

CS 598MEB

Computational Cancer Genomics

Lecture 3

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January 28, 2020



Course Project

- 1-2 students per project
- First write a proposal, which will receive feedback from instructor and fellow students
- Then, conduct research and write a paper
- Pick venue (conference/journal) and use LaTeX style for your paper

Lecture Outline

- Recap
- Two-state Perfect Phylogeny Mixtures

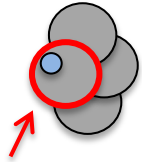
Reading

- M. El-Kebir, L. Oesper, H. Acheson-Field and B. J. Raphael. Reconstruction of clonal trees and tumor composition from multi-sample sequencing data. [Bioinformatics \(Special Issue: Proceedings of ISMB\), 31\(12\):i62-i70, 2015](#)
- Y. Qi, D. Pradhan and M. El-Kebir. Implications of non-uniqueness in phylogenetic deconvolution of bulk DNA samples of tumors. [Algorithms for Molecular Biology, 14:19, 2019.](#)

Tumorigenesis: Cell Mutation

Clonal Evolution Theory of Cancer

[Nowell, 1976]



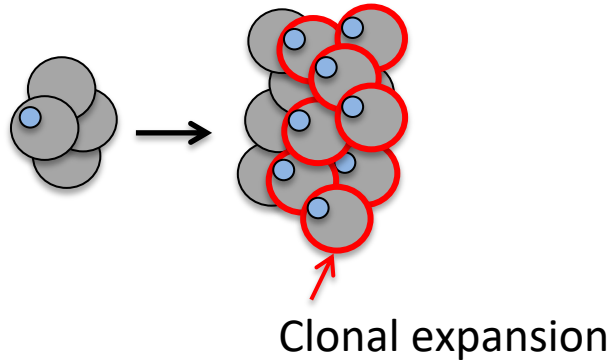
Founder
tumor cell

with somatic mutation: ●
(e.g. BRAF V600E)

Tumorigenesis: Cell Mutation

Clonal Evolution Theory of Cancer

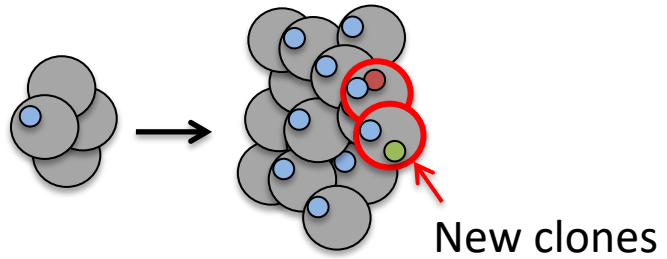
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Clonal Evolution Theory of Cancer

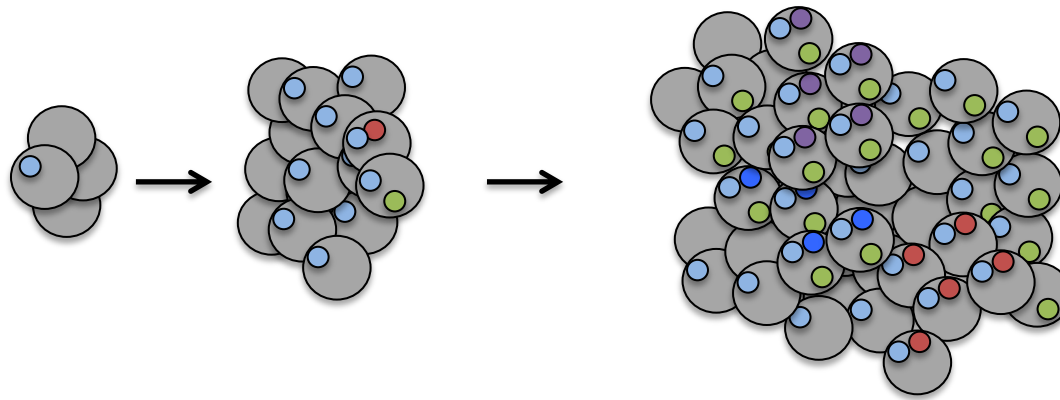
[Nowell, 1976]



Tumorigenesis: Cell Mutation & Division

Clonal Evolution Theory of Cancer

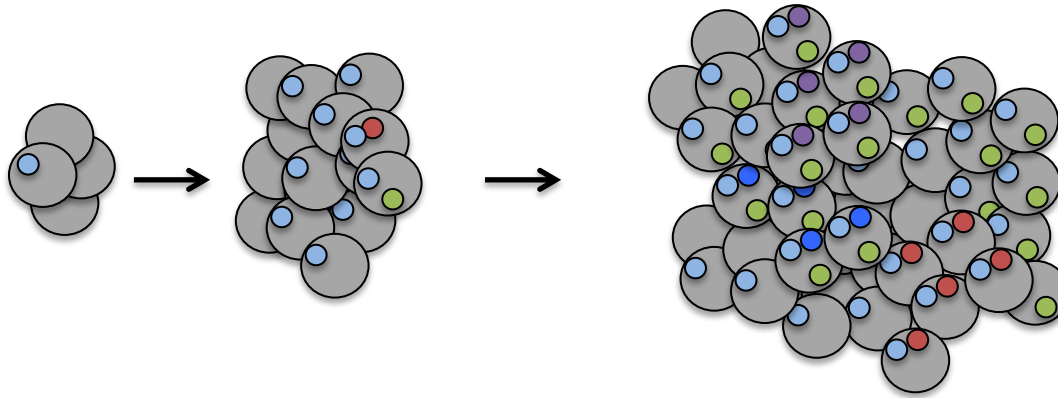
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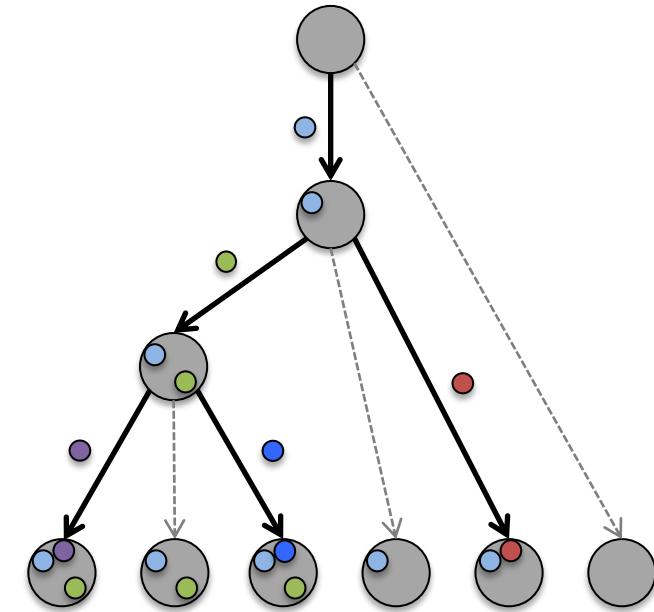
Intra-Tumor
Heterogeneity

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Clonal Evolution Theory of Cancer
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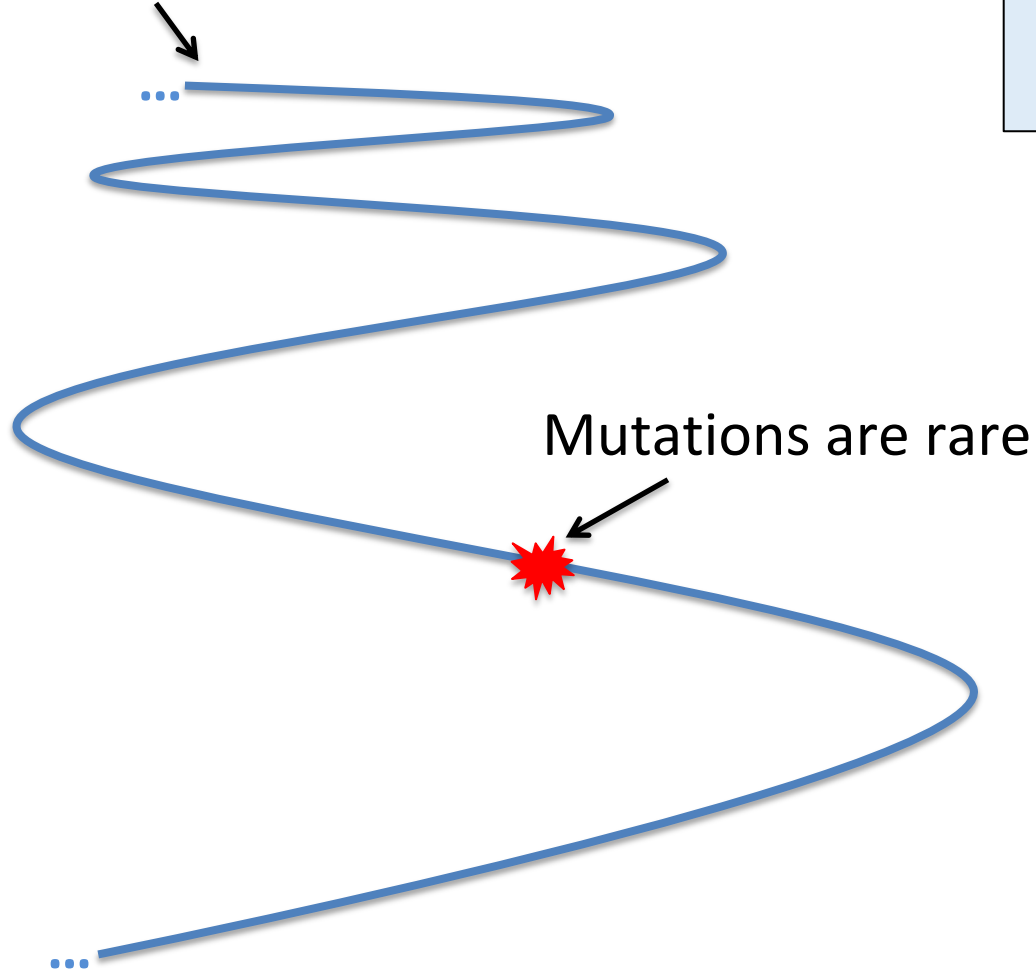
Intra-Tumor
Heterogeneity



Phylogenetic
Tree T







Infinite Sites Model

The genome is large



[Kimura, 1969]

Infinite sites model: multiple mutations never occur at the same position

		Mutated Loci					
							
Species (cancer cells)	A	0	0	0	0	1	1
	B	0	0	0	1	1	1
	C	0	0	1	0	1	0
	D	1	0	0	0	0	0
	E	1	1	0	0	0	0

1: mutated

0: not

All sites are bi-allelic: mutated or not.

Progression of Somatic Mutations

Single nucleotide mutation

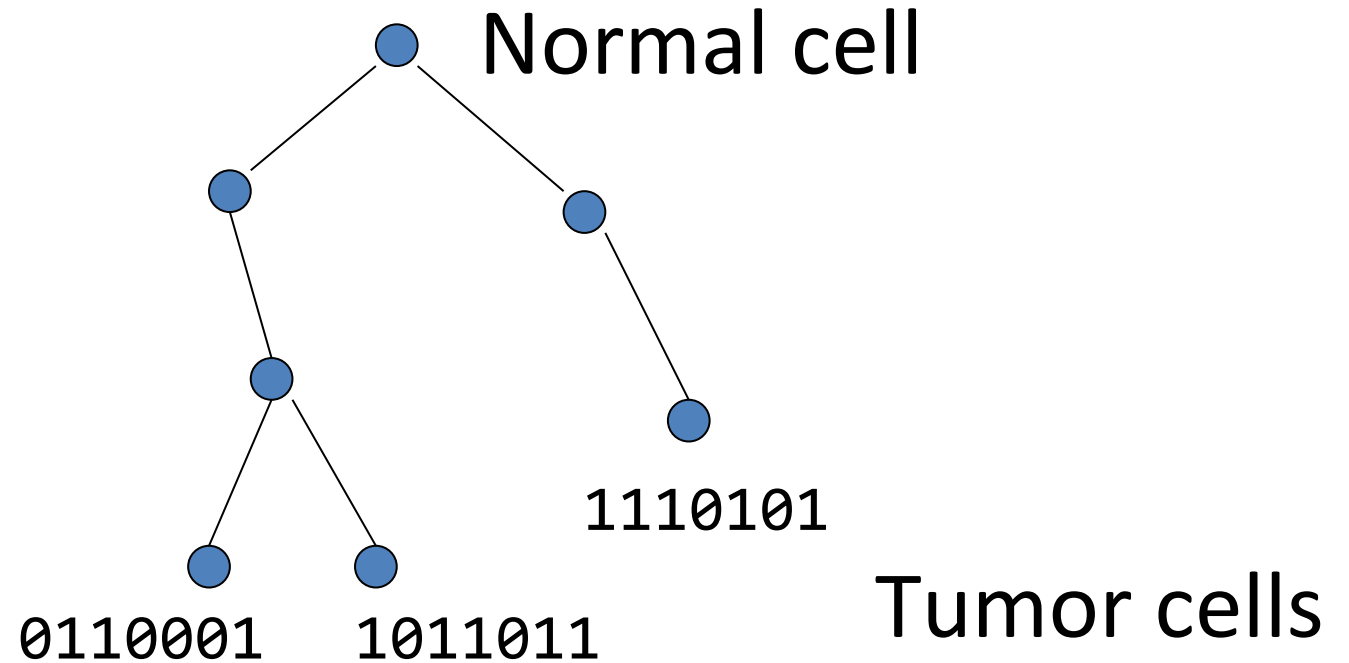
... CGT**A**TTAG ...



... CGT**C**ATTAG ...

0 = normal

1 = mutated



Root is the normal, founder cell and leaves are cells in tumor.

Infinite sites assumption: each locus mutates only once.

