

# **Reinforcement Learning**

**Nipun Batra, 1 April 2024**

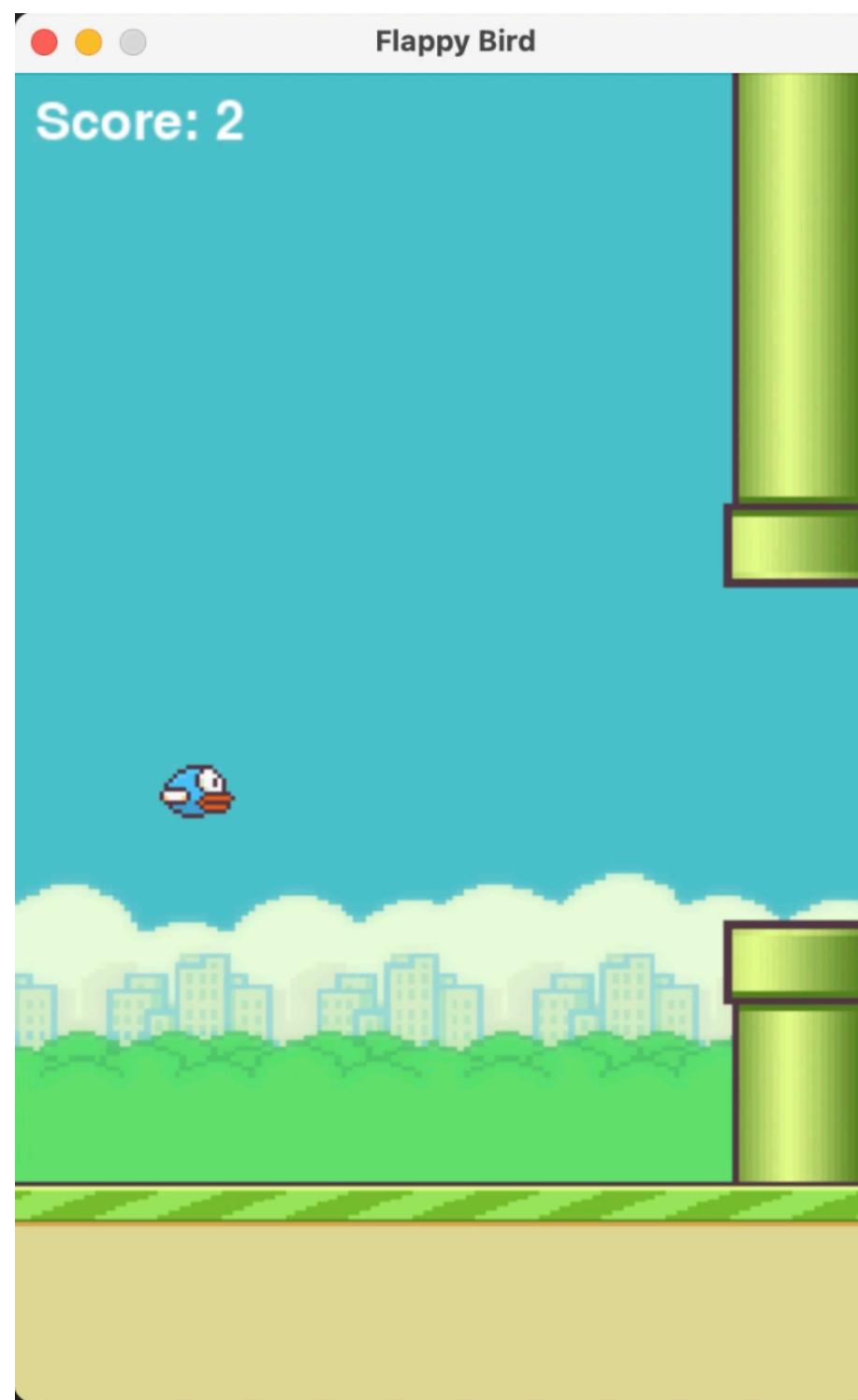
# Flappy Bird

# Flappy Bird

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

# Flappy Bird

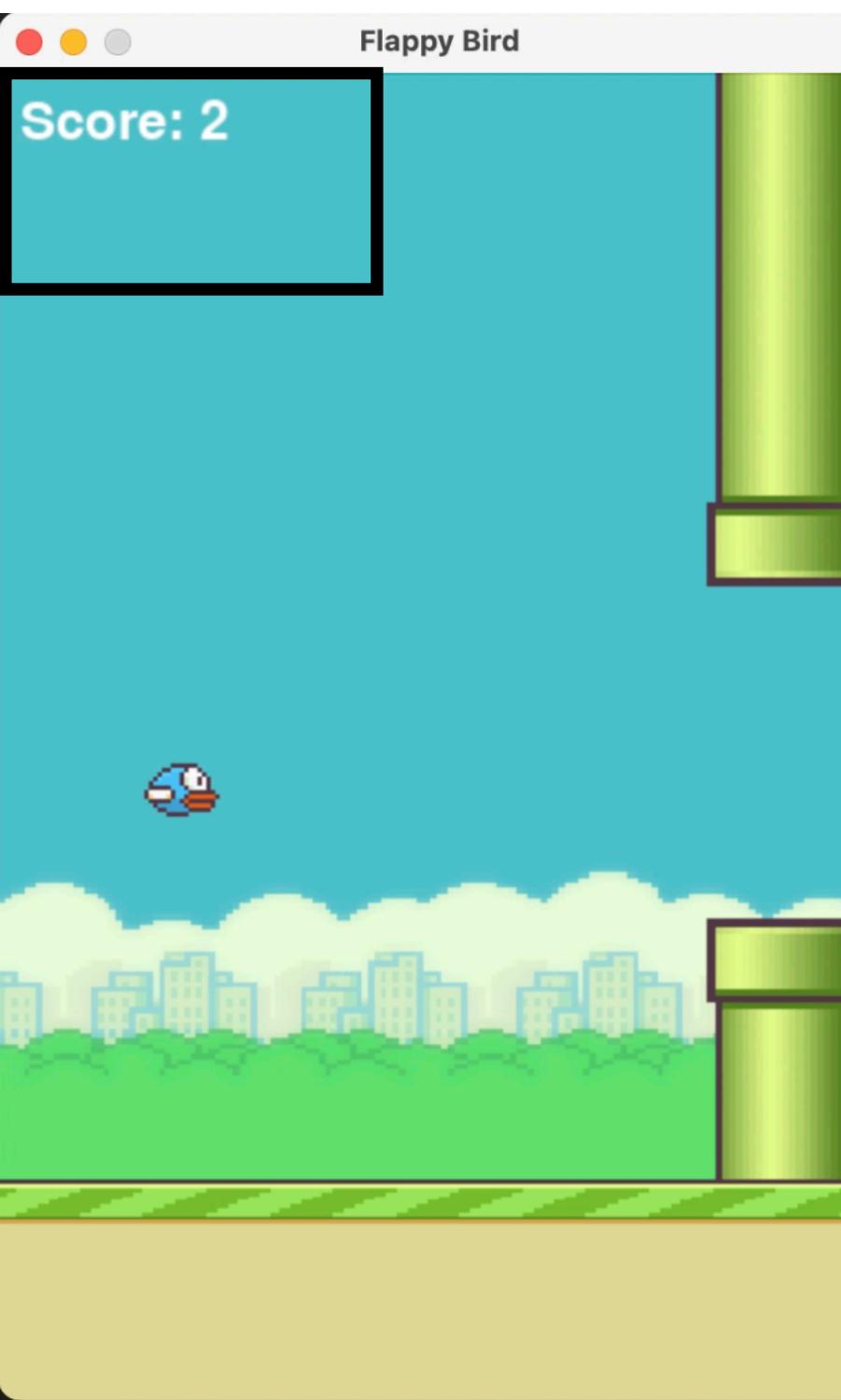
What is the goal/objective?



