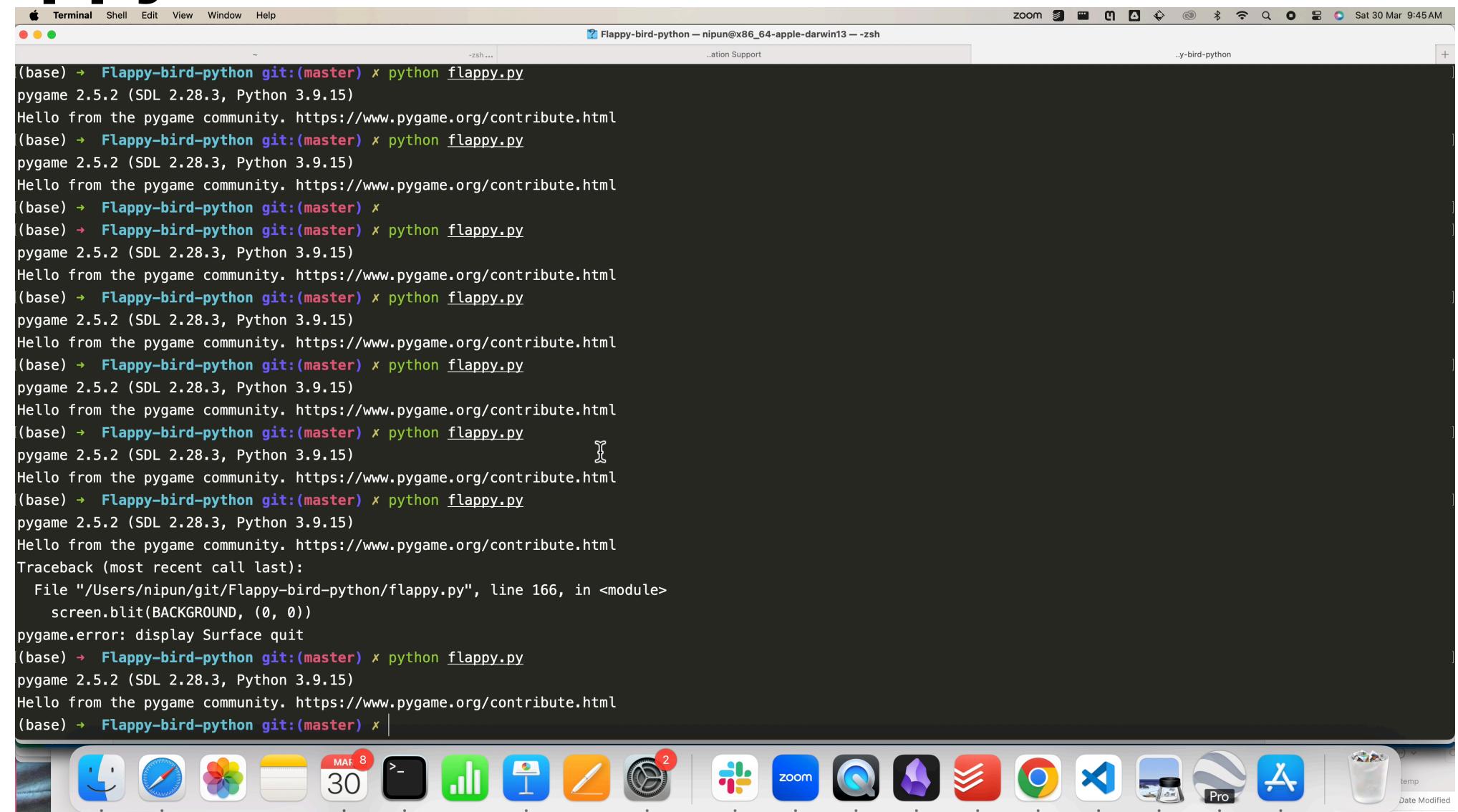
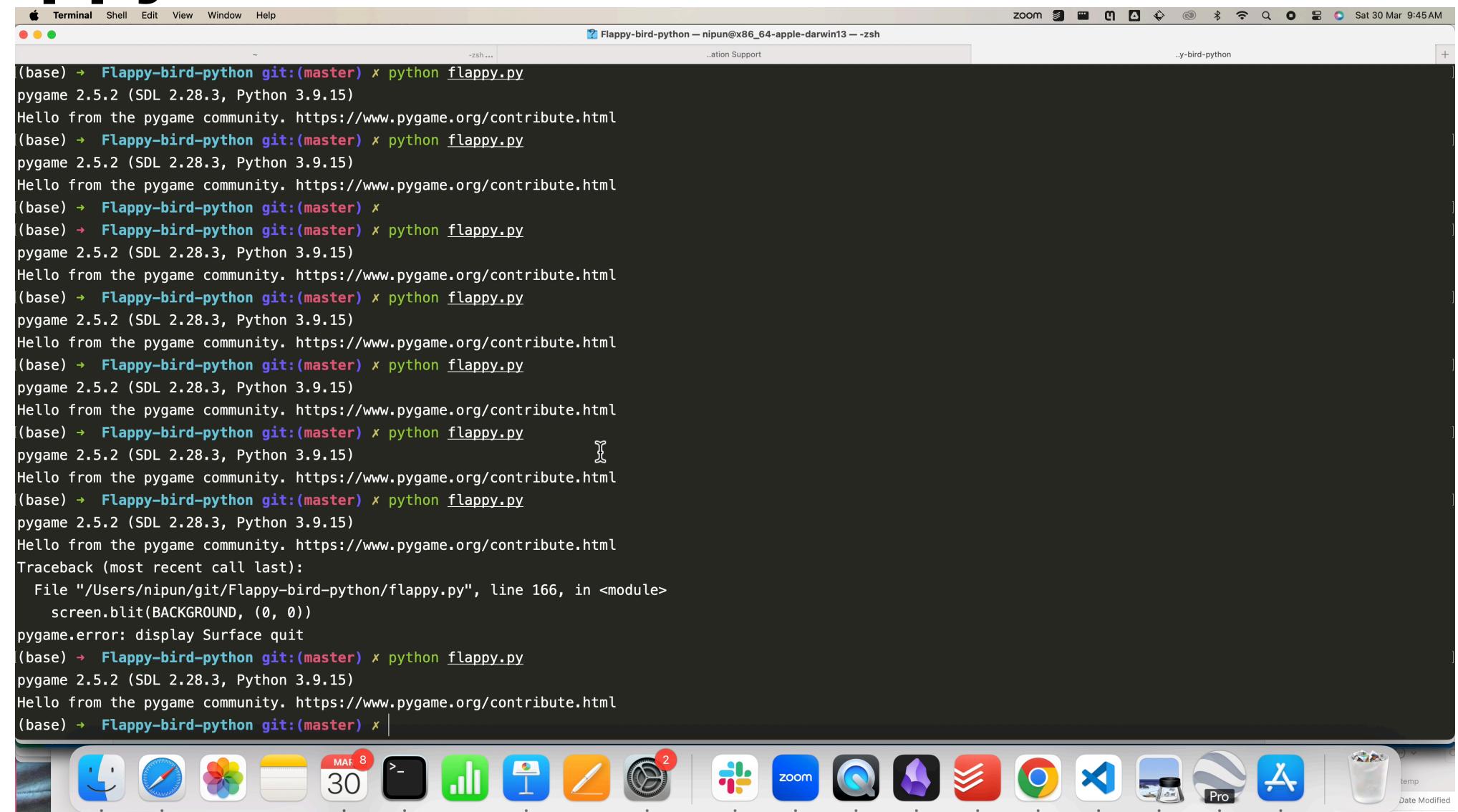
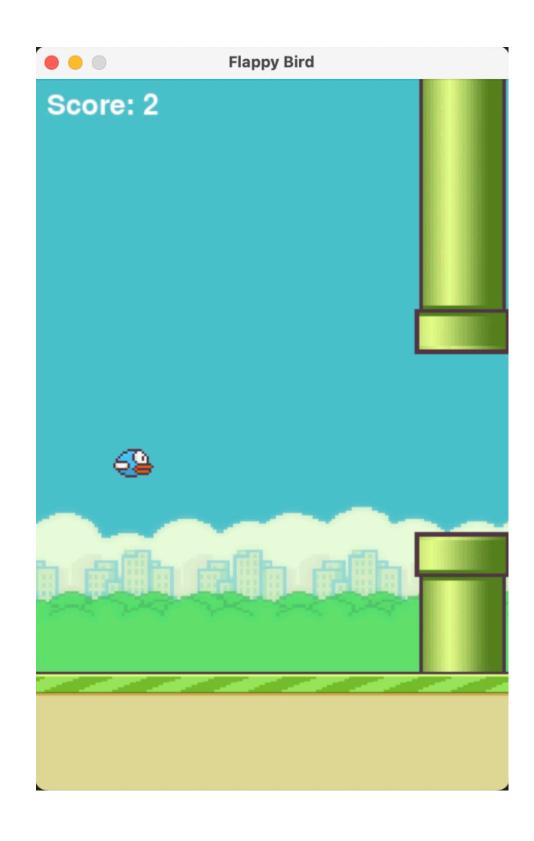
# Reinforcement Learning





