

Lab 14

Reinforcement Learning

Datalab

Department of Computer Science,
National Tsing Hua University, Taiwan

Outline

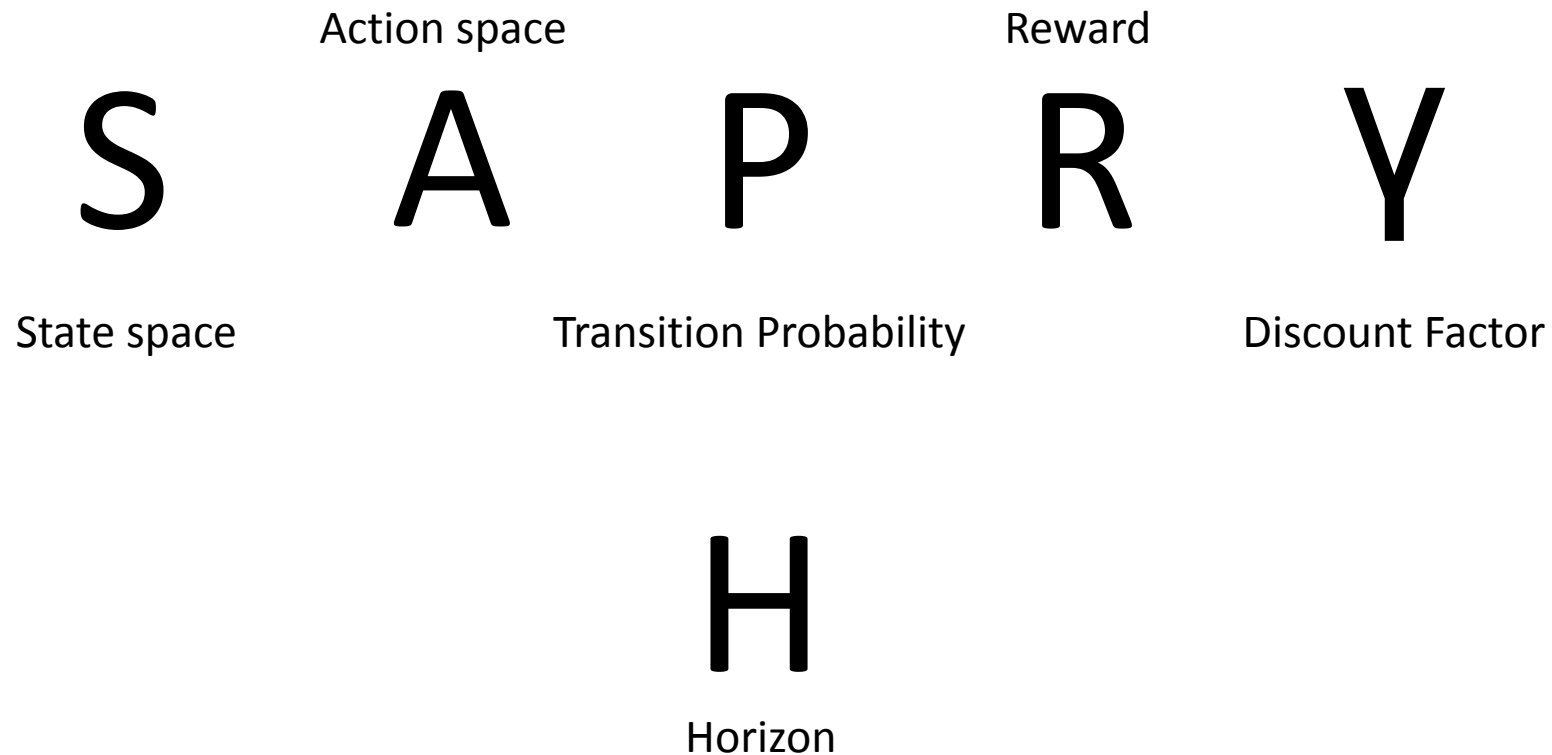
- Markov Decision Process (MDP)
 - Value Iteration
 - Policy Iteration
- Q-Learning & SARSA
- Homework

Outline

- Markov Decision Process (MDP)
 - Value Iteration
 - Policy Iteration
- Q-Learning & SARSA
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Markov Decision Process (MDP)

- A MDP is defined by



 小吃	資電	排球
綜二	台達	籃球
總圖	工三 	西門

$S = \{ \text{小吃, 資電, 排球, 綜二, 台達, 籃球, 總圖, 工三, 西門} \}$

$A = \{ \text{上, 下, 左, 右} \}$

$P = \text{no noise}$

$R(\text{工三}) = 0, R(\text{others}) = -1$

$r = 1 \quad H = \text{inf}$

We have a MDP model, then?

Goal - Find the Optimal Policy

- If the agent follow the optimal policy, it will get maximal total reward
- We can solve it via these two algorithms
 - Value Iteration
 - Policy Iteration

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Value Iteration

Input: MDP $(\mathcal{S}, \mathcal{A}, \mathbf{P}, R, \gamma, H \rightarrow \infty)$

Output: $\pi^*(s)$'s for all s 's

For each state s , initialize $V^*(s) \leftarrow 0$;

repeat

foreach s **do**

$V^*(s) \leftarrow \max_a \sum_{s'} \mathbf{P}(s'|s; a) [R(s, a, s') + \gamma V^*(s')]$;

end

until $V^*(s)$'s converge;

foreach s **do**

$\pi^*(s) \leftarrow \arg \max_a \sum_{s'} \mathbf{P}(s'|s; a) [R(s, a, s') + \gamma V^*(s')]$;

end

 小吃	資電	排球
綜二	台達	籃球
總圖	工三 	西門

$S = \{ \text{小吃, 資電, 排球, 綜二, 台達, 籃球, 總圖, 工三, 西門} \}$

$A = \{ \text{上, 下, 左, 右} \}$

$P = \text{no noise}$

$R(\text{工三}) = 0, R(\text{others}) = -1$

$r = 1 \quad H = \text{inf}$

Input: MDP $(S, A, P, R, \gamma, H \rightarrow \infty)$ 

Output: $\pi^*(s)$'s for all s 's

For each state s , initialize $V^*(s) \leftarrow 0$;

repeat

 foreach s do

$V^*(s) \leftarrow \max_a \sum_{s'} P(s'|s;a)[R(s,a,s') + \gamma V^*(s')]$;

 end

until $V^*(s)$'s converge;

foreach s do

$\pi^*(s) \leftarrow \arg \max_a \sum_{s'} P(s'|s;a)[R(s,a,s') + \gamma V^*(s')]$;

end

 小吃 0	資電 0	排球 0
綜二 0	台達 0	籃球 0
總圖 0	工三 0 	西門 0

Input: MDP $(\mathcal{S}, \mathcal{A}, \mathcal{P}, R, \gamma, H \rightarrow \infty)$

