



## Course 1: Generalities about AI

2025-10-02

Welcome to the first lesson of the AI course! I'll let AI do the introduction to this course. Demo on what modern AI systems are able to achieve (generative AI based on large language models: chatGPT and Dall-E)



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

# Global overview...

## What is AI?

- **Intelligence:** ability to **extract knowledge** from observations
- This knowledge is used to **solve tasks in different contexts and environments** (automation)

### Old way: Memorize

- Human experts code the machines
- Goods: we know what we are doing.
- Bads: requires **explicit** solutions (not available for some problems).

### Modern way: Learning

- Let machines teach themselves how to solve a problem (**implicit**).
- Goods: universally applicable
- Bads: lack of understandability/robustness.
- Requires **training**.

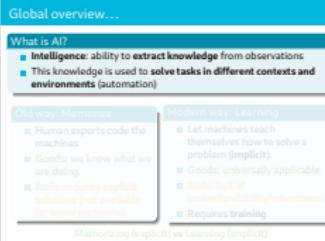
## Memorizing (explicit) vs Learning (implicit)



## Course 1: Generalities about AI

### └ Global overview...

intelligence: ability to process information to inform future decisions.  
AI: focuses on building artificial algo that can do the same thing. Historically, this has been done by explicitly telling the machines (=coding algo) how to extract the required knowledge. This had the advantage of exactly knowing how the algo was working but the strong limitation of requiring explicit solution, not available for more complex tasks. The modern way to do AI, what we call ML is to teach machines how to do is without being explicitly programmed.



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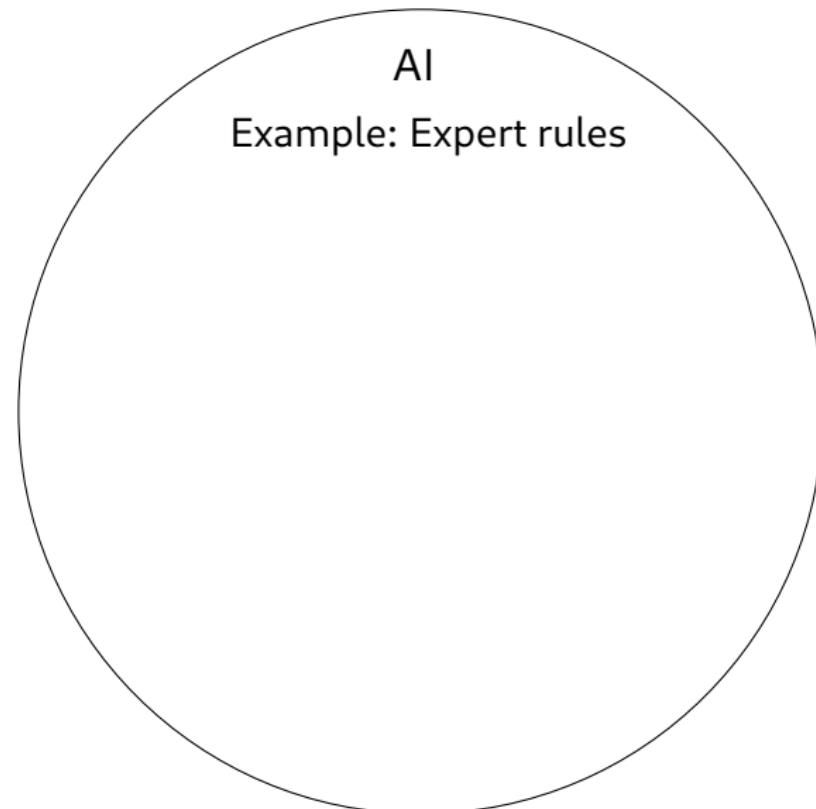
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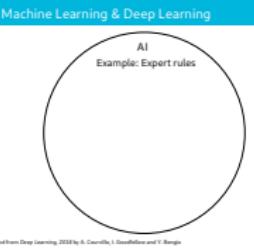
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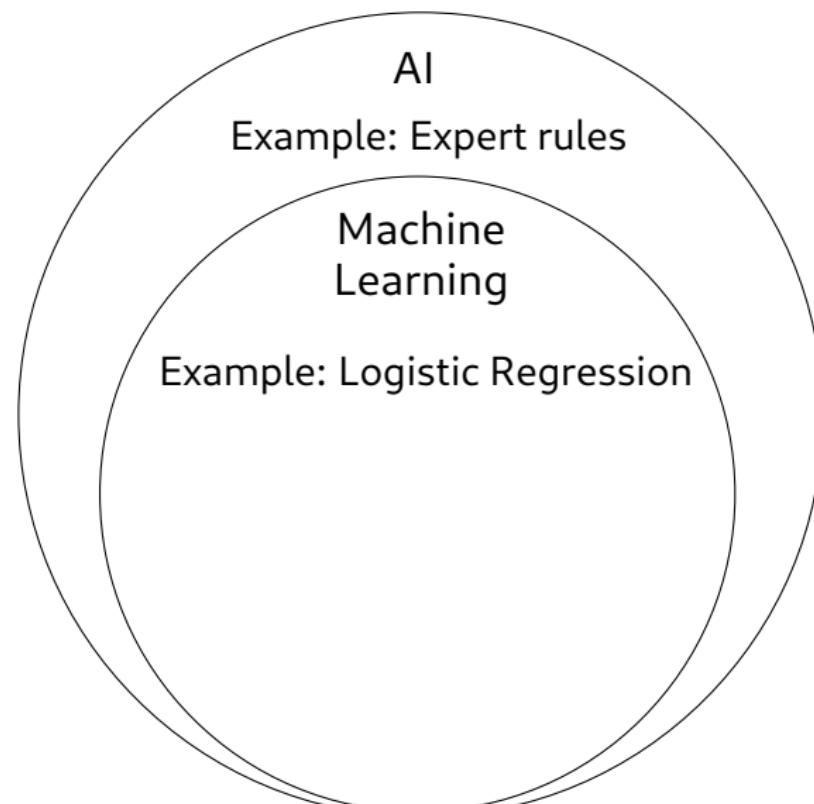
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## └ AI, Machine Learning & Deep Learning

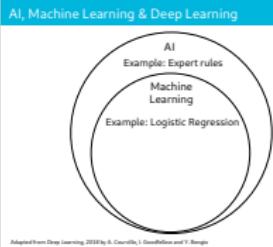
Deep Learning is a particular case of Machine Learning.

