CS 598MEB Introduction to Bioinformatics Lecture 7

Mohammed El-Kebir

February 5, 2019



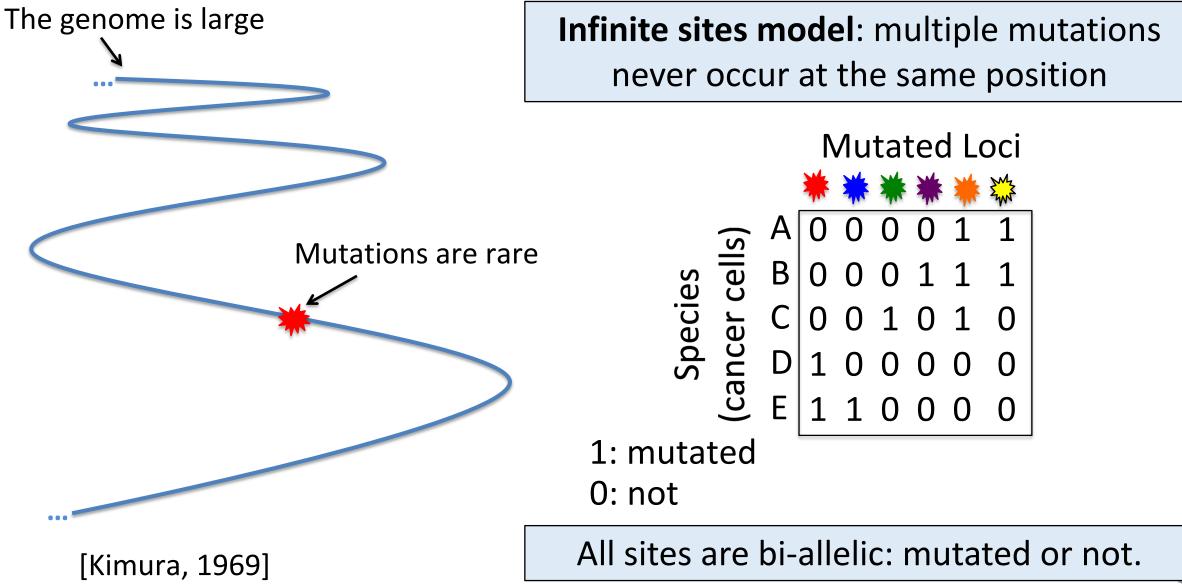
Outline

- Recap
- Tumor Phylogeny Inference from Bulk DNA-seq with Copy-Number Aberrations

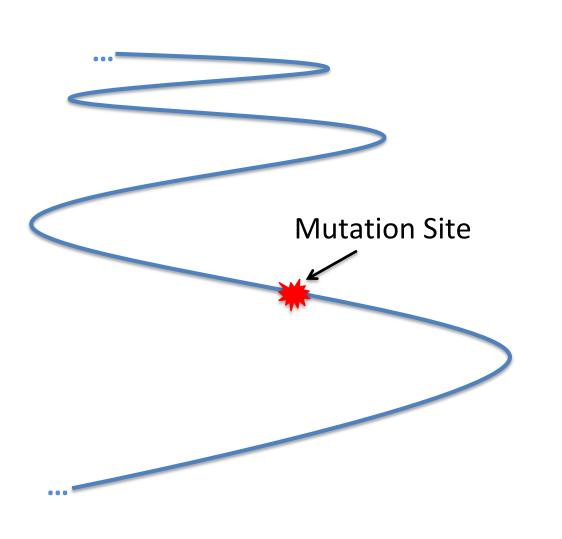
Reading:

 M. El-Kebir, G. Satas, L. Oesper and B.J. Raphael. Inferring the Mutational History of a Tumor using Multi-State Perfect Phylogeny Mixtures. <u>Cell</u> <u>Systems, 3(1):43-53, 2016</u>.

Infinite Sites Model = Two-state Perfect Phylogeny



Infinite Alleles Model = Multi-state Perfect Phylogeny



Infinite alleles model:

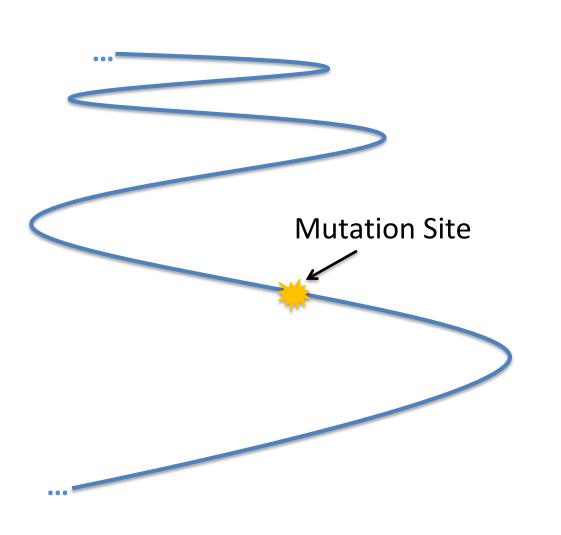
Site History:

Time

- For any mutation, there are an infinite number of possibilities of what mutation looks like (states).
- So, the same position can be mutated multiple times, but it never mutates to the same "allele" or state.

Characters have integer states

Infinite Alleles Model = Multi-state Perfect Phylogeny



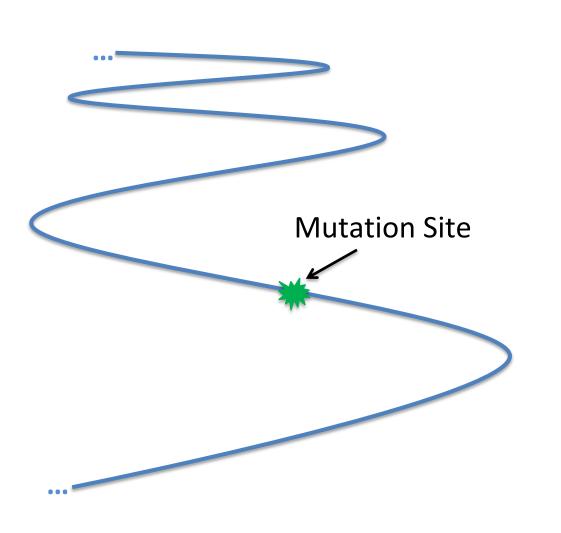
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Characters have integer states

