# CS 598MEB Computational Cancer Genomics Lecture 3

Mohammed El-Kebir February 2, 2021



# 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. <u>Bioinformatics (Special Issue: Proceedings of ISMB)</u>, 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. <u>Algorithms for Molecular Biology</u>, 14:19, 2019.

# Tumorigenesis: Cell Mutation

#### **Clonal Evolution Theory of Cancer**

[Nowell, 1976]



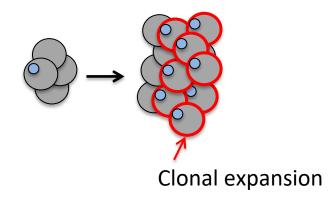
Founder tumor cell with somatic mutation: 

(e.g. BRAF V600E)

# Tumorigenesis: Cell Mutation

#### **Clonal Evolution Theory of Cancer**

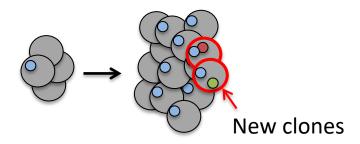
[Nowell, 1976]



# Tumorigenesis: Cell Mutation

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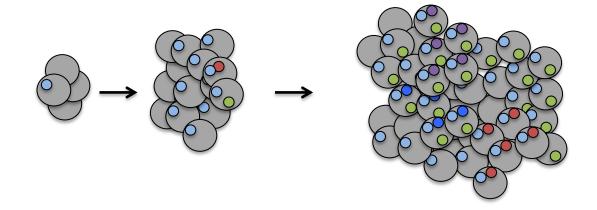
[Nowell, 1976]



# Tumorigenesis: Cell Mutation & Division

#### **Clonal Evolution Theory of Cancer**

[Nowell, 1976]

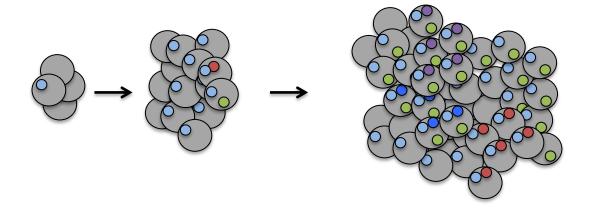


Intra-Tumor Heterogeneity

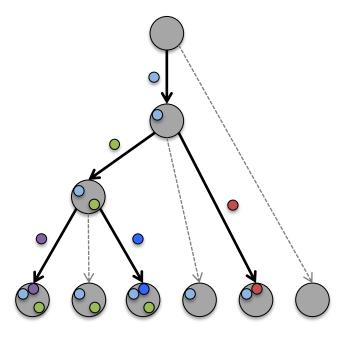
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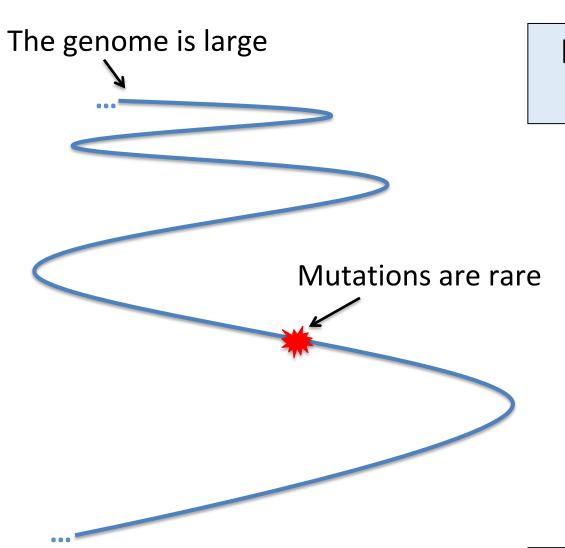


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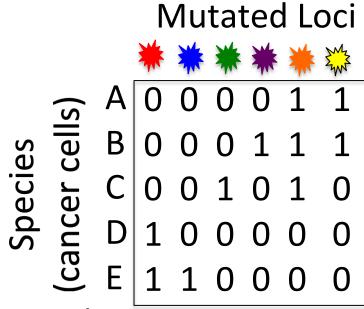


Phylogenetic Tree **T** 

# Infinite Sites Model



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



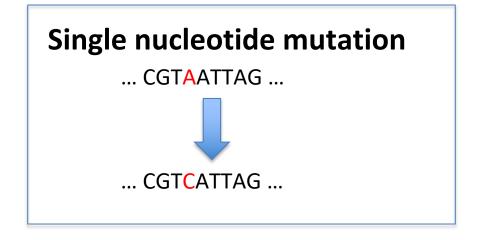
1: mutated

0: not

All sites are bi-allelic: mutated or not.

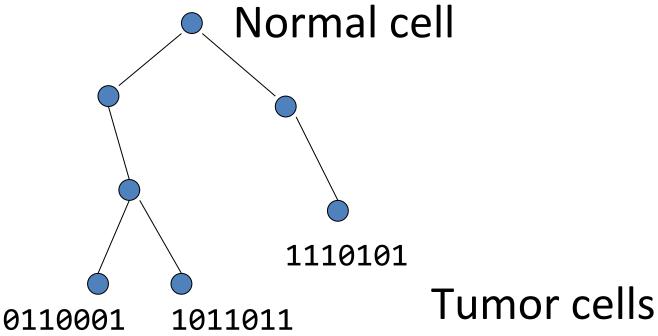
[Kimura, 1969]

# Progression of Somatic Mutations



0 = normal

1 = mutated



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

Infinite sites assumption: each locus mutates only once.

