



# Lecture 20: Conclusion





# Roadmap

## Natural language understanding

Computer vision

Summary of CS221

Next courses

History of AI

Food for thought

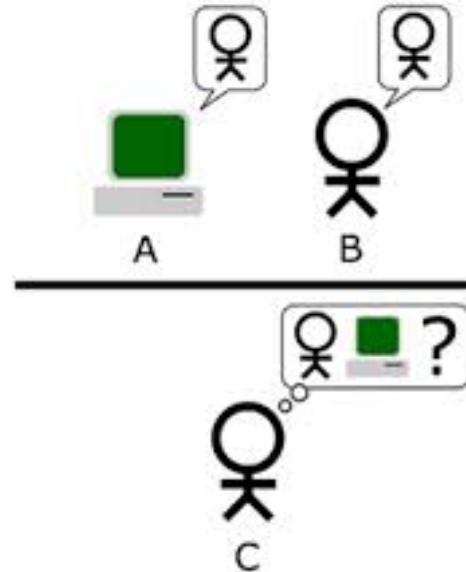
# *Natural language understanding*

# Humans are the only example



# The Imitation Game (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.

- **Behavioral test**
- ...of **intelligence**, not just natural language understanding

# Google

Google how many people live in lille

Web Maps News Shopping Images More ▾ Search tools

---

About 14,200,000 results (0.54 seconds)

**227,560 (2010)**

Lille, Population



# IBM Watson

*William Wilkinson's "An Account of the Principalities of Wallachia and Moldavia" inspired this author's most famous novel.*



# Siri



# Promise of Siri



Where is **The Hobbit** playing in **Mountain View**?

The Hobbit is playing at the Century 16 Theater.

When is **it** playing **there**?

It's playing at 2pm, 5pm, and 8pm.



OK. I'd like 1 **adult** and 2 **children** for **the first show**.  
How much would **that** cost?

Need **domain knowledge**, **discourse knowledge**, **world knowledge**

# Reality of Siri



**Colbert:** Write the show.

**Siri:** What would you like to search for?

**Colbert:** I don't want to search for anything! I want to write the show!

**Siri:** Searching the Web for "search for anything. I want to write the shuffle."

[...]

**Colbert:** For the love of God, the cameras are on, give me something?

**Siri:** What kind of place are you looking for? Camera stores or churches?

# Some headlines

*Stolen Painting Found by Tree*

*Iraqi Head Seeks Arms*

*Local HS Dropouts Cut in Half*

*Juvenile Court to Try Shooting Defendant*

*Kids Make Nutritious Snacks*

*Ban on Nude Dancing on Governor's Desk*

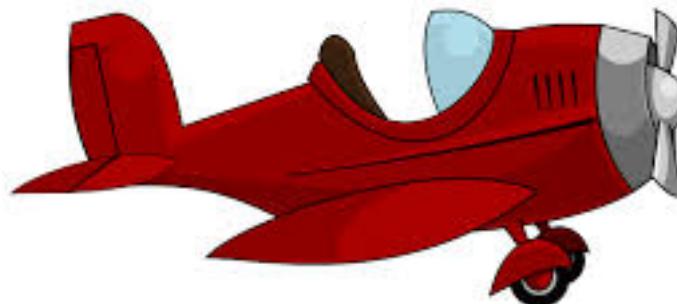
**Ambiguity** ⇒ funny for humans, wrong for machines

# Subtleties in language

*I spent three hours on **land** this afternoon.*



*I spent three hours on the **ground** this afternoon.*



# Stories

Story 1:

*The waiter came to the table. Joe went to a restaurant. Bill found five dollars. The end.*

Story 2:

*Joe went to a restaurant. Joe ordered a hamburger. When the hamburger came, it was burnt to a crisp. Joe stormed out without paying.*

- Need background knowledge to really **understand**
- Schank and Abelson developed notion of a **script** which captures this knowledge
- Same idea as frame, but tailored for event sequences

# SHRDLU [Winograd 1971]

Person: Pick up a big red block.

Computer: OK.

Person: Grasp the pyramid.

Computer: I don't understand which pyramid you mean.

Person (changing their mind): Find a block which is taller than the one you are holding and put it into the box.

Computer: By "it", I assume you mean the block which is taller than the one I am holding.

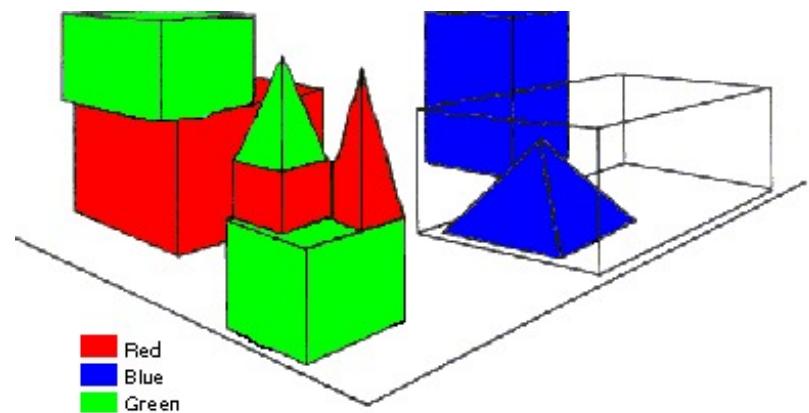
Computer: OK.

Person: What does the box contain?

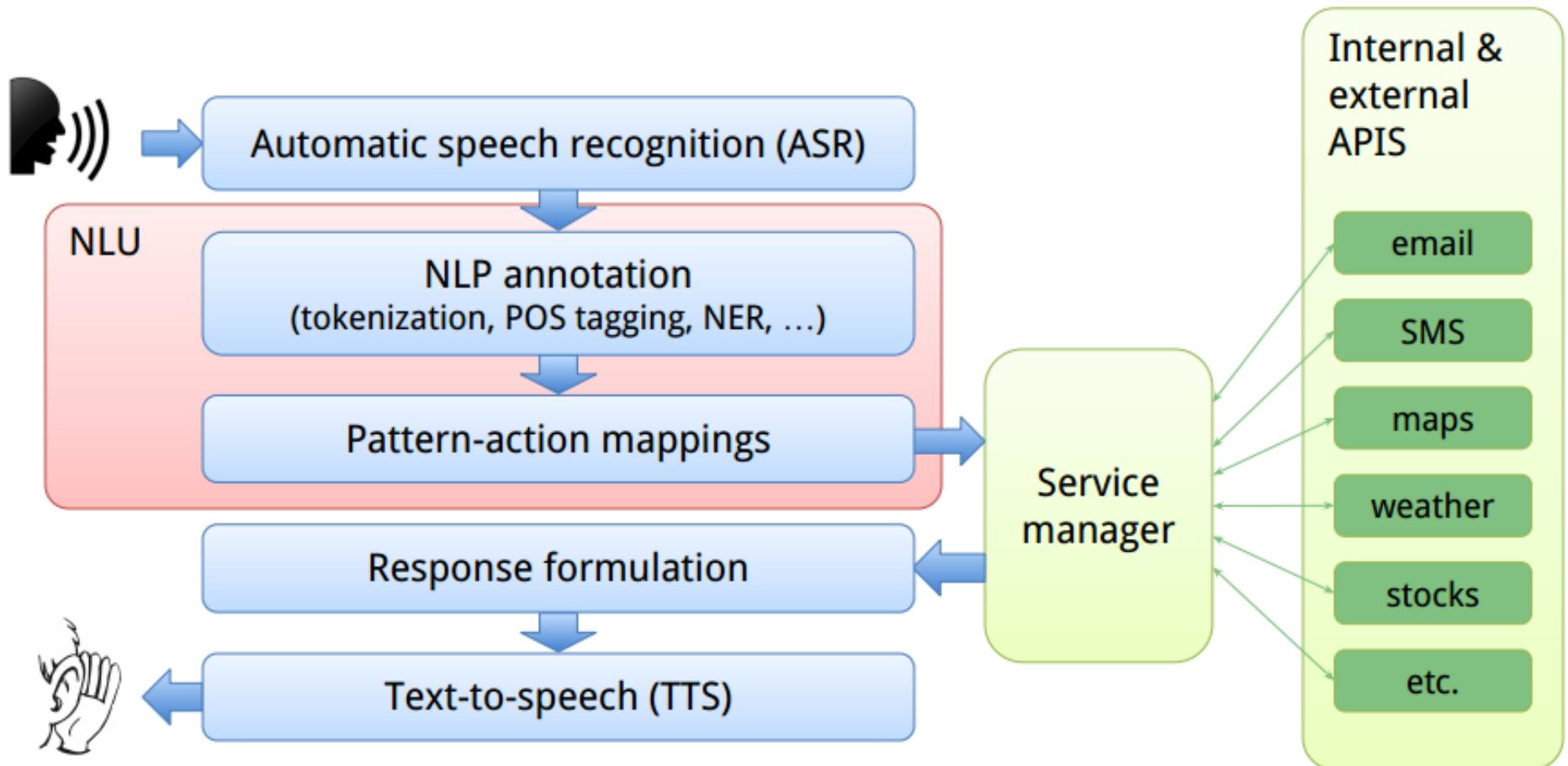
Computer: The blue pyramid and the blue block.

Person: What is the pyramid supported by?

Computer: The box.



