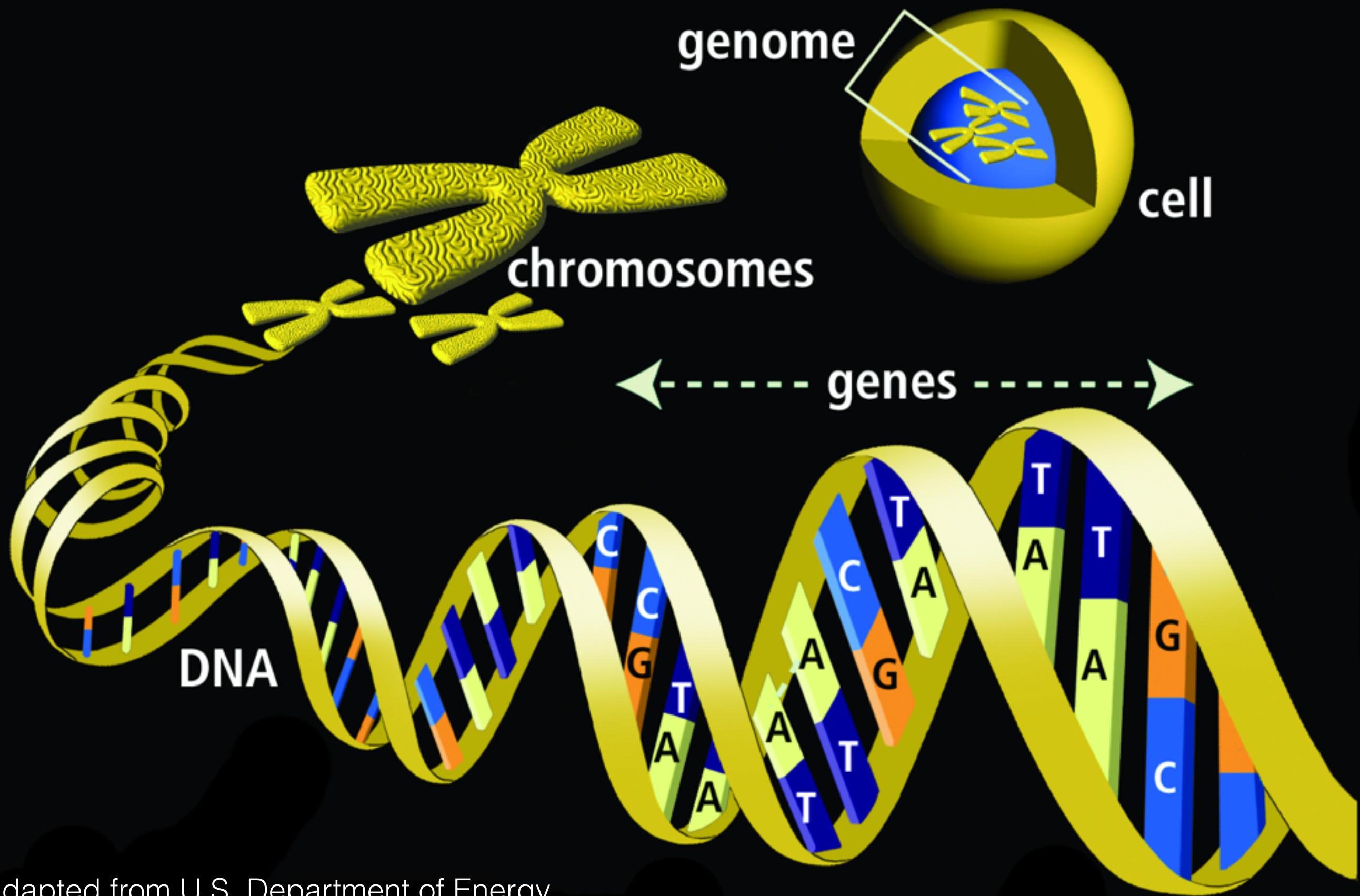


From Genes to Genomes and Beyond: a Computational Approach to Evolutionary Analysis

Kevin J. Liu, Ph.D.
Rice University Dept. of Computer Science



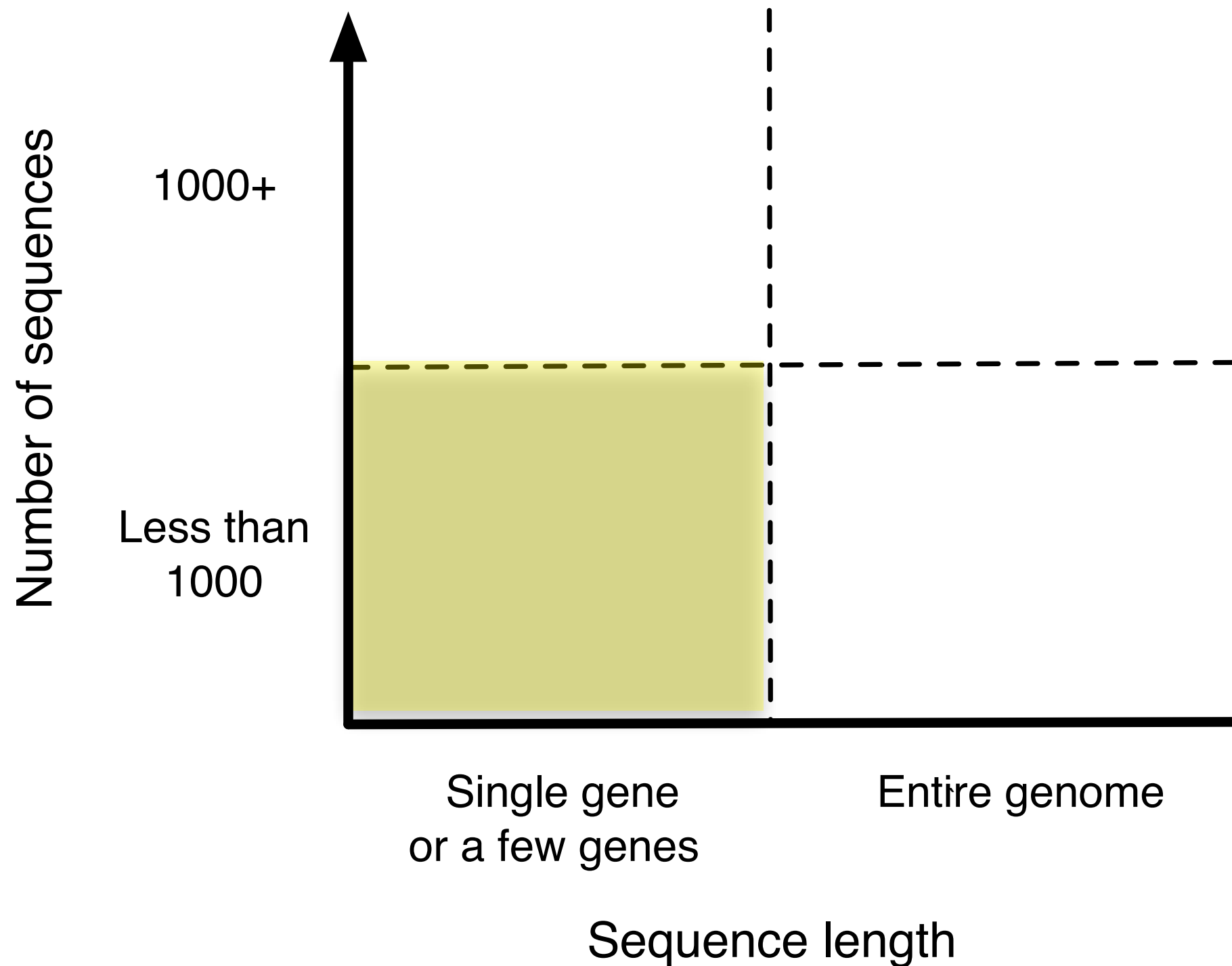
Adapted from U.S. Department of Energy
Genomic Science Program
(genomicscience.energy.gov)

Evolution: Unifying Theme

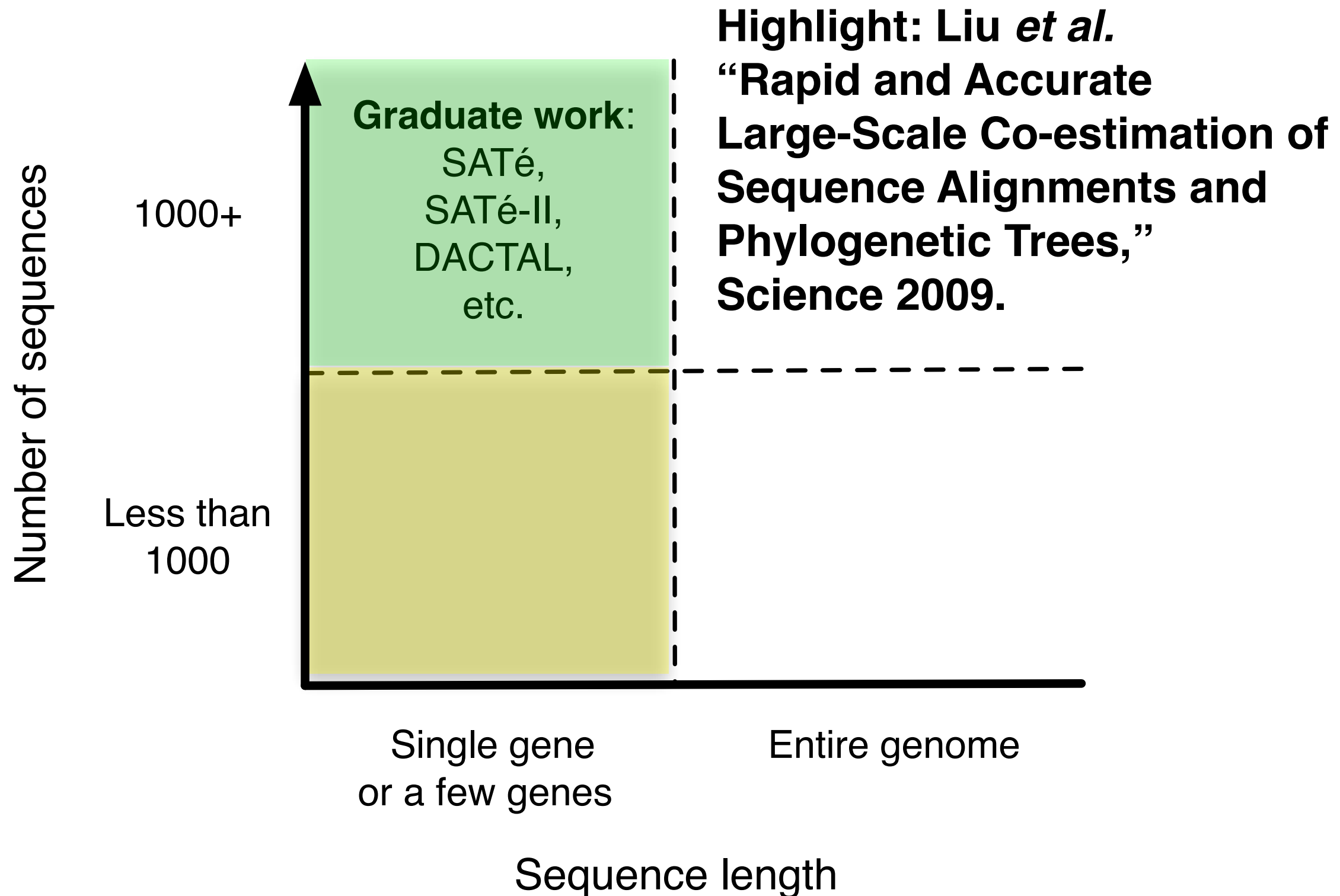
#1

- “Nothing In Biology Makes Sense Except in the Light of Evolution” – 1973 essay by T. Dobzhansky, a famous biologist
- Overarching goal: use evolutionary principles to:
 - Create computational methodology to analyze heterogeneous large-scale biological data,
 - Then apply findings to obtain new biological and biomedical discoveries

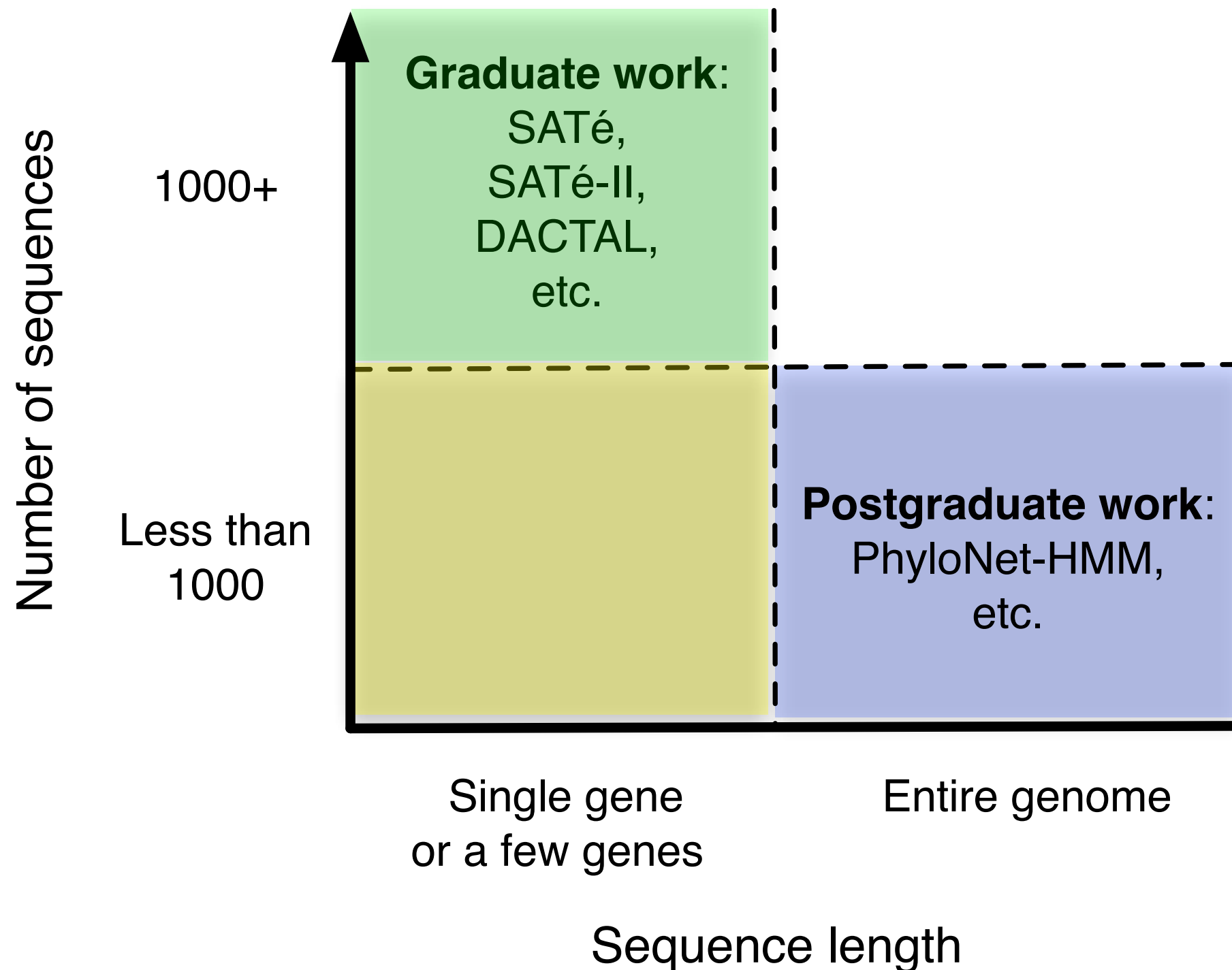
Big Data: Unifying Theme #2



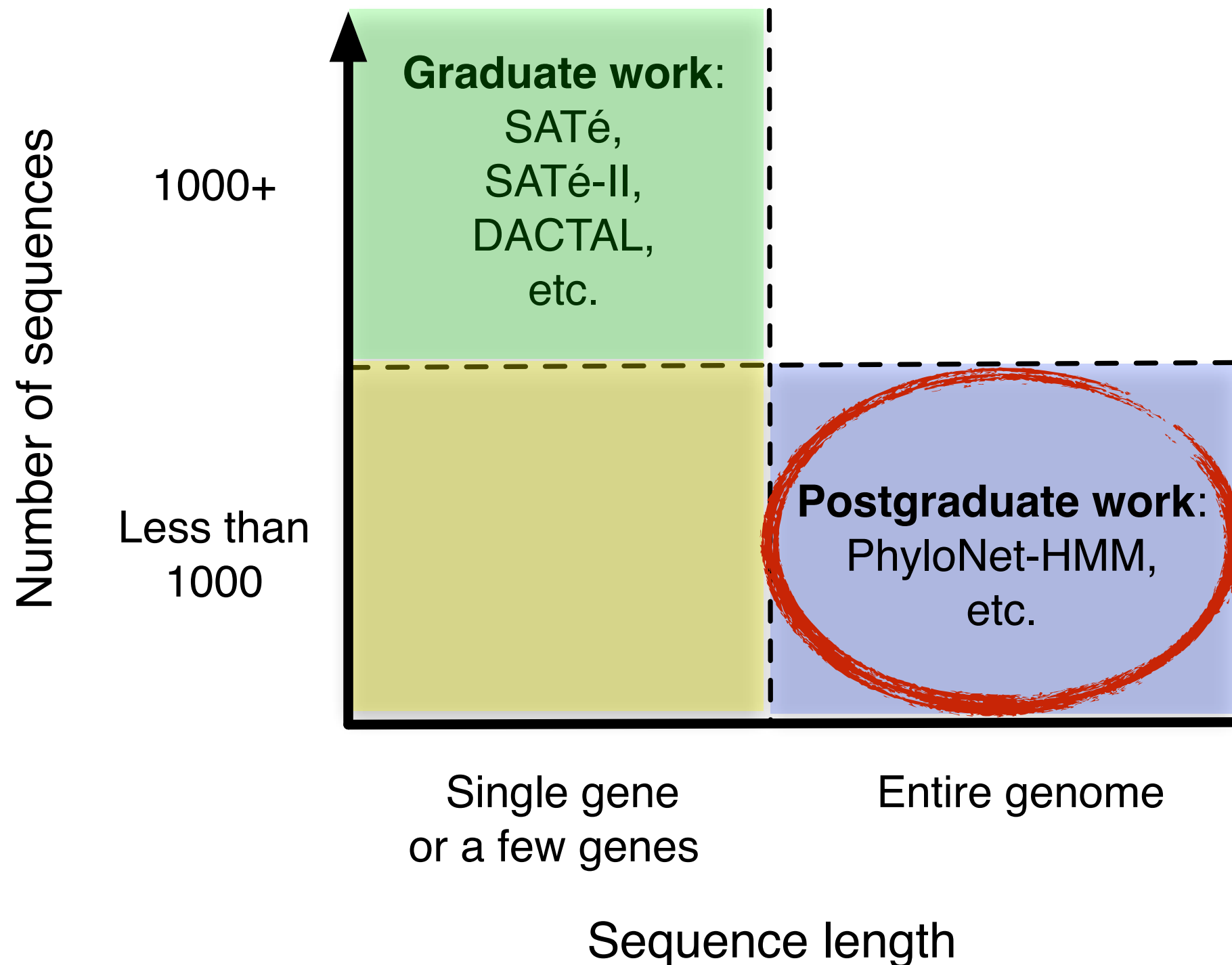
Big Data: Unifying Theme #2



Big Data: Unifying Theme #2



Big Data: Unifying Theme #2



The Spread of Warfarin Resistance Between Two Mouse Species

Current Biology 21, 1296–1301, August 9, 2011 ©2011 Elsevier Ltd All rights reserved DOI 10.1016/j.cub.2011.06.043

Report

Adaptive Introgression of Anticoagulant Rodent Poison Resistance by Hybridization between Old World Mice

Ying Song,¹ Stefan Endepols,² Nicole Klemann,³ Dania Richter,⁴ Franz-Rainer Matuschka,⁴ Ching-Hua Shih,¹ Michael W. Nachman,⁵ and Michael H. Kohn^{1,*}

¹Department of Ecology and Evolutionary Biology, Rice University, Houston, TX 77005, USA

²Environmental Science, Bayer CropScience AG, D-40789 Monheim, Germany

³D-48231 Warendorf, Germany

⁴Division of Pathology, Department of Parasitology, Charité–Universitätsmedizin, D-10117 Berlin, Germany

⁵Department of Ecology and Evolution, University of Arizona, Tucson, AZ 85721, USA

to alter blood clotting kinetics and/or in vitro VKOR activities in humans and rodents in response to exposure to anticoagulants [2]; additional SNPs in *vkorc1* await such experimental proof. A mere ~10 years after the inception of warfarin as a rodenticide in the 1950s, reports of resistant Norway rats (*Rattus norvegicus*) emerged between 1960 and 1969, followed by reports of resistant house mice (*Mus musculus* spp.) in 1964, roof rats (*R. rattus*) in 1972, and other rat species (e.g., *R. tiomanicus*, *R. r. diardii*, and *R. losea*) [3, 8–10]. Resistant rodent colonies have been discovered in Europe, the Americas, Asia, and Australia [8]. In response to such warfarin-resistant colonies, other anticoagulant rodenticides were developed that target VKOR, including coumatetralyl,

Warfarin and Adverse Events

- Warfarin is the most widely prescribed blood thinner
- Treatment is complicated because every patient is different
 - Gene mutations confer resistance or susceptibility
- Annually,
 - 85,000 serious bleeding events
 - 17,000 strokes
 - Cost: \$1.1 billion

The *Vkorc1* Gene and Personalized Warfarin Therapy



- Mutant *Vkorc1* gene contributes to warfarin resistance
- Warfarin resistant individuals require larger-than-normal dose to prevent clotting complications (like stroke)

Rost et al. Nature 427, 537-541 2004.

