

Machine Learning as a Motor for Deep Transformation?

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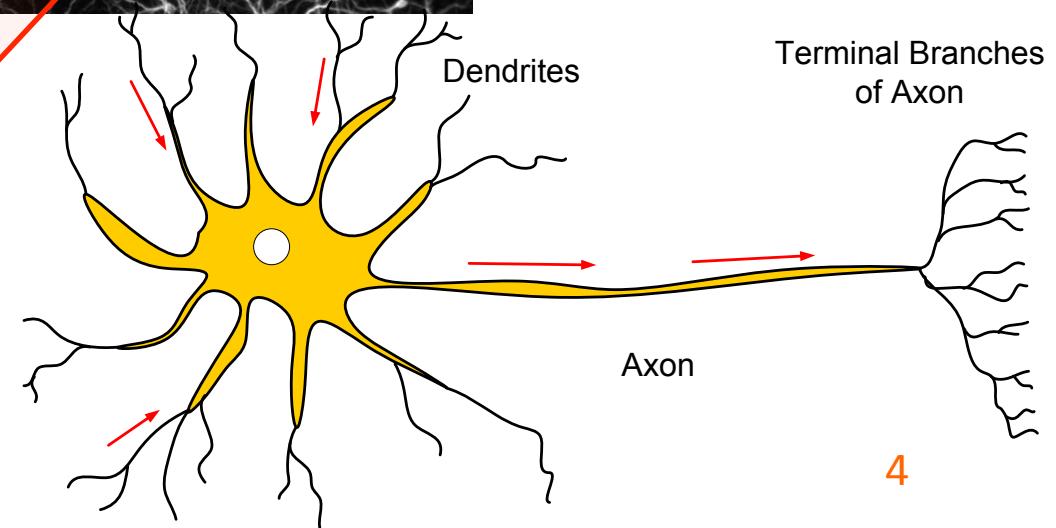
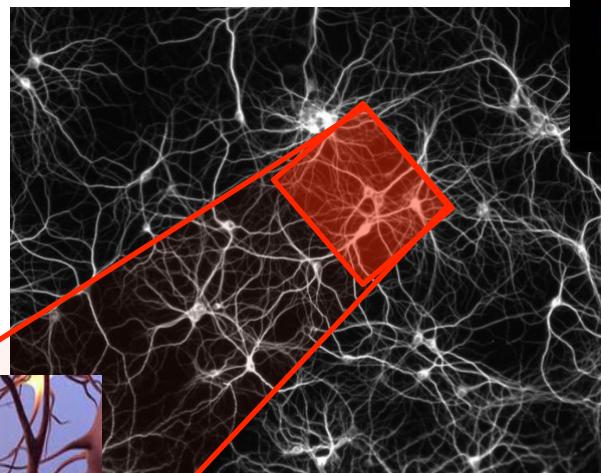
Artificial Intelligence

Dream of the pioneers

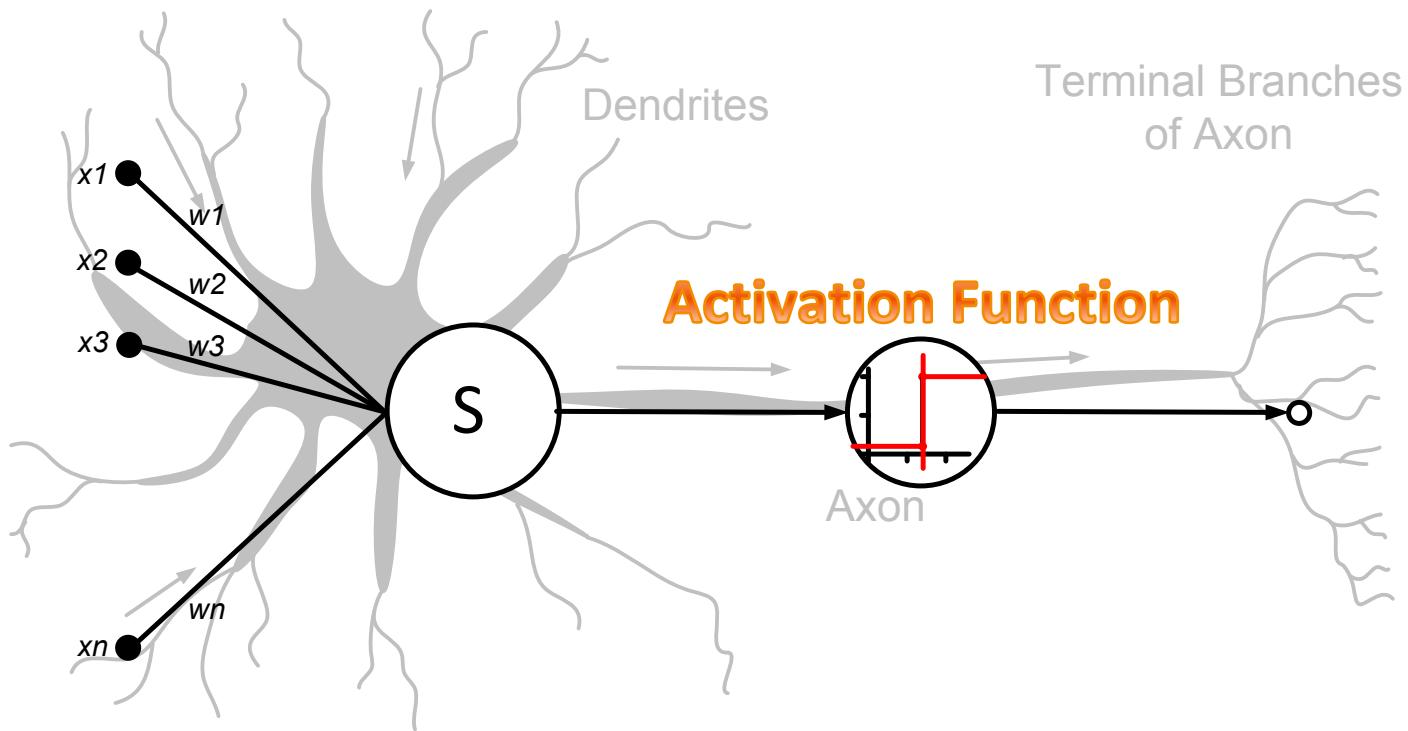
Computation

Information

Biological Neurons



1st formal model of the neuron



McCulloch & Pitts (1943)

Dream of the pioneers

1. Understanding intelligence

- Reasoning: symbolic AI Computation
- Inspired by the brain Information

2. Focused on human performances

- Playing chess
- Reasoning like humans: *planning, solving problems, analogy thinking, ...*
- Understanding texts and discourses
- Able to express itself using natural language

Outline

1. A brief history of AI
2. AI now: the triumph of deep neural networks
3. AI in the near future
4. There are limits
5. The case of XAI
6. Conclusion

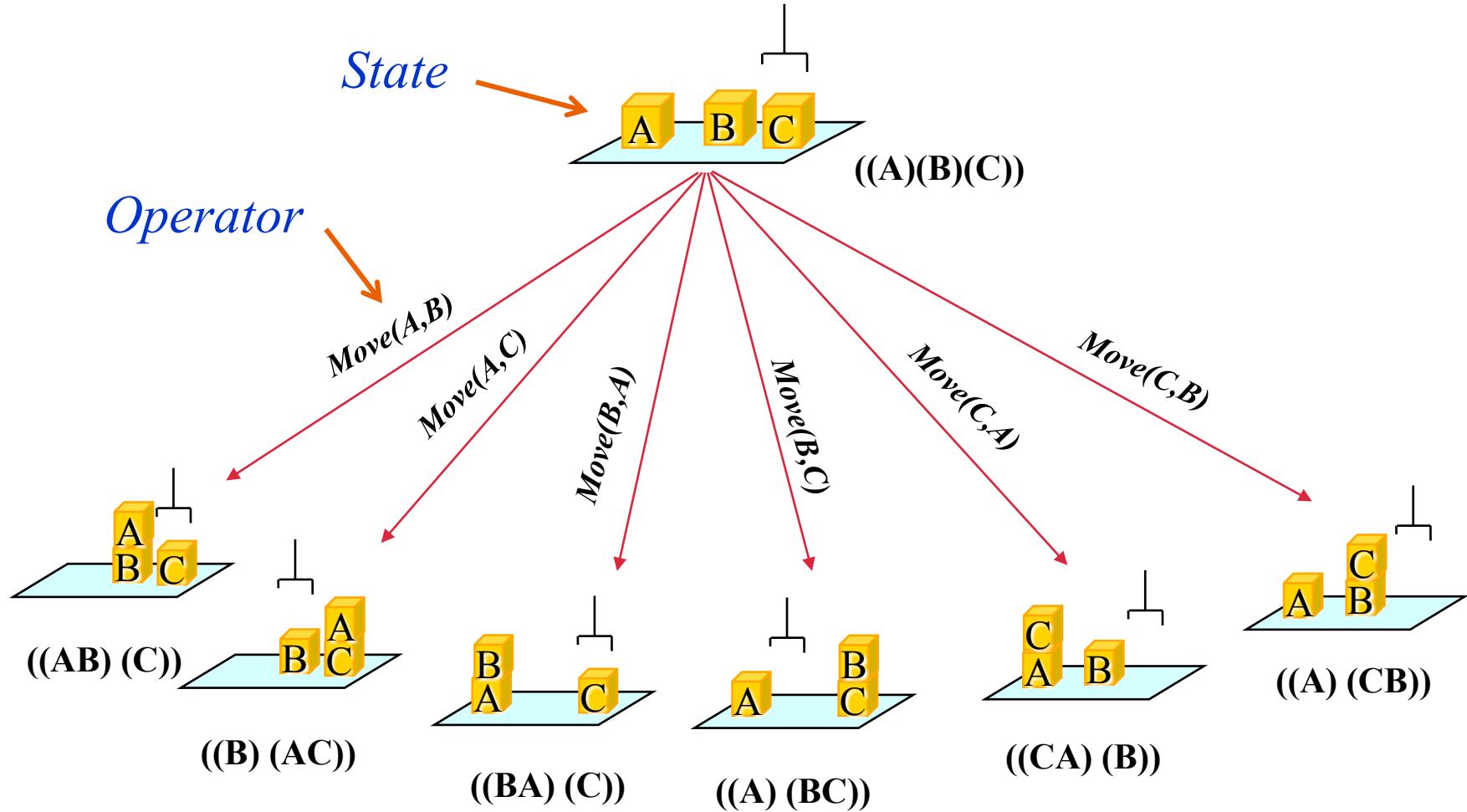
The assumption

Intelligence is

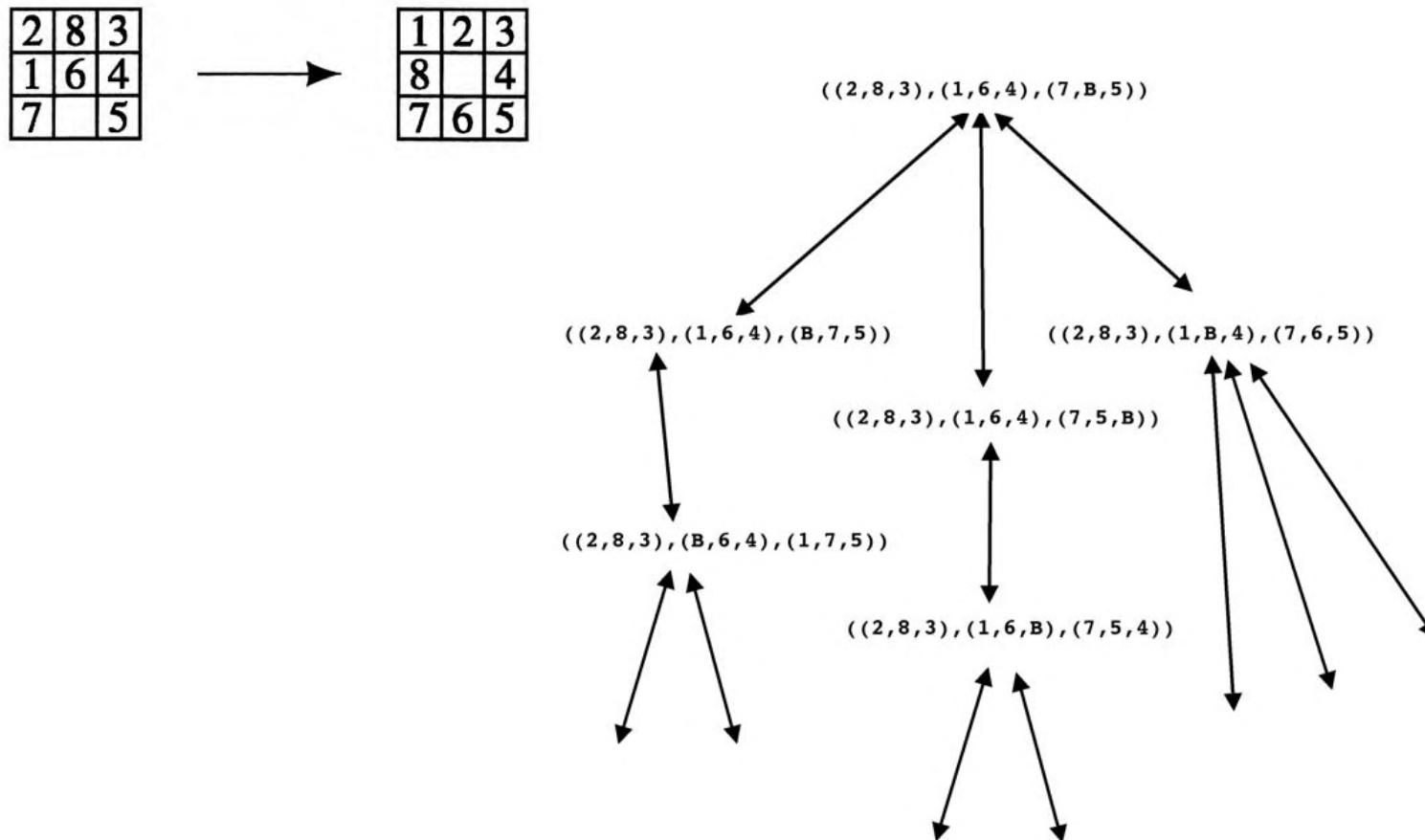
general reasoning processes

(~1956 – ~1969)

