Paradigm

Modeling

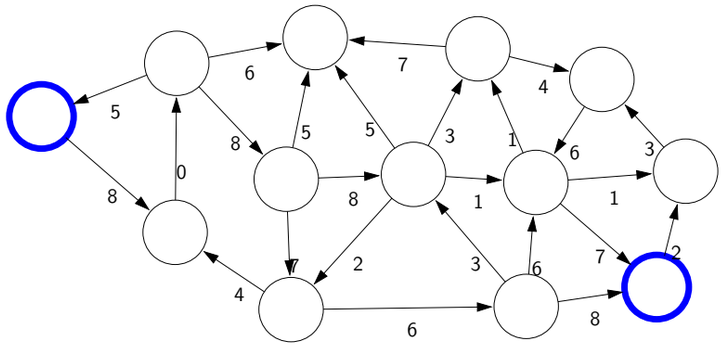
Inference **Learning**

Paradigm: modeling

Real world

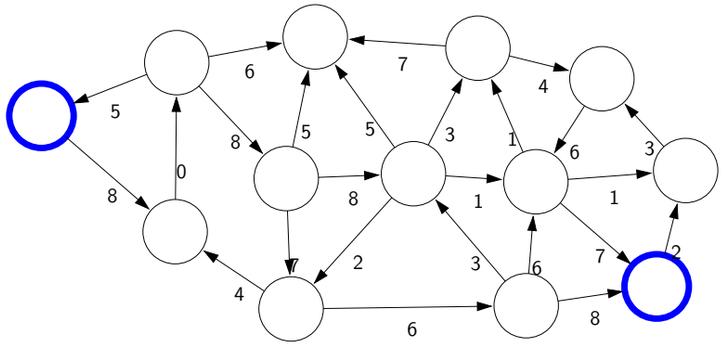
Modeling

Model



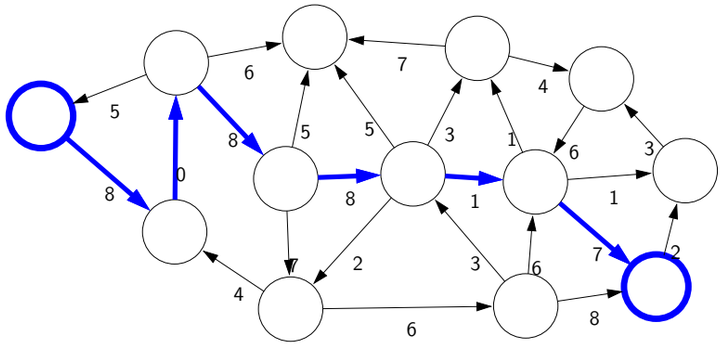
Paradigm: inference

Model



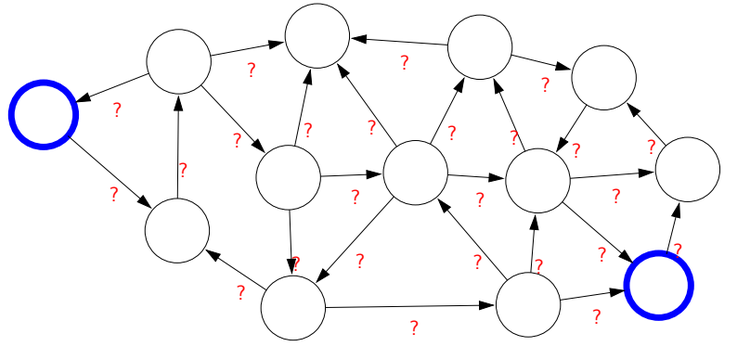
Inference

Predictions



Paradigm: learning

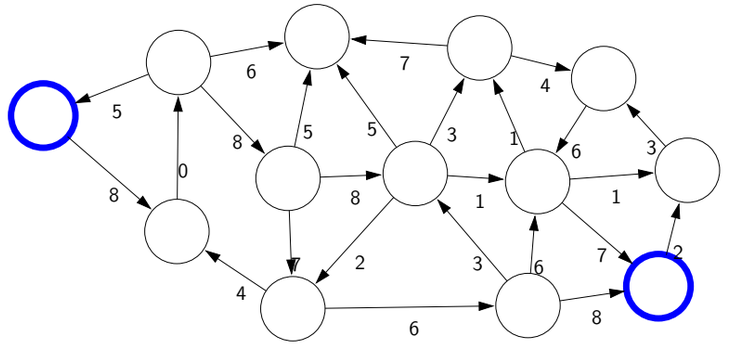
Model without parameters



+data

Learning

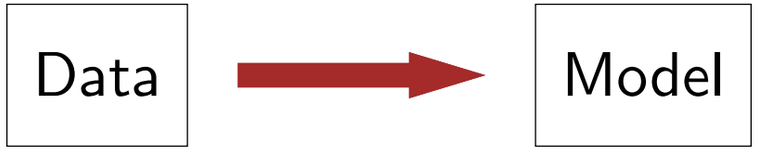
Model with parameters



Course plan

Machine learning

Machine learning



- The main driver of recent successes in AI
- Move from "code" to "data"
- Requires a leap of faith: **generalization**

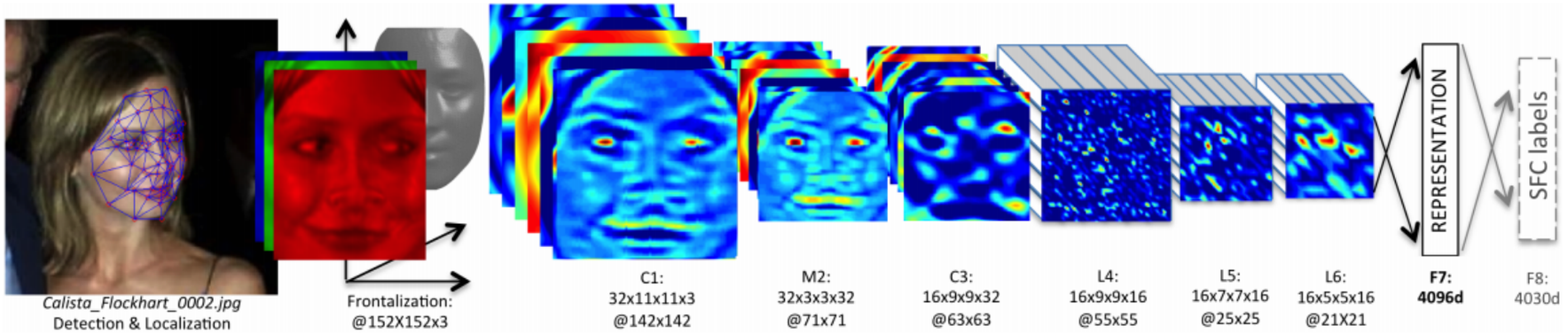
Course plan

Machine learning

What is this animal?

