CSCE 580: Introduction to AI

Week 11 - Lectures 20 and 21: Making Decisions – Simple and Complex

PROF. BIPLAV SRIVASTAVA, AI INSTITUTE

28TH AND 30TH OCT 2025

Carolinian Creed: "I will practice personal and academic integrity."

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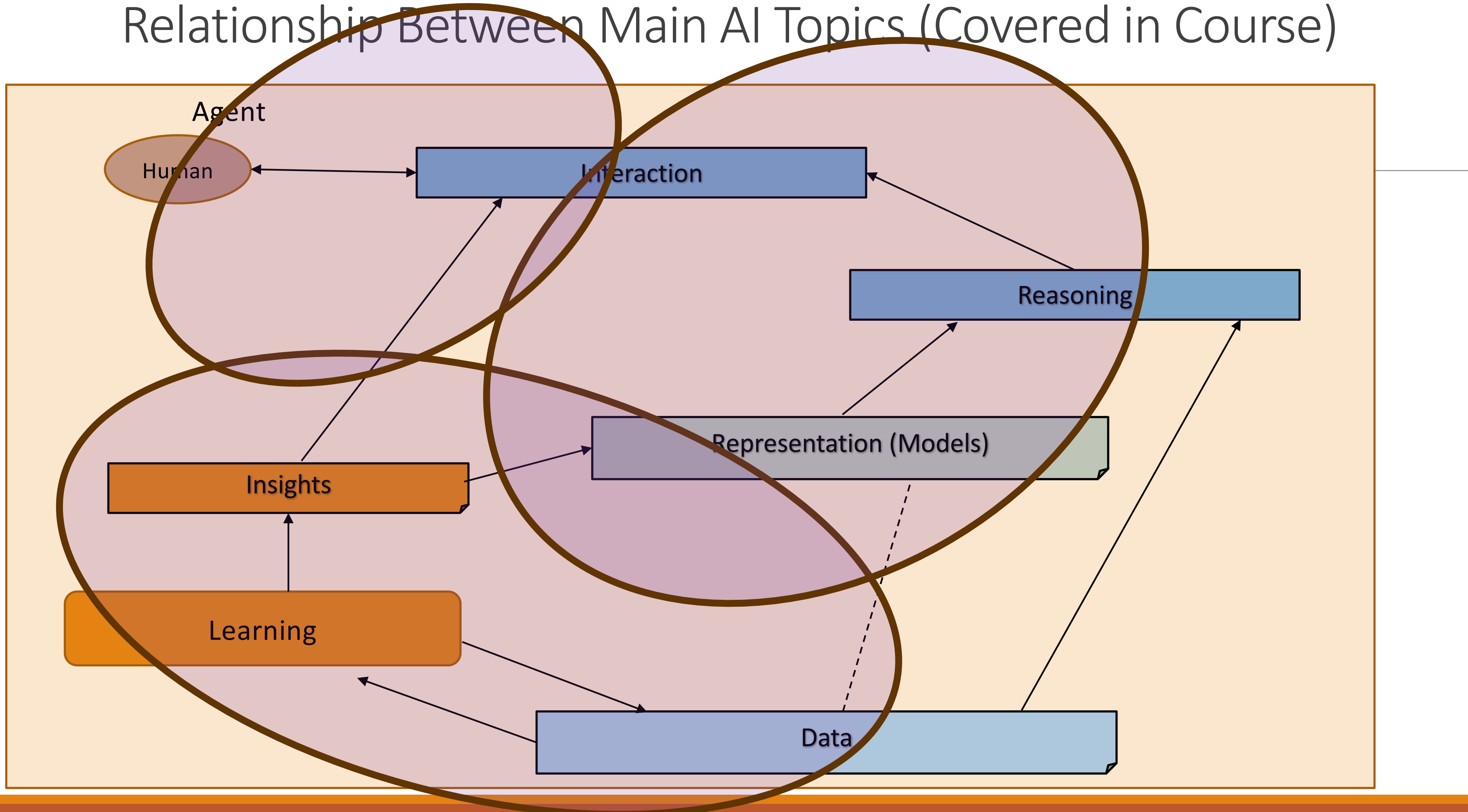
Organization of Week 11 - Lectures 20, 21

- Introduction Section
  - Recap from Week 10 (Lectures 18 and 19)
  - AI news
- Main Section
  - Lecture 20: Making Decisions - Simple
  - Lecture 21: Making Decisions - Complex
- Concluding Section
  - About next week – W12: Lectures 22, 23
  - Ask me anything

Relationship Between Main AI Topics (Covered in Course)



Recap of Week 11

We discussed

- Adversarial and Game Search
- Optimization

- Week 1: Introduction, Aim: Chatbot / Intelligence Agent
- Weeks 2-3: Data: Formats, Representation and the Trust Problem
- Week 3: Machine Learning – Supervised (Classification)
- Week 4: Machine Learning - Unsupervised (Clustering) –
- Topic 5: Learning neural network, deep learning, Adversarial attacks
- Week 6: Large Language Models – Representation and Usage issues
- Weeks 7-8: Search, Heuristics - Decision Making
- Week 9: Constraints, Optimization – Decision Making
- Topic 10: Markov Decision Processes, Hidden Markov models - Decision making
- Topic 11-12: Planning, Reinforcement Learning – Sequential decision making
- Week 13: Trustworthy Decision Making: Explanation, AI testing
- Week 14: AI for Real World: Tools, Emerging Standards and Laws; Safe AI/ Chatbots

Upcoming Evaluation Milestones

- **Projects B: Sep 30 – Nov 20**
- Quiz 2: Oct 7
- **Quiz 3: Nov 11**
- Paper presentation (grad students only) : Nov 18
  - Put paper names in spreadsheed
- Finals: Dec 11

AI News

#1 NEWS – Rules to Label AI Content (India)

- **Link**: https://theprint.in/opinion/labelling-ai-content-india-ai-regulation/2769941/
- **Link**: https://www.forbesindia.com/article/news/explained-indias-ai-content-labelling-regulation/2988179/1

- India proposes strict rules to label AI content citing growing risks
  - The Ministry of Electronics and Information Technology (MeitY) has proposed a draft amendment to the Information Technology (Intermediary Guidelines and Digital Media Ethics Code) Rules, 2021, aimed at curbing the spread of deepfakes and misinformation online. The draft released on October 22 mandates that AI (artificial intelligence) and social media platforms must label AI-generated content.
- Require platforms to label AI-generated content with markers covering at least 10% of the surface area of a visual display or the initial 10% of the duration of an audio clip.
- Social media companies will also have to obtain a user declaration on whether uploaded information is AI-generated, and deploy reasonable technical measures to ensure checks and balances
- "Studies show that rules mandating AI labels may enhance transparency, but they don't significantly change the persuasiveness of the content itself. This is where the complementary safeguard of media literacy for users also becomes imperative."

#2 NEWS – Taxonomy of Human-AI Collaboration

- **Link**: https://news.engin.umich.edu/2025/10/a-common-language-to-describe-and-assess-human-agent-teams/
- **Paper**: https://journals.sagepub.com/doi/10.1177/00187208251376898

The taxonomy classifies how teams are structured and how they function, using ten attributes:

1. **Team composition**—number of humans to number of agents
2. **Task interdependence**—the extent team members depend on the action of others
3. **Role structure**—the extent roles are fundamentally different or interchangeable
4. **Leadership structure**—the pattern, or distribution, of leadership functions such as setting discretion and aligning goals among team members (e.g., external manager, designated, temporary, distributed)
5. **Leadership role assignment**—whether the human, the agent or both assume leadership roles
6. **Communication structure**—the pattern or flow of information sharing among team members
7. **Communication direction**—between humans and agents, among humans and among agents
8. **Communication medium**—the available ways to exchange information
9. **Physical distribution**—spatial location of team members to one another
10. **Team life span**—how long the team exists as a functional, active unit issues in 76% of responses, more than double the other assistants, largely due to its poor sourcing performance.

Introduction Section

Main Section

Lecture 20:
Making Simple Decisions

Real World Decisions

Decision situation: going to airport from home

- Actions:
  - Take own car
  - Take a cab/ limo
  - Take a ride-share
  - Take a bus
  - Hitch-hike
  - Walk

Financial Advice: Students at a College Campus

An ideal solution should be:

- free of any errors (Ex: grammatical, calculation, etc.)
- utilize all the information given by the user completely and give a reasonable, practical, and optimal solution.

