

Oblivious Routing using Learning Methods

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Making Oblivious Routing Practical

Context

Routing in Networks

High volume,
Highly variable traffic

Motivation

Traffic Oblivious Routing

Stable and Robust Routing Solution
Far less complex handling of highly
varying traffic
Compatible with current day networks

Contribution

Adversarial Learning
Method

New, fast and parallelized ways to
solve optimization problems
Provide performance guarantees

Routing in Networks

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How to optimally route flows?

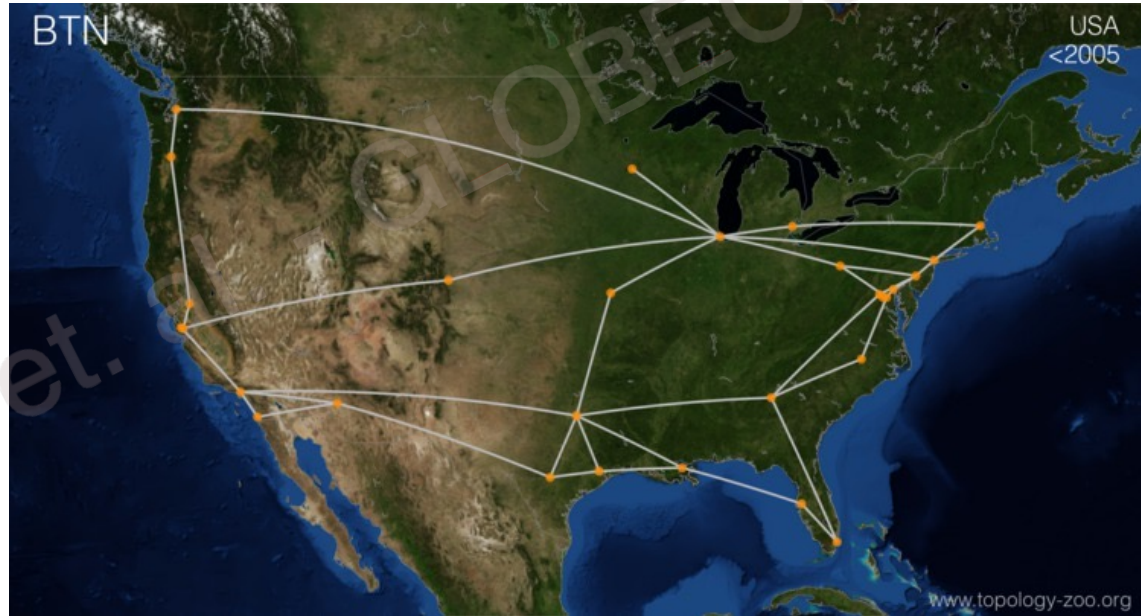
- ❑ How to satisfy all demands and constraints?
 - ❑ Solve a nice optimization problem if we can forecast what traffic to expect

min (max link utilization)

for traffic matrix:

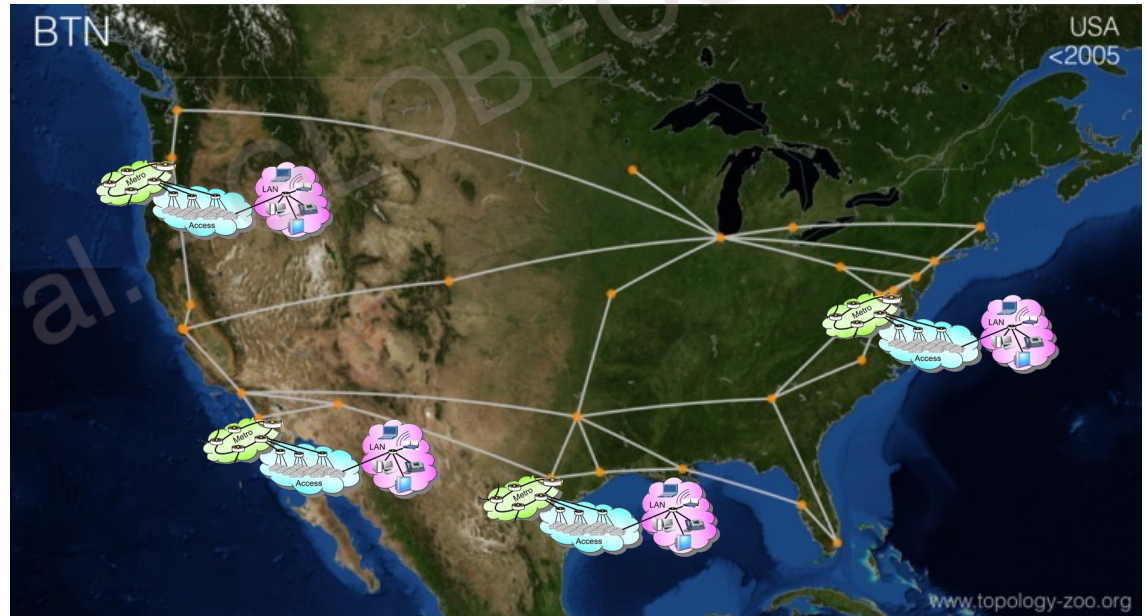
$$[t_{ij}] = \begin{bmatrix} t_{11} & t_{12} & \dots & t_{1N} \\ t_{21} & t_{22} & \dots & t_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ t_{N1} & t_{N2} & \dots & t_{NN} \end{bmatrix}$$

