Location-Aware and Budget-Constrained Service Brokering in Multi-Cloud via Deep Reinforcement Learning

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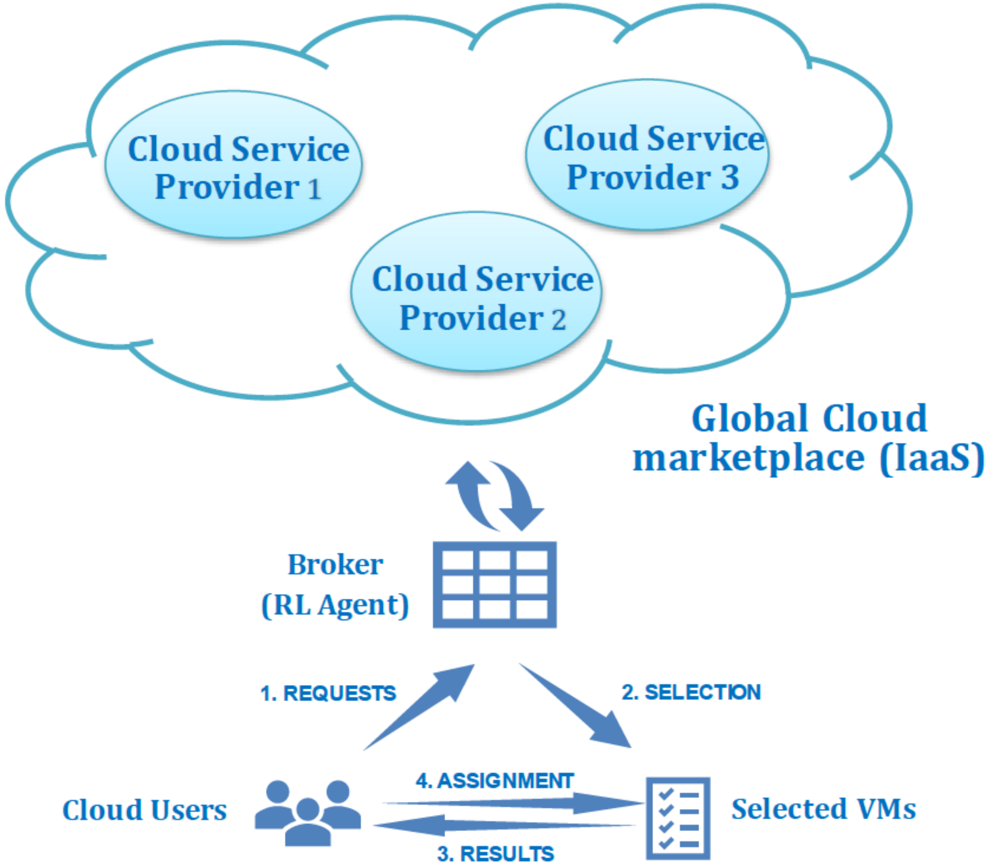
Introduction