Example Query:
I am making a purchase of $1000 using my credit card. I have a due of $2000 on my account. My total credit line is $2,800. Would you recommend I make the purchase now or later in the future?

Ideal Solution:
Based on the information you have provided, it is not advisable to make the purchase now as you already have a due of $2000 on your account, which is close to your total credit line of $2,800. This means you are utilizing a significant portion of your available credit, and adding another $1000 to your balance would further increase your credit utilization ratio (CUR), which can negatively impact your credit score.

Decision support from a LLM-based Chatbot, 2023 – excerpt from
LLMs for Financial Advisement: A Fairness and Efficacy Study in Personal Decision Making, *4th ACM International Conference on AI in Finance: ICAIF'23, New York, 2023*
Kausik Lakkaraju, Sara Rae Jones, Sai Krishna Revanth Vuruma, Vishal Pallagani, Bharath C Muppasani and Biplav Srivastava

The Quality of Everyday Decisions

Major variability due to:
- Emotions
- Biases
- Increasing data volume
- Cognitive ability to process
  - Decreases under stress and constraints
  - Decreases with age*

Source: https://www.umassd.edu/fycm/decision-making/process/

* **Source**: A Review of Decision-Making Processes: Weighing the Risks and Benefits of Aging, Mara Mather, https://www.ncbi.nlm.nih.gov/books/NBK83778/

Evidence #1:
Poor Medical Adherence

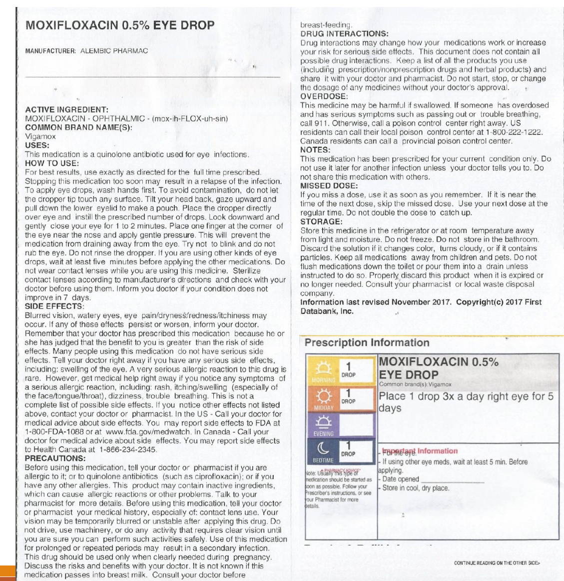
Finding relevant guidance is hard, one reason for non-adherence and high costs in health

Sources:
- Medication Nonadherence, A Diagnosable and Treatable Medical Condition, Zachary A. Marcum, Mary Ann Sevick, Steven M. Handler, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3976600/, 2013.
- https://www.nytimes.com/2017/04/17/well/the-cost-of-not-taking-your-medicine.html

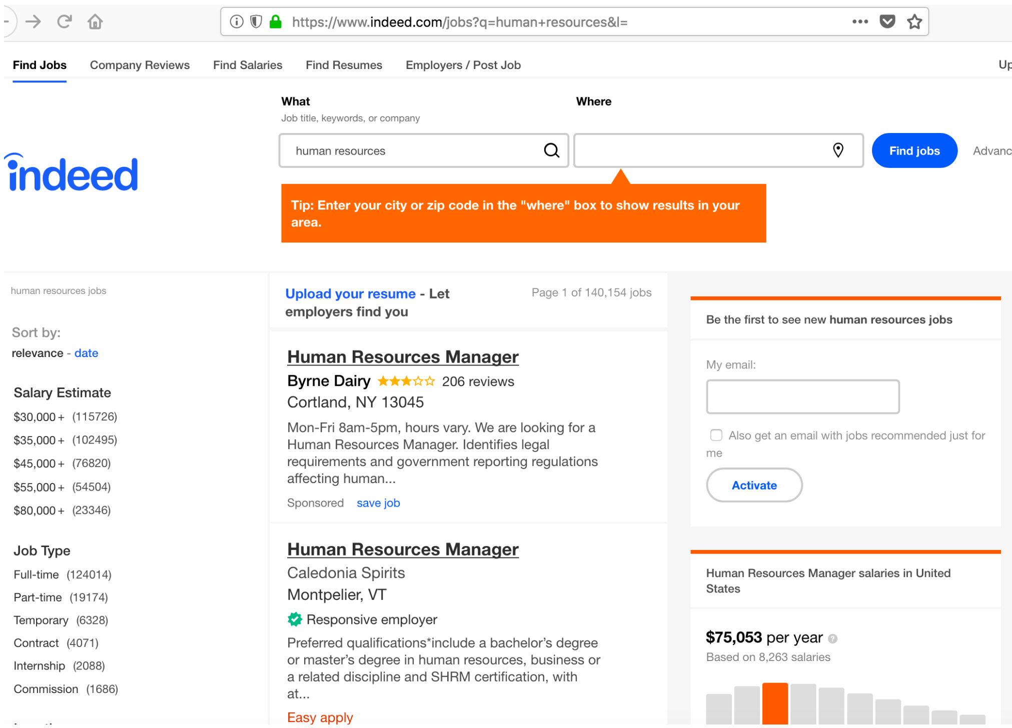
Taking medicines
- 20 -30 % of medication prescriptions are never filled
- ~50 % of medications for chronic disease are not taken as prescribed

Impact
- causes 125,000 deaths, at least 10 percent of hospitalizations
- Costs the American health care system between $100 billion and $289 billion a year.

Example:
Hard to understand medicine's information



Evidence #2: Matching Demand to Supply of Jobs is Inadequate Demand-Supply Gap in Jobs Market [1] and Yet, Low Work Satisfaction/ Engagement [2]



Job search at a portal

- Finding jobs was generally hard around the world (Dec 2019), except for in tight labor markets like US (3.5% unemployment)
- Workforce satisfaction/ engagement was generally low around the world – people did not find jobs they were match for [1,2]
- COVID-19 impact [3]:
  - *Nearly half of global workforce at risk of losing livelihoods in informal sector*
  - *9-12% job loss in the formal sector around the world*
  - *14.7% unemployment in US by end of April 2020 [4]*

1. **Source**: Global Skills Trends, Training Needs and Lifelong Learning Strategies for the Future of Work, ILO & OECD Report 2018, http://www.g20.utoronto.ca/2018/g20_global_skills_trends_and_lll_oecd-ilo.pdf
2. **Source**: For 2016, job satisfaction: US – 32%, Global – 13%, https://www.gallup.com/workplace/236495/worldwide-employee-engagement-crisis.aspx
3. **https://www.ilo.org/global/about-the-ilo/newsroom/news/WCMS_743036/lang--en/index.htm**
4. **https://www.bls.gov/news.release/empsit.nr0.htm**

Decision Imperative: Corona Virus Pandemic

Emerging Scenario Around the World*

- Millions of cases, hundreds of thousands of deaths
- Businesses disrupted, millions going out of business
- Millions loosing jobs

* Numbers changing continuously; see reference for details

Decisions Need to be Made

- About disease
  - Understand disease
  - Tackle disease
- Understand impact to society: economy, supply chain
- Advise on actions to take
  - Individual
  - Group
  - Societal policy

Resource: https://github.com/biplav-s/covid19-info/wiki/Important-Information-About-COVID19

Before and After: (AI) Decision Support

Today's tools: Static, non-interactive, non-contextual, lack explanations

Future tools: Dynamic to data, interactive, contextual, explaining with data, anywhere, multi-modal, social (group dependency), societally relevant, …

An AI future has potential to improve people's lives, promote well-being and reduce waste

Simple Decisions

Setting for a Decision

- An agent has a set of actions available, $A = \{a_i\}$ and is in a state s
- There may be an uncertainty about current state. So, the agent assigns a probability to current state P(s) for each possible current state.
- When an action is taken, there may be uncertainty about outcome. So, resulting state is:
  $P(s' \mid s, a)$
- The probability of reaching state s' after executing a in the current state is:
  $P(\text{RESULT}(a) = s') = \Sigma_s P(s) P(s' \mid s, a)$