By assigning routes to flows



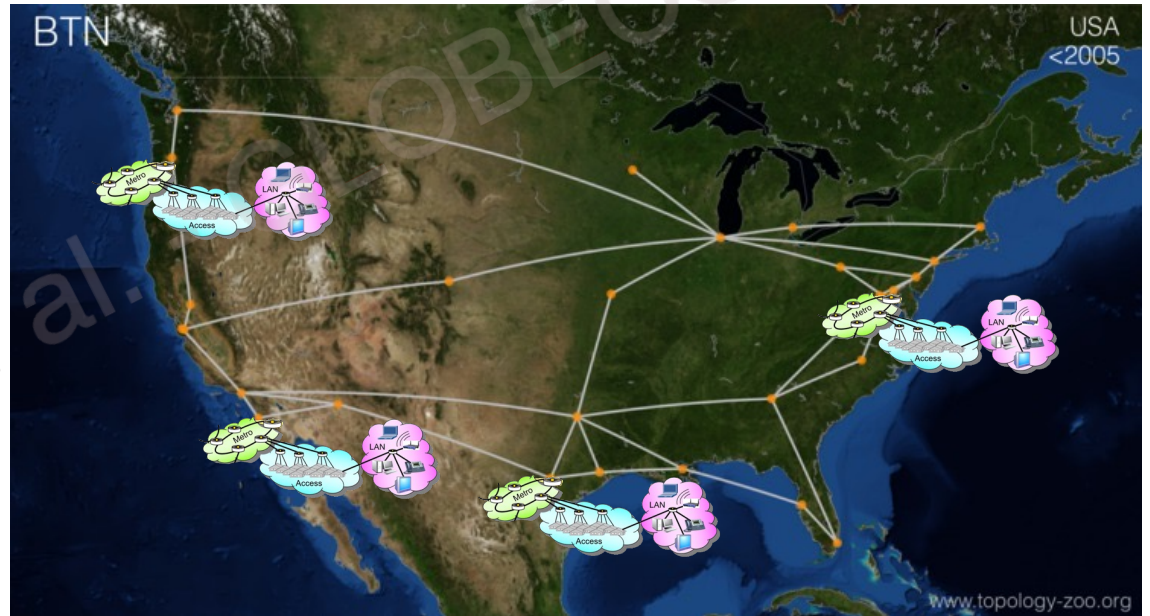
Traffic Patterns Today are Highly Variable and Harder to Predict

- ❑ High number of users
- ❑ Diverse applications
- ❑ Failures in adjacent networks
- ❑ Data Centers
- ❑ Edge Clouds
- ❑ Virtualization and Migration



How to optimize if we can't forecast traffic?

- ❑ Over-provisioning without performance guarantees?