# Flappy Bird

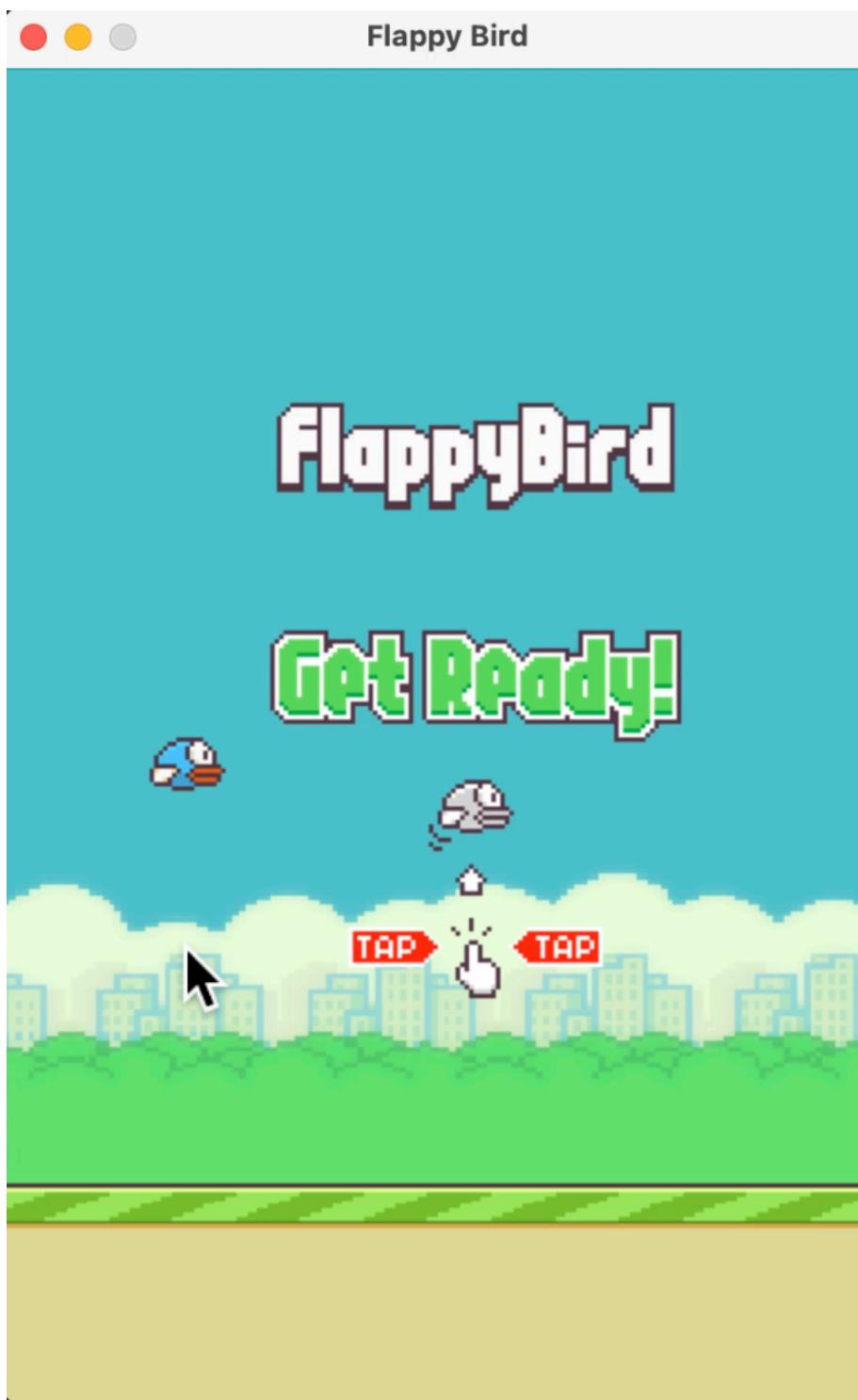
What is the goal/objective?

- Maximise score



# Flappy Bird

What are the actions we can take?



# Flappy Bird

What are the actions we can take?