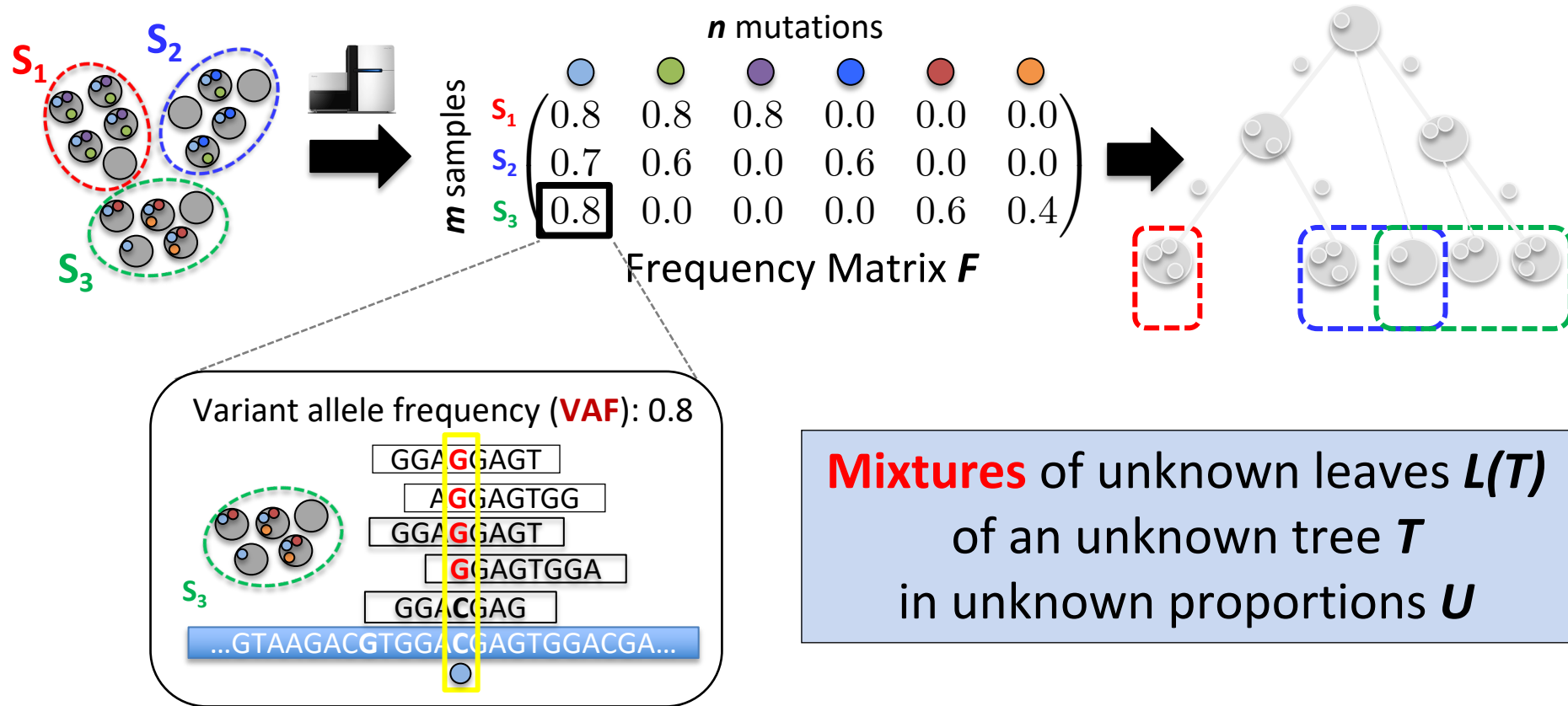
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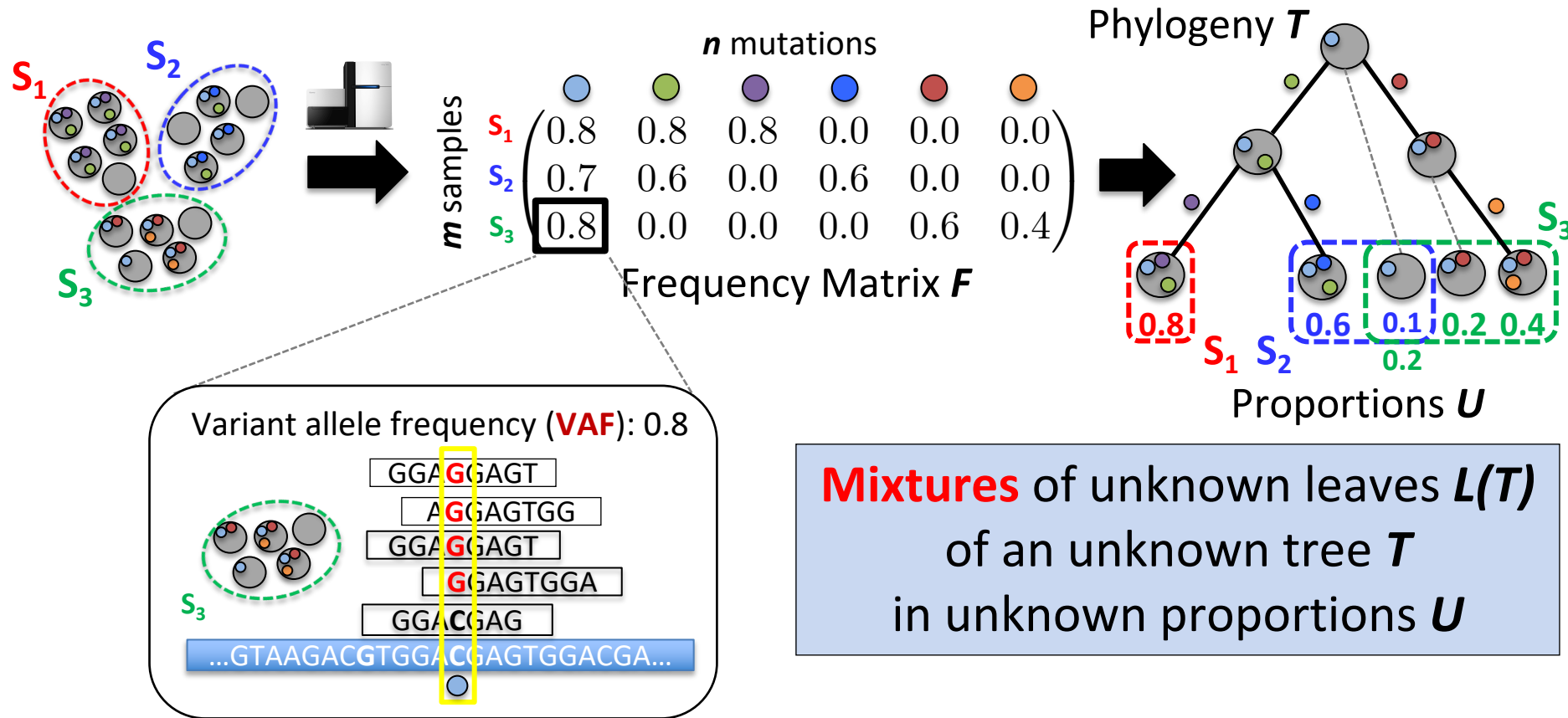
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Sequencing and Tumor Phylogeny Inference

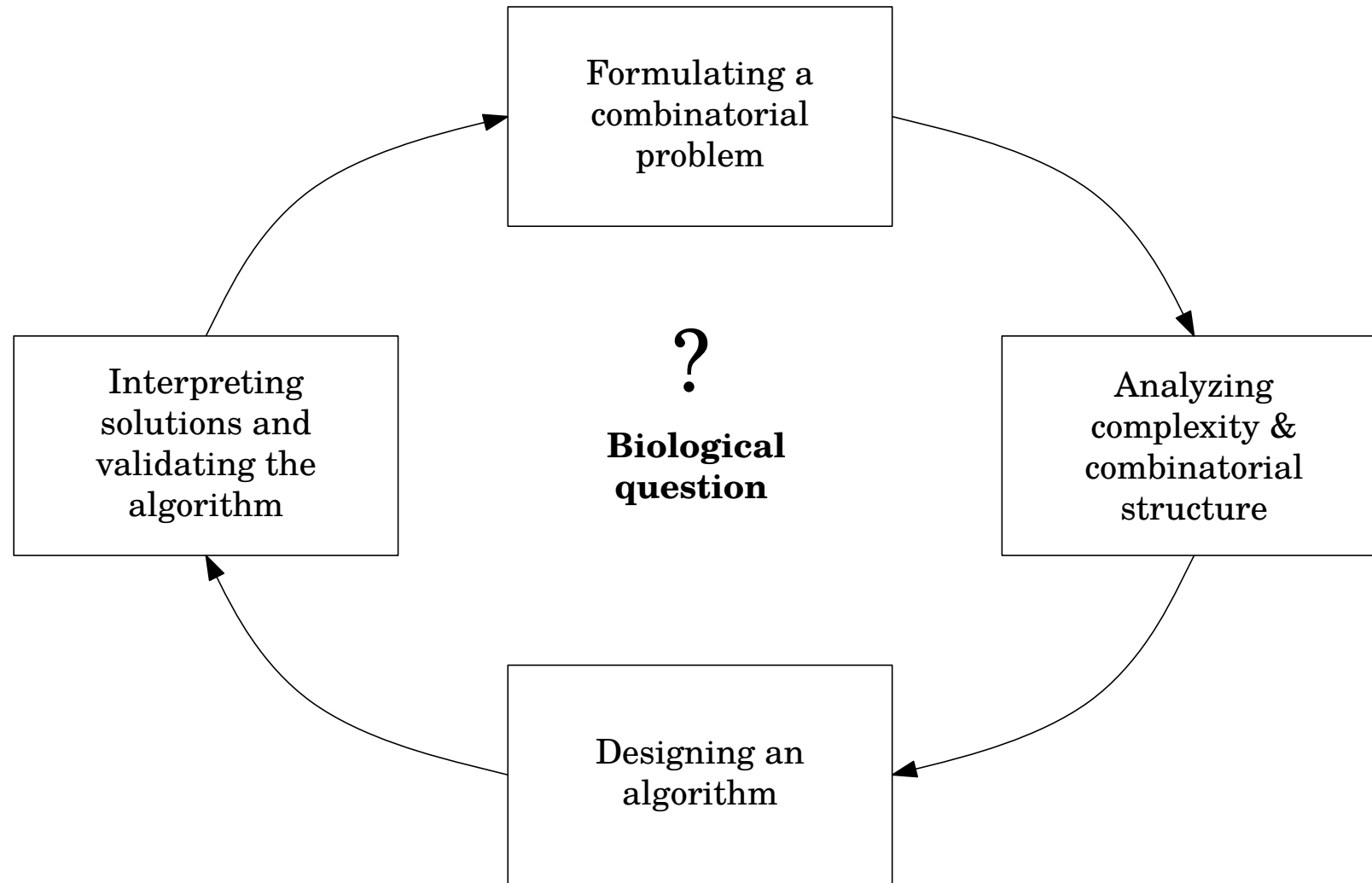


Sequencing and Tumor Phylogeny Inference



Tumor Phylogeny Inference: Given frequencies F , find phylogeny T and proportions U

Key Challenge in Computational Biology

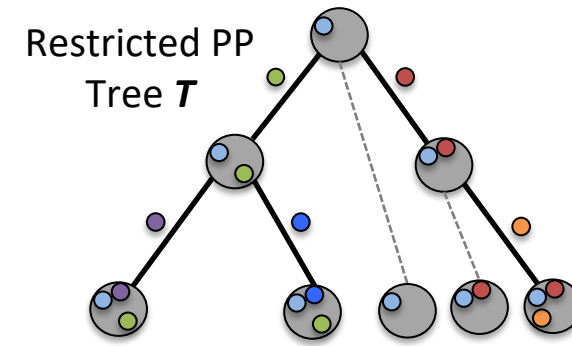


Translating a biological problem into a computational biology

Perfect Phylogeny Mixture

Assumptions:

- Infinite sites assumption: a character changes state once
- Error-free data



1-1 \updownarrow Equivalent

m samples

n mutations

$$\begin{matrix} s_1 \\ s_2 \\ s_3 \end{matrix} \begin{pmatrix} 0.8 & 0.8 & 0.8 & 0.0 & 0.0 & 0.0 \\ 0.7 & 0.6 & 0.0 & 0.6 & 0.0 & 0.0 \\ 0.8 & 0.0 & 0.0 & 0.0 & 0.6 & 0.4 \end{pmatrix}$$

Frequency Matrix F

=

m samples

clones

$$\begin{matrix} s_1 \\ s_2 \\ s_3 \end{matrix} \begin{pmatrix} 0.0 & 0.0 & 0.8 & 0.0 & 0.0 & 0.0 \\ 0.1 & 0.0 & 0.0 & 0.6 & 0.0 & 0.0 \\ 0.2 & 0.0 & 0.0 & 0.0 & 0.2 & 0.4 \end{pmatrix}$$

Mixture Matrix U

n mutations

$$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 & 1 \end{pmatrix}$$

clones

Restricted PP Matrix B

Rows of U are proportions:

$$u_{pj} \geq 0 \text{ and } \sum_j u_{pj} \leq 1$$

Perfect Phylogeny Theorem

[Estabrook, 1971]

[Gusfield, 1991]

Perfect Phylogeny Mixture: [El-Kebir*, Oesper* et al., 2015]

Given F , find U and B such that $F = UB$

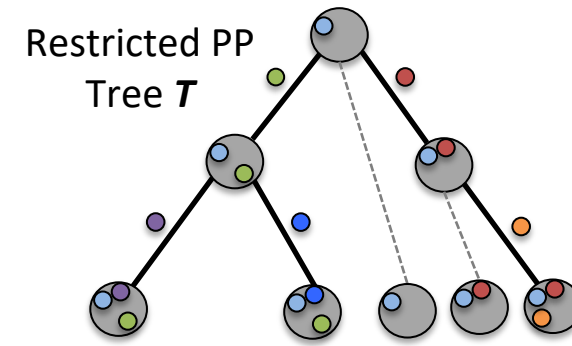
Previous Work

Variant of PPM:

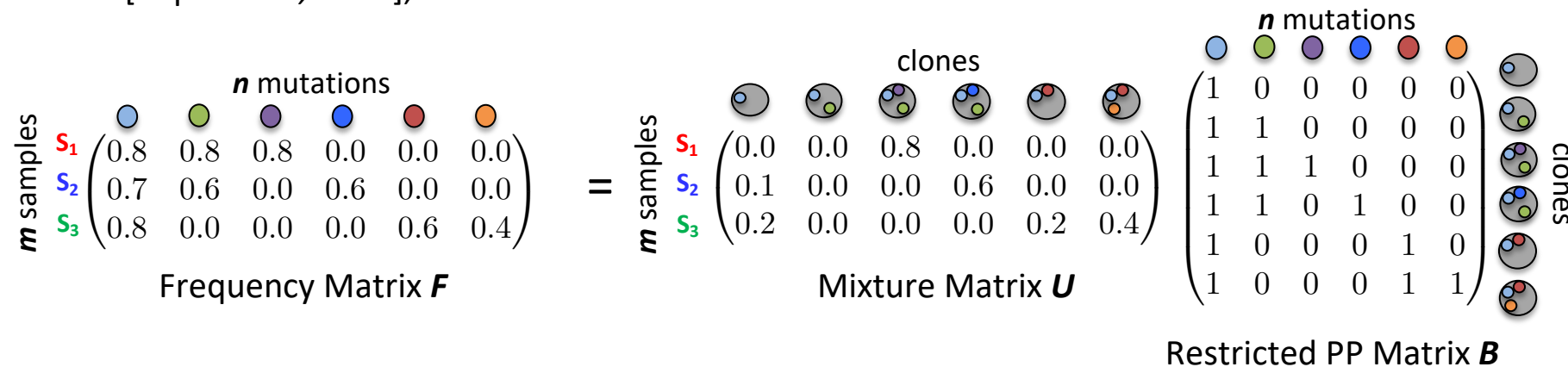
TrAp [Strino *et al.*, 2013], PhyloSub [Jiao *et al.*, 2014]

CITUP [Malikic *et al.*, 2015], BitPhylogeny [Yuan *et al.*, 2015]

LICHeE [Popic *et al.*, 2015], ...



