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# MLDS 2019 Spring

## HW4-1 - Policy Gradient

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# Time Schedule

- June 4th 19:30 Deadline
- June 8th 10:30 Deadline

# Outline

	HW4-1	HW4-2	HW4-3
Pong	PG		AC
Breakout		DQN	AC
Improved Version			

## Outline

- **Introduction**
  - Game Playing : Pong
- **Deep Reinforcement Learning**
  - Policy Gradient
  - Improvements to Policy Gradient
- **Training Hints**
- **Grading & Format**
  - Submission

# Introduction

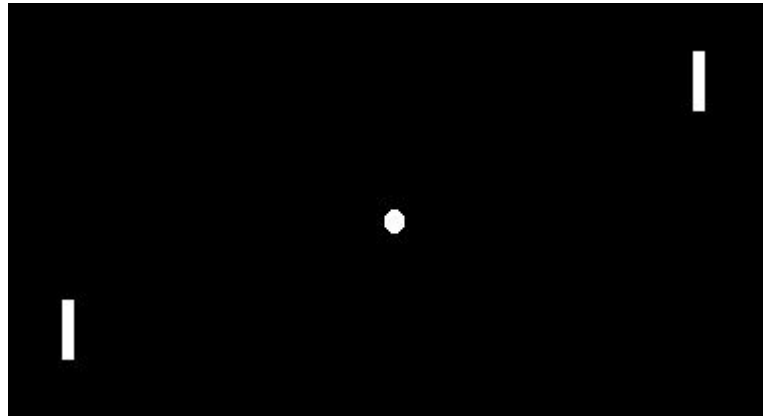
## Game Playing

- Implement an agent to play Atari games using Deep Reinforcement Learning
- In this homework, you are required to implement **Policy Gradient**
- The Pong environment is used in this homework

# Introduction

## Environment

Pong



<https://gym.openai.com/envs/>

# Deep Reinforcement Learning

## Policy Gradient

**function REINFORCE**

    Initialise  $\theta$  arbitrarily

**for** each episode  $\{s_1, a_1, r_2, \dots, s_{T-1}, a_{T-1}, r_T\} \sim \pi_\theta$  **do**

**for**  $t = 1$  to  $T - 1$  **do**

$\theta \leftarrow \theta + \alpha \nabla_\theta \log \pi_\theta(s_t, a_t) v_t$

**end for**

**end for**

**return**  $\theta$

**end function**

$s_i$  : state at time  $i$

$a_i$  : action at time  $i$

$r_i$  : reward by  $a_i$

$\pi_\theta(s, a) = P[a|s, \theta]$  :  $\theta$  is your model parameter

$v_t$  : long-term value at time  $t$

$v(s) = E[G_t | s_t = s]$

$$G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$$

- Update per step  $\rightarrow$  SGD  $\rightarrow$  High Variance
- Update per episode or by mini batch
  - episode : A player win the game (21)
  - mini batch : someone get some points

# Deep Reinforcement Learning

## REINFORCE Baseline on Pong

Training loop(simplest version):

- Play until a game is over(one player gets 21 points) with policy network  $\pi_\theta$  and store  $(s,a,r)$  tuples into memory  $m$ .
- Discount and normalize rewards in memory into  $r'$  to reduce variance
- Approximate gradient 
$$\nabla_\theta J(\theta) \approx \sum_{(s_t, a_t, r'_t) \in m} \nabla_\theta \log \pi_\theta(a_t | s_t) r'_t$$
$$\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$$
- Clear the memory  $m$



# Deep Reinforcement Learning

## Improvements to Policy Gradient

- Variance Reduction
- Natural Policy Gradient
- Trust Region Policy Optimization
- Proximal Policy Optimization