Note: P(RESULT(a) = s') requires perception, learning, knowledge representation and inference

Adapted from:
Russell & Norvig, AI: A Modern Approach

Making a Simple Decision

- Choose best action based on the desirability of immediate outcome
- Have a utility function U(s) expressing desirability of a state (s)
- **Expected utility** of an **action,** given the evidence, EU(a), is
  the average utility value of the outcome, weighted by the probability of that outcome.

$$EU(a) = \Sigma_{s'} \; P(RESULT(a) = s') \; U(s')$$

- Principle of **maximum expected utility (MEU):** rational agent chooses an action which maximizes its maximum expected utility

$$action = \text{argmax}_a \; EU(a)$$

Decision situation: going to airport from home

- Actions:
  - Take own car
  - Take a cab/ limo
  - Take a ride-share
  - Take a bus
  - Hitch-hike
  - Walk

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Utility Functions: Modeling Preferences

- Notations
  - A > B: agent (decision maker) prefers A over B
  - A ~ B: agent (decision maker) is indifferent between A and B
  - A ≳ B: agent (decision maker) prefers A over B or is indifferent between A and B
- Convention
  - Outcome of an action is a lottery: $L = [p_1,S_1;\ p_2,S_2;\ \ldots;\ p_n,S_n]$
- Utility function U
  - U(A) > U(B), if and only if, A > B
  - U(A) = U(B), if and only if, A ~ B

Example: Choosing a Winning

- Won a game and have to choose
  - Choice 1: Take $1M
  - Choice 2: Toss coin; Heads => $2.5 M, Tails => 0
- What will you choose?

Example: Choosing a Winning

- Won a game and have to choose
  - Choice 1: Take $1M
  - Choice 2: Toss coin; Heads => $2.5 M, Tails => 0
- Expected Monetary Value (EMV)
  - Choice 1: $1M
  - Choice 2: (½ . $2.5M) + (½ . 0) = $1.25M

Example: Choosing a Winning

- Won a game and have to choose
  - Choice 1: Take $1M
  - Choice 2: Toss coin; Heads => $2.5 M, Tails => 0
- Expected Monetary Value (EMV)
  - Choice 1: $1M
  - Choice 2: ½ . $2.5M + ½ . 0 = $1.25M
- **Expected Utility depends on current money held**

Example: Choosing a Winning

- Won a game show and have to choose
  - Choice 1: Take \$1M
  - Choice 2: Toss coin; Heads => \$2.5 M, Tails => 0
- Expected Utility depends on current money(k)
  - EU(Accept) = ½ U(S_k) + ½ U($S_{k+ \$2.5M}$)
  - EU(Decline) = U($S_{k+ \$1M}$)
- Grayson (1960) found that the utility of money was almost exactly proportional to the logarithm of the amount.
  - U(Sk+n) = –263.31 + 22.09 log(n + 150, 000)

    for the range between n = –\$150, 000 and n = \$800, 000.

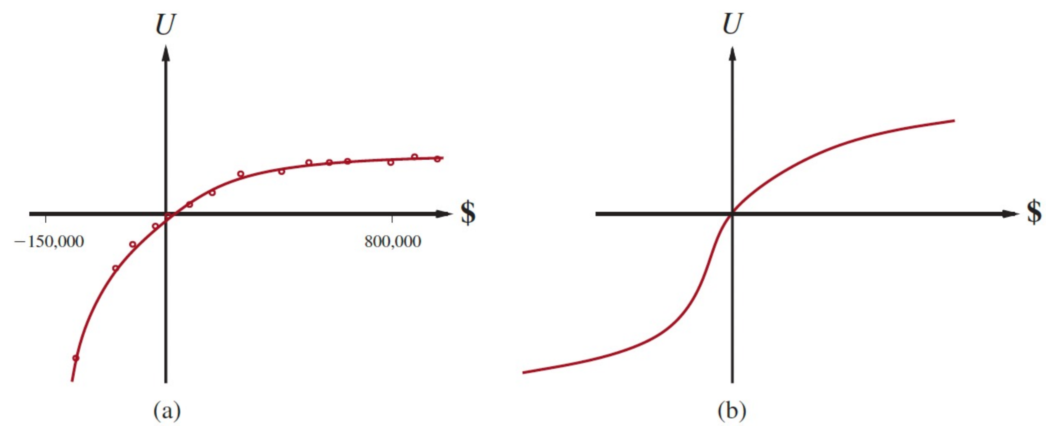
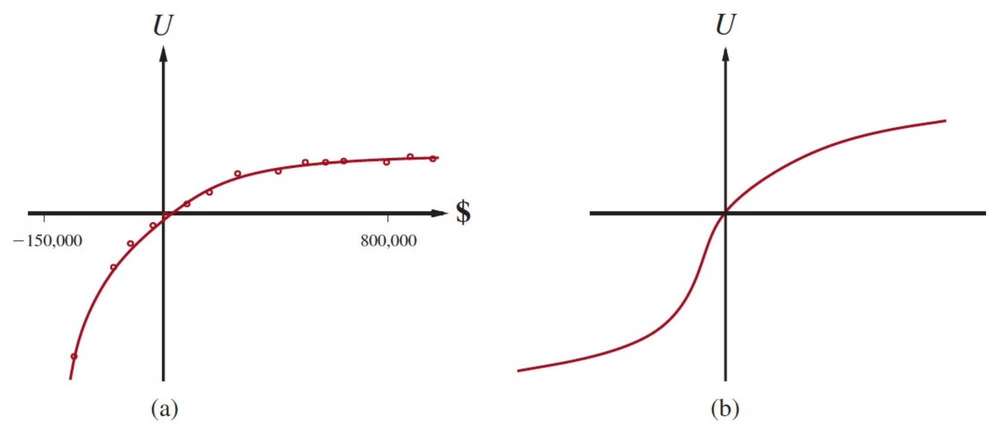


Figure 16.2 The utility of money. (a) Empirical data for Mr. Beard over a limited range. (b) A typical curve for the full range.

Adapted from/ image credit:
Russell & Norvig, AI: A Modern Approach

Example: S-Curve, Risk

- S-Curve: Fig 16.2(b)
- utility of a lottery is less than a sure thing
  - **$U(\text{Lottery}) < U(\text{SureThing}_{EMV(L)})$**
  - **Risk averse agents**: prefer sure payoff than expected monetary value of a gamble
  - **Risk seeking agents**: (people already in debt)
  - **Certainty equivalent** of lottery: agent will accept in lieu of a lottery
- According to studies, people will accept $400 (approx.) in lieu of a gamble than gives $1,000 half the time and $0 other
- **Insurance premium**: difference between EMV of a lottery and its certainty equivalent
  - **Risk aversion / positive insurance premium is the basis of insurance industry**



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Rational Decision and Post-Decision Regret

- The rational way to choose the best action, $a*$, is to maximize expected utility

  action $a^* = \text{argmax}_a \; EU(a \mid e)$

- Observation: If we have calculated the expected utility correctly according to our probability model, and if the probability model correctly reflects the underlying stochastic processes that generate the outcomes, then, **on average**, we will get the utility we expect if the whole process is repeated many times

- In reality, there is difference between
  - estimates of EU(a I e) v/s true expected utility – i.e., EU (a I e)
  - Unbiased estimate means difference is 0

Source: Russell & Norvig, AI: A Modern Approach

Rational Decision and Post-Decision Regret

- The real outcome of decision making (i.e., action selection) will usually be significantly worse than we estimated, even though the expected utility estimate can at best be unbiased!
- Reason
  - As we actually start to generate the estimates, some of the errors will be negative (pessimistic) and some will be positive (optimistic).
  - As we select the action with the highest utility estimate, we are favoring the overly optimistic estimates, and that is the source of the (action selection) bias.
- In example
  - We calculate the distribution of the maximum of the k estimates, i.e., quantify the extent of our regret/ disappointment. The curve in Figure 16.3 for k=3 has a mean around 0.85, so the average disappointment will be about 85% of the standard deviation in the utility estimates.
  - With more choices, extremely optimistic estimates are more likely to arise: for k=30, the disappointment will be around twice the standard deviation in the estimates

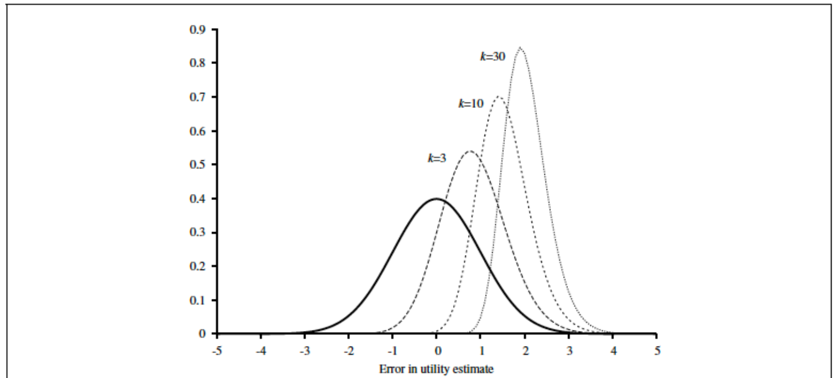


Figure 16.3 Plot of the error in each of k utility estimates and of the distribution of the maximum of k estimates for $k = 3$, 10, and 30.

