

CT Scan for Your Network: Topology Inference from End-to-End Measurements

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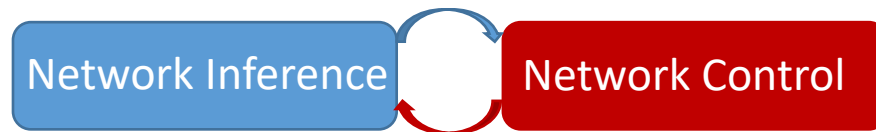
Network Sciences Research Group (NSRG)

• Interests:

- **communication networking** (network tomography, SDN, overlay, 5G, security)
- **distributed machine learning** (coreset, data reduction, federated learning)
- **mobile edge computing** (resource allocation)
- **cyber-physical systems** (smart grid, state estimation, false data injection)

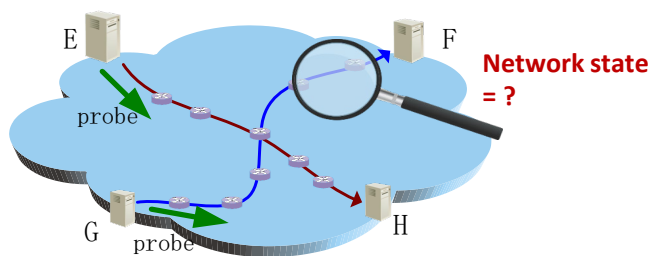
• Members:

- **Ting He, Associate Professor**
- 6 PhD students
- Alumni: 4 PhD, 6 MS (Bucknell, Google, Meta, ByteDance, HP, Amazon, Oracle)

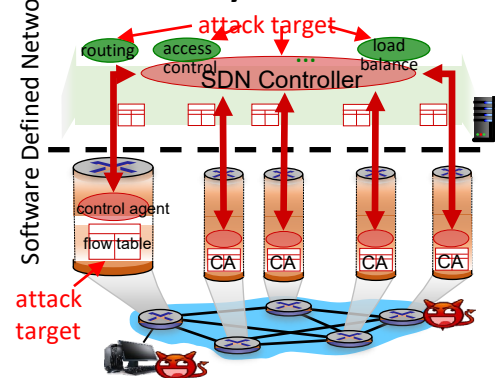


• Example projects:

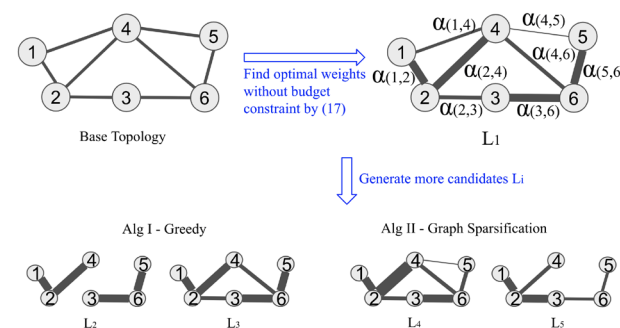
• Network tomography



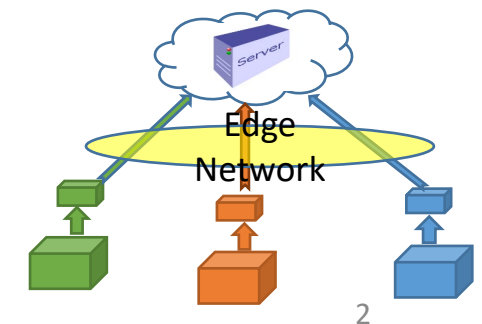
• Security in SDN



• Communication-efficient ML

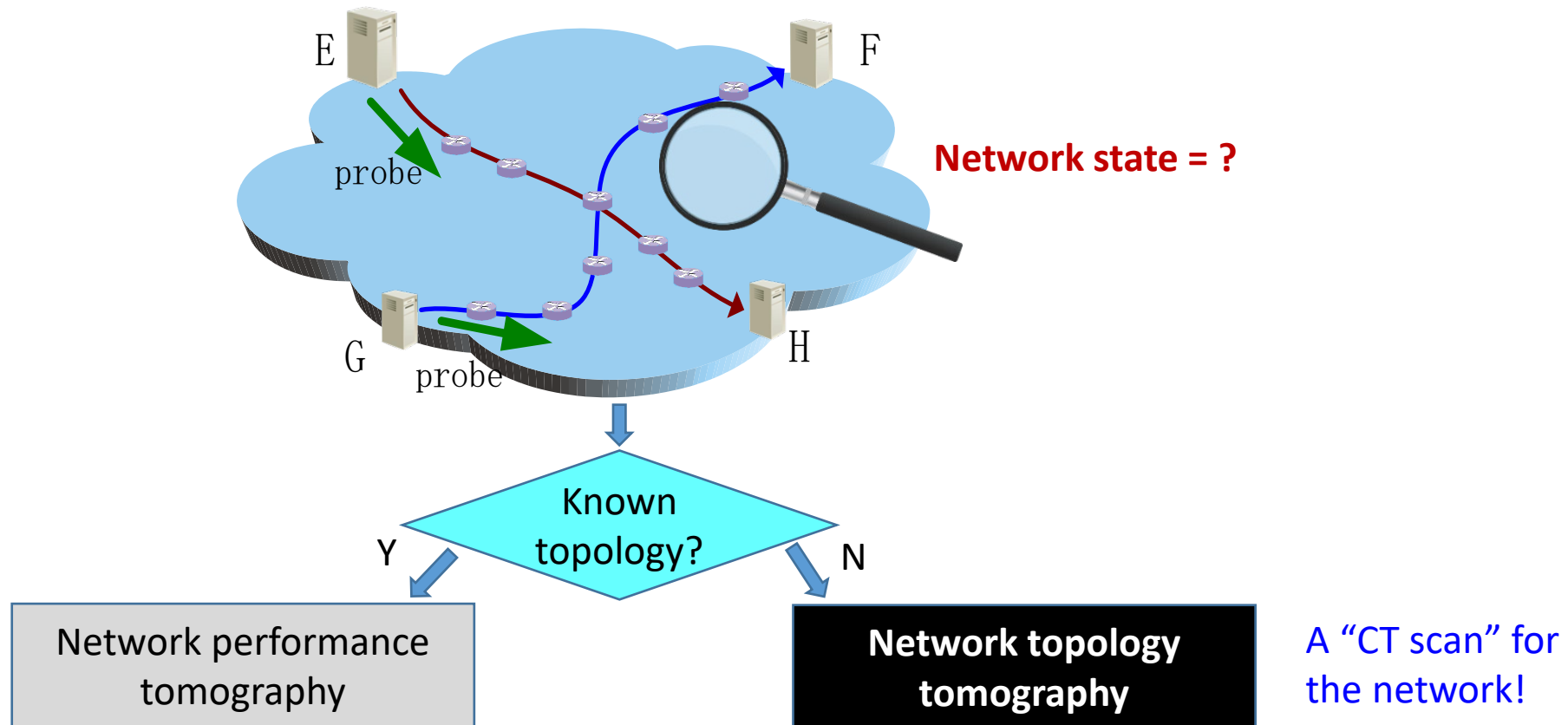


• Data reduction for ML



Overview: What is network tomography

- Using *external observations* to infer *internal network state*



Motivation: Why topology inference

- **Topology information is useful**

- Routing
- Service placement
- Client-server association
- Overlay management
- Load balancing
- Trouble shooting
- ...

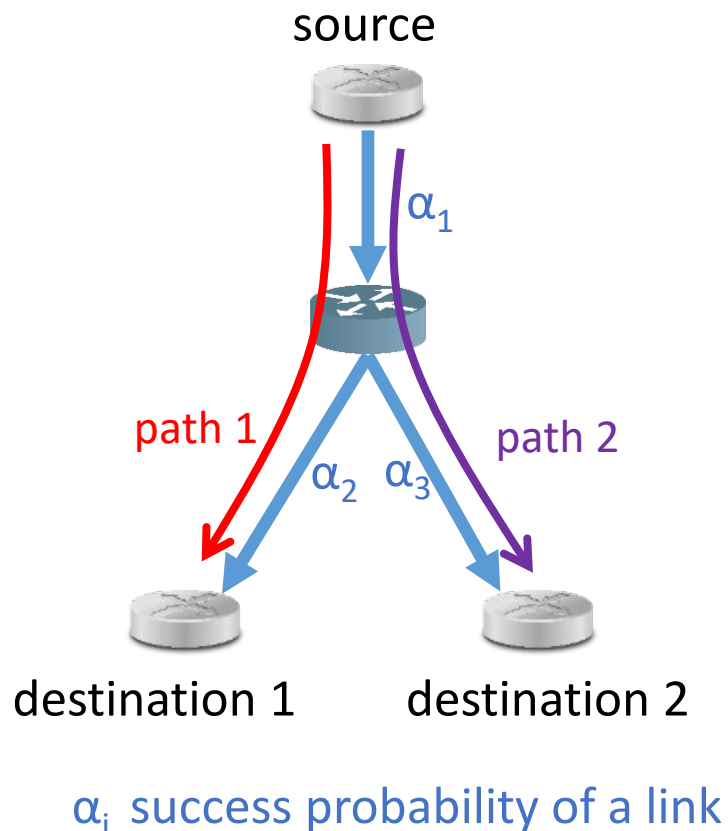
- **But it is not always observable**

- Use protocols to collect topology information (e.g., SNMP, OpenFlow) → **admin privilege**
- Use ICMP to measure topology (e.g., traceroute) → **supportive internal nodes**

Q: Is it possible to infer network topology from end-to-end measurements? If so, how?

Toy example: Why it is feasible

- Multicast measurements reveal internal topology



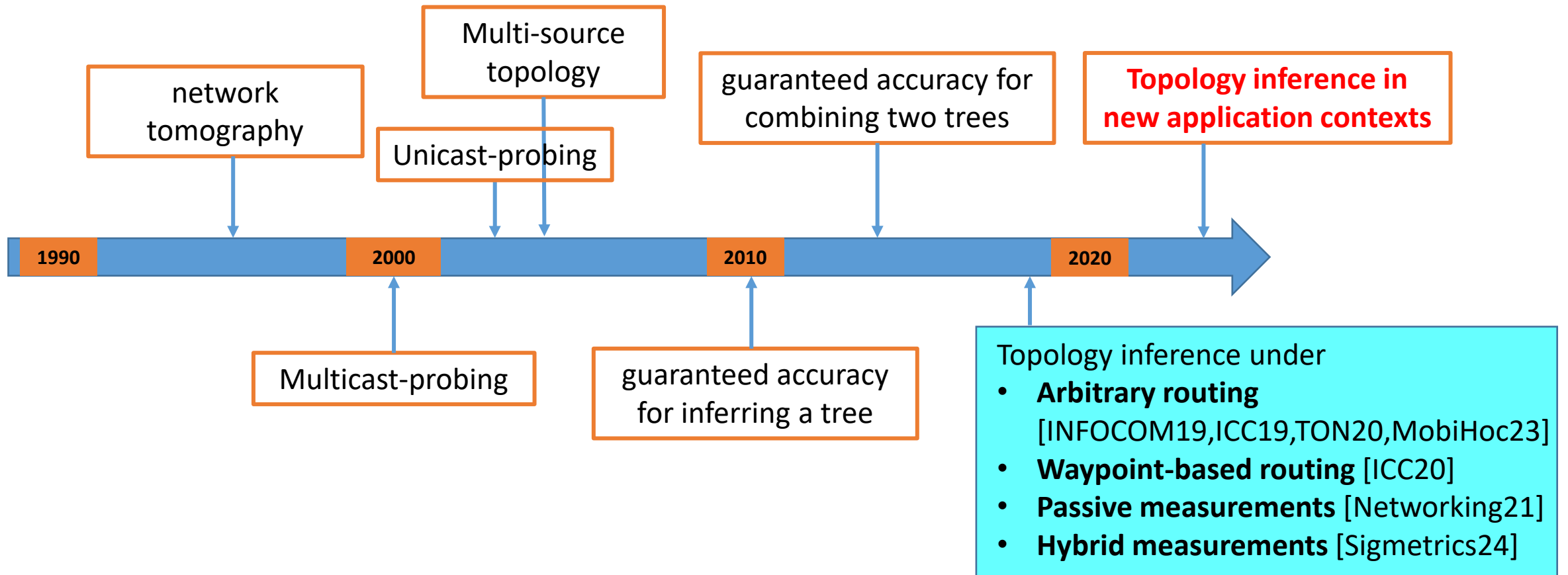
$$\begin{aligned} -\log \alpha_1 - \log \alpha_2 &= -\log \Pr\{X_{p_1} = 1\}, \\ -\log \alpha_1 - \log \alpha_3 &= -\log \Pr\{X_{p_2} = 1\}, \\ -\log \alpha_1 &= -\log \left(\frac{\Pr\{X_{p_1} = 1\} \Pr\{X_{p_2} = 1\}}{\Pr\{X_{p_1} = X_{p_2} = 1\}} \right). \end{aligned}$$

X_{p_i} : success indicator for path i

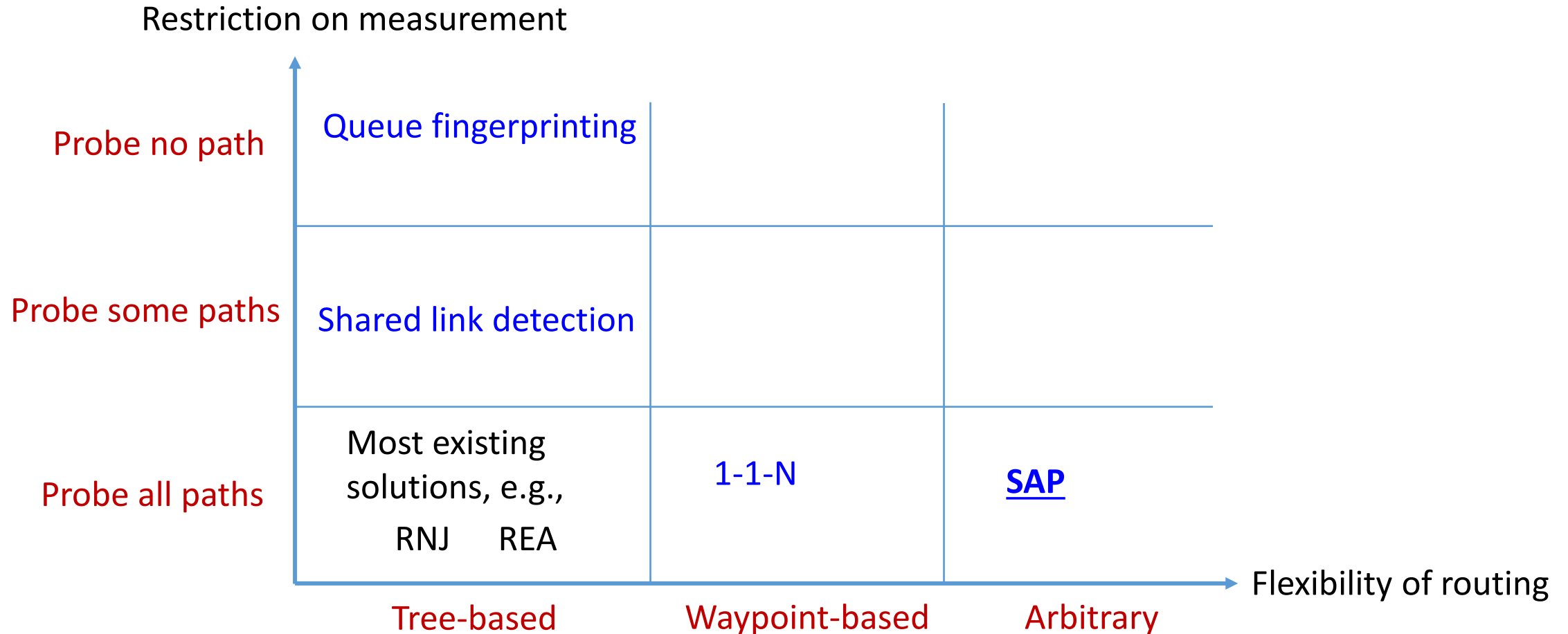
No shared link
(or sharing a lossless link) $\rightarrow -\log \alpha_1 = 0$