- Two actions
  - Tap (Space)
  - No tap



# Flappy Bird

## Who is playing?



# Flappy Bird

## Who is playing?

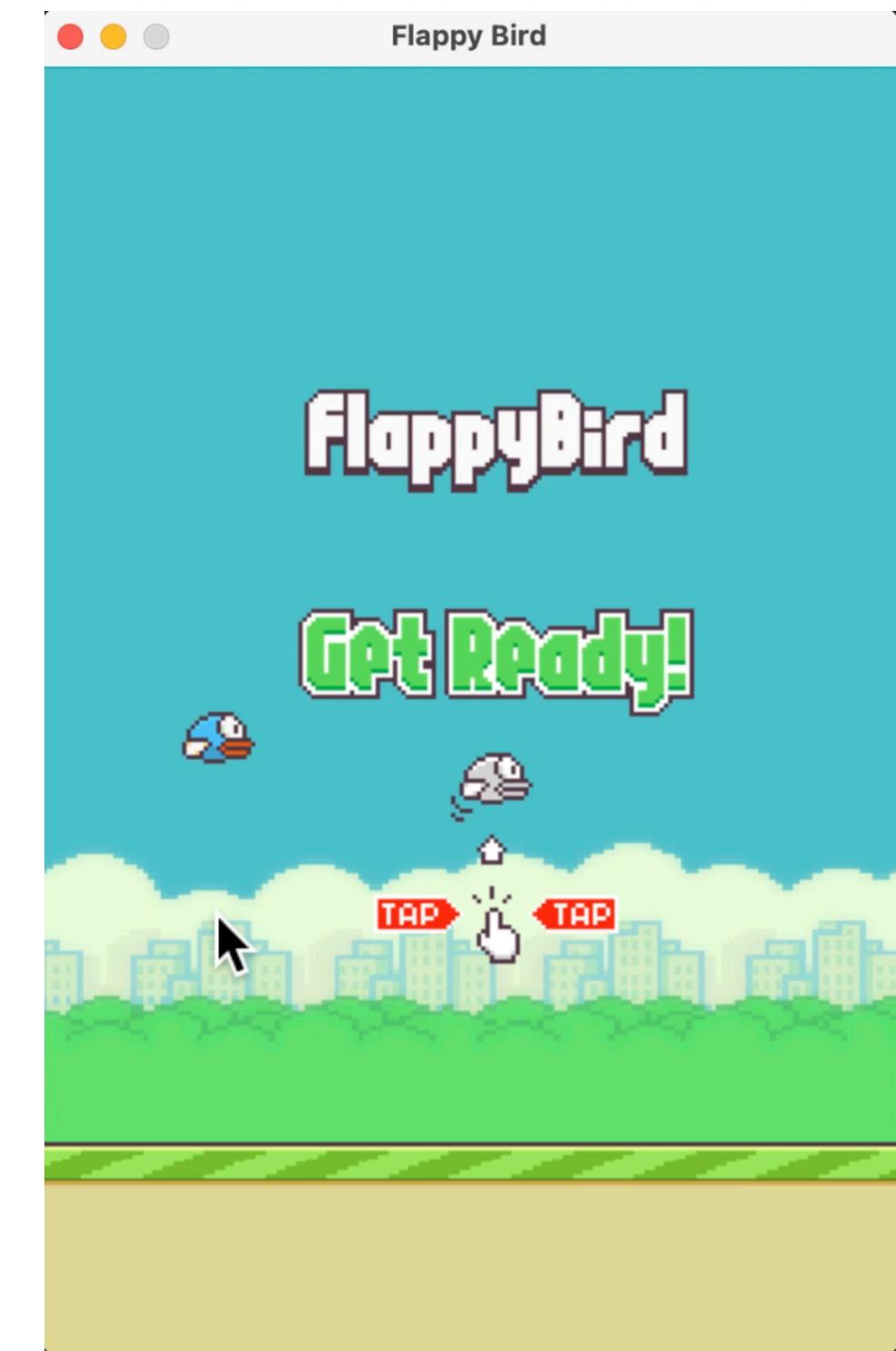
- Agent
  - You
  - Or some algorithm



# 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)  
    ground_group.draw(screen)
```

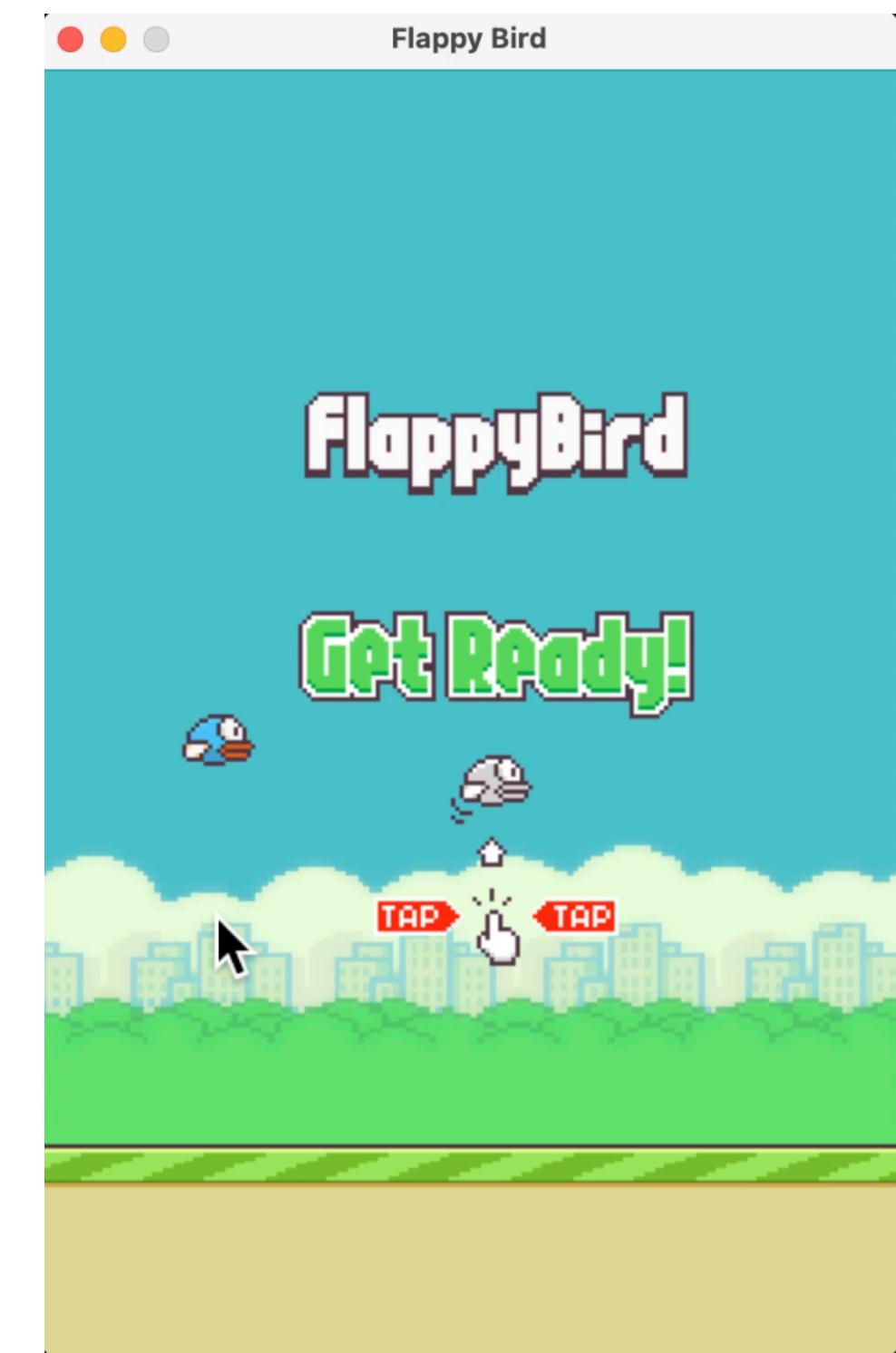


# Flappy Bird

## Where are we playing?

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

```
while begin:  
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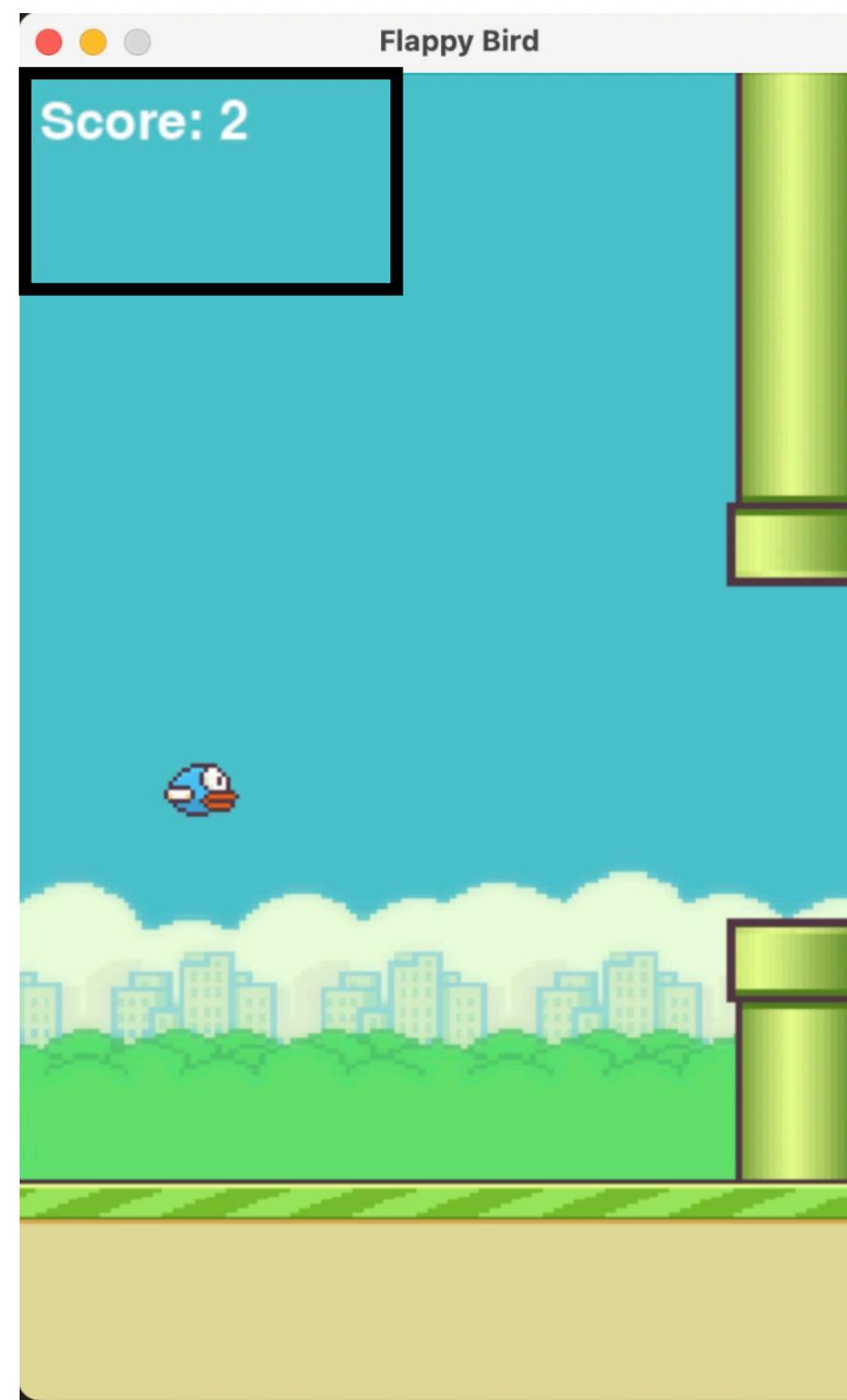
# **Flappy Bird**

**What does the environment provide to an agent?**

# Flappy Bird

What does the environment provide to an agent?

