Artificial Intelligence

CS 165A

Jun 2, 2022

Instructor: Prof. Yu-Xiang Wang

Today

→ Final Review

Logistic notes

- Project 3 submission portal (finally!) open in Gradescope

- ESCI Survey:
  - Please submit your feedback if you haven't yet.
  - Deadline is approaching.

- Final: Next Monday 12:00 pm -- 3:00 pm.
  - Open book. No digital devices.
  - 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!)

Tips for studying for the final

- Focus on the lectures and concepts
  - So you don't get tricked in T/F, MCQ questions.
- No need to make a cheatsheet, but knowing which lecture to find which topic could be useful.
- 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

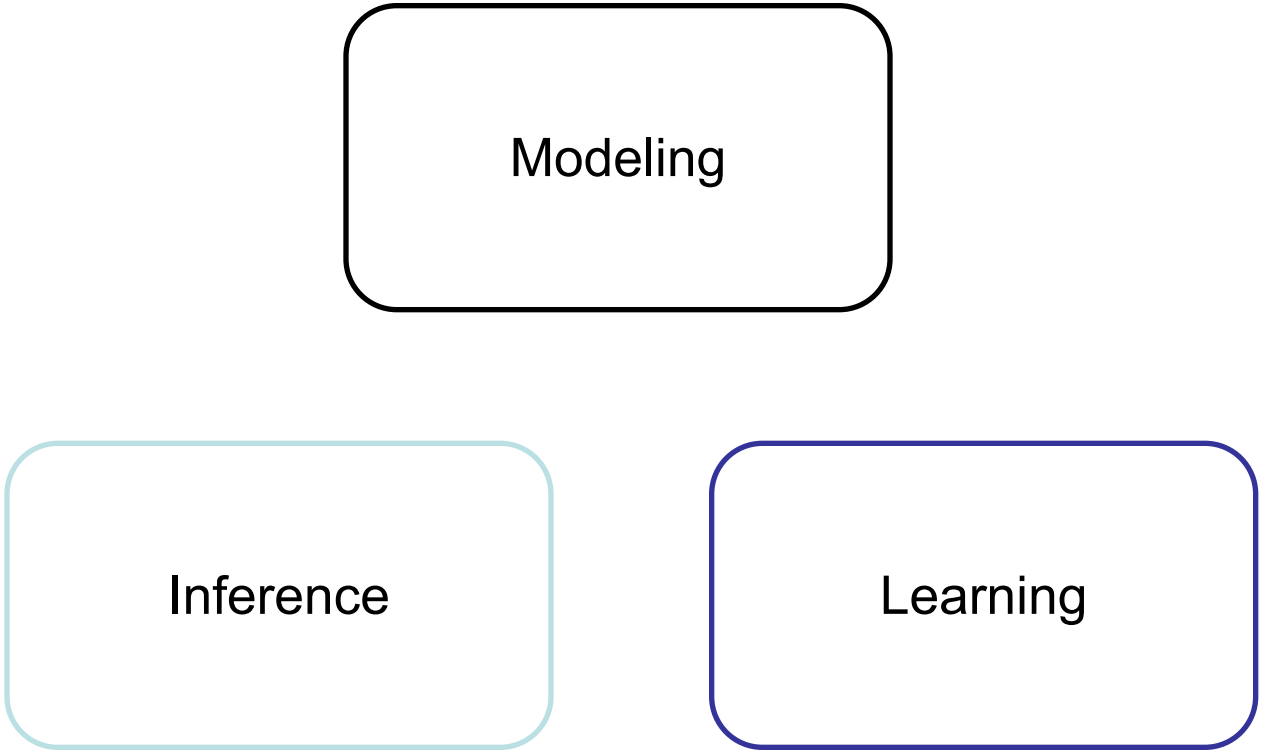
Logic

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

Classification / Regression
Bandits

Search
game playing

Markov Decision Processes
Reinforcement Learning

Logic, knowledge base
Probabilistic inference

Reflex Agents

Planning Agents

Reasoning agents

Low-level intelligence

High-level intelligence

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

Modeling-Learning-Inference Paradigm

	Modeling	**Learning**	**Inference**
Classifier agent (Spam filter)	Feature engineering Hypothesis class	Minimize Error rate	Prediction on new data points
Probabilistic Inference agent (Sherlock)	Joint distribution Draw edges in BN Conditional independences	Fitting the CPTs to Data	Marginalization (conceptually easy)
Search agents	State-Space-diagram	Environment given (learn edge weights) (Learn heuristics?)	Uninformed Search / A* Search etc…
Game playing agent	State-space-diagram	**Learn opponent model? Learn evaluation functions?**	**Minimax Search / Expetimax**

