



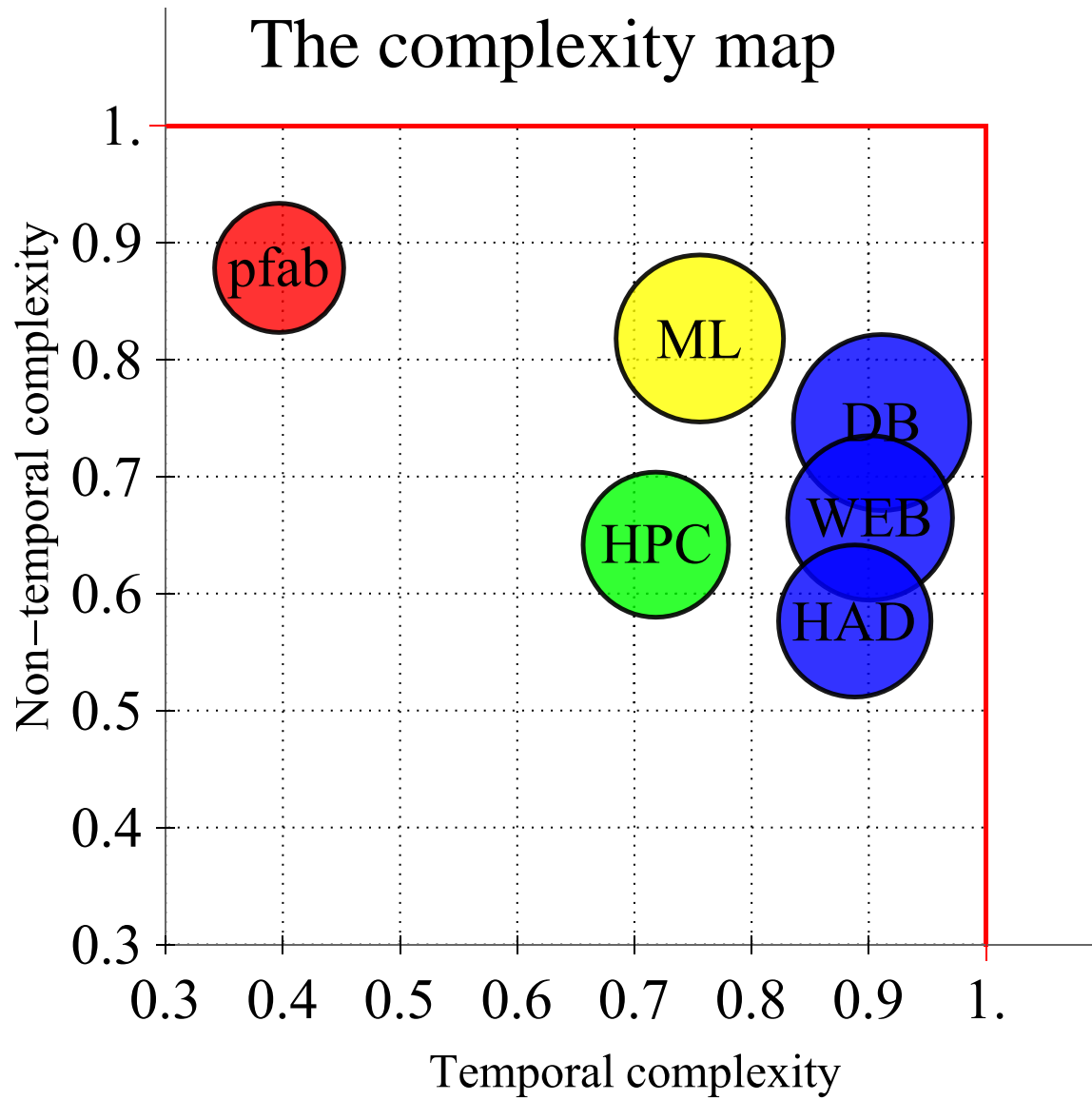
On the Complexity of Traffic Traces and Implications