Reflex-based models

- Examples: linear classifiers, deep neural networks



- Most common models in machine learning

- Fully feed-forward (no backtracking)

Course plan

Search problems

Markov decision processes

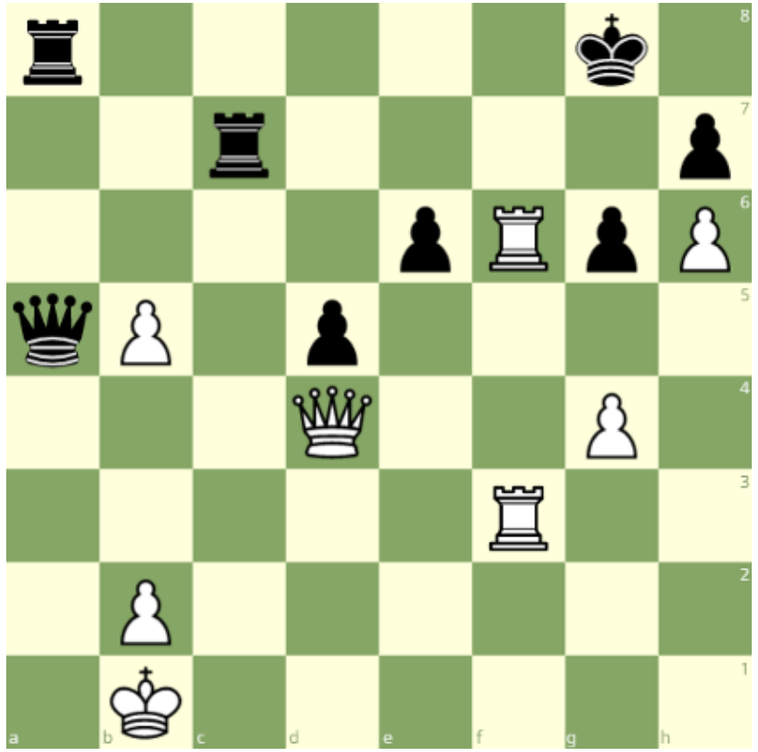
Adversarial games

Reflex **States**

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

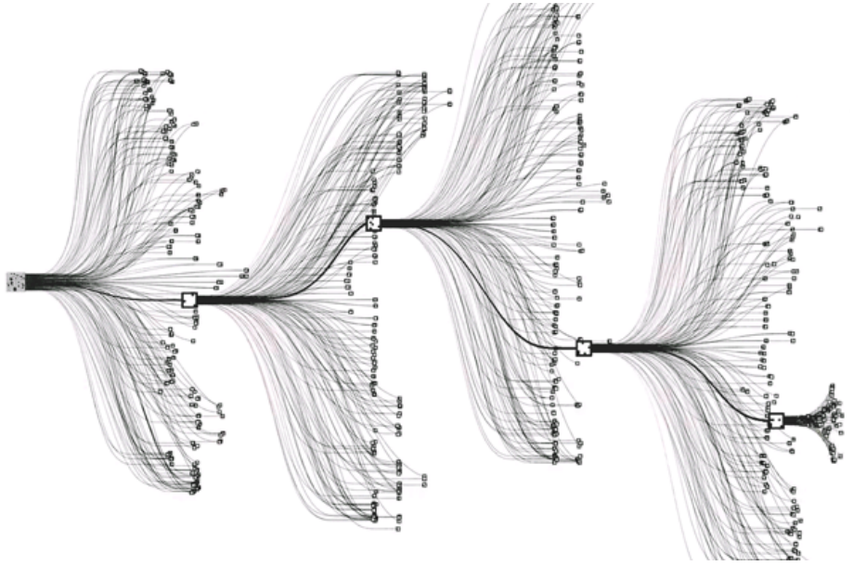
Machine learning

State-based models



White to move

State-based models

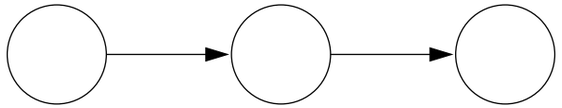


Applications:

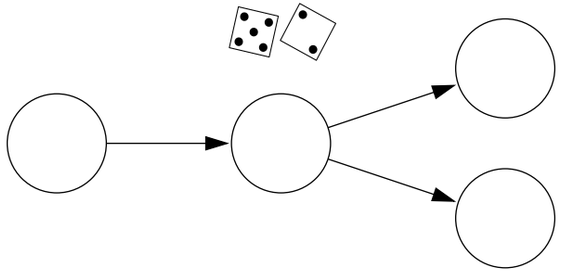
- Games: Chess, Go, Pac-Man, Starcraft, etc.
- Robotics: motion planning
- Natural language generation: machine translation, image captioning