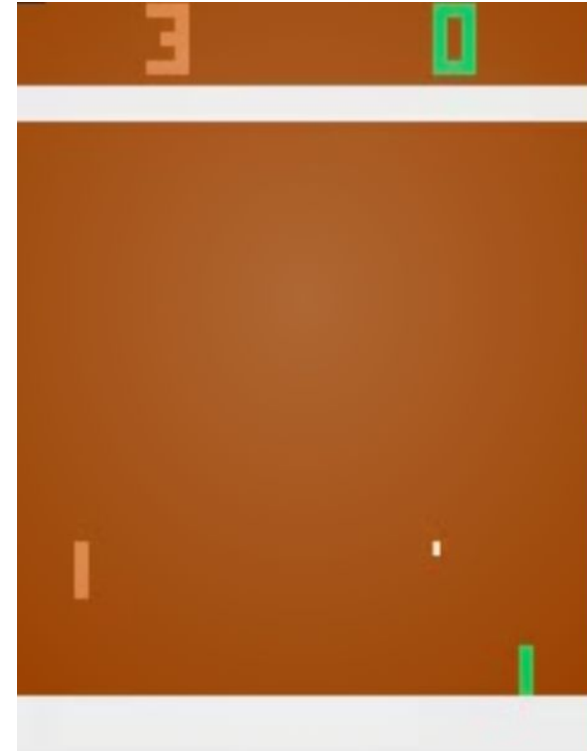
[http://rll.berkeley.edu/deeprlcourse/f17docs/lecture\\_4\\_policy\\_gradient.pdf](http://rll.berkeley.edu/deeprlcourse/f17docs/lecture_4_policy_gradient.pdf)

[http://rll.berkeley.edu/deeprlcourse/f17docs/lecture\\_13\\_advanced\\_pg.pdf](http://rll.berkeley.edu/deeprlcourse/f17docs/lecture_13_advanced_pg.pdf)

