Course 1: Generalities about AI

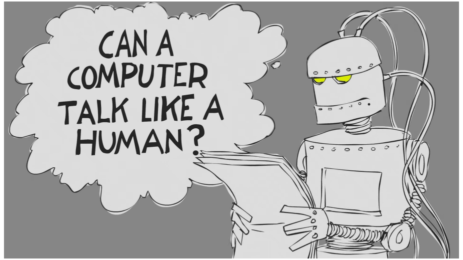
IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

2018-10-15

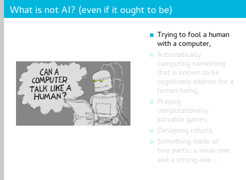
Course 1: Generalities about AI

Welcome to the first lesson of the AI course ! We will introduce a few generalities, as well as a working definition of what we will consider in this course.

What is not AI? (even if it ought to be)



- Trying to fool a human with a computer,
- Automatically computing something that is known to be cognitively intense for a human being,
- Playing computationally solvable games,
- Designing robots,
- Something made of two parts: a weak one and a strong one...



Here, we just want to briefly mention what used to be considered as the important problems in AI.

The Turing Test: is it possible to fool a human ? There used to be a lot of research to investigate whether we can build conversational systems that imitate humans. The famous Turing Test was about trying to fool a human that would not be able to tell whether it is a machine or a human. While it might be an interesting question for philosophers, it is outside of the scope of modern AI research, except maybe in the case of designing chatbots. **We won't focus on the specific questioning of AI versus Human in this course.**

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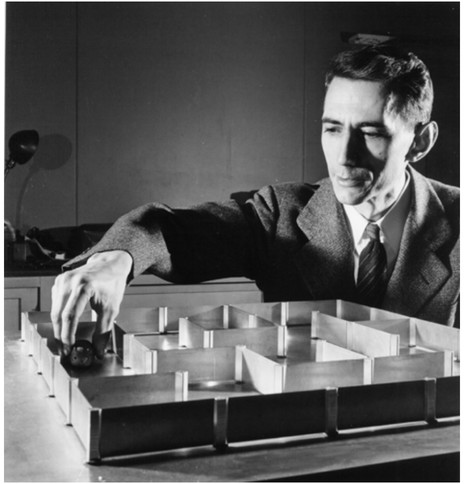

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Because computing is not learning.

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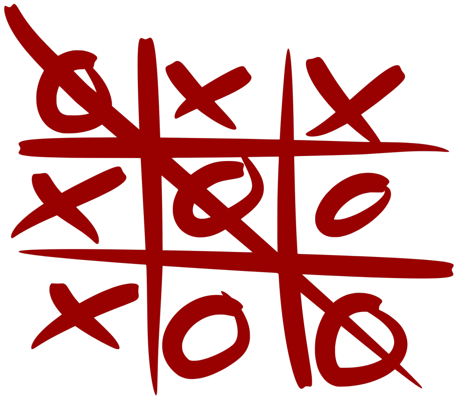

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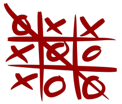

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A computationally solvable game can be solved without learning.

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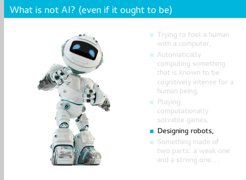

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Designing good robots is most of the time a set of optimization constraints related to moving the robot (walking, running, grasping, etc.. as well as humans do) and is related to mechanical engineering issues, on top of which difficult computational issues are to be solved.

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This relates to a taxonomy that some people use, to explain that there is Weak AI (= constrained to a task) and Strong AI (=super intelligence, surpassing the human). The monkey picture is here to illustrate the fact that if Strong AI was invented, we would be the new monkeys. There is no need to say all that, but I would say that the general point to make here is that the course is NOT about all the philosophical aspects of what is AI, NOT about the singularity, etc...

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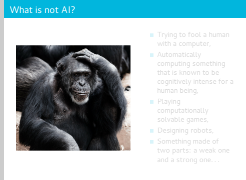

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What is AI?

A modern definition

An algorithm is said to be “intelligent” if it **generalizes** a way to take **good decisions** from (potentially annotated) **examples** and/or **trials**.

