Self-* networks: when flexibility meets algorithms

Stefan Schmid (University of Vienna)



The Trend: Flexibilities

Flexibilities: Along 3 Dimensions



Somewhere in beautiful Germany...

Flexibilities: Along 3 Dimensions



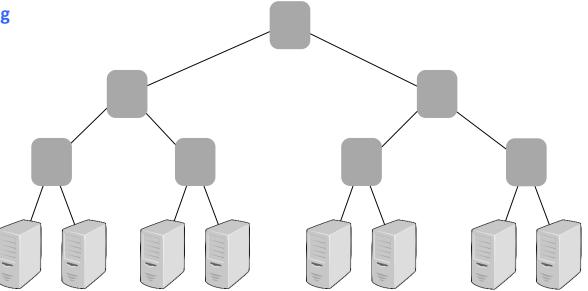
Somewhere in beautiful Germany...

Flexibilities: Along 3 Dimensions

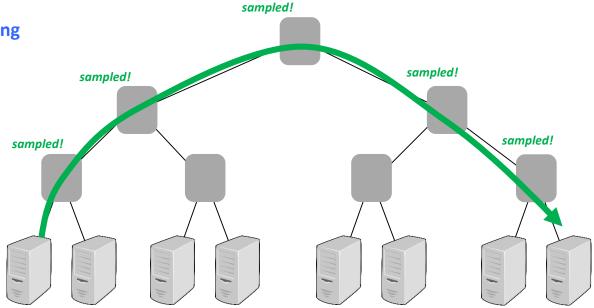


Another Trend: Improved Visibility of the Networks

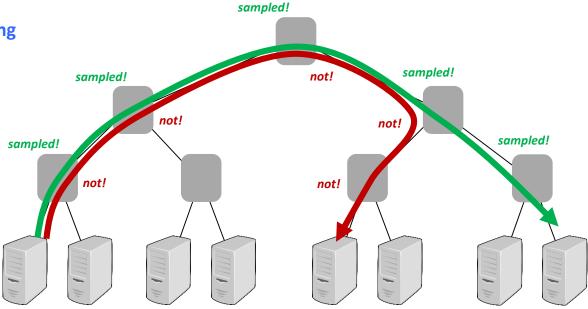
- Can also improve *security*
- Traditionally: e.g., trajectory sampling
 - Sample packets with
 hash(imm. header) ∈ [x,y]
 - See routes of *some* packets



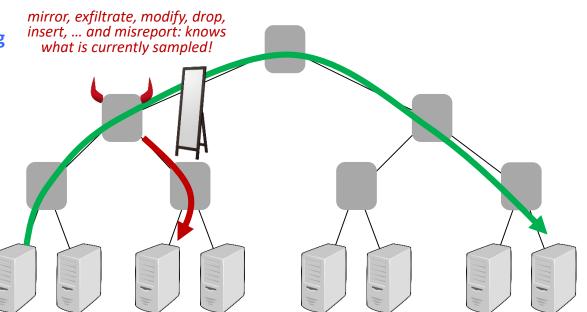
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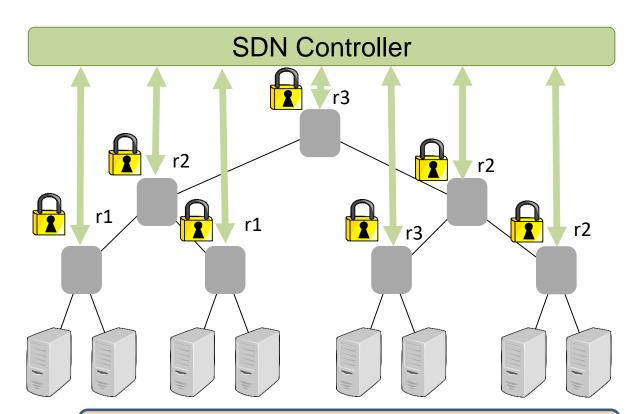
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- Can also improve *security*
- Traditionally: e.g., trajectory sampling
 - − Sample packets with
 hash(imm. header) ∈ [x,y]
 - See routes of *some* packets
 - Others not! (Usually later...)
- BSI question: What can we do if switches may be *malicious*?
 - Problem: all switches sample the same space: known!
 - Can exploit, e.g., know when unobserved.

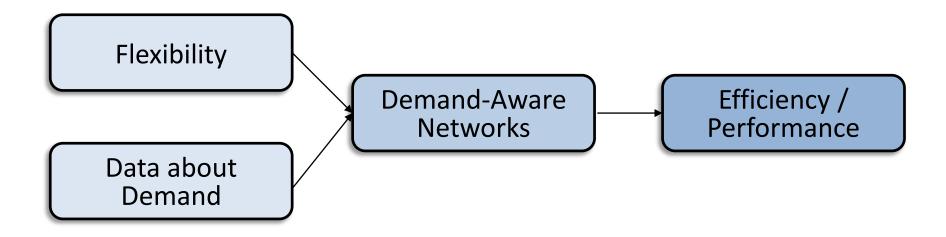


- Solution: adversarial trajectory sampling with SDN
- Idea:
 - Use secure channels between controller and switches to distribute hash ranges
 - Give different hash ranges hash ranges to different switches, but add some redundancy: risk of being caught!
- In general: obtaining live data from the network *becomes easier!*



Preacher: Network Policy Checker for Adversarial Environments. Kashyap Thimmaraju, Liron Schiff, and Stefan Schmid. SRDS 2019.

Together, Enables A Paradigm Shift: Demand-Aware Networks



A Case Study: Flexible Topologies



Enabling optical technologies for reconfigurable networks

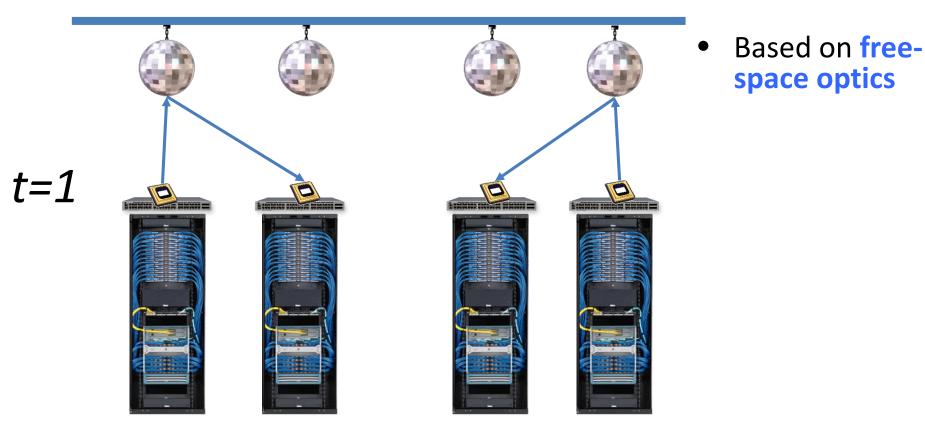


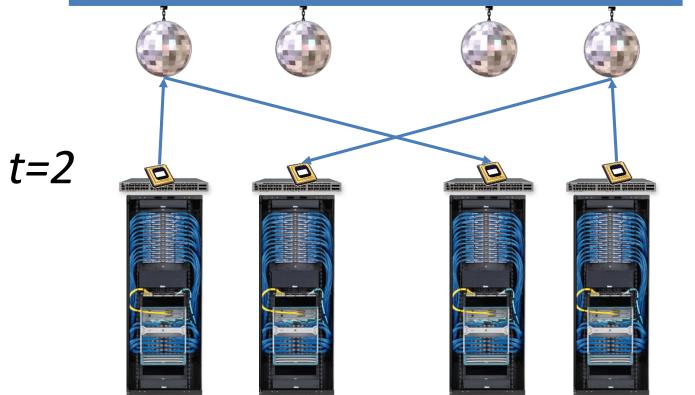
Example: Manya Ghobadi et al. *Kudos for some slides!*

Enabling optical technologies for reconfigurable networks

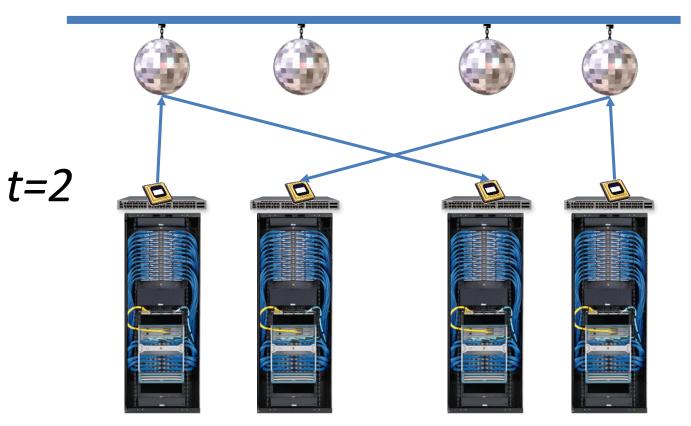


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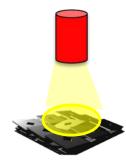




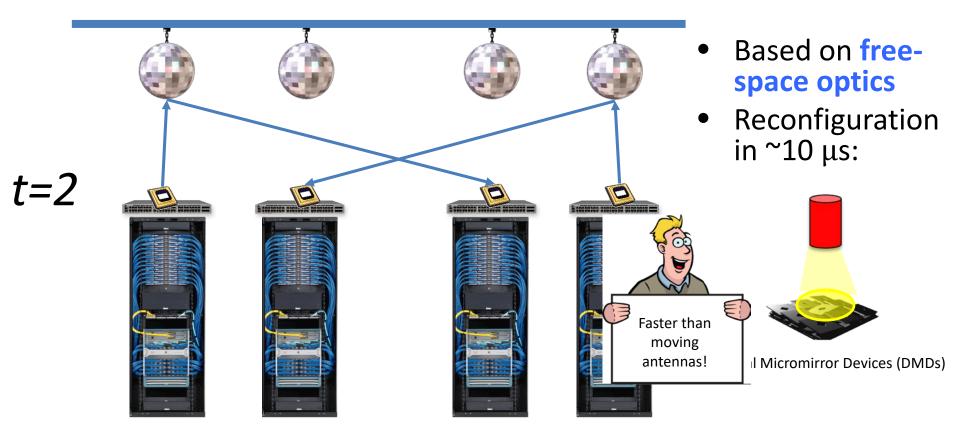
 Based on freespace optics

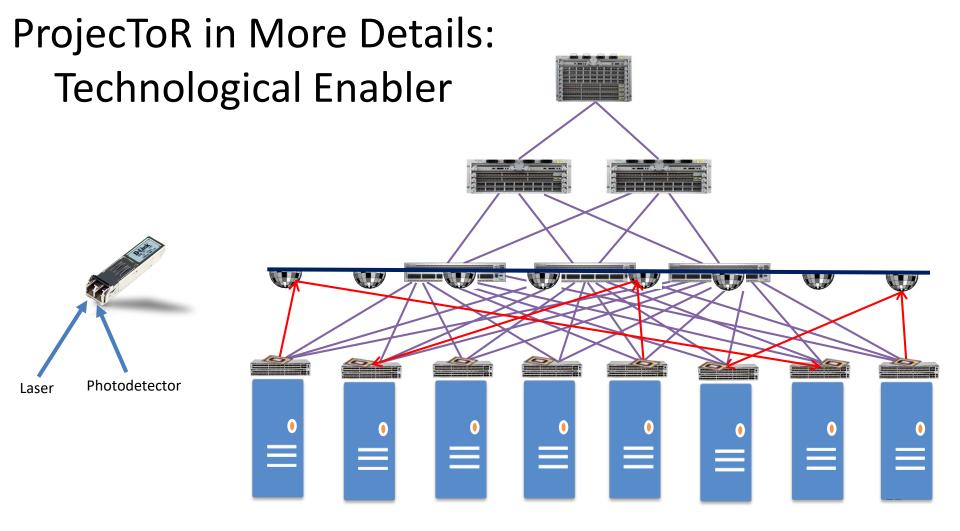


- Based on freespace optics
- Reconfiguration in ~10 μs:

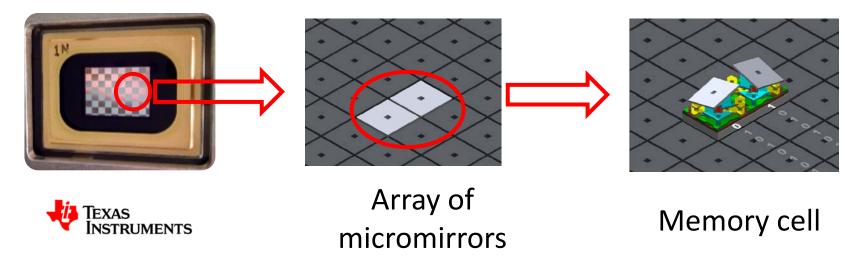


Digital Micromirror Devices (DMDs)