# Siri architecture



# Answering macro questions



By John McGarrity

Tokyo will meet carbon reduction targets without the need to use carbon credits in its emissions trading scheme, mainly as a result of increased energy efficiency after the 2011 Fukushima nuclear disaster threatened a crunch in power supply.

Japan's capital, one of the world's largest cities, became the first urban area in Asia to impose emissions caps and carbon trading at the start of the decade, blazing a trail for other cities that are using the market to control climate-changing gases.

But big cuts in emissions through energy efficiency – spurred by a 2011 catastrophic Tsunami and subsequent meltdown of a nuclear reactor – is a timely reminder of how random events and changing government priorities can blunt the effectiveness of emissions trading schemes.

"Setting an ambitious cap for emissions schemes is crucial. Carbon markets should really take the lead in reducing emissions at least cost, but also work in parallel with other policies rather than compete with them" said Sarah Deblock, European Policy Director with the International Emissions Trading Association.

[Report: Fukushima to use 100% renewable energy by 2040](#)

[Report: Japan proposes huge smart meter roll-out to cut emissions](#)

By 2015 EU member states are likely to agree how energy efficiency measures potentially hindering renewables targets and a 40%



Carbon Dioxide emissions by country						
Click heading to sort. <a href="#">Download this data</a>						
Table id	Rank, 2009	Country or region	2008, mil tonnes	2009, TOTAL, mil tonnes	2009, per capita, tonnes	% change, 2008 to 2009
225		World	30,493.23	30,398.42	4.49	-0.3
179		Asia & Oceania	12,338.41	13,264.09	3.53	7.5
188	1	China	6,803.92	7,710.50	5.83	13.3
1		North America	6,885.07	6,410.54	14.19	-6.9
7	2	United States	5,833.13	5,424.53	17.67	-7
54		Europe	4,628.98	4,310.30	7.14	-6.9
91		Eurasia	2,595.86	2,358.03	8.32	-9.2
107		Middle East	1,658.55	1,714.09	8.22	3.3
194	3	India	1,473.73	1,602.12	1.38	8.7
102	4	Russia	1,698.38	1,572.07	11.23	-7.4
8		Central & South America	1,228.65	1,219.78	2.57	0.7

*Which country has the highest CO2 emissions?*

*Which had the highest increase since last year?*

*What fraction is from the five countries with highest GDP?*

**requires aggregation / computation**

# Semantic parsing

*What is the average concentration of iron in ilmenite?*



```

(ING/BY
  (PUSH NP/ T
    (SETR SUBJ *)
    (TO VP/VP

      (* IF THE SUBJECT WAS NOT PROPERLY DETERMINED IN A
         POSS-ING COMPLEMENT, LOOK FOR IT HERE.)

    )))

(NP/
  (CAT DET T

    ((GETF POSSPRO                               (* START OF THE NP
                                                   NETWORK.))
     (ADDL ADJS (BUILDO (POSS (NP (PRO *))))))
     (SETRO DET THE

      (* IF THE DETERMINER IS A POSSESSIVE PRONOUN
         (MY, YOUR), CONSTRUCT THE POSSESSIVE MODIFIER AND USE
         'THE' FOR THE DETERMINER)

    ))
    (T (SETR DET *)))
    (TO NP/ART))
  (CAT PRO T
    (SETR N (BUILDO (PRO *)))                  (* A PRONOUN MAY PICK UP
                                                   PP MODIFIERS IN NP/HEAD)
    )
    (SETR NU (GETF NUMBER))
    (TO NP/NP))
  (MEM (WHETHER IF)
    T
    (SETR NTYPE *)
    (TO COMPL/NTYPE

      (* CONSTRUCT THE COMPLEMENT STRUCTURE FOR SENTENCES
         SUCH AS 'I DON'T KNOW WHETHER HE LEFT.')
    ))

  ))
```

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About 2,440,000 results (0.48 seconds)

[PDF] [Extraction of Titanium and Iron From Ilmenite With Fluosili...](#)

[stacks.cdc.gov/view/cdc/10135/cdc\\_10135\\_DS1.pdf](#) ▾

Extraction of Titanium and Iron From Ilmenite .... iron (Fe) from New York rock ilmenite using fluosilicic acid (HzSiF6). .... fractional amount of element leached., K.

[PDF] [Simultaneous recovery of total iron and titanium from ...](#)

[www.metalurgija.org.rs/mjom/vol18/No1/7\\_Baba\\_MME\\_1801.pdf](#) ▾

by AA Baba - Cited by 3 - Related articles

Oct 7, 2011 - and iron from ilmenite is also of particular interest and various extractants ... amount dissolved or undissolved at various time intervals up to 120 ...

[PDF] [Effects of Temperature on Ilmenite During Concentration o...](#)

[ijset.com/ijset/publication/v3s6/IJSET\\_2014\\_601.pdf](#) ▾

Jun 1, 2014 - Effects of Temperature on Ilmenite During Concentration of Iron in Laterites .... monitored by looking at the amount of charcoal consumed.

[Ilmenite - Wikipedia, the free encyclopedia](#)

[en.wikipedia.org/wiki/Ilmenite](#) ▾ Wikipedia ▾

Leucoxene is a typical component of altered gabbro and diorite and is ... It is found in large concentrations in layered intrusions where it forms as part of a .... The Balla Balla magnetite-iron-titanium-vanadium ore deposit in the Pilbara of ...

[ILMENITE \(Iron Titanium Oxide\) - Mineral Gallery](#)

[www.galleries.com/ilmenite](#) ▾

Chemical Formula: FeTiO<sub>3</sub>, Iron Titanium Oxide; Class: Oxides and Hydroxides; Group: Hematite ... Ilmenite is an economically important and interesting mineral. .... Hardness is 5 - 6; Specific Gravity is 4.5 - 5.0 (average for metallic minerals).

[How Do We Know That It's a Rock from the Moon? - Meteorites](#)

[meteorites.wustl.edu/lunar/howdoweknow.htm](#) ▾

Apr 4, 2014 - Ilmenite - An iron(II)-titanium oxide; more common in lunar basalts than .... particularly breccias, the average concentration of silica in the three ...

# Question answering via semantic parsing

*What is the largest city in states bordering California?*



semantic parsing



execute

Phoenix

# Paradigm

*[utterance: user input]*



semantic parsing

[program]



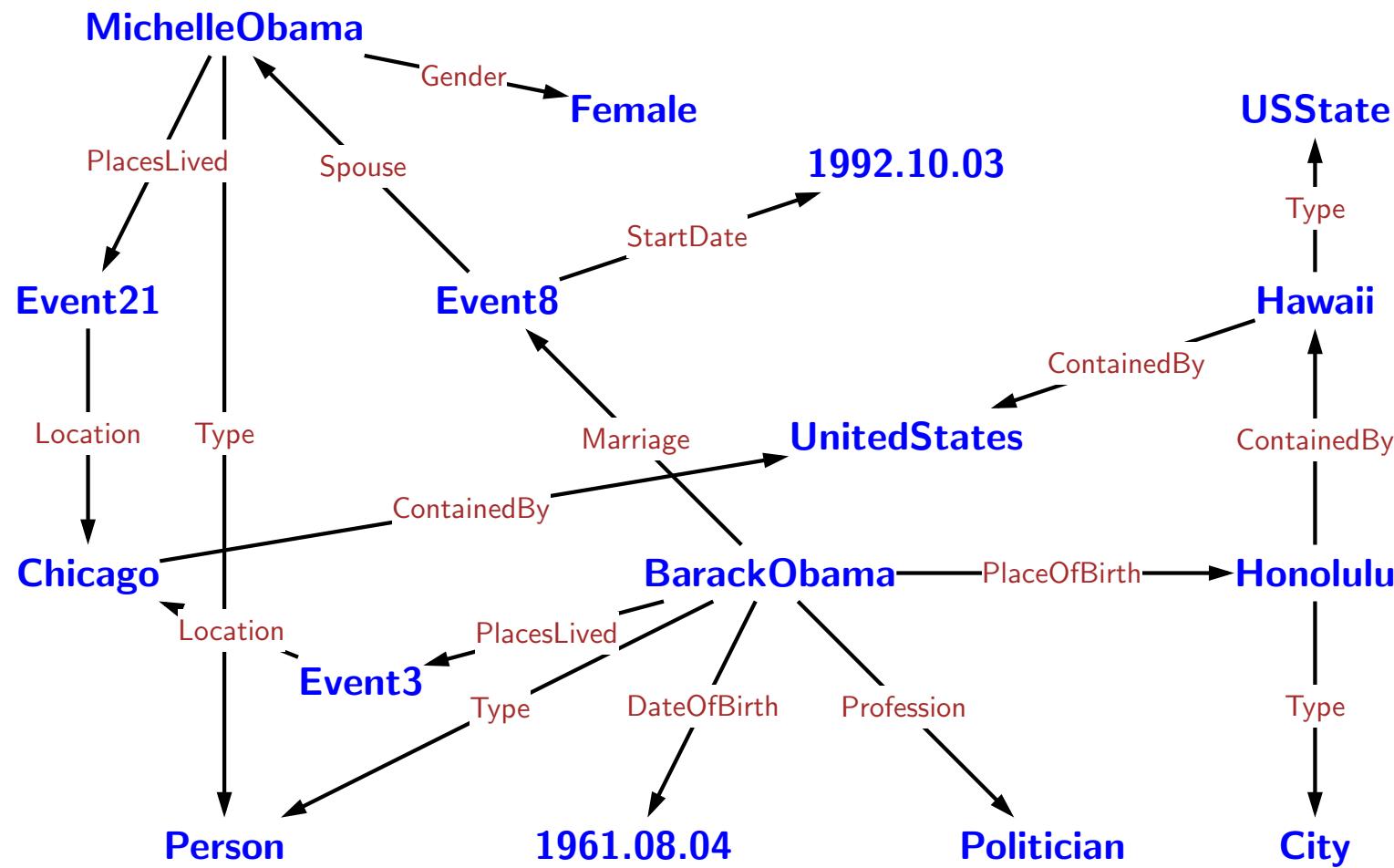
execute

[denotation: user output]