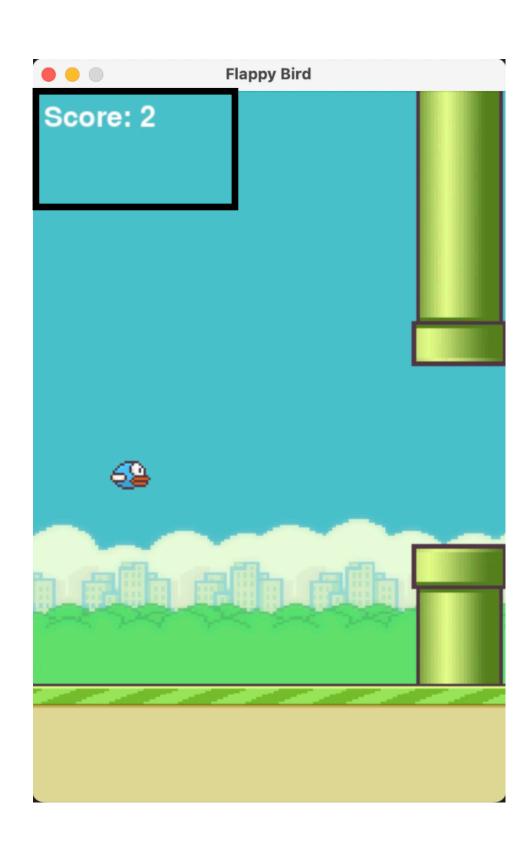
Game demo (Code modified from: <a href="https://github.com/LeonMarqs/Flappy-bird-python">https://github.com/LeonMarqs/Flappy-bird-python</a>)

What is the goal/objective?