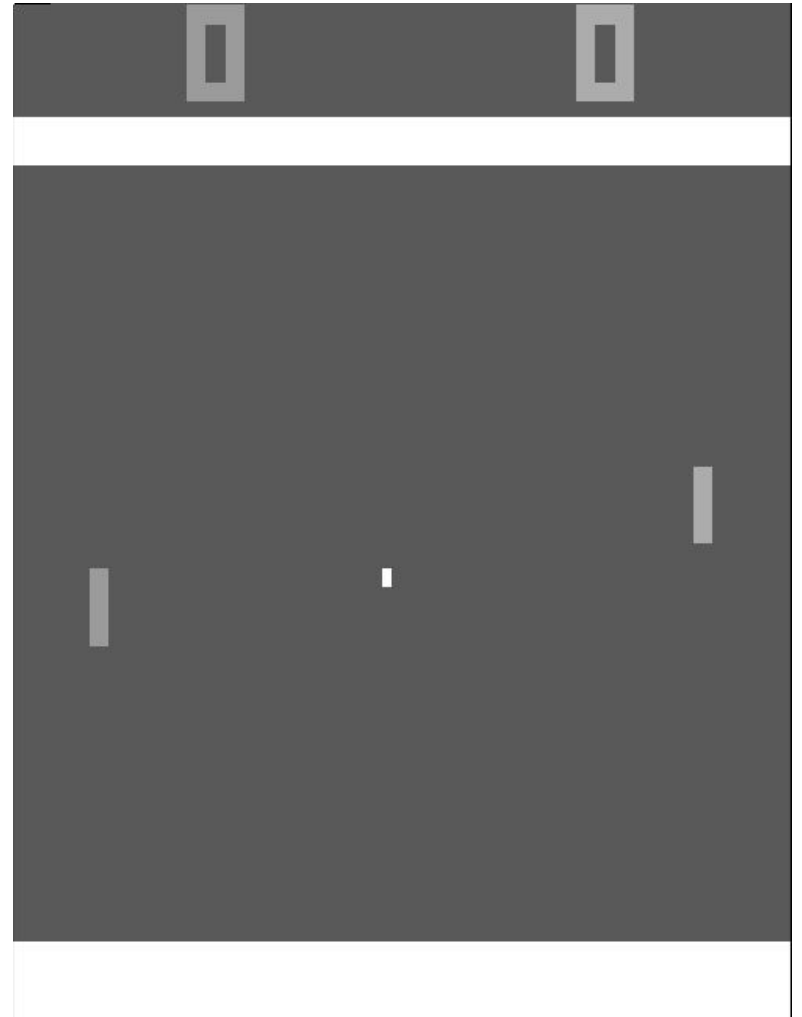
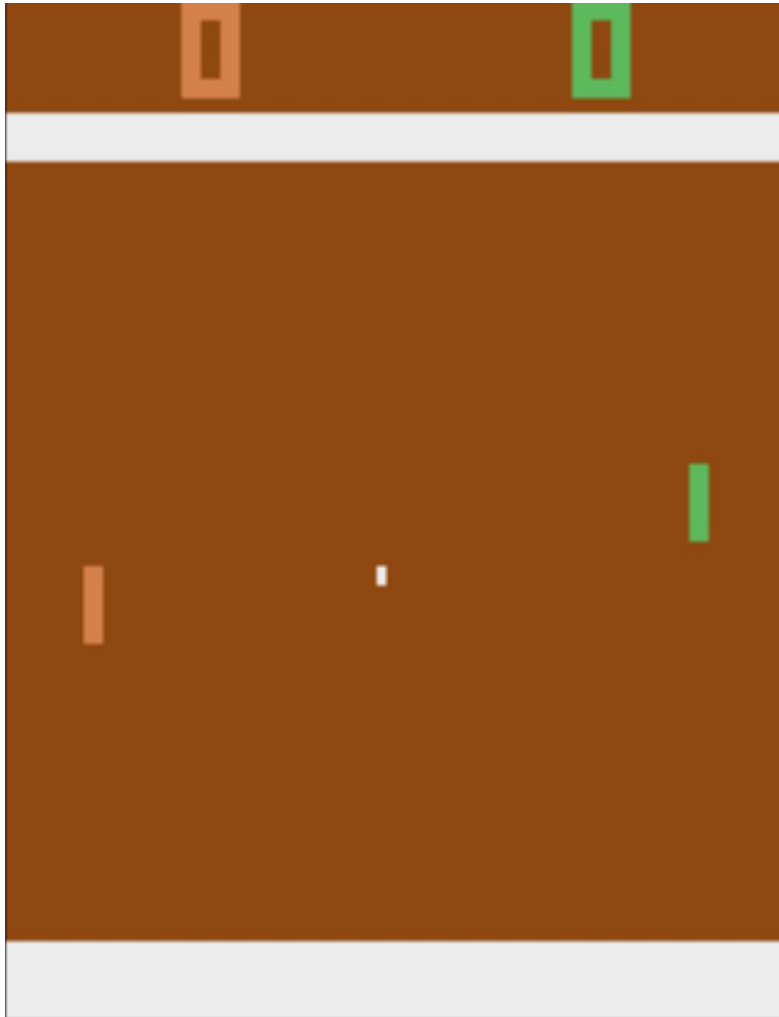
# Training Hint

