

# Learning-Augmented Online Algorithms

Stefan Schmid (TU Berlin)

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

(Folklore)

Acknowledgements:

It's a great time to be  
an algorithm researcher!



***Flexibilities*** everywhere in networked systems!

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***Flexibilities*** everywhere in networked systems!  
Enables ***self-adjusting systems***: adapt to demand.

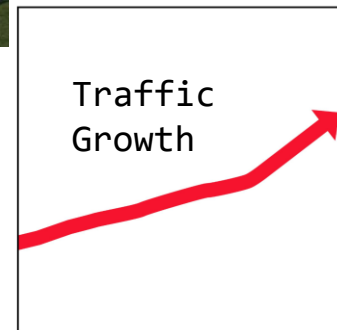
# This Talk: Datacenters

Datacenters (“hyper-scale”)



+network

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



Source: Facebook

# This Talk: Datacenters

Datacenters (“hyper-scale”)



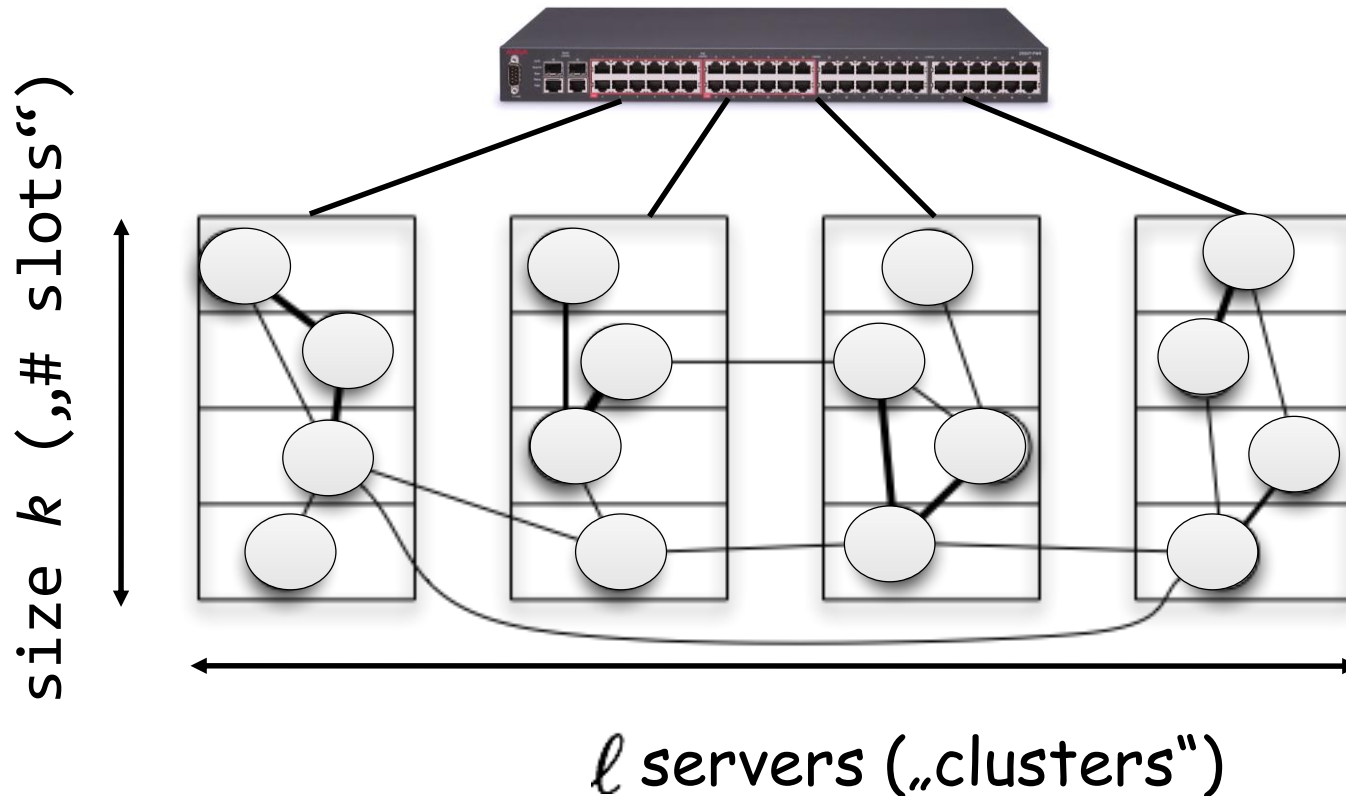
Interconnecting networks:  
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Credits: Marco Chiesa

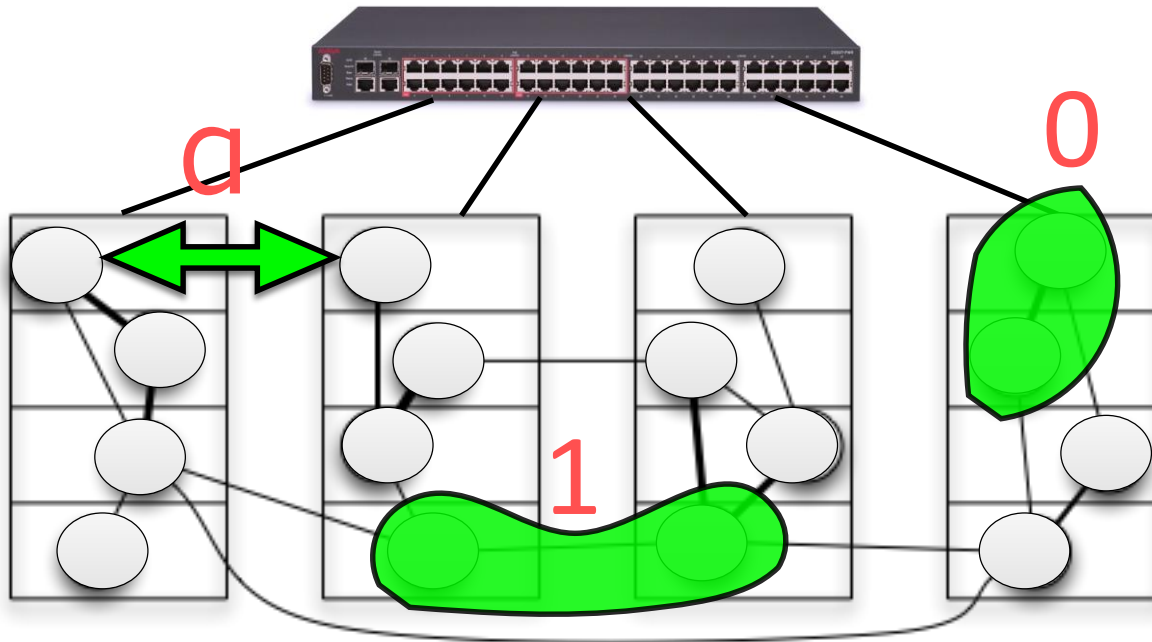
# Example 1: Scheduling

Online Re-Partitioning (Sigmetrics'19, SODA'21)



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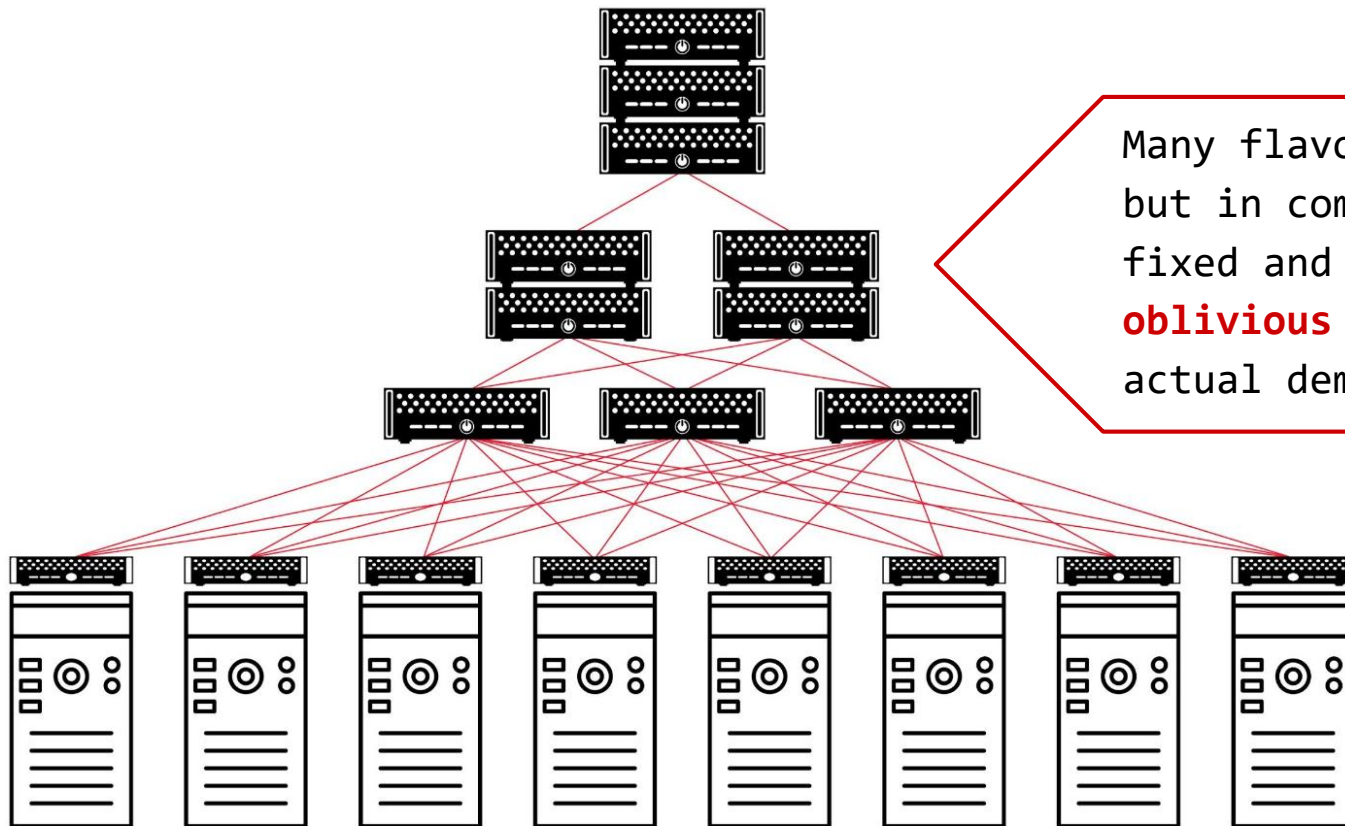
Online Re-Partitioning (Sigmetrics'19, SODA'21)



