Multi-Arm Bandit

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Machine and Reinforcement Learning in Control Applications

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Problem

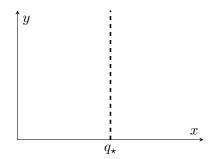
- Choose repetitively which arm to pull from those available
- Each arm returns a reward
- The objective is to maximize the expected total reward



Bandit

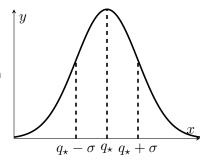
Oeterministic and stationary

- Rewards are equal to $q_{\star}(a)$
- ullet $q_{\star}(a)$'s don't change over time



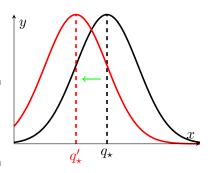
Bandit

- Oeterministic and stationary
 - Rewards are equal to $q_{\star}(a)$
 - $q_{\star}(a)$'s don't change over time
- Stochastic and stationary
 - Normally distributed rewards with mean $q_{\star}(a)$
 - $q_{\star}(a)$'s don't change over time



Bandit

- Oeterministic and stationary
 - Rewards are equal to $q_{\star}(a)$
 - $q_{\star}(a)$'s don't change over time
- Stochastic and stationary
 - Normally distributed rewards with mean $q_{\star}(a)$
 - $q_{\star}(a)$'s don't change over time
- Stochastic and non-stationary
 - Normally distributed rewards with mean $q_{\star}(a)$
 - $q_{\star}(a)$'s change over time

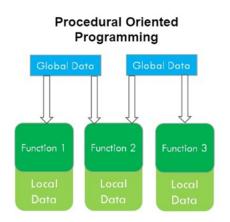


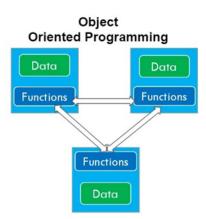
Policy

- The arm to pull is chosen according to the following policies:
 - ϵ -greedy sample-average
 - Upper confidence bound
 - Preference updates
- Comparison of the results obtained with the various policies and parameters

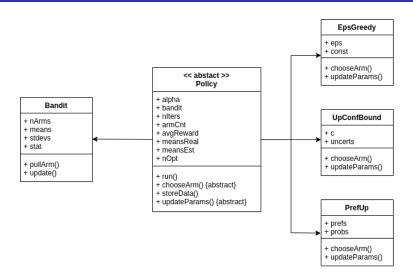
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POP vs OOP



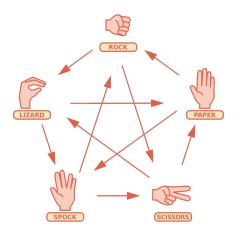


Diagram



Assignment #1

• Model the Rock, Paper, Scissors, Lizard, Spock game



Assignment #1

- Model the Rock, Paper, Scissors, Lizard, Spock game
 - See the episode 5x17 of "The Big Bang Theory" for rules
 - Choose repetitively which action to play between: Rock, Paper, Scissors, Lizard, Spock
 - The opponent plays randomly
 - Reward +1 for winning and -1 for losing
 - The objective is to maximize the rewards
 - Analyze the trends of the expected rewards for each action

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