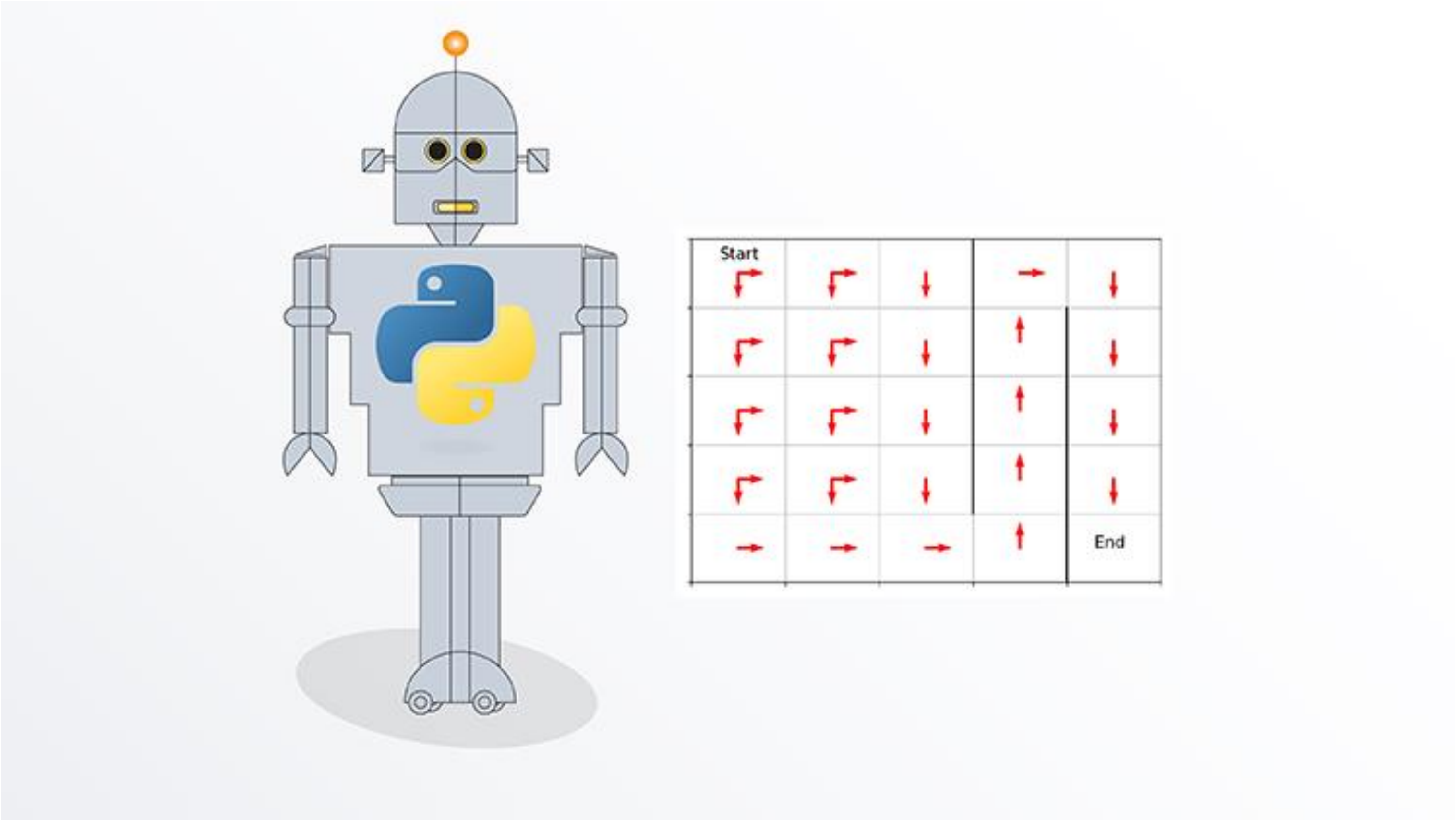
# What is Machine Learning?

