CIS 471/571 (Winter 2020): Introduction to Artificial Intelligence

Lecture 8: MDPs (Part 1)

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Source: http://ai.berkeley.edu/home.html
Reminder

- Project 2: Multi-agent Search
  - Deadline: Feb 02, 2020

- Homework 2: CSPs and Games
  - Deadline: Feb 03, 2020
Non-Deterministic Search
Example: Grid World

- A maze-like problem
  - The agent lives in a grid
  - Walls block the agent’s path

- Noisy movement: actions do not always go as planned
  - 80% of the time, the action North takes the agent North (if there is no wall there)
  - 10% of the time, North takes the agent West; 10% East
  - If there is a wall in the direction the agent would have been taken, the agent stays put

- The agent receives rewards each time step
  - Small “living” reward each step (can be negative)
  - Big rewards come at the end (good or bad)

- Goal: maximize sum of rewards
Grid World Actions

Deterministic Grid World

Stochastic Grid World
Markov Decision Processes

- An MDP is defined by:
  - A set of states \( s \in S \)
  - A set of actions \( a \in A \)
  - A transition function \( T(s, a, s') \)
    - Probability that \( a \) from \( s \) leads to \( s' \), i.e., \( P(s' \mid s, a) \)
    - Also called the model or the dynamics
  - A reward function \( R(s, a, s') \)
    - Sometimes just \( R(s) \) or \( R(s') \)
  - A start state
  - Maybe a terminal state

- MDPs are non-deterministic search problems
  - One way to solve them is with expectimax search
  - We’ll have a new tool soon
What is Markov about MDPs?

- “Markov” generally means that given the present state, the future and the past are independent.

- For Markov decision processes, “Markov” means action outcomes depend only on the current state.

\[
P(S_{t+1} = s' | S_t = s_t, A_t = a_t, S_{t-1} = s_{t-1}, A_{t-1}, \ldots S_0 = s_0)
\]

\[
= P(S_{t+1} = s' | S_t = s_t, A_t = a_t)
\]

- This is just like search, where the successor function could only depend on the current state (not the history).
Policies

- In deterministic single-agent search problems, we wanted an optimal plan, or sequence of actions, from start to a goal.

- For MDPs, we want an optimal policy $\pi^*$: $S \rightarrow A$
  - A policy $\pi$ gives an action for each state
  - An optimal policy is one that maximizes expected utility if followed
  - An explicit policy defines a reflex agent

- Expectimax didn’t compute entire policies
  - It computed the action for a single state only

Optimal policy when $R(s, a, s') = -0.03$ for all non-terminals $s$
Optimal Policies

\[
R(s) = -2.0
\]

\[
R(s) = -0.4
\]

\[
R(s) = -0.03
\]

\[
R(s) = -0.01
\]
Example: Racing
Example: Racing

- A robot car wants to travel far, quickly
- Three states: **Cool**, **Warm**, Overheated
- Two actions: **Slow**, **Fast**
- Going faster gets double reward
Racing Search Tree
Each MDP state projects an expectimax-like search tree

(s, a) is a \textit{q-state}

(s, a, s') called a \textit{transition}

\[ T(s, a, s') = P(s' \mid s, a) \]

\[ R(s, a, s') \]
Utilities of Sequences
Utilities of Sequences

- What preferences should an agent have over reward sequences?
  - More or less? \([1, 2, 2]\) or \([2, 3, 4]\)
  - Now or later? \([0, 0, 1]\) or \([1, 0, 0]\)
Discounting

- It’s reasonable to maximize the sum of rewards
- It’s also reasonable to prefer rewards now to rewards later
- One solution: values of rewards decay exponentially

![Diagram showing the discounting concept](image-url)
Discounting

- How to discount?
  - Each time we descend a level, we multiply in the discount once

- Why discount?
  - Sooner rewards probably do have higher utility than later rewards
  - Also helps our algorithms converge

- Example: discount of 0.5
  - $U([1,2,3]) = 1 \times 1 + 0.5 \times 2 + 0.25 \times 3$
  - $U([1,2,3]) < U([3,2,1])$
Stationary Preferences

