Comparison of Deep Reinforcement Learning Algorithms in Atari 2600 Games

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Abstract

The Deep Q-Network (DQN) algorithm has become very popular and several variants have been developed over it. However, it is also important to understand the intricate details in its variants, for further improvement and also to identify and exploit the most suited applications for them. In this paper, we compare DQN base algorithm along with its variants Double DQN and Dueling Double DQN algorithm. The experiments are performed on three Atari domains and extensively analyzed. We also compare a modified version of DQN with original DQN algorithm. With our experiments and analysis, we understand the differences between them and successfully make inference about the benefit of each algorithm in different situations and their suitability for different environments.

Introduction

Reinforcement Learning (RL) can be referenced as the science of sequential decision-making. Reinforcement Algorithms aim to train agents to learn the optimal behaviour in an environment to obtain maximum reward or the defined goal. This optimal behaviour is learned through interactions with the environment and observations of its response to that form of interaction in that sequence. The Reinforcement Learning problem involves an agent exploring an unknown environment to gain a maximum reward. Reinforcement Learning is based on the hypothesis that all goals can be described by the maximization of expected cumulative reward.

Advancements in Deep Learning and Reinforcement Learning combined resulted in Deep Reinforcement Learning Algorithms such as Deep Q-Networks (DQN; Mnih et al. 2013, 2015). It's a combination of Q-learning, convolutional neural networks and experience replay. This enabled it to learn, from raw pixels, how to play many Atari games at human-level performance. Since then, many extensions have been proposed that enhance its speed and stability.

Understanding the intricate differences between these variants is of pivotal importance to properly utilize their benefits and understand their drawbacks and improve upon it.

The DQN algorithm as mentioned had surpassed human experts at some Atari 2600 game environments and also most of the previous benchmark results by other RL algorithms, but it has some drawbacks.

Q-learning (Watkins, 1989) is one of the most popular basic reinforcement learning algorithms, but it is known to sometimes learn unrealistically high action values because it includes a maximization step over estimated action values, which tends to prefer overestimated to underestimated values. This same drawback applies to the DQN algorithm which is solved by Double DQN (DDQN; van Hasselt, Guez, and Silver 2016).

This algorithm is based over Double Q-learning algorithm (van Hasselt, 2010). It addresses the overestimation bias of Q-learning, by decoupling selection and evaluation of the bootstrap action. Results from this algorithm in most Atari 2600 game environments were an improvement of DQN results both in terms stability and performance. Along with the above two algorithms, we will also be comparing, Dueling Double DQN which forms a new dueling network architecture (Wang et al. 2016) which represents two separate estimators: one for the state value function and one for the state-dependent action advantage function. The main benefit of this factoring was to generalize learning across actions without imposing any change to the underlying reinforcement learning algorithm. The results show that this architecture leads to better policy evaluation in the presence of many similar-valued actions. Hence, in suitable environments, dueling architecture enabled the RL agent to outperform the previous state-of-the-art on the Atari 2600 domain games.

In this paper, the above algorithms are being compared together over 3 different Atari 2600 environments, Pong, Krull and Boxing on multiple parameters based on experiment results. Results from modifications to DQN algorithm have also been discussed.

Background

Below are the details of these algorithms and some important sub-components.

Q-Learning and Double Q-Learning

To solve sequential decision problems we can learn estimates for the optimal value of each action, defined as the expected sum of future rewards when taking that action and

following optimal policy after that. Under a given policy π, the true value of an action a in a state s is

$$Q_\pi(s,a) \equiv E\left[R_1 + \gamma R_2 + \ldots \mid S_0 = s, A_0 = a, \pi\right]$$

where $\gamma \in [0,1]$ is a discount factor that trades off the importance of immediate and later rewards. The optimal value is then $Q_*(s,a) = \max_\pi Q_\pi(s,a)$. To learn optimal action values we use Q-learning, a form of temporal difference learning. We learn a parameterized value function $Q(s,a;\theta_t)$. The standard Q-learning update for the parameters after taking action A_t in state S_t and observing the immediate reward R_{t+1} and resulting state S_{t+1} is

$$\theta_{t+1} = \theta_t + \alpha\left(Y_t^{\mathrm{Q}} - Q\left(S_t, A_t; \theta_t\right)\right)\nabla_{\theta_t} Q\left(S_t, A_t; \theta_t\right) \quad (1)$$

where α is a scalar step size and the target Y_t^{Q} is defined as

$$Y_t^{\mathrm{Q}} \equiv R_{t+1} + \gamma \max_a Q\left(S_{t+1}, a; \theta_t\right) \quad (2)$$

This update resembles stochastic gradient descent, updating the current value $Q(S_t, A_t; \theta_t)$ towards a target value Y_t^{Q}.