State-based models

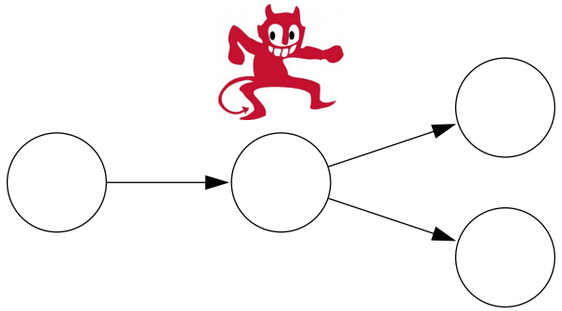
Search problems: you control everything



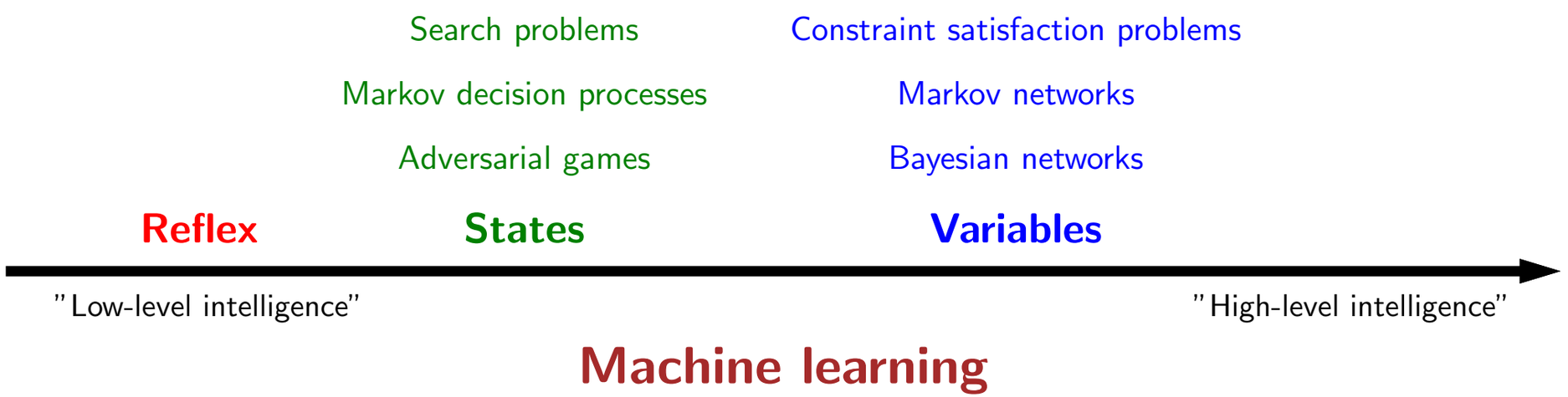
Markov decision processes: against nature (e.g., Blackjack)



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



Course plan


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

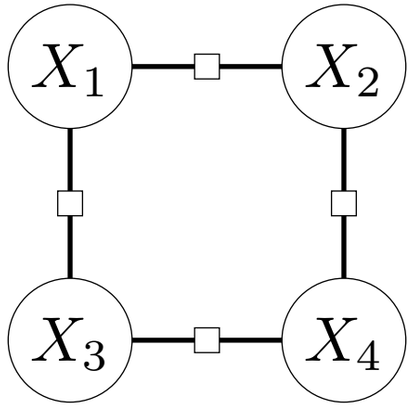
5	3	4	6	7	8	9	1	2
6	7	2	1	9	5	3	4	8
1	9	8	3	4	2	5	6	7
8	5	9	7	6	1	4	2	3
4	2	6	8	5	3	7	9	1
7	1	3	9	2	4	8	5	6
9	6	1	5	3	7	2	8	4
2	8	7	4	1	9	6	3	5
3	4	5	2	8	6	1	7	9

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

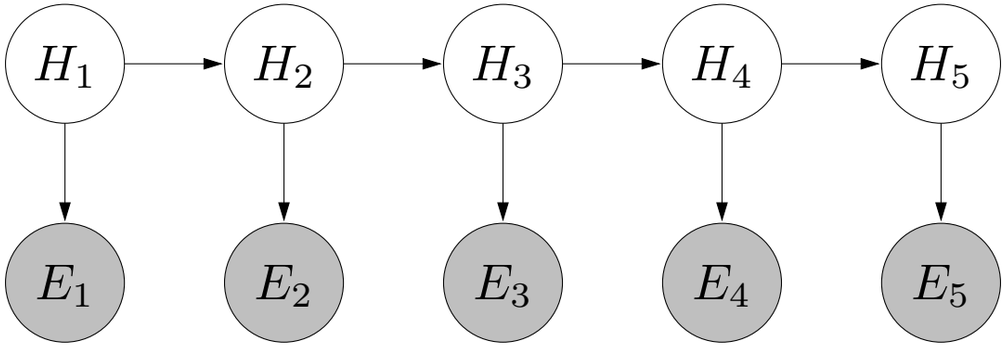
Key: order of filling squares doesn't matter in the evaluation criteria!

Variable-based models

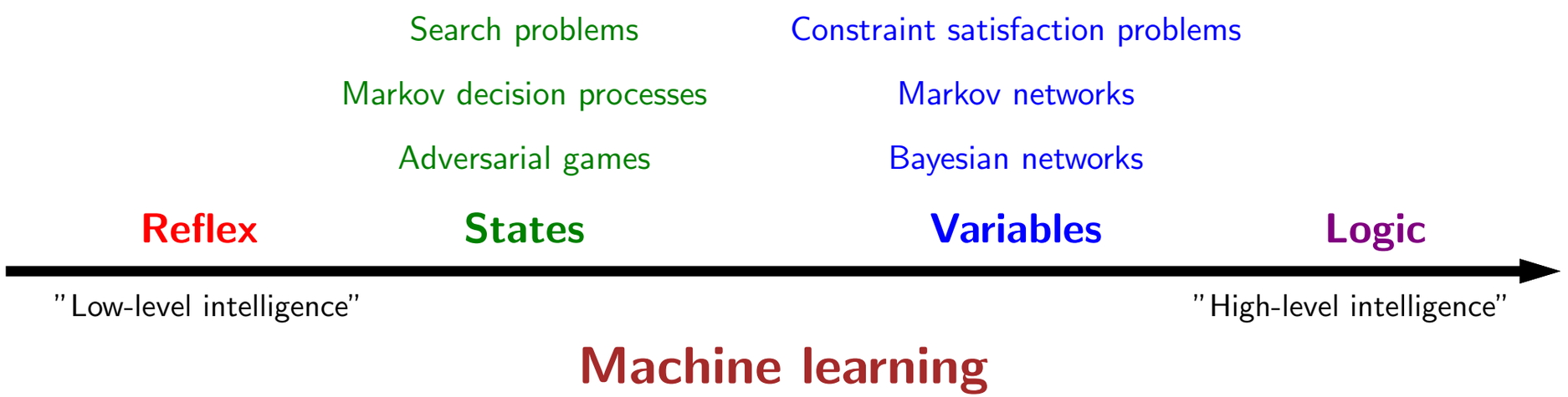
Constraint satisfaction problems: hard constraints (e.g., Sudoku, scheduling)



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



Course plan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"High-level intelligence"
Machine learning