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CHEN GRINER, STEFAN SCHMID*

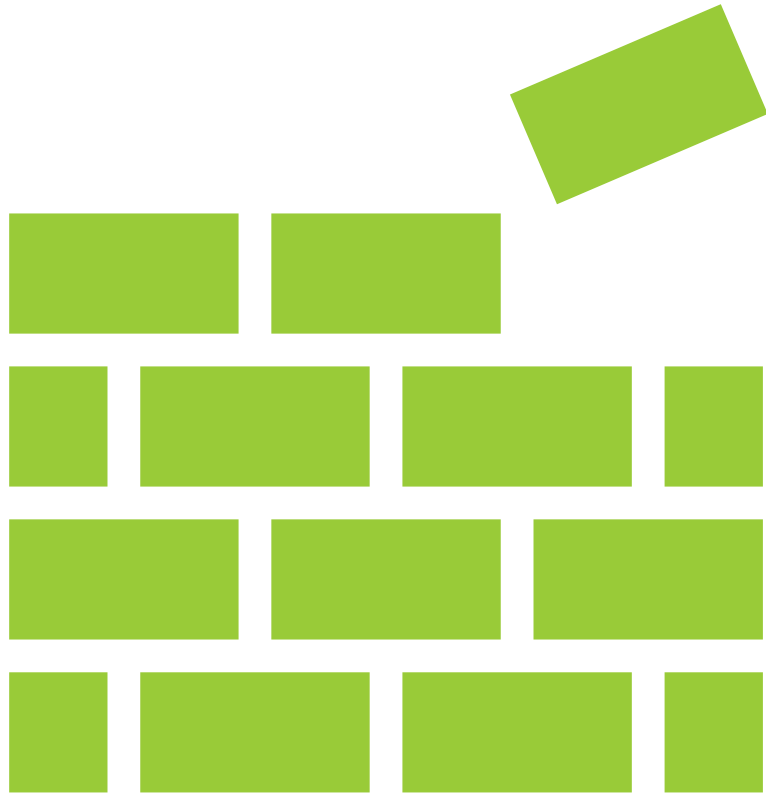
*“It is not the strongest of the species that survives,
nor the most intelligent that survives. But the one
that is most adaptable to change.”*

(Leon C. Megginson)



Mapping a Landscape of Network Traffic

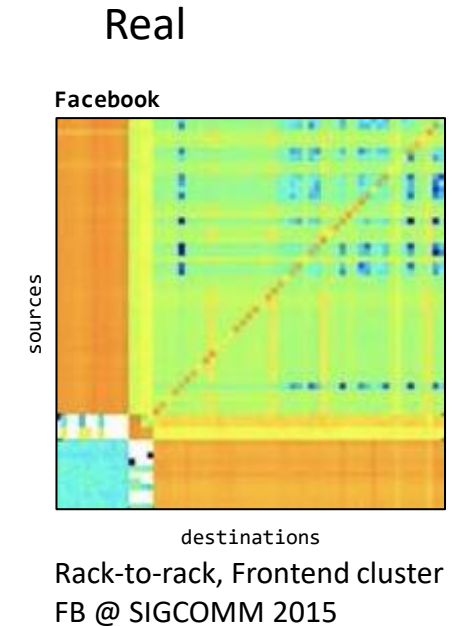
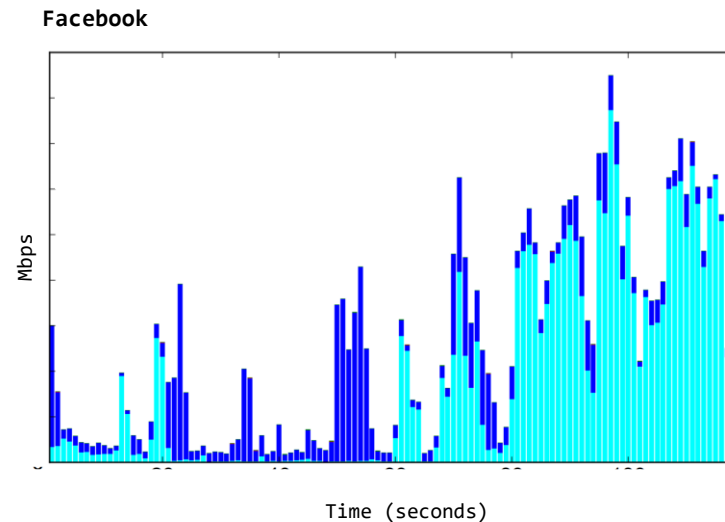
- Define
- Categorize
- Quantify
- *Map different types of structure*
- Better design of networks?



What is Structure?

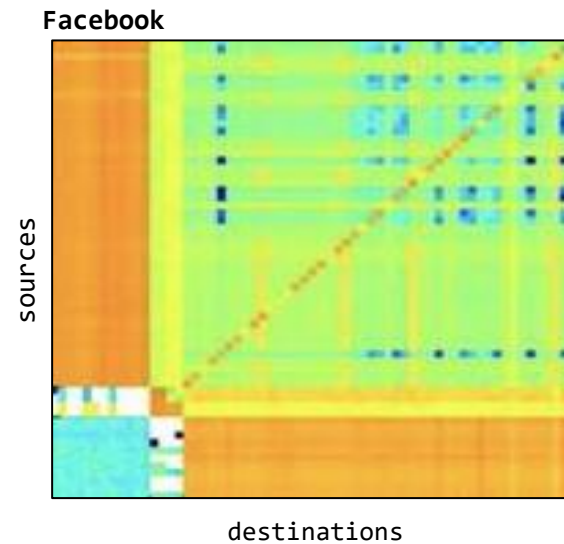
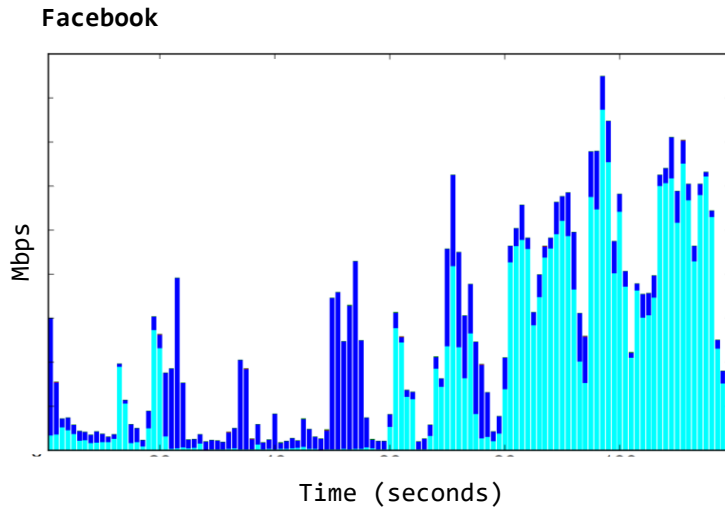
Visible Structure?

