

Stochastic Models and Algorithms for  
Large-scale Comparative Genomics under  
Complex Evolutionary Scenarios



*Kevin J. Liu*

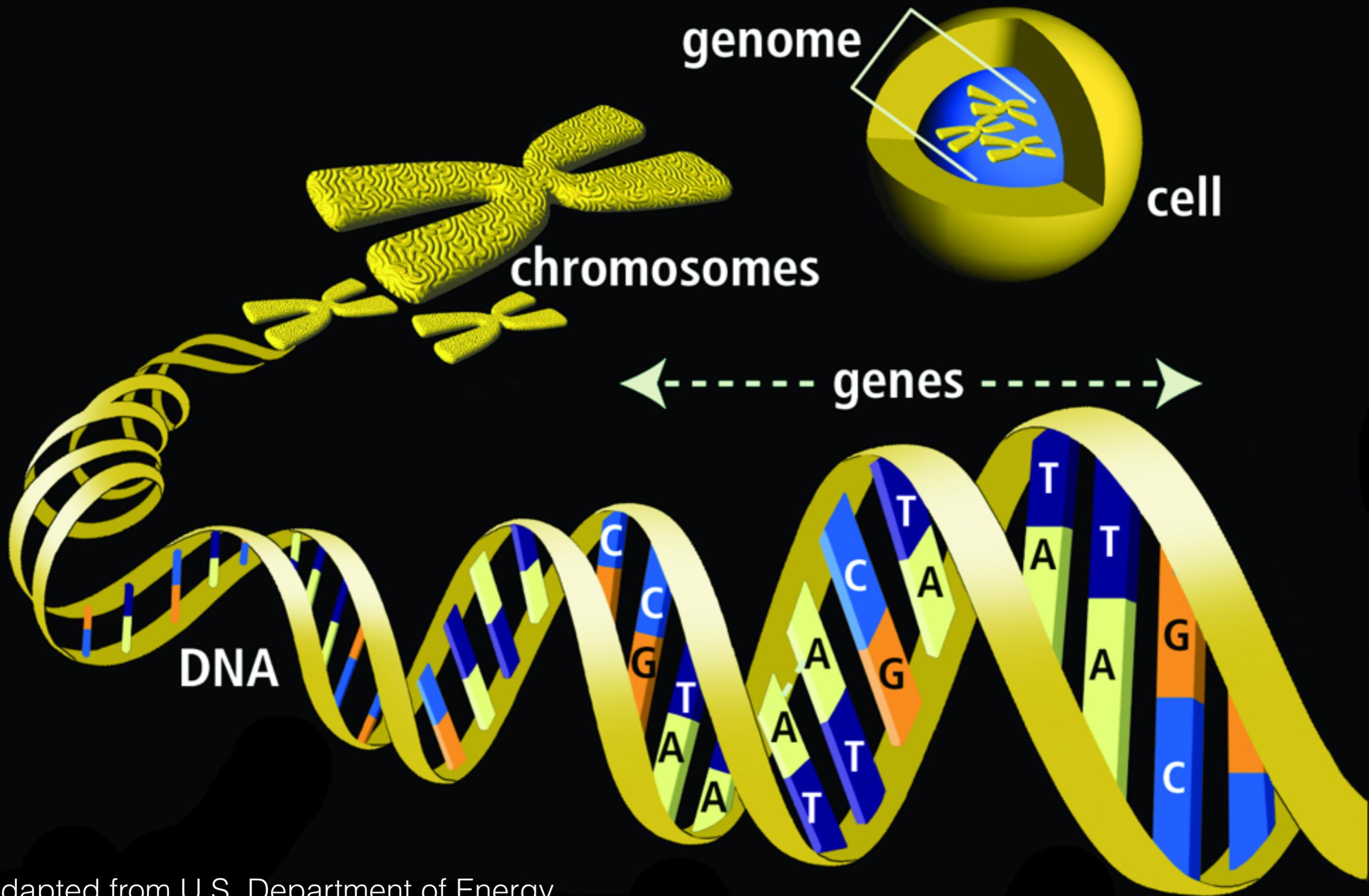
*Department of Computer Science*

*Rice University*

# Outline

- Comparative genomics: Promises and challenges
- Part I: Fast and accurate alignment and tree estimation on large-scale data sets
- Part II: Modeling and inference under more complex evolutionary scenarios
- Directions for future research and summary

# Comparative Genomics



Adapted from U.S. Department of Energy  
Genomic Science Program  
([genomicscience.energy.gov](http://genomicscience.energy.gov))

- Advanced genome sequencing technologies are generating data at an unprecedented rate.
- How do we make sense of all of this data?
- One answer: “Nothing in biology makes sense except in the light of evolution.” T. Dobzhansky

# Input and Output of An Example Comparative Genomic Study

(Nature 423 2003)



```

Scer TTATATTGAATTTTCAAAAATTCTTACTTTTTTTTTGGATGGACGCAAAGAAGTTAATAATCATATTACATGGCATTACCACCATATACA
Spar CTATGTTGATCTTTTCAGAAATTTT-CACTATATTAAAGATGGGTGCAAAGAAGTGTGATTAATTATATTACATCGCTTTCCCTATCATACACA
Smik GTATATTGAATTTTTCAGTTTTTTTTCACTATCTTCAAGGTTATGTAAAAAA-TGTCAAGATAAATTACATTTCTTACTATCATACACA
Sbay TTTTTTTGATTTCTTTAGTTTTCTTTCTTTAACTTCAAAAATTATAAAAAGAAAGTGTAGTCACATCATGCTATCT-GTCACTATCACATATA
* * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
    
```

**TBP**

```

Scer TATCCATATCTAATCTTACTTTATATGTTTGT-GGAAAT-GTAAAGAGCCCCATTATCTTAGCCTAAAAAAACC--TTCTCTTTGGAACCTTCAGTAATACG
Spar TATCCATATCTAGTCTTACTTTATATGTTTGT-GAGAGT-GTTGATAACCCCAGTATCTTAAACCCAAGAAAGCC--TT-TCATATGAAACTTGAAGTC-TACG
Smik TACCGATGCTAGTCTTACTTTATATGTTTGT-GGGAAATGTTGGTAAATCCCAGTCTCCAGATCAAAAAAGGT--CTTTCATGGAGCTTTG-CTA-TATG
Sbay TAGATATTTCTGATCTTTCTTTATATATTATAGAGAGATGCCAATAAACGTCCTACCTCGAACAAAAAGAGGGGATTTTCTGTAGGGCTTTCCCTATTTTC
** ** ** * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
    
```

**GAL4**

**GAL4**

**GAL4**

```

Scer CTTAACTGCTCATTGC-----TATATTGAAGTACGGGATTAGAAGCCCGCCAGAGGGGCACAGCCCTCCGACGGGAAGACTCTCCTCCGTGGCGTCTCGTCT
Spar CTTAACTGCTCATTGC-----AATATTGAAGTACGGGATCAGAAGCCCGCCAGAGGGGCACAGCCCTCCGACGGGAATATTCCCTCCGTGGCGTCCCGTCT
Smik TTTAGCTGTTCAAG-----ATATTGAAGTACGGGATGAGAAGCCCGCCAGAGGGGCACAGCAATTTCCCGACGGGAACATTCTCCTCCGTGGCGGCTCCTCT
Sbay TCTTATTGTCATTACTTCGCAATGTTGAAATACGGGATCAGAAGCTGCGGACGGGATGACAGTACTCCGACGGGAAGAACTGTCTCCGTGGCGAAGTCTGCTCT
** ** * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
    
```

**GAL4**

```

Scer TCACCGG-TCGCGTTCTGAAACGCAGATGTGCTCCGCGCCGCACTGCTCCGAAACAAATAAAGATTCTACAA-----TACTAGCTTTT--ATGGTTATGAA
Spar TCGTCCGGTTGTTCCCTTAA-CATCGATGTACTCCGCGCCGCCCTGCTCCGAAACAAATAAGGATTCTACAAGAAA-TACTTGTTTTTTTTATGGTTATGAC
Smik ACGTTGG-TCGCGTCCCTGAA-CATAGGTACGGCTCCGACCACCGTGGTCCGAACTATAAATACTGGCATAAAGAGGTACTAATTTCT--ACGGTGTATGCC
Sbay GTG-CGGATCACGTCCCTGAT-TACTGAAAGCGTCCGCGCCGCCATACCCCGAAACAAATGCAAAATGCAAGAACAAA-TGCCGTGTAGTG--GCAGTTATGGT
** * ** * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
    
```

**MIG1**

```

Scer GAGGA-AAAATGGCAGTAA----CCTGGCCCCACAAACCTT-CAAATTAACGAATCAAATTAACAACCATA-GGATGATAATGCCA-----TTAG--T
Spar AGGAACAAAATAAGCAGCCC----ACTGACCCCATATACCTTTTCAAACCTATTGAATCAAATTGGCCAGCATA-TGGTAATAGTACAG-----TTAG--G
Smik CAACGCAAAAATAAACAGTCC----CCCGCCCCACATACCTT-CAAATCGATGCGTAAAACTGGCTAGCATA-GAATTTTGGTAGCAA-AATATTAG--G
Sbay GAACGTGAAATGACAATTCTTGCCTT-CCCCAATATACCTTTGTTCCGTGTACAGCACACTGGATAGAACAATGATGGGGTTCGGGTCAAGCCTACTCG
** * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
    
```

**MIG1**

**TBP**

```

Scer TTTTTAGCCTTATTTCTGGGTAATTAATCAGCGAAGCG--ATGATTTTT-GATCTATTAACAGATATATAAATGCAAAGCTGCATAACCAC----TT
Spar GTTTT--TCTTATTCCTGAGACAATTCATCCGCAAAAAATAATGGTTTTT-GGTCTATTAGCAAACATATAAATGCAAAGTTGCATAGCCAC----TT
Smik TTCTCA--CCTTTCTCTGTGATAATTCATCACCAGAAATG--ATGGTTA--GGACTATTAGCAAACATATAAATGCAAAGTCCGAGAGATCA----AT
Sbay TTTTCCGTTTTACTTCTGTAGTGGCTCAT--GCAGAAAGTAATGGTTTTTCTGTTTCCTTTTTGCAAACATATAAATATGAAAGTAAGATCGCCTCAATTGTA
* * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
    
```

```

Scer TAACTAATACTTTCAACATTTTCAGT--TTGTATTACTT-CTTATTCAAAT---GTCATAAAAAGTATCAACA-AAAAATTGTTAATATACCTCTATACT
Spar TAAATAC-ATTTGCTCCTCCAAGATT--TTTAATTTCTG-TTTGTTTTATT---GTCATGGAATATTAACA-ACAAGTAGTTAATATACATCTATACT
Smik TCATTCC-ATTCGAACCTTTGAGACTAATTAATTTAGTACTAGTTTTCTTTGGAGTTATAGAAATACCAAA-AAAAATAGTCAGTATCTATACATACA
Sbay TAGTTTTCTTTATTCCGTTTGTACTTCTTAGATTTCTTATTTCGGTTTTACTTTGCTCTCCAATTATCAAAACATCAATAACAAGTATCAACATTTGT
* * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
    
```

```

Scer TTAA-CGTCAAGGA---GAAAAAAGTATA
Spar TTAT-CGTCAAGGAAA-GAACAAAGTATA
Smik TCGTTCATCAAGAA---AAAAAAGTATA
Sbay TTATCCCAAAAAAACAACAACAACATATA
* * * * * * * * * * * * * * * *
    
```

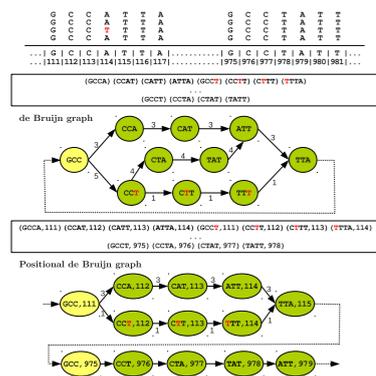
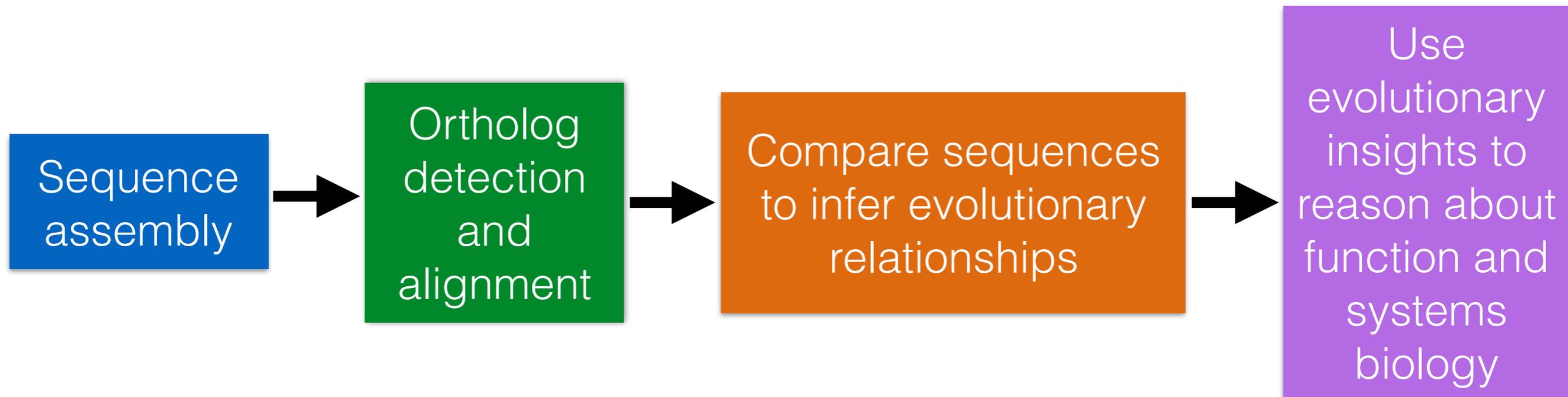


Factor footprint

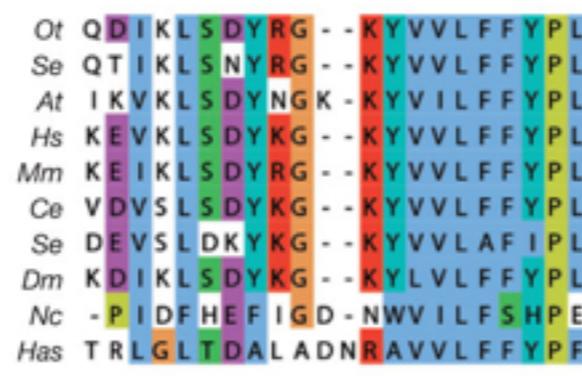


Conservation island

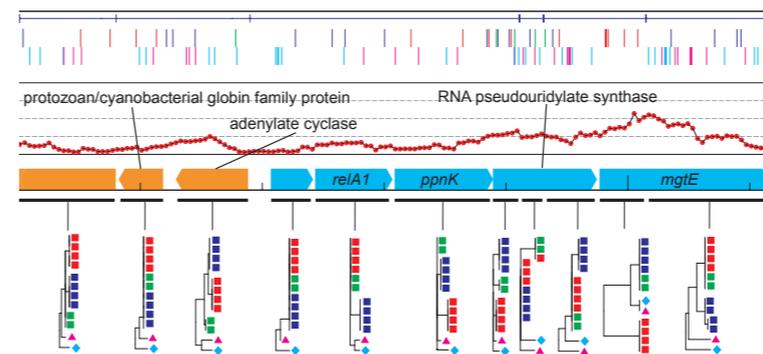
# A Comparative Genomics Pipeline



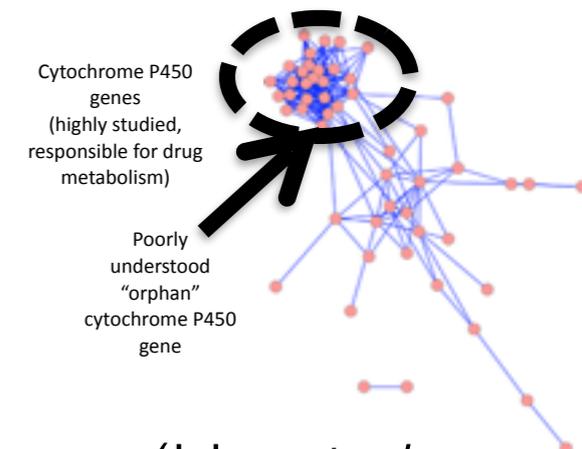
(Bioinformatics 28, 2012)



(Nature 485, 2012)



(MBE 29, 2013)



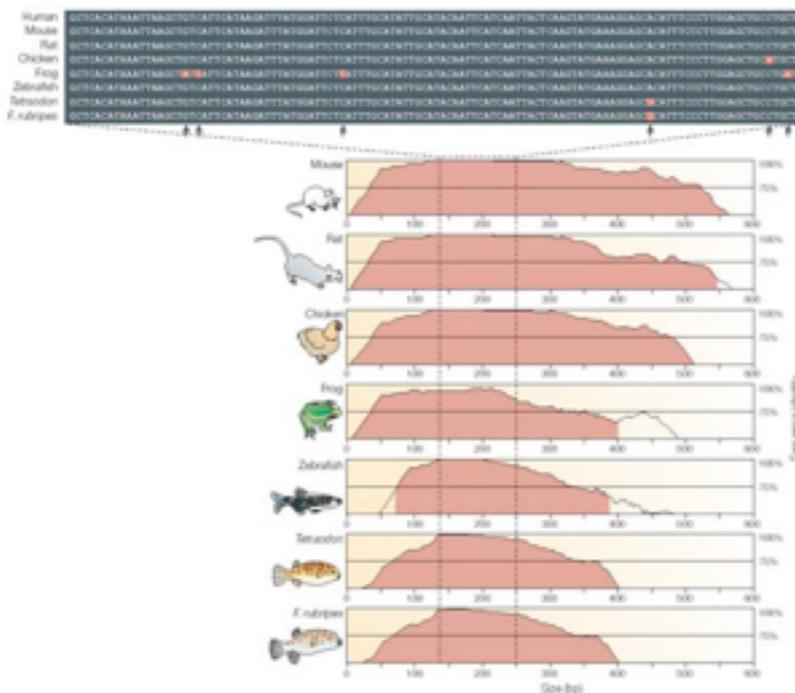
(Liu *et al.*, submitted.)

