SBAC-PAD 2019

INVENTORS FOR THE DIGITAL WORLD

Monte-Carlo Tree Search and Reinforcement Learning for Reconfiguring Data Stream Processing on Edge Computing

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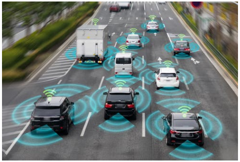
Data Stream Processing Scenarios



- Application scenarios[1]
  - Monitoring of operational infrastructure and precision agriculture
  - Anomaly detection, fraud detection
  - Smart cities, smart homes, traffic control, autonomous vehicles
  - Wearable assistance, augmented reality
- Applications generate unbounded streams of data
- Data stream processing in the Cloud
  - **Multiple tiers of data collection and processing**
  - Data in motion systems, message brokers, that increase latency
- Edge computing for data stream processing

[1] Pictures are a courtesy of Google images

Cloud and Edge Computing

Cloud

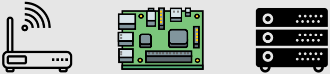
Internet

- Data storage
- Batch and stream processing
- Data warehousing
- Business applications

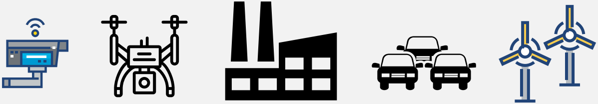
Edge

LAN/WAN

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

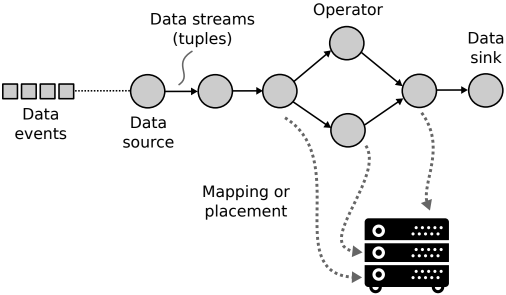


Sensors and Controlers



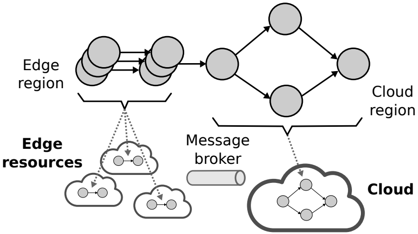
Data Stream Processing Dataflows[1]

- Applications are structured as directed graphs
- Operator properties
  - Selectivity
  - Data transformation
  - State
- Operators are assigned to resources (**placement**)



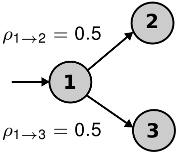
[1] M. D. Assunção *et al.*, Resource Elasticity for Distributed Data Stream Processing: A Survey and Future Directions, Journal of Network and Computer Applications, Vol. 103, pp. 1-17, Feb. 2018.

Modelling the Placement across Cloud and Edge

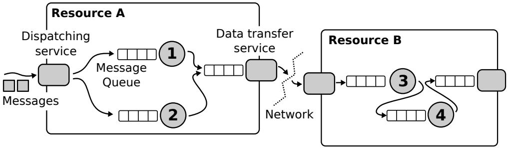


- **Infrastructure** graph $\mathcal{N} = (\mathcal{R}, \mathcal{L})$ of compute resources $\mathcal{R}$ and logical links $\mathcal{L}$
  - Resources have CPU and memory capabilities
  - Network links have bandwidth and latency

- **Application** DAG $\mathcal{G} = (\mathcal{O}, \mathcal{E})$ of operators $\mathcal{O}$ and streams $\mathcal{E}$, where an operator's requirements comprise:
  - CPU MIPS to process an event
  - Memory to load the operator
  - Selectivity
  - Data transformation
- Probability $\rho_{i \to j}$ that an output event emitted by operator *i* will flow through to operator *j*



Modelling the Placement across Cloud and Edge – Cont.



