

# Summarizing the Solution Space in Tumor Phylogeny Inference by Multiple Consensus Trees

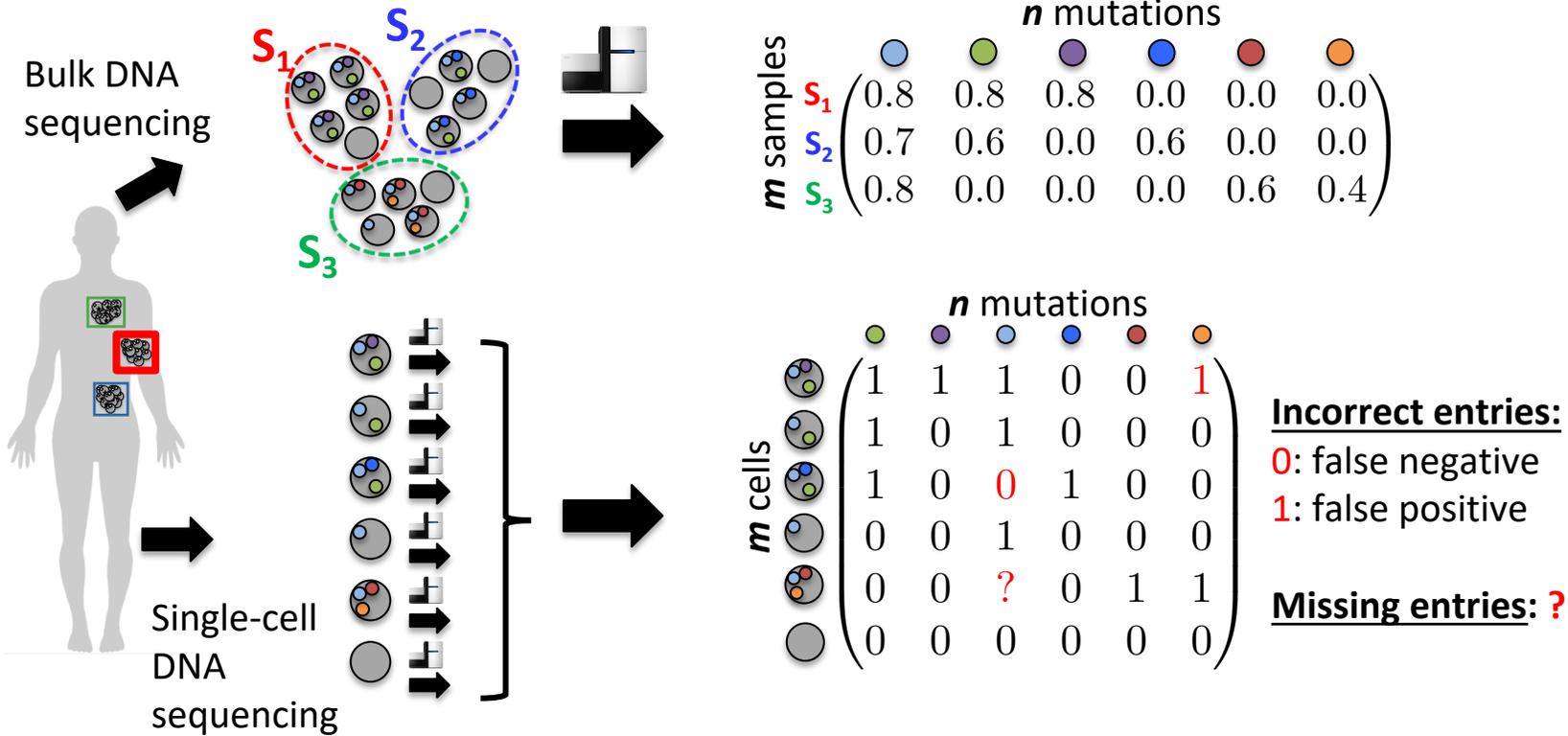
Nuraini Aguse\*, Yuanyuan Qi\* and Mohammed El-Kebir  
University of Illinois at Urbana Champaign, Department of Computer Science

RECOMB-CCB 2019



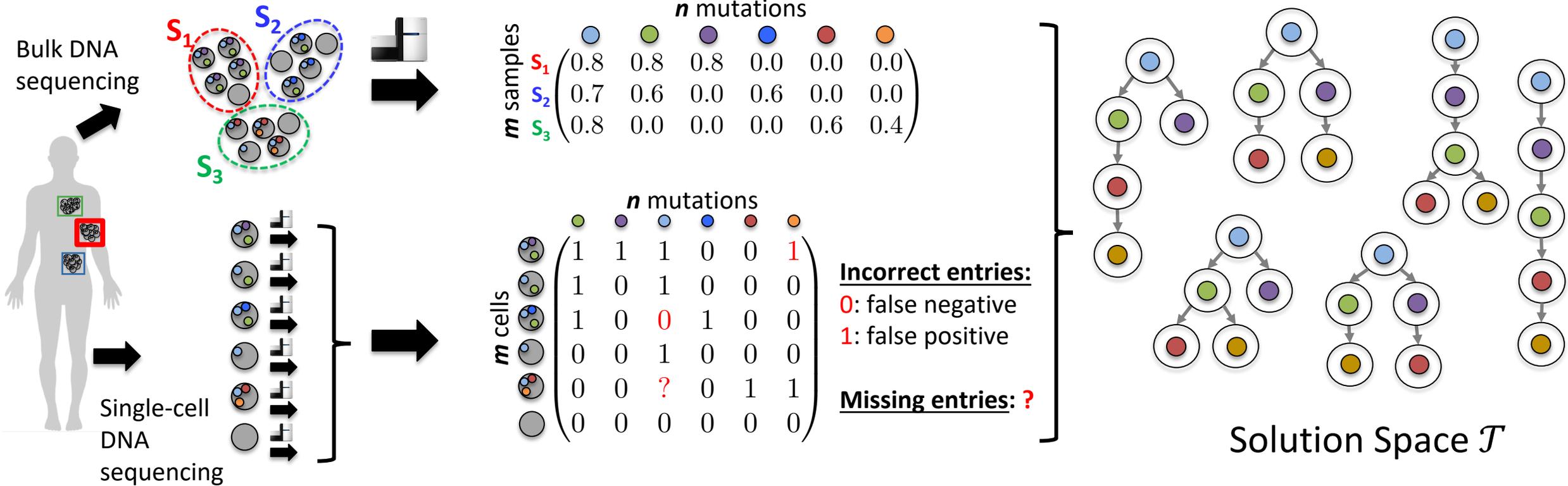
\*Joint first authorship  
Accepted at ISMB/ECCB 2019

# Additional Challenge in Cancer Phylogenetics



Phylogeny inference from mixtures of/incomplete measurements of leaves

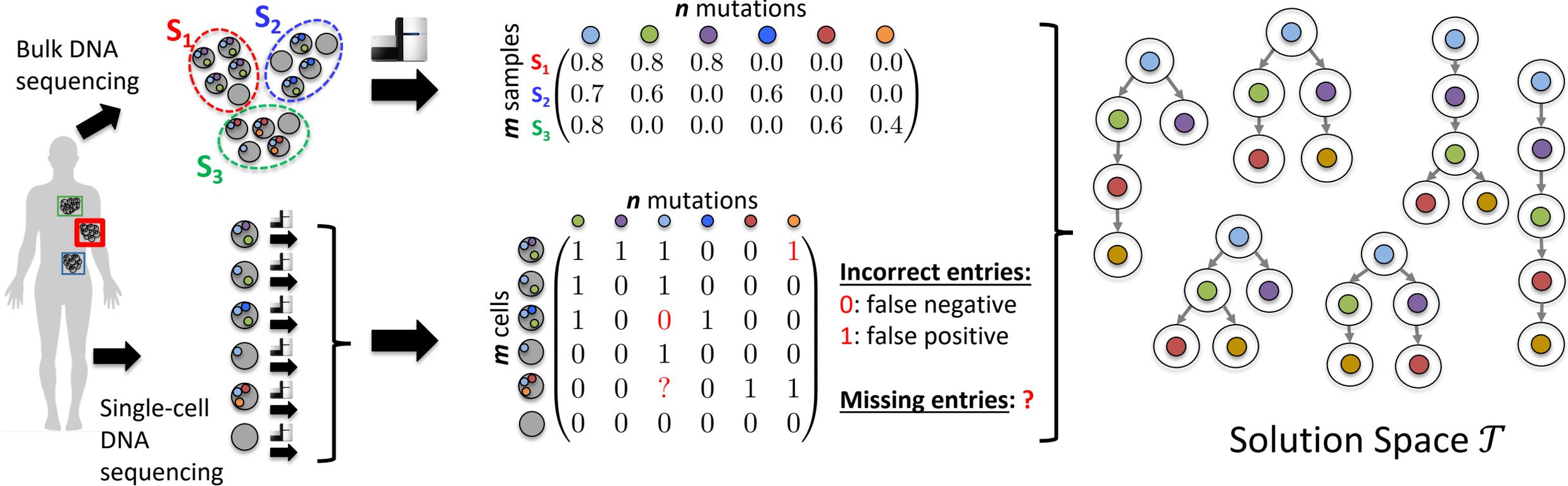
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Phylogeny inference from mixtures of/incomplete measurements of leaves

Non-uniqueness of solutions: alternative solutions with varying leaf sets

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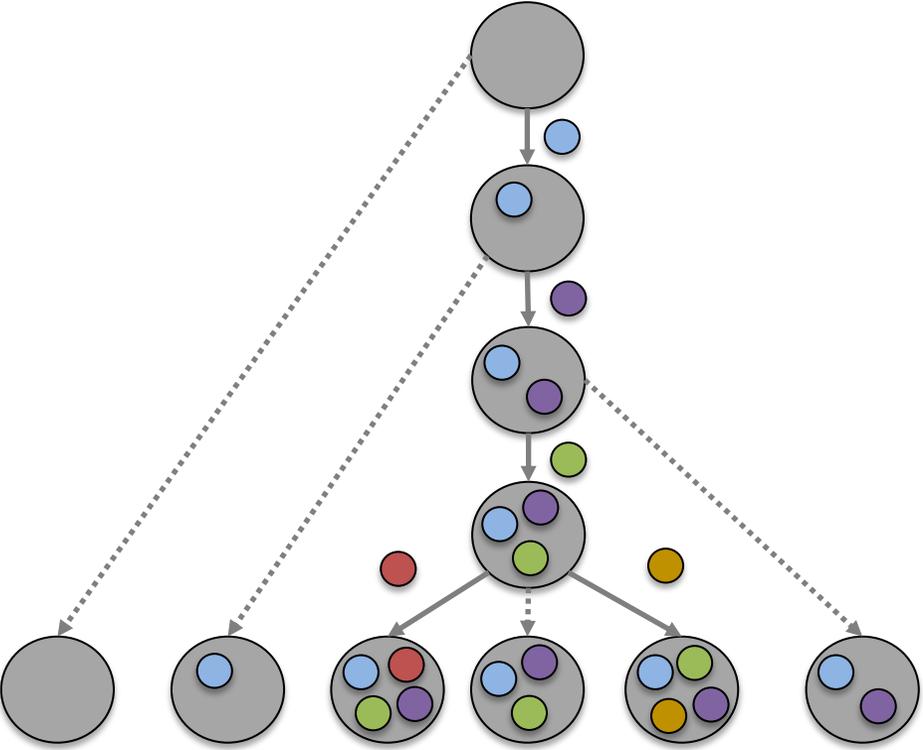
Non-uniqueness of solutions: alternative solutions with varying leaf sets

**Question:** How to **summarize solution space**  $\mathcal{T}$  in order to remove inference errors and identify dependencies among mutations?