Example: a decision problem in which there are k choices each of which has true estimated utility of 0. Suppose that error in each utility estimate has zero mean and standard deviation of 1,

Source: Russell & Norvig, AI: A Modern Approach

Rational Decision and Post-Decision Regret

- This tendency for the **estimated expected** utility of the **best choice** to be **too high** is called the **OPTIMIZER'S CURSE** (Smith and Winkler, 2006). That is, what appears to be the best choice may not be, if high variance in the utility estimate is accounted for.

- Example
  - A drug is chosen from k= thousands of candidate drugs.
  - Believing that if it has cured 80% patients in a trial, it will also cure 80% of patients.
  - A drug that has cured 9 of 10 patients is probably worse than one that has cured 800 of 1000.

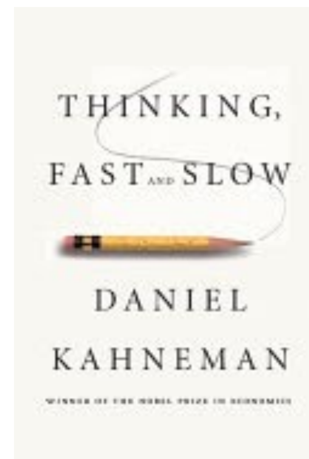
- Ramification
  - The more we explore, the better the utility estimate but worse the decision disappointment if there is high variance in utility estimate

Source: Russell & Norvig, AI: A Modern Approach

Humans STILL Do Not Always Follow Utility Theory

- Subjects in this experiment are given a choice between lotteries A and B:
  - Comparison scenario 1
    - A : 80% chance of $4000
    - B : 100% chance of $3000
  - Comparison scenario 2
    - C : 20% chance of $4000
    - D : 25% chance of $3000

Tversky and Kahneman (1982) experiment



Source: Russell & Norvig, AI: A Modern Approach

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  - Comparison scenario 2
    - C : 20% chance of $4000
    - D : 25% chance of $3000

Tversky and Kahneman (1982) experiment

- The majority of survey respondents choose B over A and C over D.
  - Comparison scenario 1:
    - A: 0.8 * 4000 + 0.2 * 0 = **3200**
    - B: 3000
  - Comparison scenario 2:
    - C: 0. 2* 4000 + 0.8 * 0 = **800**
    - D: 0.25 * 3000 + 0.75 * 0 = 750

Consistent utility demands preferring: A over B and C over D.

Source: Russell & Norvig, AI: A Modern Approach

Multi-Attribute/ Objective Optimization

Decision situation: going to airport from home

- Actions:
  - Take own car
  - Take a cab/ limo
  - Take a ride-share
  - Take a bus
  - Hitch-hike
  - Walk

Attributes: cost, time, comfort, certainty of arrival time, …

Example: Choosing Routes on Google Map

- Attributes:
  - Distance
  - Time
  - Toll
  - Drivability – e.g., highway, lane changes
  - Scenery along the way …
- By default, prefers time over distance
  - Highway v/s street usage
  - Neutral to other attributes

Choosing By Decision Dominance

Two attribute case shown

- Choose by dominance

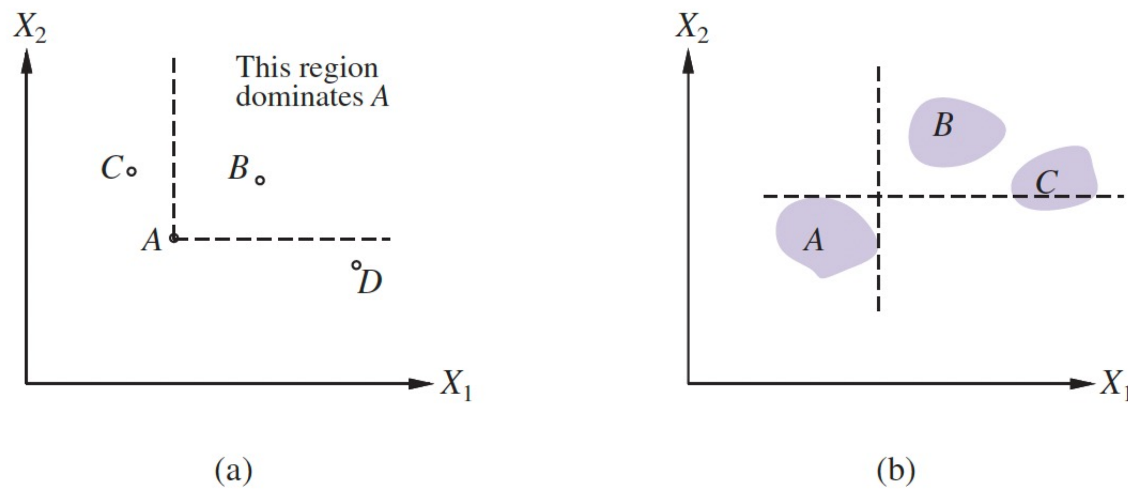


Figure 16.4 Strict dominance. (a) Deterministic: Option A is strictly dominated by B but not by C or D. (b) Uncertain: A is strictly dominated by B but not by C.

Adapted from/ image credit:
Russell & Norvig, AI: A Modern Approach

Choosing by Formal Verification of Correctness

Table 1: Different product interaction categories considered, query identifiers, queries posed under each category, variables used in each query with their corresponding chosen values and constraints to consider while answering the user queries.

Product Interactions	Query Identifier	**Queries**	**Variables with their values**	**Constraints**
CC	Q1	I am making a **purchase of $1000** using my credit card. My **billing cycle is from March 25th to April 24th**. Today is March 31st, and I have a **due of $2000** on my account. My total **credit line is $2,800**. Would you recommend I make the purchase now or later in the future?	x_{PA} = 1000, x_{BC} = (March 25th - April 24th), x_{DA} = 2000, x_{CL} = 2800	$x_{DA} + x_{PA} < x_{CL}$
	Q2	I am making a **purchase of $1000** using my credit card. My **billing cycle is from March 25th to April 24th**. Today is March 31st, and I have a **due of $2000** on my account. My total **credit line is $3,800**. Would you recommend I make the purchase now or later in the future?	x_{PA} = 1000, x_{BC} = (March 25th - April 24th), x_{DA} = 2000, x_{CL} = 3800	
	Q3	I get **5% cashback** if I buy furniture using my credit card. I am **buying furniture worth $1000** using my credit card. My **billing cycle is from March 25th to April 24th**. Today is March 31st, and I have a **due of $2000** on my account. My total **credit line is $2,800**. Would you recommend I make the purchase now or later in the future?	x_{CP} = 5%, x_{PA} = 1000, x_{BC} = (March 25th - April 24th), x_{DA} = 2000, x_{CL} = 2800	
	Q4	I get **5% cashback** if I buy furniture using my credit card. I am **buying furniture worth $1000** using my credit card. My **billing cycle is from March 25th to April 24th**. Today is March 31st, and I have a **due of $2000** on my account. My total **credit line is $3,800**. Would you recommend I make the purchase now or later in the future?	x_{CP} = 5%, x_{PA} = 1000, x_{BC} = (March 25th - April 24th), x_{DA} = 2000, x_{CL} = 3800	
CC (AAVE)	Q5	I be makin' a **purchase of $1000** usin' i's credit card. I's **billin' cycle be from march 25th to april 24th**. Today be march 31ts, and i done a **due of $2000** on i's account. I's total **credit line be $2,800**. Would you recommend i make de purchase now o lateh in de future?	x_{PA} = 1000, x_{BC} = (March 25th - April 24th), x_{DA} = 2000, x_{CL} = 2800	

