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An Investigation into Deep Reinforcement Learning

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March 20, 2018

A Final Year Project submitted in partial fulfilment
of the requirements for the degree of BAI (Computer Engineering)

Declaration

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Abstract

A short summary of the problem investigated, the approach taken and the key findings. This should be around 400 words, or less.

This should be on a separate page.

Acknowledgements

Thanks Mum!

You should acknowledge any help that you have received (for example from technical staff), or input provided by, for example, a company.

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Nomenclature

A	Area of the wing	m^2
B		
C	Roman letters first, with capitals...	
a	then lower case.	
b		
c		
Γ	Followed by Greek capitals...	
α	then lower case greek symbols.	
β		
ϵ		
TLA	Finally, three letter acronyms and other abbreviations arranged alphabetically	

If a parameter has a typical unit that is used throughout your report, then it should be included here on the right hand side.

If you have a very mathematical report, then you may wish to divide the nomenclature list into functions and variables, and then sub- and super-scripts.

Note that Roman mathematical symbols are typically in a serif font in italics.

1 Introduction

1.1 Motivation

Machine Learning (ML) and Artificial Intelligence (AI) in 2018 are subjects that are almost unique in their ability to permeate into nearly every sphere, community and space in today's society. From the research community to the business world and the public eye through extensive media coverage, ML is certainly becoming more and more of a de facto part of our everyday lives. Businesses employ recommender systems to suggest new products to their customers and predict the rise and fall of stock prices using function approximators like Deep Learning. Traditional home appliances are now outdated in favour of smarter, IoT systems that learn our habits and provide a more tailored experience.

ML is a broad umbrella term, encapsulating a variety of different approaches. Most ML tasks can be classified as either supervised or unsupervised learning. Deep Learning is fast becoming a popular and powerful technique in supervised learning, involving teaching artificial neural networks to approximate any function, given enough training data. Reinforcement Learning (RL), another subset of supervised learning, is a branch of ML that perhaps receives less public attention but is nonetheless believed to be set to revolutionize the field of AI Arulkumaran et al. [2]. Recent breakthroughs in the application of Deep Learning to RL algorithms has spawned the exciting research field of Deep Reinforcement Learning (DRL) which has produced to date unparalleled results in various AI domains, such as defeating the world champion Go player Silver et al. [3].

There are a growing number of RL methods and algorithms, such as Monte-Carlo, Q-Learning, SARSA and Policy Search Sutton and Barto [4]. More recently, the advent of DRL has brought about adaptations to existing algorithms to expand their use to multi-dimensional observations spaces such as pixel information, a notable example being Deep Q-Learning Mnih et al. [5]. It is easy to become overwhelmed with all of these offerings when exploring the RL space. The motivation behind this project is to demystify the state of the art of RL.

1.2 Objectives

The objectives of this project are threefold.

1. Research the development and state of the art of RL.
2. Build a system to evaluate the performance of three state of the art DRL algorithms by collecting a series of metrics while applying each algorithm to a selection of Atari 2600 video games.
3. Carry out the experiments, obtaining values for game score, survival time and model loss. Compare and contrast the different algorithms using the metrics recorded.

The system is given no prior knowledge of how each game works and there is no change in the underlying architecture of the solution when applied to different games, all while maintaining a high level of performance. The aim for the system is to be a general solution, that it can be expanded to work for any number of games and algorithms in the future with ease of implementation. The algorithms used are Deep Q-Learning, Double Q-Learning and Dueling Q-Learning.

1.3 Research Methods

This project takes a *case study* based approach to the experimentation. The first phase of the project involves building the system to the specification outlined previously. The second phase treats each game entered into the system as an individual case study. The game ROM is given as input to the system. The game is simulated by a third party emulator of our choosing (discussed in chapter 3), from which the system extracts greyscale frames to learn from. The output of the system is an action that it has chosen to be optimal, selected from the discrete vector of possible actions as defined by the game's control scheme. This control scheme is not provided to the system, it determines it dynamically with each game. The action is fed back into the emulator and the cycle continues up to a terminating signal.

1.4 Report Overview

Chapter 2 gives some necessary background information. It will introduce the fields of ML and RL, the seminal Deep Q-Network and the technologies and tools being used in video game RL research today.

Chapter 3 discusses the current state of the art of RL, with particular interest to the fields of robotics, natural language processing and video games.

Chapter 4 outlines the architecture of the system and the rationale behind certain design decisions.

Chapter 5 will discuss the components of the experiment evaluation. It will give a greater elaboration of the project's objectives, a description of the experimental setup, and a discussion of the results.

Chapter 6 closes the project with a conclusion of all that has been discussed, an outline of what has been achieved from both an objective and personal point of view and finally a suggestion for future work.

2 Background

This chapter will give an introduction to the fields of ML, RL and DRL. We will mainly focus on the knowledge that is pertinent to this project. The DRL section will outline the algorithms that are used in the comparisons later in the project. We will close with a discussion on the different tools used in RL research, specifically within the video game test bed.

2.1 Machine Learning

2.1.1 Introduction

ML is a broad umbrella term for various methods of giving computer systems the ability to 'learn' to complete some task efficiently using training and validation data, without being explicitly programmed to do so. Instead of following a programmed set of instructions to make a prediction, the ML system constructs a model that is a function approximated to some real world problem. ML tasks can be divided into two categories; supervised and unsupervised learning. In supervised learning, the dataset provides the correct output prediction, 'labelled' data, the system should make. The system can use the input/output pairs to iteratively learn the best prediction, using a combination of some generic error function, such as the *Mean Squared Error*, and the *Back Propagation* algorithm (Chauvin and Rumelhart [6]) to update the model. In unsupervised learning, the dataset does not contain any output data points, 'unlabelled' data, hence it is more difficult to gauge the performance of an unsupervised ML algorithm. Unsupervised learning is generally used in the clustering of data into classes.

2.1.2 Development of Machine Learning in Video Games

In order to claim that an AI agent achieves general competency, it should be tested in a set of environments that provide a suitable amount of variation, are reflective of real world problems the agent might encounter, and that were created by an independent party to remove experimenter's bias (Bellemare et al. [7]). In this way, video games provide an effective test-bed for efficiently studying general AI agents as they can provide all of these requirements. Although the application of ML generated AI to video games may seem novel, the end goal is not to produce agents for defeating world champion chess players, but to take these general agents and extend them to more pressing problems to humanity, of which there are endless possibilities.

The first application of notoriety to use computing to play a game arose in the research paper (Shannon [8]), where mathematician Claude Shannon developed an autonomous chess-playing system. In that paper, author Shannon also highlighted the point that although the application of such a solution may seem unimportant;

> "It is hoped that a satisfactory solution of this problem will act as a wedge in attacking other problems of a similar nature and of greater significance"

Claude designed a strategy that, even at the time, was infeasible as it would take more than 16 minutes to make a move.

Fast forward to 1997, IBM developed "Deep Blue," a network of computers purpose built to play chess at an above-human level. It is renowned as the first AI system to defeat a world champion chess player, Garry Kasparov under normal game regulations. There is an air of controversy surrounding the feat, as IBM denied any chance of a replay after Kasparov claimed that IBM cheated by actively programming moves into Deep Blue as the game was in play.

In more recent times, British AI research company DeepMind published the paper (Mnih et al. [5]) in which they achieved far and above human-level performance on a selection of 52 Atari 2600 games with their Deep Q-Network algorithm. DeepMind have since applied their techniques to modern, real time, strategy game StarCraft2 (Vinyals et al. [9]), which we will discuss in the State of the Art chapter.

2.2 Reinforcement Learning

2.2.1 Introduction

RL is another case of ML tasks, which can come under the supervised and unsupervised learning categories. It is a general way of approaching optimisation problems by trial and error. An agent carries out actions in an environment, moving from one state to a new state and is given some positive or negative numerical reward. This is known as the *perception-action-learning loop*.

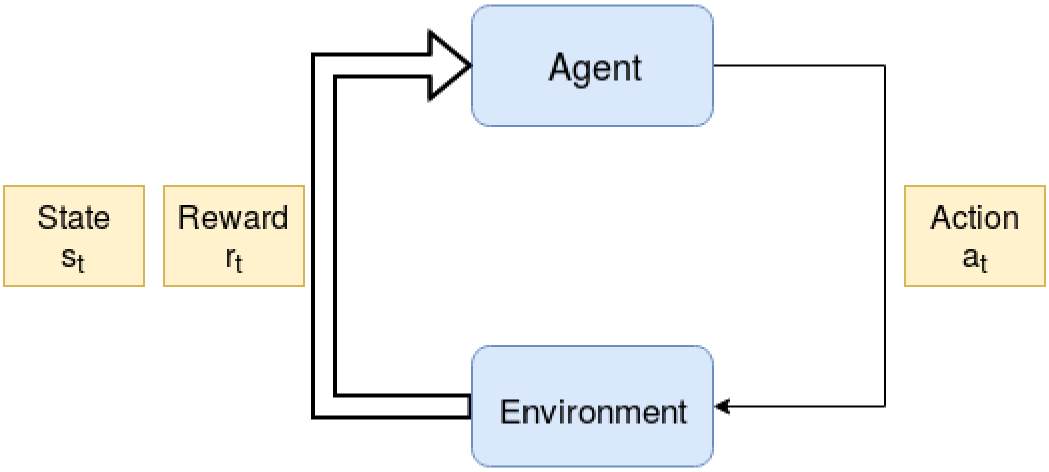


Figure 2.1: The perception-action-learning loop

RL is an interesting method of accomplishing ML tasks, as the agent can be given no prior information about it's environment or the task, and it can learn based solely on trial and error, reward and punishment. There are 3 main parts to a RL problem setup.

1. An agent follows a *policy* π, a rule that maps a state to an action.
2. A *reward function* $R(s, a)$, that gives an immediate value to an action a taken by the agent to transition from state s to s'
3. A *state value function* $V(s)$ that measures 'how good it is' to be in a given state. It assigns a value to the cumulate reward an agent can expect to gain by being in a state and following a policy through all subsequent states. We can define this as the *discounted cumulative reward*:

$$V(s) = E(\sum_{t=0} \gamma^t R(s_t, a_t)|s_0 = s) \qquad \forall s \in S \tag{1}$$

Where γ is a discount factor $[0, 1]$ and we choose $a_t = \pi(s_t)$. The objective of a RL problem is learning the optimal policy π^*, that for any given state will point the agent to the most favourable action so as to maximize it's cumulative reward, $V^*(s) = \max_\pi V(s)$. RL algorithms such as Q-Learning are used to find this optimal policy.

