Course 1: Generalities about AI

IMT Atlantique
Bretagne-Pays de la Loire
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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)

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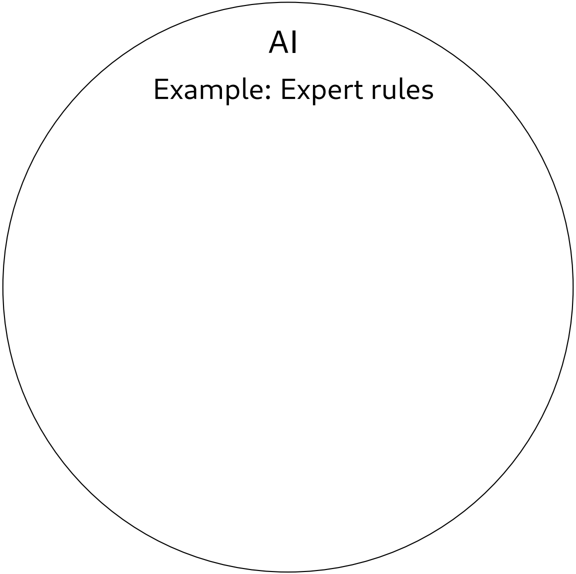
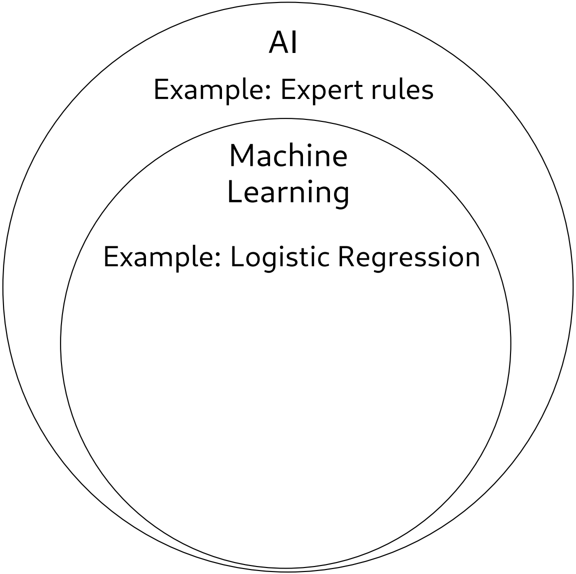
AI, Machine Learning & Deep Learning



Adapted from *Deep Learning, 2016* by A. Courville, I. Goodfellow and Y. Bengio

AI, Machine Learning & Deep Learning



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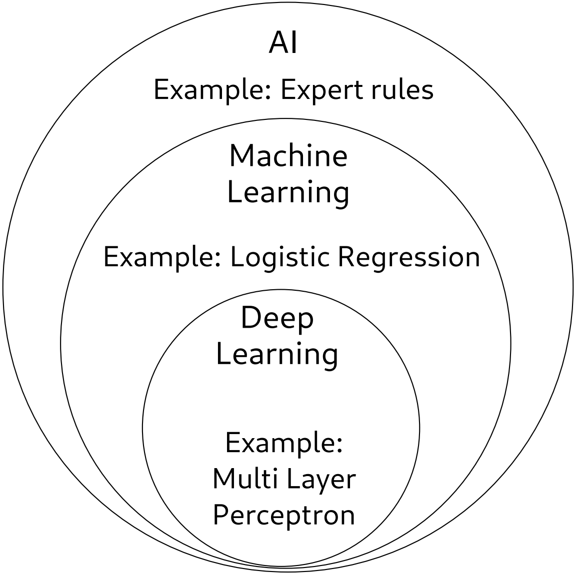