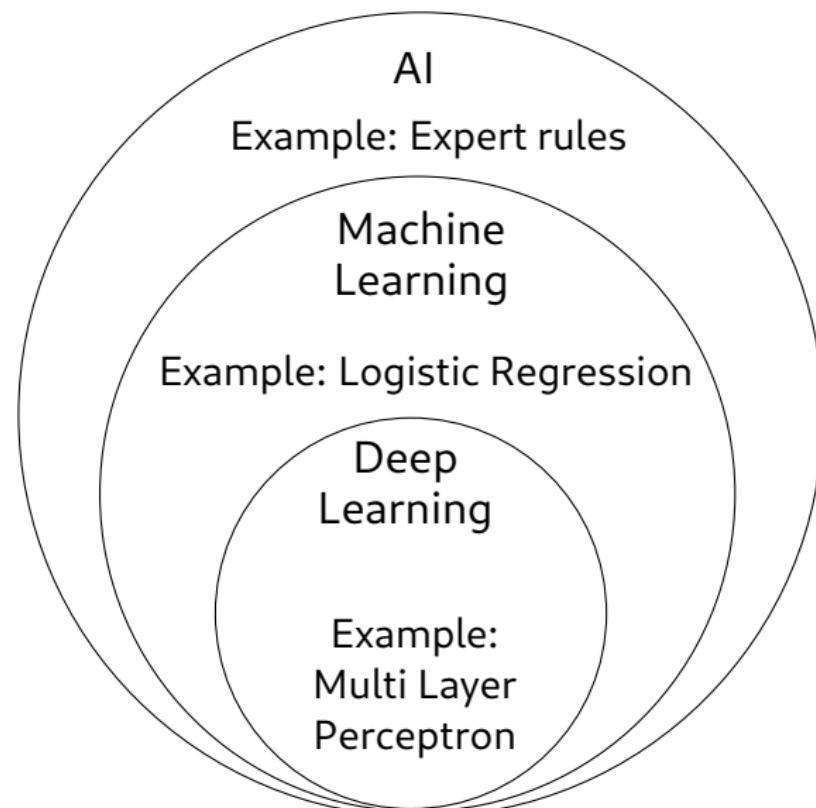




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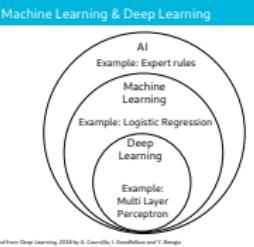
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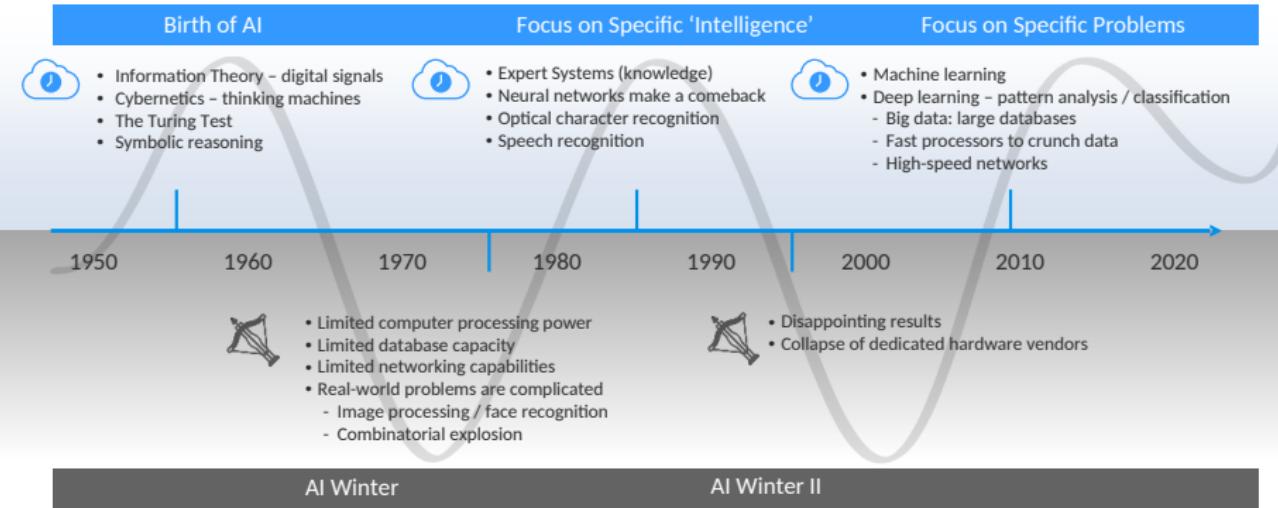
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## An AI Timeline

Source:  harmon.ie®



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## Course 1: Generalities about AI

### └ AI Timeline

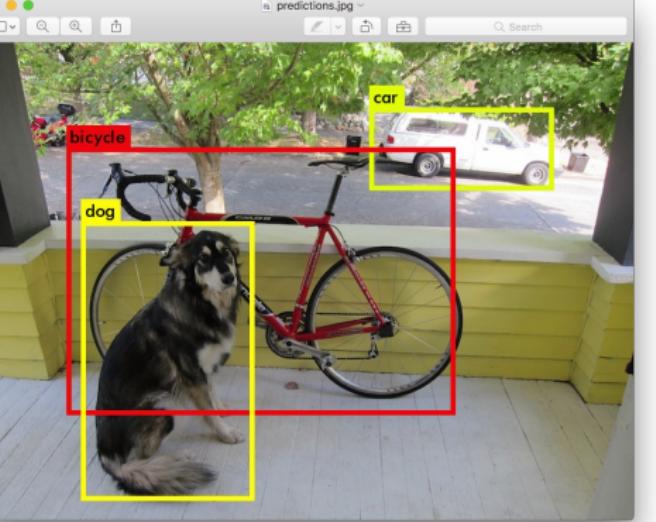
Here, we want to show that field of AI has gone through a number of "winters". This timeline shows that the basic building blocks of DL were there for decades, and algorithms to train them as well! For instance the SGD was proposed in 1952, BackPropagation in 1986. The reasons explaining the success of modern AI which is mostly based on Deep Learning are to be found in other aspects.



# Traditional application domains of AI

## Vision

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



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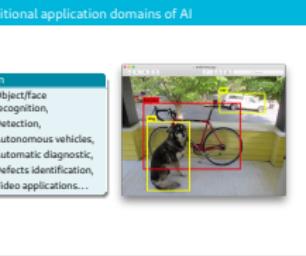
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# Traditional application domains of AI

Natural Language Processing (NLP)

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

Speak now



Cancel

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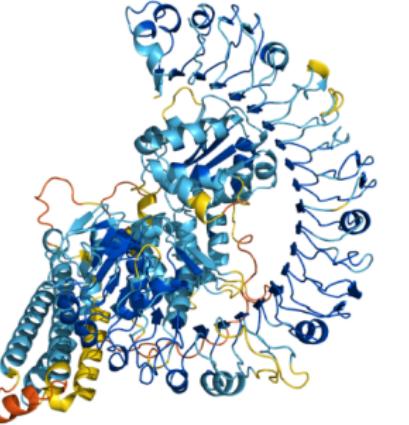
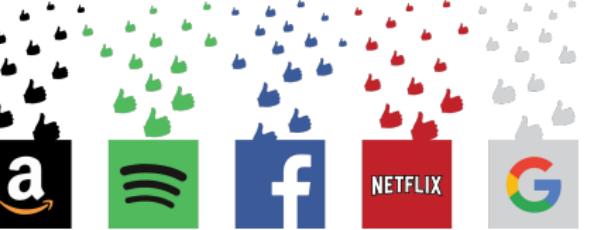
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# Traditional application domains of AI

Tons of other domains...

