Self-Adjusting Networks

Stefan Schmid

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

(Folklore)

Acknowledgements:

German-Israeli Foundation for Scientific Research and Development

European Research Council
Established by the European Commission

Trend

Data-Centric Applications

Datacenters (“hyper-scale”)

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

Source: Facebook

Trend

Data-Centric Applications

Datacenters (“hyper-scale”)

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

Credits: Marco Chiesa

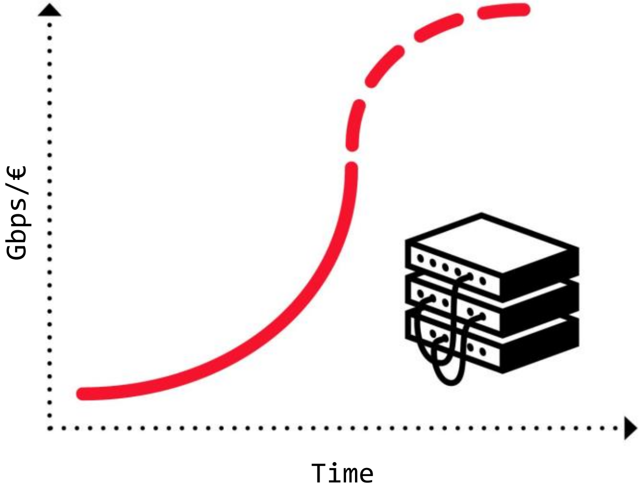
The Problem

Huge Infrastructure, Inefficient Use

- Network equipment reaching capacity limits
  - Transistor density rates stalling
  - “End of **Moore‘s Law** in networking”

- Hence: more equipment, larger networks

- Resource intensive and: **inefficient**



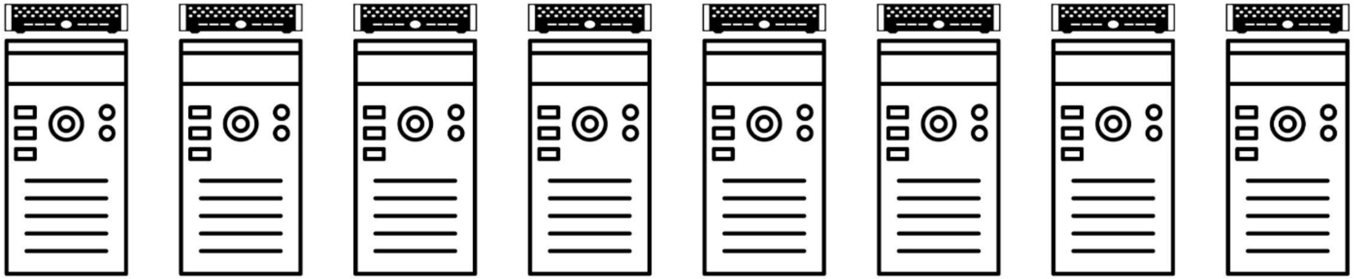
[1] Source: Microsoft, 2019

Annoying for companies, **opportunity** for researchers!

Root Cause

Fixed and Demand-Oblivious Topology

How to interconnect?



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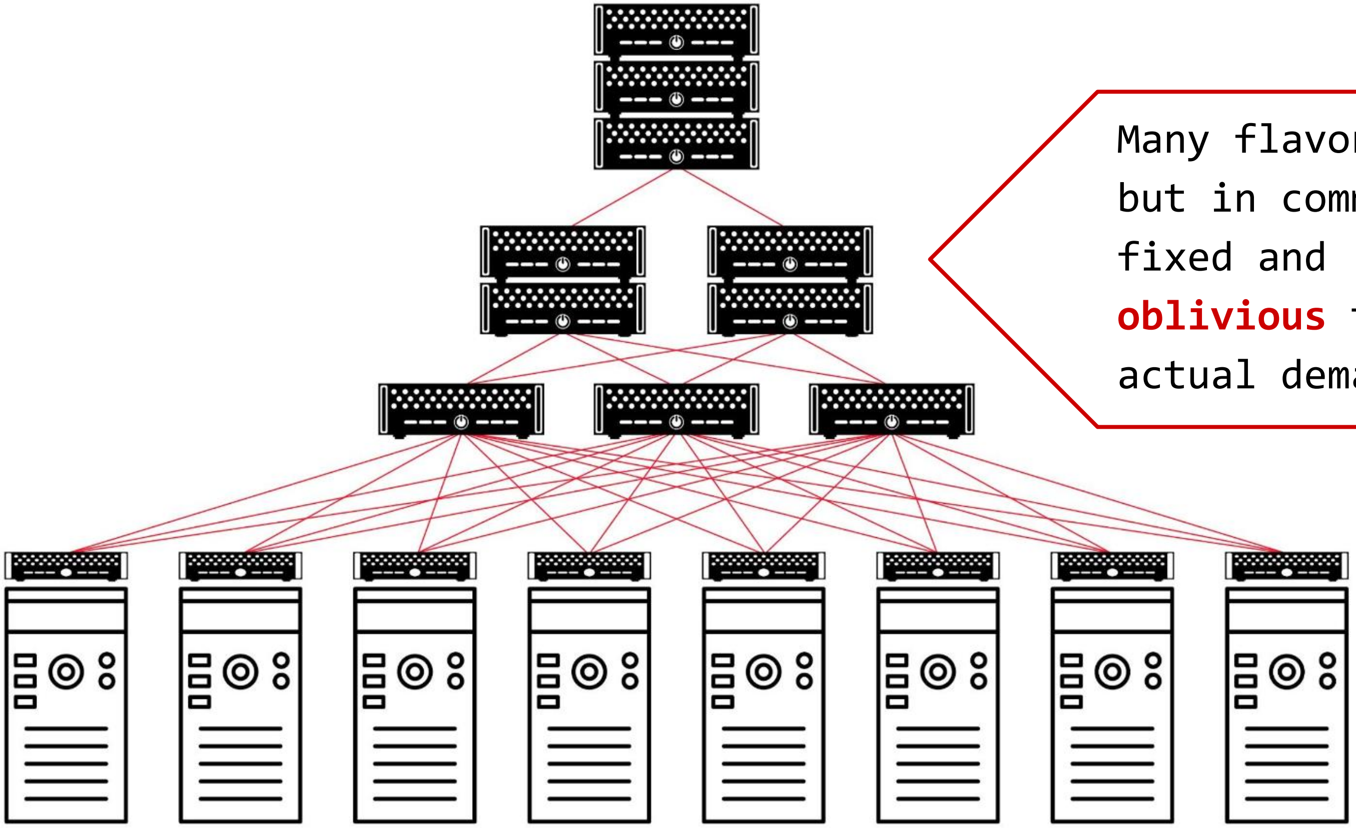

Many flavors,
but in common:
fixed and
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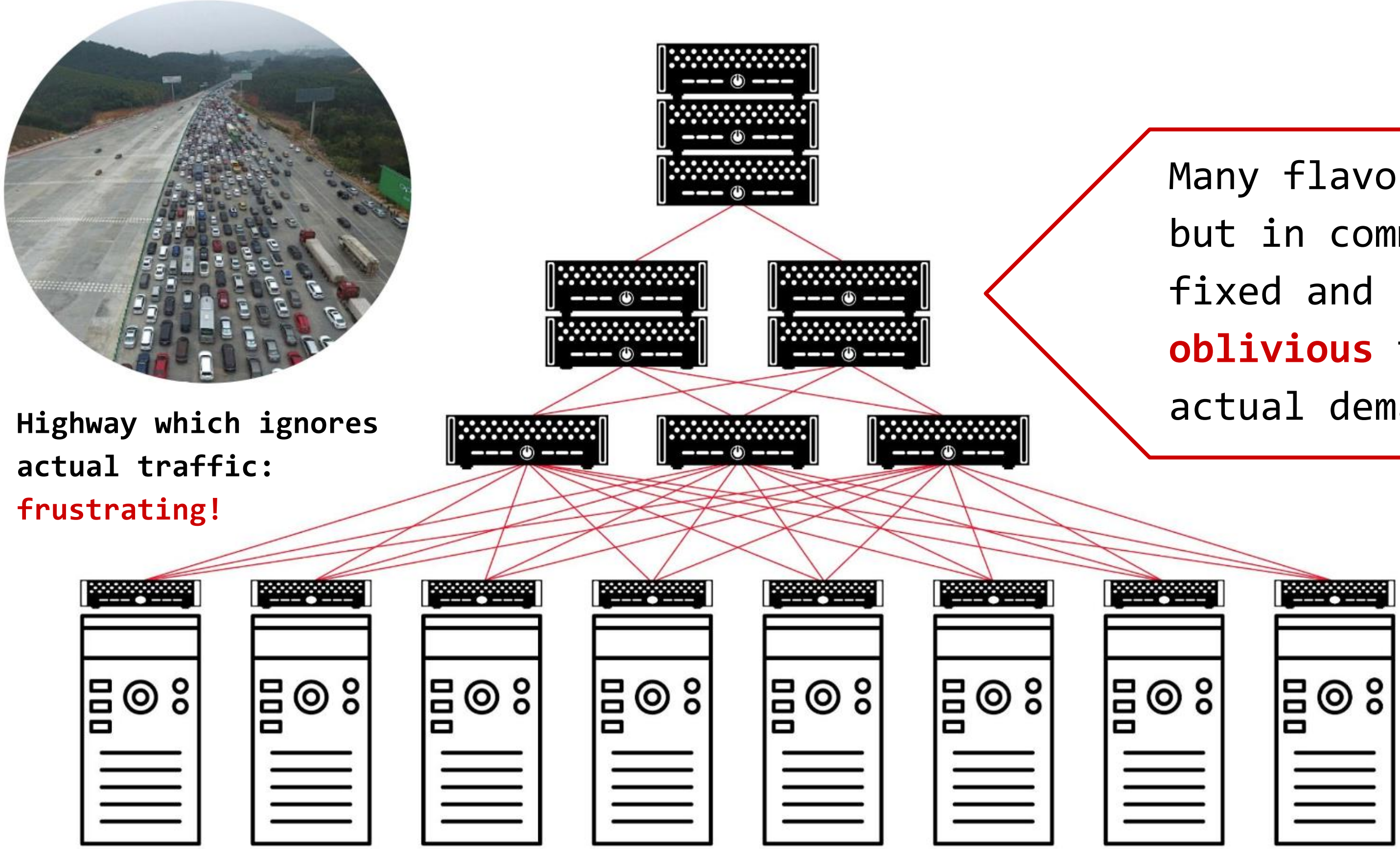
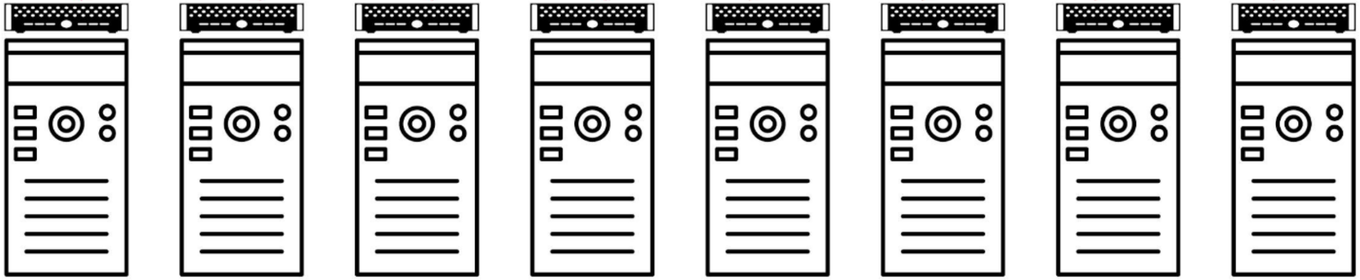


Highway which ignores actual traffic: frustrating!

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

A Vision

Flexible and Demand-Aware Topologies



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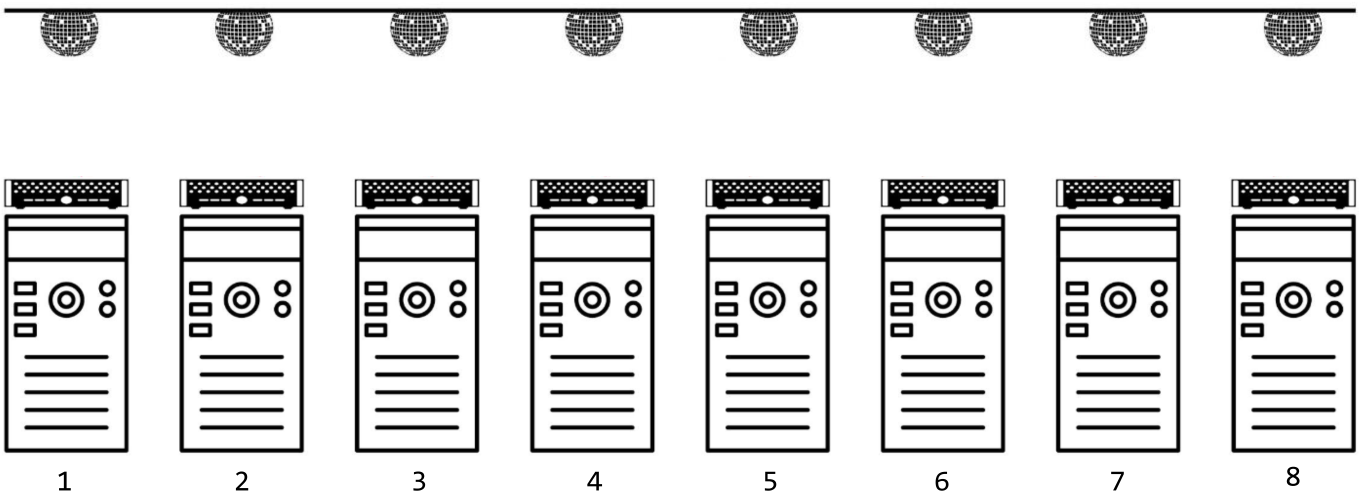
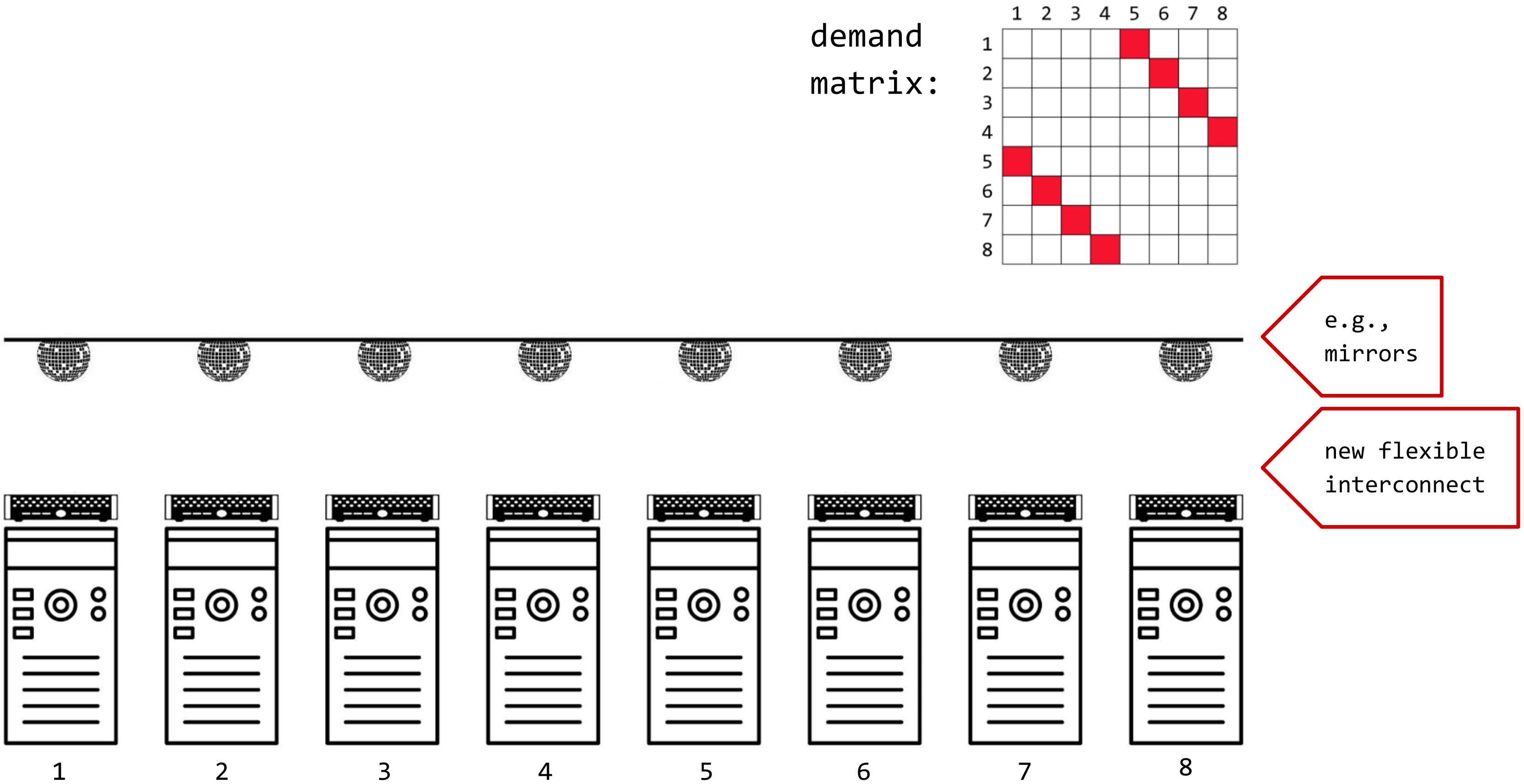


e.g., mirrors

new flexible interconnect

A Vision

Flexible and Demand-Aware Topologies



demand matrix:

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

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Flexible and Demand-Aware Topologies

Matches demand

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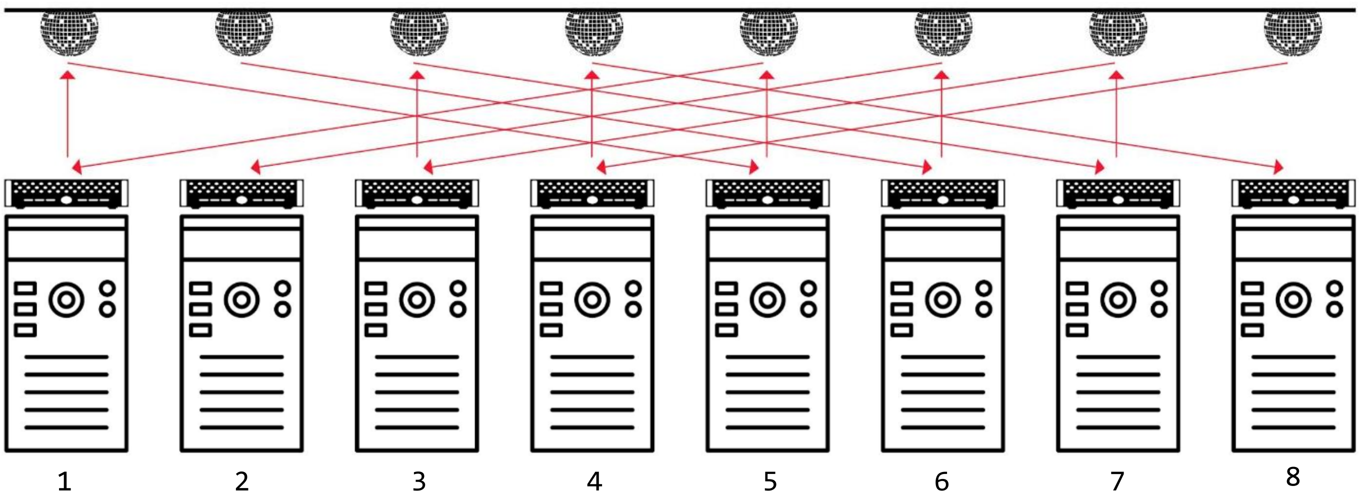

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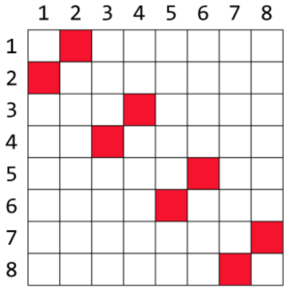
Flexible and Demand-Aware Topologies

new demand:



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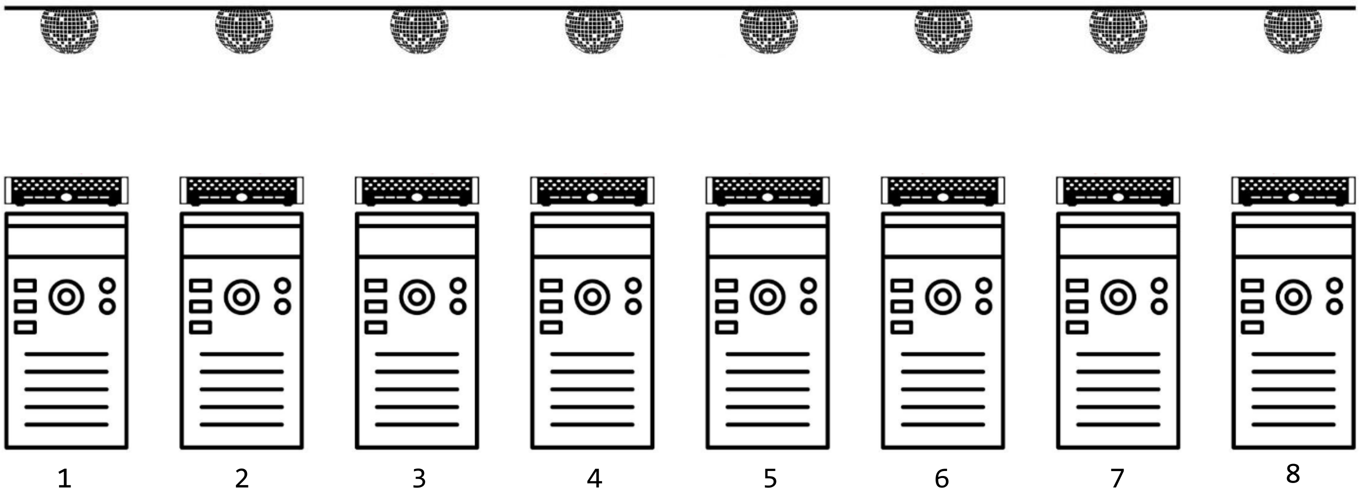

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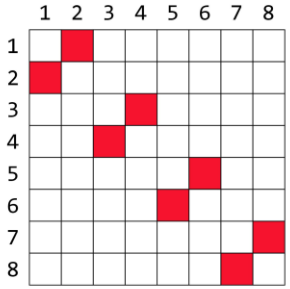

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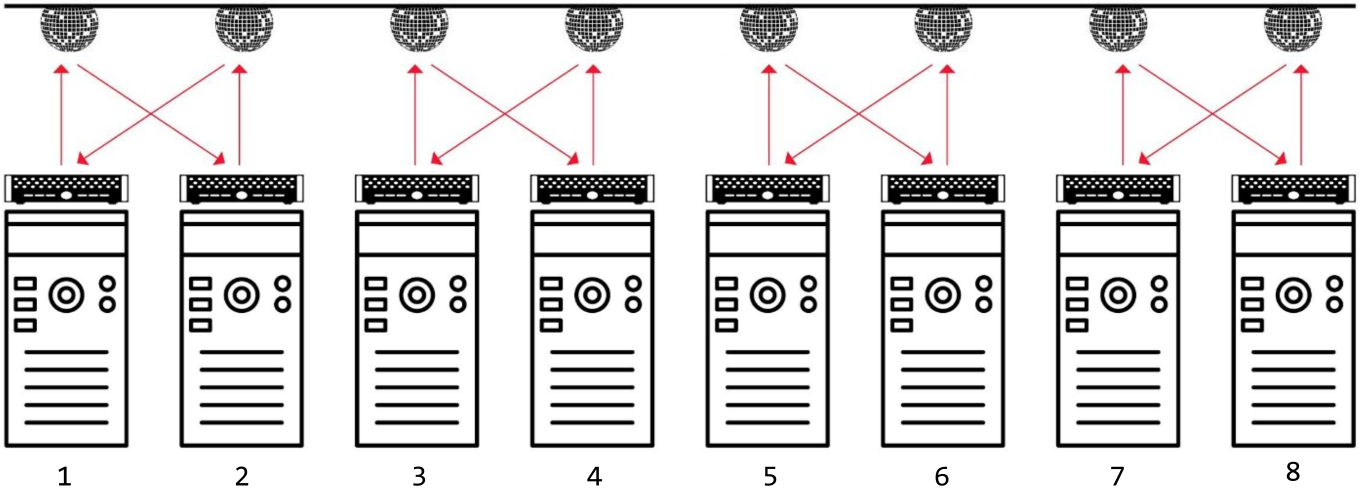

e.g., mirrors

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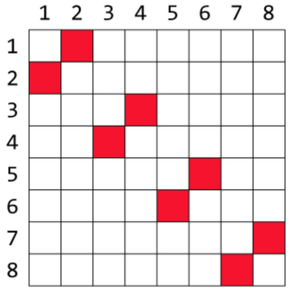
A Vision

Flexible and Demand-Aware Topologies

Self-Adjusting Networks

new demand:



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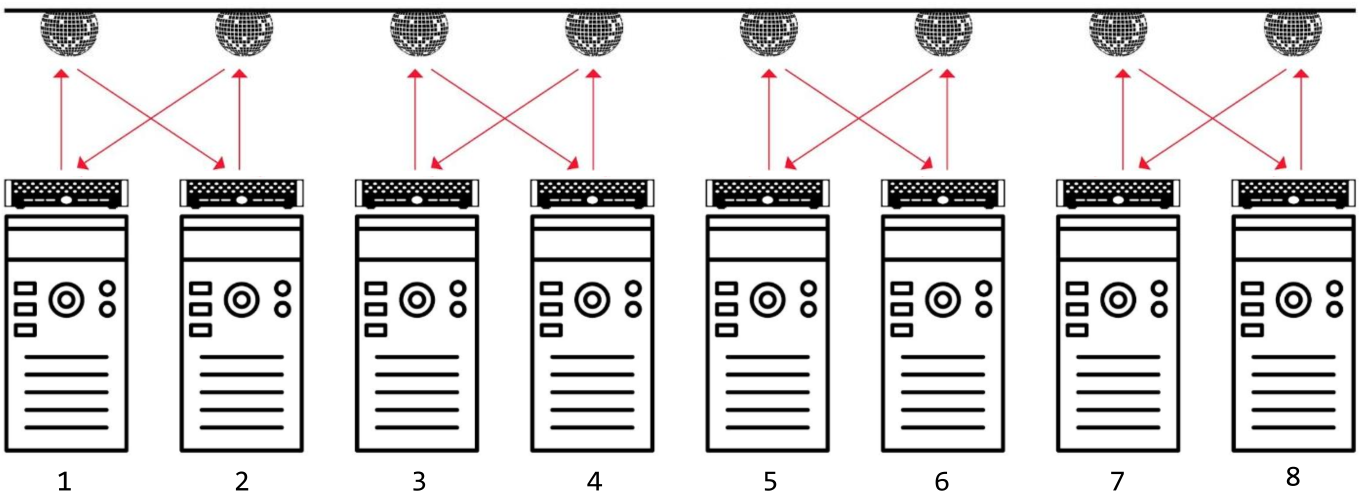


e.g., mirrors

new flexible interconnect

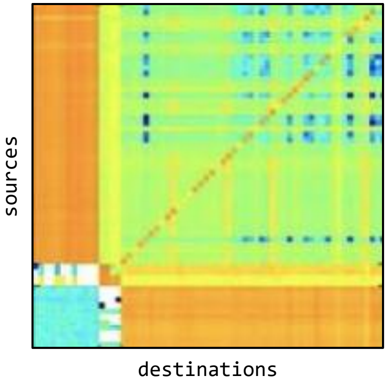
The Motivation

Much Structure in the Demand

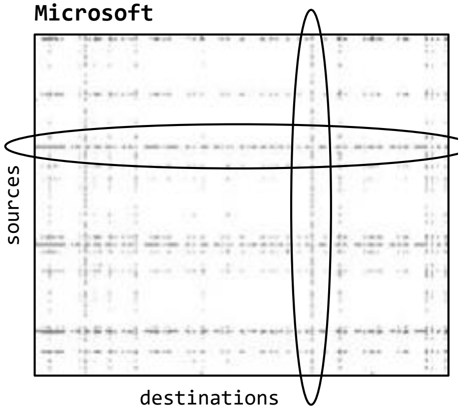
Empirical studies:

traffic matrices sparse and skewed

Facebook

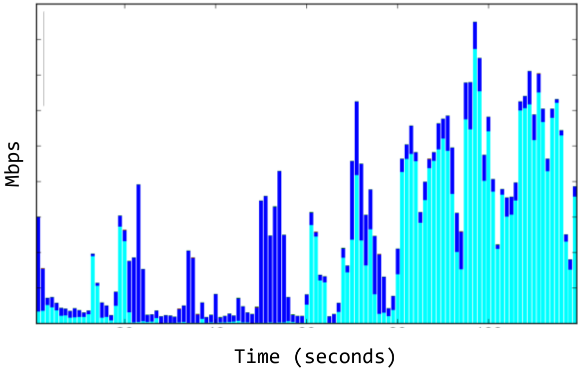


Microsoft



traffic bursty over time

Facebook



The hypothesis: can be exploited.

