Lecture 29: Artificial Intelligence

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Some slides are adapted from CS 188 (Artificial Intelligence)

Announcements

Roadmap

- Introduction
- Functions
- Data
- Mutability
- Objects
- Interpretation
- Paradigms
- Applications

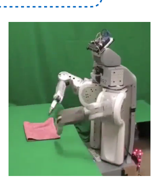
- This week (Applications), the goals are:
  - To go beyond CS 61A and see examples of what comes next
  - To wrap up CS 61A!

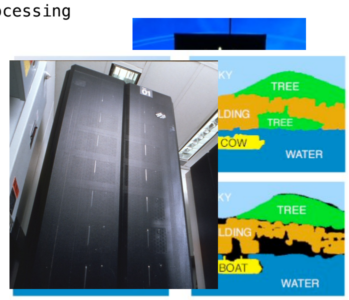
Artificial Intelligence (AI)

- The subfield of computer science that studies how to create programs that:
  - Think like humans?
    - Well, we don't really know *how* humans think
  - Act like humans?
    - Quick, what's 17548 * 44?
    - Humans can often behave *irrationally*
  - Think rationally?
    - What we really care about, though, is behavior
  - *Act rationally*
    - A better name for artificial intelligence would be *computational rationality*

Applications

- Artificial intelligence has a wide range of applications, including examples such as:
  - Natural language processing
  - Computer vision
  - Robotics
  - Game playing





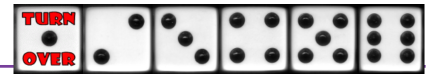
Game Playing

- Games have historically been a popular area of study in artificial intelligence, in part because they drive the study and implementation of efficient AI algorithms
  - If you're interested, two recent-ish results include playing Atari games at human expert levels and playing Go beyond top human levels
- Many breakthroughs in AI research have come from building systems that play games, including advances in:
  - Reinforcement learning (Checkers, Atari)
  - Rational meta-reasoning (Reversi/Othello)
  - Game tree search algorithms (Go)
- We will build AI systems today that play Hog and Ants!

Playing Hog

Using Markov Decision Processes

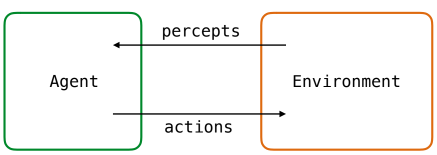
Hog



- Two player dice game
- Take turns rolling 0 to 10 dice and accumulating the sum into your overall score, until someone reaches 100
- Several special rules to keep track of:
  - Pig Out, Free Bacon, Hog Tied, Hog Wild, Hogtimus Prime
  - And the notorious Swine Swap
- In the last question of this project, you had to implement a final strategy that beats `always_roll(6)` at least 70% of the time
  - This is AI-like, except you (probably) hand-designed the "intelligence" into your strategy
  - We can get up to ~85% win rate against `always_roll(6)`! I'll show you how, using AI techniques and algorithms

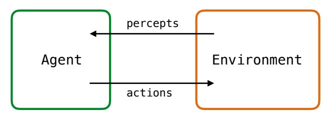
Agents and Environments

- Many, if not most, problems in AI are formalized using the concepts of an *agent* and an *environment*
- The agent *perceives* information about the environment and performs actions that may change the environment
- This is a natural way to describe many games, robotic systems, humans, and much more



Hog Agents and Environments

- In the game of Hog, who is the agent?
  - You, or the computer
- What is the environment?
  - It's the whole game!
    - Your opponent
      - (We are considering the opposing agent to be part of the environment, because it's simpler this way)
    - You and your opponent's score
    - The rules of the game
- In AI, the problem we care about is figuring out how the agent should choose its actions, given what it perceives, so as to positively shape its environment



Markov Decision Processes

- To do this for Hog, we will formalize our environment as a *Markov Decision Process* (MDP)
- This means is that we have to specify:
  - A set of *states* `S`, which are the states of the environment
    - For Hog, we just need the two scores to represent states
  - A set of *actions* `A`, which are the actions the agent can take
    - This is how many dice the agent chooses to roll
  - A *reward function* `R(s)`, which is the reward for each state `s`
    - We get a positive/negative reward only when we win/lose
  - A *transition function* `T(s, a, s')`, which tells us the probability of going to state `s'` starting from state `s` and choosing action `a`
    - We get this from dice probabilities and rules of the game

Policies

- Now, with our MDP, we can formalize our problem
- Our agent has a *policy* π, which is a function that takes in a state and outputs the action to take for that state
  - The policies that the computer uses were called strategies in the project
- Our goal is to find the *optimal policy* π^* that maximizes the expected amount of reward the agent receives
  - In our case, this means maximizing the win rate against some fixed opponent, such as `always_roll(6)`
- How do we find this optimal policy? The reward function gives us very little information because it is 0 except for winning and losing states
  - We need something that will tell us about which states are more or less likely to win from