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

<https://alphafold.ebi.ac.uk/>



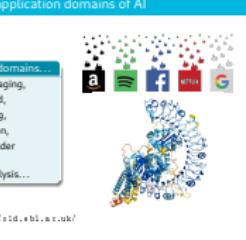
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## Traditional application domains of AI

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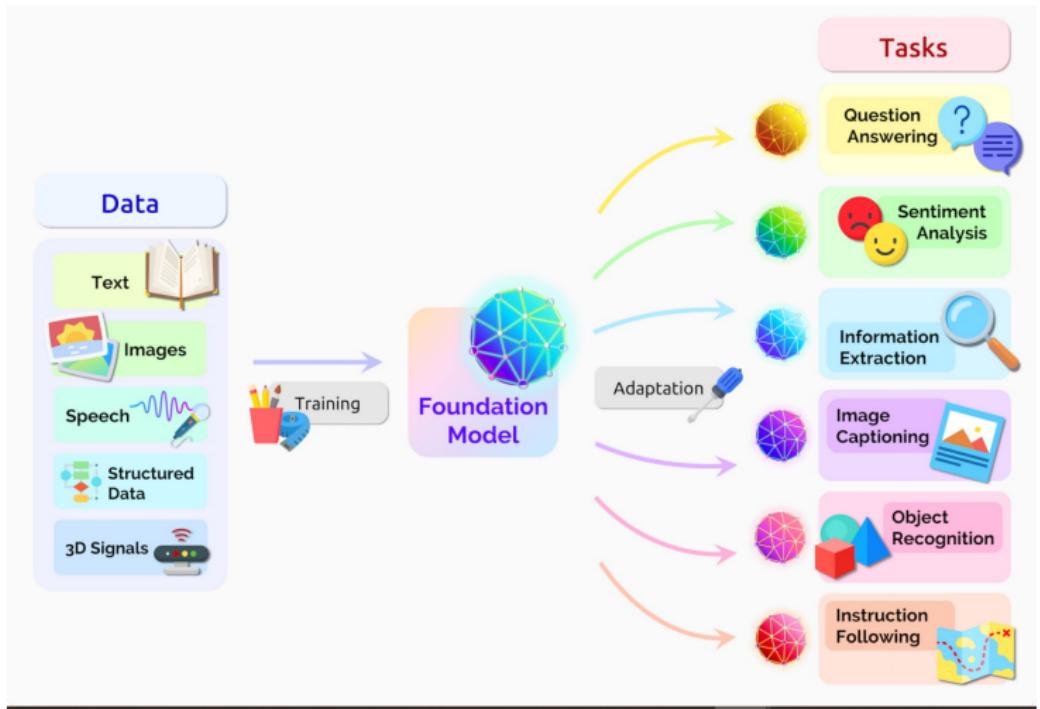
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There is probably plenty more application domains. As an example of a breakthrough it is worth mentioning AlphaFold that has revolutionized the field of bioinformatics. The AlphaFold network directly predicts the 3D coordinates of all heavy atoms for a given protein using the primary amino acid sequence. It is an AI system that contains many "ingredients" of modern DL approaches: attention mechanisms, self-distillation,...).

# Foundation models: a game changer

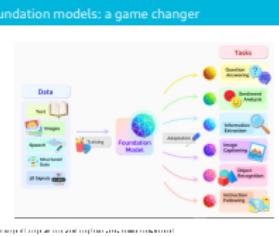


Source: <https://blogs.nvidia.com/blog/what-are-foundation-models/>

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### Foundation models: a game changer



# Generative AI: a recent breakthrough

## Text Synthesis with Large Language Models

- GPT-3, 175 billion parameters trained without explicit supervision on over 600GB of text <https://arxiv.org/abs/2005.14165>  
⇒ Model behind ChatGPT <https://openai.com/blog/chatgpt/>
- LLaMA (Meta), Gemini (Google), Mistral 8x7B (MistralAI), ... And many others!

The screenshot shows a user interface for generating text. At the top, there is a blue header bar with the text "Text Synthesis with Large Language Models". Below this is a white main area. On the left, there is a dark sidebar with a user icon and the text "Write an introduction to a master course on artificial intelligence for an engineering school". The main content area contains a message from a large language model (indicated by a green icon) stating: "Welcome to the Master's course on Artificial Intelligence (AI) at our engineering school. In this program, you will gain a comprehensive understanding of the latest advances in the field of AI and machine learning. You will learn to design and implement intelligent systems using a variety of techniques and algorithms, and you will learn to critically evaluate the performance and limitations of these systems. The course will cover a wide range of topics including supervised and unsupervised learning, deep learning, natural language processing, computer vision, and robotics. You will also have the opportunity to work on real-world projects and to collaborate with other students and faculty members on cutting-edge research. By the end of the program, you will have the skills and knowledge needed to excel in a career in AI or to pursue further research in the field." At the bottom of the main area, there is a toolbar with various icons for navigating through the text.

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### └ Generative AI: a recent breakthrough

trained on CommonCrawl, Webtext, Books, Wikipedia

The screenshot shows a presentation slide with a light gray background. At the top right, there is a small box containing the text "Generative AI: a recent breakthrough" and some bullet points. The main content area has a title "Generative AI: a recent breakthrough" and a sub-section "Text Synthesis with Large Language Models". Below this, there is a list of bullet points:

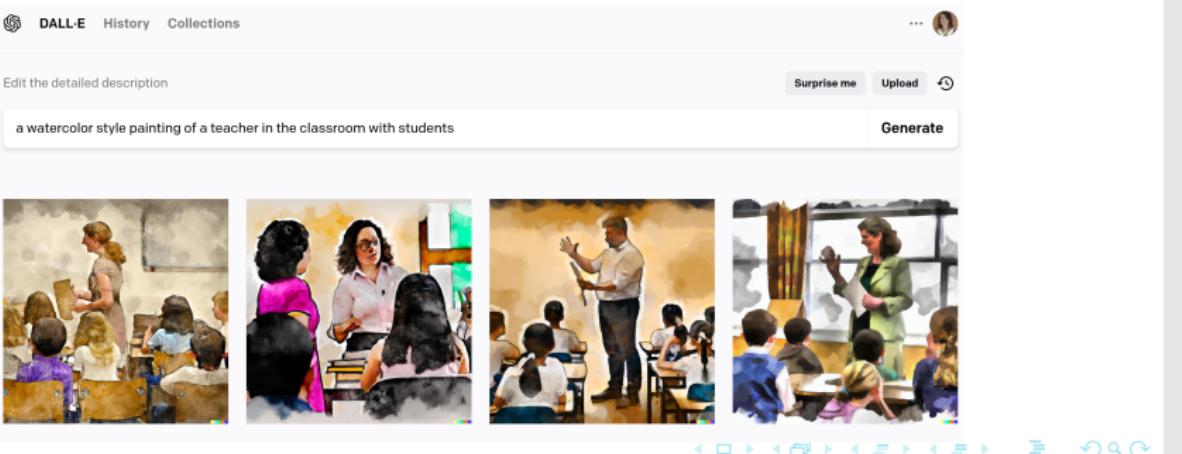
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# Generative AI: a recent breakthrough