Recent Representation of Trace Structure:

Complexity Map

● DB

● Web

● Had

● ML

● CNS

● Multi Grid

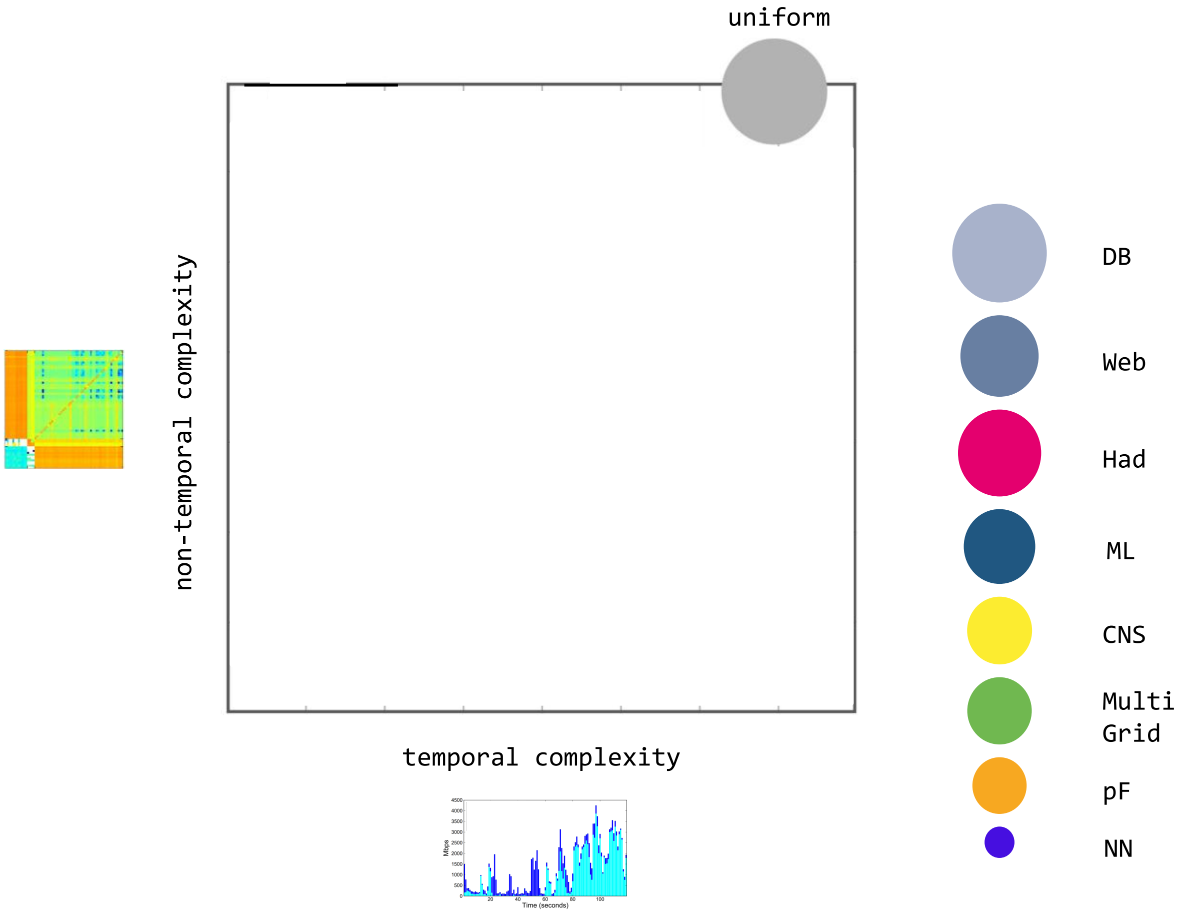
● pF

● NN

Griner et al., SIGMETRICS 2020

Recent Representation of Trace Structure:

Complexity Map



Griner et al., SIGMETRICS 2020

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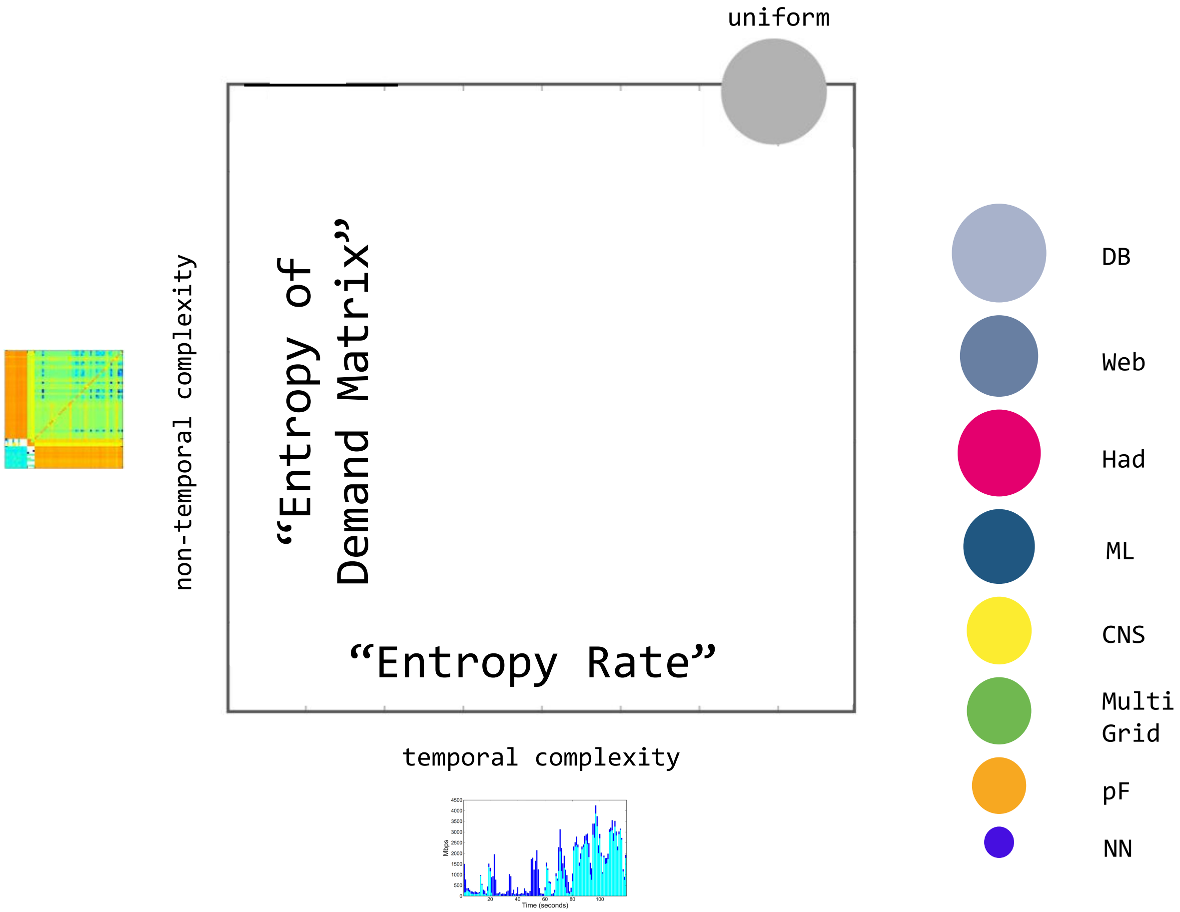

Griner et al., SIGMETRICS 2020

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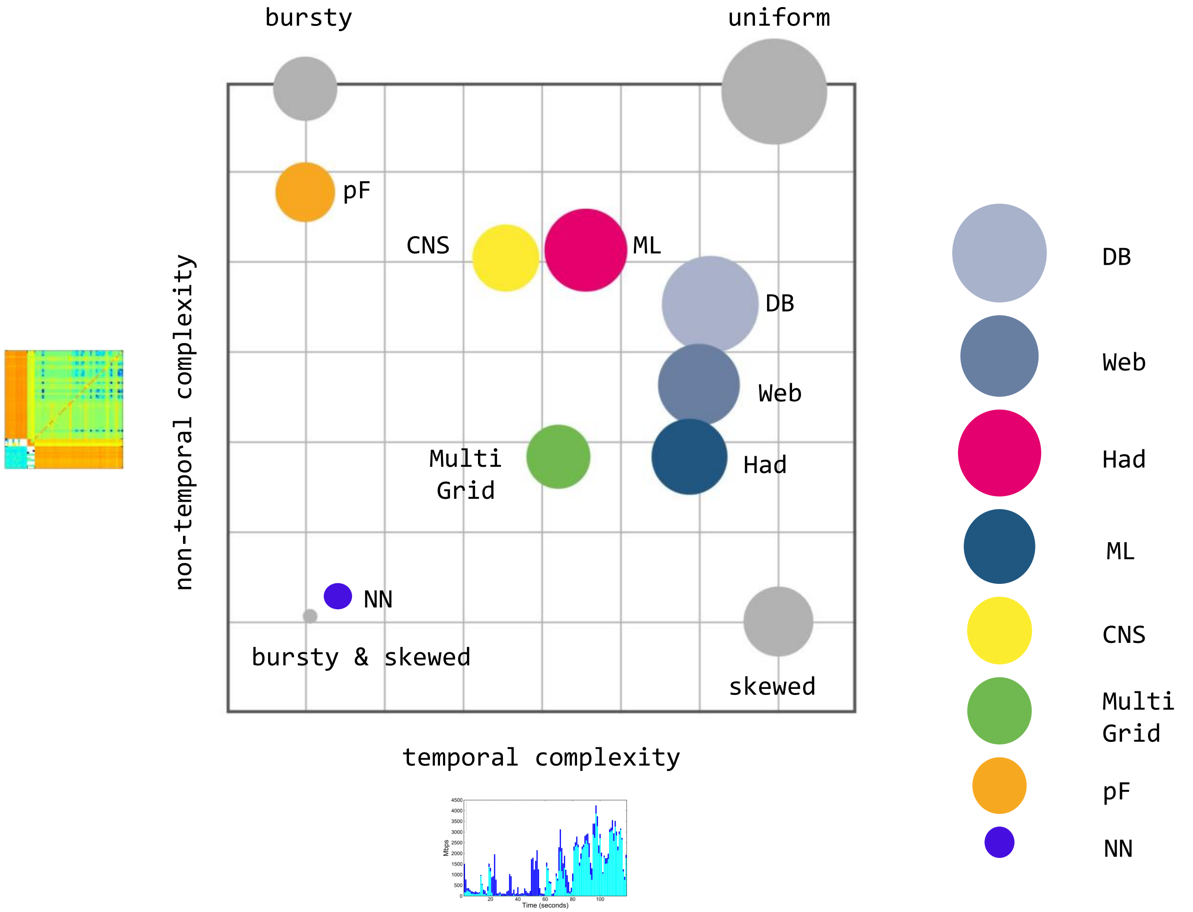
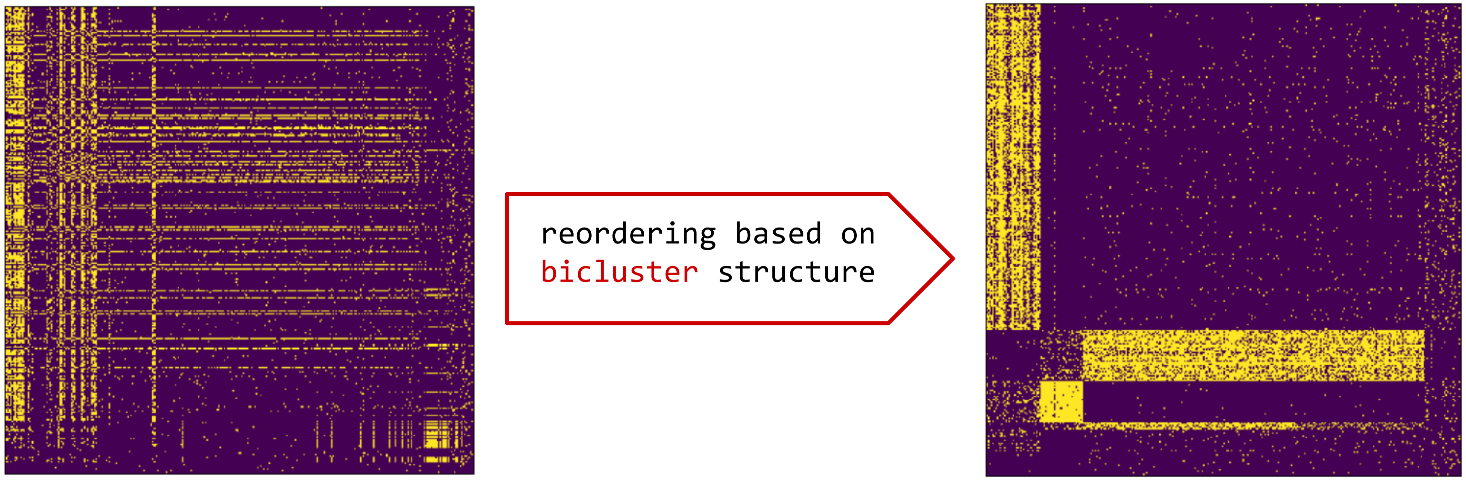


Different structures!

Griner et al., SIGMETRICS 2020

Traffic is also clustered:

Small Stable Clusters

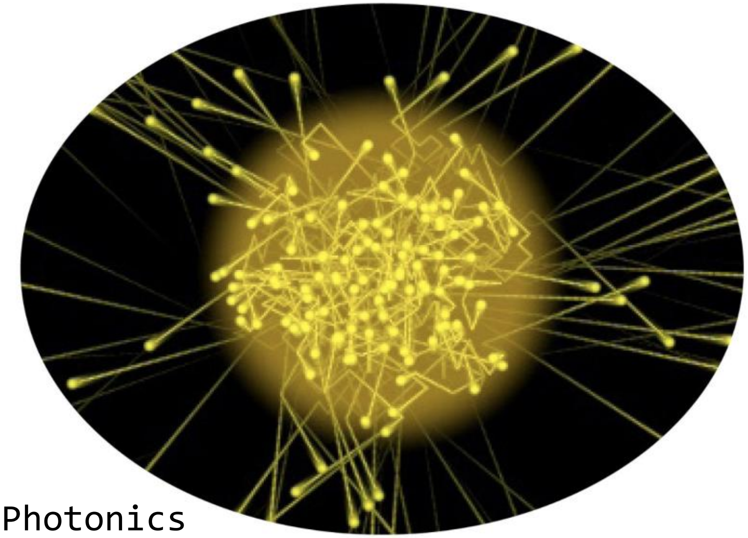


reordering based on
bicluster structure

Opportunity: *exploit* with little reconfigurations!

Förster et al., Analyzing the Communication Clusters
in Datacenters. WWW 2023

Sounds Crazy?
Emerging Enabling Technology.



Photonics

H2020:

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

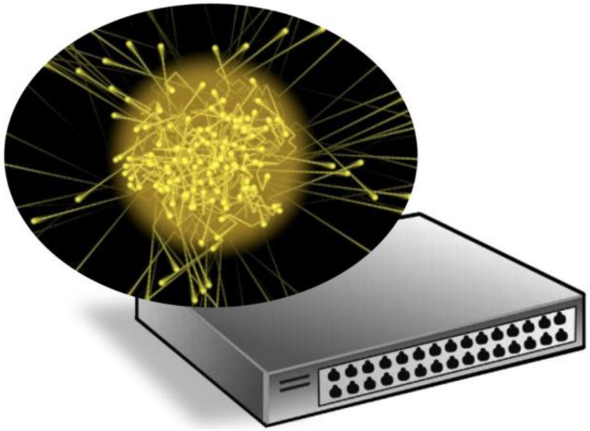
US National Research Council:

“Photons are the new Electrons.”

Enabler

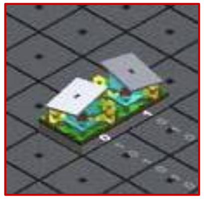
Novel Reconfigurable Optical Switches

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



Prototype 1

Moving antenna (ms)



Prototype 2

Moving mirrors (mus)

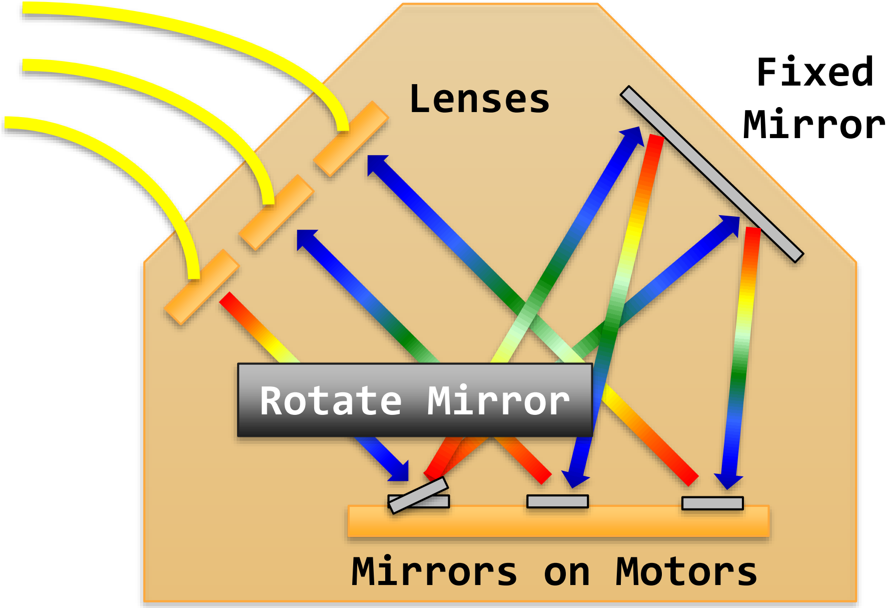
Prototype 3

Changing lambdas (ns)

Example

Optical Circuit Switch

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



Optical Circuit Switch

By Nathan Farrington, SIGCOMM 2010

First Deployments

E.g., Google

Systems

Jupiter evolving: Reflecting on Google's data center network transformation

August 24, 2022

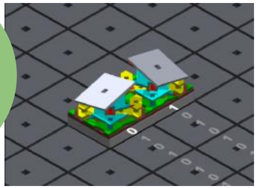
Amin Vahdat

VP & GM, Systems and Services Infrastructure

The Big Picture

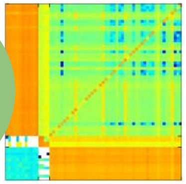
New!

Flexibility



More!

Structure



Self-Adjusting Networks

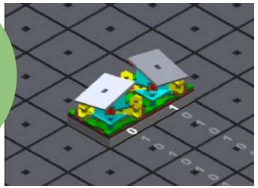
Efficiency

Now is the time!

The Big Picture

Flexibility

New!



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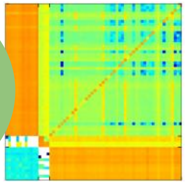


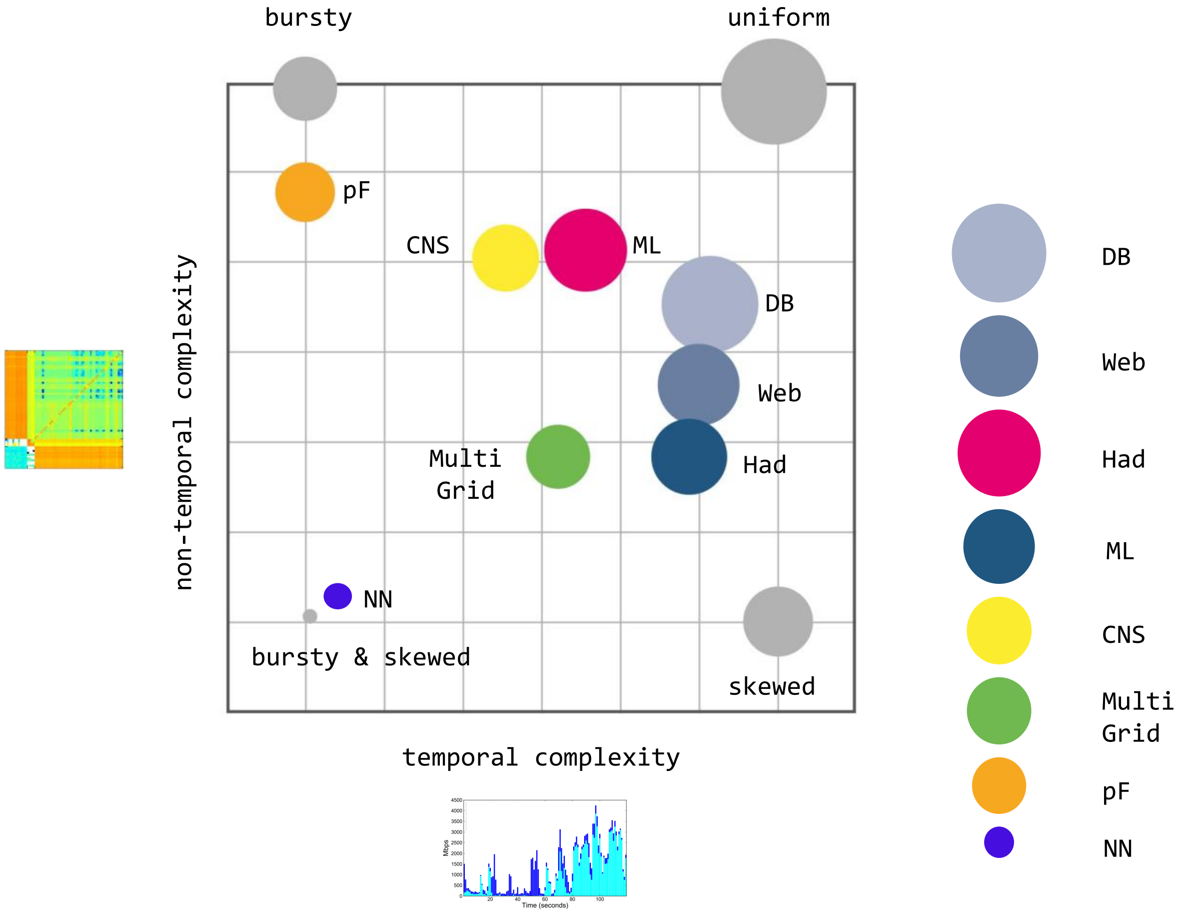
Self-Adjusting Networks

Efficiency

Now is the time!

Missing: Theoretical **foundations** of demand-aware, self-adjusting networks.

Potential Gain



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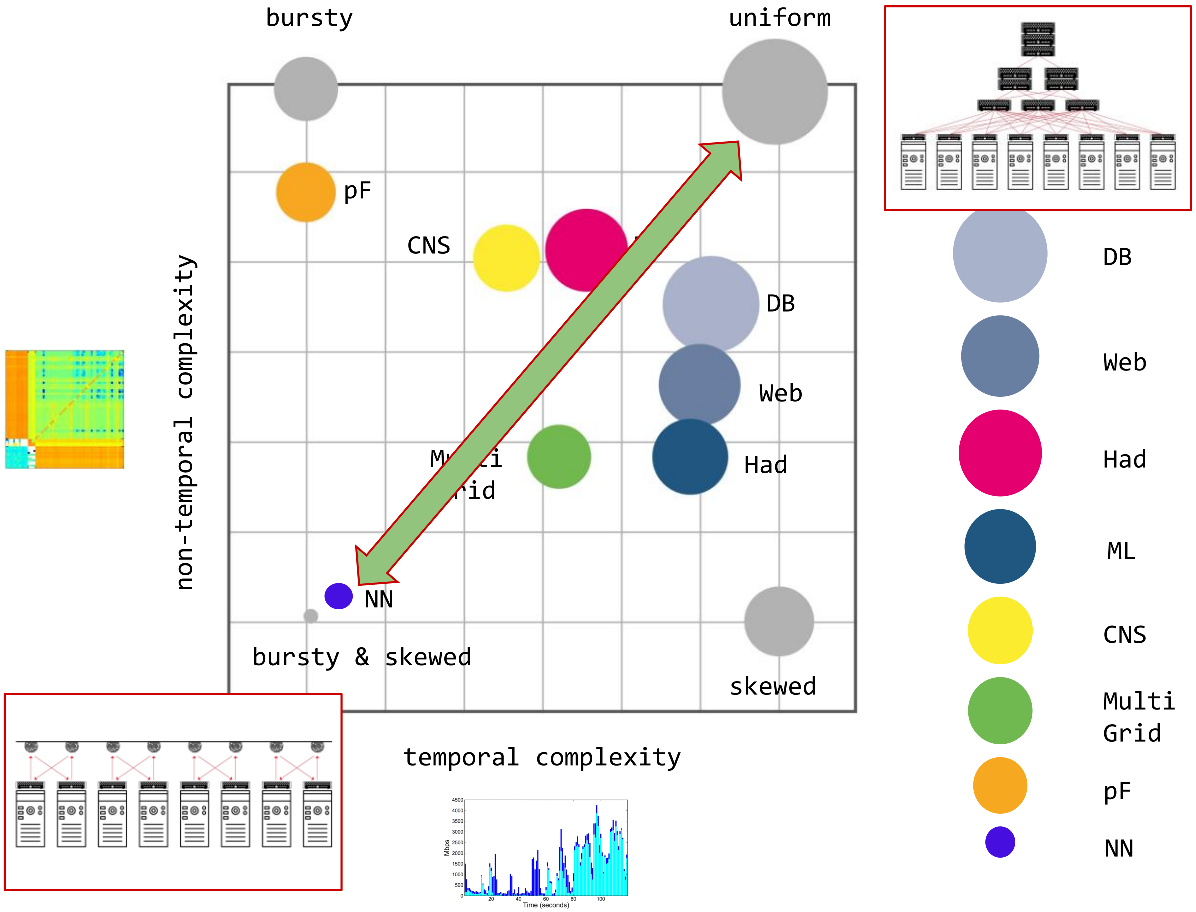


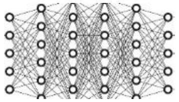
Unique Position

Demand-Aware, Self-Adjusting Systems

Everywhere, but mainly in software

Algorithmic trading

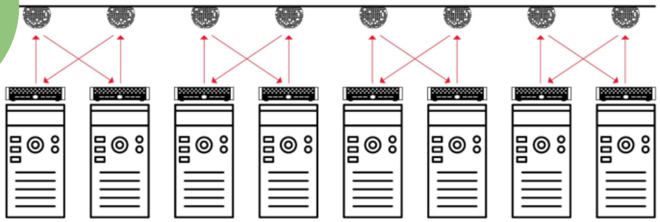
Recommender systems



Neural networks

VS

Our focus in this talk: in hardware



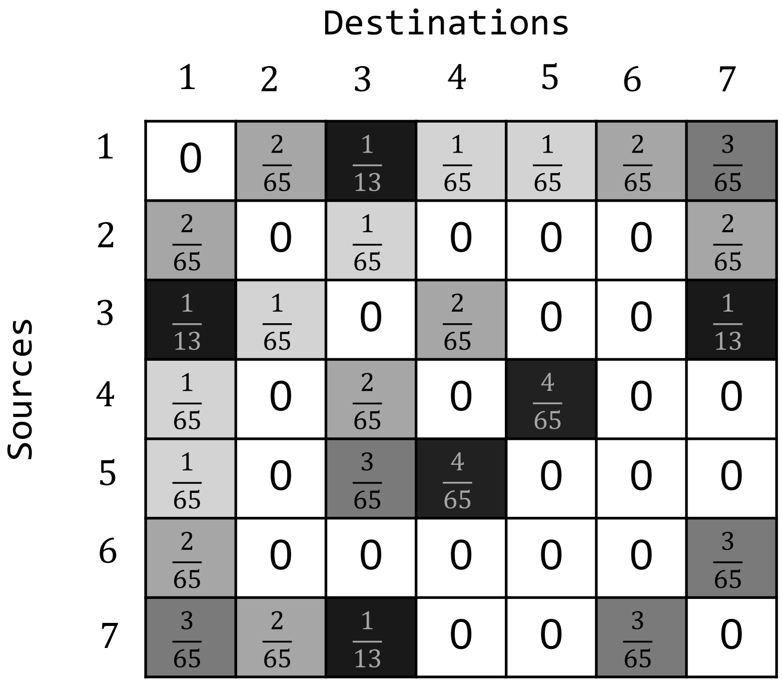
The Natural Question:

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

A first insight: entropy of the demand.

Case Study “Route Lengths”

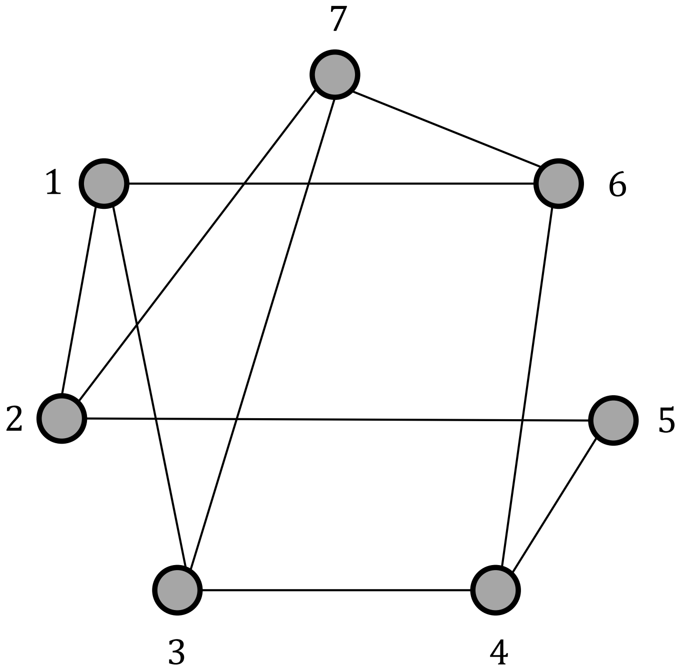
Constant-Degree Demand-Aware Network (DAN)



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



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

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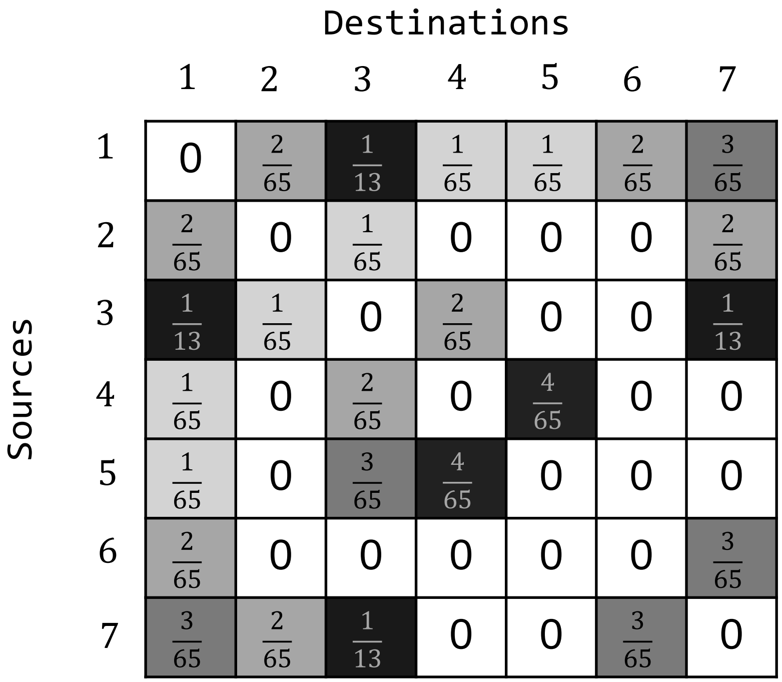

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3	$\frac{1}{13}$	$\frac{1}{65}$	0	$\frac{2}{65}$	0	0	$\frac{1}{13}$
4	$\frac{1}{65}$	0	$\frac{2}{65}$	0	$\frac{4}{65}$	0	0
5	$\frac{1}{65}$	0	$\frac{3}{65}$	$\frac{4}{65}$	0	0	0
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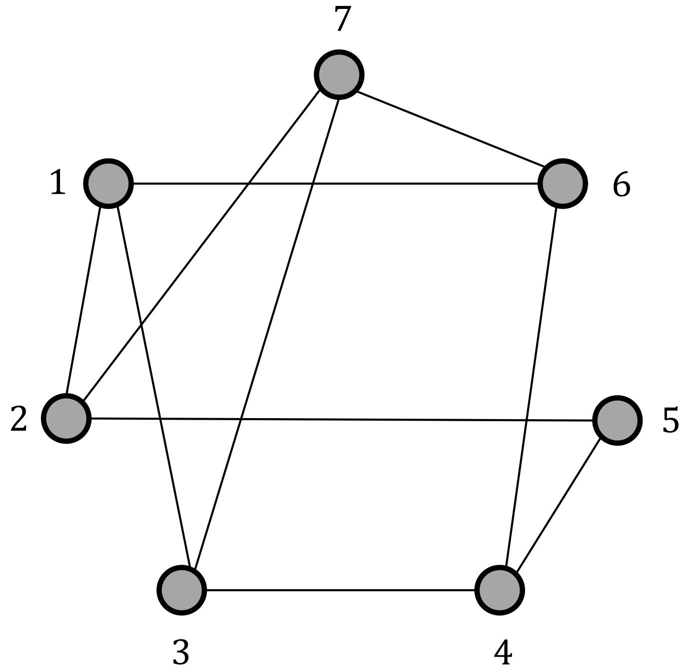

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Expected Route Length

Demand

DAN

Case Study “Route Lengths”

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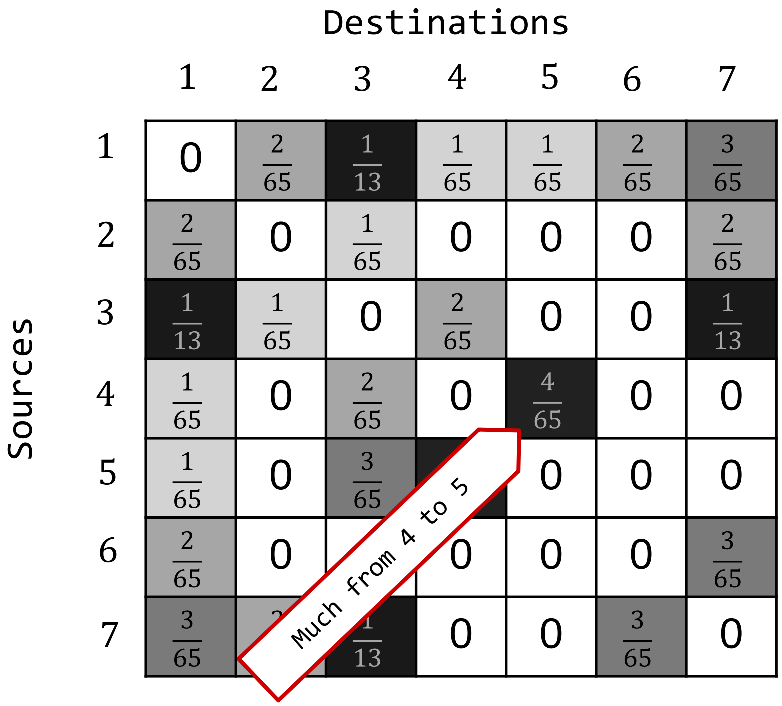

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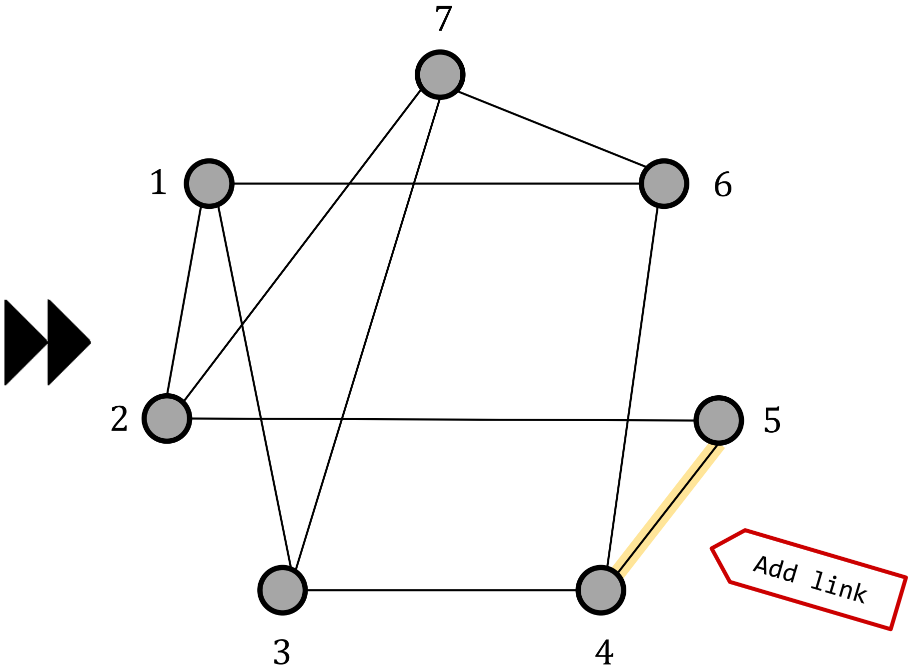
5	$\frac{1}{65}$	0	$\frac{3}{65}$	[illegible]	0	0	0
6	$\frac{2}{65}$	0	[illegible]	0	0	0	$\frac{3}{65}$
7	$\frac{3}{65}$	[illegible]	$\frac{1}{13}$	0	0	$\frac{3}{65}$	0

Much from 4 to 5



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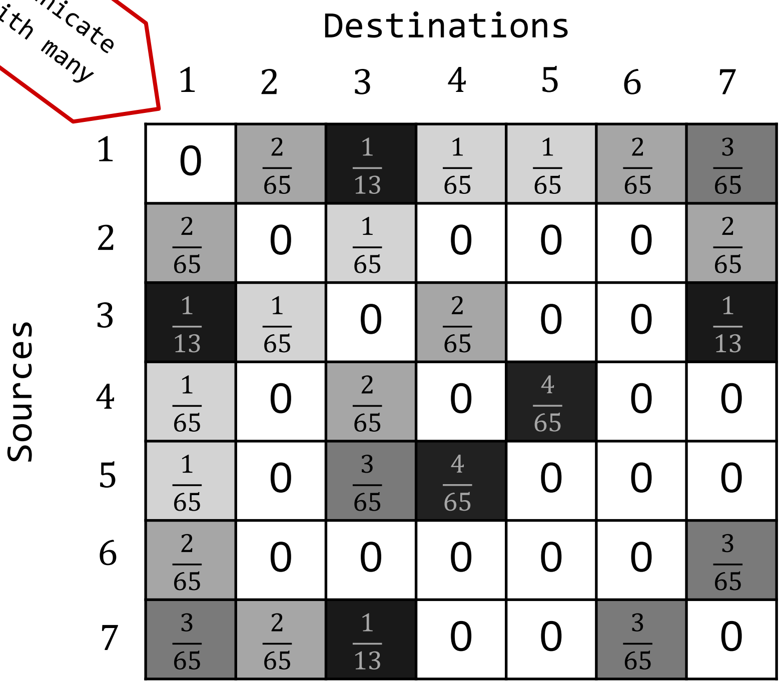
Case Study “Route Lengths”