**Migrate to reduce communication costs? Tradeoff!**

# Example 2: Topology

Self-Adjusting Datacenters (Sigmetrics'23)



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

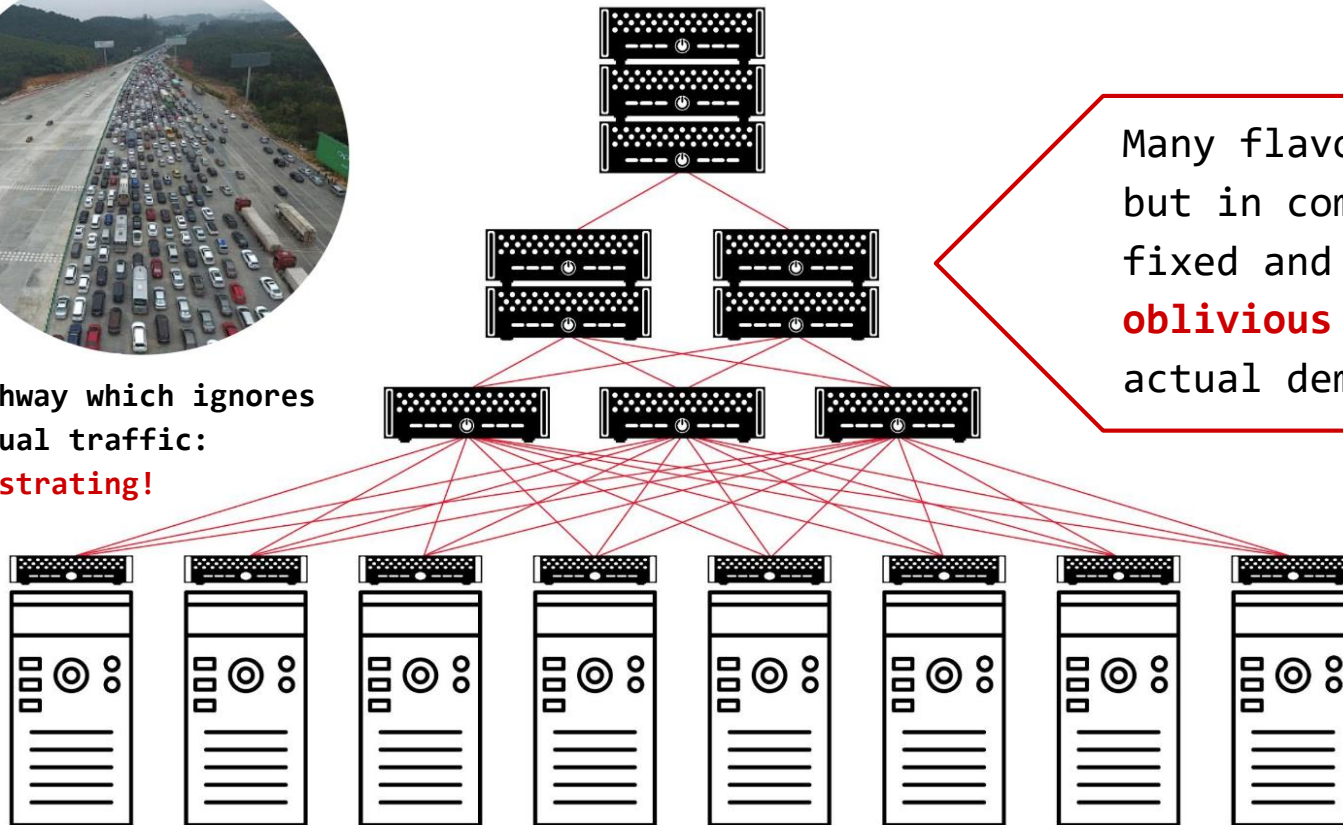


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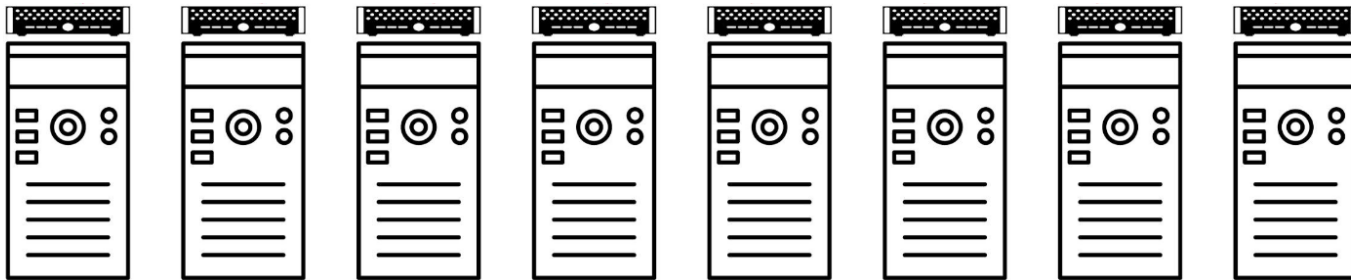
Highway which ignores  
actual traffic:  
**frustrating!**



Many flavors,  
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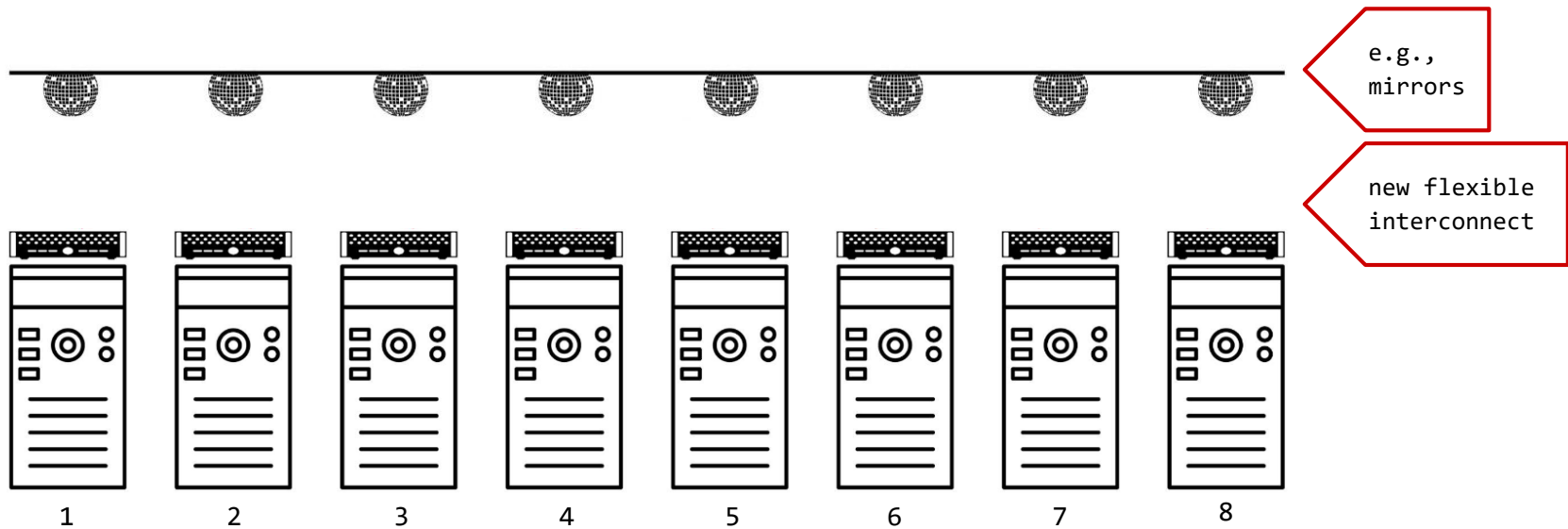
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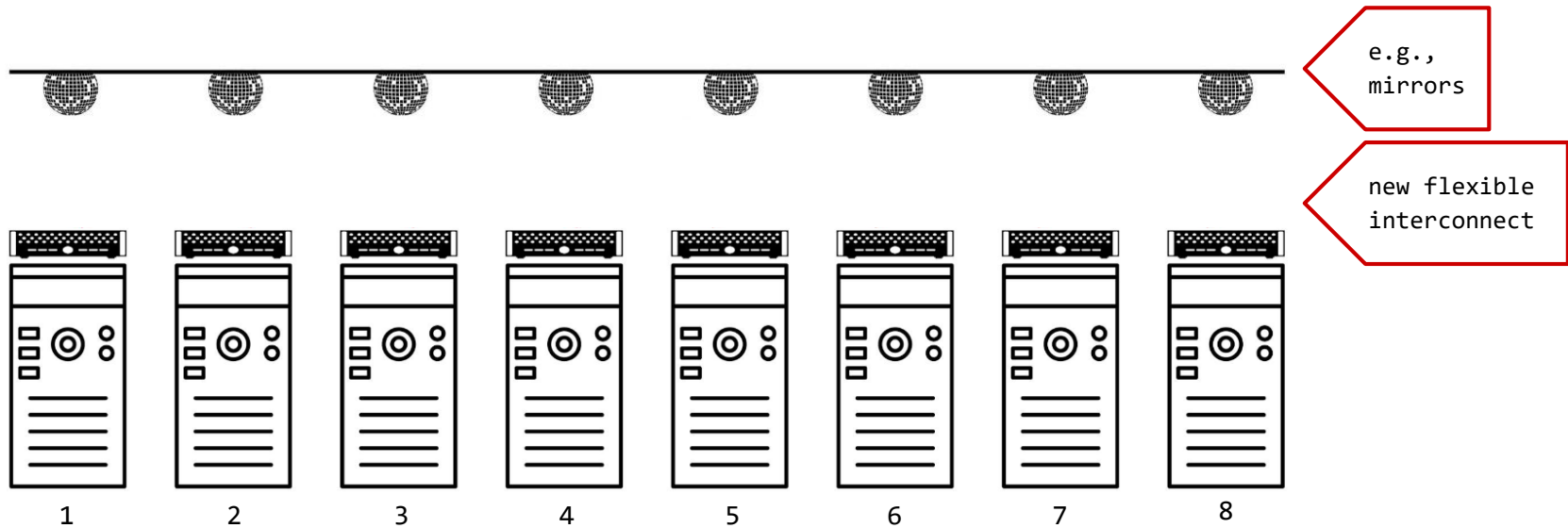
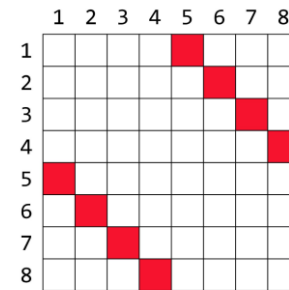
Self-Adjusting Datacenters (Sigmetrics'23)



