On the Robustness of Deep Learning-predicted Contention Models for Network Calculus

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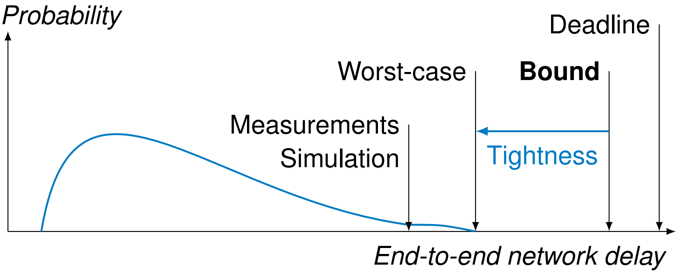
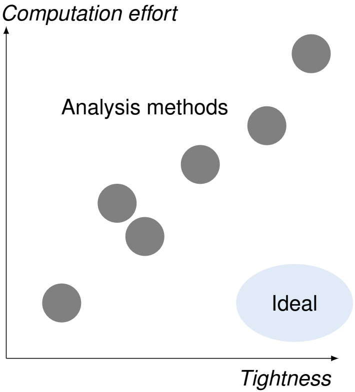
Motivation

Worst-Case End-to-End Performance Analysis

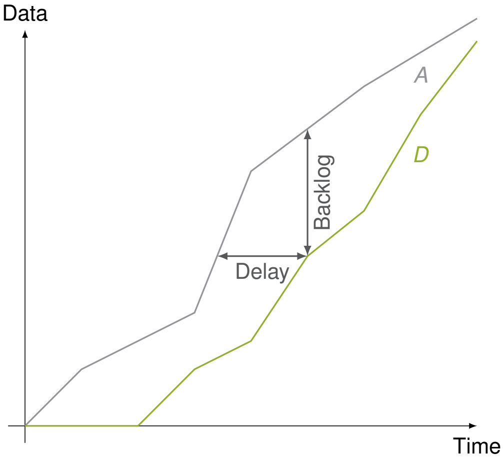


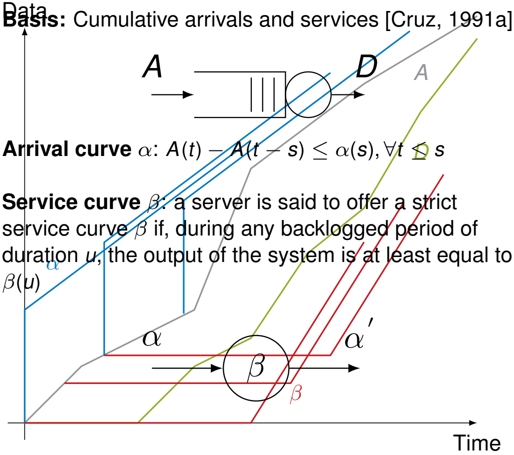


- Trade-off between computational effort and tightness
- **This talk: network analysis method with good tightness and fast execution**

Motivation

Network Calculus – Basics





Basis: Cumulative arrivals and services [Cruz, 1991a]

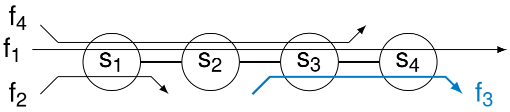
Arrival curve α: $A(t) - A(t-s) \leq \alpha(s), \forall t \geq s$

Service curve β: a server is said to offer a strict service curve β if, during any backlogged period of duration u, the output of the system is at least equal to $\beta(u)$

Motivation

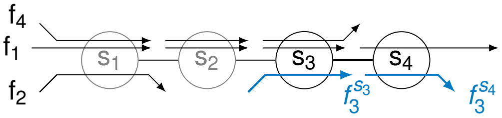
Network Calculus – Network Analysis

How to compute end-to-end performance?



