Self-Adjusting Networks

Stefan Schmid @ IIT Bhubaneswar

"We cannot direct the wind,
but we can adjust the sails."
(Folklore)

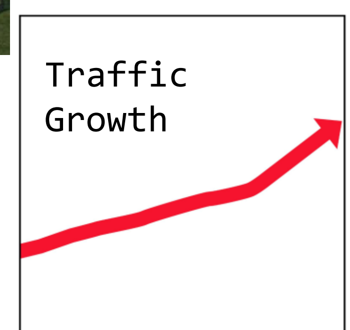
Acknowledgements:

Trend

Data-Centric Applications

Datacenters (“hyper-scale”)

+network



Source: Facebook

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

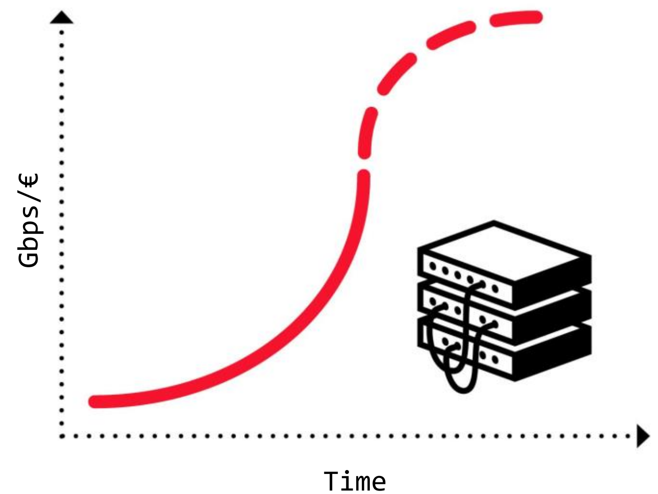
The Problem

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**



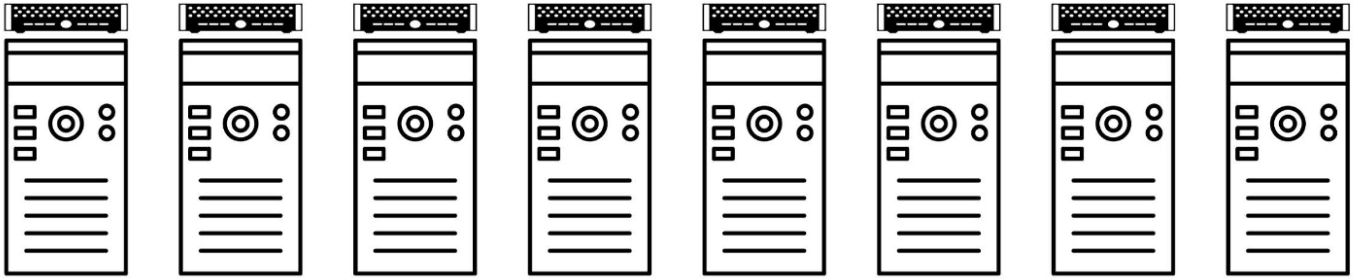
[1] Source: Microsoft, 2019

Annoying for companies, **opportunity** for researchers

Root Cause

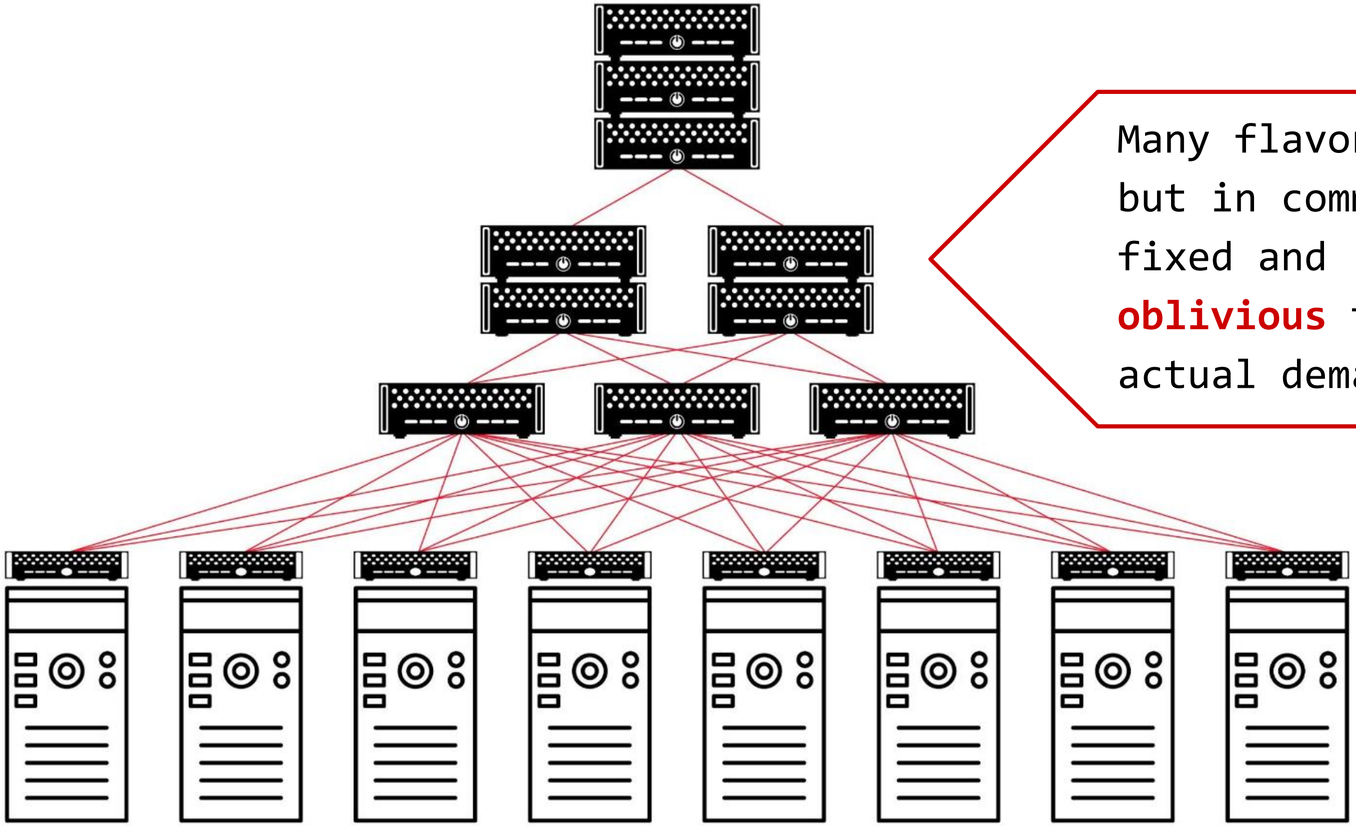
Fixed and Demand-Oblivious Topology

How to interconnect?



Root Cause

Fixed and Demand-Oblivious Topology

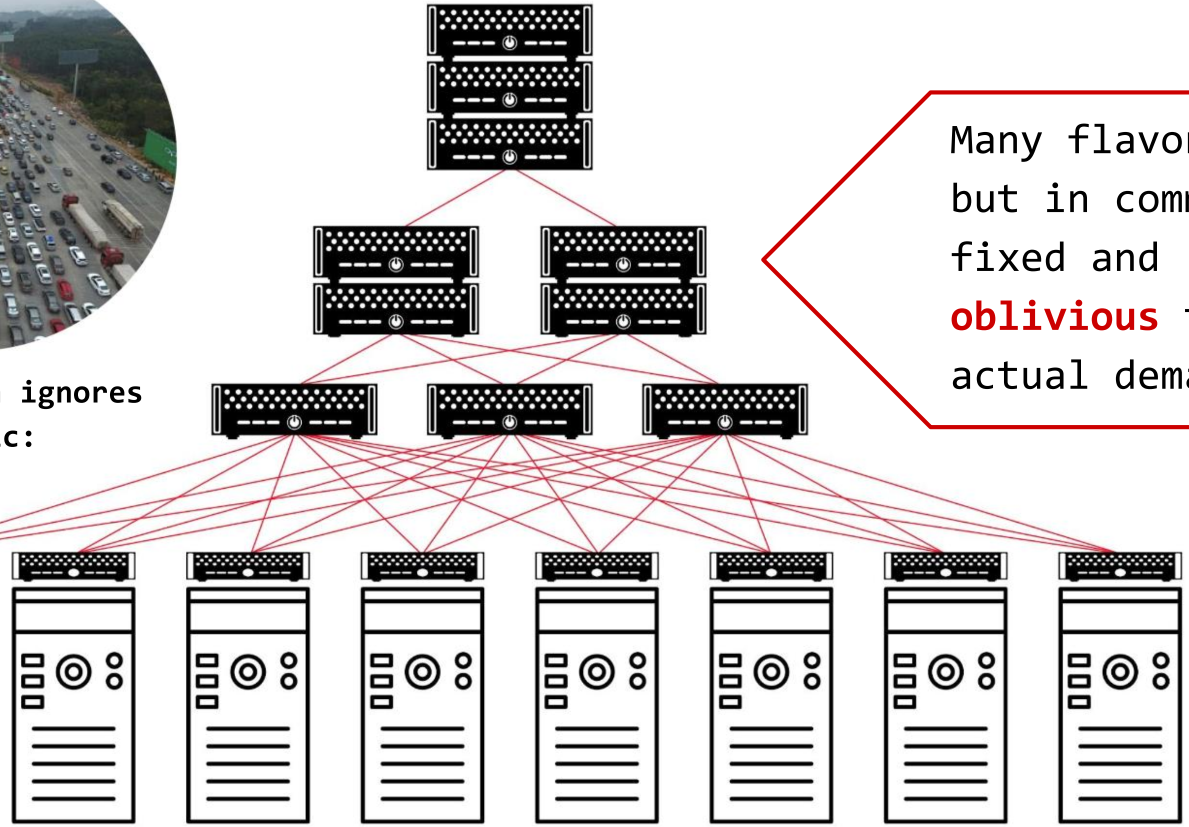


Many flavors,
but in common:
fixed and
oblivious to
actual demand.

Root Cause

Fixed and Demand-Oblivious Topology

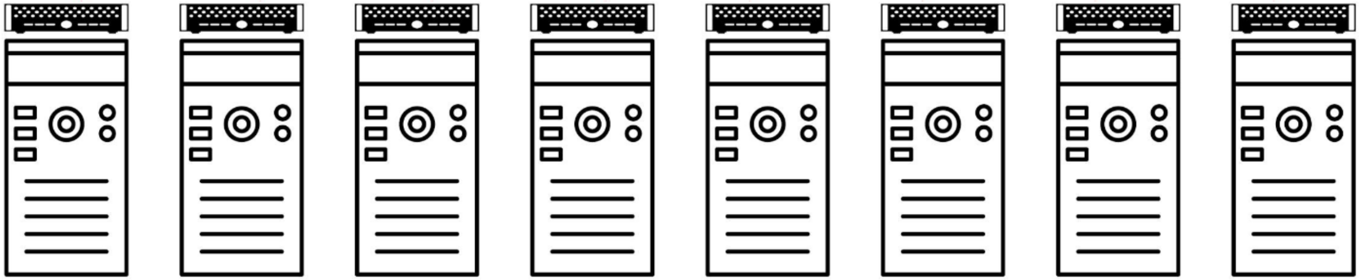
Highway which ignores actual traffic: frustrating!



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

Our Vision

Flexible and Demand-Aware Topologies



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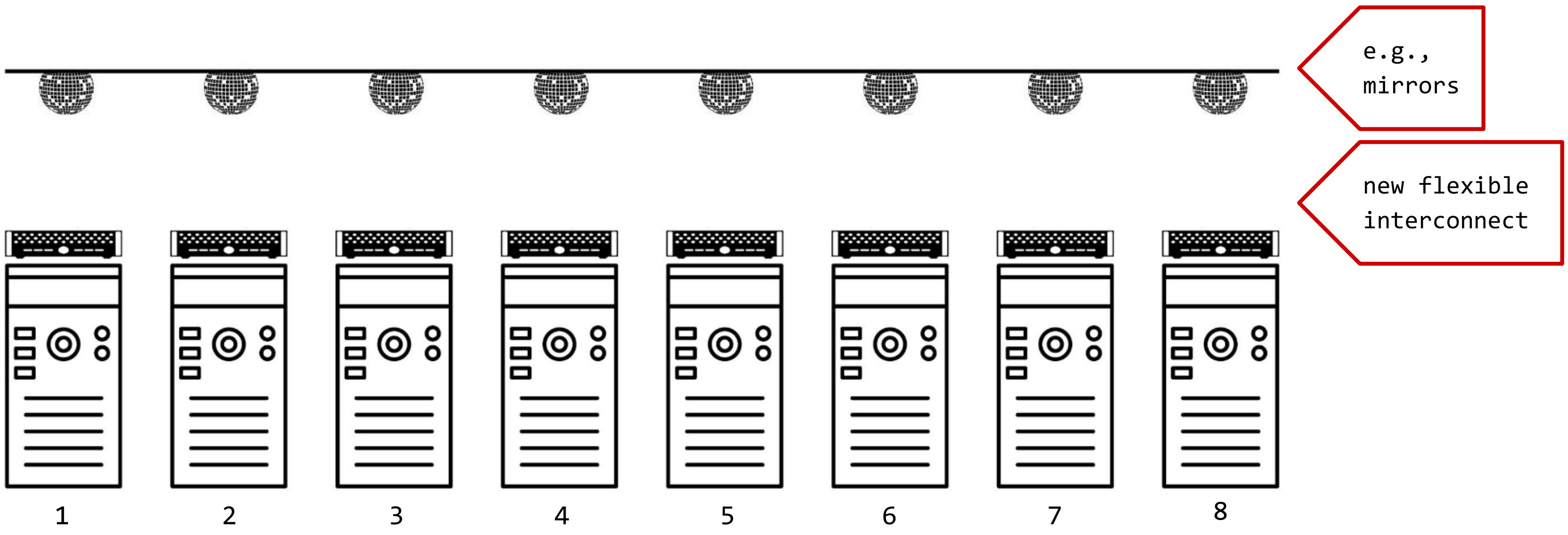

Our Vision

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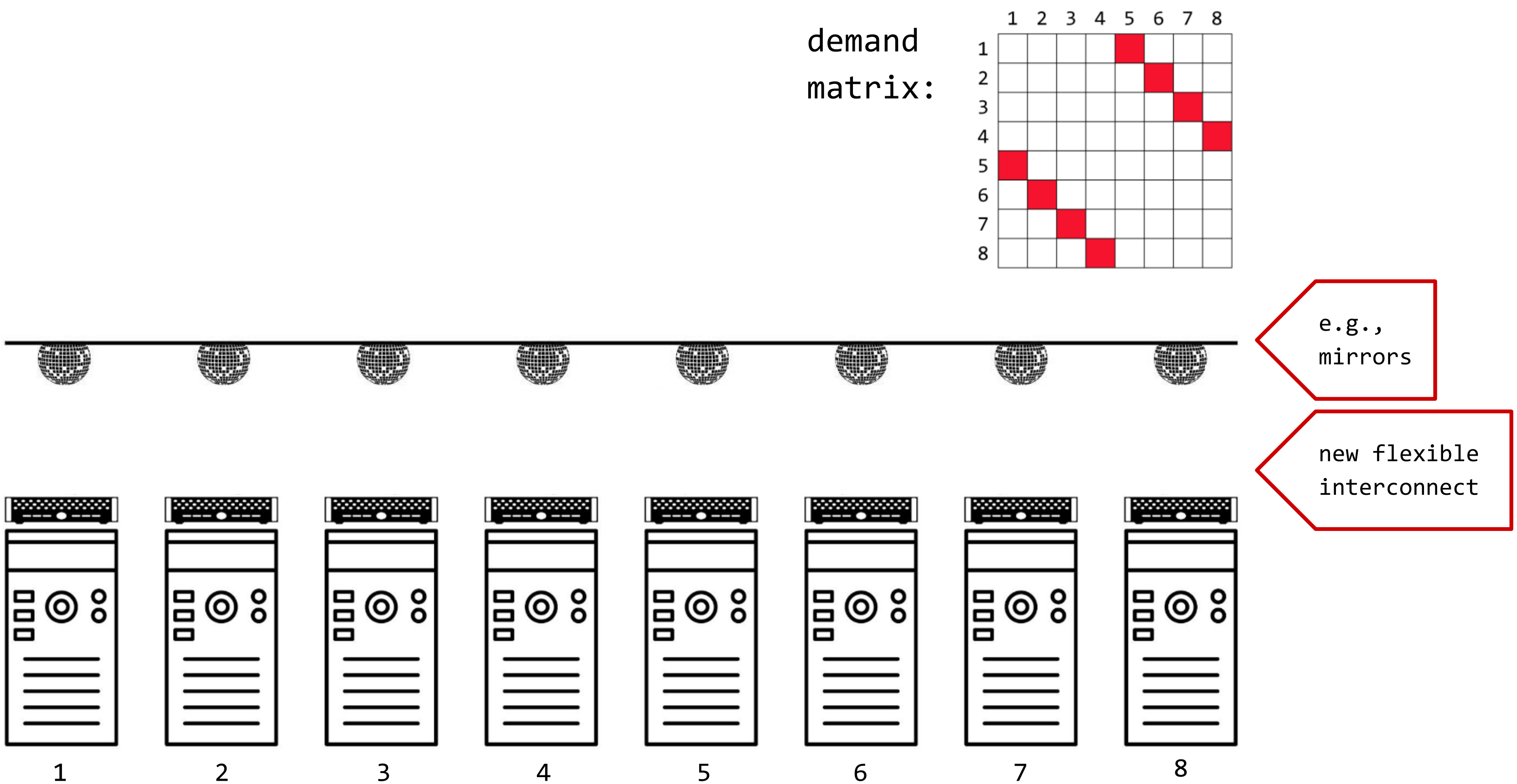
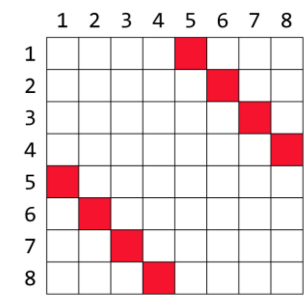


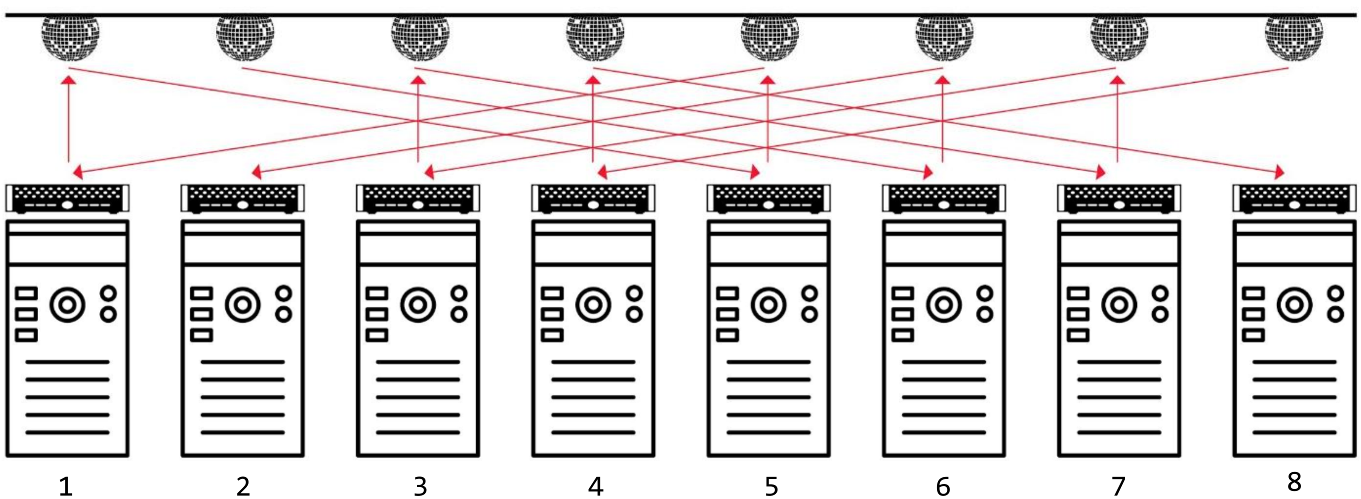
Our Vision

Flexible and Demand-Aware Topologies

Matches demand

demand matrix:



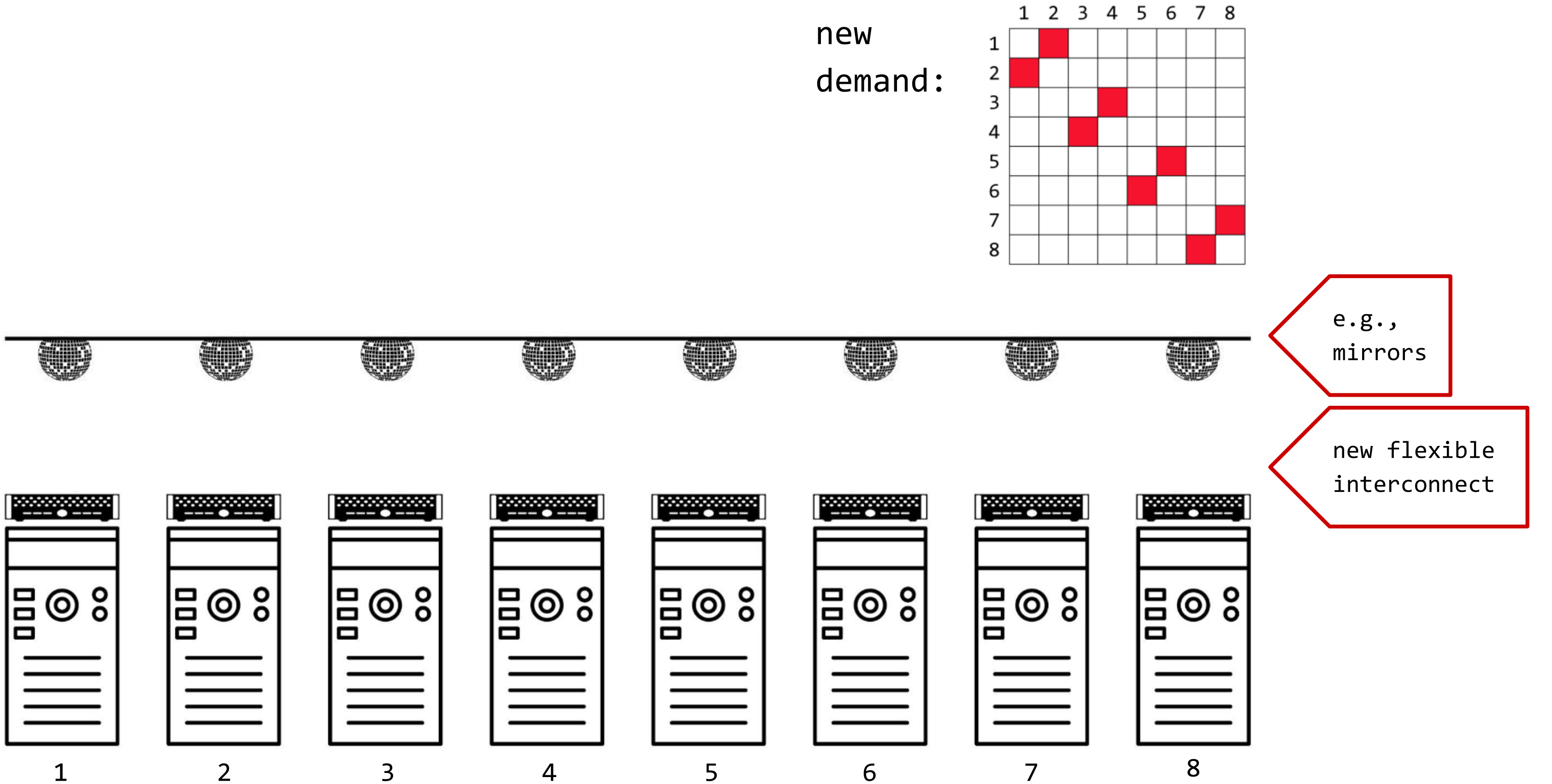


e.g., mirrors

new flexible interconnect

Our Vision

Flexible and Demand-Aware Topologies

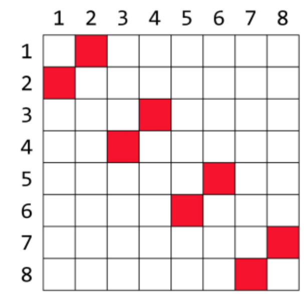


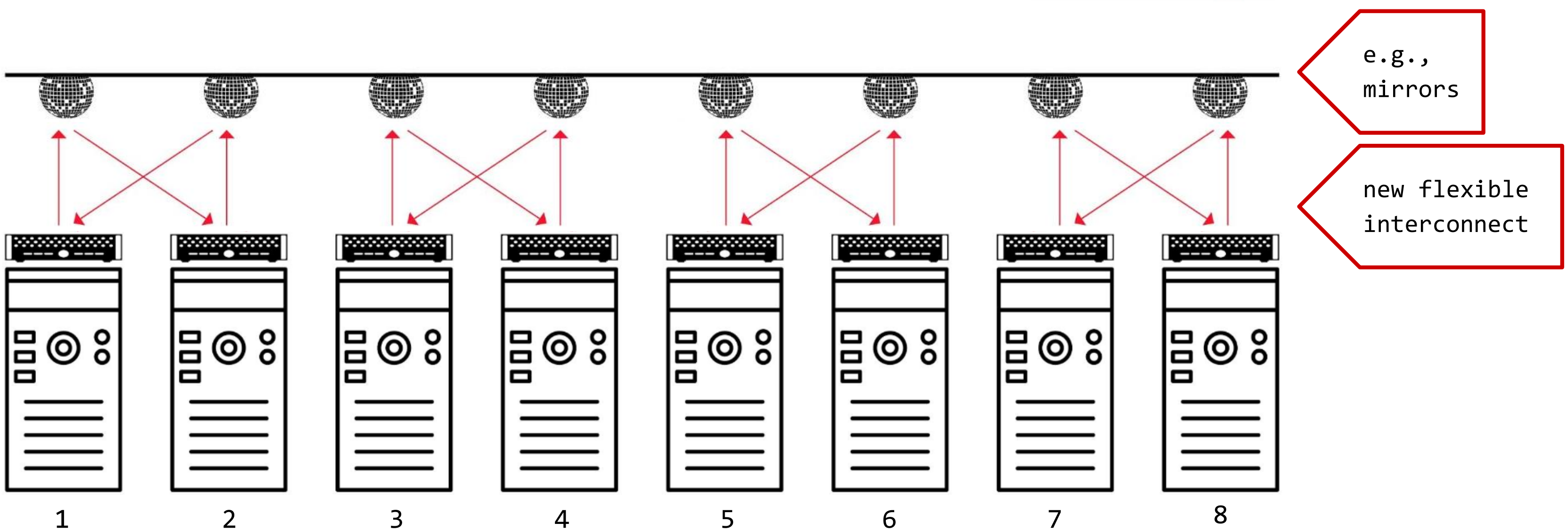
Our Vision

Flexible and Demand-Aware Topologies

Matches demand

new demand:



