SmartEntry: Mitigating Routing Update Overhead with Reinforcement Learning for Traffic Engineering

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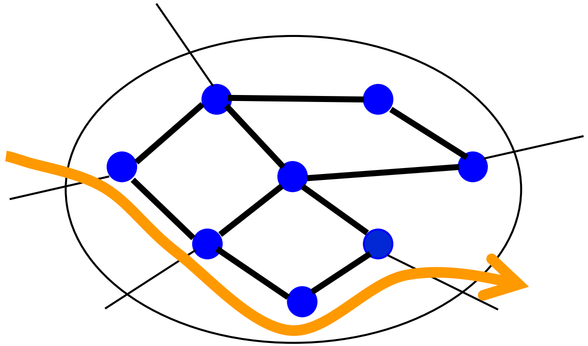
Background

- **Traffic Engineering (TE):** Configure routing to improve network performance
- **Metric:** Maximum Link Utilization (MLU) → $\frac{\text{Load}}{\text{Capacity}}$ of the most congested link



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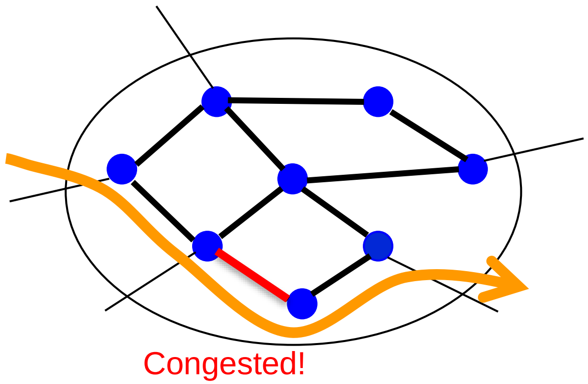

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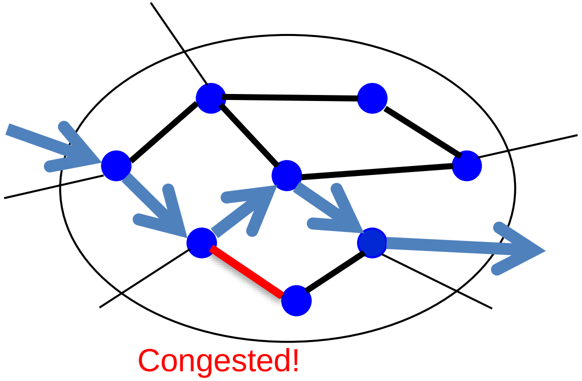
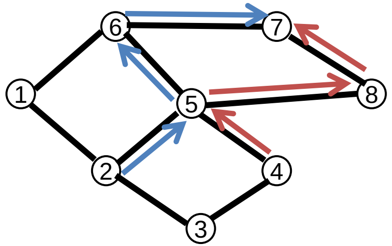


Flow-based or Destination-based Routing?

Flow-based Routing



Flow table at node 5

Match	Action
src = 2, dst = 7	Fwd to 6
src = 4, dst = 7	Fwd to 8

Two different sources can reach the same destination with different preconfigured paths

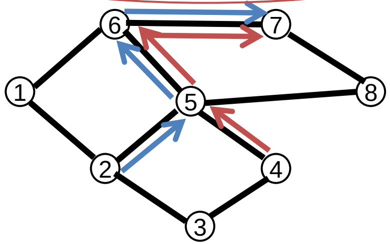
☺ Fine-grained traffic distribution control

P = # of IP routes

☹ Need to store $O(P^2)$ flow entries!

Scalability issue with limited TCAM resource

Destination-based Routing



Forwarding table at node 5

Destination	Next Hop
7	6

Paths from two different sources to same destination must coincide once they overlap

☺
- Lower forwarding complexity - $O(P)$ entries
- Widely implemented with simple RAMs

Centralized controller can be applied to update the entries when traffic changes

Motivation

However, traditional TE need to update <u>all entries</u> to improve network performance!