# Applications

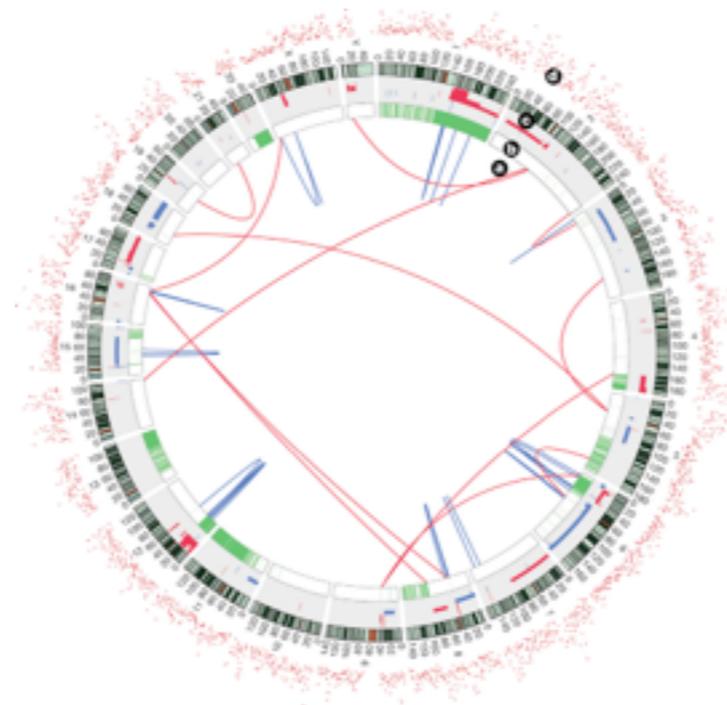
Detecting regulatory elements

Detecting cancer mutations

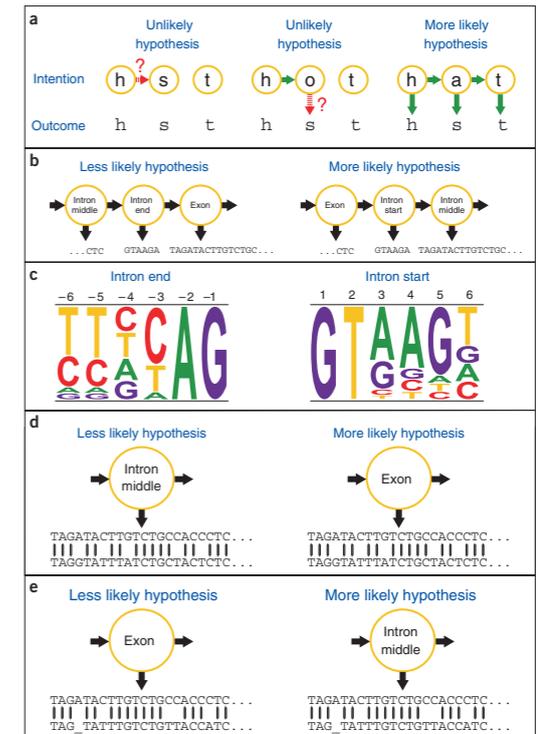
Gene finding



(Nature Reviews Genetics 5, 2004)



(Nature 465, 2010)



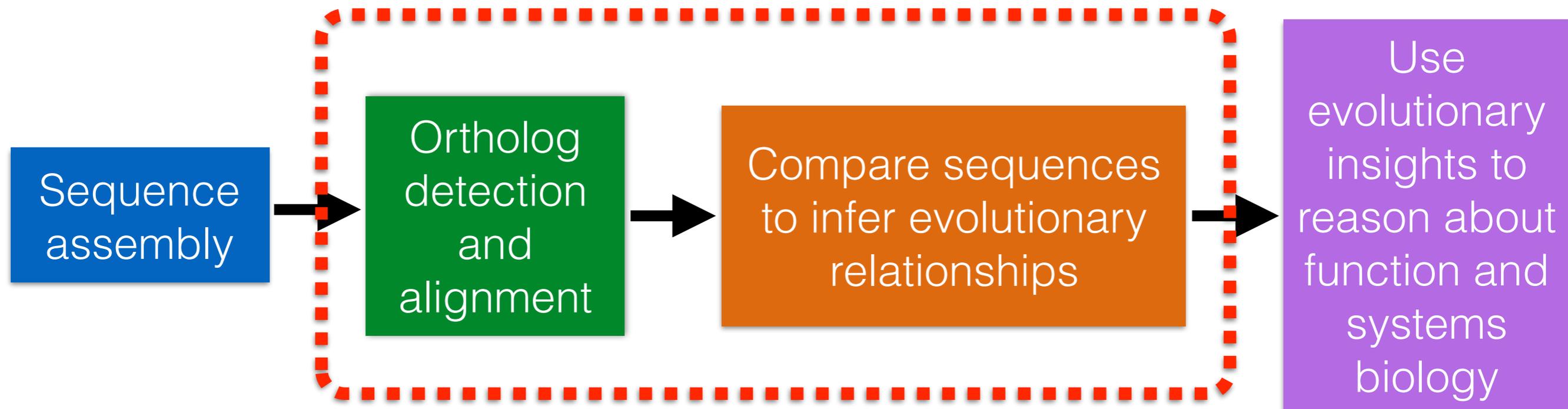
(Nature Biotechnology 25, 2007)

**And many, many more ...**

# Three Major Challenges

- **Computational challenge:** accurate and scalable algorithms and tools for large-scale analyses
- **Statistical challenge:** realistic yet tractable models of genome evolution
- **Biological challenge:** co-occurrence of multiple complex evolutionary events

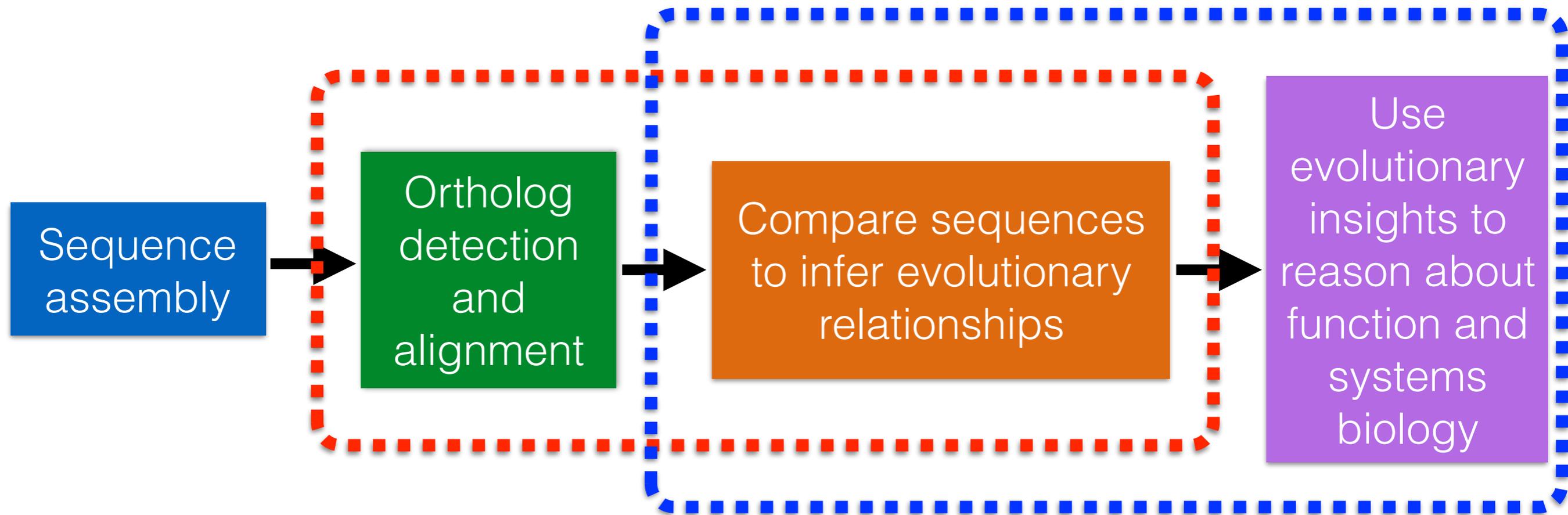
# My Contributions



## Graduate work:

SATé,  
SATé-II,  
DACTAL,  
etc.

# My Contributions



## Graduate work:

SATé,  
SATé-II,  
DACTAL,  
etc.

## Postgraduate work:

PhyloNet-HMM,  
etc.

Part I: Fast and Accurate  
Alignment and Tree Estimation  
on Large-Scale Datasets

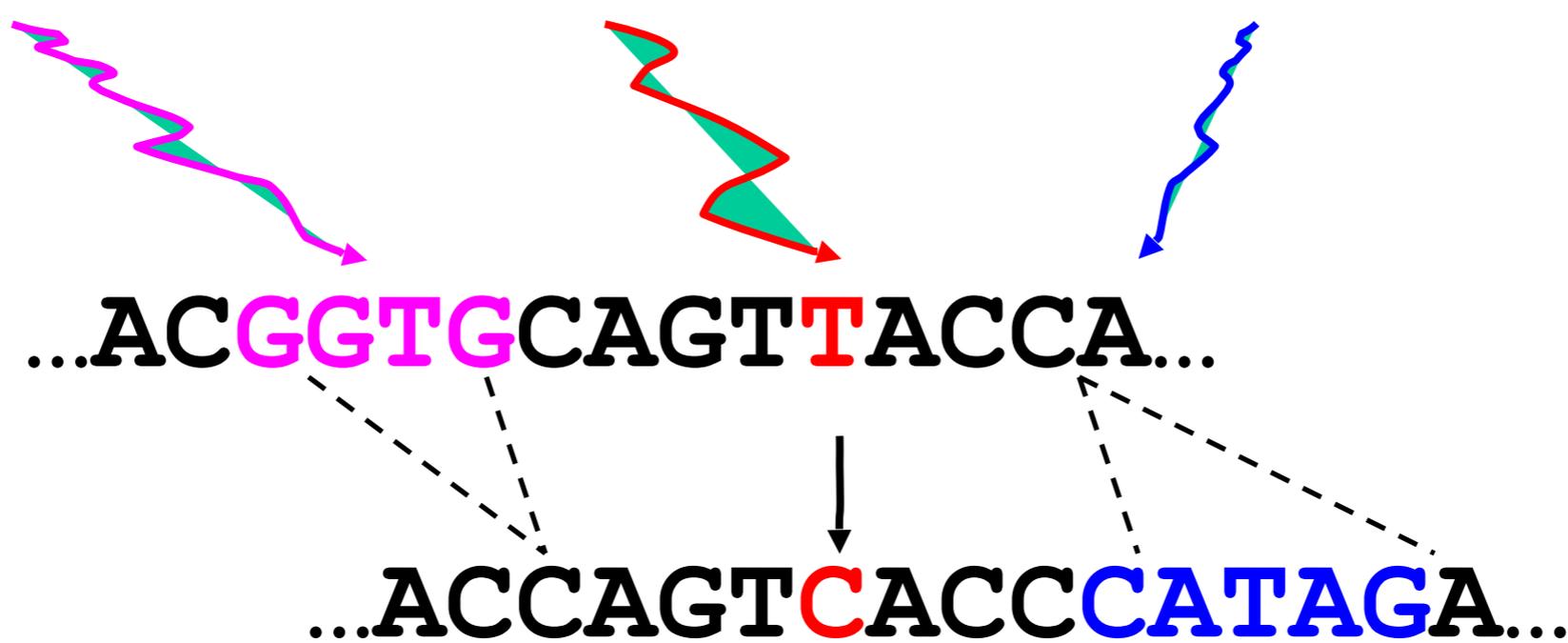
# SATé: Simultaneous Alignment and Tree estimation (Liu *et al.* Science 2009)

- Standard methods for alignment and tree estimation have unacceptably high error and/or cannot analyze large datasets
- SATé has equal or typically better accuracy than all existing methods on datasets with up to thousands of sequences
- 24 hour analyses using standard desktop computer
- SATé-II (Liu *et al.* Systematic Biology 2012) is more accurate and faster than SATé on datasets with up to tens of thousands of taxa

Deletion

Substitution

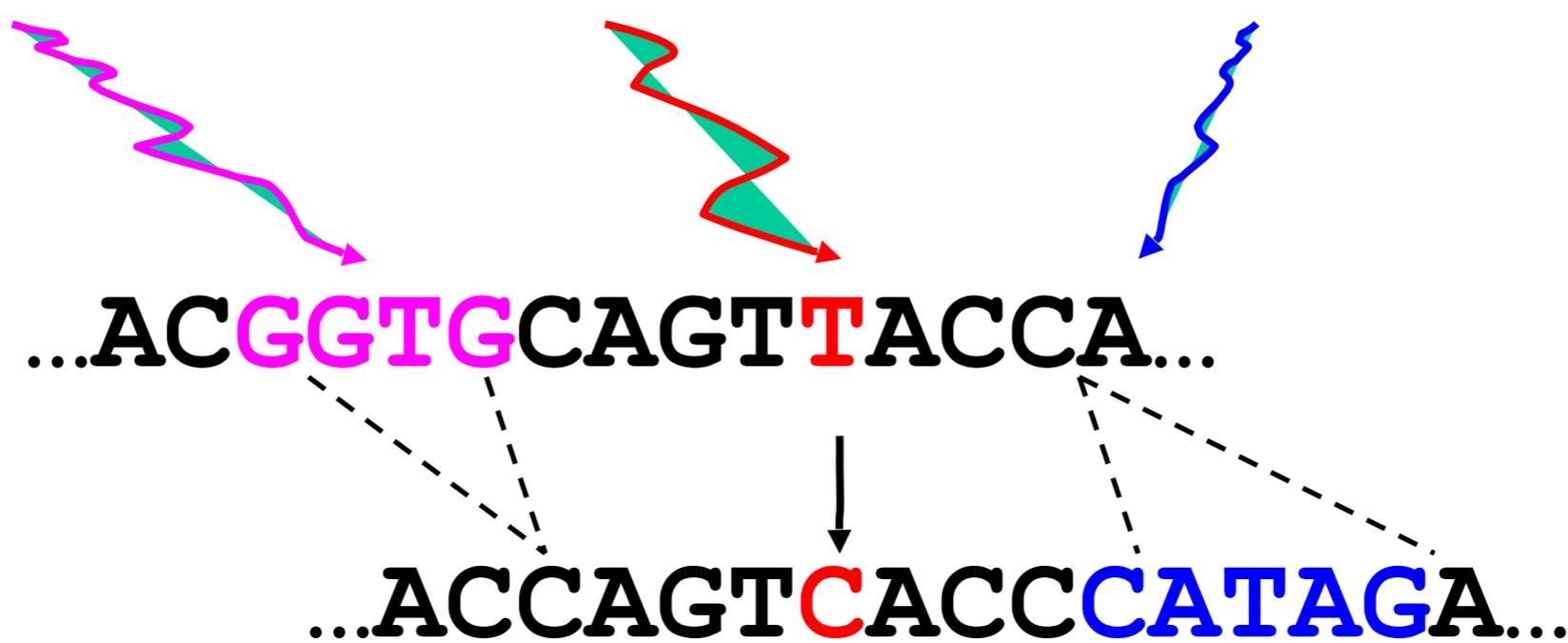
Insertion



Deletion

Substitution

Insertion



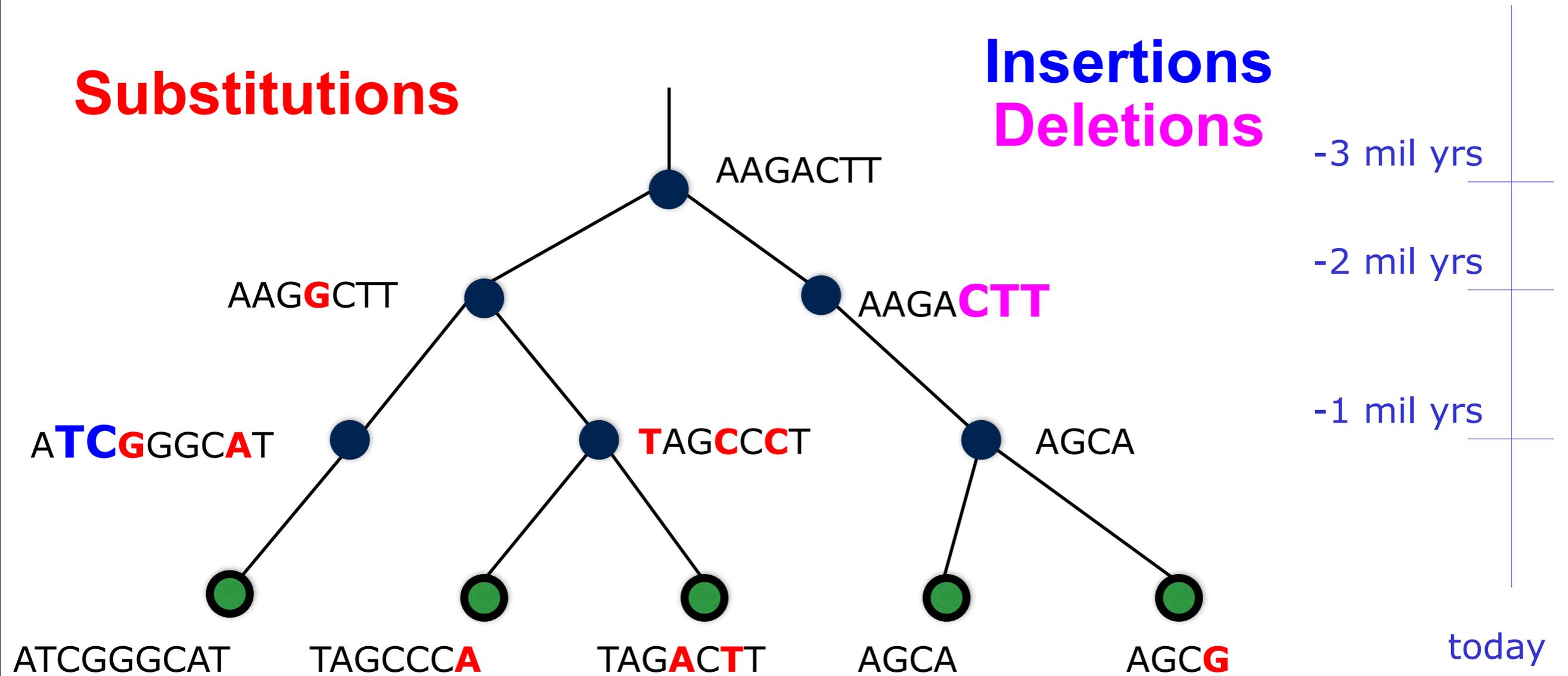
The true alignment is:

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

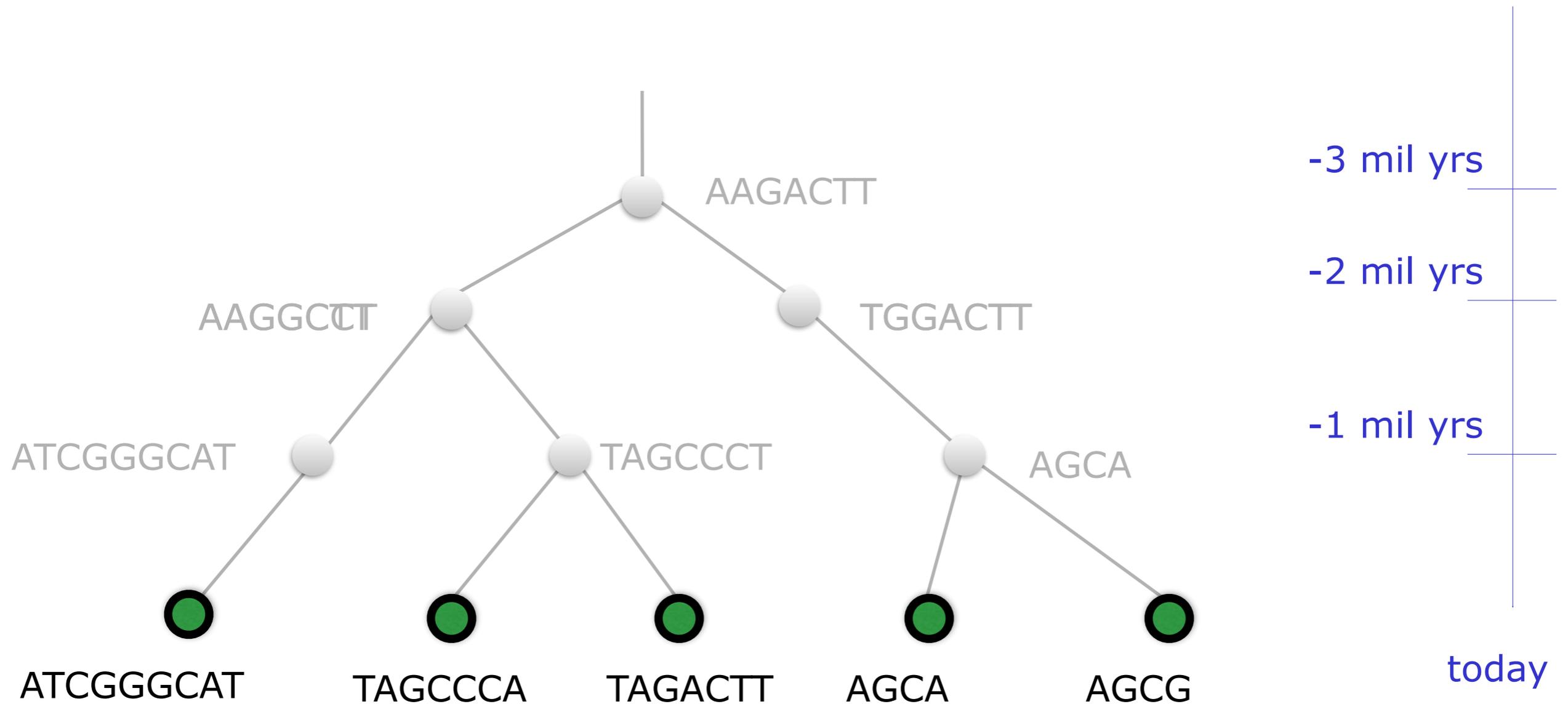
# DNA Sequence Evolution (Example)

**Substitutions**

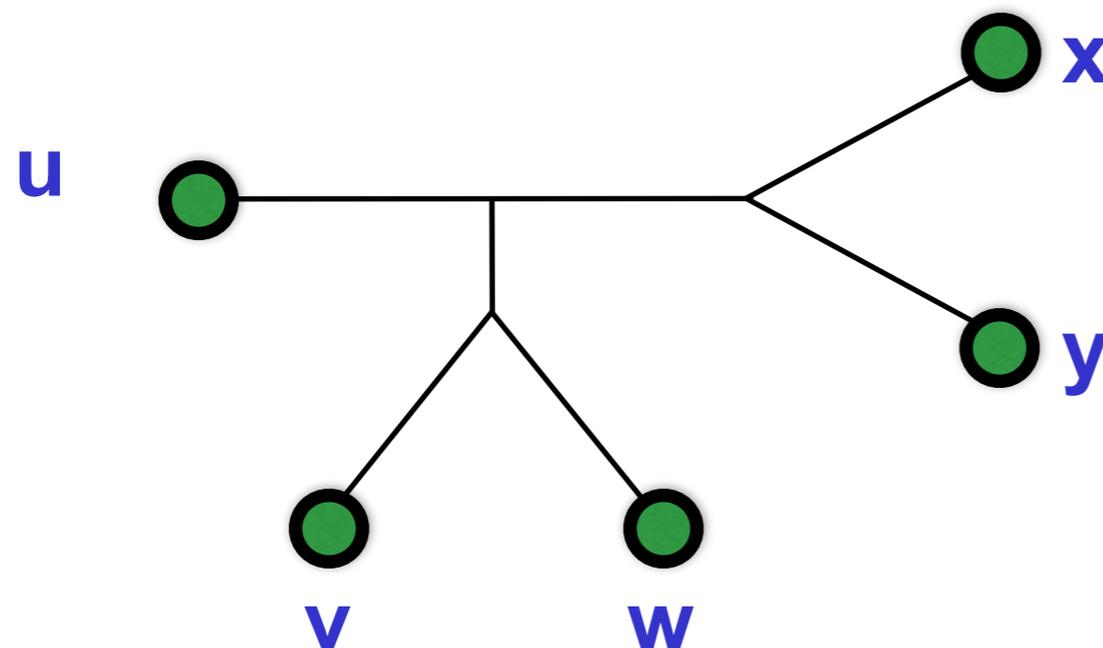
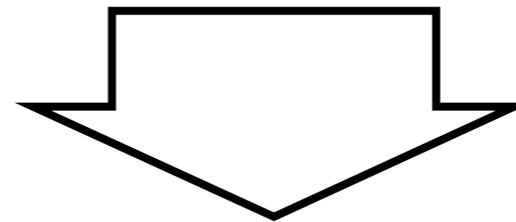
**Insertions  
Deletions**



# DNA Sequence Evolution (Example)



# Tree and Alignment Estimation Problem (Example)



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

# Many Trees and Many Alignments

- Number of trees  $|T|$  grows exponentially in  $n$ , the number of leaves:

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

- The number of alignments  $|A|$  also grows exponentially in  $n$  and the length of the longest unaligned sequence.
- All of the common and useful optimization problems are NP-hard.

# SATé Algorithm

Obtain initial alignment  
and tree



Estimate tree on new  
alignment



**Insight:**

Use tree to perform  
divide-and-conquer  
alignment

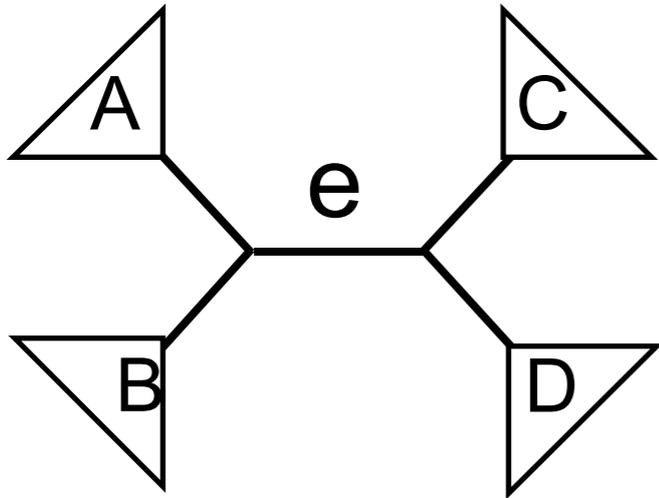
**Insight:** iterate - use a moderately accurate tree to obtain a more accurate tree

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

Repeat until convergence under the maximum likelihood optimization criterion

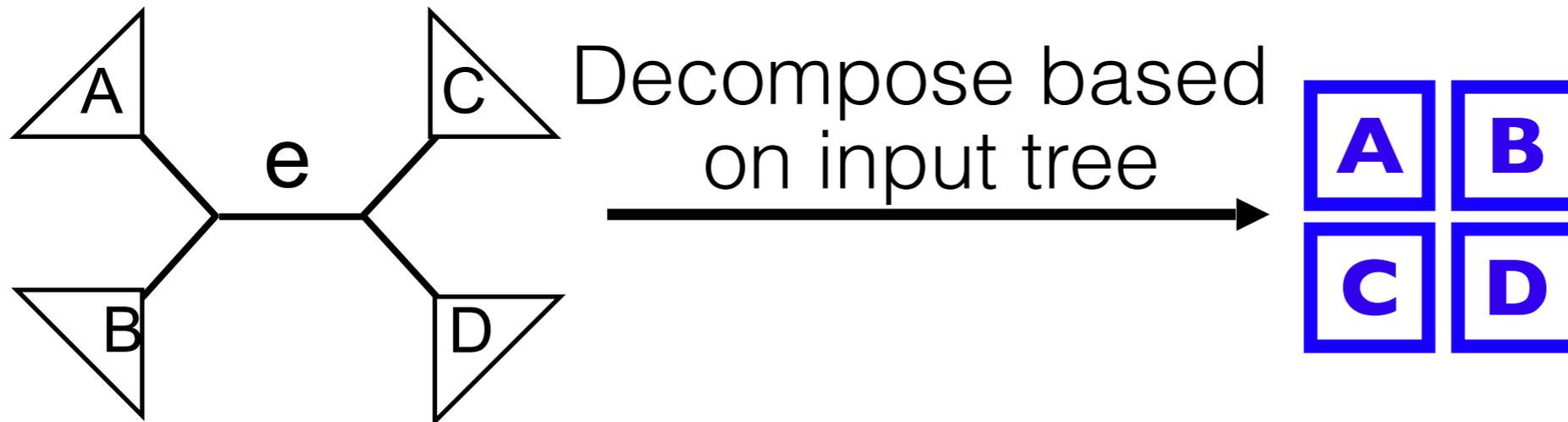
# SATé iteration

(Actual decomposition size is configurable)



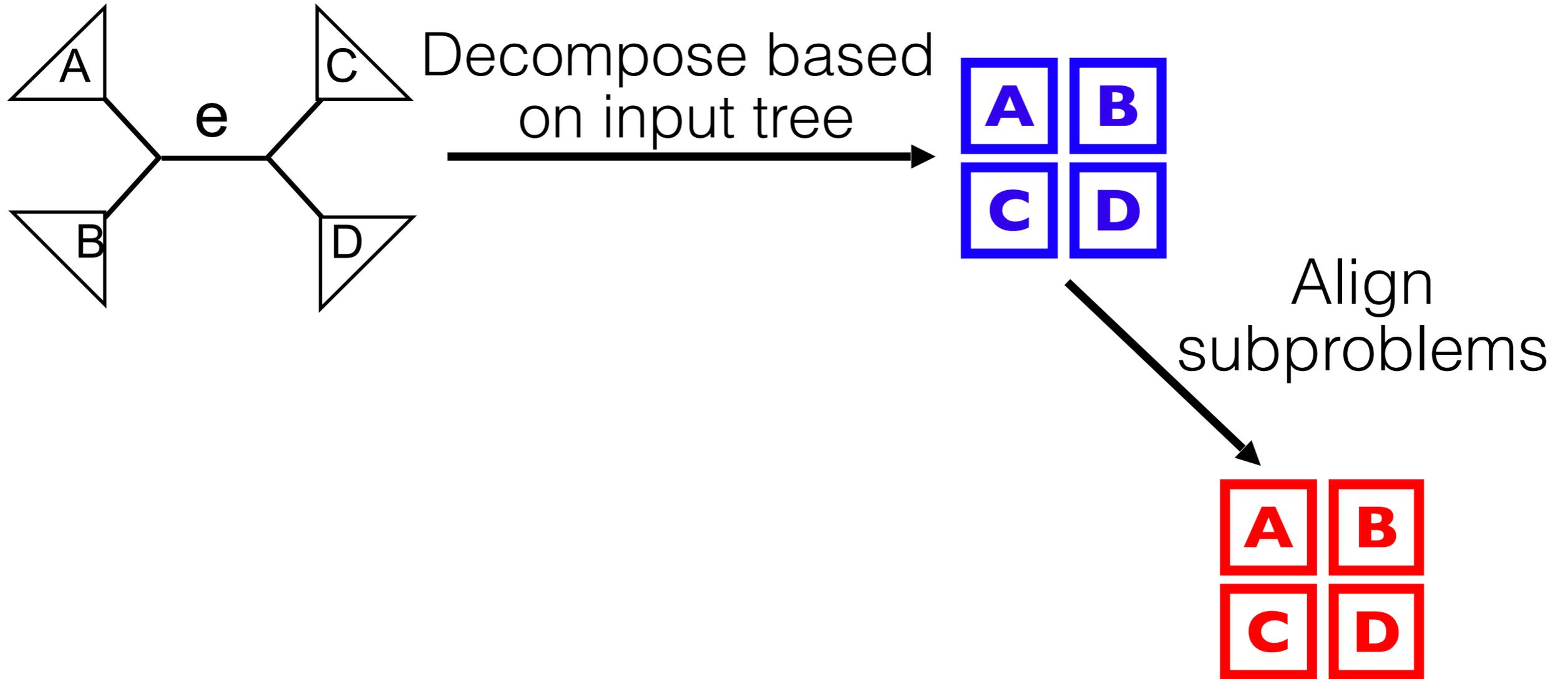
# SATé iteration

(Actual decomposition size is configurable)



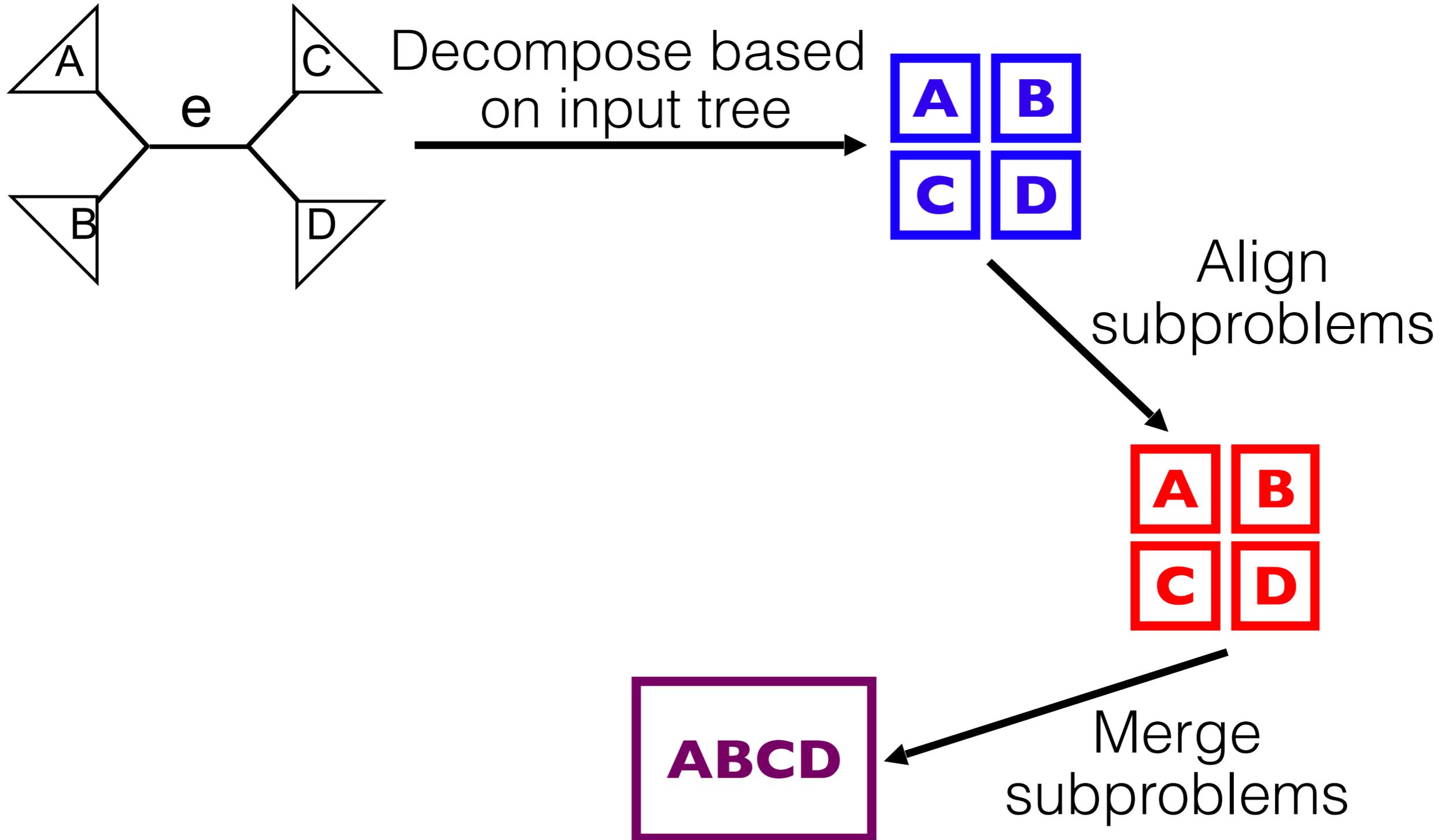
# SATé iteration

(Actual decomposition size is configurable)



