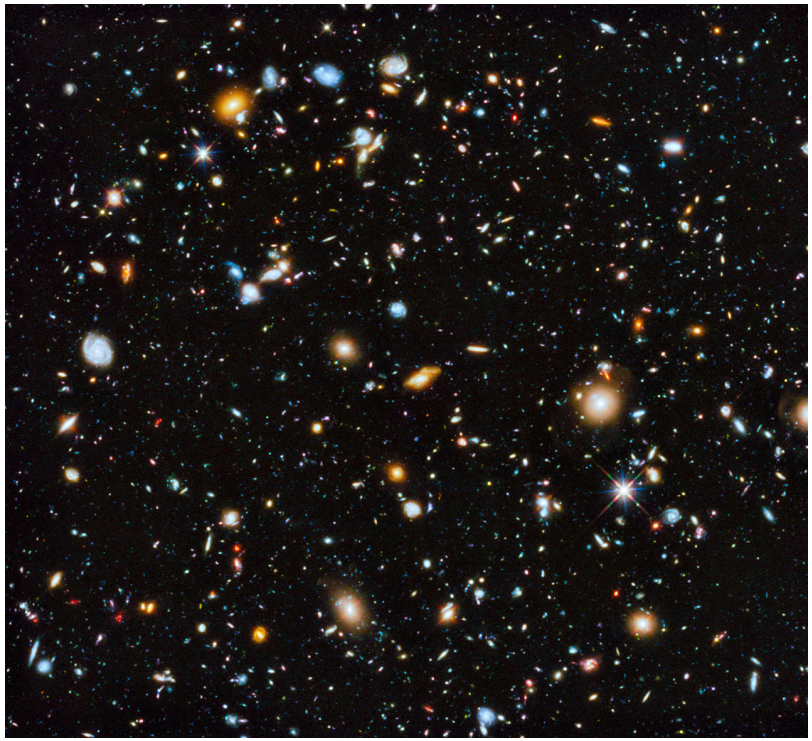
Lecture 1: Overview



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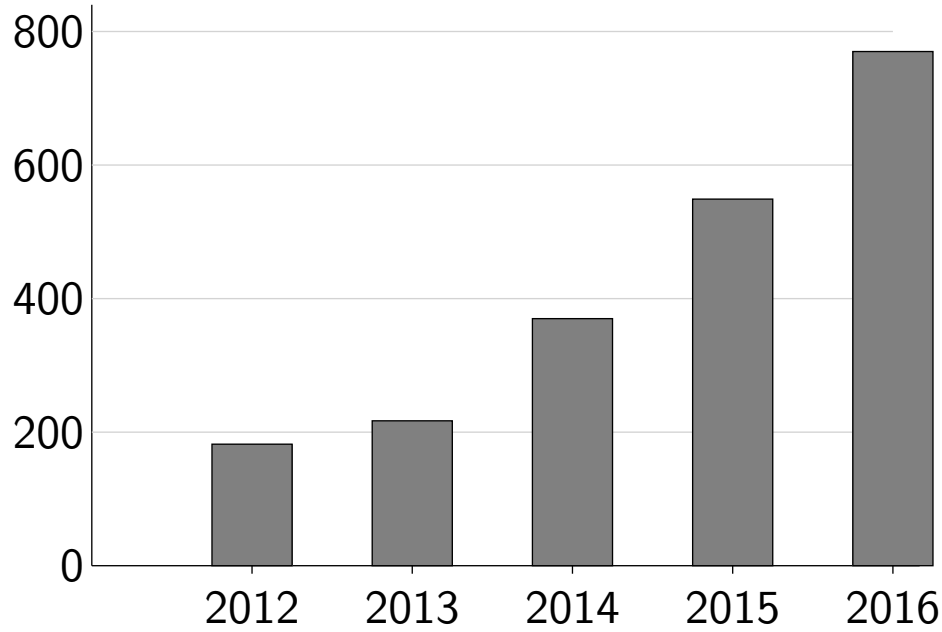
CS221 enrollments



CS221 breakdown

Freshman	1
Sophomore	26
Junior	145
Senior	159
GradYear1	164
GradYear2	156
GradYear3	50
GradYear4+	45

CS221 breakdown

...	...
Aeronautics & Astro	5
Chemical Engineering	5
Applied Physics	5
Economics	6
Materials Science & Engr	8
Mathematics	8
Physics	8
Math & Comp Science	11
Civil & Envir Engr	11
Statistics	20
Mgmt Sci & Engineering	20
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Electrical Engineering	101
Computer Science	292

Roadmap

Why learn AI?

What topics will you learn?

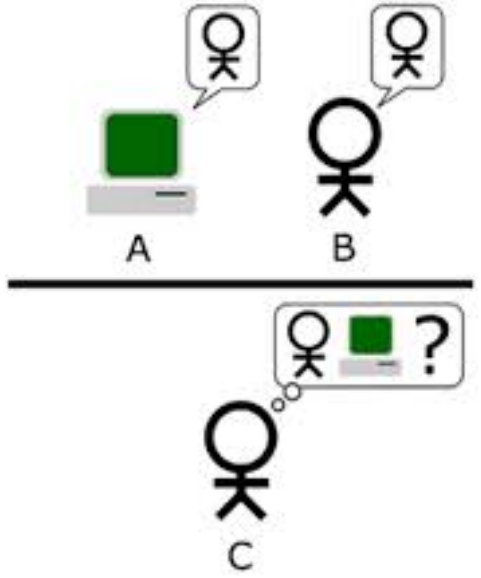
How will you learn it?

Optimization

What is AI?

The Turing Test (1950)

"Can machines think?"



Q: Please write me a sonnet on the subject of the Forth Bridge.

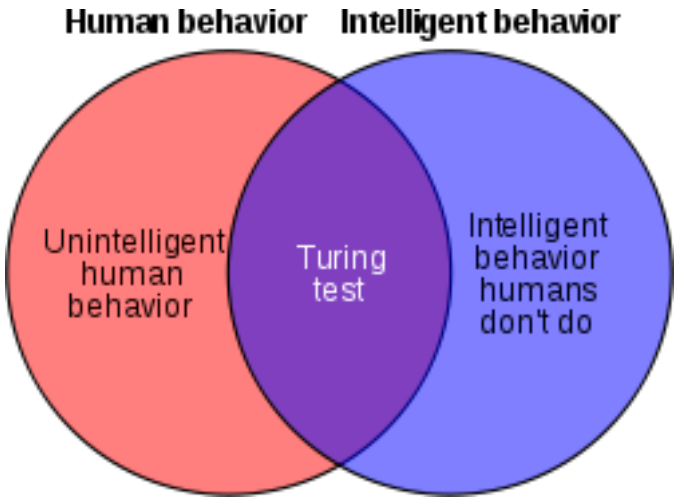
A: Count me out on this one. I never could write poetry.

Q: Add 34957 to 70764.

A: (Pause about 30 seconds and then give as answer) 105621.

Tests behavior — simple and objective

- Can machines think? This is a question that has occupied philosophers since Decartes. But even the definitions of "thinking" and "machine" are not clear. Alan Turing, the renowned mathematician and code breaker who laid the foundations of computing, posed a simple test to sidestep these philosophical concerns.
- In the test, an interrogator converses with a man and a machine via a text-based channel. If the interrogator fails to guess which one is the machine, then the machine is said to have passed the Turing test. (This is a simplification; there are more nuances in and variants of the Turing test, but these are not relevant for our present purposes.)
- The beauty of the Turing test is its simplicity and its objectivity, because it is only a test of behavior, not of the internals of the machine. It doesn't care whether the machine is using logical methods or neural networks. This decoupling of what to solve from how to solve is an important theme in this class.


Human behavior
Intelligent behavior
Unintelligent human behavior
Turing test
Intelligent behavior humans don't do

- But perhaps imitating humans is really the wrong metric when it comes to thinking about intelligence. It is true that humans possess abilities (language, vision, motor control) which currently surpass the best machines, but on the other hand, machines clearly possess many advantages over humans (e.g., speed). Why settle for human-level performance?
- The study of how humans think is fascinating and is well-studied within the field of cognitive science. In this class, however, we will primarily be concerned with the engineering goal of building intelligent systems, drawing from humans only as a source of tasks and high-level motivation.

What can AI do for you?