Examples

- Computing the length of an edge in a rectangle triangle given the two other lengths is not intelligent,
- Inferring how to find the missing length from a set of examples is intelligent,
- Winning at chess by looking at all possible plays from the current board is not intelligent,
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...and this is what we mean. Here, we will only focus on different techniques that are used to build systems that can learn on data, and generalize on unseen data.

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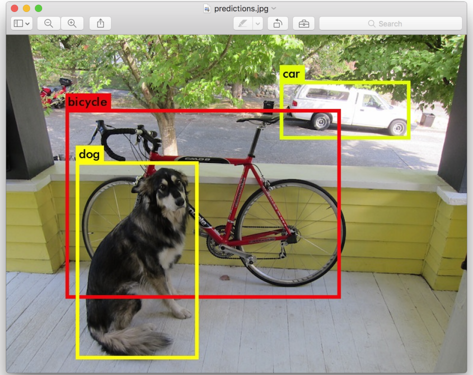
Main application domains of AI

Vision

- Object/face recognition,
- Detection,
- Autonomous vehicles,
- Automatic diagnostic,
- Defects identification,
- Video applications. . .



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Course 1: Generalities about AI

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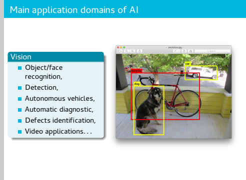
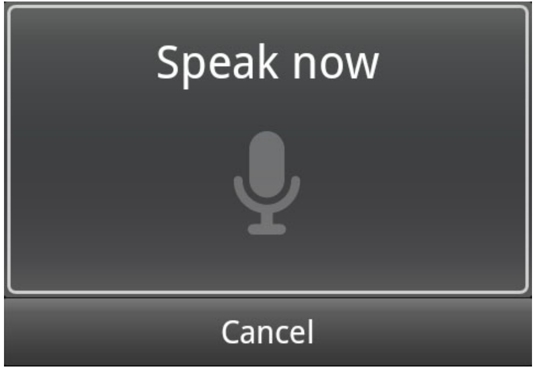


There is probably plenty more application domains.

Main application domains of AI

Natural Language Processing (NLP)

- Automatic assistant,
- Voice-to-text,
- Automatic translation,
- Automatic summarizing,
- Sentiment analysis,
- Text indexing. . .



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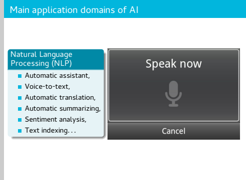

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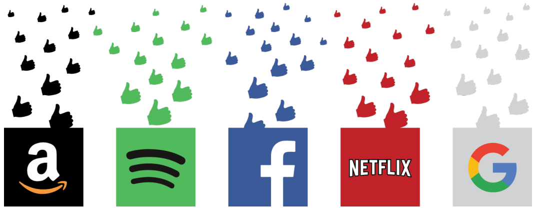
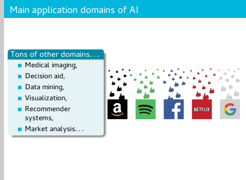
Main application domains of AI

Tons of other domains...

- Medical imaging,
- Decision aid,
- Data mining,
- Visualization,
- Recommender systems,
- Market analysis...





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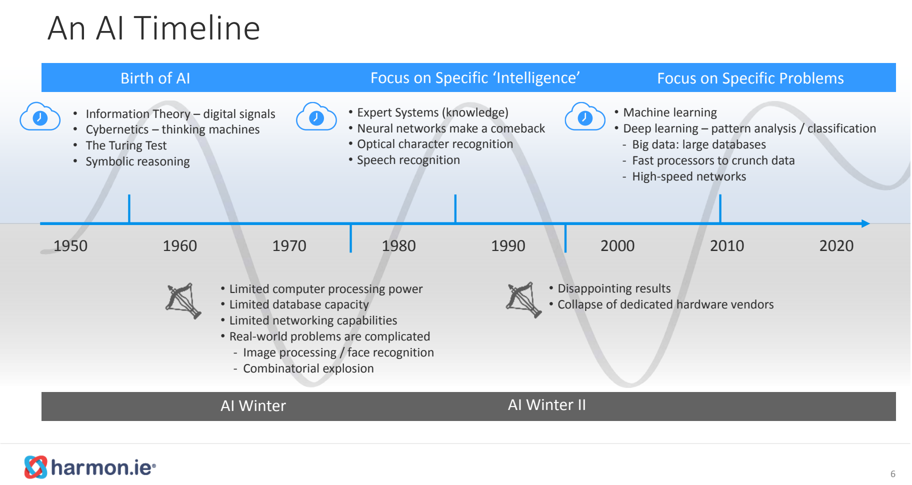
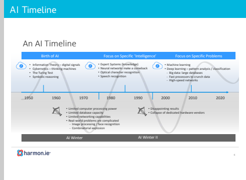
AI Timeline