Outline

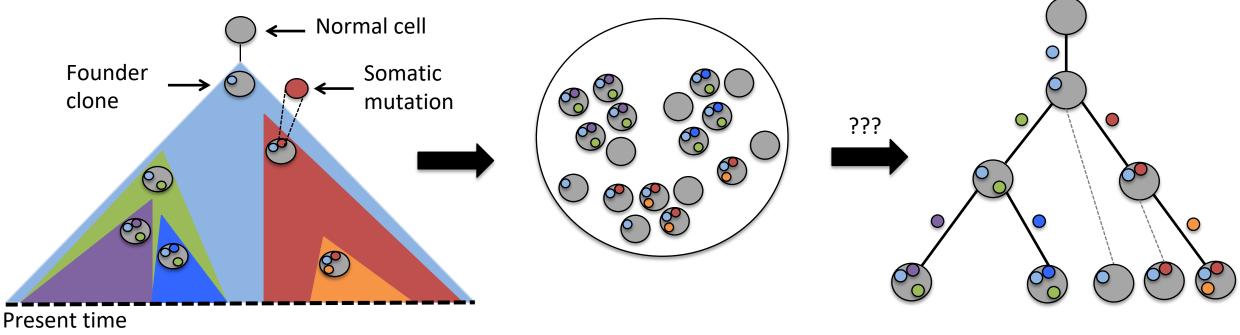
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Tumor Evolution as a Phylogenetic Tree

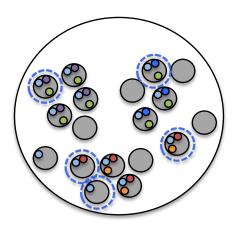
Clonal Theory [Nowell, 1976]



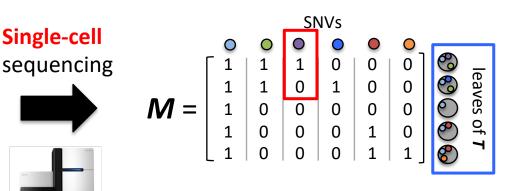
Tumor

Phylogenetic Tree

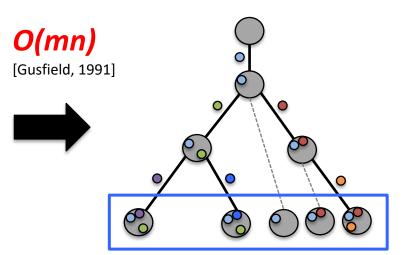
Observations are Leaves of a Perfect Phylogeny T



Tumor Snapshot



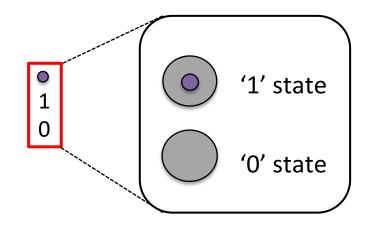
Binary Matrix **B**



Two-State Perfect Phylogeny Tree T

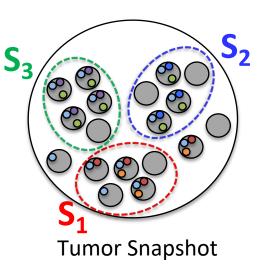
Assumptions:

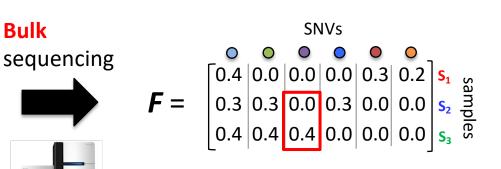
- Mutations are single nucleotide variants (SNVs)
- Infinite sites assumption



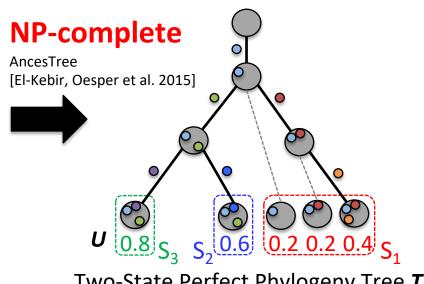
Seq. method	Inferring T	Complexity
single- cell	unmixed two-state perfect phylogeny	O(mn)

Observations are Mixtures of the Leaves of T





Variant Allele Frequencies Matrix F



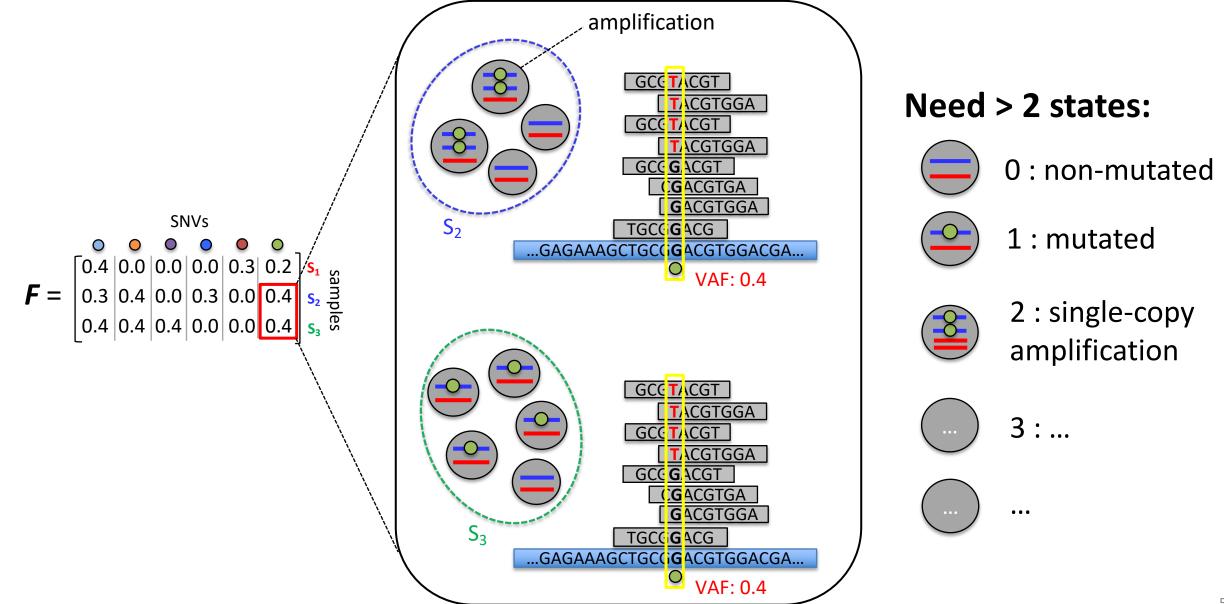
Two-State Perfect Phylogeny Tree **T** Mixing Proportions **U**