- Can we see patterns in real network traffic?
 - *Yes!*



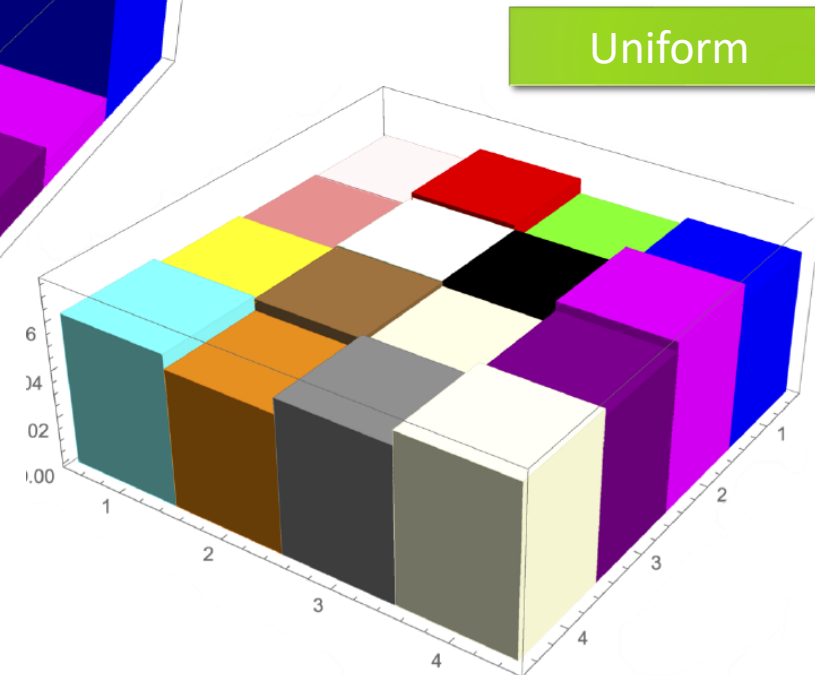
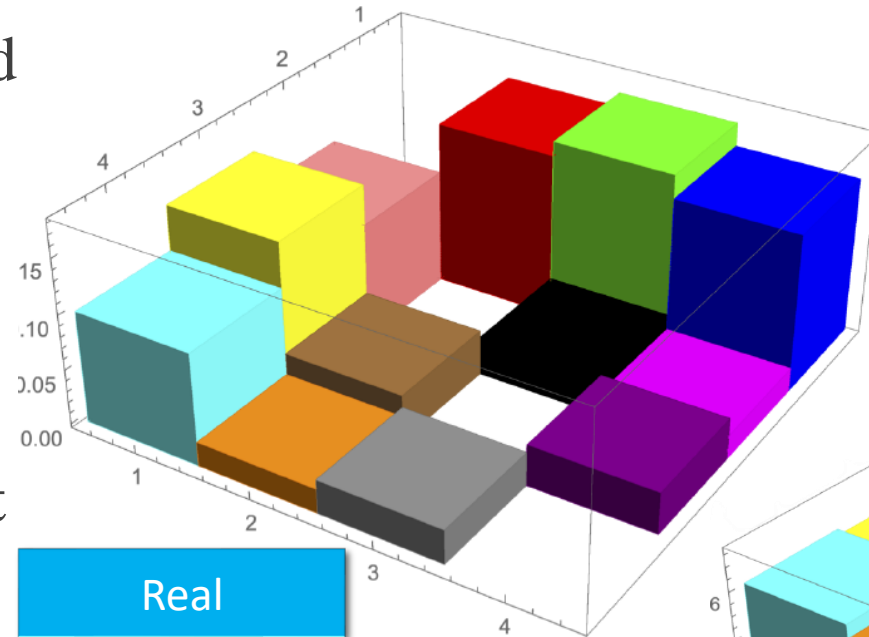
Structure: Two Types

- Temporal
- Non temporal(spatial)



