Artificial Intelligence

CS 165A

Dec 10, 2020

Instructor: Prof. Yu-Xiang Wang

Today

→ Final Review

Logistic notes

- ESCI Survey: Please go and submit your feedback!
  - Deadline is approaching. This is my final reminder.

- Final: Next Tuesday 9:00 am - Wednesday 11:59 pm.
  - 27 hours in total; for an exam that will take roughly 3 hours max.
  - Submit your take home final on gradescope.
  - Open book. NO collaboration allowed. We will check for similarities. Your questions might be subtly different from your peers.
  - Covers topics up to First Order Logic (but before FOL inference)
  - About 80% will be on topics after the midterm, 20% on earlier topics. (Note that you might be asked to apply ML or PGM on topics in the second half of the lecture!)
  - There

Tips for studying for the final

- Focus on the Lectures and HWs

- For any concepts that you are confused, check the textbook (Again, books are random access, you don't have to read chapters from the beginning to the end)
  - Stick to AIMA book for Search and Logic
  - Stick to the Sutton and Barto book for RL.

We've come a long way…

Week	Topic
1	Course Overview & Intelligent Agents
2	Machine Learning
	Machine Learning
2	Machine Learning
	Probabilistic Graphical Models
3	Probabilistic Graphical Models
	Search: Problem solving with search
4	Search: Search algorithms
	Search: Minimax search and game playing
5	Midterm Review
	Midterm (take-home)
6	RL: Intro / Markov Decision Processes
	RL: Solving MDPs
7	RL: Bandits and Exploration
	RL: Reinforcement Learning Algorithms
8	RL: Reinforcement Learning Algorithms
	Logic: Propositional Logic
9	Thanksgiving break
	Logic: First Order Logic
10	Responsible AI
	Final Review
11	Final Exam (take-home)

Machine Learning

Probabilistic Reasoning

Search

Reinforcement Learning

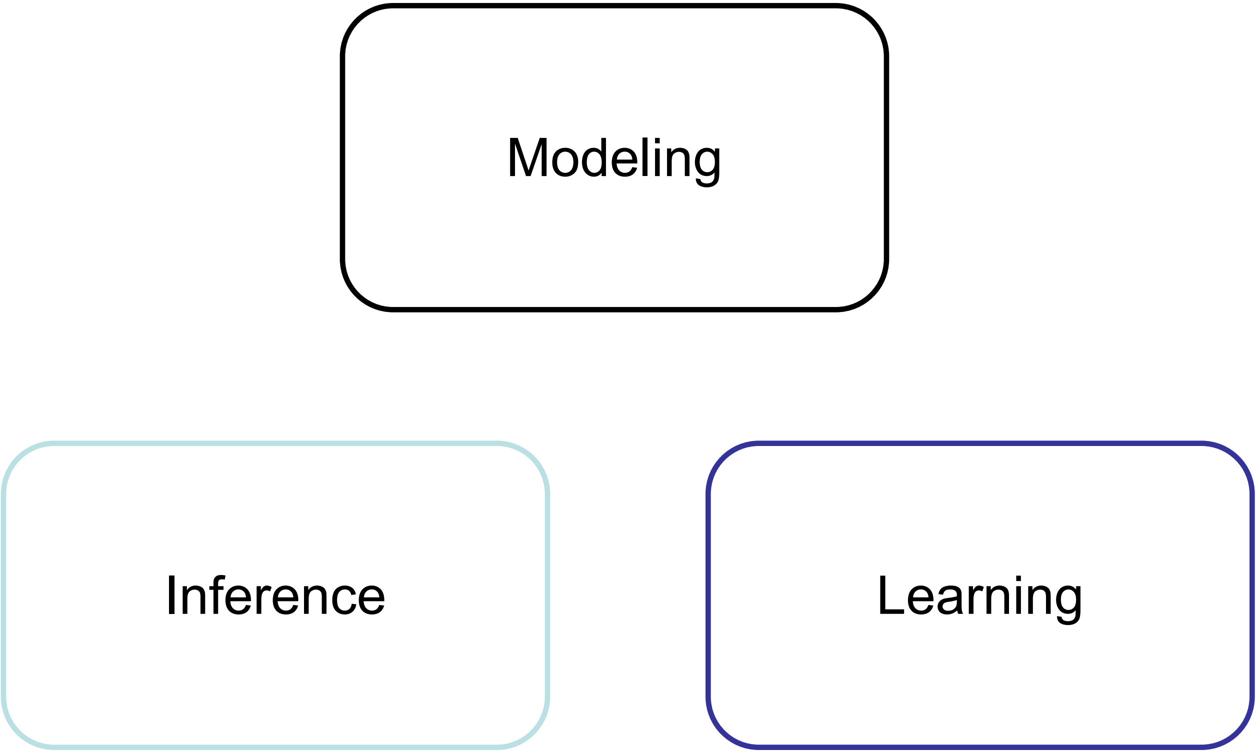
Logic

Responsible AI

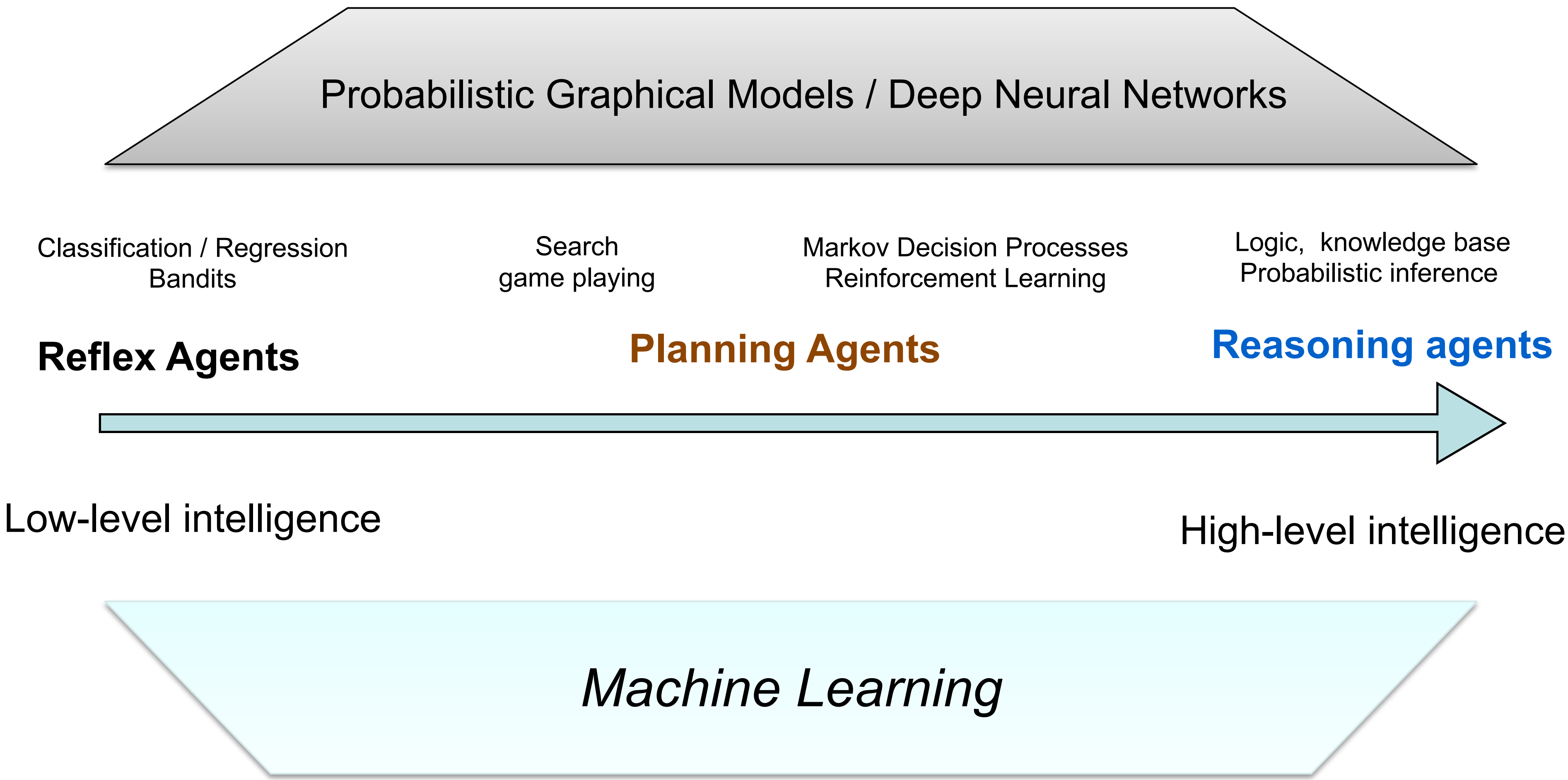
Lecture 1: AI Overview

- AI for problem solving
- Rational agents
- Examples of AI in the real world
- Modelling-Inference-Learning Paradigm

Modeling-Inference-Learning



Structure of the course



Potential question in the final: what type of agents are suitable to a given problem ?