# Outline

- Problem Statement
  - Previous work
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  - Combinatorial characterization of solutions
  - Complexity
- Method & Results
  - Exact algorithm
  - Heuristic algorithm
  - Model selection

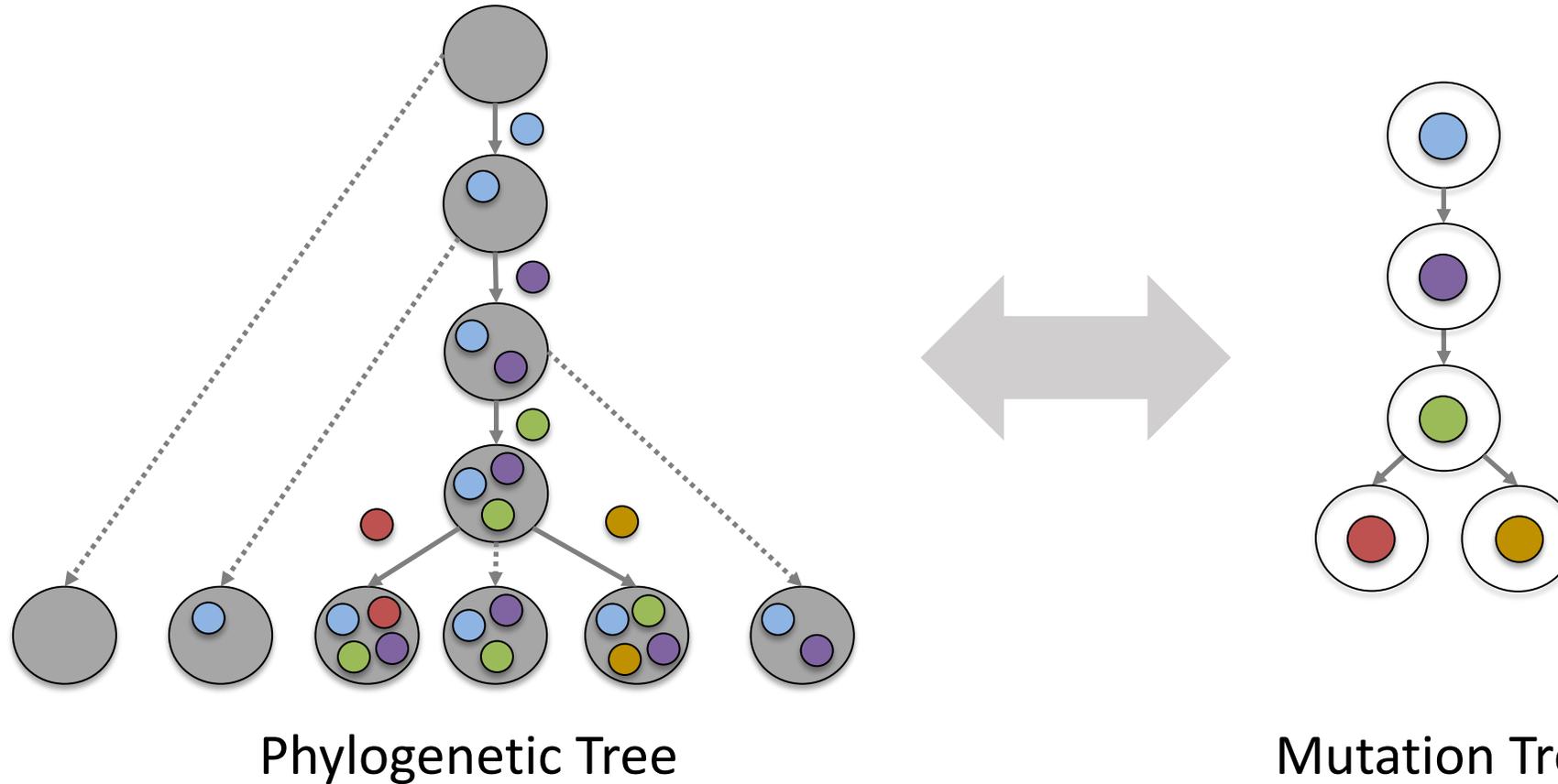
# Phylogenetic Trees vs. Mutation Trees



Phylogenetic Tree

Infinite sites assumption (ISA): each mutation is introduced once and never subsequently lost

# Phylogenetic Trees vs. Mutation Trees



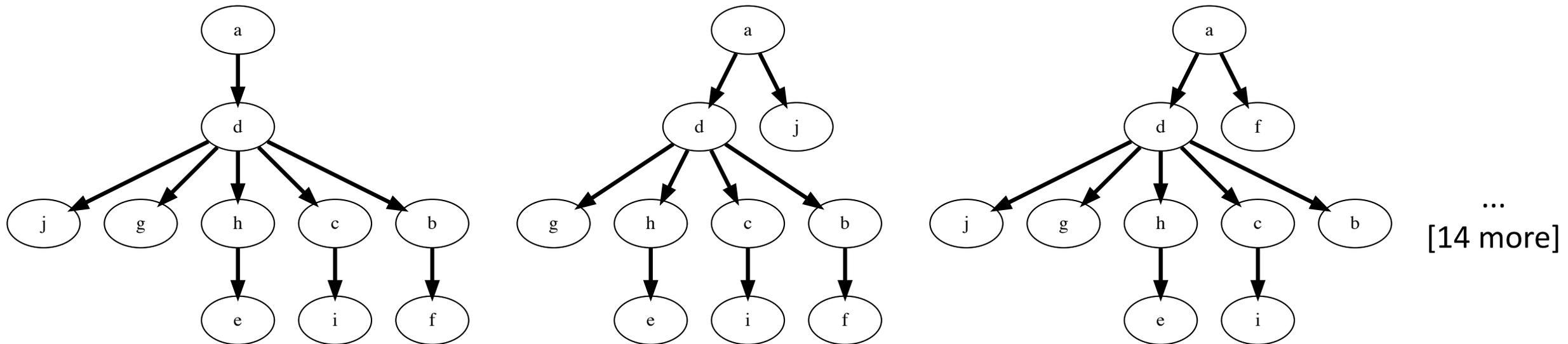
Infinite sites assumption (ISA): each mutation is introduced once and never subsequently lost

Under ISA, a phylogenetic tree may be equivalently\* represented by a mutation tree

# Solution Space of Lung Cancer Patient CRUK0037

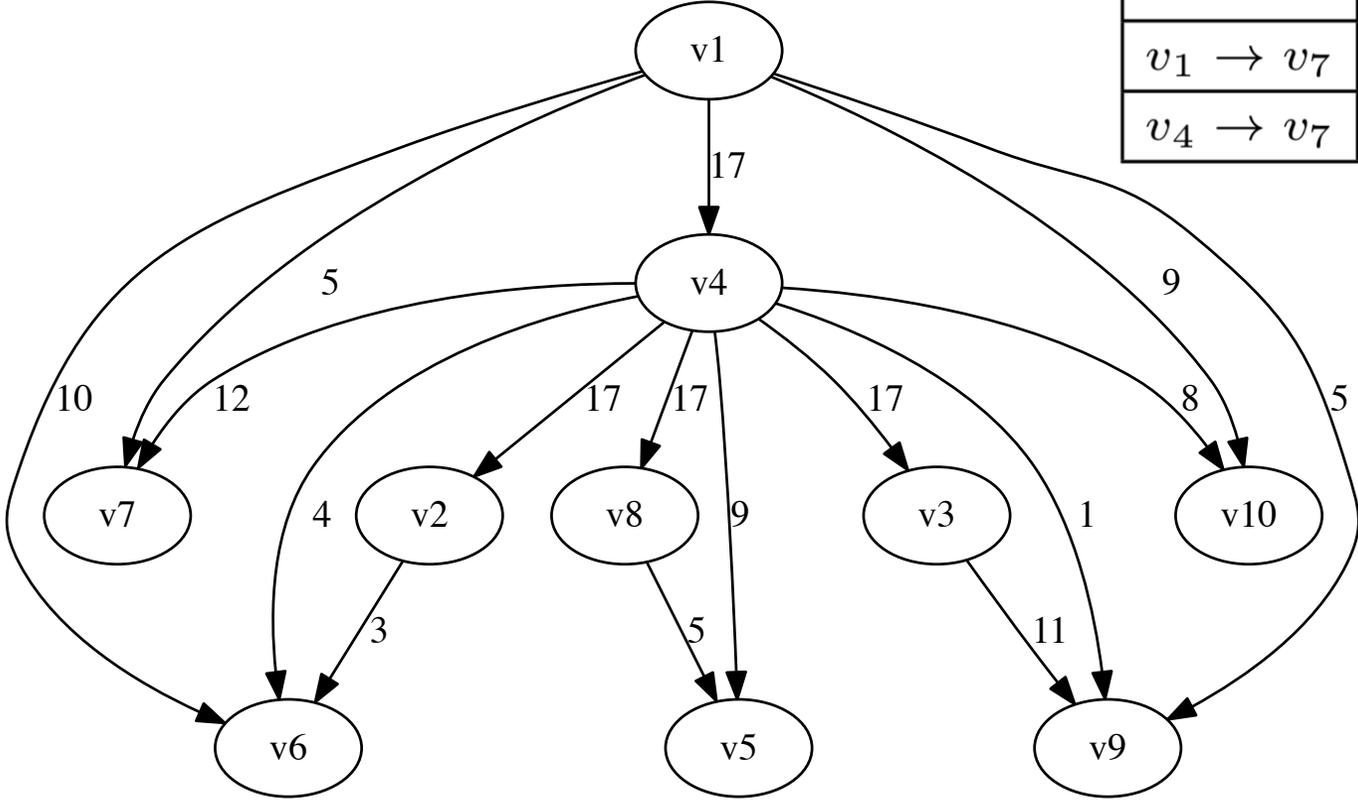
Jamal-Hanjani et al. (2017). *New England Journal of Medicine*, 376(22), 2109–2121.

Jamal-Hanjani et al. inferred 17 trees for patient CRUK0037



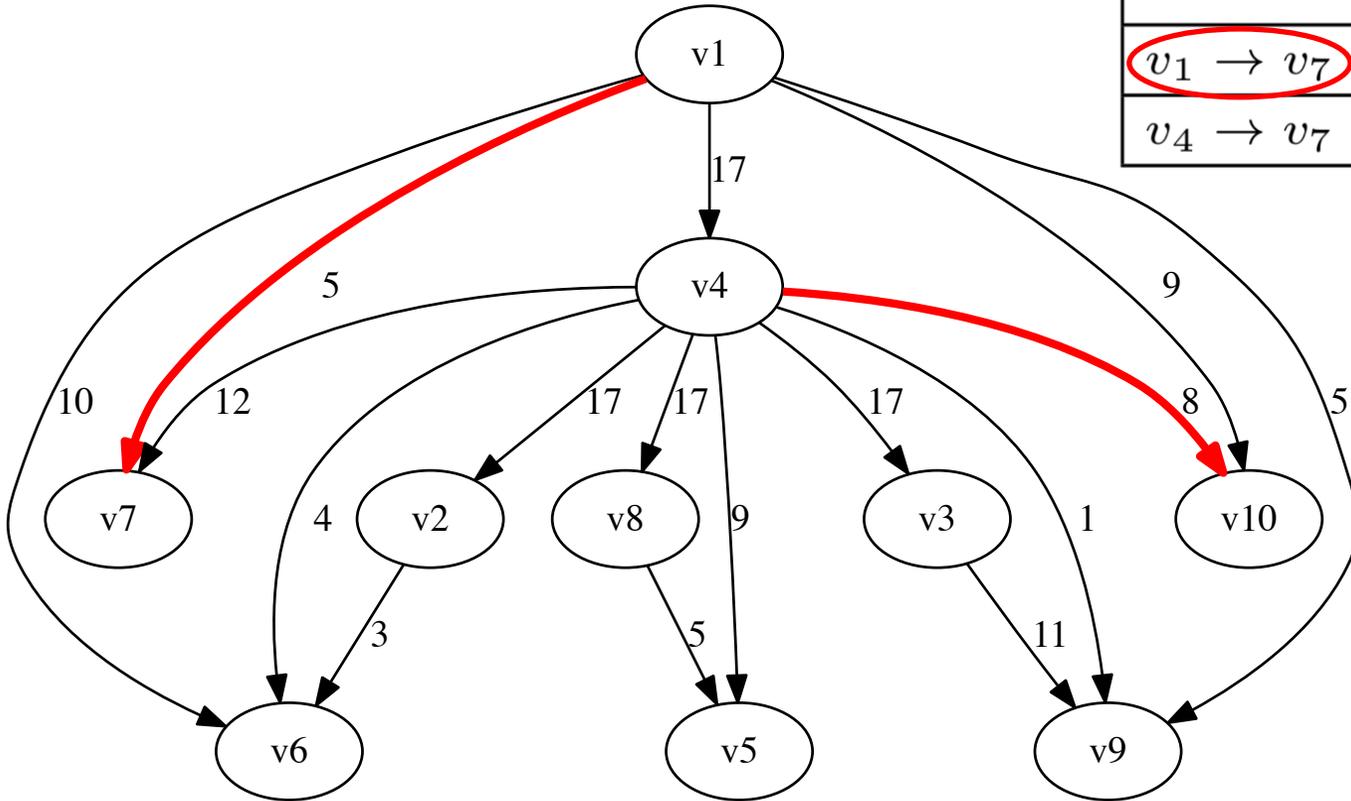
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# Parent-child Graph: Union of all Edges in $\mathcal{T}$