Reasoning / problem solving



Reasoning / problem solving



- Search in a graph

The first mobile robot: Shakey (SRI)

Vision
+ planning
+ interface through
pseudo natural
language

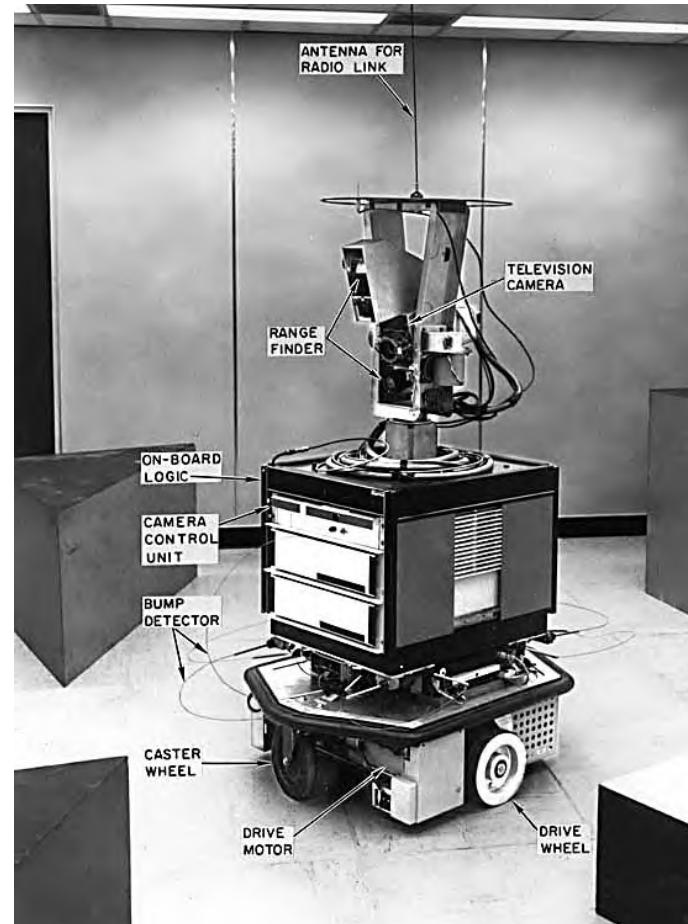


Figure 12.3: Shakey as it existed in November 1968 (with some of its components labeled). (Photograph courtesy of SRI International.)

Machine Vision

- Stanford AI Lab



Figure 8.1: Site of the Stanford AI Lab from 1966 until 1980. (Photograph courtesy of Lester Earnest.)

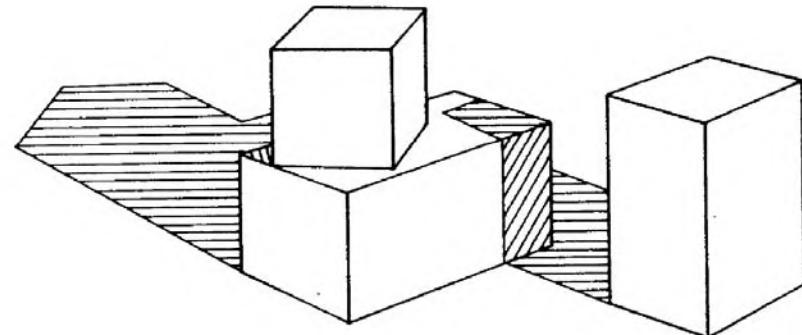
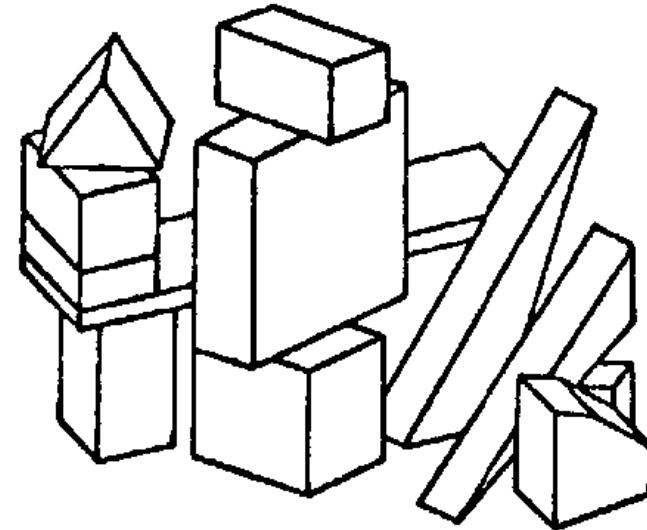


Figure 9.15: A scene with shadows analyzed by Waltz's program. (Illustration used with permission of David Waltz.)

1. pick up a big red block.

In order to pick up the red block, it had to clear it off by finding a space for the green one and moving the green one away.

OK.

The system answers "OK" when it carries out a command.

2. grasp the pyramid.

There are three pyramids in the scene, so the program does nothing.

I DON'T UNDERSTAND WHICH PYRAMID YOU MEAN.

3. find a block which is taller than the one you are holding and put it into the box.

The system has to figure out what is meant by "one" and "it," as well as using deduction to decide which block it is holding.

BY "IT," I ASSUME YOU MEAN THE BLOCK WHICH IS TALLER THAN THE ONE I AM HOLDING.

Printed out to keep us informed.

The hand has to set down the red block to pick up the taller blue one.

OK.

4. what does the box contain?

THE BLUE PYRAMID AND THE BLUE BLOCK.

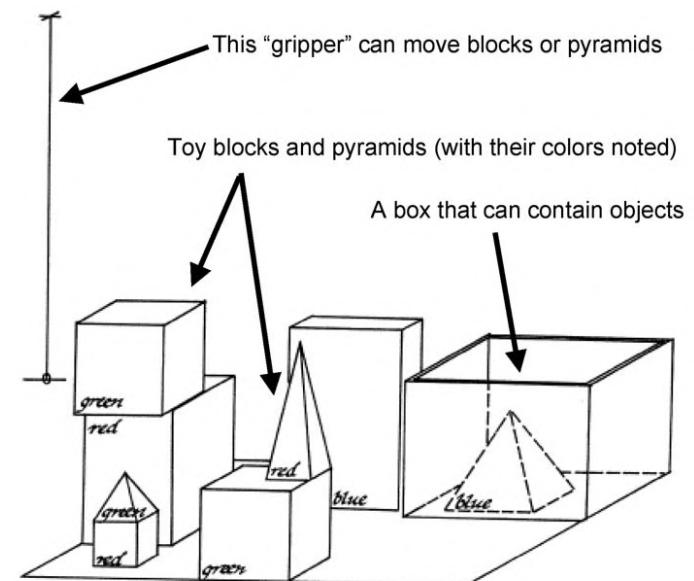
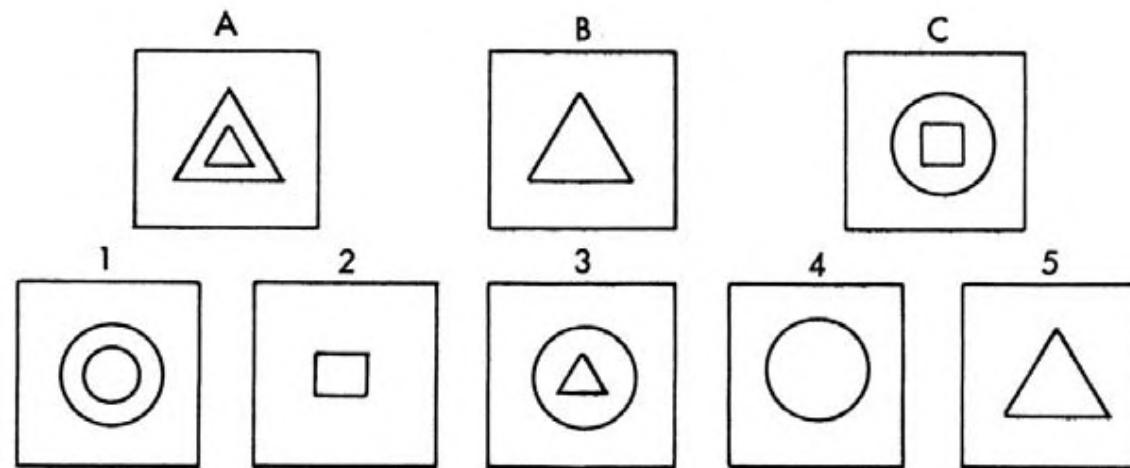


Figure 13.2: SHRDLU's world. (Illustration used with permission of Terry Winograd.)

1 9 6 8

- **Analogy making**

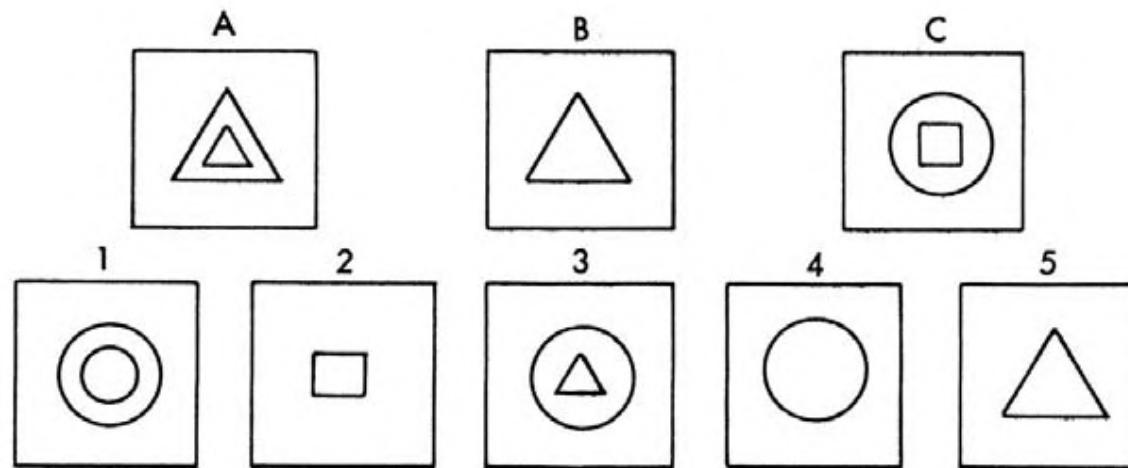


A is to B what C is to ?