0.0 0.0 S2 Image: Constraint of the second s	GACGT GACGTGA GACGTGGA GACG GACG GACGTGGACGA VAF: 0.4
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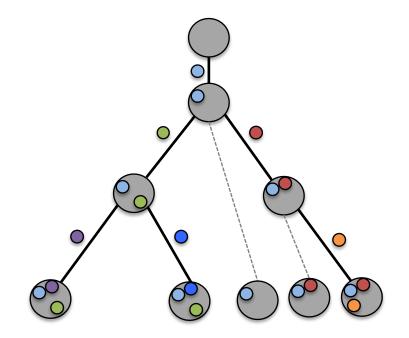
Seq. method	Inferring T	Complexity
single- cell	unmixed two-state perfect phylogeny	O(mn)
bulk	mixed two-state perfect phylogeny	NP-complete

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], ...

Copy-Number Aberrations Confound VAFs

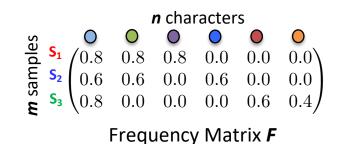


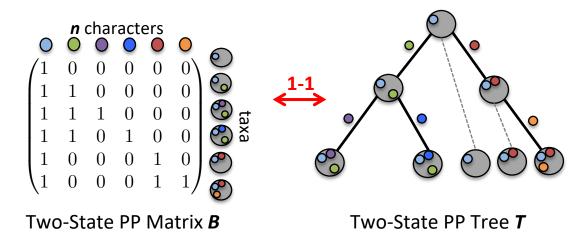
- Multi-State Perfect Phylogeny Mixture Problem
- Combinatorial Characterization of Solutions
- Application to Cancer Bulk-Sequencing Data
- Results



Infinite Sites Generalizes to Infinite Alleles

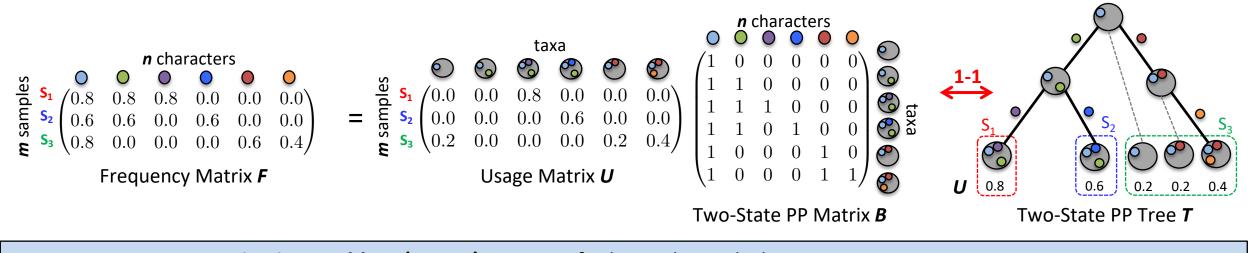
<u>Two-State Perfect Phylogeny</u> – Infinite sites assumption: a character changes state once



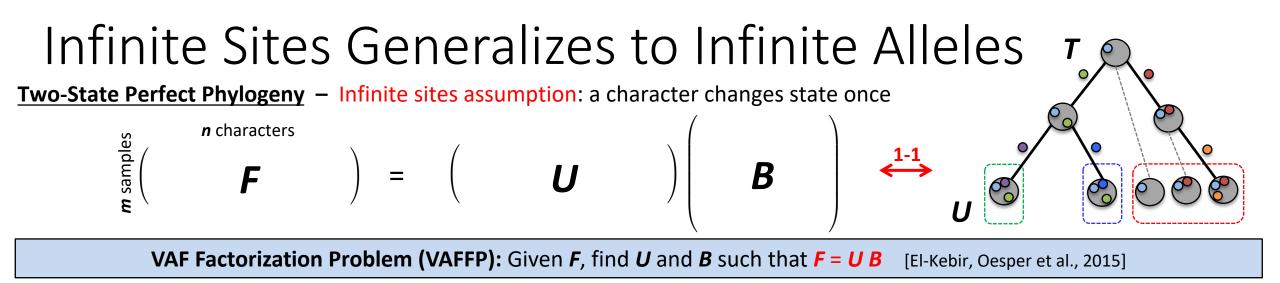


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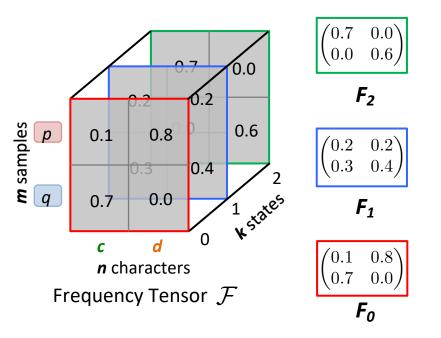
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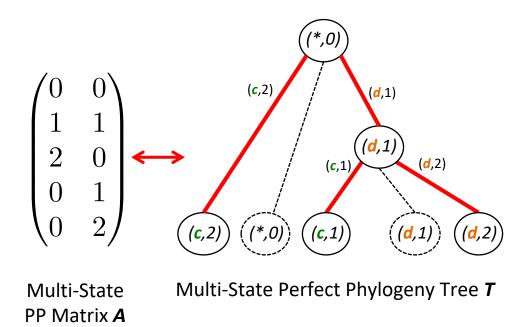