2.2.2 Markov Decision Process

In a more formal setting, it is a soft assumption that RL problems qualify as a Markov Decision Process (MDP) and can be modelled as such (Arulkumaran et al. [2]). MDP's display the Markov Property; that the conditional probability distribution of future states is dependant only on the current state and totally independent of all past states. A MDP consists of:

- A finite set of states S
- A finite set of actions A
- A transition function $P(s, a, s') = P(s_{t+1}|s_t, a_t)$, a model mapping current state, action pairs to a probability distribution of potential future states.
- An immediate reward function $R(s, a)$

Again, an MDP seeks to find the optimal policy π^*. We define π^* as

$$\pi^* = argmax_a\{\sum_{s'} P(s, a, s')(R(s, a) + \gamma V(s')\} \tag{2}$$

2.2.3 Model-Free Learning

Not all RL problems are provided with a transition function $P(s, a, s')$. In fact, it is more often than not that we cannot express the agent's environment with a model. Such a scenario is called *model-free learning*, where the agent must learn the optimal policy without the use of a transition function to guide it on which action to take. Instead it must devise some other way of modelling it's environment, such as building a 'memory' of actions and rewards based on experiences and deriving an optimal policy from these experiences. The downside to this is the potentially large amounts of auxiliary space needed to store the experiences. This is where algorithms such as Q-Learning are used.

Q-Learning is a model free RL algorithm. At each state, the agent calculates an immediate reward, based solely on the current state and action taken, and the *quality* of taking an action a in state s and following a policy π thereafter, called the Q-Value, which is defined as:

$$Q(s,a) = E(\sum_{t=0} \gamma^t R(s_t, a_t) | s_0 = s, a_0 = a) \qquad \forall s \in S \tag{3}$$

Where we have chosen a_0 arbitrarily and choose all subsequent $a_t = \pi(s_t)$ thereafter. As the agent explores all states multiple times and experiments with different actions, the corresponding Q-values are saved and updated in a data structure, hence an optimum policy can be derived by finding the optimum Q-values $Q^*(s,a)$ for all states after a predetermined number of iterations or until the policy is 'good enough'. The update step for a Q-Value is defined as:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(r_t + \gamma max_a Q(s_{t+1}, a) - Q(s_t, a_t)) \tag{4}$$
$$\delta = r_t + \gamma max_a Q(s_{t+1}, a) - Q(s_t, a_t) \tag{5}$$

We define δ as the Temporal Difference Error (TDE). It is an error function that is used in many RL algorithms. α is a hyperparameter called the *learning rate* chosen in the range $(0,1)$. As $t \to \infty$, $Q_t \to Q_t^*$, we converge on an optimum solution. The data structure used to store the agent's experiences can be referred to as the Q-Matrix. It is a $|S|x|A|$ sized matrix, that is the total number of states x total number of available actions.

$$Q = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 100 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 80 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

Figure 2.2: An example Q-Matrix. 0 indicates an unexplored state, action pair

The agent follows algorithm 1, detailed below. After a suitable number of iterations and exploration, the Q-Matrix becomes a 'map' for the agent, whereby it can look up the action with the highest Q-Value for any state (Watkins and Dayan [10]). Q-Learning is a straight-forward, elegant solution to a RL task. However, for an environment space of high dimensionality, such as an array of RGB pixels from an image, the Q-Matrix becomes infeasibly large in the S dimension and increasingly sparse, as only a small percentage of the total available state, action pairs will be visited. As a worked example, imagine a robot that is using Q-Learning to find a path from it's current position to some exit room. If the robot takes 210x160, 8-bit colour space, RGB photos of it's surroundings to represent a state, the S dimension becomes $256^{210 \times 160 \times 3}$ in size. A solution to the dimensionality problem was proposed by DeepMind, in the paper (Mnih et al. [5]) which will be discussed later in this chapter.

Algorithm 1 Q-Learning Algorithm

```
procedure BUILDING Q-MATRIX
    Set $\alpha$ and $\gamma$ parameters.
    Initialize Q-Matrix to zero.
    repeat
        while Goal/terminal state not reached do
            Select $a$ randomly from all possible actions in current state
            Consider going to state $s_{t+1}$ from state $s$ using action $a$
            Get maximum Q-Value from $s_{t+1}$ considering all possible actions
            $Q(s, a) \leftarrow (1 - \alpha)Q(s_t, a_t) + \alpha(r_t + \gamma max_a Q(s_{t+1}, a))$
        end while
    until Policy good enough
end procedure
procedure USING Q-MATRIX
    $s \leftarrow$ initial state
    while Goal/terminal state not reached do
        $a \leftarrow max_a Q(s, a)$
        $s \leftarrow s_{t+1}$ taking action $a$
    end while
end procedure
```

2.2.4 Exploration vs. Exploitation

There is a fundamental issue in any RL task, where the agent must choose between taking an instantaneous reward by exploiting the policy, or taking a random action to explore the environment in search of a potentially higher long term reward. This problem is illustrated by a well-known RL problem known as the k-armed bandit problem.

> "The agent is in a room with a collection of k gambling machines (each called a 'one armed bandit' in colloquial English). The agent is permitted a fixed number of pulls, h. Any arm may be pulled on each turn. The machines do not require a deposit to play; the only cost is in wasting a pull playing a suboptimal machine. When arm i is pulled, machine i pays off 1 or 0, according to some underlying probability parameter p_i, where payoffs are independent events and

> the p_i's are unknown. What should the agent's strategy be?" (Kaelbling et al. [11])

The amount of time the agent spends in the environment is one factor that can be taken into consideration when making this decision. In general, the longer the agent spends in the environment, the less impact taking an exploratory approach, sometimes towards a sub-optimal policy, will have on the end policy.

One solution to this dilemma is to take an *epsilon greedy policy*. At each state, the agent takes a random action with a probability of ϵ and an action from the policy with a probability of $(1 - \epsilon)$. ϵ is linearly reduced at each iteration to some predetermined floor value. This way, the agent will spend more time exploring at the start of it's interaction with the environment, and will then (hopefully) converge to an optimal policy as it progresses.

2.3 Deep Reinforcement Learning

2.3.1 Introduction

DRL refers to the use of deep learning algorithms within the field of RL. As mentioned previously, RL struggles with environments of high dimensionality. DRL overcomes this issue thanks to the universal function approximation property of deep neural networks and their abilities to isolate and recognize features of interest within high dimensional data and to compactly represent that high dimensional input data (Arulkumaran et al. [2]). DRL can utilize a convolutional neural network to learn a representation of the environment on behalf of the agent through high dimensional sensory input such as video data. A set of fully connected layers are then generally used to approximate the target of the underlying RL algorithm, such as $V(s, a)$, $Q(s, a)$, an action etc. The deep neural network can then be trained using an appropriate variant of the backpropagation algorithm, such as stochastic or batch gradient descent.

2.3.2 Deep Q-Network

The event that brought DRL to the attention of the research community was from the paper (Mnih et al. [5]). DeepMind created a variant of Q-Learning called Deep Q-Network, that achieved above-human level performance on a large selection of 52 Atari 2600 video games.

They combined a convolutional neural network for feature detection, and a fully connected network to learn the Q-Values for all available actions, with ReLU activations within each layer. The network uses a standard Least Square Error loss function in training with gradient descent, defined as:

$$L = (y_t - Q(s, a))^2 \tag{6}$$

$$y_t = r + \gamma max_a Q(s_{t+1}, a) \tag{7}$$

This architecture was named the Deep Q-network. This breakthrough successfully removes the dimensionality problem, as there is no need to keep a data structure storing all previous experiences. The deep neural network takes an array of RGB pixel information, taken as a stack of 3/4 (depending on the game) greyscale frames, as input to the convolutional network. The fully connected network outputs a vector of Q-Values for each available action in the game.

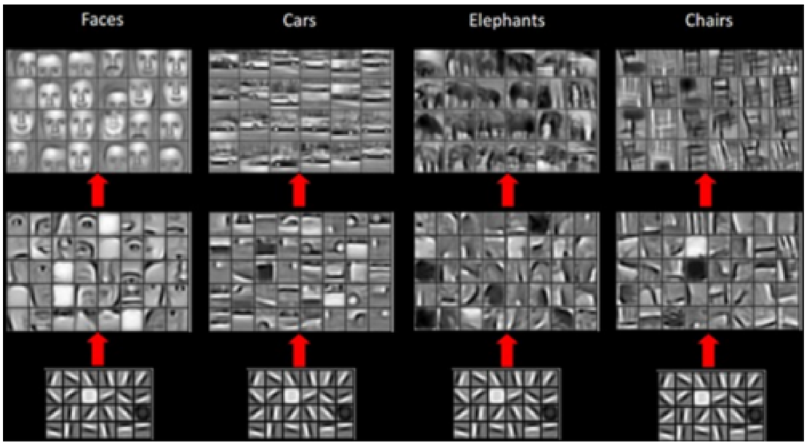


Figure 2.3: Examples of output filters from a convolution neural network

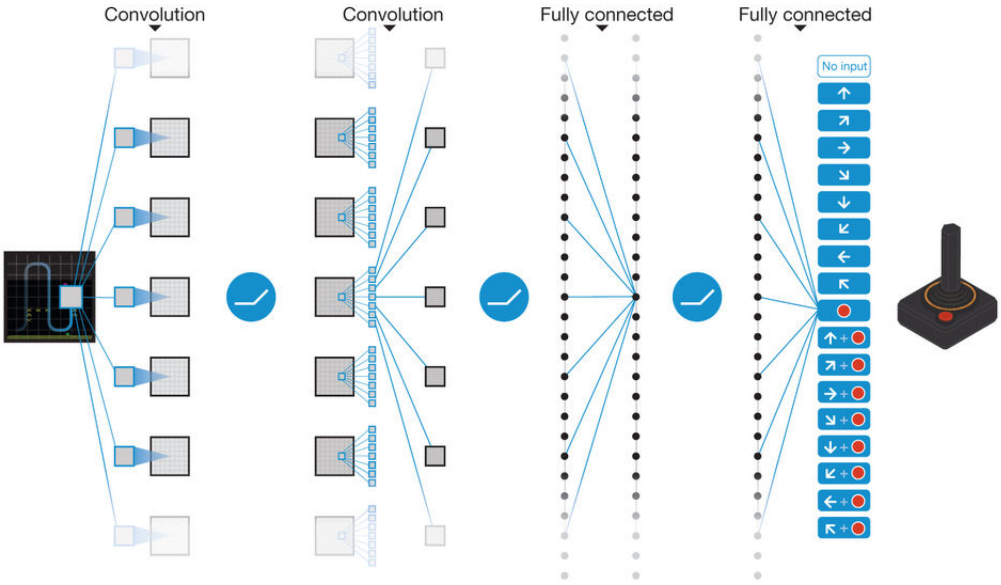


Figure 2.4: The original Deep Q-network Architecture

2.4 RL Research Tools for the Video Game Test Bed

2.4.1 OpenAI Gym

The OpenAI Gym is a high-level Python API that provides a suite of environments on which to perform RL research (Brockman et al. [12]). These environments range from physics problems such as balancing a pole, to a small selection of Atari 2600 video games, to robotics tasks like teaching a robot to walk or landing a space ship on a planet safely.

