RL Project

Peter Coates
Dept of Computer Science
University of Bath
Bath, BA2 7AY
pmc52@bath.ac.uk

Christopher Burton
Dept of Computer Science
University of Bath
Bath, BA2 7AY
cb2516@bath.ac.uk

Mirco Carciani
Dept of Computer Science
University of Bath
Bath, BA2 7AY
mc2886@bath.ac.uk

1 Problem Definition

Breakout, a 2D game. part of the classic Atari 2600 games was chosen as the "problem" to solve for this assignment. In the game of Breakout, a player controls a paddle to bounce a ball against a wall composed by a stack of 6 layers of bricks without letting the ball fall behind the paddle. Each time the ball hits a brick, the brick is destroyed and the score is increasaed by 1,4 or 7 points, depending on the color of the brick which was hit. If the ball falls behind the paddle one life is lost. The game ends when 5 lives are lost. Four actions are available at each step t, namely, fire, no operation (noop), move left and move right.

The agent has to learn to control the paddle to maximize the total final reward, meaning hit and destroy as many brinks as possible within the 5 lives available. No points are removed when a life is lost. Although Breakout seems a conceptaully easy problem to solve, its vast state space proves very challening for RL methods. The agent needs to figure out which of the available actions is best to take in each state to maximize the future reward. For the scope of this assignment, we will only consider the single player version. The highest score achievable for one player is 864; this is done by eliminating two screens of bricks worth 432 points per screen.

2 Background

2.1 DQN

One category of reinforcement learning methods that can be used to solve the game of Breakout is value-based methods which use function approximation. These methods aim to learn a function $f : (s, a, \theta) \to \mathbb{R}$, with $s \in S$, $a \in A$ and $\theta \in \mathbb{R}^n$ to estimate the action-value functions for each state and therefore determine the optimal action a to take in state s.

Deep Q-Network agent (DQN) introduced by Mnih et al., 2015, was the first value-based RL method to surpass human performances at Breakout making it the first candidate algorithm we decided to implement. Mnih et al., 2015 show how DQN was able to reach an average score of 401, compared to an average score of 31.8 reached in the same testing conditions by a professional human tester.

DQN introduced both a separate *target network* to estimate the next state maximum action value function and *experience replay memory* to avoid correlated data during training. These introductions allowed DQN to achieve stable learning and converge towards an optimal policy.

2.2 A2C

An alternative value-based methods are policy gradient methods. Policy gradient methods do not need to consult a value function and, instead, learn a parameterised policy to select actions (Sutton and Barto, 2018). In selecting actions using a parameterised policy, policy gradient methods use *action preferences* rather than action values. This distinction is crucial as it confers several benefits to policy gradient methods such as the ability to learn a stochastic optimal policy and have the policy approach a deterministic policy (Sutton and Barto, 2018).

A Policy-Gradient method that has been shown to be effective on similar tasks to Breakout is Actor-Critic. An asynchronous, extended version of Actor Critic called Asynchronous Advantage Actor-Critic (A3C) was implemented by Minh et al (2016) to mitigate issues with instability due to temporally correlated data across time-steps (Li, Bing and Yang, 2018). The Advantage component of A3C refers to the use of an advantage function in the reinforcing signals sent to the actor. This advantage value quantifies how much better or worse an action is than the average available action by using the critic's valuation of states (Graesser and Loon, 2020). A synchronous version of A3C that implements the advantage function but does not execute multiple agents in parallel is known as Advantage Actor Critic (A2C). Whilst both methods provide strong results on Breakout and similar tasks, results from Wu et al. (2017) indicate that A2C is a more suitable algorithm for the problem of Breakout than A3C.

2.3 Async Q-Learning

Mnih et al (2016) present asynchronous variants of reinforcement learning algorithms including both Q-Learning and Actor-Critic (A3C). The paper claims the asynchronous variants can produce excellent results on single multi-core CPUs with training times of just a few hours. The results published by Mnih et al (2016) are impressive and show that after 10 hours training with breakout, Async Q-Learning scored 240 and A3C scored 460, whilst DQN only managed 25.