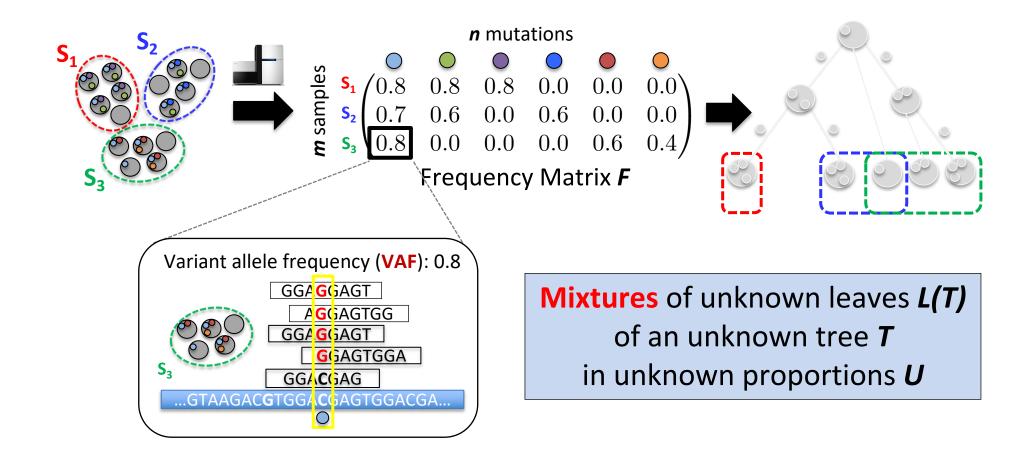
### Lecture Outline

- Recap
- Two-state Perfect Phylogeny Mixtures

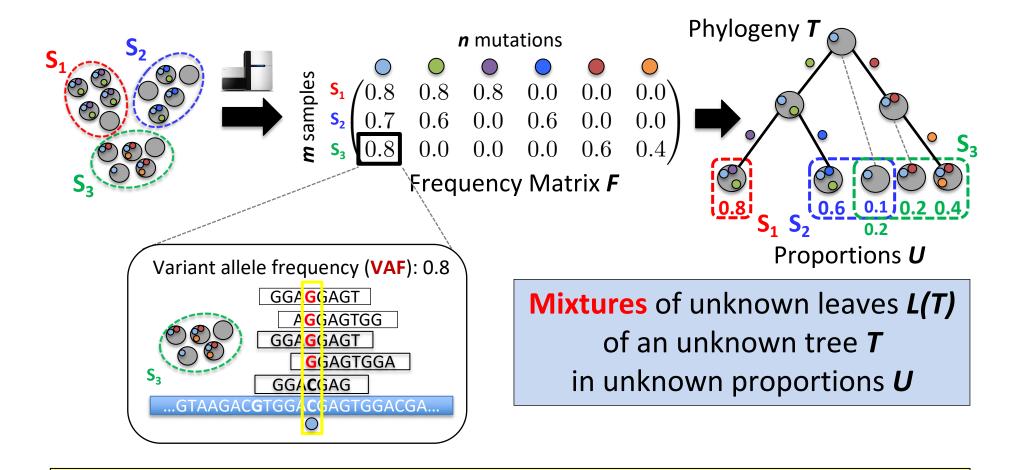
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# Sequencing and Tumor Phylogeny Inference

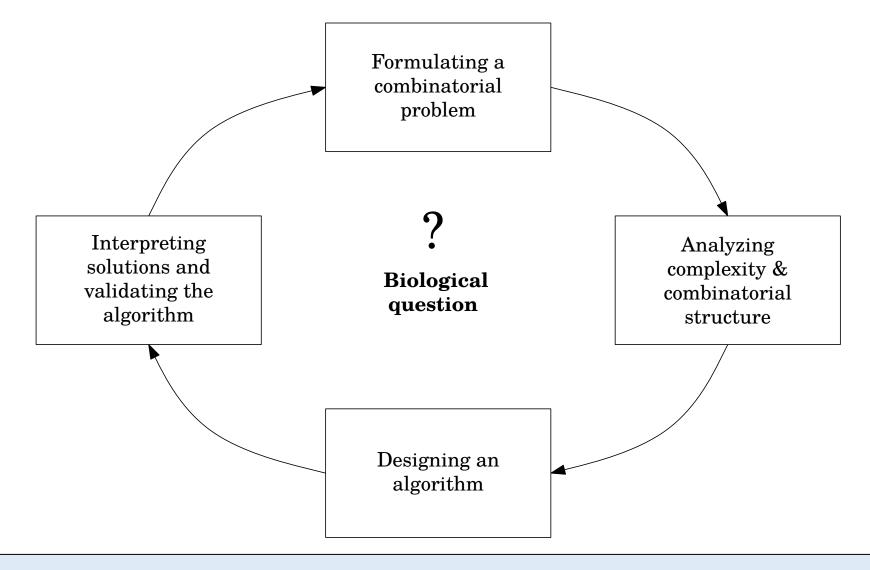


# Sequencing and Tumor Phylogeny Inference



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

# Key Challenge in Computational Biology

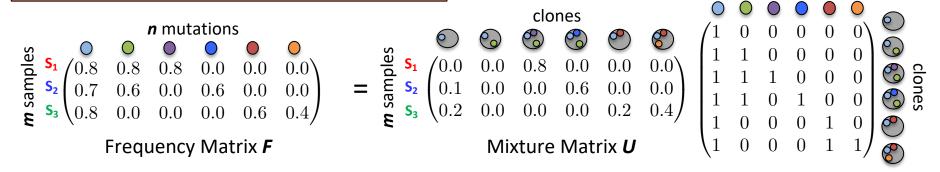


Translating a biological problem into a computational biology

# Perfect Phylogeny Mixture

#### **Assumptions:**

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



Rows of *U* are proportions:

$$u_{pj} \ge 0$$
 and  $\sum_{j} u_{pj} \le 1$ 

Perfect Phylogeny Theorem [Estabrook, 1971] [Gusfield, 1991]