☹ Take considerable time → cannot react to traffic changes in a responsive manner

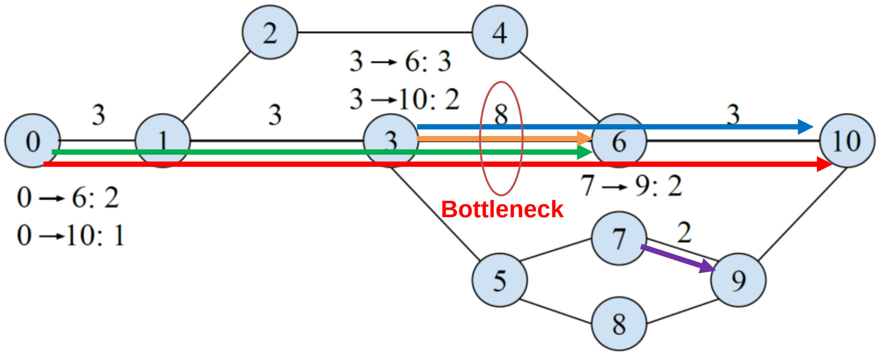
<u>Q: Can we mitigate routing update overhead?</u>

<u>A: Differentiate and route flows with a new traffic abstraction!</u>

(1) Only update some critical entries at some critical nodes to reroute traffic

(2) The remaining unaffected traffic are forwarded by ECMP

Equal-Cost Multipath (ECMP)



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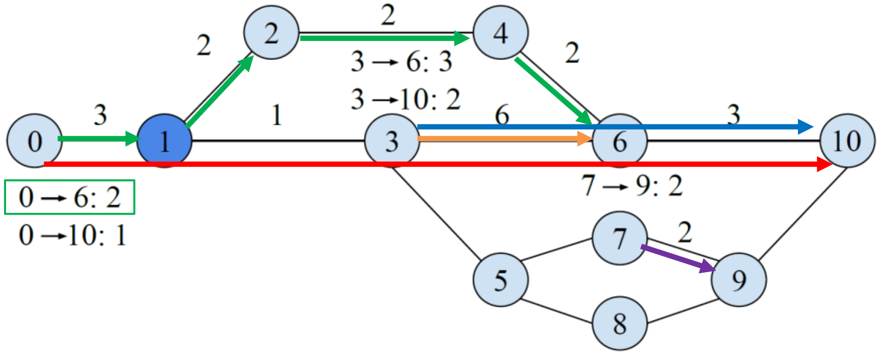
Update Critical Entries



Critical Entries

Forwarding table at node 1

Destination	Next Hop
6	2 (100%)

Motivation

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Key Problem: which pairs are 'critical'?
There are too many (node, dst) combinations!

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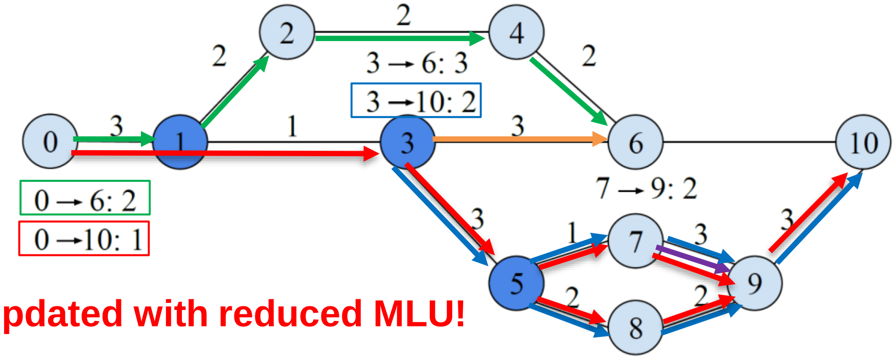
Update Critical Entries



Updated with reduced MLU!

Critical Entries

Forwarding table at node 1

Destination	Next Hop
6	2 (100%)

Forwarding table at node 3

Destination	Next Hop
10	5 (100%)