Unlike DQN, the asynchronous methods do not require an experience replay memory as multiple agents working in parallel means that the data is fragmented and sufficiently decorellated.

3 Method

3.1 DQN

DQN was derived from Q-Learning where the action-value function is estimated by a nonlinear function, more precisely, by a deep neural network, namely,

$$Q(S,A) = f(S,A,\theta) = \hat{Q}(S,A,\theta) \tag{1}$$

Bootstrapping is used to update the action value function as shown in the equation below.

$$\hat{Q}(S,A,\theta) = \hat{Q}(S,A,\theta) + \alpha * \left(r + \gamma \max_a \hat{Q}(S',a,\theta) - \hat{Q}(S,A,\theta)\right) \tag{2}$$

Where α is the learning rate and γ is the discounting factor for future rewards.

The function parameters are updated in the direction that minimizes the loss between the current action value function estimation and its update. The weight update is achieved by a single step of gradient descent as described in equation 3.

$$\theta_{t+1} = \theta_t + \alpha \left(r + \gamma \max_a \hat{Q}(S',a,\theta_t) - \hat{Q}(S,A,\theta_t)\right) \nabla_{\theta_t} \hat{Q}(S,A,\theta_t) \tag{3}$$

As a result of the weights update at each step t, the action-value function estimation $\hat{Q}(S,A,\theta_t)$ is updated towards a moving target as the next state maximum action value function $\max_a \hat{Q}(S',a,\theta_t)$ will also change. One of the major breakthroughs introduced by Mnih et al., 2015 was the introduction of separate networks. One network (q-value network), is used to estimate the action value functions of the current state S, while a separate network (target network) is used to estimate the action value functions of the next state S'. The weights of the target network are kept constant for a number of iterations before being synched with the q-value network weights. By using a constant target network, the q-value network can be updated towards a stable target limiting instability during training.

DQN also uses a replay memory buffer to store the last N interactions with the environment. At each step, the following details are recorded in the memory: state S, action A, reward R, observed next state S' and flag indicating whether or not S' is terminal.

A subset $n \in N$ of experiences is then selected and used to update the q-value network weights using equations 3. This allows the agent to train on time uncorrelated data.

Our DQN implementation tests three different methods to retrieve the experiences from the experience replay buffer.

1. Uses the implementation of Mnih et al., 2015 where the n experiences are selected at random from the buffer of capacity N.
2. Selects half randomly and half using cosine similarity to select experiences that closely matching the next state S'.
3. Uses cosine similarity to select experiences that closely matching the next state S'.

The idea behind the cosine similarity approach is to create a synthetic dejavu.

DQN uses an $\epsilon - greedy$ policy to provide exploration whilst choosing the best action $A*$ from all available actions in the next states. The exploration factor ϵ is reduced from an initial value of 1 to 0.1 over 1M steps and kept constant thereafter.

The loss function used to calculate the weight updates is the Huber loss which improve stability by clipping the gradient of the loss with respect the estimated action value function. Mnih et al., 2015 shows how this improves stability during training.

Two identical convolutional neural networks (CNN) are used as function approximations for the Q values. The raw pixel data output by whilst playing Breakout is preprocessed before being used as input to the CNNs for state S. The output of the CNNs are the Q values for each action available in that state S. The preprocessing crops the raw data, resizes to 84x84 pixel and converts to grey scale. And, to give the CNN the information about the ball trajectory, the state S is a stack of the current and 3 previous frames. DQN pseudo-code is shown in Appendix A: DQN pseudo-code

3.2 A2C

The second method chosen to solve our specific problem of Atari Breakout is Advantage Actor-Critic (A2C). In this implementation, the actor policy is parameterised by a CNN where the parameters are the weights of the neural network. The critic is also implemented as a CNN, with both architectures following a modified version of that used in Minh et al. (2015). For the Actor, the output layer uses a softmax activation function for the output layer with a single neuron for each possible action that the actor can take. This is to achieve a policy parameterisation known as softmax in action preferences (Sutton and Barto, 2018). The critic network uses the same architecture but has a single output neuron with linear activation, representing the action-value that the critic prescribes to a given state. RandomUniform initialisation is used with a small range of min and max values (0 - 0.02) as initial runs of the algorithm showed high sensitivity to initial weights on the output layers, particularly on the actor.