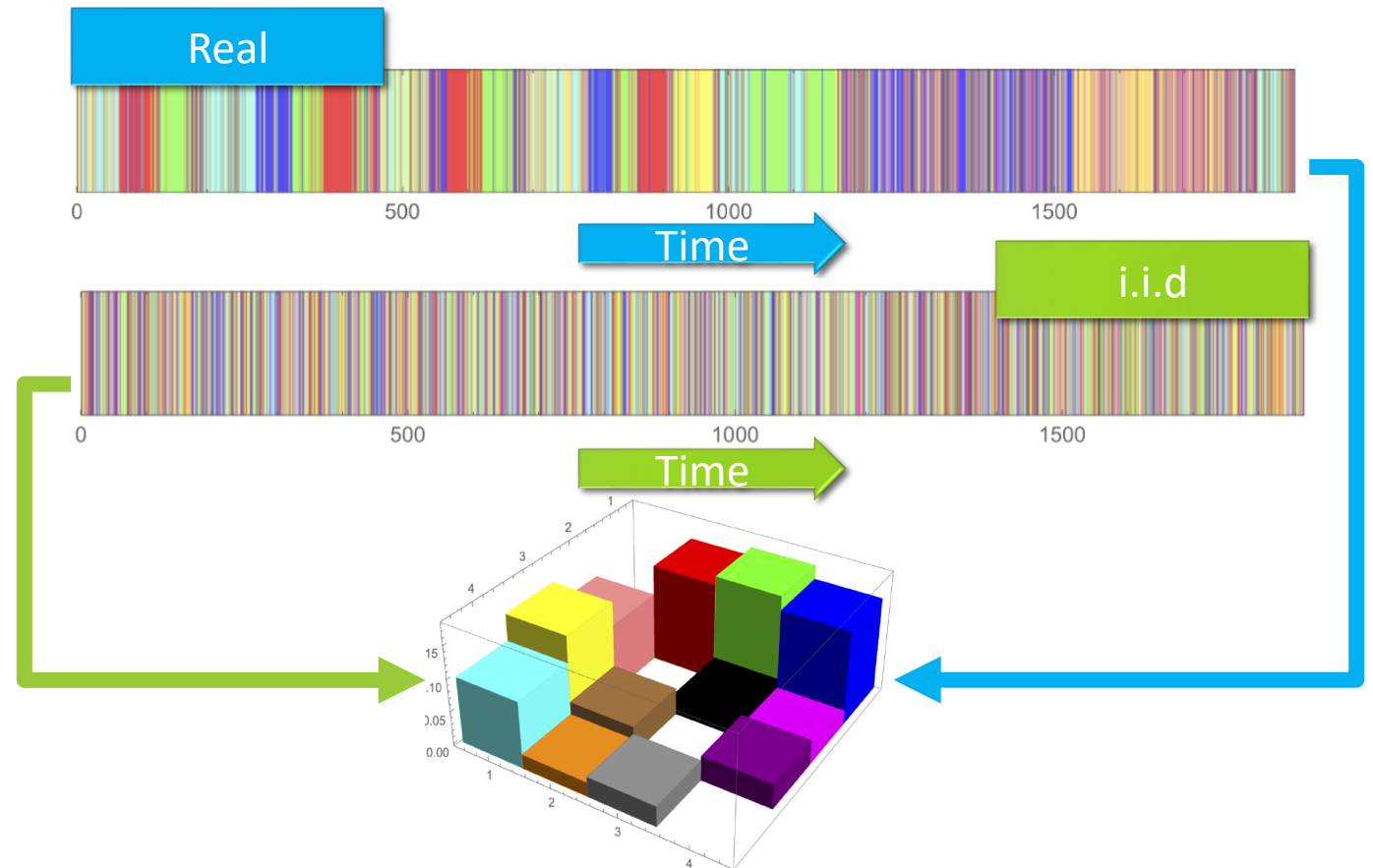
ML Example: Non temporal structure

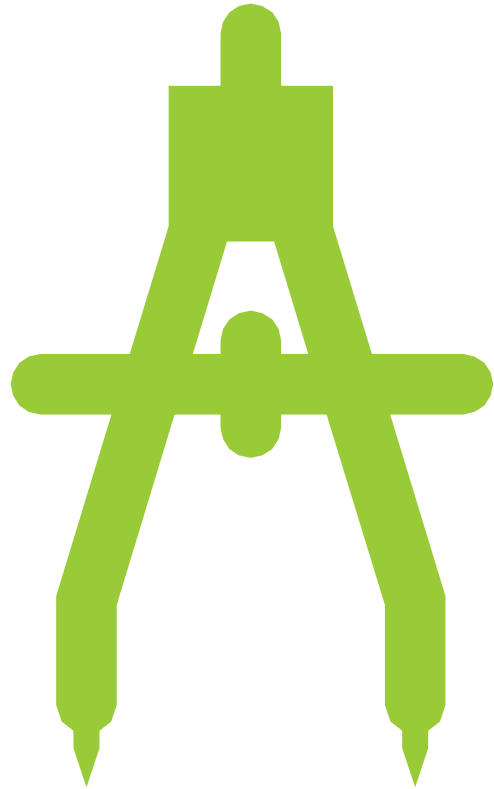
- A traffic matrix of a distributed ML application
- Source destination denoted by color
- Height denotes amount of traffic
- **How would a matrix without structure look like?**