1 9 6 8

- **Analogy making**

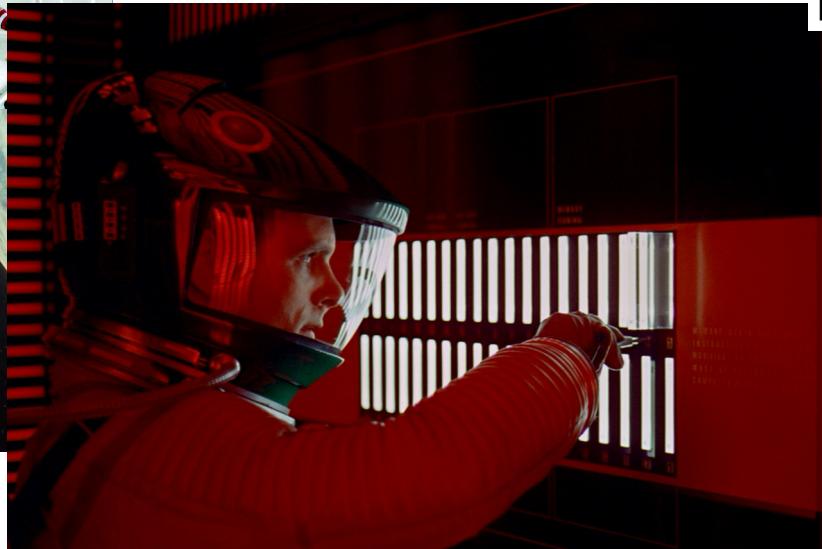
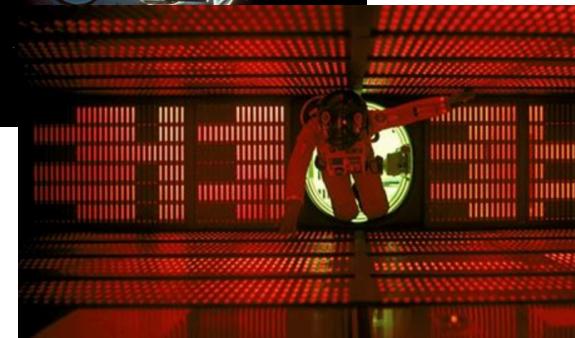
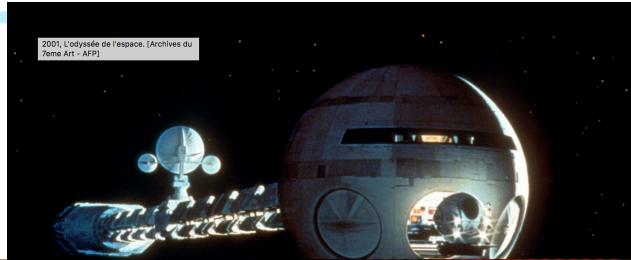
Pb: Find the best matching



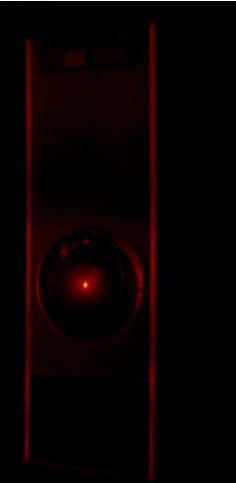
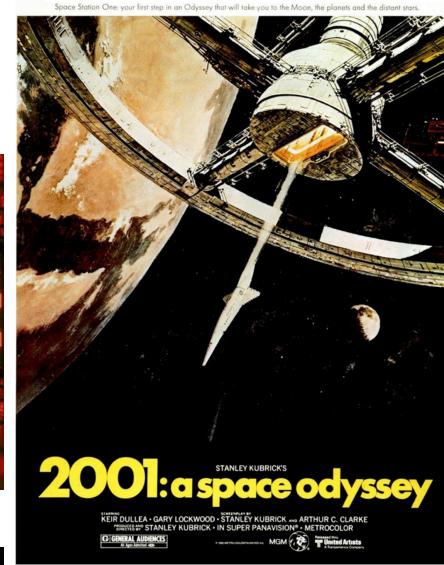
A is to B what C is to ?

2001: A Space Odyssey

- 1968 ...

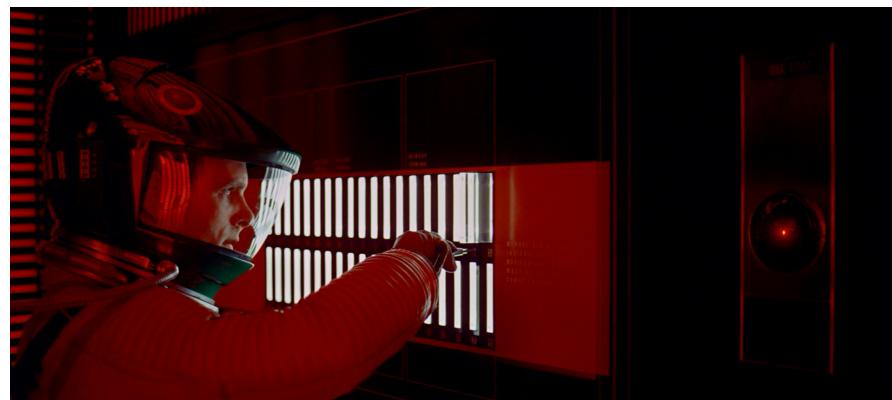
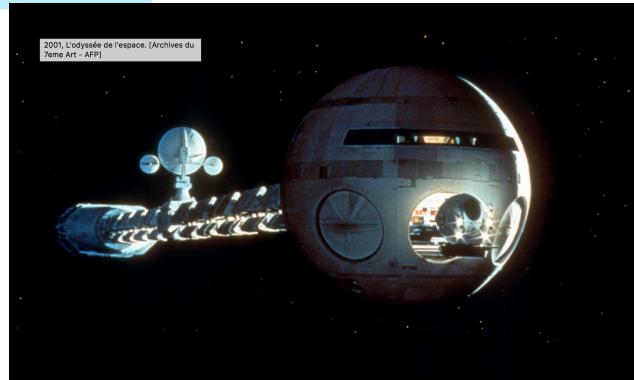


An epic drama of
adventure and exploration



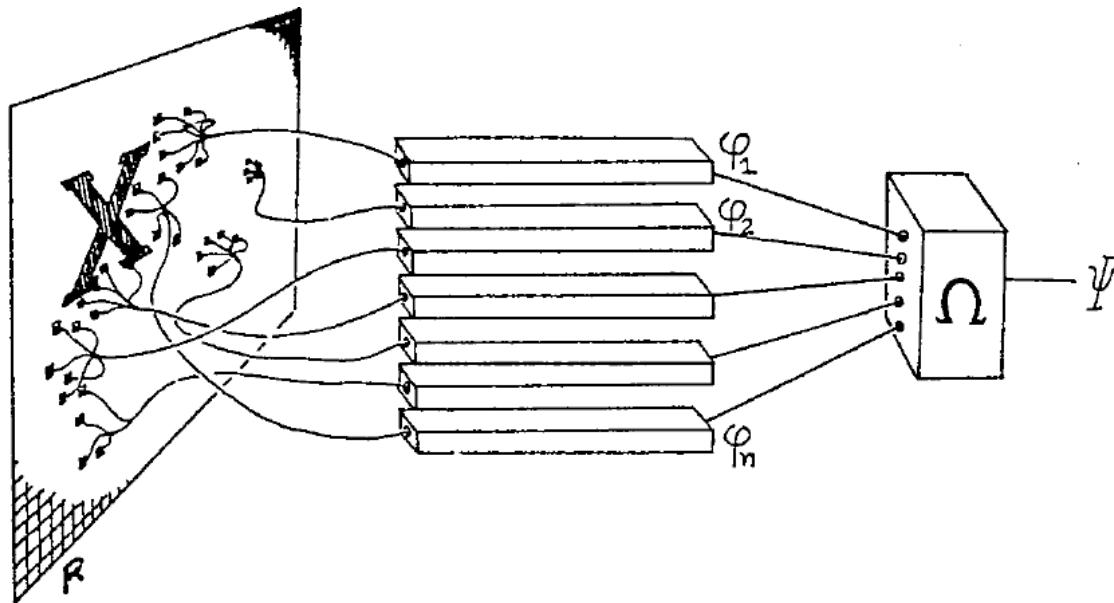
1968 -> 2001: A Space Odyssey

- Vision
- Communication
 - Lips reading
 - Conversation
- Planning complex tasks
- Reasoning
 - Plays (and wins) chess games
- Self-recoding
 - Kills the astronauts
- Emotion
 - Displays fear



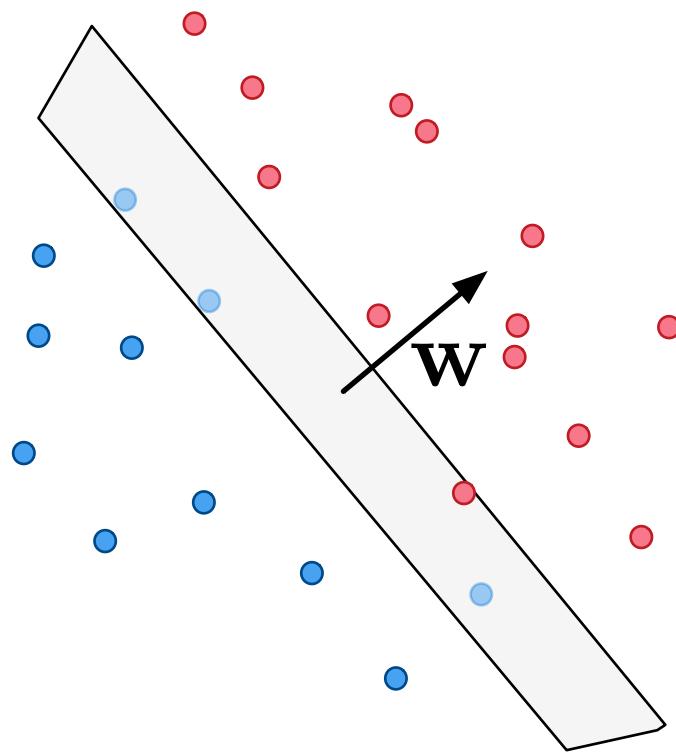
The perceptron

- Frank Rosenblatt (1958 – 1962)



$$\Psi(\mathbf{x}) = \sum_{i=1}^n w_i \phi_i(\mathbf{x})$$

The perceptron: a linear discriminant



But ... there are limits

Experts are **expert in their own domain,**
but **not on all domains**

Second assumption

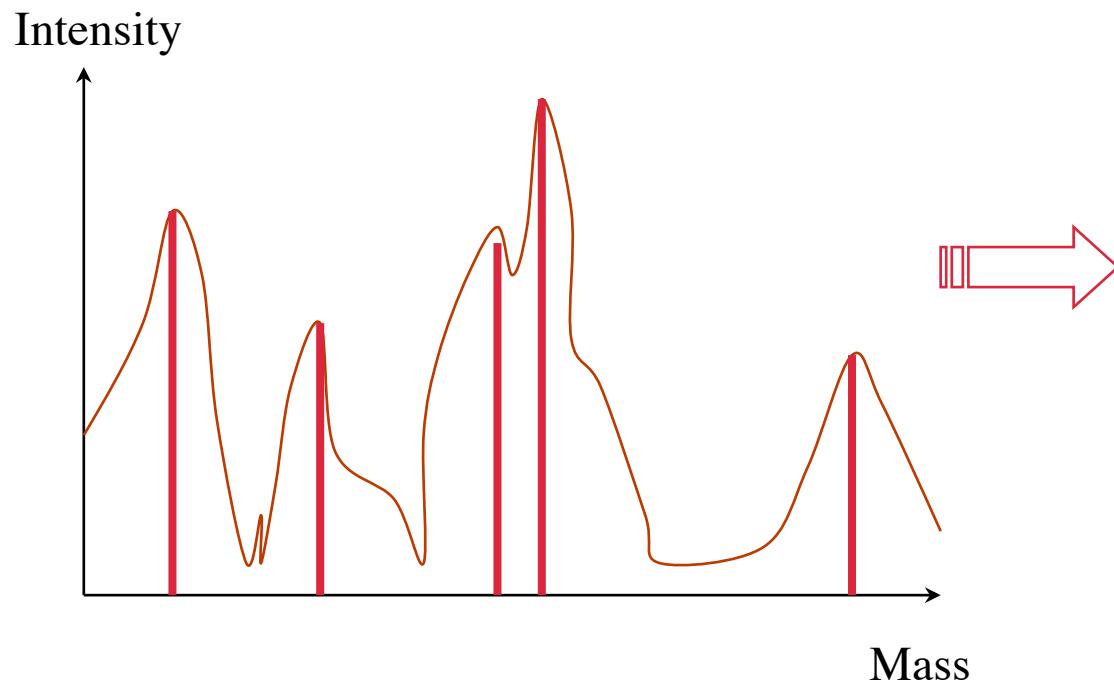
Knowledge is power

(~1970 – ~1985)

Expert Systems: DENDRAL

- A project of the NASA:
- Is there life on Mars?
- Mass spectrography

How does an expert performs this?



*The developed formula
of the molecules*

Expert Systems: DENDRAL

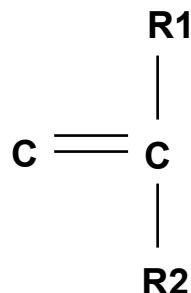
- Examples of a piece of knowledge

- Rule:

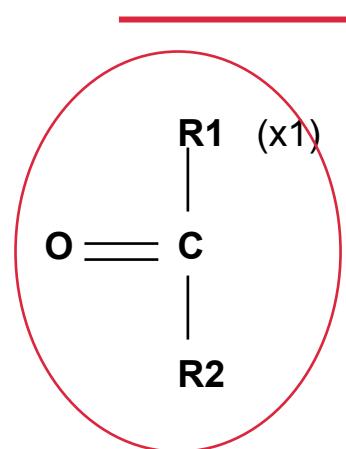
If the spectrum of the molecule has two peaks x_1 et x_2 such that:

1. $x_1 - x_2 = M + 28$
2. $x_1 - 28$ is a high peak
3. $x_2 - 28$ is a high peak
4. At least one of the peaks x_1 et x_2 is high

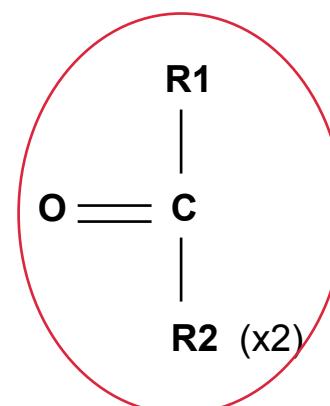
Then the molecule contains a ketone group



breaks
down in:



or in :



Expert Systems: MYCIN

MYCIN: My therapeutic recommendation will be first choice: to cover <1 2 3 5 6>, prescribe Gentamicin, dose 119 mg 98 h IV, for 10 days; Pour couvrir le point 4, prescrire de la Clindamycine, dose 595 mg 96 h IV, pendant 14 jours.