Our view of AI

- So this course is about designing rational agents
  - Constructing $\boldsymbol{f}$
  - For a given class of environments and tasks, we seek the agent (or class of agents) with the “best” performance
  - Note: Computational limitations make complete rationality unachievable in most cases

- In practice, we will focus on problem-solving techniques (ways of constructing $\boldsymbol{f}$), not agents per se

Different Ways of Looking at the AI

- Agent types / level of intelligence
  - Low-level: Reflex agents
  - Mid-level: Goal-based / Utility-based agents: planning agents
  - High-level: Knowledge-based: Logic agents

- Optimization view
  - Everything is an optimization problem

- Theoretical aspects
  - Time/space complexity
  - Algorithms and data structures
  - Statistical properties: # of free parameters / how easily can we learn them with data

Optimization perspective of AI

- A rational agent $$\max_{a_1,\ldots,a_T} \mathrm{Utility}(a_1,\ldots,a_T)$$
  - **Modelling tools:** Features / Hypothesis, PGM, State-space abstraction, agent categorization
  - **Constraints:** Computation, Data, Storage
- Discrete optimization $$\min_{p \in \mathrm{Paths}} \mathrm{Distance}(p)$$
  - **Algorithmic tool**: Search / Dynamic programming
- Continuous optimization $$\min_{\theta \in \mathbb{R}^d} \mathrm{TrainingError}(\theta)$$
  - **Algorithmic tool**: Gradient descent / Stochastic gradient descent

Different objectives to optimize in AI (first half of the course)

- PGM:
  - MLE: Maximize the log-likelihood function
  - Classifier / decision: max the posterior distribution

- Search and planning:
  - Find valid solutions with smallest path cost.
  - Minimax search / games: Maximize your worst-case pay-off (assuming your opponent plays optimally)

- Machine Learning $$\min_{\theta \in \mathbb{R}^d} \frac{1}{n} \sum_{i=1}^{n} \ell(\theta, (x_i, y_i)) + \lambda r(\theta)$$
  - (Regularized) Empirical Risk Minimization (ERM):
  - But the goal is to minimize the (unseen) expected loss.

Different objectives to optimize in AI (second half of the course)

- Markov Decision Processes / RL
  - Maximize the cumulative expected reward of "decision policy"
  - Balance Exploration and Exploitation.

- Logic / Knowledge based agent:
  - Solve a feasibility problem, find a "proof".
  - Determining "Valid, Satisfiable, Unsatisfiable"

A lot of these problems are computationally / statistically hard, but so what?

- Get help from human:
  - Use a model
  - Use abstractions at the right level
  - Use features
  - Use heuristic functions

- Get help from mathematics and computer science theory:
  - Solve an approx. solution
  - Approximate inference of a PGM
  - More iterations with less accuracy per SGD
  - A* Search
  - TD learning and Bootstrapping

Lecture 2-4: Machine Learning

- Machine learning
  - Types of machine learning models
  - Focus on Supervised Learning ---- classifier agents.
- What is a feature vector?
  - Feature engineering, feature extraction
- Hypothesis class and free parameters
  - How many are there? How to evaluate a classifier?
  - Error? On training data or on new data?
  - Overfitting, underfitting?
- How to learn (optimize)?
  - Surrogate losses, Gradient Descent, SGD

Example of a feature vector of dimension 4

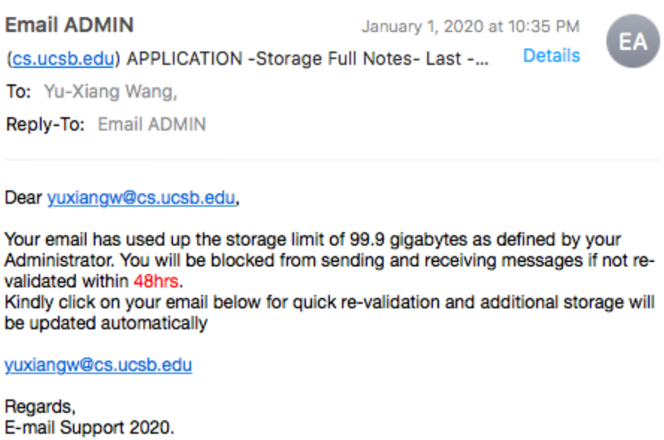
Contains hyperlinks

Proportion of misspelled words

1	**0**	**0.0375**	**80**

Whether the contact list

Length of the message


Email ADMIN January 1, 2020 at 10:35 PM
(cs.ucsb.edu) APPLICATION -Storage Full Notes- Last -... Details
To: Yu-Xiang Wang,
Reply-To: Email ADMIN

Dear yuxiangw@cs.ucsb.edu,

Your email has used up the storage limit of 99.9 gigabytes as defined by your Administrator. You will be blocked from sending and receiving messages if not re-validated within 48hrs.
Kindly click on your email below for quick re-validation and additional storage will be updated automatically

yuxiangw@cs.ucsb.edu

Regards,
E-mail Support 2020.

Step 1 in Modelling

Feature extractor:

Converting the object of interest to a vector of numerical values.

Example: Linear classifiers

- Score(x) = $w_0 + w_1$ * 1(hyperlinks) + w_2 * 1(contact list) + w_3 * misspelling + w_4 * length

- A linear classifier: h(x) = 1 if Score(x) > 0 and 0 otherwise.

- Question: What are the "free-parameters" in a linear classifier?
  - If we redefine $\mathcal{Y} = \{-1, 1\}$
  - A compact representation:

$$h(x) = \mathrm{sign}(w^T[1; x])$$

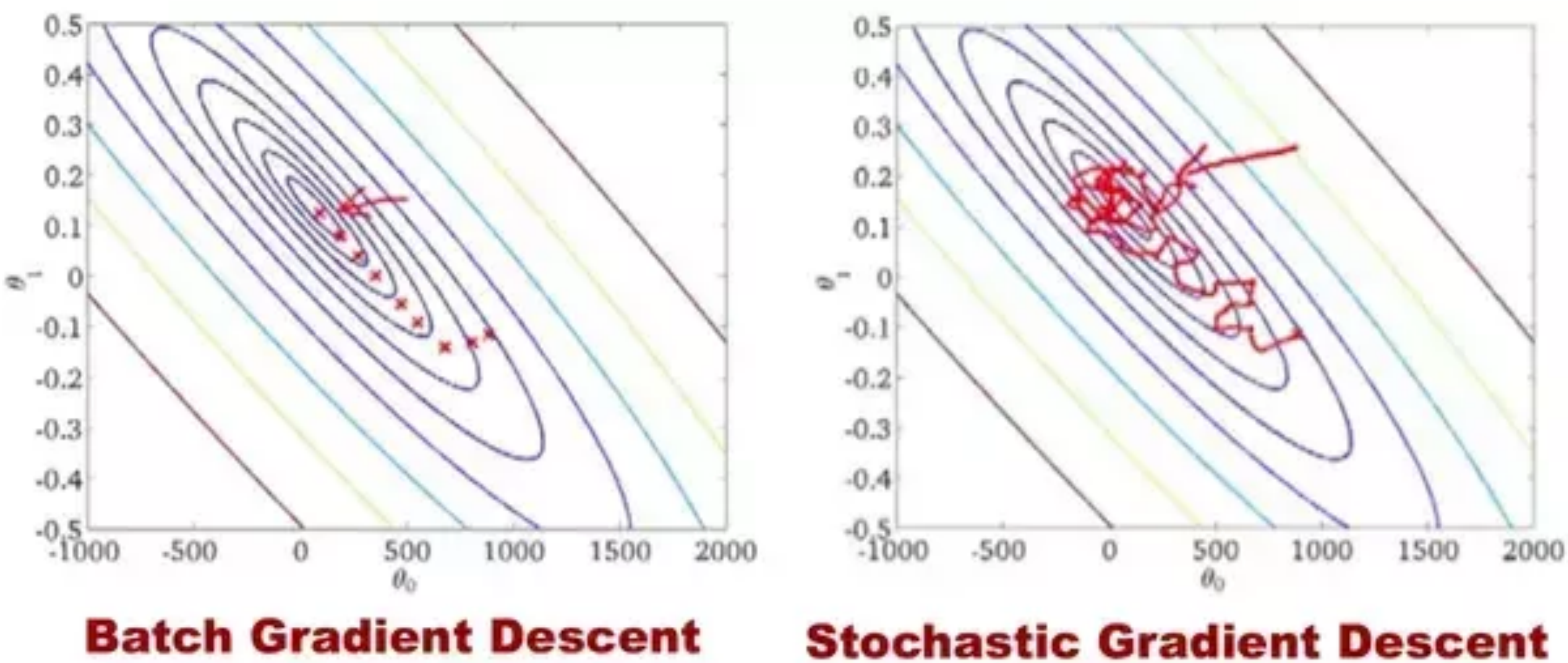
Just "relax": relaxing a hard problem into an easier one

$$\min_{w \in \mathbb{R}^d} \mathrm{Error}(w) = \frac{1}{n} \sum_{i=1}^{n} \mathbf{1}(\mathrm{sign}(w^T x_i) \neq y_i)$$

$$\Downarrow$$

$$\min_{w \in \mathbb{R}^d} \frac{1}{n} \sum_{i=1}^{n} \ell(w^T x_i, y_i).$$

Illustration of GD vs SGD



Observation: With the time gradient descent taking one step.

SGD would have already moved many steps.

One natural stochastic gradient to consider in machine learning

- Recall that

$$\min_{\theta \in \mathbb{R}^d} \frac{1}{n} \sum_{i=1}^{n} \ell(\theta, (x_i, y_i))$$

- Pick a **single** data point i uniformly at random
  - Use $$\nabla_\theta \ell(\theta, (x_i, y_i))$$
  - Show that this is an unbiased estimator!
  - Know which part of the expression is random!
  - Know how to apply the definition of expectation.