Output: $\pi^*(s)$'s for all s 's

For each state s , initialize $V^*(s) \leftarrow 0$;



repeat

foreach s **do**

$V^*(s) \leftarrow \max_a \sum_{s'} \mathcal{P}(s'|s; a) [R(s, a, s') + \gamma V^*(s')]$;

end

until $V^*(s)$'s converge;

foreach s **do**

$\pi^*(s) \leftarrow \arg \max_a \sum_{s'} \mathcal{P}(s'|s; a) [R(s, a, s') + \gamma V^*(s')]$;

end

After Initialization

 小吃 -1	資電 -1	排球 -1
綜二 -1	台達 -1	籃球 -1
總圖 -1	工三 0 	西門 -1

Input: MDP $(\mathcal{S}, \mathcal{A}, P, R, \gamma, H \rightarrow \infty)$

Output: $\pi^*(s)$'s for all s 's

For each state s , initialize $V^*(s) \leftarrow 0$;

repeat

foreach s **do**

$V^*(s) \leftarrow \max_a \sum_{s'} P(s'|s;a) [R(s,a,s') + \gamma V^*(s')]$;

end

until $V^*(s)$'s converge;

foreach s **do**

$\pi^*(s) \leftarrow \arg \max_a \sum_{s'} P(s'|s;a) [R(s,a,s') + \gamma V^*(s')]$;

end

After Iteration 1

$$V(\text{台達}) = \text{Reward} + V(\text{資電}) = -1 + 0$$

$$V(\text{台達}) = \text{Reward} + V(\text{綜二}) = -1 + 0$$

$$V(\text{台達}) = \text{Reward} + V(\text{工三}) = -1 + 0$$

$$V(\text{台達}) = \text{Reward} + V(\text{籃球}) = -1 + 0$$

 小吃 -2	資電 -2	排球 -2
綜二 -2	台達 -1	籃球 -2
總圖 -1	工三 0 	西門 -1

Input: MDP $(\mathcal{S}, \mathcal{A}, P, R, \gamma, H \rightarrow \infty)$

Output: $\pi^*(s)$'s for all s 's

For each state s , initialize $V^*(s) \leftarrow 0$;

repeat

foreach s **do**

$V^*(s) \leftarrow \max_a \sum_{s'} P(s'|s;a) [R(s,a,s') + \gamma V^*(s')]$;

end

until $V^*(s)$'s converge;

foreach s **do**

$\pi^*(s) \leftarrow \arg \max_a \sum_{s'} P(s'|s;a) [R(s,a,s') + \gamma V^*(s')]$;

end

After Iteration 2

$$V(\text{台達}) = \text{Reward} + V(\text{資電}) = -1 + -1$$

$$V(\text{台達}) = \text{Reward} + V(\text{綜二}) = -1 + -1$$

$$\max_a V(\text{台達}) = \text{Reward} + V(\text{工三}) = -1 + \mathbf{0}$$

$$V(\text{台達}) = \text{Reward} + V(\text{籃球}) = -1 + -1$$

 小吃 -3	資電 -2	排球 -3
綜二 -2	台達 -1	籃球 -2
總圖 -1	工三 0 	西門 -1

Input: MDP $(\mathcal{S}, \mathcal{A}, P, R, \gamma, H \rightarrow \infty)$

Output: $\pi^*(s)$'s for all s 's

For each state s , initialize $V^*(s) \leftarrow 0$;

repeat

foreach s **do**

$V^*(s) \leftarrow \max_a \sum_{s'} P(s'|s;a) [R(s,a,s') + \gamma V^*(s')]$;

end

until $V^*(s)$'s converge;

foreach s **do**

$\pi^*(s) \leftarrow \arg \max_a \sum_{s'} P(s'|s;a) [R(s,a,s') + \gamma V^*(s')]$;

end

After Iteration 3

$$V(\text{小吃}) = V(\text{排球}) = -1 + -2 = -3$$

 小吃 -3	資電 -2	排球 -3
綜二 -2	台達 -1	籃球 -2
總圖 -1	工三 0 	西門 -1

Iteration 4 = Iteration 3
Converge !

Input: MDP $(\mathcal{S}, \mathcal{A}, P, R, \gamma, H \rightarrow \infty)$

Output: $\pi^*(s)$'s for all s 's

For each state s , initialize $V^*(s) \leftarrow 0$;

repeat

foreach s **do**

$V^*(s) \leftarrow \max_a \sum_{s'} P(s'|s;a) [R(s,a,s') + \gamma V^*(s')]$;

