Tightening Network Calculus Delay Bounds by Predicting Flow Prolongations in the FIFO Analysis

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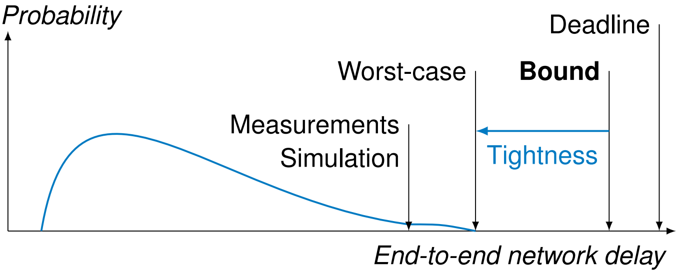
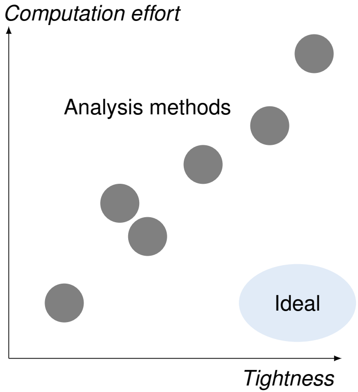
Motivation

Worst-Case End-to-End Performance Analysis

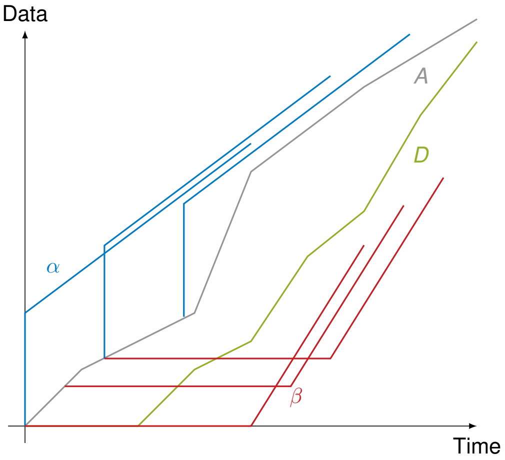




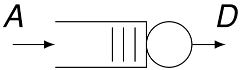
- Trade-off between computational effort and tightness
- **This talk: network analysis method with good tightness and fast execution**

Background

Network Calculus – Basics



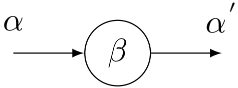
Basis: Cumulative arrivals and services [Cruz, 1991]



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

Service curve β: If the service by system $\mathcal{S}$ for a given input A results in an output D, then $\mathcal{S}$ offers a service curve $\beta \in \mathcal{F}_0$ iff

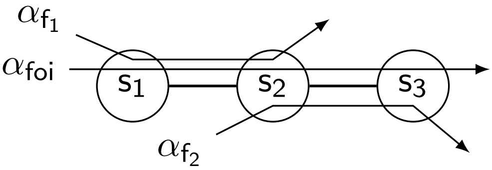
$$\forall t : D(t) \geq \inf_{0 \leq d \leq t} \{A(t-d) + \beta(d)\}.$$



Background

Network Calculus – FIFO Analysis

How to derive an end-to-end delay bound?



LUDB – Least Upper Delay Bound
[Bisti et al., 2008, Bisti et al., 2012]

Step 1: Compute the nesting tree
Step 2: Compute an end-to-end service curve by removing cross-flows step by step
Step 3: Compute the end-to-end delay bound

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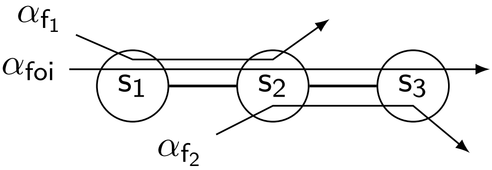

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Nesting: A sequence of servers ("tandem") is called nested if any two flows have disjunct paths or one flow is completely included in the path of the other flow.