1-1 \updownarrow Equivalent



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Combinatorial Characterization

Perfect Phylogeny Mixture: [El-Kebir*, Oesper* et al., 2015]

Given F , find U and B such that $F = U B$

Frequency Matrix F

	s_1	s_2	s_3	mut1	mut2	mut3	mut4	mut5	mut6
s_1	0.8	0.8	0.8	0.0	0.0	0.0	0.0	0.0	0.0
s_2	0.7	0.6	0.0	0.6	0.0	0.0	0.0	0.0	0.0
s_3	0.8	0.0	0.0	0.0	0.6	0.4	0.0	0.0	0.0

Mixture Matrix U

	s_1	s_2	s_3	clone1	clone2	clone3	clone4	clone5	clone6
s_1	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0
s_2	0.1	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.0
s_3	0.2	0.0	0.0	0.0	0.2	0.4	0.0	0.0	0.0

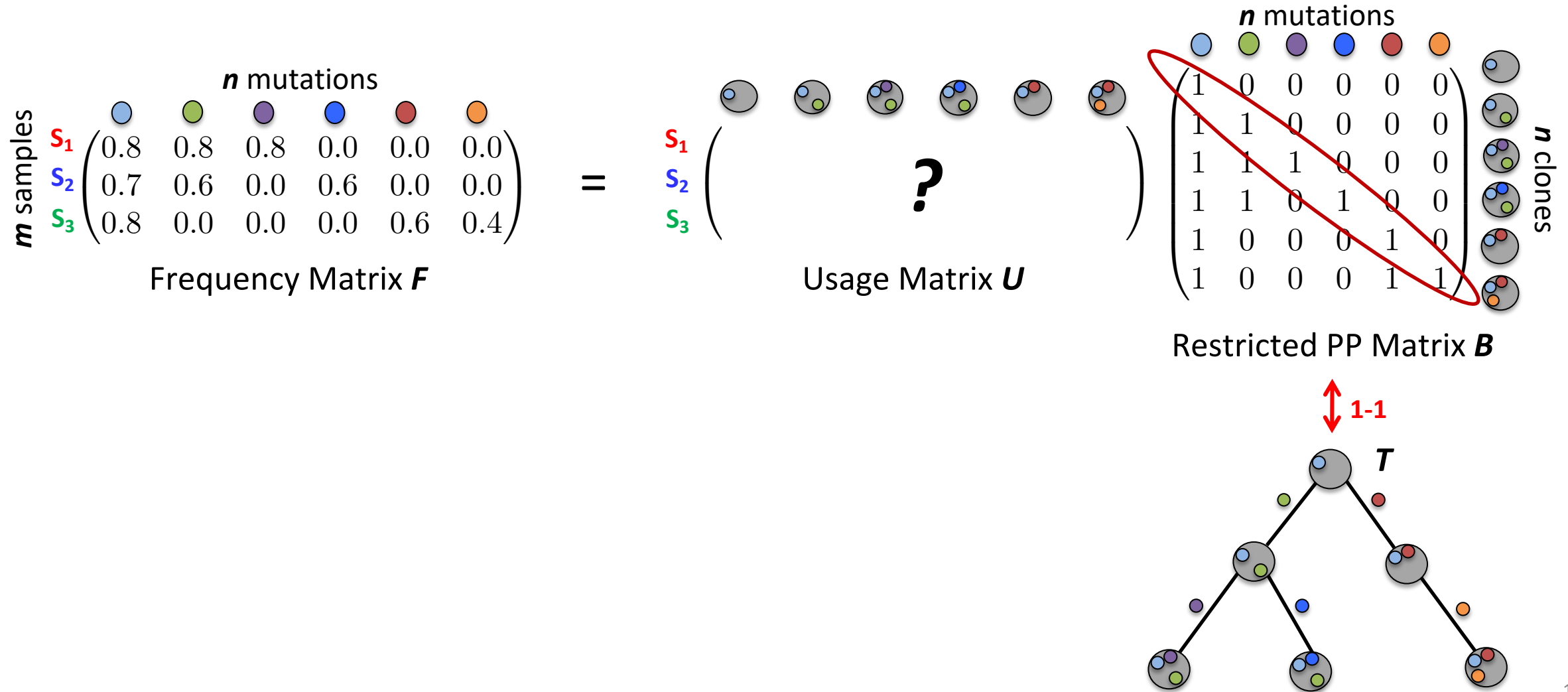
Restricted PP Matrix B

	mut1	mut2	mut3	mut4	mut5	mut6
clone1	1	0	0	0	0	0
clone2	1	1	0	0	0	0
clone3	1	1	1	0	0	0
clone4	1	1	0	1	0	0
clone5	1	0	0	0	1	0
clone6	1	0	0	0	1	1

- **Combinatorial characterization** involves investigating what (optimal) solutions look like
- This starts by asking questions!

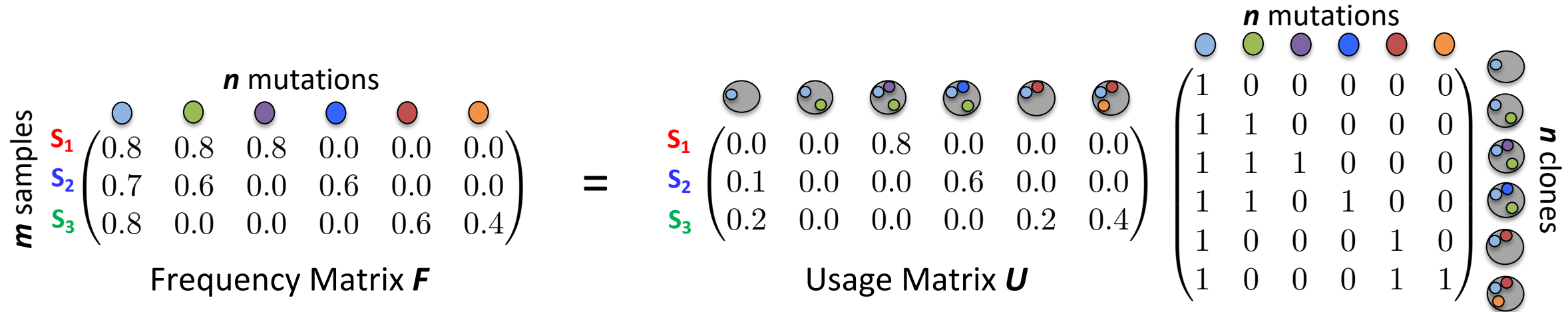
Given F and T (or B), is there a usage matrix U ?

PPM: Given F , find U and B such that $F = U B$



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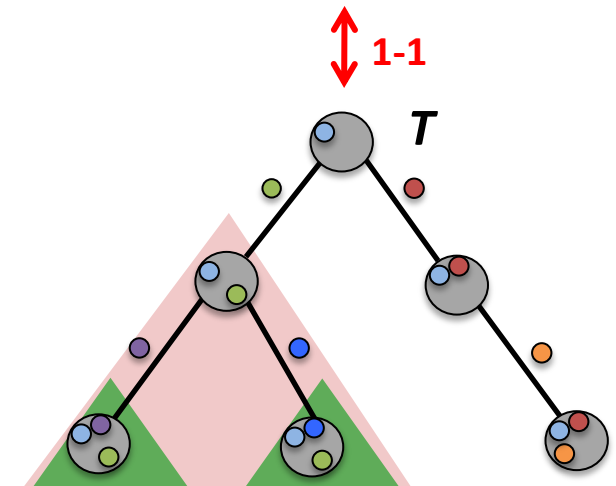


Lemma: B is invertible

➔ Given F and B , U is **unique**: $U = F B^{-1}$

Lemma:

$$u_{pj} = f_{pj} - \sum_{k \text{ child of } j} f_{pk}$$



Given F and T (or B), is there a usage matrix U ?

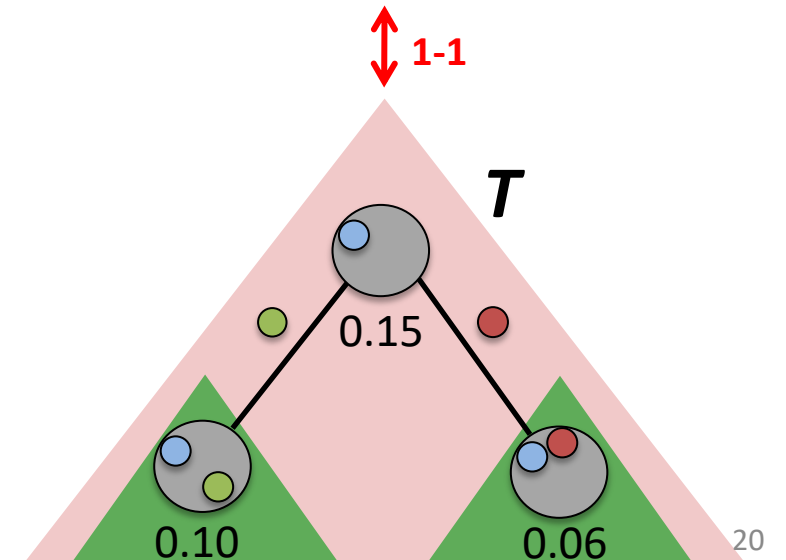
PPM: Given F , find U and B such that $F = U B$

$$\begin{array}{c}
 \begin{array}{ccc} \bullet & \bullet & \bullet \\ \text{blue} & \text{green} & \text{red} \end{array} \\
 \begin{pmatrix} \boxed{0.15} & 0.1 & 0.06 \\ 0.2 & 0.05 & 0.04 \end{pmatrix} = \begin{pmatrix} \boxed{-0.01} & 0.1 & 0.06 \\ 0.11 & 0.05 & 0.04 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix}
 \end{array}$$

Frequency Matrix F Usage Matrix U Restricted PP Matrix B

Lemma:

$$u_{pj} = \boxed{f_{pj}} - \sum_{k \text{ child of } j} \boxed{f_{pk}}$$



Combinatorial Characterization of Solutions

Lemma:







$$u_{pj} = \boxed{f_{pj}} - \sum_{k \text{ child of } j} \boxed{f_{pk}}$$

Lemma (Sum Condition):

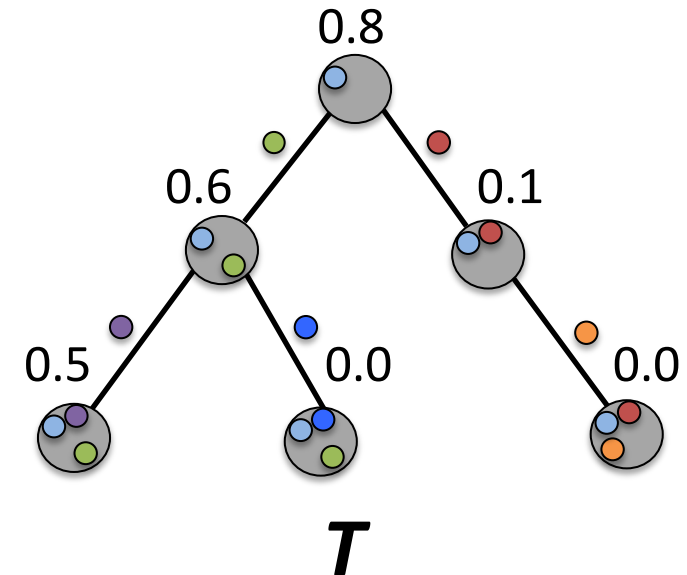
Given F and T , for all samples p and mutations j ,

$$\boxed{f_{pj}} \geq \sum_{k \text{ child of } j} \boxed{f_{pk}}$$

necessary
sufficient

					
0.8	0.6	0.5	0.0	0.1	0.0
0.7	0.6	0.0	0.6	0.0	0.0
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F









Combinatorial Characterization of Solutions

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F

Lemma (Ancestry Condition):

Given F and T , for all samples p and mutations k child of j , $f_{pj} \geq f_{pk}$







necessary

Combinatorial Characterization of Solutions

Lemma (Sum Condition):