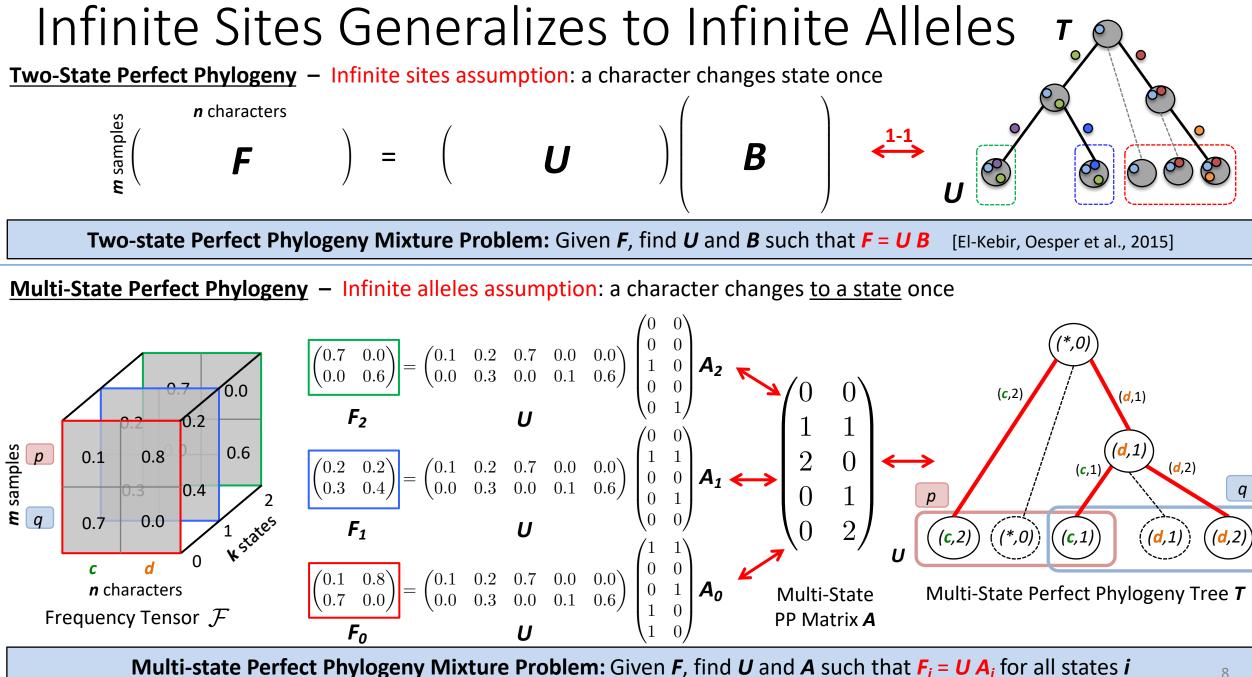
VAF Factorization Problem (VAFFP): Given *F*, find *U* and *B* such that *F* = *U B* [El-Kebir, Oesper et al., 2015]



<u>Multi-State Perfect Phylogeny</u> – Infinite alleles assumption: a character changes to a state once

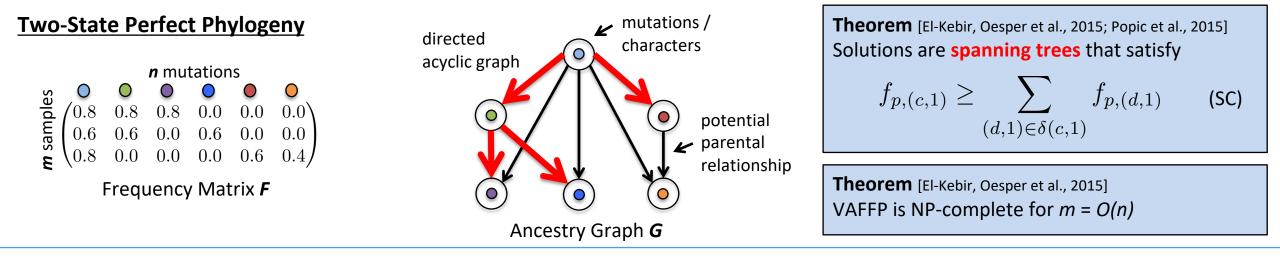




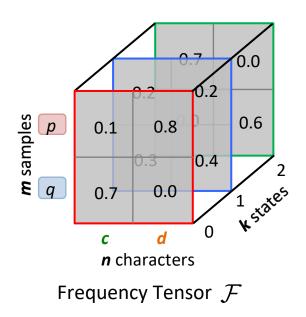


Multi-state Perfect Phylogeny Mixture Problem: Given F, find U and A such that $F_i = U A_i$ for all states i

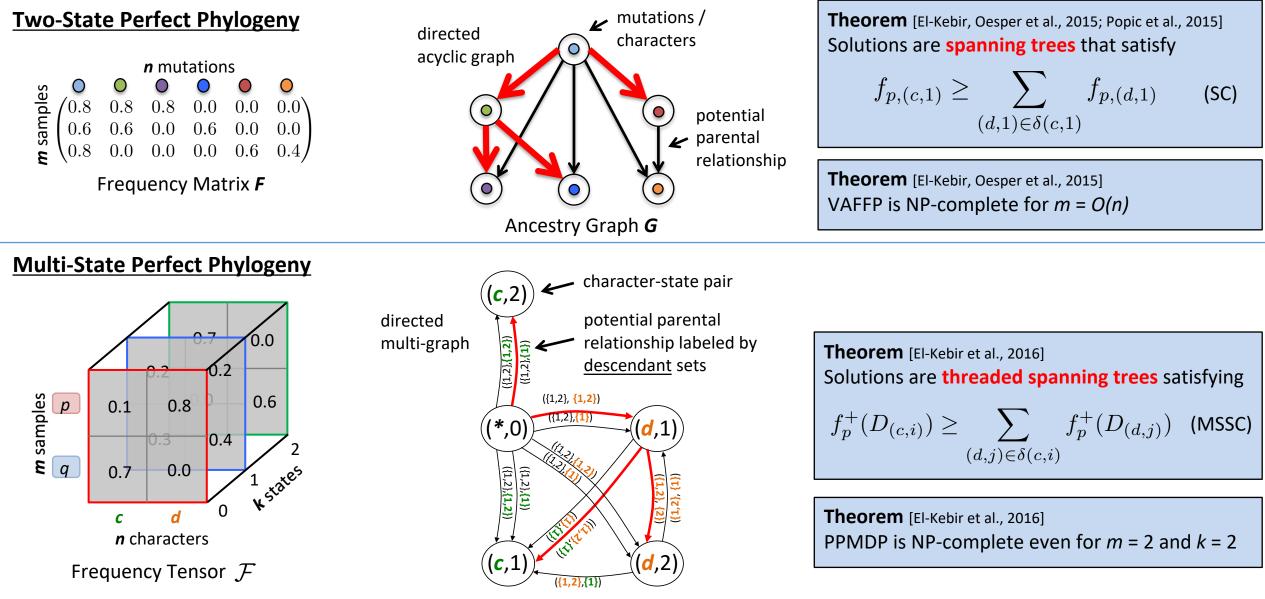
Combinatorial Characterization of Solutions