Reward

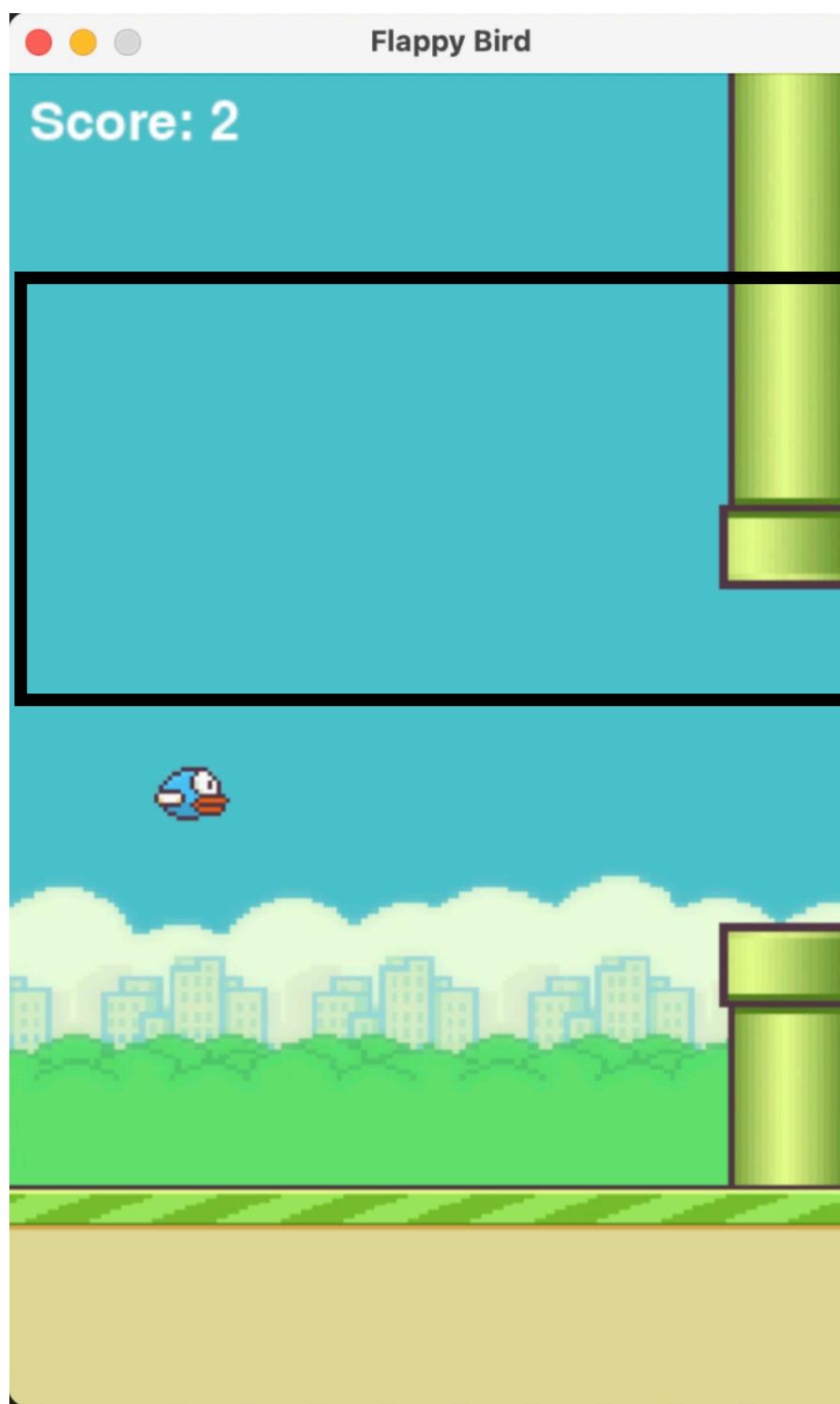


# Flappy Bird

What does the environment provide to an agent?

**Observations**

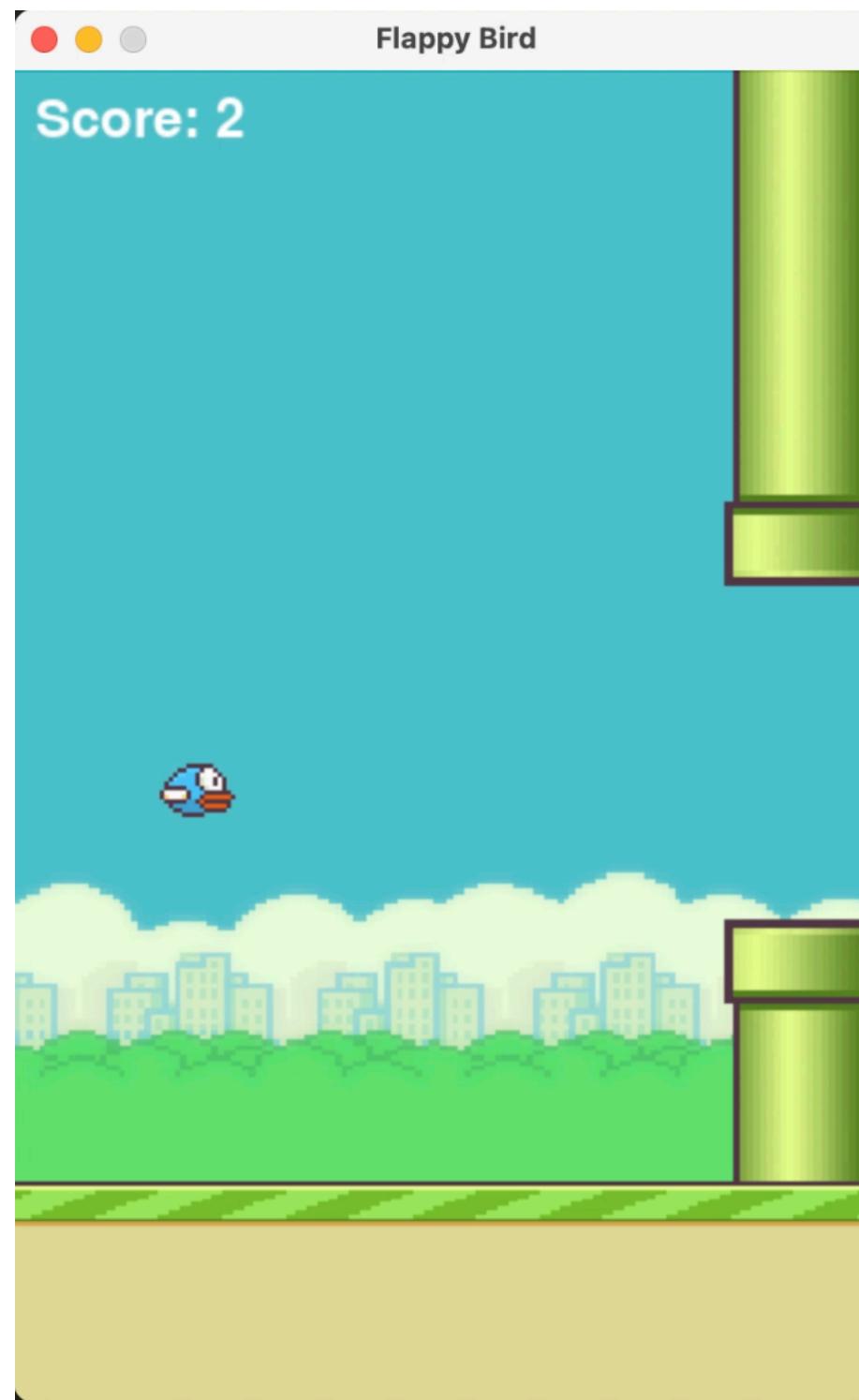
Pixel level information



# Flappy Bird

How does an agent decide what action to take?