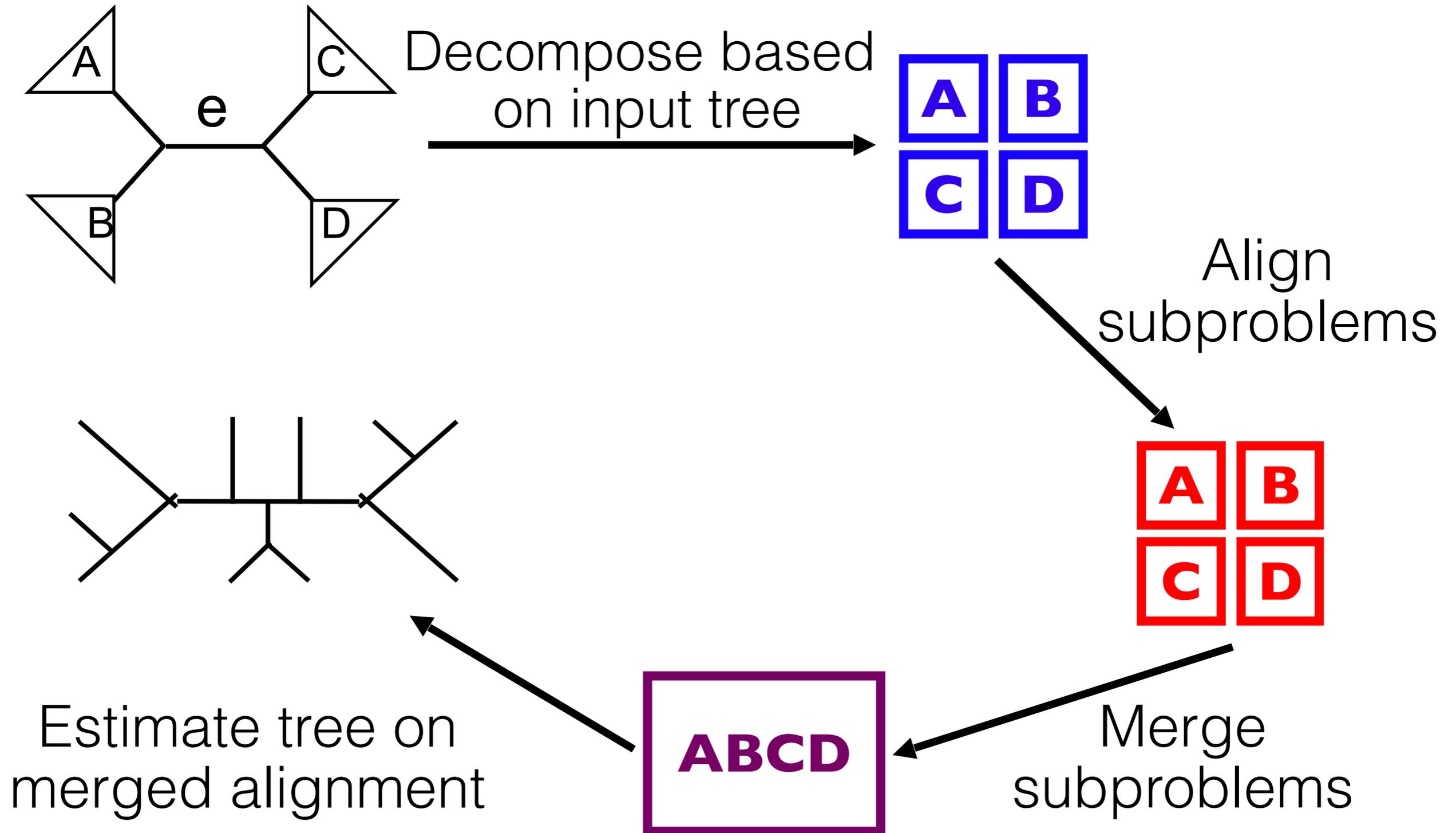
# SATé iteration

(Actual decomposition size is configurable)



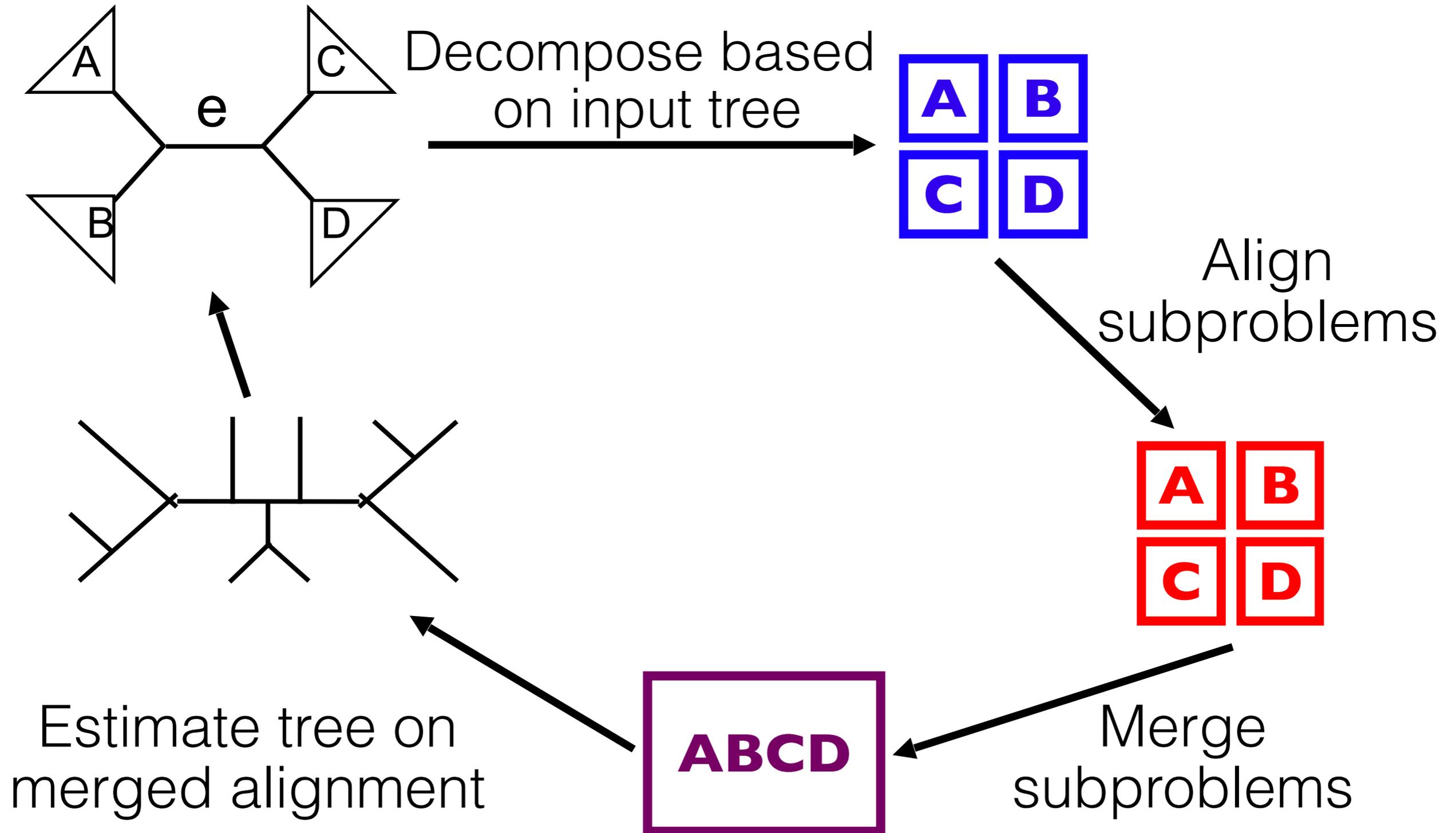
# SATé iteration

(Actual decomposition size is configurable)

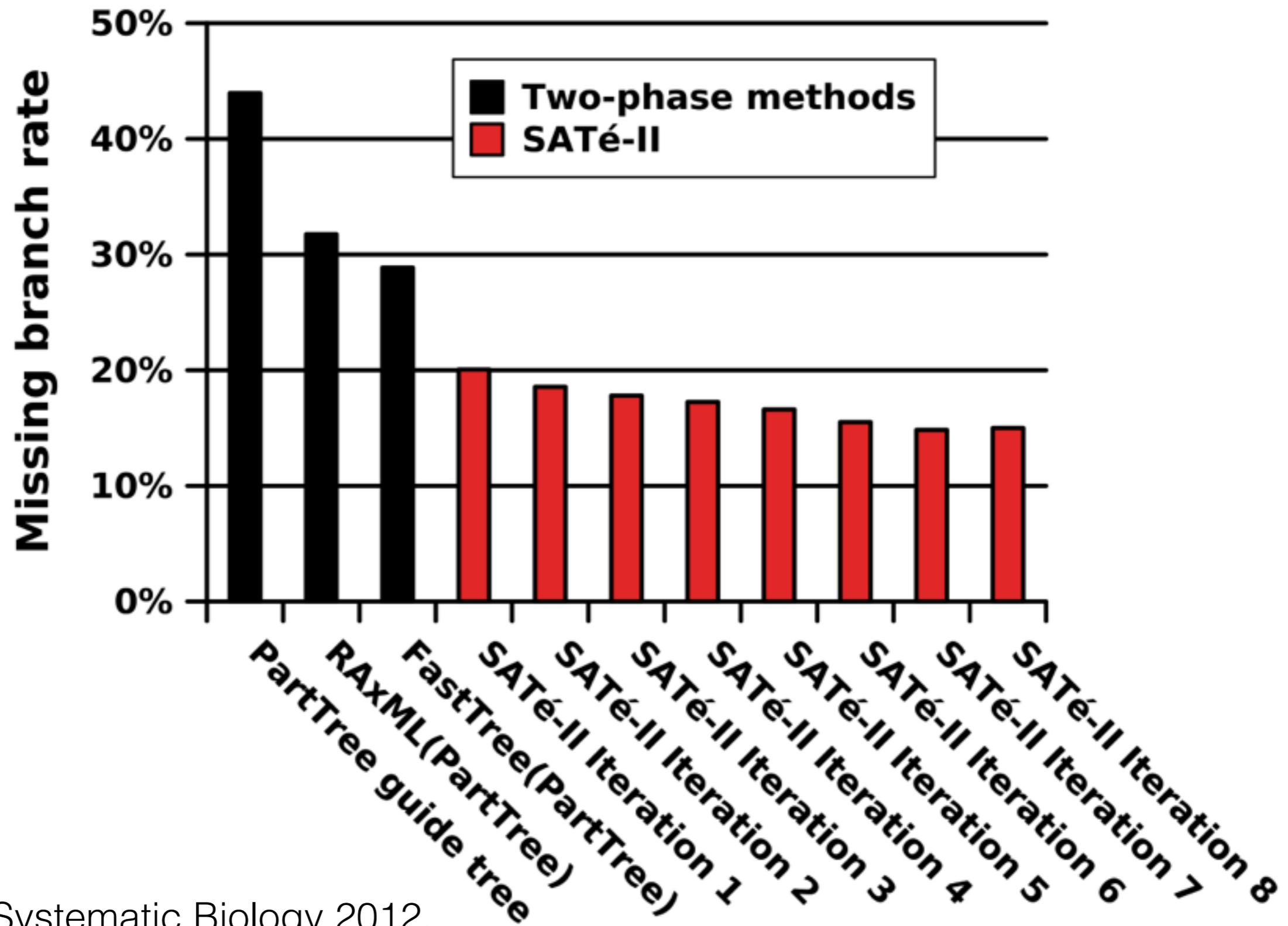


# SATé iteration

(Actual decomposition size is configurable)



# Results on a Dataset with 27,000 Sequences

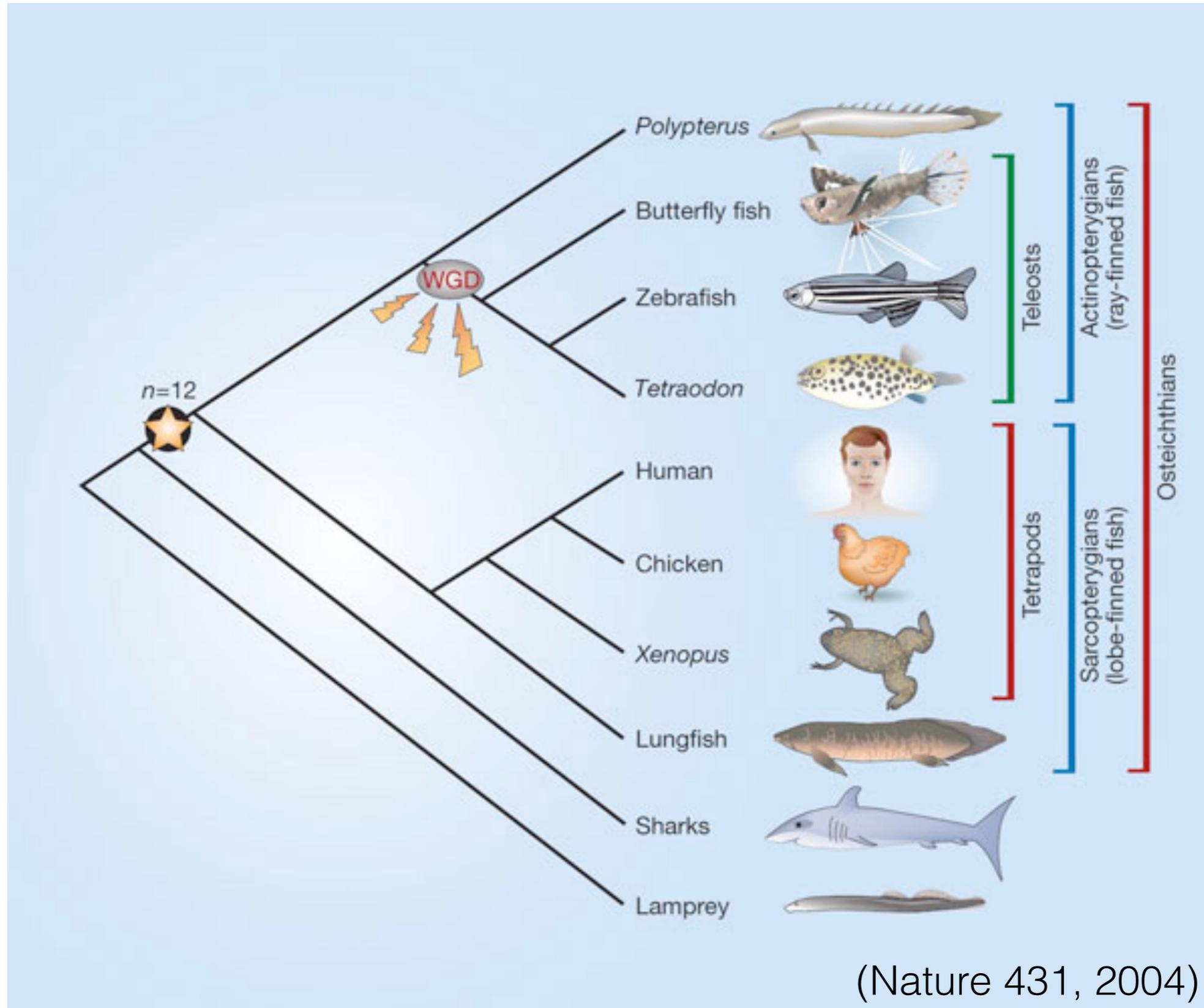


# Summary of Part I

- Created novel tree-based divide-and-conquer techniques for simultaneous alignment and tree estimation, enabling:
  - Scalability to thousands of sequences or more
  - High accuracy
- Family of algorithms included:
  - SATé (Liu *et al.* Science 2009)
  - SATé-II (Liu *et al.* Systematic Biology 2012)
  - and others

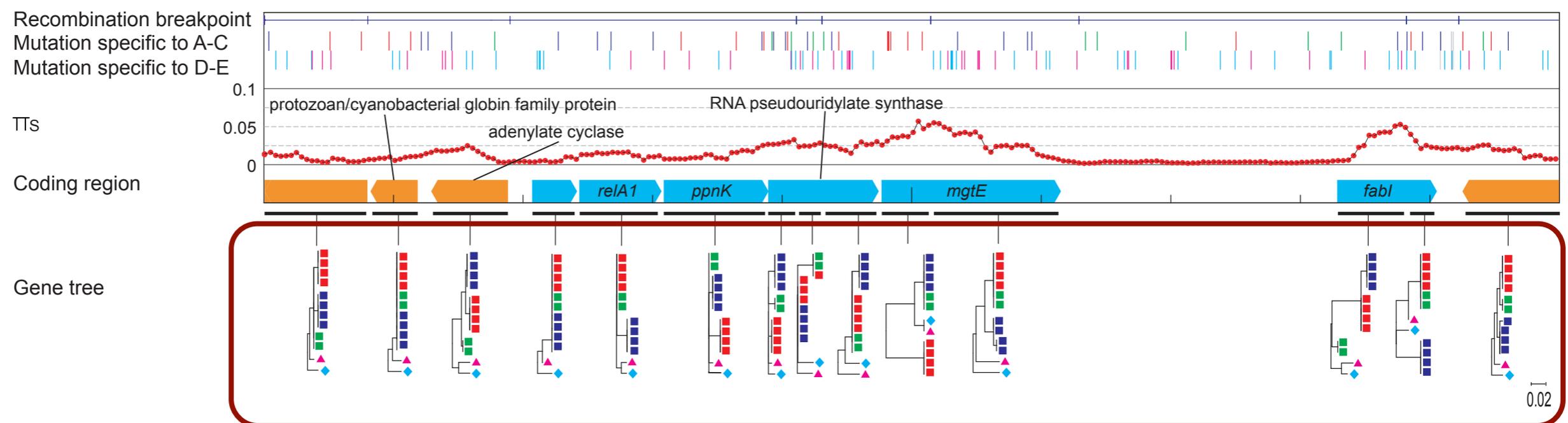
# Part II: Beyond Trees

Almost all comparative genomic approaches assume that genomes have evolved down a tree.



- However, it has been shown that:
  - different genomic regions might evolve down different trees, and
  - the set of species might not have evolved in a strictly diverging manner.

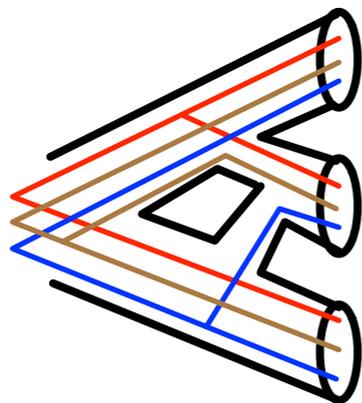
(MBE 29, 2013)



*different gene trees for different regions in the Staph aureus genomes, due to horizontal gene transfer!*

# A Machine Learning View of Comparative Genomics

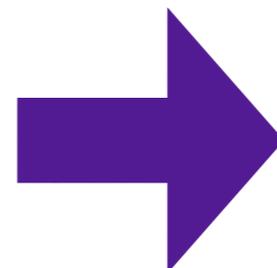
Species network  
(DAG)  
+  
gene trees



Genomes



Stochastic  
Generative  
Model



Observed Data  
(Genomic sequences)

# Overarching Goal

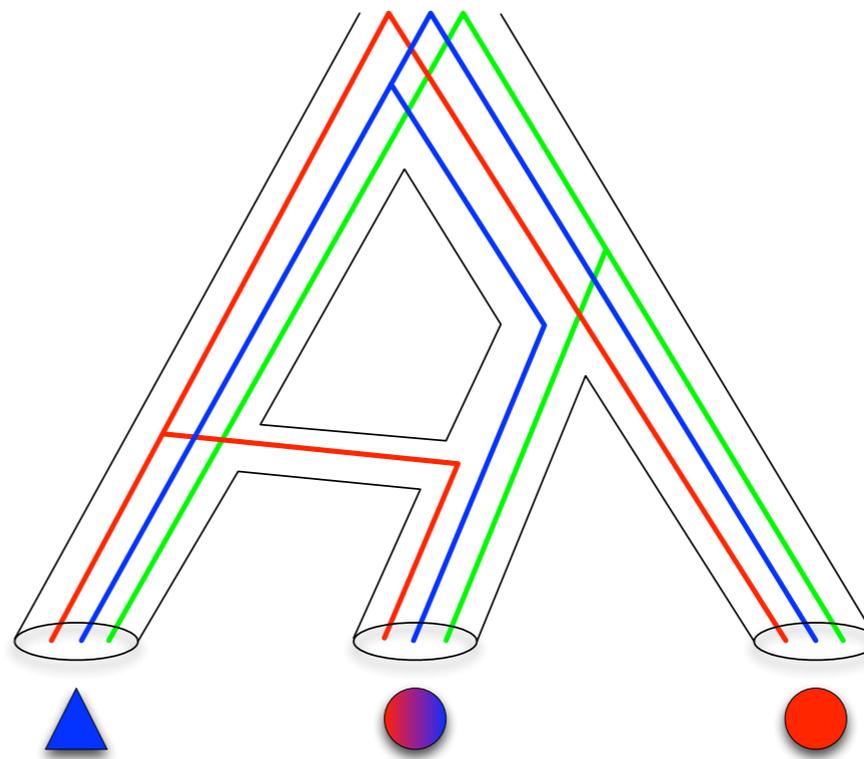
- For every site in the genome, learn:
  - the local gene tree along which the site evolved, and
  - the evolutionary trajectory that the local gene tree took within the species network.
- We also want a confidence measure for the inference.