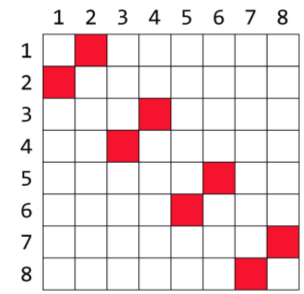


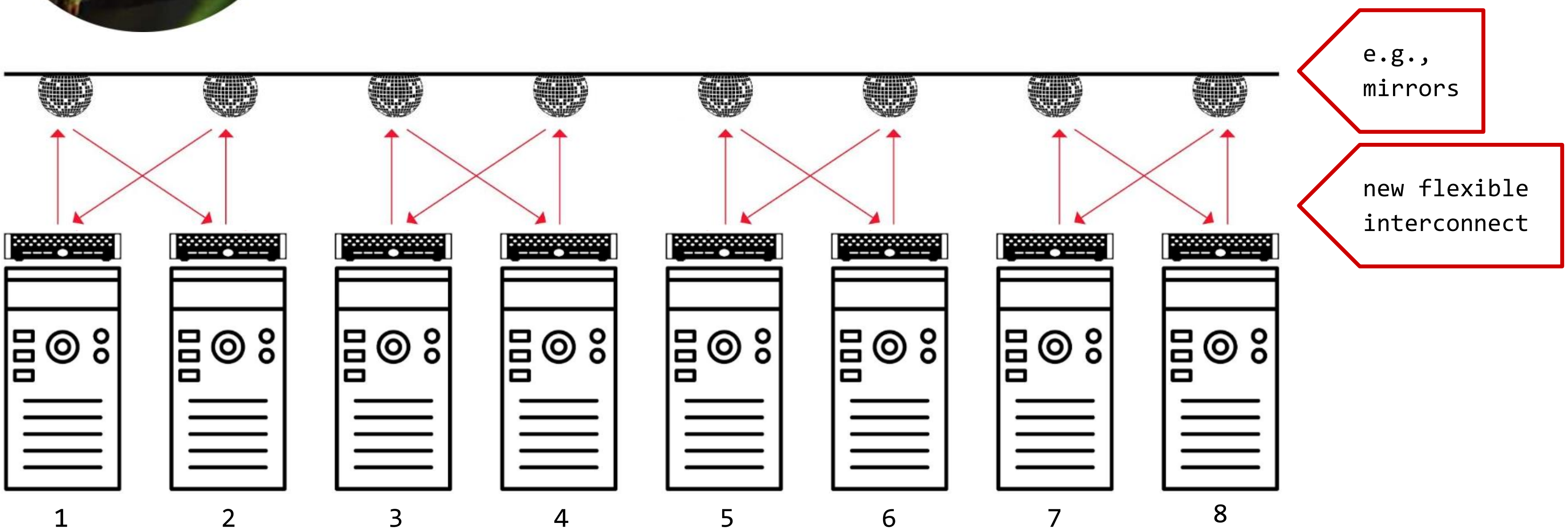
Our Vision

Flexible and Demand-Aware Topologies

Self-Adjusting Networks

new demand:





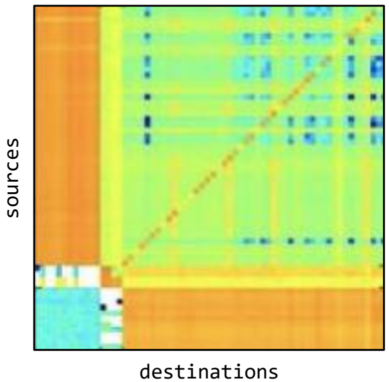
Our Motivation

Much Structure in the Demand

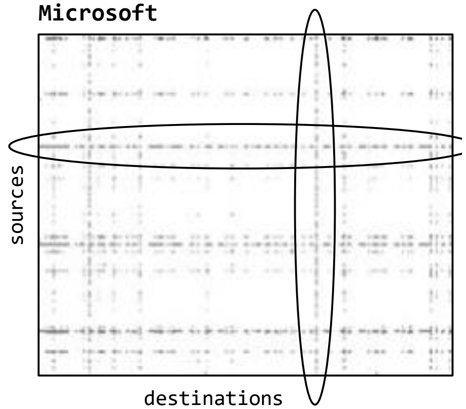
Empirical studies:

traffic matrices sparse and skewed

Facebook

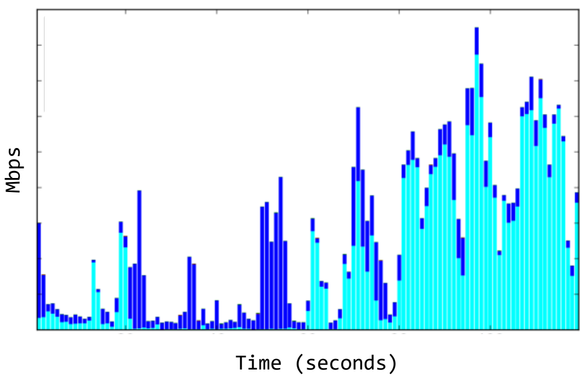


Microsoft



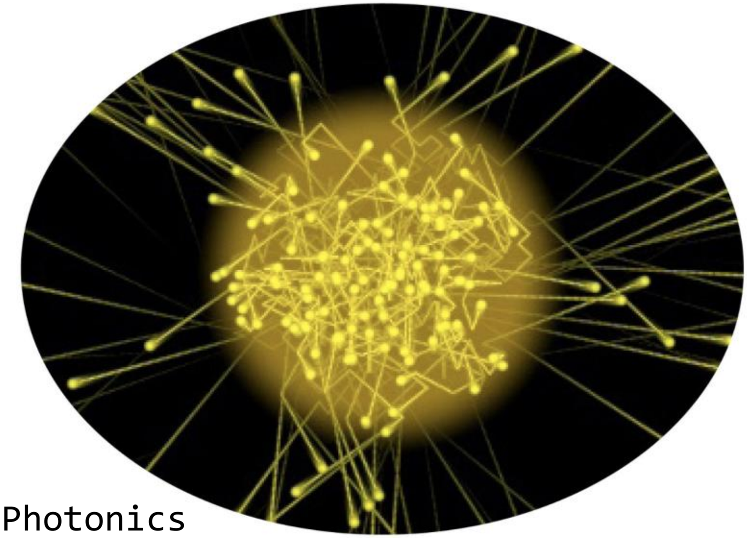
traffic bursty over time

Facebook



My hypothesis: can be exploited.

Sounds Crazy? Emerging Enabling Technology.



Photonics

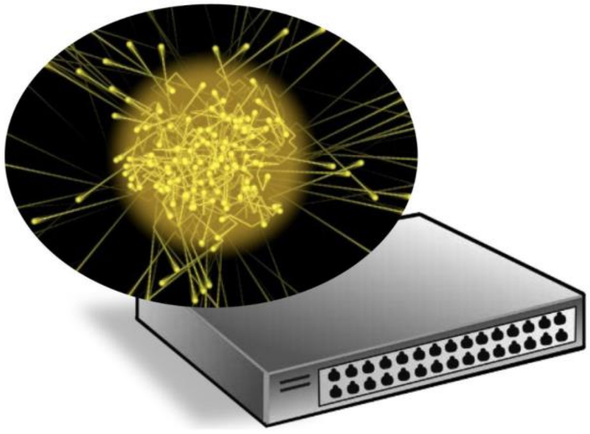
H2020:
“Photonics one of only five key enabling technologies for future prosperity.”

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

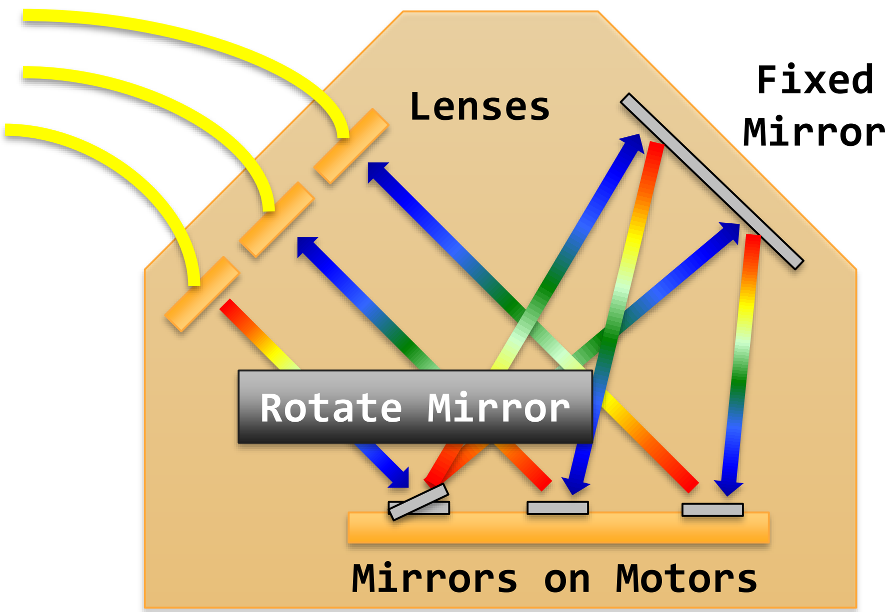
Prototype 2

Prototype 3

Example

Optical Circuit Switch

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



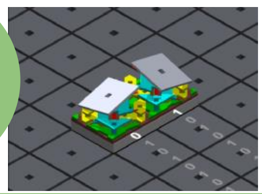
Optical Circuit Switch

By Nathan Farrington, SIGCOMM 2010

The Big Picture

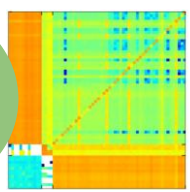
New!

Flexibility



More!

Structure



Self-Adjusting Networks

Efficiency

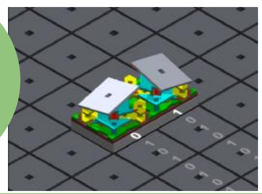
Now is the time!

The Big Picture

New!

More!

Flexibility



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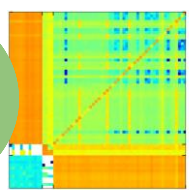


Self-Adjusting Networks

Efficiency

Now is the time!

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

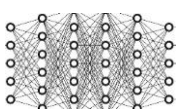
Unique Position

Demand-Aware, Self-Adjusting Systems

Everywhere, but mainly in software

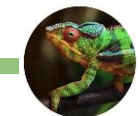
Algorithmic trading

Recommender systems

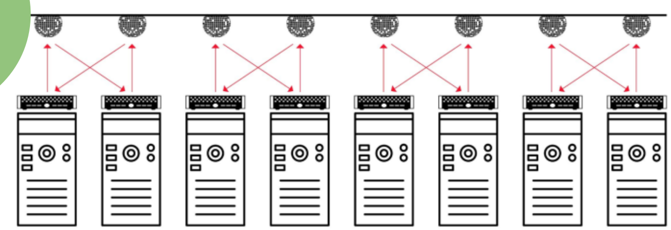


Neural networks

VS



Our focus: in hardware



Question 1:

How to Quantify such “Structure” in the Demand?

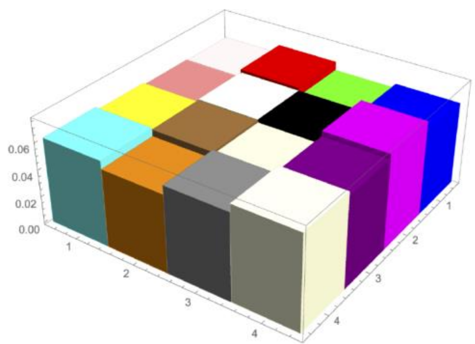
Intuition

Which demand has more structure?

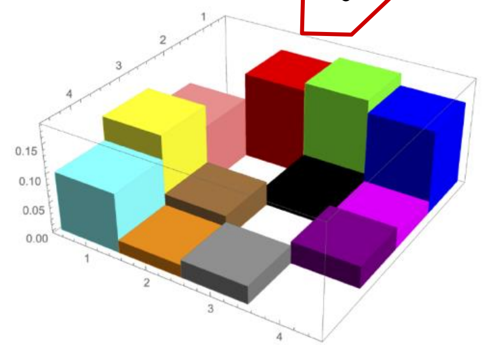
⇢ Traffic matrices of two different distributed ML applications

- ⇀ GPU-to-GPU

Color = communication pair



VS



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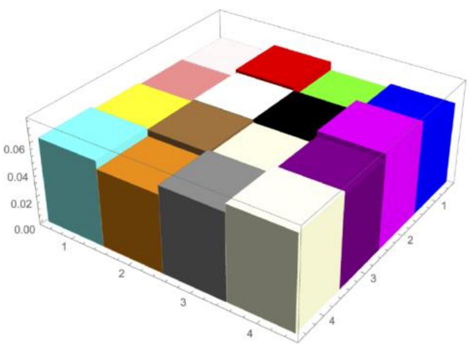

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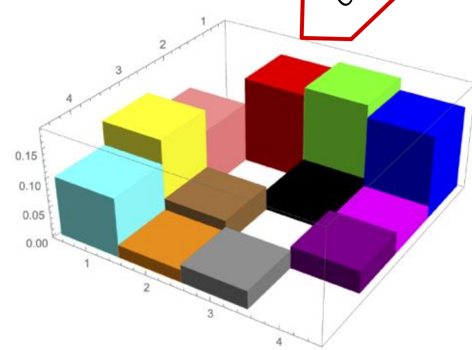


More uniform

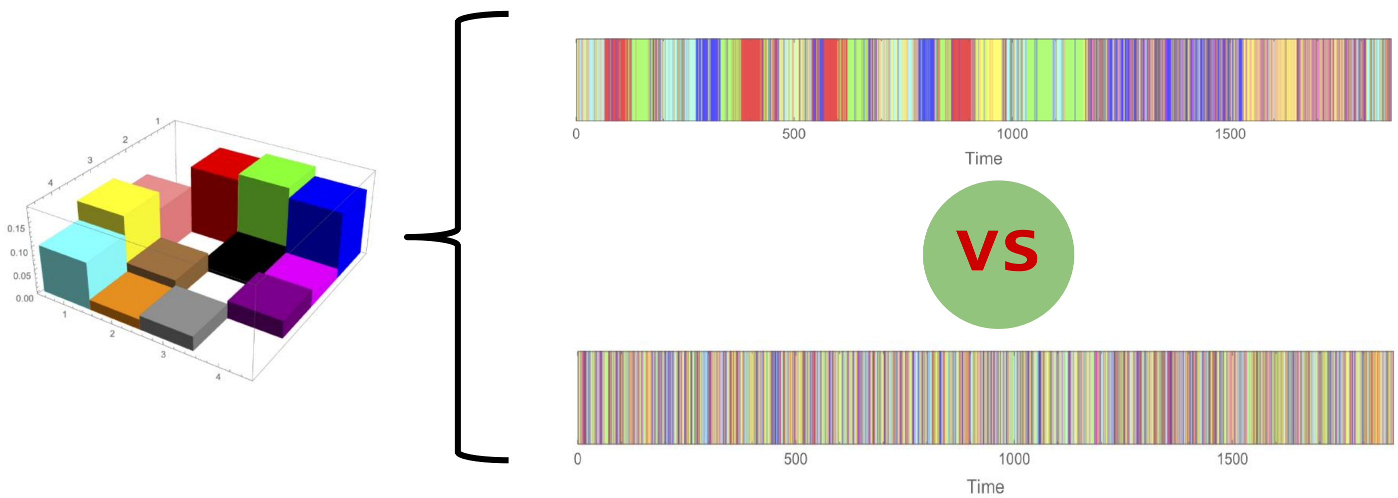
More structure

Intuition

Spatial vs temporal structure

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

⇢ Which one has more structure?



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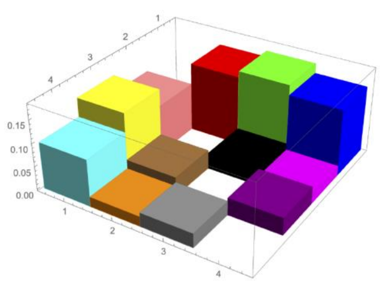
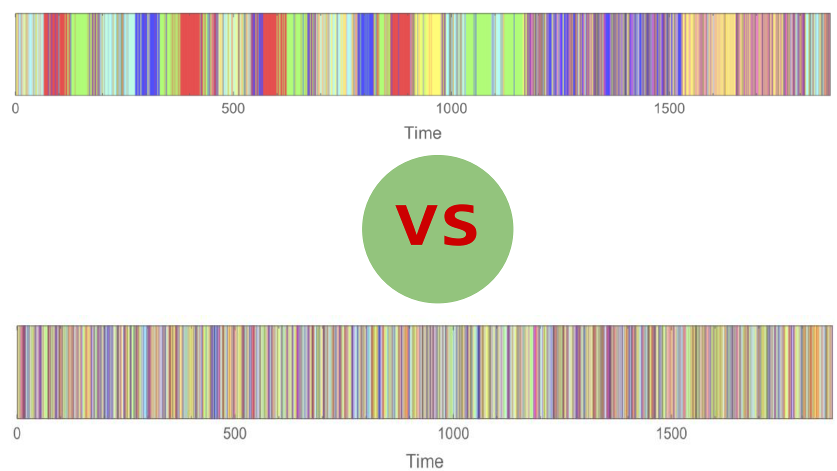


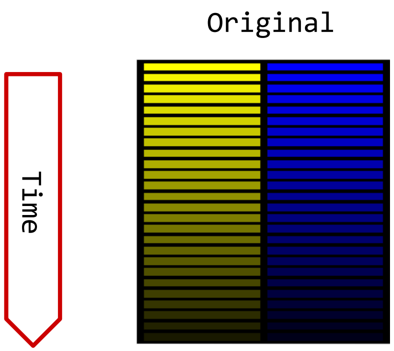


Systematically?

Trace Complexity

Information-Theoretic Approach

“Shuffle&Compress”



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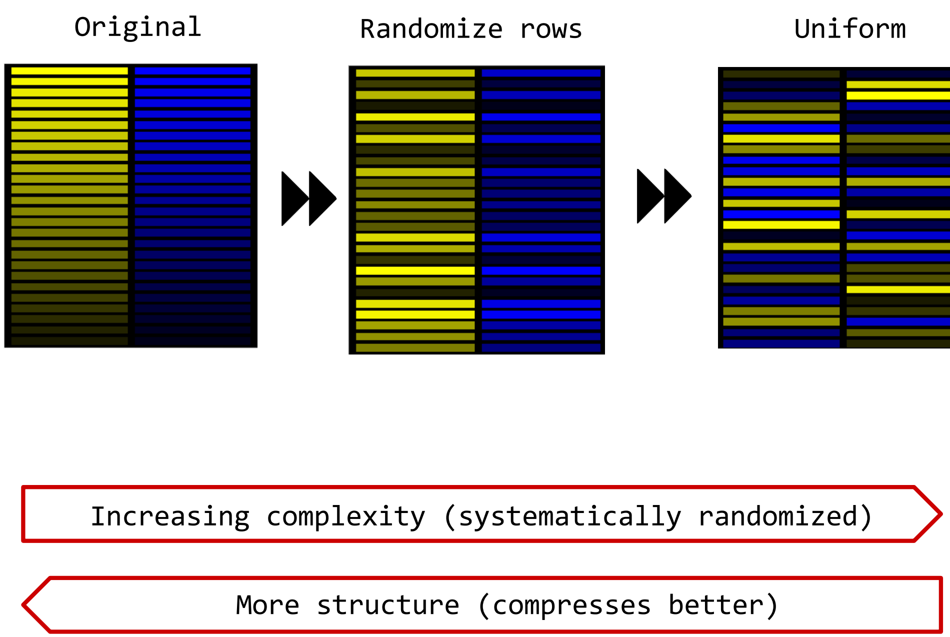

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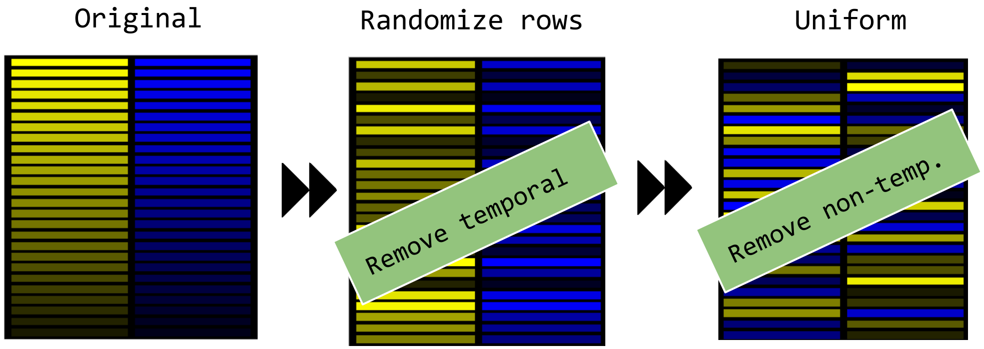

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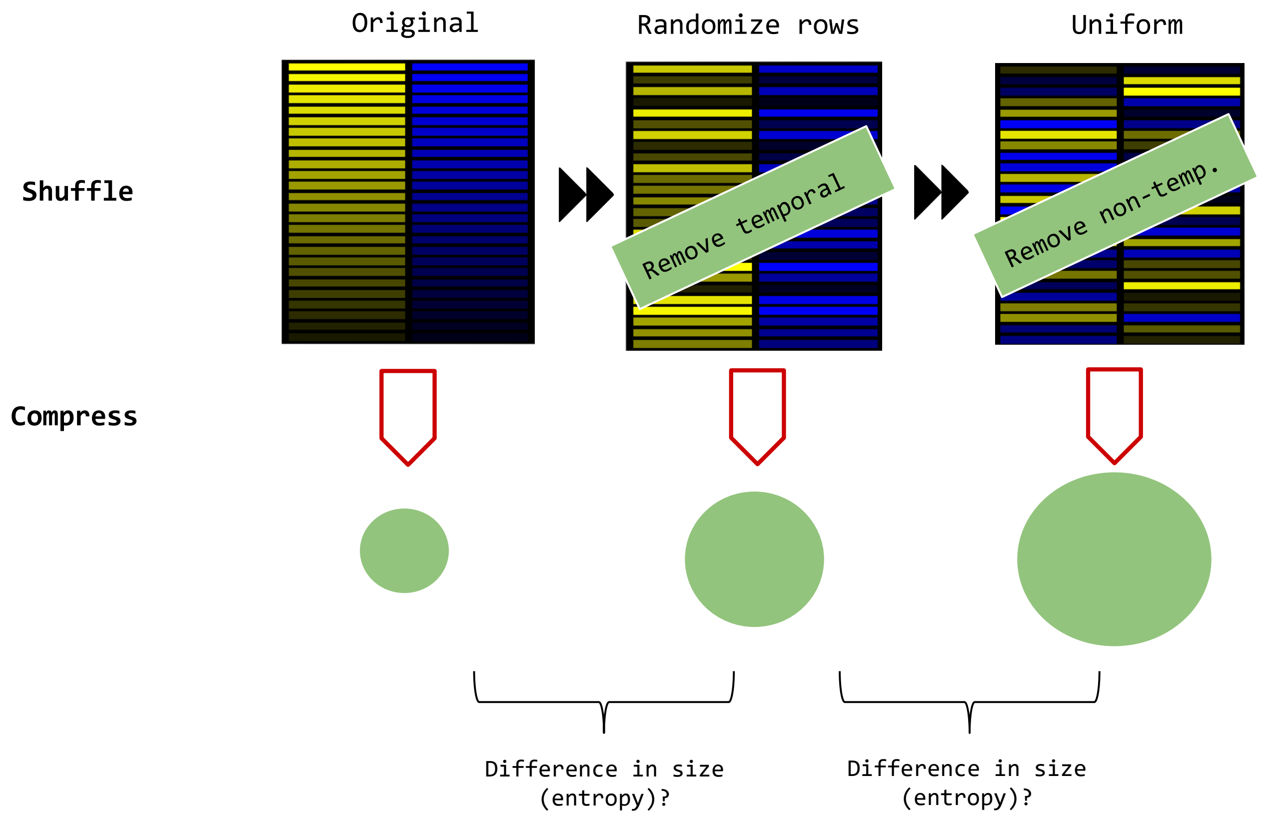