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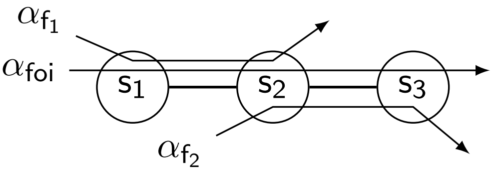

LUDB – Least Upper Delay Bound
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***Step 1:* Derive all cuts creating nested subtandems**
Step 2: Compute the nesting trees
Step 3: Compute an end-to-end service curves
Step 3a: by removing cross-flows step by step and
***Step 3b:* by concatenating the intermedite service curves**
Step 4: Compute the end-to-end delay bound

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Network Calculus – FIFO Analysis

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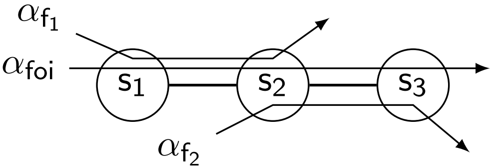

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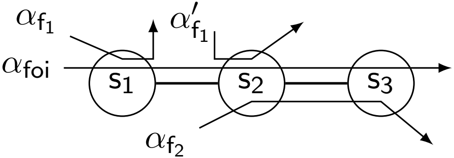
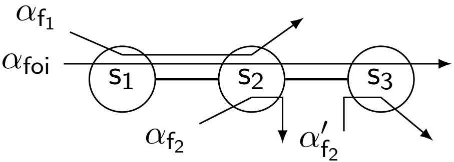
Where to cut?

Cutting alternative 1:



Cutting alternative 2:

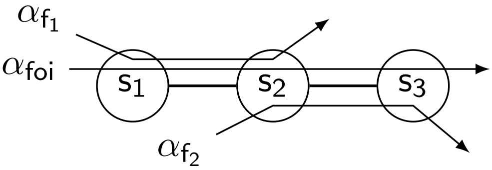


Neither alternative is strictly better than the other

Background

Network Calculus – FIFO Analysis

How to derive an end-to-end delay bound?



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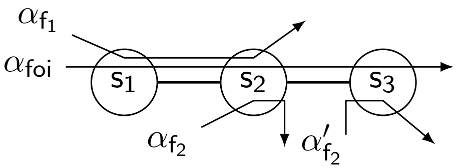
What's the problem with cutting alternative 2?



$$h(\alpha_{foi}, ((\beta_1 \otimes (\beta_2 \ominus \alpha_2)) \ominus \alpha_1) \otimes (\beta_3 \ominus (\alpha_2 \oslash (\beta_2 \ominus ((\alpha_{foi} + \alpha_1) \oslash \beta_1)))))$$

with

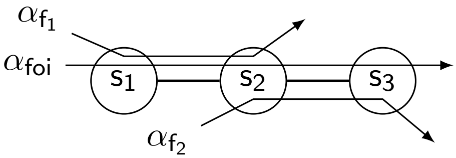
$$\text{convolution: } (f \otimes g)(d) = \inf_{0 \leq u \leq d} \{f(d-u) + g(u)\}$$

$$\text{deconvolution: } (f \oslash g)(d) = \sup_{u \geq 0} \{f(d+u) - g(u)\}$$

Contribution

Network Calculus – LUDB and Flow Prolongation

What can we do about it?



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Network Calculus – LUDB and Flow Prolongation

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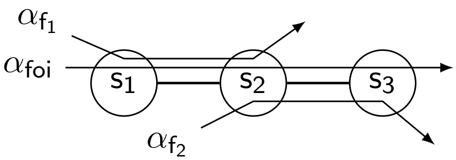
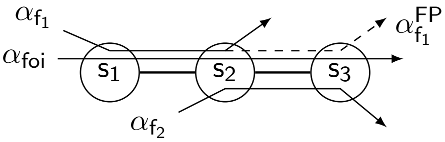


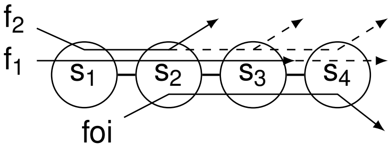
Create a nested tandem in a different way, before we face the cutting-problem!



$$h(\alpha_{foi} + \alpha_1, \beta_1 \otimes ((\beta_2 \otimes \beta_3) \ominus \alpha_2))$$

Does it Scale?