# My Approach

- Modeling: Combine species networks and hidden Markov models into one unified framework, PhyloNet-HMM.
- Inference: Using genomic sequence data, the task is to learn the model.

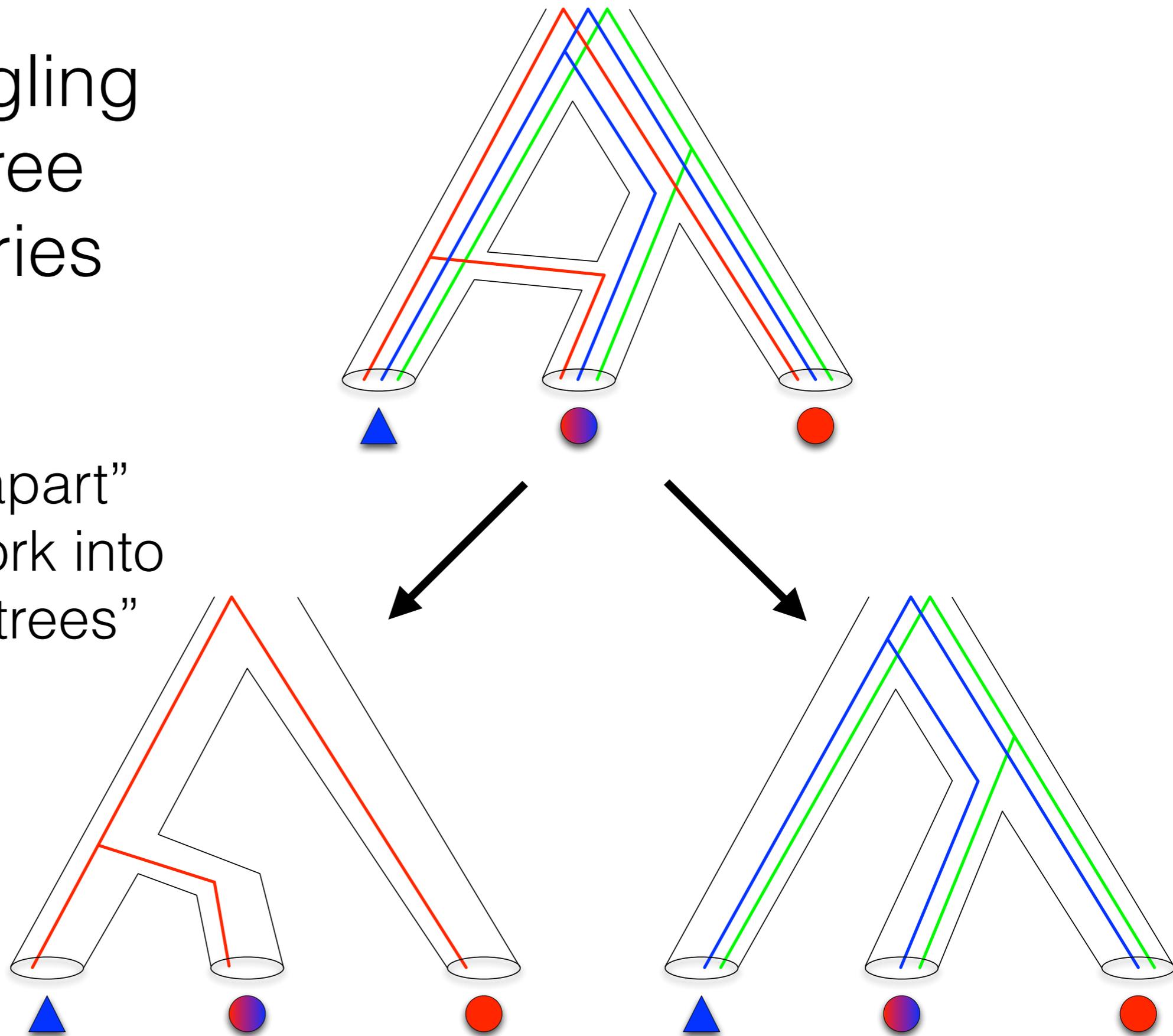


# Disentangling Gene Tree Trajectories

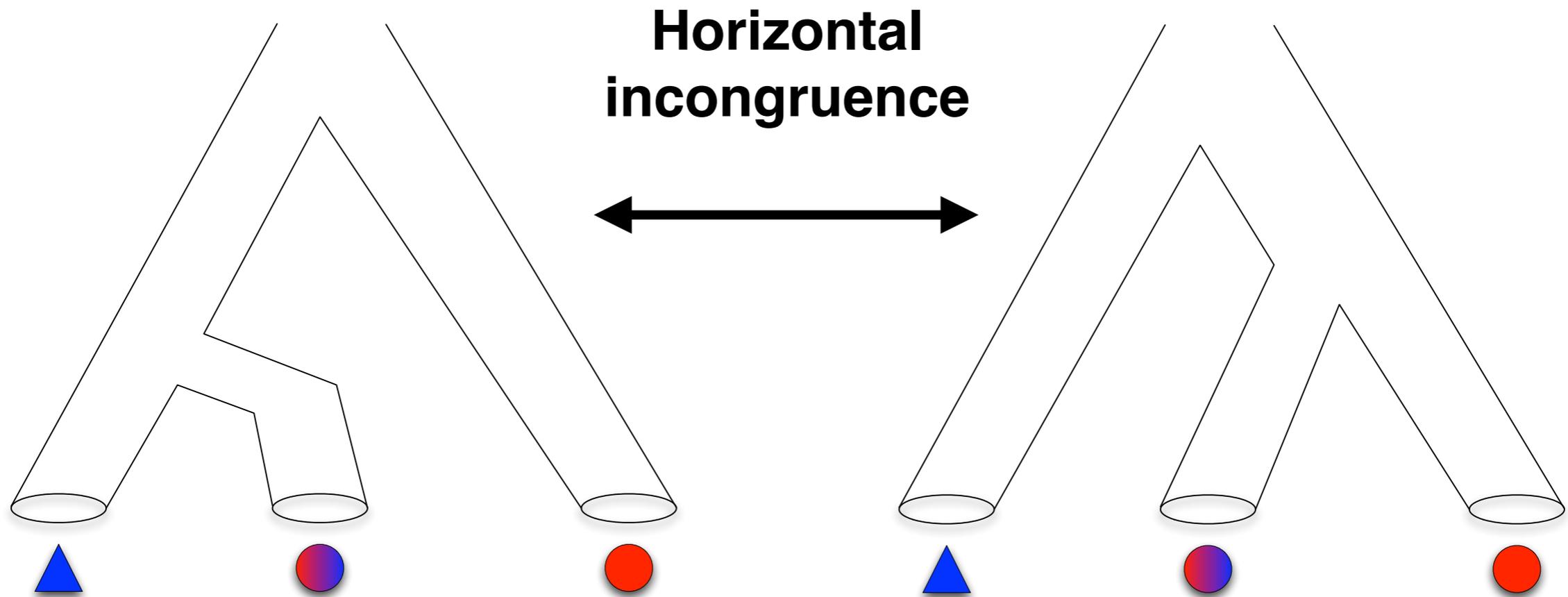


# Disentangling Gene Tree Trajectories

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



# “Horizontal” and “Vertical” Incongruence

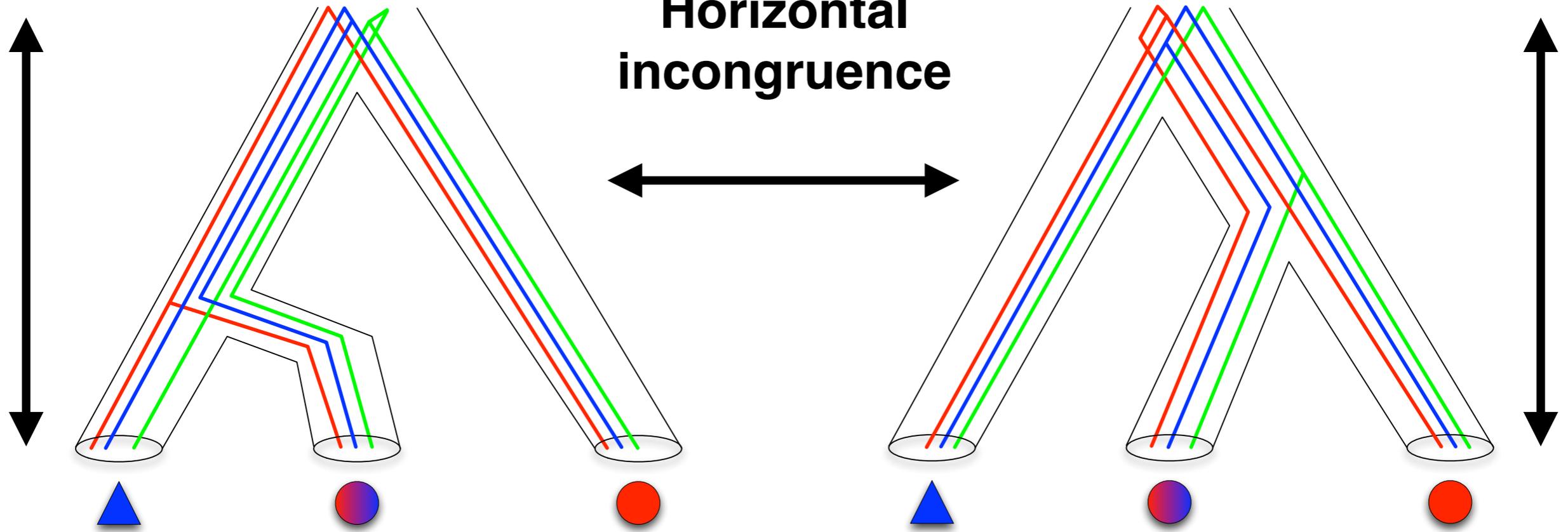


# “Horizontal” and “Vertical” Incongruence

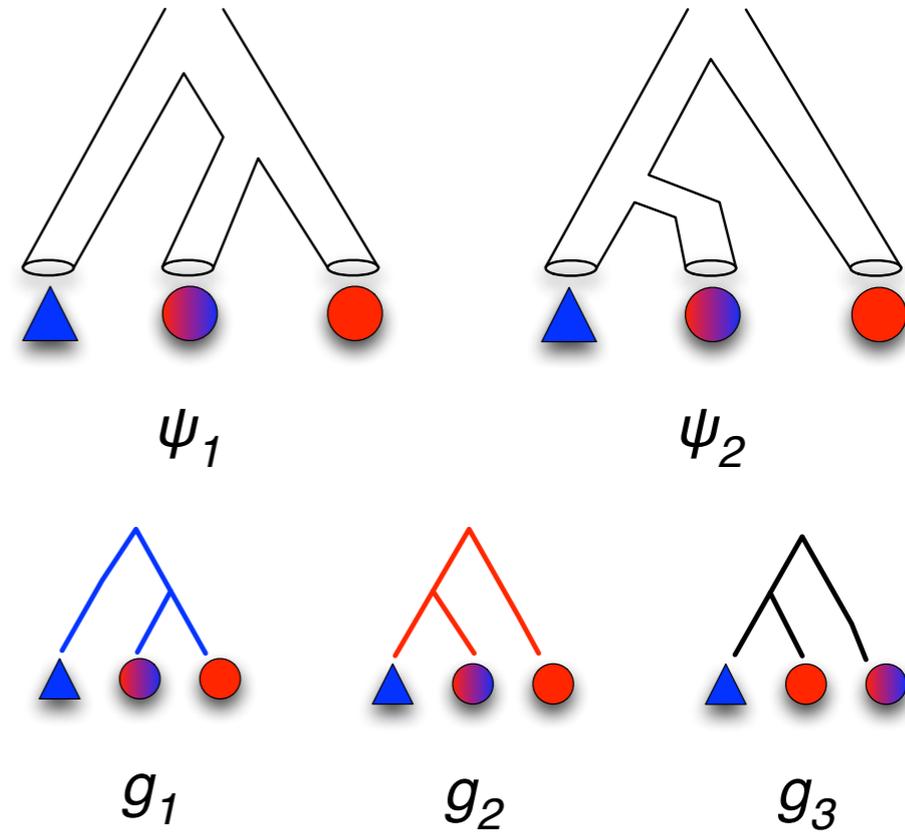
**Vertical  
incongruence**

**Vertical  
incongruence**

**Horizontal  
incongruence**



# A Sequence-Level View of Local Incongruence



$\psi_1$  region



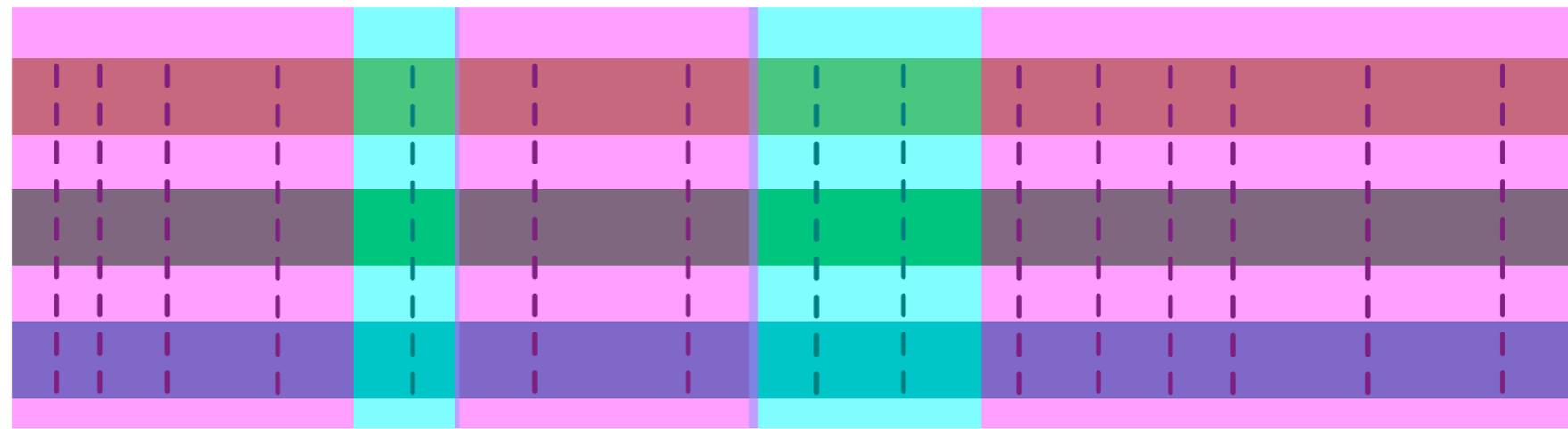
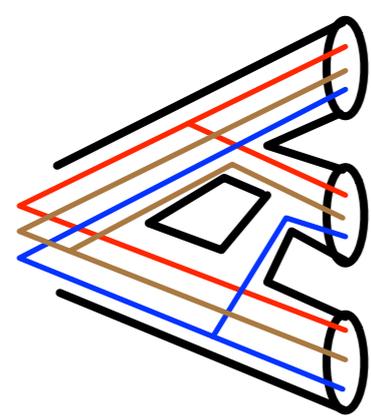
$\psi_2$  region



Gene-tree-switching  
breakpoint



I                      II                      III                      IV                      V



A  
B  
C

# 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

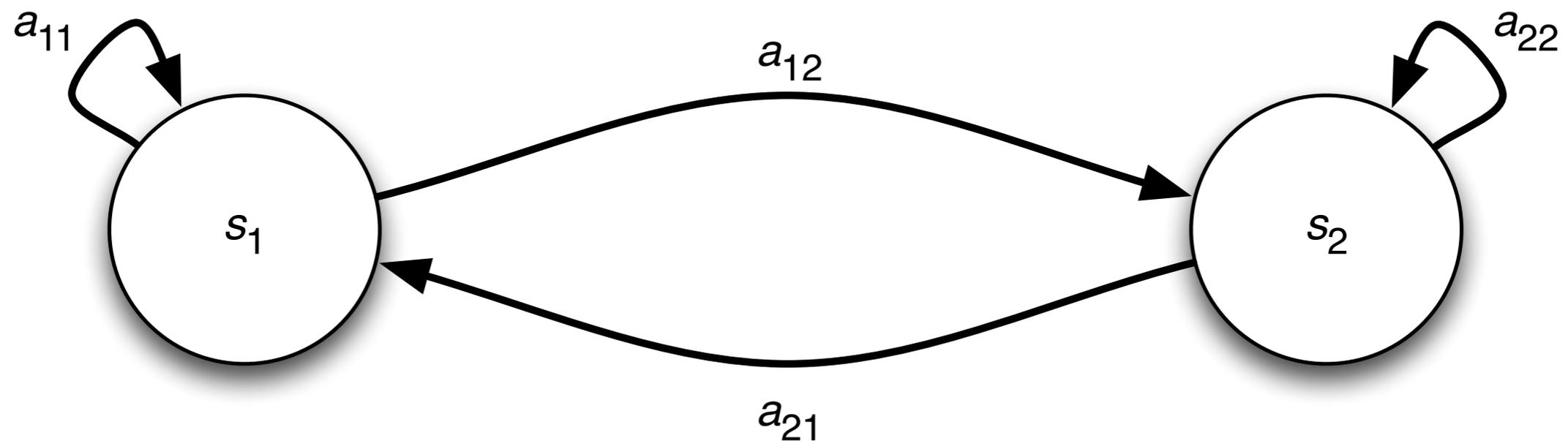
- DNA sequences are observed, not gene trees.
- Under traditional models of DNA sequence evolution, the probability  $P(s|g)$  of observing DNA sequences  $s$  given a gene tree  $g$  can be efficiently calculated using dynamic programming.