Restricted PP Matrix B

Restricted PP Tree **T** 

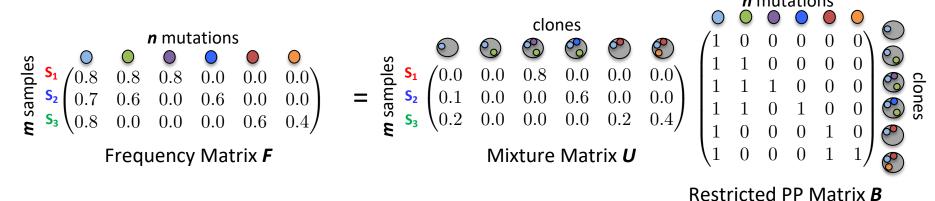
Equivalent

Perfect Phylogeny Mixture: [El-Kebir\*, Oesper\* et al., 2015] Given F, find U and B such that F = U B

#### 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], ...



Rows of *U* are proportions:

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Perfect Phylogeny Theorem [Estabrook, 1971] [Gusfield, 1991]

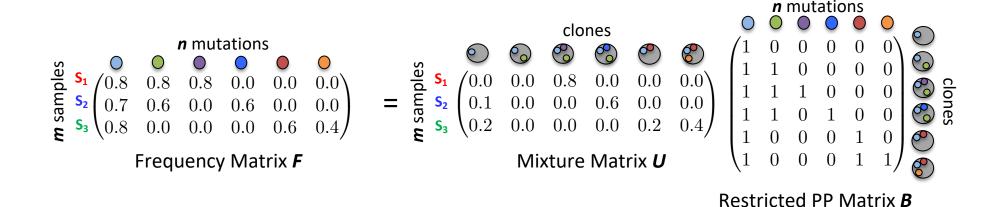
Restricted PP Tree **T** 

**1** Equivalent

Perfect Phylogeny Mixture: [El-Kebir\*, Oesper\* et al., 2015] Given F, find U and B such that F = U B

# Combinatorial Characterization

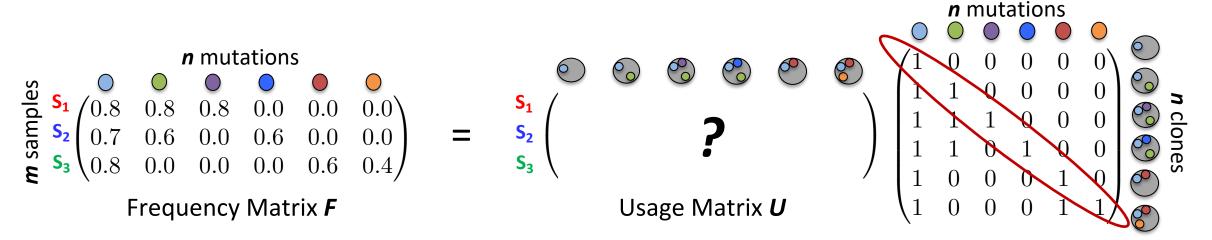
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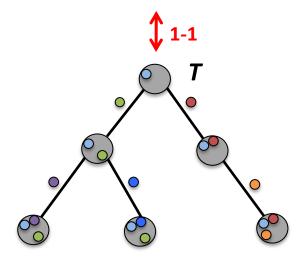
- Combinatorial characterization involves investigating what (optimal) solutions look like
- This starts by asking questions!

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

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

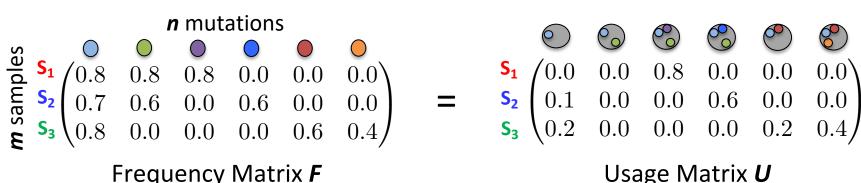


Restricted PP Matrix B

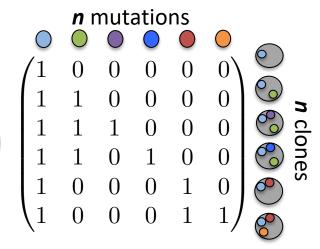


# Given F and T (or B), is there a usage matrix U?

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



Usage Matrix **U** 



Restricted PP Matrix B

#### **Lemma: B** is invertible

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

# Lemma:

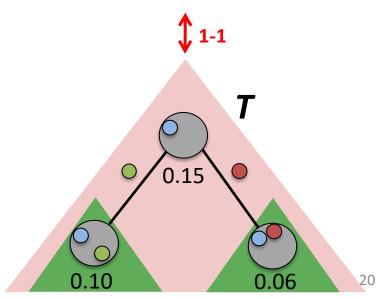
# Given F and T (or B), is there a usage matrix U?