## Image Synthesis

- Stable Diffusion Models (<https://arxiv.org/pdf/2403.03206>)
- DALL-E (<https://labs.openai.com/>)
- Midjourney (<https://docs.midjourney.com/>)

Possible thanks to **multimodality**: encoding both text and image (ex:  
CLIP (<https://arxiv.org/abs/2103.00020>) )



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### └ Generative AI: a recent breakthrough

Both use diffusion models to encode and Vision Transformer

Generative AI: a recent breakthrough

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A horizontal row of six small thumbnail images, each showing a different AI-generated scene or object, likely related to the course content.

# Generative AI: a recent breakthrough

## Many other modalities...

- Speech (Many actors, ex: Kyutai)
- Music (StableAudio, Udio, Suno, ...)
- Video (StableVideo, Sora (OpenAI), ...)
- ...
- **Multimodal** models are arising

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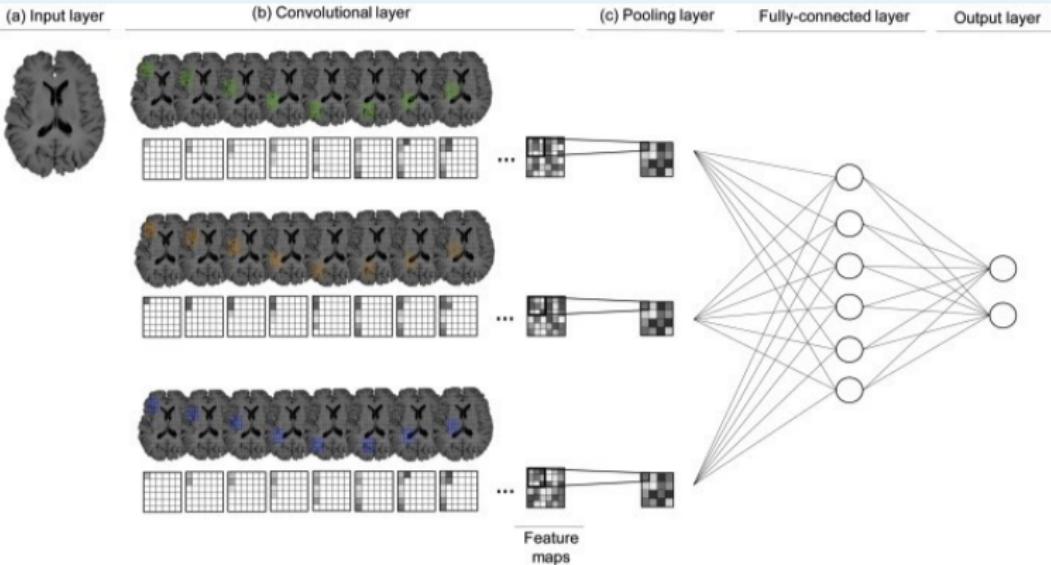
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# Some key open challenges (core AI research)

## Interpretability



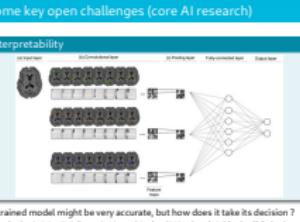
A trained model might be very accurate, but how does it take its decision ?

"Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: Methods and applications", Vieira et al. 2017.

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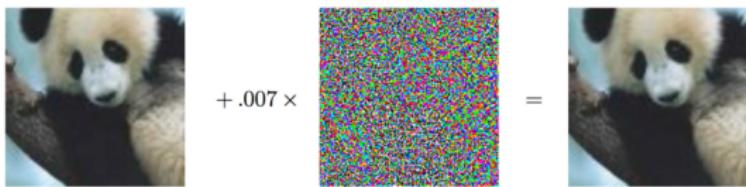
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### Some key open challenges (core AI research)



# Some key open challenges (core AI research)

## Learning what should be learned (robustness / adversarial attacks)



“panda”

57.7% confidence

noise

“gibbon”

99.3% confidence

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

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

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# Some key open challenges (core AI research)

## Computational and memory footprints

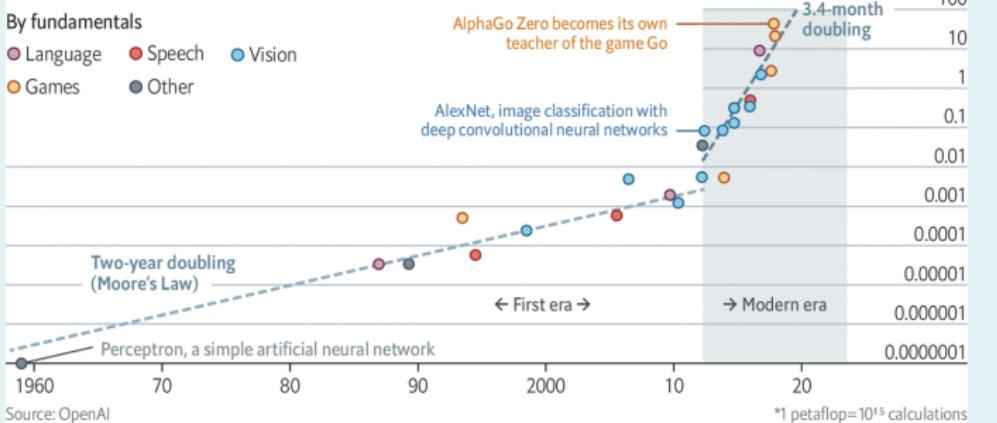
### Deep and steep

Computing power used in training AI systems

Days spent calculating at one petaflop per second\*, log scale

#### By fundamentals

- Language
- Speech
- Vision
- Games
- Other



Source: OpenAI

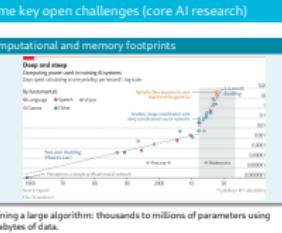
The Economist

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

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## Some key open challenges (core AI research)



Let's dive into details!