Should the agent  
tap or not?

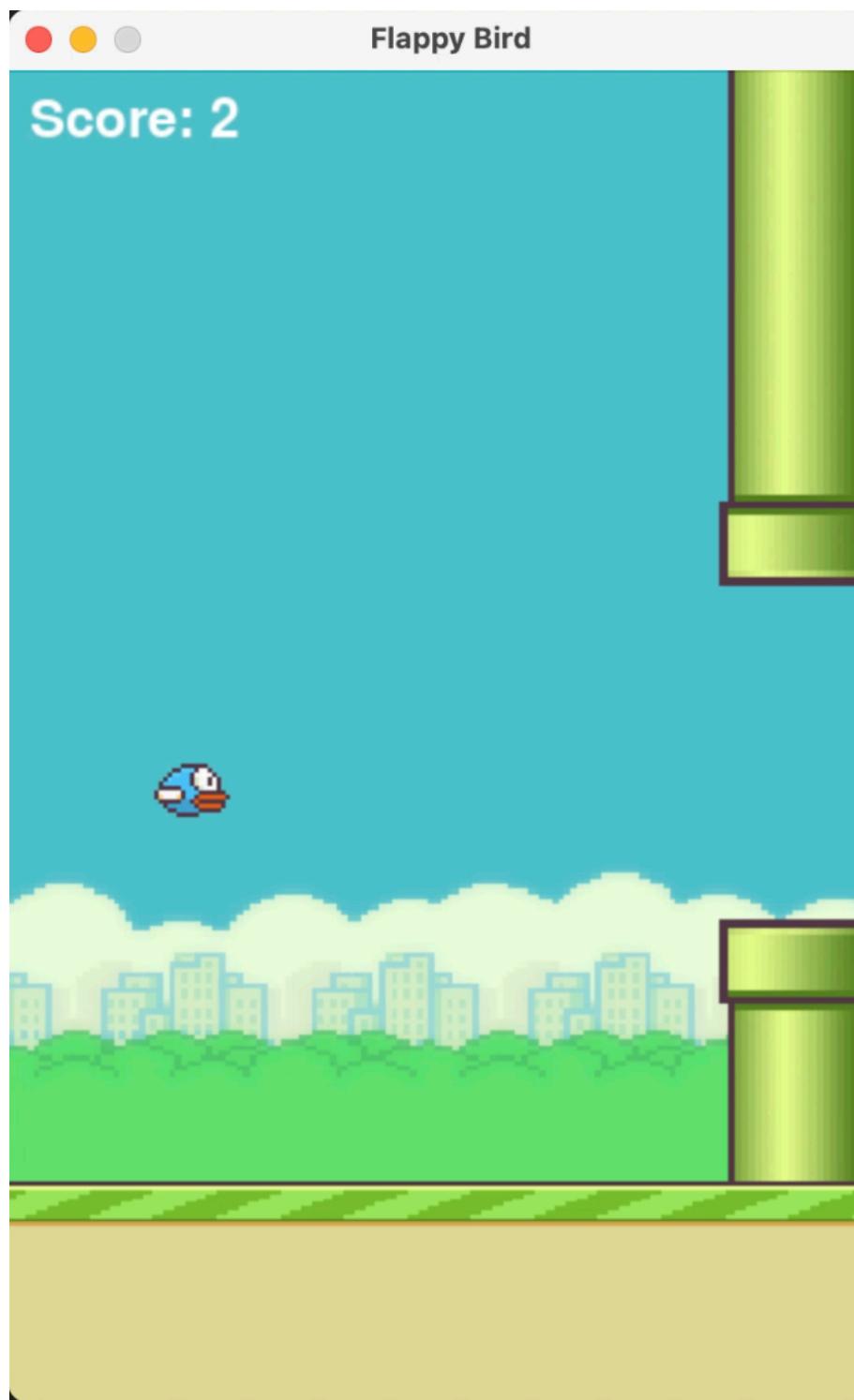


# Flappy Bird

How does an agent decide what action to take?

**State**

Process  
observation into a  
“state”

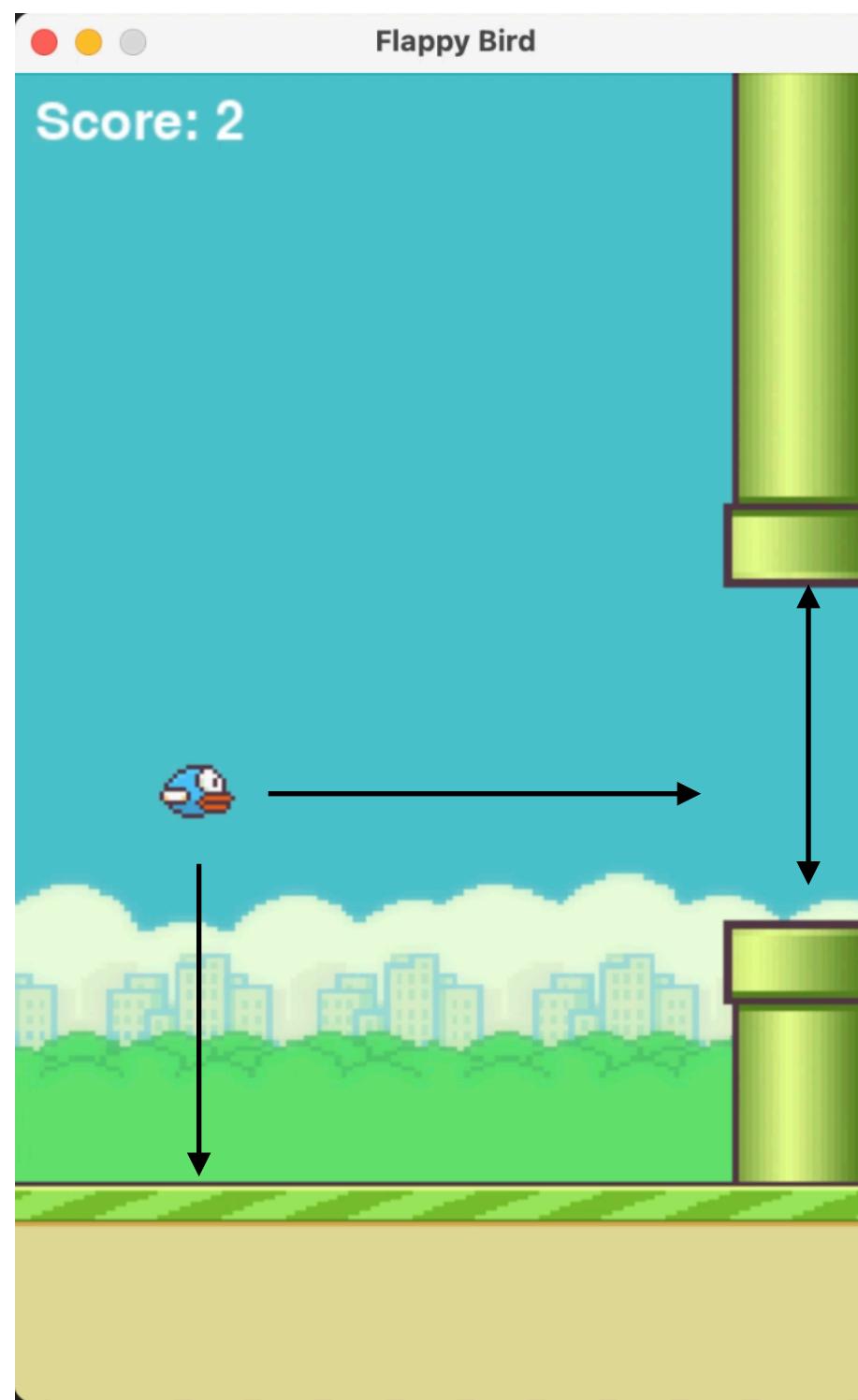


# Flappy Bird

How does an agent decide what action to take?

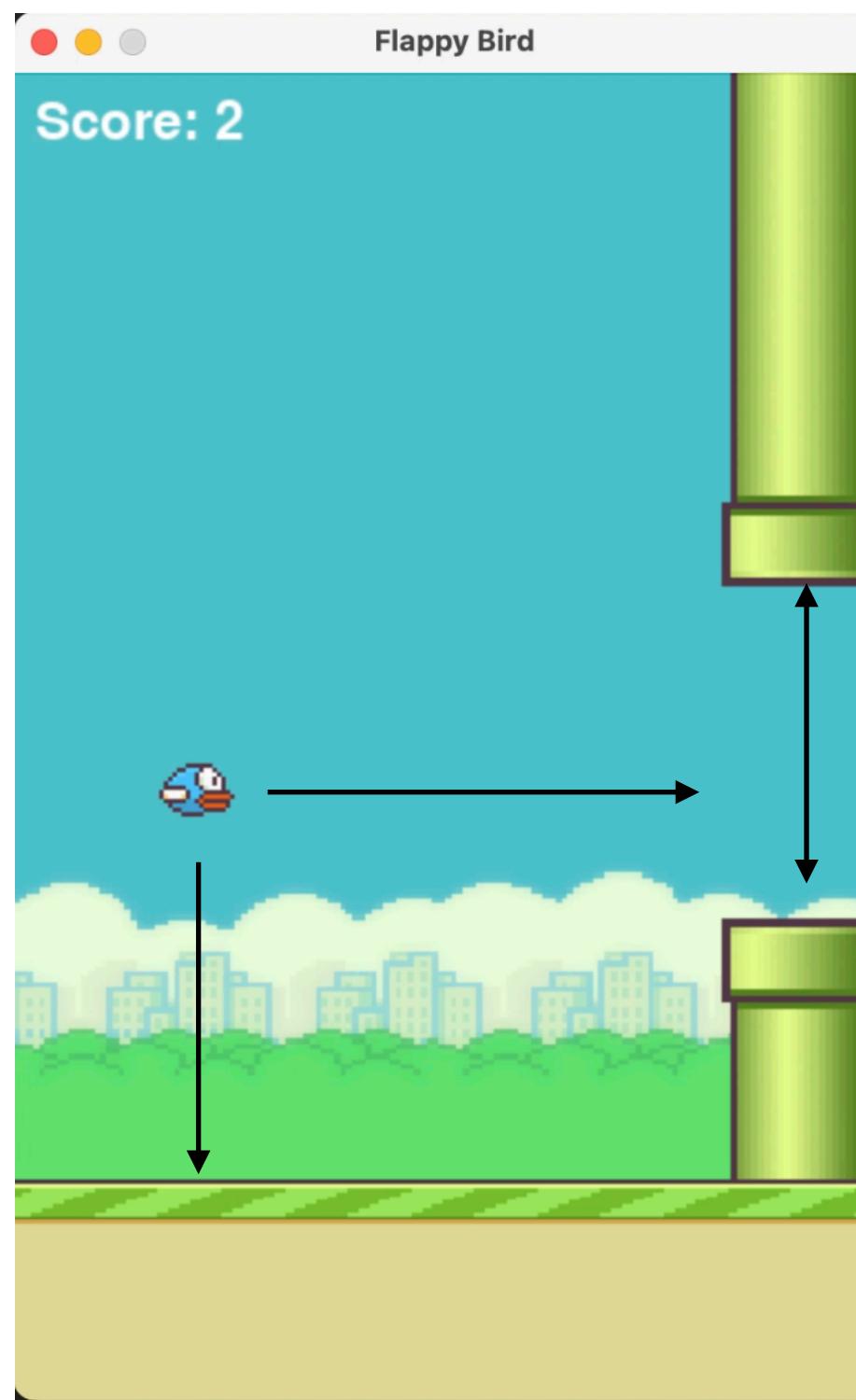
**State**

Process  
observation into a  
“state”



