Towards scalable deployment optimization in the Fog using MDPs and Function Approximation

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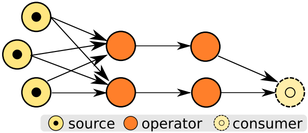
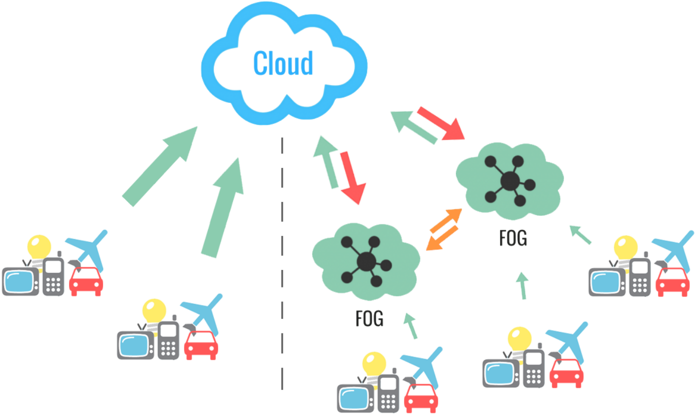
Data Stream Processing (DSP)

processing Big Data in real-time





New trend: moving computation towards data sources and consumers

Geo-distributed DSP: old and new challenges

- Non negligible network latency
- Heterogeneous computing resources (and usually less powerful...)
- Variable infrastructure conditions

$\Downarrow$

- Application deployment must be adapted at run-time:
  - how many parallel replicas for each operator? (**elasticity**)
  - where to deploy each operator?
  - when to change the deployment, incurring overhead?

Operator deployment adaptation

Operator Elasticity

- Parallelism should change over time depending on input data rate

Heterogeneous infrastructure

- Computing infrastructure composed of regions
- Several types of computing resources available (e.g., VMs with different capacity)

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Operating costs for a single operator

- resources cost: depends on amount and type of used resources
- adaptation cost: proportional to performance degradation at each deployment reconfiguration
- SLA violation: paid whenever the performance (i.e., processing latency) violates a given threshold

→ would like to minimize all of them in the long-term

MDP formulation

We model the problem as an infinite-horizon **Markov Decision Process**

- System **state**: current deployment and input data rate
- **Actions**: possible deployment adaptations

- Each state-action pair (s, a) associated with a **cost** $c(s, a)$
- We search for the optimal **policy**:

$$\text{minimize} \quad \sum_{t=0}^{\infty} \gamma^t c(s_t, a_t) \qquad \gamma \leftarrow \text{discount factor} \in [0, 1)$$

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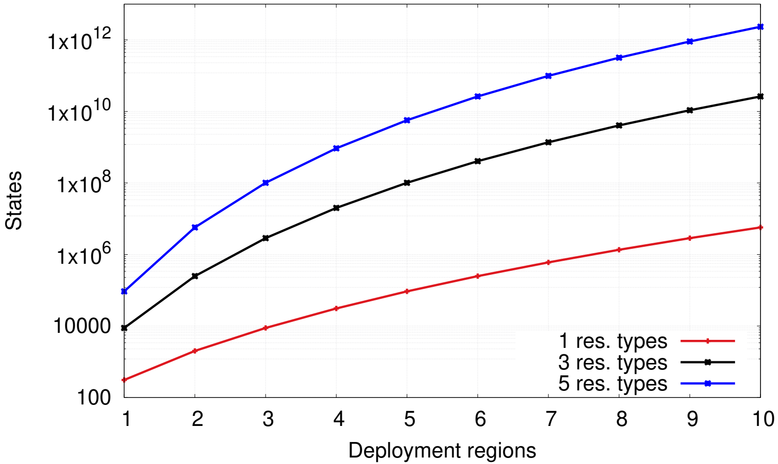
- Can be solved by DP, LP, reinforcement learning, ...
- Resolution based on the Q function
- Traditional algorithms store Q in memory: an entry for each state-action pair

Scalability



22 GB of memory to store Q with 5 regions and 3 classes of resources

Does not scale in a Fog scenario (many applications to optimize!)