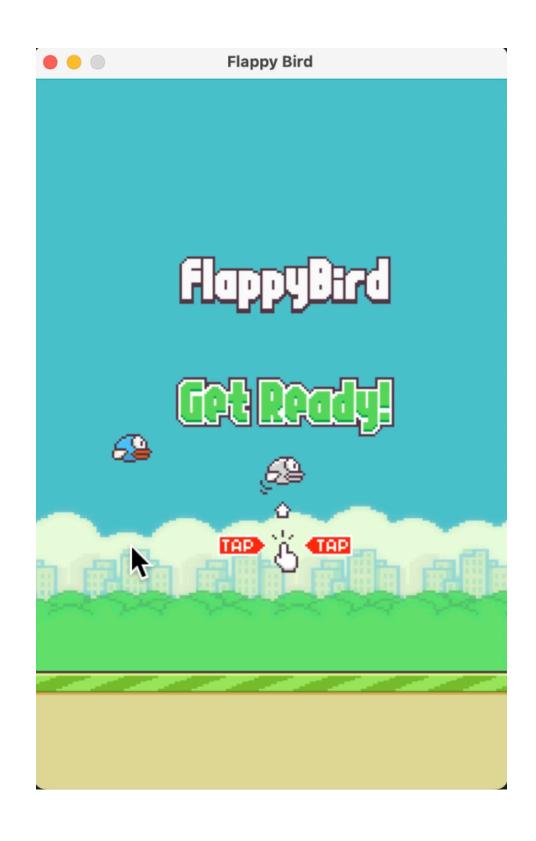


### What is the goal/objective?

Maximise score



What are the actions we can take?