Multi-State Perfect Phylogeny



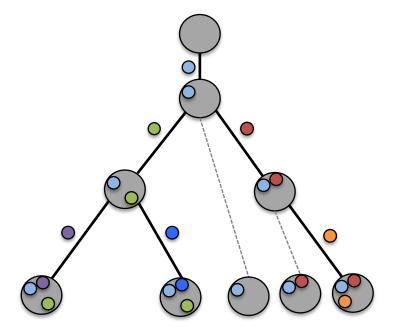
Combinatorial Characterization of Solutions



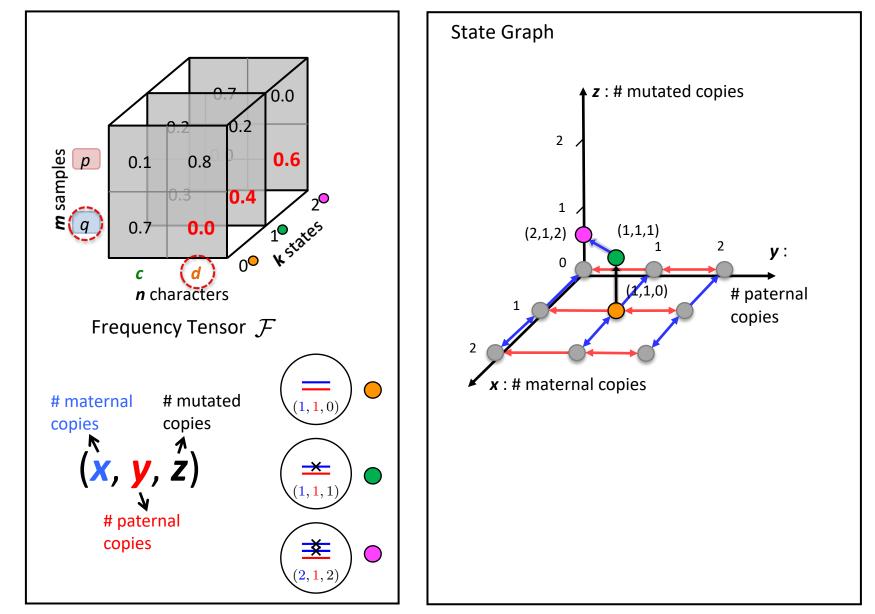
Multi-State Ancestry Graph **G**



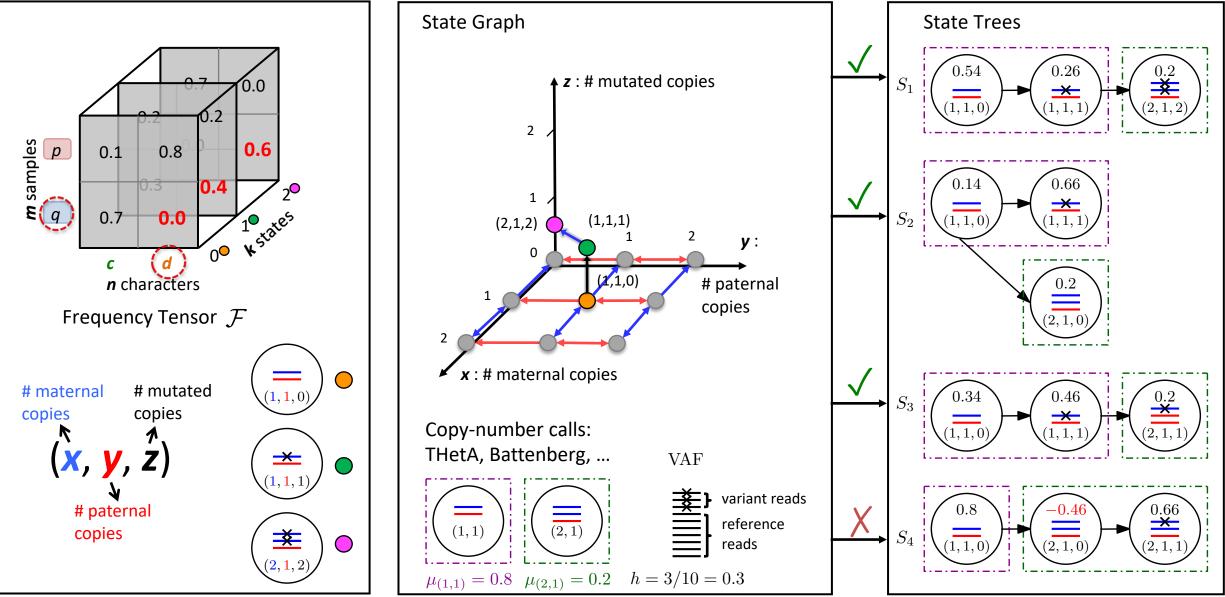
- Multi-State Perfect Phylogeny Mixture Deconvolution Problem
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Application to Cancer Bulk Sequencing