Function Approximation for MDPs

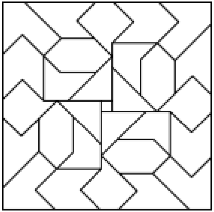
- Idea: replacing the Q table with a parametric function $\hat{Q}(s, a, \theta)$
- Need to store (and compute) only the parameters θ

- Today we focus on Linear Function Approximation:
  $\hat{Q}(s, a, \theta) = \sum_i \phi_i(s, a)\theta_i$
- Defining a good set of features $\phi_i(s, a)$ is challenging
  - More features = more parameters to compute and store
  - A small set of features may prevent the algorithm to converge

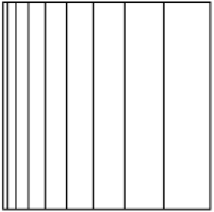
Tile Coding

Idea: cover the state space with "tilings"

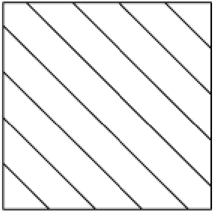
- adjacent states are aggregated in a single tile
- each state activates a tile (i.e., binary feature)
- fine-grained vs. coarse-grained tilings
- different number of dimensions and shape of tiles



a) Irregular



b) Log stripes

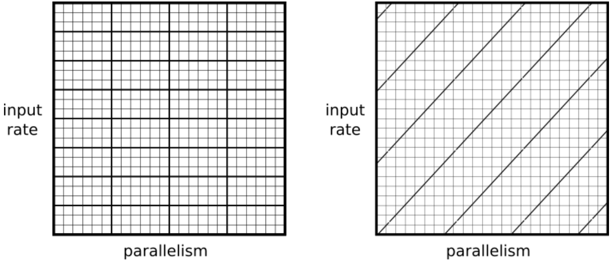


c) Diagonal stripes

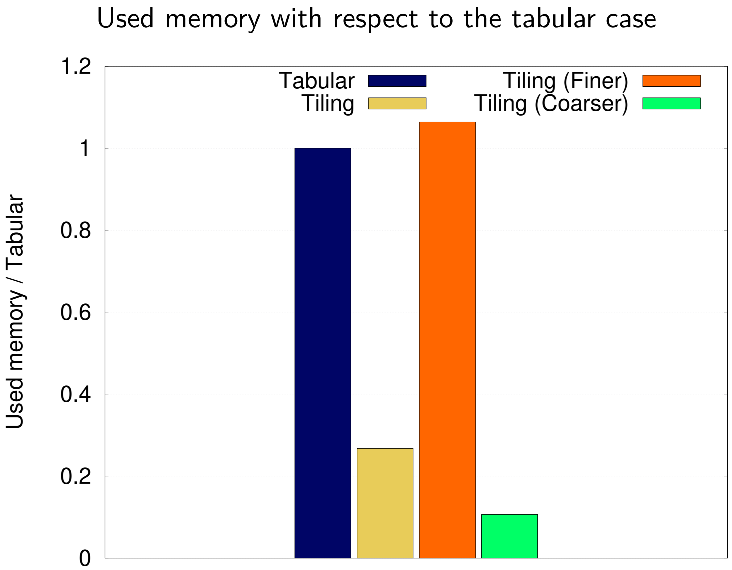
Using Tile Coding

First step: homogeneous computing resources

- A binary feature for scaling operations (scale-out, scale-in)
  $\rightarrow$ captures adaptation cost
- Rectangles-based tilings to group states with similar parallelism and input rate
- A stripes-based tiling to group states with similar load per replica
- 3 granularity settings: base, finer, coarser

