# MLDS Homework 4 Report

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## 4-1 Policy Gradient

### 4-1-1 Policy Gradient model

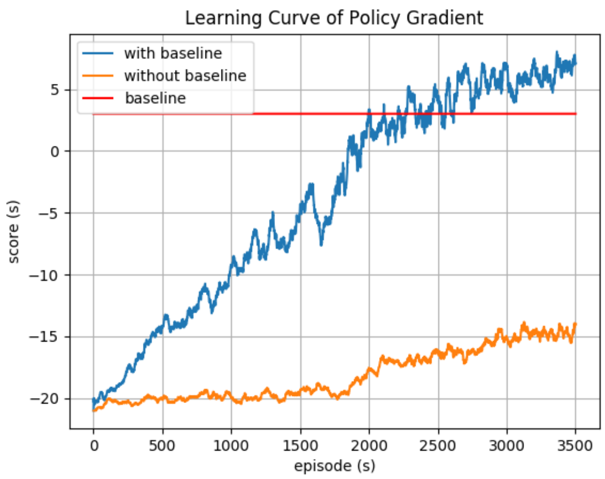
**Model**

| layer | RGB image from observation | Shape |
|---|---|---|
| perpro | TA的preprocess code. | observation -> 80*80 image |
| hidden | Dense(128 , activation='relu') | (None,6400) -> (None,128) |
| output | Dense(6,activation='softmax') | (None,128) -> (None,6) |

**Details**

| Details | Parameteres |
|---|---|
| Optimizer | pyTorch's 預設 Adam， lr=1e-4 |
| Discount value | 0.99 |

### 4-1-2 Plot the learning curve to show the performance of your Policy Gradient on Pong




### 4-1-3 Implement 1 improvement method on page 8

**Describe your tips for improvement**

- variance reduction - 加入 baseline
- 我們使用最靠近現在的10000步的rewards(包含被discount的部份)作為我們的mean。
- 要更新參數的時候，計算loss前的reward會-= mean。

**Learning curve**

- 有baseline的learning curve一起畫在上面了。

**Compare to the vallina policy gradient**

- 我們會看到一般的pg相較於reduce variance的版本，會學習的非常緩慢。因為一般的pg variance非常大。原本在計算pg的公式的時候，因為我們不會知道policy的期望值是多少，所以才用採樣的方式去逼近。但是要是原本的distribution variance非常大，那麼採樣的可信度會大幅下降。例如只要採樣時的variance變大，在同個信賴區間的機率就會變低。
- 而為什麼增加baseline就會降低variance，這件事情在課堂上已經有證明了。
- 因此，我認為一般的pg可能因為期望值預測不準確導致學習叫緩慢。

> proof : [https://en.wikipedia.org/wiki/Variance_reduction](https://en.wikipedia.org/wiki/Variance_reduction)

# 4-2 Deep Q Learning

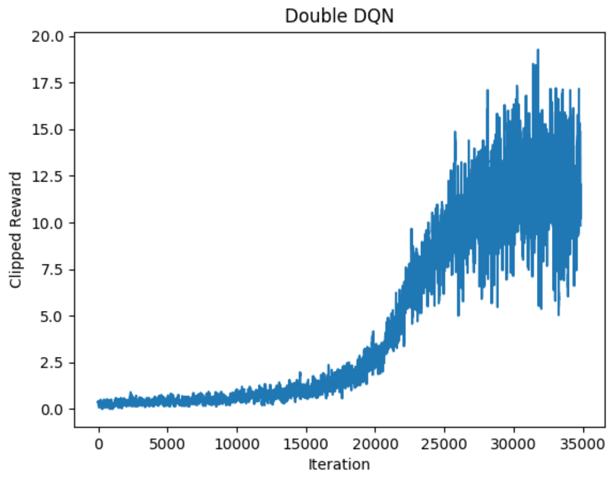
## 4-2-1 DQN Model

1. Network Structure

```
# CNN * 3 + Dense * 2
CNN (in_channel=4, out_channel=16, kernel=8, stride=4) + ReLU
CNN (in_channel=16, out_channel=32, kernel=4, stride=2) + ReLU
CNN (in_channel=32, out_channel=64, kernel=3, stride=1) + ReLU
Dense(64*7*7, 512) + ReLU
Dense(512, 4) (action數是4)
```