# Example 2: Topology

Self-Adjusting Datacenters (Sigmetrics'23)

demand  
matrix:



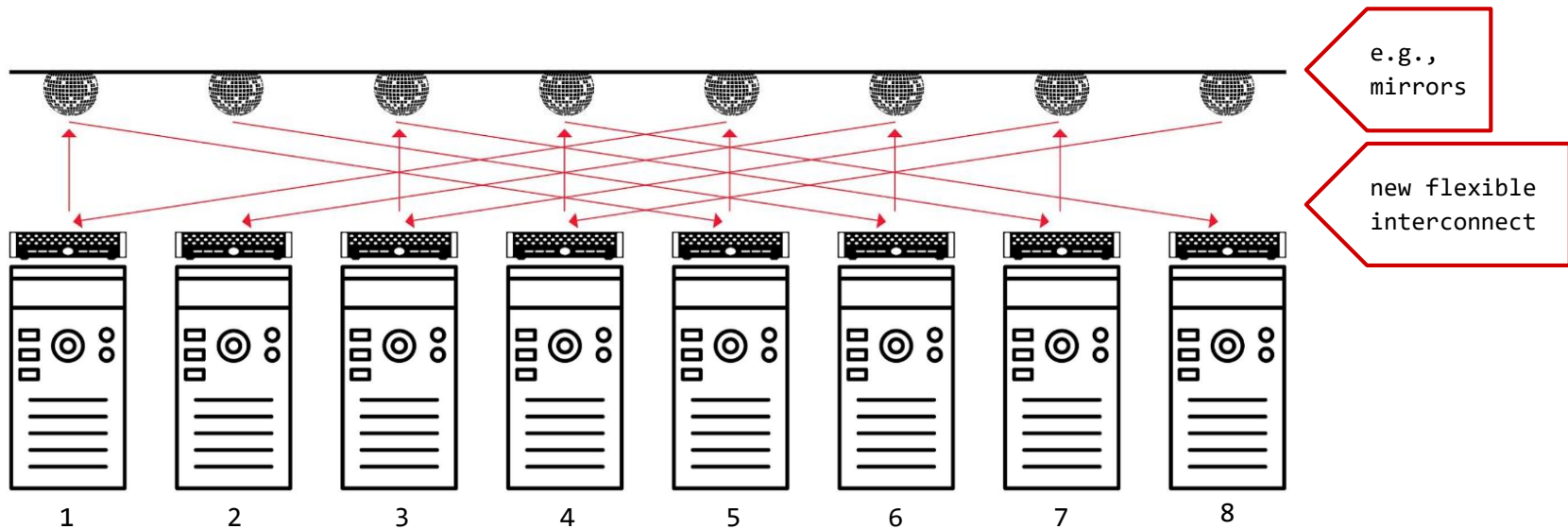
# Example 2: Topology

Self-Adjusting Datacenters (Sigmetrics'23)

Matches demand

demand  
matrix:

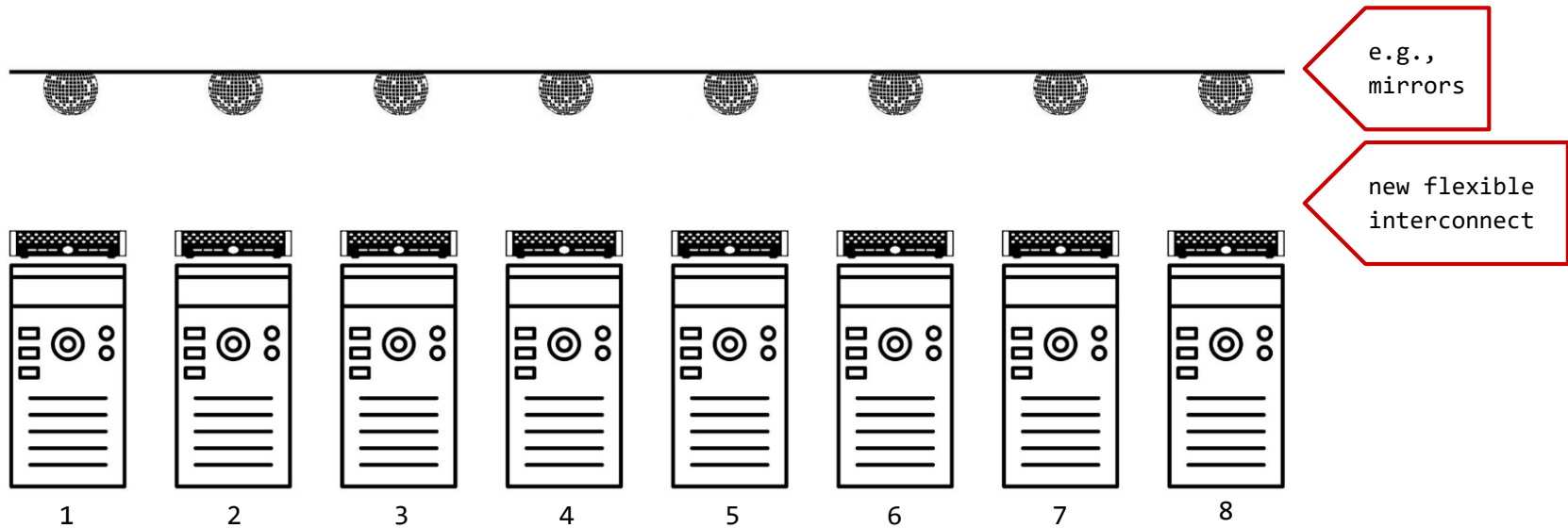
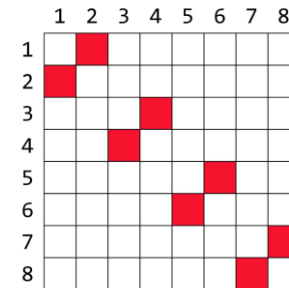
	1	2	3	4	5	6	7	8
1					■			
2						■		
3							■	
4								■
5	■							
6		■						
7			■					
8				■				



# Example 2: Topology

Self-Adjusting Datacenters (Sigmetrics'23)

new  
demand:

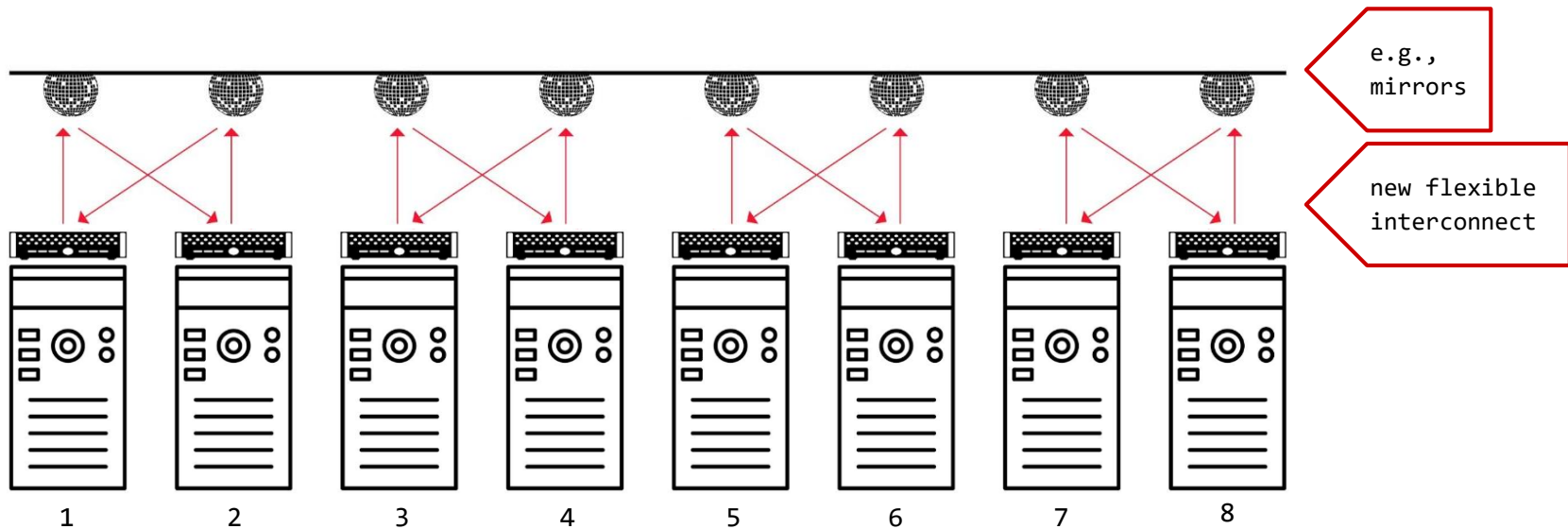
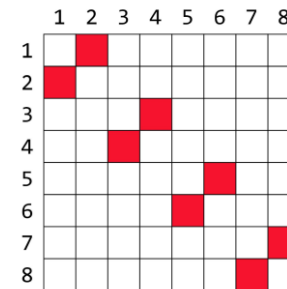


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# Example 2: Topology

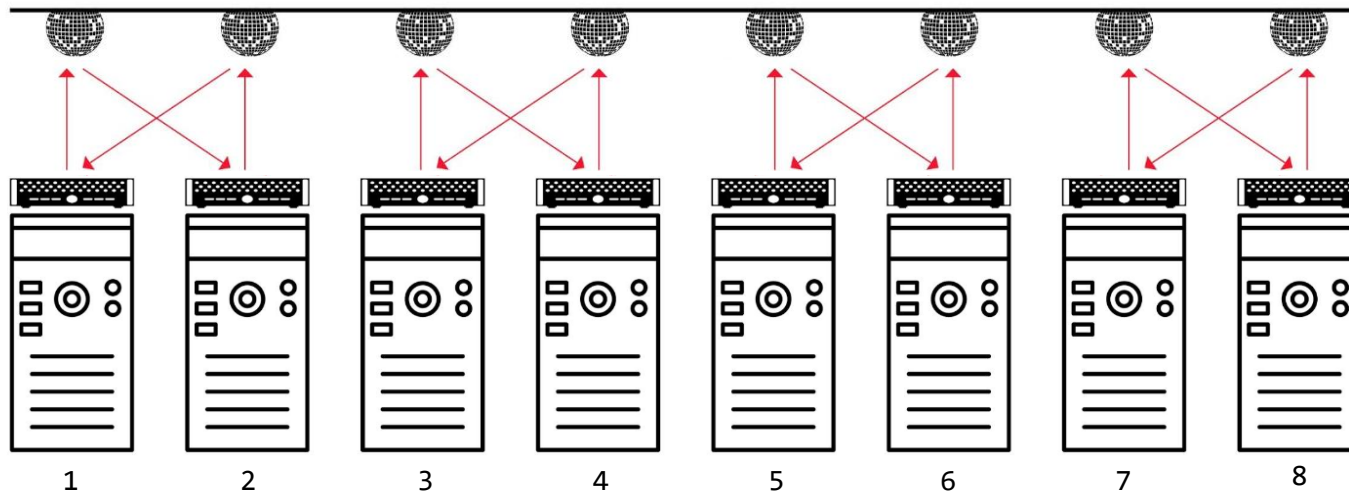
Self-Adjusting Datacenters (Sigmetrics'23)



Self-Adjusting  
Networks

new  
demand:

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



e.g.,  
mirrors

new flexible  
interconnect



# Example 2: Topology

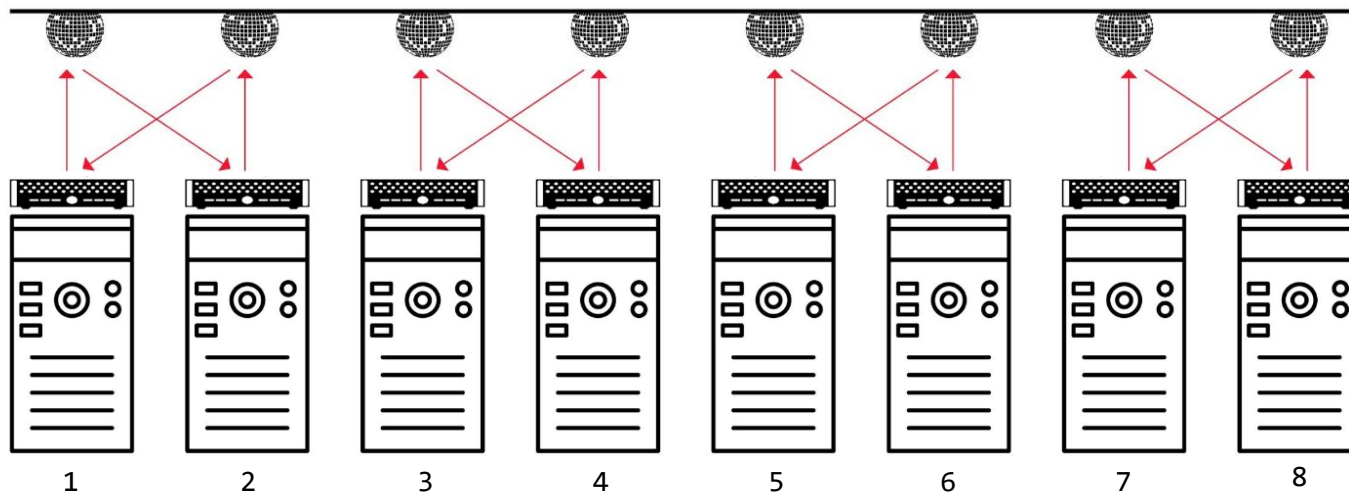
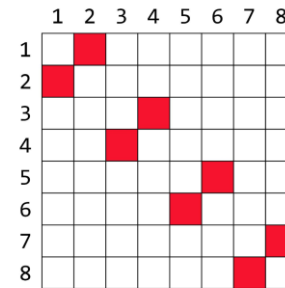
Self-Adjusting Datacenters (Sigmetrics'23)



Self-Adjusting  
Networks

**Tradeoff: benefits vs  
costs of adjustments**

new  
demand:



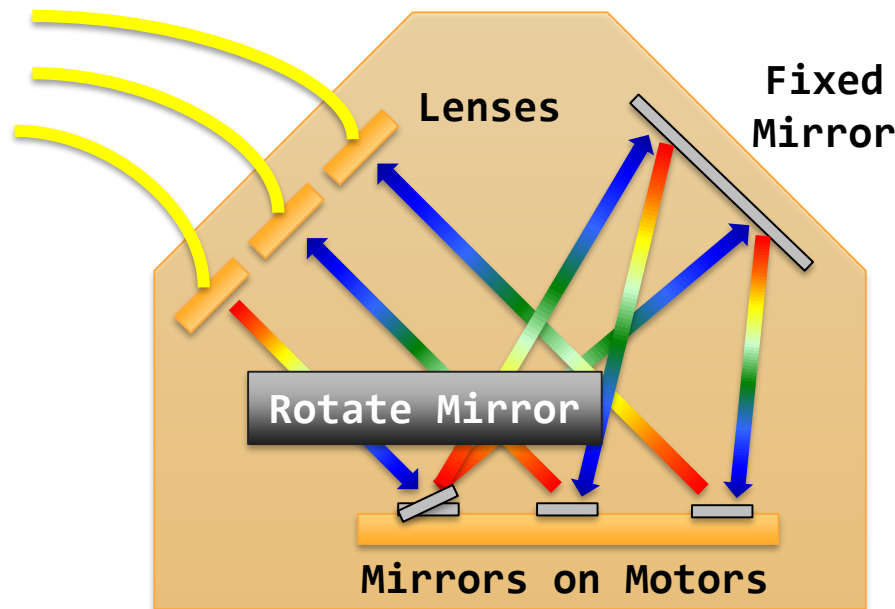
e.g.,  
mirrors

new flexible  
interconnect

# Underlying Technology

## Optical Circuit Switch

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



## Optical Circuit Switch

By Nathan Farrington, SIGCOMM 2010

# Competitive Ratio

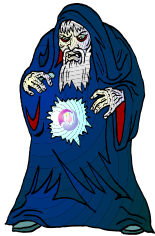
Metric for Evaluating Self-Adjusting Systems

$$\rho = \max_{\sigma} \text{Cost\_ON}(\sigma) / \text{Cost\_OFF}(\sigma)$$

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Too conservative? Demand often not “worst case”.

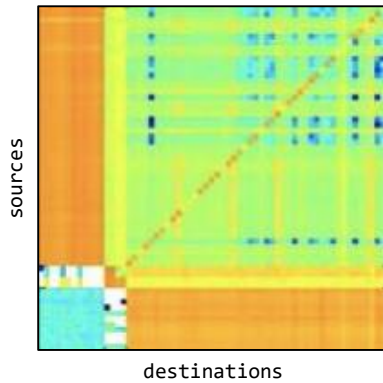
# Too Conservative?

