RL Project

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1 Problem Definition

2 Background

2.1 DQN (Mirco)

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 $f : (s, a, \theta) \to R, s \in Sa \in A\theta \in \mathbb{R}$ to estimates the action-value functions for each state and therefore determine the optimal action a to take in the state s.

Deep Q-Network agent (DQN) introduced by Mnih et al., 2015, was the first value-based RL method to achieve and surpass human performances at Breakout making it the first candidate algorithm we decided to implement. Mnih et al., 2015 shows how DQN was able to reach an average score of 401 over 30 games, compared to an average score of 31 reached in the same testing conditions by a tester professional human player.

Earlier attempts, to use nonlinear function approximations to estimate the action value function, were made before the introduction of DQN agent (find reference) but presented limited and unstable learning. DQN breakthroughs addressed these limitations, more specially the utilization of a separate target network to estimate the next state maximum action value function combined with the introduction of an experience replay memory to avoid temporally correlated data during training allowed the agent to achieve stable learning and converge to a close to optimal policy.

DQN, of course, comes with its own limitations, more specifically, the generally slow training requiring the agent to play a number of frames in the order of millions to achieve human performances translate is a slow learning process. Hasselt, Guez and Silver, 2016 showed that, like Q-learning, DQN overestimates the action value functions which may translate in a sub optimal policy. They showed that this overestimation is due to the fact that, during the bootstrapping from the next state (max operation) the same values are used to select and evaluate an action. This limitation was addressed with the introduction of DDQN agents.

2.2 A2C (Chris)

A set of alternative methods to value-based methods are policy gradient methods. Whilst value-based methods such as DQN learn values of actions and use these estimates to select actions, 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). Policy Gradient techniques have seen success in high-profile reinforcement learning breakthroughs in game-playing. Most notably, AlphaGo (Silver et al. 2016) used the REINFORCE algorithm to train the policy network used in the agent.

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. Indeed, on a set of Atari games, including Breakout, their results showed that A2C outperformed A3C and the noise introduced by the asynchronous implementation failed to deliver any performance benefit (Wu et al. 2017).

2.3 Async Q-Learning (Peter)

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.

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

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.

TODO : Weaknesses? Check publications for A3C vs A2C, I've seen comments that say A3C does not improve on A2C, but can't find anything definitive. ??

3 Method

3.1 DQN (Mirco)

As already mentioned in section 2, 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,

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

DQN as well as Q-Learning, uses bootstrapping to update the action value function as shown in the equating below.

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

where α is the learning rate and γ is the discounting factor for future rewards. With tabular RL methods, the learning process is achieved by directly updating the action value function correspondent to each state-action pair while the agent interacts with the environment. With function approximation methods, the learning happens by updating the function parameters used to estimate the action value functions. More specifically, the function parameters are update in the direction that minimize the loss between the current action value function estimation and its update via bootstrapping. The weight update is achieved by standard gradient descent.

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

DQN, as well as, Q learning belong to a class of algorithm called semi-gradient methods. These methods assume that the next state action value function estimate does not depend on the value of the function parameters. As it is shown in the equation above, the derivation of the term $\max_a \hat{Q}(S', a, \theta_t)$ is simply neglected as it is considered to be a constant.

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, as briefly mentioned in section 2, is the introduction of two separate networks for the action-value function estimation. One q-network to estimate the action value functions of state S and a separate target network to estimate the next state action value functions. The weights of the target network are kept constant for a certain number of iteration before being synched with the q network weights. By using a constant target network, the q-network can be updated towards a stable target limiting the cause on instability during training.

DQN also uses a replay memory buffer to store the last N interaction with the environment. At each step, a subset n of experienced $\in N$ is randomly selected and used to update the q-network weights using equations 3. This allows the agent to train on time uncorrelated data. Each experience stored in the replay buffer comprises of the initial state S, the action A taken while in state S, the given reward R and the resulting next state S' along an additional Boolean flag which indicates whether or not S' is a terminal state.