Lecture 5-6: Probabilities and BayesNet

- Modelling the world with a joint probability distribution
  - Number of parameters?
- CPTs
  - Count number of independent numbers to represent a CPT
- Conditional, Marginal, Probabilistic Inference with Bayes Rule
- Read off conditional independences from the graph
  - d-separation
  - Bayes ball algorithm
  - Markov Blanket

Tradeoffs in our model choices

Fully Independent

$P(X_1, X_2, \ldots, X_N)$

$= P(X_1)\, P(X_2) \ldots P(X_N)$

$$O(N)$$

Fully general

$P(X_1, X_2, \ldots, X_N)$

$$O(e^N)$$

Space / computation efficiency

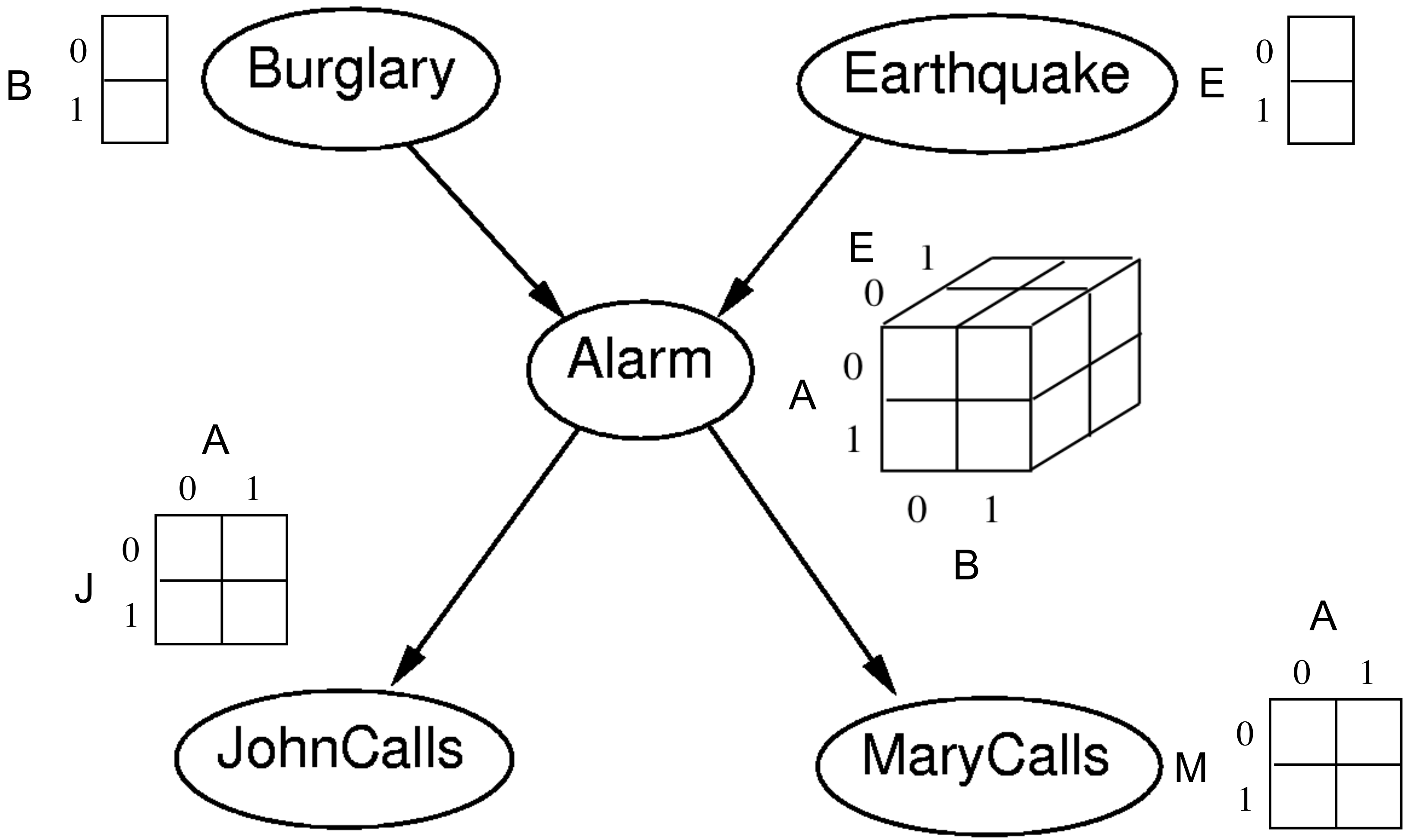
Expressiveness

Idea:

1.Independent groups of variables?

2.Conditional independences?

What are the CPTs? What are their dimensions?

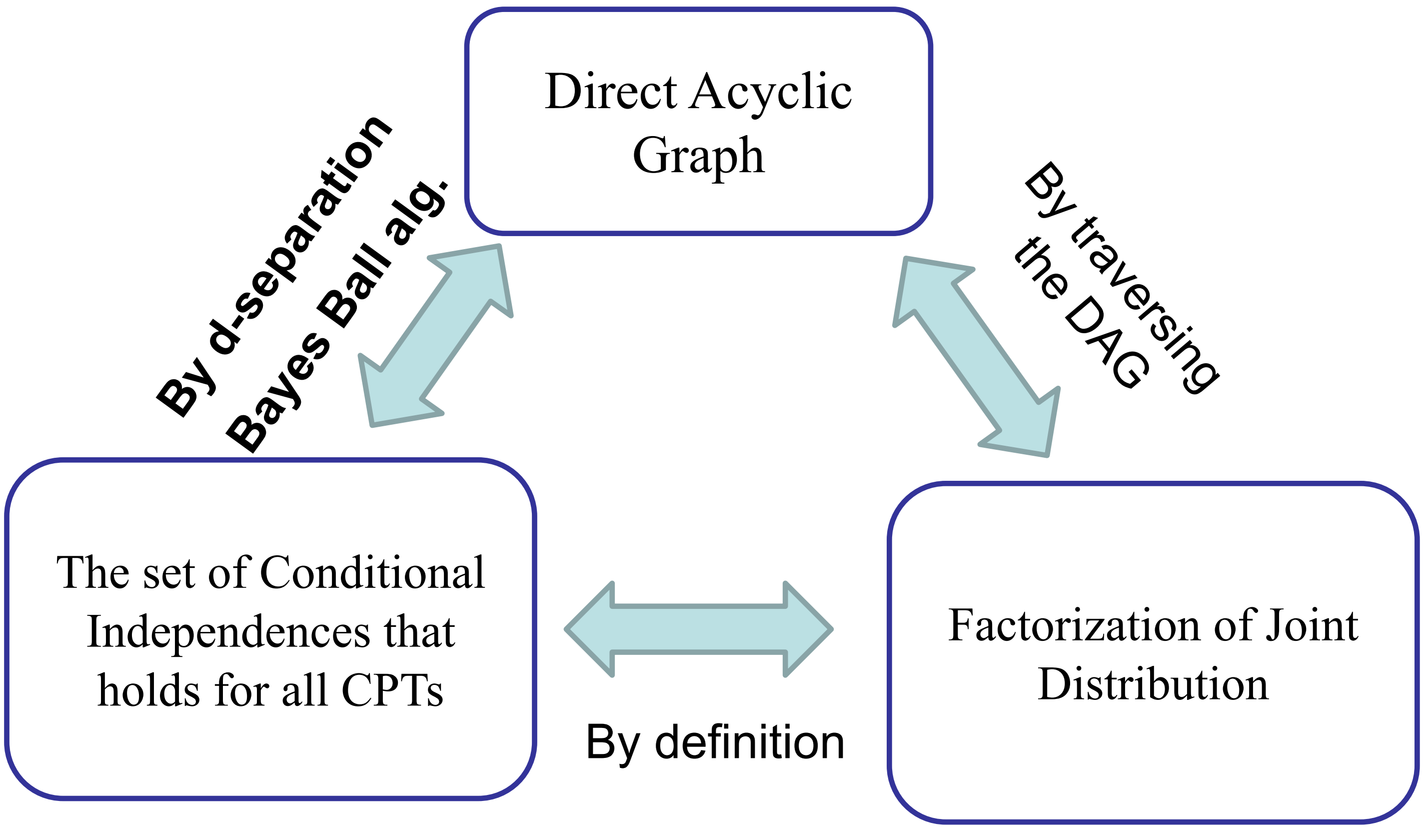


Question: How to fill values into these CPTs?

Ans: Specify by hands. Learn from data (e.g., MLE).

Big question: Is there a general way that we can answer questions about conditional independences by just inspecting the graphs?

- Turns out the answer is "Yes!"



What are the probabilistic graphical models for topics we learned in the second half?