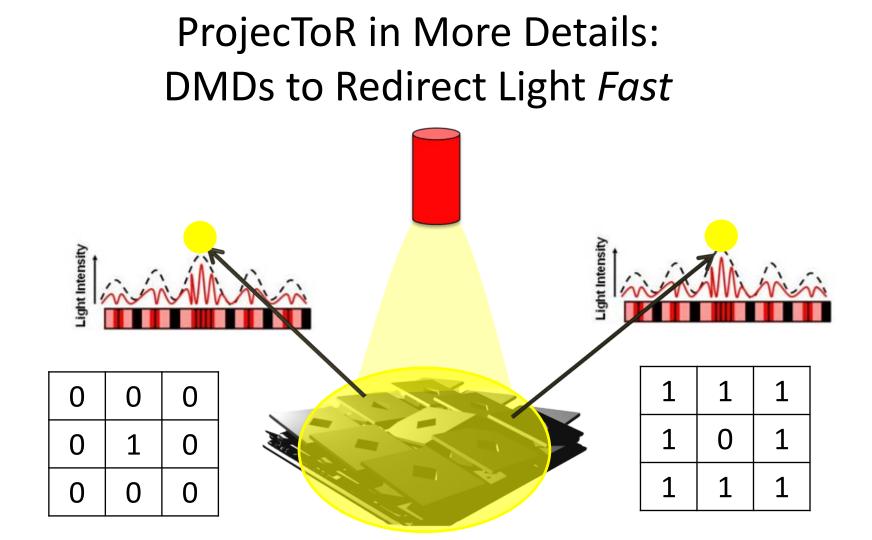


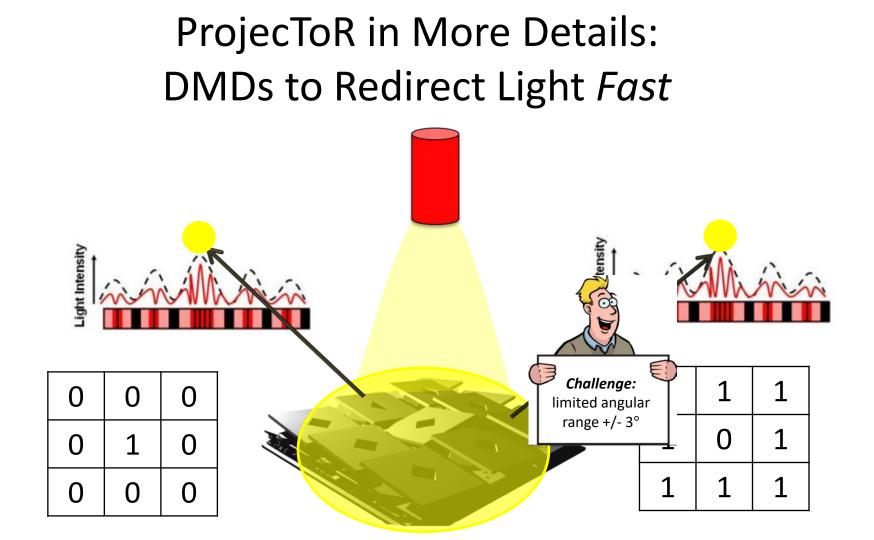


ProjecToR in More Details: DMDs

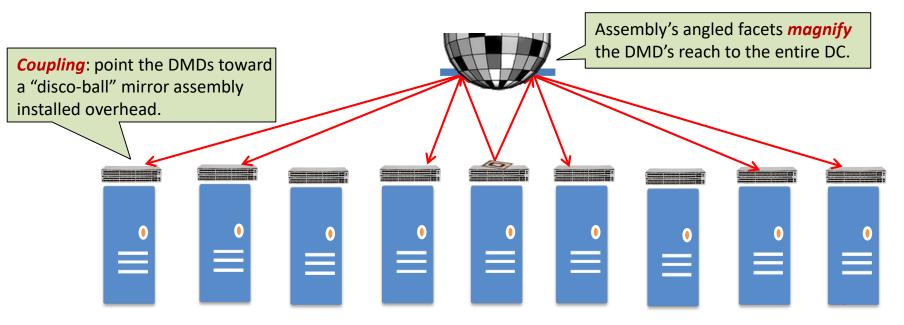


- Each micromirror can be turned on/off
- Essentially a 0/1-image: e.g., array size 768 x 1024
- Direction of the diffracted light can be finely tuned

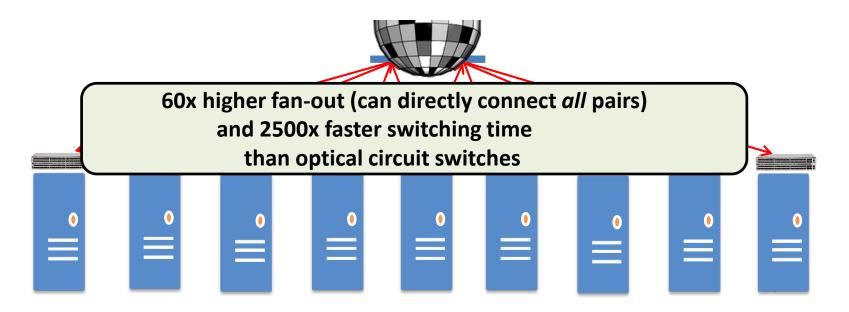




ProjecToR in More Details: Coupling DMDs with angled mirrors

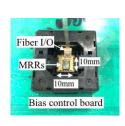


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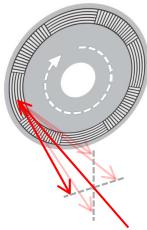
Other Technologies











Based on silicon photonics

2-NEMS

Rotating disks

Further reading:

Wade et al., A Bandwidth-Dense, Low Power Electronic-Photonic Platform and Architecture for Multi-Tbps Optical I/O [OFC'18] Porter et al., "Integrating Microsecond Circuit Switching into the Data Center", Sigcomm'13

Timeline

Reconfiguration time: from milliseconds *to microseconds* (and decentralized).

Survey of Reconfigurable Data Center Networks. Foerster and Schmid. SIGACT News, 2019.

| 2009 | - | Flyways | [51]: | Steerable | $\operatorname{antennas}$ | (narrow | beam width | at 60 | GHz | [78]) | to | serve | hotspots |
|------|---|---------|-------|-----------|---------------------------|---------|------------|-------|----------------|-------|----|-------|----------|
|------|---|---------|-------|-----------|---------------------------|---------|------------|-------|----------------|-------|----|-------|----------|

- 2010 *Helios* [33]/*c-Through* [98, 99]: Hybrid switch architecture, maximum matching (Edmond's algorithm [30]), single-hop reconfigurable connections (O(10)ms reconfiguration time).
 - Proteus [21, 89]: k reconfigurable connections per ToR, multi-hop path stitching, multi-hop reconfigurable connections (weighted b-matching [69], edge-exchanges for connectivity [72], wavelength assignment via edge-coloring [67] on multigraphs)
- 2011 Extension of *Flyways* [51] to better handle practical concerns such as stability and interference for 60GHz links, along with greedy heuristics for dynamic link placement [45]
- 2012 Mirror Mirror on the ceiling [106]: 3D-beamforming (60 Ghz wireless), signals bounce off the ceiling
- 2013 Mordia [31, 32, 77]: Traffic matrix scheduling, matrix decomposition (Birkhoff-von-Neumann (BvN) [18, 97]), fiber ring structure with wavelengths $(O(10)\mu s$ reconfiguration time)
 - SplayNets [6, 76, 82]: Fine-grained and online reconfigurations in the spirit of self-adjusting datastructures (all links are reconfigurable), aiming to strike a balance between short route lengths and reconfiguration costs
- 2014 – REACToR [56]: Buffer burst of packets at end-hosts until circuit provisioned, employs [77]
 - Firefly [14] Combination of Free Space Optics and Galvo/switchable mirrors (small fan-out)
- 2015 – Solstice [57]: Greedy perfect matching based hybrid scheduling heuristic that outperforms BvN [77]
 - Designs for optical switches with a reconfiguration latency of O(10)ns [3]
- 2016 *ProjecToR* [39]: Distributed Free Space Optics with digital micromirrors (high fan-out) [38] (Stable Matching [26]), goal of (starvation-free) low latency
 - Eclipse [95, 96]: $(1 1/e^{(1-\varepsilon)})$ -approximation for throughput in traffic matrix scheduling (single-hop reconfigurable connections, hybrid switch architecture), outperforms heuristics in [57]
- 2017 – DAN [7, 8, 11, 12]: Demand-aware networks based on reconfigurable links only and optimized for a demand snapshot, to minimized average route length and/or minimize load
 - MegaSwitch [23]: Non-blocking circuits over multiple fiber rings (stacking rings in [77] doesn't suffice)
 - Rotornet [63]: Oblivious cyclical reconfiguration w. selector switches [64] (Valiant load balancing [94])
 - Tale of Two Topologies [105]: Convert locally between Clos [24] topology and random graphs [87, 88]
- 2018 - DeepConf [81]/xWeaver [102]: Machine learning approaches for topology reconfiguration
- 2019 Complexity classifications for weighted average path lengths in reconfigurable topologies [34, 35, 36]
 - ReNet [13] and Push-Down-Trees [9] providing statically and dynamically optimal reconfigurations
 - DisSplayNets [75]: fully decentralized SplayNets
 - Opera [60]: Maintaining expander-based topologies under (oblivious) reconfiguration

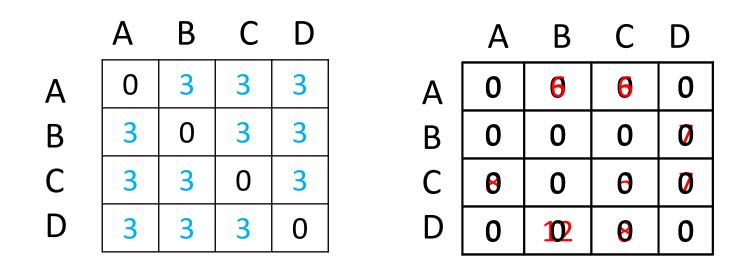
When Are Demand-Aware Networks Useful?

A Simple Answer

Demand-Oblivious Networks =



Seriously: We believe, often, in practice!



In theory: traffic matrix uniform and static In practice: skewed and dynamic

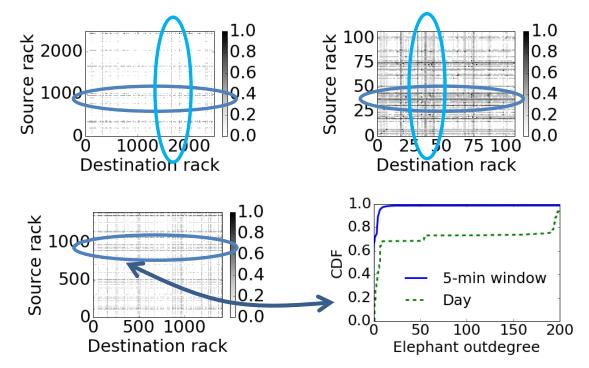
Empirical Motivation

Observation 1:

- Many rack pairs exchange little traffic
- Only some *hot rack pairs* are active

Observation 2:

 Some source racks send large amounts of traffic to many other racks



Microsoft data: 200K servers across 4 production clusters, cluster sizes: 100 - 2500 racks. Mix of workloads: MapReduce-type jobs, index builders, database and storage systems.

So: How much structure is there?



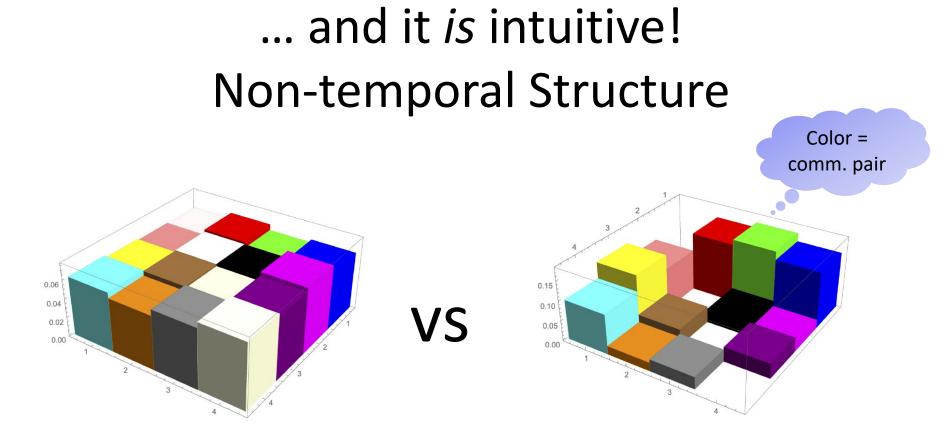
How to *measure* it? And which *types of structures*? E.g., temporal structure in addition to non-temporal structure? *Tricky*!

Often only intuitions in the literature...

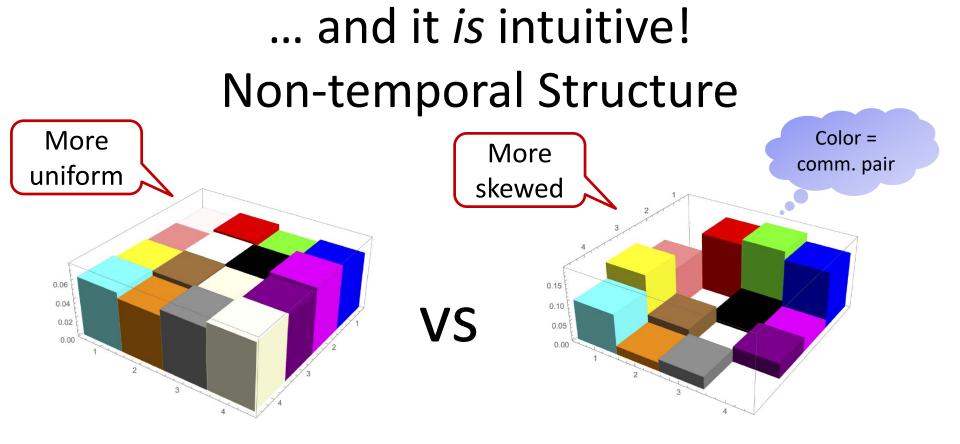
"less than 1% of the rack pairs account for 80% of the total traffic"

"only a few ToRs switches are hot and most of their traffic goes to a few other ToRs"

"over 90% bytes flow in elephant flows"

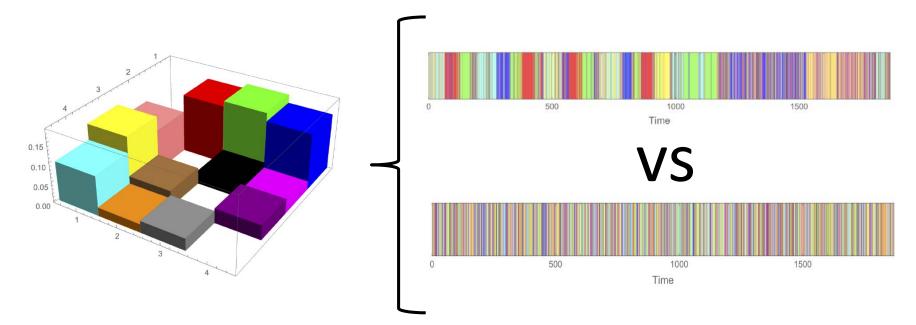


Traffic matrix of two different **distributed ML** applications (GPU-to-GPU): Which one has *more structure*?