Sharing a lossy link $\rightarrow -\log \alpha_1 > 0$

History: Where we are



Our approach: Revisiting topology inference problems in new application contexts



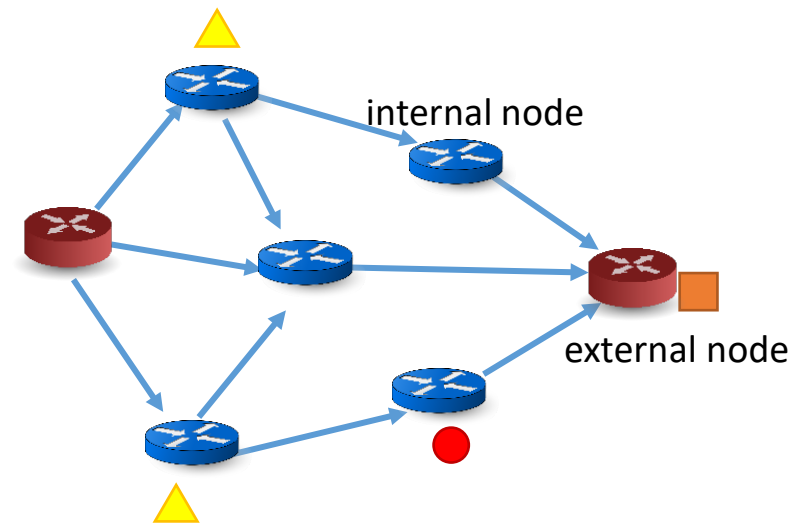
Scenario: Probe all paths, arbitrary routing

- **Motivation:** Inferring the structure and state of SDN-NFV network

- general topology
- waypoint traversal
- known service chain

- **Observation:**

- Measured: **end-to-end performance measurements** (e.g., losses)
- Inferred: lengths of paths, shared paths, union of paths
 - “length” measured by additive metric
 - E.g., $\theta_e = -\log \alpha_e$ (α_e : success prob. of edge e)
- Static: **source, destination, service chain**

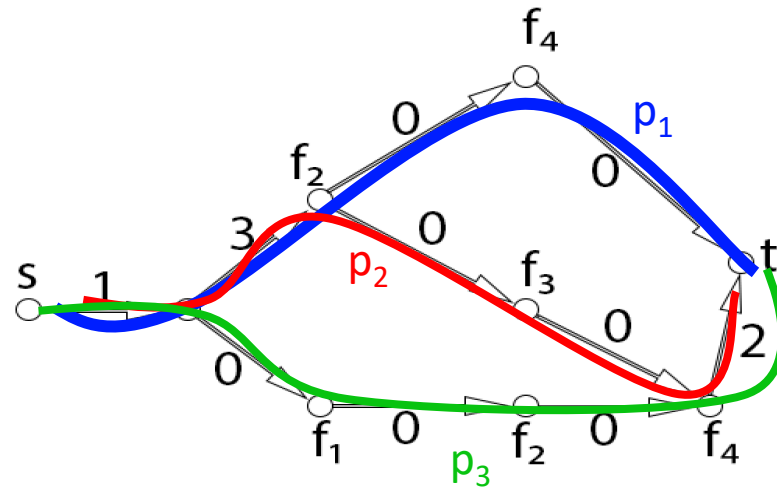


NFV network

- network function 1 (e.g., IDS)
- ▲ network function 2 (e.g., firewall)
- network function 3 (e.g., proxy)

Tree-based topology inference is insufficient

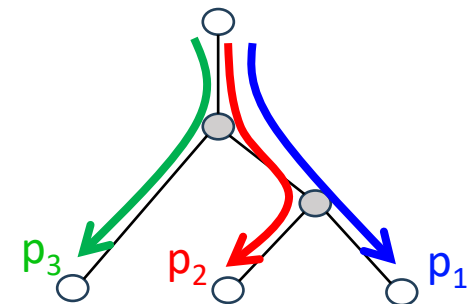
- Classic topology inference algorithms all assume tree-based routing
- But trees cannot always reconstruct the observations from a non-tree topology



$$\begin{aligned} \text{len}(p_1) &= 4 \\ \text{len}(p_2) &= 6 \\ \text{len}(p_3) &= 3 \end{aligned}$$

$$\begin{aligned} \text{len}(p_1 \cap p_2) &= 4 \\ \text{len}(p_1 \cap p_3) &= 1 \\ \text{len}(p_2 \cap p_3) &= 3 \end{aligned}$$

No tree topology reconstructs all these lengths
→ **not even guarantee a feasible solution**



Category weights are identifiable

• Weight Inference Problem:

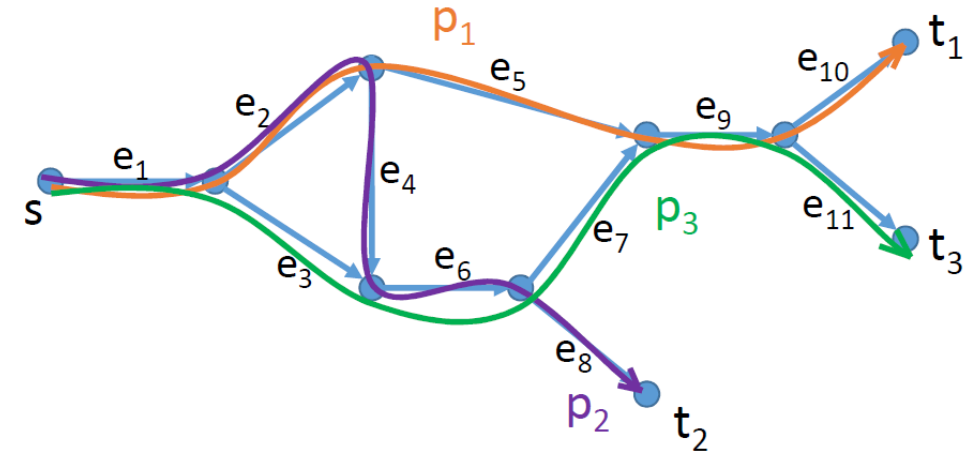
- Partition edges into $2^n - 1$ categories
 - **Category Γ_F** : set of edges traversed by and only by paths with indices in F
 - **Category weight w_F** : sum metric of edges in category Γ_F
- Observe *cast weights*, infer category weights
 - **Cast weight ρ_F** for a multicast on paths in F :

$$\rho_F := -\log(\Pr\{X_F = 1\}) = -\log\left(\prod_{e \in \bigcup_{i \in F} p_i} \alpha_e\right) = \sum_{e \in \bigcup_{i \in F} p_i} \theta_e$$

- Relationship between cast weights and category weights

Topology-agnostic

$$\rho_F = \sum_{F' \subseteq E: F' \cap F \neq \emptyset} w_{F'}, \quad \forall F \subseteq E$$



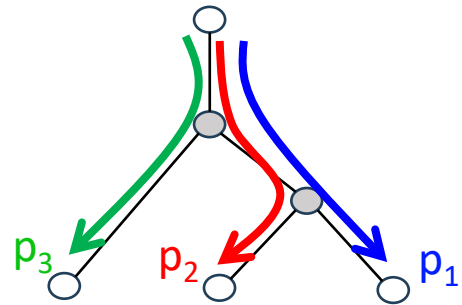
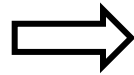
$$\begin{aligned} \rho_1 &= w_1 + w_{1,2} + w_{1,3} + w_{1,2,3} \\ \rho_2 &= w_2 + w_{1,2} + w_{2,3} + w_{1,2,3} \\ \rho_3 &= w_3 + w_{1,3} + w_{2,3} + w_{1,2,3} \\ \rho_{1,2} &= w_1 + w_2 + w_{1,2} + w_{1,3} + w_{2,3} + w_{1,2,3} \\ \rho_{1,3} &= w_1 + w_3 + w_{1,2} + w_{1,3} + w_{2,3} + w_{1,2,3} \\ \rho_{2,3} &= w_2 + w_3 + w_{1,2} + w_{1,3} + w_{2,3} + w_{1,2,3} \\ \rho_{1,2,3} &= w_1 + w_2 + w_3 + w_{1,2} + w_{1,3} + w_{2,3} + w_{1,2,3} \end{aligned}$$

Theorem: Category weights are uniquely determined by cast weights.

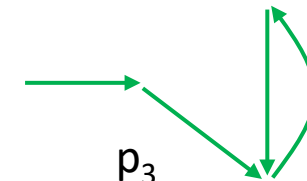
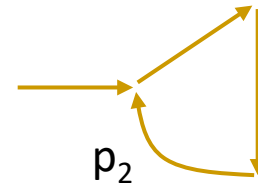
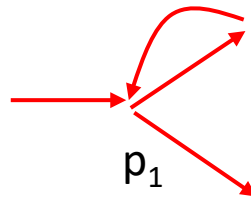
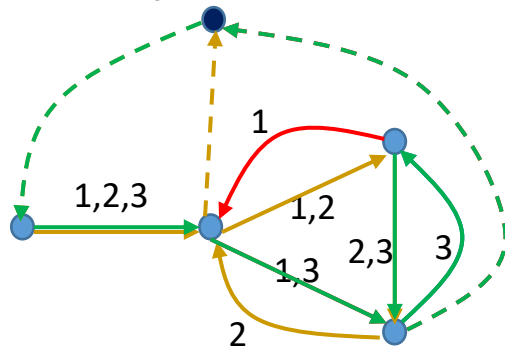
Category weights help, but are not enough

- Under mild assumption, category $\Gamma_F \neq \emptyset \Leftrightarrow w_F \neq 0$
- For trees, knowing non-empty categories \rightarrow knowing (logical) topology

$$\begin{aligned} \Gamma_{1,2,3} &\neq \emptyset \\ \Gamma_{1,2} &\neq \emptyset \\ \Gamma_1, \Gamma_2, \Gamma_3 &\neq \emptyset \end{aligned}$$



- But not so for arbitrary topology
 - E.g., can always embed the non-empty categories in a clique-like topology



Idea: Combining categories with service chain

- **String Augmentation Problem (SAP):**

- view each service chain as a string $s_i, f_{i,1}, f_{i,2}, \dots, t_i$
- insert dummy letters f_0^1, f_0^2, \dots s.t. for every positive-weight category A , $\exists a$ pair of letters appearing *only* in string i ($i \in A$)

$p'_1: s f_1 f_2 f_3 t$

$p'_2: s f_2 f_1 f_4 t$

$p'_3: s f_4 f_2 f_3 t$

$\mathcal{A}_+: \{1\}, \{2\}, \{3\},$

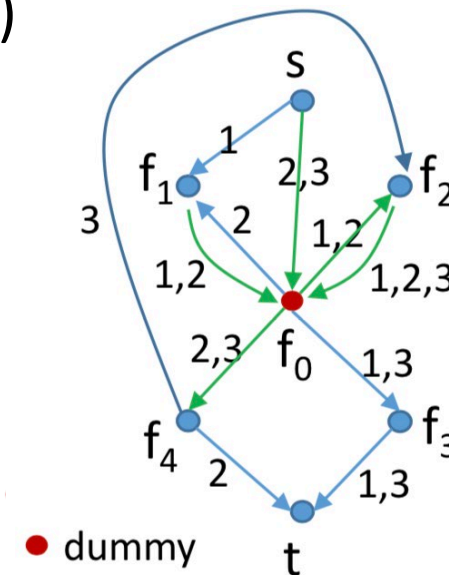
$\{1,2\}, \{1,3\}, \{2,3\},$

$\{1,2,3\}$

$p_1: s f_1 f_0 f_2 f_0 f_3 t$

$p_2: s f_0 f_2 f_0 f_1 f_0 f_4 t$

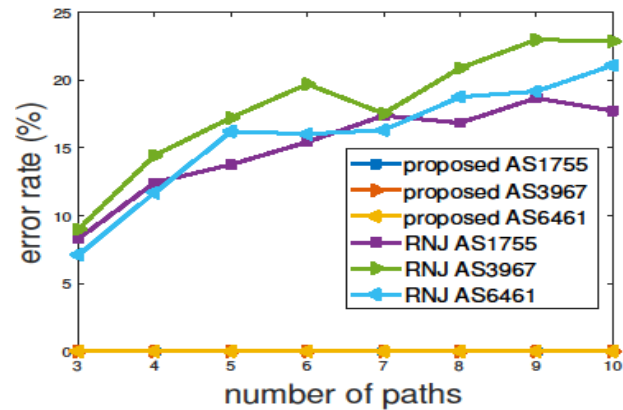
$p_3: s f_0 f_4 f_2 f_0 f_3 t$



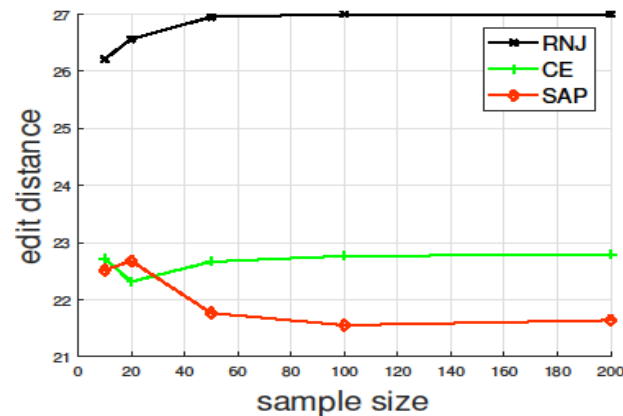
- Minimize #nodes/#links (can be formulated as an ILP)

Evaluation: VNF topology inference

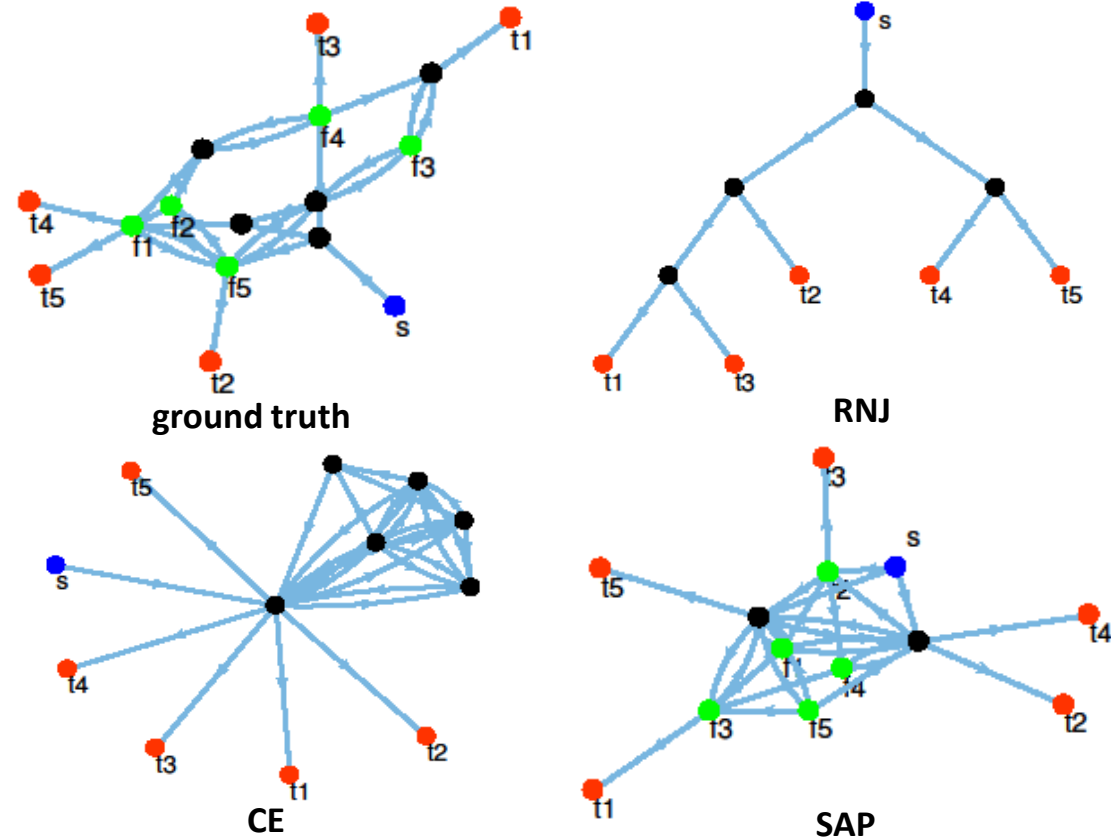
- Based on VNF overlays randomly generated on Rocketfuel AS topologies



