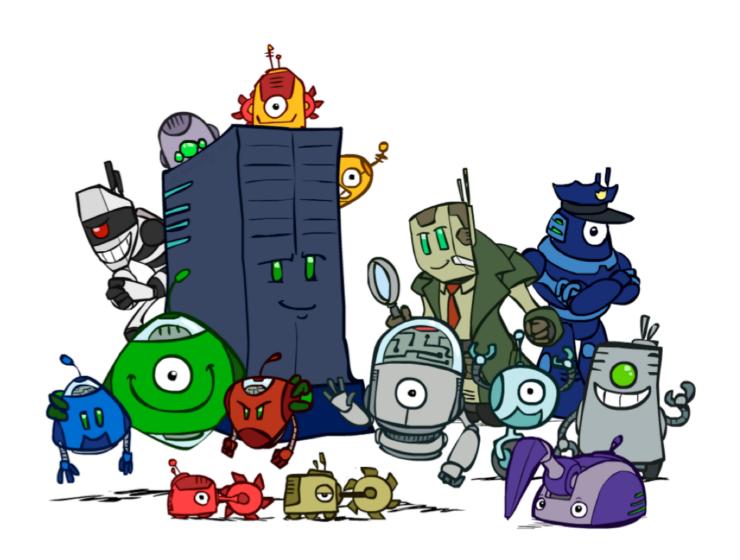
Announcements

- * Mid-term exam: June 25, 12:10pm-1:50pm
 - Closed book, 2 A4-sized cheatsheets
 - * No electronic device, no communication
- * HW5 on CSP
 - Early release today
 - Due June 30 at 11:59pm
- * P3 on MDP and RL
 - Released later today
 - Due July 5 at 11:59pm

Ve492: Introduction to Artificial Intelligence Mid-term Review



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UM-SJTU Joint Institute

Slides adapted from http://ai.berkeley.edu, AIMA, UM, CMU

What have we learned so far?

Search and planning

Define a state space, goal test; Find path from start to goal

* Game trees

Define utilities; Find path from start that maximizes utility

Decision theory and game theory

Foundation for MEU; Basic concepts in game theory

* MDPs

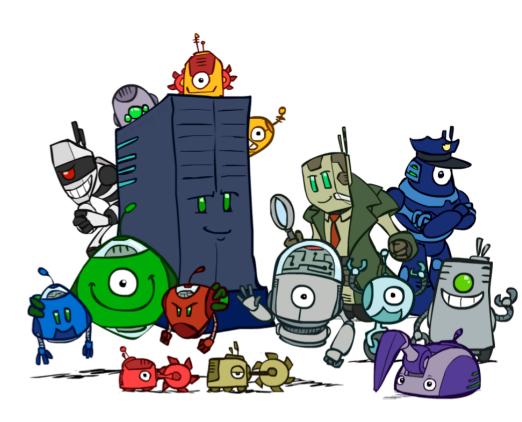
- Define rewards, utility = (discounted) sum of rewards
- Find policy that maximizes utility

Reinforcement learning

Just like MDPs, only T and/or R are not known in advance

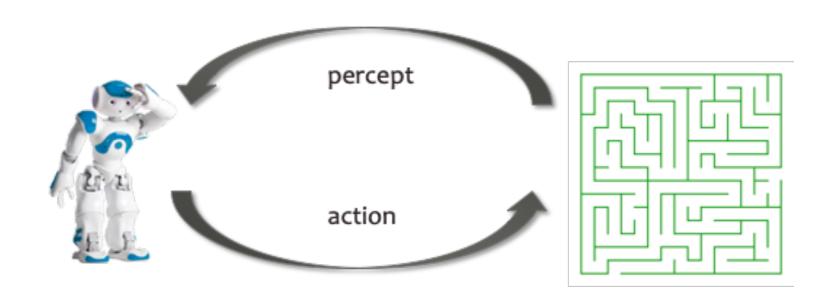
Constraint satisfaction

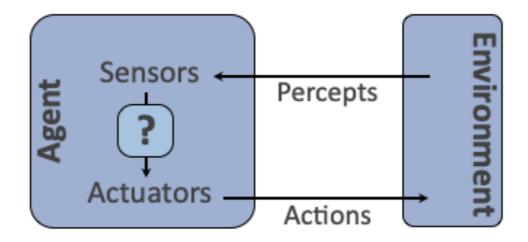
Find solution that satisfies constraints; Not just for finding a sequential plan



High-Level Framework

* How to build AI system?





Search

- Environment: single-agent, fully-observable state, deterministic transition, sequential, model known
- Search problem
 - States, transition model, goal test, initial state
 - Search tree

Algorithms

- Uninformed search
 - BFS, DFS, UCS
- Informed search
 - Greedy search, A*

Properties

- Complete, optimal
- Space and computational complexities

Search in Games

- Environment: multi-agent, fully-observable state, deterministic or stochastic transition, turn-taking, model known
- Multi-agent search problems as games
 - States, players, transition model, terminal test/values, initial state
 - Game tree
- Algorithm for adversarial agent (zero-sum game)
 - Minimax search algorithm
 - Alpha-beta pruning
 - Depth-limited search, iterative deepening
- Algorithm for random agent
 - Expectimax
- Algorithm for multi-agent search
 - Expectiminimax

Decision Theory and Game Theory

Axiomatization of Expected Utility

- Completeness, Transitivity, Independence, Continuity
- Unicity of utility function up to positive affine transformation
- Preference elicitation

Game theory

- Extensive form vs normal form
- Best response, dominant/dominated strategies
- Nash equilibrium (pure or mixed)
- Pareto optimal, correlated equilibrium