	$v_4 \rightarrow v_5$		$v_8 \rightarrow v_5$	
	$v_1 \rightarrow v_{10}$	$v_4 \rightarrow v_{10}$	$v_1 \rightarrow v_{10}$	$v_4 \rightarrow v_{10}$
$v_1 \rightarrow v_7$	2	0	3 (d)	0
$v_4 \rightarrow v_7$	2 (b)	5 (e)	2	3

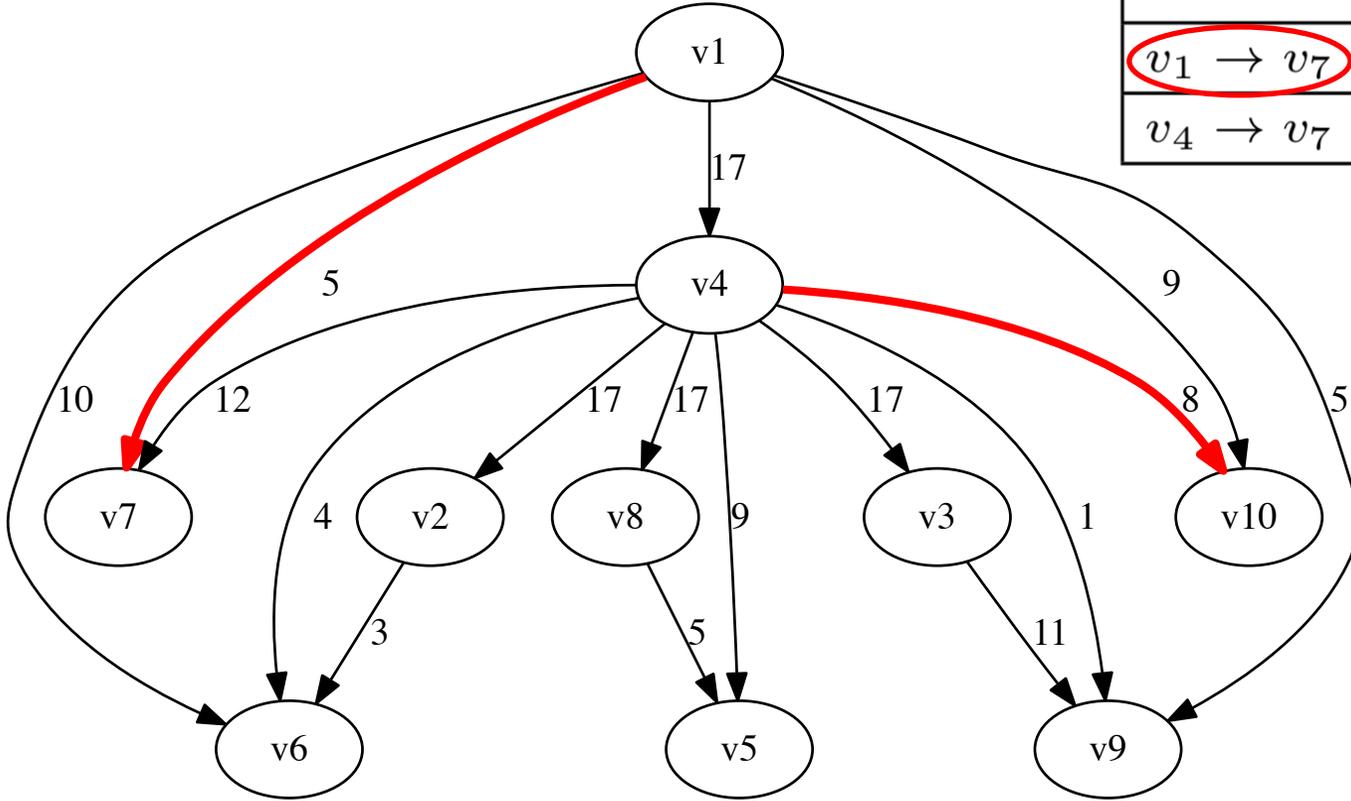
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The parent-child graph does not capture patterns of mutual exclusivity

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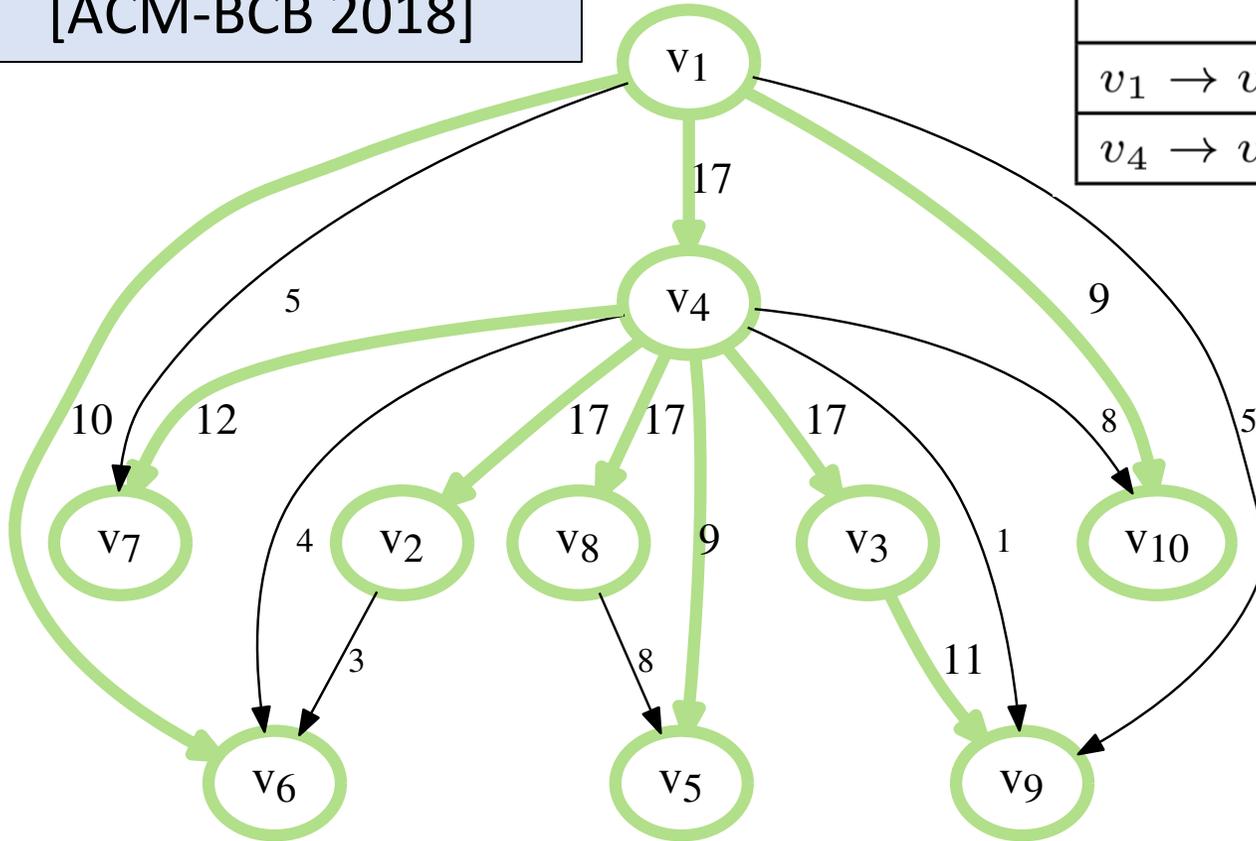
The parent-child graph does not capture patterns of mutual exclusivity

**Question:** Can we infer a single consensus tree?

# Single Consensus Tree: Max Weight Spanning Tree

Oesper and colleagues.  
[ACM-BCB 2018]

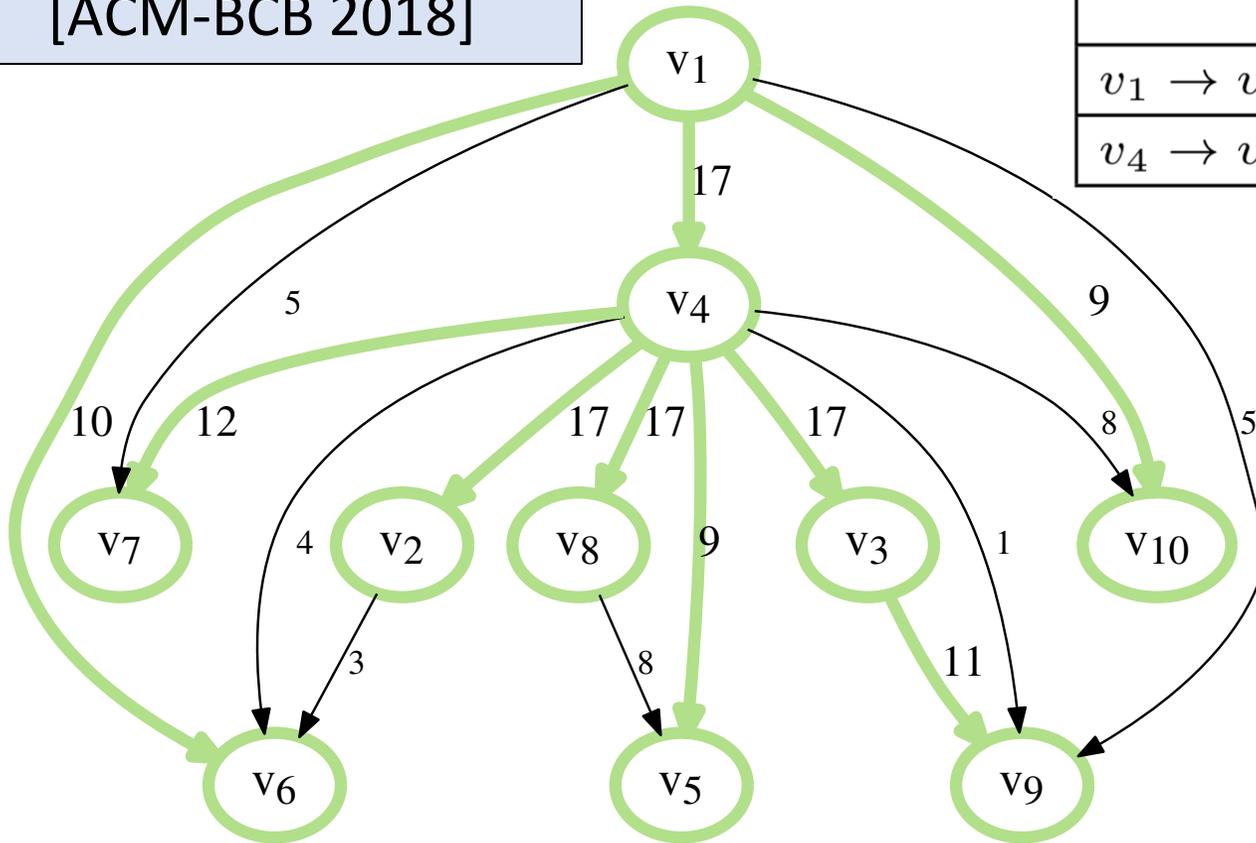
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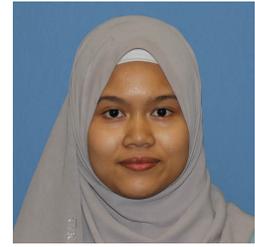