Flow prolongation in general does not [Bondorf, 2017], e.g., see:



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Network Calculus – LUDB and Flow Prolongation

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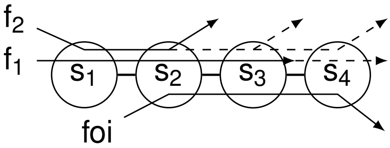

Not if you try to search exhaustively,
not even when considering the objective to convert non-nested tandems to nested tandems.

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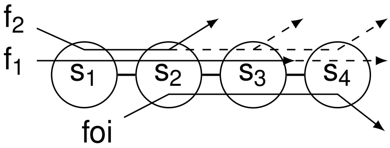

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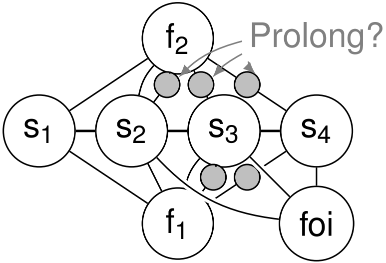
Thus, we converted the tandem into a Graph Neural Network:



We call the new analysis *DeepFP*.

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

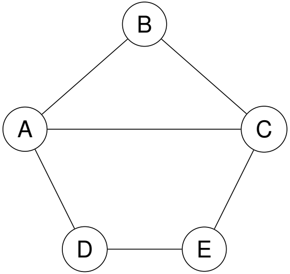
- Each node has a *hidden* vector $\mathbf{h}_v \in \mathbb{R}^k$
- . . . computed according to the vector of its neighbors
- . . . and are propagated through the graph

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 $READOUT\left(\mathbf{h}_v^{(T)}\right)$

Heuristic based on Graph Neural Networks

Graph Neural Networks – Illustration



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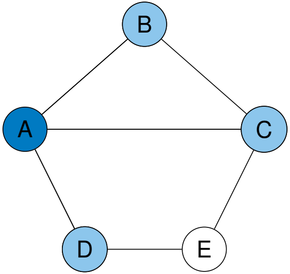

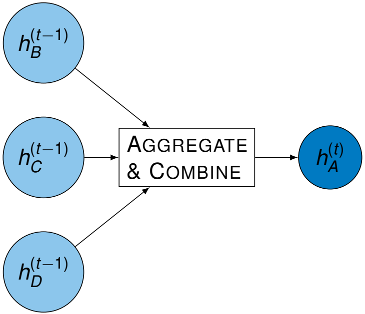

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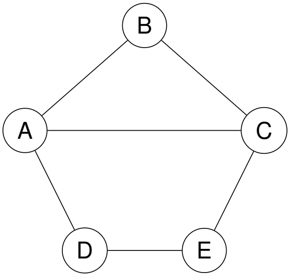

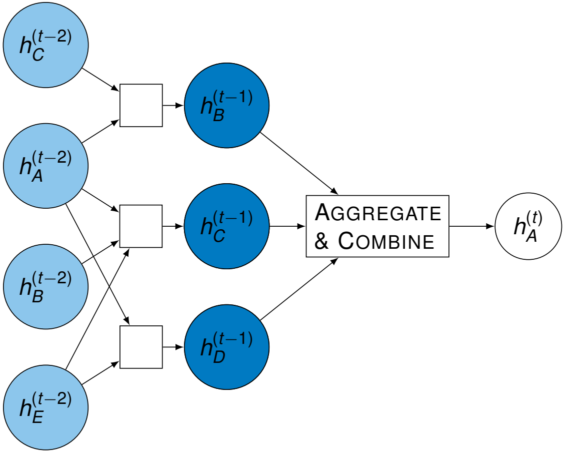

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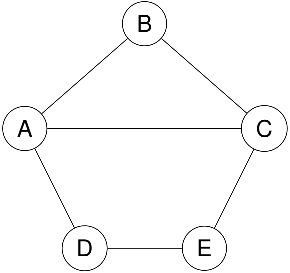