**Induce hidden program to accomplish end goal**

# Freebase

100M entities (nodes)    1B assertions (edges)



# Training intuition

*Where did Mozart tupress?*

~~PlaceOfBirth.WolfgangMozart~~ → Salzburg

PlaceOfDeath.WolfgangMozart ⇒ Vienna

PlaceOfMarriage.WolfgangMozart ⇒ Vienna

**Vienna**

*Where did Hogarth tupress?*

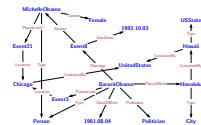
PlaceOfBirth.WilliamHogarth ⇒ London

PlaceOfDeath.WilliamHogarth ⇒ London

~~PlaceOfMarriage.WilliamHogarth~~ → Paddington

**London**

*hiking trails near Palo Alto  
dishes at Oren's Hummus  
ACL 2014 papers*



# Fewer than 10% of web questions answerable via Freebase

**dog-friendly hiking trails near Palo Alto**  
**spicy dishes at Oren's Hummus**  
**ACL 2014 papers about semantic parsing**

Year	Competition	Venue	Position	Event	Notes
<b>Representing  Poland</b>					
2001	World Youth Championships	Debrecen, Hungary	2nd	400 m	47.12
			1st	Medley relay	1:50.46
	European Junior Championships	Grosseto, Italy	1st	4x400 m relay	3:06.12
2003	European Junior Championships	Tampere, Finland	3rd	400 m	46.69
			2nd	4x400 m relay	3:08.62
2005	European U23 Championships	Erfurt, Germany	11th (sf)	400 m	46.62
			1st	4x400 m relay	3:04.41
	Universiade	Izmir, Turkey	7th	400 m	46.89
			1st	4x400 m relay	3:02.57
2006	World Indoor Championships	Moscow, Russia	2nd (h)	4x400 m relay	3:06.10
	European Championships	Gothenburg, Sweden	3rd	4x400 m relay	3:01.73
2007	European Indoor Championships	Birmingham, United Kingdom	3rd	4x400 m relay	3:08.14
	Universiade	Bangkok, Thailand	7th	400 m	46.85
			1st	4x400 m relay	3:02.05
2008	World Indoor Championships	Valencia, Spain	4th	4x400 m relay	3:08.76
	Olympic Games	Beijing, China	7th	4x400 m relay	3:00.32
2009	Universiade	Belgrade, Serbia	2nd	4x400 m relay	3:05.69

*How many times has this competitor placed 5th or better in competition?*

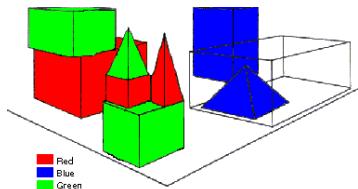
# Breadth

information retrieval

Google™ bing™



Objective: to develop semantic parsers with the modern sensibilities of web search.