- Expectimax
- MDP
- Bandits / Contextual Bandits
- Reinforcement Learning

Lecture 7-10: Search

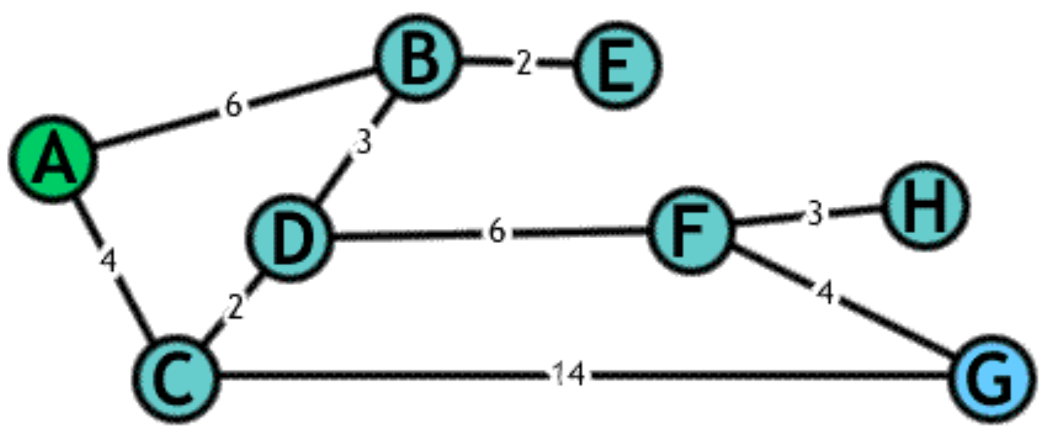
- Problem solving by search
  - Abstraction, problem formulation
  - State-space diagram
  - Count the number of states, number of actions.
- Uniformed Search algorithms
  - Four evaluation criteria
- Informed (heuristic) search
  - Admissible / consistent heuristics
  - Tree-search vs graph search
- **Minimax Search and Game playing**
  - Know how to do minimax / expectimax by hand!
  - Pruning

Problem Formulation and Search

- Problem formulation
  - State-space description < **{S}, S_0, {S_G}, {O}, {g}** >
    - **S**: Possible states
    - $\mathbf{S_0}$: Initial state of the agent
    - $\mathbf{S_G}$: Goal state(s)
      - Or equivalently, a goal test **G(S)**
    - **O**: Operators O: {S} => {S}
      - Describes the possible actions of the agent
    - **g**: Path cost function, assigns a cost to a path/action
- At any given time, which possible action $\boldsymbol{O_i}$ is best?
  - Depends on the goal, the path cost function, the future sequence of actions….
- Agent's strategy: Formulate, Search, and Execute
  - This is *offline* problem solving

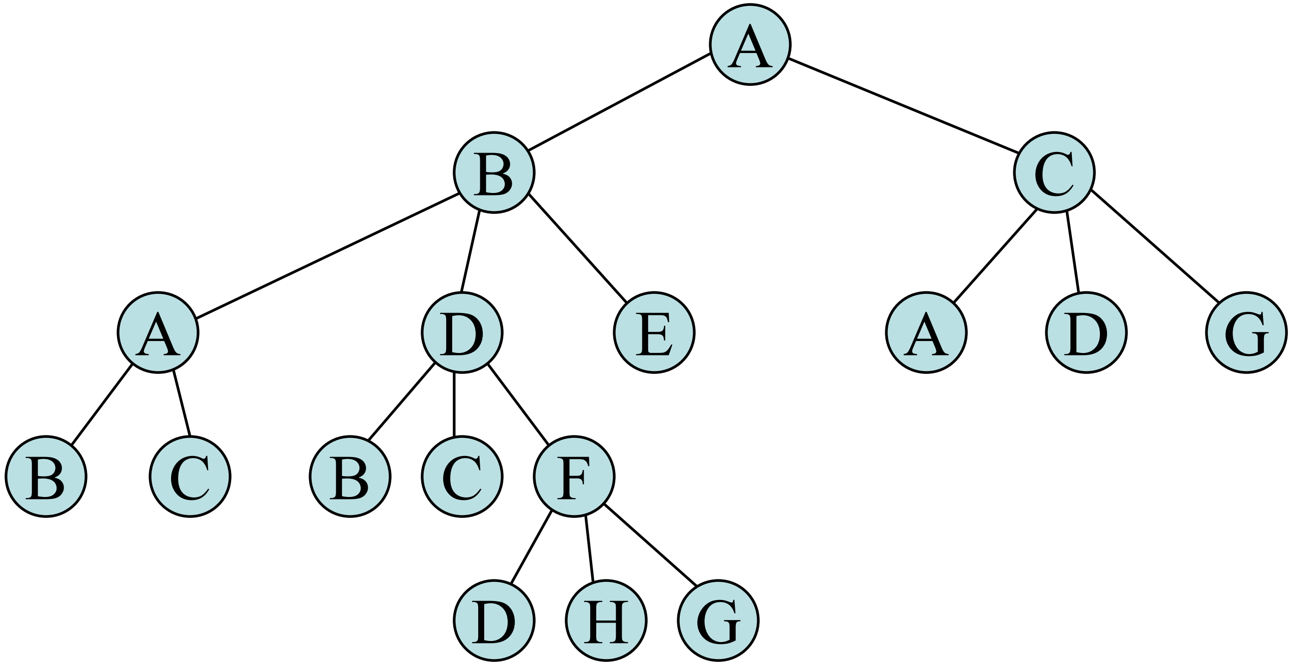
State-Space Diagrams

- State-space description can be represented by a state-space diagram, which shows
  - States (incl. initial and goal)
  - Operators/actions (state transitions)
  - Path costs



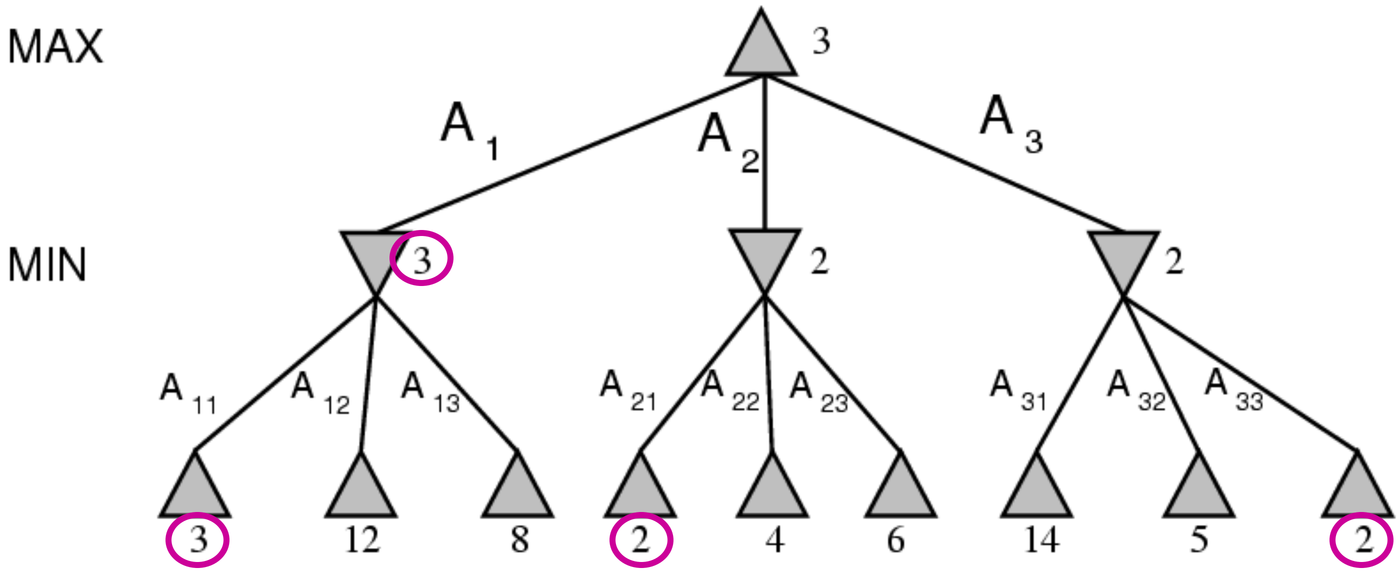
State Space vs. Search Tree (cont.)

Search tree (partially expanded)



