# Announcements

- **Project Milestone 2 due tonight at 8pm**

- Homework 6 released tonight
  - Due Wednesday, April 19 at 8pm

# Lecture 22: Reinforcement Learning

CIS 4190/5190

Spring 2023

# Recap

- **Q iteration:** Compute optimal Q function when the transitions and rewards are known

- **Q learning:** Compute optimal Q function when the transitions and rewards are unknown

- **Extensions**
  - Various strategies for exploring the state space during learning
  - Handling large or continuous state spaces

# Q Learning

- Iteratively perform the following update:

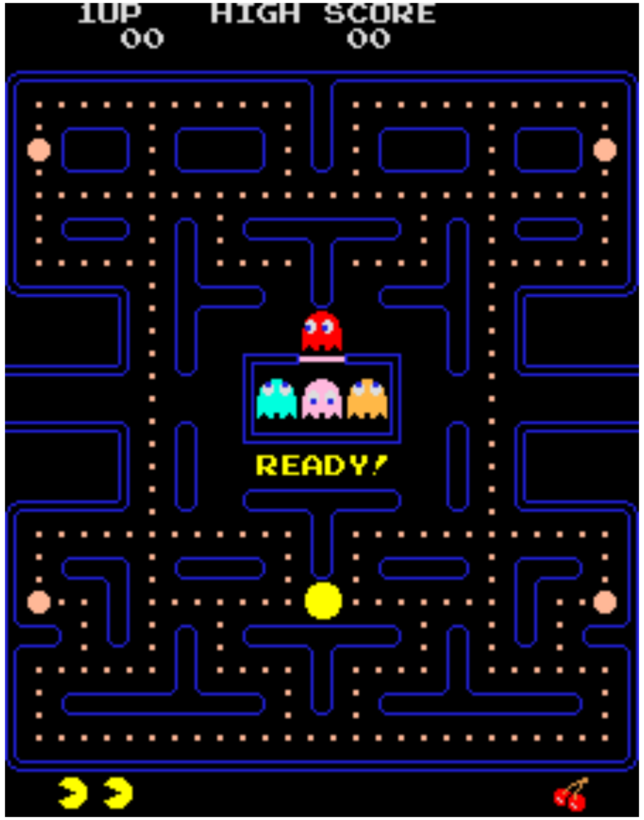
$$Q_{i+1}(s,a) \leftarrow (1-\alpha)\cdot Q_i(s,a) + \alpha \cdot \left(R(s,a,s') + \gamma \cdot \max_{a' \in A} Q_i(s',a')\right)$$

# Agenda

- Deep Q learning & actor-critic
- Multi-armed bandits
- Exploration in reinforcement learning
- Offline reinforcement learning

# Curse of Dimensionality

- How large is the state space?
  - **Gridworld:** One for each of the $n$ cells
  - **Pacman:** State is $(\text{player}, \text{ghost}_1, \ldots, \text{ghost}_k)$, so there are $n^k$ states!
- **Problem:** Learning in one state does not tell us anything about the other states!
- Many states → learn very slowly



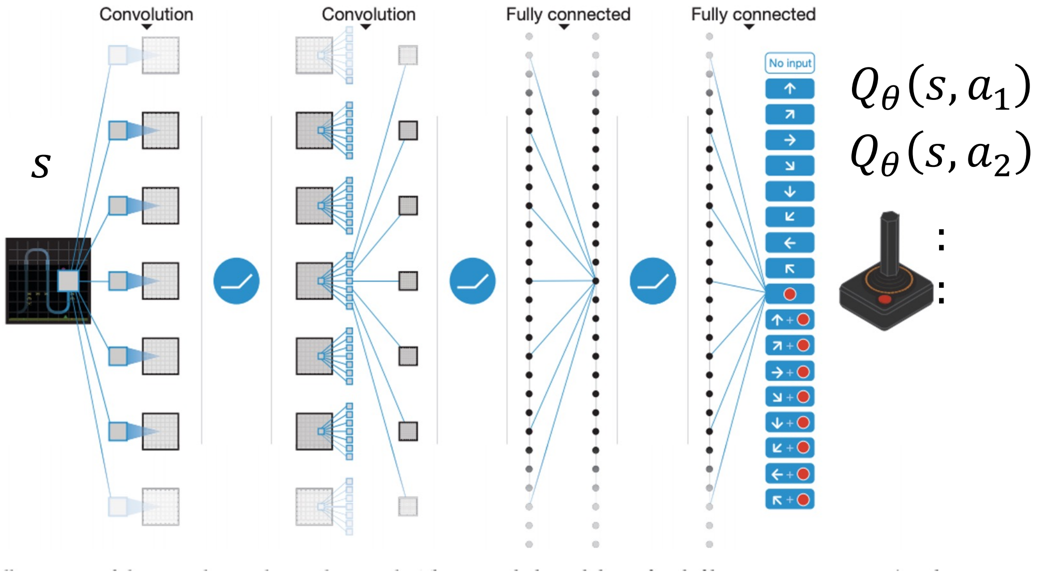
# State-Action Features

- Can we learn **across** state-action pairs?

- Yes, use features!
  - $\phi(s, a) \in \mathbb{R}^d$
  - Then, learn to predict $Q^*(s, a) \approx Q_\theta(s, a) = f_\theta\big(\phi(s, a)\big)$
  - Enables generalization to similar states

# Neural Network $Q$ Function

- **Examples:** Distance to closest ghost, distance to closest dot, etc.
  - Can also use neural networks to **learn** features (e.g., represent Pacman game state as an image and feed to CNN)!