(a) reconstruction error

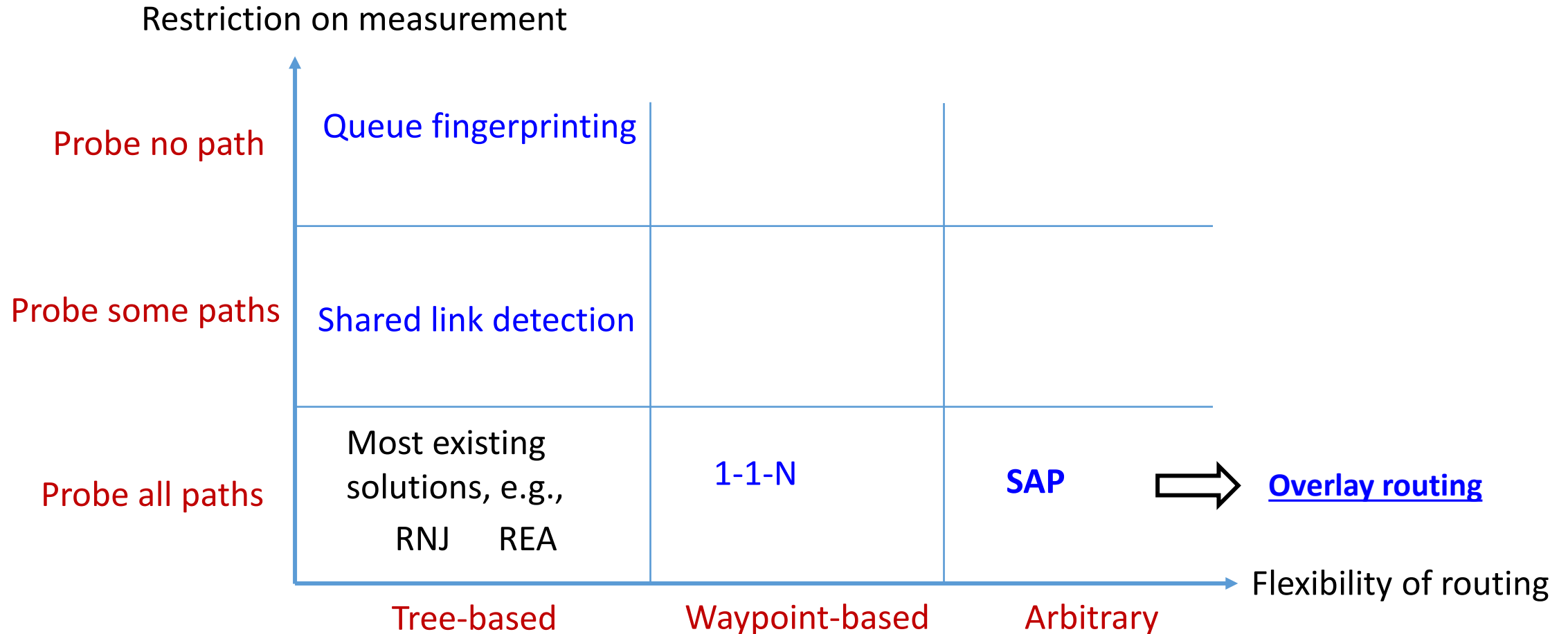


(b) convergence



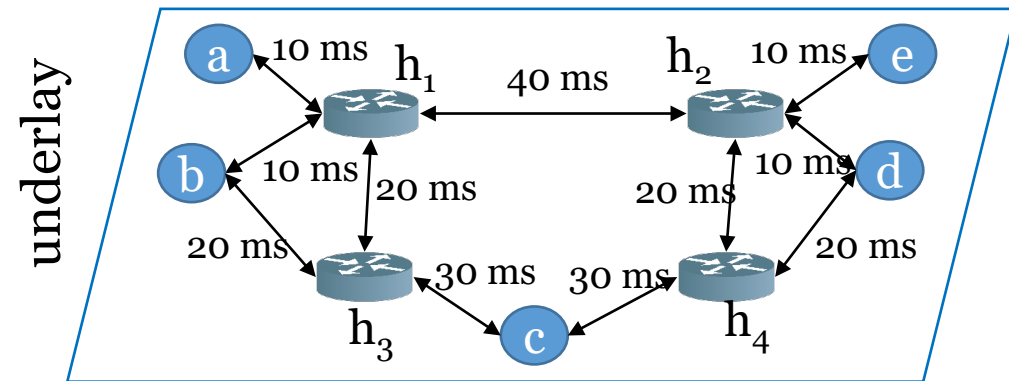
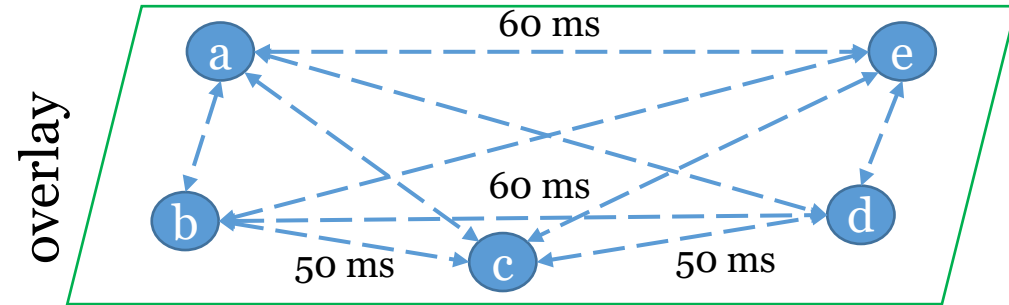
(c) inferred topologies

Topology inference from the perspective of upper-layer application



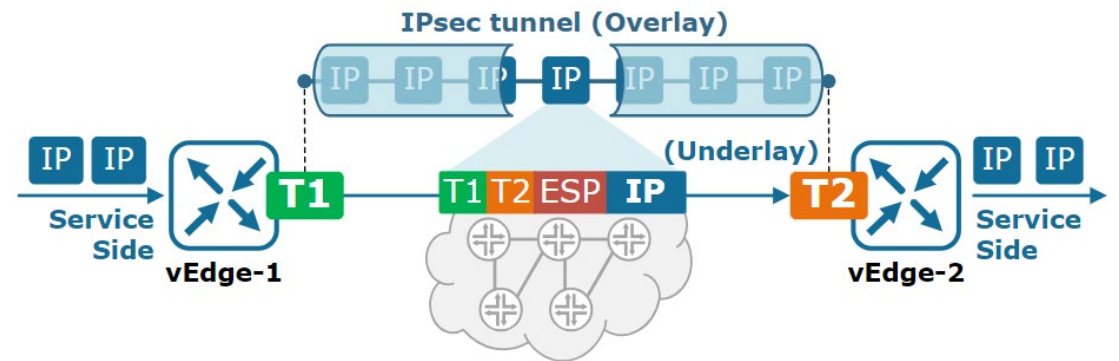
Overlay Network

- A logical network running on top of an underlying communication infrastructure (underlay network)
 - Enhance best-effort IP-based underlay network
 - Caching, traffic engineering (service-chaining, multicast), fast failover, network slicing, ...
 - Focus: **overlay-based routing**
- Example: SD-WAN
 - Software-Defined Wide-Area Networks



Managed SD-WAN Solutions

AT&T SD-WAN solutions can improve your network's agility and provide centralized control and improve total cost of ownership.



Cisco SD-WAN overlay fabric

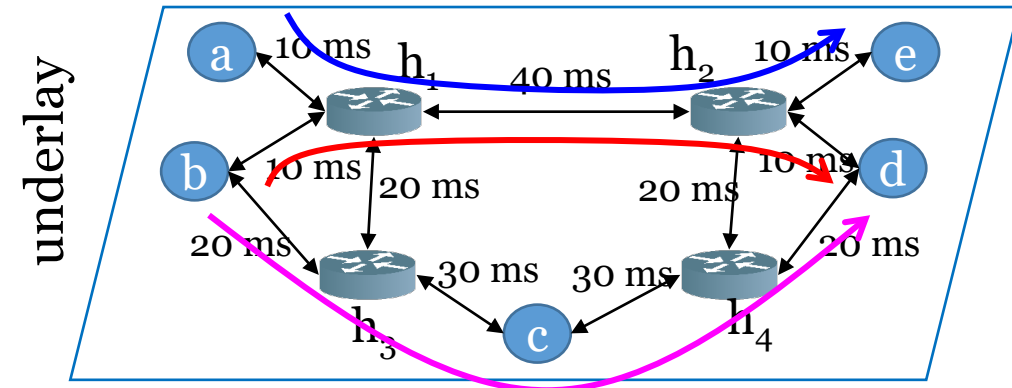
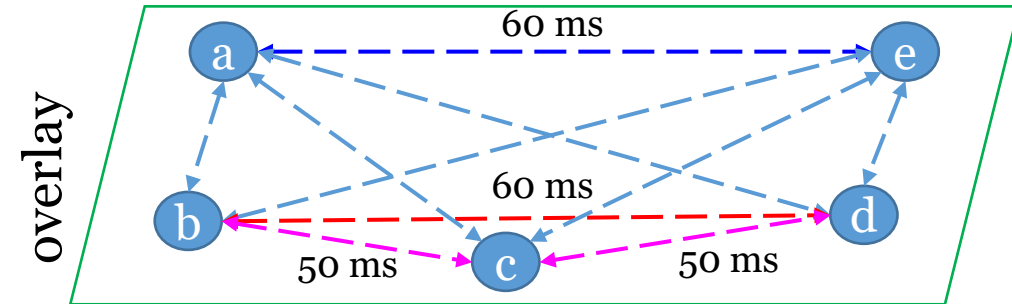
Routing in Overlay Network is Challenging

- Challenges

- Seemingly independent tunnels share underlay links
 - Congestion
- Uncooperative underlay
 - No direct underlay topology information

Q: Do we need the full topology for overlay routing?

A: No!



- Flow: a->e and b->d
- Direct tunnel: both traverse $h_1 \rightarrow h_2$
- Congestion-free overlay routing:
 - a->e
 - b->c->d

Overlay Routing Problem

$$\min_x \sum_{all_tunnels} tunnel_cost \sum_{all_demands} demand \cdot x_{tunnel}^{demand}$$

$$s.t. \quad x_{tunnel}^{demand} \in \{0,1\}$$

flow conservation constraints

Depend on routing & link
capacities in underlay

$$\sum_{tunnels_traverse_link} \sum_{demands} f_{tunnel}^{demand} \leq link_capacity, \forall links$$

Q: What is the **minimum information** for imposing **capacity constraints** for an **uncooperative underlay**?

Recall: Underlay Link Categorization

- (Underlay) link category

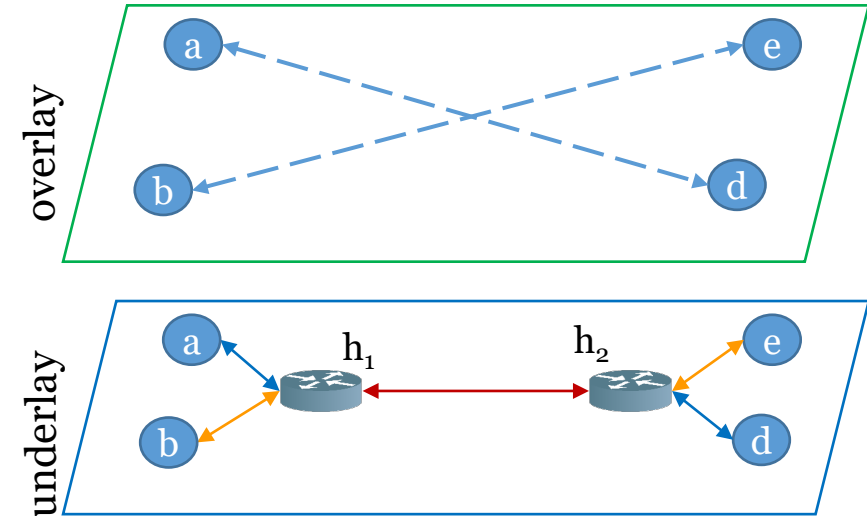
- $\Gamma_F(E)$: A **category of links traversed by F out of E** ($F \subseteq E$) is the set of underlay links traversed **by and only by** the tunnels in F out of all the tunnels in E

- i.e., $\Gamma_F(E) := \frac{\left(\bigcap_{(i,j) \in F} \underline{p}_{i,j} \right)}{\left(\bigcup_{(i,j) \in E \setminus F} \underline{p}_{i,j} \right)}$

Links shared by F All links traversed by $E \setminus F$

- Category weight: $w_F(E) := \sum_{\underline{e} \in \Gamma_F(E)} \theta_{\underline{e}}$

Observation: Knowledge of **link categories suffices for congestion-free overlay routing**



Example: $E = \{(a, d), (b, e)\}$

- $F_1 = \{(a, d), (b, e)\}$
 - $\Gamma_{F_1}(E) = \{(h_1, h_2)\}$
- $F_2 = \{(a, d)\}$
 - $\Gamma_{F_2}(E) = \{(a, h_1), (h_2, d)\}$
- $F_3 = \{(b, e)\}$
 - $\Gamma_{F_3}(E) = \{(b, h_1), (h_2, e)\}$

Category-based Capacity Constraints



Links in the same category receive the same traffic load from the overlay

Full topology

information – which tunnels traverse each link



Partial topology

information – which tunnels exclusively share links, i.e., $\Gamma_F(E) \neq \emptyset$

Per-link constraints:

$$\sum_{\text{tunnels_traverse_link}} \sum_{\text{demands}} f_{\text{tunnel}}^h \leq \text{link_capacity}$$



Per-category constraints:

$$\sum_{\text{tunnels_in_category}} \sum_{\text{demands}} f_{\text{tunnel}}^h \leq \text{category_capacity}$$

Full capacity information

– what is the capacity of each link



Partial capacity information

– what is the min link capacity in each category

Challenge of Category Inference

Measurements in overlay $\rightarrow \rho_F$

$$\rho_F := \sum_{\underline{e} \in \bigcup_{(i,j) \in F} \underline{p}_{i,j}} \theta_{\underline{e}}$$

Candidate category weight w_F

$$w_F(E) := \sum_{\underline{e} \in \Gamma_F(E)} \theta_{\underline{e}}$$

$$\rho_F = \sum_{F' \subseteq E: F' \cap F \neq \emptyset} w_{F'}(E), \forall F \subseteq E$$

- **Full rank** linear system
- $w_F(E) > 0 \implies \Gamma_F(E) \neq \emptyset$

Q: Is problem solved?