Much Structure in the Demand

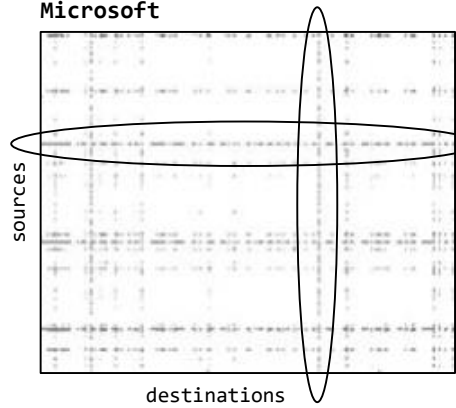
Empirical studies:

traffic matrices **sparse** and **skewed**

Facebook

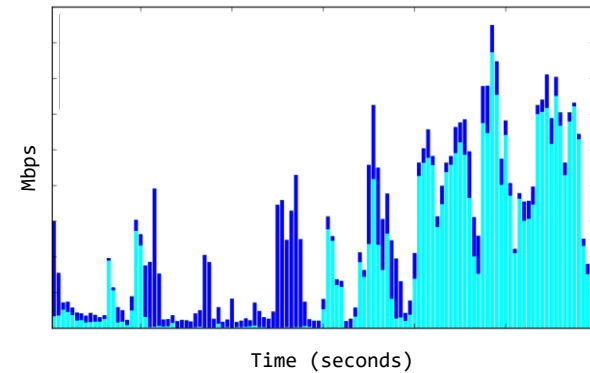


Microsoft



traffic **bursty** over time

Facebook



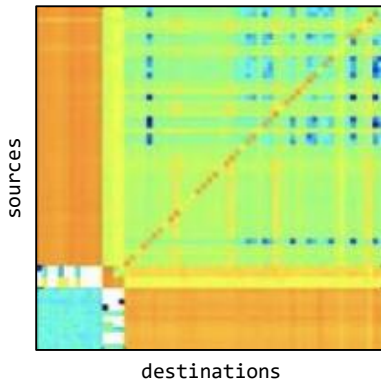
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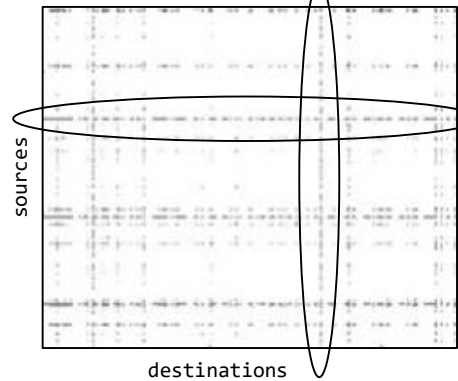
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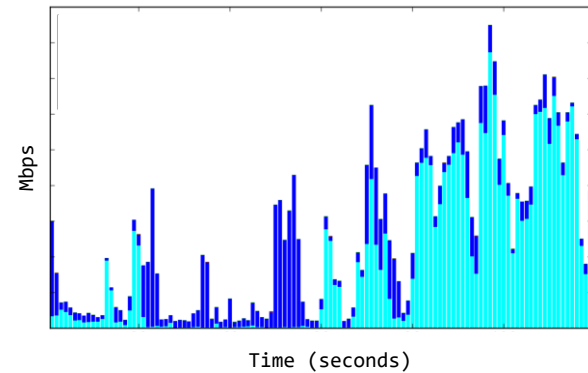


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The **hypothesis**: can be learned/predicted/exploited.

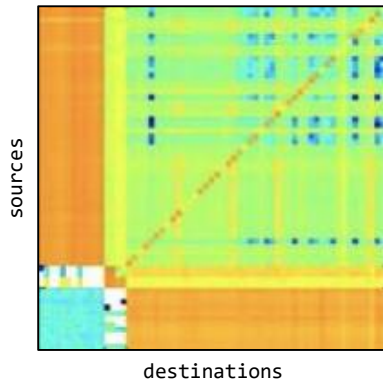
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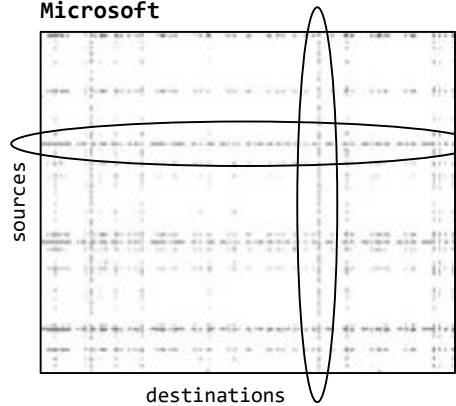
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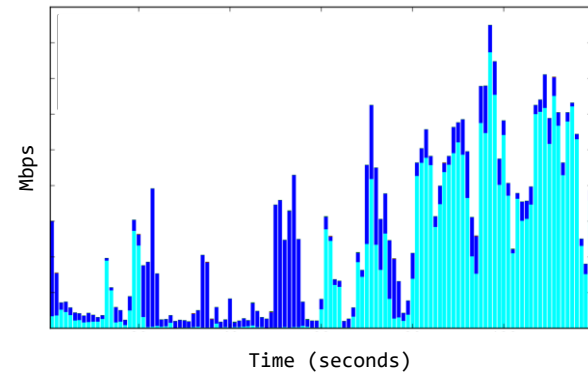


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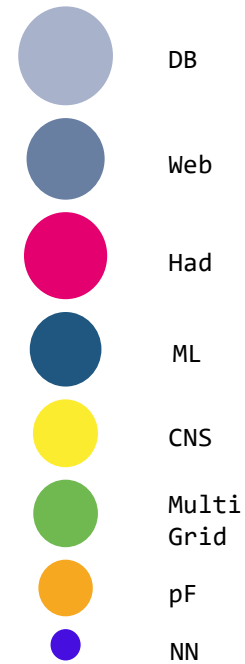
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Check out [trace complexity website!](#)

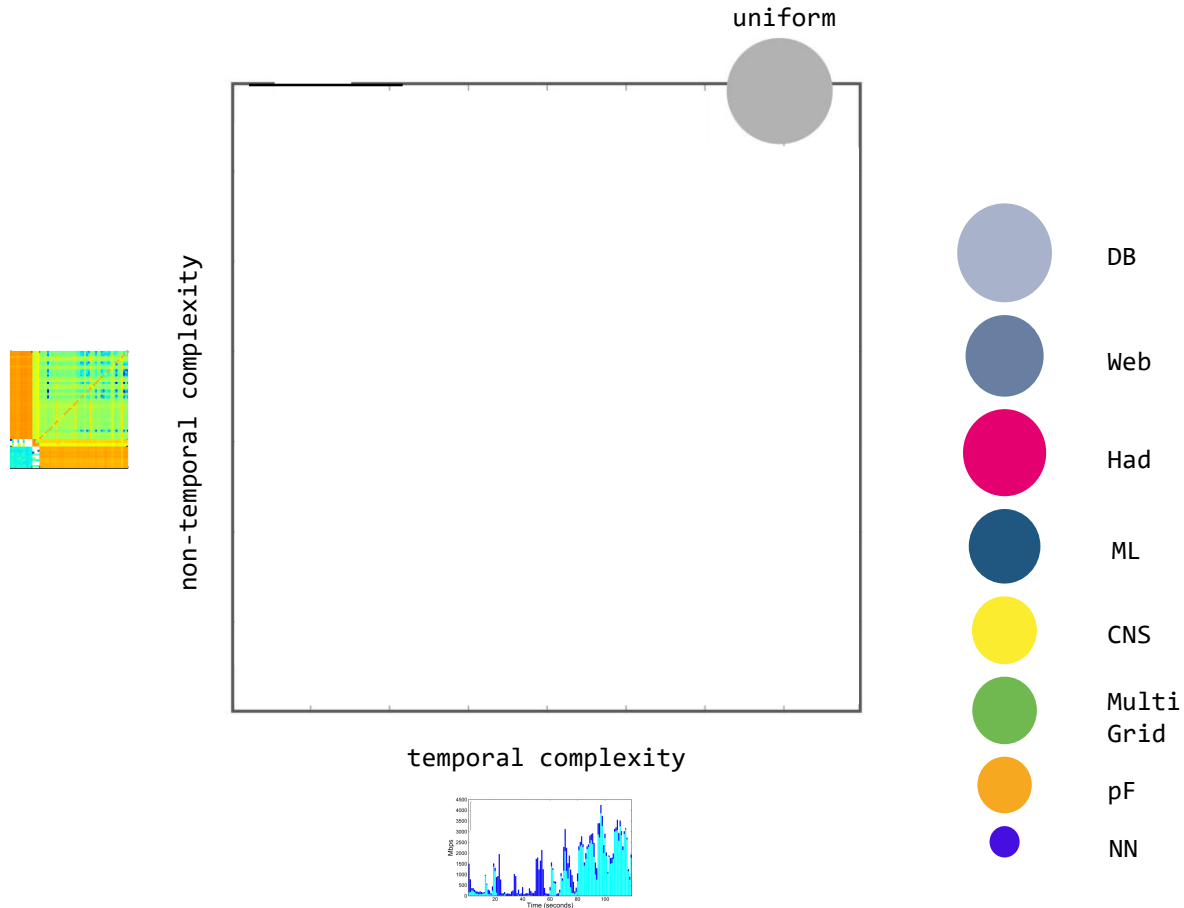


Recent Representation of Trace Structure:

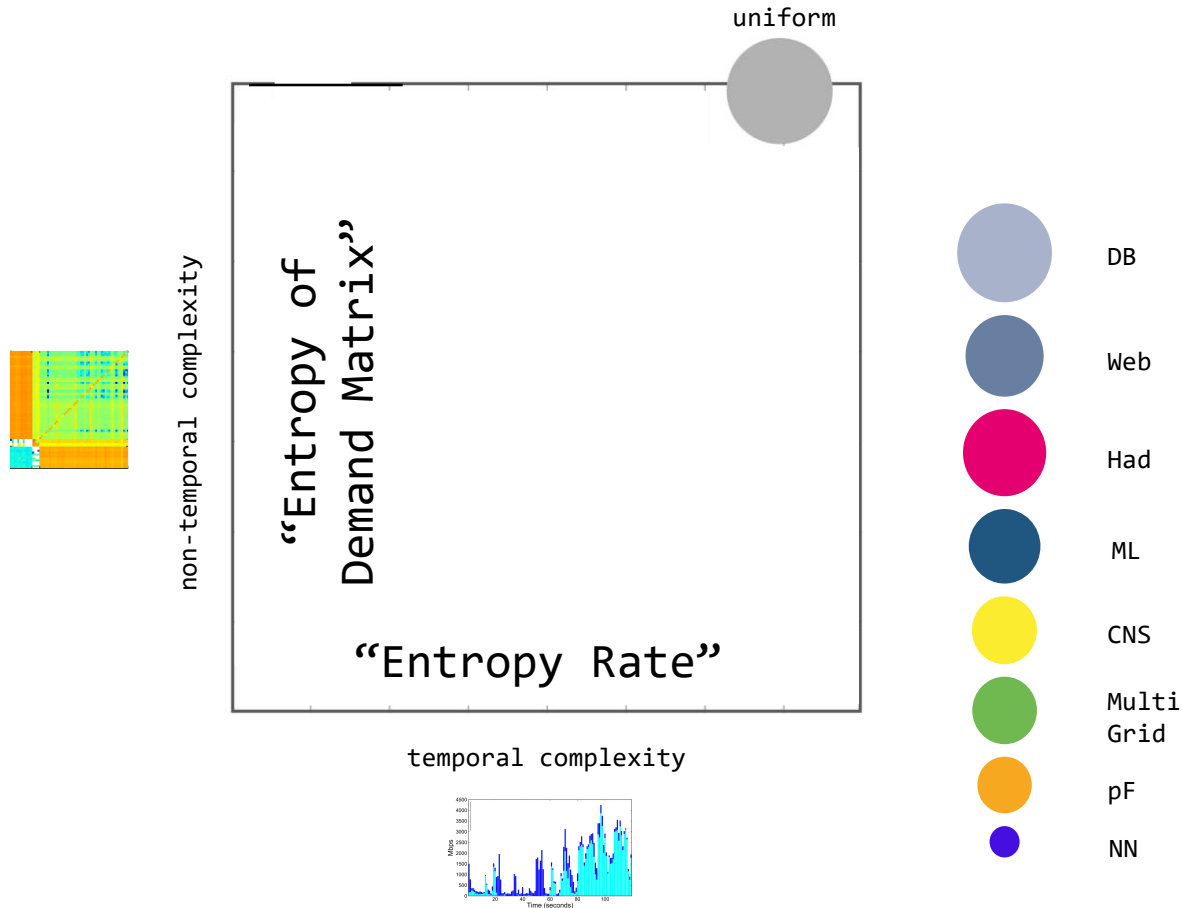
# Complexity Map (Sigmetrics'20)



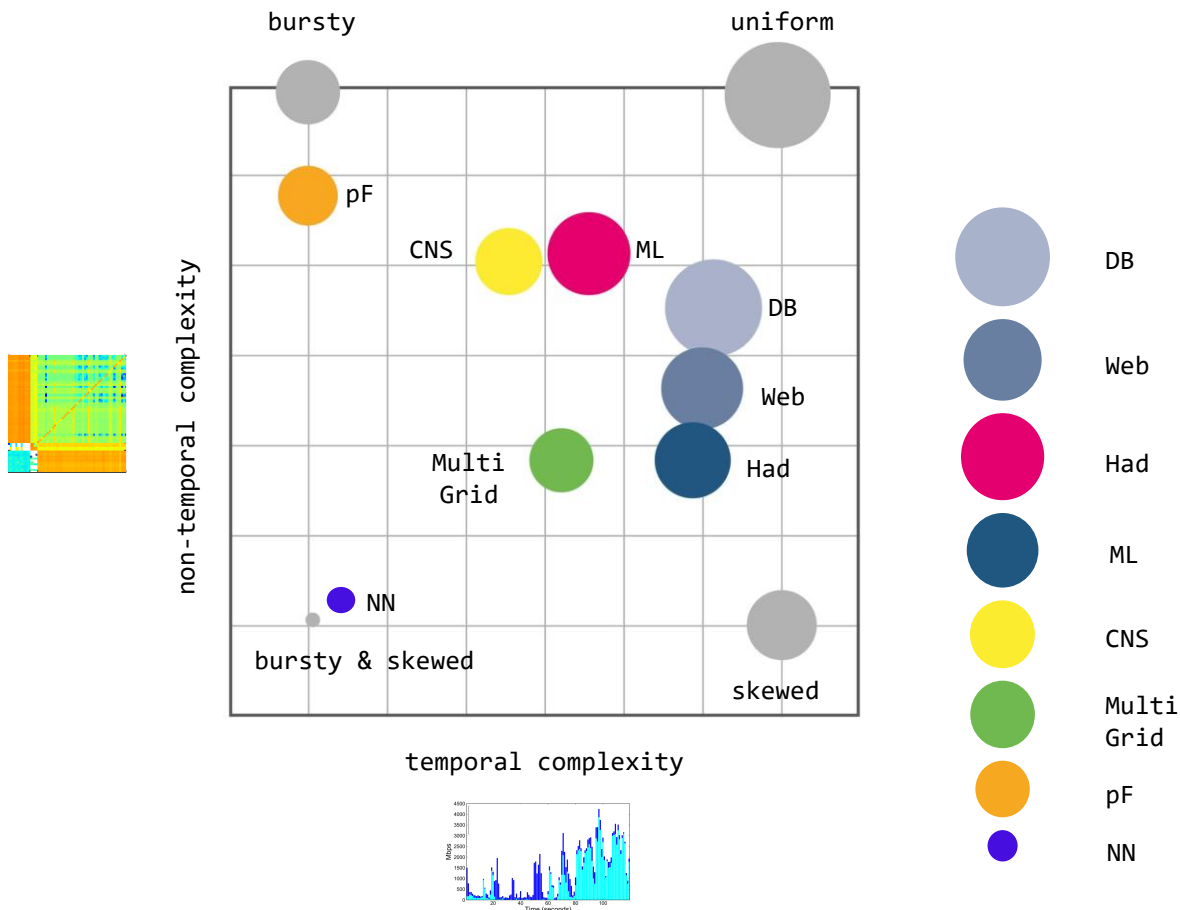
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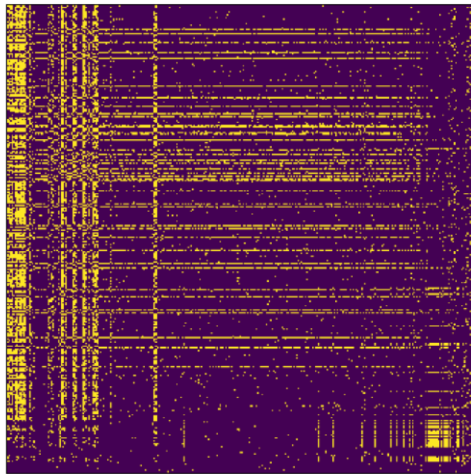
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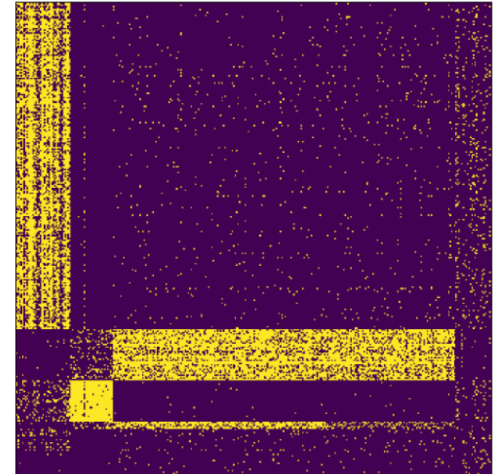
**Different structures!**

Traffic is also clustered (WWW'23):

# Small Stable Clusters



reordering based on  
*bicluster* structure



Opportunity: *exploit* with little reconfigurations!

# Beyond Worst-Case

Many approaches, also for online algorithms!



- **Restricting inputs:** random arrival order, locality of reference, access graph, smoothed analysis, independent sampling, diffused adversaries, distributional analysis, ...
- **Deviating from competitive analysis:** resource augmentation, loose competitiveness, and competitiveness with high probability
- **Advice:** Next slide 😊

# Advice Models

Advice from an oracle: *side-loaded information* about the future helps online algorithms to make better decisions.