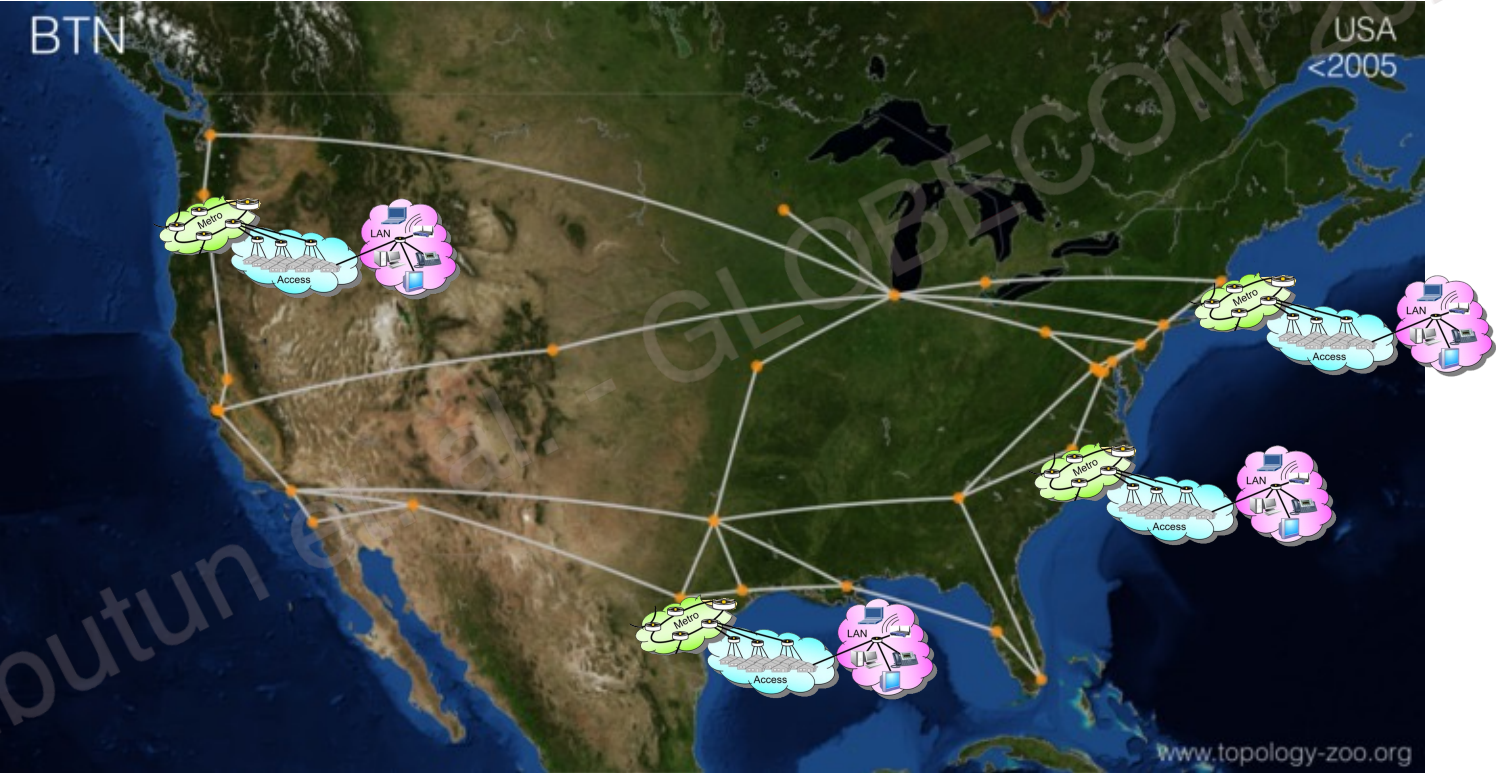


Oblivious Routing

with Hose Constraints

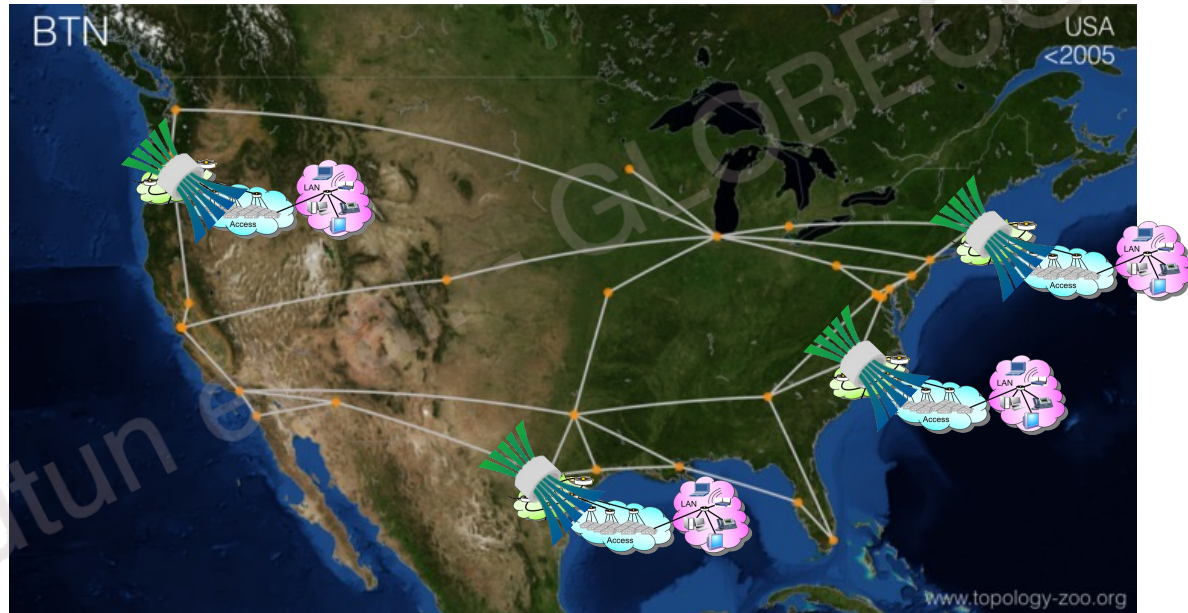


We know link capacities

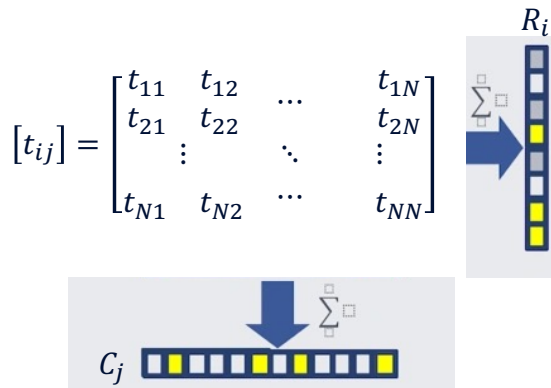


We know one more thing about the network:

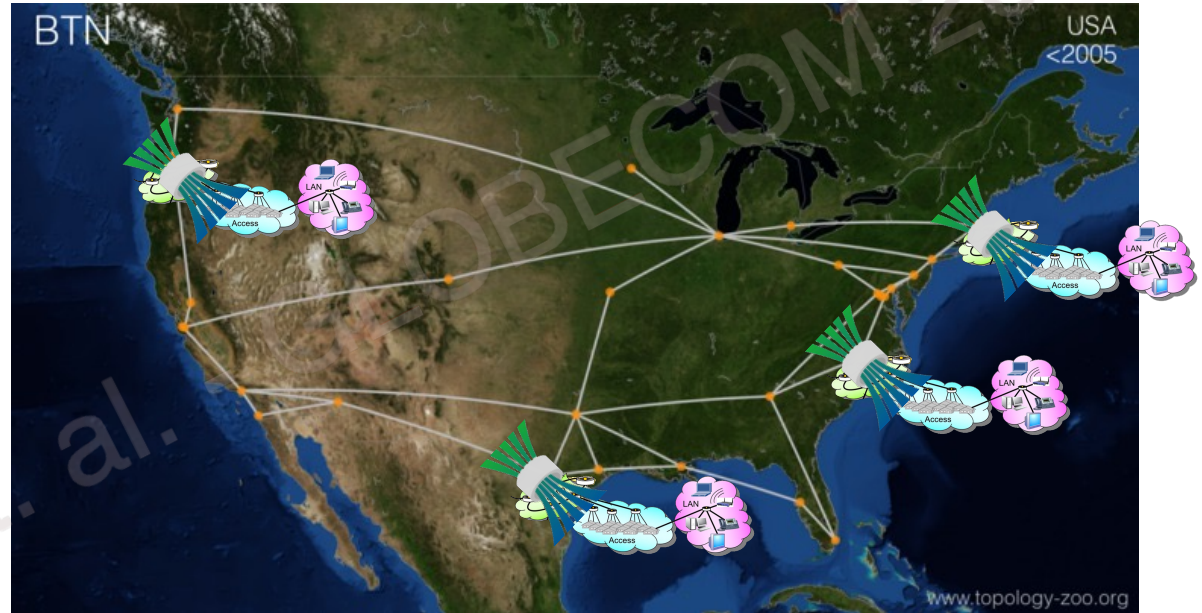
- ❑ The capacity of the physical connection of the network with the outside: The Hose



Find a fixed routing rule by solving for all possible traffic matrices



$$\mathcal{T}(\vec{R}, \vec{C}) = \left\{ [t_{ij}] \mid \sum_{j \neq i} t_{ij} \leq R_i \text{ and } \sum_{j \neq i} t_{ji} \leq C_i \forall i \right\}$$



- Stable and robust scheme reducing network complexity
- However, we need to optimize for infinitely many traffic matrices. A complex optimization problem!

Learning Methods

Machine Learning is a Natural Way of Solving Large Problems

- ❑ High performance, highly parallelized and optimized ways of solving **unconstrained** optimization problems
 - ❑ Using variants of Gradient Descent
- ❑ Challenges to ML methods for Oblivious Routing:
 - ❑ Incorporating the **constraints**
 - ❑ Representing and solving for **infinitely many** traffic matrices
- ❑ Can we use this toolset to solve our complex routing problem?
 - ❑ Yes!

How?

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How do we engineer traffic?

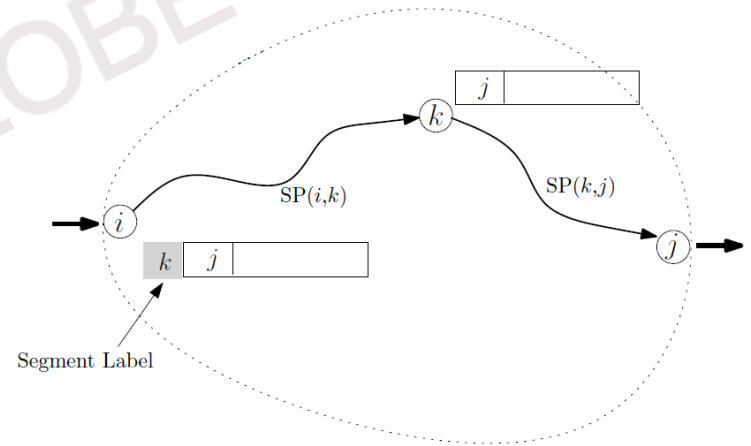
- ❑ We need flexibility with split choices:
 - ❑ **Segment Routing** is a recent and widely deployed non-shortest path technique

- ❑ 2-Segment Routing: $i \rightarrow k \rightarrow j$

- ❑ Choose an intermediate node k
- ❑ Set what fraction of $i \rightarrow j$ should go through k : α_{ij}^k
- ❑ $\sum_k \alpha_{ij}^k = 1, \forall i, j$

- ❑ We embed constraints into the objective function!