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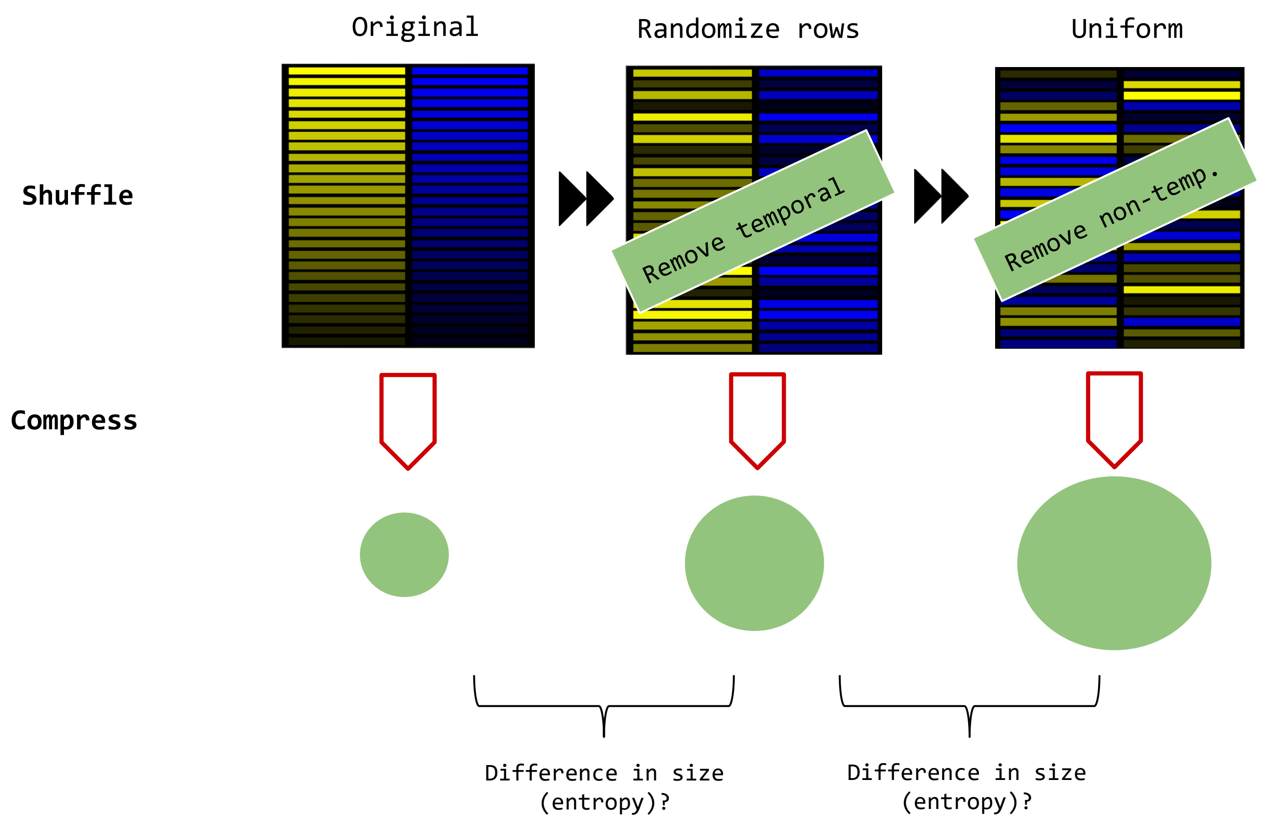
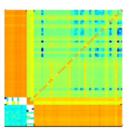
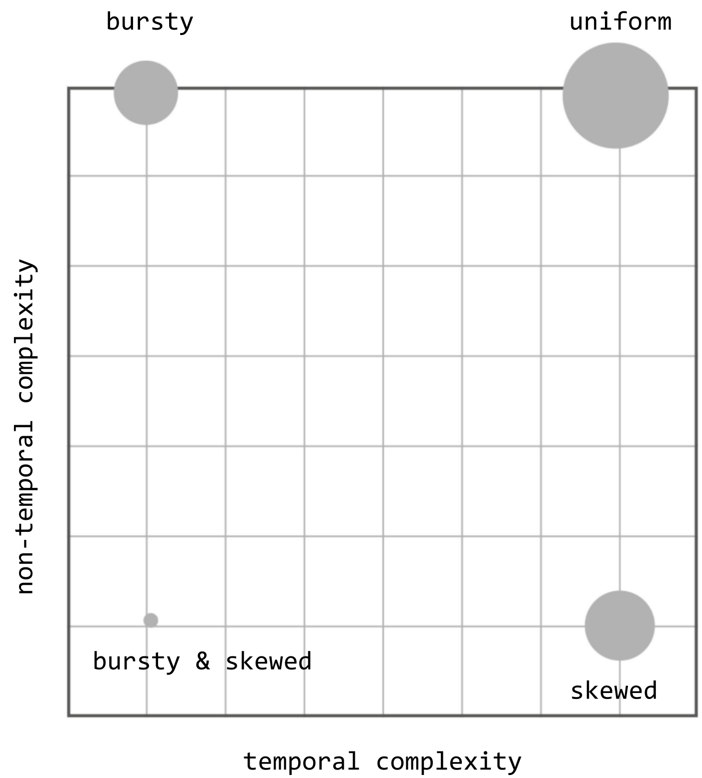


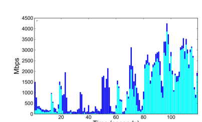
Can be used to define 2-dimensional complexity map!

Our Methodology

Complexity Map





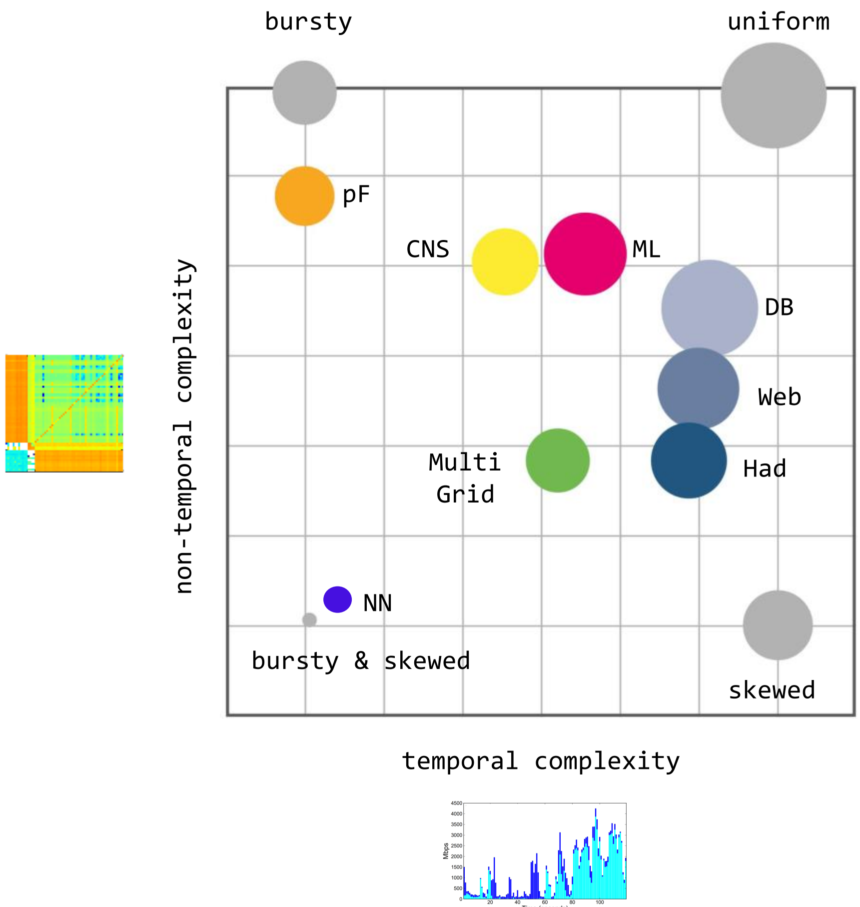


No structure

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

Our Methodology

Complexity Map



No structure

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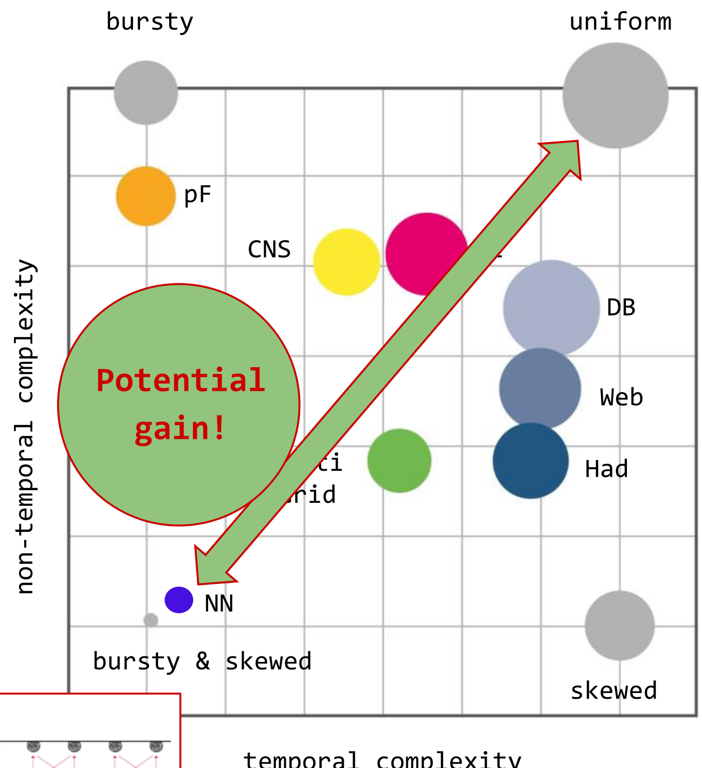
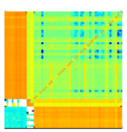
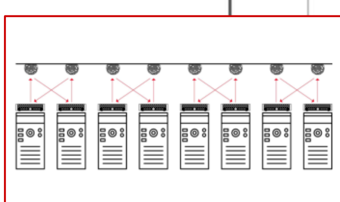
Different structures!

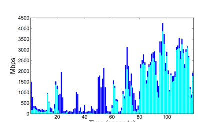
Our Methodology

Complexity Map









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

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

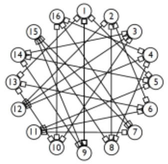
Question 2:

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

A first insight: entropy of the demand.

Models and Connection to Datastructures & Coding

Oblivious networks
(worst-case traffic)



More structure: **lower routing cost**

Models and Connection to Datastructures & Coding

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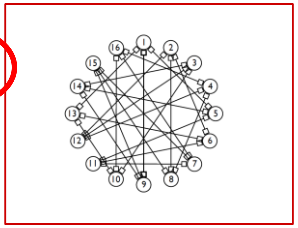

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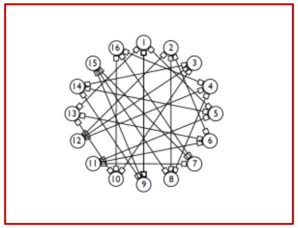
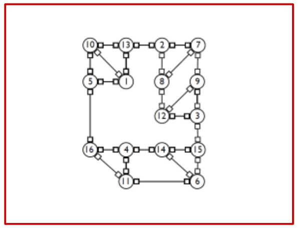


Demand-aware networks
(spatial structure)



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Models and Connection to Datastructures & Coding

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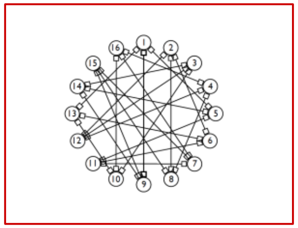

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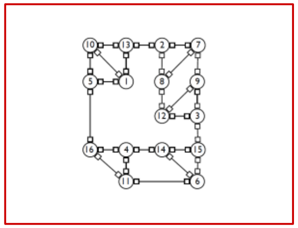
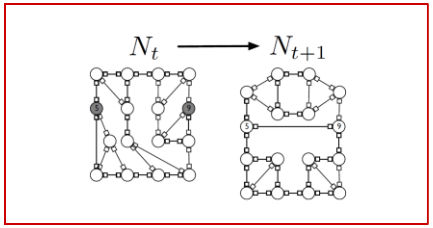


Self-adjusting networks
(temporal structure)



More structure: **lower routing cost**

Models and Connection to Datastructures & Coding

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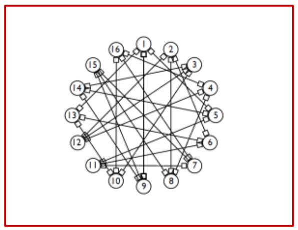

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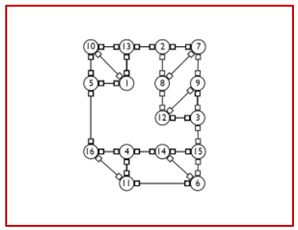
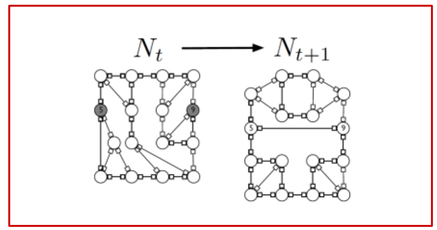
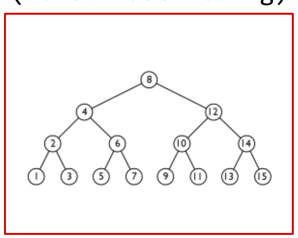


Self-adjusting networks
(temporal structure)

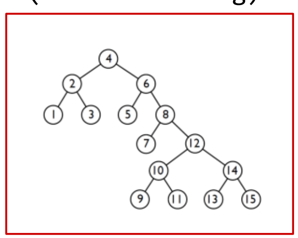


More structure: **lower routing cost**

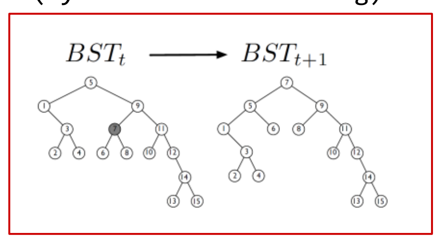
Traditional BST
(Worst-case coding)



Demand-aware BST
(Huffman coding)



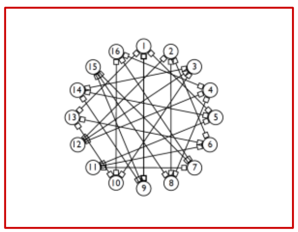
Self-adjusting BST
(Dynamic Huffman coding)



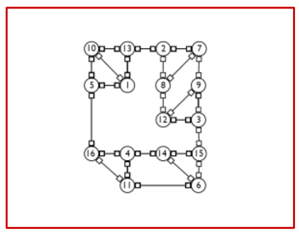
More structure: improved **access cost** / shorter **codes**

Models and Connection to Datastructures & Coding

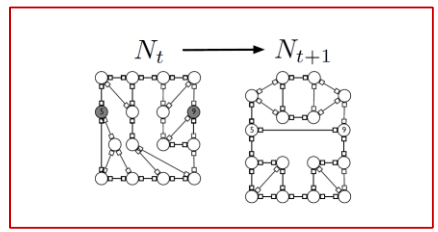
Oblivious networks
(worst-case traffic)



Demand-aware networks
(spatial structure)



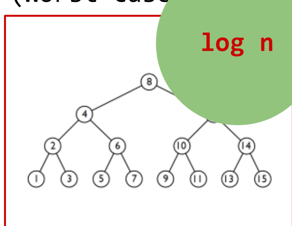
Self-adjusting networks
(temporal structure)



More structure: **lower routing cost**

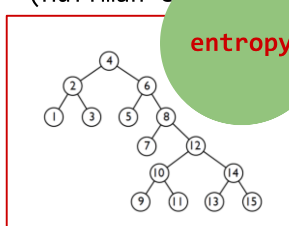
Traditional BST
(Worst-case

log n



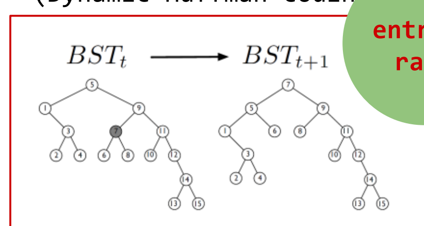
Demand-aware BST
(Huffman c

entropy



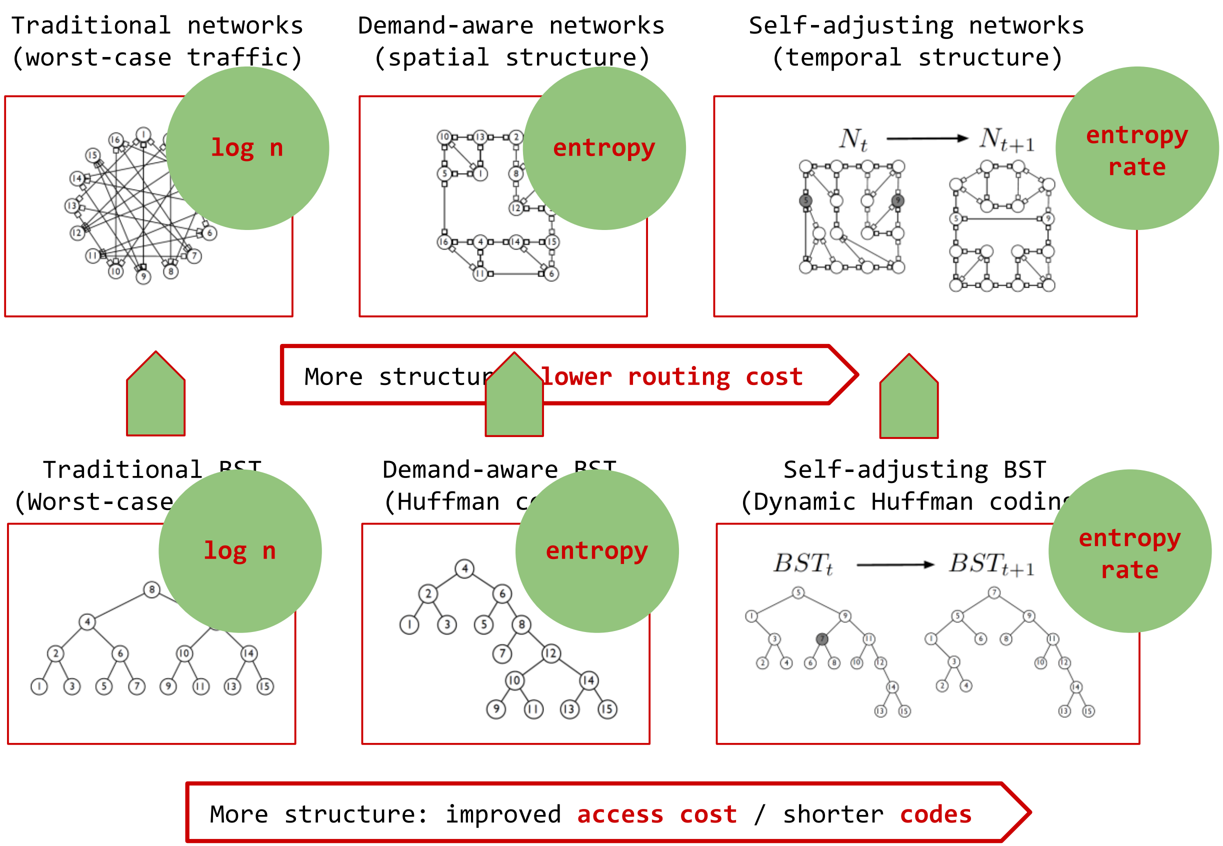
Self-adjusting BST
(Dynamic Huffman codin

entropy rate



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

Models and Connection to Datastructures & Coding



More than
an analogy!

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

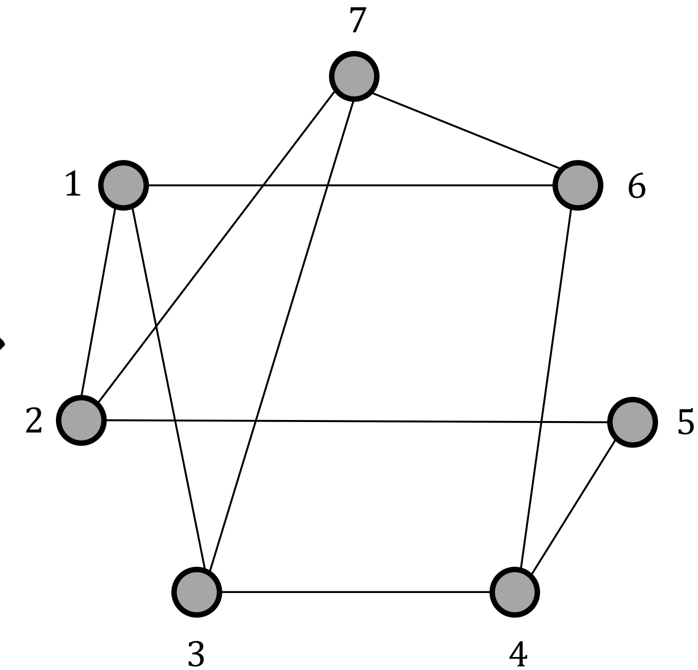
First result:
Demand-aware networks of asymptotically optimal route lengths.