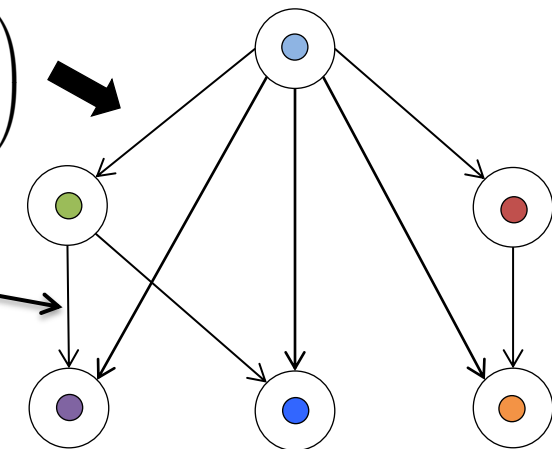
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F

potential parental
relationship



Ancestry Graph $G = (V, A)$

Lemma (Ancestry Condition):

Given F and T , for all samples p and mutations k child of j , $f_{pj} \geq f_{pk}$

necessary

Ancestry graph $G = (V, A)$; given F

- Vertex for every mutation
- Edge $(j, k) \in A$ iff $f_{pj} \geq f_{pk}$ for all samples p

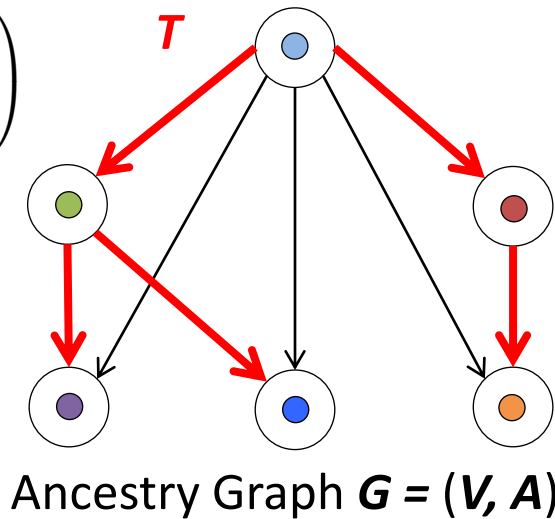
Combinatorial Characterization of Solutions

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Given F and T , for all samples p and mutations j , $f_{pj} \geq \sum_{k \text{ child of } j} f_{pk}$

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●	●	●	●	●	●
(0.8	0.6	0.5	0.0	0.1	0.0)
0.7	0.6	0.0	0.6	0.0	0.0)
0.8	0.0	0.0	0.0	0.6	0.4)
F					



Theorem 2:

PPM is NP-complete

Lemma (Ancestry Condition):

Given F and T , for all samples p and mutations k child of j , $f_{pj} \geq f_{pk}$

necessary

Ancestry graph $G = (V, A)$; given F

- Vertex for every mutation
- Edge $(j, k) \in A$ iff $f_{pj} \geq f_{pk}$ for all samples p

Theorem 1:

T is a solution to the PPM if and only if T is a spanning tree of G satisfying the Sum Condition

Solving the PPM problem: ILP formulation

$$\max \sum_{(v_j, v_k) \in A'} x_{jk}$$

**Find the largest
set of edges in G**

$$\text{s.t.} \quad \sum_{v_j \in \delta^+(v_r)} x_{rj} = 1$$

Exactly one root node

$$x_{kl} \leq \sum_{v_j \in \delta^-(v_k)} x_{jk}$$

$\forall (v_k, v_l) \in A$ **Connectivity**

$$\sum_{v_j \in \delta^-(v_k)} x_{jk} \leq 1$$

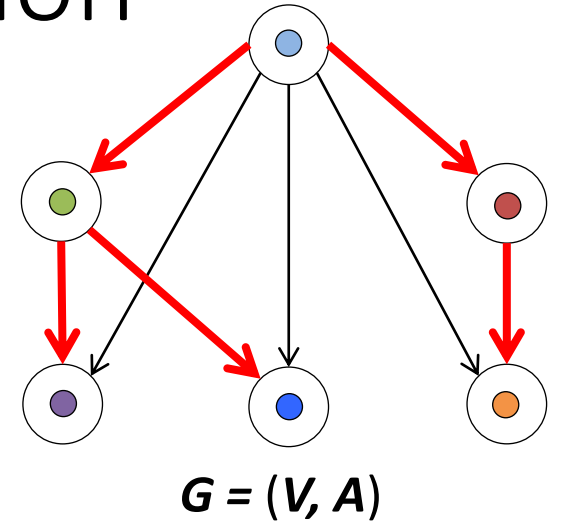
$\forall v_k \in V$ **Tree**

$$\sum_{v_j \in \delta^-(v_k)} f_{pk} x_{jk} \geq \sum_{v_l \in \delta^+(v_k)} f_{pl} x_{kl} \quad \forall p \in [m], v_k \in V$$

Sum condition

$$x_{jk} \in \{0, 1\}$$

$$\forall (v_j, v_k) \in A'$$

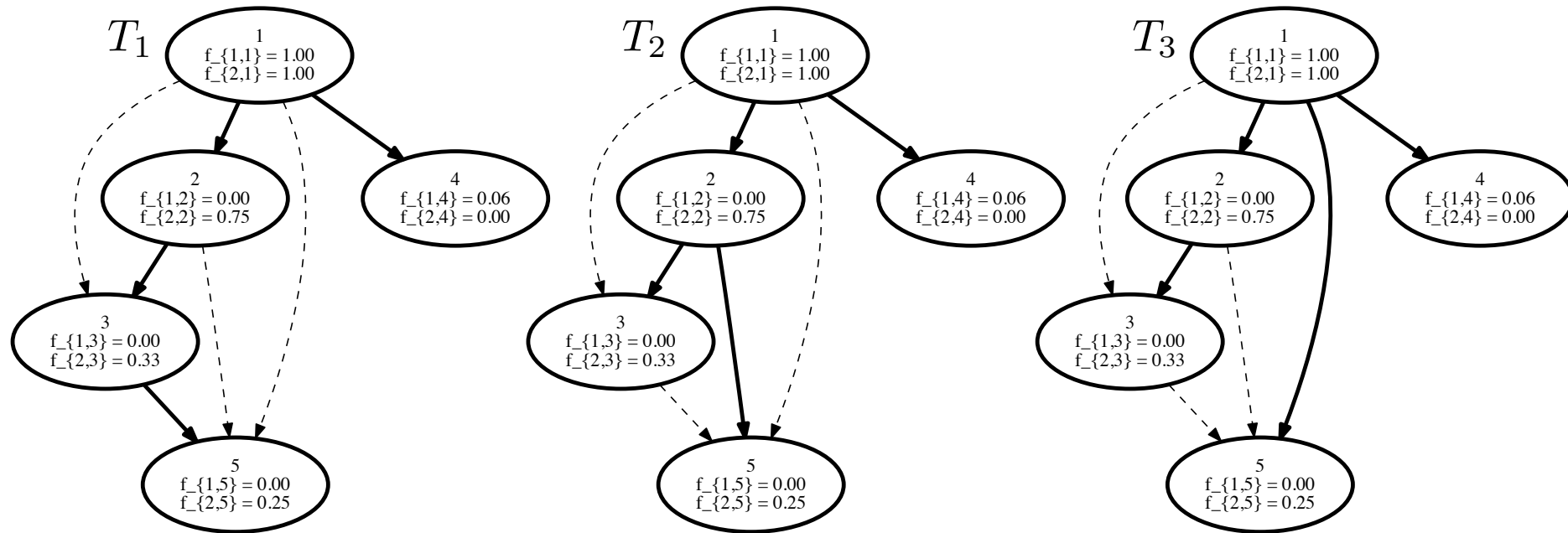


Non-uniqueness of Solutions to PPM

$$F = \begin{pmatrix} 1 & 0 & 0 & 0.06 & 0 \\ 1 & 0.75 & 0.33 & 0 & 0.25 \end{pmatrix}$$

Question 0: Reconstruct all solutions?

Non-uniqueness of Solutions to PPM



$$F = \begin{pmatrix} 1 & 0 & 0 & 0.06 & 0 \\ 1 & 0.75 & 0.33 & 0 & 0.25 \end{pmatrix}$$

Question 1: Can we determine the number of solutions?

Question 2: Can sample solutions uniformly at random?

Question 3: How to enumerate solutions?

Recall: Different Types of Problems!

Problem Π with instance X and solution set $\Pi(X)$:

- Decision problem:
 - Is $\Pi(X) = \emptyset$?
- Optimization problem:
 - Find $y^* \in \Pi(X)$ s.t. $f(y^*)$ is optimum.
- Counting problem:
 - Compute $|\Pi(X)|$.
- Sampling problem:
 - Sample uniformly from $\Pi(X)$.
- Enumeration problem:
 - Enumerate all solutions in $\Pi(X)$

Algorithms:

Set of instructions for solving problem.

- Exact
- Heuristic

On the Complexity of #PPM (new results)

Question 1: Can we determine the number of solutions?

Question 2: Can sample solutions uniformly at random?

#PPM: Given F , count the number of pairs (U, B) composed of mixture matrix U and perfect phylogeny matrix B such that $F = U B$

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#P is the complexity class of counting problems whose decision problems are in NP

Every problem in #P can be reduced in polynomial time to any problem in #P-complete, preserving cardinalities

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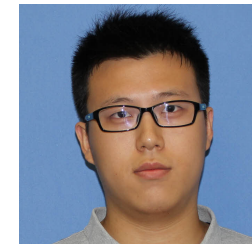
#P is the complexity class of counting problems whose decision problems are in NP

Every problem in #P can be reduced in polynomial time to any problem in #P-complete, preserving cardinalities

Theorem: #PPM is #P-complete

Theorem: There is no FPRAS for #PPM

Theorem: There is no FPAUS for PPM



Yuanyuan Qi

Outline

Background and theory:

- Perfect Phylogeny Mixture (PPM) problem
- Combinatorial characterization of solutions
- #PPM: exact counting and uniform sampling

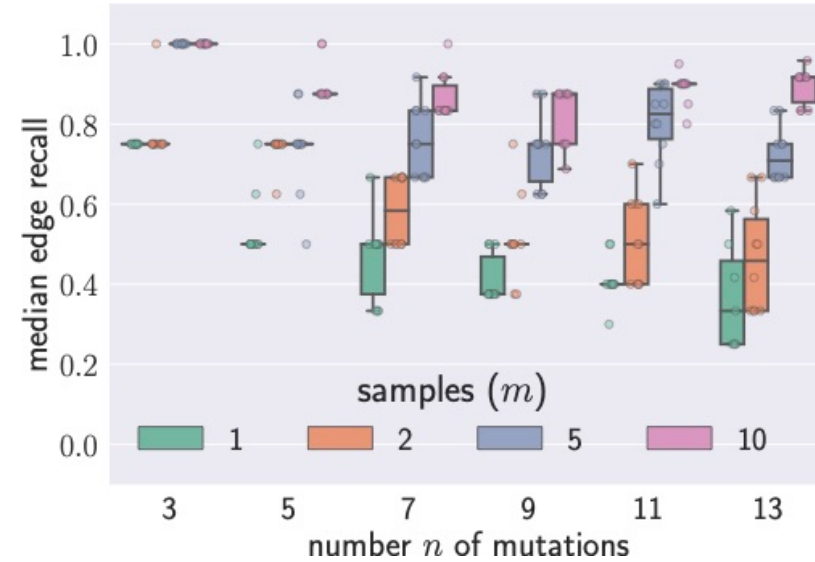
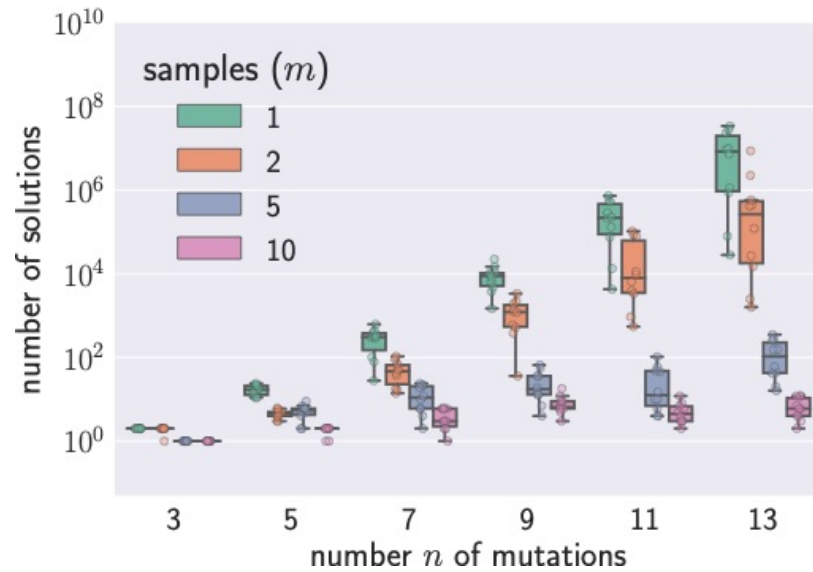
Simulation results:

- What contributes to non-uniqueness?
- How to reduce non-uniqueness?
- How does non-uniqueness affect current methods?

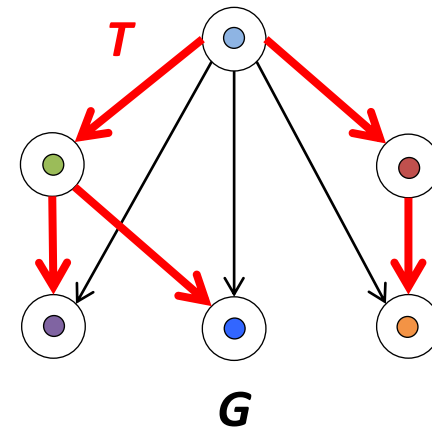
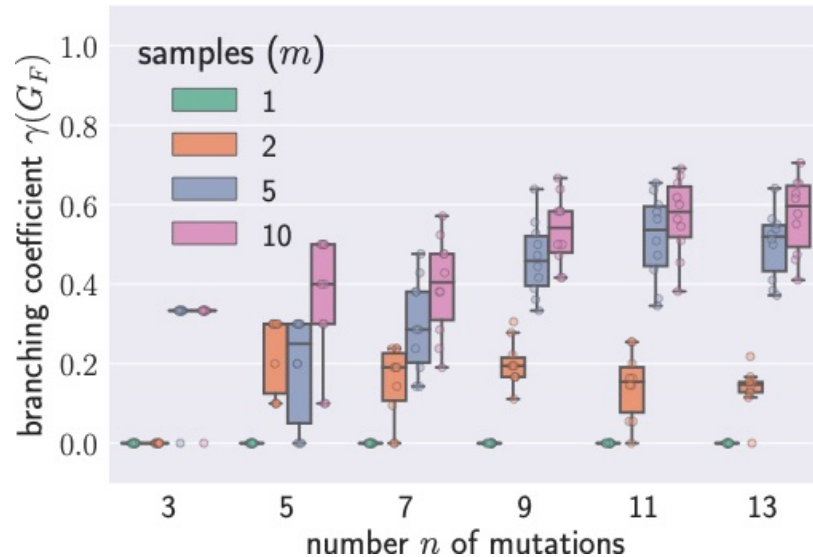
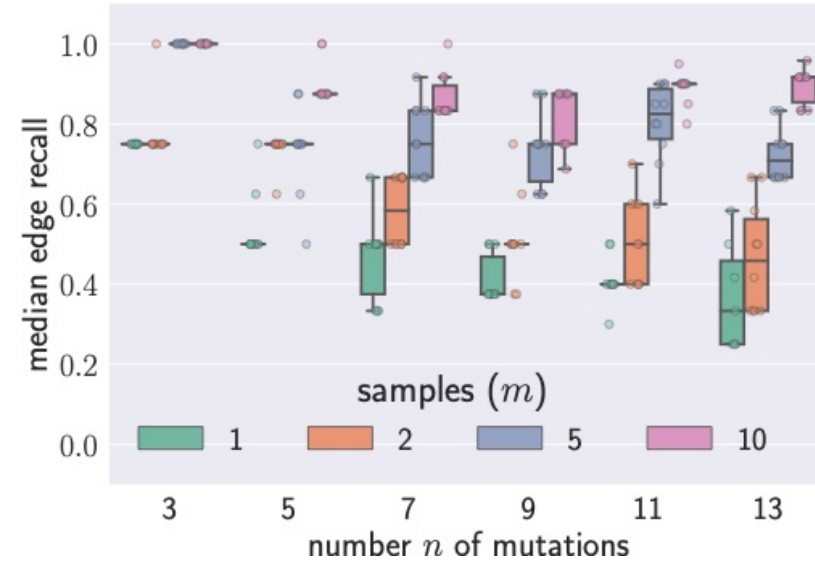
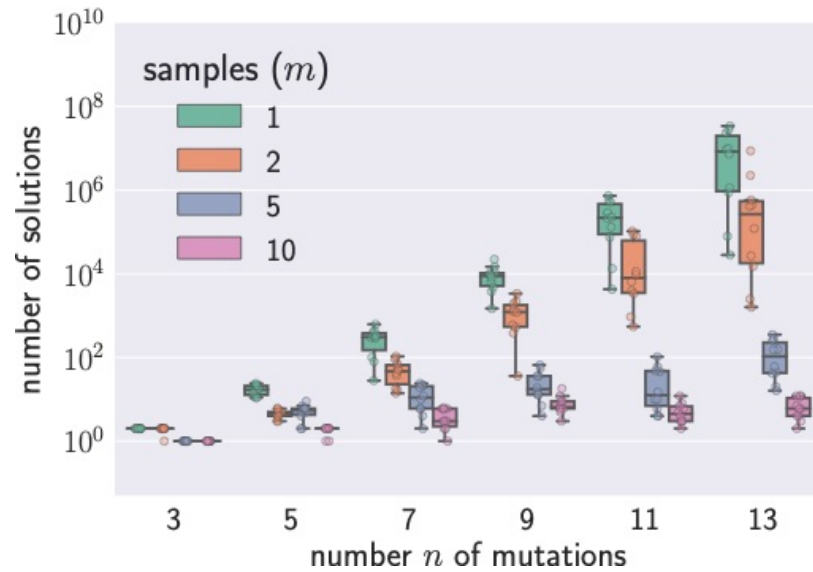


Dikshant Pradhan

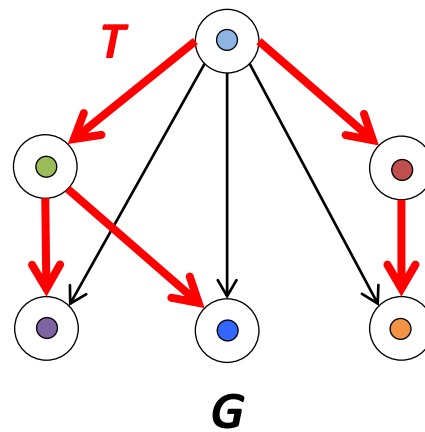
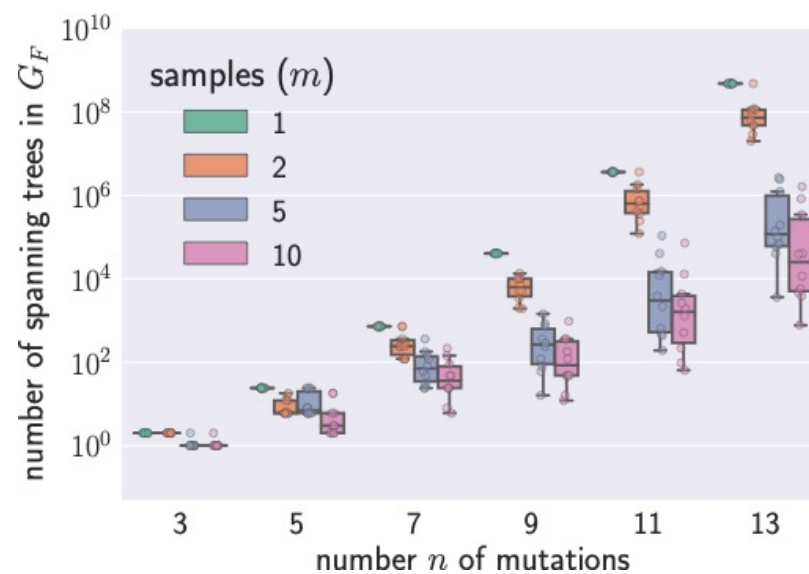
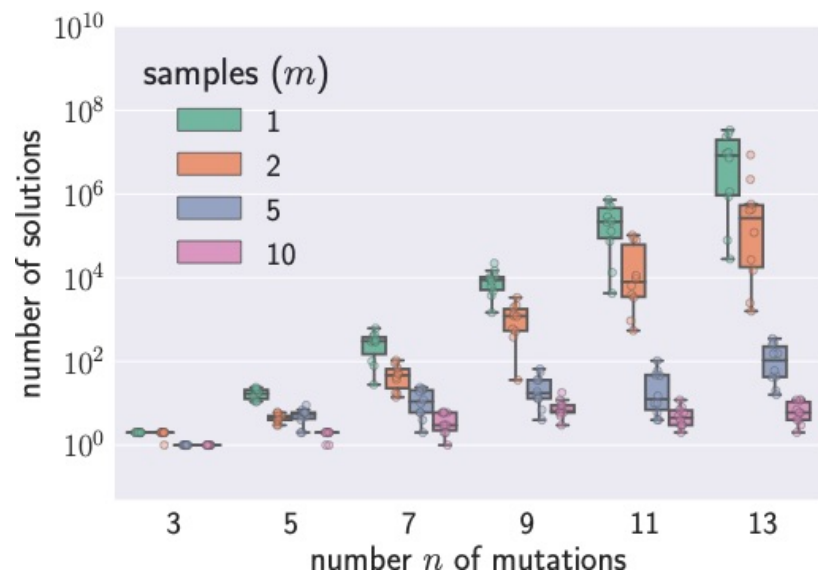
What Contributes to Non-uniqueness?



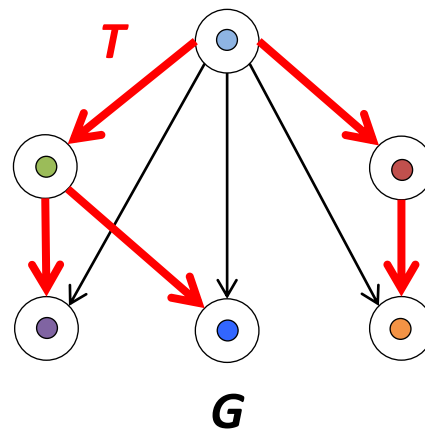
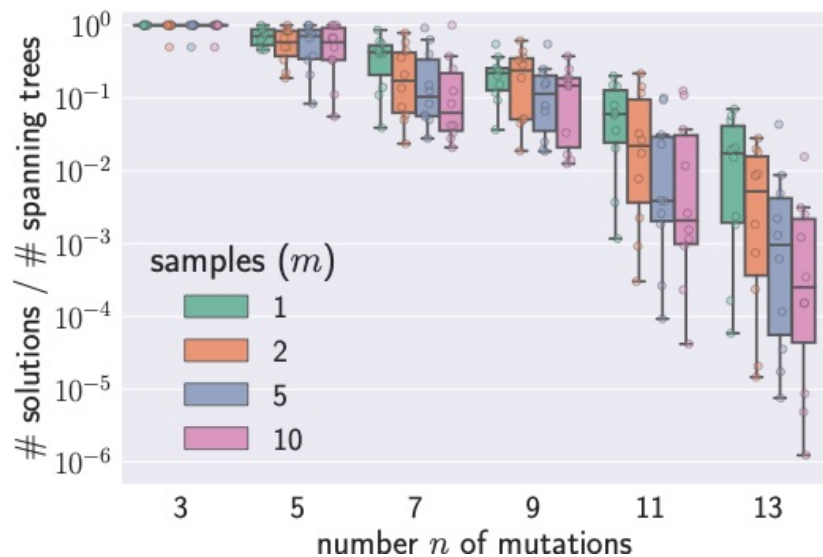
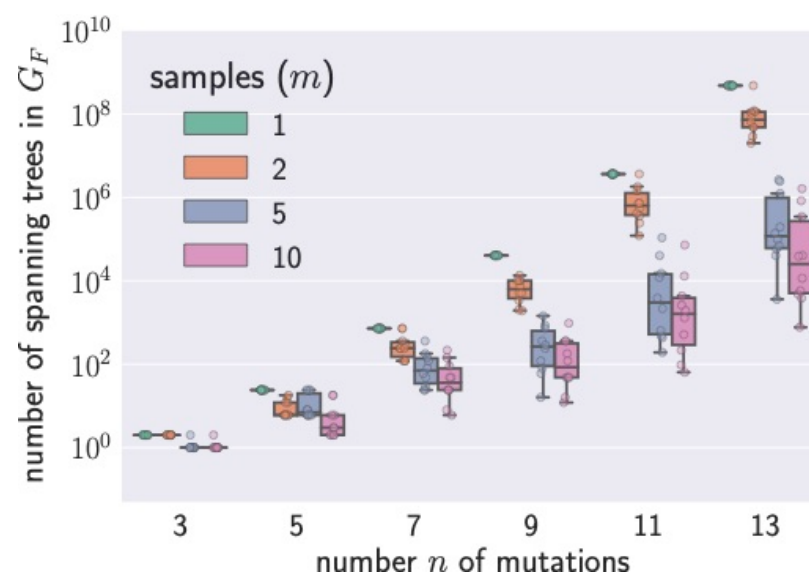
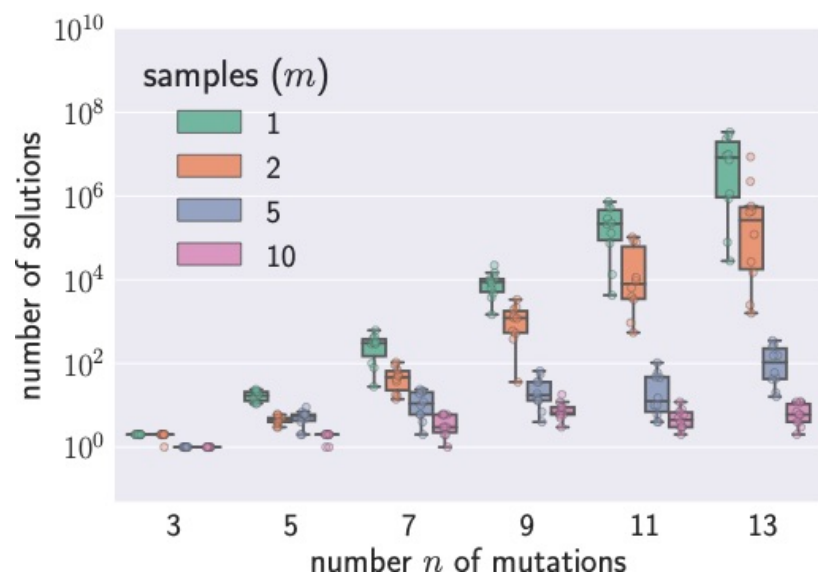
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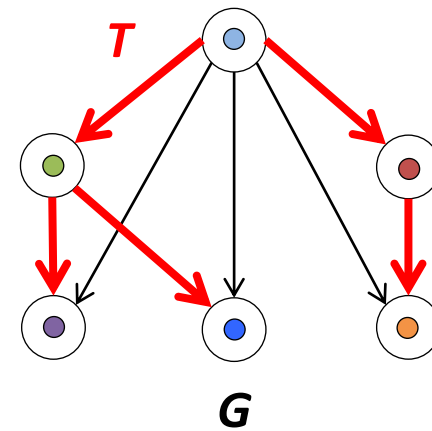
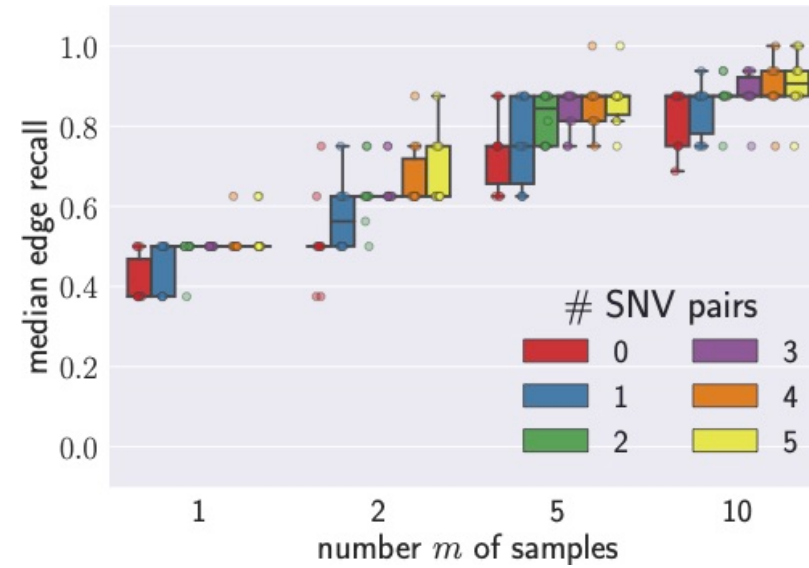
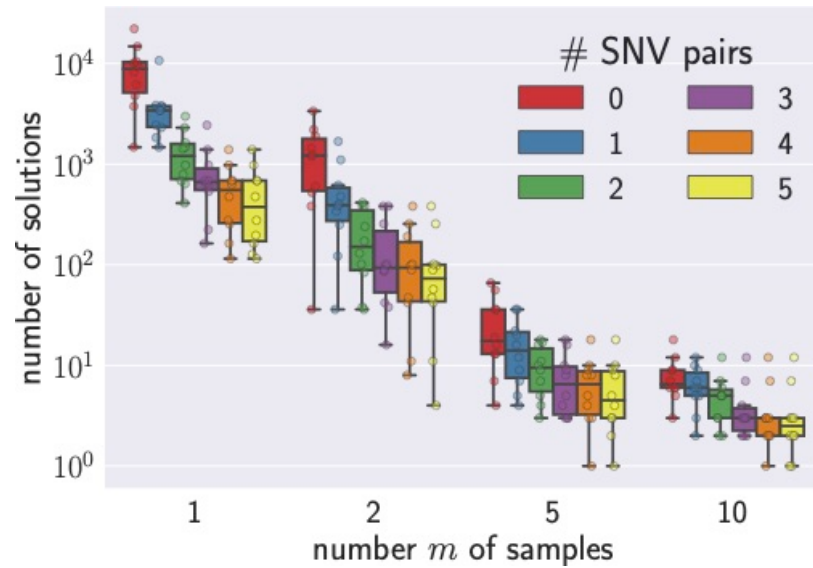
An Upper Bound for Number of Solutions