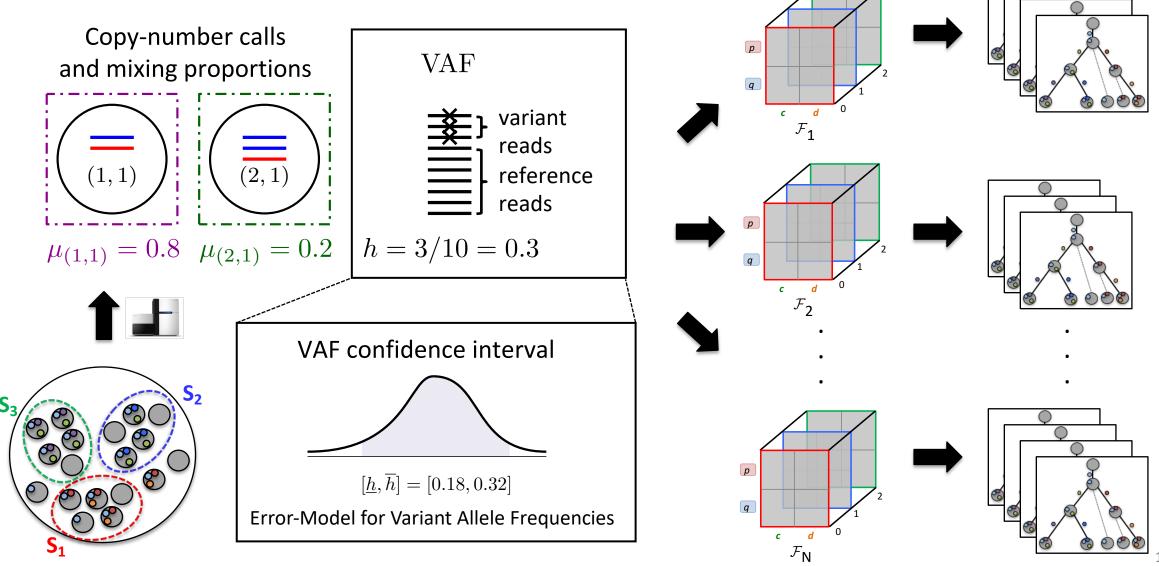


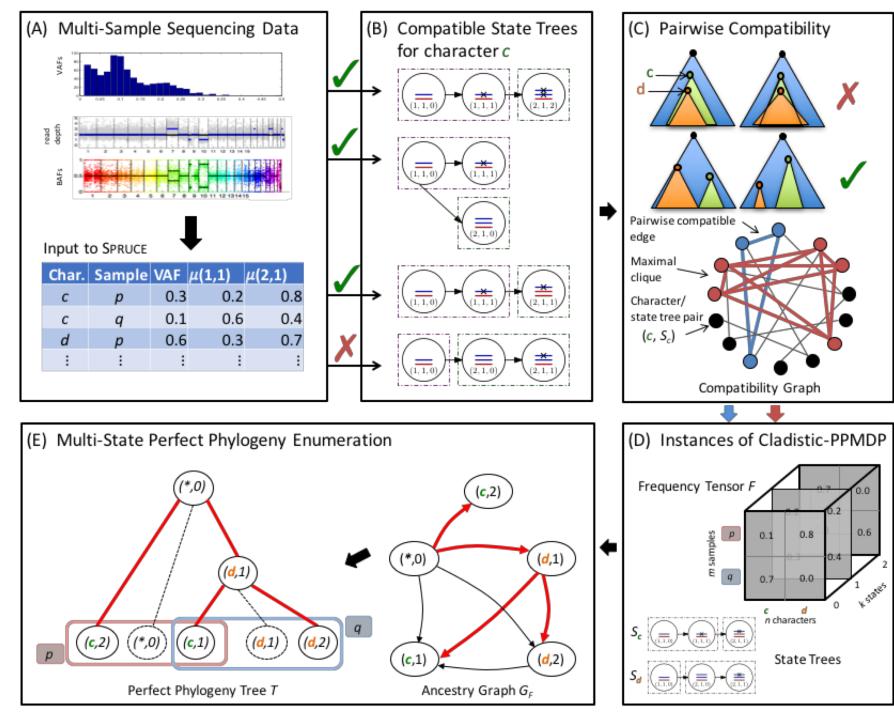
Application to Cancer Bulk Sequencing



SPRUCE Enumerates Phylogenies

<u>Somatic</u> <u>Phylogeny</u> <u>Reconstruction</u> <u>Using</u> <u>Combinatorial</u> <u>Enumeration</u> Available at: http://compbio.cs.brown.edu/projects/spruce/

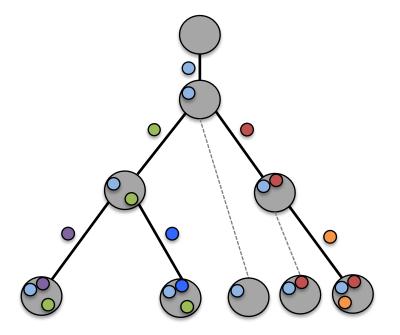




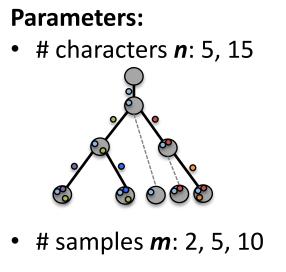
SPRUCE: Somatic Phylogeny Reconstruction Using Combinatorial Enumeration

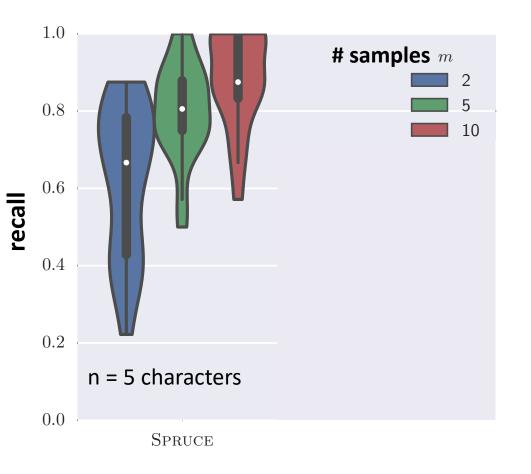


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SPRUCE Accurately Recovers Simulated Trees



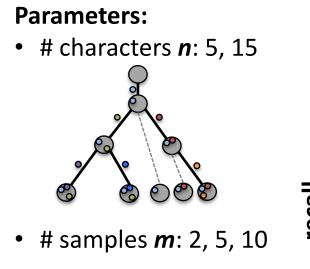


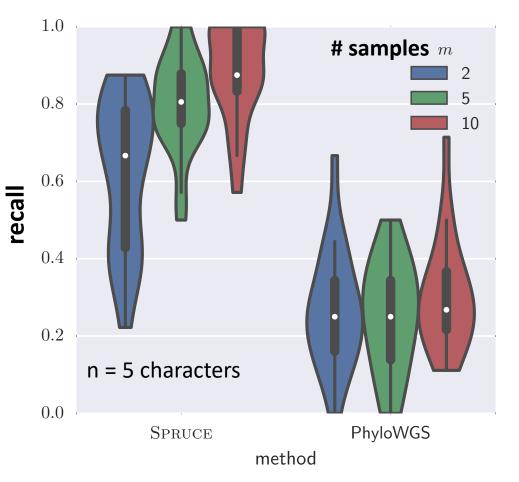
Methods:

- SPRUCE
- PhyloWGS [Deshwar et al., 2015]

