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Computer Science

Prioritized Experience Replay via Learnability Approximation

Noam Ringach (nomir), Megumi Sano (megsano)

Experience replay is a key technique in RL in which the agent repeatedly learns on previous experiences stored in a buffer in order to improve sample efficiency. **Prioritized Experience Replay** (PER) weights experiences by their TD errors to prioritize important experiences during replay. We propose **Cluster-wise Learnability Experience Replay** (CLER) that prioritizes experiences based on their learnability approximated by cluster-wise regression on TD error. Results suggest further improved sample efficiency.

Goal: **Develop a prioritization method for experience replay to improve sample efficiency.**

Prior work on ER

Experience Replay[1]

for k = 1, …, m:
  Observe (s, a, r, s'), place in buffer
  for j = 1, …, M:
    Uniformly sample transitions
    Accumulate weight change
  Update weights
  Update target network

Prioritized Experience Replay[2]

for k = 1, …, m:
  Observe (s, a, r, s'), place in buffer with maximal priority
  for j = 1, …, M:
    Sample transitions from buffer according to weighted probabilities
    Compute TD errors
    Set probabilities to TD error
    Accumulate weight change
  Update weights
  Update target network

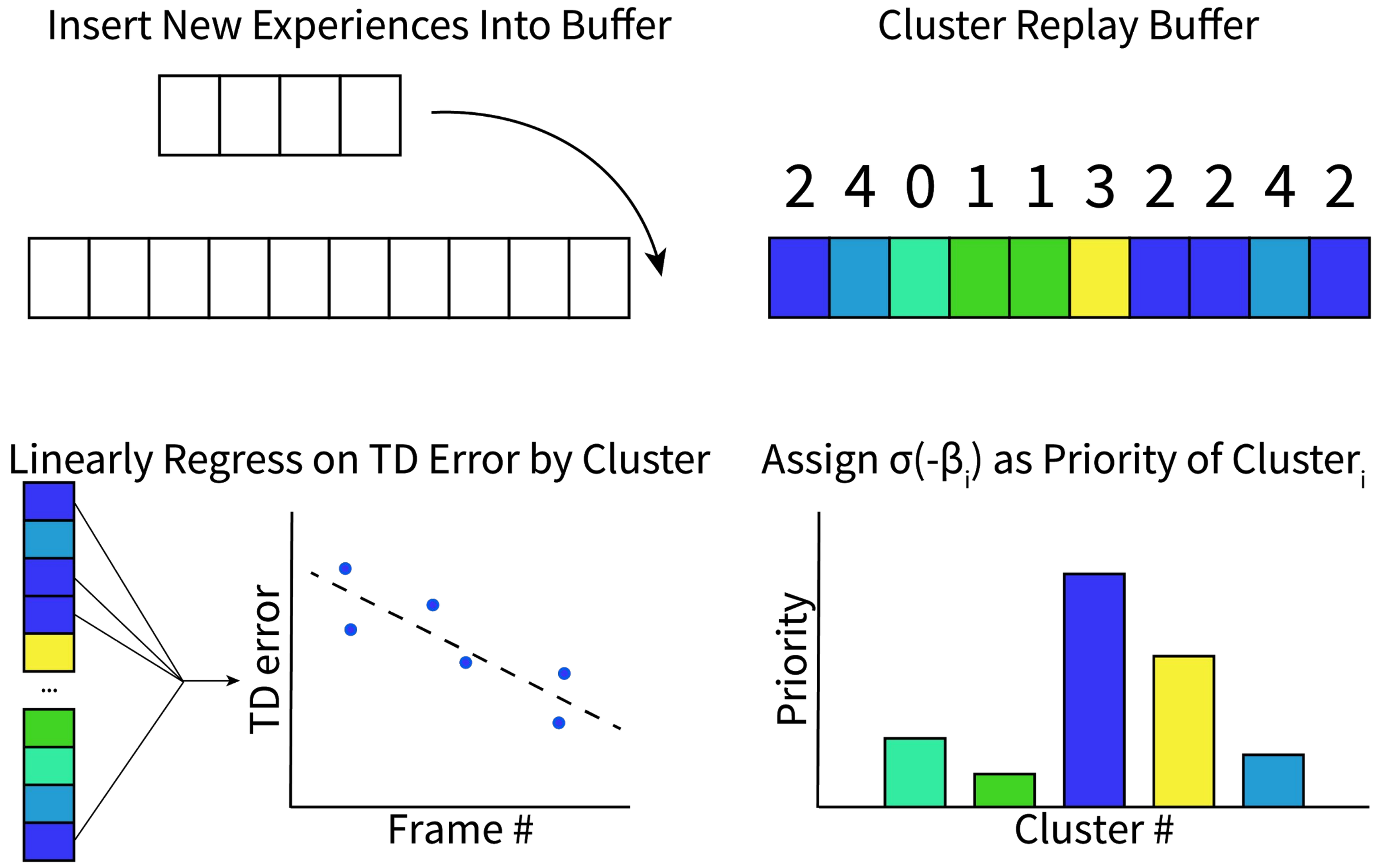
Our prioritization algorithm

Cluster-wise Learnability Experience Replay (CLER)

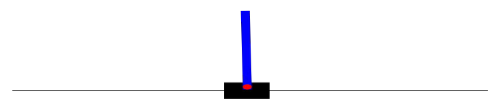
For k = 1, …, m:
  Observe (s, a, r, s'), place in buffer
  Cluster buffer using mean shift
  For j = 1, …, M:
    Sample transition from buffer according to weighted probabilities
    Compute TD errors
    For i = 1, …, number of clusters:
      Linearly regress on TD errors in the i-th cluster to obtain slope β
      Set probabilities of all experiences in the i-th cluster to $\sigma(-\beta)$
      (learnability approx.)
    Accumulate weight change
  Update weights
  Update target network

Mean shift is a clustering algorithm that uses a sliding window to compute new centroids and can remove duplicate centroids.