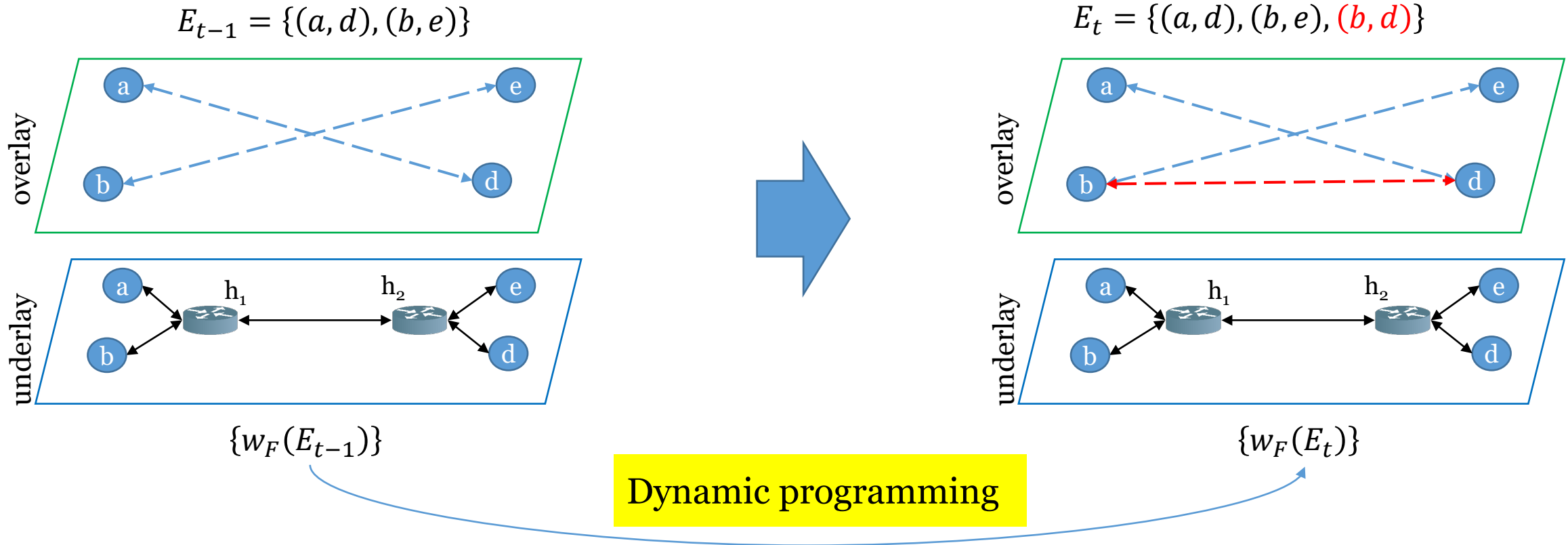
A: Unfortunately, **no**

- **Exponential complexity!** #variables = $2^{|E|} = 2^{O(|V|^2)}$
- Example: $|V| = 10$, number of candidate categories: 2^{90}

Taming the Complexity in Category Inference

Idea: Given $\{w_F(E_{t-1})\}$ and $E_t \leftarrow E_{t-1} \cup \{e_t\}$, augment it into $\{w_F(E_t)\}$

→ Dynamic programming

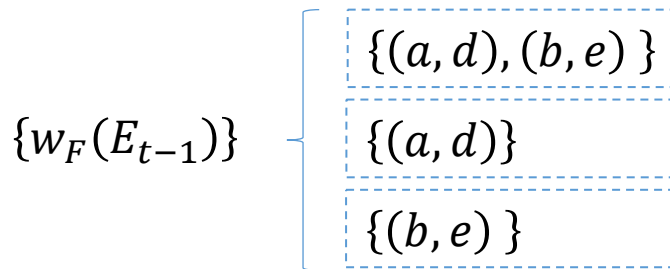
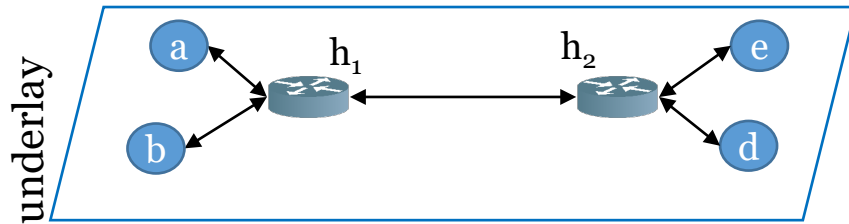
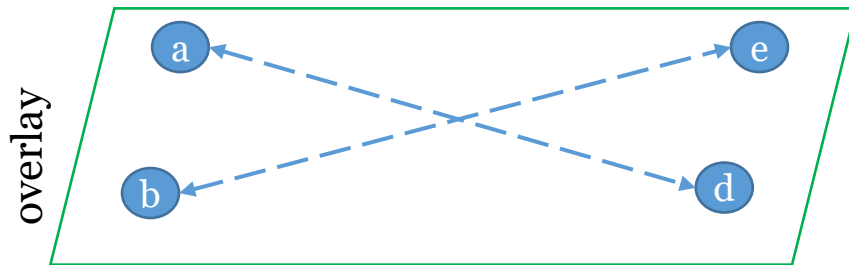


Idea for Dynamic Programming

- Category weights are decomposed gradually

- For any $E' \subset E$ and $e \in E \setminus E'$, $w_F(E') = w_{F \cup \{e\}}(E' \cup \{e\}) + w_F(E' \cup \{e\})$

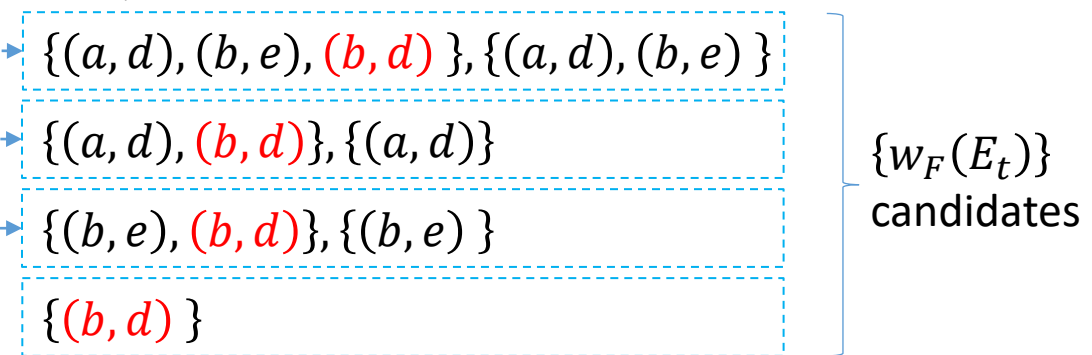
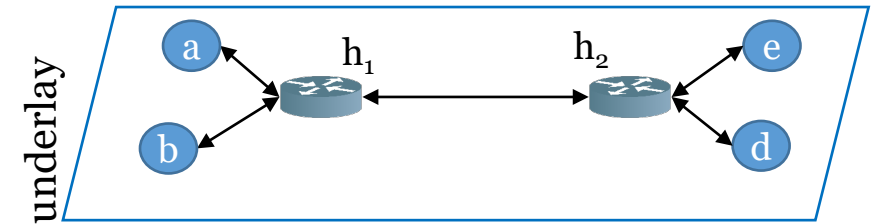
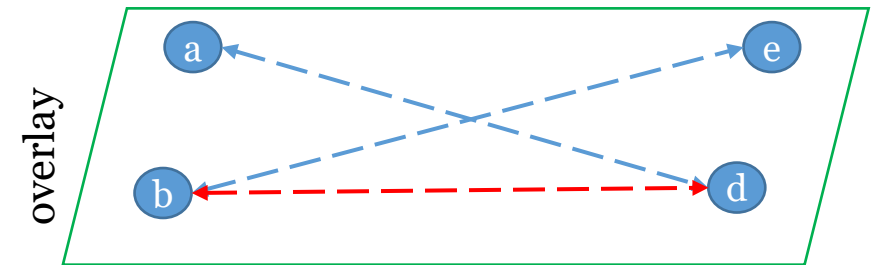
$$E_{t-1} = \{(a, d), (b, e)\}$$



$$|\text{supp}(\mathbf{w}(E_{t-1}))| \leq |E|$$

(#non-empty categories \leq #underlay links)

$$E_t = \{(a, d), (b, e), (b, d)\}$$



$$\# \text{variables} = 2|\text{supp}(\mathbf{w}(E_{t-1}))| + 1$$

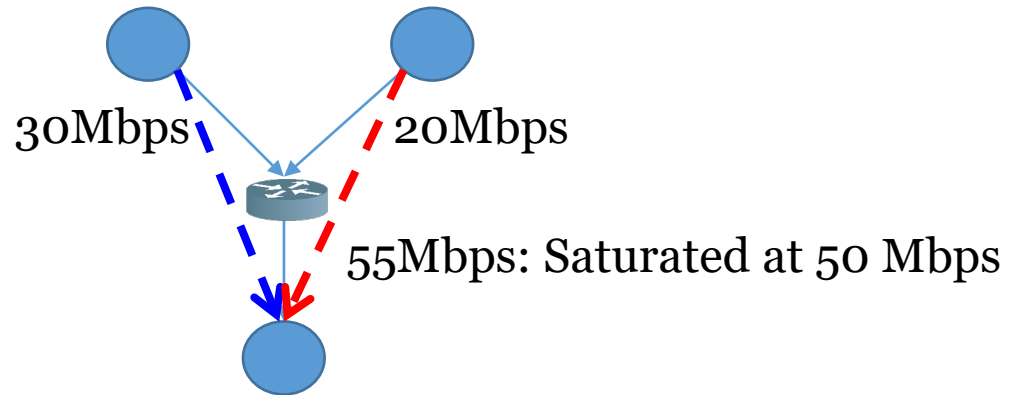
Algorithm for Category Inference

- Dynamic programming with the update rule:
 - $E_t \leftarrow E_{t-1} \cup \{e\}$
 - $w_{\{e\}}(E_t) \leftarrow \rho_{E_t} - \rho_{E_{t-1}}$
 - For $F \in \text{supp}(w(E_{t-1}))$ in an increasing order of $|F|$:
 - $w_{F \cup \{e\}}(E_t) \leftarrow \rho_{(E_{t-1} \setminus F) \cup \{e\}} - \rho_{E_{t-1} \setminus F} - w_{\{e\}}(E_t) - \sum_{F' \subset F: F \in \text{supp}(w(E_{t-1}))} w_{F' \cup \{e\}}(E_t)$
 - $w_F(E_t) \leftarrow w_F(E_t) - w_{F \cup \{e\}}(E_t)$
- #variables = $2|\text{supp}(w(E_{t-1}))| + 1 = O(|E|)$

- In each iteration, solve a **linear system** whose size is **linear in the underlay network size**.
- In total $|E|$ iterations, **linear in the overlay network size**
- The first **polynomial-time** algorithm for category inference

Effective Category Capacity Inference

- The minimum capacity of the links in a category may not be measurable



- Effective Category Capacity: maximum flow through the tunnels associated with the category

- $\tilde{C}_F := \max_{(f_e)_{e \in E}} \sum_{e \in F} f_e$ (f_e : flow assigned to tunnel e)

s.t. $\sum_{e' \in F'} f_{e'} \leq C_{F'}$, $\forall F' \subseteq E, \Gamma_{F'} \neq \emptyset$
 $f_e \geq 0, \forall e \in E$ UNKNOWN

Effective Category Capacity Estimation

[1] Jain M, Dovrolis C. "End-to-end available bandwidth: measurement methodology, dynamics, and relation with TCP throughput," IEEE/ACM TNET, 2003.

• Algorithm:

Algorithm 3: Effective Category Capacity Estimation

input : set \mathcal{F} of category indices of interest (e.g.,
 $\mathcal{F} := \{F \subseteq E : \hat{w}_F > \eta\}$)
output : Estimated effective category capacities $\{\hat{C}_F\}_{F \in \mathcal{F}}$

- 1 **for** each $F := \{e_{i_1}, \dots, e_{i_{|F|}}\} \in \mathcal{F}$ **do**
- 2 $f_{e_{i_1}} \leftarrow \hat{C}_{e_{i_1}}(\mathbf{0});$ \longrightarrow Initialize all flows f_e to zero
- 3 **for** $j = 2, \dots, |F|$ **do**
- 4 $f_{e_{i_j}} \leftarrow \hat{C}_{e_{i_j}}(\mathbf{f});$ \longrightarrow Subroutine [1]: test the residual capacity of a tunnel given flow assignment
- 5 $\hat{C}_F \leftarrow \sum_{j=1}^{|F|} f_{e_{i_j}};$ \longrightarrow Sum of flow rates
- 6 **return** $\{\hat{C}_F\}_{F \in \mathcal{F}};$

• Performance guarantee

- If Line~4 is accurate, then Algorithm 3 achieves $1/q_F$ approximation
 - $q_F := \max_{e \in F} |\{F' \subseteq E : e \in F', \Gamma_{F'} \neq \emptyset, |F' \cap F| > 1\}|$
 - maximum number of nonempty categories a tunnel in F traverses that are shared by at least another tunnel in \bar{F}

Resulting Overlay Routing Problem

$$\min_x \sum_{all_tunnels} tunnel_cost \sum_{all_demands} demand \cdot x_{tunnel}^{demand}$$

$$s.t. \quad x_{tunnel}^{demand} \in \{0,1\}$$

flow conservation constraints

$$\sum_{tunnels_in_category} \sum_{demands} f_{tunnel}^h \leq category_capacity$$

Partial topology information

– which tunnels exclusively share links

Partial capacity information

– what is the effective category capacity

NS3-Based Simulation

- Topologies from Internet Topology Zoo

	AttMpls	AboveNet	GTS-CE	BellCanada
$ V $	25	23	149	48
$ E $	114	62	386	130
C_e (Gbps)	1	1	1	1
Link delays (us)	[206,4973]	[100, 13800]	[5,1081]	[78, 6160]

- **Background traffic**
 - ON-OFF process for each link independently
 - Duration follows Pareto distribution
 - Utilization: [10%,40%]
- **Probing**
 - Number of overlay nodes: 10
 - 50-byte packets for probing; 1000-byte packets for routings
 - Measurements: end-to-end delays
- **Routing cost: link (propagation) delays**

Performance of Inference

Non-Empty Category Detection

	AttMpls	AboveNet	GTS-CE	BellCanada
#empty cat.	$2^{90} - 69$	$2^{90} - 52$	$2^{90} - 59$	$2^{90} - 51$
#nonempty cat.	69	52	59	51
#false alarms	603	542	2159	1695
#misses	20	27	40	30

- **Low false alarm rate** although the absolute number is not small
- **High miss rate:** Inaccurate estimation of ρ_F if (1) $|F|$ is large or (2) tunnels in F have different sources

Effective Category Capacity Estimation

	AttMpls	AboveNet	GTS-CE	BellCanada
ideal subroutine	0.10%	0.13%	0.13%	0.4%
Pathload	1.07%	1.18%	1.15%	1.49%

- **Highly accurate capacity estimation:** *False alarms will not hurt* in most case, but *misses may lead to congestions.*

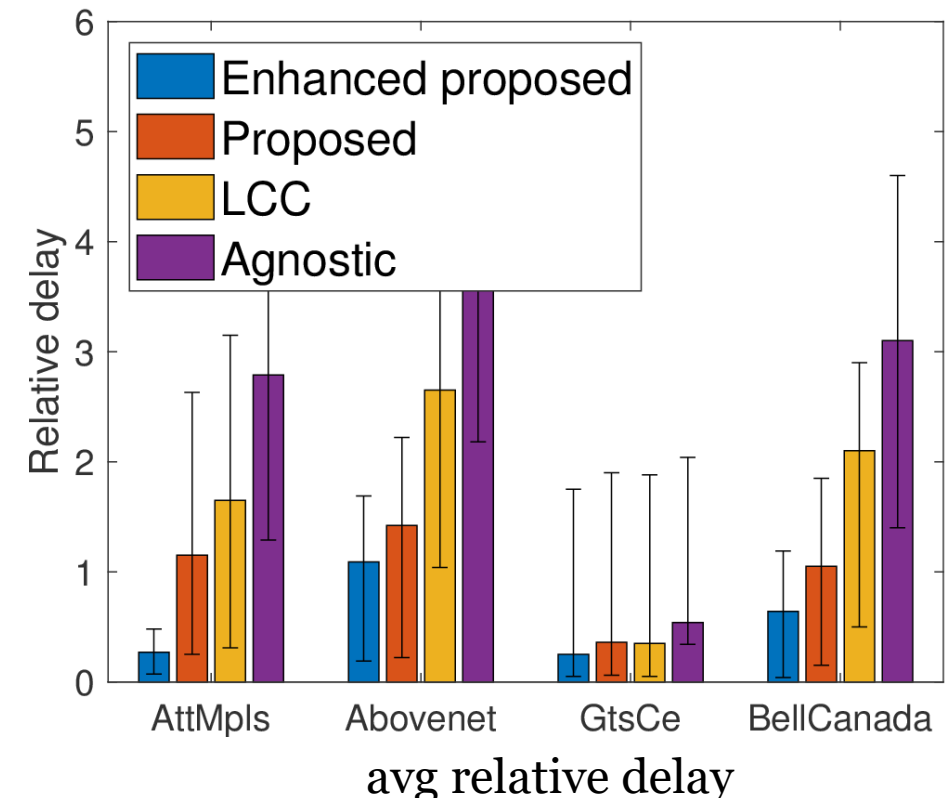
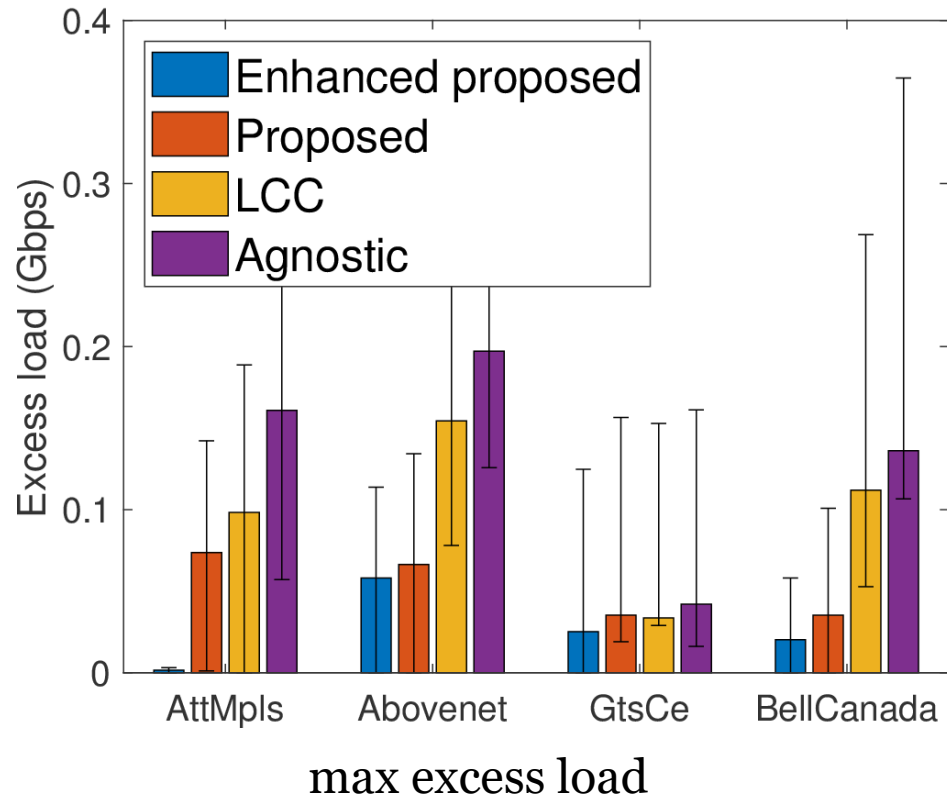
Performance of Overlay Routing

