université PARIS-SACLAY

DE L'INTELLIGENCE ARTIFICIELLE AUX MODÈLES DE FONDATION

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GDR RADIA

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MIA PARIS-SACLAY
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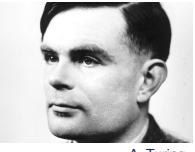
AGROPARISTECH
Institut des Sciences et Industries du Vivant et de l'Environnement

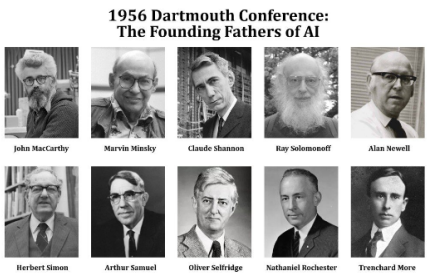
From AI to machine-learning

Historique rapide de l'IA

Naissance de l'informatique... Et de l'Intelligence Artificielle



A. Turing



Dartmouth conference creation of IA

G. Hinton

Y. Lecun
Automated cheque reading

E. Dickmanns : 1000km in autonomous vehicle

IBM Deeper Blue

First computer

DARPA

Backpropagation

1941 1950 1956 1958 1963 1965 1972 1979 1986 1987 1990 1992 1993 1994 1997

Dynamic programming

LISP Language
Perceptron

PROLOG

1st Neural Network

DARPA MUC

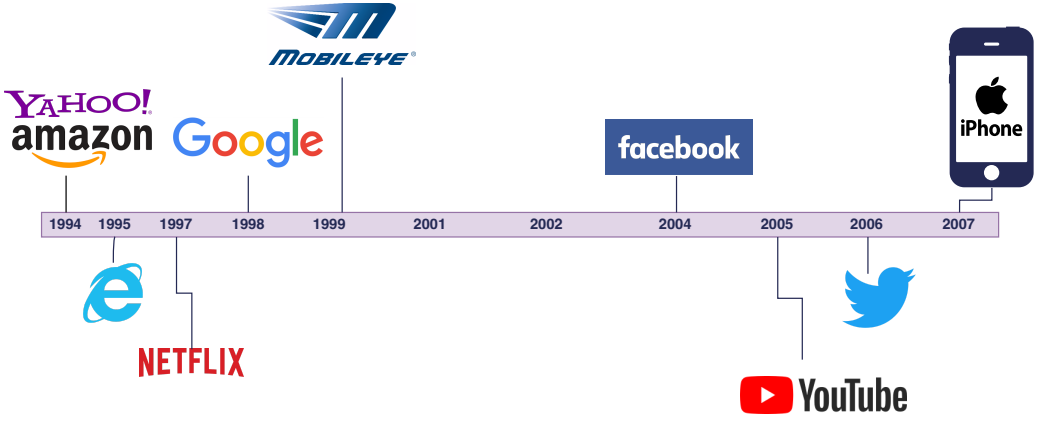
DARPA TREC

SVM

C4.5
Decision Tree

Historique rapide de l'IA

Emergence (ou refondation) des GAFAM/GAMMA



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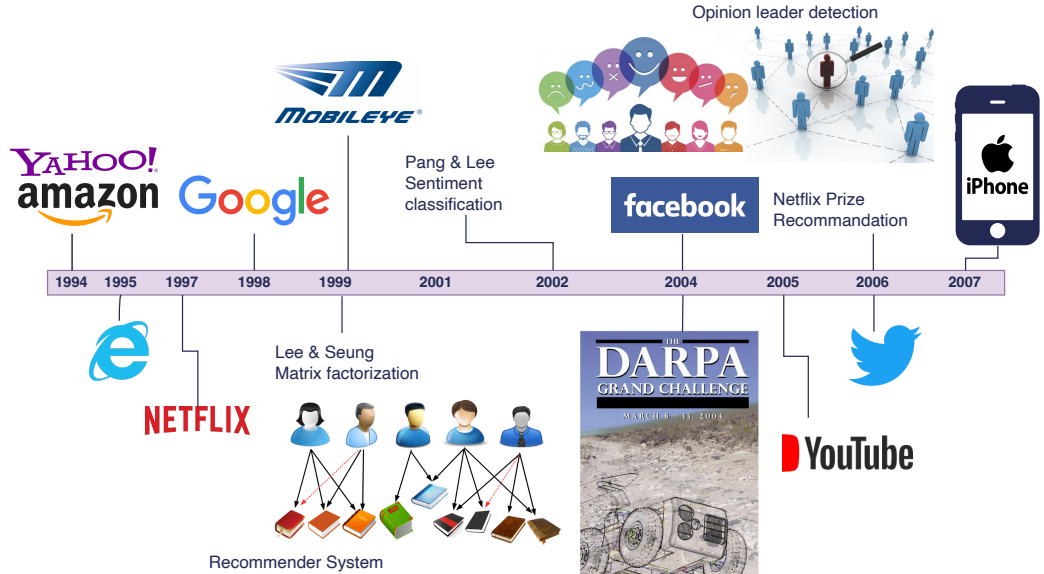
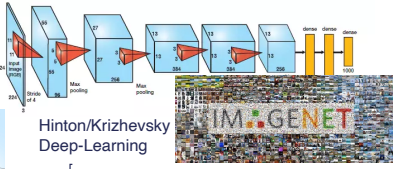


Historique rapide de l'IA

Formation d'une vague de l'Intelligence Artificielle

Thrun:
DARPA Gd Challenge
victory

Google
car



Hinton/Krizhevsky
Deep-Learning

K. Cho
Traduction auto.

Translate (v2)

AlphaGo

ChatGPT

2005 2007 2008 2009 2010 2011 2012 2014 2015 2016 2017 2020 2023

Y. Koren
Challenge
Netflix

kaggle

SIRI

amazon alexa

Google
DeepMind
Acquisition : $400M

IBM Jeopardy win

MOBILEYE
An intel company
Acquisition :
$15B

AlphaFold

OpenAI
DALL·E 2

Ingrédients de l'Intelligence Artificielle

Intelligence Artificielle & Machine Learning

Input (**X**)		Output (**Y**)	Application
email	→	spam? (0/1)	spam filtering
audio	→	text transcript	speech recognition
English	→	Chinese	machine translation
ad, user info	→	click? (0/1)	online advertising
image, radar info	→	position of other cars	self-driving car
image of phone	→	defect? (0/1)	visual inspection

IA : programmes informatiques qui s'adonnent à des tâches qui sont, pour l'instant, accomplies de façon plus satisfaisante par des êtres humains car elles demandent des processus mentaux de haut niveau.

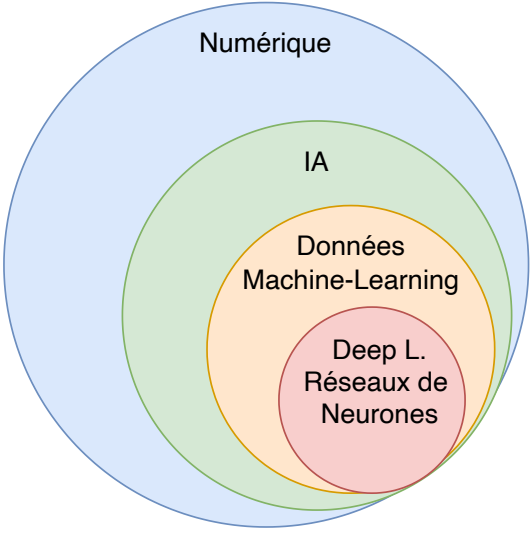
Marvin Lee Minsky, 1956

N-AI (Narrow Artificial Intelligence), dédiée à une tâche

$\neq$ **G-AI (General AI)** qui remplace l'humain dans des systèmes complexes.

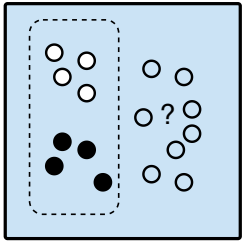
Andrew Ng, 2015

Place de l'IA dans le numérique

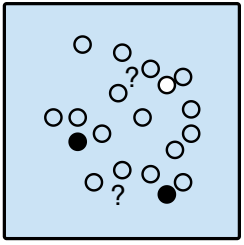


- Caisse automatique du supermarché
- Google Maps
- Système prédictif (e.g. marché immobilier), recommandation
- chatGPT

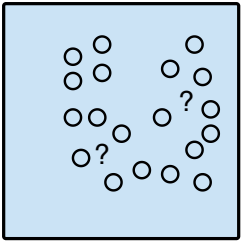
Cadres en machine-learning



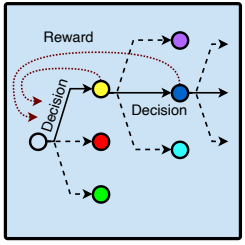
Apprentissage supervisé



Apprentissage semi-supervisé



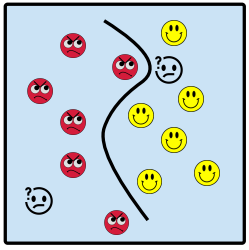
Apprentissage non-supervisé



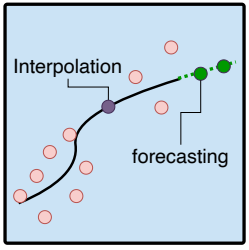
Apprentissage par renforcement

- Différentes **modalités** de données (images, textes, données numériques...)
- Différents **étiquetages**

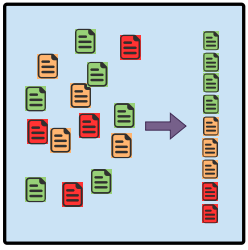
Cadres en machine-learning



Classification



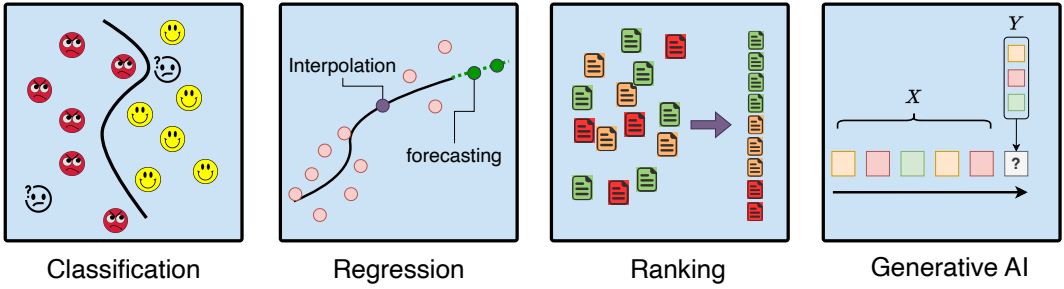
Regression



Ranking

- Différentes **modalités** de données (images, textes, données numériques...)
- Différents **étiquetages**
- Différentes types de **prédictions**

