Reinforcement Learning Based Policies for Elastic Stream Processing on Heterogeneous Resources

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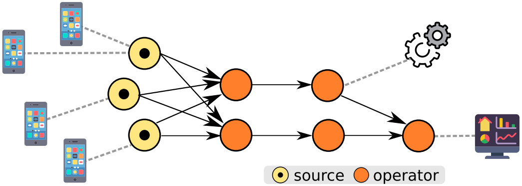
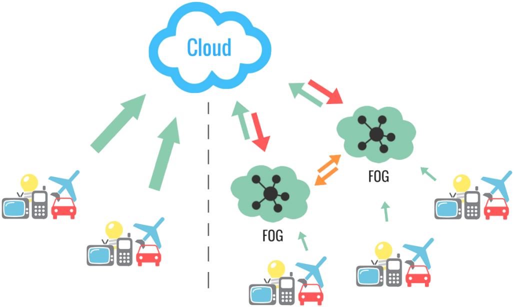
Distributed Data Stream Processing

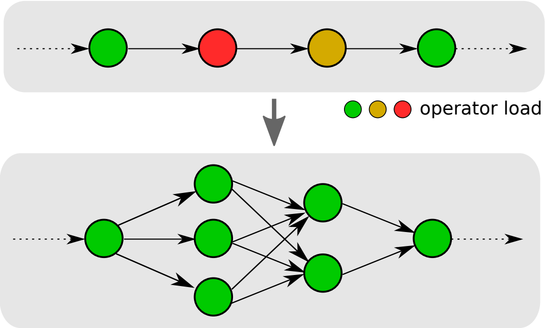


New pervasive services enabled by real-time stream processing



New trend:
moving applications towards users (and data!)

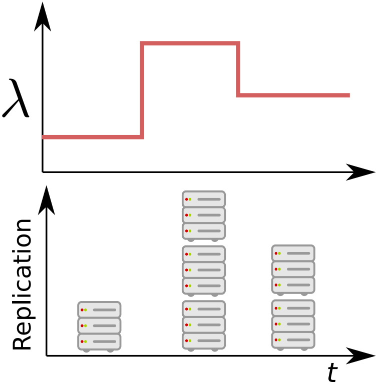
Elasticity for DSP



- A key feature for modern DSP systems
- Many approaches in the literature: queueing theory, control theory, threshold-based heuristics, ...
- Common assumption: homogeneous computing resources

Elasticity on Heterogeneous Resources

- Computing resources in Fog/Edge environments can be highly heterogeneous
- Trade-offs between cost, capacity, energy consumption, ...
- Elasticity policies should take it into account!



Goals

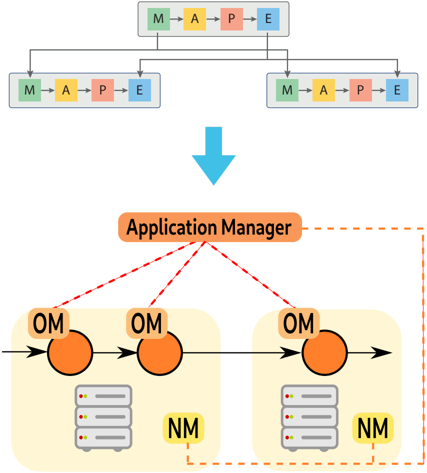
Decentralized elasticity on heterogeneous resources

- Problem formulation based on Markov Decision Process
- Efficient resolution through Function Approximation techniques
- Dealing with uncertainty: reinforcement learning

A Framework for Decentralized Elasticity

Based on Hierarchical MAPE:

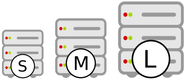
- An Application Manager for each application
- An Operator Manager for each operator



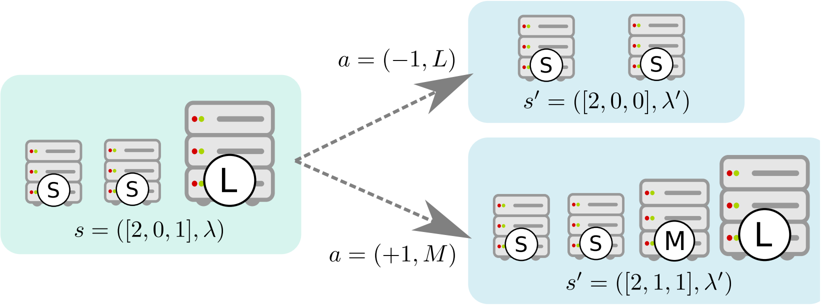
V. Cardellini, F. Lo Presti, M. Nardelli, G. Russo Russo, "Decentralized self-adaptation for elastic data stream processing", *Future Generation Computing Systems*, Vol. 87, pp. 171-185, October 2018.