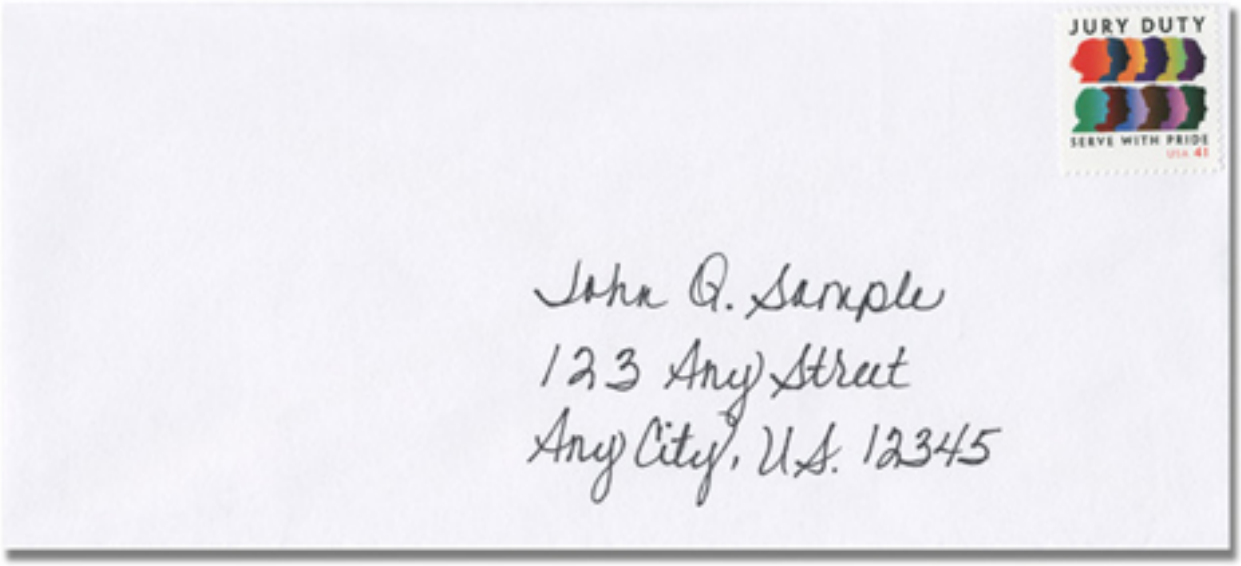
cs221.stanford.edu/q

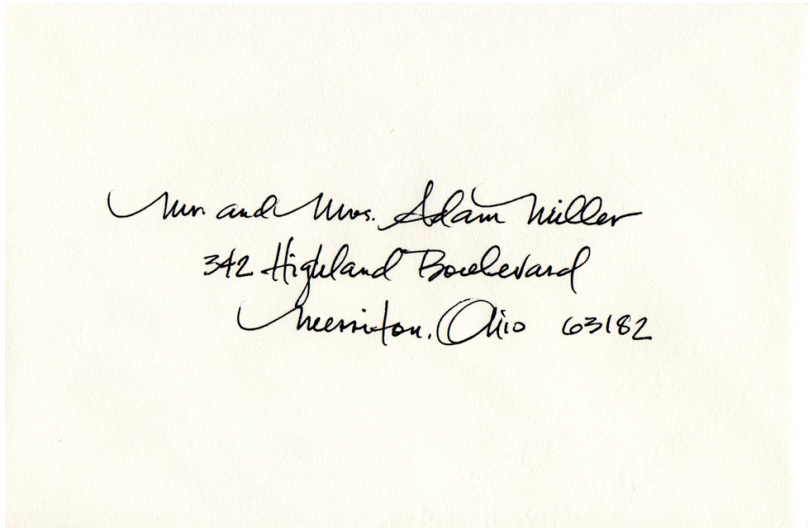
Question

In what area do you think AI will have the most important societal impact? Keep your response to 1-3 words.

- Instead of asking what AI is, let us turn to the more pragmatic question of what AI can do for you. We will go through some examples where AI has already had a substantial impact on society.

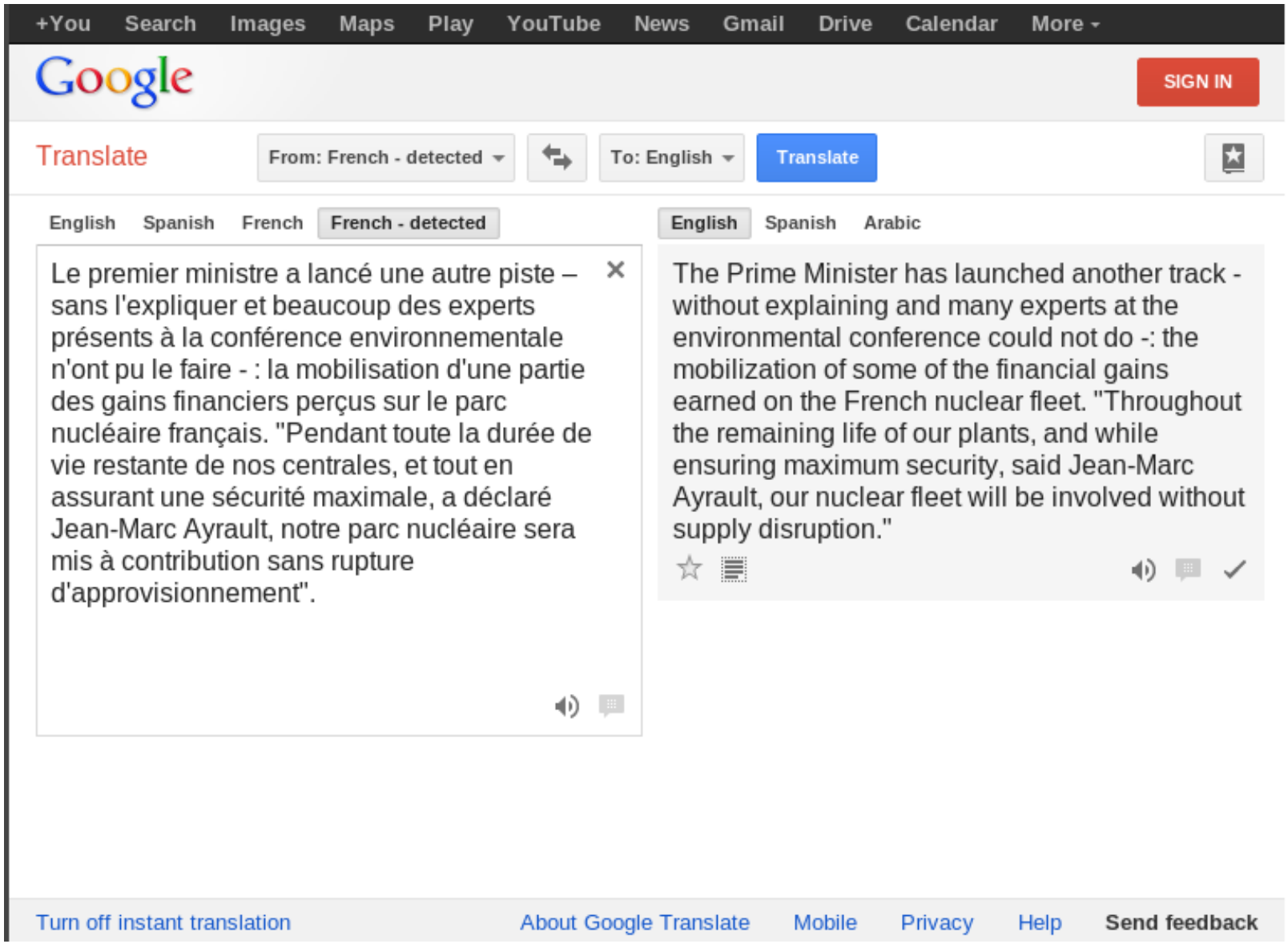
Handwriting recognition





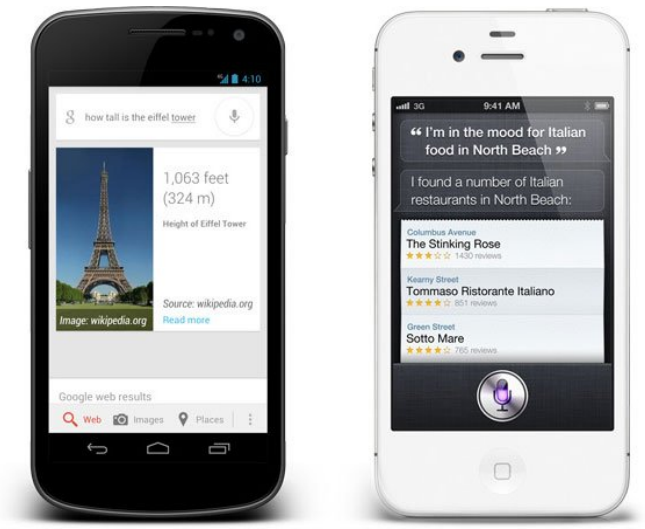
- In 1983, the United States Postal Service (USPS) and the University of Buffalo started a collaboration to automatically recognize handwritten zip code digits.
- In 1989, Yann LeCun and colleagues published a paper on using convolutional neural networks to recognize handwritten zip codes.
- The first system was then deployed in 1997, saving 100 million dollars.
- Today, 83% of the 70 million handwritten addresses per day are automatically sorted, and the methods have been refined to use the full context of the address.