Constant-Degree Demand-Aware Network (DAN)

Communicated with many



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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	$\frac{3}{65}$
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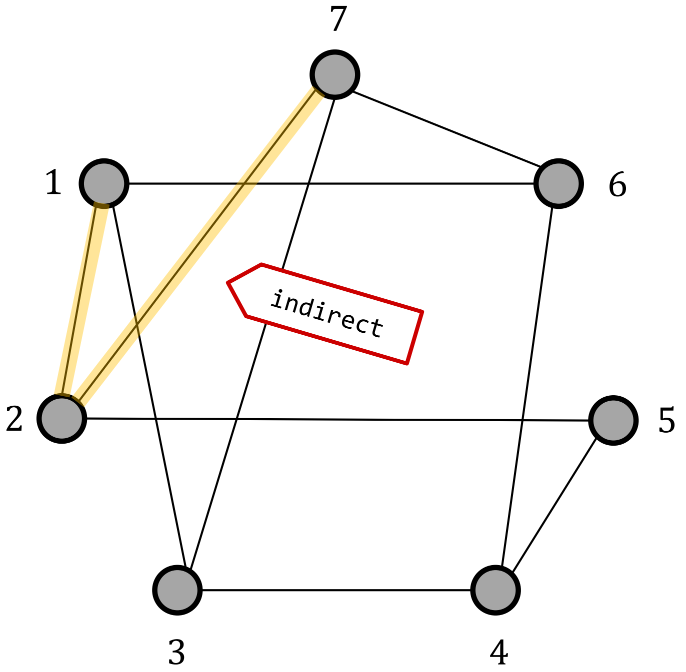

indirect

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

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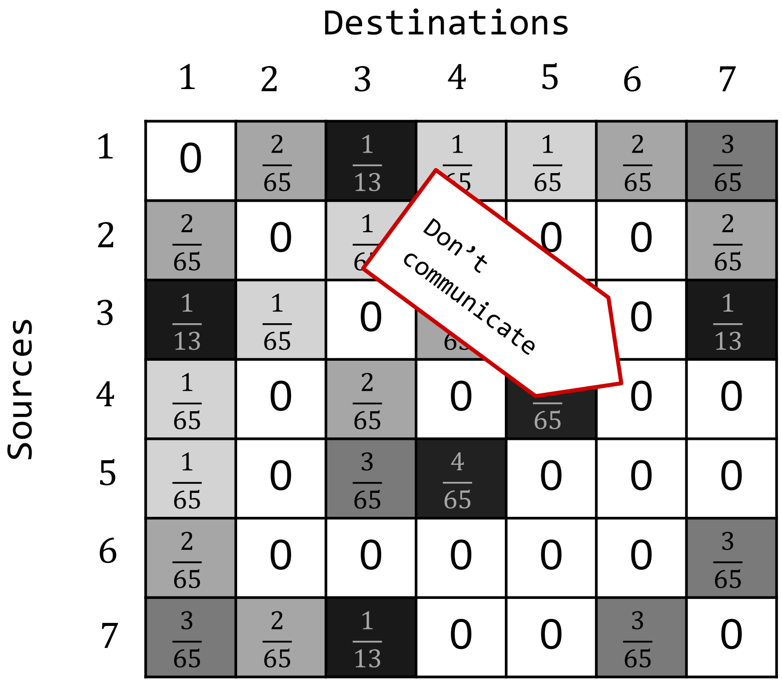

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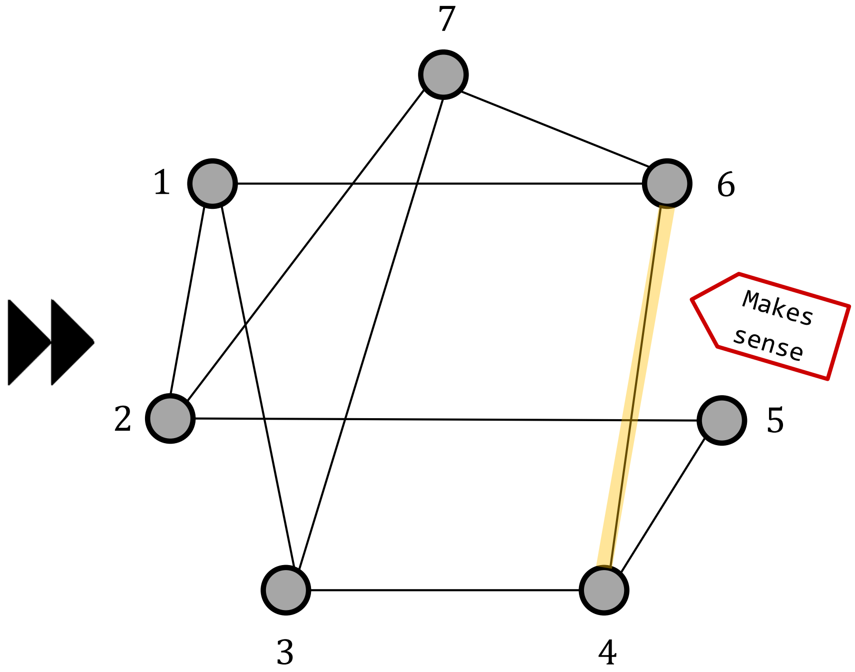
2	$\frac{2}{65}$	0	[illegible]	[illegible]	0	0	$\frac{2}{65}$
3	$\frac{1}{13}$	$\frac{1}{65}$	0	[illegible]	[illegible]	0	$\frac{1}{13}$
4	$\frac{1}{65}$	0	$\frac{2}{65}$	0	[illegible]	0	0
5	$\frac{1}{65}$	0	$\frac{3}{65}$	$\frac{4}{65}$	0	0	0
6	$\frac{2}{65}$	0	0	0	0	0	$\frac{3}{65}$
7	$\frac{3}{65}$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

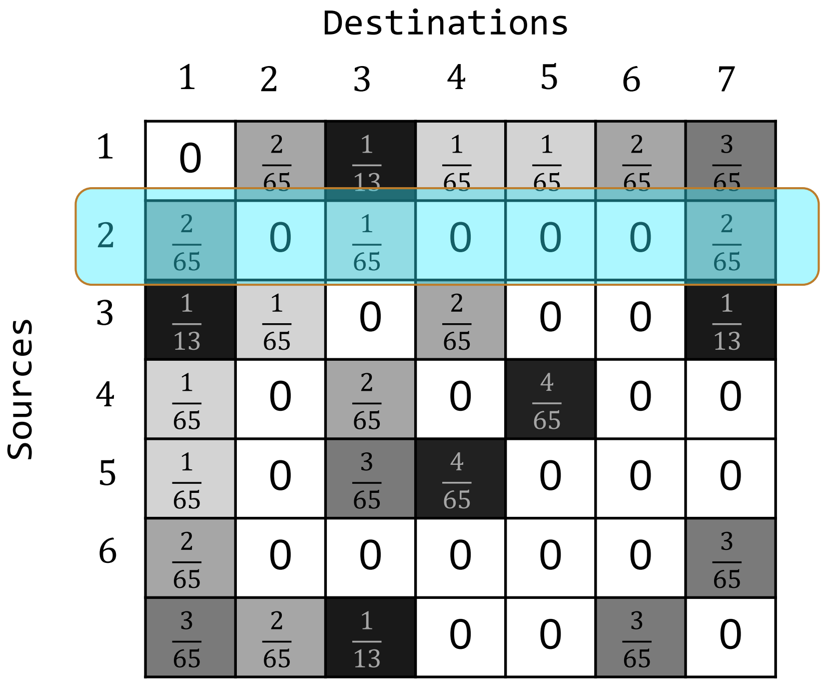
Don’t communicate



Makes sense

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

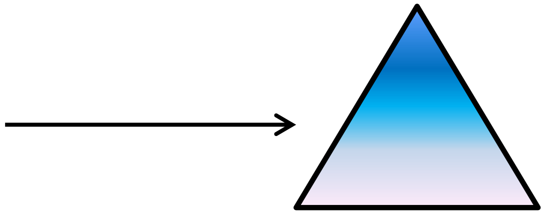
Algorithm: Idea



Destinations

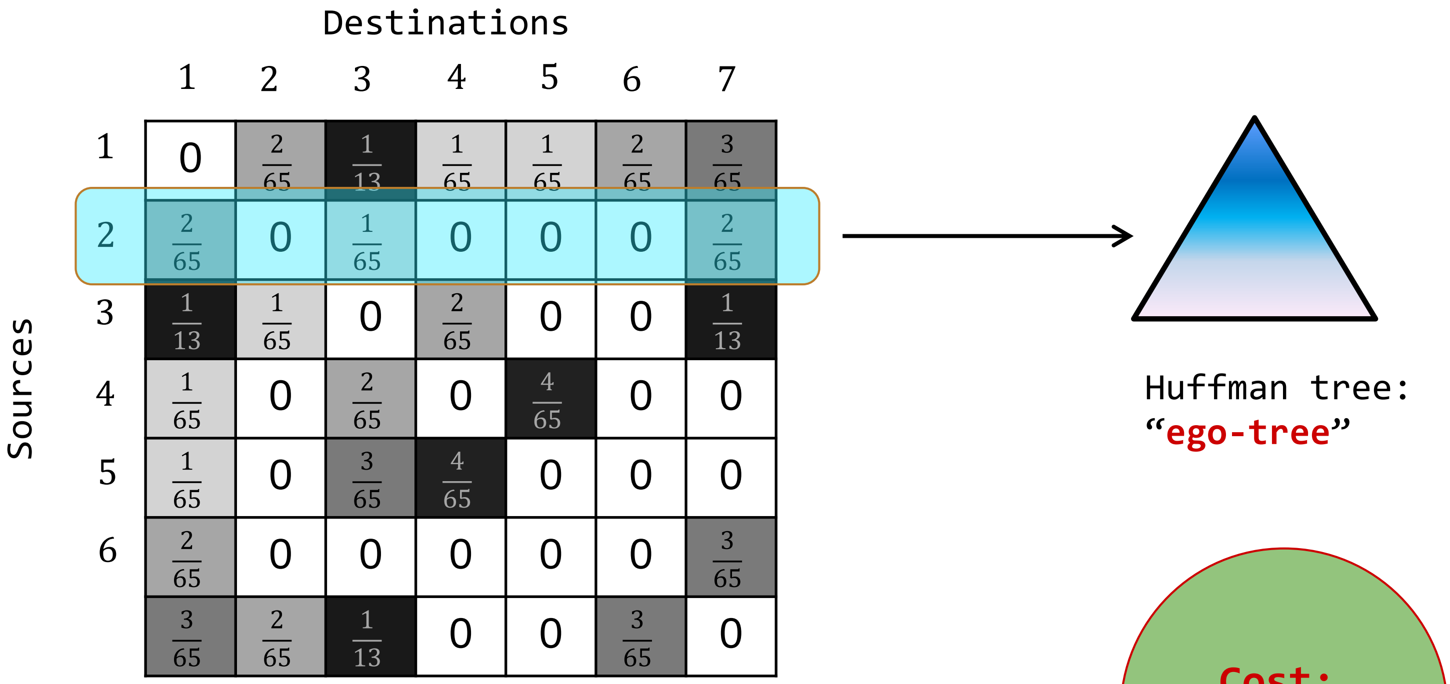
Sources

	1	2	3	4	5	6	7
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**”

Algorithm: Idea



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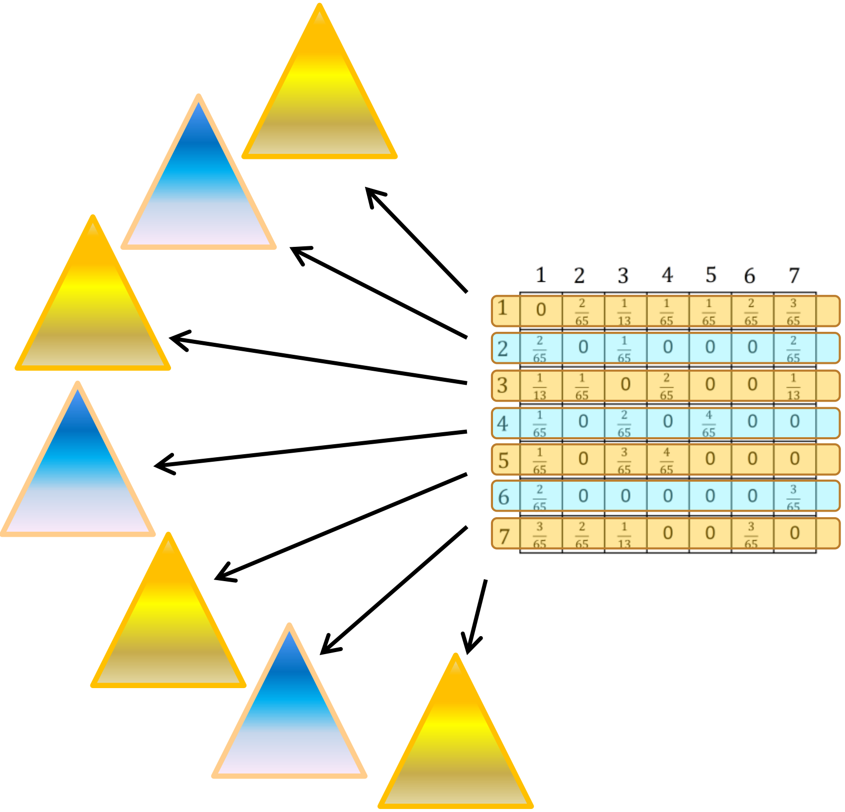
2	$\frac{2}{65}$	0	$\frac{1}{65}$	0	0	0	$\frac{2}{65}$
3	$\frac{1}{13}$	$\frac{1}{65}$	0	$\frac{2}{65}$	0	0	$\frac{1}{13}$
4	$\frac{1}{65}$	0	$\frac{2}{65}$	0	$\frac{4}{65}$	0	0
5	$\frac{1}{65}$	0	$\frac{3}{65}$	$\frac{4}{65}$	0	0	0
6	$\frac{2}{65}$	0	0	0	0	0	$\frac{3}{65}$
	$\frac{3}{65}$	$\frac{2}{65}$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

Huffman tree:
“**ego-tree**”

Cost:
Entropy!

Entropy Upper Bound

- Idea for algorithm:
  - Union of trees
  - Reduce degree
  - But keep distances

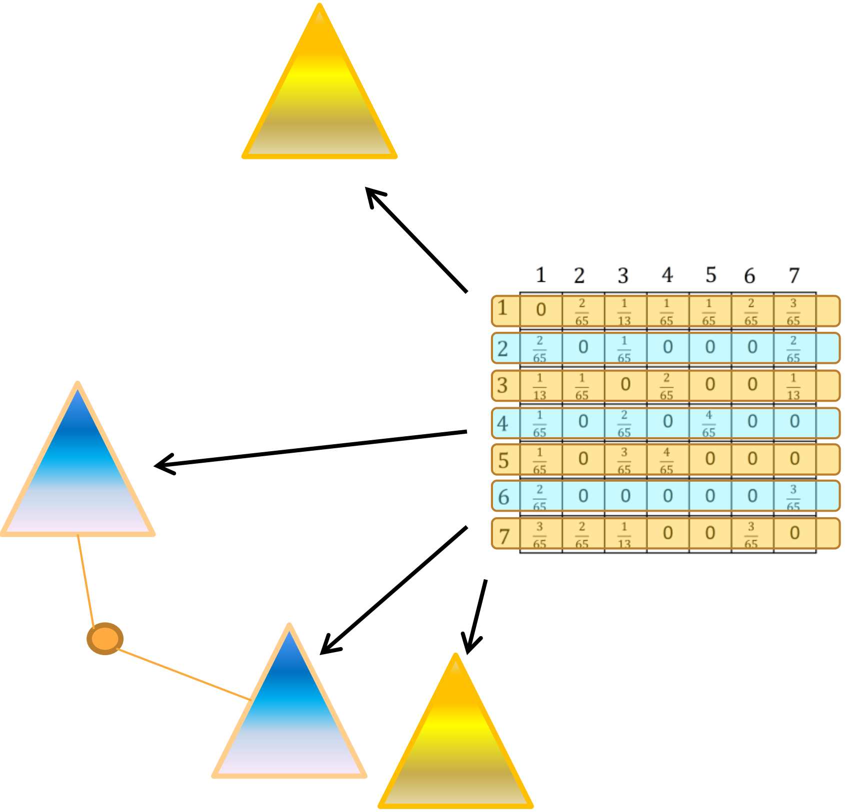


	1	2	3	4	5	6	7
1	0	$\frac{2}{65}$	$\frac{1}{13}$	$\frac{1}{65}$	$\frac{1}{65}$	$\frac{2}{65}$	$\frac{3}{65}$
2	$\frac{2}{65}$	0	$\frac{1}{65}$	0	0	0	$\frac{2}{65}$
3	$\frac{1}{13}$	$\frac{1}{65}$	0	$\frac{2}{65}$	0	0	$\frac{1}{13}$
4	$\frac{1}{65}$	0	$\frac{2}{65}$	0	$\frac{4}{65}$	0	0
5	$\frac{1}{65}$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

Entropy Upper Bound

- Idea for algorithm:
  - Union of trees
  - Reduce degree
  - But keep distances

- **For sparse demands**:
  - Make trees for high-degree nodes only
  - Use low-degree nodes as helpers to connect pairs of high-degree nodes



	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

Entropy Upper Bound

- Idea for algorithm:
  - Union of trees
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  - But keep distances
- **For sparse demands**:
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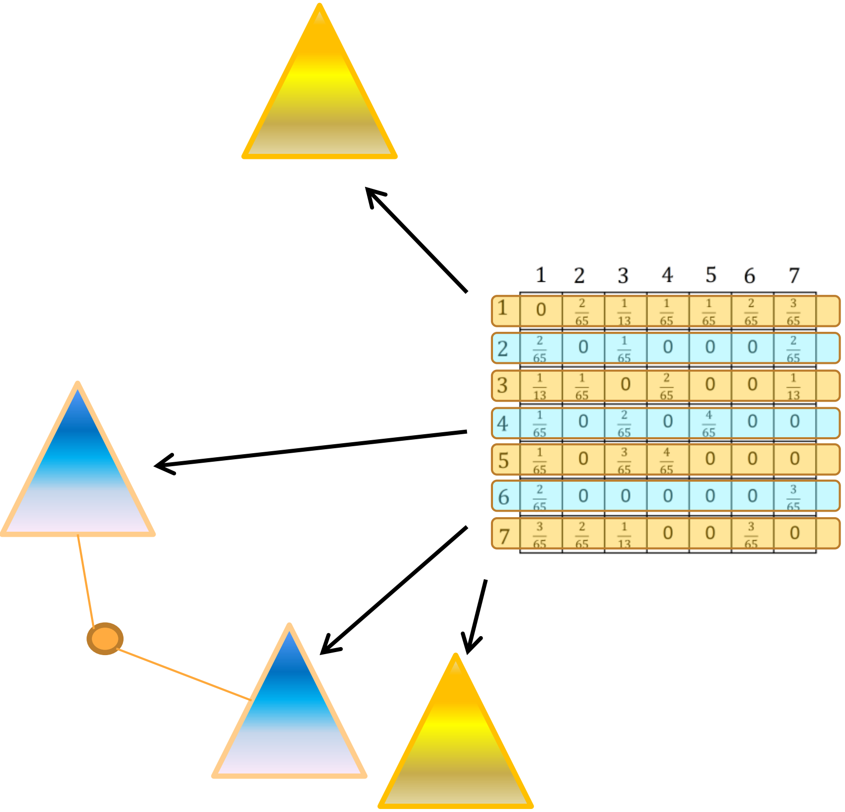
Dense?
Congestion?
Dynamic?
Distributed?

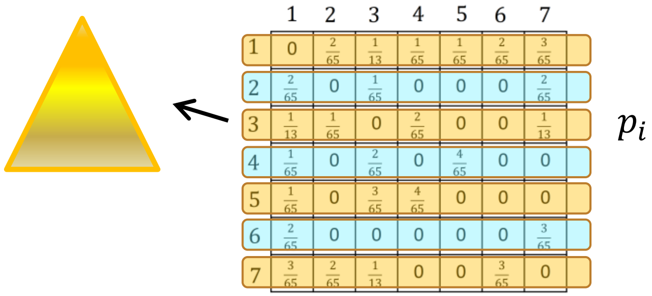


	1	2	3	4	5	6	7
1	0	$\frac{2}{65}$	$\frac{1}{13}$	$\frac{1}{65}$	$\frac{1}{65}$	$\frac{2}{65}$	$\frac{3}{65}$
2	$\frac{2}{65}$	0	$\frac{1}{65}$	0	0	0	$\frac{2}{65}$
3	$\frac{1}{13}$	$\frac{1}{65}$	0	$\frac{2}{65}$	0	0	$\frac{1}{13}$
4	$\frac{1}{65}$	0	$\frac{2}{65}$	0	$\frac{4}{65}$	0	0
5	$\frac{1}{65}$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

Optimality: Lower Bound

⇢ For each single row:

$$\mathrm{EPL}(p_i, T) + 1 \geq \frac{1}{\log(\Delta+1)} H_\Delta(p_i)$$



	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

Optimality: Lower Bound

- For each single row:

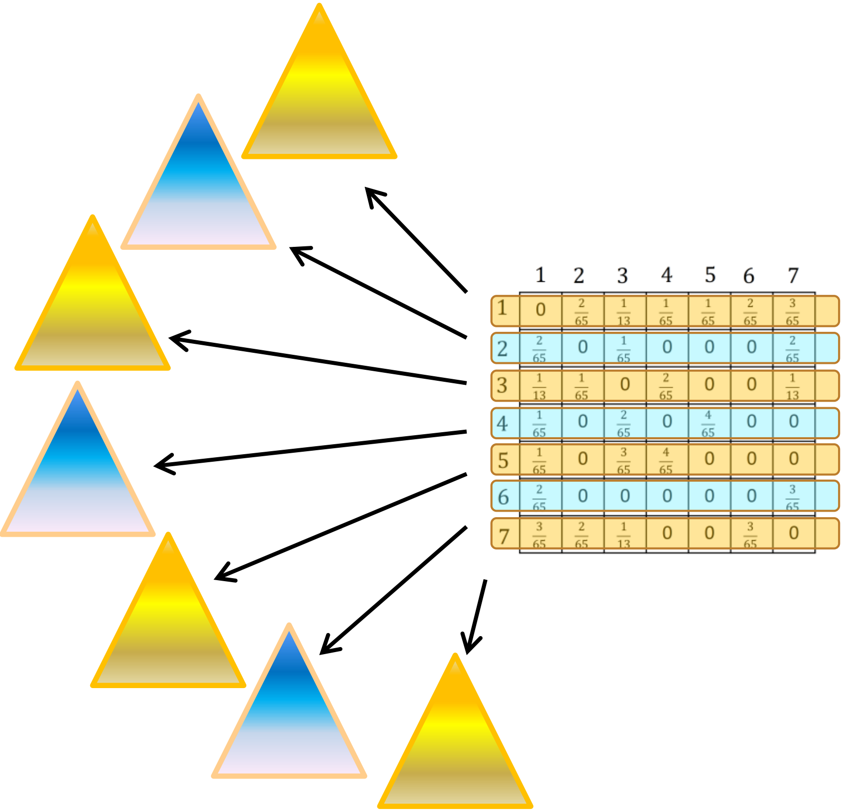
$$\text{EPL}(p_i, T) + 1 \geq \frac{1}{\log(\Delta+1)} H_\Delta(p_i)$$

- For all trees:

$$\geq \Omega(\max(H_\Delta(Y|X) + H_\Delta(X|Y)))$$

destinations

sources



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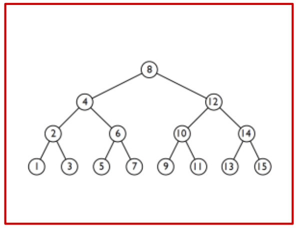
3	$\frac{1}{13}$	$\frac{1}{65}$	0	$\frac{2}{65}$	0	0	$\frac{1}{13}$
4	$\frac{1}{65}$	0	$\frac{2}{65}$	0	$\frac{4}{65}$	0	0
5	$\frac{1}{65}$	0	$\frac{3}{65}$	$\frac{4}{65}$	0	0	0
6	$\frac{2}{65}$	0	0	0	0	0	$\frac{3}{65}$
7	$\frac{3}{65}$	$\frac{2}{65}$	$\frac{1}{13}$	0	0	$\frac{3}{65}$	0

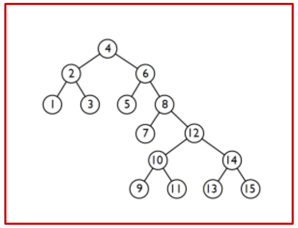
Insight:

Connection to Datastructures

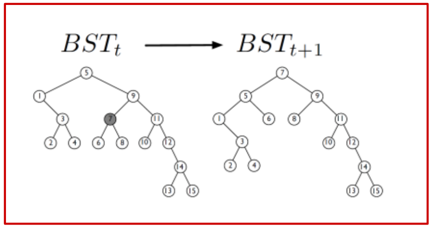
Traditional BST



Demand-aware BST



Self-adjusting BST

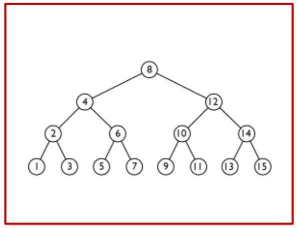


More structure: improved **access cost**

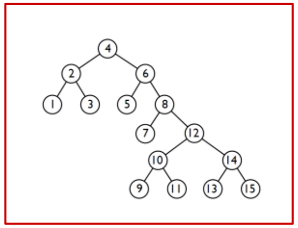
Insight:

Connection to Datastructures & Coding

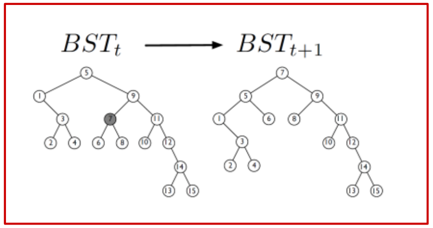
Traditional BST
(Worst-case coding)



Demand-aware BST
(Huffman coding)



Self-adjusting BST
(Dynamic Huffman coding)



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

Insight:

Connection to Datastructures & Coding

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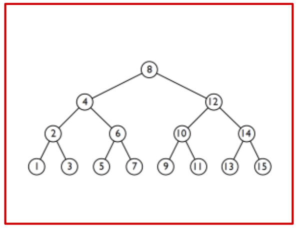

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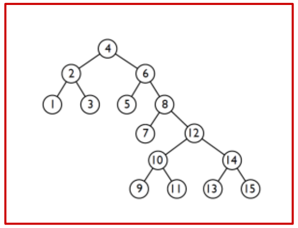

Self-adjusting BST
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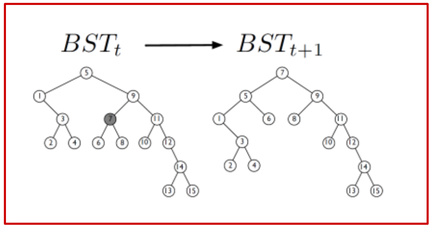

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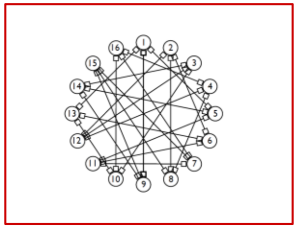

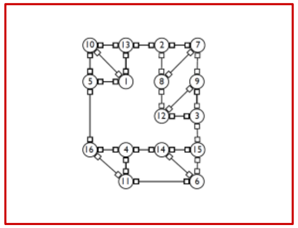

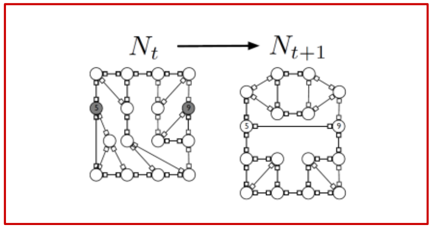

Similar **benefits**?

Insight:

Connection to Datastructures & Coding

Traditional BST
(Worst-case coding)

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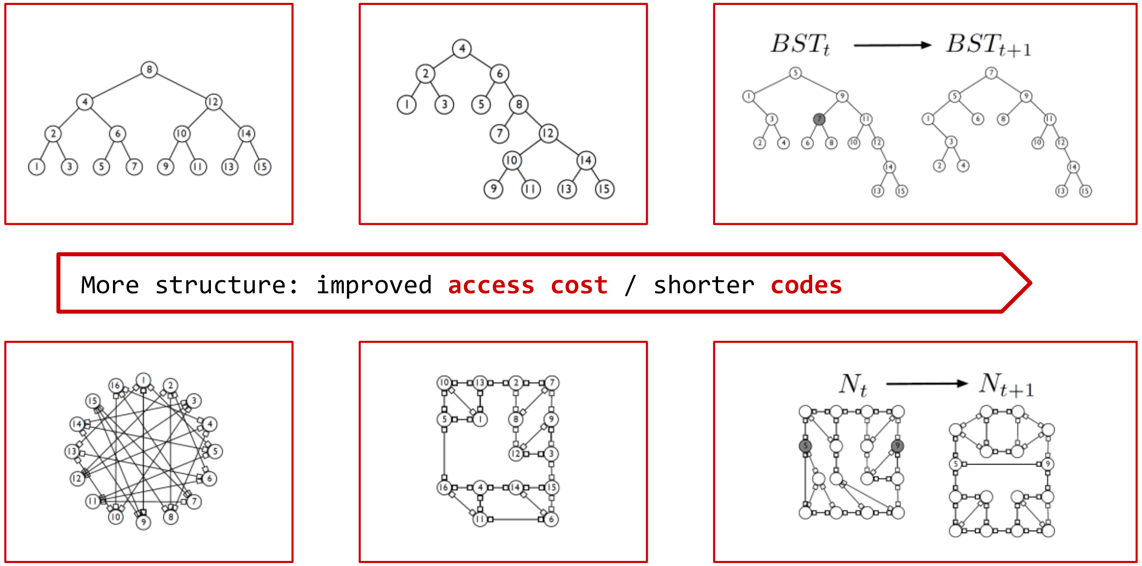
(Huffman coding)

Self-adjusting BST
(Dynamic Huffman coding)



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

Similar **benefits**?

More than
an analogy!

Insight:

Connection to Datastructures & Coding

Traditional BST
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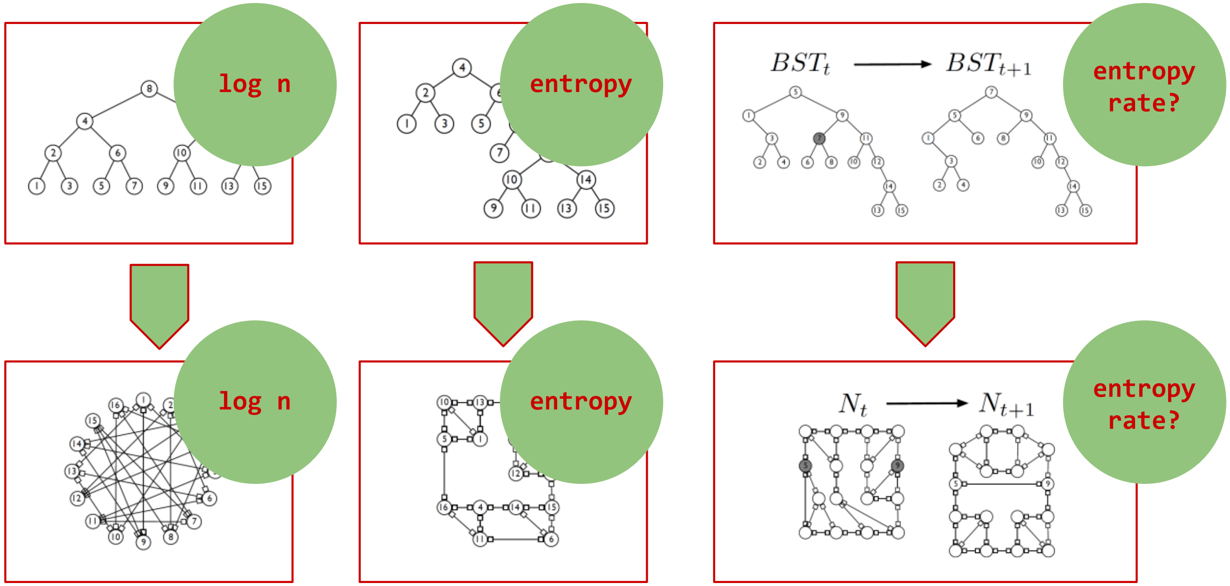


Reduced expected **route lengths**!

More than
an analogy!

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

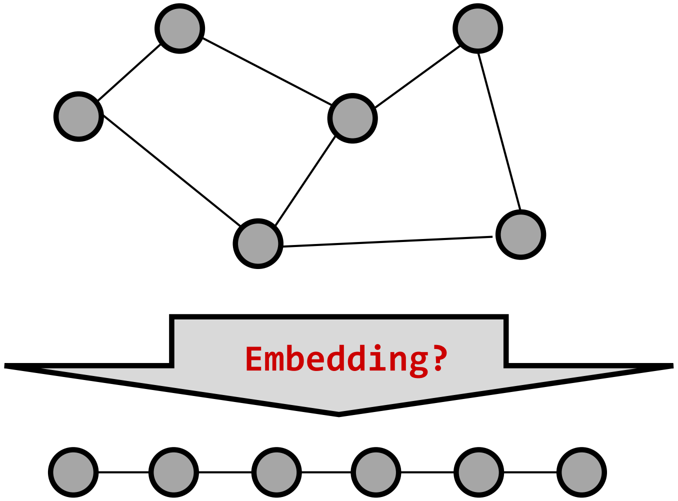
First result:
Demand-aware networks of asymptotically optimal route lengths.