LET'S DIVE INTO DETAILS!

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Course 1: Generalities about AI

Let's dive into details!



## Examples

- Learning to play chess through playing games,
- Learning to recognize dogs and cats in images from annotated examples ...

## Machine learning

- Supervised: Learning from **inputs** and **human annotations**
- Unsupervised: Learning from **inputs** only (patterns)
- Self-supervised: Learning by reconstructing the **inputs** from distorted versions

## Generalization

- Generalization refers to the ability to infer **good decisions or representations from examples**.
- Goal: transfer knowledge from a dataset to another

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## Course 1: Generalities about AI

### └ Machine Learning

The most common framework in ML is Supervised Learning: we learn a function from inputs/examples/data and their outputs/labels. In this setting, labels are given by humans (ex: cat pictures, with the annotation "cat"). A second framework is Unsupervised Learning, where the function is learned from the data only. In general, it consists of finding repeated patterns or structure in data. A third framework, very popular nowadays, consist of leveraging the data itself to compute the annotations, and remove the human in the loop. It can be very powerful if a relevant way to compute annotations is found. A particular example, used for most Large Language Models: remove one word in a sentence, and train the network to find this word.

One key challenge in ML is Generalization. It can be seen as the ability to generalize on unseen data (different from data (inputs/labels) the model has been trained on). In this course 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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## Input/output

- **Goal:** infer a function of parameters  $\mathbf{W}$  from an input (often tensor) space to an output (often tensor) space,  $\mathbf{y} = f(\mathbf{x}, \mathbf{W})$ .
- **Example:** input can be an image, output a vector where the largest value indicate the category the image belongs to.

## Error/Loss

- **Loss  $\mathcal{L}$ :** nonnegative measure of the discrepancy between expected output  $\hat{\mathbf{y}}$  and obtained output  $\mathbf{y}$ .
- **Example:** output should be  $[0, 1]$  but is  $[0.2, 0.8]$ .

## Parameters

- $f(\cdot, \mathbf{W})$  contains **parameters  $\mathbf{W}$**  to be trained,
- In most cases, an ideal  $f(\cdot, \mathbf{W})$  exists but is **hard to find in practice**,
- Learning is a **regression ill-posed problem**.

### └ Global formalism

Loss: it's a way to tell the model when it is wrong and train the model accordingly. The model contains parameters (model weights and bias) and usually, given a task, an optimal set of parameters exist but again finding it is ill posed problem (many solutions exist)

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- **Goal:** Infer a function of parameters  $\mathbf{W}$  from an input (often tensor) space to an output (often tensor) space,  $\mathbf{y} = f(\mathbf{x}, \mathbf{W})$ .
- **Example:** input can be an image, output a vector where the largest value indicate the category the image belongs to.

#### Error/Loss

- **Loss  $\mathcal{L}$ :** nonnegative measure of the discrepancy between expected output  $\hat{\mathbf{y}}$  and obtained output  $\mathbf{y}$ .
- **Example:** output should be [0, 1] but is [0.2, 0.8].

#### Parameters

- $f(\cdot, \mathbf{W})$  contains parameters  $\mathbf{W}$  to be trained.
- In most cases, an ideal  $f(\cdot, \mathbf{W})$  exists but is hard to find in practice.
- Learning is a regression ill-posed problem.

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### └ Global formalism

Loss: it's a way to tell the model when it is wrong and train the model accordingly. The model contains parameters (model weights and bias) and usually, given a task, an optimal set of parameters exist but again finding it is ill posed problem (many solutions exist)

## Input/output

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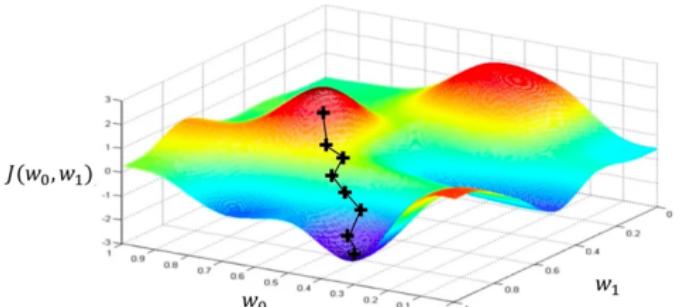
# Global formalism

- Loss:  $J(\mathbf{W}) = \sum_i \mathcal{L}(f(\mathbf{x}^{(i)}, \mathbf{W}), \mathbf{y}^{(i)})$ ,  $i = \text{examples}$
- Model parameters:  $\mathbf{W}^* = \text{argmin}(J(\mathbf{W}))$

## Training Algorithm

### Gradient Descent:

- Randomly Initialize model weights
- Compute Gradient of the Loss  $\frac{\partial J(\mathbf{W})}{\partial \mathbf{W}}$
- Update weights  $\mathbf{W} \leftarrow \mathbf{W} - \eta \frac{\partial J(\mathbf{W})}{\partial \mathbf{W}}$
- Repeat until convergence



from MIT course [introtodeeplearning.com](http://introtodeeplearning.com)

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### └ Global formalism

The total loss  $J$  (Empirical Risk, Objective function) is the average of Loss for each input/example and the optimal model parameters are those that minimize it. But how to find them? In other words, how to train the model? Here is a simplified description of the training algorithm at the base of modern DL, gradient descent. Repeat until reaching a local minimum (as illustrated in the figure for a simple example where we have only 2 parameters. We'll see that the function becomes much more complicated for millions of parameters -modern neural networks.)

Global formalism

■ Loss:  $J(\mathbf{W}) = \sum_i \mathcal{L}(f(\mathbf{x}^{(i)}, \mathbf{W}), \mathbf{y}^{(i)})$ ,  $i = \text{examples}$

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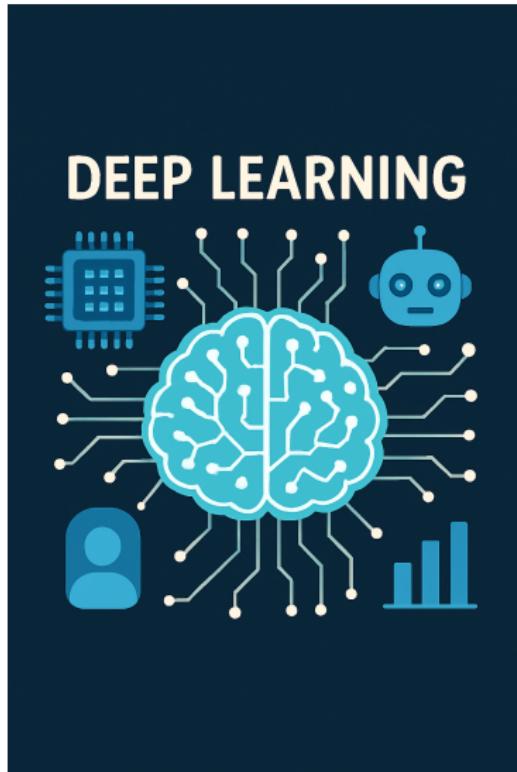
# Deep Learning