Machine translation



- Machine translation research started in the 1960s (the US government was quite keen on translating Russian into English). Over the subsequent decades, it went through quite a few rough turns.
- In the 1990s and 2000s, statistical machine translation, aided by large amounts of example translations, helped vastly improve translation quality.
- As of 2015, Google Translate supports 90 languages and serves over 200 million people daily. The translations are nowhere near perfect, but they are very useful.

Virtual assistants



- Apple's Siri, Google Now, Microsoft Cortana, Amazon Echo, and other virtual assistants are also becoming real.
- A large part of this is due to the dramatic improvements in speech recognition in the last seven years (thanks to deep neural networks).
- However, speech recognition is only one part of the story; the other is understanding the text, which is a much harder problem. Current systems don't handle much more than simple utterances and actions (e.g., setting an alarm, sending a text, etc.), but the area of natural language understanding is growing rapidly.

Autonomous driving

- Research in autonomous cars started in the 1980s, but the technology wasn't there.
- Perhaps the first significant event was the 2005 DARPA Grand Challenge, in which the goal was to have a driverless car go through a 132-mile off-road course. Stanford finished in first place. The car was equipped with various sensors (laser, vision, radar), whose readings needed to be synthesized (using probabilistic techniques that we'll learn from this class) to localize the car and then to generate control signals for the steering, throttle, and brake.
- In 2007, DARPA created an even harder Urban Challenge, which was won by CMU.
- In 2009, Google started a self-driving car program, and since then, their self-driving cars have driven over 1 million miles on freeways and streets.
- In January 2015, Uber hired about 50 people from CMU's robotics department to build self-driving cars.
- While there are still technological and policy issues to be worked out, the potential impact on transportation is huge.

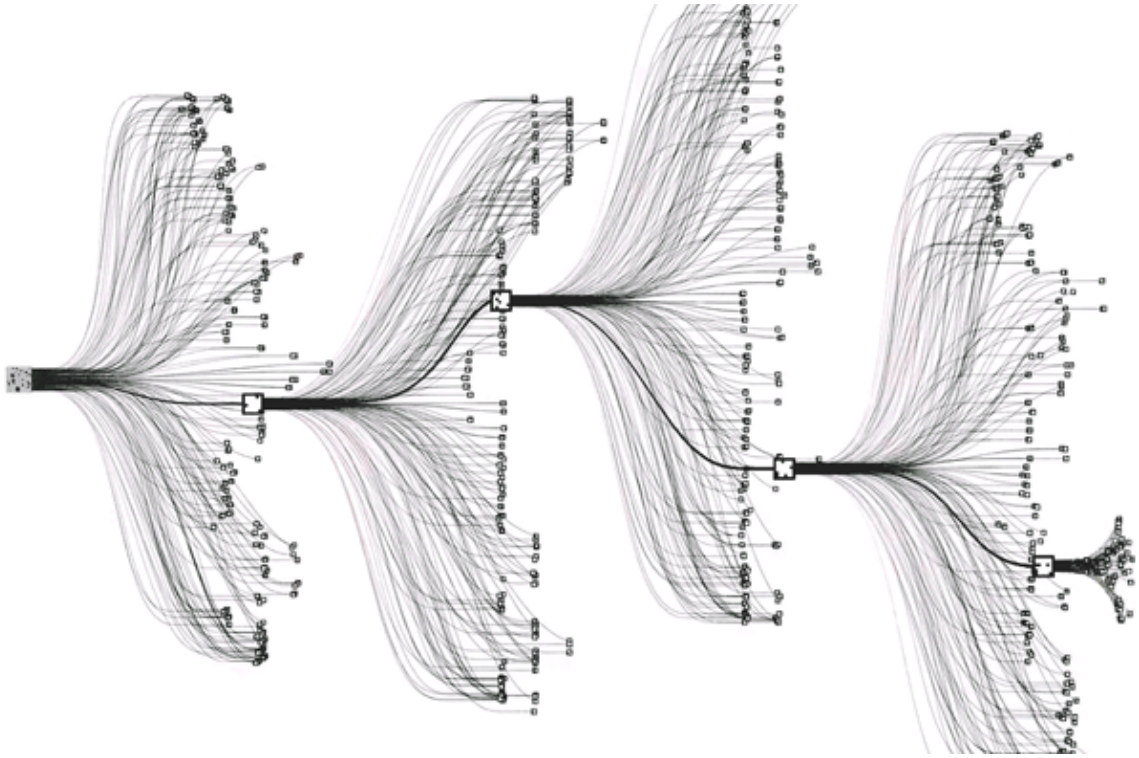
Humans versus machines

1997: Deep Blue (chess)

2011: IBM Watson (Jeopardy!)

- Perhaps the aspect of AI that captures the public's imagination the most is in defeating humans at their own games.
- In 1997, Deep Blue defeated Gary Kasparov, the world chess champion. In 2011, IBM Watson defeated two of the biggest winners (Brad Rutter and Ken Jennings) at the quiz show Jeopardy! (IBM seems to be pretty good at performing these kind of stunts.)
- One could have argued that Deep Blue won simply by the sheer force of its computational prowess, whereas winning Jeopardy! involved understanding natural language, and this defeat hit closer to home.

Humans versus machines



- March 2016 gave us another seminal result in game playing, this time in the ancient game of Go. Unlike chess, which fell to efficient search algorithms, Go styimed computer programs for a very long time, as the the space of possible moves in Go is much larger.
- Google DeepMind created a program called AlphaGo, which used deep neural networks and reinforcement learning (techniques we'll cover later in this class), defeating Lee Sedol, a 9-dan professional, 4-1 in a stunning five-game match, surprising not only the master Go player but many AI researchers as well.

The Atlantic SUBSCRIBE SEARCH MENU

BUSINESS

Technology

Stephen Hawking warns artificial intelligence could end mankind

By Rory Cellan-Jones
Technology correspondent

2 December 2014 | Technology

Stephen Hawking: "Humans, who are limited by slow biological evolution, couldn't compete and would be superseded"

lappen. Let's Prepare For

pen, what's the best way for it to happen?"

2 COMMENTS

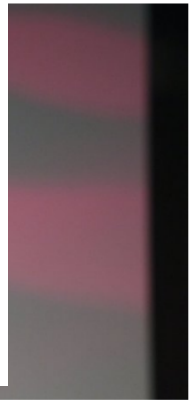
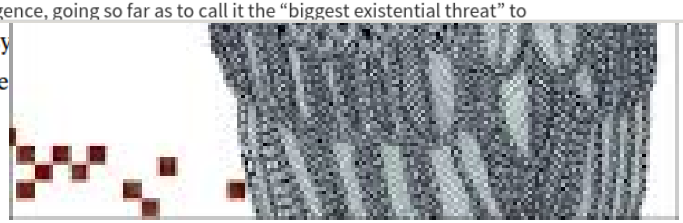


IMAGE: Getty Images

Elon Musk has emerged as a leading voice in speaking out on the potential dangers of artificial intelligence, going so far as to call it the "biggest existential threat" to

The advances we'
humanoid robots, speech recognition and sy
Jeopardy!-champion computers—are not the



TODAY'S MUST READS

17 Speaking Habits That Make You Sound, Like, Totally Unprofessional

How Playing the Long Game Made Elizabeth Holmes a Billionaire

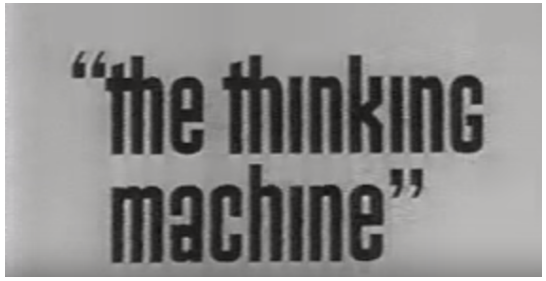
5 Holy Knickknacks to Celebrate Pope Francis's Visit

Inside the Mind of Facebook's Sheryl Sandberg

Take a Video Tour of Facebook's Frank Gehry-Designed New York City Office

HIT THE ROAD

- According to many articles and popular books, it seems like human-level AI is right around the corner, for better or for worse.