Motivation: virtual assistant

Tell information

Ask questions

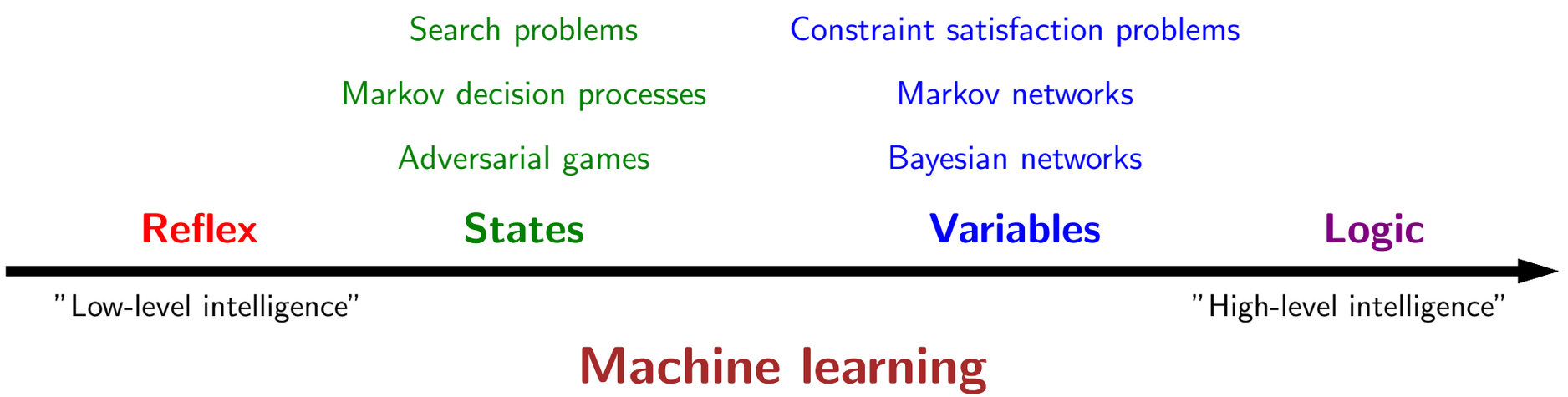
Use natural language!

[demo]

Need to:

- Digest **heterogenous** information
- Reason **deeply** with that information

Course plan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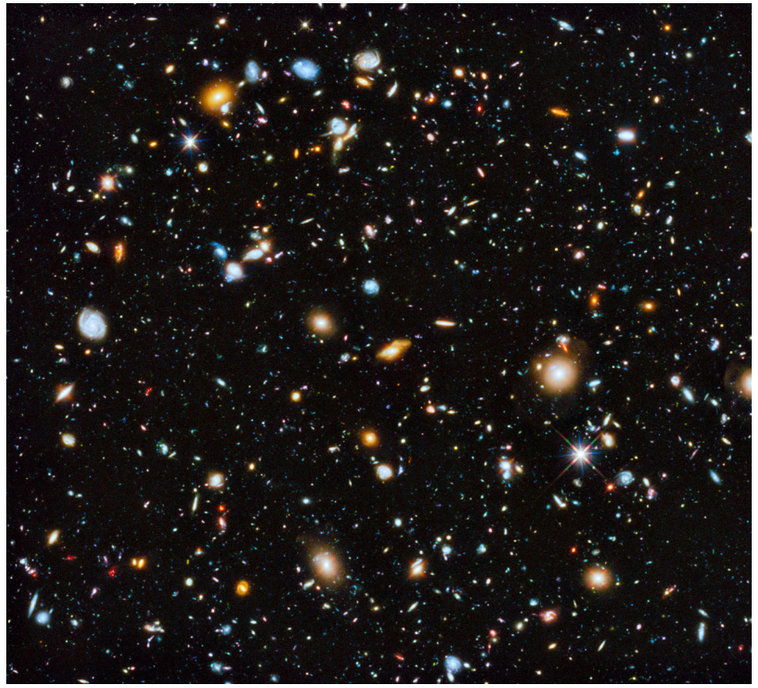
General: AI history



. LIX. No. 236.] [October, 1950

MIND

A QUARTERLY REVIEW

OF

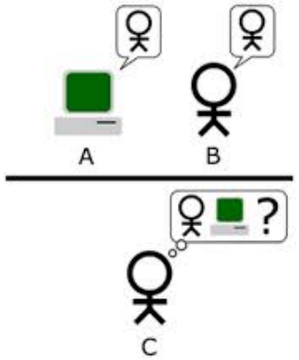
PSYCHOLOGY AND PHILOSOPHY

I.—COMPUTING MACHINERY AND INTELLIGENCE

By A. M. Turing

1. *The Imitation Game.*

I propose to consider the question, 'Can machines think?' This should begin with definitions of the meaning of the terms 'machine' and 'think'. The definitions might be framed so as to



objective specification

Many people think that a very abstract activity, like the playing of chess, would be best. It can also be maintained that it is best to provide the machine with the best **sense organs** *that money can buy, and then teach it to understand and speak English. This process could follow the normal* **teaching of a child**. *Things would be pointed out and named, etc. Again I do not know what the right answer is, but I think both approaches should be tried.*

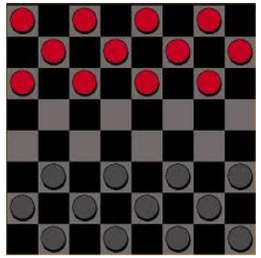
Birth of AI

1956: John McCarthy organized workshop at Dartmouth College

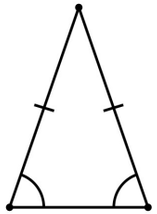
Every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it.

general principles

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.

Within 10 years the problems of artificial intelligence will be substantially solved.

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

...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, first AI winter

Implications of early era

Problems:

- **Limited computation**: search space grew exponentially, outpacing hardware
- **Limited information**: complexity of AI problems (number of words, objects, concepts in the world)

Useful contributions (John McCarthy):

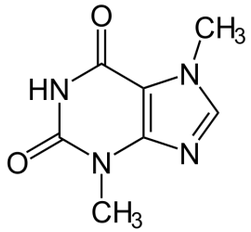
- Lisp
- Garbage collection
- Time-sharing

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

Knowledge-based systems

Wins:

- Knowledge helped both the **information** and **computation** gap
- First **real application** that impacted industry

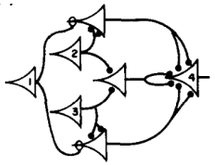
Problems:

- Deterministic rules couldn't handle the **uncertainty** of the real world
- Rules quickly became too **complex** to create and maintain

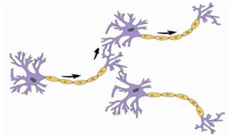
A number of people have suggested to me that large programs like the SHRDLU program for understanding natural language represent a kind of dead end in AI programming. Complex interactions between its components give the program much of its power, but at the same time they present a formidable obstacle 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

1987: Collapse of Lisp machines and second AI winter

Artificial neural networks



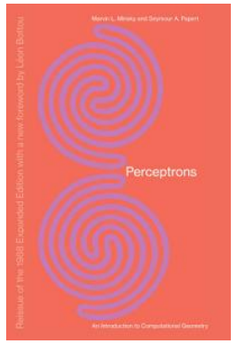
1943: artificial neural networks, relate neural circuitry and mathematical logic (McCulloch/Pitts)



1949: "cells that fire together wire together" learning rule (Hebb)

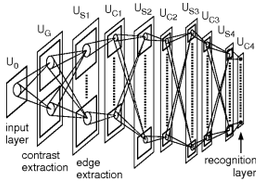
1958: Perceptron algorithm for linear classifiers (Rosenblatt)