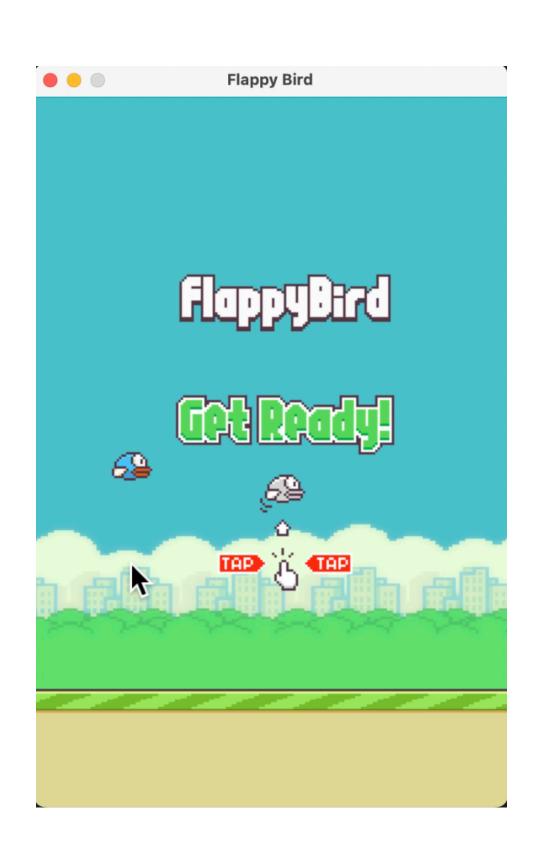


### What are the actions we can take?

- Two actions
  - Tap (Space)
  - No tap

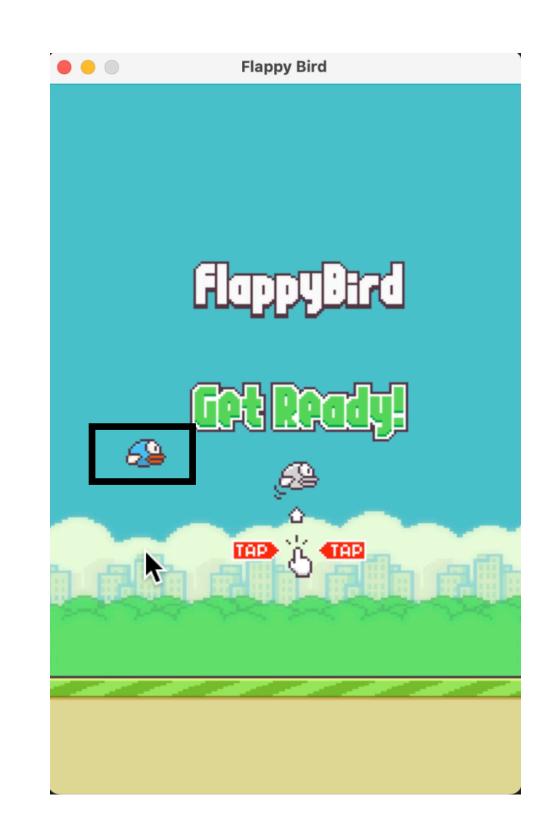


# Flappy Bird Who is playing?



# Flappy Bird Who is playing?

- Agent
  - You
  - Or some algorithm



# Flappy Bird Where are we playing?

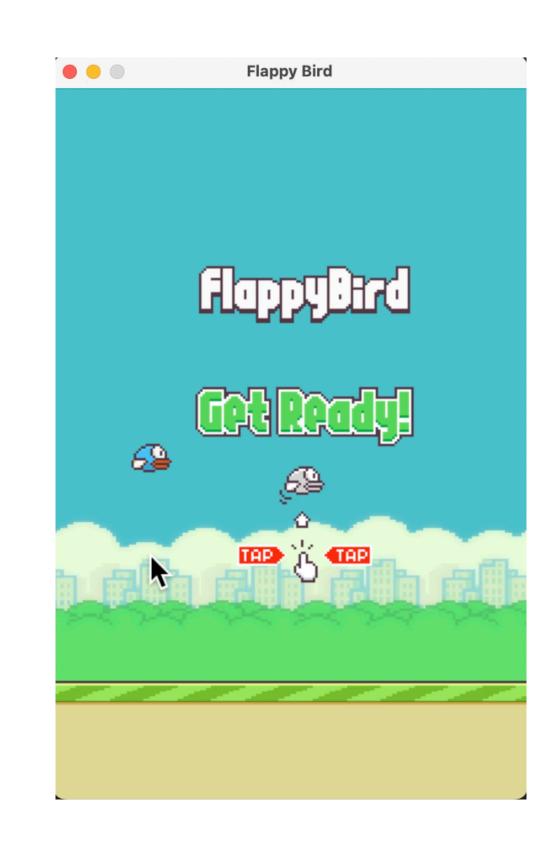
```
while begin:
   clock.tick(15)
   for event in pygame.event.get():
       if event type == QUIT:
           pygame.quit()
       if event.type == KEYDOWN:
           if event.key == K_SPACE or event.key == K_UP:
               bird.bump()
               pygame.mixer.music.load(wing)
               pygame.mixer.music.play()
               begin = False
   screen.blit(BACKGROUND, (0, 0))
   screen.blit(BEGIN_IMAGE, (120, 150))
   if is_off_screen(ground_group.sprites()[0]):
       ground_group.remove(ground_group.sprites()[0])
       new_ground = Ground(GROUND_WIDHT - 20)
       ground_group.add(new_ground)
   bird.begin()
   ground_group.update()
   bird_group.draw(screen)
```



### Where are we playing?

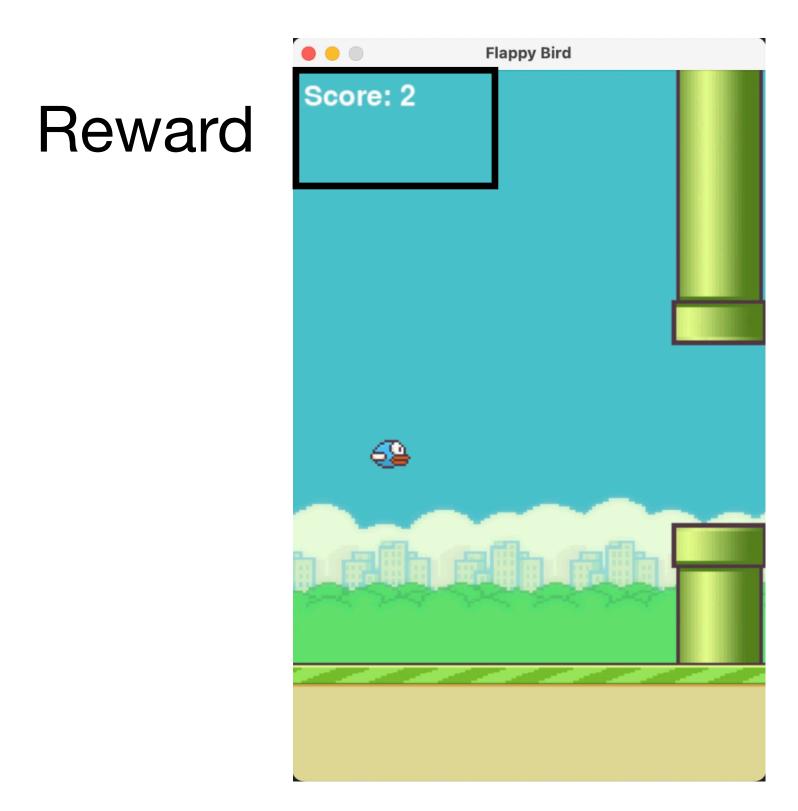
- Environment
  - Code
    - generating the graphics
    - Physics rules
      - What happens when you tap
      - What happens when you hit pipe

```
while begin:
    clock.tick(15)
    for event in pygame.event.get():
       if event.type == QUIT:
           pygame.quit()
       if event.type == KEYDOWN:
            if event.key == K_SPACE or event.key == K_UP:
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               pygame.mixer.music.load(wing)
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       new_ground = Ground(GROUND_WIDHT - 20)
       ground_group.add(new_ground)
    bird.begin()
   ground_group.update()
   bird_group.draw(screen)
```



What does the environment provide to an agent?