- Operators and communication services handle events in a FCFS basis
- Both services are modelled as M/M/1 queues

- L_{p_i}: end-to-end latency of path p_i is the sum of the computation time of all operators in p_i and the communication time to stream events along p_i
- **Placement goal**: find a mapping $\mathcal{M} : \mathcal{O} \rightarrow \mathcal{R}, \mathcal{E} \rightarrow \mathcal{L}$ that minimises the Aggregate end-to-end Latency (AL) of all paths:

$$AL = \min \sum_{p_i \in \mathcal{P}} L_{p_i}$$

where $\mathcal{P}$ is the set of all paths in the application DAG[a]

[a] A. Veith *et al.*, Latency-Aware Placement of Data Stream Analytics on Edge Computing, ICSOC 2018, pp. 215-229, Hangzhou, China, Nov. 2018.

Need for Application Reconfiguration and its Goal

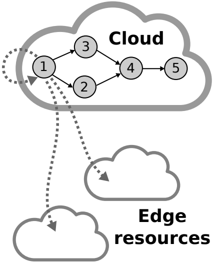
- Data stream processing applications are long-running
- Workload conditions may change over time
- Initial placement might not be ideal
- Resources at the edge are more failure prone

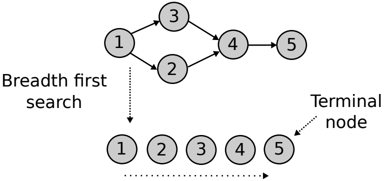
Reconfiguration goal: Find a new mapping $\mathcal{M} : \mathcal{O} \rightarrow \mathcal{R}, \mathcal{E} \rightarrow \mathcal{L}$ that improves the current Aggregate end-to-end Latency

Markov Decision Process (MDP) and Reconfiguration

- **MDP** comprises a set of states $\mathcal{S}$, where each state $s \in \mathcal{S}$ has a number of possible actions $\mathcal{A}(s)$ and a reward function $R(s)$
  - State s contains a mapping $\mathcal{M} : \mathcal{O} \rightarrow \mathcal{R}, \mathcal{E} \rightarrow \mathcal{L}$
  - Action $a \in \mathcal{A}(s)$ is either migrating an operator to another resource or maintaining its current mapping
  - The reward $R(s)$ reflects how much the aggregate end-to-end latency is improved under state s:

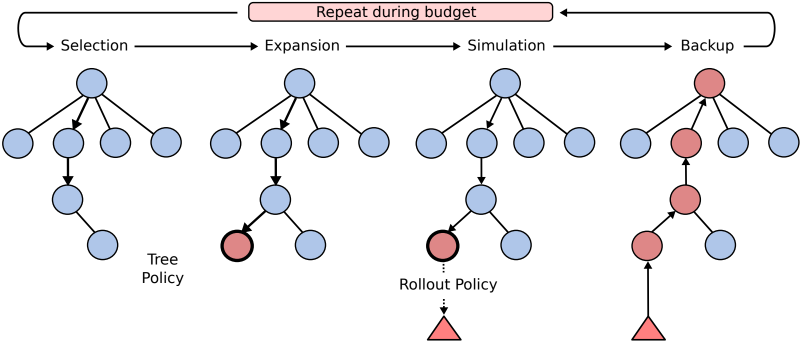
$$R(s) = AL_{s_0} - AL_s$$





- **An episode** is a set of transitions from an initial state to a terminal state
- **An optimal policy** defines the transitions from states to actions that maximise the reward

Monte-Carlo Tree Search[1]



- In addition to a valid placement, a node/state *s* contains:
  - A count $N(s)$ with number of times the state was visited
  - An action value $Q(s, a)$ for each action
  - A count $N(s, a)$ of times an action *a* was picked
- Simulated episode is created using *tree policy* and *rollout policy*
  - Exploration versus exploitation dilemma
- Generated return is used to update/initialise the action values

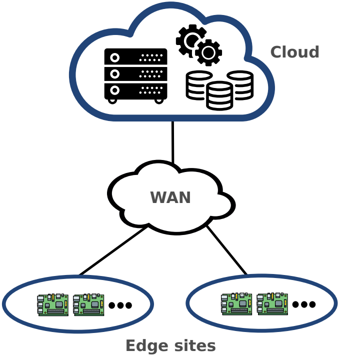
[1] R. S. Sutton and A. G. Barto, Reinforcement Learning: An introduction. MIT press, 2018.