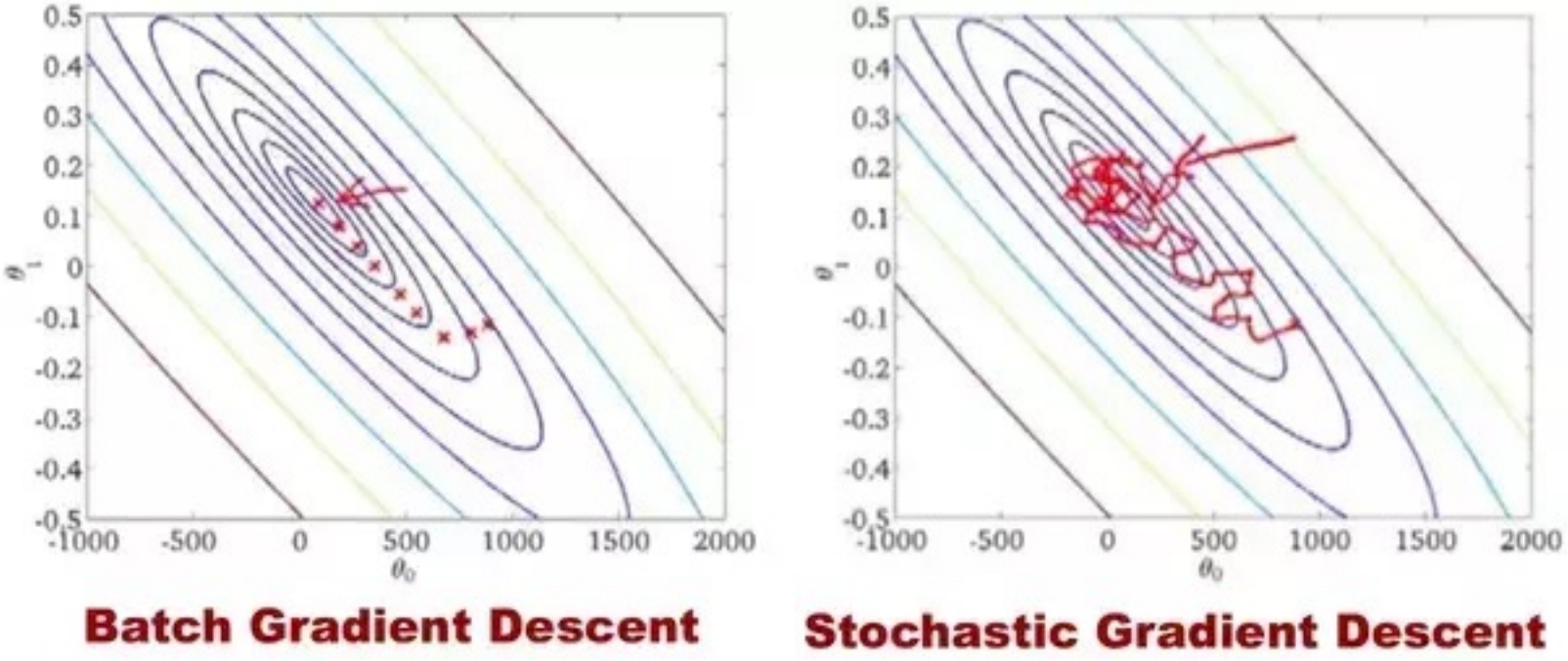
Modeling-Learning-Inference Paradigm

	Modeling	Learning	Inference
Planning Agent	MDPs: State-representation / reward design	Not much	Value Iteration / Policy iterations /
Reinforcement Learning Agent	Same as above. But also function approximation	Model based: Estimate MDP parameter + VI / PI Model free: Monte Carlo. SARSA. Q-Learning (with linear function approx) . Policy Gradient	
Logic Agent	Formal logic: Syntax / Semantics Representing the knowledge using FOL	n.a.	Logic inference: CNF / Resolution Modus Ponens

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

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

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

$O(e^N)$

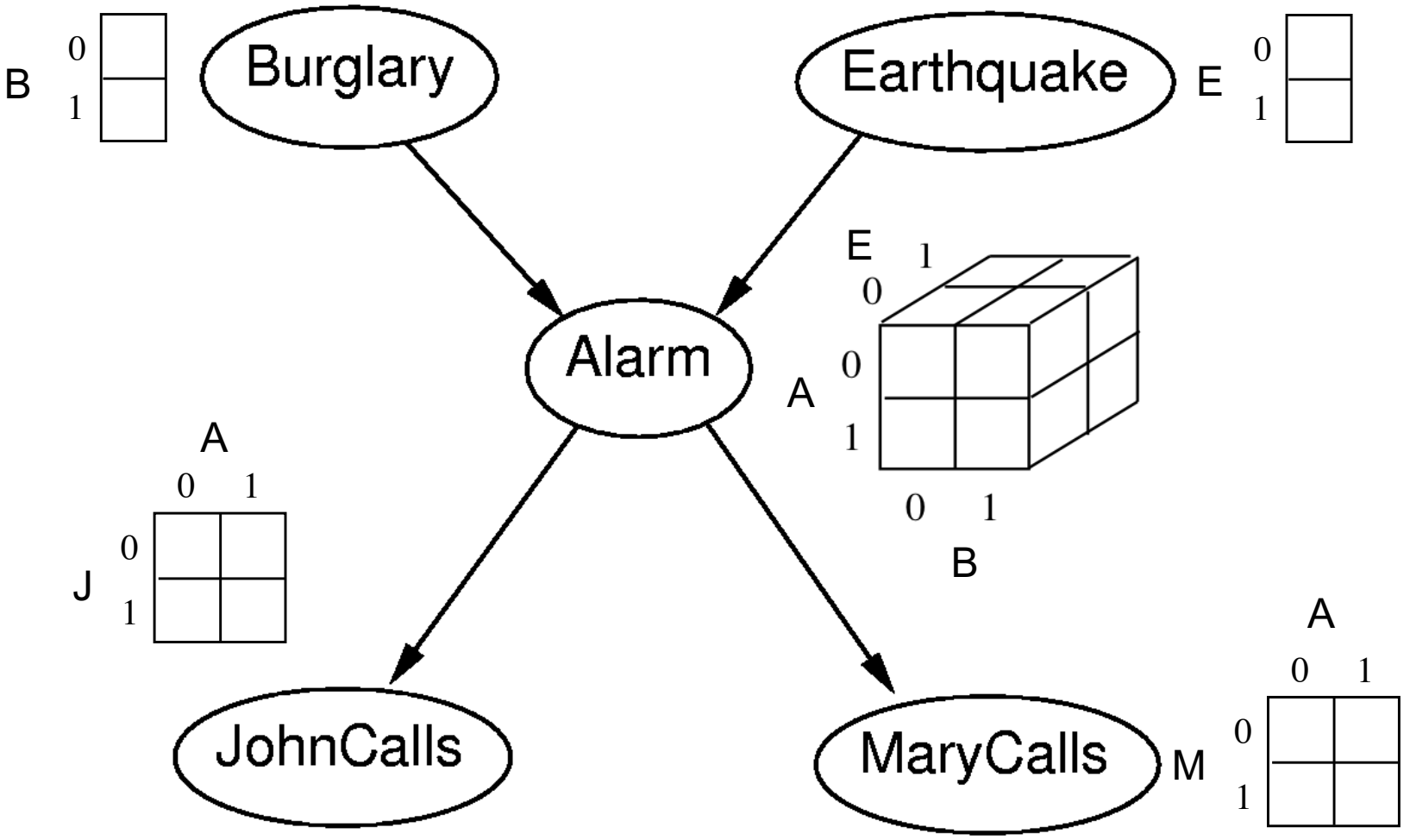
Space / computation efficiency

Expressiveness

Idea:

1. Independent groups of variables?
2. **Conditional independences?**

What are the CPTs? What are their dimensions?