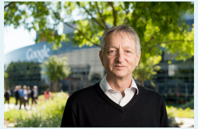




Here, we want to show that field of AI has gone through a number of "winters". It can be interesting to briefly mention the reasons of the winters, and to make a transition to the success of modern AI which is mostly based on Deep Learning.

The great elders of modern AI

Geoffrey Hinton



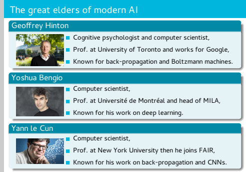
- Cognitive psychologist and computer scientist,
- Prof. at University of Toronto and works for Google,
- Known for back-propagation and Boltzmann machines.

Yoshua Bengio

- Computer scientist,
- Prof. at Université de Montréal and head of MILA,
- Known for his work on deep learning.

Yann le Cun

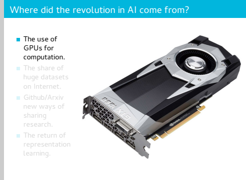
- Computer scientist,
- Prof. at New York University then he joins FAIR,
- Known for his work on back-propagation and CNNs.



The reason why we mention them is because their work has mostly enabled to get out of the last two AI winters.

Where did the revolution in AI come from?

- The use of GPUs for computation.
- The share of huge datasets on Internet.
- Github/Arxiv new ways of sharing research.
- The return of representation learning.



A few more explanation on Representation learning. As we will see in the next lessons, finding a good representation of the data is a very difficult thing. Deep Learning has enabled to search / decompose the data automatically to find such representations.

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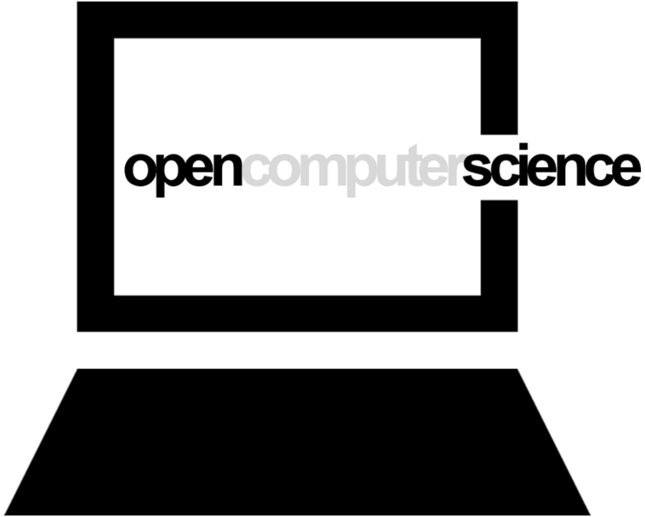

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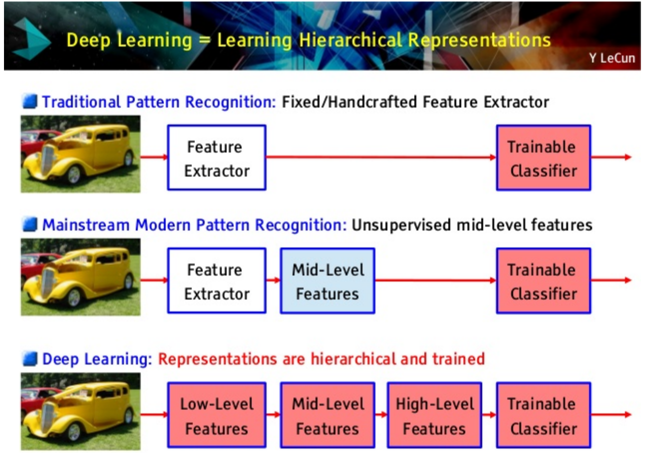