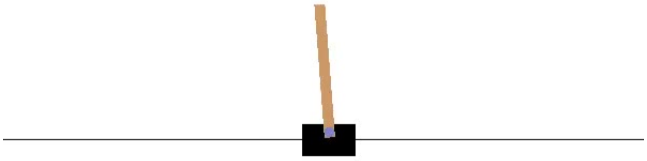


Figure 2.5: The CartPole environment, where an agent must move the cart left and right to keep the pole balanced

```
        state = env.reset() # create starting state
        action = agent.act(state) # agent chooses first action

        nxt_state, reward, done, info = env.step(action)
        if done:
            break
        ...

```

Figure 2.6: Typical code snippet from OpenAI Gym Python API

The user must write their own agents to interact with the provided environments. In the above code snippet, the `env` object is one of the environments provided by the API, and the `agent` object would be written by the user, including the `act(state)` method. The `(nxt_state, reward, done, info)` tuple is about the extent of the information about the environment that can be gathered using the API. For this reason, as will be discussed in the Design chapter, OpenAI Gym was not used in the implementation of this project. However, it remains an excellent tool for a beginner to become acquainted with RL problems.

2.4.2 The Arcade Learning Environment

The Arcade Learning Environment (ALE) (Bellemare et al. [7]) is a framework for assisting RL researchers in testing AI agents on Atari 2600 video games. It is similar to OpenAI Gym, in fact OpenAI Gym uses the ALE under the hood for it's Atari 2600 environments, however it is much more low level. It's main supported language is C++, it will provide full functionality to any agents written in C++. There is however an excellent Python interface with almost complete functionality; more than enough for the purposes of this project. For languages other than C++ or Python there is an intelligent text based mechanism using pipes called the FIFO Interface that allows *any* programming language to use the ALE with a restricted set of services.

The ALE provides much more functionality than OpenAI Gym without being much more complex to program with. We can load a selection of 52 supported Atari 2600 ROMs to experiment with, all having different graphics, control schemes, scoring mechanisms etc. hence the ALE provides a nicely varied selection of environments against which to test AI agents. Just some of the features we can extract while an agent is running are:

- The current game screen as an RGB or greyscale array of pixels.
- The number of frames the agent has played in total and since the last game reset.

- A list of all available actions on the Atari 2600 and a tailored list of actions used in the specific game being played.
- The number of lives (if provided) the agent has remaining.
- Query at any time if the game has terminated (game over), not just after a state transition as in OpenAI Gym
- Change difficulty mode, if the specified game supported it on the original Atari 2600.
- Video and sound recording
- The internal state of the 128-byte RAM of the game.
- Load and save states.

As well as all of the expected features such as processing an action in the environment and returning a reward. By default, the returned reward is the difference in game score during the state transition caused by an action.

The ALE provides many more practical features than OpenAI Gym, however there are some drawbacks to using the ALE. The researcher is restricted to using just Atari 2600 environments, which means an inherently high-dimensional problem as the agent will more than likely represent a state as an array of pixels. OpenAI Gym provides a lot more lower-dimensional environments, such as the physics based CartPole where the state is represented as a much shorter tuple of `(cart position, cart velocity, pole angle, pole velocity)`.

3 State of the Art

The current state of the field of RL is vast. More and more it is being utilized as the next step towards more efficient and intelligent ML systems (Arulkumaran et al. [2]). This section will be divided into two discussions. The first will give a basic survey of the types of different applications of RL today. The second section will discuss the state of the art for RL research within the video game test bed.

3.1 Robotics

Robotics is a field very suited to RL techniques. It closely follows the basic definition of an RL task involving an agent exploring an environment through trial and error to maximize some reward function. Although it is well suited, there are many challenges that face RL techniques in robotics. The recent work of (Mnih et al. [13]), the A3C algorithm (see subsequent section for an explanation of the algorithm), is an example of state of the art RL techniques addressing one of the most pressing issues for RL in robotics: the 'curse of dimensionality' with respect to the navigation of a robot through a complex environment. Coincidentally A3C has provided state of the art results in video game AI agent research results.

The representation of state in robotics is often imperfect and noisy due to it's high levels of dimensionality and the resolution reduction of continuous physical measurements to discrete digital computer/controller representations. A mechanical representation of state such as robot limb position, or any other physical measurement can have many degrees of freedom (DOF). In addition to state complexity, the action space in contrast to the Atari domain which is fixed and simple, can reach high dimensionality due to multiple DOF and the hardware complexity of most modern robots, where there can be a large number of motors and other components working in tandem, each adding to the complexity of the total action space.

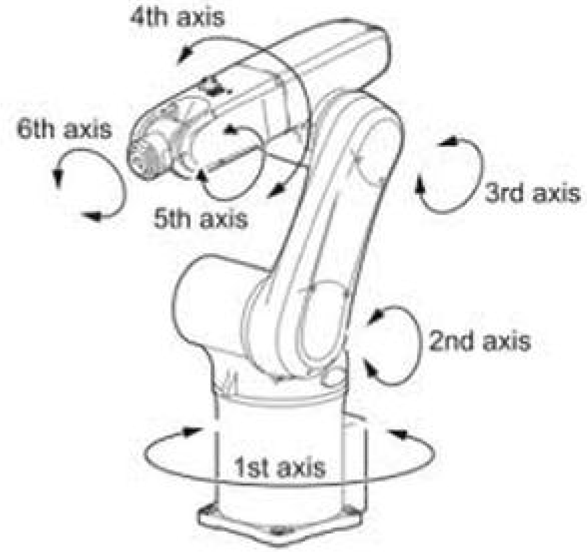


Figure 3.1: Example DOF figure of a robotic arm

With respect to a robot that navigates through a complex, partially observable environment with dynamic obstacles, in addition to the high dimensional state size, the memory efficiency of remembering past experiences becomes a pressing issue as it is of utmost importance for a robot learning to navigate to be able to utilize past experiences to map its surroundings. A3C abandons experience replay in favour of a stacked Long Short Term Memory (LSTM) network running multiple agents that are exploring the environment in parallel, providing a wider range of experiences that scales with the number of parallel agents employed. This dramatically increased the memory efficiency of the implementation.

3.2 Natural Language Processing

Deep learning, more so than DRL, has been permeating into the field of Natural Language Processing (NLP). There have been many exciting revelations in NLP in recent years that interface with users regularly, such as chat bots, text prediction and machine translation (MT) etc.

MT is simply defined as the sub-field of computer linguistics that investigates the use of software to translate text or speech from one language to another. The ability for systems to recognize full phrases and sentences and translate those accurately instead of simply substituting words is what defines good MT systems from others, as the latter will almost always be rife with grammatical errors in the target language. Neural Machine Translation (NMT) introduces deep learning into the MT sphere, to further the ability to recognize phrases and sentences. Recurrent neural networks (RNNs) are popular in NTM systems, owing to their internal memory which is suited to picking out patterns and phrases, as opposed to fully feed forward networks with no concept of internal remembrance. The basic architecture involves two RNN's, an encoding layer at the input sentence and a decoding layer at the translated sentence output.

The current state of the art in NMT is Google's Neural Machine Translation (GNMT) system Wu et al. [14]. It tackles the issues of speed of translation/inference, robustness in the face of translating sentences containing 'rare' words and incomplete translations. These are three issues that have *severely* hampered the deployment of MT systems into production. The network architecture consists of an LSTM encoder with 8 layers and the same at the output. The residual connections between layers in the encoder and decoder, to introduce parallelism, and low-precision arithmetic during inference computations are used to tackle the speed of translation problem. Breaking up words into sub-word units or 'wordpieces' reduces the chances of finding 'rare' words by translating on sections rather than full words, but provides a balance of compute time over single character scale translation. Finally, a beam search technique to tackle the issue of incomplete translations. With these three features, GNMT has proved itself as a state of the art for MT and is in fact used in production at Google today.

3.3 Deep Reinforcement Learning

3.3.1 Improvements to Deep Q-Network

In 2013, the DQN breakthrough was the state of the art. Since then, many improvements and adaptations have been made on this model, by DeepMind and other research groups. Such examples include the Double Q-Network adaptation (Van Hasselt et al. [15]) and the Dueling Q-network architecture (Wang et al. [16]). Experience replay and target networks were two techniques added to the original architecture by DeepMind to add more stability to the learning process. Prioritized experience replay was then built on from experienced replay providing even better performance.

Experience Replay and Target Network

Instead of learning from the immediately previous experience when training the network, a large memory of past experiences are stored as tuples of $(s_t, a_t, r_t, s_{t+1}, \mathit{term})$, where *term* is a boolean indicating if this state transition was terminal (a gameover). The network is then trained from a random sampling of past experiences from this replay memory. It was found to greatly reduce the number of interactions the agent needed to have with the environment. However, this technique *is somewhat* limited as there is no way to differentiate important experiences from unimportant ones.

The target network is a secondary network $\hat{Q}$ cloned from the online Q-network Q, that is used to predict the targets y_i when training Q. The weights of $\hat{Q}$ are cloned from Q every τ training steps. This modification makes the algorithm more stable, as an increase to $Q(s_t, a_t)$ was often found to also increase $Q(s_{t+1}, a)$ for all a, thus also increasing the targets y_i. This can create a diverging solution in some cases. Freezing the weights makes the updates to Q and the targets y further apart, decreasing the likelihood of divergence (Mnih et al. [1]).