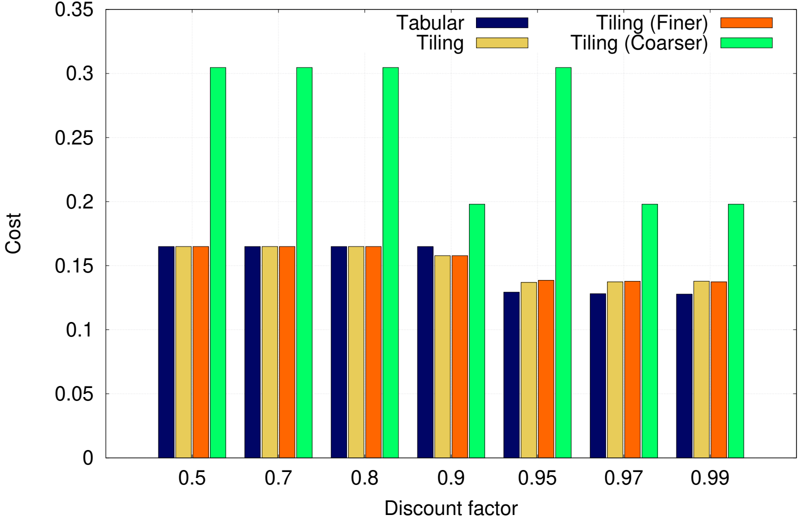


Results: used memory



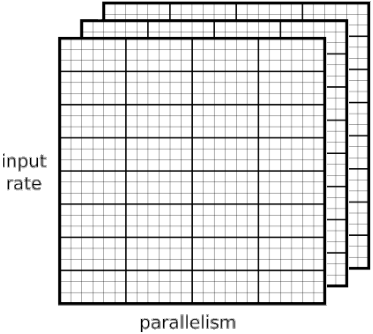
Simulation results: average cost

Base scenario, with homogeneous resources

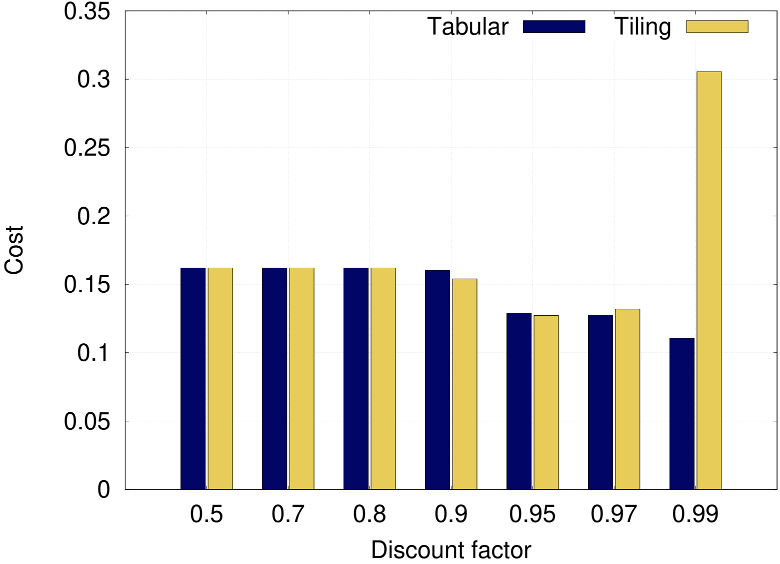


Features for the heterogeneous scenario

- Considering parallelism is not enough any more: computing resources with different cost and performance
- Would need a N-dimensional tiling: input rate + amount of resources of each type
- Simpler idea, adding only a third dimension to the current tilings: parallelism, input rate, type of the less powerful used resource



Preliminary results: 3 types of comp. resources



Near-optimal results for $\gamma < 0.99$, using 2% of the memory

Conclusion

- A MDP-based framework for optimizing deployment in the Fog
- Function Approximation techniques are promising for scalability

Still work to do for better performance:

- Automatic feature engineering (e.g., adaptive tiling)
- Artificial Neural Networks

+ Extend to similar resource allocation problems in the Fog

Thanks for your attention!

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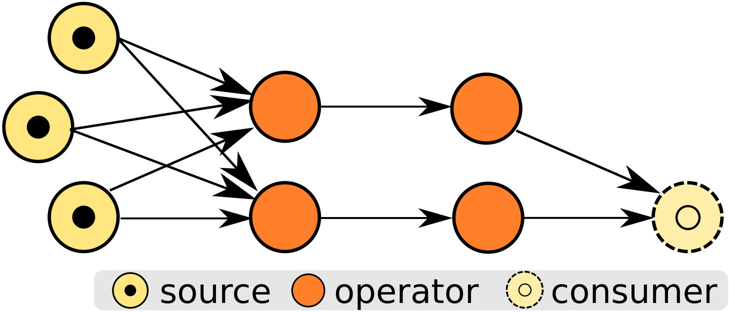
Data Stream Processing (DSP)

- A computational paradigm for **real-time Big Data analysis**
- Continuous processing of unbounded sequences: data streams
- Data processed "on the fly"