semantic parsing





# Roadmap

Natural language understanding

**Computer vision**

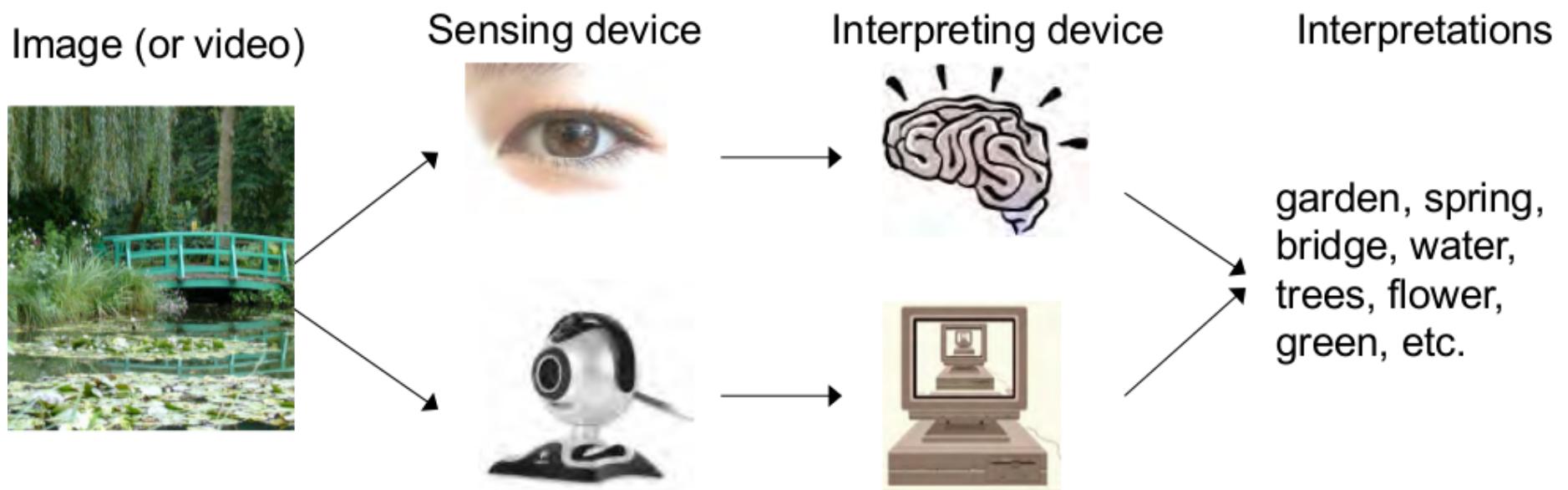
Summary of CS221

Next courses

History of AI

Food for thought

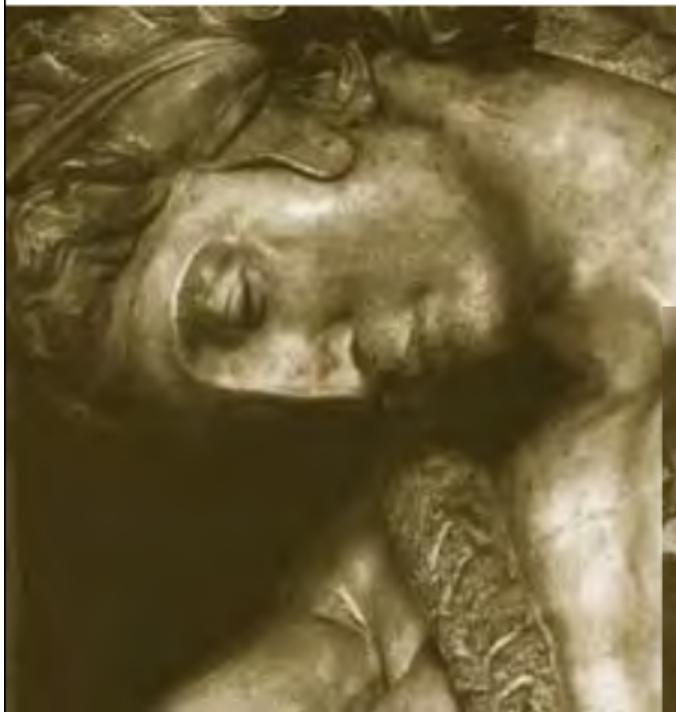
# Computer vision



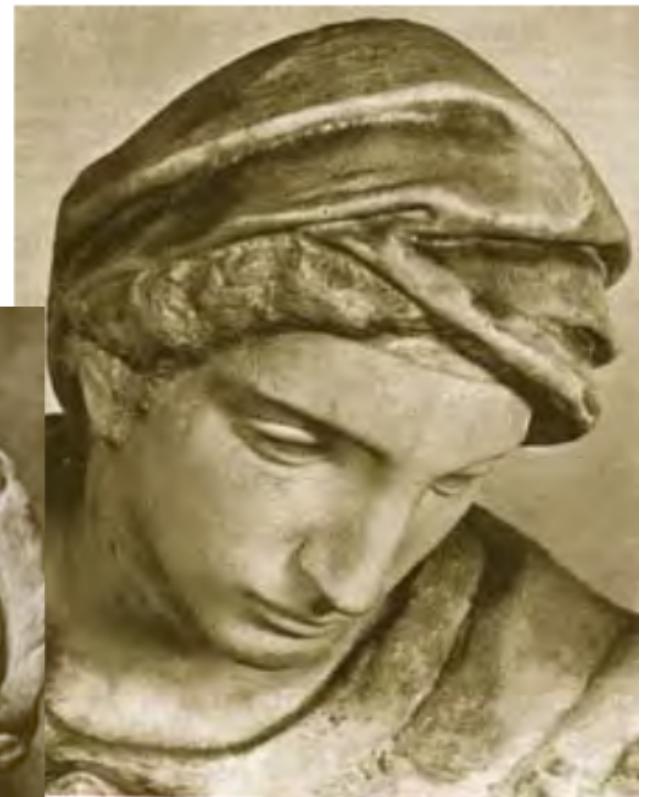
# Long-term goal: scene understanding



# Challenge: variation in viewpoint

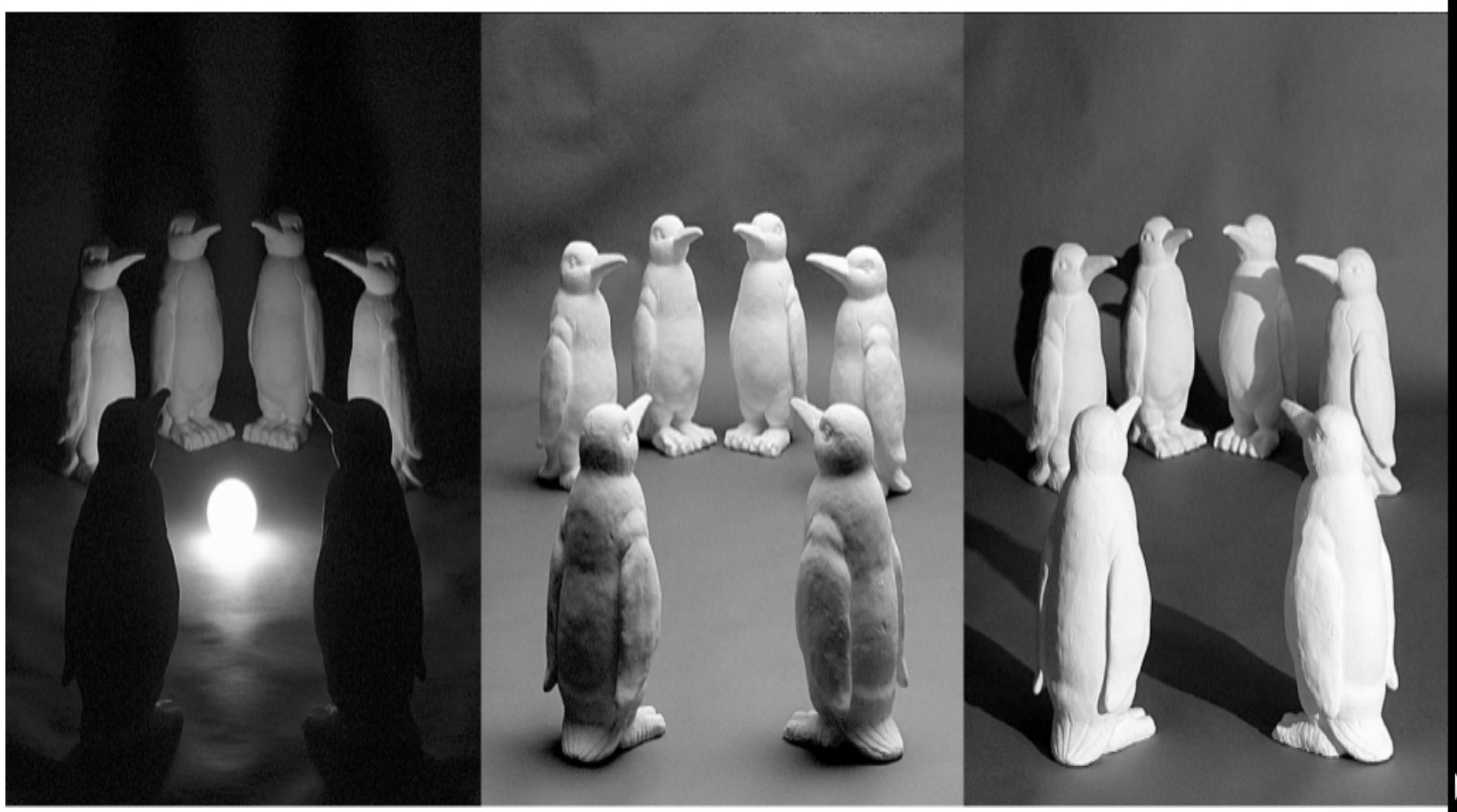


Michelangelo 1475-1564



[slide credit: Fei-Fei Li, J. Koenderink]

# Challenge: variation in illumination



[slide credit: Fei-Fei Li, Fergus, Torralba]

# Challenge: intra-class variation



# Summer Vision Project

*The summer vision project is an attempt to use our summer workers effectively in the construction of a significant part of a visual system.*  
—Seymour Papert, 1966

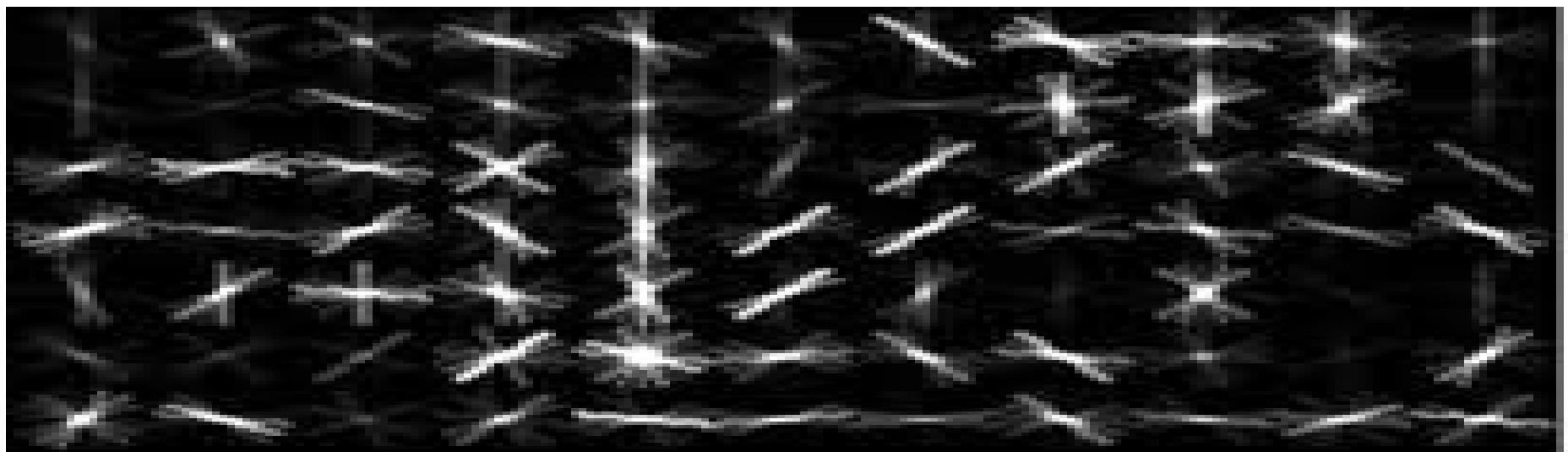


IN CS, IT CAN BE HARD TO EXPLAIN  
THE DIFFERENCE BETWEEN THE EASY  
AND THE VIRTUALLY IMPOSSIBLE.

# Features

Problem: pixel features are very poor features

Desiderata: features invariant to translation, rotation, scaling, deformation



Basic approach: measure changes in intensity between adjacent pixels, aggregate over local neighborhood

# Features

Hand-engineered features:

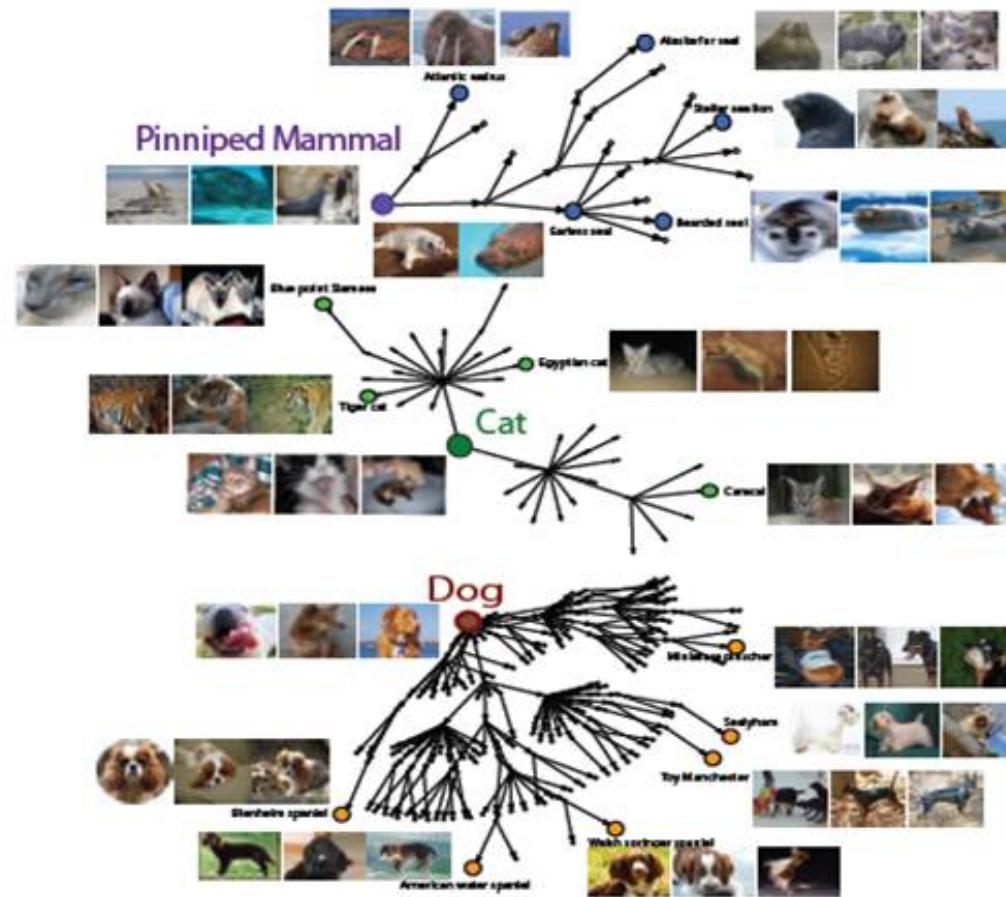
- Scale-invariant feature transform (SIFT) [Lowe, 1999]
- Histogram of oriented gradients (HOG) [Dalal, Triggs, 2005]