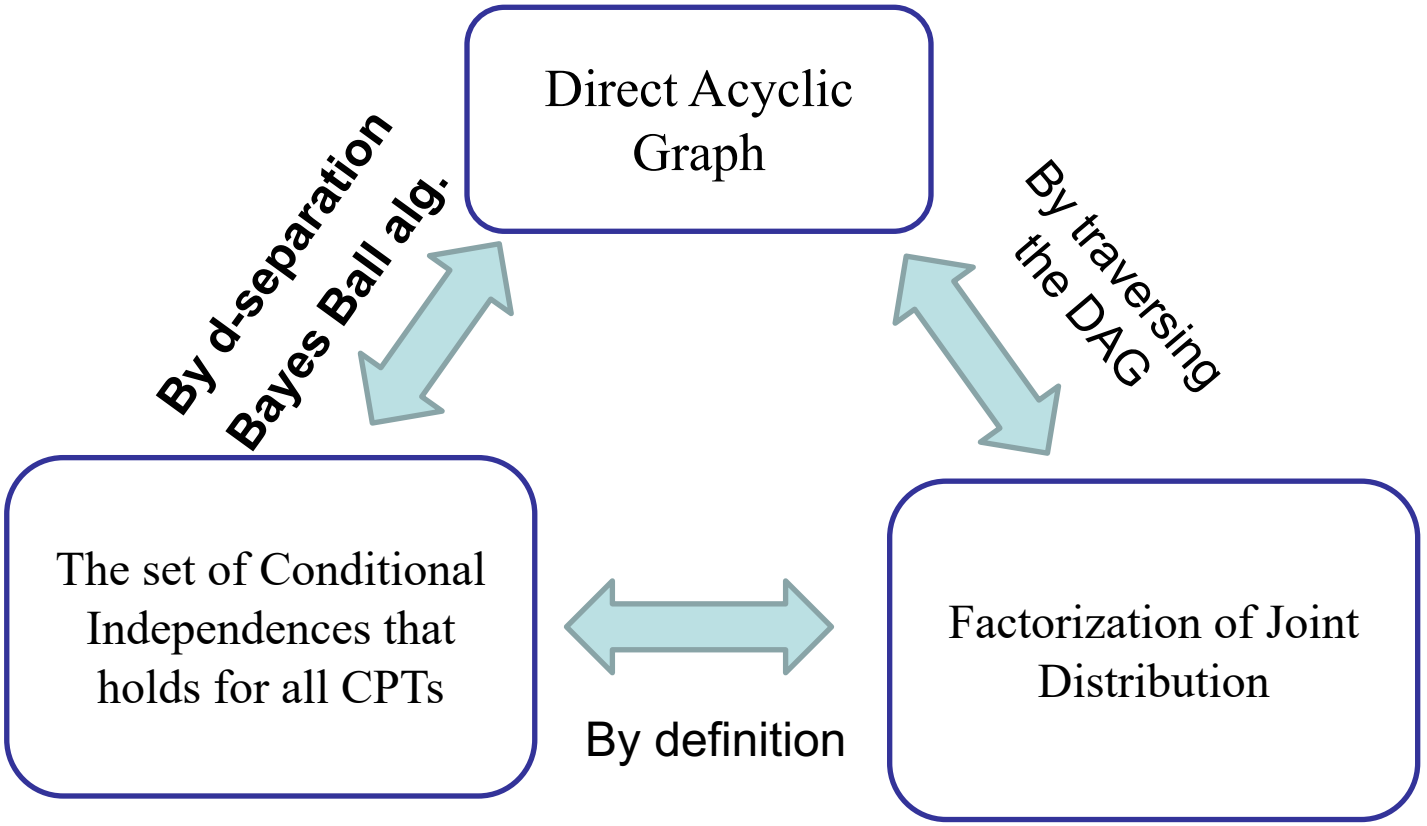


Question: How to fill values into these CPTs?

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

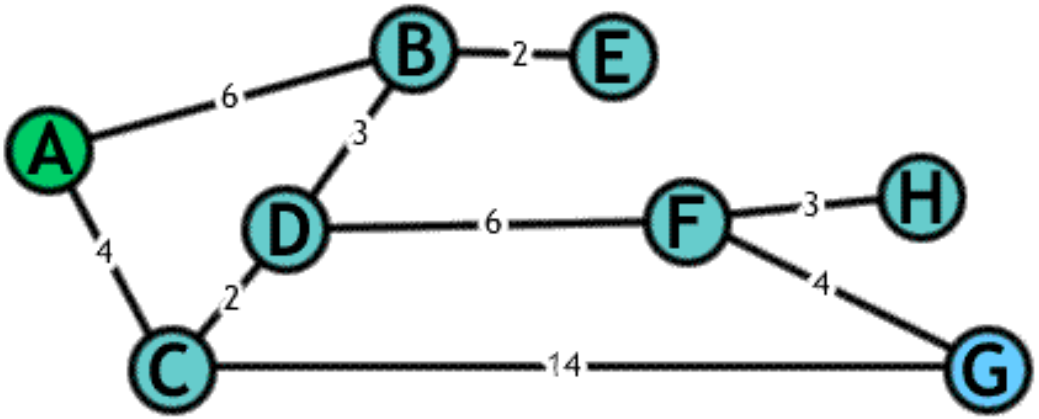
- Problem solving by search
  - Abstraction, problem formulation
  - State-space diagram
  - Count the number of states, number of actions.
- Uniformed Search algorithms
  - Four evaluation criteria
- Informed (heuristic) search
  - Admissible / consistent heuristics
  - Tree-search vs graph search
- **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
    - **S_0**: Initial state of the agent
    - **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 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