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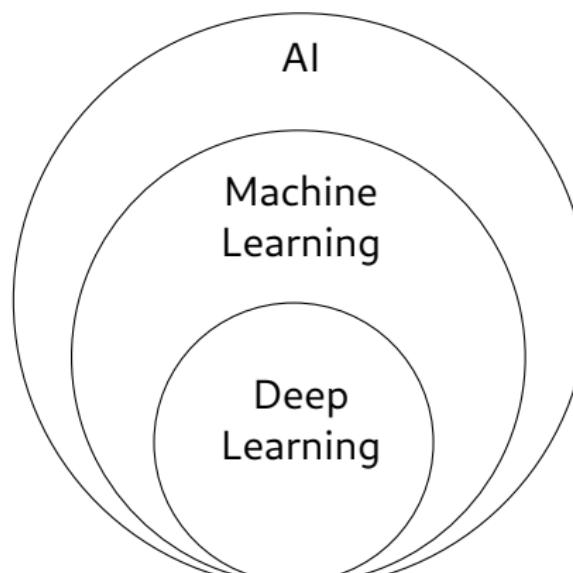
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Deep Learning

Deep Learning



# Deep Learning: A Particular Case of Machine Learning



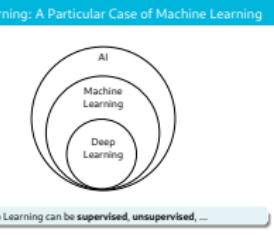
A Venn diagram consisting of three nested circles. The outermost circle is labeled "AI". Inside it is a smaller circle labeled "Machine Learning". Inside that is another circle labeled "Deep Learning".

Hence, Deep Learning can be **supervised, unsupervised, ...**

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Deep Learning: A Particular Case of Machine Learning

Deep Learning: A Particular Case of Machine Learning

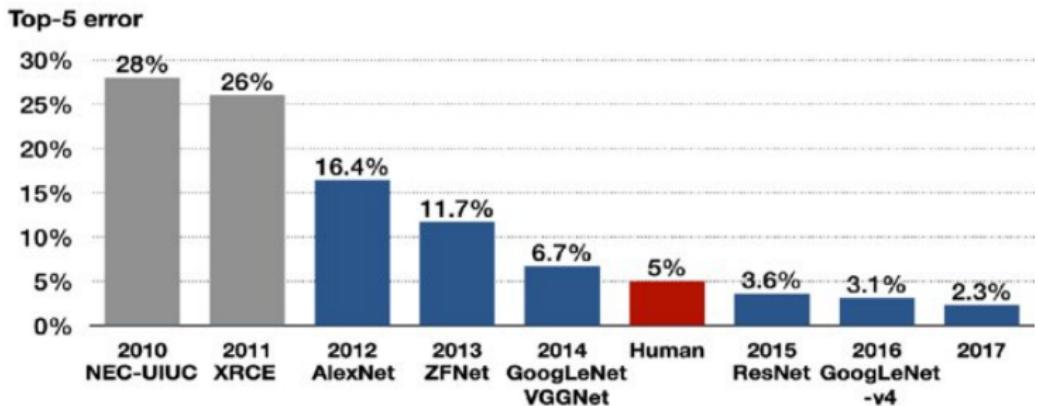


A diagram showing three concentric circles. The outermost circle is labeled "AI". The middle circle is labeled "Machine Learning". The innermost circle is labeled "Deep Learning". Below the circles is the text: "Hence, Deep Learning can be supervised, unsupervised, ...".

# A turning point: AlexNet (2012)

## Started the reign of Deep Learning

- Using **deep** neural networks and **large** datasets
- A major breakthrough in image classification:



Source: Kang, D. Y., Duong, H. P., & Park, J. C. (2020). Application of deep learning in dentistry and implantology. Journal of implantology and applied sciences, 24(3), 148-181.

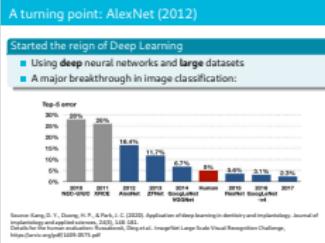
Details for the human evaluation: Russakovsky, Dieg et al.. ImageNet Large Scale Visual Recognition Challenge,  
<https://arxiv.org/pdf/1409.0575.pdf>

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### └ A turning point: AlexNet (2012)

The landscape of Machine Learning changed in 2012: Deep Neural Networks, a technique used in a minority of cases until then, suddenly won the Image Classification contest on ImageNet, a standard image classification dataset. From this point, Deep Neural Networks became mainstream, and the performance of Deep Neural Network models skyrocketed.



# The great elders of Deep Learning (Turing Prize 2018)

## 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.

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### └ The great elders of Deep Learning (Turing Prize 2018)

The reason why we mention them is because their work has mostly enabled to get out of the last two AI winters. It is also worth noting that they won the Turing prize in 2018, which is the highest distinction in computer science.

The great elders of Deep Learning (Turing Prize 2018)

<b>Geoffrey Hinton</b> <ul style="list-style-type: none"><li>Cognitive psychologist and computer scientist,</li><li>Prof. at University of Toronto and works for Google,</li><li>Known for back-propagation and Boltzmann machines.</li></ul>	<b>Yoshua Bengio</b> <ul style="list-style-type: none"><li>Computer scientist,</li><li>Prof. at Université de Montréal and head of MILA,</li><li>Known for his work on deep learning.</li></ul>	<b>Yann le Cun</b> <ul style="list-style-type: none"><li>Computer scientist,</li><li>Prof. at New York University then he joins FAIR,</li><li>Known for his work on back-propagation and CNNs.</li></ul>
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# Where did the Deep Learning revolution came from?

- The use of GPUs for computation.
- The share of huge datasets on Internet.
- HuggingFace / Github / Arxiv: easy and open-source share of research.
- The rise of representation learning.



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- └ Where did the Deep Learning revolution came from?

DL training algorithms are highly parallelizable, and can benefit from modern GPU

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## Course 1: Generalities about AI

### Where did the Deep Learning revolution came from?

We are in a data pervasive era, massive amount of digitale data is available and has been shared. This benefits DL algo that are extremely data hungry

Where did the Deep Learning revolution came from?