## Model 1: perfect advice

- Assumes a powerful, fully *trustworthy oracle*
- Provides algorithm with any information about the future
- Question *how many bits* of the advice an online algorithm needs to achieve a certain competitive ratio  $c$

## Model 2: predictions (untrusted advice)

- Introduced by Mitzenmacher and Vassilvitskii: predictor may be faulty, and the competitive ratio depends on its error
- For small error, algorithm should perform close to the offline optimum (*consistency*), for large error, not worse than non-augmented online algorithms (*robustness*)

## Model 3: lookahead

- Related to local algorithms of distributed computing\*

# Limitations



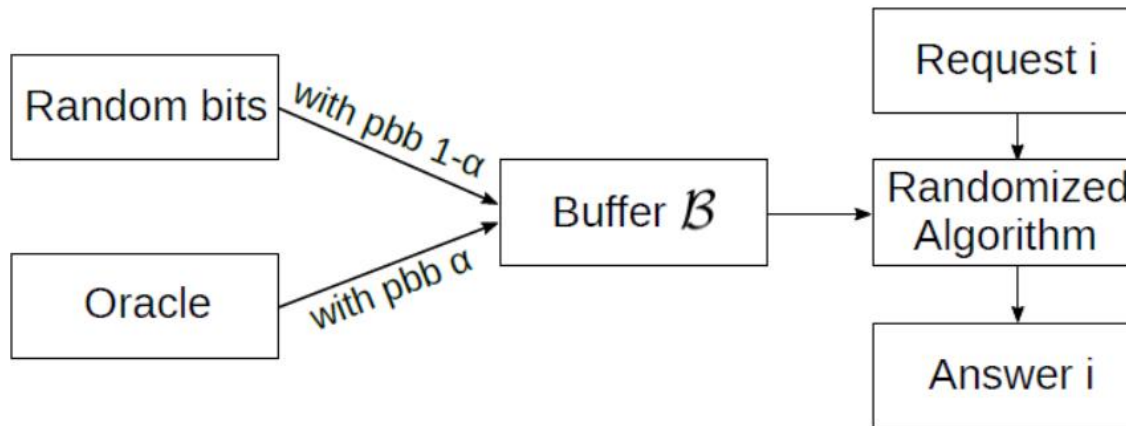
- All these models require new algorithmic features (e.g., a *designated advice tape*)
- Hence not applicable to *existing online algorithms*
- Bounds also depend on choice of error function



# Infused Advice Model

An alternative

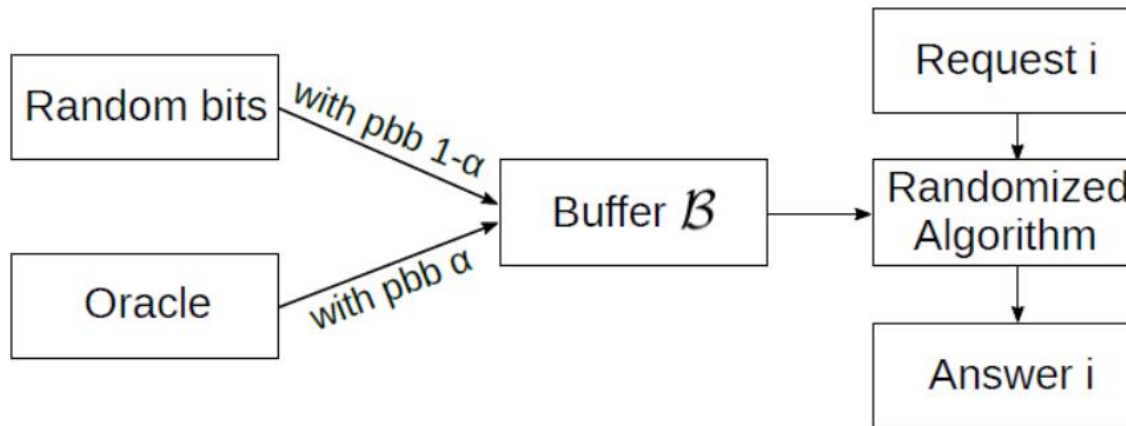
→ Idea: for randomized online algorithms, we may feed advice „*non-intrusively*“ via the random bits tape



# Infused Advice Model

An alternative

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Works also for existing online algorithms

# First Results (ESA'23)

- Applies to: *paging*, *uniform metrical task systems*, *online set cover*, etc.
- New *upper bounds* which improve when the infusion parameter  $\alpha$  increases
- Often tight lower bounds (assuming algorithm cannot access buffer of previous rounds)

Problem	upper bound	lower bound
Caching	$\min\{2H_k, \frac{2}{\alpha}\}$	$\min\{H_k, \frac{1}{\alpha}\}$
Uniform MTS	$\min\{2H_n, \frac{2}{\alpha} + 2\}$	$\min\{H_{n-1}, \frac{1}{\alpha}\}$
Online set cover	$O(\min\{\log d \log n, \frac{\log n}{\alpha}\})$	$\min\{\frac{1}{2} \log d, \frac{1}{2\alpha}\}$

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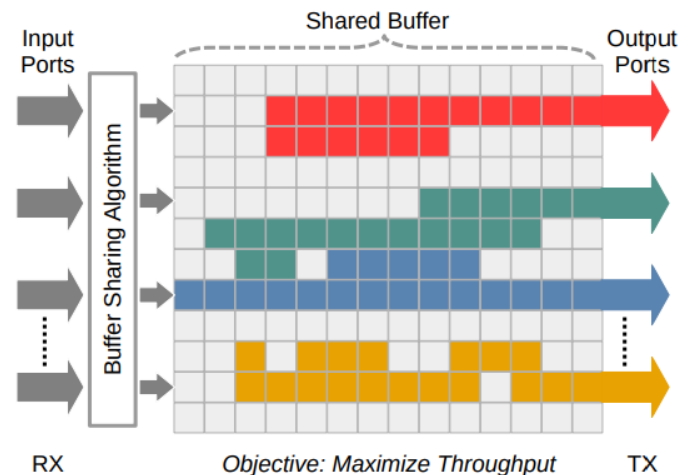
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**Application domains for augmentation?**

# Emerging Applications

## Example: Programmable Network Switches

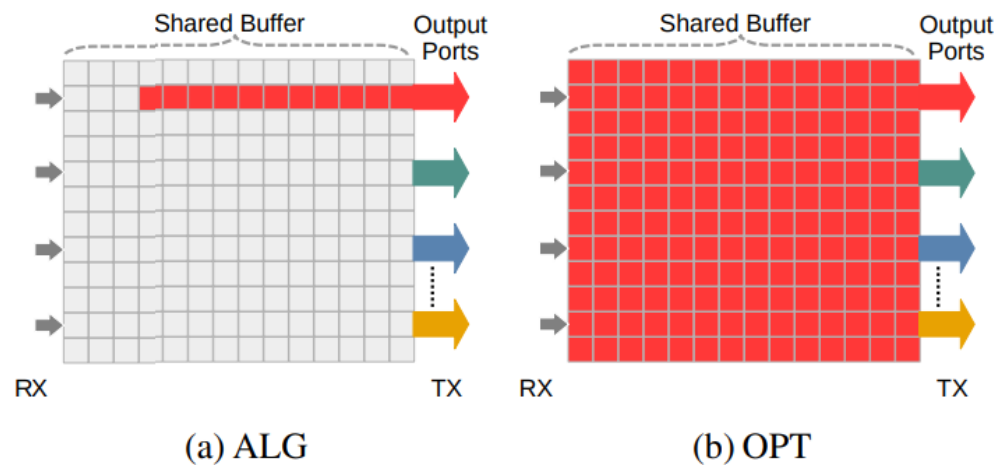
- Classic *buffer sharing* algorithm:  
which packets to accept/drop?
- Typically *no pushout*: once  
packet admitted to buffer,  
cannot be dropped later
- Future arrivals unknown:  
how to *maximize throughput*?
- Programmable switches enable  
new applications: running ML  
models *in the data plane*



# Emerging Applications

## Example: Programmable Network Switches

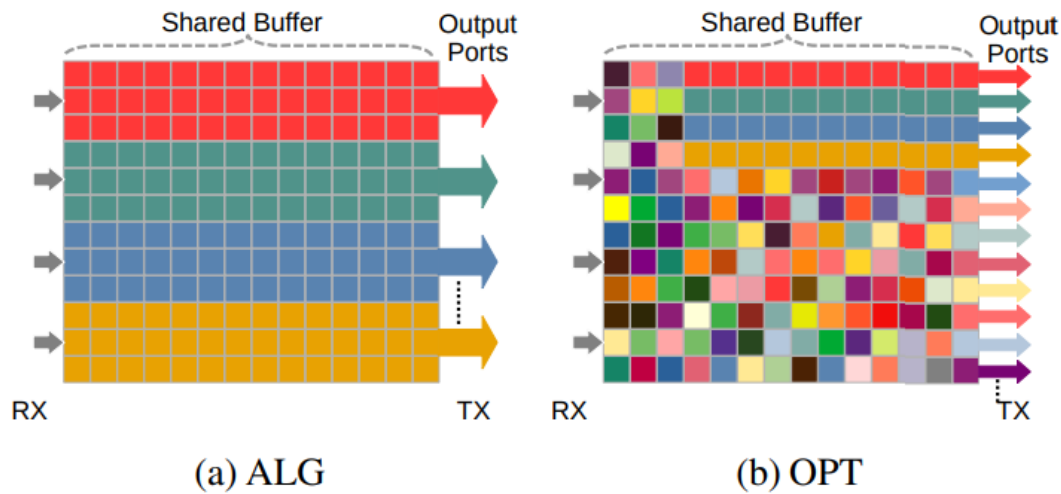
- Challenge: **drop tail algorithms** may drop red packets in order to keep buffer for other ports (and transmit in parallel)
- **Not competitive**: if not differently colored packets arrive



# Emerging Applications

## Example: Programmable Network Switches

→ Alternatively: if drop tail algorithm *absorbs burst*, it may lead to reactive drops in future and low throughput



# Emerging Applications

Example: Programmable Network Switches

- Augment switches with predictions
- Simple *random forest* approach significantly improves competitive ratio
- Depending on prediction error
- Can be implemented on switch *hardware*...