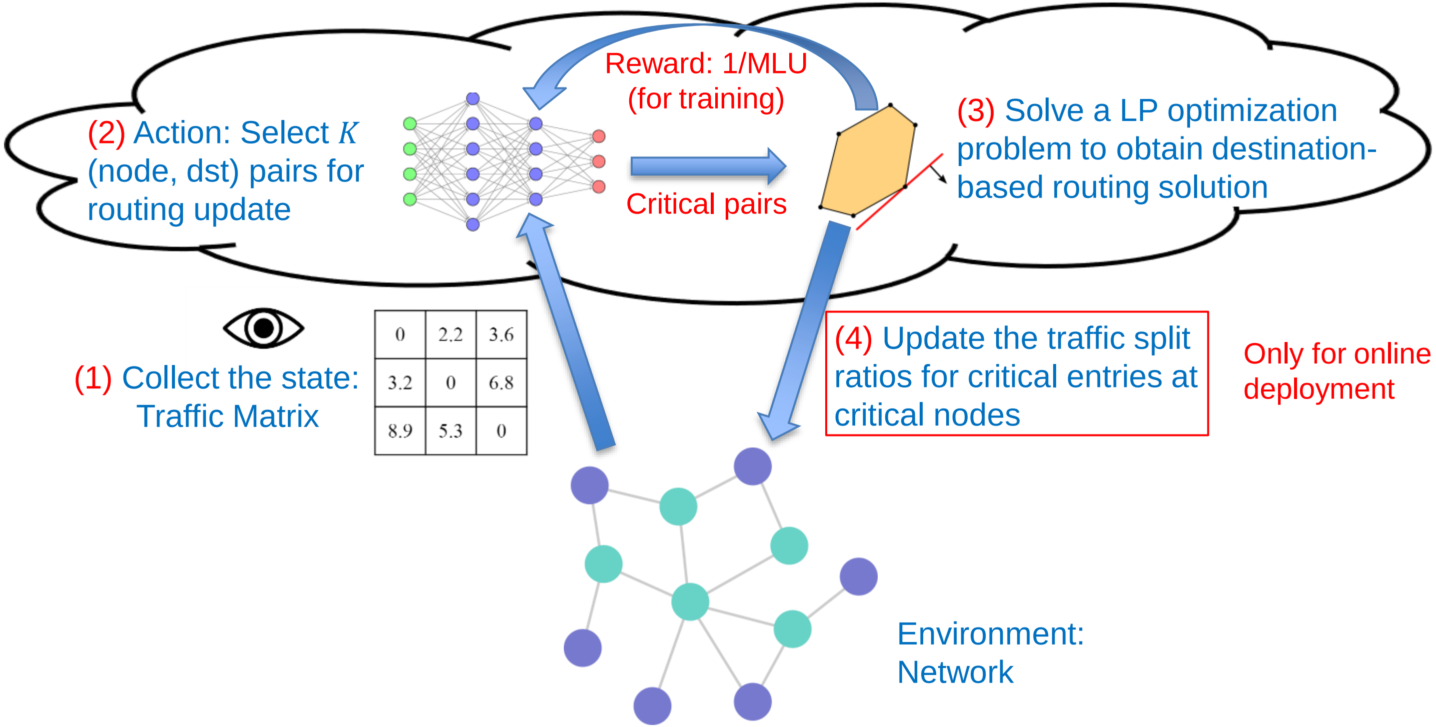
Forwarding table at node 5

Destination	Next Hop
10	7 (33.3%), 8 (66.6%)

SmartEntry: RL + LP combined approach

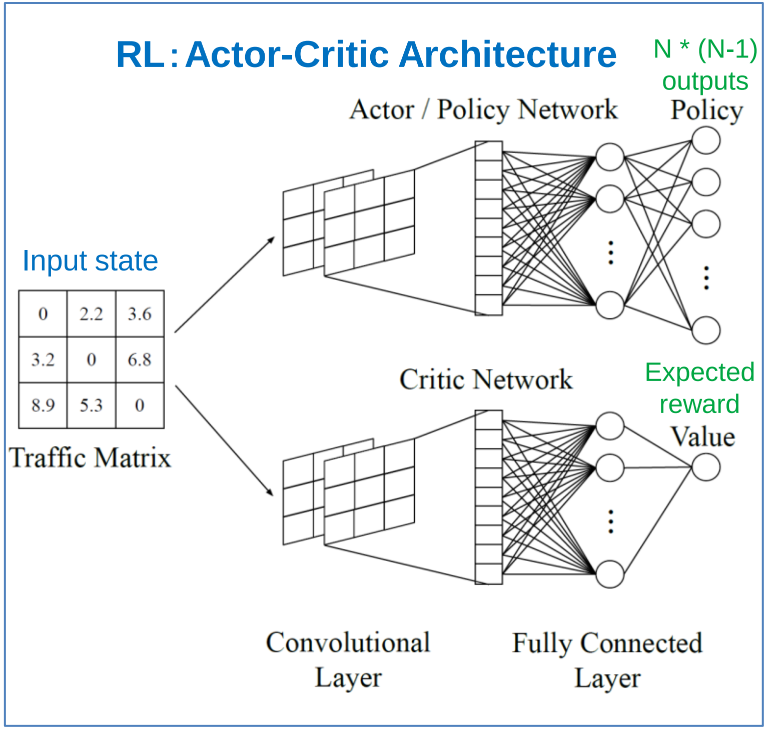
Idea: (1) Using **Reinforcement Learning (RL)** to smartly select critical pairs for routing update

(2) Solve a **Linear Programming (LP)** optimization problem to obtain destination-based routing solution



Why is RL + LP powerful?