1959: ADALINE device for linear regression (Widrow/Hoff)

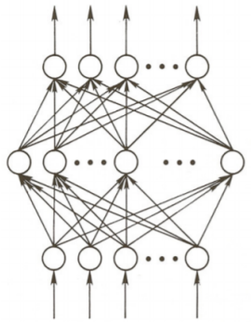


1969: Perceptrons book showed that linear models could not solve XOR, killed neural nets research (Minsky/Papert)

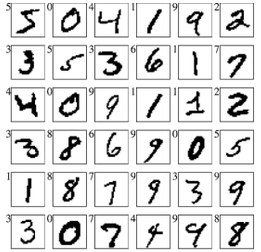
Revival of connectionism



1980: Neocognitron, a.k.a. convolutional neural networks for images (Fukushima)

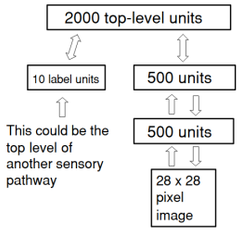


1986: popularization of backpropagation for training multi-layer networks (Rumelhardt, Hinton, Williams)



1989: applied convolutional neural networks to recognizing handwritten digits for USPS (LeCun)

Deep learning

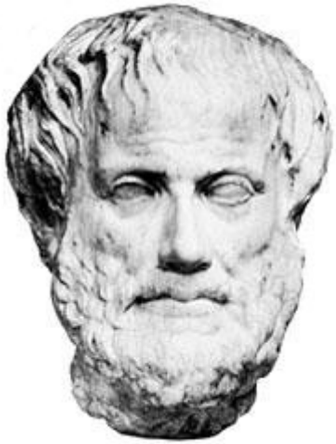


2006: unsupervised layerwise pre-training of deep networks (Hinton et al.)

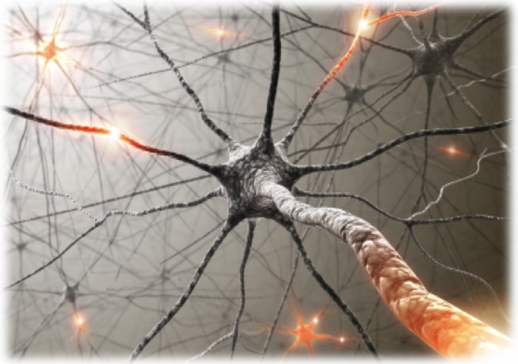
2012: AlexNet obtains huge gains in object recognition; transformed computer vision community overnight

2016: AlphaGo uses deep reinforcement learning, defeat world champion Lee Sedol in Go

Two intellectual traditions



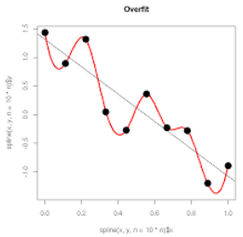
symbolic AI



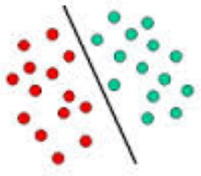
neural AI

Food for thought: deep philosphical differences, but deeper connections (McCulloch/Pitts, AlphaGo)?

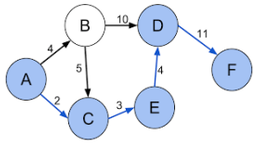
Early ideas from outside AI



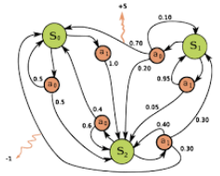
1801: linear regression (Gauss, Legendre)



1936: linear classification (Fisher)

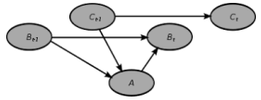


1956: Uniform cost search for shortest paths (Dijkstra)

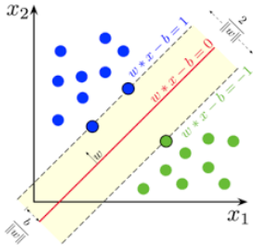


1957: Markov decision processes (Bellman)

Statistical machine learning

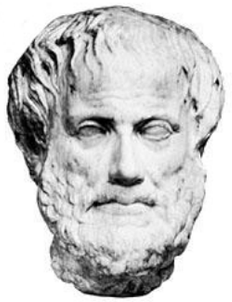


1985: Bayesian networks (Pearl)

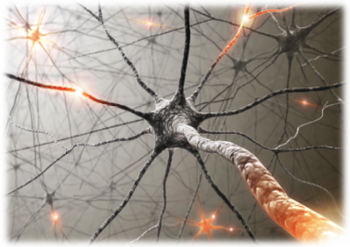


1995: Support vector machines (Cortes/Vapnik)

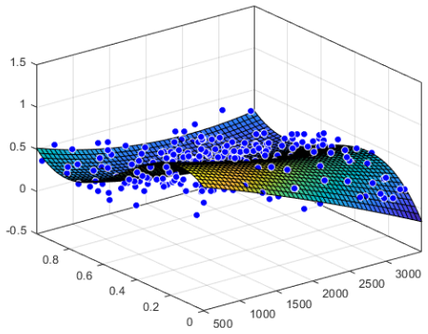
Three intellectual traditions



symbolic AI



neural AI



statistical AI

Further reading

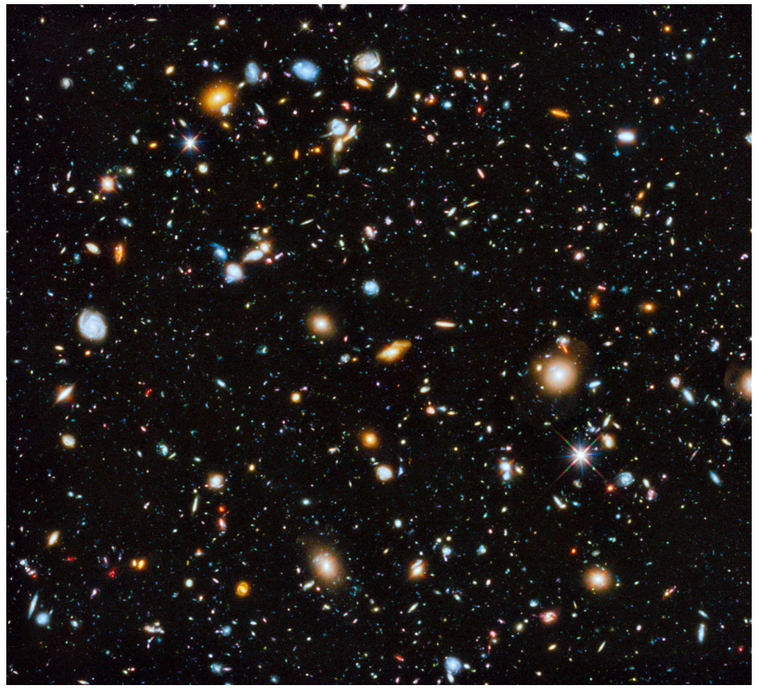
Wikipedia article: https://en.wikipedia.org/wiki/History_of_artificial_intelligence