Do you want to eliminate certain medications?

Doctor: Yes, Clindamycine.

MYCIN: To cover <2 3 4 5 6> give Chloramphenicol, dose 1 g 96 h IV, for 14 days;

** Monitor the patient's white blood cell count.

To cover point 1, give gentamicin, dose 119 mg 98 h IV, for 10 days.

** Modify the dose in case of renal weakness.

Explanations in Expert Systems

- Mycin: Is meningitis a hospital acquired illness?
- Doctor: Why?
- Mycin: **This will aid in** determining the organism that might be causing the infection
 - It has already been established that
 - [2.1] the infection that requires therapy is meningitis
 - [2.2] organisms were not seen on the stain of this pending csf culture
 - [2.3] the type of infection is bacterial
 - [2.4] neurosurgery is not one of the relevant items of patient 100
 - [2.5] the age of patient 100 is greater than 25
 - therefore** if [2.6] the infection was acquired while the patient was in hospital then there is evidence that the organisms that might be causing the infection are
 - E coli(0.75) staphylococcus-coag-pos(0.3)
 - pseudomonas-aeruginosa(0.3)
 - klebsiella-pneumoniae(0.5)

Explanations in Expert Systems

- Doctor: Why didn't you consider the possibility that the organism be a streptocoque?
- Mycin:
Rule 33 should have been used to identify the organism as streptococcus, but the second clause "the morphology is shell-like" was already known to be wrong and rule 33 was never tried.

BORIS [Dyer,82]

"Richard *hadn't* heard from his *college roommate* Paul for years.

Richard had *borrowed money* from Paul which was *never paid back*.

But now he had no idea where to find his *old friend*. When *a letter finally*

arrived from San Francisco, Richard was anxious to find out how Paul was."

~1970 ... ~1985

- “Knowledge is power”

Everything is OK

- Explicit Reasoning
- Explications
- Dialogue

BUT ...

The truth...

- Necessitates **Knowledge** Engineering
 - A **painful** and **lengthy** process
 - Quite **artisanal**
 - **Difficult to maintain** Expert Systems

Third assumption (~1985 - ...)

Intelligence involves a lot of knowledge

that can be obtained through ...

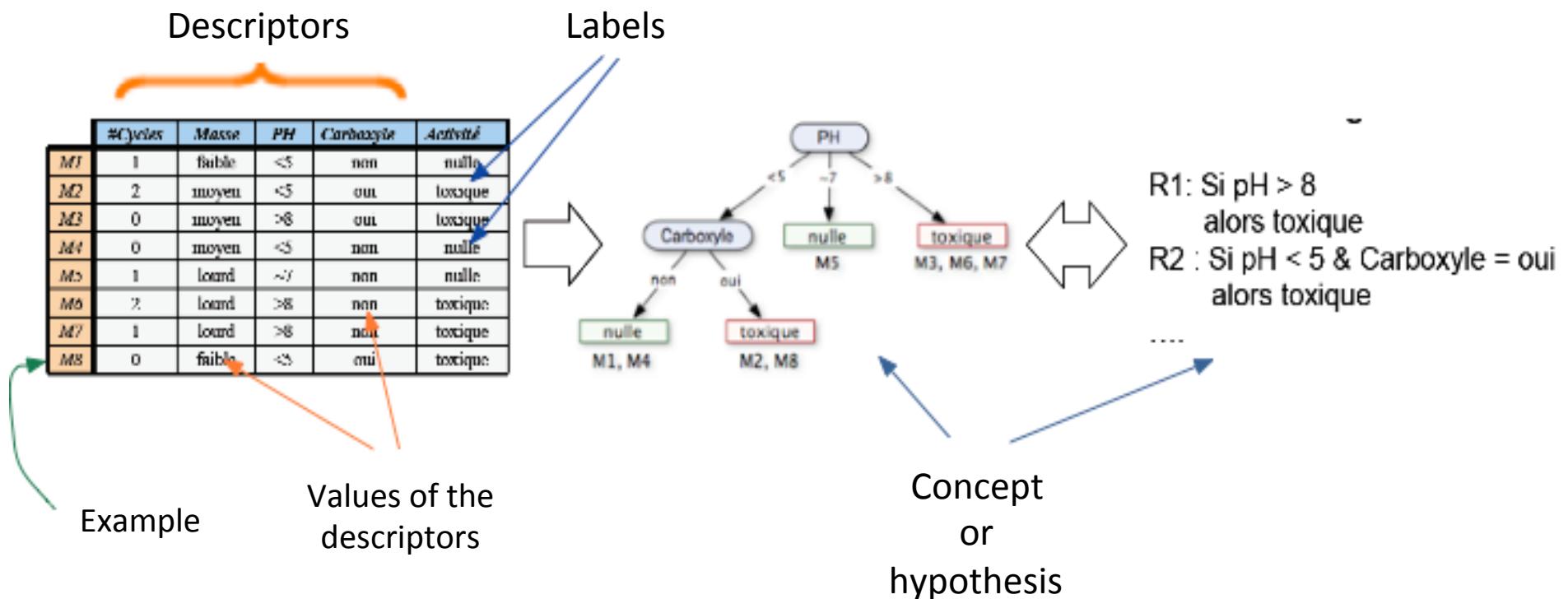
Third assumption (~1985 - ...)

Intelligence involves a lot of knowledge

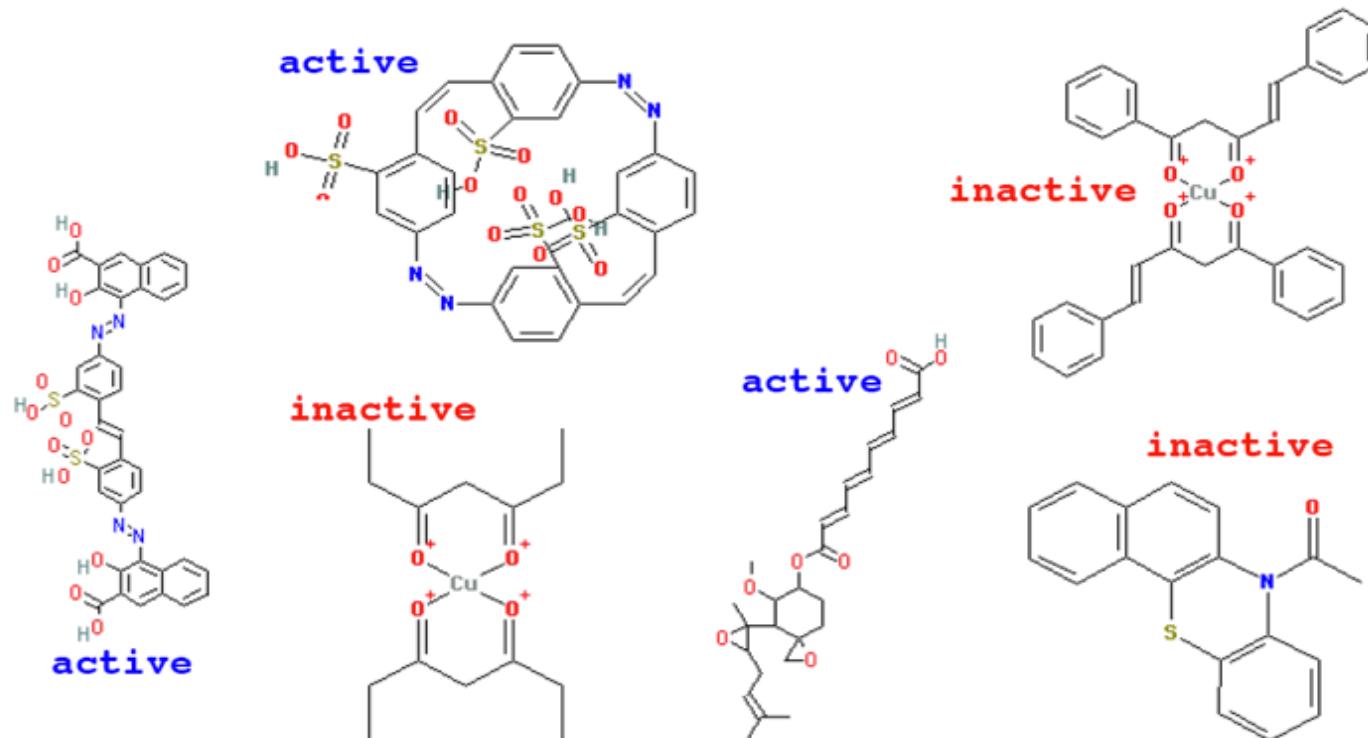
that can be obtained through general learning processes

Why not learn everything from data?

Supervised Induction



Supervised learning

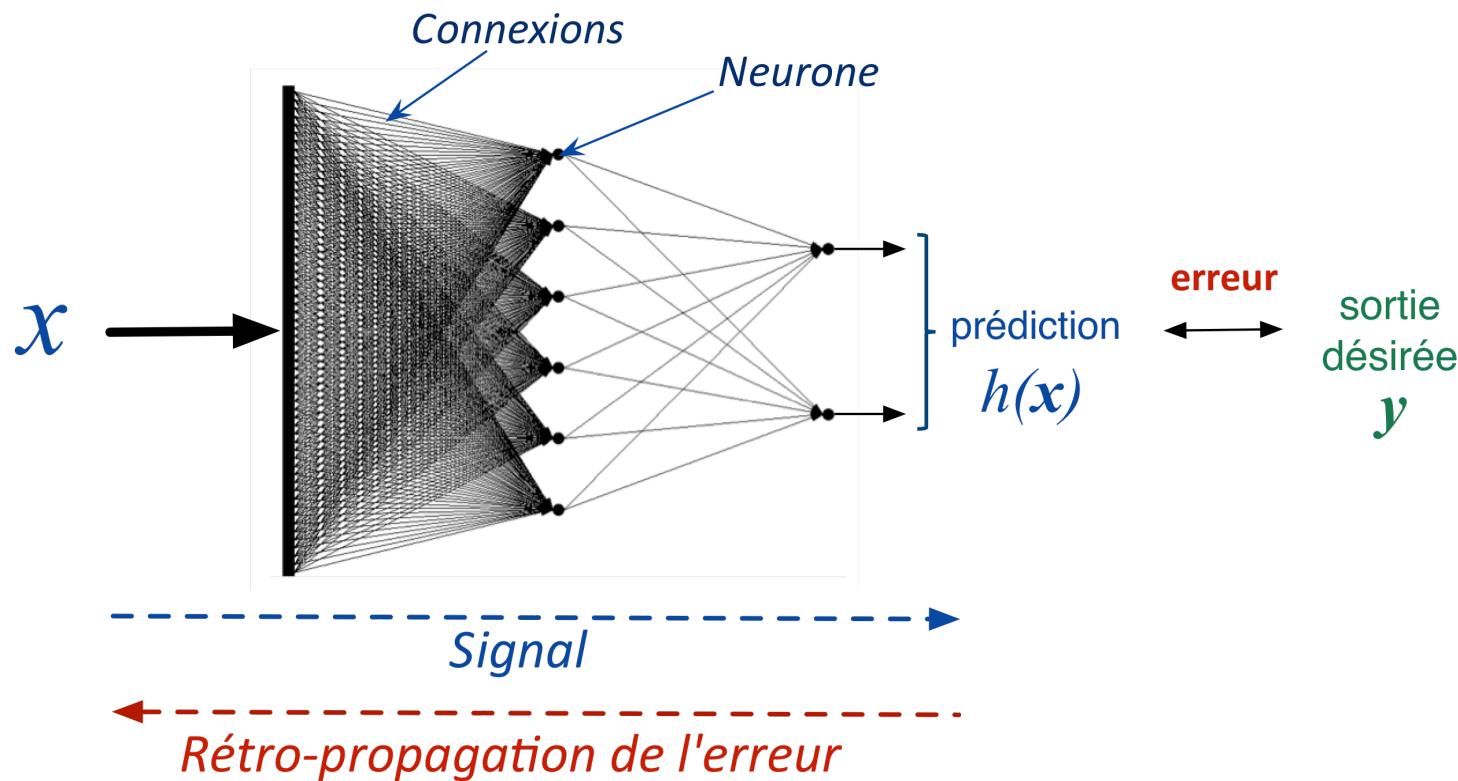


NCI AIDS screen results (from <http://cactus.nci.nih.gov>).