# Chapter 4: Reinforcement Learning



# Reinforcement Learning

Definition (see Wikipedia page on Reinforcement Learning)

- Area of machine learning concerned with how software agents should take actions in an environment to maximize the cumulative reward

Informal Definition:

- Learn strategy to maximize the cumulative reward

# K Bandit Problem

- One-armed bandit is a nickname for a slot machine
- K Bandit problem:
  - K slot machines n=1,2,…,K each with own mean $M_n$ and payoffs drawn from a normal distribution
  - If means are not known, what strategy to follow to maximize cumulative payoff after many pulls

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# K Bandit Problem

Optimal strategy to get greatest cumulative reward: pull lever for machine with largest mean reward

Agent does not know which machine has largest mean reward -> needs to learn

Greedy Strategy:

- Track sample mean reward for each slot machine
- Pull lever for slot machine with largest current sample mean

Consider example with 2 slot machines

- Machine 1 has actual mean reward = 1
- Machine 2 has actual mean reward = 2

| Action | Reward | Cumulative Reward | Machine 1 # Pulls | Machine 1 Total Reward | Machine 1 Sample Mean | Machine 2 # Pulls | Machine 2 Total Reward | Machine 2 Sample Mean |
|---|---|---|---|---|---|---|---|---|
| Initial | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Random: Pull M1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| Greedy: Pull M1 | -2 | -1 | 2 | -1 | -0.5 | 0 | 0 | 0 |
| Greedy: Pull M2 | 1 | 0 | 2 | -1 | -0.5 | 1 | 1 | 1 |
| Greedy: Pull M2 | 3 | 3 | 2 | -1 | -0.5 | 2 | 4 | 2 |

# Exploit versus Explore in Reinforcement Learning

Issue with Greedy Approach:

- May get stuck pulling lever of machine with lower mean
- Leads to Exploit versus Explore dilemma

Exploit:

- At current position, take action to maximize immediate reward

Explore:

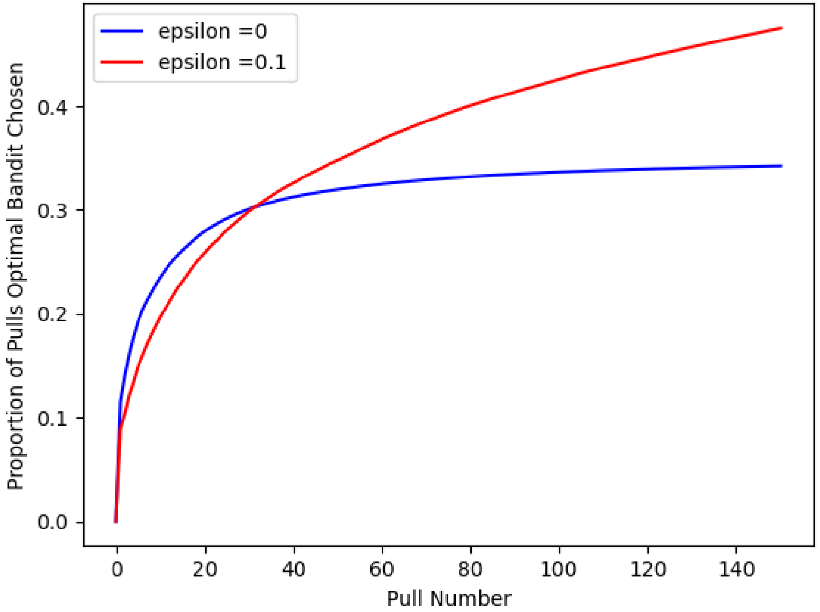
- At current position, take action to learn about environment
- Information acquired in exploration to be used later to hopefully increase cumulative reward

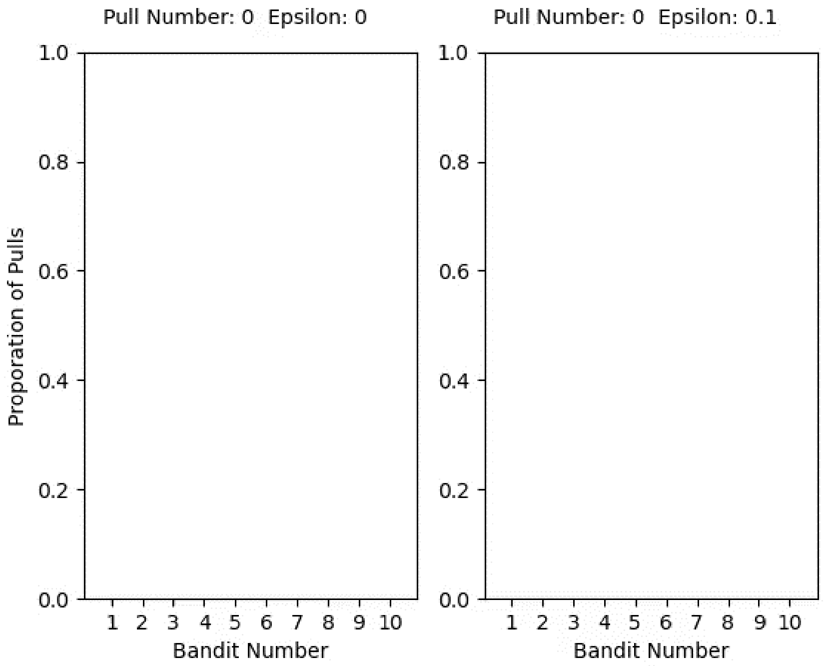
Epsilon Greedy Strategy:

- For $\epsilon$ proportion of time pull lever of slot machine at random
- For 1 - $\epsilon$ proportion of time pull lever of machine with largest current sample mean

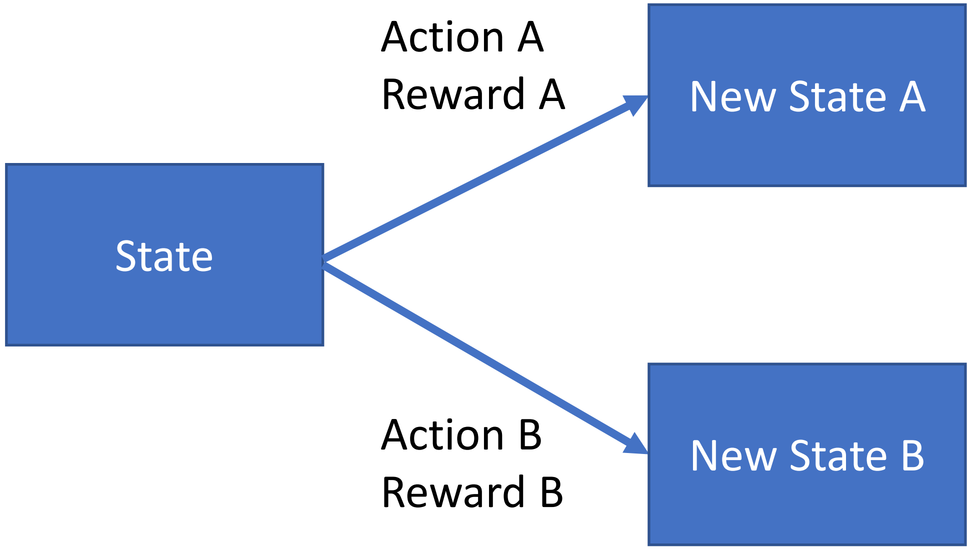
# K Bandit Problem - Simulation

- 10 slot machines
- Means drawn from standard normal distribution
- Results averaged over 1000 simulations
- Compare Greedy and Epsilon Greedy Approach with $\epsilon = 0.1$



# General Formulation for Reinforcement Learning

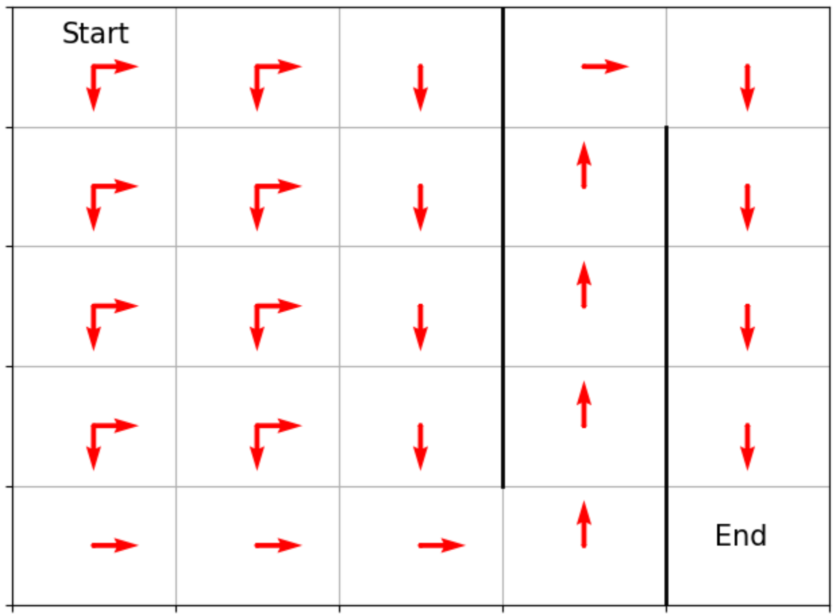



Starting at State

- Agent is allowed to take a number of possible actions, each with a specified reward and leading to a new state, where process is repeated
- Process continues forever or until reaching a terminal state
- Goal: find optimal strategy (action at each state) to maximize total cumulative reward (which may involve discounting)

# Maze Problem

- State is location in maze
- Actions: up, down, left or right (stay in same place if action means hitting a wall)
- Reward is -1 for each step (including if hit wall)
- Cumulative reward is (-1) * number of step to go to End
- Goal: find strategy that maximizes cumulative reward from Start to End (equivalent to minimizing number of steps)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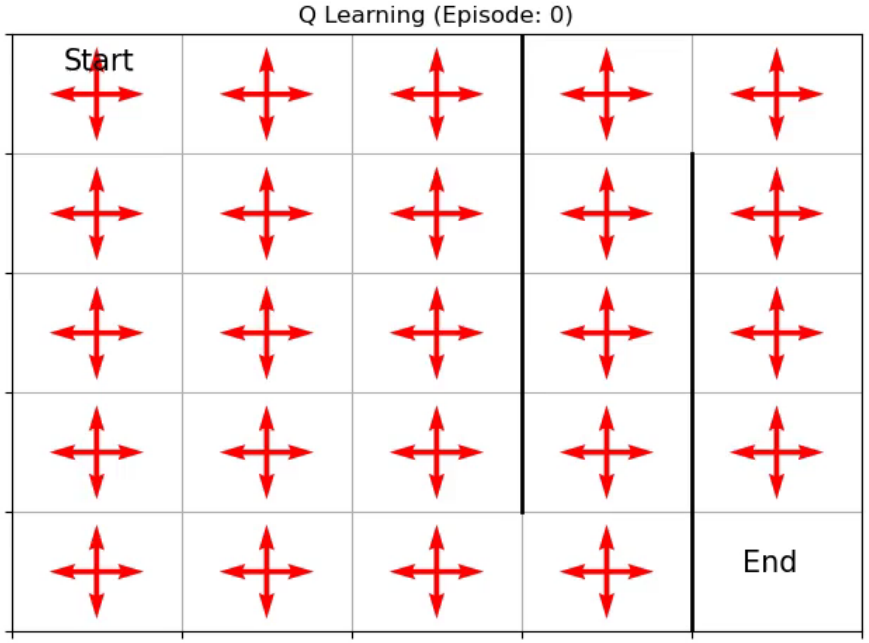
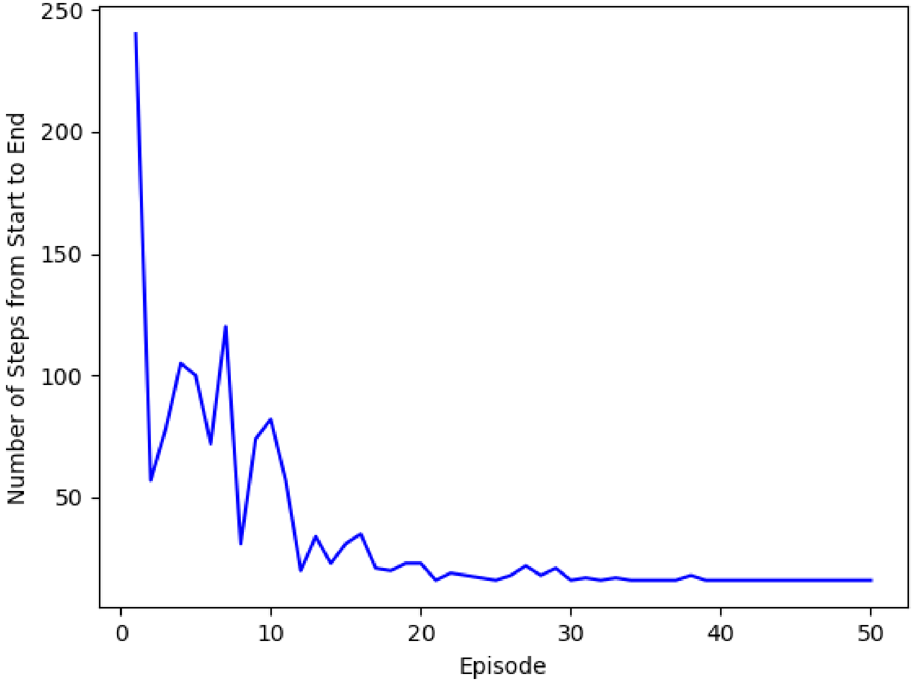
# Q Learning Approach to Finding Path

- Use "Q Learning" approach
  - Simulate "episode" (sequence state/action/state/action… to go from Start to Finish)
  - Start with equal probability for up, down, left, or right actions at each state
  - Update "action-value" function Q(s,a) which tracks cumulative reward for each state/action pair
  - Follow greedy strategy -> take action that maximizes cumulative reward
  - Repeat for many episodes
  - This process yields optimal strategy, obtained as maximum of action-value function over all possible actions at each state

# Maze: Results from Q Learning

- Animation shows how strategy evolves from initial equally likely actions to optimal actions (actions updated after each episode)
- Plot shows Number of Moves from Start to End as a function of episode
  - Settles down at 16 steps = minimum number of steps from Start to End



# Reinforcement Learning: Applications

| Application | Notes |
|---|---|
| Industrial Control | States: location on factory floor, battery status<br>Actions: perform tasks or return to home base for charging<br>Rewards: positive rewards for performing task, negative reward for running out of power in middle of factory floor |
| Game Playing | States: configuration of pieces on the game board<br>Actions: allowable moves<br>Rewards: typically positive reward for winning game (may be additional intermediate rewards for other accomplishments during play) |

# Reinforcement Learning: Notes

| Component | Notes: |
|---|---|
| Q Learning and related algorithms | Suitable if reasonable number of states and actions:<br>• Maze problem has 24 states/4 actions per state -> 96 action values to learn |
| | Must use alternative approaches if there are many states/actions<br>• Chess has astronomical number of configurations of pieces on the board<br>• Use approximation methods to estimate action values for state/action pairs (can use ideas from Supervised Learning) |
| AlphaZero | Effort to create artificial intelligence program to play chess, shogi and go (see AlphaZero Wikipedia page and see AlphaGo movie on Youtube)<br>• Trained using self play only<br>• Beat other state of the art programs in chess, go, shogi |