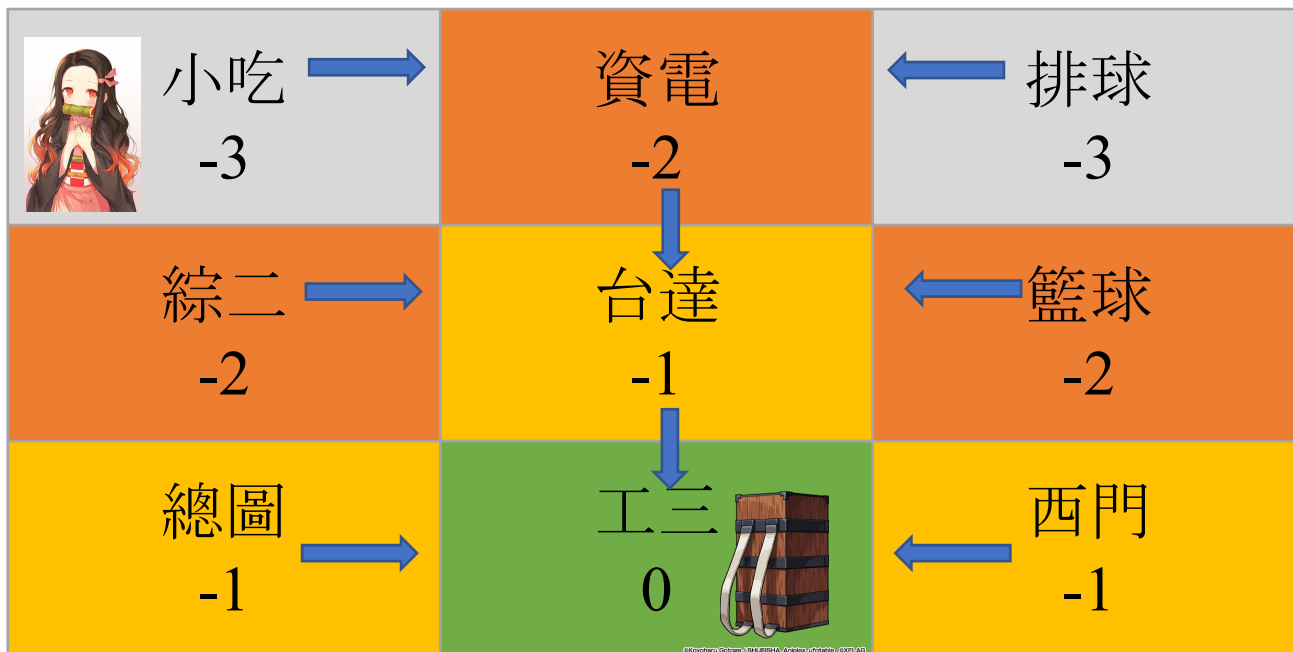
end

until $V^*(s)$'s converge; ←

foreach s **do**

$\pi^*(s) \leftarrow \arg \max_a \sum_{s'} P(s'|s;a) [R(s,a,s') + \gamma V^*(s')]$;

end



Input: MDP $(\mathcal{S}, \mathcal{A}, \mathcal{P}, R, \gamma, H \rightarrow \infty)$

Output: $\pi^*(s)$'s for all s 's

For each state s , initialize $V^*(s) \leftarrow 0$;

repeat

foreach s **do**

$V^*(s) \leftarrow \max_a \sum_{s'} P(s'|s;a) [R(s,a,s') + \gamma V^*(s')]$;

end

until $V^*(s)$'s converge;

foreach s **do**

$\pi^*(s) \leftarrow \arg \max_a \sum_{s'} P(s'|s;a) [R(s,a,s') + \gamma V^*(s')]$;

end

Now we have the optimal policy

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Policy Iteration

Input: MDP $(\mathcal{S}, \mathcal{A}, P, R, \gamma, H \rightarrow \infty)$

Output: $\pi(s)$'s for all s 's

For each state s , initialize $\pi(s)$ randomly;

repeat

 For each state s , initialize $V_\pi(s) \leftarrow 0$;

repeat

foreach s **do**

$V_\pi(s) \leftarrow \sum_{s'} P(s'|s; \pi(s)) [R(s, \pi(s), s') + \gamma V_\pi(s')]$;

end

until $V_\pi(s)$'s converge;

foreach s **do**

$\pi(s) \leftarrow \arg \max_a \sum_{s'} P(s'|s; a) [R(s, a, s') + \gamma V_\pi(s')]$;

end

until $\pi(s)$'s converge;

Policy evaluation

Policy improvement

 小吃	資電	排球
綜二	台達	籃球
總圖	工三 	西門

$S = \{ \text{小吃, 資電, 排球, 綜二, 台達, 籃球, 總圖, 工三, 西門} \}$

$A = \{ \text{上, 下, 左, 右} \}$

$P = \text{no noise}$

$R(\text{工三}) = 0, R(\text{others}) = -1$

$r = 1 \quad H = \text{inf}$

Input: MDP $(S, A, P, R, \gamma, H \rightarrow \infty)$



Output: $\pi(s)$'s for all s 's

For each state s , initialize $\pi(s)$ randomly;

repeat

For each state s , initialize $V_\pi(s) \leftarrow 0$;

repeat

foreach s do

Policy evaluation

$V_\pi(s) \leftarrow \sum_{s'} P(s'|s; \pi(s)) [R(s, \pi(s), s') + \gamma V_\pi(s')];$

end

until $V_\pi(s)$'s converge;

foreach s do

Policy improvement

$\pi(s) \leftarrow \arg \max_a \sum_{s'} P(s'|s; a) [R(s, a, s') + \gamma V_\pi(s')];$

end

until $\pi(s)$'s converge;

 小吃 ↓	↓ 資電	↓ 排球
綜二 ↓	↓ 台達	↓ 籃球
總圖 ↓	↓ 工三 	↓ 西門

Random initialize a policy
Let's say all goes down!

Input: MDP $(\mathcal{S}, \mathcal{A}, P, R, \gamma, H \rightarrow \infty)$

Output: $\pi(s)$'s for all s 's

For each state s , initialize $\pi(s)$ randomly; ←

repeat

For each state s , initialize $V_{\pi}(s) \leftarrow 0$;

repeat

foreach s do ← **Policy evaluation**

$V_{\pi}(s) \leftarrow \sum_{s'} P(s'|s; \pi(s)) [R(s, \pi(s), s') + \gamma V_{\pi}(s')]$;

end

until $V_{\pi}(s)$'s converge;

foreach s do ← **Policy improvement**

$\pi(s) \leftarrow \arg \max_a \sum_{s'} P(s'|s; a) [R(s, a, s') + \gamma V_{\pi}(s')]$;

end

until $\pi(s)$'s converge;

 小吃 0 ↓	↓ 資電 0	↓ 排球 0
綜二 0 ↓	↓ 台達 0	↓ 籃球 0
總圖 0 ↓	↓ 工三 0 	↓ 西門 0

After initialization of V_{π}

Input: MDP $(\mathcal{S}, \mathcal{A}, P, R, \gamma, H \rightarrow \infty)$

Output: $\pi(s)$'s for all s 's

For each state s , initialize $\pi(s)$ randomly;

repeat

For each state s , initialize $V_{\pi}(s) \leftarrow 0$; ←

repeat

foreach s do

| $V_{\pi}(s) \leftarrow \sum_{s'} P(s'|s; \pi(s)) [R(s, \pi(s), s') + \gamma V_{\pi}(s')]$; ← **Policy evaluation**

end

until $V_{\pi}(s)$'s converge;

foreach s do ← **Policy improvement**

| $\pi(s) \leftarrow \arg \max_a \sum_{s'} P(s'|s; a) [R(s, a, s') + \gamma V_{\pi}(s')]$;

end

until $\pi(s)$'s converge;