The max operator in standard Q-learning, in (2), uses the same values both to select and to evaluate an action. This makes it more likely to select overestimated values, resulting in overoptimistic value estimates. To prevent this, we can decouple the selection from the evaluation which forms idea of Double Q-learning.

$$Y_t^{DQ} \equiv R_{t+1} + \gamma Q\left(S_{t+1}, argmax_a Q\left(S_{t+1}, a; \theta_t\right); \theta_t'\right) \quad (3)$$

Here we use two value functions are learned by assigning each experience randomly to update one of the two value functions, such that there are two sets of weights, θ and θ'. For each update, one set of weights is used to determine the greedy policy and the other to determine its value.

Experience Replay

During learning, the agent accumulates a dataset of experiences from many episodes. When training the Q-network, instead of only using the current experience as prescribed by standard temporal difference learning, the network is trained by sampling mini-batches of experiences from D uniformly at random. Experience replay increases data efficiency through re-use of experience samples in multiple updates and, importantly, it reduces variance as uniform sampling from the replay buffer reduces the correlation among the samples used in the update.
Another advantage is that when the algorithm "Forgets" about previously learned experience, the sampling uniform data from buffer can allow it to learn it again.

Deep Q Networks (DQN)

A deep Q network (DQN) is a multi-layered neural network that for a given state s outputs a vector of action values $Q(s,\cdot;\theta)$, where θ are the parameters of the network. For an n-dimensional state space and an action space containing m actions, the neural network is a function from R^n to R^m. Two important components of the DQN algorithm as proposed by Mnih et al. (2015) are the use of a target network, and the use of experience replay. The target network, with parameters θ^-, is the same as the online network except that its parameters are copied every τ steps from the online network, so that then $\theta_t^- = \theta_t$, and kept fixed on all other steps. The target used by DQN is then

$$Y_t^{\mathrm{DQN}} \equiv R_{t+1} + \gamma \max_a Q\left(S_{t+1}, a; \theta_t^-\right).$$

Both the target network and the experience replay dramatically improve the performance of the algorithm (Mnih et al., 2015).

Double Deep Q Networks (DDQN)

A DDQN follows complete methodology of DQN with the enhancement of using Double Q-Learning algorithm's concept instead of Q-Learning which reduces overestimation of values and results in better stability and performance of algorithm. Although, the target network gives estimated values too, compared to behavior network (or first network) it has very less updates and hence has more stable values.
The update equation for Double DQN is:

$$Y_t^{DDQN} \equiv R_{t+1} + \gamma Q\left(S_{t+1}, argmax_a Q\left(S_{t+1}, a; \theta_t\right), \theta_t^-\right)$$

Dueling Double Deep Q Networks (DDQN)

This algorithm has a new duel architecture which is combined with DDQN and hence named Dueling DDQN.

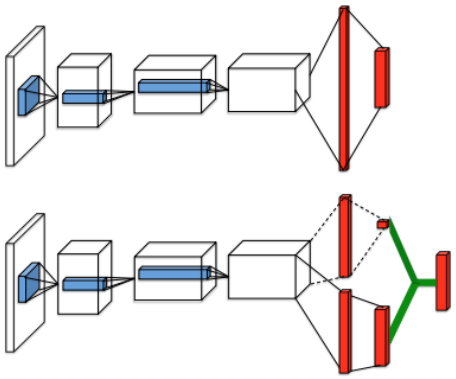

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Figure 1: Duel Network Architecture (Wang et al. 2016)