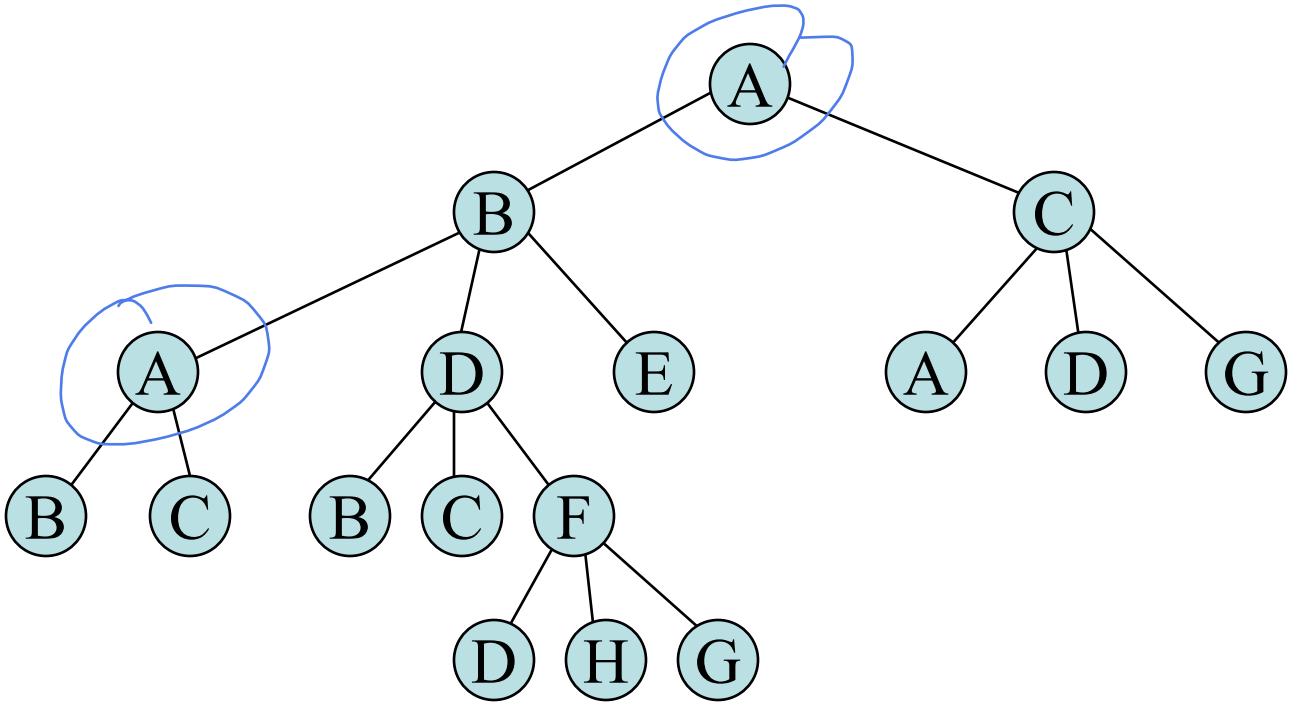
State-Space Diagrams

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



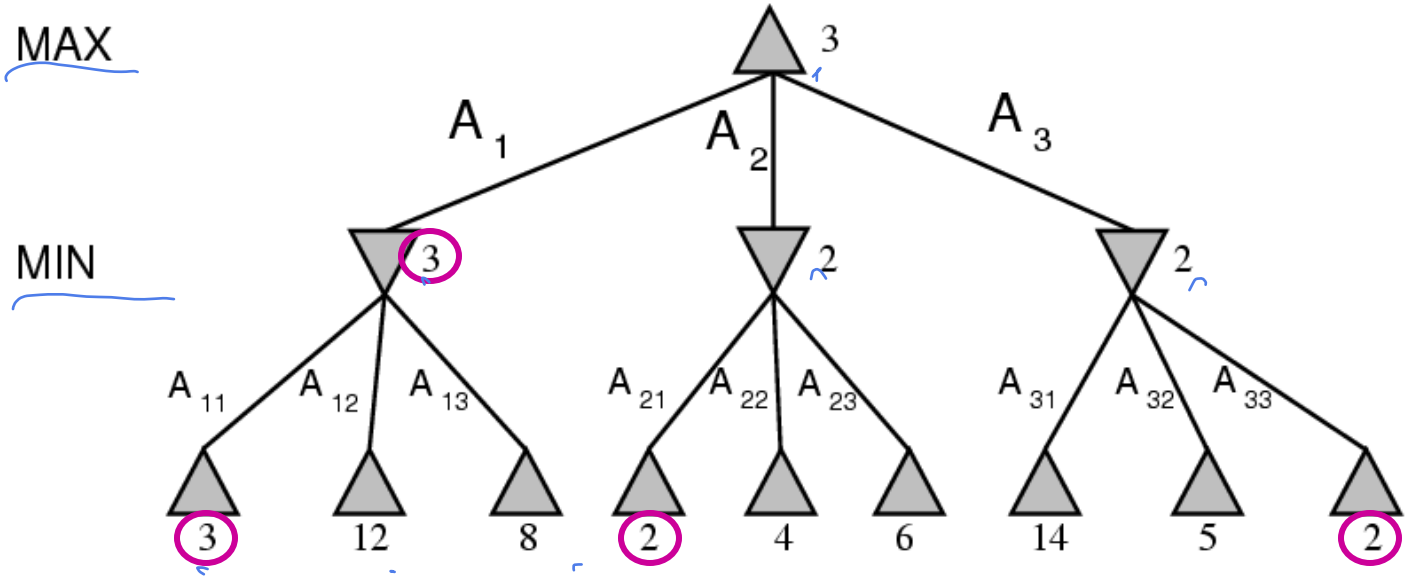
State Space vs. Search Tree (cont.)

Search tree (partially expanded)



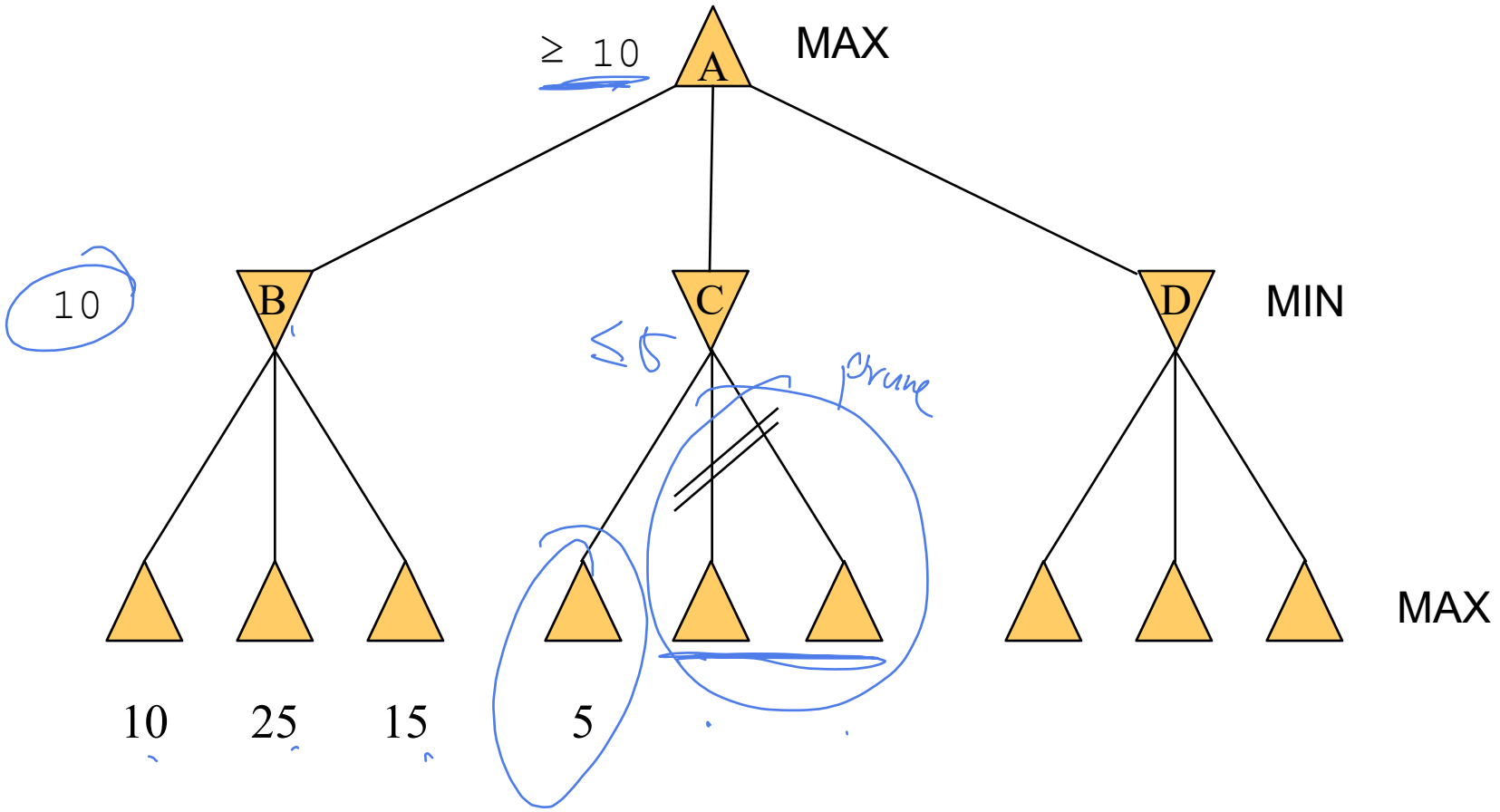
Minimax example

Which move to choose?