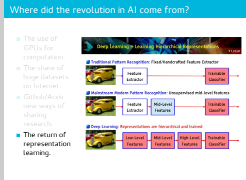

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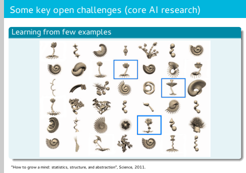
Some key open challenges (core AI research)

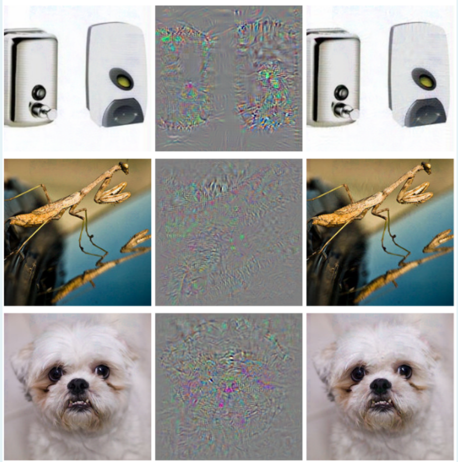
Learning from few examples

"How to grow a mind: statistics, structure, and abstraction", Science, 2011.



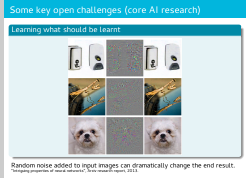
About Learning from few examples: this picture is from the science paper from Josh Tenenbaum, and is explained in the following way. It is very easy for humans with just a few examples of these three weird objects (let's call them "tufas"), and if I ask you where are the other ones, you can tell me right away. However it is a difficult problem for current AI approaches.

Learning what should be learnt



Random noise added to input images can dramatically change the end result.

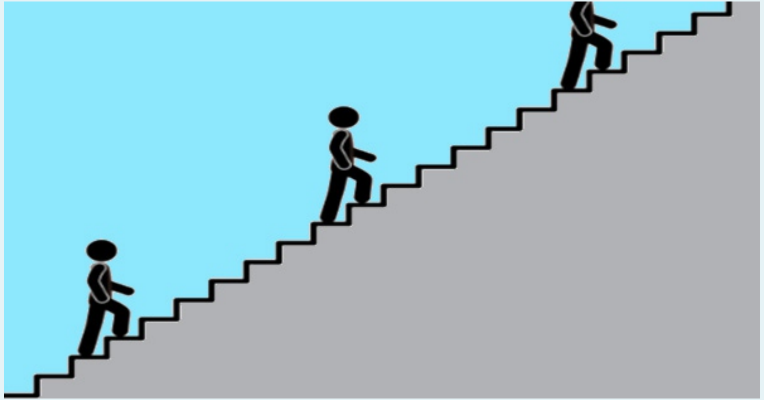
“Intriguing properties of neural networks”, Arxiv research report, 2013.



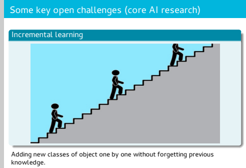
Learning what should be learnt: the point here is to talk about adversarial noise (but there is no need to say the phrase "adverserial noise / examples"). The actual classes that are represented are "soap dispenser", "praying mantis" and "dog", and when the noise is added, the algorithm recognises the three images as "ostrich".

Some key open challenges (core AI research)

Incremental learning

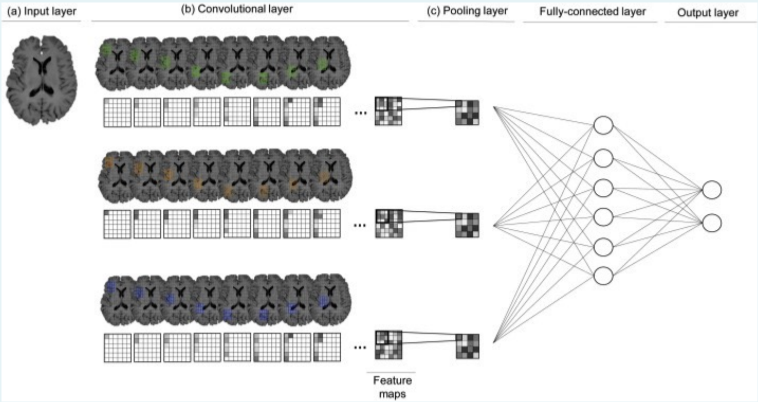


Adding new classes of object one by one without forgetting previous knowledge.