# Deep Q Learning

- **Learning:** Gradient descent with the squared Bellman error loss:

$$\Bigg(\underbrace{\Big(R(s,a,s') + \gamma \cdot \max_{a'} Q_\theta(s',a')\Big)}_{\text{“Label” } y} - Q_\theta(s,a)\Bigg)^2$$

# Deep Q Learning

- **Iteratively perform the following:**
  - Take an action $a_i$ and observe $(s_i, a_i, s_{i+1}, r_i)$
  - $y_i \leftarrow r_i + \gamma \cdot \max_{a' \in A} Q_\theta(s_{i+1}, a')$
  - $\phi \leftarrow \phi - \alpha \cdot \frac{d}{d\theta}(Q_\theta(s_i, a_i) - y_i)^2$

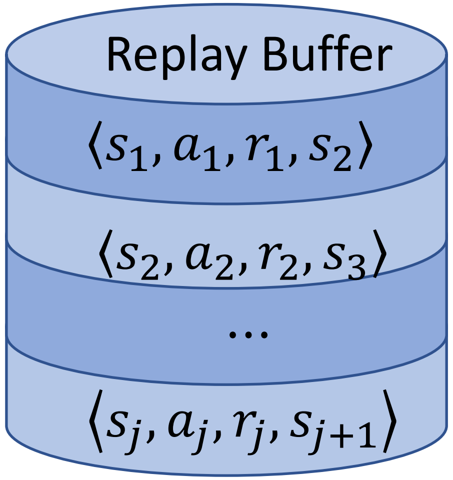
- **Note:** Pretend like $y_i$ is constant when taking the gradient

- For finite state setting, recover incremental update if the "parameters" are the Q values for each state-action pair

Based on slide by Sergey Levine

# Experience Replay Buffer

- **Problem**
  - Sequences of states are highly correlated
  - Tend to overfit to current states and forget older states
- **Solution**
  - Keep a **replay buffer** of observations (as a priority queue)
  - Gradient updates on samples from replay buffer instead of current state
- **Advantages**
  - Breaks correlations between consecutive samples
  - Can take multiple gradient steps on each observation

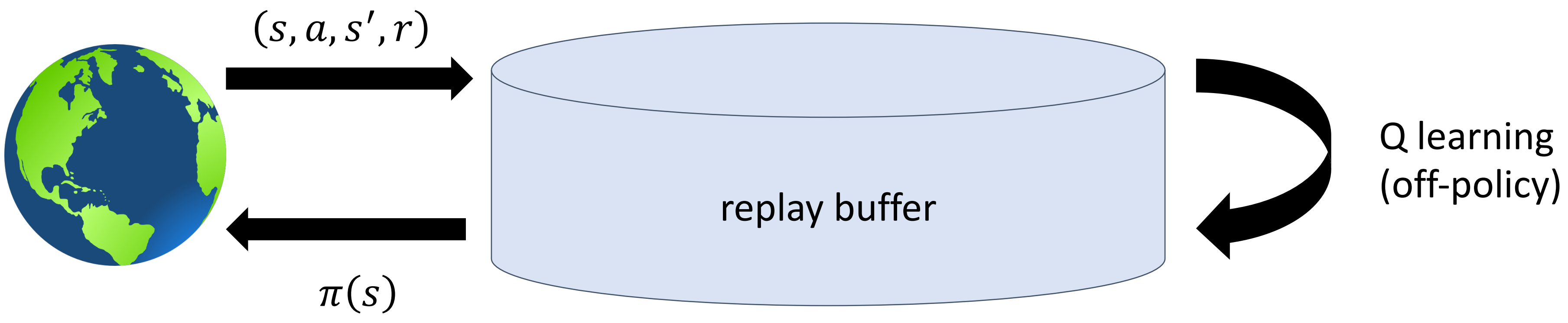



Priority Queue

Based on slide by Sergey Levine

# Deep Q Learning with Replay Buffer

- **Iteratively perform the following:**
  - Take an action $a_i$ and add observation $(s_i, a_i, s_{i+1}, r_i)$ to replay buffer $D$
  - For $k \in \{1, \ldots, K\}$:
    - Sample $(s_{i,k}, a_{i,k}, s_{i+1,k}, r_{i,k})$ from $D$
    - $y_{i,k} \leftarrow r_{i,k} + \gamma \cdot \max_{a' \in A} Q_\theta(s_{i+1,k}, a')$
    - $\theta \leftarrow \theta - \alpha \cdot \frac{d}{d\theta}\left(Q_\theta(s_{i,k}, a_{i,k}) - y_{i,k}\right)^2$




Based on slide by Sergey Levine

# Target Q Network

- **Problem**
  - Q network occurs in the label $y_i$!
  - $\theta \leftarrow \theta - \alpha \cdot \frac{d}{d\theta}\left(Q_\theta(s_i, a_i) - r_i + \gamma \cdot \max_{a' \in A} Q_\theta(s_{i+1}, a')\right)^2$
  - Thus, labels change as Q network changes (distribution shift)

- **Solution**
  - Use a separate **target Q network** for the occurrence in $y_i$
  - Only update target network occasionally
  - $\theta \leftarrow \theta - \alpha \cdot \frac{d}{d\theta}\left(\underbrace{Q_\theta(s_i, a_i)}_{\text{Original Q Network}} - r_i + \gamma \cdot \max_{a' \in A} \underbrace{Q_{\theta'}(s_{i+1}, a')}_{\text{Target Q Network}}\right)^2$

Based on slide by Sergey Levine

# Deep Q Learning with Target Q Network

- **Iteratively perform the following:**
  - Take an action $a_i$ and add observation $(s_i, a_i, s_{i+1}, r_i)$ to replay buffer $D$
  - For $k \in \{1, \dots, K\}$:
    - Sample $(s_{i,k}, a_{i,k}, s_{i+1,k}, r_{i,k})$ from $D$
    - $y_{i,k} \leftarrow r_{i,k} + \gamma \cdot \max_{a' \in A} Q_{\theta'}(s_{i+1,k}, a')$
    - $\theta \leftarrow \theta - \alpha \cdot \frac{d}{d\theta}\left(Q_\theta(s_{i,k}, a_{i,k}) - y_{i,k}\right)^2$
  - Every $N$ steps, $\theta' \leftarrow \theta$

Based on slide by Sergey Levine

# Deep Q Learning for Atari Games

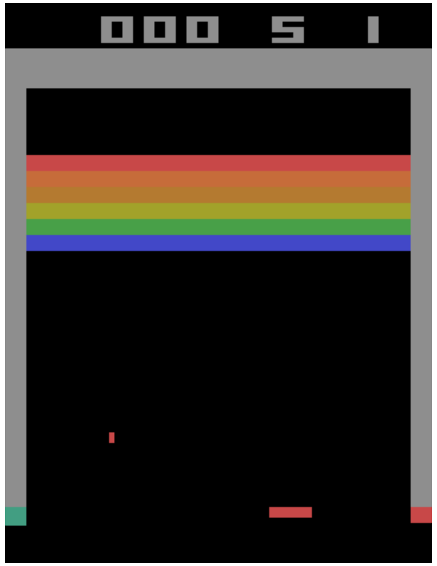




Image Sources:
https://towardsdatascience.com/tutorial-double-deep-q-learning-with-dueling-network-architectures-4c1b3fb7f756
https://deepmind.com/blog/going-beyond-average-reinforcement-learning/
https://jaromiru.com/2016/11/07/lets-make-a-dqn-double-learning-and-prioritized-experience-replay/