[2] Y. Zhu and B. Li, "Overlay networks with linear capacity constraints," IEEE TPDS, 2008

- **Benchmarks**

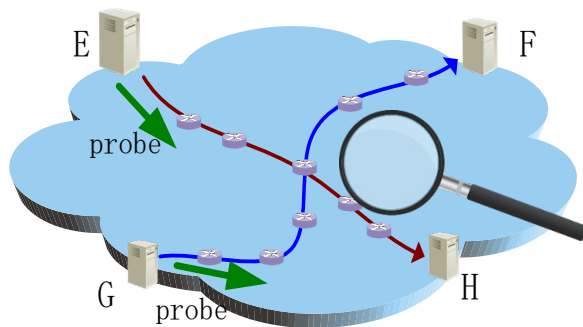
- **“Agnostic”**: an underlay-agnostic routing
- **“LCC”**: the state-of-the-art solution from [2]
- **“Proposed”**
- **“Enhanced proposed”**: “Proposed” + “LCC”

Improved overlay routing performance despite notable estimation errors



Concluding Remark

- Topology inference: **Jointly infer network *internal structure & state* from *external observations***
 - What structures are possible, what measurements are allowed
 - A tool for **application-layer network optimization** (e.g., overlay routing)



**Network structure
& state = ?**

Restriction on measurement

Probe no path	Queue fingerprinting		
Probe some paths	Shared link detection		
Probe all paths	Most existing solutions, e.g., RNJ REA	1-1-N	SAP
	Tree-based	Waypoint-based	Arbitrary

Flexibility of routing

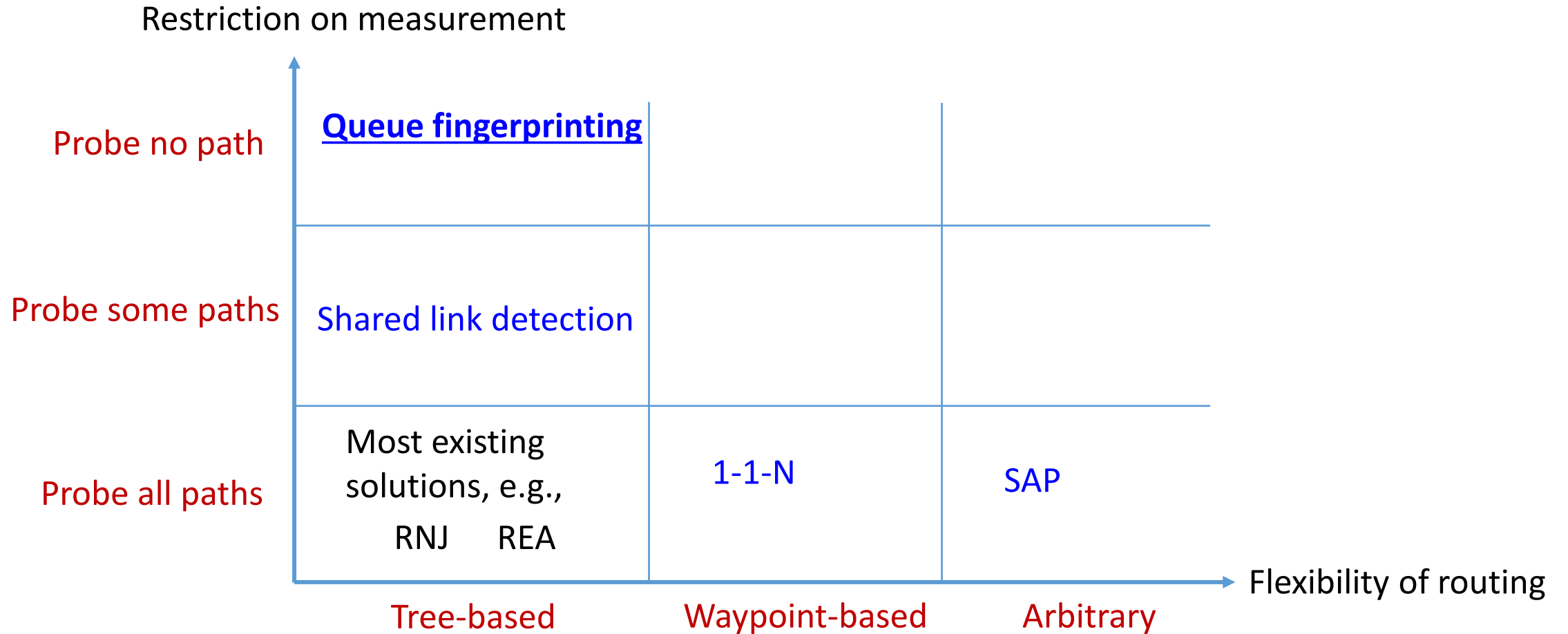
CT Scan for Your Network: Topology Inference from End-to-End Measurements

Ting He, tinghe@psu.edu

THANK YOU

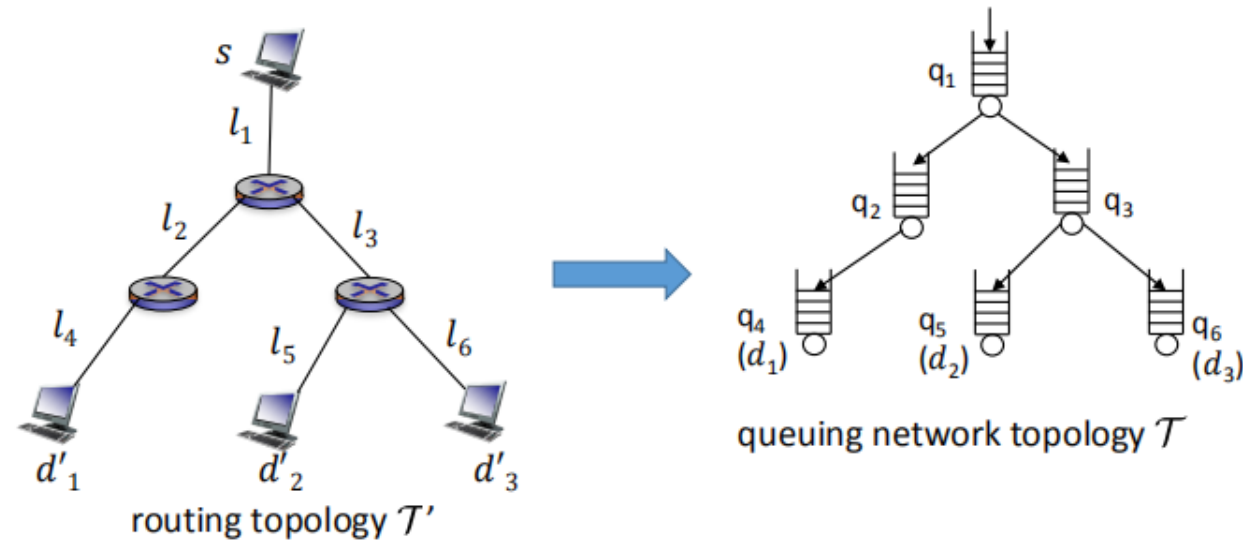
Backup slides

Outline



Scenario: Passive monitoring only

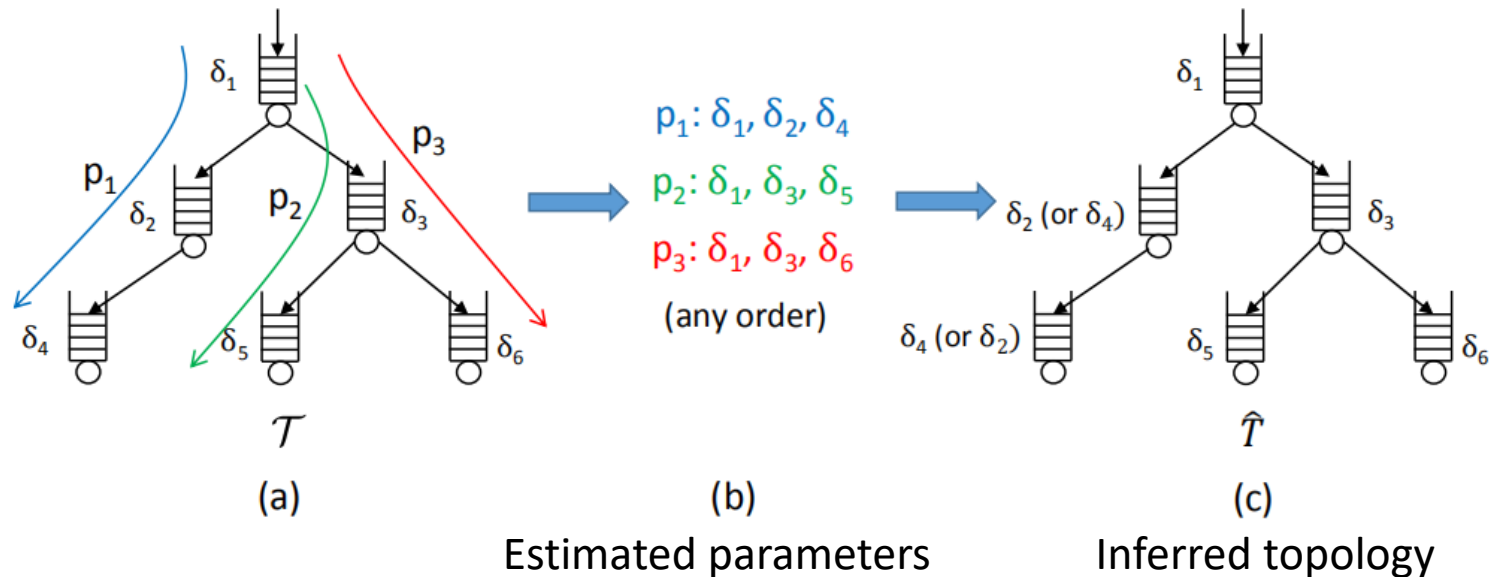
- A network of independent M/M/1 queues



- **Goal:** Address two key limitations of existing solutions
 - Active probing \rightarrow **passive monitoring**
 - Logical topology \rightarrow **physical topology**

Why it is feasible

- Queue parameter: $\delta_i = \mu_i - \lambda_i$ (residual capacity)
- Sojourn time: exponential r.v. with PDF $\delta_i e^{-\delta_i t}$
- End-to-end delay: hypoexponential r.v. with parameters $\boldsymbol{\delta} := (\delta_i)_{i=1}^K$
- Idea: **Queue fingerprinting**



Parameter estimation for tandem of M/M/1 queues: Estimator

- Idea 1: **MLE**

$$\hat{\delta} = \operatorname{argmax}_{\delta} \sum_{h=1}^n \log g(x_h; \delta)$$

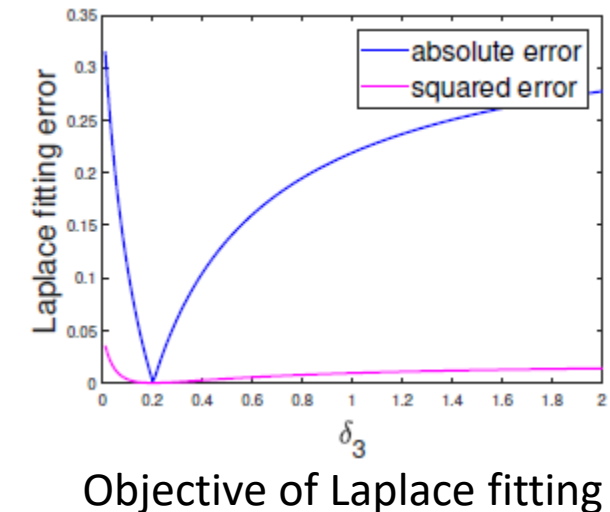
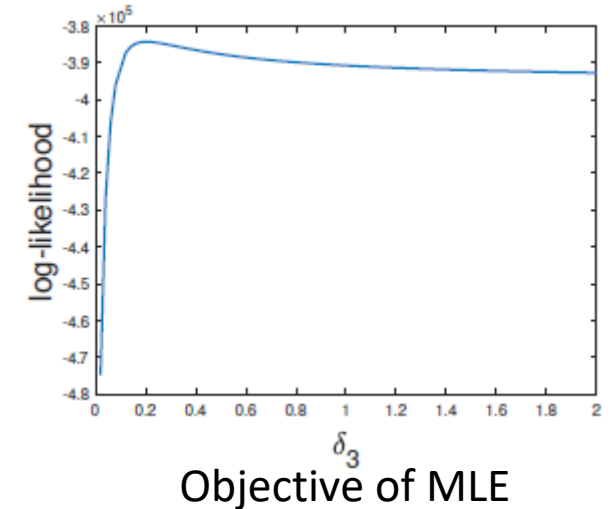
- PDF:
$$g(x; \delta) = \sum_{i=1}^K \delta_i e^{-x\delta_i} \left(\prod_{j=1, j \neq i}^K \frac{\delta_j}{\delta_j - \delta_i} \right)$$

- Idea 2: **Fitting Laplace transform**

- Laplace transform:
$$L(s; \delta) := \prod_{i=1}^K \frac{\delta_i}{\delta_i + s}, \quad s > -\min_{i=1, \dots, K} \delta_i.$$