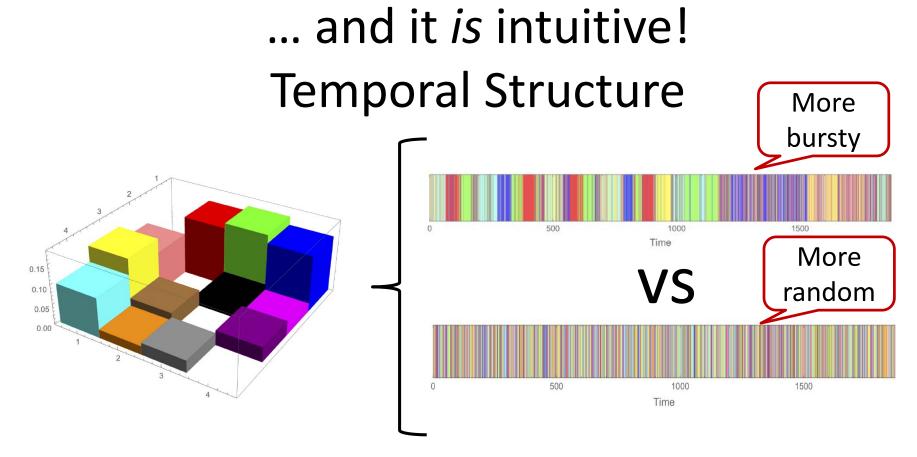


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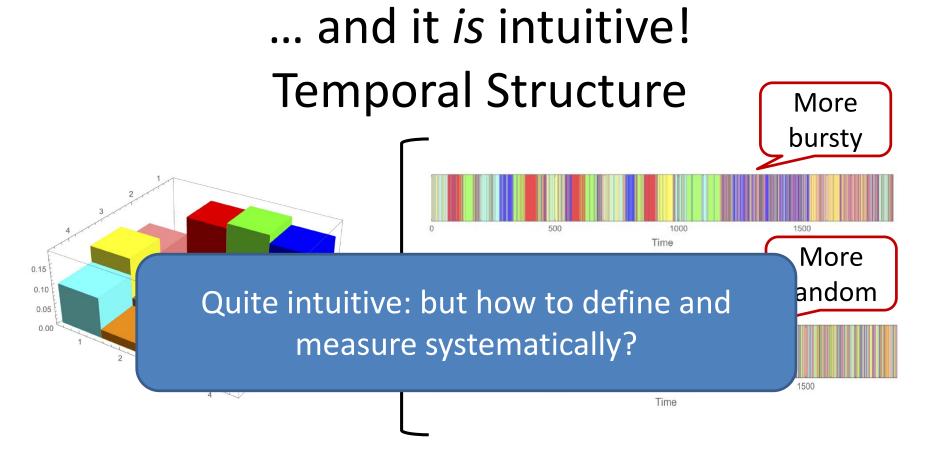
... and it *is* intuitive! Temporal Structure



Two different ways to generate *same traffic matrix* (same non-temporal structure): Which one has *more structure*?

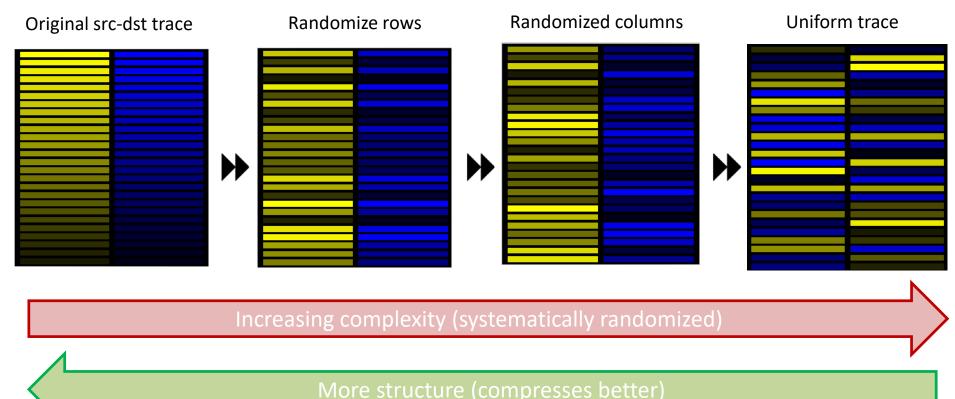


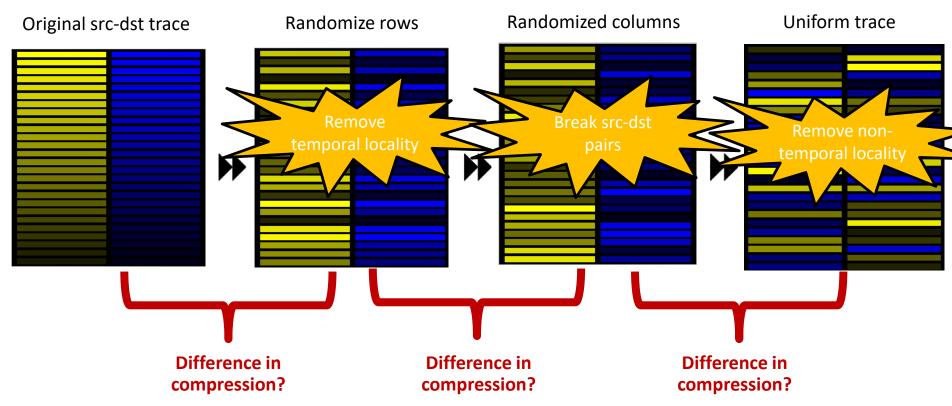
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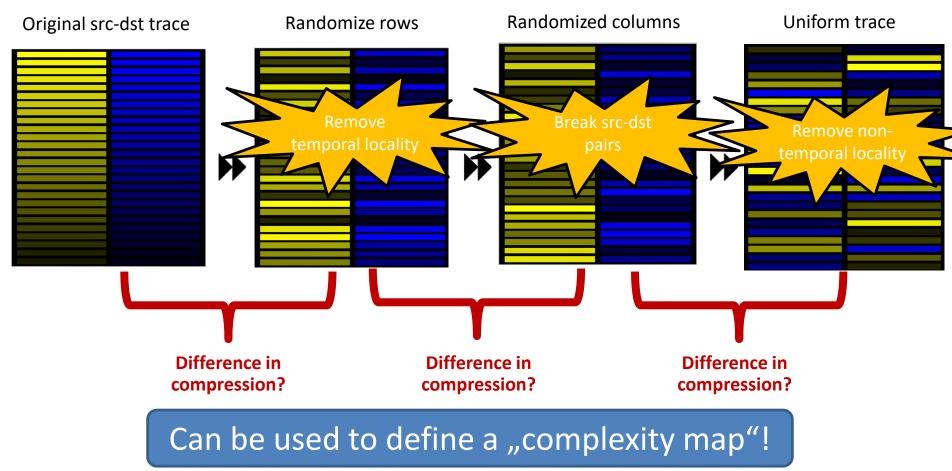


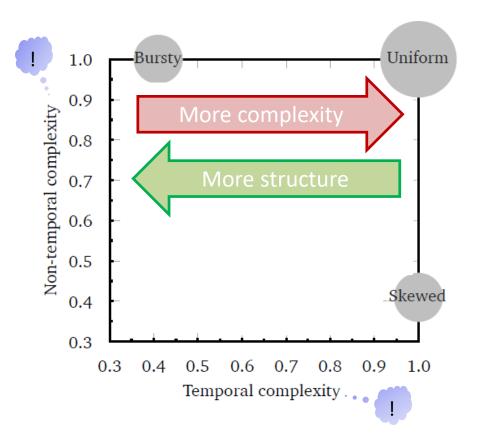
Two different ways to generate *same traffic matrix* (same non-temporal structure): Which one has *more structure*?

- An information-theoretic approach: how can we *measure the entropy* (rate) of a traffic trace?
- Henceforth called the trace complexity
- Simple approximation: "shuffle&compress"
 - Remove structure by iterative *randomization*
 - Difference of compression *before and after* randomization: structure

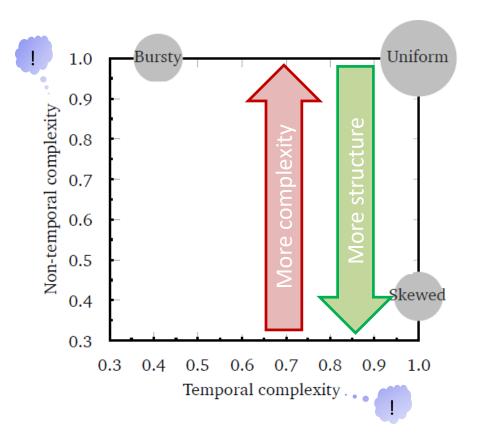




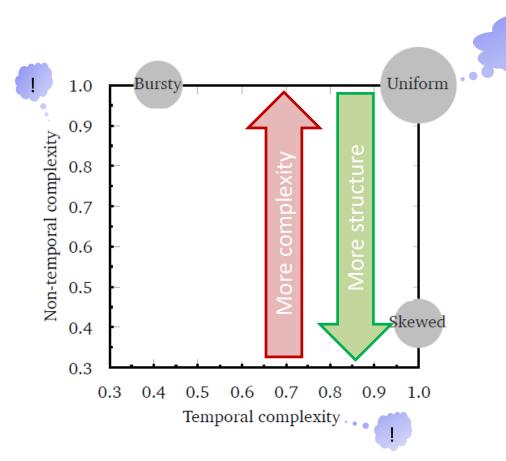




Complexity Map: Entropy ("complexity") of traffic traces.

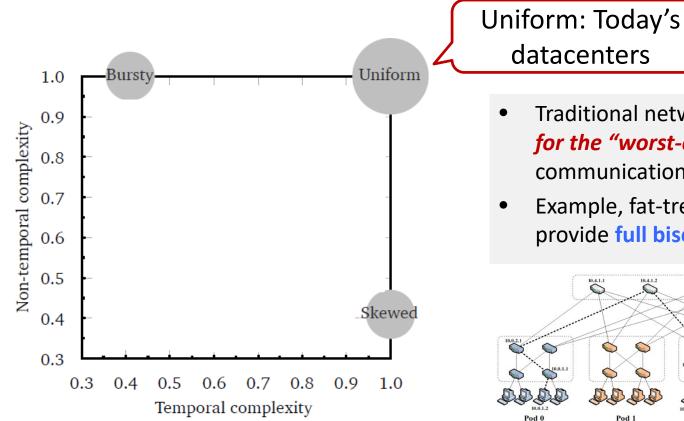


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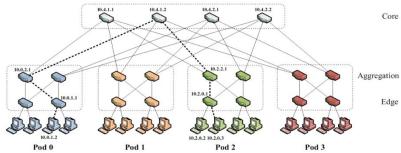


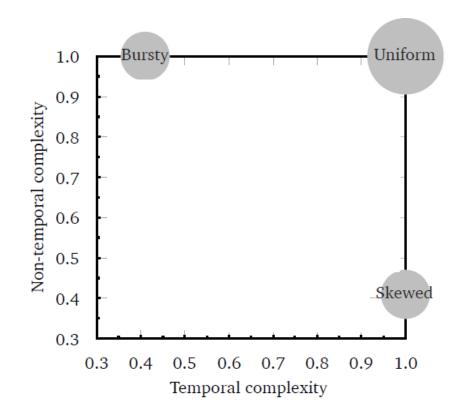
Size = product of entropy

Complexity Map: Entropy ("complexity") of traffic traces.

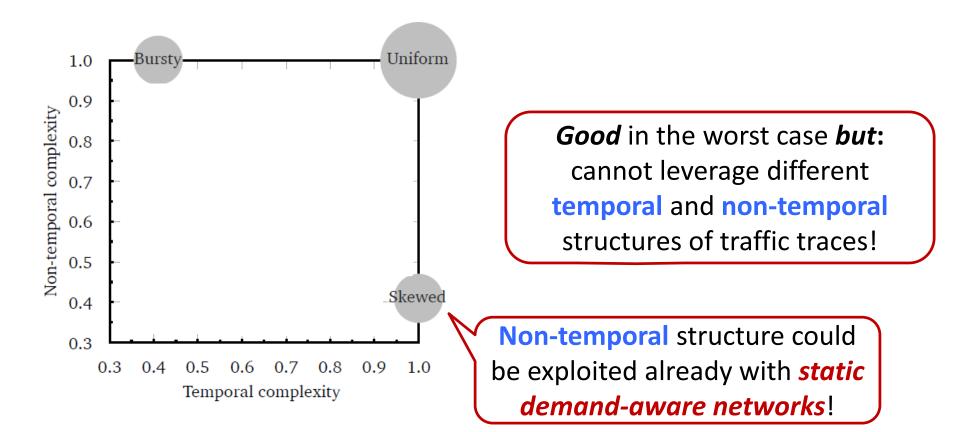


- Traditional networks are optimized for the "worst-case" (all-to-all communication traffic)
- Example, fat-tree topologies: provide full bisection bandwidth

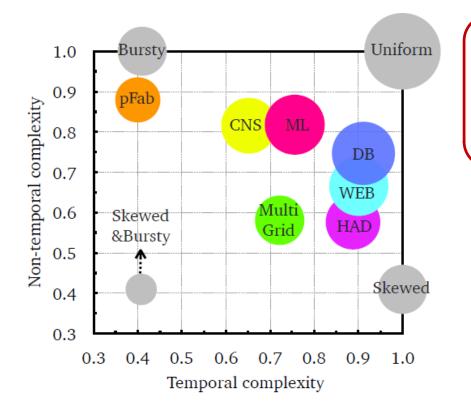




Good in the worst case **but**: cannot leverage different **temporal** and **non-temporal** structures of traffic traces!

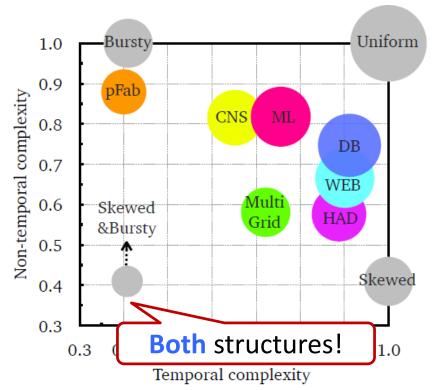


To exploit **temporal** structure, plexity Map need adaptive demand-aware ("self-adjusting") networks. Uniform Bursty 1.00.9 Non-temporal complexity *Good* in the worst case *but*: 0.8 cannot leverage different 0.7 temporal and non-temporal 0.6 structures of traffic traces! 0.5 Skewed 0.4 Non-temporal structure could 0.3 0.3 0.9 be exploited already with *static* 0.4 0.81.00 Temporal complexity demand-aware networks!

