

# Deep Q-Learning With Recurrent Neural Networks

Clare Chen, Vincent Ying, Dillon Laird  
Stanford, 2016

## Abstract

Deep reinforcement learning models have proven to be successful at learning control policies im- age inputs. They have, however, struggled with learning policies that require longer term infor- mation. Recurrent neural network architectures have be used in tasks dealing with longer term dependencies between data points. We investi- gate these architectures to overcome the difficul- ties arising from learning policies with long term dependencies.

## 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).
- Deep Q-networks are limited in that they learn a mapping from a single previous state which consist of a small number of game screens.
- We explore the concept of a deep recurrent Q-network (DRQN), a combination of a recurrent neural network (RNN) and a deep Q-network (DQN)
- In addition to vanilla RNN architectures we also examine augmented RNN architectures such as attention RNNs.

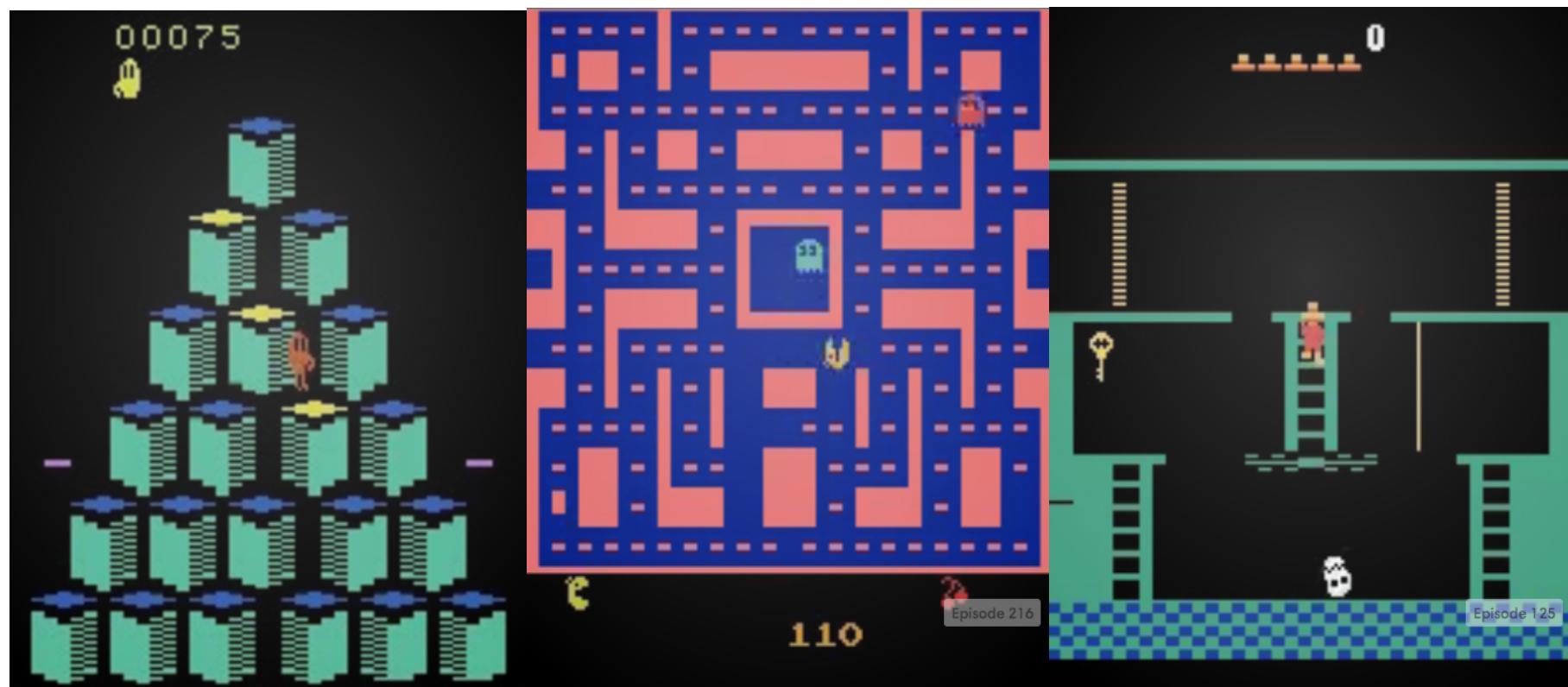


Figure 1: Q\*bert, Ms. Pac-Man and Montezuma’s Revenge

## Background

## Attention Deep Recurrent Q-Learning

## Title

### Box

Text or image?

## References

### Box

- item

## Deep Recurrent Q-Learning

## Title

- The architecture of DRQN augments DQN’s fully connected layer with a LSTM.
- We accomplish this by looking at the last  $L$  states:

$$\{s_{t-(L-1)}, \dots, s_t\}$$

- We feed these into a convultion neural network (CNN) to get intermediate outputs and finally send those through the RNN:

$$\begin{aligned} \text{CNN}(s_{t-i}) &= x_{t-i} \\ \text{RNN}(x_{t-i}, h_{t-i-1}) &= h_{t-i} \end{aligned}$$

- The final output is used to predict the  $Q$  value.