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

$$\begin{pmatrix}
0.15 & 0.1 & 0.06 \\
0.2 & 0.05 & 0.04
\end{pmatrix} = \begin{pmatrix}
-0.01 & 0.1 & 0.06 \\
0.11 & 0.05 & 0.04
\end{pmatrix} \begin{pmatrix}
1 & 0 & 0 \\
1 & 1 & 0 \\
1 & 0 & 1
\end{pmatrix}$$
Frequency Matrix  $\boldsymbol{F}$ 

Usage Matrix  $\boldsymbol{U}$ 

Restricted PP Matrix B



#### Lemma:

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

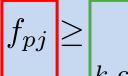
# Lemma:

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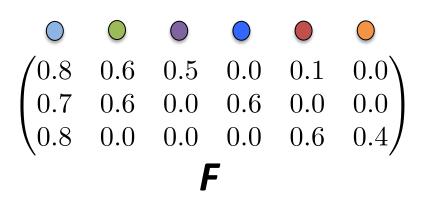
### Lemma (Sum Condition):

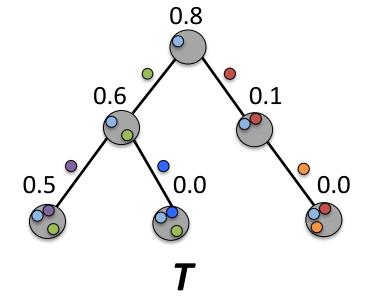
Given **F** and **T**, for all samples **p** and

mutations j,



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





#### **Lemma (Sum Condition):**

Given  ${\it F}$  and  ${\it T}$ , for all samples  ${\it p}$  and mutations  ${\it j}$ ,  $f_{pj} \geq \sum_{i} f_{pk}$ 

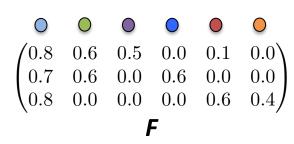
k child of j

necessary sufficient

#### **Lemma (Ancestry Condition):**

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

necessary



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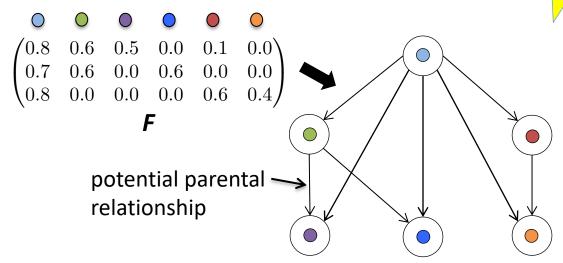
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necessary



#### Ancestry Graph G = (V, A)

#### 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

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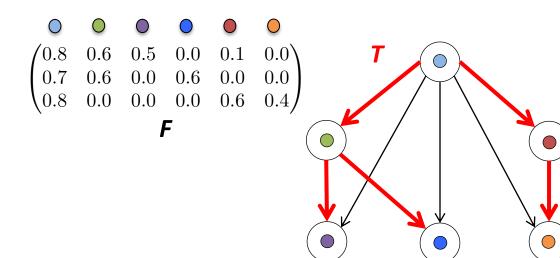
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#### Ancestry Graph G = (V, A)

#### **Theorem 2:**

PPM is NP-complete

#### 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 ifT is a spanning tree of G satisfying the SumCondition

Solving the PPM problem: ILP formulation

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

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

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

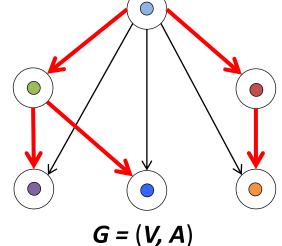
$$\sum_{v_j \in \delta^-(v_k)} x_{jk} \le 1$$

$$\sum_{v_j \in \delta^-(v_k)} f_{pk} x_{jk} \ge \sum_{v_l \in \delta^+(v_k)} f_{pk} x_{jk}$$

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

Find the largest set of edges in G

**Exactly one root node** 



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

$$\forall v_k \in V$$
 Tree

$$\sum f_{pk}x_{jk} \geq \sum f_{pl}x_{kl} \quad \forall p \in [m], \, v_k \in V \quad ext{Sum condition}$$

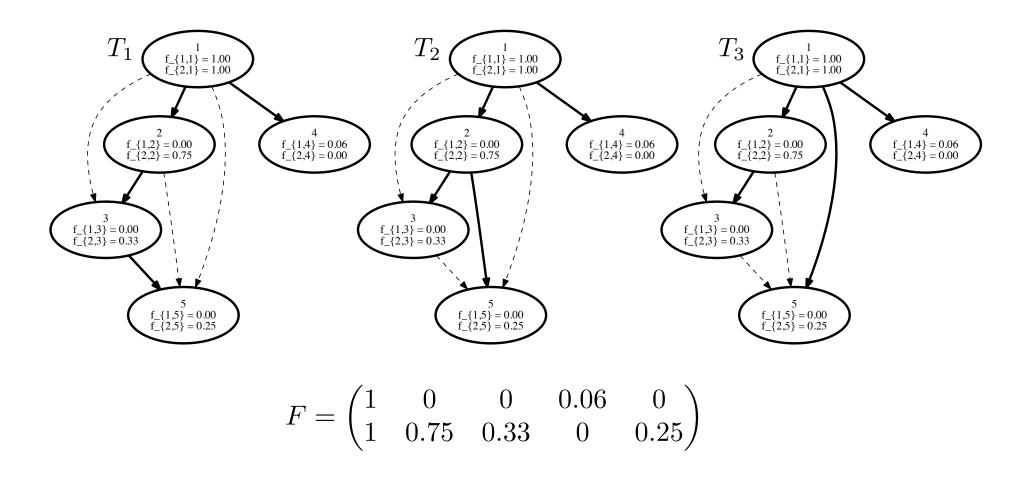
$$\forall (v_j, v_k) \in A'$$

# 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



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

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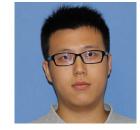
#P is the complexity class of counting problems whose decision problems are in NP