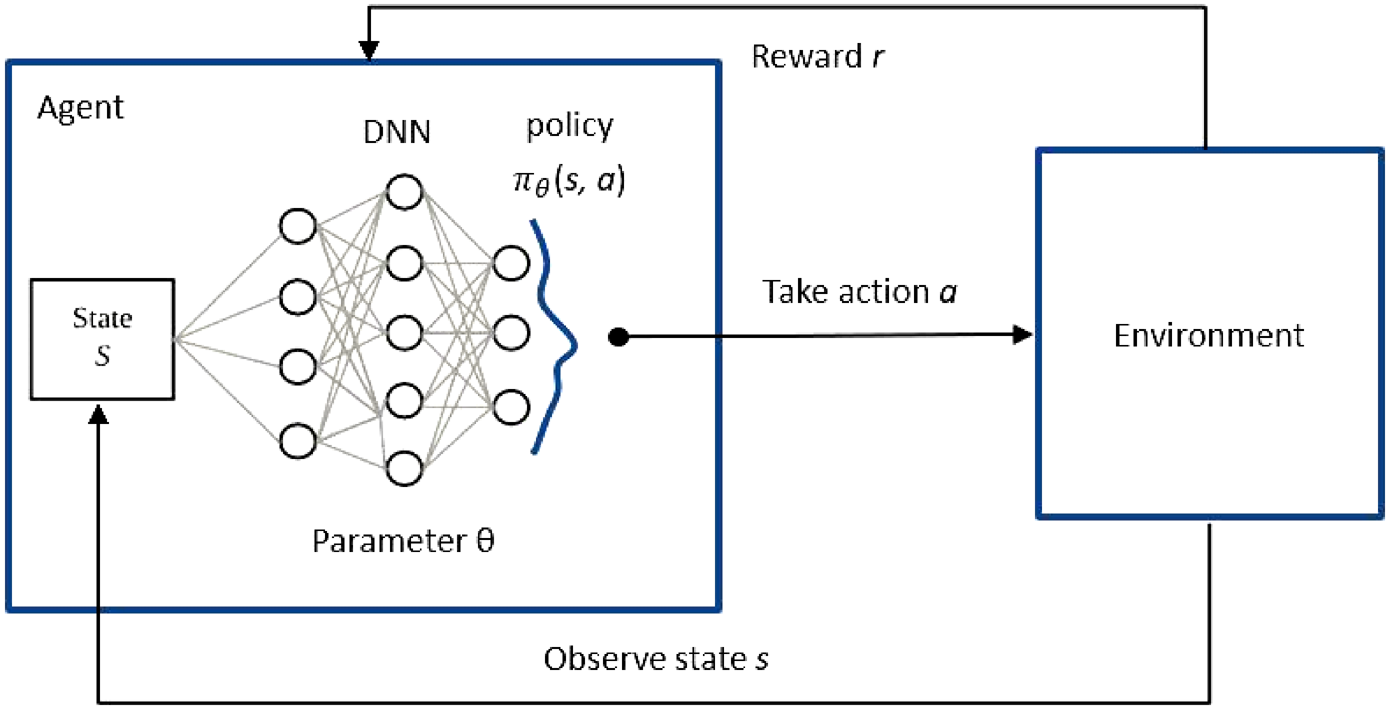
Service Brokering in Multi-Cloud

- Multi-cloud
  - High quality of services
  - Low operation cost
  - Avoid vendor lock-in
- Broker
  - Deployment and management of cloud services
- Location
  - Network latency
  - Cost
- Budget
  - Budgetary control to ensure financial viability



- Location-aware and Budget-constrained Service Brokering in Multi-cloud: LBSBM

Deep Reinforcement Learning (DRL)



- Maximize the overall reward during a long period of system operation
- Computationally efficient selection

Introduction

Challenges of DRL for LBSBM

- Unlimited VM instances available in multi-cloud
  - Novel components: state extractor and action executor

- Meet the budgetary constraint
  - New penalty-based reward function

Problem Description

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Location-aware and Budget-constrained Service Brokering in Multi-cloud: LBSBM

➢ VM types

- Capacities: CPU, memory
- Available regions

➢ Requests

- Resource requirements: CPU, memory
- Arrival time, duration
- User location
- Capacity-feasible assignment

➢ Assumptions

- The same VM instance can be used to process one request or multiple requests sequentially.
- Each request can only be assigned to a single VM instance.
- VM usage is charged on an hourly rate.

Problem Description

Location-aware and Budget-constrained Service Brokering in Multi-cloud: LBSBM

- Total cost (TC) and average network latency (ANL)

$$TC = \sum_{v \in V} \sum_{r \in R_v} C_{v,r} x_{v,r}, \ ANL = \frac{1}{N} \sum_{i=1}^{N} \sum_{v \in V} \sum_{r \in R_v} L_{i,r} y_{i,v,r}$$