Learning with Multi-Layer Perceptrons

Performs **magic!**

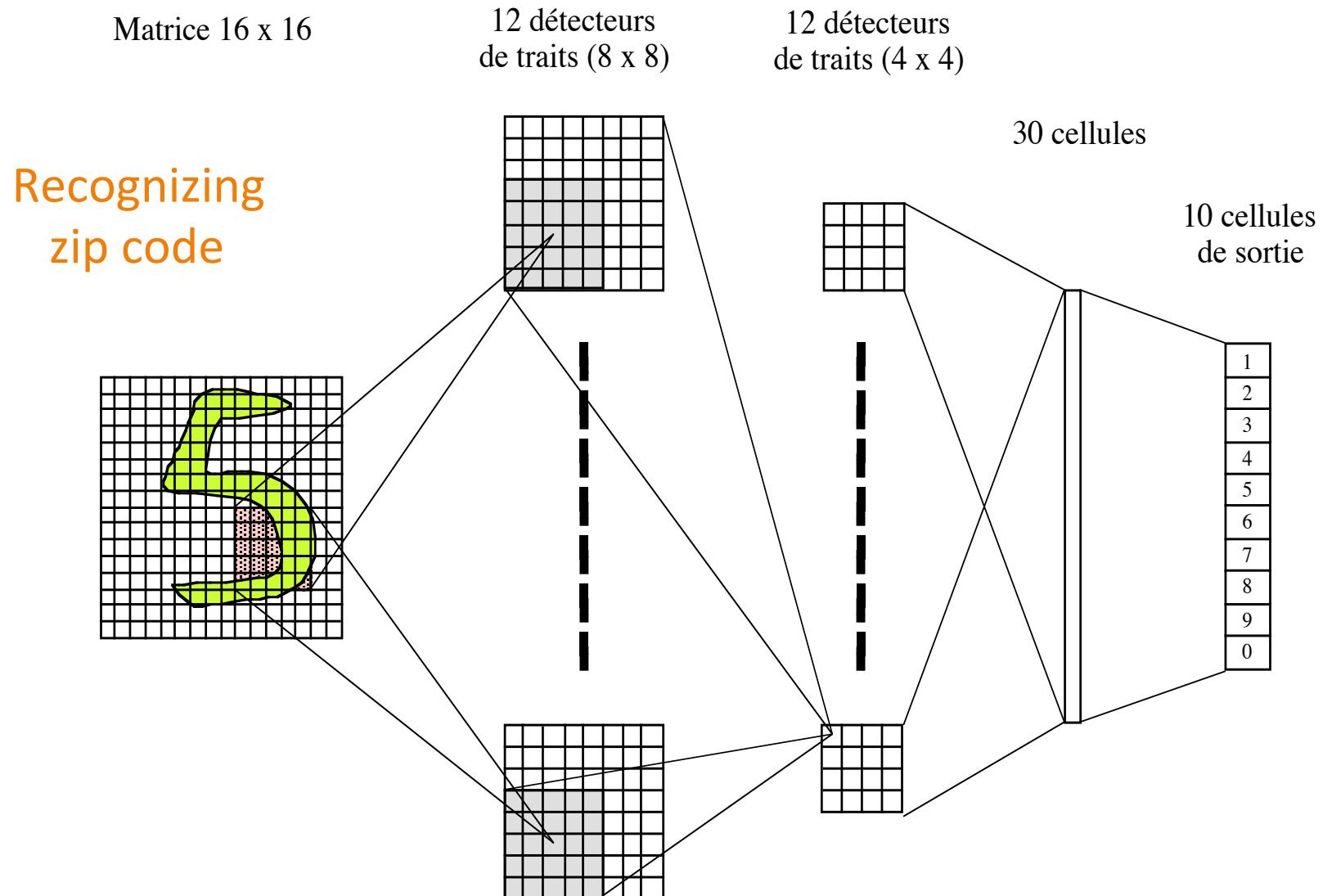
- Automatically **self-adapt** from the data
- And **resistant** to **noisy data**



The database

65473	60198	68544
<u>70065</u>	<u>70117</u>	<u>19032</u>
27260	61828	19559
74136	1937	43101
20878	60521	3800*
48640-2398	<u>20907</u>	14868

Convolutionnal Neural Networks: the ancestor

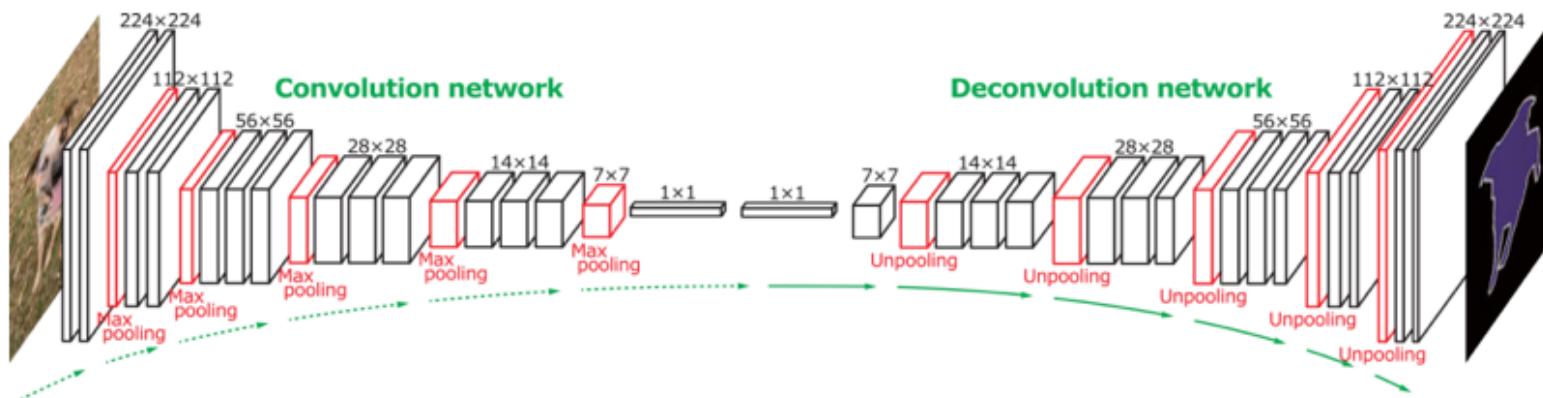


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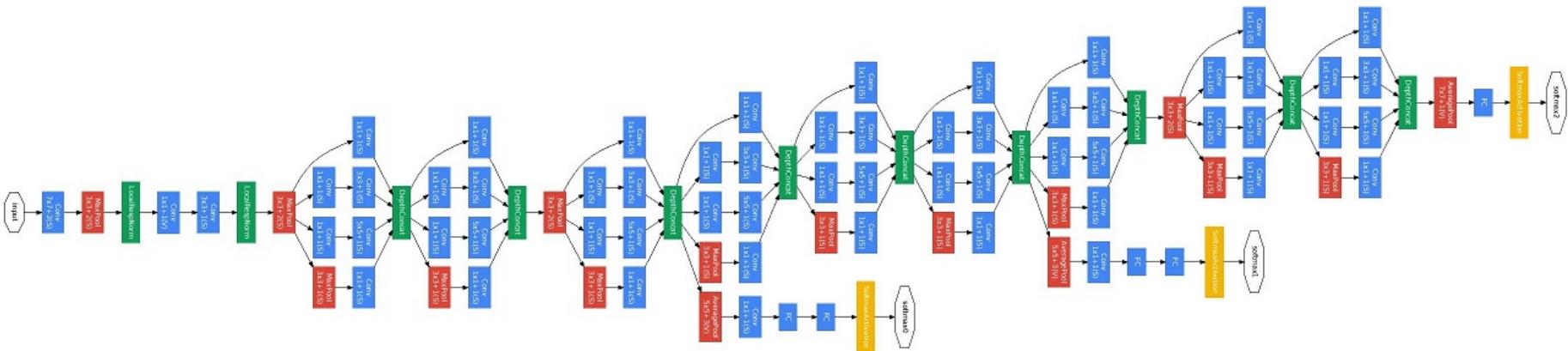
“Deep Neural Networks”

- Artificial Neural Networks with
 - A large number of **layers** (possibly > 100)
 - A very large number of **parameters** ($10^7 – 10^9$ parameters)

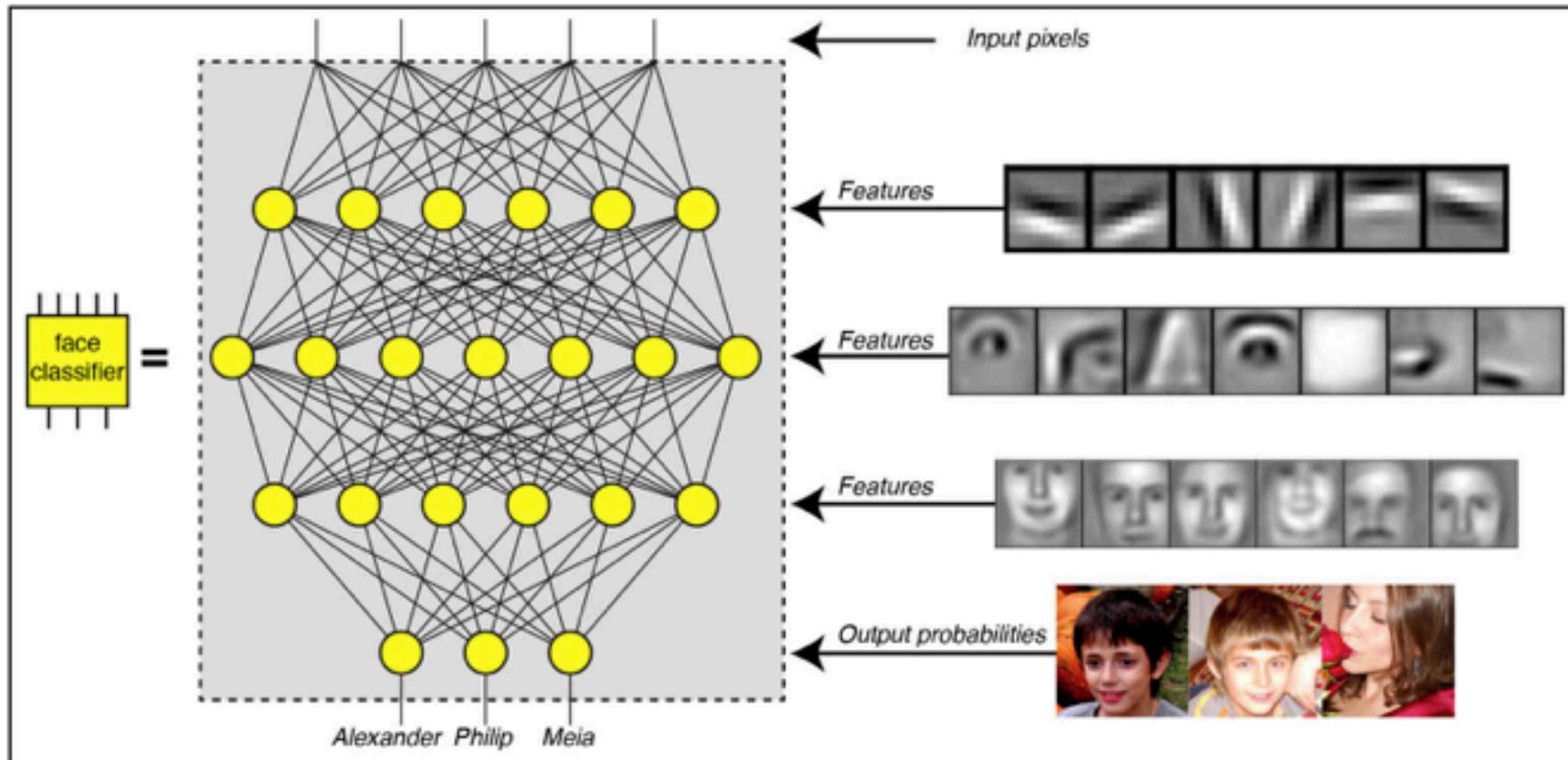


GoogleNet

- Illustration



Face recognition



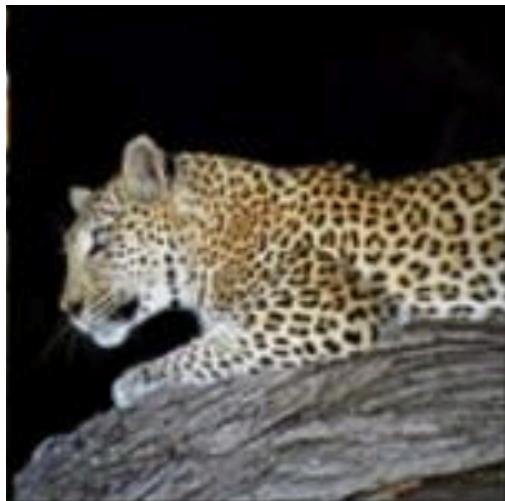
The ImageNet competition

- Over 15M labeled high resolution images
- Roughly 22K categories
- Collected from the Web and labeled by Amazon Mechanical Turk



Goal

- Image classification



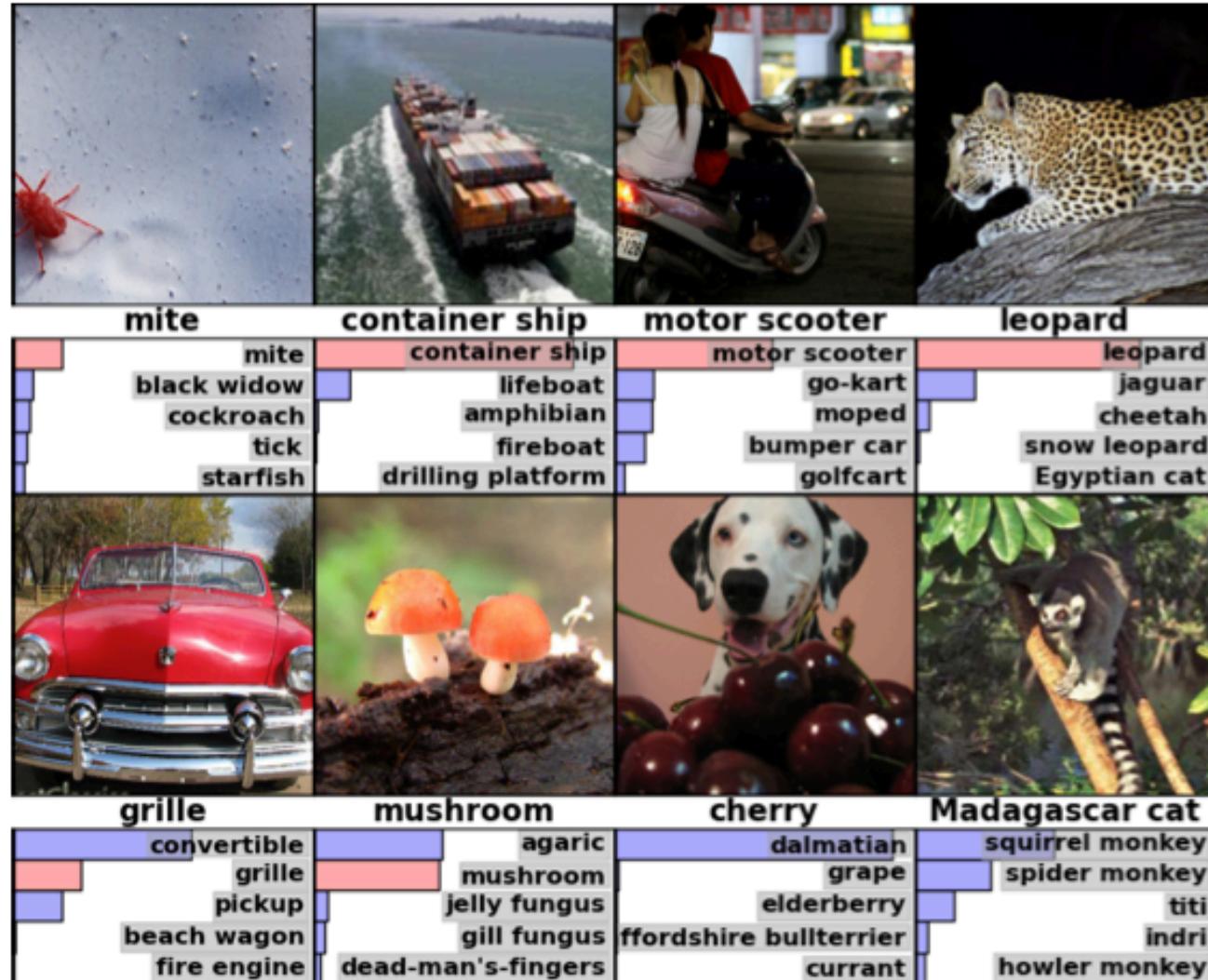
Classification



leopard
leopard
jaguar
cheetah
snow leopard
Egyptian cat

Results: 8 ILSVRC-2010 test images

- Results



Semantic Image Segmentation



Model trained with a maximum range of 40m and EFS.

- Autonomous vehicles

And YOU?

- Machine **translation**
- Change of **paradigm**
- A set of **new tools**
 - **Data analysis** (e.g. neural networks)
 - **Simulation** (e.g. Multi-Agent systems)
 - **New goals** (e.g. recommendation)

1. Old paradigm

- Construct a hypothesis (e.g. such and such treatment should have such and such an effect)
- Build an experimental design to test the validity of the hypothesis
- The experimental design and the data collected serve only to test the given hypothesis

1. Old paradigm

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- The experimental design and the data collected serve only to test the given hypothesis

2. New paradigm

- Be “open” minded: we are ready to look for (unexpected) patterns in the mass of available data
- Infinite re-use of data is possible (even though they were not collected for this specific purpose)

This is « **data mining** »

(Almost) all field are concerned

- Environment
 - Follow the **dynamics** of urban areas, of coastal erosion, of the Arctic ocean, ... From satellite images
 - The **climate change**
 - The Harvard forest (Long Term Ecological Project). 1600ha, of which 20 are equipped with electric heaters.
 - Understand the **interplay between species** in an ecosystem
 - What are the **genes** that participate in the resistance to hydraulic stress
- Nutrition
 - What are the **determinant** of our preferences for animal proteins
- Sociology
 - How **rumors** are born and spread

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Where one speaks of “data flood”

- Our data is captured in abundance whenever we go **on Internet**
 - Which sites are visited
 - Which time, for how long, the clicks, what has been bought, ...
- **Smartphones**
 - **Location** even when you did not agree
 - A lot of apps **full of curiosity**
- **Connected Bracelets**
- **Means of payment** (bank)
- Sensors in **vehicles** (insurance)
- Linky meters

« data flood » in the field

- Agriculture

- Sensors in the **field**
- Sensors in the **soil**
- Sensors on **animals**, in the farm
- **Drones**
- Data on the **local markets** (e.g. in India)
- Data on the **stock markets**
- Metereological data
- Data on the **social networks**: producers and consumers
- **Cold chains and distribution**



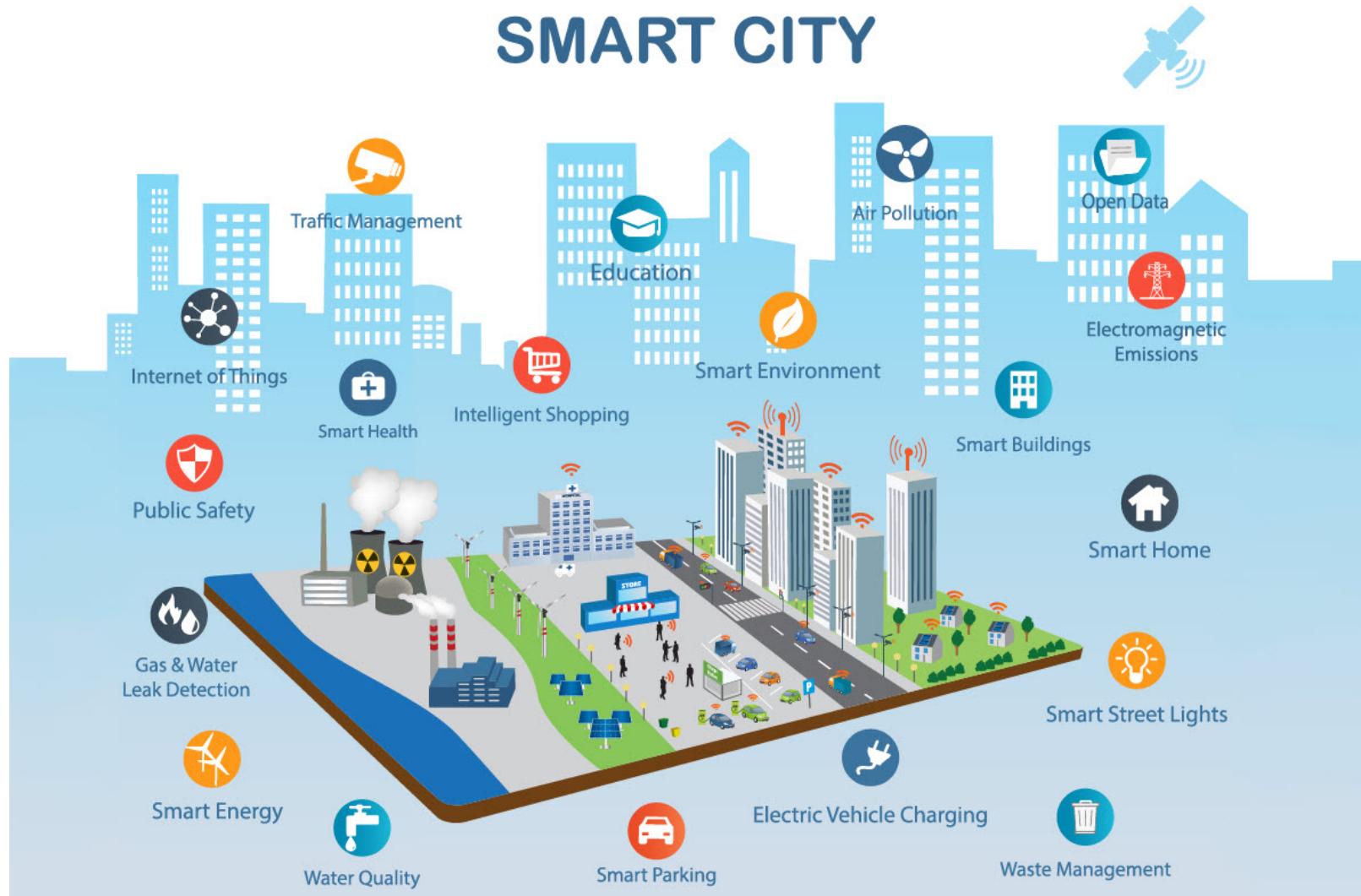
The world is yours

AI + Internet of Things

- It cares for you ... or so it seems
 - Sensors, cameras, smartphones, car, ... **EVERYWHERE** and **ALL THE TIME**
- Scenario
 - You enter your local supermarket. You are recognized by the camera or thanks to your smartphone. An automatic concierge greets you:
 - “Hi, Mr. Smith, I understand that your wife’s birthday is coming up. We know she loves Napa wines. We’ve just got a shipment of some fantastic Napa wines, ...”
 - “We can also recommend you some travel place for your next vacation ...”

Completely **fluid** and **targeted to you**

The world is yours



Other AI goodies

- **Personal assistant**
 - Help you **plan** your next holiday vacation
 - Help you **optimize** your revenue declaration
 - Help you **choose** the best meal
- **Personal assistant for scientists**
 - A **super Mathematica**
 - **Alpha fold**: discovering the 3D conformation of proteins
- **Specialized devices**
 - “be my eyes” for the blind and vision impaired people

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One example can says a lot

- Examples are described by:

Number (1 or 2); **size** (small or large); **shape** (circle or square); **color** (red or green)

Description	Your prediction	True class
1 large red square		-
1 large green square		+
2 small red squares		+
2 large red circles		-
1 large green circle		+
1 small red circle		+

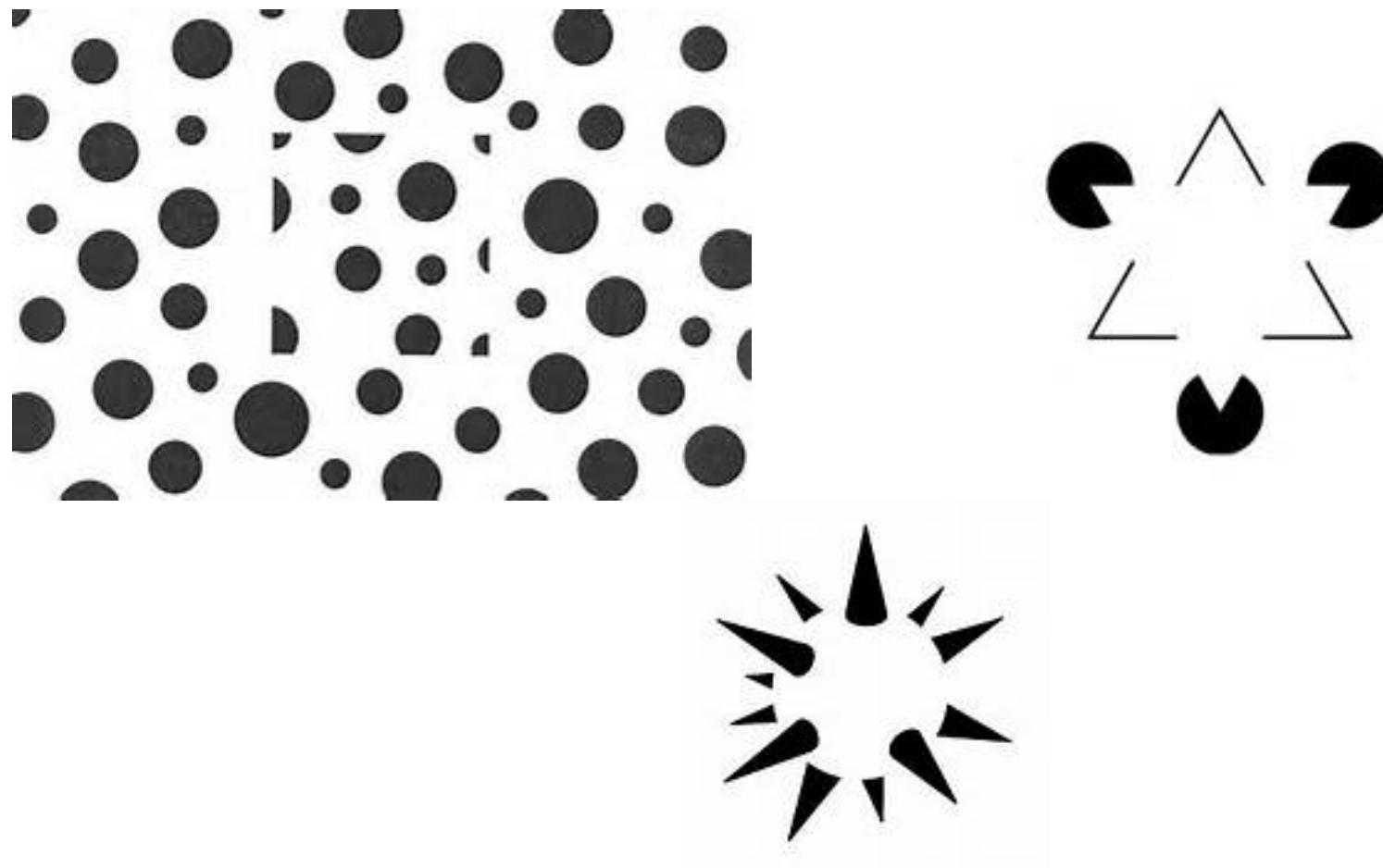
How many possible functions altogether from X to Y ?

$$2^2 = 2^{16} = 65,536$$

How many functions do remain after 6 training examples?

$$2^{10} = 1024$$

Learning is induction



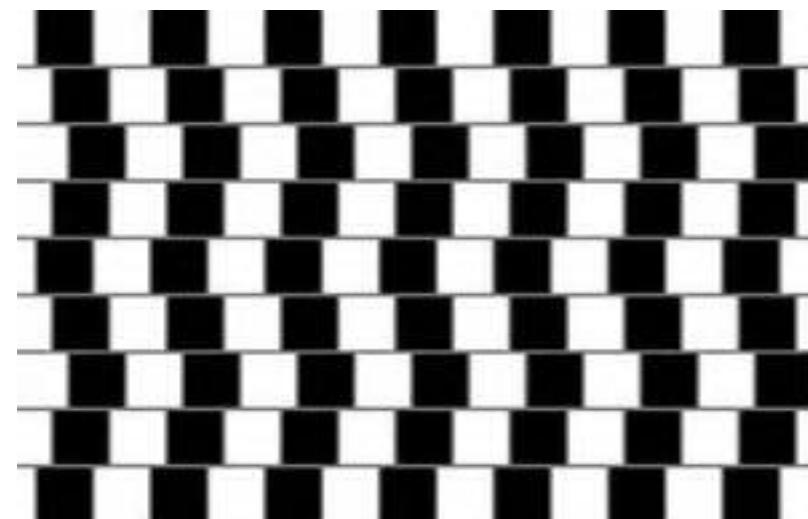
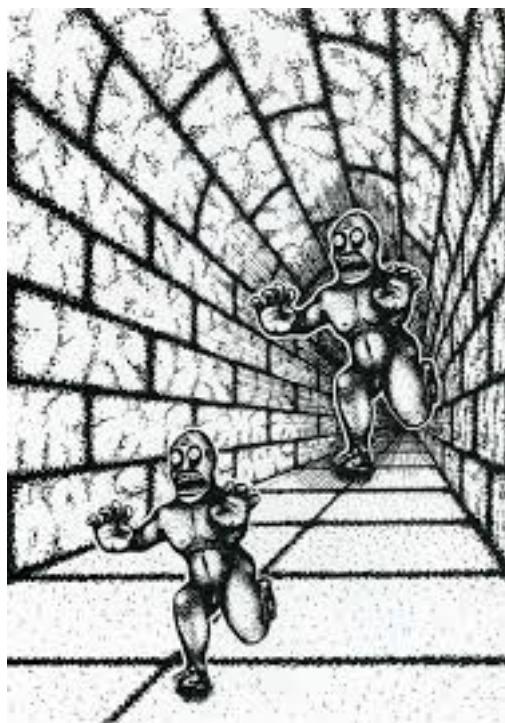
Learning is induction

- There are ambiguities



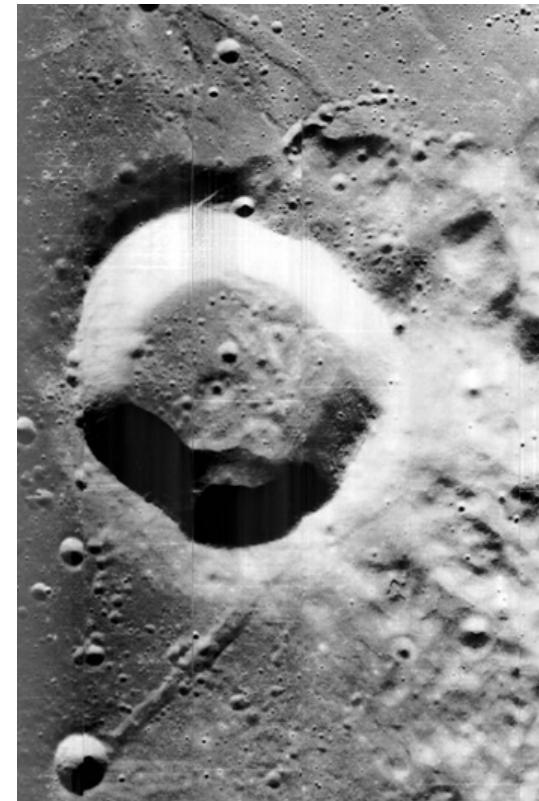
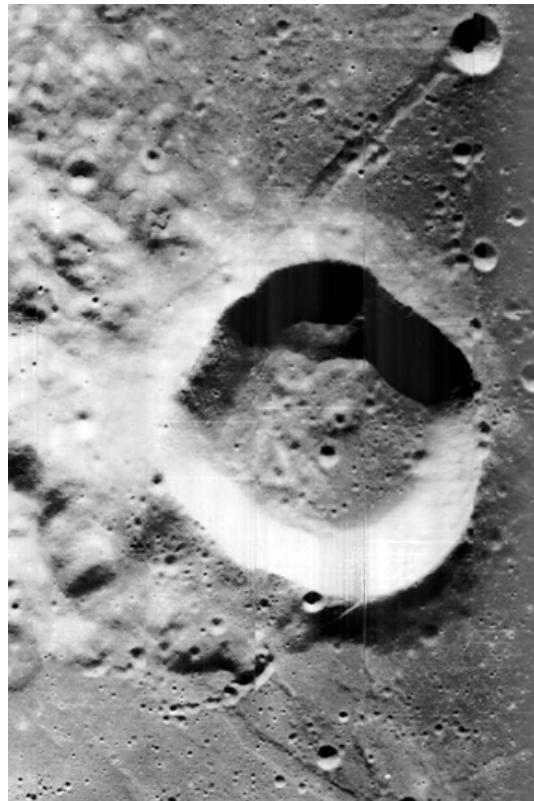
Learning is induction

- ... therefore fallible



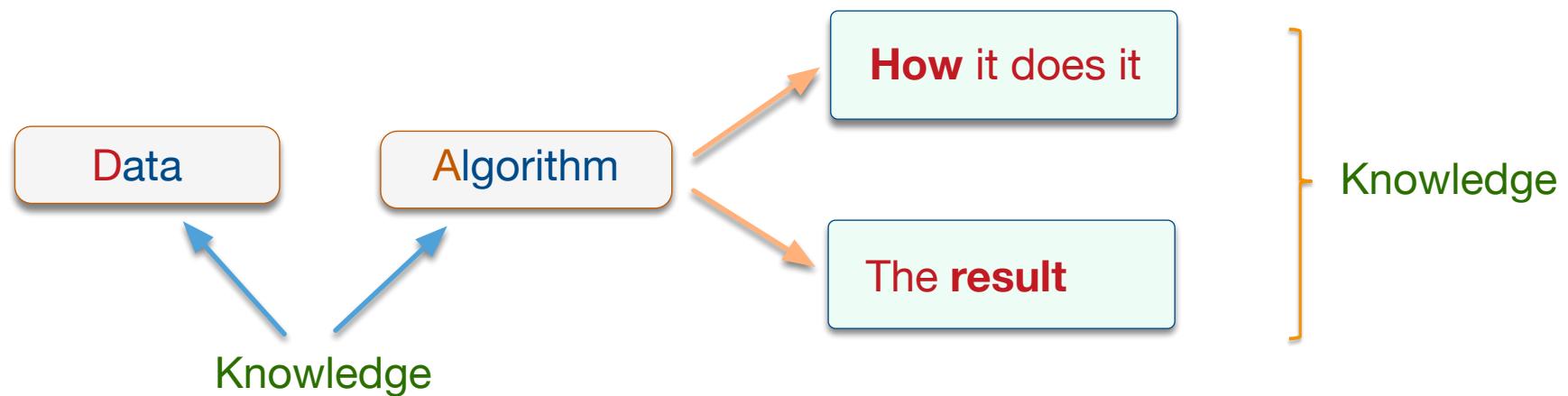
Learning is induction

- There are **uncertainties**



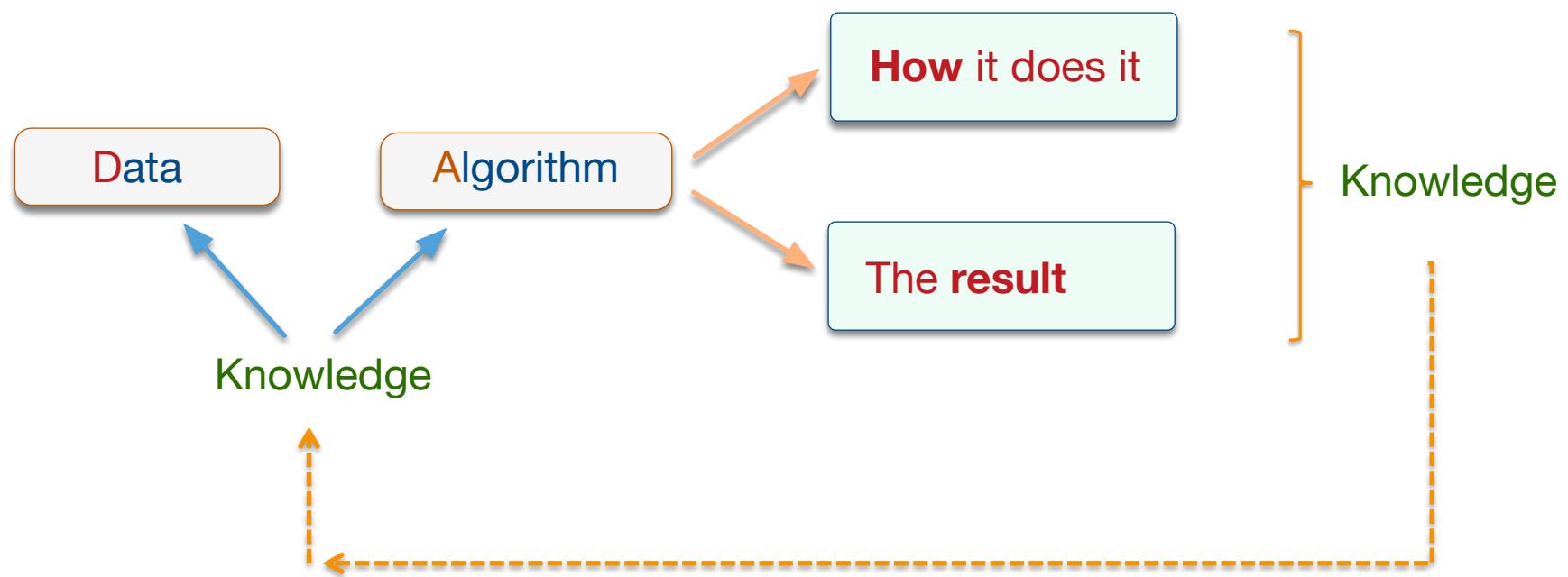
Crater or hill?

Inductive learning: what it does



...

Inductive learning: what it does



...

Induction is a **risky** business

1. You have to **invest a lot**
2. And **be very careful** about the yield

Machine Learning DOES NOT produce absolute truths

Do not give up your **critical sense** at every step!

Machine translation

- Very **impressive** and **useful** (see DeepL)
- But

Le drone volait à
une altitude de 30m
au-dessus du sol

The drone was flying at
an altitude of 30 m \$
above the ground

Machine translation

- Very **impressive** and **useful** (see DeepL)

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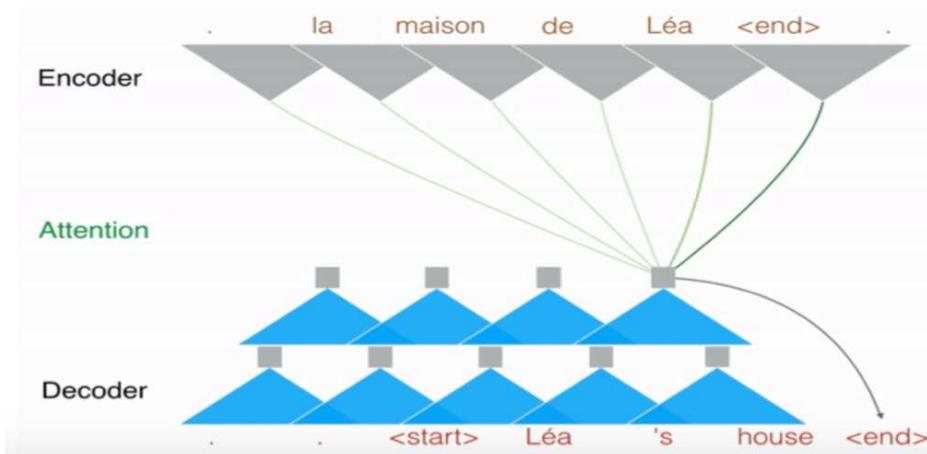
Le drone volait à
une altitude de 30m
au-dessus du sol

The drone was flying at
an altitude of 30 m \$
above the ground

???