Warfarin is Really Glorified Rodent Poison



Reproduced from UTMB.

Recasting the Study of Introgression as a Computational Question

- Humans inadvertently started a gigantic drug trial by giving warfarin to mice in the wild
- Mice shared genes (including one that confers warfarin resistance) to survive (Song *et al.* 2011)
 - Gene sharing occurred between two different species (introgression)
- To find out results from the drug trial, we just need to analyze the genomes of introgressed mice and locate the introgressed genes

Related Applications

- Similar computational approaches can be used to study gene flow between species in other contexts
 - Constitutes basic research of interest to the NSF
- Wide range of applications of interest to different funding agencies, including:
 - The role of horizontal gene transfer in the spread of antibiotic resistance in bacteria (NIH)
 - Metabolism of hybrid yeast species, with applications in metabolic engineering (DOE)
 - Disease resistance of hybrid plant species (USDA)

Problem:
Computational
Introgression
Detection

Input:

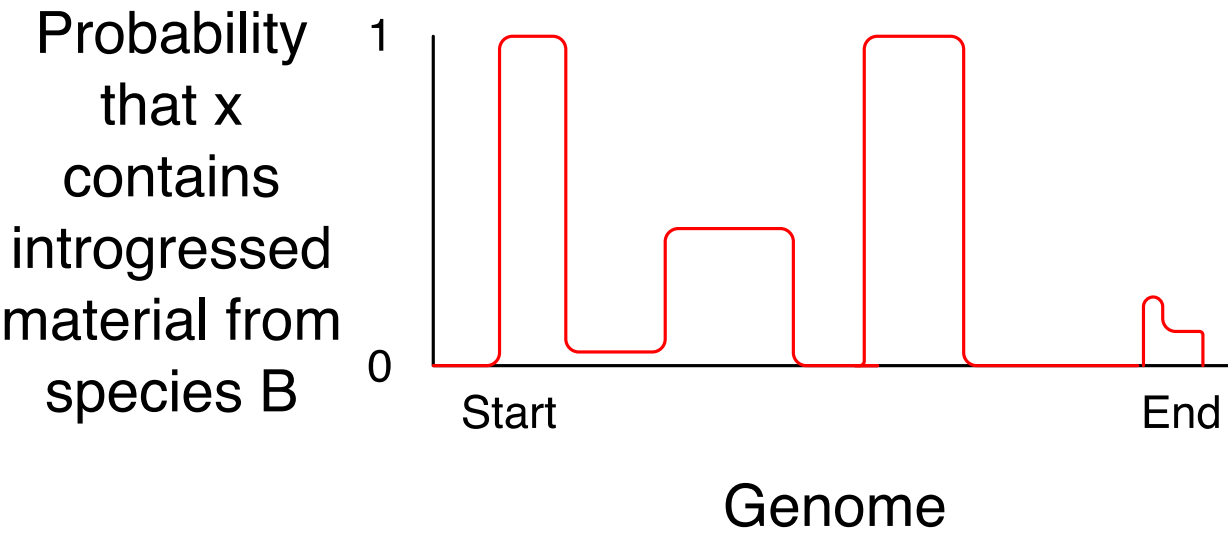
Species	Genome ID	Introgressed?
A	x	Unknown
A	a ₁	No
...
A	a _k	No
B	b ₁	No
...
B	b _l	No

Problem:
Computational
Introgression
Detection

Input:

Species	Genome ID	Introgressed?
A	x	Unknown
A	a ₁	No
...
A	a _k	No
B	b ₁	No
...
B	b _l	No

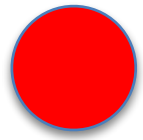
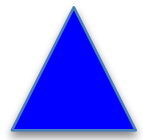
Output:



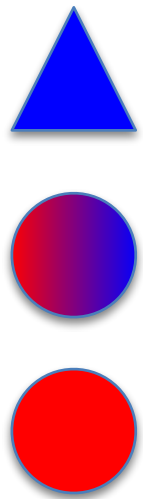
Naïve Sliding Windows

1. Break the genome into segments using a sliding-window (or other approaches)
2. Estimate a local tree in between every pair of breakpoints

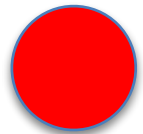
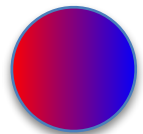
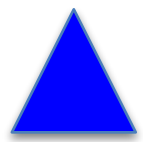
Sliding Windows (Example)



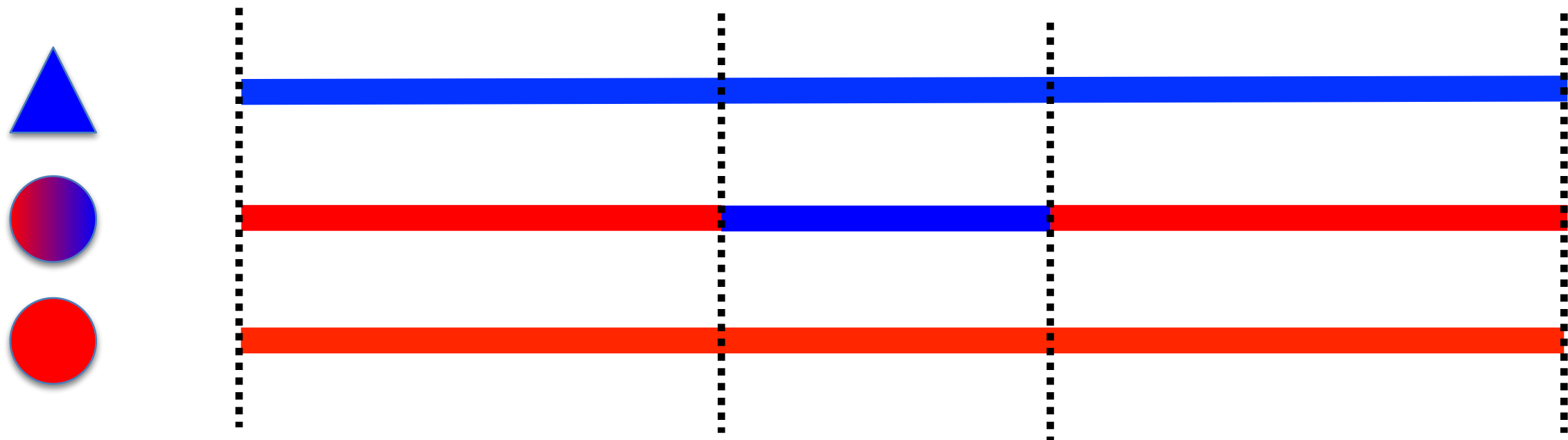
Sliding Windows (Example)



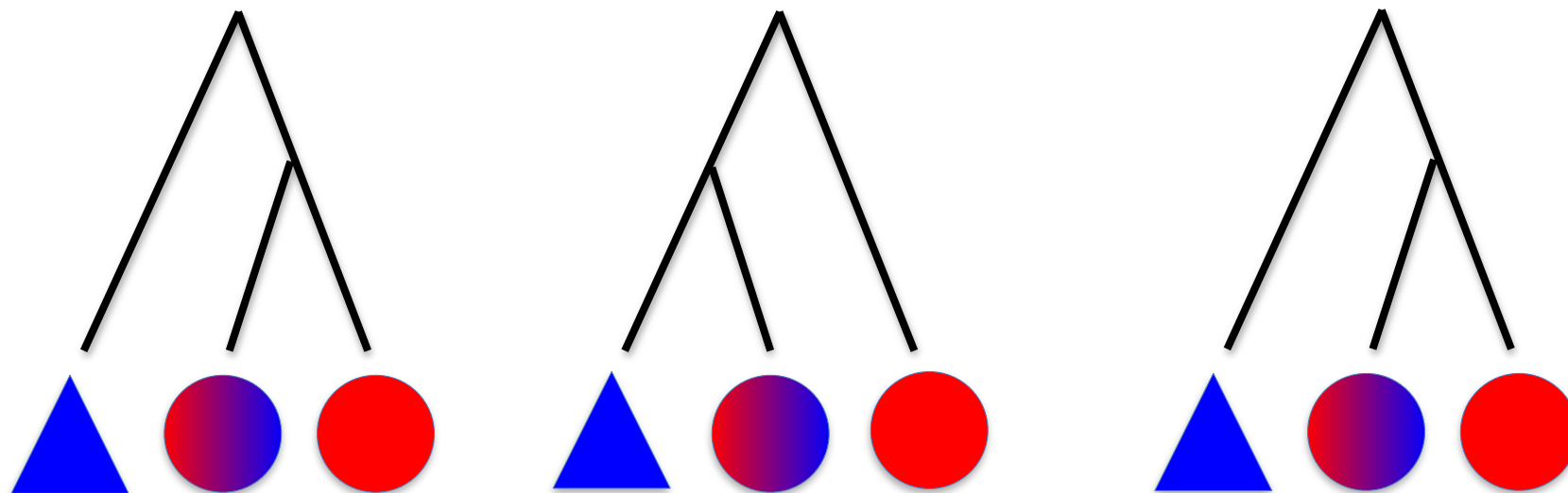
Sliding Windows (Example)



Sliding Windows (Example)

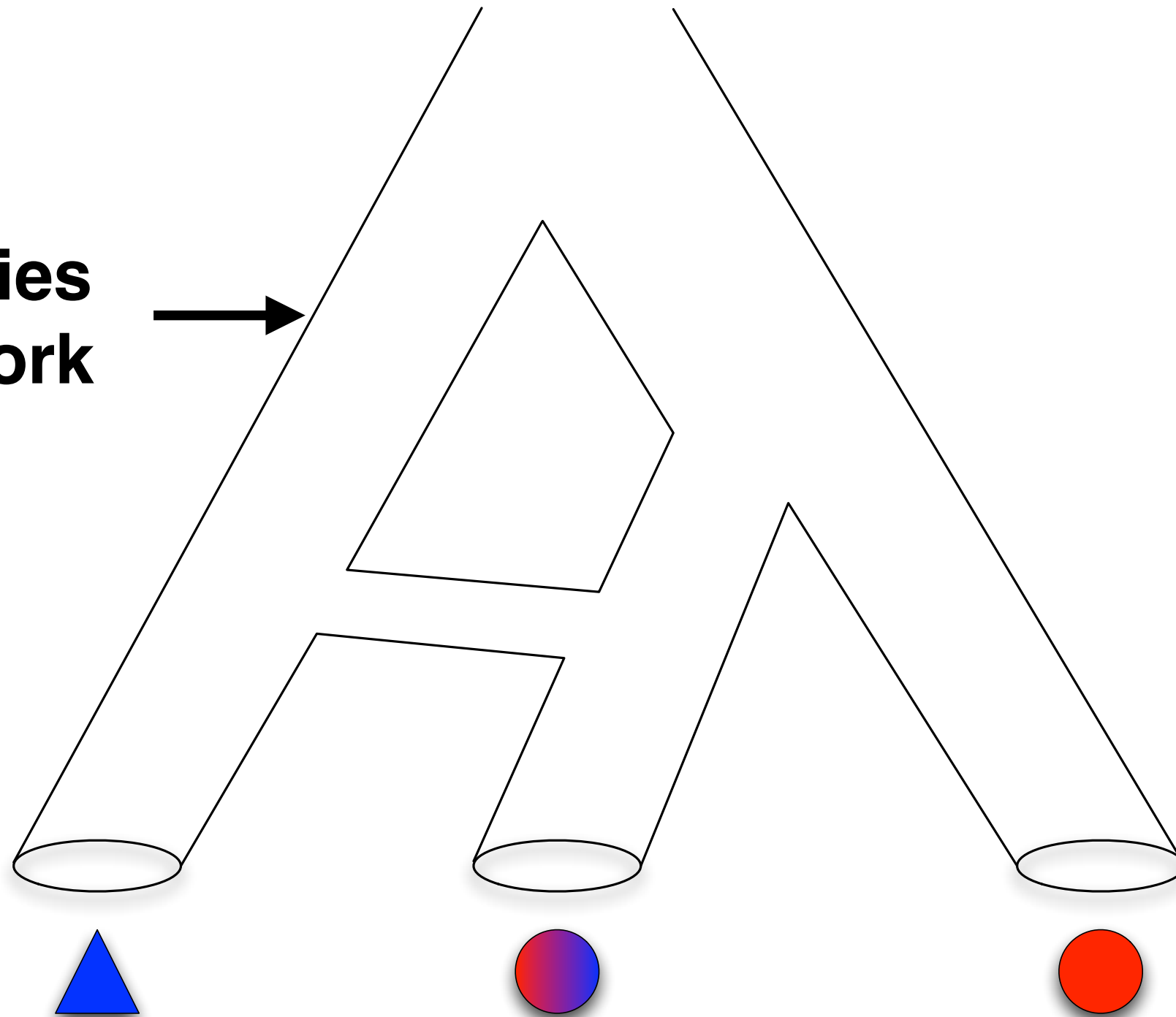


**Gene tree
incongruence!**

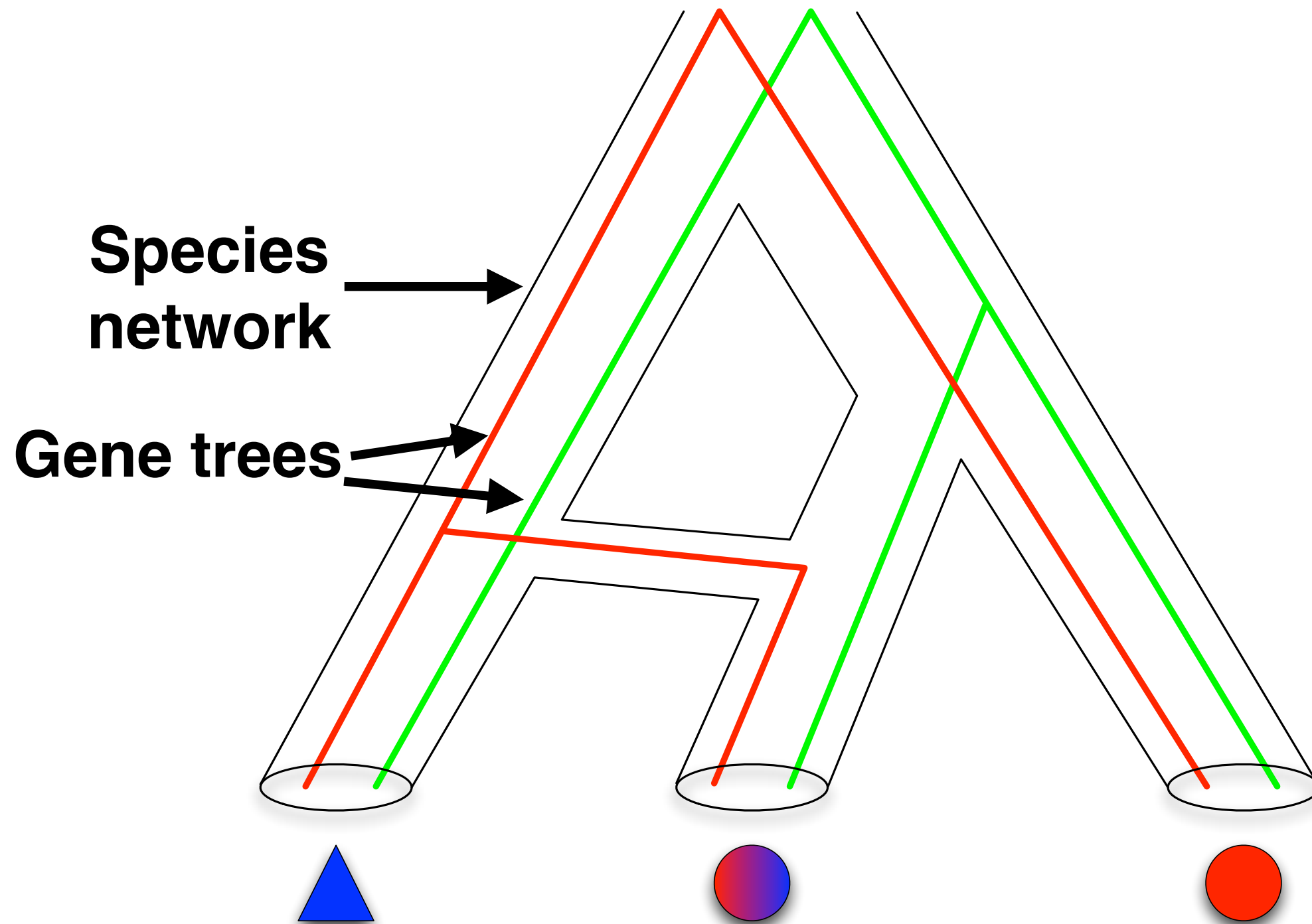


“Horizontal” Gene Tree Incongruence (Example)

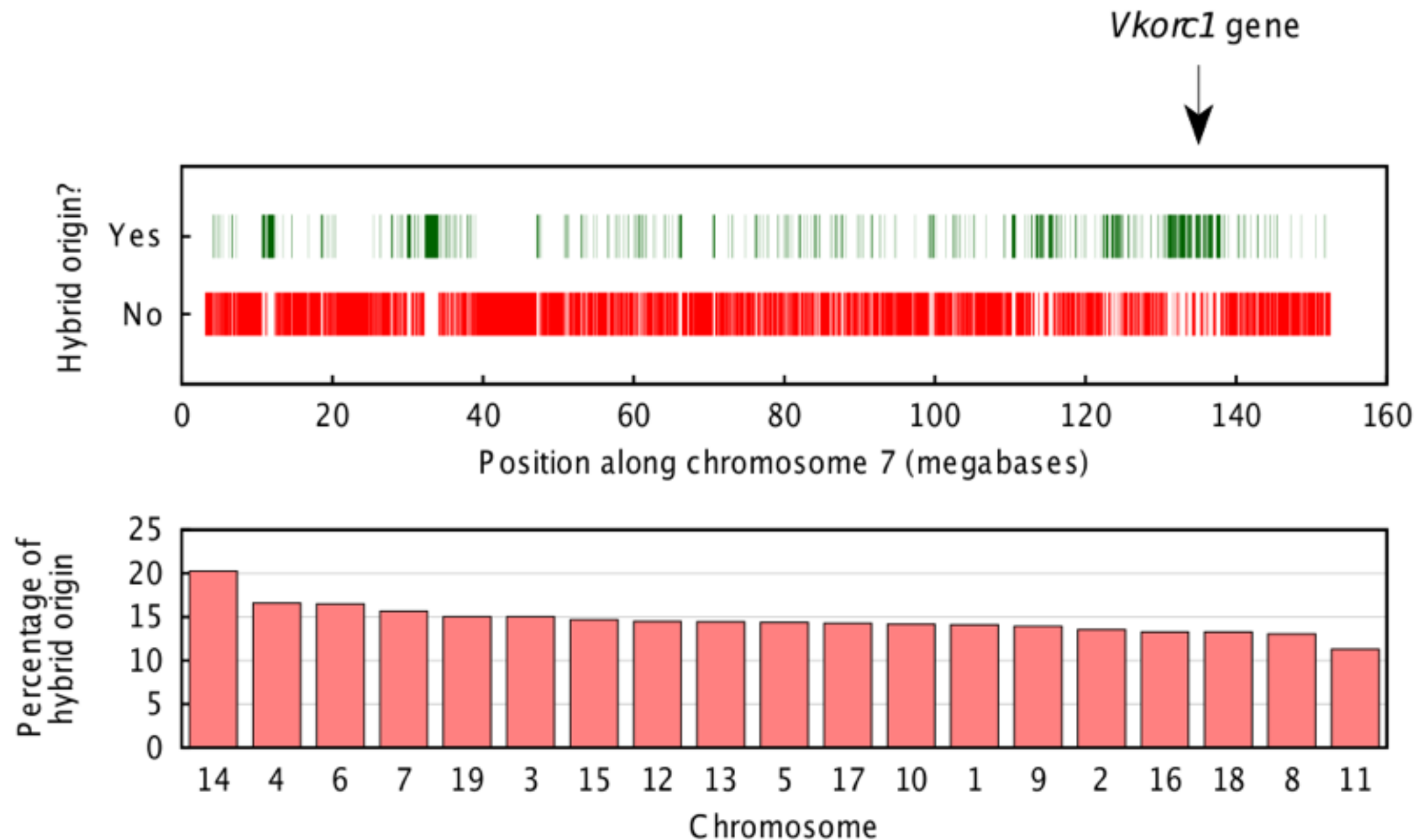
**Species
network**



“Horizontal” Gene Tree Incongruence (Example)