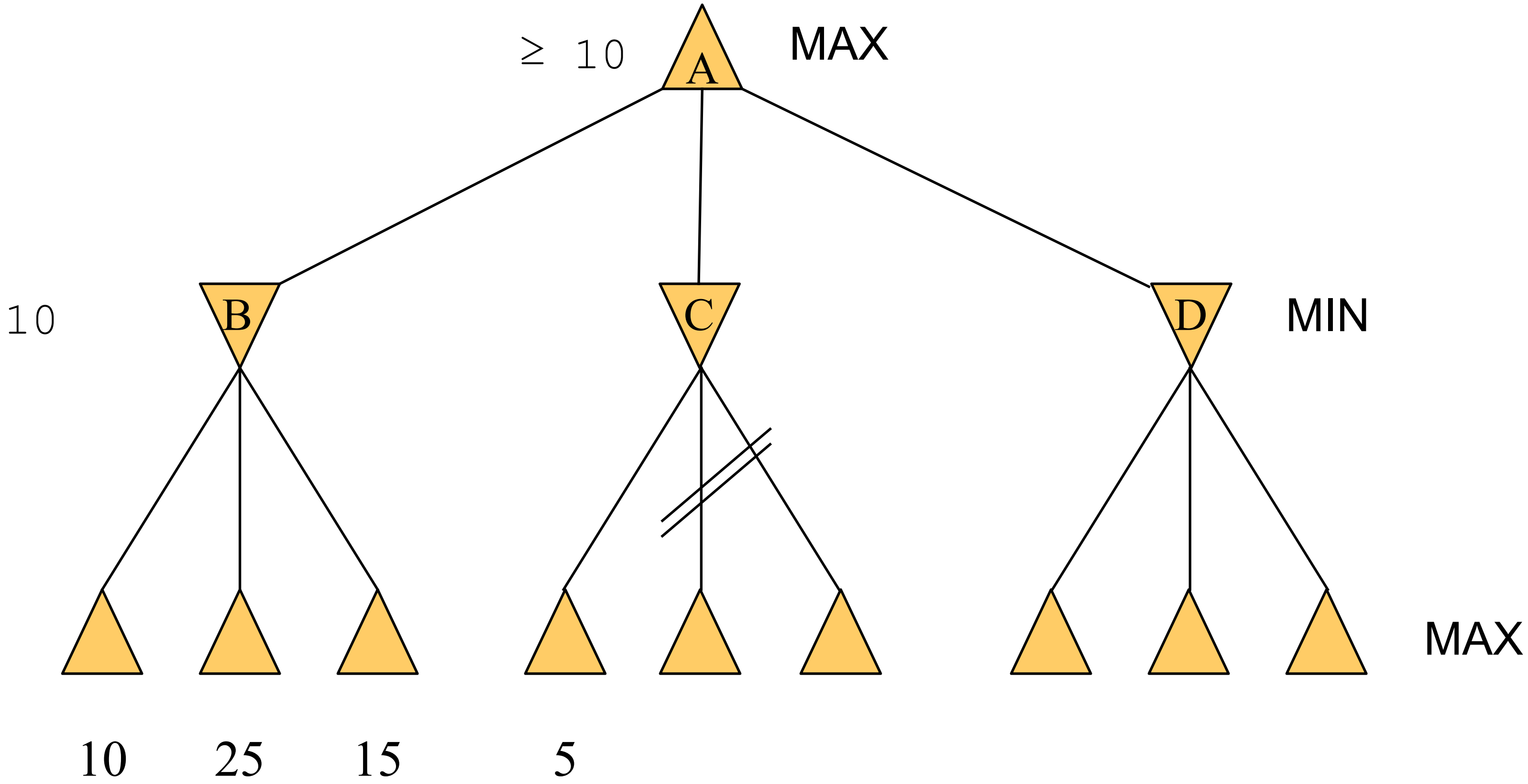
Minimax example

Which move to choose?

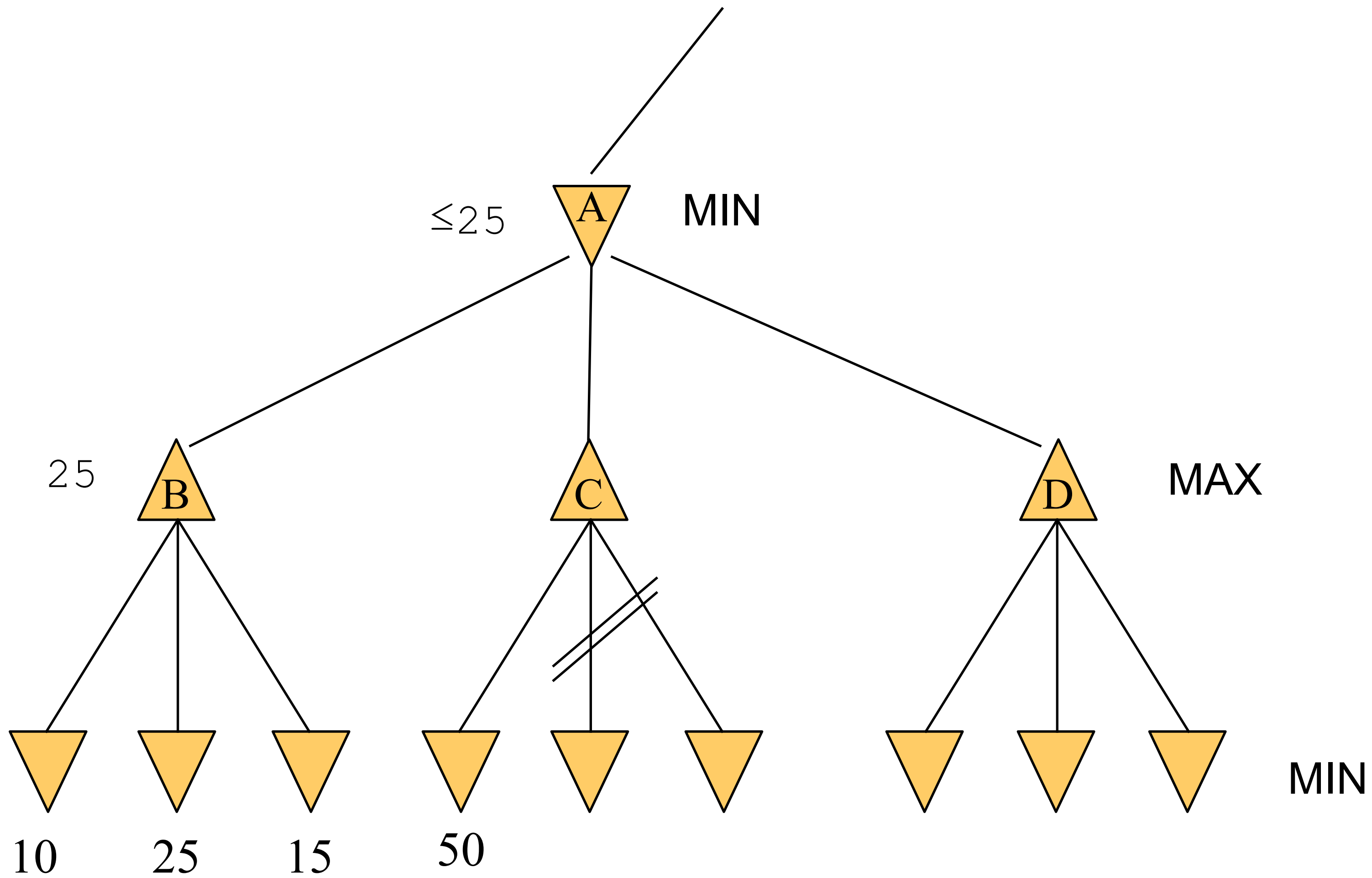


The **minimax decision** is move $\mathbf{A_1}$

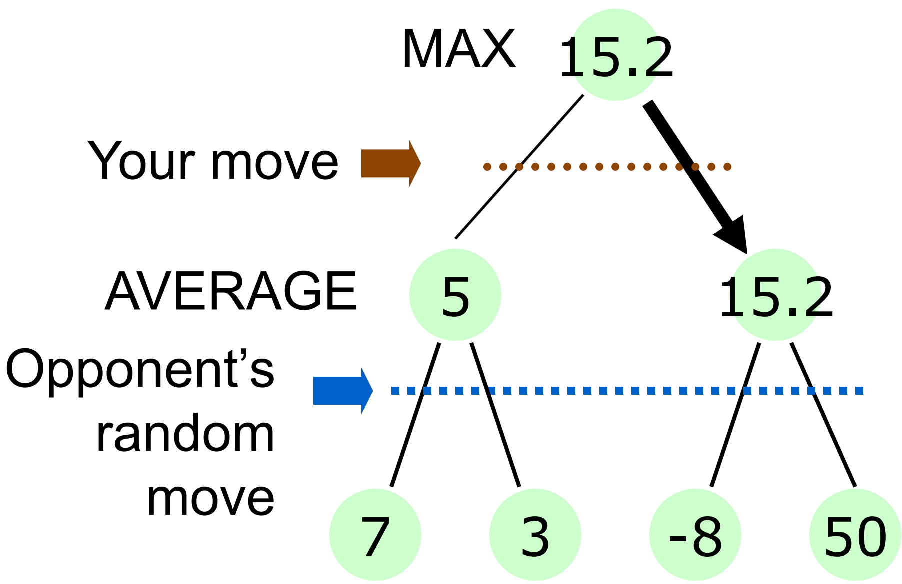
Alpha pruning



Beta pruning



Expectimax



- Your opponent behave randomly with a given probability distribution,
- If you move left, your opponent will select actions with probability [0.5,0.5]
- If you move right, your opponent will select actions with [0.6,0.4]