The first architecture in Figure 1 is used by DDQN and DQN. The second neural network architecture is dueling architecture which is designed for value based RL. It features two streams of computation, the value and advantage streams, sharing a convolutional encoder, and merged by a special aggregator as shown in Figure 1 (Wang et al. 2016). This corresponds to the following factorization of action values:

$$Q(s,a;\theta,\alpha,\beta) = V(s;\theta,\beta) +$$

$$\left(A(s,a;\theta,\alpha) - \frac{1}{|\mathcal{A}|}\sum_{a'} A\left(s,a';\theta,\alpha\right)\right).$$

The Q-values of the state are sum of the expected state-value and Advantage function of action. Where the stream $V(s;\theta,\beta)$ provides an estimate of the value function, while the other stream produces an estimate of the advantage function. Also, θ denotes the parameters of the convolutional layers, while α and β are the parameters of the two streams of fully-connected layers.
The dueling architecture can better approximate value of states and distinguish higher ones from lower ones, without having to learn the effect of each action for each state. This is particularly useful in states where its actions do not affect the environment in any relevant way. The dueling architecture can also more quickly identify the correct action during policy evaluation as redundant or similar actions are added to the learning problem.
With every update of the Q values in the dueling architecture, the value stream V is updated, this contrasts with the updates in a single-stream architecture where only the value for one of the actions is updated, the values for all other actions remain untouched.

Related Work

There has been a lot of development in this series of DQN algorithms, with many variants including Multi-step Learning, Prioritized replay, Distributional RL, Noisy Nets and also multiple combination of these which are called Rainbow Algorithm's variant. Rainbow algorithm encompasses all the mentioned DQN variants here and DQN, DDQN and Dueling DDQN.
Each of these algorithms improve an aspect of DQN algorithm.

In Multi-step learning we perform n-step bootstrap in contrast to Q-learning which is one step boostrapping. This also reduces the deadly triad effect due to n-step bootstrapping which increases variance and reduces bias. Hence, this algorithm has the potential to exploit a good balance between variance and bias of the bootstrapped values and results in better performance and stability with fine-tuning.

Prioritized DQN uses a Prioritized Experience Replay buffer which samples the data based on TD-error as priority. This has multiple advantages as it makes trains the agent with the best states hence, improving performance.

Noisy Nets are improving the exploration aspect of DQN and similar algorithms. Here, learned perturbations of the network weights are used to drive exploration. The key insight is that a single change to the weight vector can induce a consistent, and potentially very complex, state-dependent change in policy over multiple time steps unlike dithering approaches where de-correlated noise (example: e-greedy) is added to the policy at every step. The perturbations are sampled from a noise distribution. The variance of the perturbation is a parameter that can be considered as the energy of the injected noise. These variance parameters are learned using gradients from the reinforcement learning loss function, along side the other parameters of the agent. This way of inducing stochasticity by adding noise to weight values enables better exploration and agent's policy results in greater results although with some increase in computation.

Distributional Reinforcement Learning, approximates distribution of the return instead of computing typical expected return. It uses a distributional perspective to design a new algorithm which applies Bellman's equation to the learning of approximate value distributions. This algorithm also achieves state of the art results.

The final variant Rainbow combines all these methods in a single algorithm and evaluates performance on all Atari 2600 games, where it demonstrated state of the art results for most games among DQN variants.

Project Description

In this project, focus is on the DQN, Double DQN and Dueling DDQN algorithms and extensively comparing them on 3 Atari game domains. A modified version of DQN has also been compared.

Image Processing and Environment Wrappers

Since the state space is in RGB image format, it can be resource intensive and inefficient to directly train on those state spaces. Hence, below are some modification methods used for image processing.
After extensive research and experiment, OpenAI gym wrappers have been selected for the pre-processing and also some environment modifications.