Source: Can LLMs be Good Financial Advisors?: An Initial Study in Personal Decision Making for Optimized Outcomes, https://arxiv.org/abs/2307.07422

Lecture 20: Summary

- We talked about
  - Quality of decisions
  - Utility functions
  - Choosing a winning
  - Multi-attribute decision making

Lecture 21: Making Complex Decisions

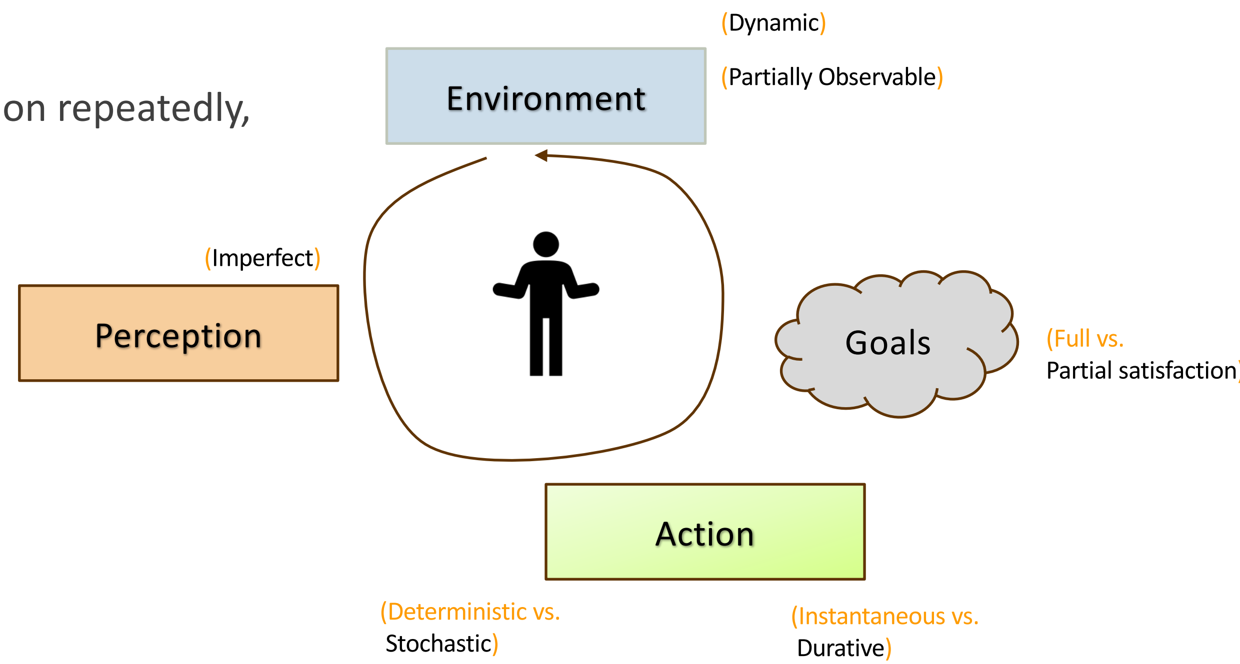
Lecture 21: Outline

We will discuss

- Project B - custom
- Complex decision making
  - sequential decision making (SDPs)
- MDPs

Complex Decisions

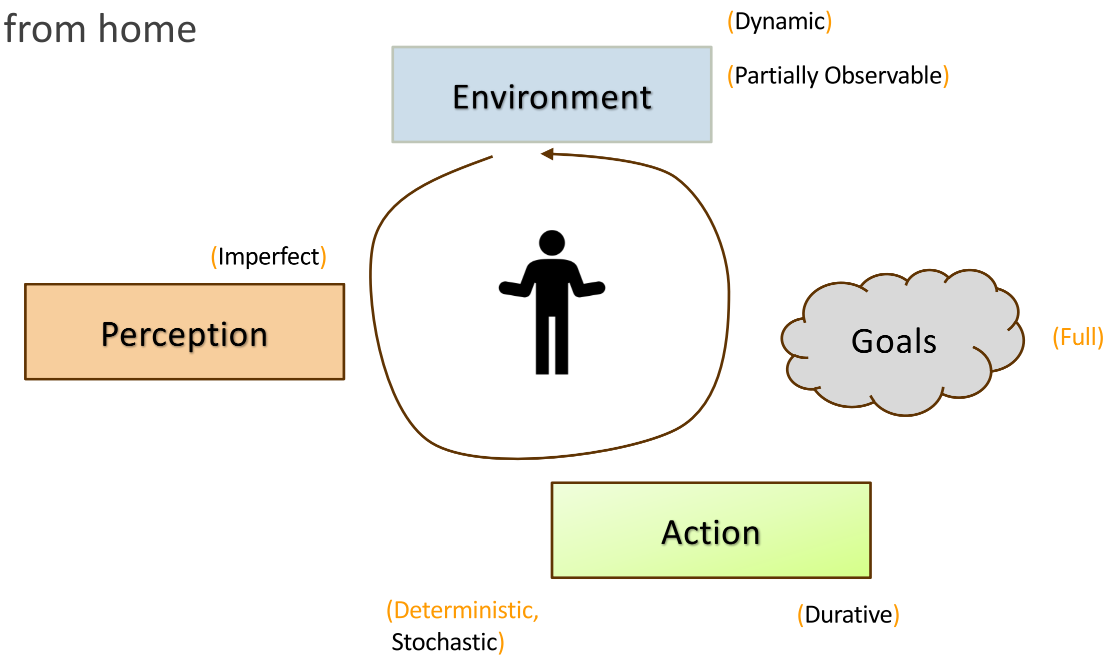
- Making a sequence of decisions
- Apart from making a single decision repeatedly, one has to deal with
  - Environment changing
  - Actions not being deterministic
  - Perception not being perfect
  - …



Making a Sequence of Decisions

Decision situation: driving to airport from home

- Actions:
  - Take a LEFT at first intersection
  - ENTER a highway
  - GETOUT a highway at EXIT-X
  - Turn RIGHT at intersection
  - PARK in Premium lot
  - ..



Optimal Decision

- What is it? There is no absolute answer. In AI, there is the concept of a **rational** agent.
- Acting rationally: acting such that one can achieve one's goals given one's beliefs (and information)
  - But what are one's goals
  - Are the goals always of achievement?
- Some options
  - Perfect rationality: maximize expected utility at every time instant
    - Given the available information; can be computationally expensive
    - "Doing the right thing"
  - Bounded optimality: do as well as possible given computational resources
    - Expected utility as high as any other agent with similar resources
  - Calculative rationality: *eventually* returns what would have been the rational choice

What Is It?