Related Problem: Remember Bernardetta’s Talk

Virtual Network Embedding Problem (VNEP)

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

- ⇀ Minimizes sum of virtual edges



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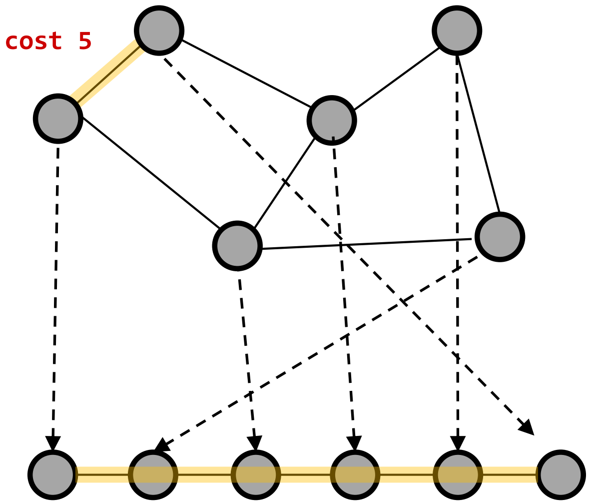

Bad!

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Virtual Network Embedding Problem (VNEP)

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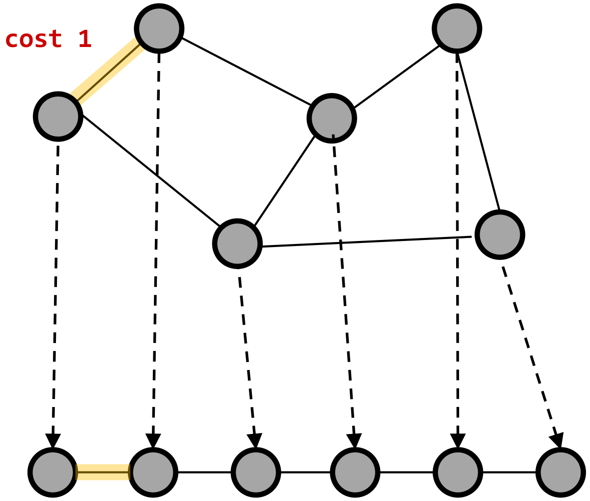

Good!

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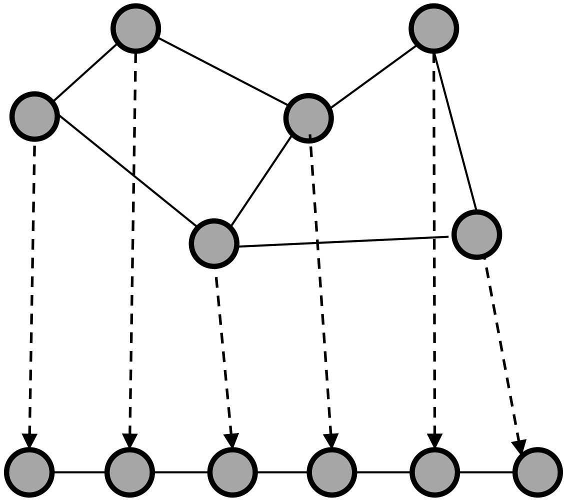
MLA is **NP-hard**

⇀ … and so is our problem!



Related Problem: Remember Bernardetta's Talk

Virtual Network Embedding Problem (VNEP)

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- ⇀ Minimizes sum of virtual edges

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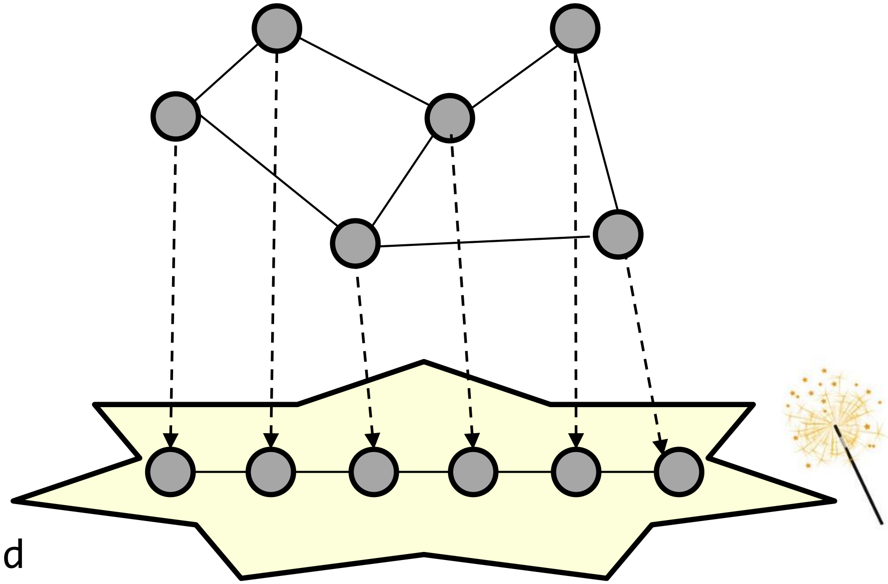
But what about **△>2**?

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



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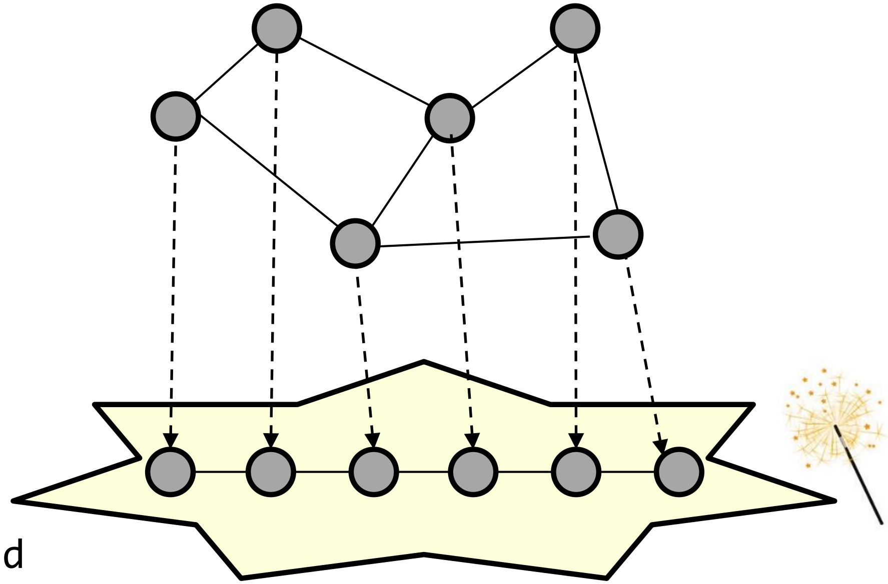
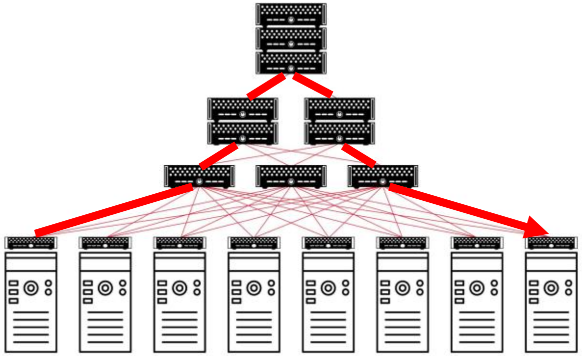


Simplifies problem?!

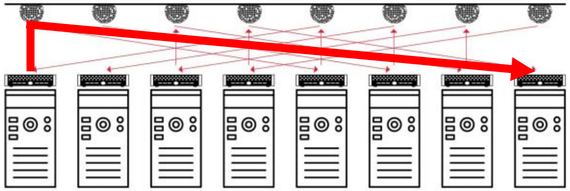
Reality more complicated

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



6 hops

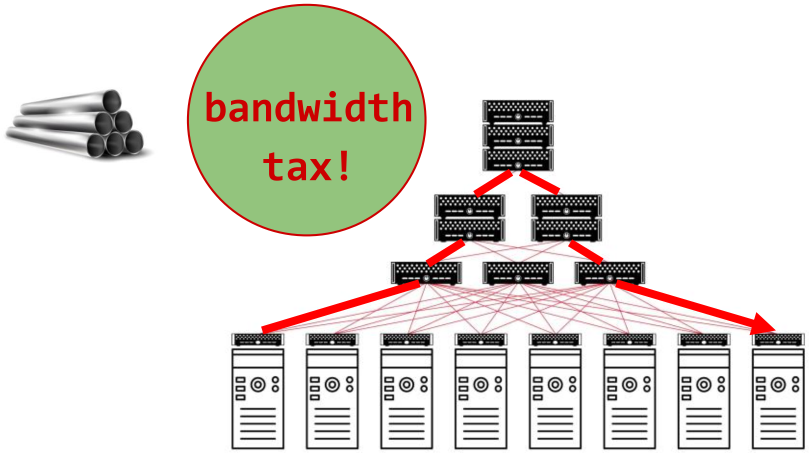
vs



1 hop

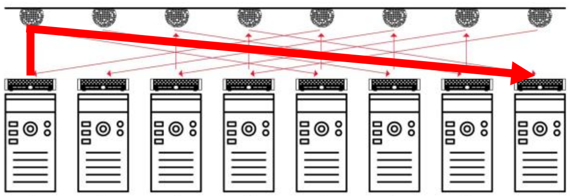
Reality more complicated

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



6 hops

vs

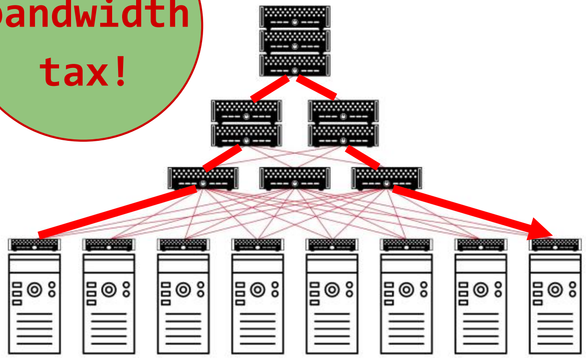


1 hop

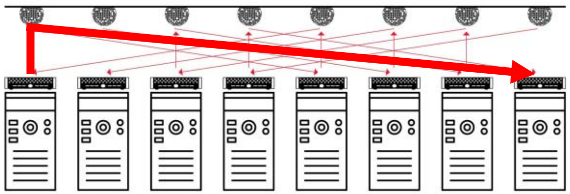
Reality more complicated

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

bandwidth tax!



vs



6 hops

1 hop

⇀ However, requires optimization and adaption, which takes time

Reality more complicated

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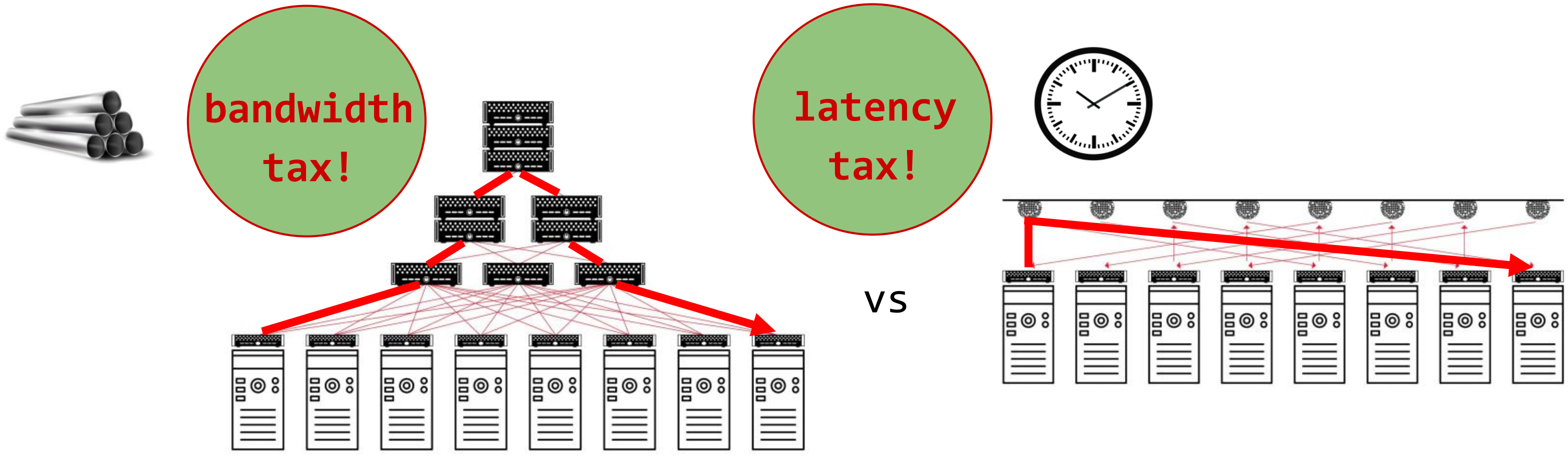


bandwidth tax!

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

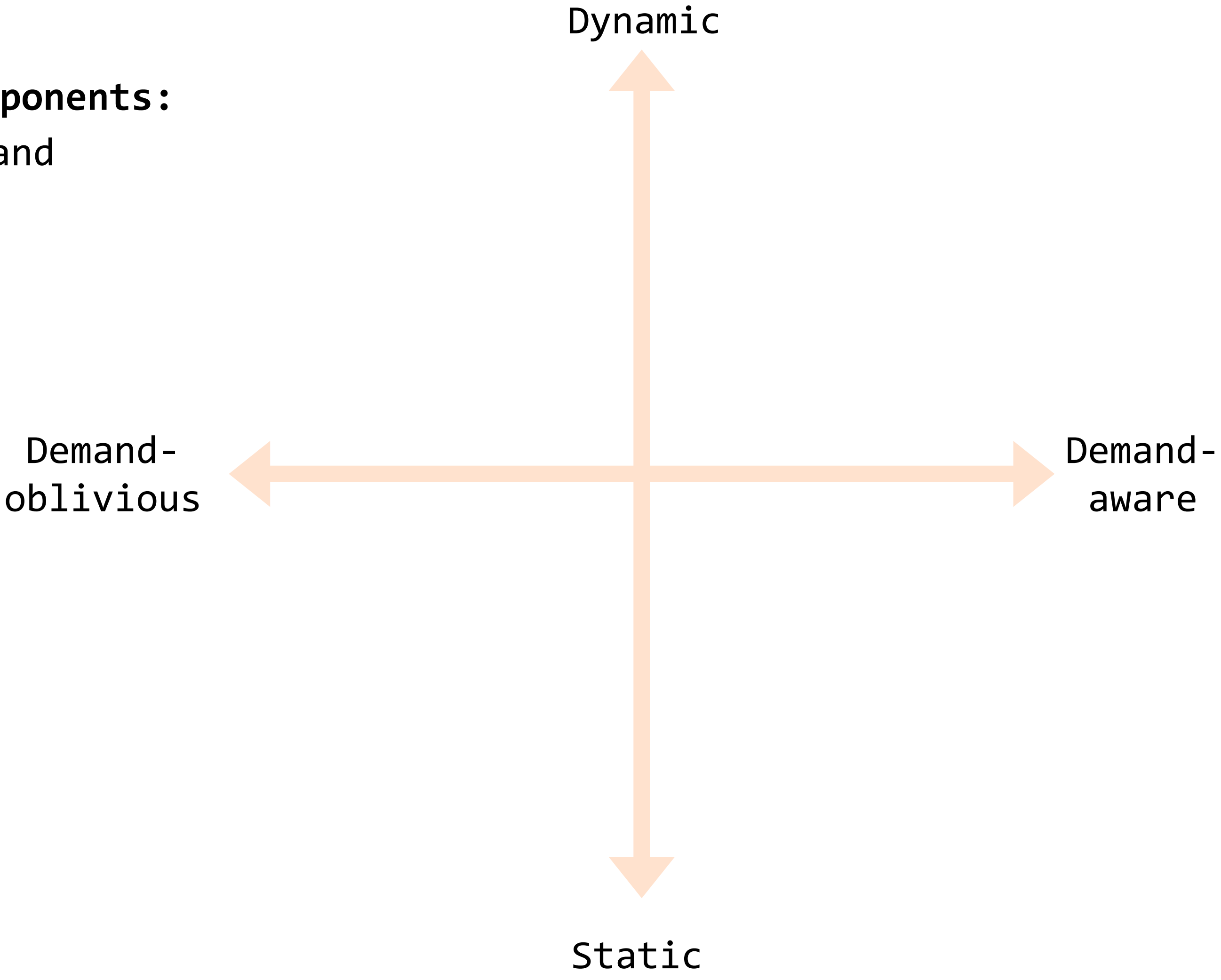
Demand-aware

Opportunity: Tech Diversity

Diverse topology components:

⇀ demand-oblivious and
  demand-aware

⇀ static vs dynamic



Opportunity: Tech Diversity

Diverse topology components:

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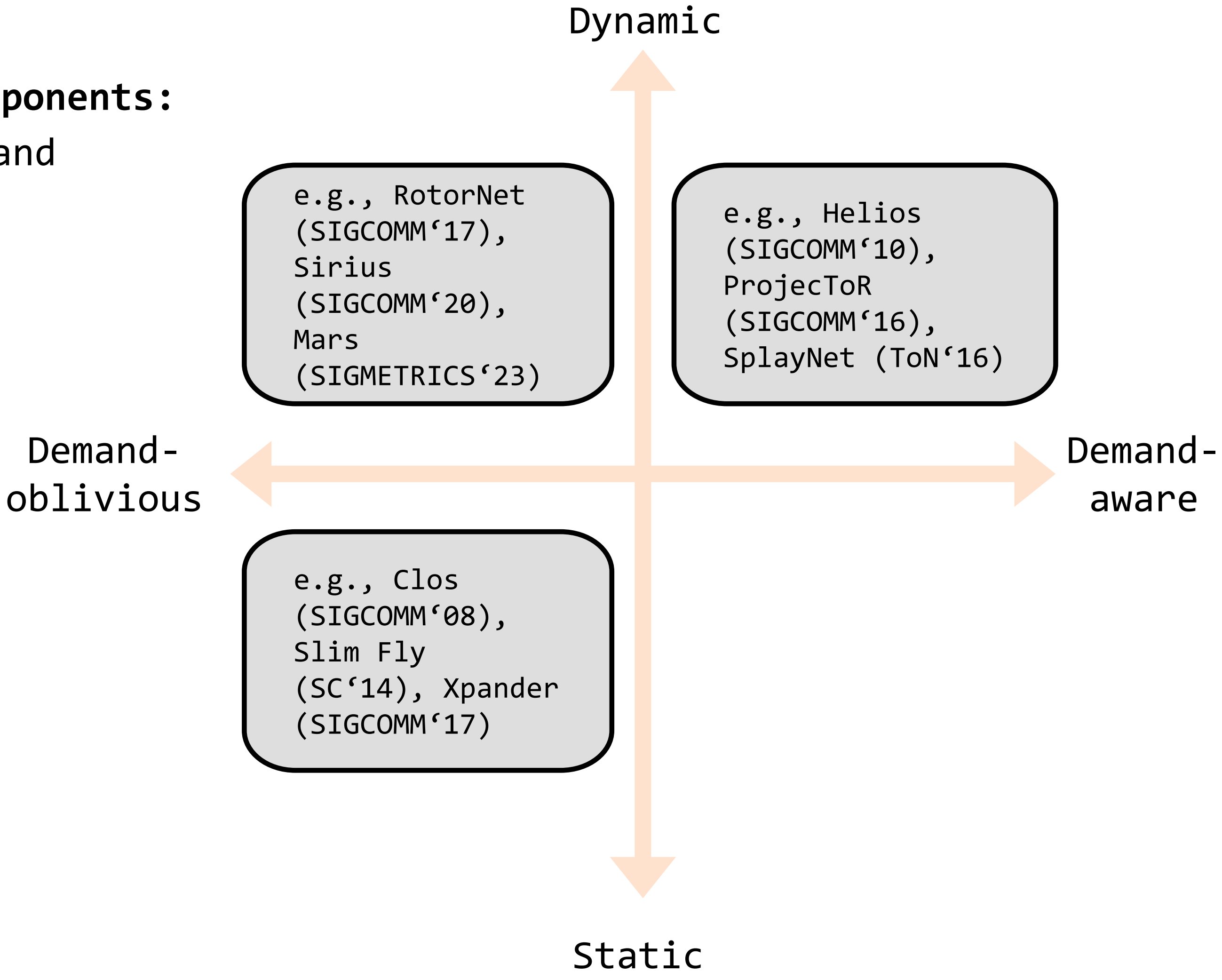


Dynamic

e.g., RotorNet (SIGCOMM‘17), Sirius (SIGCOMM‘20), Mars (SIGMETRICS‘23)

e.g., Helios (SIGCOMM‘10), ProjecToR (SIGCOMM‘16), SplayNet (ToN‘16)

Demand-oblivious

Demand-aware

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

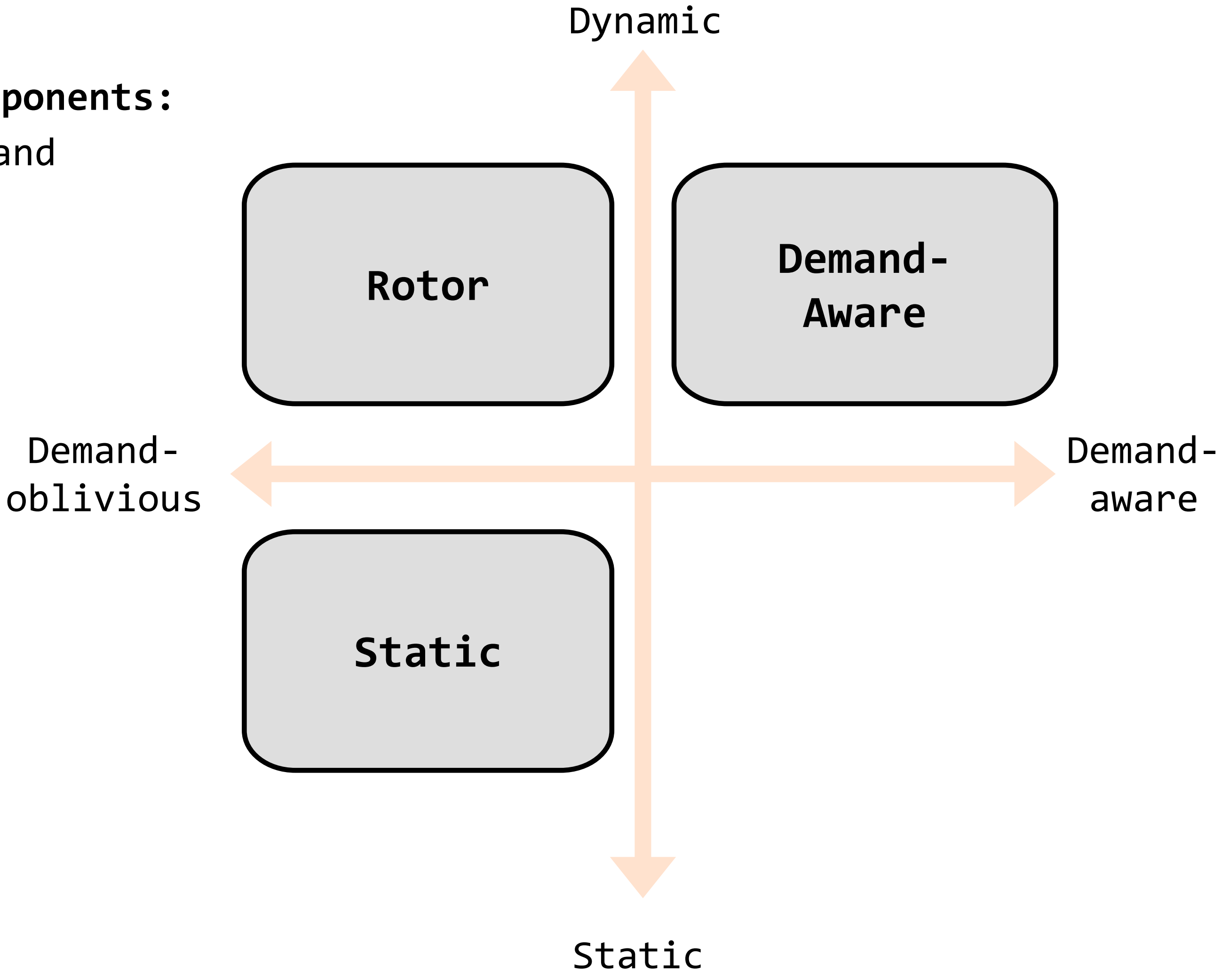
Static

Opportunity: Tech Diversity

Diverse topology components:

⇀ demand-oblivious and
  demand-aware

⇀ static vs dynamic



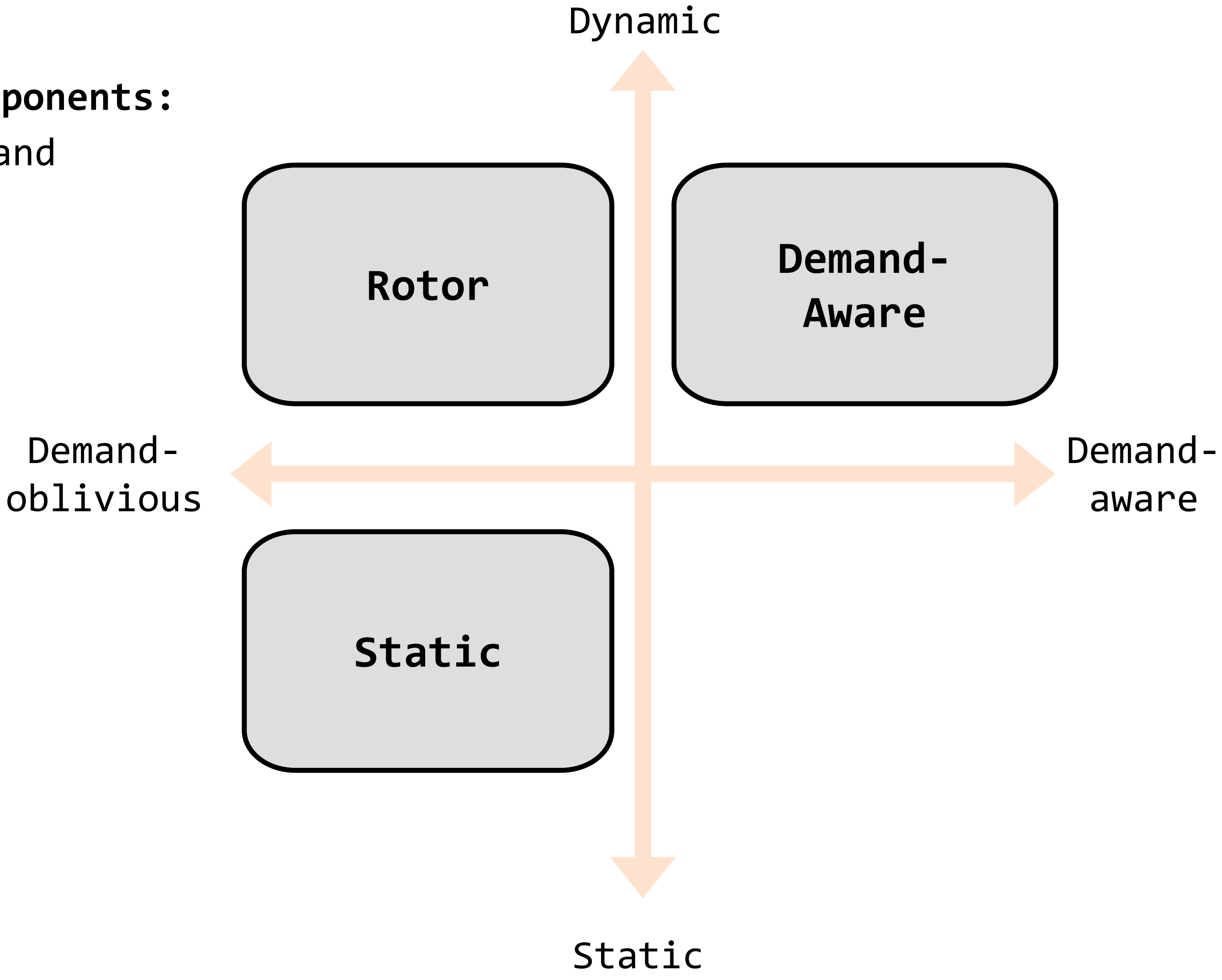
Opportunity: Tech Diversity

Diverse topology components:

⇀ demand-oblivious and demand-aware

⇀ static vs dynamic

Which approach is best?

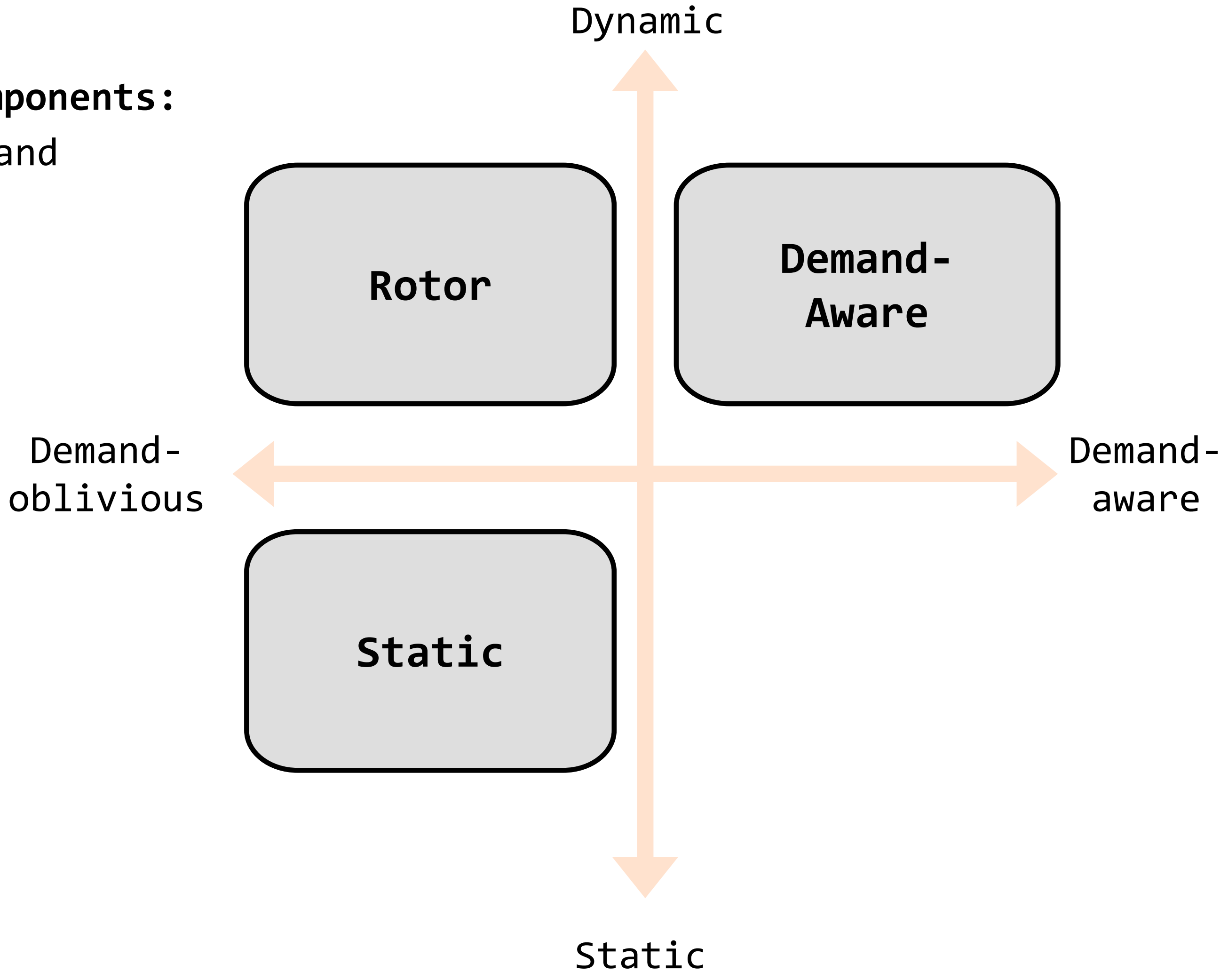


Opportunity: Tech Diversity

Diverse topology components:

⇀ demand-oblivious and demand-aware

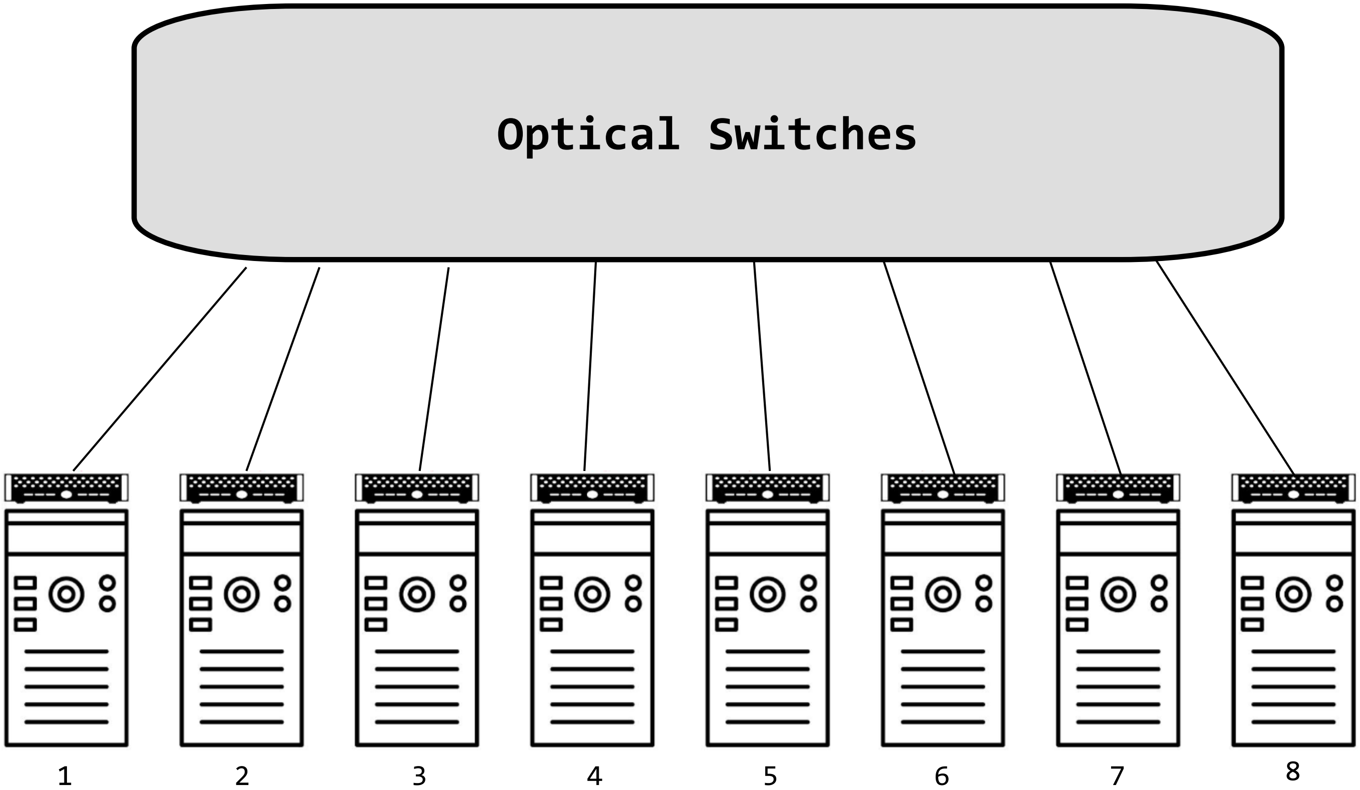
⇀ static vs dynamic



Which approach is best?