Automatically learned features:

- Convolutional neural networks [LeCun, 1998, etc.]
- Important part of "deep learning"

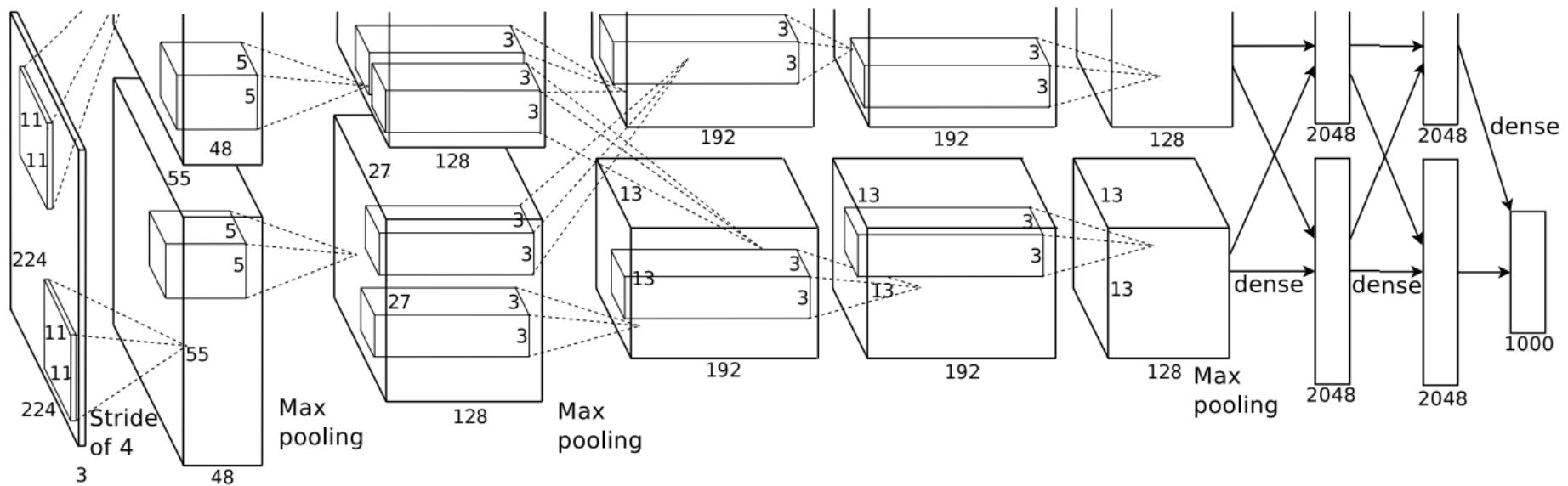
# ImageNet

14 million images, 22K categories [browse]



# ImageNet using CNNs

Convolutional neural network:

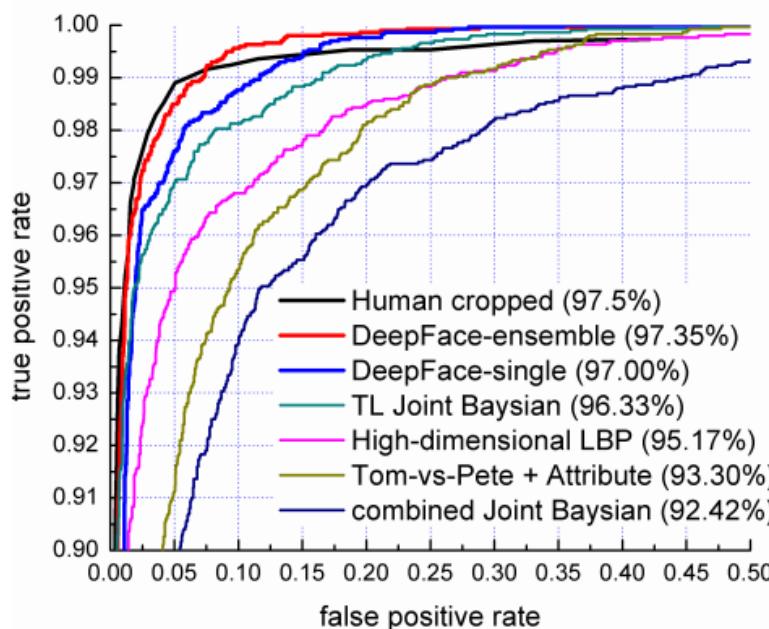
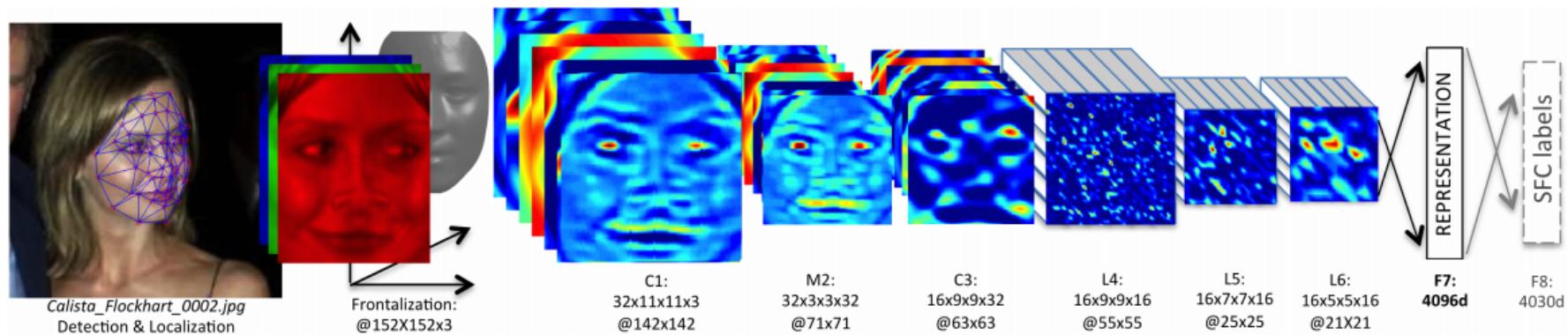


1st place: Krizhevsky et al. (16.4% error)

2nd place: non-CNNs (26.2% error)

# Face recognition

120 million parameters, 4 million faces, 4000 people



Humans: 97.53%  
DeepFace: 97.35%

# Generating image descriptions



*little girl is eating piece of cake*

Multimodal recurrent neural network:

<http://cs.stanford.edu/people/karpathy/deepimagesent/>



# Roadmap

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# Paradigm

Real-world task

## Modeling

search problems, MDPs, games, CSPs, Markov/Bayesian networks, first-order logic, etc.



Formal task (model)

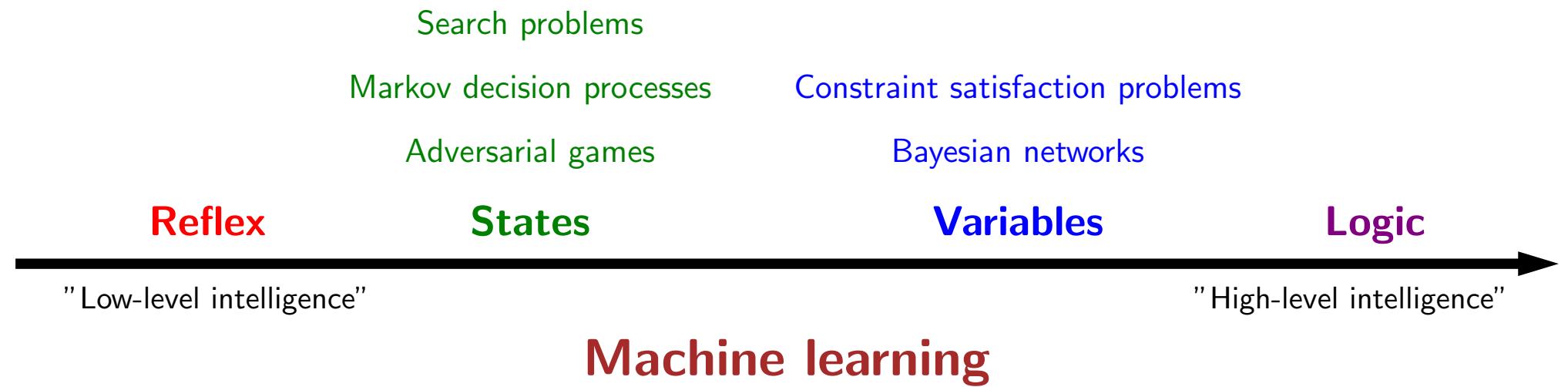
## Algorithms

UCS, DP, value iteration, variable elimination, particle filtering, Gibbs sampling, etc.

