Reinforcement Learning in Latent Space

We, the authors

Abstract

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Keywords: some important words

1 Introduction

1.1 Research Questions

1.2 Approach

1.3 Related Work

Early work on transfer learning for reinforcement learning mostly relied on human intervention to create a mapping between source and target tasks (e.g. Taylor and Stone, 2007). Taylor and Stone (2007), for example, developed a method called *Rule Transfer*. Their algorithm learns a policy in the source task that gets transformed into rules, serving as advise to the agent when training in the new environment. To use these rules in the target task, hand-coded translation functions were applied. In contrast, Taylor, Kuhlmann, and Stone (2008) published the first system that automatically mapped source and target task. They use little data from a short exploration period in the target task to approximate a one-to-many mapping between the state and action space. This is achieved by comparing all possible state-state and action-action pairs and choosing the ones with the smallest MSE when predicting the next action using neural networks trained on the target task observations. While their method effectively facilitated learning in the target task, it needs to be noted that transfer was performed on modifications of the same task. Hence, they were fairly similar and there was no attempt to tackle cross-domain transfer.

Gupta et al. (2017) used a proxy task learnt in both the source and target domains, and a test task where transfer should occur. Firstly, with the proxy task, pairs of corresponding states are found using time-based alignment or dynamic time warping. Based on these state pairs, a common latent state space is learnt by minimizing reconstruction errors and pairwise distances. In the test task, to incentivize policy transfer from source to task, the distance to source optimal policy in the common space is incorporated the reward function.

Gupta et al. (2018) uses the latent space and meta-learning to improve the exploration phase for the new task the agent is tackling. To do so, model-agnostic meta-learning is used to generate knowledge that could be easily adapted for different tasks (latent space). In addition, policy gradients methods in conjunction with meta-learning are utilized to generate and train the policies.

In the following sections ...

2 Tasks & Experiments

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3 Results

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4 Discussion

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4.1 Future Work

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5 Conclusion

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