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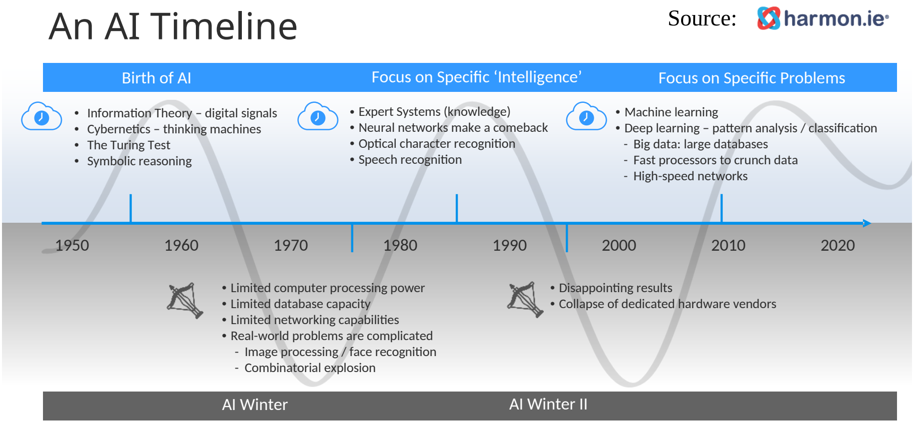
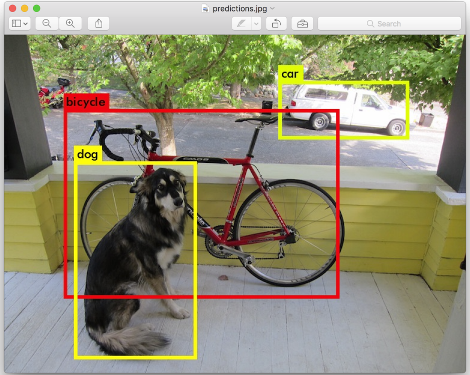
AI Timeline


An AI Timeline
Source: harmon.ie
Birth of AI
Focus on Specific 'Intelligence'
Focus on Specific Problems
• Information Theory – digital signals
• Cybernetics – thinking machines
• The Turing Test
• Symbolic reasoning
• Expert Systems (knowledge)
• Neural networks make a comeback
• Optical character recognition
• Speech recognition
• Machine learning
• Deep learning – pattern analysis / classification
- Big data: large databases
- Fast processors to crunch data
- High-speed networks
1950
1960
1970
1980
1990
2000
2010
2020
• Limited computer processing power
• Limited database capacity
• Limited networking capabilities
• Real-world problems are complicated
- Image processing / face recognition
- Combinatorial explosion
• Disappointing results
• Collapse of dedicated hardware vendors
AI Winter
AI Winter II

Traditional application domains of AI

Vision

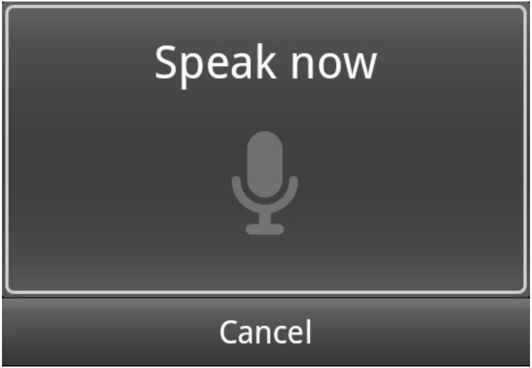
- Object/face recognition,
- Detection,
- Autonomous vehicles,
- Automatic diagnostic,
- Defects identification,
- Video applications...



Traditional application domains of AI

Natural Language Processing (NLP)

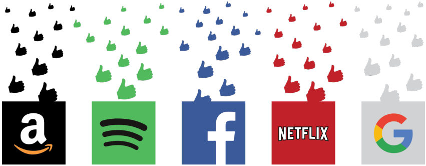
- Automatic assistant,
- Voice-to-text,
- Automatic translation,
- Automatic summarizing,
- Sentiment analysis,
- Text indexing...