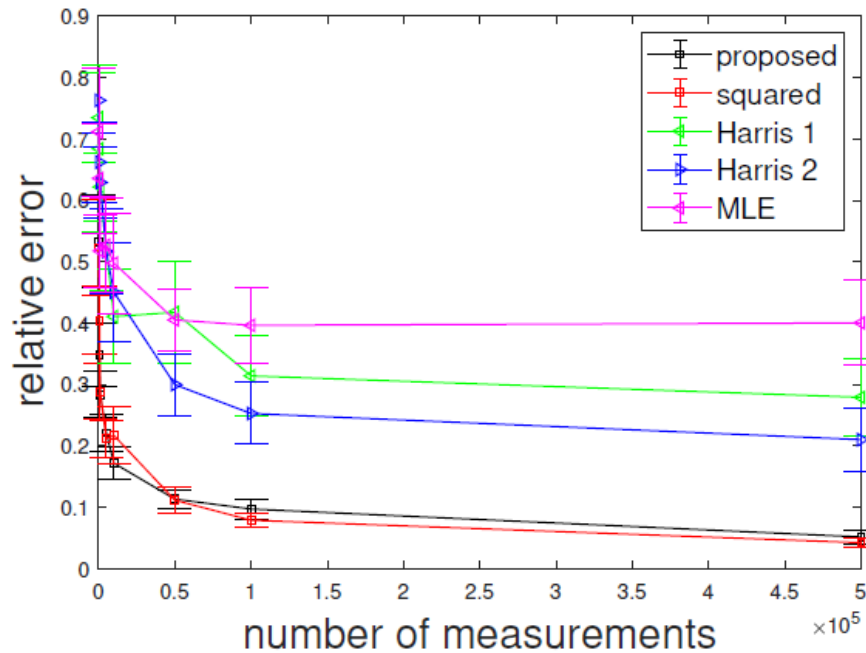
- Empirical Laplace transform:
$$\hat{L}(s; \mathbf{x}) := \frac{1}{n} \sum_{h=1}^n e^{-sx_h}$$

$$\begin{aligned} \rightarrow \quad & \min \sum_{s \in S} |L(s; \delta) - \hat{L}(s; \mathbf{x})| \\ & \text{s.t. } 0 < \delta_1 \leq \dots \leq \delta_K, \end{aligned}$$

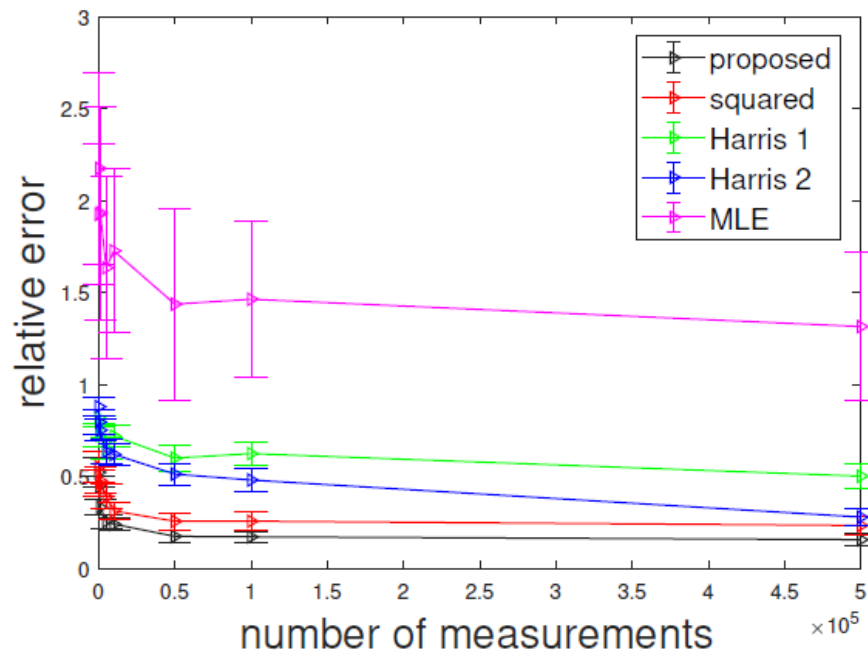


Parameter estimation for tandem of M/M/1 queues: Performance

- **Theorem.** As $n \rightarrow \infty$, Laplace fitting has a unique optimal solution that equals the ground truth δ if $|S| > K$.



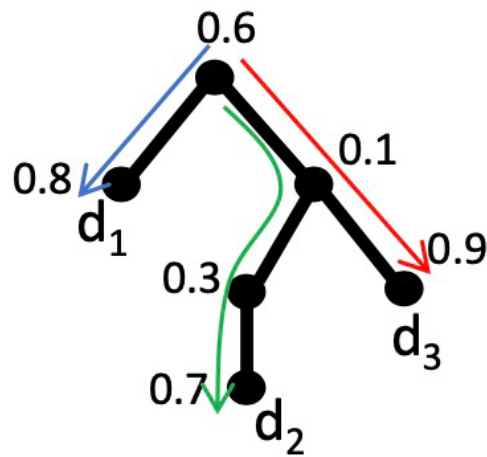
$K = 3$



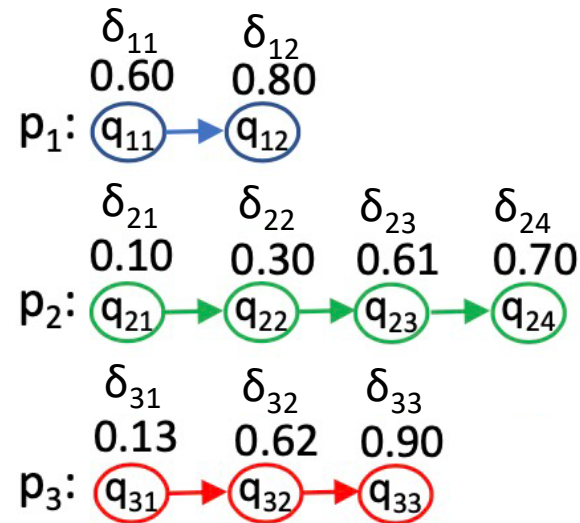
$K = 4$

Queueing topology inference: idea

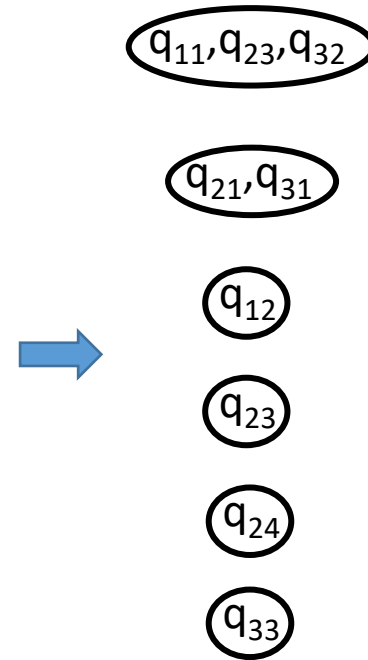
- Ideal case:



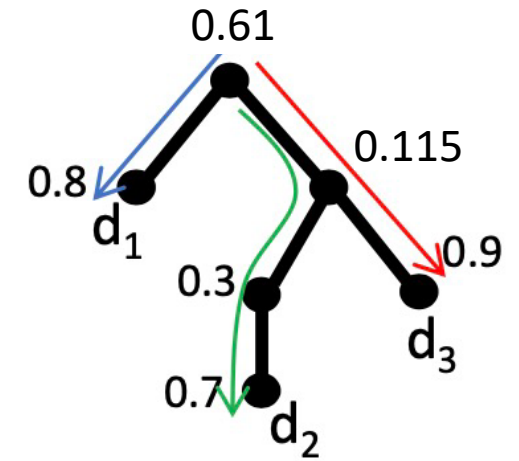
Ground truth topology



Estimated parameters



Parameters associated with the same queue



Inferred topology

Queueing topology inference: challenges

- Parameter estimation is not perfect

- An upper bound Δ , such that

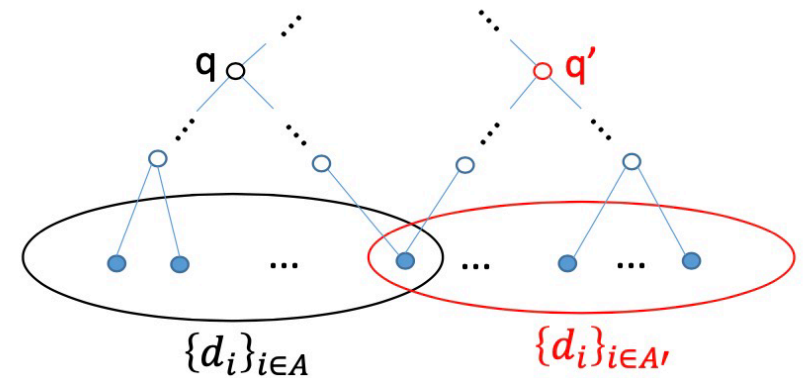
$$D_{\{q_{i_1 j_1}, \dots, q_{i_k j_k}\}} := \max\{\delta_{i_1 j_1}, \dots, \delta_{i_k j_k}\} - \min\{\delta_{i_1 j_1}, \dots, \delta_{i_k j_k}\} \leq \Delta$$

- Topology is not arbitrary

- Partially overlapping categories cannot coexist

- Exponential complexity if brute-forcing

- $O(K^N)$ ways to merge queues



Queueing topology inference: solution

- A *greedy* algorithm with *progressively constructed search space* to infer estimated parameters associated with the same queue
 - $O(K^4 N^5)$ time complexity, $O(K^2 N^3)$ space complexity
 - Correct if estimated parameters are sufficiently accurate

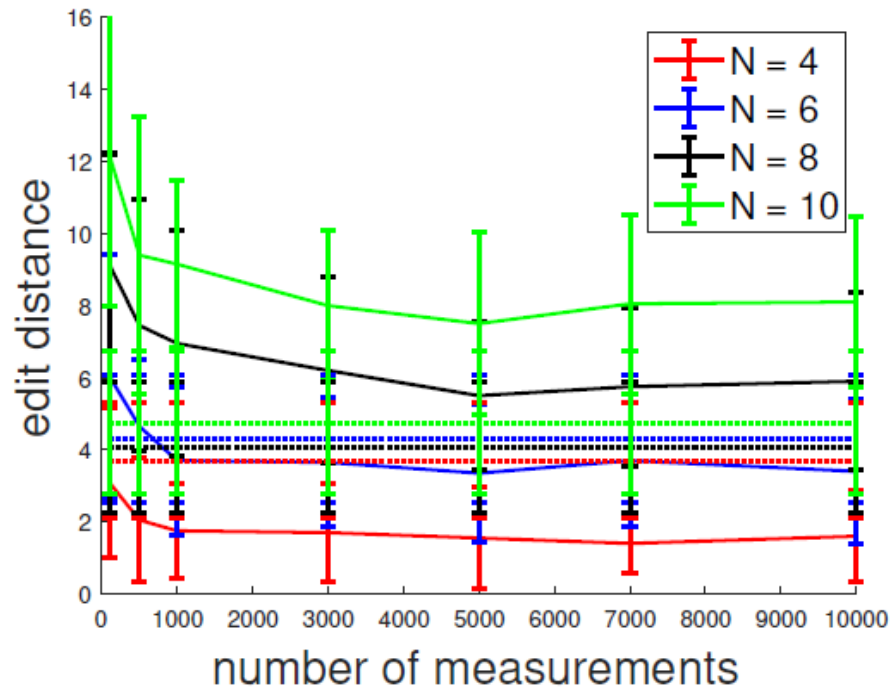
- **Theorem.** All parameters for the same queue are correctly identified if

$$|\delta_{ij} - \delta_{ij}^*| \leq \frac{\Delta}{2} < \frac{\Delta^*}{4} \quad (\text{where } \Delta^* := \min_{e \neq e'} |\delta_e^* - \delta_{e'}^*|)$$

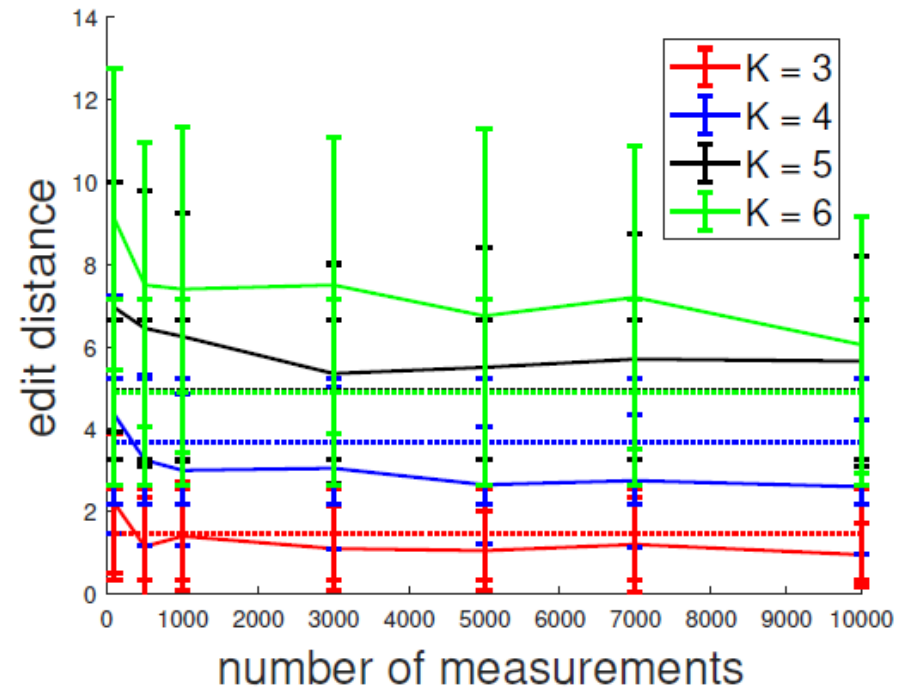
→ Under this condition, **the inferred topology will be identical to the ground truth**, up to a permutation of queues on the same branch.

Performance evaluation

- Routing trees generated from AS6461 of Abovenet



(a) vary N ($K = 4$)

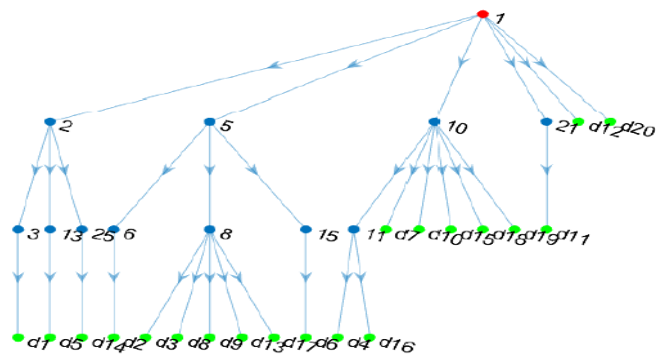


(b) vary K ($N = 5$)

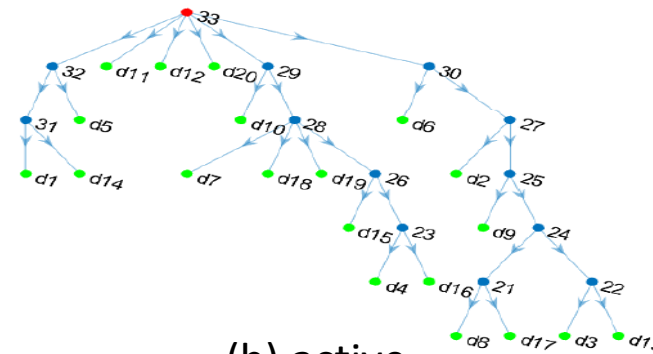
solid line: edit distance for inferred topology; dotted line: edit distance for multicast tree

How to improve the scalability

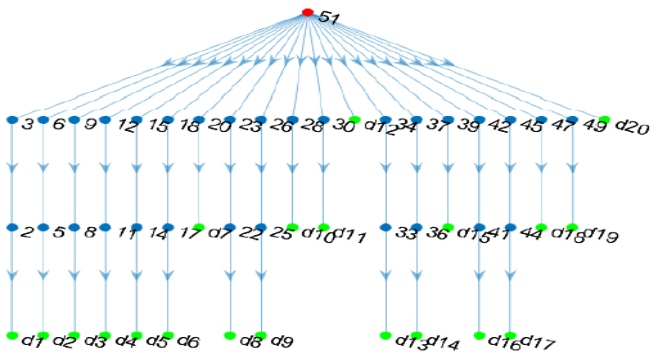
- Idea: Combining passive & active measurements
 - Passive measurements → queue fingerprints
 - Active measurements → shared path length