- NoopResetEnv(30): This class has three functions, init(), reset() and step(). It samples initial states by taking random number of no-ops on reset. Here, No-op is assumed to be action 0. It takes random number of no-op actions in reset() bounded by specified range which is this case is 30.
- FireResetEnv(): This class takes action on reset for environments that are fixed until firing.
- MaxAndSkipEnv(4): This class boosts performance speed of training by choosing maximum reward resulting observation of N observations (four in this case) and returns this as an observation for the step combining reward from all N observations. It takes the maximum of every pixel in the last two frames and sends it as an observation.
- ProcessFrame84(): This class converts the input state image from dimensions $(210, 160, 3)$ to $(84, 84, 1)$ using gray-scale conversion. It crops non-relevant parts of the image and then scales them down.
- BufferWrapper(4): This class stacks 4 images to the state, to increase the observation of game dynamics.
- ImageToPyTorch(): This class converts the input state from $(84, 84, 4)$ to $(4, 84, 84)$. Basically shifting the channel or in our case, number of stacked states.
- ScaledFloatFrame(): This class converts the grayscale pixel input values $[0, 255]$ to float value $[0.0, 1.0]$ and is applied at the end of processing.

Algorithm 1: deep Q-learning with experience replay

Input:Initialize replay memory D to capacity N
Input:Initialize action-value function Q with random weights θ
Input:Initialize target action-value function Q with weights $\theta^{-} = \theta$
For episode $= 1, M$ do
  Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$
  For $t = 1,$ T do
    With probability ε select a random action a_t
    otherwise select $a_t = argmax_{\mathrm{r}} Q(\phi(s_t), a; \theta)$
    Execute action a_t in emulator and observe reward r_t and image x_{i+1}
    Set $s_{t+1} = s_t, a_t, x_{\mathrm{t}+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in D
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from D
    Set $y_j = \begin{cases} r_j & if A \\ r_j + \gamma \max_{\alpha'} \dot{Q}(\phi_{j+1}, a'; \theta^{-}) & else \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ with respect to the network parameters θ
    Every C steps reset $\dot{Q} = Q$
  End For
End For

Where Condition A is $j + 1$ episode being terminal.

DQN

For DQN the Algorithm 1 from (Mnih et al.,2015) has been implemented in PyTorch. The states in this algorithm are pre-processed using the wrappers discussed in previous sub section.
In all the three algorithms, the epsilon value is linear decayed till Final Exploration Frame mentioned in hyperparameter table in next section.

Neural Network Architecture:
Convolution layer 1: 32 channels, filter size 8*8, stride 4
Convolution layer 2: 64 channels, filter size 4*4, stride 2
Convolution layer 3: 64 channels, filter size 3*3, stride 1
Linear Layer 1: Hidden Dimension 512
Linear Layer 2: Output Dimension: Number of actions

Double DQN

For Double DQN, the same algorithm and same network architecture as DQN has been implemented with just the replacement of Target value being (3).

$$Y_t^{DQ} \equiv R_{t+1} + \gamma Q(S_{t+1}, argmax_a Q(S_{t+1}, a; \theta_t); \theta_t')$$

Dueling DDQN

This algorithm has been implemented using Double DQN algorithm with the difference being in Network Architecture.
Additionally, the gradient norms in Dueling DDQN have been clipped to value of 10 for stability.

Convolution layer 1: 32 channels, filter size 8*8, stride 4
Convolution layer 2: 64 channels, filter size 4*4, stride 2
Convolution layer 3: 64 channels, filter size 3*3, stride 1

Value Network:
Linear Layer 1: Hidden Dimension 512
Linear Layer 2: Output Dimension: 1

Advantage (State-Action)
Linear Layer 1: Hidden Dimension 512
Linear Layer 2: Output Dimension: Number of actions

Further hyperparameters are in Experiments Section.

Experiments and Analysis

Atari 2600 game domains are popular environments to evaluate Deep Reinforcement Learning Algorithms. They range from simple to moderately complex environments. By training our Agents on them we can have a good understanding of the flaws and possible improvements in a resource efficient manner. These environments can be used as a substitution or a simulation of real world scenarios.

The domains chosen for current algorithm comparison are Pong, Krull and Boxing. These have good amount of variance in complexity of environment and also have the potential to bring out the uniqueness of our chosen algorithms, hence they can be properly evaluated and their positive effects and negative effects will be potentially observed.