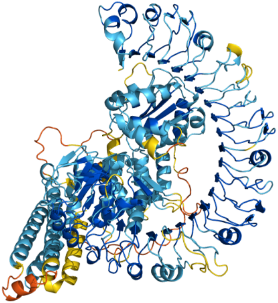


Traditional application domains of AI

Tons of other domains…

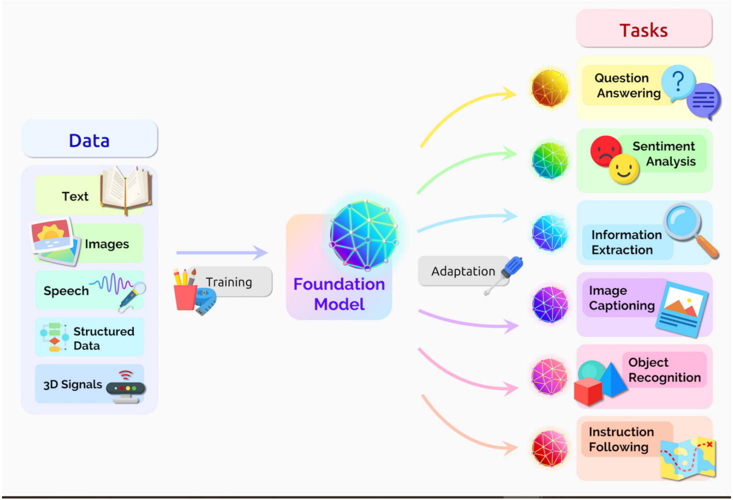
- Medical imaging,
- Decision aid,
- Data mining,
- Visualization,
- Recommender systems,
- Market analysis…





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

Foundation models: a game changer

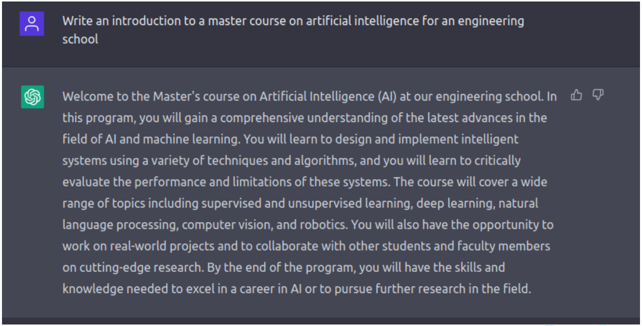


Source: `https://blogs.nvidia.com/blog/what-are-foundation-models/`

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`
  $\Rightarrow$ Model behind ChatGPT `https://openai.com/blog/chatgpt/`
- LLaMA (Meta), Gemini (Google), Mistral 8x7B (MistralAI), ... And many others!

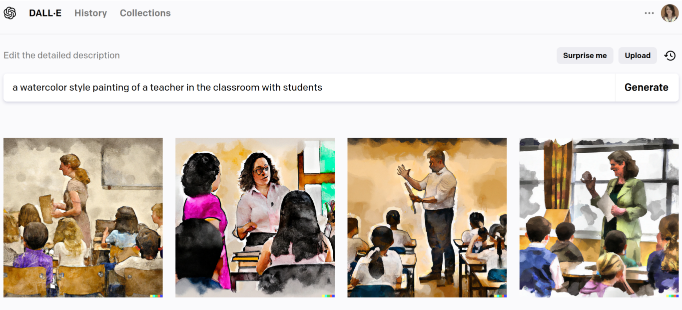


Generative AI: a recent breakthrough

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))



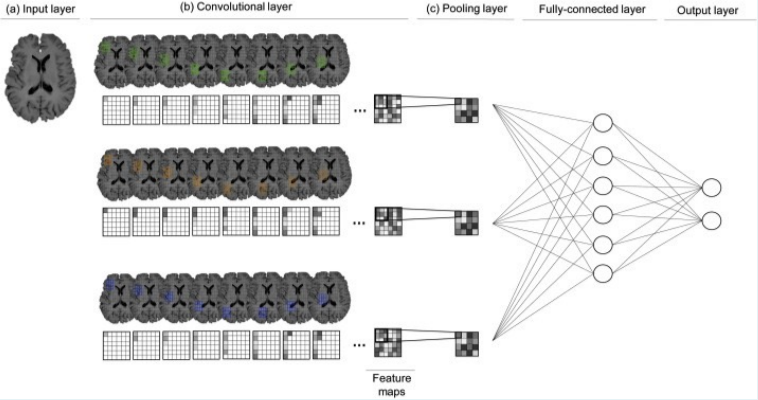
Generative AI: a recent breakthrough

Many other modalities...