Lecture 11-16 Reinforcement Learning

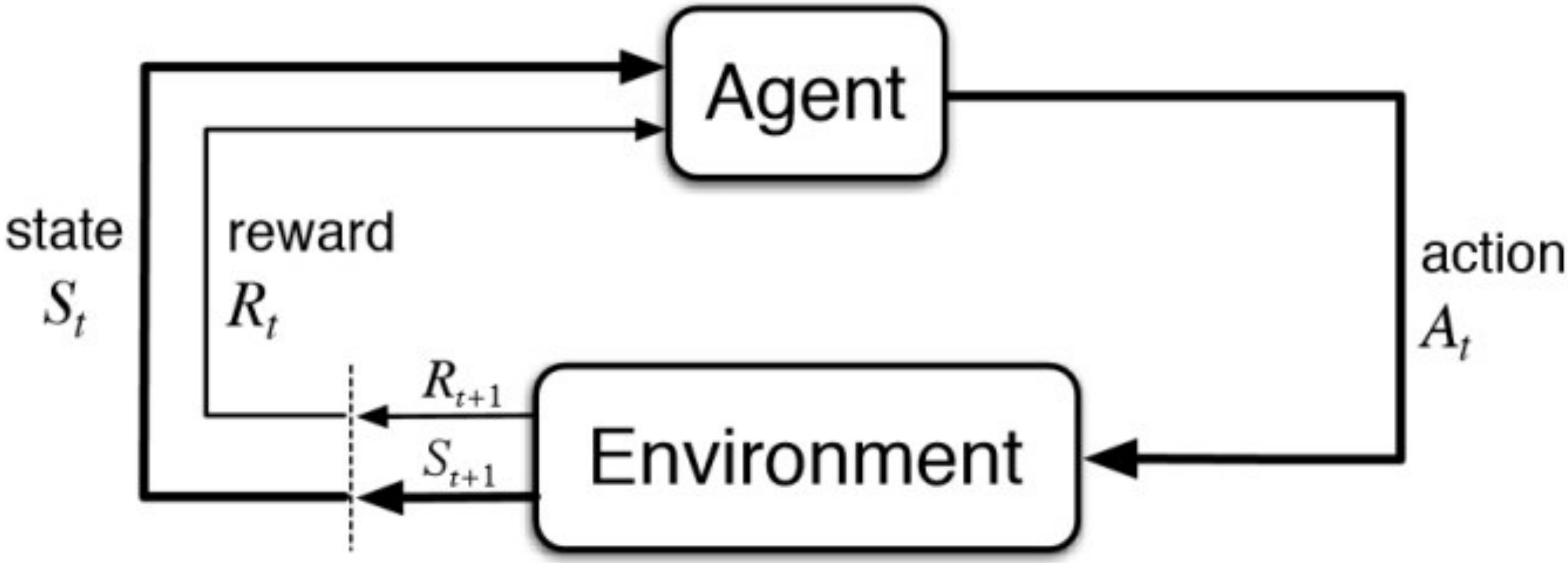
- Markov Decision Processes
  - New concepts: reward, value function, policy, transition dynamics
  - Bellman equations
  - Iterative algorithms for finding the optimal policy

- Bandits / Contextual bandits
  - The notion of regret
  - Explore-exploit

- Reinforcement Learning
  - Model-based learning
  - Model-free learning
  - Bootstrapping with Temporal Difference Learning

Reinforcement learning problem setup

- State, Action, Reward
- Unknown reward function, unknown state-transitions.
- Agents might not even observe the state



Reinforcement learning problem setup

- State, Action, Reward and Observation

$$S_t \in \mathcal{S} \quad A_t \in \mathcal{A} \quad R_t \in \mathbb{R} \quad O_t \in \mathcal{O}$$

- Policy:
  - When the state is observable: $\pi : \mathcal{S} \rightarrow \mathcal{A}$
  - Or when the state is not observable

$$\pi_t : (\mathcal{O} \times \mathcal{A} \times \mathbb{R})^{t-1} \rightarrow \mathcal{A}$$

- Learn the best policy that maximizes the expected reward
  - Finite horizon (episodic) RL: $\pi^* = \arg\max_{\pi \in \Pi} \mathbb{E}[\sum_{t=1}^{T} R_t]$ T: horizon
  - Infinite horizon RL: $\pi^* = \arg\max_{\pi \in \Pi} \mathbb{E}[\sum_{t=1}^{\infty} \gamma^{t-1} R_t]$

γ: discount factor

Reinforcement learning is, arguably, the most general AI framework.

- RL: State, Action, Reward, Nothing is known.

- Simplified RL models:
  - iid state → Contextual bandits
  - No state, tabular action → Multi-arm bandits
  - iid state, no reward → Supervised Learning
  - Known dynamics / reward → Markov Decision Processes (Control/Cybernetics)
  - No reward / Unknown dynamics → System Identification

Let us tackle different aspects of the RL problem one at a time

- Markov Decision Processes:
  - Dynamics are given no need to learn
- Bandits: Explore-Exploit in simple settings
  - RL without dynamics
- Full Reinforcement Learning
  - Learning MDPs

Tabular MDP

- Discrete State, Discrete Action, Reward and Observation

$$S_t \in \mathcal{S} \quad A_t \in \mathcal{A} \quad R_t \in \mathbb{R} \quad \cancel{O_t \in \mathcal{O}}$$

- Policy:
  - When the state is observable: $\pi : \mathcal{S} \rightarrow \mathcal{A}$
  - ~~Or when the state is not observable~~

$$\cancel{\pi_t : (\mathcal{O} \times \mathcal{A} \times \mathbb{R})^{t-1} \rightarrow \mathcal{A}}$$

- Learn the best policy that maximizes the expected reward
  - Finite horizon (episodic) MDP: $\pi^* = \arg\max_{\pi \in \Pi} \mathbb{E}[\sum_{t=1}^{T} R_t]$ T: horizon
  - Infinite horizon MDP: $\pi^* = \arg\max_{\pi \in \Pi} \mathbb{E}[\sum_{t=1}^{\infty} \gamma^{t-1} R_t]$

γ: discount factor

Reward function and Value functions

- Immediate reward function r(s,a,s')
  - expected **immediate** reward

    $$r(s,a,s') = \mathbb{E}[R_1 | S_1 = s, A_1 = a, S_2 = s']$$

    $$r^{\pi}(s) = \mathbb{E}_{a \sim \pi(a|s)}[R_1 | S_1 = s]$$

- state value function: $V^{\pi}(s)$
  - expected **long-term** return when starting in *s* and following π

    $$V^{\pi}(s) = \mathbb{E}_{\pi}[R_1 + \gamma R_2 + ... + \gamma^{t-1} R_t + ... | S_1 = s]$$

- state-action value function: $Q^{\pi}(s,a)$
  - expected **long-term** return when starting in *s*, performing *a,* and following π

    $$Q^{\pi}(s,a) = \mathbb{E}_{\pi}[R_1 + \gamma R_2 + ... + \gamma^{t-1} R_t + ... | S_1 = s, A_1 = a]$$

Bellman equations – the fundamental equations of MDP and RL

- An alternative, recursive and more useful way of defining the V-function and Q function
  - V^π function Bellman equation

$$V^\pi(s) = \sum_a \pi(a|s) \sum_{s'} P(s'|s,a)[r(s,a,s') + \gamma V^\pi(s')]$$

  - Q^π function Bellman equation

$$Q^\pi(s,a) = \sum_{s'} P(s'|s,a)[r(s,a,s') + \gamma \sum_{a'} \pi(a'|s') Q^\pi(s',a')]$$

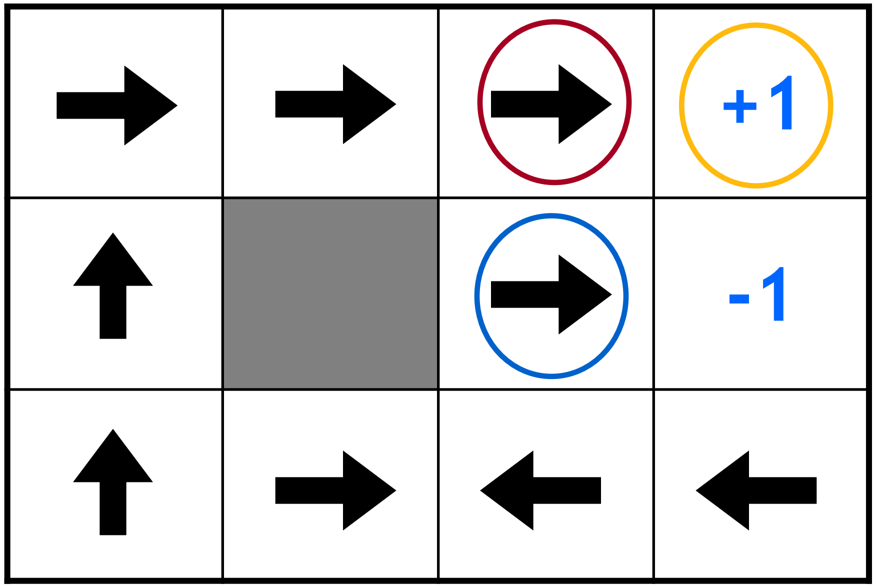
  - V* function Bellman (optimality) equation

$$V^*(s) = \max_a \sum_{s'} P(s'|s,a)[r(s,a,s') + \gamma V^*(s')]$$

  - Q* function Bellman (optimality) equation

$$Q^*(s,a) = \sum_{s'} P(s'|s,a)[r(s,a,s') + \gamma \max_{a'} Q^*(s',a')]$$

Let's work out the Value function for a specific policy



actions: UP, DOWN, LEFT, RIGHT

UP

80%	move UP
10%	move LEFT
10%	move RIGHT

- reward +1 at [4,3], -1 at [4,2]
- reward -0.04 for each step

$$V^\pi(s) = \sum_a \pi(a|s) \sum_{s'} P(s'|s,a)[r(s,a,s') + \gamma V^\pi(s')] = \sum_a \pi(a|s) Q^\pi(s,a)$$

1.0

0.8 * (+1-0.04 + 0)

+ 0.1 * (-0.04 + V^π([3,2]))

+ 0.1 * (-0.04 + V^π([3,3]))

Inference problem: given an MDP, how to compute its optimal policy?