 小吃 -∞ ↓	↓ 資電 -2	↓ 排球 -∞
綜二 -∞ ↓	↓ 台達 -1	↓ 籃球 -∞
總圖 -∞ ↓	↓ 工三 0 	↓ 西門 -∞

After Policy Evaluation

Input: MDP $(\mathcal{S}, \mathcal{A}, P, R, \gamma, H \rightarrow \infty)$

Output: $\pi(s)$'s for all s 's

For each state s , initialize $\pi(s)$ randomly;

repeat

 For each state s , initialize $V_\pi(s) \leftarrow 0$;

repeat

foreach s **do** ← Policy evaluation

$V_\pi(s) \leftarrow \sum_{s'} P(s'|s; \pi(s)) [R(s, \pi(s), s') + \gamma V_\pi(s')]$;

end

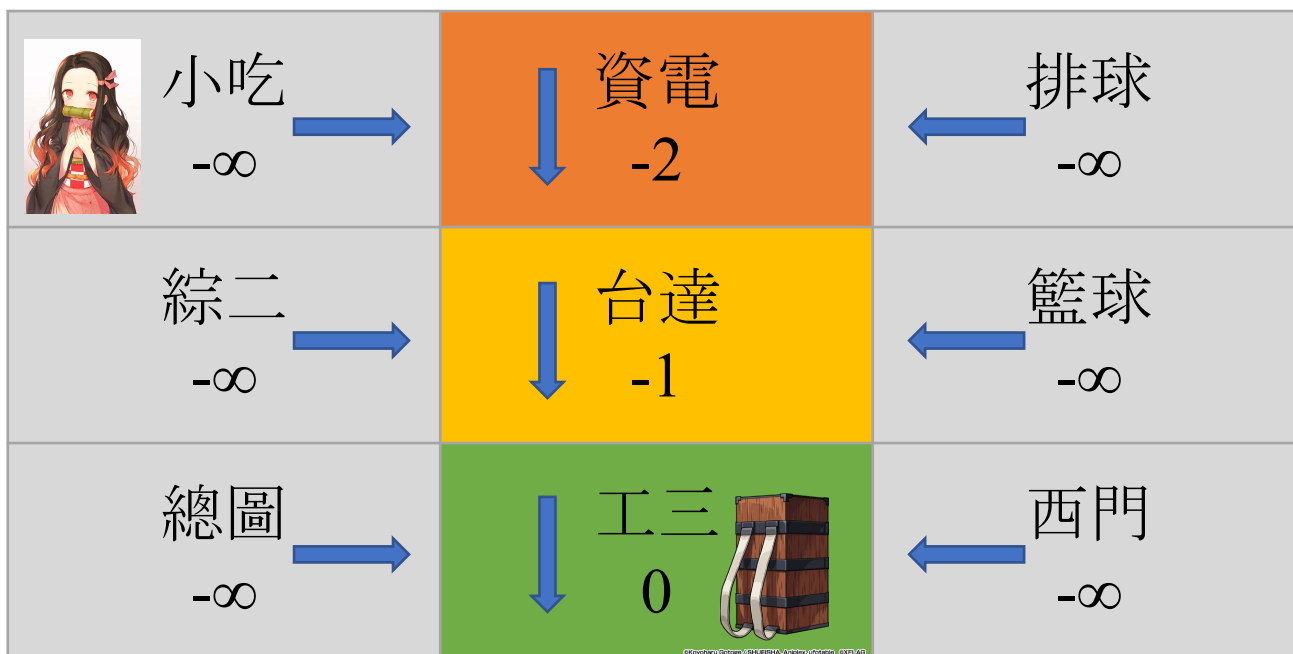
until $V_\pi(s)$'s converge;

foreach s **do** ← Policy improvement

$\pi(s) \leftarrow \arg \max_a \sum_{s'} P(s'|s; a) [R(s, a, s') + \gamma V_\pi(s')]$;

end

until $\pi(s)$'s converge;



Input: MDP $(\mathcal{S}, \mathcal{A}, P, R, \gamma, H \rightarrow \infty)$

Output: $\pi(s)$'s for all s 's

For each state s , initialize $\pi(s)$ randomly;

repeat

For each state s , initialize $V_\pi(s) \leftarrow 0$;

repeat

foreach s do

Policy evaluation

$V_\pi(s) \leftarrow \sum_{s'} P(s'|s; \pi(s)) [R(s, \pi(s), s') + \gamma V_\pi(s')]$;

end

until $V_\pi(s)$'s converge;

foreach s do

Policy improvement

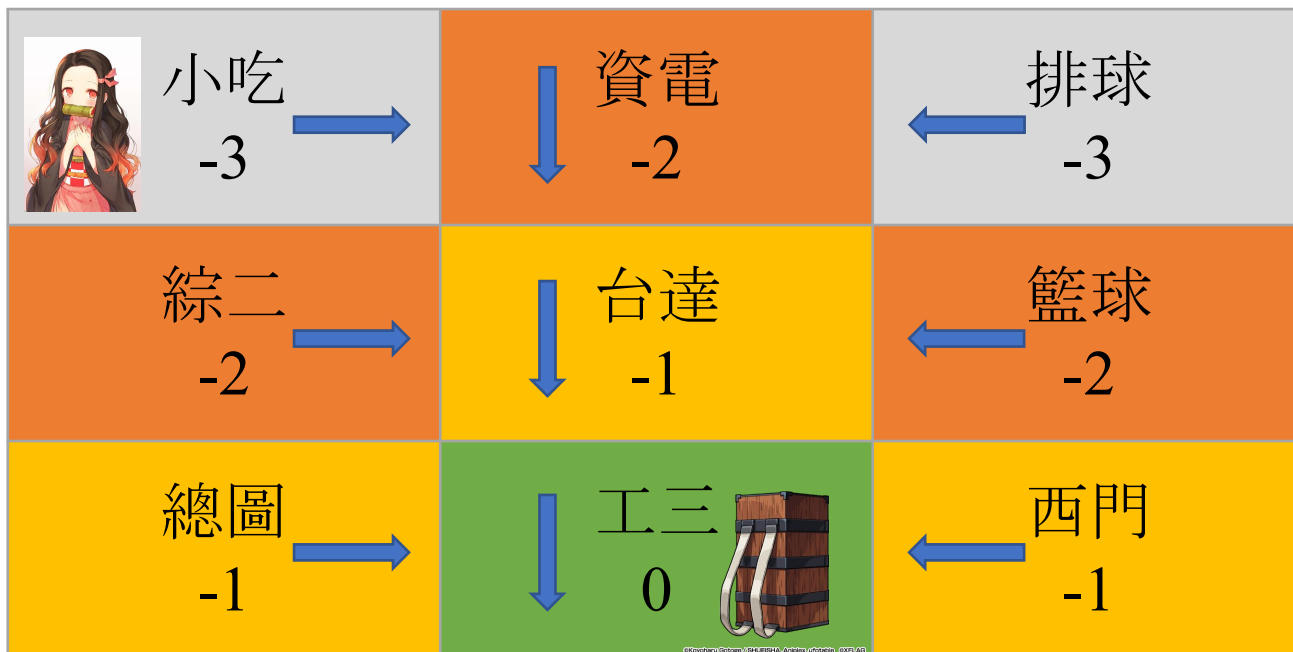
$\pi(s) \leftarrow \arg \max_a \sum_{s'} P(s'|s; a) [R(s, a, s') + \gamma V_\pi(s')]$;

end

until $\pi(s)$'s converge;