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

Some key open challenges (core AI research)

Interpretability

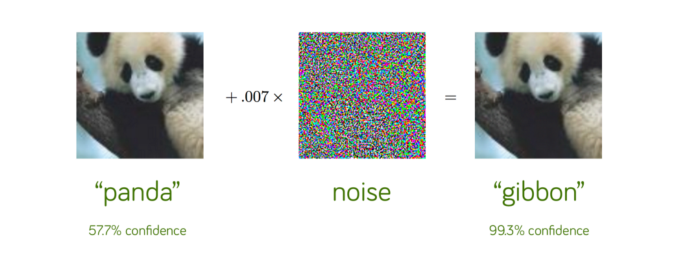


A trained model might be very accurate, but how does it take its decision ?

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

Some key open challenges (core AI research)

Learning what should be learned (robustness / adversarial attacks)

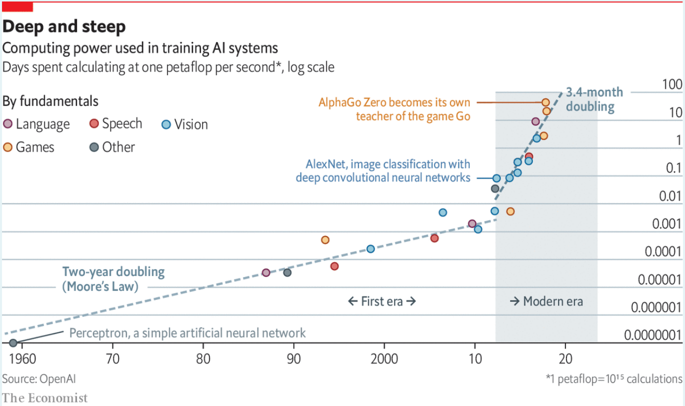


Random noise added to input images can dramatically change the result.

"Intriguing properties of neural networks", Arxiv research report, 2013.

Some key open challenges (core AI research)

Computational and memory footprints



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

Let's dive into details!

Machine Learning

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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Global formalism

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 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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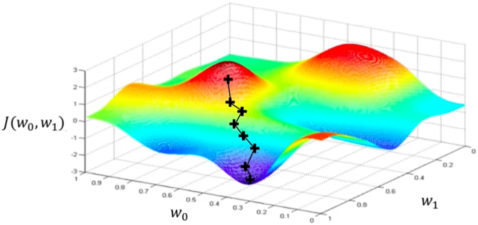
Global formalism

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

Training Algorithm

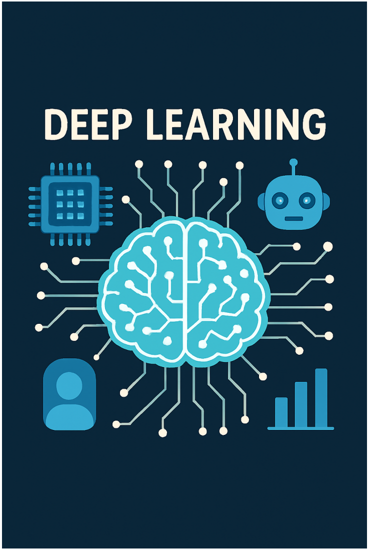
Gradient Descent:

- 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

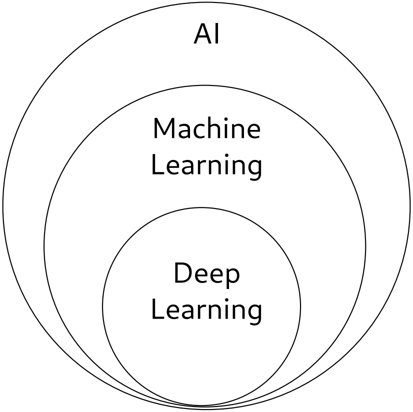


from MIT course `introtodeeplearning.com`

Deep Learning



Deep Learning: A Particular Case of Machine Learning

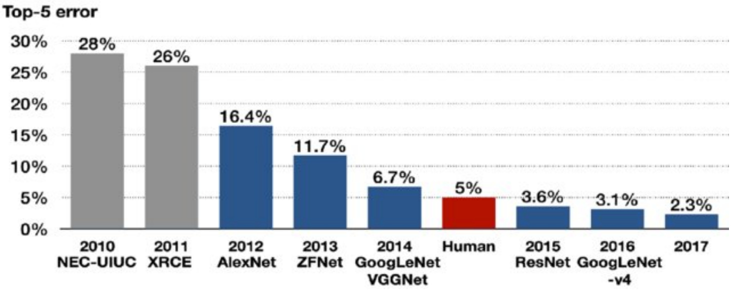


Hence, Deep Learning can be **supervised**, **unsupervised**, ...

A turning point: AlexNet (2012)

Started the reign of Deep Learning

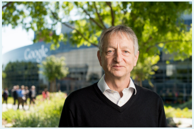
- Using **deep** neural networks and **large** datasets
- A major breakthrough in image classification:



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: Russakovsk, Dieg *et al.*. ImageNet Large Scale Visual Recognition Challenge, https://arxiv.org/pdf/1409.0575.pdf

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.

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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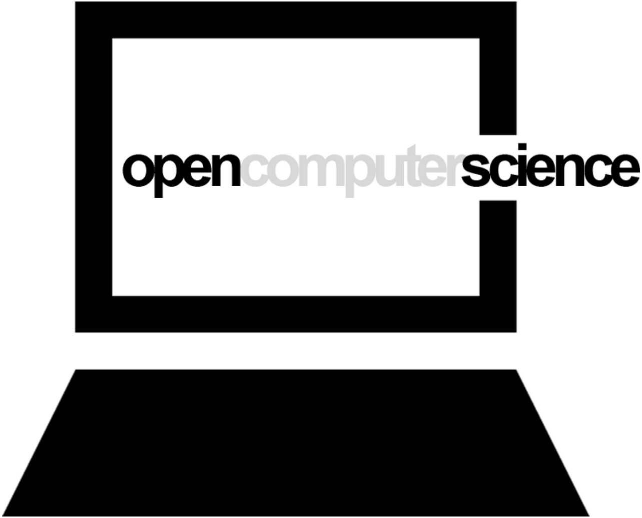

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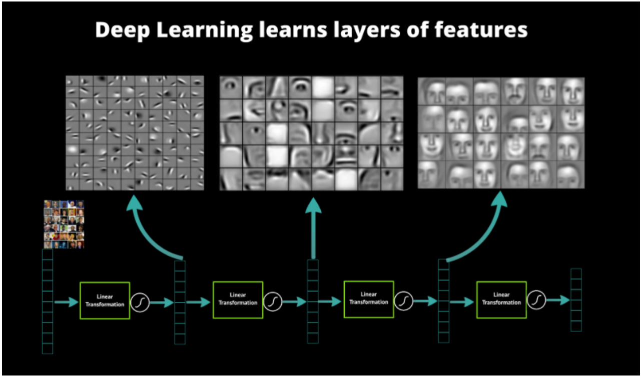
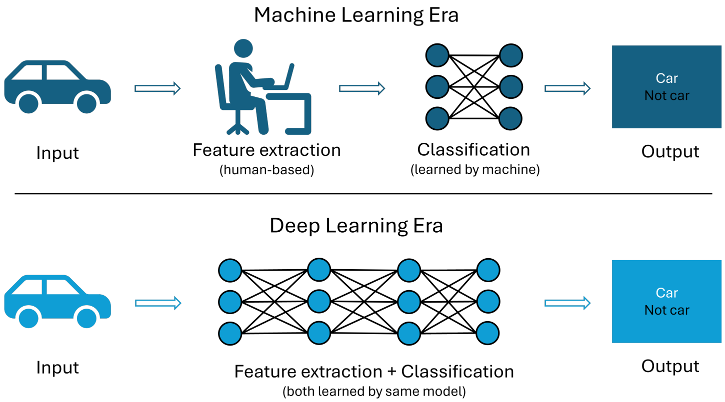


