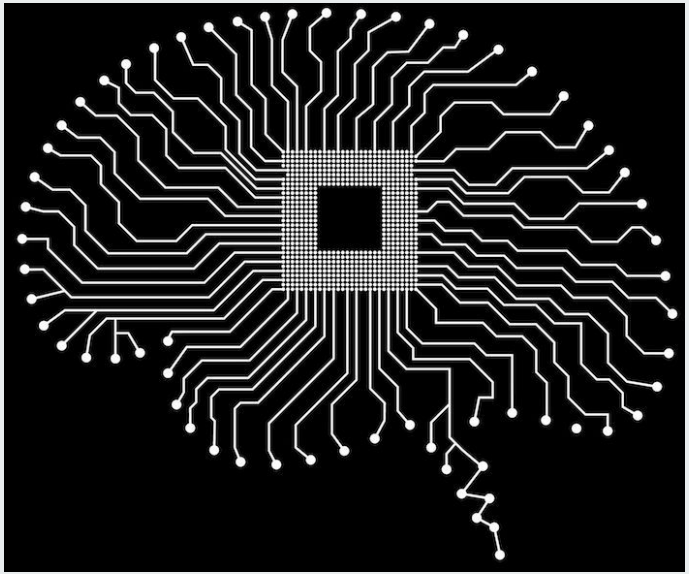
Introduction to A.I.

With Dylan Moore

Welcome!



Ice breaker

- Learn three interesting things about the person next to you (and his/her name!)

Course Logistics:

Course Content:
https://github.com/dmoore2/tumo_ai

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dylanedwardmoore@gmail.com

Today’s focus:

Today's focus:
Data, Data, and more Data



But first: An overview

Microsoft creates AI that can read a document and answer questions about it as well as a person

January 15, 2018 | Allison Linn

Microsoft researchers achieve new conversational speech recognition milestone

August 20, 2017 | By Xuedong

June 24, 2014

DeepFace: Closing Performance in Fa

Conference on Computer Vision and Pattern Recognition (CVPR)

By: **Yaniv Taigman**, Ming Yang, **Marc'Aurelio Ranzato**, **Lior Wolf**

Abstract

In modern face recognition, the conventional pipeline co
classify. We revisit both the alignment step and the repre
modeling in order to apply a piecewise affine transforma
layer deep neural network. This deep network involves m
locally connected layers without weight sharing, rather tl
trained it on the largest facial dataset to-date, an identity
belonging to more than 4,000 identities.

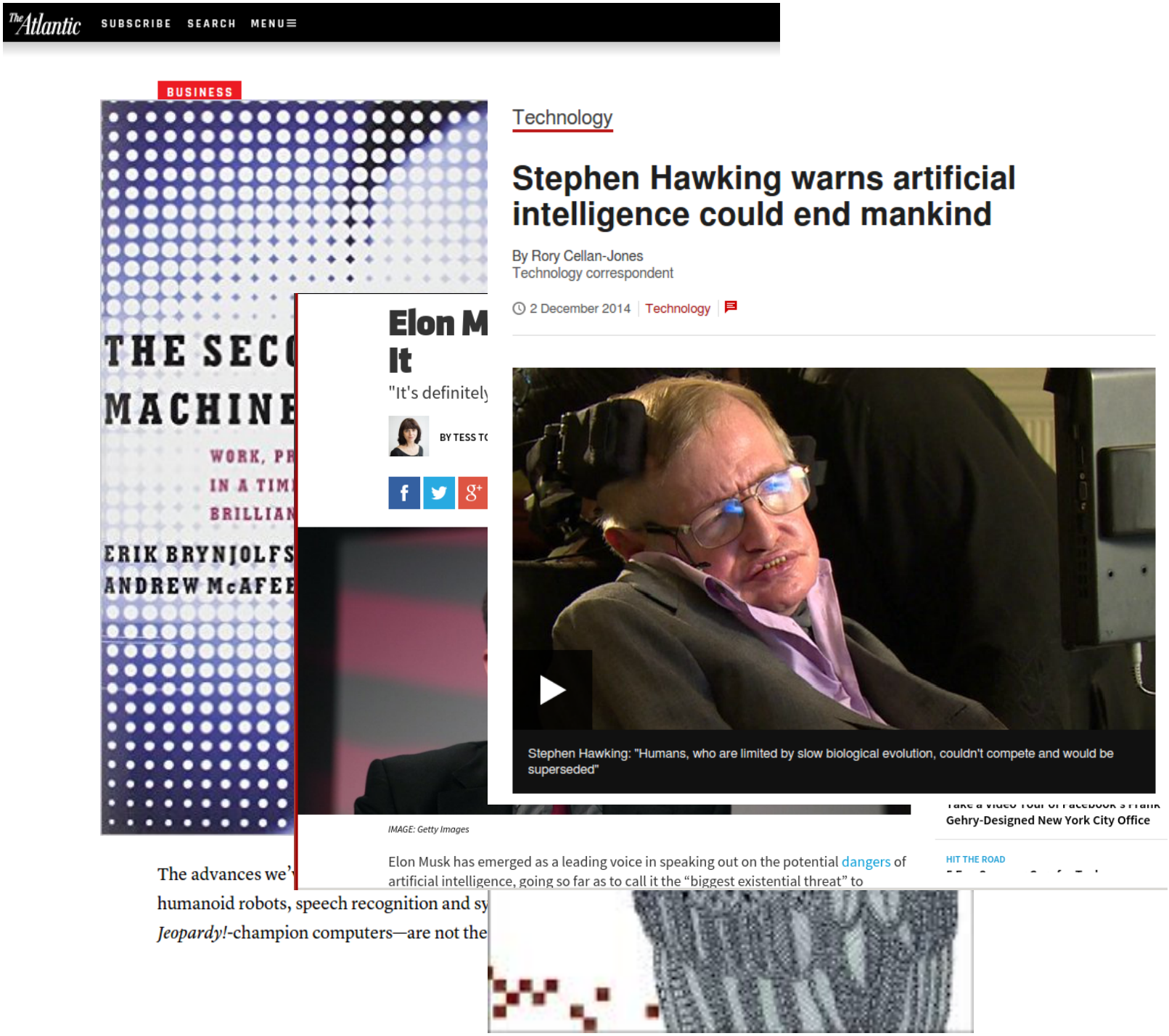
If you think AI will never replace radiologists—you may want to think again

May 14, 2018 | Michael Walter | Artificial Intelligence

It's one of the most frequently discussed questions in radiology today: What kind of long-term impact will artificial intelligence (AI) have on radiologists?

Robert Schier, MD, a radiologist for RadNet, shared his own thoughts on the topic in a new commentary published by the *Journal of the American College of Radiology*—and he's not quite as optimistic as some of his colleagues throughout the industry.

- It is hard these days to escape hearing about AI — in the news, on social media, in cafe conversations. We see both reports triumphs of superhuman performance in games such as Jeopardy! (IBM Watson, 2011) and Go (DeepMind's AlphaGo, 2016), as well as on benchmark tasks such as reading comprehension, speech recognition, face recognition, and medical imaging (though it is important to realize that these are about performance on one benchmark, which is a far cry from the general problem).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Stephen Hawking warns artificial intelligence could end mankind
By Rory Cellan-Jones
Technology correspondent
2 December 2014 | Technology
Elon M
It
"It's definitely
BY TESS TO
Stephen Hawking: "Humans, who are limited by slow biological evolution, couldn't compete and would be superseded"
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
Gehry-Designed New York City Office
HIT THE ROAD
The advances we'
humanoid robots, speech recognition and sy
Jeopardy!-champion computers—are not the

- We also see speculation about the future: that it will bring about sweeping societal change due to automation, resulting in massive job loss, not unlike the industrial revolution, or that AI could even surpass human-level intelligence and seek to take control.