Inaccurate summary for diverse solution spaces

**Question:** How about inferring multiple consensus trees?

# Multiple Consensus Trees Problem

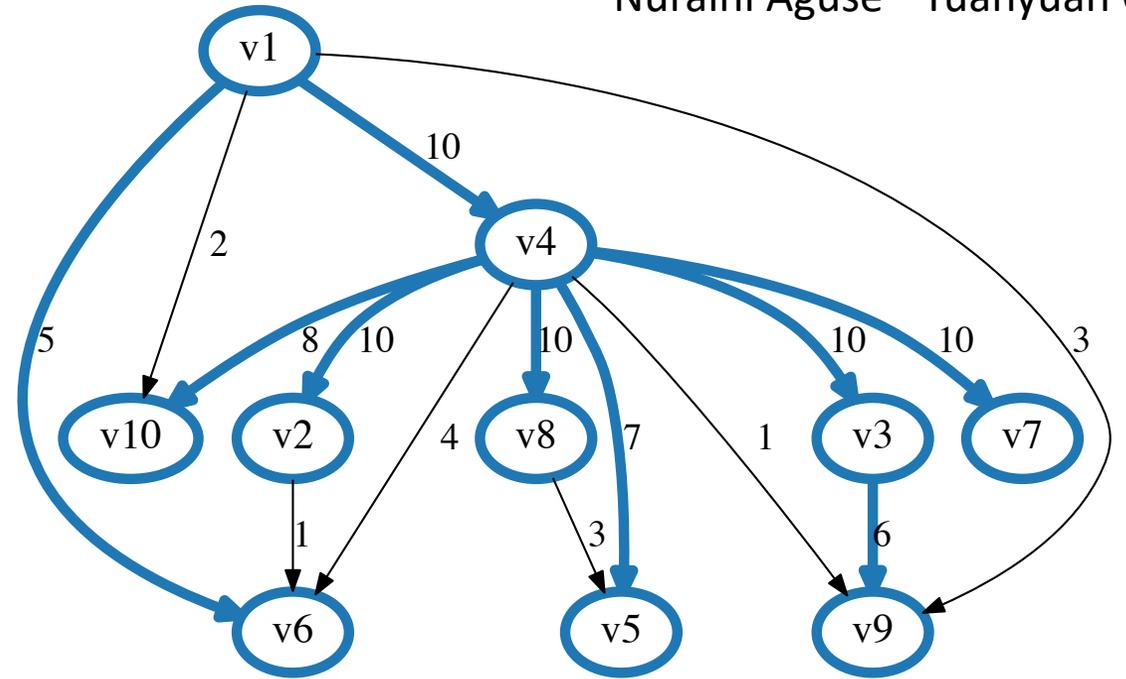
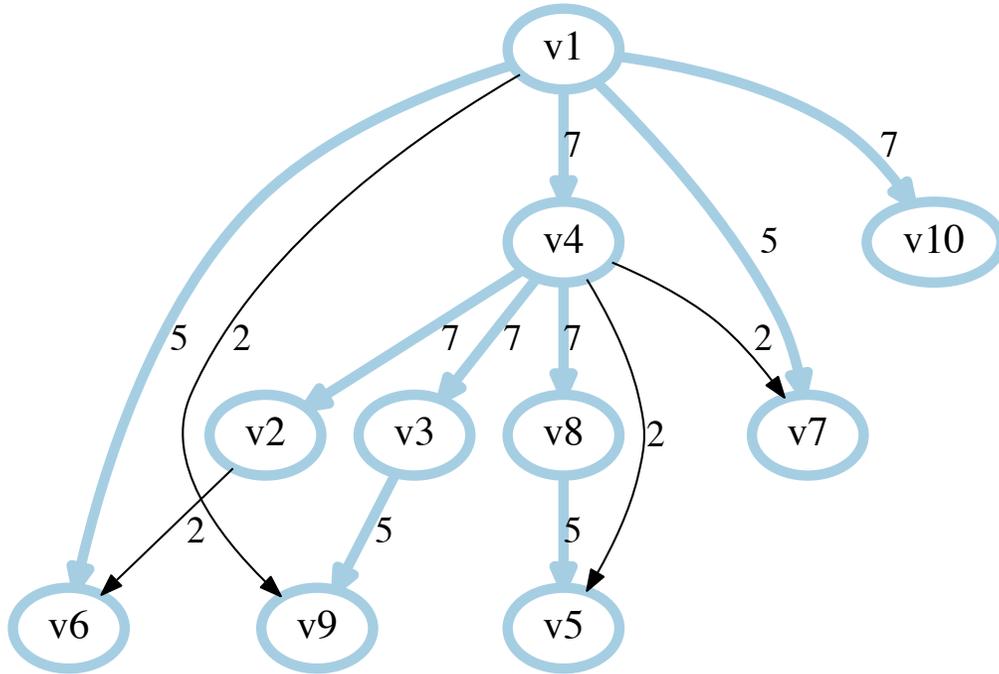
Simultaneous clustering and consensus tree inference



Nuraini Aguse

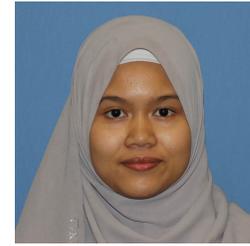


Yuanyuan Qi



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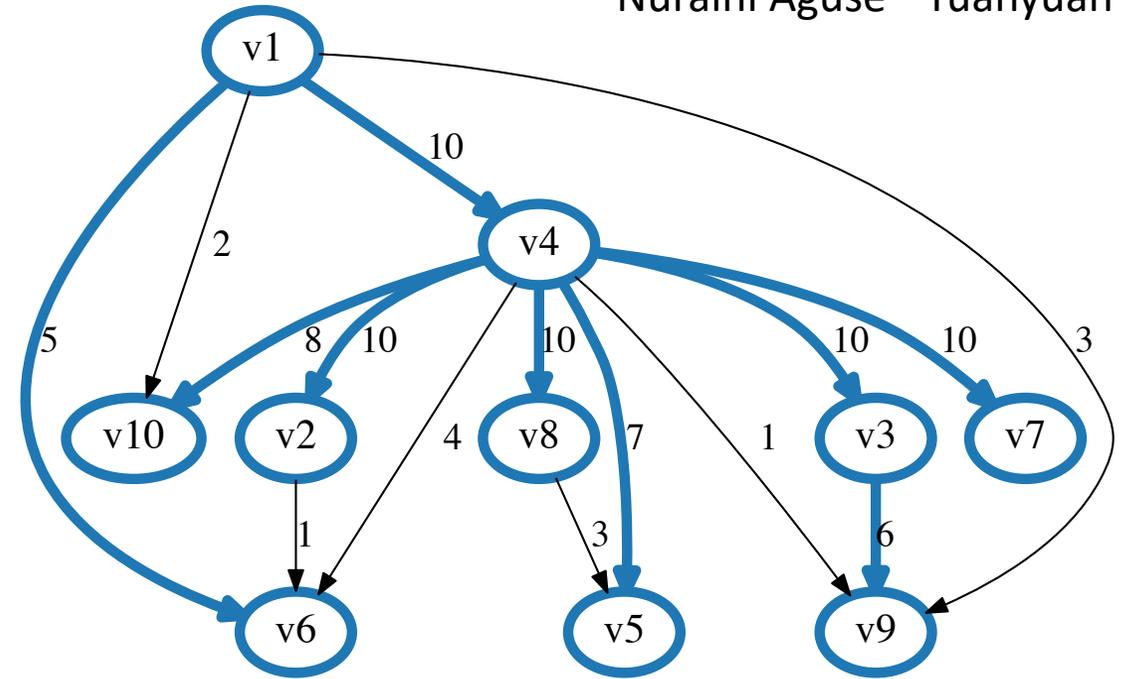
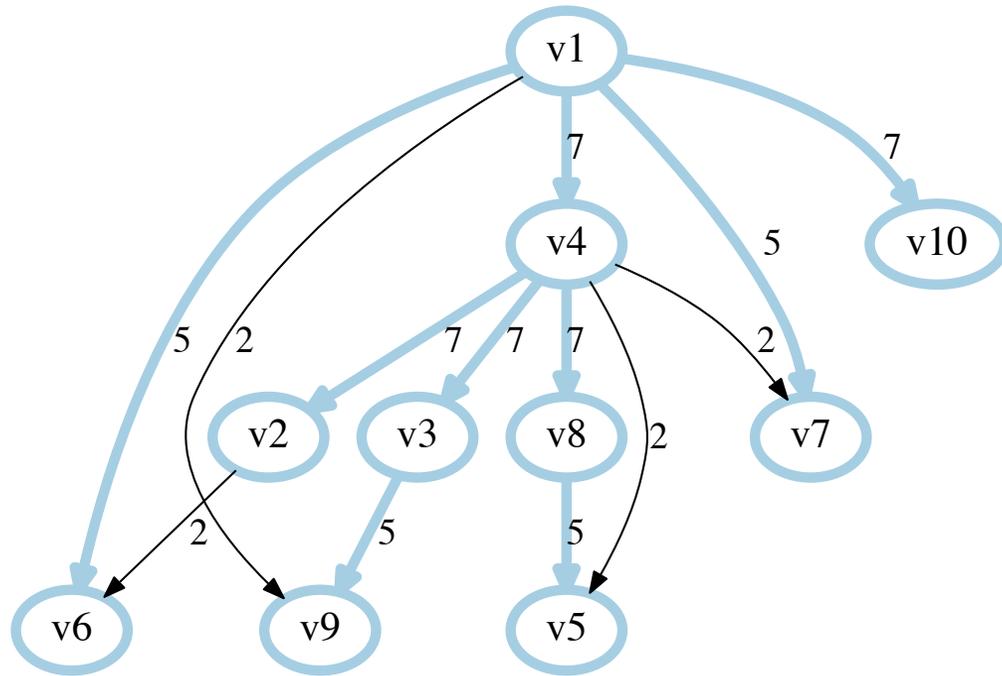
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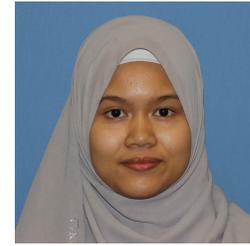


**Multiple Consensus Trees (MCT):** [ISMB/ECCB 2019]

Given trees  $\mathcal{T} = \{T_1, \dots, T_n\}$  and  $k > 0$ , find surjective clustering  $\sigma : [n] \rightarrow [k]$  and consensus trees  $\mathcal{R} = \{R_1, \dots, R_k\}$  s.t.  $\sum_{i=1}^n d(T_i, R_{\sigma(i)})$  is minimum