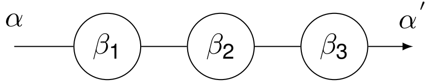
TFA – Total Flow Analysis [Cruz, 1991b]

Step 1: Compute delay at each server on the path



Step 2: Sum delays

Server concatenation [Le Boudec and Thiran, 2001]



(min, +) algebra gives us:

$$\alpha \longrightarrow \boxed{\beta_1 \otimes \beta_2 \otimes \beta_3} \longrightarrow \alpha'$$

$\rightarrow$ Pay Bursts Only Once principle

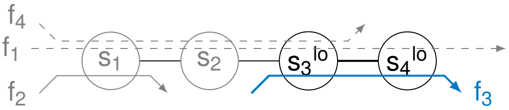
Motivation

Network Calculus – Network Analysis

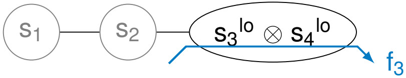
SFA – Separate Flow Analysis

[Le Boudec and Thiran, 2001]

Step 1: Compute per-server residual service



Step 2: Concatenate the servers

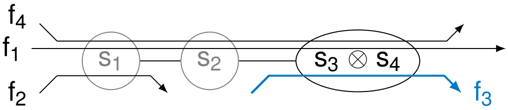


Step 3: Compute delay over concatenated server

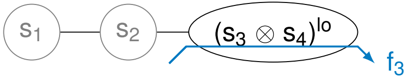
PMOO – Pay Multiplexing Only Once

[Schmitt et al., 2008b]

Step 1: Concatenate the servers



Step 2: Compute residual service



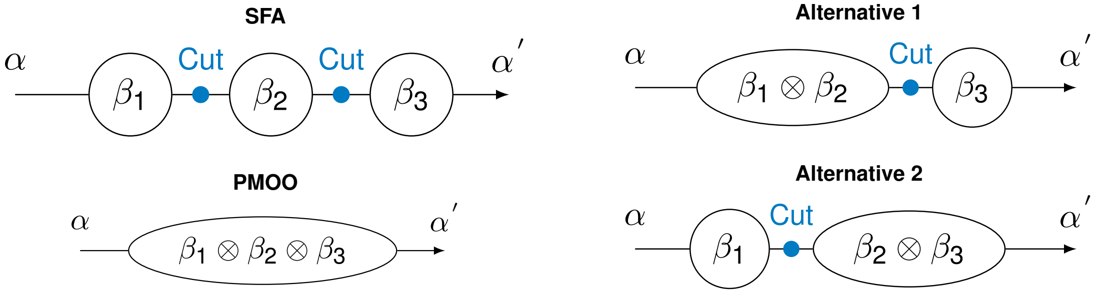
Step 3: Compute delay over concatenated server

Motivation

Network Calculus – TMA

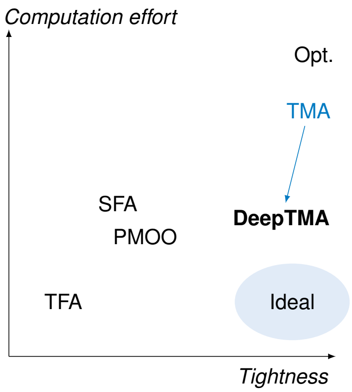
TMA – Tandem Matching Analysis [Bondorf et al., 2017]

- Main concept: apply concatenation only for some servers
- Exhaustive search to find which concatenations will result in the tightest end-to-end delay $\rightarrow \mathcal{O}\left(2^{n-1}\right)$



Motivation

Network Calculus – DeepTMA



Opt.: [Schmitt et al., 2008a][Bouillard et al., 2010]

Approach: Avoid TMA's exhaustive search using ML [Geyer and Bondorf, 2019]

→ **DeepTMA:**

- **Main idea: use neural networks for predicting best cuts**
- Even if the heuristic is wrong, the bounds are still valid

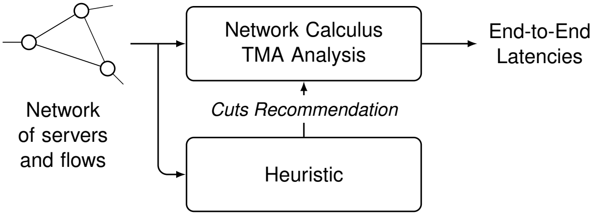


Figure 1: Approach

Motivation

Network Calculus – Contributions

[Geyer and Bondorf, 2019] introduced DeepTMA, but did not explore it's scalability or robustness

New results: Explore the robustness of DeepTMA

- Influence of network size (number of flows and servers) and topology type on accuracy and tightness?
- Scalability on larger networks (up to 10 000 s of flows)?
- Importance of features used by the machine learning algorithm?

