# Self-Adjusting Networks

Stefan Schmid

> “We cannot direct the wind,
> but we can adjust the sails.”

(Folklore)

Acknowledgements:

# Trend

## Data-Centric Applications

Datacenters (“hyper-scale”)

Interconnecting networks:
a **critical infrastructure**
of our digital society.

Source: Facebook

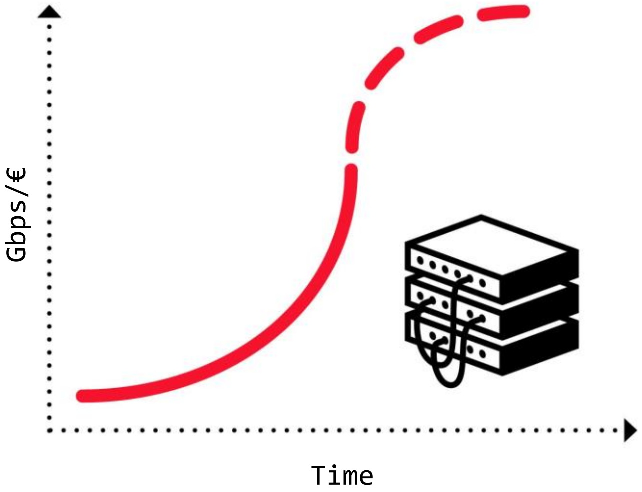
# The Problem

## Huge Infrastructure, Inefficient Use

⇢ Network equipment reaching capacity limits
  ⇀ Transistor density rates stalling
  ⇀ “End of **Moore‘s Law** in networking” [1]

⇢ Hence: more equipment, larger networks

⇢ Resource intensive and: **inefficient**



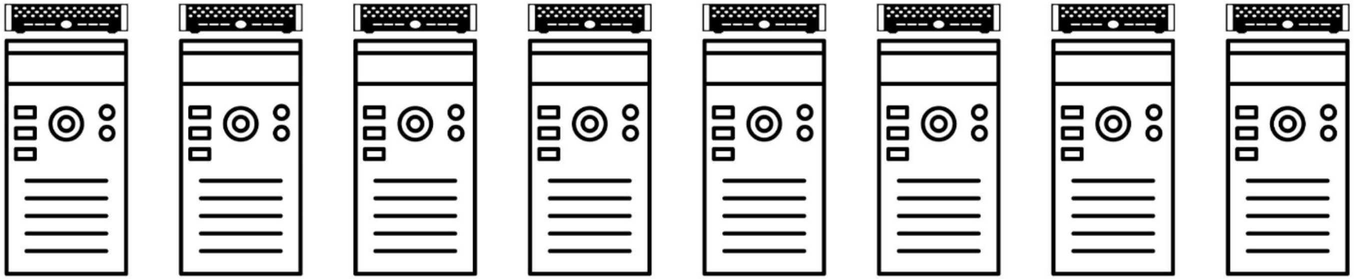
[1] Source: Microsoft, 2019

Annoying for companies,
**opportunity** for researchers

# Root Cause

## Fixed and Demand-Oblivious Topology

How to interconnect?



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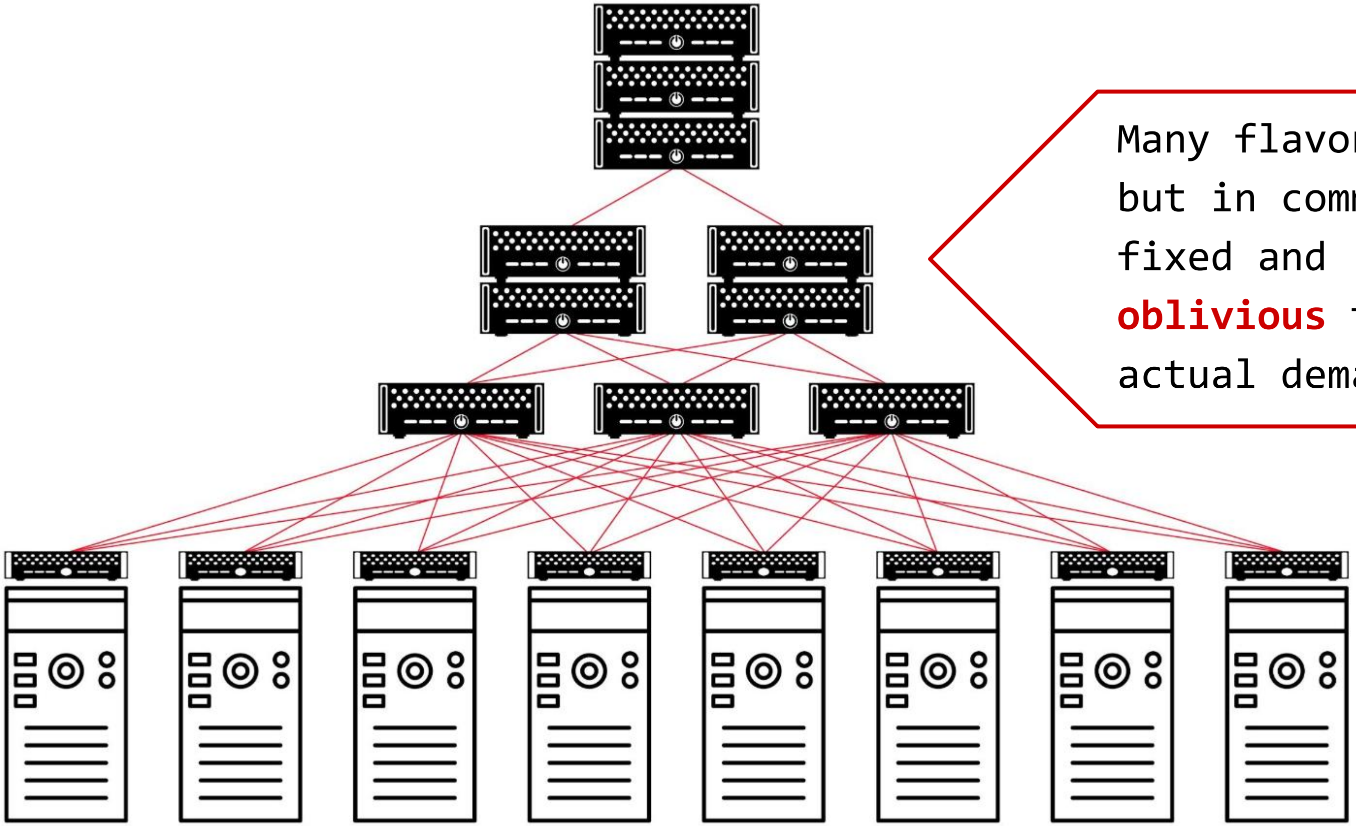

Many flavors,
but in common:
fixed and
**oblivious** to
actual demand.

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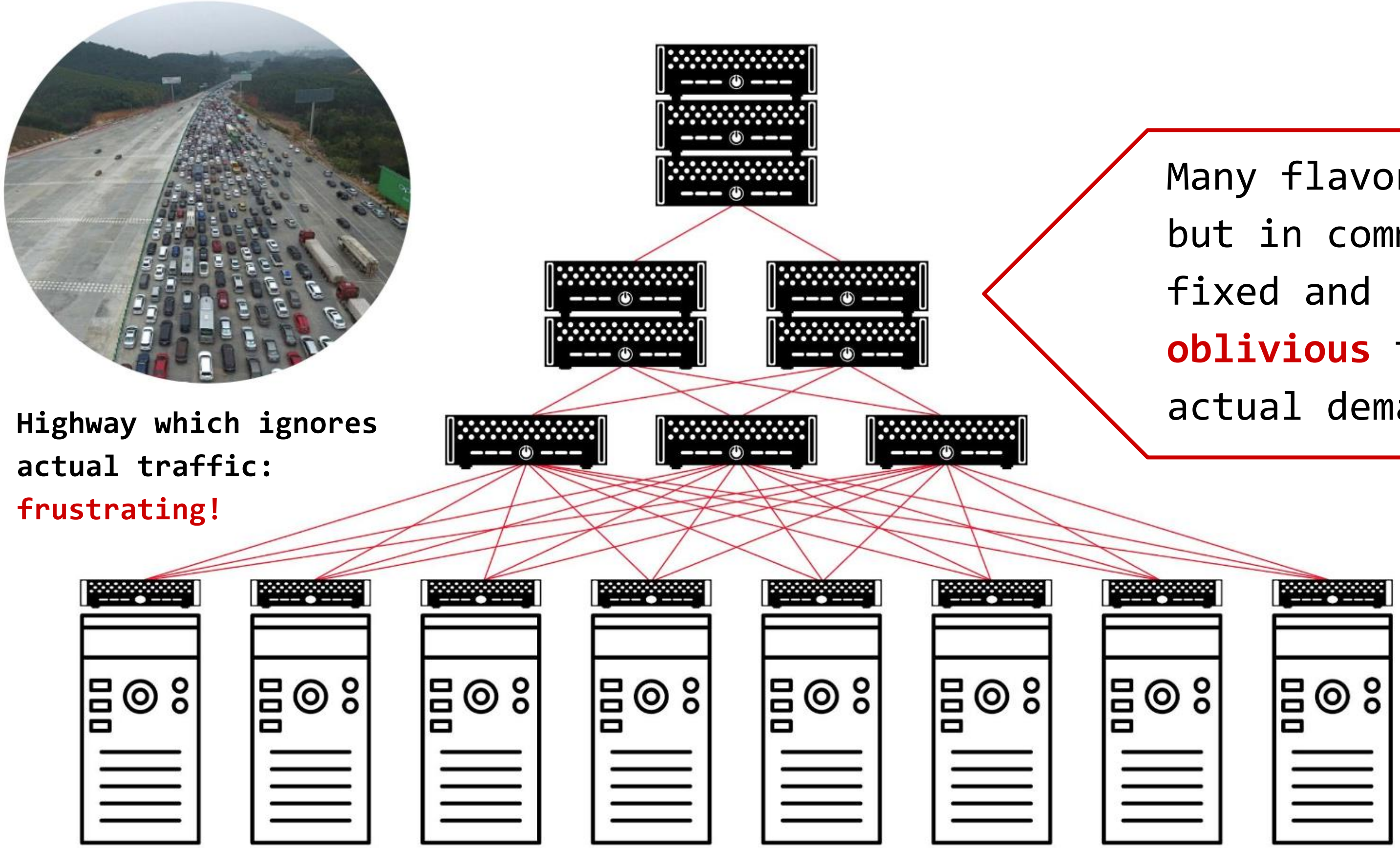
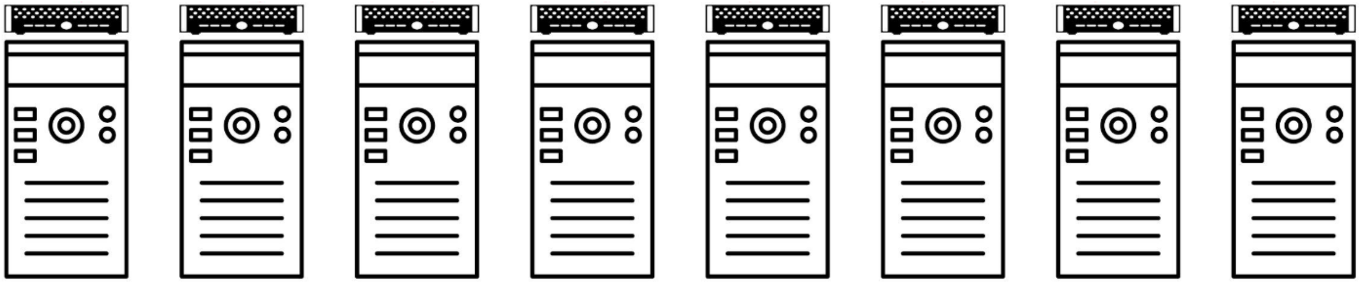


**Highway which ignores actual traffic: frustrating!**

Many flavors, but in common: fixed and **oblivious** to actual demand.

# Our Vision

## Flexible and Demand-Aware Topologies



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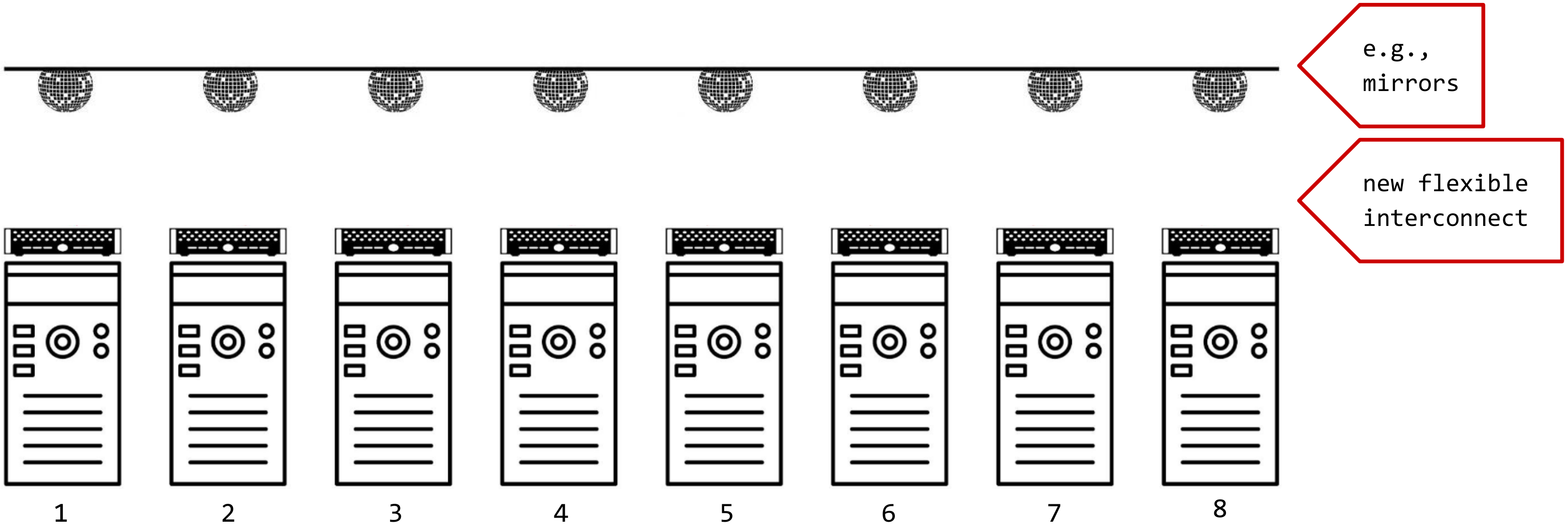


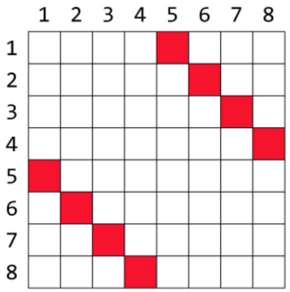
e.g., mirrors

new flexible interconnect

# Our Vision

## Flexible and Demand-Aware Topologies

demand matrix:



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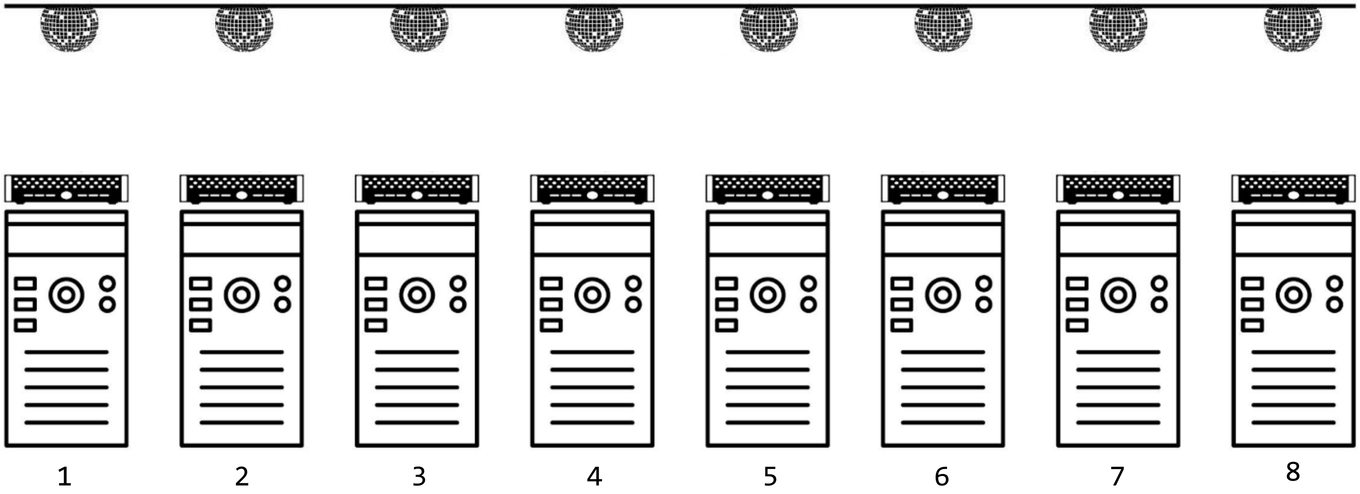

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## Flexible and Demand-Aware Topologies

Matches demand

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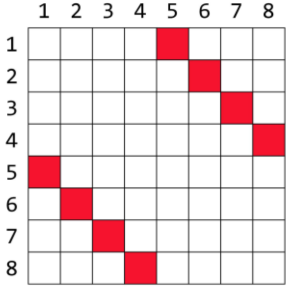

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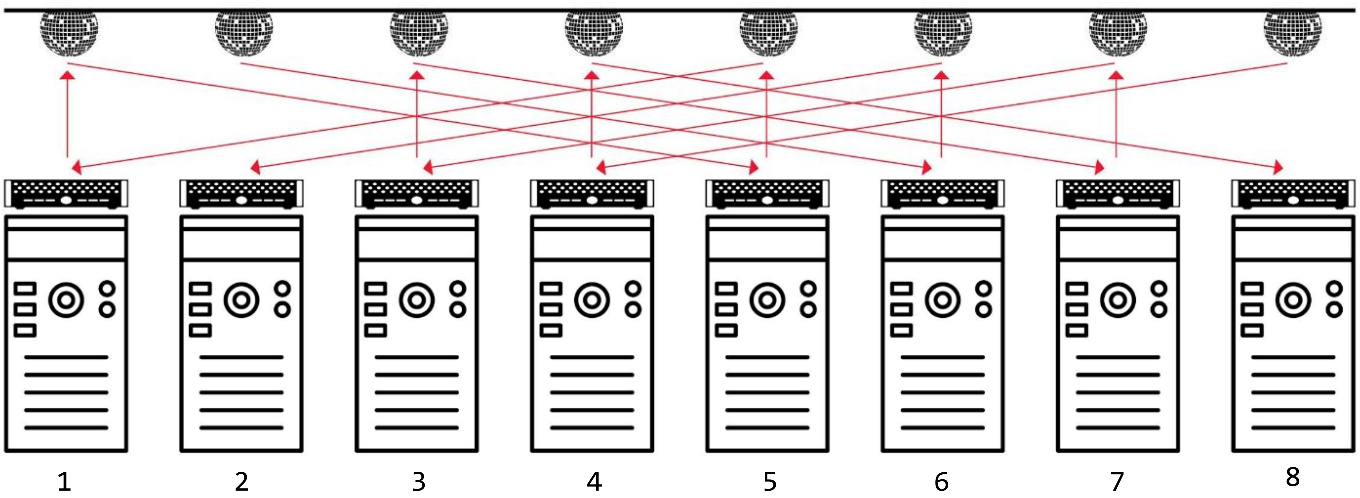

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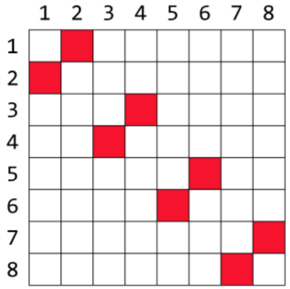
# Our Vision

## Flexible and Demand-Aware Topologies

new demand:



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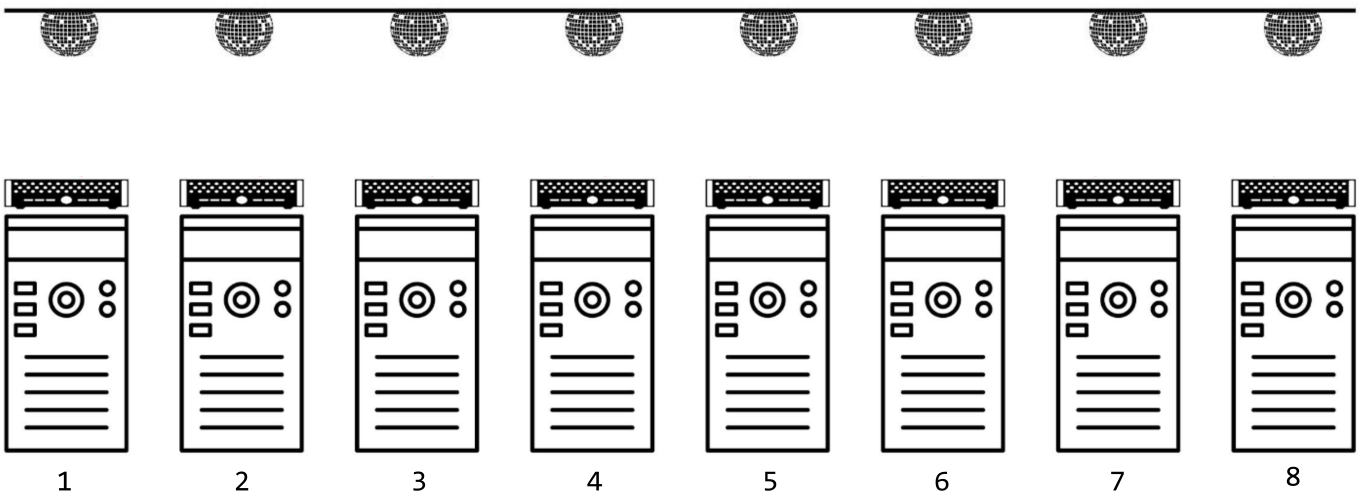

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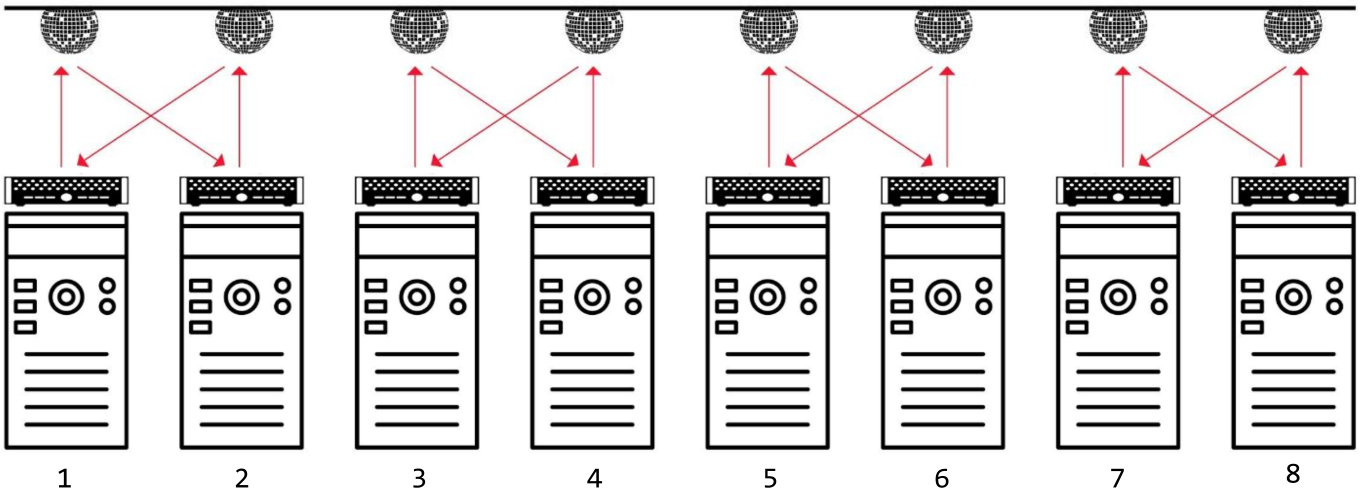

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Self-Adjusting Networks

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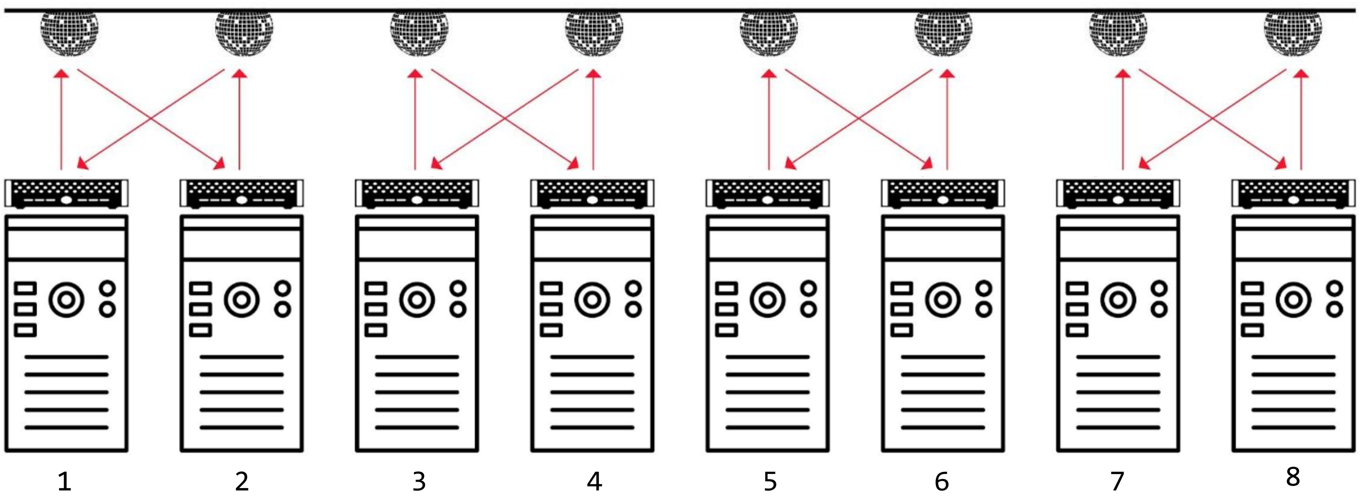

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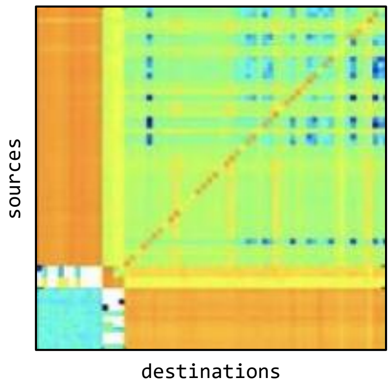
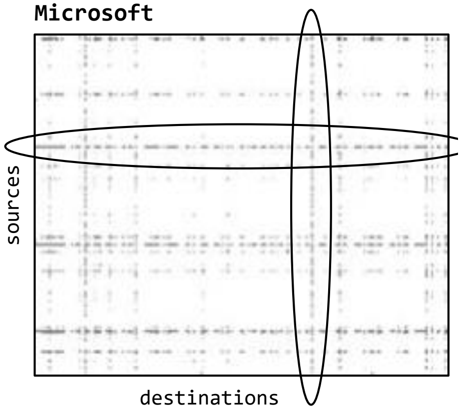
# Our Motivation

## Much Structure in the Demand

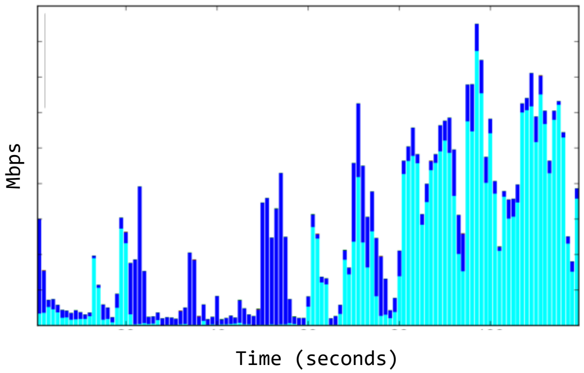
Empirical studies:

traffic matrices sparse and skewed


**Facebook**


**Microsoft**

traffic bursty over time


**Facebook**

**My hypothesis: can be exploited.**

## Recent Representation of Trace Structure:

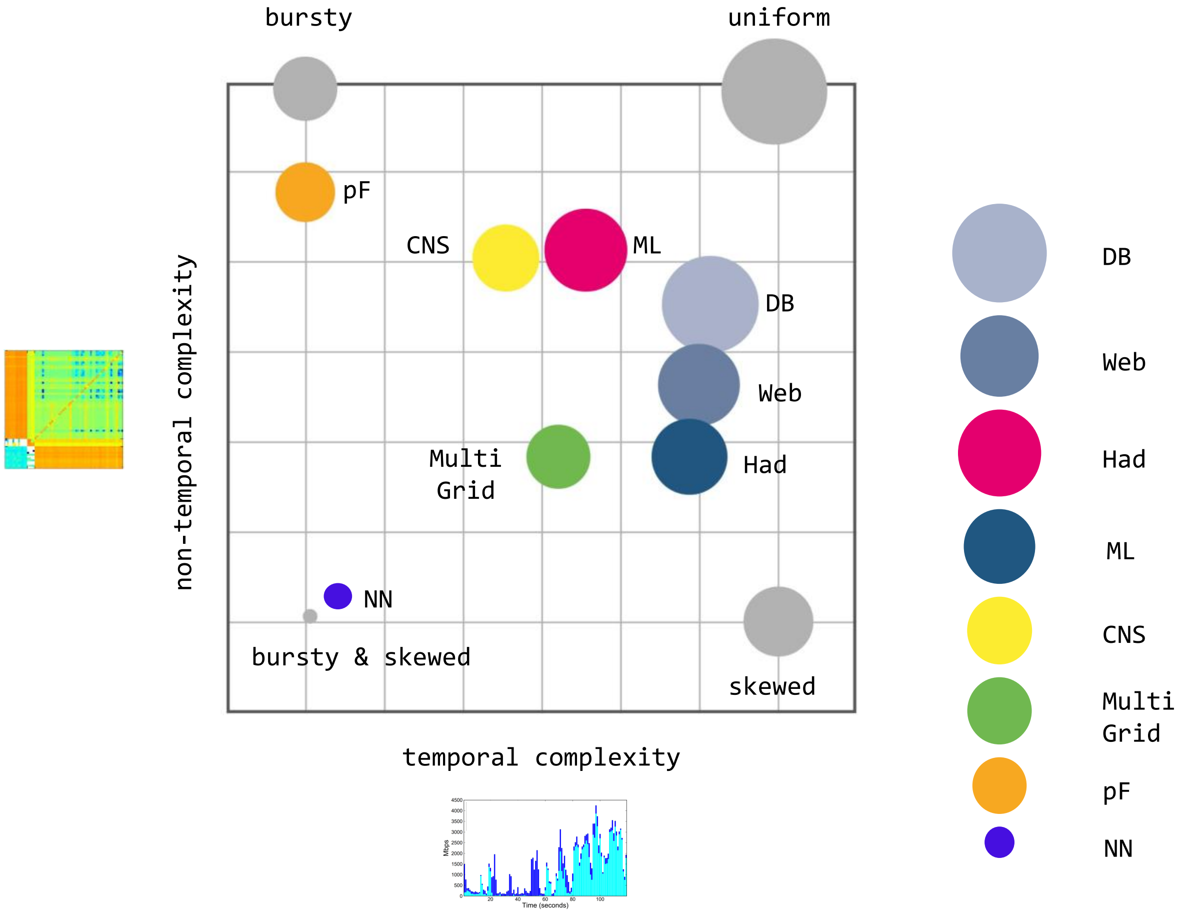
# Complexity Map

● DB
● Web
● Had
● ML
● CNS
● Multi Grid
● pF
● NN

Griner et al., SIGMETRICS 2020

Recent Representation of Trace Structure:

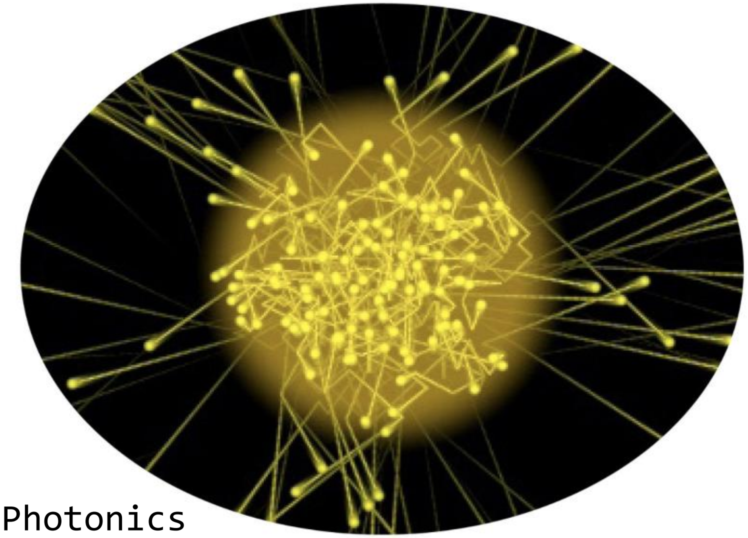
# Complexity Map



**Different structures!**

Griner et al., SIGMETRICS 2020

# Sounds Crazy?
# Emerging Enabling Technology.



Photonics

H2020:

**“Photonics one of only five key enabling technologies for future prosperity.”**

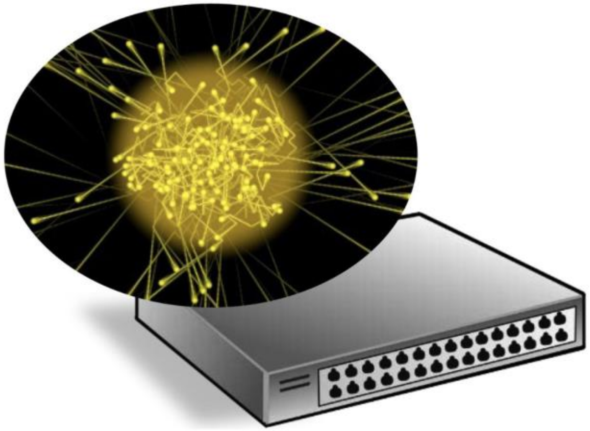
US National Research Council:

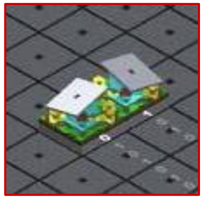
**“Photons are the new Electrons.”**

# Enabler

## Novel Reconfigurable Optical Switches

- **Spectrum** of prototypes
  - Different sizes, different reconfiguration times
  - From our last year’s ACM **SIGCOMM** workshop OptSys





Prototype 1

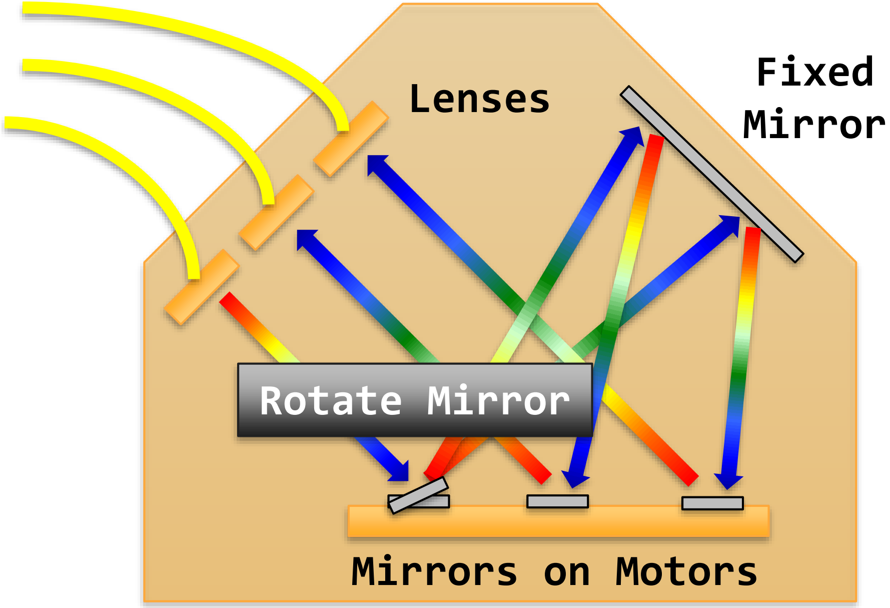
Prototype 2

Prototype 3

# Example

## Optical Circuit Switch

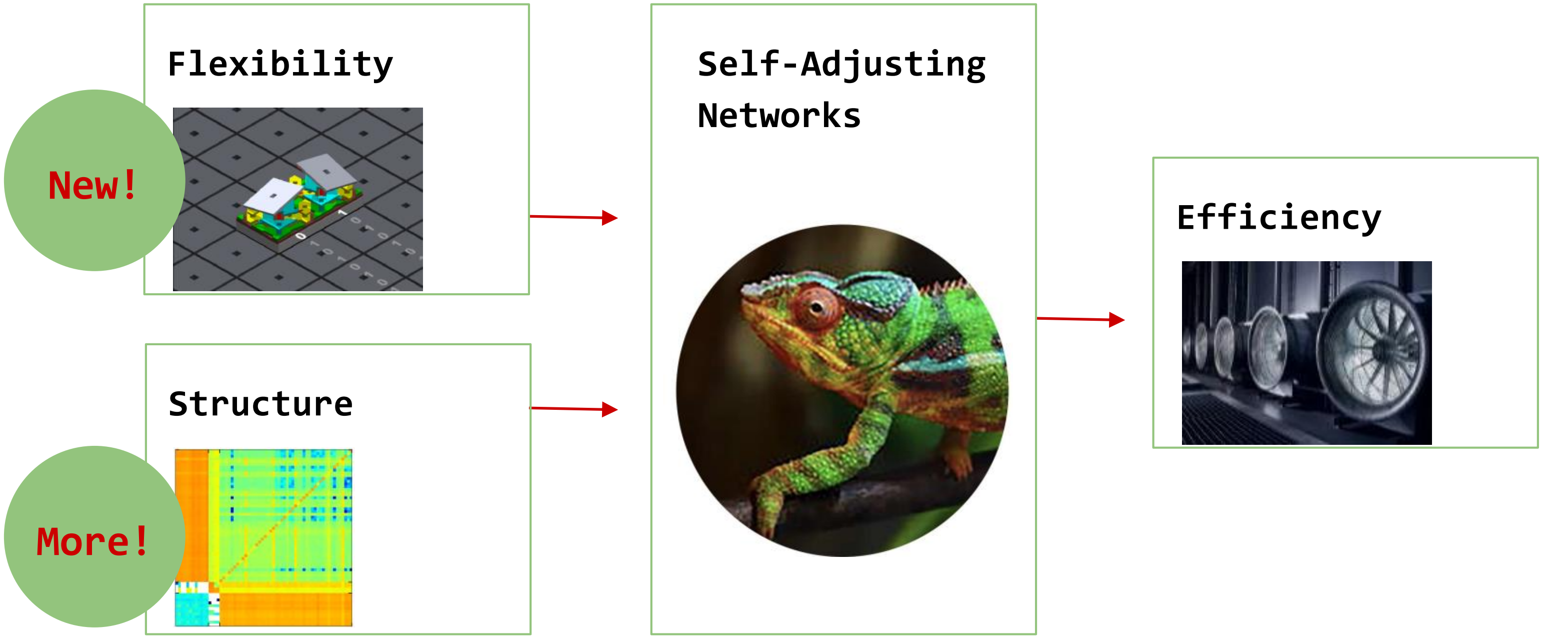
- ⇢ Optical Circuit Switch rapid adaption of physical layer
    - ⇀ Based on rotating mirrors



Optical Circuit Switch

By Nathan Farrington, SIGCOMM 2010

# The Big Picture



New!

**Flexibility**

More!

**Structure**

**Self-Adjusting Networks**

**Efficiency**

Now is the time!

# The Big Picture

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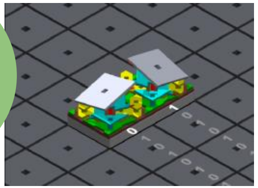

More!

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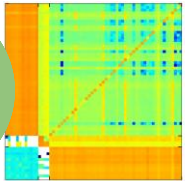


**Self-Adjusting Networks**

Now is the time!

**Efficiency**

**Our goal:** Develop the theoretical **foundations** of demand-aware, self-adjusting networks.

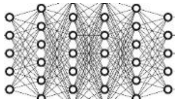
# Unique Position

## Demand-Aware, Self-Adjusting Systems

Everywhere, but mainly in software

Algorithmic trading

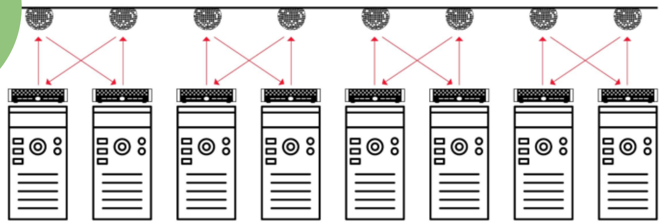
Recommender systems



Neural networks

**VS**

**Our focus: in hardware**



The Natural Question:

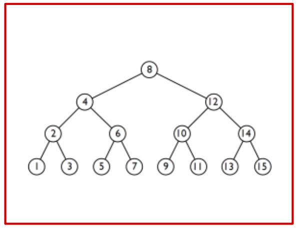
# Given This Structure, What Can Be Achieved? Metrics and Algorithms?

A first insight: entropy of the demand.

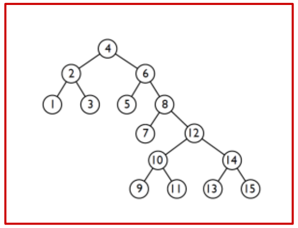
Our Insight:

# Connection to Datastructures

Traditional BST



Demand-aware BST



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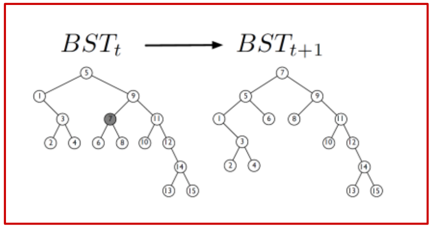
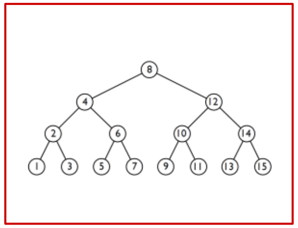


More structure: improved **access cost**

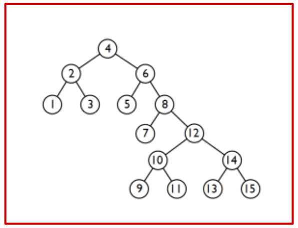
## Our Insight:

# Connection to Datastructures & Coding

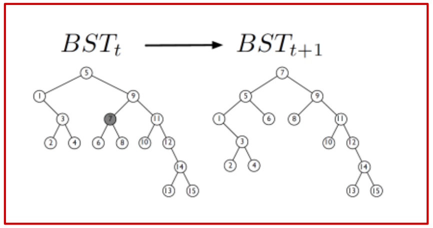
Traditional BST
(Worst-case coding)



Demand-aware BST
(Huffman coding)



Self-adjusting BST
(Dynamic Huffman coding)



More structure: improved **access cost** / shorter **codes**

Our Insight:

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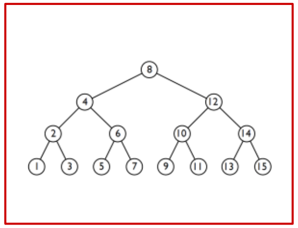

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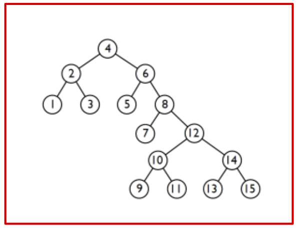

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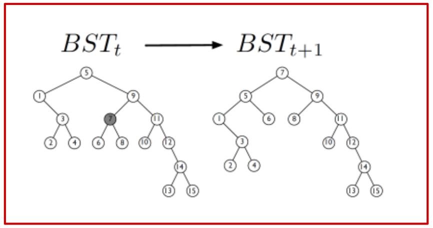

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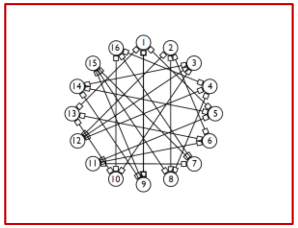

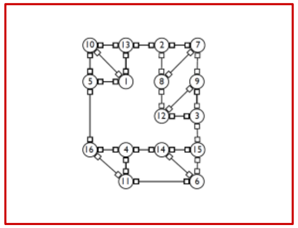

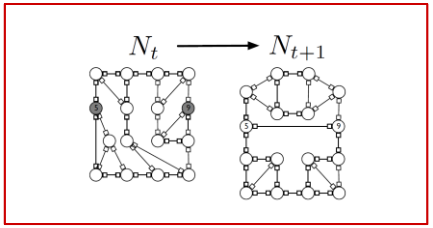

Similar **benefits**?

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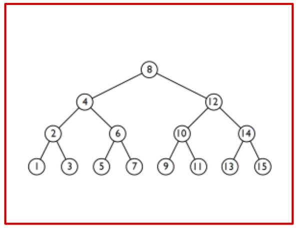

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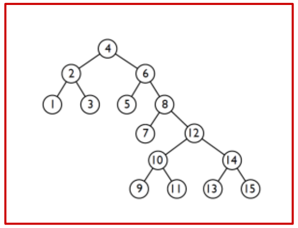

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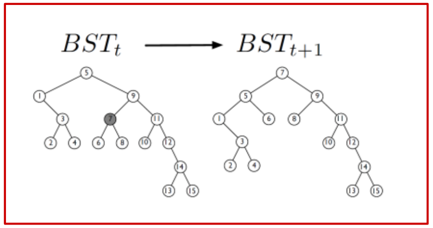
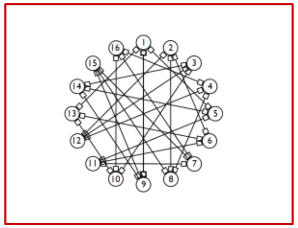
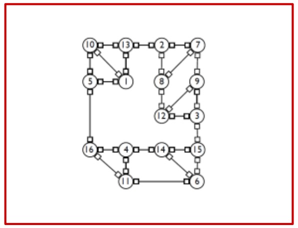
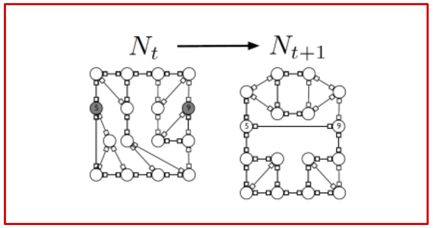


More than
an analogy!

More structure: improved **access cost** / shorter **codes**







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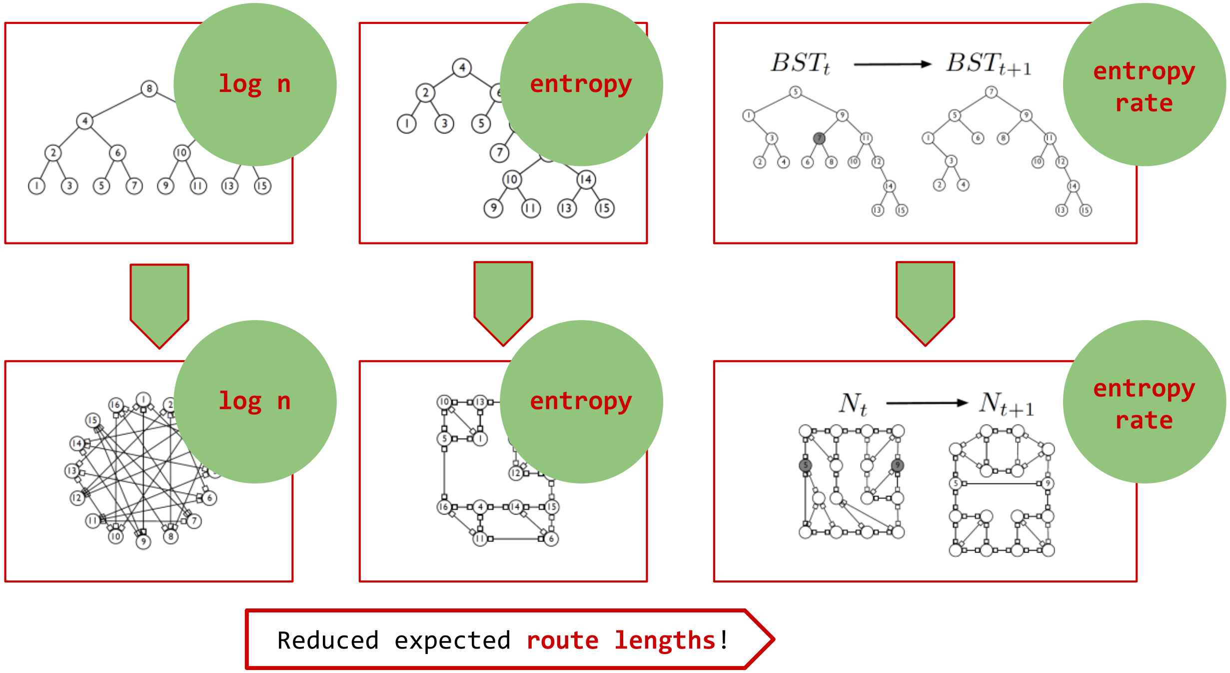


Reduced expected **route lengths**!

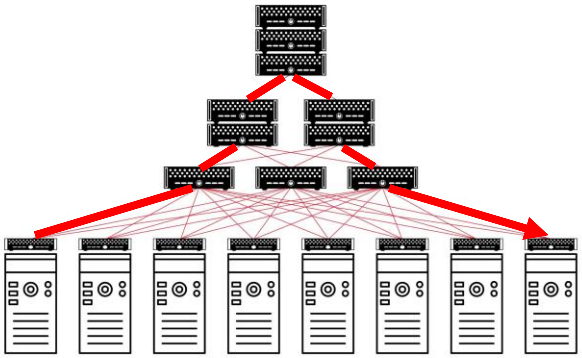
More than
an analogy!

**Generalize methodology:**
**... and transfer entropy bounds and algorithms of data-structures to networks.**

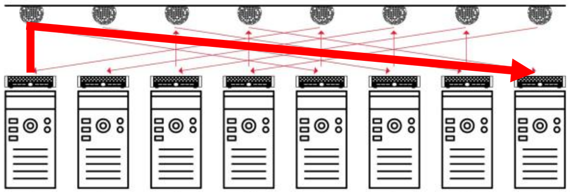
**First result:**
**Demand-aware networks of asymptotically optimal route lengths.**

# It is more complicated…

→ Self-adjusting networks may be really useful to serve large flows (elephant flows): avoiding multi-hop routing



vs



**6 hops**

**1 hop**

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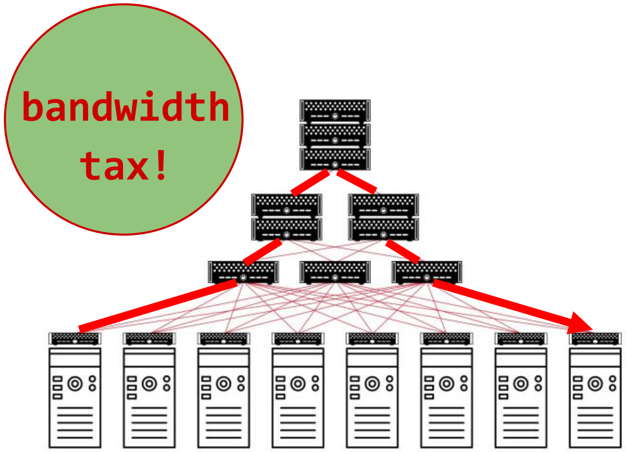
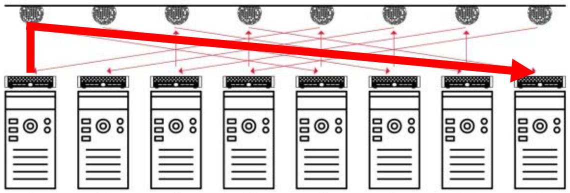


**bandwidth tax!**

vs



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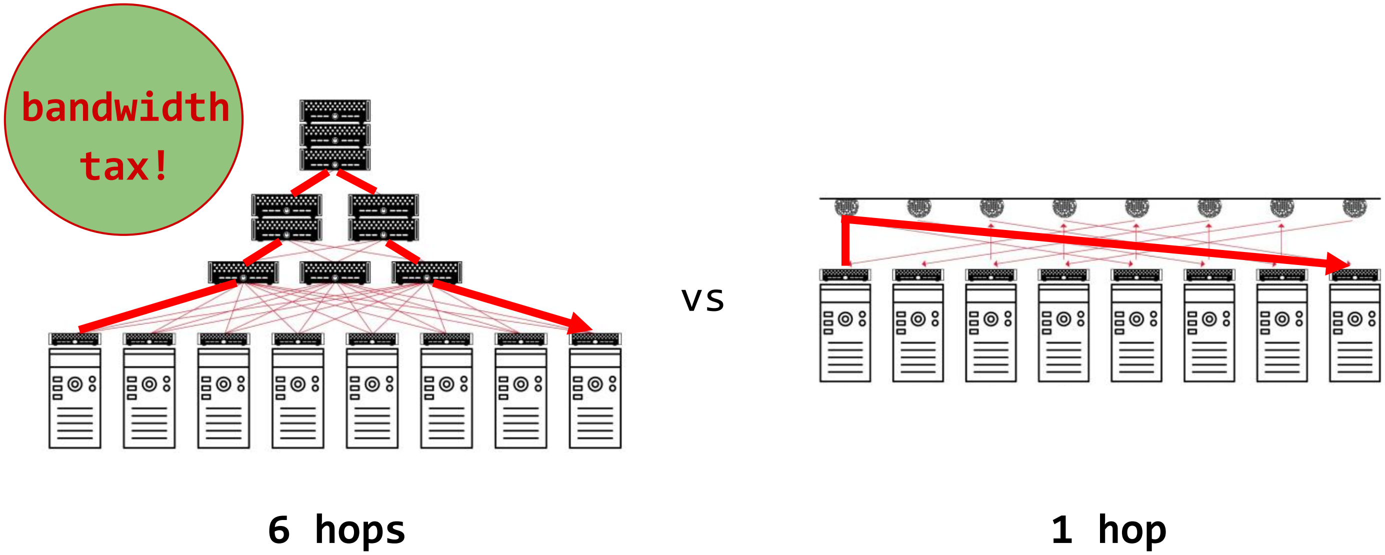

⇀ However, requires optimization and adaption, which takes time

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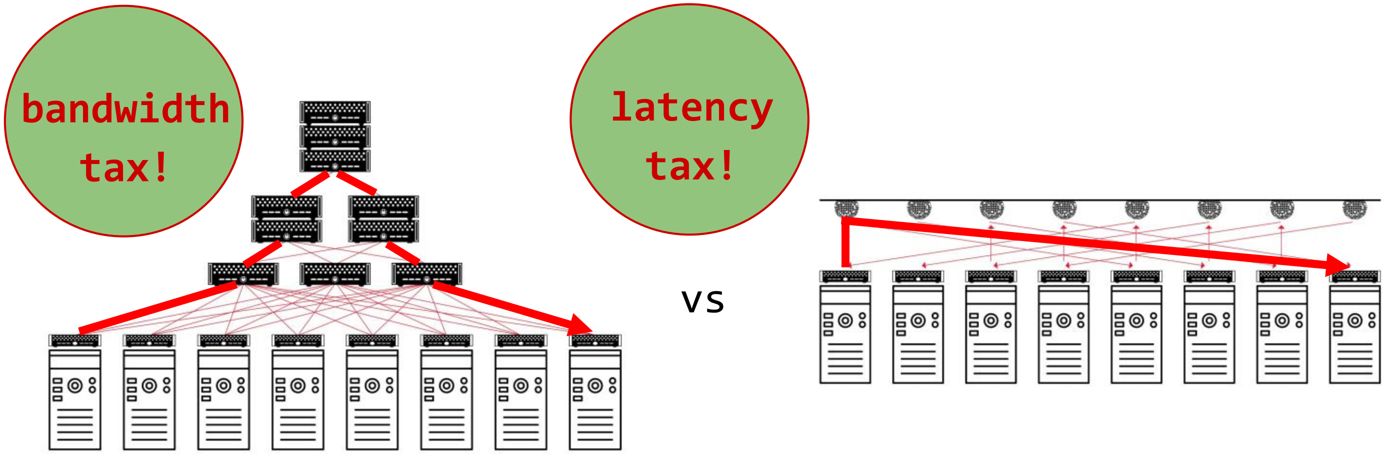


bandwidth tax!

latency tax!

vs

**6 hops**

**1 hop**

⇀ However, requires optimization and adaption, which takes time

Indeed, it is more complicated than that…

# Challenge: Traffic Diversity

**Diverse patterns:**

⇀ Shuffling/Hadoop: all-to-all

⇀ All-reduce/ML: ring or tree traffic patterns

  ⇀ Elephant flows

⇀ Query traffic: skewed

  ⇀ Mice flows

⇀ Control traffic: does not evolve but has non-temporal structure

**Diverse requirements:**

⇀ ML is bandwidth hungry, small flows are latency-sensitive

Shuffling

All-to-All

ML

Large flows

Delay sensitive

Telemetry / control

# Opportunity: Tech Diversity

**Diverse topology components:**

⇀ demand-oblivious and
demand-aware

Demand-oblivious

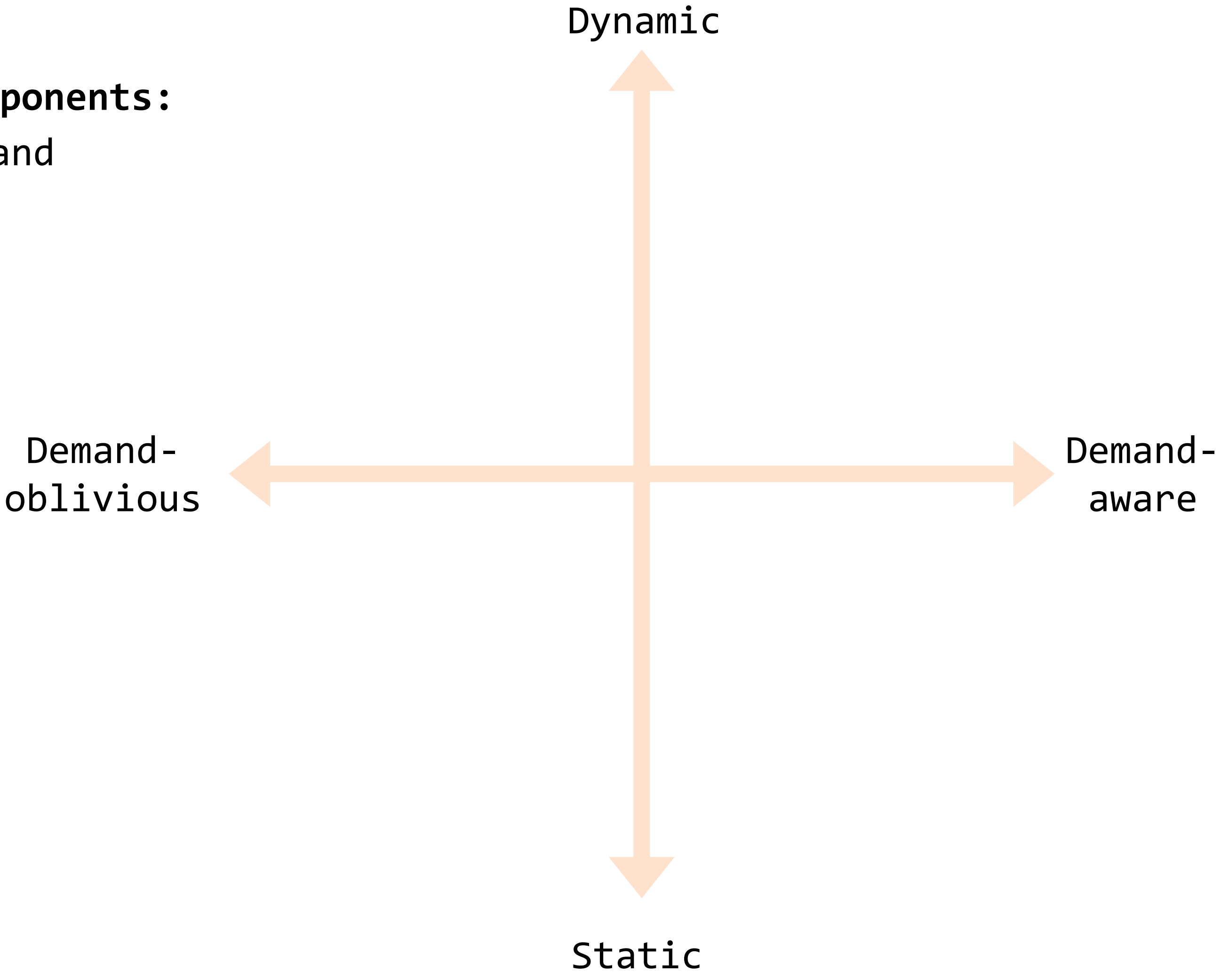
Demand-aware

# Opportunity: Tech Diversity

**Diverse topology components:**

⇀ demand-oblivious and
  demand-aware

⇀ static vs dynamic

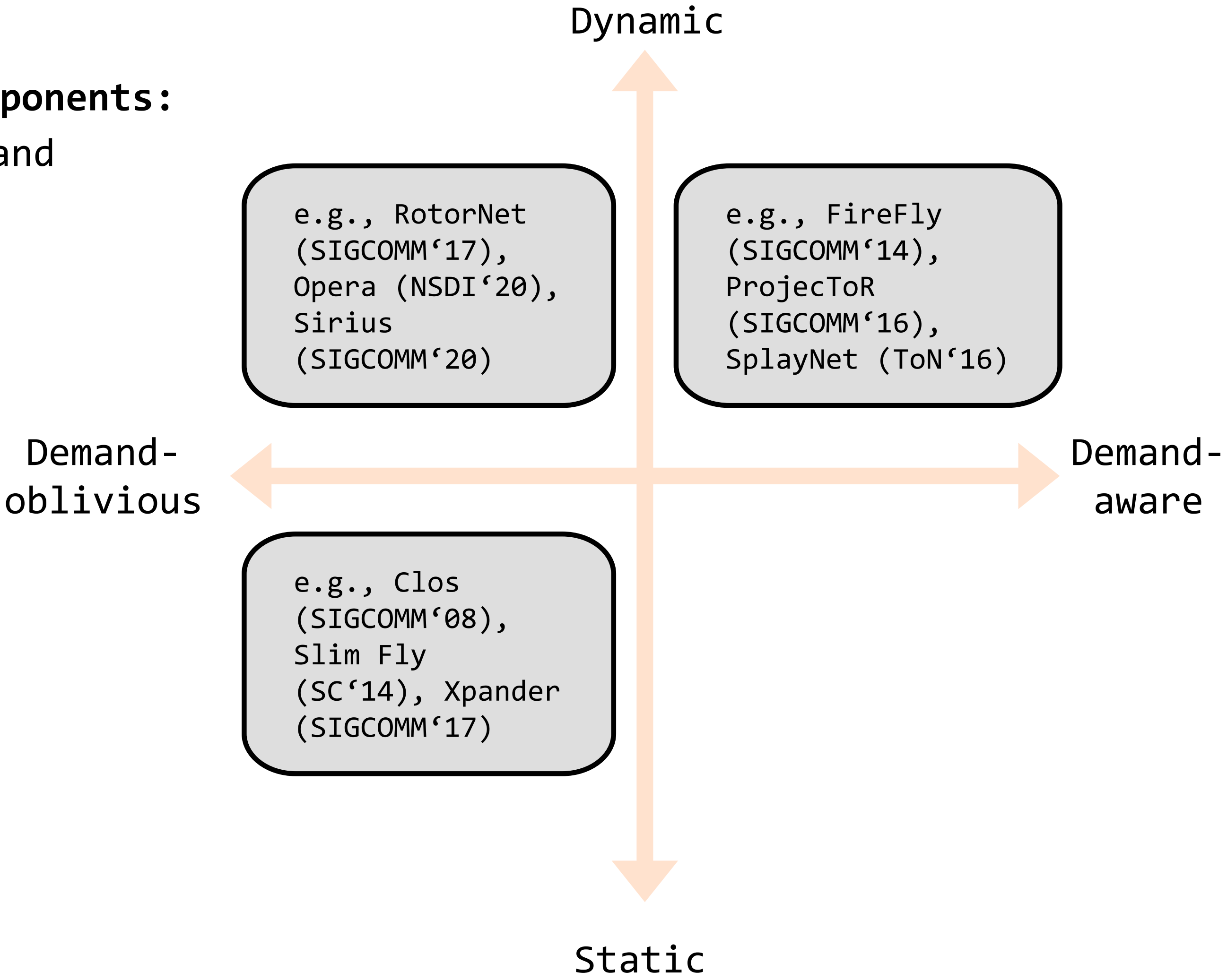


# Opportunity: Tech Diversity

**Diverse topology components:**

⇀ demand-oblivious and
demand-aware

⇀ static vs dynamic



Dynamic

e.g., RotorNet (SIGCOMM‘17), Opera (NSDI‘20), Sirius (SIGCOMM‘20)

e.g., FireFly (SIGCOMM‘14), ProjecToR (SIGCOMM‘16), SplayNet (ToN‘16)