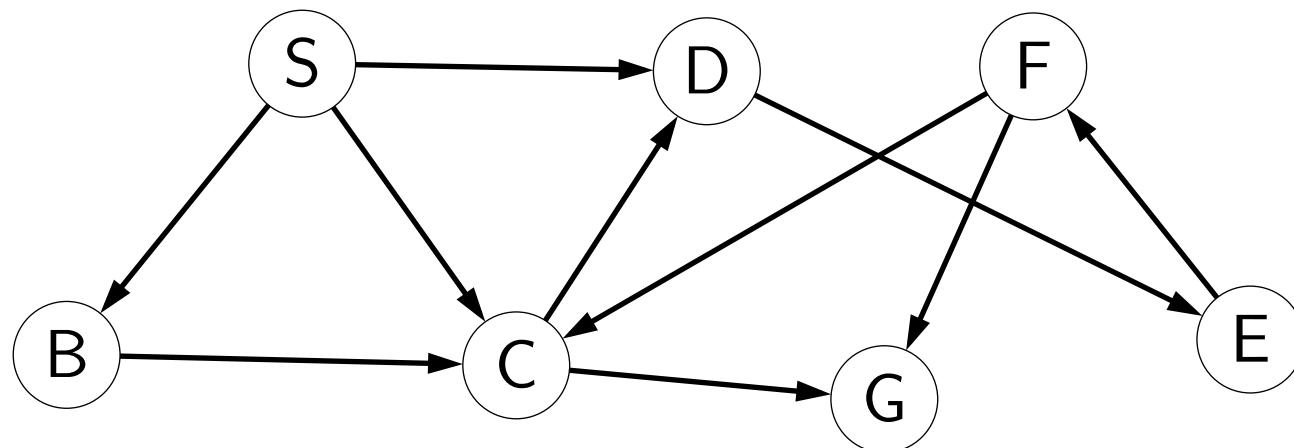


Program

# Course plan



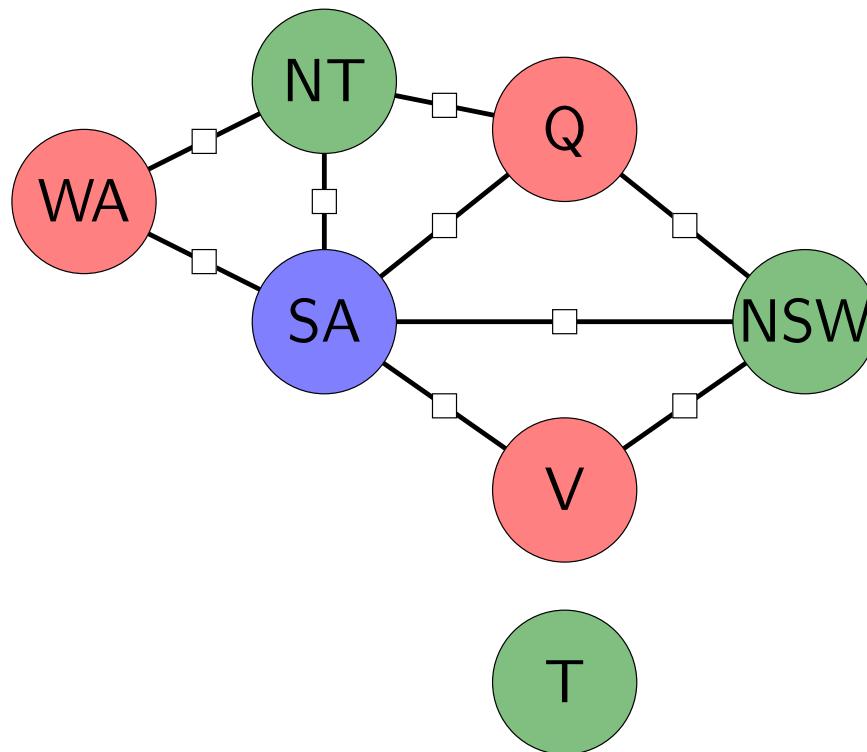
# State-based models



**Key idea: state**

A **state** is a summary of all the past actions sufficient to choose future actions **optimally**.

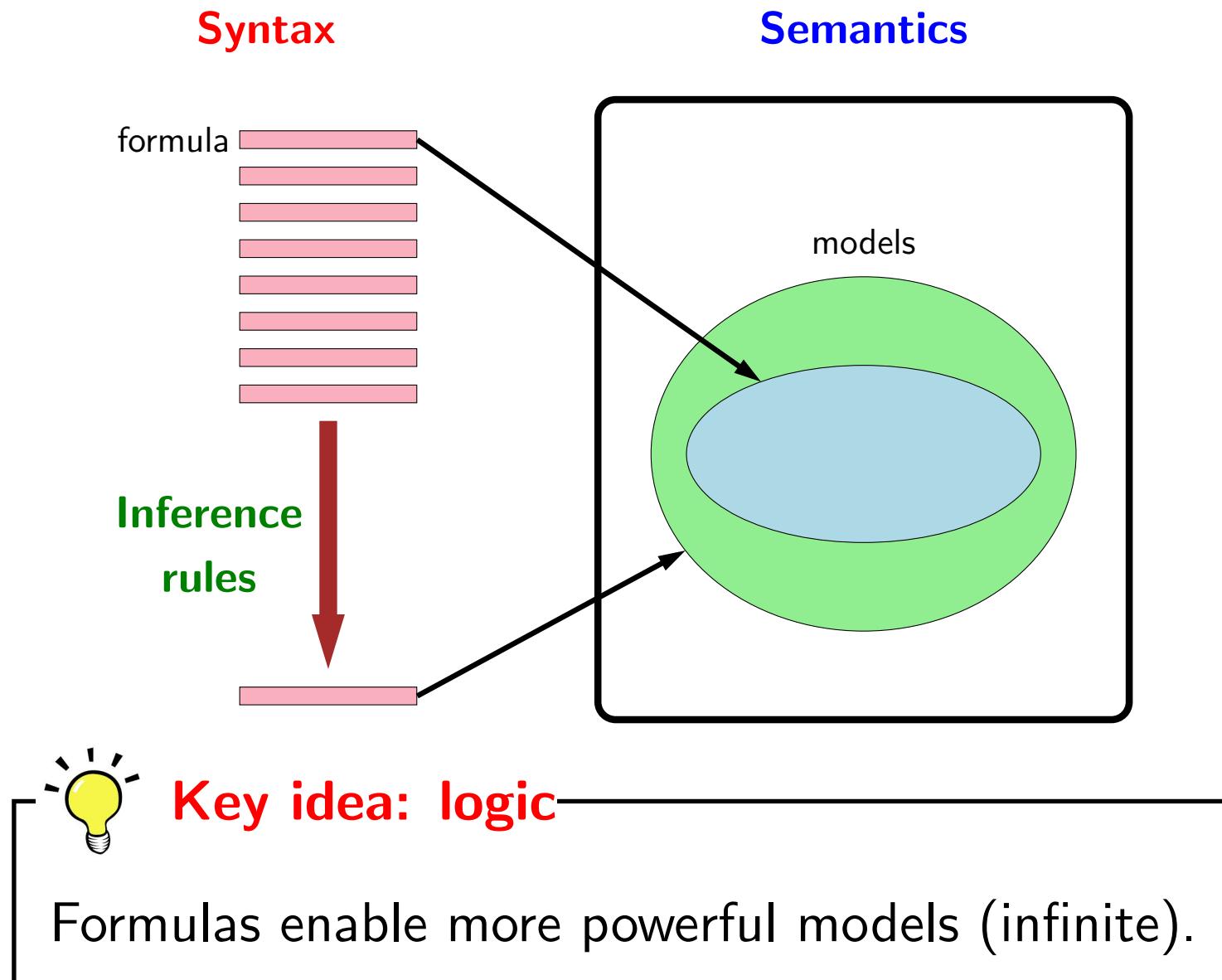
# Variable-based models



**Key idea: factor graphs**

Graph structure captures conditional independence.

# Logic-based models



# Machine learning

Objective: loss minimization

$$\min_{\mathbf{w}} \sum_{(x,y) \in \mathcal{D}_{\text{train}}} \text{Loss}(x, y, \mathbf{w})$$

Algorithm: stochastic gradient descent

$$\mathbf{w} \rightarrow \mathbf{w} - \eta_t \underbrace{\nabla \text{Loss}(x, y, \mathbf{w})}_{\text{prediction} - \text{target}}$$



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# Other AI-related courses

<http://ai.stanford.edu/courses/>

## Foundations:

- CS228: Probabilistic Graphical Models
- CS229: Machine Learning
- CS229T: Statistical Learning Theory
- CS334A: Convex Optimization
- ...

## Applications:

- CS224N: Natural Language Processing
- CS276: Information Retrieval and Web Search
- CS231A: Introduction to Computer Vision
- CS224W: Social and Information Network Analysis

# Machine learning (CS229)

- Boosting, bagging, feature selection
- Discrete  $\Rightarrow$  continuous
- K-means  $\Rightarrow$  mixture of Gaussians
- Q-learning  $\Rightarrow$  policy gradient

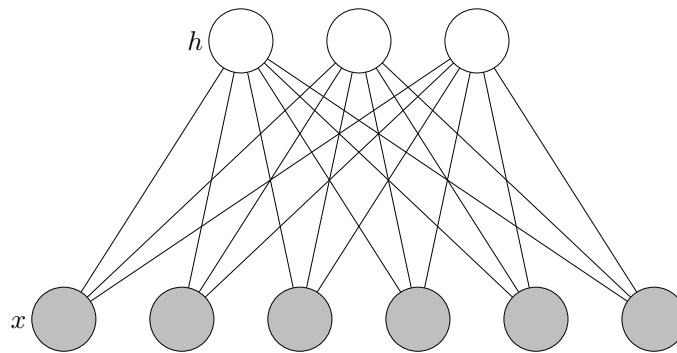
# Statistical learning theory (CS229T)

Question: what are the mathematical principles behind learning?