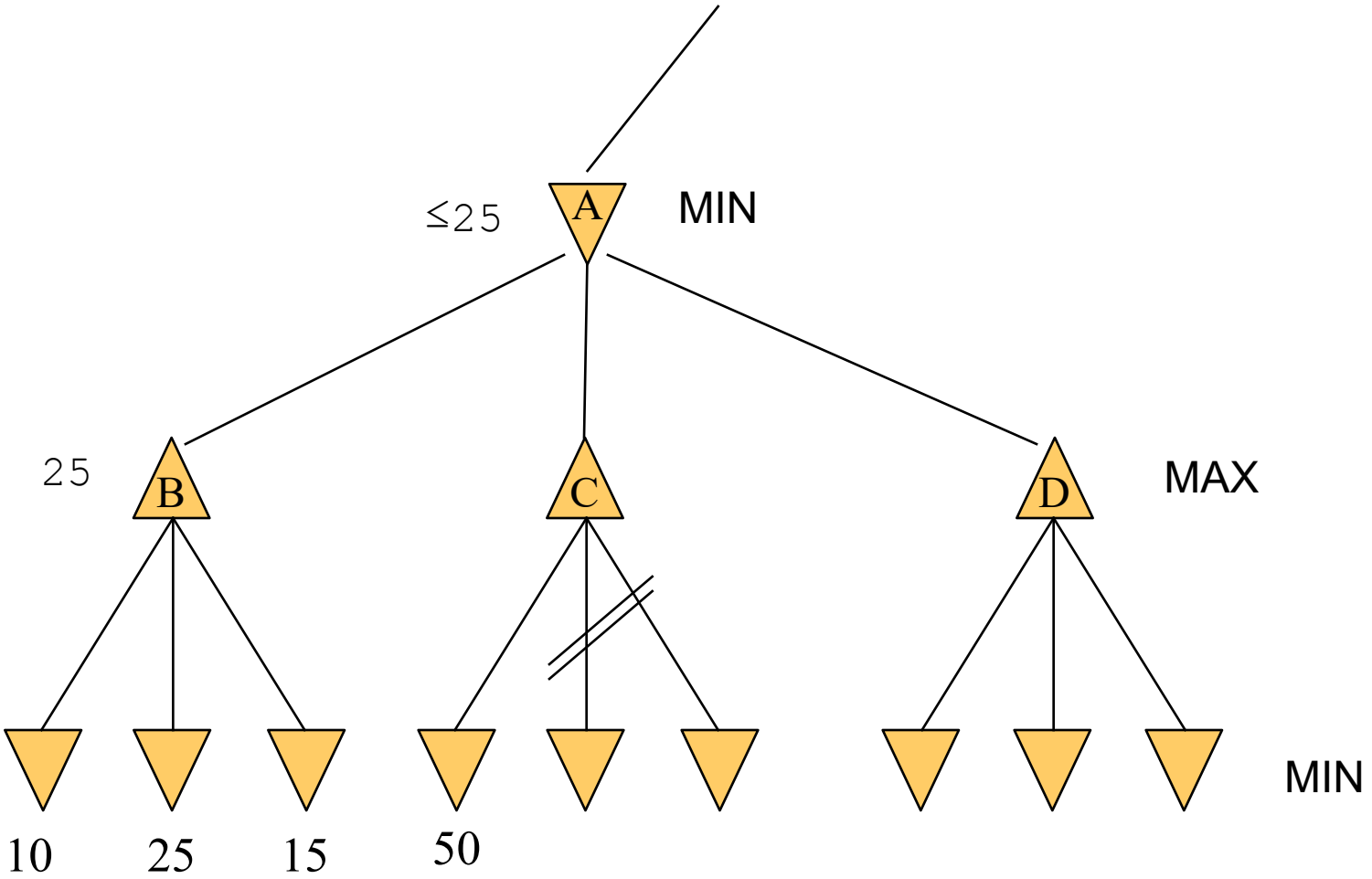


The **minimax decision** is move $\mathbf{A_1}$

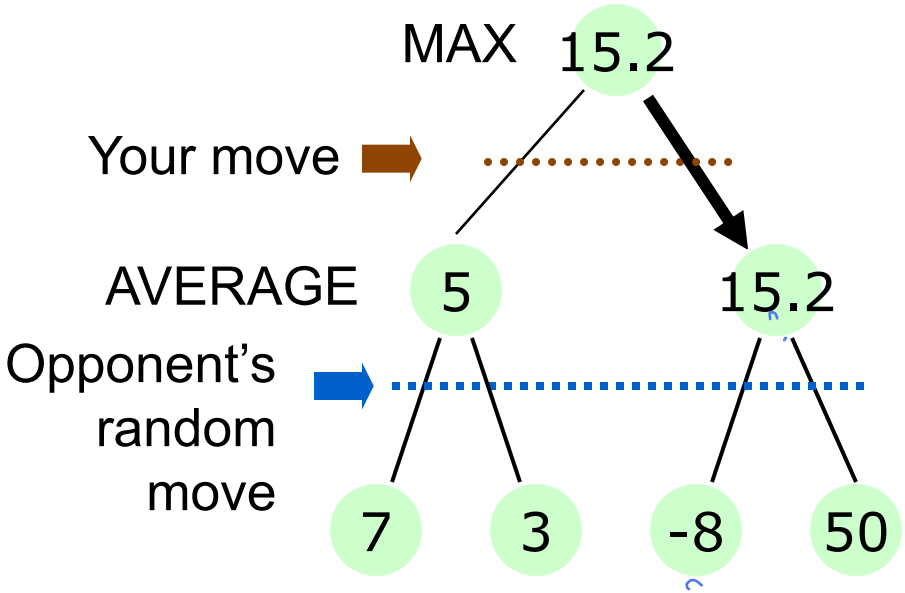
Alpha pruning



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

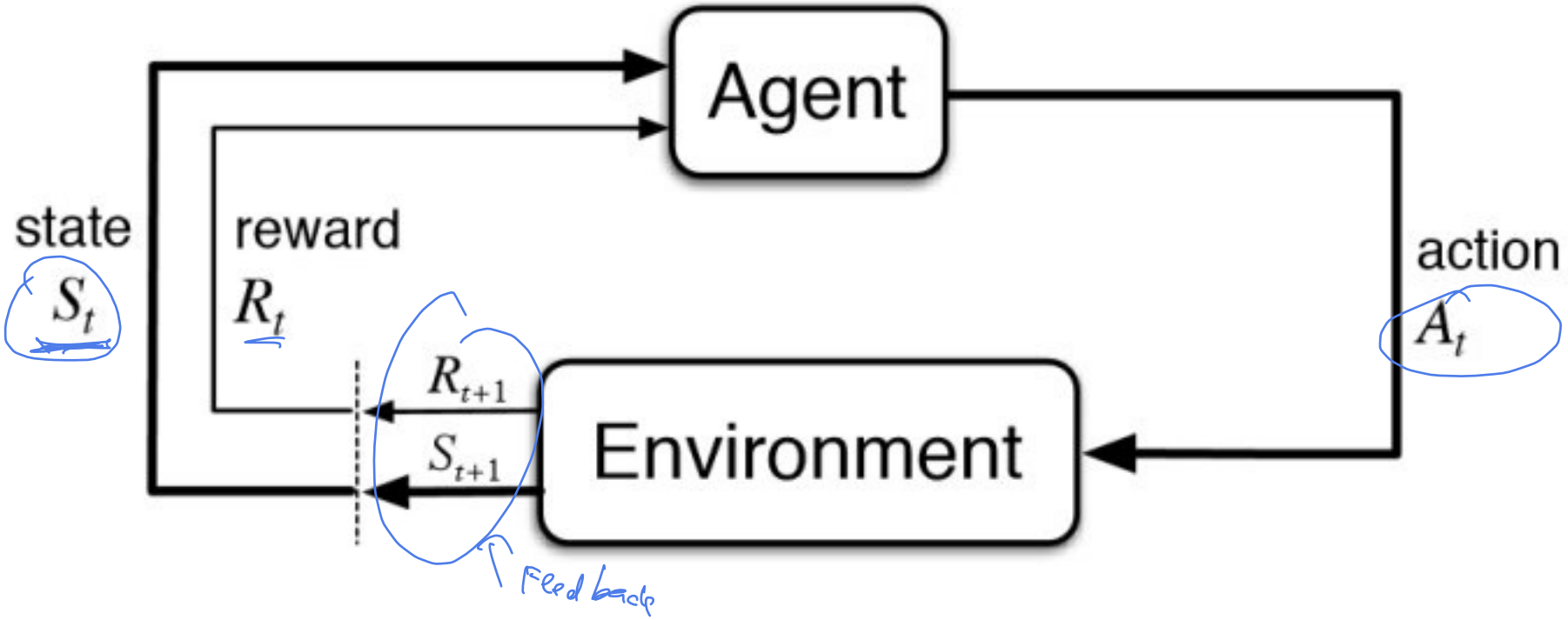
- Markov Decision Processes
  - New concepts: reward, value function, policy, transition dynamics
  - Bellman equations
  - Iterative algorithms for finding the optimal policy

- 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

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

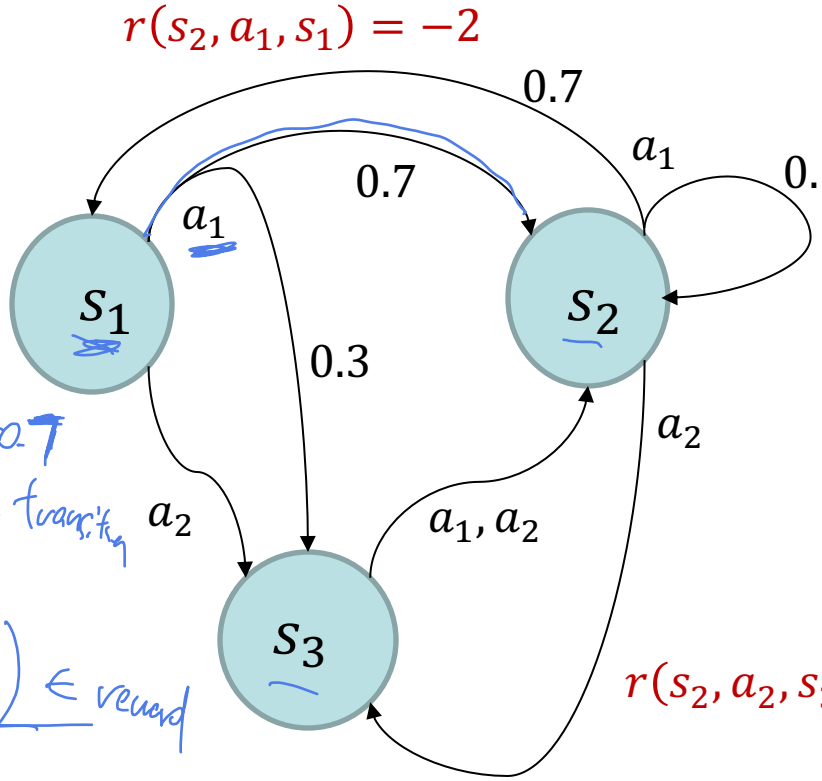
- Policy:
  - When the state is observable: $\pi : \mathcal{S} \to \mathcal{A}$
  - ~~Or when the state is not observable~~

