Finding State-Action Similarities in Tabular Reinforcement Learning Using Low-Dimensional Embeddings

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Abstract

This paper proposes a method to automatically detect state-action similarities in temporal difference learning methods. Previous work showed that domain-specific state-action similarity functions can be used to speed up the training process of these learning methods on many domains, such as the popular video-game *Super Mario Bros*. In this paper, I will briefly detail the technical aspects of this method, the project deadlines and milestones, and why I believe that this automatic approach is capable of performing at least as well as the domain-specific one.

Introduction

Reinforcement learning (Sutton et al. 1998) methods are the state-of-the-art solutions in a variety of domains, from autonomous robots (Riedmiller et al. 2009) to recent developments that enabled agents to master classic video-games (Mnih et al. 2015). Such methods require an agent to learn by training: the agent explores and interacts with an unknown environment for several time-steps in order to learn how to perform an episodic or continuous task. However, this training process can often be expensive resource-wise and time consuming.

Many methods were developed in order to speed up an agent's training process from a designer's perspective, such as using domain-specific knowledge to shape it's rewards (Ng, Harada, and Russell 1999) and custom strategies (Ribeiro 1995). Recent work (Rosenfeld, Taylor, and Kraus 2017) introduced a new method called SASS that can speed up this training process significantly for temporal difference reinforcement learning methods, such as Q-Learning (Watkins and Dayan 1992), by *spreading* the Q-function estimates of an state to other similar states. SASS considers a custom similarity function that relies on a designer's input in order to compare state-action pairs. However, it is often desirable to automatize such designer-dependent processes in order to achieve a generalized solution as opposed to a custom one for each domain.

This paper proposes a novel method for automatically finding state-action similarities by comparing the distance between their low-dimensional embeddings (Nikol'skii 2012). These embeddings will be generated by an autoencoder (Hinton and Salakhutdinov 2006) that can be trained with state-action data from the domain.

In the following sections I will describe the technical aspects of my solution and how I plan to validate my implementation. Then, I will detail the schedule that I will follow in order to complete this project.

Automatic State-Action Similarity Detection Using Embeddings

Reinforcement learning problems and domains are usually represented through a Markov Decision Process (MDP). MDPs are a classical formalization of sequential decision making, where an agent interact with an environment through a set of actions. Taking actions yield immediate and delayed rewards to the agent, and changes the environment configuration (state). This change is expressed as a transition from one state to another. The environment have an action-space A and a state-space S which contain all the possible actions and states respectively. Temporal difference methods, such as *Q-Learning*, learn to estimate the value of taking action a from state s by means of a function called Q-function that receives an action-state pair as input, or (a, s) in this case .

A typical method for finding similarities in data is to compare the distance of elements in the data using some distance metric, such as the Euclidian distance. In reinforcement learning, a state is often represented as a vector of features that describe the environment's current state of affairs. For complex environments, states can have many features and their vector representation will consequently be in a high dimensional space. Working with elements in high dimensions can lead to the *curse-of-dimensionality* (Aggarwal 2005): it is often computationally expensive, hard to visualize, and prune to over-fitting.

Low-dimensional embeddings are lower dimensional representations of high dimensional data that can hold

the *semantics* of the original data. Embeddings can be generated by a type of neural network called autoencoder (Hinton and Salakhutdinov 2006). Figure 1 illustrates the structure of an autoencoder: It receives input data through an encoder that encode the incoming data into a low-dimensional embedding (or encoding), then, it decodes this embedding back to it's original dimensionality. An autoencoder is trained by gradually adjusting the network's weights based on the difference (or error) of the input x to the output x'.

This paper's main contribution is to create a similarity function $\sigma : S \times A \times S \times A \mapsto [0, 1]$, where A is the action-space and S is the state-space of a certain domain, that calculates the similarity of state-action pairs by comparing the distance between their embeddings. This function will then be implemented in an SASS agent (Rosenfeld, Taylor, and Kraus 2017) that will utilize it to *spread* Q-function estimates from one state to other similar states.

In order to evaluate my similarity function, I will compare it's performance to that of the custom made similarity function from previous work on an SASS agent that will be trained on the Super Mario Bros domain. I chose to test my implementation on the Super Mario domain since it is a popular benchmark for reinforcement learning agents (Karakovskiy and Togelius 2012) and it was one of the domains used to test the SASS agent, which will serve as the baseline for this paper.

Even though comparing state-actions using their embeddings distances may lead to sub-optimal similarity measures, the SASS agent is still capable of yielding superior results compared to other temporal difference techniques (Rosenfeld, Taylor, and Kraus 2017). Because of this, I believe that the proposed approach can yield at least comparable speed-up and winning rate when tested next to the custom SASS solution, which would be a great result, since the proposed approach is automatic and domain-independent.

Project Management

In order to implement the method proposed in this paper, I will divide the project in several milestones that will eventually lead to the whole solution, paper and presentation. Timeline 1 shows the dates and milestones considered, where: the first milestone is the Super Mario domain implementation, which should be complete in 10 days. After that, I leave 11 days for the autoencoder implementation and training, finishing all this *preparatory* work before November. In the first week of November, I will focus on the similarity method implementation, followed by another week of optimization and fine-tuning. Finally, I reserve the last week of work for writing the paper, getting the results and preparing my presentation.

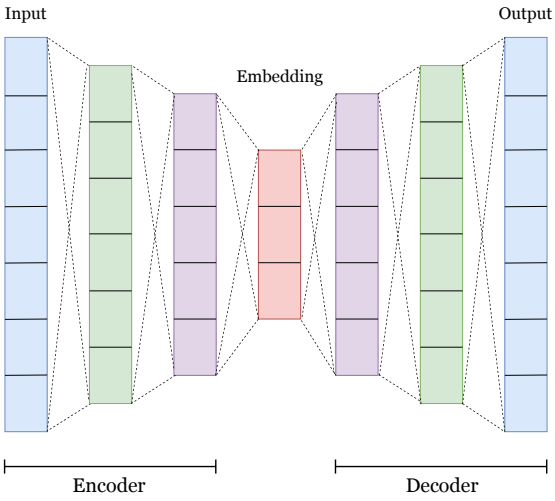

Figure 1: Autoencoder schematic structure.

TIMELINE 1: *Project Milestones*

Oct. 11	Project start
Oct. 21	Super Mario domain implementation
Nov. 1	Autoencoder implementation
Nov. 8	Similarity method implementation
Nov. 19	Optimization and fine-tuning
Nov. 26	Paper and Results
Nov. 29	Presentation

Conclusion

By the end of this project, I hope to confirm my believes that the proposed method is capable of similar or better performance to that the original SASS agent. With a generalized approach to finding state-action similarities, the SASS agent becomes a viable and interesting option from a research perspective, since it would be easier and quicker to implement.

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