Algorithm	Competitive Ratio
Complete Sharing [26]	$N+1$
Dynamic Thresholds [20, 26]	$O(N)$
Harmonic [33]	$\ln(N)+2$
LQD (push-out) [9, 26]	1.707
LateQD (clairvoyant) [14]	1
CREDENCE	$\min(1.707 \eta, N)$

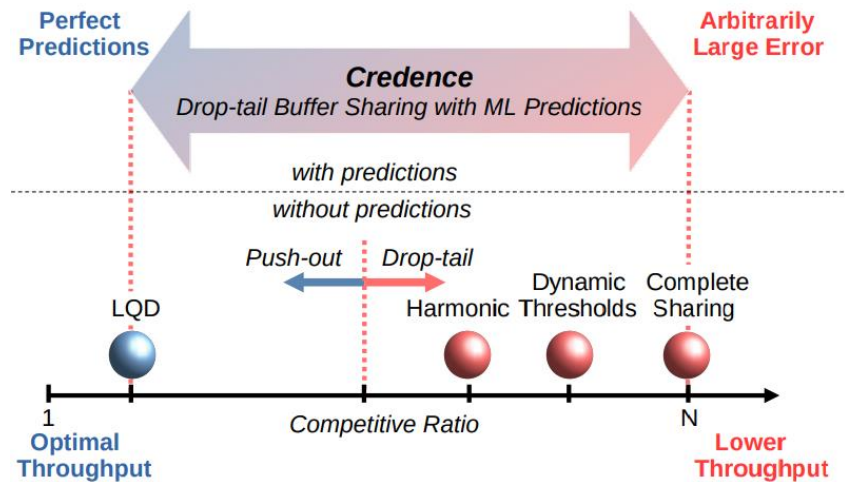


# Emerging Applications

Example: Programmable Network Switches

→ Further reading: NSDI'24

→ Video: <https://www.youtube.com/watch?v=sAPe78RFsz0>



# Conclusion

- Augmenting online algorithms with learning can benefit competitive ratio *in theory but also in practice* as input is skewed and predictable
- Network equipment supports such augmentations to some extent
- *Infused advice* approach allows to augment existing algorithms
- Interesting use cases in networked systems, much to explore

# Data Available

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

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

WEBSITE LAUNCHED!  
MARCH 17, 2010

Download Slides

<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
esact_BotLB_MultiGhd_C_Large_1024.csv	High Performance Computing Traces	Traces	17,947,800	151.3 MB	Download
esact_BotLB_CNS_NoSpec_Large_1024.csv	High Performance Computing Traces	Traces	1,108,068	9.3 MB	Download
cesar_NakBone_1024.csv	High Performance Computing Traces	Traces	21,745,229	184.0 MB	Download

<https://trace-collection.net/>  
Trace collection website

# Selected References

## **On the Complexity of Traffic Traces and Implications**

Chen Avin, Manya Ghobadi, Chen Griner, and Stefan Schmid.  
ACM SIGMETRICS, Boston, Massachusetts, USA, June 2020.

## **Survey of Reconfigurable Data Center Networks: Enablers, Algorithms, Complexity**

Klaus-Tycho Foerster and Stefan Schmid.  
SIGACT News, June 2019.

## **Analyzing the Communication Clusters in Datacenters**

Klaus-Tycho Foerster, Thibault Marette, Stefan Neumann, Claudia Plant, Ylli Sadikaj, Stefan Schmid, and Yllka Velaj.  
The Web Conference (WWW), Austin, Texas, USA, April 2023.

## **Tight Bounds for Online Graph Partitioning**

Monika Henzinger, Stefan Neumann, Harald Räcke, and Stefan Schmid.  
ACM-SIAM Symposium on Discrete Algorithms (SODA), Alexandria, Virginia, USA, January 2021.

## **Efficient Distributed Workload (Re-)Embedding**

Monika Henzinger, Stefan Neumann, and Stefan Schmid.  
ACM/IFIP SIGMETRICS/PERFORMANCE, Phoenix, Arizona, USA, June 2019, and ACM Performance Evaluation Review (PER).

## **Duo: A High-Throughput Reconfigurable Datacenter Network Using Local Routing and Control**

Johannes Zerwas, Csaba Györgyi, Andreas Blenk, Stefan Schmid, and Chen Avin.  
ACM SIGMETRICS and ACM Performance Evaluation Review (PER), Orlando, Florida, USA, June 2023.

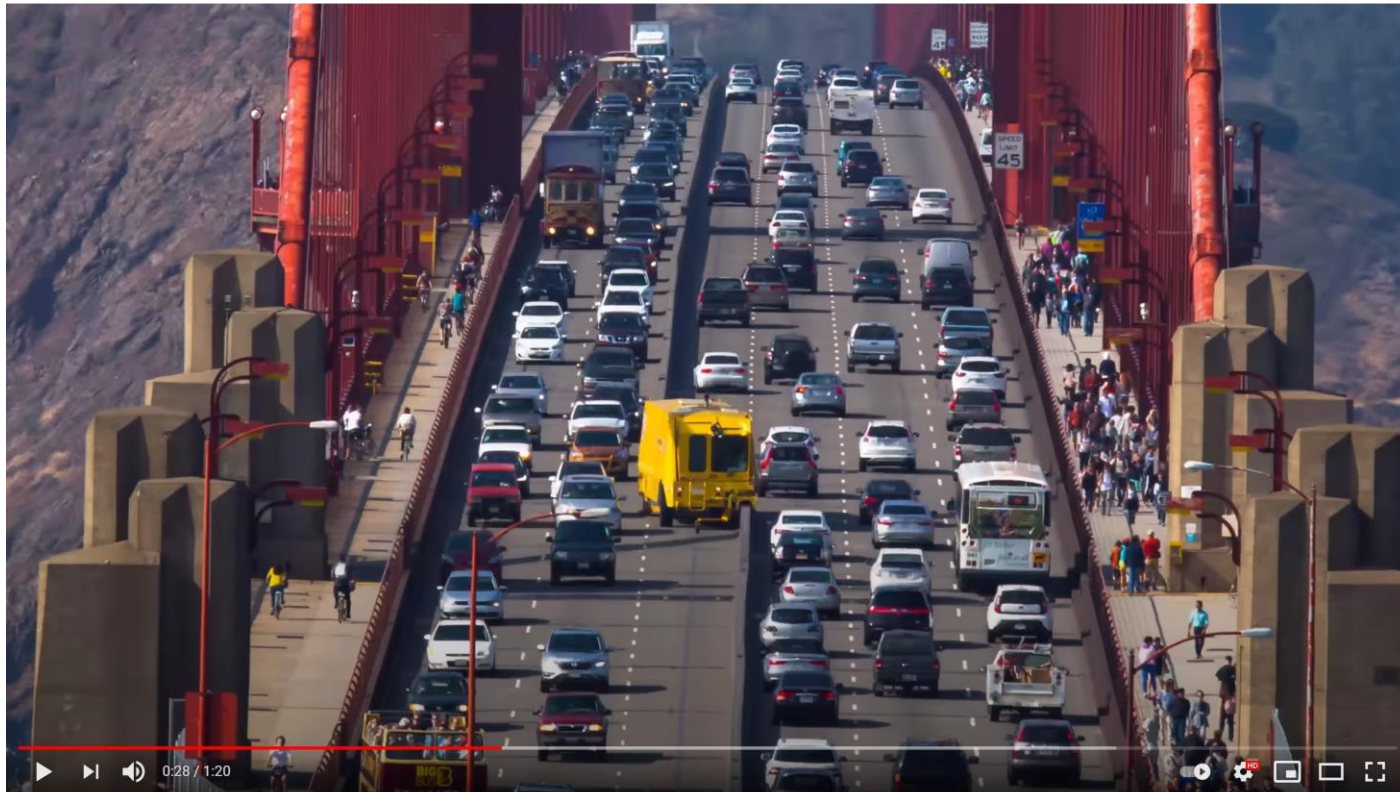
## **Online Algorithms with Randomly Infused Advice**

Yuval Emek, Yuval Gil, Maciej Pacut, and Stefan Schmid.  
European Symposium on Algorithms (ESA), Amsterdam, Netherlands, September 2023.

## **Credence: Augmenting Datacenter Switch Buffer Sharing with ML Predictions**

Vamsi Addanki, Maciej Pacut, and Stefan Schmid.  
21st USENIX Symposium on Networked Systems Design and Implementation (NSDI), Santa Clara, California, USA, April 2024.

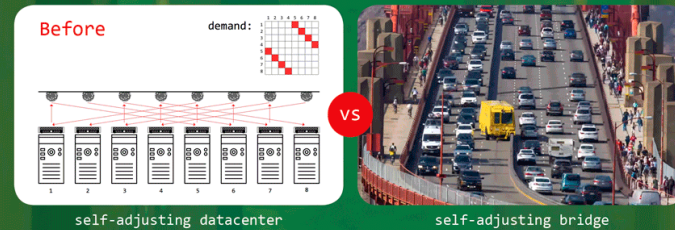
# Thank you! Questions?



Golden Gate Zipper

# Online Video Course

Invitation to  
**Self-Adjusting Networks**  
A short video course



“ 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>



# Bonus Material



Hogwarts Stair