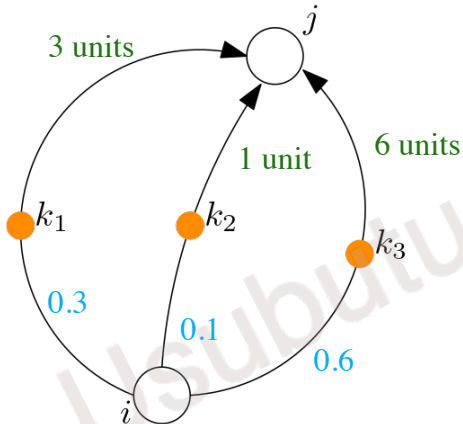
- ❑ Segment Routing renders paths enumerable!
- ❑ *Softmax* function trick!
(see paper for details!)



How to Solve an Oblivious Routing Problem Using ML?

- Follow an adversarial approach

Start with
random split
fractions α_{ij}^k

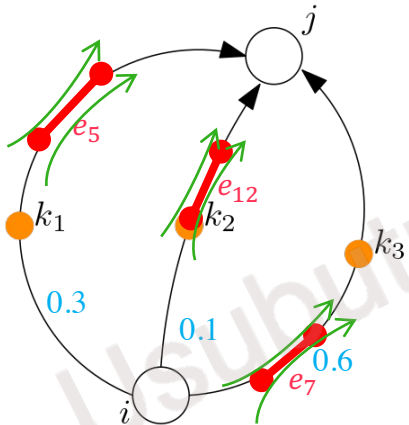


Traffic $i \rightarrow j$: 10 units

How to Solve an Oblivious Routing Problem Using ML?

- Follow an adversarial approach

Start with
random split
fractions α_{ij}^k



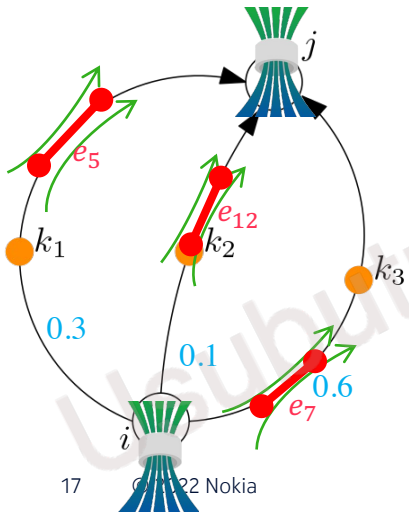
How to Solve an Oblivious Routing Problem Using ML?

- Follow an adversarial approach

Adversarial Step

Start with random split fractions α_{ij}^k

Generate the worst possible traffic matrices $[t_{ij}]^{(l)}$ for the current routing fractions α_{ij}^k and add to the set of bad matrices \mathcal{L}