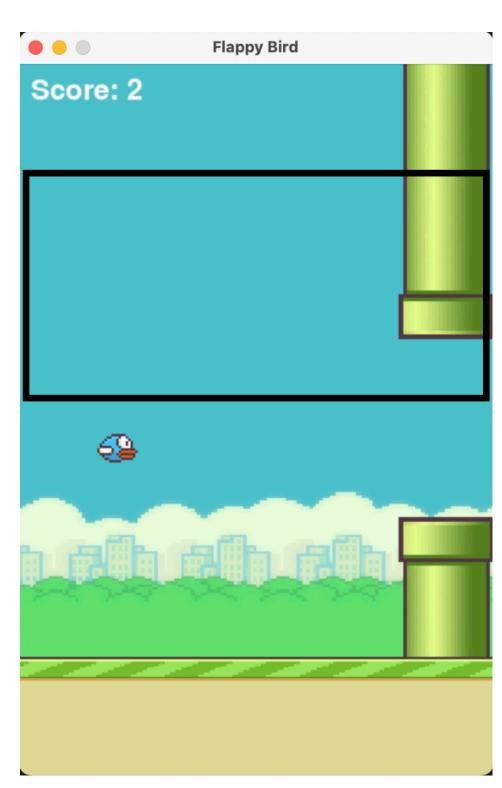
What does the environment provide to an agent?



What does the environment provide to an agent?

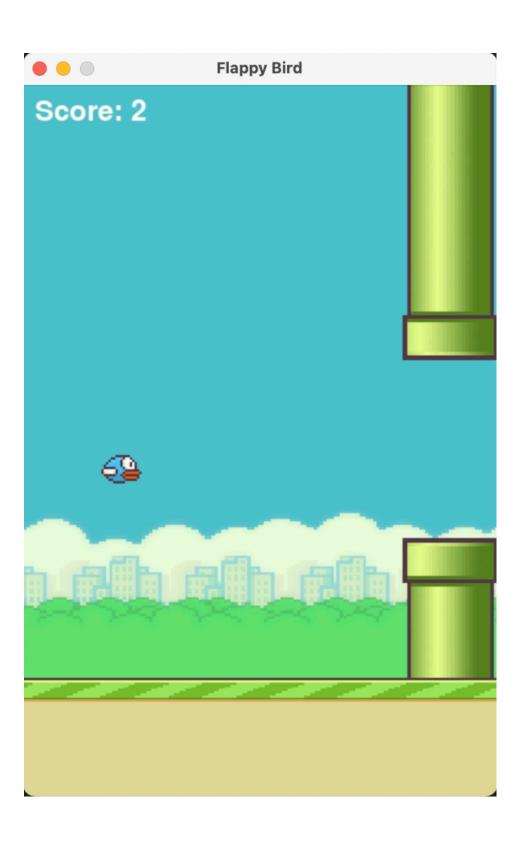
#### **Observations**

Pixel level information



How does an agent decide what action to take?

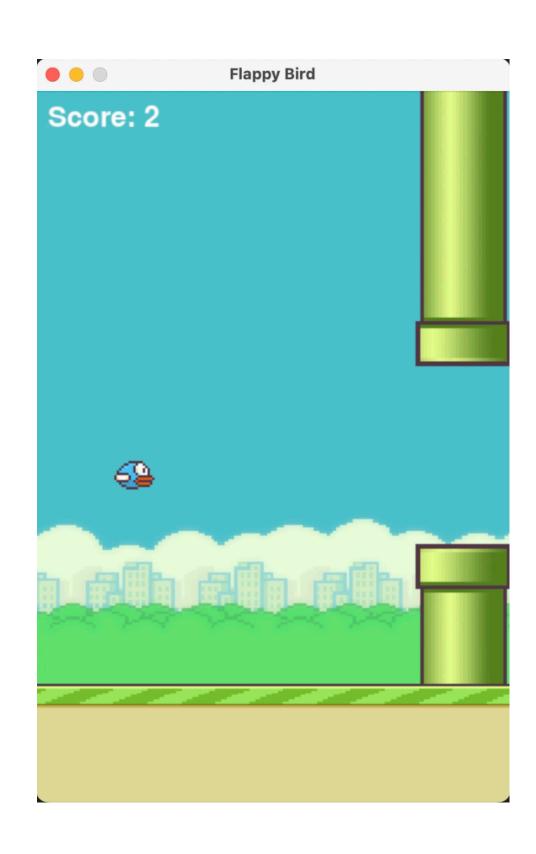
Should the agent tap or not?



How does an agent decide what action to take?

### **State**

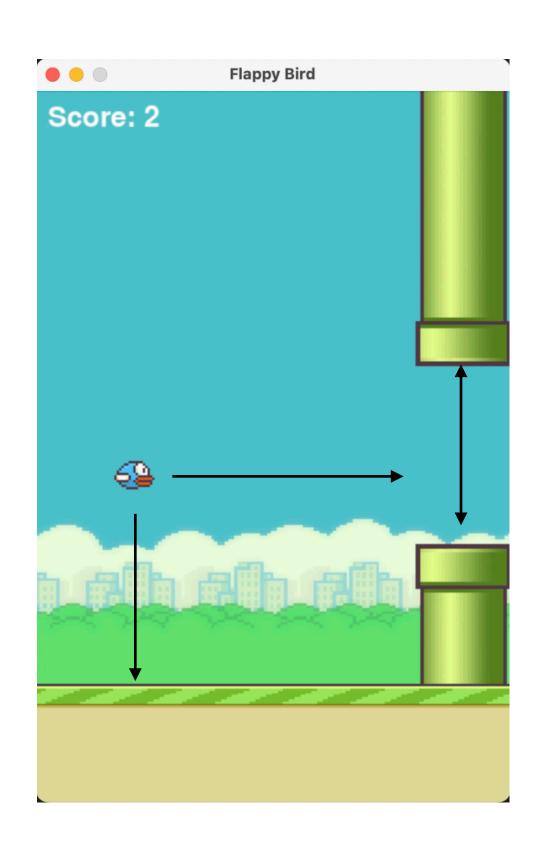
Process observation into a "state"