Temporal structure

- Not all structure is related to frequency
- *Temporal* structure, represents the dependency of future events on recent events
 - Example: bursts of traffic
 - Both traces have the same traffic matrix but are different in time

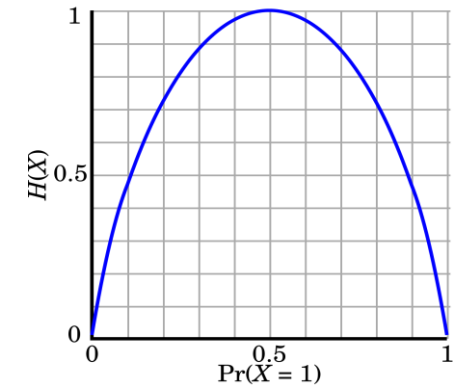




How to Measure Structure

An information theoretic perspective

- In Information theory *entropy* (entropy rate) is a measure “randomness”
- Lower *entropy* \Rightarrow More predictable traffic
- Traffic with more “structure” is less “complex”
- *Compression* offers a way to estimate *entropy*
- But how to represent traffic?



Traffic as a Network Trace

Source	Destination
(192.168.1.3)=s ₀	(192.168.1.1)=d ₀
s ₁	d ₁
s ₂	d ₂
s ₃	d ₃
s ₄	d ₄
s ₅	d ₅
s ₆	d ₆

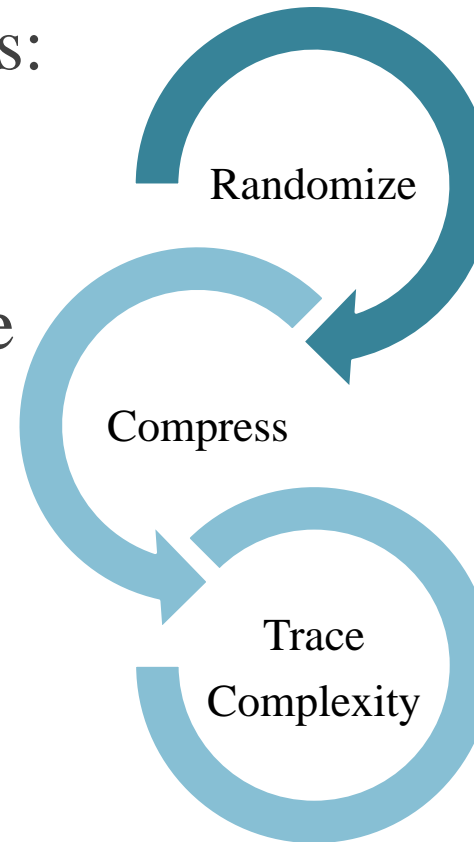
Time

- A Simplified **time ordered** list of **source-destination** pairs
- How to use it?

Methodology

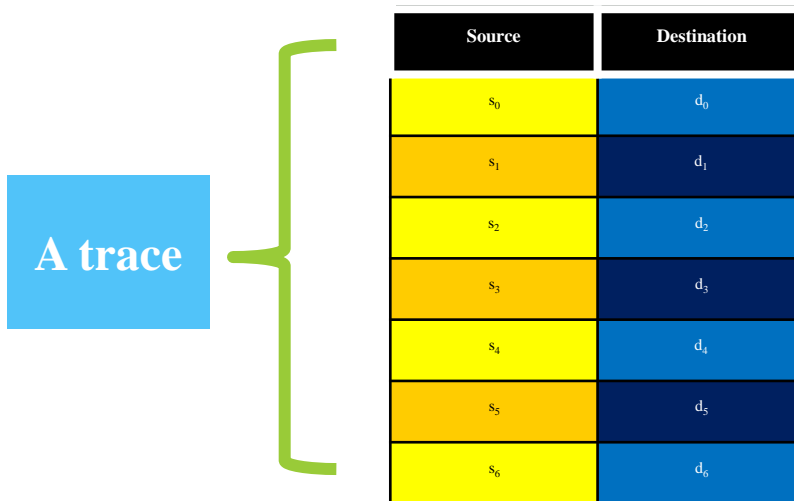
- Measuring complexity with two steps:

1. Sequentially randomize a trace, remove a specific types of structure
2. Compress the trace, compare their size.



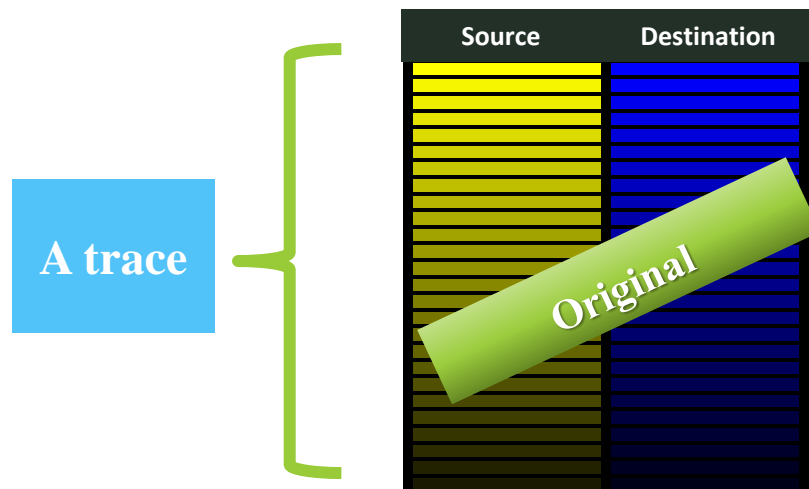
Source	Destination
s_0	d_0
s_1	d_1
s_2	d_2
s_3	d_3
s_4	d_4
s_5	d_5
s_6	d_6

Systematic randomization



Systematic randomization

Increasing complexity



Original trace σ

- ✓ Temporal
- ✓ Non Temporal

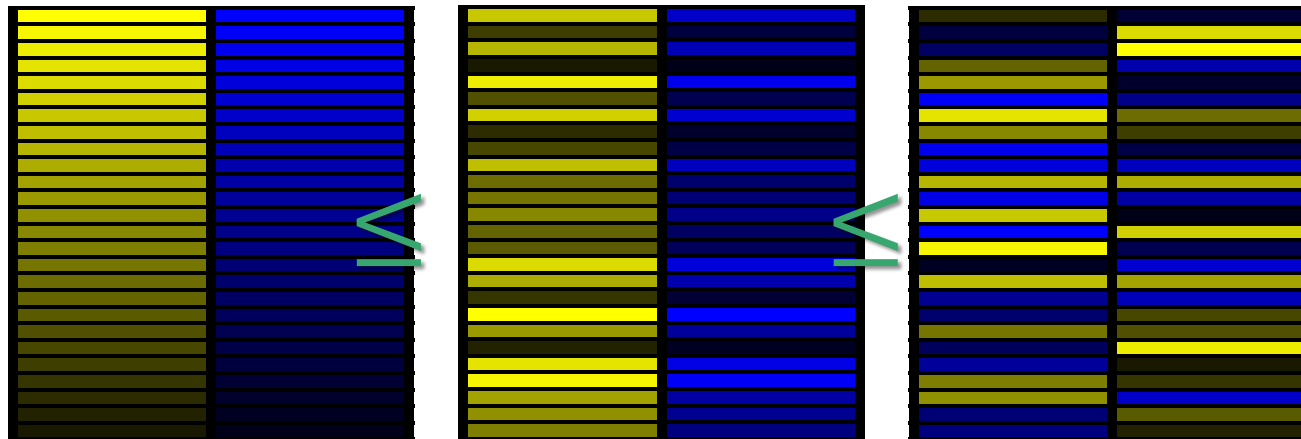
Row Randomized $\Gamma(\sigma)$

X	Temporal
✓	Non Temporal

Uniform Trace $\mathbf{u}(\sigma)$

- X Temporal
- X Non Temporal

Compression



Formal Definitions of Trace Complexity

Let $c(\sigma)$ is the *size* of a compressed trace σ :

We define:

Total complexity: $\psi(\sigma) = \frac{c(\sigma)}{c(u(\sigma))}$

Uniform
transformation

Temporal complexity: $T(\sigma) = \frac{c(\sigma)}{c(\Gamma(\sigma))}$

Row
transformation

Non-temporal complexity: $NT(\sigma) = \frac{c(\Gamma(\sigma))}{c(u(\sigma))}$

Complexity is in the range of $[0 \dots 1]$

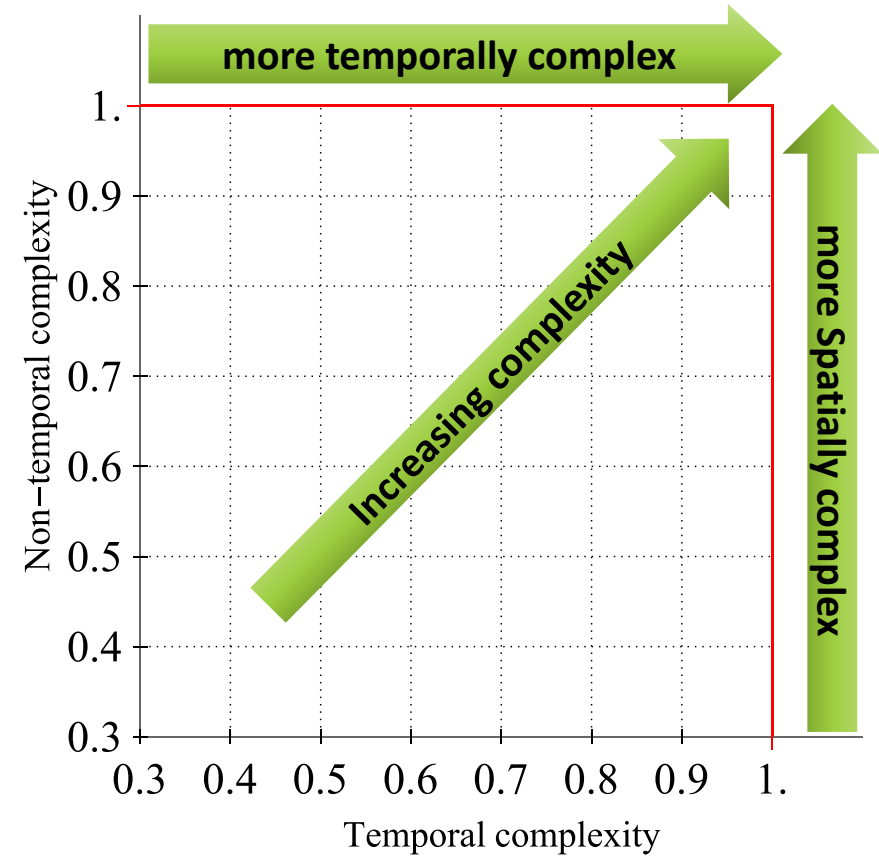




Mapping Trace Complexity

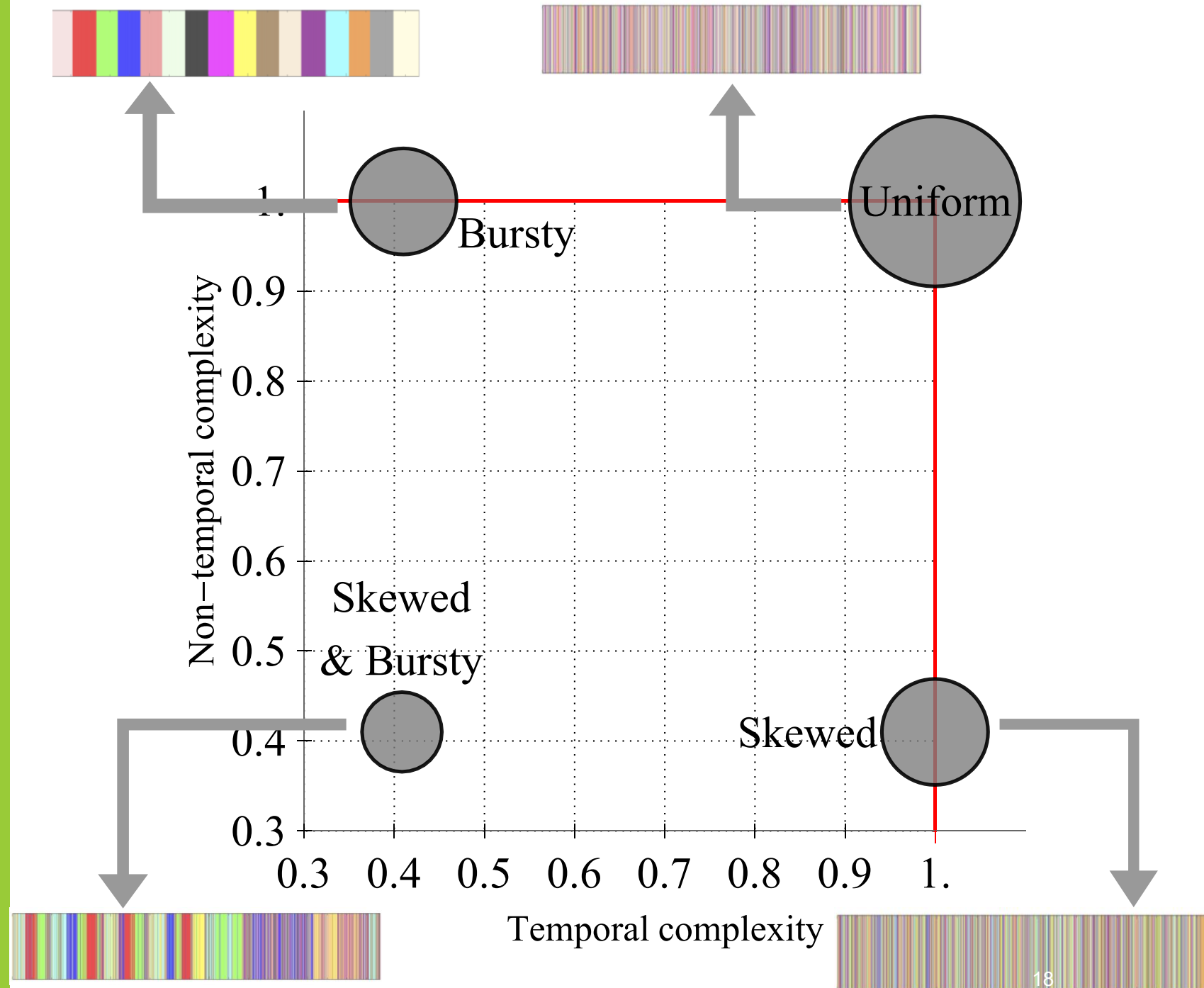
The Complexity Map

- X axis: temporal complexity
- Y axis: non-temporal complexity
- Rule of thumb:
Closer to the axis's origin, means lower complexity