# Actor-Critic Policy Update

- Policy gradient:

$$\theta \leftarrow \theta + \eta \cdot \frac{1}{N} \sum_{i=1}^{N} \left( \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta \left( a_{i,t} \middle| s_{i,t} \right) \sum_{t'=t}^{T} \gamma^{t'-t} r_{t'} \right)$$

# Actor-Critic Policy Update

- Actor-critic policy gradient:

$$\theta \leftarrow \theta + \eta \cdot \frac{1}{N} \sum_{i=1}^{N} \left( \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(a_{i,t} | s_{i,t}) \, \hat{Q}_\phi(s_{i,t}, a_{i,t}) \right)$$

- **Important:** Policy Q learning instead of optimal Q learning!
  - Target is $\hat{Q}_\phi(s', \pi(s'))$ instead of $\max_a \hat{Q}_\phi(s', a)$
  - Value is $\hat{V}_\phi(s) = \mathbb{E}_{a \sim \pi(\cdot|s)}[\hat{Q}_\phi(s, a)]$ instead of $\hat{V}_\phi(s) = \max_a \hat{Q}_\phi(s, a)$

- **Exploration:** Use policy to take actions

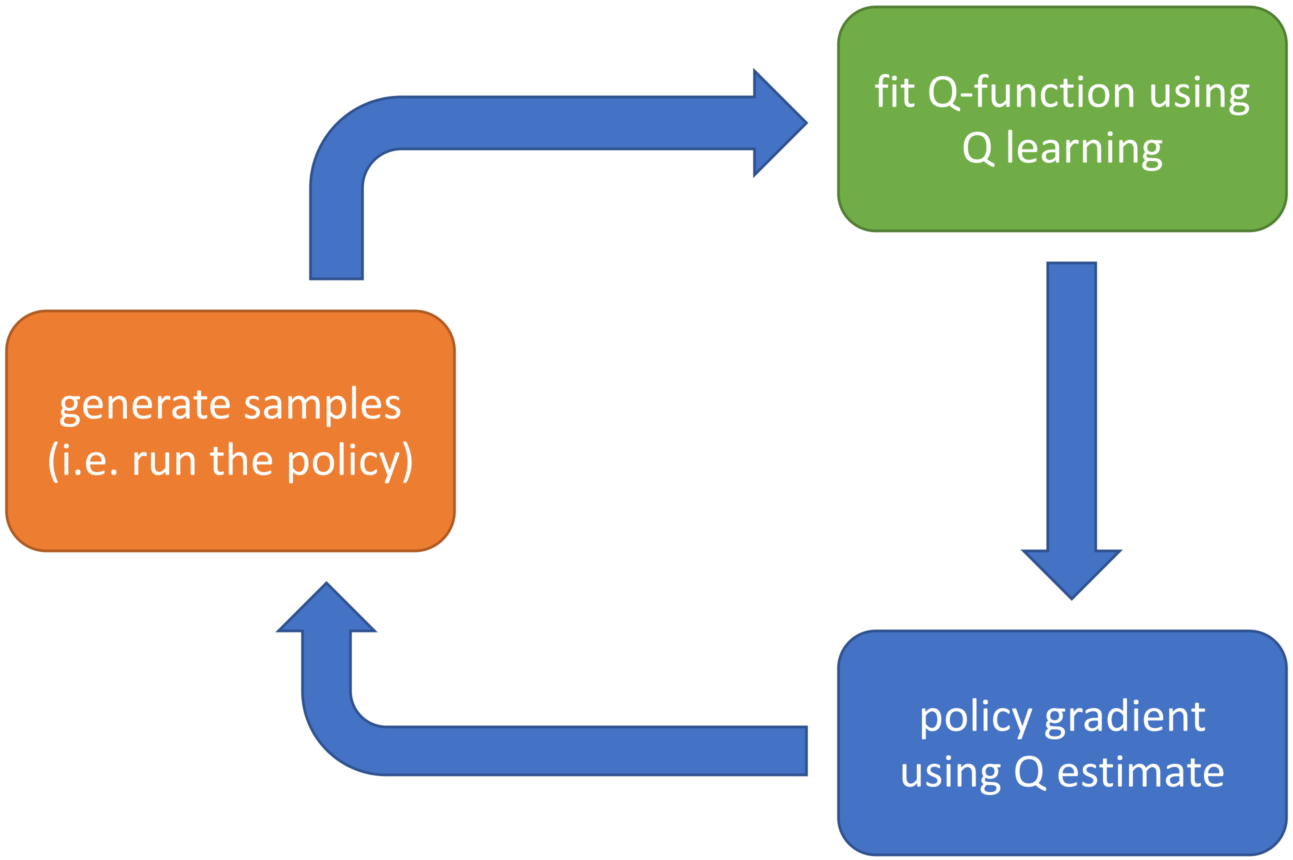
# Actor-Critic Policy Update

- What about the baseline?
  - The value function is a good baseline!

- Advantage actor-critic:

$$\phi \leftarrow \phi + \eta \cdot \frac{1}{N} \sum_{i=1}^{N} \left( \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta \left( a_{i,t} \middle| s_{i,t} \right) \left( \hat{Q}_\phi \left( s_{i,t}, a_{i,t} \right) - \hat{V}_\phi \left( s_{i,t} \right) \right) \right)$$

# Actor-Critic Training Strategy



# Actor-Critic with Experience Replay

- **Iteratively perform the following:**
  - Take an action $a_i \sim \pi_\theta(s_i)$ and add $(s_i, a_i, s_{i+1}, r_i)$ to replay buffer $D$
  - For $k \in \{1, \ldots, K\}$:
    - Sample $(s_{i,k}, a_{i,k}, s_{i+1,k}, r_{i,k})$ from $D$
    - $y_{i,k} \leftarrow r_{i,k} + \gamma \cdot \max_{a' \in A} Q_\phi(s_{i+1,k}, a')$
    - $\phi \leftarrow \phi - \alpha \cdot \frac{d}{d\phi}\left(Q_\phi(s_{i,k}, a_{i,k}) - y_{i,k}\right)^2$
  - $\theta \leftarrow \theta + \eta \cdot \nabla_\theta J(\theta)$

- **Key intuition:** Actor-critic can learn using **past data**, whereas policy gradient can only learn using **current data**
  - Reduces sample complexity in real-world interactions

# Agenda

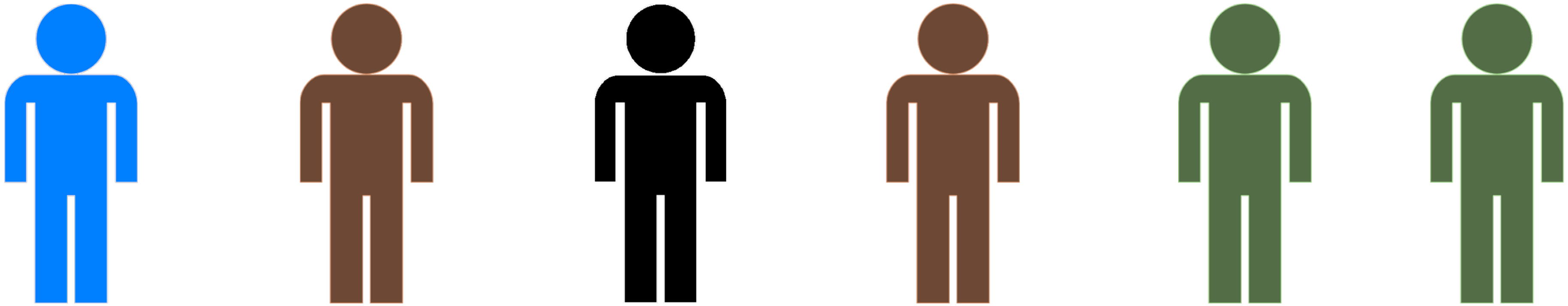
- Deep Q learning & actor-critic
- Multi-armed bandits
- Exploration in reinforcement learning
- Offline reinforcement learning

# Multi-Armed Bandits

- **State:** None! (To be precise, a single state $S = \{s_0\}$)
- **Action:** Item to recommend (often called **arms**)
- **Transitions:** Just stay in the same state
- **Rewards:** Random payoff for each arm
  - Denote $R(a) = R(s_0, a)$, where $a$ is the chosen action

# Example: Ad Targeting

- **Setting**
  - Google wants to show the most popular ad for a search term (e.g., “lawyer”)
  - There are a fixed number of ads to choose from



| | | | | | |
|---|---|---|---|---|---|
| Ad 3 | Ad 1 | Ad 2 | Ad 3 | Ad 2 | Ad 3 |
| Click | No Click | Click | No Click | Click | ?? |

# Multi-Armed Bandits

- **Many applications**
  - Cold-start for news/ad/movie recommendations
  - A/B testing
  - Flagging potentially harmful content on a social media platform
  - Prioritizing medical tests

- Learning dynamically

- Many practical RL problems are multi-armed bandits

# Exploration-Exploitation Tradeoff

- For $t \in \{1,2,\dots,T\}$
  - Compute reward estimates $r_{t,a} = \frac{\sum_{i=1}^{t-1} r_i \cdot 1(a_i=a)}{\sum_{i=1}^{t-1} 1(a_i=a)}$
  - Choose action $a_t$ based on reward estimates
  - Add $(a_t, r_t)$ to replay buffer

- **Question:** How to choose actions?
  - **Exploration:** Try actions to better estimate their rewards
  - **Exploitation:** Use action with the best estimated reward to maximize payoff

# Multi-Armed Bandit Algorithms

- **Naïve strategy:** $\epsilon$-Greedy
  - Choose action $a_t \sim \mathrm{Uniform}(A)$ with probability $\epsilon$
  - Choose action $a_t = \arg\max_{a \in A} r_{t,a}$ with probability $1 - \epsilon$

- Can we do better?

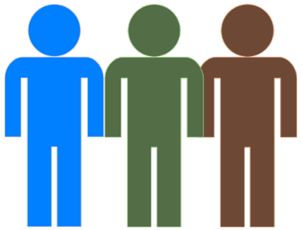
# Multi-Armed Bandit Algorithms

- **Upper confidence bound (UCB)**
  - Choose action $a_t = \arg\max_{a \in A} \left\{ r_{t,a} + \frac{\text{const}}{\sqrt{N_t(a)}} \right\}$
  - $N_t(a) = \sum_{i=1}^{t-1} 1(a_i = a)$ is the number of times action $a$ has been played

- **Thompson sampling**
  - Choose action $a_t = \arg\max_{a \in A} \{ r_{t,a} + \epsilon_{t,a} \}$, where $\epsilon_{t,a} \sim N\left(0, \frac{\text{const}}{\sqrt{N_t(a)}}\right)$

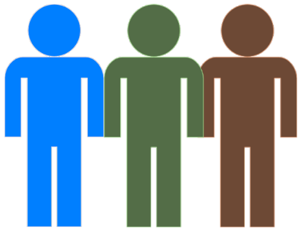
- Both come with theoretical guarantees

# Application: Targeted COVID-19 Testing



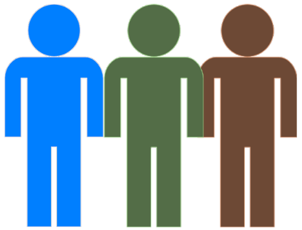
Test Blue

Negative



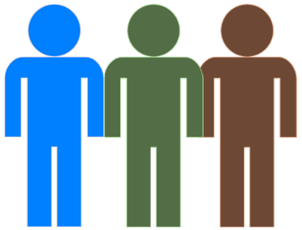
Test Green

Positive



Test Green

Negative



Test Brown

Negative

H. Bastani, K. Drakopoulos, V. Gupta, et al. Efficient and Targeted COVID-19 Border Testing via Reinforcement Learning.

# EVA

30k-100k passengers

24 hours prior to travel

PLF form

Travelers report:

- Origin
- Demographics
- Destination
- Contact

Use prior testing results to allocate tests efficiently at every point of entry

Labs submit positive results to central database with ~2-day delay

EVA

test (6k-8k)

no test

QR code scanned to link sample with PLF info

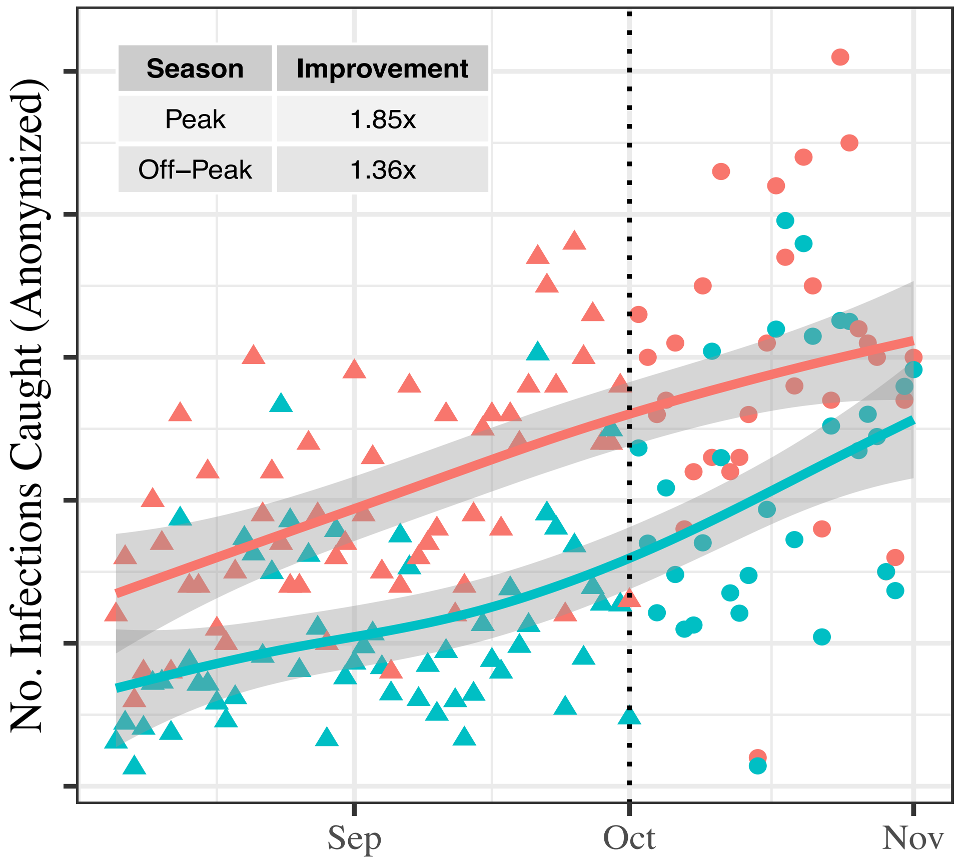
# Why Bandits?

- **Bandit feedback**
  - Only observe positive/negative if the traveler is tested
  - Technically “semi-bandit feedback”

- **Nonstationarity**
  - Infection rate for different passenger types changes over time
  - Need to continue to explore and collect data over time

# Cases Caught

- 1.85× improvement compared to random testing
- 1.25-1.45× improvement vs. targeting based on public data

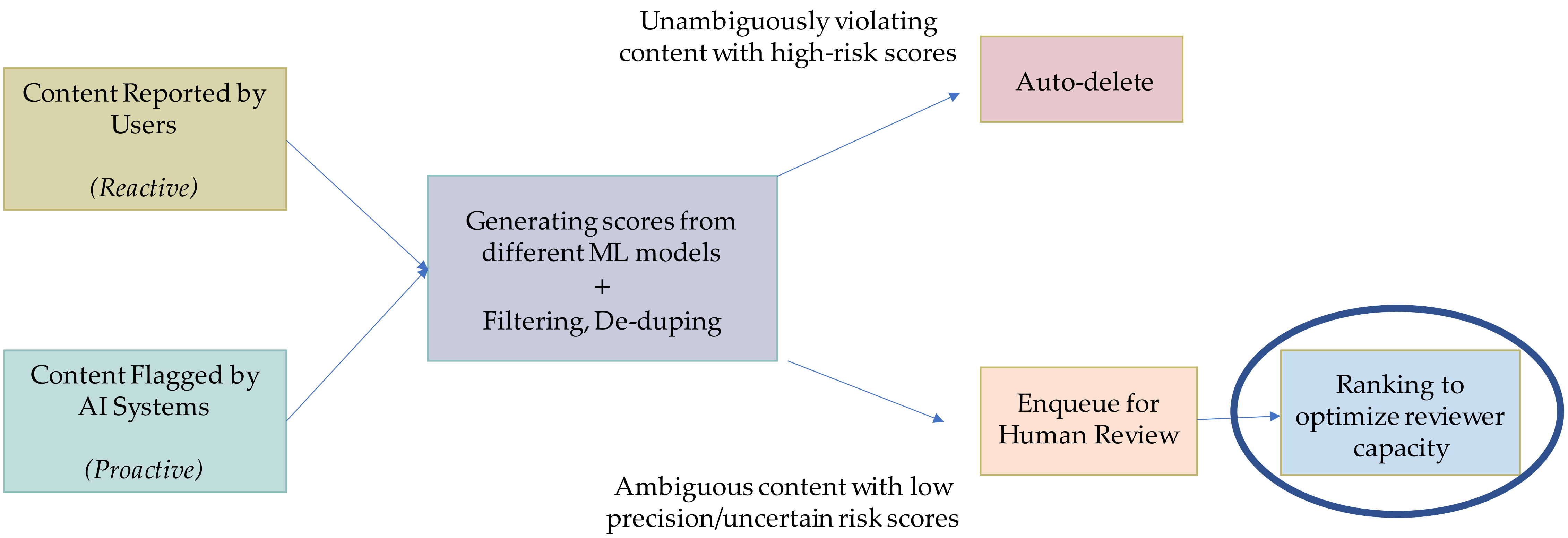


# Application: Content Moderation

- **Problem**
  - Millions of pieces of content are posted on Meta platforms each day
  - Too much to manually review all content
  - How to moderate to make sure no harmful?
- **Solution**
  - ML to prioritize potentially harmful content for manual review
  - Featurize content and predict likelihood that it is harmful

V. Avadhanula, O. Baki, H. Bastani, O. Bastani, et al. Bandits for Online Calibration: An Application to Content Moderation on Social Media Platforms

# Application: Content Moderation



# Application: Content Moderation

- What about new “types” of content?
  - E.g., new kind of racial slur
  - Cold start problem!

- Use multi-armed bandits!