Operator Manager: controlling elasticity

- N_{res} types of resources: $\tau_1, \tau_2, \ldots, \tau_{N_{res}}$



- We model the problem as a Markov Decision Process (MDP)
- System **state**: $s = (\mathbf{k}, \lambda)$
  k_τ = num. of replicas deployed on resources of type τ
  λ = current input data rate
- **Actions**: possible deployment adaptations



Operator Manager: controlling elasticity (2)

- **Cost** $c(s, a, s')$ paid after executing action a in state s, entering s'
- $c(s, a, s')$ weighted sum of normalized cost terms
- Resources cost

$$c_{res}(s, a, s') = \sum_{\tau \in T_{res}} k'_\tau c_\tau$$

- Reconfiguration cost

$$c_{rcf}(s, a, s') = \mathbb{1}_{\{\text{deployment changed}\}}$$

- SLO violation penalty

$$c_{SLO}(s, a, s') = \mathbb{1}_{\{R(s') > R_{max}\}}$$

- The optimal **policy** minimizes $\sum_{t=0}^{\infty} \gamma^t c(s_t, a_t, s_{t+1}) \quad \gamma \in (0, 1)$

Scalability issues

- The optimal policy can be computed under different settings:
  - the model is completely known (e.g., using Value Iteration)
  - the model is (partially) unknown (using reinforcement learning)
- Most algorithms rely on the **Q function**:
  expected long-term cost of every action in every state
- Standard algorithms use the Q table to represent Q:
  an entry for each state-action pair in memory ... cannot scale!

State	**Action**	**Q**
s_1	a_1	$Q(s_1, a_1)$
s_2	a_2	$Q(s_2, a_2)$
...	...	...

Function Approximation for MDPs

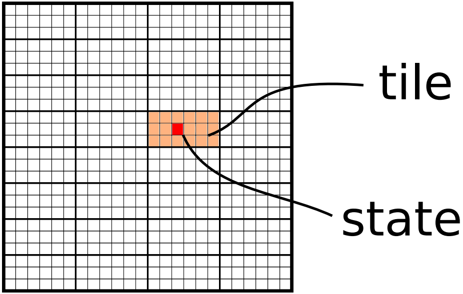
- Idea: replacing the Q table with a parametric function $\hat{Q}(s, a, \theta)$
- Need to store (and compute) only the parameters θ
- We focus on linear Function Approximation:

$$\hat{Q}(s, a, \boldsymbol{\theta}) = \sum_i \phi_i(s, a)\theta_i$$

- Weights $\boldsymbol{\theta}$: updated using Stochastic Gradient Descent
- Features $\boldsymbol{\phi}$: critical choice for good accuracy!

Defining features: Tile Coding

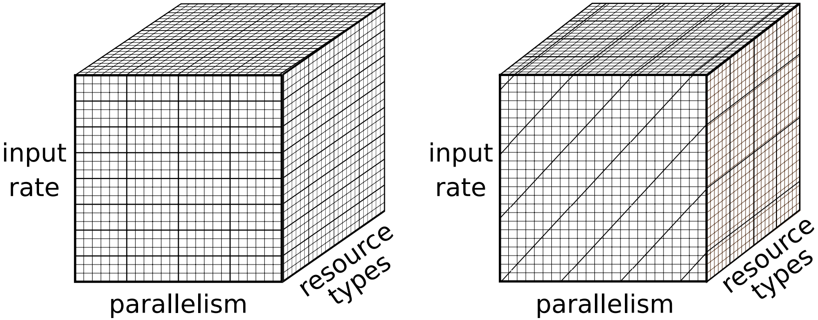
- Manually defining a good set of features is not feasible
- **Tile Coding**: cover the state space with “tilings”
- “similar” states covered by a single tile (i.e., a single feature)
- different number and shape of tiles
- multiple overlapping tilings combined for increased accuracy



Defining features: Tile Coding (2)

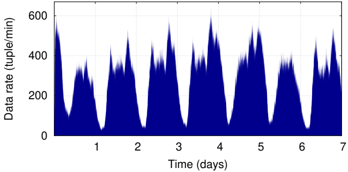
We aggregate "similar" states along 3 dimensions:

- input rate
- parallelism
- set of used resource types



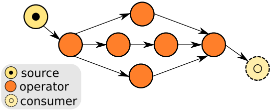
Evaluation

- We consider different sets of resource types
  - characterized by speedup and cost
- Standard and FA-based algorithms (including Q-learning) compared through a numerical evaluation
- Two threshold-based heuristic policies included in the comparison
  - CPU utilization threshold used for scaling
  - **TH-cost** picks the cheapest resource when needed
  - **TH-speedup** picks the resource with max speedup when needed
- Realistic workload, from DEBS 2015 Grand Challenge



Results: comparing algorithms

We compare SLO violations, deployment reconfigurations and resources cost when using different policies



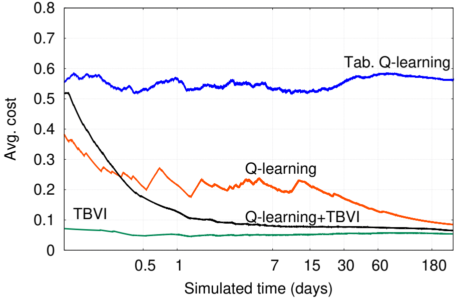
3 types of resources

Algorithm	Viol (%)	Reconf. (%)	Res.	
TH-cost	100.0	3.31	2.8	✗
TH-speedup	0.12	0.01	90.6	✗
VI	0.0	0.0	12.0	✓
TBVI (VI + FA)	0.0	0.30	11.4	✓

10 types of resources

Algorithm	Viol (%)	Reconf. (%)	Res.	
TH-cost	100.0	4.11	2.8	✗
TH-speedup	0.12	0.01	90.6	✗
VI	-	-	-	✗
TBVI (VI + FA)	0.10	0.03	17.7	✓

Results: learning algorithms

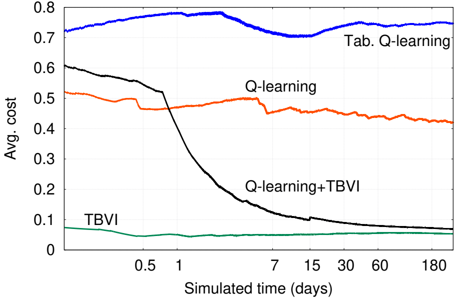


Average cost during a single experiment

← 3 types of resources

TBVI (model-based)

Tabular Q-learning
Q-learning with FA
Q-learning initialized with an approximate model



← 10 types of resources

Results: different sets of features

We solve the MDP using different tiling configurations, varying the size of tiles:

- coarse-grained ($\approx$ 1000 features)
- standard ($\approx$ 2500 features)
- fine-grained ($\approx$ 6000 features)

Features	**Avg. cost**
Tile Coding (coarser)	0.059
Tile Coding	0.054
Tile Coding (finer)	0.070

Conclusion

- Decentralized policies for elasticity on heterogeneous resources
- Reinforcement learning allows to deal with model uncertainty
- Function Approximation techniques required for scalability
- An approach likely re-usable for solving similar problems with self-adaptive distributed systems

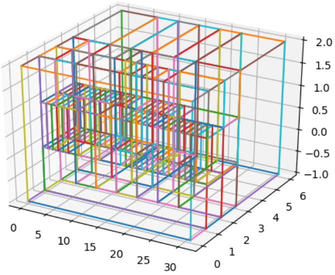
Future work:

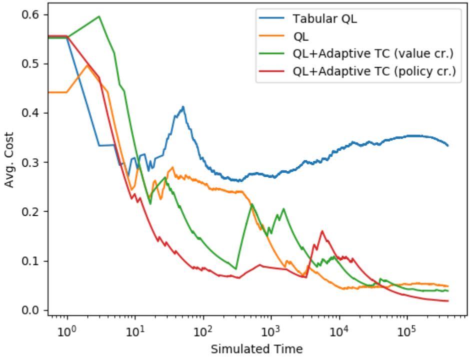
- Implementation on top of existing DSP framework
- Non-linear FA, including Neural Networks
- Adaptive Tile Coding

Adaptive Tile Coding (preview)

- Tile Coding still requires expertise to choose size/shape of tiles
- If the problem changes, may need new tilings

- Adaptive Tile Coding: identify best partitioning in an automated way
- Start with one large tile, then iteratively split to increase accuracy





Thanks for your attention!

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