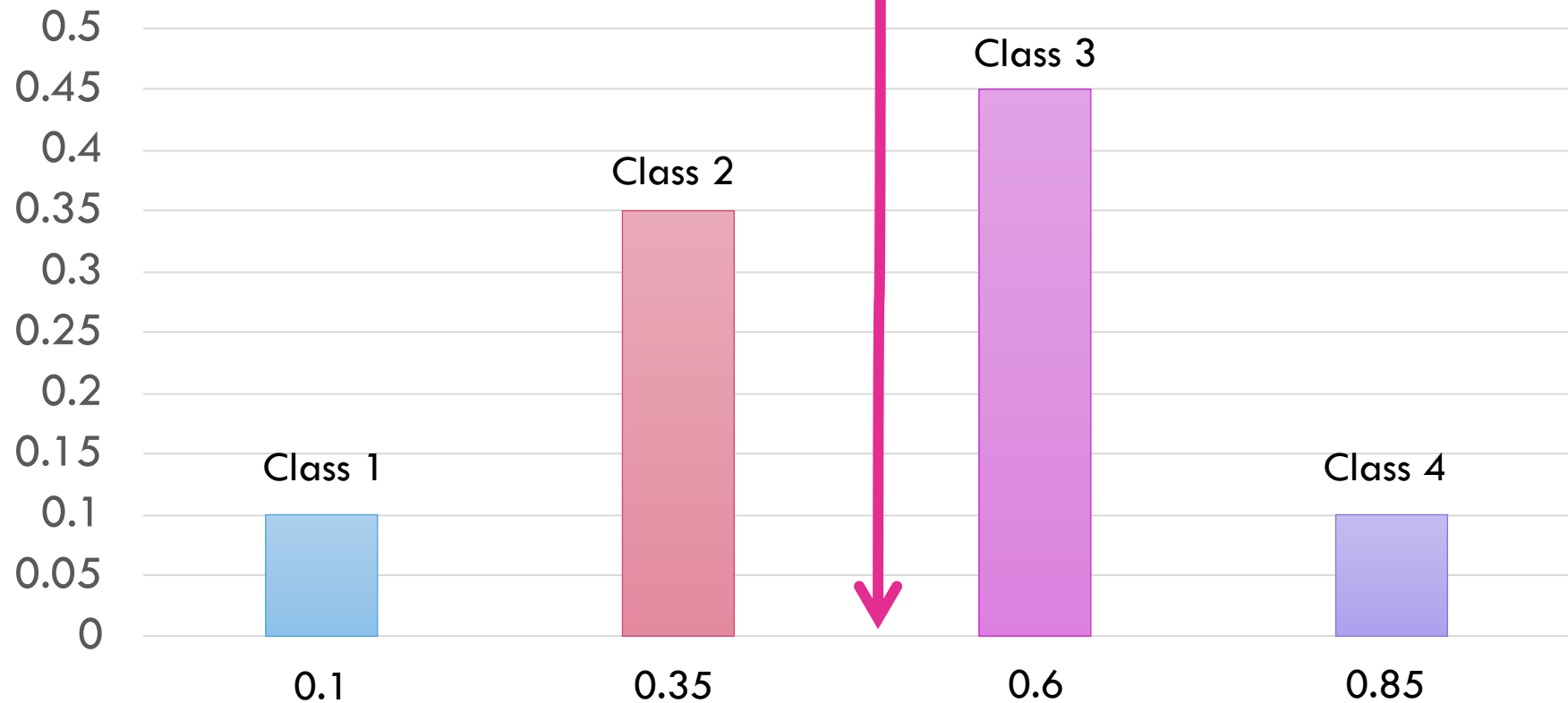
E.g.: Posterior mean site frequency for 'G' at a given site x, with a 4 class mixture model



E.g.: Posterior mean site frequency for 'G' at a given site x, with a 4 class mixture model

$$E[f_G] = (0.1 \times 0.1) + (0.35 \times 0.35) + (0.6 \times 0.45) + (0.85 \times 0.1) = 0.5$$

Probability
 $P(c \mid \text{data})$ of
each class at
site x



Frequency (f_G) of amino acid G in each of 4 'site classes'

PMSF (Posterior Mean Site Frequency) model

- 1) Reconstruct an ML tree under a 'reasonably good' model
- 2) Using the ML tree, estimate, for each site x , the posterior probability of each amino-acid class c of your preferred mixture model (e.g.: C60)

Posterior probability of 'class c ' at site x

$$P(c|x) = \frac{w_c \times P(x|c)}{\sum_c w_c \times P(x|c)}$$

- 3) For each site x , estimate the posterior mean frequency of each amino acid j

Posterior mean frequency of amino acid j
at site x over all c classes ($f_{j,x}$)

$$f_{j,x} = \sum_c f_{j,c} \times P(c|x)$$

- 4) Now, every site x has its own $\Pi =$

$$\Pi = \begin{bmatrix} \pi_A & 0 & 0 & 0 \\ 0 & \pi_R & 0 & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \pi_v \end{bmatrix}$$

PMSF (Posterior Mean Site Frequency) model

5) You estimate the ML tree using these pre-computed site-specific Q matrices: LG exchangeabilities + custom frequencies

➔ **Equivalent to LG+F, where F would be different for every site**

➔ Barely more computationally intensive than using the 'native' LG matrix

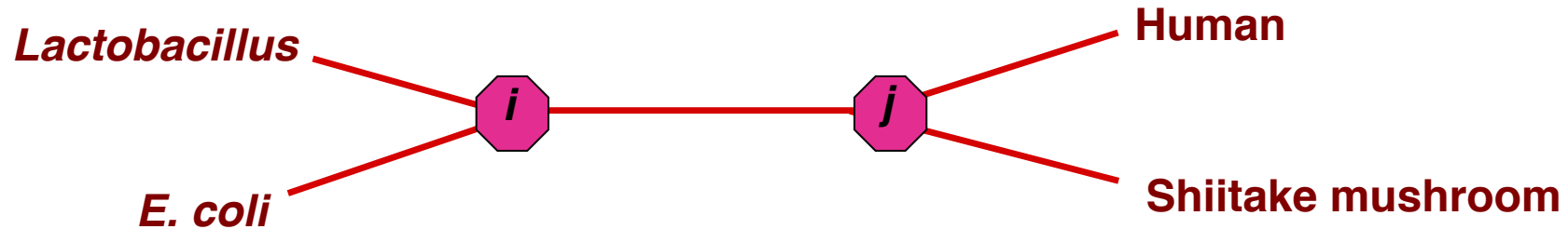
➔ Bootstrapping is dramatically faster

Take home

- Models are idealizations of the actual process of protein evolution
- Model misspecification (single-matrix models) often means systematic error (LBA)
- Mixture models deal with site-specific heterogeneity but are computationally expensive
- PMSF models provide a viable alternative for bootstrap analyses

Other types of mixture models

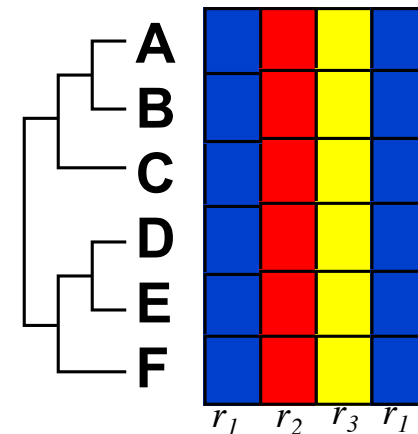
Probability of going from amino acid i to j
at site x , evolving at rate r_v on branch t_e



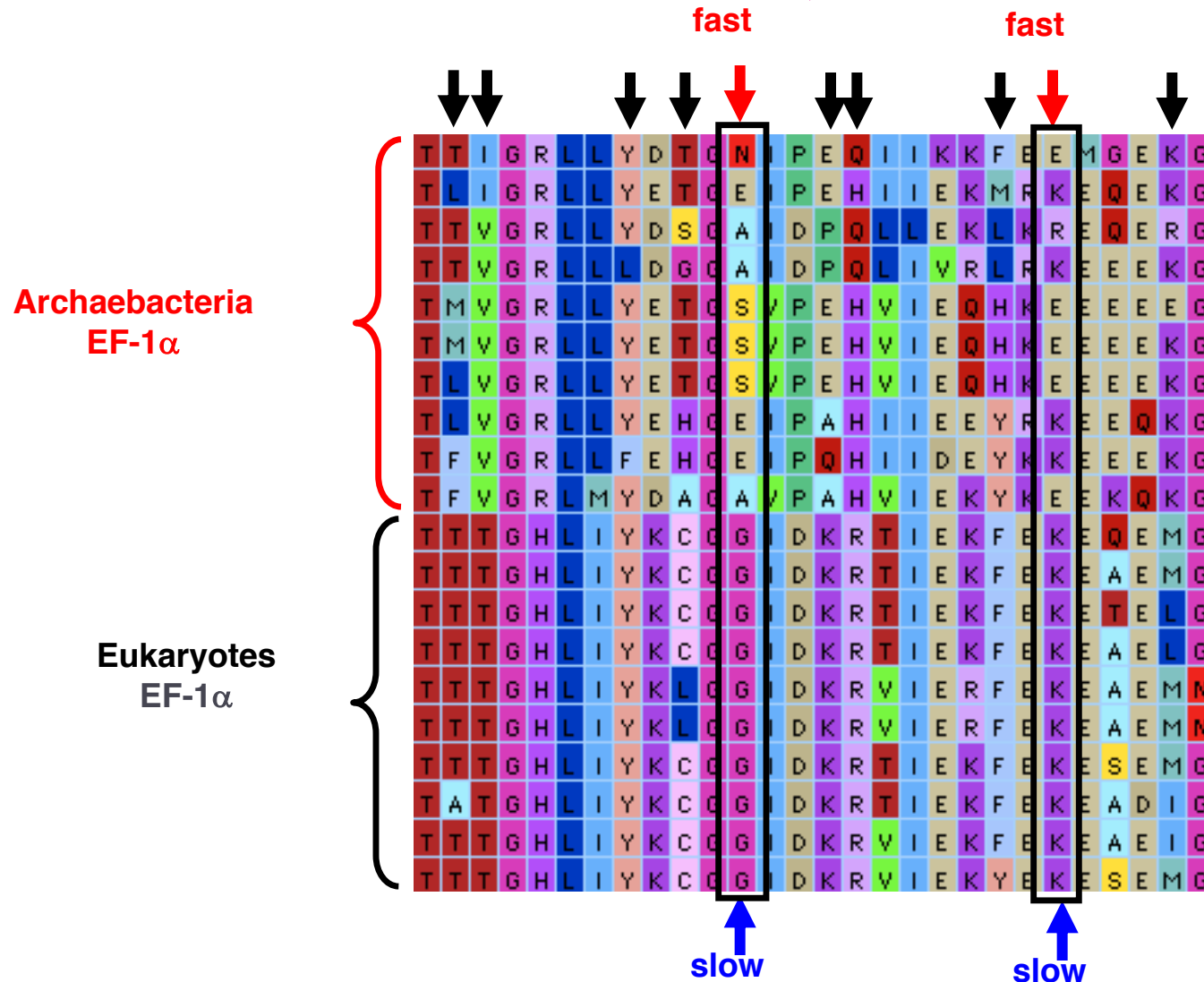
$$P(j | i; t) = \left[\exp(R \times \Pi \times t_e \times \underline{r_v}) \right]_{ij}$$

Assumptions

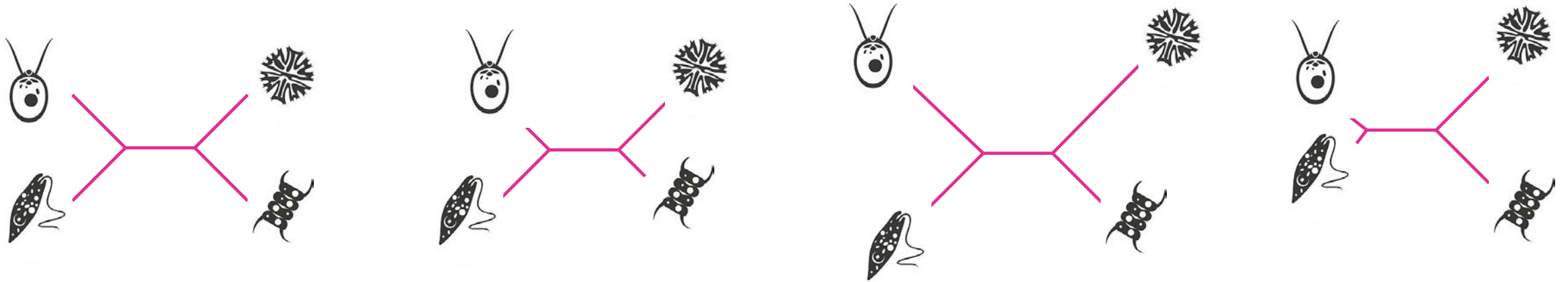
- 'fast-evolving' positions are always fast and slow-evolving positions are always slow
- Sites have the same rate of evolution (r_v) on different branches of tree



Changing rates of evolution at sites in different parts of the tree of life (=heterotachy)



Changing rates of evolution at sites in different parts of the tree of life (=heterotachy)



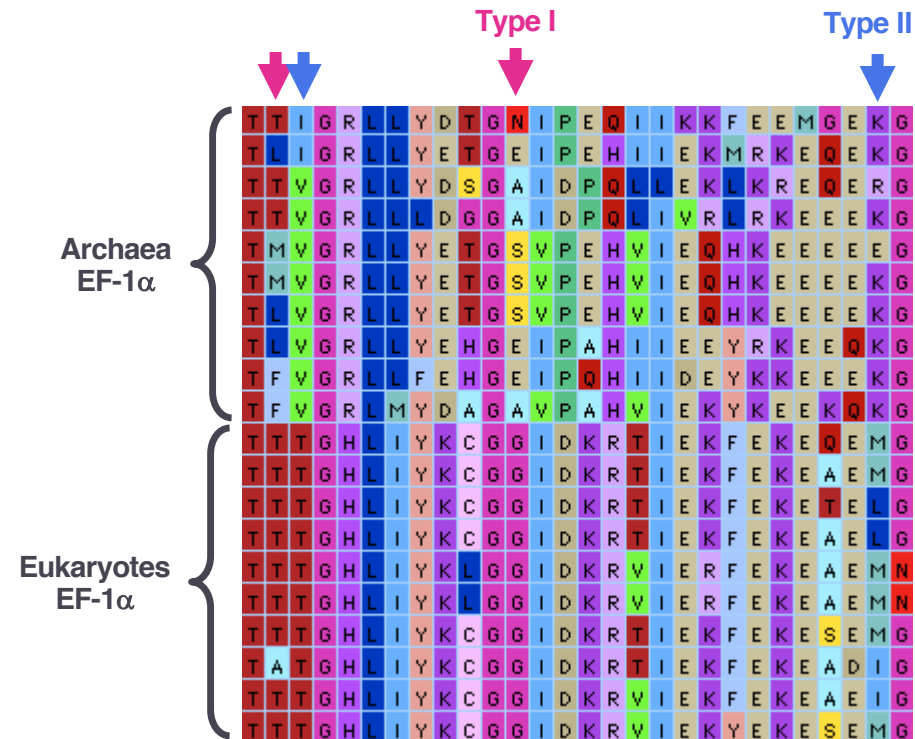
Models that deal with heterotachy (changing site rates across the tree)

- Covarion models (cf Joe's lecture)
 - Allow the sites “switch” between high rates and low rates over the tree
 - Computationally intensive
- Rate-shift models
 - Allows rates at many different sites to change abruptly on one branch
- Mixture of branch-length models
 - Allows different branch-lengths for different sites

Functionally divergent sites generate heterotachy

Functional shifts (functional divergence)

- Type I: 'rate-shifting' sites (sites that are conserved in one phylogenetic sub-group but not another).
- Type II: conserved-but-different' (conservation within both sub-groups of a phylogenetic tree but for amino acids with differing physico-chemical properties).



Functionally divergent sites generate heterotachy

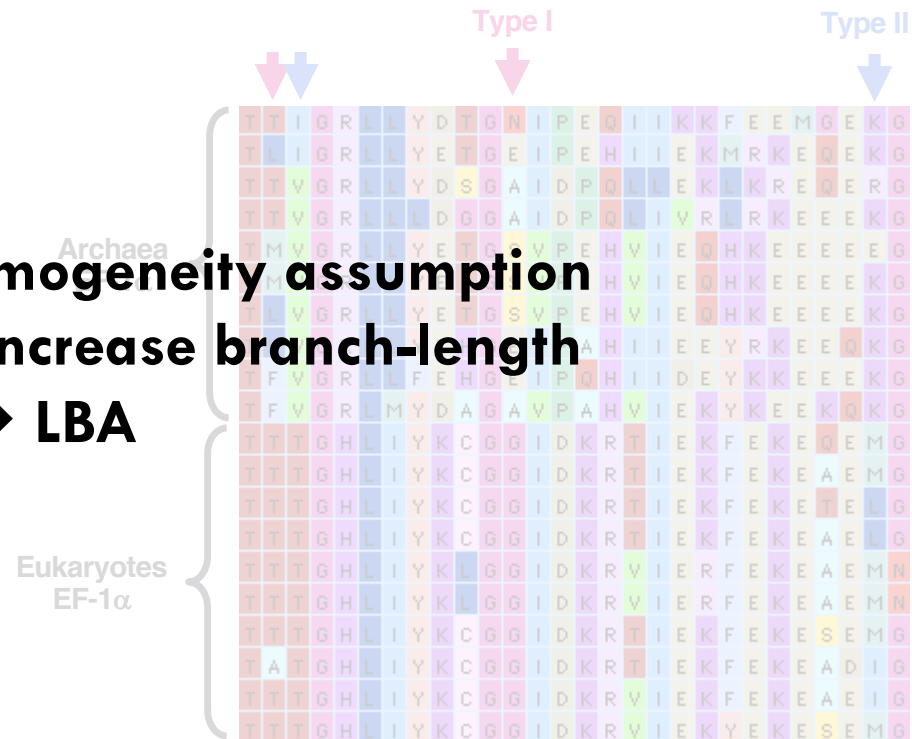
Functional shifts (functional divergence)

- Type I: 'rate-shifting' sites (sites that are conserved in one phylogenetic sub-group but not another).

FD sites violate homogeneity assumption and artefactually increase branch-length

→ LBA

- Type II: conserved-but-different' (conservation within both sub-groups of a phylogenetic tree but for amino acids with differing physico-chemical properties).



Functionally divergent sites generate heterotachy

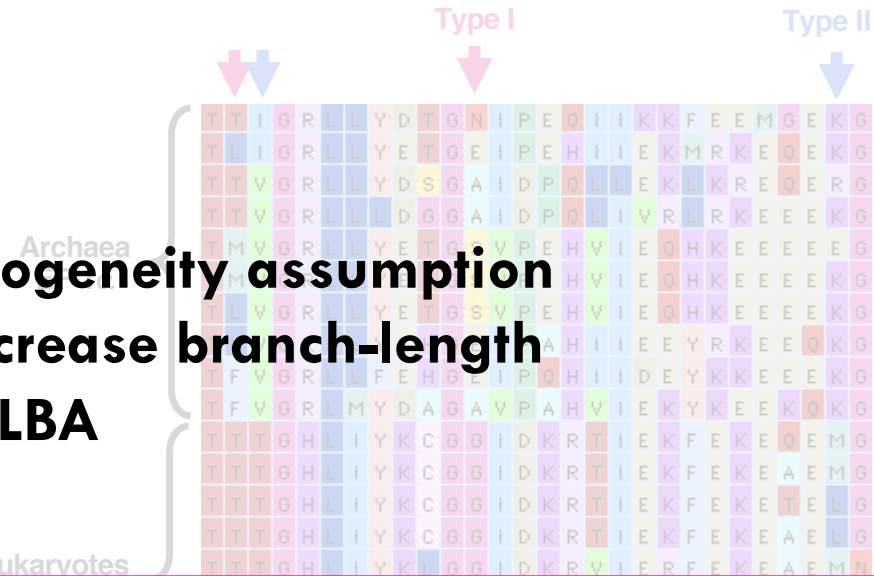
Functional shifts (functional divergence)

- Type I: 'rate-shifting' sites (sites that are conserved in one phylogenetic sub-group but not another).

FD sites violate homogeneity assumption and artefactually increase branch-length

→ LBA

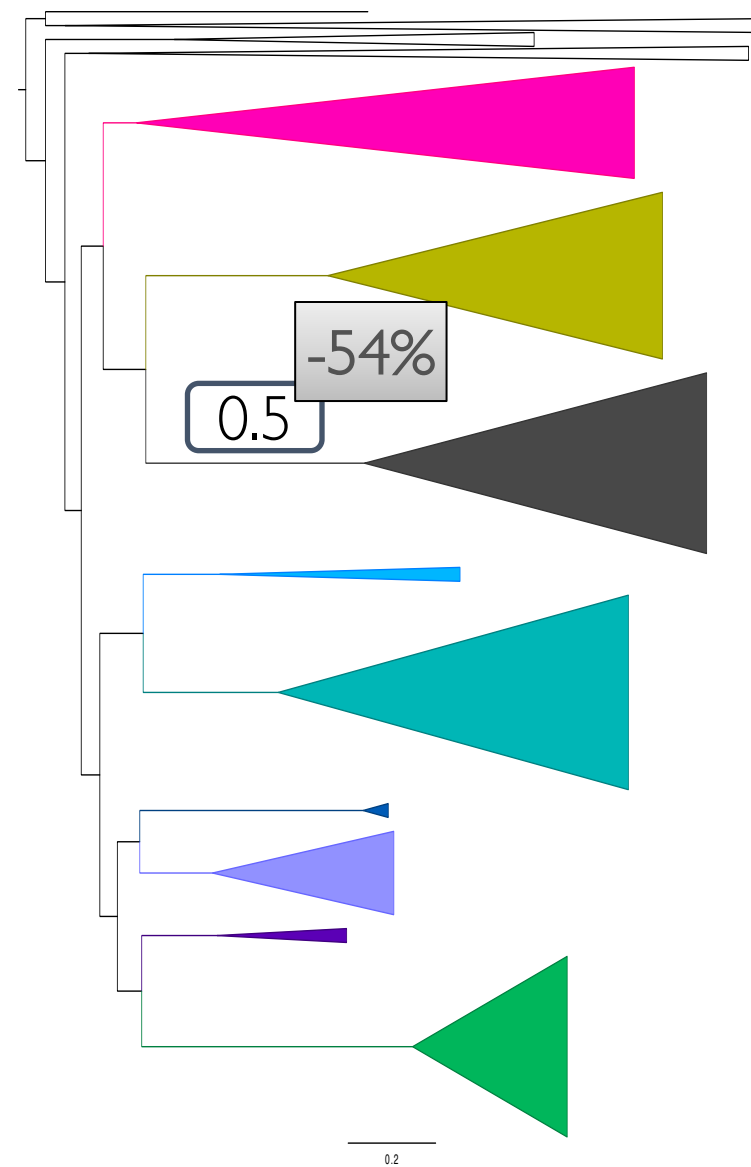
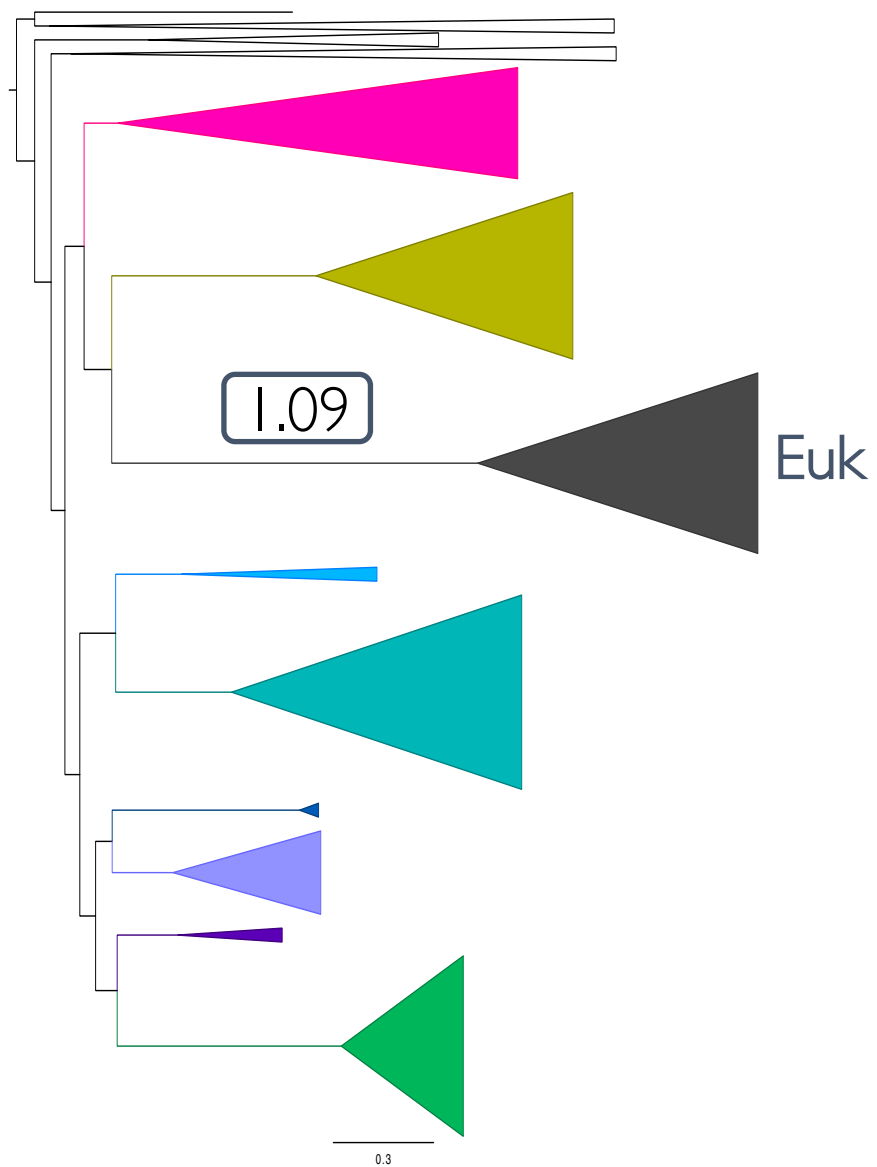
- Type II: conserved-but-different' (conservation within both sub-groups of a phylogenetic tree but for