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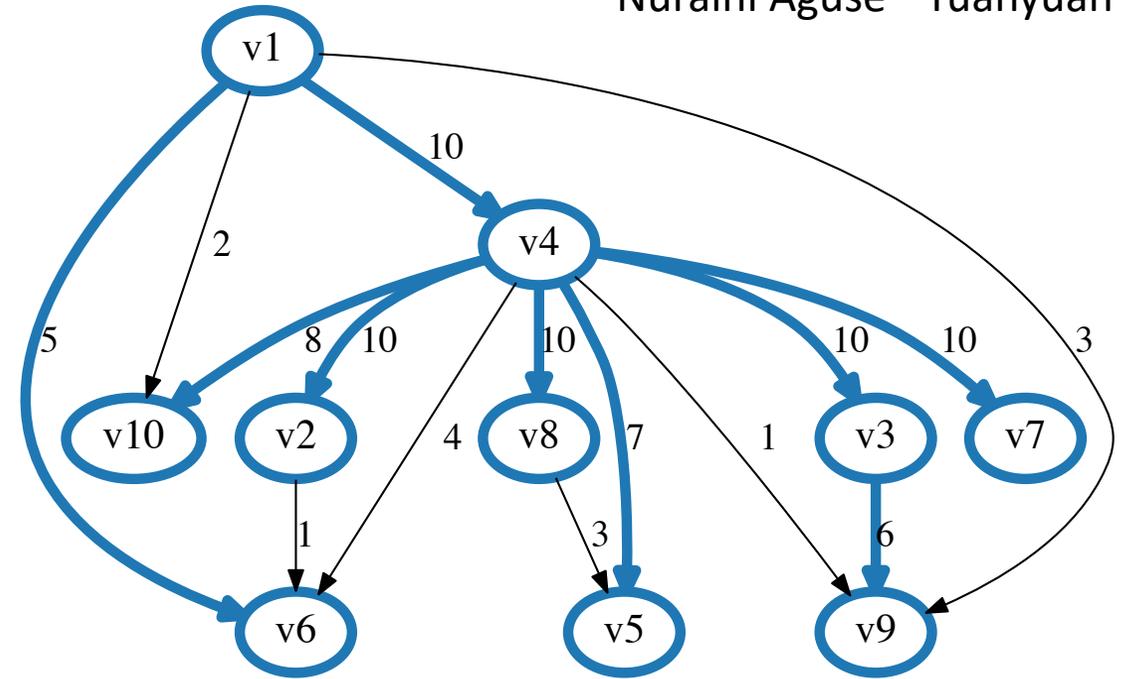
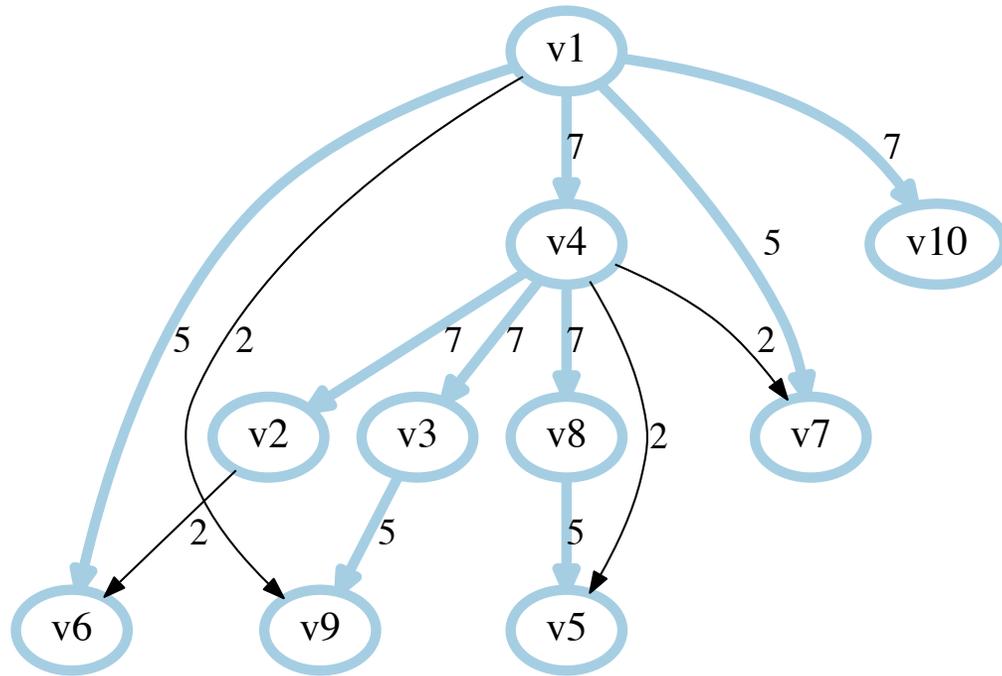
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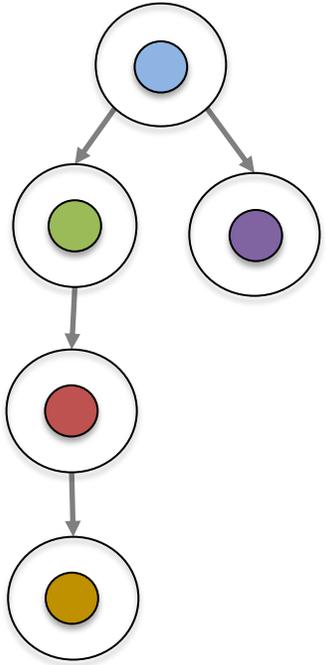
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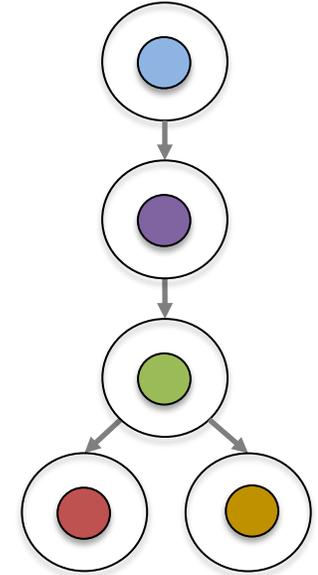
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# Parent-child Distance Function

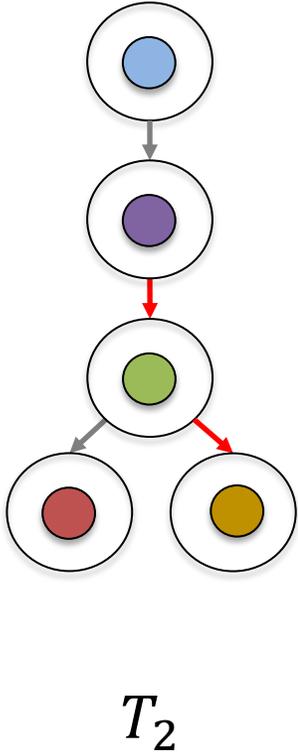
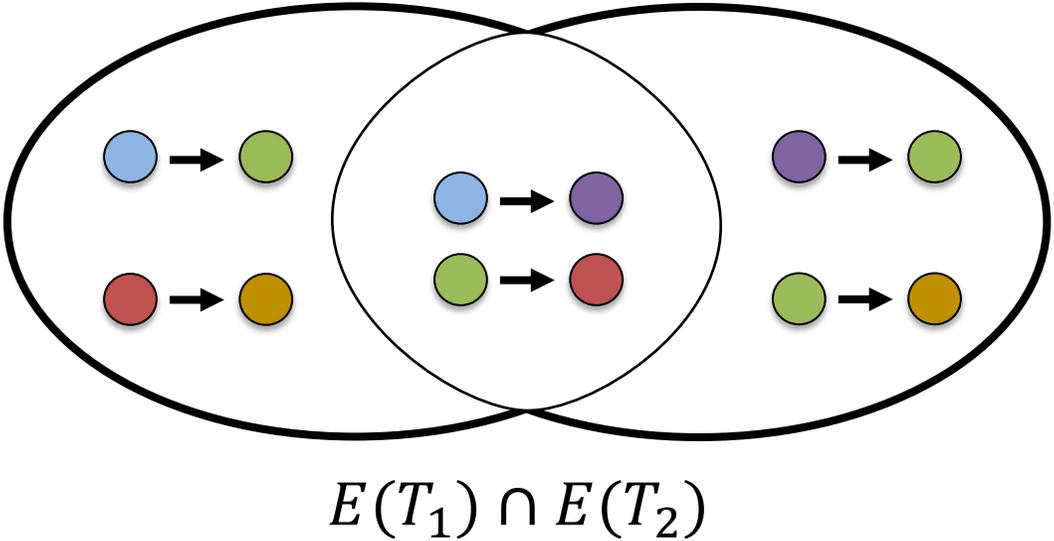
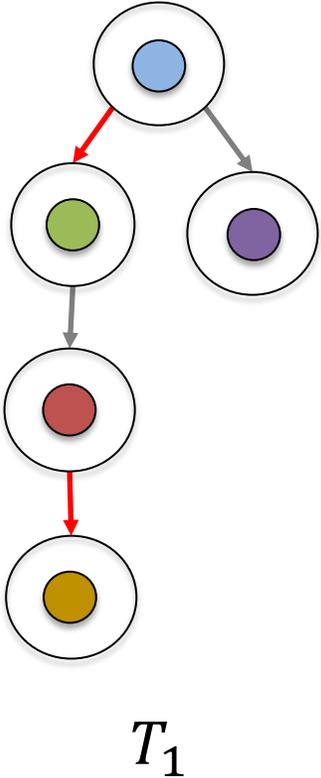


$T_1$

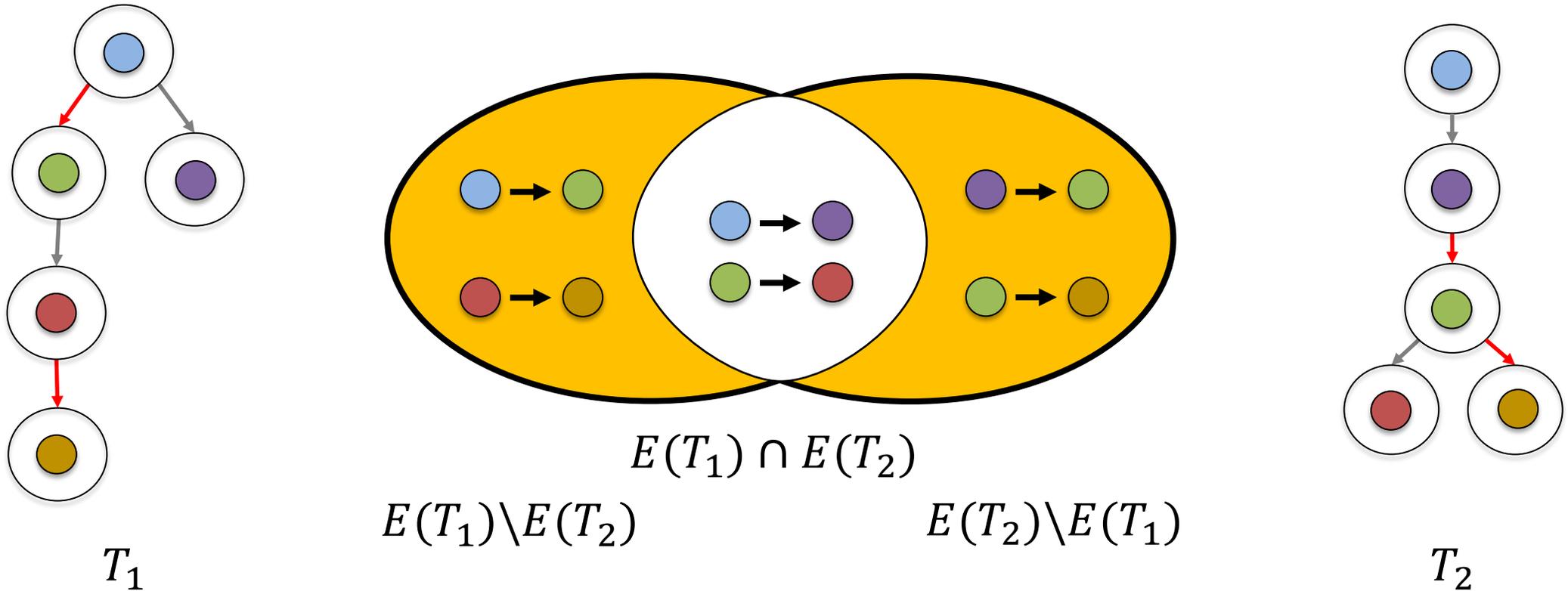


$T_2$

# Parent-child Distance Function



# Parent-child Distance Function



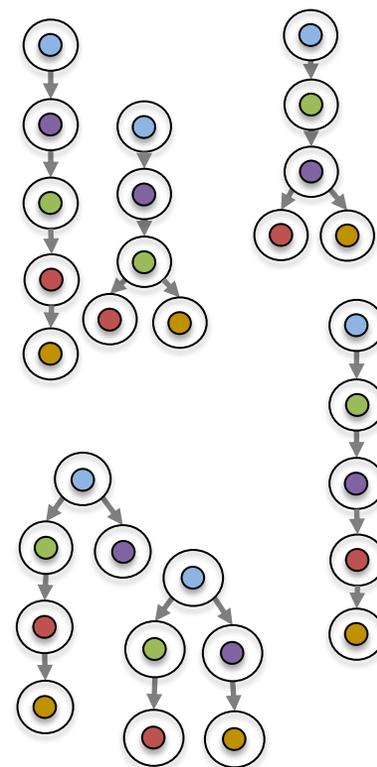
Parent-child distance  $d(T_1, T_2)$  is the size of the symmetric difference of the edge sets

$$\text{Here, } d(T_1, T_2) = |E(T_1) \setminus E(T_2)| + |E(T_2) \setminus E(T_1)| = 4.$$

# Combinatorial Characterization of Solutions to MCT

**Single Consensus Trees (SCT):** [Govek et al., ACM-BCB 2018]

Given  $\mathcal{T} = \{T_1, \dots, T_n\}$ , find consensus tree  $R$  s.t.  
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Solution Space  $\mathcal{T}$

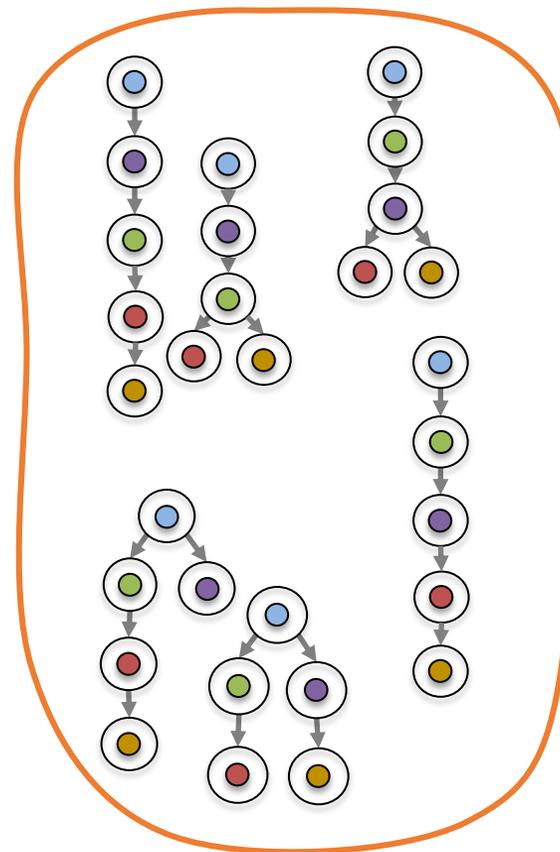
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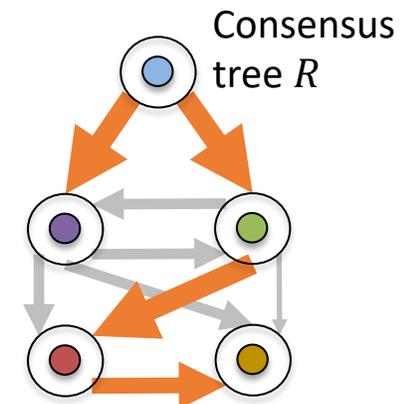
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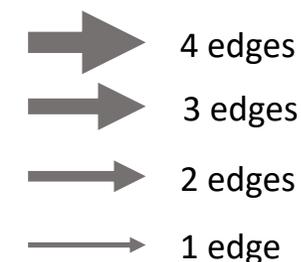
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Parent-child graph  $G_{\mathcal{T}}$



