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Embedding expert demonstrations into clustering buffer for effective deep reinforcement learning

Key words: Reinforcement learning; Sample efficiency; Sampling process; Clustering methods; Autonomous driving

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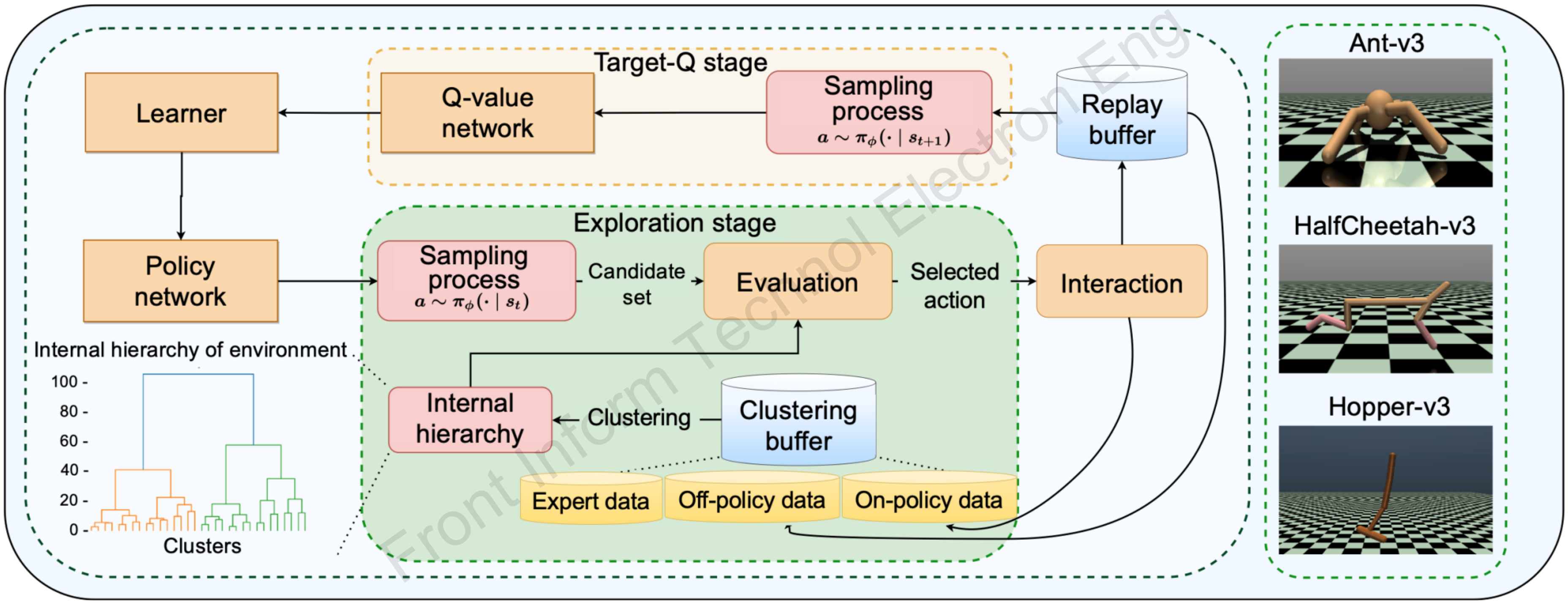
Motivation

- As one of the most fundamental topics in reinforcement learning (RL), sample efficiency is essential to the deployment of deep RL algorithms. Existing researches tried to alleviate the need for samples by solving the credit assignment problem or introducing expert demonstration. On the other hand, existing exploration methods sample an action from different types of posterior distributions. However, these methods neglect the importance of expert demonstration in exploration.
- To deploy deep RL algorithms to some costly domains, such as robotic manipulation and autonomous driving, it is of paramount importance to model the internal hierarchy of the environment.

Framework



Structure of selective sampling

Method

- We focus on the policy sampling process and propose an efficient selective sampling approach to improve the sample efficiency by modeling the internal hierarchy of the environment.
- We first employ clustering methods on the policy sampling process, which generates an action candidate set. Then we introduce a clustering buffer for modeling the internal hierarchy, which consists of on-policy data, off-policy data, and expert data, to evaluate actions in the action candidate set in the exploration stage.
- Selective sampling has played an essential role in the exploration stage and is able to take more advantage of the supervision information in the expert demonstration data.