Outline

DeepTMA: Heuristic based on Graph Neural Networks

Introduction

Principle: Replace exhaustive search by a fast heuristic [Geyer and Bondorf, 2019]

Heuristic

- **Use Graph Neural Network**
- **Classification problem for cuts**

Graph formulation

- Nodes: flows, servers, cuts
- Edges: relationships between elements
- Prediction if cut is applied or not

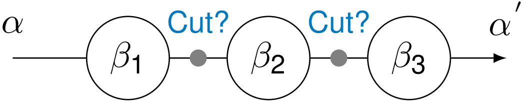


Figure 2: Classification problem

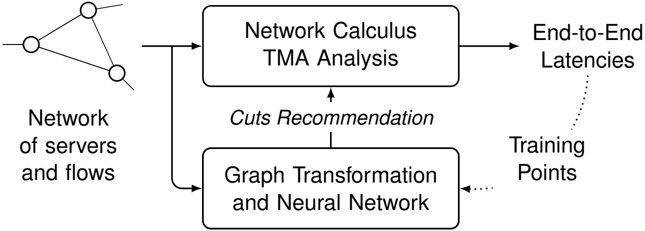
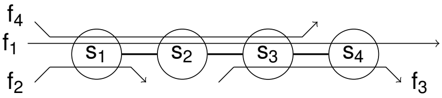
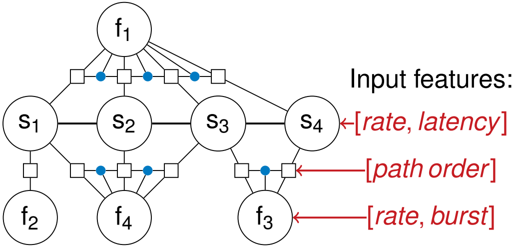


Figure 3: Approach

DeepTMA: Heuristic based on Graph Neural Networks

Problem formulation as graph





DeepTMA: Heuristic based on Graph Neural Networks

Graph Neural Networks – Introduction

Graph Neural Networks [Scarselli et al., 2009] and related architectures are able to process general graphs and predict feature of nodes $\mathbf{o}_v$

Principle

- Each node has a *hidden* vector $\mathbf{h}_v \in \mathbb{R}^k$
- ... computed according to the vector of its neighbors
- ... and are propagated through the graph

Algorithm

- Initialize $\mathbf{h}_v^{(0)}$ according to features of nodes
- for $t = 1, \ldots, T$ do
  - $\mathbf{a}_v^{(t)} = AGGREGATE\left(\left\{\mathbf{h}_u^{(t-1)} \mid u \in Nbr(v)\right\}\right)$
  - $\mathbf{h}_v^{(t)} = COMBINE\left(\mathbf{h}_v^{(t-1)}, \mathbf{a}_v^{(t)}\right)$
- return $READOUT\left(\mathbf{h}_v^{(T)}\right)$

DeepTMA: Heuristic based on Graph Neural Networks

Graph Neural Networks – Implementation

Implementation (simplified)

- Initialize $\mathbf{h}_v^{(0)}$ according to features of nodes
- for $t = 1, \ldots, T$ do
  - *AGGREGATE* $\rightarrow \mathbf{a}_v^{(t)} = \sum_{u \in Nbr(v)} \mathbf{h}_u^{(t-1)}$
  - *COMBINE* $\rightarrow \mathbf{h}_v^{(t)} = \textit{Neural Network}\left(\mathbf{h}_v^{(t-1)}, \mathbf{a}_v^{(t)}\right)$
- *READOUT* $\rightarrow$ return *Neural Network* $\left(\mathbf{h}_v^{(T)}\right)$

Training

- Using standard gradient descent techniques

Different approaches

- **Gated-Graph Neural Network**
- Graph Convolution Network
- Graph Attention Networks
- Graph Spatial-Temporal Networks
- ...