Encyclopedia of Philosophy article: https://plato.stanford.edu/entries/artificial-intelligence

Turing's Computing Machinery and Intelligence: https://www.csee.umbc.edu/courses/471/papers/turing.pdf

History and Philosophy of Neural Networks: https://research.gold.ac.uk/10846/1/Bishop-2014.pdf

General: AI today



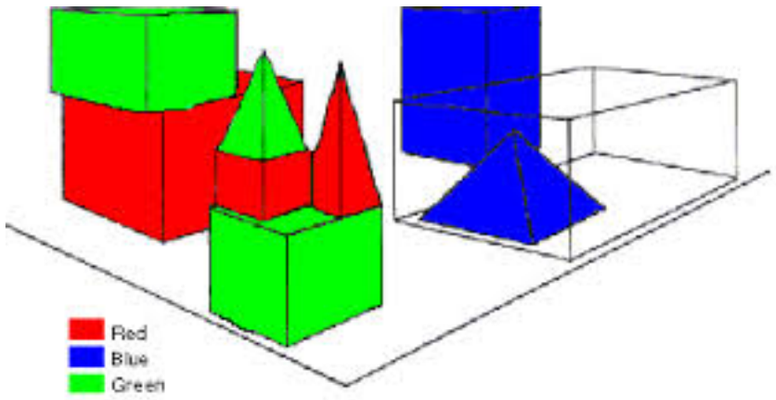
Prior to 2012, AI results closely tracked Moore's Law, with compute doubling every two years. Post-2012, compute has been **doubling every 3.4 months**.

In 2019, the largest AI conference, **NeurIPS**, *expects 13,500 attendees, up 41% over 2018 and over* **800% relative to 2012**.

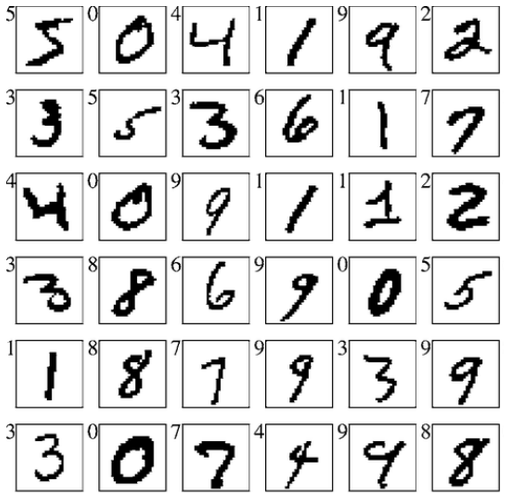
In the US, the share of **jobs** *in AI-related topics increased from* **0.26% of total jobs posted in 2010 to 1.32% in October 2019**.

In vitro

SHRDLU

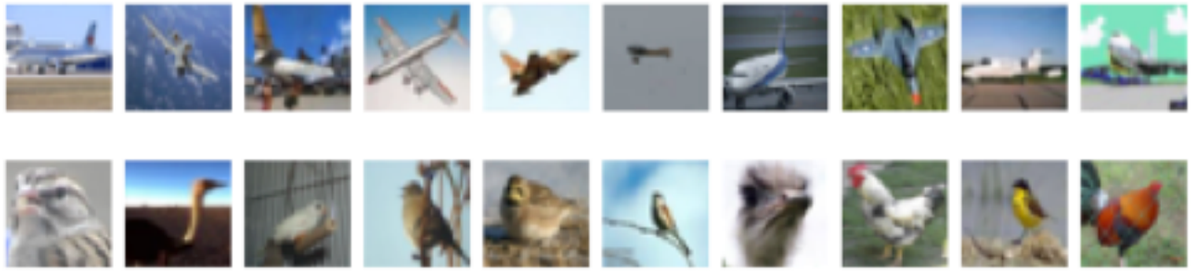


MNIST



Atari

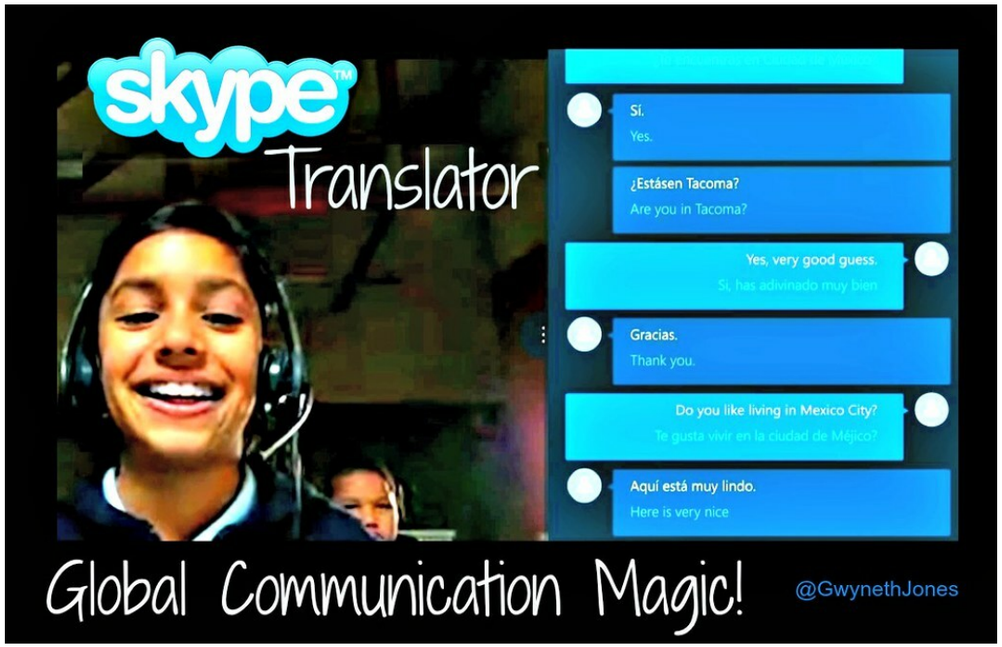
CIFAR-10



Virtual assistants

Machine translation

Input sentence:	*Translation (PBMT):*	*Translation (GNMT):*	*Translation (human):*
李克強此行將啟動中加總理年度對話機制，與加拿大總理杜魯多舉行兩國總理首次年度對話。	Li Keqiang premier added this line to start the annual dialogue mechanism with the Canadian Prime Minister Trudeau two prime ministers held its first annual session.	Li Keqiang will start the annual dialogue mechanism with Prime Minister Trudeau of Canada and hold the first annual dialogue between the two premiers.	Li Keqiang will initiate the annual dialogue mechanism between premiers of China and Canada during this visit, and hold the first annual dialogue with Premier Trudeau of Canada.