- 1956: Dartmouth workshop, John McCarthy coined "AI"
- 1960: checkers playing program, Logical Theorist
- 1966: ALPAC report cuts off funding for translation
- 1974: Lighthill report cuts off funding in UK
- 1970-80s: expert systems (XCON, MYCIN) in industry
- 1980s: Fifth-Generation Computer System (Japan); Strategic Computing Initative (DARPA)
- 1987: collapse of Lisp market, government funding cut
- 1990-: rise of machine learning
- 2010s: heavy industry investment in deep learning

- But this is also what people thought in the 1960s. Ok, so maybe people misjudged the difficulty of the problem. But it happened again in the 1980s, leading to another AI winter. During these AI winters, people eschewed the phrase "artificial intelligence" as not to be labeled as a hype-driven lunatic.
- In the latest rebirth, we have new machine learning techniques, tons of data, and tons of computation. So each cycle, we are actually making progress. Will this time be different?
- We should be optimistic and inspired about the potential impact that advances in AI can bring. But at the same time, we need to be grounded and not be blown away by hype. This class is about providing that grounding, showing how AI problems can be treated rigorously and mathematically. After all, this class is called "Artificial Intelligence: Principles and Techniques".

Many AI applications

...

Web search

Speech recognition

Handwriting recognition

Machine translation

Information extraction

Document summarization

Question answering

Spelling correction

Image recognition

3D scene reconstruction

Human activity recognition

Autonomous driving

Music information retrieval

Automatic composition

Social network analysis

...

...

Product recommendation

Advertisement placement

Smart-grid energy optimization

Household robotics

Robotic surgery

Robot exploration

Spam filtering

Fraud detection

Fault diagnostics

AI for video games

Character animation

Financial trading

Dynamic pricing

Protein folding

Medical diagnosis

Medical imaging

...

- We have already talked about some AI applications, but there are many more. Note that many of them extend beyond computer science and involving topics one would perhaps not traditionally think of as AI.

Characteristics of AI tasks

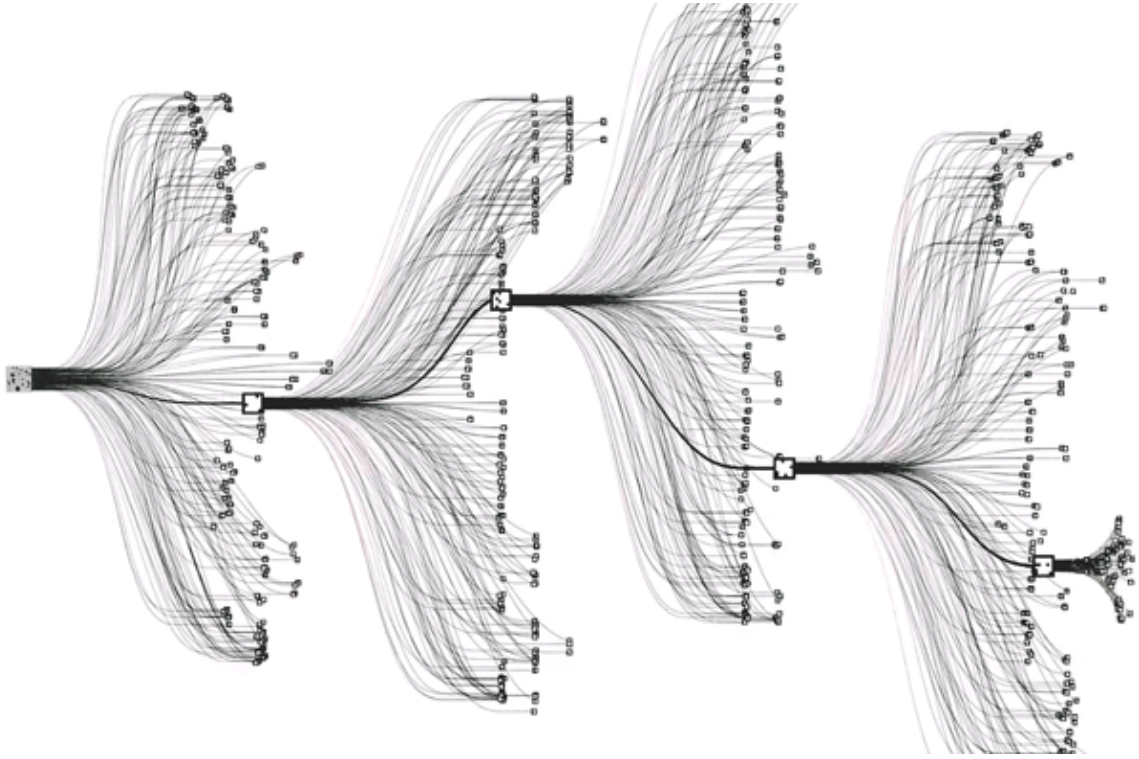
High societal impact (affect billions of people)

Diverse (language, games, robotics)

Complex (really hard)

- What's in common with all of these examples?
- It's clear that AI applications tend to be very **high impact**.
- They are also incredibly **diverse**, operating in very different domains, and requiring integration with many different modalities (natural language, vision, robotics). Throughout the course, we will see how we can start to tame this diversity with a few fundamental principles and techniques.
- Finally, these applications are also mind-bogglingly **complex** to the point where we shouldn't expect to find solutions that solve these problems perfectly.

Two sources of complexity...



Computational complexity: exponential explosion

- There are two sources of complexity in AI tasks.
- The first, which you, as computer scientists, should be familiar with, is **computational complexity**. We can solve useful problems in polynomial time, but most interesting AI problems — certainly the ones we looked at — are NP-hard. We will be constantly straddling the boundary between polynomial time and exponential time, or in many cases, going from exponential time with a bad exponent to exponential time with a less bad exponent.
- For example, in the game of Go, there are up to 361 legal moves per turn, and let us say that the average game is about 200 turns. Then, as a crude calculation, there might be 361^{200} game trajectories that a player would have to consider to play optimally. Of course, one could be more clever, but the number of possibilities would still remain huge.

这是什么意思?

Even infinite computation isn't enough...need to somehow *know* stuff.

Information complexity: need to acquire knowledge

- The second source of complexity, which you might not have thought of consciously, is **information complexity**.
- (Note that there are formal ways to characterize information based on Shannon entropy, but we are using the term information rather loosely here.) Suppose I gave you (really, your program) literally infinite computational resources, locked you (or your program) in a room, and asked you to translate a sentence. Or asked you to classify an image with the type of bird (it's a Weka from New Zealand, in case you're wondering).
- In each of these cases, increasing the amount of computation past a certain point simply won't help. In these problems, we simply need the information or knowledge about a foreign language or ornithology to make optimal decisions. But just like computation, we will be always information-limited and therefore have to simply cope with **uncertainty**.

Resources

Computation (time/memory)

Information (data)

- We can switch vantage points and think about resources to tackle the computational and information complexities.
- In terms of computation, **computers** (fast CPUs, GPUs, lots of memory, storage, network bandwidth) is a resource. In terms of information, **data** is a resource.
- Fortunately for AI, in the last two decades, the amount of computing power and data has skyrocketed, and this trend coincides with our ability to solve some of the challenging tasks that we discussed earlier.

How do we ~~solve~~ tackle these challenging AI tasks?

How?

Real-world task

- So having stated the motivation for working on AI and the challenges, how should we actually make progress?
- Given a complex real-world task, at the end of the day, we need to write some code (and possibly build some hardware too). But there is a huge chasm between the real-world task and code.

Paradigm

Real-world task 

Modeling

Formal task (model) 

Algorithms

Program 

- A useful paradigm for solving complex tasks is to break them up into two stages. The first stage is modeling, whereby messy real-world tasks are converted into clean formal tasks called **models**. The second stage is algorithms, where we find efficient ways to solve these formal tasks.

Algorithms (example)

Formal task:

- Input: list $L = [x_1, \ldots, x_n]$ and a function $f : X \mapsto \mathbb{R}$
- Output: k highest-scoring elements

Example ($k = 2$):

L:	A	B	C	D
f:	(3)	2	(7)	1

Two algorithms:

- Scan through to find largest, scan through again to find the second largest, etc.
- Sort L based on f, return first k elements

- Let's start with something that you're probably familiar with: algorithms. When you study algorithms, you are generally given a well-defined formal task, something specified with mathematical precision, and your goal is to solve the task. A solution either solves the formal task or it doesn't, and in general, there are many possible solutions with different computational trade-offs.
- As an example, suppose you wanted to find the k largest elements in a list of $L = [x_1, \ldots, x_n]$ according to given a scoring function f that maps each element into a real-valued score.
- Solving a formal task involves coming up with increasingly more efficient algorithms for solving the task.