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



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

Case Study “Route Lengths”

Constant-Degree Demand-Aware Network

Destinations

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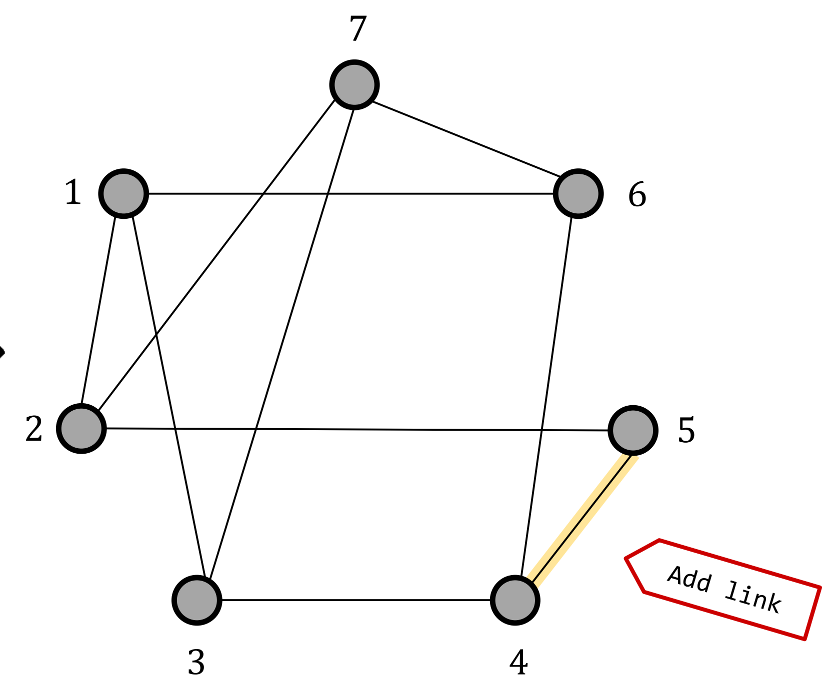
3	$\frac{1}{13}$	$\frac{1}{65}$	0	$\frac{2}{65}$	0	0	$\frac{1}{13}$
4	$\frac{1}{65}$	0	$\frac{2}{65}$	0	$\frac{4}{65}$	0	0
5	$\frac{1}{65}$	0	$\frac{3}{65}$	[illegible]	0	0	0
6	$\frac{2}{65}$	0	[illegible]	0	0	0	$\frac{3}{65}$
7	$\frac{3}{65}$	[illegible]	$\frac{1}{13}$	0	0	$\frac{3}{65}$	0

Much from 4 to 5



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

Case Study “Route Lengths”

Constant-Degree Demand-Aware Network

Communicated with many

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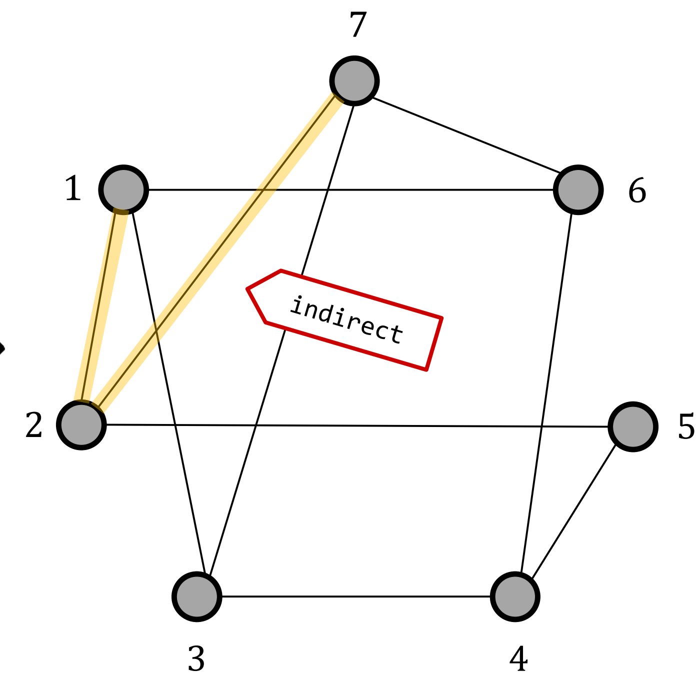
5	$\frac{1}{65}$	0	$\frac{3}{65}$	$\frac{4}{65}$	0	0	0
6	$\frac{2}{65}$	0	0	0	0	0	$\frac{3}{65}$
7	$\frac{3}{65}$	$\frac{2}{65}$	$\frac{1}{13}$	0	0	$\frac{3}{65}$	0



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Case Study “Route Lengths”

Constant-Degree Demand-Aware Network

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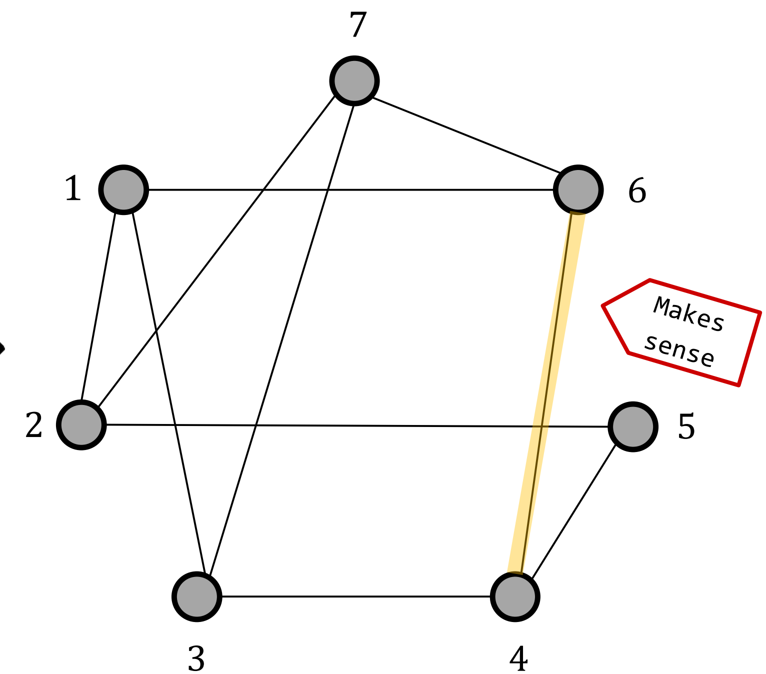
2	$\frac{2}{65}$	0	[illegible]	[illegible]	0	0	$\frac{2}{65}$
3	$\frac{1}{13}$	$\frac{1}{65}$	0	[illegible]	[illegible]	0	$\frac{1}{13}$
4	$\frac{1}{65}$	0	$\frac{2}{65}$	0	[illegible]	0	0
5	$\frac{1}{65}$	0	$\frac{3}{65}$	$\frac{4}{65}$	0	0	0
6	$\frac{2}{65}$	0	0	0	0	0	$\frac{3}{65}$
7	$\frac{3}{65}$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

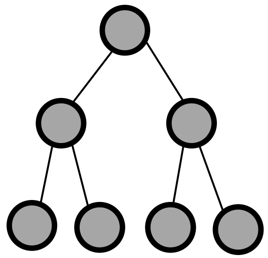
Don’t communicate



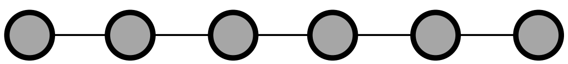
$$\mathrm{ERL}(\mathcal{D},\mathrm{N}) = \sum_{(u,v)\in\mathcal{D}} p(u,v)\cdot d_N(u,v)$$

Examples

- DAN for △=3
  - E.g., complete **binary tree** would be **log n**
  - Can we do better?



- DAN for △=2
  - Set of **lines** and **cycles**



Examples

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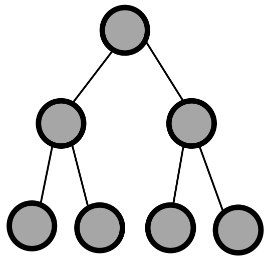

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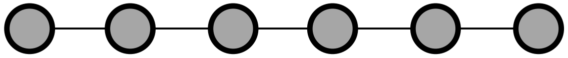


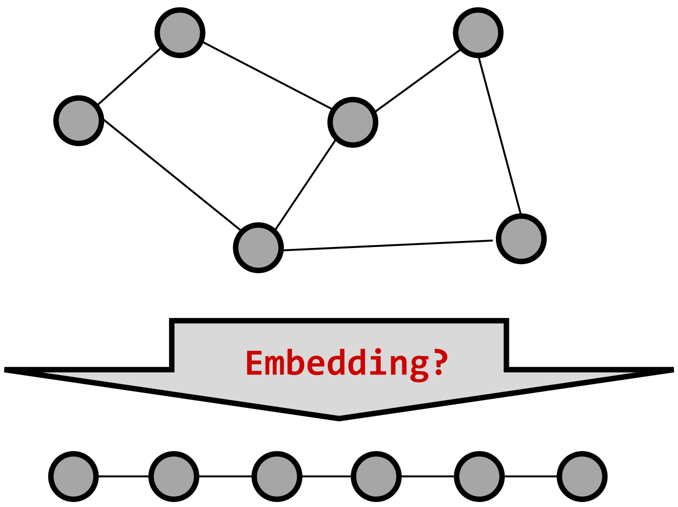
How hard?

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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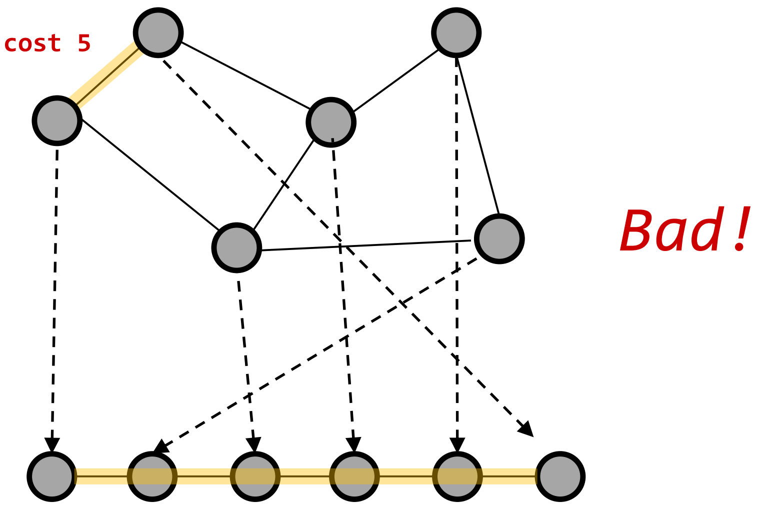

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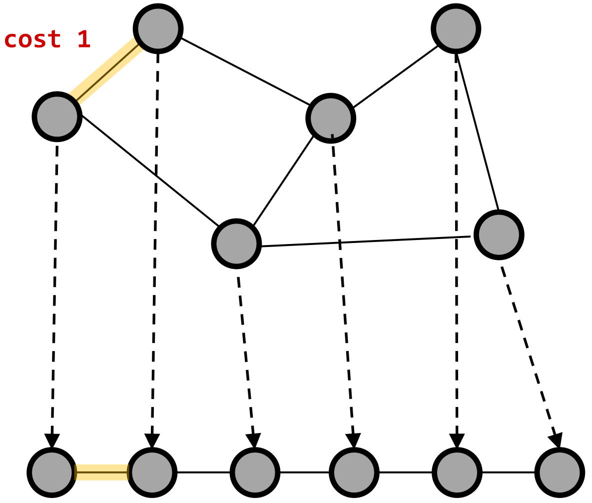

Good!

Related Problem

Virtual Network Embedding Problem (VNEP)

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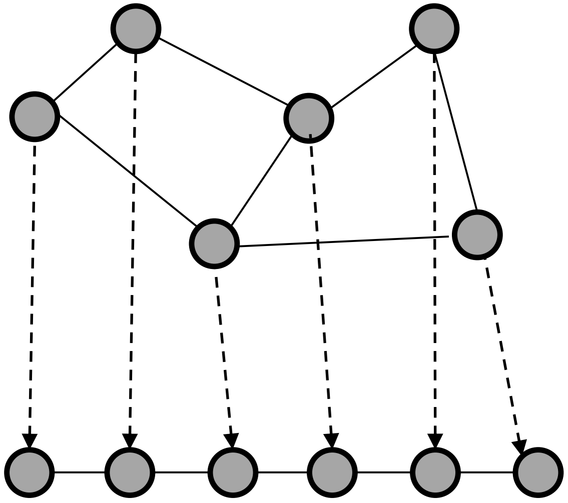
⇀ Minimizes sum of virtual edges

MLA is **NP-hard**

⇀ … and so is our problem!



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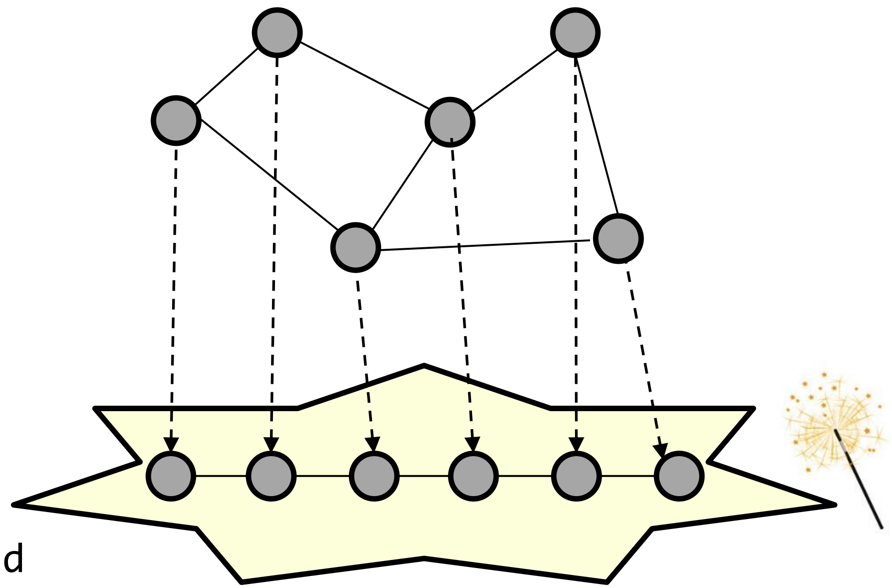
But what about **△>2**?

→ Embedding problem still hard

→ But we have a new **degree of freedom**!



Related Problem

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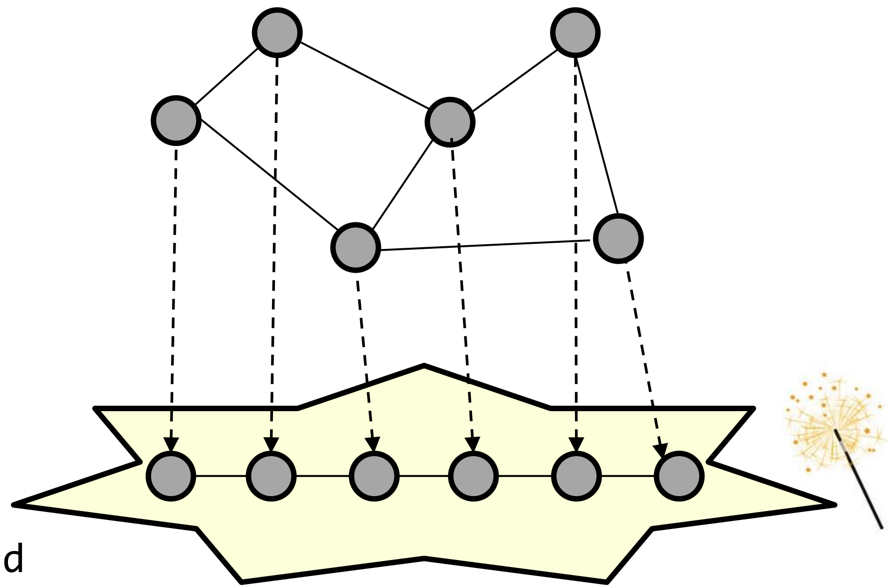
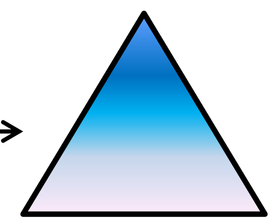


Simplifies problem?!

Algorithm: Idea

Destinations

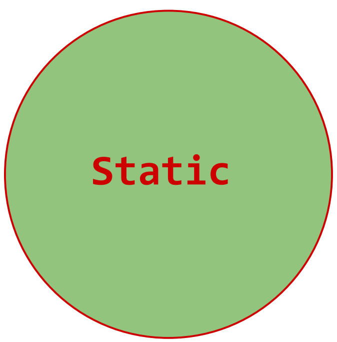
Sources	1	2	3	4	5	6	7
1	0	$\frac{2}{65}$	$\frac{1}{13}$	$\frac{1}{65}$	$\frac{1}{65}$	$\frac{2}{65}$	$\frac{3}{65}$
2	$\frac{2}{65}$	0	$\frac{1}{65}$	0	0	0	$\frac{2}{65}$
3	$\frac{1}{13}$	$\frac{1}{65}$	0	$\frac{2}{65}$	0	0	$\frac{1}{13}$
4	$\frac{1}{65}$	0	$\frac{2}{65}$	0	$\frac{4}{65}$	0	0
5	$\frac{1}{65}$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

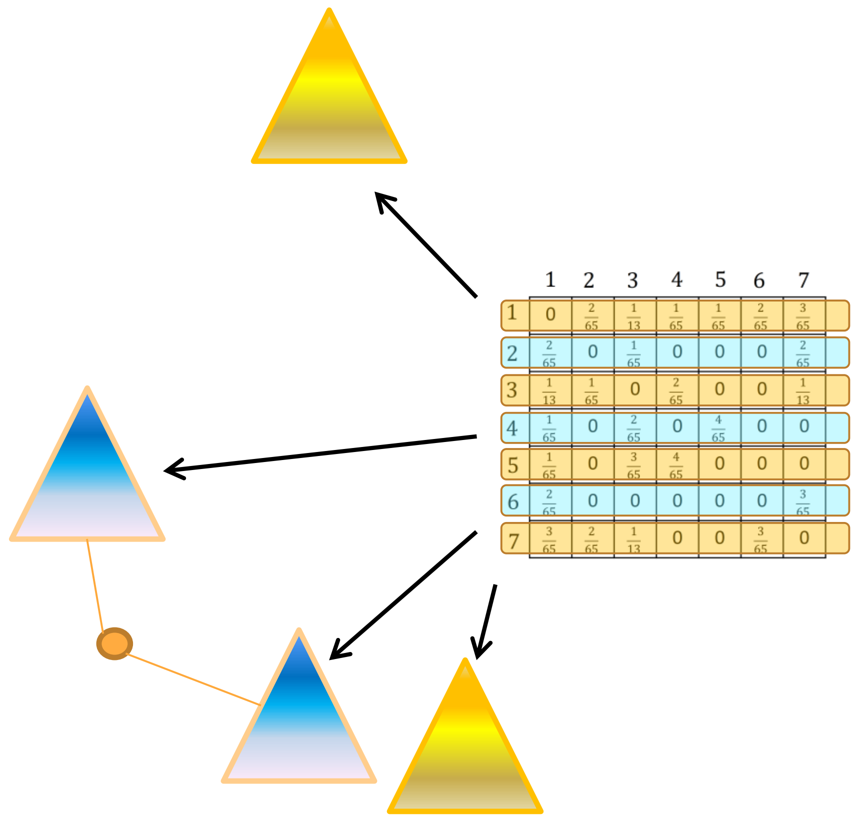


Huffman tree:
"**ego-tree**"

Entropy Upper Bound

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





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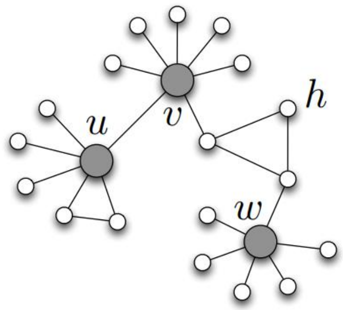
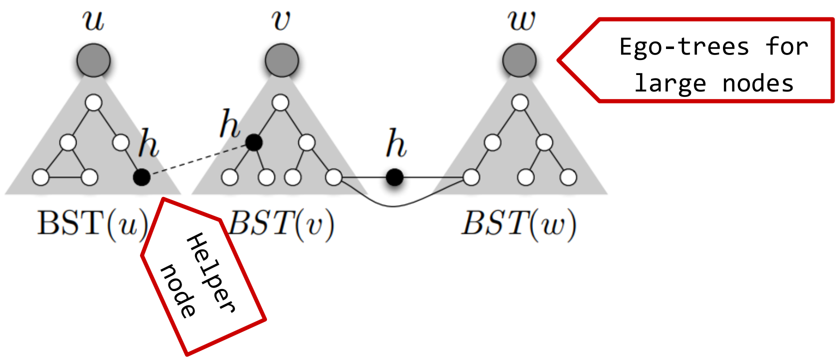
6	$\frac{2}{65}$	0	0	0	0	0	$\frac{3}{65}$
7	$\frac{3}{65}$	$\frac{2}{65}$	$\frac{1}{13}$	0	0	$\frac{3}{65}$	0

Intuition of Algorithm

Demand graph:



Demand-aware network:



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]

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Aalborg University, Denmark
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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

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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 datas-

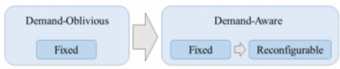

Figure 1: Taxonomy of topology optimization

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 σ. 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

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Ben Gurion University of the Negev, Israel

Kaushik Mondal
Communication Systems Engineering Dept.
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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.,

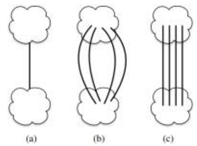
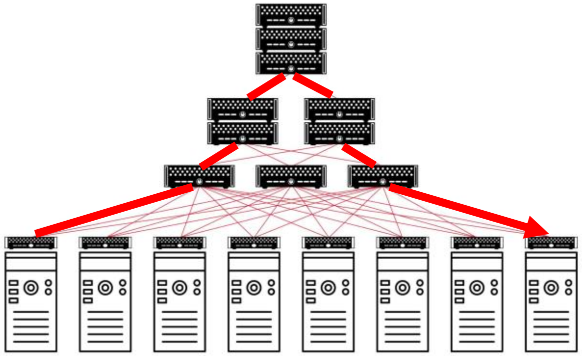


Fig. 1. Challenge of designing demand-aware networks: (a) Optimizing for route lengths only may result in bottlenecks and high loads. (b) Optimizing for congestion only, by distributing load across multiple paths, can result in long routes. (c) Ideally, we aim to design networks that minimize both congestion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

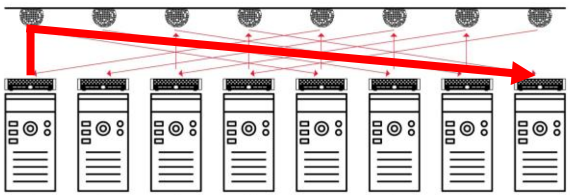
However, only little is known today about the *algorithmic* challenge of designing demand-aware networks which provide low congestion ***and*** short routes (in the number of hops), for

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

It is more complicated…

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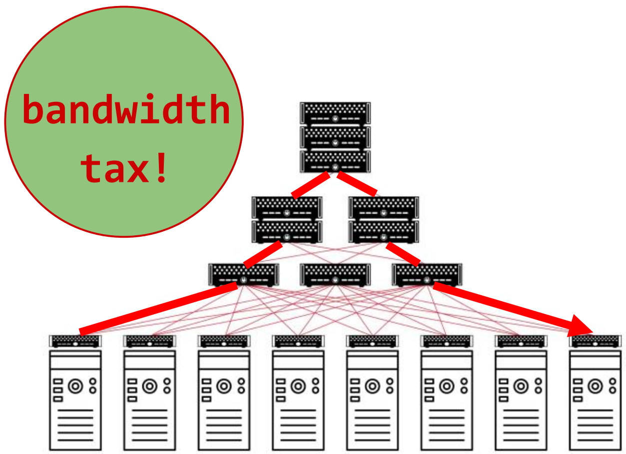

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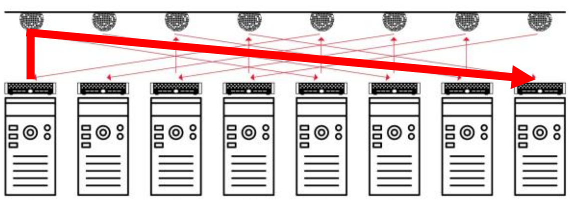