Uniform convergence: with probability at least  $1 - \delta$ ,

$$\text{TestError}(h) \leq \text{TrainError}(h) + \sqrt{\frac{\text{Complexity}(\mathcal{H})}{n}}$$

# Probabilistic graphical models (CS228)



- Forward-backward  $\Rightarrow$  message passing, variational methods
- Gibbs sampling  $\Rightarrow$  MCMC
- Structure learning

# Cognitive science

Question: How does the human mind work?

- Cognitive science and AI grew up together
- Humans can learn from few examples on many tasks

Computation and cognitive science (PSYCH204):

- Cognition as Bayesian modeling — probabilistic program [Tenenbaum, Goodman, Griffiths]

# Online materials

- Online courses (Coursera, edX)
- Videolectures.net: tons of recorded talks from major leaders of AI (and other fields)
- arXiv.org: latest research (pre-prints)

# Conferences

- AI: IJCAI, AAAI
- Machine learning: ICML, NIPS, UAI, COLT
- Data mining: KDD, CIKM, WWW
- Natural language processing: ACL, EMNLP, NAACL
- Computer vision: CVPR, ICCV, ECCV
- Robotics: RSS, ICRA



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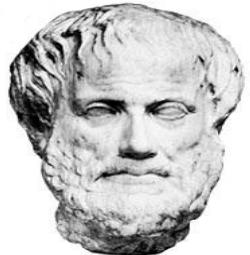
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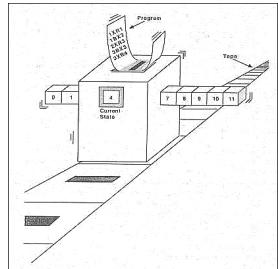
**History of AI**

Food for thought

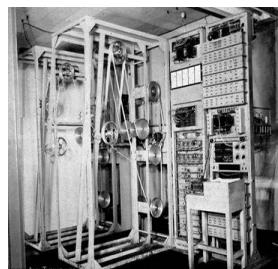
# Pre-AI developments



Philosophy: **intelligence** can be achieved via mechanical computation (e.g., Aristotle)



Church-Turing thesis (1930s): any computable function is **computable** by a Turing machine



Real computers (1940s): actual **hardware** to do it: Heath Robinson, Z-3, ABC/ENIAC

# Birth of AI

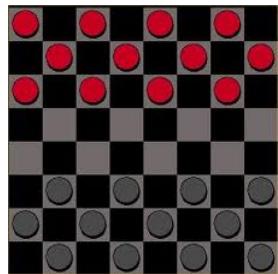
1956: Workshop at Dartmouth College; attendees: John McCarthy, Marvin Minsky, Claude Shannon, etc.



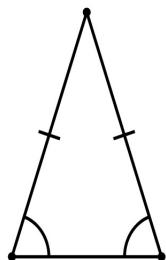
Aim for **general principles**:

*Every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it.*

# Birth of AI, early successes



**Checkers (1952)**: Samuel's program learned weights and played at strong amateur level



**Problem solving (1955)**: Newell & Simon's Logic Theorist: prove theorems in Principia Mathematica using search + heuristics; later, General Problem Solver (GPS)

# Overwhelming optimism...

*Machines will be capable, within twenty years, of doing any work a man can do.* —Herbert Simon

*Within 10 years the problems of artificial intelligence will be substantially solved.* —Marvin Minsky

*I visualize a time when we will be to robots what dogs are to humans, and I'm rooting for the machines.* —Claude Shannon

# ...underwhelming results

Example: machine translation

*The spirit is willing but the flesh is weak.*



(Russian)



*The vodka is good but the meat is rotten.*

1966: ALPAC report cut off government funding for MT

# Implications of early era

## Problems:

- **Limited computation**: search space grew exponentially, outpacing hardware ( $100! \approx 10^{157} > 10^{80}$ )
- **Limited information**: complexity of AI problems (number of words, objects, concepts in the world)

## Contributions:

- Lisp, garbage collection, time-sharing (John McCarthy)
- **Key paradigm**: separate **modeling** (declarative) and **algorithms** (procedural)

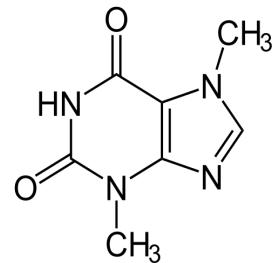
# Knowledge-based systems (70-80s)



Expert systems: elicit specific domain knowledge from experts in form of rules:

if [premises] then [conclusion]

# Knowledge-based systems (70-80s)



DENDRAL: infer molecular structure from mass spectrometry



MYCIN: diagnose blood infections, recommend antibiotics



XCON: convert customer orders into parts specification; save DEC \$40 million a year by 1986

# Knowledge-based systems

## Contributions:

- First **real application** that impacted industry
- Knowledge helped curb the exponential growth

## Problems:

- Knowledge is not deterministic rules, need to model **uncertainty**
- Requires considerable **manual effort** to create rules, hard to maintain

# Modern AI (90s-present)

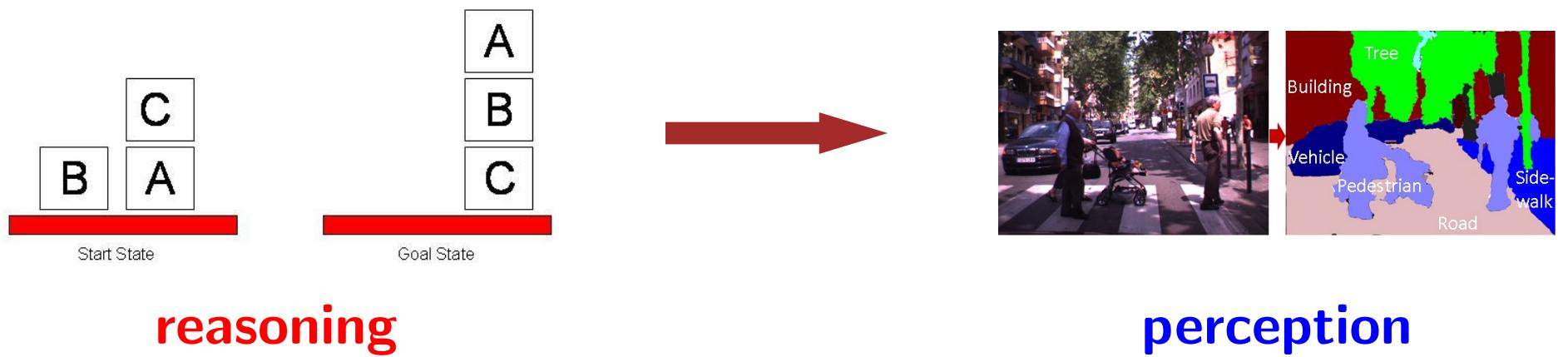
- **Probability**: Pearl (1988) promote Bayesian networks in AI to **model uncertainty** (based on Bayes rule from 1700s)

model → predictions

- **Machine learning**: Vapnik (1995) invented support vector machines to **tune parameters** (based on statistical models in early 1900s)

data → model

# Modern AI (90s-present)



# The Complexity Barrier

A number of people have suggested to me that large programs like the SHRDLU program for understanding natural language represent a kind of dead end in AI programming. Complex interactions between its components give the program much of its power, but at the same time they present a formidable obstacle to understanding and extending it. In order to grasp any part, it is necessary to understand how it fits with other parts, presents a dense mass, with no easy footholds. Even having written the program, I find it near the limit of what I can keep in mind at once.

— Terry Winograd (1972)



