# LAB 3

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**Deadline: 2024/11/10 (Sun) 23:59**

**Demo: 2024/11/11 (Mon)**

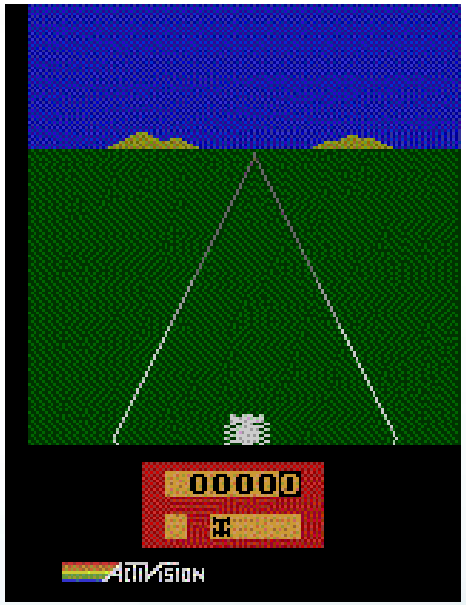
In this lab,

**Must use sample code,**
**otherwise no credit.**

# Enduro-v5

- Introduction:
  - You are a racer in the National Enduro, a long-distance endurance race. You must overtake a certain amount of cars each day to stay on the race. The first day you need to pass 200 cars, and 300 for each following day. The game ends if you do not meet your overtake quota for the day
- Observation space:
  - The whole image
- Action space:

| Num | Action |
|---|---|
| 0 | NOOP |
| 1 | UP |
| 2 | RIGHT |
| 3 | LEFT |
| 4 | DOWN |
| 5 | UPRIGHT |
| 6 | UPLEFT |
| 7 | DOWNRIGHT |
| 8 | DOWNLEFT |