DQN, as well as Q-Learning is an off-policy method. A behavioral $\epsilon - greedy$ policy is used for exploration while the agent policy is updated by taking choosing the best action $A*$ (leading to the maximum future expected reward) 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 CNN are used as function approximations for the Q values, whose input are the raw pixel data outputted by the environments. Preprocessing is applied to the input image to reduce the amount of computation. More specifically, the image is cropped, resized to 84x84 pixel and converted to grey scale. To give the CNN the information about the ball trajectory, the state S is a concatenation of 4 consecutive states experienced by the agent. The output of the CNN are the Q values for each action available in state S.

3.2 A2C (Chris)

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 convolutional neural network (CNN) where the parameters are the weights of the neural network. The critic is also implemented as a convolutional neural network, 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 uses 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 a pre-processed 84x84x4 image that represents a state the Breakout environment. The preprocessing applied is similar to that applied in Minh et al. (2015), including greyscale, image cropping and frame-skip. This is implemented using an OpenAIGym provided Atari wrapper that follows the guidelines in Machado et al. (2018) The 4 channels of the image are implemented using the StateHistory class which includes the current frame and the 3 previous frames, giving the agent context to the current frame such as the direction the ball is travelling in.

The critic uses a TD update to adjust its estimate of the value of a state. Each step of the environment, the critic network calculates a value estimate for both the previous state and the next-state that the agent is in. In a similar fashion to TD(0), the critic uses the 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 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. The use of log probabilities in the calculation of the actor loss yields a loss function similar to categorical cross entropy with the negative log probabilities being multiplied by an advantage adjusted delta term to represent the action taken and the probabilities of taking each action. Using log probabilities offer benefits over the use of raw probabilities since log probabilities do not tend to 0 when multiplied and thus, 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 one action every time, making it incapable of sampling other actions. 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 (Peter)

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

Like DQN, Async Q-Learning uses an e-greedy policy based on a value network to select actions to take and then uses a target network to get an action value 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 keeps a local copy of the value and target networks to calculate the losses and gradients which it then applies to the shared networks every few steps. Once the worker agent has updated the shared network, it resets the weights in its own copies to match shared ones. As the worker agent takes a number of steps before updating the shared network, the updates are done like mini-batches and the chances of one worker agent overwritting changes being made by another are reduced.

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.

Having multiple worker agents running at the same time, and the non-deterministic nature of breakout 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 e-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 a single test meant a thorough examination of the impacts of both of these hyperparameters was not possible.

A controller process handles the creation of multiple workers as different processes. The controller gives each worker a queue which allows communication between controller and workers. Each worker starts the atari environment and plays games of breakout. An episode is a complete game, and at the end of each episode the worker sends some details to the controller.

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 based on the shared value network with an epsilon of 0.01 to provide a measure of how well the policy performs.

TODO : Maybe a diagram of the different processes would help here?

4 Results

4.1 DQN (Mirco)

Different DQN agent with different configurations of memory buffer size and experience 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.