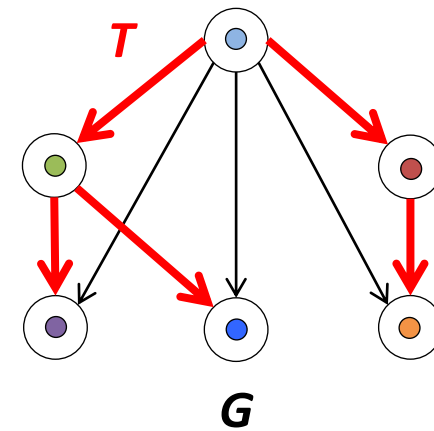
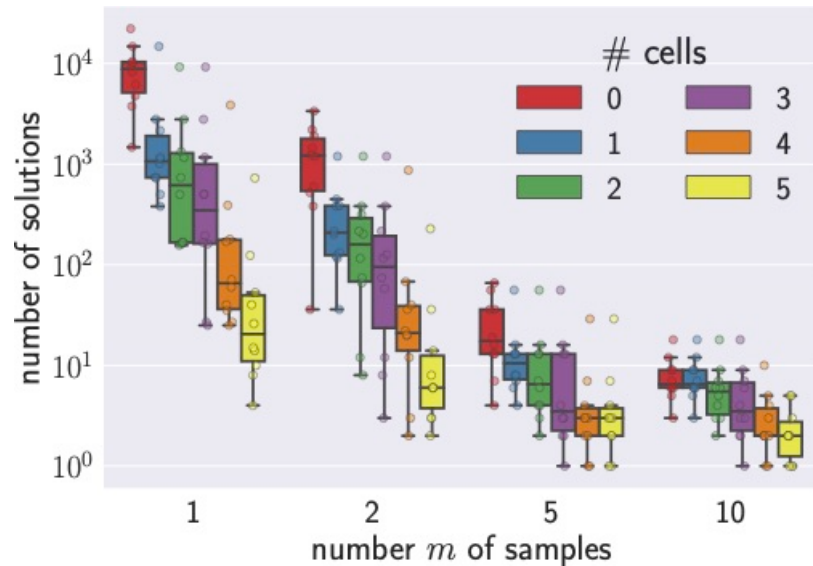
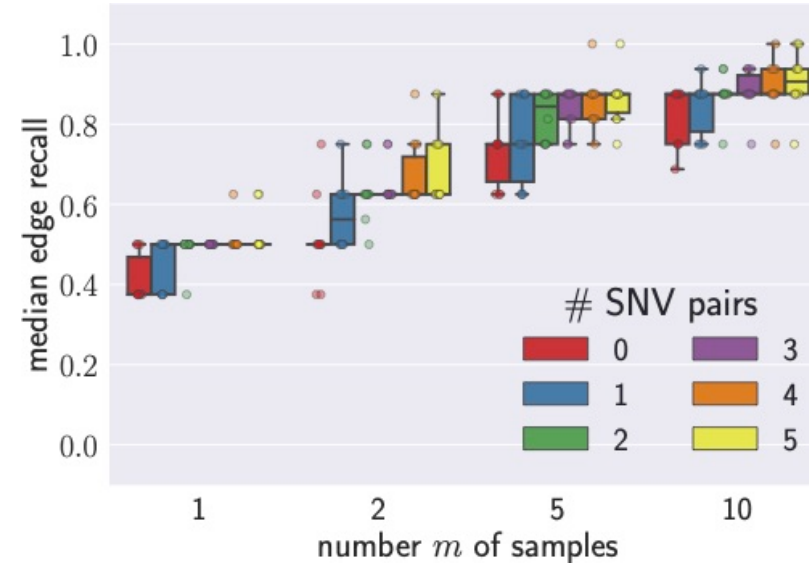
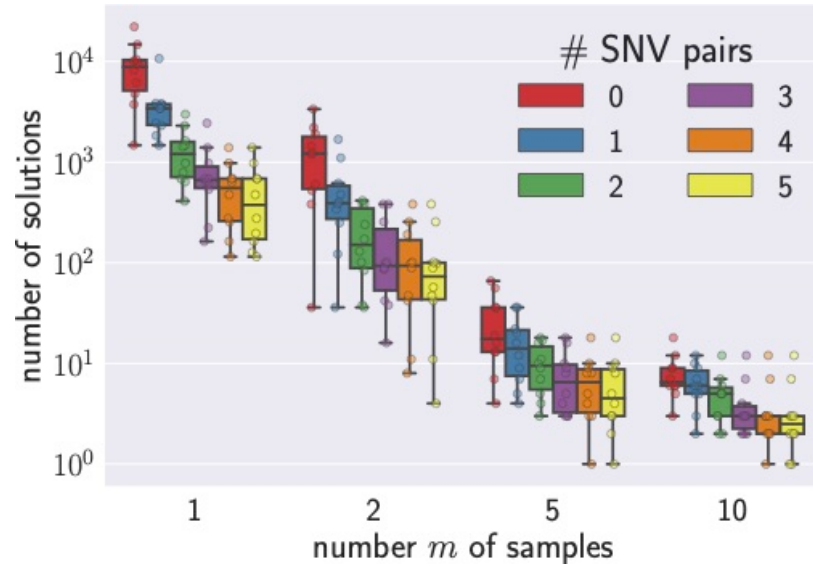
An Upper Bound for Number of Solutions



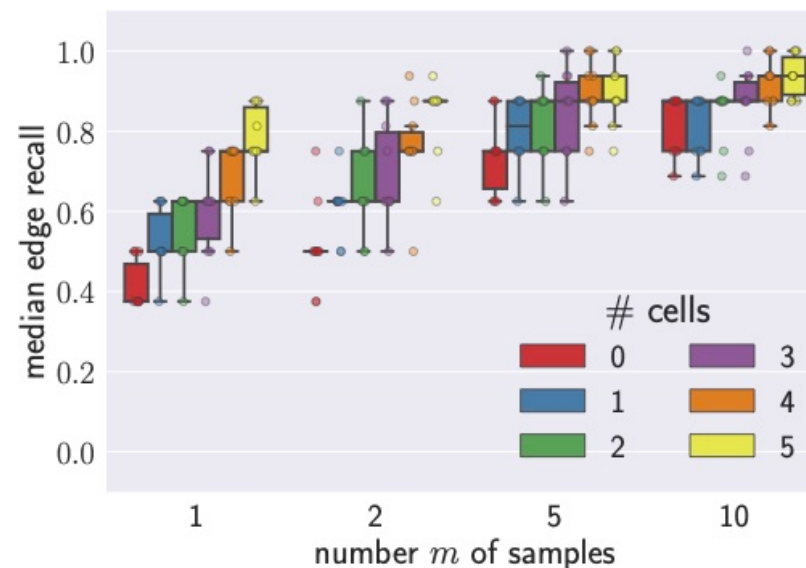
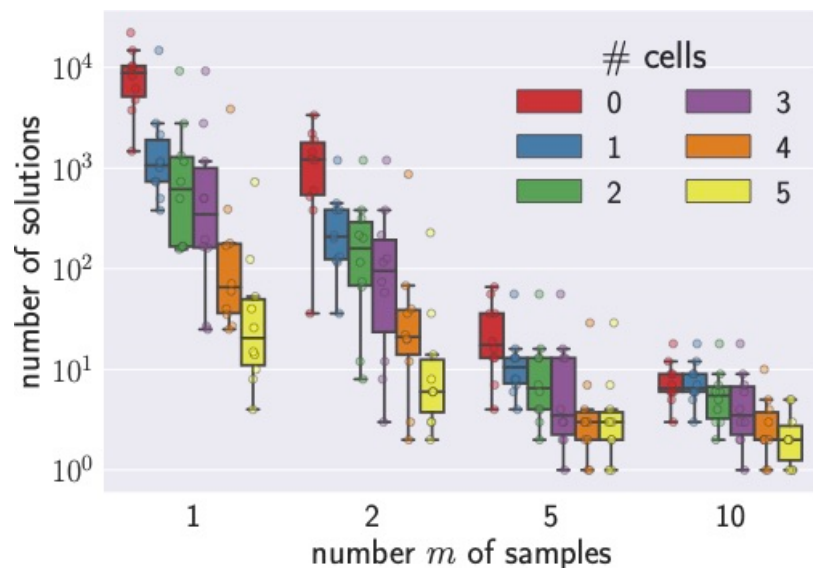
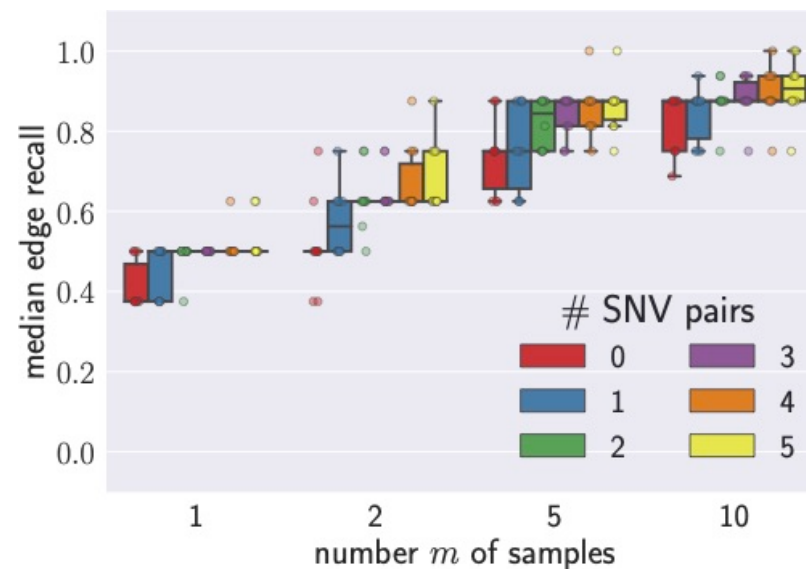
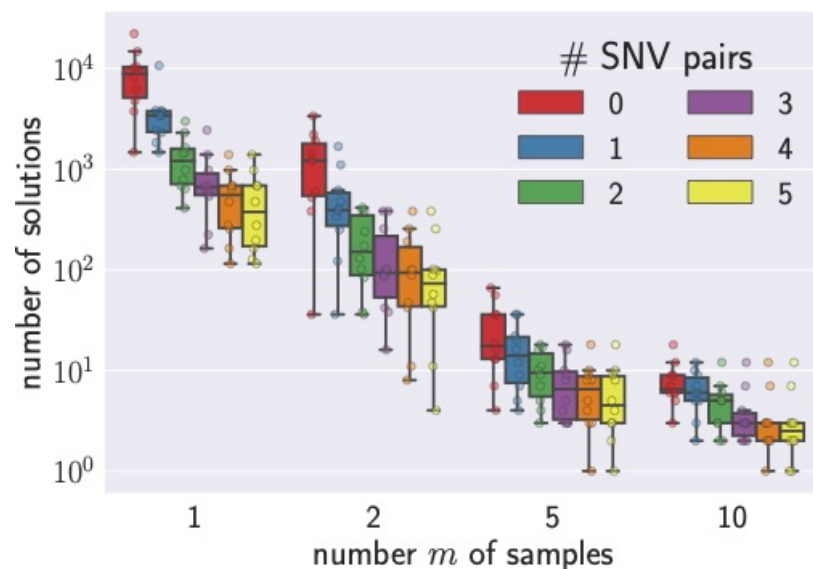
How to Reduce Non-Uniqueness?