Companies

"An important shift from a mobile first world to an AI first world" [CEO Sundar Pichai @ Google I/O 2017]

Created AI and Research group as 4th engineering division, now 8K people [2016]

Created Facebook AI Research, Mark Zuckerberg very optimistic and invested

Others: IBM, Amazon, Apple, Uber, Salesforce, Baidu, Tencent, etc.

Governments

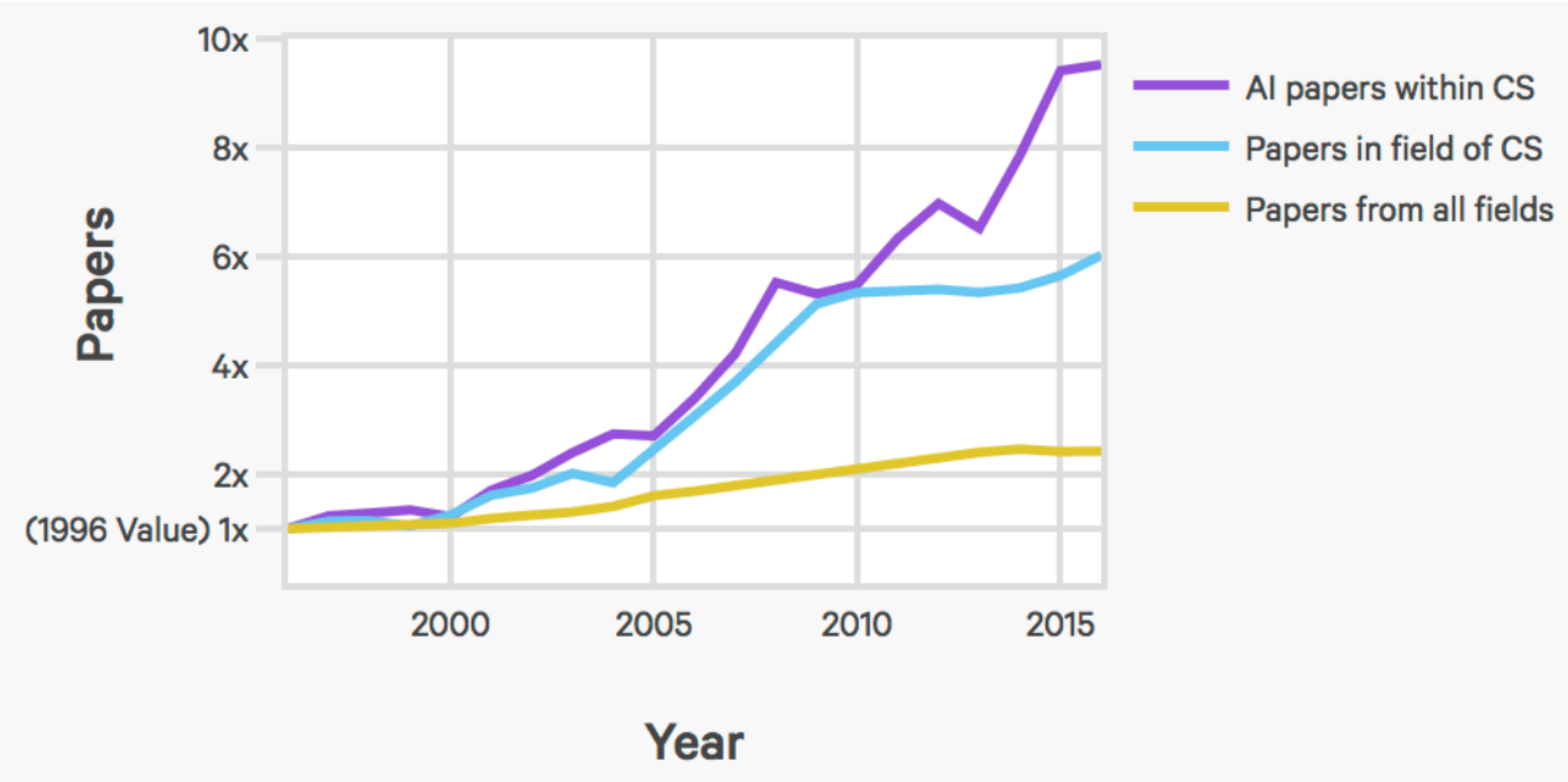
"AI holds the potential to be a major driver of economic growth and social progress" [White House report, 2016]

Released domestic strategic plan to become world leader in AI by 2030 [2017]

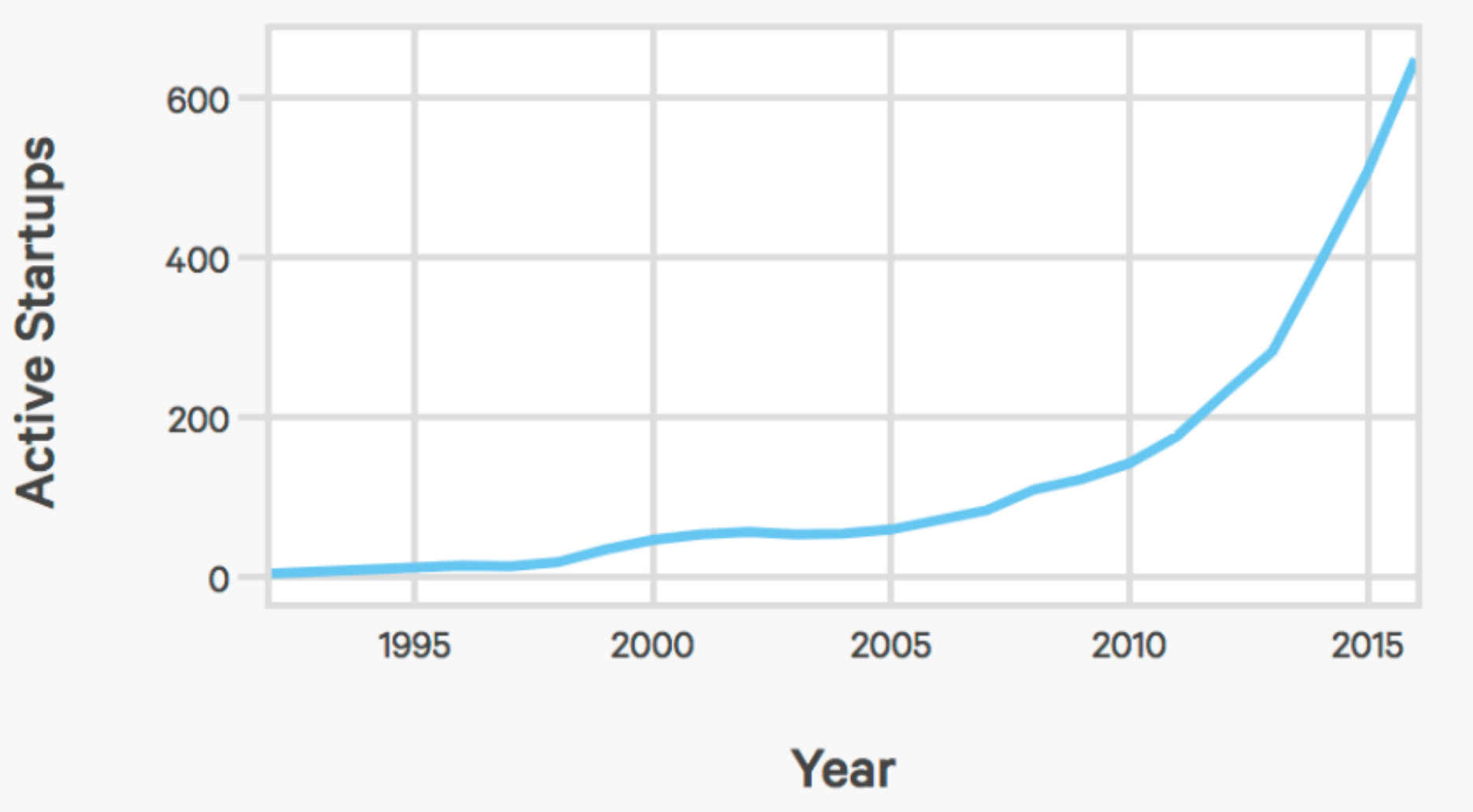
"Whoever becomes the leader in this sphere [AI] will become the ruler of the world" [Putin, 2017]