## Preprocessing for States

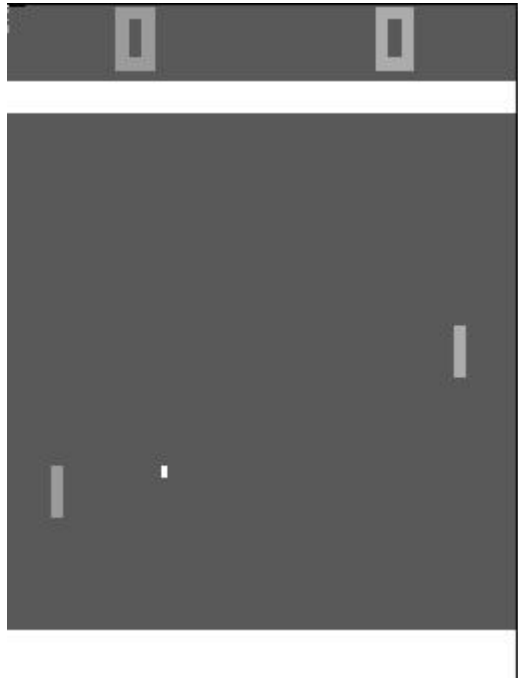
- Which is better ?
  - rgb channel or gray scale
    - $0.2126 * \text{Red} + 0.7152 * \text{Green} + 0.0722 * \text{Blue}$
  - single or residual
    - $s'(t) = s(t+1) - s(t)$
    - represent change of pixel
  - scoreboard yes or no?



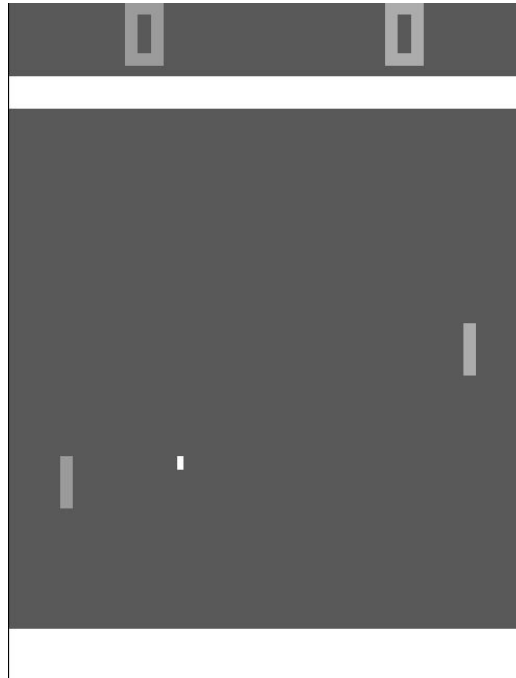
# RGB vs Gray scale



# Residual State



S2



S1



S1'