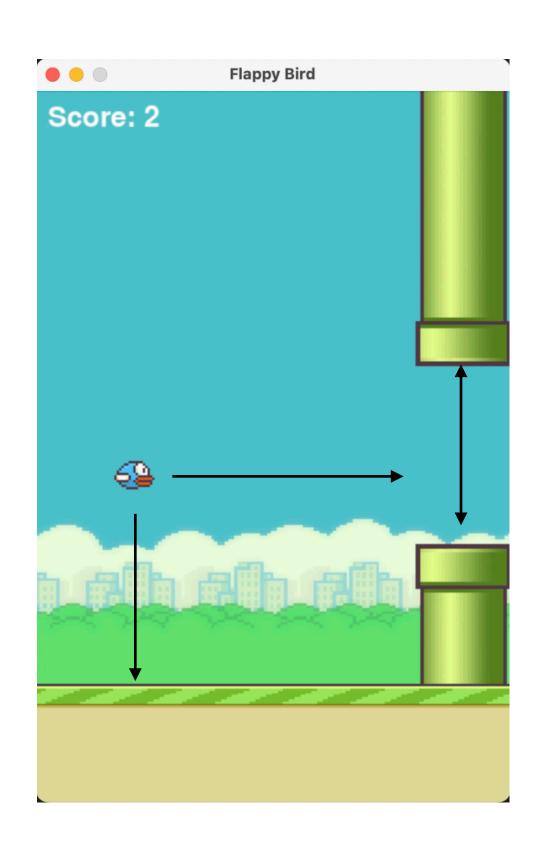
How does an agent decide what action to take?

### **State**

Process observation into a "state"



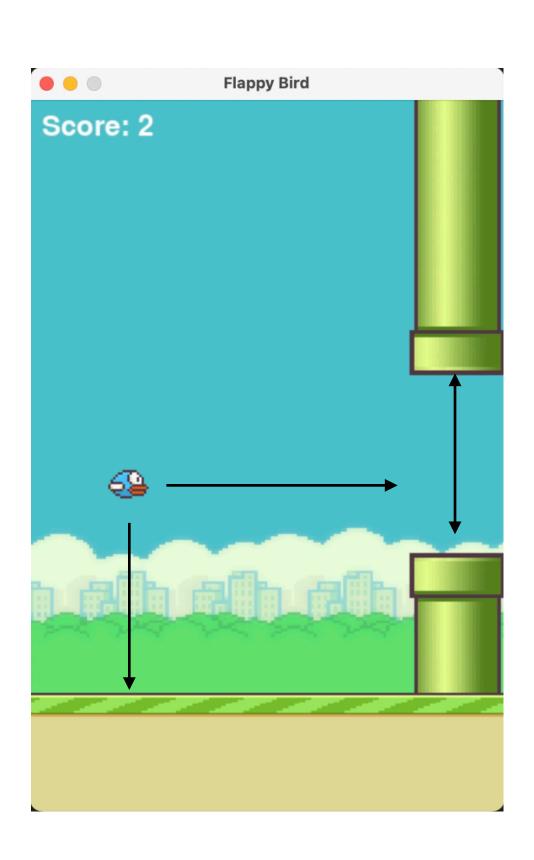
# Flappy Bird Is time important?