- While media hype is real, it is true that both companies and governments are heavily investing in AI. Both see AI as an integral part of their competitive strategy.

AI index: number of published AI papers



AI index: number of AI startups



- The reality is that there is a lot of uncertainty over what will happen, and there is a lot of nuance that's missing from these stories about what AI is truly capable of. The goal of this class is to help you understand these nuances, so that you can form your own opinion.

Ok, really, what is AI?

Two views of AI

AI agents: how can we re-create intelligence?

AI tools: how can we benefit society?

- There are two ways to look at AI philosophicaly.
- The first is what one would normally associate with the AI: the science and engineering of building "intelligent" agents. The inspiration of what constitutes intelligence comes from the types of capabilities that humans possess: the ability to perceive a very complex world and make enough sense of it to be able to manipulate it.
- The second views AI as a set of tools. We are simply trying to solve problems in the world, and AI techniques happen to be quite useful for that.
- However, both views boil down to many of the same day-to-day activities (e.g., collecting data and optimizing a training objective), the philosophical differences do change the way AI researchers approach and talk about their work. And moreover, the conflation of these two can generate a lot of confusion.

AI agents...

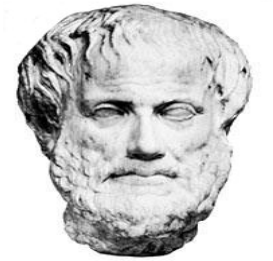
An intelligent agent

Perception Robotics Language

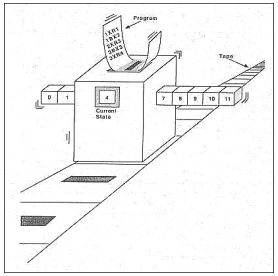
Knowledge Reasoning Learning

- The starting point for the agent-based view is ourselves.
- As humans, we have to be able perceive the world (computer vision), perform actions in it (robotics), and communicate with other agents.
- We also have knowledge about the world (from how to ride a bike to knowing the capital of France), and using this knowledge we can draw inferences and make decisions.
- Finally, last but not least, we learn and adapt over time. Indeed machine learning has become the primary driver of many of the AI applications we see today.

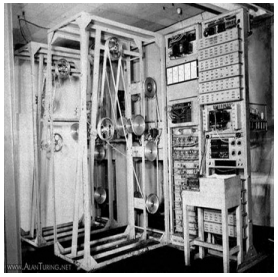
Pre-AI developments



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



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



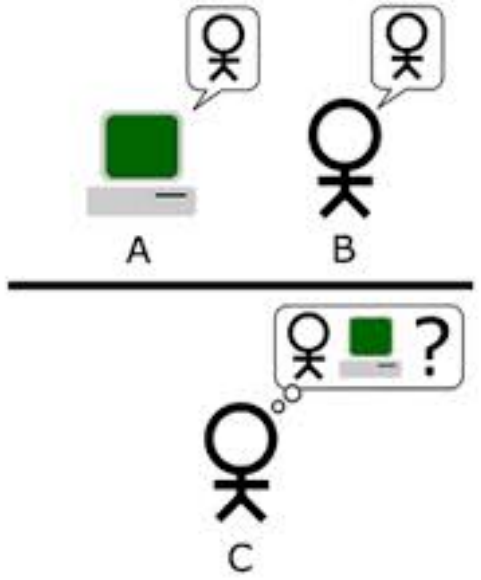
Real computers (1940s): actual **hardware** to do it: Heath Robinson, Z-3, ABC/ENIAC

- Why might one even think that it is even possible to capture this rich behavior?
- While AI is a relatively young field, one can trace back some of its roots back to Aristotle, who formulated a system of syllogisms that capture the reasoning process: how one can mechanically apply syllogisms to derive new conclusions.
- Alan Turing, who laid the conceptual foundations of computer science, developed the Turing machine, an abstract model of computation, which, based on the Church-Turing thesis, can implement any computable function.
- In the 1940s, actual devices that could actually carry out these computations started emerging.
- So perhaps one might be able to capture intelligent behavior via a computer. But how do we define success?

The Turing Test (1950)

[Turing, 1950. Computing Machinery and Intelligence]

"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 Descartes. 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 but it suffices for our present purposes.)
- Although the Turing test is not without flaws (e.g., failure to capture visual and physical abilities, emphasis on deception), the beauty of the Turing test is its simplicity and objectivity. 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.

A very brief history

- 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

- AI started out with a bang. People were ambitious and tried to develop things like General Problem Solver that could solve anything. Despite some successes, certain tasks such as machine translation were complete failures, which lead to the cutting of funding and the first AI winter. It happened again in the 1980s, this time with expert systems, though the aims were scoped more towards industrial impact. But again, expectations exceeded reality, 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".

[Li et al., 2016]

Open-domain dialogue

A: How old are you?

B: I'm 16. Why are you asking?

A: I thought you were 12.

B: What made you think so?

A: I don't know what you are talking about.

B: You don't know what you are saying.