How to Reduce Non-Uniqueness?



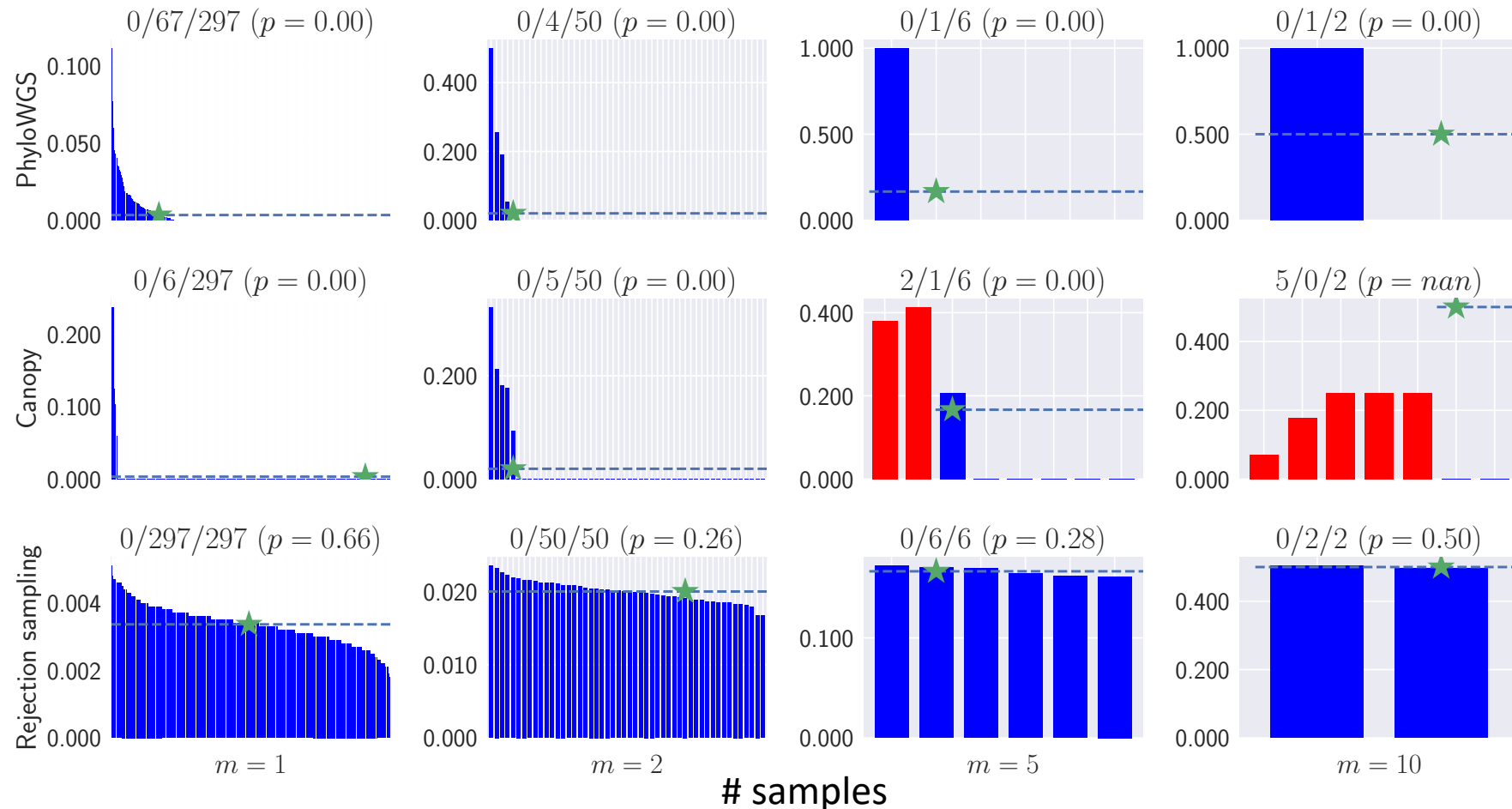
How to Reduce Non-Uniqueness?



How Does Non-uniqueness affect Methods?

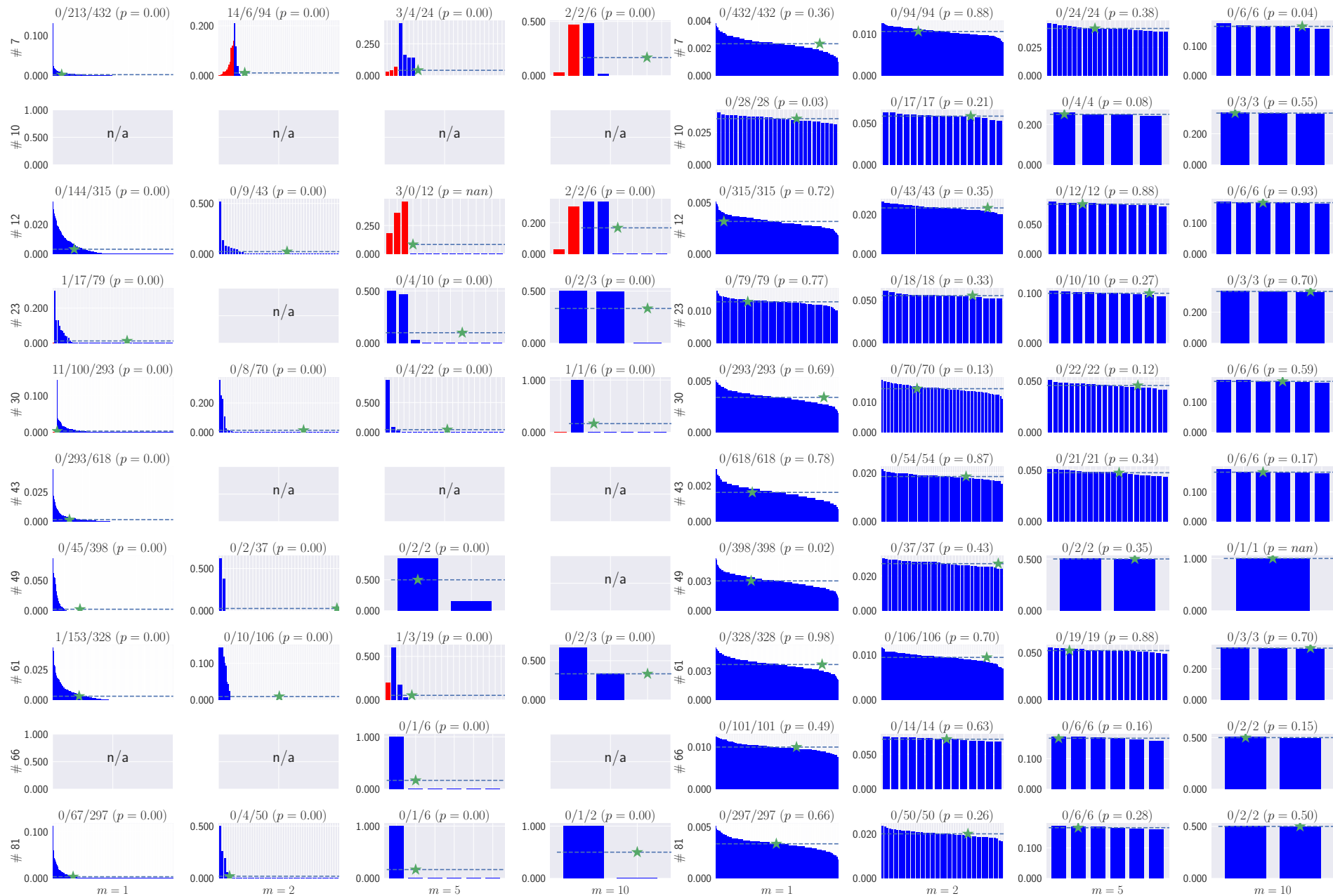
Two current MCMC methods using default parameters:

- PhyloWGS, Deshwar et al., Genom. Biol., 2015 [10,000 samples]
- Canopy, Jiang et al., PNAS, 2016 [~300 samples]

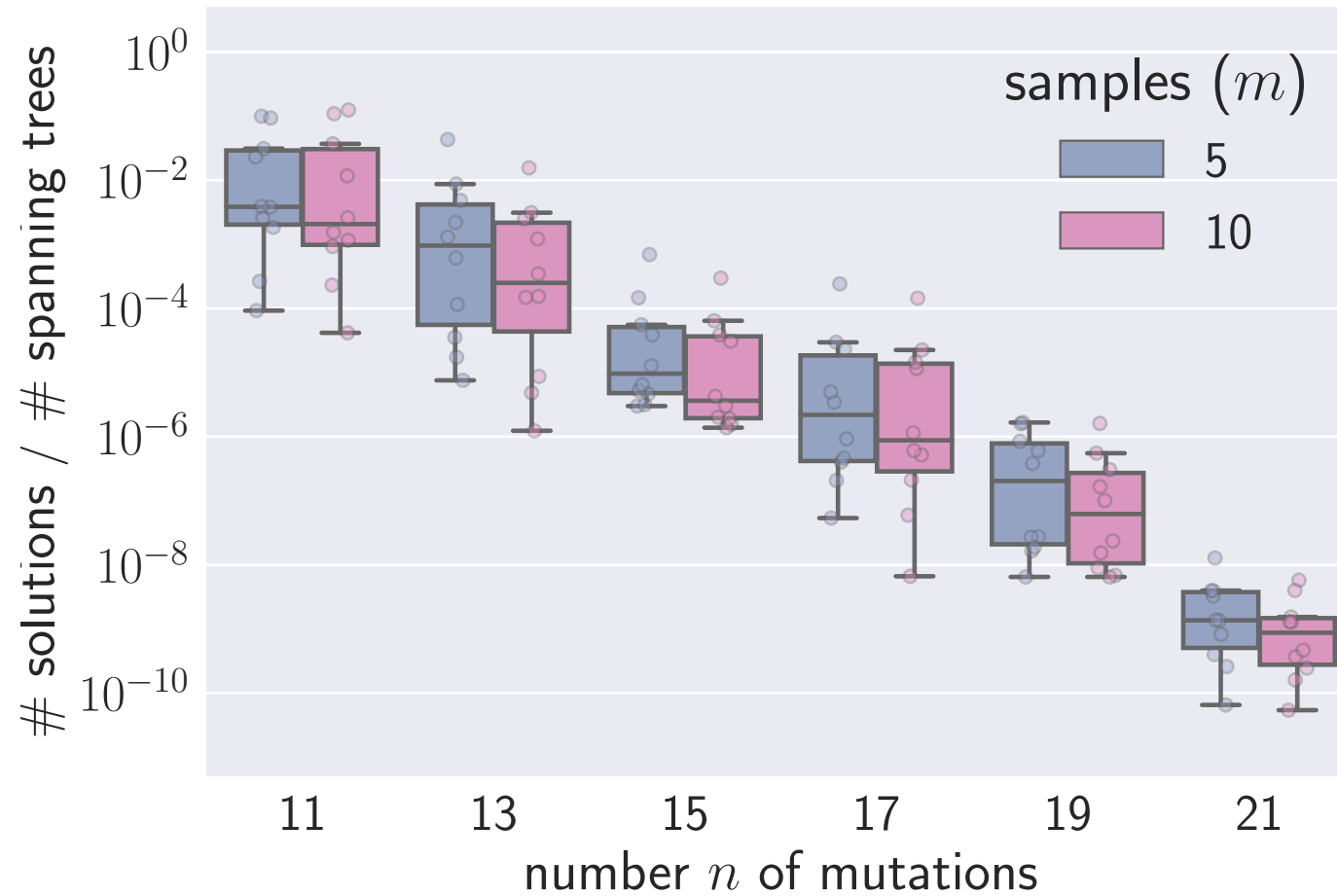


PhyloWGS

Rejection Sampling



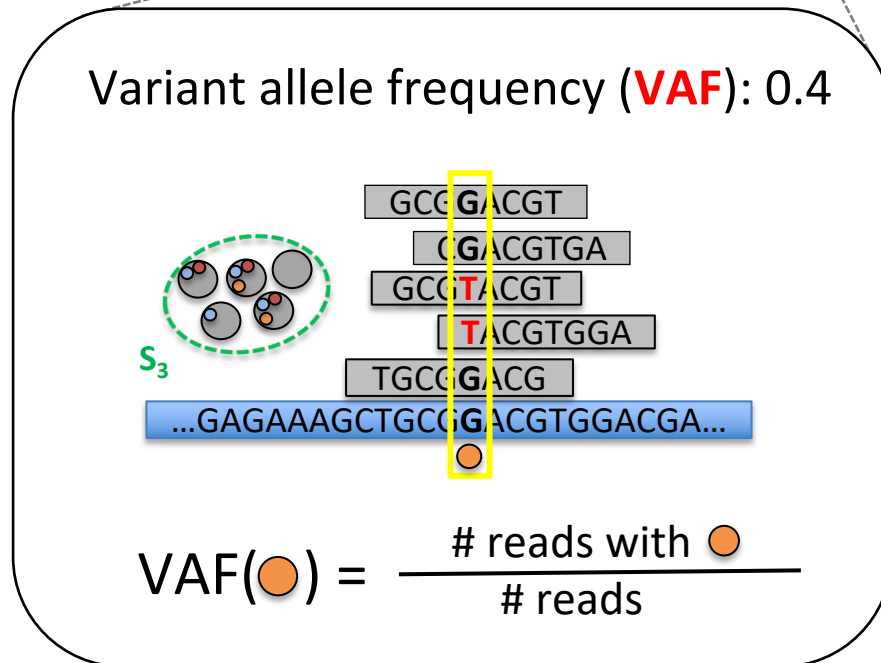
Rejection Sampling Does Not Scale



Probabilistic Model for Noisy Measurements

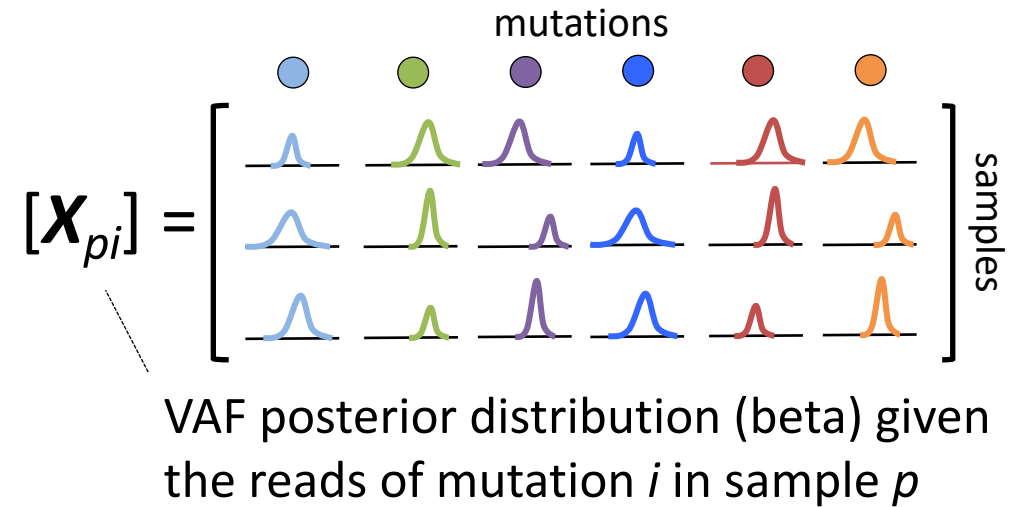
$$\mathbf{F} = [f_{pi}] = \begin{pmatrix} 0.8 & 0.8 & 0.8 & 0.0 & 0.0 & 0.0 \\ 0.7 & 0.6 & 0.0 & 0.6 & 0.0 & 0.0 \\ 0.8 & 0.0 & 0.0 & 0.0 & 0.6 & \boxed{0.4} \end{pmatrix}$$