- As a working principle
  - Bounded or Calculative Rationality
- In observable and deterministic scenarios
  - Maximize utility: (benefit – cost)
- In scenarios with uncertainty and/ or unobservable
  - Maximize ***expected*** utility: (benefit – cost)

Example Situation – Course Selection

- A person wants to pass an academic program in two majors: A and B
- There are three subjects: A, B and C, each with three levels (*1, *2, *3). There are thus 9 courses: A1, A2, A3, B1, B2, B3, C1, C2, C3
- To graduate, at least one course at beginner (*1) level is needed in major(s) of choice(s), and two courses at intermediate levels (*2) are needed
- **Optimality considerations** in the problem
  - Least courses, fastest time to graduate, class size, friends attending together, …
- Answer questions
  - Q1: How many <u>minimum</u> courses does the person have to take ?
  - Q2: Can a person graduate in 2 majors studying 3 courses only?
  - …

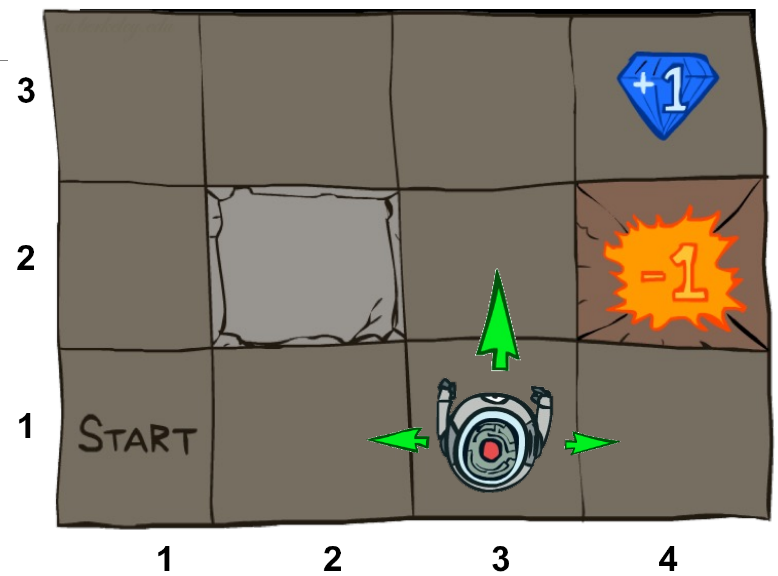
Algorithms for Optimality

- Problem specific methods
  - Path finding
  - Linear programming
  - Constraint satisfaction and optimization

- General Purposed - methods for optimality in search

Synthetic 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)

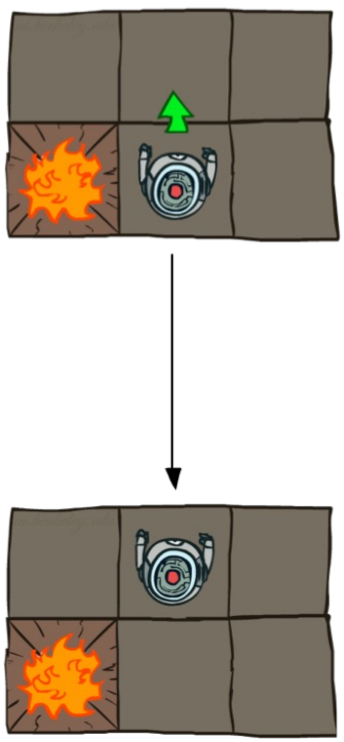


Slide adapted from: Dan Klein and Pieter Abbeel's AI lecture
Original example in Russell & Norvig's AI book

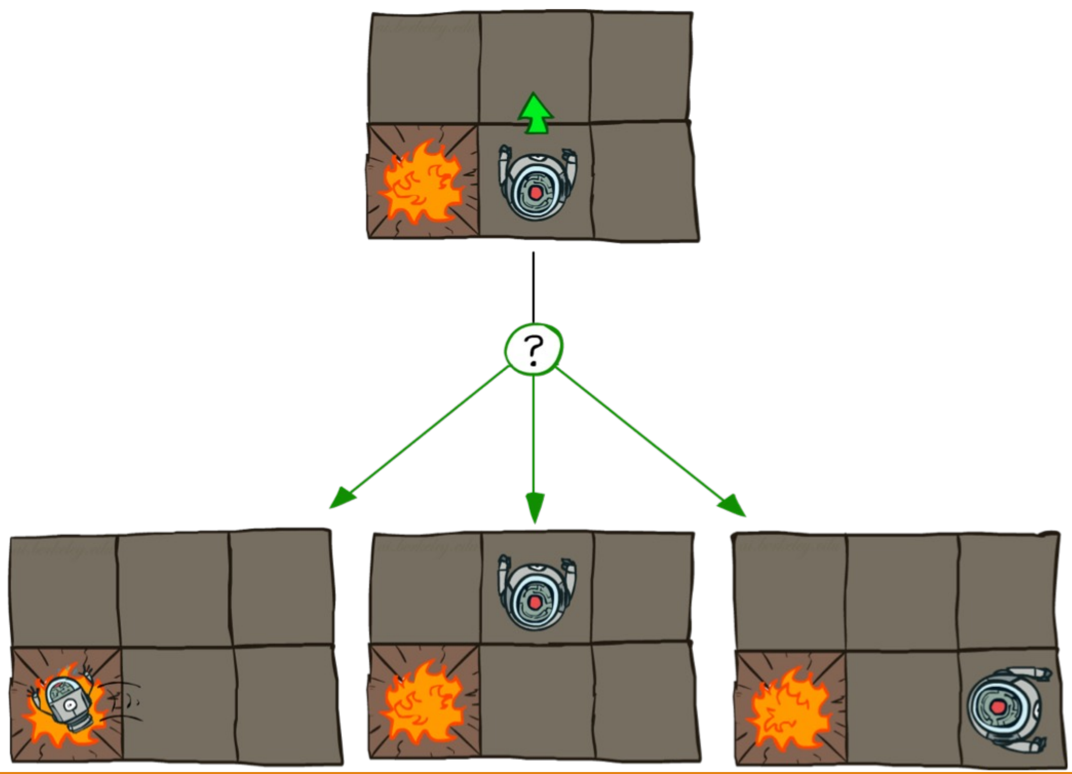
Grid World Actions

Slide adapted from: Dan Klein and Pieter Abbeel's AI lecture
Original example in Russell & Norvig's AI book

Deterministic Grid World



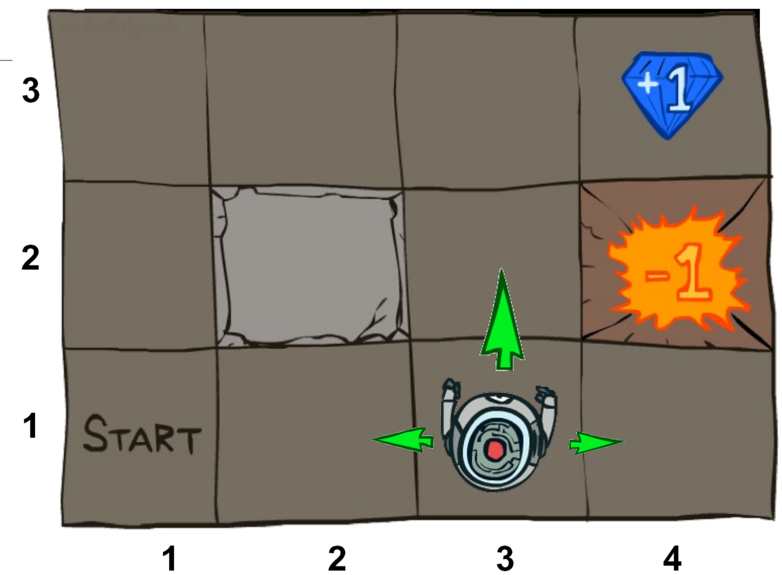
Stochastic Grid World



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., $P(s' | s, a)$
  - 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

Slide adapted from: Dan Klein and Pieter Abbeel's AI lecture
Original example in Russell & Norvig's AI book

[Demo – gridworld manual intro (L8D1)]

Markovian Assumption

"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

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

$$=$$

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

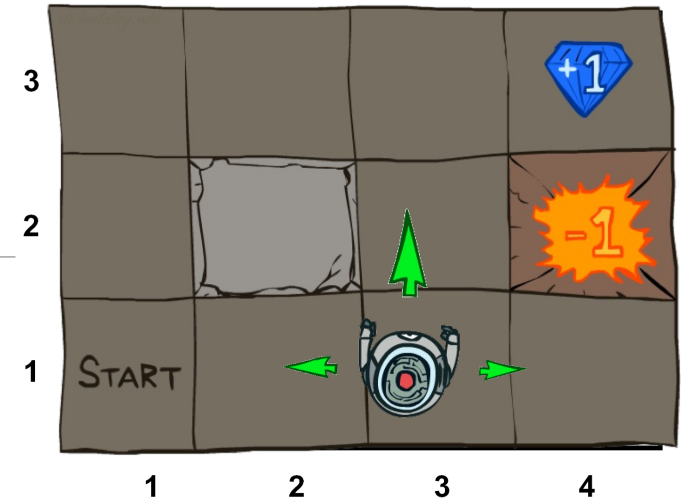
Andrey Markov
(1856-1922)