- RL can model complex selection policies as neural networks to map "raw" observations to actions
- LP generates reward signal for RL to learn a better combination selection policy (minimize MLU)



Gradient update

Actions

LP

Produce reward signal

$$\text{minimize} \quad U_{max} + \epsilon \cdot \sum_{\langle i,j\rangle \in E} \sum_{d \in V} y^d_{i,j}$$

subject to

$$\sum_{d \in V} y^d_{i,j} = l_{i,j} \qquad i,j : \langle i,j\rangle \in E$$

$$l_{i,j} \le c_{i,j} \cdot U_{max} \qquad i,j : \langle i,j\rangle \in E$$

$$\sum_{k:\langle k,i\rangle \in E} y^d_{k,i} - \sum_{k:\langle i,k\rangle \in E} y^d_{i,k} = -t^{i,d} \qquad i,d : \tau^d_i \in \tau_K$$

$$y^d_{i,k} = \begin{cases} \dfrac{\sum_{n:\langle n,i\rangle \in E} y^d_{n,i} + t^{i,d}}{|\mathrm{ENH}^d_i|} & \text{if } k \in \mathrm{ENH}^d_i \\ 0 & \text{otherwise} \end{cases}$$

$$i,d : \tau^d_i \in \tau_{N*(N-1)-K},\ k : \langle i,k\rangle \in E$$

$$\sum_{k:\langle k,d\rangle \in E} y^d_{k,d} - \sum_{k:\langle d,k\rangle \in E} y^d_{d,k} = \sum_{s \in V, s \neq d} t^{s,d} \qquad d \in V$$

$$y^d_{i,j} \ge 0 \qquad d \in V,\ i,j : \langle i,j\rangle \in E$$

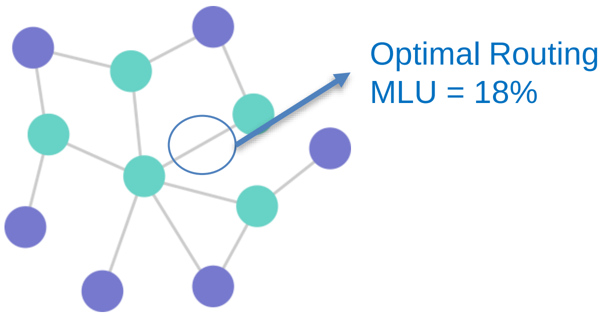
Experiment setup

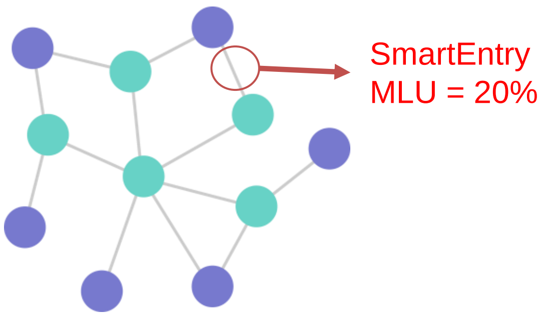
- We use 4 real networks to evaluate SmartEntry

Topology	Nodes	Directed Links
Abilene	12	30
GÉANT	23	74
EBONE	23	76
Tiscali	49	172

- Baseline Methods
  - ECMP: Distributes traffic evenly among available next hops along the shortest paths
  - Weighted ECMP: extends ECMP to allow weighted traffic splitting with shortest paths

- Evaluation Metric: **Performance Ratio (PR)**
  - Compare against optimal flow-based routing in terms of MLU
  - $PR = MLU_{optimal} / MLU_{SmartEntry}$