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

- 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

State-space diagram representation of an MDP: An example with 3 states and 2 actions.



$|S| = 3$

$|A| = 2$

$O(S^2A)$ → $P(S' | S, A=a)$ ∈ transition $a = a_1$

$P(R | S, A, S')$ ∈ reward

$P(S_1)$ – initial state distribution

$E[R | S, A, S']$

$O(S^2A)$

0

* The reward can be associated with only the state s' you transition into.
* Or the state that you transition from s and the action a you take.
* Or all three at the same time.

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

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

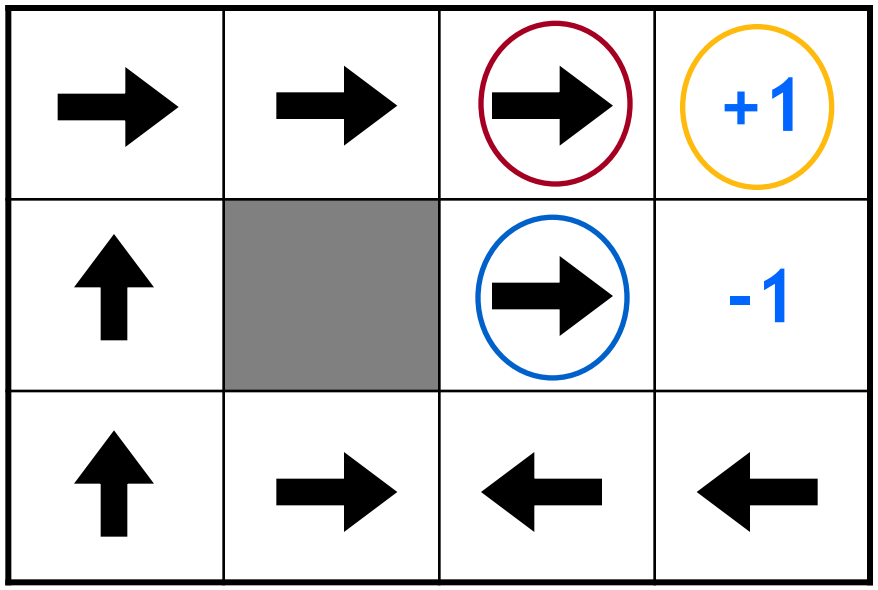
  - V* function Bellman (optimality) equation

