Deep Q-Learning with Recurrent Neural Networks

Clare Chen
cchen9@stanford.edu

Vincent Ying
vincenthying@stanford.edu

Dillon Laird
dalaird@cs.stanford.edu

Abstract

Deep reinforcement learning models have proven to be successful at learning control policies image inputs. They have, however, struggled with learning policies that require longer term information. Recurrent neural network architectures have be used in tasks dealing with longer term dependencies between data points. We investigate these architectures to overcome the difficulties arising from learning policies with long term dependencies.

1 Introduction

Recent advances in Reinforcement Learning have led to human-level or greater performance on a wide variety of games (e.g. Atari 2600 Games). However, training these networks can take a long time, and the techniques presented in the state of the art [add reference] perform poorly on several games that require long term planning. Deep Q-Networks learn to estimate the Q-Values (long term discounted returns) of selecting each possible action from the current game state.

Deep Q-networks are limited in the sense that they learn a mapping from a limited number of past states, or game screens. In practice, DQN is trained using an input consisting of the last four states (or game screens). Thus, DQN performs poorly at games that require the agent to remember information more than four screens ago. In other words, the game could no longer be modeled as a true Markov Decision Process; all of the information needed to make an optimal action would no longer be contained in a single state. We explore the concept of a Deep Recurrent Q-network, a combination of a Long Short Term Memory (LSTM) [add reference] and a Deep Q-network. We wish to demonstrate that introducing recurrent network architecture into the Deep Q-network, the network can retain information from previous frames of the game and achieve good performance on games that require long term planning.

In addition, recent achievements of visual attention models have introduced people to exploring the possibility of incorporating attention mechanisms into the structure of the DRQN algorithm. The advantage of using attention mechanisms is that DRQN acquires the ability to select and focus on small informative regions of an input image, thus helping to reduce the total number of parameters in the deep neural network and computation operations needed for training and testing.

Deep Q-Networks (DQNs) have had success playing Atari 2600 games [0] but have struggled with particular games involving policies that require longer term information. This is evident from the types of games that DQNs perform poorly at, near or below human-level, which includes Q*bert, Ms. Pac-Man, and in an extreme case Montezuma's Revenge.

Recurrent neural networks (RNNs) have been used in modeling longer sequences and is one way to overcome DQNs difficulties with learning policies that require longer term information. We investigate augmenting DQN architecture proposed in [0], utilizing a convolutional neural network (CNN), with an RNN.

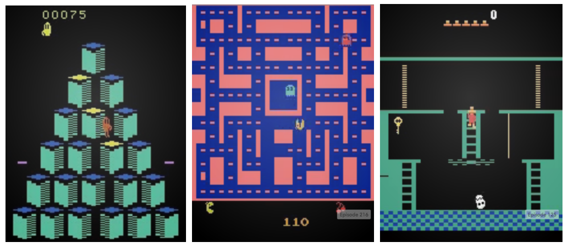

Figure 1: Q*bert, Ms. Pac-Man and Montezuma's Revenge

2 Recurrent Deep Q-Learning

We propose two architectures for the Recurrent Deep Q-Network (RDQN). The first is a very basic extension of DQN. We look at the last L states, $\{s_{t-(L+1)}, \ldots, s_t\}$ and feed these into a convolutional neural network (CNN) to get intermediate outputs $\text{CNN}(s_{t-i}) = x_{t-i}$. These are then fed into a RNN, $\text{RNN}(x_{t-i}) = h_{t-i}$, and the final output h_t is used to predict the Q value.

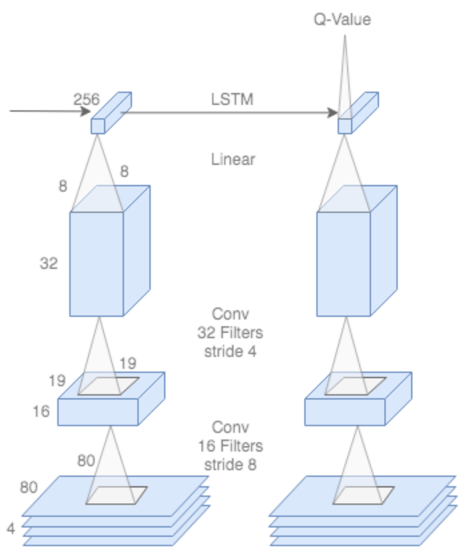

Figure 2: Architecutre of the RDQN

Another architecture we used was a version of an attention RNN. For the attention RNN we take the L hidden states outputted by the RNN, $\{h_{t-(L+1)}, \ldots, h_t\}$ and we take the inner product with a learned vector v_a, $\{v_a^T h_{t-(L+1)}, \ldots, v_a^T h_t\}$. We then take a softmax over these values, $a_{t-i} = \text{softmax}(v_a^T h_{t-i})$. We use this softmax to take a weighted sum over the hidden states to get a context vector, $c_t = \sum_{i=0}^{L-1} a_{t-i} h_{t-i}$. This context vector is then used to predict the Q value.

3 Experiments

Experiments.

References

[0] "Human-level control through deep reinforcement learning" Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves, Martin Riedmiller, Andreas K. Fidjeland, Georg Ostrovski, Stig Petersen, Charles Beattie, Amir Sadik, Ioannis Antonoglou, Helen King, Dharshan Kumaran, Daan Wierstra, Shane Legg & Demis Hassabis

[1] "Playing Atari with Deep Reinforcement Learning" Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, Martin Riedmiller

[2] "Neural Machine Translation By Jointly Learning To Align and Translate" Dzmitry Bahdanau, Kyunghyun Cho, Yoshua Bengio

[3] "Deep Recurrent Q-Learning for Partially Observable MDPs" Matthew Hausknecht and Peter Stone

[4] "Prioritized Experience Replay" Tom Schaul, John Quan, Ioannis Antonoglou, and David Silver

[5] "Effective Approaches to Attention-based Neural Machine Translation" Minh-Thang Luong, Hieu Pham, and Christopher D. Manning

[6] "Neural Machine Translation By Jointly Learning To Align And Translate" Dzmitry Bahdanau, KyungHyun Cho, and Yoshua Bengio

[7] "Deep Attention Recurrent Q-Network" Ivan Sorokin, Alexey Seleznev, Mikhail Pavlov, Aleksandr Fedorov, and Anastasiia Ignateva