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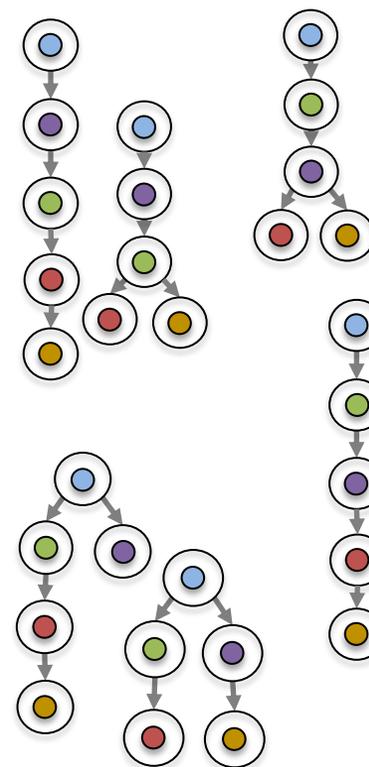
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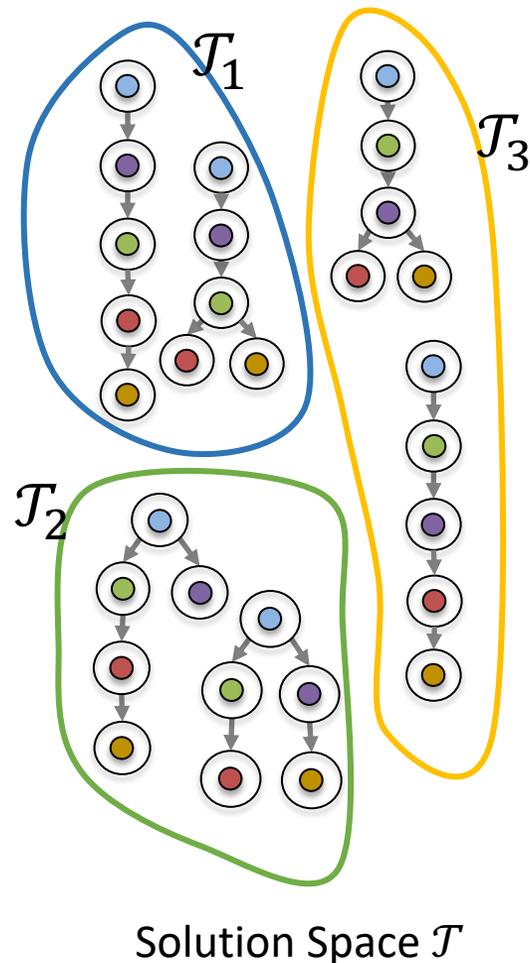
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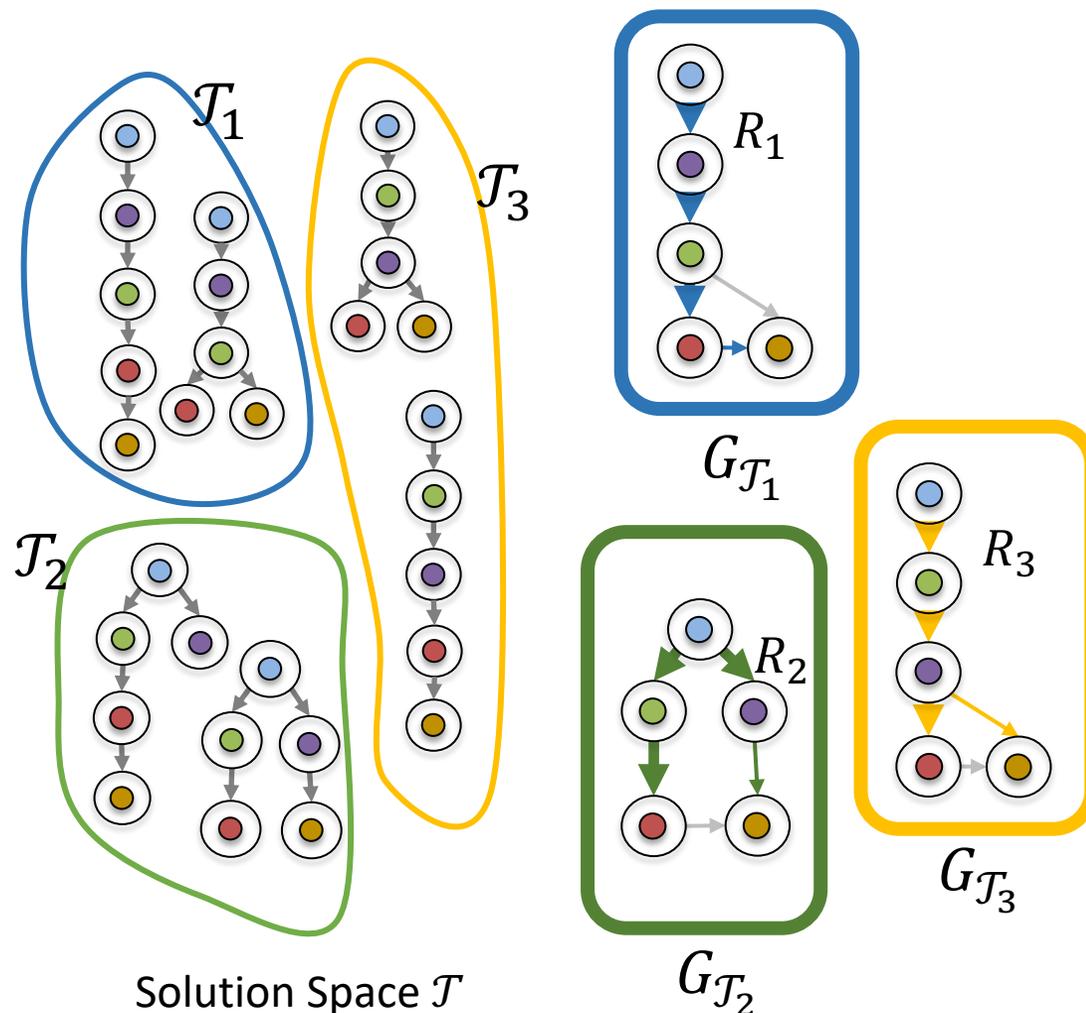
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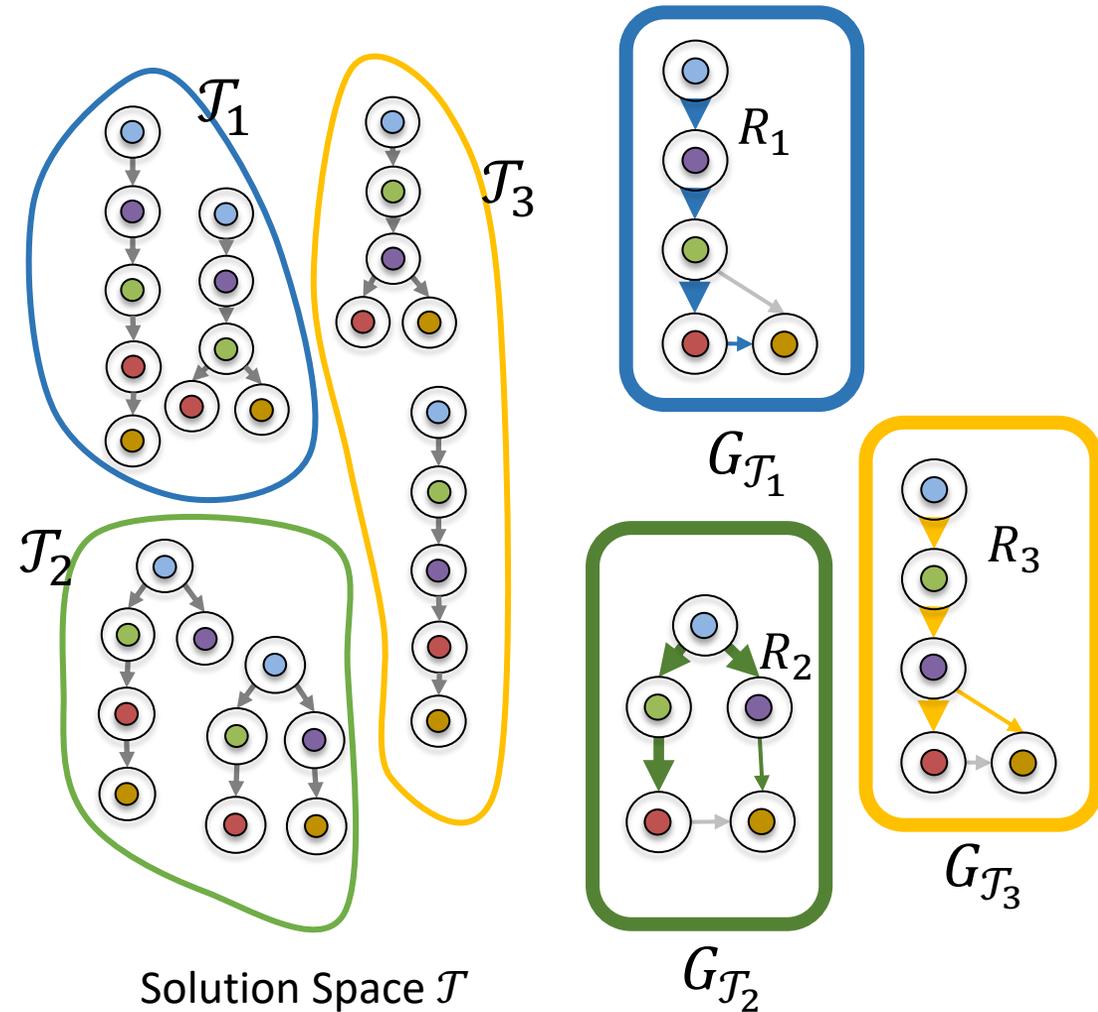
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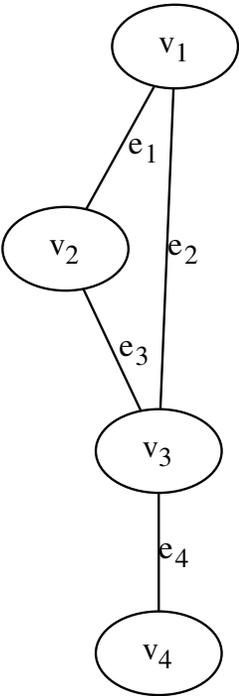


**Question:** How to find  $\sigma^*$ ?

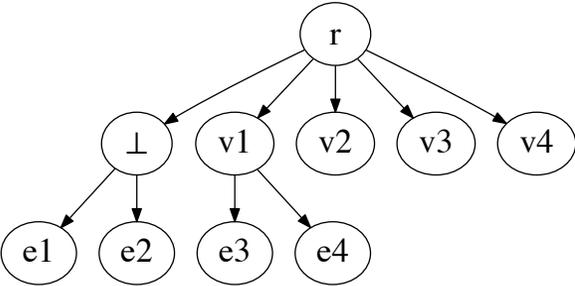
# Complexity

## Multiple Consensus Trees (MCT):

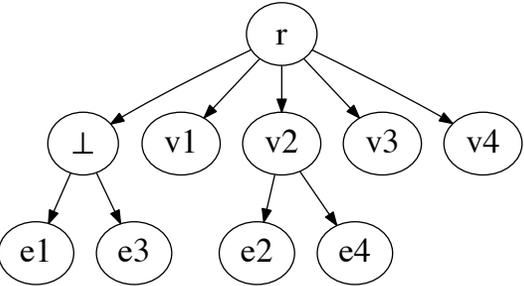
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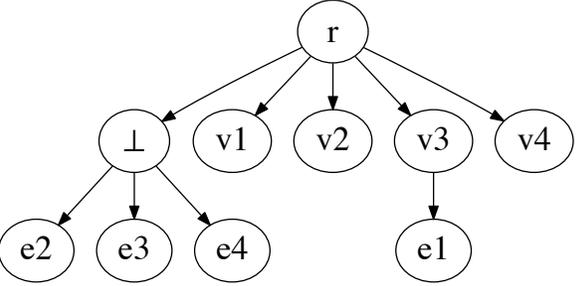
(a)