The input to both networks is similar to that used for DQN, and, is implemented using an OpenAIGym provided Atari wrapper that follows the guidelines in Machado et al. (2018). The current and the 3 previous frames are stacked to give the agent context such as the direction the ball is travelling in.

The critic uses a TD update. At each step, the critic network calculates a value estimate for both the previous state and the next-state that the agent is in. The critic uses a bootstrapped estimate of the next state, the reward at $t + 1$ and the discount factor to calculate a target value for the state. The mean squared difference between the critic's initial value of the state and the target value is used to update the critic and adjust its estimate of the state closer to the target value. The target TD value is used also to calculate the advantage function for the actor loss by subtracting the critic's valuation of the previous state from the target TD update. The full A2C actor update rule from Yoon (2019) is given below:

$$\nabla_\theta J(\theta) = \sum_{t=0}^{T-1} \nabla_\theta \log \pi_\theta(a_t|s_t) A(s_t, a_t) \tag{4}$$

Where:

$$A(s_t, a_t) = Q_w(s_t, a_t) - V_v(s_t) = r_{t+1} + \gamma V_v(s_{t+1}) - V_v(s_t) \tag{5}$$

The first component of the actor loss function is the gradient in parameter space (delta). This value represents the action taken and whether it followed or went against the current actor policy. The delta term implementation in this assignment follows an extended version of the method followed by Wang (2021).The advantage component, which represents the reinforcement signal from the critic, tells the actor whether the action taken was better than the average reward for that state (Positive advantage) or worse (Negative advantage). By multiplying the gradient of action selection with respect to the current policy and a positive or negative advantage value, the actor evaluates the action taken and current policy against the valuation states from the critic. The agent is encouraged to reinforce the current policy if the action taken follows the current policy and the action taken resulted in a value better than the average value for that state or the action taken went against policy which resulted in a lower than average value. Conversely, the agent is encouraged to update away from the current policy if the action followed the current policy and resulted in a worse value than average for the state or if the agent went against current policy and the resulting value was better than the average for the state. Since log probabilities do not tend to 0 when multiplied, they provide better numerical stability during training.

Initial runs showed that even with very small learning rates (1e-5 and below), the agent would find a local minima, selecting the same action every time. Thus, an entropy term has been added to improve training stability. The entropy term, originally proposed by William and Peng (1991) for use with the REINFORCE algorithm, encourages the actor to output a distribution with higher entropy (More even probabilities) by penalising low entropy outputs through the loss function. For example, in an environment with four actions such as Breakout, a maximum entropy output distribution would have a 0.25 probability of selecting each action. The inclusion of the entropy term yields a new update equation below where β is the entropy weight, which is a hyperparameter that controls how much the actor loss comprises of the entropy value.

$$\nabla_\theta J(\theta) = \sum_{t=0}^{T-1} -\nabla_\theta \log \pi_\theta(a_t|s_t) A(s_t, a_t) + \beta H_t \tag{6}$$

3.3 Async Q-Learning

Async Q-Learning was chosen as it is similar to DQN, but promises improved learning in a shorter time. Appendix C: Async Q-Learning pseudo-code

Like DQN, Async Q-Learning uses an ϵ-greedy policy based on a value network to select actions to take and then uses a target network to estimate an action value that is used to calculate the loss. The weights in the target network are occasionally reset to match the value network.

Where Async Q-Learning differs from DQN is that it runs multiple worker agents in separate processes which share the value and target networks. Each worker agent uses local copies of the value and target networks to calculate the losses and gradients, then applies them to the shared networks every few steps as a single batch. Once the worker agent has updated the shared network, it refreshes the weights in its local copies to match shared ones.

As the updates are done in batches, it is easy to also implement the n-step variant of Async Q-Learning, which according to Mnih et al (2016) offers further performance improvements. (Appendix D: Async n-step Q-Learning pseudo-code)

Having multiple worker agents running at the same time means that different areas of the game will be explored at the same time. The different worker agents were also given different epsilon values for their ϵ-greedy policies to further increase the variety of exploration. Some experimentation was also done using both decaying epsilon values, and learning rates. However, the time taken to run tests meant a thorough examination of the impacts of these hyperparameters was not possible.

A controller process handles the creation of multiple workers and a stats collector. The controller gives each worker a queue which allows communication between controller and workers. Each worker starts the ALE environment and plays games of breakout letting the controller know the results of each game. The controller keeps track of the total number of episodes completed by all the workers, and uses another process to play games with a policy created from a copy of the shared value network to provide a measure of how well the training is going.

4 Results

The DQN implementation was tested against v5 of the ALE framework, whilst the A2C implemtnations was tested against v4 of the ALE framework. The main difference between the two ALE versions is that v5 introduces a *repeat_action_probability=0.25*. This means that 25% of the time the action sent to ALE is ignored, and the previous action is used instead. This makes the ALE environment stochastic and harder to train an agent against. For the following results, DQN was trained against v5, A2C was trained against v4, and Asynch Q-Learning was trained against both.

4.1 DQN

Different DQN agents with different configurations of memory capacity and experience replay selection were initially tested for 7 million Frames to attest the best hyper-parameter set. The picture below shows the test score trajectories of 4 different DQN agent configurations.

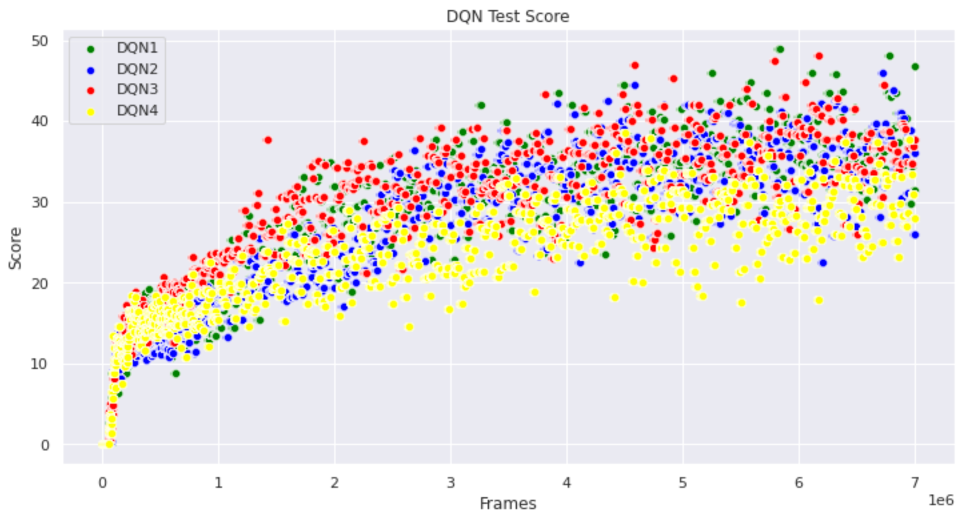
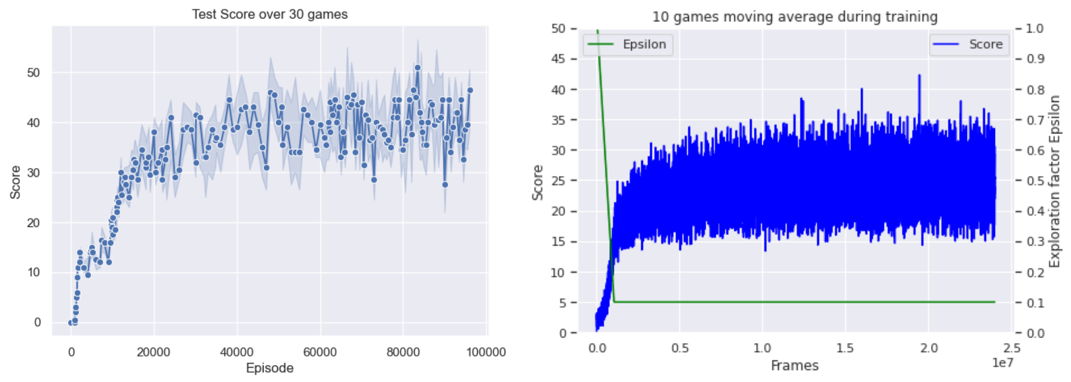


Figure 1. DQN agent performances comparison over 7M frames. DQN1: N=200k, random experience replay selection. DQN2: N=1M, random experience replay selection. DQN3: N=200k, half prioritized experience replay selection. DQN4: N=500k, full prioritized experience replay selection.

Due to the amount of time required to train multiple agent, the training process was then resumed until 24M frames with DQN2 agent only. There was no clearcut winner from the initial test, so DQN2 was chosen because its hyper-parameters mimic the values used by Mnih et al., 2015 which gives a clear baseline for performance comparison.



(a) Test score over 30 games with epsilon = 0 **(b) 10 games score moving average during training**

Figure 2. DQN2 performances

4.2 A2C

From episode 1000, the agent shows steady and notable improvement, maintaining a running average of over 10 points by episode 2500.

The agent performance peaks around episode 3750 with a 10 game average of 41.4 and peak single game performance of 233.

Beyond this point the agent shows evidence of overtraining. Performance significantly deteriorates to the level seen in the earliest episodes.

Observing the actor's softmax output, we see that the agent is outputting almost the same probabilities for every state with very little change in the distribution between states or between episodes.

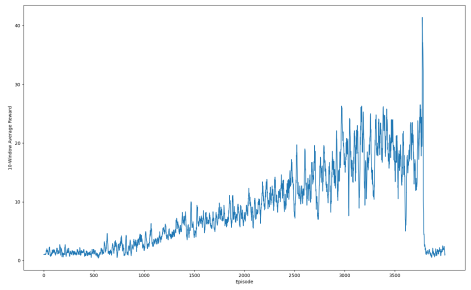
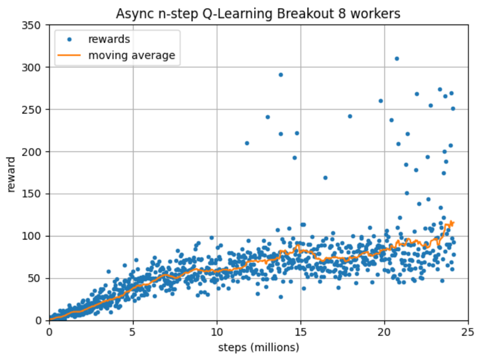


Figure 3. 10-episode running average for Breakout A2C agent over 4000 episodes

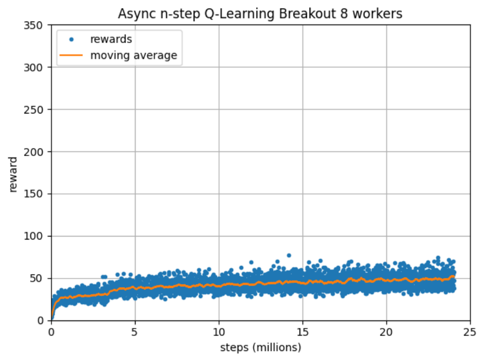
4.3 Async Q-Learning

As expected Asynch n-step Q-Learning (using n=8) learnt more quickly than the single step version. So, the majority of tests were performed with the n-step vesion.

The figures below show the results from a long run of approximately 40 hours (24 million frames). A learning rate of 0.0001, epsilon values in the ϵ-greedy policies varied in different processes and were reduced from a maximum of 0.4 down to 0.1 after approximately a million frames.



(a) Run against ALE v4



(b) Run against ALE v5

Figure 4. Long runs of Async n-step Q-Learning against v4 and v5 of the ALE

The figures clearly show that v5 of the ALE with *repeat_action_probability=0.25* is harder to train against than v4 of the ALE which does not have repeat action. Scores achieved with v5 tended to improve at about half of the rate of scores achieved with v4.

5 Discussion

5.1 DQN

Mnih et al., 2015 report a maximum average score of 401 after 50M frames. We were not able to replicate the same level of performance. The best average score recorded in our implementation of DQN is 51 at around 21M frames (83500-th episode) Although we could not match Mnih et al., 2015 results, our agent reaches 160% of human performance.

Human (Baseline)	DQN Implementation	Mnih et al (2015) DQN (50M frames)
31.8	51	401

It was interesting to notice the early difference in performances amongst DQN agents having different memory buffer sizes and experience replay selection methods shown in Figure1. DQN1 and DQN2 differ in the size of the memory buffer (200K vs 1M), but, no appreciable difference was seen between the two. Comparable results were obtained selecting half of the training samples using cosine similarity. An overall degradation in performances was recorded while only selecting experiences which resemble the agent observed state S'. This might suggest that by only selecting experiences which are similar to the current observation a form of data correlation is introduced.

5.2 A2C

Human (Baseline)	A2C Implementation	Wu et al. (2017) A2C (50M frames)
31.8	41.4	581.6

The A2C implementation was able to significantly outperform a professional human game tester, reaching 130.19% of human performance. This was achieved in 3,750 episodes (8 hours) of training. The implementation outperforms the human baseline, so, the agent has solved the chosen problem relatively well. Wu et al. (2017) required 14,464 episodes to surpass human performance, whereas our A2C implementation only required 3,774. This shows that our implementation learns quickly.

However, the implementation does not come close to achieving the 100 game running average of 581.6 achieved by the A2C implementation in Wu et al. (2017). The agent training becomes unstable significantly before the timesteps taken in Wu et al. (2017). Interestingly, across several runs, the instability and subsequent local minima appear after a particularly high score (In this case 233), indicating that a potential cause is a very large update to the networks that the agent is unable to properly incorporate. This suggests that a potential route to match the high scores reached in the literature is to reduce the learning rate and training the agent for significantly longer or implementing reward clipping.

5.3 Async Q-Learning

The performance of Async n-step Q-Learning and DQN was similar with both achieving an average score around 50 after processing 24 million frames with v5 of the ALE.

Comparing the results from Async n-step Q-Learning and A2C when trained against v4 of the ALE shows that the configuration used for A2C learns more quickly. Async n-step Q-Learning was slower, but kept on increasing, managing an average score of over 100 after processing 24 million frames.

The results obtained from running Async n-step Q-Learning did not match the results and time scales achieved by Mnih et al (2016). However, they completed approx 25 epochs in 10 hours to get scores in excess of 250. A single epoch being 4 million frames giving 100 million frames in 10 hours. In contrast our implementation is 16 times slower, processing about 6 million frames in 10 hours.

Our results compare favourably with those from Mnih et al (2016), as we reached average scores of 50 in approximately half the number of frames. Although, we have not trained for long enough to compare final scores.

6 Future Work

6.1 DQN

Experience replay is a key ingredient in the success of DQN agent. In this assignment random experience replay was implemented, and, although effective, Schaul et al., 2016 work prove that rank-based and proportional based prioritized experience replay improves the agent performances. Narasimhan et al., 2015 also suggest an alternative method of resampling the experiences. The method separates experience into two buckets, one for positive and one for negative rewards. The experiences are then picked from the two buckets by a fixed ratio.

6.2 A2C

In the A2C implementation used, the advantage function is calculated using n-step (Where n=1) returns. This only includes one step of actual rewards. Since rewards are generated from a single trajectory, they tend to have high variance but are unbiased. However, the state valuation reflects all trajectories seen so far and thus has lower variance but introduces bias. As a result, the value of n controls the bias-variance tradeoff (Graesser and Loon, 2020).Thus, using 1 step returns provides us with a tradeoff of low variance but introduces significant bias through the reliance on state value.

In contrast, Generalised Advantage Estimate (GAE) overcomes the need to set n as a hyperparameter by using an exponentially-weighted average of advantages calculated with different values of n (Schulman et al., 2015). GAE provides a method by which the low-variance, high-bias one step advantage is most heavily weighted but the lower-weighted contributions from higher values of n still contribute. By tweaking the decay rate of contribution from these higher-variance estimators with higher values of n, GAE allows a more finely controlled tradeoff between bias and variance than the hard cut-off tradeoff in n-step methods (Graesser and Loon, 2020). In comparison to the 1-step method implemented, this is likely to allow a significant reduction in bias whilst controlling the increase in variance.

6.3 Async Q-Learning

Having multiple processes gives scope for using different hyperparameters at the same time. So, it would be interesting to try and produce a version of the code that attempts to tune itself.

It would also be interesting to investigate the asynchronous version of advantage actor critic (A3C) to see how it compares to A2C.

7 Personal Experience

7.1 Mirco

DQN was quite fiddly to tune. Parameters that seems not to bear a great deal of impotance over the training process actaully affected results quite heavily. For instance, a key factor for the agent learning stability was frequency at which the q-value network are updated. I found that updating the agent policy at every step triggered some form of instabiity and led to the agent to forget all the prevoius learning after few hundred of thousen of frames. By updaing the network weights every four actions the learning was much more stable. The experience batch size also had a somewhat sizable impact on the training outcome. Batches of size 64 presented a more unstable behaviour with respect of batches of size 32.

7.2 Chris

In the training of the A2C agent, one factor that was both a difficulty and a surprise was the sensitivity of the agent to changes in the algorithm hyperparameters. For example, the entropy weight was found to be a very important and sensitive hyperparameter. If set slightly too low the agent would revert to selecting a single action with certainty every time. If set too high, the agent would not move significantly from a random sample across the four actions. However, the difference between these outcomes was often a very small change. It is, however, possible that this sensitivity may have been mitigated at the cost of increased training time by reducing the learning rate of the networks.

7.3 Peter

Creating a multiprocessing application in python using Keras seemed to be a little awkward, however, PyTorch offered much better support and it became much more straightforward once swapping to use that. It was nice to get a chance to try out PyTorch, and from first use, it seems to be a nicer API than keras.

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Appendices

Appendix A: DQN pseudo-code

Taken from the course notes.

```
 1: Initialise replay memory $D$ to capacity $N$
 2: Initialise action-value network $\hat{q}_1$ with parameters $\boldsymbol{\theta}_1 \in \mathbb{R}^d$ arbitrarily
 3: Initialise target action-value network $\hat{q}_2$ with parameters $\boldsymbol{\theta}_2 = \boldsymbol{\theta}_1$
 4: for each episode do
 5:     Initialise $S$
 6:     for for each step of episode do
 7:         Choose action $A$ in state $S$ using policy derived from $\hat{q}_1(S, \cdot, \theta_1)$
 8:         Take action $A$ observe reward $R$ and next-state $S'$
 9:         Store transition $(S, A, R, S')$ in $D$
10:         for each transition $(S_j, A_j, R_j, S'_j)$ in minibatch sampled from $D$ do
11:             $y = \begin{cases} R_j & \text{if } S'_j \text{ is terminal} \\ R_j + \gamma \max_{a'} \hat{q}_2(S'_j, a', \boldsymbol{\theta}_2) & \text{otherwise} \end{cases}$
12:             $\hat{y} = \hat{q}_1(S_j, A_j, \boldsymbol{\theta}_1)$
13:             Perform gradient descent step $\nabla_{\theta_1} L_\delta(y, \hat{y})$
14:         Every $C$ time-steps, update $\boldsymbol{\theta}_2 = \boldsymbol{\theta}_1$
```

Appendix B: TD Advantage Actor Critic (A2C) pseudo-code

From Steinbach (2018)

```
 1: Randomly initialise critic network $V_\pi^U(s)$ and actor network $\pi^\theta(s)$ with weights U and $\theta$
 2: Initialise environment $E$
 3: for episode = 1, M do
 4:     Receive initial observation state $s_0$ from $E$
 5:     for t=0, T do
 6:         Sample action $a_t \sim \pi(a|\mu, \sigma) = \mathcal{N}(a|\mu, \sigma)$ according to current policy
 7:         Execute action $a_t$ and observe reward $r$ and next state $s_{t+1}$ from $E$
 8:         Set TD target $y_t = r + \gamma \cdot V_\pi^U(s_{t+1})$
 9:         Update critic by minimising loss: $\delta_t = (y_t - V_\pi^U(s))^2$
10:         Update actor by minimising loss: $Loss = -\log(\mathcal{N}(a|\mu(s_t), \sigma(s_t))) \cdot \delta_t$
11:         Update $s_t \leftarrow s_{t+1}$
```

Appendix C: Async Q-Learning pseudo-code

From Mnih et al (2016)

```
 1: // Assume global shared $\theta$, $\theta^-$, and counter $T = 0$
 2: Initialise thread step counter $t \leftarrow 0$
 3: Initialise target network weights $\theta^- \leftarrow \theta$
 4: Initialise network gradients $d\theta \leftarrow 0$
 5: Get initial stats $s$
 6: while $T <= T_{\max}$ do
 7:     Take action $a$ with $\epsilon$-greedy policy based on $Q(s, a; \theta)$
 8:     Receive new state $s'$ and reward $r$
 9:     $y = \begin{cases} r & \text{for terminal } s' \\ r + \gamma \max_{a'} Q(s', a', \theta^-) & \text{for non terminal } s' \end{cases}$
10:     Accumulate gradients wrt $\theta$: $d\theta \leftarrow d\theta + \frac{\delta(y - Q(s,a,\theta))^2}{\delta\theta}$
11:     $s = s'$
12:     $T \leftarrow T + 1$ and $t \leftarrow t + 1$
13:     if $T$ mod $I_{target} == 0$ then
14:         Update the target network $\theta^- \leftarrow \theta$
15:     if $t$ mod $I_{AsyncUpdate} == 0$ or $s$ is terminal then
16:         Perform asynchronous update ot $\theta$ using $d\theta$
```

```
17:         Clear gradients $d\theta \leftarrow 0$
```

Appendix D: Async n-step Q-Learning pseudo-code

From Mnih et al (2016)

```
 1: *// Assume global shared $\theta$, $\theta^{-}$, and counter $T = 0$*
 2: Initialise thread step counter $t \leftarrow 0$
 3: Initialise target network weights $\theta^{-} \leftarrow \theta$
 4: Initialise network gradients $d\theta \leftarrow 0$
 5: Initialise thread-specific parameters $\theta' \leftarrow \theta$
 6: Get initial stats $s$
 7: while $T <= T_{\max}$ do
 8:     Clear gradients $d\theta \leftarrow 0$
 9:     Synchronize thread-specific parameters $\theta' \leftarrow \theta$
10:     $t_{start} = t$
11:     Get state $s_t$
12:     while not terminal $s_t$ and $t - t_{start} < t_{max}$ do
13:         Take action $a_t$ with $\epsilon$-greedy policy based on $Q(s_t, a; \theta')$
14:         Receive new state $s_{t+1}$ and reward $r_t$
15:         $t \leftarrow t + 1$
16:         $T \leftarrow T + 1$
17:     $R = \begin{cases} 0 & \text{for terminal } s_t \\ \max_a Q(s_t, a, \theta^{-}) & \text{for non terminal } s_t \end{cases}$
18:     for $i \in \{t-1, ..., t_{start}\}$ do
19:         $R \leftarrow r_i + \gamma R$
20:         Accumulate gradients wrt $\theta'$: $d\theta \leftarrow d\theta + \frac{\delta(y - Q(s,a,\theta\prime))^2}{\delta\theta\prime}$
21:     Perform asynchronous update ot $\theta$ using $d\theta$
22:     if $T$ mod $I_{target} == 0$ then
23:         Update the target network $\theta^{-} \leftarrow \theta$
```

Appendix E: