CAP 6635 – Artificial Intelligence

Lecture 9a: Foundations of AI (Part 4)

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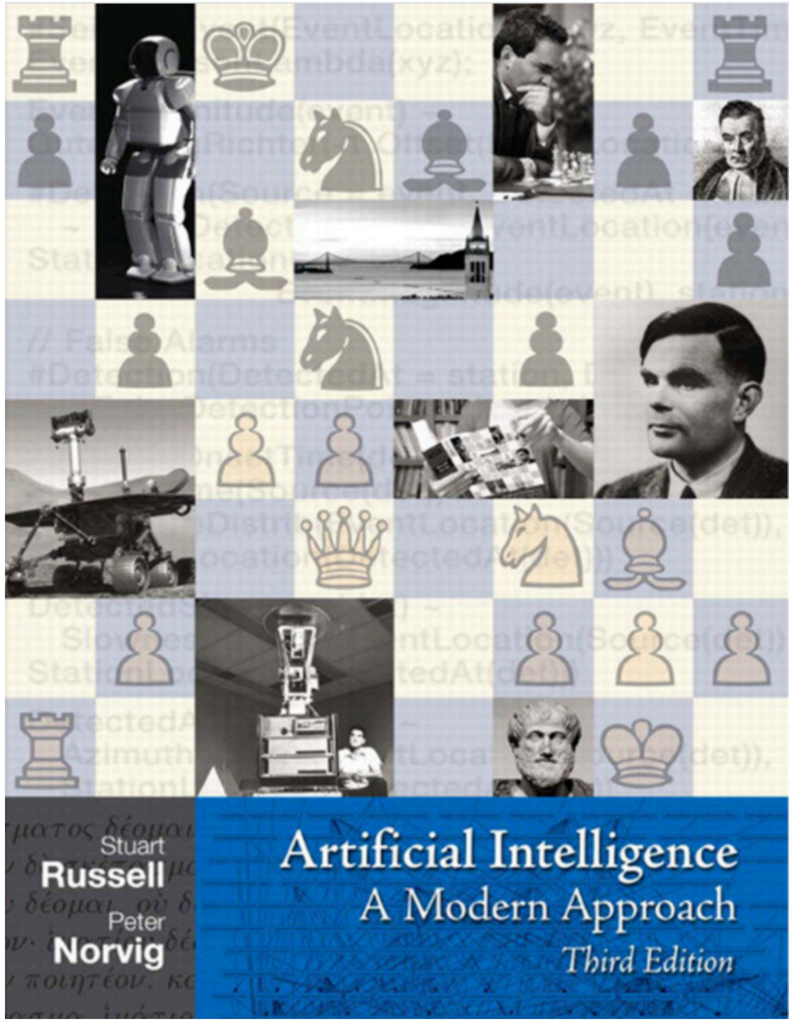

A whirlwind tour of Russell & Norvig 3/e

Outline

- Introduction
- Intelligent agents and their environments
- Solving problems by searching
- Adversarial search and games
- Constraint satisfaction problems (CSPs)
- Logical Agents
- Planning
- Knowledge representation
- Uncertain knowledge and reasoning
- Learning
- Communicating, perceiving, and acting

Outline

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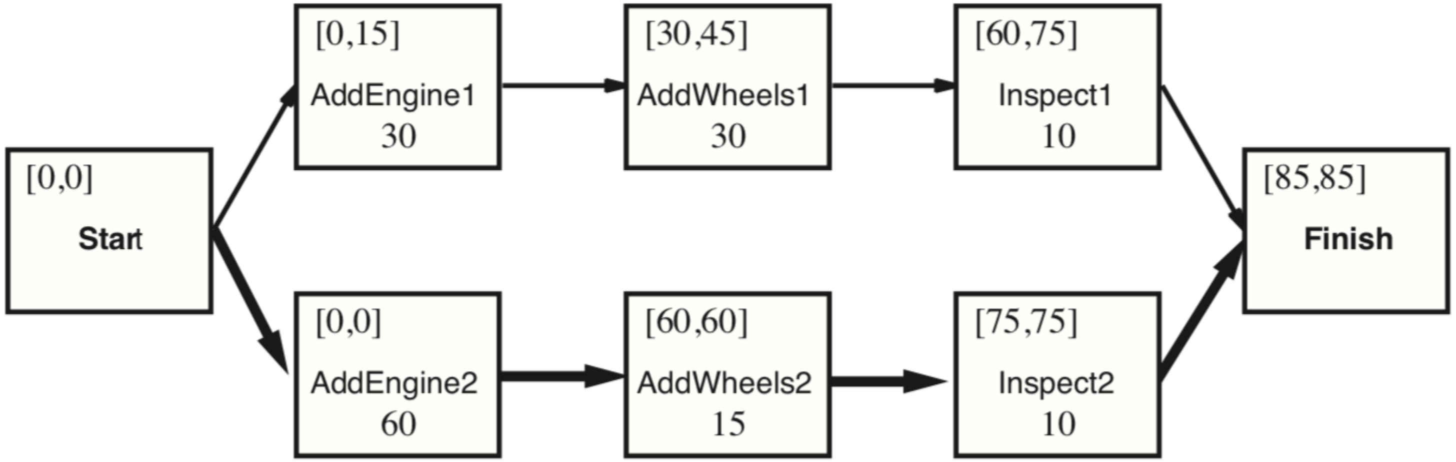
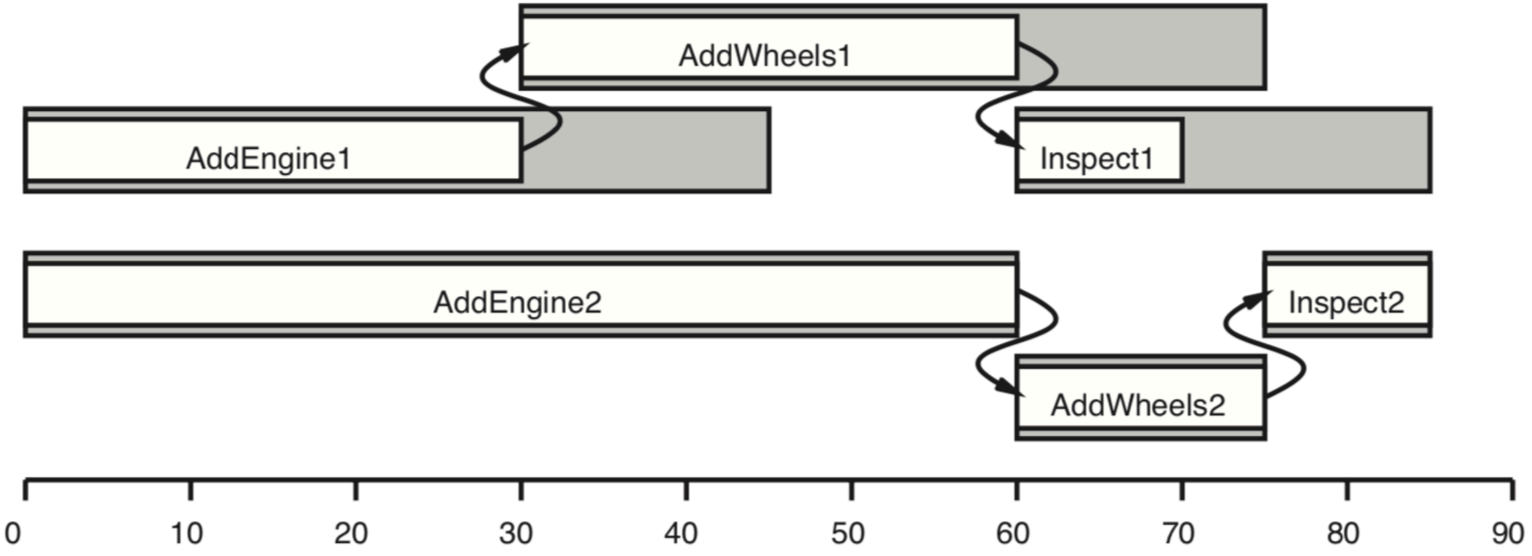
Planning

In which we see how an agent can take advantage of the structure of a problem to construct complex plans of action.

Example: job-shop scheduling (no constraints)





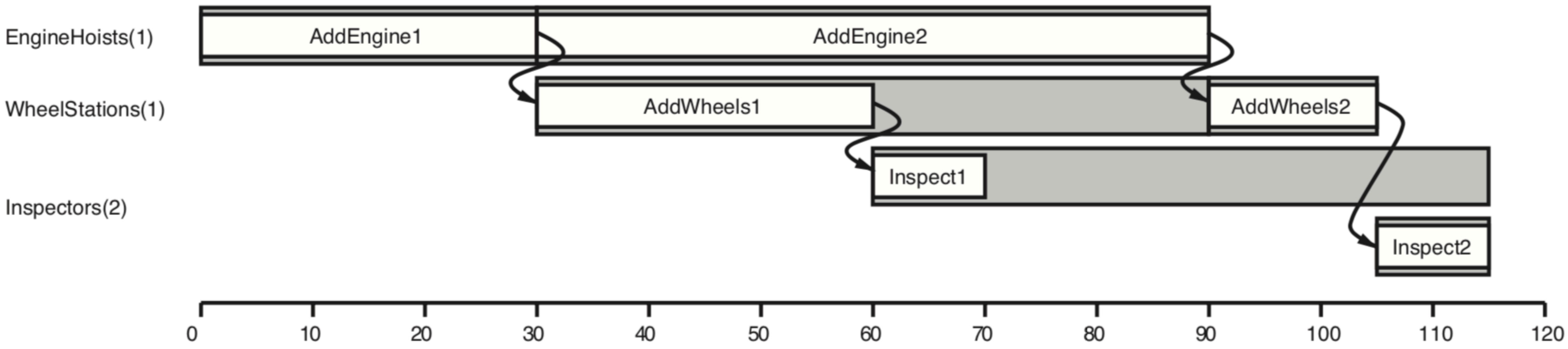
Example: Assembling two cars with resource constraints

$$
\begin{aligned}
&Jobs(\{AddEngine1 \prec AddWheels1 \prec Inspect1\},\\
&\qquad \{AddEngine2 \prec AddWheels2 \prec Inspect2\})
\end{aligned}
$$

$$Resources(EngineHoists(1),\ WheelStations(1),\ Inspectors(2),\ LugNuts(500))$$

$$
\begin{aligned}
&Action(AddEngine1, \text{DURATION}{:}30,\\
&\qquad \text{USE}{:}EngineHoists(1))\\
&Action(AddEngine2, \text{DURATION}{:}60,\\
&\qquad \text{USE}{:}EngineHoists(1))\\
&Action(AddWheels1, \text{DURATION}{:}30,\\
&\qquad \text{CONSUME}{:}LugNuts(20), \text{USE}{:}\ WheelStations(1))\\
&Action(AddWheels2, \text{DURATION}{:}15,\\
&\qquad \text{CONSUME}{:}LugNuts(20), \text{USE}{:}\ WheelStations(1))\\
&Action(Inspect_i, \text{DURATION}{:}10,\\
&\qquad \text{USE}{:}Inspectors(1))
\end{aligned}
$$

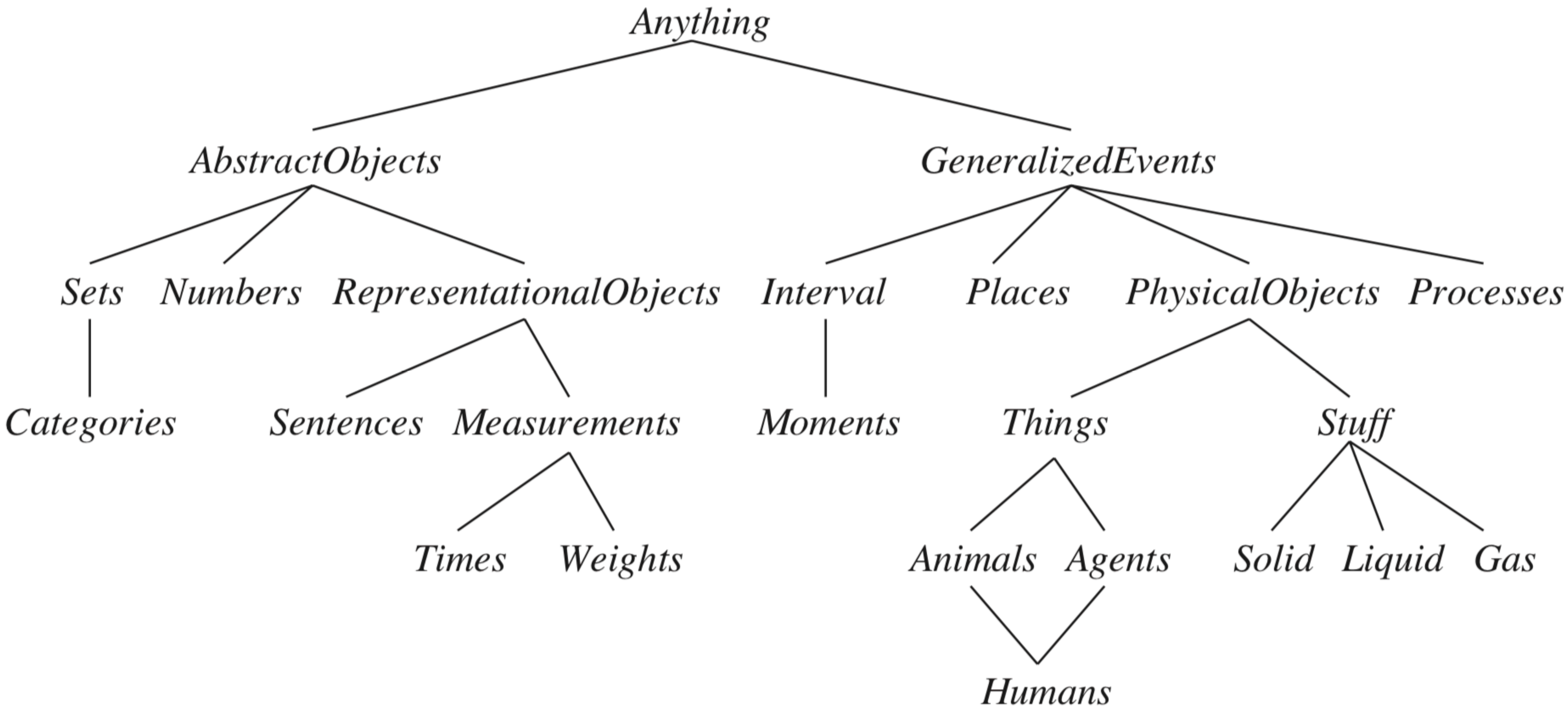
Example: job-shop scheduling (with constraints)



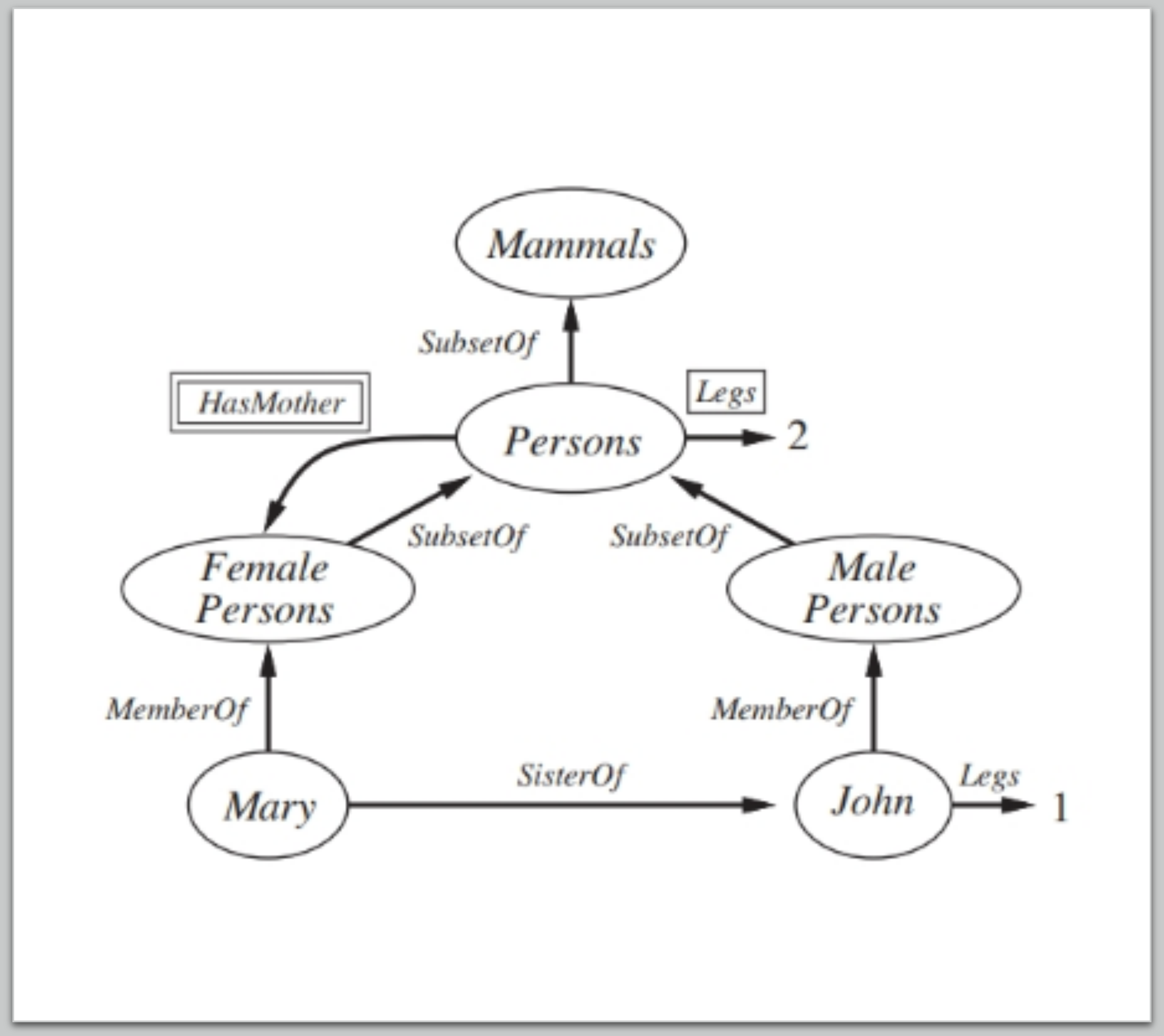
Knowledge Representation

In which we show how to use first-order logic to represent the most important aspects of the real world, such as action, space, time, thoughts, and shopping.

“The upper ontology of the world”



Semantic network: example



Sidebar: the CYC project

Cyc

Project

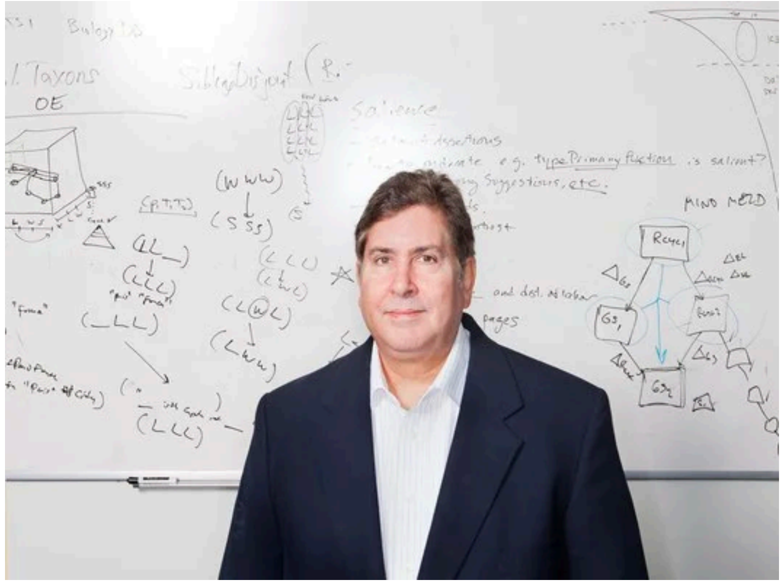
“The most notorious failure in the history of AI”
-- Pedro Domingos

Cyc is a long-living artificial intelligence project that aims to assemble a comprehensive ontology and knowledge base that spans the basic concepts and rules about how the world works. Hoping to capture common sense knowledge, Cyc focuses on implicit knowledge that other AI platforms may take for granted. Wikipedia

Start date: 1984

Developer(s): Cycorp, Inc

Original author(s): Douglas Lenat



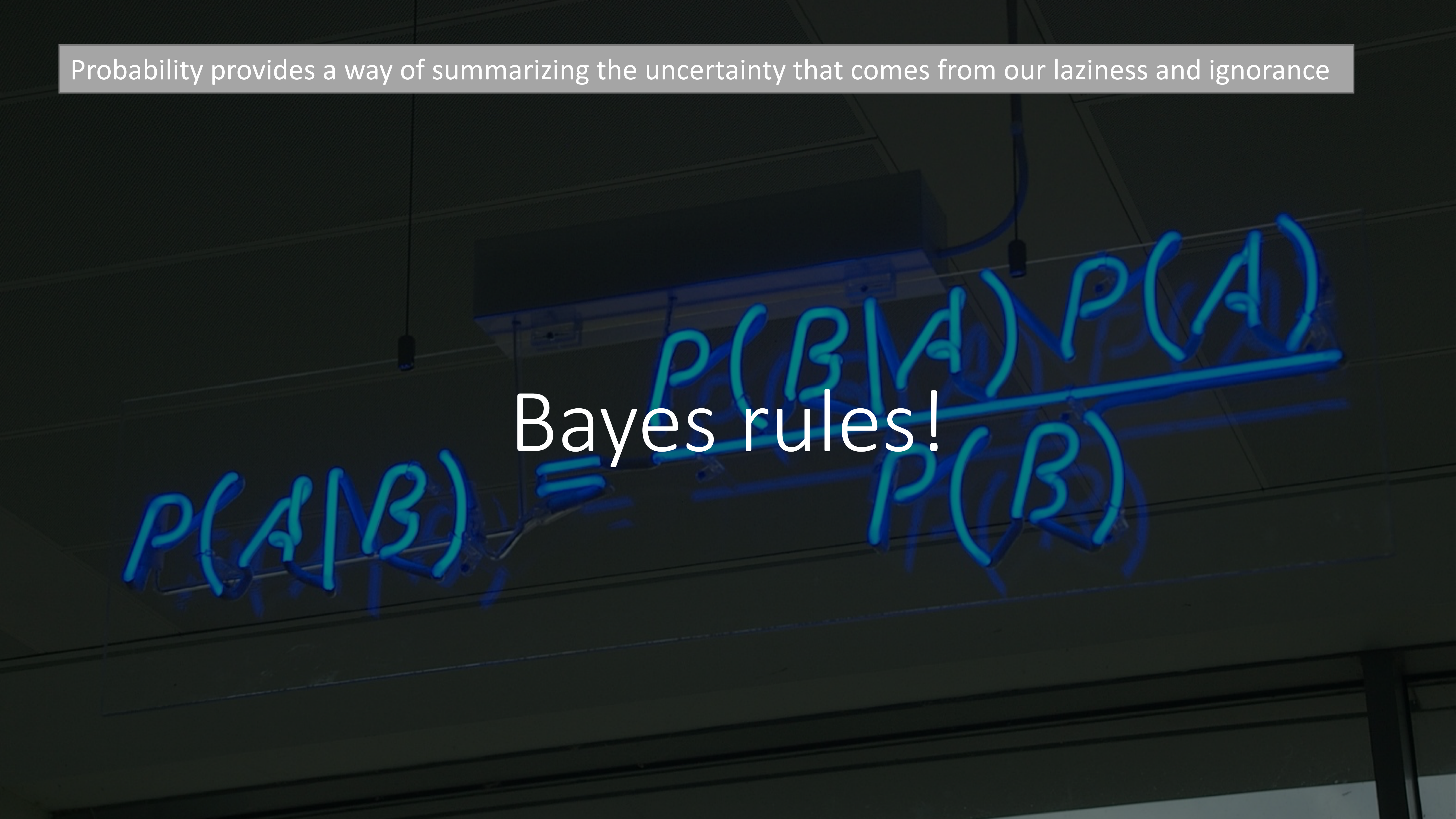
- See story at: https://www.wired.com/2016/03/doug-lenat-artificial-intelligence-common-sense-engine/

Uncertain knowledge and reasoning

In which we see how an agent can tame uncertainty with degrees of belief.

Probability provides a way of summarizing the uncertainty that comes from our laziness and ignorance

Bayes rules!



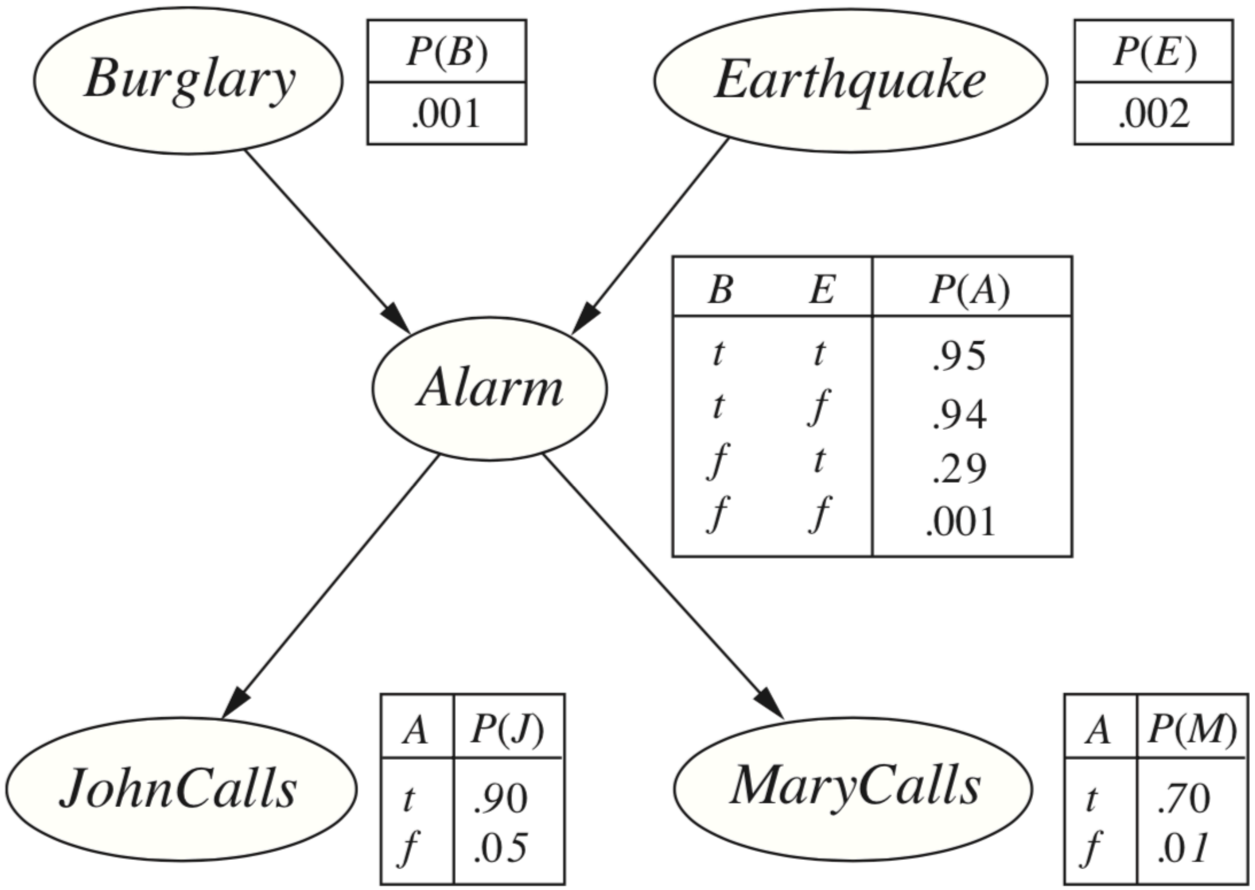
Probabilistic reasoning: example

You have a new burglar alarm installed at home. It is fairly reliable at detecting a burglary, but also responds on occasion to minor earthquakes.

You also have two neighbors, John and Mary, who have promised to call you at work when they hear the alarm.

- John nearly always calls when he hears the alarm, but sometimes confuses the telephone ringing with the alarm and calls then, too.
- Mary, on the other hand, likes rather loud music and often misses the alarm altogether.

Given the evidence of who has or has not called, we would like to estimate the probability of a burglary.



Learning

In which we describe agents that can improve their behavior through diligent study of their own experiences.

Reasons to learn

An agent is learning if it improves its performance on future tasks after making observations about the world.

Why would we want an agent to learn?

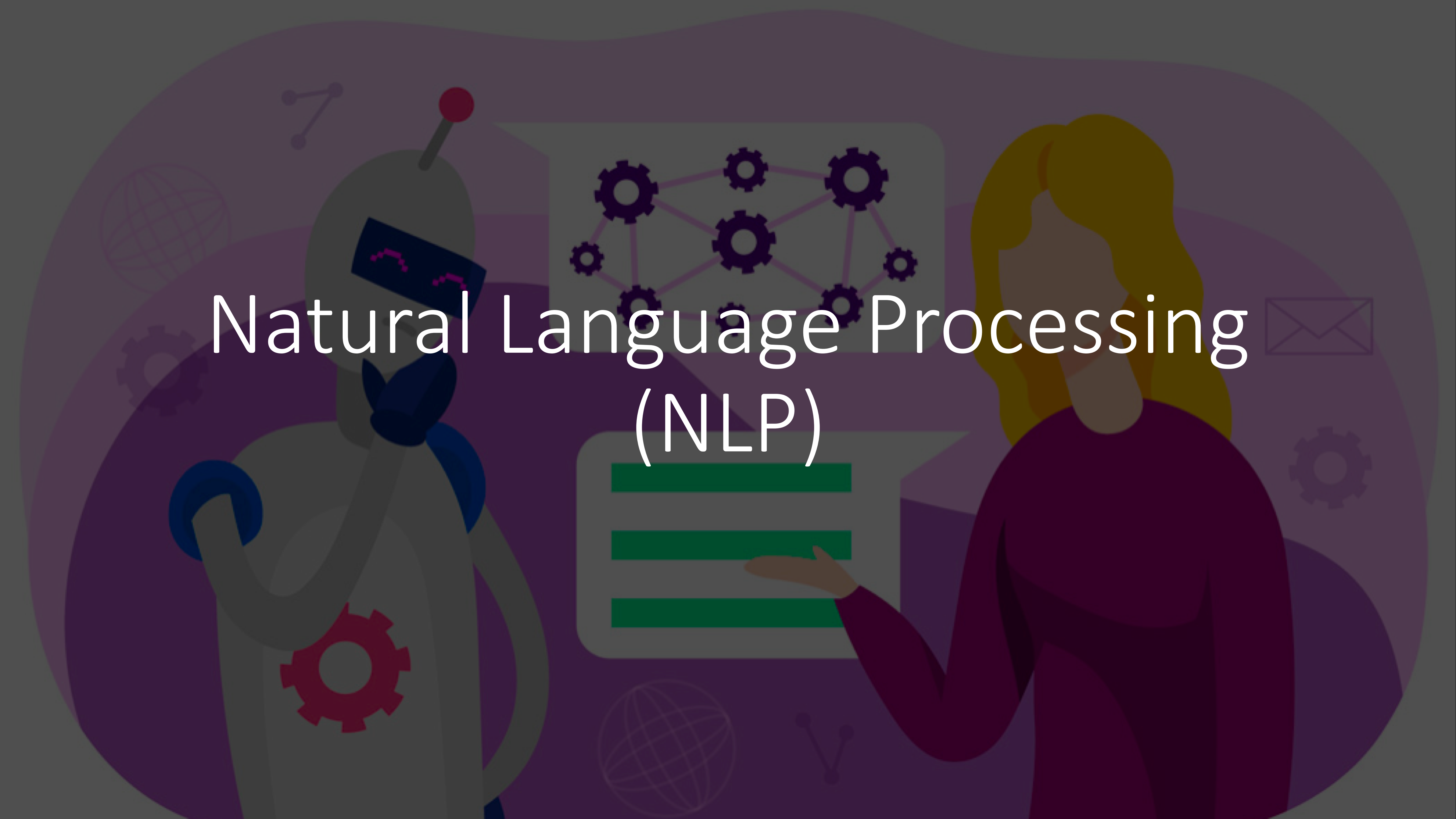
1. Designers cannot anticipate all possible situations that the agents might find themselves in.
2. Designers cannot anticipate all changes over time.
3. Sometimes human programmers have no idea how to program a solution themselves ▶ their solutions will consist of <u>building models that can learn from examples</u>.

Learning Algorithms

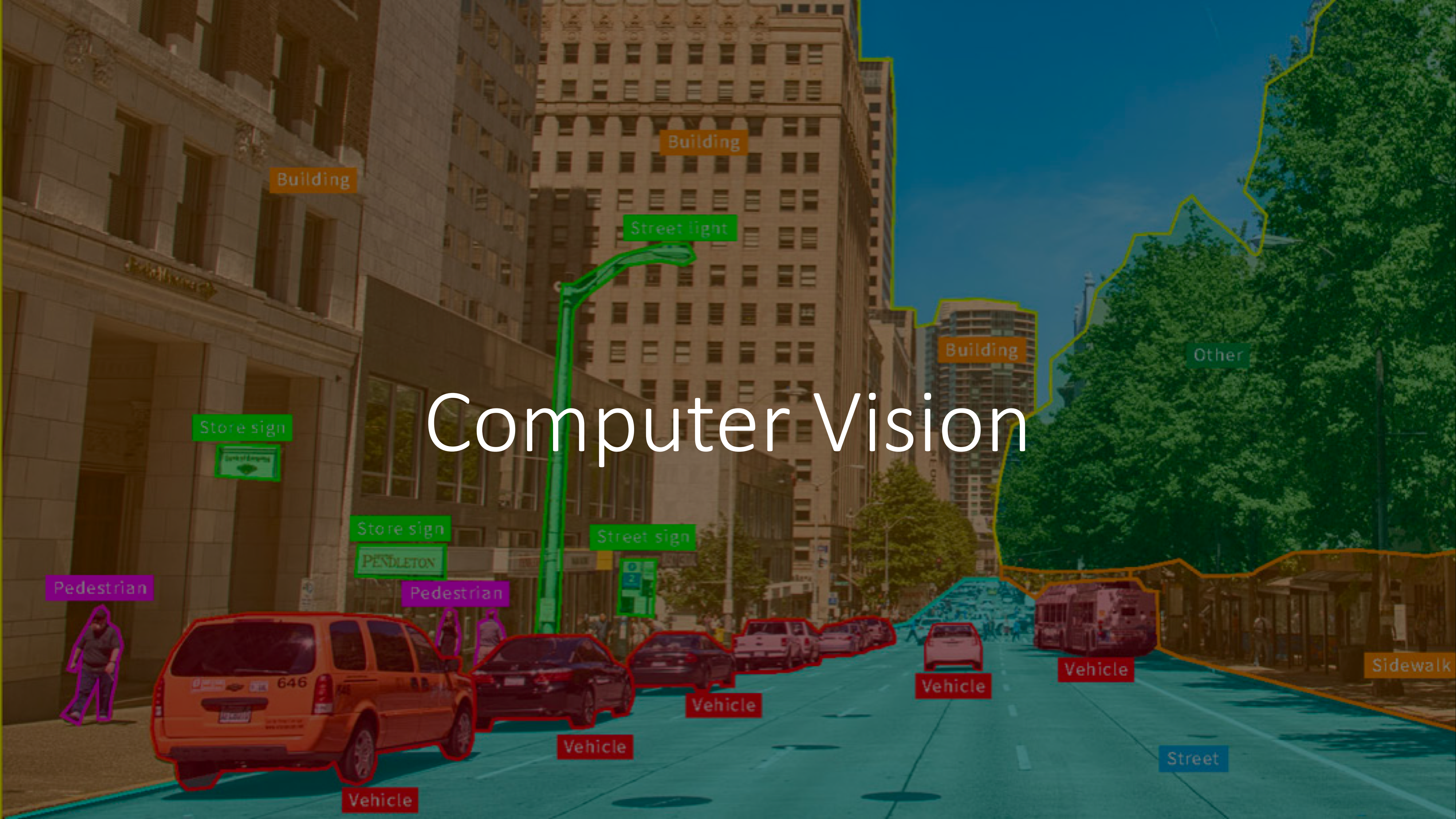
Coming up soon…

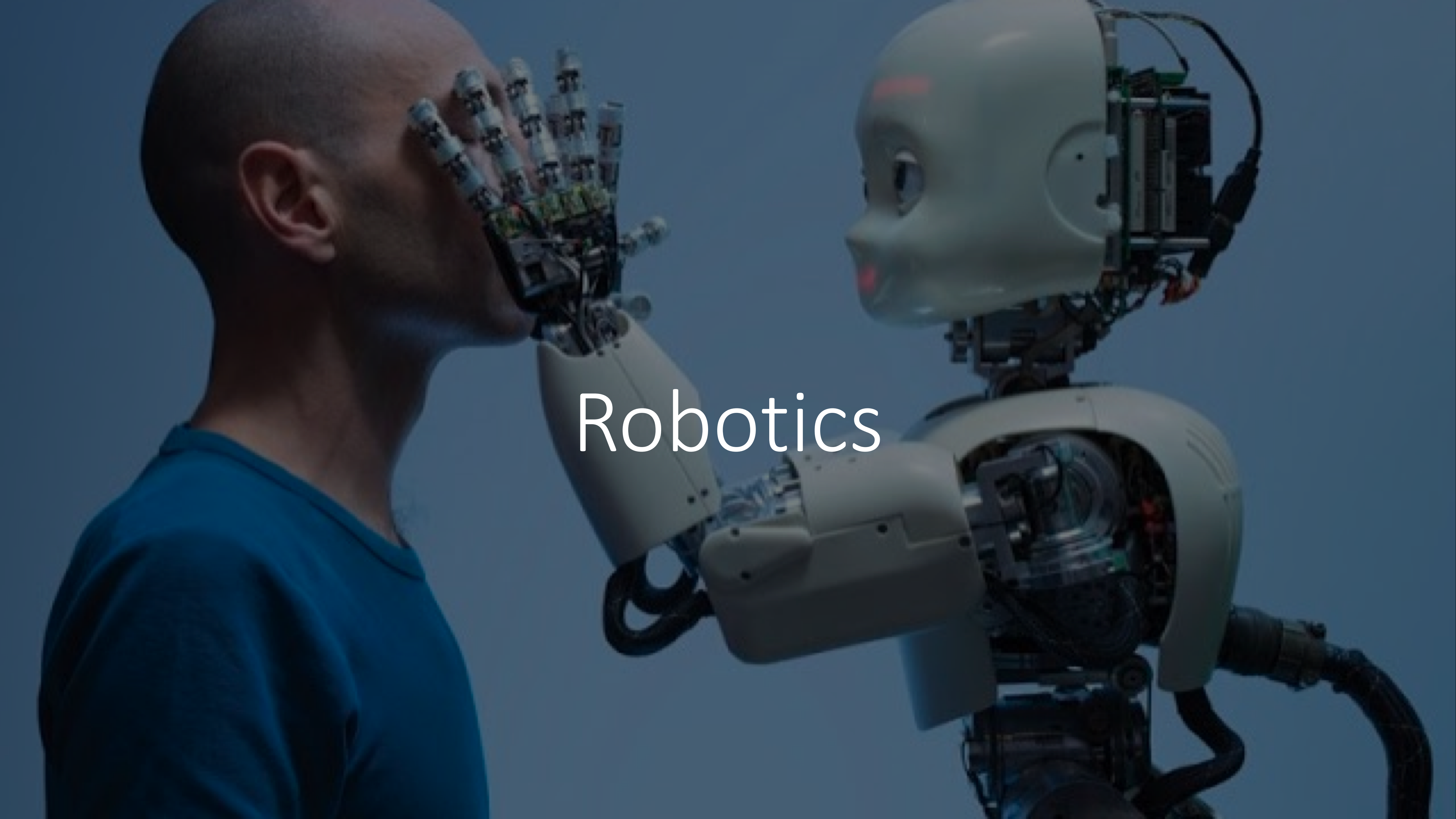
Communicating, perceiving, and acting

Natural Language Processing (NLP)



Computer Vision





Robotics

Speech Recognition

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Lecture 9b: How do machines learn? (Part 1)

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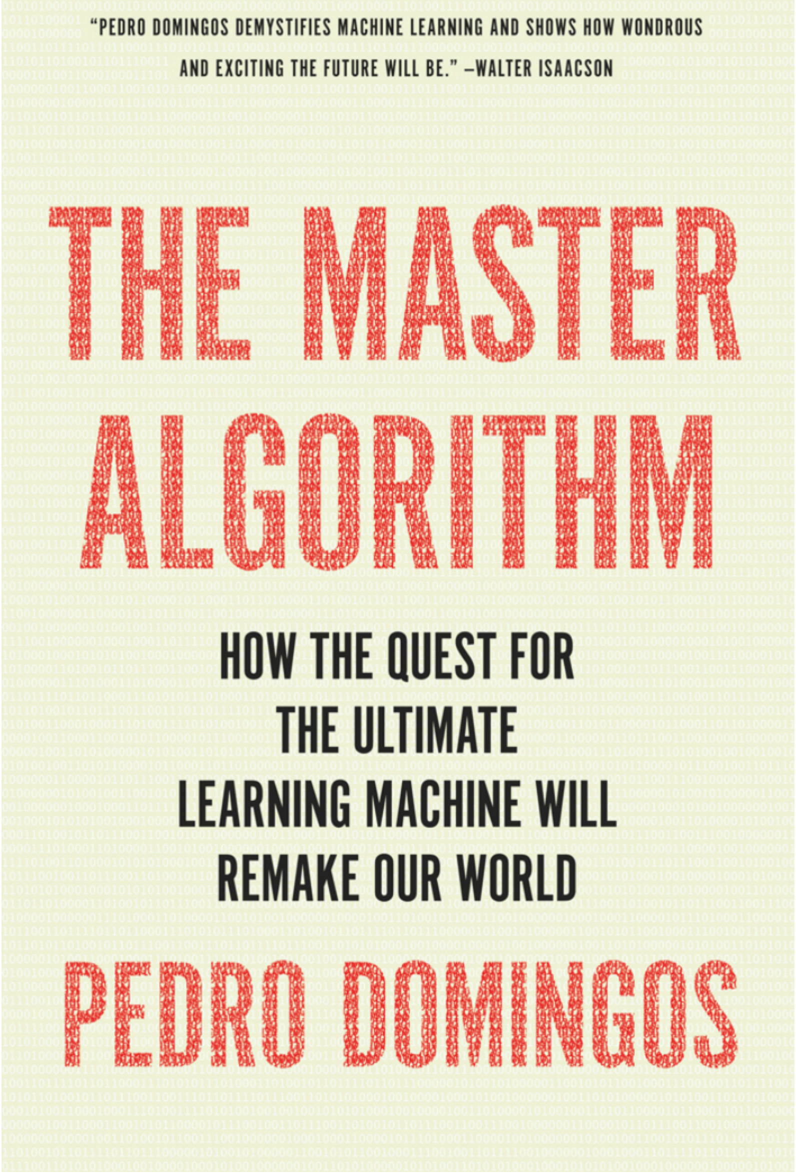
The Master Algorithm

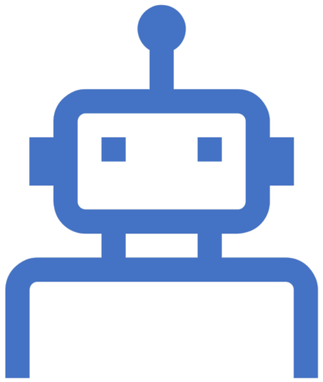
(by Pedro Domingos)

"All knowledge—past, present, and future—can be derived from data by a single, universal learning algorithm."



How Do Machines Learn?

- Neuroscience
- Evolution
- Physics
- Statistics
- Computer Science



Sidebar: Jeff Hawkins and Numenta

The Thousand Brains Theory of Intelligence

Numenta

About	Developing machine intelligence through neocortical theory
Established	Feb 4, 2005 · Redwood City, CA
Employees	15

The New York Times

Jeff Hawkins Is Finally Ready to Explain His Brain Research

The core concepts in our cortical theory were first described in this book titled **On Intelligence**, which was written by Jeff Hawkins with Sandra Blakeslee.

This book still provides background and a great introduction to our theory, though many of the ideas in chapter 6 ("How the Cortex Works") are currently being revised.

Machine Learning vs. Knowledge Engineering

- Machine Learning has become the predominant approach to AI
- This is not without objection
  - Marvin Minsky – Society of Mind
    - Supporter of the Cyc project
  - Noam Chomsky – “language is innate”
  - Jerry Fodor – “modularity of the mind”
  - (many others)

Objections to Machine Learning

- The “black swan” effect (novelty, surprise)

- “Data can’t replace human intuition.”

- “In fact, it’s the other way around: human intuition can’t replace data. Intuition is what you use when you don’t know the facts, and since you often don’t, intuition is precious”. -- Pedro Domingos.

How complex should the master algorithm be?

- “In machine learning the complexity is in the data; all the Master Algorithm has to do is assimilate it, so we shouldn’t be surprised if it turns out to be simple.
- The human hand is simple—four fingers, one opposable thumb—and yet it can make and use an infinite variety of tools.
- The Master Algorithm is to algorithms what the hand is to pens, swords, screwdrivers, and forks.”

Potential impact vs. odds of success

- “Because the potential impact is so great, it would behoove us to try to invent the Master Algorithm even if the odds of success were low.
- And even if it takes a long time, searching for a universal learner has many immediate benefits. ”

What if the Master Algorithm falls into wrong hands?

- “The first line of defense is to make sure the good guys get it first—or, if it’s not clear who the good guys are, to make sure it’s open-sourced.
- The second is to realize that, no matter how good the learning algorithm is, it’s only as good as the data it gets.
  - He who controls the data controls the learner.

- Control of data and ownership of the models learned from it is what many of the twenty-first century’s battles will be about—between governments, corporations, unions, and individuals. But you also have an ethical duty to share data for the common good. Machine learning alone will not cure cancer; cancer patients will, by sharing their data for the benefit of future patients.”

The power of a theory

- “The power of a theory lies in how much it simplifies our description of the world.”

- “Unlike the theories of a given field, which only have power within that field, the Master Algorithm has power across all fields.”

The Master Algorithm in one equation

$$U(x) = 0$$

The 5 tribes of Machine Learning - Symbolists

- For symbolists, all intelligence can be reduced to manipulating symbols, in the same way that a mathematician solves equations by replacing expressions by other expressions.
- Symbolists understand that you can’t learn from scratch: you need some initial knowledge to go with the data.
- They’ve figured out how to incorporate preexisting knowledge into learning, and how to combine different pieces of knowledge on the fly in order to solve new problems.
- Their master algorithm is inverse deduction, which figures out what knowledge is missing in order to make a deduction go through, and then makes it as general as possible.

The 5 tribes of Machine Learning - Connectionists

- For connectionists, learning is what the brain does, and so what we need to do is reverse engineer it.
- The brain learns by adjusting the strengths of connections between neurons, and the crucial problem is figuring out which connections are to blame for which errors and changing them accordingly.
- The connectionists' master algorithm is backpropagation, which compares a system's output with the desired one and then successively changes the connections in layer after layer of neurons so as to bring the output closer to what it should be.

The 5 tribes of Machine Learning - Evolutionaries

- Evolutionaries believe that the mother of all learning is natural selection. If it made us, it can make anything, and all we need to do is simulate it on the computer.
- The key problem that evolutionaries solve is learning structure: not just adjusting parameters, like backpropagation does, but creating the brain that those adjustments can then fine-tune.
- The evolutionaries' master algorithm is genetic programming, which mates and evolves computer programs in the same way that nature mates and evolves organisms.

The 5 tribes of Machine Learning - Bayesians

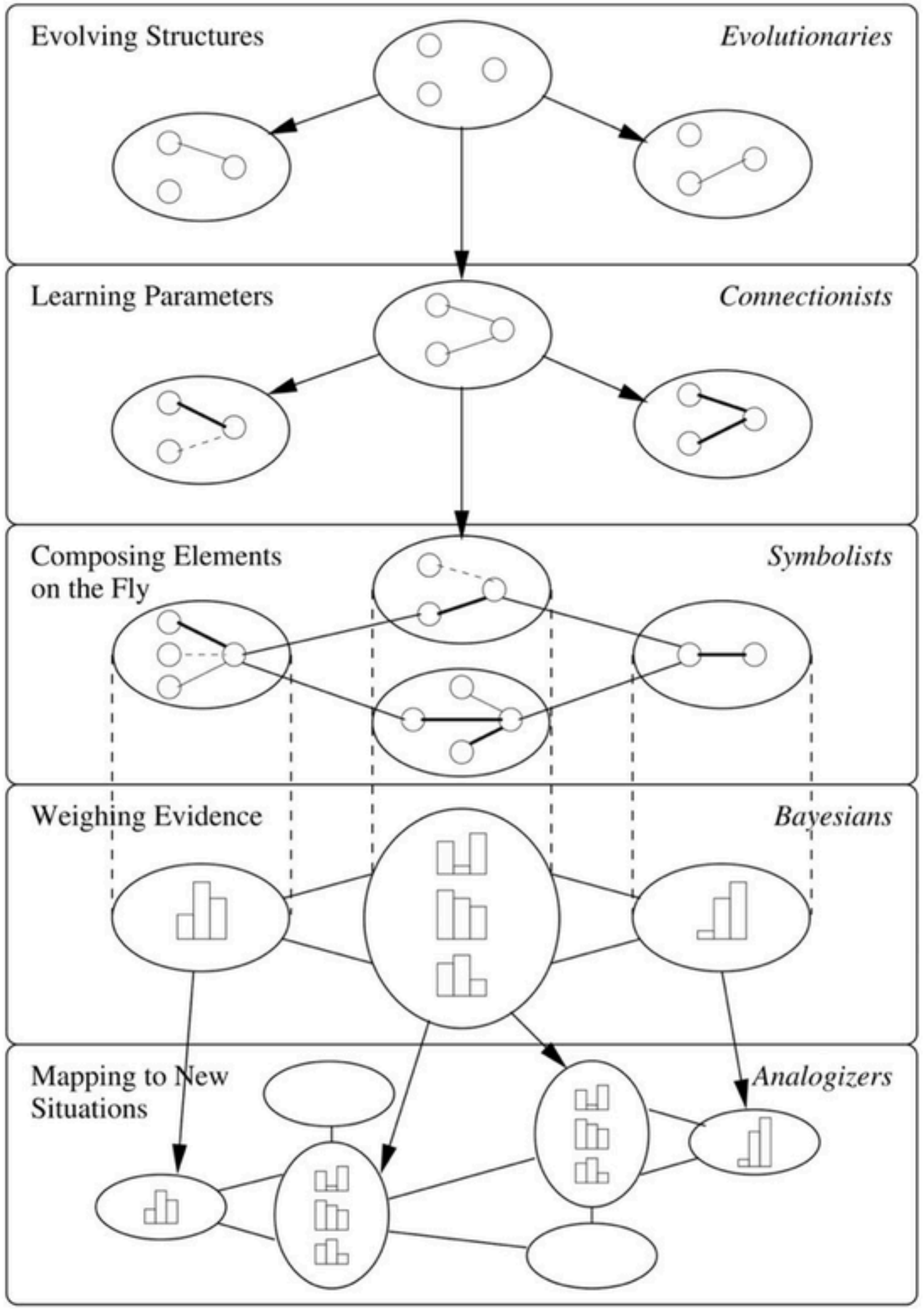
- Bayesians are concerned above all with uncertainty.
- All learned knowledge is uncertain, and learning itself is a form of uncertain inference.
- The problem then becomes how to deal with noisy, incomplete, and even contradictory information without falling apart.
- The solution is probabilistic inference, and the master algorithm is Bayes' theorem and its derivates.
- Bayes' theorem tells us how to incorporate new evidence into our beliefs, and probabilistic inference algorithms do that as efficiently as possible.

The 5 tribes of Machine Learning - Analogizers

- For analogizers, the key to learning is recognizing similarities between situations and thereby inferring other similarities.
  - If two patients have similar symptoms, perhaps they have the same disease.
- The key problem is judging how similar two things are.
- The analogizers’ master algorithm is the support vector machine, which figures out which experiences to remember and how to combine them to make new predictions.

The 5 tribes

- “Each tribe’s solution to its central problem is a brilliant, hard-won advance. But the true Master Algorithm must solve all five problems, not just one.”
- Careful with the border crossings…



The symbolists

No free lunch theorem- David Wolpert and William Macready (1997)

- “Any two optimization algorithms are equivalent when their performance is averaged across all possible problems.”
- “The practical consequence of the “no free lunch” theorem is that there’s no such thing as learning without knowledge. Data alone is not enough. Starting from scratch will only get you to scratch. Machine learning is a kind of knowledge pump: we can use it to extract a lot of knowledge from data, but first we have to prime the pump.” -- Pedro Domingos

Overfitting

- “Overfitting is the central problem in machine learning.”
- “Learning algorithms are particularly prone to overfitting, though, because they have an almost unlimited capacity to find patterns in data.”
- “Overfitting happens when you have too many hypotheses and not enough data to tell them apart.”
- “Bottom line: learning is a race between the amount of data you have and the number of hypotheses you consider.”