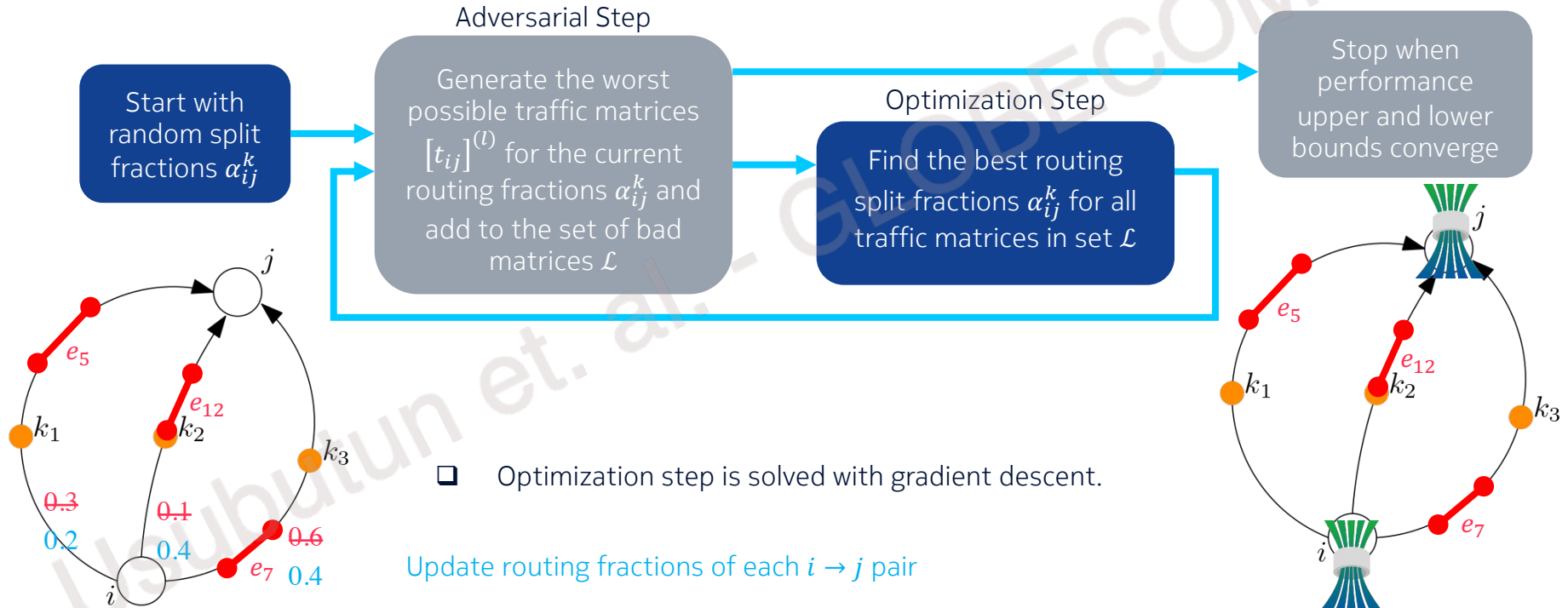


Generate a traffic matrix corresponding to each edge:

- from the hose constraints
- that maximizes the load

How to Solve an Oblivious Routing Problem Using ML?

- Follow an adversarial approach

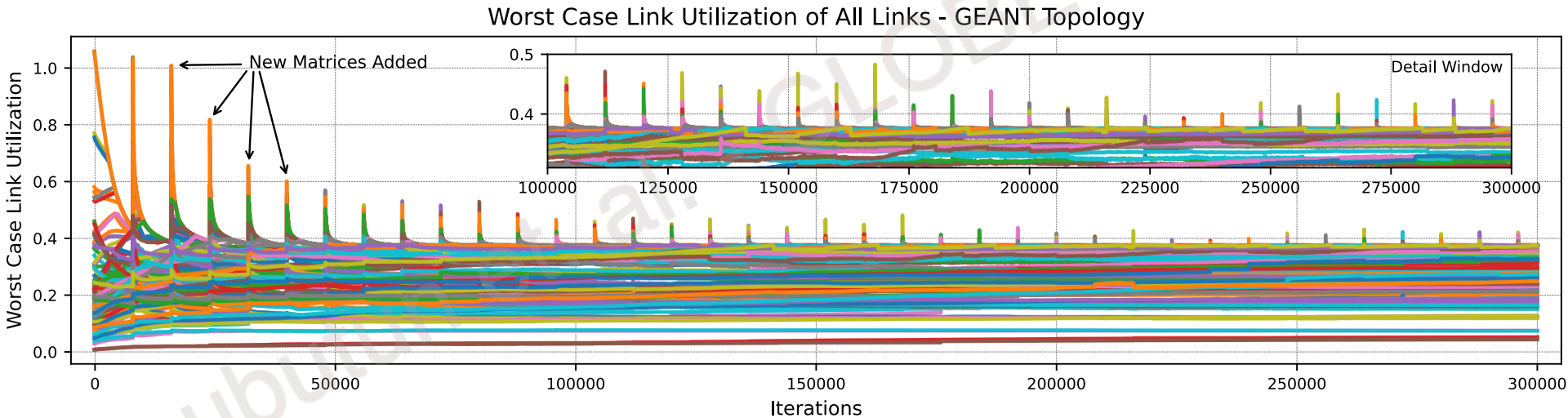


Results



The Adversarial Approach converges to the optimal solution

- ❑ Worst case utilization of each link on the network is depicted as split fractions are tuned.
- ❑ Adversarial traffic matrices are periodically added.



We Can Solve Large Scale Problems Using the ML Approach

- ❑ The Hose-Oblivious Routing problem can be solved using the Adversarial Learning Approach.
- ❑ The method scales well with network sizes and is able to handle hundreds of nodes
- ❑ For each solution obtained, we have a performance guarantee for the worst-case scenario.
- ❑ Our method is compatible with:
 - ❑ Legacy shortest path routing extensions (e.g., MPLS)
 - ❑ Software Defined Networking
- ❑ Also available in our paper:
 - ❑ Two computationally simple relaxations of this problem –providing bounding solutions

Thank You

Oblivious Routing using Learning Methods

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Backup Slides

How do we incorporate 2-Segment Routing into the problem formulation?