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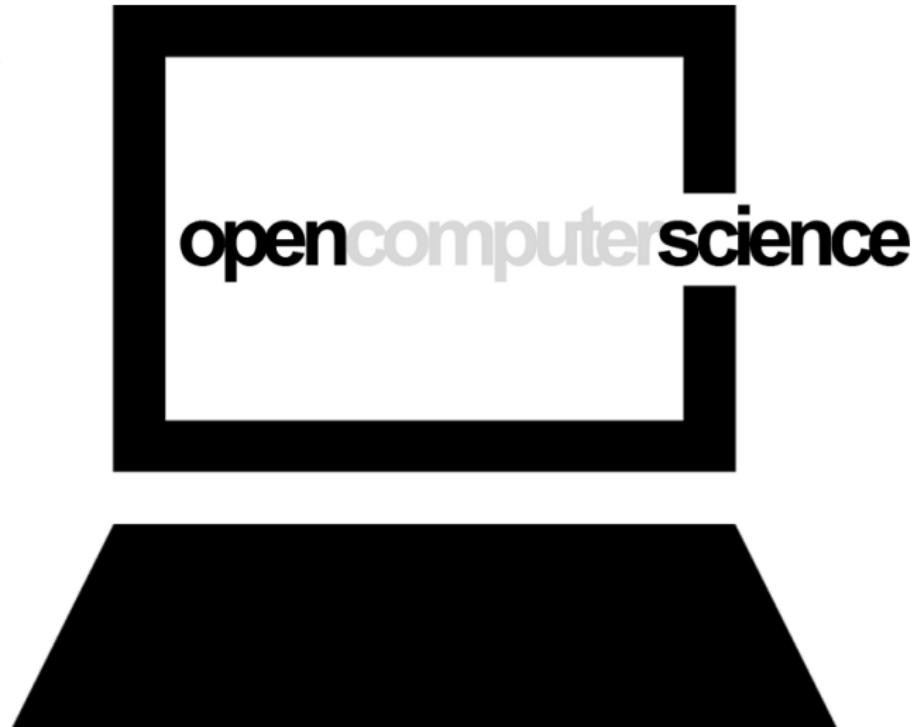
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Where did the Deep Learning revolution came from?

The availability of open source toolboxes such as pytorch and tensorflow and the practice of sharing research content and tools makes implementing and training DL models much easier, and you will find out in this course

Where did the Deep Learning revolution came from?

The use of GPUs for computation.

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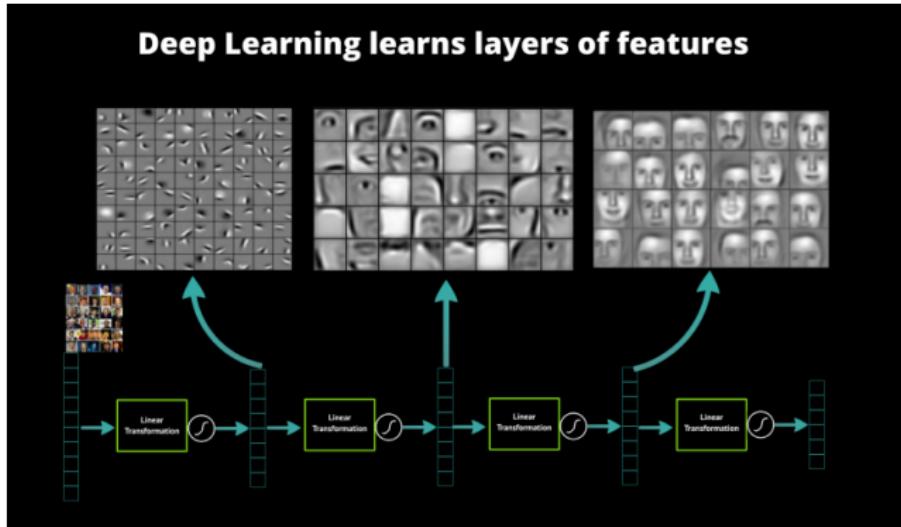
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opencomputerscience

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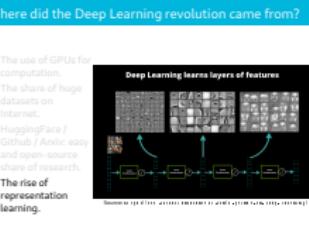
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## Course 1: Generalities about AI

- Where did the Deep Learning revolution came from?



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. In traditional pattern recognition, features were extracted using a priori expert knowledge on the data (eg looking for orange round objects to recognize oranges, by filter the colour orange, and extracting round objects). In mainstream pattern recognition, mathematical functions (eg wavelets) are used to automatically decompose images in sets of features that are more abstract, but still expertly chosen depending on the data. In Deep Learning: the features are trained end to end.

# Traditional Deep Learning (before 2020)

Machine Learning Era

```
graph LR; A[Input] --> B[Feature extraction<br/>(human-based)]; B --> C[Classification<br/>(learned by machine)]; C --> D[Output: Car, Not car];
```

---

Deep Learning Era

```
graph LR; A[Input] --> B[Feature extraction + Classification<br/>(both learned by same model)]; B --> D[Output: Car, Not car];
```

Inspired from: <https://www.softwaretestinghelp.com/data-mining-vs-machine-learning-vs-ai/>

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## Traditional Deep Learning (before 2020)

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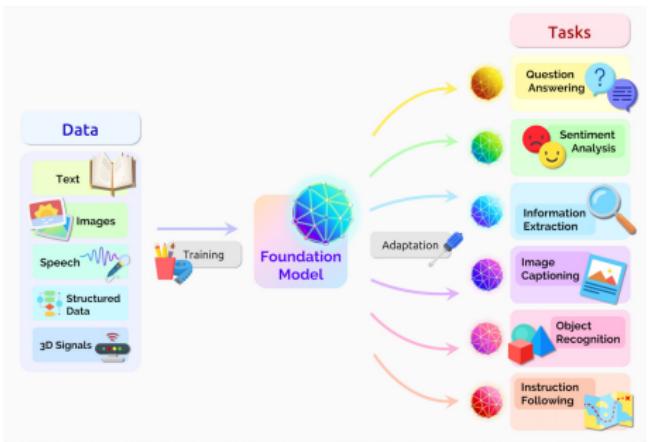
```
graph TD; subgraph ML_Era [Machine Learning Era]; A[Input] --> B[Feature extraction<br/>(human-based)]; B --> C[Classification<br/>(learned by machine)]; C --> D[Output]; end; subgraph DL_Era [Deep Learning Era]; A[Input] --> E[Feature extraction + Classification<br/>(learned by same model)]; E --> F[Output]; end;
```

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- Model trained on an Internet scale dataset
- Self-Supervised training: pretext tasks
- Generalization is not a problem anymore! All is about **particularization**