Hyperparameters

The hyperparameters for Pong, Krull and Boxing environments have been provided in Figure 3 and Figure 4, respectively. These parameters have been tuned by multiple trial and error, utilizing Ray Tune library from PyTorch and referring to Algorithm specific original papers. It was observed that learning rate, Target network update step, and epsilon decay, total amount of training steps have dominant effect on learning of algorithm.

Training Platform

The Training platform for this project was Google Colab Pro on CUDA (GPU) and partially on local machine CPU. These have been resource intensive experiments.

Pong Experiment Analysis

Pong is relatively simpler domain of Atari 2600 yet complex enough for the algorithms to be tested over it for evaluation. It has action-space of size 6 and reward +1 and -1 over interaction in the environment, with the goal of reaching to a score of 21 before the opponent. It is a deterministic version

environment.
Environment Reference: PongNoFrameskip-V4
The results in the graph (Figure 2) have been averaged by a sliding window of range 5. The algorithms took about 2 hours for training, but slightly more for Dueling DDQN, perhaps due to the dueling architecture and hence more weights to update.
Based on the graph results, it can be observed that all three algorithms converge almost to the optimal/goal value, with Dueling DDQN (duel) receiving 20.5 test score, Double DQN test score of 19.7 and DQN test score of 19.1. (Since it's deterministic environment, there's no need to average test scores) Further, it can be observed that Dueling DQN (duel) most of the time had higher score and rate of learning compared to DDQN and DQN. There can be seen an instance where for short duration overestimated state-action values in DQN had higher rate of score increment (slope) than Dueling DDQN, however the Dueling overcame it soon.
Double DQN (DDQN) initially performed similar to DQN however fell behing DQN, but later it recovered its learning speed having learned optimal State-Action pairs compared to DQN and performed better. Dueling DDQN having the benefits of DDQN, also has the benefit of its dueling network structure which it seems gave it an advantage to distinguish between optimal states and the optimal state-action values at those states. It converged approximately 5 percent episodes before DDQN and 10 percent episodes before DQN based on the given results.
Another point to mention is without sliding window average, it could be observed that DQN had highest local variance followed by DDQN.

Krull Experiment Analysis

Krull can be deemed moderate-high complexity domain of Atari 2600 with 18 action-spaces and many states. The agent receives multiple types of rewards while interacting with the environment (basically killing different types of monsters and even the same monsters gives different rewards if they have different speeds) The reward earning potential is spread over multiple states in this environment. The game ends when the player loses all lives. It is a deterministic version environment, however, as game proceeds difficulty level increases (Monsters have higher speeds and change their pattern).
Environment Reference: KrullNoFrameskip-V4
Due to high variance, the results in the graph have been averaged by a sliding window of range 11. The DDQN and DQN algorithms took about 6.5 hours for training, with around 7.5 hours for Dueling DDQN, due to the same reason as mentioned above.
Based on the graph (Figure 5) results, it can be observed that training by all three algorithms result in agent learning how to maximize rewards in the environment, with Dueling DDQN (duel) converging at 9,014 test score, Double DQN 7481 test score and DQN 6272 test score.
Further, it can be observed that Dueling DQN (duel) most of the time had higher score and rate of learning compared to DDQN and DQN. It can be seen that due to the maxi-

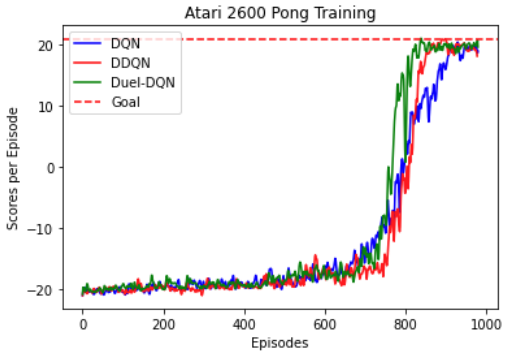

Figure 2: Atari 2600 Pong Results

PONG

Mini-Batch Size	32
Replay Memory Size	50_000
Action Repeat	4
Target Network Update Frequency	10_000
Behavior Network Update Frequency	4
Discount Factor	0.99
Agent History Length	4
Learning Rate (DQN, DDQN)	2.25e-4
Learning Rate (Dueling DDQN)	1.25e-4
Initial Exploration (e)	1.0
Final Exploration (e)	0.01
Final Exploration Frame	1_600_000
Replay start size	5000
No-op max	30
Total Time steps	1_800_000
Maximum Episode Length	15000