- It suffices to compute its Q* function, because:

$$\pi^*(s) = \arg\max_a Q^*(s,a)$$

- It suffices to compute its V* function, because:

$$Q^*(s,a) = \sum_{s'} P(s'|s,a)[r(s,a,s') + \gamma V^*(s')]$$

MDP inference problem: Policy Evaluation (prediction) vs Policy Optimization (control)

- Policy Evaluation (prediction):
  - Simulate Bellman equation w.r.t. policy \pi until it converges
- Policy Optimization (control):
  - Policy evaluation, policy improvement, PE, PI, …
  - Value iterations: simulate Bellman optimality equation

How to calculate value functions given MDP parameters? Policy Iterations and Value Iterations

- What are these algorithms for?
  - Algorithms of computing the V* and Q* functions from MDP parameters

- Policy Iterations

$$\pi_0 \longrightarrow^E V^{\pi_0} \longrightarrow^I \pi_1 \longrightarrow^E V^{\pi_1} \longrightarrow^I \dots \longrightarrow^I \pi^* \longrightarrow^E V^*$$

- Value iterations

$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} P(s'|s,a)[r(s,a,s') + \gamma V_k(s')]$$

- How do we make sense of them?
  - Recursively applying the Bellman equations until convergence.

Multi-arm bandits: Problem setup

- No state. k-actions $a \in \mathcal{A} = \{1, 2, ..., k\}$

- You decide which arm to pull in every iteration

$$A_1, A_2, ..., A_T$$

- You collect a cumulative payoff of $\sum_{t=1}^{T} R_t$

- The goal of the agent is to maximize the expected payoff.
  - For future payoffs?
  - For the expected cumulative payoff?

How do we measure the performance of an **online learning agent**?

- The notion of "Regret":
  - I wish I have done things differently.
  - Comparing to the best actions in the hindsight, how much worse did I do.

- For MAB, the regret is defined as follow

$$T \max_{a \in [k]} \mathbb{E}[R_t | a] - \sum_{t=1}^{T} \mathbb{E}_{a \sim \pi} \left[\mathbb{E}[R_t | a] \right]$$

Regret of different MAB algorithms

- Greedy $$O(T)$$

- ExploreFirst $$O(T^{2/3}k^{1/3})$$

- eps-Greedy $$O(T^{2/3}k^{1/3})$$

- Upper Confidence Bound: $$O(T^{1/2}k^{1/2})$$

RL algorithms

- Model-based approach (plug-in an empirically estimated MDP, run VI / PI)

- Model-free approach:
  - Monte Carlo (average converges to mean) e.g., First visit Monte Carlo
  - Combining Monte Carlo with Dynamic Programming (e.g., VI)
  - Temporal difference learning

Revisit the dynamic programming approach

- Policy Evaluation

$$V_{k+1}^{\pi}(s) \leftarrow \sum_a \pi(a|s) \sum_{s'} \cancel{P(s'|s,a)}[\cancel{r(s,a,s')} + \gamma V_k^{\pi}(s')]$$

- Policy improvement

$$\pi'(s) = \arg\max_a Q^{\pi}(s,a)$$
$$= \arg\max_a \sum_{s'} \cancel{P(s'|s,a)}[\cancel{r(s,a,s')} + \gamma V_k^{\pi}(s')]$$

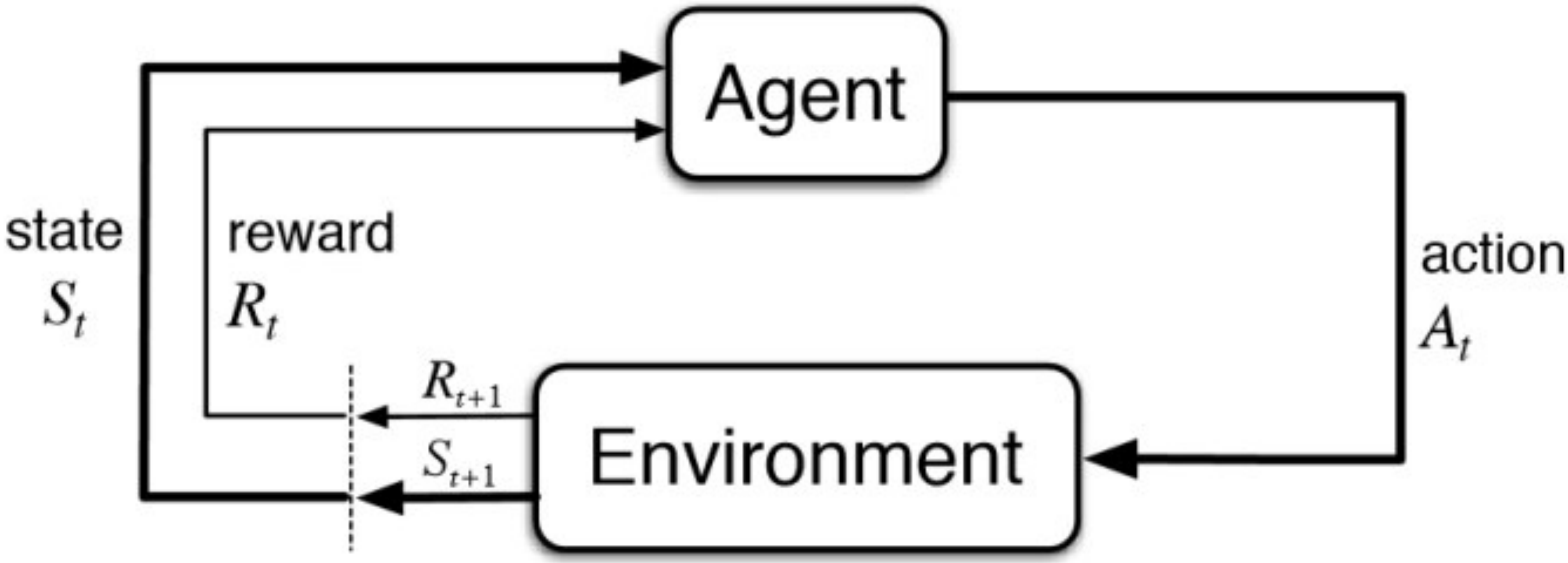
- Value iterations

$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} \cancel{P(s'|s,a)}[\cancel{r(s,a,s')} + \gamma V_k(s')]$$

***We do not have the MDP parameters in RL!**

Reinforcement learning agents have "online" access to an environment

- State, Action, Reward
- Unknown reward function, unknown state-transitions.
- Agents can "act" and "experiment", rather than only doing offline planning.



TD policy optimization (TD-control)

- SARSA (On-Policy TD-control)
  - Update the Q function by bootstrapping Bellman Equation

$$Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma Q(S', A') - Q(S, A)\big]$$

  - Choose the next A' using Q, e.g., eps-greedy.

- Q-Learning (Off-policy TD-control)
  - Update the Q function by bootstrapping Bellman Optimality Eq.

$$Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma \max_a Q(S', a) - Q(S, A)\big]$$

  - Choose the next A' using Q, e.g., eps-greedy, or any other policy.

Q-Learning with function approximation

$$Q(s,a) = w_1 f_1(s,a) + w_2 f_2(s,a) + \ldots + w_n f_n(s,a)$$

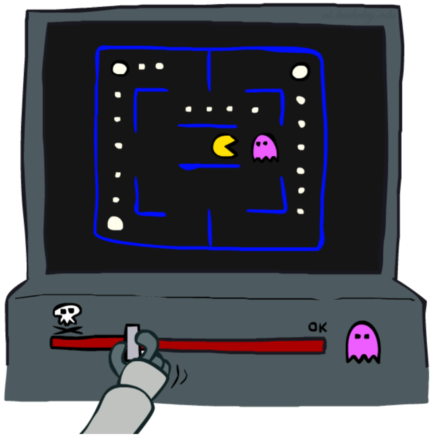
- Q-learning with linear Q-functions:

$$\text{transition } = (s, a, r, s')$$

$$\text{difference} = \left[r + \gamma \max_{a'} Q(s', a')\right] - Q(s,a)$$

$$Q(s,a) \leftarrow Q(s,a) + \alpha\,[\text{difference}]$$ Exact Q's

$$w_i \leftarrow w_i + \alpha\,[\text{difference}]\, f_i(s,a)$$ Approximate Q's



- Intuitive interpretation:
  - Adjust weights of active features
  - E.g., if something unexpectedly bad happens, blame the features that were on: disprefer all states with that state's features
- Formal justification: online least squares (Read the textbook!)

Policy gradient

- Let's not worry about states, dynamics, Q function.
  - We might not even observe the true state.
  - Let's specify a class of parametrized policy and hope to compare to the best within this class

- Objective function to maximize: $J(\boldsymbol{\theta}) \doteq v_{\pi_{\boldsymbol{\theta}}}(s_0),$

- Do SGD: $\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t + \alpha \widehat{\nabla J(\boldsymbol{\theta}_t)},$

- Policy gradient theorem:

$$\nabla J(\boldsymbol{\theta}) = \sum_s d^\pi(s) \sum_a Q^\pi(s,a) \nabla_{\boldsymbol{\theta}} \pi(a|s,\boldsymbol{\theta})$$

*Note how this theorem is non-trivial… The first two terms depends on π, but we did not take the gradient w.r.t. them.

Special case of policy gradient theorem in contextual bandits?

- Gradient of the IPS-estimator (or Importance Sampling estimator that you've seen) w.r.t. the parameter θ of the policy π

$$\hat{v}^{\pi}_{\mathrm{IPS}} = \frac{1}{n}\sum_{i=1}^{n}\frac{\pi(a_i|x_i)}{\mu(a_i|x_i)}r_i$$

- Connections to the policy gradient?