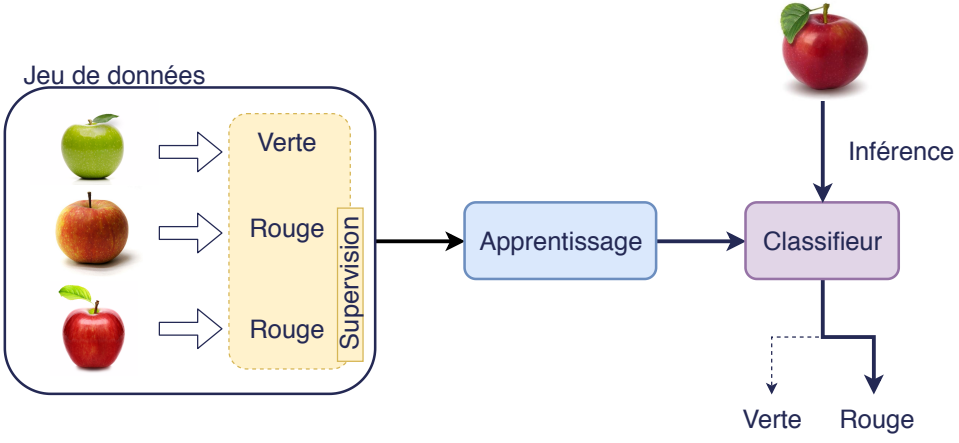
Cadres en machine-learning



Classification Regression Ranking Generative AI

- Différentes **modalités** de données (images, textes, données numériques...)
- Différents **étiquetages**
- Différentes types de **prédictions**

Chaine de traitements supervisée & modèles



- Promesse = construire un modèle *uniquement* à partir des observations

Chaine de traitements supervisée & modèles

Extraction de caractéristiques

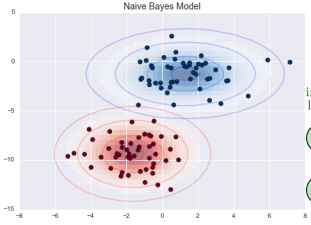
Diamètre
Texture
Niveau de rouge
Niveau de bleu
...

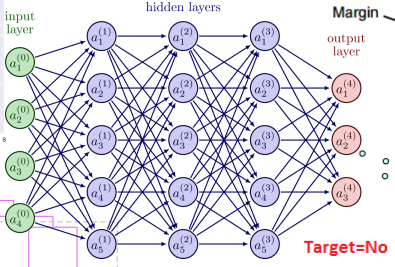
Niveau de bleu

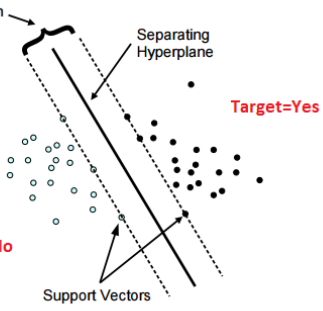
f( ) = pred

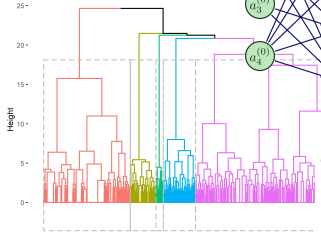
supervision

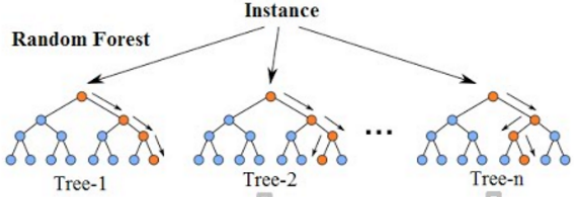
Chaine de traitements supervisée & modèles











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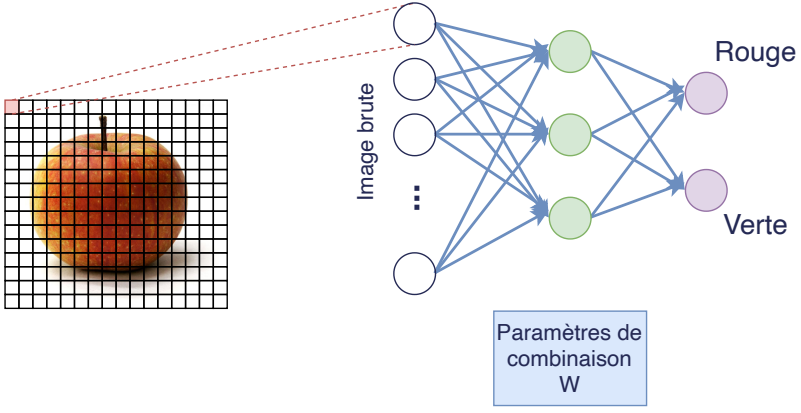
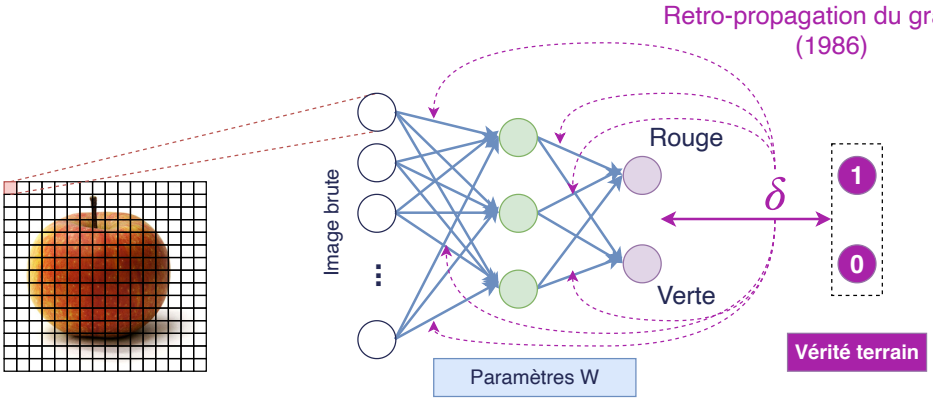


- Initialisation aléatoire...

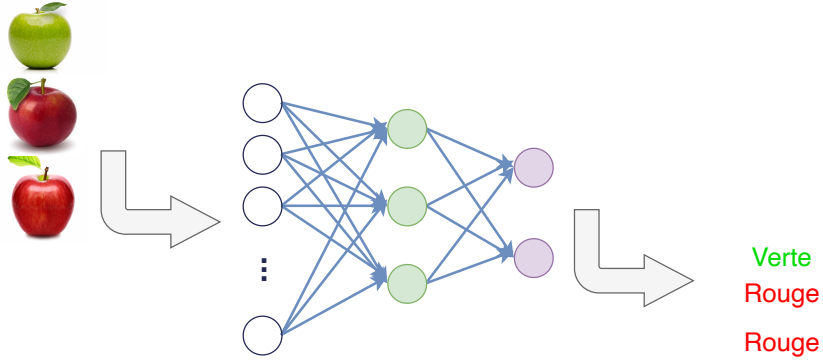
Et décision aléatoire (au début!)

Chaine de traitements supervisée & modèles



- Mise à jour des poids
- Pas à pas epsilonesque, nombreuses itérations sur les données

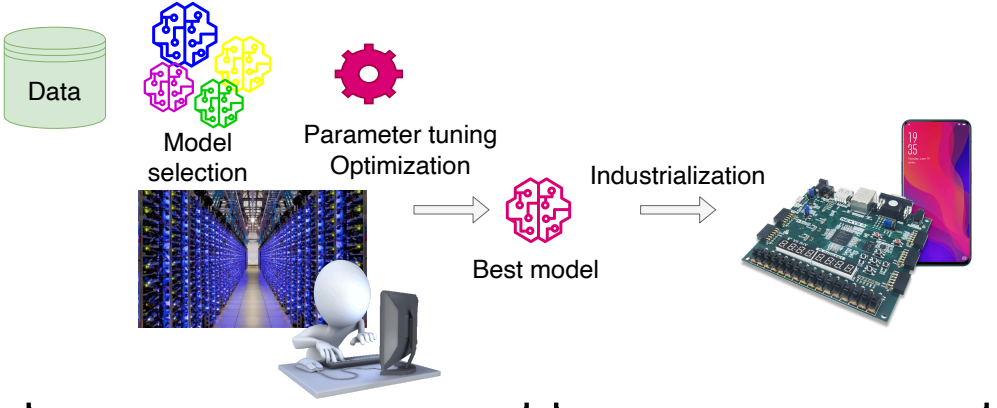
Chaine de traitements supervisée & modèles



- **Apprentissage** lent et couteux
- **Inférence** (beaucoup plus) rapide

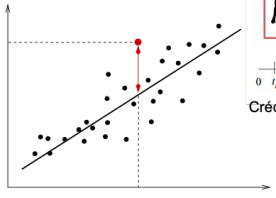
Chaine de traitements supervisée & modèles

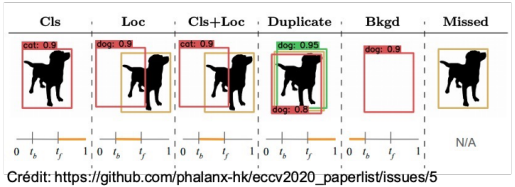
Différentes étapes en machine-learning



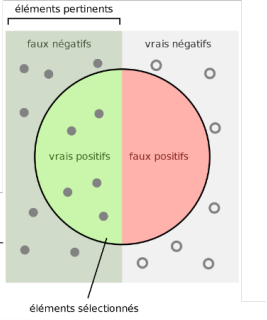
Mesurer les performances

Estimer les performances (en généralisation)...
Est aussi important que l'apprentissage du modèle lui-même!