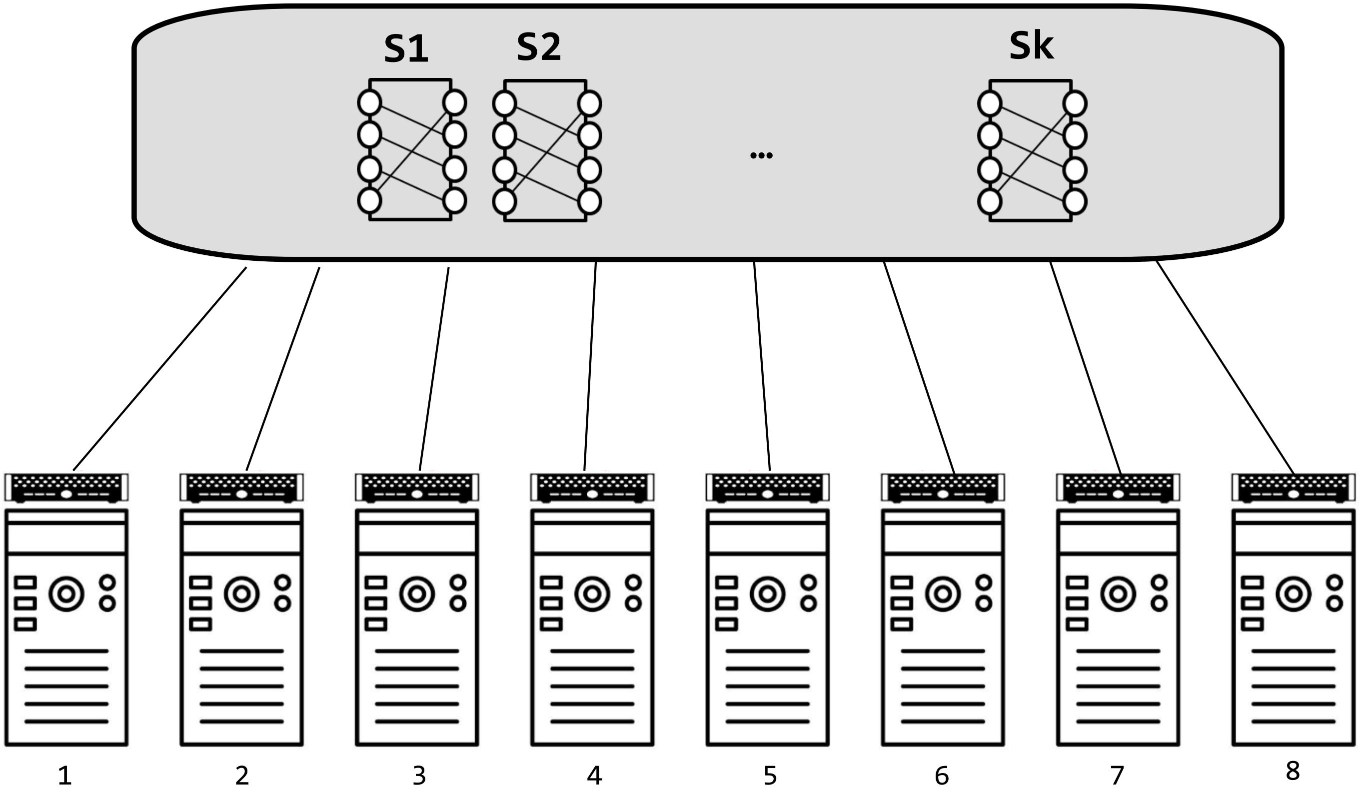
As always in CS:
It depends…

Rack Interconnect



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

Rack Interconnect



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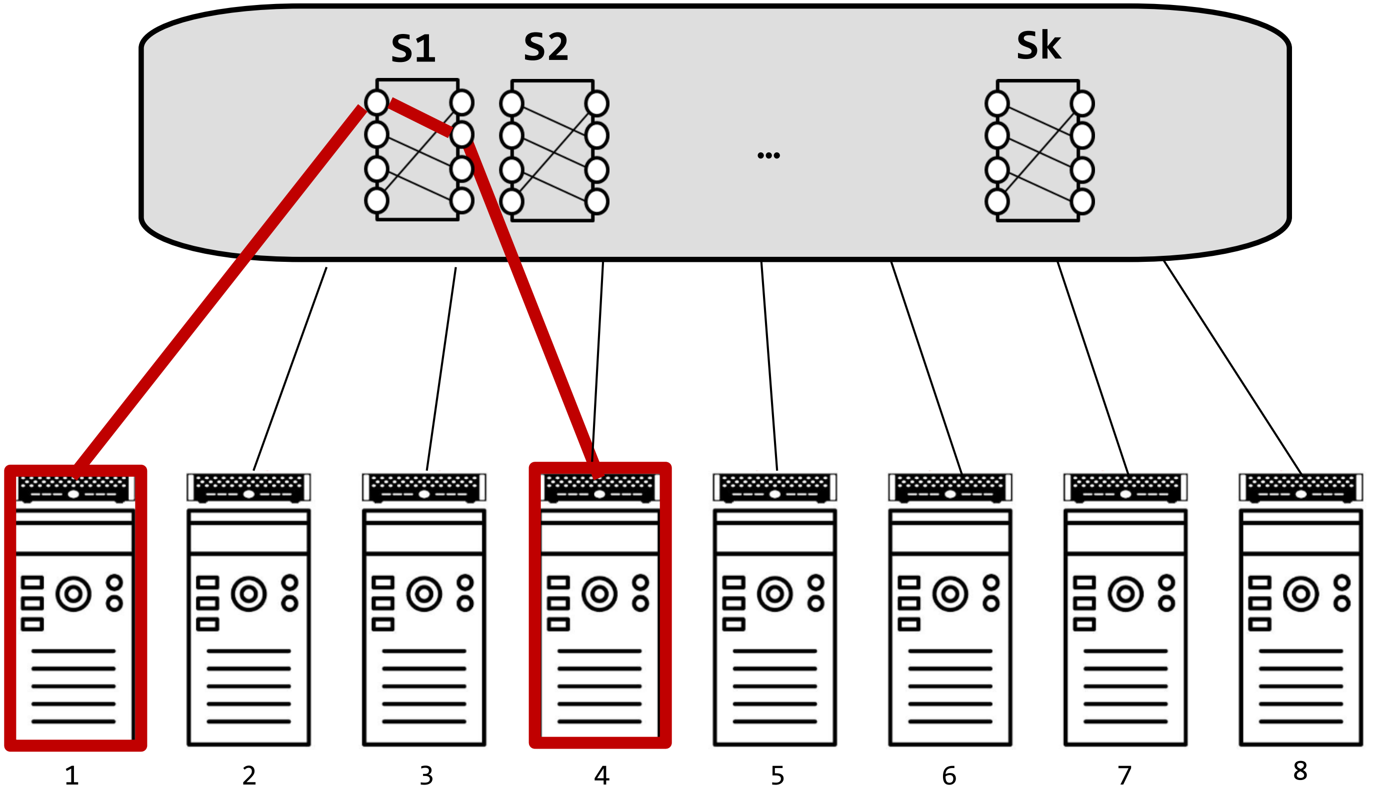

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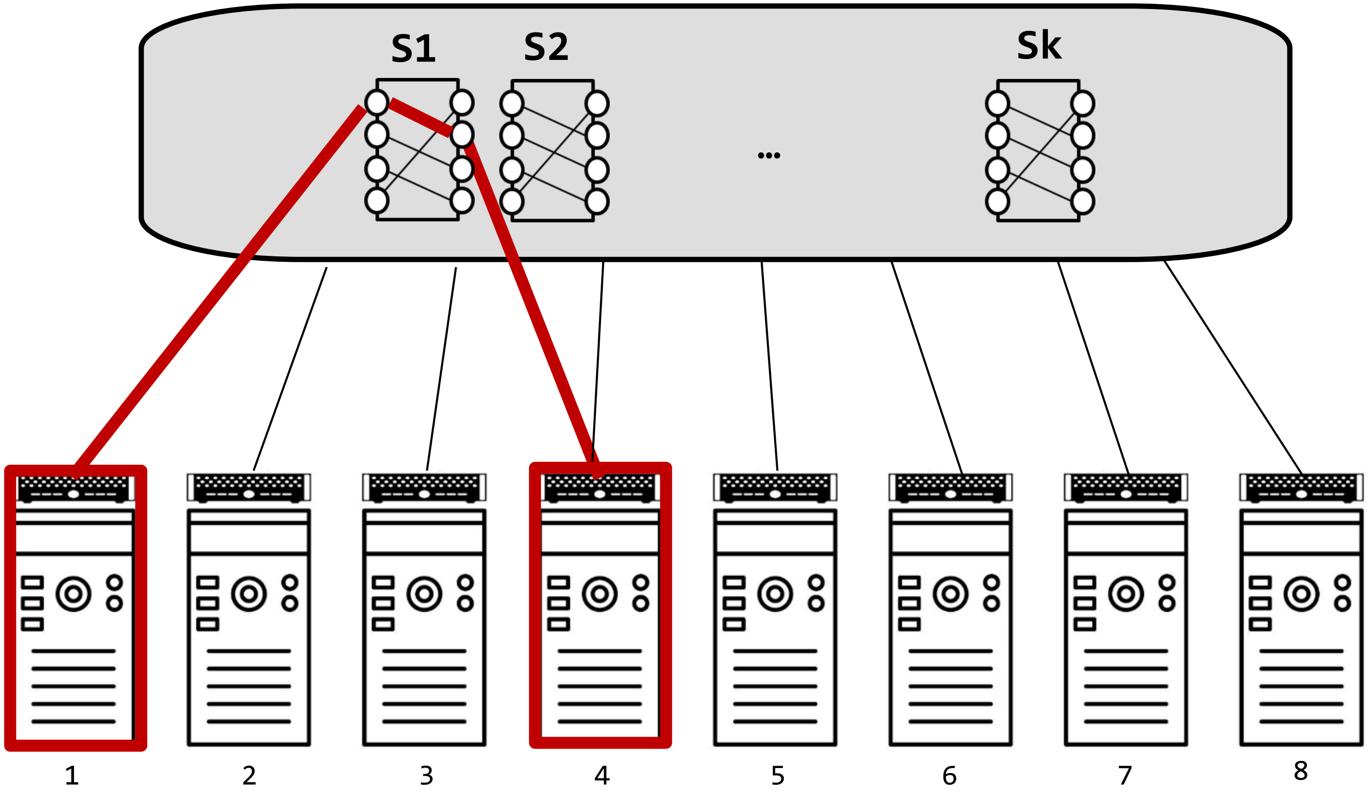
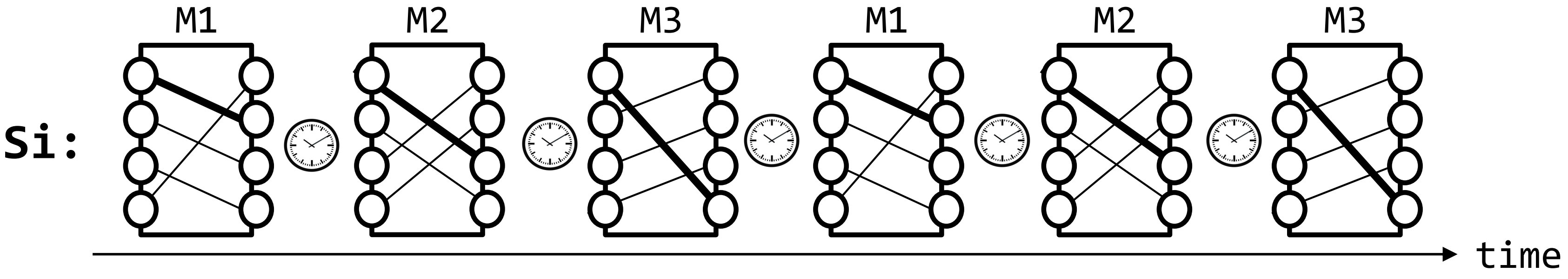


… a motivation for b matchings, Arie and Jenny! ☺

Details: Switch Types

Periodic Switch (aka Rotor Switch)

Rotor switch: periodic matchings (demand-oblivious)



Details: Switch Types

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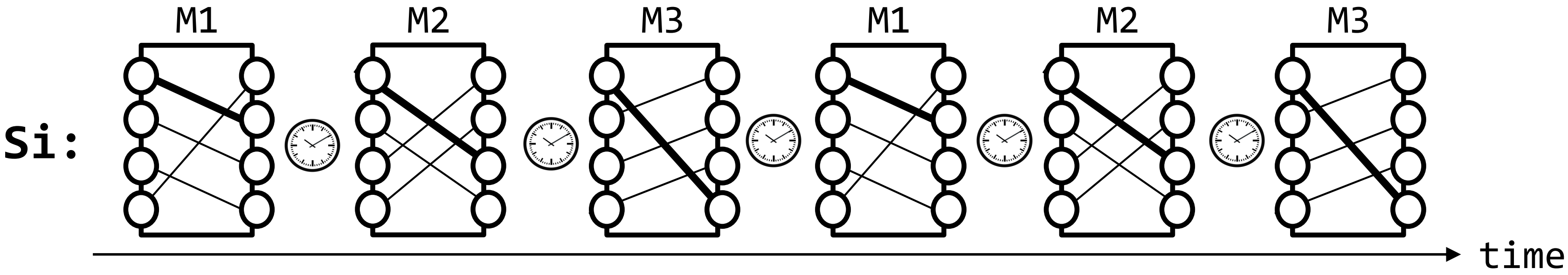
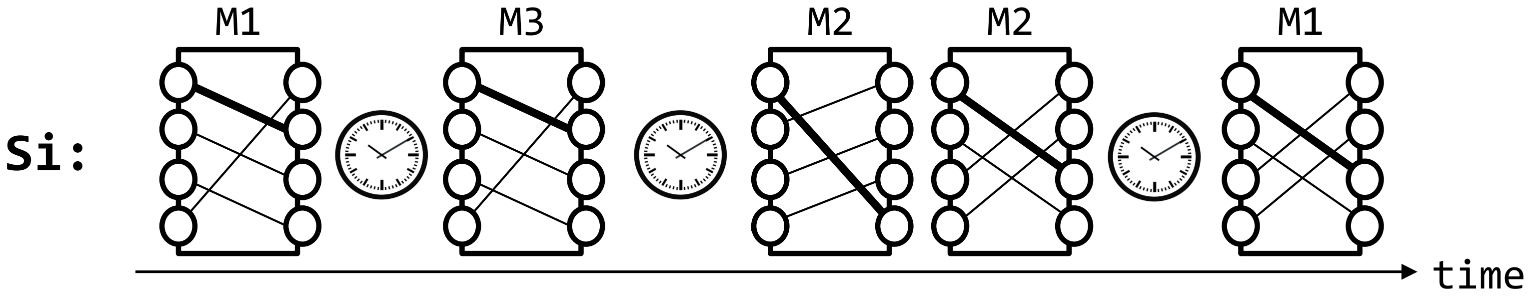


Essentially: evolving graphs with reconfiguration times!

Details: Switch Types

Demand-Aware Switch

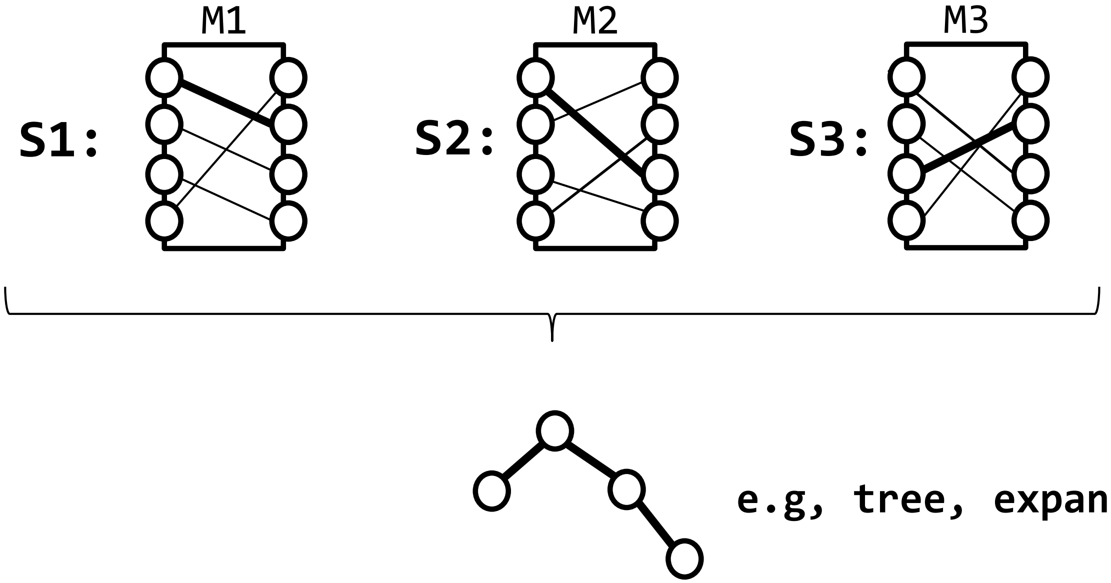
Demand-aware switch: optimized matchings



Details: Switch Types

Static Switch

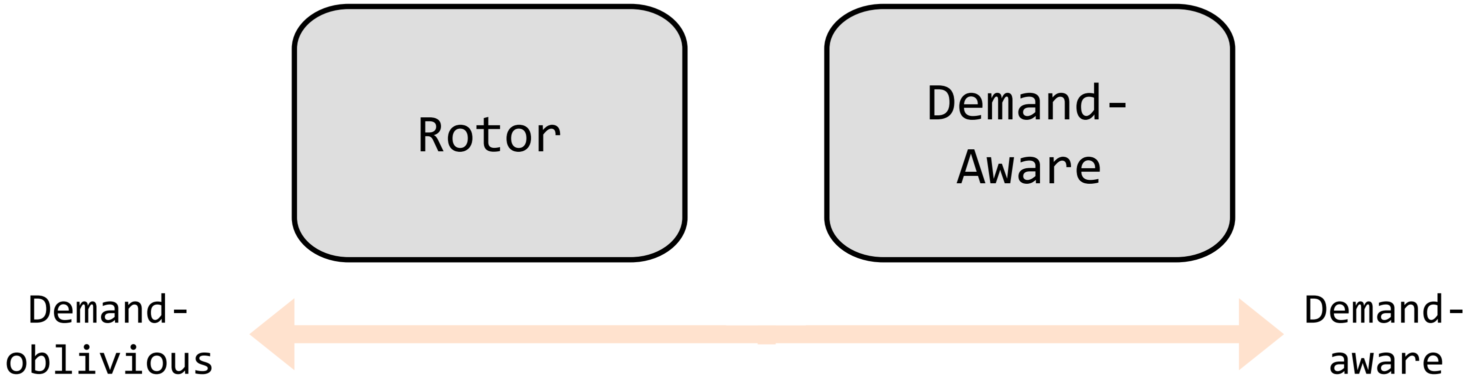
Static switches: combine for optimized static topology



e.g, tree, expander

Design Tradeoffs (1)

The “Awareness-Dimension”



Rotor

Demand-Aware

Demand-oblivious

Demand-aware

Good for all-to-all traffic!

⇀ oblivious: very fast periodic direct connectivity

⇀ no control plane overhead

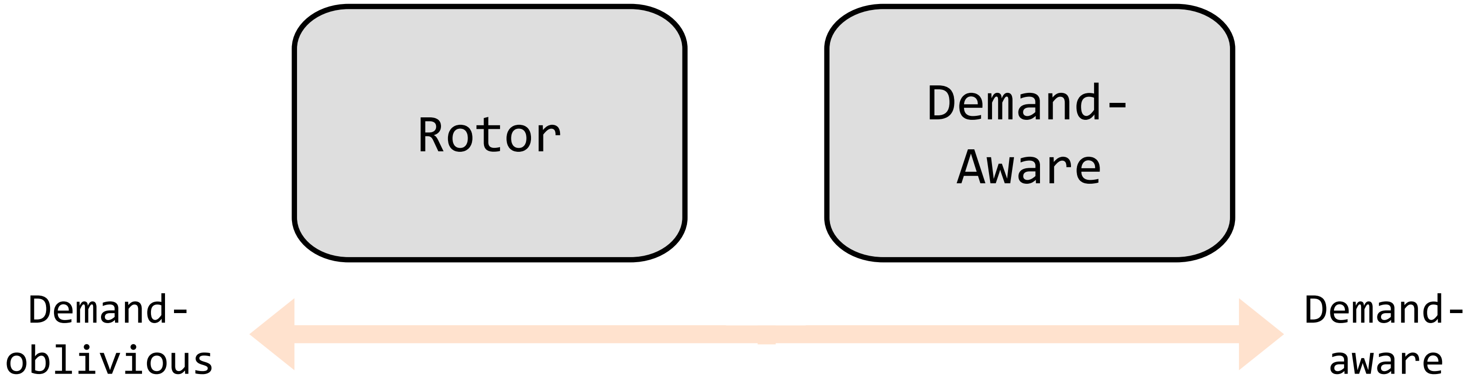
Good for elephant flows!

⇀ optimizable toward traffic

⇀ but slower

Design Tradeoffs (1)

The “Awareness-Dimension”



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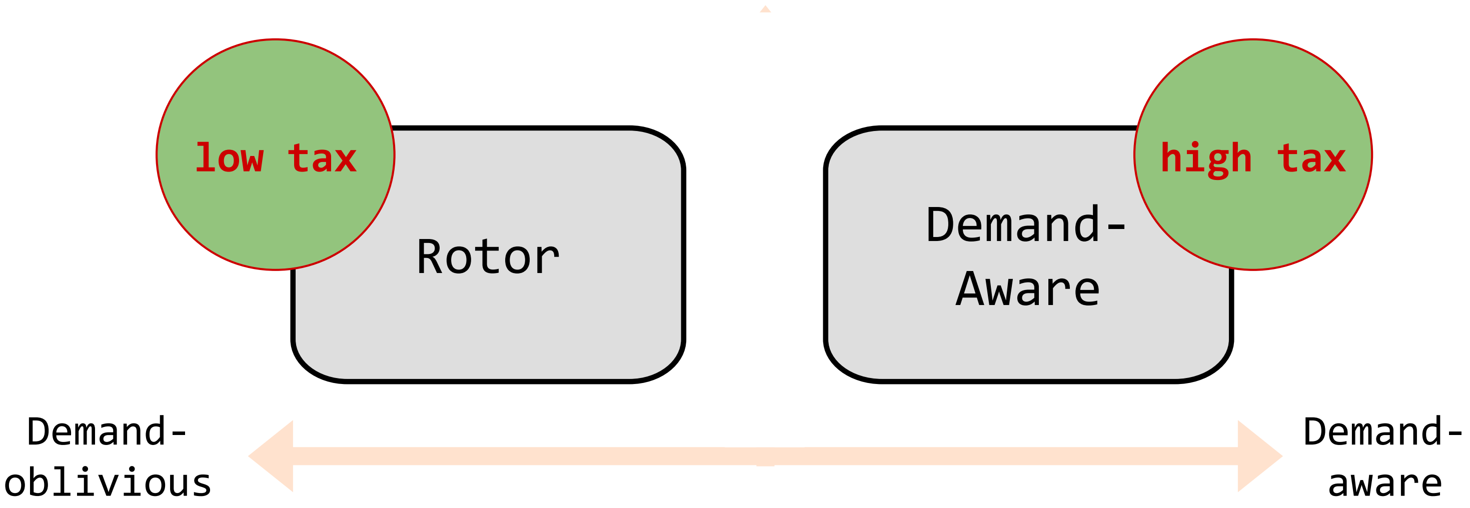
Compared to static networks: latency tax!

Design Tradeoffs (1)

The “Awareness-Dimension”



low tax

Rotor

Demand-Aware

high tax

Demand-oblivious

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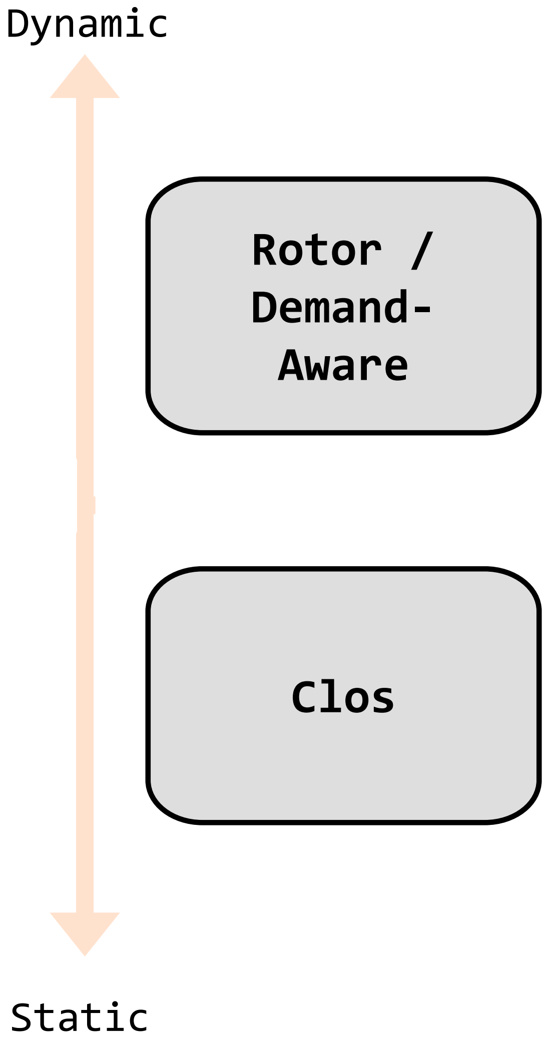
⇀ but slower

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”

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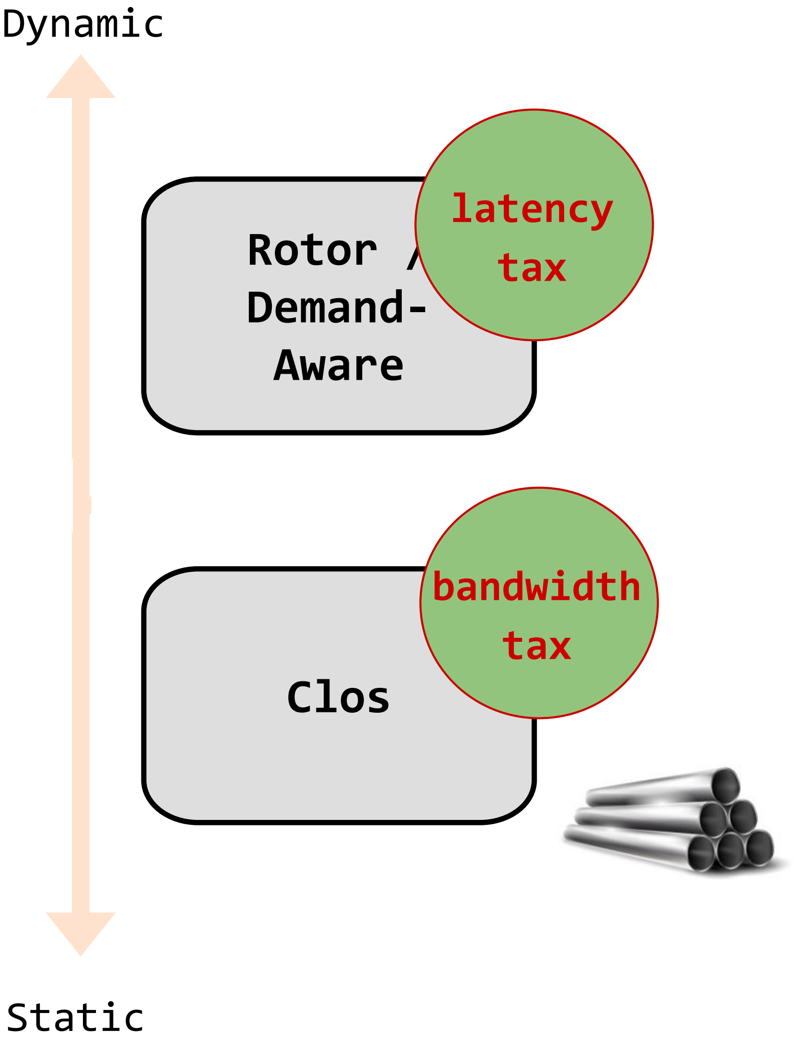
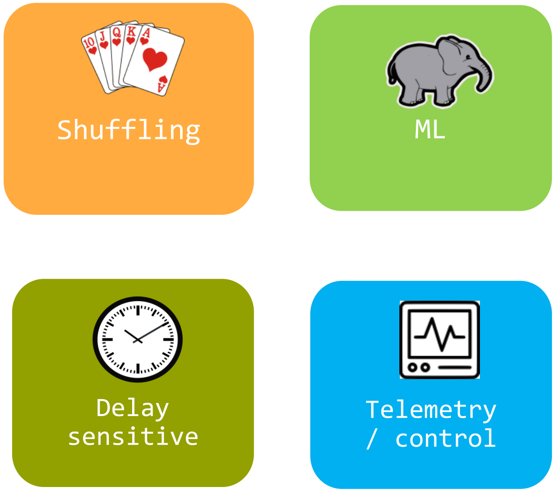


First Observations

- **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?