Machine translation

- Still far from perfect, but ...



From Hofstädter (2018)

Traduction

Anglais Français Arabe DéTECTER la langue ↗



Français Anglais Arabe ↘

Traduire

Chez eux, ils ont tout en double. Il y a sa voiture à elle et sa voiture à lui, ses serviettes à elle et ses serviettes à lui, sa bibliothèque à elle et sa bibliothèque à lui.



175/5000

At home, they have everything in double. There is her car and her car, her towels and towels, her own library and her own library.



DésACTIVER la traduction instantanée

Explanations and deep neural networks

Optical illusions: how to explain them?



Boxer: 0.40 Tiger Cat: 0.18

(a) Original image



Airliner: 0.9999

(b) Adversarial image

!!??

[Selvaraju et al. (2017) « Grad-CAM: Visual explanations from deep networks via gradient-based localization »]

Annotation d'images

-



Figure 2.11: “A group of young people playing a game of frisbee”—that caption was written by a computer with no understanding of people, games or frisbees.

Exemple en médecine

MACHINE LEARNING

Science

Adversarial attacks on medical machine learning

Emerging vulnerabilities demand new conversations

22 March 2019

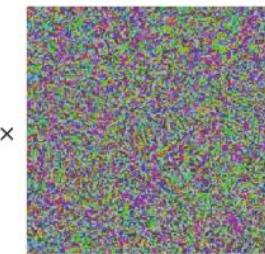
The anatomy of an adversarial attack

Demonstration of how adversarial attacks against various medical AI systems might be executed without requiring any overtly fraudulent misrepresentation of the data.

Original image



Adversarial noise



Adversarial example



+ 0.04 ×

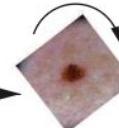
Dermatoscopic image of a benign melanocytic nevus, along with the diagnostic probability computed by a deep neural network.



Diagnosis: Benign



Adversarial rotation (8)



Diagnosis: Malignant

The patient has a history of **back pain** and chronic **alcohol abuse** and more recently has been seen in several...

Opioid abuse risk: High

277.7 Metabolic syndrome
429.9 Heart disease, unspecified
278.00 Obesity, unspecified

Reimbursement: Denied

Adversarial text substitution (9)

The patient has a history of **lumbago** and chronic **alcohol dependence** and more recently has been seen in several...

Opioid abuse risk: Low

Adversarial coding (13)

401.0 Benign essential hypertension
272.0 Hypercholesterolemia
272.2 Hyperglyceridemia
429.9 Heart disease, unspecified
278.00 Obesity, unspecified

Reimbursement: Approved

Car in a swimming pool

- ... or not ... ?

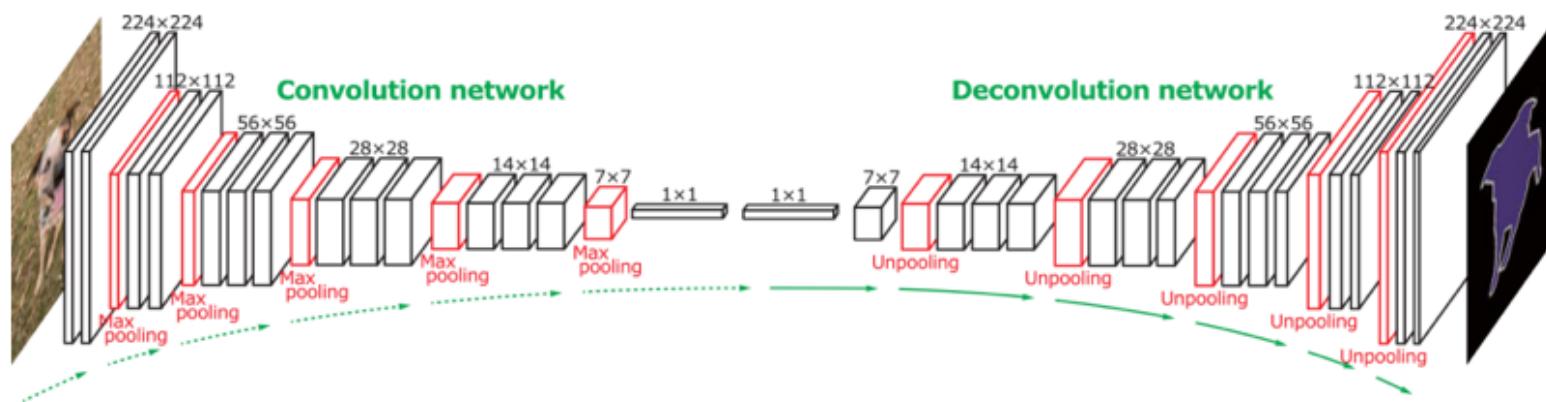


Is this less of a car
because the context is wrong?

[Léon Bottou (ICML-2015, invited talk) « *Two big challenges in Machine Learning* »]

Neural networks are “black boxes”

- A very large number of numbers ($10^7 - 10^9$ parameters)



Outline

1. A brief history of AI
2. AI now: the triumph of deep neural networks
3. AI in the near future
4. There are limits
5. The case of XAI
6. Conclusion

The case AlphaGo

- Plays like an “alien”
- An amazing game
- Revolutionizes the way we play
- Effervescence in go schools



A collage of three images. On the left is the cover of the book "AlphaGo And The Hand Of God" by Brady Daniels, featuring a brown background and a stack of Go stones. In the center is a screenshot of a video player showing a Go match between Lee Sedol and AlphaGo. The video player interface includes a title bar, a toolbar with icons, and a grid-based Go board with stones. On the right is a close-up photograph of a man with glasses and a beard, looking directly at the camera.

Autonomous vehicle

- The National Highway Traffic Safety Administration (NHTSA) is currently investigating 23 accidents related to Tesla's Autopilot system
- Questions
 - Who is **responsible?**
 - The driver?
 - Tesla (the programmer)?
 - The other person?
 - What is **the reason** for the accident?
 - So as to correct the autopilot system (and systems around)

Problem

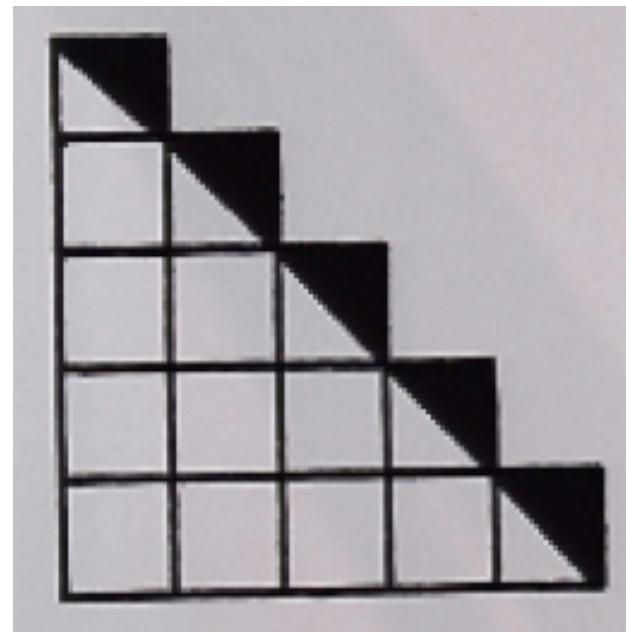
- So far efficient predictors are often black boxes
- This is an issue for a number of applications (e.g. in medicine)
 - We want to be able to be **confident** in the system
 - It can justify its **decisions**
 - It can justify its **reasoning**

The ability of providing explanations is **required** in Europe since May 2018 (GDPR, Recital 71)

XAI: Explainable Artificial Intelligence

Lots of types of “explanations”

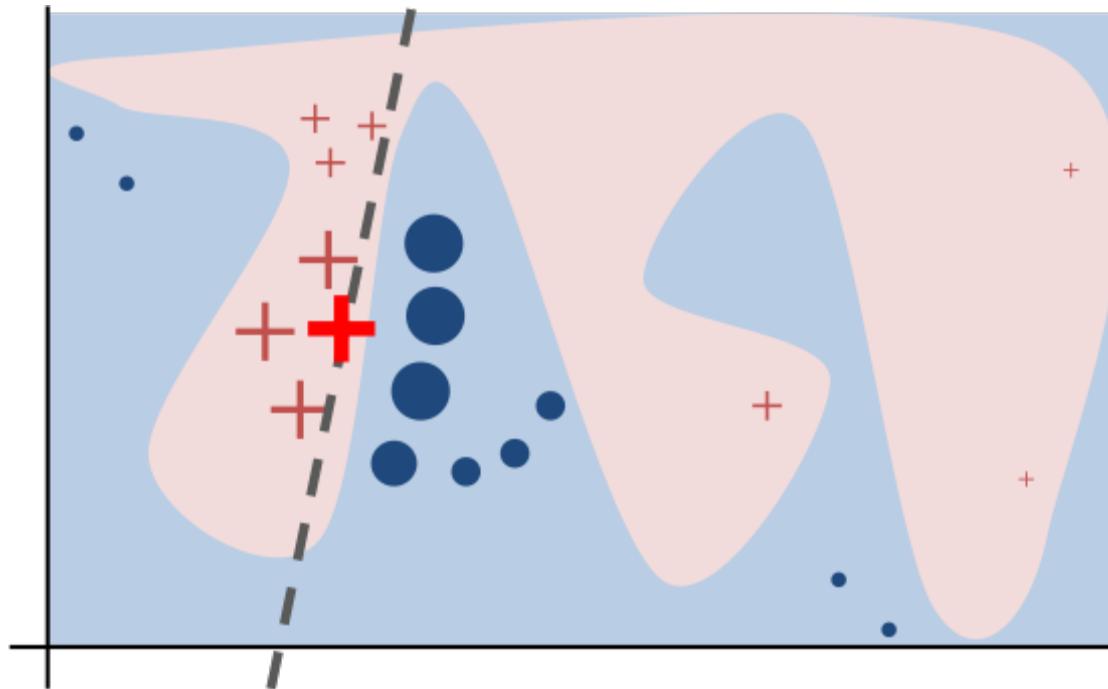
$$1 + 2 + 3 + \dots + n = \frac{n^2}{2} + \frac{n}{2}$$



Counterfactuals

- If James Dean had **taken the train** the day of his car accident, he **would not** have died

Local simplification



- LIME

Sensitivity analysis



- The pixels that best “explain”
 - The recognition of a **electric guitar**
 - The recognition of an **acoustic guitar**
 - The recognition of a **dog**

-
- Still very rudimentary

What kind of knowledge can we extract?

- When interpretability is **NOT** needed?

What kind of knowledge can we extract?

- When interpretability is **NOT** needed?
 - When **low risk** associated with the decision
 - E.g. *recommendation for a movie*
 - When **good guarantees** on performance exist
 - E.g. *character recognition*

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- When interpretability **IS** needed?
 1. With **high risk decisions**
 - *E.g. chirurgical operation*
 - *E.g. shutting down a nuclear plant*
 - *E.g. autonomous vehicle*

What kind of knowledge can we extract?

- When interpretability **IS** needed?
 1. With **high risk decisions**
 - *E.g. surgical operation*
 - *E.g. shutting down a nuclear plant*
 - *E.g. autonomous vehicle*
 2. Satisfying **curiosity** (what science is about)
 - *E.g. explain surprising results*
 - *E.g. when no easy explanation exists*
 - *E.g. when the decision function must be included in a larger inference system (a domain theory)*

What kind of knowledge can we extract?

- When interpretability **IS** needed?

3. Debugging

- *E.g. why is that decision wrong (counterfactual)*
- *E.g. if a bicycle is recognized because it has two wheels, what if one is hidden behind side bags?*
- *E.g. why the system seems gender biased?*

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4. Interpretability demands higher standard predictive systems

- *An interpretable system **can be manipulated***
 - *E.g. if someone knows that a loan is granted if you have more than 2 credit cards*
- ➡ • *In order **not to be manipulated**,
the predictive system **must use causal factors***

-
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 - **Interpretability of the process**
 - **Gaining a better understanding of the world**
when including the learned decision function in an existing theory

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Somehow, we have to **change**
the **inductive criterion** used in Machine Learning

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-
- There are **reasons** to be stunned
 - Enormous **progress** the last few years
 - In combination with **IoT**, a new era is coming
 - But also to be **cautious**
 - These systems **do not understand**
 - They **do not explain**
 - They are essentially **black boxes**
 - And not well understood yet

A lot remains
to be done

Some of us still dream
the old dream

Towards a General Artificial Intelligence?

- AI far surpasses humans at **narrow tasks** that can be **optimized based on data**
- BUT, it **cannot** engage in **cross-domain thinking** on **creative tasks** or ones requiring **complex strategies**
- For **future** research:
 - **Multidomain learning**
 - **Real understanding**
 - **Common sense reasoning**
 - Learning from very **few examples**
 - Understanding **humor**
 - Self-awareness?