MDP formulation

We model the problem as an infinite-horizon **Markov Decision Process**

- System **state**: $s = (\mathbf{K}, \lambda)$
  $k_{r,\tau}$ = replicas deployed in region r using instances of type τ
  λ = current input data rate for the operator (discretized)
- **Actions**:
  - add a replica on a resource of type t in region r
  - kill one of the active replicas
  - do nothing
- Each state-action pair associated with a **cost** $c(s, a)$:
  $c(s, a) = w_R c_{resources}(s, a) + w_A c_{adaptation}(s, a) + w_S c_{SLA}(s, a)$
- We search for the optimal **policy** $\pi^* : \mathcal{S} \rightarrow \mathcal{A}$:

$$\text{minimize} \quad \sum_{t=0}^{\infty} \gamma^t c(s_t, a_t) \qquad \gamma \leftarrow \text{discount factor} \in [0, 1)$$

Solving the MDP

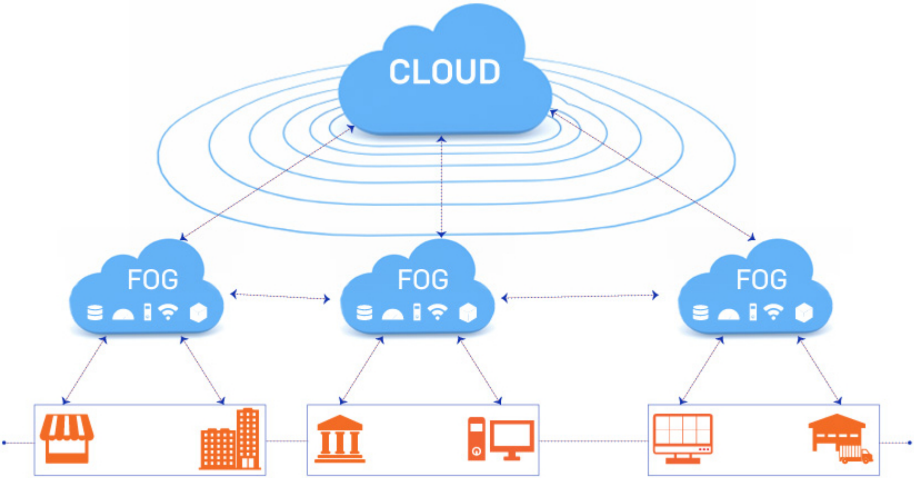
<1-| handout:0> An optimal policy can be found by standard techniques:
linear programming, dynamic programming, reinforcement learning, ...

- Classical DP algorithms (e.g., Value Iteration) rely on **Q function**: expected long-term cost of every action in every state
- Computed iteratively until convergence
- Q function stored in a Q table in memory: an entry for each state-action pair