# Training Hint

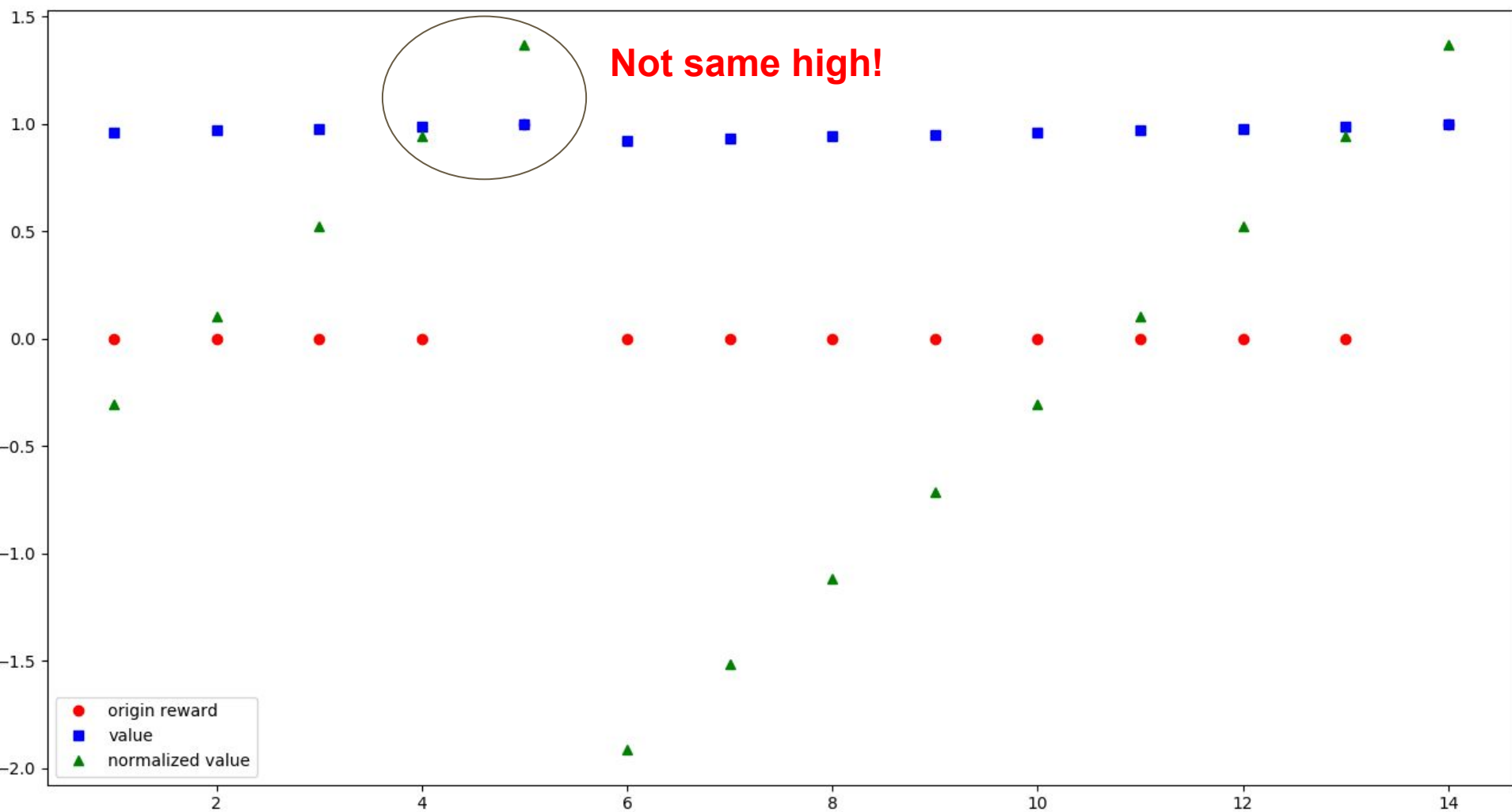
## Reward and Action

- Reward normalization
  - More stable
  - <http://karpathy.github.io/2016/05/31/rl>
  - <https://arxiv.org/pdf/1506.02438.pdf>
- Action space reduction
- Reset the running add of discounted reward to zero if a player scores (Pong specific)

# Action space reduction

```
ACTION_MEANING = {  
    0: "NOOP",  
    1: "FIRE",  
    2: "UP",  
    3: "RIGHT",  
    4: "LEFT",  
    5: "DOWN",  
    6: "UPRIGHT",  
    7: "UPLEFT",  
    8: "DOWNRIGHT",  
    9: "DOWNLEFT",  
    10: "UPFIRE",  
    11: "RIGHTFIRE",  
    12: "LEFTFIRE",  
    13: "DOWNFIRE",  
    14: "UPRIGHTFIRE",  
    15: "UPLEFTFIRE",  
    16: "DOWNRIGHTFIRE",  
    17: "DOWNLEFTFIRE",  
}
```