Increasing number of samples decreases ambiguity

SPRUCE Accurately Recovers Simulated Trees



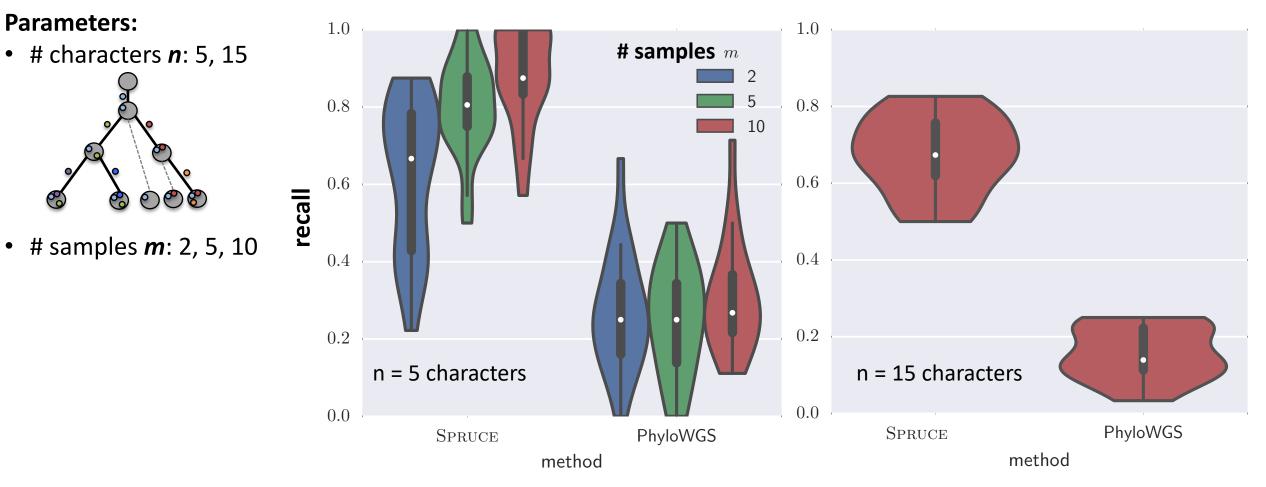


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SPRUCE Accurately Recovers Simulated Trees

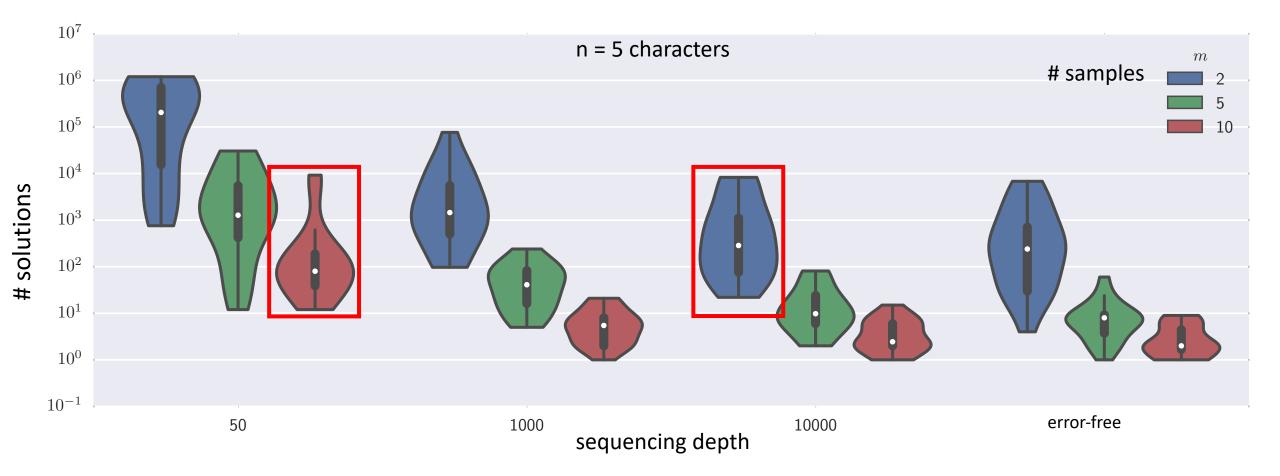


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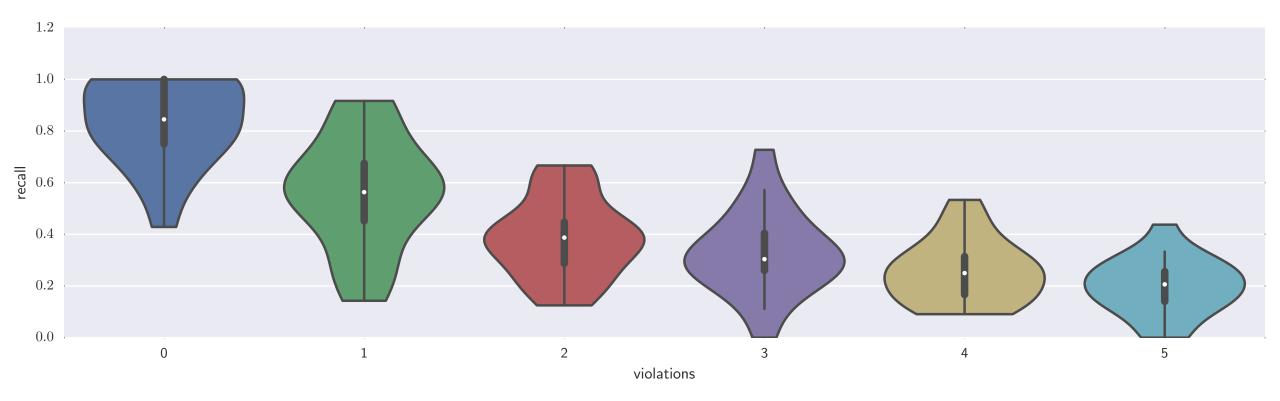
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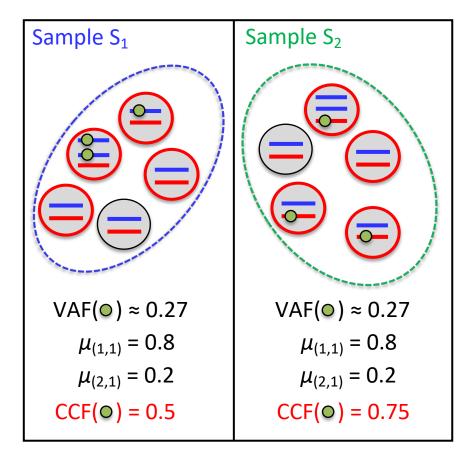
More Samples vs. More Coverage