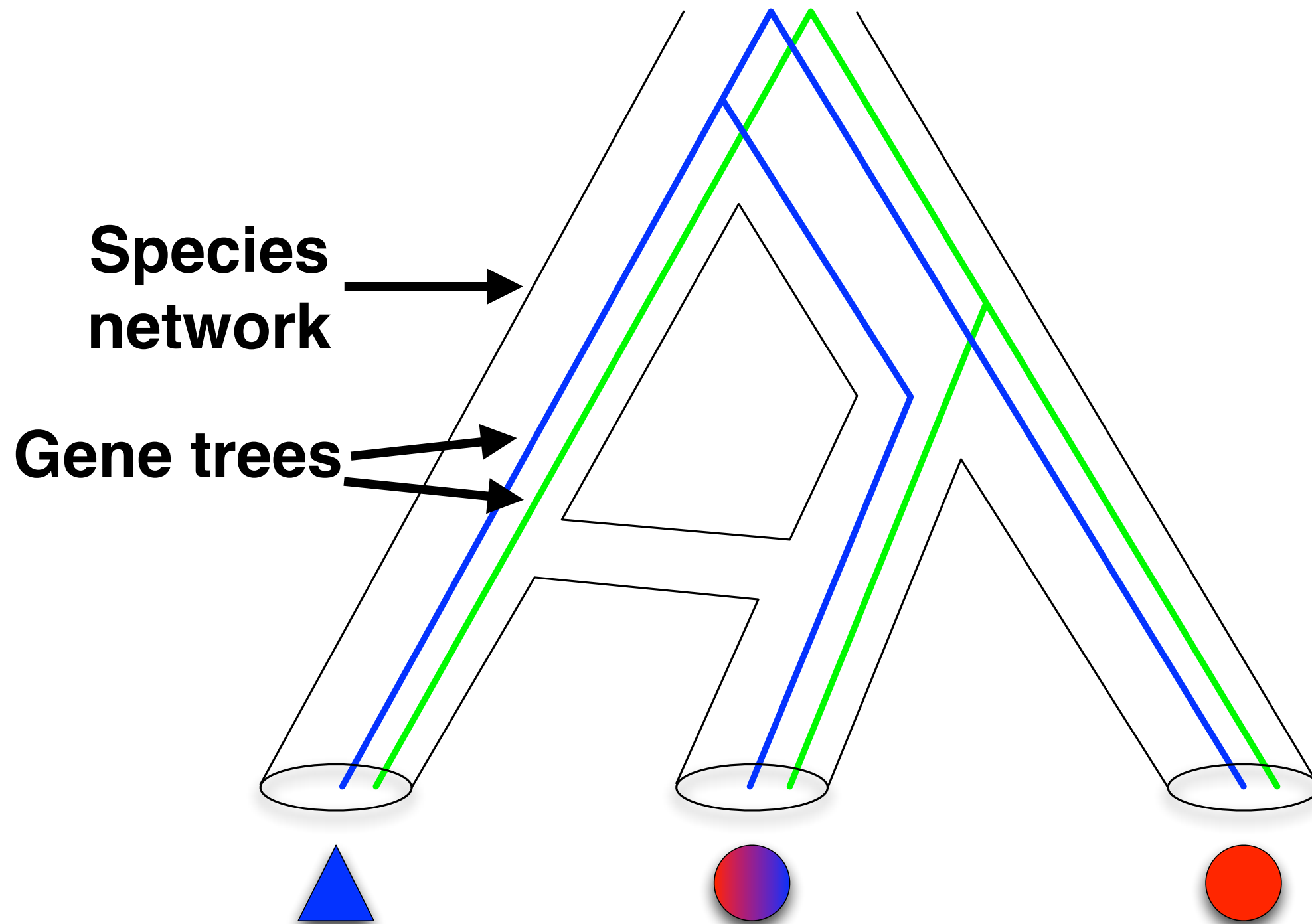
Sliding Windows: Results



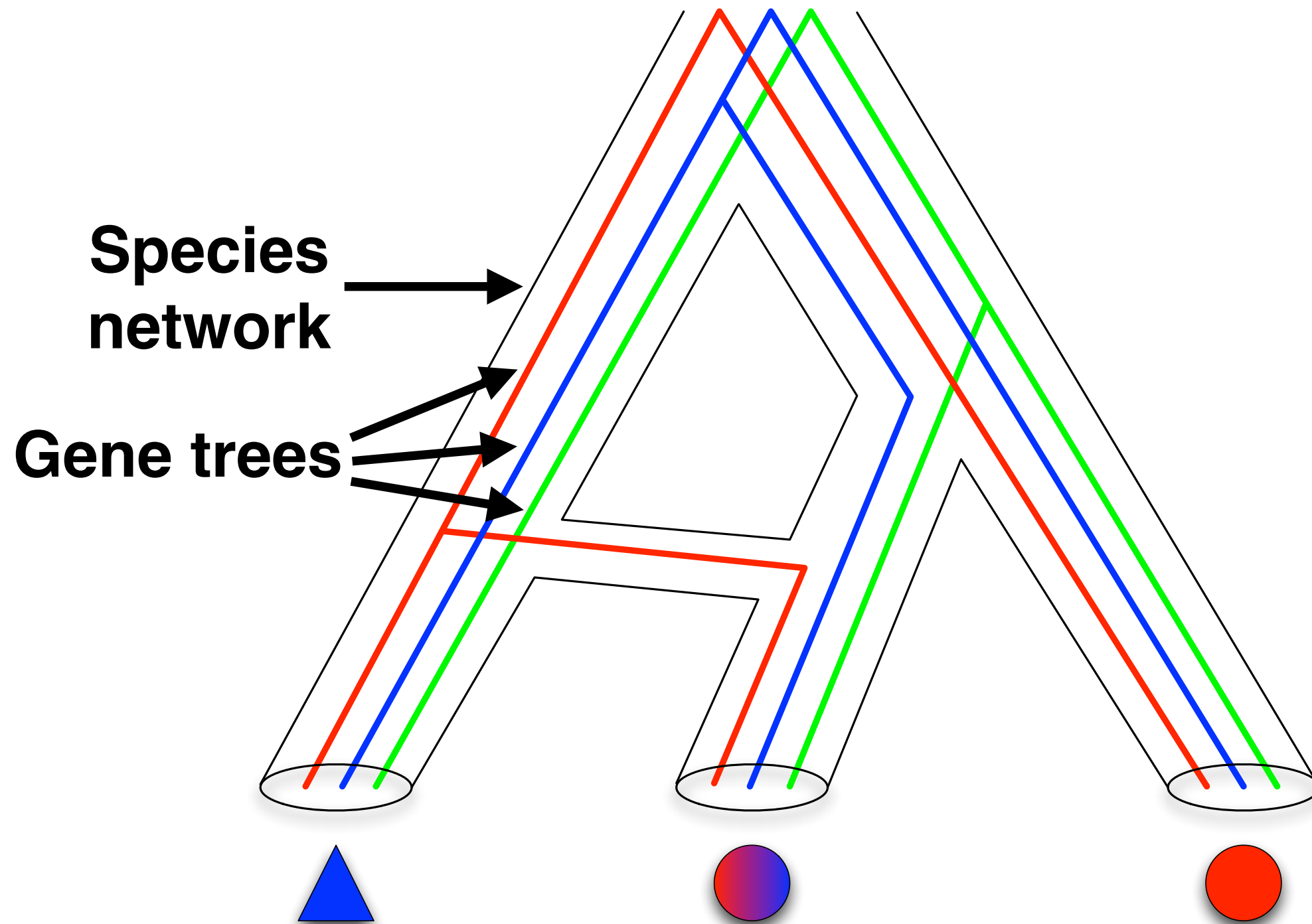
Sliding Windows Approach Is Too Simplistic

- Gene tree incongruence can occur for reasons other than introgression
- The organisms in our study included “vertical” gene tree incongruence due to:
 - Incomplete lineage sorting
 - Recombination

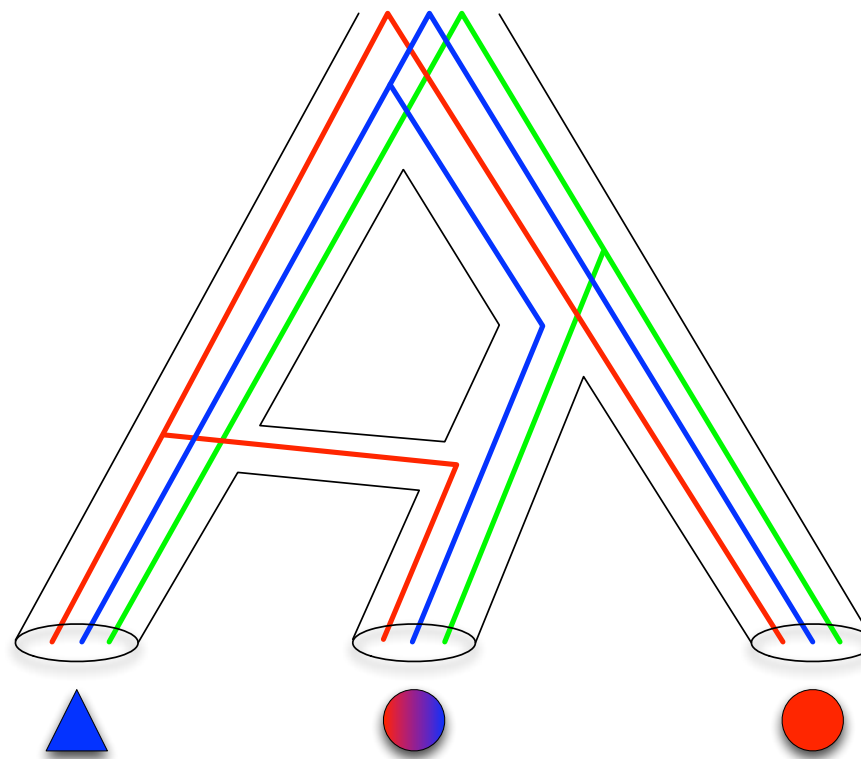
“Vertical” Gene Tree Incongruence (Example)



How to Disentangle “Horizontal” and “Vertical” Gene Tree Incongruence?

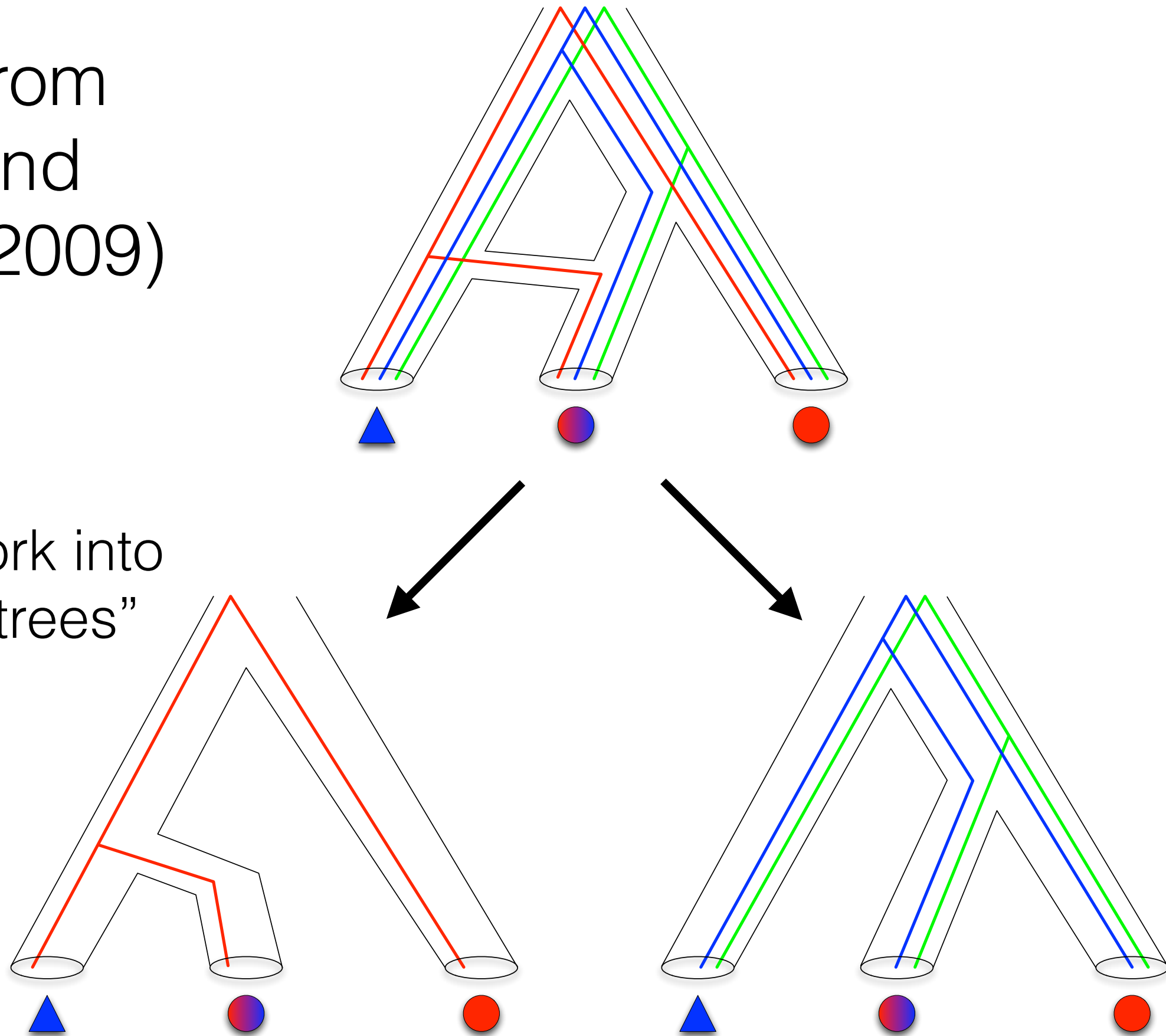


Insight from Meng and Kubratko (2009)

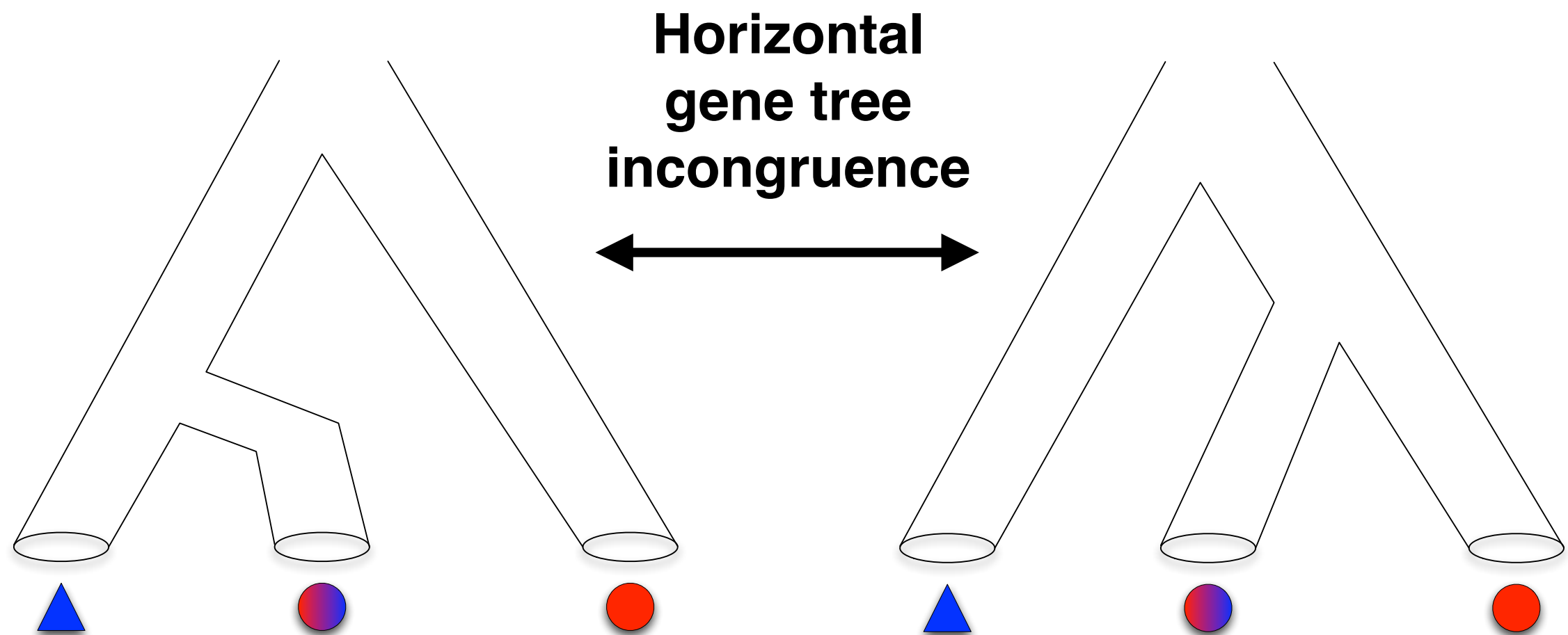


Insight from Meng and Kubatko (2009)

“Pull apart”
species network into
two “parental trees”