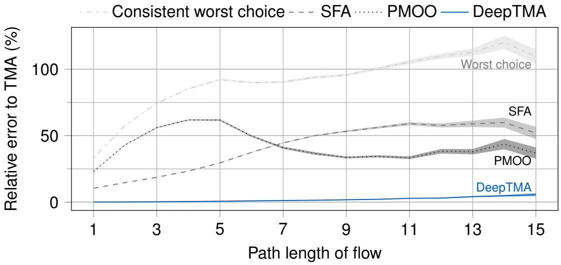
$\rightarrow$ Hot area of research in the ML community

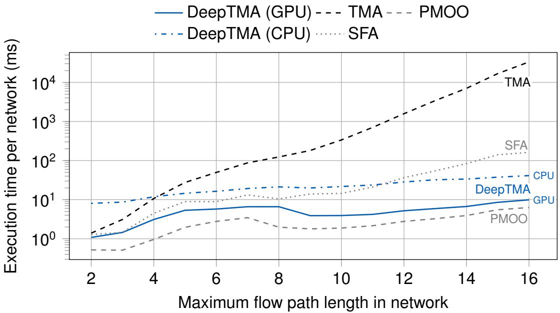
Numerical evaluation

Previous results from [Geyer and Bondorf, 2019]

- We already showed that DeepTMA is a fast and accurate method
- Relative error: metric used for estimating tightness:

$$RelErr_{f_i} = \frac{Delay_{f_i}^{DeepTMA} - Delay_{f_i}^{TMA}}{Delay_{f_i}^{TMA}} \quad (1)$$





Numerical evaluation

Dataset generation for training

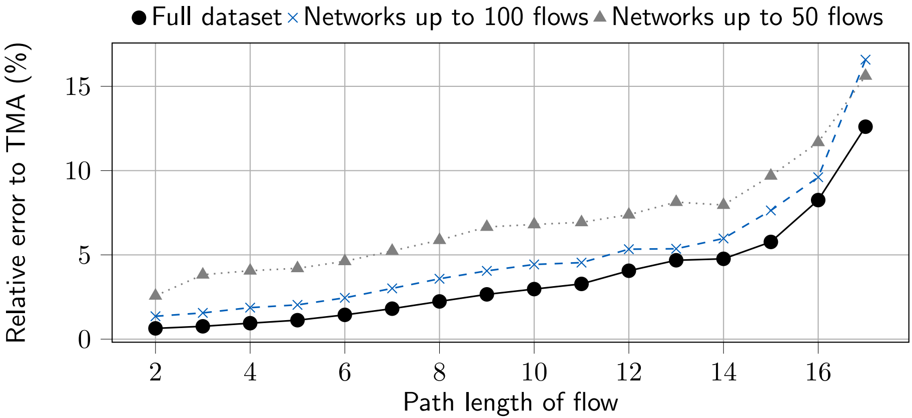
- Generation of 172 374 networks with tandem, tree or random graph topology
- Random generation of curve parameters for servers and flows
- Evaluation of each network using DiscoDNC and extract intermediary results of TMA
- Dataset available online: `https://github.com/fabgeyer/dataset-deeptma-extension`

Parameter	Min	Max	Mean	Median
# of servers	2	41	14.6	12
# of flows	3	203	101.2	100
# of tandem combinations	2	197 196	1508,5	384
# of nodes in analyzed graph	10	2093	545.2	504
# of tandem combination per flow	2	65 536	19.4	4
# of flows per server	1	173	18.1	10

Table 1: Statistics about the generated dataset.