# **Application:** Content Moderation

- Multi-armed bandit
  - Each “step” corresponds to one piece of content

- **Action:** Whether to manually review content

- **Reward:** 1 if content is harmful, 0 otherwise
  - **Intuition:** Goal is to maximize amount of harmful content caught
  - Include an $\alpha$ penalty for flagging content to avoid flagging everything

# Application: Training ChatGPT

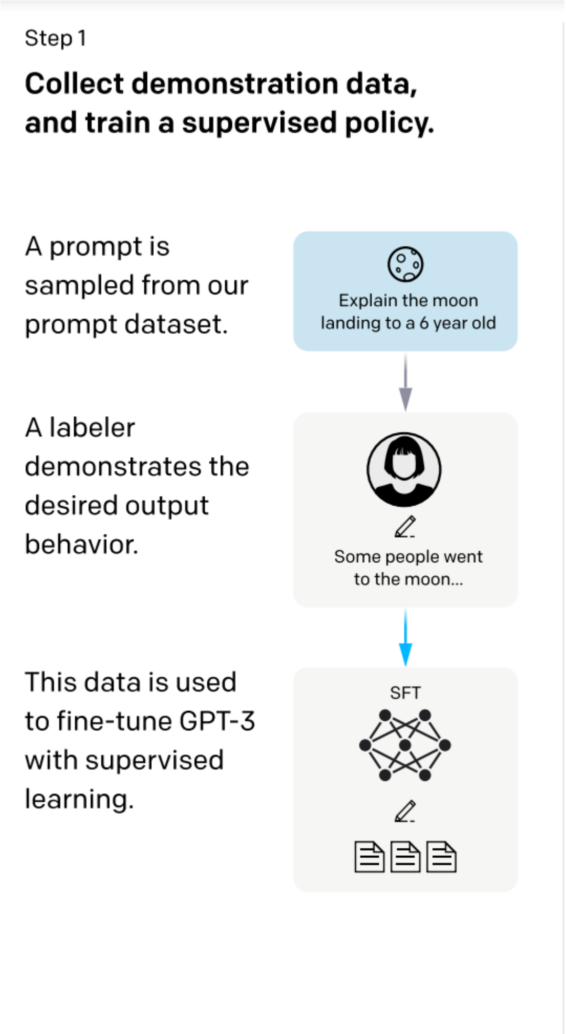
- **Problem**
  - Language models are trained using **unsupervised learning**
  - Generating from these models mimics training data rather than human preferences

- **Solution**
  - **Step 1:** Predict human preferences over possible generations (the reward)
  - **Step 2:** Finetune GPT using reinforcement learning, where it is rewarded for generating content preferred by humans

# Application: Training ChatGPT

Source: Ouyang et al., Training language models to follow instructions with human feedback.

# Application: Training ChatGPT

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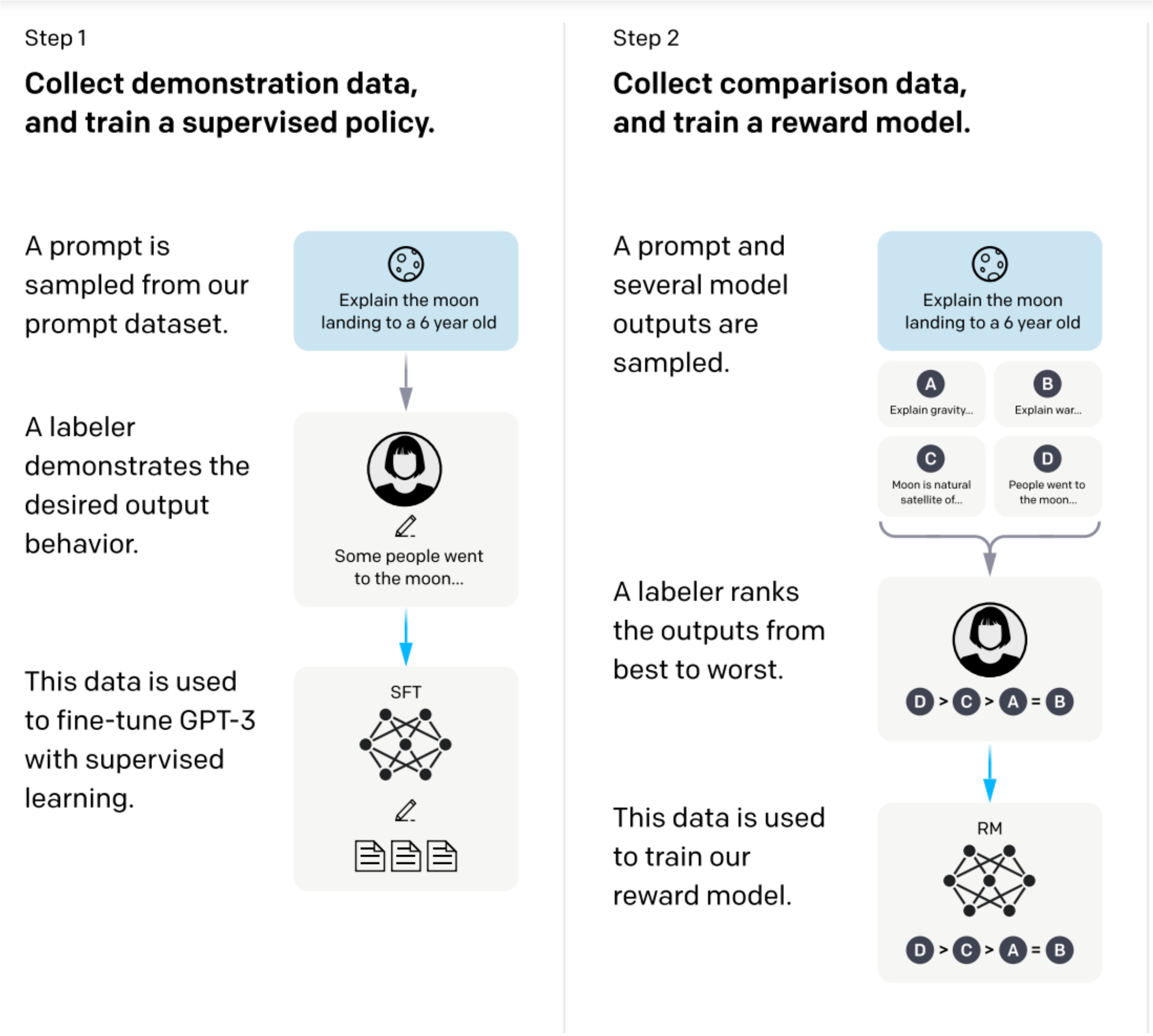
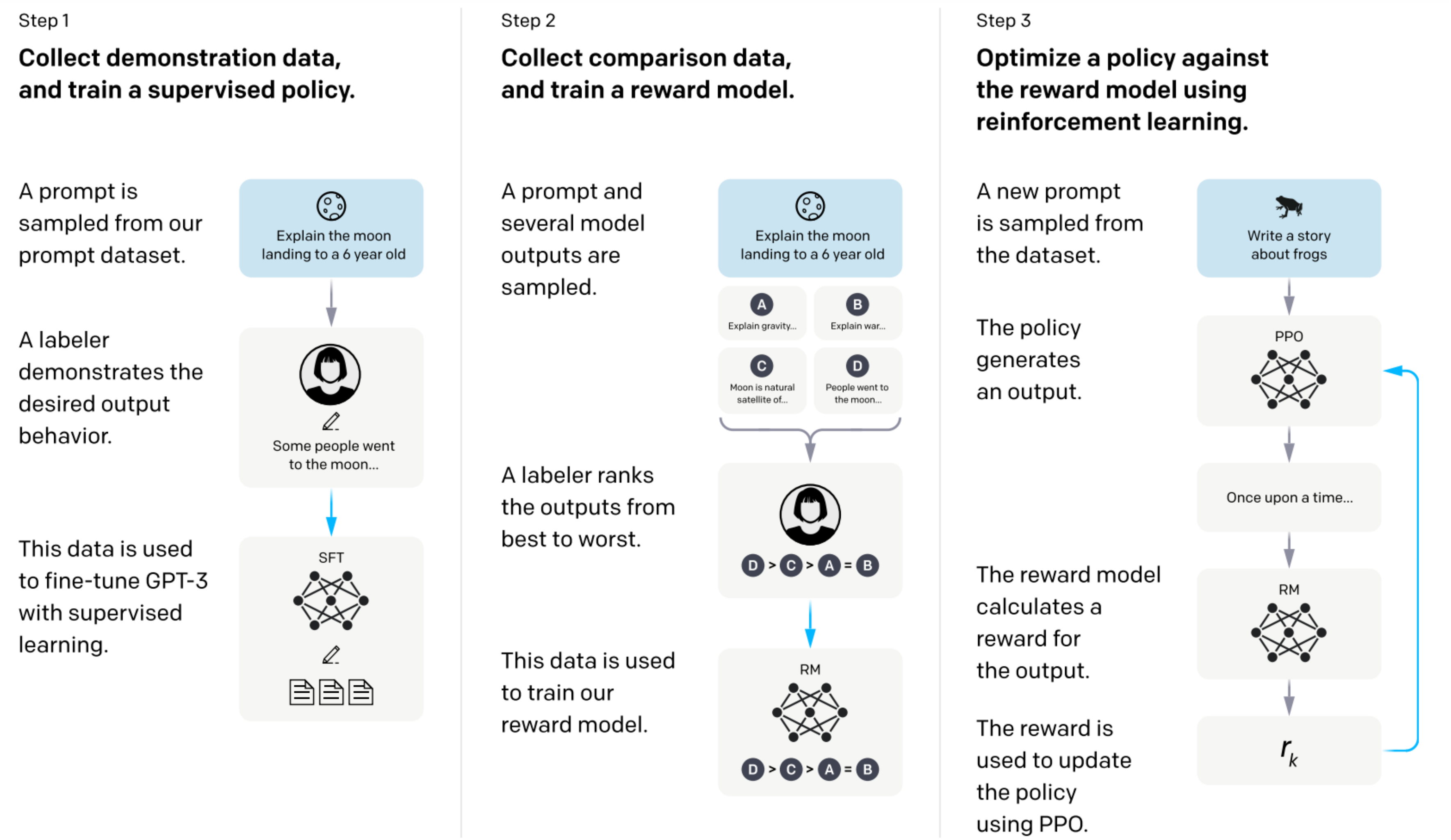
# Application: Training ChatGPT




Source: Ouyang et al., Training language models to follow instructions with human feedback.

# Application: Training ChatGPT




Source: Ouyang et al., Training language models to follow instructions with human feedback.

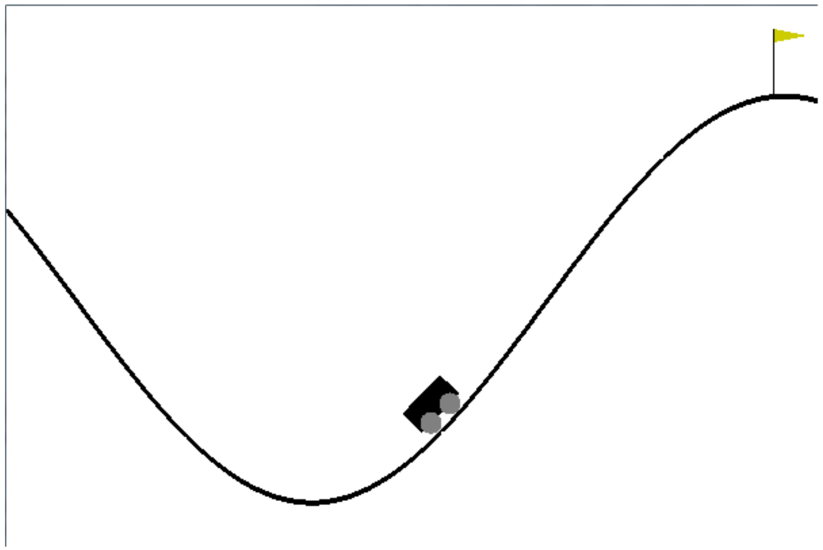
# Agenda

- Deep Q learning & actor-critic
- Multi-armed bandits
- Exploration in reinforcement learning
- Offline reinforcement learning

# Exploration in Reinforcement Learning

- $\epsilon$-greedy suffers additional issues due to state space

- Policy learning is an effective practical solution
  - No theoretical guarantees due to local minima



# Exploration in Finite MDPs

- **Upper confidence bound (UCB)**
  - Choose action $a_t = \arg\max_{a \in A} \left\{ Q_t(s,a) + \frac{\text{const}}{\sqrt{N_t(s,a)}} \right\}$
  - $N_t(s,a) = \sum_{i=1}^{t-1} 1(s_i = s, a_i = a)$ is the number of times action $a$ has been played in state $s$

- **Thompson sampling**
  - Choose action $a_t = \arg\max_{a \in A} \{ Q_t(s,a) + \epsilon_{t,s,a} \}$, where $\epsilon_{t,s,a} \sim N\left(0, \frac{\text{const}}{\sqrt{N_t(s,a)}}\right)$

- Both come with theoretical guarantees

# Exploration in Continuous MDPs

- Can we adapt these ideas to continuous MDPs?
  - Thompson sampling is more suitable

- **Bootstrap DQN**
  - Train ensemble of $k$ different $Q$-function estimates $Q_{\theta_1}, \dots, Q_{\theta_k}$ in parallel
  - Original idea was to use online bootstrap, but training from different random initial $\theta$'s worked as well
  - In each episode, act optimally according to $Q_{\theta_i}$ for $i \sim \mathrm{Uniform}(\{1, \dots, k\})$

# Exploration in Continuous MDPs

- Can we adapt these ideas to continuous MDPs?
  - Thompson sampling is more suitable

- **Soft Q-learning**
  - Sample actions according to $a \sim \mathrm{Softmax}\left(\left[\beta \cdot \hat{Q}_\theta(s, a)\right]_{a \in A}\right)$

# Curiosity

- **Intuition:** Rather than focus on optimism with respect to reward, focus on exploring where we are uncertain
- **How to determine uncertainty?**
- **Candidate strategy**
  - Train a **dynamics model** to predict $s' = f(s, a)$
  - Take actions where $f(s, a)$ has high variance (e.g., use bootstrap)
- **Problems?**
  - What if $s'$ includes spurious components, like a TV screen playing a movie?

# Curiosity

- Learn a feature map $\phi(s) \in \mathbb{R}^d$
- **Model 1:** Train a model to predict state transitions:

$$\hat{\phi}(s') = f_\theta(\phi(s), a)$$

  - Feature map lets the model "ignore" spurious components of $s$ such as a TV
  - **Problem:** We could just learn $\phi(s) = \vec{0}$?

# Curiosity

- Learn a feature map $\phi(s) \in \mathbb{R}^d$
- **Model 1:** Train a model to predict state transitions:

$$\hat{\phi}(s') = f_\theta(\phi(s), a)$$

- **Model 2:** Train a model to predict action to achieve a transition:

$$\hat{a} = g_\theta\big(\phi(s), \phi(s')\big)$$

  - "Inverse dynamics model" that avoids collapsing $\phi$

# Curiosity

- Curiosity reward is

$$R(s, a, s') = \left\| \hat{\phi}(s') - \phi(s') \right\|_2^2$$

- In other words, reward agent for exercising transitions that $f$ cannot yet predict accurately

# Agenda

- Deep Q learning & actor-critic
- Multi-armed bandits
- Exploration in reinforcement learning
- Offline reinforcement learning

# Offline Reinforcement Learning

- **Offline reinforcement learning:** How can we learn **without** actively gathering new data?
  - E.g., learn how to perform a task from videos of humans performing the task
  - Also known as **off-policy** or **batch** reinforcement learning

- **Recall:** Drawback of Q learning was we need an exploration strategy

- However, this also enables us to use Q learning with offline data!

# Offline Reinforcement Learning

- **Iteratively perform the following:**
  - Take an action $a_i$ and add observation $(s_i, a_i, s_{i+1}, r_i)$ to replay buffer $D$
  - For $k \in \{1, \dots, K\}$:
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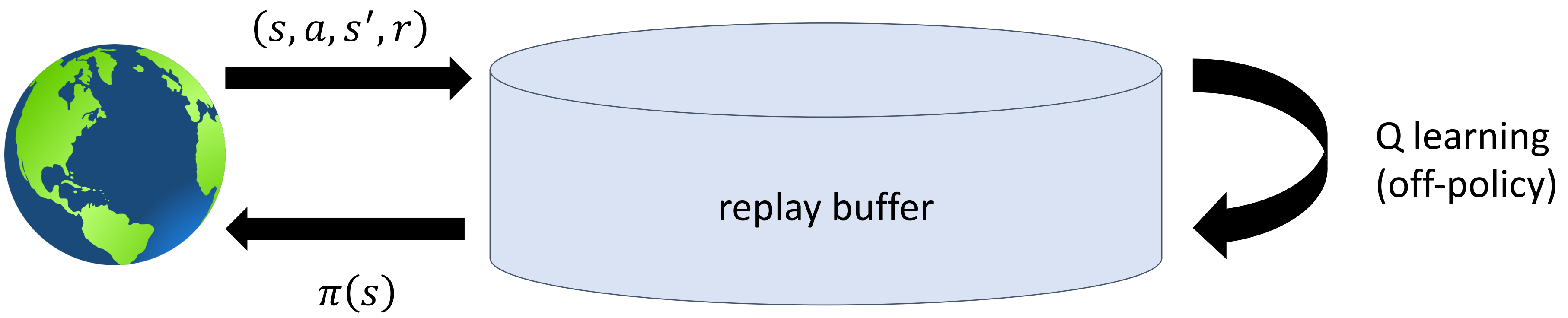

# Offline Reinforcement Learning

- **Iteratively perform the following:**
  - ~~Take an action $a_i$ and add observation $(s_i, a_i, s_{i+1}, r_i)$ to replay buffer $D$~~
  - For $k \in \{1, \dots, K\}$:
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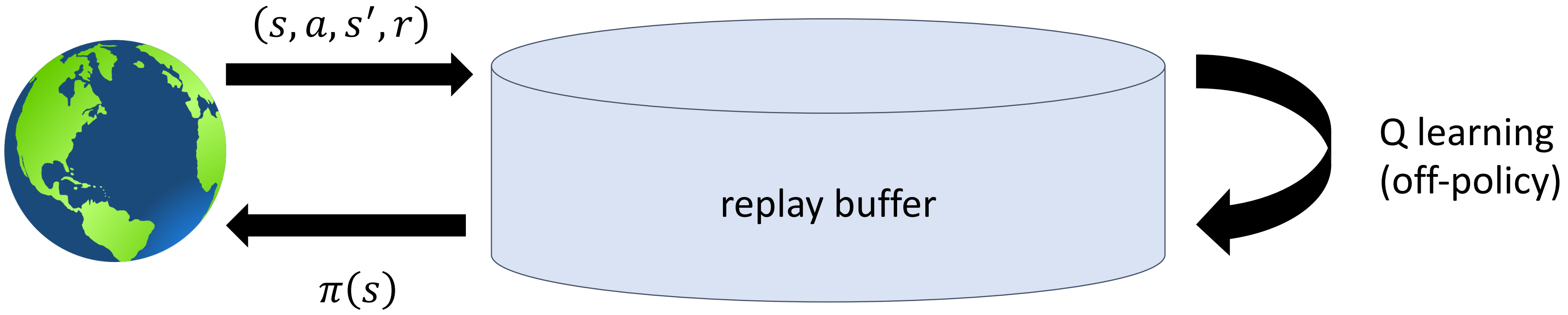

# Summary