- Objective

Minimize *ANL*

- Constraint

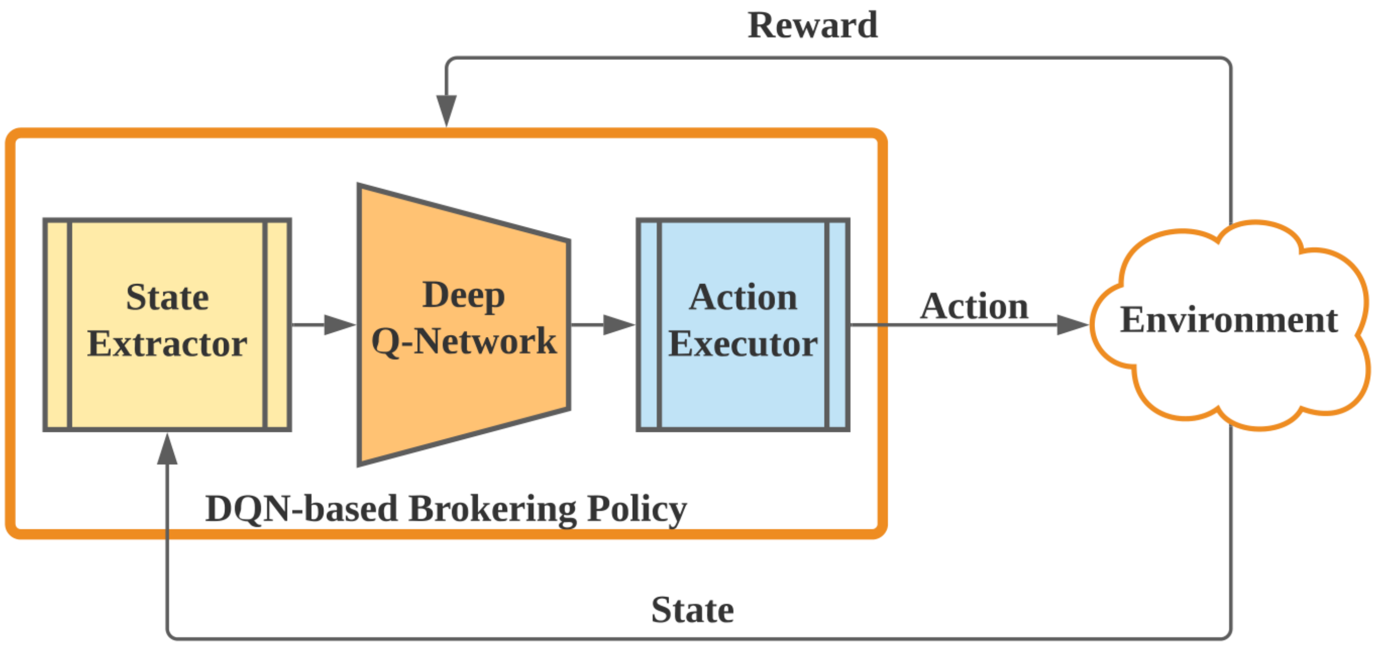
$$TC \le \sum_{i=1}^{N} b_i$$

$$b_i = C_{i,min} t_i + k \cdot (C_{i,max} t_i - C_{i,min} t_i)$$

DeepBroker: A DRL-Based Algorithm

DRL system

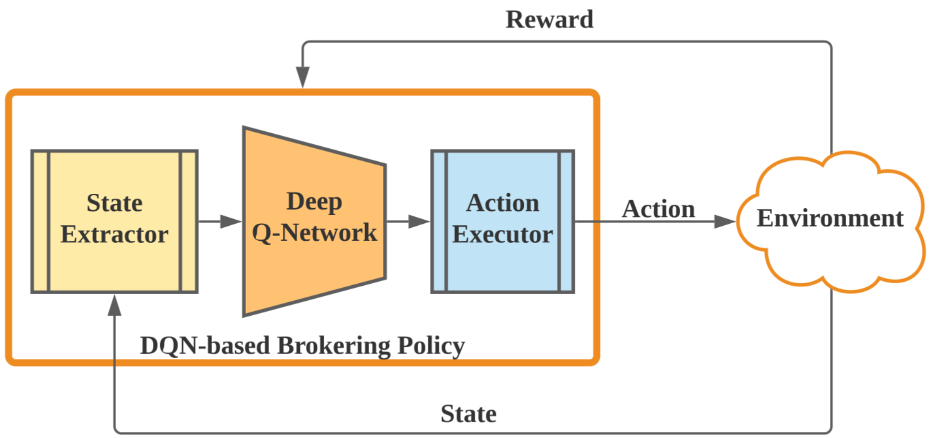
- State: The observed state includes the new request and currently leased VM instances.
- Action: To select a specific instance of capacity-feasible VM types, i.e., an idle VM instance or a newly selected VM instance, for request.