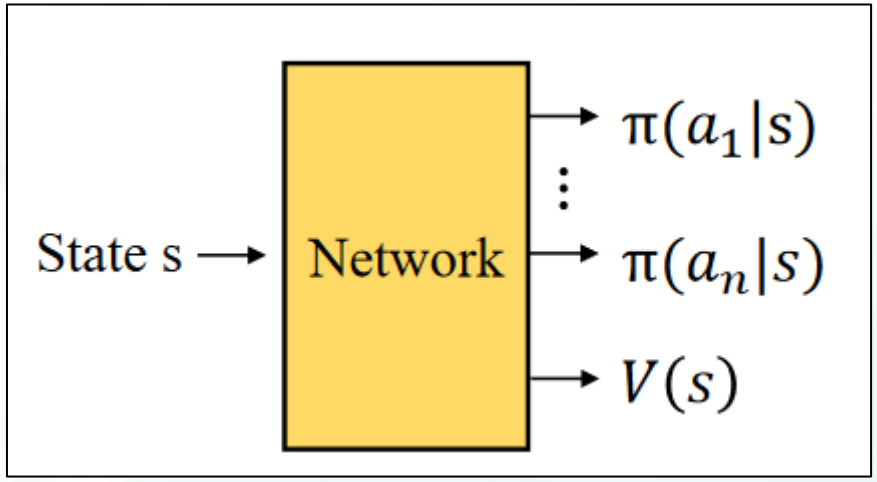


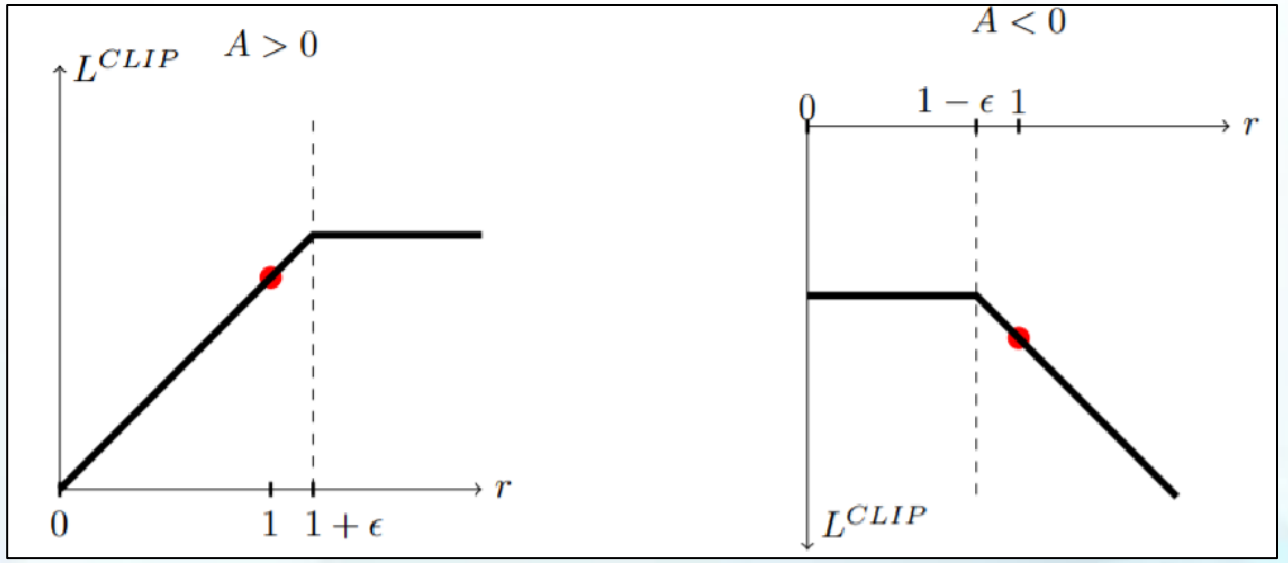

https://www.gymlibrary.dev/environments/atari/enduro/

# Proximal Policy Optimization (PPO-clip)

$$\max_{\theta} E_{s\sim d_{\mu}^{\pi_{\theta_k}}, a\sim\pi_{\theta_k}(.|s)} [\min( \frac{\pi_\theta(a|s)}{\pi_{\theta_k}(a|s)} A^{\theta_k}(s,a), \quad clip(\frac{\pi_\theta(a|s)}{\pi_{\theta_k}(a|s)}, 1-\epsilon, 1+\epsilon) A^{\theta_k}(s,a))]$$

$ratio * A(s,a)$ $\qquad$ $clipped\_ratio * A(s,a)$



# Proximal Policy Optimization (PPO)

Algorithm –Proximal Policy Optimization (PPO):

**for** iteration=$1, 2, \ldots$ **do**
  **for** actor=$1, 2, \ldots, N$ **do**
    Run policy $\pi_{\theta_{\text{old}}}$ in environment for $T$ timesteps
    Compute advantage estimates $\hat{A}_1, \ldots, \hat{A}_T$
  **end for**
  Optimize surrogate $L$ wrt $\theta$, with $K$ epochs and minibatch size $M \leq NT$
  $\theta_{\text{old}} \leftarrow \theta$
**end for**

# TODO

- Solve Enduro-v5 using PPO.
- (Bonus) Answer questions:
  1. PPO is an on-policy or an off-policy algorithm? Why?
  2. Explain how PPO ensures that policy updates at each step are not too large to avoid destabilization.
  3. Why is GAE-lambda used to estimate advantages in PPO instead of just one-step advantages? How does it contribute to improving the policy learning process?
  4. Please explain what the lambda parameter represents in GAE-lambda, and how adjusting the lambda parameter affects the training process and performance of PPO? Please explain what the lambda parameter represents in GAE-lambda, and how adjusting the lambda parameter affects the training process and performance of PPO?