mutations: (columns) ● ● ● ● ● ●
 samples: s_1 (red), s_2 (blue), s_3 (green)
 VAF of mutation i in sample p



Uncertainty due to:

- (i) sequencing errors
- (ii) mapping errors
- (iii) sampling



Probabilistic Model for Noisy Measurements

$$\mathbf{F}^- = [f_{pi}^-] = \begin{matrix} & \begin{matrix} \text{mutations} \end{matrix} & & & & & \\ \begin{matrix} \text{samples} \end{matrix} & \begin{matrix} s_1 \\ s_2 \\ s_3 \end{matrix} & \begin{matrix} \text{blue} & \text{green} & \text{purple} & \text{blue} & \text{red} & \text{orange} \end{matrix} & \begin{pmatrix} 0.75 & 0.78 & 0.77 & 0.0 & 0.0 & 0.0 \\ 0.55 & 0.43 & 0.0 & 0.54 & 0.0 & 0.0 \\ 0.56 & 0.0 & 0.0 & 0.0 & 0.57 & 0.34 \end{pmatrix} \end{matrix}$$

Consider $(1 - \alpha)$ confidence intervals:

Interval PPM (I-PPM)
 Given \mathbf{F}^- and \mathbf{F}^+ , find \mathbf{F} , \mathbf{U} and \mathbf{B} such that $\mathbf{F} = \mathbf{U} \mathbf{B}$
 and $f_{pi}^- \leq f_{pi} \leq f_{pi}^+$ for all samples p and mutations i

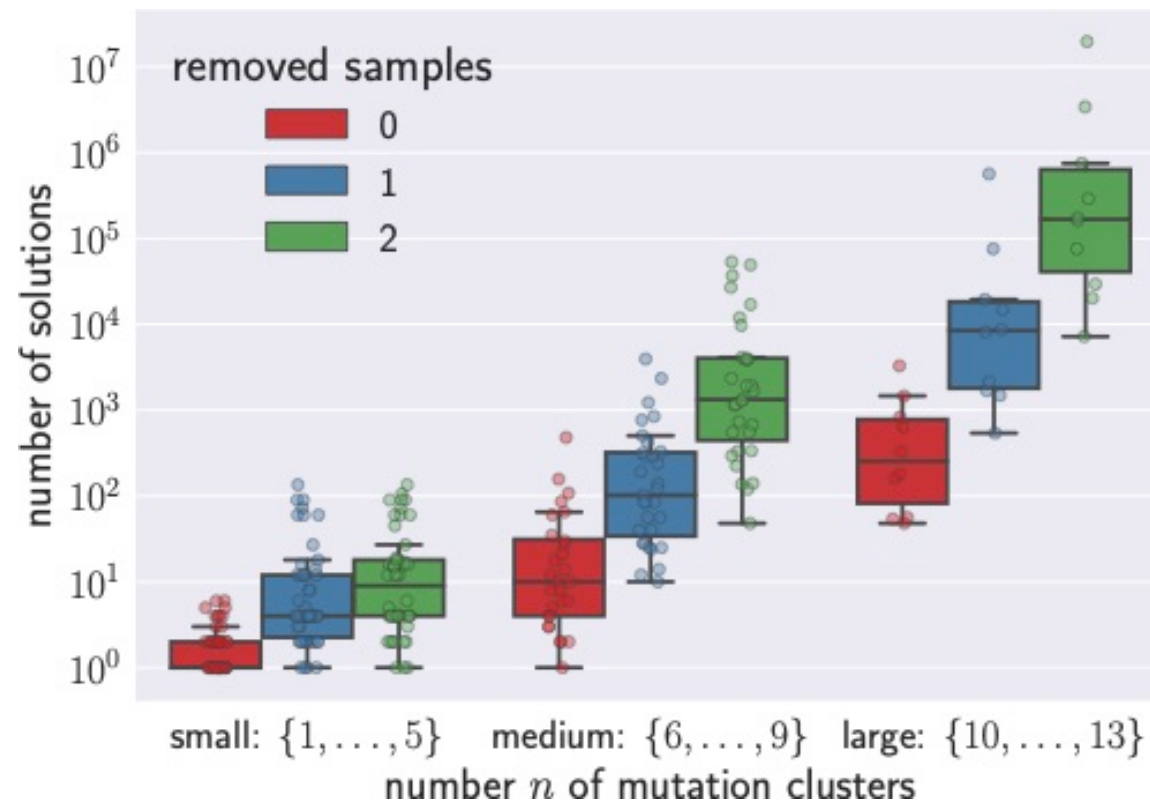
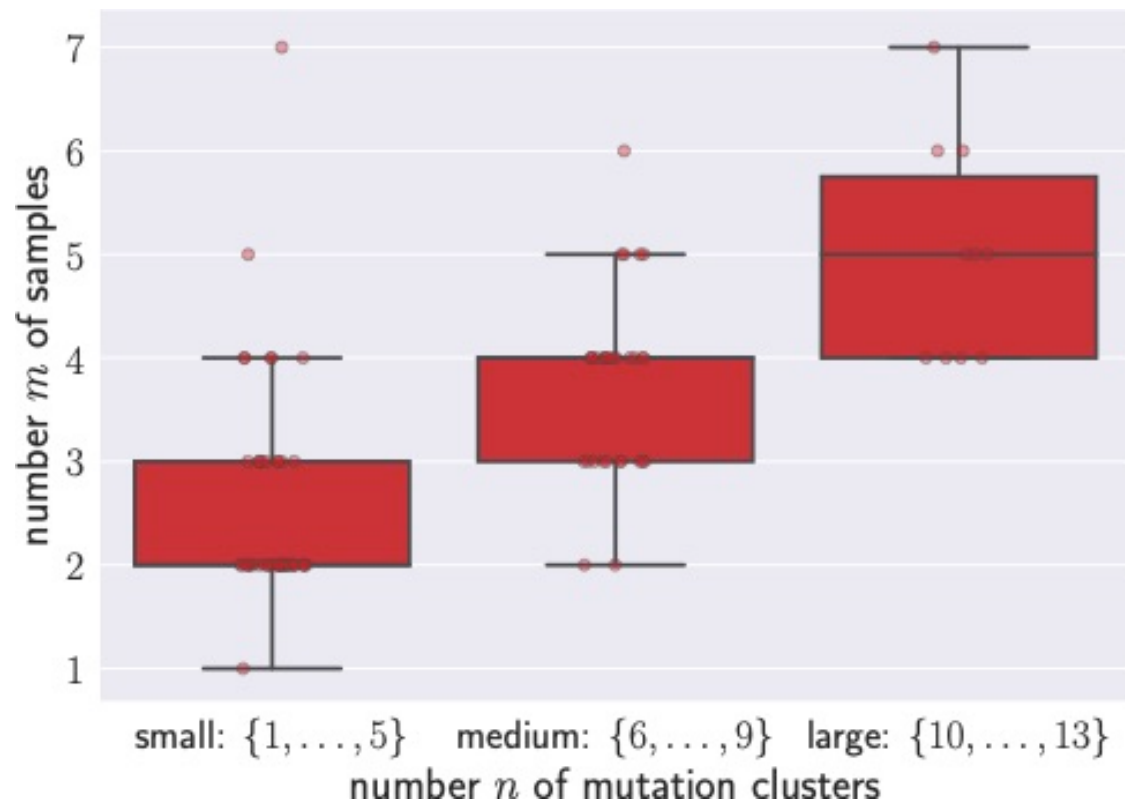
$$[\mathbf{X}_{pi}] = \begin{matrix} & \begin{matrix} \text{mutations} \end{matrix} & & & & & \\ \begin{matrix} \text{samples} \end{matrix} & \begin{matrix} s_1 \\ s_2 \\ s_3 \end{matrix} & \begin{matrix} \text{blue} & \text{green} & \text{purple} & \text{blue} & \text{red} & \text{orange} \end{matrix} & \left[\begin{array}{cccccc} \text{---} & \text{---} & \text{---} & \text{---} & \text{---} & \text{---} \\ \text{---} & \text{---} & \text{---} & \text{---} & \text{---} & \text{---} \\ \text{---} & \text{---} & \text{---} & \text{---} & \text{---} & \text{---} \end{array} \right] \end{matrix}$$

VAF posterior distribution (beta) given the reads of mutation i in sample p

$$\mathbf{F}^+ = [f_{pi}^+] = \begin{matrix} & \begin{matrix} \text{mutations} \end{matrix} & & & & & \\ \begin{matrix} \text{samples} \end{matrix} & \begin{matrix} s_1 \\ s_2 \\ s_3 \end{matrix} & \begin{matrix} \text{blue} & \text{green} & \text{purple} & \text{blue} & \text{red} & \text{orange} \end{matrix} & \begin{pmatrix} 0.9 & 0.85 & 0.87 & 0.05 & 0.0 & 0.0 \\ 0.75 & 0.65 & 0.05 & 0.68 & 0.0 & 0.0 \\ 0.83 & 0.0 & 0.04 & 0.0 & 0.67 & 0.48 \end{pmatrix} \end{matrix}$$

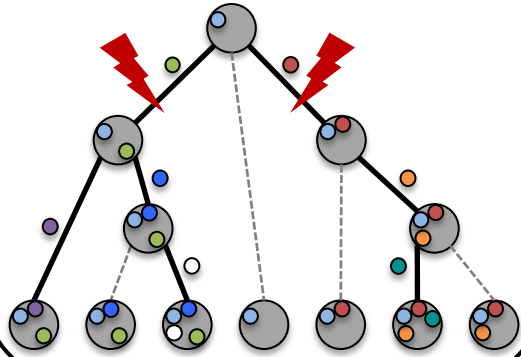
Real Data

- Cohort of 100 lung cancers [Jamal-Hanjani, NEJM 2017]
- 90% confidence intervals

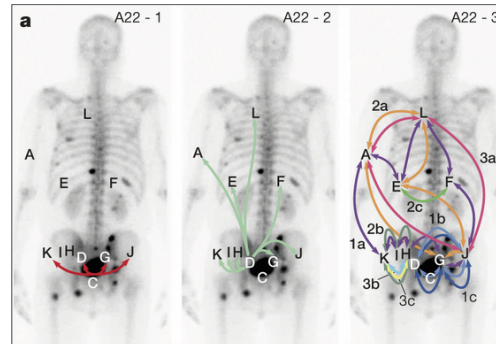


Challenges

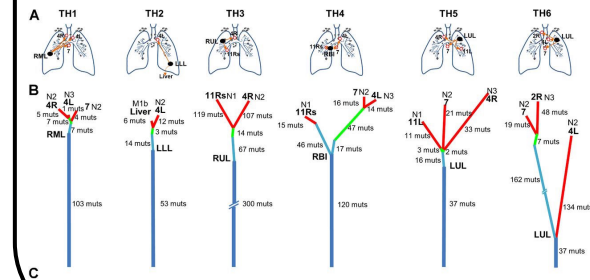
Identify targets for treatment



Understand metastatic development



Recognize common patterns of tumor evolution across patients



Downstream analyses in cancer genomics **critically rely** on accurate tumor phylogeny inference

Challenge I

Novel algorithms that sample uniformly at random from the space of PPM solutions

Challenge II

Algorithms to accurately summarizing solution space (consensus trees)

Conclusion

Background and theory:

- Perfect Phylogeny Mixture (PPM) problem
- Combinatorial characterization of solutions
- #PPM: exact counting and uniform sampling

Simulation results:

- What contributes to non-uniqueness?
- How to reduce non-uniqueness?
- How does non-uniqueness affect current methods?

Summary of Lectures 1, 2 and 3

- DNA, RNA and proteins are sequences
 - Central dogma of molecular biology: DNA -> RNA -> protein
- Problem != algorithm
- Key challenge in computational biology is translating a biological problem into a computational problem
- Cancer is a genetic disease caused by somatic mutations
- Inter-tumor heterogeneity and intra-tumor heterogeneity:
 - *Not only is every tumor different, but so is every tumor cell...*
- **Non-uniqueness of solutions in phylogeny reconstruction from bulk DNA samples**