DeepBroker: A DRL-Based Algorithm

State Extractor

- New request
  - Resource requirements: CPU, memory
  - Duration
  - User location: Latency vector including the network latency between the user location and all the regions covered by multi-cloud data centers.
- Leased VM instances
  - For each VM type in each available region
  - Capacity feasible?
  - Idle? Maximum remaining time



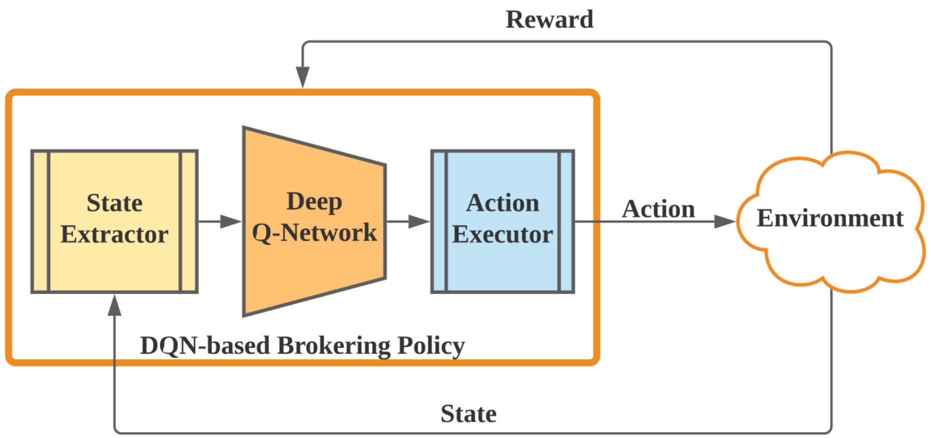
DeepBroker: A DRL-Based Algorithm

DRL for Training DQN

- Penalty-based reward function

$$r_i = -L_{i,r} - \max(0, (C_{v,r} t_i - b_i))$$

- Q-learning
- DQNs as function approximators
- Experience replay

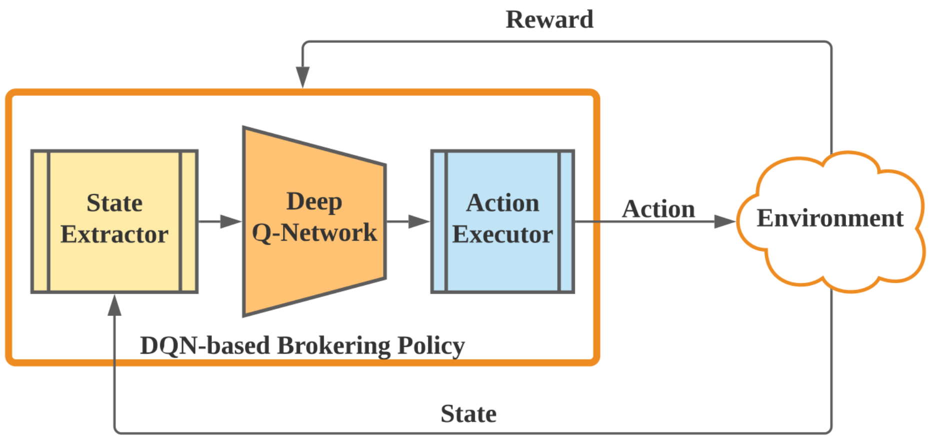


DeepBroker: A DRL-Based Algorithm

Action Executor

- Mask
  - Zero probabilities for capacity-infeasible VM types

- Specify VM instances
  - Idle? Maximum remaining time
  - New VM instance



Evaluation

Datasets

- VMs
  - Three leading cloud providers, i.e., Amazon Web Services (AWS), Microsoft Azure and Alibaba Elastic Compute Service (ECS)
  - 12 different VM types (4 from each)
  - 8 regions for major AWS, Azure and Alibaba data centers, i.e., Northern Virginia, Dublin, Singapore, Tokyo, Sydney, Northern California, Sao Paulo, and Mumbai.
- Requests
  - Public VM request workload in the Azure dataset [1]
- Network latency evaluation
  - Sprint IP backbone network databases

[1] Cortez, E., Bonde, A., Muzio, A., Russinovich, M., Fontoura, M., Bianchini, R.: Resource central: understanding and predicting workloads for improved resource management in large cloud platforms. In: Proceedings of the 26th Symposium on Operating Systems Principles, pp. 153–167 (2017)

Algorithm Implementation

- PyTorch
- Two fully-connected hidden layers, each with 64 nodes
- ReLUs, MSE, Adam
- Initial and minimum probability that DRL randomly chooses an action: 0.2 and 0.01
- Learning rate and discount factor: 0.001and 1.0
- Mini-batch size: 32

Evaluation

Baseline

➢ Greedy

- Assigns each user request to the best possible VM instance in terms of the weighted sum of the normalized cost and network latency.
- Tune an appropriate combination of weights based on the training workload.