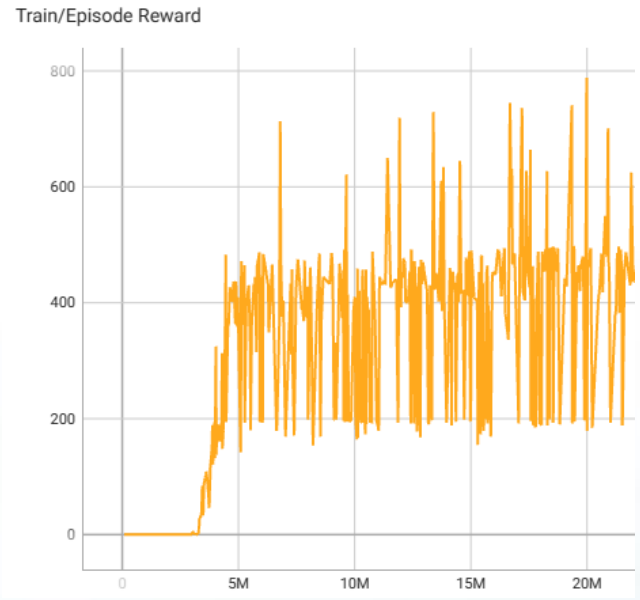
# TODO

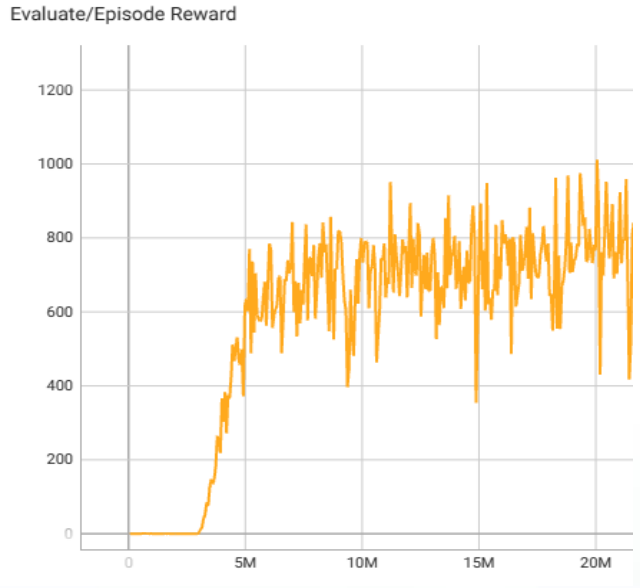
- Find the #TODO comments and hints, remove the raise NotImplementedError.
- Implement the forward function in neural network.
- Inherit from the "PPOBaseAgent" and override the "decide_agent_actions" and "update" functions.
- Screenshot of Tensorboard training curve and testing results and put it on the report.

# TODO

- Screenshot of Tensorboard training curve and testing results and put it on the report.

Training curve:



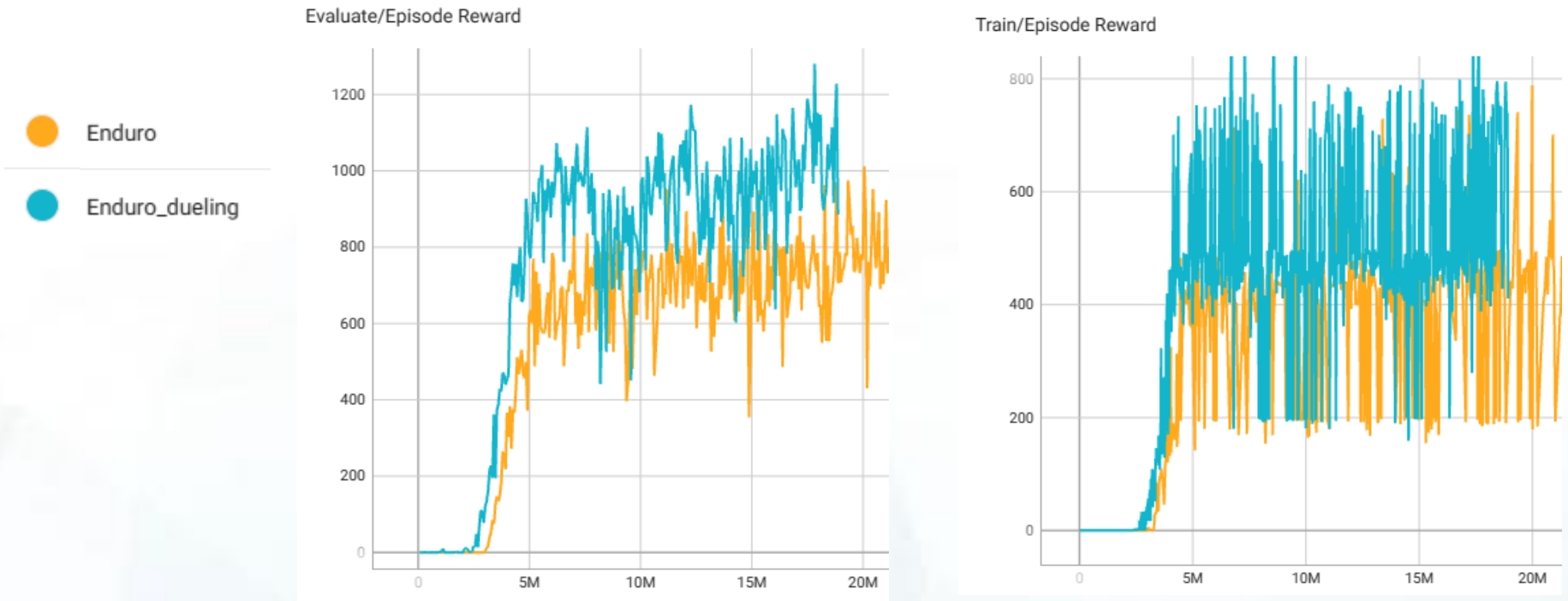




Testing results (5 games):

```
Episode: 1      Length: 13301   Total reward: 1040.00
Episode: 2      Length: 13307   Total reward: 1066.00
Episode: 3      Length: 9969    Total reward: 705.00
Episode: 4      Length: 13286   Total reward: 1059.00
Episode: 5      Length: 16630   Total reward: 1318.00
average score: 1037.6
```

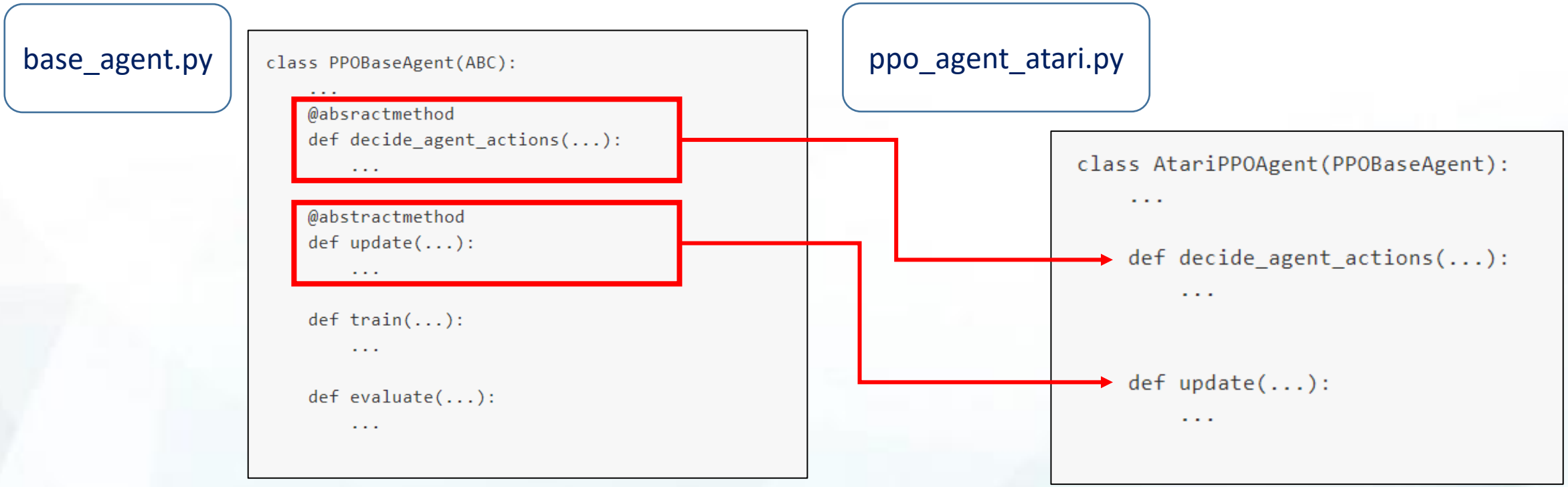
# TODO

- Screenshot of Tensorboard training curve and testing results and put it on the report.