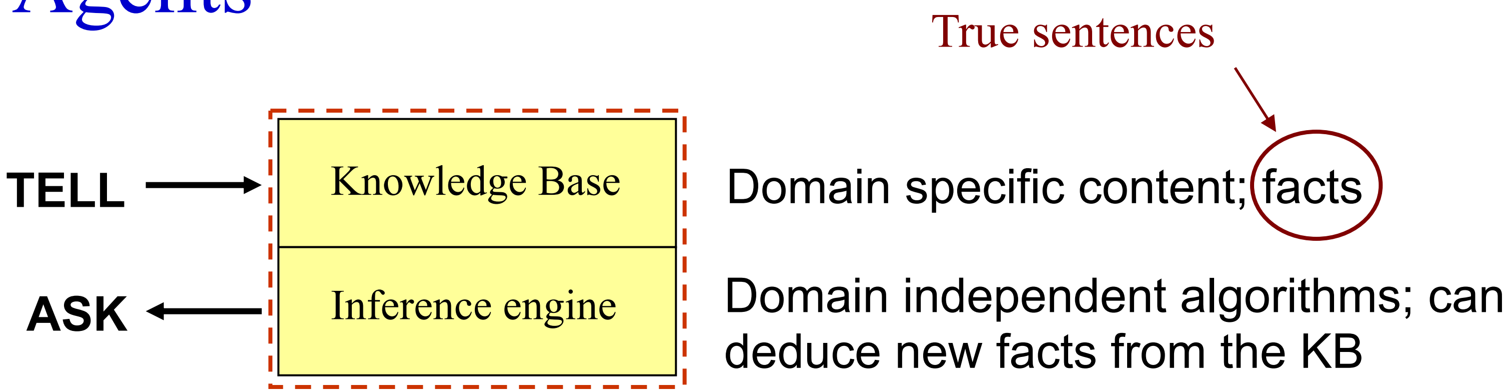
Most important concepts in MDP / RL

- Make sure you understand
  - Problem setup, evaluation criteria
  - Definition of the policy, state, action, immediate reward, value, value function …
- Bellman equations
- Policy / Value iterations
  - Finding fixed points of Bellman equations
  - Finding eigenvector of a matrix
- SARSA, Q-Learning
  - SGD-style Stochastic simulation of Bellman equations

Lecture 16-17: Logic

- Logic agent
  - Know how to play, e.g., Minesweeper and know how to explain your reasons.
- Knowledge Base
  - Tell operation
  - Ask operation
- Components of a formal mathematical logic system
  - Syntax, Semantics
- Inference Algorithms.

KB Agents

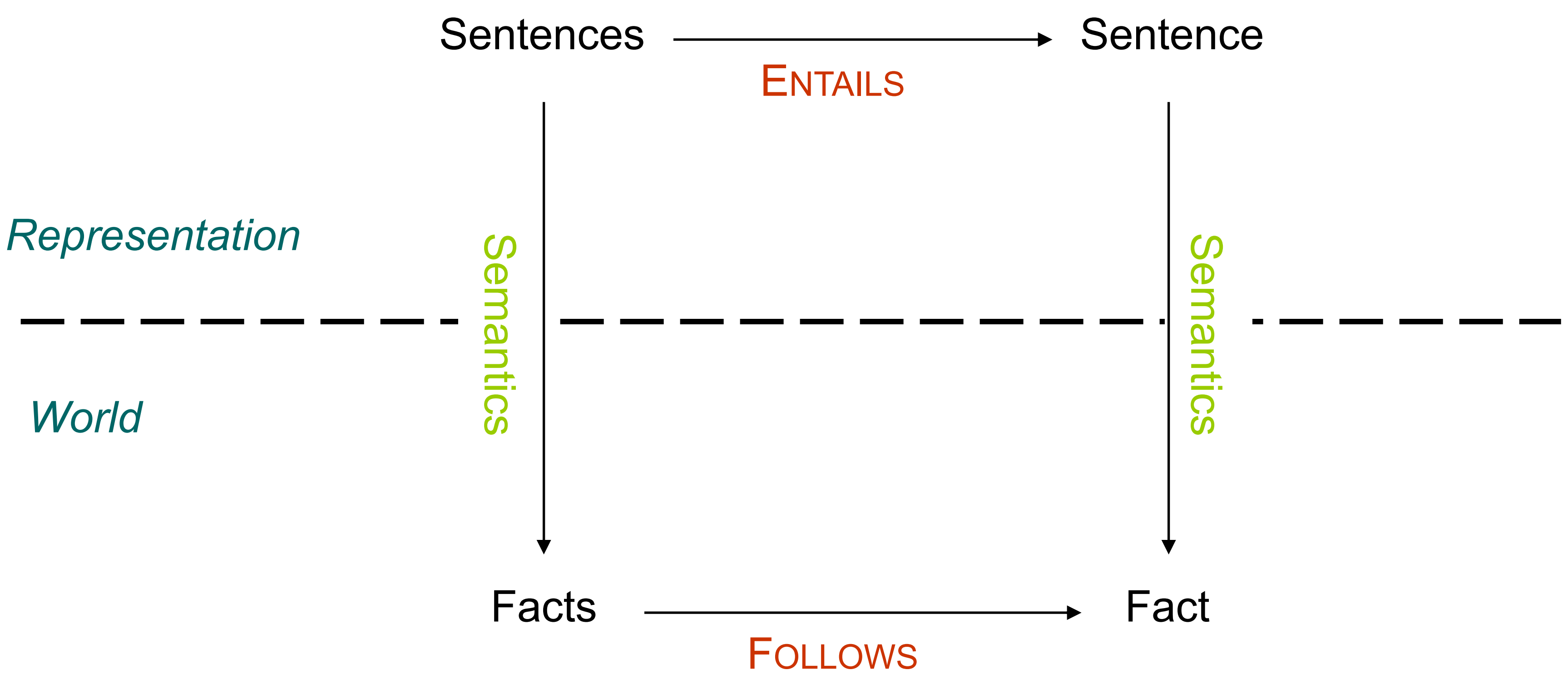


- Need a formal logic system to work
- Need a data structure to represent known facts
- Need an algorithm to answer ASK questions

Syntax and semantics

- Two components of a logic system
- Syntax --- How to construct sentences
  - The symbols
  - The operators that connect symbols together
  - A precedence ordering
- Semantics --- Rules the assignment of sentences to truth
  - For every possible worlds (or "models" in logic jargon)
  - The truth table is a semantics

Entailment



A is entailed by B, if A is true in all possible worlds consistent with B under the semantics.

Inference procedure

- Inference procedure
  - Rules (algorithms) that we apply (often recursively) to derive truth from other truth.
  - Could be specific to a particular set of semantics, a particular realization of the world.
- Soundness and completeness of an inference procedure
  - Soundness: All truth discovered are valid.
  - Completeness: All truth that are entailed can be discovered.

Propositional Logic

- Syntax:
  - *True, false,* propositional symbols
  - ( ) , $\neg$ (not), $\wedge$ (and), $\vee$ (or), $\Rightarrow$ (implies), $\Leftrightarrow$ (equivalent)

- **Semantics**:
  - Five rules (the following truth table)

P	Q	$\neg P$	$P \wedge Q$	$P \vee Q$	$P \Rightarrow Q$	$P \Leftrightarrow Q$
False	*False*	*True*	*False*	*False*	*True*	*True*
False	*True*	*True*	*False*	*True*	*True*	*False*
True	*False*	*False*	*False*	*True*	*False*	*False*
True	*True*	*False*	*True*	*True*	*True*	*True*

- **Inference rules**:
  - Modus Pronens etc.   Most important: Resolution

Propositional logic agent

- Representation: Conjunctive Normal Forms
  - Represent them in a data structure: a list, a heap, a tree?
  - Efficient TELL operation

- Inference: Solve ASK question
  - Use “Resolution” only on CNFs is Sound and Complete.
  - Equivalent to SAT, NP-complete, but good heuristics / practical algorithms exist

- Possible answers to ASK:
  - Valid, Satisfiable, Unsatisfiable

First order logic

- More expressive language
  - Relations and functions of objects.
  - Quantifiers such as, All, Exists.
- Easier to construct a KB.
  - Need much smaller number of sentences to capture a domain.
- Follow the same structure: Symbols, Semantics
- Dedicated inference algorithms
- (FOL inference is not covered in the Final)

Potential types of questions in FOL

- Translate FOL sentence to natural language or the other way round.

- Translate the rule of a simple game to FOL.

Lecture 18: Responsible AI

- What are the typical pitfalls in AI applications
  - Privacy: Data sharing,   data use, data ownership
  - Fairness of AI Decision making: Recidivism prediction, Admission / Recruiting
  - Polarizing effects of recommendation systems
  - Fake news / fake videos
  - Social impacts: unemployment / rich gets richer
  - Robustness and Safety: adversarial examples, self-driving cars

- What are your thoughts on overcoming them?
  - Potentially a case / short essay question.

- Your thoughts on Weak AI vs Strong AI.
  - And artificial general Intelligence…

Thank you and stay in touch!

- It’s a challenging quarter for everyone of us.
- It’s my pleasure to work with you!
- I hope the course is / will be useful.

- AI Research at UCSB
  - Machine Learning Lab
  - Natural Language Processing Lab
  - Center for Responsible Machine Learning
  - Center for Information Technology and Society
  - The Mellichamp Initiative in Mind & Machine Intelligence
  - Data Science Initiative