FunDi : identifies FD sites along a specific branch taking into account the phylogeny (ML framework)

(Gaston, Susko, Roger, *Bioinformatics*)

Downside: you have to decide *a priori* which branch to analyze



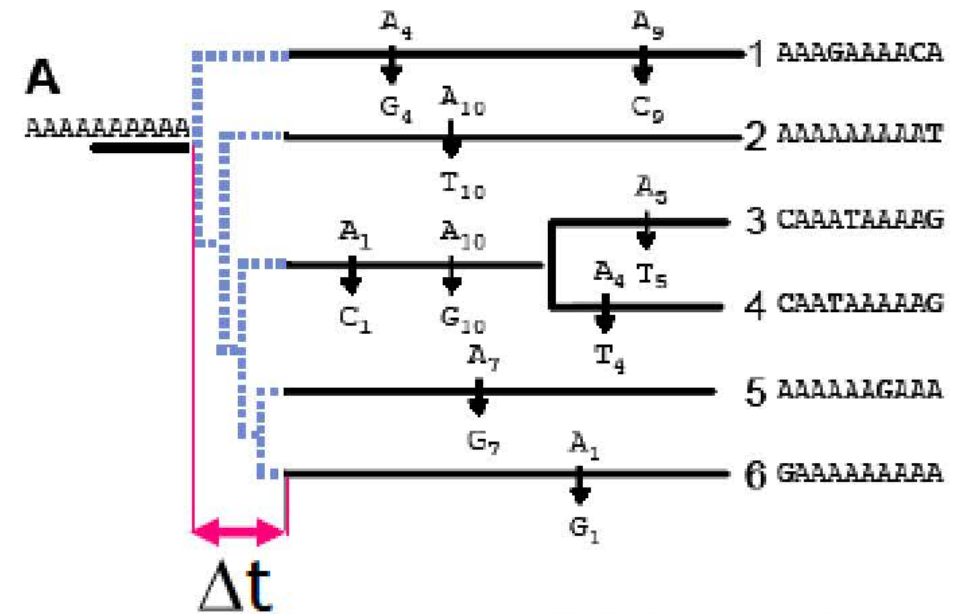
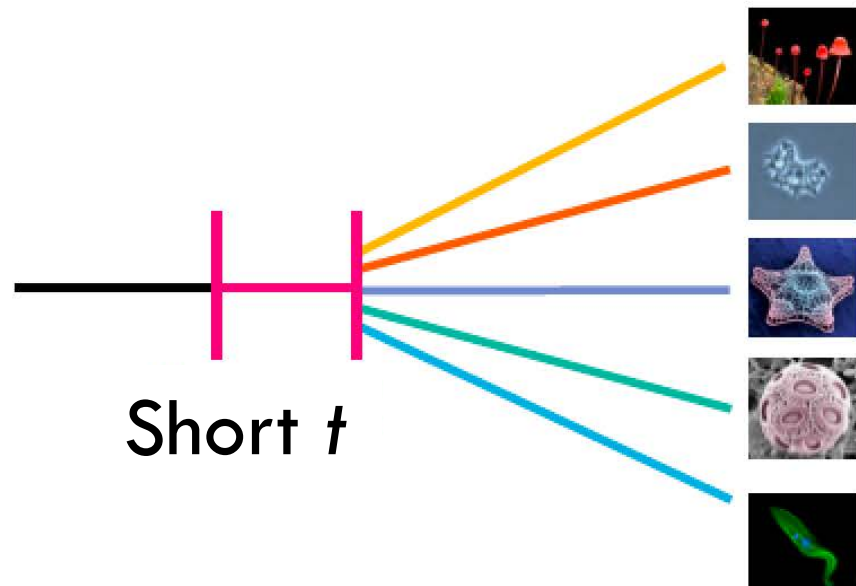
PART 2

Reconstructing 'deep' phylogenies

(aka large-scale species trees)

Single gene trees are not enough to resolve 'ancient relationships'

Rapid radiation: little signal recorded during diversification

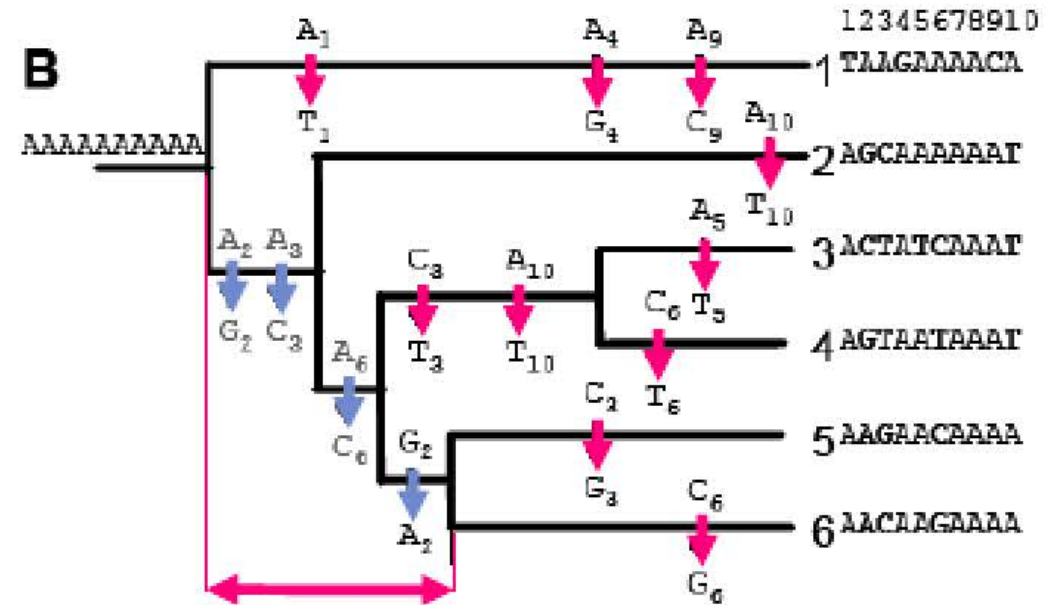
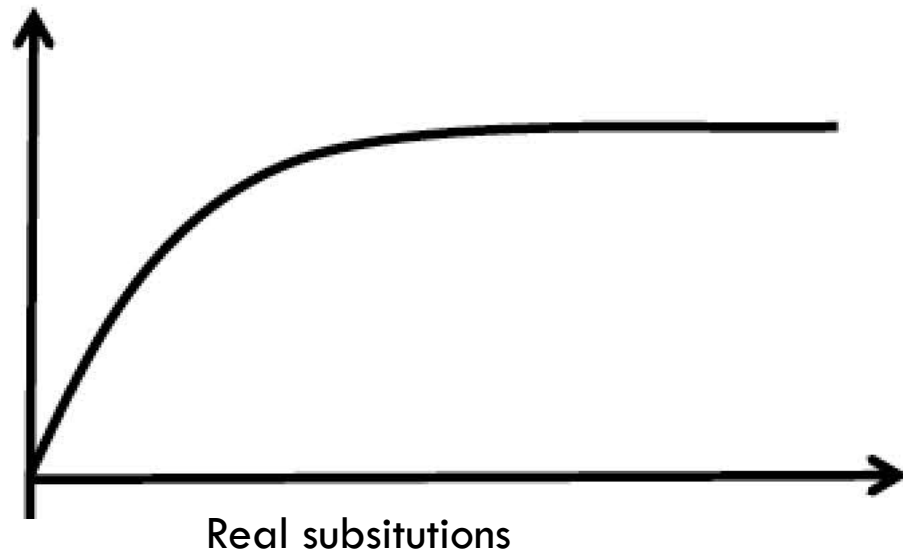


Gribaldo & Brochier 2009

Single gene trees are not enough to resolve ‘ancient relationships’

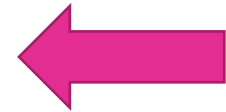
“Ancient” signal erased by more recent substitutions

Observed substitutions



How to improve phylogenetic signal

- Improve models
- Identify 'rare' genomic events (indels, gene fusions) used as synapomorphies (be wary of convergences)
- Improve taxonomic sampling
- Increase number of analyzed sites (multi-gene analyses)



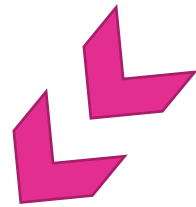
How to combine phylogenetic signal from several genes?

- Supermatrices
- Supertrees
- Reconciliation methods

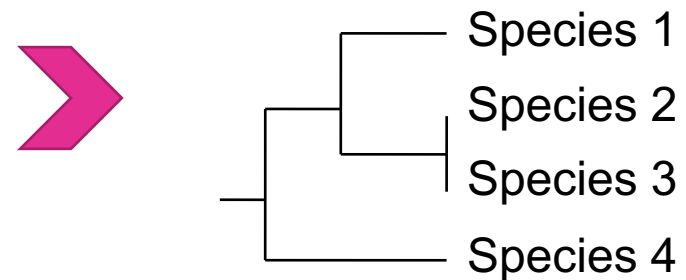
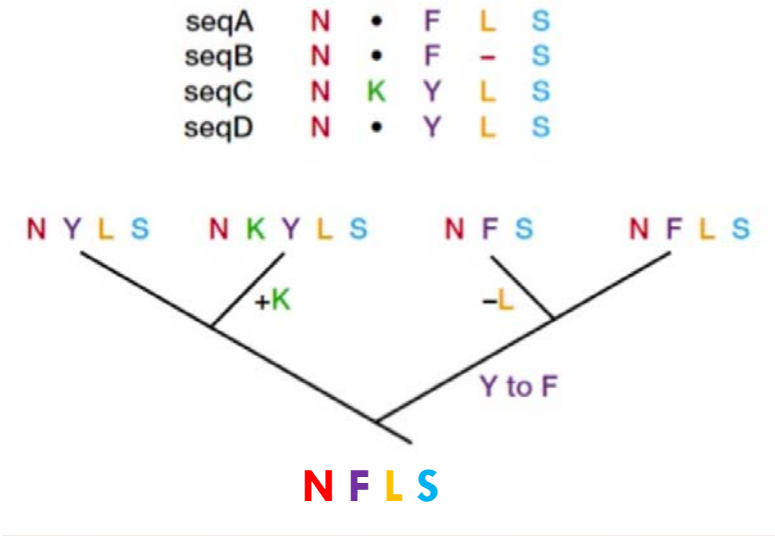
Supermatrices

Typical phylogenetic analysis (one protein):

TAXA		SEQUENCES
Species 1		GOODMORNING
Species 2		GODMORGON
Species 3		GOEDEMORGEN
Species 4		GUTEMORGEN

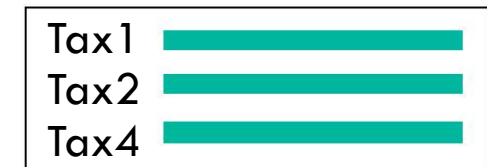
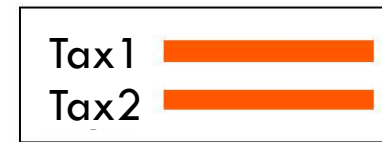
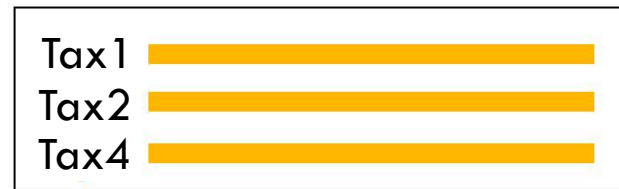


ALIGNMENT		SITE SELECTION
GOOD-MORNING		GODMORN N
GO-D-MORGON-		GODMORGN
GOEDEMORGEN-		GODMORGN
GU-TEMORGEN-		G U TMORGN

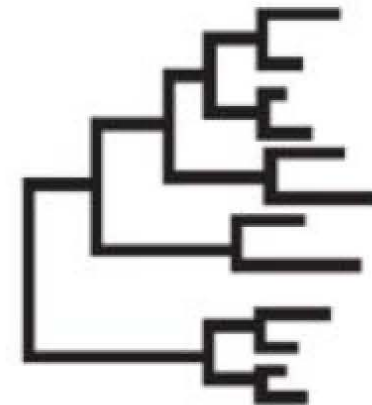
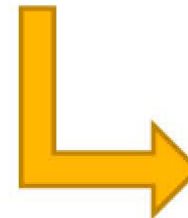


Supermatrices

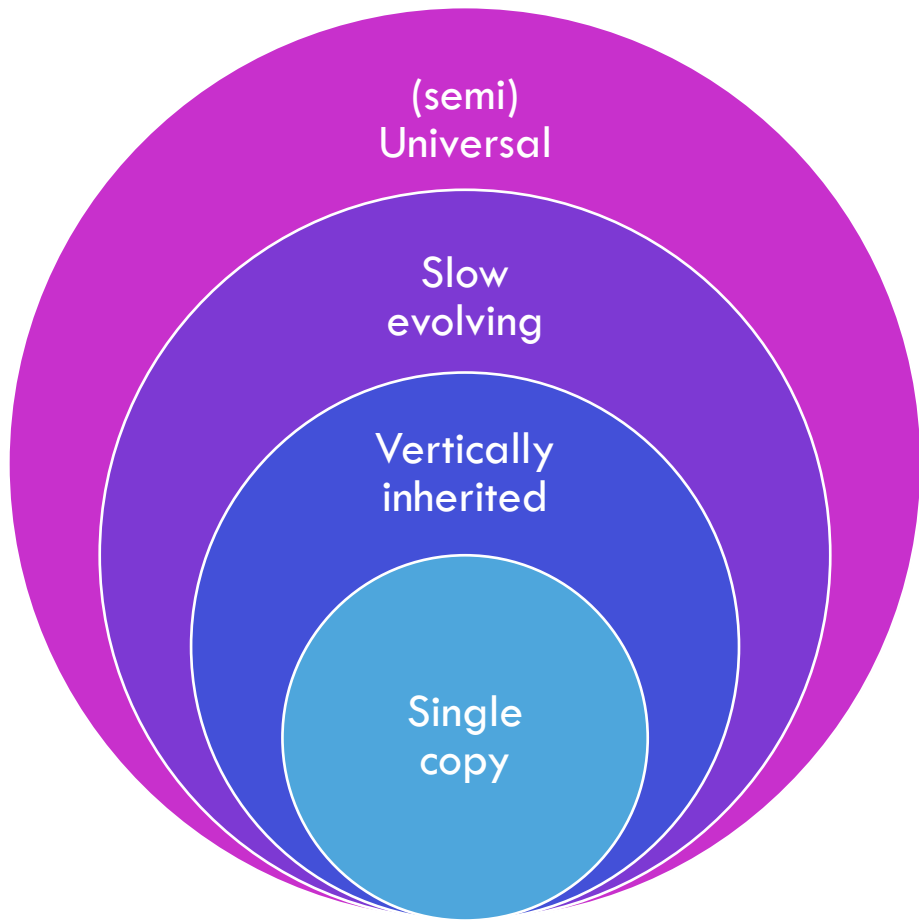
Combine weak phylogenetic (historical) signal from many genes
Attenuate individual bias (IF RANDOM)



CHECK FOR CONGRUENCE!



How to select multiple markers



Phylogenomic analysis
"pipeline" software tools:

- PhyloGenie
- Scafos
- AMPHORA
- Orthoselect
- iPhy
- PhyloTOL

Precomputed 'orthologous'
databases

- EggNOG
- HOMEOPEN
- OrthoMCL

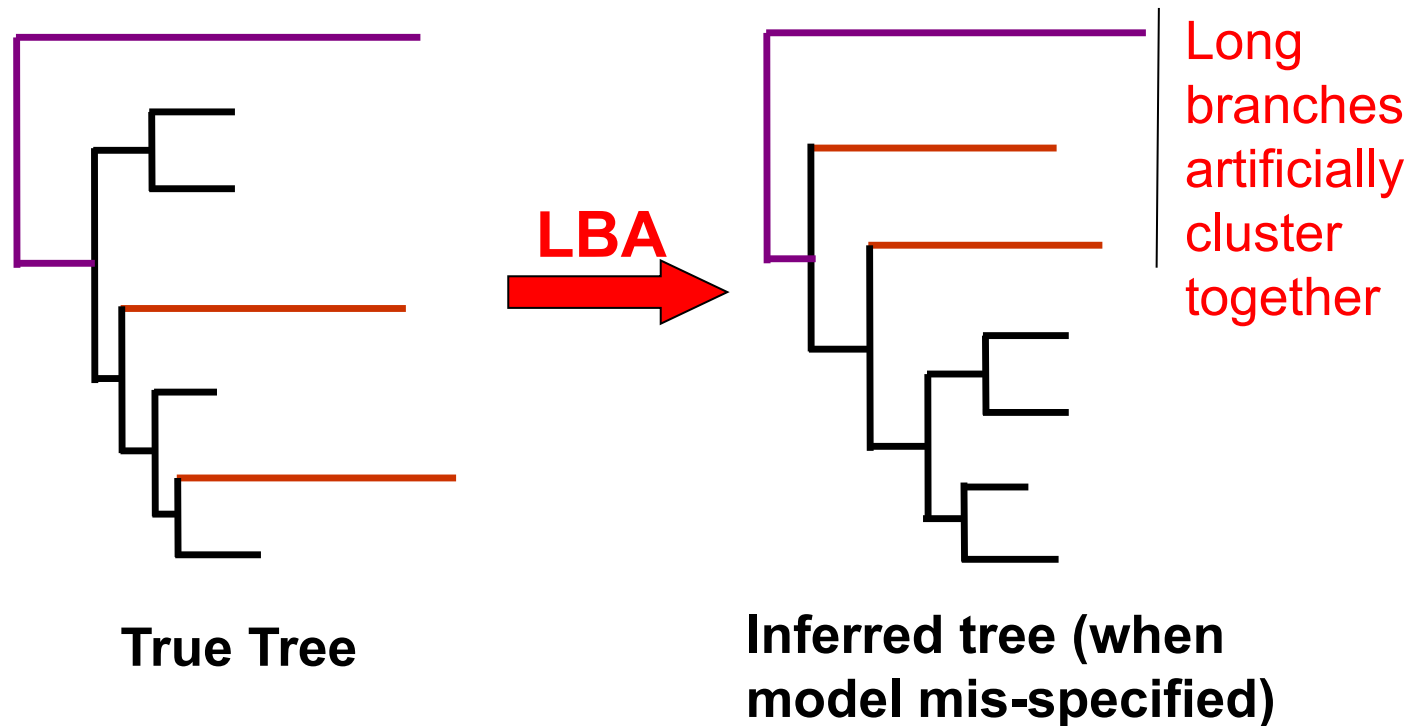
What can affect your topology

- Taxon sampling
 - Long branching taxa
 - Taxa with compositional bias
 - Contaminated data
- Gene/site sampling
 - Heterotachy
 - Saturated sites
- Model misspecification
 - LBA
- Highways of HGT
 - Consistently conflicting with vertical signal
- (and many other things...)

Minimazing potential artefacts

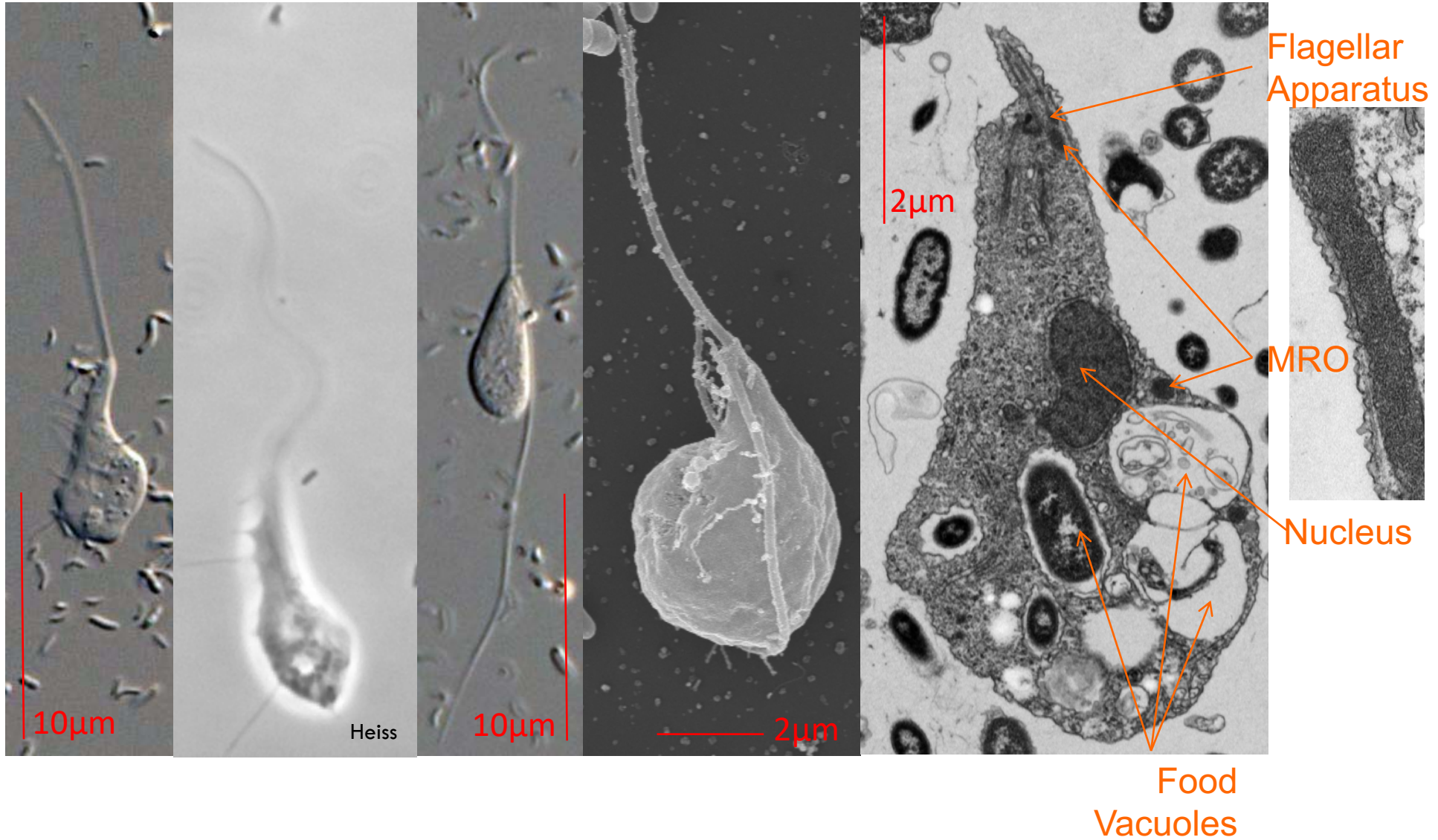
Model misspecification or over-simplistic: statistical inconsistency

Long Branch Attraction (LBA) Artefact



Adding more data *strengthens* artefact
→ statistical inconsistency

Pygsuia biforma n. gen. n. sp.