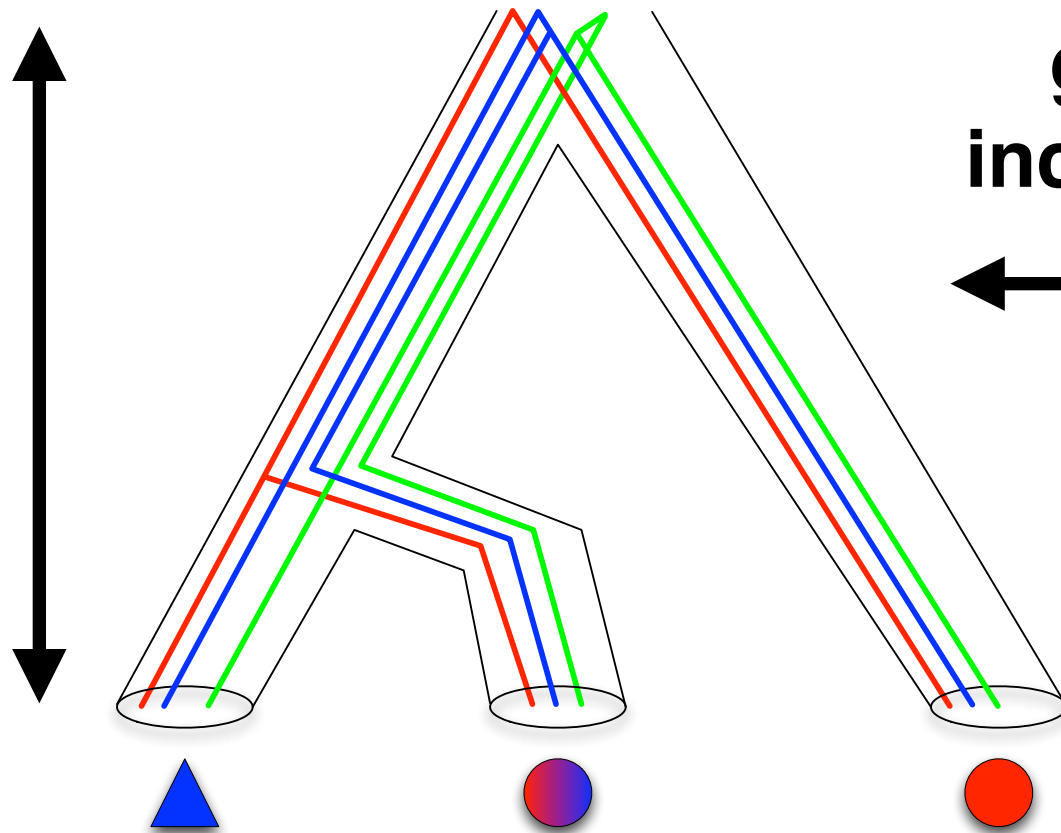


Disentangling “Horizontal” and “Vertical” Gene Tree Incongruence



Disentangling “Horizontal” and “Vertical” Gene Tree Incongruence

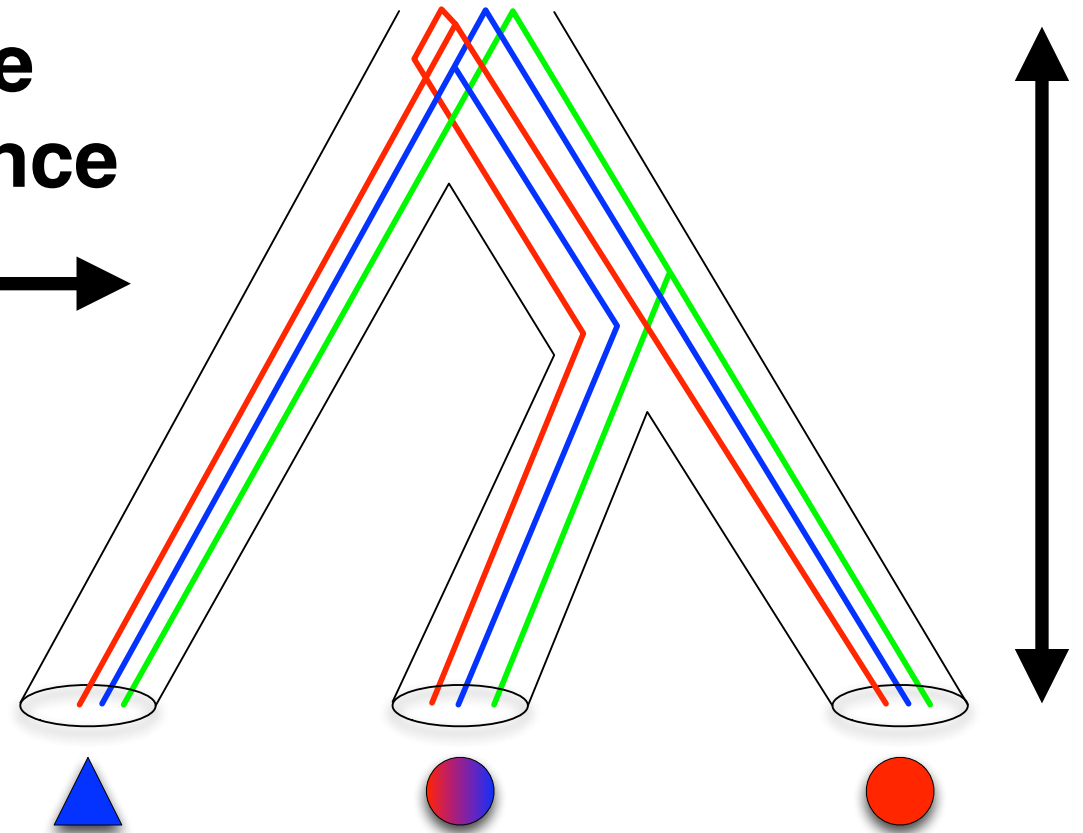
**Vertical
gene tree
incongruence**



**Horizontal
gene tree
incongruence**



**Vertical
gene tree
incongruence**



Insight #1

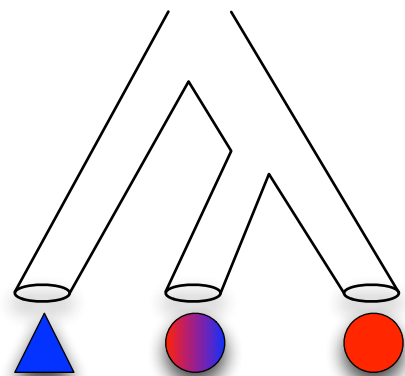
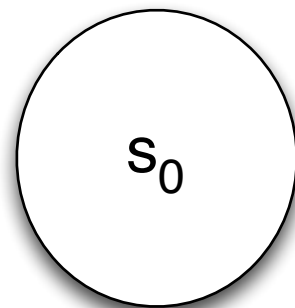
- “Horizontal” and “vertical” incongruence between neighboring gene trees represent two different types of dependence
- Model the two dependence types using two classes of transitions in a graphical model

Insight #2

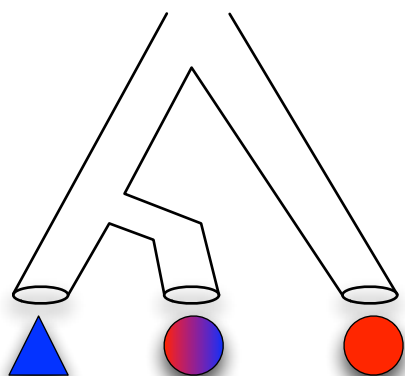
- DNA sequences are observed, not gene trees
- Under traditional models of DNA sequence evolution, the probability $P[s|g]$ of observing DNA sequences s given a gene tree g can be efficiently calculated using dynamic programming (Felsenstein's pruning algorithm)

Insight #1 + Insight #2 =
Use a Hidden Markov
Model (HMM)

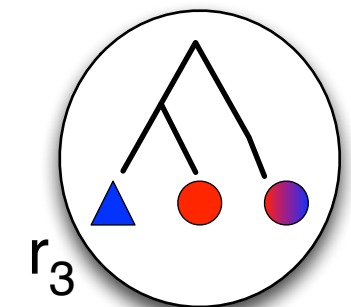
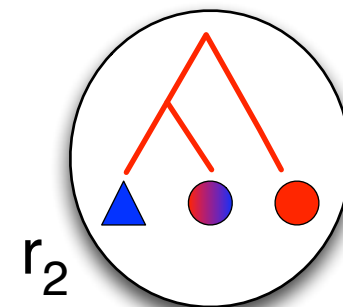
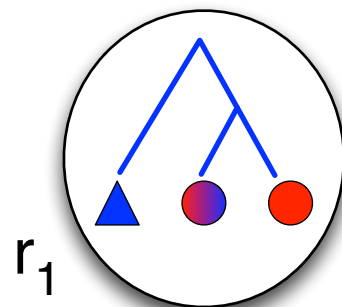
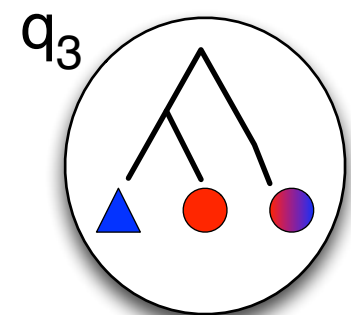
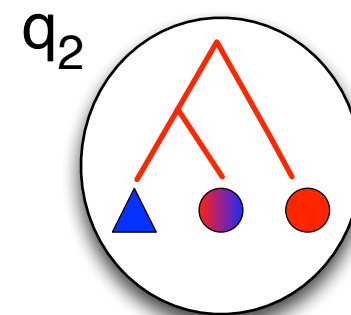
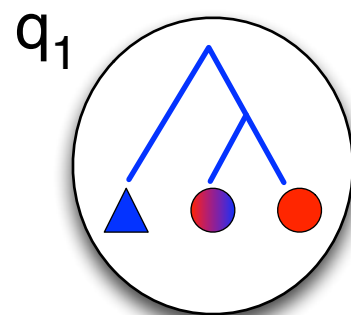
PhyloNet-HMM: Hidden States



Non-introgressed



Introgressed



PhyloNet-HMM

- Each hidden state s_i is associated with a gene tree $g(s_i)$ contained within a “parental” tree $f(s_i)$
- The set of HMM parameters λ consists of
 - The initial state distribution π
 - Transition probabilities $a_{ij} = \begin{cases} P[g(s_i)|f(s_i)] \cdot \gamma & \text{if } s_i \text{ and } s_j \text{ in different rows} \\ P[g(s_i)|f(s_i)] \cdot (1 - \gamma) & \text{if } s_i \text{ and } s_j \text{ in same row} \end{cases}$

where γ is the “vertical” parental tree switching frequency and $\Pr[g(s_i)|f(s_i)]$ is calculated using formula of Degnan and Salter (2005)
 - The emission probabilities $b_i = \Pr[O_t|g(s_i)]$
 - Use a model of nucleotide substitution like Jukes-Cantor (1969)

Three HMM-related Problems

1. What is the likelihood of the model given the observed DNA sequences?
2. Which sequence of hidden states best explains the observed DNA sequences?
3. How do we choose parameter values that maximize the model likelihood?

First HMM-related Problem

- Let q_t be PhyloNet-HMM's hidden state at time t , where $1 \leq t \leq k$ and k is the length of the input observation sequence O .
- What is the likelihood of the model given the observed DNA sequences O ?
 - Forward algorithm calculates “prefix” probability $\alpha_t(i)$
 - Backward algorithm calculates “suffix” probability $\beta_t(i)$
 - Model likelihood is $P[O|\lambda] = \sum_{i=1}^N \alpha_k(i)$.

Second HMM-related Problem

- Which sequence of states best explains the observation sequence?
 - Posterior decoding probability $\gamma_t(i)$ is the probability that the HMM is in state s_i at time t , which can be computed as:

$$\gamma_t(i) = \frac{\alpha_t(i)\beta_t(i)}{P[O|\lambda]}.$$

Third HMM-related Problem

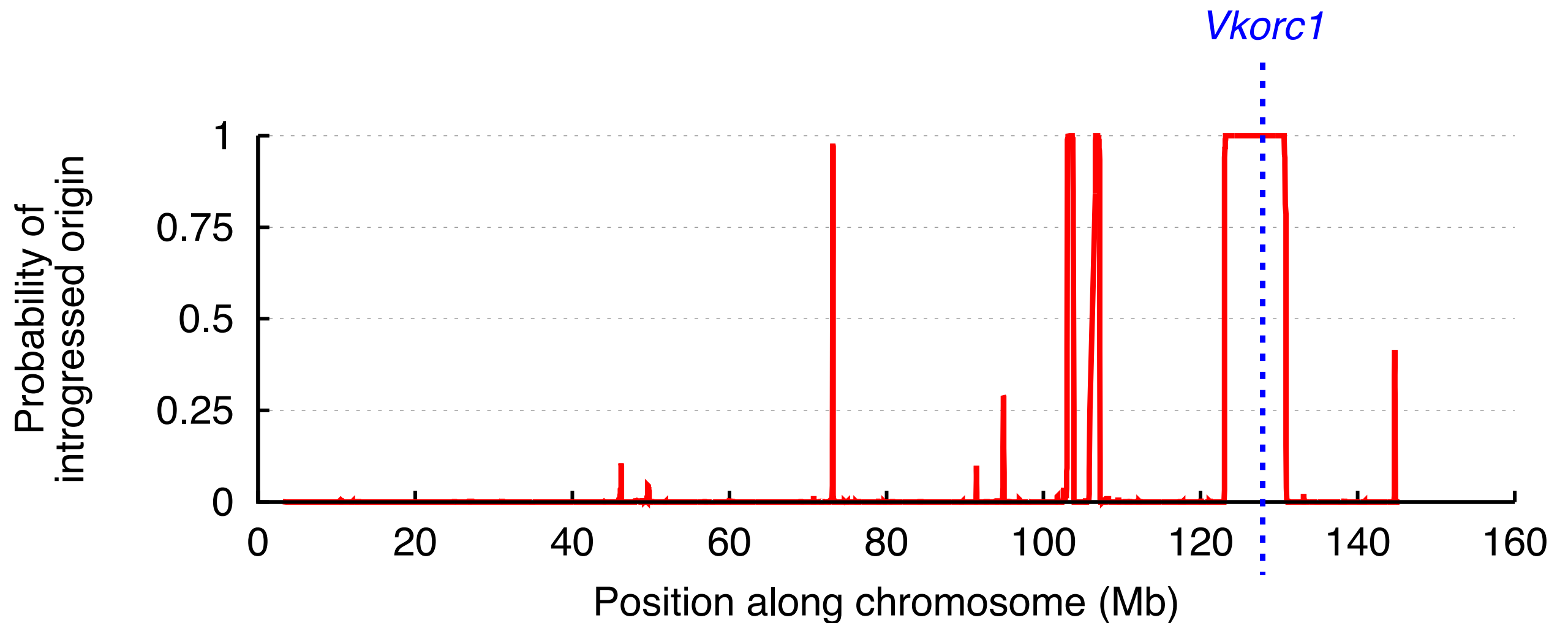
- How do we choose parameter values that maximize the model likelihood?
 - Perform local search to optimize the criterion

$$\arg \max_{\lambda} P[O|\lambda]$$

Related HMM-based Approaches

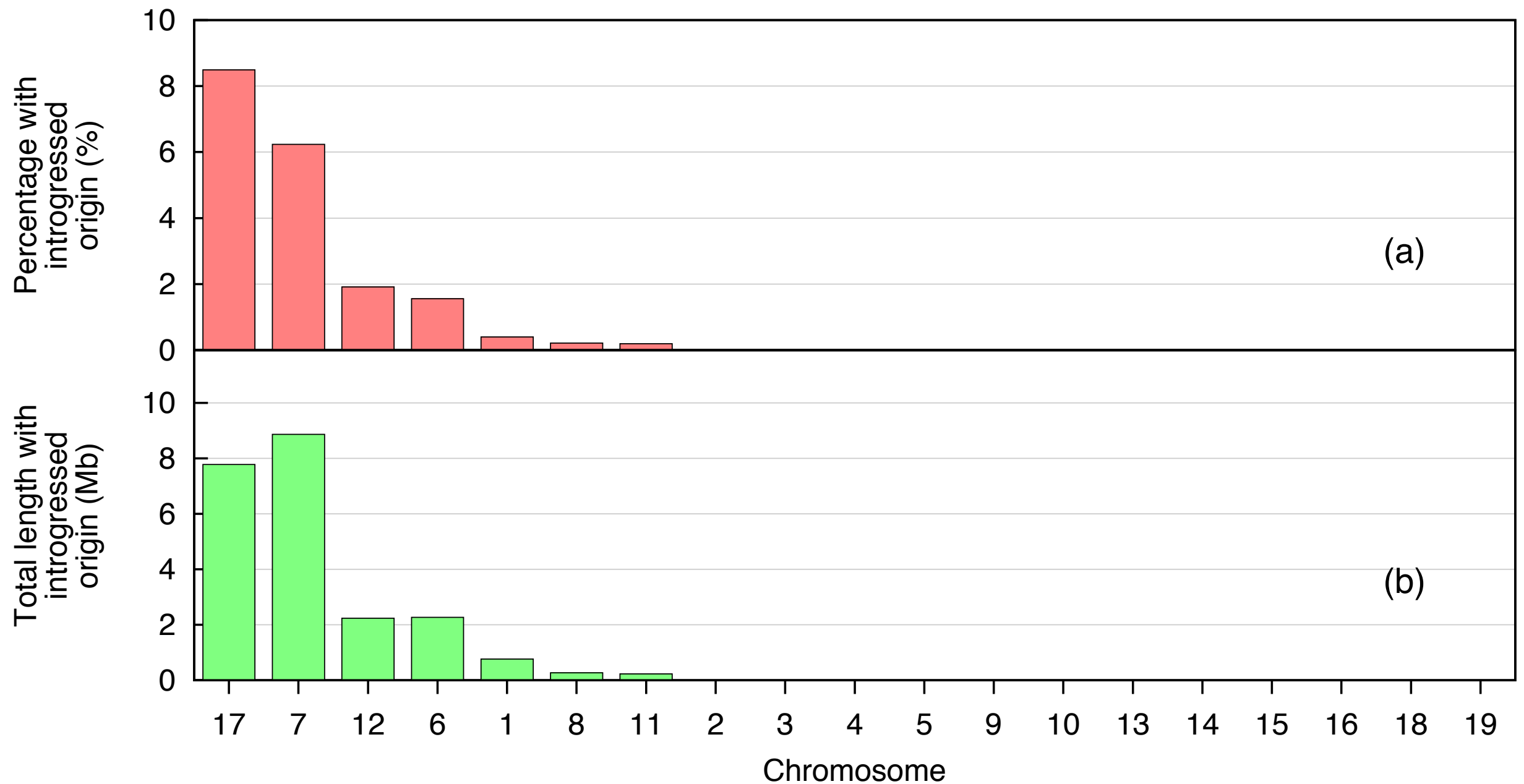
- CoalHMM (Mailund *et al.* 2012)
 - Models introgression + incomplete lineage sorting + recombination (with a simplifying assumption)
 - Currently supports two sequences only
 - Assumes that time is discretized
- Other approaches that don't account for introgression (*e.g.*, Hobolth *et al.* 2007)

PhyloNet-HMM Scan of Chromosome 7



Liu et al. submitted to
Nature Genetics and
PLoS Computational Biology.

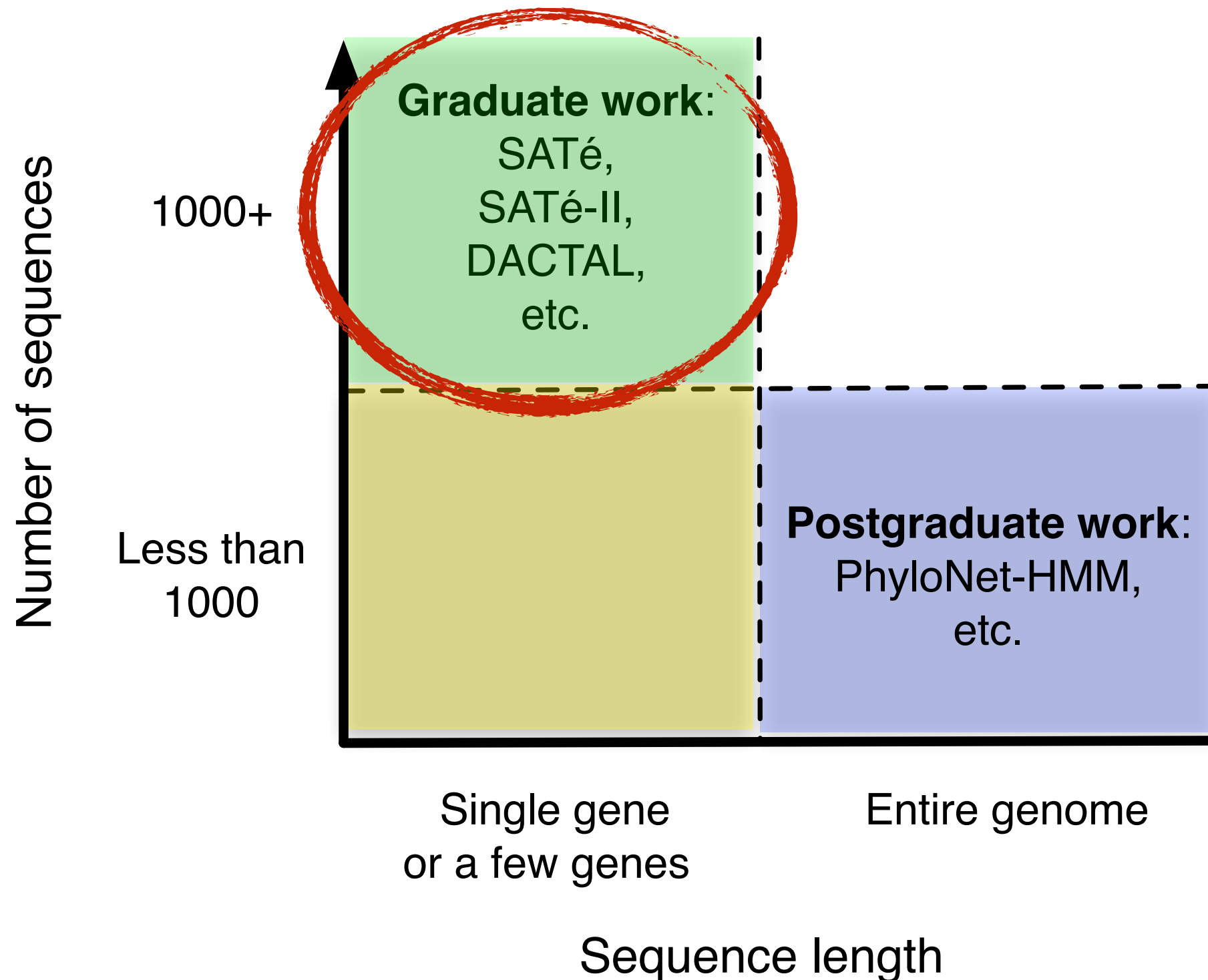
PhyloNet-HMM Scan of Whole Genome



Scaling PhylpNet-HMM

- Previous analyses (at most five genomes and a single introgression event) required more than a CPU-month on a large cluster
- Problem is combinatorial in both the number of genomes and the number of introgression events
- Challenge: efficient and accurate introgression detection from hundreds of genomes or more