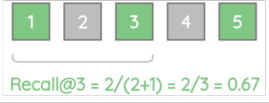


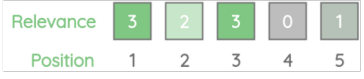


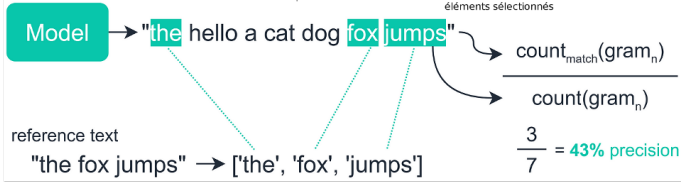
Crédit: https://github.com/phalanx-hk/eccv2020_paperlist/issues/5



$$\text{Précision} = \frac{\text{vrais positifs}}{\text{éléments sélectionnés}} \qquad \text{Rappel} = \frac{\text{vrais positifs}}{\text{éléments pertinents}}$$







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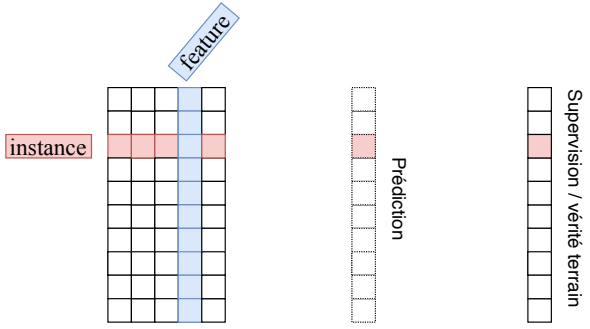

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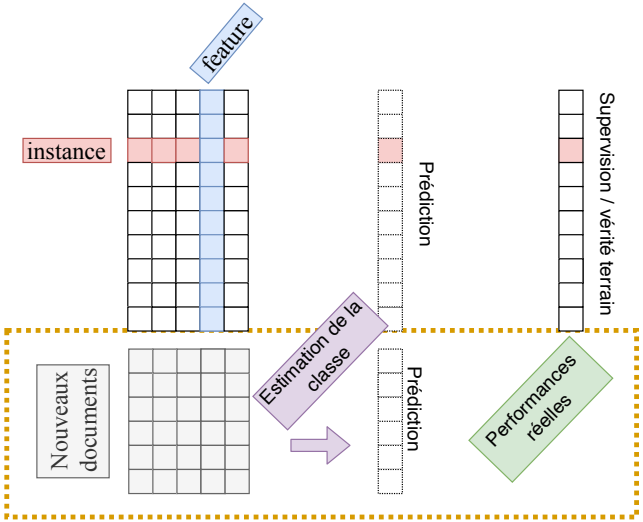
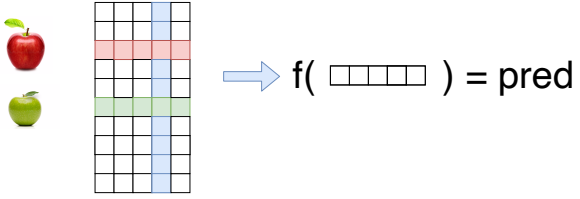


Deep-Learning & NLP*

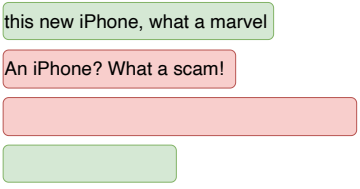
[* Traitement Automatique de la Langue Naturelle]

From tabular data to text

- Tabular data
  - Fixed dimension
  - Continuous values



- Textual data
  - Variable length
  - Discrete values

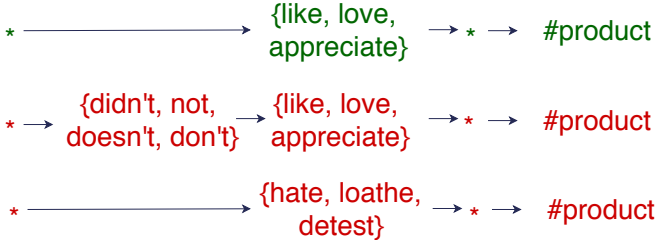


AI + Textual Data: Natural Language Processing (NLP)

NLP = largest scientific community in AI

Linguistics [1960-2010]

Rule-based Systems:



- Requires expert knowledge
- Rule extraction $\Leftrightarrow$ very clean data
- Very high precision
- Low recall
- Interpretable system

AI + Textual Data: Natural Language Processing (NLP)

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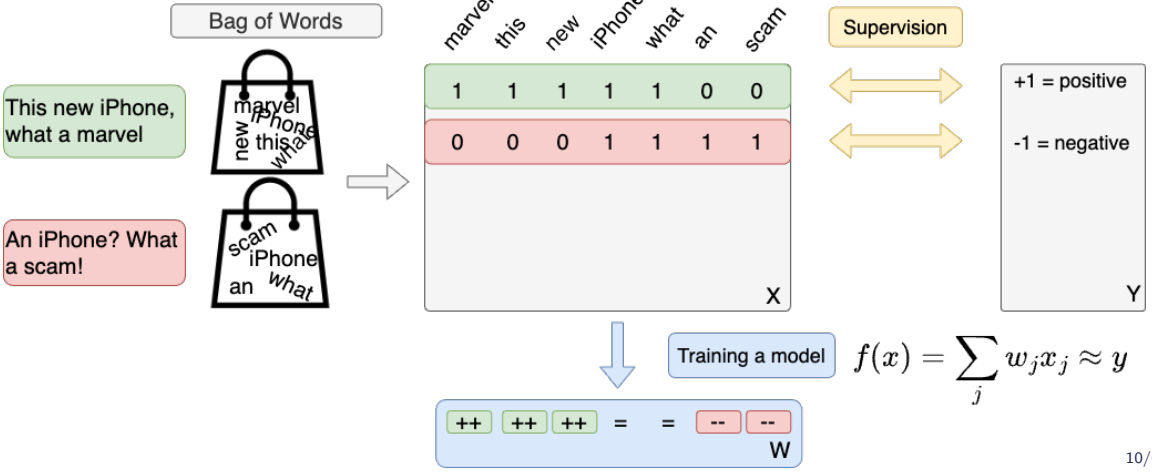
Machine Learning [1990-2015]



AI + Textual Data: Natural Language Processing (NLP)

NLP = largest scientific community in AI

Linguistics [1960-2010]

- Requires expert knowledge
- Rule extraction $\Leftrightarrow$ very clean data

\+ Interpretable system
\+ Very high precision
− Low recall

Machine Learning [1990-2015]

- Little expert knowledge needed
- Statistical extraction $\Leftrightarrow$ robust to noisy data

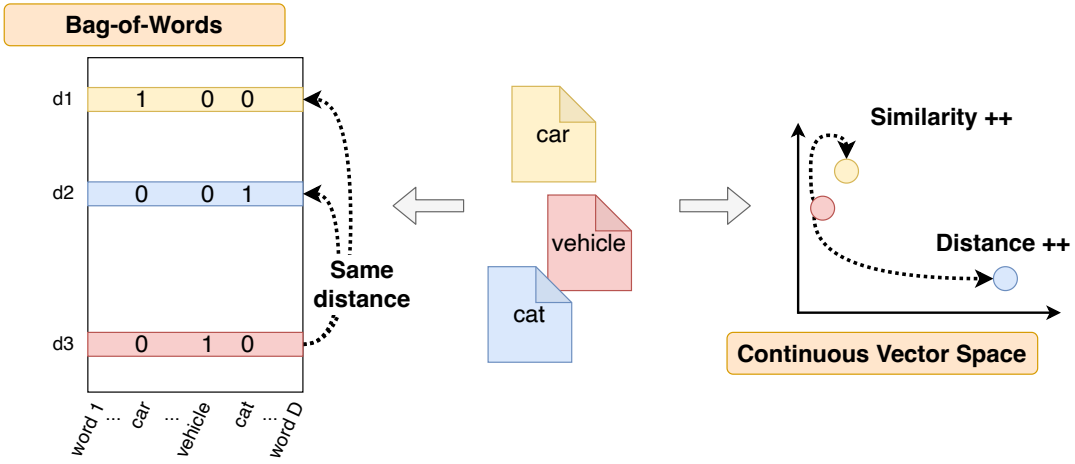
$\approx$ Less interpretable system
− Lower precision
\+ Better recall

Precision = criterion for acceptance by industry

→ Link to metrics

Deep/Representation Learning for Text Data

From Bag of Words to Vector Representations [2008, 2013, 2016]

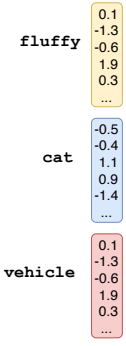


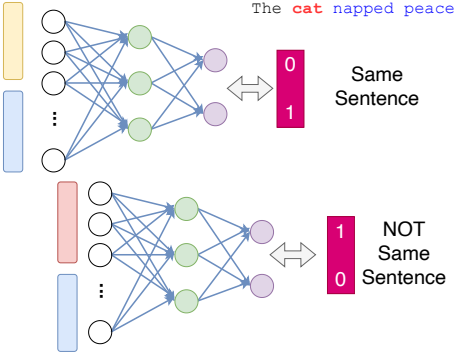
LeCun, Y., Bengio, Y., Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.

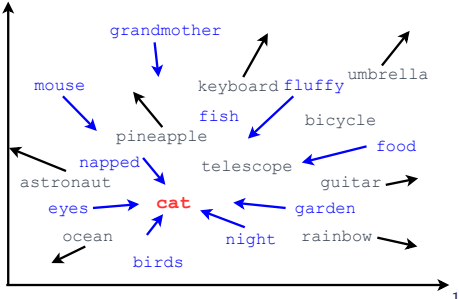
Deep/Representation Learning for Text Data

From Bag of Words to Vector Representations [2008, 2013, 2016]

The fluffy cat napped lazily in the sunbeam.
I adopted a stray cat from the shelter last week.
My cat loves to chase after toy mice.
The black cat stealthily crept through the dark alley.
I often find my cat perched on the windowsill, watching birds.
She gently stroked her cat's fur as it purred contentedly.
Our neighbor's cat frequently visits our backyard.
My cat has a preference for fish flavored cat food.
The cat stealthily stalked a mouse in the garden.
My grandmother has a collection of porcelain cat figurines.
The cat napped peacefully in the warm sunlight.



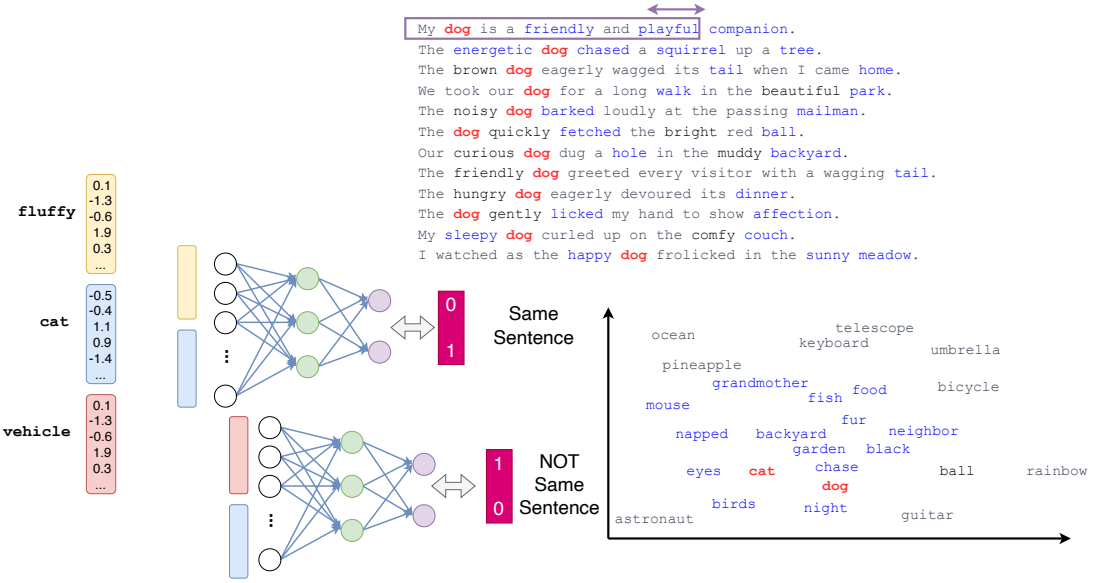




Deep/Representation Learning for Text Data

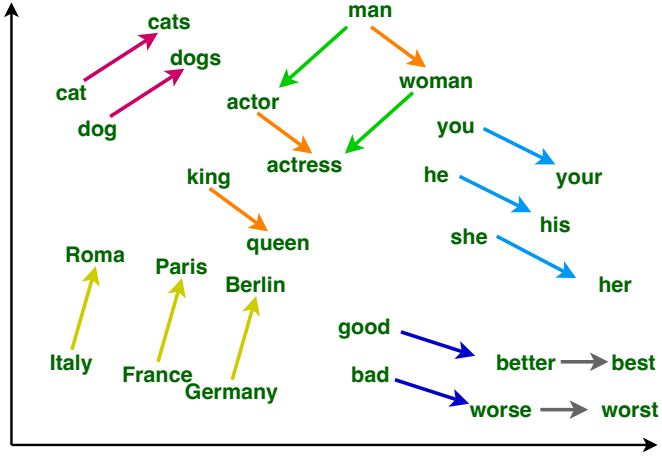
From Bag of Words to Vector Representations [2008, 2013, 2016]

My **dog** is a friendly and playful companion.
The energetic **dog** chased a squirrel up a tree.
The brown **dog** eagerly wagged its tail when I came home.
We took our **dog** for a long walk in the beautiful park.
The noisy **dog** barked loudly at the passing mailman.
The **dog** quickly fetched the bright red ball.
Our curious **dog** dug a hole in the muddy backyard.
The friendly **dog** greeted every visitor with a wagging tail.
The hungry **dog** eagerly devoured its dinner.
The **dog** gently licked my hand to show affection.
My sleepy **dog** curled up on the comfy couch.
I watched as the happy **dog** frolicked in the sunny meadow.



Deep/Representation Learning for Text Data

From Bag of Words to Vector Representations [2008, 2013, 2016]



- Semantic Space:
  similar meaning
  $\Leftrightarrow$
  close position
- Structured Space:
  grammatical regularities,
  basic knowledge, ...

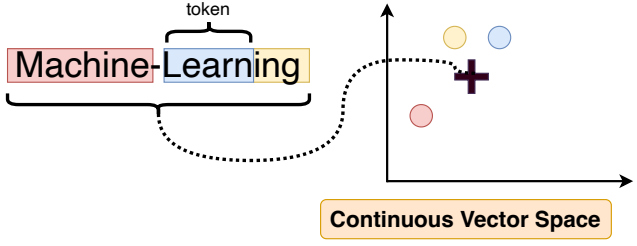
Distributed representations of words and phrases and their compositionality, Mikolov et al. NeurIPS 2013

Deep/Representation Learning for Text Data

From Bag of Words to Vector Representations [2008, 2013, 2016]

From Words to Tokens

Word Piece statistical split

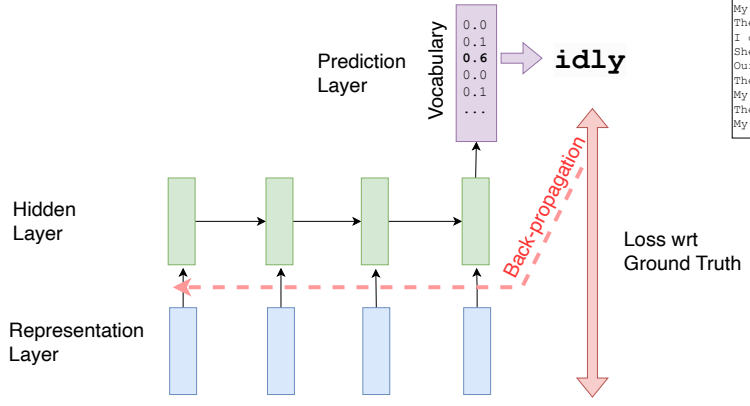


- Representation of unknown words
- Adaptation to technical domains
- Resistance to spelling errors

Enriching word vectors with subword information. Bojanowski et al. TACL 2017.

Aggregating word representations: towards generative AI

- Generation & Representation
- New way of learning word positions



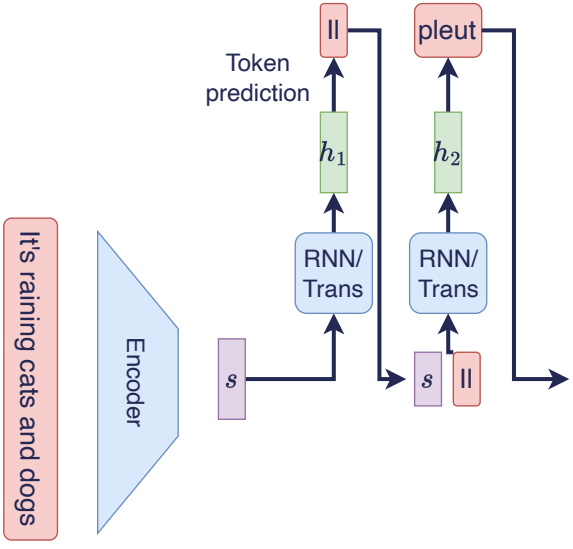
The fluffy cat napped lazily in the sunbeam.
I adopted a stray cat from the shelter last week.
My cat loves to chase after toy mice.
The black cat stealthily crept through the dark alley.
I often find my cat perched on the windowsill, watching birds.
She gently stroked her cat's fur as it purred contentedly.
Our neighbor's cat frequently visits our backyard.
The playful cat swatted at the dangling string with its paw.
My cat has a preference for fish flavored cat food.
The cat stealthily stalked a mouse in the garden.
My grandmother has a collection of porcelain cat figurines.

Corpus

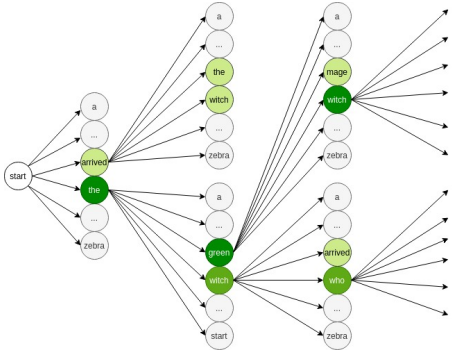
The fluffy cat napped lazily in the sunbeam.

Sequence to Sequence Learning with Neural Networks, Sutskever et al. NeurIPS 2014

Inference & Beam Search



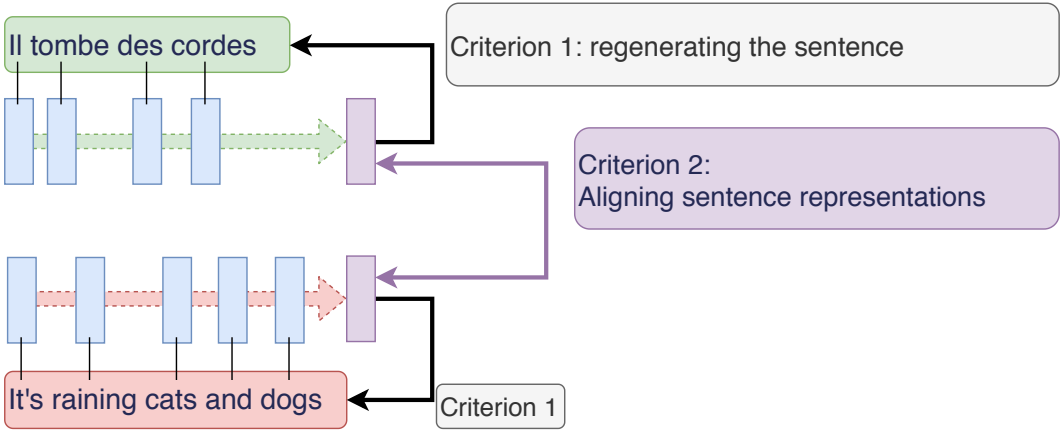
- High cost $\approx$ 1 call / token
- Max. likelihood principle
- NLP historical task =
  - specific classif./scoring archi.
  - constraint and/or post processing on generative archi.



Use-Case: Machine Translation

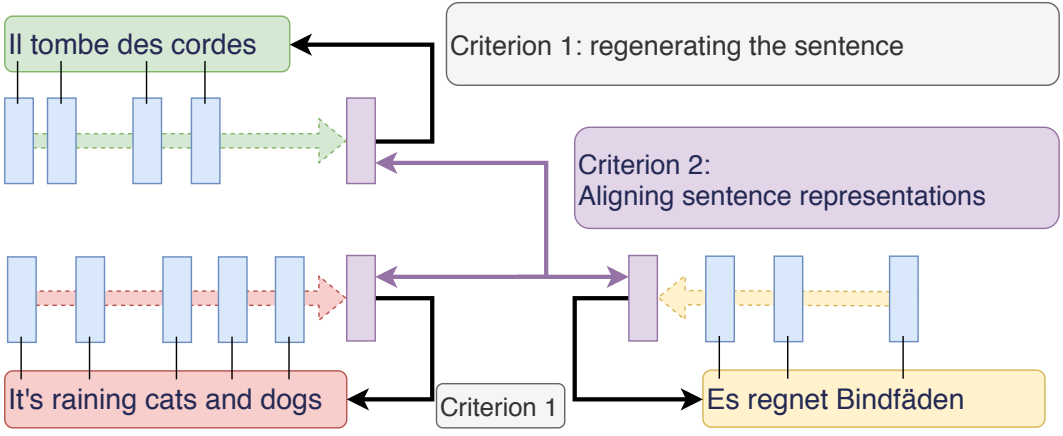
Beyond word-for-word translation, multilingual representation of sentences

Use-Case: Machine Translation



Beyond word-for-word translation, multilingual representation of sentences

Use-Case: Machine Translation

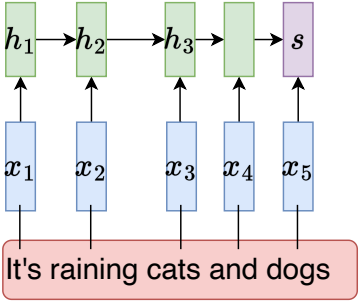


Beyond word-for-word translation, multilingual representation of sentences

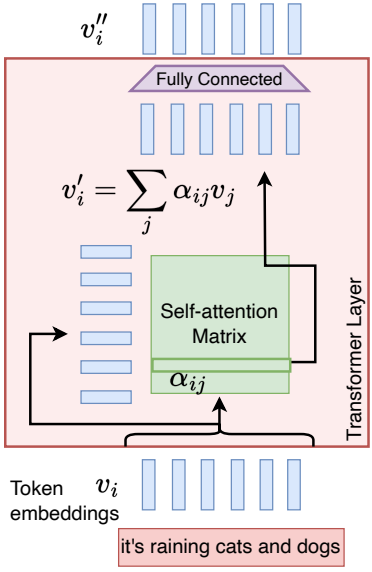
Transformer architecture: state-of-the-art aggregation

Recurrent Neural Network:

$$h_{t+1} = h_t W_1 + x_{t+1} W_2$$



Transformer:



Attention is all you need, Vaswani et al. NeurIPS 2017

Sequence to Sequence Learning with Neural Networks, Sutskever et al. NeurIPS 2014

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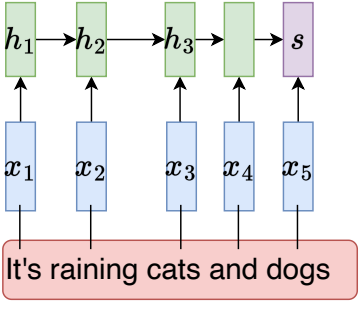
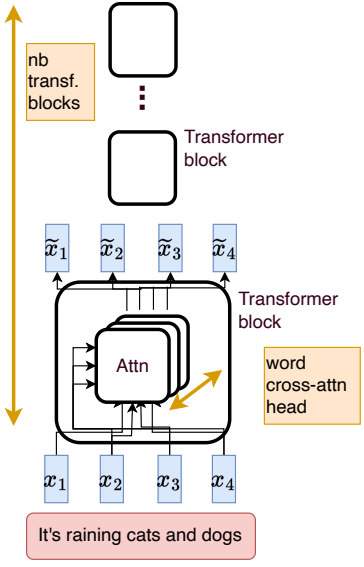


Transformer:



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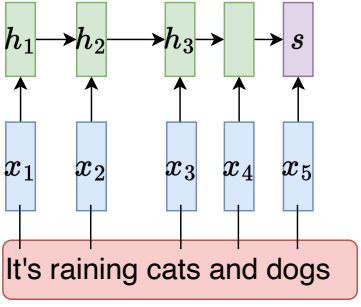
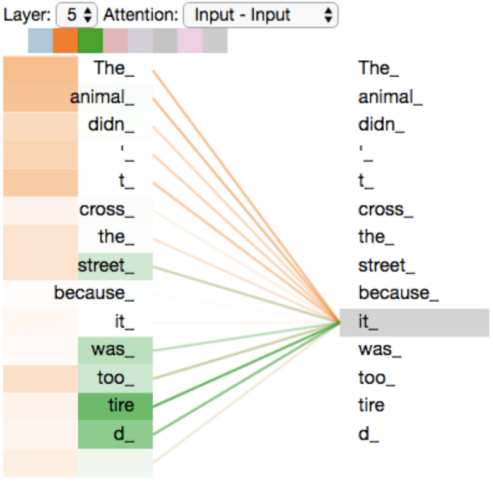


Transformer:



Attention is all you need, Vaswani et al. NeurIPS 2017

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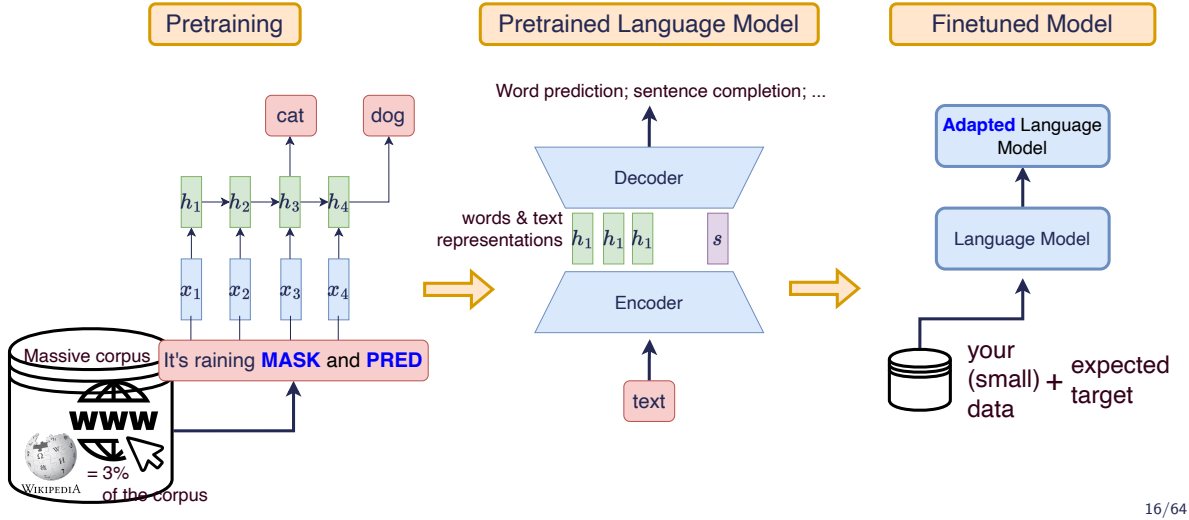
A new developpement paradigm since 2015

- Huge dataset + huge archi. $\Rightarrow$ unreasonable training cost
- Pre-trained architecture + 0-shot / finetuning



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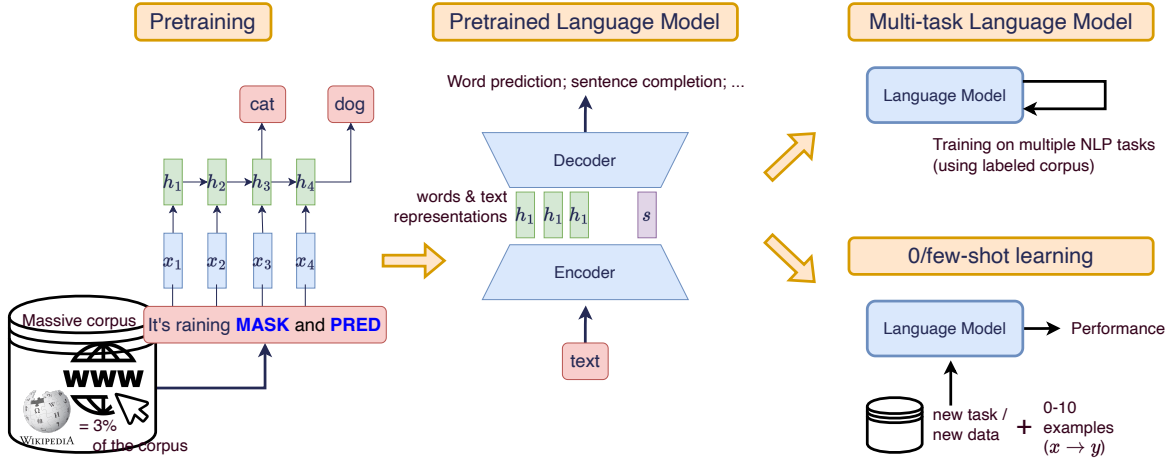


chatGPT

November 30, 2022

1 million users in 5 days
100 million by the end of January 2023
1.16 billion by March 2023

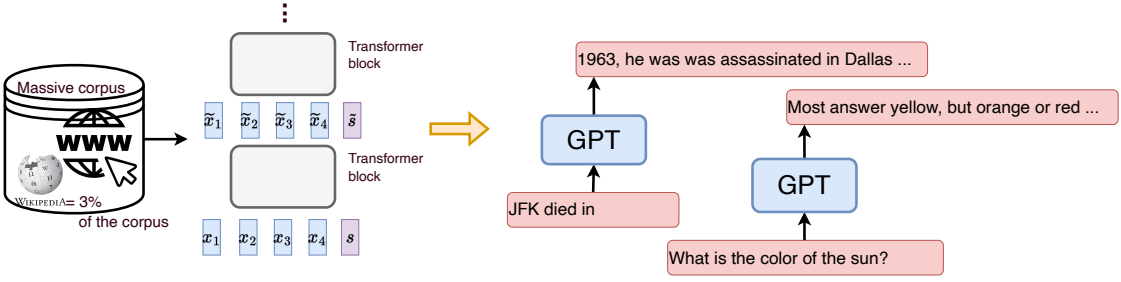
The Ingredients of chatGPT

0. Transformer + massive data (GPT)

Huge +Filtered dataset

Huge Transformer architecture

Causal pretraining



- Grammatical skills: singular/plural agreement, tense concordance
- Knowledges

Language Models are Few-Shot Learners, Brown et al. 2020

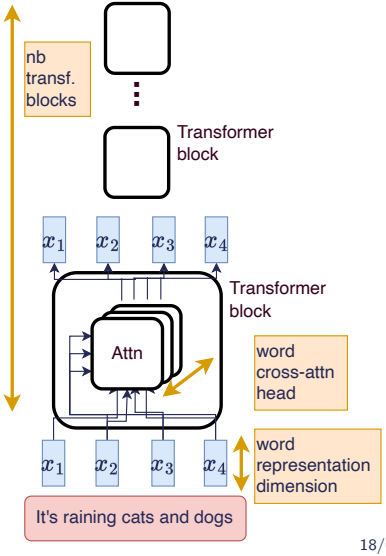
The Ingredients of chatGPT

1. More is better! (GPT)

+ more input words [500 ⇒ 2k, 32k, 100k]
+ more dimensions in the word space [500-2k ⇒ 12k]
+ more attention heads [12 ⇒ 96]
+ more blocks/layers [5-12 ⇒ 96]

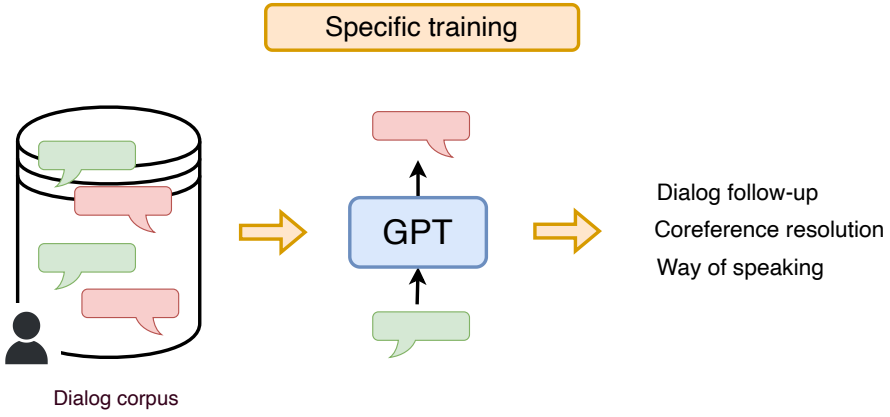
175 Billion parameters... What does it mean?

- $1.75 \cdot 10^{11} \Rightarrow$ 300 GB + 100 GB (data storage for inference) $\approx$ 400GB
- NVidia A100 GPU = 80GB of memory (=20k€)
- Cost for (1) training: 4.6 Million €



The Ingredients of chatGPT

2. Dialogue Tracking

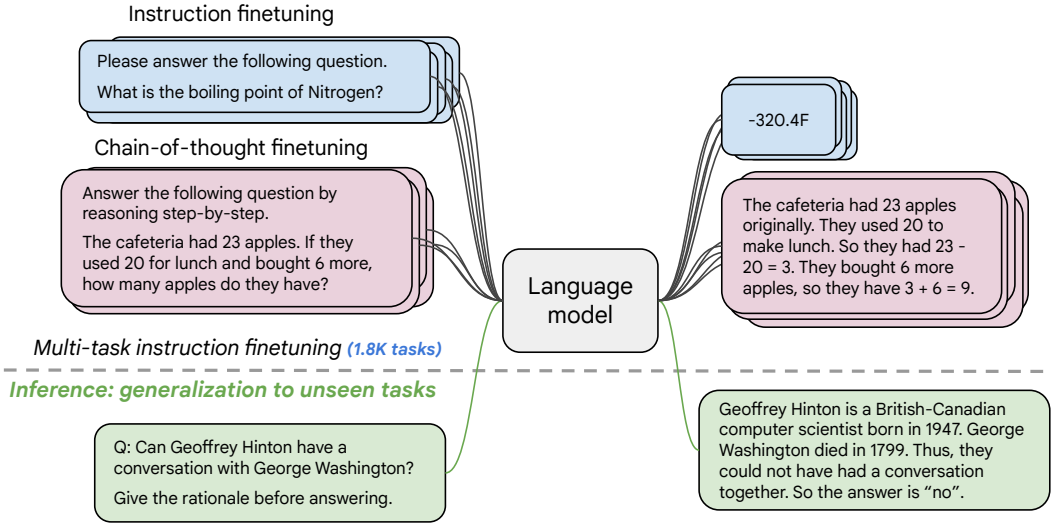


- **Very clean** data

Data generated/validated/ranked by humans

The Ingredients of chatGPT

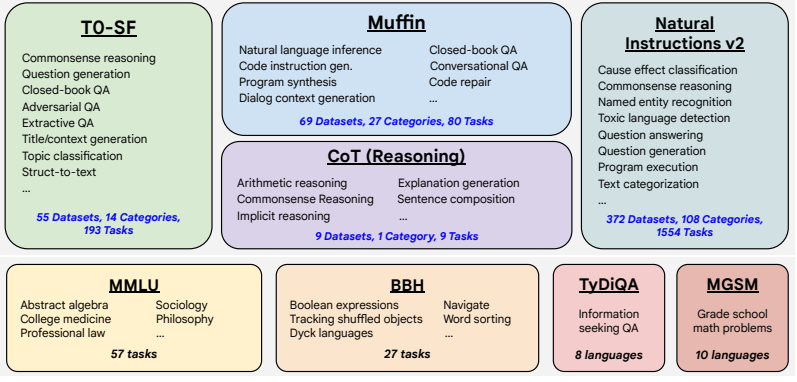
3. Fine-tuning on different (±) complex reasoning tasks

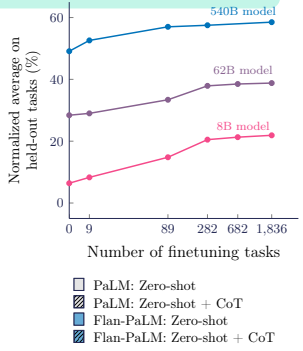


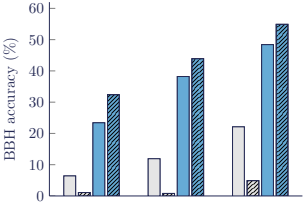
Scaling Instruction-Finetuned Language Models, Chung et al., JMLR 2024

The Ingredients of chatGPT

3. Fine-tuning on different (±) complex reasoning tasks



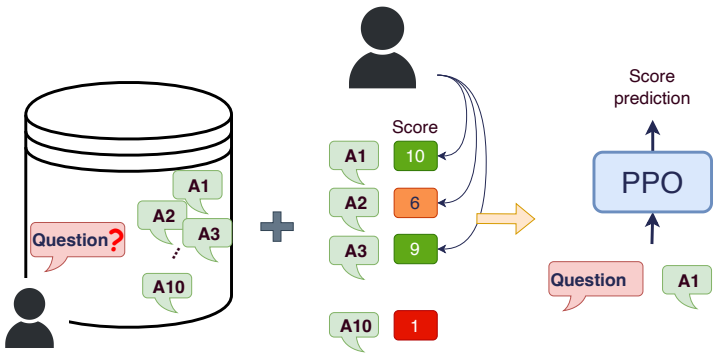


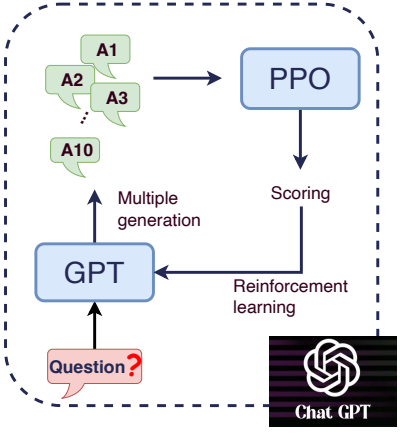


Scaling Instruction-Finetuned Language Models, Chung et al., JMLR 2024

The Ingredients of chatGPT

4. Instructions + answer ranking





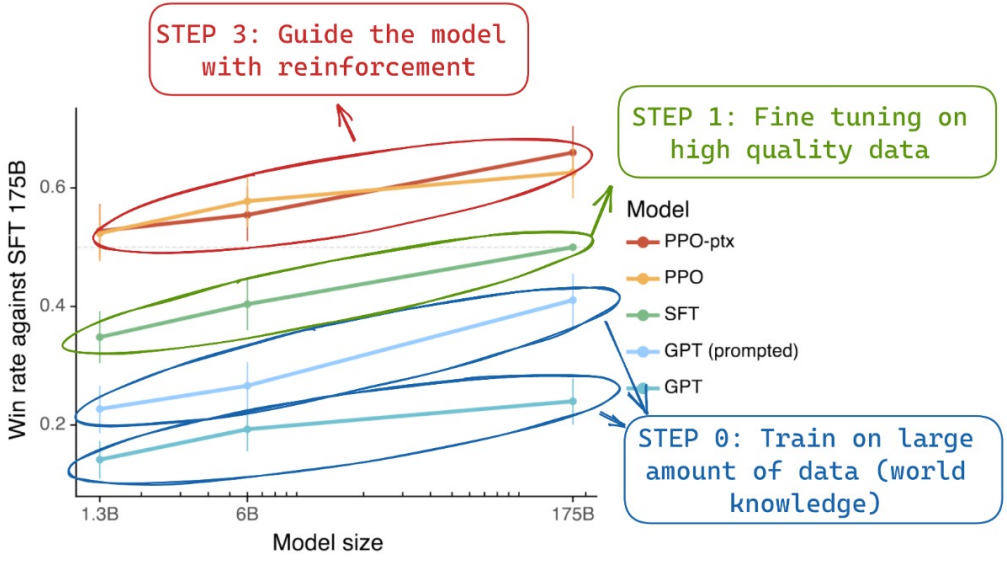
- Database created by humans
- Response improvement

- ... Also a way to avoid critical topics = censorship

Training language models to follow instructions with human feedback, Ouyang et al., 2022

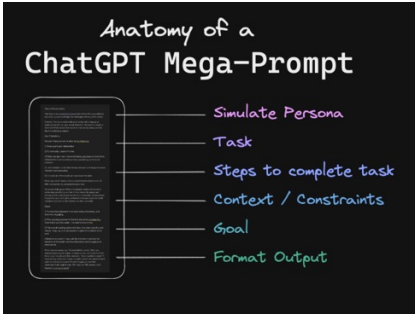
Steps & Performance

Massive data ⇒ HQ data (dialogue) ⇒ Tasks ⇒ RLHF



Usage of chatGPT & Prompting

- Asking chatGPT = skill to acquire ⇒ *prompting*
  - Asking a question well: *... in detail*, *... step by step*
  - Specify number of elements e.g. : *3 qualities for ...*
  - Provide context : *cell* for a biologist / legal assistant
- Don't stop at the first question
  - Detail specific points
  - Redirect the research
  - Dialogue
- Rephrasing
  - Explain like I'm 5, like a scientific article, bro style, ...
  - Summarize, extend
  - Add mistakes (!)

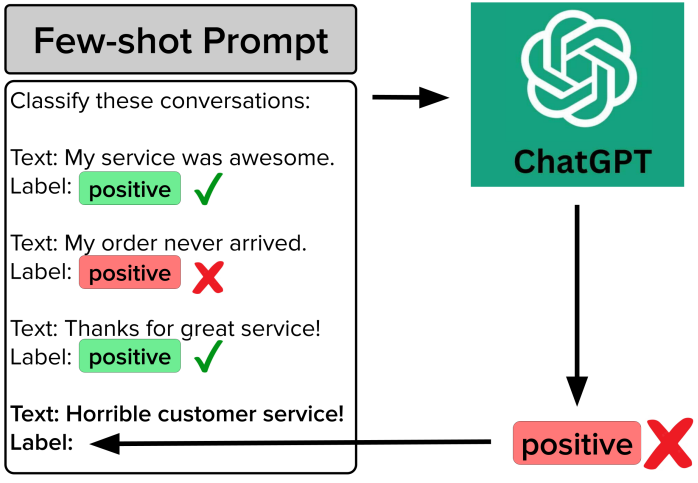


https://chatgptprompts.guru/what-makes-a-good-chatgpt-prompt/

⇒ Need for **practice** [1 to 2 hours], discuss with colleagues

Towards *few-shot learning*

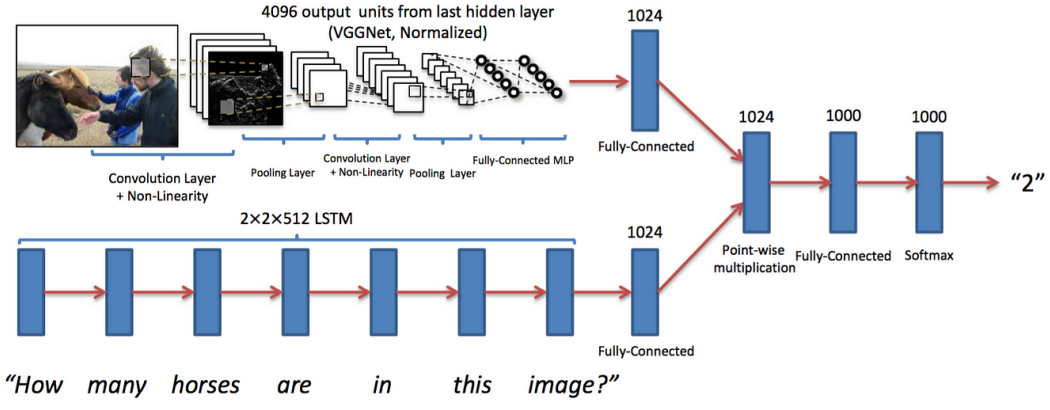
- Learning without modifying the model = examples in the prompt



GPT4 & Multimodality

Merging information from text & image. **Learning** to exploit information jointly

The example of VQA: visual question answering

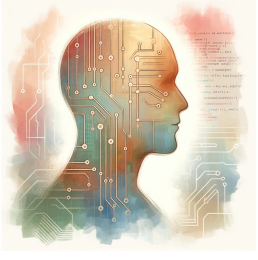


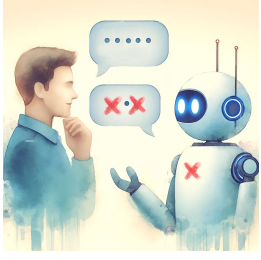
$\Rightarrow$ Backpropagate the error $\Rightarrow$ modify word representations + image analysis

VQA: Visual Question Answering, arXiv, 2016 , A. Agrawal et al.

Why So Much Controversy?

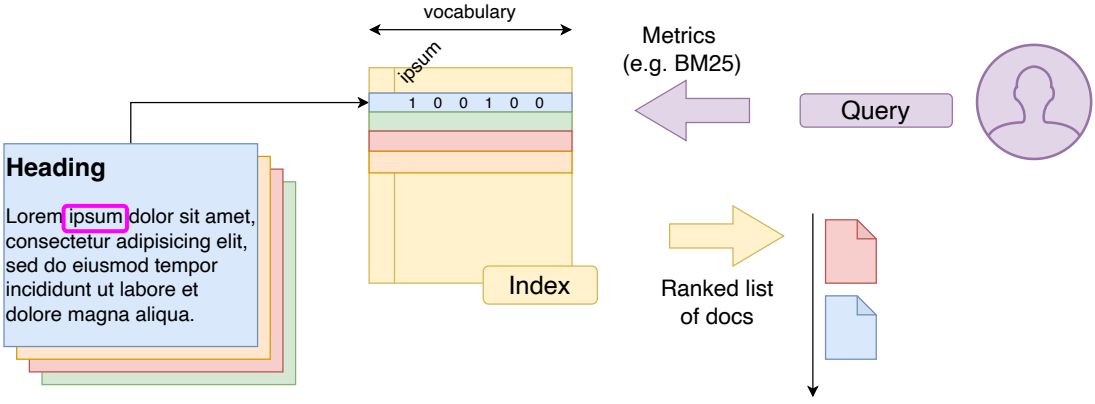
- New tool [December 2022]
- + Unprecedented adoption speed [1M users in 5 days]
- Strengths and weaknesses... Poorly understood by users
  - Significant productivity gains
  - Surprising / sometimes absurd uses
  - Bias / dangerous uses / risks
- Misinterpreted feedback
  - Anthropomorphization of the algorithm and its errors
- Prohibitive cost: what economic, ecological, and societal model?





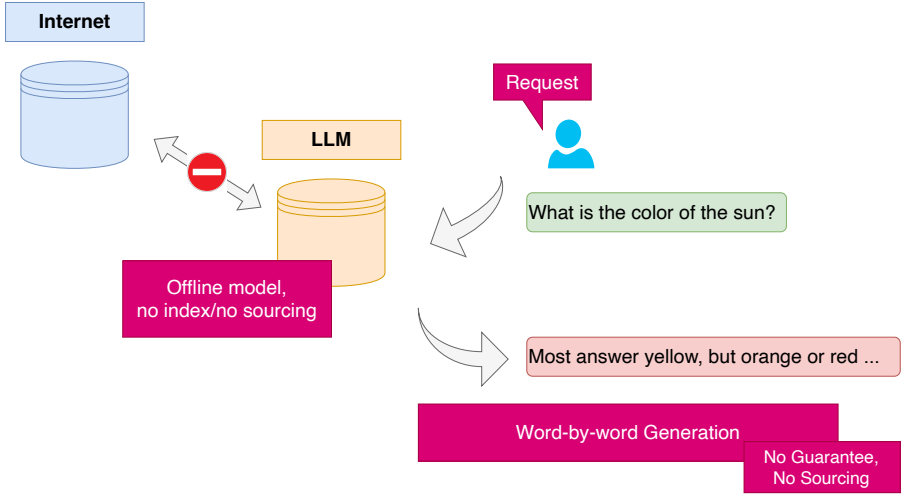
Large Language Models Uses

LLM & Information Retrieval



Information access: from word index to RAG

- Asking for information from ChatGPT... A surprising use!
- But is it reasonnable? [Real Open Question (!)]



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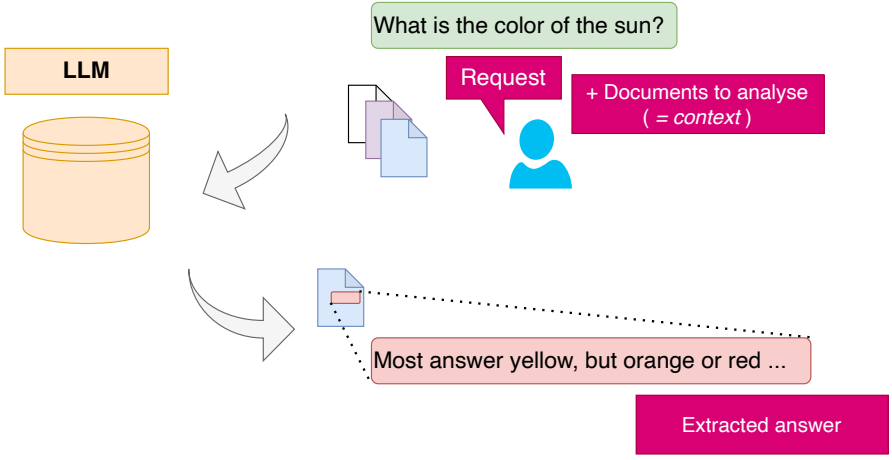
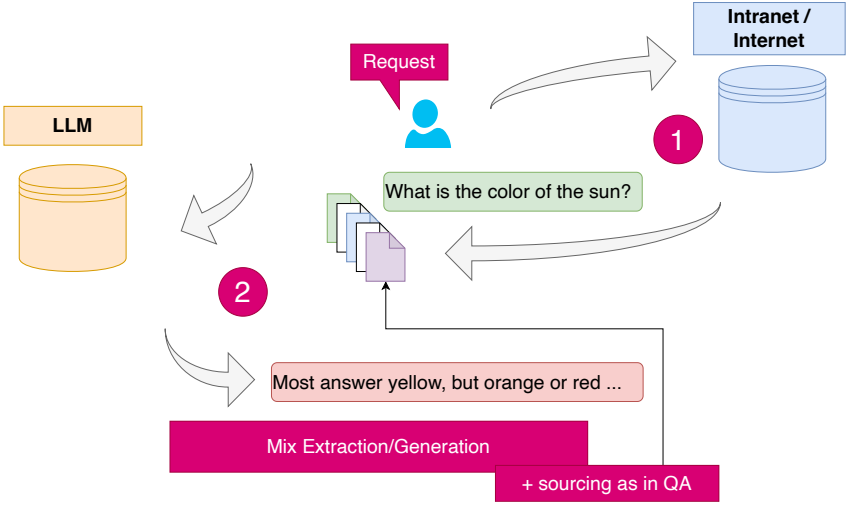


- Web query + analysis, automatic summary, rephrasing, meeting reports...
- (Current) limit on input size (2k then 32k tokens)
- = *pre chatGPT use of LLM for question answering*

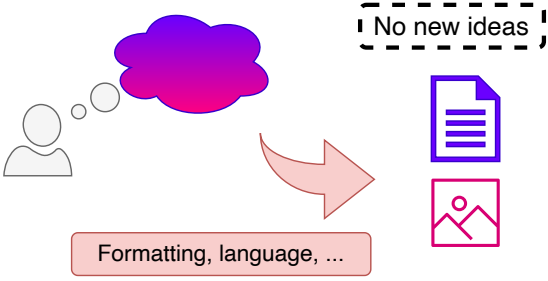
Information access: from word index to RAG



- RAG: Retrieval Augmented Generation
- (Current) limit on input size (2k then 32k tokens)

Other Uses of Generative AIs

A fantastic tool for **formatting**

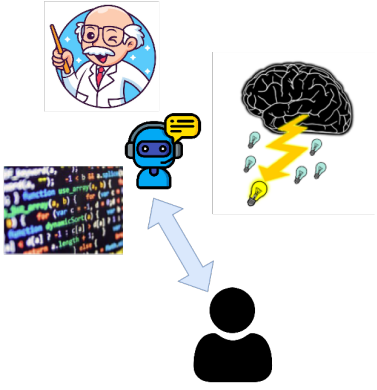


- Personal assistant
  - Standard letters, recommendation letters, cover letters, termination letters
  - Translations
- Meeting reports
  - Formatting notes
- Writing scientific articles
  - Writing ideas, in French, in English
- Document analysis
  - Information extraction, question-answering, ...

Other Uses of Generative AIs

And a tool for **reflection**!

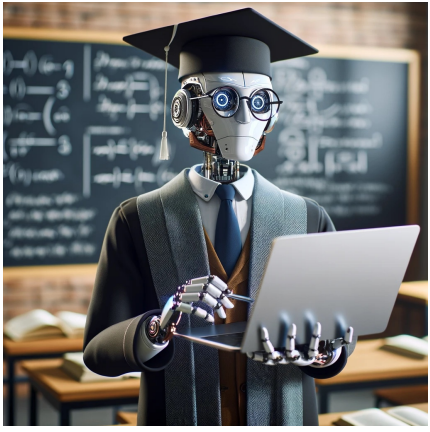
- Information Access
  - Risky but so convenient
- Brainstorming
  - Argument development, contradiction search
- Assistant for software development
  - Code generation, error search, ...
  - Documentation
- Educational assistant
  - Wikipedia ++, proposal of outlines for essays,
  - Code explanation / correction proposals



LLM & Teaching opportunities

- A great opportunity to have a 24/7 available teacher
- In particular for coding:
  - Learning python
  - Learning machine learning

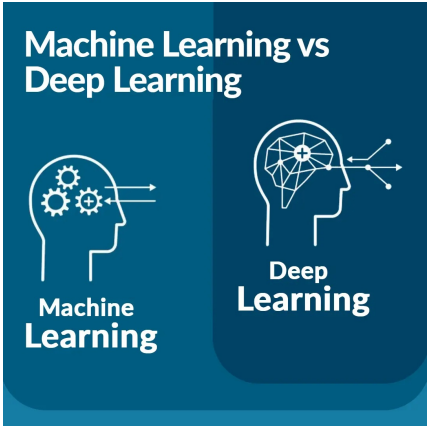
$\Rightarrow$
1. Generate a small program
2. Ask question about the different functions



LLM can do your homeworks... But LLM can explain you, answer questions about the solution, teach you!