### Is time important?

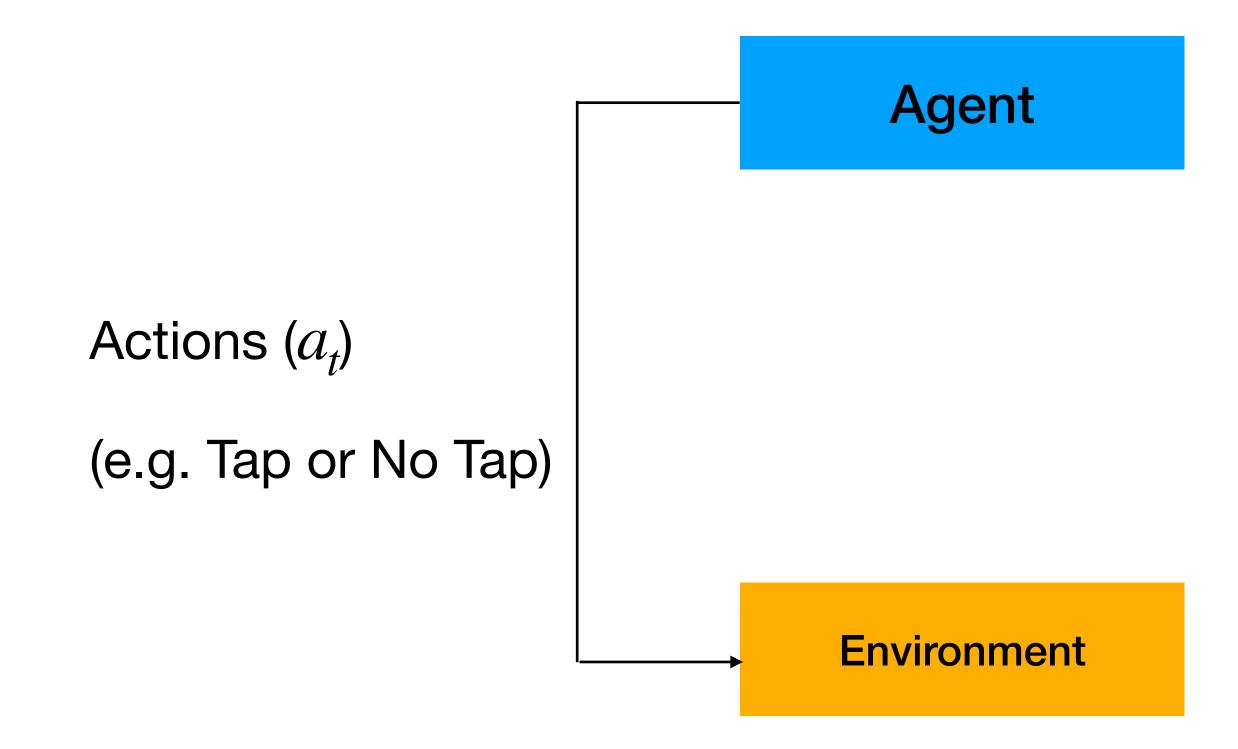
#### Yes

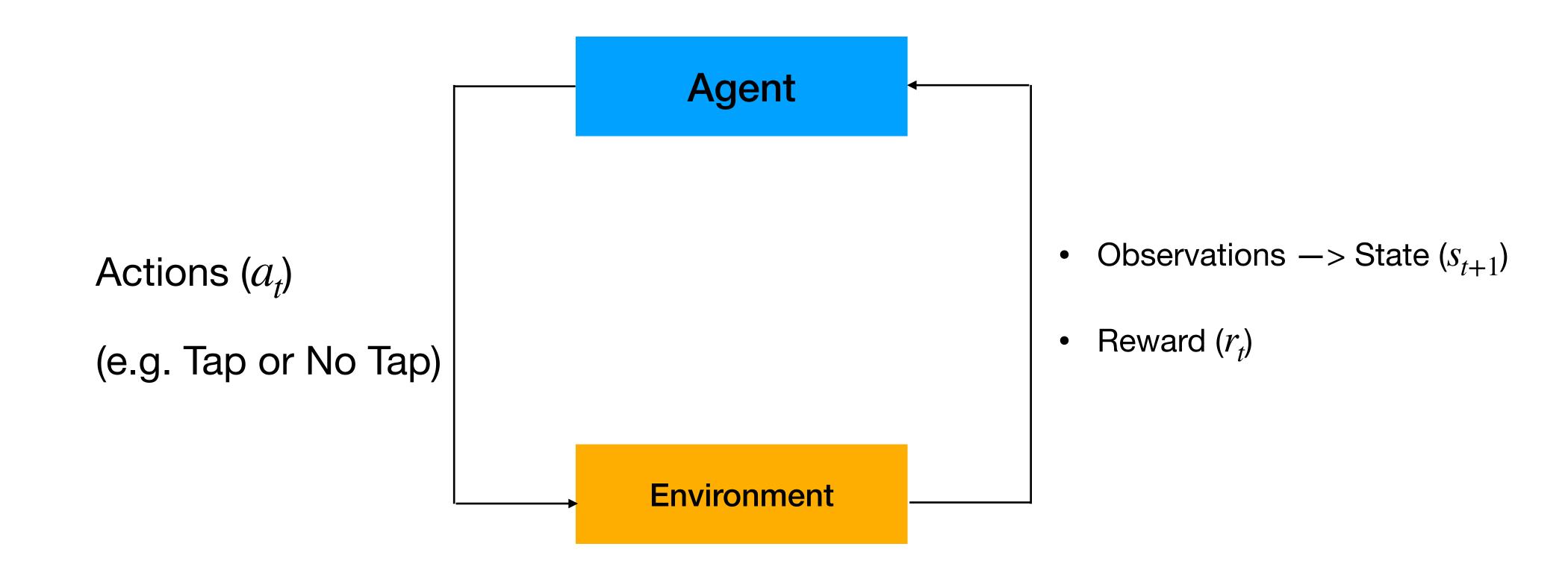
Agent's current state depends on previous state and action