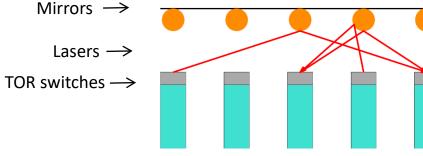


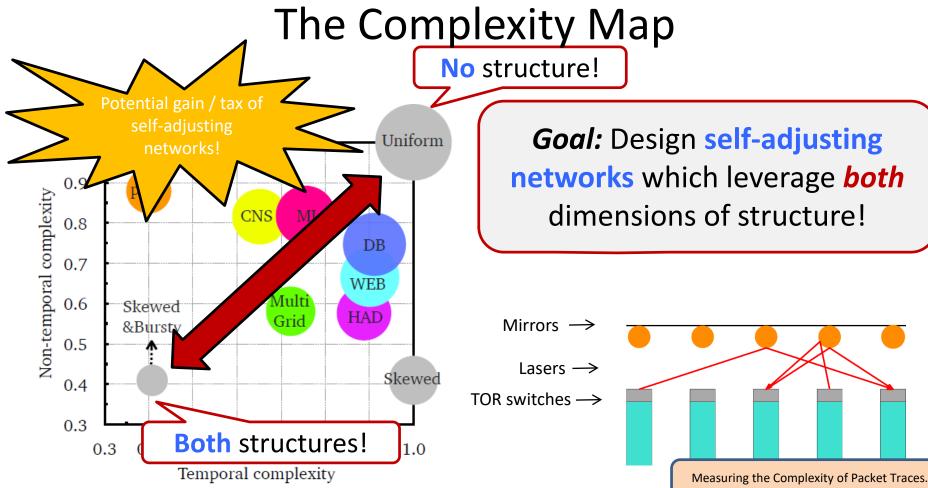
Observation: different applications feature quite significant (and different!) temporal and nontemporal structures.

- Facebook clusters: DB, WEB, HAD
- **HPC** workloads: CNS, Multigrid
- Distributed Machine Learning (ML)
- Synthetic traces like **pFabric**



Goal: Design self-adjusting networks which leverage *both* dimensions of structure!





Avin, Ghobadi, Griner, Schmid. ArXiv 2019.

So: How to design networks which exploit this structure? How good can they be?

Metrics again!

Roadmap

- Entropy: A metric for demand-aware networks?
 - Intuition
 - A lower bound
 - Algorithms achieving entropy bounds
- From static to dynamic demand-aware networks
 - Empirical motivation
 - A connection to self-adjusting datastructures



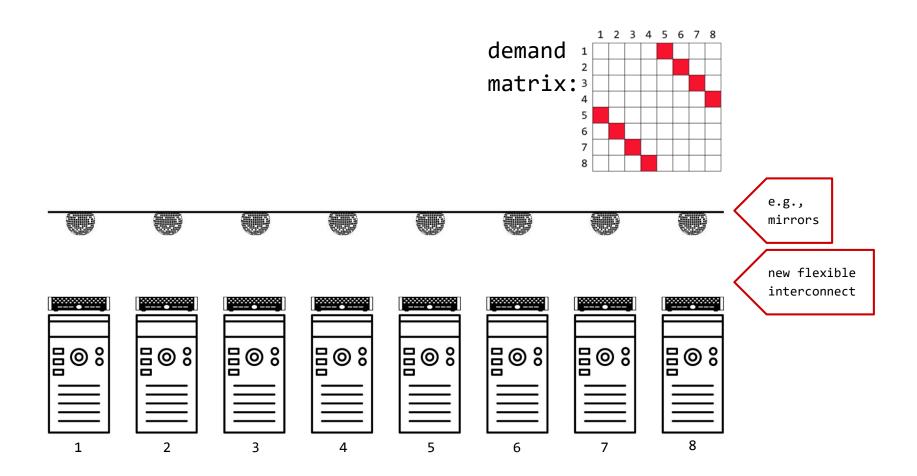
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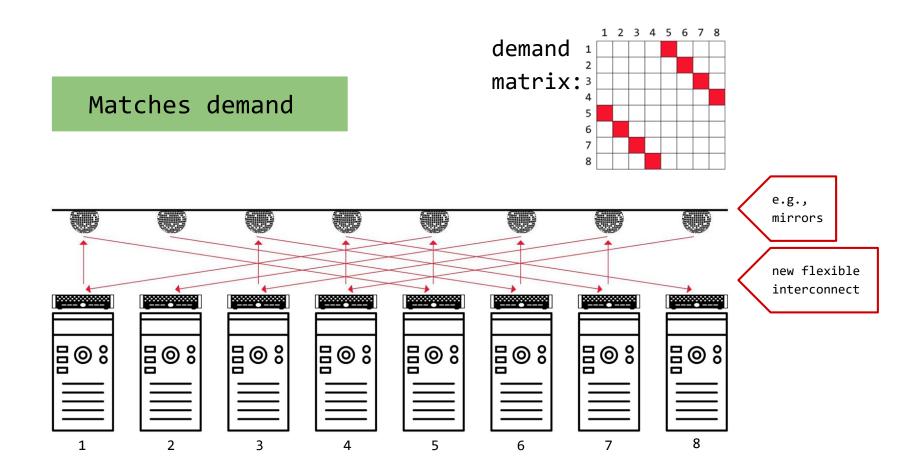
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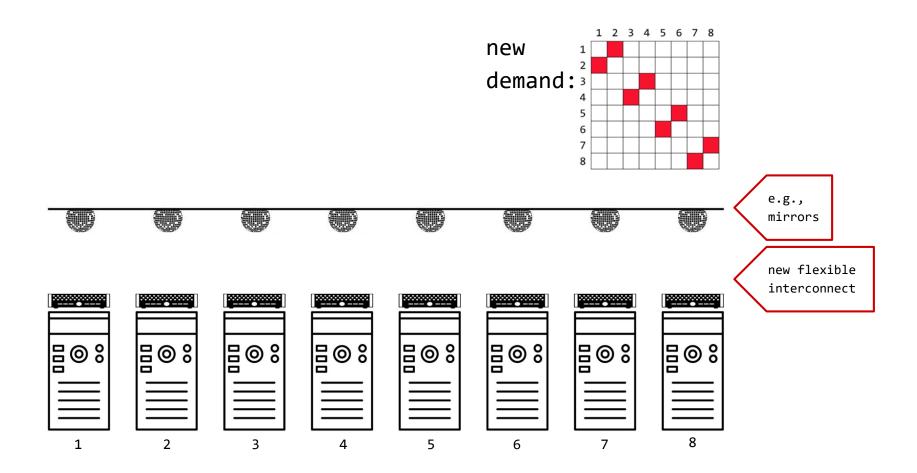


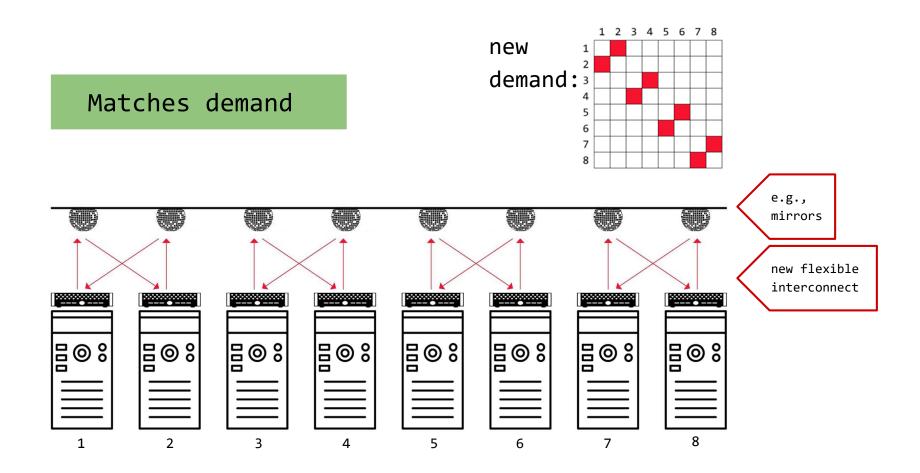
A Simple Example

Demand-Aware Network Designs of Bounded Degree Chen Avin, Kaushik Mondal, and Stefan Schmid. 31st International Symposium on Distributed Computing (**DISC**), Vienna, Austria, October 2017.







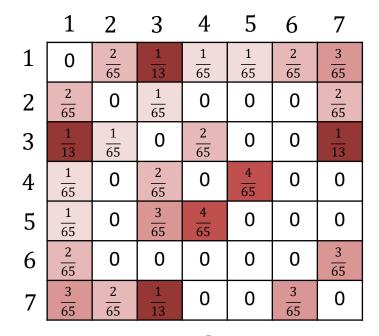


More Formally

Input: Workload

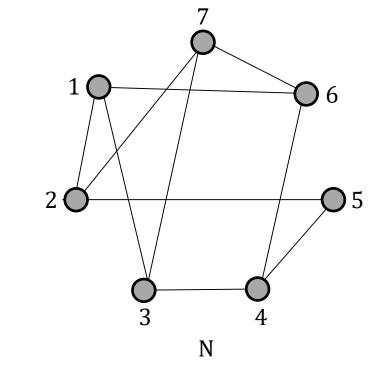
Output: Constant-Degree DAN

Destinations

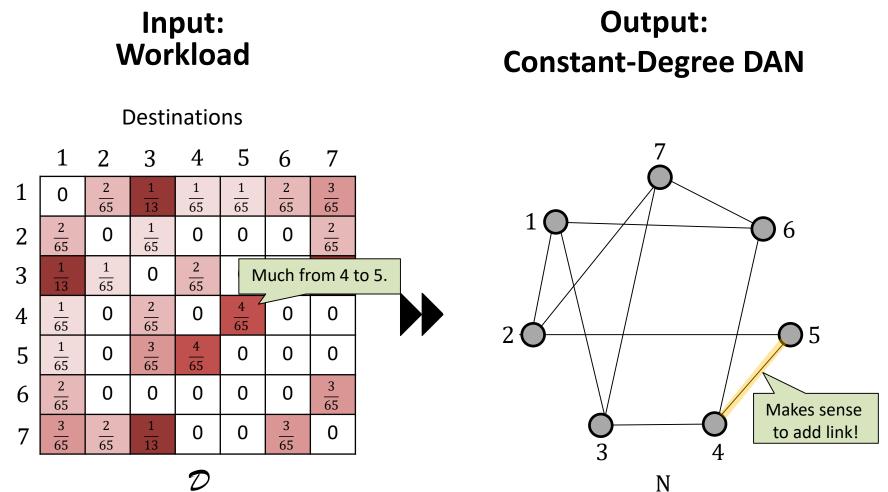


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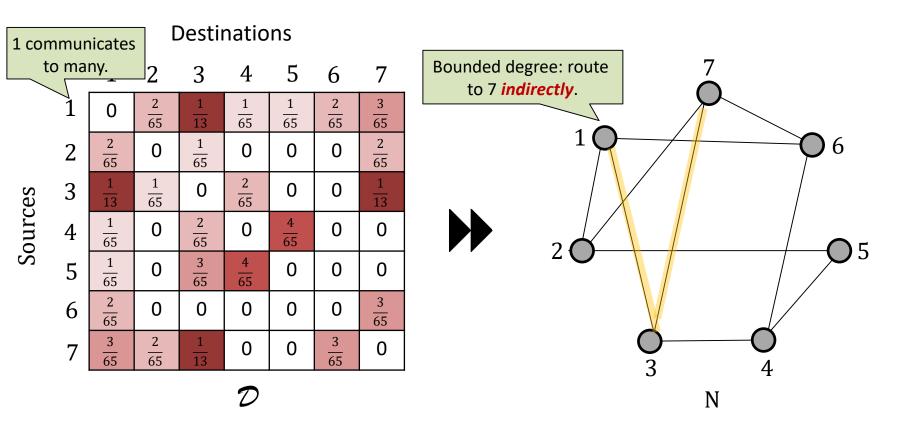
Sources

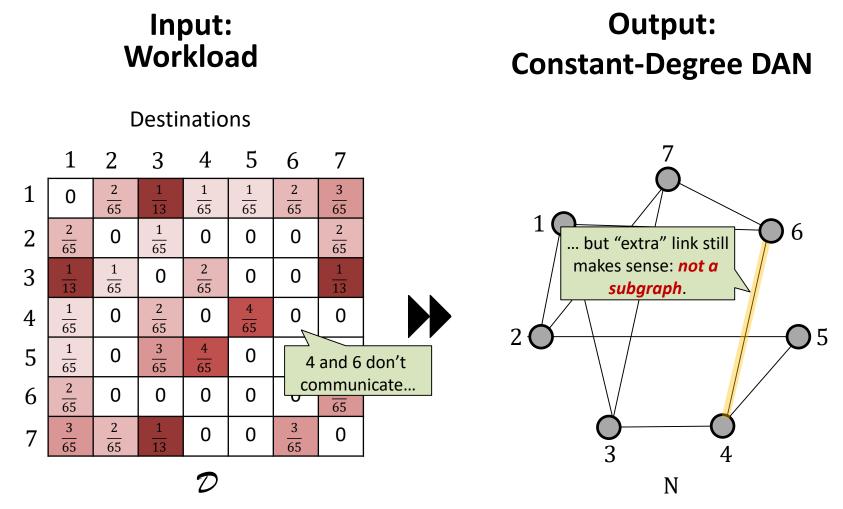


Sources

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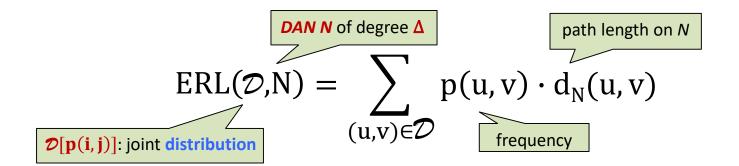
Output: Constant-Degree DAN





Sources

Objective: Expected Route Length

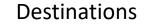


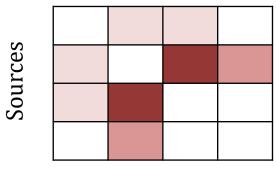
Remark

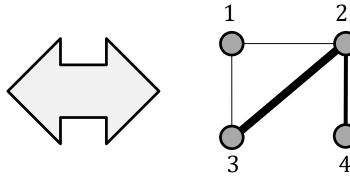
• Can represent demand matrix as a **demand graph**

sparse distribution $\boldsymbol{\mathcal{D}}$

sparse graph $G(\mathcal{D})$

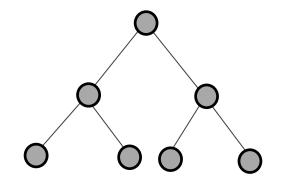






Some Examples

- DANs of $\Delta = 3$:
 - E.g., complete binary tree
 - $d_N(u,v) \le 2 \log n$
 - Can we do **better** than **log n**?