Demand-oblivious

Demand-aware

e.g., Clos (SIGCOMM‘08), Slim Fly (SC‘14), Xpander (SIGCOMM‘17)

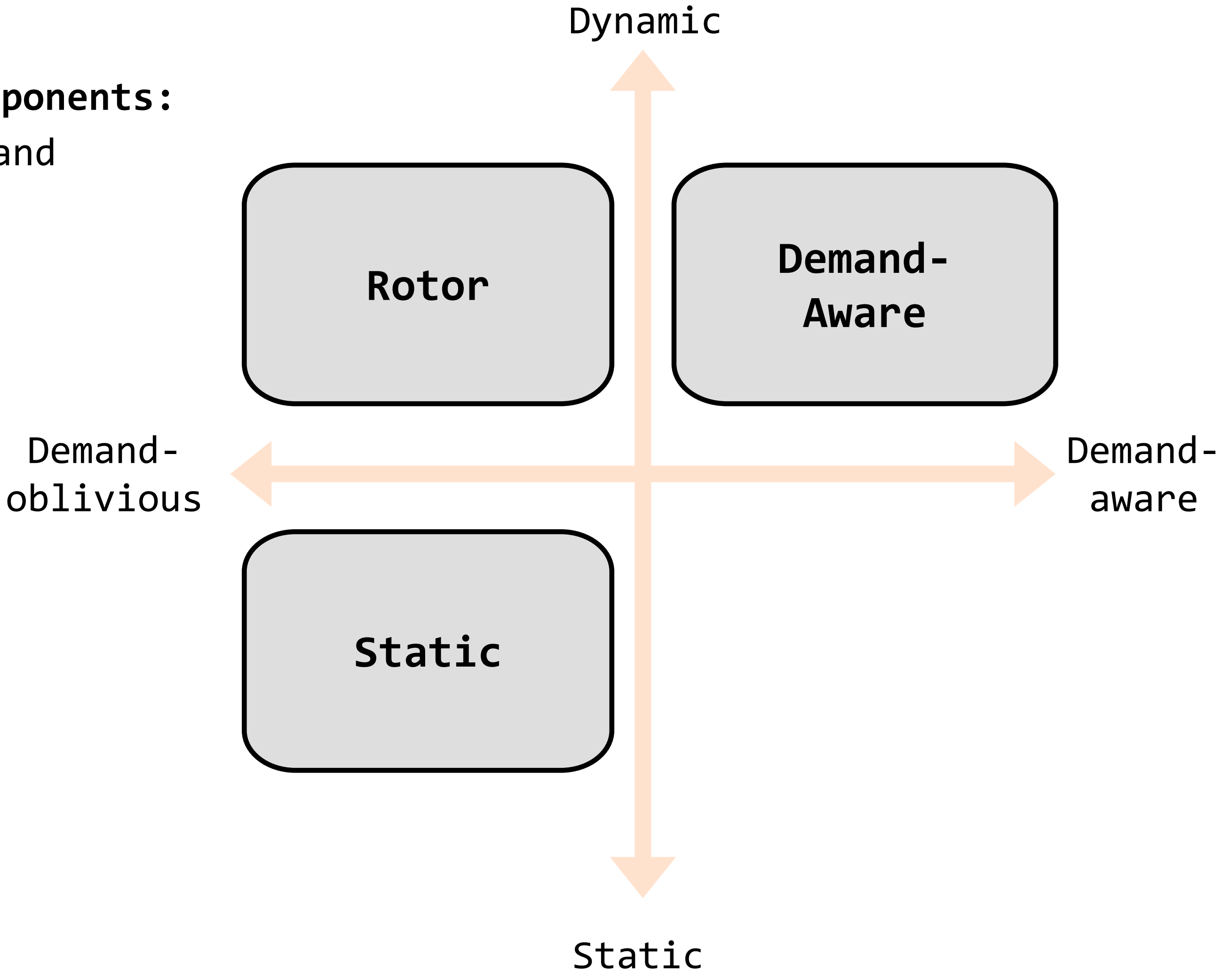
Static

# Opportunity: Tech Diversity

**Diverse topology components:**

⇀ demand-oblivious and
demand-aware

⇀ static vs dynamic



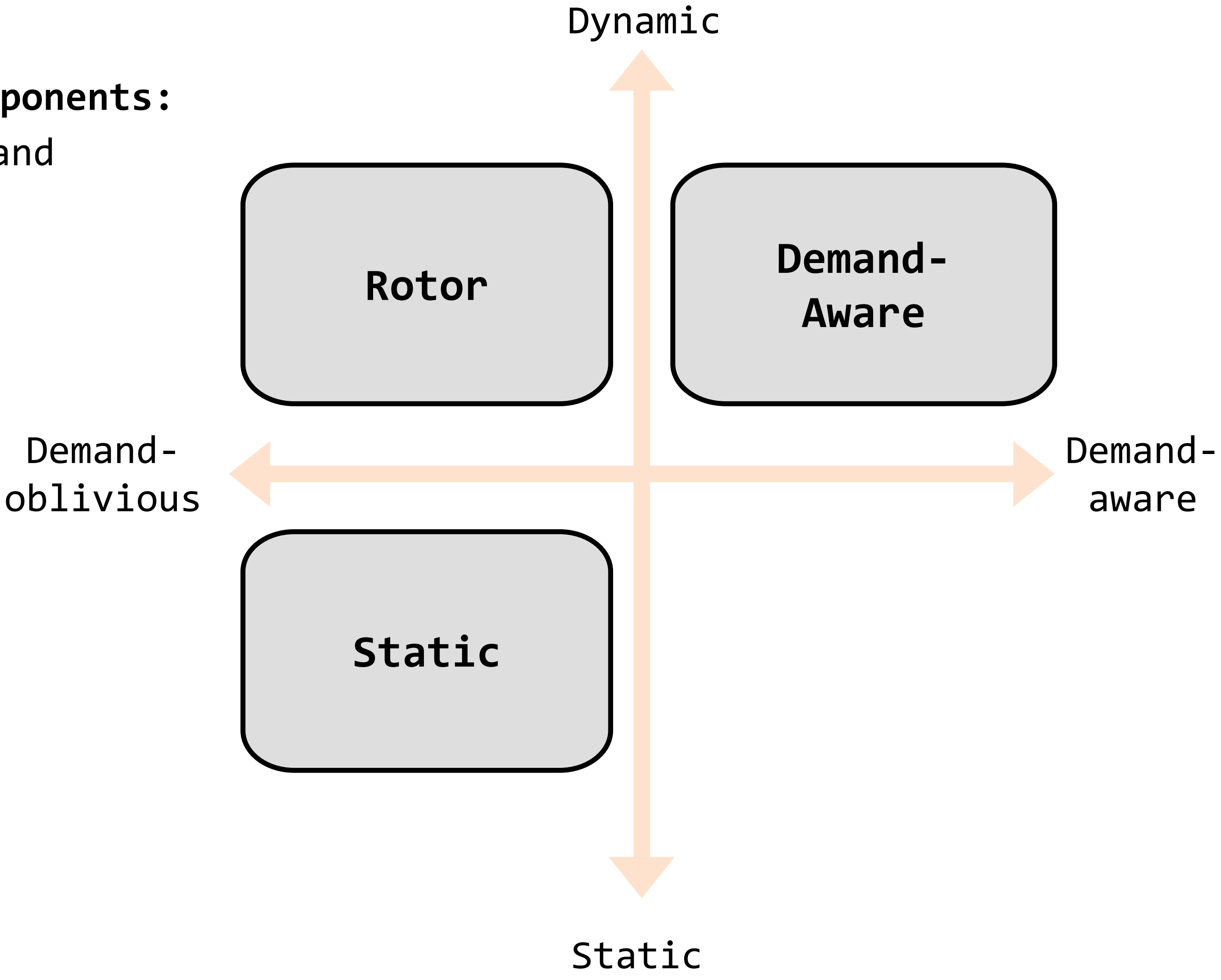
# Opportunity: Tech Diversity

**Diverse topology components:**

⇀ demand-oblivious and demand-aware

⇀ static vs dynamic

**Which approach is best?**

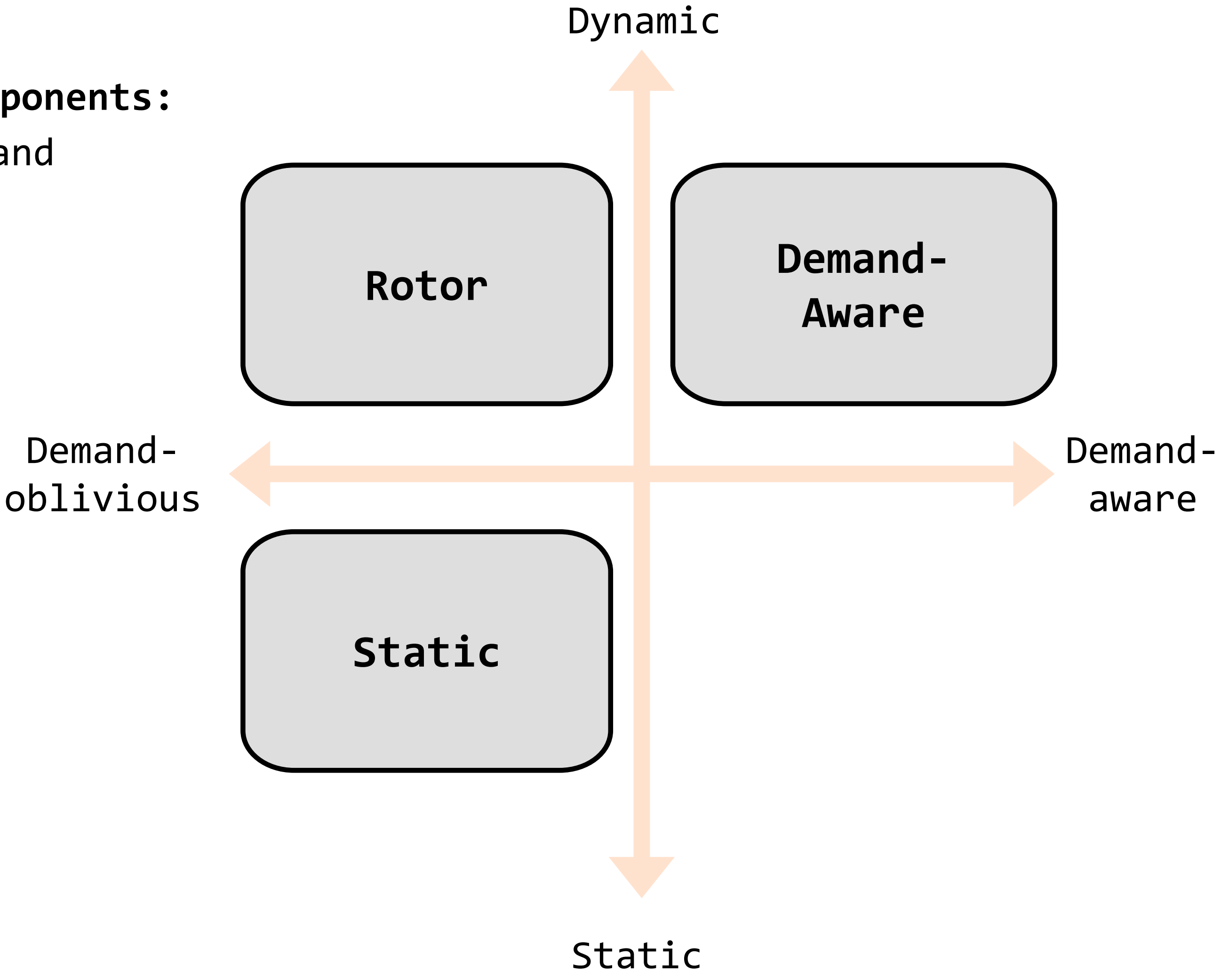


# Opportunity: Tech Diversity

**Diverse topology components:**

⇀ demand-oblivious and
 demand-aware

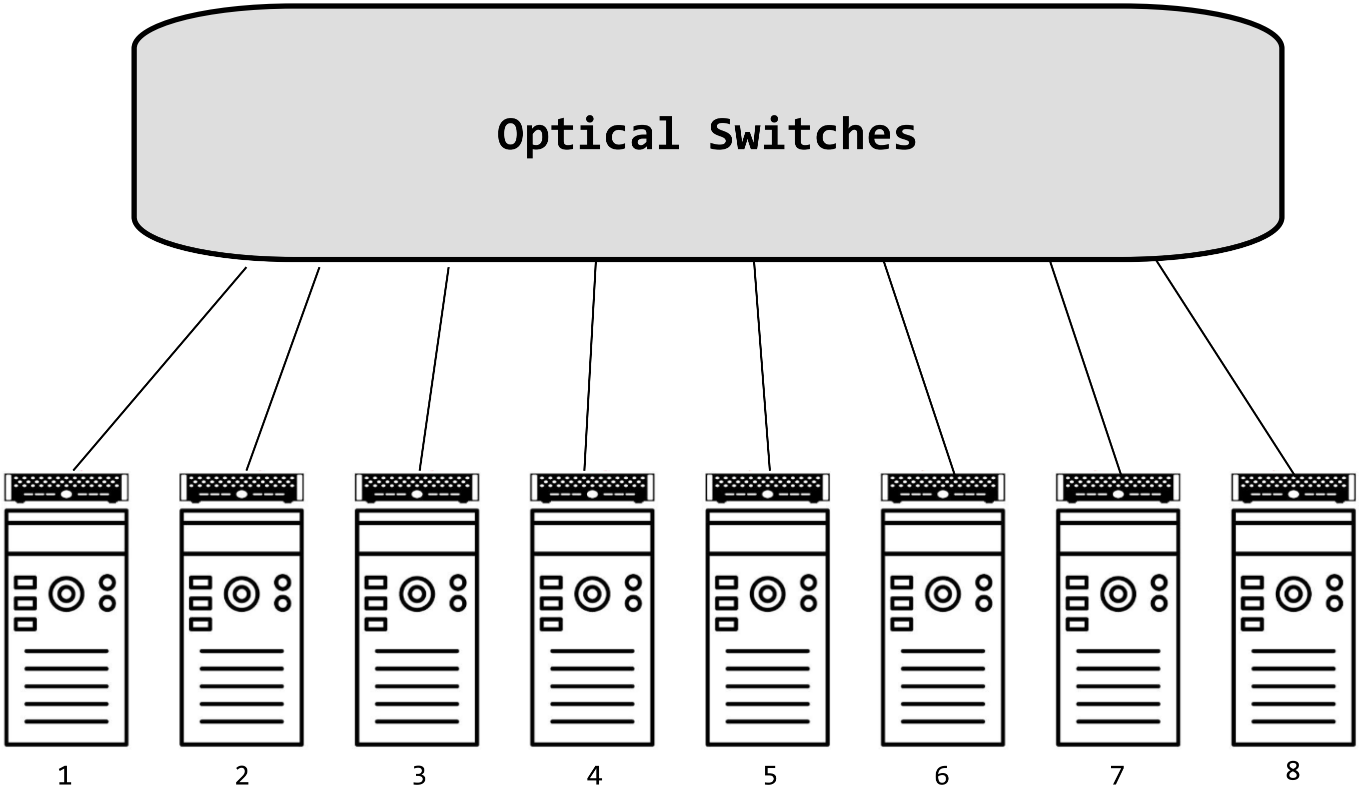
⇀ static vs dynamic



**Which approach is best?**

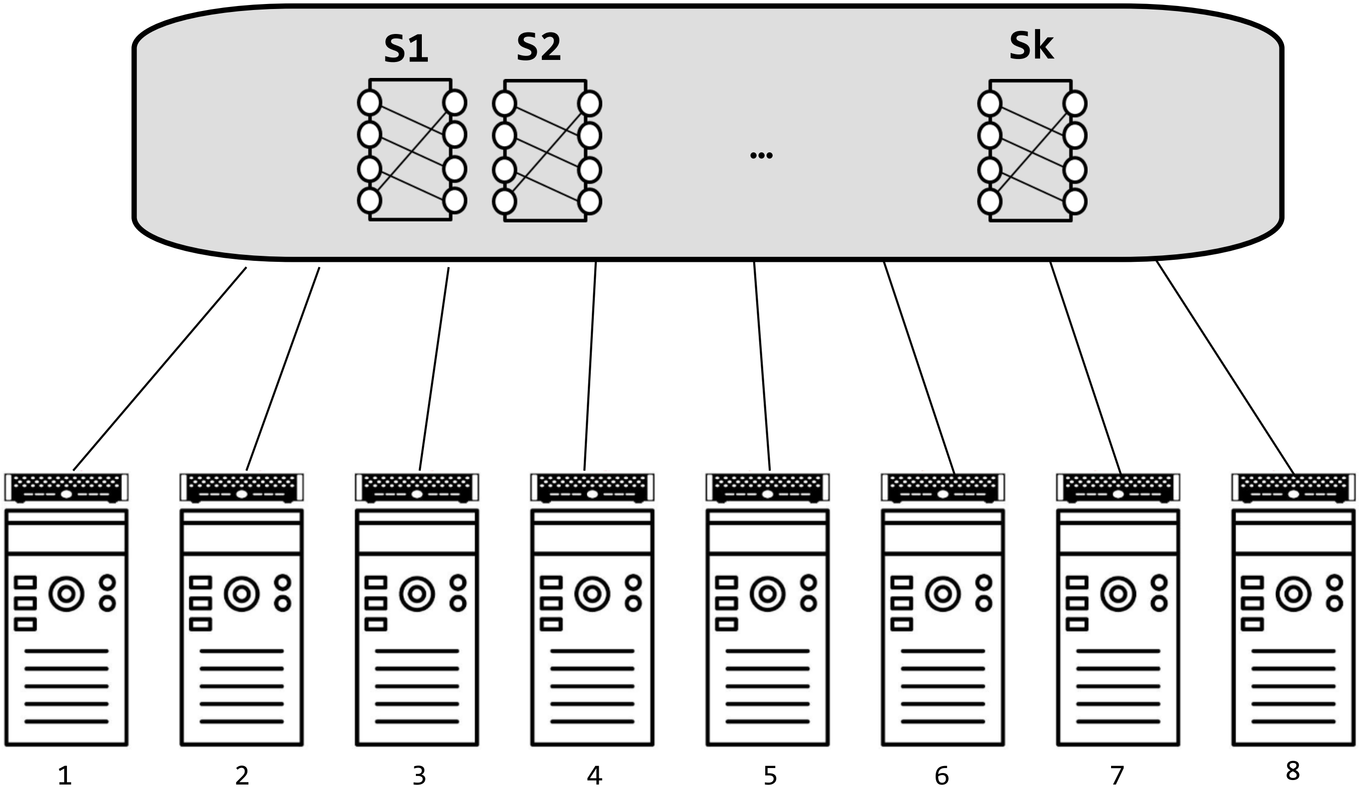
**As always in CS:**
**It depends…**

# Rack Interconnect



**Typical rack internconnect: ToR-Matching-ToR (TMT) model**

# Rack Interconnect

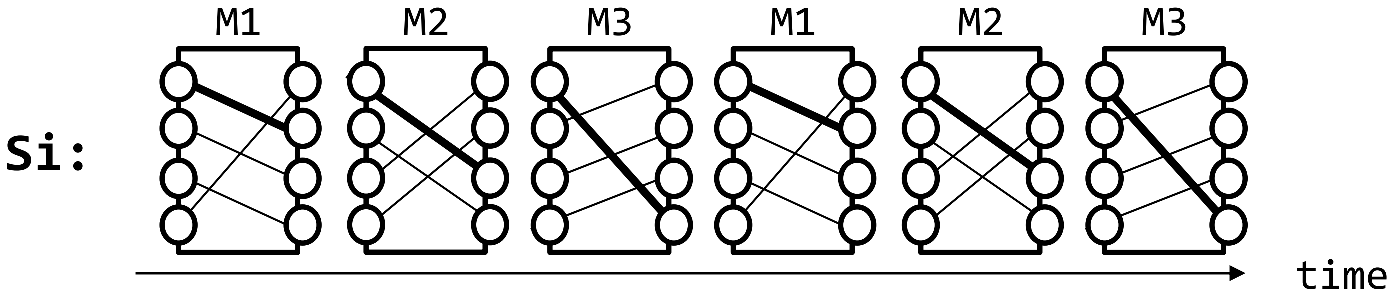


**Typical rack internconnect: ToR-Matching-ToR (TMT) model**

# Details: Switch Types

## Periodic Switch (aka Rotor Switch)

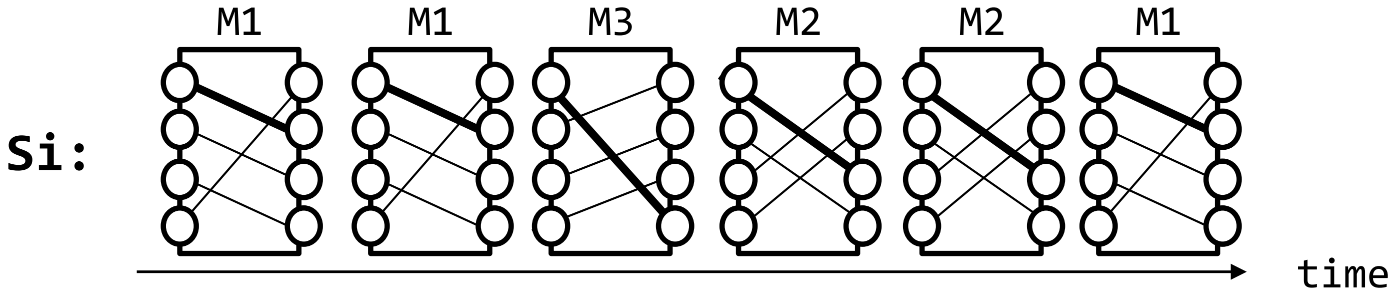
**Rotor switch: periodic matchings (demand-oblivious)**



# Details: Switch Types

## Demand-Aware Switch

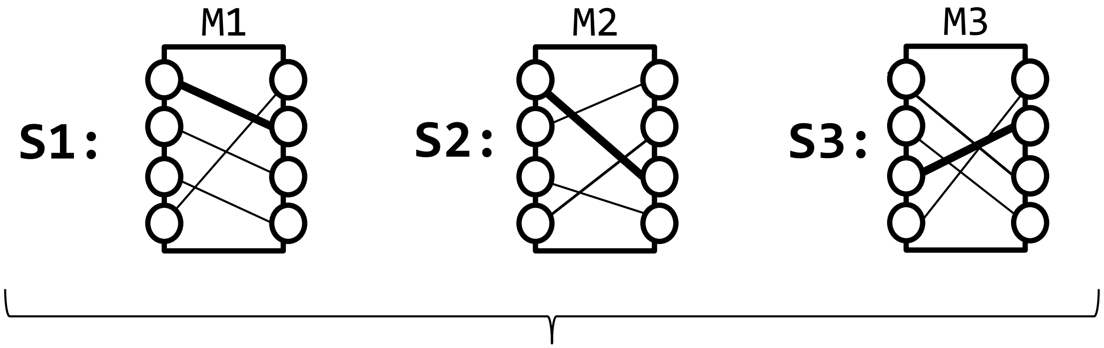
**Demand-aware switch: optimized matchings**

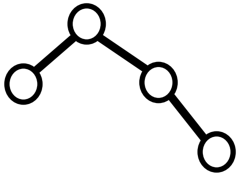


# Details: Switch Types

## Static Switch

**Static switches: combine for optimized static topology**

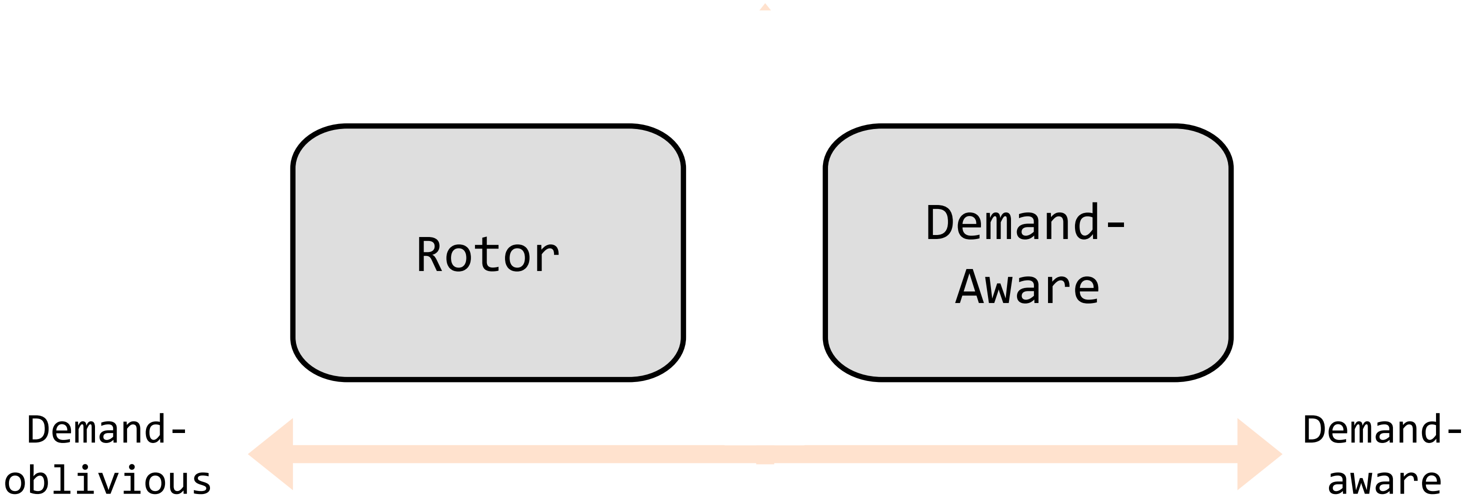




**e.g, tree, expander**

# Design Tradeoffs (1)

## The “Awareness-Dimension”



**Good for all-to-all traffic!**

⇀ oblivious: very fast periodic direct connectivity

⇀ no control plane overhead

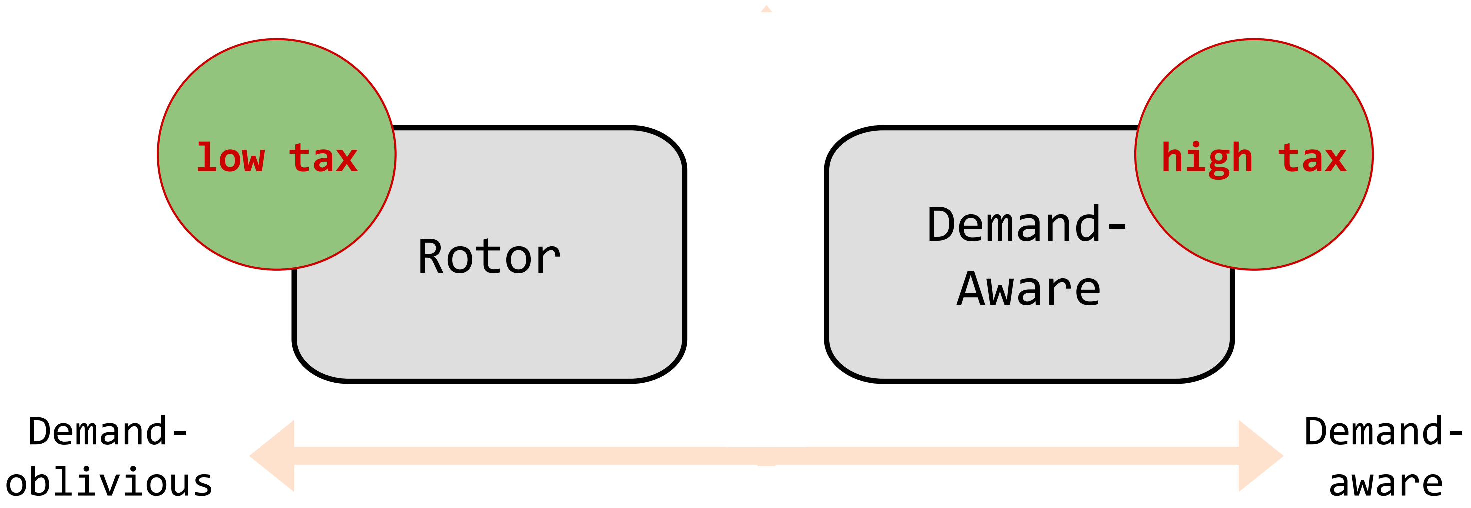
**Good for elephant flows!**

⇀ optimizable toward traffic

⇀ but slower

# Design Tradeoffs (1)

## The “Awareness-Dimension”



low tax

Rotor

Demand-Aware

high tax

Demand-oblivious

Demand-aware

**Good for all-to-all traffic!**

→ oblivious: very fast periodic direct connectivity

→ no control plane overhead

**Good for elephant flows!**

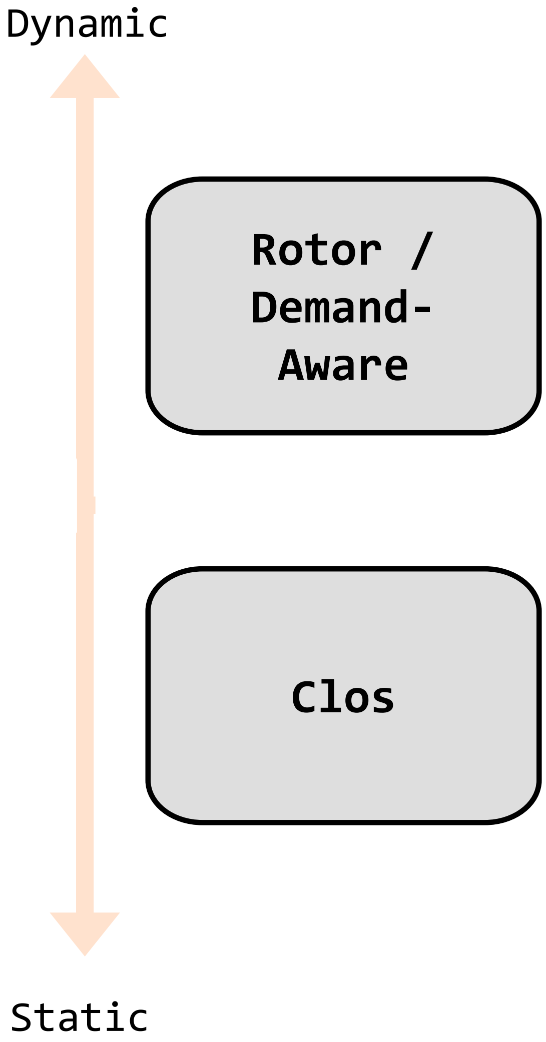
→ optimizable toward traffic

→ but slower

**Compared to static networks: latency tax!**

# Design Tradeoffs (2)

## The “Flexibility-Dimension”



**Good for high throughput!**
→ direct connectivity saves bandwidth along links

**Good for low latency!**
→ no need to wait for reconfigurable links
→ **compared to dynamic: bandwidth tax (multi-hop)**

# Design Tradeoffs (2)

## The “Flexibility-Dimension”

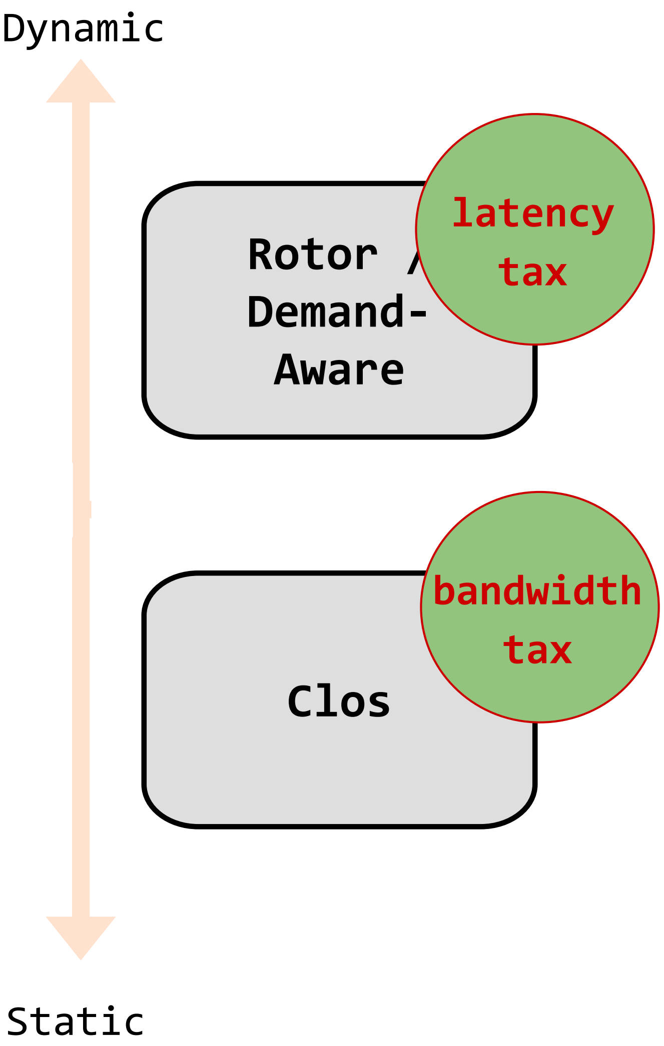
**Good for high throughput!**

⇀ direct connectivity saves bandwidth along links

**Good for low latency!**

⇀ no need to wait for reconfigurable links

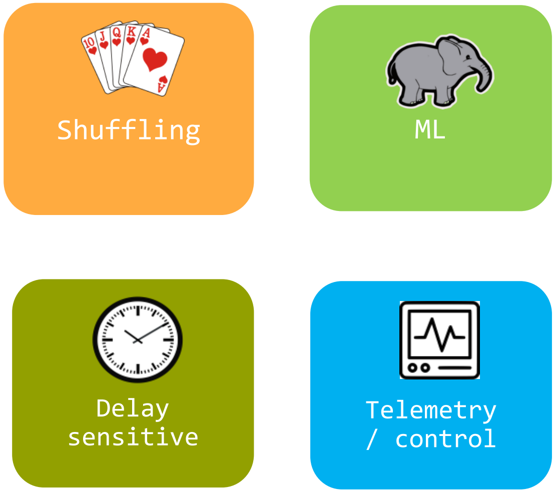
⇀ **compared to dynamic: bandwidth tax (multi-hop)**



# First Observations

- **Observation 1:** Different topologies provide different tradeoffs.
- **Observation 2:** Different traffic requires different topology types.
- **Observation 3:** A **mismatch of demand** and topology can increase **flow completion times**.