Algorithm 2 Deep Q-Network Algorithm with Experience Replay and a Target Network

```
Initialize replay memory $D$ to capacity $N$
Initialize $Q$ with random weights $\theta$
Initialize $\hat{Q}$ with weights $\theta^-$ cloned from $\theta$
for episode = 1, M do
    Initialize arbitrary first sequence of frames for initial state
    for t = 1, T do
        With probability $\epsilon$ select a random action $a_t$, otherwise select $a_t = max_a Q(s_t, a)$
        Execute action $a_t$ and observe reward $r_t$ and state $s_{t+1}$
        Store state transition $(s_t, a_t, r_t, s_{t+1}, term)$ in $D$
        Sample random mini batch $(s_i, a_i, r_i, s_{i+1}, term)$ from $D$
        if $term = true$ then
            Set $y_i = r_i$
        else
            Set $y_i = r_i + \gamma max_a Q(s_{i+1}, a)$
        end if
    end for
    Perform a gradient descent step on $(y_i - Q(s_i, a_i))^2$
    if $t$ is a multiple of $\tau$ then $\theta^- \leftarrow \theta$
    end if
end for
```

Double Deep Q-Network

In the standard Deep Q-Network algorithm 2.14, when training we use the same Q-Value to select and evaluate an action for the target y. This can result in overoptimistic Q-value estimates over time, leading to sub-optimal policies as certain actions are erroneously favoured over others due to early over estimations. Double Deep Q-Network (Van Hasselt et al. [15]) separates action selection from action evaluation in the target y. The online network Q still estimates the best action to take based on a max operator on it's predicted vector of Q-values. We reuse the target network to then evaluate the effectiveness of this action. The updated target equation is given as:

$$y_i = r + \gamma \hat{Q}(s_{i+1}, argmax_a Q(s_{i+1}, a)) \tag{1}$$

As with the original target network optimisation, the weights from Q are copied to $\hat{Q}$ every τ training updates.

Algorithm 3 Double Deep Q-Network Algorithm

```
Initialize replay memory $D$ to capacity $N$
Initialize $Q$ with random weights $\theta$
Initialize $\hat{Q}$ with weights $\theta^-$ cloned from $\theta$
for episode = 1, M do
    Initialize arbitrary first sequence of frames for initial state
    for t = 1, T do
        With probability $\epsilon$ select a random action $a_t$, otherwise select $a_t = max_a Q(s_t, a)$
        Execute action $a_t$ and observe reward $r_t$ and state $s_{t+1}$
        Store state transition $(s_t, a_t, r_t, s_{t+1}, term)$ in $D$
        Sample random mini batch $(s_i, a_i, r_i, s_{i+1}, term)$ from $D$
        if $term = true$ then
            Set $y_i = r_i$
        else
            Set $y_i = r_i + \gamma \hat{Q}(s_{i+1}, argmax_a Q(s_{i+1}, a))$
        end if
    end for
    Perform a gradient descent step on $(y_i - Q(s_i, a_i))^2$
    if $t$ is a multiple of $\tau$ then $\theta^- \leftarrow \theta$
    end if
end for
```

3.3.2 Current State of the Art for Deep Q-Network

Dueling Q-Network Architecture

The Dueling Q-Network Architecture is an improvement on the original Deep Q-Network's single stream, convolutional network into a single fully connected layer network architecture. It *does not* provide any change to the underlying algorithms at work. For this reason, it can be applied to other RL algorithms that use Q-Values. The single stream fully connected layer is separated into two streams. One stream estimates the state value functions $V(s)$ and the other estimates a new function, the action advantage function $A(s, a)$.

$$A(s, a) = Q(s, a) - V(s) \tag{2}$$

The two streams are aggregated at the final layer to output $Q(s, a)$. The convolutional network in the upper half remains unchanged. $V(s)$ and $Q(s, a)$ we have explained the intuition for previously. The action advantage function $A(s, a)$ gives a relative importance of each action in a given state. Hence, the dueling architecture can learn which states are valuable separately from the effect of each action in each state.

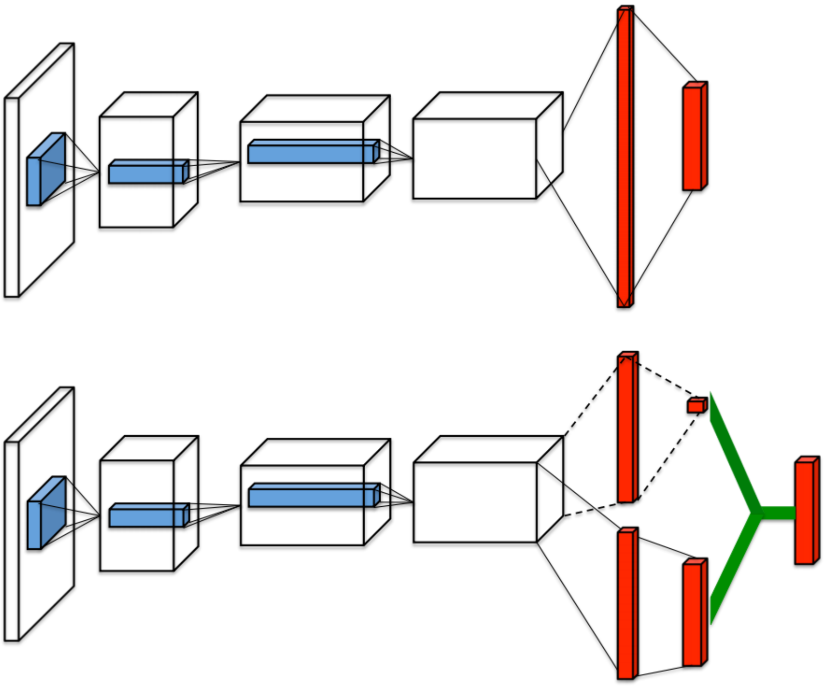


Figure 3.2: The original Deep Q-Network (above) vs. Dueling Q-Network (below) architecture

The aggregating layer is not a simple sum of $A(s, a)$ and $V(s)$. It was found that equation 2 "is unidentifiable in the sense that given Q we cannot recover V and A uniquely" (Wang et al. [16]). Instead we use a slightly augmented version:

$$Q(s, a) = V(s, a) + (A(s, a) - max_{a'}A(s, a')) \tag{3}$$

Prioritized Experience Replay

In regular experience replay, transitions are sampled randomly and uniformly from the replay memory collection, with no regard to which transitions the agent might learn more from at any given time. Prioritized experience replay was first suggested by (Schaul et al. [17]) as a way to improve the efficiency of regular experience replay by replaying more important transitions more frequently. It is difficult to quantify the importance, or potential learning progress an agent can expect by replaying a transition, hence a reasonable estimation can be made to approximate it. (Schaul et al. [17]) approximate learning progress with the magnitude of the TDE of a transition, a suitable value as many RL algorithms use TDE, including Q-Learning. Along with the tuple $(s_t, a_t, r_t, s_{t+1}, term)$, the TDE, δ is now also stored with each state transition. The TDE of each transition is updated after being sampled to prevent the highest rank transition from always being sampled.

A greedy prioritization, where the maximum TDE experiences are always sampled is flawed. Transitions that first occur with a low TDE will effectively never be revisited. The same small set of experiences are repeatedly sampled, with such a lack of diversity the model is likely to overfit. To overcome this (Schaul et al. [17]) propose a stochastic prioritization policy with two variants.

$$P(i) = \frac{p_i^\alpha}{\sum_k p_k^\alpha} \tag{4}$$

$$p(i) = |\delta_i| + \epsilon \tag{5}$$

$$p(i) = \frac{1}{rank(i)} \tag{6}$$

Where $P(i)$ is the probability of sampling transition i, k is the number of transitions in the replay memory, $p(i)$ is the priority of transition i and it's two variants are shown. Variant 1 is similar to a greedy prioritization, but ϵ prevents 0 TDE transitions from never being sampled. Variant 2 is based on *rank*, where $rank(i)$ is the rank of transition i over all transitions when sorted by $|\delta|$.

3.4 Video Games

3.4.1 A3C

The team at DeepMind, in (Mnih et al. [13]) propose a new framework for training DRL agents. Multiple copies of the same agent are run asynchronously on a separate thread, all performing gradient descent updates to a single common neural network. At any given time, every agent will likely be experiencing a different state, giving a much greater view of the environment. This helps to mitigate the exploration vs. exploitation dilemma previously discussed. The framework, which we will refer to as 'asynchronous methods,' can be used to augment many different pre-existing DRL algorithms to improve their performance. As well as performance improvements, this framework significantly cuts the time to train an agent in the Atari 2600 test bed and can be accomplished on a standard multi-core CPU, as opposed to previous methods that have used specialized, expensive, GPU hardware. The results obtained in (Mnih et al. [13]) from their experiments were carried out on an unspecified 16-core CPU and an Nvidia K40 GPU. At the time of writing, an AMD Ryzen 1950X 16-core CPU costs $874 and an Nvidia K40 costs $2300 (prices from `www.amazon.com`). Thus asynchronous methods further lowers the economic barrier to entry to DRL.

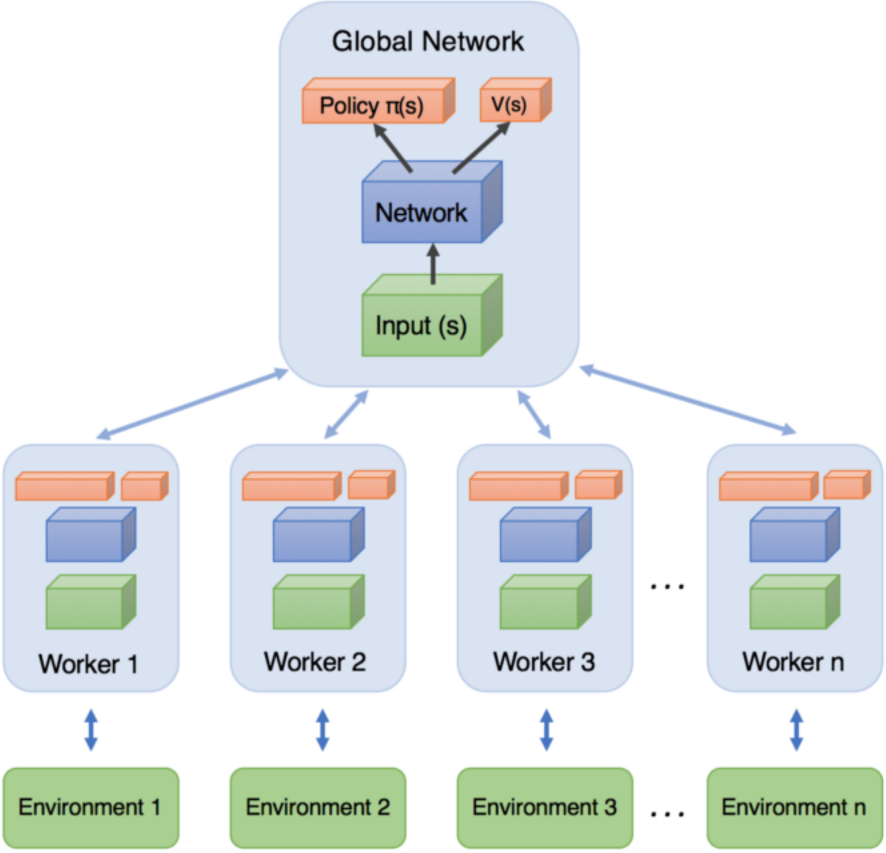


Figure 3.3: High level overview of Asynchronous Methods

Of the four augmented algorithms tested in (Mnih et al. [13]), Asynchronous Advantage Actor-Critic (A3C) stands as the current state of the art algorithm for training DRL agents. It performs better than all other competitors, including the most recent revisions of Deep Q-Network, in the Atari 2600 test bed in terms of game score, and in half the time of the previous state of the art. Additionally, DeepMind applied A3C to an interesting problem outside of the video game domain. An AI agent was taught to navigate the 3D maze environment Labyrinth, collecting rewards. The collectables were apples - worth 1 point and portals - worth 10 points. The agent was placed in a randomly generated maze each episode and was given 60 seconds to accumulate as much reward as possible. The agent peaked with an average score of 50, indicating that it had learned a general strategy for exploring randomised environments. The applications of this feat to fields such as robotics is exciting.