After Policy Improvement

$$\arg \max_a \begin{aligned} V(\text{籃球}) &= \text{reward} + V(\text{西門}) = -1 + -\infty \\ V(\text{籃球}) &= \text{reward} + V(\text{台達}) = -1 + -1 \\ V(\text{籃球}) &= \text{reward} + V(\text{排球}) = -1 + -\infty \end{aligned}$$



Policy Evaluation Again!

Input: MDP $(\mathcal{S}, \mathcal{A}, P, R, \gamma, H \rightarrow \infty)$

Output: $\pi(s)$'s for all s 's

For each state s , initialize $\pi(s)$ randomly;

repeat

For each state s , initialize $V_\pi(s) \leftarrow 0$;

repeat

foreach s do

Policy evaluation

$V_\pi(s) \leftarrow \sum_{s'} P(s'|s; \pi(s)) [R(s, \pi(s), s') + \gamma V_\pi(s')]$;

end

until $V_\pi(s)$'s converge;

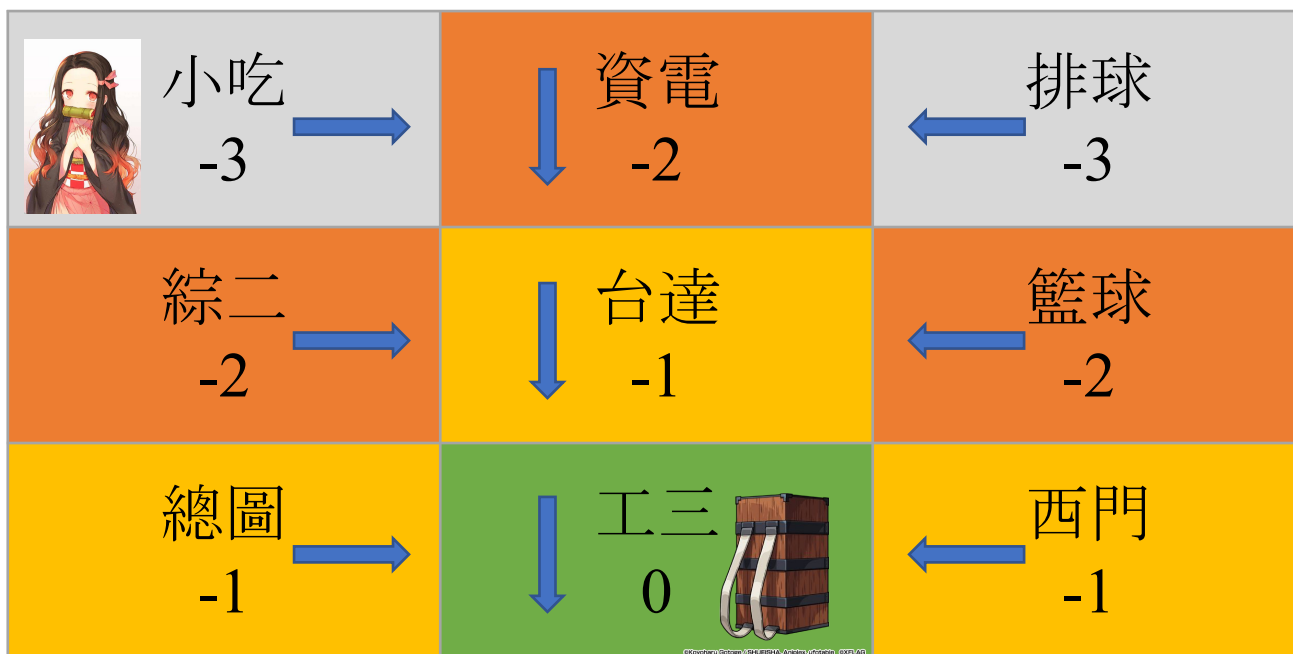
foreach s do

Policy improvement

$\pi(s) \leftarrow \arg \max_a \sum_{s'} P(s'|s; a) [R(s, a, s') + \gamma V_\pi(s')]$;

end

until $\pi(s)$'s converge;



Policy Improvement.
Nothing Changed!
Converge!!

Input: MDP $(\mathcal{S}, \mathcal{A}, P, R, \gamma, H \rightarrow \infty)$

Output: $\pi(s)$'s for all s 's

For each state s , initialize $\pi(s)$ randomly;

repeat

For each state s , initialize $V_\pi(s) \leftarrow 0$;

repeat

foreach s do

Policy evaluation

$V_\pi(s) \leftarrow \sum_{s'} P(s'|s; \pi(s)) [R(s, \pi(s), s') + \gamma V_\pi(s')];$

end

until $V_\pi(s)$'s converge;

foreach s do

Policy improvement

$\pi(s) \leftarrow \arg \max_a \sum_{s'} P(s'|s; a) [R(s, a, s') + \gamma V_\pi(s')];$

end

until $\pi(s)$'s converge;

Did agent Interact with the Environment?

- No ! We model every transition and every reward
- But it is impossible to solve more complex problems like Flappy Bird
- We need model-free algorithms
 - Q-Learning
 - SARSA

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Q-Learning

- Flappy bird



Q-Learning

- States: $(\Delta x, \Delta y)$
- Actions: { fly, none }
- Reward:
 - +1: pass through a pipe
 - -5: die



Q-Learning

- Q-table(finite):

状態	飛	不飛
$(\Delta x_1, \Delta y_1)$	1	20
$(\Delta x_1, \Delta y_2)$	20	-100
...
$(\Delta x_m, \Delta y_{n-1})$	-100	2
$(\Delta x_m, \Delta y_n)$	50	-200



- Update rule: $Q(S, A) \leftarrow Q(S, A) + \alpha [R + \gamma \max_a Q(S', a) - Q(S, A)]$

Q-Learning

- Algorithm

Q-learning: An off-policy TD control algorithm

Initialize $Q(s, a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\text{terminal-state}, \cdot) = 0$