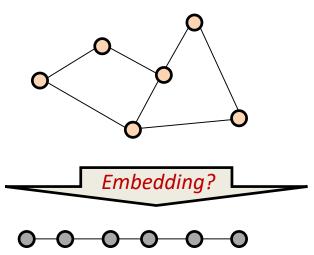


- DANs of $\Delta = 2$:
 - E.g., set of lines and cycles

Remark: Hardness Proof

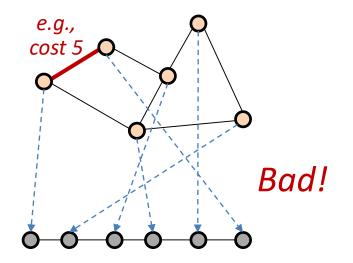
DAN design can be NP-hard

- Example Δ = 2: A Minimum Linear Arrangement (MLA) problem
 - A "Virtual Network Embedding Problem", VNEP
 - *Minimize sum* of lengths of virtual edges



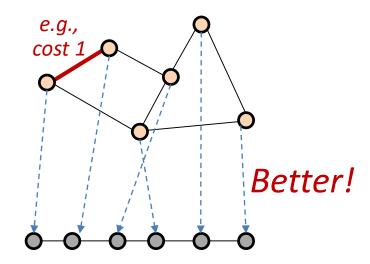
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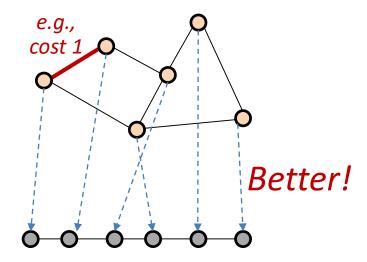
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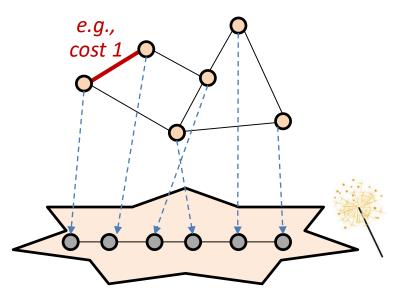
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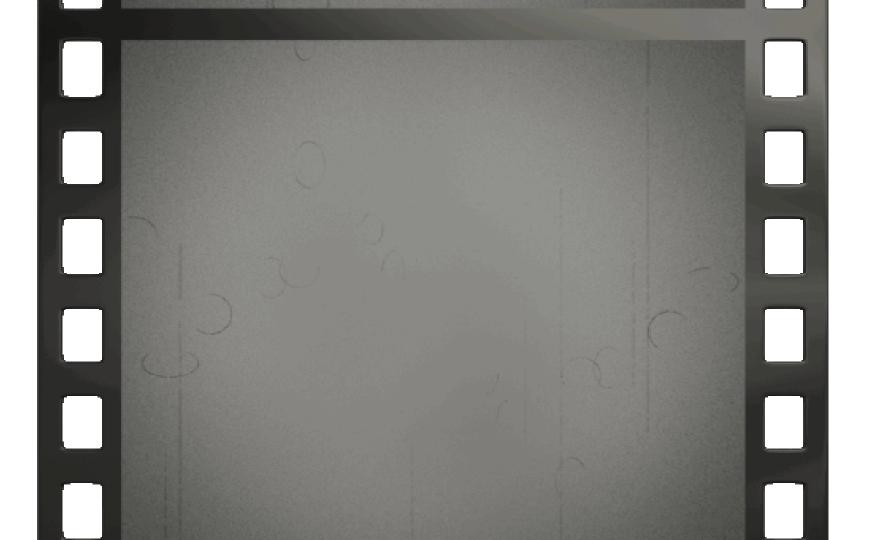
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- But what about > 2? *Embedding* problem still hard, but we have an additional degree of freedom:

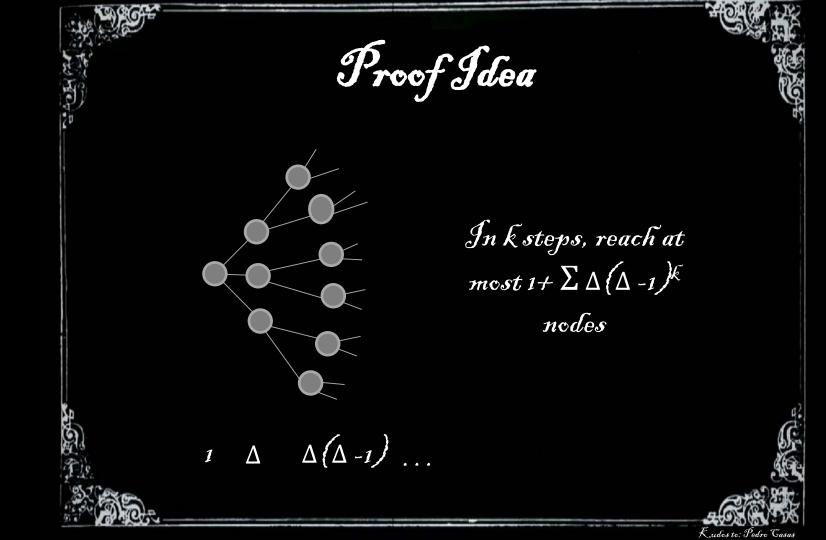
Do topological flexibilities make problem easier or harder?!



A new knob for optimization!



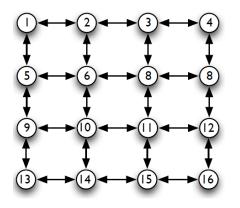
Rewinding the Glock: Degree-Diameter Tradeoff \mathcal{E} ach network with n nodes and max degree Δ >2 must have a diameter of at least $\log(n)/\log(\Delta-1)-1$. Example: constant Δ , $\log(n)$ diameter K.udosto: Pedr



Is there a better tradeoff in DANs?

Sometimes, DANs can be much better!

Example 1: low-degree demand

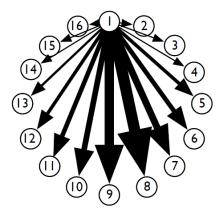


If **demand graph** is of degree Δ , it is trivial to design a **DAN** of degree Δ which achieves an *expected route length of 1*.

Just take DAN = demand graph!

Sometimes, DANs can be much better!

Example 2: skewed demand

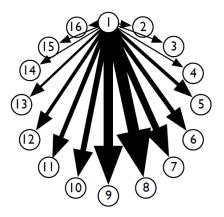


If **demand** is highly skewed, it is also possible to achieve an *expected route length of O(1)* in a constant-degree DAN.



Sometimes, DANs can be much better!

Example 2: skewed demand



Toward Demand-Aware Networking: A Theory for Self-Adjusting Networks. Chen Avin and Stefan Schmid. ACM SIGCOMM CCR, October 2018 If **demand** is highly skewed, it is also possible to achieve an *expected route length of O(1)* in a constant-degree DAN.



So on what does it depend?

So on what does it depend?



We argue (but still don't know!): on the **"entropy" of the demand**!





Intuition: Entropy Lower Bound

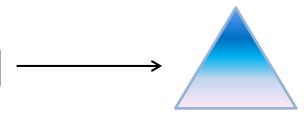


Lower Bound Idea: Leverage Coding or Datastructure

Destinations

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---------|---|----------------|----------------|----------------|----------------|----------------|----------------|----------------|--|
| Sources | 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 | |

• DAN just for a *single (source) node 3*



- How good can this tree be? Cannot do better than Δ-ary Huffman tree for its destinations
- Entropy lower bound on ERL known for binary trees, e.g. *Mehlhorn* 1975

Lower Bound Idea: Leverage Coding or Datastructure

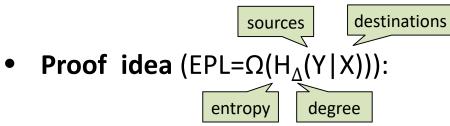
An optimal "ego-tree" for this source!

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---------|---|----------------|----------------|----------------|----------------|----------------|----------------|----------------|--|
| Sources | 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 | |

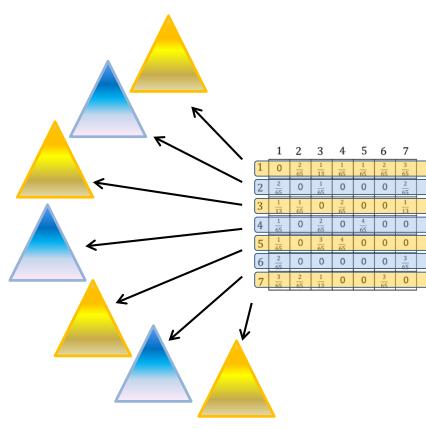
Destinations

- DAN just for a *single (source) node 3*
- How good can this tree be? Cannot do better than Δ-ary Huffman tree for its destinations
- Entropy lower bound on ERL known for binary trees, e.g. *Mehlhorn* 1975

So: Entropy of the Entire Demand

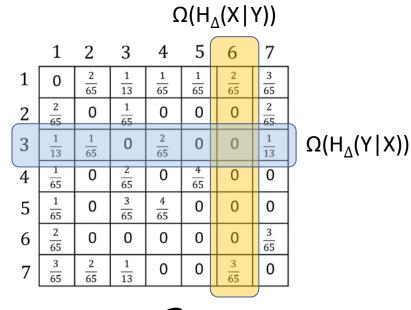


- Compute ego-tree for each source node
- Take *union* of all ego-trees
- Violates *degree restriction* but valid lower bound



Entropy of the *Entire* Demand: Sources *and* Destinations

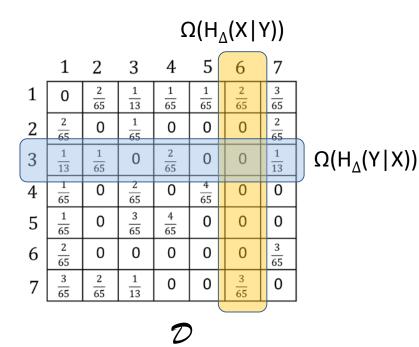
Do this in **both dimensions**: EPL $\geq \Omega(\max\{H_{\Delta}(Y|X), H_{\Delta}(X|Y)\})$



 \mathcal{D}

Entropy of the *Entire* Demand: Sources *and* Destinations

Do this in **both dimensions**: EPL $\geq \Omega(\max\{H_{\Delta}(Y|X), H_{\Delta}(X|Y)\})$



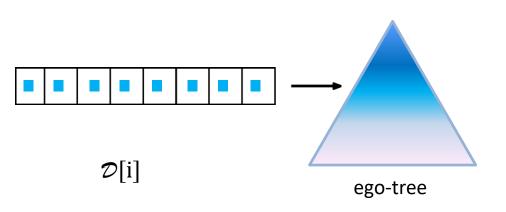
Demand-Aware Network Designs of Bounded Degree. Chen Avin, Kaushik Mondal, and Stefan Schmid. **DISC**, 2017.

Achieving Entropy Limit: Algorithms



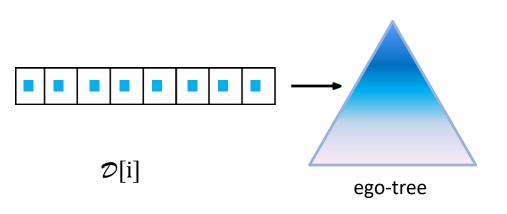
Ego-Trees Revisited

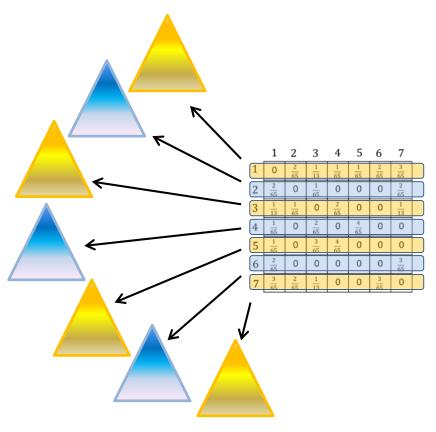
 ego-tree: optimal tree for a row (= given source)



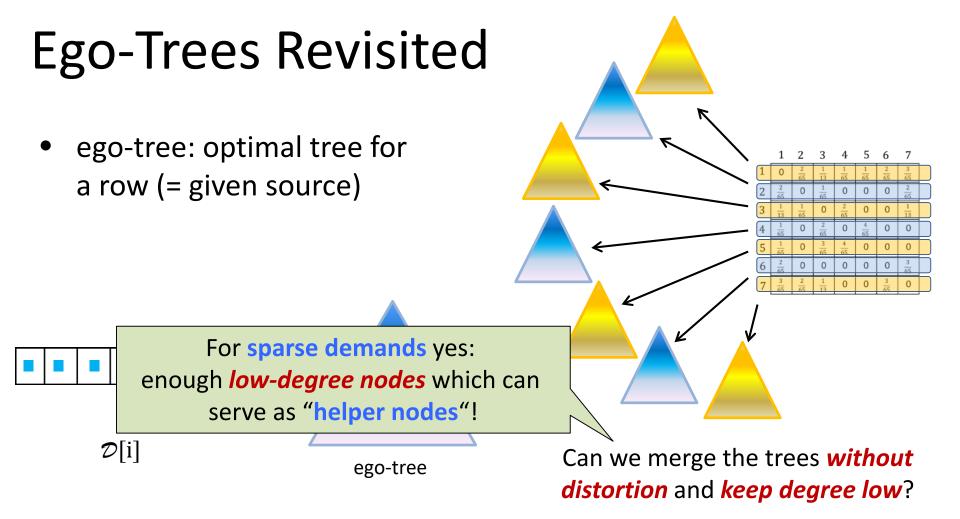
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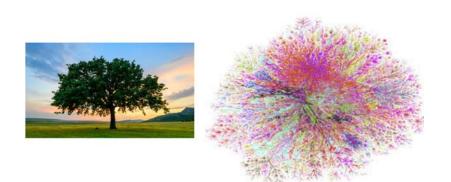




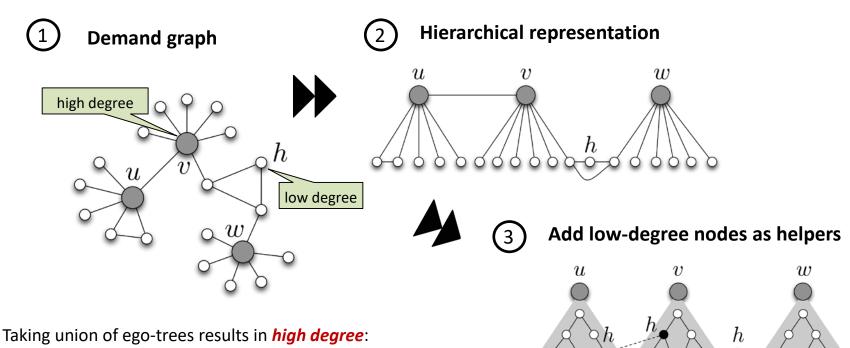
Can we merge the trees *without distortion* and *keep degree low*?