Big Data: Unifying Theme #2

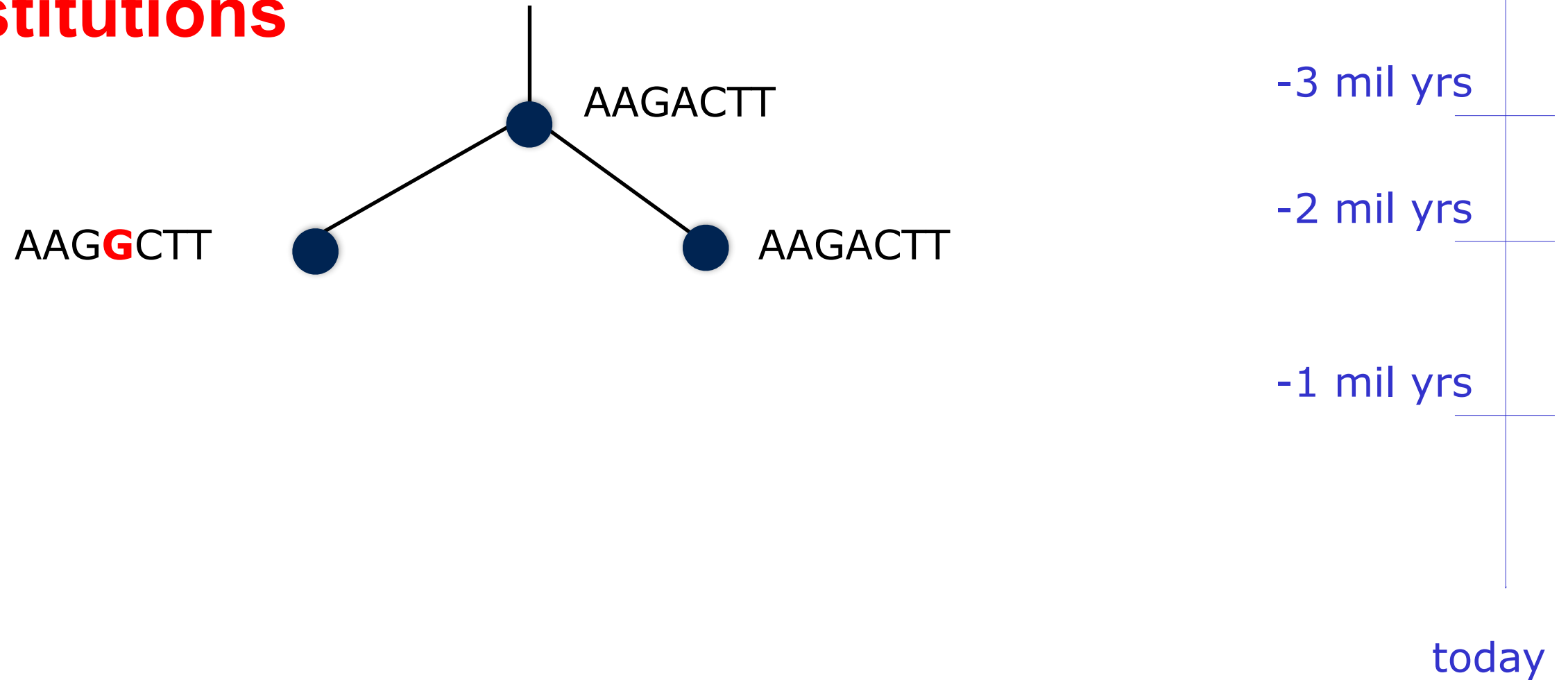


SATé: Simultaneous Alignment and Tree estimation (Liu *et al.* Science 2009)

- Standard methods for alignment and tree estimation have unacceptably high error and/or cannot analyze large datasets
- SATé is more accurate than all existing methods on datasets with up to thousands of taxa
- 24 hour analyses using standard desktop computer
- SATé-II (Liu *et al.* Systematic Biology 2011) is more accurate and faster than SATé on datasets with up to tens of thousands of taxa using a standard desktop computer

DNA Sequence Evolution (Example)

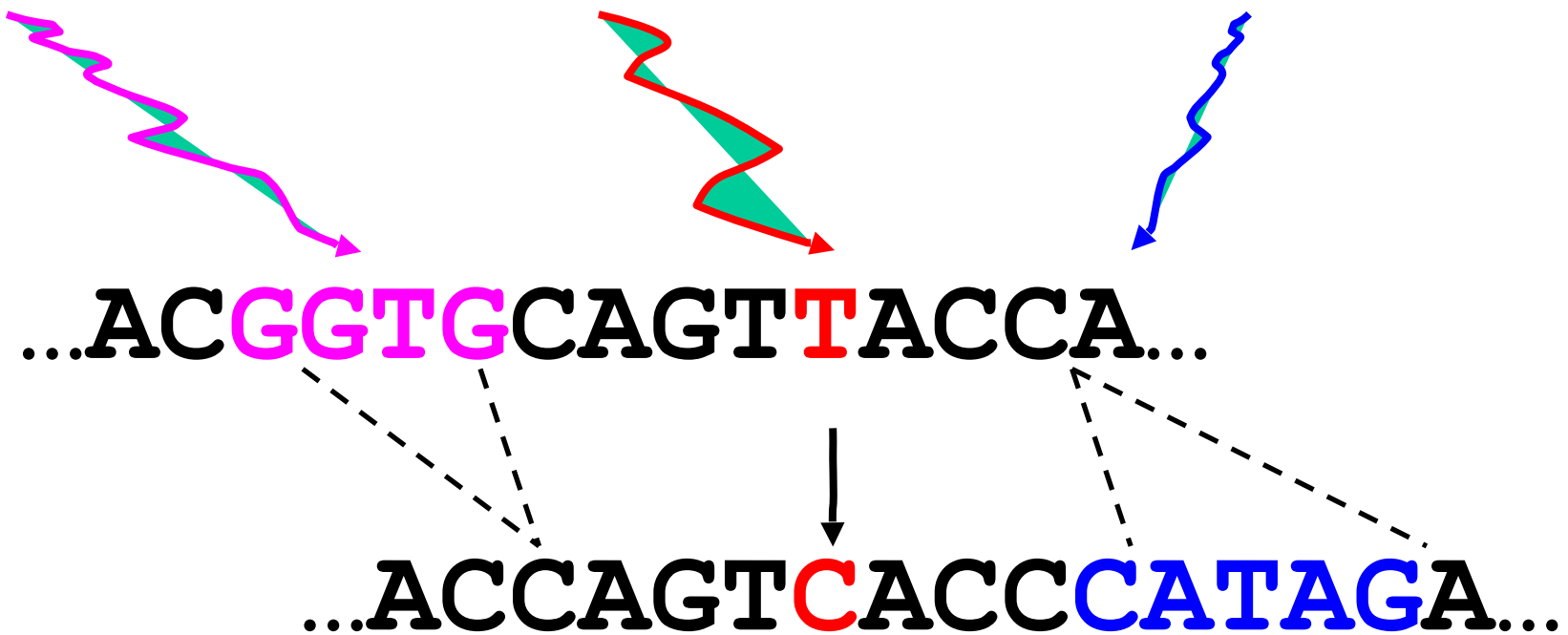
Substitutions



Deletion

Substitution

Insertion



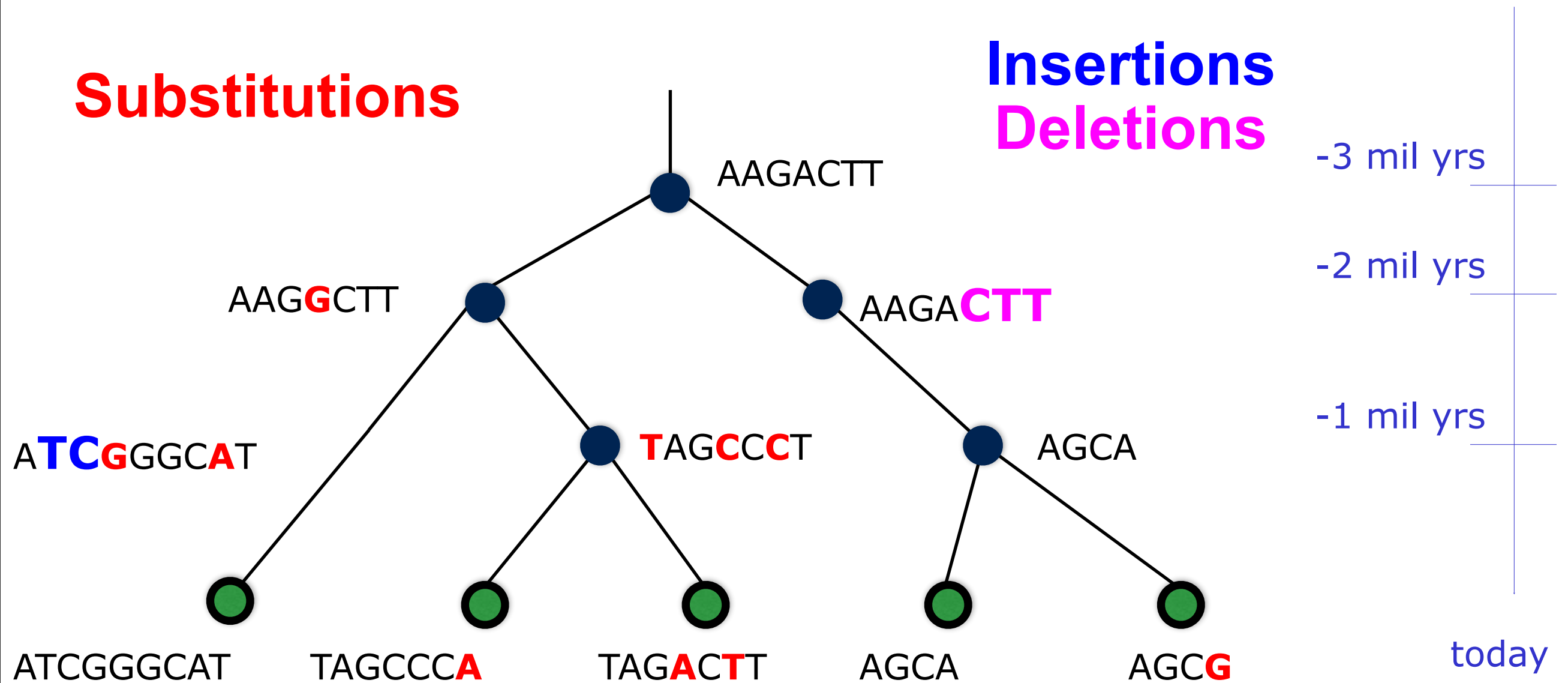
The true alignment is:

...ACGGTG CAGT TACC-----A...
...AC-----CAGT C ACC CATAGA...

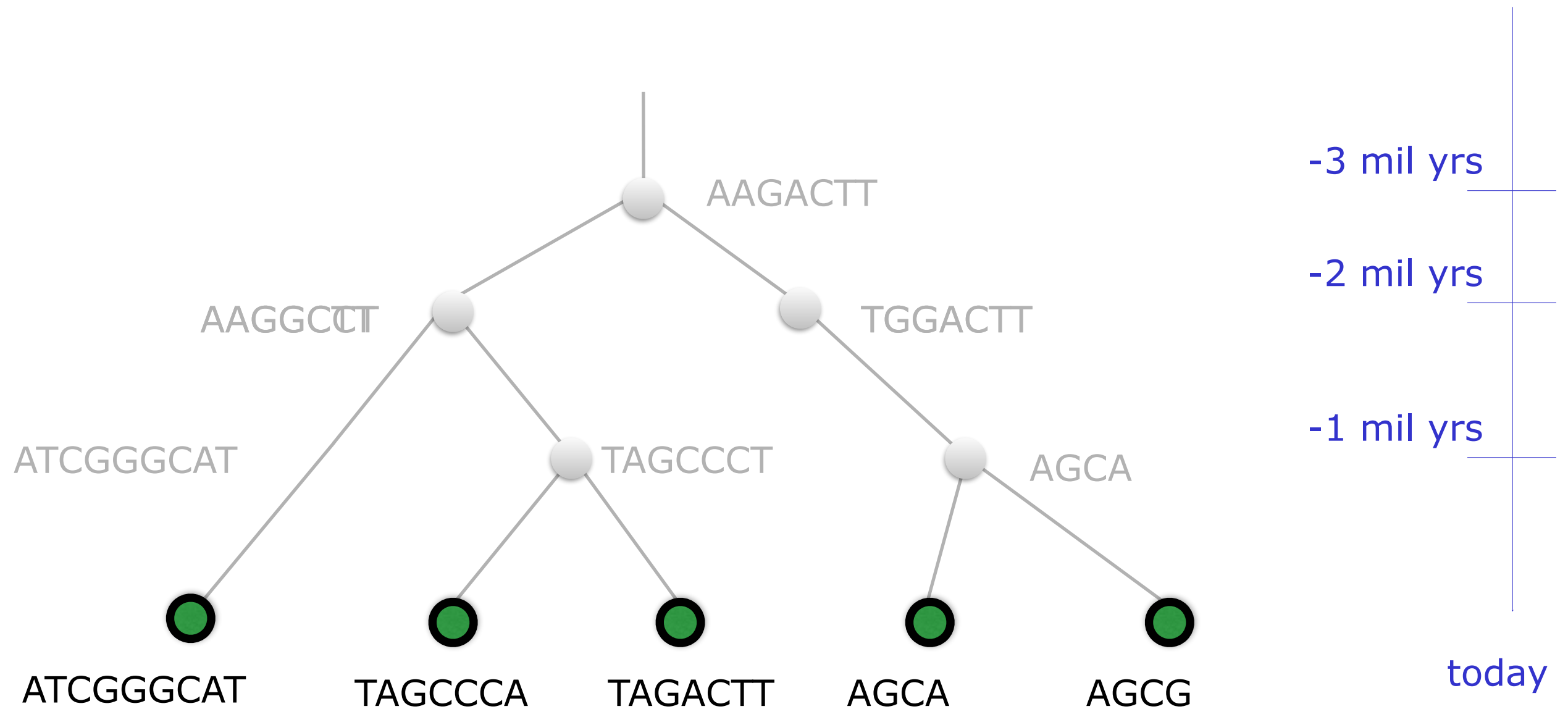
DNA Sequence Evolution (Example)

Substitutions

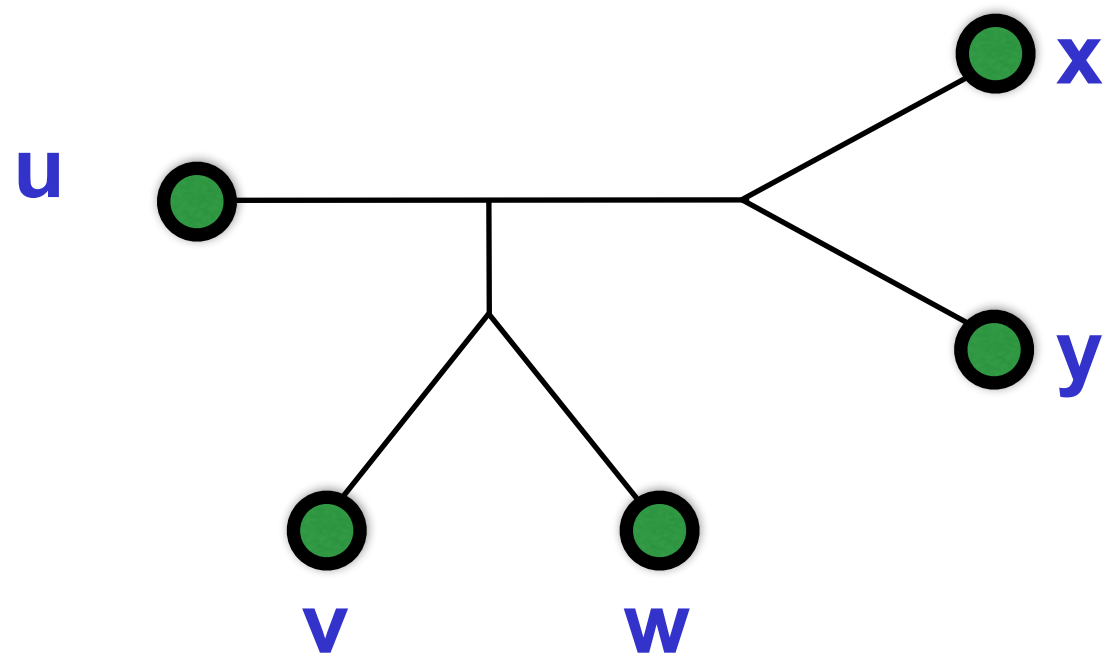
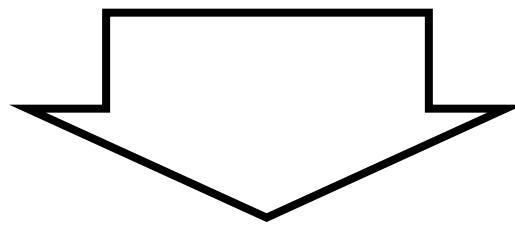
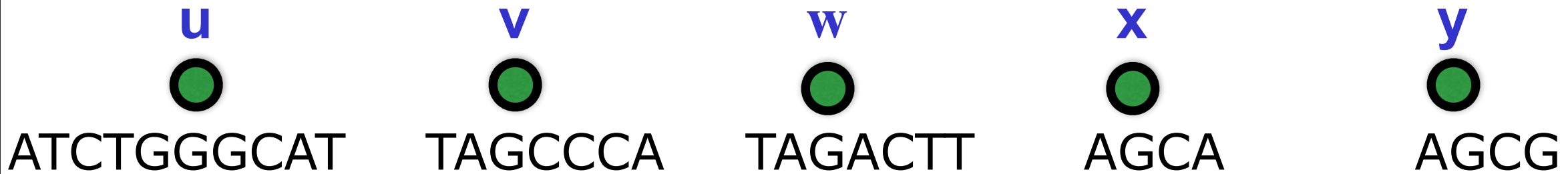
**Insertions
Deletions**



DNA Sequence Evolution (Example)



Tree and Alignment Estimation Problem (Example)



u = ATCTGGGCAT
v = T--AGCCCA
w = T--AGACTT
x = AGCA-----
y = AGCG-----

Many Trees

- Number of trees $|T|$ grows exponentially in the number of species n

$$|T| = (2n - 5)!!$$

- NP-hard optimization problems

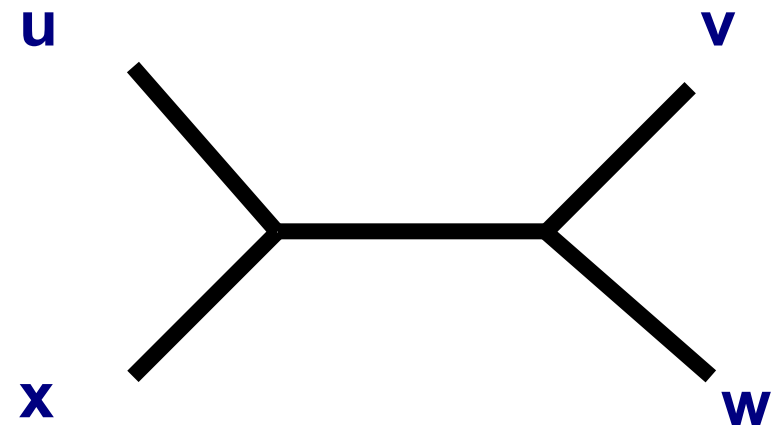
Two-phase Methods

u = AGGCTATCACCTGACCTCCA
v = TAGCTATCACGACCGC
w = TAGCTGACCGC
x = TCACGACCGACA

→
Phase 1:
Align

u = -AGGCTATCACCTGACCTCCA
v = TAG-CTATCAC--GACCGC--
w = TAG-CT-----GACCGC--
x = -----TCAC--GACCGACA

↓
Phase 2:
Estimate Tree



Many Methods

Alignment method

- **ClustalW**
- **MAFFT**
- **Muscle**
- **Prank**
- Opal
- Probcons (and Probtree)
- Di-align
- T-Coffee
- Etc.

Many Methods

Alignment method

- **ClustalW**
- **MAFFT**
- **Muscle**
- **Prank**
- Opal
- Probcons (and Probtree)
- Di-align
- T-Coffee
- Etc.

Phylogeny method

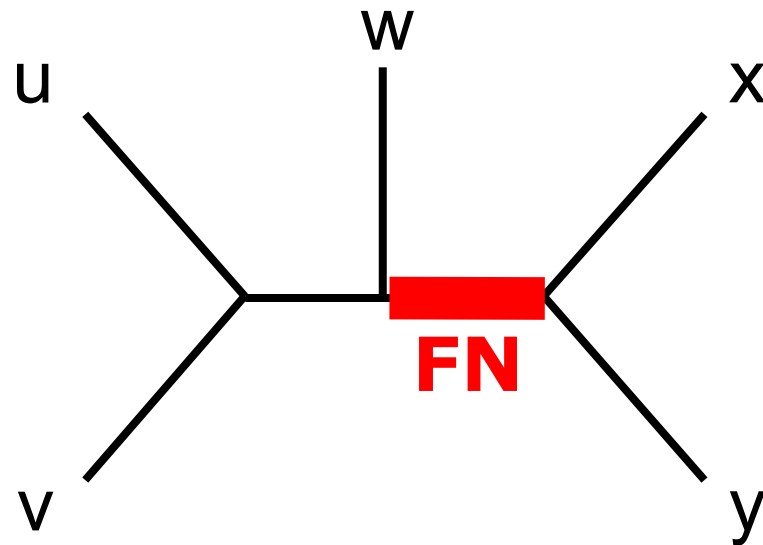
- **Maximum likelihood (ML)**
 - **RAxML**
- Bayesian MCMC
- Maximum parsimony
- Neighbor joining
- UPGMA
- Quartet puzzling
- Etc.