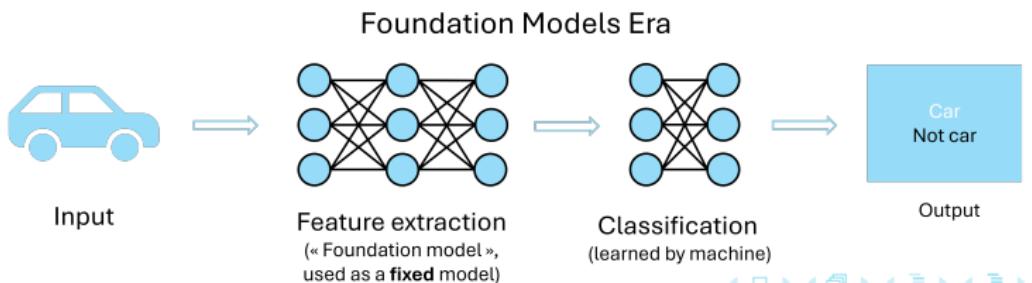
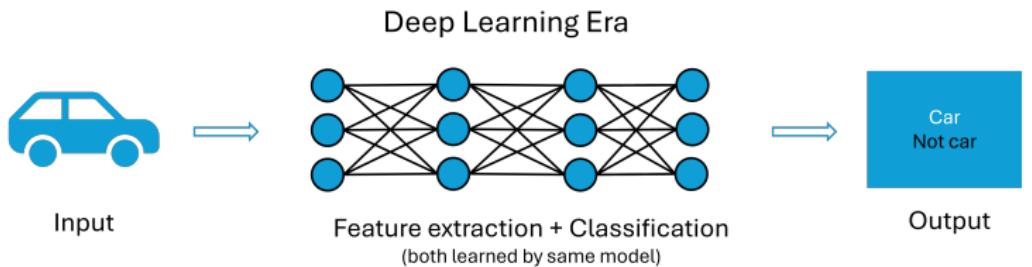
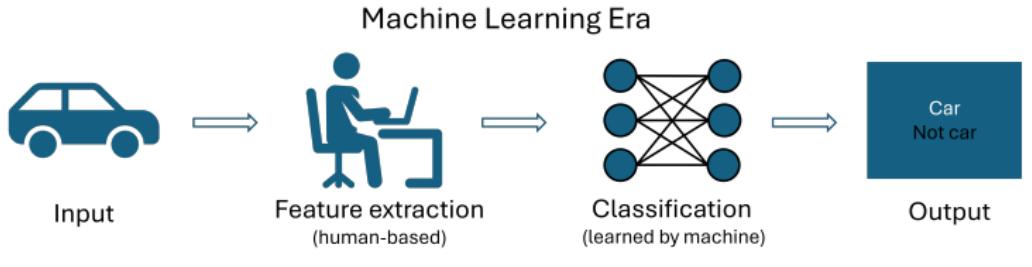
Source: <https://blogs.nvidia.com/blog/what-are-foundation-models/>

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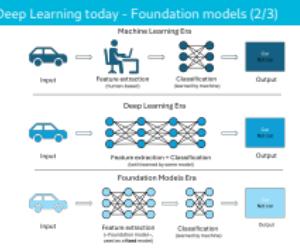
### Deep Learning today - Foundation models (1/3)



# Deep Learning today - Foundation models (2/3)



## Deep Learning today - Foundation models (2/3)



## ■ Foundation models are really hard to train...

- Requires a lot (a lot!) of data
- Requires a lot of computing power
- Requires a lot of time

## ■ ... But they can be used as powerful feature extractor!

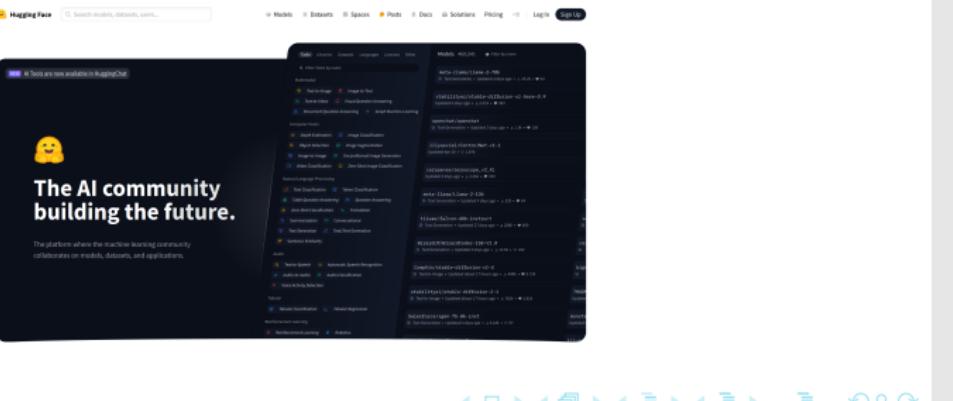
- Some open-source Foundation models exist, and are available on HuggingFace <https://huggingface.co/>
- We will use such algorithms during our labs sessions.

## └ Deep Learning today - Foundation models (3/3)

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— Deep Learning today - Foundation models  
(3/3)

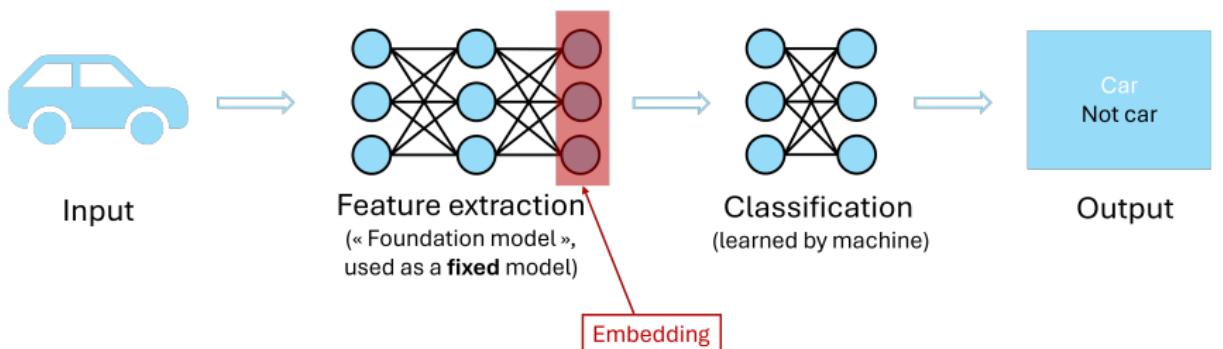
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## Take-home messages (for now):

- Foundation models represent data with meaningful and rich information ("embeddings");
- They can be used to represent a set of data, and extract features.

Embeddings: leveraging représentations learned in Foundation models



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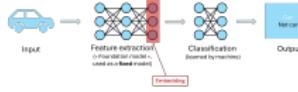
Lab Session 1

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# Lab Session 1

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- Introduction to data visualization for Machine Learning,
- Choose one modality (Text, Image, Audio)
- Tests on some examples of each modality (embeddings are pre-computed for you).

Link to the lab: <https://mee-labs.gitlab-pages.imt-atlantique.fr/intro2ai/lab1/>

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