From Trees to Networks



Idea: Degree Reduction



Taking union of ego-trees results in *high degree u* and *v* will appear in many ego-trees

Demand-Aware Network Designs of Bounded Degree. Chen Avin, Kaushik Mondal, and Stefan Schmid. **DISC**, 2017. Node *h* **helps edge (u, v)** by participating in *ego-tree(u)* as a relay node toward *v* and *in ego-tree(v)* as a relay toward *u*

But: How to design DANs which also leverage *temporal structure*?



Inspiration from self-adjusting datastructures again!

Roadmap

- Entropy: A metric for demand-aware networks?
 - Empirical motivation
 - A lower bound
 - Algorithms achieving entropy bounds
- From static to dynamic demand-aware networks
 - A connection to self-adjusting datastructures

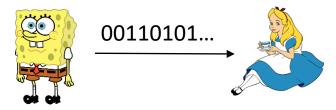


An Analogy

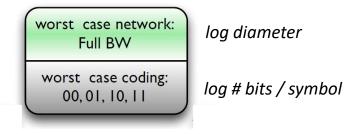
Static vs dynamic demandaware networks!?

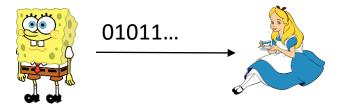
DANs vs SANs?

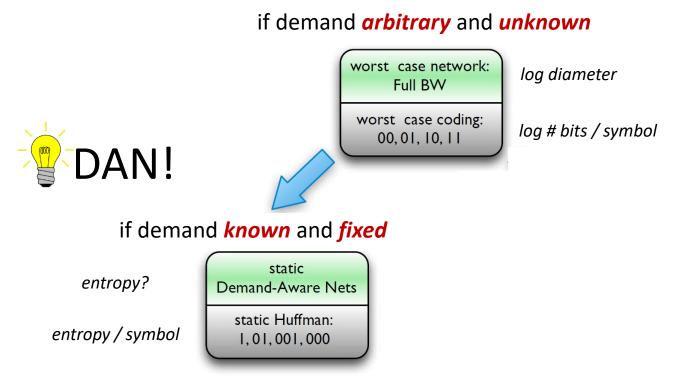
An Analogy to Coding

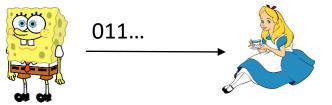


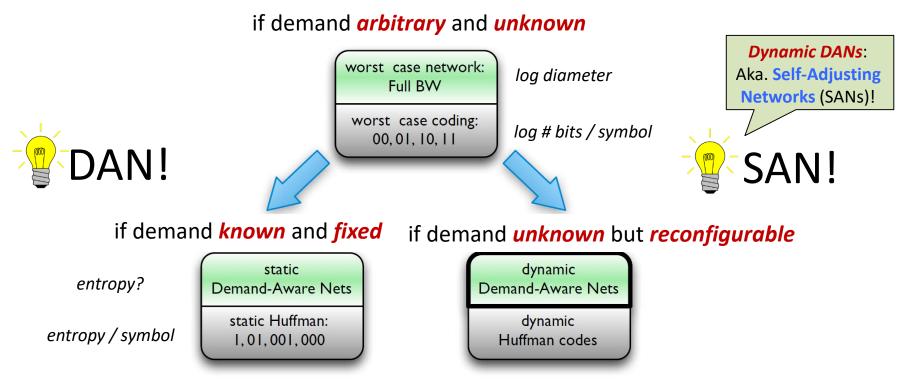
if demand *arbitrary* and *unknown*

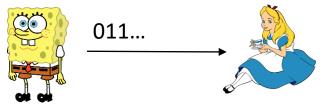


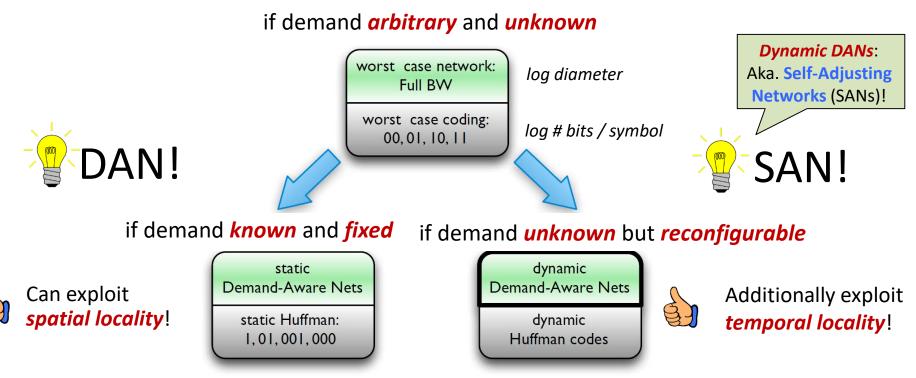


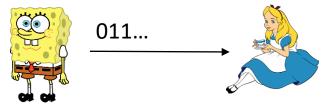


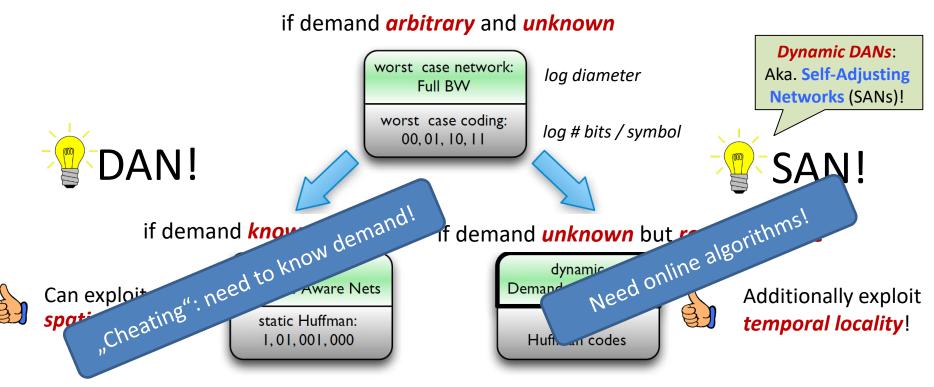












Analogous to *Datastructures*: Oblivious...

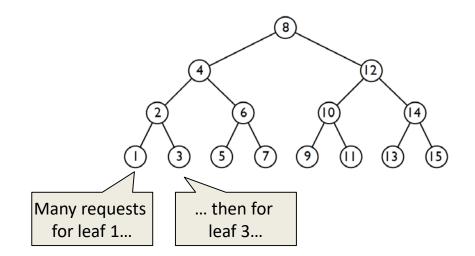
- Traditional, fixed BSTs do not rely on any assumptions on the demand
- Optimize for the worst-case
- Example demand:

 $1, \dots, 1, 3, \dots, 3, 5, \dots, 5, 7, \dots, 7, \dots, \log(n), \dots, \log(n)$ $\longleftrightarrow \qquad \longleftrightarrow \qquad \longleftrightarrow \qquad \longleftrightarrow \qquad \longleftrightarrow \qquad \longleftrightarrow \qquad$ *many many many many many many many*

 Items stored at O(log n) from the root, uniformly and independently of their

frequency

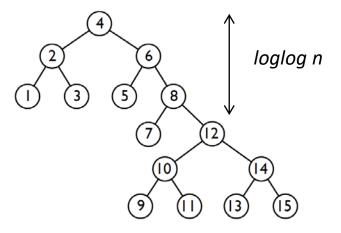
Corresponds to max possible demand!



... Demand-Aware ...

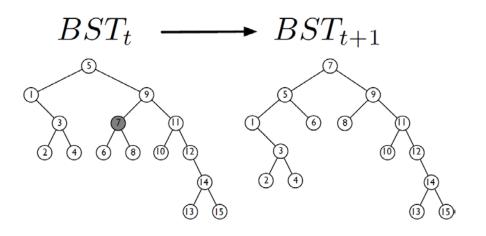
- Demand-aware fixed BSTs can take advantage of *spatial locality* of the demand
- E.g.: place frequently accessed elements close to the root
- E.g., Knuth/Mehlhorn/Tarjan trees
- Recall example demand: 1,...,1,3,...,3,5,...,5,7,...,7,...,log(n),...,log(n)
 - Amortized cost O(loglog n)

Amortized cost corresponds to *empirical entropy of demand*!



... Self-Adjusting!

- Demand-aware reconfigurable BSTs can additionally take advantage of temporal locality
- By moving accessed element to the root: amortized cost is *constant*, i.e., O(1)
 - Recall example demand:
 1,...,1,3,...,3,5,...,5,7,...,7,...,log(n),...,log(n)

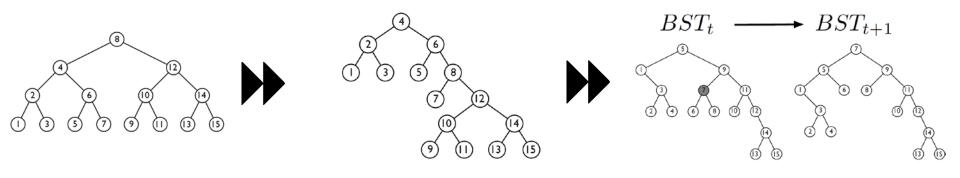


Datastructures

Oblivious

Demand-Aware

Self-Adjusting



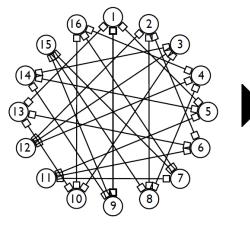
Lookup *O(log n)* Exploit spatial locality: empirical entropy O(loglog n) Exploit temporal locality as well: O(1)

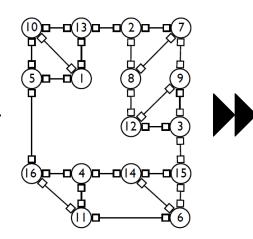
Analogously for Networks

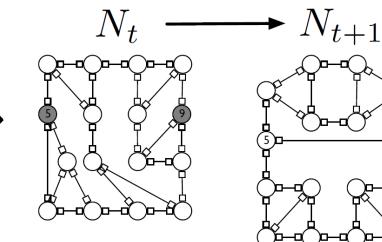


DAN









Const degree (e.g., expander): route lengths O(log n)

Exploit spatial locality

Exploit temporal locality as well

Avin, S.: Toward Demand-Aware Networking: A Theory for Self-Adjusting Networks. **SIGCOMM CCR** 2018.

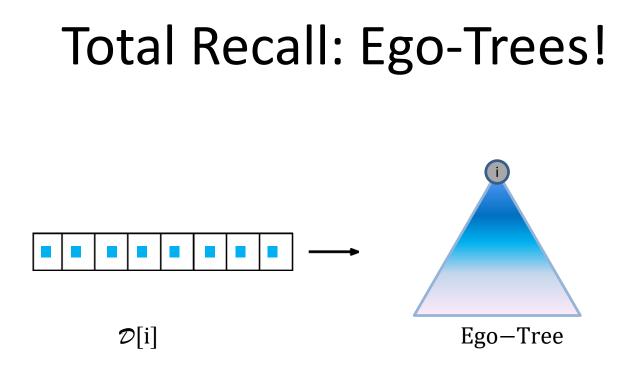
Algorithms for Self-Adjusting Networks



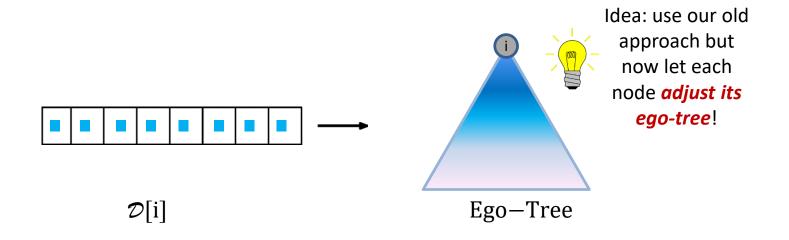
From trees to networks!



Ego-trees strike back!



Total Recall: Ego-Trees!

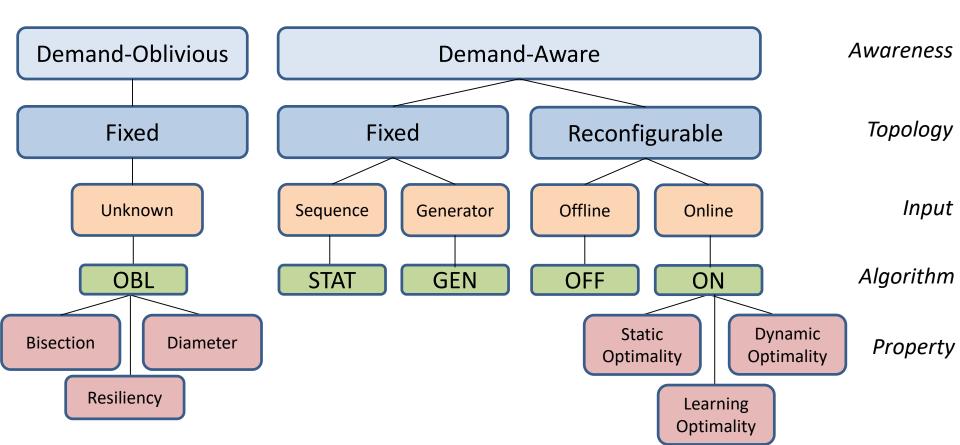


A Dynamic Ego-Tree: Splay Tree



Uncharted Landscape!

Toward Demand-Aware Networking: A Theory for Self-Adjusting Networks. **SIGCOMM CCR**, 2018.