Value Functions

- Reward function: `R(s)` = reward of being in state `s`
- *Value function*: `V(s)` = value of being in state `s`
- The value is the *long-term expected reward*
- How do we determine the value of a state? With recursion!
  - The value of a state is the reward of the state plus the value of the state we end up in next.

$$V(s) = R(s) + \max_a \sum_{s'} T(s, a, s')V(s')$$

- We take a maximum over all possible actions because we want to find the value for the optimal policy
- We use a summation and `T(s, a, s')` because there may be several different states we could end up in

Value Iteration

- We may have to compute `V(s)` multiple times in order to get it right, because the value of later states `s'` can change and this can affect the value of `s`
- This leads us to an algorithm known as *value iteration*:
- Repeat:
  - For all states `s`, determine `V(s)`

$$V(s) = R(s) + \max_a \sum_{s'} T(s, a, s')V(s')$$

  - If `V` doesn't change, return the policy π that, given a state `s`, chooses the action `a` that maximizes the expected value of the next state `s'`

$$\pi^*(s) = \arg\max_a \sum_{s'} T(s, a, s')V(s')$$

- We can show that this policy is optimal, under the correct assumptions! But let's not do the math

Algorithms for MDPs (demo)

- We now have an algorithm that will find us the optimal policy for playing against `always_roll(6)`!
  - It also does quite well against other opponents
- This algorithm, value iteration, is just a special case of a family of algorithms for solving MDPs by alternating between two steps:
  - *Policy evaluation:* Determine the value of each state `s`, but using the current policy rather than the optimal
  - *Policy iteration:* Improve the current policy to a new policy using the value function found in the first step
  - Value iteration combines these two steps into one!
- Let's see the optimal policy in action

Playing Ants

Using rollout-based methods

Reinforcement Learning (RL)

- In the *reinforcement learning* setting, we still model our environment as an MDP, except now we don't know our reward function `R(s)` or transition function `T(s, a, s')`
- This is very much like the real world, and here's an analogy: suppose you go on a date with someone
- You are the agent, the other person and the setting are the environment, and you don't know the environment that well
- At the beginning of the date, you might not know how to act, so you try different things to see how the other person responds
- As the date goes on, you slowly figure out how you should act based on what you've tried so far, and how it went
- With some luck, and the right algorithm, you may learn how to act optimally!

RL Algorithms

- Algorithms for reinforcement learning must solve a more general problem than algorithms like value iteration, because we don't know how our environment works
- We have to make sure to try different actions to determine which ones work well in our environment
  - This is called *exploration*
- However, we also want to make sure to use actions that we have already found to be good
  - This is called *exploitation*
- Balancing exploration and exploitation is a key problem that RL algorithms must address, and there are many different ways to handle this

RL for Ants

- It's a little weird to use MDPs and RL for Ants. Why?
  - Everything is *deterministic*
  - This means that we don't need a transition function, and we actually do know how our environment works
- However, the state space for Ants is very, very large
  - So even though we could specify how our environment works, it is very difficult to code it and for our program to utilize all of this information
  - A more reasonable approach is thus to only look at a subset of states and actions, e.g., the more likely ones, and find an approximation that hopefully works for all states
  - Now, it makes sense to use MDPs and RL for Ants

Rollout-based Policy Iteration (demo)

- In reinforcement learning and some other settings, a *rollout* is essentially a simulation, where the agent takes a certain number of actions in the environment
- Algorithms that use rollouts to find a policy are sometimes called rollout-based algorithms
- One such algorithm is *rollout-based policy iteration*, which approximates the value function `V(s)` using rollouts
  - For every state seen during the rollouts, the value of that state is the average of the rewards after that state for every rollout that included that state
  - For the unseen states, we assign them values by looking at the seen states that seem the most similar
  - We balance exploration and exploitation by sometimes selecting a random action, rather than using our policy
- Let's see a policy trained using this algorithm in action

Summary

- Artificial intelligence is all about building programs that act rationally, i.e., *computational rationality*
- Game playing is an important and natural domain for much of artificial intelligence research and development
  - We built an agent that plays Hog optimally against `always_roll(6)`, using MDPs and value iteration
  - We built an agent that plays Ants pretty well, using reinforcement learning and rollout-based methods
- However, applications of AI go far beyond games and stretch into almost every area of everyday life
- If you're interested, take:
  - CS 188 (Introduction to Artificial Intelligence)
  - CS 189 (Introduction to Machine Learning)

Thank you