



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**.

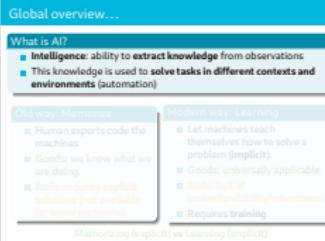
Memorizing (explicit) vs Learning (implicit)



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.



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.

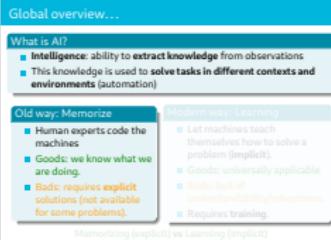
Memorizing (explicit) vs Learning (implicit)



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.



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)



└ 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.

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

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

- 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)

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)

└ Global overview...

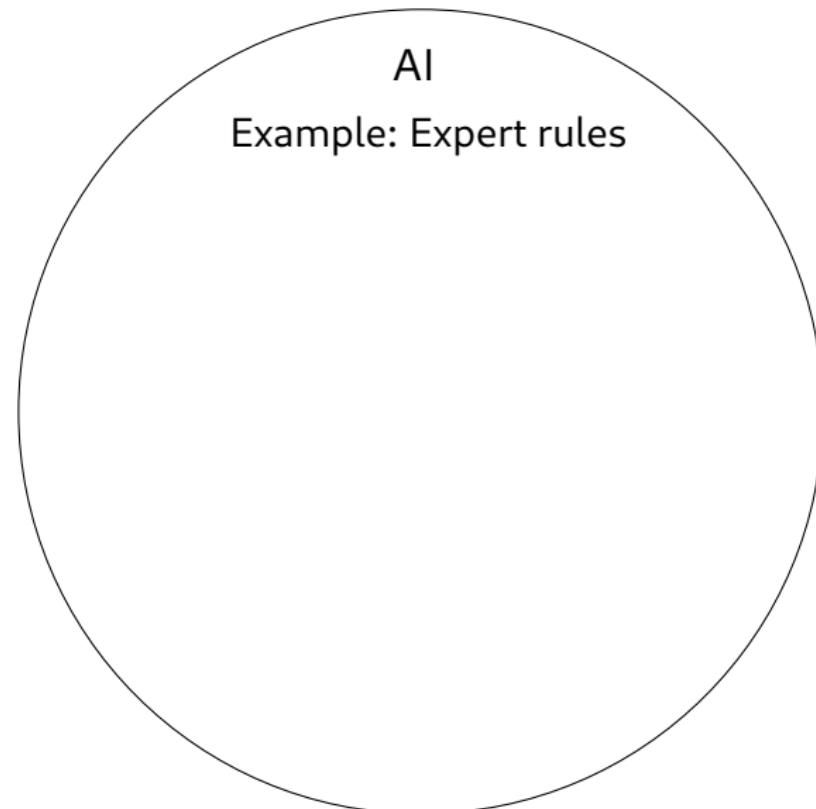
- Intelligence: ability to extract knowledge from observations
- This knowledge is used to solve tasks in different contexts and environments (automation)

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

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

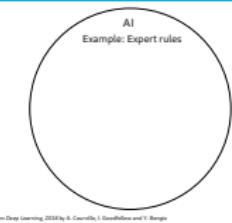
Memorizing (explicit) vs Learning (implicit)

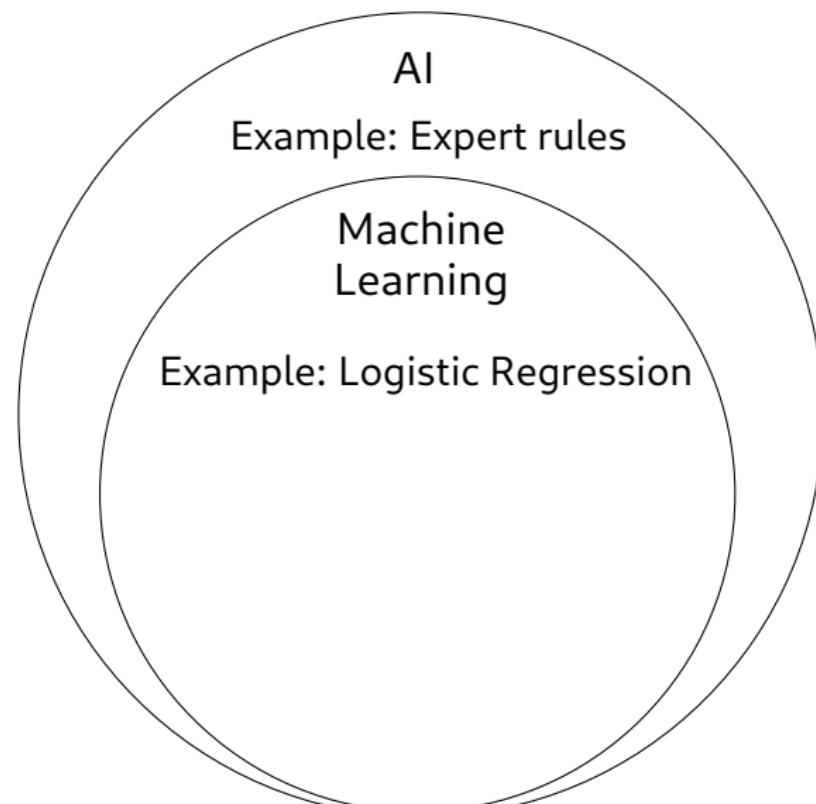
intelligence: ability to process information to inform future decisions.
AI: focuses on building artificial algo that can do the same thing. Historically, this has been done by explicitly telling the machines (=coding algo) how to extract the required knowledge. This had the advantage of exactly knowing 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.



└ AI, Machine Learning & Deep Learning

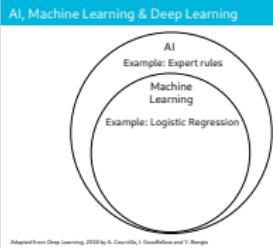
Deep Learning is a particular case of Machine Learning.

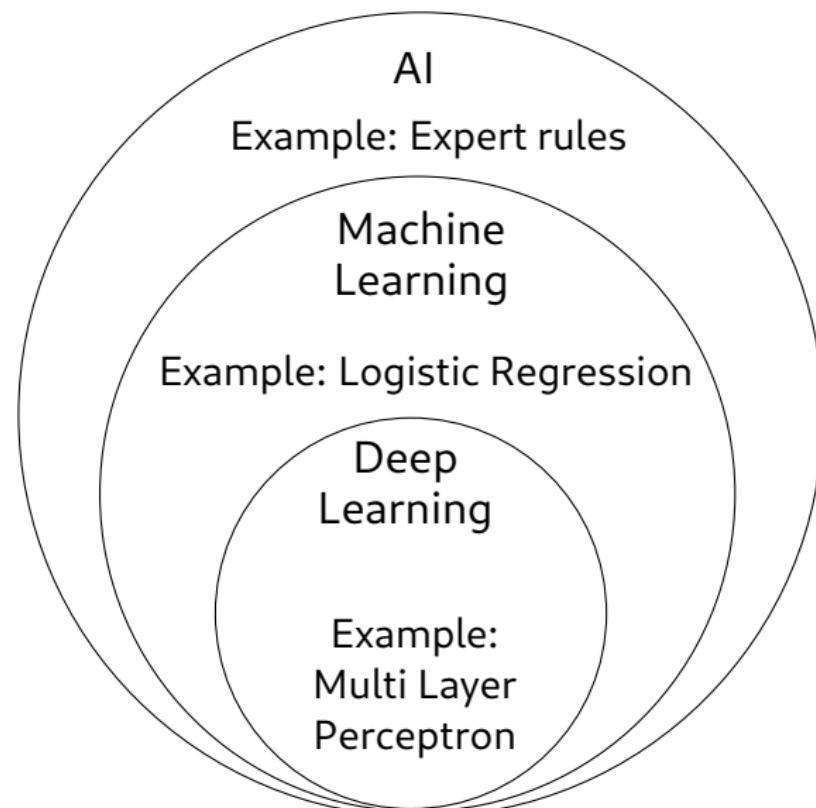




└ AI, Machine Learning & Deep Learning

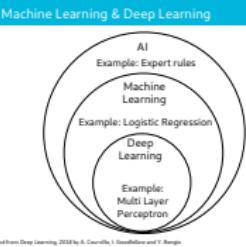
Deep Learning is a particular case of Machine Learning.





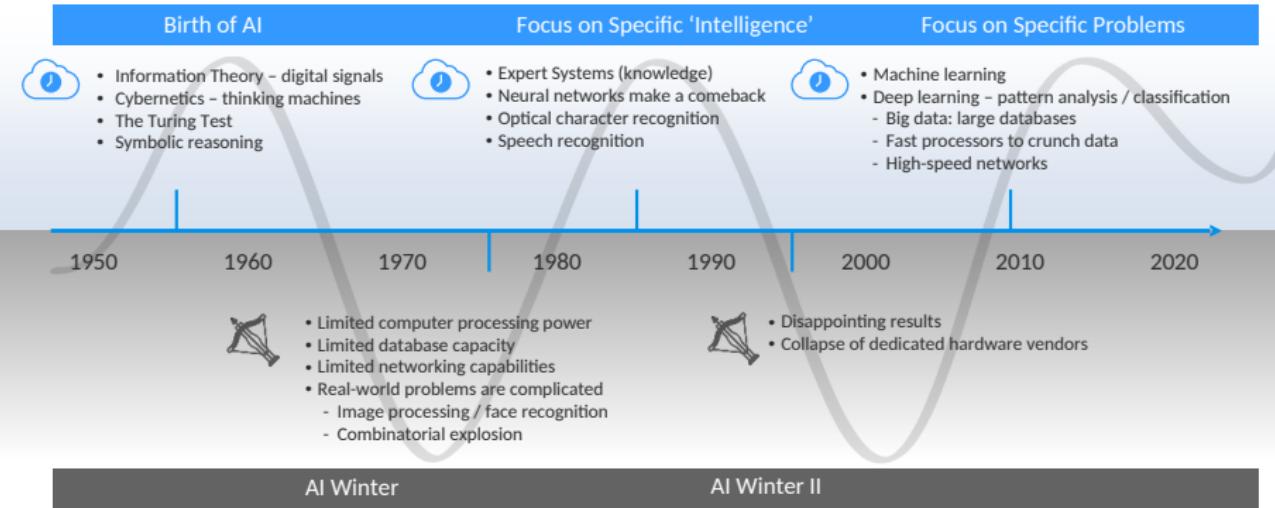
└ AI, Machine Learning & Deep Learning

Deep Learning is a particular case of Machine Learning.



An AI Timeline

Source:  harmon.ie®



2025-10-02

Course 1: Generalities about AI

└ AI Timeline

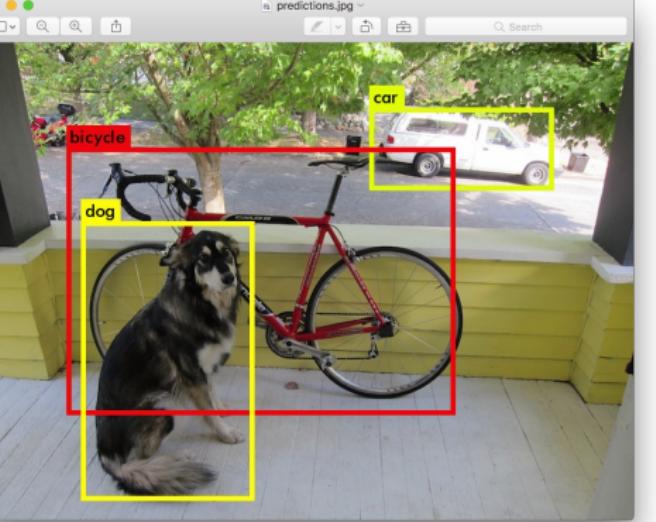
Here, we want to show that field of AI has gone through a number of "winters". This timeline shows that the basic building blocks of DL were there for decades, and algorithms to train them as well! For instance the SGD was proposed in 1952, BackPropagation in 1986. The reasons explaining the success 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...



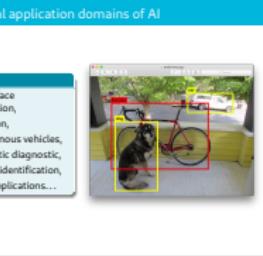
IMT-Atlantique Course 1: Generalities about AI

2025-10-02 Course 1: Generalities about AI

Traditional application domains of AI

Vision

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



Traditional application domains of AI

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

2025-10-02

Course 1: Generalities about AI

Traditional application domains of AI

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



IMT-Atlantique

Course 1: Generalities about AI

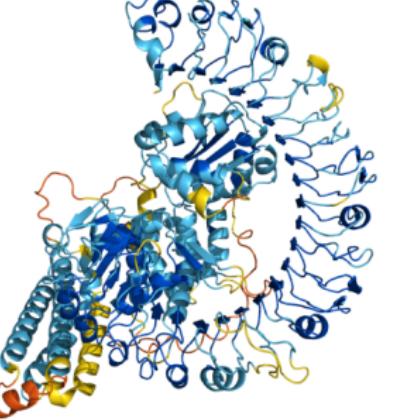
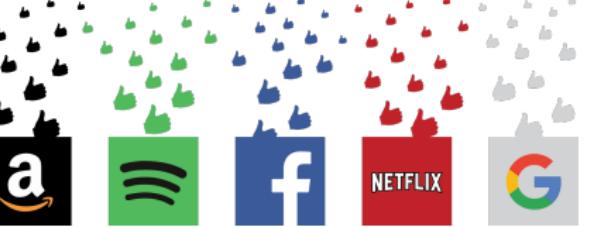
5 / 22

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/>



Course 1: Generalities about AI

2025-10-02

Traditional application domains of AI

Tons of other domains...

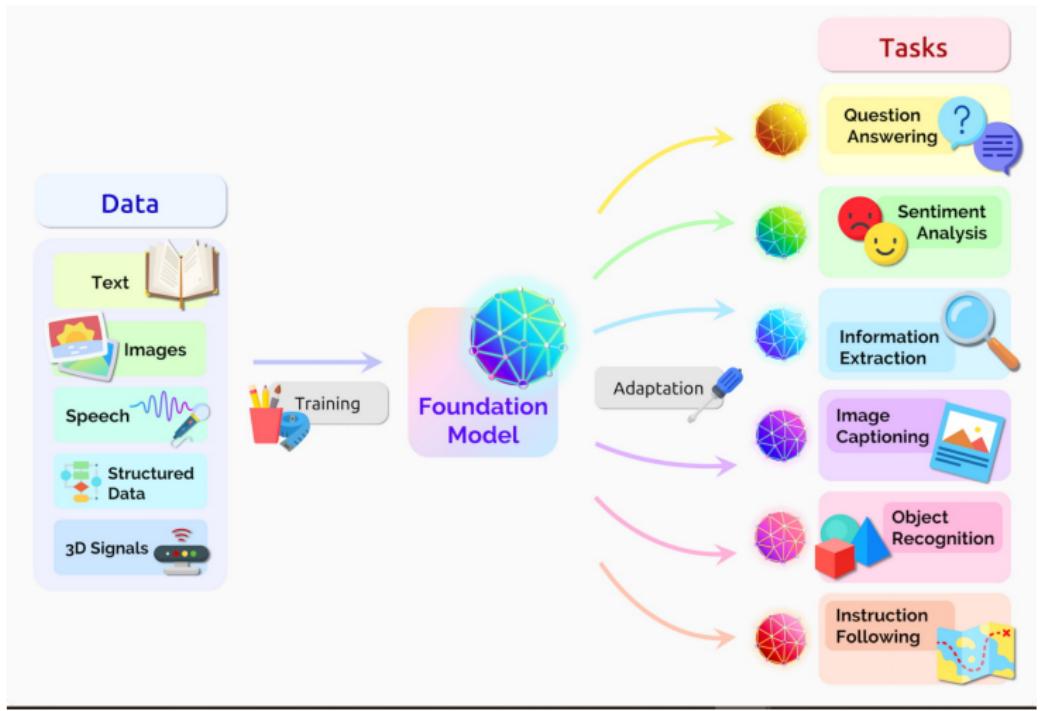
- Medical imaging,
- Decision aid,
- Data mining,
- Visualization,
- Recommender systems,
- Market analysis...

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



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

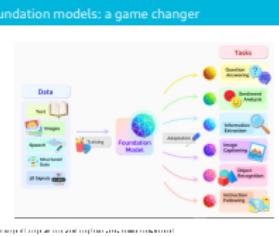


Source: <https://blogs.nvidia.com/blog/what-are-foundation-models/>

Course 1: Generalities about AI

2025-10-02

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, the main content area has a light gray background. On the left, there is a dark gray sidebar containing a user icon and the text "Write an introduction to a master course on artificial intelligence for an engineering school". The main content area starts with a green icon representing a document or message, followed by the text: "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 content area, there is a series of small, semi-transparent navigation icons.

2025-10-02

Course 1: Generalities about AI

└ Generative AI: a recent breakthrough

trained on CommonCrawl, Webtext, Books, Wikipedia

The screenshot shows a presentation slide with a white background. At the top right, there is a small section titled "Generative AI: a recent breakthrough" with some bullet points. The main content area has a light gray background. It contains a large, bold title "Generative AI: a recent breakthrough" at the top. Below the title, there is a list of bullet points:

- 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!

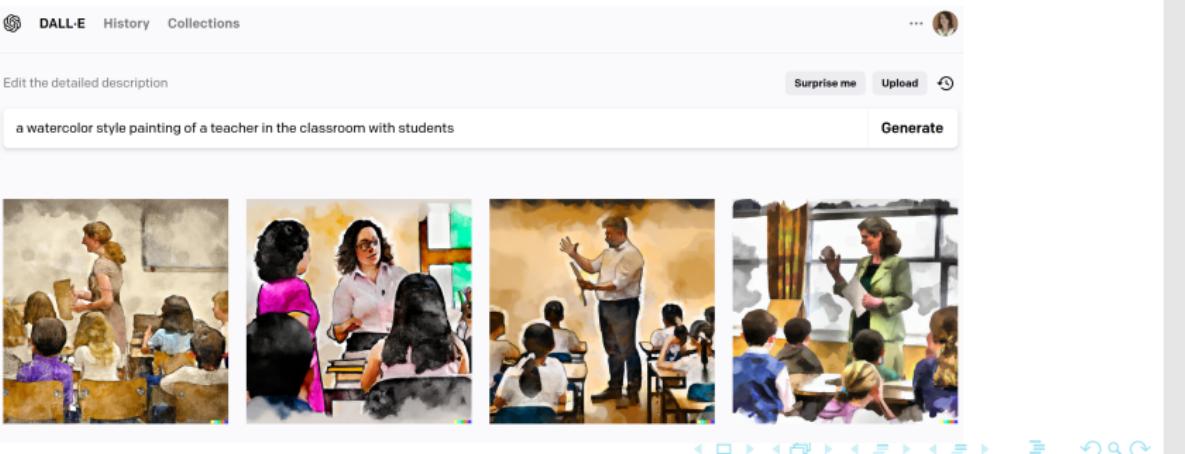
At the bottom of the slide, there is a small footer with the text "Text Synthesis with Large Language Models".

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>))



Course 1: Generalities about AI

└ Generative AI: a recent breakthrough

Both use diffusion models to encode and Vision Transformer

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>))

A screenshot of a presentation slide titled 'Generative AI: a recent breakthrough'. It features a section titled 'Image Synthesis' with three bullet points: 'Stable Diffusion Models', 'DALL-E', and 'Midjourney'. Below this is a note about 'multimodality'. On the right side of the slide, there is a large image showing several thumbnail versions of AI-generated images, likely generated by DALL-E or similar models, depicting various scenes such as people in classrooms and landscapes.

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

Course 1: Generalities about AI

2025-10-02

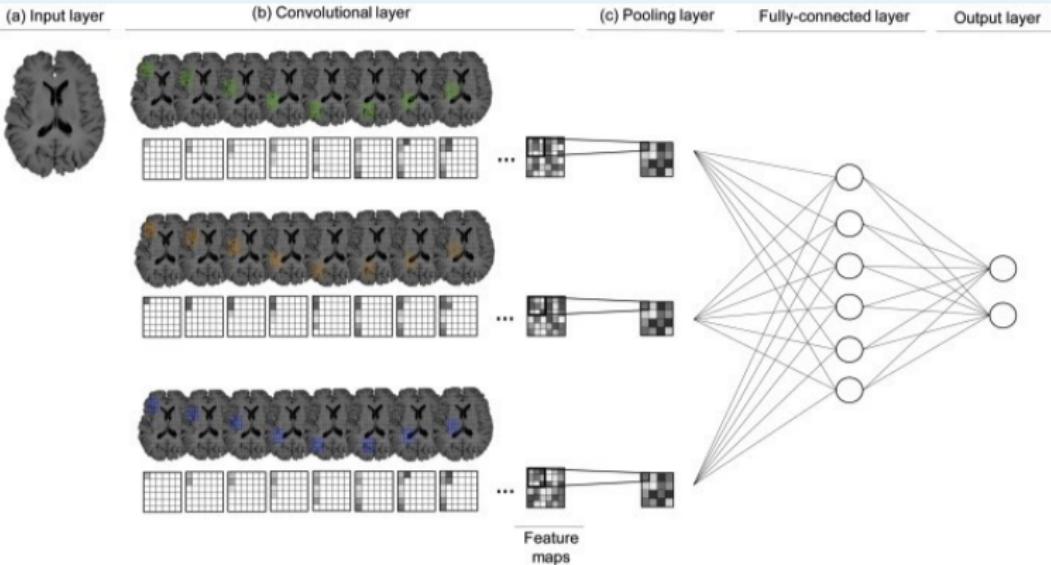
└ Generative AI: a recent breakthrough

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



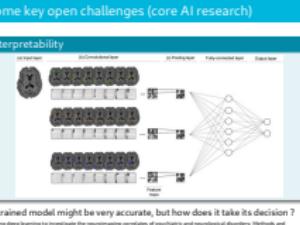
A trained model might be very accurate, but how does it take its decision ?

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

Course 1: Generalities about AI

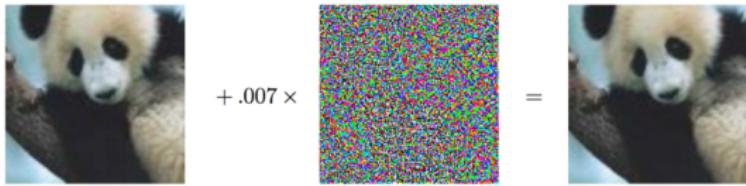
2025-10-02

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.

Course 1: Generalities about AI

2025-10-02

Some key open challenges (core AI research)

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

Deep and steep

Computing power used in training AI systems

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

By fundamentals

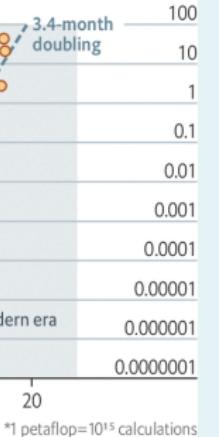
- Language
- Speech
- Vision
- Games
- Other

Two-year doubling
(Moore's Law)

Perceptron, a simple artificial neural network

AlphaGo Zero becomes its own teacher of the game Go

AlexNet, image classification with deep convolutional neural networks



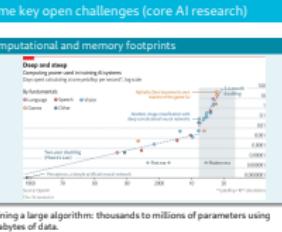
Source: OpenAI
The Economist

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

Course 1: Generalities about AI

2025-10-02

Some key open challenges (core AI research)



Let's dive into details!



LET'S DIVE INTO DETAILS!

2025-10-02

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

2025-10-02

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.

Machine Learning

Examples

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

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

2025-10-02

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.

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

- **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

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

2025-10-02

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.

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

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)

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

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**.

Course 1: Generalities about AI

2025-10-02

└ 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)

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 \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.

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)

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.

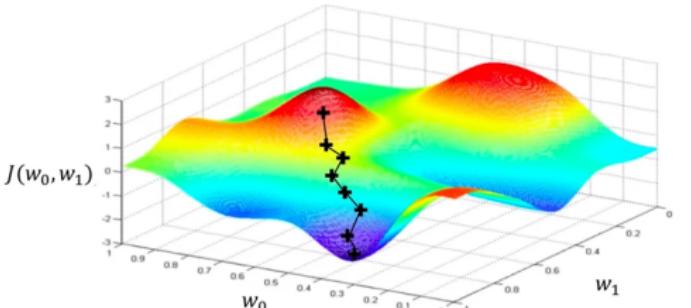
Global formalism

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

2025-10-02

Course 1: Generalities about AI

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

■ Model parameters: $\mathbf{W}^* = \text{argmin}(J(\mathbf{W}))$

Training Algorithm

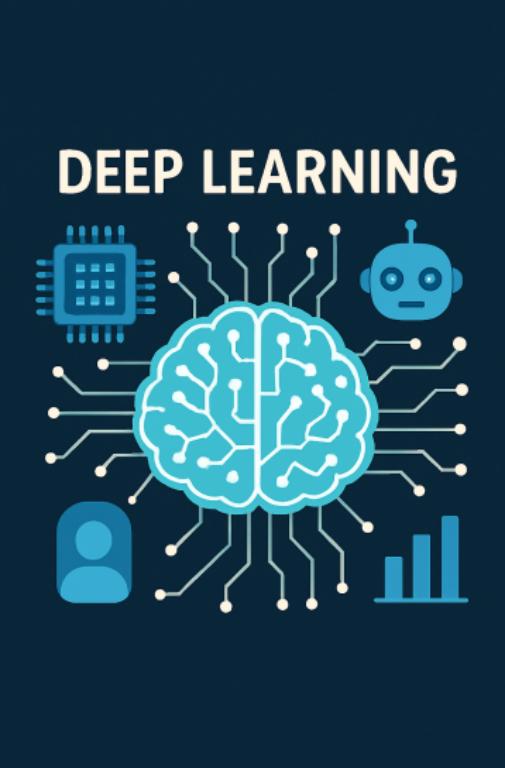
Gradient Descent:

- 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

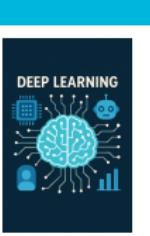
Deep Learning

2025-10-02 Course 1: Generalities about AI

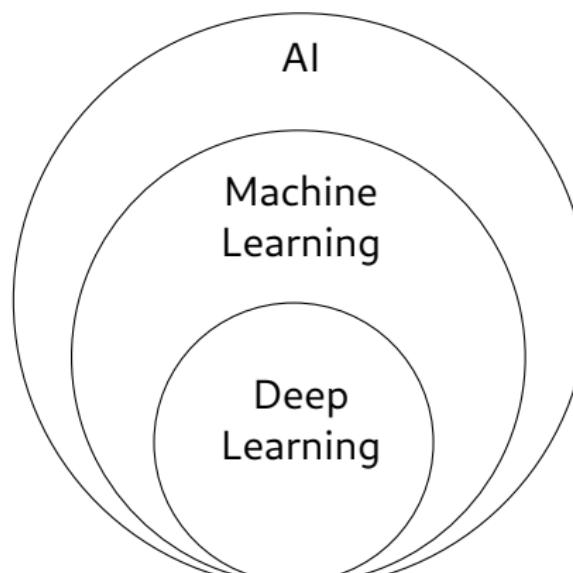
Deep Learning



DEEP LEARNING



Deep Learning: A Particular Case of Machine Learning



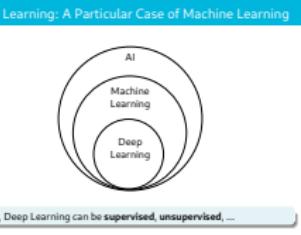
A Venn diagram consisting of three nested circles. The outermost circle is labeled "AI". Inside it is a smaller circle labeled "Machine Learning". Inside that is another circle labeled "Deep Learning".

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

2025-10-02 Course 1: Generalities about AI

Deep Learning: A Particular Case of Machine Learning

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



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

IMT-Atlantique

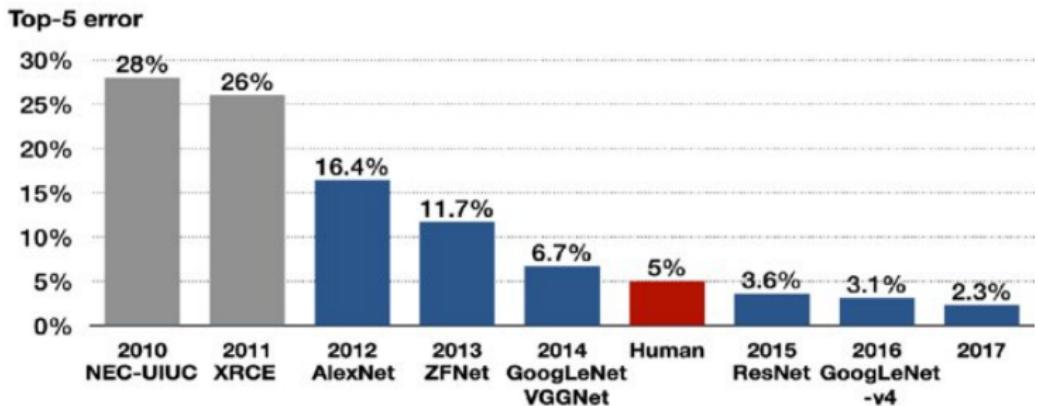
Course 1: Generalities about AI

14/22

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.

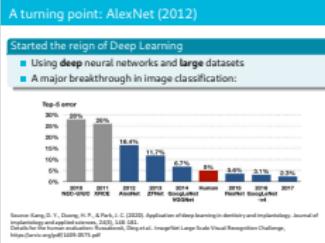
Details for the human evaluation: Russakovsky, Dieg et al.. ImageNet Large Scale Visual Recognition Challenge,
<https://arxiv.org/pdf/1409.0575.pdf>

Course 1: Generalities about AI

2025-10-02

└ 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.

Course 1: Generalities about AI

2025-10-02

└ 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)

Geoffrey Hinton <ul style="list-style-type: none">Cognitive psychologist and computer scientist,Prof. at University of Toronto and works for Google,Known for back-propagation and Boltzmann machines.	Yoshua Bengio <ul style="list-style-type: none">Computer scientist,Prof. at Université de Montréal and head of MILA,Known for his work on deep learning.	Yann le Cun <ul style="list-style-type: none">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.



Course 1: Generalities about AI

2025-10-02

- └ Where did the Deep Learning revolution came from?

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

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.

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.



2025-10-02

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?

- 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.



IMT-Atlantique

Course 1: Generalities about AI

17/22

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.



2025-10-02

Course 1: Generalities about AI

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.

The share of huge datasets on Internet.

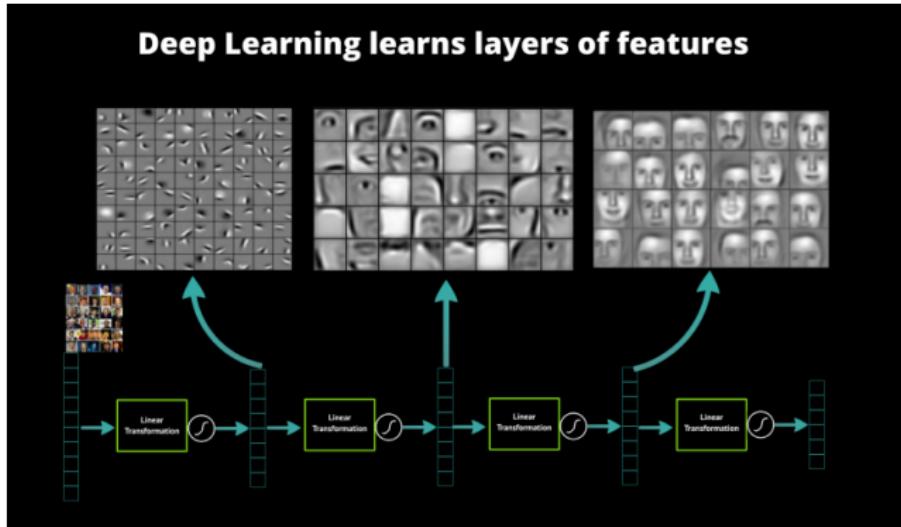
HuggingFace / Github / Arxiv: easy and open-source share of research.

The rise of representation learning.

opencomputerscience

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.



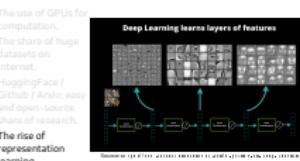
2025-10-02

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.

Where did the Deep Learning revolution came from?



Traditional Deep Learning (before 2020)

Machine Learning

```
graph LR; A[Input] --> B[Feature extraction]; B --> C[Classification]; C --> D[Output: Car | Not car]
```

Deep Learning

```
graph LR; A[Input] --> B[Feature extraction + Classification]; B --> D[Output: Car | Not car]
```

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

2025-10-02 Course 1: Generalities about AI

Traditional Deep Learning (before 2020)

Traditional Deep Learning (before 2020)

Traditional Deep Learning (before 2020)

Machine Learning

Input → Feature extraction → Classification → Output: Car | Not car

Deep Learning

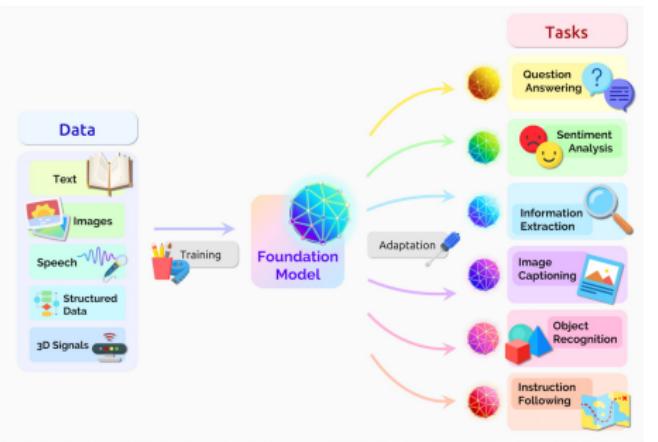
Input → Feature extraction + Classification → Output: Car | Not car

IMT-Atlantique

Course 1: Generalities about AI

18 / 22

- 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/>

2025-10-02

Deep Learning today - Foundation models (1/3)



Deep Learning today - Foundation models (2/3)

2025-10-02 Course 1: Generalities about AI

Deep Learning today - Foundation models (2/3)

The diagram illustrates the progression of AI models:

- Machine Learning:** An input image of a car is processed by a person performing "Feature extraction", which is then fed into a "Classification" step using a simple neural network. The output is "Car" or "Not car".
- Deep Learning:** An input image of a car is processed directly by a complex, multi-layered neural network that performs both "Feature extraction + Classification". The output is "Car" or "Not car".
- Foundation models:** An input image of a car is processed by a two-stage pipeline. First, it undergoes "Feature extraction (fixed model)" using a pre-trained neural network. Then, the extracted features are processed by a "Classification" step using a smaller neural network. The output is "Car" or "Not car".

Legend for the diagram icons:

- Machine Learning: Car icon → Person icon → Network icon → Blue square icon.
- Deep Learning: Car icon → Network icon → Blue square icon.
- Foundation models: Car icon → Network icon → Network icon → Blue square icon.

Machine Learning

```
graph LR; Input[Input] --> FE[Feature extraction]; FE --> CL[Classification]; CL --> Output[Output: Car | Not car];
```

Input → Feature extraction → Classification → Output

Deep Learning

```
graph LR; Input[Input] --> DL[Deep Learning]; DL --> Output[Output: Car | Not car];
```

Input → Deep Learning → Output

Foundation models

```
graph LR; Input[Input] --> FE[Feature extraction]; FE --> CL[Classification]; CL --> Output[Output: Car | Not car];
```

Input → Feature extraction (fixed model) → Classification → Output

IMT-Atlantique

Course 1: Generalities about AI

20/22

■ 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!

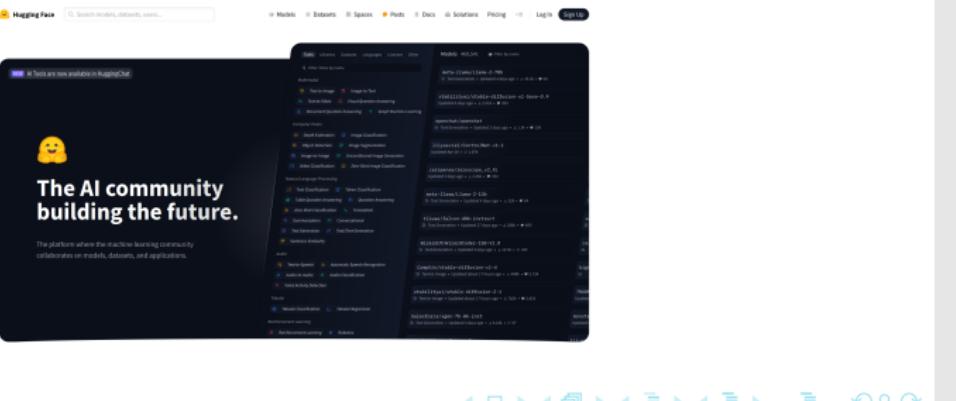
- Some open-source Foundation models exist, and are available on HuggingFace <https://huggingface.co/>
- We will use such algorithms during our labs sessions.

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

- 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)

- 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.



The screenshot shows the Hugging Face homepage. At the top, there's a search bar and navigation links for Models, Datasets, Spaces, Posts, Docs, Signin, and Login. Below the header, a large banner features the text "The AI community building the future." with a yellow emoji of a smiling face. To the right of the banner is a sidebar with categories like "All models", "All datasets", and "All spaces". The main content area displays a grid of cards representing different AI models and datasets, each with a thumbnail, name, and a brief description.

2025-10-02

Course 1: Generalities about AI

Deep Learning today - Foundation models (3/3)

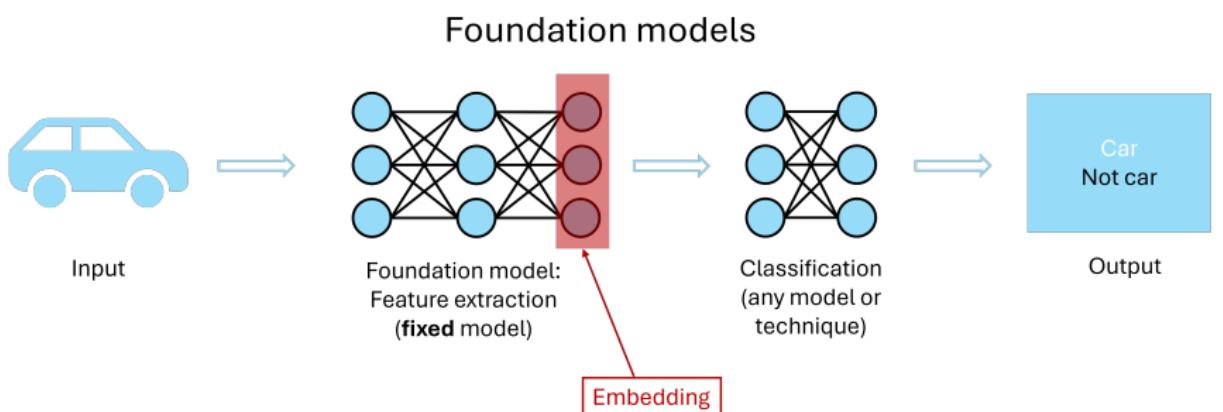
Deep Learning today - Foundation models (3/3)

- 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.



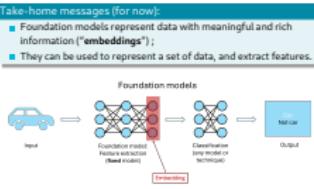
Take-home messages (for now):

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



2025-10-02

Lab Session 1



Lab Session 1

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.

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/>

Course 1: Generalities about AI

2025-10-02

Lab Session 1

Lab Session 1

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.

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/>