Figure 3: Atari 2600 Pong Hyperparameters

Boxing and Krull

Mini-Batch Size	32
Replay Memory Size	50_000
Action Repeat	4
Target Network Update Frequency	10_000
Behavior Network Update Frequency	4
Discount Factor	0.99
Agent History Length	4
Learning Rate (DQN, DDQN)	2.25e-4
Learning Rate (Dueling DDQN)	1.25e-4
Initial Exploration (e)	1.0
Final Exploration (e)	0.01
Final Exploration Frame	4_250_000
Replay start size	5000
No-op max	30
Total Time steps	5_000_000
Maximum Episode Length	20000

Figure 4: Krull And Boxing Hyperparameters

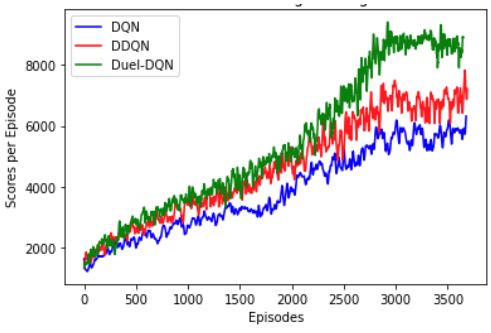

Figure 5: Atari 2600 Boxing Results

mization bias DQN over-estimated certain state-actions and had a drop in scoring rate. Even though it did improve later it still converged to a lower score than DDQN and Dueling DQN.

It can be observed that DDQN score is lower than Duel DQN most of the time, however, it is still higher than DQN and has more stable learning compared DQN. However, once it reached its maximum score, it seems the environment difficulty increased (Monster patterns and speed changed) its score reduced for those episodes as it didn't have the optimal state-action for those scenarios.

This however, can only be seen slightly affecting the Dueling DQN value. The advantage of having a better approximated state value and perhaps a generalized Q-value can be seen here. Agent is able to adapt better to changing patterns. This doesn't seem to affect the DQN values perhaps due to the overestimated state-action values were in general applicable to the situation.

It can be seen that Dueling DDQN also had, a sudden increase in score rate increment in between training. Perhaps this was due to having learned considerable amount of optimal values of state and the optimal state-action values till those episodes that enabled distinguishing them and hence choosing better state and actions at those states. Finally, Dueling DDQN scored around 20 percent higher than DDQN and 42 percent higher compared to DQN.

Boxing Experiment Analysis

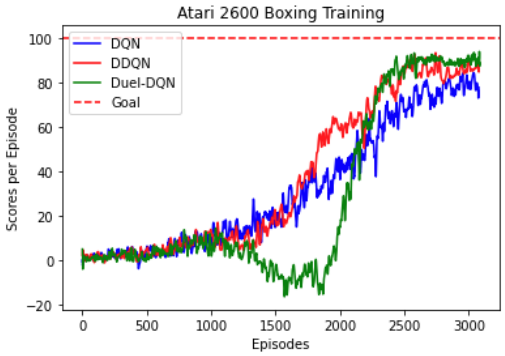

Figure 6: Atari 2600 Boxing Results

Boxing can be deemed moderate complexity domain of Atari 2600 with 18 action-spaces and multiple states. The agent receives multiple types of rewards, specifically two different rewards for two different types of punches +1 and +2 and -1 and -2 if get punched by opponent. The reward earning potential is spread over multiple states in this environment. The game ends if anyone of the player the scores 100, winner is the one who scores it first.