# Examples:
# Match or Mismatch?



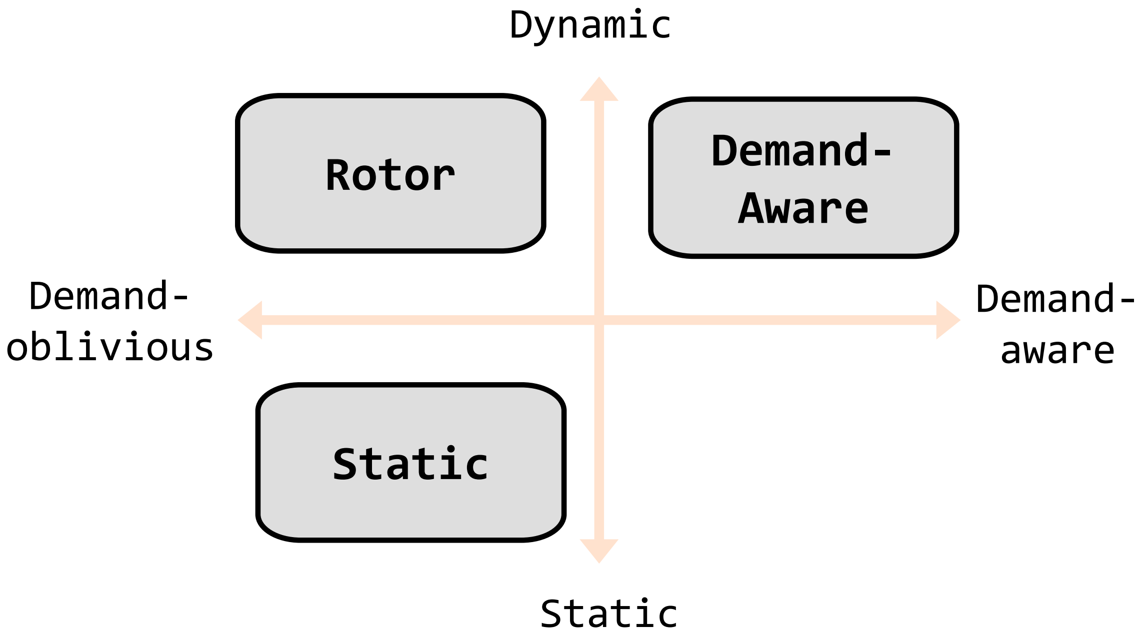
Shuffling

ML

Delay sensitive

Telemetry / control

**Demand**



Dynamic

**Rotor**

**Demand-Aware**

Demand-oblivious

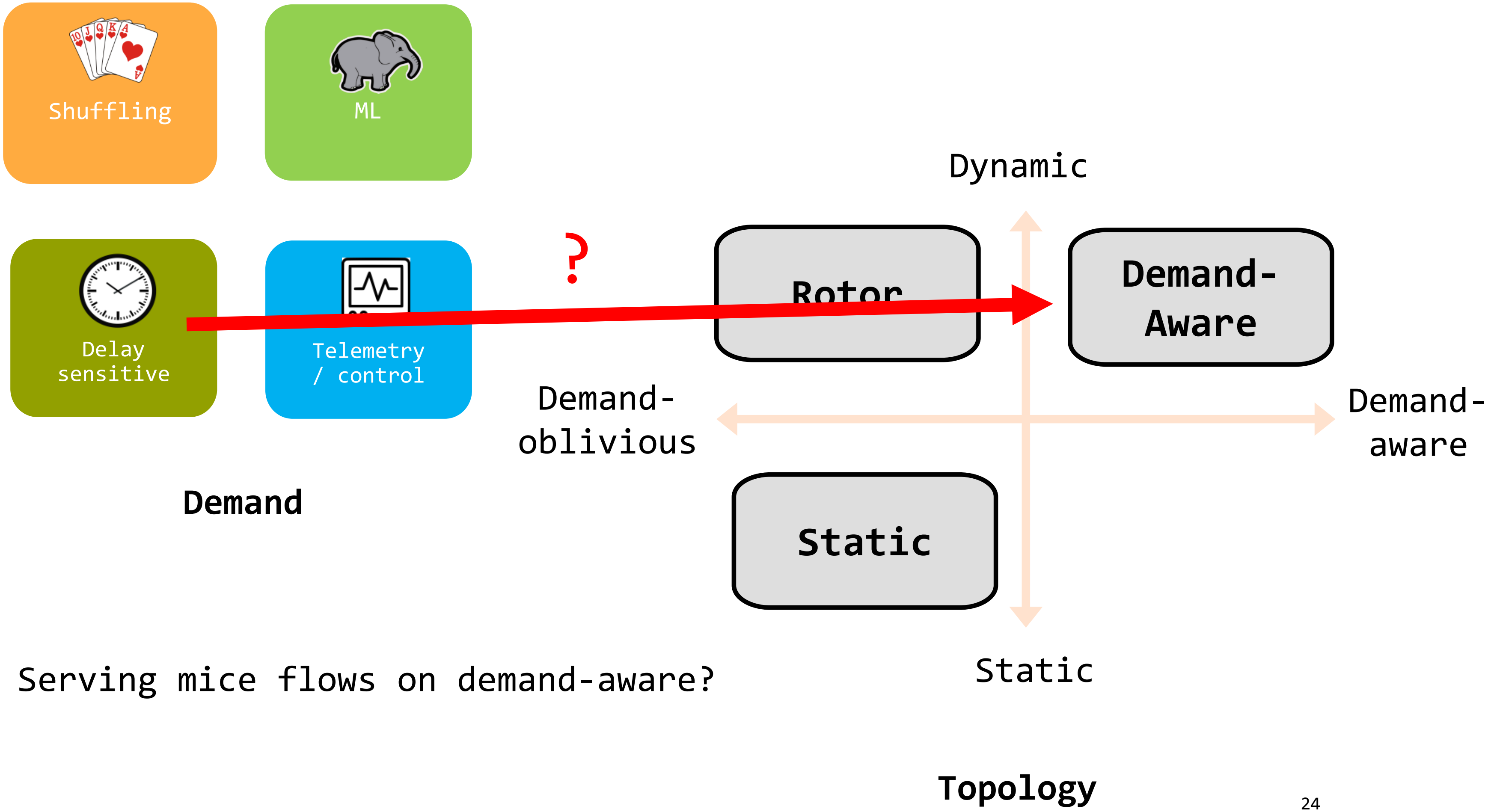
Demand-aware

**Static**

Static

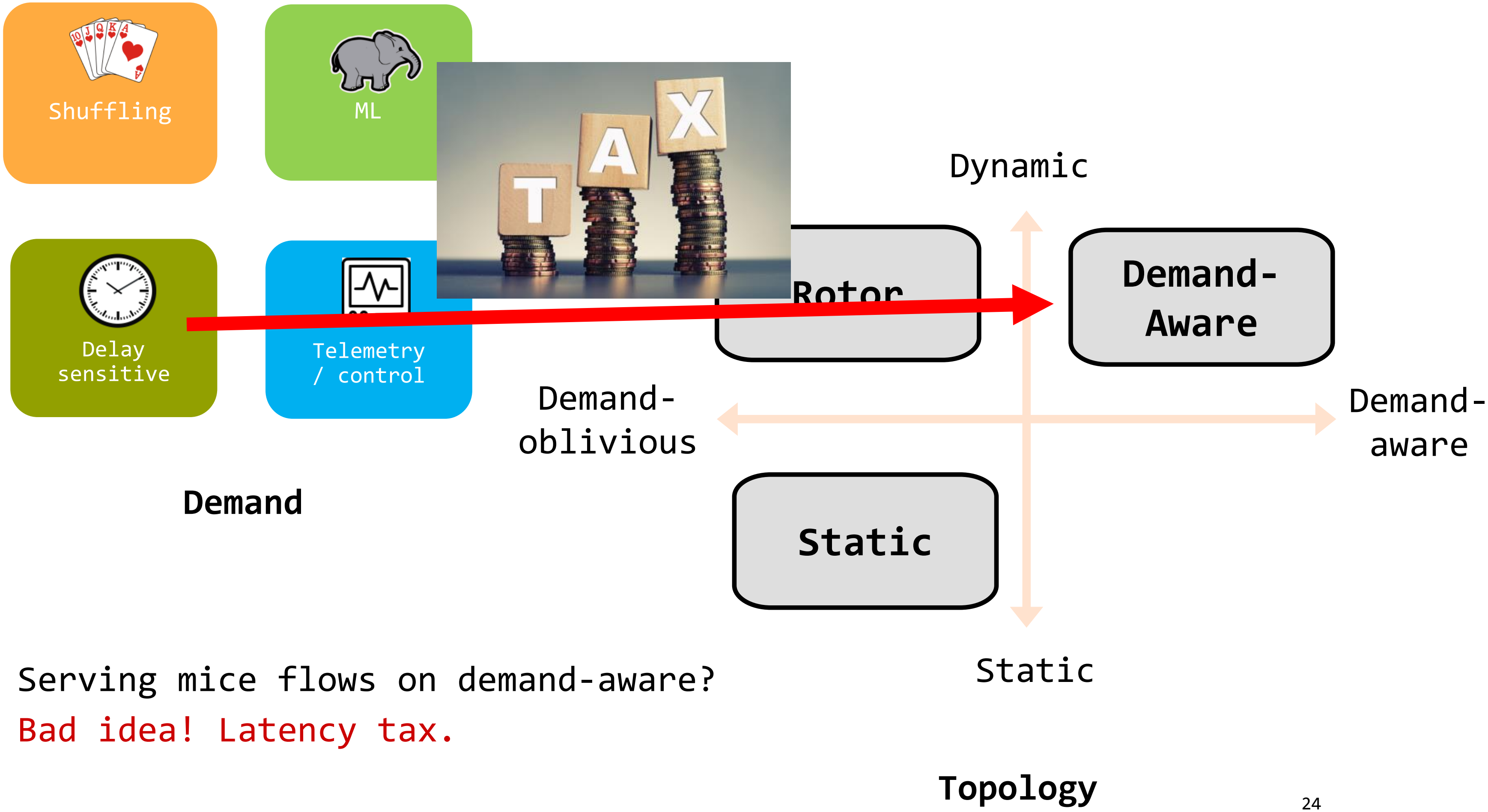
**Topology**

# Examples:
# Match or Mismatch?



Serving mice flows on demand-aware?

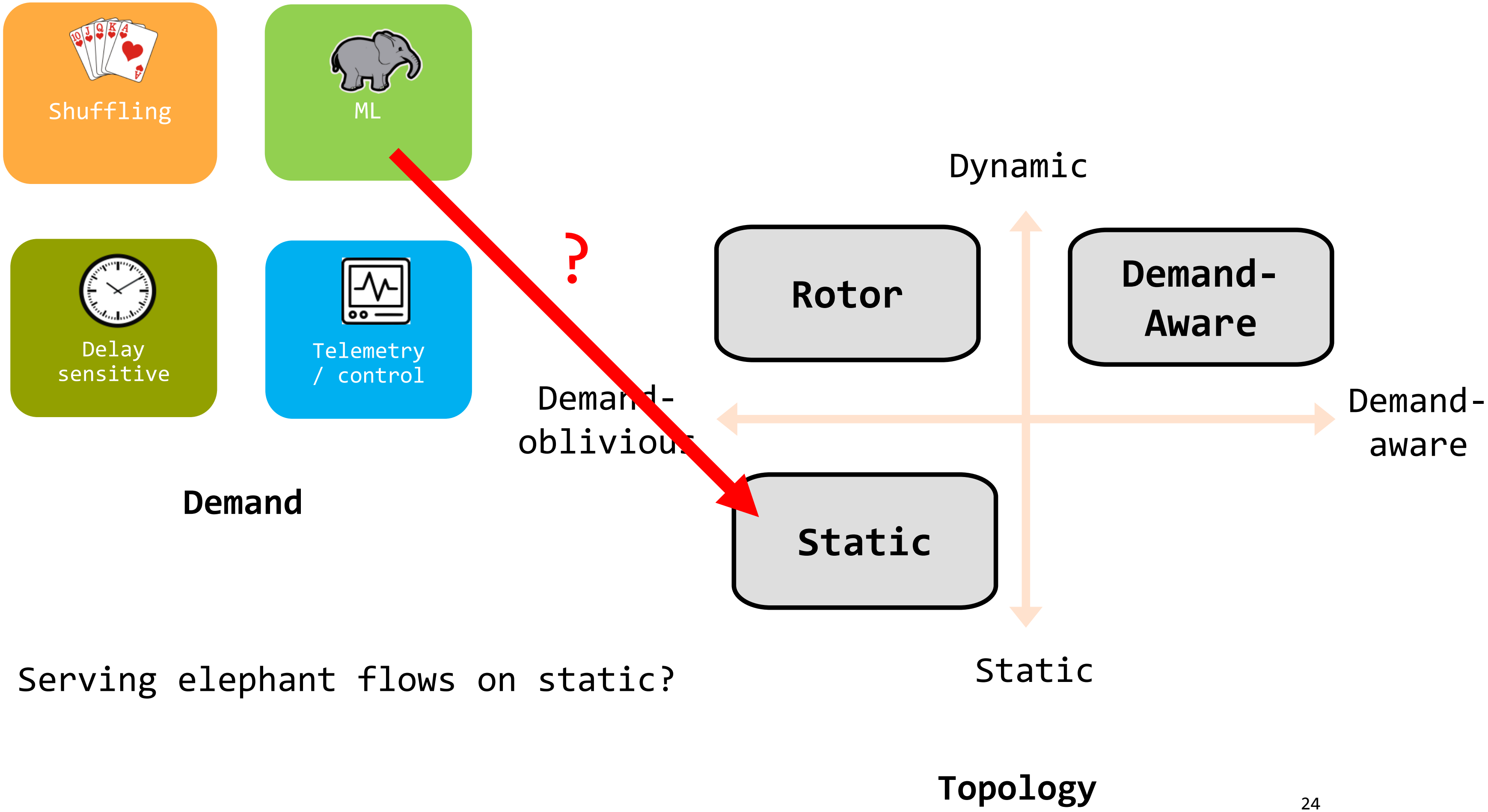
# Examples:
# Match or Mismatch?



Serving mice flows on demand-aware?

Bad idea! Latency tax.

# Examples:
# Match or Mismatch?



Shuffling

ML

Delay sensitive

Telemetry / control

**Demand**

?

Dynamic

Rotor

Demand-Aware

Demand-oblivious

Demand-aware

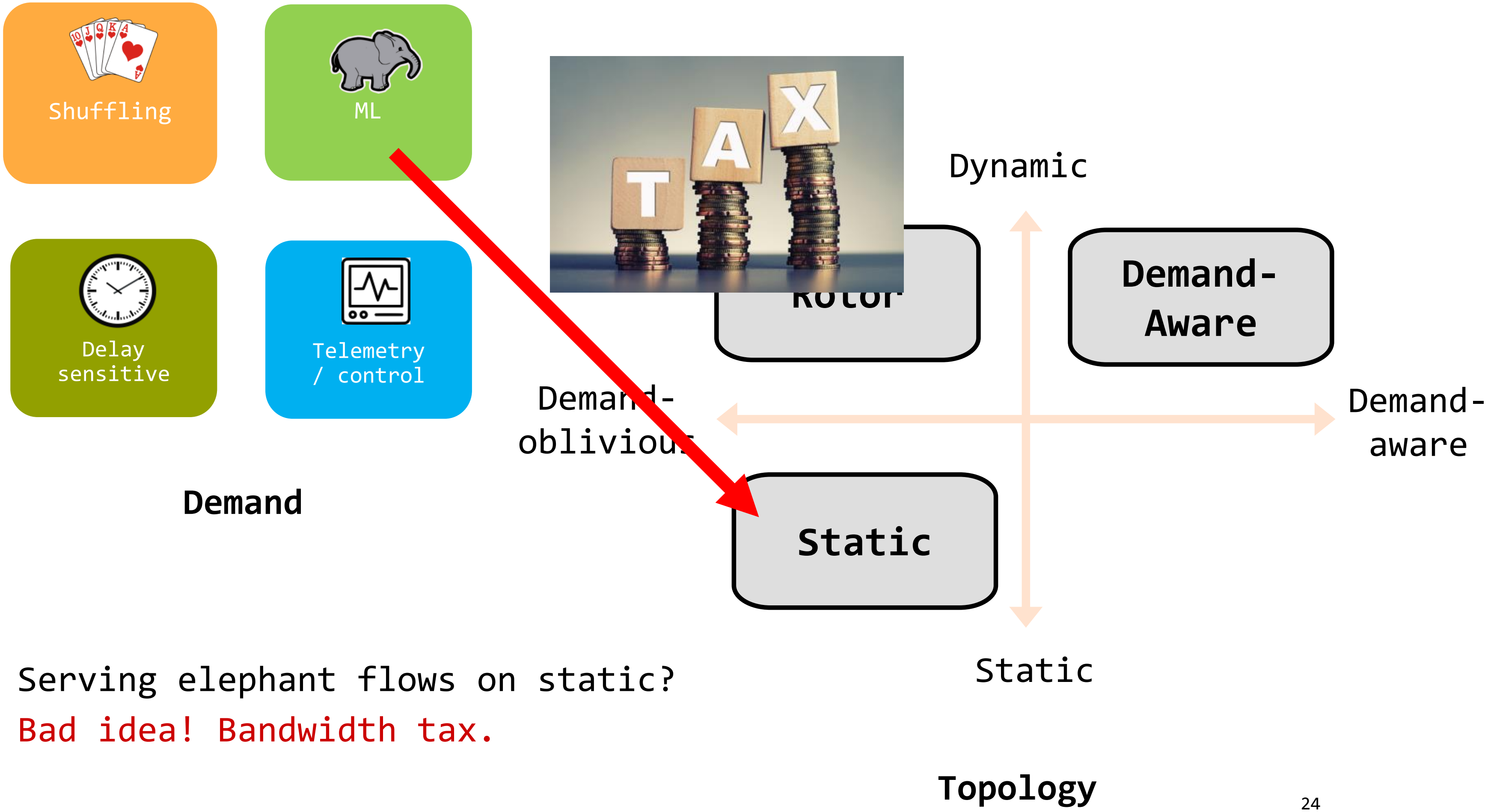
Static

Static

**Topology**

Serving elephant flows on static?

# Examples:
# Match or Mismatch?



Shuffling

ML

Delay sensitive

Telemetry / control

**Demand**

Dynamic

**Rotor**

**Demand-Aware**

Demand-oblivious

Demand-aware

**Static**

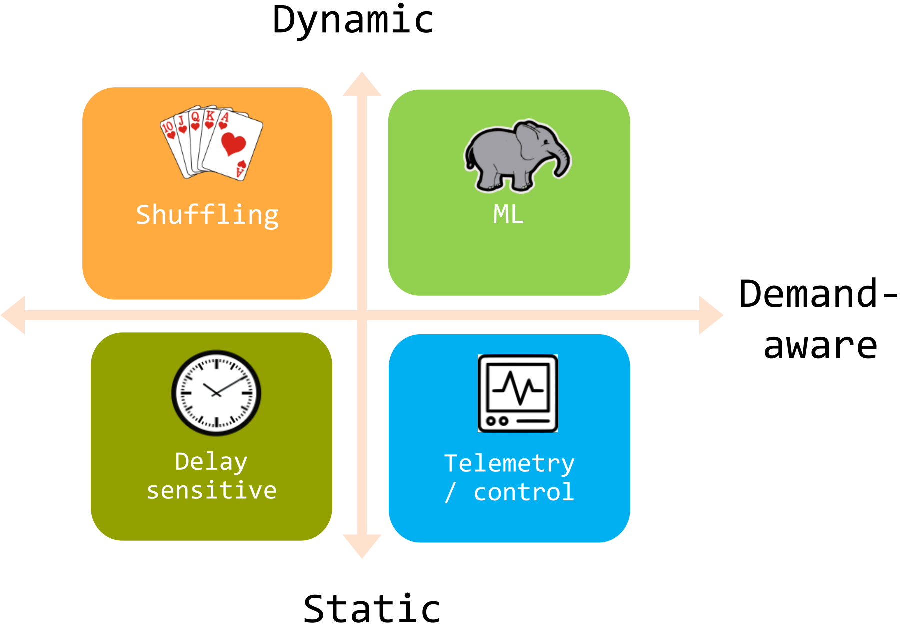
Static

**Topology**

Serving elephant flows on static?

Bad idea! Bandwidth tax.

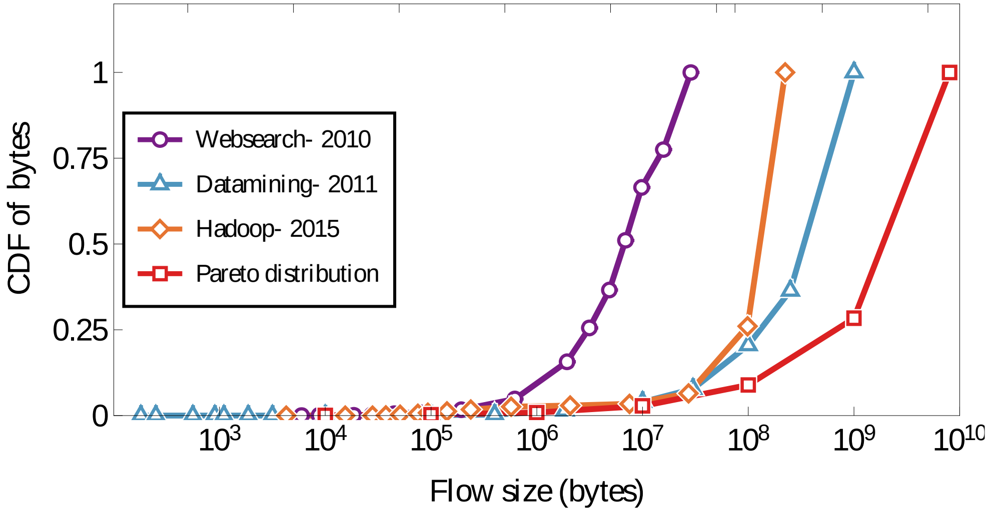
# Cerberus: It's a Match!



Our system Cerberus* serves traffic on the “best topology”!

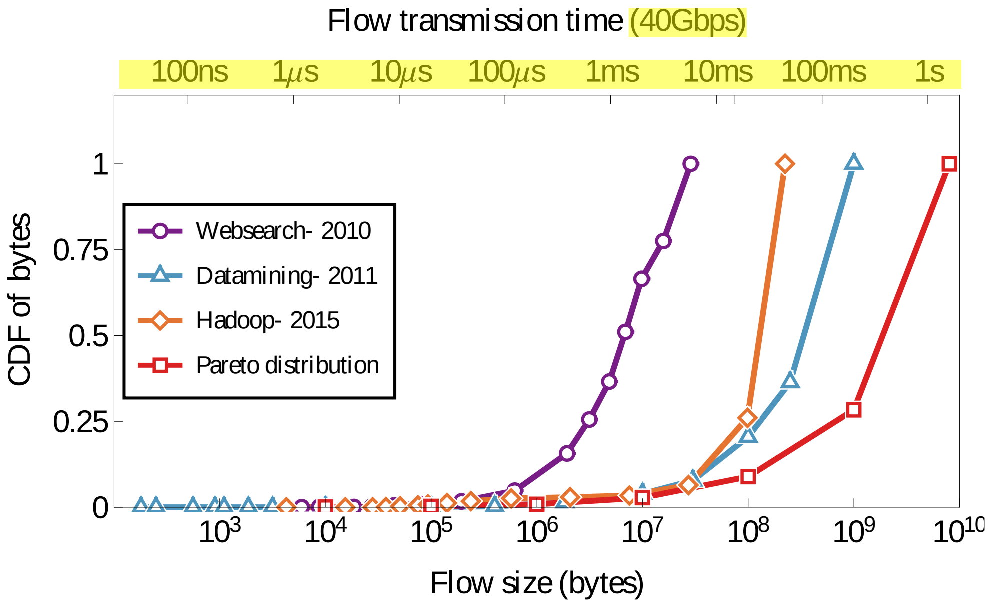
* Griner et al., ACM SIGMETRICS 2022

# Flow Size Matters



⇢ **Observation 1:** Different apps have different flow size distributions.

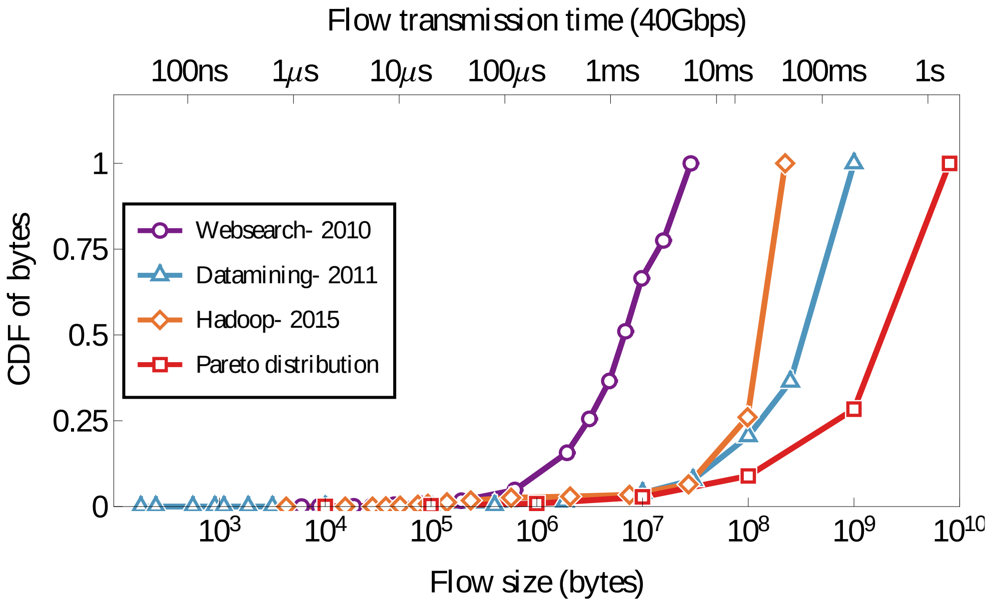
# Flow Size Matters



⇢ **Observation 1:** Different apps have different flow size distributions.

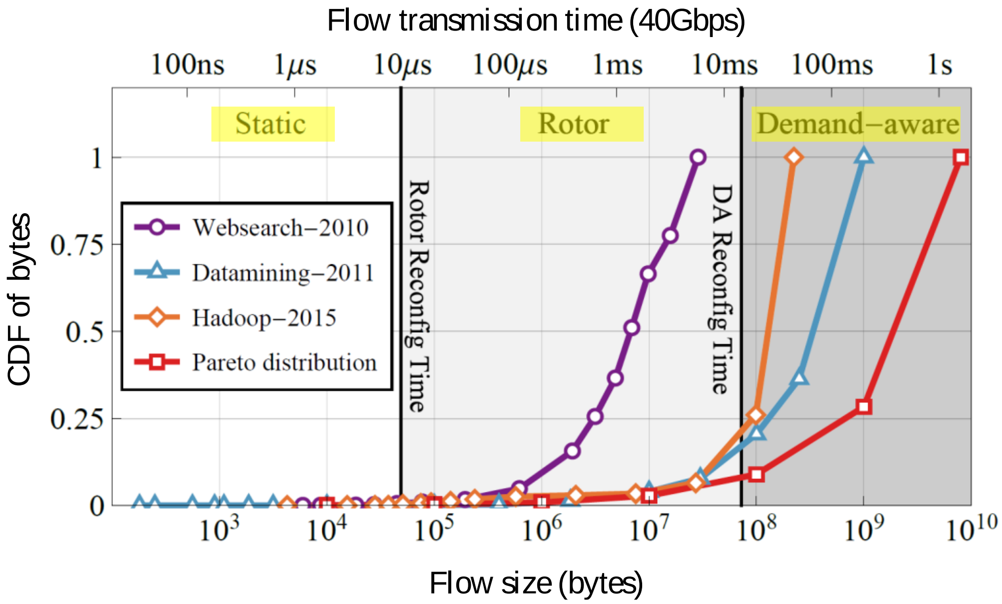
⇢ **Observation 2:** The transmission time of a flow depends on its size.

# Flow Size Matters



- **Observation 1:** Different apps have different flow size distributions.
- **Observation 2:** The transmission time of a flow depends on its size.
- **Observation 3:** For small flows, flow completion time suffers if network needs to be reconfigured first.
- **Observation 4:** For large flows, reconfiguration time may amortize.

# Flow Size Matters



It's a Match!