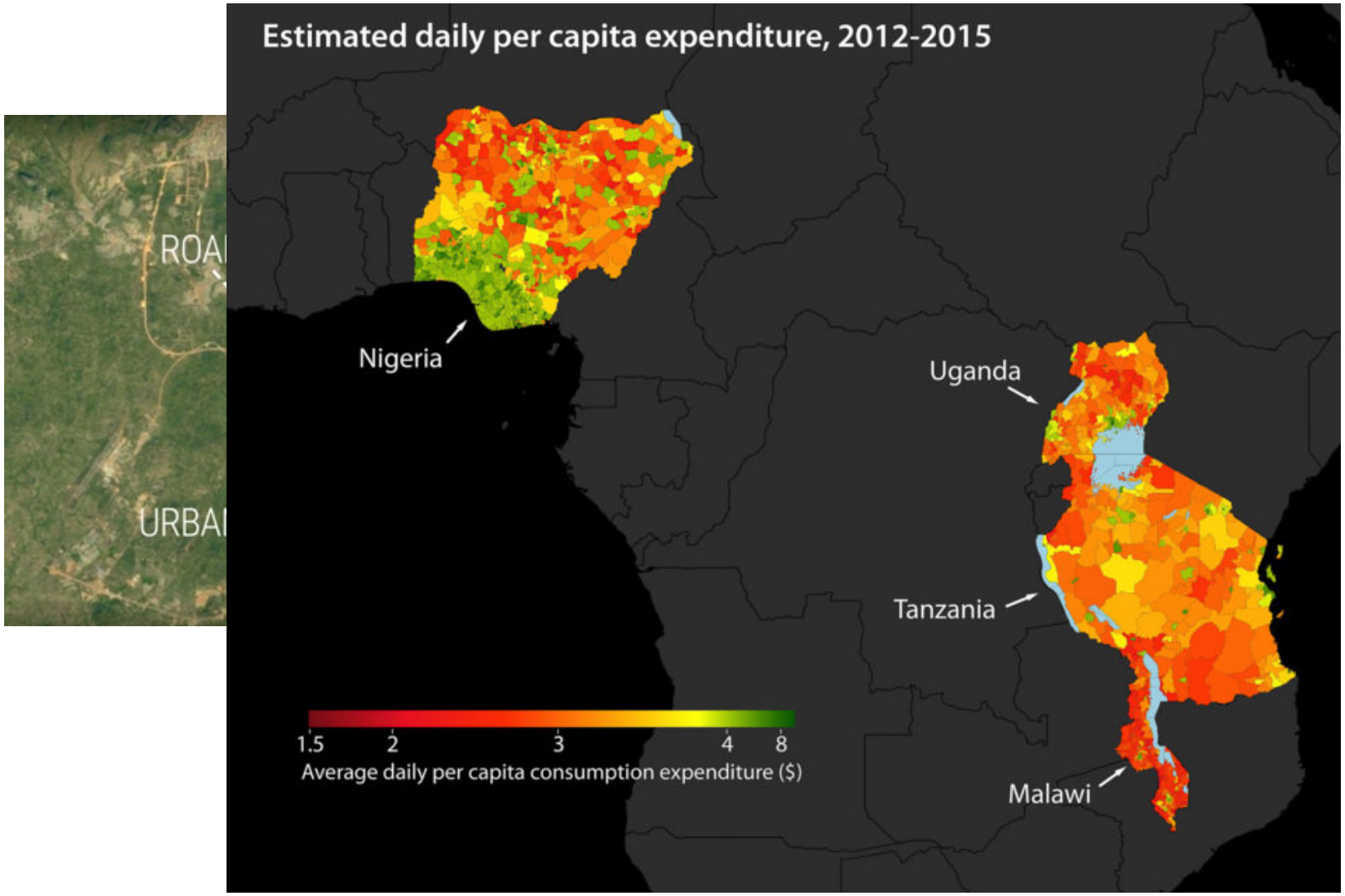
- We still don't have computers that we have a natural conversation with. While training deep neural networks on huge amounts of data has worked beautifully for speech recognition and machine translation, recent attempts in open-domain dialogue have not produced such sensible results. Models get confused by the sheer complexity of dialogue and often fall back to generic responses as shown here.

AI tools...

- The AI agents view is an inspiring quest to undercover the mysteries of intelligence and tackle the tasks that humans are good at. While there has been a lot of progress, we still have a long way to go along some dimensions: for example, the ability to learn quickly from few examples or the ability to perform commonsense reasoning.
- At the same time, the current level of technology is already being deployed widely in practice. These settings are often not particularly human-like (targeted advertising, news or product recommendation, web search, supply chain management, etc.)

[Jean et al. 2016]

