Lecture 9: ε-Greedy k-Arm Bandit Problem

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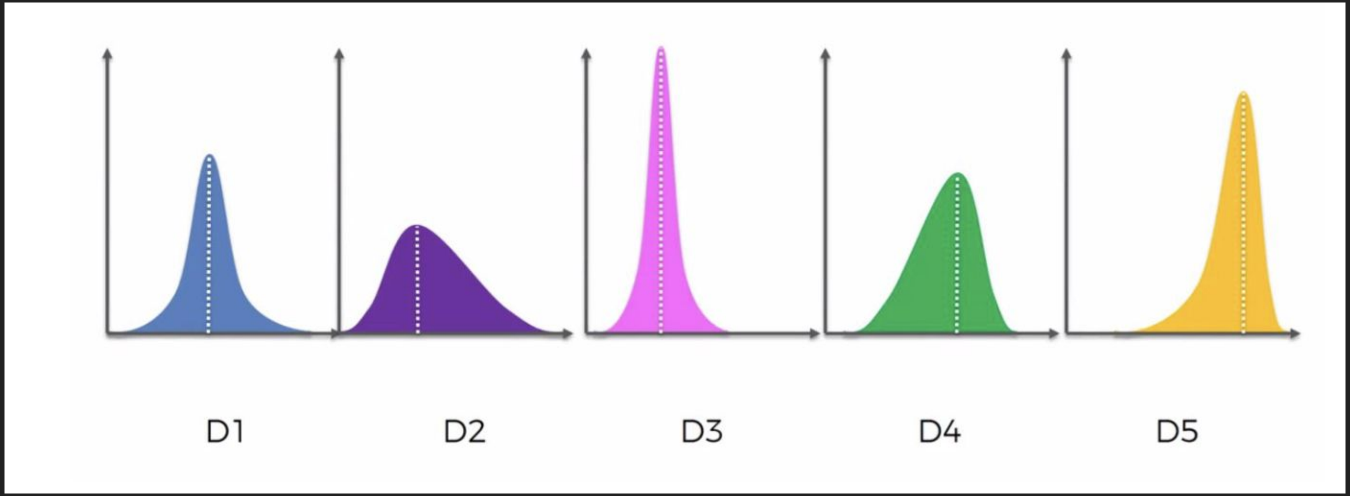
What is the k-Arm Bandit Problem?

- Imagine a slot machine with k levers (arms)
- Each arm provides a random reward from an unknown distribution
- Goal: Maximize cumulative reward over a sequence of pulls

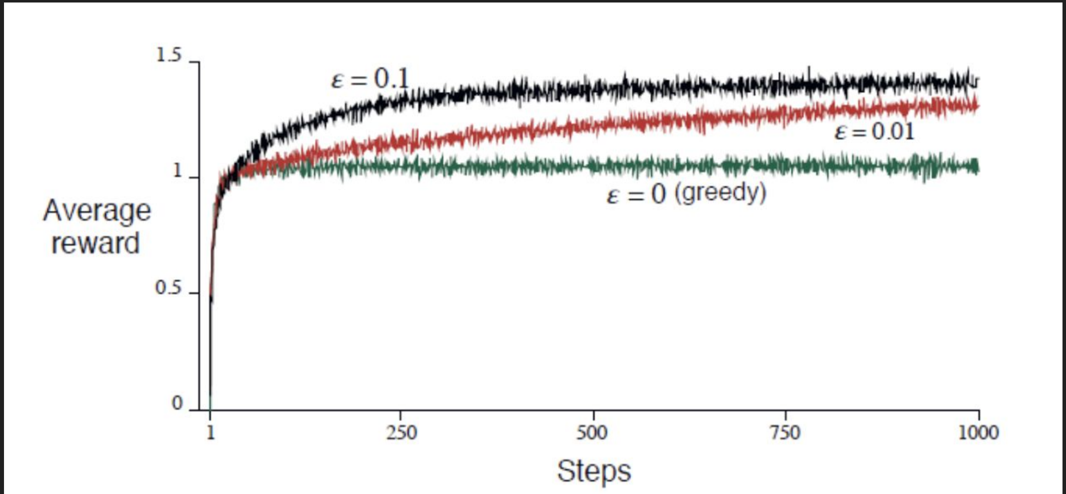
Core Challenge: Exploration vs. Exploitation

- Exploration: Try different arms to learn about their rewards
- Exploitation: Select the arm with the highest known reward
- Balancing both is crucial for optimal performance



The ε-Greedy Algorithm

- Choose a random arm with probability ε (exploration)
- Choose the best-known arm with probability 1-ε (exploitation)
- ε is a small constant (e.g., 0.1)



Reward and Update Approach

- After selecting an arm and receiving a reward:
- Update the estimated reward based on previous experience and the new reward
- Weighted approach to balance past knowledge with new information

$$q(a) = \mathbb{E}[R_t | A_t = a], a \in A$$

Advantages and limitations

- Simple and effective
- Balances exploration and exploitation
- Suitable for dynamic environments

- Fixed ε does not adapt over time
- Early vs. late-stage learning may require different strategies
- Potential for suboptimal exploration

Conclusion

- The ε-greedy k-arm bandit is a foundational concept in reinforcement learning
- It introduces the critical exploration-exploitation trade-off
- Practical applications in online advertising, finance, and more
- Quick Q&A and implementation.