Repeat (for each episode):

Initialize S

Repeat (for each step of episode):

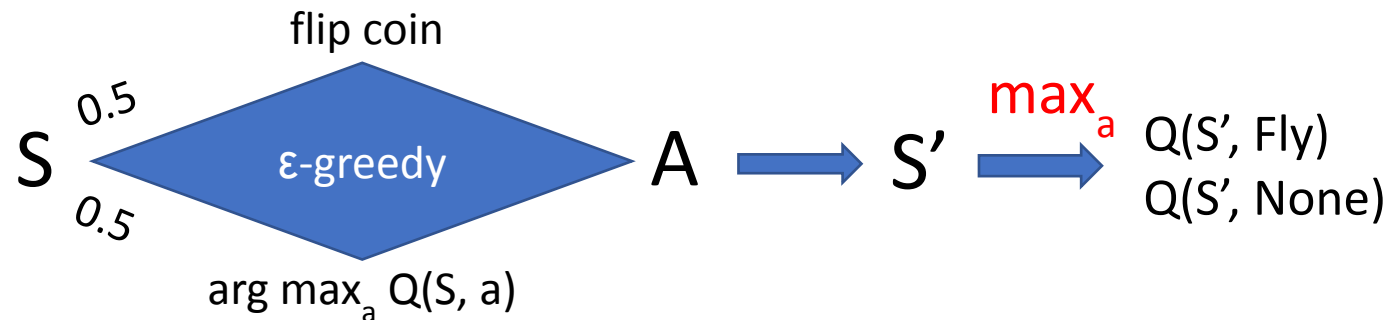
Choose A from S using policy derived from Q (e.g., ϵ -greedy)

Take action A , observe R, S'

$Q(S, A) \leftarrow Q(S, A) + \alpha [R + \gamma \max_a Q(S', a) - Q(S, A)]$

$S \leftarrow S'$

until S is terminal



Q-Learning

- Reference
 - <https://www.zhihu.com/question/26408259>

SARSA

- Algorithm

Sarsa: An on-policy TD control algorithm

Initialize $Q(s, a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\text{terminal-state}, \cdot) = 0$

Repeat (for each episode):

 Initialize S

 Choose A from S using policy derived from Q (e.g., ϵ -greedy)

 Repeat (for each step of episode):

 Take action A , observe R, S'

 Choose A' from S' using policy derived from Q (e.g., ϵ -greedy)

$Q(S, A) \leftarrow Q(S, A) + \alpha[R + \gamma Q(S', A') - Q(S, A)]$

$S \leftarrow S'; A \leftarrow A';$

 until S is terminal

SARSA

- Q-table(finite):

状態	飛	不飛
$(\Delta x_1, \Delta y_1)$	1	20
$(\Delta x_1, \Delta y_2)$	20	-100
...
$(\Delta x_m, \Delta y_{n-1})$	-100	2
$(\Delta x_m, \Delta y_n)$	50	-200



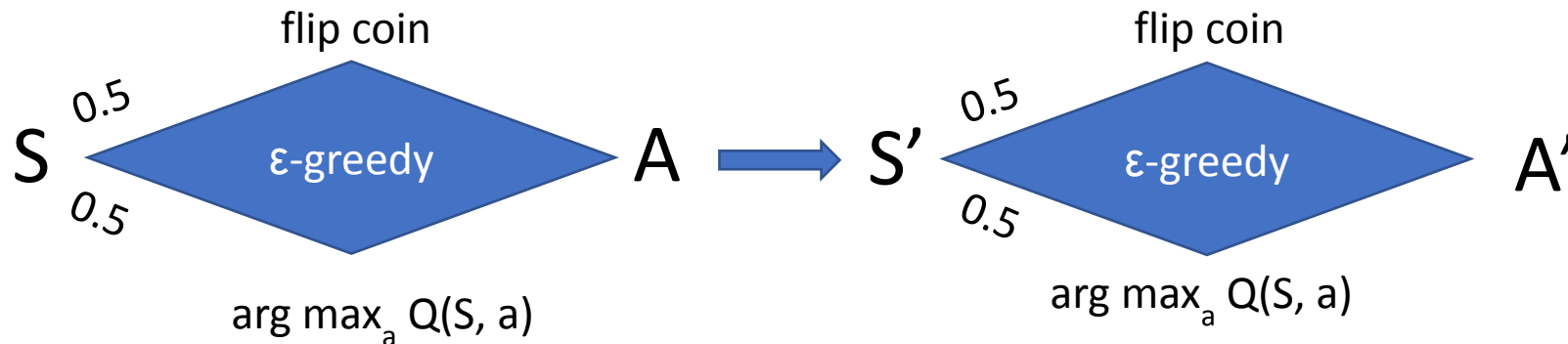
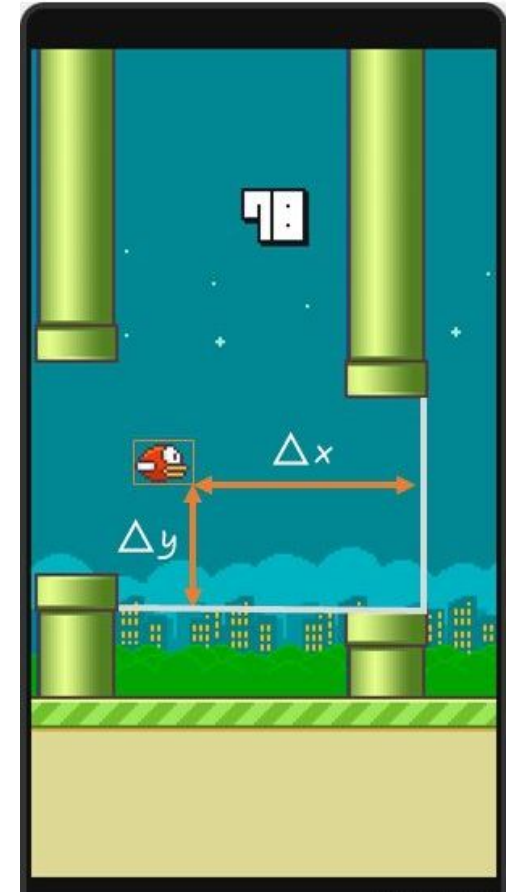
- Update rule: $Q(S, A) \leftarrow Q(S, A) + \alpha [R + \gamma Q(S', A') - Q(S, A)]$