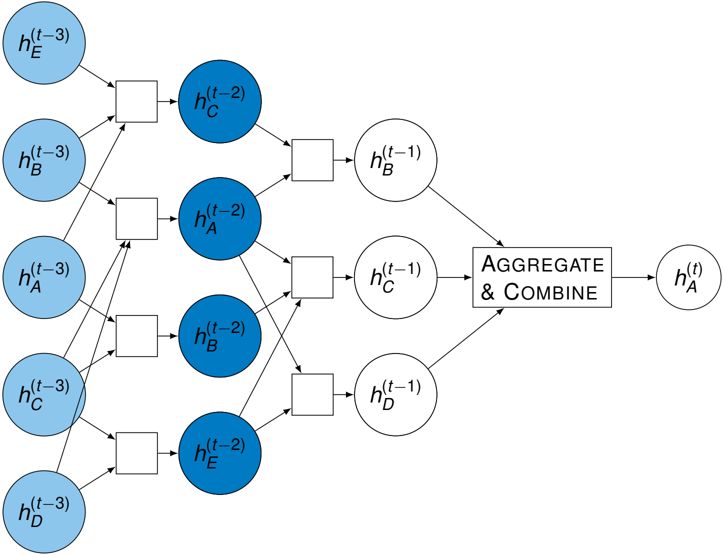

Heuristic based on Graph Neural Networks

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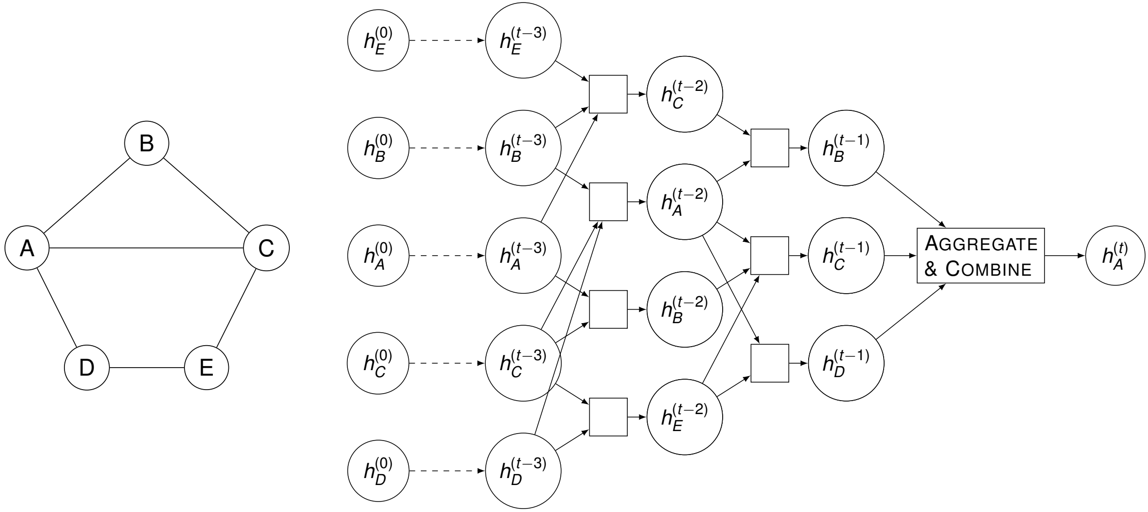
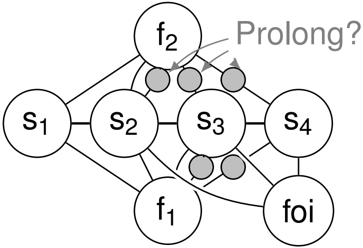