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**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

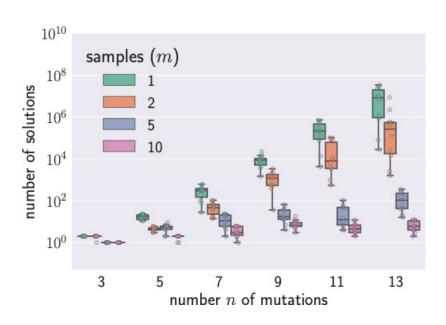
#### **Simulation results:**

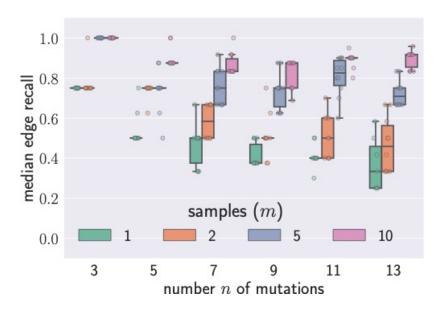
- What contributes to non-uniqueness?
- How to reduce non-uniqueness?
- How does non-uniqueness affect current methods?



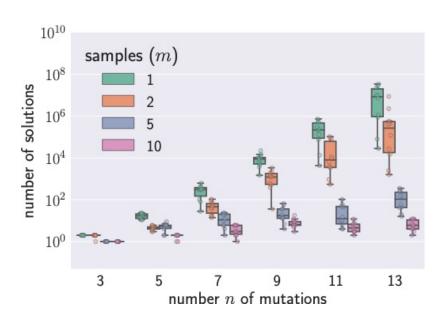
**Dikshant Pradhan** 

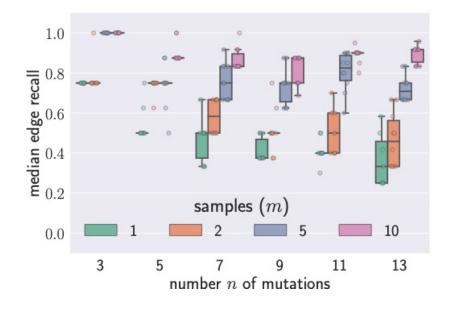
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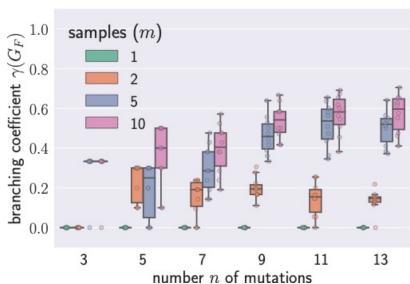


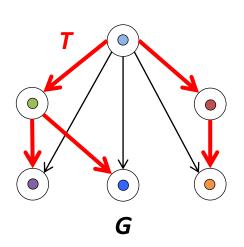


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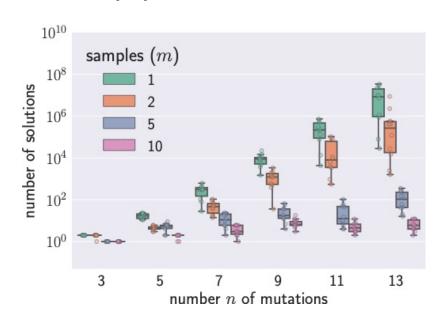


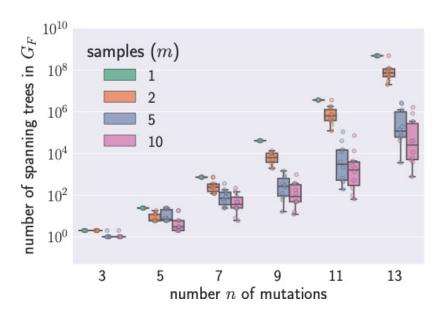


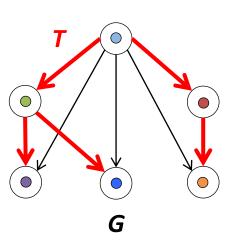




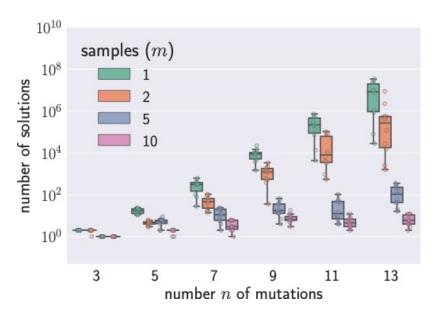
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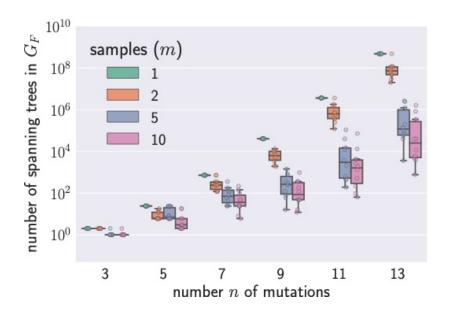