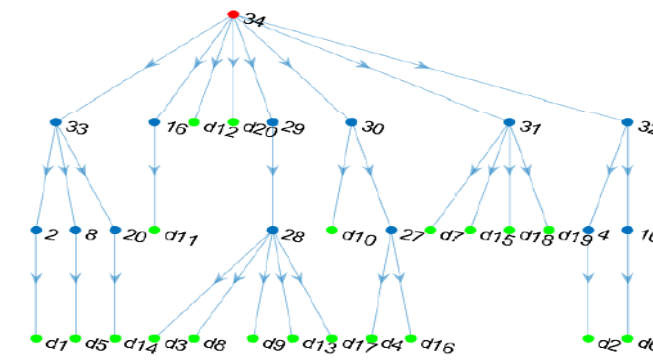
a) ground truth



(b) active

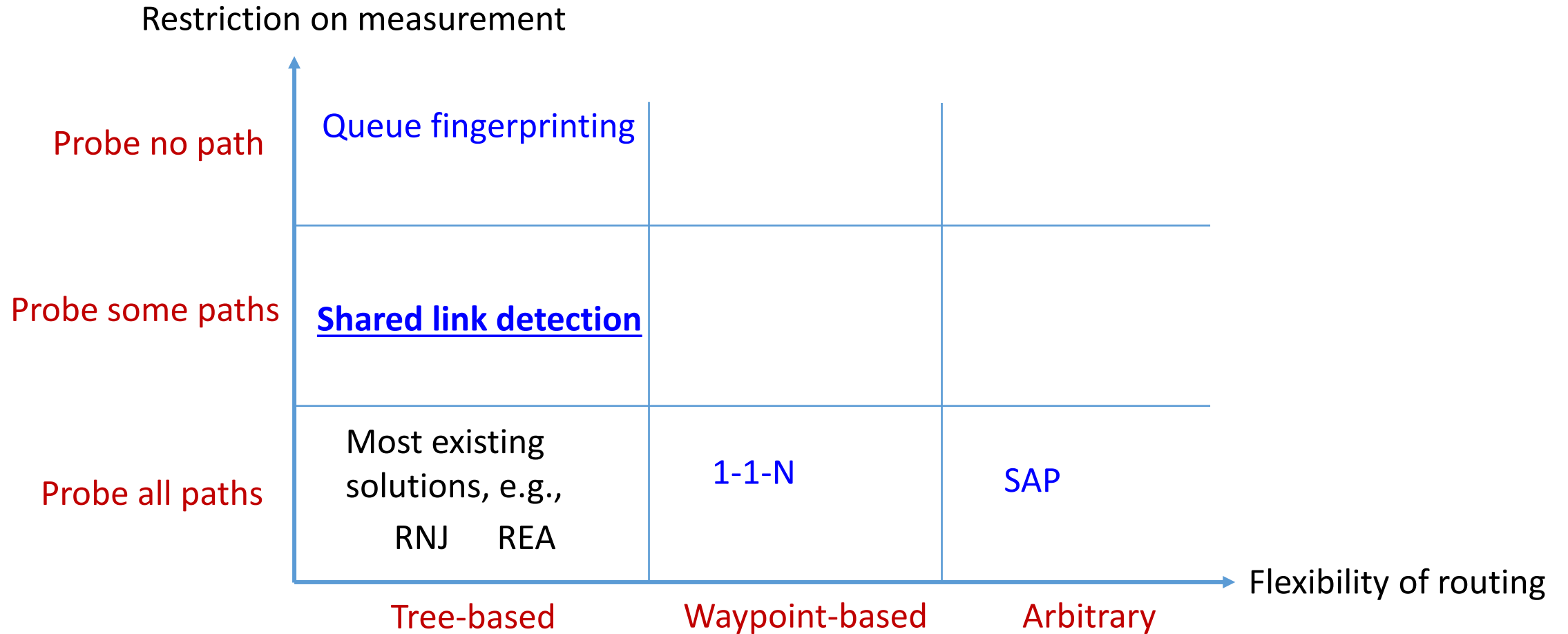


(c) passive



(d) combined

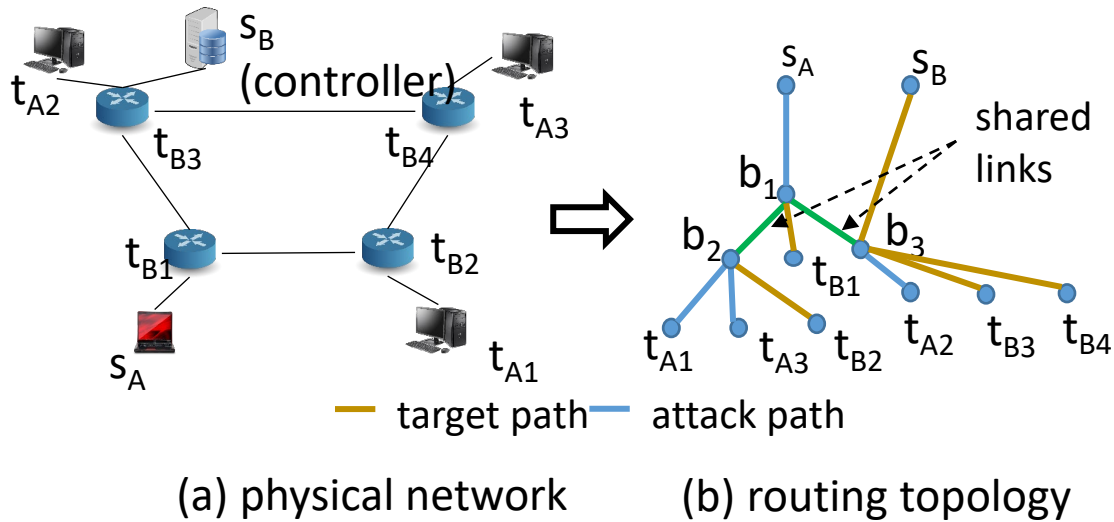
Outline



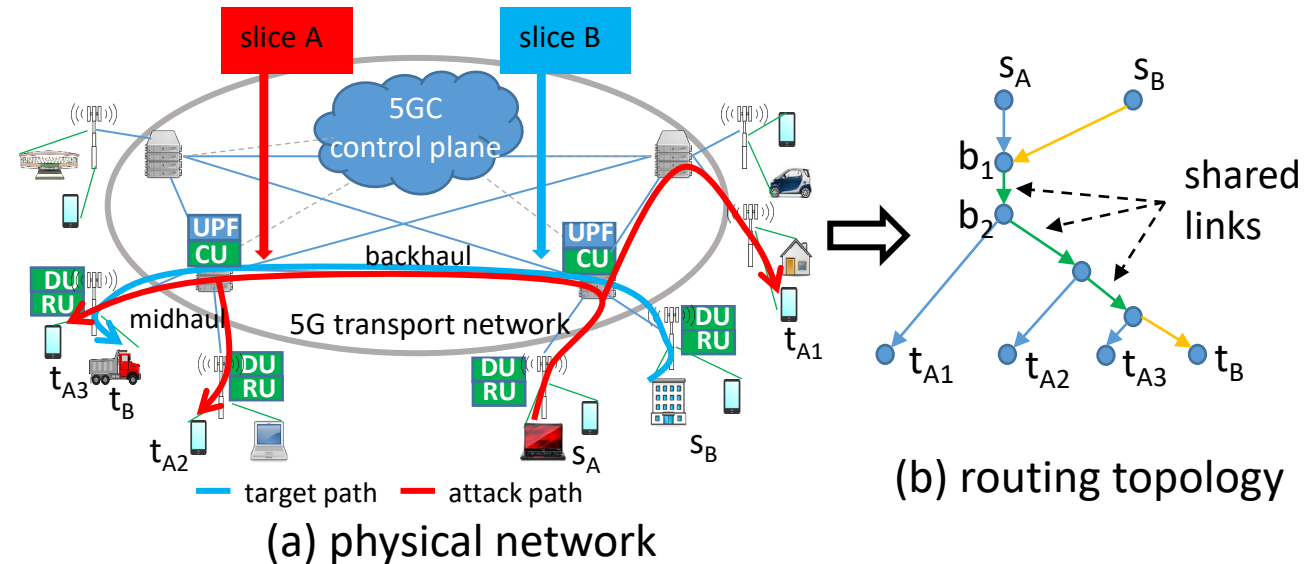
Scenario: Cross-path attack

- An attacker in control of a set of *attack paths* wants to launch indirect DoS attack on a set of *target paths* by consuming shared resources

Example 1: Data → Control Plane Attack in SDN



Example 2: Cross-slice Attack in 5G



Cross-path attack: A high-level description

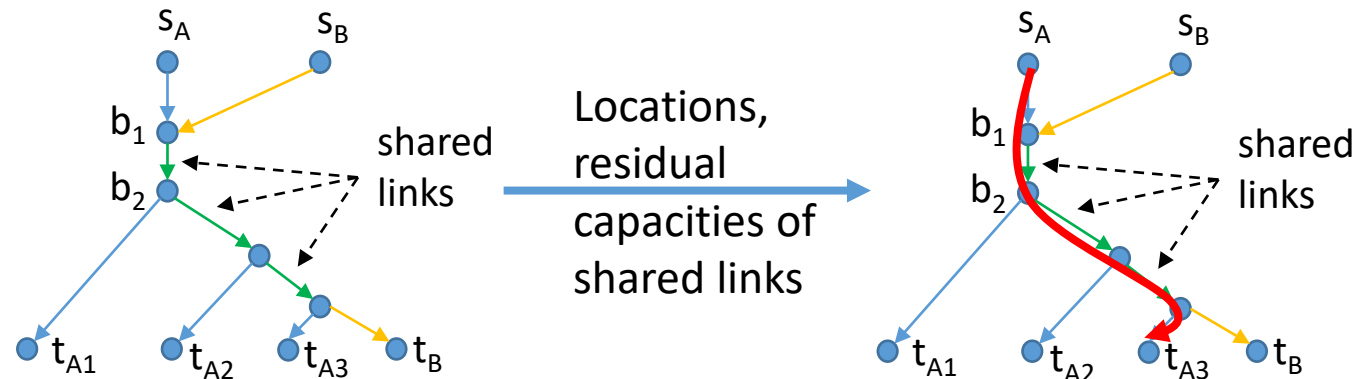
- Cross-path attack contains a *reconnaissance phase* and an *active attack phase*

Which attack paths share resource with target paths?
What is the capacity of the shared resource?

Which attack paths to use?
How much traffic to send?

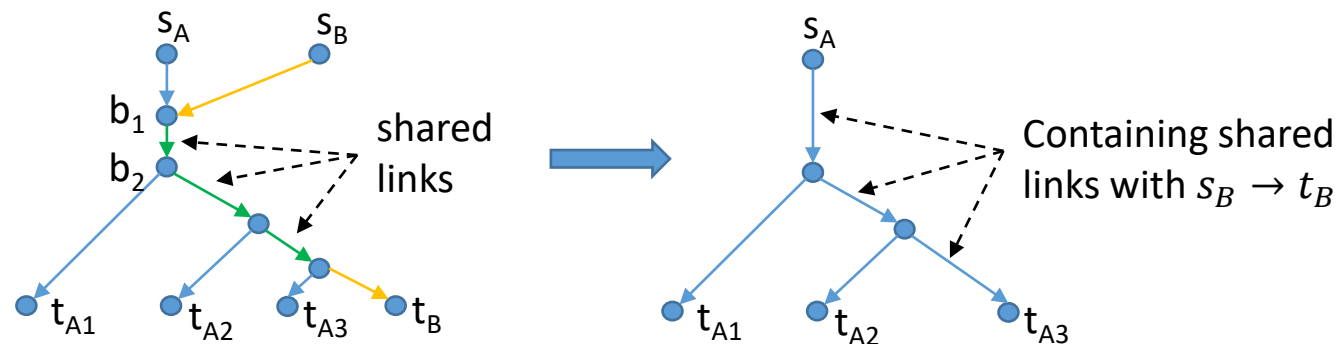
Adversarial Reconnaissance

Active DoS Attack



Adversarial reconnaissance: A topology inference problem

- **Observation model:** *Active probing* on attack paths, *passive monitoring* on target paths
- **Goal:** Support optimal attack design
 - Knowing the true routing topology formed by all attack/target paths is sufficient, but not necessary
- **Idea:** Use mimicked multicast to infer “attack paths + 1 target path” topologies



Adversarial reconnaissance: Results

- Recursive algorithm to **detect shared links**

• **Theorem.** If all shared links have non-zero metrics and **category weights are estimated accurately**, then all **shared links will be correctly detected**.

- Recursive algorithm to **estimate parameters of detected shared links**

- Modeled as M/M/1, M/D/1, or G/G/1 queue
- Estimated by fitting average delay under K different probing rates

• **Theorem.** If all shared links are correctly detected, and the **average delays on target paths are accurately estimated**, then the **parameters of shared links will be accurately estimated** if (i) $K > 2$ under M/M/1 or M/D/1, and (ii) $K > 4$ under G/G/1

Attack design: Objectives and results

- Objective 1: Delay maximization

$$\begin{aligned} \max f(\bar{\lambda}) &:= \sum_{i=1}^{N_B} \beta_i \sum_{e \in \mathcal{T}: W_{ie} > 0} d(\xi_{ie}; \sum_{k=1}^{N_A} h_{ek} \bar{\lambda}_k) \\ \text{s.t.} \quad &\sum_{k=1}^{N_A} \bar{\lambda}_k \leq \lambda, \\ &\sum_{k=1}^{N_A} h_{ek} \bar{\lambda}_k \leq \tilde{r}_e, \forall e \in \mathcal{T}, \\ &\bar{\lambda}_k \geq 0, k = 1, \dots, N_A, \end{aligned}$$

- Objective 2: Overload maximization

$$\begin{aligned} \max_{\bar{\lambda}} \max_{e \in \mathcal{T}: \exists W_{ie} > 0} &\left(\sum_{k=1}^{N_A} h_{ek} \bar{\lambda}_k - \min_{i \in \{1, \dots, N_B\}: W_{ie} > 0} r_{ie} \right) \\ \text{s.t.} \quad &\sum_{k=1}^{N_A} \bar{\lambda}_k \leq \lambda, \quad \sum_{k=1}^{N_A} h_{ek} \bar{\lambda}_k \leq \tilde{r}_e, \forall e \in \mathcal{T}, \quad \bar{\lambda}_k \geq 0, k = 1, \dots, N_A, \end{aligned}$$

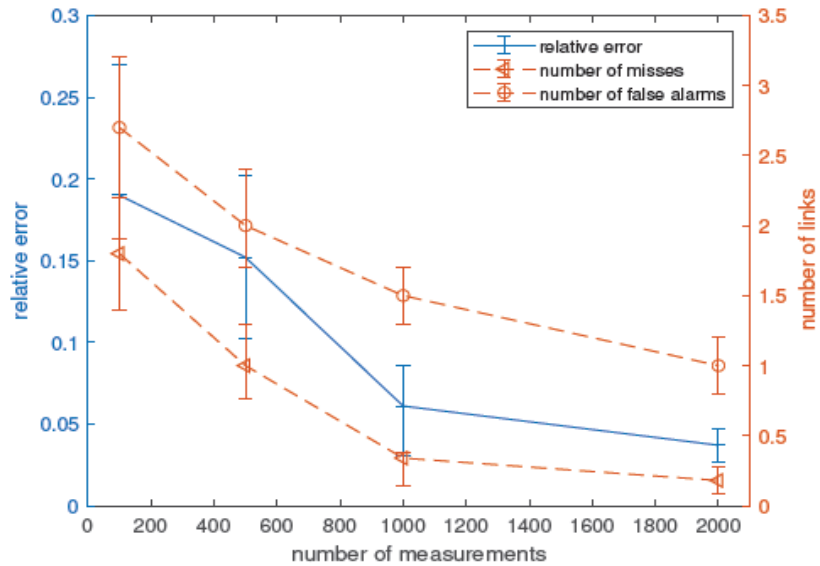
Both maximizing convex function under linear constraints