- Theorem: if we assume stationary preferences:

\[ [a_1, a_2, \ldots] \succeq [b_1, b_2, \ldots] \]
\[ \iff \]
\[ [r, a_1, a_2, \ldots] \succeq [r, b_1, b_2, \ldots] \]

- Then: there are only two ways to define utilities
  - Additive utility: \[ U([r_0, r_1, r_2, \ldots]) = r_0 + r_1 + r_2 + \cdots \]
  - Discounted utility: \[ U([r_0, r_1, r_2, \ldots]) = r_0 + \gamma r_1 + \gamma^2 r_2 \cdots \]
Quiz: Discounting

- Given:
  
  \[
  \begin{array}{cccccc}
  10 & & & & 1 \\
  a & b & c & d & e
  \end{array}
  \]

  - Actions: East, West, and Exit (only available in exit states a, e)
  - Transitions: deterministic

  - Quiz 1: For \( \gamma = 1 \), what is the optimal policy?
  
  \[
  \begin{array}{cccccc}
  10 & & & & 1 \\
  a & b & c & d & e
  \end{array}
  \]

  - Quiz 2: For \( \gamma = 0.1 \), what is the optimal policy?
  
  \[
  \begin{array}{cccccc}
  10 & & & & 1 \\
  a & b & c & d & e
  \end{array}
  \]

  - Quiz 3: For which \( \gamma \) are West and East equally good when in state d?
Infinite Utilities?!

- **Problem:** What if the game lasts forever? Do we get infinite rewards?

- **Solutions:**
  - **Finite horizon:** (similar to depth-limited search)
    - Terminate episodes after a fixed $T$ steps (e.g. life)
    - Gives nonstationary policies ($\pi$ depends on time left)
  - **Discounting:** use $0 < \gamma < 1$
    \[
    U([r_0, \ldots r_\infty]) = \sum_{t=0}^{\infty} \gamma^t r_t \leq R_{\text{max}}/(1 - \gamma)
    \]
    - Smaller $\gamma$ means smaller “horizon” – shorter term focus
  - **Absorbing state:** guarantee that for every policy, a terminal state will eventually be reached (like “overheated” for racing)
Recap: Defining MDPs

- Markov decision processes:
  - Set of states $S$
  - Start state $s_0$
  - Set of actions $A$
  - Transitions $P(s'|s,a)$ (or $T(s,a,s')$)
  - Rewards $R(s,a,s')$ (and discount $\gamma$)

- MDP quantities so far:
  - Policy = Choice of action for each state
  - Utility = sum of (discounted) rewards
Solving MDPs
Optimal Quantities

- The value (utility) of a state $s$:
  \[ V^*(s) = \text{expected utility starting in } s \text{ and acting optimally} \]

- The value (utility) of a q-state $(s,a)$:
  \[ Q^*(s,a) = \text{expected utility starting out having taken action } a \text{ from state } s \text{ and (thereafter) acting optimally} \]

- The optimal policy:
  \[ \pi^*(s) = \text{optimal action from state } s \]
Snapshot of Demo – Gridworld V

Values

VALUES AFTER 100 ITERATIONS

0.64   0.74   0.85   1.00
0.57   0.57   -1.00
0.49   0.43   0.48   0.28

Noise = 0.2
Discount = 0.9
Living reward = 0
Snapshot of Demo – Gridworld Q Values

Noise = 0.2
Discount = 0.9
Living reward = 0
Values of States

- Fundamental operation: compute the (expectimax) value of a state
  - Expected utility under optimal action
  - Average sum of (discounted) rewards
  - This is just what expectimax computed!

- Recursive definition of value:

\[ V^*(s) = \max_a Q^*(s, a) \]

\[ Q^*(s, a) = \sum_{s'} T(s, a, s') \left[ R(s, a, s') + \gamma V^*(s') \right] \]

\[ V^*(s) = \max_a \sum_{s'} T(s, a, s') \left[ R(s, a, s') + \gamma V^*(s') \right] \]
Racing Search Tree
Racing Search Tree
Racing Search Tree

- We’re doing way too much work with expectimax!