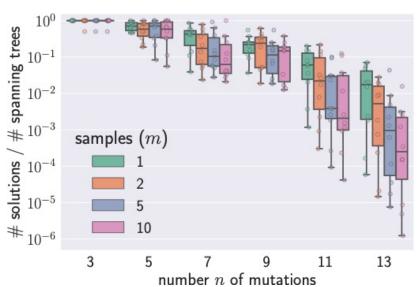


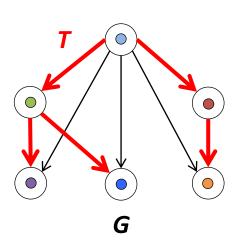


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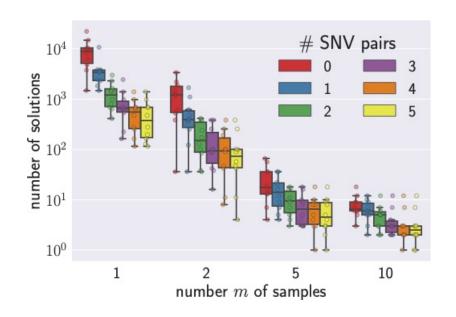


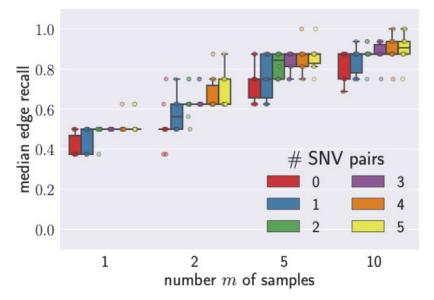


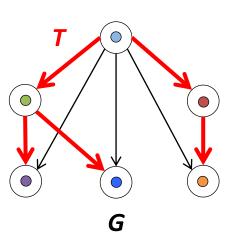




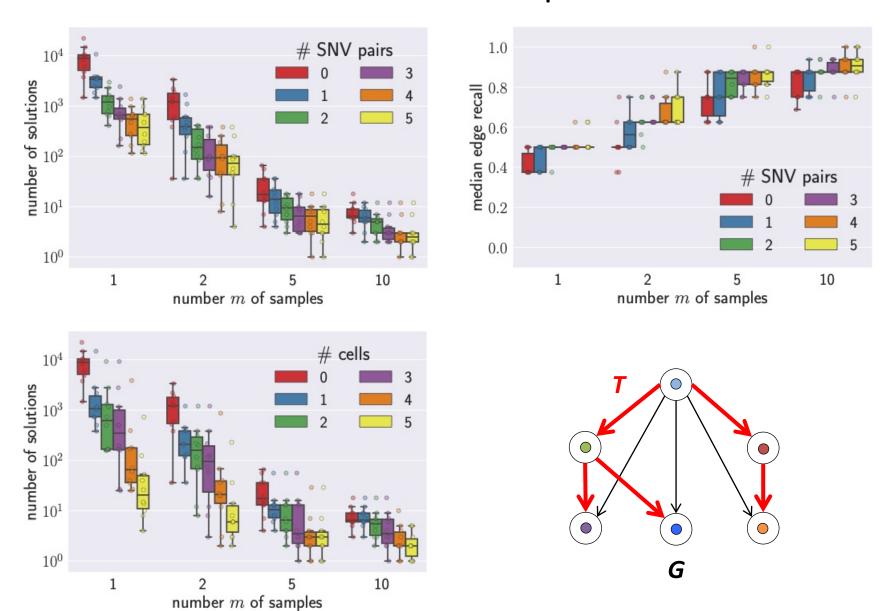
## How to Reduce Non-Uniqueness?