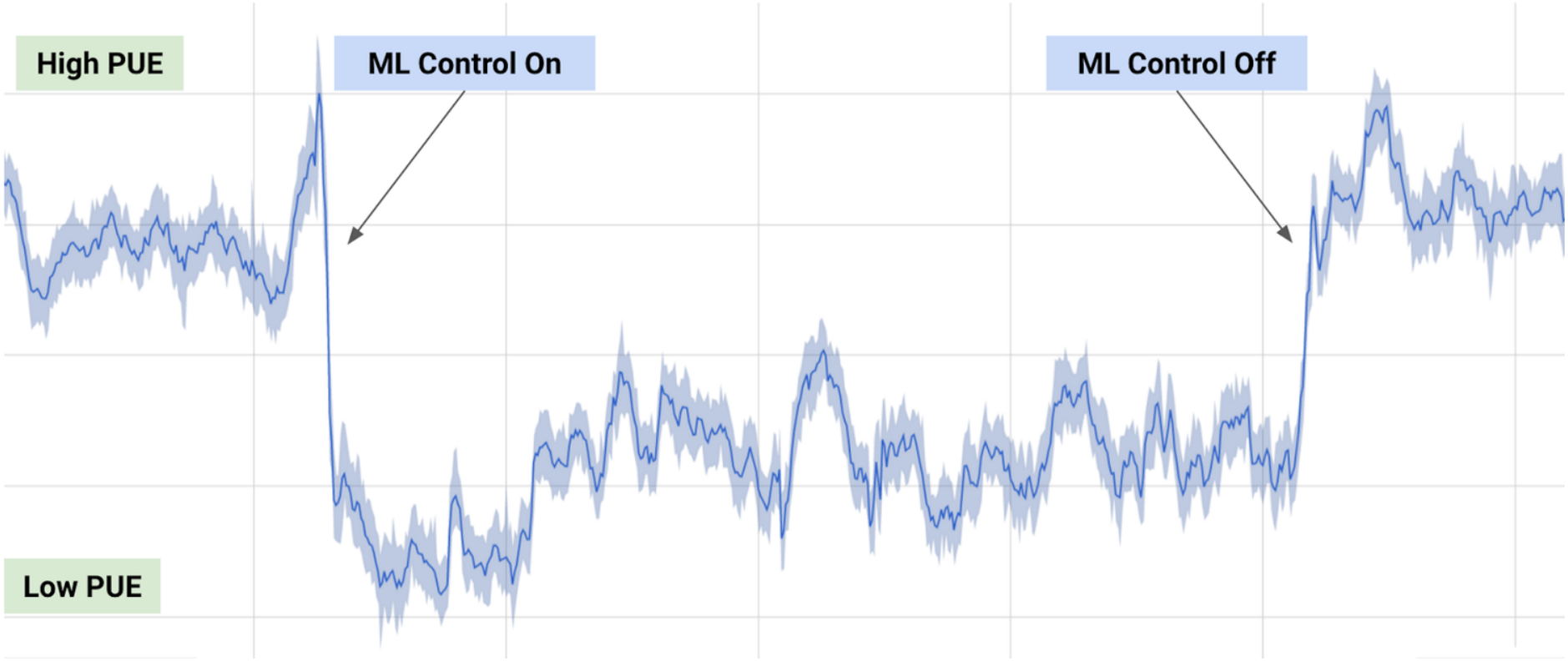
Predicting poverty



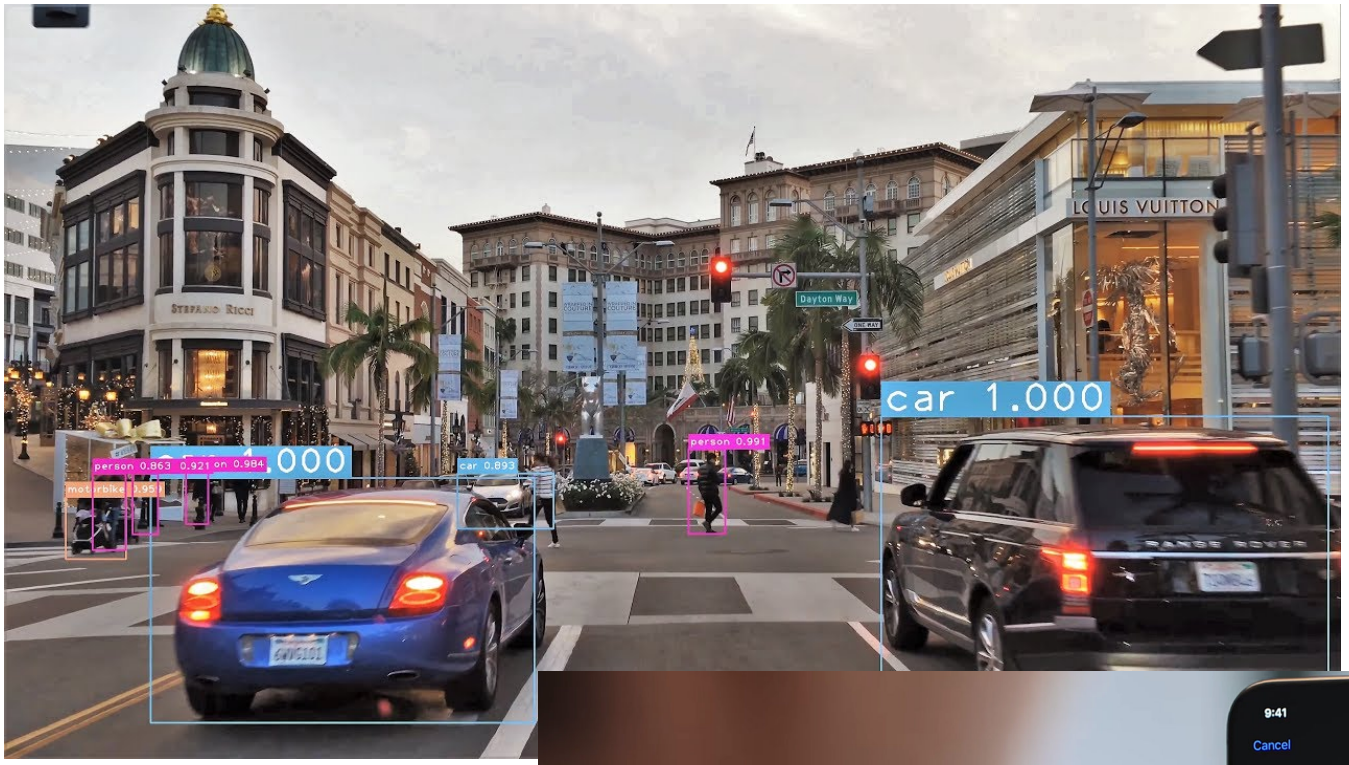
- The same computer vision techniques used to recognize objects can be used to tackle social problems. Poverty is a huge problem, and even identifying the areas of need is difficult due to the difficulty in getting reliable survey data. Recent work has shown that one can take satellite images (which are readily available) and predict various poverty indicators.

[DeepMind]

Saving energy by cooling datacenters



- Machine learning can also be used to optimize the energy efficiency of datacenters, which given the hunger for compute these days makes a big difference. Some recent work from DeepMind show how to significantly reduce Google's energy footprint by using machine learning to predict the power usage effectiveness from sensor measurements such as pump speeds, and using that to drive recommendations.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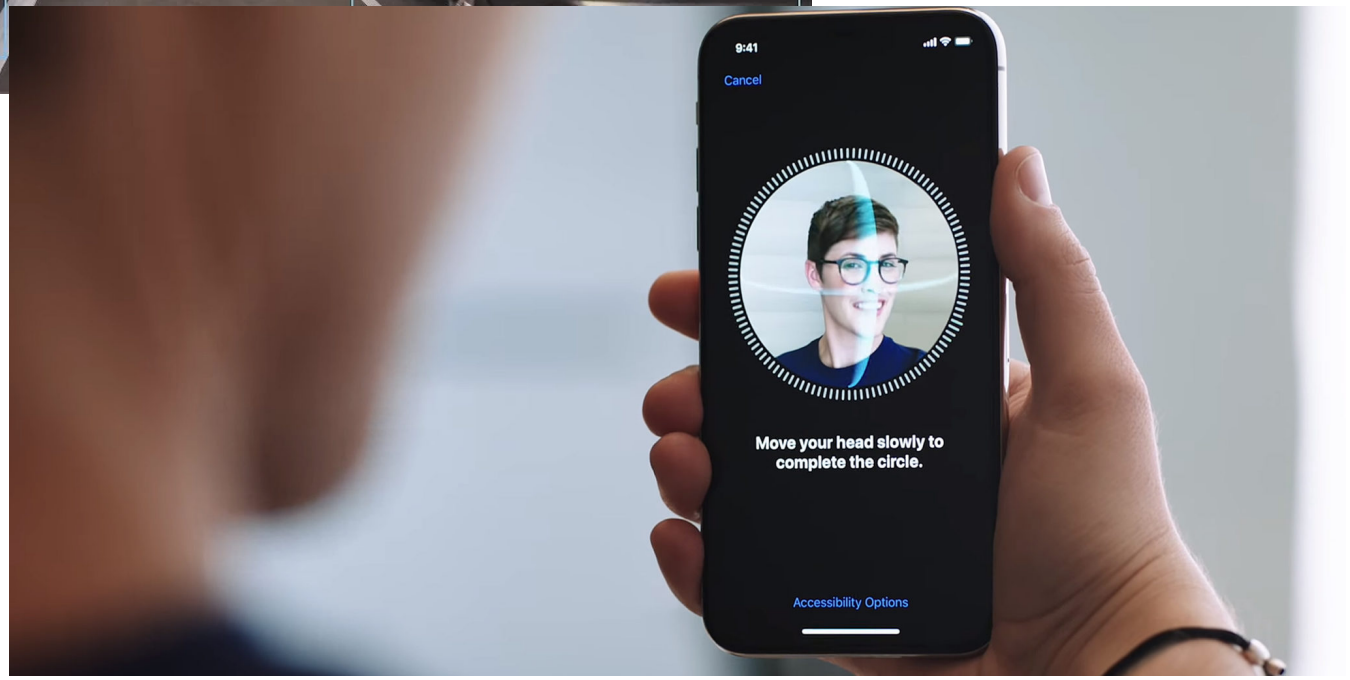
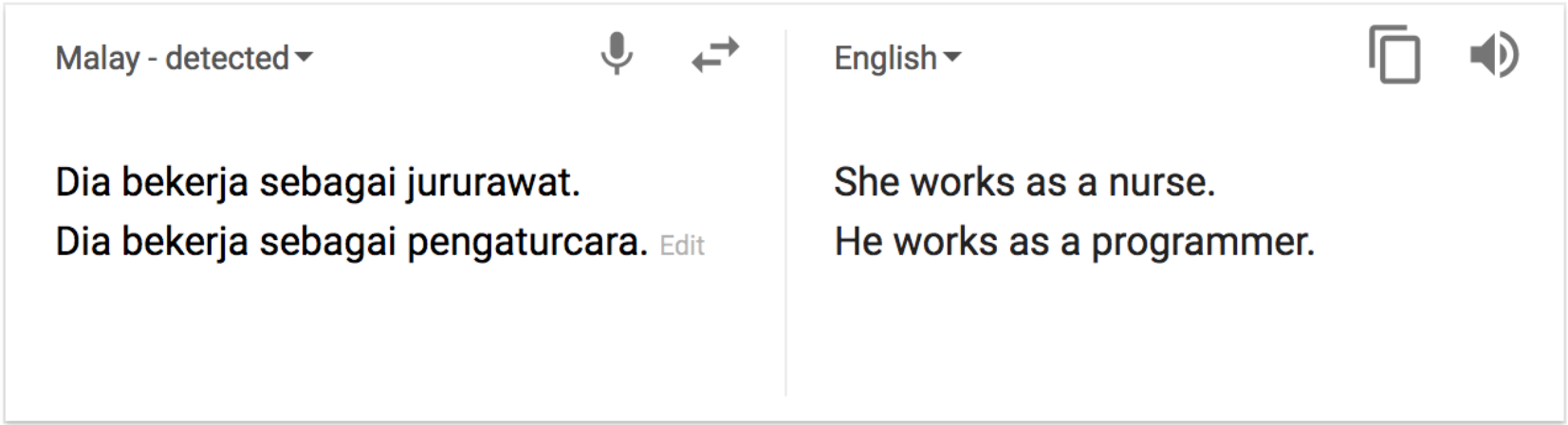