Contribution

Network Calculus – LUDB and Flow Prolongation and Predictions

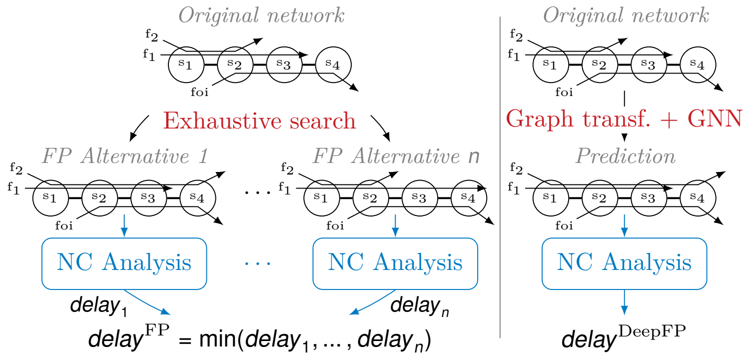


DeepFP$_n$

- Converts the Network Calculus graph into a GNN network
- Predicts a score for each prolongation node, ranking the top prolongation choices
- Let's Network Calculus pick the top $n \geq 1$ combinations of prolongations, to compute n valid delay bounds

DeepFP Overview

... and Related Work



DeepFP Overview

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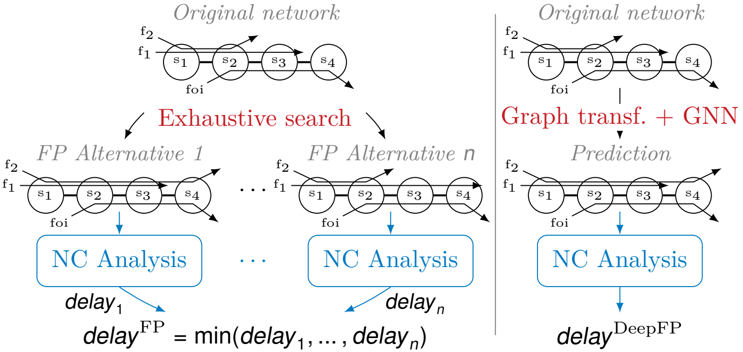
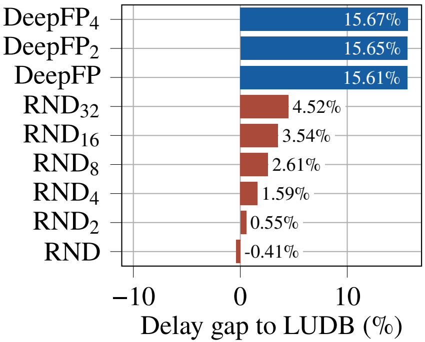
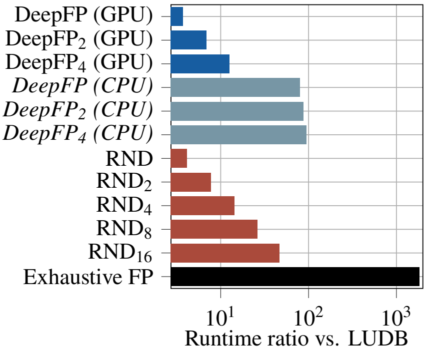


Related Work on NC + GNN:
[Geyer and Carle, 2018,
Geyer and Bondorf, 2019,
Geyer and Bondorf, 2020],
all of which focuses on the
complexities in FIFO systems.

Evaluation

Benchmark to LUDB and Random Heuristic





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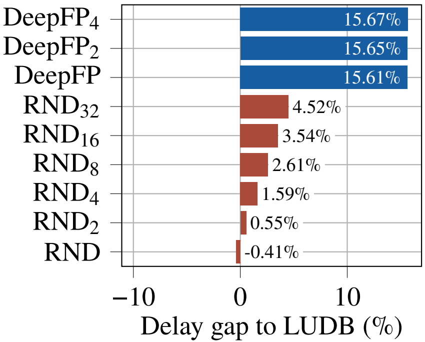

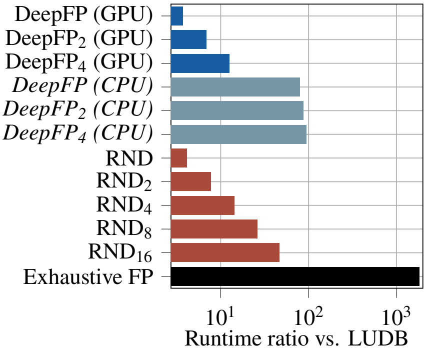

That's it, thank you for your attention!

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