Numerical evaluation

Tightness vs. network size used for training



Numerical evaluation

Evaluation dataset

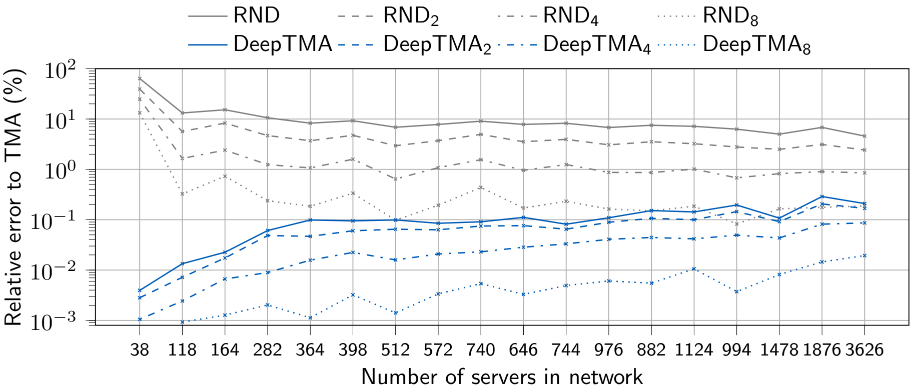
- Evaluated also on dataset from [Bondorf et al., 2017] with larger networks
- Up to 2 orders of magnitude larger in terms of number of servers and flows per network
- Neural network **not trained** on such large networks

Parameter	Min	Max	Mean	Median
# of servers	38	3626	863.0	693
# of flows	152	14 504	3452,0	2772
# of tandem combinations	2418	121 860	24 777,6	18 869
# of nodes in analyzed graph	1358	113 162	25 137,7	19 518
# of tandem combination per flow	2	512	7.3	8
# of flows per server	1	467	16.4	12

Table 2: Statistics about the set of networks from [Bondorf et al., 2017].

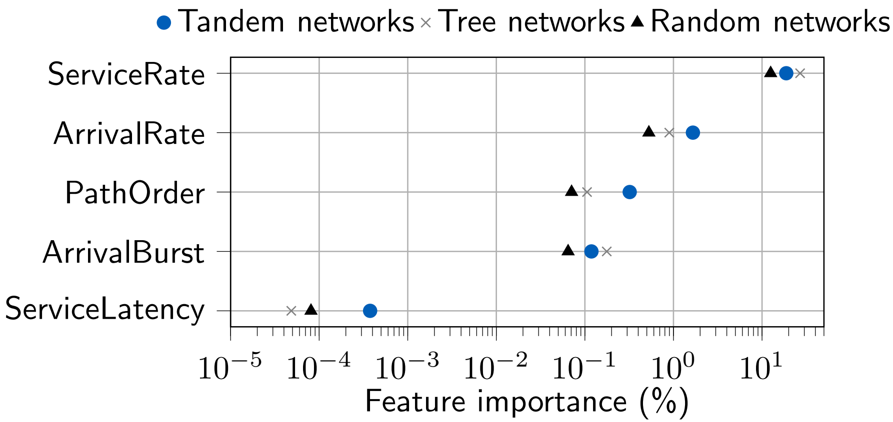
Numerical evaluation

Tightness in larger dataset



Numerical evaluation

Feature importance



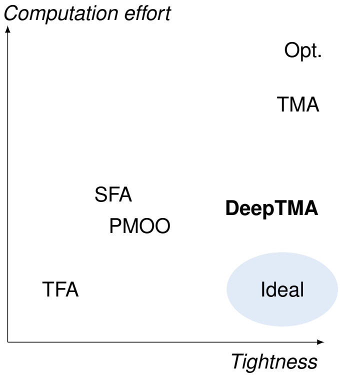
Conclusion

Contributions

- **Framework combining network calculus and graph-based deep learning**
- **Results show scalabilty on networks larger by 2 orders of magnitude**
- Feature importance will guide next iterations of the method
- Dataset available online for reproducing our results:
  - → `https://github.com/fabgeyer/dataset-deeptma-extension`

Future work

- Applicability at other problems in Network Calculus
- Extension to other formal methods for network verification



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