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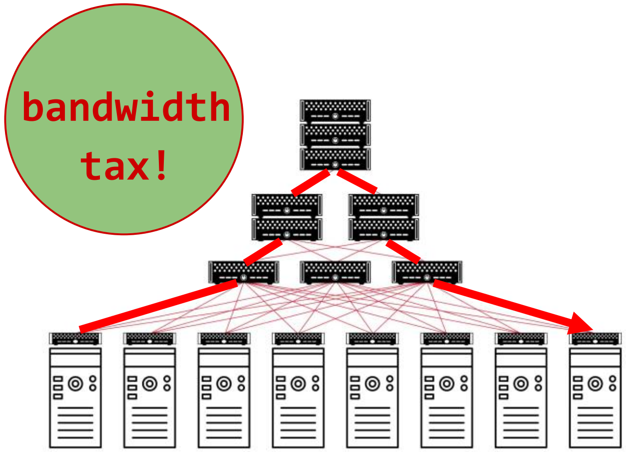
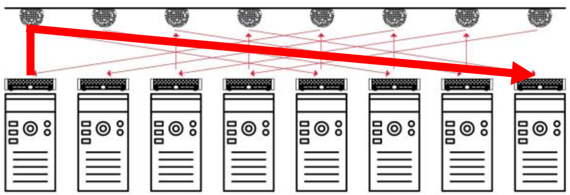


vs

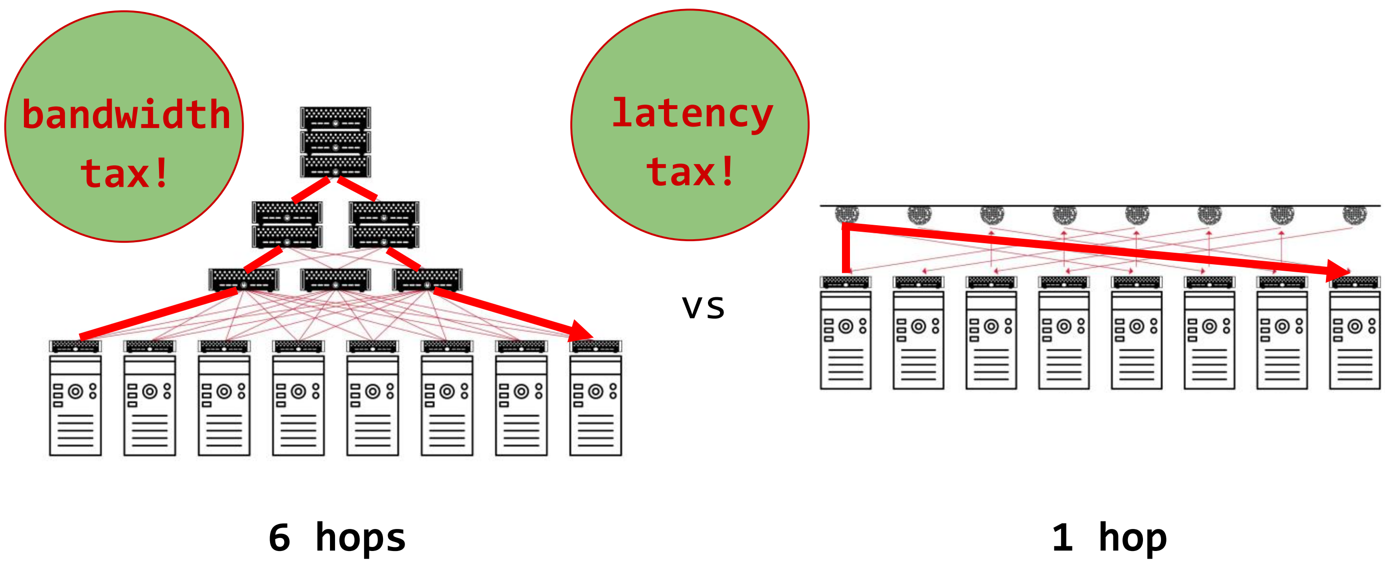


6 hops **1 hop**

→ However, requires optimization and adaption, which takes time

It is more complicated…

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



→ 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

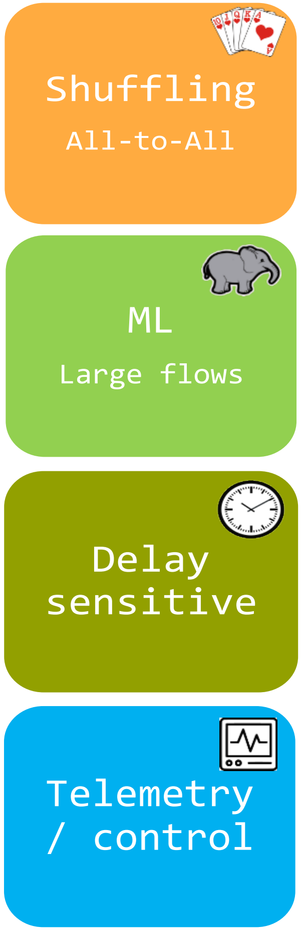
⇀ Query traffic: skewed

⇀ Mice flows

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

Diverse requirements:

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



Opportunity: Tech Diversity

Diverse topology components:

⇀ demand-oblivious and
demand-aware

Demand-
oblivious

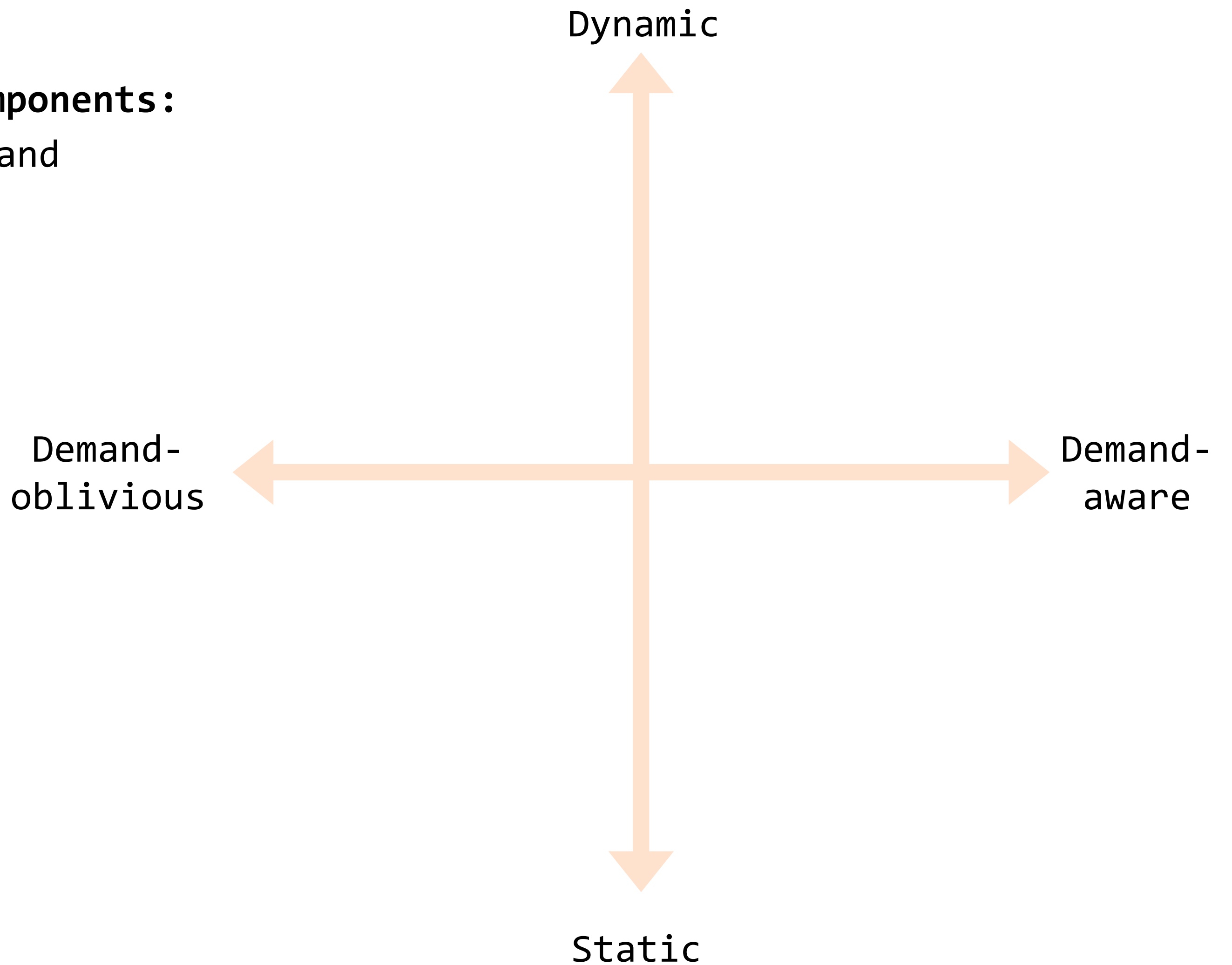
Demand-
aware

Opportunity: Tech Diversity

Diverse topology components:

⇀ demand-oblivious and
  demand-aware

⇀ static vs dynamic

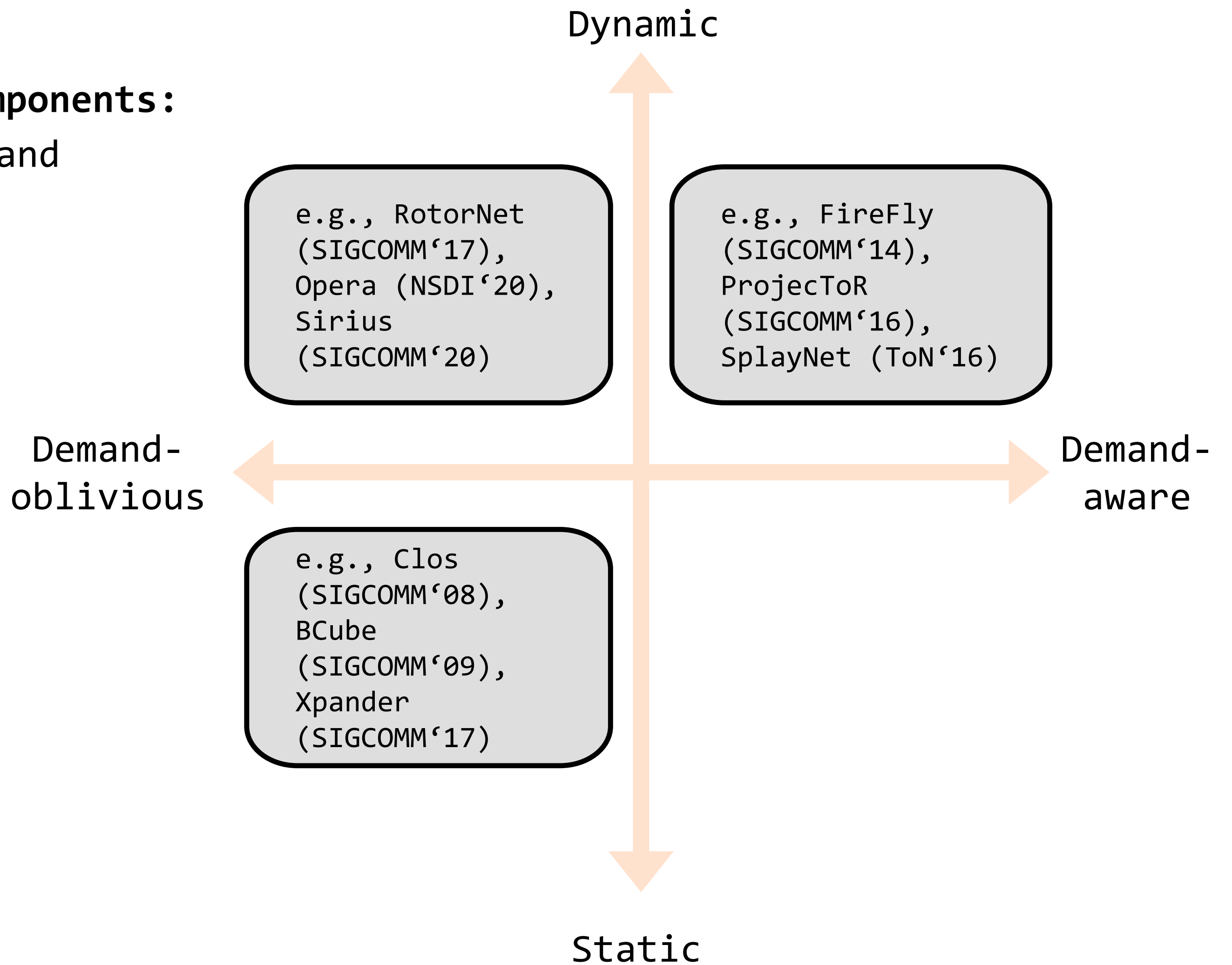


Opportunity: Tech Diversity

Diverse topology components:

⇀ demand-oblivious and demand-aware

⇀ static vs dynamic

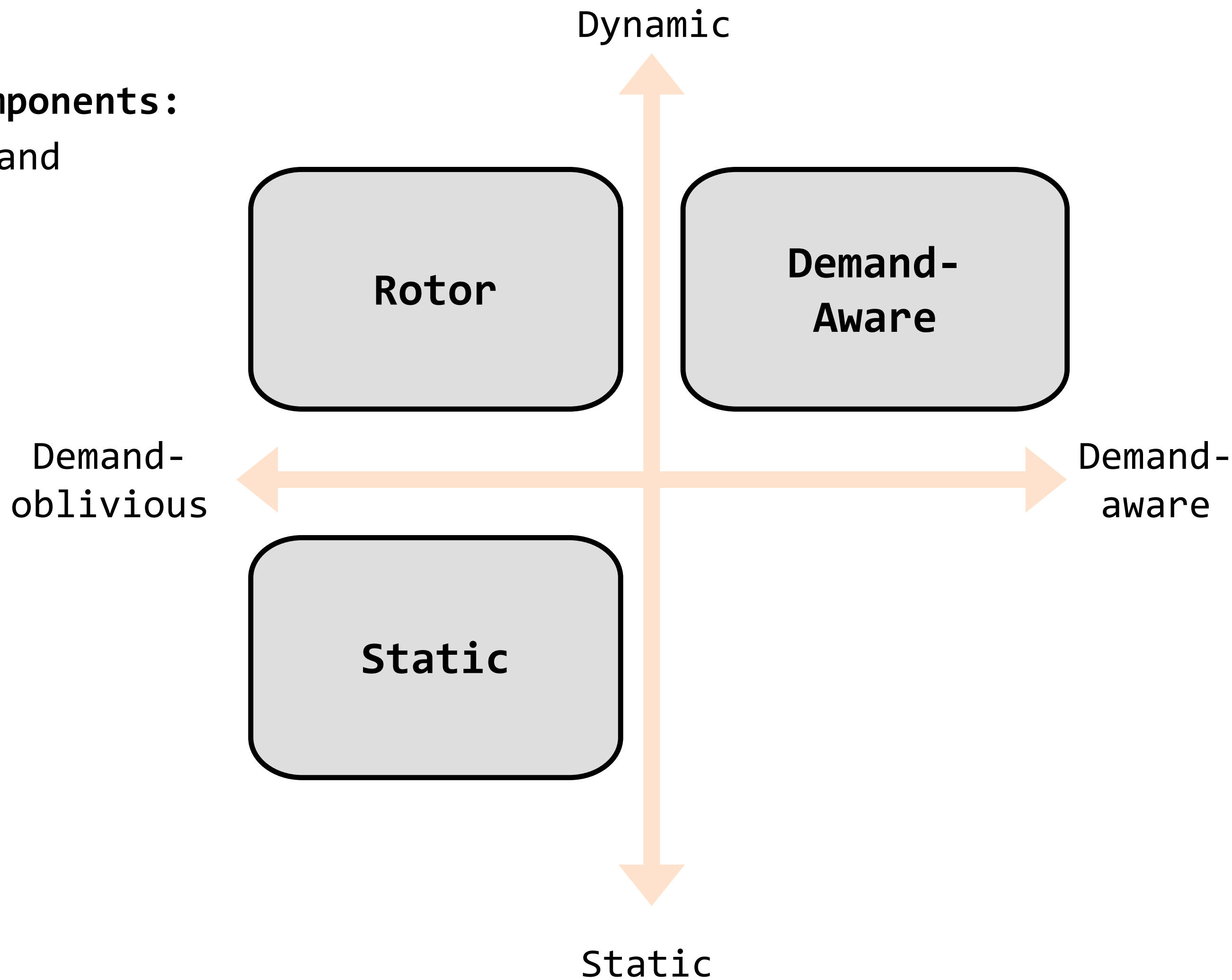


Opportunity: Tech Diversity

Diverse topology components:

⇀ demand-oblivious and demand-aware

⇀ static vs dynamic



Opportunity: Tech Diversity

Diverse topology components:

→ demand-oblivious and
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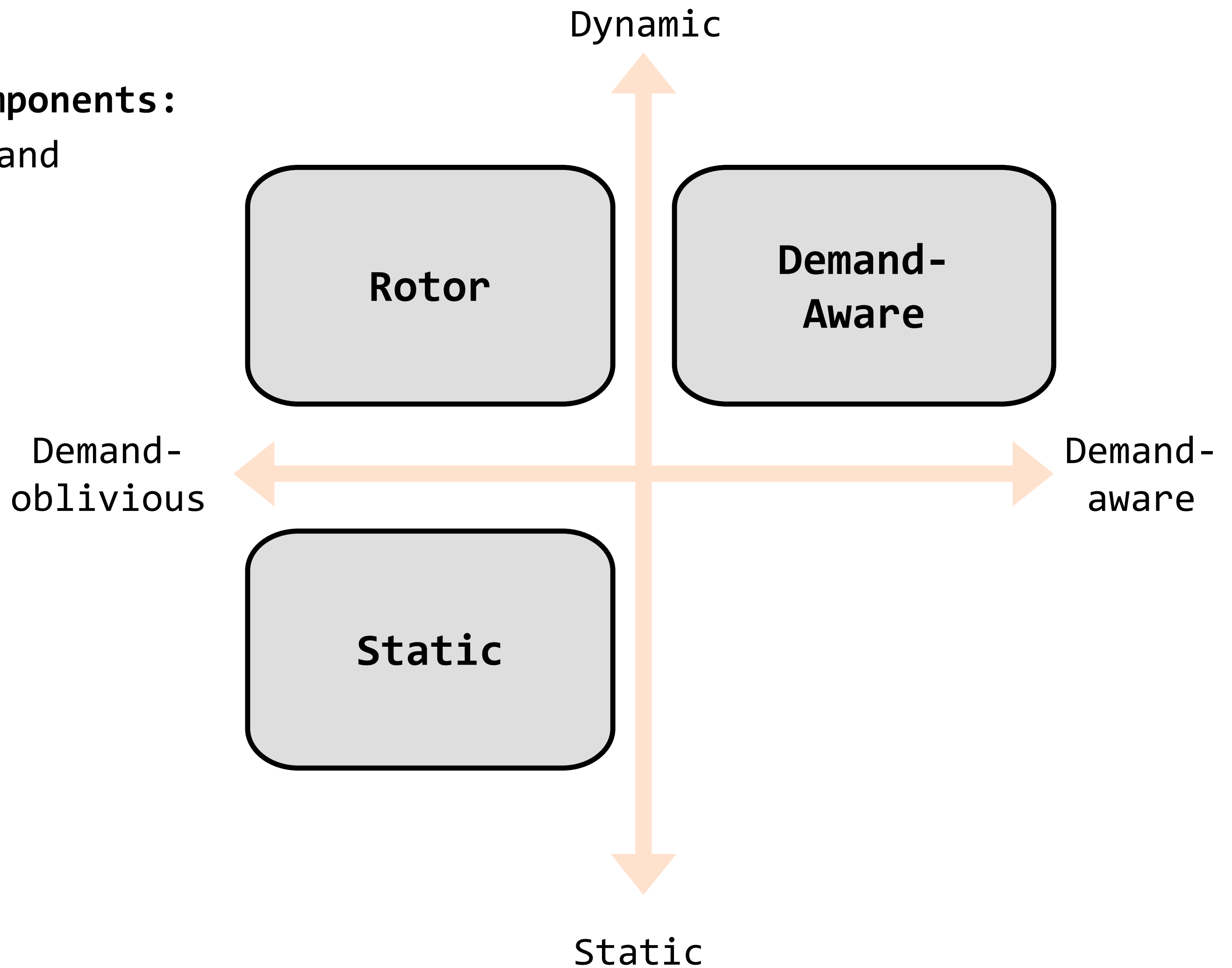
→ static vs dynamic



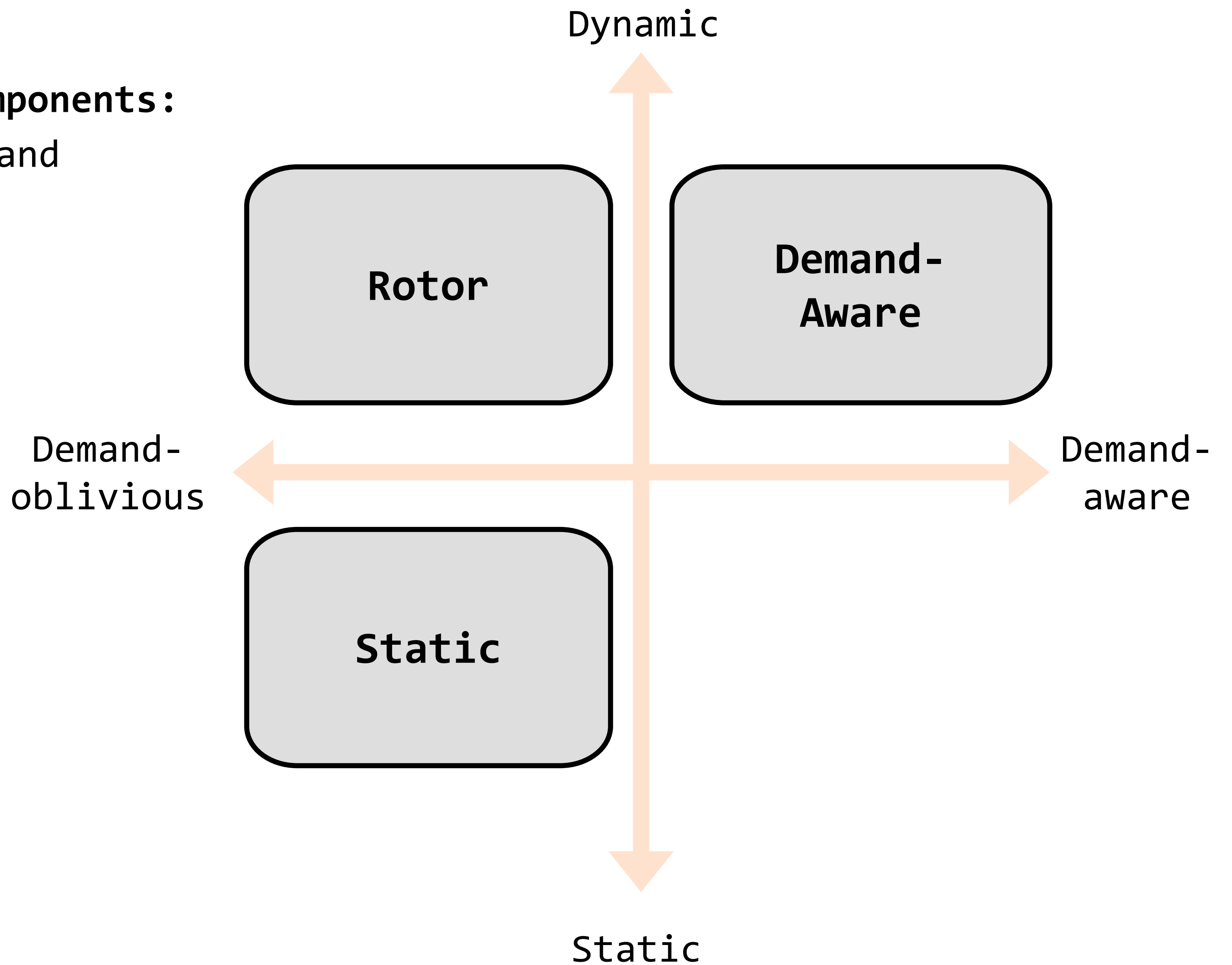
Which approach is best?

Opportunity: Tech Diversity

Diverse topology components:

⇀ demand-oblivious and
demand-aware

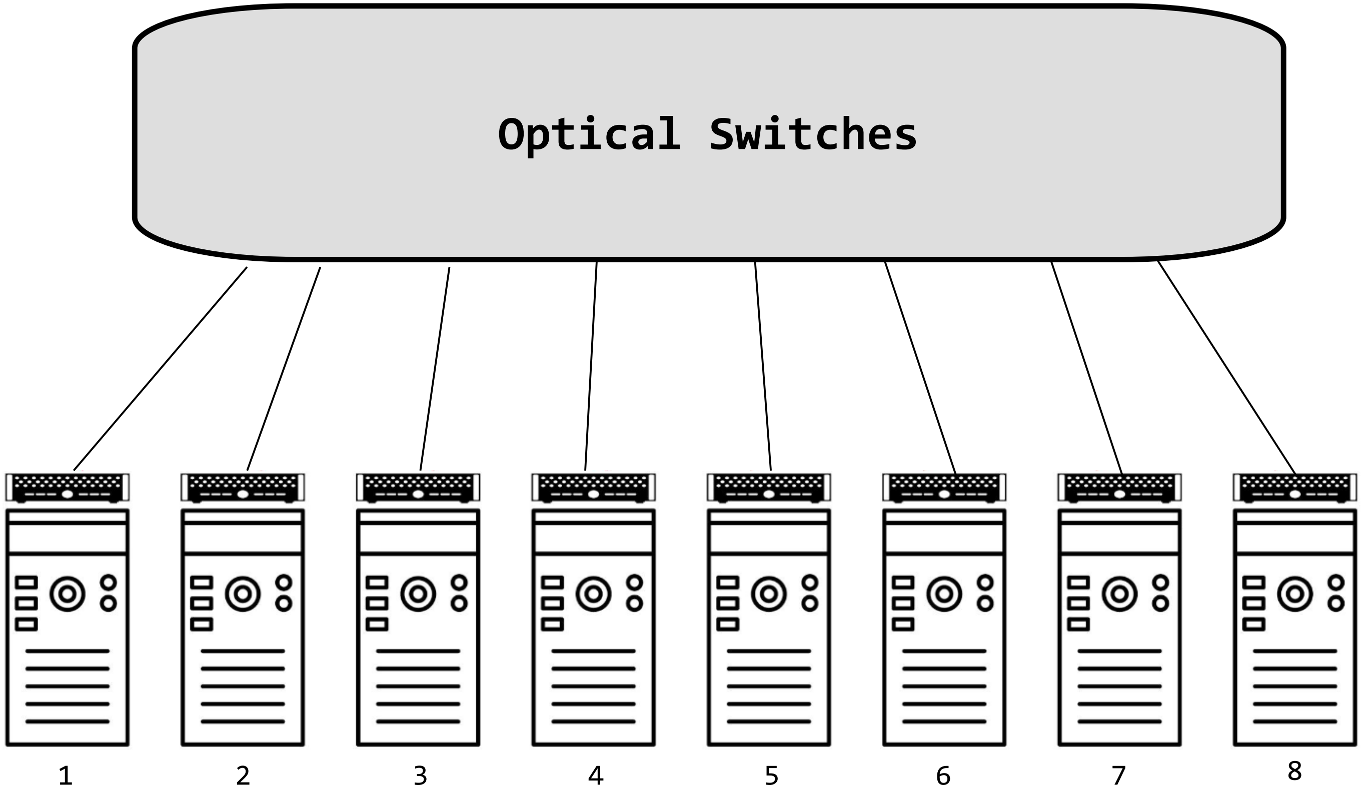
⇀ static vs dynamic



Which approach is best?