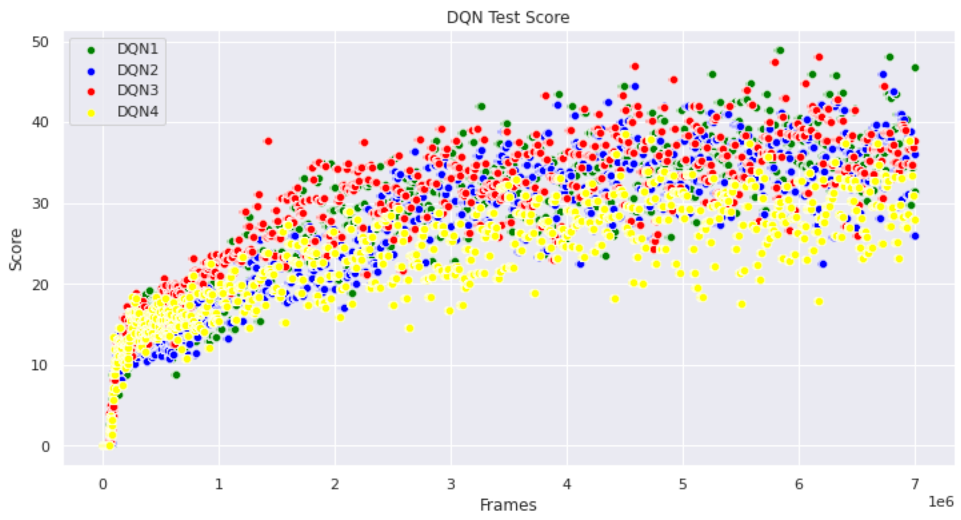


Figure 1. DQN agent performances comparison over 7M frames. DQN1: N=200k, random experience replay selection. DQN2: N=1M, random experience replay selection. DQN3: N=200k, half prioritized experience replay selection. DQN5: N=500k, full prioritized experience replay selection.

Due to the amount of time required to train multiple agent, the training process was then resumed until 24M frames with DQ2 agent only. DQN2 was chosen for two main reasons. DQN2 hyper-parameters mimic the values used by Mnih et al., 2015 which gives a clear baseline for performance comparison. Although the performance between DQN1, DQN2 and DQN3 agents do slightly vary, there is not clear cut winner. DQN4 does seem to perform the worse between the tested configurations. More details are given in section 5.

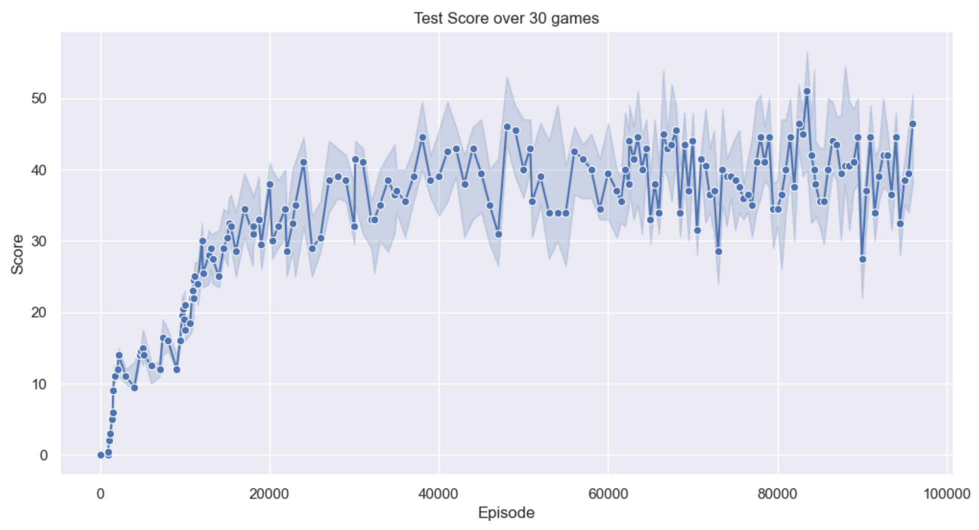


Figure 2. DQN2 test score calculated as simple average over 10 games with epsilon = 0

Figure 2 report the median test score calculated as the meadian over 30 games using a determinist policy, namely, $\epsilon = 0$. The faded bands represent the 95% confidence interval.

Figure 3 shows in blue the moving average of the score over 10 games during training. The green trajectory shows the decaying exploration factor ϵ over the first 1 million frames.