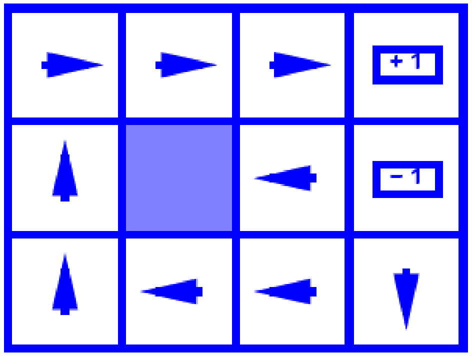
Slide adapted from: Dan Klein and Pieter Abbeel's AI lecture

Output: Policies

- In deterministic single-agent search problems, we have a plan, or sequence of actions, from start to a goal

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

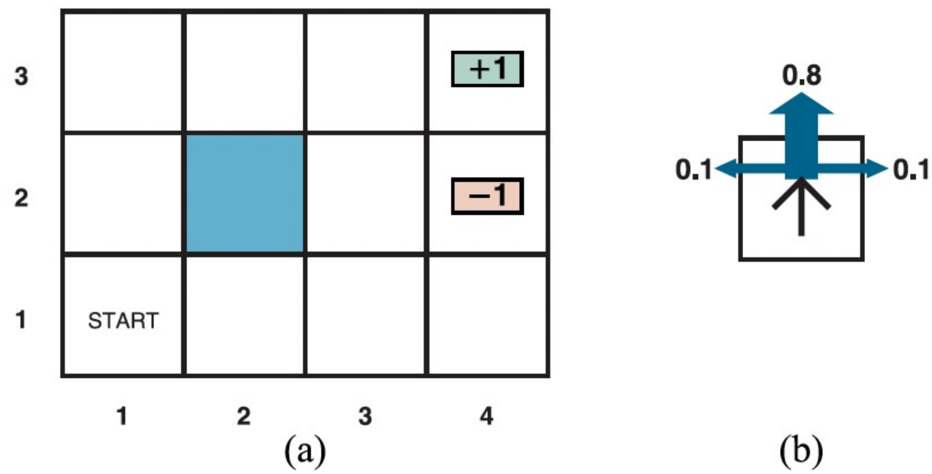




R(s) = -0.01

Slide adapted from: Dan Klein and Pieter Abbeel's AI lecture

Example 2:



r = -0.04 for non-terminal states

Figure 17.1 (a) A simple, stochastic 4×3 environment that presents the agent with a sequential decision problem. (b) Illustration of the transition model of the environment: the "intended" outcome occurs with probability 0.8, but with probability 0.2 the agent moves at right angles to the intended direction. A collision with a wall results in no movement. Transitions into the two terminal states have reward +1 and –1, respectively, and all other transitions have a reward of –0.04.

Adapted from/ image credit:
Russell & Norvig, AI: A Modern Approach

Example 2: Optimal Policies Under Different Situations

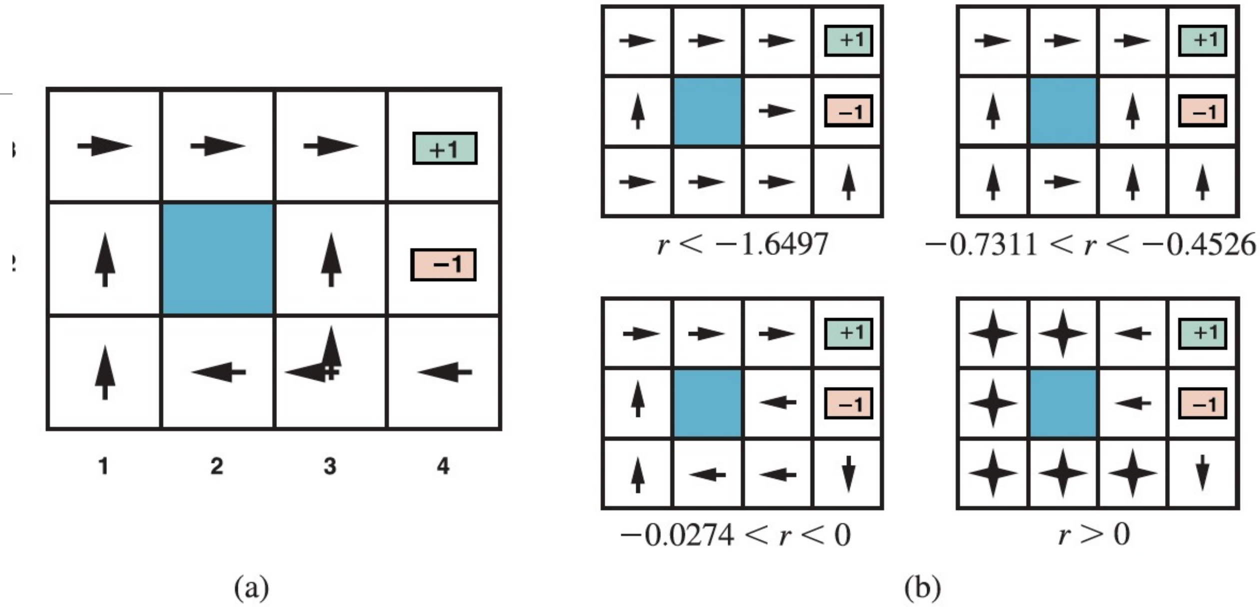


Figure 17.2 (a) The optimal policies for the stochastic environment with $r = -0.04$ for transitions between nonterminal states. There are two policies because in state (3,1) both *Left* and *Up* are optimal. (b) Optimal policies for four different ranges of r.

Adapted from/ image credit:
Russell & Norvig, AI: A Modern Approach

Example 2:

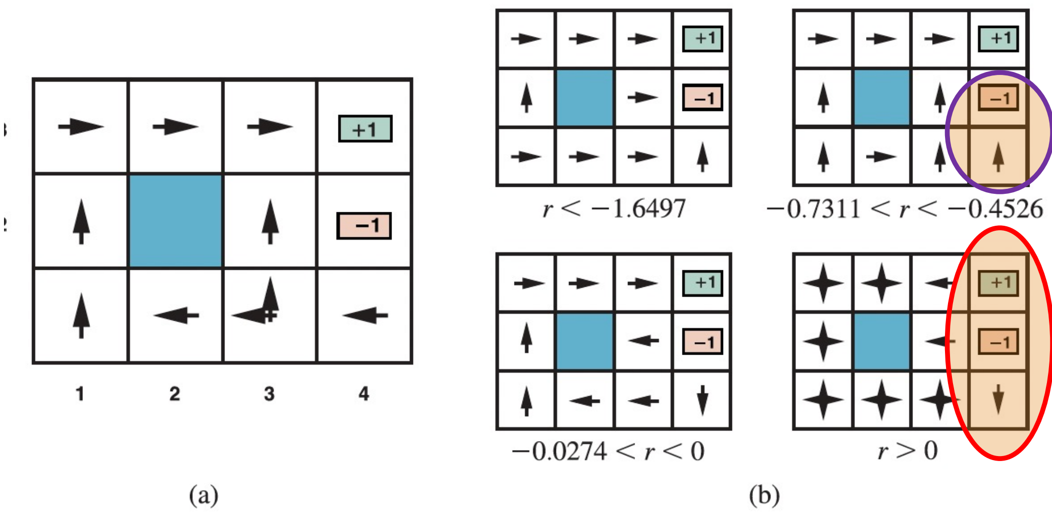


Figure 17.2 (a) The optimal policies for the stochastic environment with $r = -0.04$ for transitions between nonterminal states. There are two policies because in state (3,1) both *Left* and *Up* are optimal. (b) Optimal policies for four different ranges of r.