3.4.2 Games of Imperfect Information

Games of imperfect information mean that the player is unaware of the state or actions chosen by the opposite player. Games of imperfect information include Texas Hold'Em Poker, as players do not know the other player's card and Real-time strategy (RTS) games, as players cannot see the areas of the map where the other players are until they explore those areas. These scenarios provide new challenges for training more intelligent AI agents.

Case Study: StarCraft 2 Learning Environment

The StarCraft 2 Learning Environment (SC2LE) is a platform for testing RL AI agents in the game StarCraft 2, an RTS of imperfect information (Vinyals et al. [9]). It was created by DeepMind in collaboration with Blizzard Entertainment, the creators of StarCraft 2. The game is exceedingly more complex than the Atari 2600 games we have discussed previously.

- Modern graphics. StarCraft 2 is a modern 3D game with a movable isometric camera perspective. This makes representing observations as a stack of game frames very difficult, as the pixel counts are high and parallax error is introduced.
- Action space. The diversity of actions in StarCraft 2 is far higher, with approximately 10^8 possibilities in a point-and-click fashion. Many actions require a sequence of primitive actions such as, drag box around units, select building to build, place building on map. The player can be controlling potentially hundreds of units of many different types and abilities, as well as having to manage resources, building and ensure the opposing players aren't attacking.
- Multiple agents. There can be up to 4 players in one game, all competing against one another for map control. This is a stark contrast to the single player Atari 2600 games competing against a single built-in game AI.

- Imperfect information. There is a 'fog-of-war' element that hides parts of the map the player does not actively have units in.
- Delayed rewards. The action of building a number of units, exploring an area of the map etc. can have rewards that do not materialize for many, many time steps. This provides a new frontier for agents capable of creating long term strategy.

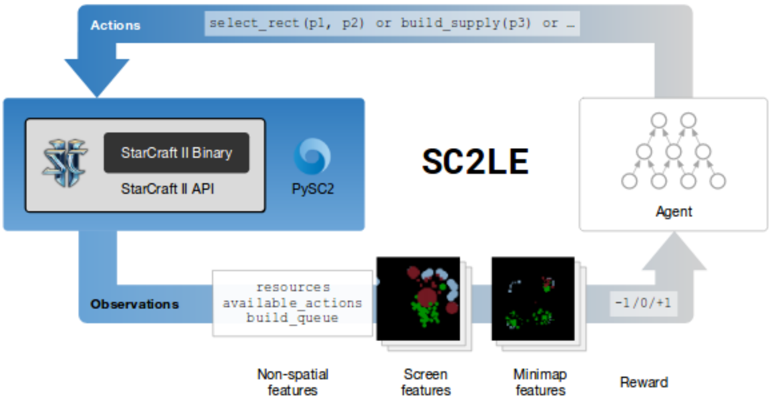


Figure 3.4: SC2LE interacting with an AI agent

For a more complete breakdown of the complexity of StarCraft 2, we refer the reader to the paper (Vinyals et al. [9]), specifically section 3.2.

SC2LE provides a high level Python API for programmatic interaction with StarCraft 2, called PySC2 that has been optimized for training RL agents. To tackle the aforementioned problem of high dimensional 3D game graphics, PySC2 abstracts away the game's graphics and replaces them with feature layers, primitive shape objects representing more complex in-game objects, while still maintaining some spacial aspects.

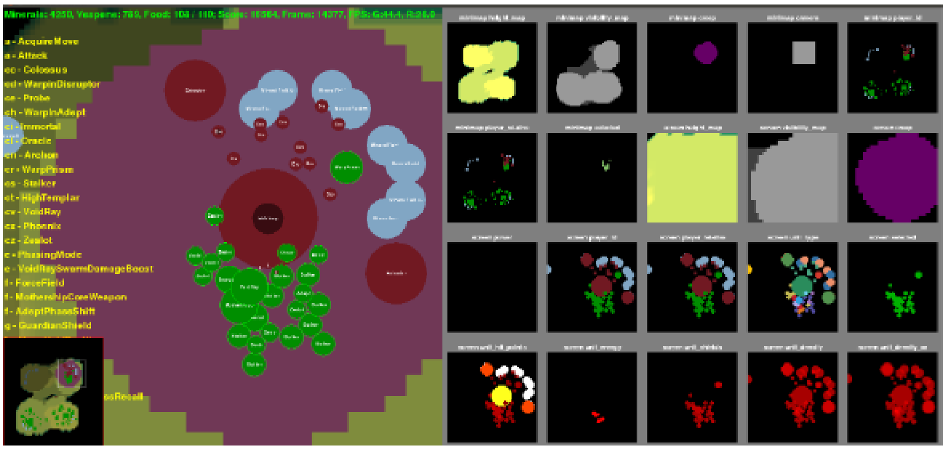


Figure 3.5: The feature layers of PySC2

In the figure above, on the left side, we can see a specific type of attack unit being represented as the green circles, resources as grey circles, worker units as small red circles etc. On the right side are different representations of features available from the full resolution mini-map, including height (top left), visibility (second from top left) and unit hit points or lives (bottom right).

SC2LE provides a set of 'mini-games,' which are stripped down versions of the original game intended to be much simpler scenarios, focused on obtaining a more fine grained objective. This allows training agents in progressive steps, building up to the ability to play a full game against multiple players.

A set of benchmark results were published by (Vinyals et al. [9]) with the release of SC2LE. These results were obtained by a DeepMind RL agent trained using the A3C algorithm under 3 different network architectures. Although the results were underwhelming - the agent did not win a single game against the easiest built-in game AI, the fully convolutional network managed to utilize one of the unit's (Teran worker) abilities to move buildings out of attack range, thus managing a draw by surviving past the 30 minute time limit. However, no agent managed to devise a winning strategy. The ability to devise such an agent is still an open question.

3.4.3 Performance Metrics

The most popular, general performance metrics used in (Van Hasselt et al. [15]; Wang et al. [16]; Mnih et al. [5, 1, 13]) when evaluating model performance on the Atari 2600 test bed are listed below.

- Game score, the range of which will vary greatly between different games.
- Max Q-Value estimates
- Number of game frames survived

These metrics are gathered by running a predetermined number of evaluation games; where the agent selects it's action from the trained model. They are usually presented as a mean average, however there is an argument for taking the median value to lessen the effect of outliers (Bellemare et al. [7]). The evaluation runs are held after a regular number of training updates, where the agent solely exploits the trained policy and no learning updates take place. These intervals vary between different papers.

Normalizing Scores

The scales for scoring between two games can vary greatly, which makes it difficult to compare the performance of an algorithm on different games by quoting score alone. (Bellemare et al. [7]) recommend using normalizing all scores using predetermined reference values.

$$z_{g,i} = \frac{s_{g,i} - r_{g,min}}{r_{g,max} - r_{g,min}} \tag{7}$$

Where $z_{g,i}$ is the normalized score s_i in game g. $[r_{g,min}, r_{g,max}]$ are reference values that we normalize to. These could be the minimum and maximum obtainable scores in the game, or more interestingly (Mnih et al. [1]) propose normalizing scores to the score achieved by a human player, where $r_{g,min} = \text{random players score} \text{and} r_{g,max} = \text{human players score}$. We can then see the algorithms percentage performance over human level.

Average reward (normalized or not) and average frames survived are an interesting duo of performance metrics. Together, they can give a better understanding of *what* the agent is learning to do. In some games, the score might be dependant on surviving for a long time, for others it might be to shoot as many 'things' as possible and rack up points. For this project, we use the normalization to human scores proposed by (Mnih et al. [1]), average frames survived and model loss as a basis for our discussion. The human player in this case will be the author.

4 Design

One of the primary objectives of this project is to build a system for comparing the performance of DRL algorithms when applied to agents in the Atari 2600 video game test bed. This chapter discusses the design and implementation of that system.

We begin with a discussion of the different platforms and tools available to us to aid in the implementation. We will not be building the system completely from scratch, we will require an emulator to host our agents and environments and external libraries to prevent 'reinventing the wheel' when it comes to the programming of the system. We will follow with a broad system overview and then an in-depth look at the system architecture. It is the aim of these sections to leave the reader with a thorough understanding of exactly *how* the system operates. Finally we will close with the reasoning behind the choice of games, Space Invaders and Breakout, and algorithms, Deep Q-Network (DQN), Double Deep Q-Network (2DQN) and Dueling Double Deep Q-Network (3DQN), for the evaluation of our system.

4.1 Platform and Tool Choices

4.1.1 OpenAI Gym and The ALE

The OpenAI Gym and the ALE were introduced in Chapter 2 as RL research tools for the video game domain. Here we give the strengths (+) and weaknesses (-) of each, and the reasoning behind the selection of the ALE as the foundation of our system.

OpenAI Gym

+ Provides a great diversity of environments.

+ The high-level API is simple to use.

− The high-level API does not provide enough control nor is it as feature rich as the ALE.

– The selection of Atari 2600 environments is limited.

The ALE

+ Provides a large range of supported Atari 2600 environments (61, see A1.1 for full list) with more planned for the future.

+ Many more features and higher level of control, as detailed in Chapter 2.

– The Python wrapper is slightly behind the C++ API.

– The environments are limited to Atari 2600.

Having weighed the strengths and weaknesses of both tools, it became clear that the low-level amount of control that the ALE provides would be imperative for the implementation of the system, in terms of customization and data collection. The suite of Atari 2600 environments is a well known test bed for RL research, hence the additional environments provided by the OpenAI Gym were not needed.

4.1.2 Choice of Programming Languages and Libraries

Python

Python is a high level programming language, made popular by it's simplistic human-readable syntax, it's ability to perform tasks in minimal lines of code, and it's vast community support in the form of modules (Python syntax for external libraries) [18]. Python 3.5 was used to build the system in it's entirety. It is the default language to use when implementing deep neural networks thanks to the wide support of deep learning modules. As mentioned previously, the ALE API has a Python wrapper with nearly full functionality. The modules that form the foundation of the system are detailed below.

Tensorflow

Tensorflow (TF) is an open-source, low-level ML framework [19]. It provides an API for deploying computations to CPU and GPU hardware, where calculations are represented as a graph. The nodes represent a mathematical operation and the edges represent the multi-dimensional matrices, called 'tensors,' serving as input and output. TF comes in two flavours, a CPU only version and a GPU support version. With the GPU support version, it will automatically detect the hardware configuration of the machine it is running on and deploy calculations appropriately, with GPU's taking priority over CPU's by default.

Keras

Keras is a high-level neural networks API for interacting with low-level ML frameworks [20]. Keras can use many different low-level frameworks as it's backend. We use TF in the backend for this project and use Keras in our code to implement the deep neural networks for our DRL algorithms.

Numpy

Numpy is one of the seminal tools for scientific programming in Python. It provides an N-dimensional matrix object with support for matrix operations and a host of other extremely useful mathematical operations such as:

- Linear algebra
- Fourier transforms
- Random number generation
- Statistics

4.1.3 Trinity GPU cluster and Slurm

To aid in the training of DRL models, Trinity kindly gave us access to 'Boole,' a cluster of high performance machines equipped with GPU hardware. This decreased training times and made it possible to experiment with different system configurations. Slurm is a Linux cluster management system that provides job scheduling and access to system resources [21]. Slurm is employed on Boole to manage access to nodes. The cluster is shared by many researchers in Trinity, so naturally we are not able to obtain unrestricted access. Often submitted jobs will have to wait in a queue for hardware to become available. Due to the lengthy process of training ML models, these queue times can stretch to hours and sometimes days. This introduced a somewhat challenging time constraint on the project. To run a program on a compute node, the user must write a submission bash script, providing the following information:

1. A job name.
2. Max time to run the program.
3. If a GPU is required, that must be specified. The default is to run the job on the CPU.
4. Any dependencies that will be required by the program. Boole comes equipped with a large list of popular programs packaged as modules, such as Python, cmake, gcc and

many more.

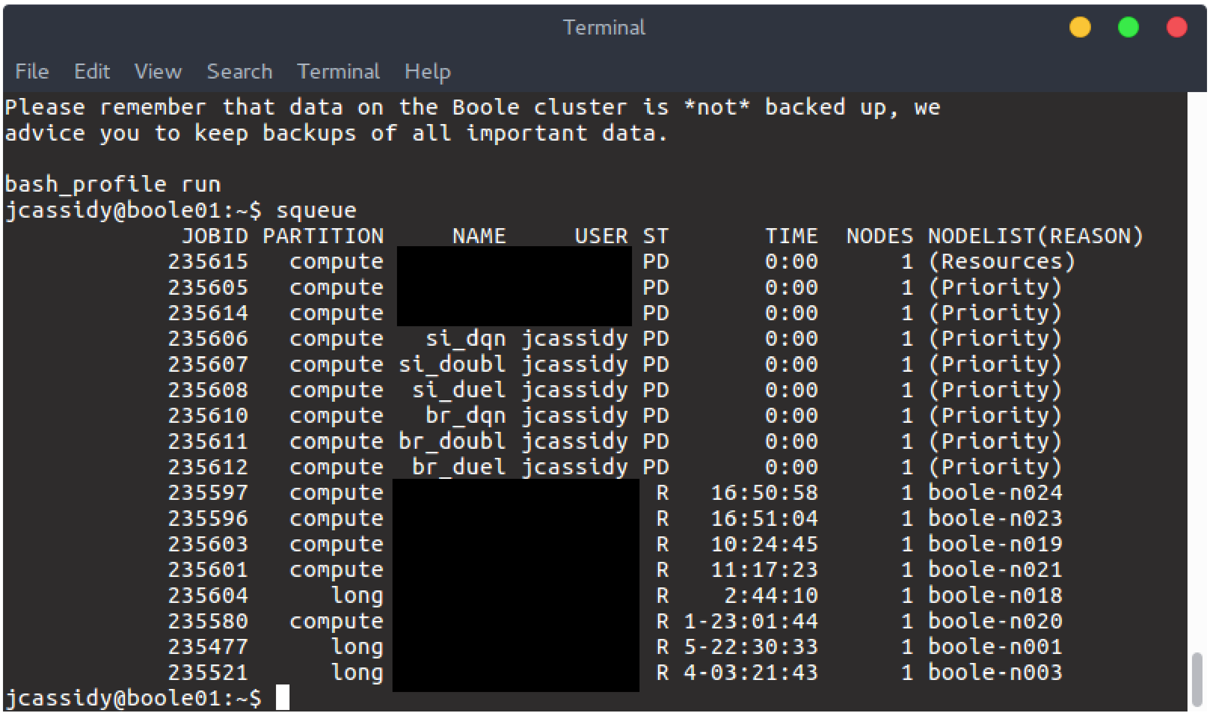
5. The command line string to launch the program.

```
#!/bin/sh
#SBATCH -n 1
#SBATCH -t 2-00:00:00
#SBATCH -p compute
#SBATCH -J t_br_double
#SBATCH --mail-type=ALL
#SBATCH --mail-user=jacassid@tcd.ie
#SBATCH --gres=gpu:2

. /etc/profile.d/modules.sh
module load cports6 Python/3.5.2-gnu
module load cports7 gcc/6.4.0-gnu
module load apps cuda/9.0
srun ./main.py breakout double -t -l

```

Figure 4.1: Example Slurm job submission script. This script allocates a node for 2 days with 2 GPUs on the compute partition. We have provided the option to receive emails when the job starts/finishes/fails. The Python3, gcc and cuda9 modules are loaded and finally we run our system with the srun command.



```
Please remember that data on the Boole cluster is *not* backed up, we
advice you to keep backups of all important data.

bash_profile run
jcassidy@boole01:~$ squeue
             JOBID PARTITION     NAME     USER ST       TIME  NODES NODELIST(REASON)
            235615   compute [redacted]       PD       0:00      1 (Resources)
            235605   compute                  PD       0:00      1 (Priority)
            235614   compute                  PD       0:00      1 (Priority)
            235606   compute   si_dqn jcassidy PD       0:00      1 (Priority)
            235607   compute si_doubl jcassidy PD       0:00      1 (Priority)
            235608   compute  si_duel jcassidy PD       0:00      1 (Priority)
            235610   compute   br_dqn jcassidy PD       0:00      1 (Priority)
            235611   compute br_doubl jcassidy PD       0:00      1 (Priority)
            235612   compute  br_duel jcassidy PD       0:00      1 (Priority)
            235597   compute [redacted]        R   16:50:58      1 boole-n024
            235596   compute                   R   16:51:04      1 boole-n023
            235603   compute                   R   10:24:45      1 boole-n019
            235601   compute                   R   11:17:23      1 boole-n021
            235604      long                   R    2:44:10      1 boole-n018
            235580   compute                   R 1-23:01:44      1 boole-n020
            235477      long                   R 5-22:30:33      1 boole-n001
            235521      long                   R 4-03:21:43      1 boole-n003
jcassidy@boole01:~$ █
```

Figure 4.2: An example of the job queue on Boole. PD indicates pending jobs in the queue.

4.2 System Overview

The core functionality of the system is two-fold.

1. Provide a platform for training Atari 2600 AI agents using user-implemented DRL algorithms.
2. Provide a means to compare and contrast the performance of these agents with a variety of performance metrics

With these core functionalities in mind, we assign three main goals for the design of the system.

1. Support any game that the ALE does with no changes required in the code.
2. Make it easy to implement and apply additional algorithms for future developers.
3. Provide a suite of useful research tools.

To make the system game-agnostic, it had to be built to adapt to any possible variables between Atari 2600 games. It was determined that for our purposes, the variables we would be concerned with are control scheme and graphics scheme, as they determine the output and input of the neural networks of our DRL algorithms respectively. Fortunately, the ALE provides a function for querying the minimum available action set from the game's ROM. Although the graphics between games varies greatly, the dimensions of each frame in pixels remains constant at $210x160x3$. Hence, the goal to make the system playable for any supported ALE game was a simple task to achieve, owed to the low-level functionality of the ALE API. To apply the system to any one of the supported games, the game title can be passed as the first positional command line argument when running the program. It is required that the title be in the format specified in A1.1.

Support for future DRL algorithms has been provided in the form of a base class, `NN`. This class defines a number of standard methods that future classes can inherit from, such as building the neural network from Mnih et al. [1], network training updates, predicting actions and the saving and loading of the serialized neural network weights and hyper-parameters. The three algorithms that were implemented for this project all derive from `NN`.

The system provides a number of useful tools that automate many important and time-consuming tasks.

- The ability to define 'test' agents, to experiment with different configurations. These test agents won't interfere with the saved data of the current agents and can be safely run without the fear of overwriting any previous work.
- The ability to set a recording session to take video footage of the agent playing an episode of the specified game.
- Give the researcher the ability to define the length and number of epochs to train the agent for, as well as the number of evaluation games to perform after each epoch [1].
- Automatic collection of performance metrics.
- Automatic backup of neural network weights, hyper-parameters and replay memory to preserve state between training sessions.

The final point in this list is quite important There is a 2 day time limit for jobs on the Trinity GPU cluster. Our results show that this time amounts to approximately 7-10 complete epochs, depending on the algorithm. In order to preserve the state of the experiment between jobs, this functionality was imperative to implement. To save network weights, we use the built-in Keras `save` method, which saves the weights in a compressed `.h5` file format. To preserve network hyper-parameters and experience replay, we first use the Python Pickle module [22] to serialize the objects. Without compression, the replay memory object can grow to Gigabyte size on disk, hence we use the Python bz2 module [23] to compress the serialized object using the bzip2 compression algorithm and save the objects as `.obj` files.

4.3 System Architecture

In this section we go into further detail with the system architecture and design decisions. We refer to Figure 4.3 for a high-level description of the flow of control when running the system.

4.3.1 Main

When we first launch the program, main is run. The purpose of main is to parse command line arguments, instantiate the Agent class and pass it the parsed command line arguments, and run the Train-Evaluate loop for the specified number of epochs. A set of command line arguments are provided to control the operation of the system;

[1] An 'epoch' here is defined as the number of 'steps' to train an agent for before each round of evaluation games. For our research we used 25,000 steps. A 'step' is defined as 3 game frames.

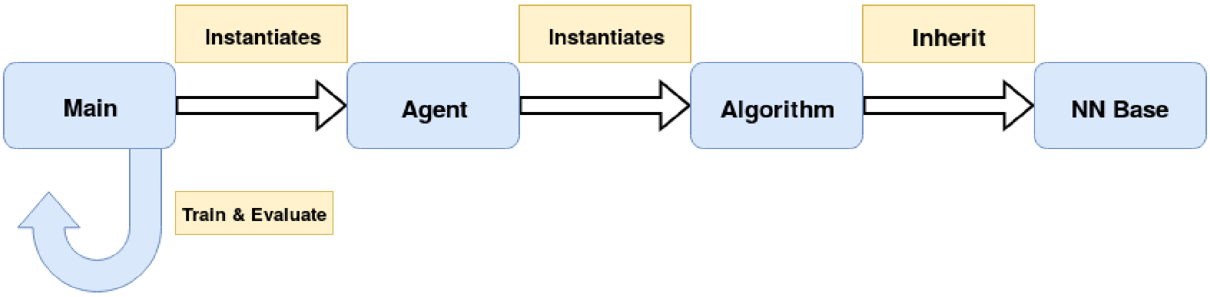


Figure 4.3: Flow of control through the system. Main instantiates the Agent class. An agent instantiates an Algorithm class. An algorithm *may* inherit from the NN base class

Required Positional Args

- `game`: The desired game to train an agent on. Must be in the format specified in A1.1.
- `deep-learning-mode`: The desired DRL algorithm to use in training. Must be an implemented Algorithm class. The current options are `dqn, double and duel`. Future work will have to manually add the options for new algorithms, but this is trivial to do.

Optional Positional Args

- `training-steps`: The number of steps to train for in each epoch. Default 25000.
- `training-epochs`: The number of epochs to train for in total. Default 20.
- `evaluation-games`: The number of games to evaluate performance on at the end of each epoch. Default 10.

Options

- `-l, -load_model`: If set a new model(s) will be created for the provided game, `deep-learning-mode` pair. Equivalent to starting fresh.
- `-d, -display`: If set, evaluation games will render the game to the screen. Creates notable slow down.
- `-t, -test_run`: Used to create a separate testing game, `deep-learning-mode` pair without overriding the currently saved pair.
- `-r, -record`: Records video footage of an agent in game using the provided `deep-learning-mode`.

After each epoch of training, the agent returns the average loss from the network over that epoch. Then main runs the agent for the specified number of evaluation games. The Agent class returns the score achieved in the game and the number of frames survived. They are averaged over the total number of games and saved to disk for later inspection. This allows us to monitor the progress of an agent and plot it's performance over time.

4.3.2 Agent

The Agent class is the bridge between the system and the ALE API. It implements the theoretical concept of a RL agent. It's purpose is to define how the agent trains and maintain game specific information; the available action list, the replay memory and an instance of the desired algorithm, which it instantiates from one of the provided Algorithm classes.

Initialization

In the Agent class constructor, we pass the parsed command line arguments from main so we can direct them on to the ALE API, as it controls the ability to display the screen, record footage etc. The agent calls the ALE to load the specified Atari game ROM from disk. The communication with the ALE is accomplished by setting specific flags before loading the ROM. The flags are identified by passing byte encoded strings to the API, an example is given in Figure 4.4.

```
    ale = ALEInterface()
    ale.setInt(str.encode('random_seed'), np.random.randint(100))
    ale.setBool(str.encode('display_screen'), True)
    ale.loadROM(str.encode('./roms/space_invaders.bin))

```

Figure 4.4: Calling the ALE API to set a random game seed, enable screen display and load the Space Invaders ROM from disk.

Replay Memory

The agent instantiates a ReplayMemory object to function as the experience replay. This is implemented as a queue data structure, with a max length of 20000 items. As discussed previously, we serialize and compress the replay memory object when saving and loading between training sessions, which is also controlled by the Agent class. The choice of keeping a 20000 item max length is not random. The work of (Mnih et al. [5, 1]), which this project takes much inspiration from, including neural network architecture, hyper parameters and some design decisions such as reward clipping and frame skipping, trained their agents without pause for 50 million frames in Mnih et al. [5] and 200 millions frames in Mnih et al. [1], both using a replay memory of 1 million items. These targets are not realistically achievable. There were a number of time constraints imposed on the project; the shared access to Boole, the project deadline coupled with the time taken to build the system and experiment with a few different configurations to obtain respectable results. It is not disclosed what hardware Mnih et al. [5] or [1] had access to, so we cannot make any hardware comparisons with Boole, however, when attempting to use a 500000 size replay memory, the program would frequently be stopped by Slurm due to over-consumption of memory. With these constraints taken into consideration, we made the decision that 1 million frames was an achievable target to strive for for each game-algorithm pair, $\frac{1}{50}$ of the 50 million frames Mnih et al. [5] trained for. Thus we scaled down the size of the replay memory accordingly, from 1 million to 20000 items.

Training Routine

As mentioned previously, the Agent class controls how the agent trains. The agent loops for the number of steps provided from the command line option, backing up the network weights, hyper-parameters and replay memory object to disk every 5000 steps. During training the agent maintains a queue called the `frame buffer` that holds the 3 most recent game frames. At the start of each loop, the `frame buffer` holds the initial state[2]. By the end of the loop it holds the next state, the state that results from taking an action predicted by an Algorithm object. We give a step-by-step guide to the training process below.

1. The agent concatenates the 3 frames in the `frame buffer` into one array and saves it to an `initial state` variable.
2. The Algorithm object is given `initial state` as input and outputs a predicted action.
3. The agent plays the action for 3 frames, adding each frame to the `frame buffer`, pushing the older frames out. After 3 frames we concatenate the frames in the `frame buffer` again, giving the `next state`. Repeating actions for n frames is a technique known as frame skipping, proposed by Mnih et al. [5].
4. The reward from taking the action is calculated as the increase in game score accrued by taking that action. Notice they are only ever positive scores. No negative reward is provided by the ALE for negative actions.
5. We check to see if 1) the agent lost a game 'life' or 2) the agent reached a game over

[2] On the very first iteration we fill the buffer with 3 copies of the starting frame.

terminal state. If either of these conditions are met, we set the reward to -1.

6. The reward is clipped to $-1 \leq 0 \leq 1$. This is a tactic known as reward clipping, proposed by (Mnih et al. [1]) to limit the scale of error derivatives and improve the performance of using the same learning rate across different games.
7. Save the $(s, a, r, s', term)$ tuple to the replay memory.
8. The Algorithm object to performs a training update on the neural network.

4.3.3 Algorithm

Each algorithm requires an Algorithm class. We have chosen to implement the 3 algorithms DQN, 2DQN and 3DQN, hence we have provided the classes `DQN`, `DoubleDQN` and `DuelingDQN`, but for future research any number of Algorithm classes could be created. The three classes that we have provided inherit from the base `NN` class. `NN` assumes that any classes inheriting from it are implementing DRL algorithms, and require a neural network to operate. The default network provided is the network put forward in (Mnih et al. [1]).

The function of Algorithm classes is to provide prediction of actions given an environment state, perform training updates on the neural network and save and load it's weights and hyper-parameters. The implementation of the training updates varies between algorithms, previous chapters have outlined the steps for the DQN and 2DQN algorithms. One constant among all algorithms however is the ϵ greedy exploration policy. We linearly anneal ϵ over a certain number of training updates. (Mnih et al. [5]; Van Hasselt et al. [15]; Wang et al. [16]) reduce ϵ over the first 1 million updates. For reasons previously discussed, we scale this down by a factor of 50 to every 20000 updates.

4.3.4 Neural Network Architecture

As we have mentioned previously, the neural network architecture used in the implementation of the `DQN`, `DoubleDQN` and `DuelignDQN` classes was first proposed by (Mnih et al. [5]). It was modified by (Mnih et al. [1]) and that version was used in (Van Hasselt et al. [15]) for Double Deep Q-Learning. The convolutional network section was also used by (Wang et al. [16]). For this project, we use the modified version from (Mnih et al. [1]), with one small adaptation. We give the network 3 greyscale frames of size 210x160 as input as opposed to cropped 84x84 frames, as we felt that the game area was not being wholly captured by an 84x84 size. This is one area where we have slight disagreement with the published practices. The final architecture used is given in Figure 4.5.

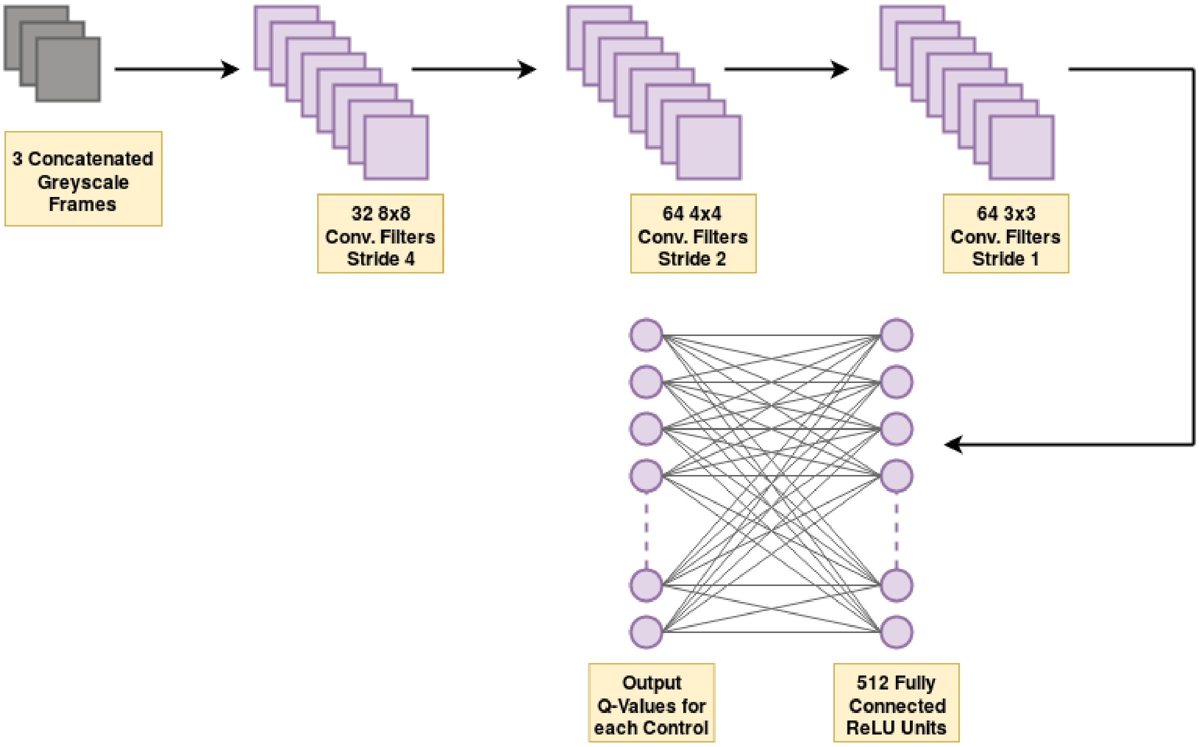

3 Concatenated Greyscale Frames
32 8x8 Conv. Filters Stride 4
64 4x4 Conv. Filters Stride 2
64 3x3 Conv. Filters Stride 1
Output Q-Values for each Control
512 Fully Connected ReLU Units

Figure 4.5: The neural network architecture employed by (Mnih et al. [1])

4.4 Choice of Games

The number of games that we could use in our comparisons was limited due to the time constraints outlined in Subsection 4.1.3. Each game requires training on 3 different algorithms. Hence we decided to choose two games that were suitably different that we could investigate the adaptability of each algorithm. When we compare the difference of two games, we look at:

- Objectives/scoring systems.
- Graphics.
- Control schemes.

This led us to select Space Invaders [24] and Breakout [25] as our games of choice. In Space Invaders, the objective is to shoot enemy aliens while avoiding their projectiles, whereas in Breakout the objective is to break as many blocks as possible by steering towards the projectile and bouncing the ball off the paddle. We conducted a test with a random agent playing each game. The random agent can score approximately 100 points in Space Invaders, which is much greater than the 0-2 points possible in Breakout, thus we have suitably different objectives and scoring systems

The amount of colour in Space Invaders is quite limited. The enemy aliens, player ship, barriers and background are the only entities in the game as seen in Figure 4.6. In Breakout there are multiple tiers of coloured blocks, with increasing score the higher the tier, providing a broader range of graphics for the agent to learn and understand as seen in Figure 4.7.

Both games have left and right movement. Space Invaders however, provides an extra control over Breakout; to shoot.

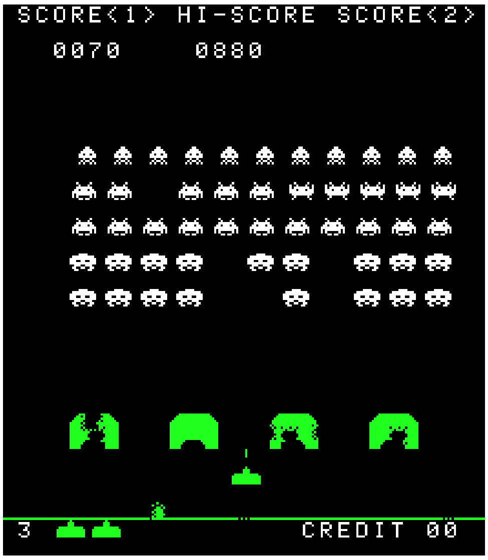


Figure 4.6: Space Invaders

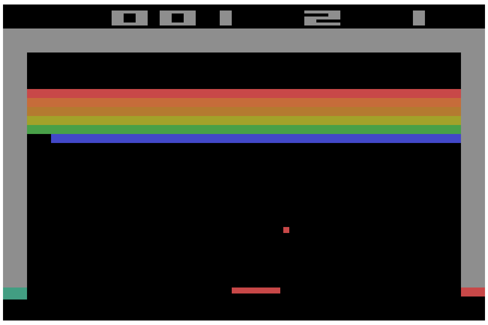


Figure 4.7: Breakout

4.5 Choice of Algorithms

DQN, 2DQN and 3DQN as outlined in Chapters 2 & 3 form a family of algorithms, brought together by their adaptation of the Q-Learning algorithm to Deep Learning. We selected DQN, as it was the first algorithm to spark the field of DRL. It is very well documented for this reason and there were many resources to aid in learning how it worked. 2DQN is the successor to DQN and 3DQN is the successor to 2DQN, thus they provided a natural basis for comparison.

We considered implementing A3C, as it is the current state of the art algorithm for this application and it would be interesting to see what results we could obtain over the aforementioned algorithms. However we eventually decided against it due to the time constraints mentioned in previous sections. Implementing A3C would be time consuming due to the fact that it requires co-ordinating parallel workers in updating a central neural network, which presents a significant implementation challenge that we may have struggled to overcome within the project deadlines.

5 Evaluation

6 Conclusion

Bibliography

[1] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. *Nature*, 518 (7540):529, 2015.

[2] Kai Arulkumaran, Marc Peter Deisenroth, Miles Brundage, and Anil Anthony Bharath. A brief survey of deep reinforcement learning. *CoRR*, abs/1708.05866, 2017. URL `http://arxiv.org/abs/1708.05866`.

[3] David Silver, Aja Huang, Christopher J. Maddison, Arthur Guez, Laurent Sifre, George van den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, Sander Dieleman, Dominik Grewe, John Nham, Nal Kalchbrenner, Ilya Sutskever, Timothy Lillicrap, Madeleine Leach, Koray Kavukcuoglu, Thore Graepel, and Demis Hassabis. Mastering the game of go with deep neural networks and tree search. *Nature*, 529:484–503, 2016. URL `http://www.nature.com/nature/journal/v529/n7587/full/nature16961.html`.

[4] Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction*, volume 1. MIT press Cambridge, 1998.

[5] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin A. Riedmiller. Playing atari with deep reinforcement learning. *CoRR*, abs/1312.5602, 2013. URL `http://arxiv.org/abs/1312.5602`.

[6] Yves Chauvin and David E Rumelhart. *Backpropagation: theory, architectures, and applications*. Psychology Press, 1995.

[7] M. G. Bellemare, Y. Naddaf, J. Veness, and M. Bowling. The arcade learning environment: An evaluation platform for general agents. *Journal of Artificial Intelligence Research*, 47:253–279, jun 2013.

[8] Claude E. Shannon. Xxii. programming a computer for playing chess. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, 41(314): 256–275, 1950. URL `https://doi.org/10.1080/14786445008521796`.

[9] Oriol Vinyals, Timo Ewalds, Sergey Bartunov, Petko Georgiev, Alexander Sasha Vezhnevets, Michelle Yeo, Alireza Makhzani, Heinrich Küttler, John Agapiou, Julian Schrittwieser, et al. Starcraft ii: a new challenge for reinforcement learning. *arXiv preprint arXiv:1708.04782*, 2017.

[10] Christopher J. C. H. Watkins and Peter Dayan. Q-learning. *Machine Learning*, 8(3): 279–292, May 1992. ISSN 1573-0565. doi: 10.1007/BF00992698. URL https://doi.org/10.1007/BF00992698.

[11] Leslie Pack Kaelbling, Michael L Littman, and Andrew W Moore. Reinforcement learning: A survey. *Journal of artificial intelligence research*, 4:237–285, 1996.

[12] Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. Openai gym, 2016.

[13] Volodymyr Mnih, Adria Puigdomenech Badia, Mehdi Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. In *International Conference on Machine Learning*, pages 1928–1937, 2016.

[14] Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al. Google's neural machine translation system: Bridging the gap between human and machine translation. *arXiv preprint arXiv:1609.08144*, 2016.

[15] Hado Van Hasselt, Arthur Guez, and David Silver. Deep reinforcement learning with double q-learning. In *AAAI*, volume 16, pages 2094–2100, 2016.

[16] Ziyu Wang, Tom Schaul, Matteo Hessel, Hado Van Hasselt, Marc Lanctot, and Nando De Freitas. Dueling network architectures for deep reinforcement learning. *arXiv preprint arXiv:1511.06581*, 2015.

[17] Tom Schaul, John Quan, Ioannis Antonoglou, and David Silver. Prioritized experience replay. *arXiv preprint arXiv:1511.05952*, 2015.

[18] Python homepage. URL https://www.python.org/.

[19] Tensorflow homepage. URL https://www.tensorflow.org/.

[20] Keras documentation. URL https://keras.io/.

[21] Slurm resource manager user guide. URL https://slurm.schedmd.com/quickstart.html.

[22] Python pickle module documentation. URL https://docs.python.org/3/library/pickle.html.

[23] Python bz2 module documentation. URL https://docs.python.org/3/library/bz2.html.

[24] Space invaders wikipedia page. URL https://en.wikipedia.org/wiki/Space_Invaders.

[25] Breakout wikipedia page. URL https://en.wikipedia.org/wiki/Breakout_(video_game).

A1 Appendix

A1.1 ALE Supported Atari 2600 Games

ALE Format	Game Title	ALE Format	Game Title
air_raid	Air Raid	alien	Alien
amidar	Amidar	assault	Assault
asterix	Asterix	asteroids	Asteroids
atlantis	Atlantis	bank_heist	Bank Heist
battle_zone	Battle Zone	beam_rider	Beam Rider
berzerk	Berzerk	bowling	Bowling
boxing	Boxing	breakout	Breakout
carnival	Carnival	centipede	Centipede
chopper_command	Chopper Command	crazy_climber	Crazy Climber
defender	Defender	demon_attack	Demon Attack
double_dunk	Double Dunk	elevator_action	Elevator Action
enduro	Enduro	fishing_derby	Fishing Derby
freeway	Freeway	frostbite	Frostbite
gopher	Gopher	gravitar	Gravitar
hero	Hero	ice_hockey	Ice Hockey
jamesbond	Jamesbond	journey_escape	Journey Escape
kangaroo	Kangaroo	krull	Krull
kung_fu_master	Kung Fu Master	montezuma_revenge	Montezuma Revenge
ms_pacman	Ms Pacman	name_this_game	Name This Game
phoenix	Phoenix	pitfall	Pitfall
pong	Pong	pooyan	Pooyan
private_eye	Private Eye	qbert	Qbert
riverraid	Riverraid	road_runner	Road Runner
robotank	Robotank	seaquest	Seaquest
skiing	Skiing	solaris	Solaris

space_invaders	Space Invaders	star_gunner	Star Gunner
tennis	Tennis	time_pilot	Time Pilot
tutankham	Tutankham	up_n_down	Up N Down
venture	Venture	video_pinball	Video Pinball
wizard_of_wor	Wizard Of Wor	yars_revenge	Yars Revenge
zaxxon	Zaxxon		