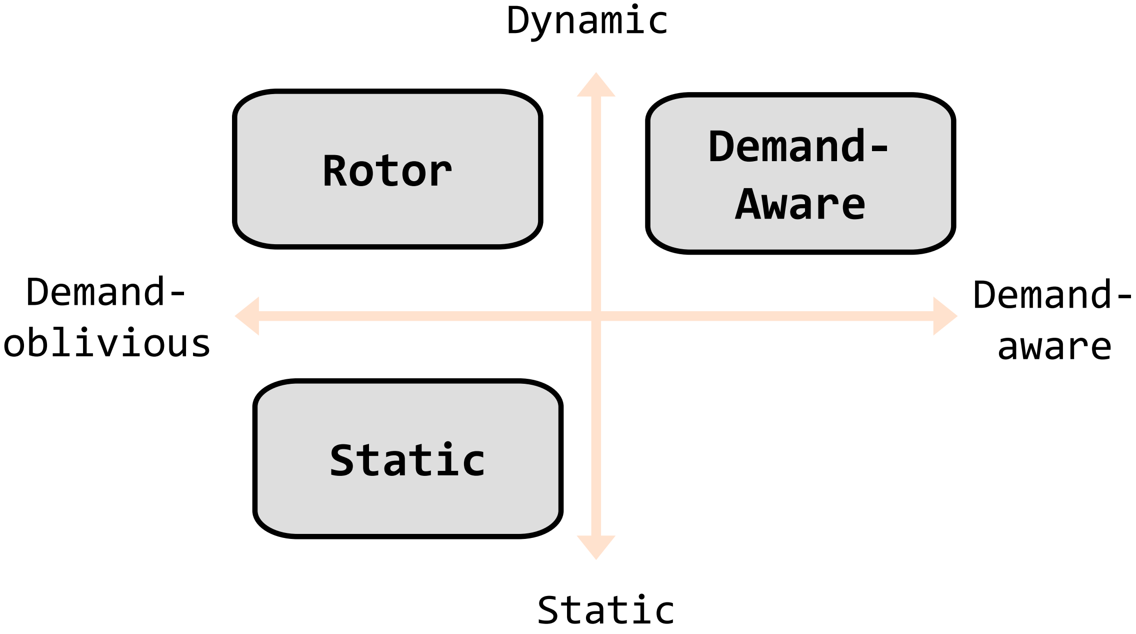

Shuffling

ML

Delay sensitive

Telemetry / control

Demand


Dynamic

Rotor

Demand-Aware

Demand-oblivious

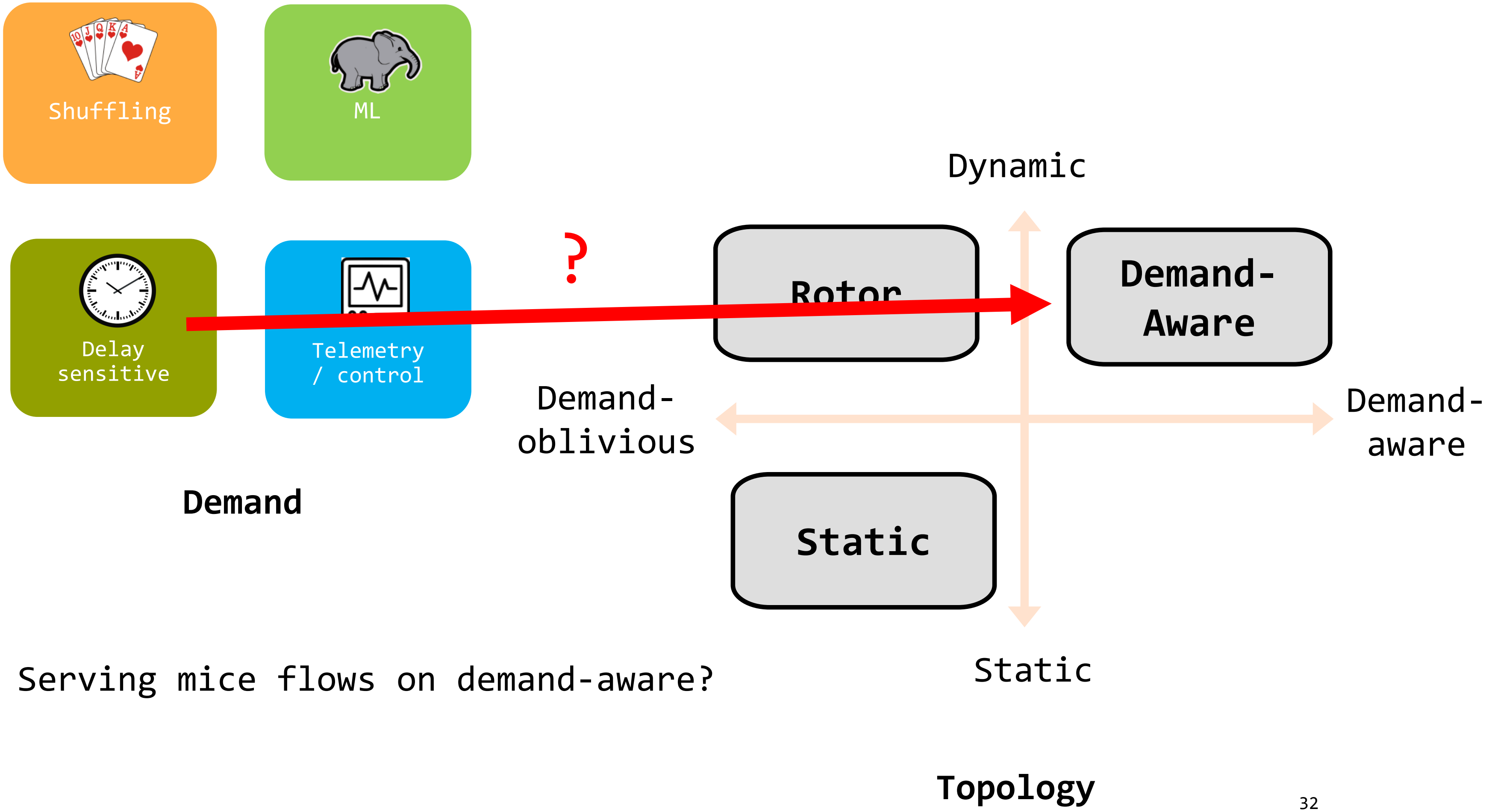
Demand-aware

Static

Static

Topology

Examples:
Match or Mismatch?



Shuffling

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?

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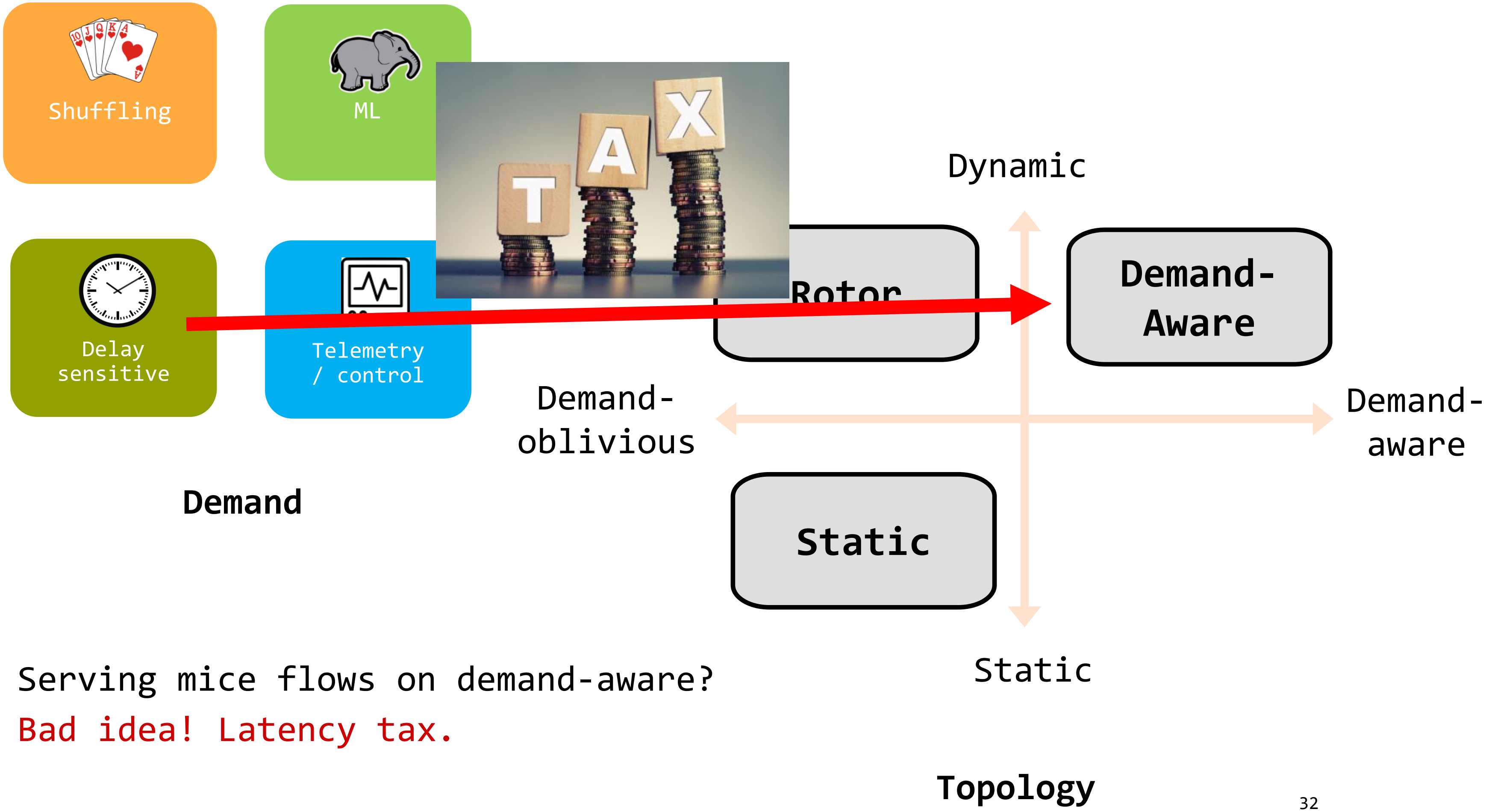
Static

Static

Topology

Serving mice flows on demand-aware?

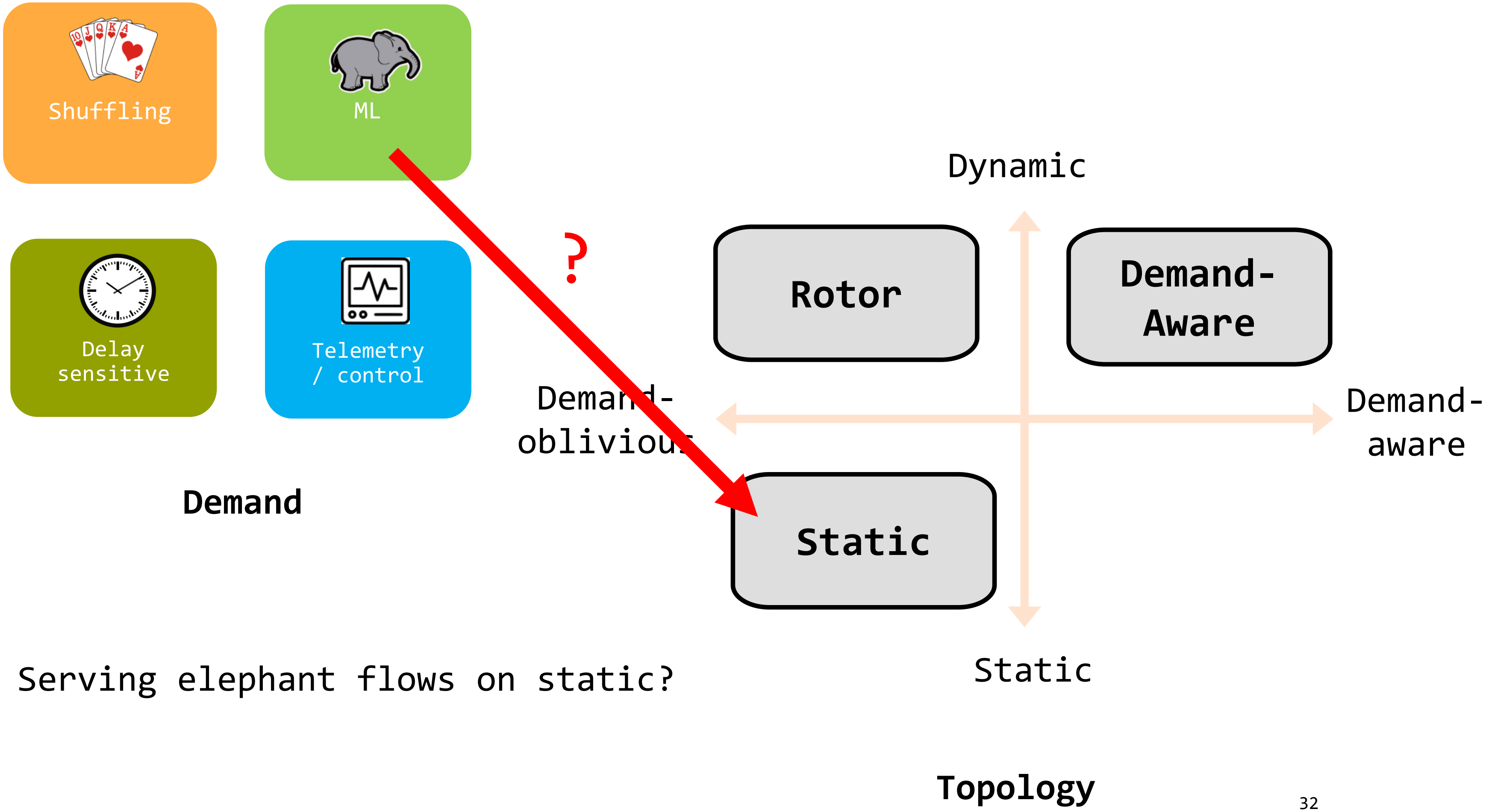
Examples:
Match or Mismatch?



Serving mice flows on demand-aware?

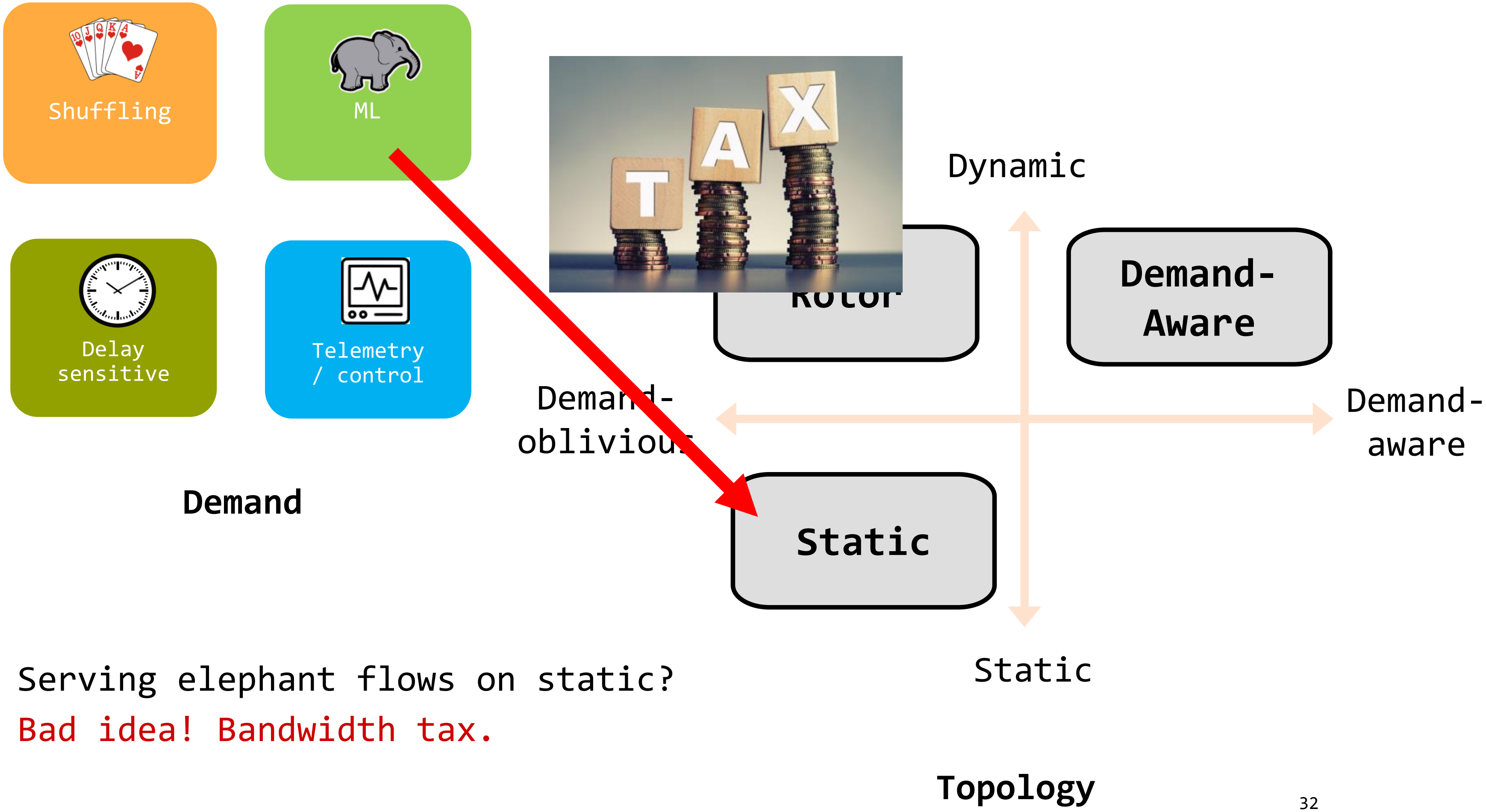
Bad idea! Latency tax.

Examples:
Match or Mismatch?



Serving elephant flows on static?

Examples:
Match or Mismatch?



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Bad idea! Bandwidth tax.

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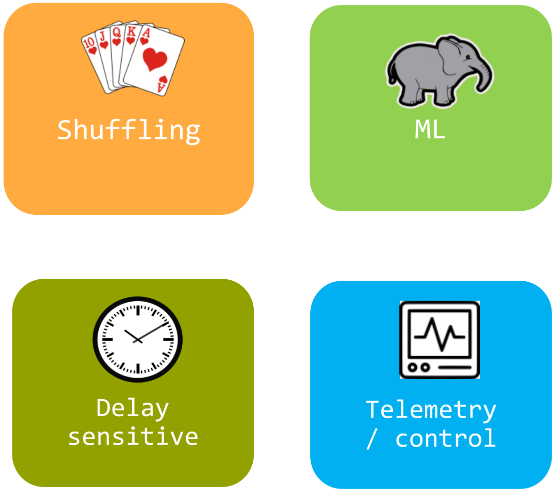
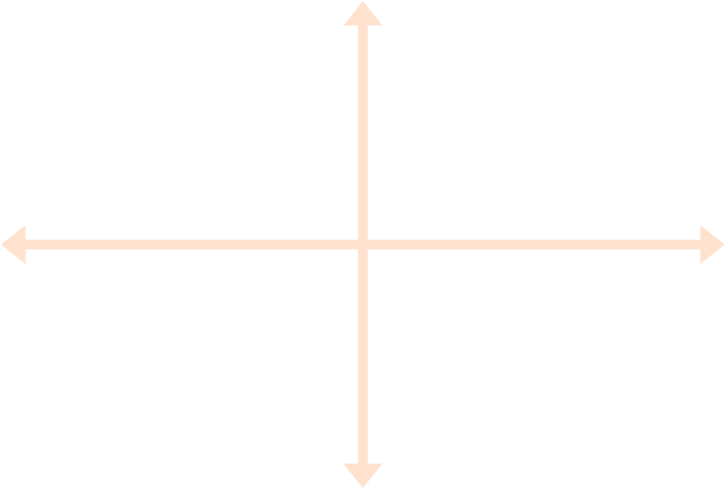


Demand

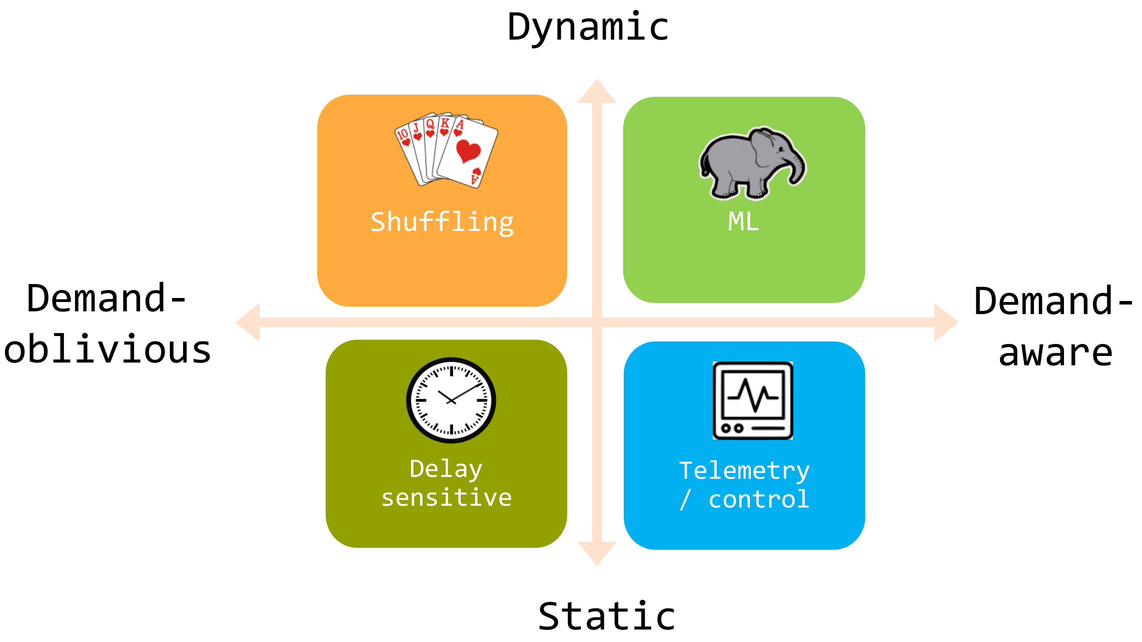


Topology

Serving elephant flows on static?

Bad idea! Bandwidth tax.

Optimal Solution: It's a Match!


Dynamic

Shuffling

ML

Demand-oblivious

Demand-aware

Delay sensitive

Telemetry / control

Static

We have a first approach:

Cerberus** serves traffic on the “best topology”! (Optimality open)

* Griner et al., ACM SIGMETRICS 2022

Flow Size Matters

On what should topology type depend? We argue: flow size.

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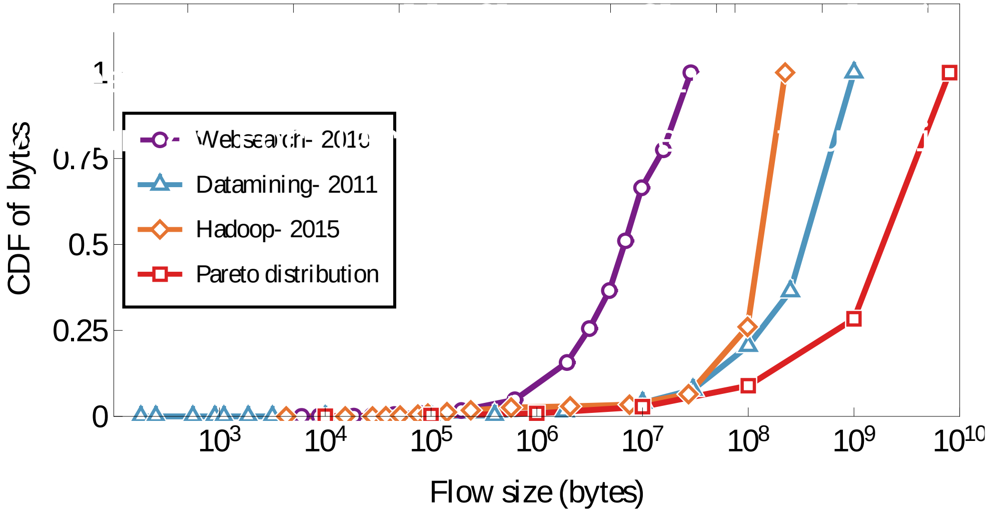
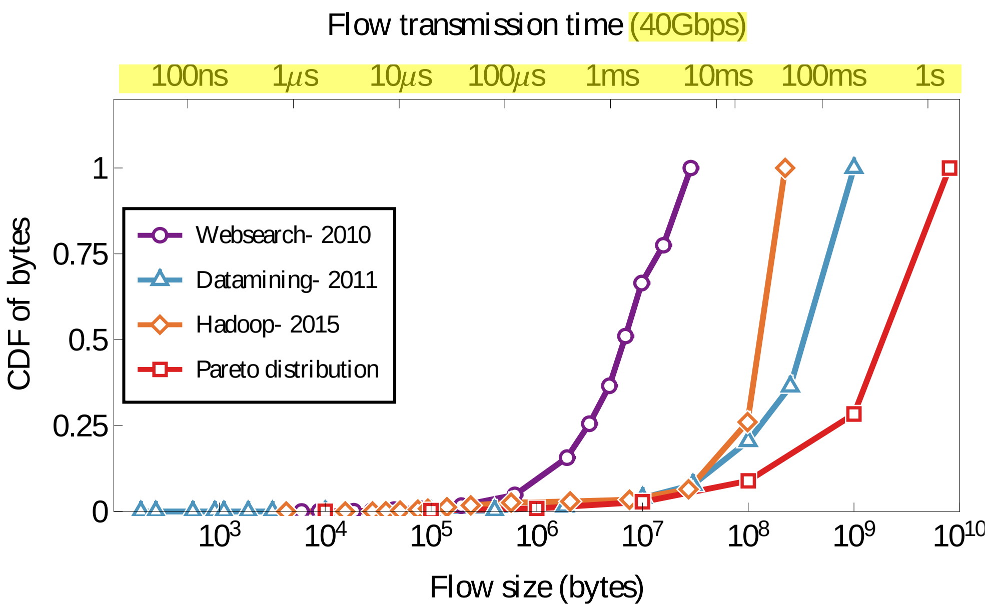


⇢ **Observation 1:** Different apps have different flow size distributions.

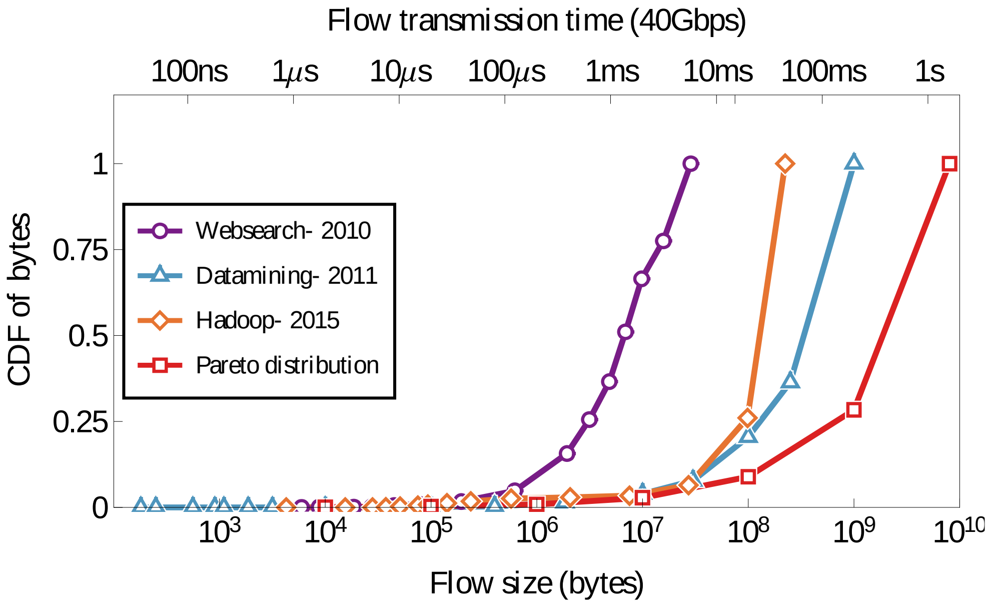
Flow Size Matters



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

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

Flow Size Matters



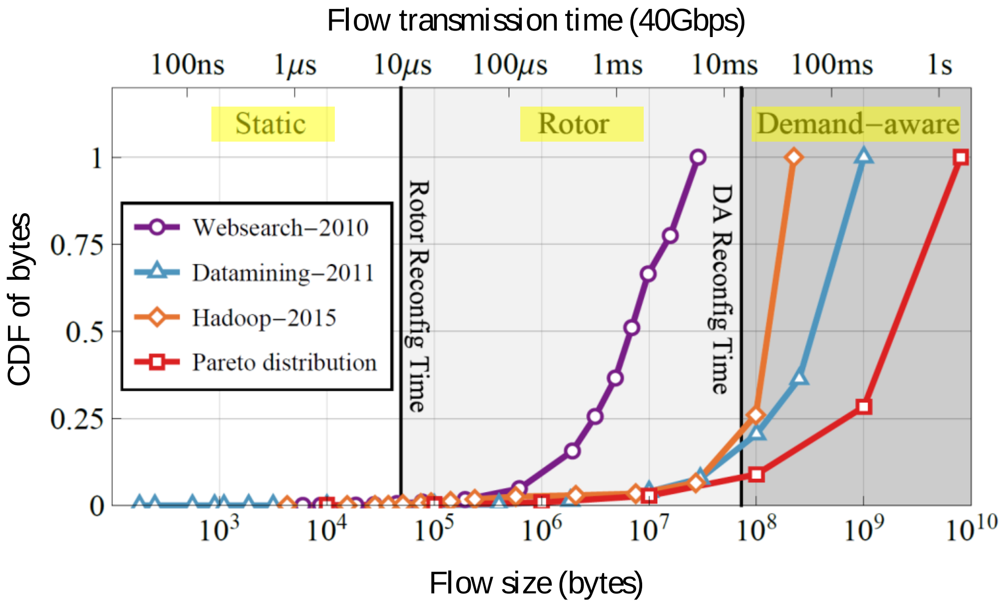
⇢ **Observation 1:** Different apps have different flow size distributions.

⇢ **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!

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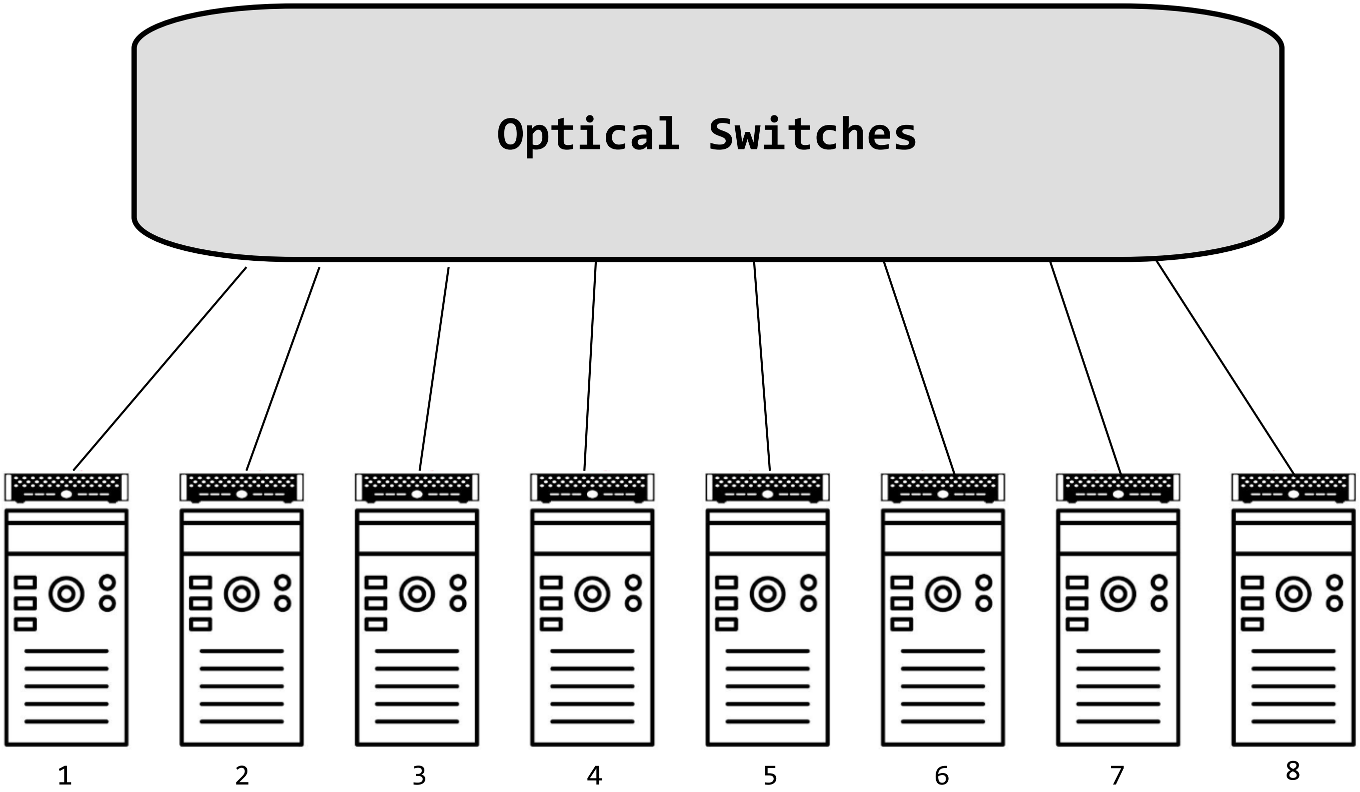
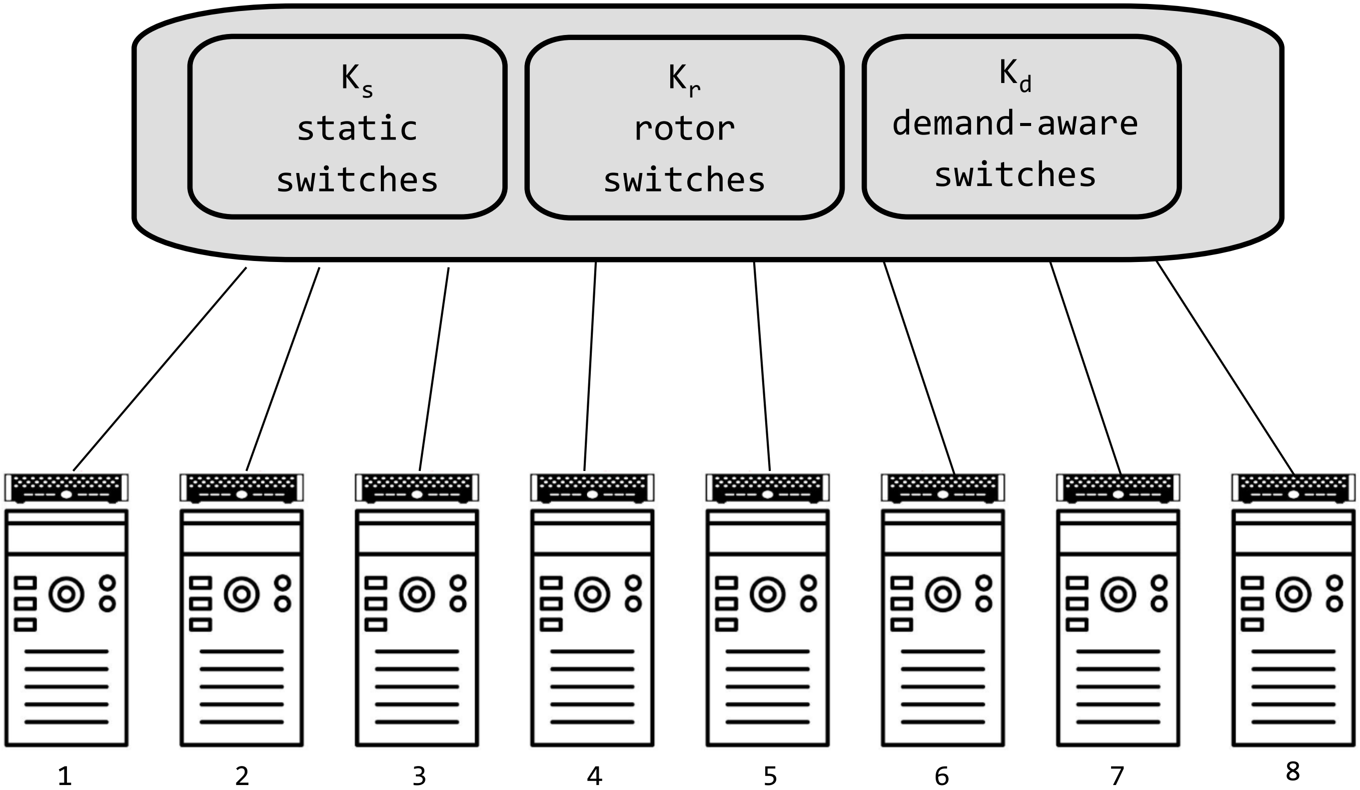
Cerberus