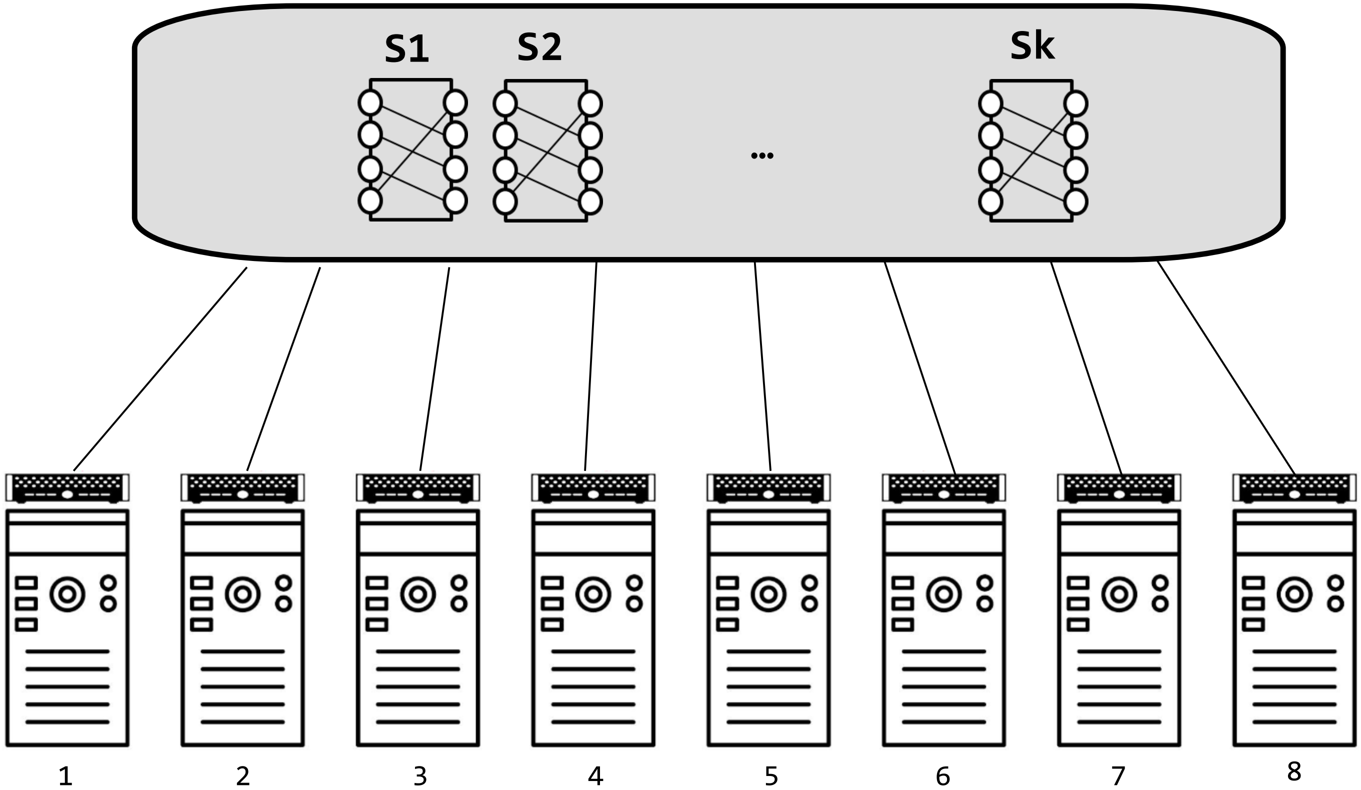
As always in CS:
It depends…

Rack Interconnect



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

Rack Interconnect

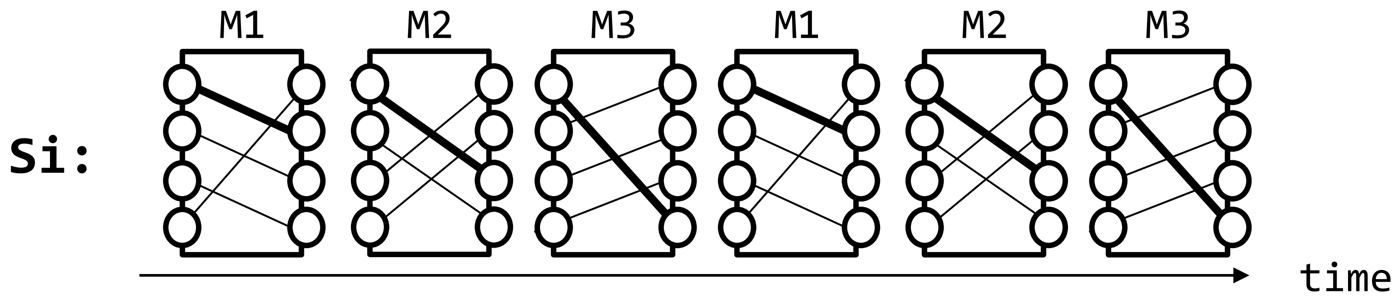


Typical rack internconnect: ToR-Matching-ToR (TMT) model

Details: Switch Types

Periodic Switch (aka Rotor Switch)

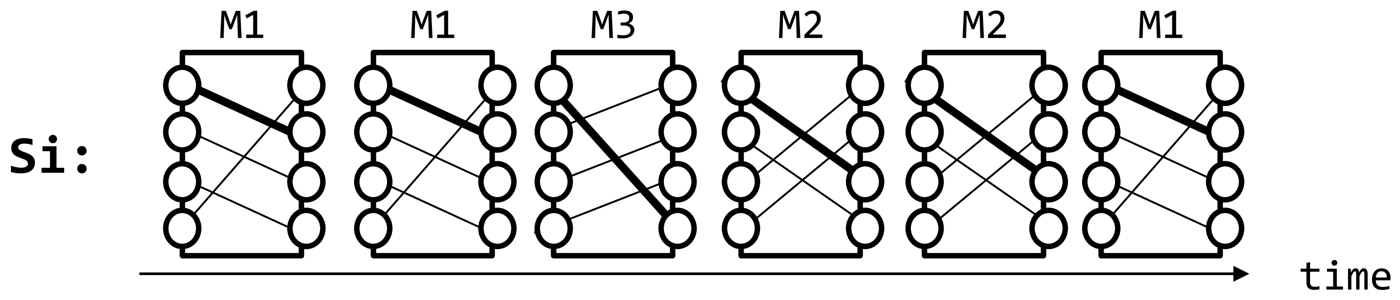
Rotor switch: periodic matchings (demand-oblivious)



Details: Switch Types

Demand-Aware Switch

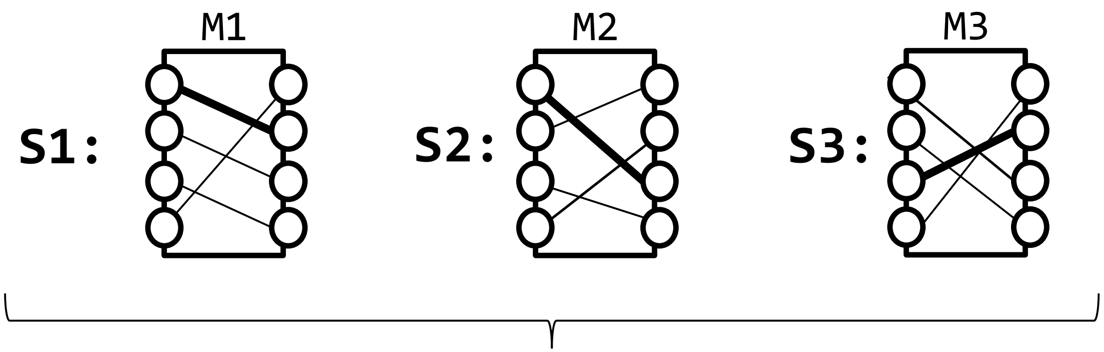
Demand-aware switch: optimized matchings

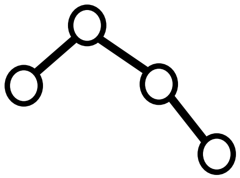


Details: Switch Types

Static Switch

Static switches: combine for optimized static topology

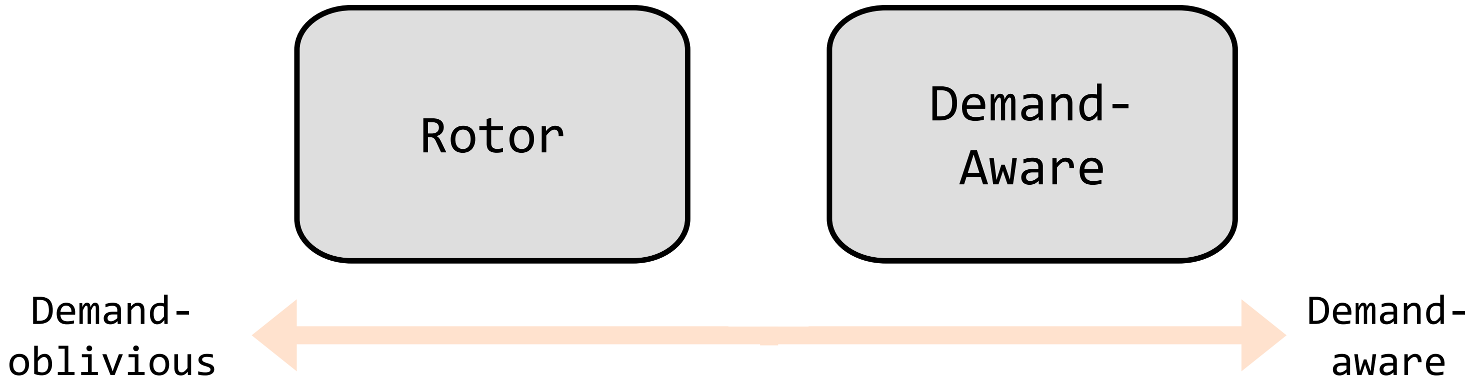




e.g, tree, expander

Design Tradeoffs (1)

The “Awareness-Dimension”



Good for all-to-all traffic!

→ oblivious: very fast periodic direct connectivity

→ no control plane overhead

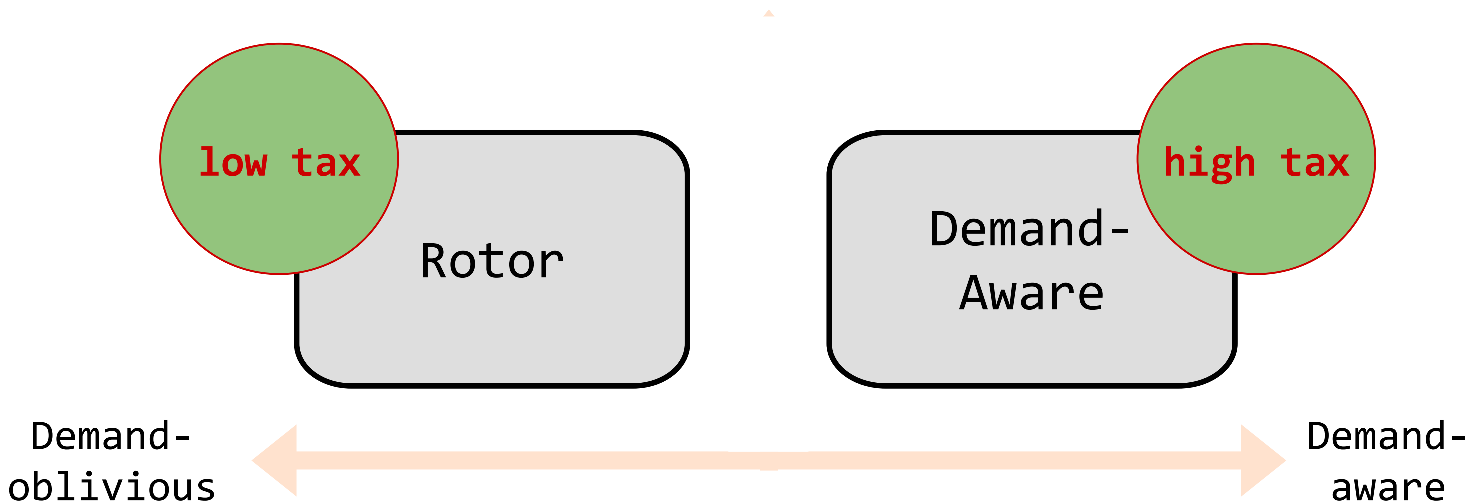
Good for elephant flows!

→ optimizable toward traffic

→ but slower

Design Tradeoffs (1)

The “Awareness-Dimension”



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

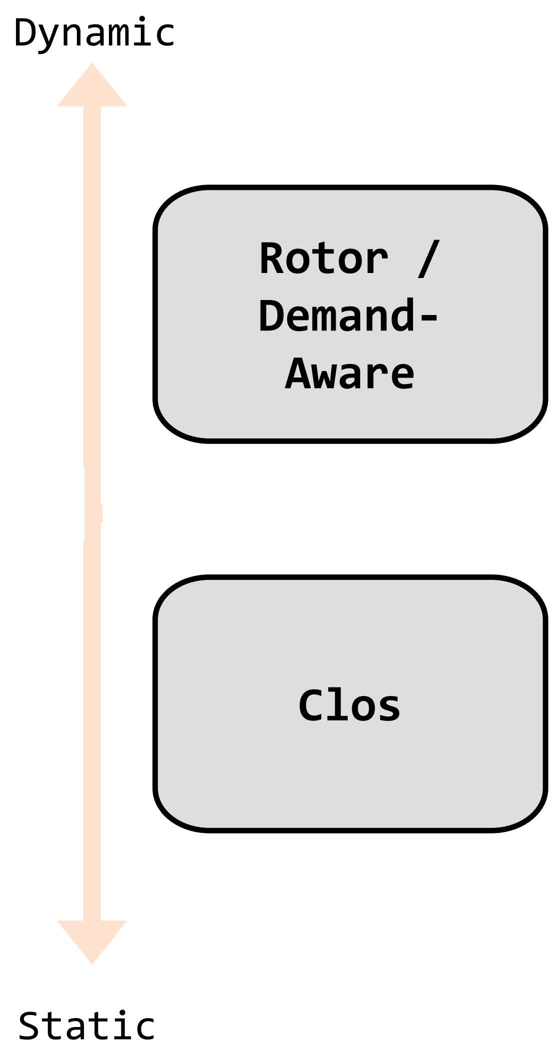
Compared to static networks: latency tax!

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)

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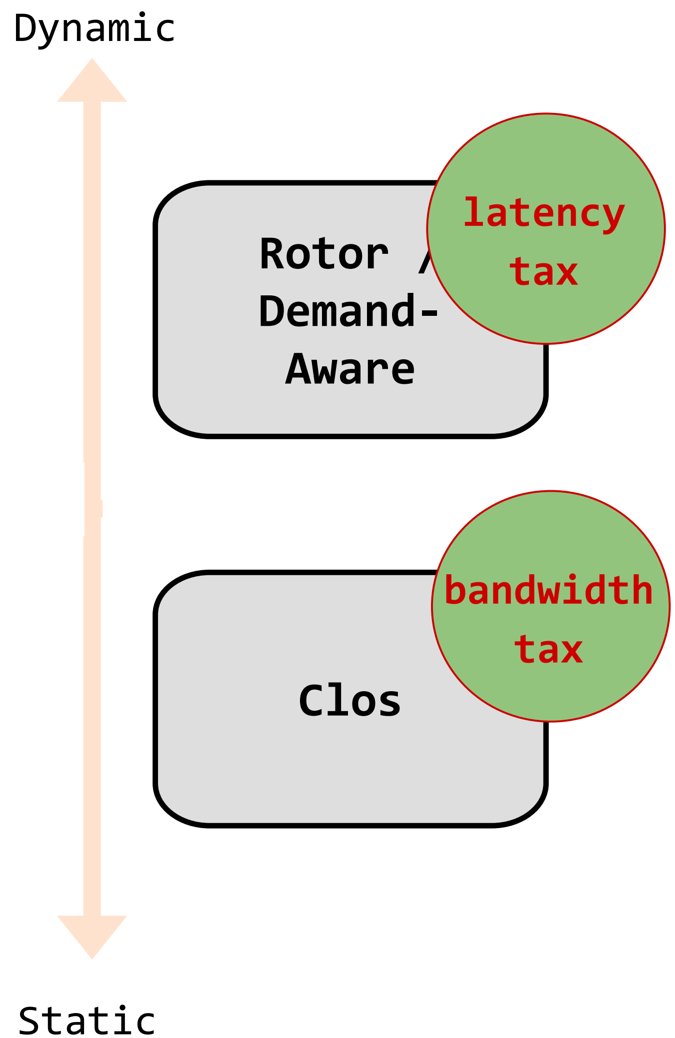
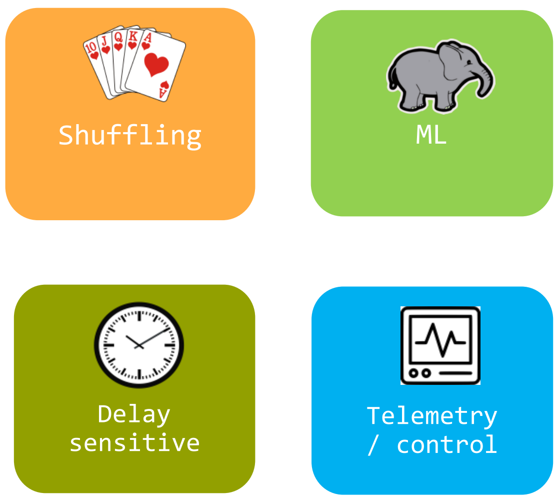


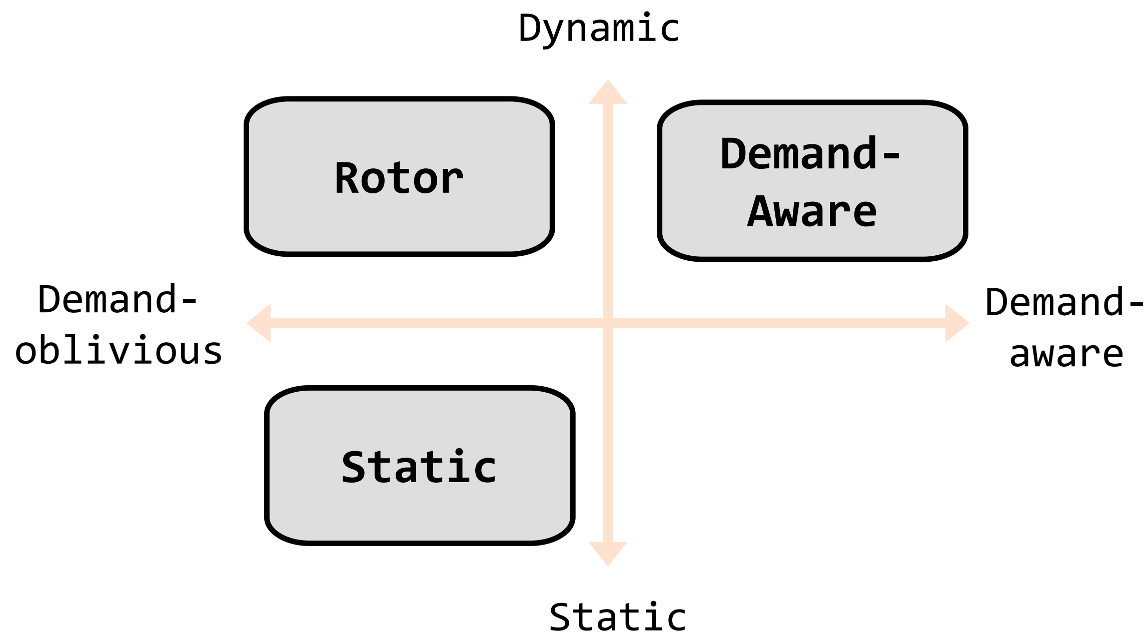
First Observations

- **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?

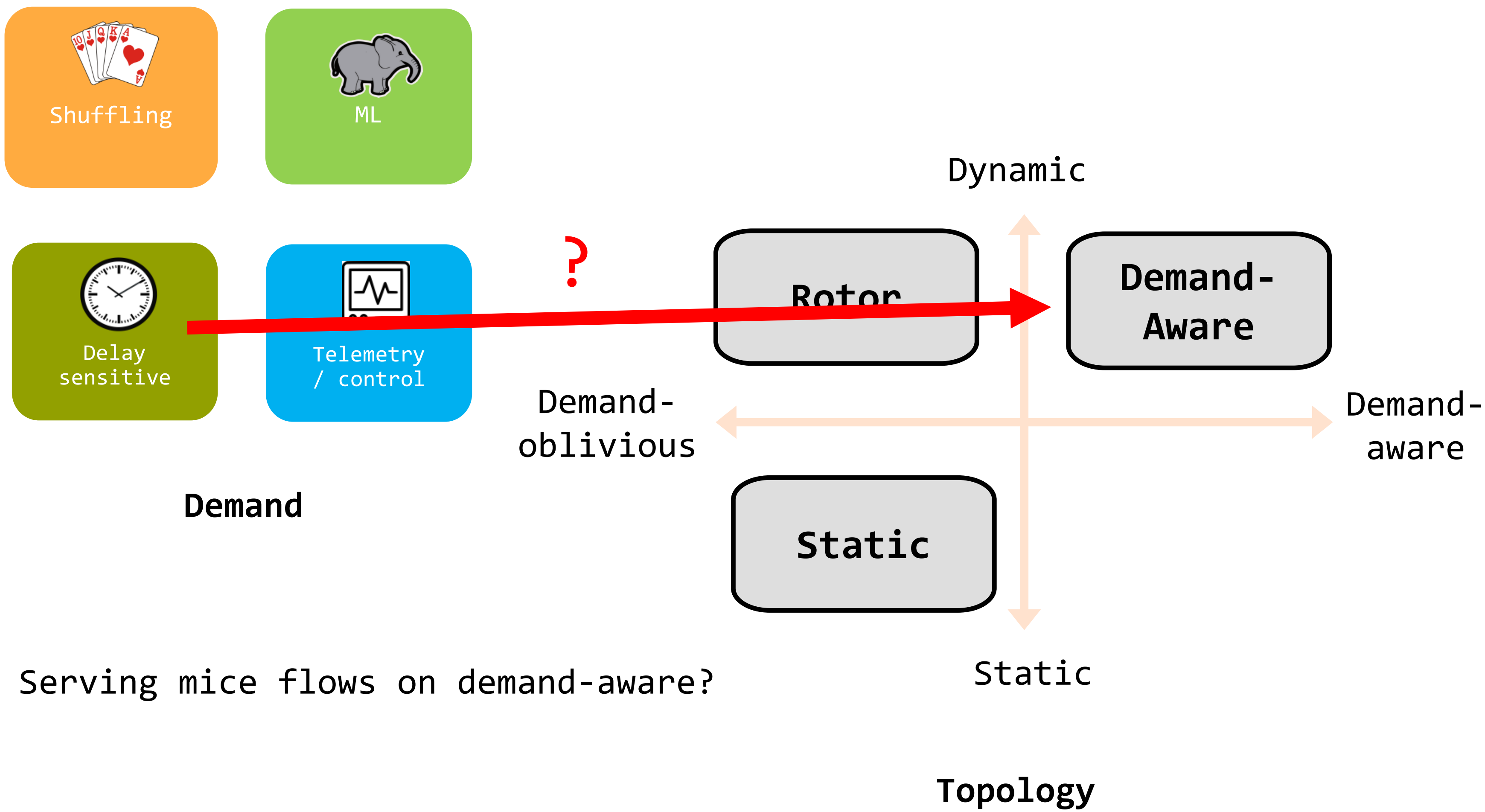


Demand



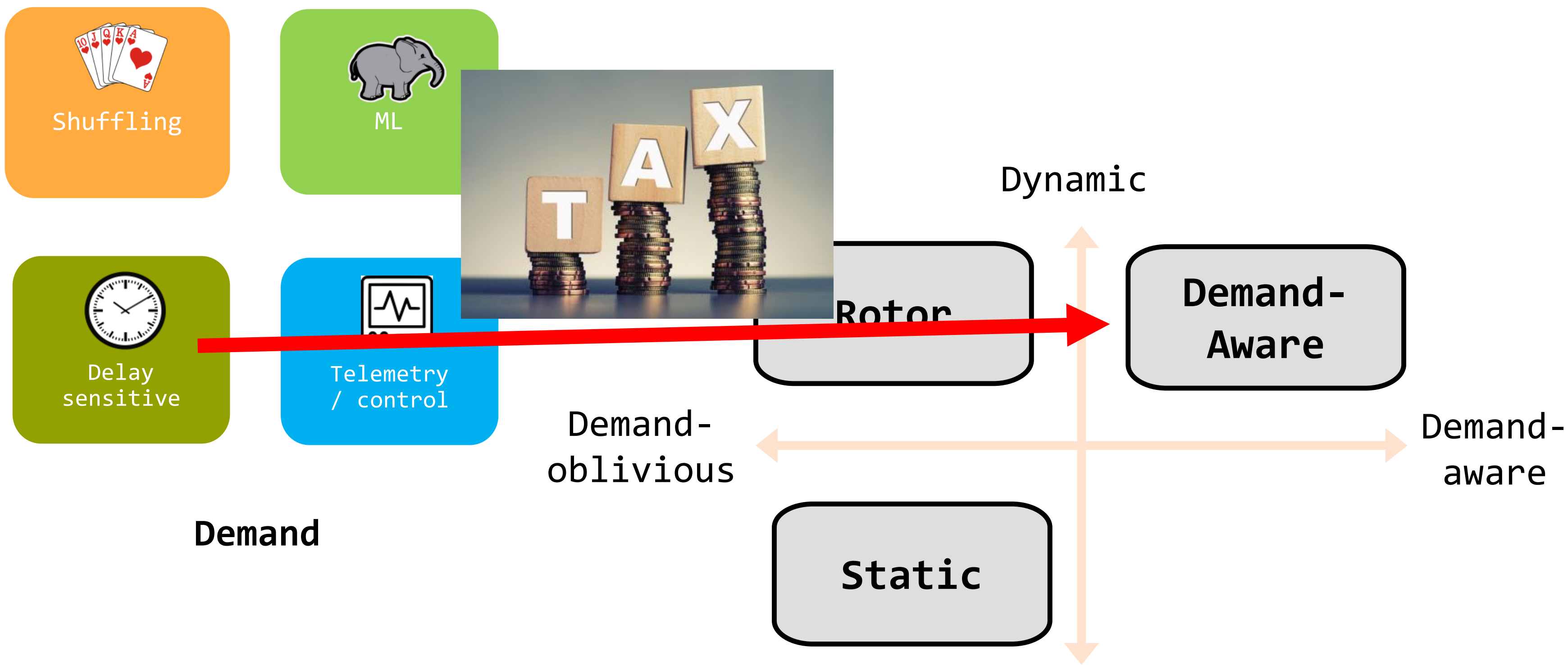
Topology

Examples:
Match or Mismatch?