9:41
Cancel
Move your head slowly to complete the circle.
Accessibility Options

Bias in machine translation



society $\Rightarrow$ data $\Rightarrow$ predictions

cs221.stanford.edu/q

Question

What inspires you more?

Building agents with human-level intelligence

Developing tools that can benefit society

Summary so far

- AI dream of achieving human-level intelligence is ongoing
- Still lots of open research questions
- AI is having huge societal impact
- Need to think carefully about real-world consequences

And back to:
Data, Data, and more Data



How do we solve AI tasks?

- How should we actually solve these AI tasks? The real world is complicated. At the end of the day, we need to write some code (and possibly build some hardware too). But there is a huge chasm.

Paradigm

Modeling

Inference **Learning**

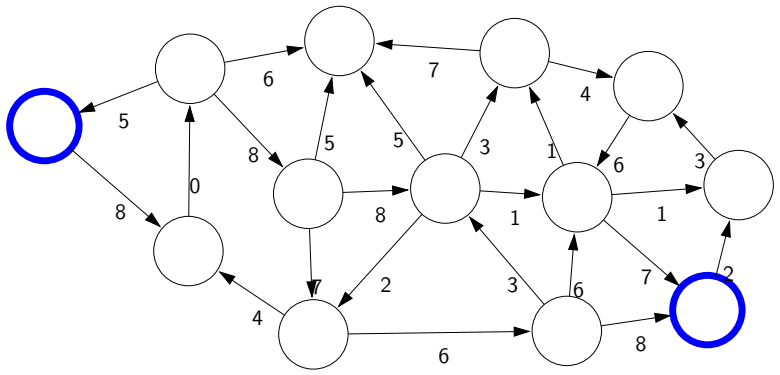
- In this class, we will adopt the **modeling-inference-learning** paradigm to help us navigate the solution space. In reality, the lines are blurry, but this paradigm serves as an ideal and a useful guiding principle.

Paradigm: modeling

Real world

Modeling

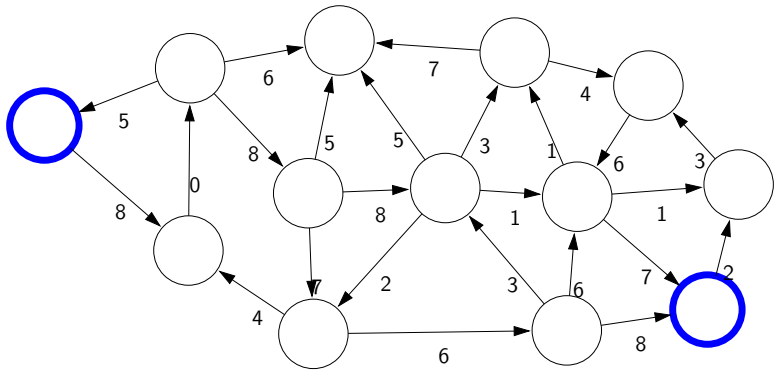
Model



- The first pillar is modeling. Modeling takes messy real world problems and packages them into neat formal mathematical objects called **models**, which can be subject to rigorous analysis but is more amenable to what computers can operate on. However, modeling is lossy: not all of the richness of the real world can be captured, and therefore there is an art of modeling: what does one keep versus ignore? (An exception to this is games such as Chess or Go or Sodoku, where the real world is identical to the model.)
- As an example, suppose we're trying to have an AI that can navigate through a busy city. We might formulate this as a graph where nodes represent points in the city.

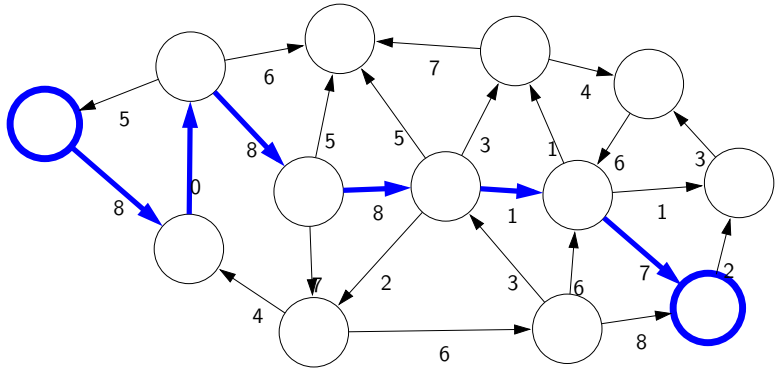
Paradigm: inference

Model



Inference

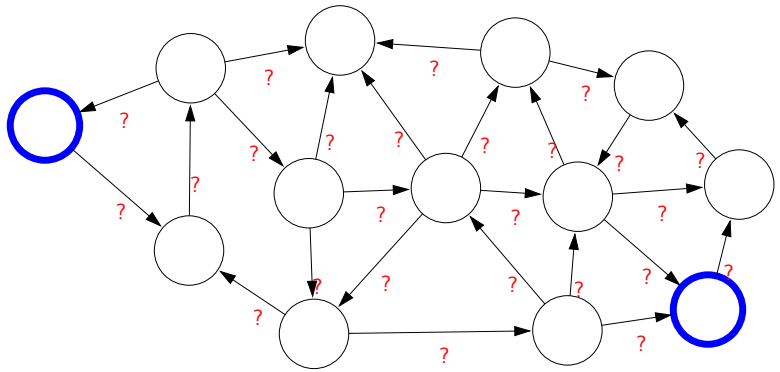
Predictions



- The second pillar is inference. Given a model, the task of **inference** is to answer questions with respect to the model. For example, given the model of the city, one could ask questions such as: what is the shortest path? what is the cheapest path?
- For some models, computational complexity can be a concern (games such as Go), and usually approximations are needed.