Autonomous driving

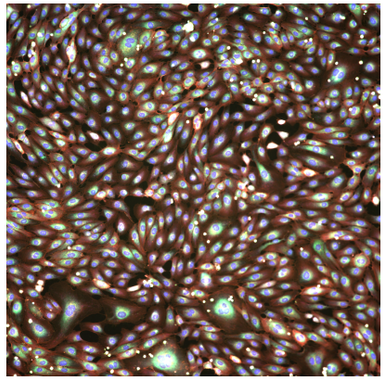
Visual assistive technology

Healthcare

Chest radiology

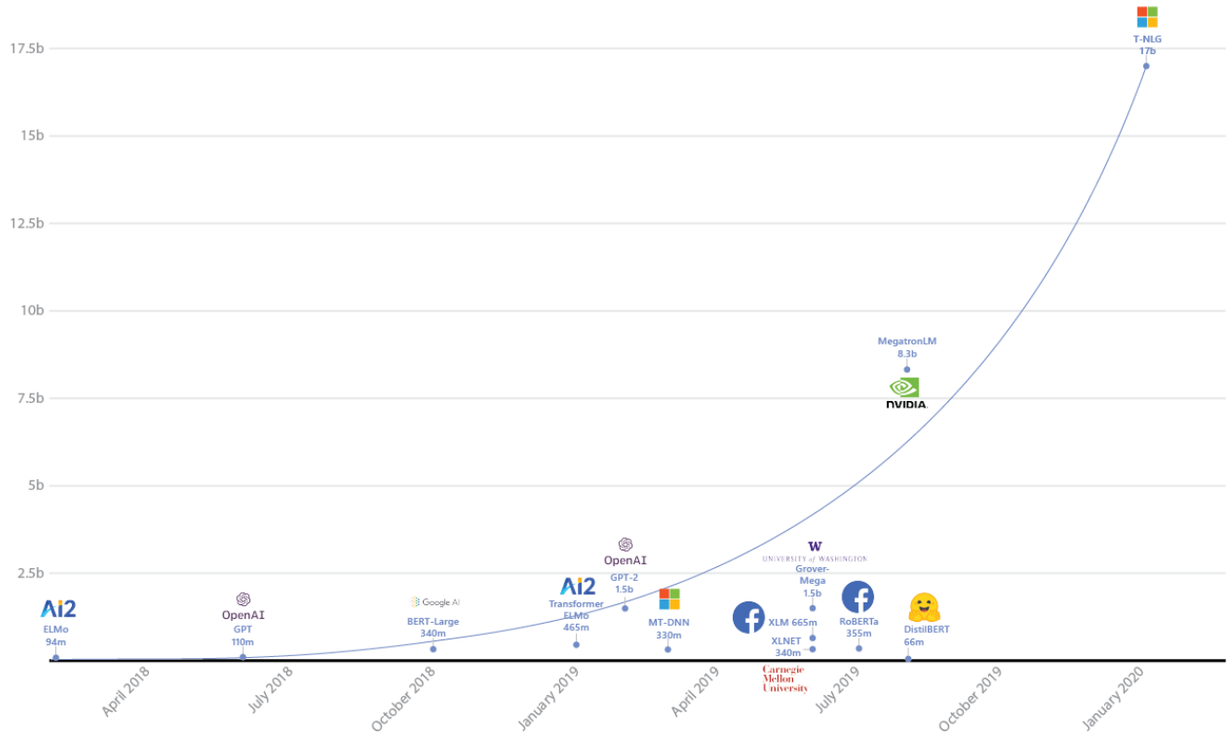
Diabetic retinopathy

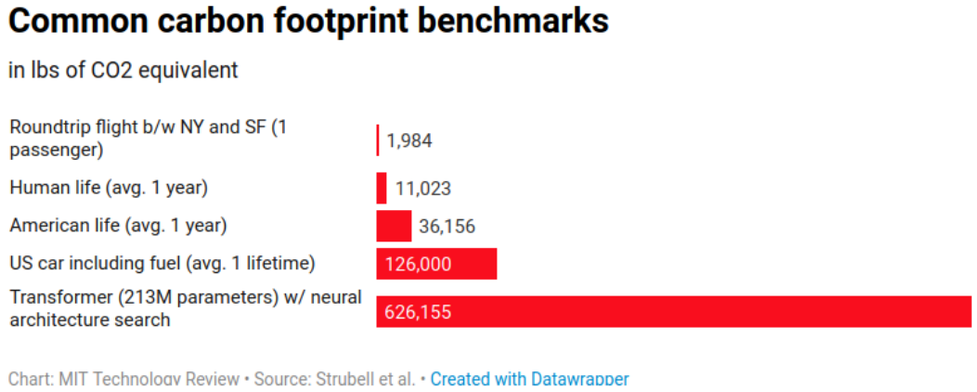
Drug screening for COVID-19



Risks

Energy consumption





GPT-3 (released May 2020) from OpenAI has **175 billion** parameters

Privacy

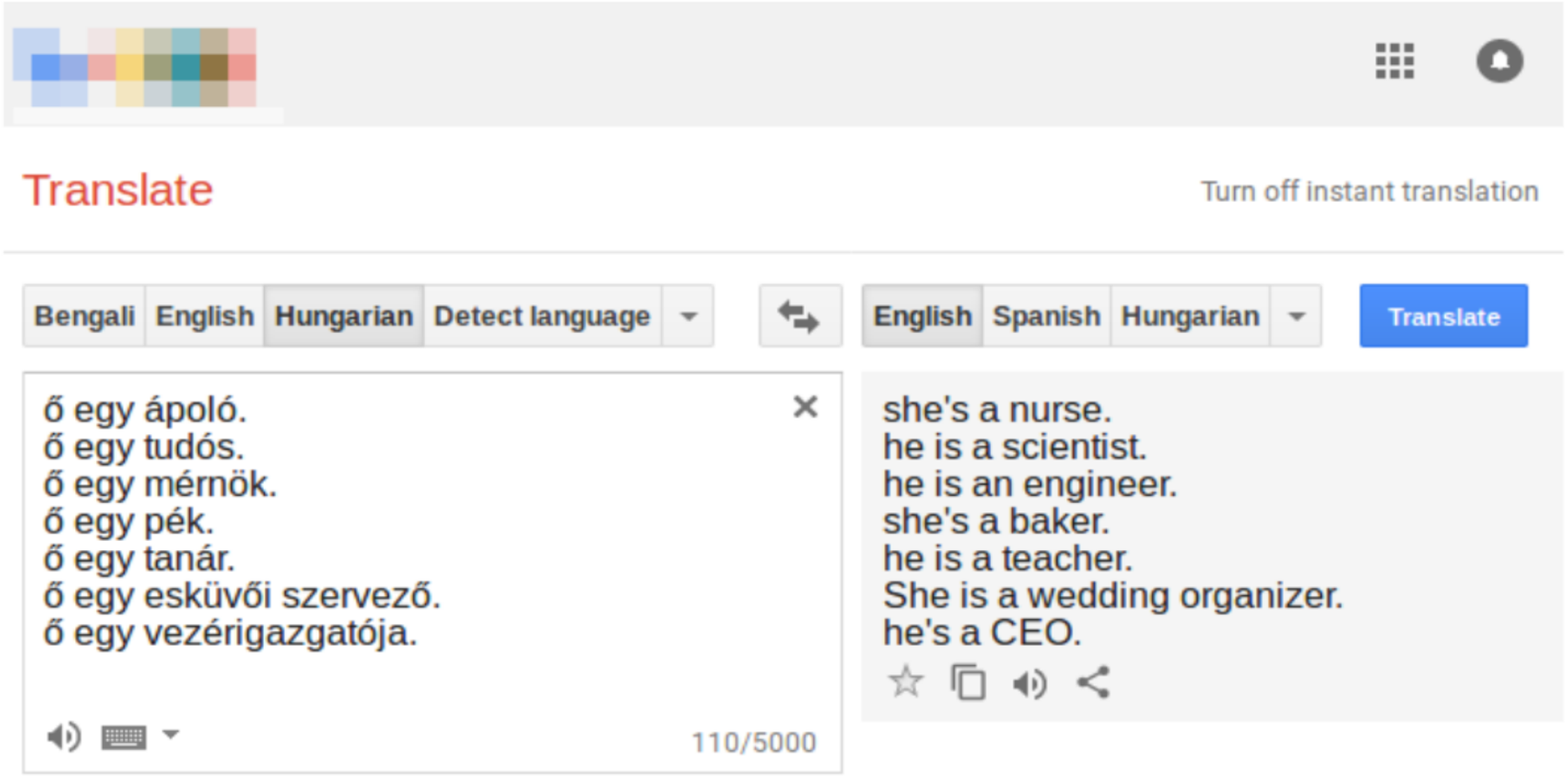
Security

[Evtimov+ 2017]

[Sharif+ 2016]

[Prates+ 2018]

Bias



Fairness

- Northpointe: COMPAS predicts criminal risk score (1-10)
- ProPublica: given that an individual did not reoffend, Black people 2x likely to be (wrongly) classified 5 or above
- Northpointe: given a risk score of 7, 60% of White people reoffended, 60% of Black people reoffended

Generating fake content

In order to get something done, maybe we need to think less. Seems counter-intuitive, but I believe sometimes our thoughts can get in the way of the creative process. We can work better at times when we "tune out" the external world and focus on what's in front of us.