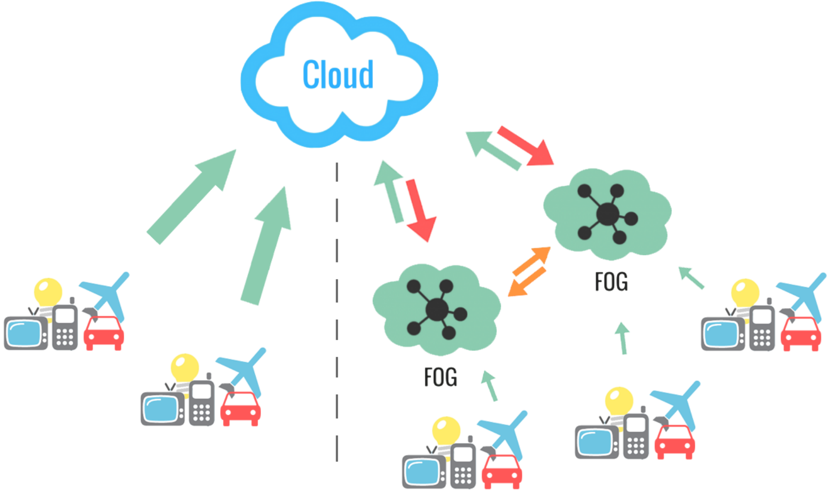
Trajectory Based Value Iteration

Algorithm 3: Trajectory Based Value Iteration (TBVI)	Complexity
Input: MDP, α, L_1	
Output: π	
$\boldsymbol{\theta} \leftarrow$ Initialize arbitrarily	
while *time left* **do**	
for $\langle s, a \rangle$ *in a trajectory following* π^ϵ **do**	
Create L_1 samples: $s'_j \sim \mathcal{P}^a_{s\cdot}, j = 1, ..., L_1$	
$Q^+(s, a) \leftarrow \frac{1}{L_1} \sum_{j=1}^{L_1} \mathcal{R}^a_{ss'_j} + \gamma \max_{a'} Q(s'_j, a'),$	$\mathcal{O}(nL_1\|\mathcal{A}\|)$
$\delta \leftarrow Q^+(s, a) - Q(s, a)$	
$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha\delta\phi(s, a)$	$\mathcal{O}(n)$
return π greedy with respect to Q	

Fog Computing



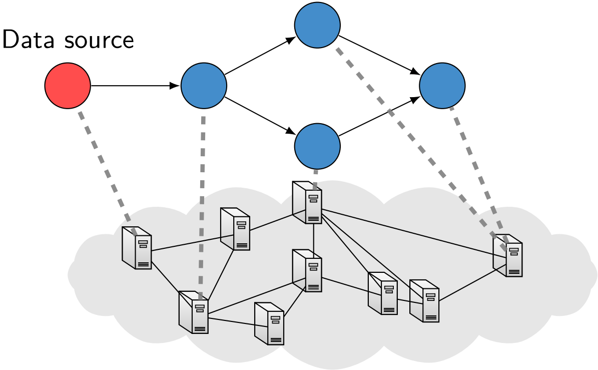
New trends for Big Data: geo-distributed processing



From large data centers in the Cloud to. . . **everywhere**

Executing DSP applications: placement

How to **place** the application components
over a computing infrastructure?



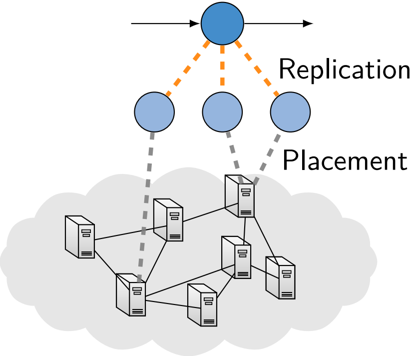
Network latency and resource heterogeneity impact the QoS!

A (centralized) optimization problem

EDRP

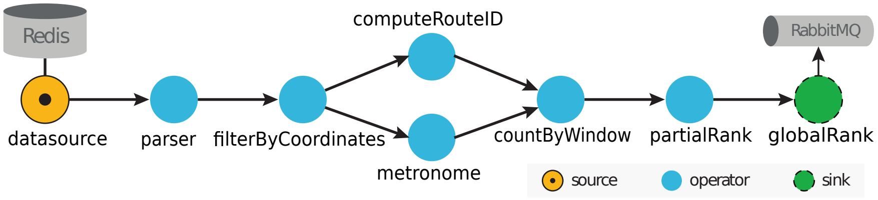
Elastic DSP Replication and Placement

- ILP model
- Optimizes trade-off between response time, resource usage, and reconfiguration cost
- Requires full characterization of the application and the infrastructure
- Does not scale!
- No foresight

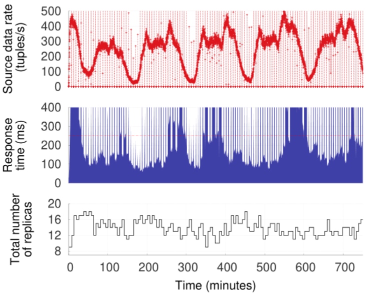


V. Cardellini, F. Lo Presti, M. Nardelli, G. Russo Russo, "Optimal operator deployment and replication for elastic distributed data stream processing", *Concurrency and Computation: Pract Exper.*, 2017

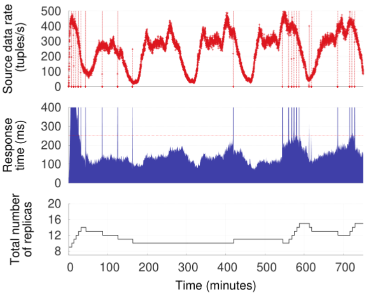
DEBS 2015 Grand Challenge application



EDF + Reinforcement learning



Q-learning



Q-learning, with token bucket