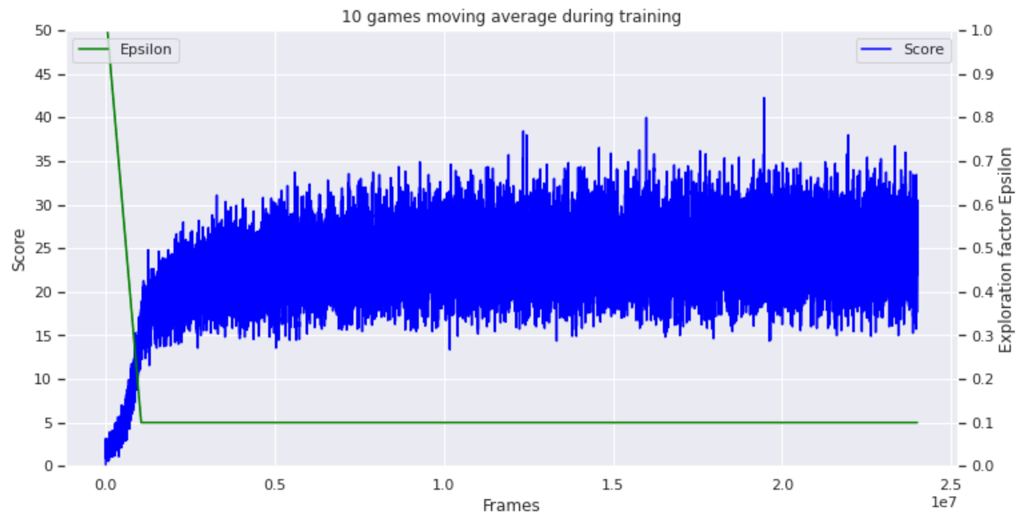
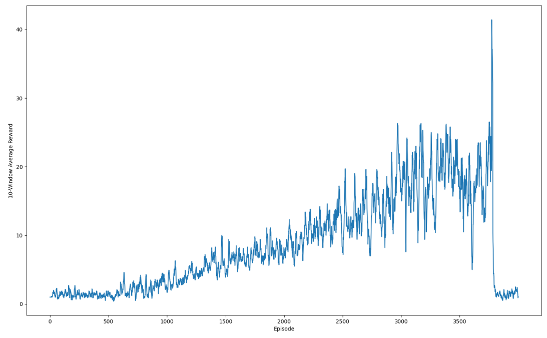


Figure 3

4.2 A2C (Chris)

Figure 4.1: 10-episode running average for Breakout A2C agent over 4000 episodes

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. The performance significantly deteriorates to the level seen in the earliest episodes. Observing the softmax output from the actor during this period shows the agent is outputting almost the same probabilities for every state with very little change in the distribution between states or between episodes.



4.3 Async Q-Learning (Peter)

Initial results were encouraging, but the performance tended to level off quite quickly and often started to decrease.

The figure below shows a comparison of the single step Asynch Q-Learning and n-step, using n=8. The n-step approach showed a marked improvement over the single step. TODO : get better example image.

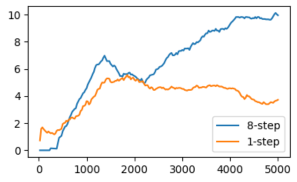
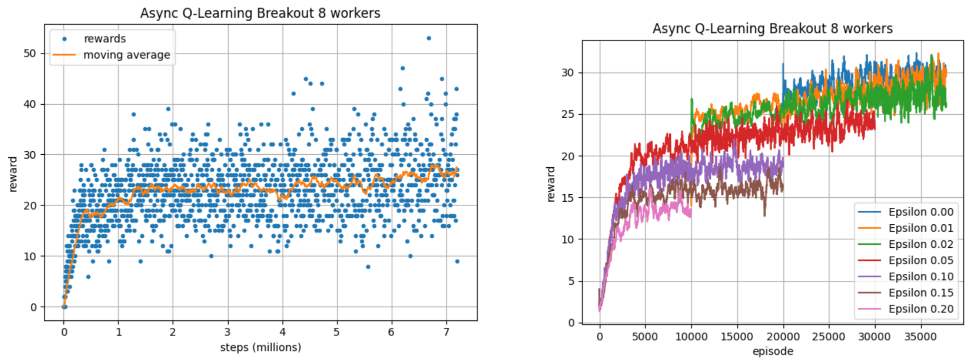