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

  - 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

$$\pi_0 \rightarrow^E V^{\pi_0} \rightarrow^I \pi_1 \rightarrow^E V^{\pi_1} \rightarrow^I \ldots \rightarrow^I \pi^* \rightarrow^E V^*$$

- 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

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

- Policy improvement

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

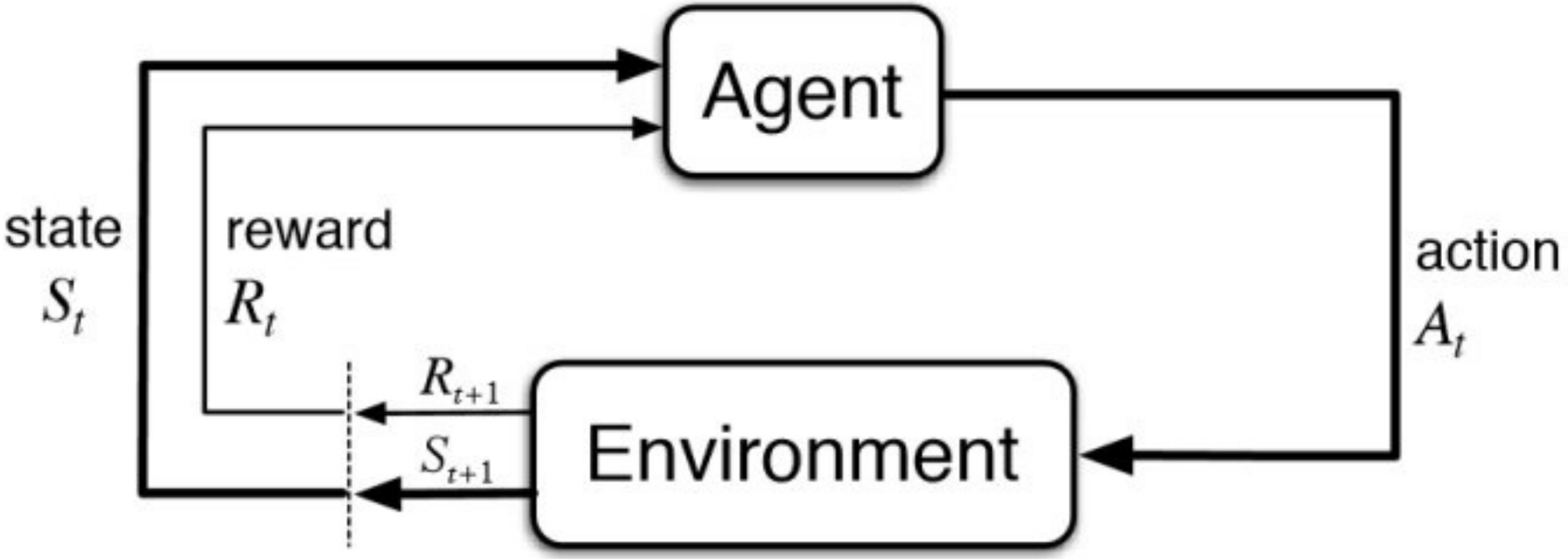
- Value iterations

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

***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

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

  - 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.

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

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

Q-Learning with function approximation

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

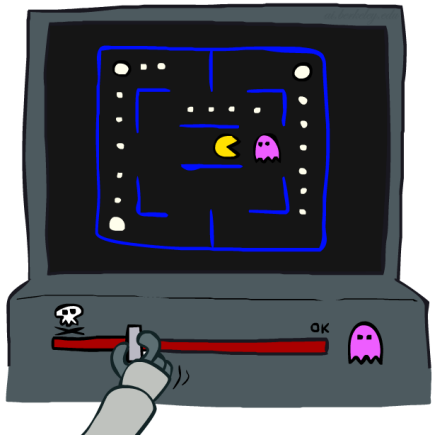
- Q-learning with linear Q-functions:

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

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

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

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



- 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.

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
- 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.

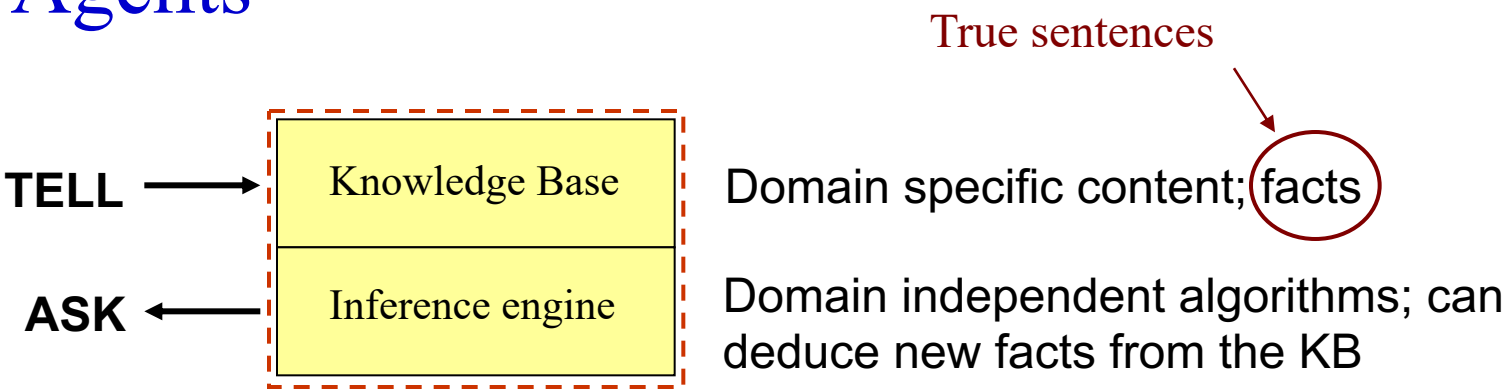
- Knowledge Base
  - Tell operation
  - Ask operation