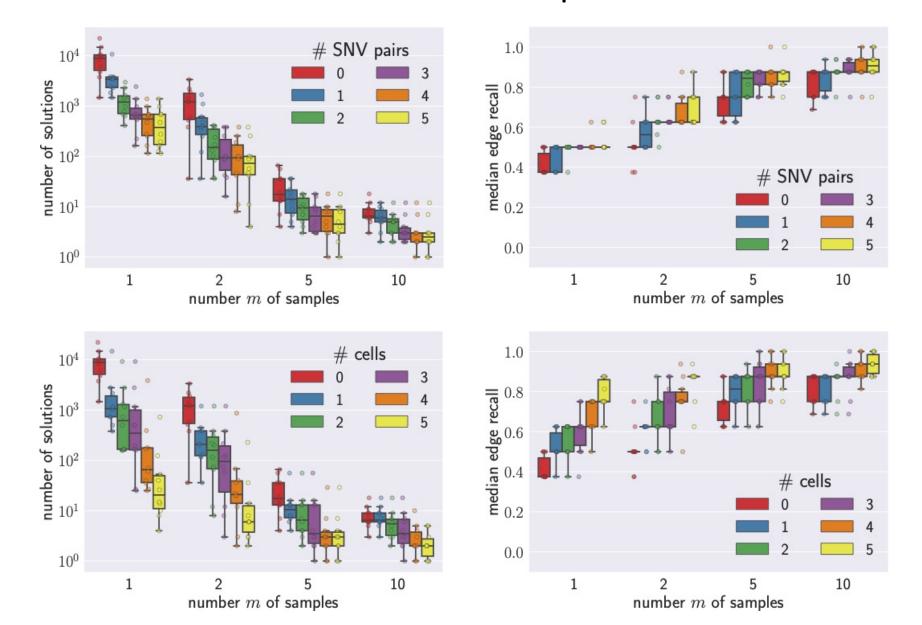




## How to Reduce Non-Uniqueness?



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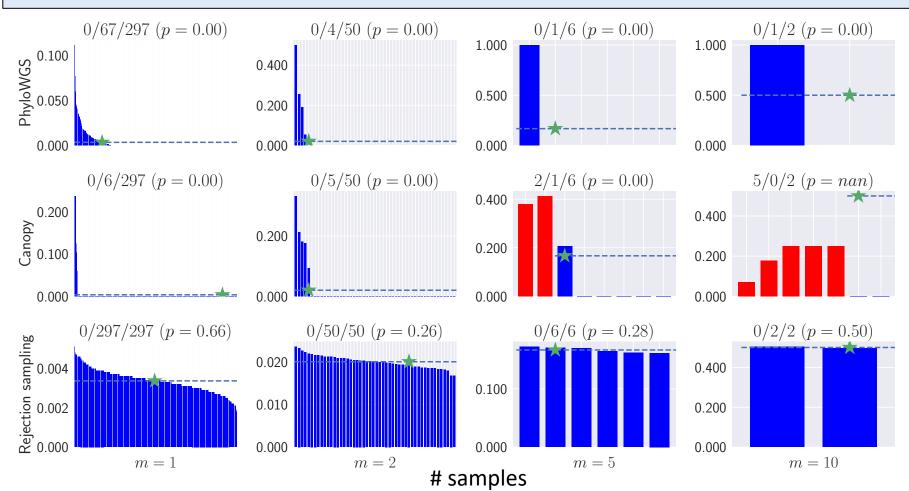


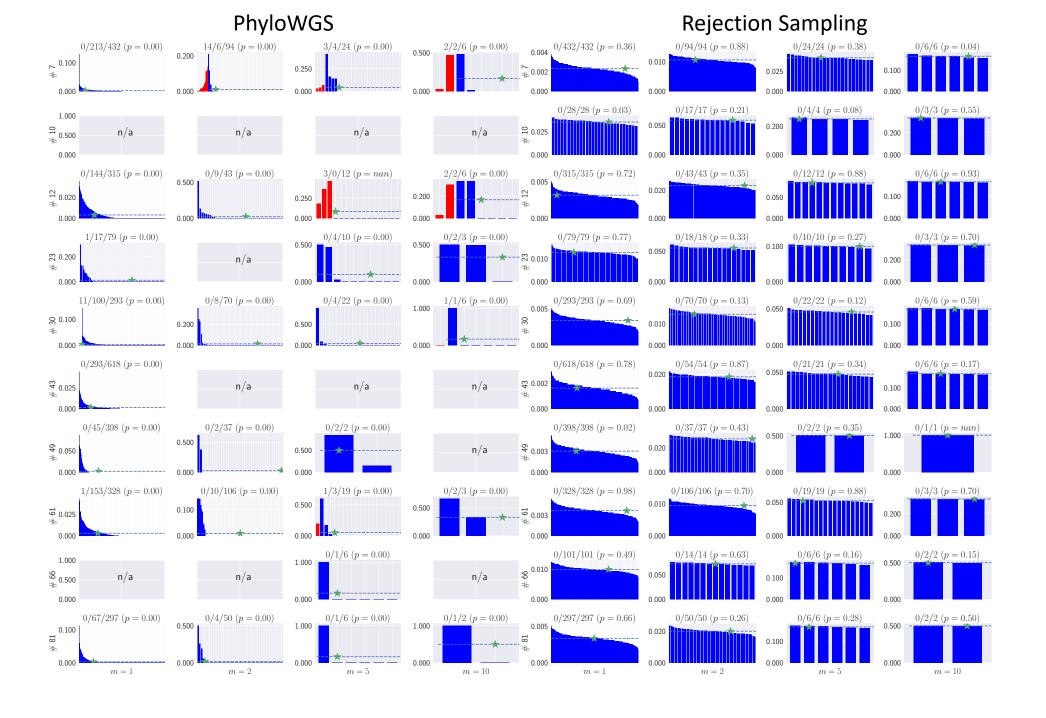
### How Does Non-uniqueness affect Methods?

Two current MCMC methods using default parameters:

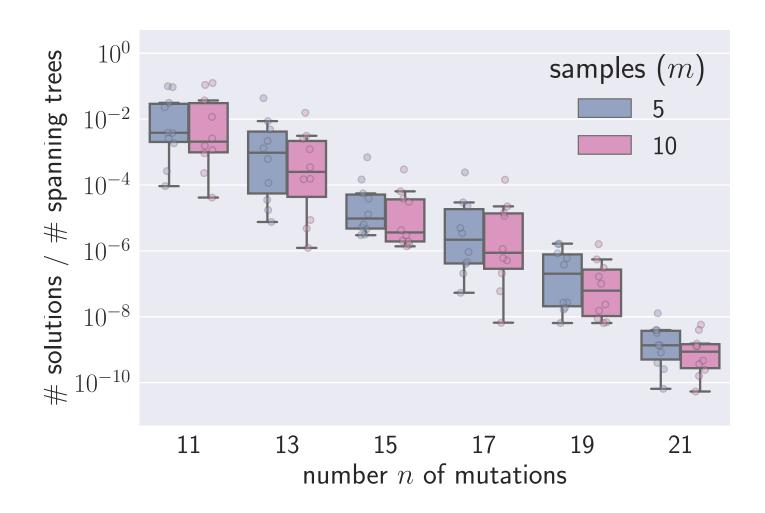
- PhyloWGS, Deshwar et al., Genom. Biol., 2015 [10,000 samples]
- Canopy, Jiang et al., PNAS, 2016

[~300 samples]