SARSA

- Algorithm

Sarsa: An on-policy TD control algorithm

Initialize $Q(s, a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\text{terminal-state}, \cdot) = 0$
Repeat (for each episode):
 Initialize S
 Choose A from S using policy derived from Q (e.g., ϵ -greedy)
 Repeat (for each step of episode):
 Take action A , observe R, S'
 Choose A' from S' using policy derived from Q (e.g., ϵ -greedy)
 $Q(S, A) \leftarrow Q(S, A) + \alpha [R + \gamma Q(S', A') - Q(S, A)]$
 $S \leftarrow S'; A \leftarrow A';$
 until S is terminal

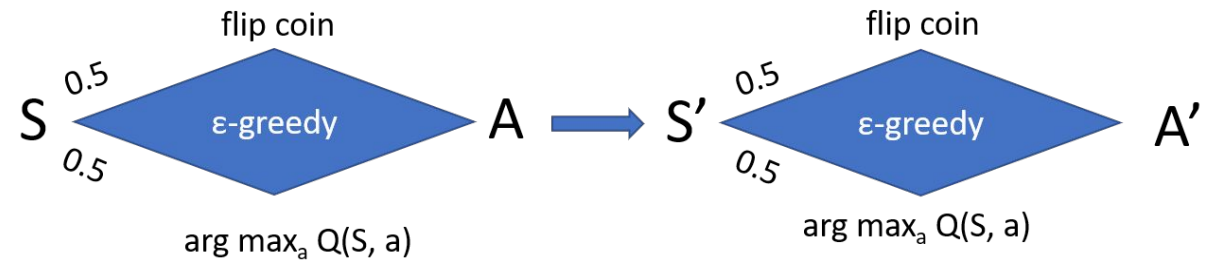


Q-Learning VS. SARSA

• Difference

Initialize $Q(s, a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\text{terminal-state}, \cdot) = 0$
 Repeat (for each episode):
 Initialize S
 Choose A from S using policy derived from Q (e.g., ϵ -greedy)
 Repeat (for each step of episode):
 Take action A , observe R, S'
 Choose A' from S' using policy derived from Q (e.g., ϵ -greedy)
 $Q(S, A) \leftarrow Q(S, A) + \alpha[R + \gamma Q(S', A') - Q(S, A)]$
 $S \leftarrow S'; A \leftarrow A'$
 until S is terminal

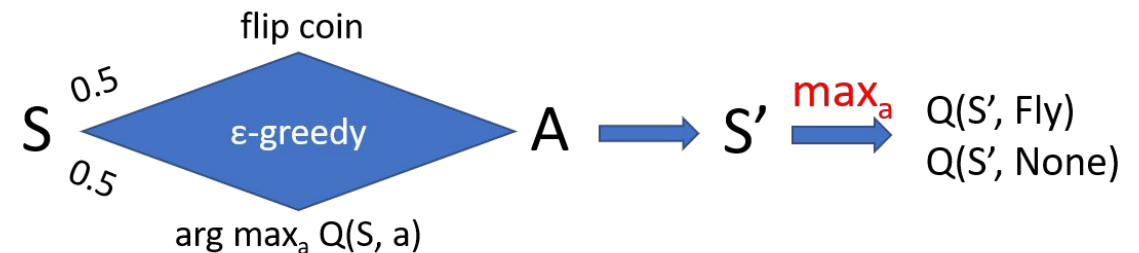
Figure 6.9: Sarsa: An on-policy TD control algorithm.



Initialize $Q(s, a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\text{terminal-state}, \cdot) = 0$
 Repeat (for each episode):
 Initialize S
 Repeat (for each step of episode):
 Choose A from S using policy derived from Q (e.g., ϵ -greedy)
 Take action A , observe R, S'
 $Q(S, A) \leftarrow Q(S, A) + \alpha[R + \gamma \max_a Q(S', a) - Q(S, A)]$
 $S \leftarrow S';$ **what about A'?**
 until S is terminal

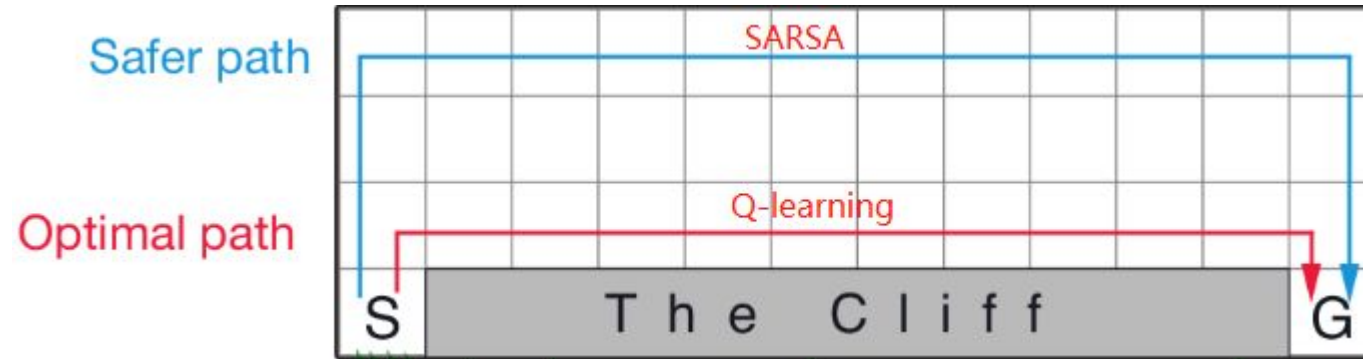
this is like following a greedy policy (e.g. $\epsilon=0$, NO exploration)

Figure 6.12: Q-learning: An off-policy TD control algorithm.



Q-Learning VS. SARSA

- [Cliff Walking](#)



Outline

- MDP(value iteration & policy iteration)
- Q-Learning & SARSA
- Homework

Homework

- Train an agent to play Flappy Bird game(SARSA)



Install PLE and Pygame

- Clone the repo

```
$ git clone https://github.com/ntasfi/PyGame-Learning-Environment
Cloning into 'PyGame-Learning-Environment'...
remote: Enumerating objects: 1118, done.
remote: Total 1118 (delta 0), reused 0 (delta 0), pack-reused 1118
Receiving objects: 100% (1118/1118), 8.06 MiB | 800.00 KiB/s, done.
Resolving deltas: 100% (592/592), done.
```

- Install PLE(in the PyGame-Learning-Environment folder)
 - cd PyGame-Learning-Environment
 - pip install -e .

```
$ pip install -e .
Obtaining file:///E:/DL/Lab/RL/PyGame-Learning-Environment
Requirement already satisfied: numpy in c:\users\vincent\anaconda3\lib\site-pack
ages (from ple==0.0.1) (1.16.4)
Requirement already satisfied: Pillow in c:\users\vincent\anaconda3\lib\site-pac
kages (from ple==0.0.1) (6.1.0)
Installing collected packages: ple
  Found existing installation: ple 0.0.1
    Uninstalling ple-0.0.1:
      Successfully uninstalled ple-0.0.1
  Running setup.py develop for ple
Successfully installed ple
```

- pip install pygame

Homework

- What you should do:
 - Change the update rule from Q-learning to **SARSA** (**with the same episodes**).
 - Give a brief report to discuss the result (compare Q-learning with SARSA based on the game result).