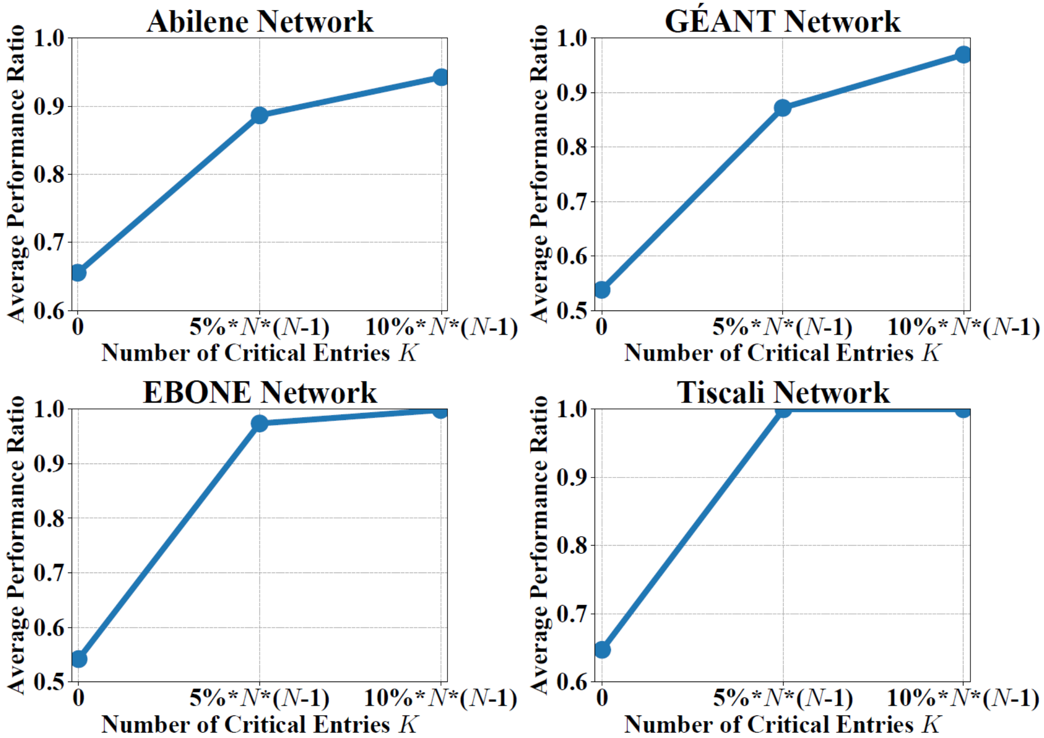




$$PR = \frac{18\%}{20\%} = 0.9$$

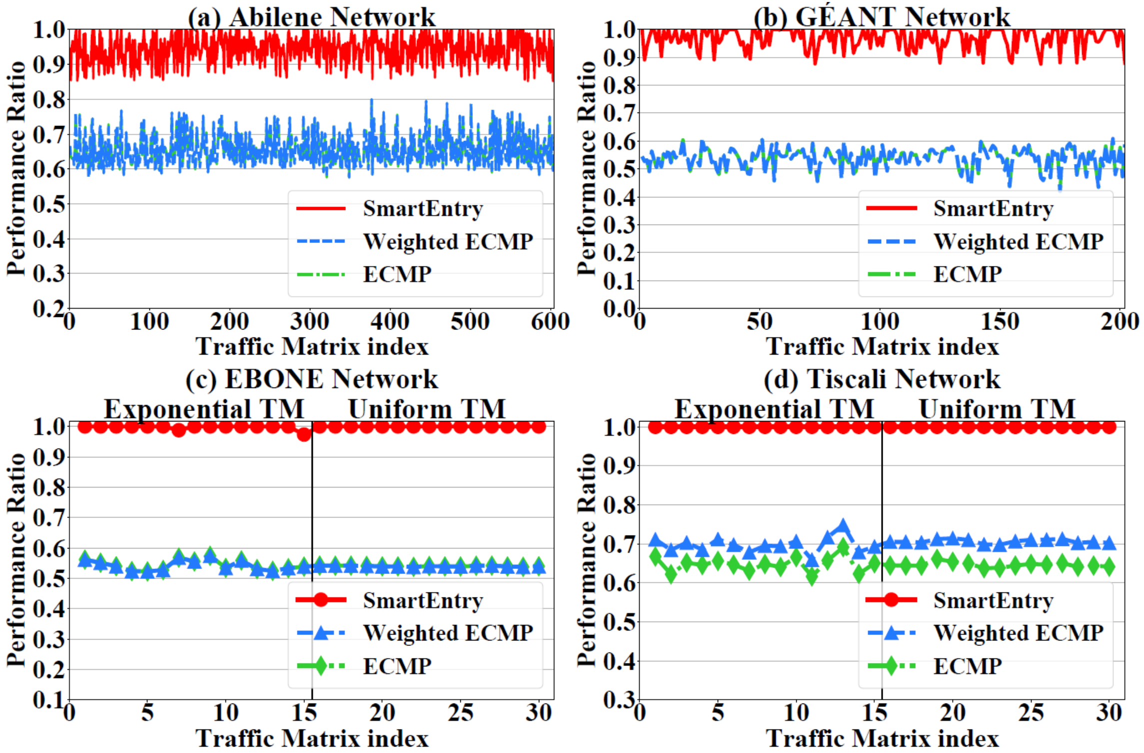
Number of critical entries

- SmartEntry achieves near-optimal performance with only 10% entries updated



Comparison in different networks

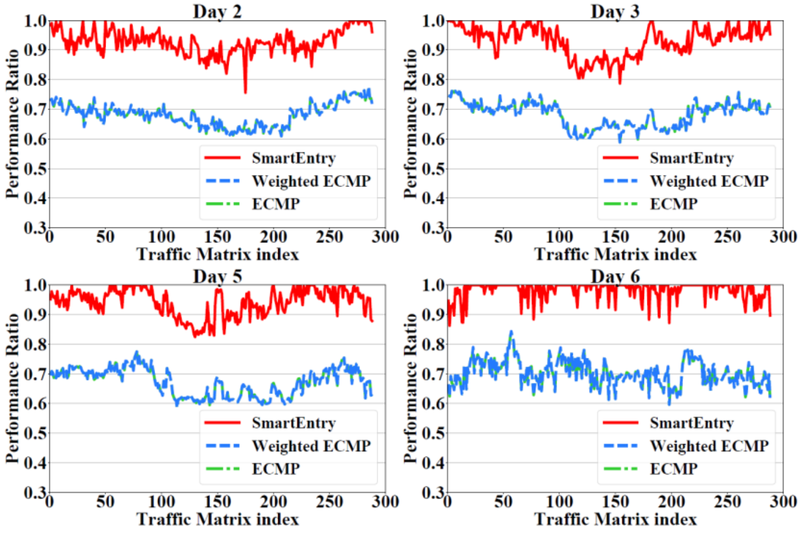
➢ SmartEntry performs consistently well on real and synthesized traffic matrices



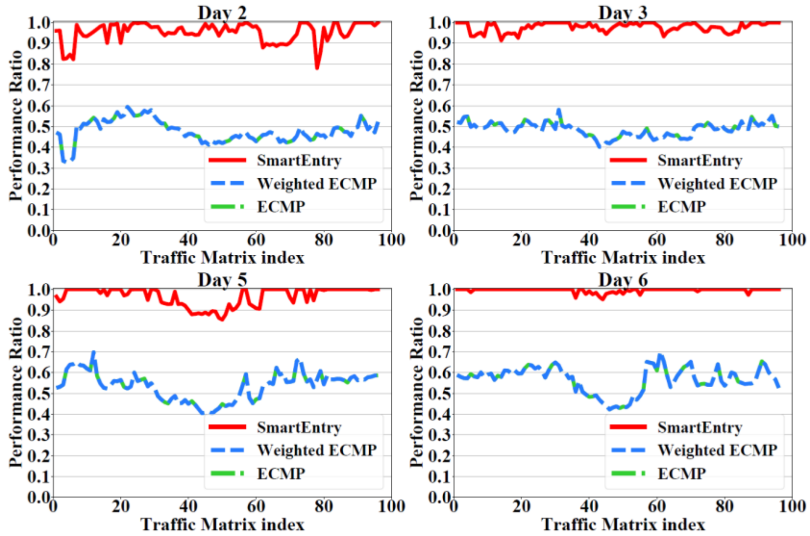
Generalization test

- ➢ Training on week 1, test on week 2
- ➢ SmartEntry generalizes well to unseen traffics

Abilene Network



GÉANT Network



Conclusion

- With an objective of minimizing maximum link utilization in a network and mitigating routing update overhead, we proposed SmartEntry, a scheme that learns a combination selection policy automatically using reinforcement learning, without any domain specific rule-based heuristic.

- SmartEntry smartly selects a combination of K node-destination pairs for each given traffic matrix and reroutes the selected traffic to achieve load balancing of the network by solving a rerouting optimization problem.

- Extensive evaluations show that SmartEntry achieves near-optimal performance and generalizes well to traffic matrices for which it was not explicitly trained.