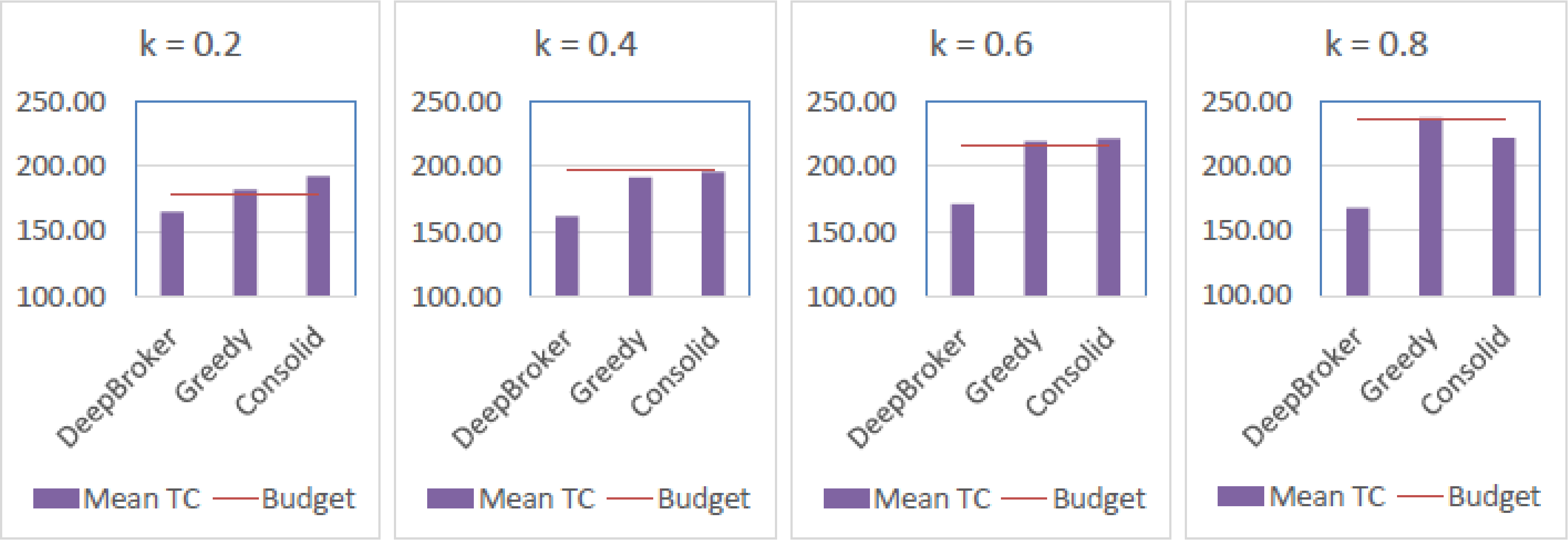
➢ Consolid

- Identifies a set of eligible processors with enough resources that can process the arriving request.
- Assigns the request to the processor with the highest post-allocation utilization.

Evaluation

Results: Budget Compliance

- Training workload: one day's workload with 365 user requests
- Test workload: the following day’s workload with 362 user requests
- 4 budget factors: 0.2, 0.4, 0.6, and 0.8,



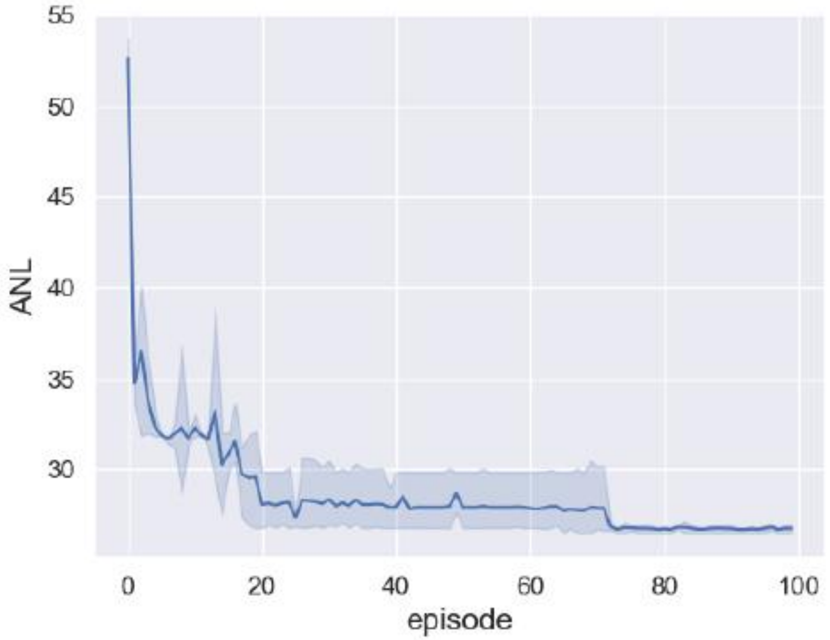
Results: ANL Comparison and VM Instance Numbers