- Problem: States are repeated
  - Idea: Only compute needed quantities once

- Problem: Tree goes on forever
  - Idea: Do a depth-limited computation, but with increasing depths until change is small
  - Note: deep parts of the tree eventually don’t matter if $\gamma < 1$
Time-Limited Values

- Key idea: time-limited values

- Define $V_k(s)$ to be the optimal value of $s$ if the game ends in $k$ more time steps
  - Equivalently, it’s what a depth-$k$ expectimax would give from $s$
\(k=0\)

VALUES AFTER 0 ITERATIONS

Noise = 0.2
Discount = 0.9
Living reward = 0
$k=1$

VALUES AFTER 1 ITERATIONS

Noise = 0.2
Discount = 0.9
Living reward = 0
$k=2$

VALUES AFTER 2 ITERATIONS

Noise = 0.2
Discount = 0.9
Living reward = 0
$k = 3$

VALUES AFTER 3 ITERATIONS

Noise = 0.2
Discount = 0.9
Living reward = 0
k=4

VALUES AFTER 4 ITERATIONS

Noise = 0.2
Discount = 0.9
Living reward = 0
$k=5$

VALUES AFTER 5 ITERATIONS

Noise = 0.2
Discount = 0.9
Living reward = 0
k=6

VALUES AFTER 6 ITERATIONS

Noise = 0.2
Discount = 0.9
Living reward = 0
\[ k = 7 \]

VALUES AFTER 7 ITERATIONS

Noise = 0.2
Discount = 0.9
Living reward = 0
$k=8$

VALUES AFTER 8 ITERATIONS

Noise = 0.2
Discount = 0.9
Living reward = 0
$k = 9$

VALUES AFTER 9 ITERATIONS

Noise = 0.2  
Discount = 0.9  
Living reward = 0
k=10

VALUES AFTER 10 ITERATIONS

Noise = 0.2
Discount = 0.9
Living reward = 0
k=11

VALUES AFTER 11 ITERATIONS

Noise = 0.2
Discount = 0.9
Living reward = 0
$k=12$

VALUES AFTER 12 ITERATIONS

Noise = 0.2
Discount = 0.9
Living reward = 0
k=100

VALUES AFTER 100 ITERATIONS

Noise = 0.2
Discount = 0.9
Living reward = 0
Computing Time-Limited Values
Value Iteration
Value Iteration

- Start with $V_0(s) = 0$: no time steps left means an expected reward sum of zero

- Given vector of $V_k(s)$ values, do one ply of expectimax from each state:

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

- Repeat until convergence

- Complexity of each iteration: $O(S^2A)$

- Theorem: will converge to unique optimal values
  - Basic idea: approximations get refined towards optimal values
  - Policy may converge long before values do
Example: Value Iteration

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_2$</td>
<td>3.5</td>
<td>2.5</td>
<td>0</td>
</tr>
<tr>
<td>$V_1$</td>
<td>2</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>$V_0$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Assume no discount!

$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} T(s, a, s') \left[ R(s, a, s') + \gamma V_k(s') \right]$$
Convergence

- How do we know the $V_k$ vectors are going to converge?

- Case 1: If the tree has maximum depth $M$, then $V_M$ holds the actual untruncated values

- Case 2: If the discount is less than 1
  - Sketch: For any state $V_k$ and $V_{k+1}$ can be viewed as depth $k+1$ expectimax results in nearly identical search trees
  - The difference is that on the bottom layer, $V_{k+1}$ has actual rewards while $V_k$ has zeros
  - That last layer is at best all $R_{\text{MAX}}$
  - It is at worst $R_{\text{MIN}}$
  - But everything is discounted by $\gamma^k$ that far out
  - So $V_k$ and $V_{k+1}$ are at most $\gamma^k \max |R|$ different
  - So as $k$ increases, the values converge