Modeling (example)

Real-world task:

- Input: list of 1000 web pages
- Output: 10 most relevant web pages

Modeling

$L =$ list of web pages

$f(x) = 10 \cdot \text{QueryMatch}(x) + 3 \cdot \text{PageRank}(x)$

Formal task:

- Input: list $L = [x_1, \ldots, x_n]$ and a function $f : X \to \mathbb{R}$
- Output: k highest-scoring elements

- However, real-world tasks are not well-defined. For example, the web ranking task is to output the 10 most pages relevant to a user's query. What does "relevant" mean?
- Our strategy is not to develop algorithms for solving real-world tasks directly, but rather to convert them via a process called **modeling** into formal tasks.
- In our example, we would have to decide on the appropriate scoring function $f(x)$, which could be the number of words in x that are also in the user's query, the PageRank of x which measures how popular x is, or some combination of the two.
- The advantage of modeling is that now we can entertain increasingly sophisticated scoring functions f without bothering about the details of how we're going to compute it.

Modeling and algorithms

- Separate **what** to compute (**modeling**) from **how** to compute it (**algorithms**)

- Advantage: divison of labor

- This class: providing a toolbox of different types of models and associated algorithms

- This modularity between modeling and algorithms is a powerful abstraction that is the basis for successful methods, not only in AI but in many disciplines.
- The advantage is a division of labor: we can think about the real-world task at a higher-level of abstraction (via the model), while people who are good at coming up with clever algorithms have some formal specification to latch onto.
- The purpose of this class is to introduce you to a set of different model types which are useful in a variety of different settings. We will both develop efficient algorithms for these formal tasks and, more importantly, practice the art of modeling: converting real-world tasks into models.

Summary so far

- Applications of AI: high-impact, diverse

- Challenges: computational/information complexity

- Paradigm: modeling + algorithms

Roadmap

Why learn AI?

What topics will you learn?

How will you learn it?

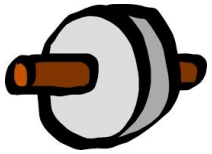
Optimization

Course plan

"Low-level intelligence" "High-level intelligence"

Machine learning

- We now embark on our tour of the topics in this course. The topics correspond to types of models that we can use to represent real-world tasks. The topics will in a sense advance from low-level intelligence to high-level intelligence, evolving from models that simply make a reflex decision to models that are based on logical reasoning.



Traditional approach

A spell checker:

Problem: complexity becomes unwieldy

Machine learning approach

Training examples

hte ⇒ the
jeapardy ⇒ jeopardy
affedave ⇒ affidavit
misilous ⇒ miscellaneous

Learning algorithm

input → **simple program** **parameters = [3.2,1.2,...]** → output

- Supporting all of these models is **machine learning**.
- In the non-machine learning approach, one would write a complex program (remember, we are solving tasks of significant complexity), but this gets very tedious. For example, how should a spellchecker know that for "hte", "the" (transposition) is more likely to be the correct output as compared to "hate" (insertion)?
- The machine learning approach is to instead write a really simple program with unknown parameters (e.g., numbers measuring how bad it is to transpose or insert characters). Then, we obtain a set of training examples that partially specifies the desired system behavior. A learning algorithm takes these training examples and sets the parameters of our simple program so that the resulting program approximately produces the desired system behavior.
- Abstractly, machine learning allows us to shift the complexity from the program to the data, which is much easier to obtain (either naturally occurring or via crowdsourcing).

Machine learning

Key idea: generalization

Learning algorithm maximizes accuracy on **training** examples.

But we only care about accuracy on future **test** examples.

How to **generalize** from training to test?

- The main conceptually magical part of learning is that if done properly, the trained program will be able to produce good predictions beyond the set of training examples. This leap of faith is called **generalization**, and is, explicitly or implicitly, at the heart of any machine learning algorithm. This can even be formalized using tools from probability and statistical learning theory.

Course plan


Reflex
"Low-level intelligence"
"High-level intelligence"
Machine learning

What is this animal?

Sentiment analysis

Input: movie review

Shows moments of promise
but ultimately succumbs to
cliches and pat storytelling.

Output: sentiment

POSITIVE or **NEGATIVE**

- To demonstrate reflex-models, let us take the example application of sentiment analysis. For concreteness, consider the real-world task of determining whether a movie review expresses a positive or negative sentiment. Sentiment analysis (opinion mining) has been quite popular in recent years. For example, companies are quite interested in mining Twitter and other social media to find out what people think of their products.

Reflex-based models

Input: x

Output: $f(x)$, a simple function of x

Example: f is set of simple rules

If x contains "cliches", return NEGATIVE.

If x contains "promise", return POSITIVE.

...

- The idea of a reflex-based model is to take an input x and perform a very simple calculation based on x to produce some output $f(x)$. For example, in sentiment classification, x is a review and $f(x)$ is the prediction of whether the review is postive or negative.
- Reflex-based models could consist of a small set of deterministic rules that look at various superficial properties of the input, e.g., what words it contains.
- We use the term "reflex-based" more intuitively than formally, as there is not really an official definition of what constitutes a very simple calculation.

Reflex-based models

Use scores to capture nuances...

Example: f is based on scores

Set score $= 0$.

If x contains "cliches", score -= 10.

If x contains "promise" , score $+= 5$.

If score > 0, return POSITIVE.

More generally...

Key idea: linear classifier

$$f(x) = \text{sign}(w_1\phi_1(x) + \cdots + w_d\phi_d(x))$$

- Fancier reflex-based models are based on features and weights (think soft rules): If x has a **feature** (e.g., x contains "cliches"), then the score is updated with the feature's weight (e.g., -10).
- Abstractly, we can think of having d features $\phi_1(x), \ldots, \phi_d(x)$, each of which capture some property of x (in general, $\phi_j(x) \in \mathbb{R}$, but for intuition, you can think of them as 0 or 1). Each feature $\phi_j(x)$ is associated with a weight $w_j \in \mathbb{R}$ which represents how much support $\phi_j(x)$ provides to either a positive or negative classification.
- The final prediction $f(x) = \text{sign}(\sum_{j=1}^{d} w_j \phi_j(x))$ is based on taking the weighted sum over all the features to get a score. If the score is positive, then we output POSITIVE; otherwise, we output NEGATIVE.
- Where do the weights come from? We can use machine learning to set them automatically from data.
- As we'll see later, linear classifiers have certain limitations that can be overcomed by using non-linear classifiers such as neural networks. The idea of deep learning is to push on this insight and develop larger and more powerful neural networks models.

Sentiment detection

[demo]

Course plan

Search problems

Markov decision processes

Adversarial games

Reflex **States**

"Low-level intelligence" "High-level intelligence"

Machine learning

Text reconstruction

Chinese is written without spaces:

这 是 什么 意思 ?

Arabic omits (some) vowels:

Remove vowels and spaces from an English phrase:

rtfclntllgnc

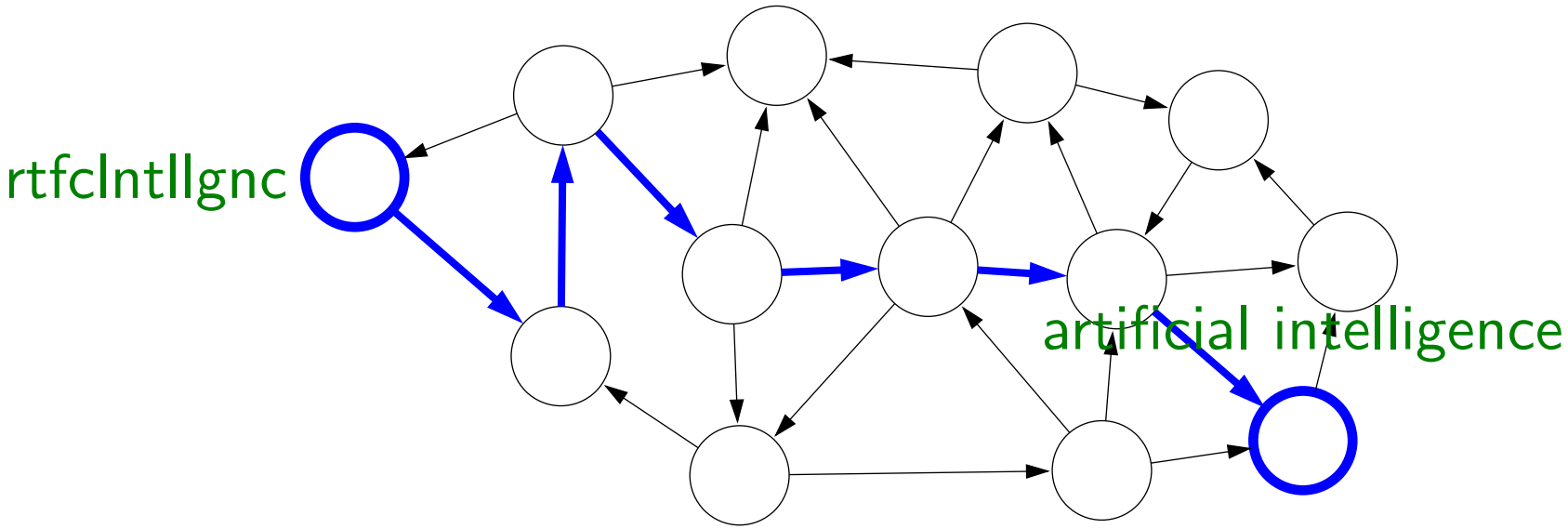
- Reflex-based models are normally used for classification tasks where the output is one of a small set (think multiple choice). However, in many problems (e.g., speech recognition, machine translation), the outputs are more complicated (e.g., an entire sentence).
- Consider a simple version of text reconstruction, where we are given some incomplete form of a sentence (such as missing vowels/spaces), and the goal is to recover them. In this class, you will build a system that does this.