Method

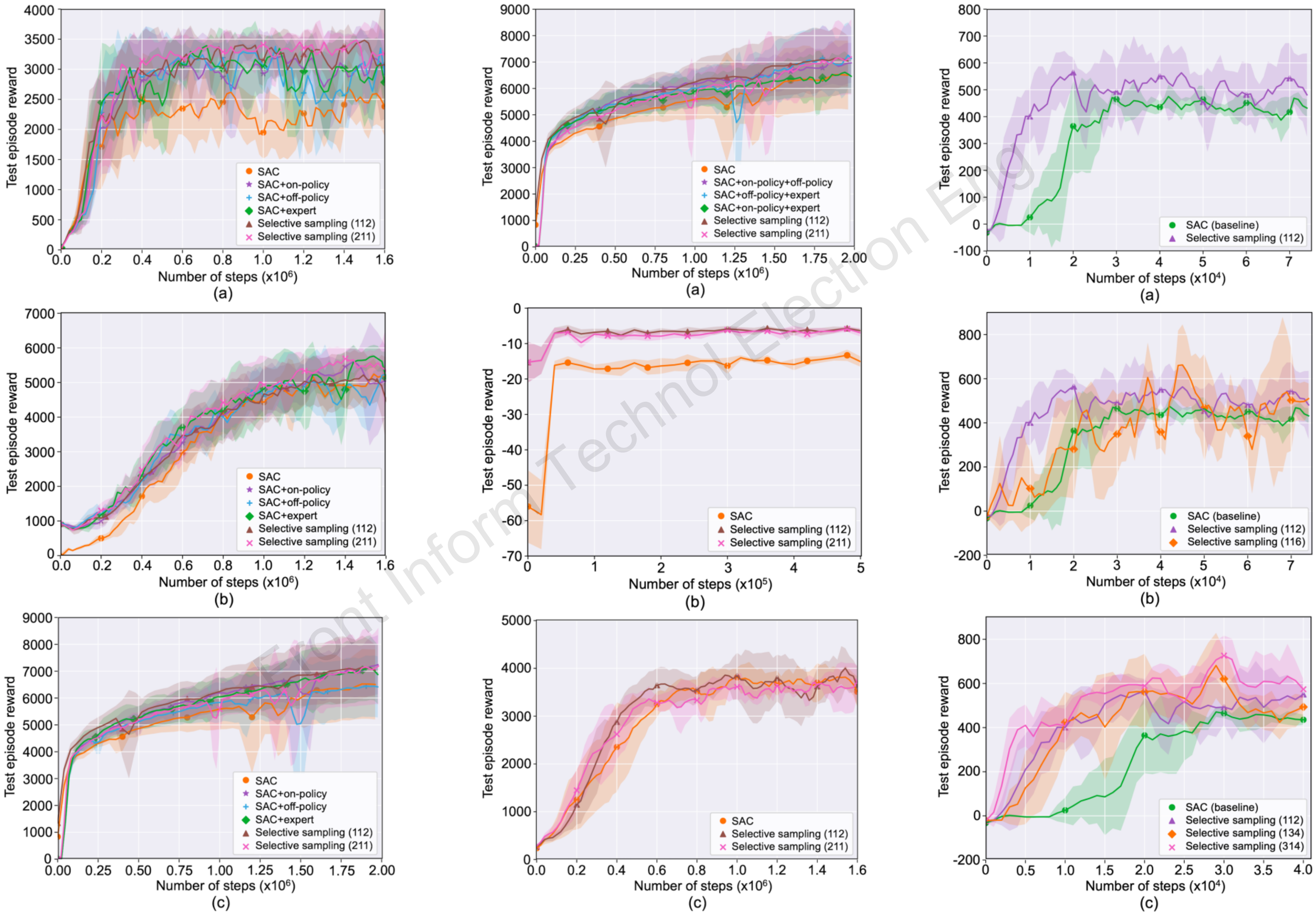
Algorithm 1 Selective sampling

Require: on-policy data $\mathcal{D}_{\text{on}}$, off-policy data $\mathcal{D}_{\text{off}}$, expert data $\mathcal{D}_{\text{E}}$

Ensure: learned policy $\pi_\phi(a \mid s)$

Initialize network parameters θ, θ^-, ϕ
for each environment step **do**
  $\mathcal{D}_{\text{s}} \leftarrow a \sim \pi_\phi(\cdot \mid s_t)$
  $\mathcal{D}_{\text{c}} \leftarrow (\mathcal{D}_{\text{on}}, \mathcal{D}_{\text{off}}, \mathcal{D}_{\text{E}})$
  $N_{\text{c}} \leftarrow \text{AgglomerativeClustering}(\mathcal{D}_{\text{c}})$
  $\mathcal{C} \leftarrow K\text{-means}(\mathcal{D}_{\text{c}}, N_{\text{c}}, \mathcal{D}_{\text{s}})$
  for each c in $\mathcal{C}$ **do**
    $V_\eta(c) \leftarrow \frac{1}{n_h} \sum_{k=i}^{i+n_h-1} \eta(s_k, a_k)$
  end for
  $a_{\text{selected}} \leftarrow \text{Random}(\text{Softmax}_{c \in \mathcal{C}} V_\eta(c))$
  $s_{t+1} \sim \mathcal{T}(\cdot \mid s_t, a_{\text{selected}})$
  $\mathcal{D}_{\text{Q}} \leftarrow \mathcal{D}_{\text{Q}} \cup \{s_t, a_{\text{selected}}, r_t, s_{t+1}\}$
  for each gradient step **do**
    $\theta \leftarrow \theta - \lambda_{\text{Q}} \nabla_\theta \mathcal{B}_\theta(Q)$
    $\phi \leftarrow \phi - \lambda_\pi \nabla_\phi \mathcal{J}_\phi(\pi)$
    $\theta^- \leftarrow \lambda_{\text{target}} \theta + (1 - \lambda_{\text{target}}) \theta^-$
  end for
end for

Major results



Convergence curves of training in Mujoco (left & middle) and LGSVL (right) tasks

Conclusions

- This paper presents a novel sampling approach, selective sampling, to improve the sample efficiency of RL. Experiments on six different continuous locomotion environments demonstrate superior RL performance and faster convergence of selective sampling. In particular, on the LGSVL task, our method can reduce the number of convergence steps by 46.7% and the convergence time by 28.5%.
- In the implementation of selective sampling, we recommend to increase the expert data and on-policy data in costly domains, such as robotic manipulation and autonomous driving. The ward setting and average setting are recommended for the linkage criterion.

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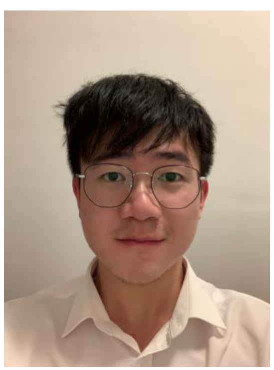

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