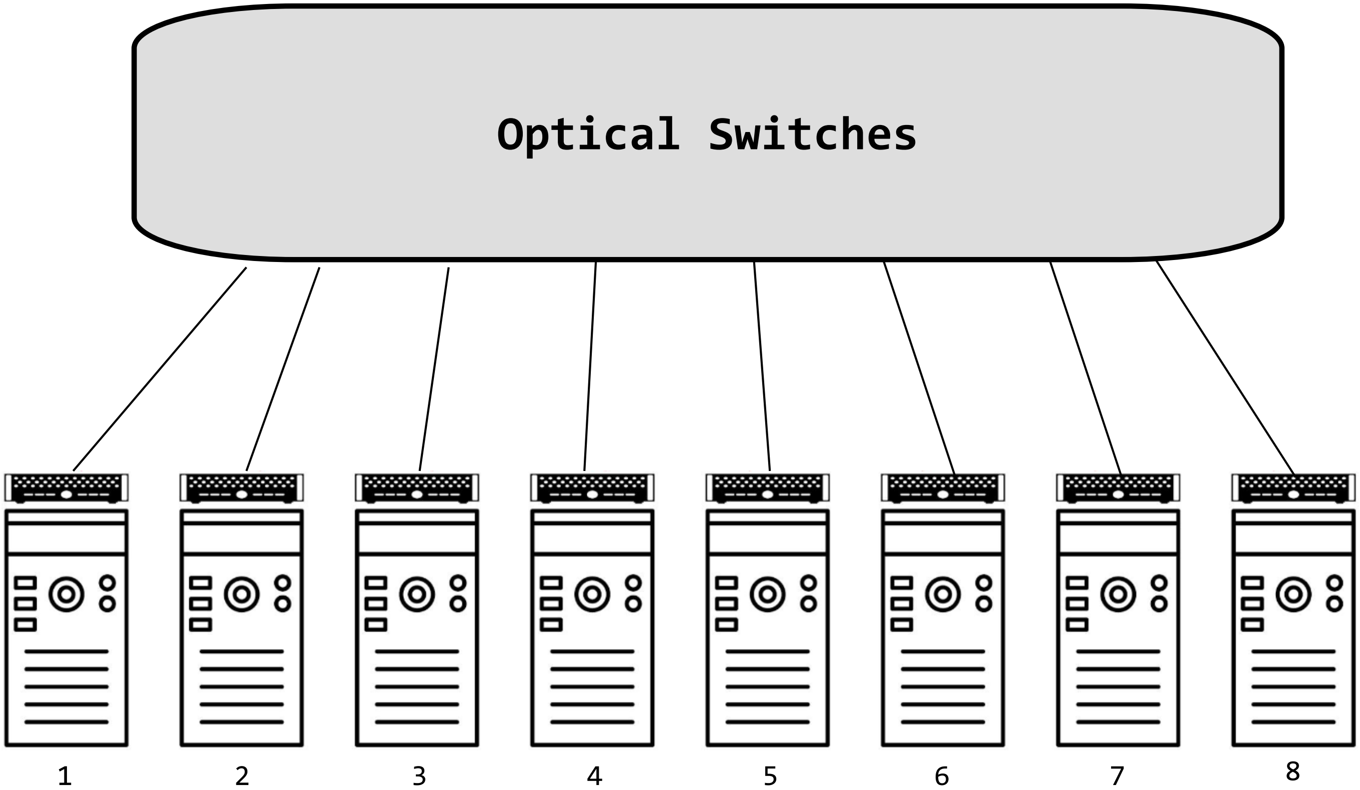
⇢ **Observation 1:** Different apps have different flow size distributions.

⇢ **Observation 2:** The transmission time of a flow depends on its size.

⇢ **Observation 3:** For small flows, flow completion time suffers if network needs to be reconfigured first.

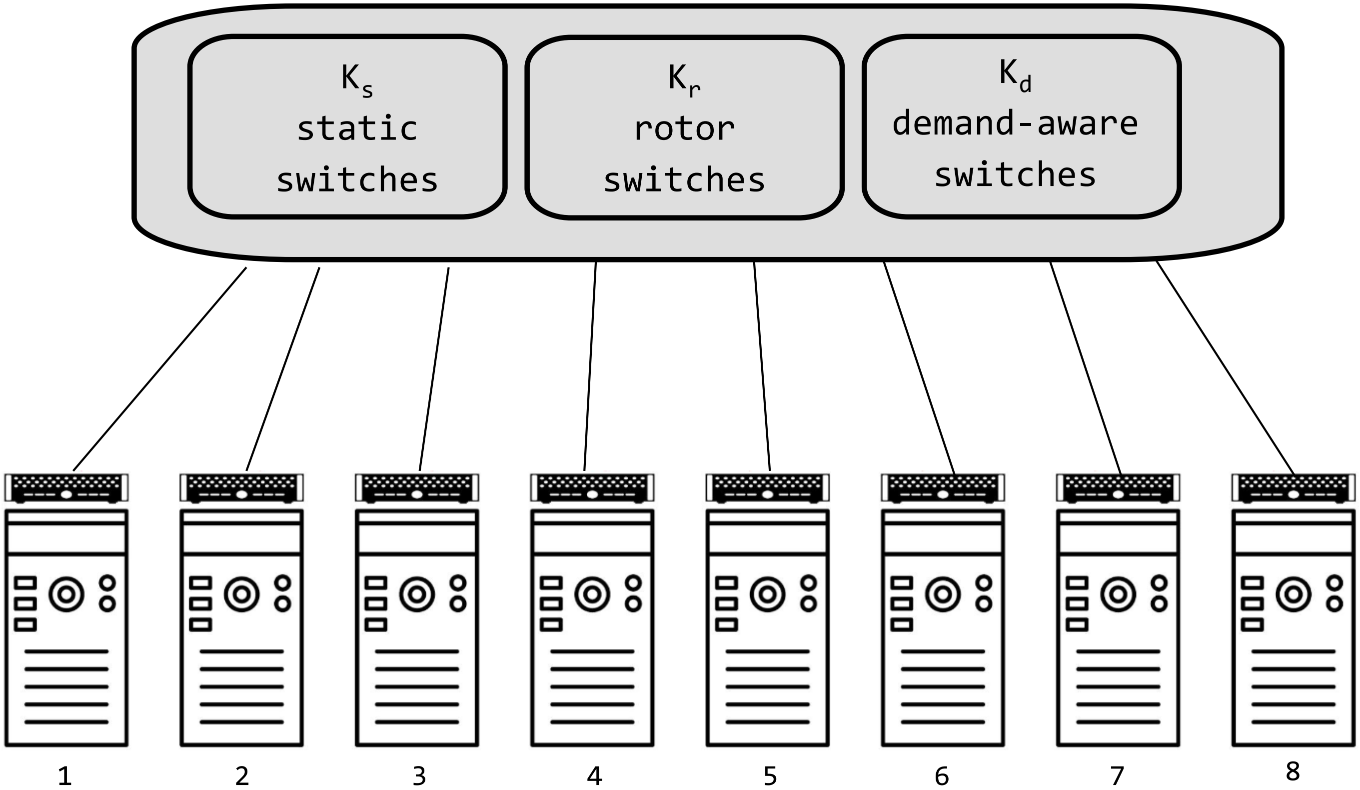
⇢ **Observation 4:** For large flows, reconfiguration time may amortize.

# Cerberus



Optical Switches

# Cerberus

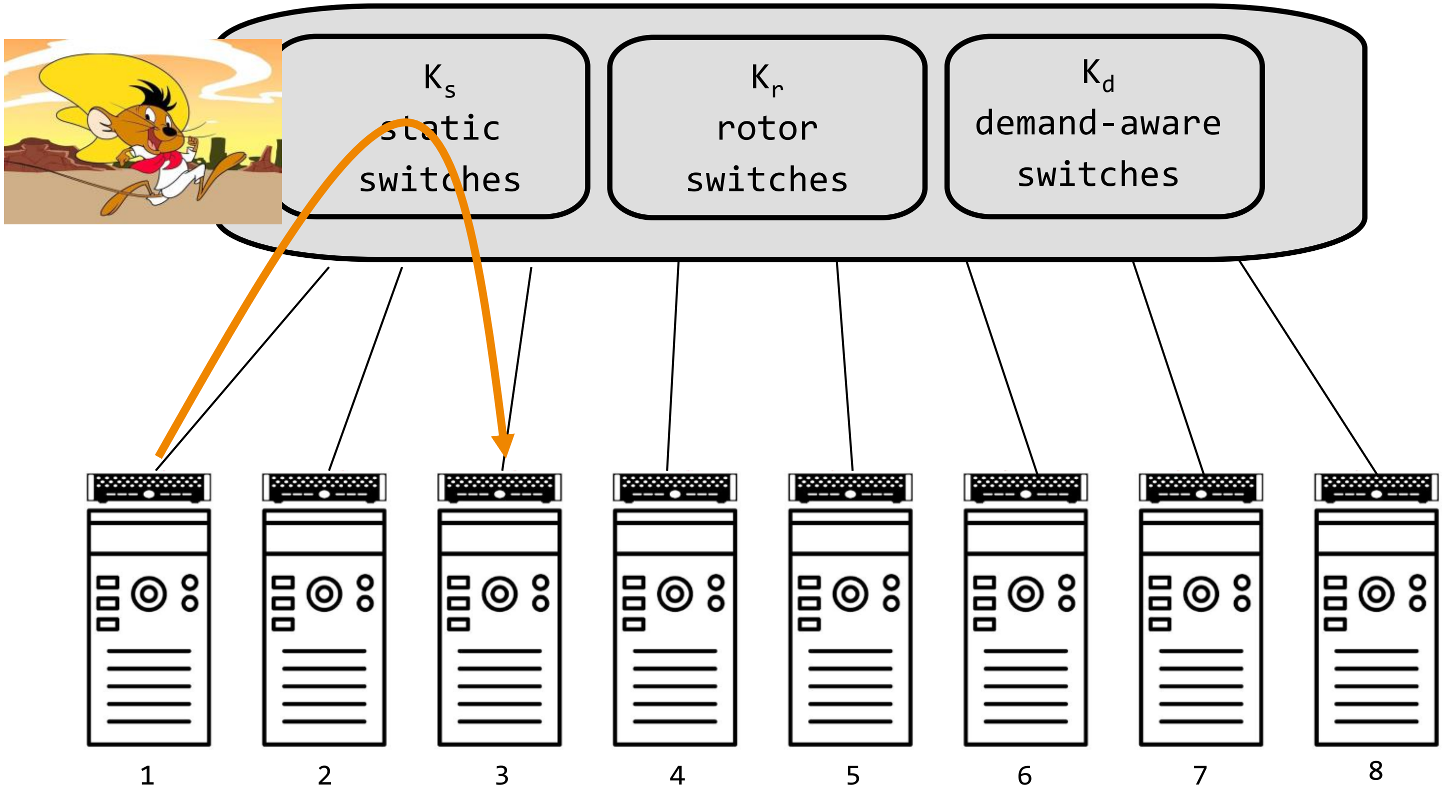


$K_s$
static
switches

$K_r$
rotor
switches

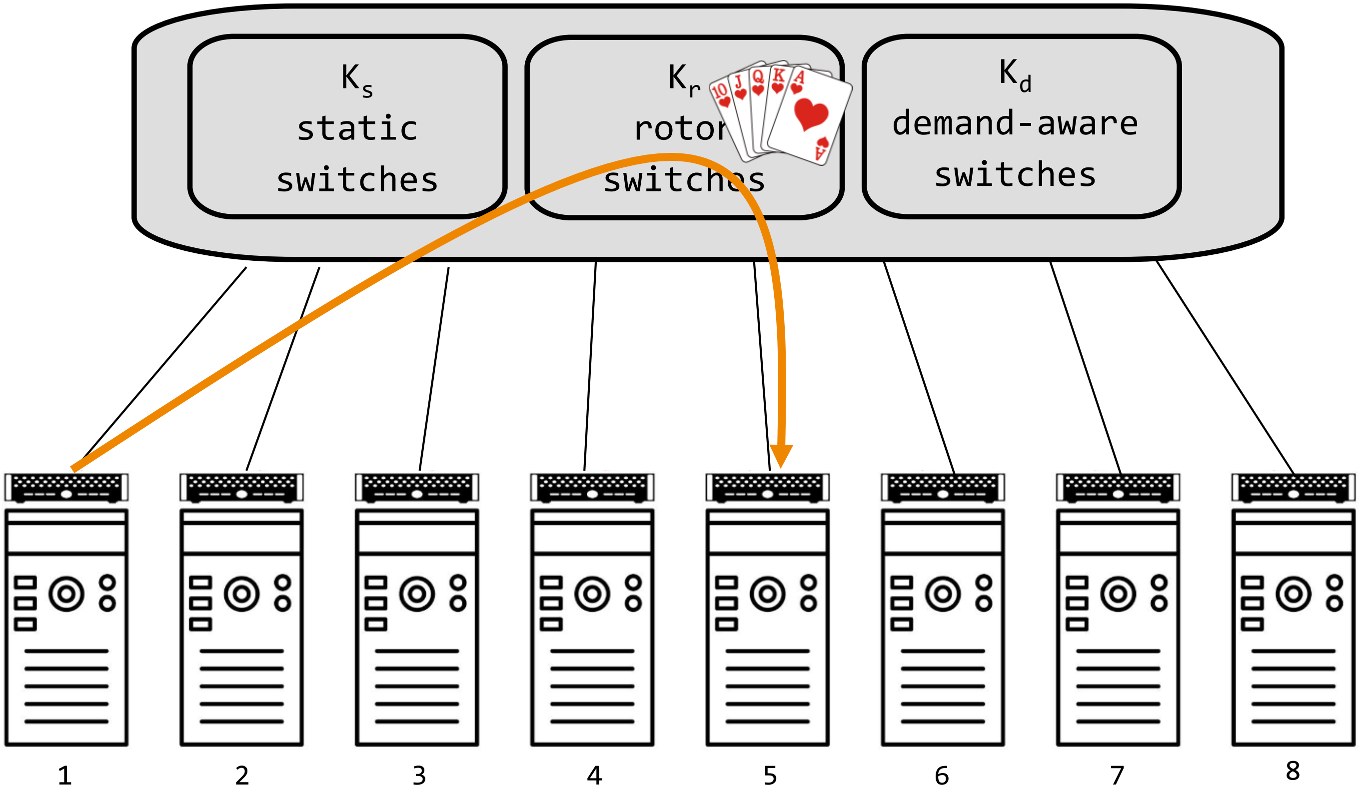
$K_d$
demand-aware
switches

# Cerberus



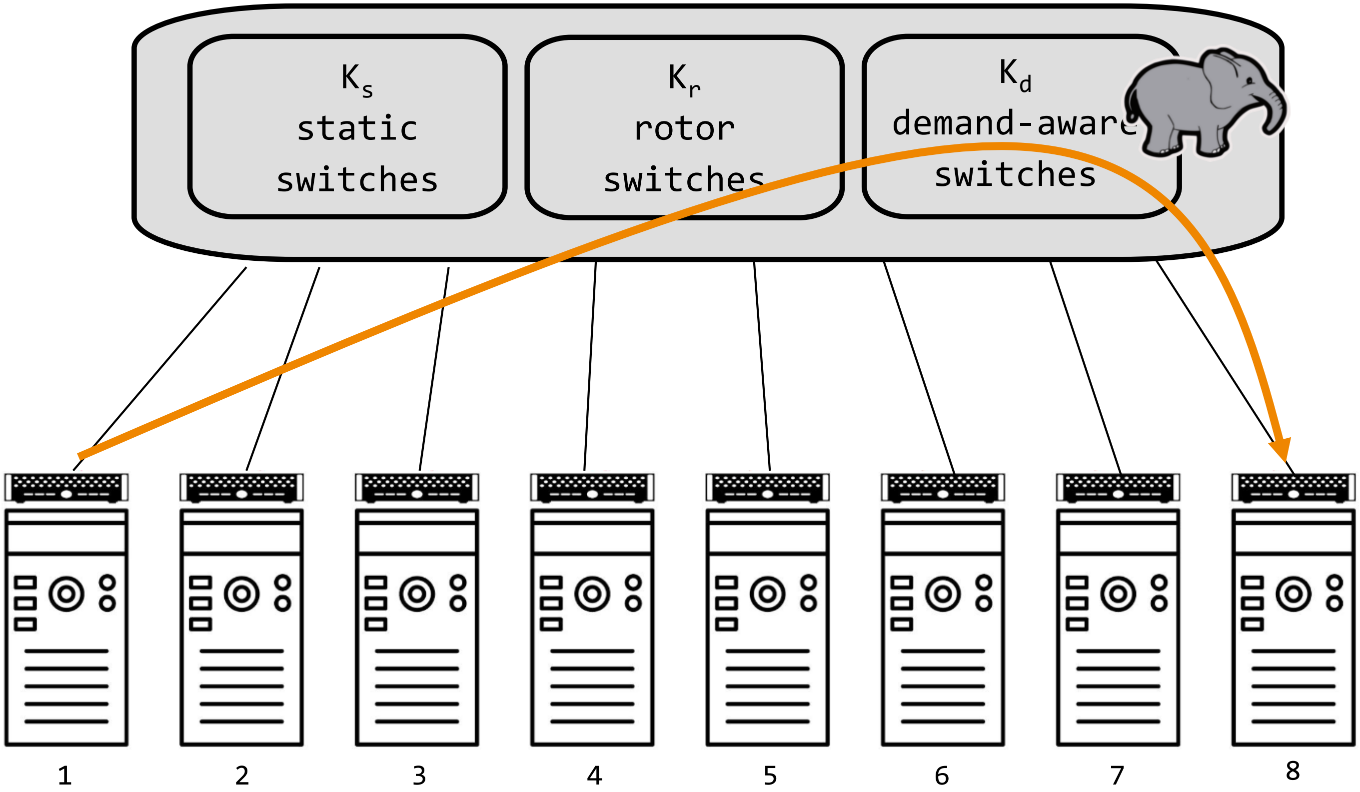
**Scheduling:** Small flows go via static switches…

# Cerberus



**Scheduling:** … medium flows via rotor switches…

# Cerberus

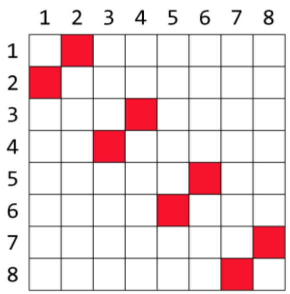


**Scheduling:** … and large flows via demand-aware switches (if one available, otherwise via rotor).

# Throughput Analysis

Demand Matrix

$T$

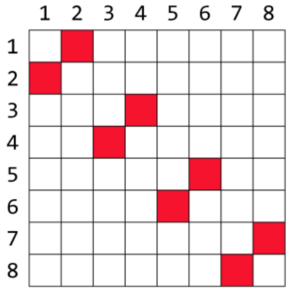


| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1 | | 🟥 | | | | | | |
| 2 | 🟥 | | | | | | | |
| 3 | | | | 🟥 | | | | |
| 4 | | | 🟥 | | | | | |
| 5 | | | | | | 🟥 | | |
| 6 | | | | | 🟥 | | | |
| 7 | | | | | | | | 🟥 |
| 8 | | | | | | | 🟥 | |

**Metric:** throughput of a demand matrix…

# Throughput Analysis

Demand Matrix



| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1 | | 🟥 | | | | | | |
| 2 | 🟥 | | | | | | | |
| 3 | | | | 🟥 | | | | |
| 4 | | | 🟥 | | | | | |
| 5 | | | | | | 🟥 | | |
| 6 | | | | | 🟥 | | | |
| 7 | | | | | | | | 🟥 |
| 8 | | | | | | | 🟥 | |

$$T \times \theta(T)$$

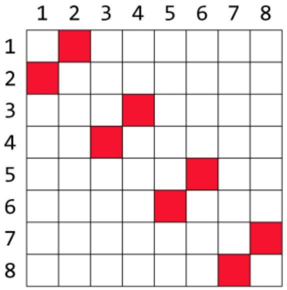
**Metric:** throughput of a demand matrix…

… is the maximal scale down factor by which traffic is feasible.

# Throughput Analysis

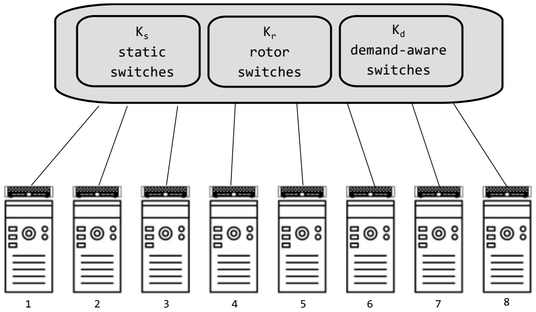
Demand Matrix

$T$



| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1 | | 🟥 | | | | | | |
| 2 | 🟥 | | | | | | | |
| 3 | | | | 🟥 | | | | |
| 4 | | | 🟥 | | | | | |
| 5 | | | | | | 🟥 | | |
| 6 | | | | | 🟥 | | | |
| 7 | | | | | | | | 🟥 |
| 8 | | | | | | | 🟥 | |

$\times \ \theta(T) \quad \Rightarrow$

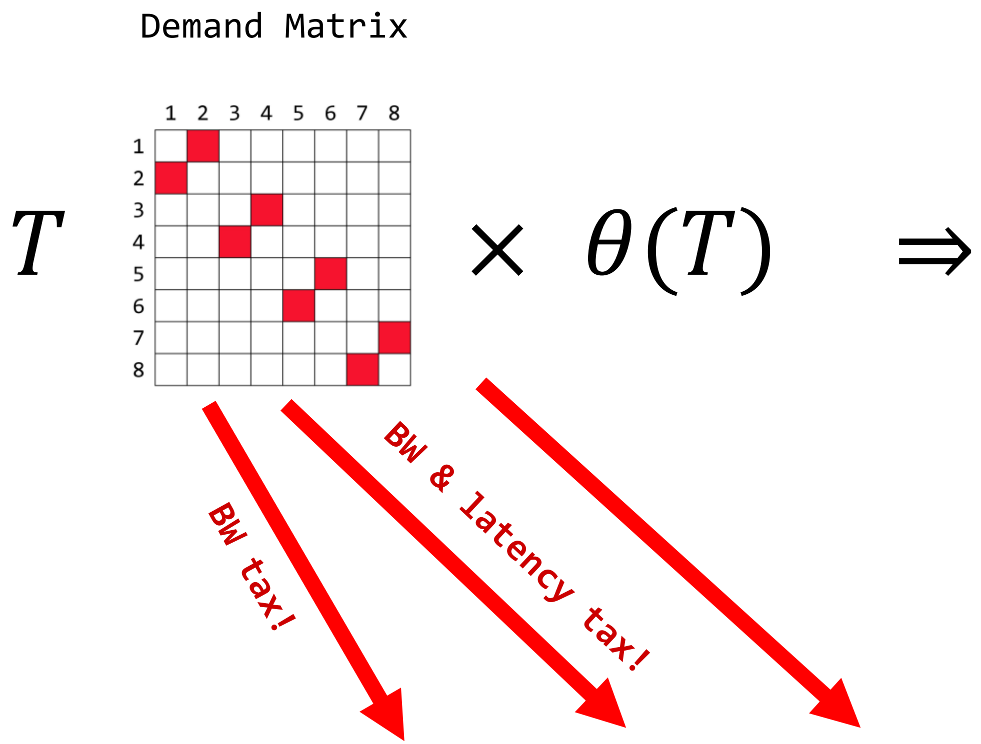


**Metric:** throughput of a demand matrix…

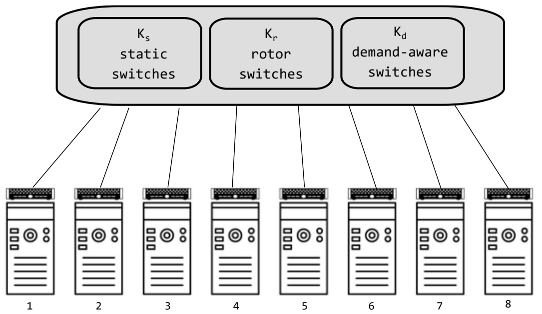
… is the maximal scale down factor by which traffic is feasible.

Throughput of network $\theta^*$: worst case $T$

# Throughput Analysis

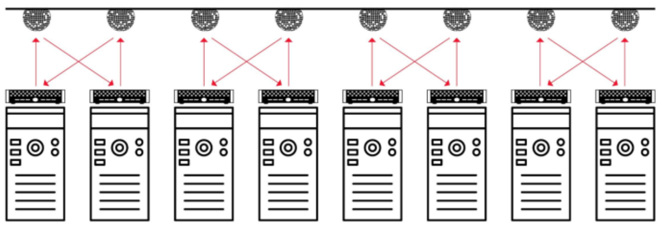


| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1 | | 🟥 | | | | | | |
| 2 | 🟥 | | | | | | | |
| 3 | | | | 🟥 | | | | |
| 4 | | | 🟥 | | | | | |
| 5 | | | | | | 🟥 | | |
| 6 | | | | | 🟥 | | | |
| 7 | | | | | | | | 🟥 |
| 8 | | | | | | | 🟥 | |



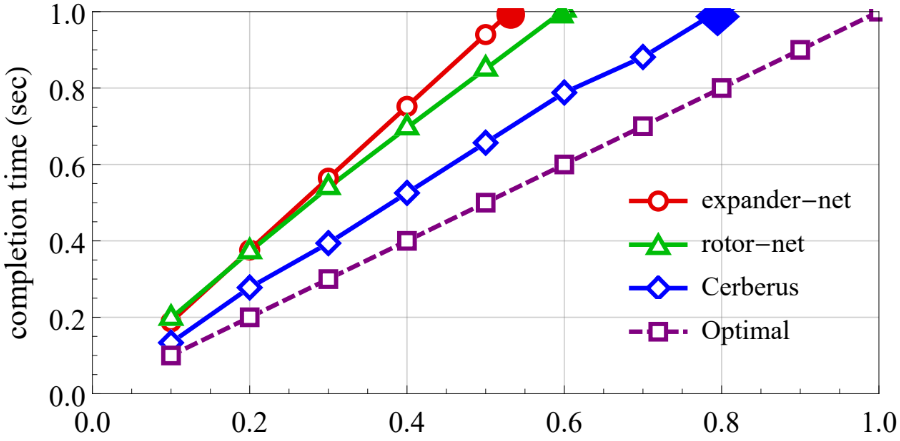
Worst demand matrix for static and rotor: permutation. Best case for demand-aware!

| | *expander-net* | *rotor-net* | CERBERUS |
|---|---|---|---|
| BW-Tax | ✓ | ✓ | ✗ |
| LT-Tax | ✗ | ✓ | ✓ |
| $\theta(T)$ | Thm 2 | Thm 3 | Thm 5 |
| $\theta^*$ | 0.53 | 0.45 | Open |
| Datamining | 0.53 | 0.6 | 0.8 (+33%) |
| Permutation | 0.53 | 0.45 | ≈ 1 (+88%) |
| Case Study | 0.53 | 0.66 | 0.9 (+36%) |



# Completion Time

- Demand completion time: How long does it take to serve a demand matrix?



Data mining workload

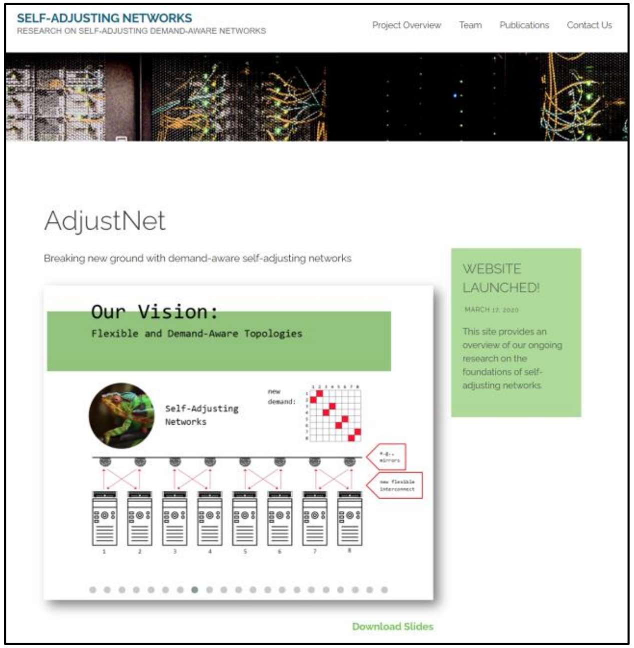
- Also useful in analysis: throughput can be computed more easily via demand completion time.

# Conclusion

- Diverse traffic requires diverse technologies
- Cerberus aims to assign traffic to its best topology
  - Depending on flow size
- Many challenges
  - Impact on routing and congestion control
  - Sensitivity analysis
  - Prototyping

**Thank you!**

# Websites



SELF-ADJUSTING NETWORKS

RESEARCH ON SELF-ADJUSTING DEMAND-AWARE NETWORKS

AdjustNet

Breaking new ground with demand-aware self-adjusting networks

Our Vision:

Flexible and Demand-Aware Topologies

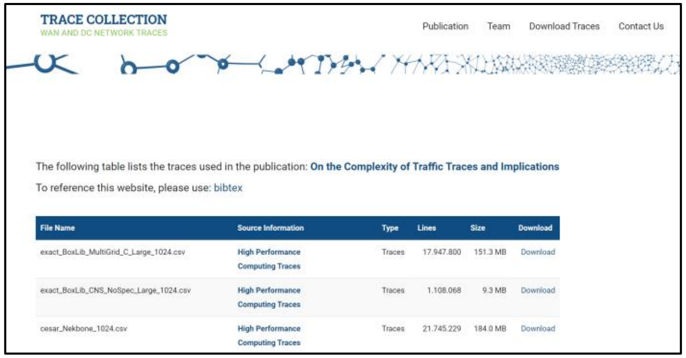
Self-Adjusting Networks

WEBSITE LAUNCHED!

MARCH 17, 2020

This site provides an overview of our ongoing research on the foundations of self-adjusting networks.

**http://self-adjusting.net/**
**Project website**



TRACE COLLECTION

WAN AND DC NETWORK TRACES

The following table lists the traces used in the publication: **On the Complexity of Traffic Traces and Implications**

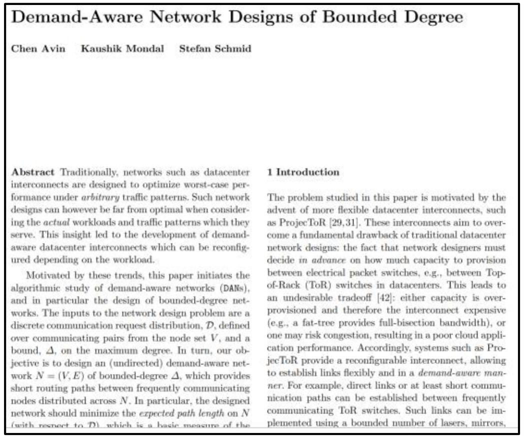
To reference this website, please use: bibtex

| File Name | Source Information | Type | Lines | Size | Download |
|---|---|---|---|---|---|
| exact_BoxLib_MultiGrid_C_Large_1024.csv | High Performance Computing Traces | Traces | 17.947.800 | 151.3 MB | Download |
| exact_BoxLib_CNS_NoSpec_Large_1024.csv | High Performance Computing Traces | Traces | 1.108.068 | 9.3 MB | Download |
| cesar_Nekbone_1024.csv | High Performance Computing Traces | Traces | 21.745.229 | 184.0 MB | Download |

**https://trace-collection.net/**
**Trace collection website**

# Further Reading

## Static DAN



### Demand-Aware Network Designs of Bounded Degree

**Chen Avin** **Kaushik Mondal** **Stefan Schmid**

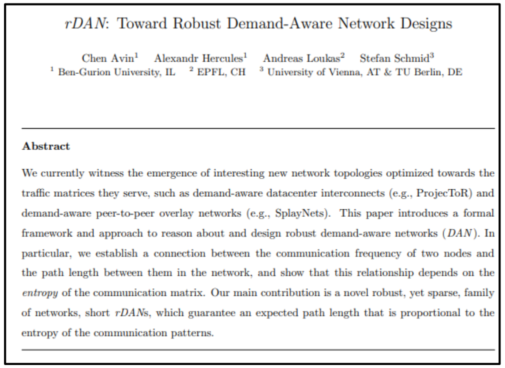
**Abstract** Traditionally, networks such as datacenter interconnects are designed to optimize worst-case performance under *arbitrary* traffic patterns. Such network designs can however be far from optimal when considering the *actual* workloads and traffic patterns which they serve. This insight led to the development of demand-aware datacenter interconnects which can be reconfigured depending on the workload.