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

# Hidden Markov Model (HMM) Example

- Coin tossing experiment:
  1. An experimenter flips one of two hidden coins with unknown bias and tells you the result.
  2. Repeat for a total of  $k$  trials, resulting in observation sequence  $O$ .

# Hidden Markov Model (HMM) Example



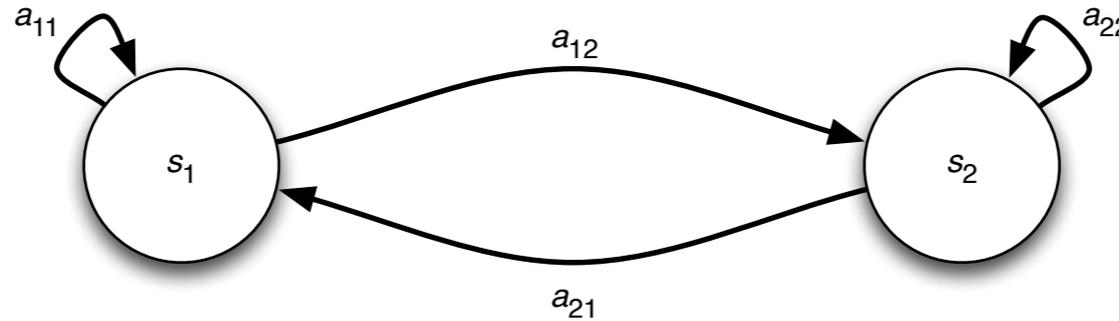
$$\mathbf{P}(H|q_t = s_1) = b_1$$

$$\mathbf{P}(T|q_t = s_1) = 1 - b_1$$

$$\mathbf{P}(H|q_t = s_2) = b_2$$

$$\mathbf{P}(T|q_t = s_2) = 1 - b_2$$

# Hidden Markov Model (HMM) Example



- The HMM has  $N=2$  states.
- The HMM is in state  $q_t$  at time  $t$ , where  $1 \leq t \leq k$ .
- The set of HMM parameters  $\lambda$  consists of:
  - The transition probability matrix  $A = \{a_{ij}\}$
  - The emission probabilities  $B = \{b_i\}$
  - The initial state distribution  $\pi_i = \mathbf{P}(q_1 = s_i)$

# Three Problems Addressed Using HMMs

1. What is the likelihood of the model given the observation sequence?

- Forward algorithm calculates prefix probability  $\alpha_t(i) = \mathbf{P}(O_1, O_2, \dots, O_t, q_t = S_i | \lambda)$

- Backward algorithm calculates suffix probability  $\beta_t(i) = \mathbf{P}(O_{t+1}, O_{t+2}, \dots, O_k | q_t = S_i, \lambda)$

- Model likelihood is  $\mathbf{P}(O | \lambda) = \sum_{i=1}^N \alpha_k(i)$

2. Which sequence of hidden states best explains the observation sequence?

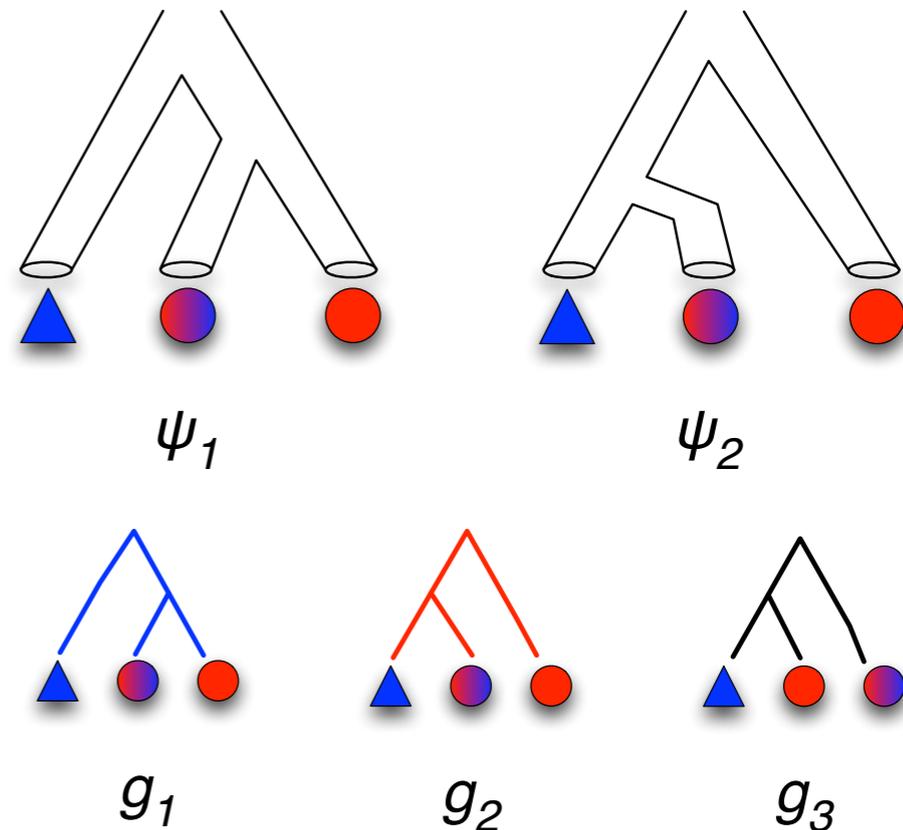
- Posterior decoding probability  $\gamma_t(i)$  is the probability that HMM is in state  $s_i$  at time  $t$ , calculated as:

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

3. How do we choose parameter values that maximize the model likelihood?

- Apply Baum-Welch algorithm to search for  $\arg \max_{\lambda} \mathbf{P}(O|\lambda)$

# PhyloNet-HMM: Problem Definition



For each site  $1 \leq i \leq k$ , let  $\pi_i$  be a random variable that takes a value from the set  $(g_x, \psi_y) : g_x \in G(n), \psi_y \in \Psi$ .

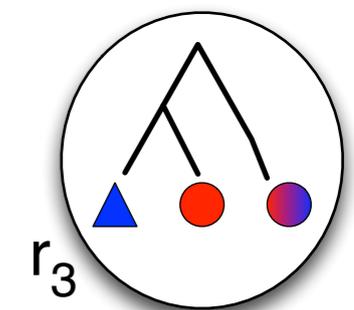
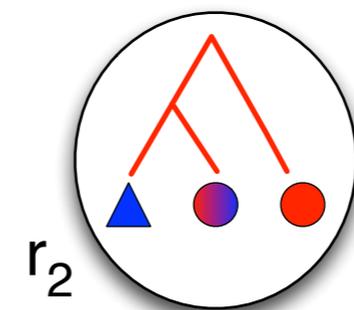
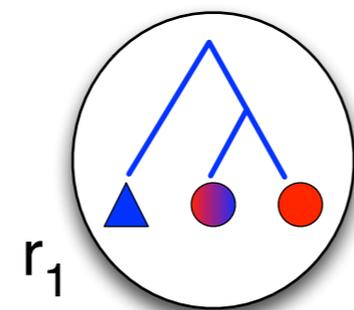
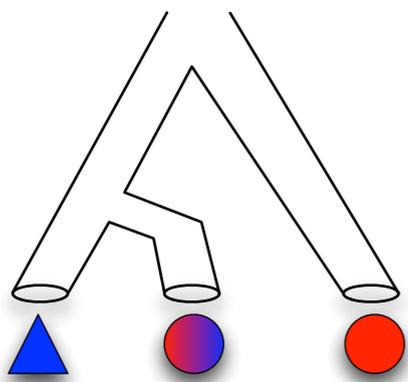
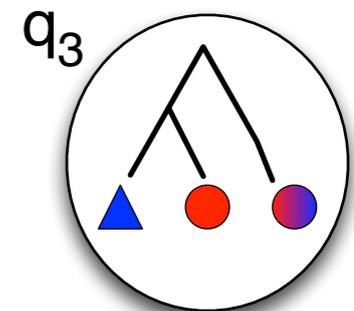
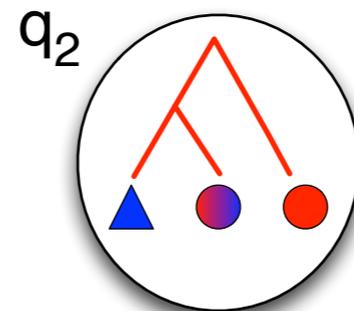
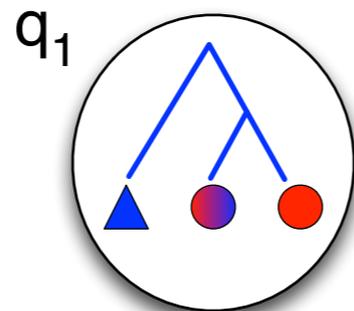
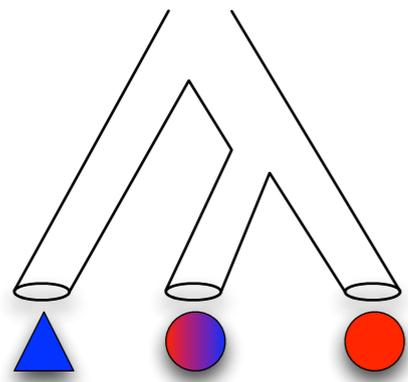
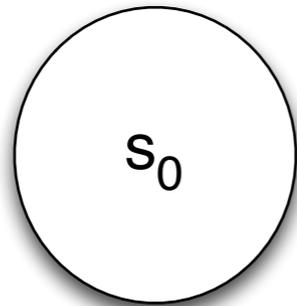
**Input:** A set  $S$  of  $n$  aligned genomes, each of length  $k$ , and a set  $\Psi$  of parental trees corresponding to a species network.

**Output:** For each site  $1 \leq i \leq k$ , the probability

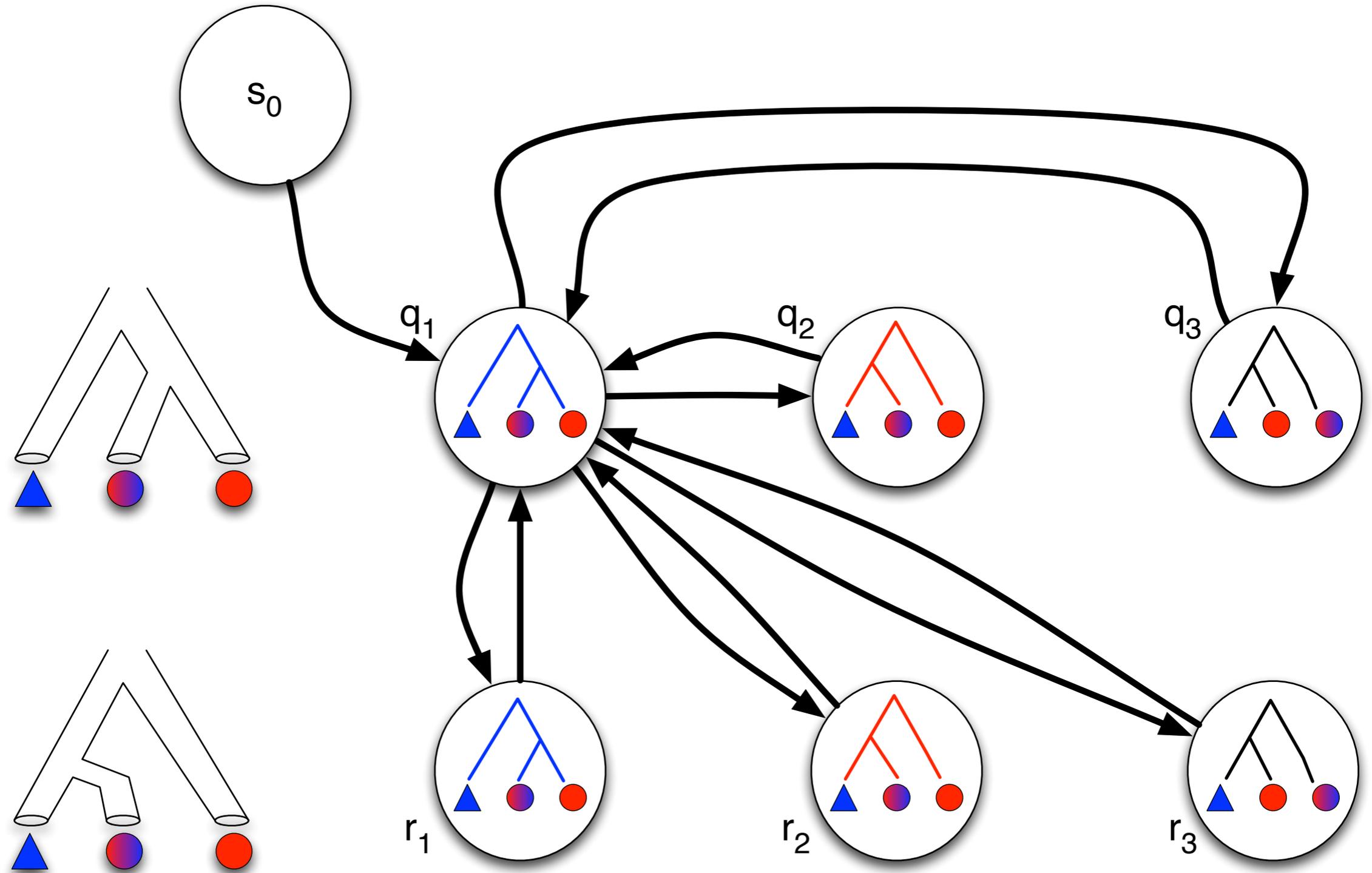
$$\mathbf{P}(\pi_i = (g_x, \psi_y) | S)$$

for every  $g_x \in G(n)$  and  $\psi_y \in \Psi$ .

# PhyloNet-HMM: Hidden States



# PhyloNet-HMM: Hidden States and Transitions Involving $q_1$



# 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  $\lambda$  consists of
  - The initial state distribution  $\pi$
  - Transition probabilities

$$a_{ij} = \begin{cases} \mathbf{P}(g(s_i)|f(s_i)) \cdot \gamma & \text{if } s_i \text{ and } s_j \text{ in different rows} \\ \mathbf{P}(g(s_i)|f(s_i)) \cdot (1 - \gamma) & \text{if } s_i \text{ and } s_j \text{ in same row} \end{cases}$$

where  $\gamma$  is the “horizontal” parental tree switching frequency.

- The emission probabilities  $b_i = \mathbf{P}(O_t|g(s_i))$

# PhyloNet-HMM: Two Calculations

- The probability of a gene tree topology  $g$  given a containing species tree  $(\Psi, \lambda)$  (Degnan and Salter 2005):

$$P_{\Psi, \lambda}(G = g) = \sum_{\mathbf{h} \in H_{\Psi}(g)} \frac{w(\mathbf{h})}{d(\mathbf{h})} \prod_{b=1}^{n-2} \frac{w_b(\mathbf{h})}{d_b(\mathbf{h})} p_{u_b(\mathbf{h})v_b(\mathbf{h})}(\lambda_b).$$

- The probability of observing DNA sequences  $S$  given a gene tree  $(g, \omega)$  can be efficiently computed using dynamic programming (Felsenstein 1981).

# Three Problems Addressed Using PhyloNet-HMM

1. What is the likelihood of the model given the observed DNA sequences?

- Forward algorithm calculates prefix probability  $\alpha_t(i) = \mathbf{P}(O_1, O_2, \dots, O_t, q_t = S_i | \lambda)$

- Backward algorithm calculates suffix probability  $\beta_t(i) = \mathbf{P}(O_{t+1}, O_{t+2}, \dots, O_k | q_t = S_i, \lambda)$

- Model likelihood is  $\mathbf{P}(O | \lambda) = \sum_{i=1}^N \alpha_k(i)$

2. Which sequence of hidden states best explains the observed DNA sequences?

- Posterior decoding probability  $\gamma_t(i)$  is the probability that HMM is in state  $s_i$  at time  $t$ , calculated as:

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

3. How do we choose parameter values that maximize the model likelihood?

- Apply E-M to optimize  $\arg \max_{\lambda} \mathbf{P}(O | \lambda)$

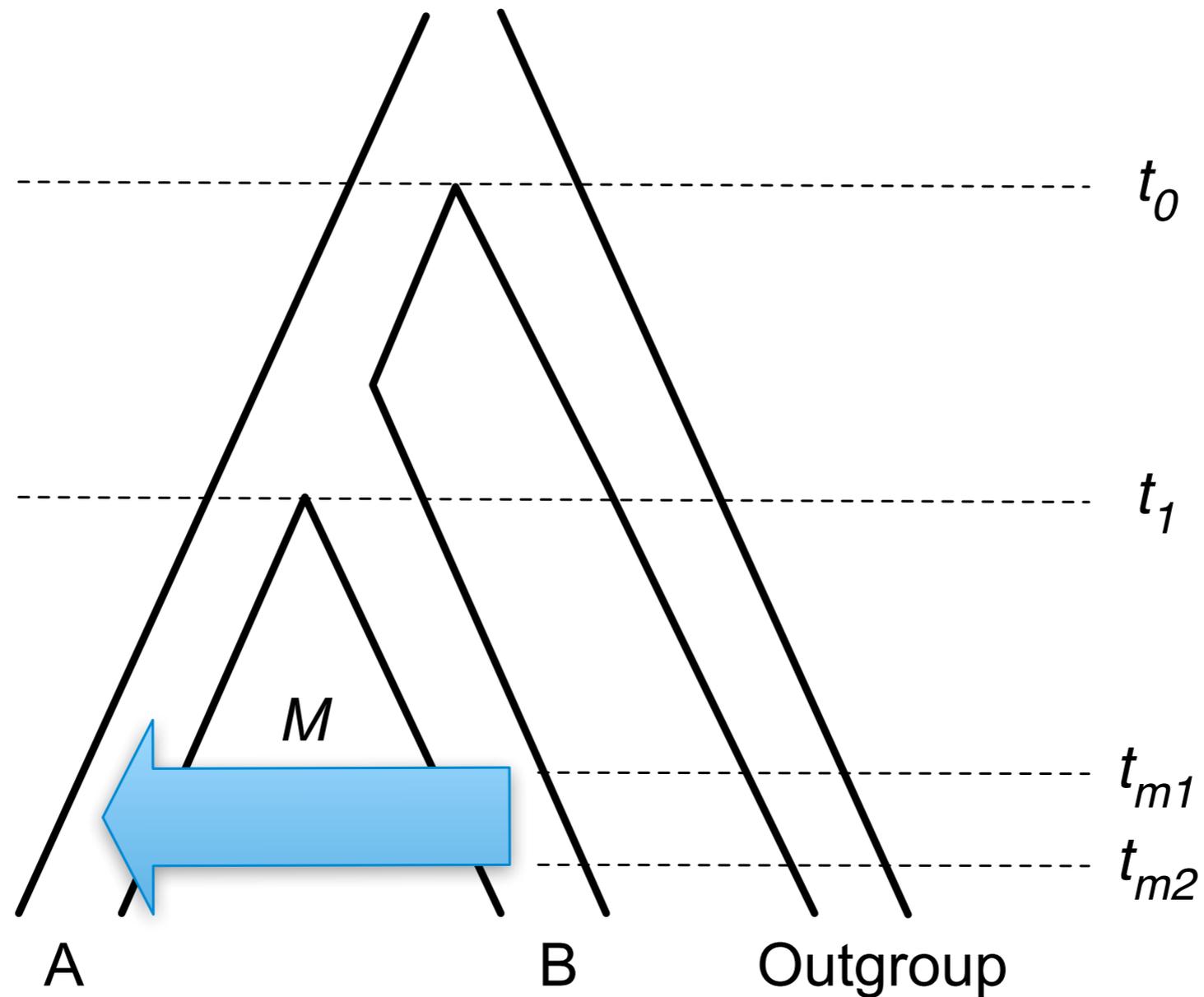
# Related Methods

- Current methods for inference under species networks fall into two classes:
  1. Methods that work for at most three genomes, e.g.
    - D-statistic (Durand *et al.* 2012)
    - CoalHMM (Mailund *et al.* 2012)
  2. Methods that consider vertical incongruence or horizontal incongruence but not both, e.g.
    - CoalHMM (Hobolth *et al.* 2007, Schierup *et al.* 2009)
    - RechMM (Westesson and Holmes 2009)

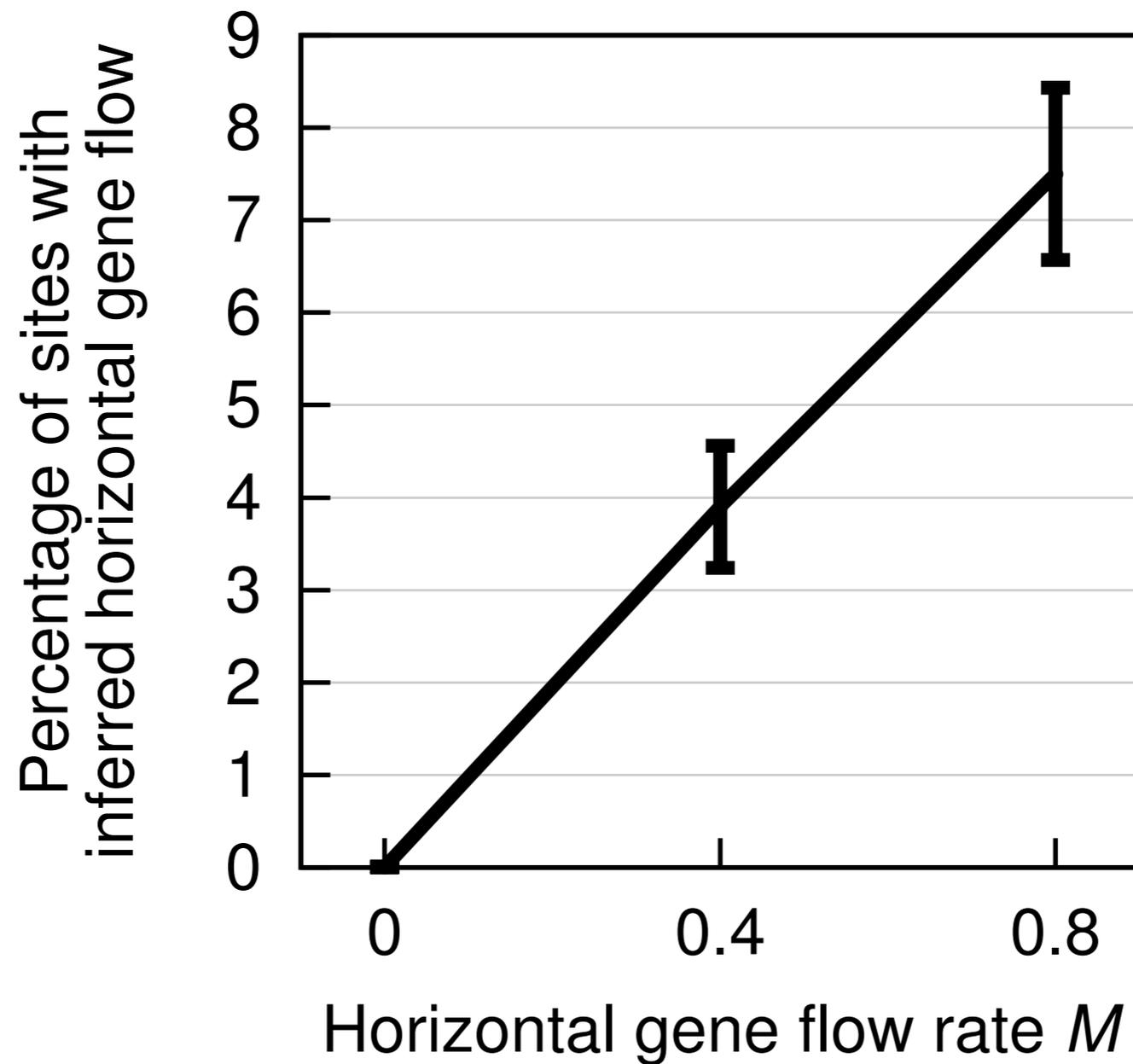
# Evaluating PhylpNet-HMM

- Simulation study using:
  - Species tree model
  - Species network model
- Empirical study of different sets of mouse genomes:
  - Controls: lab mice, wild mice from populations that lacked gene flow
  - Additional wild mice from populations where gene flow was suspected

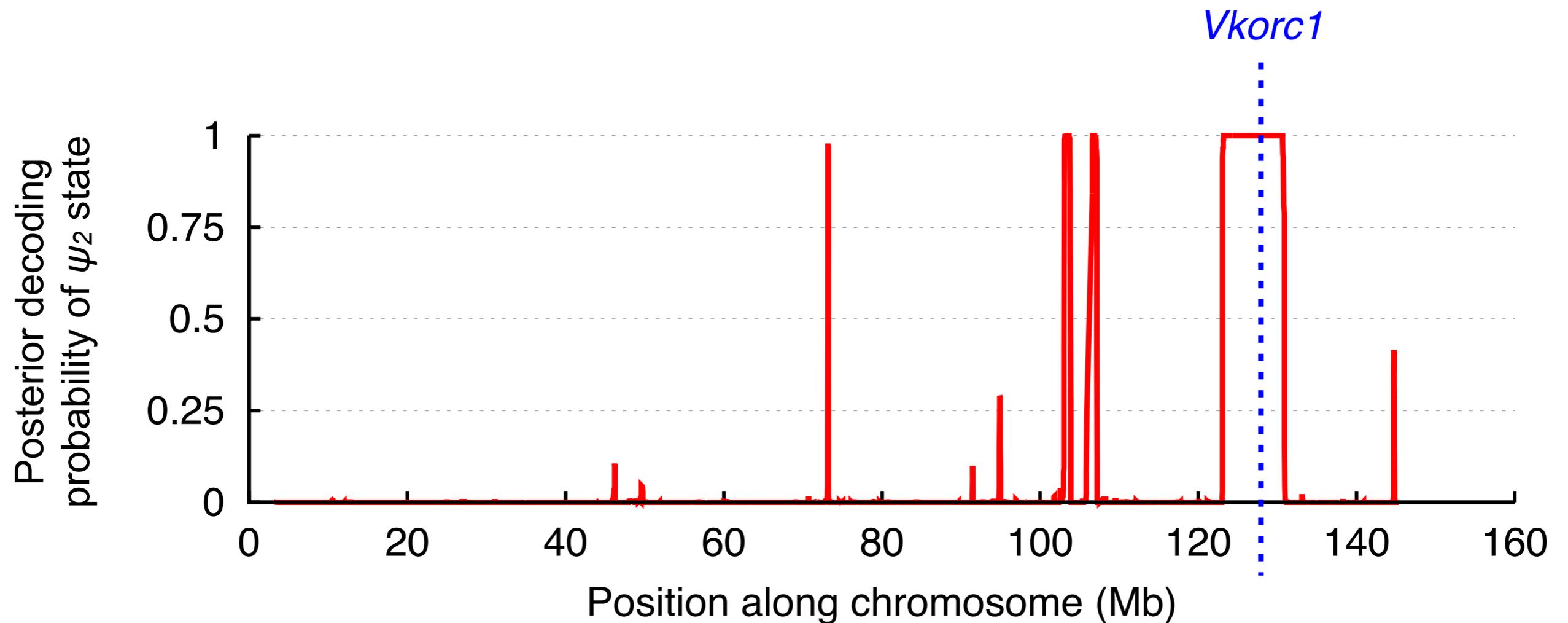
# Simulation Model



# Simulation Study Results



# Empirical Study: Non-control Mice (Chromosome 7)



Liu *et al.*, revision under review,  
PLoS Computational Biology.

# The *Vkorc1* Gene and Personalized Warfarin Therapy



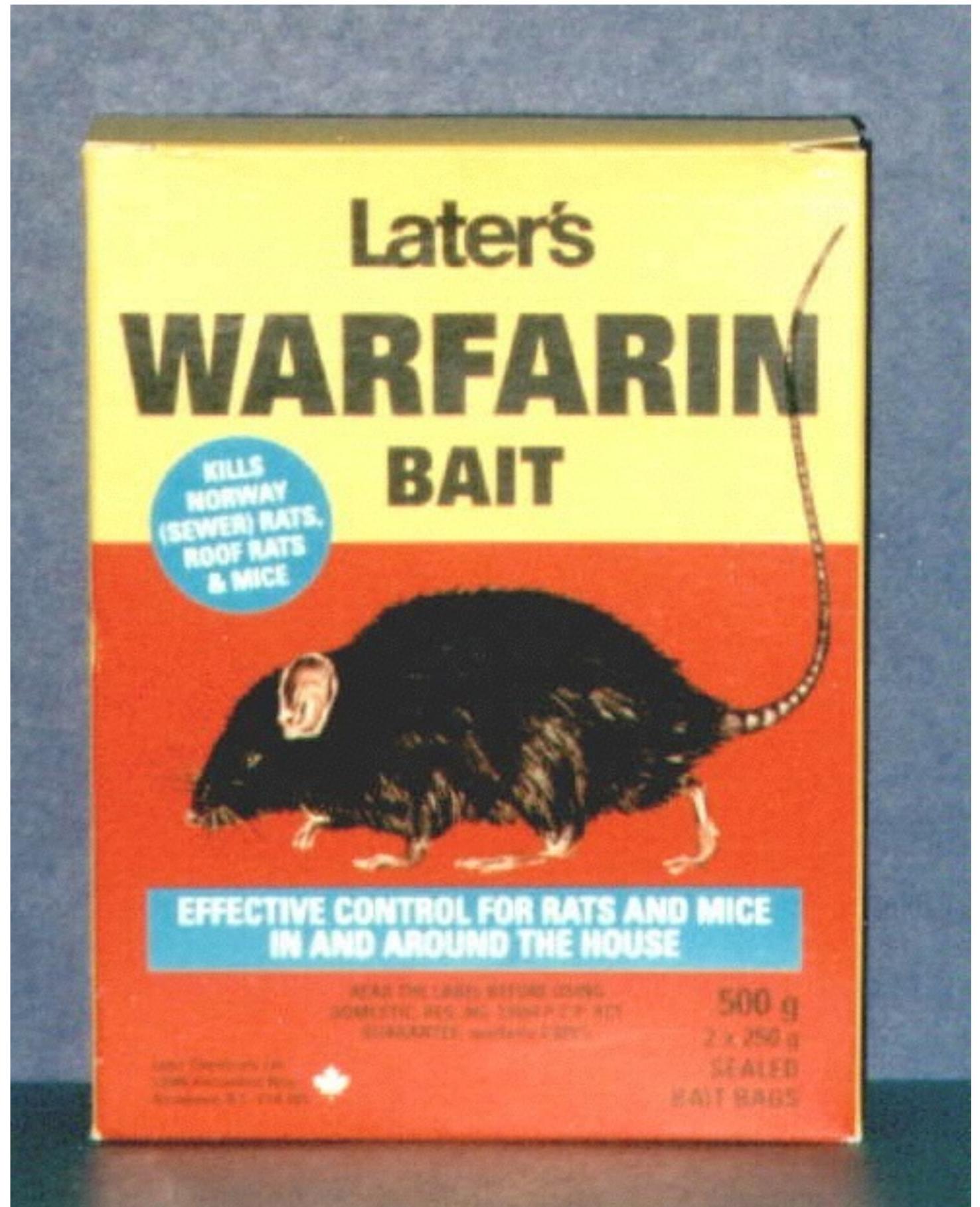
- Mutant *Vkorc1* gene contributes to warfarin resistance
- Warfarin resistant individuals require larger-than-normal dose to prevent clotting complications (like stroke)

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

# Warfarin 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

# Warfarin is Really Glorified Rodent Poison



Reproduced from UTMB.

# The Spread of Warfarin Resistance in Wild Mice

- 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

# Summary of Part II

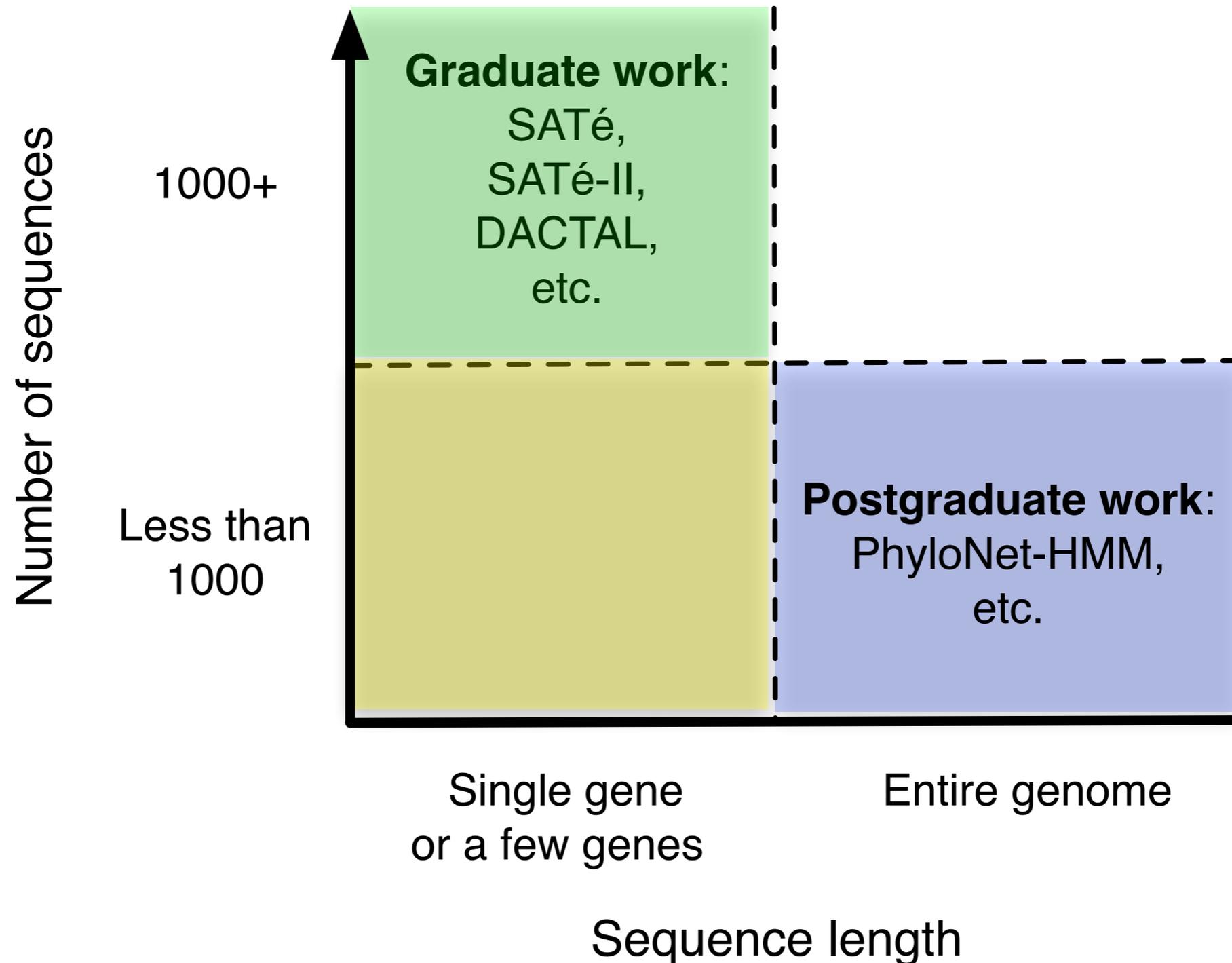
- PhyloNet-HMM generalizes the basic coalescent model, one of the most widely used models in population genetics, by using a DAG in place of a tree
- Simulated and empirical data sets with tree-like and non-tree-like evolution were used to validate PhyloNet-HMM
- PhyloNet-HMM found non-tree-like evolution in multiple mouse chromosomes
  - Introgressed mouse genes confer warfarin resistance, many with related human genes
  - New candidate genes to target for improved personalization of warfarin therapy
- Study of non-tree-like evolution is a fundamentally important research topic in biology