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# Causality

$T$ : Treatment

$S$ : Survival



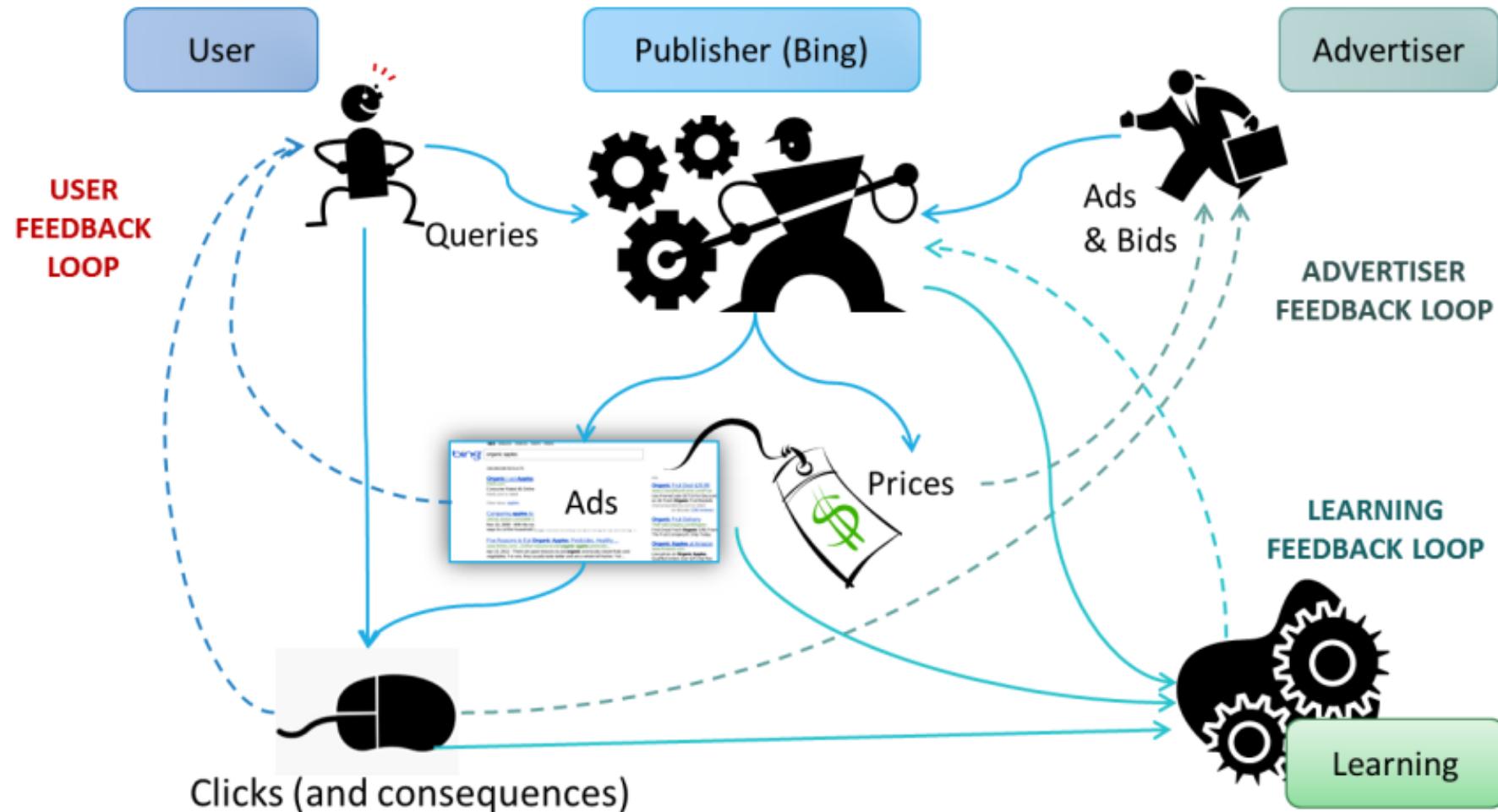
Suppose:

$$\mathbb{P}(S = 1 \mid T = 0) = 0.8 \quad \mathbb{P}(S = 1 \mid T = 1) = 0.3$$

What can we conclude about the treatment?

Nothing! Sick people are more likely to undergo treatment...

# AI in the real world



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# Machine Learning: The High-Interest Credit Card of Technical Debt

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## Abstract

Machine learning offers a fantastically powerful toolkit for building complex systems quickly. This paper argues that it is dangerous to think of these quick wins as coming for free. Using the framework of *technical debt*, we note that it is remarkably easy to incur massive ongoing maintenance costs at the system level when applying machine learning. The goal of this paper is highlight several machine learning specific risk factors and design patterns to be avoided or refactored where possible. These include boundary erosion, entanglement, hidden feedback loops, undeclared consumers, data dependencies, changes in the external world, and a variety of system-level anti-patterns.

Machine learning  $\Rightarrow$  software

## Traditional software:

```
def sort(numbers): ...
```

## Machine learning software:



- Improve parser?
- Add a new feature?
- Feedback loops: predict web pages based on what people click on...

**Everything depends on everything**

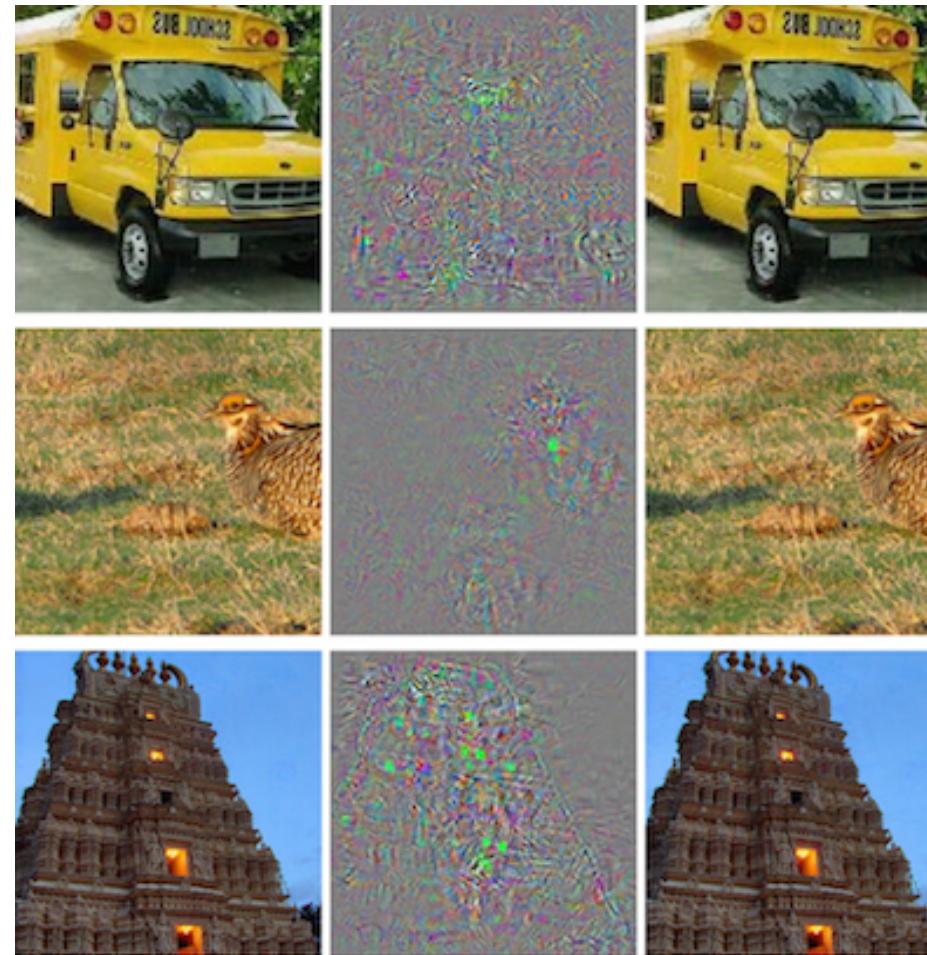
# Safety guarantees

- For air-traffic control, threshold level of safety: probability  $10^{-9}$  for a catastrophic failure (e.g., collision) per flight hour
- Move from human designed rules to a numeric Q-value table?

yes

# Adversarial examples

AlexNet predicts correctly on the left



AlexNet predicts **ostritch** on the right

# Fairness

Prediction task:

personal information  $\Rightarrow$  grant insurance?

Fallacy 1: it's just math, right?

learning algorithms  $\Leftarrow$  data  $\Leftarrow$  reflection of our society

Fallacy 2:

personal information – race, gender, etc.  $\Rightarrow$  grant insurance?

# Tools

- CS221 provides a set of tools to solve real-world problems



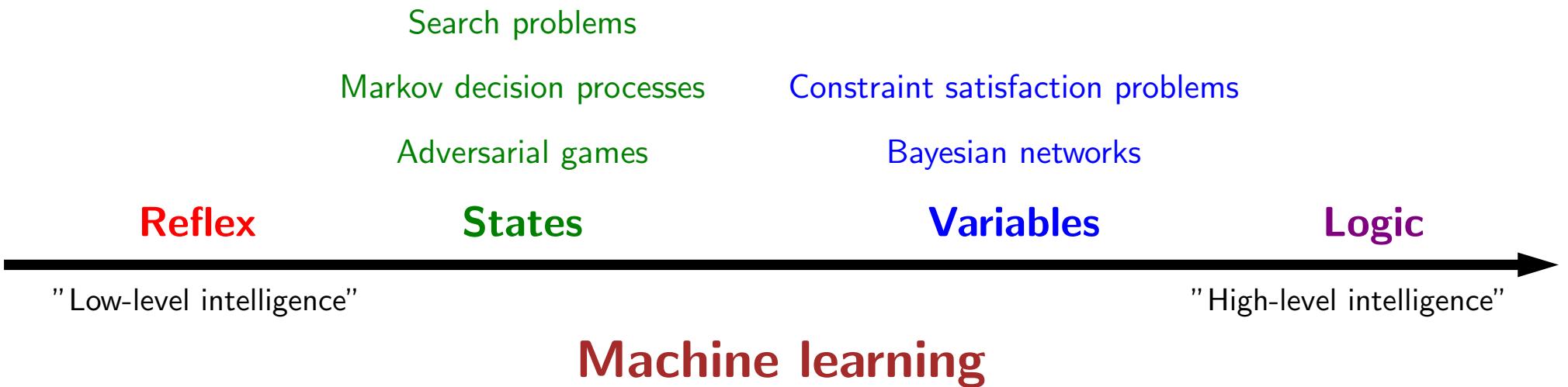
- Start with the nail, and figure out what tool to use

# Societal and industrial impact

Efficiency, communication, safety, health, environment



Self-driving cars, energy efficient, drug discovery, etc.



Please fill out course evaluations on Axess.

Thanks for an exciting quarter!