Motivated by these trends, this paper initiates the algorithmic study of demand-aware networks (DANs), and in particular the design of bounded-degree networks. The inputs to the network design problem are a discrete communication request distribution, $\mathcal{D}$, defined over communicating pairs from the node set $V$, and a bound, $\Delta$, on the maximum degree. In turn, our objective is to design an (undirected) demand-aware network $N = (V, E)$ of bounded-degree $\Delta$, which provides short routing paths between frequently communicating nodes distributed across $N$. In particular, the designed network should minimize the *expected path length* on $N$

**1 Introduction**

The problem studied in this paper is motivated by the advent of more flexible datacenter interconnects, such as ProjecToR [29,31]. These interconnects aim to overcome a fundamental drawback of traditional datacenter network designs: the fact that network designers must decide *in advance* on how much capacity to provision between electrical packet switches, e.g., between Top-of-Rack (ToR) switches in datacenters. This leads to an undesirable tradeoff [42]: either capacity is over-provisioned and therefore the interconnect expensive (e.g., a fat-tree provides full-bisection bandwidth), or one may risk congestion, resulting in a poor cloud application performance. Accordingly, systems such as ProjecToR provide a reconfigurable interconnect, allowing to establish links flexibly and in a *demand-aware manner*. For example, direct links or at least short communication paths can be established between frequently communicating ToR switches. Such links can be implemented using a bounded number of lasers, mirrors,

## Robust DAN



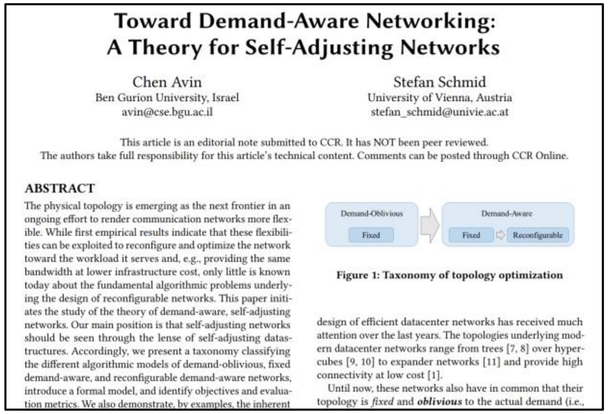
### *rDAN*: Toward Robust Demand-Aware Network Designs

Chen Avin[1] Alexandr Hercules[1] Andreas Loukas[2] Stefan Schmid[3]
[1] Ben-Gurion University, IL [2] EPFL, CH [3] University of Vienna, AT & TU Berlin, DE

**Abstract**

We currently witness the emergence of interesting new network topologies optimized towards the traffic matrices they serve, such as demand-aware datacenter interconnects (e.g., ProjecToR) and demand-aware peer-to-peer overlay networks (e.g., SplayNets). This paper introduces a formal framework and approach to reason about and design robust demand-aware networks (*DAN*). In particular, we establish a connection between the communication frequency of two nodes and the path length between them in the network, and show that this relationship depends on the *entropy* of the communication matrix. Our main contribution is a novel robust, yet sparse, family of networks, short *rDAN*s, which guarantee an expected path length that is proportional to the entropy of the communication patterns.

## Overview: Models



### Toward Demand-Aware Networking: A Theory for Self-Adjusting Networks

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This article is an editorial note submitted to CCR. It has NOT been peer reviewed.
The authors take full responsibility for this article's technical content. Comments can be posted through CCR Online.

**ABSTRACT**

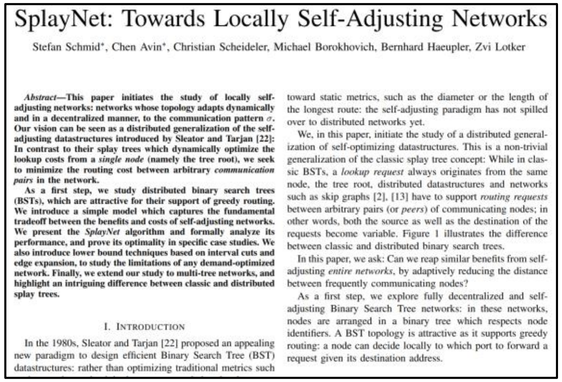
The physical topology is emerging as the next frontier in an ongoing effort to render communication networks more flexible. While first empirical results indicate that these flexibilities can be exploited to reconfigure and optimize the network toward the workload it serves and, e.g., providing the same bandwidth at lower infrastructure cost, only little is known today about the fundamental algorithmic problems underlying the design of reconfigurable networks. This paper initiates the study of the theory of demand-aware, self-adjusting networks. Our main position is that self-adjusting networks should be seen through the lense of self-adjusting datastructures. Accordingly, we present a taxonomy classifying the different algorithmic models of demand-oblivious, fixed demand-aware, and reconfigurable demand-aware networks, introduce a formal model, and identify objectives and evaluation metrics. We also demonstrate, by examples, the inherent

**Figure 1: Taxonomy of topology optimization**

design of efficient datacenter networks has received much attention over the last years. The topologies underlying modern datacenter networks range from trees [7, 8] over hypercubes [9, 10] to expander networks [11] and provide high connectivity at low cost [1].

Until now, these networks also have in common that their topology is *fixed* and ***oblivious*** to the actual demand (i.e.,

## Dynamic DAN



### SplayNet: Towards Locally Self-Adjusting Networks

Stefan Schmid*, Chen Avin*, Christian Scheideler, Michael Borokhovich, Bernhard Haeupler, Zvi Lotker

***Abstract*—This paper initiates the study of locally self-adjusting networks: networks whose topology adapts dynamically and in a decentralized manner, to the communication pattern $\sigma$. Our vision can be seen as a distributed generalization of the self-adjusting datastructures introduced by Sleator and Tarjan [22]: In contrast to their splay trees which dynamically optimize the lookup costs from a *single node* (namely the tree root), we seek to minimize the routing cost between arbitrary *communication pairs* in the network.**

**As a first step, we study distributed binary search trees (BSTs), which are attractive for their support of greedy routing. We introduce a simple model which captures the fundamental tradeoff between the benefits and costs of self-adjusting networks. We present the *SplayNet* algorithm and formally analyze its performance, and prove its optimality in specific case studies. We also introduce lower bound techniques based on interval cuts and edge expansion, to study the limitations of any demand-optimized network. Finally, we extend our study to multi-tree networks, and highlight an intriguing difference between classic and distributed splay trees.**

I. INTRODUCTION

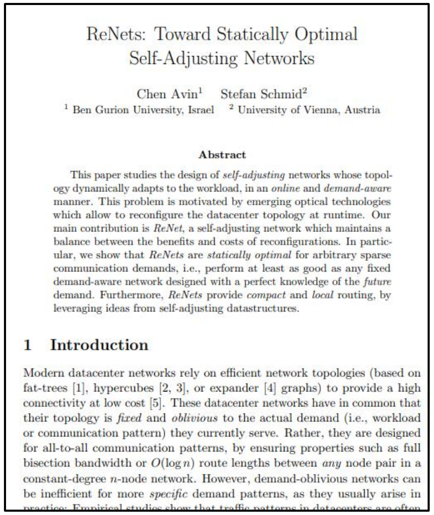
In the 1980s, Sleator and Tarjan [22] proposed an appealing new paradigm to design efficient Binary Search Tree (BST) datastructures: rather than optimizing traditional metrics such toward static metrics, such as the diameter or the length of the longest route: the self-adjusting paradigm has not spilled over to distributed networks yet.

We, in this paper, initiate the study of a distributed generalization of self-optimizing datastructures. This is a non-trivial generalization of the classic splay tree concept: While in classic BSTs, a *lookup request* always originates from the same node, the tree root, distributed datastructures and networks such as skip graphs [2], [13] have to support *routing requests* between arbitrary pairs (or *peers*) of communicating nodes; in other words, both the source as well as the destination of the requests become variable. Figure 1 illustrates the difference between classic and distributed binary search trees.

In this paper, we ask: Can we reap similar benefits from self-adjusting *entire networks*, by adaptively reducing the distance between frequently communicating nodes?

As a first step, we explore fully decentralized and self-adjusting Binary Search Tree networks: in these networks, nodes are arranged in a binary tree which respects node identifiers. A BST topology is attractive as it supports greedy routing: a node can decide locally to which port to forward a request given its destination address.

## Static Optimality



### ReNets: Toward Statically Optimal Self-Adjusting Networks

Chen Avin[1] Stefan Schmid[2]
[1] Ben Gurion University, Israel [2] University of Vienna, Austria

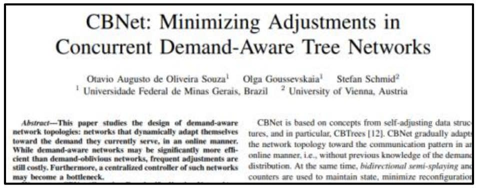
**Abstract**

This paper studies the design of *self-adjusting* networks whose topology dynamically adapts to the workload, in an *online* and *demand-aware* manner. This problem is motivated by emerging optical technologies which allow to reconfigure the datacenter topology at runtime. Our main contribution is *ReNet*, a self-adjusting network which maintains a balance between the benefits and costs of reconfigurations. In particular, we show that *ReNets* are *statically optimal* for arbitrary sparse communication demands, i.e., perform at least as good as any fixed demand-aware network designed with a perfect knowledge of the *future* demand. Furthermore, *ReNets* provide *compact* and *local* routing, by leveraging ideas from self-adjusting datastructures.

**1 Introduction**

Modern datacenter networks rely on efficient network topologies (based on fat-trees [1], hypercubes [2, 3], or expander [4] graphs) to provide a high connectivity at low cost [5]. These datacenter networks have in common that their topology is *fixed* and *oblivious* to the actual demand (i.e., workload or communication pattern) they currently serve. Rather, they are designed for all-to-all communication patterns, by ensuring properties such as full bisection bandwidth or $O(\log n)$ route lengths between *any* node pair in a constant-degree $n$-node network. However, demand-oblivious networks can be inefficient for more *specific* demand patterns, as they usually arise in

## Concurrent DANs



### CBNet: Minimizing Adjustments in Concurrent Demand-Aware Tree Networks

Otavio Augusto de Oliveira Souza[1] Olga Goussevskaia[1] Stefan Schmid[2]
[1] Universidade Federal de Minas Gerais, Brazil [2] University of Vienna, Austria

***Abstract*—This paper studies the design of demand-aware network topologies: networks that dynamically adapt themselves toward the demand they currently serve, in an online manner. While demand-aware networks may be significantly more efficient than demand-oblivious networks, frequent adjustments are still costly. Furthermore, a centralized controller of such networks may become a bottleneck.**

CBNet is based on concepts from self-adjusting data struc
tures, and in particular, CBTrees [12]. CBNet gradually adapt
the network topology toward the communication pattern in a
online manner, i.e., without previous knowledge of the deman
distribution. At the same time, *bidirectional semi-splaying* an
counters are used to maintain state, minimize reconfiguratio

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**On the Complexity of Traffic Traces and Implications**
Chen Avin, Manya Ghobadi, Chen Griner, and Stefan Schmid.
ACM SIGMETRICS, Boston, Massachusetts, USA, June 2020.

**Survey of Reconfigurable Data Center Networks: Enablers, Algorithms, Complexity**
Klaus-Tycho Foerster and Stefan Schmid.
**SIGACT News**, June 2019.

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Chen Avin and Stefan Schmid.
ACM SIGCOMM Computer Communication Review (**CCR**), October 2018.

**Dynamically Optimal Self-Adjusting Single-Source Tree Networks**
Chen Avin, Kaushik Mondal, and Stefan Schmid.
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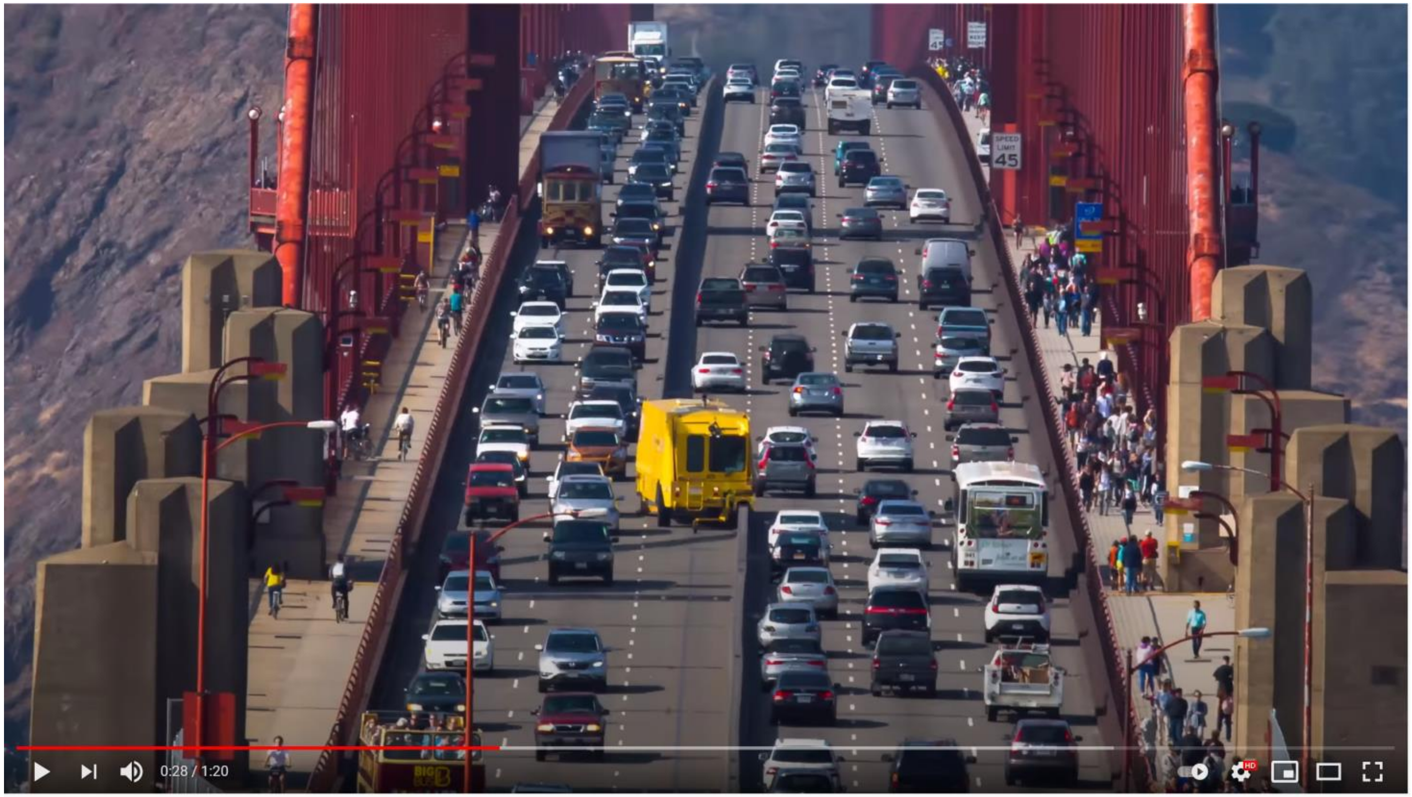
**SplayNet: Towards Locally Self-Adjusting Networks**
Stefan Schmid, Chen Avin, Christian Scheideler, Michael Borokhovich, Bernhard Haeupler, and Zvi Lotker.
IEEE/ACM Transactions on Networking (**TON**), Volume 24, Issue 3, 2016. Early version: IEEE **IPDPS** 2013.

**Characterizing the Algorithmic Complexity of Reconfigurable Data Center Architectures**
Klaus-Tycho Foerster, Monia Ghobadi, and Stefan Schmid.
ACM/IEEE Symposium on Architectures for Networking and Communications Systems (**ANCS**), Ithaca, New York, USA, July 2018.

# Bonus Material

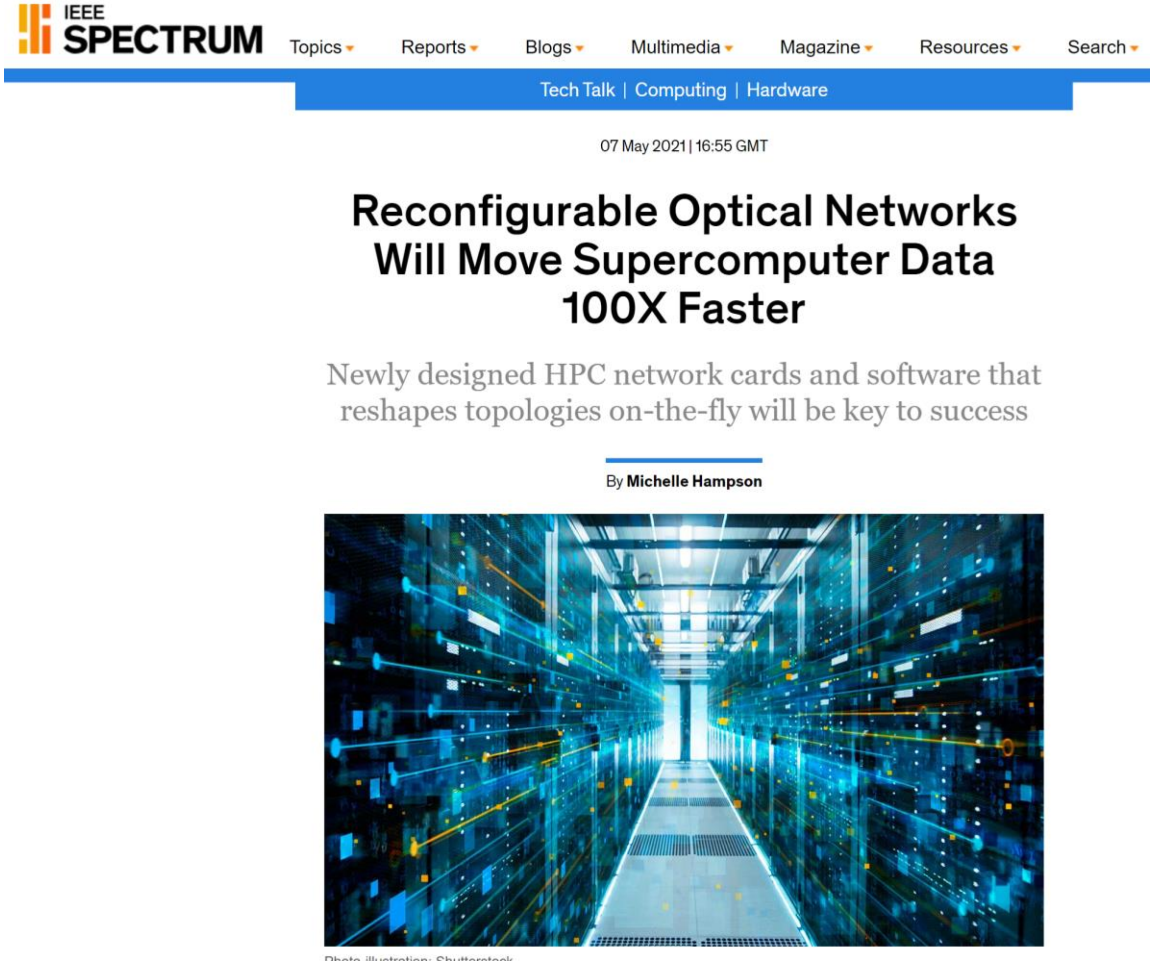
Hogwarts Stair

# Bonus Material



Golden Gate Zipper

# Bonus Material



07 May 2021 | 16:55 GMT

## Reconfigurable Optical Networks Will Move Supercomputer Data 100X Faster

Newly designed HPC network cards and software that reshapes topologies on-the-fly will be key to success

By **Michelle Hampson**

In HPC

Question:

# How to Quantify such “Structure” in the Demand?

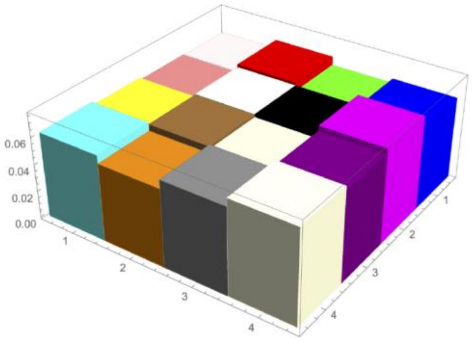
# Intuition

## Which demand has more structure?

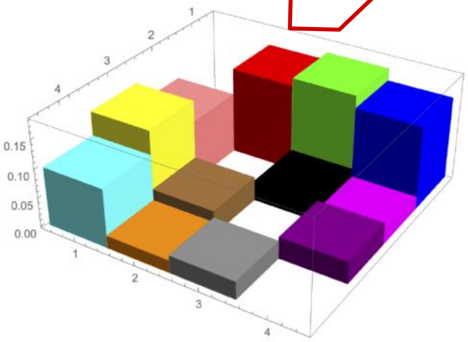
⇢ Traffic matrices of two different distributed ML applications

- → GPU-to-GPU

Color = communication pair



**VS**



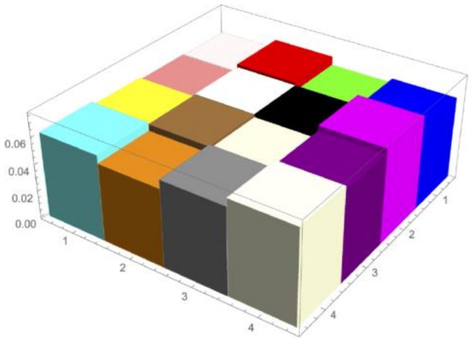
# Intuition

## Which demand has more structure?

⇢ Traffic matrices of two different distributed ML applications

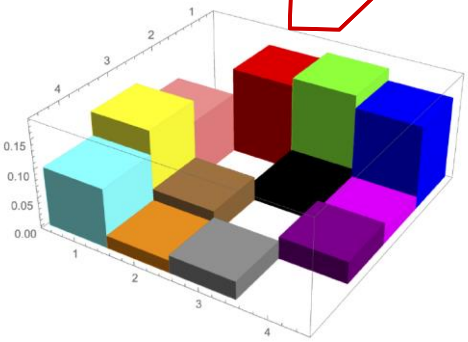
- → GPU-to-GPU

Color = communication pair



**More uniform**

vs



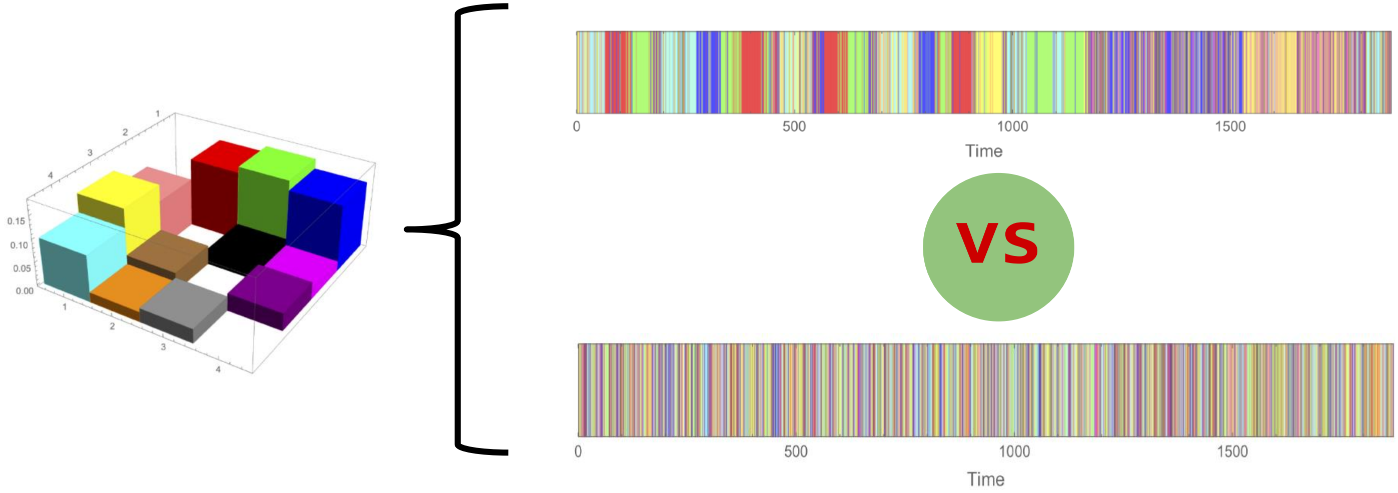
**More structure**

# Intuition

## Spatial vs temporal structure

⇢ Two different ways to generate same traffic matrix:
  ⇀ Same non-temporal structure

⇢ Which one has more structure?

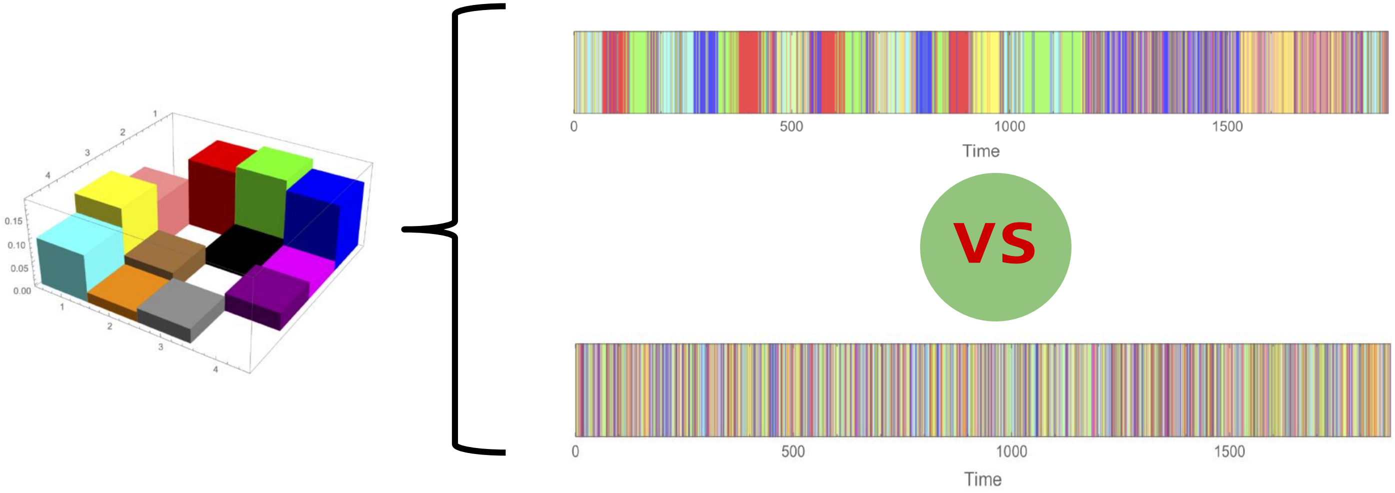


# Intuition

## Spatial vs temporal structure

- ⇢ Two different ways to generate same traffic matrix:
  - ⇀ Same non-temporal structure

- ⇢ Which one has more structure?

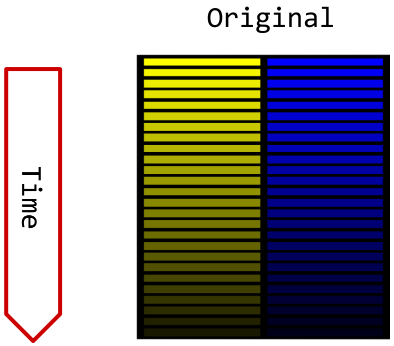


Systematically?

# Trace Complexity

## Information-Theoretic Approach

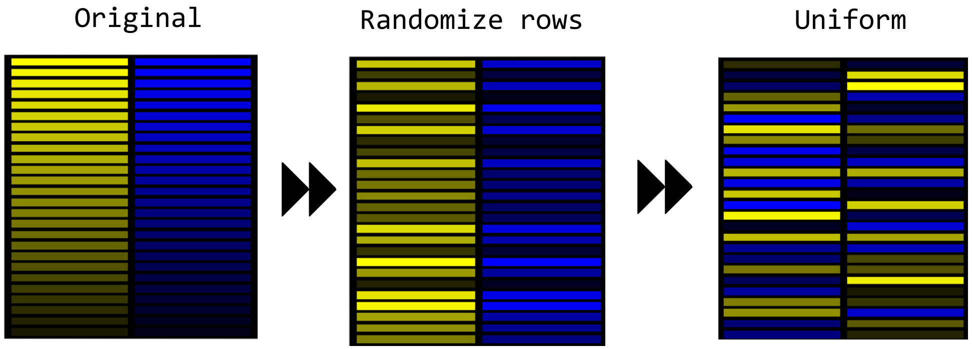
“Shuffle&Compress”



# Trace Complexity

## Information-Theoretic Approach

“Shuffle&Compress”



Original

Randomize rows

Uniform

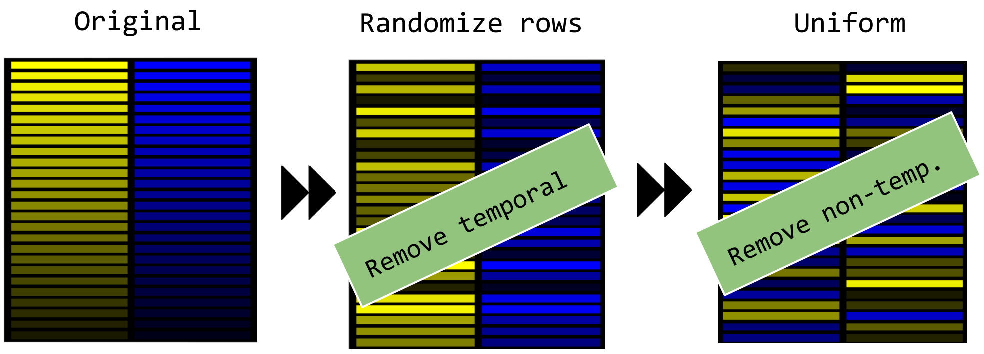
Increasing complexity (systematically randomized)

More structure (compresses better)

# Trace Complexity

## Information-Theoretic Approach

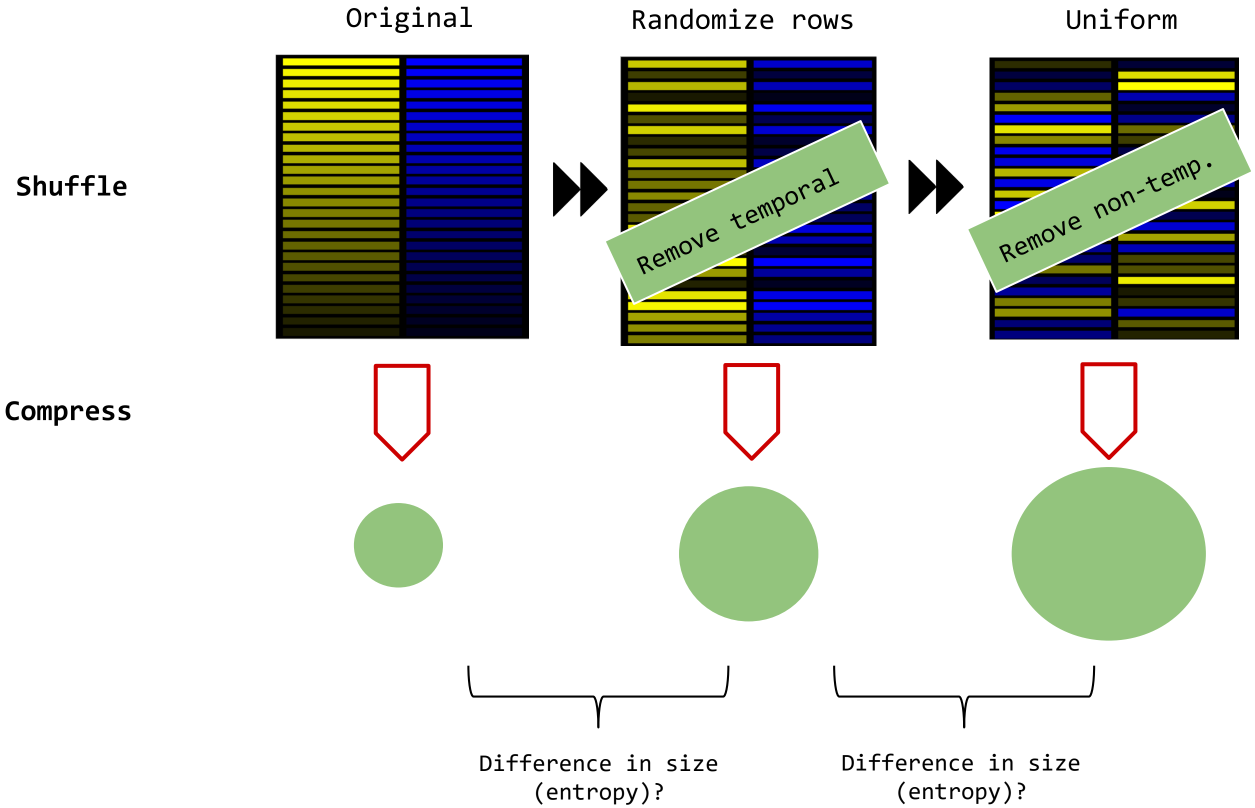
“Shuffle&Compress”



# Trace Complexity

## Information-Theoretic Approach

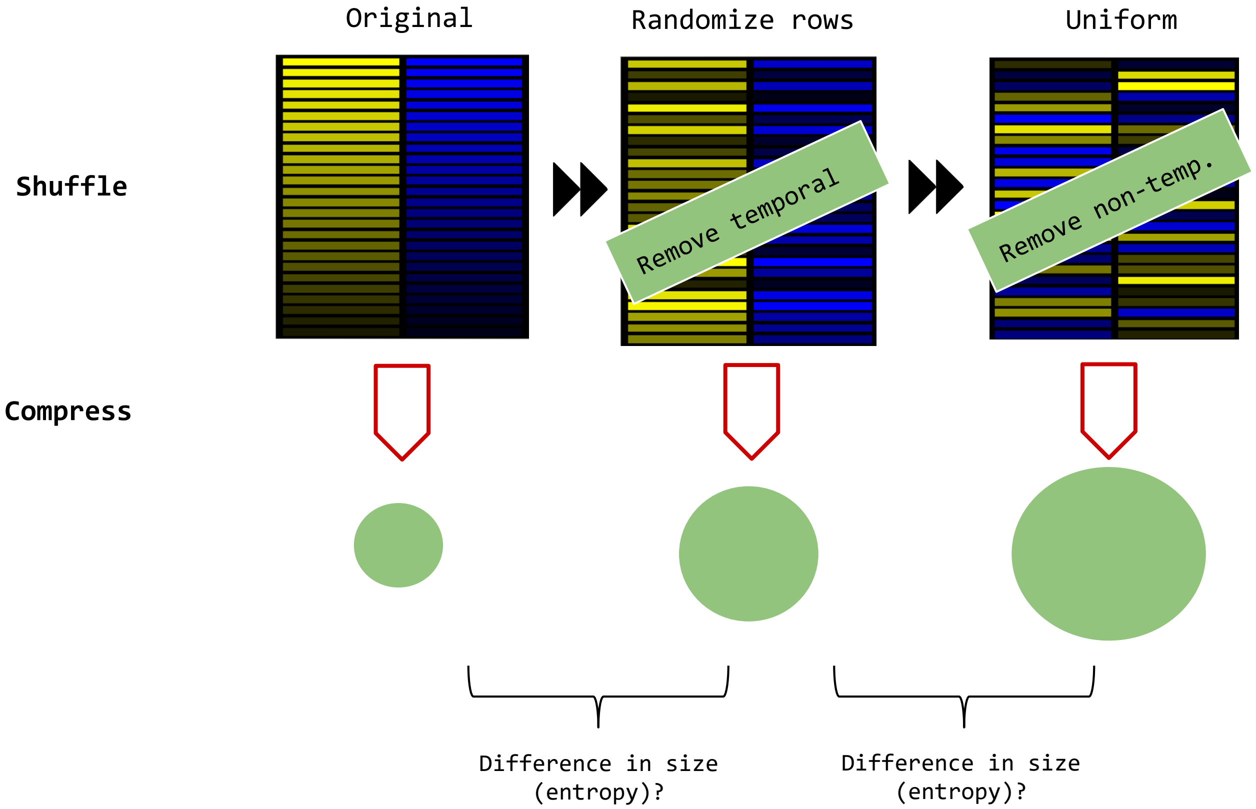
## “Shuffle&Compress”



# Trace Complexity

## Information-Theoretic Approach

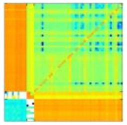
## “Shuffle&Compress”

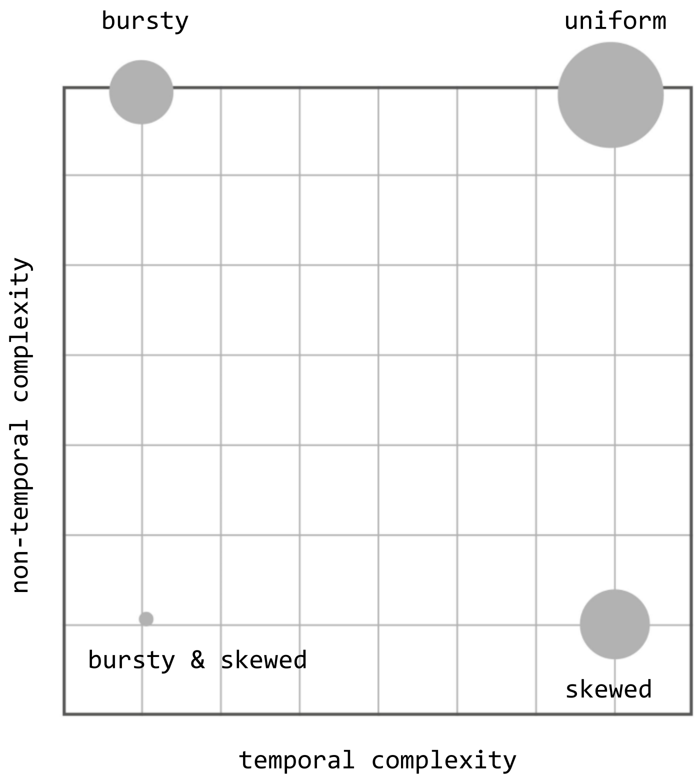


**Can be used to define 2-dimensional complexity map!**

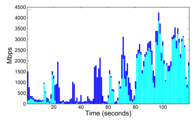
Our Methodology

# Complexity Map





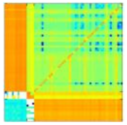
No structure

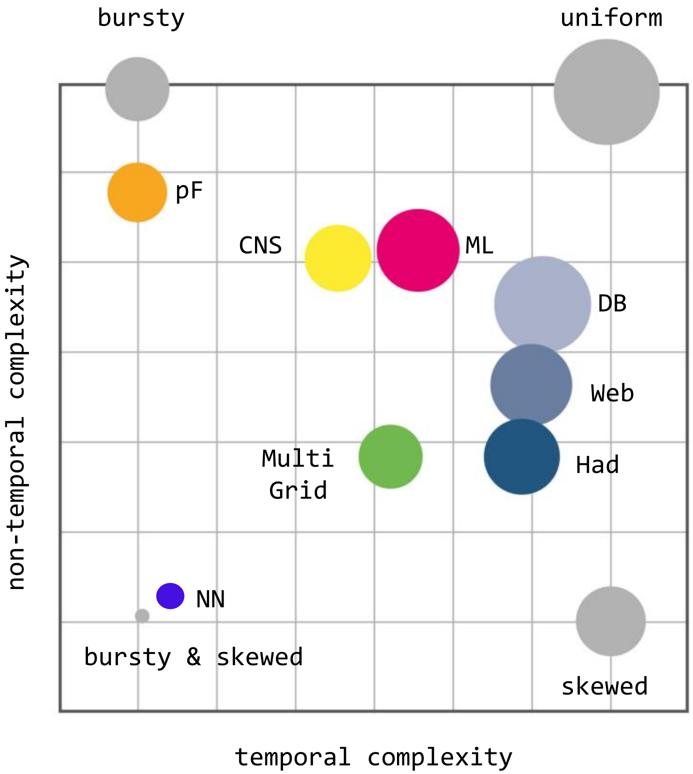


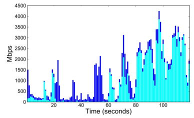
Our **approach**: iterative **randomization and compression** of trace to identify dimensions of structure.

Our Methodology

# Complexity Map







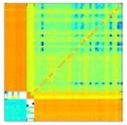
No structure

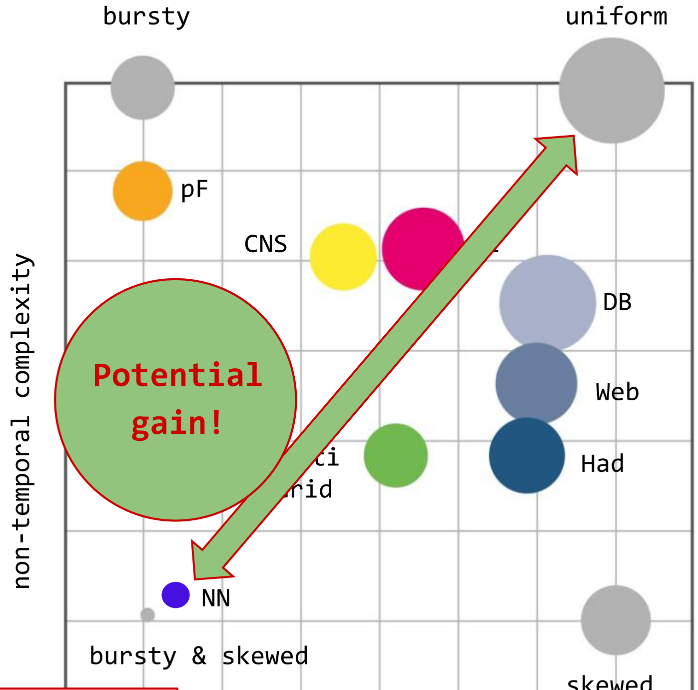
Our **approach**: iterative **randomization and compression** of trace to identify dimensions of structure.

**Different structures!**

Our Methodology

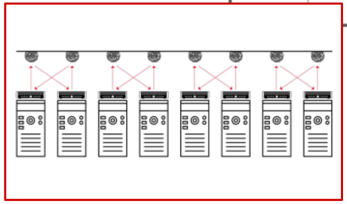
# Complexity Map



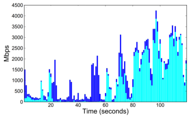


**Potential gain!**

Our **approach**: iterative **randomization and compression** of trace to identify dimensions of structure.



temporal complexity



**Different structures!**

Further Reading

# ACM SIGMETRICS 2020

## On the Complexity of Traffic Traces and Implications

CHEN AVIN, School of Electrical and Computer Engineering, Ben Gurion University of the Negev, Israel
MANYA GHOBADI, Computer Science and Artificial Intelligence Laboratory, MIT, USA
CHEN GRINER, School of Electrical and Computer Engineering, Ben Gurion University of the Negev, Israel
STEFAN SCHMID, Faculty of Computer Science, University of Vienna, Austria

This paper presents a systematic approach to identify and quantify the types of structures featured by packet traces in communication networks. Our approach leverages an information-theoretic methodology, based on iterative randomization and compression of the packet trace, which allows us to systematically remove and measure dimensions of structure in the trace. In particular, we introduce the notion of *trace complexity* which approximates the entropy rate of a packet trace. Considering several real-world traces, we show that trace complexity can provide unique insights into the characteristics of various applications. Based on our approach, we also propose a traffic generator model able to produce a synthetic trace that matches the complexity levels of its corresponding real-world trace. Using a case study in the context of datacenters, we show that insights into the structure of packet traces can lead to improved demand-aware network designs: datacenter topologies that are optimized for specific traffic patterns.

CCS Concepts: • **Networks** → **Network performance evaluation**; **Network algorithms**; **Data center networks**; • **Mathematics of computing** → *Information theory*;

Additional Key Words and Phrases: trace complexity, self-adjusting networks, entropy rate, compress, complexity map, data centers

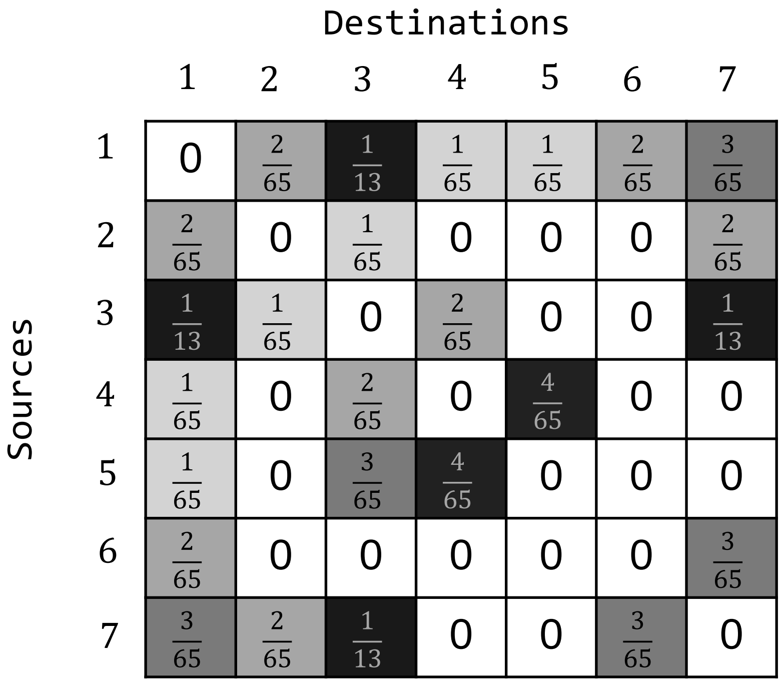
**ACM Reference Format:**
Chen Avin, Manya Ghobadi, Chen Griner, and Stefan Schmid. 2020. On the Complexity of Traffic Traces and Implications. *Proc. ACM Meas. Anal. Comput. Syst.* 4, 1, Article 20 (March 2020), 29 pages. https://doi.org/10.1145/3379486

### 1 INTRODUCTION

Packet traces collected from networking applications, such as datacenter traffic, have been shown to feature much *structure*: datacenter traffic matrices are sparse and skewed [16, 39], exhibit

Case Study “Route Lengths”

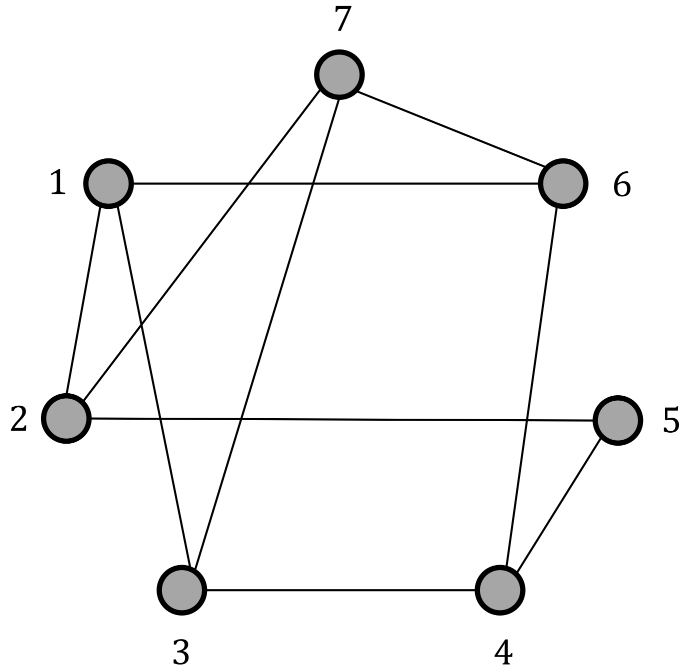
# Constant-Degree Demand-Aware Network



Destinations

Sources

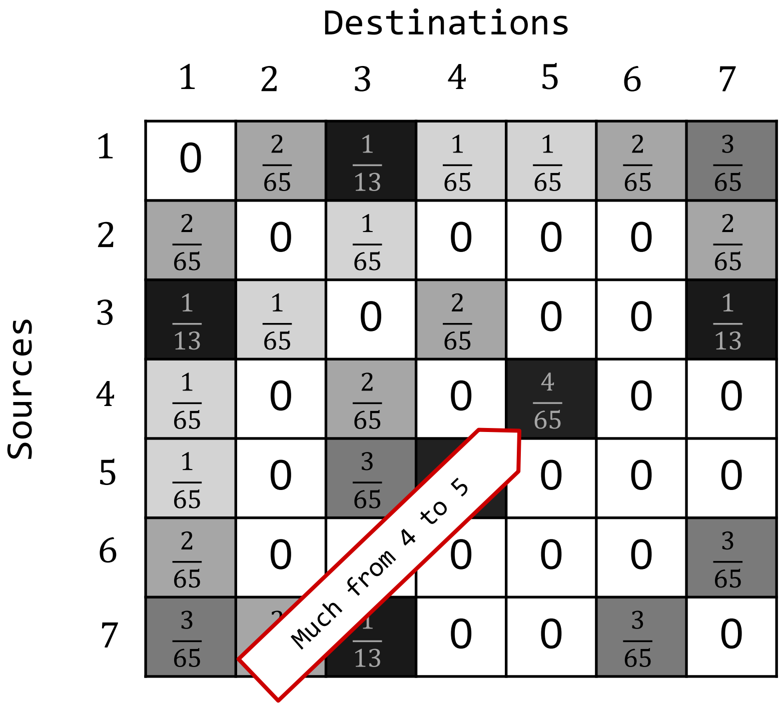
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1 | 0 | $\frac{2}{65}$ | $\frac{1}{13}$ | $\frac{1}{65}$ | $\frac{1}{65}$ | $\frac{2}{65}$ | $\frac{3}{65}$ |
| 2 | $\frac{2}{65}$ | 0 | $\frac{1}{65}$ | 0 | 0 | 0 | $\frac{2}{65}$ |
| 3 | $\frac{1}{13}$ | $\frac{1}{65}$ | 0 | $\frac{2}{65}$ | 0 | 0 | $\frac{1}{13}$ |
| 4 | $\frac{1}{65}$ | 0 | $\frac{2}{65}$ | 0 | $\frac{4}{65}$ | 0 | 0 |
| 5 | $\frac{1}{65}$ | 0 | $\frac{3}{65}$ | $\frac{4}{65}$ | 0 | 0 | 0 |
| 6 | $\frac{2}{65}$ | 0 | 0 | 0 | 0 | 0 | $\frac{3}{65}$ |
| 7 | $\frac{3}{65}$ | $\frac{2}{65}$ | $\frac{1}{13}$ | 0 | 0 | $\frac{3}{65}$ | 0 |



$$\mathrm{ERL}(\mathcal{D},\mathrm{N}) = \sum_{(u,v)\in\mathcal{D}} p(u,v)\cdot d_N(u,v)$$

Case Study “Route Lengths”

# Constant-Degree Demand-Aware Network



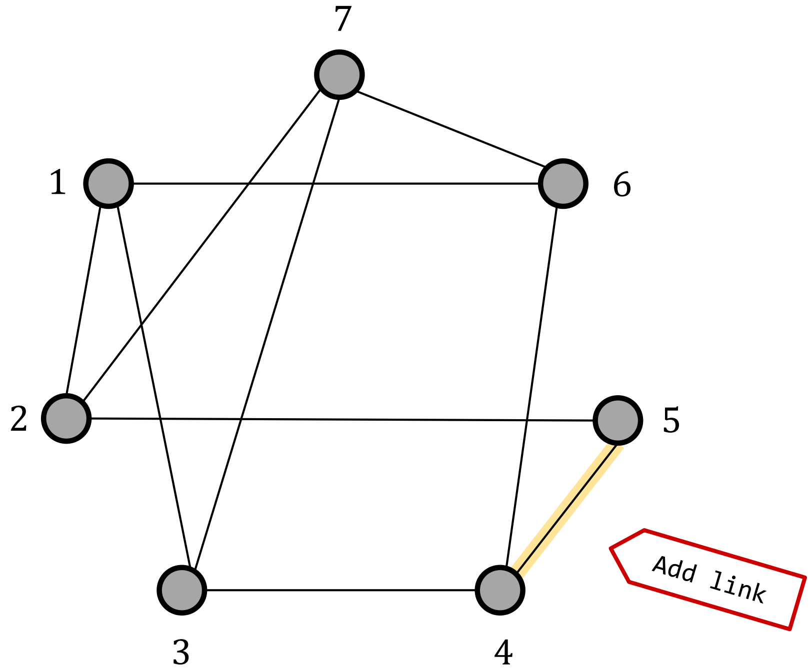
Destinations

Sources

|  | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1 | 0 | $\frac{2}{65}$ | $\frac{1}{13}$ | $\frac{1}{65}$ | $\frac{1}{65}$ | $\frac{2}{65}$ | $\frac{3}{65}$ |
| 2 | $\frac{2}{65}$ | 0 | $\frac{1}{65}$ | 0 | 0 | 0 | $\frac{2}{65}$ |
| 3 | $\frac{1}{13}$ | $\frac{1}{65}$ | 0 | $\frac{2}{65}$ | 0 | 0 | $\frac{1}{13}$ |
| 4 | $\frac{1}{65}$ | 0 | $\frac{2}{65}$ | 0 | $\frac{4}{65}$ | 0 | 0 |
| 5 | $\frac{1}{65}$ | 0 | $\frac{3}{65}$ | [illegible] | 0 | 0 | 0 |
| 6 | $\frac{2}{65}$ | 0 | [illegible] | 0 | 0 | 0 | $\frac{3}{65}$ |
| 7 | $\frac{3}{65}$ | [illegible] | $\frac{1}{13}$ | 0 | 0 | $\frac{3}{65}$ | 0 |

Much from 4 to 5

▶▶



Add link

$$\mathrm{ERL}(\mathcal{D},\mathrm{N}) = \sum_{(u,v)\in\mathcal{D}} p(u,v)\cdot d_{N}(u,v)$$

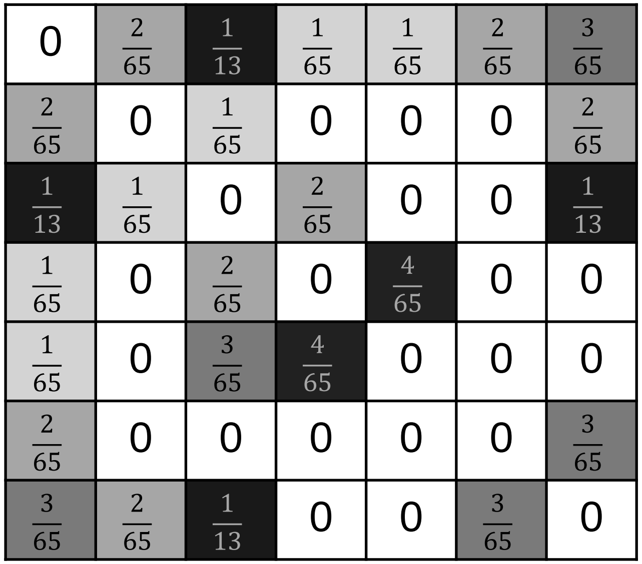
Case Study “Route Lengths”

# Constant-Degree Demand-Aware Network

Communicated with many

Destinations

Sources



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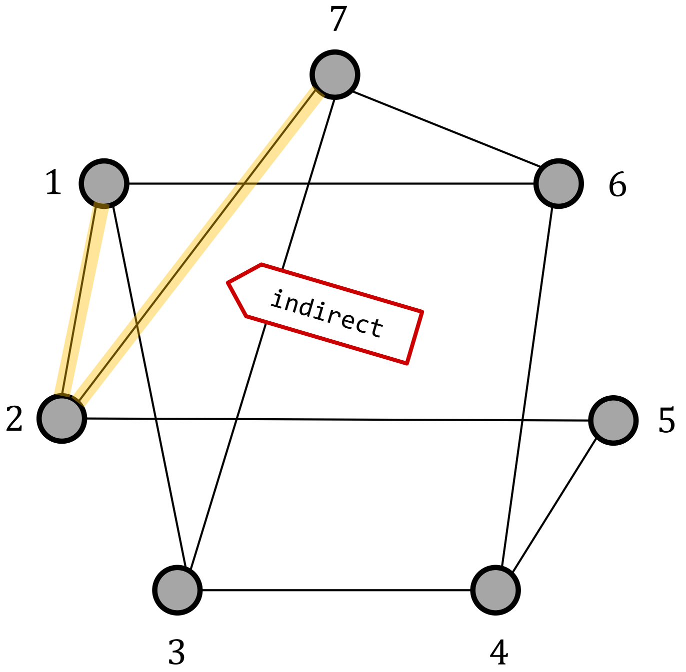
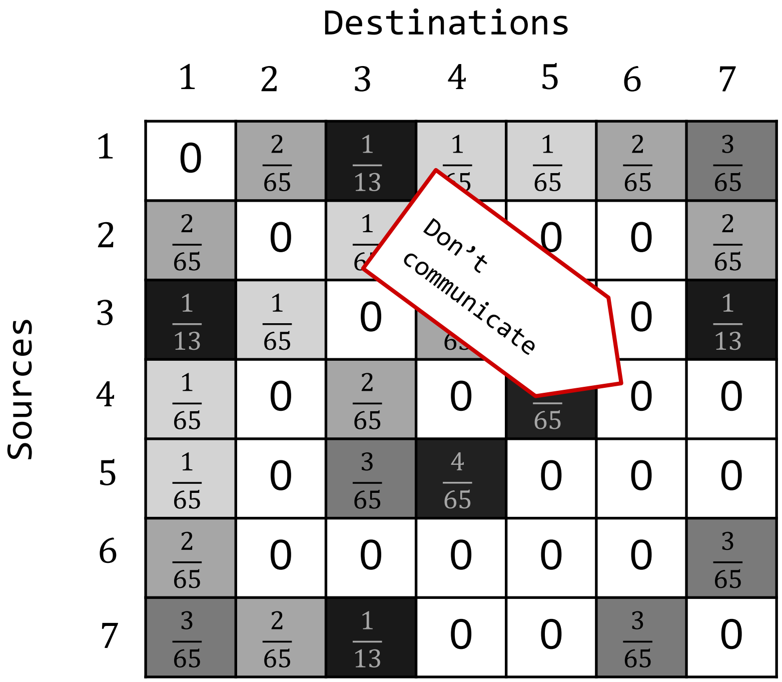


$$\mathrm{ERL}(\mathcal{D},\mathrm{N}) = \sum_{(u,v)\in\mathcal{D}} p(u,v)\cdot d_N(u,v)$$

Case Study “Route Lengths”

# Constant-Degree Demand-Aware Network



Destinations

Sources

|  | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
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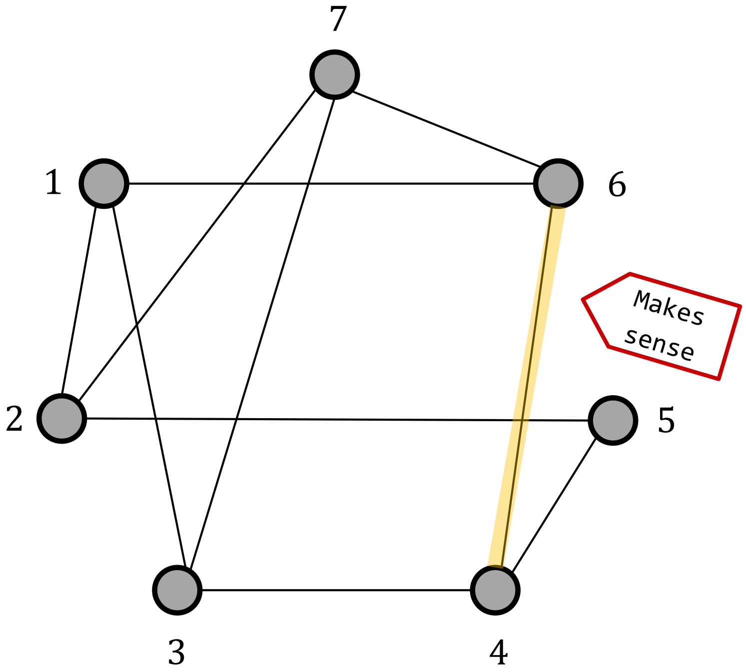
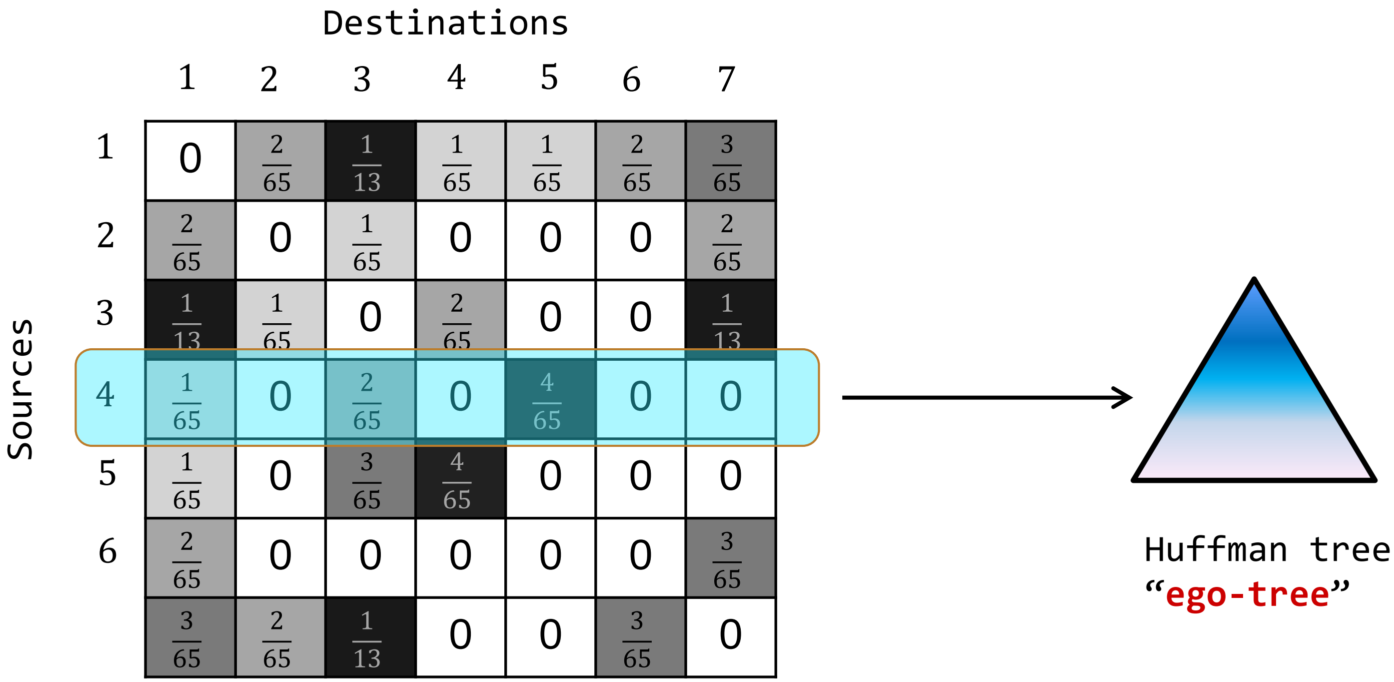
Don’t communicate



Makes sense

$$\mathrm{ERL}(\mathcal{D},N) = \sum_{(u,v)\in\mathcal{D}} p(u,v) \cdot d_N(u,v)$$

# Algorithm: Idea



Destinations

Sources

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
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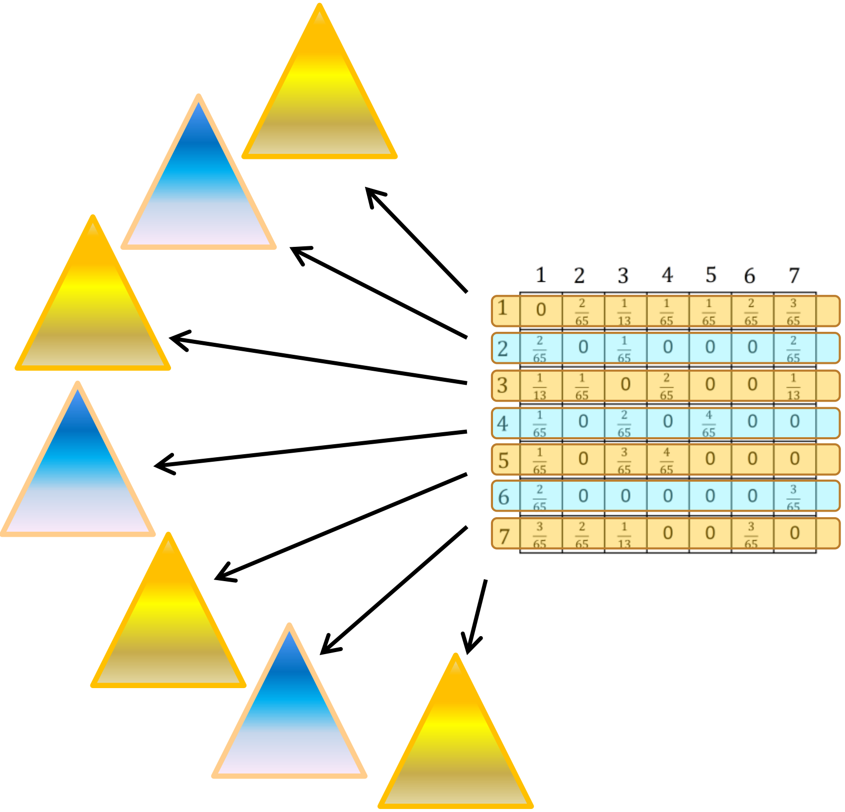
| | $\frac{3}{65}$ | $\frac{2}{65}$ | $\frac{1}{13}$ | 0 | 0 | $\frac{3}{65}$ | 0 |

Huffman tree:
“**ego-tree**”

# Entropy Upper Bound

⇢ Idea for algorithm:

  → union of trees



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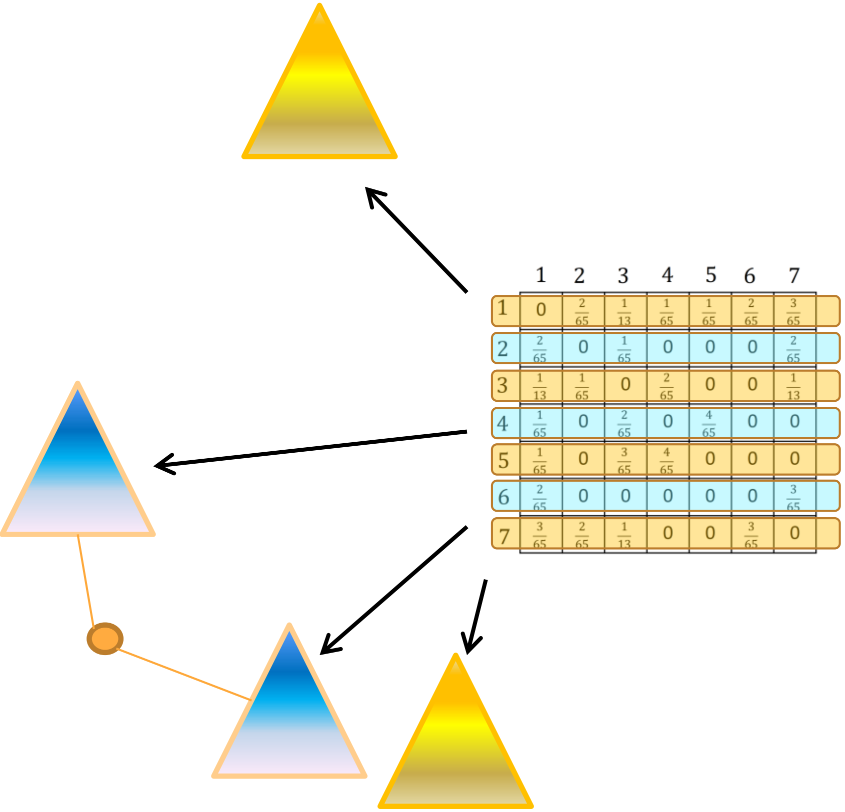
| 7 | $\frac{3}{65}$ | $\frac{2}{65}$ | $\frac{1}{13}$ | 0 | 0 | $\frac{3}{65}$ | 0 |

# Entropy Upper Bound

- Idea for algorithm:
  - union of trees
  - reduce degree
  - but keep distances



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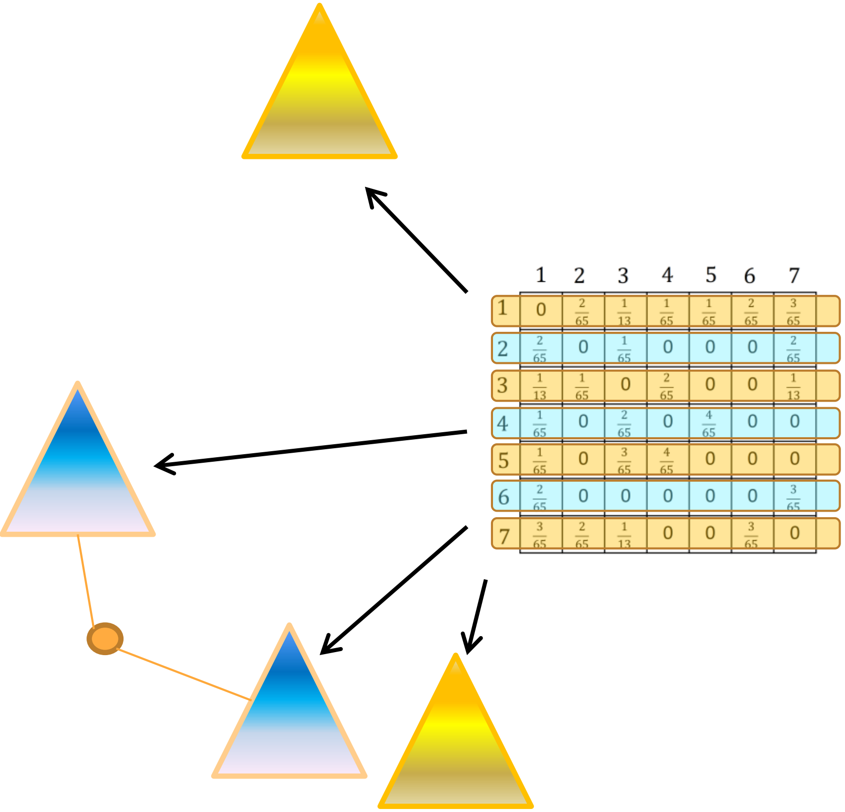
| 7 | $\frac{3}{65}$ | $\frac{2}{65}$ | $\frac{1}{13}$ | 0 | 0 | $\frac{3}{65}$ | 0 |

# Entropy Upper Bound

- ⇢ Idea for algorithm:
  - ⇀ union of trees
  - ⇀ reduce degree
  - ⇀ but keep distances

- ⇢ Ok for sparse demands
  - ⇀ not everyone gets tree
  - ⇀ helper nodes



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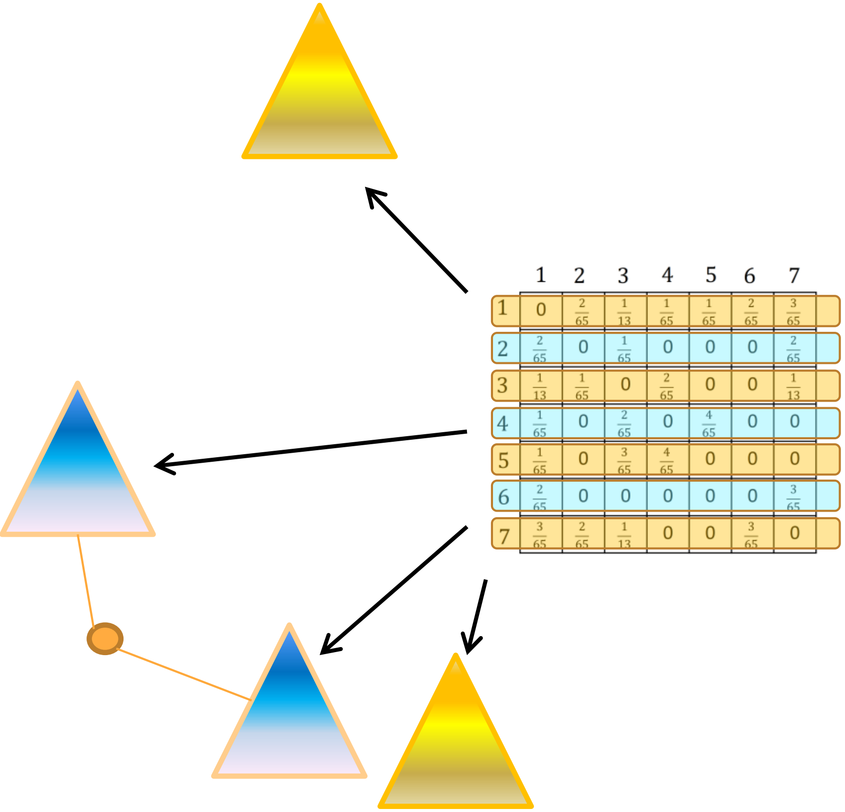
# Entropy Upper Bound

- Idea for algorithm:
  - union of trees
  - reduce degree
  - but keep distances
- Ok for sparse demands
  - not everyone gets tree
  - helper nodes

**Static**



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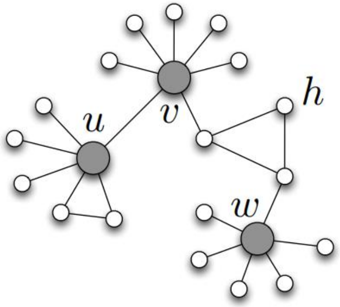
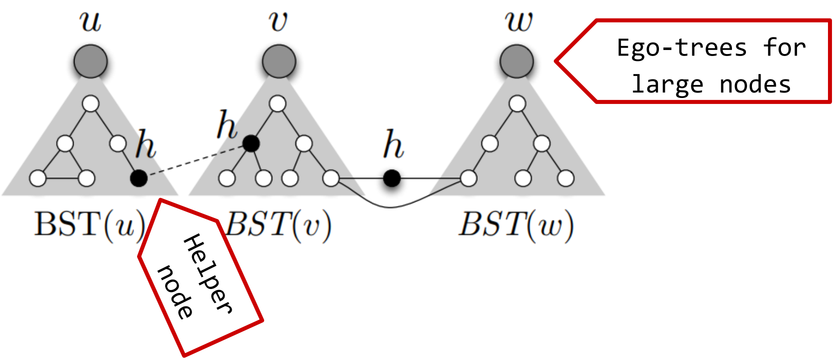
| 7 | $\frac{3}{65}$ | $\frac{2}{65}$ | $\frac{1}{13}$ | 0 | 0 | $\frac{3}{65}$ | 0 |

# Intuition of Algorithm

Demand graph:



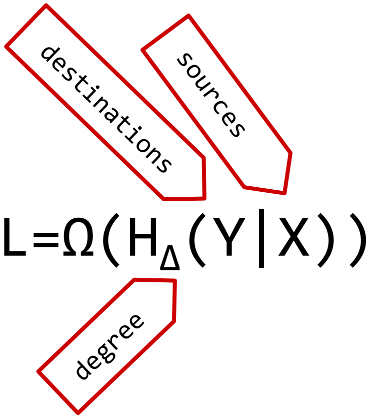
Demand-aware network:



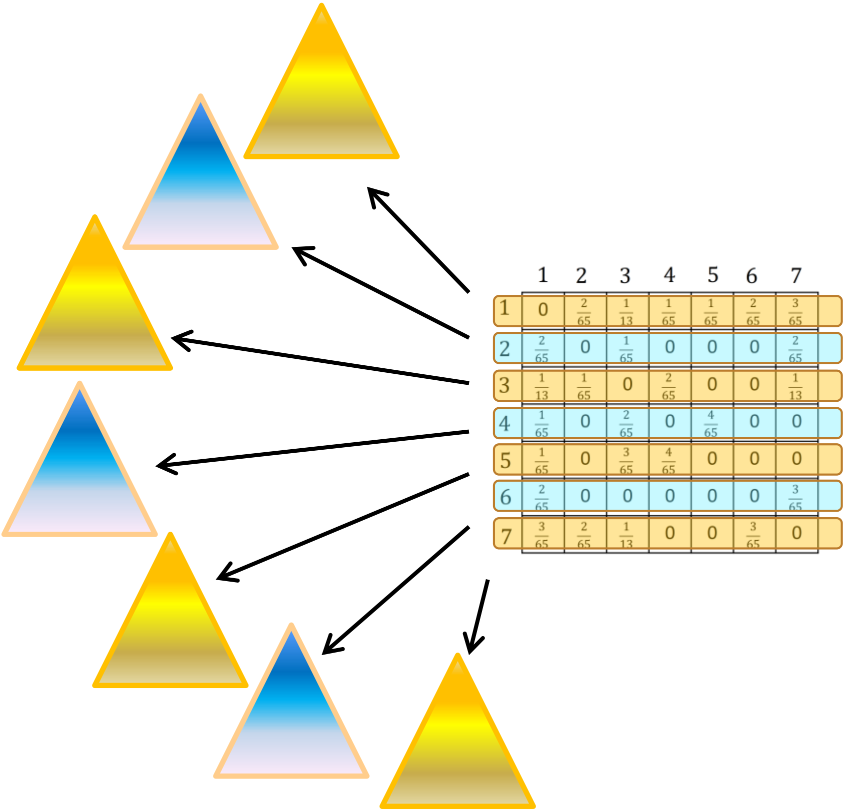
Ego-trees for large nodes

Helper node

# Entropy Lower Bound



$$ERL=\Omega(H_{\Delta}(Y|X))$$



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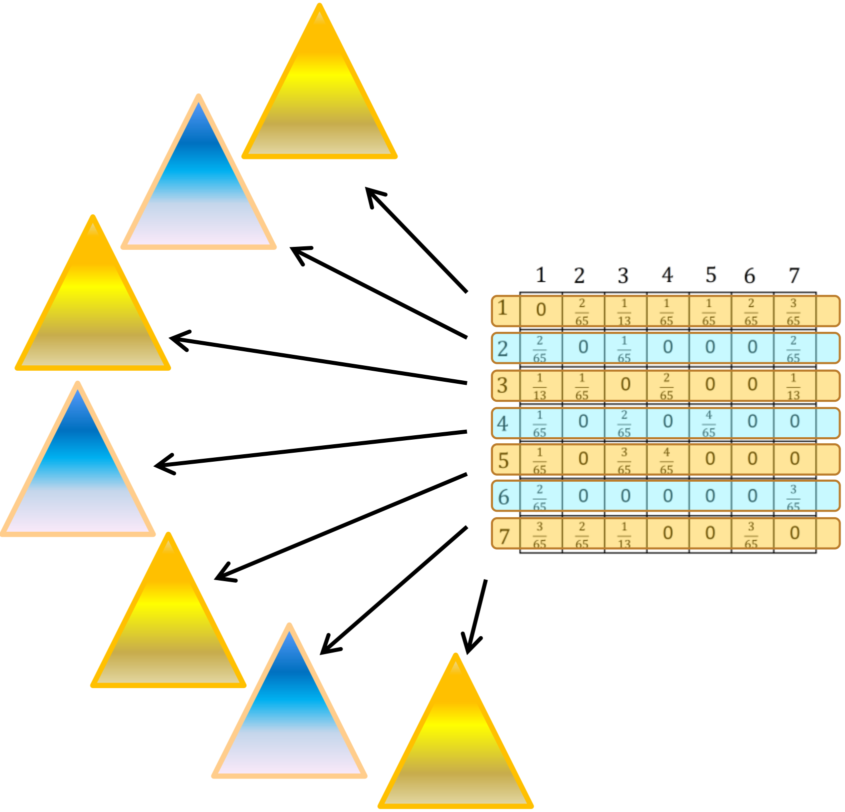
| 7 | $\frac{3}{65}$ | $\frac{2}{65}$ | $\frac{1}{13}$ | 0 | 0 | $\frac{3}{65}$ | 0 |

# Dynamic Algorithm

**Dynamic**



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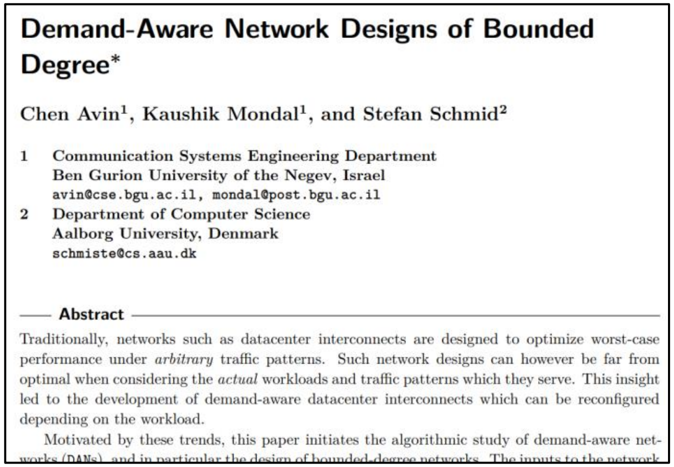
| 7 | $\frac{3}{65}$ | $\frac{2}{65}$ | $\frac{1}{13}$ | 0 | 0 | $\frac{3}{65}$ | 0 |

Further Reading

# TON 2016, DISC 2017, CCR 2019, INFOCOM 2019



## Demand-Aware Network Designs of Bounded Degree*

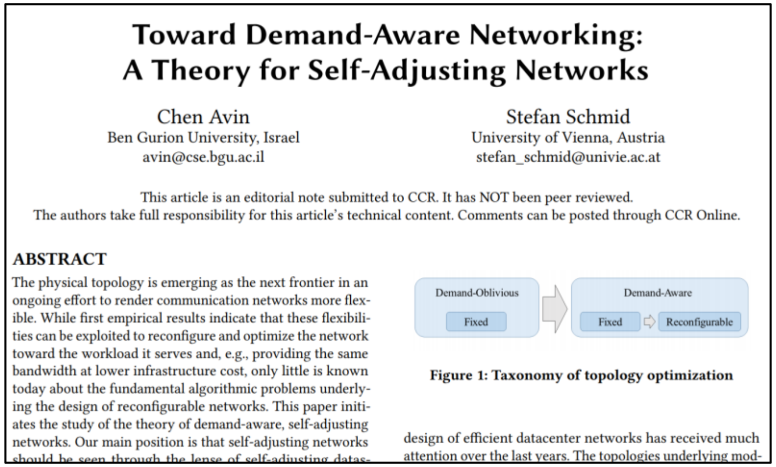
Chen Avin[1], Kaushik Mondal[1], and Stefan Schmid[2]

1 Communication Systems Engineering Department
Ben Gurion University of the Negev, Israel
avin@cse.bgu.ac.il, mondal@post.bgu.ac.il
2 Department of Computer Science
Aalborg University, Denmark
schmiste@cs.aau.dk

**Abstract**

Traditionally, networks such as datacenter interconnects are designed to optimize worst-case performance under *arbitrary* traffic patterns. Such network designs can however be far from optimal when considering the *actual* workloads and traffic patterns which they serve. This insight led to the development of demand-aware datacenter interconnects which can be reconfigured depending on the workload.

Motivated by these trends, this paper initiates the algorithmic study of demand-aware networks (DANs), and in particular the design of bounded-degree networks. The inputs to the network



## Toward Demand-Aware Networking: A Theory for Self-Adjusting Networks

Chen Avin
Ben Gurion University, Israel
avin@cse.bgu.ac.il

Stefan Schmid
University of Vienna, Austria
stefan_schmid@univie.ac.at

This article is an editorial note submitted to CCR. It has NOT been peer reviewed.
The authors take full responsibility for this article's technical content. Comments can be posted through CCR Online.

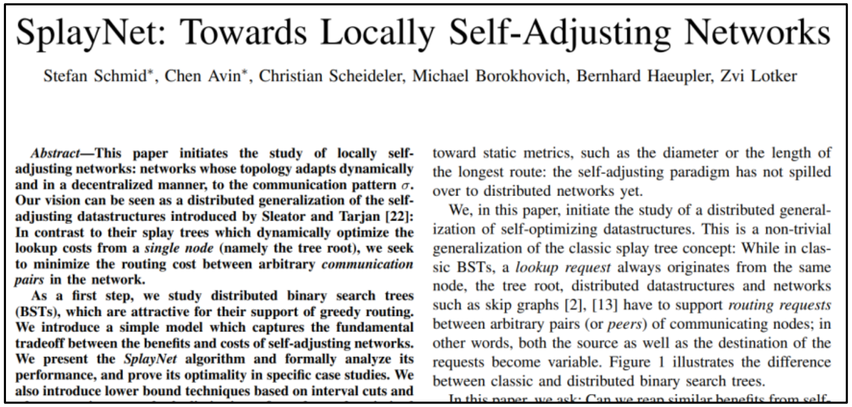
**ABSTRACT**

The physical topology is emerging as the next frontier in an ongoing effort to render communication networks more flexible. While first empirical results indicate that these flexibilities can be exploited to reconfigure and optimize the network toward the workload it serves and, e.g., providing the same bandwidth at lower infrastructure cost, only little is known today about the fundamental algorithmic problems underlying the design of reconfigurable networks. This paper initiates the study of the theory of demand-aware, self-adjusting networks. Our main position is that self-adjusting networks should be seen through the lense of self-adjusting datas-

Demand-Oblivious | Fixed → Demand-Aware | Fixed → Reconfigurable

**Figure 1: Taxonomy of topology optimization**

design of efficient datacenter networks has received much attention over the last years. The topologies underlying mod-



## SplayNet: Towards Locally Self-Adjusting Networks

Stefan Schmid*, Chen Avin*, Christian Scheideler, Michael Borokhovich, Bernhard Haeupler, Zvi Lotker

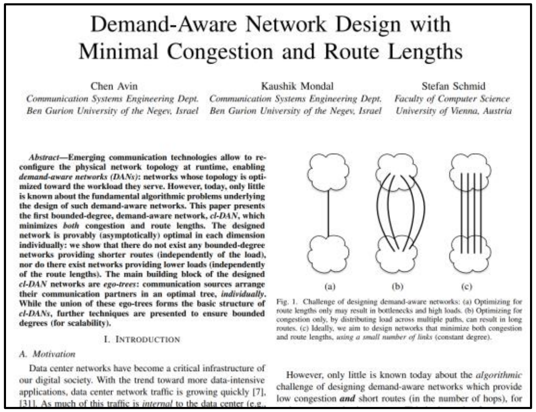
***Abstract*—This paper initiates the study of locally self-adjusting networks: networks whose topology adapts dynamically and in a decentralized manner, to the communication pattern $\sigma$. Our vision can be seen as a distributed generalization of the self-adjusting datastructures introduced by Sleator and Tarjan [22]: In contrast to their splay trees which dynamically optimize the lookup costs from a *single node* (namely the tree root), we seek to minimize the routing cost between arbitrary *communication pairs* in the network.**

**As a first step, we study distributed binary search trees (BSTs), which are attractive for their support of greedy routing. We introduce a simple model which captures the fundamental tradeoff between the benefits and costs of self-adjusting networks. We present the *SplayNet* algorithm and formally analyze its performance, and prove its optimality in specific case studies. We also introduce lower bound techniques based on interval cuts and**

toward static metrics, such as the diameter or the length of the longest route: the self-adjusting paradigm has not spilled over to distributed networks yet.

We, in this paper, initiate the study of a distributed generalization of self-optimizing datastructures. This is a non-trivial generalization of the classic splay tree concept: While in classic BSTs, a *lookup request* always originates from the same node, the tree root, distributed datastructures and networks such as skip graphs [2], [13] have to support *routing requests* between arbitrary pairs (or *peers*) of communicating nodes; in other words, both the source as well as the destination of the requests become variable. Figure 1 illustrates the difference between classic and distributed binary search trees.

In this paper, we ask: Can we reap similar benefits from self-



## Demand-Aware Network Design with Minimal Congestion and Route Lengths

Chen Avin
*Communication Systems Engineering Dept.*
*Ben Gurion University of the Negev, Israel*

Kaushik Mondal
*Communication Systems Engineering Dept.*
*Ben Gurion University of the Negev, Israel*

Stefan Schmid
*Faculty of Computer Science*
*University of Vienna, Austria*

***Abstract*—Emerging communication technologies allow to reconfigure the physical network topology at runtime, enabling *demand-aware networks (DANs)*: networks whose topology is optimized toward the workload they serve. However, today, only little is known about the fundamental algorithmic problems underlying the design of such demand-aware networks. This paper presents the first bounded-degree, demand-aware network, *cl-DAN*, which minimizes *both* congestion and route lengths. The designed network is provably (asymptotically) optimal in each dimension individually: we show that there do not exist any bounded-degree networks providing shorter routes (independently of the load), nor do there exist networks providing lower loads (independently of the route lengths). The main building block of the designed *cl-DAN* networks are *ego-trees*: communication sources arrange their communication partners in an optimal tree, *individually*. While the union of these ego-trees forms the basic structure of *cl-DANs*, further techniques are presented to ensure bounded degrees (for scalability).**

I. INTRODUCTION

*A. Motivation*

Data center networks have become a critical infrastructure of our digital society. With the trend toward more data-intensive applications, data center network traffic is growing quickly [7], [31]. As much of this traffic is *internal* to the data center (e.g.,

(a) (b) (c)

Fig. 1. Challenge of designing demand-aware networks: (a) Optimizing for route lengths only may result in bottlenecks and high loads. (b) Optimizing for congestion only, by distributing load across multiple paths, can result in long routes. (c) Ideally, we aim to design networks that minimize both congestion and route lengths, *using a small number of links* (constant degree).

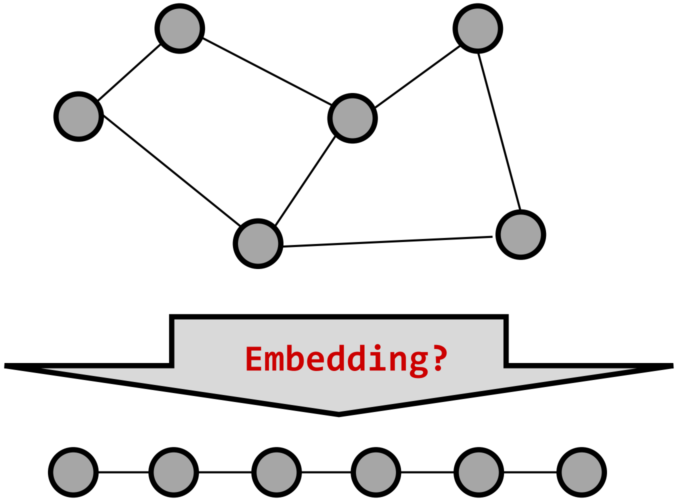
However, only little is known today about the *algorithmic* challenge of designing demand-aware networks which provide low congestion ***and*** short routes (in the number of hops), for

Related Problem

# Virtual Network Embedding Problem (VNEP)

Example △=2: A Minium Linear Arrangement (**MLA**) Problem

- → Minimizes sum of virtual edges



Related Problem

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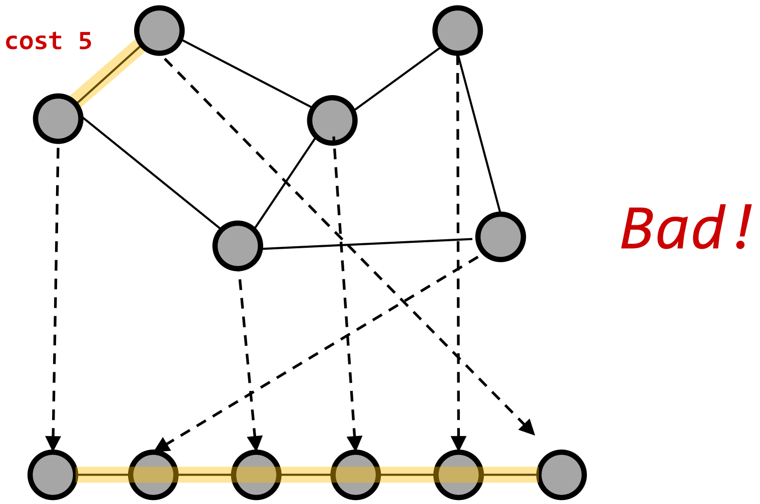

Related Problem

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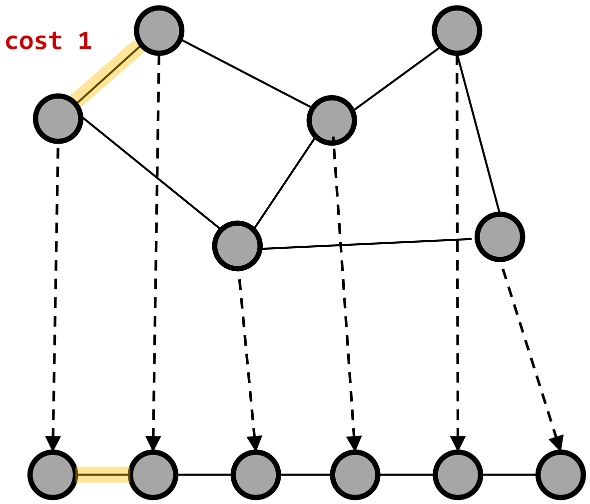


*Good!*

Related Problem

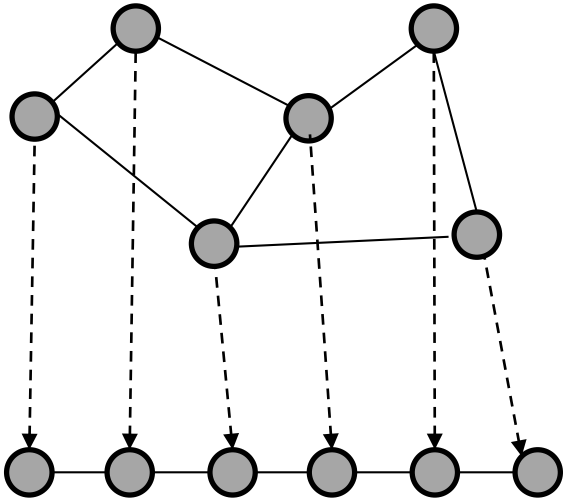
# Virtual Network Embedding Problem (VNEP)

Example △=2: A Minium Linear Arrangement (**MLA**) Problem

⇀ Minimizes sum of virtual edges

MLA is **NP-hard**

⇀ … and so is our problem!



Related Problem

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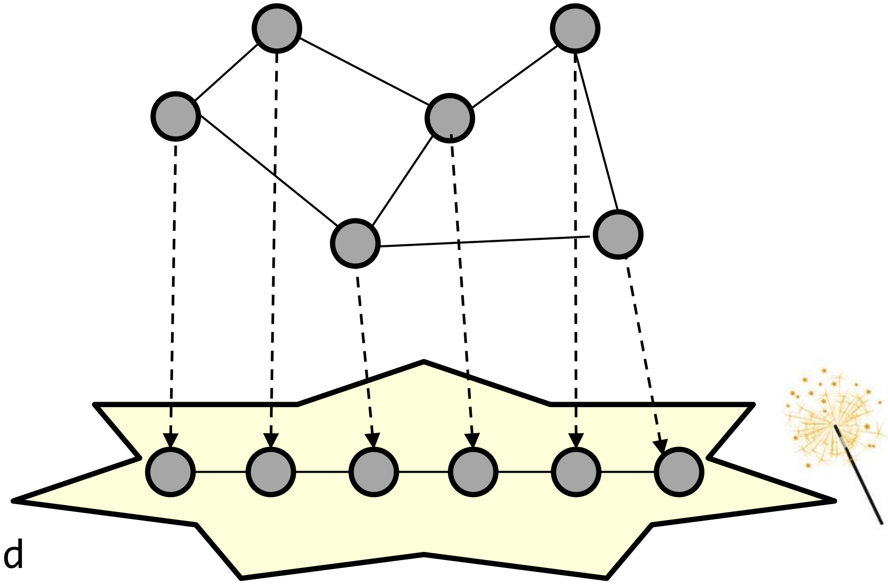
But what about **△>2**?

- ⇀ Embedding problem still hard
- ⇀ But we have a new **degree of freedom**!



Related Problem

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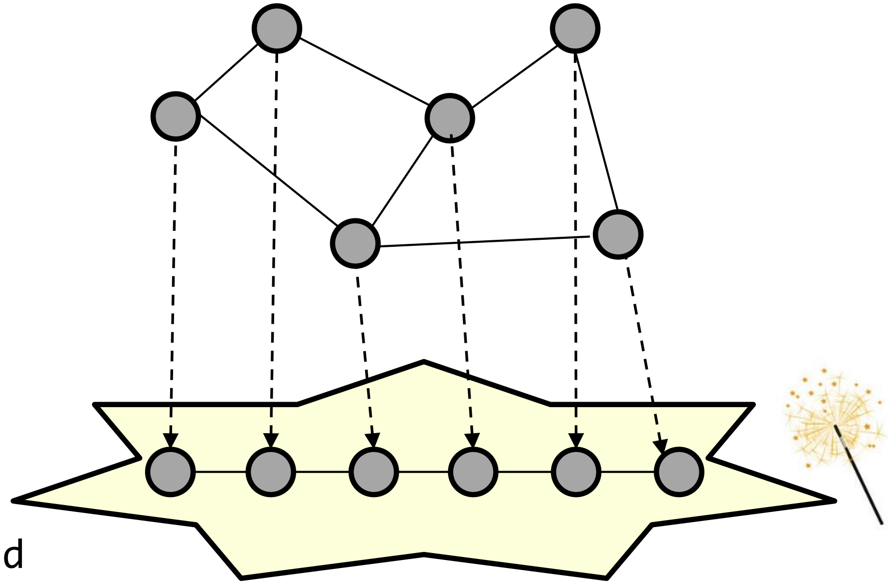

Simplifies problem?!