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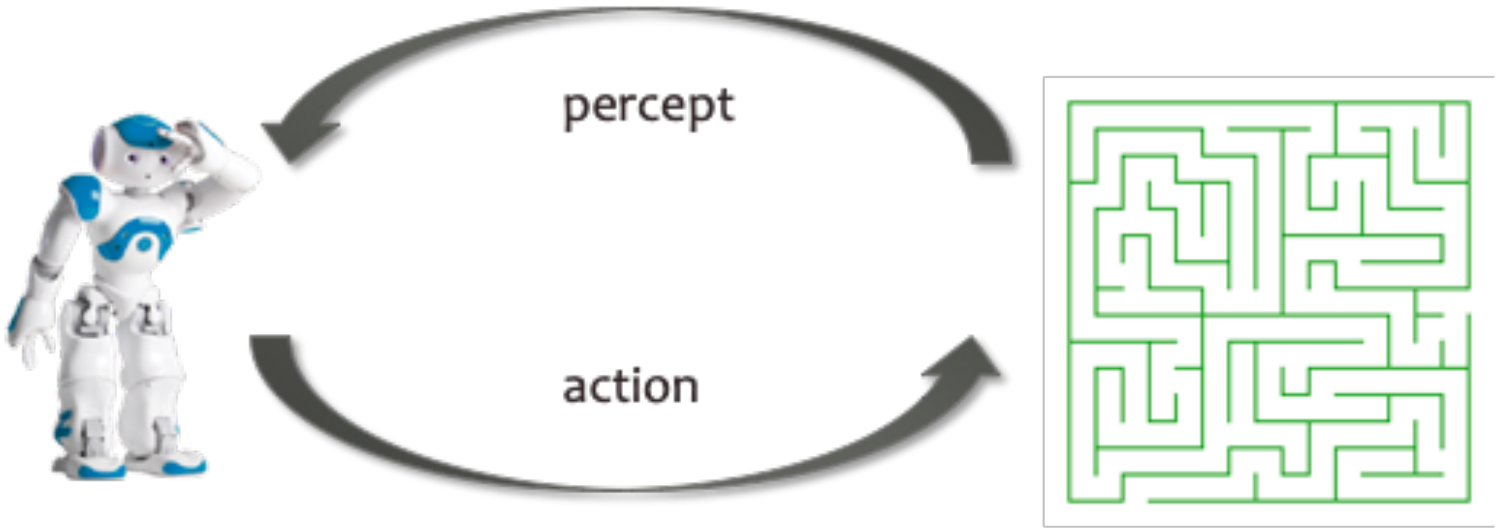
Slides adapted from http://ai.berkeley.edu, AIMA, UM, CMU

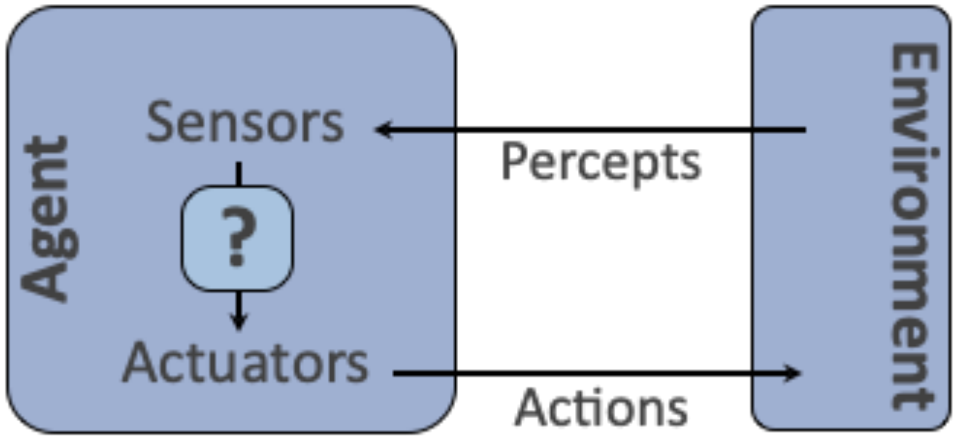
What have we learned so far?

- 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 $\epsilon > 0$. 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
  - can reduce computation time by pruning portions of the game tree
  - is generally faster than minimax, but loses the guarantee of optimality
  - always returns the same value as minimax for the root of the tree
  - 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.
  - A large, negative living reward ($\ll 0$) 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

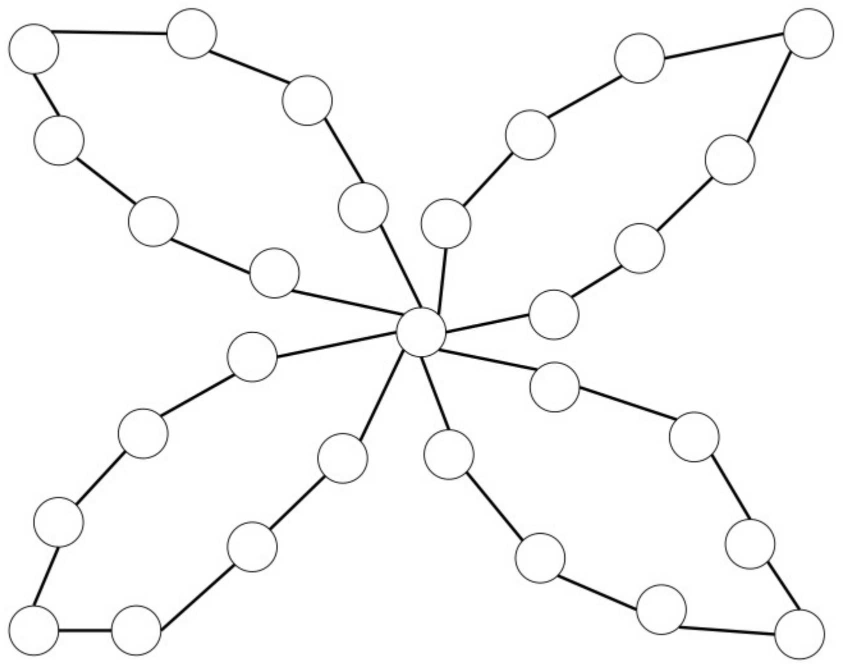
- Value iteration can converge only if the discount factor (γ) satisfies $0 < \gamma < 1$.
- Policies found by value iteration may be superior to policies found by policy iteration.
- Policies found by policy iteration may be superior to policies found by value iteration.
- In some problems, value iteration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

Quiz: Reinforcement Learning

- Assume that the agent observes the true reward with some Gaussian noise $\mathcal{N}(0,1)$, Q-learning would still converge
- Q-learning can learn the optimal Q-function Q^* without ever executing the optimal policy.
- 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
a	Erecting walls	7	none
b	Carpentry for roof	3	a
c	Roof	1	b
d	Installations	8	a
e	Facade painting	2	c & d
f	Windows	1	c & d
g	Garden	1	c & d
h	Ceilings	3	a
i	Painting	2	f & h
j	Moving in	1	i