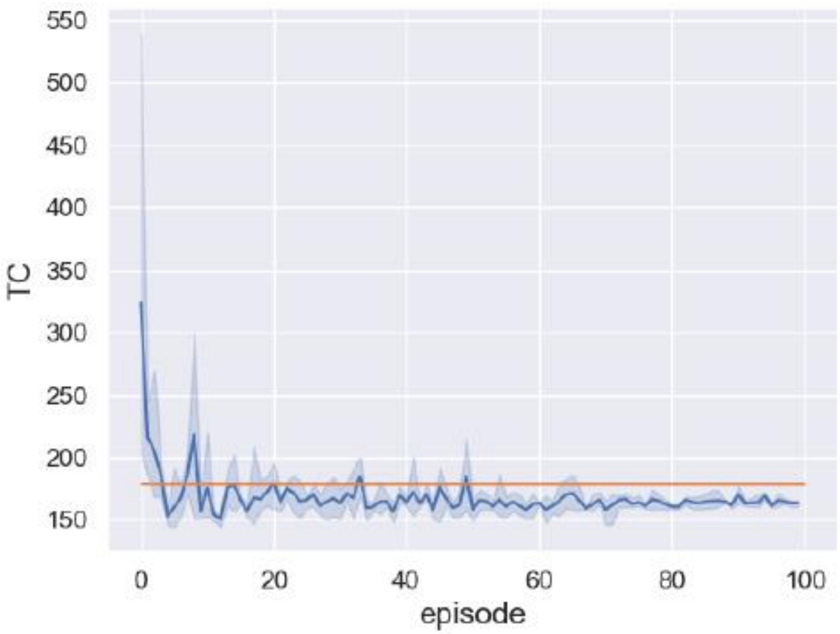
Algorithm performance comparison for the *LBSBM* problem under different budget factors (*ANL* in ms., Total budget and *TC* in USD, the best is bold).

k	Total budget	DeepBroker			Greedy based on [3]					Consolid based on [13]		
		ANL	TC	n	ANL	TC	ω_1	ω_2	n	ANL	TC	n
0.2	178.71	$\mathbf{26.83 \pm 0.23}$	164.98 ± 4.8	249	124.4 ± 0	182.21 ± 0	1.00	0.00	181	105.73 ± 0	192.39 ± 0	172
0.4	197.68	$\mathbf{26.93 \pm 0.3}$	162.18 ± 3.61	253	61.83 ± 0	191.75 ± 0	0.95	0.05	221	97.53 ± 0	196.1 ± 0	171
0.6	216.65	$\mathbf{26.86 \pm 0.2}$	171.65 ± 5.83	245	38.17 ± 0	219.09 ± 0	0.85	0.15	225	73.35 ± 0	221.56 ± 0	172
0.8	235.62	$\mathbf{27.01 \pm 0.29}$	167.82 ± 6.58	249	26.55 ± 0	237.6 ± 0	0.75	0.25	230	73.35 ± 0	221.56 ± 0	172

Evaluation

Convergence Analysis and Computational Overhead





- Training time: less than 30 min
- Computational overhead: within 1ms

Conclusions

Conclusions

- The paper studies the LBSBM problem, i.e., selecting VMs for arriving user requests to minimize the average network latency of VMs subject to the total budget over a time span.

- We propose a DRL-based algorithm, named DeepBroker, with the problem-specific state extractor, action executor, and penalty-based reward function to train the DQN-based service brokering policies.

- The experiments based on the real-world datasets show the trained brokering policies significantly outperform several heuristic-based algorithms in terms of both average network latency and budget satisfaction.

Thank You
Q&A

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