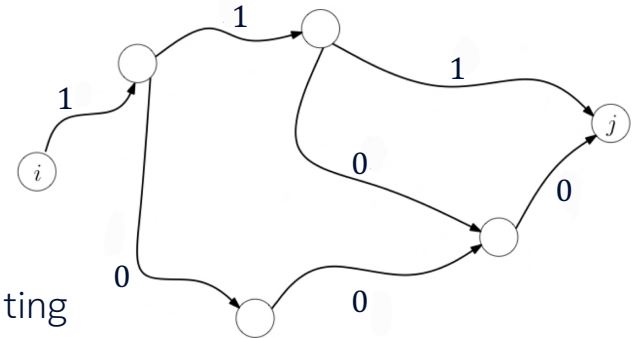
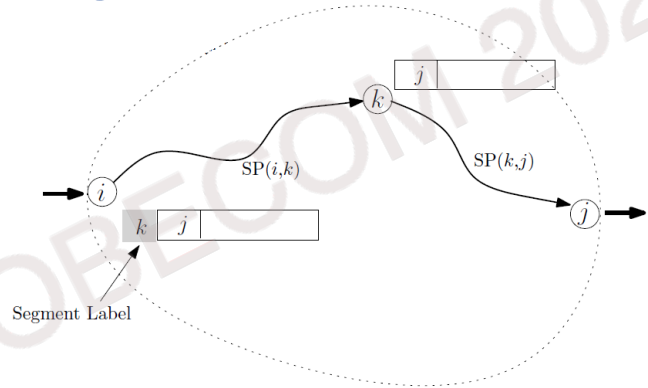
□ 2-Segment Routing: $i \rightarrow k \rightarrow j$

- Choose an intermediate node k
- Set what fraction of $i \rightarrow j$ should go through k
- $\sum_k \alpha_{ij}^k = 1, \forall i, j$

□ Define an indicator function $f_{ij}(e) \in \{0,1\}$ where e is an edge

- If a link e is on the shortest path from i to j : set $f_{ij}(e)$ to 1
- Otherwise: set $f_{ij}(e)$ to 0

□ Define $g_{ij}^k(e) = f_{ik}(e) + f_{kj}(e)$ to accommodate 2-Segment Routing



ECMP Extension

- ❑ Define an indicator function $f_{ij}(e) \in \{0,1\}$ where e is an edge
 - ❑ If a link e is on the shortest path from i to j : set $f_{ij}(e)$ to 1
 - ❑ Otherwise: set $f_{ij}(e)$ to 0

- ❑ ECMP Extension

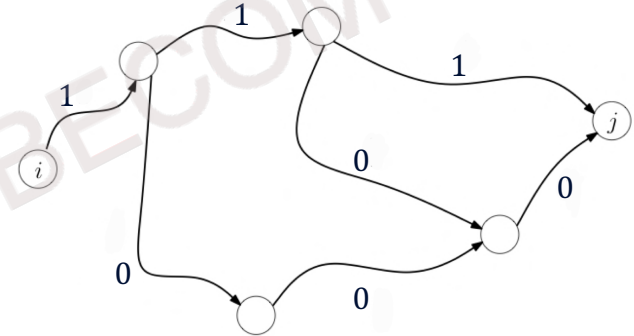
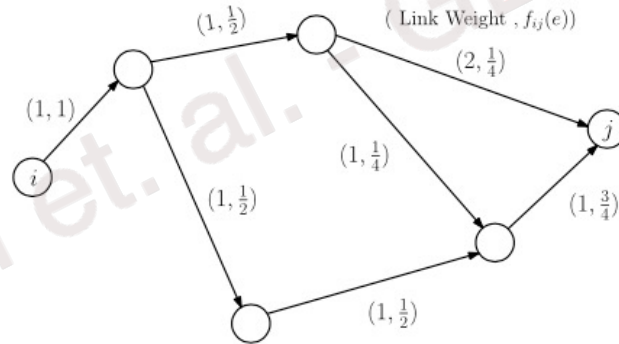


Fig. 1. Definition of $f_{ij}(e)$ with ECMP. The first number next to the link represents the link weight and the second number is $f_{ij}(e)$. The shortest path length is 4 and there are three shortest paths.

Formulating a 2-Segment Routing Problem

- Total traffic from i to j traveling over node k :

$$t_{ij}\alpha_{ij}^k$$

- The load on a link e caused by traffic from i to j thru k :