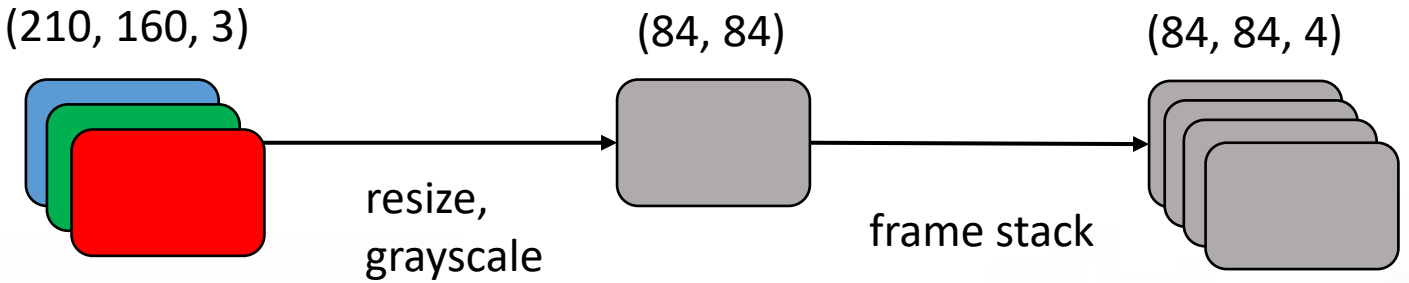
# TODO

- Inherit from the "PPOBaseAgent" and override the "decide_agent_actions" and "update" functions.



# Hint

- You can add any trick you want. E.g.:
  - Frame stack
  - Clip reward
  - Grayscale observation
  - ……




- You can use OpenAI Gym Wrapper.
  - https://www.gymlibrary.dev/api/wrappers/

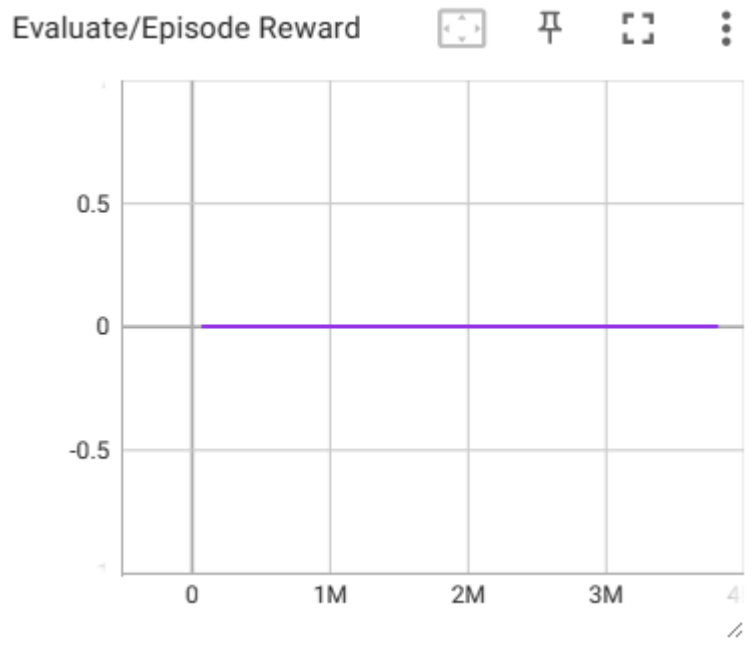
# Scoring Criteria

- Your Score = report (30%) + report bonus (20%) + demo performance (50%) + demo questions (20%)
- Report contains two parts:
  - Experimental Results (30%)
    - Screenshot of Tensorboard training curve and testing results on PPO.
  - Answer the questions (bonus) (20%)
    1. PPO is an on-policy or an off-policy algorithm? Why? (5%)
    2. Explain how PPO ensures that policy updates at each step are not too large to avoid destabilization. (5%)
    3. Why is GAE-lambda used to estimate advantages in PPO instead of just one-step advantages? How does it contribute to improving the policy learning process? (5%)
    4. Please explain what the lambda parameter represents in GAE-lambda, and how adjusting the lambda parameter affects the training process and performance of PPO? (5%)