Serving mice flows on demand-aware?

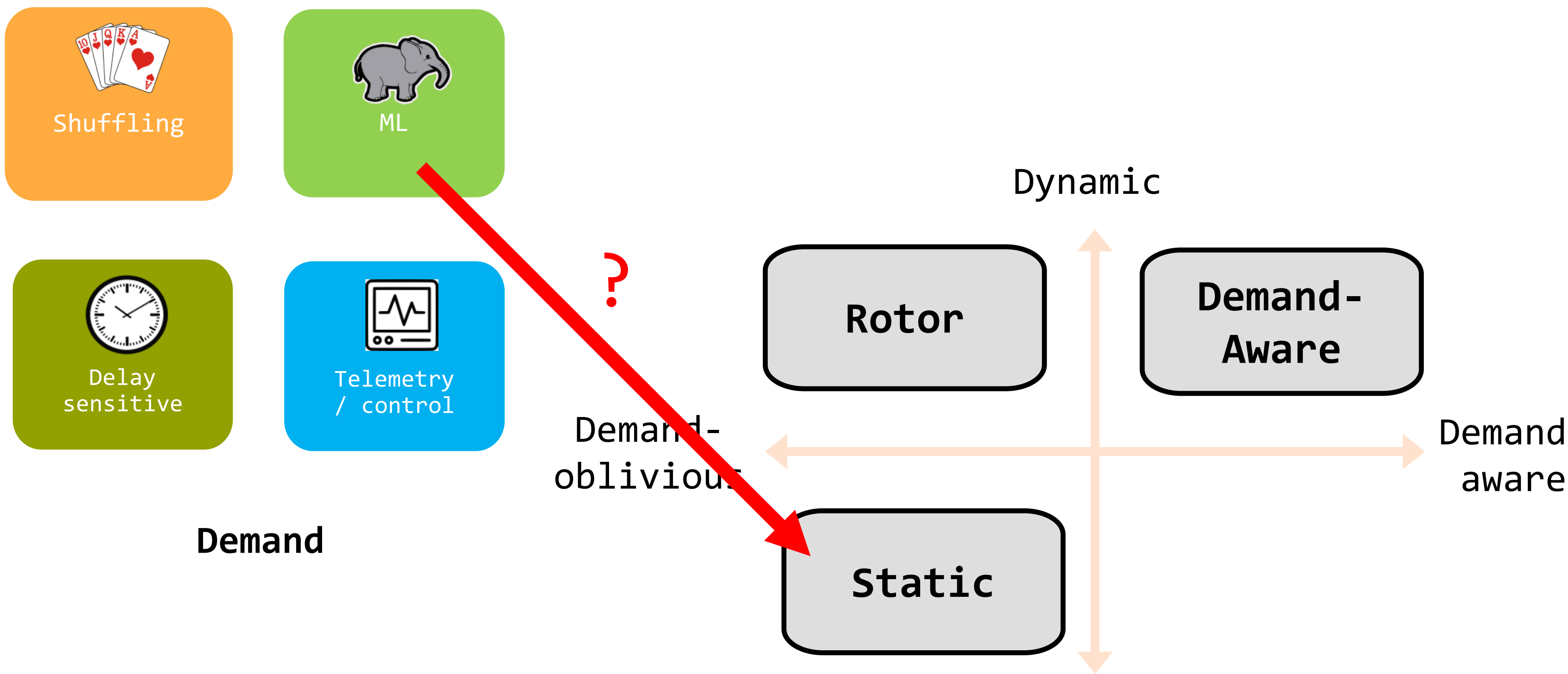
Examples:
Match or Mismatch?



Serving mice flows on demand-aware?

Bad idea! Latency tax.

Examples:
Match or Mismatch?

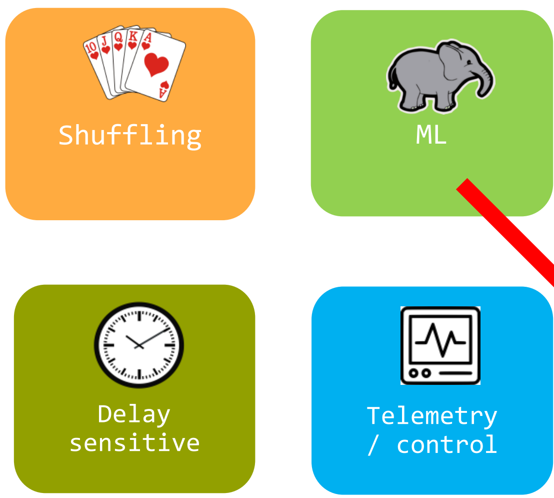


Serving elephant flows on static?

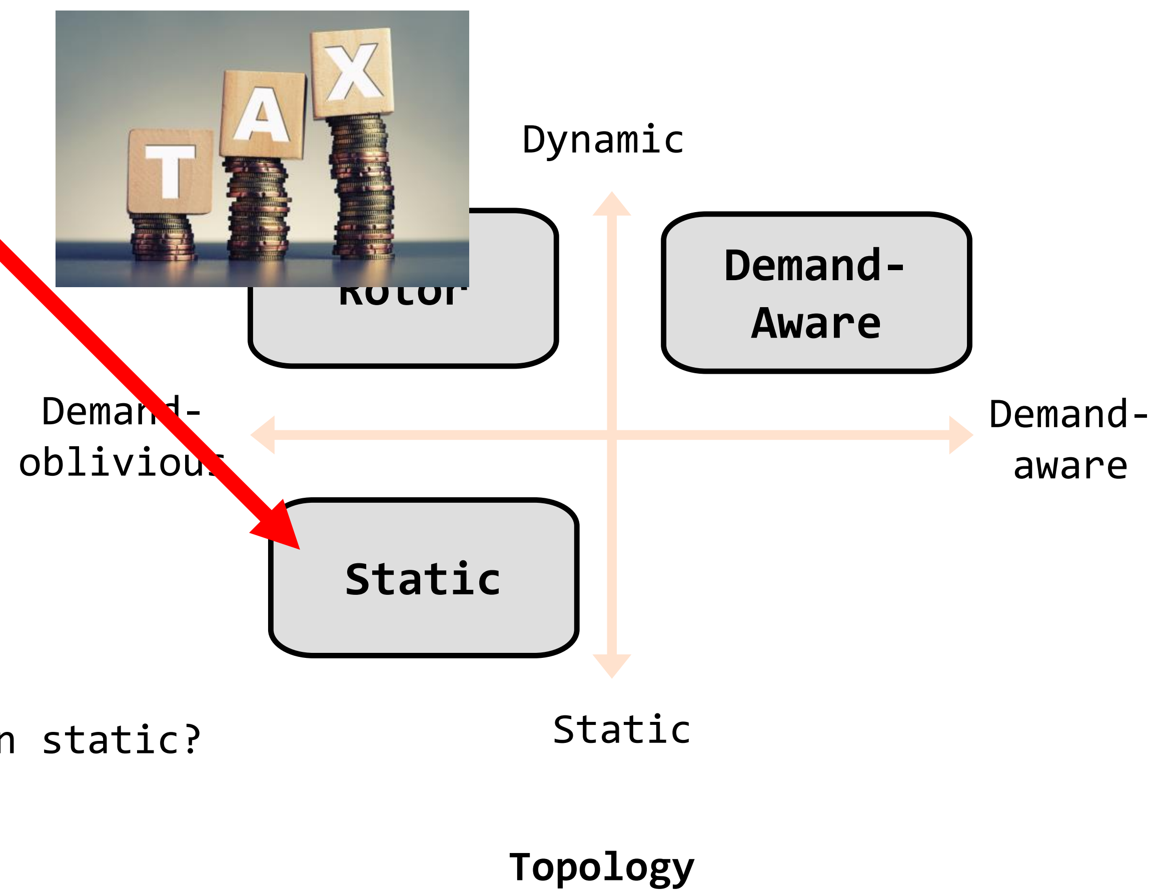
Static

Topology

Examples:
Match or Mismatch?



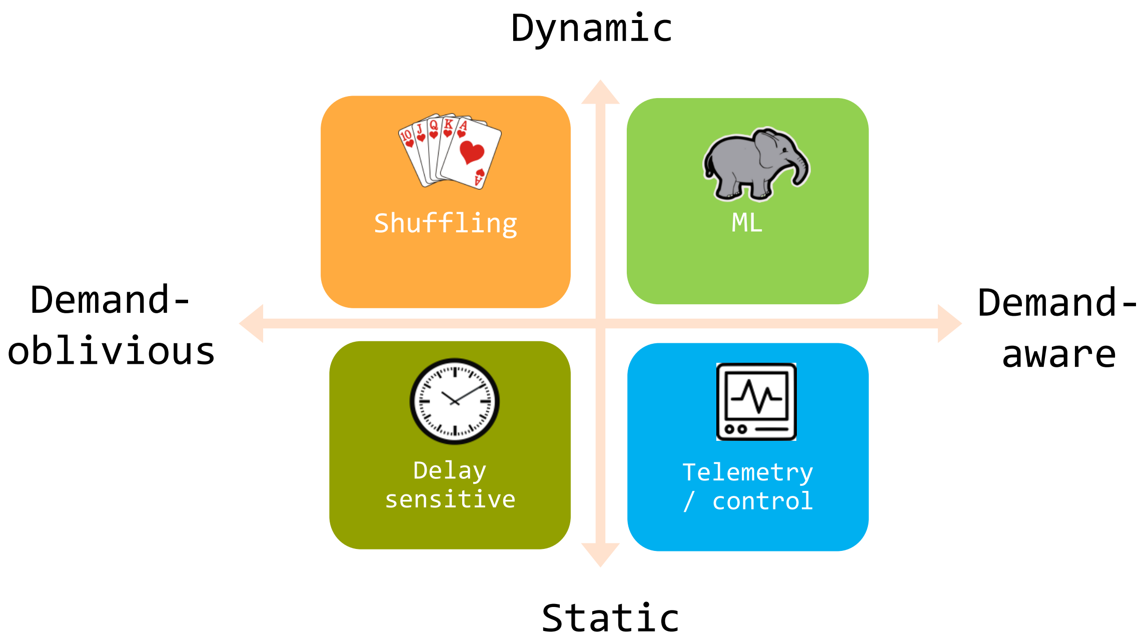
Demand



Serving elephant flows on static?

Bad idea! Bandwidth tax.

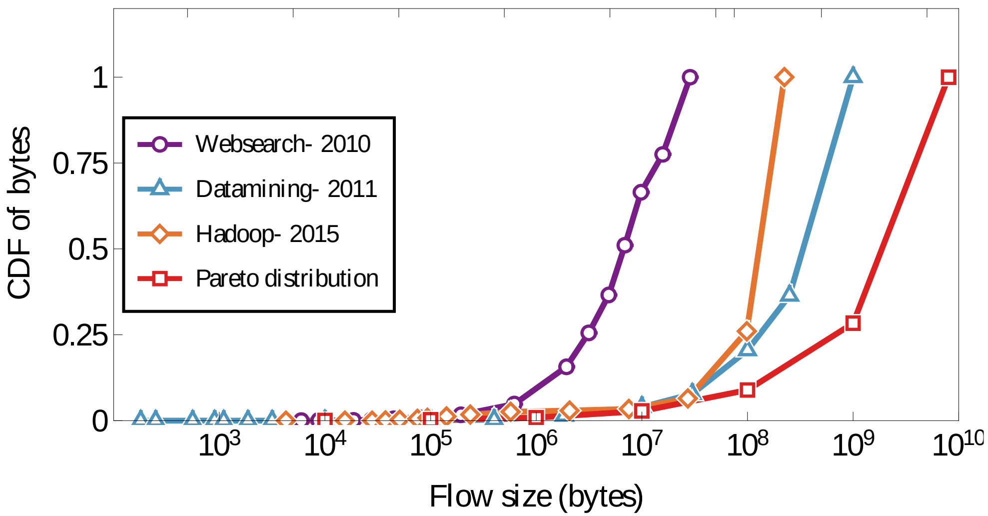
Cerberus: It's a Match!



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

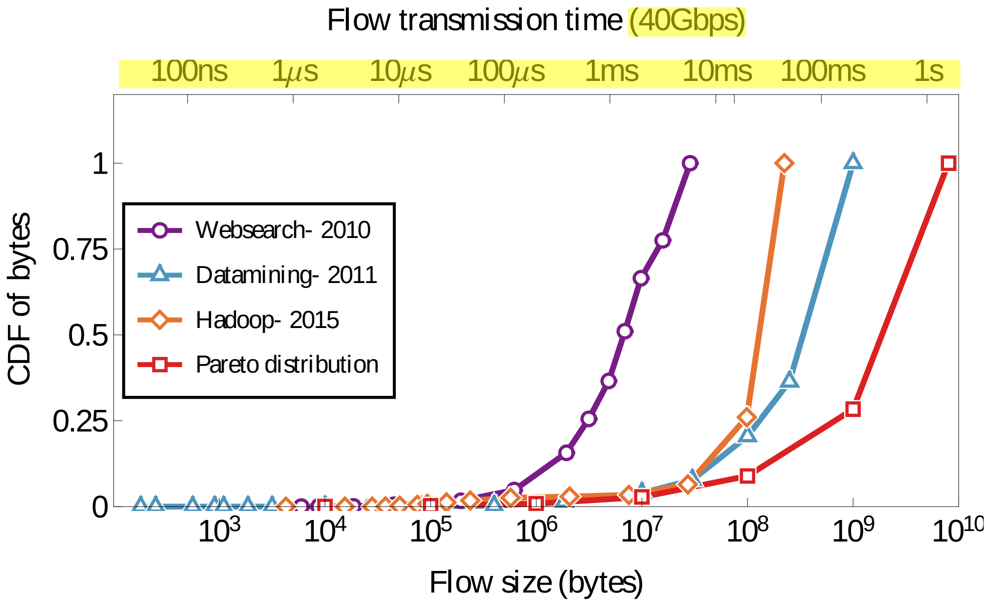
* Griner et al., ACM SIGMETRICS 2022

Flow Size Matters



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

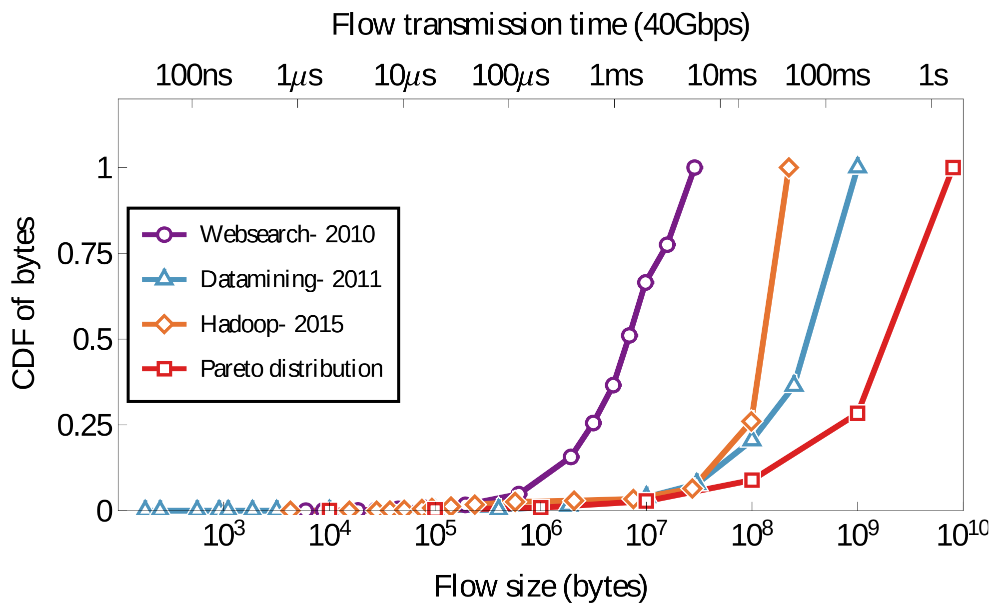
Flow Size Matters



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

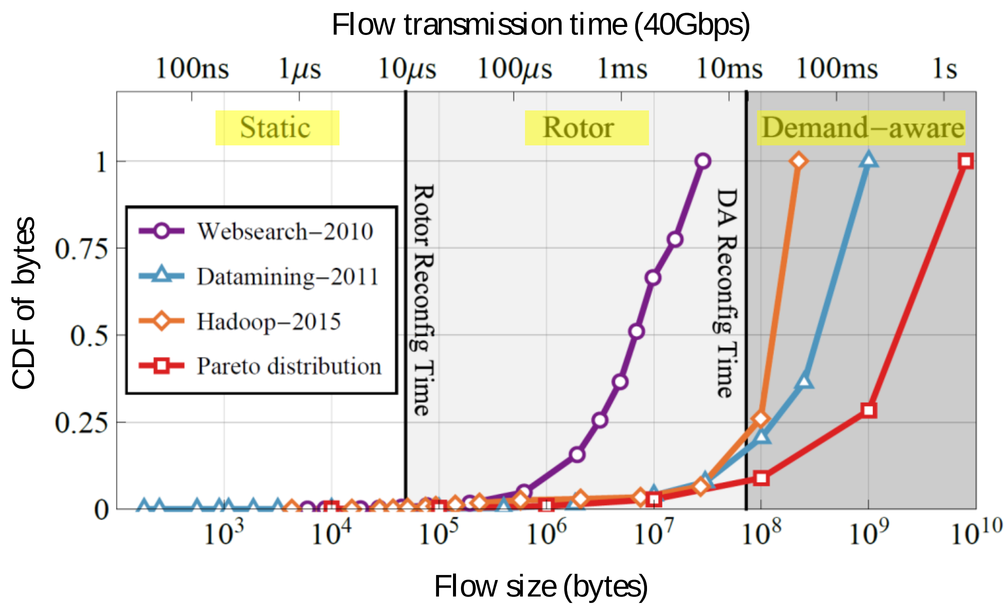
⇢ **Observation 2:** The transmission time of a flow depends on its size.

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.
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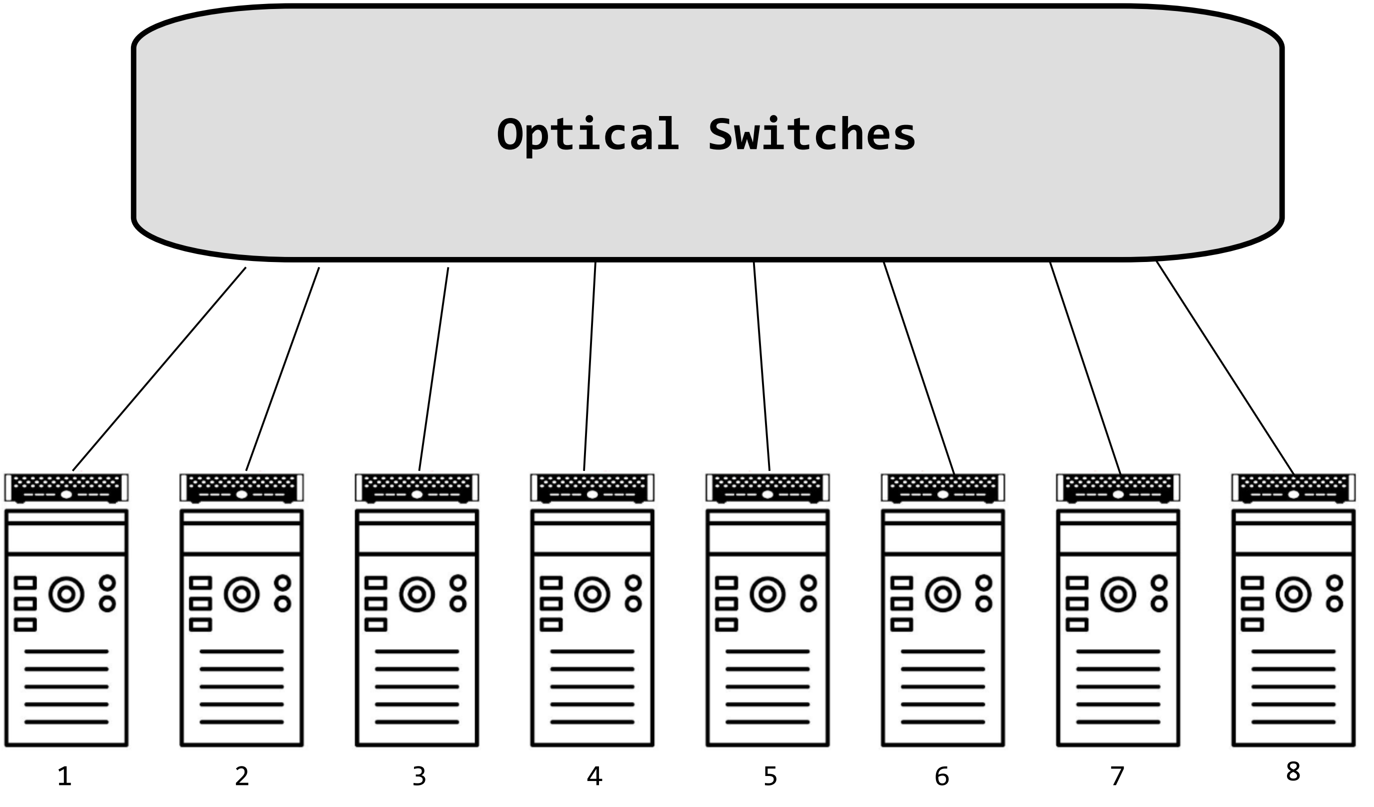
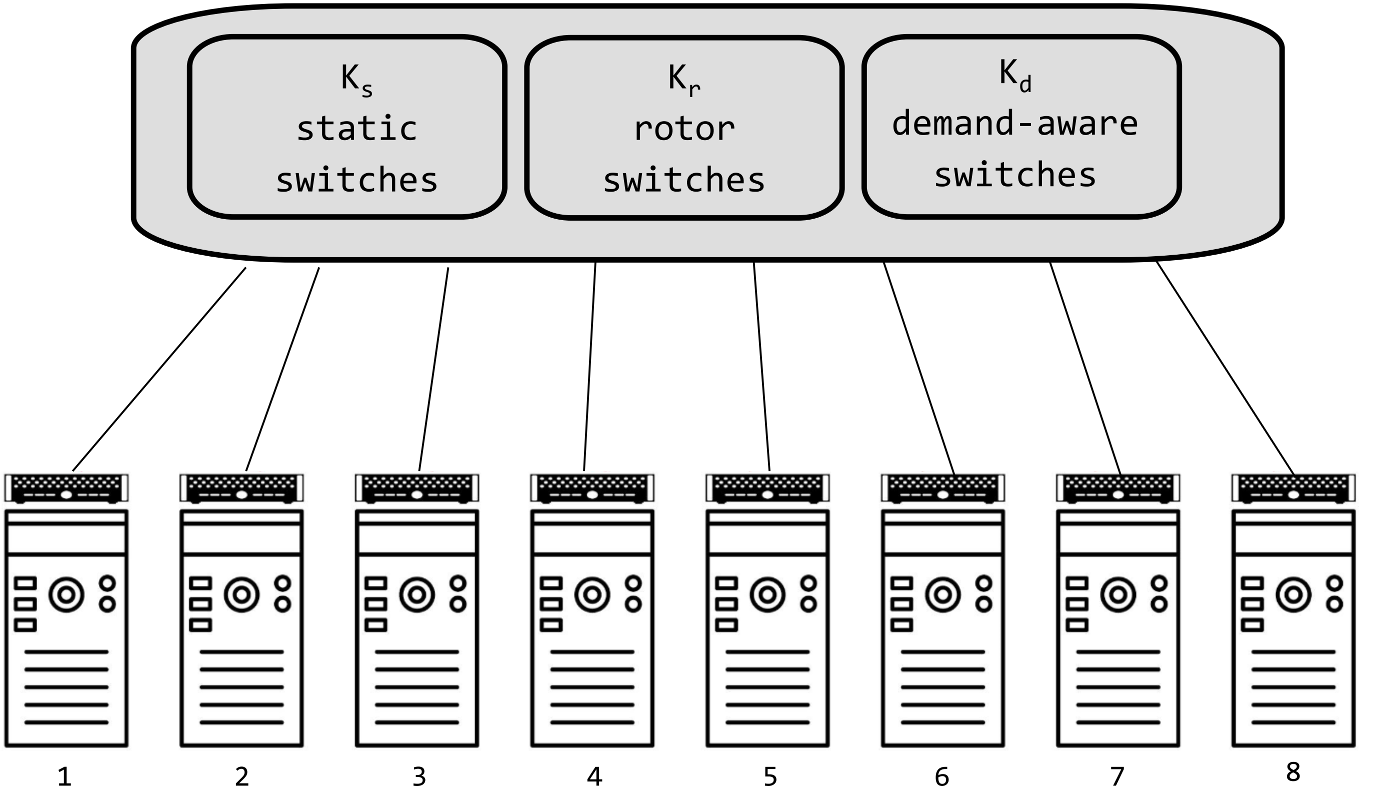
Cerberus