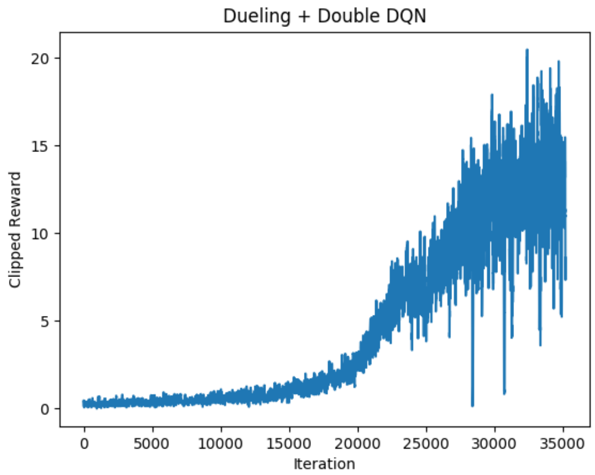
2. Training method
    - batch size: 32
    - Optimizer: RMSProp, lr = $1.5 \times 10^{-4}$
    - Loss function: mse
3. DQN parameter
    - 使用Double DQN
    - 更新online network的頻率：4 timestamp
    - 更新target network的頻率：1000 timestamp
    - $\gamma = 0.99$
    - $\epsilon$ greedy使用Linear Decay，總共訓練500萬個iteration，不過只有在前面$0.3 \times 5000000$個iteration從1降到0.025。其餘的iteration都是$\epsilon = 0.025$

## 4-2-2 Learning Curve




### 4-2-3 Implement 1 improvement method

1. Tips
   - 基於第一題的Double DQN再加上Dueling上去
   - 基本上就按照投影片上面所述在最後一層做分岔然後再加起來
2. Learning Curve




3. Compare to origin one
   - 由圖看出有沒有多加上Dueling在收斂時間上並沒有太大的差距，另外在最終的表現上也差不多
   - 由圖看出在Dueling + Dobule DQN在後期會有大震盪的狀況，而這是在原本只有Double DQN不曾出現的狀況

## 4-3 Actor Critic

### 4-3-1 Actor Critic Model

**Pong**

```
# Dense * 2
Input (80 * 80)
Linear (6400, 256) + ReLU
-> Actor  : Linear (256, 2) + Softmax
-> Critic : Linear (256, 1)
```

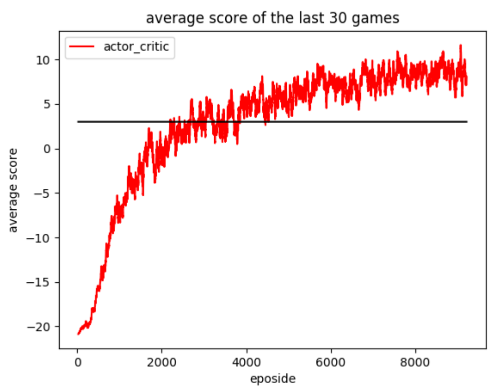
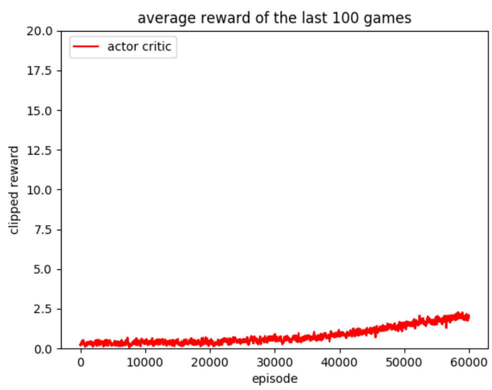
其他參數：

- Optimizer: adam, lr=$10^{-4}$
- Reward Discount: 0.99

**Breakout**

```
# CNN * 3 + Dense * 2
CNN (in_channel=4, out_channel=16, kernel=8, stride=4) + ReLU
CNN (in_channel=16, out_channel=32, kernel=4, stride=2) + ReLU
CNN (in_channel=32, out_channel=64, kernel=3, stride=1) + ReLU
-> Actor :
    Linear (64 * 7 * 7, 512) + ReLU -> Linear (512, 4) + Softmax
-> Critic :
    Linear (64 * 7 * 7, 512) + ReLU -> Linear (512, 1)
```

