Bio-Medical Computing Lab, BMCL

PRIORITIZED EXPERIENCE REPLAY

Google DeepMind, 2016 ICLR

Bio-Medical Computing Laboratory

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INTRODUCTION

- How prioritizing which transitions are replayed can make experience replay more efficient and effective than if all transitions are replayed uniformly.
- Some transitions may not be immediately useful to the agent, but might become so when the agent competence increases (Schmidhuber, 1991).
- Propose to more frequently replay transitions with high expected learning progress, as measured by the magnitude of their temporaldifference (TD) error.



PRIORITIZING WITH TD-ERROR

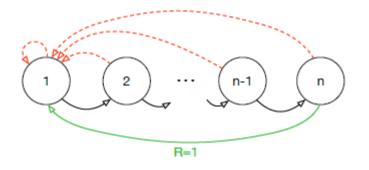
- The central component of prioritized replay is the criterion by which the importance of each transition is measured (TD error δ).
- **TD** error , which indicates how 'surprising' or unexpected the transition is.
- The TD-error can be a poor estimate in some circumstances as well, e.g. when rewards are noisy
- 7 The transition with the largest absolute TD error is replayed from the memory.

$$V(S_t) \leftarrow V(S_t) + \alpha \Big[R_{t+1} + \gamma V(S_{t+1}) - V(S_t) \Big].$$

"They learn a guess from a guess"



STOCHASTIC PRIORITIZATION

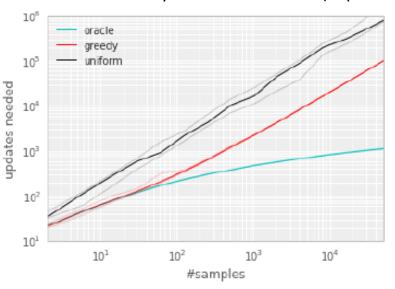


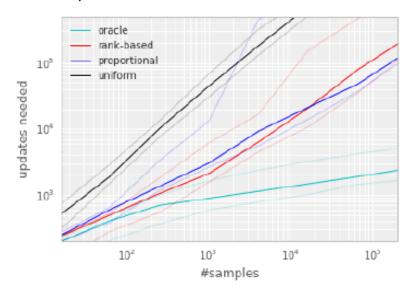
- there are two actions, a 'right' and a 'wrong' one
- 2. Taking the 'right' action progresses through a sequence of n states at the end of which lies a final reward of 1, reward is 0 elsewhere.



STOCHASTIC PRIORITIZATION

oracle: Priority learned in advance (impossible in real world)







STOCHASTIC PRIORITIZATION

- Greedy TD-error prioritization has several issues.
- Transitions that have a low TD error on first visit may not be replayed for a long time (which means effectively never).
- Further, it is sensitive to noise spikes (e.g. when rewards are 7 stochastic), which can be exacerbated by bootstrapping.
- lack of diversity that makes the system prone to over-fitting.
- To overcome these issues, they introduce a stochastic sampling method that interpolates between pure greedy prioritization and uniform random sampling.

$$P(i) = \frac{p_i^{\alpha}}{\sum_k p_k^{\alpha}}$$



Variant 1: proportional prioritization

$$p_i = |\delta_i| + \epsilon.$$

∈ is a small positive constant that prevents the edge-case of transitions not being revisited once their error is zero. δ is the TD-error

Variant 2: rank-based prioritization

$$p_i = \frac{1}{\operatorname{rank}(i)}$$

rank(i) is the rank of transition i when the replay memory is sorted according to δi latter is likely to be more robust, as it is insensitive to outliers

They expected Variant 2 is likely to be more robust, as it is insensitive to outliers.

But, both variants perform similarly in practice.



Both variants of stochastic prioritization lead to large speed-ups over the uniform baseline

ANNEALING THE BIAS

In typical reinforcement learning scenarios, the unbiased nature of the updates is most important near convergence at the end of training, as the process is highly non-stationary anyway, due to changing policies, state distributions and bootstrap targets.



ANNEALING THE BIAS

- Prioritized replay introduces bias because it changes this distribution in an uncontrolled fashion. We can correct this bias by using importancesampling (IS) weights.
- Note that the choice of this hyperparameter interacts with choice of prioritization exponent; increasing both simultaneously prioritizes sampling more aggressively at the same time as correcting for it more strongly.
- In practice, we linearly anneal from its initial value 0 to 1.

$$w_i = \left(\frac{1}{N} \cdot \frac{1}{P(i)}\right)^{\beta}$$

$$V(S_t) \leftarrow V(S_t) + \alpha \Big[R_{t+1} + \gamma V(S_{t+1}) - V(S_t) \Big].$$



These weights can be folded into the Q-learning update by using $w_i \delta_i$ instead of δ_i

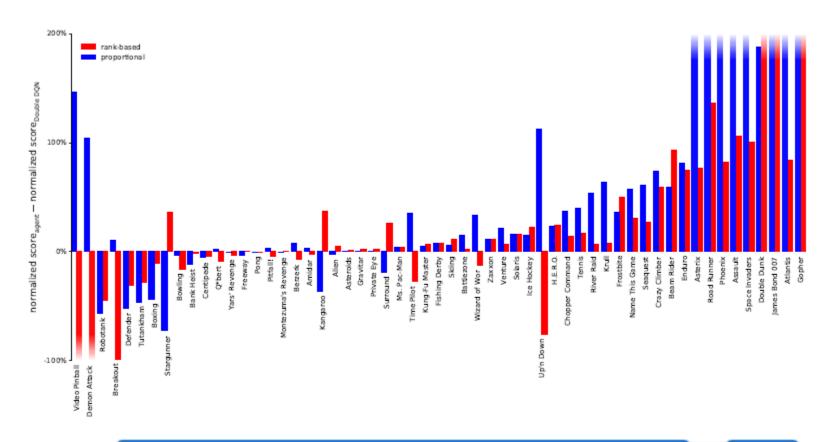


Figure 3: Difference in normalized score (the gap between random and human is 100%) on 57 games with human starts, comparing Double DQN with and without prioritized replay (rank-based variant in red, proportional in blue), showing substantial improvements in most games. Exact scores are in Table 6. See also Figure 9 where regular DQN is the baseline.