# Flappy Bird

## Is time important?

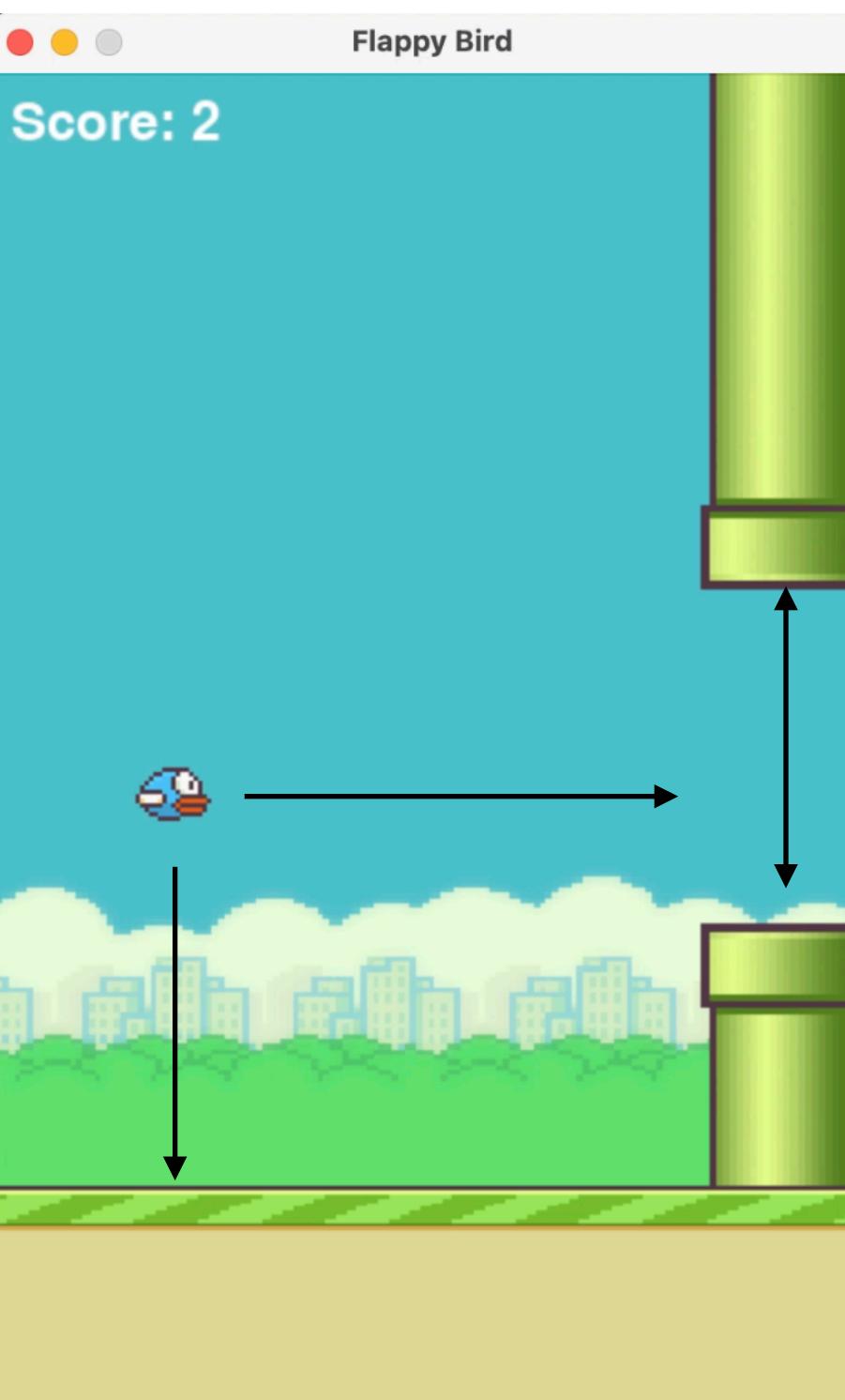


# Flappy Bird

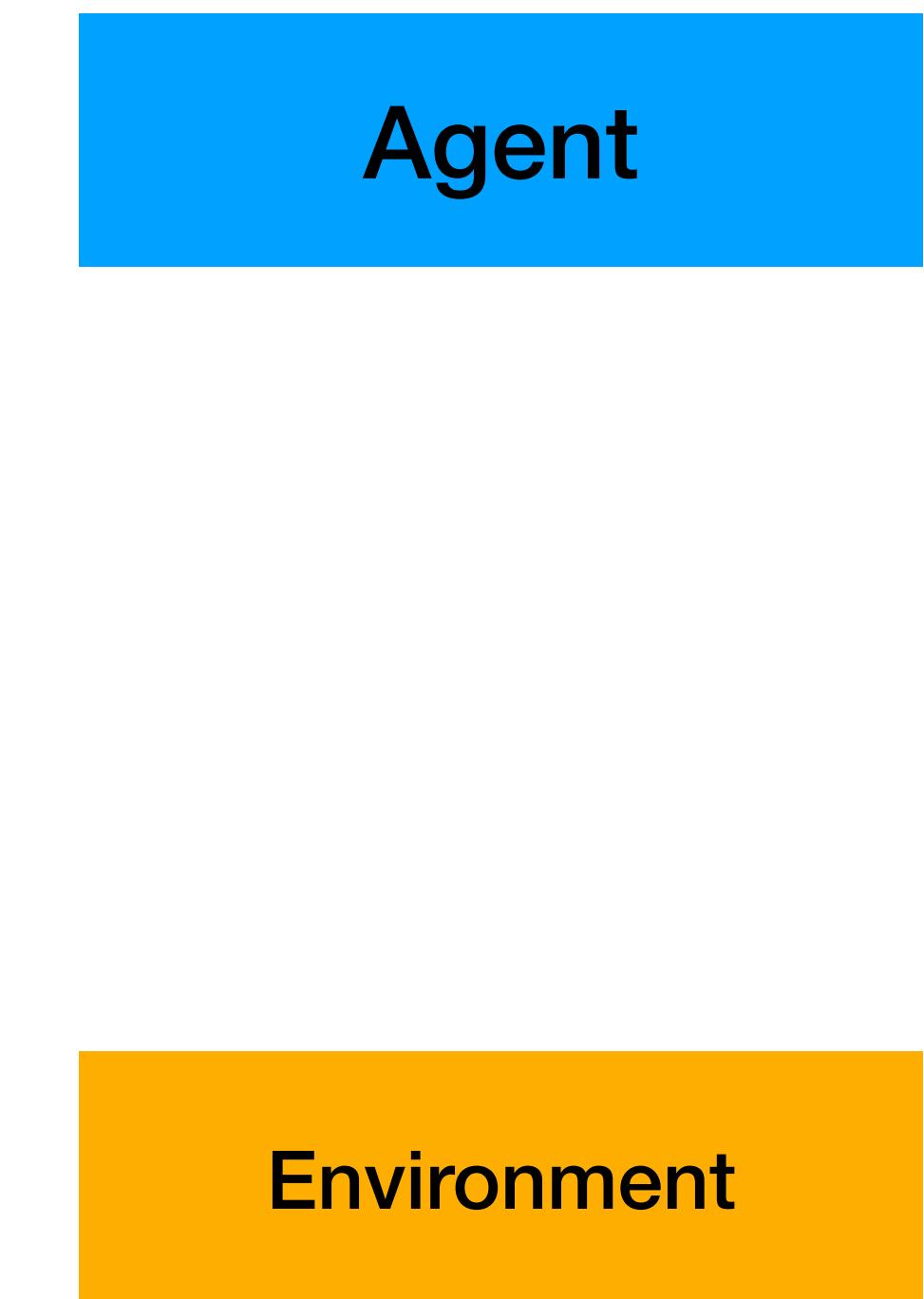
## Is time important?

**Yes**

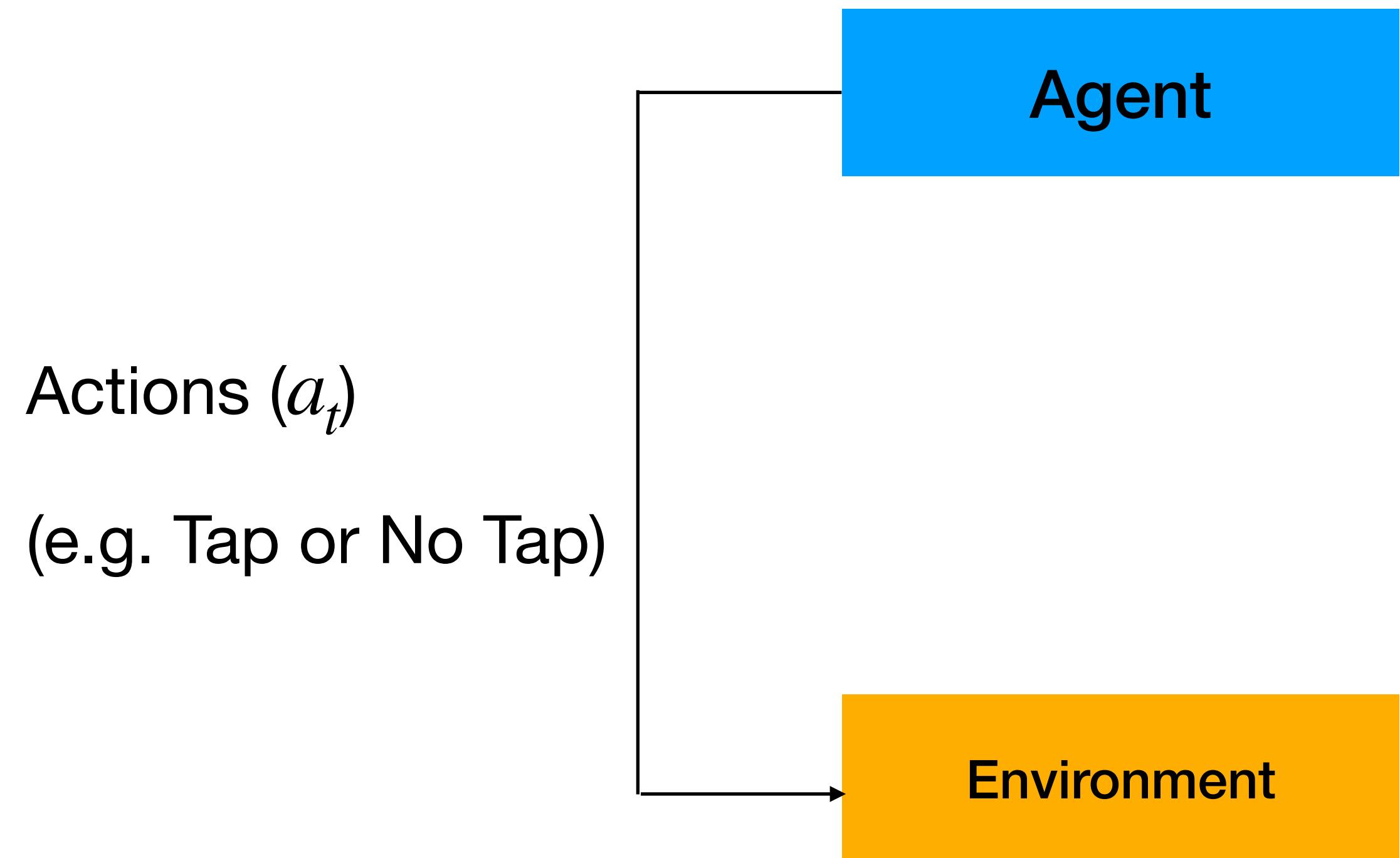
Agent's current state depends on previous state and action



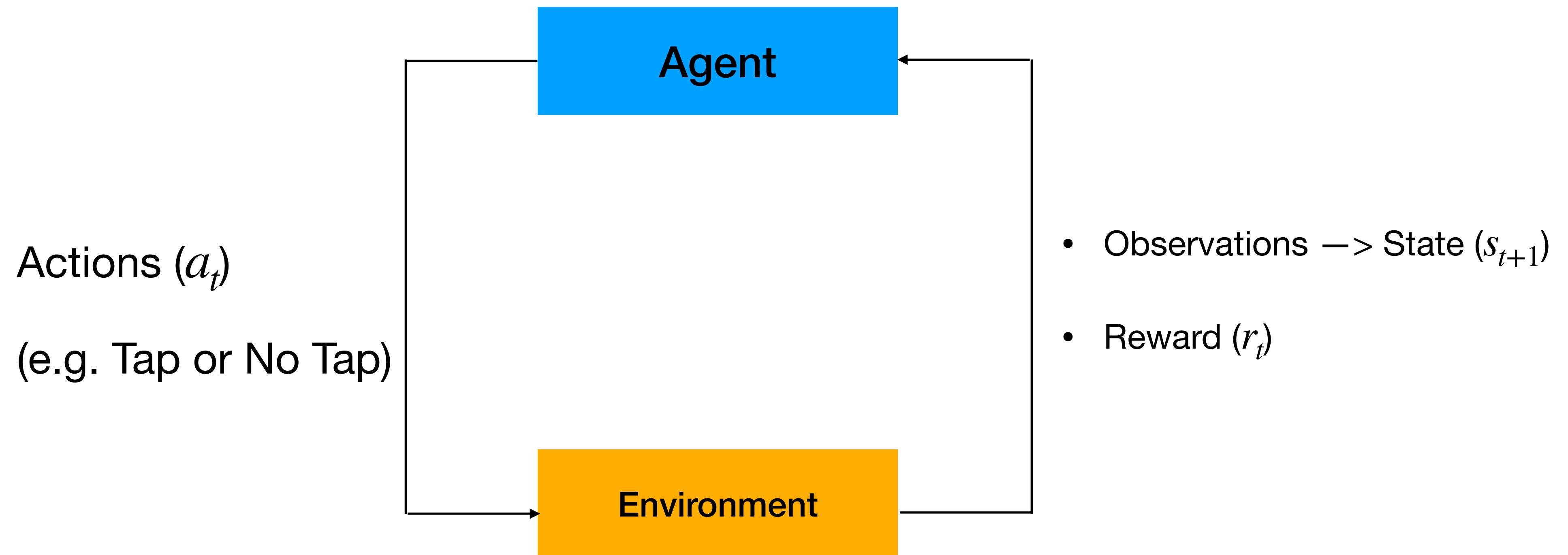
# Block Diagram



# Block Diagram



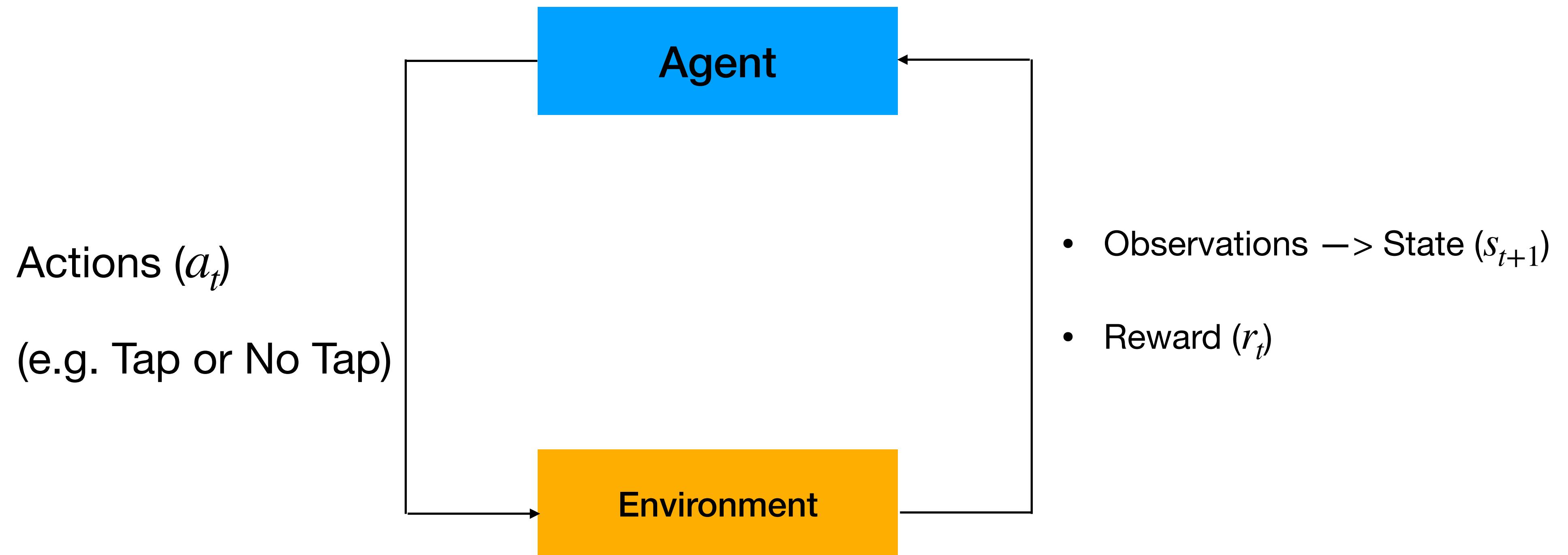
# Block Diagram



# OpenAI Gym Environment

- Mountain Car
  - Actions?
  - State?

# Block Diagram



# 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)
$$R_t = \sum_{i=t}^{\infty} \gamma^i r_i = \gamma^t r_t + \gamma^{t+1} r_{t+1} \dots + \gamma^{t+n} r_{t+n} + \dots$$
- $Q(s_t, a_t) = \mathbb{E}[R_t | s_t, a_t]$
- Q-function captures the expected total future reward an agent can achieve by taking an action.

# Q table

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

# Q table

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?

# Q table

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)

# Q table

State <Position, Velocity>	Action 1	Action 2	Action 3
<-5, -2>	?	?	?
...	?	?	?
...			
...	?	?	?

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

# Q table

State $\langle \text{Position}, \text{Velocity} \rangle$	Action 1	Action 2	Action 3
$\langle [-5, -4], [-2, -1] \rangle$	?	?	?
$\langle [-5, -4], [-1, 0] \rangle$	?	?	?
...			
...	?	?	?

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)
$$R_t = \sum_{i=t}^{\infty} \gamma^i r_i = \gamma^t r_t + \gamma^{t+1} r_{t+1} \dots + \gamma^{t+n} r_{t+n} + \dots$$
- $Q(s_t, a_t) = \mathbb{E}[R_t | s_t, a_t]$
- 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  $a$ .
- $R(s, a)$  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.