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

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: $s = (k, \lambda)$
  - $k_\tau =$ num. of replicas deployed on resources of type $\tau$
  - $\lambda =$ current input data rate
- Actions: possible deployment adaptations

\[ s = ([2, 0, 1], \lambda) \]
\[ a = (-1, L) \]
\[ s' = ([2, 0, 0], \lambda') \]
\[ a = (+1, M) \]
\[ s' = ([2, 1, 1], \lambda') \]
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**
  \[
  c_{rcf}(s, a, s') = 1_{\{\text{deployment changed}\}}
  \]
- **SLO violation penalty**
  \[
  c_{SLO}(s, a, s') = 1_{\{R(s') > R_{max}\}}
  \]
- The optimal **policy** minimizes
  \[
  \sum_{t=0}^{\infty} \gamma^t c(s_t, a_t, s_{t+1}) \quad \gamma \in (0, 1)
  \]
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!

<table>
<thead>
<tr>
<th>State</th>
<th>Action</th>
<th>Q</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s_1$</td>
<td>$a_1$</td>
<td>$Q(s_1, a_1)$</td>
</tr>
<tr>
<td>$s_2$</td>
<td>$a_2$</td>
<td>$Q(s_2, a_2)$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>
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 $\theta$
- We focus on linear Function Approximation:
  
  $$\hat{Q}(s, a, \theta) = \sum_i \phi_i(s, a) \theta_i$$

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

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Viol (%)</th>
<th>Reconf. (%)</th>
<th>Res.</th>
</tr>
</thead>
<tbody>
<tr>
<td>TH-cost</td>
<td>100.0</td>
<td>3.31</td>
<td>2.8</td>
</tr>
<tr>
<td>TH-speedup</td>
<td>0.12</td>
<td>0.01</td>
<td>90.6</td>
</tr>
<tr>
<td>VI</td>
<td>0.0</td>
<td>0.0</td>
<td>12.0</td>
</tr>
<tr>
<td>TBVI (VI + FA)</td>
<td>0.0</td>
<td>0.30</td>
<td>11.4</td>
</tr>
</tbody>
</table>

3 types of resources

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Viol (%)</th>
<th>Reconf. (%)</th>
<th>Res.</th>
</tr>
</thead>
<tbody>
<tr>
<td>TH-cost</td>
<td>100.0</td>
<td>4.11</td>
<td>2.8</td>
</tr>
<tr>
<td>TH-speedup</td>
<td>0.12</td>
<td>0.01</td>
<td>90.6</td>
</tr>
<tr>
<td>VI</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>TBVI (VI + FA)</td>
<td>0.10</td>
<td>0.03</td>
<td>17.7</td>
</tr>
</tbody>
</table>

10 types of resources
## 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

<table>
<thead>
<tr>
<th>Avg. cost</th>
<th>Simulated time (days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>1</td>
</tr>
<tr>
<td>0.1</td>
<td>7</td>
</tr>
<tr>
<td>0.2</td>
<td>15</td>
</tr>
<tr>
<td>0.3</td>
<td>30</td>
</tr>
<tr>
<td>0.4</td>
<td>60</td>
</tr>
<tr>
<td>0.5</td>
<td>180</td>
</tr>
</tbody>
</table>

TBVI

Q-learning

Q-learning+TBVI

→ 10 types of resources
Results: different sets of features

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

- coarse-grained (≈ 1000 features)
- standard (≈ 2500 features)
- fine-grained (≈ 6000 features)

<table>
<thead>
<tr>
<th>Features</th>
<th>Avg. cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tile Coding (coarser)</td>
<td>0.059</td>
</tr>
<tr>
<td>Tile Coding</td>
<td>0.054</td>
</tr>
<tr>
<td>Tile Coding (finer)</td>
<td>0.070</td>
</tr>
</tbody>
</table>
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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