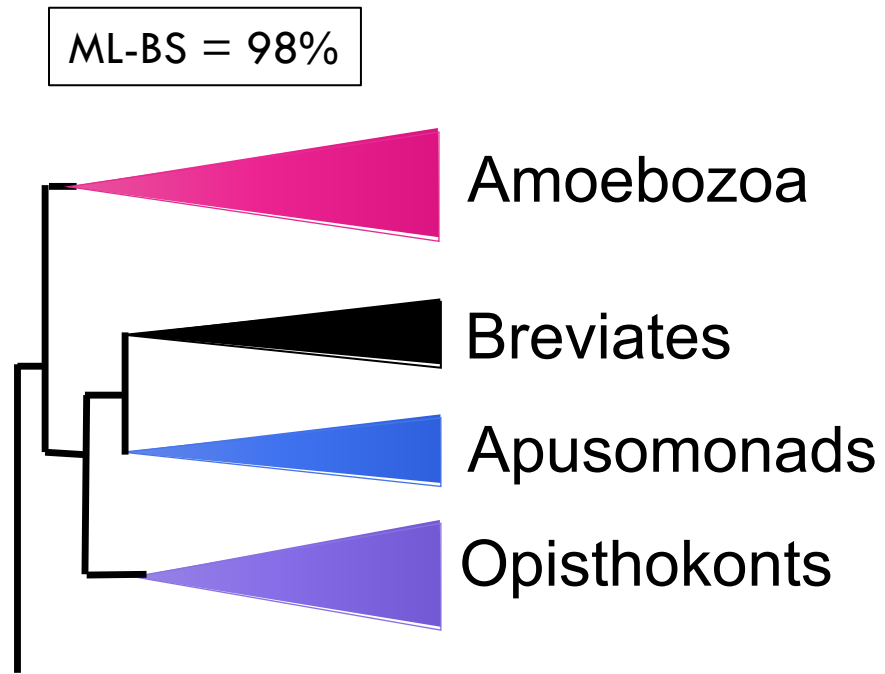


Two different topologies within Obazoa are supported by different phylogenetic models

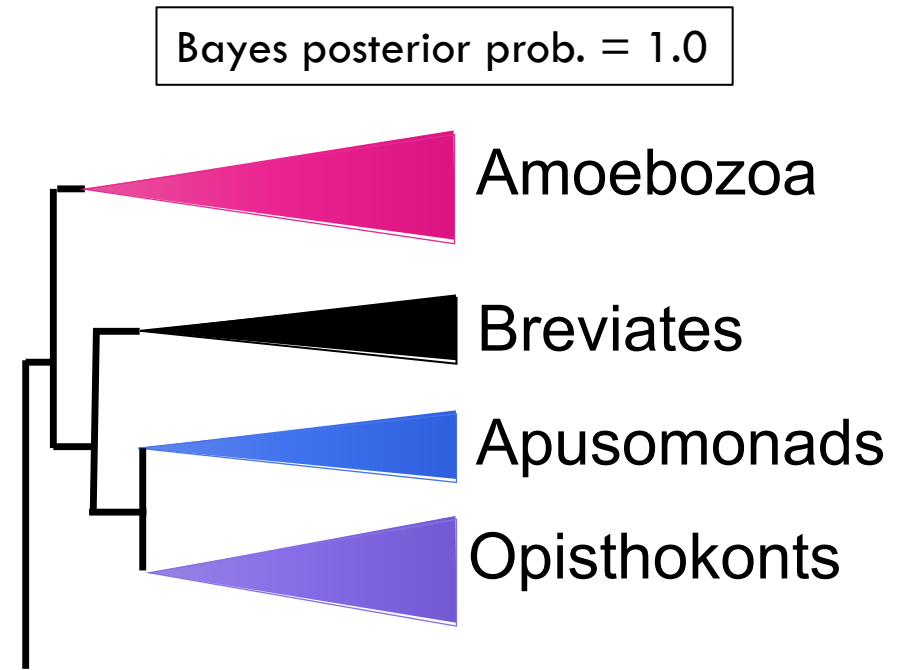


Opisto + Breviata + Apusomonads = OBAzoa

Two different topologies within Obazoa are supported by different phylogenetic models



ML – LG+ Γ
Bayes – LG+ Γ



Bayes – CAT-Poisson+ Γ
Bayes – CAT-GTR+ Γ

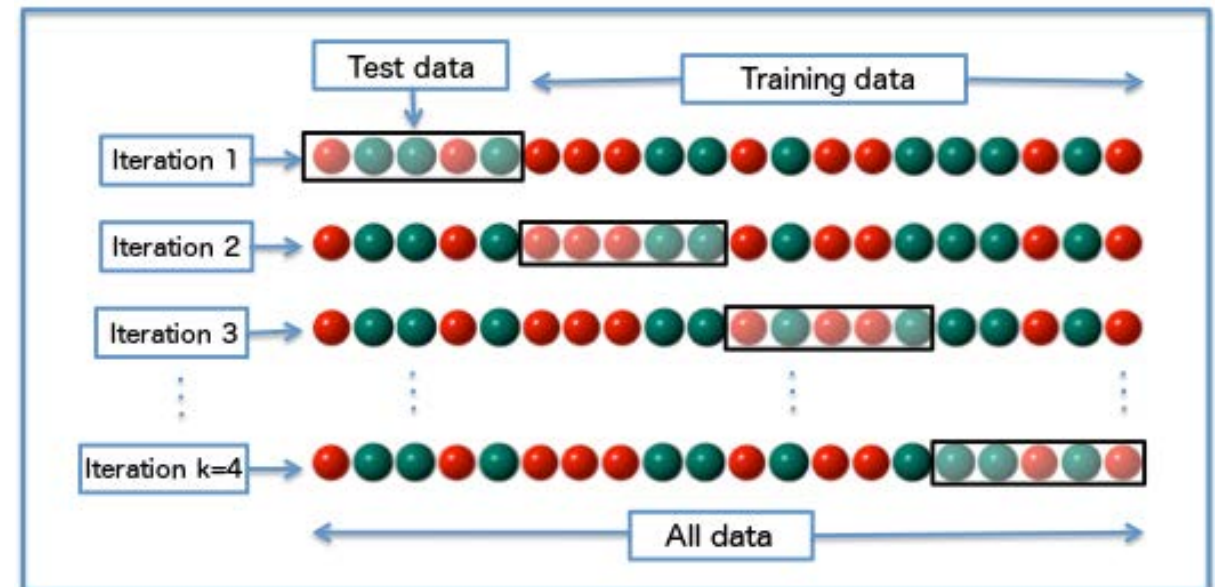
How to decide which is real and which is artefact?

- One of two topologies is likely artefactual resulting from misspecified model
- Test which substitution model fits better
 - E.g., Cross-validation, Bayes factors, Posterior prediction

How to decide which is real and which is artefact?

Cross-validation:

- 1) parameters of the model estimated on the learning set
- 2) these parameter values are then used to compute the likelihood of the test set = **how well the test set is 'predicted' by the model?**
- 3) Repeat over all partitions and average the likelihood
- 4) Repeat for each model and compare



Cross-validation favors CAT-GTR over LG

ML-BS = 98%



ML – LG+ Γ
Bayes – LG+ Γ

Bayes posterior prob. = 1.0



Bayes – CAT-Poisson+ Γ
Bayes – CAT-GTR+ Γ



Cross validation

How do decide which is real and which is artefact?

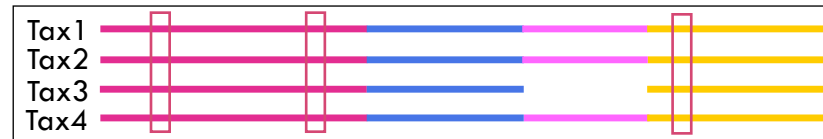
- One of two topologies is likely artefactual resulting from misspecified model
- Test which substitution model fits better
 - Cross-validation
- Try to eliminate 'noisiest' data
 - Fast-evolving site removal
 - Fast-evolving gene removal
 - Fast-evolving taxon removal
 - Recoding

Removal of fast-evolving sites

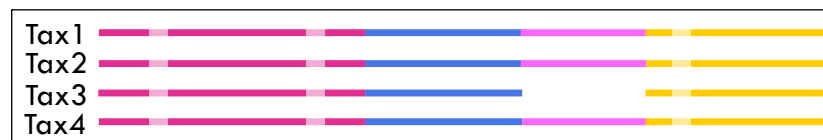
Fast Evolving Sites removal

Fast-evolving sites : carry the ‘noisiest’ signal (most saturated sites)

Initial alignment



Iteration 1

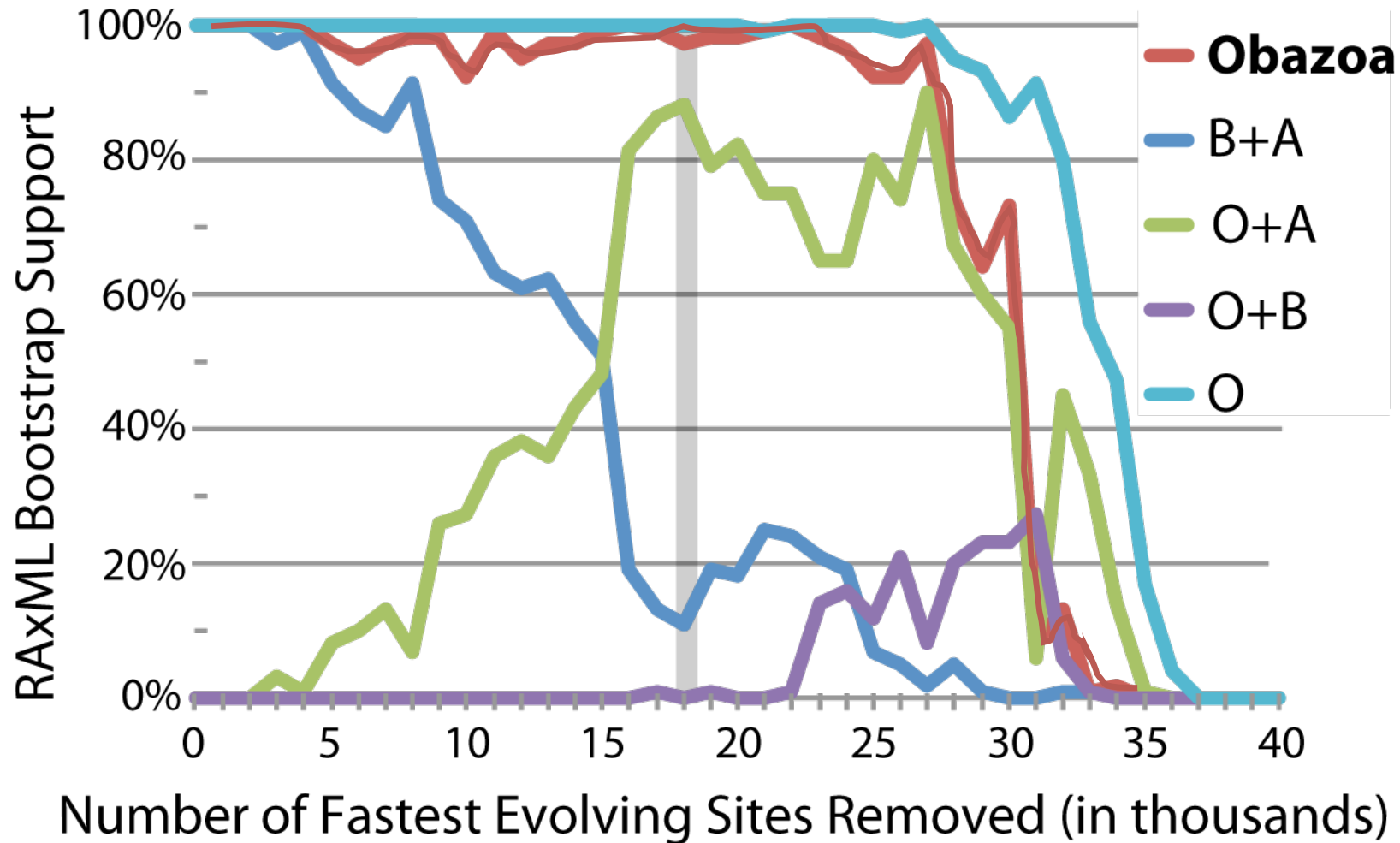


Reconstruct tree

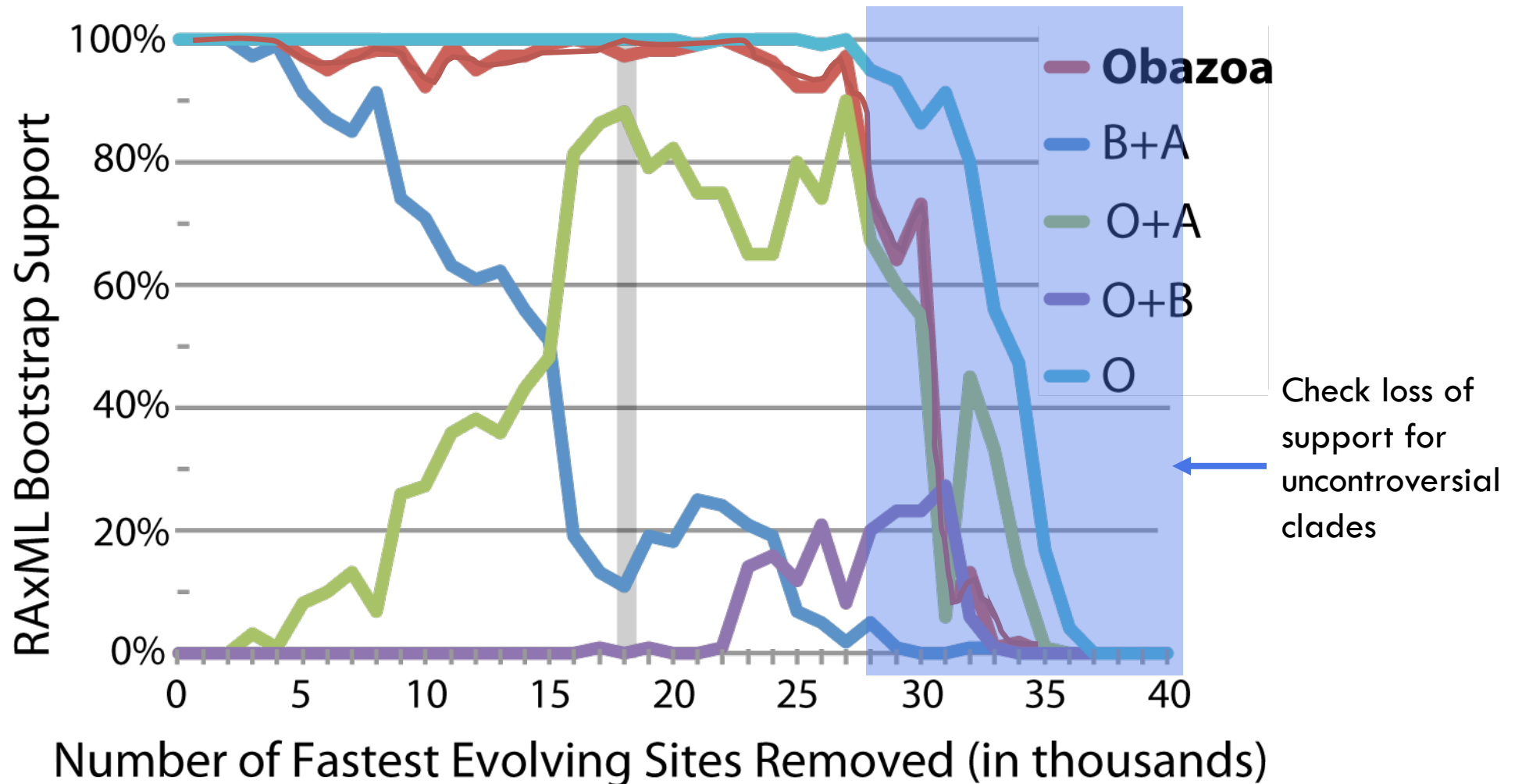
→ 40 steps of removal of 1000 sites (evolutionary rates estimated by IQTREE for example)

Step	# sites left	
1	43615	Tree 1
2	42615	Tree 2
...		
4	40615	Tree 4
...		
40	3615	Tree 40

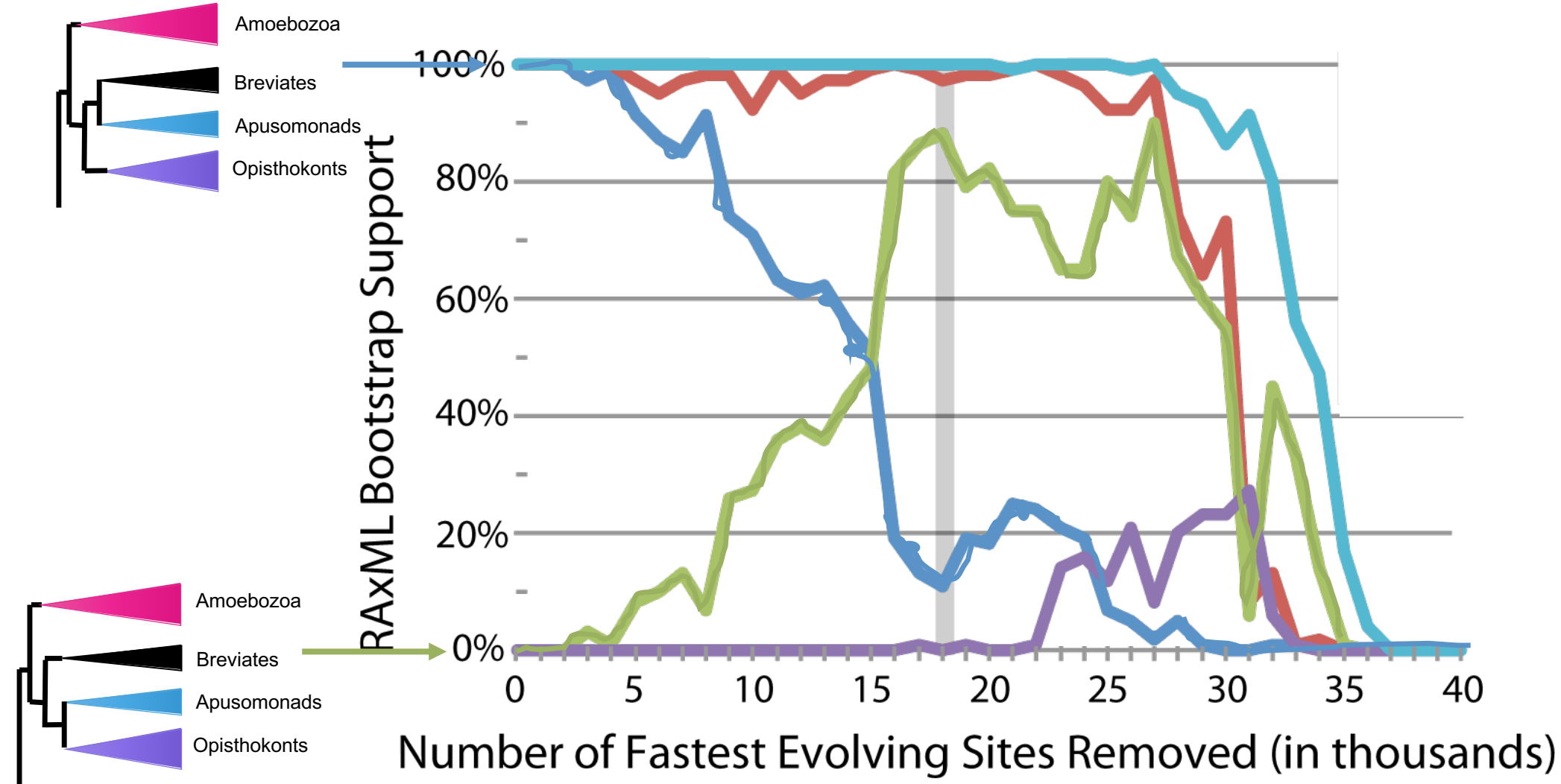
Estimate BS for various clades as we remove Fast-Evolving Sites

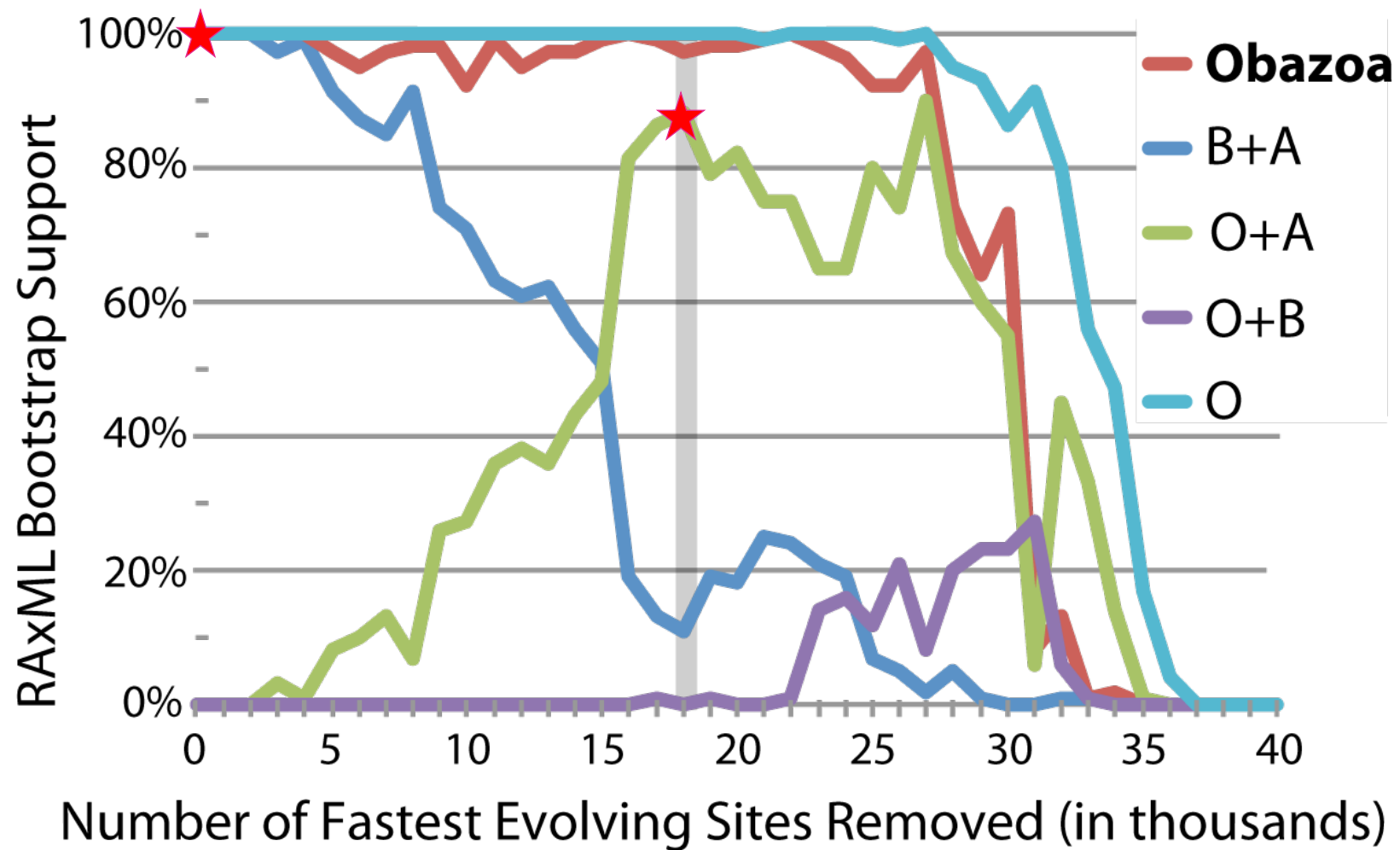


Estimate BS for various clades as we remove Fast-Evolving Sites



Breviates+Apusomonads (B+A) topology vs. Apusomonads+Opisthokonts (O+A)