Text reconstruction

[demo]

State-based models

Solutions are represented as paths through a graph



- Reflex-based models are too simple for tasks that require more forethought (e.g., in playing chess or planning a big trip). State-based models overcome this limitation.
- The key idea is, at a high-level, to model real-world tasks as finding (minimum cost) paths through graphs. This reduction is useful because we understand graphs well and have a lot of efficient algorithms for operating on graphs.

State-based models

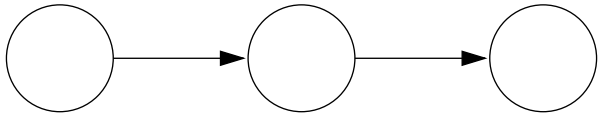
Key idea: state

A **state** captures all the relevant information about the past in order to act optimally in the future.

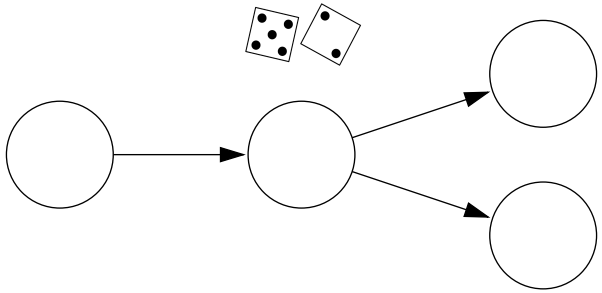
- The simplest case is a **search problem**, where the solution to the original task is a path through the graph from a start to a goal.
- The central concept in using state-based models are **states**, which correspond to the nodes in the graph. Intuitively, a state must contain all the relevant information about the past needed to make optimal choices in the future.
- Consider the task of finding the cheapest way to travel from city A to city B via a sequence of intermediate cities. In this case, the state should contain the current city but perhaps also the amount of gas or the time of day, depending on the task. We will discuss these design issues in much more detail later in the course.

State-based models

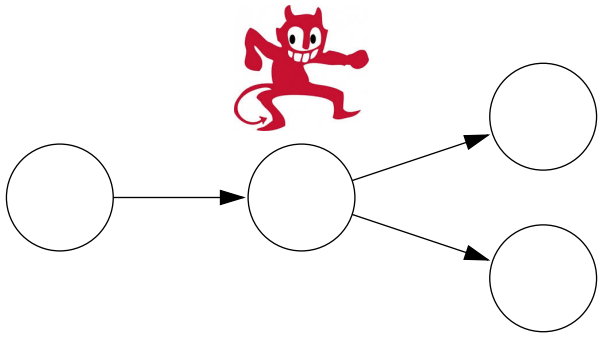
Search problems: you control everything



Markov decision processes: against nature (e.g., Blackjack)

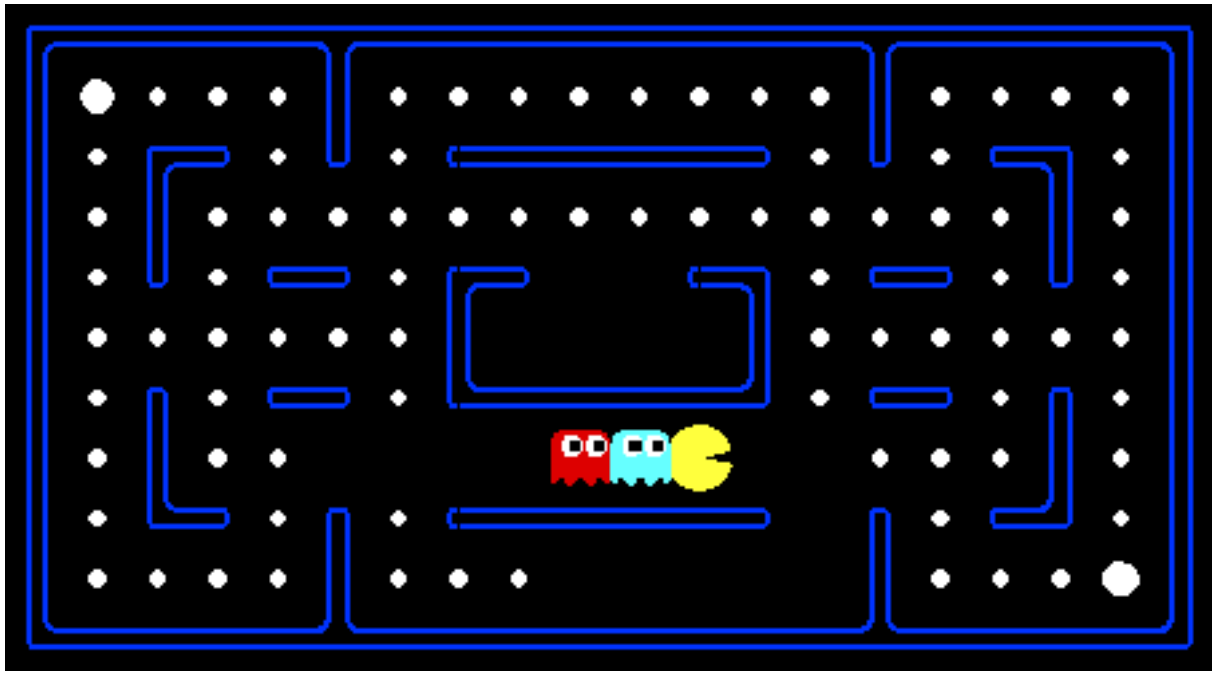


Adversarial games: against opponent (e.g., chess)



- Search problems are adequate models when you are operating in environment that has no uncertainty. However, in many realistic settings, there are other forces at play.
- **Markov decision processes** handle tasks with an element of chance (e.g., Blackjack), where the distribution of randomness is known (reinforcement learning can be employed if it is not).
- **Adversarial games**, as the name suggests, handle tasks where there is an opponent who is working against you (e.g., chess).

Pac-Man



[demo]

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Question

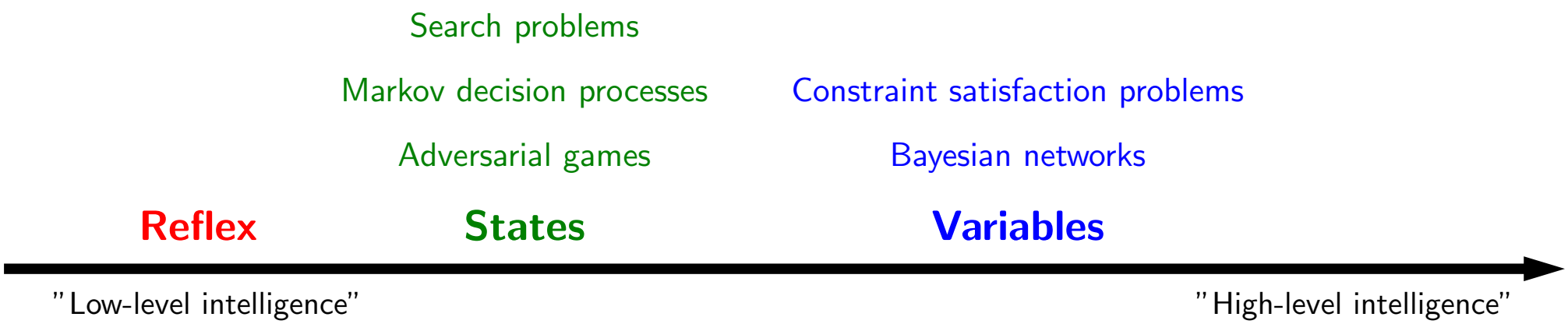
What kind of model is appropriate for playing Pac-Man against ghosts that move into each valid adjacent square with equal probability?

search problem

Markov decision process

adversarial game

Course plan



Machine learning

Sudoku

5	3			7				
6			1	9	5			
	9	8					6	
8				6				3
4			8		3			1
7				2				6
	6					2	8	
			4	1	9			5
				8			7	9

5	3	4	6	7	8	9	1	2
6	7	2	1	9	5	3	4	8
1	9	8	3	4	2	5	6	7
8	5	9	7	6	1	4	2	3
4	2	6	8	5	3	7	9	1
7	1	3	9	2	4	8	5	6
9	6	1	5	3	7	2	8	4
2	8	7	4	1	9	6	3	5
3	4	5	2	8	6	1	7	9

Goal: put digits in blank squares so each row, column, and 3x3 sub-block has digits 1–9

Note: order of filling squares doesn't matter in the evaluation criteria!