CLER (step by step)



Task / Environment:

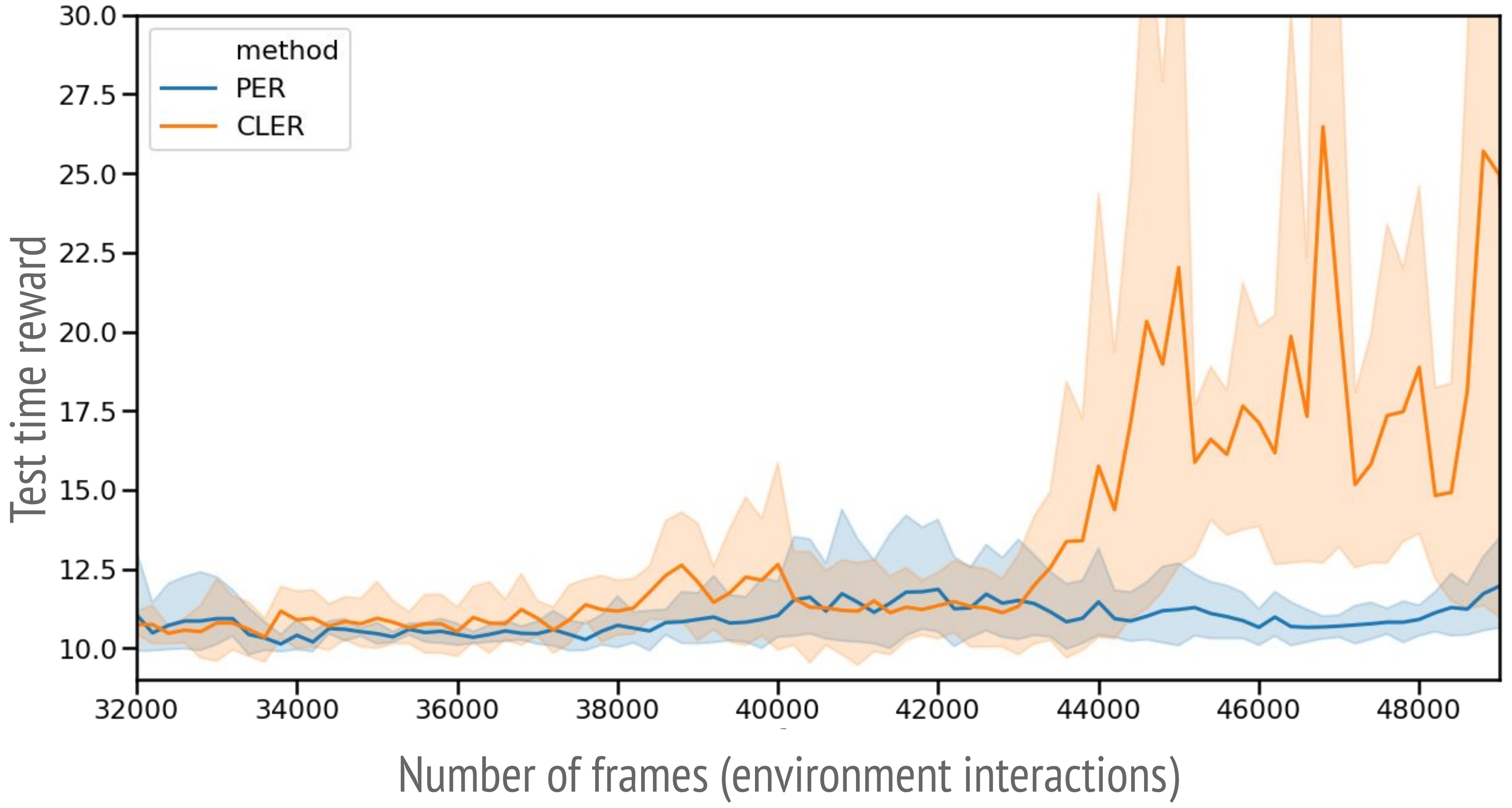


We modified CartPole-v0 from OpenAI Gym[3] such that at each frame, with probability ε, a random action is taken to create noisy states.

Policy / Architecture:

We use Q-learning with epsilon-greedy exploration. Our Q-function is a two-layer fully connected network with 128 hidden units.

Experimental results: *Can we achieve lower sample complexity?*



Discussion:

- Compared to PER, our learnability-based CLER algorithm obtains significantly higher test time reward at about 11% fewer environment interactions, showing **lower sample complexity**.
- We hypothesize that CLER performs better because it is able to **ignore states with high TD error and low learnability**, such as when the pole will definitely fall.

Future directions:

- **Better ways to approximate learnability** and speed up CLER
- Explore **probabilistic and theoretical guarantees** on performance
- More rigorous **hyperparameter tuning** e.g. number of clusters, clustering method

Works Cited

1. Lin, Long-Ji. Self-improving reactive agents based on reinforcement learning, planning and teaching. Machine learning, 8(3-4):293–321, 1992.
2. Tom Schaul, John Quan, Ioannis Antonogloy, and David Silver. Prioritized Experience Replay. ICLR, 2016.
3. G. Brockman, V. Cheung, L. Pettersson, J. Schneider, J. Schulman, J. Tang, and W. Zaremba. OpenAI Gym, 2016.