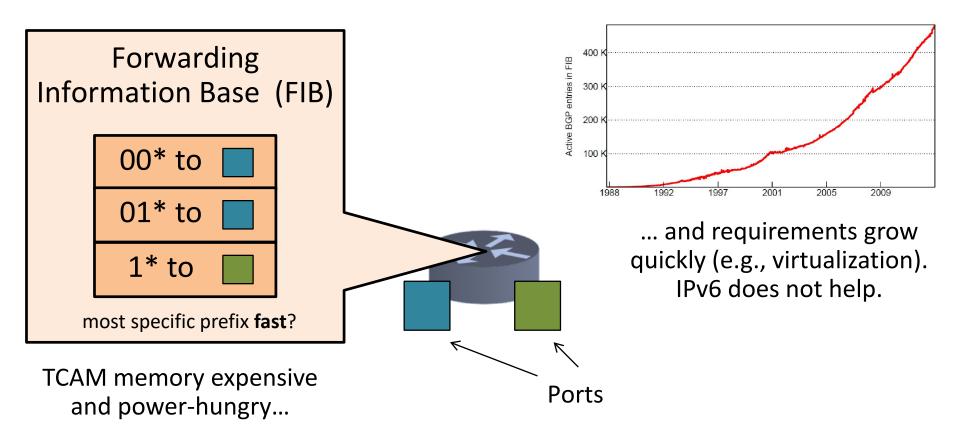


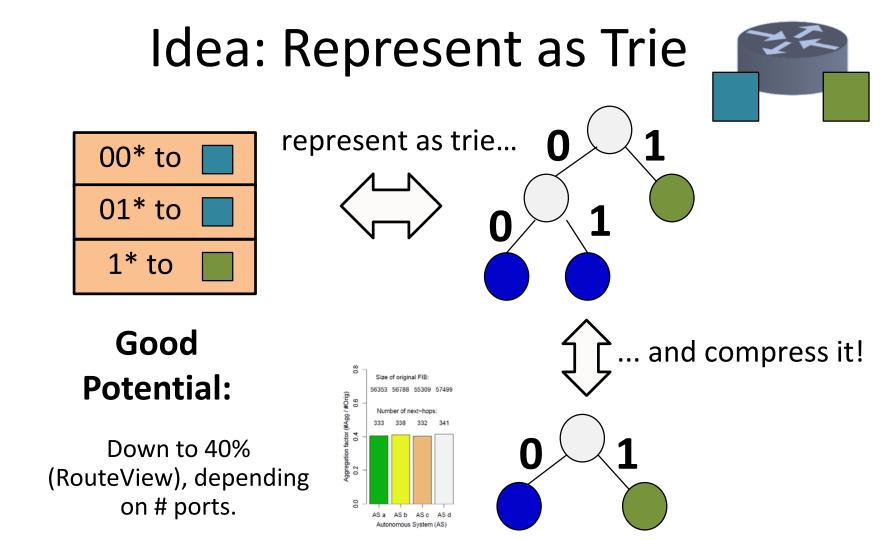
Flexibilities and Algorithms: Opportunities and Challenges

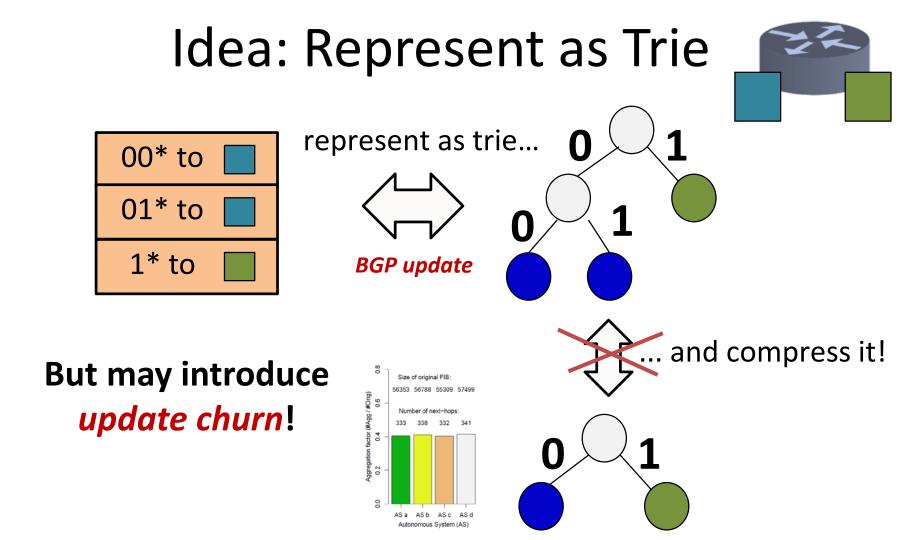
Optimizing Individual Routers

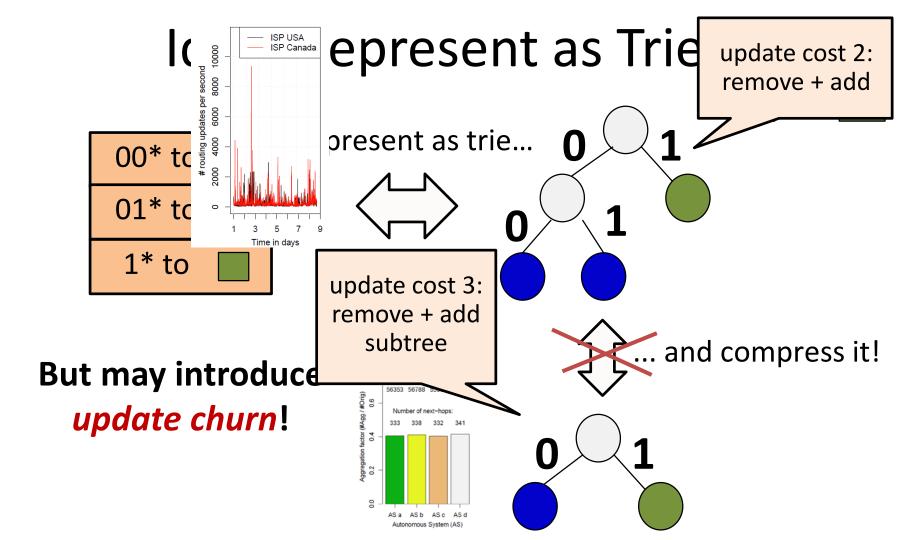
Online Aggregation of the Forwarding Information Base: Accounting for Locality and Churn. Marcin Bienkowski, Nadi Sarrar, Stefan Schmid, and Steve Uhlig. IEEE/ACM Transactions on Networking (**TON**), 2018.

Poor IP Routers

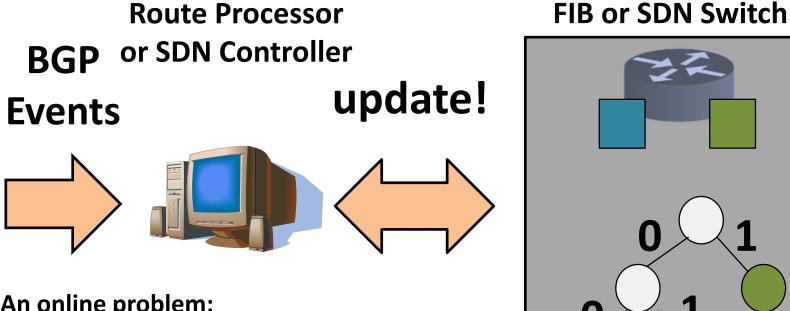








An Optimization Problem



An online problem:

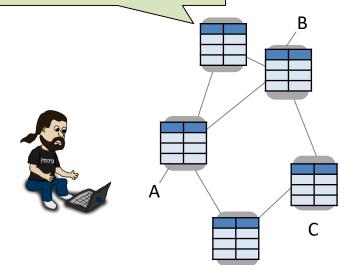
- Forwarding must always be correct 1. (equivalent)
- 2. Minimize update cost and memory size

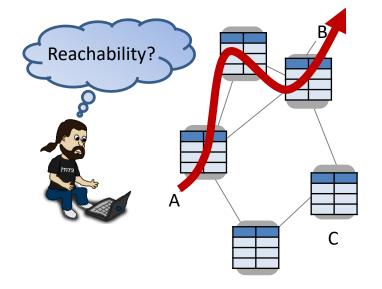
Optimization of Local Fast Failover

P-Rex: Fast Verification of MPLS Networks with Multiple Link Failures. Jesper Stenbjerg Jensen, Troels Beck Krogh, Jonas Sand Madsen, Stefan Schmid, Jiri Srba, and Marc Tom Thorgersen. ACM **CoNEXT**, Heraklion/Crete, Greece, December 2018.

Polynomial-Time What-If Analysis for Prefix-Manipulating MPLS Networks Stefan Schmid and Jiri Srba. IEEE **INFOCOM**, Honolulu, Hawaii, USA, April 2018.

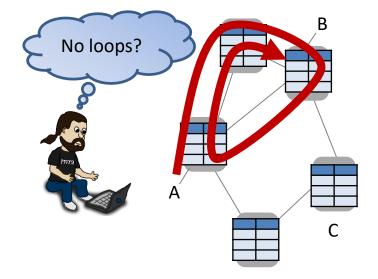
Routers and switches store list of forwarding rules, and conditional failover rules.





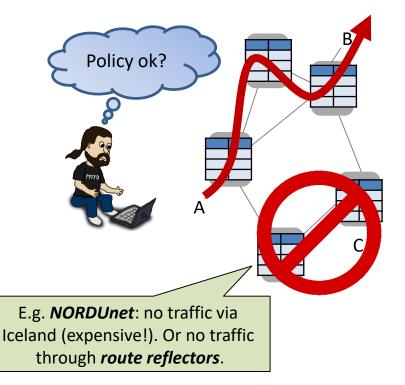
Sysadmin responsible for:

• **Reachability:** Can traffic from ingress port A reach egress port B?



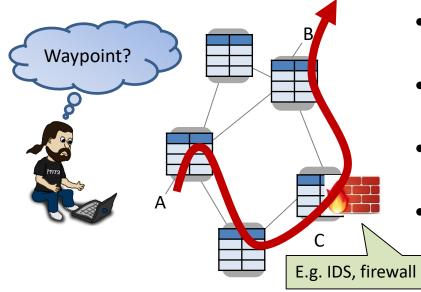
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- Waypoint enforcement: Is it ensured that traffic from A to B is always routed via a node C?



k failures = possibilities А E.g. IDS, firewall

Sysadmin responsible for:

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- **Policy:** Is it ensured that traffic from A to B never goes via C?
- Waypoint enforcement: Is it ensured that traffic from A to B is always routed via a node C?

... and everything even under multiple failures?!

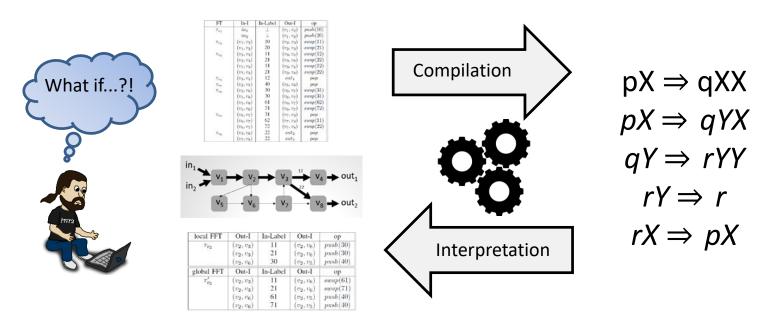
Can we automate such tests or even self-repair?

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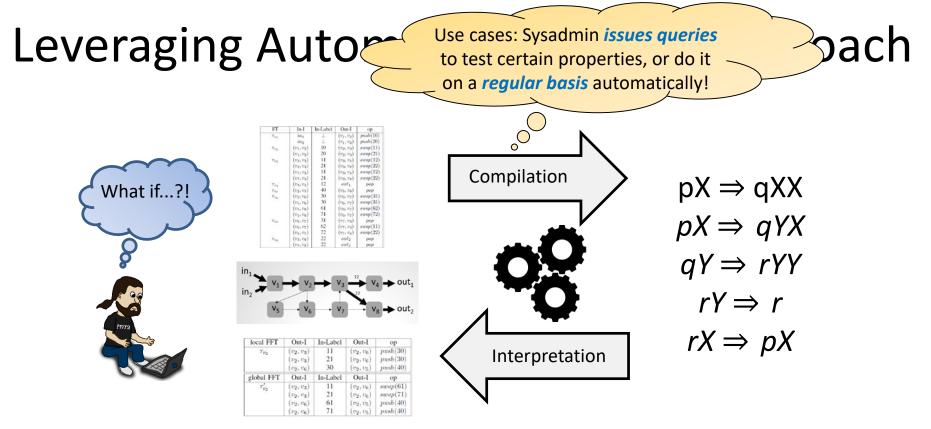


Yes! Encouraging: sometimes even *fast*: What-if Analysis Tool for MPLS and SR

Leveraging Automata-Theoretic Approach



MPLS configurations, Segment Routing etc. Pushdown Automaton and Prefix Rewriting Systems Theory



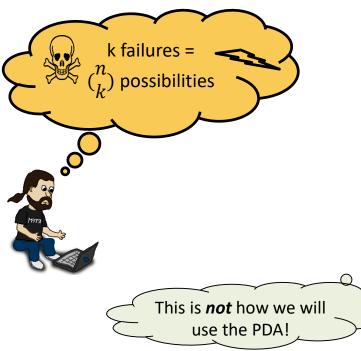
MPLS configurations, Segment Routing etc. Pushdown Automaton and Prefix Rewriting Systems Theory

A Complex and Big Formal Language! Why Polynomial Time?!



- Arbitrary number k of failures: How can I avoid checking all ⁿ_k many options?!
- Even if we reduce to **push-down automaton**: simple operations such as emptiness testing or intersection on Push-Down Automata (PDA) is computationally non-trivial and sometimes even undecidable!

A Complex and Big Formal Language! Why Polynomial Time?!



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A Complex and Big Formal Language! Why Polynomial Time?!



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- Even if we reduce to **push-down automaton**: simple operations such as emptiness testing or intersection on Push-Down Automata (PDA) is computationally non-trivial and sometimes even **undecidable**!

The words in our language are sequences of pushdown stack symbols, not the labels of transitions.

Time for Automata Theory (from Switzerland)!