Homework

- Only need CPU resources.
- It will take you more than 13 hours to train, please reserve enough time.

Homework

- Precautions:
 - If you encounter this problem, just stop.
 - It means your bird plays well and the recorded frames is too long to save.

```
~\Anaconda3\lib\site-packages\moviepy\video\io\html_tools.py in html_embed(clip, filetype, maxduration, rd_kwargs, center, **html_k
wargs)
    105
    106     return html_embed(filename, maxduration=maxduration, rd_kwargs=rd_kwargs,
--> 107                          center=center, **html_kwargs)
    108
    109     filename = clip

~\Anaconda3\lib\site-packages\moviepy\video\io\html_tools.py in html_embed(clip, filetype, maxduration, rd_kwargs, center, **html_k
wargs)
    140     if duration > maxduration:
    141         raise ValueError("The duration of video %s (%.1f) exceeds the 'maxduration' '%(filename, duration)+
--> 142                          "attribute. You can increase 'maxduration', by passing 'maxduration' parameter"
    143                          "to ipython_display function."
    144                          "But note that embedding large videos may take all the memory away !")

ValueError: The duration of video __temp__.mp4 (129.8) exceeds the 'maxduration' attribute. You can increase 'maxduration', by passing 'max
duration' parameter to ipython_display function. But note that embedding large videos may take all the memory away !
```

Homework

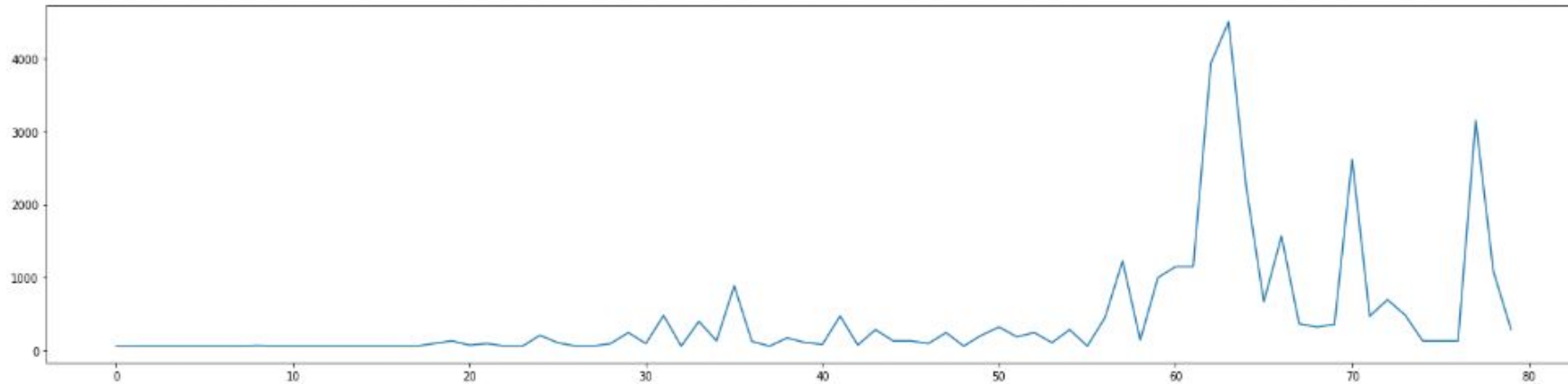
- Requirements:
 - Write a brief report in the notebook
 - Upload both ipynb and **mp4** to google drive
 - Lab14_{student_id}.ipynb
 - Lab14_{student_id}.mp4
 - Notebook cannot display videos well, that's why we need html
 - Share your drive's link via **eeclash**
 - Please make sure that TA can access your google drive!!!
- Deadline: 2023-12-28(Thur) 23:59

Homework

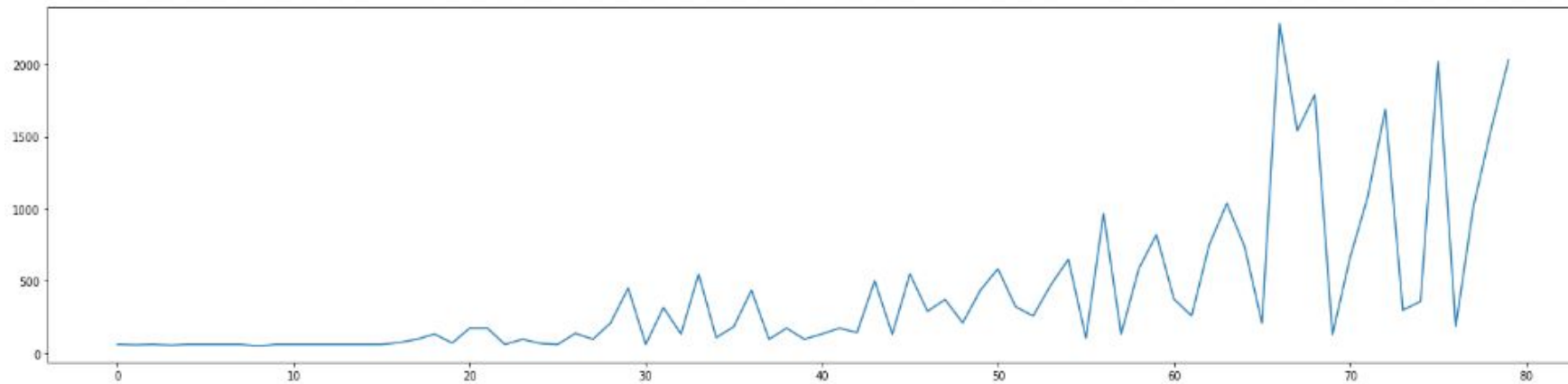
- Hints(report):
 - You can compare life time or reward against training episodes for both two algorithms.

Homework

- Hints(report):



Q-learning



SARSA

Thanks! Be a Happy Bird