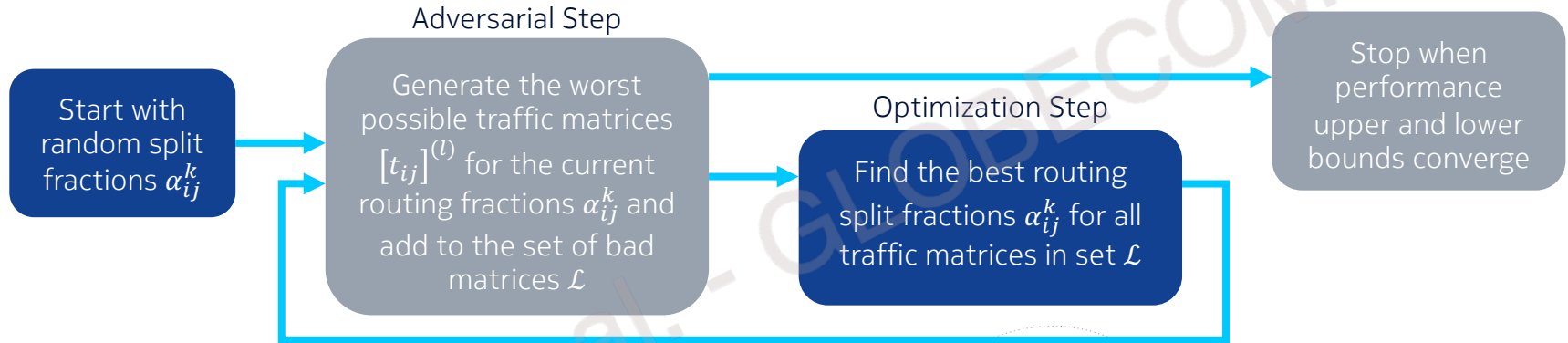
$$t_{ij}\alpha_{ij}^k g_{ij}^k(e)$$

- The total load on a link e :

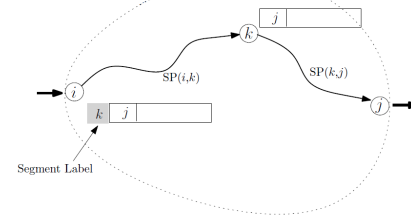
$$\sum_{ijk} t_{ij}\alpha_{ij}^k g_{ij}^k(e)$$

How to Solve an Oblivious Routing Problem Using ML?

- Follow an adversarial approach



$$\mathcal{I}(\vec{R}, \vec{C}) = \left\{ [t_{ij}] \mid \sum_{j \neq i} t_{ij} \leq R_i \text{ and } \sum_{j \neq i} t_{ji} \leq C_i \forall i \right\}$$



- Optimization step is solved with gradient descent.

Formulating a 2-Segment Oblivious Routing Problem

- Let the capacity of a given link e is u_e . The optimization problem becomes:

$$\begin{aligned} & \min_{\alpha_{ij}^k} \mu \text{ s. t.} \\ & \sum_{ijk} t_{ij} \alpha_{ij}^k g_{ij}^k(e) \leq \mu u_e, \quad \forall i, j, \forall e, \forall [t_{ij}] \in T(\vec{R}, \vec{C}) \\ & \sum_k \alpha_{ij}^k = 1, \quad \forall i, j \\ & \alpha_{ij}^k \geq 0, \quad \forall i, j, k \end{aligned}$$

$$T(\vec{R}, \vec{C}) = \left\{ [t_{ij}] \mid \sum_{j \neq i} t_{ij} \leq R_i \text{ and } \sum_{j \neq i} t_{ji} \leq C_i \forall i \right\}$$

- How do we work with infinitely many traffic matrices?

How to Solve an Oblivious Routing Problem Using ML?

The Optimization Step

- Reshape the 2-segment routing problem to embed some constraints into the objective function

$$\begin{aligned} & \min_{\alpha_{ij}^k} \mu \text{ s. t.} \\ & \sum_{ijk} t_{ij}^{(l)} \alpha_{ij}^k g_{ij}^k(e) \leq \mu u_e, \quad \forall i, j, \forall l, \forall e \\ & \sum_k \alpha_{ij}^k = 1, \quad \forall i, j \\ & \alpha_{ij}^k \geq 0, \quad \forall i, j, k \end{aligned}$$



$$\begin{aligned} & \min_{\alpha_{ij}^k} \left\{ \max_{e,l} \frac{\sum_{ijk} t_{ij}^{(l)} \alpha_{ij}^k g_{ij}^k(e)}{u_e} \right\} \text{ s. t.} \\ & \sum_k \alpha_{ij}^k = 1, \quad \forall i, j \\ & \alpha_{ij}^k \geq 0, \quad \forall i, j, k \end{aligned}$$



- Use the *softmax* function to keep solutions in the feasible set.

$$\alpha_{ij}^k = SM(y_{ij}^k) = \frac{e^{y_{ij}^k}}{\sum_k e^{y_{ij}^k}}, \quad \forall i, j$$



$$\min_{\alpha_{ij}^k} \left\{ \max_{e,l} \frac{\sum_{ijk} t_{ij}^{(l)} SM(y_{ij}^k) g_{ij}^k(e)}{u_e} \right\} \text{ s. t.}$$

Generate worst case matrices: The Adversarial Step

Given a choice of split fractions α_{ij}^k

Generate one worst case traffic matrix for each link e

Append all new matrices to set \mathcal{L}

$$[t_{ij}]^{(l)} = \arg \max_{[t_{ij}]} \sum_{ijk} t_{ij} \alpha_{ik}^k g_{ij}^k(e) \quad \text{s.t.}$$

$$\sum_i t_{ij} \leq C_j, \quad \forall j$$

$$\sum_j t_{ij} \leq R_i, \quad \forall i$$

$$t_{ij} \geq 0, \quad \forall i, j$$

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