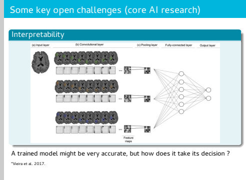
The problem of incremental learning comes from the fact that most methods can't be retrained after they have been trained. Therefore, they suffer from what is called "catastrophic forgetting", which is the fact that previously learnt knowledge is erased by the new knowledge, so the algorithm performs poorly on the newly learnt knowledge.

Interpretability



A trained model might be very accurate, but how does it take its decision ?

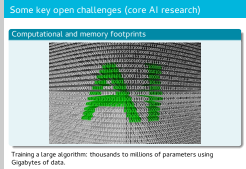
"Vieira et al. 2017.



Interpretability : the image is here to illustrate a usecase (neuroimaging) in which it can be difficult to know if the network has learnt correctly. The reason is easier to understand when comparing with a more classical image recognition task : a human can check whether an AI that learns to classify dogs versus cats is performing well by just checking the images. But with brain images (let's say recognizing Parkinson Disease from brain structure), we can't do that, because we don't know necessarily what a Parkinson brain looks like.

Computational and memory footprints

Training a large algorithm: thousands to millions of parameters using Gigabytes of data.



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Sessions

1. Generalities about AI (today),
2. Supervised learning,
3. Unsupervised learning,
4. Practical ethics in AI,
5. Combinatorial game theory,
6. Reinforcement learning,
7. Challenge.

Lab Sessions and Challenge

By groups of two, you are given a machine with complete access.

Sessions schedule

Each session has the same structure:

- Short written exam about the previous lesson (10 min),
- Short lesson (20 min),
- Lab Session including an introductory "TP" (50 min),
- Project (1h20)
- Sessions 2, 3, 5 and 7 include students' presentations

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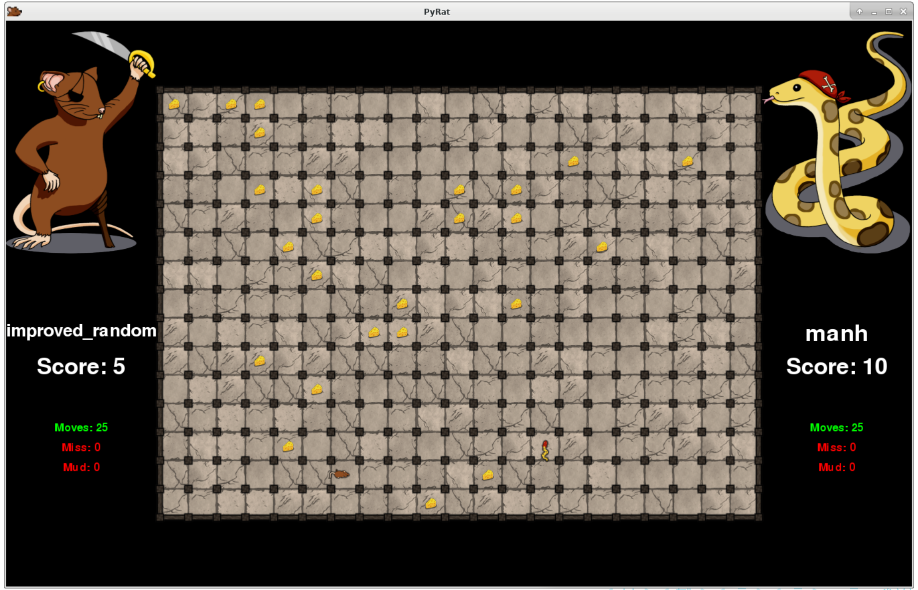

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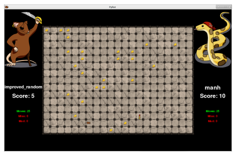

Lab Session 1 and assignments for Session 2

Introductory TP (TP0)

- Introduction to Jupyter Notebook
- Crash course in Numpy, Scipy
- Visualisation using Matplotlib

Project 0 (P0)

You will be assigned a topic on an application of AI.
You have to prepare a 7 minutes presentation (for session 2) in which you quickly explain :

- What the topic is about
- What solutions already exist
- Examples of companies / existing products on this topic
- Example of ethical considerations related to the topic
- Current limitations and hard problems

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