# Future Research and Summary

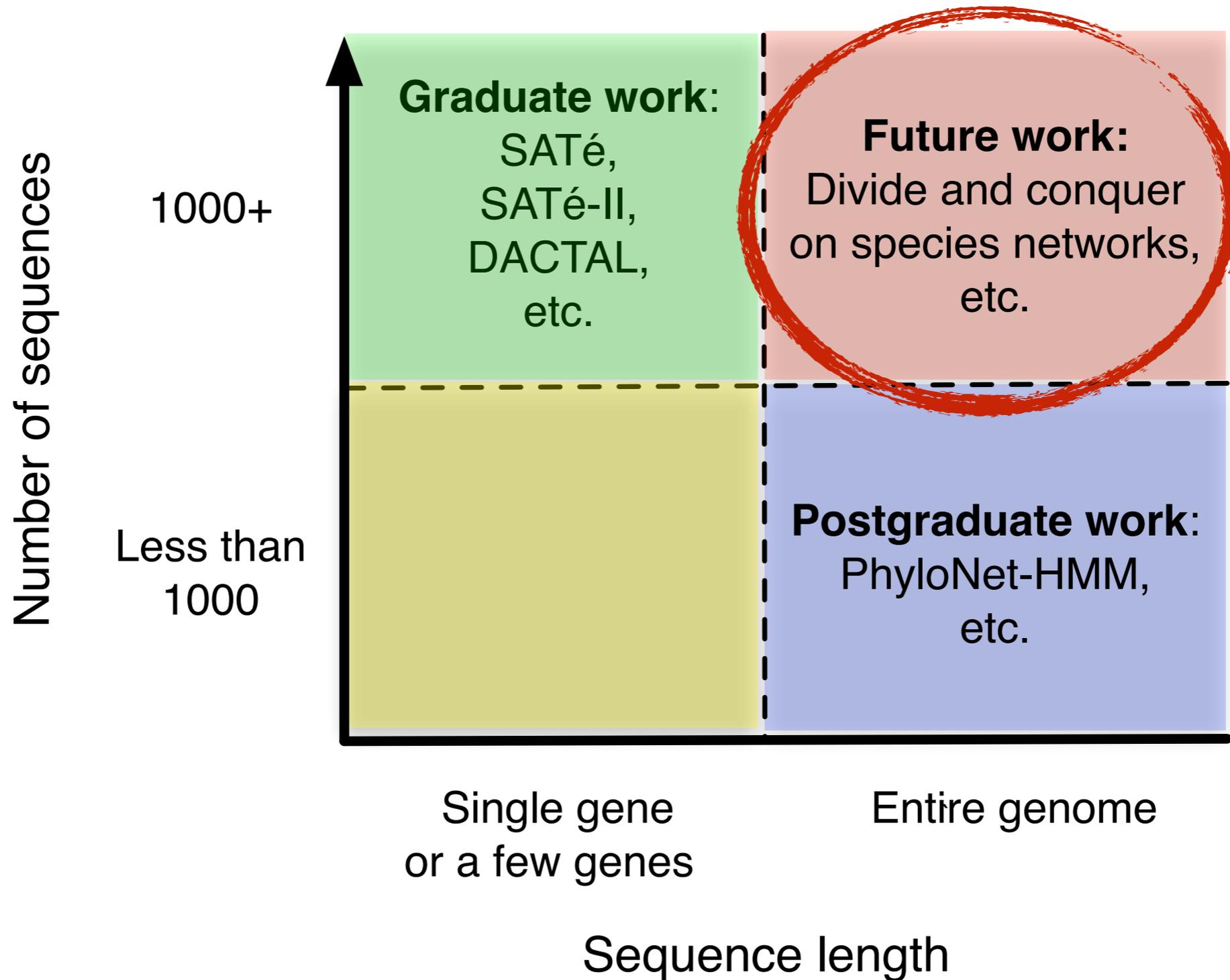
# Future Direction #1

- Previous analyses (at most five genomes and a single network edge) required more than a CPU-month on a large cluster
- Problem is combinatorial in both the number of genomes and the number of network edges
- Challenge: efficient and accurate network-based inference from hundreds of genomes or more

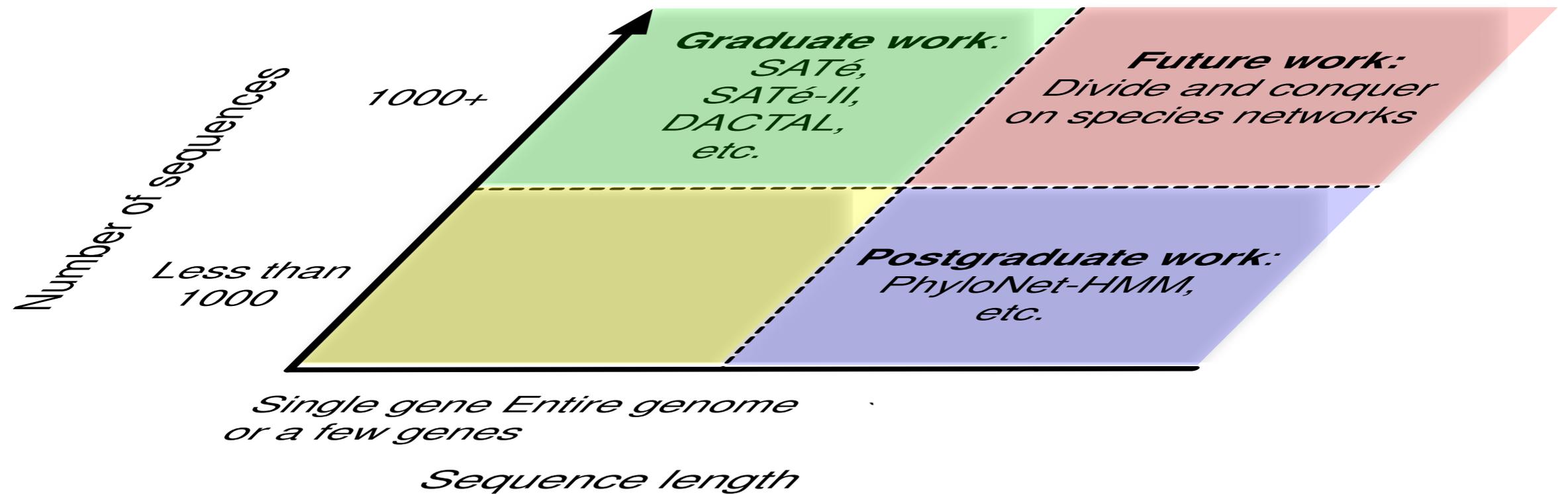
# My Contributions: A Big Data Perspective



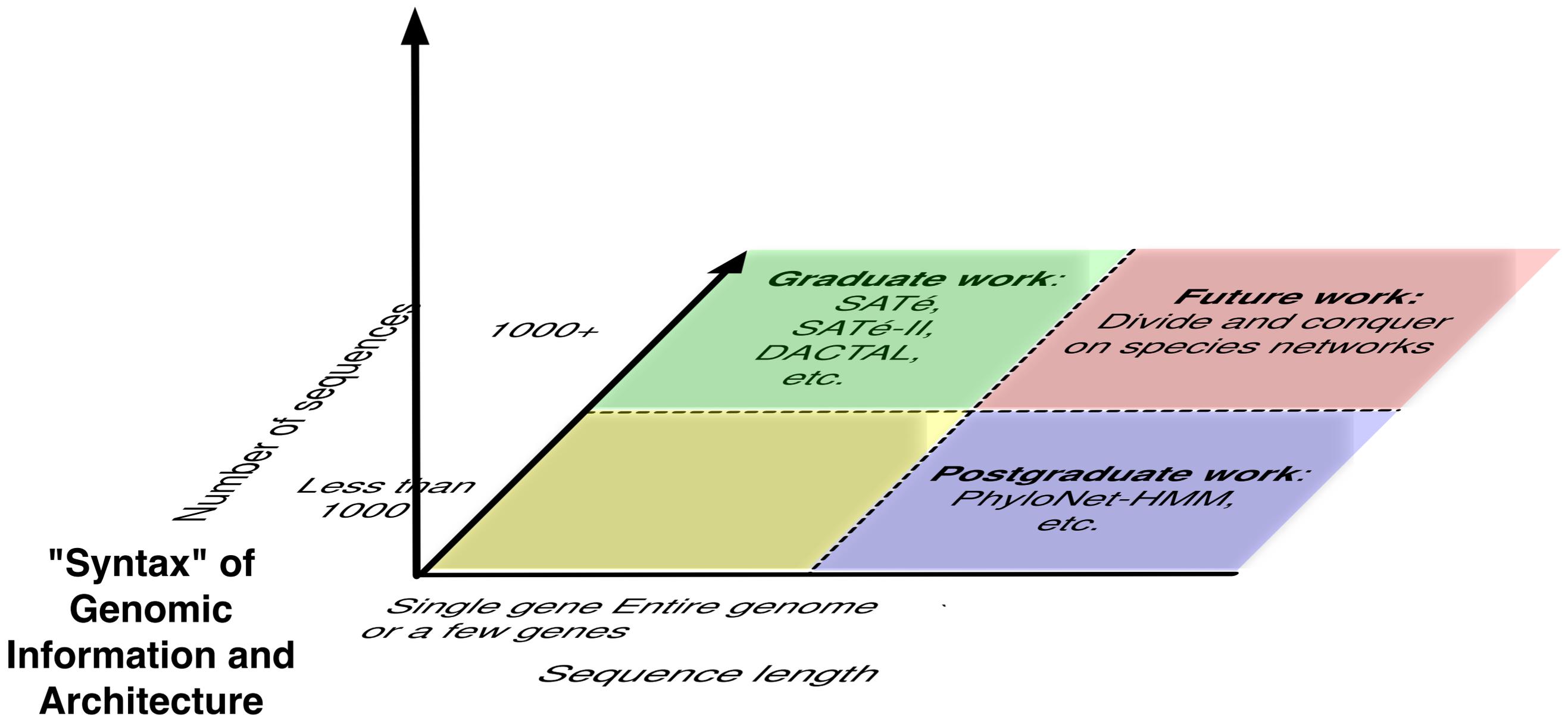
# Future Direction #1



# Future Direction #2



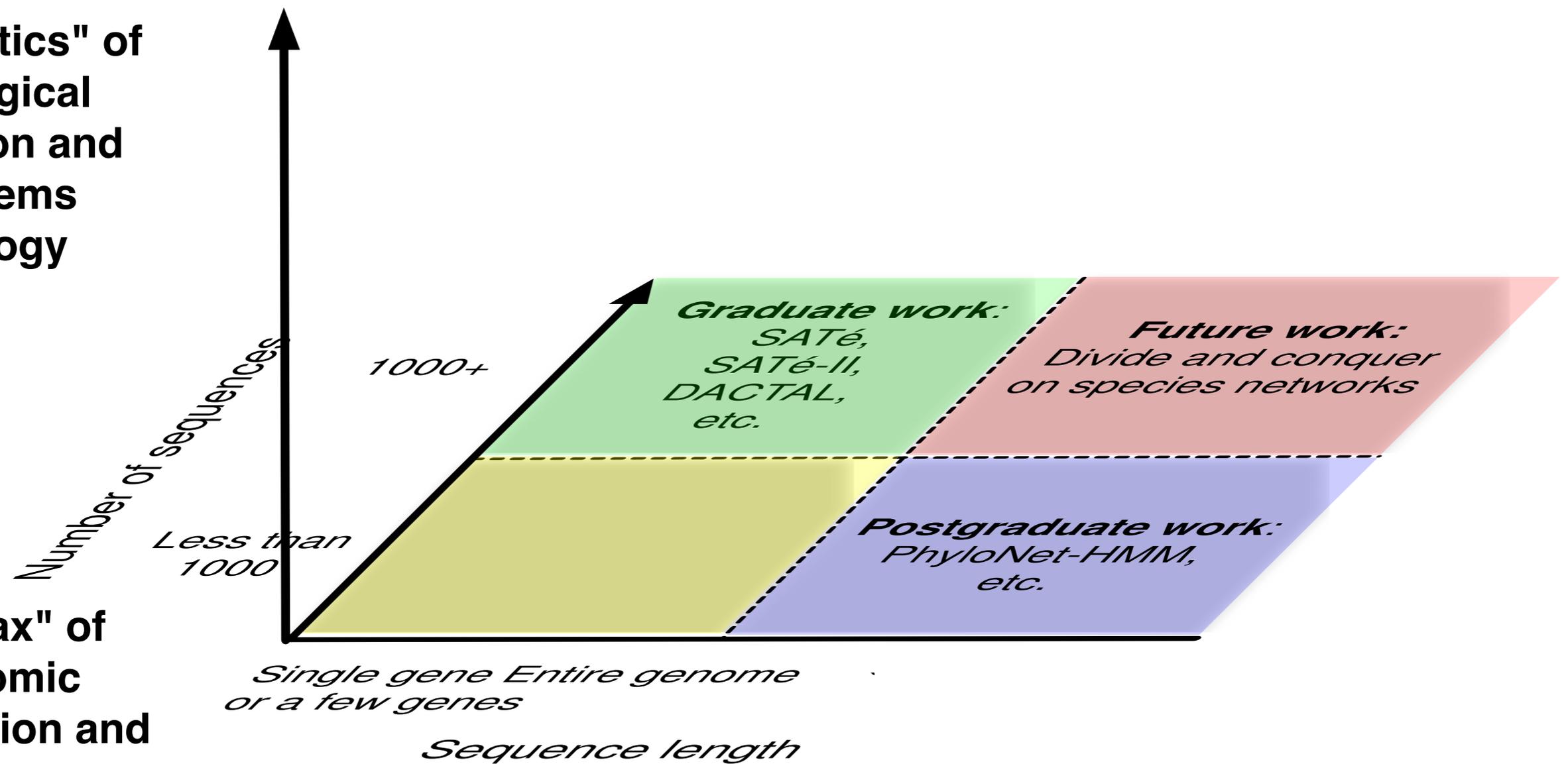
# Future Direction #2



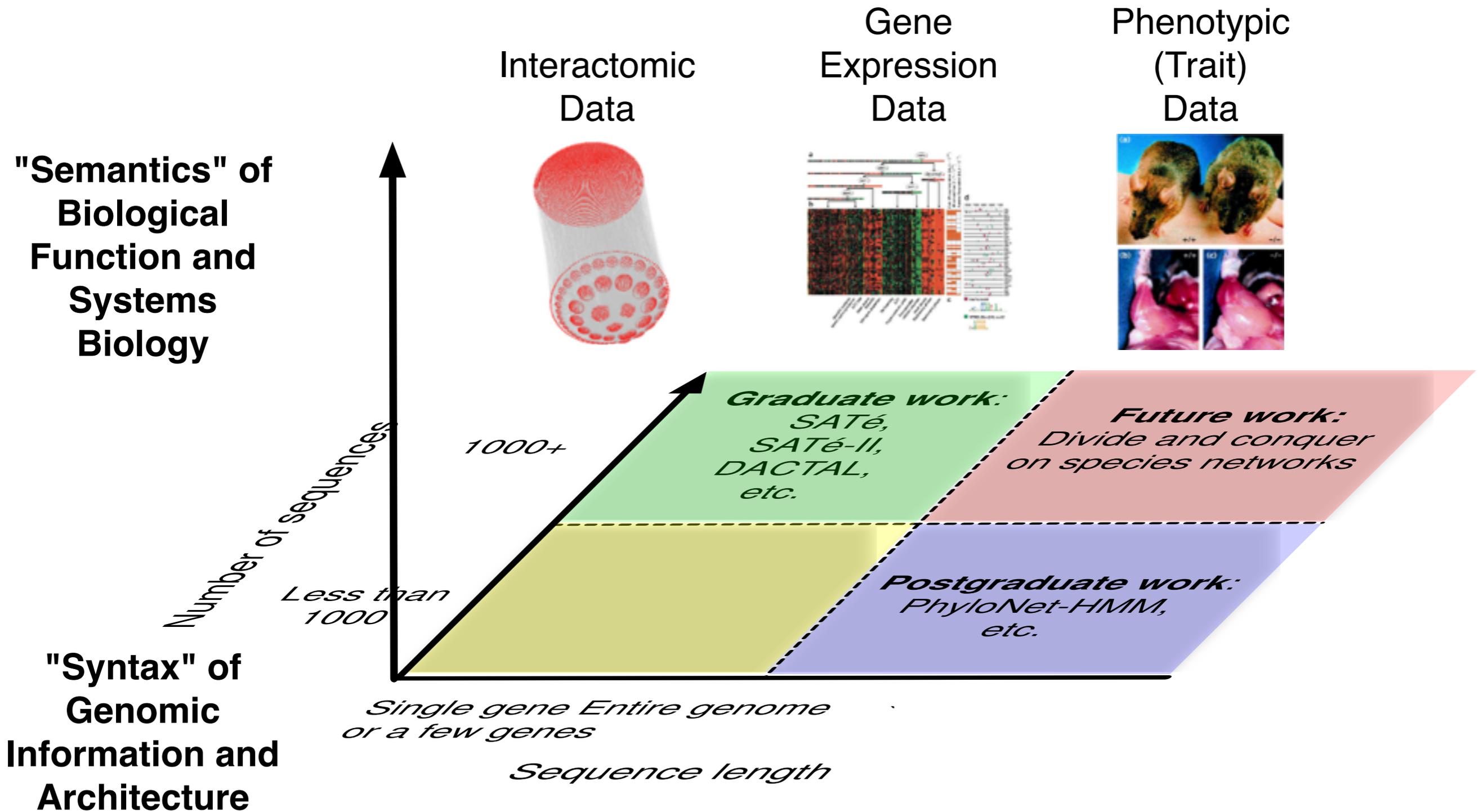
# Future Direction #2

"Semantics" of  
Biological  
Function and  
Systems  
Biology

"Syntax" of  
Genomic  
Information and  
Architecture



# Future Direction #2



# Funding Opportunities for My Work

- Computational approaches constitute basic research of interest to NSF (IIS, ABI)
- Wide range of applications of interest to different funding agencies, including:
  - The role of introgression in the spread of pesticide resistance in wild mice, with applications to personalized warfarin therapy (NIH)
  - The role of horizontal gene transfer in the spread of antibiotic resistance in bacteria (NIH)
  - Bacterial genomics (DOE)
  - Hybridization in plants (USDA)

# Summary

- I have created:
  - new iterative divide-and-conquer techniques, which were used to develop methods for fast and accurate inference of alignments and trees from large-scale data sets, and
  - PhyloNet-HMM, a new inference method utilizing a DAG-based stochastic model, which is capable of disentangling “vertical” and “horizontal” evolution.
- My future research directions include:
  - developing divide-and-conquer methods for fast and accurate analysis of non-tree-like evolution using large-scale genomic data sets, and
  - synthesizing evolutionary analysis with interactomic and other functional analyses.

# Acknowledgments



Luay Nakhleh  
CS



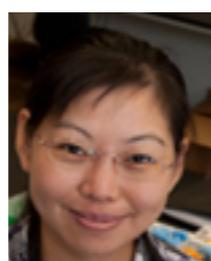
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- NLM (Grant No. R01LM00949405 to Luay Nakhleh)
- NHLBI (Grant No. R01HL09100704 to Michael Kohn)

# Questions?

- My website:  
<http://www.cs.rice.edu/~kl23>
- Nakhleh lab website:  
<http://bioinfo.cs.rice.edu>
- Warnow lab website:  
<http://www.cs.utexas.edu/~phylo>