- In state-based models, solutions are procedural: they specify step by step instructions on how to go from A to B. In many applications, the order in which things are done isn't important.

5	3			7				
6			1	9	5			
	9	8					6	
8				6				3
4			8		3			1
7				2				6
	6					2	8	
			4	1	9			5
				8			7	9

Example: Sudoku

Variables: $X_{i,j} \in \{1, \ldots, 9\}$ for $1 \leq i, j \leq 9$

Constraints: Each row of X contains $\{1, \ldots, 9\}$

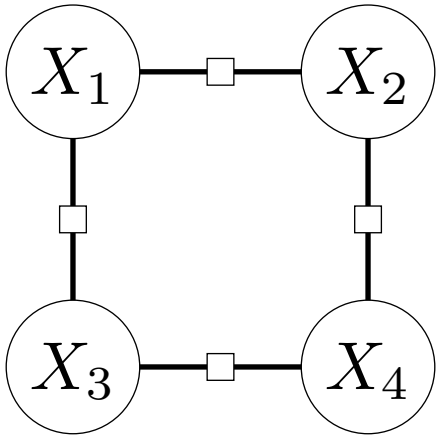
Each column of X contains $\{1, \ldots, 9\}$

Each sub-block of X contains $\{1, \ldots, 9\}$

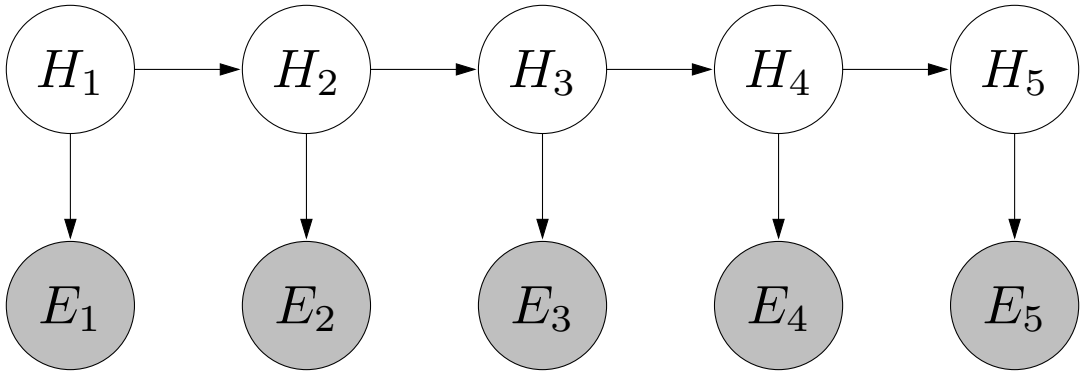
- For example, in Sodoku, it doesn't matter what order the squares are filled in. For these applications, **variable-based models** are more appropriate models. In these models, a solution corresponds to an assignment of values (e.g., digits) to variables (e.g., squares).

Variable-based models

Constraint satisfaction problems: hard constraints (e.g., Sudoku, scheduling)

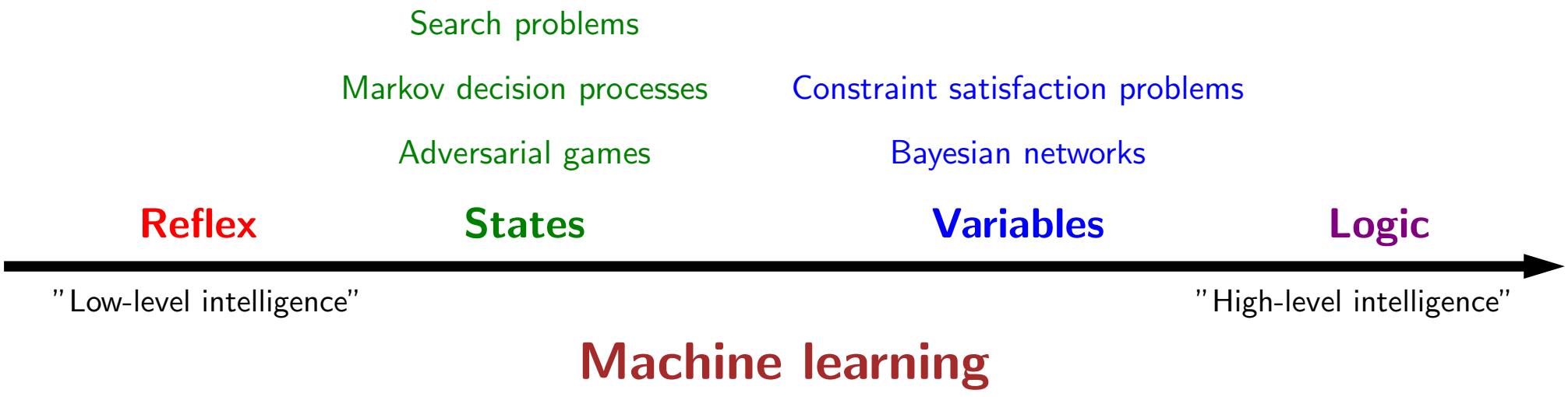


Bayesian networks: soft dependencies (e.g., tracking cars from sensors)



- **Constraint satisfaction problems** are variable-based models where we only have hard constraints. For example, in scheduling, we can't have two people in the same place at the same time.
- **Bayesian networks** are variable-based models where variables are random variables which are dependent on each other. For example, the true location of an airplane H_t and its radar reading E_t are related, as are the location H_t and the location at the last time step H_{t-1}. The exact dependency structure is given by the graph structure and formally defines a joint probability distribution over all the variables. This topic is studied thoroughly in probabilistic graphical models (CS228).

Course plan


Search problems
Markov decision processes
Adversarial games
Constraint satisfaction problems
Bayesian networks
Reflex
States
Variables
Logic
"Low-level intelligence"
"High-level intelligence"
Machine learning

Question

You get extra credit if you write a paper and you solve the problems. You didn't get extra credit, but you did solve the problems. Did you write a paper?

yes

no

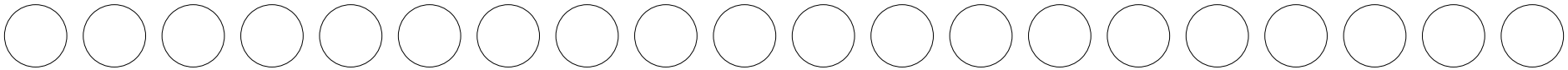
Implicit representation

All students work hard.

John is a student.

Therefore, John works hard.

Variable-based models would explicitly represent all the students — this is inefficient.



Higher-order reasoning

John believes *it will rain*.

Will it rain?

Does John believe *it will not rain* (assuming John is logical)?

Need **expressive power** of logic to represent this...

- Our last stop on the tour is **logic**. Even more so than variable-based models, logic provides a compact language for modeling, which gives us more expressivity.
- It is interesting that historically, logic was one of the first things that AI researchers started with in the 1950s. While logical approaches were in a way quite sophisticated, they did not work well on complex real-world tasks with noise and uncertainty. On the other hand, methods based on probability and machine learning naturally handle noise and uncertainty, which is why they presently dominate the AI landscape. However, they have yet to be applied successfully to tasks that require really sophisticated reasoning.
- In this course, we will appreciate the two as not contradictory, but simply tackling different aspects of AI — in fact, in our schema, logic is a class of models which can be supported by machine learning. An active area of research is to combine the modeling richness of logic with the robustness and agility of machine learning.

Language and logic

Components:

- Natural language parsing
- Knowledge representation
- Logical inference

[demo]

Course plan

Search problems

Markov decision processes

Adversarial games

Constraint satisfaction problems

Bayesian networks

Reflex **States** **Variables** **Logic**

"Low-level intelligence" "High-level intelligence"

Machine learning

Roadmap

Why learn AI?

What topics will you learn?

How will you learn it?

Optimization

Course objectives

Before you take the class, you should know...