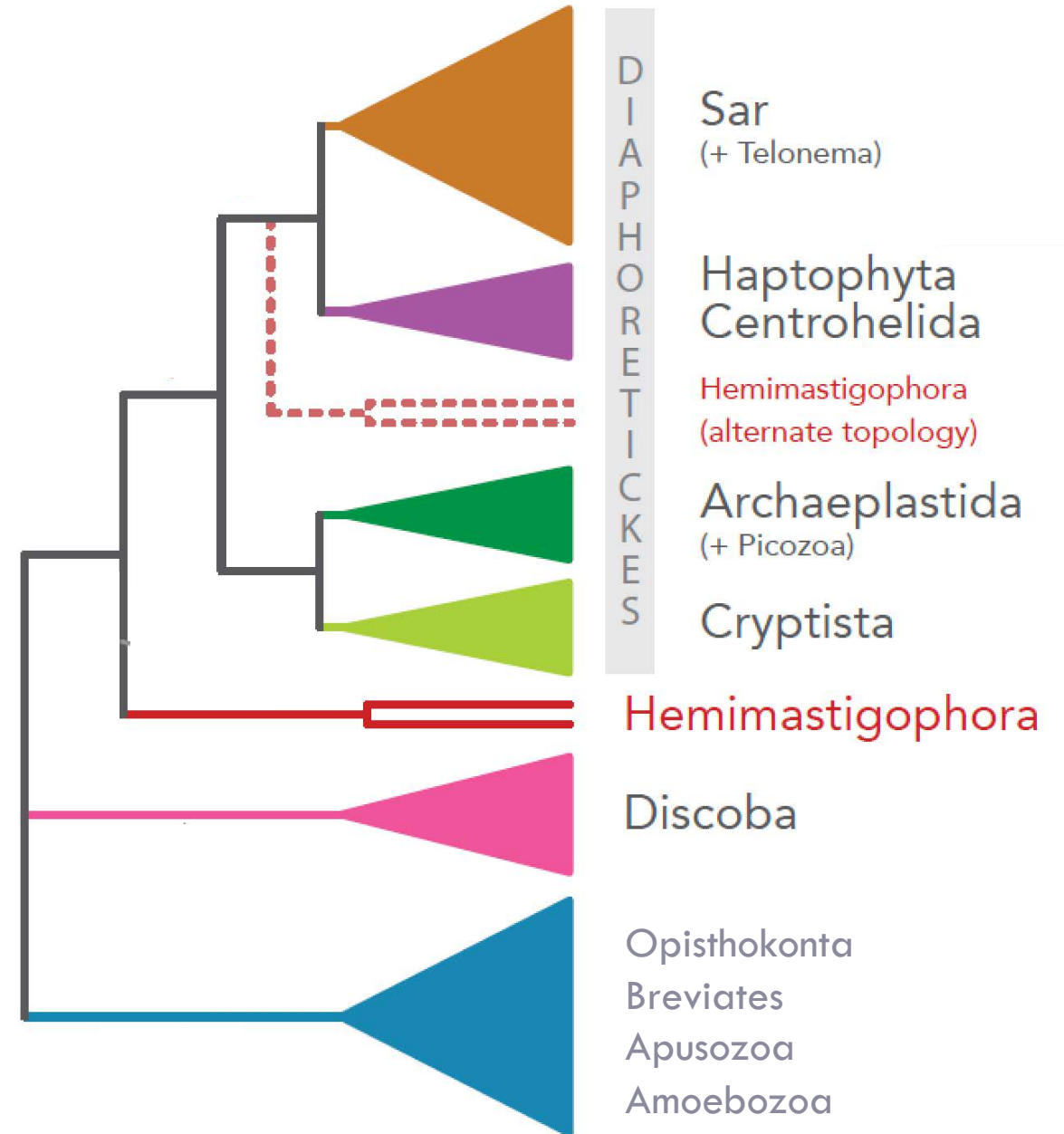
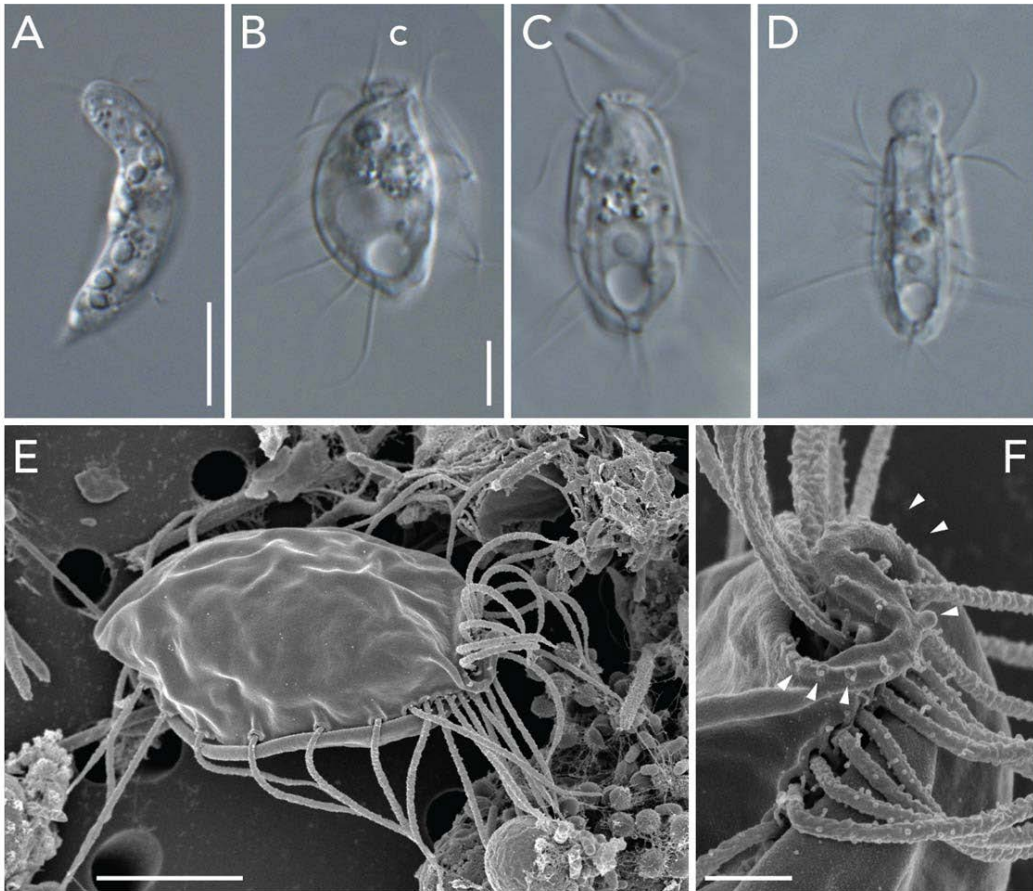
Removal of 18,000 fastest-evolving sites



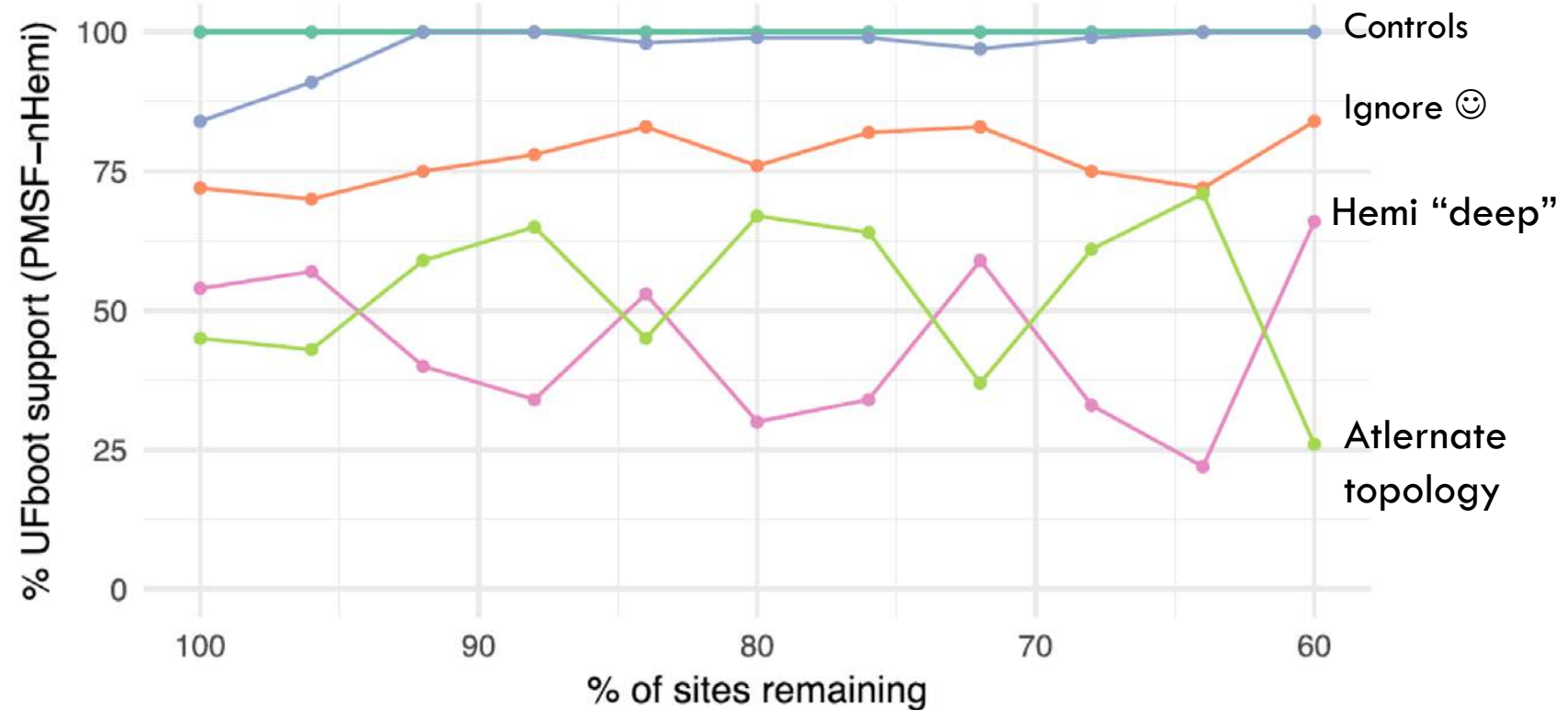
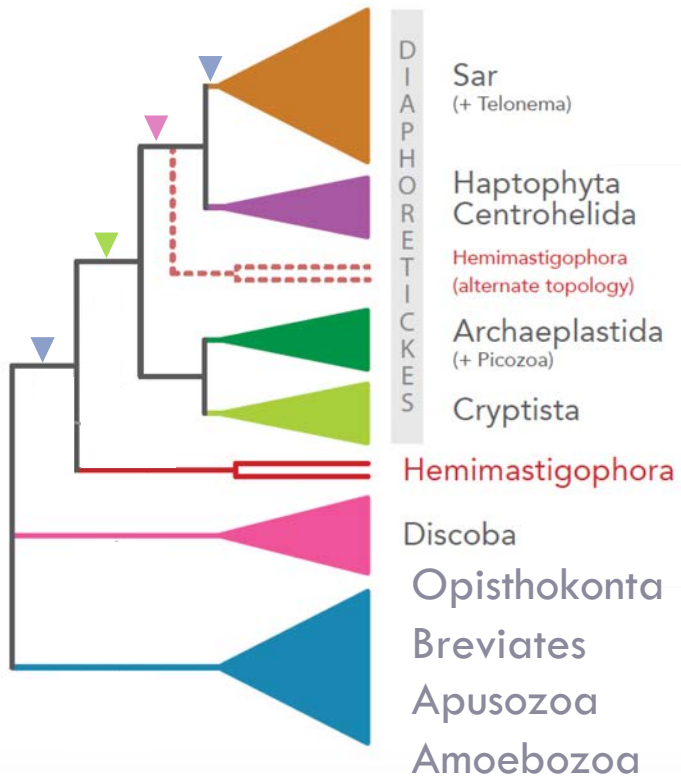
Fast-evolving site removal: warning

- Very poor proxy for heterotacheous site removal
 - Fast sites in themselves are not a problem if they are fast across the entire tree
- In practice, fast sites seem to overlap to some extent with sites whose rate varies across the tree and are improperly modelled by most widely used models.
- You also remove the most saturated sites, which are usually poorly modelled

FES removal is not the key to all conflictual signal



FES removal is not the key to all conflictual signal



Removal of long-branching genes

Long-branching genes removal

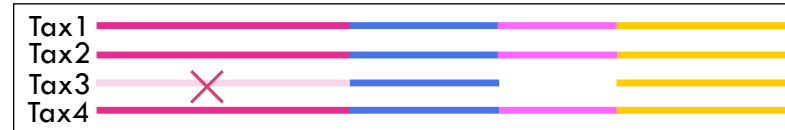
Initial alignment



Individual trees

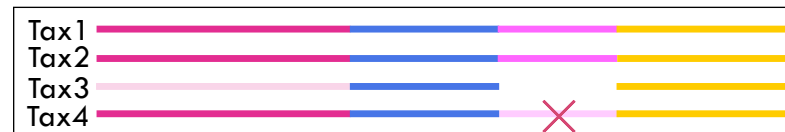


Iteration 1



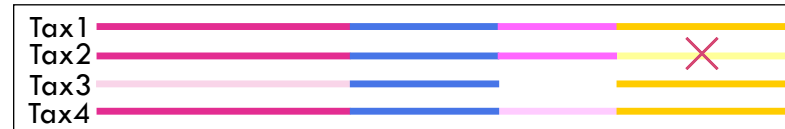
➡ Tree 1

Iteration 2



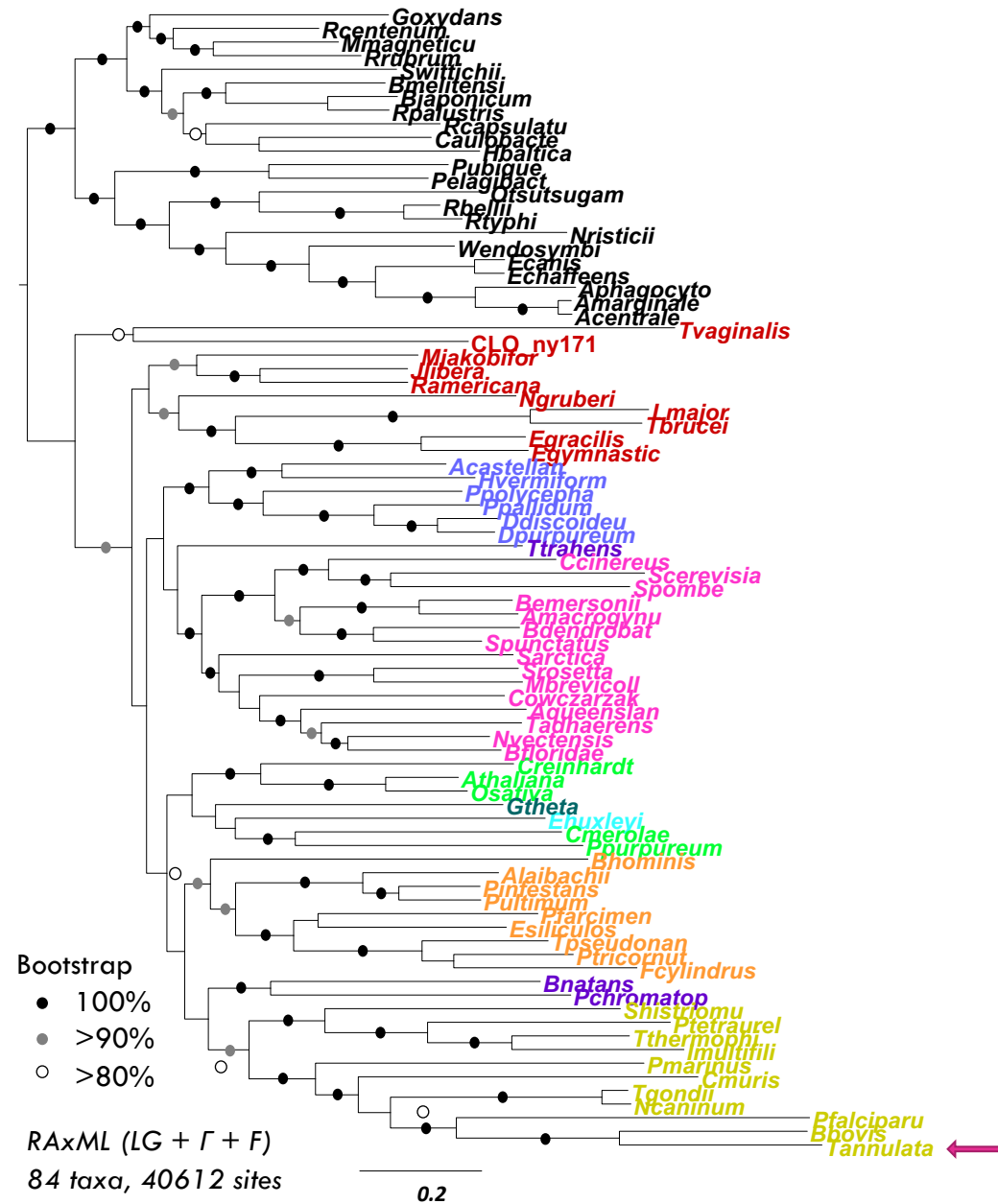
➡ Tree 2

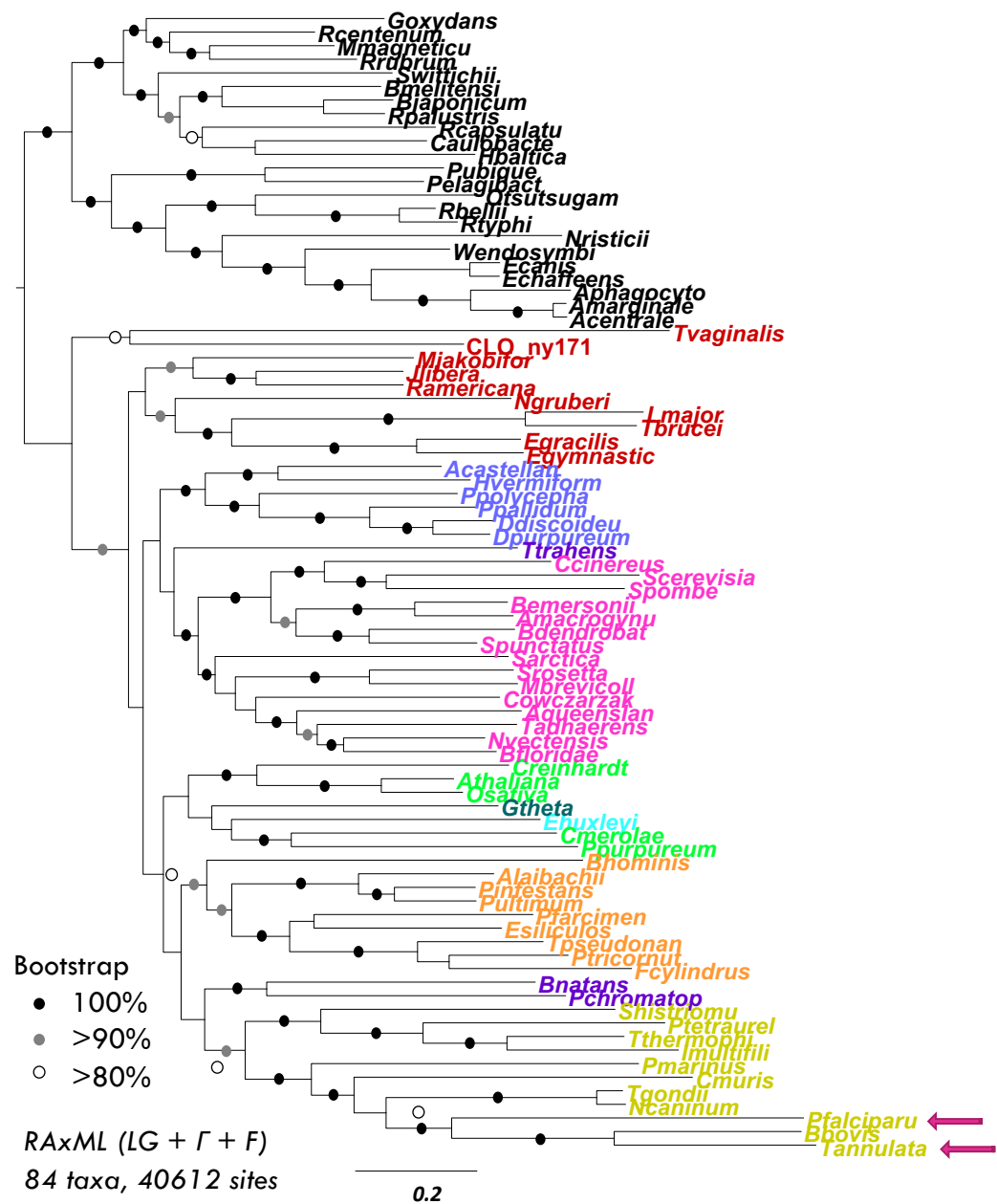
Iteration 3

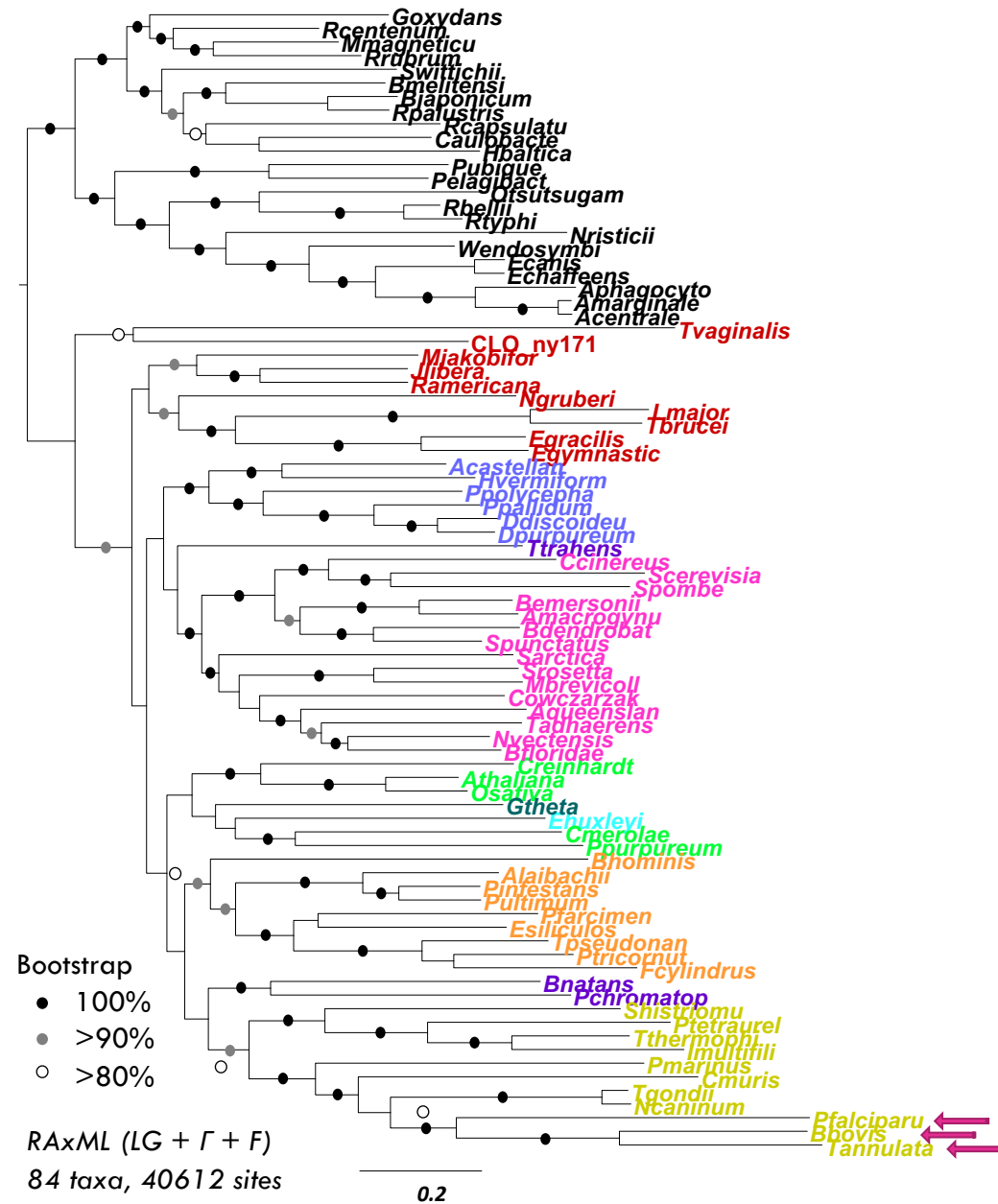


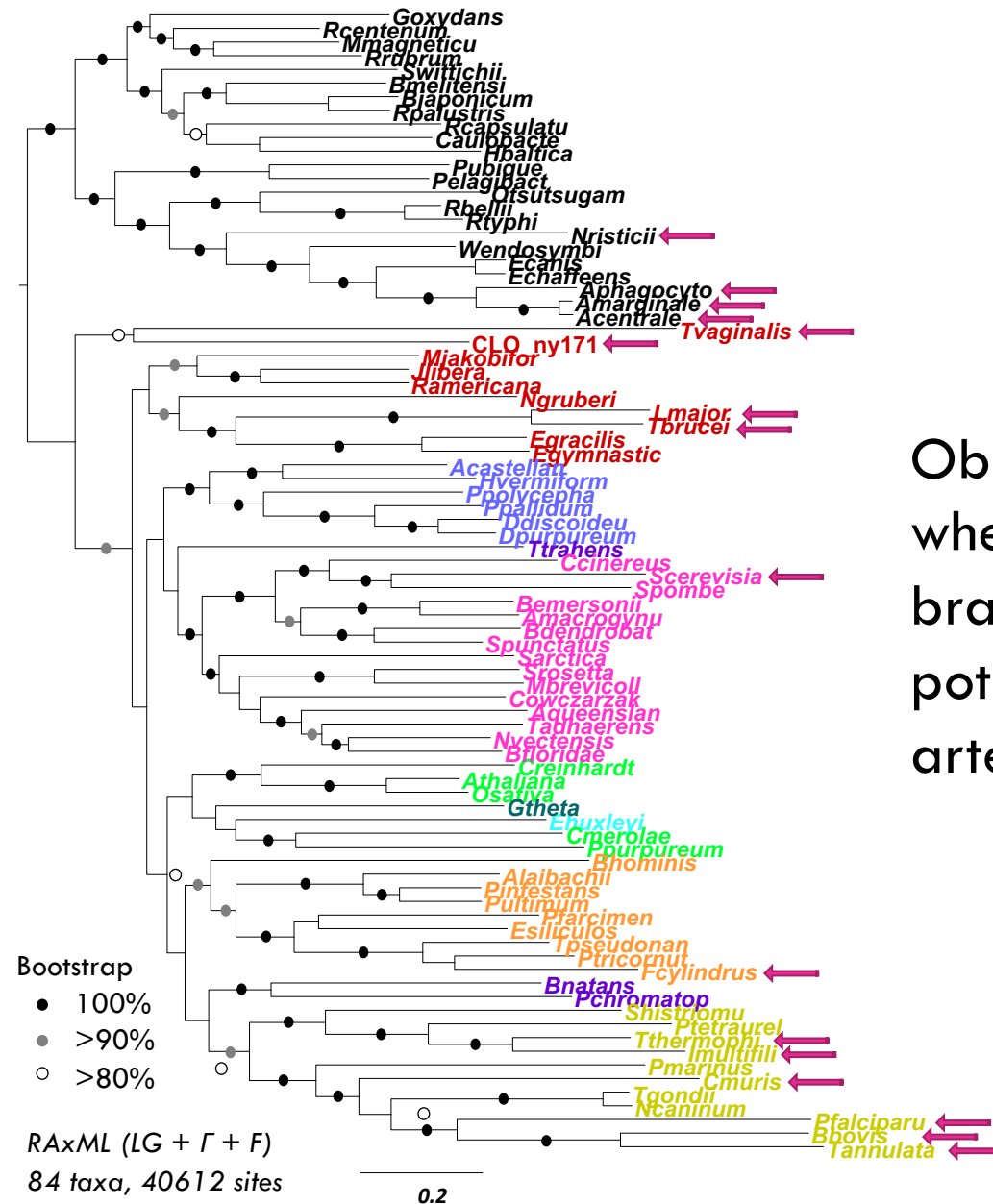
➡ Tree 3

Removal of long-branching taxa









Observing a shift of topology when removing long branching taxa suggests a potential reconstruction artefact