I've been thinking about this lately, so I thought it would be good to write an article about it.

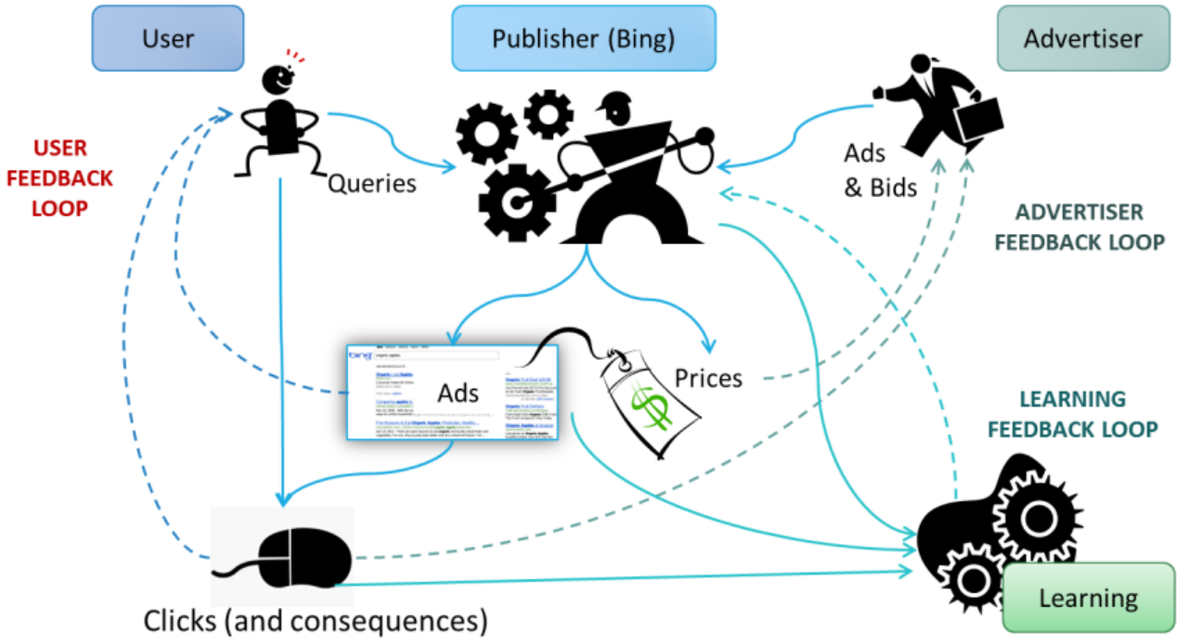
So what exactly does this mean? Well, for starters, let's start with some definitions.

Definition #1: Creative Thinking (CT) is the act of using your mind to come up with ideas that are not already present in reality or that have never existed before. It is a form of mental activity that involves the use of logic and reason.

Definition #2: Over-Thinking (OT) is the act of trying to come up with ideas that have already been thought through by someone else. OT usually results in ideas that are impractical, impossible, or even stupid.

Feedback loops in learning

[Leon Bottou]



Prospects and risks of AI

AI technology is an amplifier

🙂 Can reduce accessibility barriers and improve efficiency

☹️ Can amplify bias, security risks, centralize power

Can build it $\neq$ should build it