Source: `https://www.datasciencecentral.com/a-primer-on-deep-learning/`

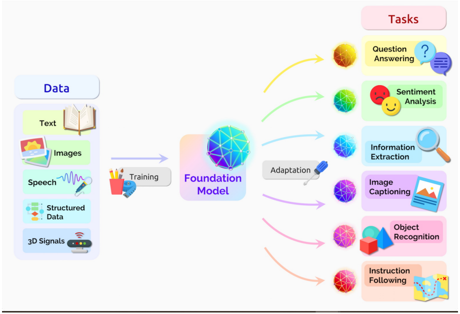
Traditional Deep Learning (before 2020)



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

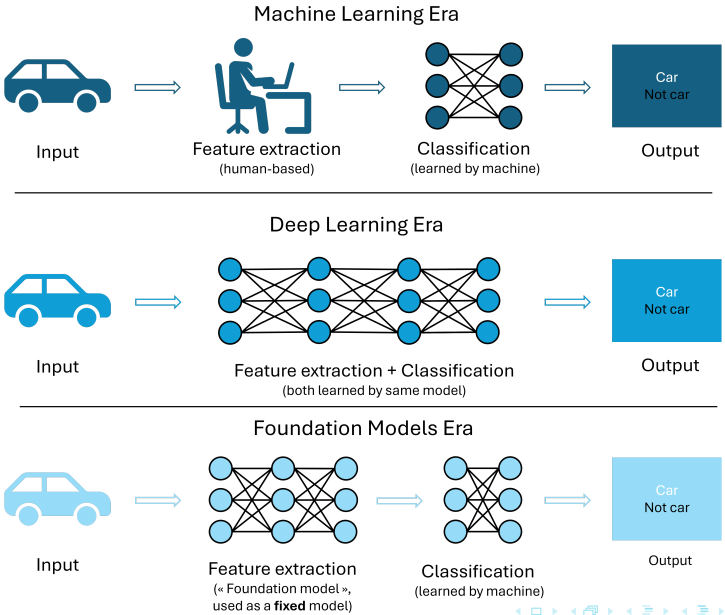
Deep Learning today - Foundation models (1/3)

- 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/`

Deep Learning today - Foundation models (2/3)



Deep Learning today - Foundation models (3/3)

- 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.

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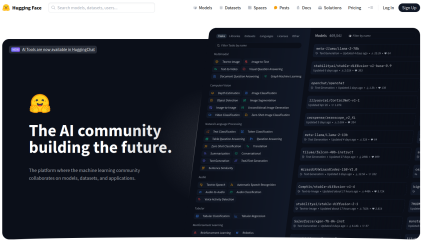
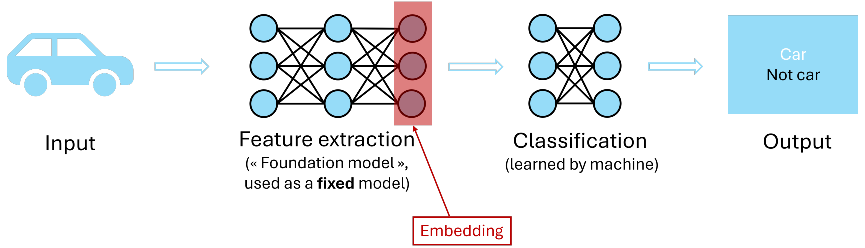


Take-home messages (for now):

- 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



Lab Session 1

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Lab assignments:

- Introduction to Python, Environments, Numpy, etc,
- 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/`