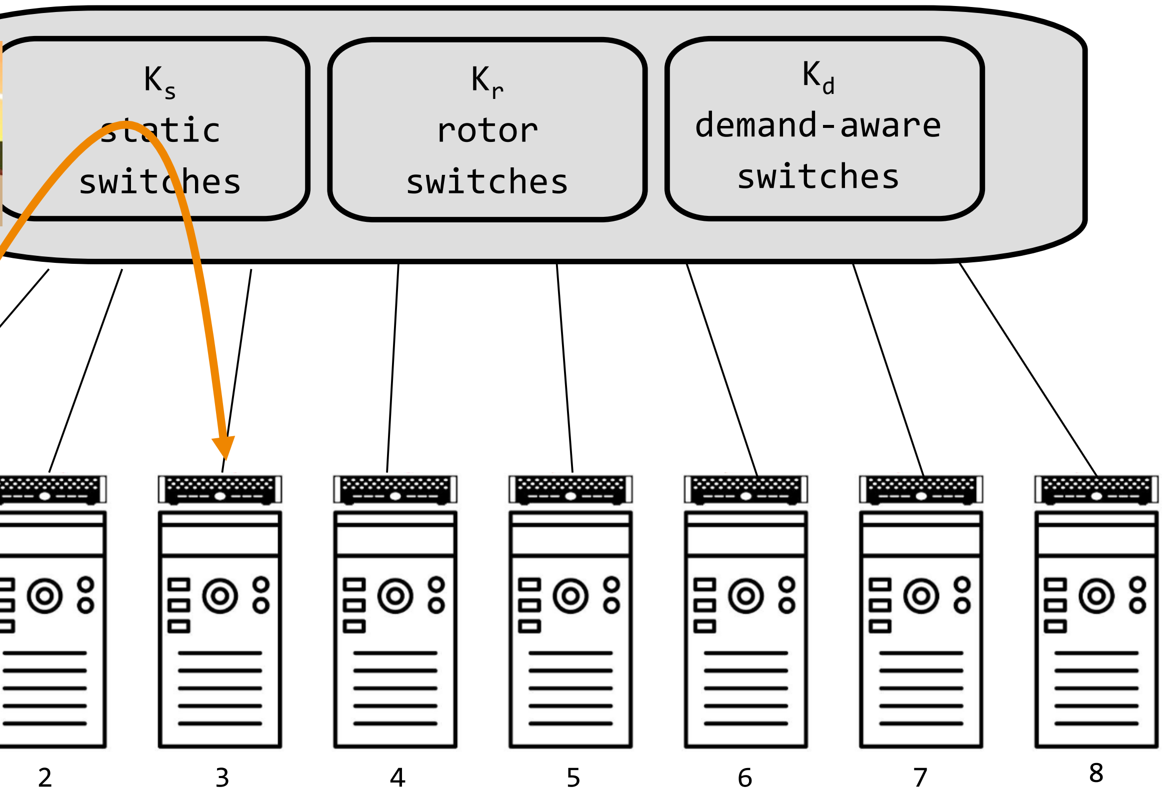


Cerberus



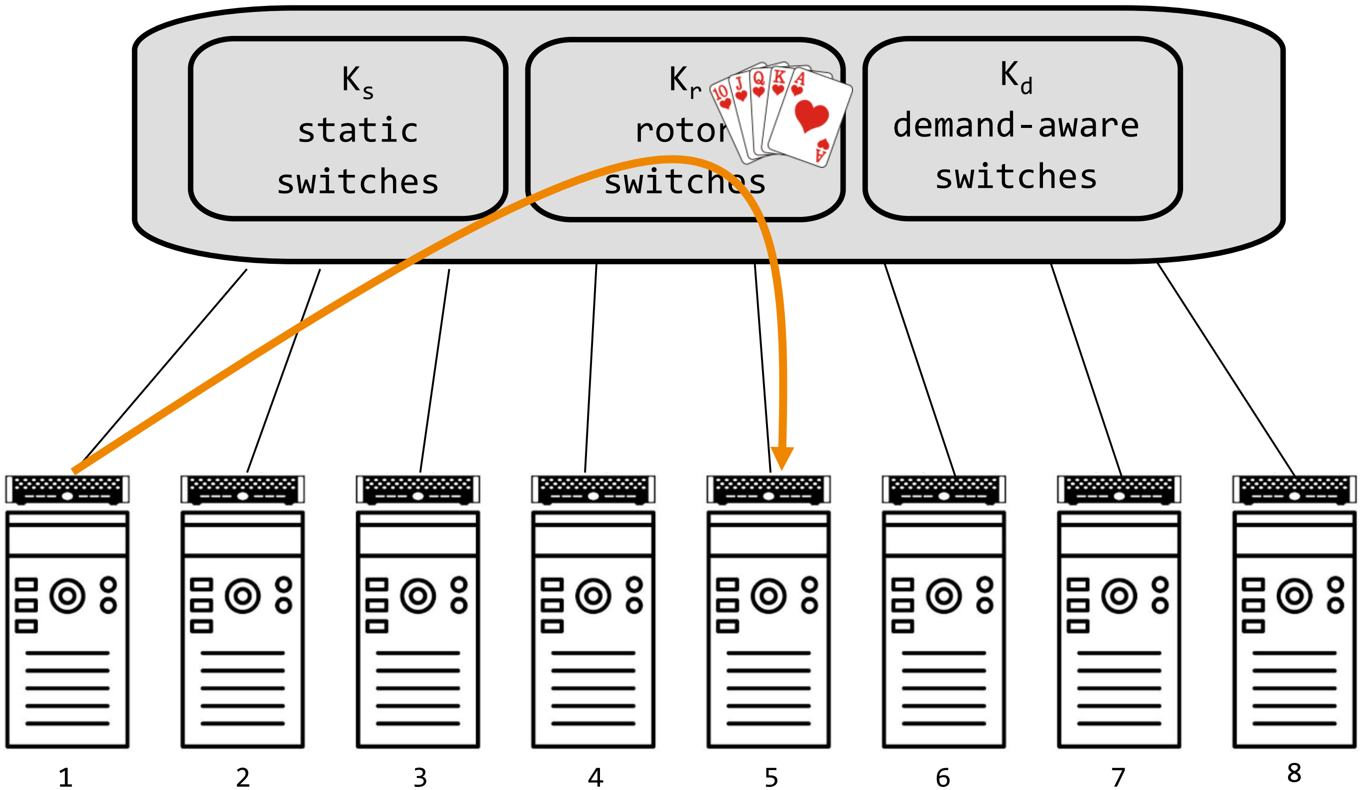
K_s
static
switches
K_r
rotor
switches
K_d
demand-aware
switches
1
2
3
4
5
6
7
8

Cerberus



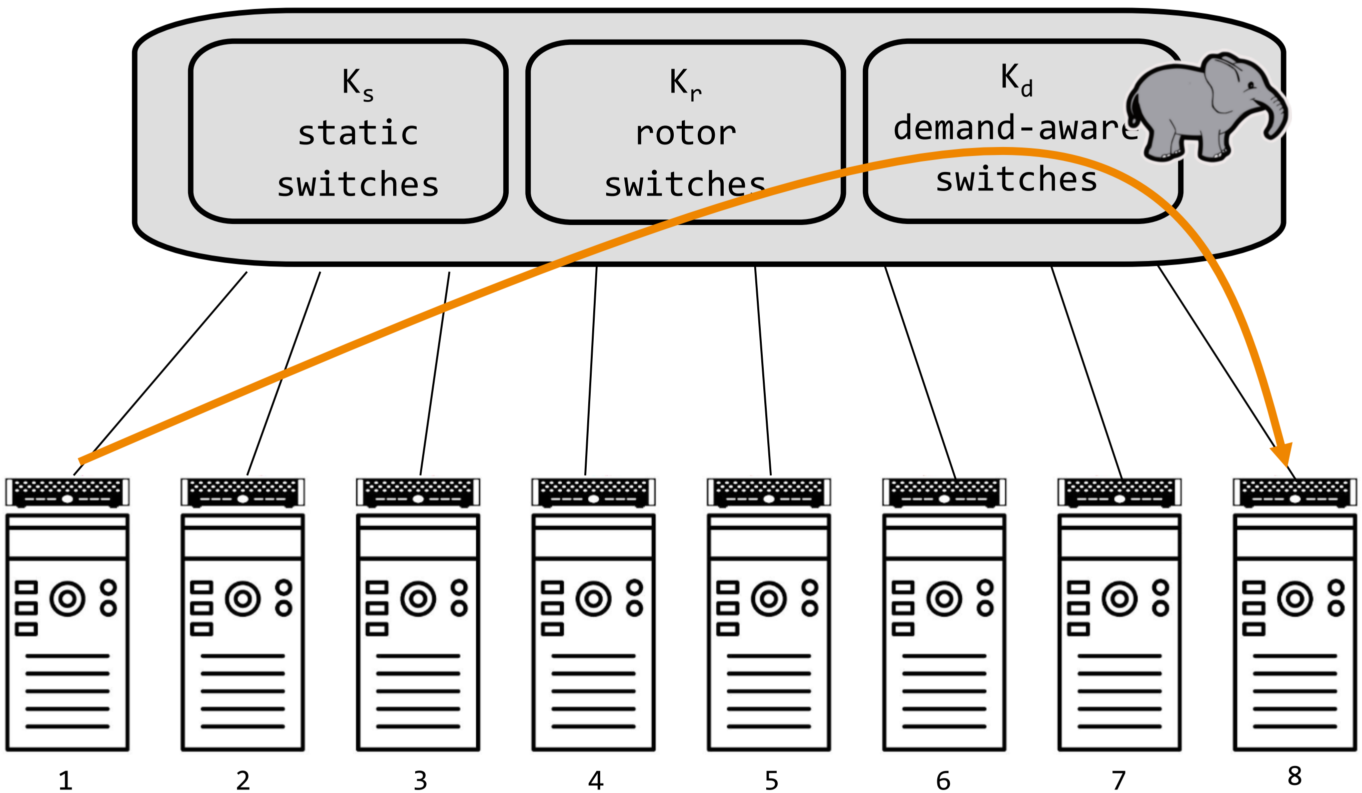
Scheduling: Small flows go via static switches…

Cerberus



Scheduling: … medium flows via rotor switches…

Cerberus

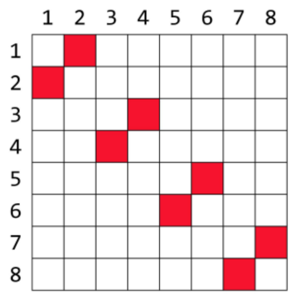


Scheduling: … and large flows via demand-aware switches
(if one available, otherwise via rotor).

Throughput Analysis

Demand Matrix

T

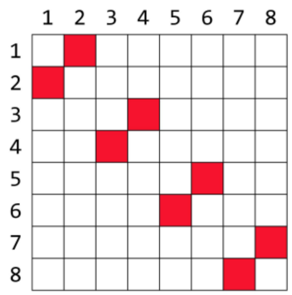


Metric: throughput of a demand matrix…

Throughput Analysis

Demand Matrix

T



$\times \ \theta(T)$

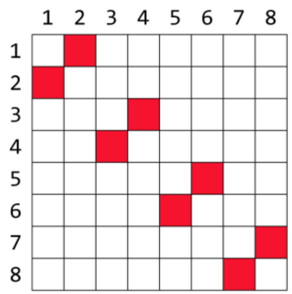
Metric: throughput of a demand matrix…

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

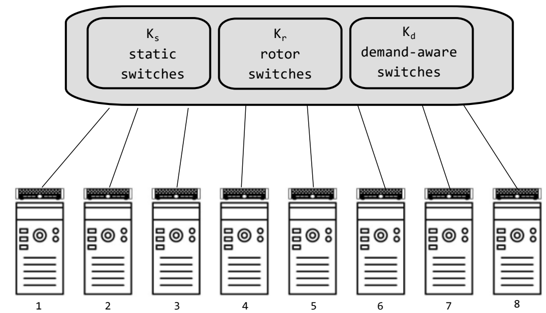
Throughput Analysis

Demand Matrix

T



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



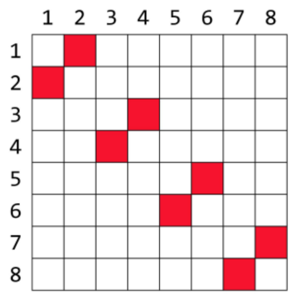
Metric: throughput of a demand matrix…

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

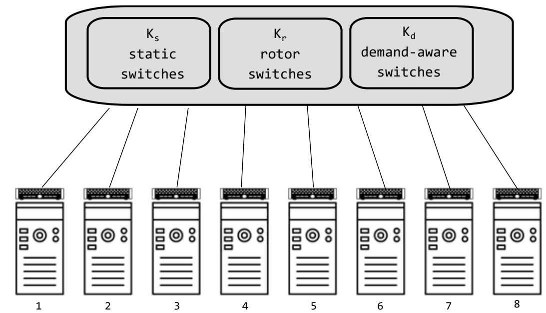
Throughput of network θ^*: worst case T

Throughput Analysis

Demand Matrix



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

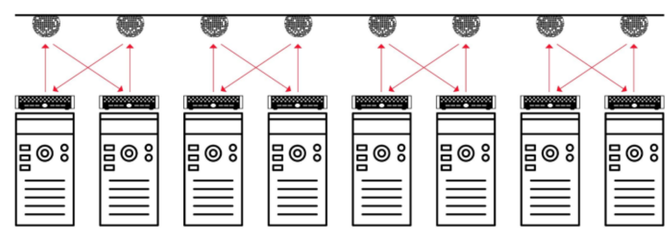


BW tax!

BW & latency tax!

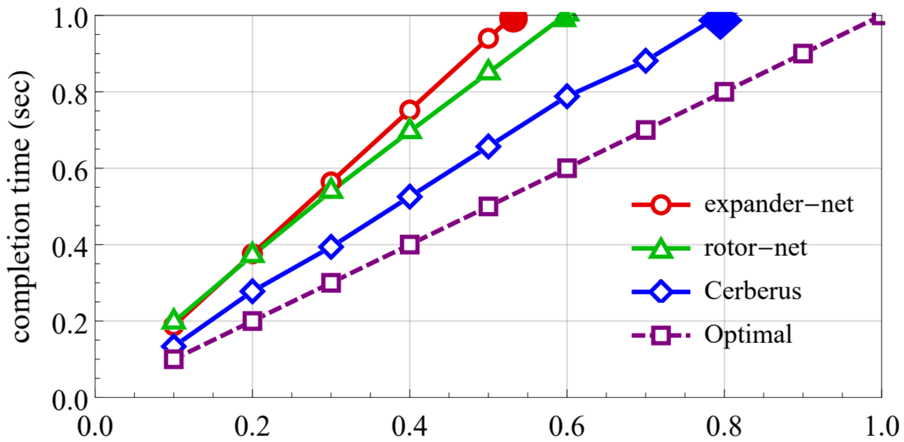
Worst demand matrix for static and rotor: permutation. Best case for demand-aware!

	expander-net	*rotor-net*	CERBERUS
BW-Tax	✓	✓	✗
LT-Tax	✗	✓	✓
$\theta(T)$	Thm 2	Thm 3	Thm 5
θ^*	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

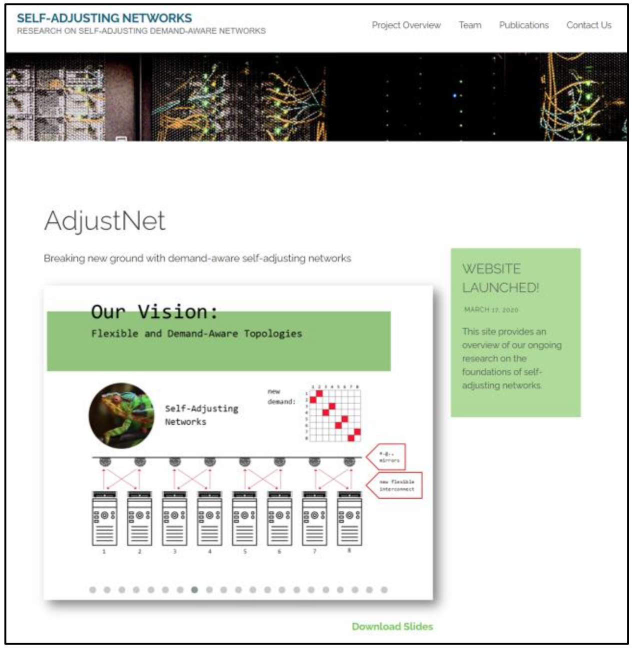
⇢ Diverse traffic requires diverse technologies

⇢ Cerberus aims to assign traffic to its best topology
  - ⇀ Depending on flow size

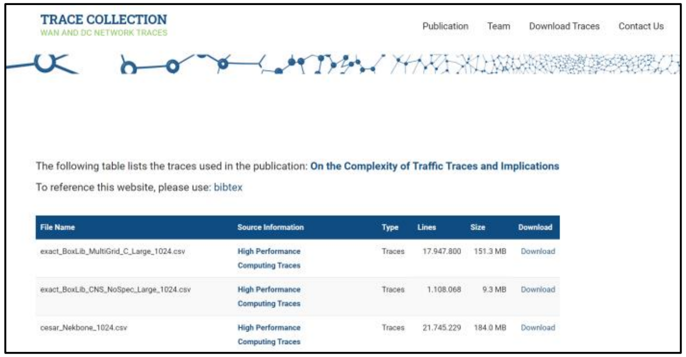
⇢ Many challenges
  - ⇀ Impact on routing and congestion control
  - ⇀ Sensitivity analysis
  - ⇀ Prototyping

Thank you!

Websites



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



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, Δ, on the maximum degree. In turn, our objective is to design an (undirected) demand-aware network $N = (V, E)$ of bounded-degree Δ, 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 (with respect to $\mathcal{D}$), which is a basic measure of the

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,

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.,

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 practice: Empirical studies show that traffic patterns in datacenters are often

Robust DAN

rDAN: Toward Robust Demand-Aware Network Designs

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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.

Dynamic DAN

SplayNet: Towards Locally Self-Adjusting Networks

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***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 σ. 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.

Concurrent DANs

CBNet: Minimizing Adjustments in Concurrent Demand-Aware Tree Networks

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***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 structures, and in particular, CBTrees [12]. CBNet gradually adapts the network topology toward the communication pattern in an online manner, i.e., without previous knowledge of the demand distribution. At the same time, *bidirectional semi-splaying* and counters are used to maintain state, minimize reconfiguration

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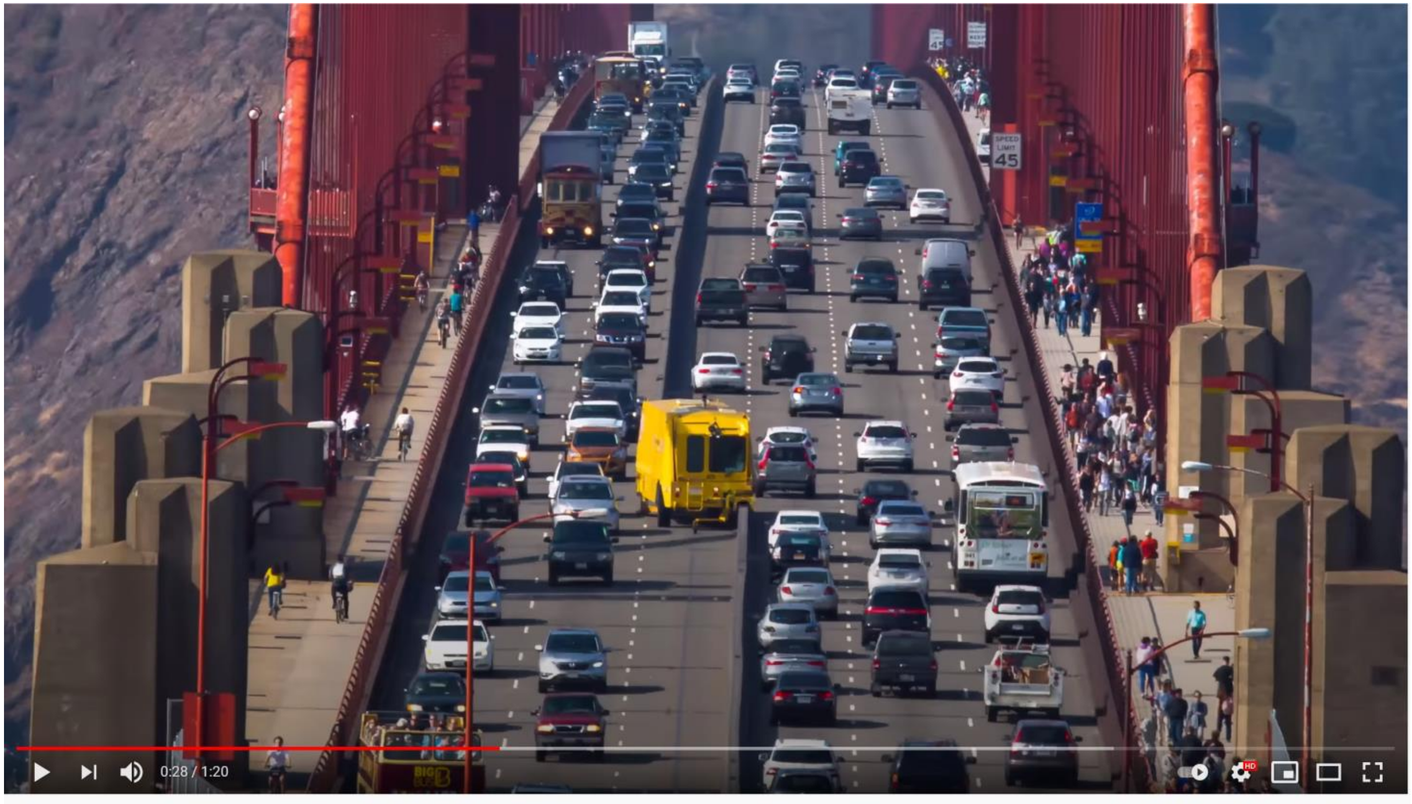
Bonus Material

Hogwarts Stair

Bonus Material



Golden Gate Zipper

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