- Programming (CS 106A, CS 106B, CS 107)
- Discrete math (CS 103)
- Probability (CS 109)

At the end of this course, you should...

- Be able to tackle real-world tasks with the appropriate models and algorithms
- Be more proficient at math and programming

Coursework

- Homeworks (60%)
- Exam (20%)
- Project (20%)

Homeworks

- 8 homeworks, mix of written and programming problems, centers on an application

Introduction	foundations
Machine learning	sentiment classification
Search	text reconstruction
MDPs	blackjack
Games	Pac-Man
CSPs	course scheduling
Bayesian networks	car tracking
Logic	language and logic

- Some have competitions for extra credit
- When you submit, programming parts will be sanity checked on basic tests; your grade will be based on hidden test cases

Exam

- Goal: test your ability to use knowledge to solve new problems, not know facts
- All written problems, similar to written part of homeworks
- Closed book except one page of notes
- Covers all material up to and including preceding week
- Tue Nov. 29 from 6pm to 9pm (3 hours)

Project

- Goal: choose any task you care about and apply techniques from class
- Work in groups of up to 3; find a group early, your responsibility to be in a good group
- Milestones: proposal, progress report, poster session, final report
- Task is completely open, but must follow well-defined steps: task definition, implement baselines/oracles, evaluate on dataset, literature review, error analysis (read website)
- Help: assigned a CA mentor, come to any office hours

Policies

Late days: 8 total late days, max two per assignment

Regrades: come in person to the owner CA of the homework

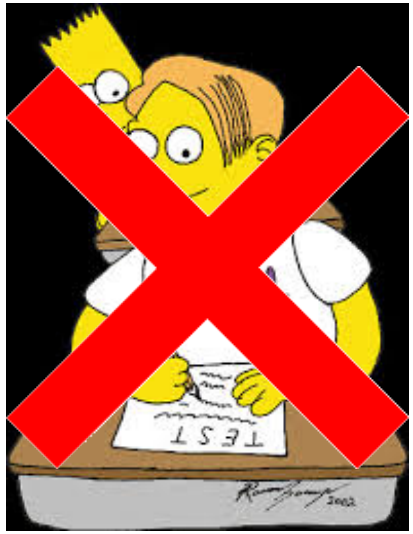
Piazza: ask questions on Piazza, don't email us directly

Piazza: extra credit for students who help answer questions

All details are on the course website

THE HONOR CODE

- Do collaborate and discuss together, but write up and code independently.
- Do not look at anyone else's writeup or code.
- Do not show anyone else your writeup or code or post it online.
- When debugging, only look at input-output behavior.
- We will run MOSS periodically to detect plagarism.



Lecture slides

- Ask questions and provide feedback on individual slides
- Keyboard shortcuts under [Help]
- Lecture notes are available interleaved with slides

Different ways to view the slides:

- One page (press 'p'): make screen large enough for notes to be side-by-side
- Presentation with slide builds (press 'shift-d')
- Text-only outline (press 'shift-o'): for fast loading
- PDF (1pp or 6pp)

Roadmap

Why learn AI?

What topics will you learn?

How will you learn it?

Optimization

Paradigm

Real-world task 

Modeling

Formal task (model) 

Algorithms

Program 

Optimization

Models are optimization problems:

$$\min_{x \in C} F(x)$$

Discrete optimization: x is a discrete object

$$\min_{x \in \{\text{abcd,xyz}\}} \text{Length}(x)$$

Algorithmic tool: dynamic programming

Continuous optimization: x is a vector of real numbers

$$\min_{x \in \mathbb{R}} (x - 5)^2$$

Algorithmic tool: gradient descent

- We are now done with the high-level motivation for the class. Let us now dive into some technical details. Recall that modeling converts real-world tasks to models and algorithms solves these models. In this course, we will express our models as **optimization problems**, which provides a mathematical specification of what we want to compute.
- In total generality, optimization problems ask that you find the x that lives in a constraint set C that makes the function $F(x)$ as small as possible.
- There are two types of optimization problems we'll consider: discrete optimization problems and continuous optimization problems. Both are backed by a rich research field and are interesting topics in their own right. For this course, we will use the most basic tools from these topics: **dynamic programming** and **gradient descent**.
- Let us do two practice problems to illustrate each tool. For now, we are assuming that the model (optimization problem) is given and only focus on **algorithms**.

Problem: computing edit distance

Input: two strings, s and t

Output: minimum number of character insertions, deletions, and substitutions it takes to change s into t

Examples:

"cat", "cat"	$\Rightarrow$	0
"cat", "dog"	$\Rightarrow$	3
"cat", "at"	$\Rightarrow$	1
"cat", "cats"	$\Rightarrow$	1
"a cat!", "the cats!"	$\Rightarrow$	4

[live solution]

- Let's consider the formal task of computing the edit distance (or more precisely the Levenshtein distance) between two strings. These measures of dissimilarity have applications in spelling correction, computational biology (applied to DNA sequences).
- As a first step, you should think to break down the problem into subproblems. Observation 1: inserting into s is equivalent to deleting a letter from t (ensures subproblems get smaller). Observation 2: perform edits at the end of strings (might as well start there).
- Consider the last letter of s and t. If these are the same, then we don't need to edit these letters, and we can proceed to the second-to-last letters. If they are different, then we have three choices. (i) We can substitute the last letter of s with the last letter of t. (ii) We can delete the last letter of s. (iii) We can insert the last letter of t at the end of s.
- In each of those cases, we can reduce the problem into a smaller problem, but which one? We simply try all of them and take the one that yields the minimum cost!
- We can express this more formally with a mathematical recurrence. These types of recurrences will show up throughout the course, so it's a good idea to be comfortable with them. Before writing down the actual recurrence, the first step is to express the quantity that we wish to compute. In this case: let $d(m, n)$ be the edit distance between the first m letters of s and the first n letters of t. Then we have

$$d(m,n) = \begin{cases} m & \text{if } n = 0 \\ n & \text{if } m = 0 \\ d(m-1, n-1) & \text{if } s\_m = t\_n \\ 1 + \min\{d(m-1,n-1), d(m-1,n), d(m,n-1)\} & \text{otherwise.} \end{cases}$$

- Once you have the recurrence, you can code it up. The straightforward implementation will take exponential time, but you can **memoize** the results to make it $O(n^2)$ time. The end result is the dynamic programming solution: recurrence + memoization.

Problem: finding the least squares line

Input: set of pairs $\{(x_1, y_1), \ldots, (x_n, y_n)\}$

Output: $w \in \mathbb{R}$ that minimizes the squared error

$$F(w) = \sum_{i=1}^{n} (x_i w - y_i)^2$$

Examples:

$$\begin{aligned} \{(2,4)\} &\Rightarrow 2 \\ \{(2,4),(4,2)\} &\Rightarrow ? \end{aligned}$$

[live solution]

- The formal task is this: given a set of n two-dimensional points (x_i, y_i) which defines $F(w)$, compute the w that minimizes $F(w)$.
- A brief detour to explain the modeling that might lead to this formal task. **Linear regression** is an important problem in machine learning, which we will come to later. Here's a motivation for the problem: suppose you're trying to understand how your exam score (y) depends on the number of hours you study (x). Let's posit a linear relationship $y = wx$ (not exactly true in practice, but maybe good enough). Now we get a set of training examples, each of which is a (x_i, y_i) pair. The goal is to find the slope w that best fits the data.
- Back to algorithms for this formal task. We would like an algorithm for optimizing general types of $F(w)$. So let's **abstract away from the details**. Start at a guess of w (say $w = 0$), and then iteratively update w based on the derivative (gradient if w is a vector) of $F(w)$. The algorithm we will use is called **gradient descent**.
- If the derivative $F'(w) < 0$, then increase w; if $F'(w) > 0$, decrease w; otherwise, keep w still. This motivates the following update rule, which we perform over and over again: $w \leftarrow w - \eta F'(w)$, where $\eta > 0$ is a **step size** that controls how aggressively we change w.
- If η is too big, then w might bounce around and not converge. If η is too small, then we w might not move very far to the optimum. Choosing the right value of η can be rather tricky. Theory can give rough guidance, but this is outside the scope of this class. Empirically, we will just try a few values and see which one works best. This will help us develop some intuition in the process.
- Now to specialize to our function, we just need to compute the derivative, which is an elementary calculus exercise: $F'(w) = \sum_{i=1}^{n} 2(x_i w - y_i)x_i$.

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Question

What was the most surprising thing you learned today?

Summary

- AI applications are high-impact and complex
- Think in terms of modeling + algorithms
- Models: learning + [reflex, states, variables, logic]
- Section this Thursday: review of foundations
- Homework [foundations]: due next Tuesday 11pm
- Course will be fast-paced and exciting!