## 4-3-2 Learning Curve

| Pong | Breakout |
| --- | --- |
|   |   |

## 4-3-3 One improvement method of Actor-Critic

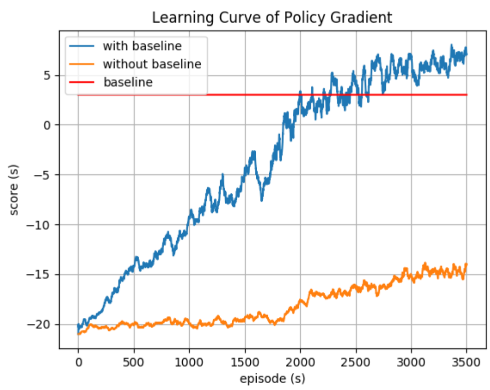
**Model Description**

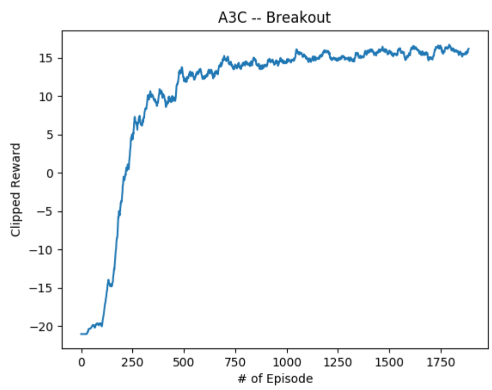
```
# A3CLSTM
CNN (in_channel=4, out_channel=32, kernel=5, stride=1) + Maxpooling + ReLU
CNN (in_channel=32, out_channel=32, kernel=5, stride=1) + Maxpooling + ReLU
CNN (in_channel=32, out_channel=64, kernel=3, stride=1) + Maxpooling + ReLU
h, c = LSTM(1024, 512)
-> Actor  : Linear (512, action_num) + Softmax
-> Critic : Linear (512, 1)
```

其他參數：

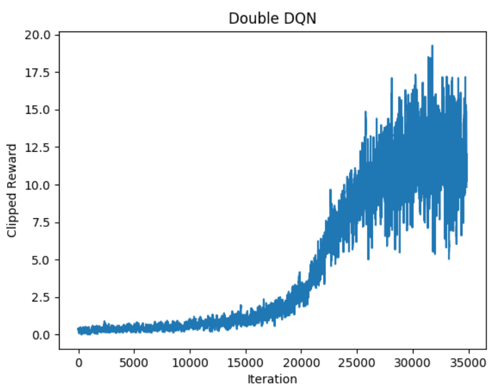
- Optimizer: Shared Adam, lr=$10^{-4}$
- Number of process: 4

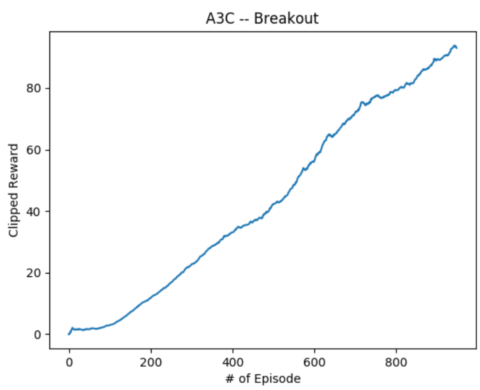
### Learning Curve

<table>
<tr><th>Policy Gradient</th><th>A3C</th></tr>
<tr><td>


</td><td>


</td></tr>
</table>

<table>
<tr><th>Double DQN</th><th>A3C</th></tr>
<tr><td>


</td><td>


</td></tr>
</table>

上面第一個表格是pong的Learning Curve，下面第二個表格則是breakout的Learning Curve。可以明顯看到使用A3C的效能遠高於我們原本的DQN以及Policy Gradient。

### Reference

- https://github.com/dgriff777/rl_a3c_pytorch

## 分工表

- 4-1: b05902127 劉俊緯
- 4-2: b05902013 吳宗翰
- 4-3: b05902013 吳宗翰