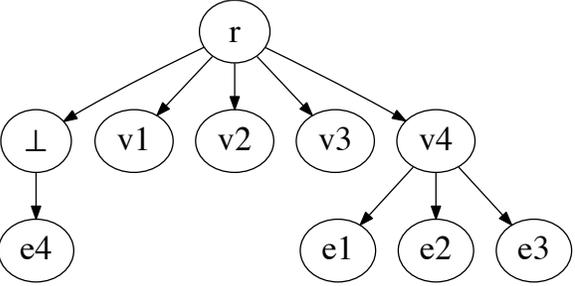
(b)



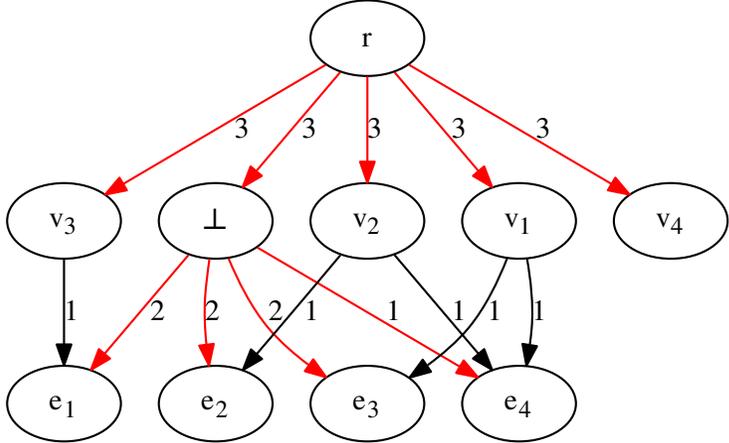
(c)



(d)



(e)



(f)

**Theorem:** MCT is NP-hard for general  $k$  (by reduction from CLIQUE).

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# Mixed Integer Linear Program

**Theorem:** MCT is NP-hard for general  $k$  (by reduction from CLIQUE).

$$\min n(m-1) - \sum_{i=1}^n \sum_{s=1}^k \sum_{p=1}^m \sum_{q=1}^m w_{i,s,p,q}$$

$$\text{s.t. } \sum_{s=1}^k x_{i,s} = 1 \quad \forall i \in [n]$$

$$\sum_{i=1}^n x_{i,s} \geq 1 \quad \forall s \in [k]$$

$$\sum_{p=1}^m z_{s,p} = 1 \quad \forall s \in [k]$$

$$\sum_{q=1}^m y_{s,p,q} = 1 - z_{s,p} \quad \forall s \in [k], p \in [m]$$

$$y_{s,p,q} \leq b_{p,q} \quad \forall s \in [k], p, q \in [m]$$

$$\sum_{(p,q) \in \delta^-(U)} y_{s,p,q} + \sum_{p \in U} z_{s,p} \geq 1 \quad \forall s \in [k], U \subseteq [m]$$

$$w_{i,s,p,q} \leq a_{i,p,q} \quad \forall i \in [n], s \in [k], p, q \in [m]$$

$$w_{i,s,p,q} \leq x_{i,s} \quad \forall i \in [n], s \in [k], p, q \in [m]$$

$$w_{i,s,p,q} \leq y_{s,p,q} \quad \forall i \in [n], s \in [k], p, q \in [m]$$

$$w_{i,s,p,q} \geq 0 \quad \forall i \in [n], s \in [k], p, q \in [m]$$

$$y_{s,p,q} \leq \sum_{i=1}^n a_{i,p,q} x_{i,s} \quad \forall s \in [k], p, q \in [m]$$

$$y_{s,p,q} \geq \sum_{i=1}^n a_{i,p,q} x_{i,s} - \sum_{i=1}^n x_{i,s} + 1 \quad \forall s \in [k], p, q \in [m]$$

$$\sum_{i=1}^n x_{i,s} \geq \sum_{i=1}^n x_{i,s+1} + 1 \quad \forall s \in [k-1]$$

$$x_{i,s} \in \{0, 1\} \quad \forall i \in [n], s \in [k]$$

$$y_{s,p,q} \geq 0 \quad \forall s \in [k], p, q \in [m]$$

$$z_{s,p} \geq 0 \quad \forall s \in [k], p \in [m]$$

# Mixed Integer Linear Program

**Theorem:** MCT is NP-hard for general  $k$  (by reduction from CLIQUE).

$x_{i,s} \in \{0, 1\}$  Tree  $T_i$  is assigned to cluster  $s$   
 $y_{s,p,q} \geq 0$  Edge  $(p, q)$  is present in consensus tree  $R_s$   
 $z_{s,p} \geq 0$  Vertex  $p$  is root of consensus tree  $R_s$

$$\min n(m-1) - \sum_{i=1}^n \sum_{s=1}^k \sum_{p=1}^m \sum_{q=1}^m w_{i,s,p,q}$$

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$$\sum_{(p,q) \in \delta^-(U)} y_{s,p,q} + \sum_{p \in U} z_{s,p} \geq 1 \quad \forall s \in [k], U \subseteq [m]$$

$$w_{i,s,p,q} \leq a_{i,p,q} \quad \forall i \in [n], s \in [k], p, q \in [m]$$

$$w_{i,s,p,q} \leq x_{i,s} \quad \forall i \in [n], s \in [k], p, q \in [m]$$

$$w_{i,s,p,q} \leq y_{s,p,q} \quad \forall i \in [n], s \in [k], p, q \in [m]$$

$$w_{i,s,p,q} \geq 0 \quad \forall i \in [n], s \in [k], p, q \in [m]$$

$$y_{s,p,q} \leq \sum_{i=1}^n a_{i,p,q} x_{i,s} \quad \forall s \in [k], p, q \in [m]$$

$$y_{s,p,q} \geq \sum_{i=1}^n a_{i,p,q} x_{i,s} - \sum_{i=1}^n x_{i,s} + 1 \quad \forall s \in [k], p, q \in [m]$$

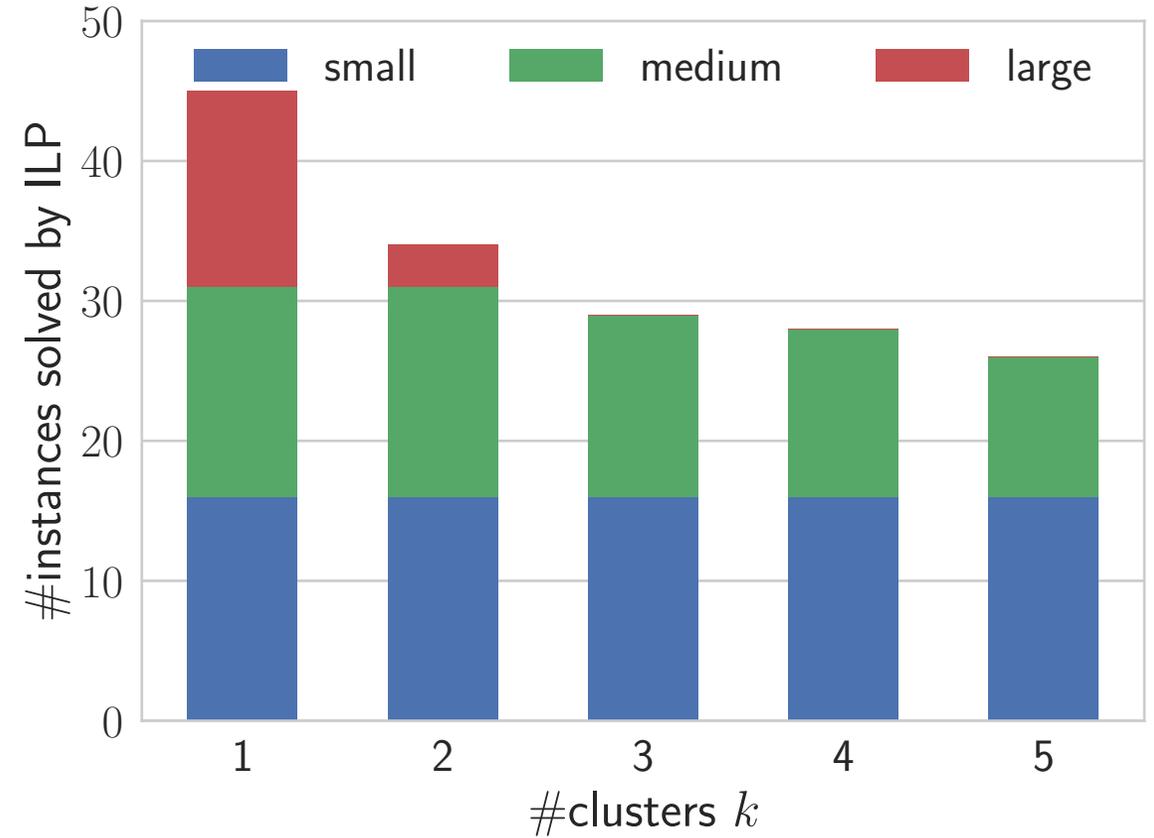
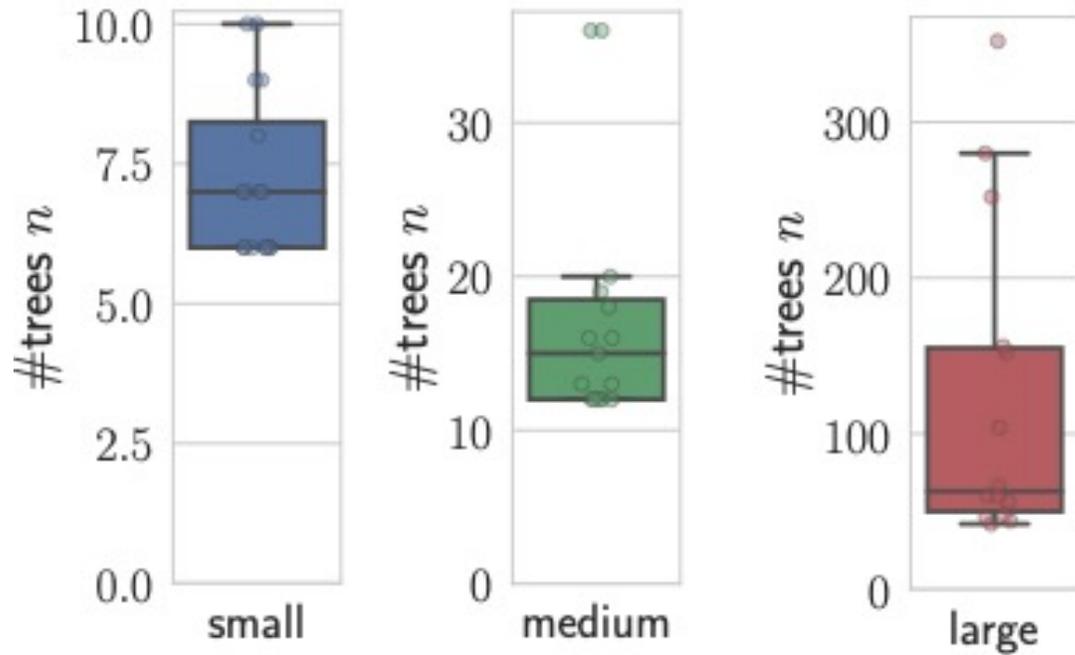
$$\sum_{i=1}^n x_{i,s} \geq \sum_{i=1}^n x_{i,s+1} + 1 \quad \forall s \in [k-1]$$

$$x_{i,s} \in \{0, 1\} \quad \forall i \in [n], s \in [k]$$

$$y_{s,p,q} \geq 0 \quad \forall s \in [k], p, q \in [m]$$

$$z_{s,p} \geq 0 \quad \forall s \in [k], p \in [m]$$

# MILP does not scale well with $k$ and $n$



# Coordinate Ascent (akin to k-means)

**Proposition:** [Aguse et al., ISMB 2019]

Given fixed clustering  $\sigma : [n] \rightarrow [k]$ , MCT decomposes into  $k$  independent SCT instances