Paradigm: learning

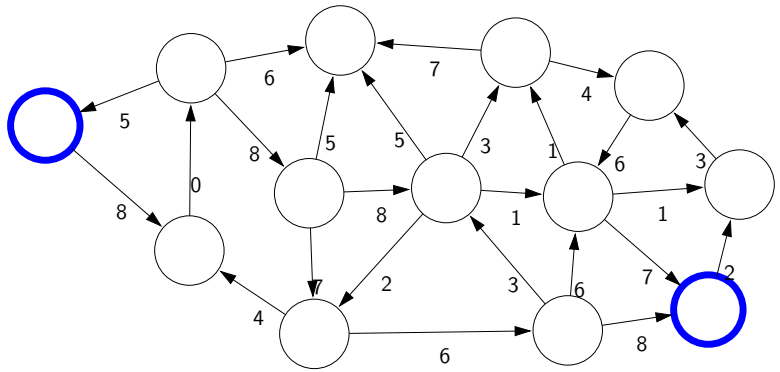
Model without parameters



+data

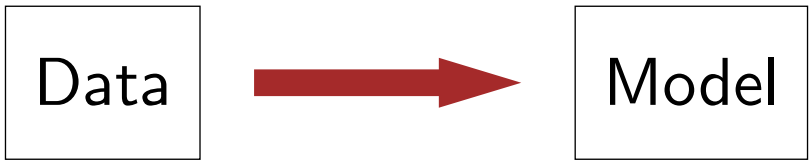
Learning

Model with parameters



- But where does the model come from? Remember that the real world is rich, so if the model is to be faithful, the model has to be rich as well. But we can't possibly write down such a rich model manually.
- The idea behind (machine) **learning** is to instead get it from data. Instead of constructing a model, one constructs a skeleton of a model (more precisely, a model family), which is a model without parameters. And then if we have the right type of data, we can run a machine learning algorithm to tune the parameters of the model.

Machine learning

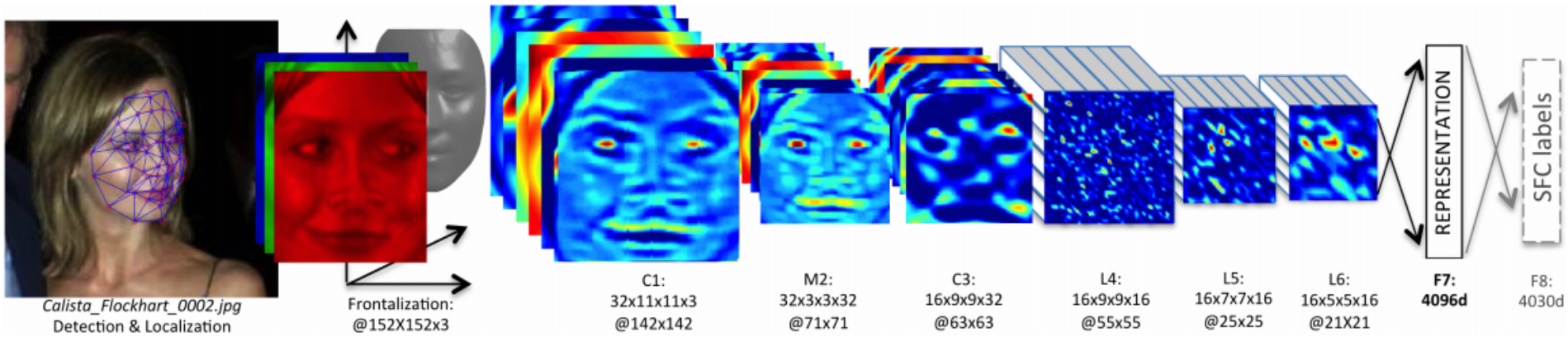


- The main driver of recent successes in AI
- Move from "code" to "data" to manage the information complexity
- Requires a leap of faith: **generalization**

- Supporting all of these models is **machine learning**, which has been arguably the most crucial ingredient powering recent successes in AI. Conceptually, machine learning allows us to shift the information complexity of the model from code to data, which is much easier to obtain (either naturally occurring or via crowdsourcing).
- The main conceptually magical part of learning is that if done properly, the trained model 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.

Reflex-based models

- Examples: linear classifiers, deep neural networks

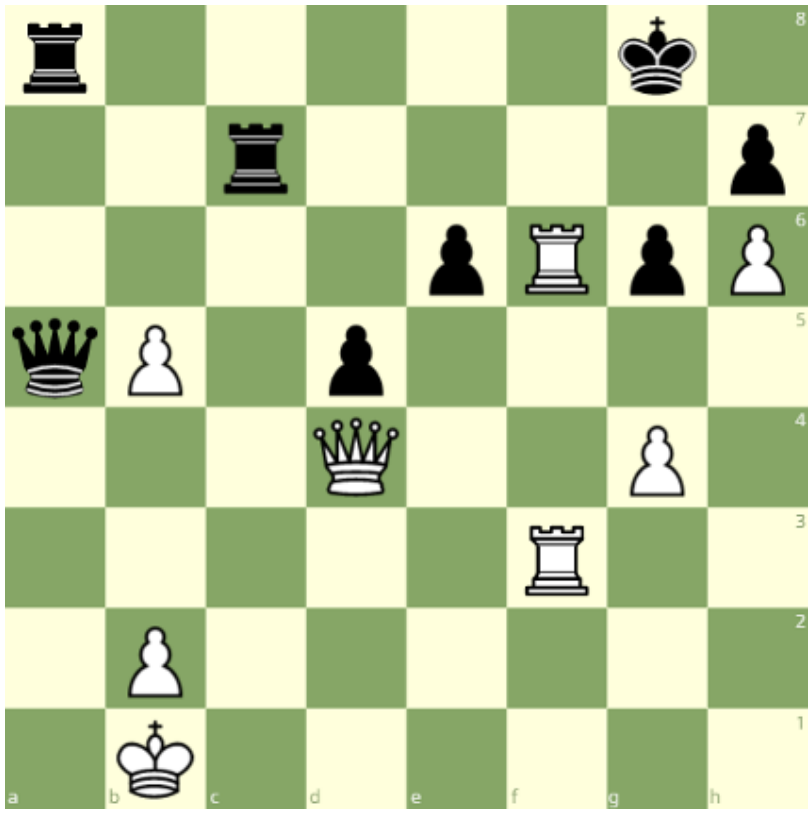


- Most common models in machine learning

- Fully feed-forward (no backtracking)