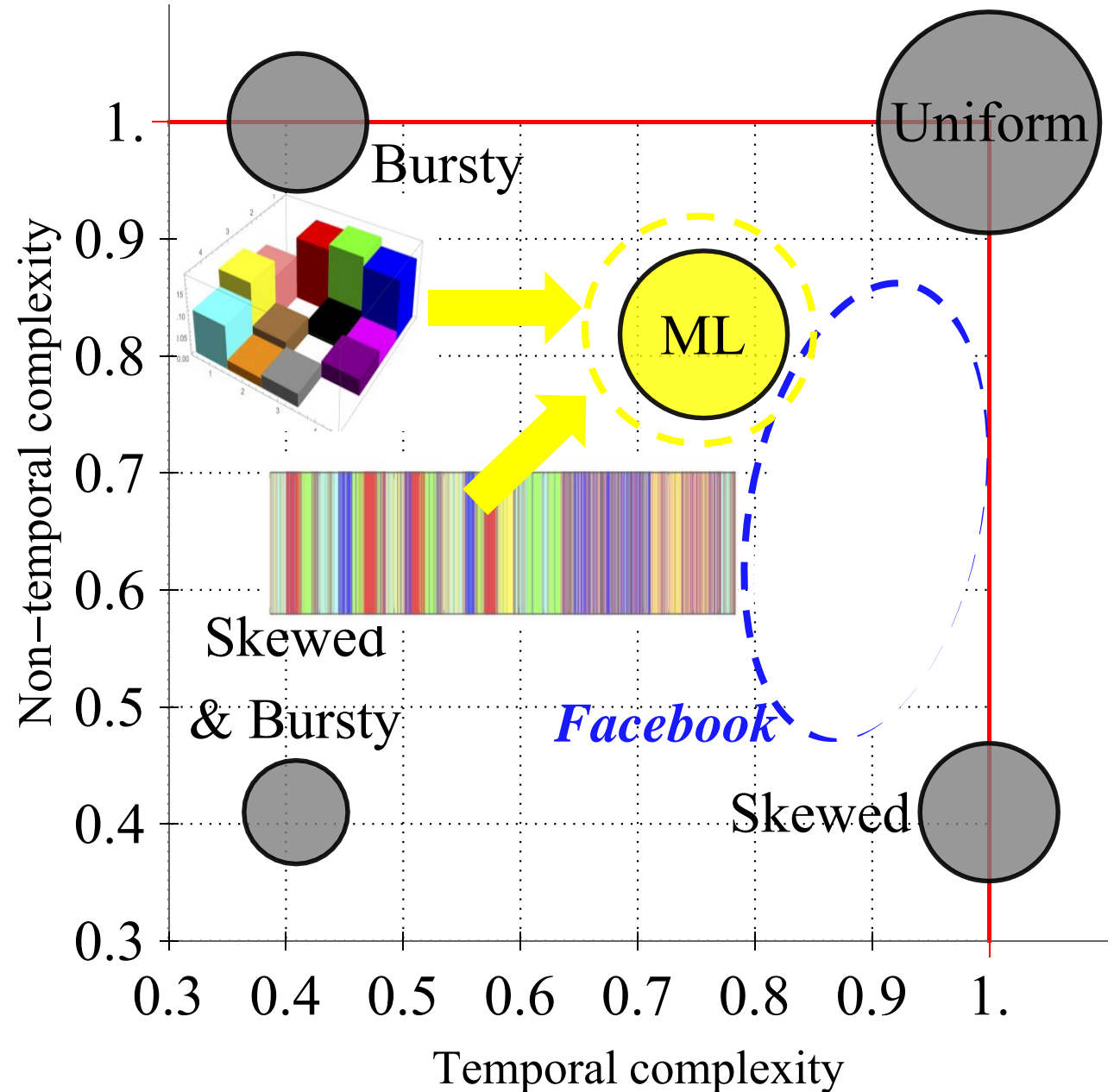
The Complexity Map

- Uniform Traffic
 - Lacking any structure, maximal entropy
- Bursty Traffic
 - Has temporal correlations
- Skewed Traffic
 - From a skewed distribution
- Skewed & Bursty Traffic
 - Has both temporal and non temporal elements



Case Study

- ML
- Facebook
 - Database, Web, Hadoop
- High Power Computing (HPC)
- pFabric



What can we expect to learn from trace complexity?



Lower complexity means better optimization



Identify and quantify different structures



Compare different traces?



Differentiate between different workloads?

Future work

- Test trace with more metadata
 - Interarrival times, ports etc
- What are the other dimensions of complexity?
- Practical implementation of complexity in online algorithms?
- Trace website:
 - <https://self-adjusting.net>
- Further details are found in the paper:

On the Complexity of Traffic Traces and Implications.

*Chen Avin, Manya Ghobadi, Chen Griner, Stefan Schmid. **Sigmetrics 2020***