Identifying conflict between
single-gene trees

Detecting conflict between single-gene trees

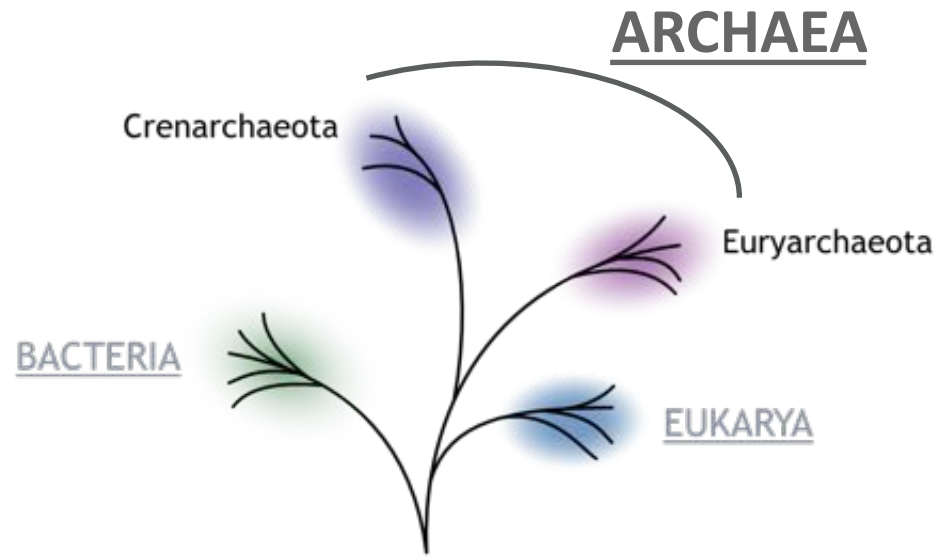
Characteristics of Popular Congruence Tests

Test	H_0	Algorithmic Complexity ^a	Identification of Multiple Subsets?	Interpretation of Missing Taxa
MAST (Lapointe and Rissler 2005 ; de Vienne et al. 2007)	Incongruence	$O(n)$	Yes ^b	Pruned and ignored ^b
CADM (Campbell et al. 2009)	Incongruence	$O(n^2)$	Yes	N/A
ILD (Farris et al. 1994)	Congruence	$O(n)^c$	No	N/A
Multiple ILD (Planet and Sarkar 2005)	Congruence	$O(n^2)$	Yes	Pruned and ignored
LRT (Huelsenbeck and Bull 1996)	Congruence	$O(n)^c$	No	N/A
Concatenation hierarchical LRT (Leigh et al. 2008)	Congruence	$O(n^2)$	Yes	Pruned and ignored
LRT (Waddell et al. 2000)	Congruence	$O(nm)$	No	N/A
Likelihood-based topology tests	Congruence	$O(nm)$	No	Pruned and ignored
Principal component analysis	Congruence	$O(nm)$	No	Pruned and ignored
Heatmaps	Congruence	$O(nm)$	Yes	Pruned and ignored
Likelihood-based topology tests	Congruence ^d	$O(nm)$	No	N/A

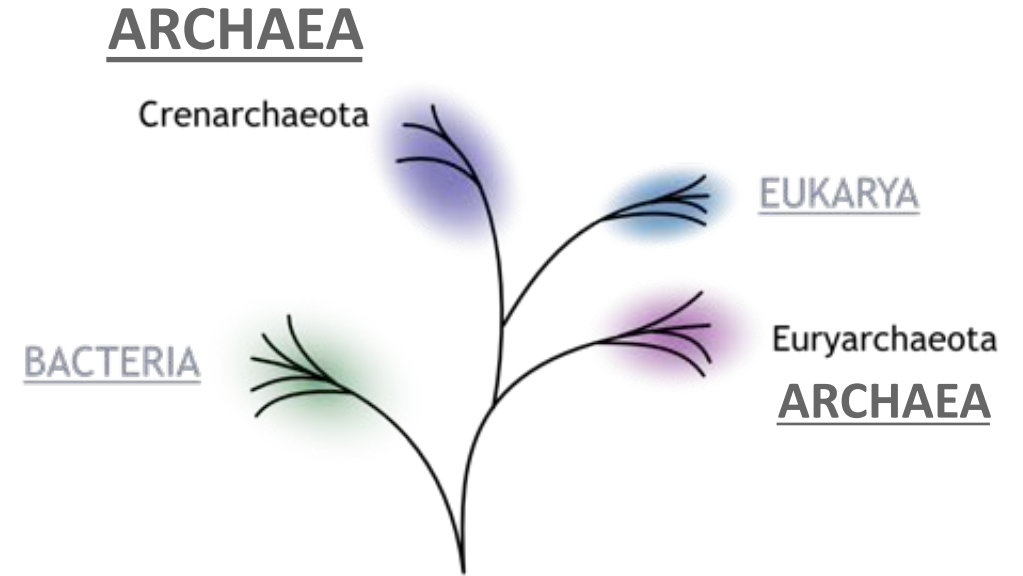
Small systematic bias leads to large artefacts in concatenations

An example from my recent research

Archaea as **sister-group** or as **ancestors** of eukaryotes?



Three domain
tree of Life

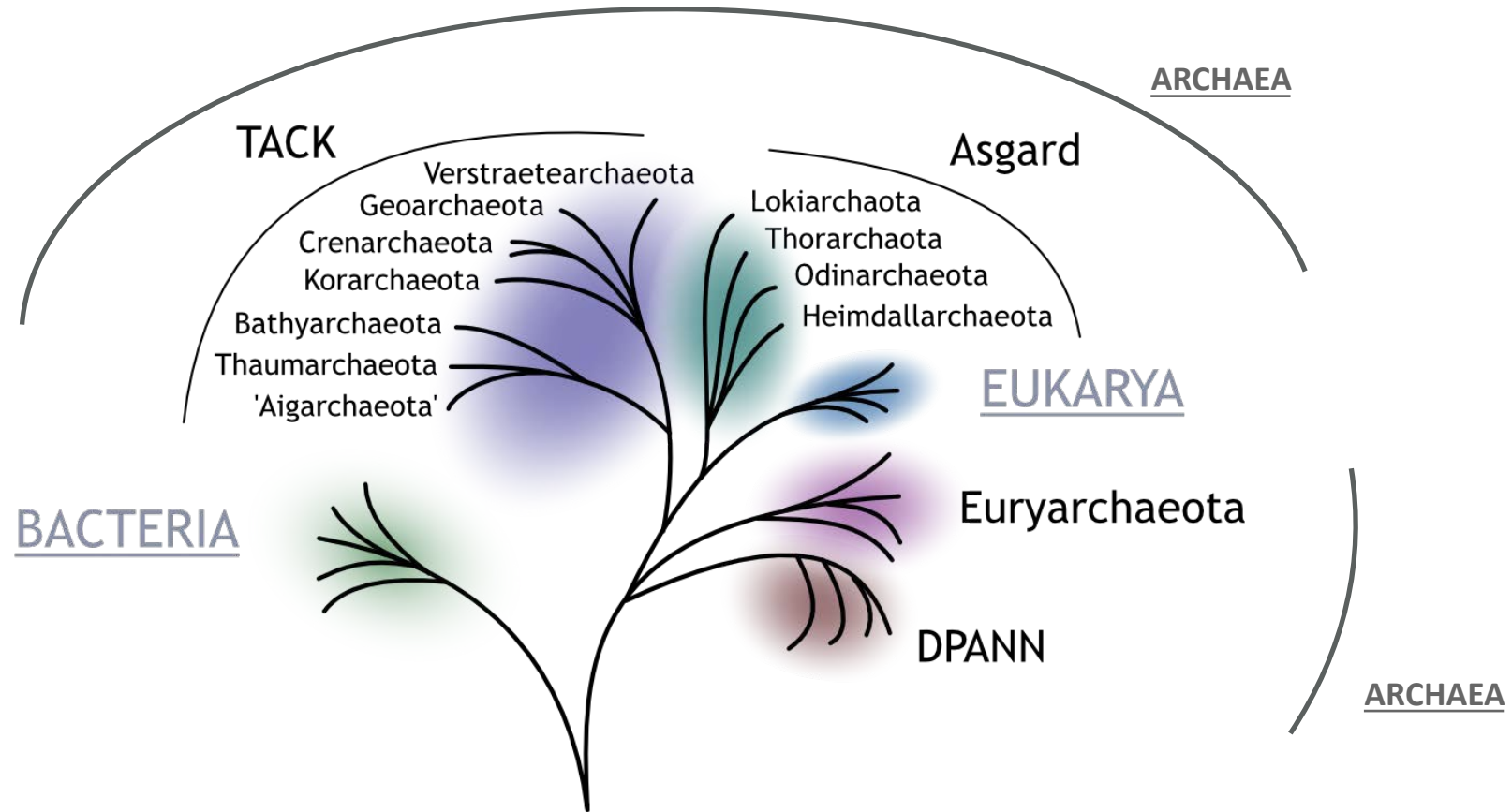


Two domain
tree of Life

1990s-2000s: Phylogenetic analyses: few genes; few cultivated organisms

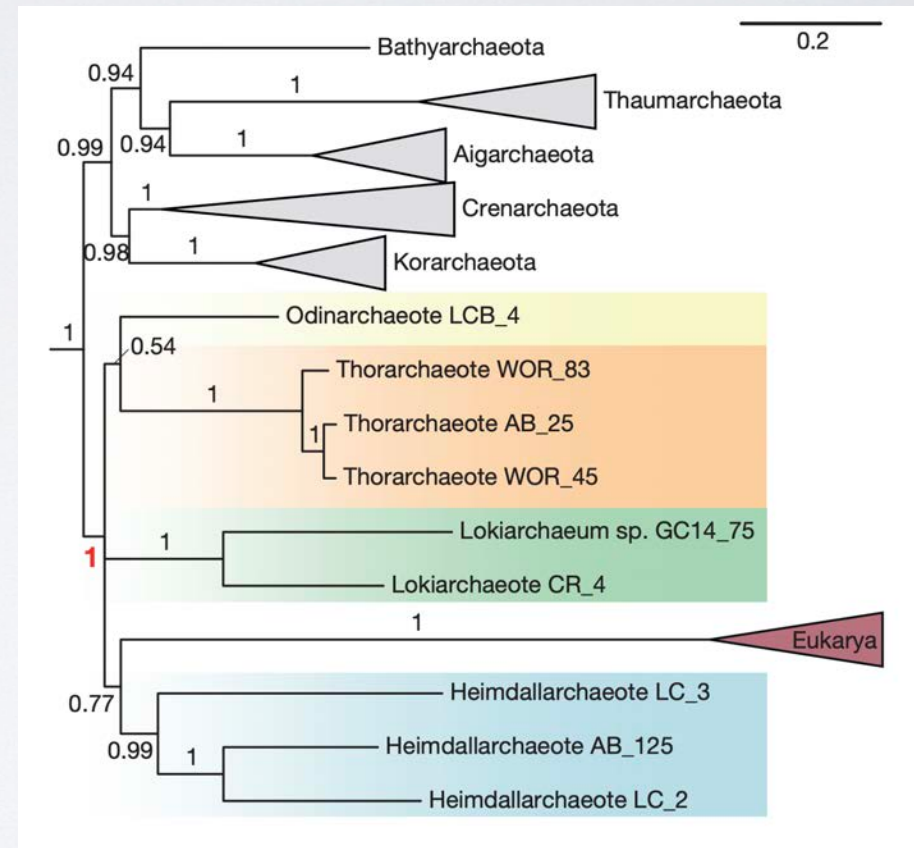
Culture-independent genomics (e.g. metagenomics)

Archaea as **ancestors** of eukaryotes



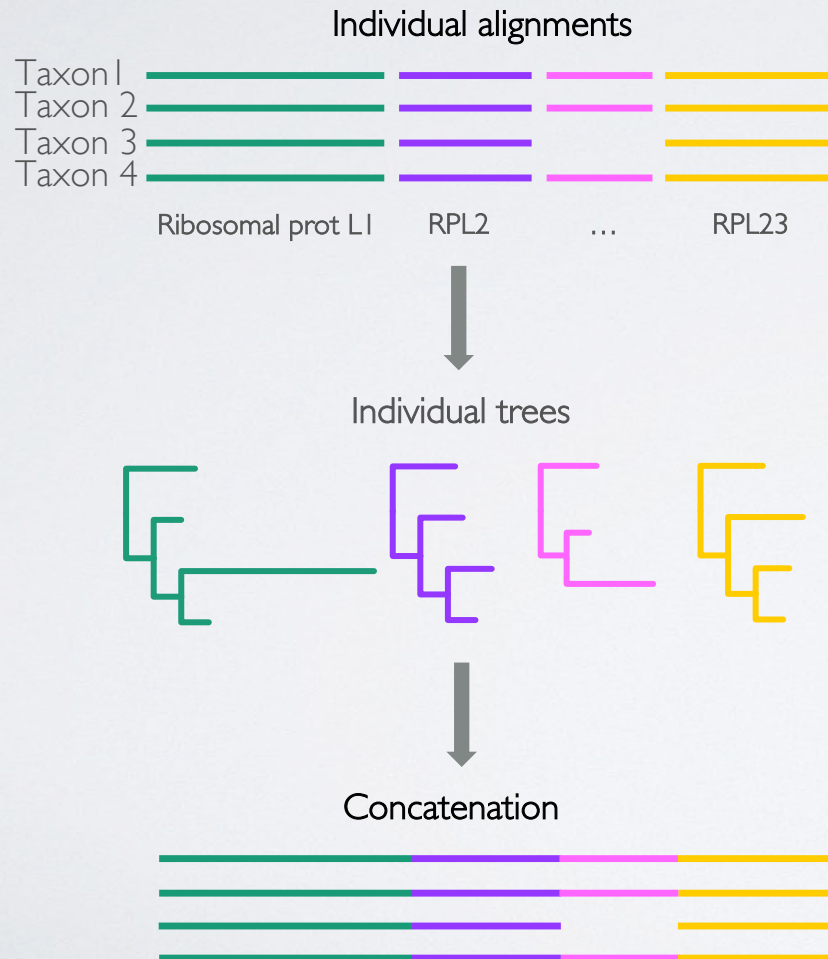
Culture-independent genomics (e.g. metagenomics)

Eukaryotes: within or sister to Asgard ?

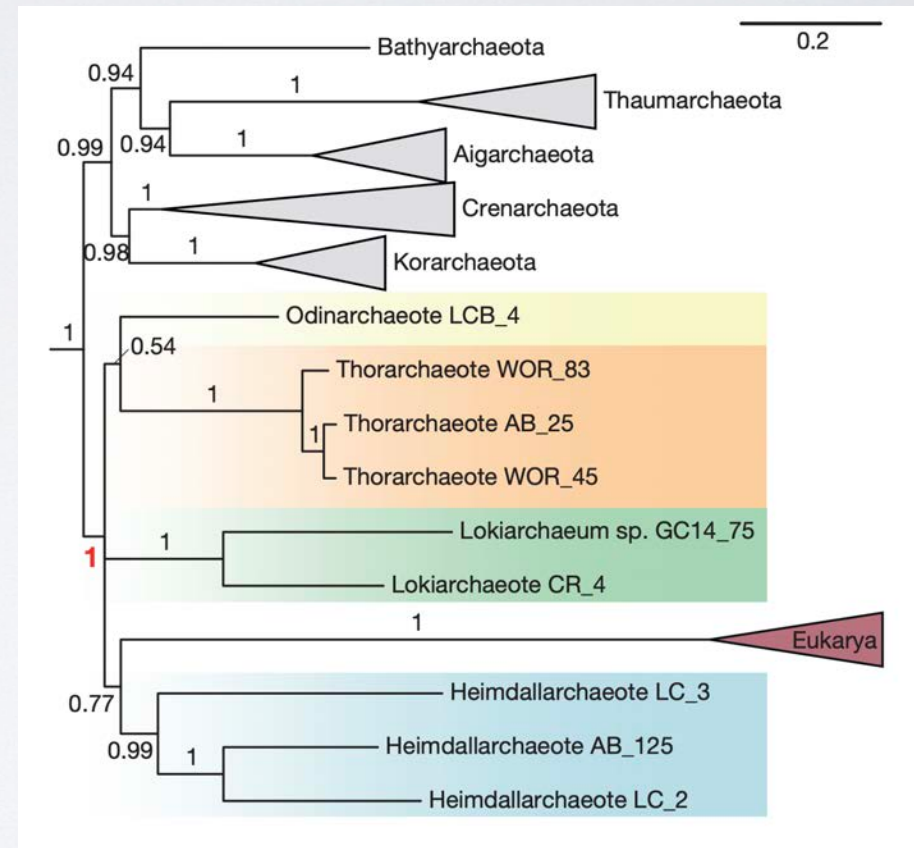


Zaremba-Niedzwiedzka *et al.*, Nature 2017

9 asgard genomes
56 ribosomal proteins



Eukaryotes:
within or sister to Asgard ?

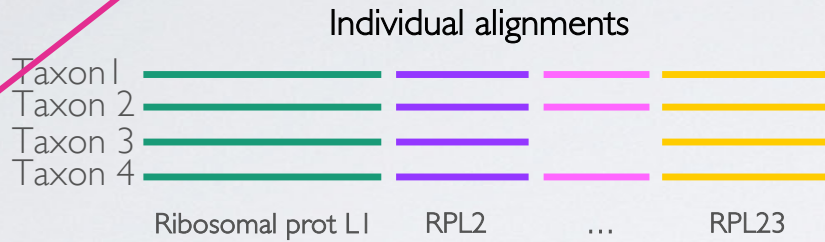


Zaremba-Niedzwiedzka *et al.*, Nature 2017

Increase taxon
sampling

9 asgard genomes
56 ribosomal proteins

Increase
concatenation
size



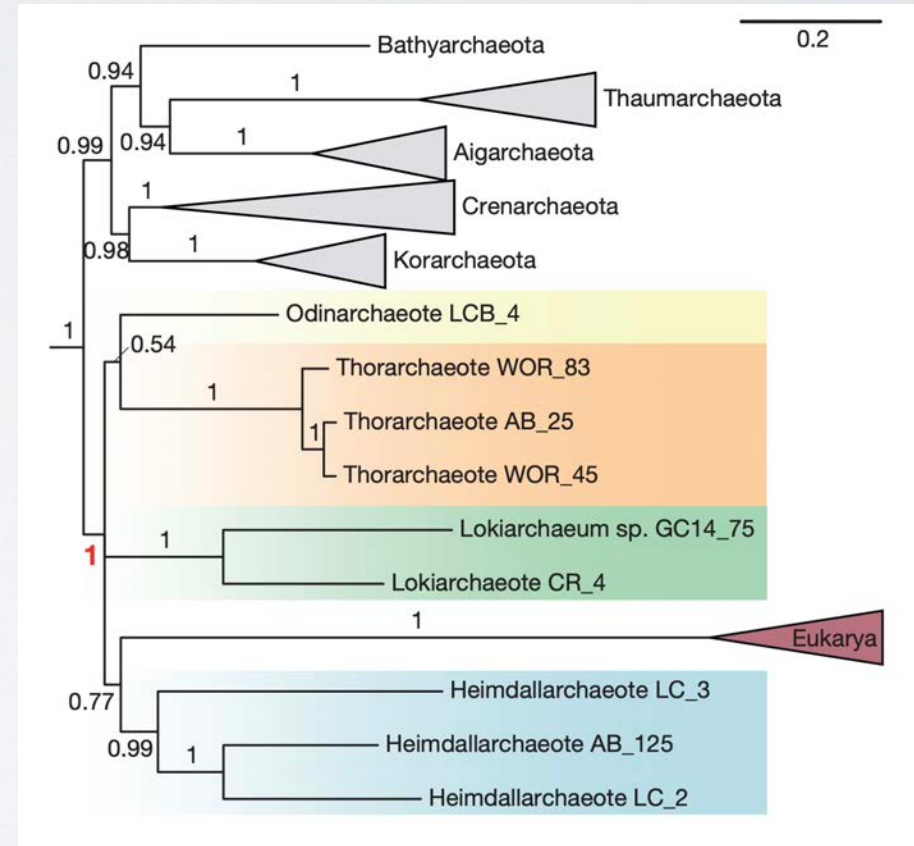
Individual trees



Concatenation

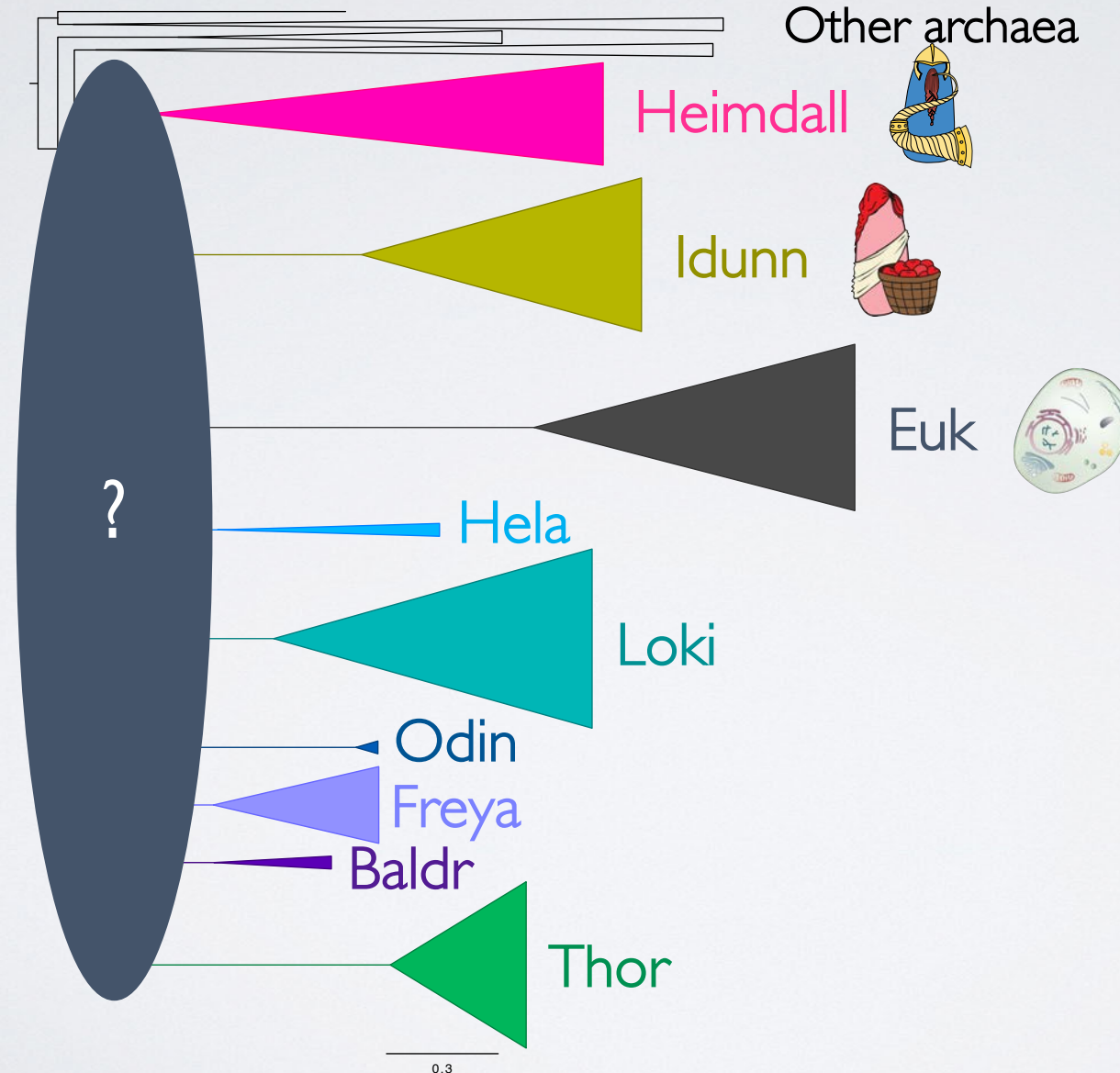


Eukaryotes:
within or sister to Asgard ?



Zaremba-Niedzwiedzka et al., Nature 2017

60 new Asgard genomes and many new major lineages



➔ Identifying new
phylogenomic
markers



Ribosomal proteins (RP) vs New markers (NM)

Ribosomal proteins:

Slow evolving

Universal

Short

Functional divergence

Ribosomal proteins (RP) vs New markers (NM)

Ribosomal proteins:

Slow evolving
Universal
Short
Functional divergence

New markers:

200 archaeal markers (Petitjean *et al.*, MBE 2015)



$\geq 10/14$ euks
Of archaeal origin in euks
Present in all Asgard phyla
Manual + automated check for HGT



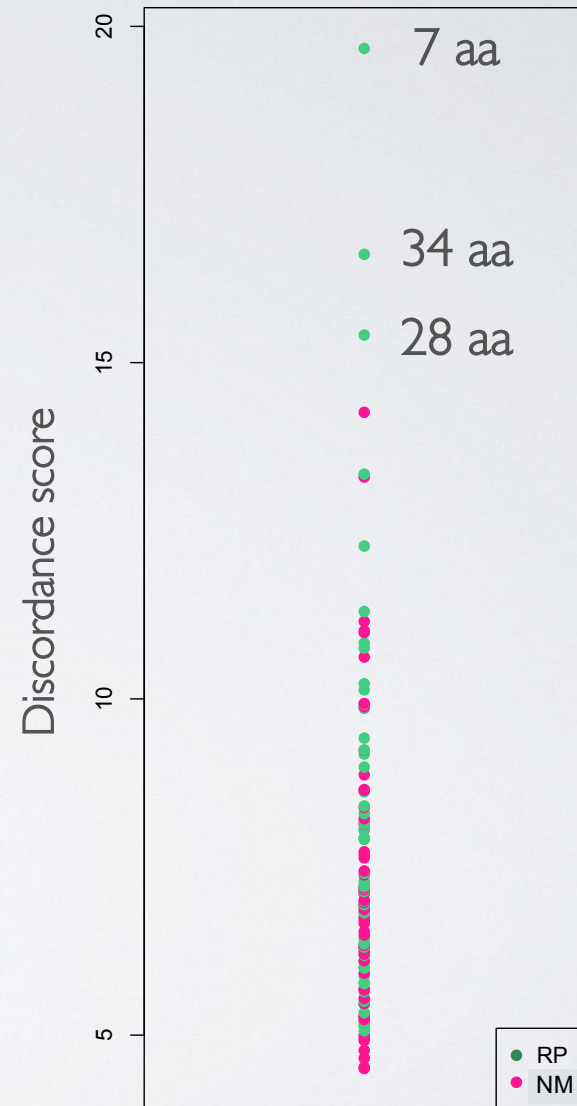
57 new markers

Testing for congruence: Discordance score

Discordance score:

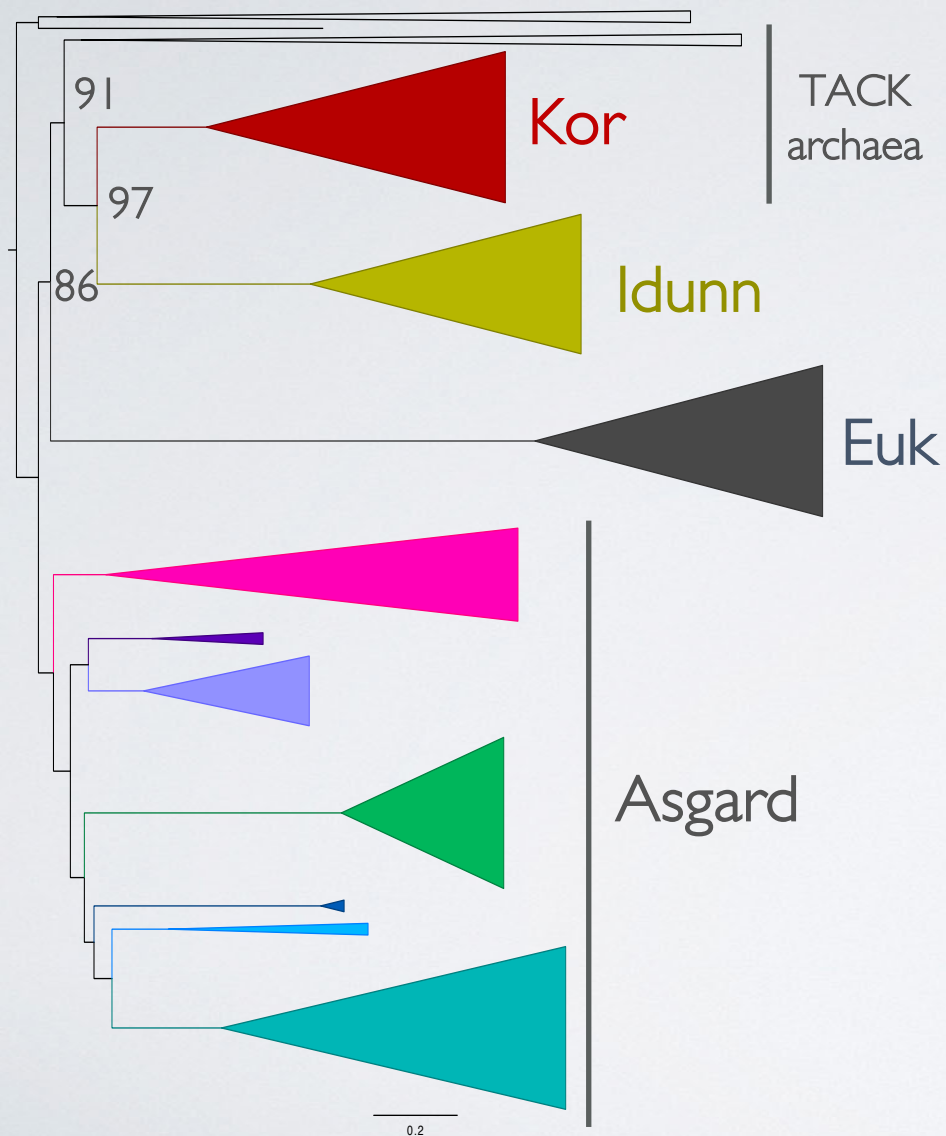
~proportional to the frequency of
incompatible (highly supported)
bipartitions between a tree and all others.

~All trees appear congruent
(or more so, “not incongruent”)



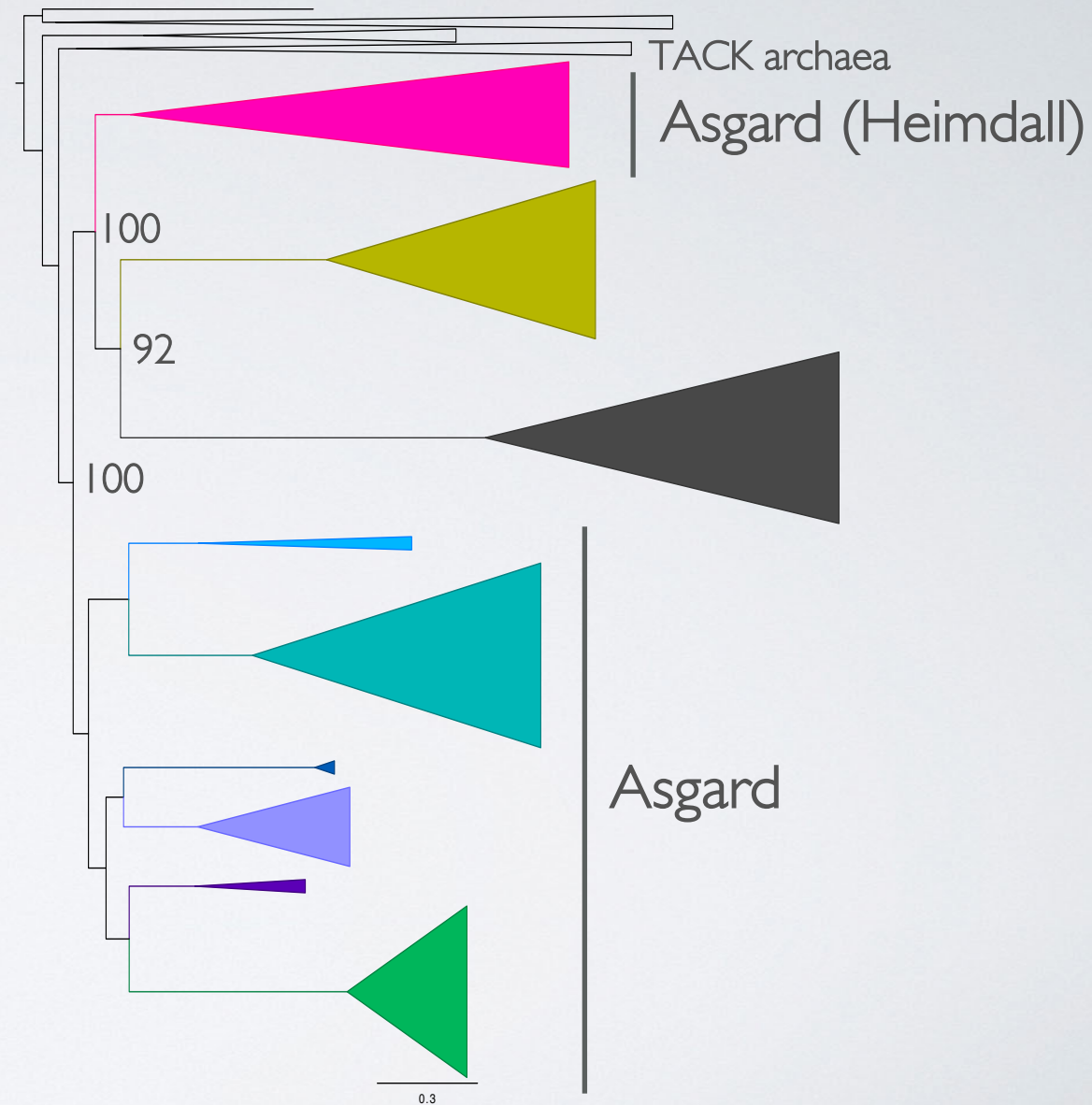
56 ribosomal proteins (5647 aa), 195 taxa

IQ-tree C60+LG+F+G



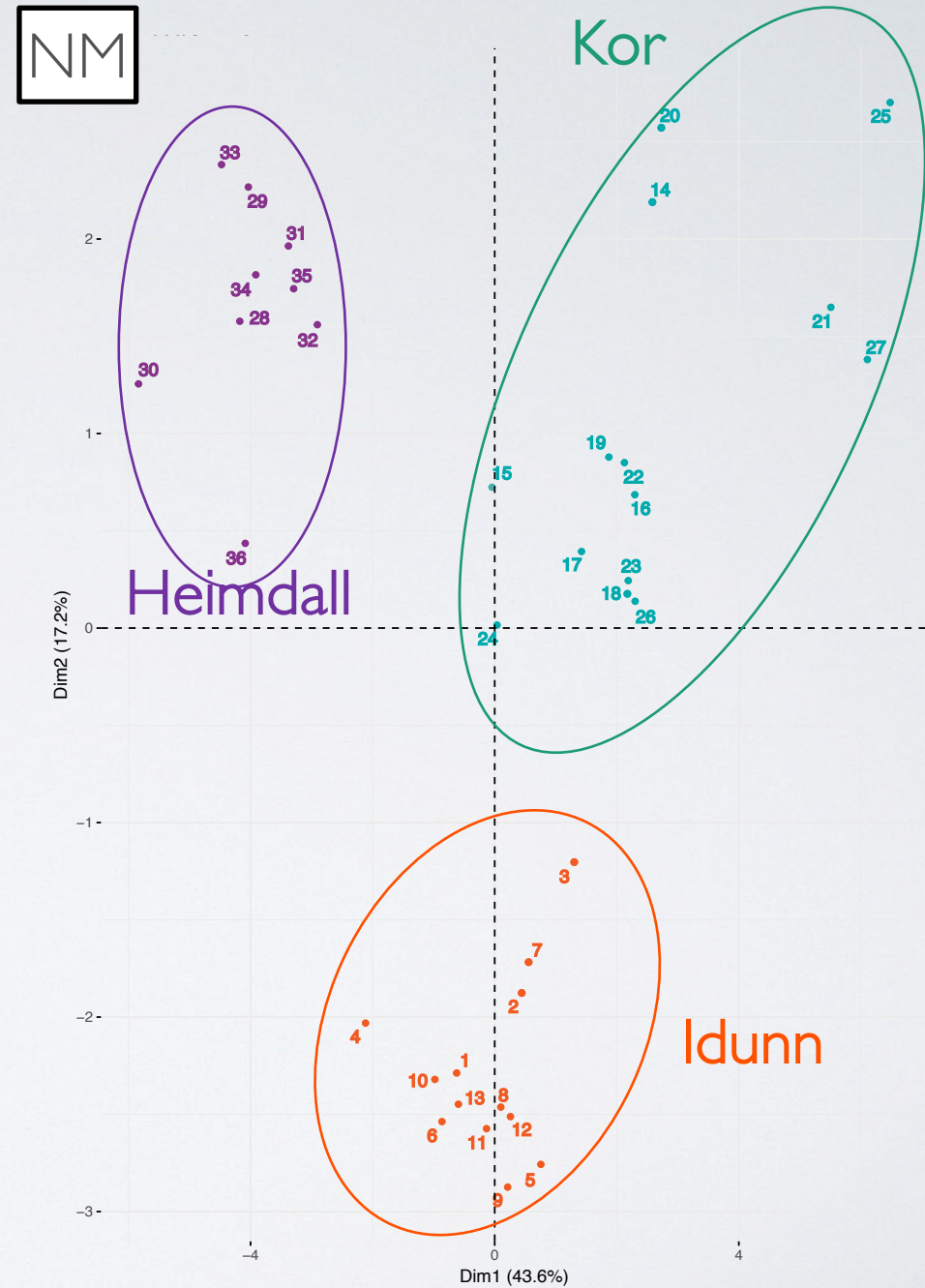
57 new markers (13485 aa), 195 taxa

IQ-tree C60+LG+F+G

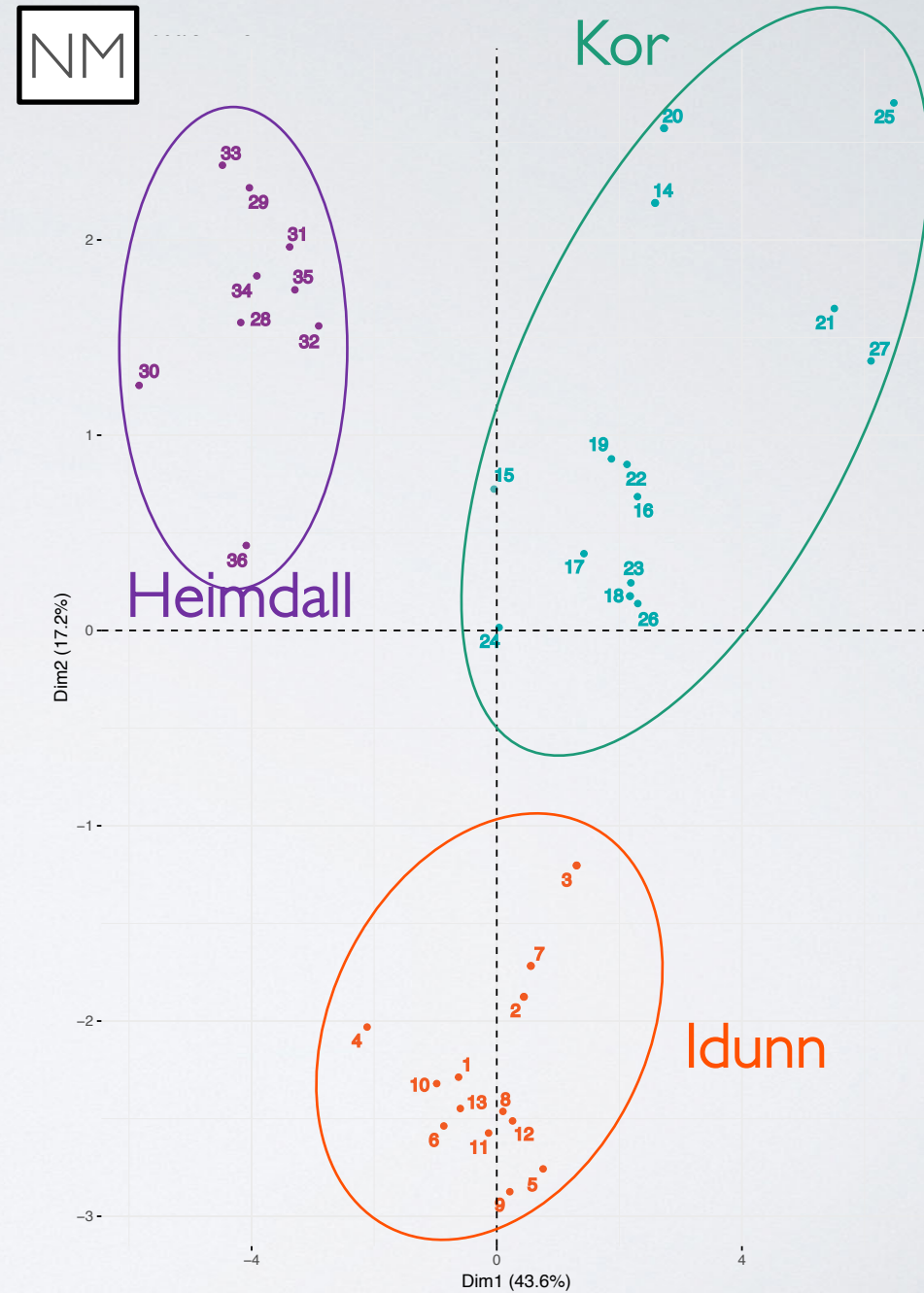
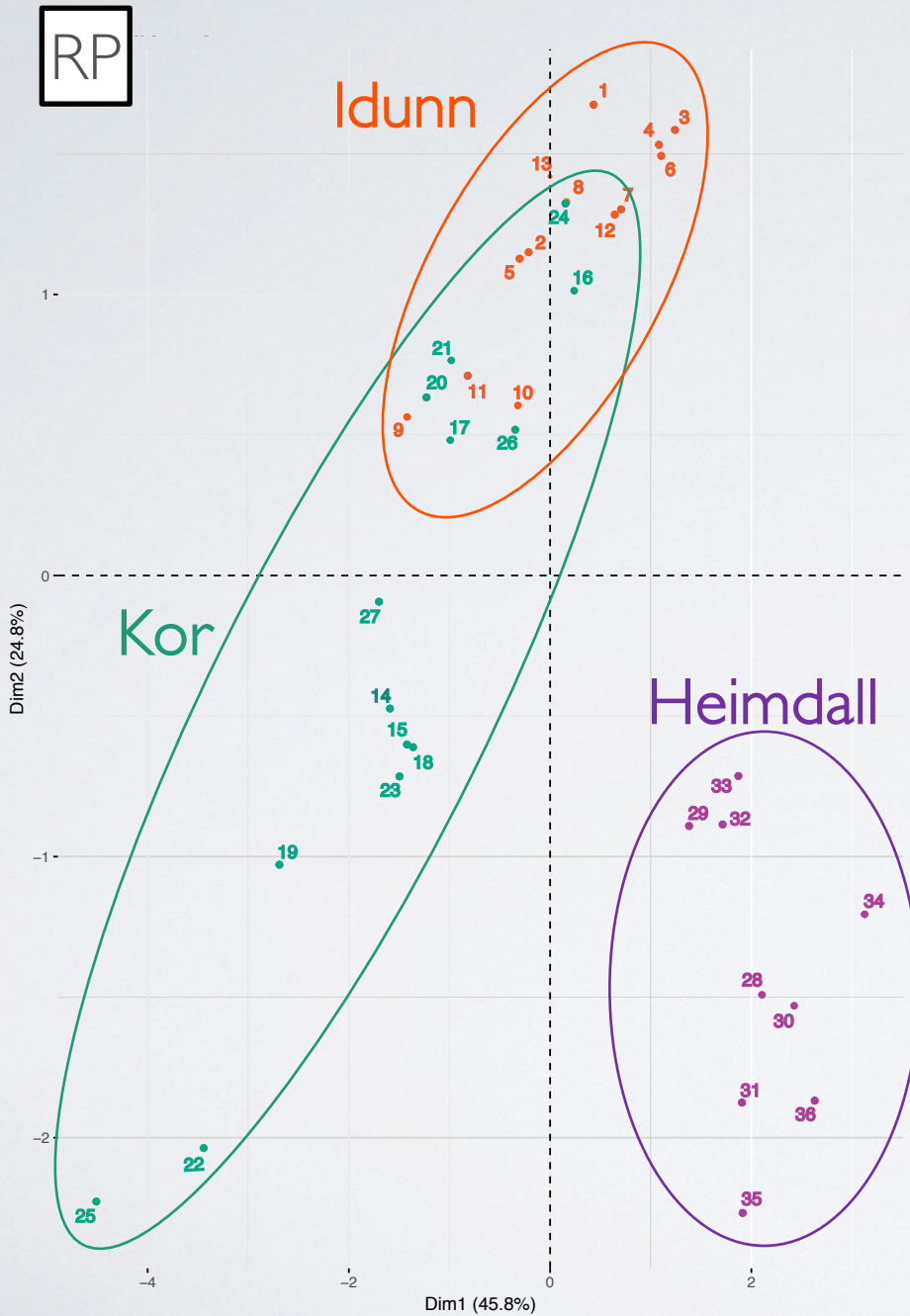


Investigating the discrepancy between RP and NM

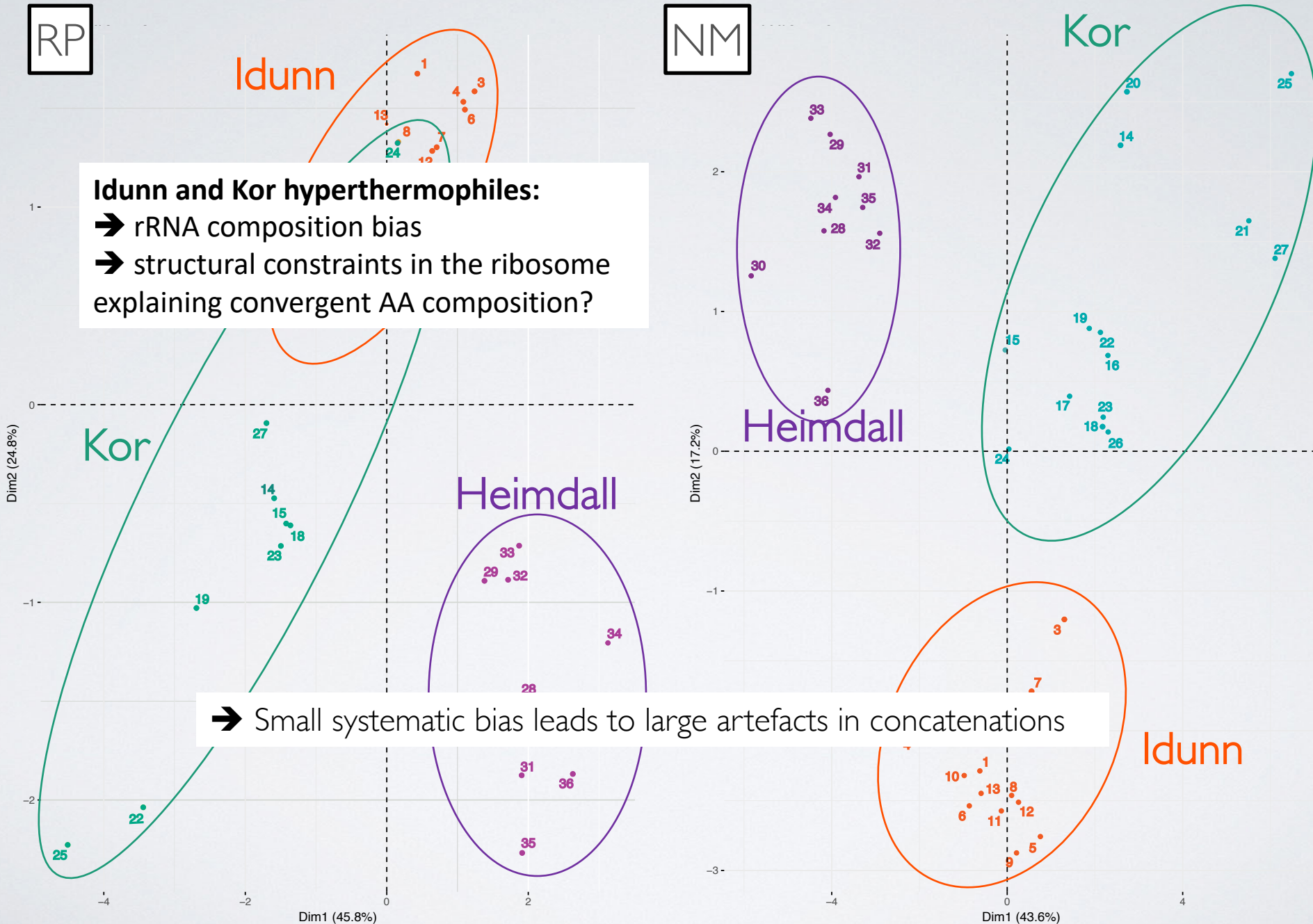
PCA based on aminoacid composition



PCA based on aminoacid composition



PCA based on aminoacid composition



Recoding

Recoding AA

- Recoding with the same state AAs which often substitutes for one another.
Eg: SR4 recoding scheme: AGNPST CHWY DEKQR FILMV
- Accommodates compositional biases and saturation
- Allows the use of more complex models because it reduces computational intensity

But...

- Reduces the amount of phylogenetic information

Other elements that impact your tree reconstruction

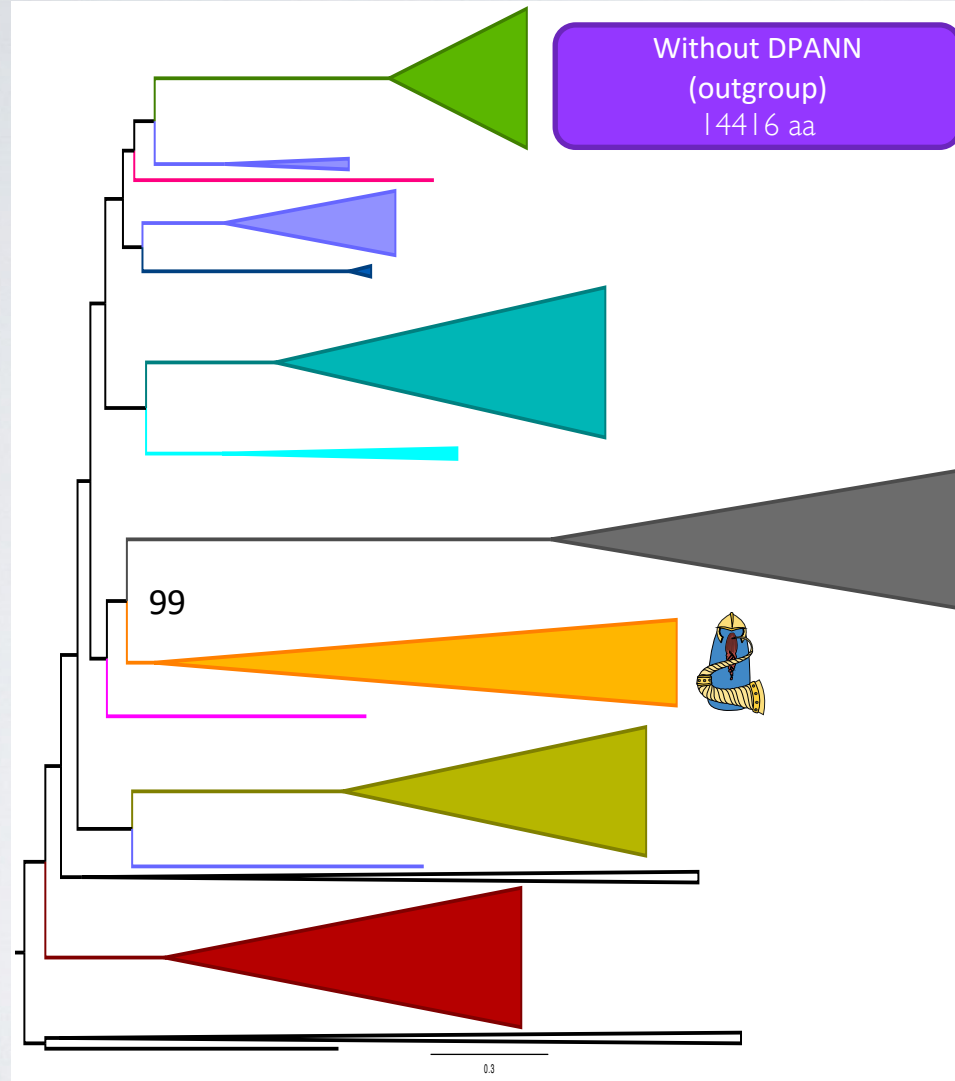
Alignment and trimming

The effect of realigning

Might be obvious but...

At this evolutionary scale, we need to realign for each taxon sampling, even for “well conserved” markers

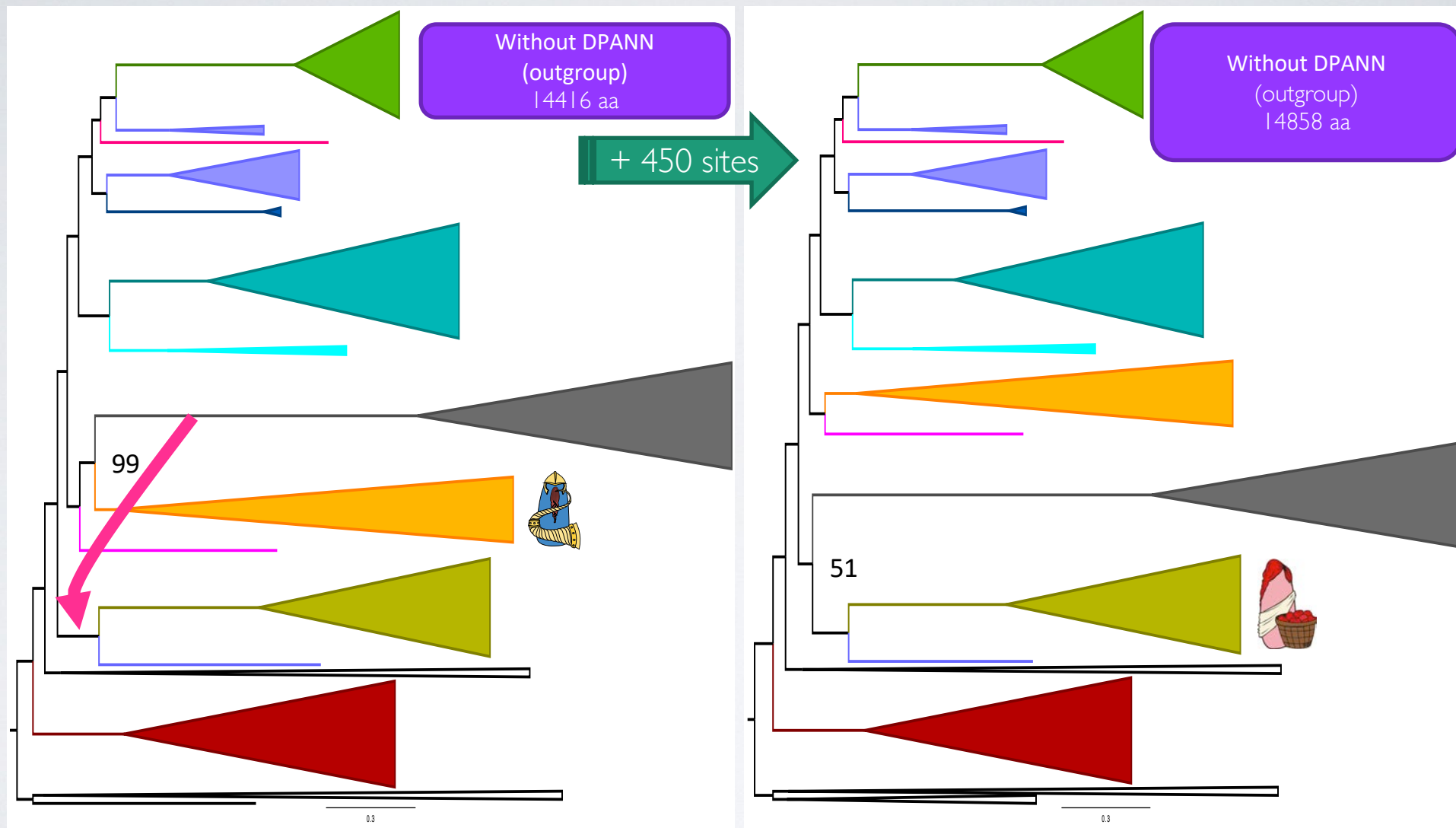
- ➔ Better quality alignments
- ➔ More sites after trimming



In agreement with Zaremba 2017

IQ-TREE (LG+C60+F+G+PMSF)

Realigned + trimmed after removing outgroups



IQ-TREE (LG+C60+F+G+PMSF)

If 3% of sites make such a difference...

ALIGNMENT AND TRIMMING STRATEGIES

MAFFT-LINSI



T-COFFEE

PROBCONS

Forward

MAFFT-LINSI



T-COFFEE

PROBCONS

Reverse

ALIGNMENT AND TRIMMING STRATEGIES

MAFFT-LINSI



T-COFFEE

PROBCONS

Forward

MAFFT-LINSI



T-COFFEE

PROBCONS

Reverse



ALIGNMENT AND TRIMMING STRATEGIES

I decided not to decide...

ALIGNMENT AND TRIMMING STRATEGIES

I decided not to decide...

- Trimal consensus mode (-ct 0.95)
 - ➔ Selects for 'consensually aligned sites' across the 6 alignments
- Allows to be less stringent about gaps and block sizes
 - ➔ Important at this evolutionary scale

parts of the backbone)

ALIGNMENT AND TRIMMING STRATEGIES

I decided not to decide...

- Trimal consensus mode (-ct 0.95)
 - ➔ Selects for 'consensually aligned sites' across the 6 alignments
- Allows to be less stringent about gaps and block sizes
 - ➔ Important at this evolutionary scale
 - ➔ Allows to keep putative synapomorphies (indels supporting specific parts of the backbone)

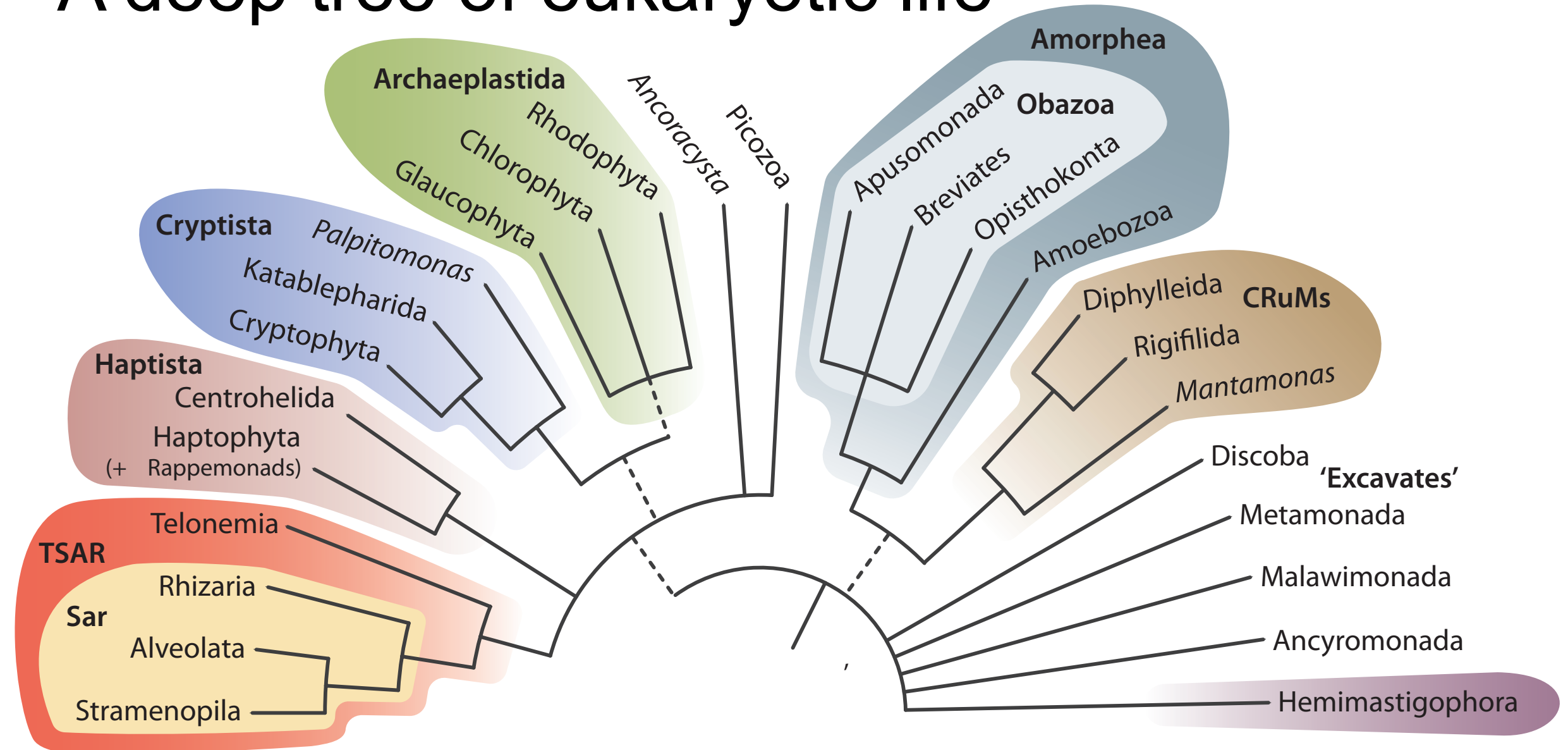
Useful tools

PHYLOFISHER

A phylogenetically aware pipeline for phylogenomic dataset construction

David Žihala, Alexander K. Tice, Tomáš Pánek, Serafim Nenarokov, Eric Salomaki,
Andrew J. Roger, Martin Kolísko, Fabien Burki, Laura Eme, Marek Eliáš,
Matthew W. Brown

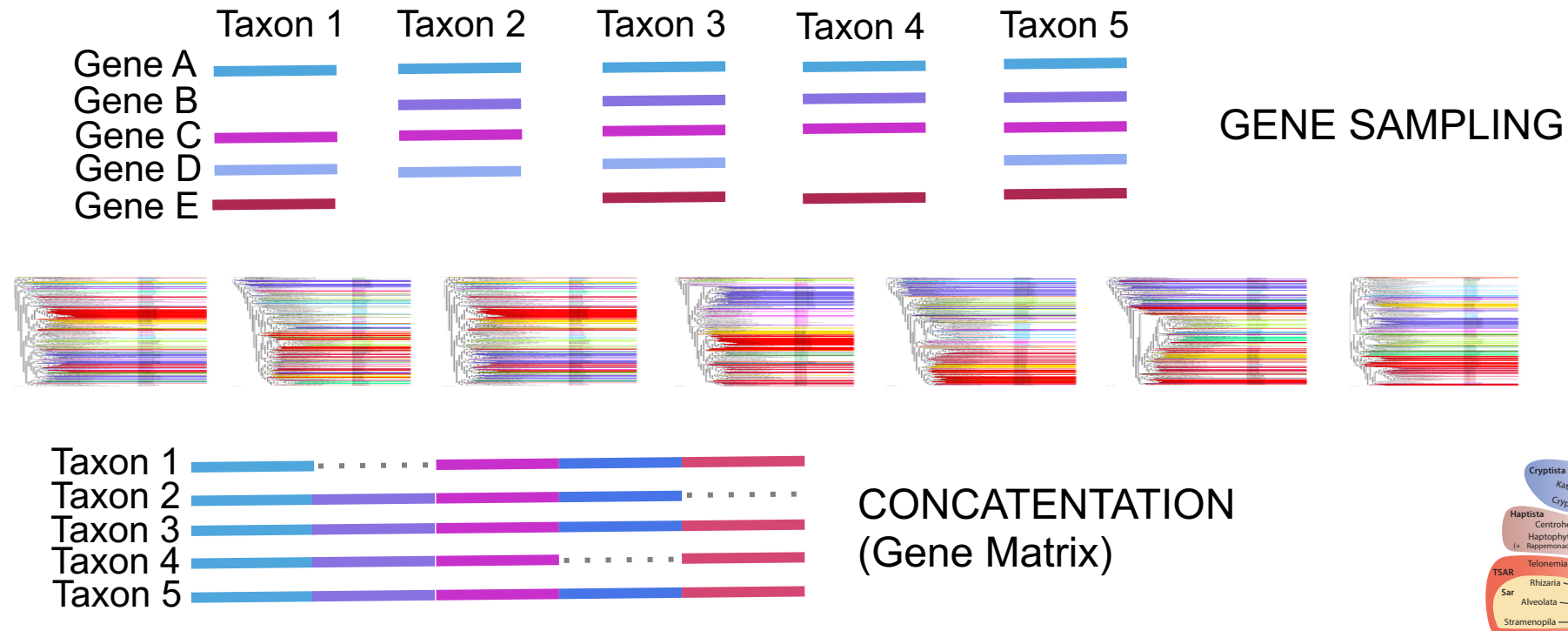
A deep tree of eukaryotic life



Edited from Burki et al. Under Revision - TREE

Multigene Phylogenetics – Phylogenomics

- Take multiple genes and infer a phylogeny
 - Genes A+B+C+D+E
- Offers more data
- Can handle missing data from taxa
- Concatenation
 - implies 1 taxon = 1 orthologous sequence



Selection of orthologs and orthologous sequences in them is critical



- Contamination
 - On sequencer
 - Endosymbionts
 - Prey (or predators)
- Paralogs
 - Genomic duplication
 - Deep- (i.e., a- vs b-tubulin)
 - Mid- (within a group)
 - In- (within a species (or genus))
- Phylogenetically informative
 - Broad taxonomic sampling
- To do this requires trees and careful consideration of them
 - Eyes

PHYLOFISHER

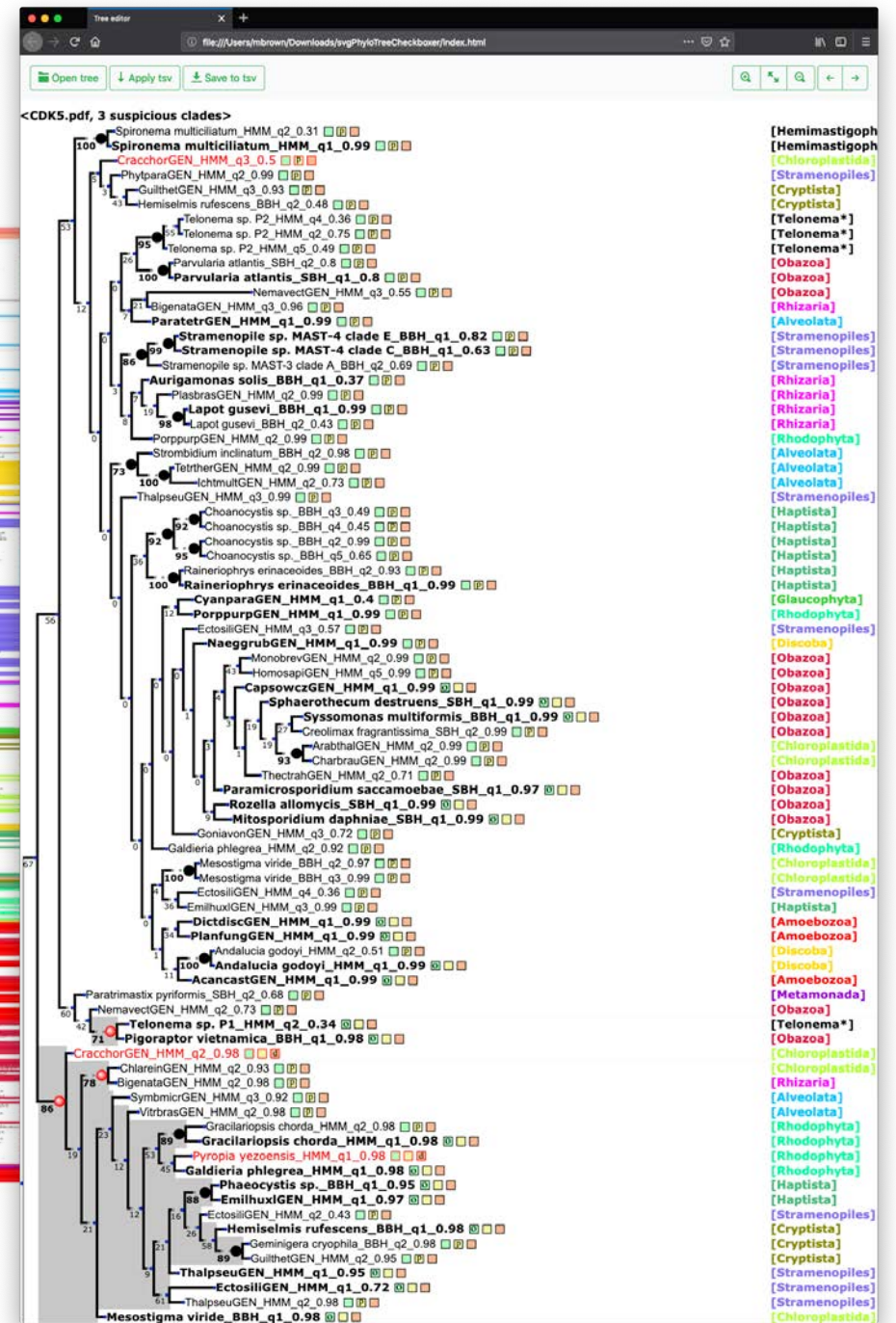
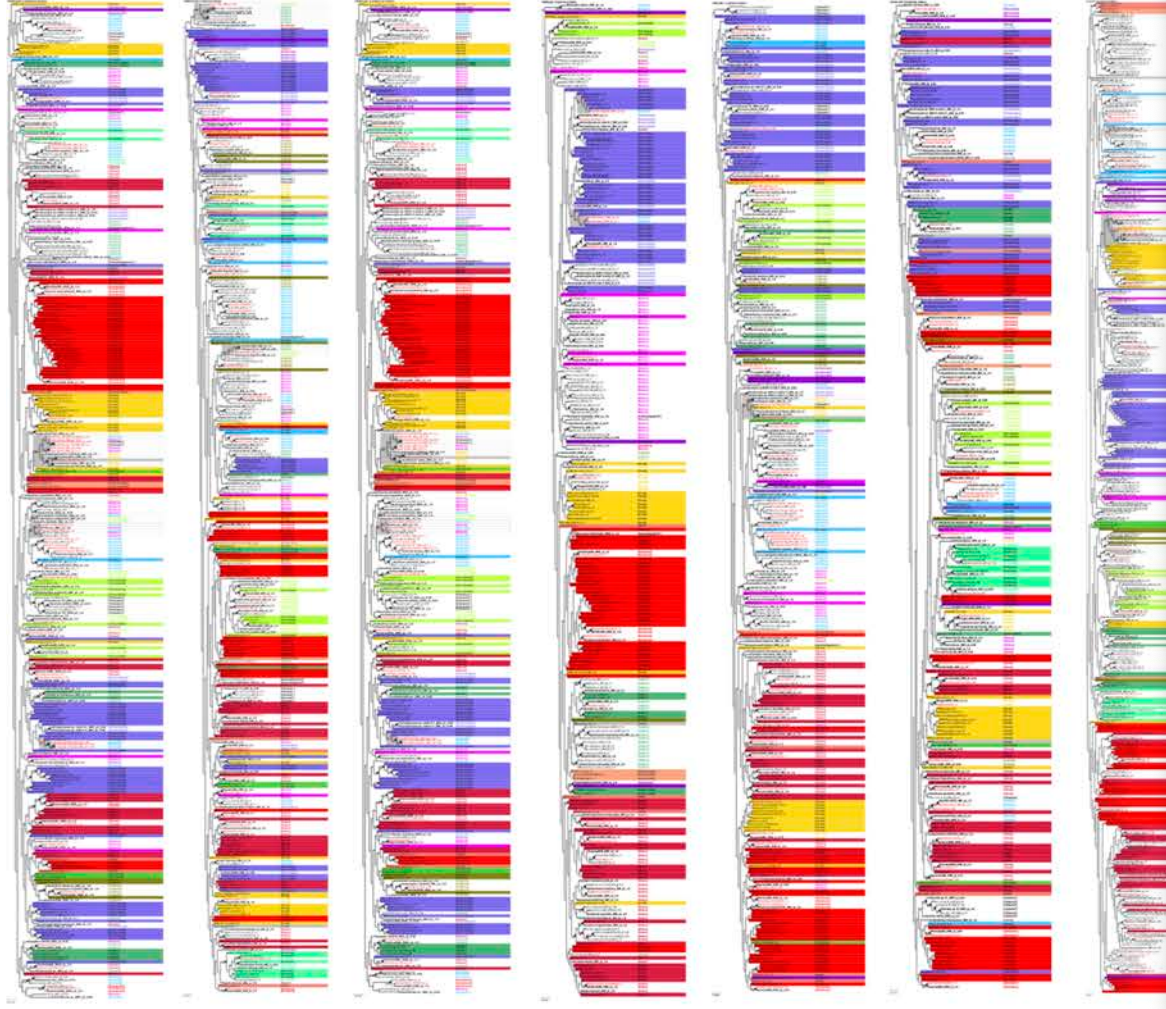
New method (and tool) allows for others to simply do phylogenomics

- Ships with a phylogenomic matrix and tool (via GitHub)
 - 310 Taxa, covering all deep eukaryotic groups
 - 240 Orthologs (whittled down from Brown et al. 2018)
- Coded in Python in a easy to to install CONDA environment
 - All dependencies are automatically installed



```
conda env create -f fisher_env.yml
```

Tree Inspection

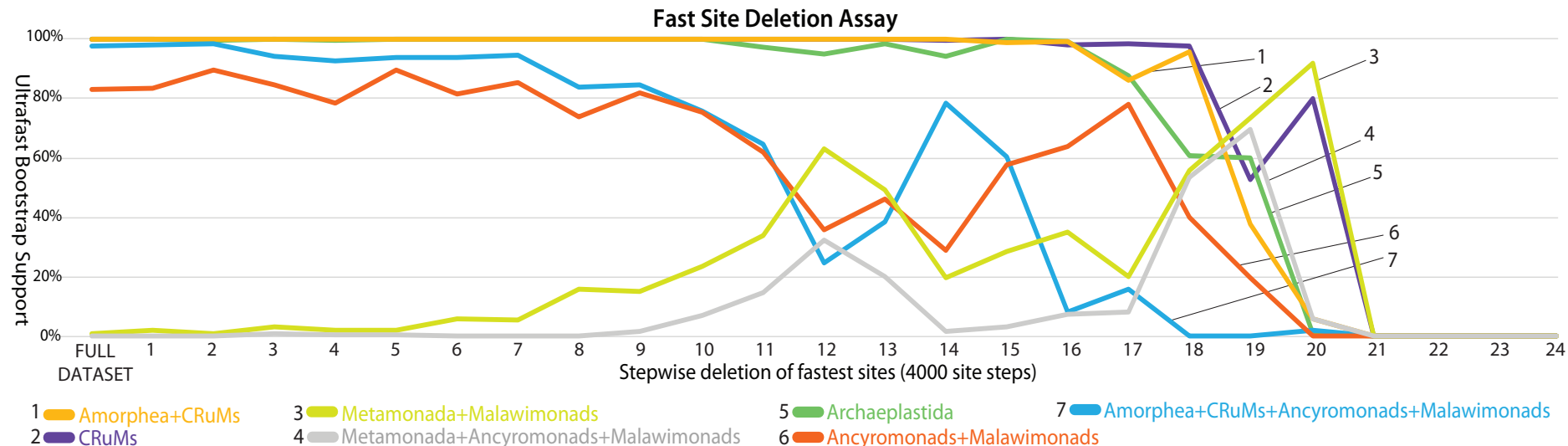


Tree Inspection



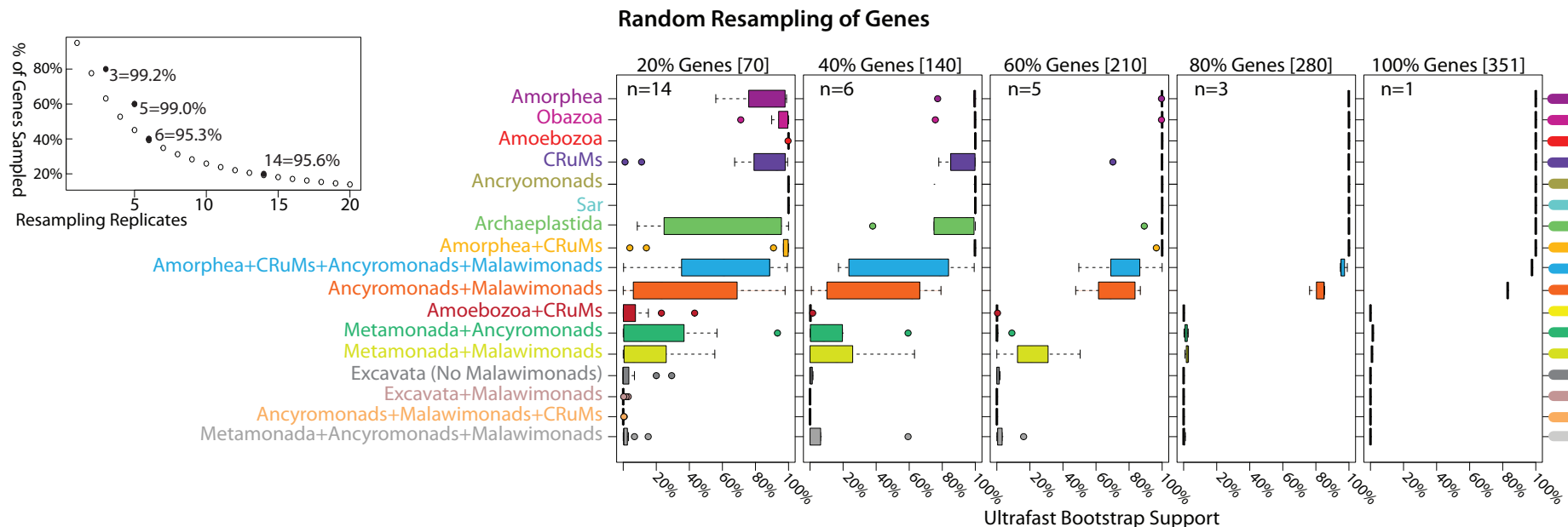
PHYLOFISHER

- Easily installed and simple usage
- Ships with our dataset
 - Includes Paralogs for tree building, more accurate identification
- Your own gene sets can be incorporated or used independently
- Tools for post-phylogenomic analyses



PHYLOFISHER

- Easily installed and simple usage
- Ships with our dataset
 - Includes Paralogs for tree building, more accurate identification
- Your own gene sets can be incorporated or used independently
- Tools for post-phylogenomic analyses



ETE3

A Python framework for the analysis and visualization of trees.

[Download](#)[Python API](#)[Cookbook](#)[Phylogenomic tools](#)[Contribute](#)

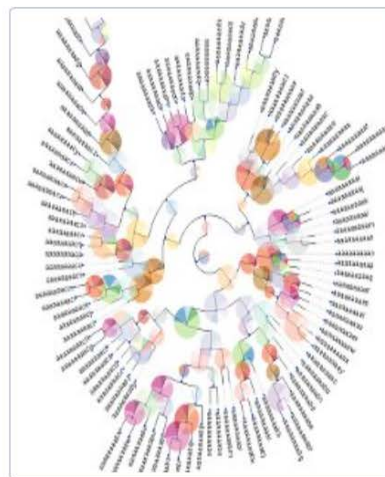
```
from ete3 import Tree
tree = Tree('((A,B), D);')

print tree
#      /-A
#     /-|
#    --| \-B
#     |  \-D

A = tree & "A"
A.up.show()
```

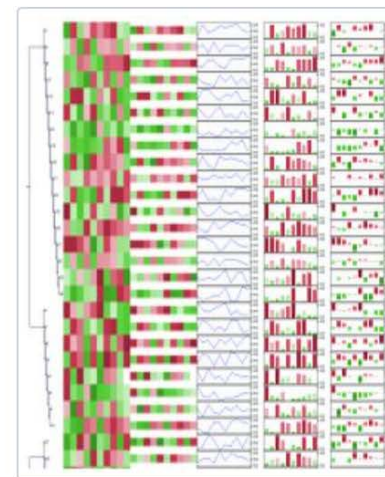
Trees as Python objects

Load, create, traverse, search, prune, or modify hierarchical tree structures with ease using the ETE Python API.



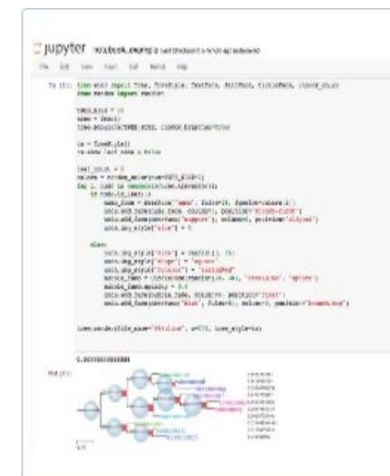
Programmatic tree visualization

Get full control of your tree images. Browse them interactively or render SVG, PNG or PDF images.



Tree annotation

Custom node attributes can be rendered as graphical elements. Choose among external images, charts, symbols, text labels, and



Jupyter notebook support

Prototype your methods using the Jupyter notebook framework including inline visualization of trees.

Signal in your data can be 'real'
(non artefactual) and still not
reflect the species tree

Gene trees may or may not = Species trees

Three main reasons:

- (A) Deep coalescence of alleles *(but usually ignored at this evolutionary scale)*
- (B) paralogy and orthology
- (C) lateral gene transfer (xenology)

Throw out data that is inconsistent

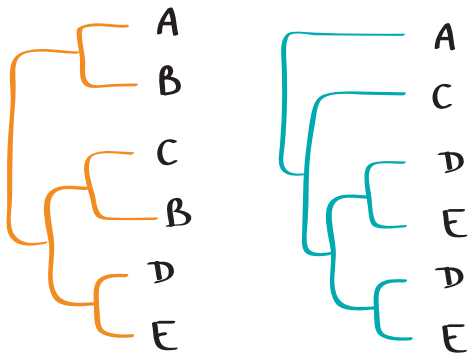
Try to model these events

Gene tree / Species tree reconciliation methods

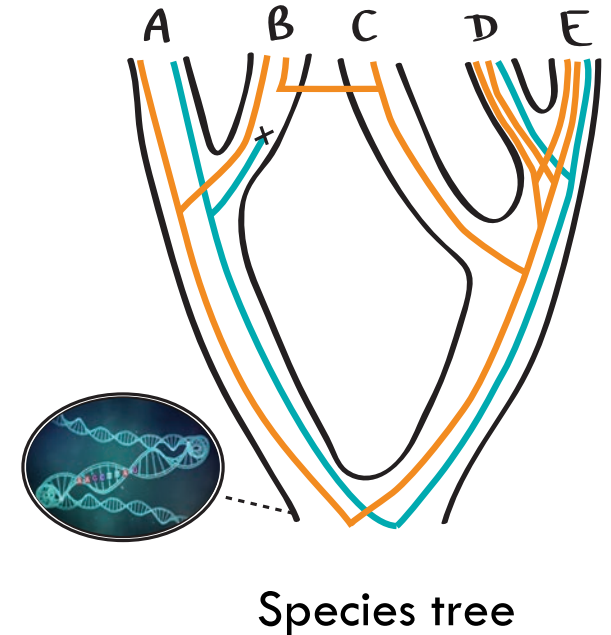
Reconciliation approaches

ALE
Phyldog
BUCKy
ecceTERA

Reconciliation



- Rooted species tree
- Losses and/or duplications and/or transfers and/or coalescence
- Ancestral gene content
- Use HGT to date clades

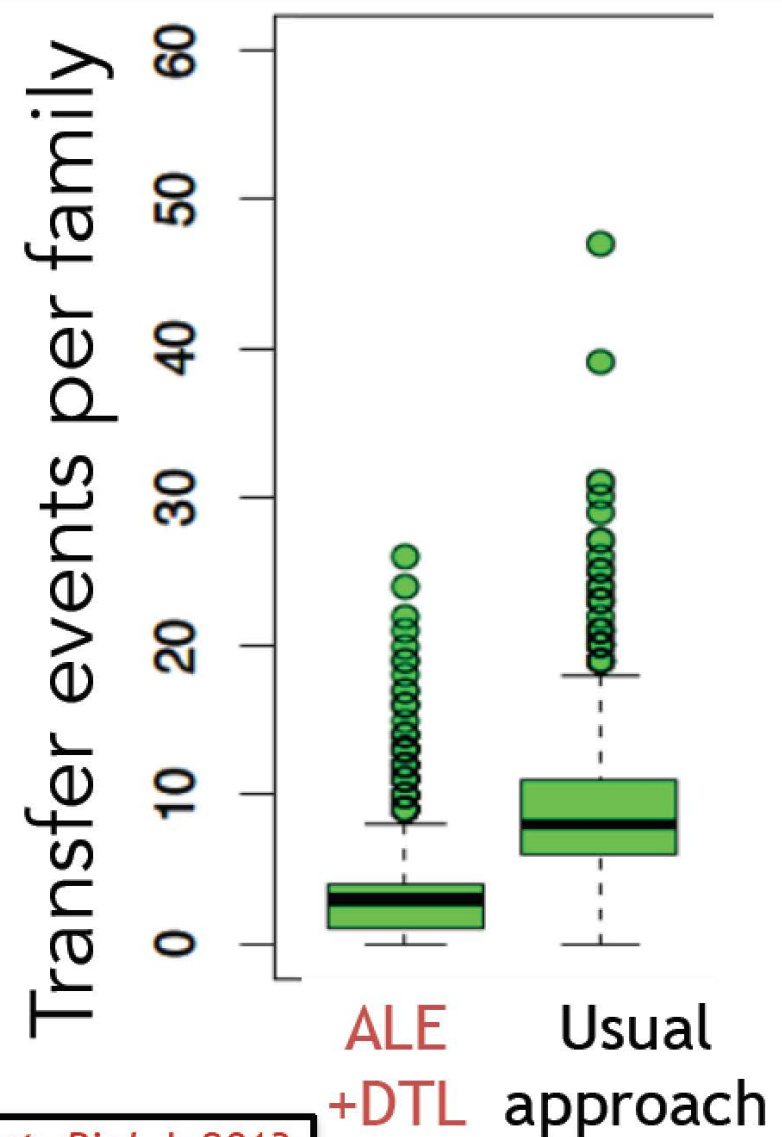
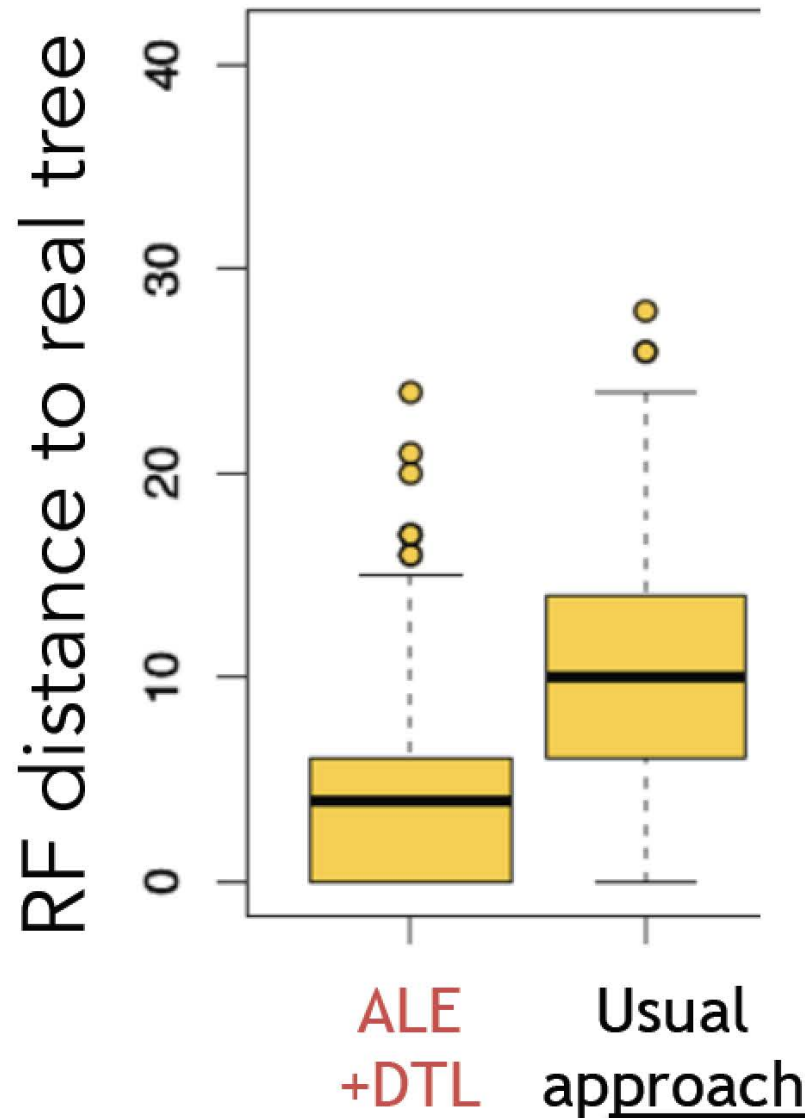


exODT: a model of gene duplication, transfer, and loss

Assumptions

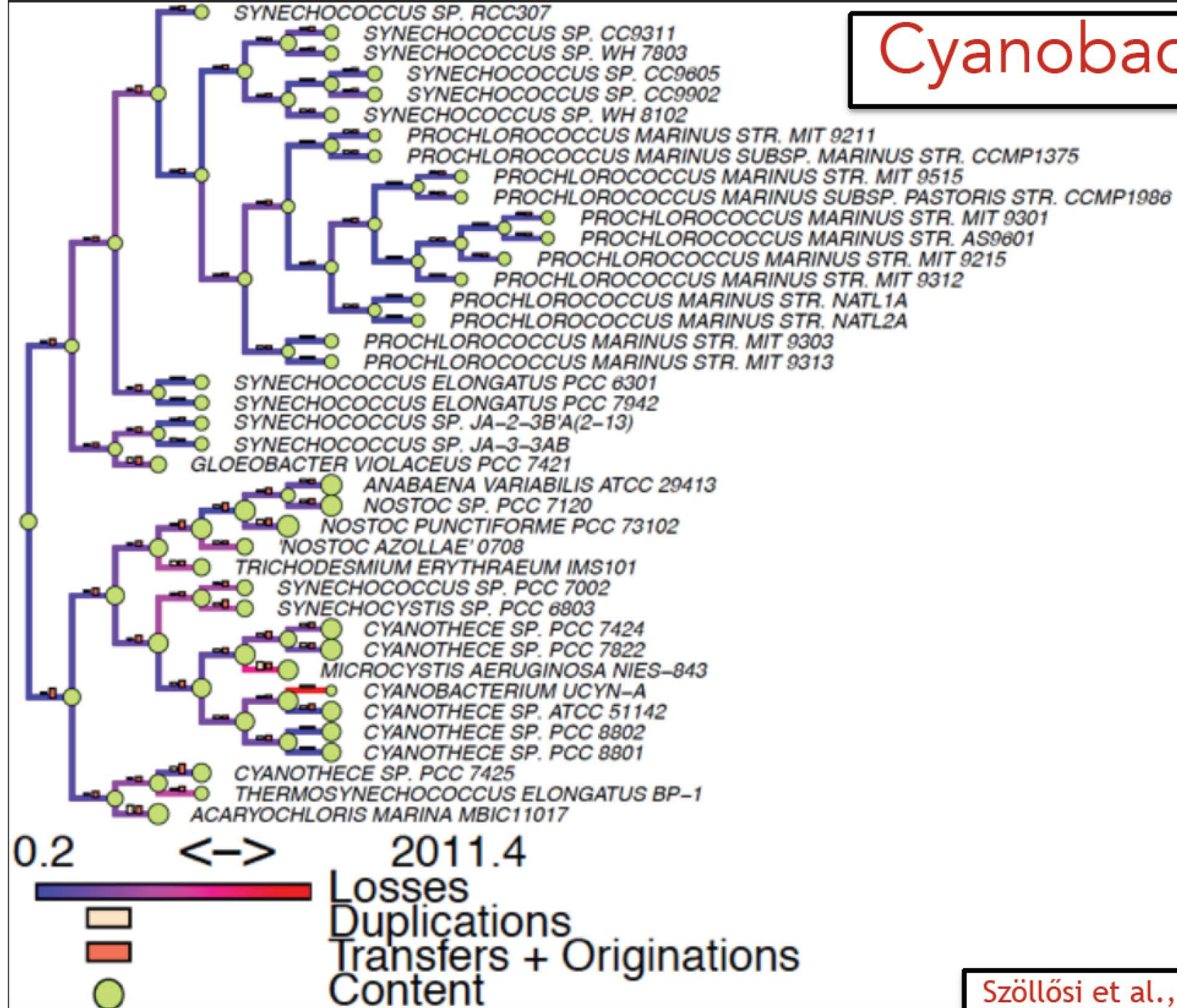
- Genes evolve along the species tree:
 - birth events:
 - duplications (rate of duplication)
 - transfers (rate of receiving a gene)
 - death events:
 - losses (rate of loss)
- Each gene family is independent of other genes
- Each gene copy is independent of other copies
- Transfers can go through unsampled/extinct species

Better gene trees, fewer transfers

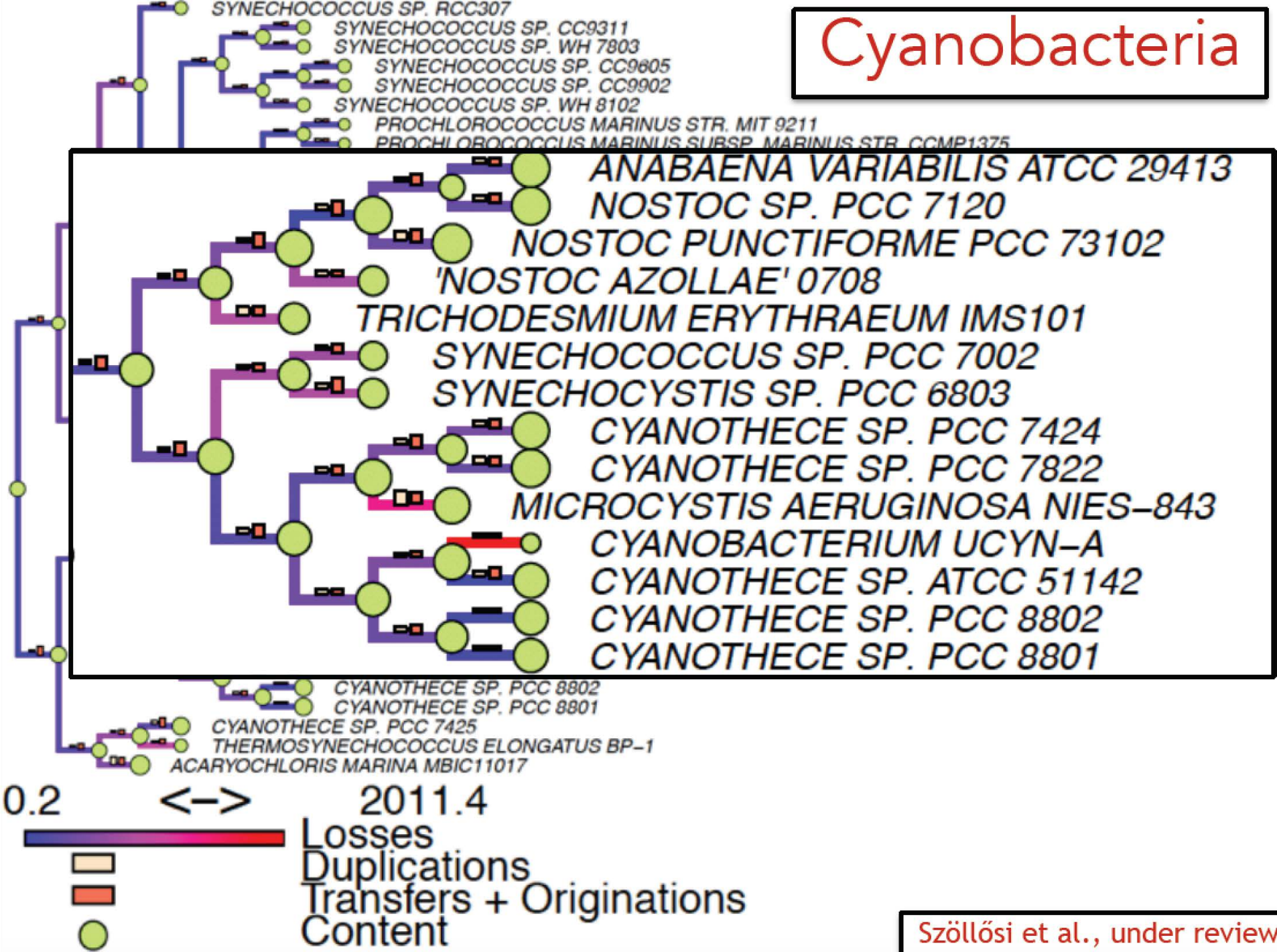


Szöllősi et al., *Syst. Biol.* b 2013

Cyanobacteria



Cyanobacteria



Using transfers to date clades