MCTS-Best-UCT and Deployment Hierarchy (DH)

- MCTS-UCT:
  - It assigns a bonus to the uncertainty in the value of a state-action
  - Its tree policy picks the action that maximises the Upper Confidence Bound (UCB)
- **MCTS-Best-UCT**:
  - It maintains a list of visited nodes with their UCB values
  - Instead of starting the tree search from the root node, its "tree policy" picks the node with the best UCT value from the list
- Deployment Hierarchy:
  - Action space can be large as the number of resources grows
  - Operators on a path with a sink on the edge have priority
  - DH sorts operators by their potential impact on end-to-end latency[1]

[1] A. Veith *et al.*, Latency-Aware Placement of Data Stream Analytics on Edge Computing, ICSOC 2018, pp. 215-229, Hangzhou, China, Nov. 2018.

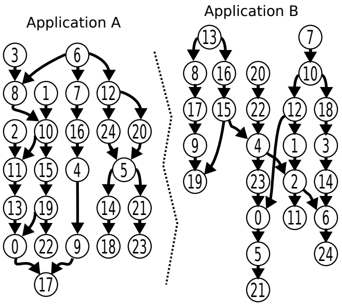
Experimental Setup



- Discrete-event simulation (OMNET++)
- One cloud with 2 servers and two edge sites with 20 resources each
  - Cloud servers are modelled as AMD Ryzen 7 1800x
  - Edge servers as Raspberry Pi's model 2
- Edge resources are interconnected by a LAN whereas the communication among sites is done via a WAN (Internet)
- Network latency is modelled based on experiments conducted in previous work[1]

[1] W. Hu *et al.*, Quantifying the impact of edge computing on mobile applications, in 7th ACM SIGOPS Asia-Pacific Workshop on Systems, pp. 5:1–5:8, New York, USA 2016.

Evaluated Applications



- The number of operators is based on the graph order of RIoTBench[1] applications
- For each application, 15 different configurations were created by varying the following operator properties:

Operator property	Value
cpu	1–100 MIPS
Data transf. ratio	10–100%
mem	100–7,500 Bytes
Input event size	100–2500 Bytes
Selectivity	10–100%
Input event rate	1,000–10,000 messages

- The initial placement of sources and sinks changes in each configuration
- The sink on the critical path is always placed on the cloud

[1] https://github.com/dream-lab/riot-bench

Performance Evaluation Scenarios

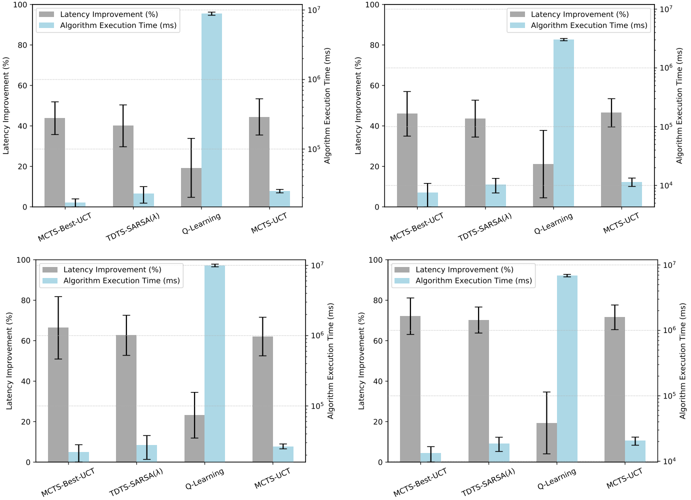
- **Scenario 1:** Reinforcement algorithms receive a cloud-only deployment as initial placement (all operators placed in the cloud)
  - Q-learning, TDTS-Sarsa(λ)
  - With and without Deployment Hierarchy
- **Scenario 2:** Evaluating the aggregate end-to-end latency, it considers all reinforcement learning algorithms and previously proposed solutions
  - Taneja's algorithm, RTR and RTR-RP