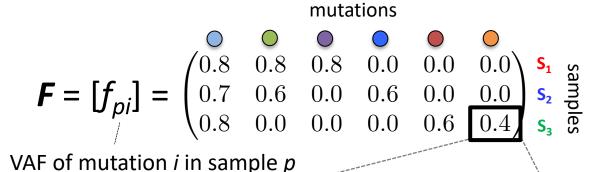




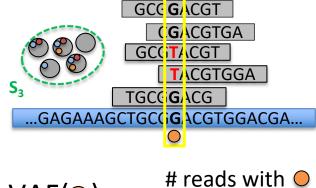
### Rejection Sampling Does Not Scale



## Probabilistic Model for Noisy Measurements

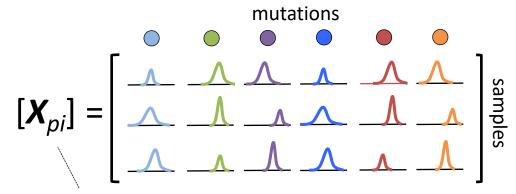


Variant allele frequency (VAF): 0.4



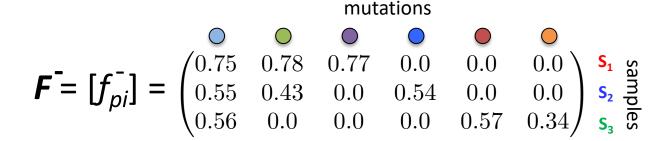
#### **Uncertainty** due to:

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



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

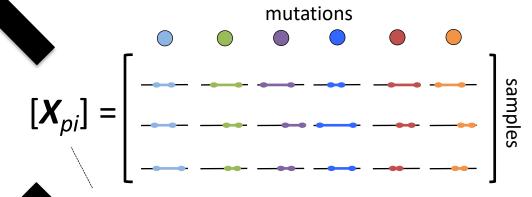
## Probabilistic Model for Noisy Measurements



#### **Interval PPM (I-PPM)**

Given  ${\it F}^-$  and  ${\it F}^+$ , find  ${\it F}$ ,  ${\it U}$  and  ${\it B}$  such that  ${\it F}$  =  ${\it U}$   ${\it B}$  and  $f_{pi}^- \le f_{pi} \le f_{pi}^+$  for all samples  ${\it p}$  and mutations  ${\it i}$ 

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

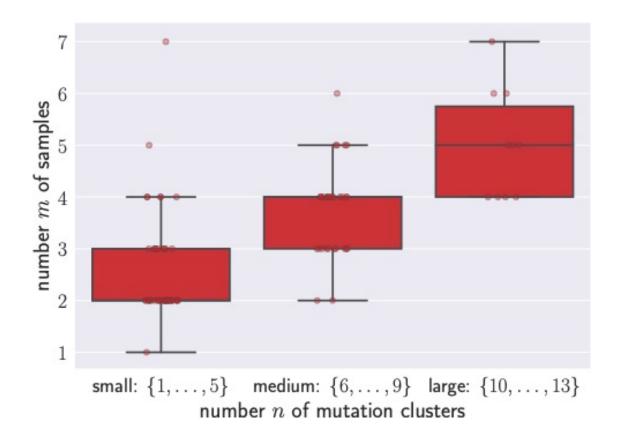


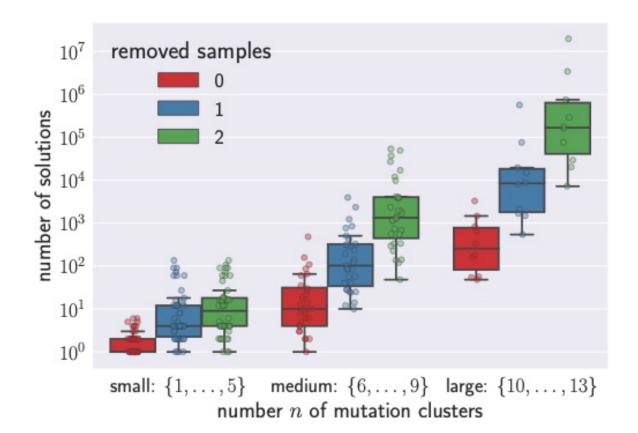
VAF posterior distribution (beta) given the reads of mutation *i* in sample *p* 

$$\mathbf{F} = [\mathbf{f}_{pi}^{+}] = \begin{pmatrix} 0.9 & 0.85 & 0.87 & 0.05 & 0.0 & 0.0 \\ 0.75 & 0.65 & 0.05 & 0.68 & 0.0 & 0.0 \\ 0.83 & 0.0 & 0.04 & 0.0 & 0.67 & 0.48 \end{pmatrix} \begin{array}{c} \mathbf{S}_{1} & \mathbf{S}_{2} & \mathbf{S}_{3} & \mathbf$$

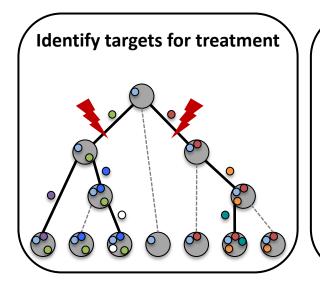
### Real Data

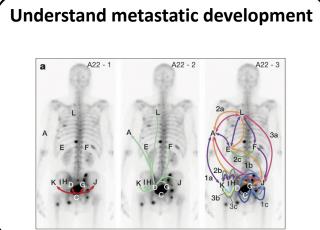
- Cohort of 100 lung cancers [Jamal-Hanjani, NEJM 2017]
- 90% confidence intervals

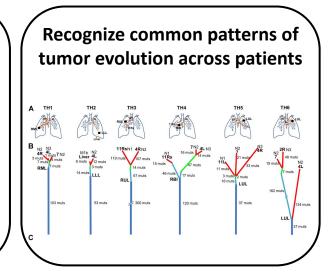




## Challenges







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