Optical Switches

Cerberus

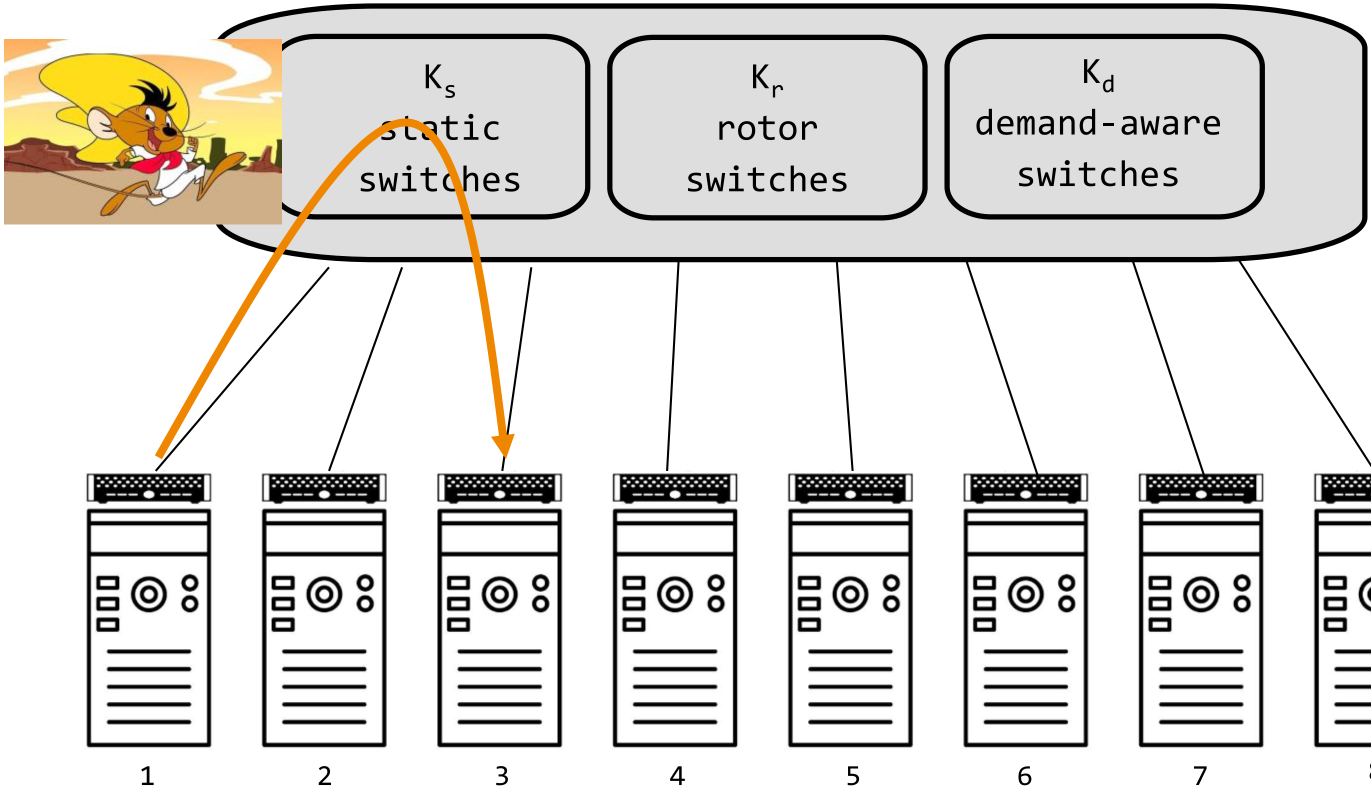


K_s
static
switches

K_r
rotor
switches

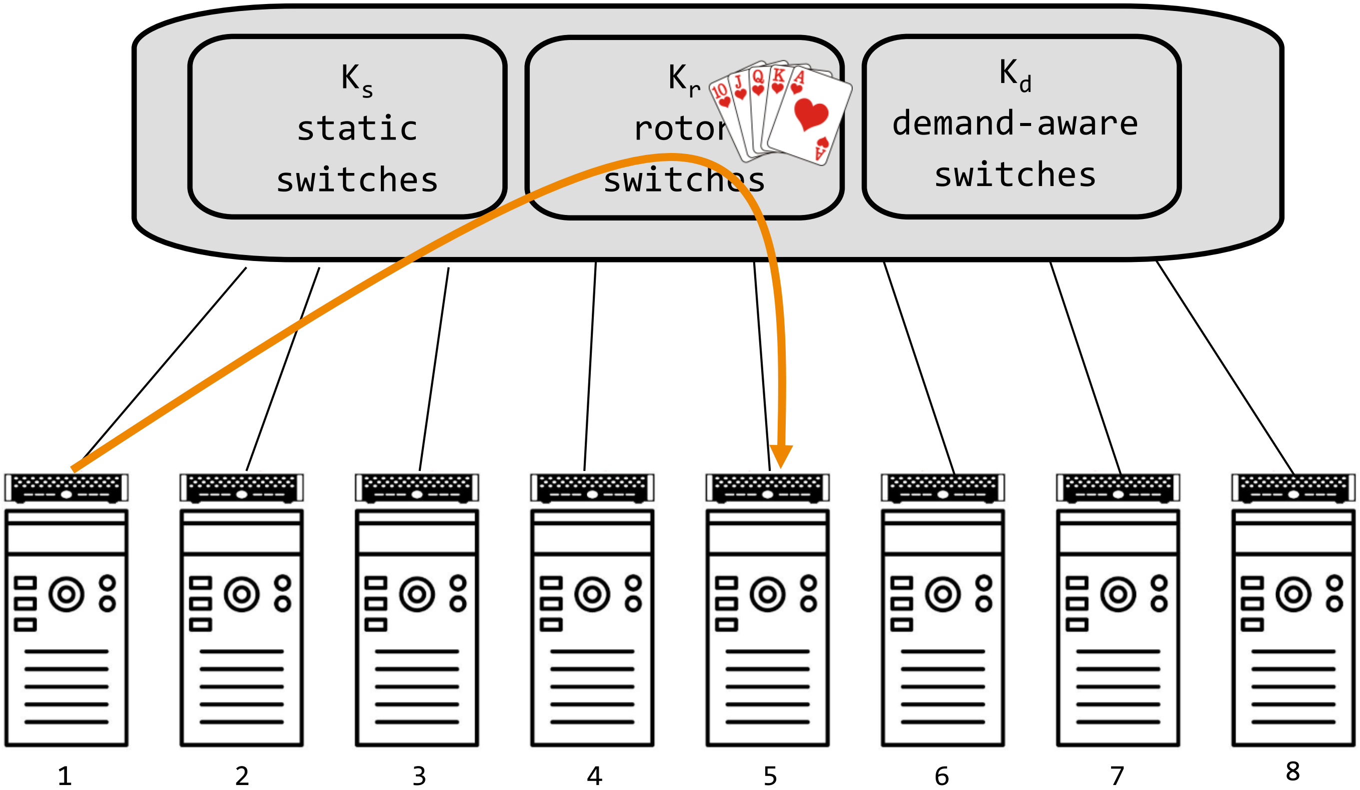
K_d
demand-aware
switches

Cerberus



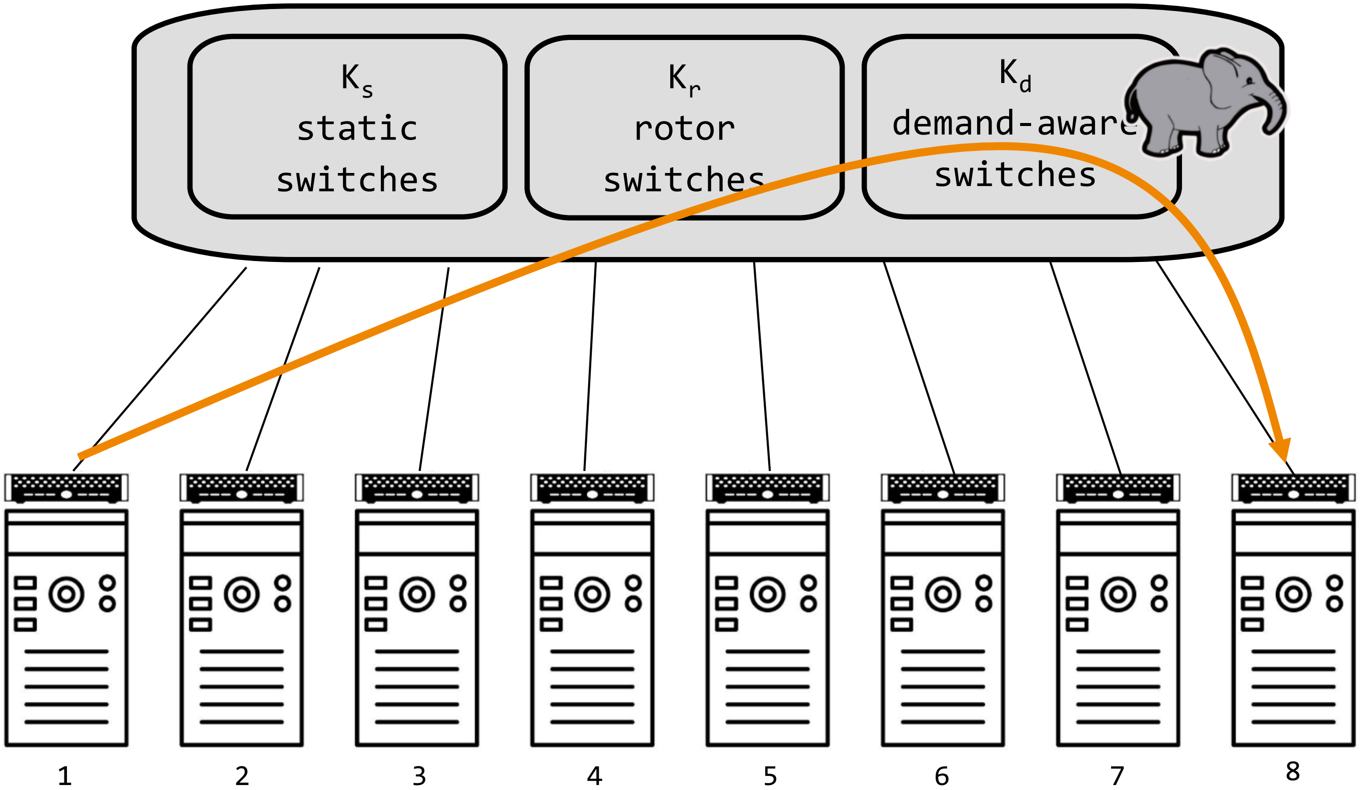
Scheduling: Small flows go via static switches…

Cerberus



Scheduling: … medium flows via rotor switches…

Cerberus

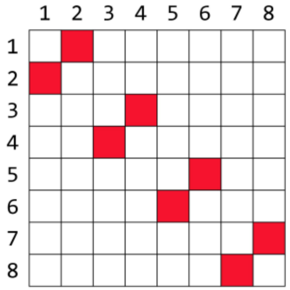


Scheduling: … and large flows via demand-aware switches
(if one available, otherwise via rotor).

Throughput Analysis

Demand Matrix

T



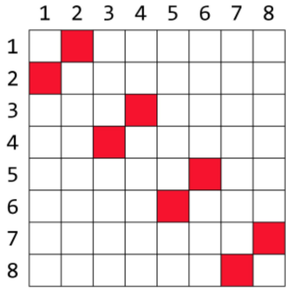
	1	2	3	4	5	6	7	8
1		🟥						
2	🟥							
3				🟥				
4			🟥					
5						🟥		
6					🟥			
7								🟥
8							🟥	

Metric: throughput
of a demand matrix…

Throughput Analysis

Demand Matrix

T



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

$\times \ \theta(T)$

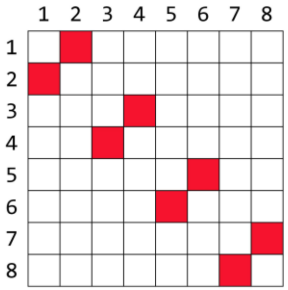
Metric: throughput of a demand matrix…

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

Throughput Analysis

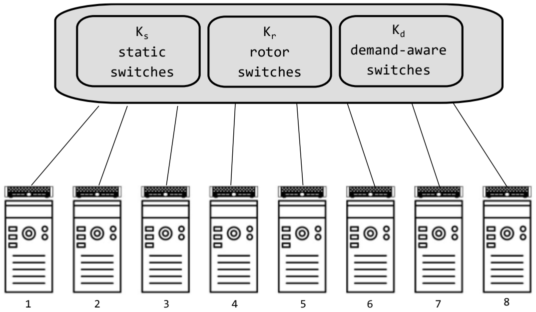
Demand Matrix

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…

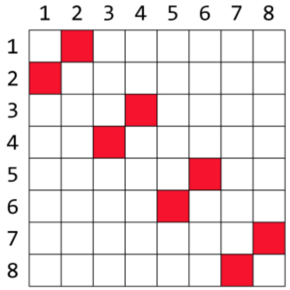
… is the maximal scale down factor by which traffic is feasible.

Throughput of network θ^*: worst case T

Throughput Analysis

Demand Matrix

T



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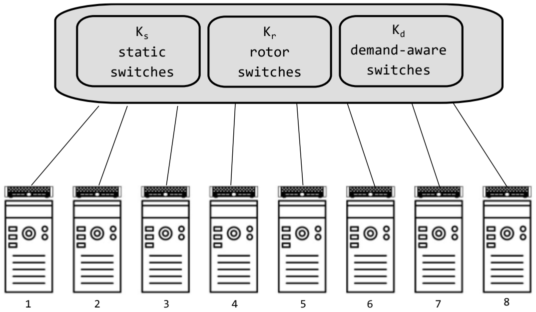
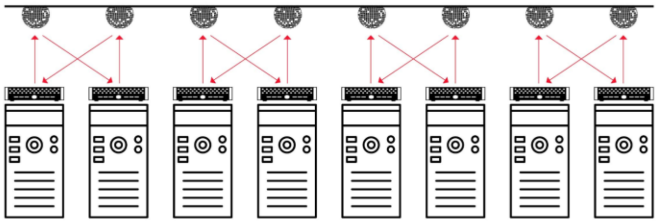


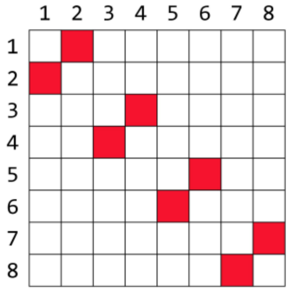
Worst demand matrix for static and rotor: permutation. Best case for demand-aware!



Throughput Analysis

Demand Matrix

T



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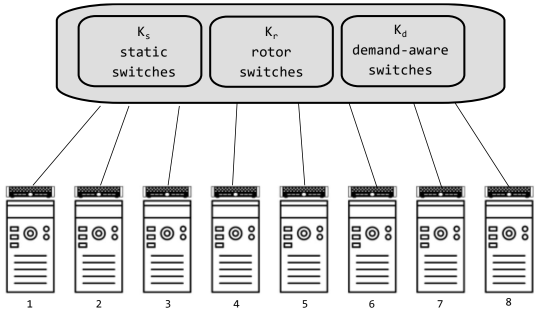
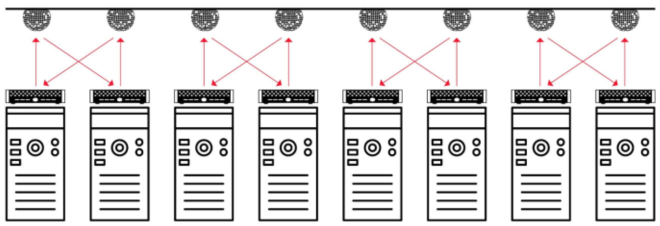


Worst demand matrix for static and rotor: permutation. Best case for demand-aware!

BW tax!

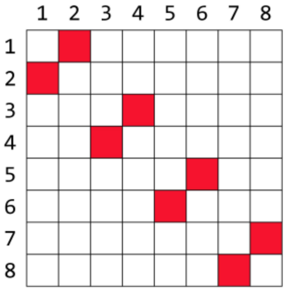
BW & latency tax!



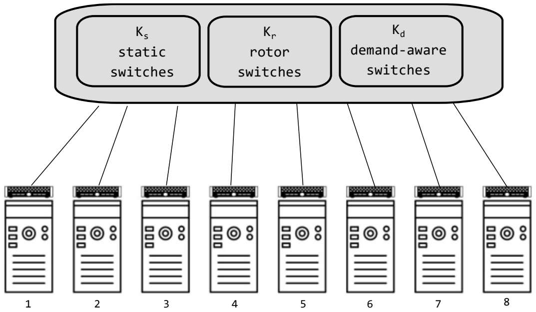
	expander-net	*rotor-net*	CERBERUS
BW-Tax	✓	✓	✗
LT-Tax	✗	✓	✓
$\theta(T)$	Thm 2	Thm 3	Thm 5
θ^*	0.53	0.45	Open
Datamining	0.53	0.6	0.8 (+33%)
Permutation	0.53	0.45	≈ 1 (+88%)
Case Study	0.53	0.66	0.9 (+36%)

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!

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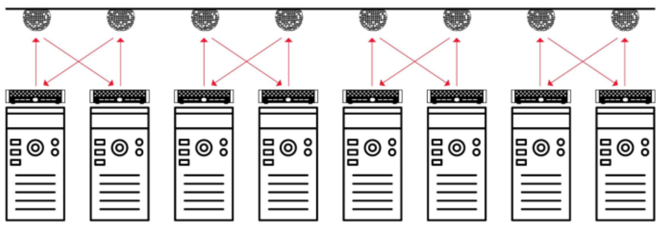


Summary

- Opportunity: *structure* in demand and *reconfigurable* networks
- How to measure demand? A first metric: *entropy*
- New algorithmic problem: demand-aware and *self-adjusting graphs*
  - At least for sparse demands we know how
  - ***Open questions:*** What about general demand? Load? Distributed algorithms? ***Hybrid*** networks (i.e., demand-aware on top of a fixed Clos topology)?
- Cerberus aims to assign traffic to its best topology
  - Depending on flow size
  - ***Open questions:*** Analysis of throughput? Optimality?

“Zukunftsmusik”

- ⇢ So far: tip of the iceberg

- ⇢ Many more challenges
  - ⇀ Shock wave through *layers*: impact on routing and congestion control?
  - ⇀ *Scalability* of control in dynamic graphs: *local algorithms*? Greedy routing?
  - ⇢ Complexity of demand-aware graphs (*pure vs hybrid*, e.g., SplayNet)
  - ⇀ *Application-specific* self-adjusting networks: e.g., for AI, or similar to *active dynamic networks* (independent sets, consensus, …)
  - ⇀ etc.

Thank you!

Online Video Course

Invitation to

Self-Adjusting Networks

A short video course

self-adjusting datacenter

self-adjusting bridge

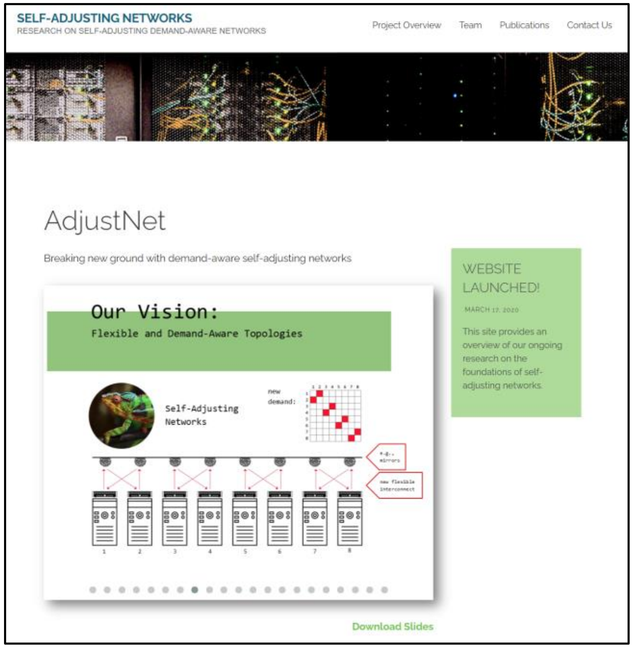
> We cannot direct the wind,
> but we can adjust the sails.
>
> (Folklore)

Prof. Chen Avin
(BGU, Israel)

Prof. Stefan Schmid
(TU Berlin, Germany)

https://self-adjusting.net/course

Websites



SELF-ADJUSTING NETWORKS
RESEARCH ON SELF-ADJUSTING DEMAND-AWARE NETWORKS

Project Overview Team Publications Contact Us

AdjustNet

Breaking new ground with demand-aware self-adjusting networks

Our Vision:
Flexible and Demand-Aware Topologies

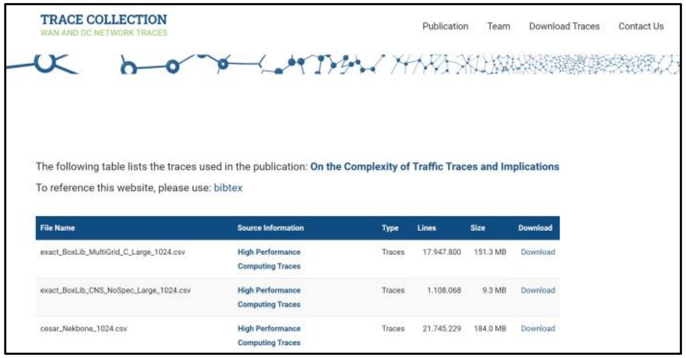
Download Slides

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

Publication Team Download Traces Contact Us

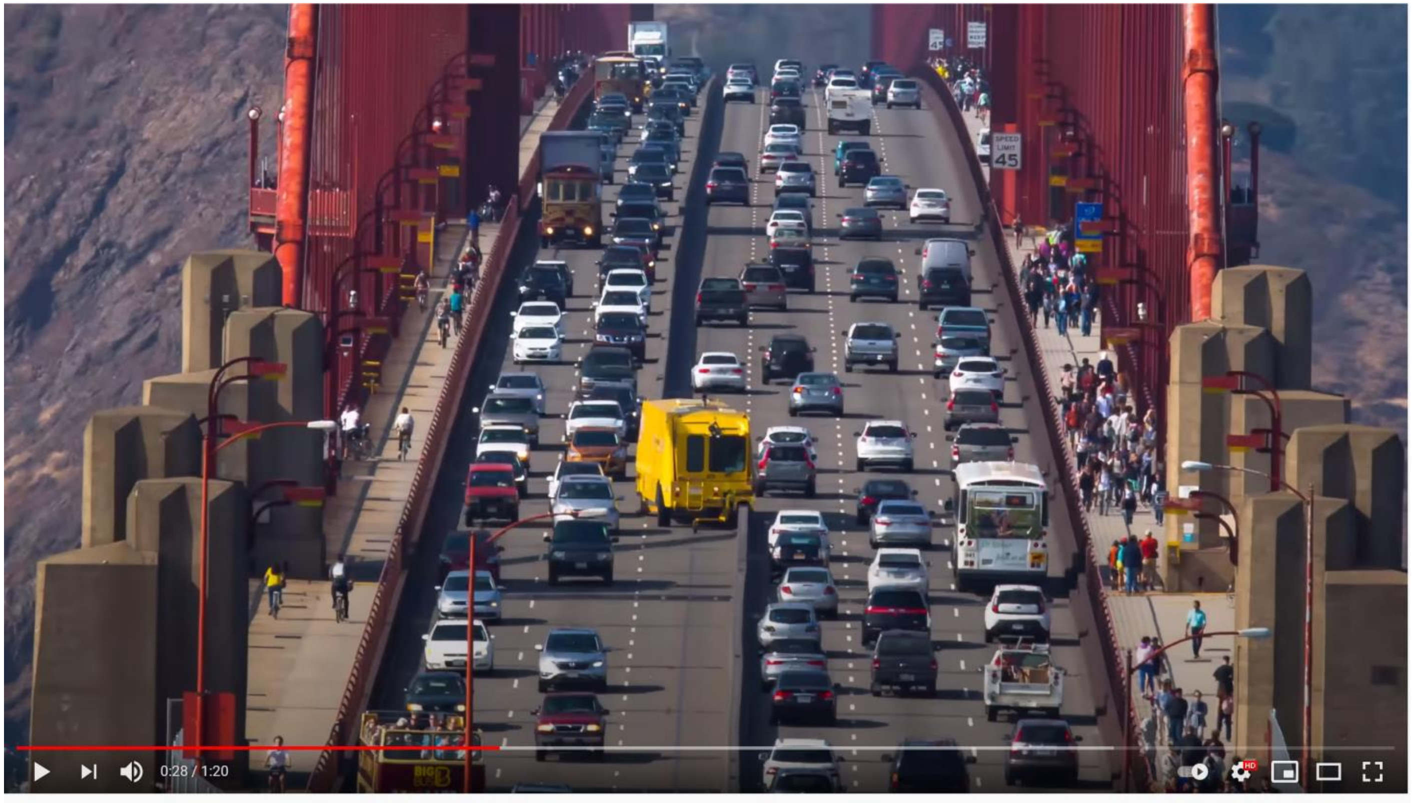
The following table lists the traces used in the publication: **On the Complexity of Traffic Traces and Implications**

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

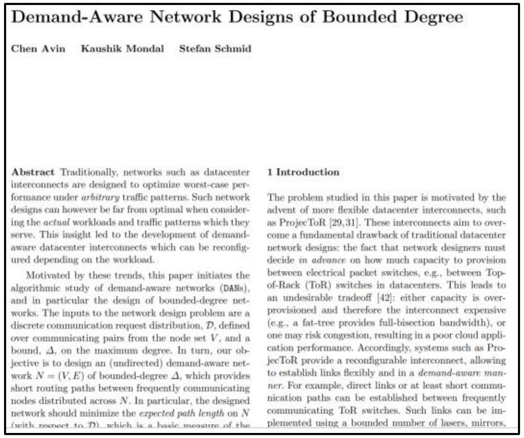
Questions?



Golden Gate Zipper

Further Reading

Static DAN



Demand-Aware Network Designs of Bounded Degree

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

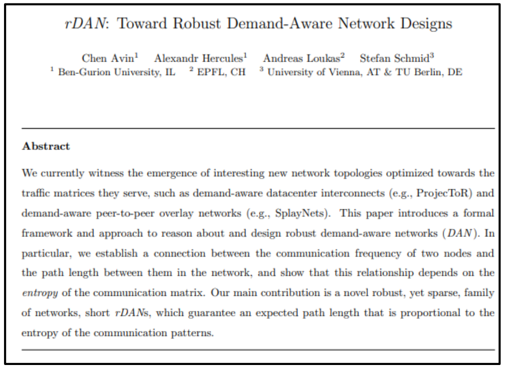
Abstract Traditionally, networks such as datacenter interconnects are designed to optimize worst-case performance under *arbitrary* traffic patterns. Such network designs can however be far from optimal when considering the *actual* workloads and traffic patterns which they serve. This insight led to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

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



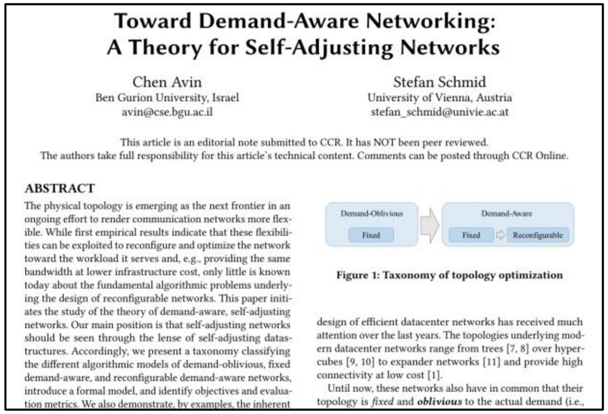
rDAN: Toward Robust Demand-Aware Network Designs

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

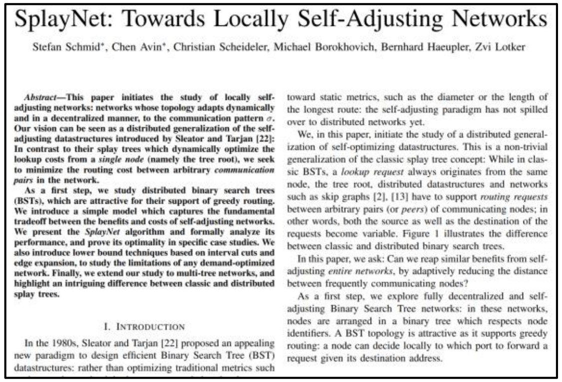
The physical topology is emerging as the next frontier in an ongoing effort to render communication networks more flexible. While first empirical results indicate that these flexibilities can be exploited to reconfigure and optimize the network toward the workload it serves and, e.g., providing the same 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 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

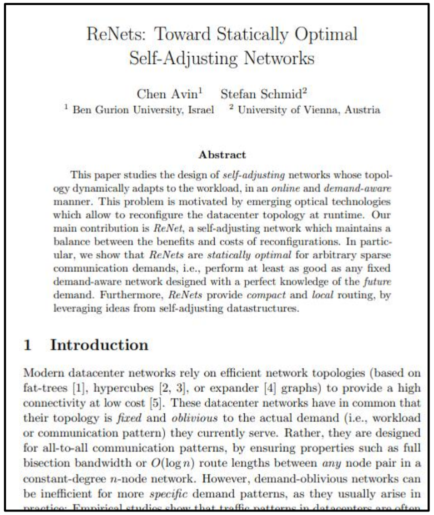
In the 1980s, Sleator and Tarjan [22] proposed an appealing new paradigm to design efficient Binary Search Tree (BST) datastructures: rather than optimizing traditional metrics such toward static metrics, such as the diameter or the length of the longest route: the self-adjusting paradigm has not spilled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

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

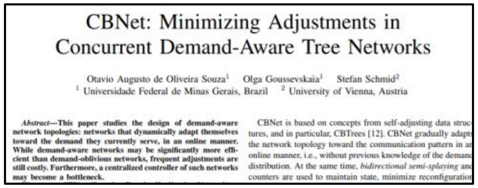
Abstract

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 structures, 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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SplayNet: Towards Locally Self-Adjusting Networks
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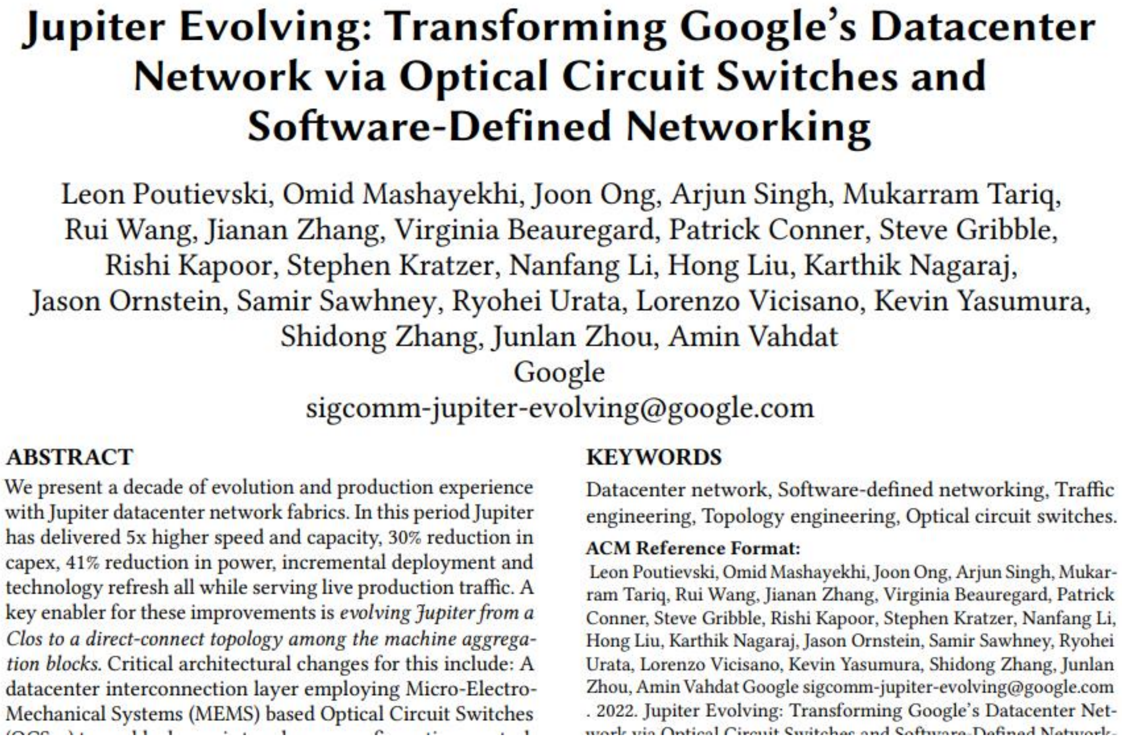
Bonus Material

Hogwarts Stair

Industry Moving Forward!