Environment Reference: BoxingNoFrameskip-V4

Due to high variance, the results in the graph have been averaged by a sliding window of range 11. The DDQN and DQN algorithms took about 6-7 hours for training, with

around 7 hours for Dueling DDQN.
Based on the graph results, it can be observed that training by all three algorithms result in agent learning how to maximize rewards in the environment, with Dueling DDQN (duel) converging at 92.4 test score, Double DQN 85.1 test score and DQN 78.9 test score.
This graph (Figure 6) has multiple points. First considerable amount of score in Dueling during training was first in negative reward. For DDQN this observation is comparatively less and DQN even less, perhaps due to restricted exploration of "seemingly" un-optimal state spaces. First, for Double DQN, the initial drop in learning was perhaps due to biased state-action values which was corrected and it overcame DQN quickly. In case of DQN, there was no apparent considerable drop and maximization bias didn't affect much initially however, after mid-way point in training it's slow score increment rate/slope was noticeable and it converged to a lower score value due to biased/overestimated state-action pair values.

Dueling DDQN is beneficial in scenarios where the action results are similar and state values hold significant importance. In this scenario, the right action at the right state, both are important. In this case, Dueling DDQN had similar starting score rate/slope as the other two, however, the negative rewards it received were more than the positive rewards per state. This occurrence happening multiple times lead to the state value being negative and hence also reducing State-action pair (Q-values) for all actions. At this stage perhaps the algorithm started to explore the values at other states which were non-negative/relatively higher. With more training it was able to finally distinguish the relative importance of state values and then started stabilizing and then choosing the right action at the right state. After being trained with this, the agent was able to make better choices and soon its rate of score increment overcame the other two algorithms and converged to a higher value compared to them.
Finally, Dueling DDQN scored around 8 percent higher than DDQN and 17 percent higher compared to DQN.

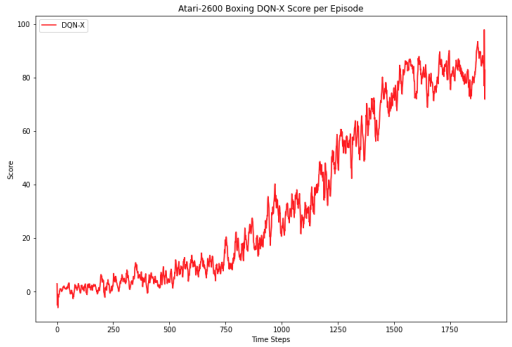

Figure 7: Atari 2600 Boxing Result DQN-X

In Boxing, along with the three general algorithms, a new experiment was done with DQN.
In this DQN the learning rate was set to be 2.5e-4 and the gradients were clipped to norm of 10 as in Dueling DDQN. This modification can be called DQN-X. The result (Figure 7) showed DQN-X converging in close to 60 percent time steps as compared to standard DQN algorithm in Boxing environment.
The reason can be that clipping the gradients resulted in counteracting the overestimation bias of DQN. Further, increment in learning rate also gave it a boost and it converged to an average test value of 82.5, higher than standard DQN (trained in 5M training steps), in just over 2.5 million training steps.
With this we can understand that the learning rates for DQN and DDQN can be further tuned, by slightly increasing it.
Hyperparameters for DQN-X algorithm are shown in Figure 8.

DQN-X Boxing

Mini-Batch Size	32
Replay Memory Size	50_000
Action Repeat	4
Target Network Update Frequency	10_000
Behavior Network Update Frequency	4
Discount Factor	0.99
Agent History Length	4
Learning Rate (DQN-X)	2.5e-4
Initial Exploration (e)	1.0
Final Exploration (e)	0.01
Final Exploration Frame	2_200_000
Replay start size	5000
No-op max	30
Total Time steps	2_500_000
Maximum Episode Length	20000
Gradient Clip	10

Figure 8: DQN-X Hyperparameters

Conclusion

Here we have learnt the differences between three variant of DQN algorithms Double DQN (DDQN), Dueling DDQN and its base form algorithm on three Atari domains. A modified version of DQN was also compared with DQN, emphasizing importance of reducing maximization bias in DQN algorithm. In general, we can now comment that DDQN performs better than DQN, however, in some situations the benefit may not be significant if the number of actions or variance in environment are less or all actions give similar impact in environment. We also clearly identified the dominance of Dueling DDQN in large state

and action spaces and understand that it typically has better performance than DDQN and DQN. We also get an understanding that Dueling DDQN may lose its advantage in environments that have less states and action spaces and have unique conditions that result in the expected state values to become ineffective for sequential decision making.

Code Link has been provided below.

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Experiment Code Link

CODE LINK