Figure 4. n-step better than single step

The figures below show that the rapid initial learning slows, but with management of the epsilon value in the e-greedy policy, it does continue to improve. TODO : Getter neater graphs with matching ranges



(a) Reward sampled every 25 episodes **(b) Rewards every episode for different processes**

Figure 6. long run showing gradual improvements

5 Discussion

5.1 DQN (Mirco)

Mnih et al., 2015 reports a maximum average score of 401 after 50M frames. We were not able to replicate the same level of performances. The best average score recorded in our implementation of DQN is 75 around 22M frames. Figure reffig:DQNTestScore shows that although the test score trend appears to be upward, from a simple visual analysis, its first derivative with respect to the number of Frames seem to be too low to match the score of 401 at 50M frames. Although we could no match Mnih et al., 2015 results, our agent reaches 236% of human performances.

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

5.2 A2C (Chris)

Human (Baseline)	A2C Implementation	Wu et al. (2017) A2C (50mil timesteps)
31.8	41.4	581.6

Table 5.1: Col 1- Human performance on Breakout from a professional games tester (Mnih et al., 2015). Col2 - Peak performance of A2C implementation in this assignment averaged over 10 episodes. Col3 - Performance of A2C implementation in Wu et al. (2017) after 50 million timesteps averaged over 100 episodes

As shown in Table 5.1, using an average over 10 games, the A2C implementation was able to significantly outperform a professional human game tester, reaching 130.19% of human performance. This was achieved in 3750 episodes of training which equated to approximately 8 hours training time on CPU. As the implementation outperforms the human baseline, this indicates the agent has solved the chosen problem relatively well and achieves superhuman performance.

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). Thus, whilst the agent does solve the problem effectively enough to achieve superhuman performance, it does not match similar implementations in the literature. 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 for the deterioration in performance is a very large update to the networks that the agent is unable to properly incorporate. This suggests that, given more time and resources in the assignment, 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.

A2C Implementation	Wu et al. (2017) A2C (50mil timesteps)
3774	14464

Table 5.2: Col 1- Episodes required for 10 episode average to surpass human performance Col2 - Episodes required for Wu et al. (2017) A2C implementation to surpass human performance over 100 episode average.

Table 5.2 compounds the idea that the agent implemented in this paper learns quickly but that this may be the cause of the instability. Whilst the episode average windows are of different sizes, the difference number of episodes required for the A2C to surpass human performance over the chosen window is relatively large. This suggests that although the agent is unable to match the final performance of similar implementations in the literature, the agent in this implementation learns quickly. This, again, suggests that with more time and resources, a lower learning rate and a greater training time may allow this implementation to reach scores comparable to those in the literature.

5.3 Async Q-Learning (Peter)

As expected, the Asynch n-step Q-Learning produced better results than single step. However, they did not match the results in the time scales achieved by Mnih et al (2016). On further examination of figures published by Mnih et al (2016) the scores on the data efficiency and training time graphs show that they completed approx 25 epochs in 10 hours giving scores in excess of 250. A single epoch is 4 million frames giving 100 million frames in 10 hours. In contrast our implementation for asynch Q-Learning processed about 7.5 million frames in 10 hours, so approximately 13 times slower.

That being the case, it gives us an expectation of 2 days processing time to acheive a score in excess of 250. The results we obtained actually compare favourably with those from Mnih et al (2016), with average scores of 25 being acheived in less than half the number of steps.

TODO : Discussion of all the different hyper parameters?

6 Future Work

6.1 A2C (Chris)

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.

7 Personal Experience

7.1 A2C (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.

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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 $Q\left(s_t, a; \theta'\right)$
14:         Receive new state $s_{t+1}$ and reward $r_t$
15:         $t \leftarrow t + 1$
16:         $T \leftarrow T + 1$
17:     $R = \begin{cases} 0 & \text{for terminal } s_t \\ \max_a Q\left(s_t, a, \theta^{-}\right) & \text{for non terminal } s_t \end{cases}$
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: