Lecture 29: Artificial Intelligence

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08/10/2016

Some slides are adapted from CS 188 (Artificial Intelligence)
Announcements
This week (Applications), the goals are:
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- To go beyond CS 61A and see examples of what comes next
Roadmap

- 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)
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  - Think like humans?
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    - What we really care about, though, is behavior
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  - Act *rationally*
    - A better name for artificial intelligence would be *computational rationality*
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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
Hog

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  • We can get up to ~85% win rate against always_roll(6)! I’ll show you how, using AI techniques and algorithms
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• 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
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    - We get this from dice probabilities and rules of the game
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• We need something that will tell us about which states are more or less likely to win from
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  - 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
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    \]

• We can show that this policy is optimal, under the correct assumptions! But let’s not do the math
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Playing Ants

Using rollout-based methods
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- You are the agent, the other person and the setting are the environment, and you don’t know the environment that well
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• This is very much like the real world, and here's an analogy: suppose you go on a date with someone.

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  Do you like cats?
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Ew, no.
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Oh... yeah, me neither.
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So... do you like dogs?
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I love dogs!
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Omg me too!!
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• Balancing exploration and exploitation is a key problem that RL algorithms must address, and there are many different ways to handle this
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Now, it makes sense to use MDPs and RL for Ants.
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Thank you