(Deep) Reinforcement Learning

COMP 4630 | Winter 2025

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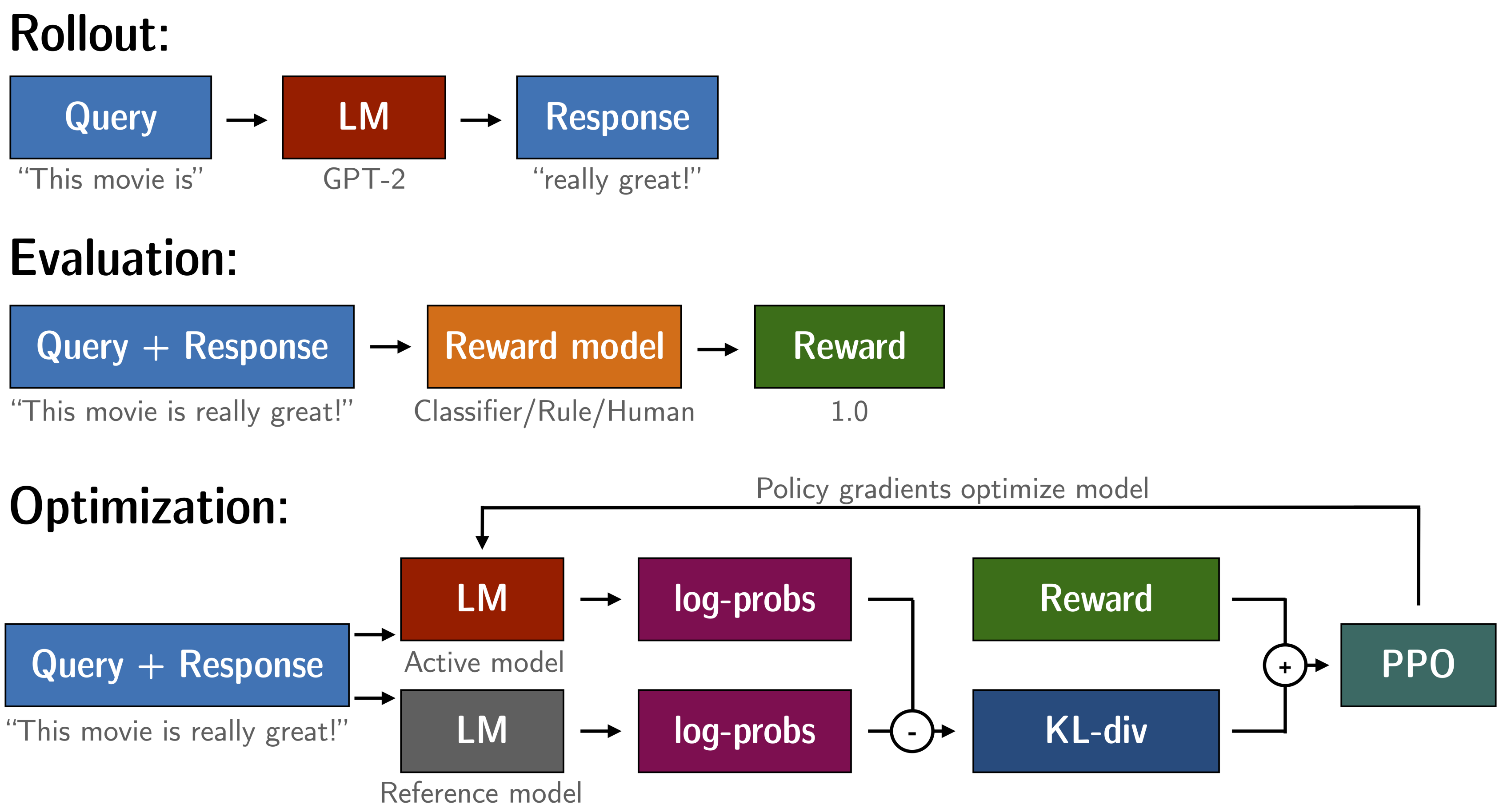
Overview

- Terminology and fundamentals
- Q-learning
- Deep Q Networks
- References and suggested reading:
    - Scikit-learn book: Chapter 18
    - d2l.ai: Chapter 17

Reinforcement Learning + LLMs



Terminology

- **Agent**: the learner or decision maker
- **Environment**: the world the agent interacts with
- **State**: the current situation
- **Reward**: feedback from the environment
- **Action**: what the agent can do
- **Policy**: the strategy the agent uses to make decisions

> *Classic example: Cartpole*

The Credit Assignment Problem

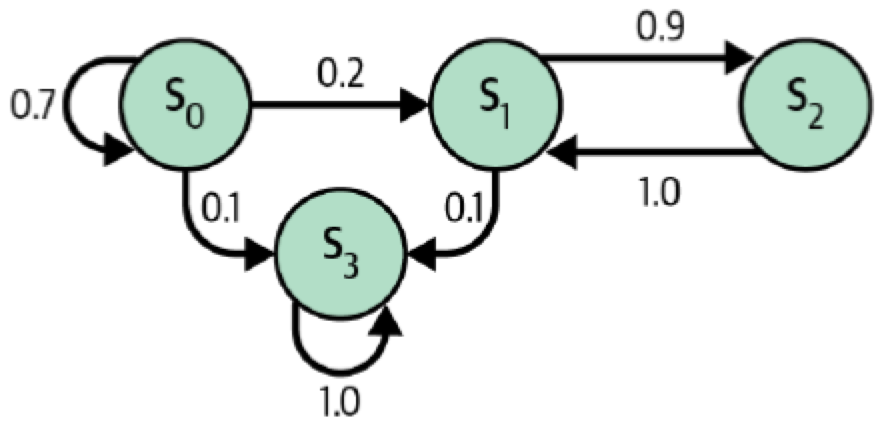
- Problem: If we've taken 100 actions and received a reward, which ones were "good" actions contributing to the reward?
- Solution: Evaluate an action based on the sum of all future rewards
  - Apply a **discount factor** γ to future rewards, reducing their influence
  - Common choice in the range of $\gamma = 0.9$ to $\gamma = 0.99$
  - Example of actions/rewards:
    - Action: Right, Reward: 10
    - Action: Right, Reward: 0
    - Action: Right, Reward: -50

Policy Gradient Approach

- If we can calculate the gradient of the **expected reward** with respect to the **policy parameters**, we can use gradient descent to find the best policy
- Approach:
    i. Play the game several times. At each step, compute the gradient (but don't update the policy yet).
    ii. After several episodes, compute each action's **advantage** (relative sum of discounted rewards).
    iii. Multiply each gradient vector by the advantage
    iv. Compute the mean of all gradients and update the policy via gradient descent

Markov Chains

- A **Markov Chain** is a model of random states where the future state depends **only** on the current state (a **memoryless** process)



- Used to model real-world processes, e.g. Google's PageRank algorithm
- ❓ Which of these is the **terminal state**?

Figure 18-7 from the Scikit-learn book

Markov Decision Processes

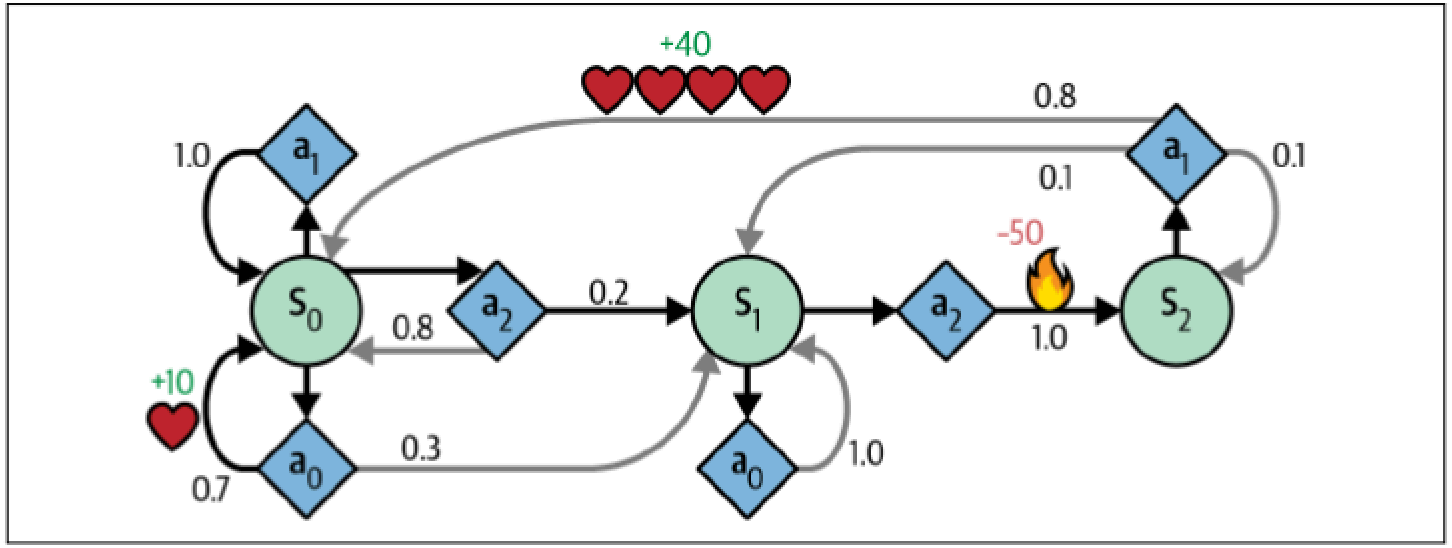


Figure 18-8. Example of a Markov decision process

- Like a Markov Chain, but with **actions** and **rewards**
- Bellman optimality equation:

$$V^*(s) = \max_a \sum_{s'} T(s,a,s')[R(s,a,s') + \gamma V^*(s')] \text{ for all } s$$

Iterative solution to Bellman's equation

Value Iteration:

1. Initialize $V(s) = 0$ for all states
2. Update $V(s)$ using the Bellman equation
3. Repeat until convergence

$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} T(s,a,s')[R(s,a,s') + \gamma V_k(s')] \text{ for all } s$$

> *Problem: we still don't know the optimal policy*

Q-Values

Bellman's equation for Q-values (optimal state-action pairs):

$$Q_{k+1}(s,a) \leftarrow \sum_{s'} T(s,a,s')[R(s,a,s') + \gamma \max_{a'} Q_k(s',a')]$$

Optimal policy $\pi^*(s)$:

$$\pi^*(s) = \arg\max_a Q^*(s,a)$$

For small spaces, we can use **dynamic programming** to iteratively solve for Q^*

Q-Learning

- **Q-Learning** is a variation on Q-value iteration that learns the **transition probabilities** and **rewards** from experience
- An **agent** interacts with the environment and keeps track of the estimated Q-values for each state-action pair
- It's also a type of **temporal difference learning** (TD learning), which is kind of similar to stochastic gradient descent
- Interestingly, Q-learning is "off-policy" because it learns the optimal policy while following a different one (in this case, totally random exploration)

Q-Learning Update rule

- At each iteration, the Q estimate is updated according to:

$$Q(s,a) \leftarrow (1-\alpha)\cdot Q(s,a) + \alpha \cdot \left[r + \gamma \cdot \max_{a'} Q(s',a')\right]$$

- Where:
  - $Q(s,a)$ is the estimated value of taking action a in state s
  - α is the learning rate (decreasing over time)
  - r is the immediate reward
  - γ is the discount factor
  - $\max_{a'} Q(s',a')$ is the maximum Q-value for the next state

Exploration policies

- ❓ How do you balance short-term rewards, long-term rewards, and exploration?
- Our small example used a purely random policy
- ϵ-greedy chooses to explore randomly with probability ϵ, and **greedily** with probability $1 - \epsilon$
- Common to start with high $epsilon$ and gradually reduce (e.g. 1 down to 0.05)

Challenges with Q-Learning

- ❓ We just converged on a 3-state problem in 10k iterations. How many states are in something like an Atari game?
- ❓ How do we handle **continuous** state spaces?

One approach: **Approximate** Q-learning:

- $Q_\theta(s, a)$ approximates the Q-value for any state-action pair
- The number of parameters θ can be kept manageable
- [Turns out] that **neural networks** are great for this!

Deep Q-Networks

- We know states, actions, and observed rewards
- We need to estimate the Q-values for each state-action pair
- Target Q-values: $y(s, a) = r + \gamma \cdot \max_{a'} Q_\theta(s', a')$
  - r is the observed reward, s' is the next state
  - $Q_\theta(s', a')$ is the network's estimate of the future reward
- Loss function: $\mathcal{L}(\theta) = ||y(s, a) - Q_\theta(s, a)||^2$
- Standard MSE, backpropagation, etc.

Challenges with DQNs

- **Catastrophic forgetting**: just when it seems to converge, the network forgets what it learned about old states and comes crashing down
- The **learning environment keeps changing**, which isn't great for gradient descent
- The **loss value** isn't a good indicator of performance, particularly since we're estimating both the target and the Q-values*
- Ultimately, reinforcement learning is inherently **unstable**!

The last topic: Geneterative AI and ethics