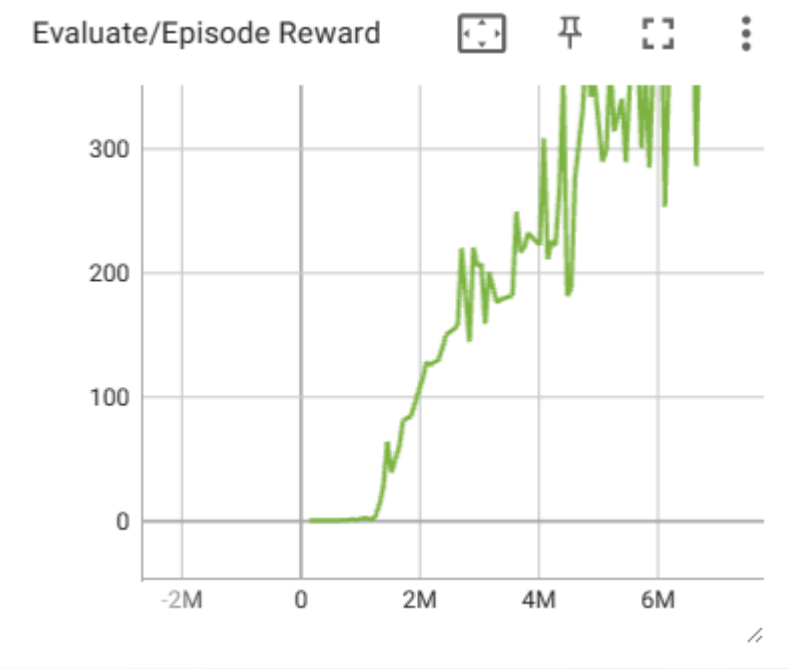
# Scoring Criteria

- Screenshot of Tensorboard training curve and testing results and put it on the report.

✖ No score

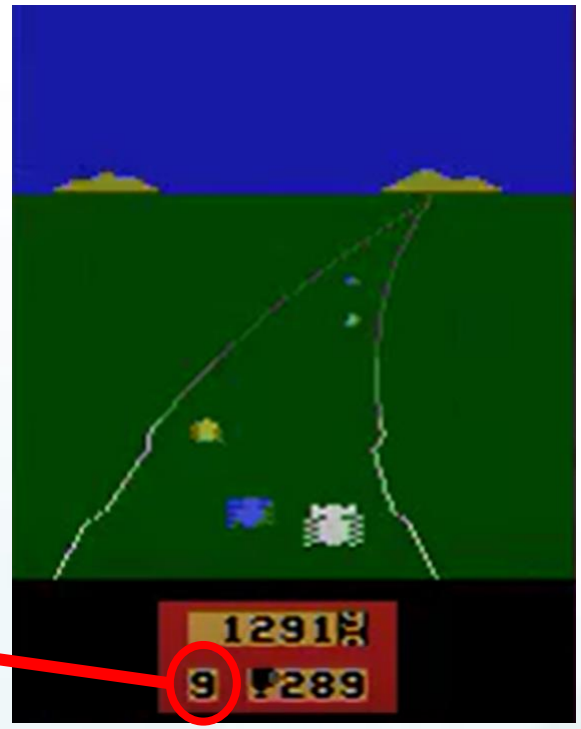



○ Get score (30%)



# Scoring Criteria - Demo Performance

- Test your best model for one game.
- You have to show the video while testing. You can use env.render() or save video function to achieve this.
- You can use a fixed random seed to reproduce your best game score