Agent

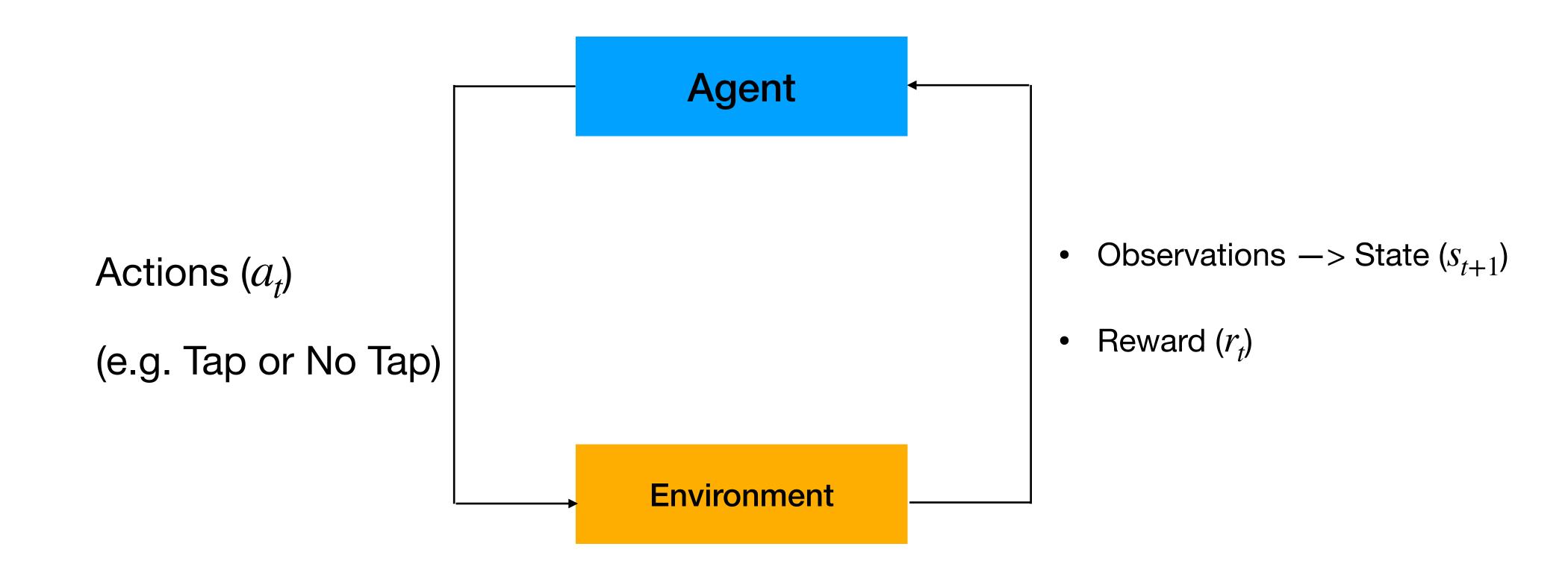
Environment





### OpenAl Gym Environment

- Mountain Car
  - Actions?
  - State?



### Goal: Maximise total (discounted) reward

Total Reward (Return) 
$$R_t = \sum_{i=t}^{\infty} r_i = r_t + r_{t+1} \dots + r_{t+n} + \dots$$

• Total Reward (Discounted Return)

$$R_{t} = \sum_{i=t}^{\infty} \gamma^{i} r_{i} = \gamma^{t} r_{t} + \gamma^{t+1} r_{t+1} \dots + \gamma^{t+n} r_{t+n} + \dots$$

•  $\gamma$ : discount factor;  $0 < \gamma < 1$ 

### **Q** function

- What we want?
  - Given a state choose an "action" that maximises total discounted reward
- Total Reward (Discounted Return)

$$R_{t} = \sum_{i=t}^{\infty} \gamma^{i} r_{i} = \gamma^{t} r_{t} + \gamma^{t+1} r_{t+1} \dots + \gamma^{t+n} r_{t+n} + \dots$$

• 
$$Q(s_t, a_t) = \mathbb{E}[R_t \mid s_t, a_t]$$

 Q-function captures the expected total future reward an agent can achieve by taking an action.

State	Action 1	Action 2	Action 3
S1	10	20	15
S2	20	30	5
SN	-5	10	20

State	Action 1	Action 2	Action 3
S1	10	20	15
S2	20	30	5
SN	-5	10	20

What action will you choose if you are in state S2?

State	Action 1	Action 2	Action 3
S1	10	20	15
S2	20	30	5
SN	-5	10	20

What action will you choose if you are in state S2?

Action 2 (as it gives us highest return)

State <position, Velocity&gt;</position, 	Action 1	Action 2	Action 3
<-5, -2>	?	?	?
	?	?	?
•••	?	?	?

How do we define states for problems like Mountain car where these numbers are not discrete?

State <position, Velocity&gt;</position, 	Action 1	Action 2	Action 3
<[-5, -4], [-2, -1]>	?	?	?
<[-5, -4], [—1, 0]>	?	?	?
<b></b>			
• • •	?	?	?

How do we define states for problems like Mountain car where these numbers are not discrete?

Discretisation (notebook)

### Q function (revision)

- What we want?
  - Given a state choose an "action" that maximises total discounted reward
- Total Reward (Discounted Return)

$$R_{t} = \sum_{i=t} \gamma^{i} r_{i} = \gamma^{t} r_{t} + \gamma^{t+1} r_{t+1} \dots + \gamma^{t+n} r_{t+n} + \dots$$

- $Q(s_t, a_t) = \mathbb{E}[R_t \mid s_t, a_t]$
- Q-function captures the expected total future reward an agent can achieve by taking an action.

### Bellman Equation

The Bellman equation for Q-values is given by:

$$Q(s,a) = R(s,a) + \gamma \cdot \max_{a'} Q(s',a')$$

#### where:

- Q(s, a) is the Q-value of taking action
- R(s, a) is the immediate reward of taking action a in state s.
- $\gamma$  is the discount factor that determines the importance of future rewards.
- s' is the next state after taking action a.
- $\max_{a'} Q(s', a')$  is the maximum Q-value over all possible actions in state s'.

## Q-learning Update Bellman Equation

$$Q(s,a) = R(s,a) + \gamma \cdot \max_{a'} Q(s',a')$$

Q-learning update rule is derived by using the Bellman equation in an iterative manner:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \cdot \left( R(s,a) + \gamma \cdot \max_{a'} Q(s',a') - Q(s,a) \right)$$

- $\alpha$  is the learning rate that controls the extent to which new information overrides old information.
- $R(s,a) + \gamma \cdot \max_{a'} Q(s',a') Q(s,a)$  is the temporal difference (TD) error, representing the discrepancy between the expected Q-value and the observed reward.