Violations of Infinite Alleles Assumption



Cancer Cell Fractions (CCFs) Cannot Be Inferred A Priori



$$\mathsf{CCF}(\bigcirc) = \frac{\# \operatorname{tumor} \operatorname{cells} \operatorname{with} \bigcirc}{\# \operatorname{tumor} \operatorname{cells}}$$

CCFs are used extensively in studying intra-tumor heterogeneity and tumor evolution:

1. Timing of driver mutations

- Andor et al. Nature (2015)
- McGranahan et al. Science Translational Medicine (2015)

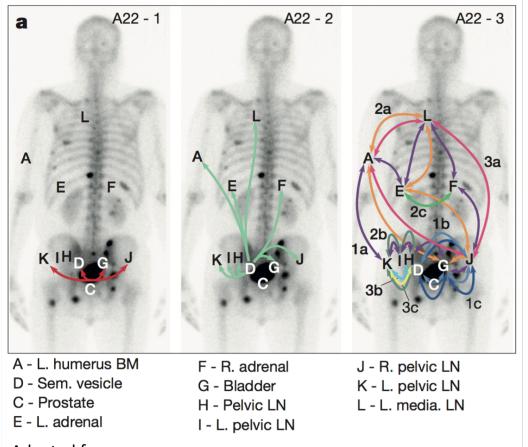
2. Tumor evolution and phylogeny reconstruction

- Bolli et al. Nature communications (2014)
- Nik-Zainal et al. The life history of 21 breast cancers. Cell (2012)
- Sanborn et al. PNAS (2015)
- Sottoriva et al. Nature Genetics (2015)

3. Developmental patterns of metastases

- Brastianos et al. Cancer Discovery, (2015)
- Gundem *et al*. *Nature* (2015)

Metastatic Evolution in Prostate Tumor



Adapted from:

Gundem *et al.* (2015). *Nature*.

The evolutionary history of lethal metastatic prostate cancer

Input:

 10 samples: whole-genome & targeted sequencing

DNAJA4

FLG

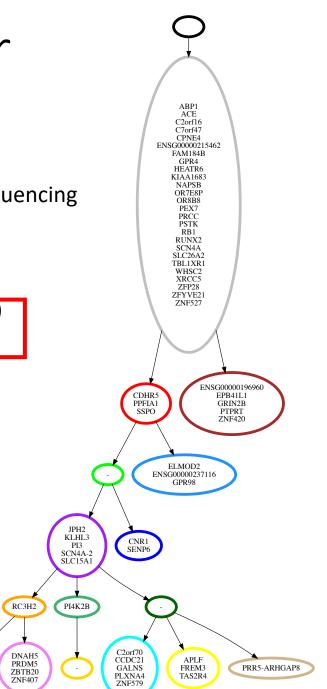
TFB1M

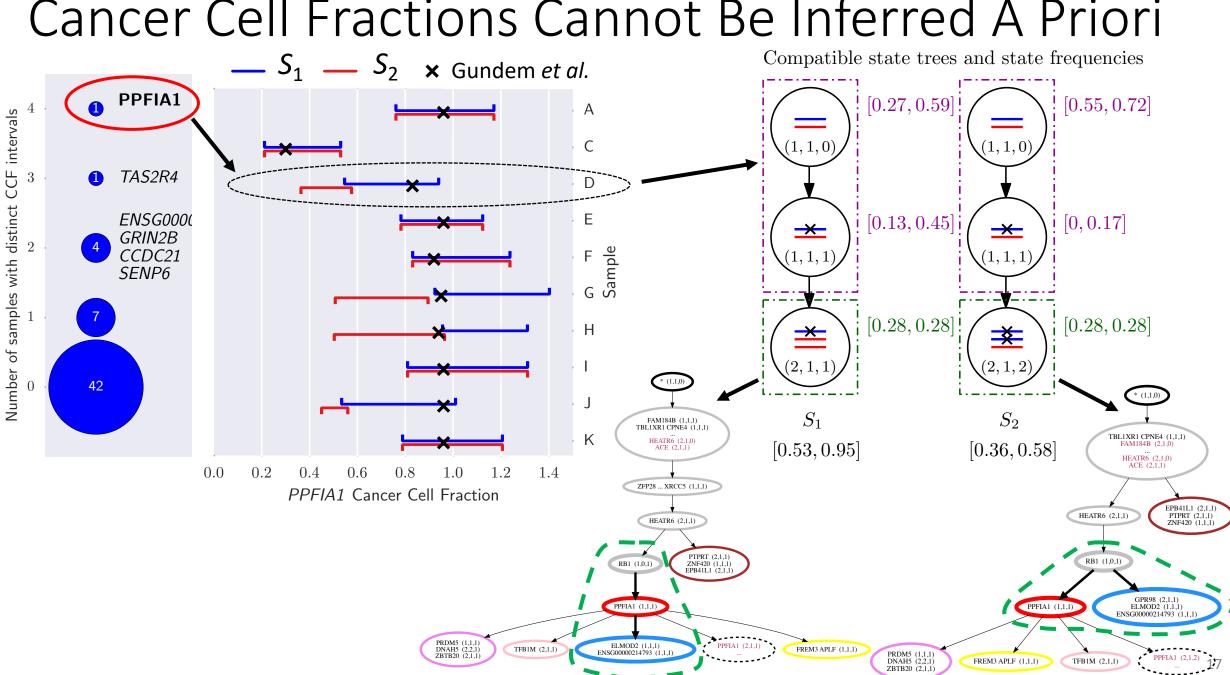
ZNF396

• ~110 SNVs

Tree building:

- Infer cancer cell fraction (CCF) for each SNV in each sample
- 2. Cluster SNVs by CCFs across samples
- Construct tree using Pigeon-Hole-Principle (Sum Condition)





Cancer Cell Fractions Cannot Be Inferred A Priori

Conclusions

- Copy-number aberrations confound variant allele frequencies
 - SNVs and CNAs must be considered jointly in phylogeny reconstruction
- Generalization of infinite sites for SNVs is infinite alleles for SNVs + CNAs
 - Multi-state Perfect Phylogeny Mixture Problem (PPM)
- Complete combinatorial characterization of the problem
 - Solutions are constrained spanning trees in a directed multi-graph
 - PPM is NP-complete for *k* = 2 and *m* = 2
- Using combinatorial structure, SPRUCE accurately recovers simulated trees
- Cancer cell fractions cannot be uniquely inferred *a priori* by considering SNVs in isolation
- Precise mathematical models are needed to describe evolutionary process in cancer