→ Optimum at a vertex

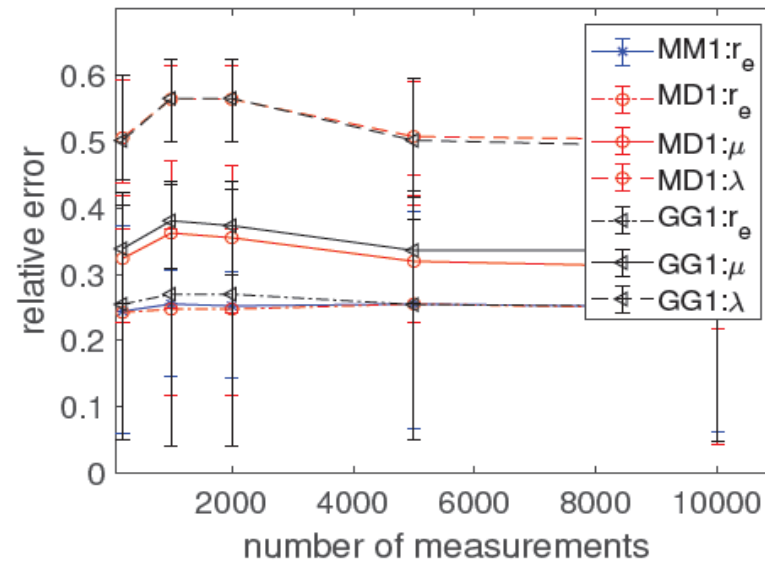
→ If attack rate $\lambda \leq \min_{e \in \mathcal{T}} \tilde{r}_e$, optimal

to send all attack traffic on one attack path

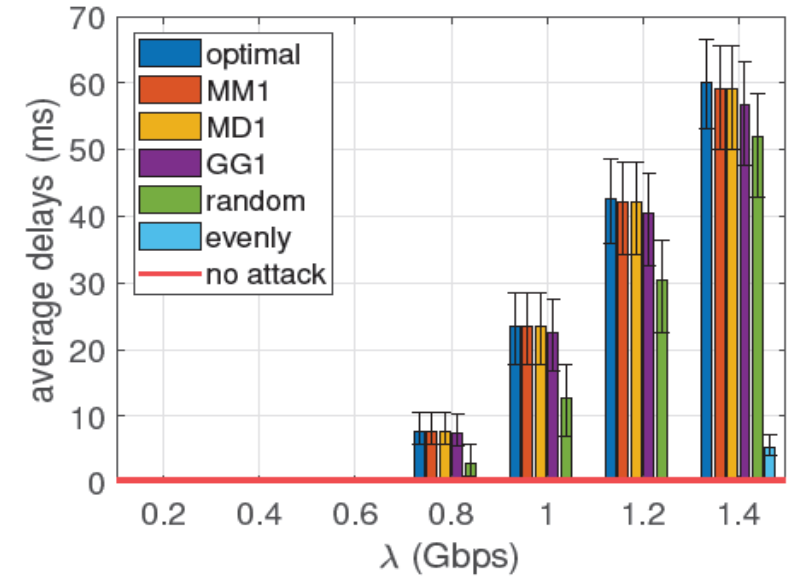
Performance evaluation: Results



(a)



(b)

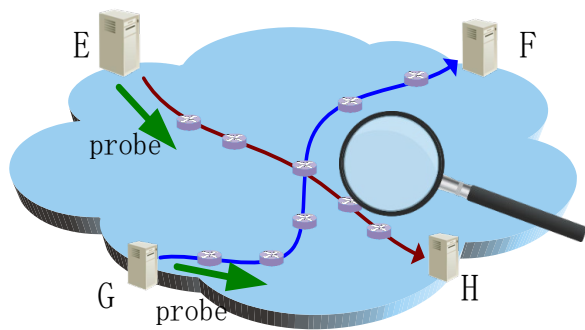


(c)

- a) Can detect most of the shared links
- b) Notable error in estimated parameters
- c) Near-optimal performance in attack design

Concluding Remark

- Topology inference: Jointly infer network *internal structure* from *external observations*
 - what “internal structure” to infer, what structures are possible, what measurements are allowed
 - A double-sided sword (overlay management vs. adversarial reconnaissance)



**Network structure
& state = ?**

	Restriction on measurement			
Probe no path	Queue fingerprinting			
Probe some paths	Shared link detection			
Probe all paths	Most existing solutions, e.g., RNJ REA	1-1-N	SAP	
	Tree-based	Waypoint-based	Arbitrary	Flexibility of routing

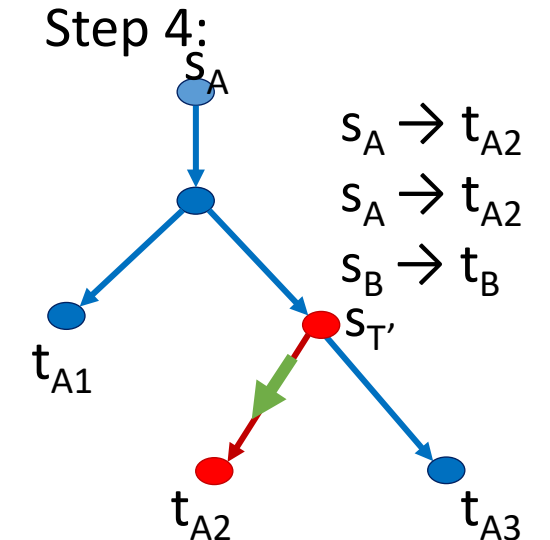
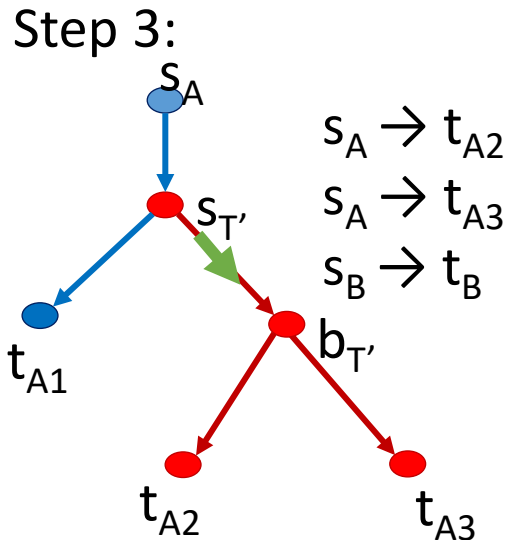
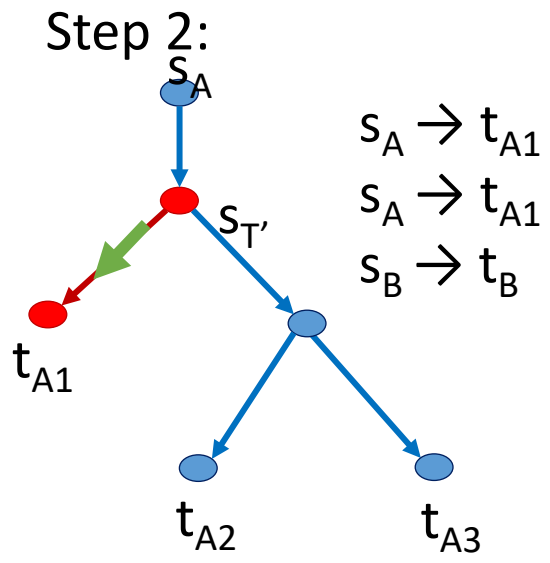
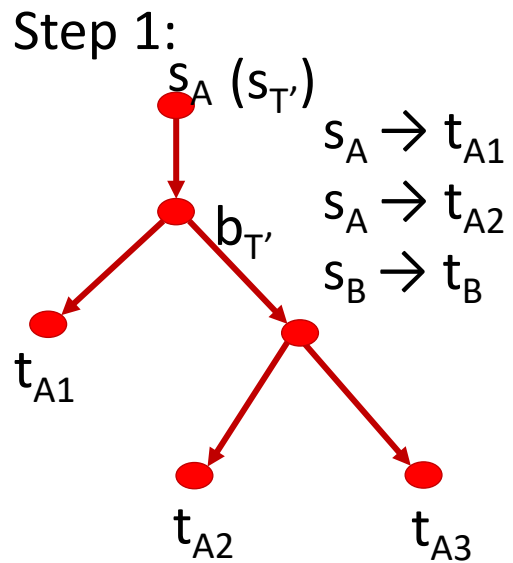
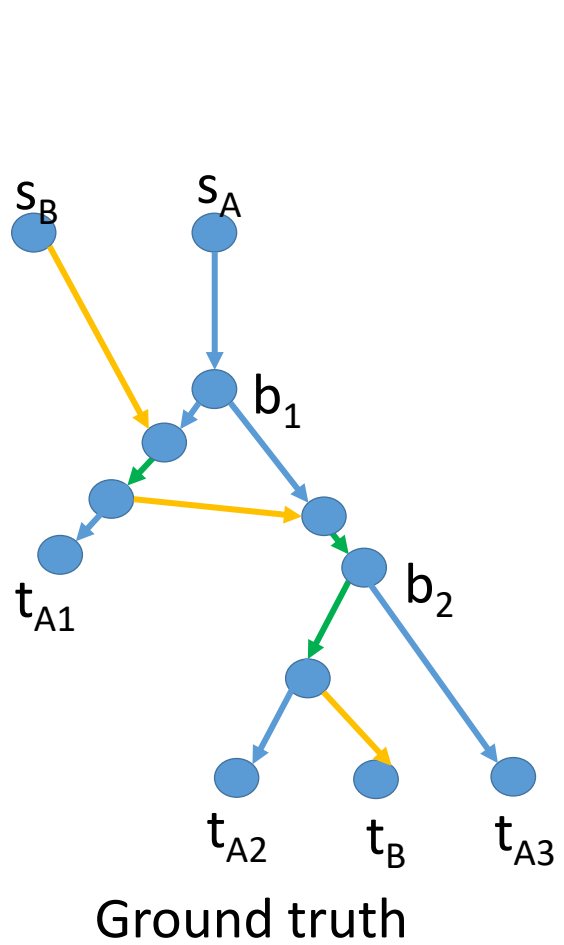
CT Scan for Network: Topology Inference from End-to-End Measurements

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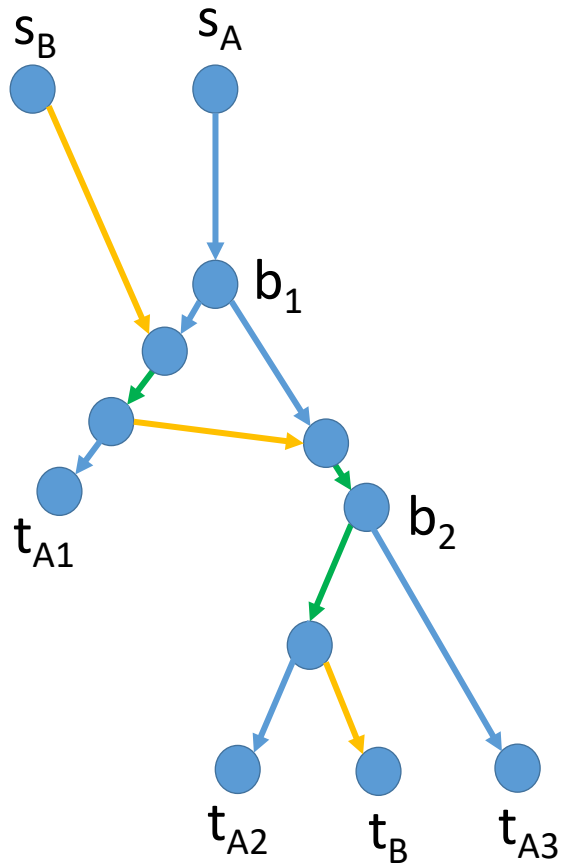
THANK YOU

Backup slides

Example: Shared link detection

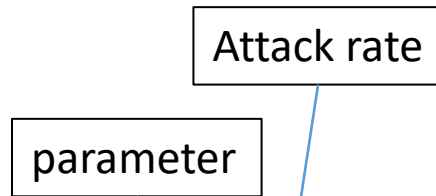


Parameter Estimation



Ground truth

Top-down: One queue at a time

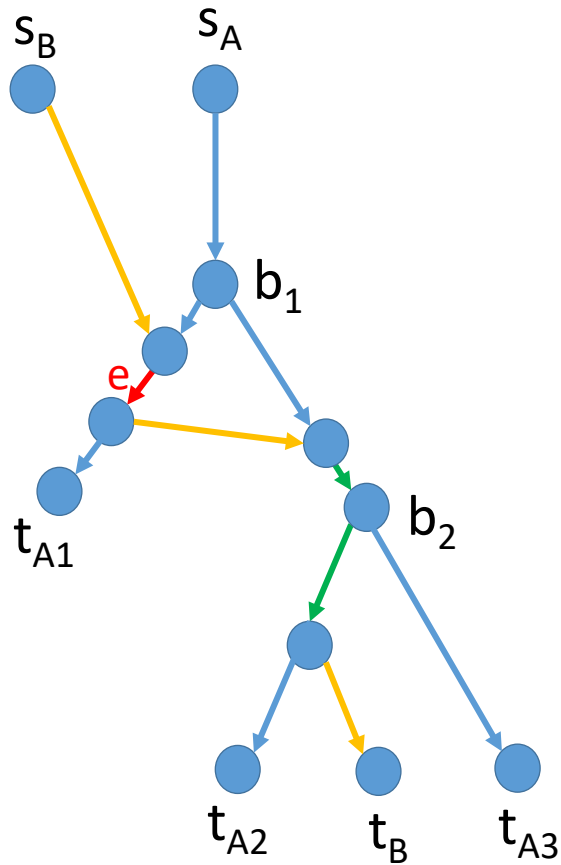


$$M/M/1: d(r_e; \bar{\lambda}) = \frac{1}{r_e - \bar{\lambda}}$$

$$M/D/1: d(\lambda_e, \mu_e; \bar{\lambda}) = \frac{2\mu_e - \lambda_e - \bar{\lambda}}{2\mu_e(\mu_e - \lambda_e - \bar{\lambda})}$$

$$G/G/1: d(\lambda_e, \mu_e, \sigma_{ae}, \sigma_{se}; \bar{\lambda}) \approx \frac{1}{2\mu_e} \frac{\lambda_e + \bar{\lambda}}{\mu_e - \lambda_e - \bar{\lambda}} \left(\sigma_{ae}^2 (\lambda_e + \bar{\lambda})^2 + \sigma_{se}^2 \mu_e^2 \right) + \frac{1}{\mu_e}$$

Parameter Estimation

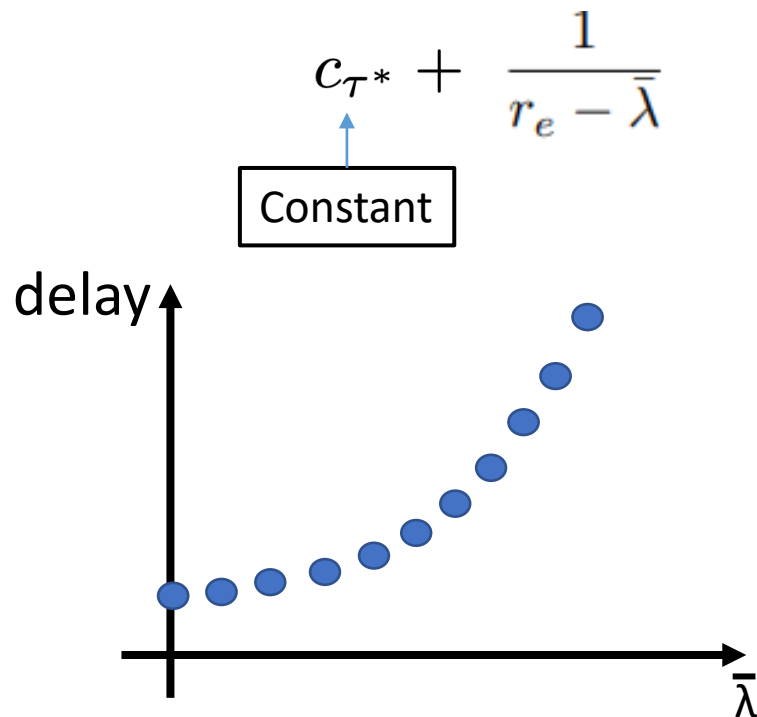


Ground truth

$$M/M/1: d(r_e; \bar{\lambda}) = \frac{1}{r_e - \bar{\lambda}}$$

Send probes $s_A \rightarrow t_{A1}$ with rate $\bar{\lambda} = 0, \dots, r/2$

Measure delay of path $s_B \rightarrow t_B$



Theorem:

Accurate delay
& enough dimension



Accurate parameter