- Components of a formal logic system
  - Syntax, Semantics

- Definition of Valid / Unsatisfiable

- Conversion to CNF

KB Agents



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

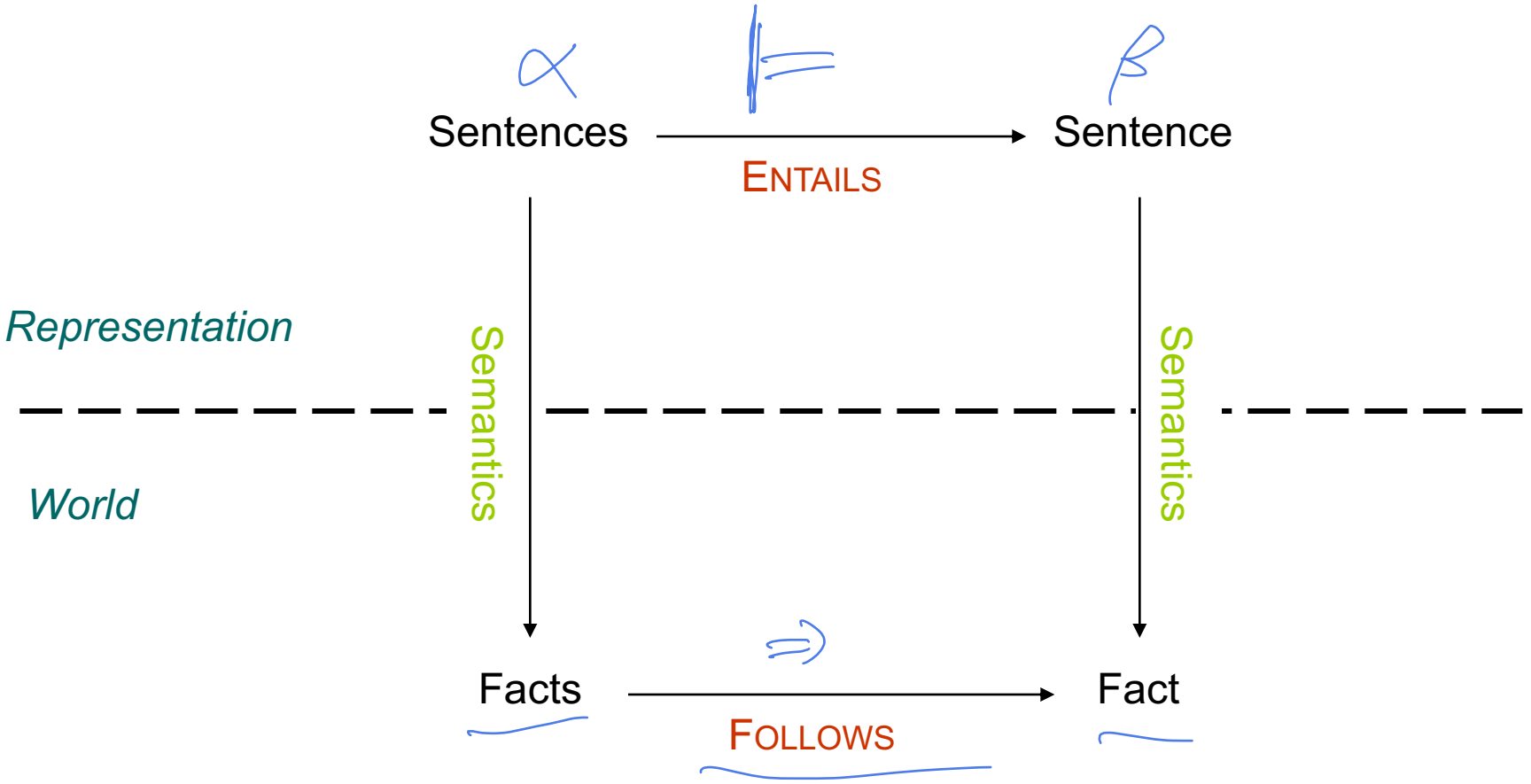
Syntax and semantics

- 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 facts from other facts.
  - 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
  - ( ) , ¬ (not), ∧ (and), ∨ (or), ⇒ (implies), ⇔ (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 / 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

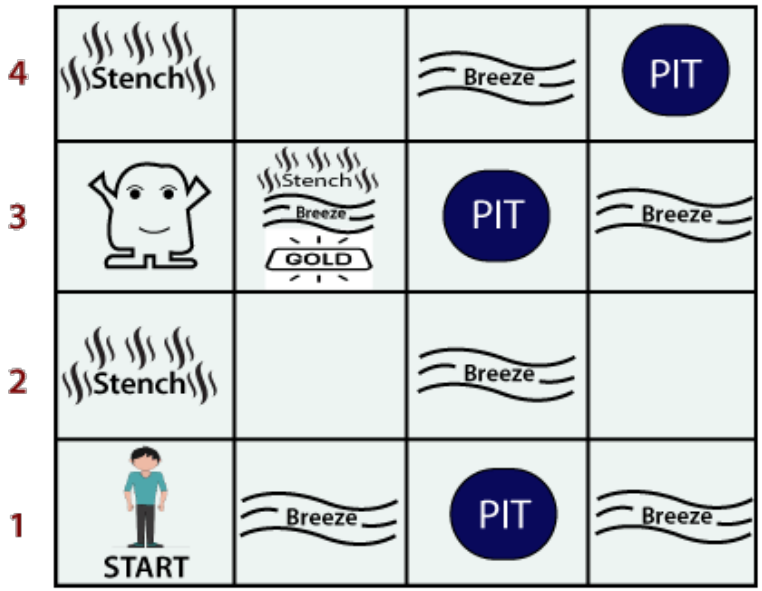
- More expressive language
  - Relations and functions of objects.
  - Quantifiers such as, All, Exists.
- Easier to construct a KB.
  - Need much smaller number of sentences to capture a domain.
- Follow the same structure: Symbols, Semantics
- Dedicated inference algorithms
- (FOL inference is not 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.
  - e.g., how would you describe the rules of Wumpus world using FOL?

FOL Description of a Wumpus world



$\forall\ (i,j)$

$Wumpus((i,j)) \Rightarrow \forall x\ Stench(x) \wedge Neighbor(x,(i,j))$

- What are the rules? How to write them down in FOL?

$\forall x,y\ \ Neighbor(x,y) \Rightarrow$ $\left(\left(|x(0)-y(0)|=1 \vee |x(1)-y(1)|=0\right) \vee \left(|x(0)-y(0)|=0 \wedge |x(1)-y(1)|=1\right)\right)$

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
  - Generative models: ethics and copyright

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

Courses to take next on the AI track

- CS165B Machine Learning (almost every quarter)
  - Undergraduate level intro to ML
  - Expanded version of Part 1 in this course

- CS291K (2022 Fall): Machine Learning
  - Co-taught by Lei Li and myself
  - Graduate level intro to ML (also open to advanced undergrads)
  - https://sites.cs.ucsb.edu/~lilei/course/ml22fa/index.html

- Other advanced topics courses in AI:
  - Deep Learning, Natural Language Processing, Computer vision, Convex Optimization, Reinforcement Learning

Thank you and stay in touch!

- 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