Markov Decision Process

- Environment: single-agent, fully-observable state, stochastic transition, sequential, model known
- * Model
 - States, actions, transition function, reward function
- * Algorithms
 - Policy evaluation
 - Policy extraction
 - Value iteration
 - Policy iteration

Reinforcement Learning

- Environment: single-agent, fully-observable state, stochastic transition, sequential, model unknown
- * MDP Model, but unknown!
 - States, actions, transition function, reward function

* Algorithms

- Policy evaluation with TD learning
- Policy learning with Q-learning
- Approximate Q-learning
- * Action selection with ϵ -greedy or exploration function

Constraint Satisfaction

* CSP

- Set of variables, set of domains, set of constraints
- Find assignments to variables such that all constraints are satisfied

Algorithms

- Backtracking search
 - Filtering, forward-checking, arc consistency, k-consistency
 - Ordering of variables and values
- Structure of constraint graph
 - Two-pass algorithm for tree-structured constraint graph
 - Cutset conditioning
- Iterativement improvement
- Local search

Quiz: Search

- * Consider a graph search problem where for every action, the cost is at least ϵ , with ϵ >0. Assume the used heuristic is consistent.
 - Greedy graph search is guaranteed to return an optimal solution.
 - * A* graph search is guaranteed to return an optimal solution.
 - * A* graph search is guaranteed to expand no more nodes than depth-first graph search.
 - A* graph search is guaranteed to expand no more nodes than uniform-cost graph search.

Quiz: A* Heuristics

- * Let H_1 and H_2 both be admissible heuristics.
 - * $max(H_1, H_2)$ is necessarily admissible
 - * $min(H_1, H_2)$ is necessarily admissible
 - * $(H_1 + H_2)/2$ is necessarily admissible
 - * $max(H_1, H_2)$ is necessarily consistent

Quiz: Search under Uncertainty

- * You are given a game tree for which you are the maximizer, and in the nodes in which you don't get to make a decision an action is chosen uniformly at random amongst the available options. Your objective is to maximize the probability you win \$10 or more (rather than the usual objective to maximize your expected value).
- Running expectimax will result in finding the optimal strategy to maximize the probability of winning \$10 or more.
- Running minimax, where chance nodes are considered minimizers, will result in finding the optimal strategy to maximize the probability of winning \$10 or more.
- Running expectimax in a modified game tree where every pay-off of \$10 or more is given a value of 1, and every pay-off lower than \$10 is given a value of 0 will result in finding the optimal strategy to maximize the probability of winning \$10 or more.
- Running minimax in a modified game tree where every pay-off of \$10 or more is given a value of 1, and every pay-off lower than \$10 is given a value of 0 will result in finding the optimal strategy to maximize the probability of winning \$10 or more.

Quiz: Adversarial Search

- * In the context of adversarial search, α - β pruning
- ├ ❖ is generally faster than minimax, but loses the guarantee of optimality
- ↑ always returns the same value as minimax for the root of the tree
- F * always returns the same value as minimax for all nodes of the tree

Game Theory: Zero-Sum Game

- * Two players choose simultaneously a coin of 10 cents, 50 cents or 1 dollar, which they show to each other.
- If they chose the same coin, player I wins. Otherwise, player II wins.
- Write this game in normal form. Is there any pure NE?
- Express a system of inequalities to find a mixed NE.

Quiz: MDP

- For Markov Decisions Processes (MDPs), we have that:
- A small discount (close to 0) encourages shortsighted, greedy behavior.
- \lnot * A large, negative living reward (< 0) encourages shortsighted, greedy behavior.
 - * A negative living reward can always be expressed using a discount<1.
 - * A discount<1 can always be expressed as a negative living reward.

Quiz: MDP

- Value iteration can converge only if the discount factor
- \vdash (γ) satisfies $0 < \gamma < 1$.
- Policies found by value iteration may be superior to policies found by policy iteration.
- Policies found by policy iteration may be superior to policies found by value iteration.
- * In some problems, value iteration can converge even though policy iteration may not.

Quiz: Reinforcement Learning

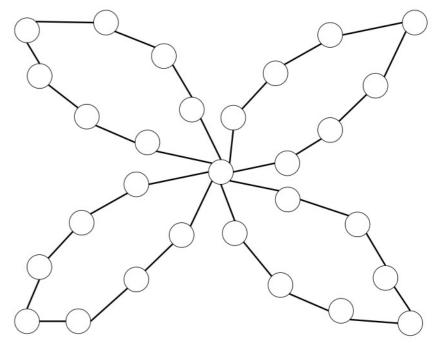
- * Assume that the agent observes the true reward with some \Box Gaussian noise $\mathcal{N}(0,1)$, Q-learning would still converge
- * If an MDP has a transition model T that assigns non-zero probability for all triples T (s, a, s') then Q-learning will fail.
- In Q-learning, we decide to explore every k steps, i.e., if t = 0 [k] we choose a random action with a uniform distribution, otherwise we choose the greedy action. This version would still converge.

Quiz: CSP

- * Assume given a CSP whose constraint graph is given below and that all the variables have the same domain.
- * What is the complexity of solving it with a direct application of backtracking search?

* Which efficient strategy could you apply to solve it?

What would be the complexity?



CSP Problem: Job Scheduling

When can I move in?

Task	Description	Duration	Predecessor
а	Erecting walls	7	none
b	Carpentry for roof	3	а
С	Roof	1	b
d	Installations	8	а
е	Facade painting	2	c & d
f	Windows	1	c & d
g	Garden	1	c & d
h	Ceilings	3	а
i	Painting	2	f & h
j	Moving in	1	i