1. Fix clustering  $\sigma$  at random
2. Compute consensus tree  $R_s$  for each cluster  $s$
3. Reassign each input trees  $T_i$  to cluster  $s$  where  $d(T_i, R_s)$  is minimum
4. Go to 2

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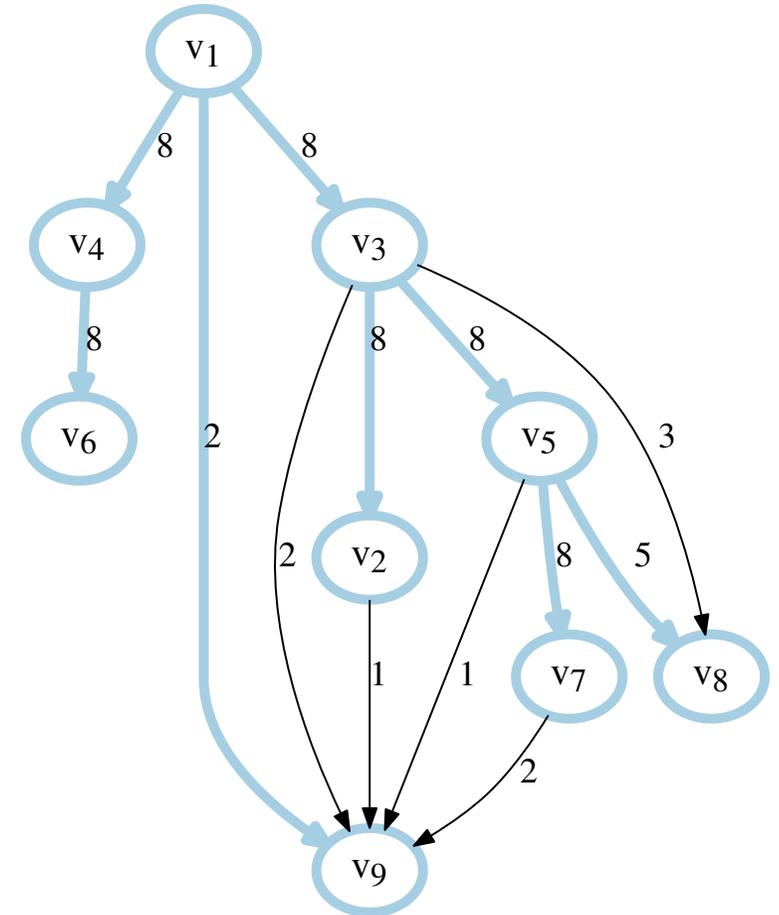
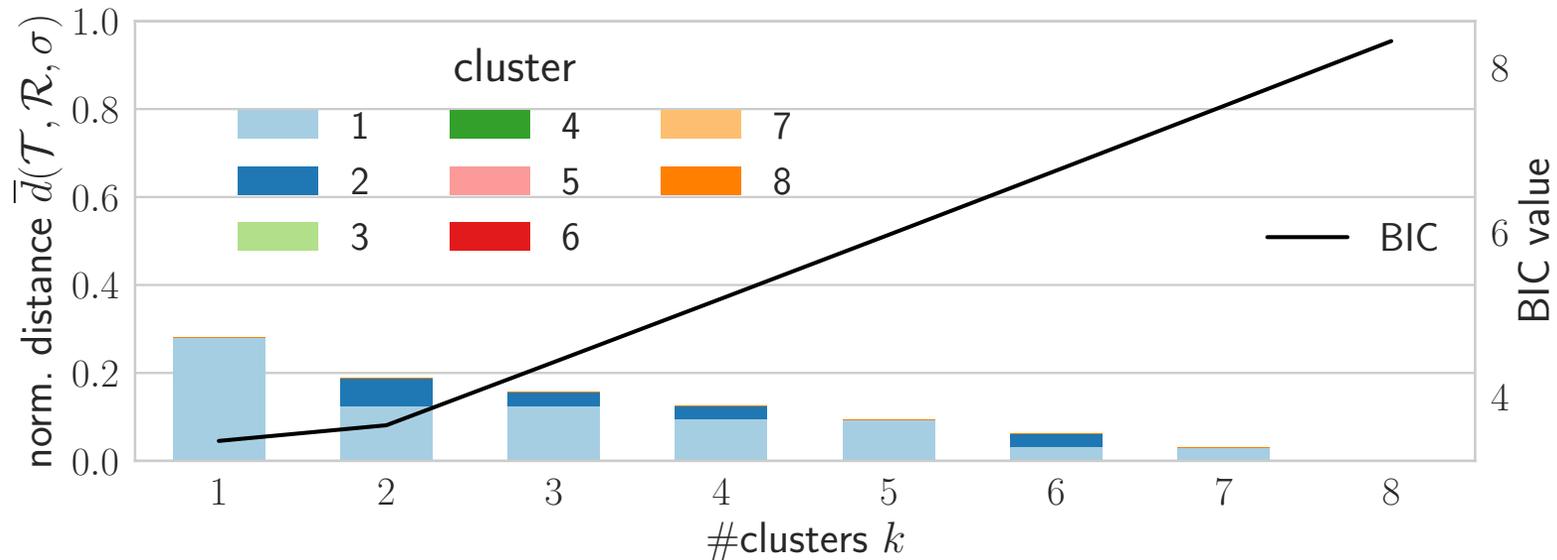
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4. Go to 2

	#clusters $k$	MILP (1 h)	BF (1 h)	CA (1 h)	CA (100 r.)
small (16)	2	16	16	16	16
	3	16	16	16	16
	4	16	16	16	16
	5	16	14	16	16
medium (15)	2	15	13	15	15
	3	13	7	13	13
	4	12	0	12	12
	5	10	0	10	10
large (14)	2	3	0	3	3
	3	0	0	0	0
	4	0	0	0	0
	5	0	0	0	0

# Bayesian Information Criterion

Jamal-Hanjani et al. (2017). *NEJM*.

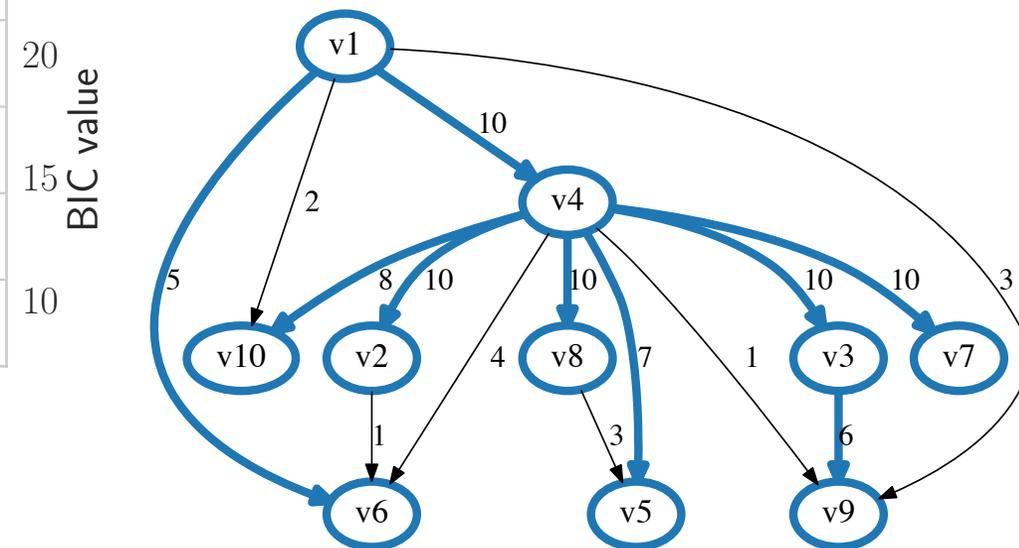
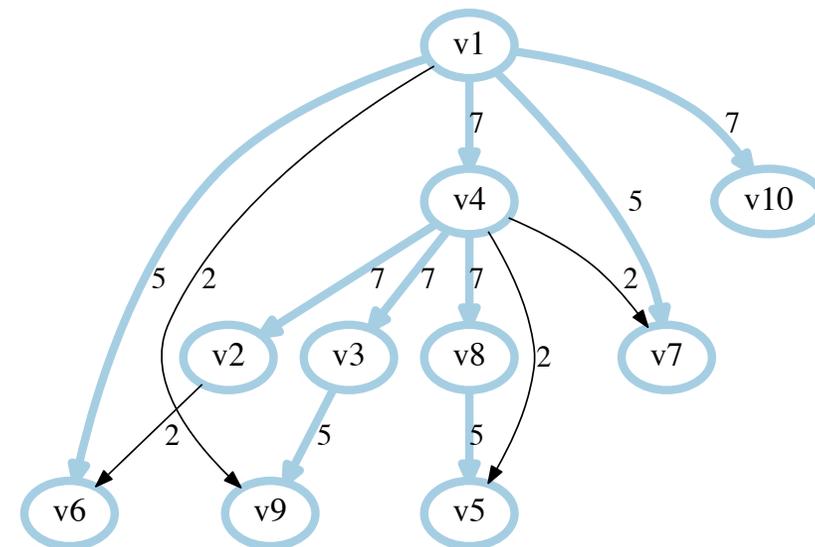
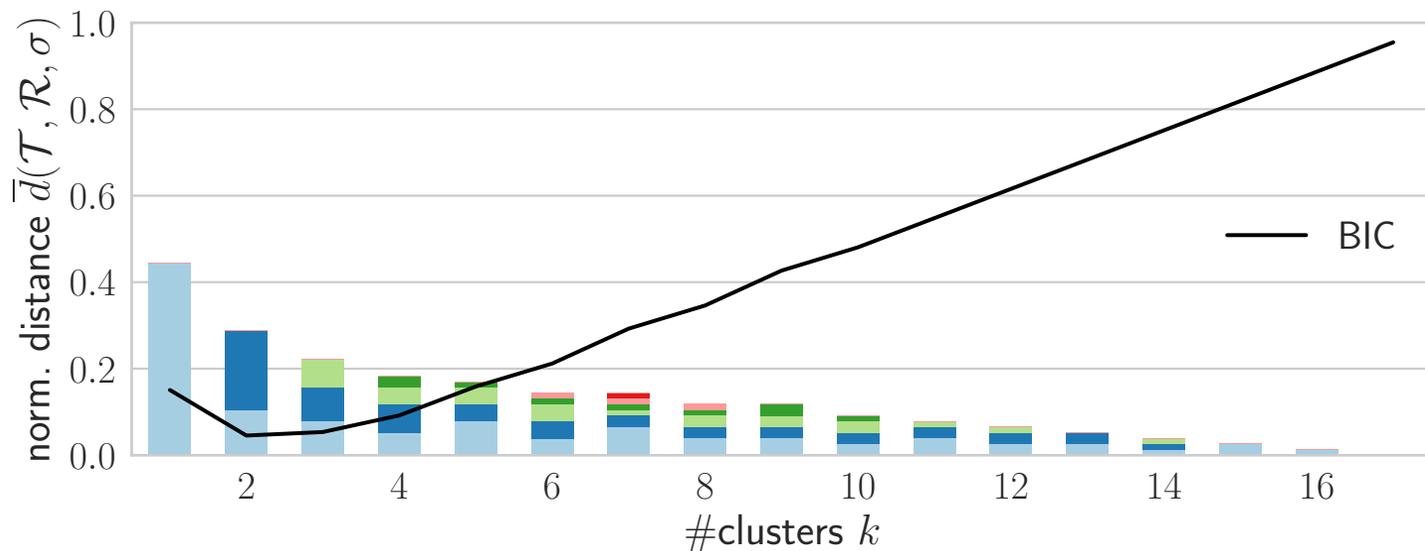
Jamal-Hanjani et al. inferred 8 trees for patient CRUK0013



# Bayesian Information Criterion

Jamal-Hanjani et al. (2017). *NEJM*.

Jamal-Hanjani et al. inferred 17 trees for patient CRUK0037



# Conclusion

- Introduced the Multiple Consensus Tree (MCT) problem
- Characterized combinatorial structure of optimal solutions
- Showed that MCT is NP-hard
- Presented a mixed integer linear program
- Presented an efficient heuristic and showed that it finds optimal solutions
- Model selection for the number of clusters

## **Future directions**

- Relax infinite sites assumption
- Use medoids rather than centroids