# Reward normalization



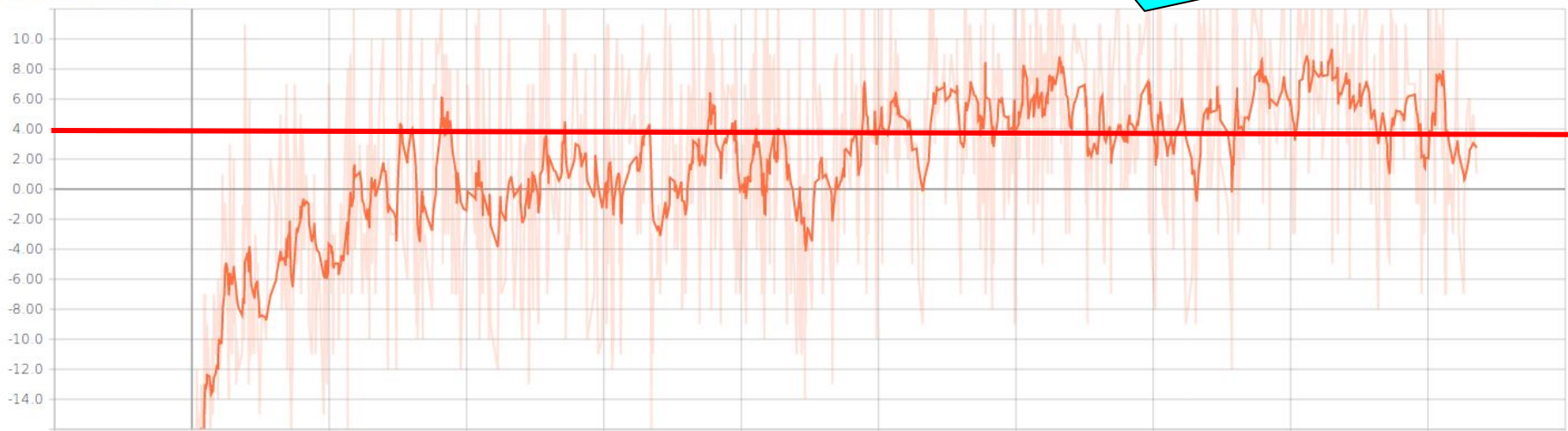
# Training Hint

## Training Plot

- The unit of x-axis is 1000 episode
- Around 6000 episode to reach baseline in “average”
- Mind your preprocessing if your curve differs from this too much
- Baseline Network Structure : Flatten + Two-layer FNN
  - 256 dimension hidden layer
  - output layer (action space size)
- Update per episode (21 point game)

**Freeze random seed!**

summaries/Episode\_Reward





## Baseline

- Policy Gradient
  - Getting averaging reward in 30 episodes over **0** in **Pong**
  - Without OpenAI's Atari wrapper & reward clipping
  - Improvements to Policy Gradient are allowed

# Grading & Format

## Code Format

- Please download the sample files from [github](#)
- Follow the instructions in README to install required packages
- **Four** functions you should implement in [agent\\_pg.py](#)
  1. `__init__(self, env, args)`
  2. `init_game_setting(self)`
  3. `train(self)`
  4. `make_action(self, state, test)`
- **DO NOT** add any parameter in `__init__()`, `init_game_setting()` and `make_action()`
- You can add new methods in the [agent\\_pg.py](#)
- You can add your arguments in [argument.py](#)

# Grading & Format

## Submission

- Submit your presentation files to: [google drive](#)

## Presentation Files

- Describe your Policy Gradient model
- Plot the learning curve to show the performance of your Policy Gradient on Pong
  - X-axis: number of time steps
  - Y-axis: average reward in last 30 episodes
- Implement **1** improvement method on page 8
  - Describe your tips for improvement
  - Learning curve
  - Compare to the vanilla policy gradient
- Github link

# Outline

HW4-1

HW4-2

HW4-3

Pong

PG

AC

Breakout

DQN

AC

Improved  
Version



# Related Materials

- Course & Tutorial:
  - [Berkeley Deep Reinforcement Learning, Fall 2017](#)
  - [David Silver RL course](#)
  - [Nips 2016 RL tutorial](#)
- Blog:
  - [Andrej Karpathy's blog](#)
  - [Arthur Juliani's Blog](#)
  - [Openai](#)
- Text Book:
  - [Reinforcement Learning: An Introduction](#)
- Repo:
  - <https://github.com/williamFalcon/DeepRLHacks>