Simulation Study (Liu et al. Science 2009)

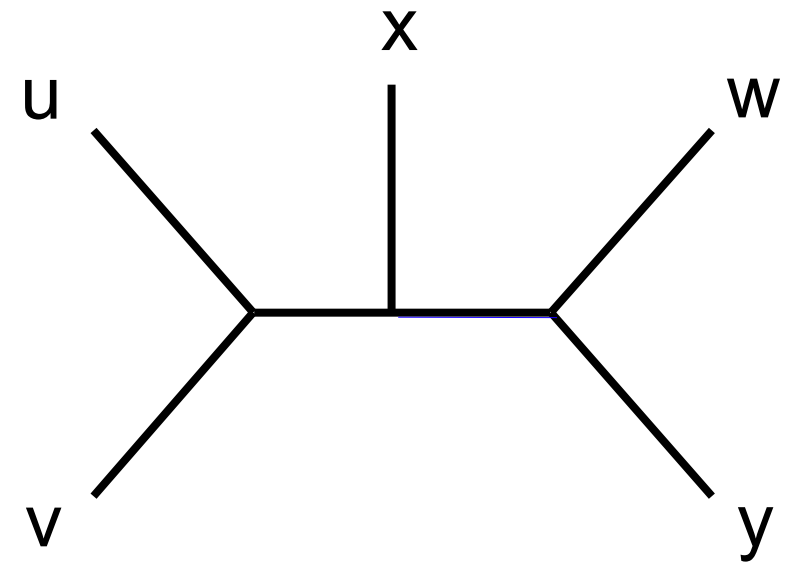
Simulation using ROSE

- Model trees with 1000 taxa
- Biologically realistic model with:
 - Varied rates of substitutions
 - Varied rates of insertions and deletions
 - Varied gap length distribution
 - Long
 - Medium
 - Short

Tree Error



True Tree



Estimated Tree

- **False Negative (FN)**: an edge in the true tree that is missing from the estimated tree
- **Missing branch rate**: the percentage of edges present in the true tree but missing from the estimated tree

Alignment Error

FN

AACAT T
A-CC G

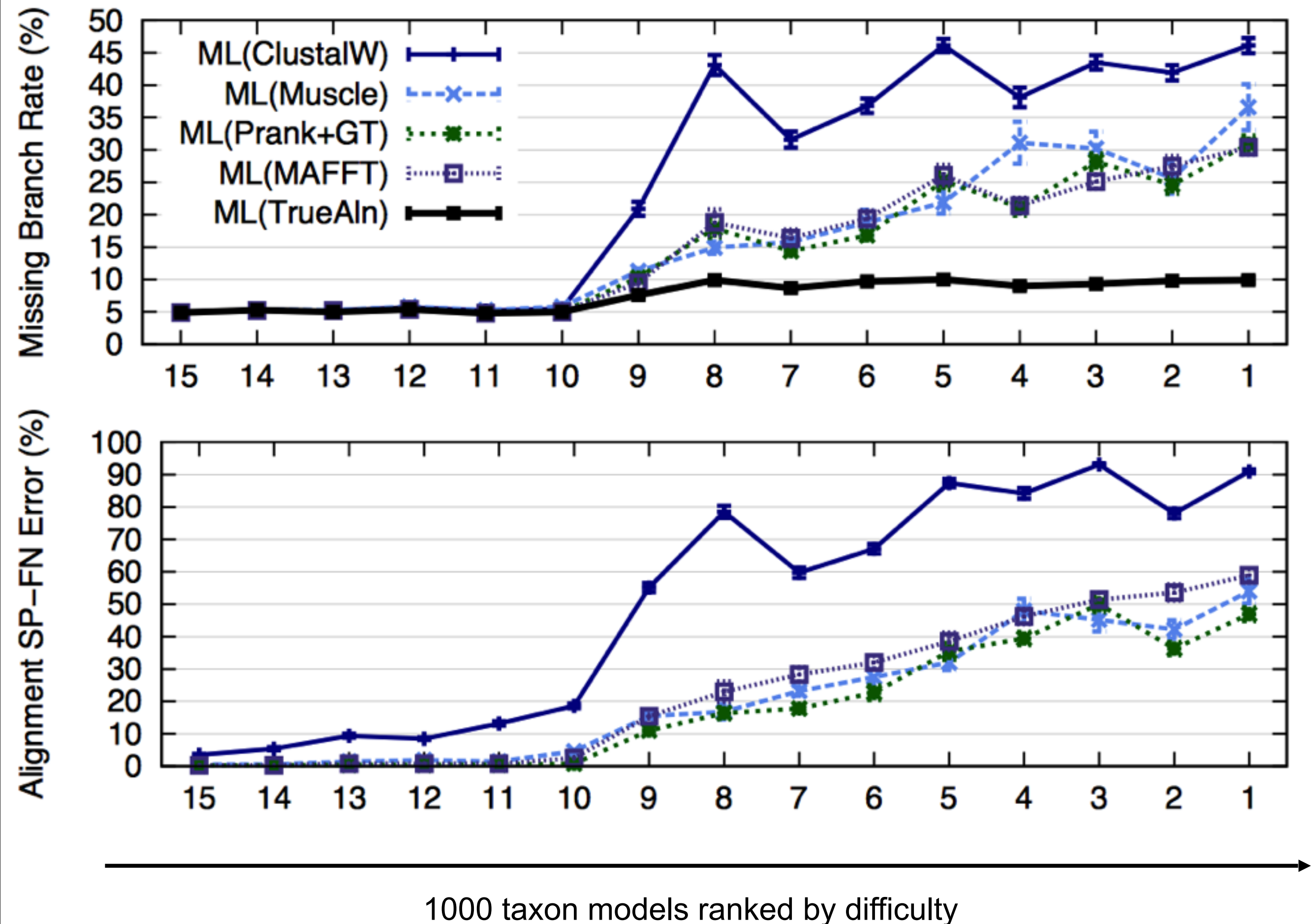
True Alignment

AACAT-
A-CC-G

Estimated Alignment

- **False Negative (FN)**: pair of nucleotides present in true alignment but missing from estimated alignment
- **Alignment SP-FN error**: percentage of paired nucleotides present in true alignment but missing from estimated alignment

Results

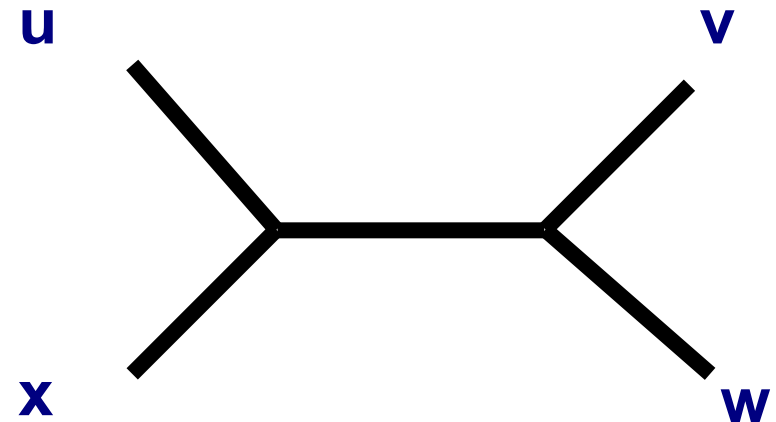
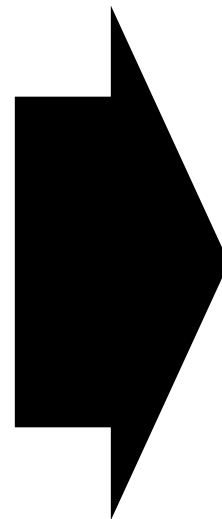


Problem with Two-phase Approach

- **Problem:** two-phase methods fail to return reasonable alignments and accurate trees on large and divergent datasets
 - manual alignment
 - unreliable alignments excluded from phylogenetic analysis

Simultaneous Estimation of a Tree and Alignment

u = AGGCTATCACCTGACCTCCA
v = TAGCTATCACGACCGC
w = TAGCTGACCGC
x = TCACGACCGACA



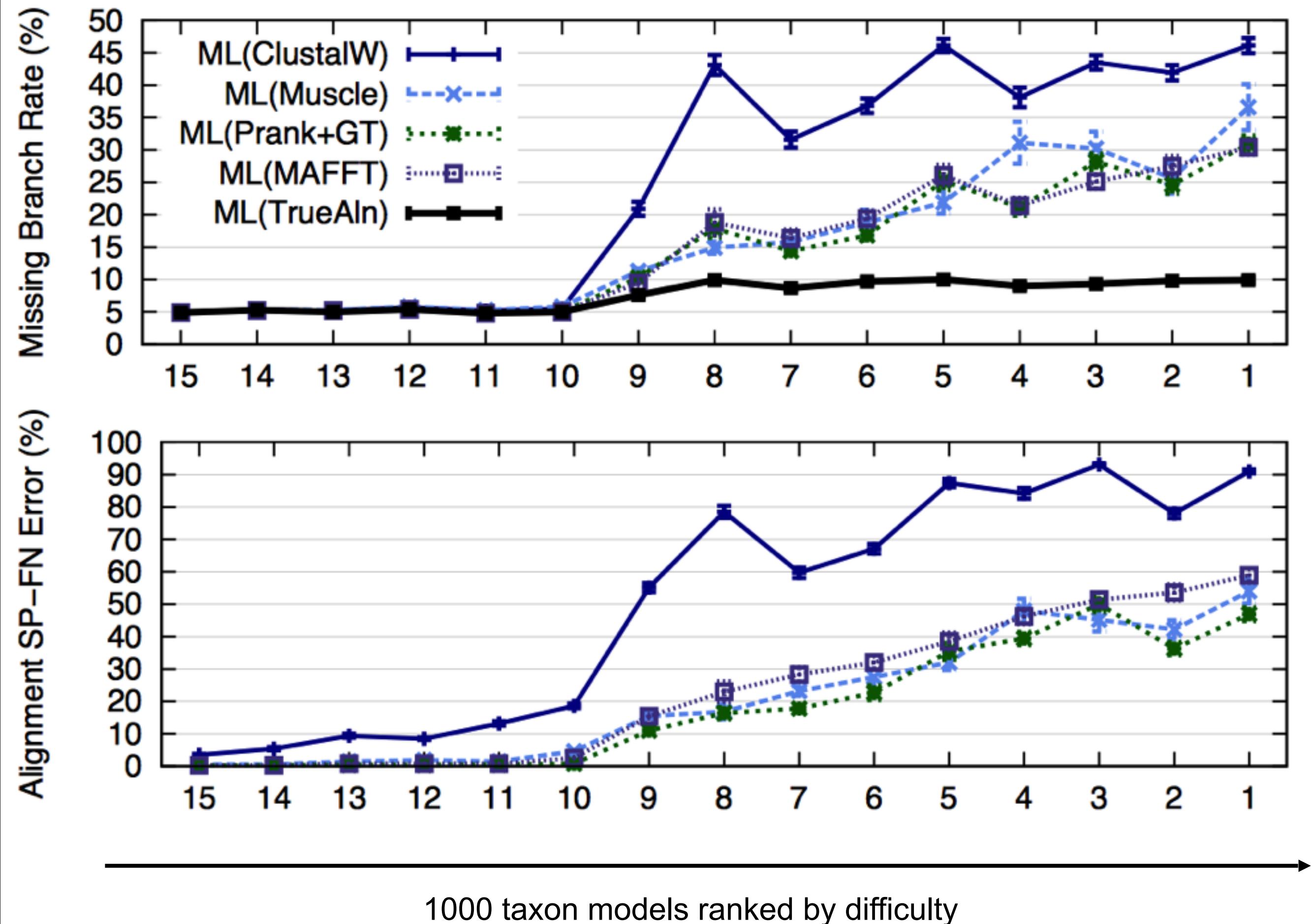
and

u = -AGGCTATCACCTGACCTCCA
v = TAG-CTATCAC--GACCGC--
w = TAG-CT-----GACCGC--
x = -----TCAC--GACCGACA

Simultaneous Estimation Methods

- Methods based on statistical models
 - Limited to datasets with a few hundred taxa
 - Unknown accuracy on larger datasets
- Parsimony-based methods
 - Slower than two-phase methods
 - No more accurate than two-phase methods

Results



Problem with Two-phase Approach

- **Problem:** two-phase methods fail to return reasonable alignments and accurate trees on large and divergent datasets
- **Insight:** divide-and-conquer to constrain dataset divergence and size

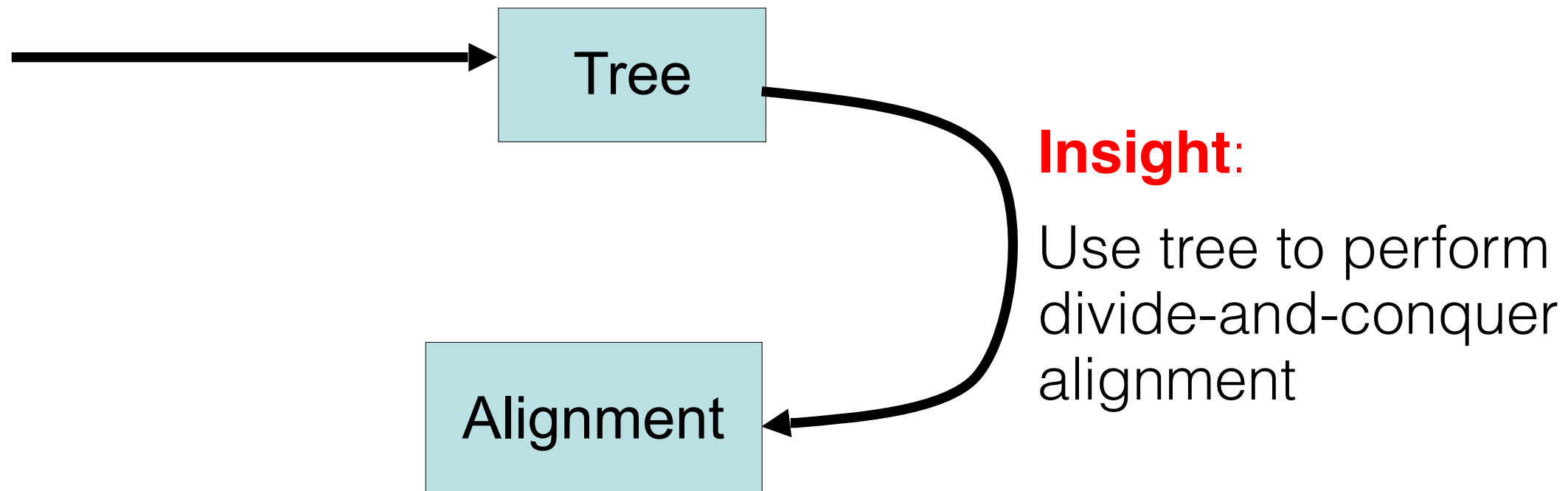
SATé Algorithm

Obtain initial alignment and
estimated ML tree



SATé Algorithm

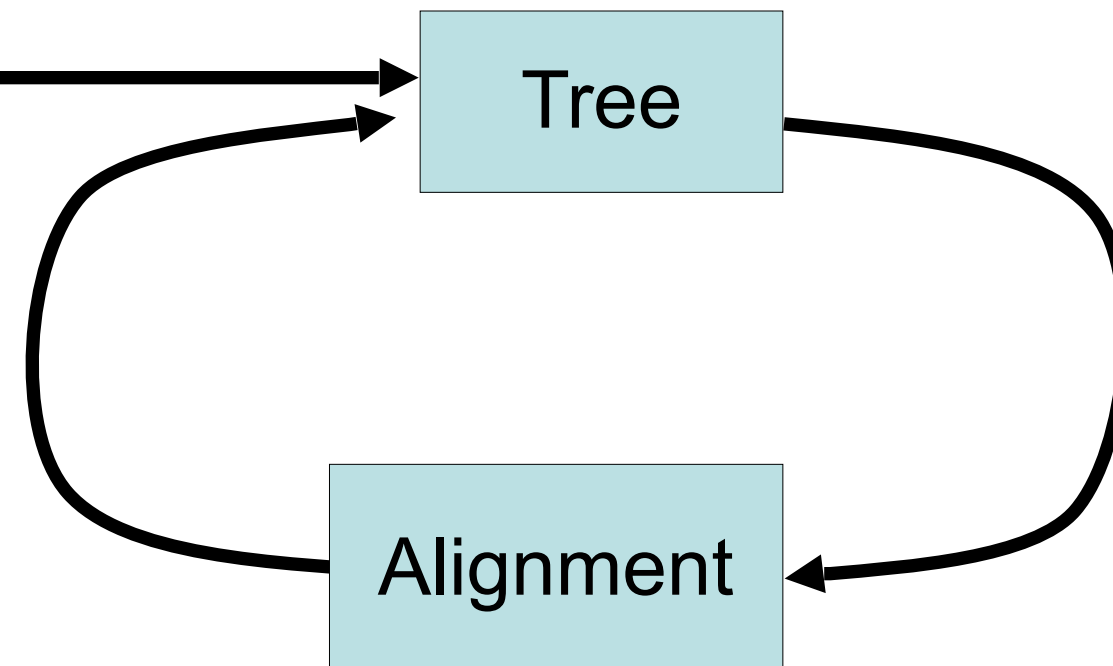
Obtain initial alignment and
estimated ML tree



SATé Algorithm

Obtain initial alignment and
estimated ML tree

Estimate ML tree on
new alignment

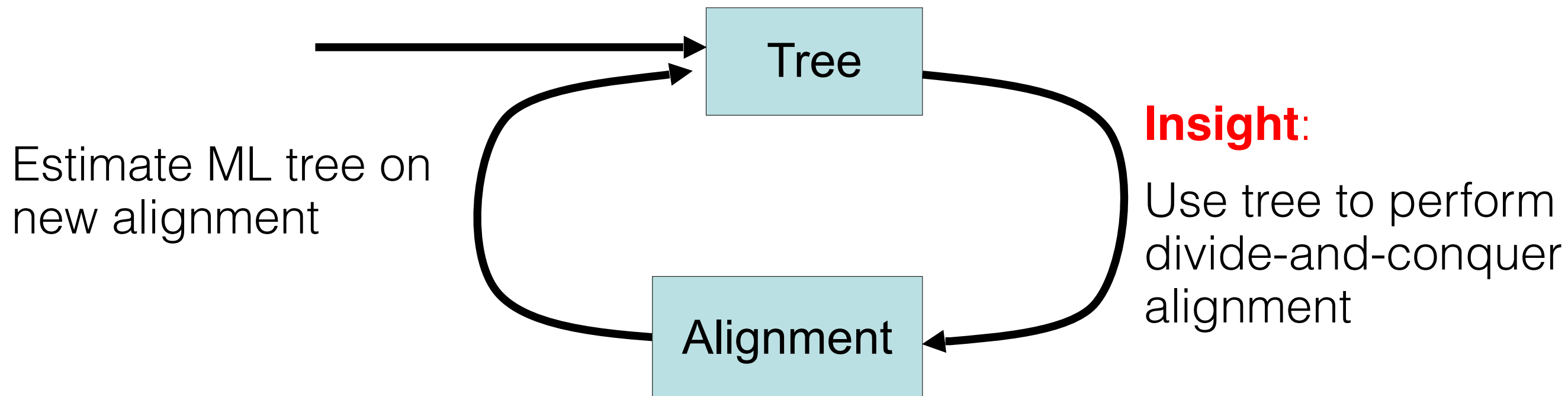


Insight:

Use tree to perform
divide-and-conquer
alignment

SATé Algorithm

Obtain initial alignment and estimated ML tree



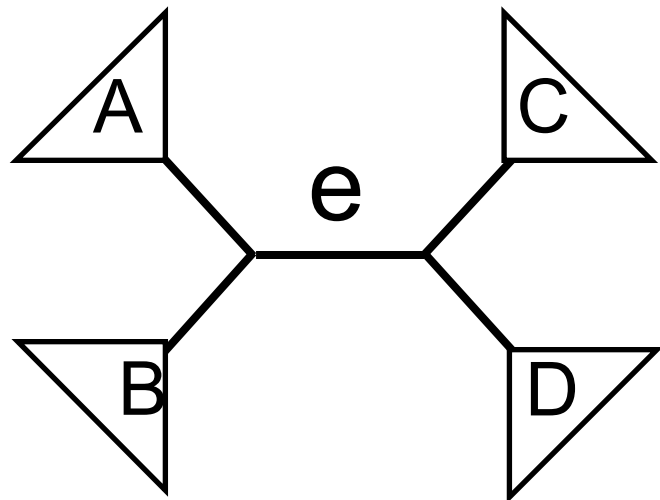
Insight: iterate - use a moderately accurate tree to obtain a more accurate tree

If new alignment/tree pair has worse ML score, realign using a different decomposition

Repeat until termination condition (typically, 24 hours)

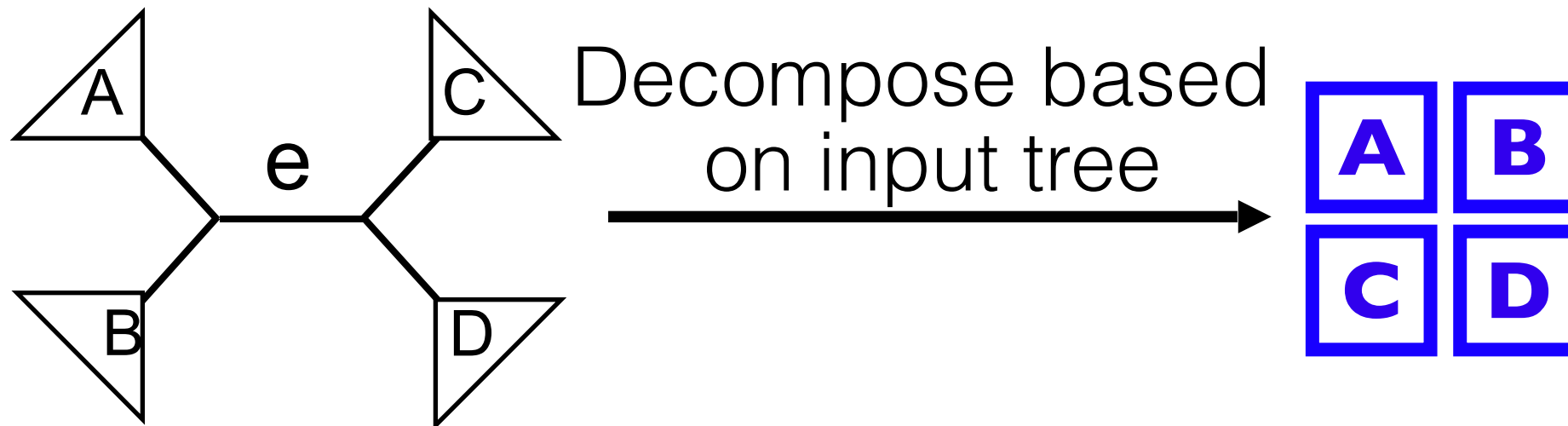
SATé iteration

(Actual decomposition produces 32 subproblems)



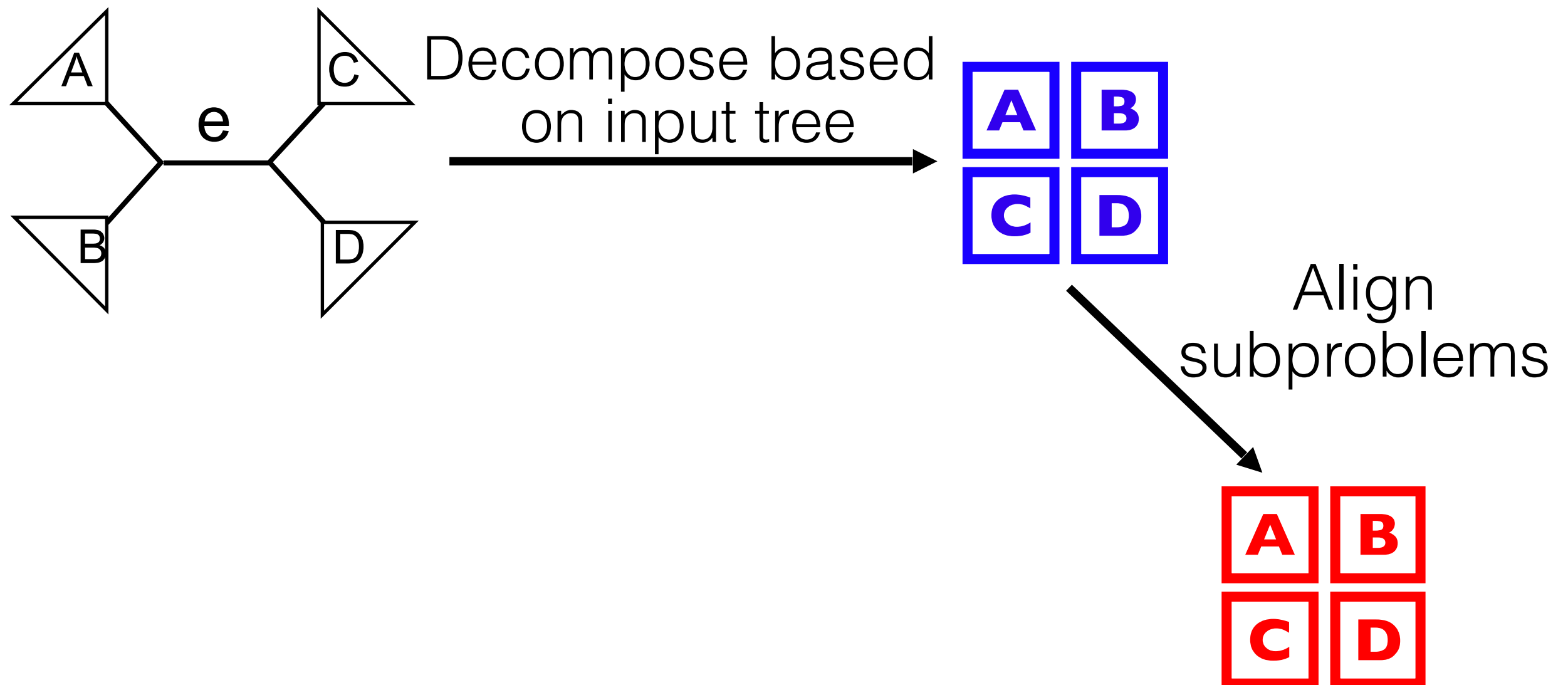
SATé iteration

(Actual decomposition produces 32 subproblems)



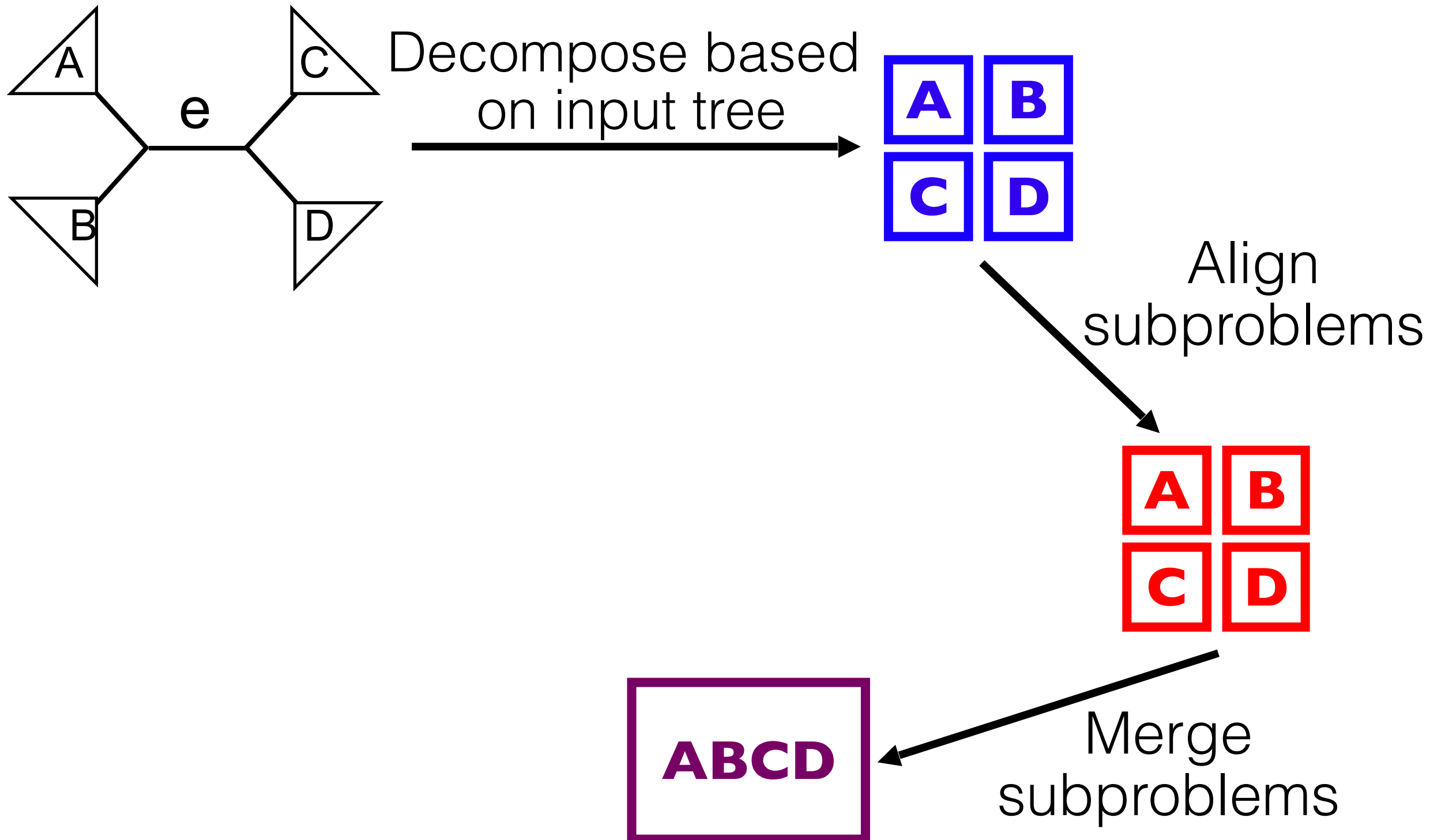
SATé iteration

(Actual decomposition produces 32 subproblems)



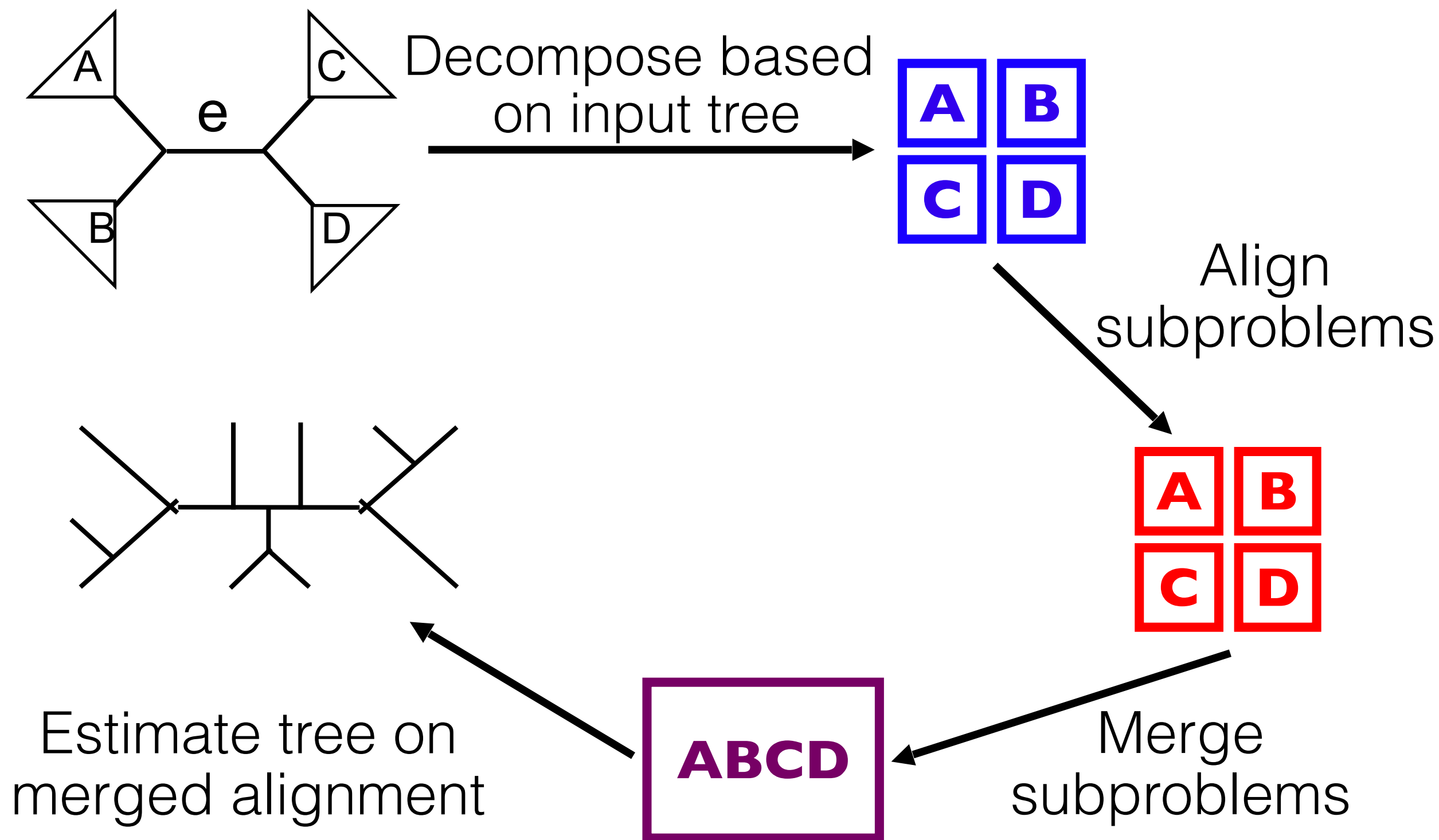
SATé iteration

(Actual decomposition produces 32 subproblems)



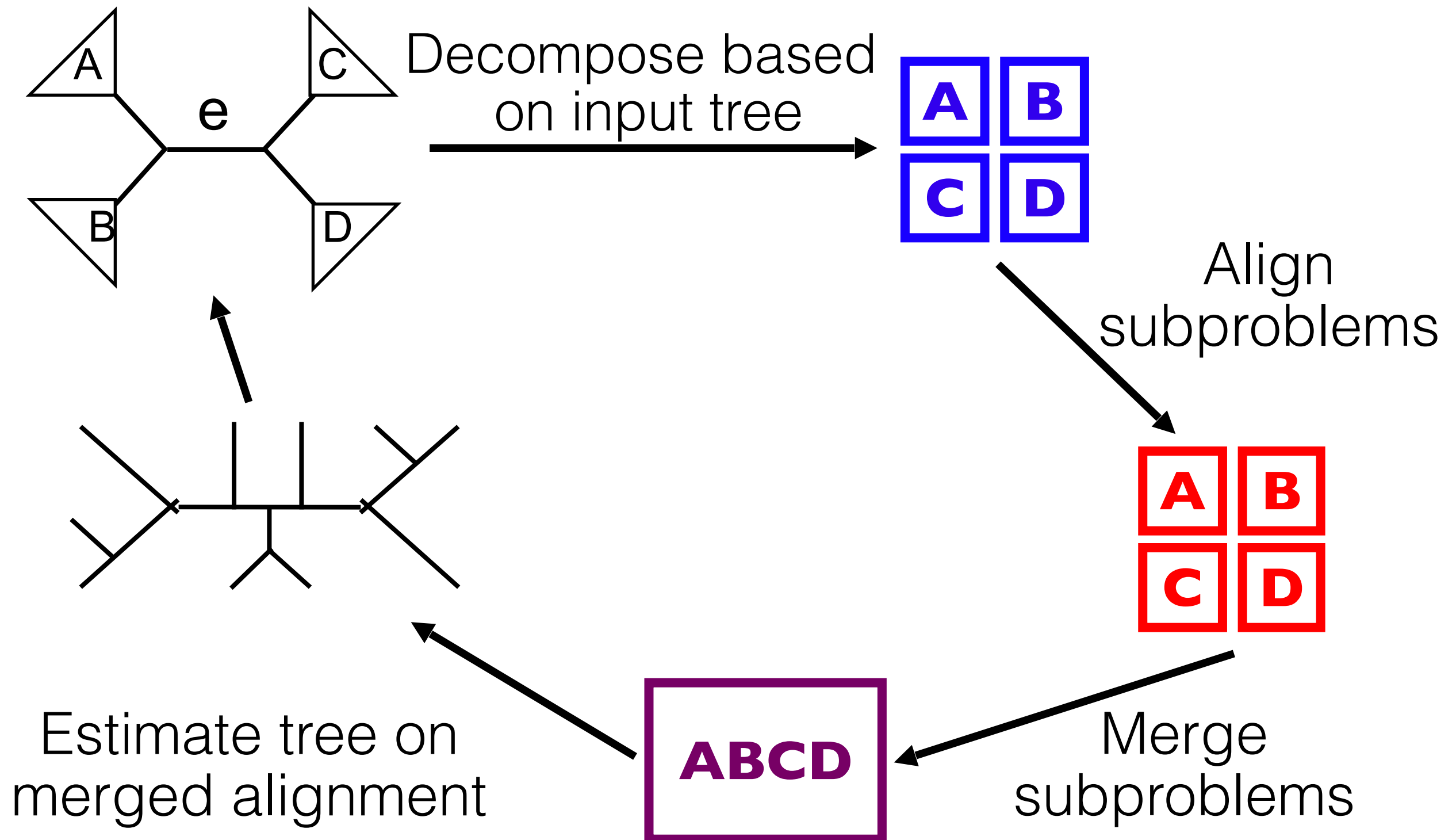
SATé iteration

(Actual decomposition produces 32 subproblems)

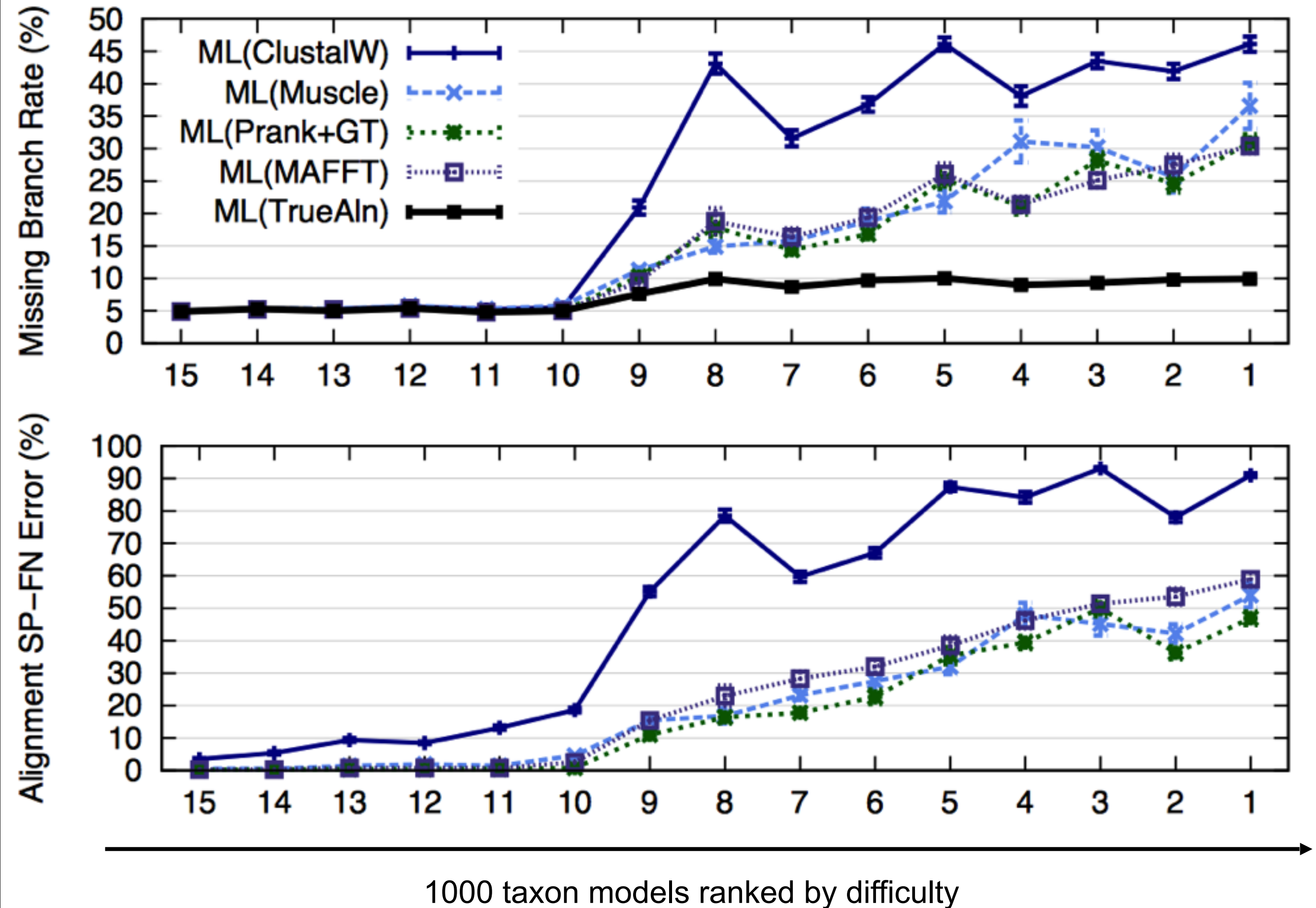


SATé iteration

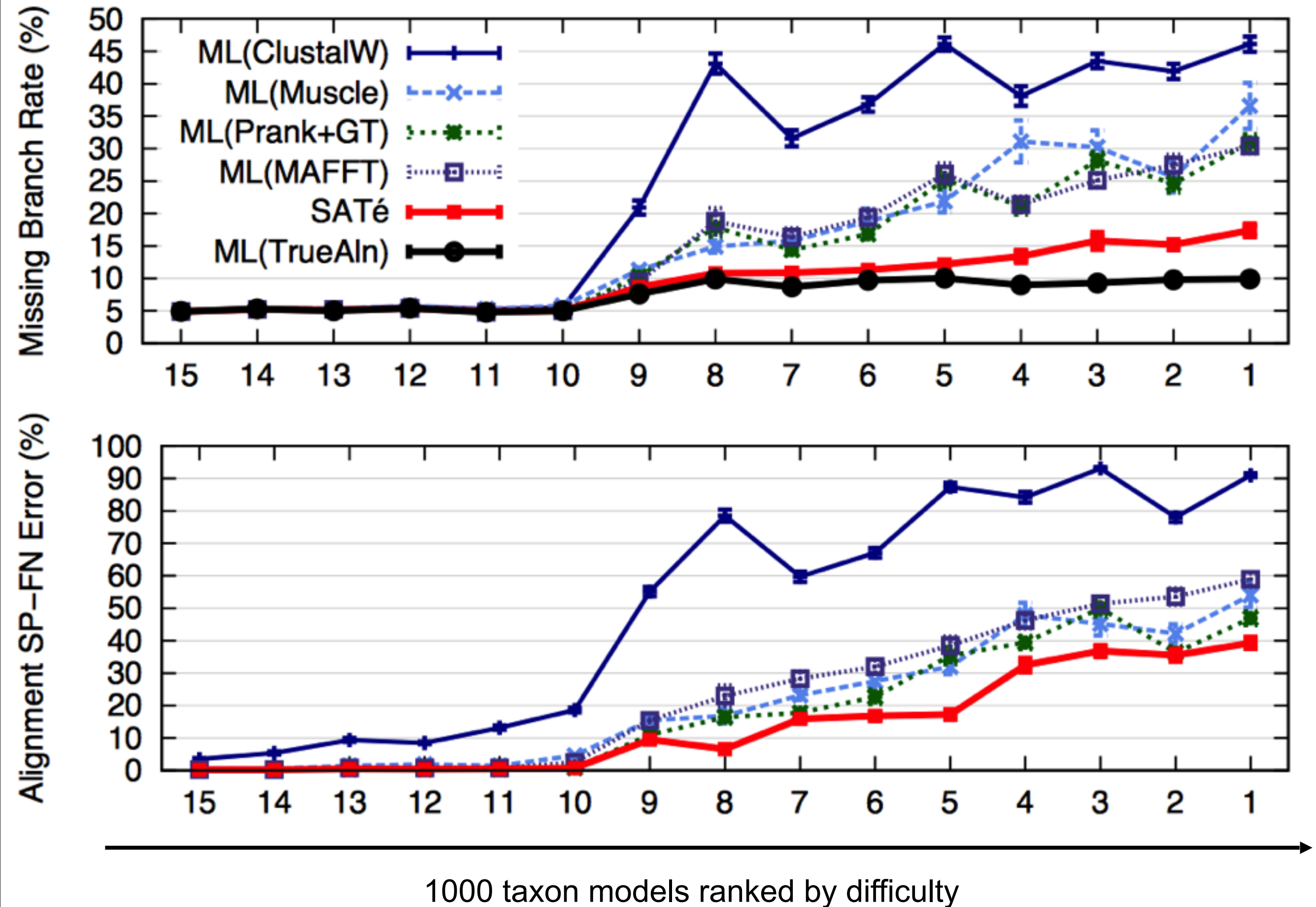
(Actual decomposition produces 32 subproblems)



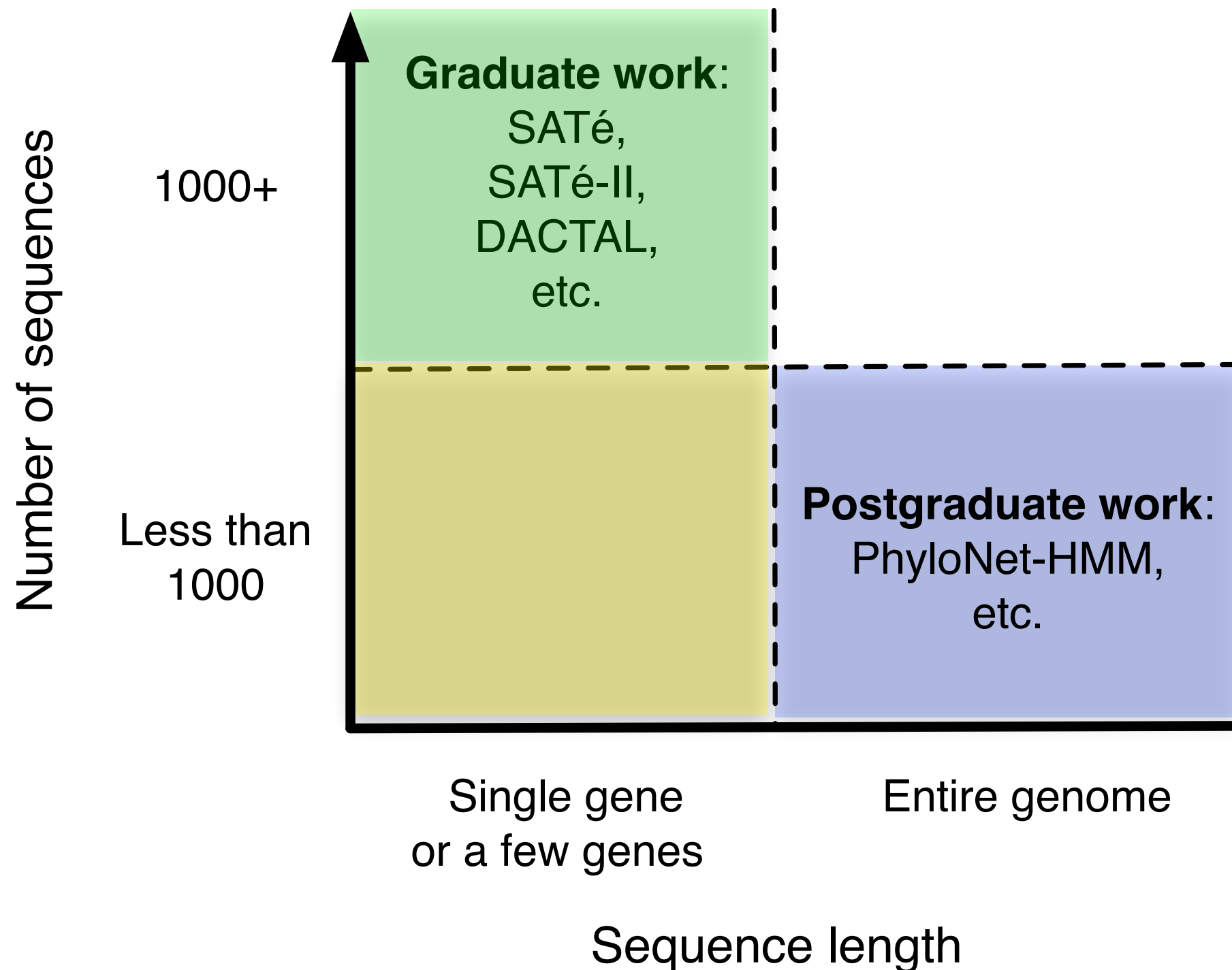
Results



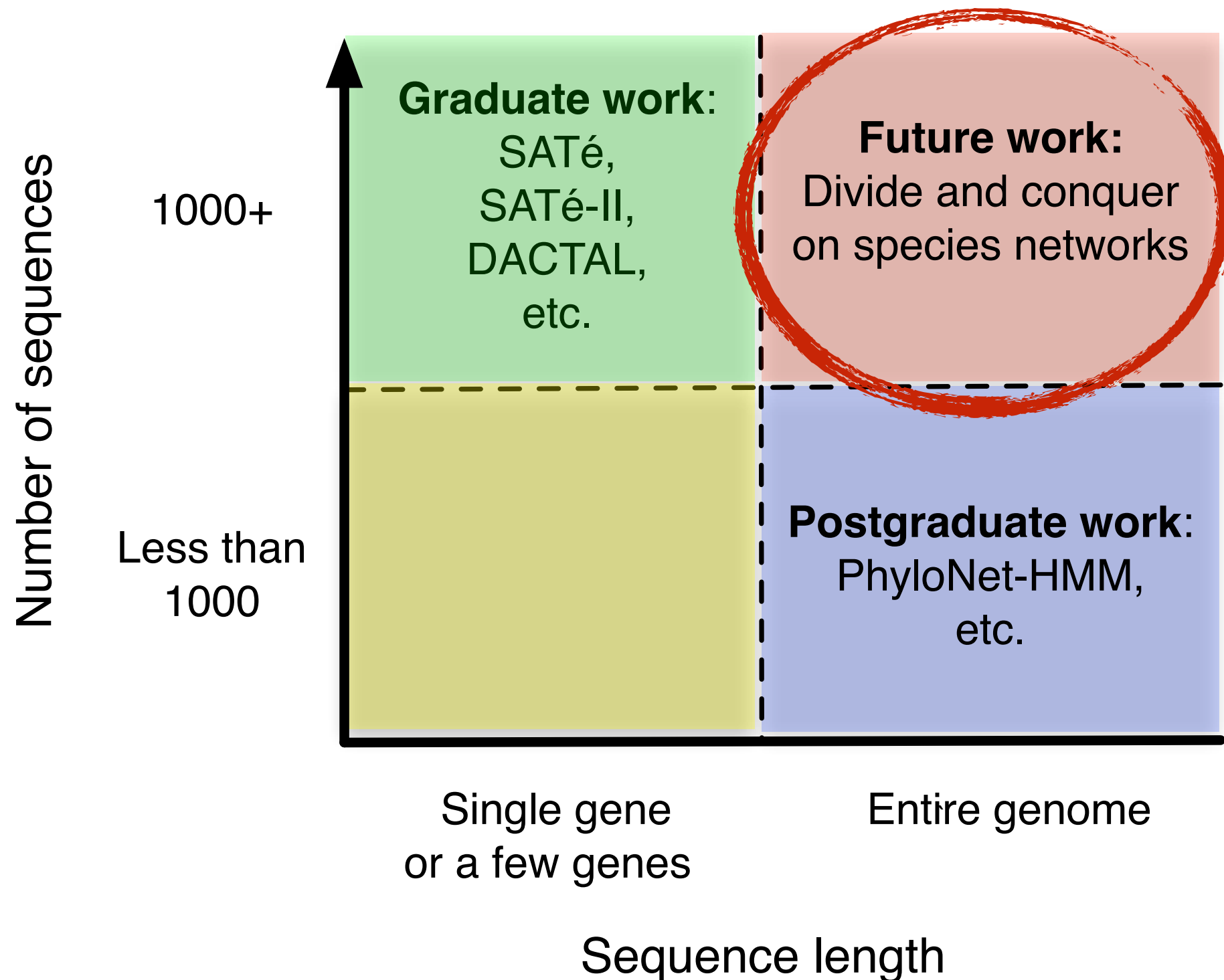
Results



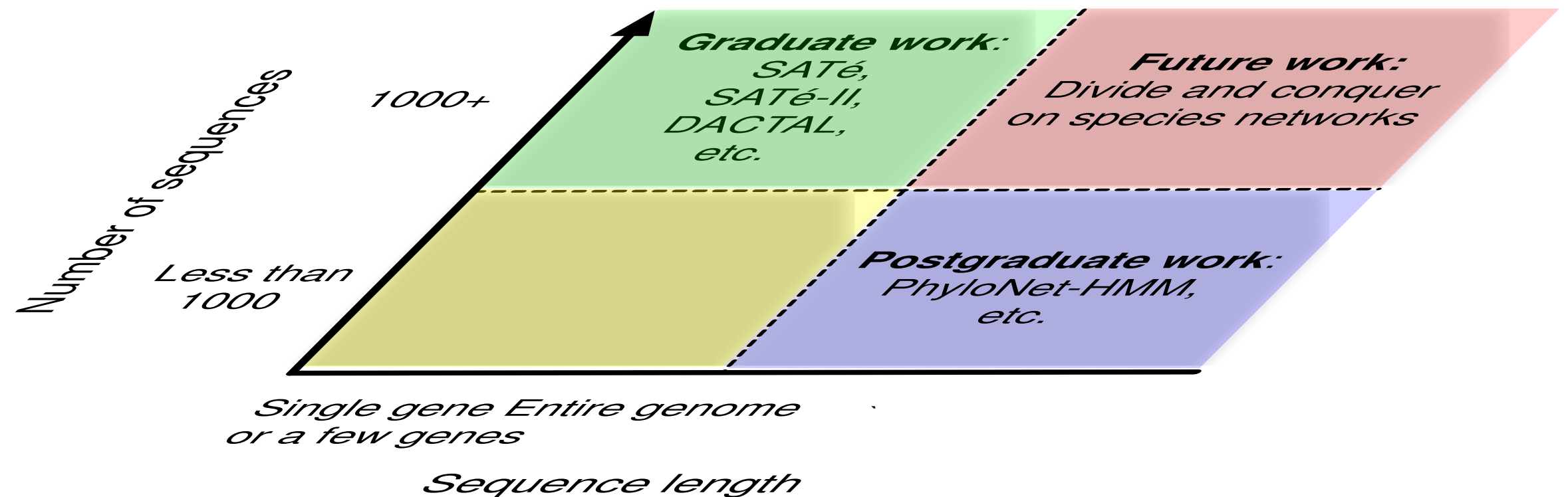
Selected Current Contributions



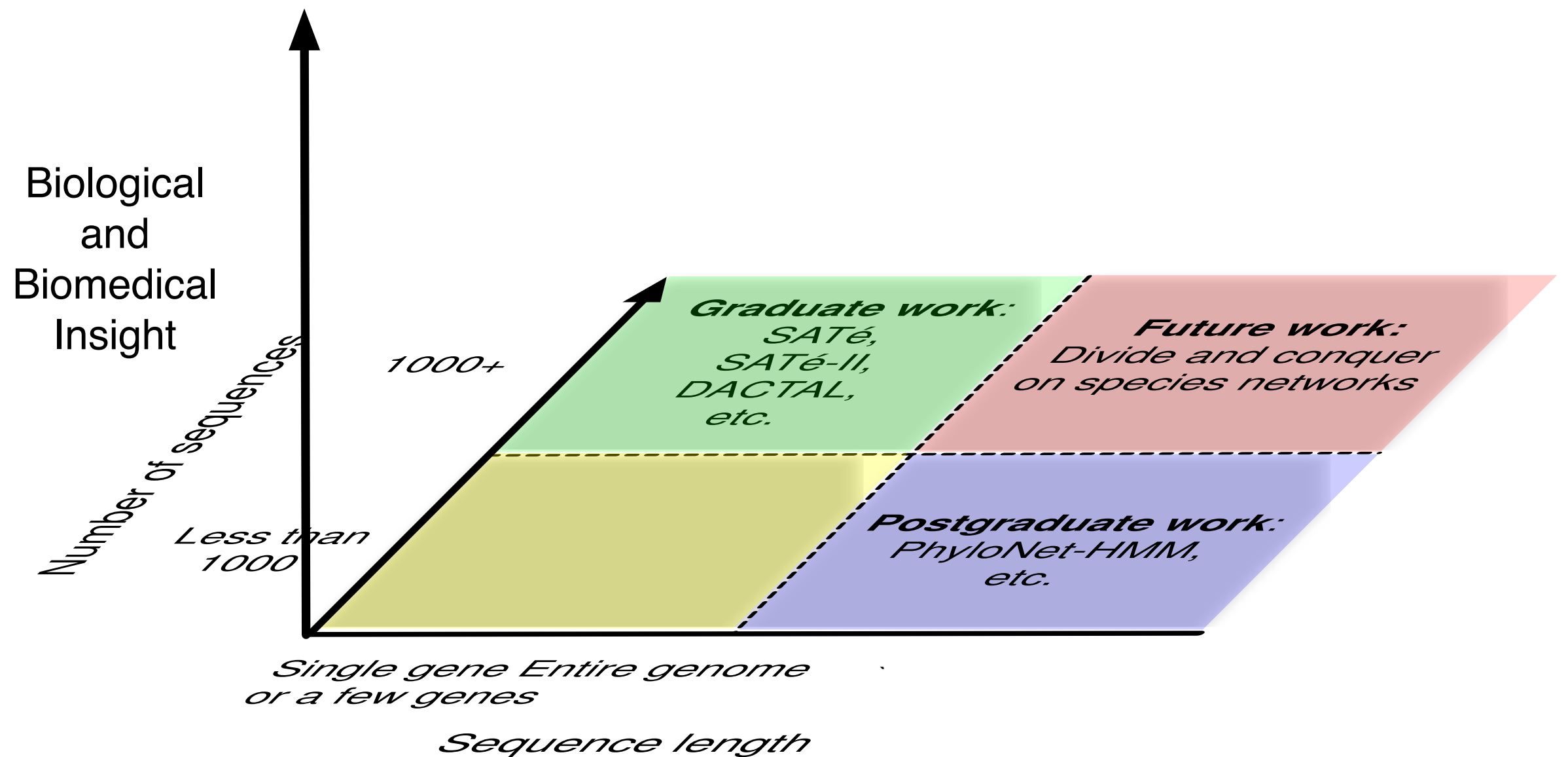
Future Work: Topic #1



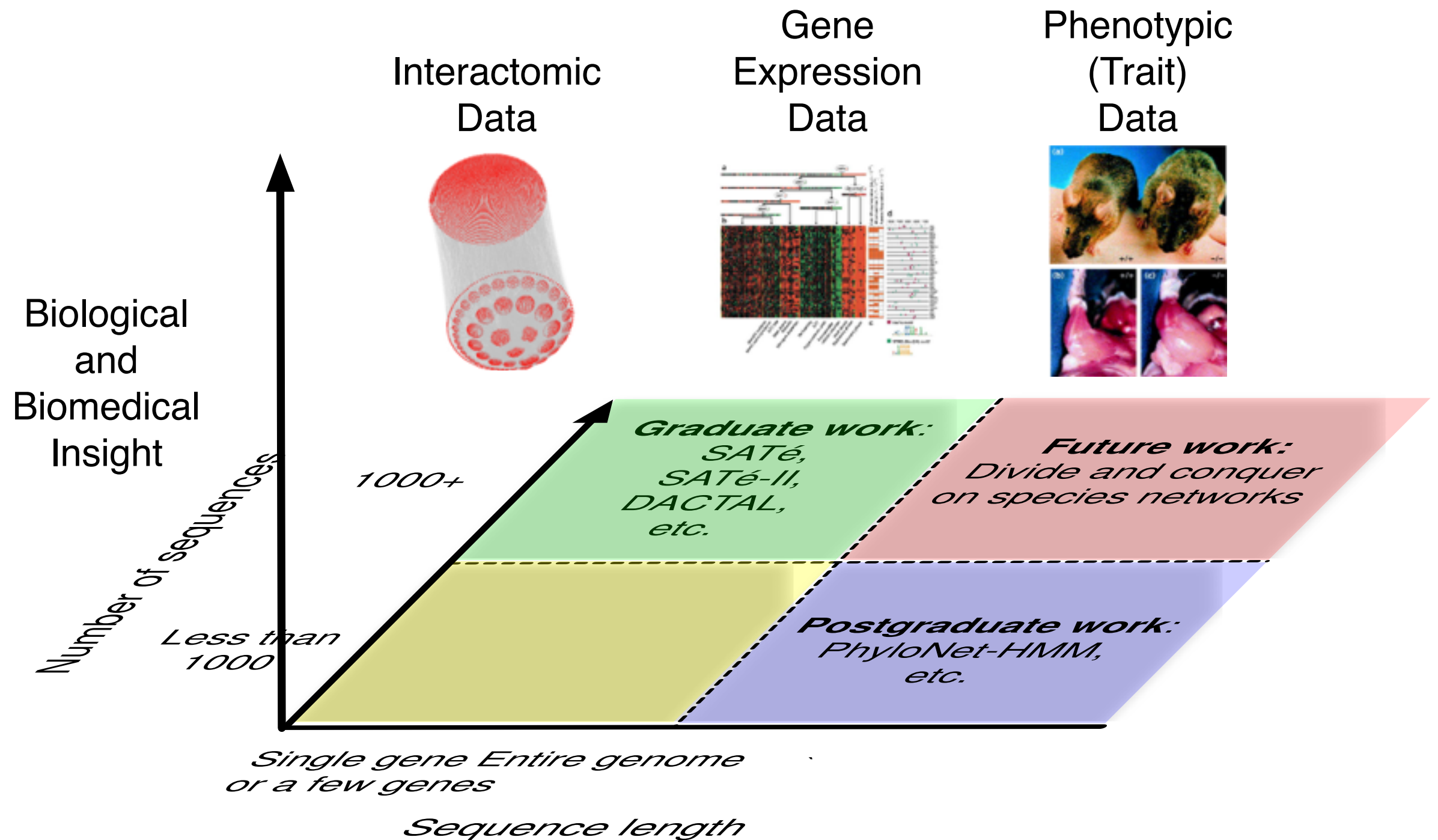
Future Work: Topic #2



Future Work: Topic #2



Future Work: Topic #2



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Questions?

- My website can be found at <http://www.cs.rice.edu/~kl23>
- Nakhleh lab website can be found at <http://bioinfo.cs.rice.edu/>