Terminated in day 9

# Scoring Criteria - Demo Performance

- Demo performance – Score table:


Terminated in day 9

| Day | Cars | Reward | Points (50%) |
|---|---|---|---|
| 1 | 200 | 0~200 | 0 |
| 2 | 300 | 200~500 | 10 |
| 3 | 300 | 500~800 | 20 |
| 4 | 300 | 800~1100 | 25 |
| 5 | 300 | 1100~1400 | 30 |
| 6 | 300 | 1400~1700 | 35 |
| 7 | 300 | 1700~2000 | 40 |
| 8 | 300 | 2000~2300 | 45 |
| 9 | 300 | 2300~2600 | 50 |

# Tensorboard Remote Server

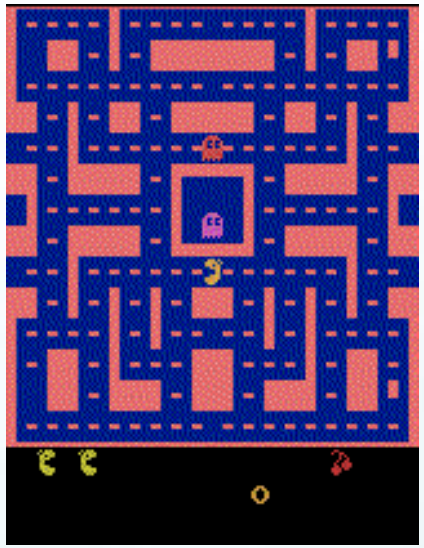
- ssh -p [your port] -L 6006:localhost:6006 pp037@140.113.215.196
- tensorboard --logdir log/dqn
- Open your browser locally and input 127.0.0.1:6006

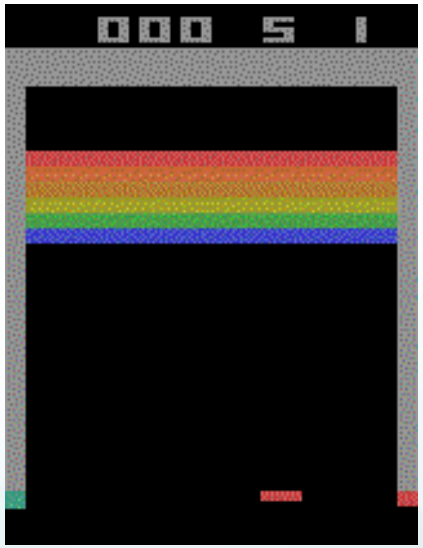
# Recommended Package Version

- gym 0.26.2
- numpy 1.25.2
- pytorch 2.0.1
- tensorboard 2.14.0
- opencv-python 4.8.0.76
- moviepy 1.0.3

# Reminders

- Your network architecture and hyper-parameters can differ from the defaults.
- Ensure the shape of tensors all the time especially when calculating the loss.
- with no_grad() : scope is the same as xxx.detach()
- Be aware of the indentation of hints.
- You can use simpler environments to check if your PPO implementation is correct, such as MsPacman, Breakout.





# References


1. Mnih, Volodymyr et al. “Playing Atari with Deep Reinforcement Learning.” ArXiv abs/1312.5602 (2013).
2. Silver, David et al. “Deterministic Policy Gradient Algorithms.” ICML (2014).
3. Schulman, John, et al. "Proximal policy optimization algorithms." arXiv preprint arXiv:1707.06347 (2017).
4. OpenAI. “OpenAI Gym Documentation.” Retrieved from Getting Started with Gym: https://gym.openai.com/docs/.
5. PyTorch. “Reinforcement Learning (DQN) Tutorial.” Retrieved from PyTorch Tutorials: https://pytorch.org/tutorials/intermediate/reinforcement_q_learning.html.
6. Huang, et al., "The 37 Implementation Details of Proximal Policy Optimization", ICLR Blog Track, 2022. url: https://iclr-blog-track.github.io/2022/03/25/ppo-implementation-details/