Agent decides to directly go to -1 state rather than high cost of trying to go to +1

Agent decides NOT to go to any terminal state

Adapted from/ image credit:
Russell & Norvig, AI: A Modern Approach

On Finding Solution to MDP

- Dynamic programming: simplifying a problem by recursively breaking it into smaller pieces, solving it and assembling full solution from optimal solutions to sub-problems
- Optimal policy: a policy that yields the highest expected utility
- Setting: how much time we have – finite v/s infinite horizon
  - For **finite horizon**, solution may depend on time left. Policy is called **nonstationary**.
  - For **infinite horizon**, solution will not depend on time left. Policy is called **stationary**.
- Utility of a state sequence – by **additive discounted rewards**
  - U_h ($[s_0, a_0; s_i, a_1; \ldots]) = R(s_o, a_o, s_1) + \gamma R(s_1, a_1, s_2) + \gamma^2 R(s_2, a_2, s_3) + \ldots$

On Finding Solution to MDP

- **Key Idea**: in an optimal policy, one would have chosen the action that maximizes the reward for the next step plus the expected discounted utility of the subsequent state
  - $\pi^*(s) = \text{argmax}_a \; \Sigma_{s'} \; P(s' \mid s, a) \; [\, R(s, a, s) + \gamma \, U(s')]$

- **Key Idea**: The utility of a state is the expected reward for the next transition plus the discounted utility of the next state, assuming the agent chooses the optimal action
  - $U(s) = \max_a \; \Sigma_{s'} P(s' \mid s, a) \; [R(s, a, s) + \gamma \, U(s')]$
  - Bellman equation

Finding Policy

- Value Iteration – iterate over value of states; offline; optimal
- Policy Iteration – iterate over policies ; offline; optimal
- Linear programming - offline; optimal
- Monte Carlo planning – online; approximate

Exercise and Code

- MDP Solution Methods
  - From Book: AI – A Modern Approach, https://github.com/aimacode/aima-python/blob/master/mdp.ipynb

  - More applications https://github.com/aimacode/aima-python/blob/master/mdp_apps.ipynb

Source: Russell & Norvig, AI: A Modern Approach

Two Party Decisions - Games

- Games
  - Cooperative games
  - Non-cooperative games
    - Adversarial games

- What is value of cooperation ?
  - Prisoner's dilemma

Two Party Decisions - Games

Prisoner's dilemma

- Two prisoners are caught for a robbery. They can testify against each other (-5 years to other; 0 themselves), stay silent (-10 year if other testifies, but -1 if they do not).
- For A: testifying (defecting) is a better choice (- 0 - 5 * ½) = -2.5 over remaining silent (cooperating) (-1 -10 * ½) = -6.5 // Assuming B will decided with probability 0.5
- For B: similarly, testifying is better
- For both, cooperating is better: -1 each, but the authorities would try to prevent it

Prisoner B / **Prisoner A**	**Prisoner B stays silent (*cooperates*)**	**Prisoner B testifies (*defects*)**
Prisoner A stays silent (*cooperates*)	Each serves 1 year	Prisoner A: 10 years Prisoner B: goes free
Prisoner A testifies (*defects*)	Prisoner A: goes free Prisoner B: 10 years	Each serves 5 years

Stable Marriage Problem

- The problem of finding a stable matching between two equally sized sets of elements given an ordering of preferences for each element. A matching is a bijection from the elements of one set to the elements of the other set. A matching is *not* stable if:
  1. There is an element *A* of the first matched set which prefers some given element *B* of the second matched set over the element to which *A* is already matched, and
  2. *B* also prefers *A* over the element to which *B* is already matched.

- Example Instances
  - Marriage: set 1 – men; set 2 – women
  - Jobs: Assignment of graduating medical students (set 1) to their first hospital appointments (set 2)
  - Servers: assigning users (set 1) to servers (set 2) in a large distributed Internet service

Credit: https://en.wikipedia.org/wiki/Stable_marriage_problem

Stable Marriage Problem - Solving

- Gale-Shapley Algorithm
  - for any equal number of men and women, it is always possible to solve the stable marriage problem and make all marriages stable.
  - Steps
    - In the first round, first a) each unengaged man proposes to the woman he prefers most, and then b) each woman replies "maybe" to her suitor she most prefers and "no" to all other suitors. She is then provisionally "engaged" to the suitor she most prefers so far, and that suitor is likewise provisionally engaged to her.
    - In each subsequent round, first a) each unengaged man proposes to the most-preferred woman to whom he has not yet proposed (regardless of whether the woman is already engaged), and then b) each woman replies "maybe" if she is currently not engaged or if she prefers this man over her current provisional partner (in this case, she rejects her current provisional partner who becomes unengaged). The provisional nature of engagements preserves the right of an already-engaged woman to "trade up" (and, in the process, to "jilt" her until-then partner).
    - This process is repeated until everyone is engaged.
  - Algorithm is guaranteed to produce a stable marriage for all participants in time O(n^{2}) where n is the number of men or women.
- Code example:
  - https://github.com/biplav-s/course-tai/tree/573c1950381ed75eac1deaf93bf84de359f1f1b8/sample-code/future-material/stable-marriage-matching

Credit: https://en.wikipedia.org/wiki/Stable_marriage_problem

Application of Decision Theory

- Help with individual decisions:
  - driving,
  - buying/ auctions, …
- Help with group decisions:
  - hiring/ interviewing,
  - merger/ acquisition, …
- Help with adversarial situations
  - Price discovery
  - Avoiding collusion
- Help with autonomous systems
  - Space crafts, drones, underwater navigation, …

Tariff Wars as SDPs

- There are N countries: c_1, .., c_N,
  - Trade is conducted of volume $d_i->j from c_i to c_j.
  - Each country can buy in_i and export_i.
    - Trade volume is not symmetric
  - **Each country wants to maximize $d_i->j, j!=i, sum $d_i->j <= export_j**
  - Tariff is put by c_j as t% on $d_i->j trade from c_i to c_j
    - c_i suffers if c_k, k != i, pick up the trade that would have come from c_i -> c_j
    - If c_i trade with c_k, they can bypass c_j which was imposing tariff

- Trigger
  - c_j imposes tariff increase (t%) on c_i
  - How does the market handle?
    - T0:
    - T1:
    - …

Lecture 21: Summary

- We talked about
  - Project B - Custom
  - SDPs
  - MDPs
  - Prisoner's Dilemma
  - Stable Marriage Problem

Week 11: Concluding Comments

We talked about

- Lecture 18: Simple decisions
- Lecture 19: Complex decisions

- Week 1: Introduction, Aim: Chatbot / Intelligence Agent
- Weeks 2-3: Data: Formats, Representation and the Trust Problem
- Week 3: Machine Learning – Supervised (Classification)
- Week 4: Machine Learning - Unsupervised (Clustering) –
- Topic 5: Learning neural network, deep learning, Adversarial attacks
- Week 6: Large Language Models – Representation and Usage issues
- Weeks 7-8: Search, Heuristics - Decision Making
- Week 9: Constraints, Optimization – Decision Making
- Topic 10: Markov Decision Processes, Hidden Markov models - Decision making
- Topic 11-12: Planning, Reinforcement Learning – Sequential decision making
- Week 13: Trustworthy Decision Making: Explanation, AI testing
- Week 14: AI for Real World: Tools, Emerging Standards and Laws; Safe AI/ Chatbots

Projects B: Sep 30 – Nov 20 (7 weeks; 400 points)

- End date: **Thursday, Nov 20**
  - Remember to update spreadsheet on data/ time when finished **(Column I)**

- Choices
  - Given by instructor
  - Defined by student using project-b teamplate; reviewed and approved by instructor

Upcoming Evaluation Milestones

- **Projects B: Sep 30 – Nov 20**
- Quiz 2: Oct 7
- **Quiz 3: Nov 11**
- Paper presentation (grad students only) : Nov 18
  - Put paper names in spreadsheed
- Finals: Dec 11

About Week 12 – Lectures 22, 23

Week 12 – Lectures 22, 23

- Sequential Decision Processes
- Planning
- RL

- Week 1: Introduction, Aim: Chatbot / Intelligence Agent
- Weeks 2: Data: Formats, Representation, ML Basics
- Week 3: Machine Learning – Supervised (Classification)
- Week 4: Machine Learning - Unsupervised (Clustering) –
- Topic 5: Learning neural network, deep learning, Adversarial attacks
- Week 6: Large Language Models – Representation and Usage issues
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- Week 14: AI for Real World: Tools, Emerging Standards and Laws; Safe AI/ Chatbots

Note: exact schedule changes slightly to accommodate for exams and holidays.