Novelty-Guided Proximal Curriculum Learning

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- need lots of exploration
- sparse rewards -> infrequent learning signal
- curriculum learning for appriориate task difficulty

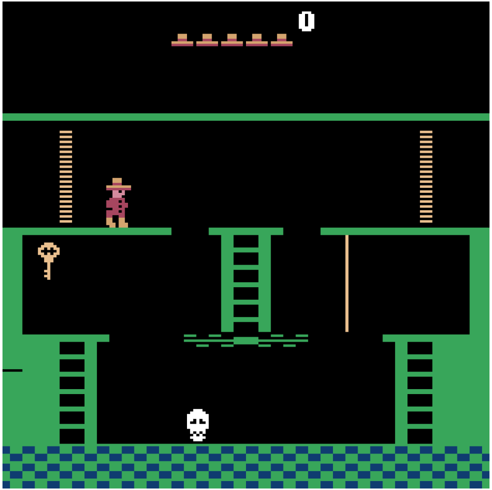
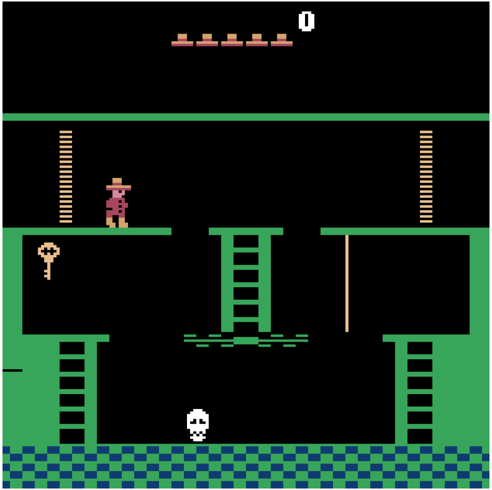


Figure: https://images.openai.com/blob/2c736f64-38dc-4c65-a1dd-aabe2ceb8ddf/learning-montezumas-revenge-from-a-single-demonstration.png

- need lots of exploration
- sparse rewards -> infrequent learning signal
- curriculum learning for appriorate task difficulty
- *How to set proper tasks?*
- current approaches often rigid and demonstration-based



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Proximal Curriculum Learning (PCL) [Tzannetos et al. 2023]

- starting state based on *probability of success* PoS
- $PoS \approx 0.5$
- distribution over S_{init}
- Approximate PoS via agents value function V (scaled to $[0, 1]$)

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Problems:

- V initialized randomly
- V inaccurate for seldomly seen states
- states may get PoS of 0 or 1 and never get chosen

State Novelty

Exploration may help us fix the problem.

- state novelty $\sim$ V inaccuracy

$\rightarrow$ explore seldomly seen states

- set starting state based on state novelty

Novelty-Guided Proximal Curriculum Learning (NGPCL)

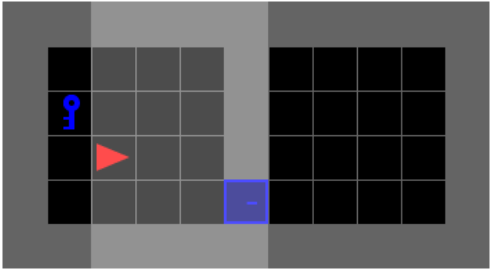
- incorporate novelty by creating distribution over S_{init}

$\rightarrow$ faster V convergence

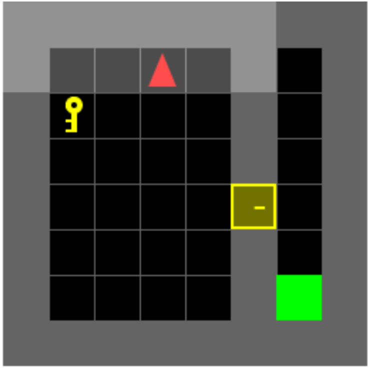
$\rightarrow$ skip environment steps needed for intrinsic reward

- overlay both distributions by using weighted sum

Environments



(a) Unlock

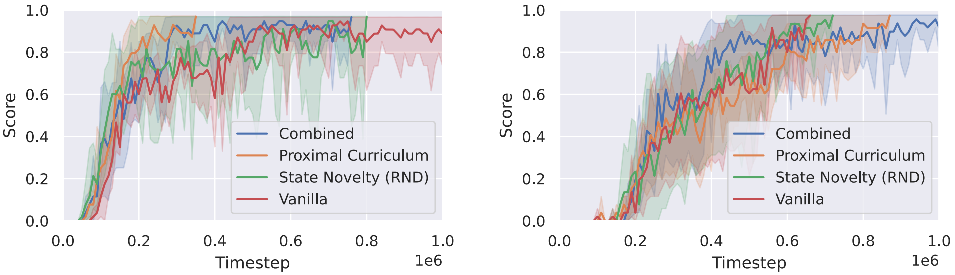


(b) DoorKey-8x8

Figure: Environments used for experiments [Chevalier-Boisvert et al. 2023]. Key was added to observation.

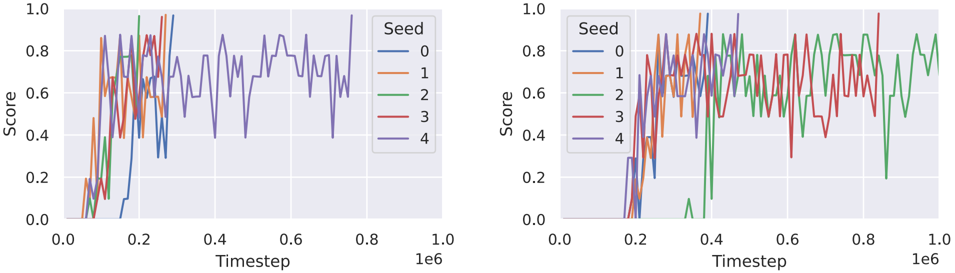
Setup

- S_{init} over all states, not evolving
- Random Network Distillation (RND) [Burda et al. 2018] as state novelty implementation
- Hyperparameters and architectures optimized by bayesian optimization using SMAC [Lindauer et al. 2022]



(a) Unlock (b) Doorkey-8x8

Figure: Rewards over training steps starting from usual starting state (NGPCL). 5 seeds with 95% CI.



(a) Unlock (b) Doorkey-8x8

Figure: Rewards over the training steps given seed (NGPCL).

Discussion

Results:

- some seeds showed fast learning
- ... others failed to solve the environment
- performance differs per environment

Possible causes:

- distribution overlaying may be destructive
- Hyperparameters could be set poorly (especially for RND)

Future Work

Things to try:

- schedule for overlay parameter
- interleave PCL with RND
- try other state novelty approaches
- (dynamic) S_{init} determination

Environments to evaluate:

- dense rewards
- big/continuous state- and/or action-spaces
- reward space not being convex

References

Burda, Yuri et al. (2018). "Exploration by Random Network Distillation". In: *CoRR* abs/1810.12894. arXiv: 1810.12894. URL: http://arxiv.org/abs/1810.12894.

Chevalier-Boisvert, Maxime et al. (2023). "Minigrid & Miniworld: Modular & Customizable Reinforcement Learning Environments for Goal-Oriented Tasks". In: *CoRR* abs/2306.13831.

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Tzannetos, Georgios et al. (2023). "Proximal Curriculum for Reinforcement Learning Agents". In: *Trans. Mach. Learn. Res.* 2023. URL: https://openreview.net/forum?id=8WUyeeMxMH.