#### Latency-Aware Placement of Data Stream Analytics on Edge Computing

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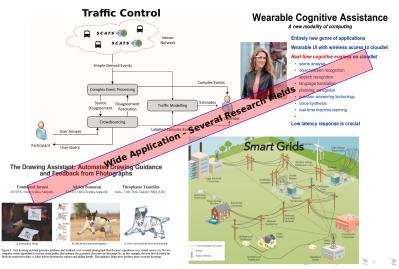
26th June 2018

#### Context

Problem Statement Solution Evaluation Conclusions and Future Work

Data Stream Analytics

#### Data Stream Analytics



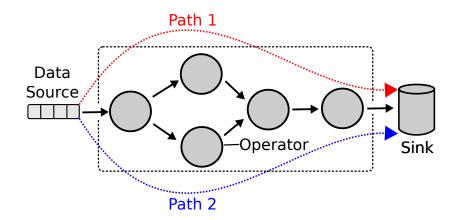
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Data Stream Analytics

# What are latency-aware applications composed of?

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#### Applications and their characteristics



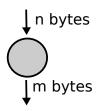
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#### Applications and their characteristics



# Selectivity

The ratio of number of input messages to output messages



# Data compression/ expansion factor

The ratio of the size of input events to the size of output events

4 3 6 4 3

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# Where are the latency-aware applications deployed?



#### Context

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#### Classic Data Center



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# Generating opportunities to deploy applications **closer** where **data are generated**

#### Context

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#### Micro Data Centers







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# Solutions are exploring computational resources even closer where data are generated

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#### Edge Devices and Sensors

#### Raspberry Pi 2

#### Galileo





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## How are the applications deployed across Cloud and Edge Computing?

#### Context

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#### CLOUD

Data storage Batch and stream processing Data warehousing Business applications



#### NETWORK

#### EDGE

Real-time data processing Basic analytics Data filtering, optimization Data caching, buffering



#### SENSORS AND CONTROLLERS



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## Is there any **method** for **deploying** the applications **dynamically** onto edge and cloud?



#### Problem Statement / Methodology

#### Minimize metrics such as end-to-end application latency and energy consumption by placing operators onto cloud and edge resources

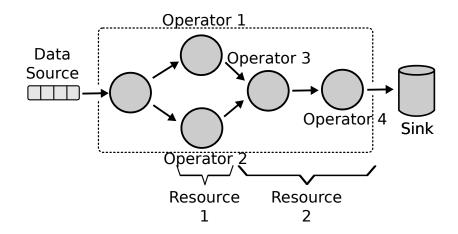
Physical infrastructure capabilities

- CPU and memory
- Network latencies and bandwidth

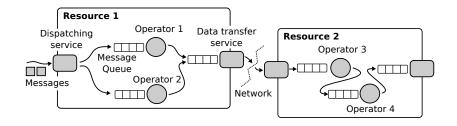
Application requirements

- Selectivity
- Data compression rate
- CPU and Memory
- Data sources and sinks localization

#### Our proposal model



#### Our proposal model



Model is based on **Queueing Theory** - M/M/1 Two queues: **Computation** and **Communication Response time** is equal to the sum of computation and communication into a path.

A 3 b

## We aim to **minimize the sum of the response times** (all paths)

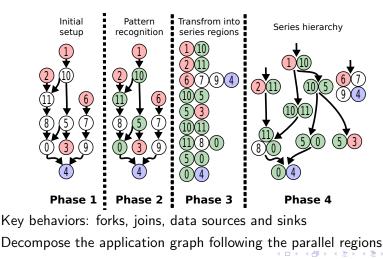


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Finding Application Patterns - Contribution Latency-Aware Strategies - Contribution

#### Finding Application Patterns



Finding Application Patterns - Contribution Latency-Aware Strategies - Contribution

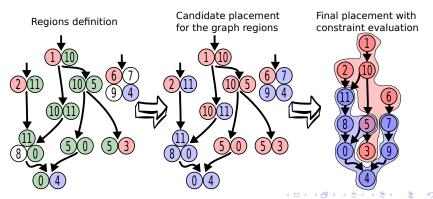
Response Time Rate (RTR) Strategy

- Response Time Rate for computational resource based on the end-to-end application latency
- Sequentially estimate the operator response time following the upstream(s) and downstream(s) connections
- Evaluate memory, CPU, and bandwidth constraints

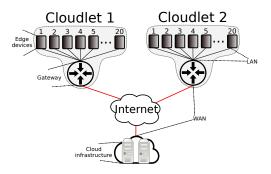
Finding Application Patterns - Contribution Latency-Aware Strategies - Contribution

# Response Time Rate with Region Patterns (RTR+RP) Strategy

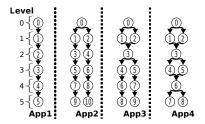
- Split the application graph following the pathways
- Calculate the Response Time Rate only to the edge side



#### Experimental Setup

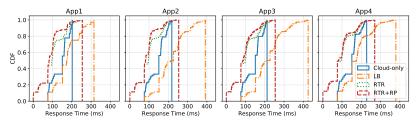


#### Experimental Setup - Microbenchmarks



Messages sizes: text - 10 bytes, pictures/objects - 50KB, and voice records - 200KB Input event rates: Each message size has three input event rates CPU requirements: 10 bytes - 3.7952 IPS, 50 KB-18976 IPS, and 200 KB - 75904 IPS Selectivity and data compression rates: 100, 75, 50 and 25

#### Results on Response Time - Microbenchmarks

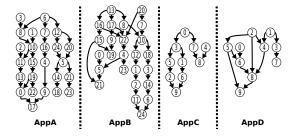


**432 experiments** (4 selectivities, 4 data compression rates, 3 input event rates, 3 sink locations and 3 input event sizes)

**RTR and RTR+RP** have shown to be over 95% more efficient than cloud-only approach and LB

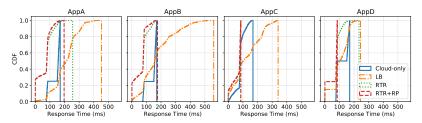
**Cloud-only** achieved 5% better results (when the blue line crosses the red at approx. 200ms)

#### Experimental Setup - More Complex Applications



1160 graphs randomly applying multiple selectivities, data compression rates, sink and source locations, input event sizes and rates, memory, and CPU requirements
Large (AppA and AppB) containing 25 operators
Small (AppC and AppD) holding 10 operators.

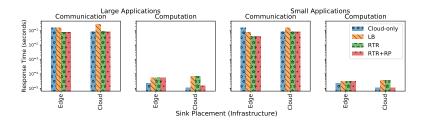
#### Results on Response Time - More Complex Applications



Our strategies outperformed cloud-only in over **6%** and **50%** under small and large applications, respectively.

Similarly, we improve the response times in over **23%** (small) and **57%** (large applications) compared to the LB approach.

Results on Response Time - More Complex Applications



The communication cost for sinks placed on cloudlets at cloud-only was about **160 ms**, and RTR+RP was **76 ms**.

Our solution outperformed cloud-only in up to 52%, but sinks on the cloud, RTR+RP had a slight performance loss of 3%

#### Conclusions and Future Work

Summary

- A model and the DSP placement problem formalization
- Two strategies to improve the response time
- A performance comparison using a simulated environment

#### Conclusions

- The key behaviors (forks and joins) of the dataflows directed us to our strategies
- Our strategies using the dataflow aspects allow us to be 50% better in response time

Future Work

- An evaluation using a real environment
- Determine the optimal value and compare with our solutions
- A model to deal with the reconfiguration phase

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### Questions?

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