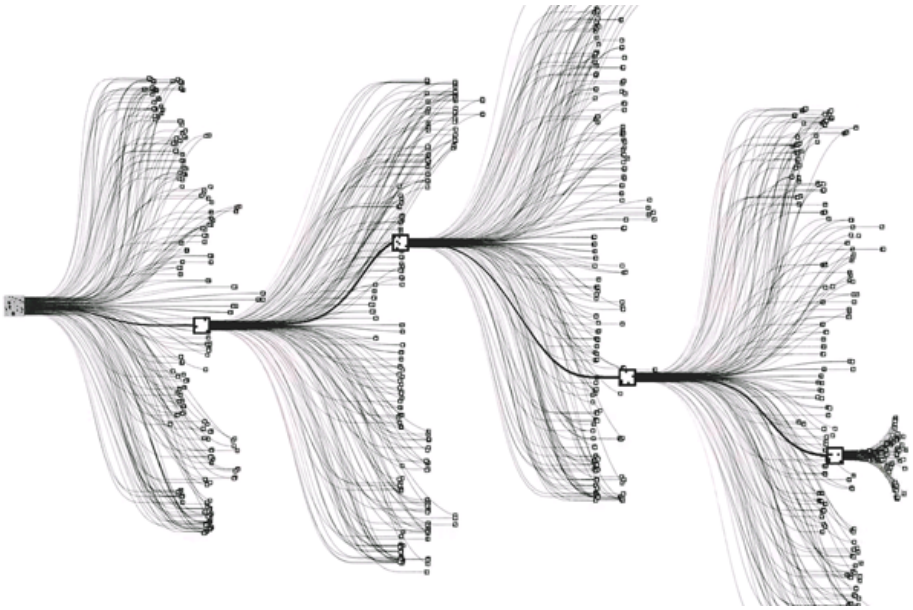
- The idea of a reflex-based model simply performs a fixed sequence of computations on a given input. Examples include most models found in machine learning from simple linear classifiers to deep neural networks. The main characteristic of reflex-based models is that their computations are feed-forward; one doesn't backtrack and consider alternative computations. Inference is trivial in these models because it is just running the fixed computations, which makes these models appealing.

State-based models



White to move

State-based models



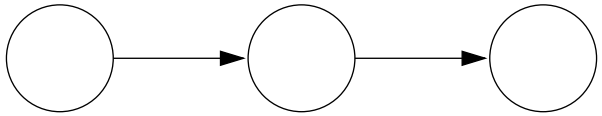
Applications:

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

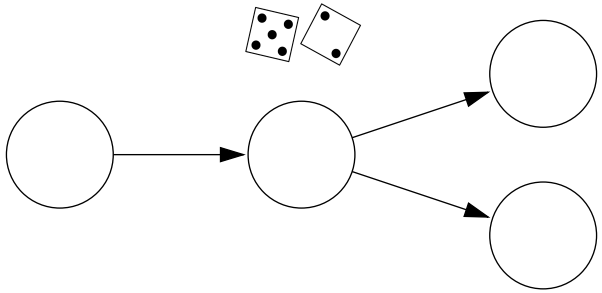
- Reflex-based models are too simple for tasks that require more forethought (e.g., in playing chess or planning a big trip). State-based models overcome this limitation.
- The key idea is, at a high-level, to model the **state** of a world and transitions between states which are triggered by actions. Concretely, one can think of states as nodes in a graph and transitions as edges. This reduction is useful because we understand graphs well and have a lot of efficient algorithms for operating on graphs.

State-based models

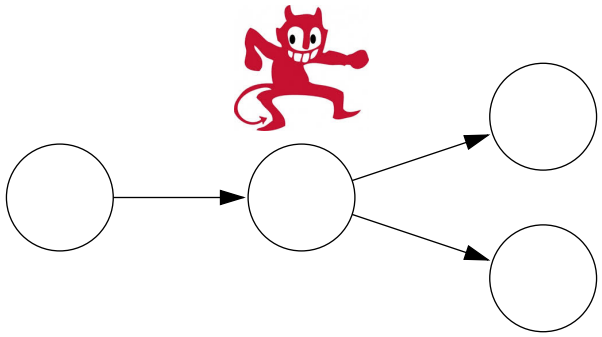
Search problems: you control everything



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

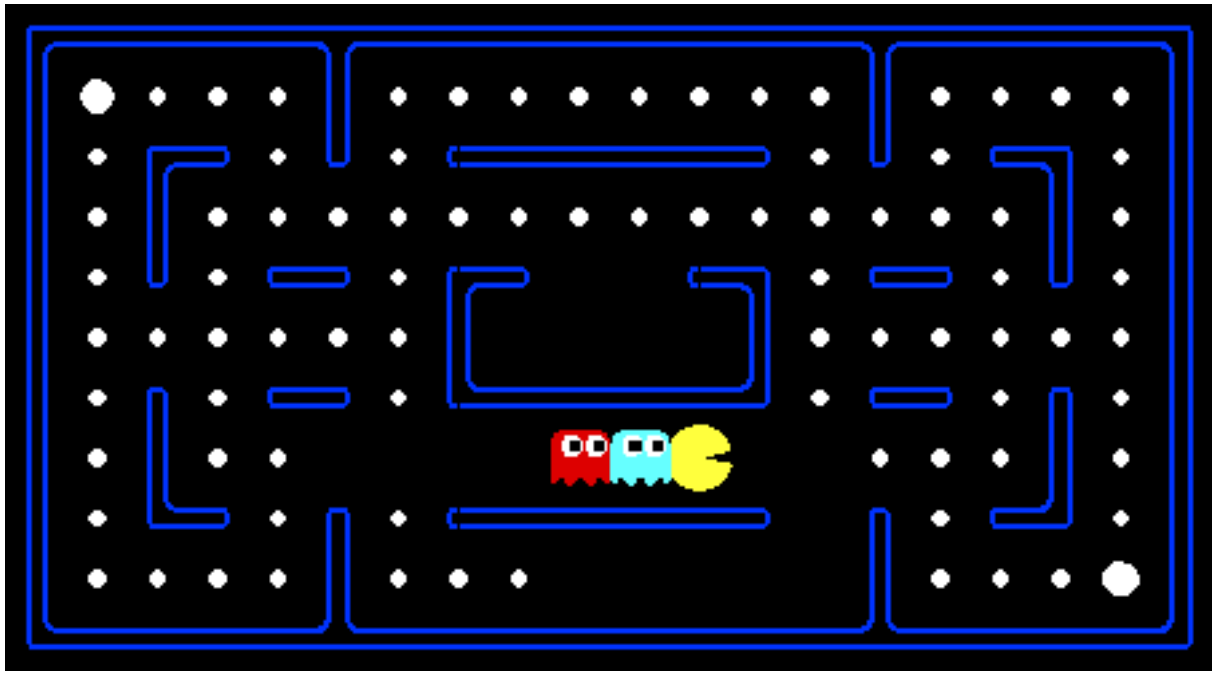


Adversarial games: against opponent (e.g., chess)



- 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

Optimization

Discrete optimization: a discrete object

$$\min_{p \in \text{Paths}} \text{Distance}(p)$$

Algorithmic tool: dynamic programming

Continuous optimization: a vector of real numbers

$$\min_{\mathbf{w} \in \mathbb{R}^d} \text{TrainingError}(\mathbf{w})$$

Algorithmic tool: gradient descent

- We are now done with the high-level motivation for the class. Let us now dive into some technical details. Let us focus on the inference and the learning aspect of the **modeling-inference-learning** paradigm.
- We will approach inference and learning from an **optimization** perspective, which allows us to decouple the mathematical specification of **what** we want to compute from the algorithms for **how** to compute it.
- 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 (mostly for inference) and continuous optimization problems (mostly for learning). 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**.