- Execution budget is 10,000 iterations/episodes
- Initial placement is run for 300 seconds or until all application paths have processed at least 500 messages each

Performance Metrics

- Latency improvement
- Algorithm execution time
- Time to best latency
- Number of operator migrations
- Minimum aggregate end-to-end latency

Latency Improvement



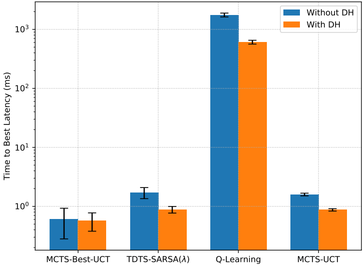
Application A

Application B

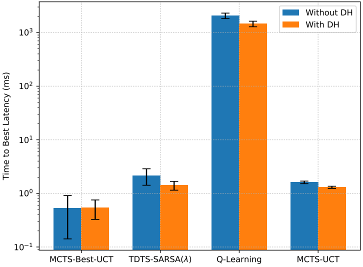
(a) Without DH

(b) With DH

Time to Achieve the Best Latency



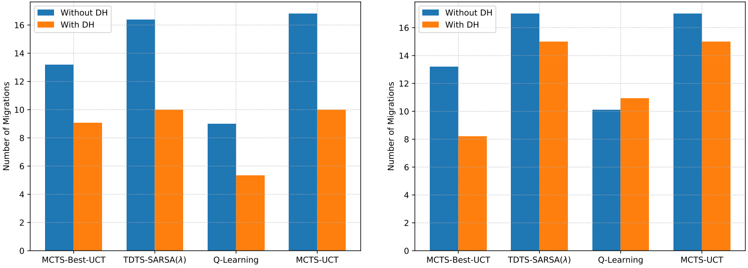
(a) Application A



(b) Application B

- **Application A:** MCTS-Best-UCT performs at least 64% better that MCTS-UCT without DH and 33% with DH
- **Application B:** MCTS-Best-UCT also performs best

Number of Operator Migrations

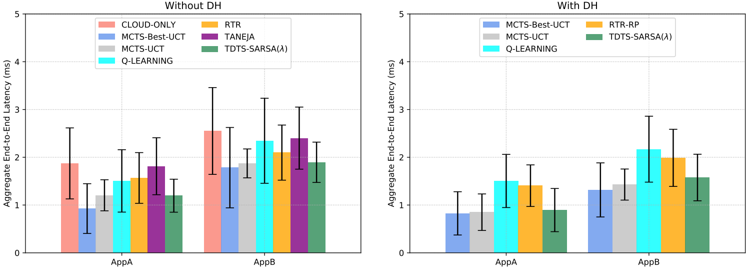


(a) Application A

(b) Application B

- MCTS-Best-UCT discovers earlier on the operators that have the biggest impact on latency (*i.e.*, operators that are selective) and migrates them to edge resources

Minimum Aggregate End-to-End Latency



- The reinforcement learning algorithms improve the latency compared to other solutions from the state of the art
- Expect for MCTS-Best-UCT and Q-learning, the solutions proposed by the reinforcement learning algorithms are more stable

Conclusions and Future Work

- Summary and conclusions:
  - Markov Decision Process for DSP application reconfiguration
  - Evaluation of reinforcement learning algorithms
  - MCTS-Best-UCT improves the *time to best latency*
  - MCTS-Best-UCT is also able to achieve *end-to-end latency* similar to other algorithms under a smaller budget

- Future work:
  - Evaluate the algorithms on a real testbed
  - Use other machine learning techniques to approximate the Q-values (deep reinforcement learning)
  - Use energy consumption as an optimisation metric

Questions?

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