Jupiter Evolving: Transforming Google's Datacenter Network via Optical Circuit Switches and Software-Defined Networking

Leon Poutievski, Omid Mashayekhi, Joon Ong, Arjun Singh, Mukarram Tariq,
Rui Wang, Jianan Zhang, Virginia Beauregard, Patrick Conner, Steve Gribble,
Rishi Kapoor, Stephen Kratzer, Nanfang Li, Hong Liu, Karthik Nagaraj,
Jason Ornstein, Samir Sawhney, Ryohei Urata, Lorenzo Vicisano, Kevin Yasumura,
Shidong Zhang, Junlan Zhou, Amin Vahdat
Google
sigcomm-jupiter-evolving@google.com

ABSTRACT

We present a decade of evolution and production experience with Jupiter datacenter network fabrics. In this period Jupiter has delivered 5x higher speed and capacity, 30% reduction in capex, 41% reduction in power, incremental deployment and technology refresh all while serving live production traffic. A key enabler for these improvements is *evolving Jupiter from a Clos to a direct-connect topology among the machine aggregation blocks*. Critical architectural changes for this include: A datacenter interconnection layer employing Micro-Electro-Mechanical Systems (MEMS) based Optical Circuit Switches

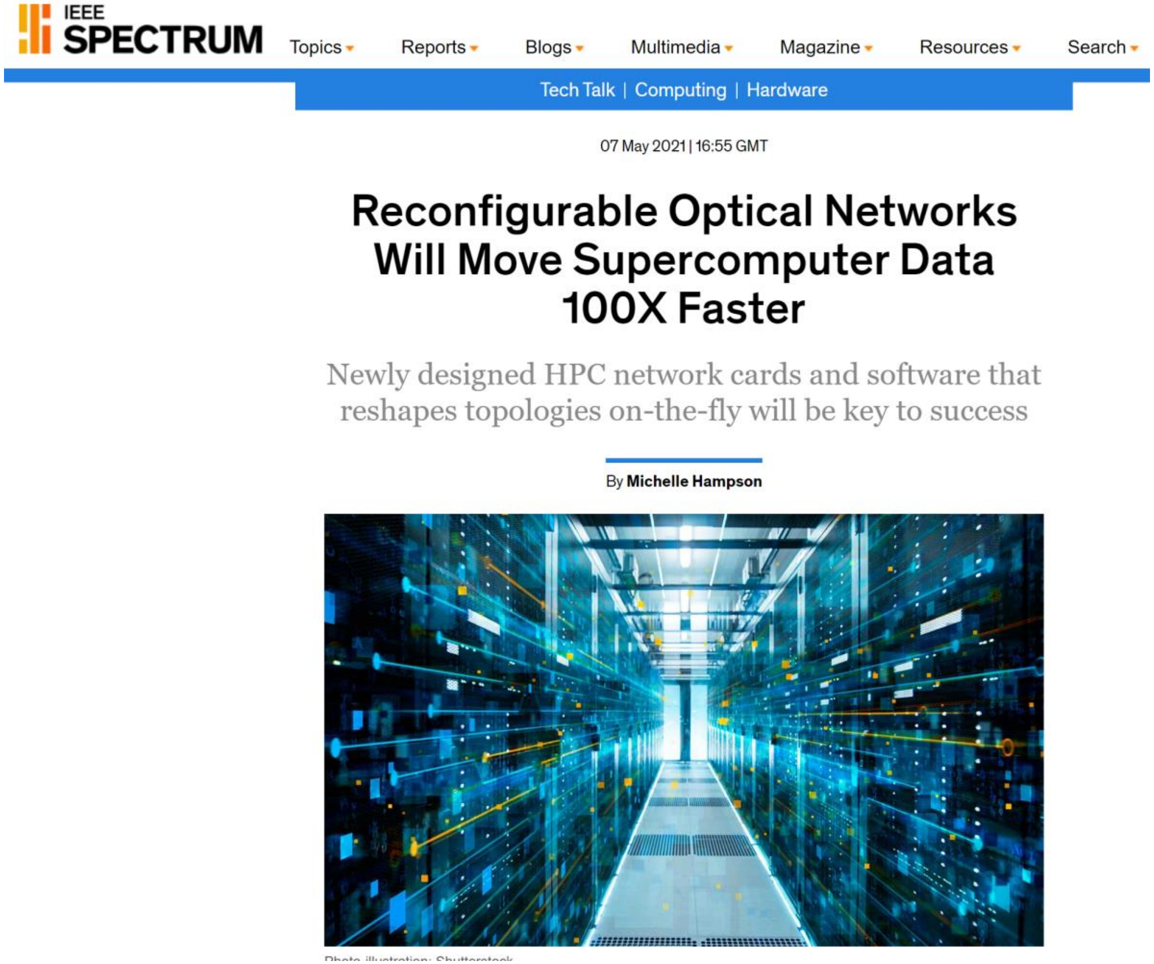
KEYWORDS

Datacenter network, Software-defined networking, Traffic engineering, Topology engineering, Optical circuit switches.

ACM Reference Format:

Leon Poutievski, Omid Mashayekhi, Joon Ong, Arjun Singh, Mukarram Tariq, Rui Wang, Jianan Zhang, Virginia Beauregard, Patrick Conner, Steve Gribble, Rishi Kapoor, Stephen Kratzer, Nanfang Li, Hong Liu, Karthik Nagaraj, Jason Ornstein, Samir Sawhney, Ryohei Urata, Lorenzo Vicisano, Kevin Yasumura, Shidong Zhang, Junlan Zhou, Amin Vahdat Google sigcomm-jupiter-evolving@google.com . 2022. Jupiter Evolving: Transforming Google's Datacenter Net-

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:

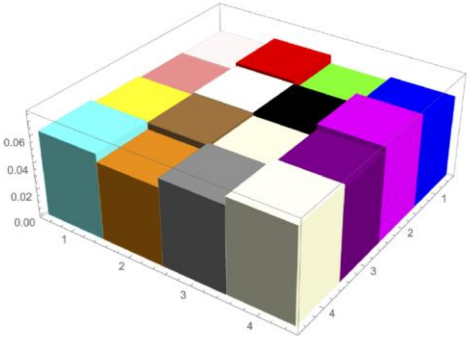
How to Quantify such “Structure” in the Demand?

Intuition

Which demand has more structure?

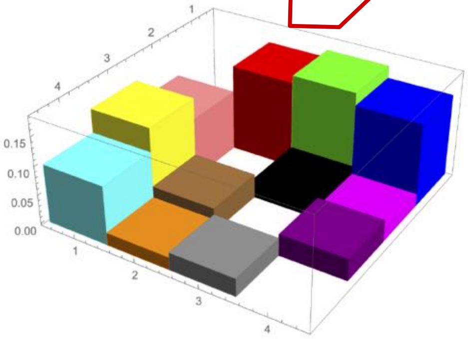
⇢ Traffic matrices of two different distributed ML applications

  ⇀ GPU-to-GPU



VS

Color = communication pair



Intuition

Which demand has more structure?

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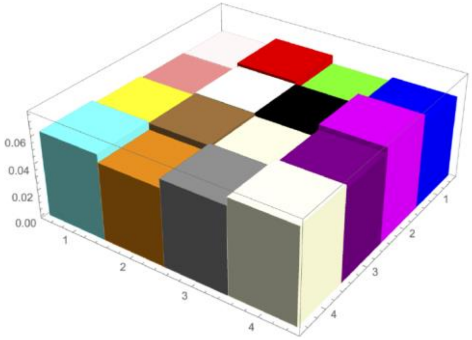
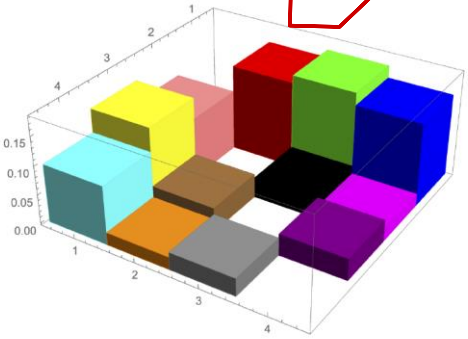
  - ⇀ GPU-to-GPU



More uniform

VS

Color = communication pair



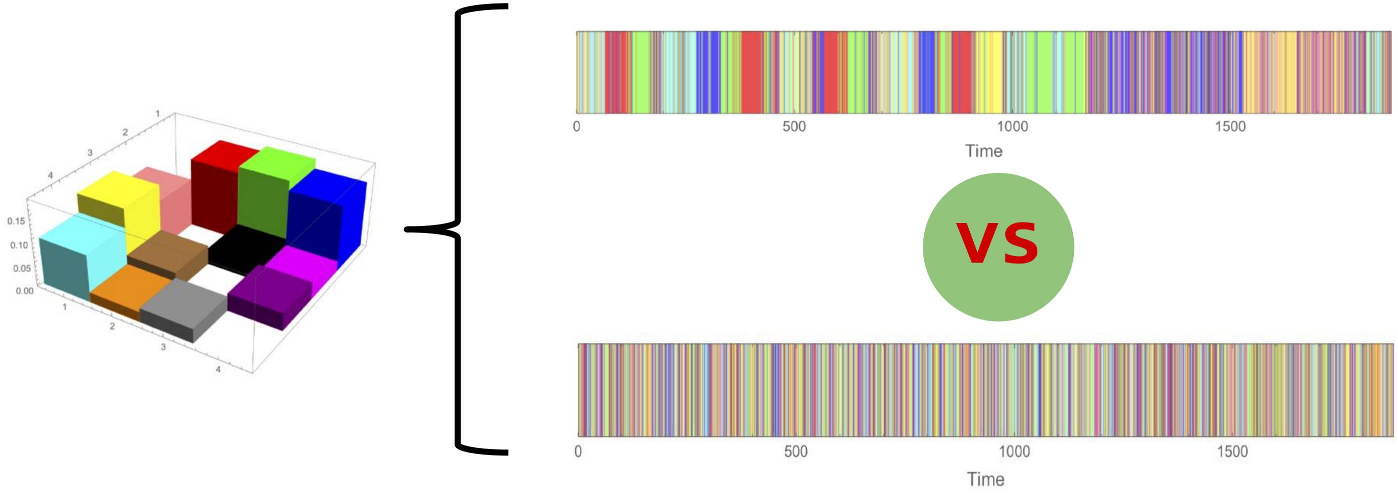
More structure

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

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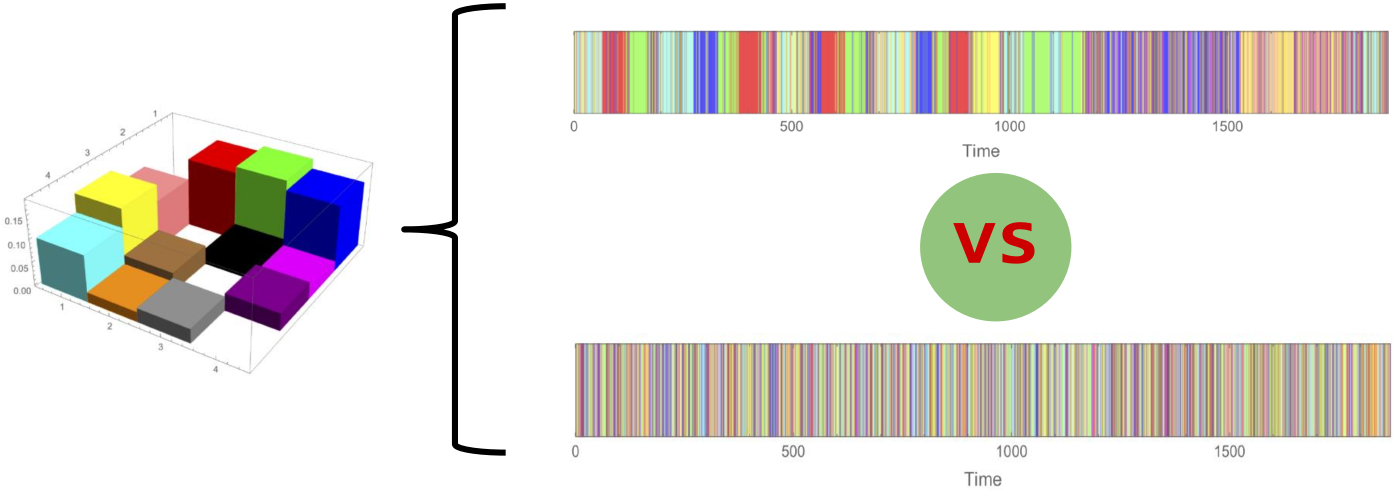
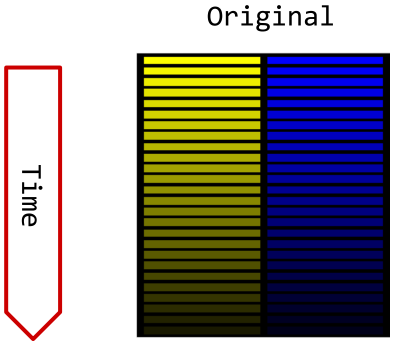


Systematically?

Trace Complexity

Information-Theoretic Approach

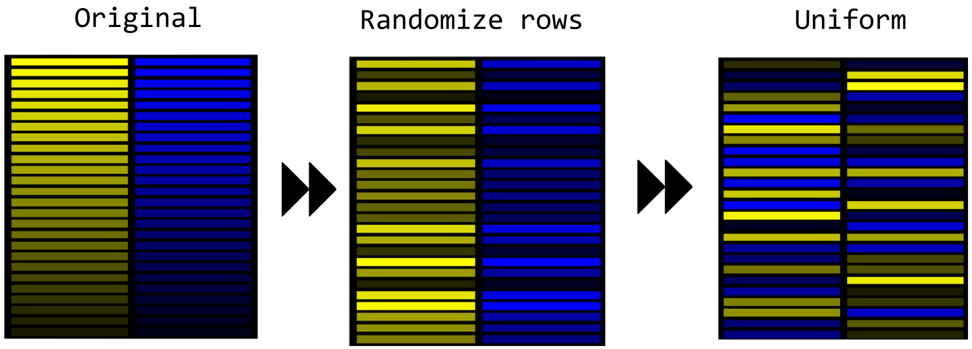
“Shuffle&Compress”



Trace Complexity

Information-Theoretic Approach

“Shuffle&Compress”



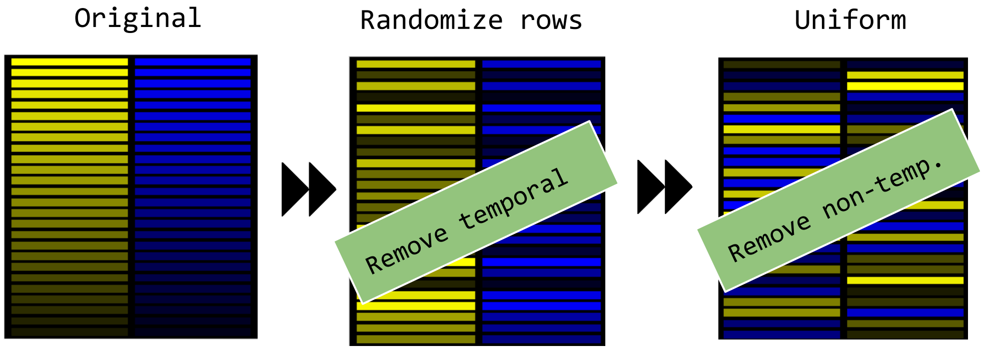
Increasing complexity (systematically randomized)

More structure (compresses better)

Trace Complexity

Information-Theoretic Approach

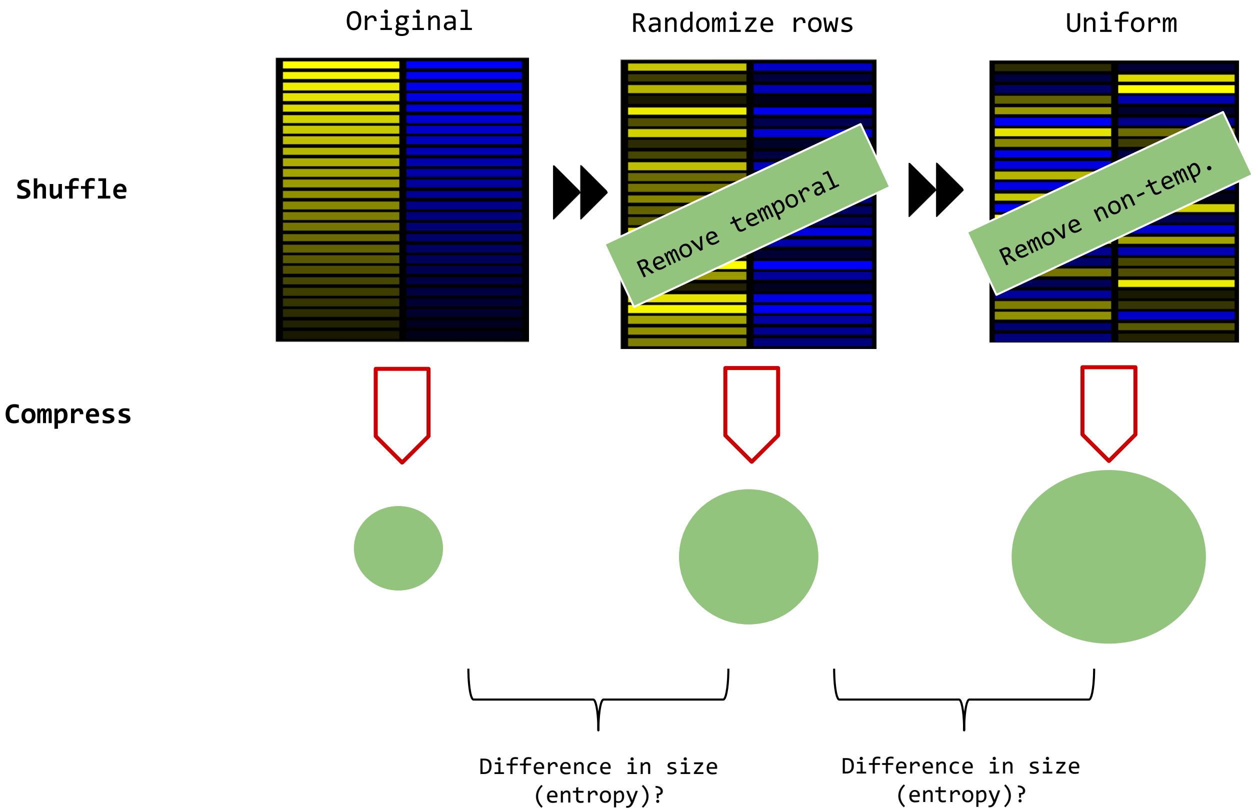
“Shuffle&Compress”



Trace Complexity

Information-Theoretic Approach

“Shuffle&Compress”



Original

Randomize rows

Uniform

Shuffle

Remove temporal

Remove non-temp.

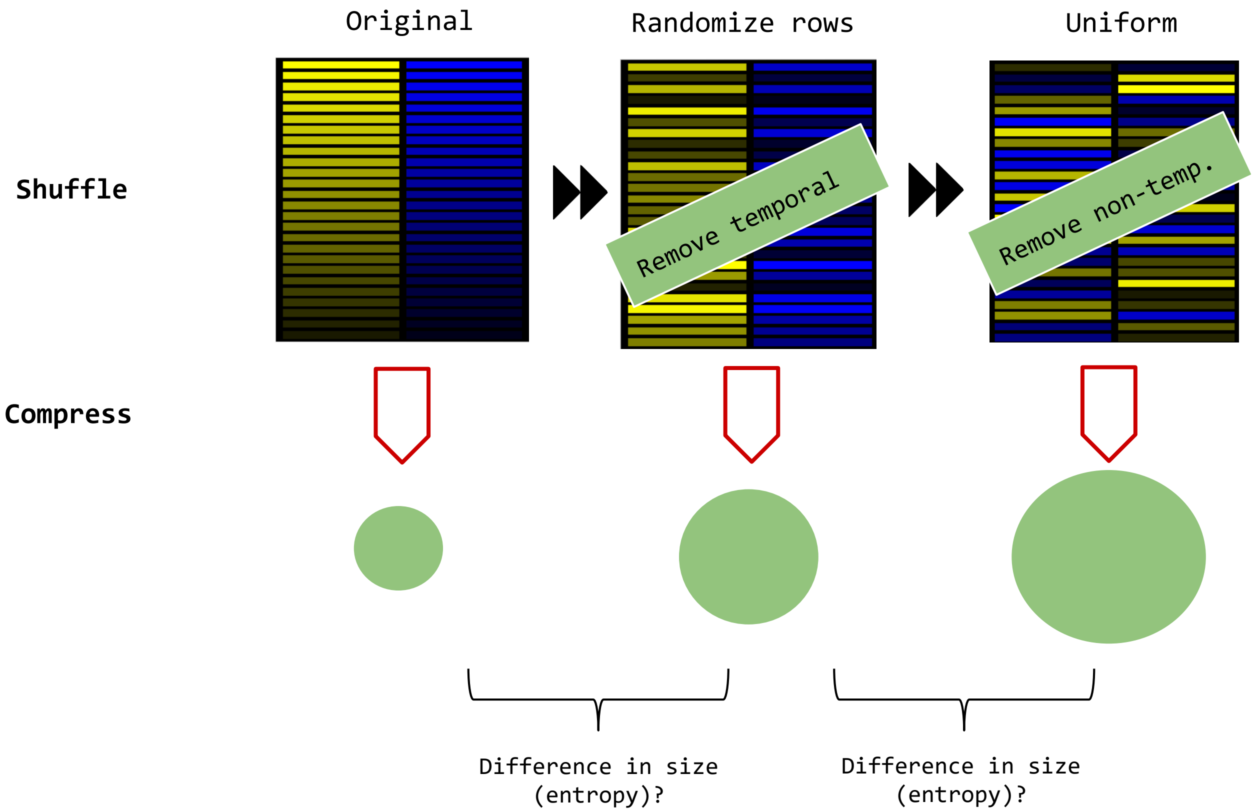
Compress

Difference in size (entropy)?

Difference in size (entropy)?

Trace Complexity

Information-Theoretic Approach
“Shuffle&Compress”



Original

Randomize rows

Uniform

Shuffle

Remove temporal

Remove non-temp.

Compress

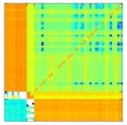
Difference in size
(entropy)?

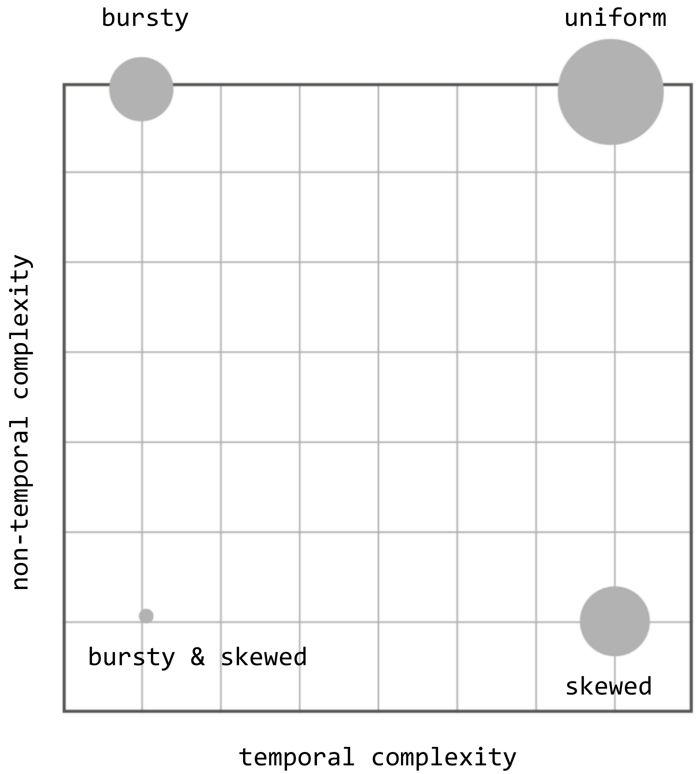
Difference in size
(entropy)?

Can be used to define 2-dimensional complexity map!

Our Methodology

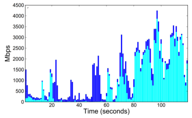
Complexity Map





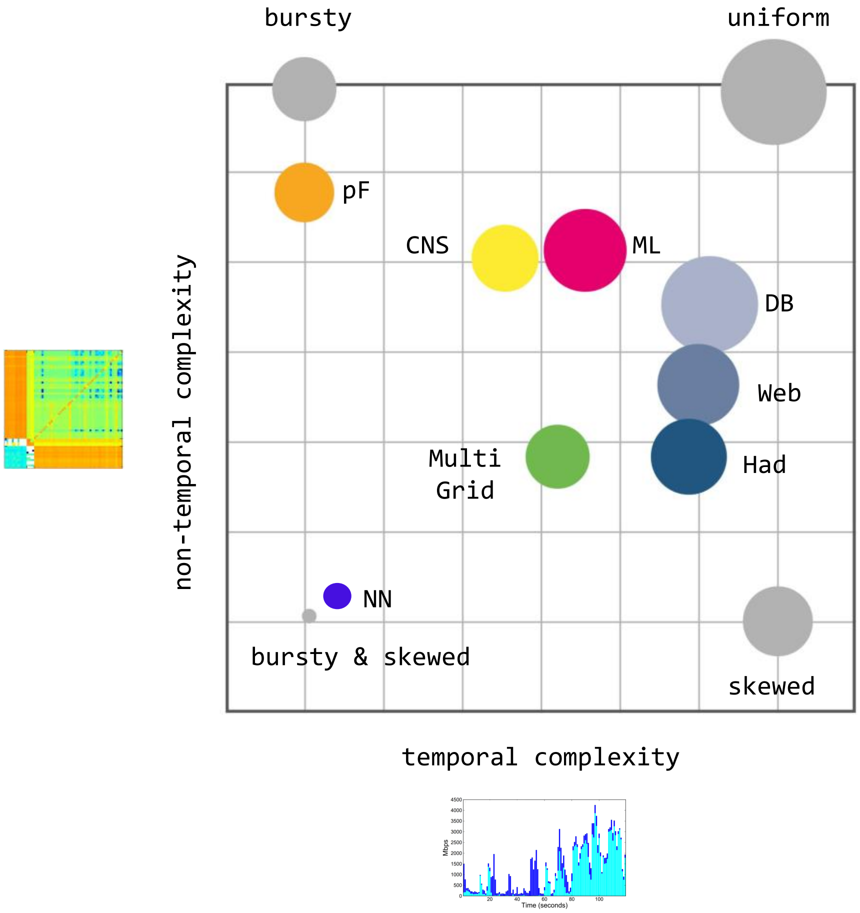
No structure

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



Our Methodology

Complexity Map



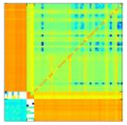
No structure

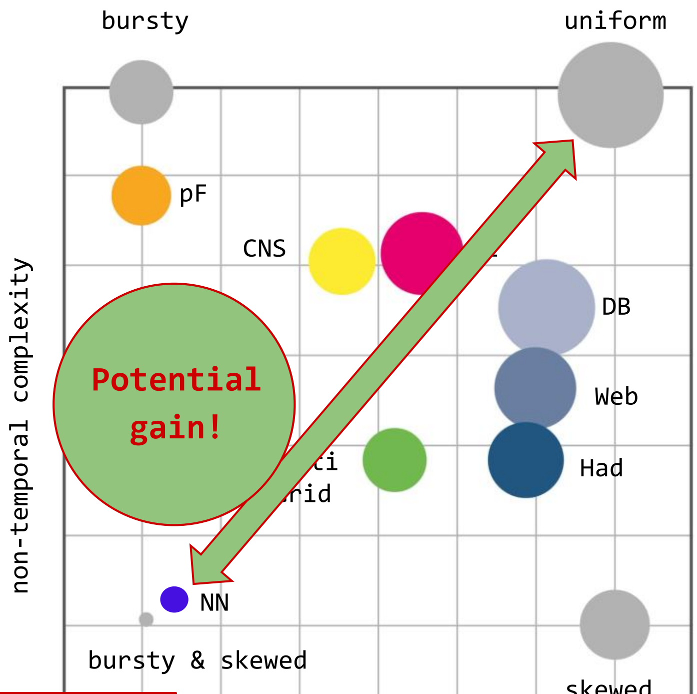
Our **approach**: iterative **randomization and compression** of trace to identify dimensions of structure.

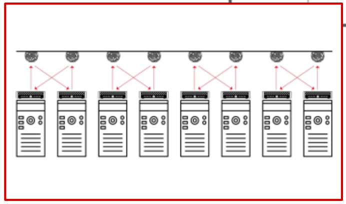
Different structures!

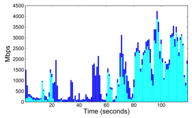
Our Methodology

Complexity Map









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

Another Related Problem

Low Distortion Spanners

- Classic problem: find *sparse*, *distance-preserving* (low-distortion) spanner of a graph

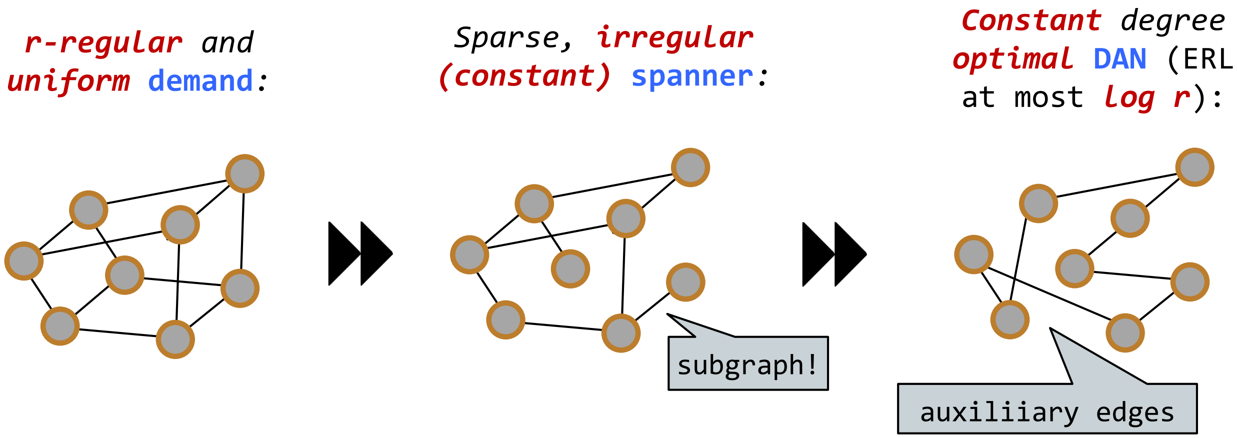
- But:
  - Spanners aim at low distortion *among all pairs*; in our case, we are only interested in the local distortion, 1-hop communication neighbors
  - We allow *auxiliary edges* (not a subgraph): similar to geometric spanners
  - We require *constant degree*

From Spanners to DANs

An Algorithm

⇢ Yet, can leverage the connection to spanners sometimes!

Theorem: If demand matrix is regular and uniform, and if we can find a constant distortion, linear sized (i.e., constant, sparse) spanner for this request graph: then we can design a constant degree DAN providing an optimal expected route length *(i.e., $O(H(X|Y)+H(Y|X))$).*



r-regular *and* ***uniform demand****:*

Sparse, ***irregular (constant) spanner****:*

Constant *degree* ***optimal*** **DAN** (ERL at most ***log r***):

From Spanners to DANs

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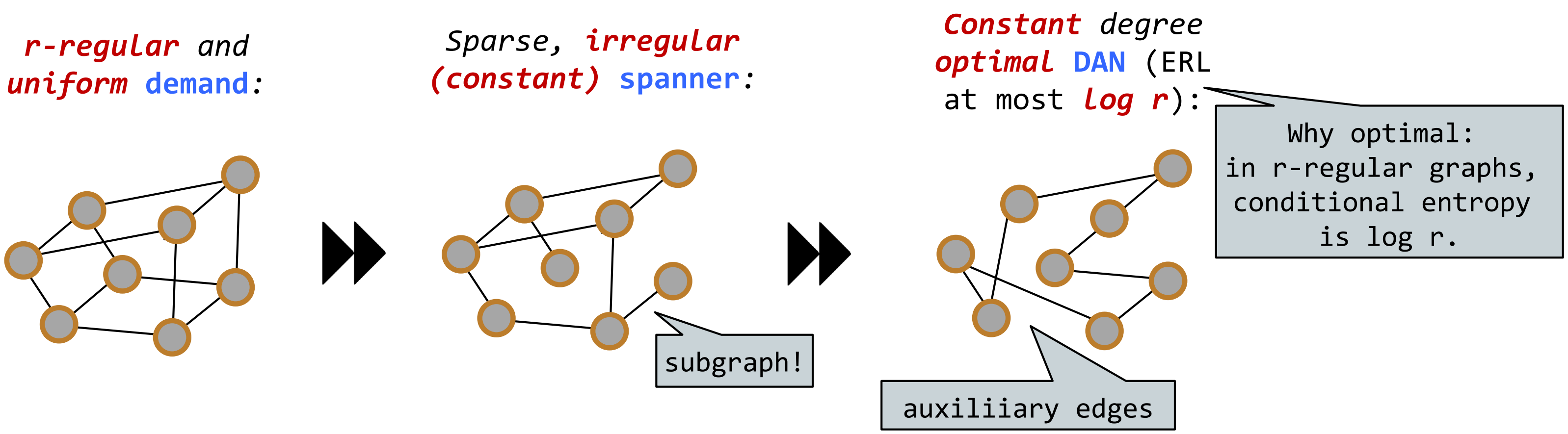

Our degree reduction trick again!

r-regular *and* ***uniform*** **demand**:

Sparse, ***irregular (constant)*** **spanner**:

Constant *degree* ***optimal*** **DAN** (ERL at most ***log r***):

Why optimal: in r-regular graphs, conditional entropy is log r.

subgraph!

auxiliiary edges