- Classic result by **Büchi** 1964: the set of all reachable configurations of a pushdown automaton a is regular set
- Hence, we can operate only on Nondeterministic Finite Automata (NFAs) when reasoning about the pushdown automata



Julius Richard Büchi 1924-1984 Swiss logician

- The resulting **regular operations** are all **polynomial time**
 - Important result of model checking

Tool and Query Language

Part 1: Parses query and constructs Push-Down System (PDS)

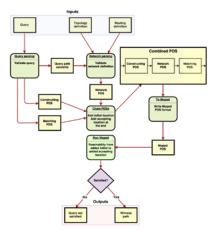
• In Python 3

Part 2: Reachability analysis of constructed PDS

• Using *Moped* tool

failures header path header header header header

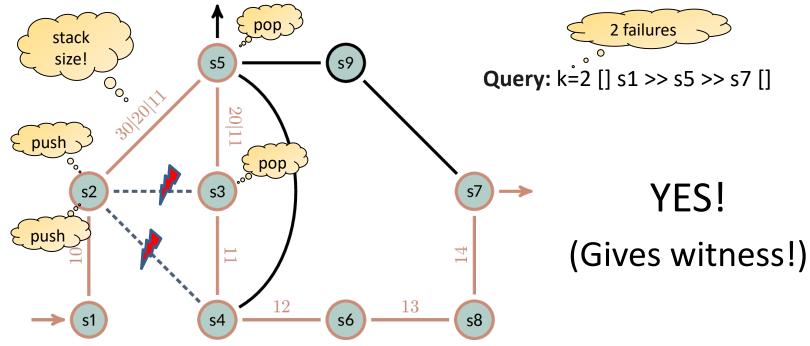
Regular query language



query processing flow

Example: Traversal Testing With 2 Failures

Traversal test with k=2: Can traffic starting with [] go through s5, under up to k=2 failures?

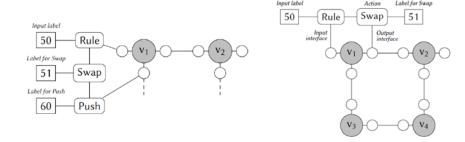


Formal methods are nice (give guarantees!)... But what about ML...?!

DeepMPLS: Fast Analysis of MPLS Configurations Using Deep Learning. Fabien Geyer and Stefan Schmid. **IFIP Networking**, Warsaw, Poland, May 2019.

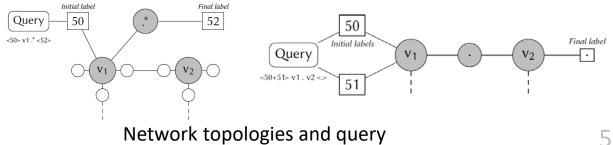
Speed Up Further and Synthesize: Deep Learning (s. talk by Fabien Geyer)

- Yes sometimes without losing guarantees
- Extend graph-based neural networks



Network topologies and MPLS rules

Predict counter-examples and fixes



Challenges of Self-* Networks

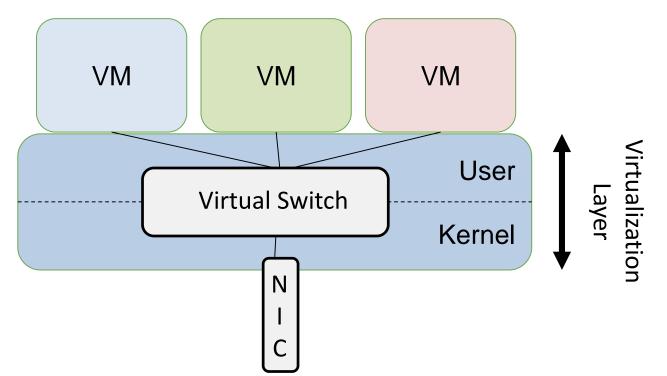
- Can a self-* network realize its limits?
- E.g., when quality of **input data** is not good enough?
- When to hand over to human? Or fall back to "safe/oblivious mode"?
- Can we learn from self-driving cars?



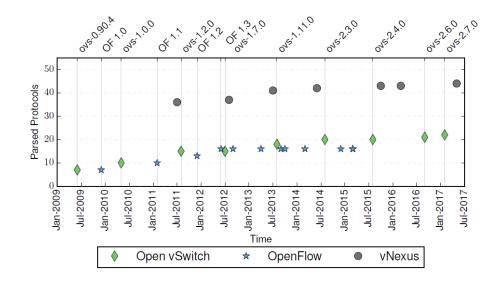
Security Challenges of More Flexible Networks

MTS: Bringing Multi-Tenancy to Virtual Switches. Kashyap Thimmaraju, Saad Hermak, Gabor Retvari, and Stefan Schmid. USENIX **ATC**, 2019.

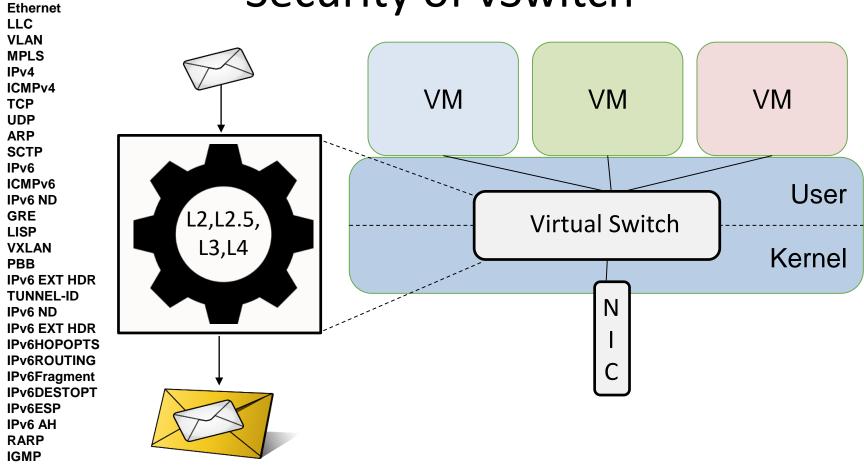
> Taking Control of SDN-based Cloud Systems via the Data Plane. Kashyap Thimmaraju et al. ACM **SOSR**, USA, March 2018.

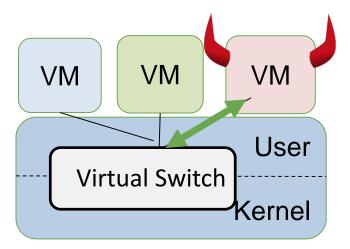


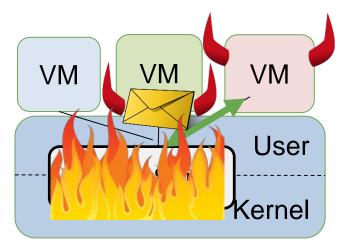
Virtual switches reside in the **server's virtualization layer** (e.g., Xen's Dom0). Goal: provide connectivity and isolation.

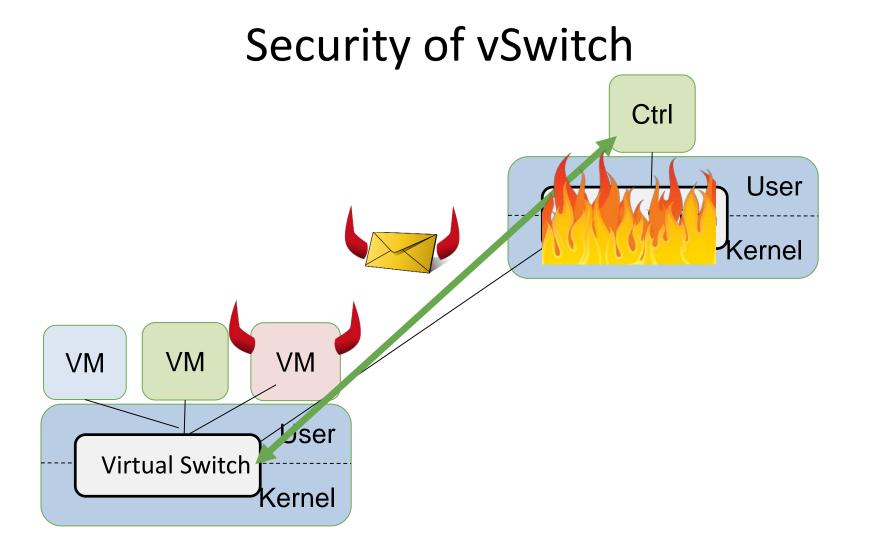


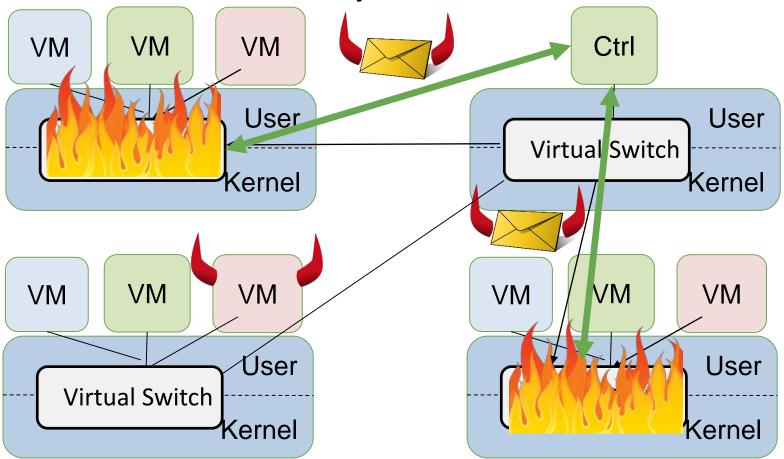
Number of parsed high-level protocols constantly increases...

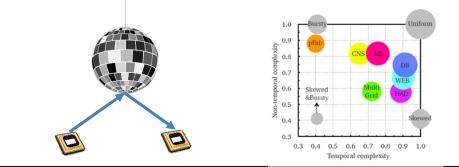




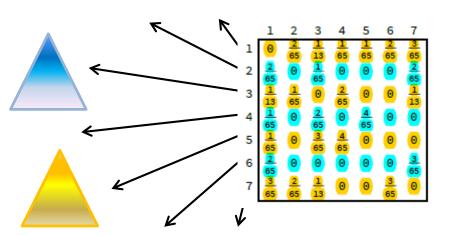








Thank you! Questions?



Demand-aware networks

Survey of Reconfigurable Data Center Networks: Enablers, Algorithms, Complexity Klaus-Tycho Foerster and Stefan Schmid. SIGACT News, June 2019. Toward Demand-Aware Networking: A Theory for Self-Adjusting Networks (Editorial) Chen Avin and Stefan Schmid. ACM SIGCOMM Computer Communication Review (CCR), October 2018. Measuring the Complexity of Network Traffic Traces Chen Griner, Chen Avin, Manya Ghobadi, and Stefan Schmid. arXiv, 2019. Demand-Aware Network Design with Minimal Congestion and Route Lengths Chen Avin, Kaushik Mondal, and Stefan Schmid. 38th IEEE Conference on Computer Communications (INFOCOM), Paris, France, April 2019. **Distributed Self-Adjusting Tree Networks** Bruna Peres, Otavio Augusto de Oliveira Souza, Olga Goussevskaia, Chen Avin, and Stefan Schmid. 38th IEEE Conference on Computer Communications (INFOCOM), Paris, France, April 2019. Efficient Non-Segregated Routing for Reconfigurable Demand-Aware Networks Thomas Fenz, Klaus-Tycho Foerster, Stefan Schmid, and Anaïs Villedieu. IFIP Networking, Warsaw, Poland, May 2019. DaRTree: Deadline-Aware Multicast Transfers in Reconfigurable Wide-Area Networks Long Luo, Klaus-Tycho Foerster, Stefan Schmid, and Hongfang Yu. IEEE/ACM International Symposium on Quality of Service (IWQoS), Phoenix, Arizona, USA, June 2019. Demand-Aware Network Designs of Bounded Degree Chen Avin, Kaushik Mondal, and Stefan Schmid. 31st International Symposium on Distributed Computing (DISC), Vienna, Austria, October 2017. SplayNet: Towards Locally Self-Adjusting Networks Stefan Schmid, Chen Avin, Christian Scheideler, Michael Borokhovich, Bernhard Haeupler, and Zvi Lotker. IEEE/ACM Transactions on Networking (TON), Volume 24, Issue 3, 2016. Early version: IEEE IPDPS 2013. Characterizing the Algorithmic Complexity of Reconfigurable Data Center Architectures Klaus-Tycho Foerster, Monia Ghobadi, and Stefan Schmid. ACM/IEEE Symposium on Architectures for Networking and Communications Systems (ANCS), Ithaca, New York, USA, July 2018.

A survey!

What-if analysis

P-Rex: Fast Verification of MPLS Networks with Multiple Link Failures

Jesper Stenbjerg Jensen, Troels Beck Krogh, Jonas Sand Madsen, Stefan Schmid, Jiri Srba, and Marc Tom Thorgersen. 14th ACM International Conference on emerging Networking EXperiments and Technologies (**CoNEXT**), Heraklion/Crete, Greece, December 2018.

Polynomial-Time What-If Analysis for Prefix-Manipulating MPLS Networks

Stefan Schmid and Jiri Srba.

37th IEEE Conference on Computer Communications (INFOCOM), Honolulu, Hawaii, USA, April 2018.

Secure sampling and dataplane

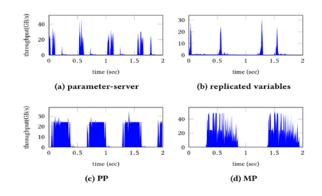
Preacher: Network Policy Checker for Adversarial Environments Kashyap Thimmaraju, Liron Schiff, and Stefan Schmid. 38th International Symposium on Reliable Distributed Systems (SRDS), Lyon, France, October 2019. MTS: Bringing Multi-Tenancy to Virtual Switches Kashyap Thimmaraju, Saad Hermak, Gabor Retvari, and Stefan Schmid. USENIX Annual Technical Conference (ATC), Renton, Washington, USA, July 2019. Taking Control of SDN-based Cloud Systems via the Data Plane (Best Paper Award) Kashyap Thimmaraju, Bhargava Shastry, Tobias Fiebig, Felicitas Hetzelt, Jean-Pierre Seifert, Anja Feldmann, and Stefan Schmid. ACM Symposium on SDN Research (SOSR), Los Angeles, California, USA, March 2018.

Backup Slides

How Predictable is Traffic?

Even if reconfiguration fast, control plane (e.g., data collection) can become a bottleneck. However, many good examples:

- Machine learning applications
- Trend to disaggregation (specialized racks)
- Datacenter communication dominated by elephant flows
- Etc.



ML workload (GPU to GPU): deep convolutional neural network *Predictable from their dataflow graph*