IA générative *vs* IA classique

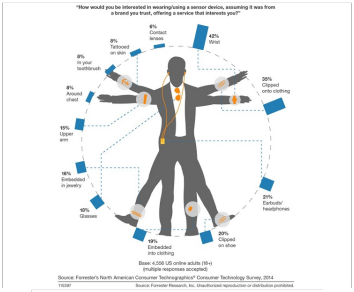
- Prédiction de séries temporelles, maintenance prédicitive
- Prédiction des prix (voitures, immobilier, ...)
- Diagnostic médical sur des données numériques, EEG, ECG, ...
- Systèmes de recommandation

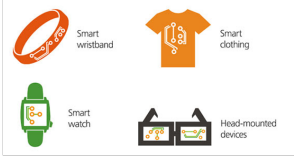


Why do tree-based models still outperform deep learning on typical tabular data?
L Grinsztajn, E Oyallon, G Varoquaux, NeurIPS 22

Des très nombreuses application d'IA embarquée

1. Bracelet connecté, vêtements, lunettes





- Séries temporelles, diagnostic, recherche d'anomalie
- Médecine ou gadget?

Des très nombreuses application d'IA embarquée

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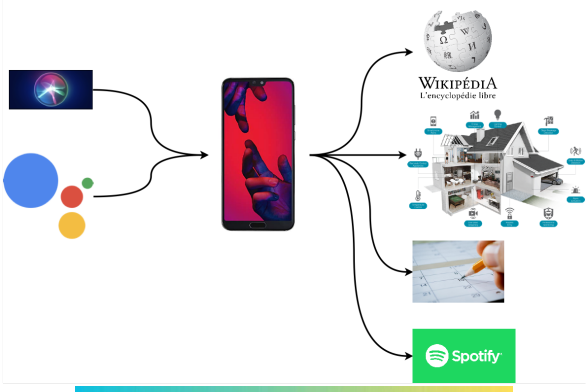
2. Assistant intelligent, Chatbot



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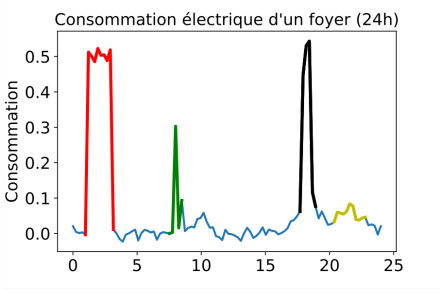

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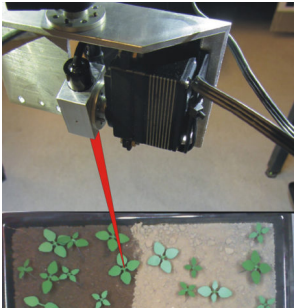
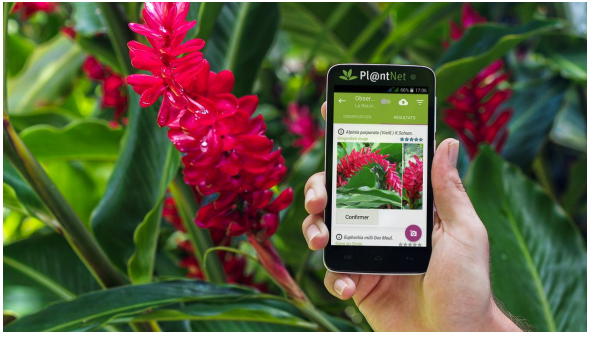
5. Robotique

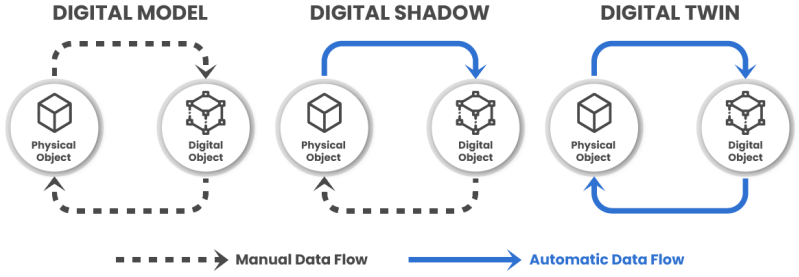


Des très nombreuses application d'IA embarquée

1. Bracelet connecté, vêtements, lunettes
2. Assistant intelligent, Chatbot
3. Compteur intelligent (e.g. Linky)
4. Cabine télémédecine
5. Robotique
6. ... Et plein d'autres choses ! Smartphone?



Définition(s) des jumeaux numériques & PINNs

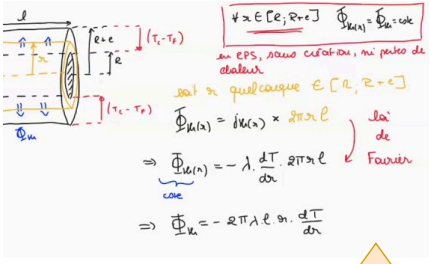


- Optimiser les décisions de gestion du jumeau réel en temps réel (lien capteurs / actionneurs)
- Réaliser des expériences numériques $\Rightarrow$ tester les conséquences des modifications avant de les mettre en œuvre.

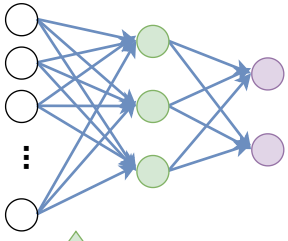
Définition(s) des jumeaux numériques & PINNs

Plusieurs types de modèles:

Mecanistic model / simulation



Data driven



Boundary conditions
Calibration

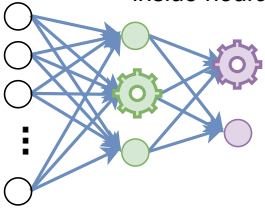
Data

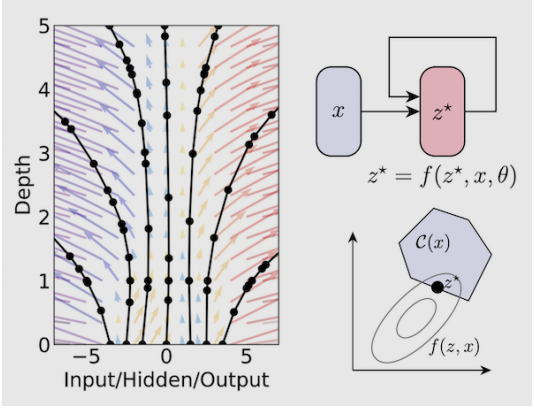
Model training

Définition(s) des jumeaux numériques & PINNs

Combiner modèles mécanistes et approches fondées sur les données:
PINNs - Physics Informed Neural Networks

Physical constraints
Differential equation modeling
inside neural architecture

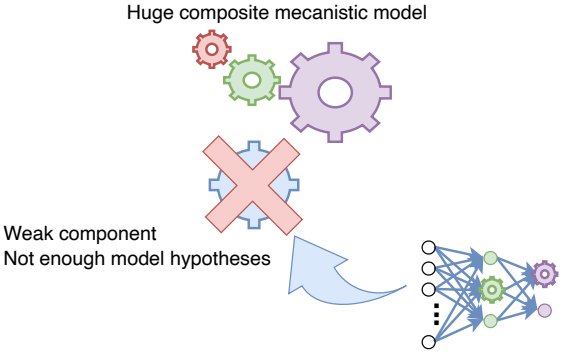




Neural ordinary differential equations. Chen et al. NeurIPS 2018

Définition(s) des jumeaux numériques & PINNs

Vers des architectures hybrides:

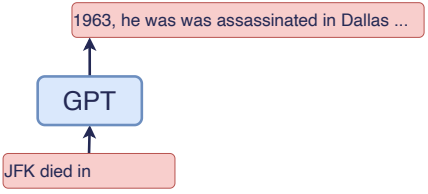


- Données de simulation
- Données réelles
- Données générées

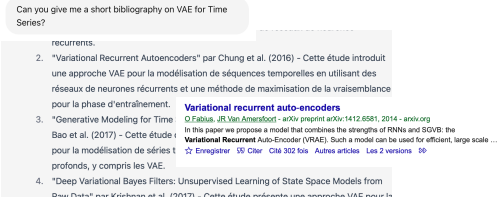
Machine Learning Limits

chatGPT and the relationship with truth

1. Plausibility = grammar, agreement, tense concordance, logical sequences...
   $\Rightarrow$ Repeated knowledge
2. Predict the most **plausible** word...
   $\Rightarrow$ produces **hallucinations**
3. **Offline** functioning
4. chatGPT $\neq$ **knowledge graphs**
5. Brilliant answers...
   And silly mistakes!
   + we cannot predict the errors



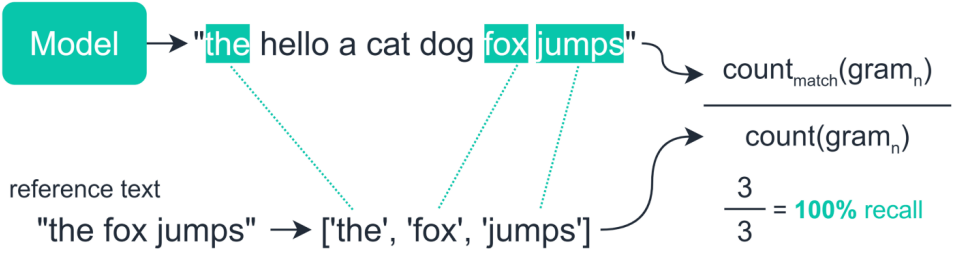
Example: producing a bibliography



Generative AI: how to evaluate performance?

The critical point today

- How to evaluate against ground truth?
- How to evaluate system confidence / plausibility of generation?



The Ultimate Performance Metric in NLP, J. Briggs, Medium 2021

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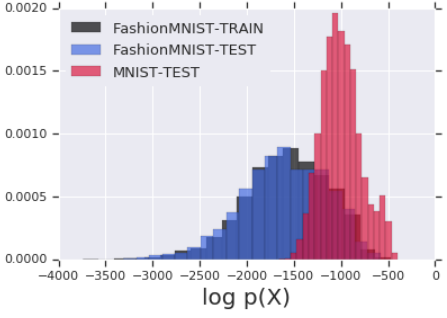


Plausibility

Train

Test

Do Large Language Models Know What They Don't Know?, Yin et al. , ACL, 2023
Do Deep Generative Models Know What They Don't Know?, Nalisnick et al. , ICLR, 2019

Stability/predictability

- Difficult to bound a behavior
- Impossible to predict good/bad answers

$\Rightarrow$ Little/no use in video games

V how old is Obama

Barack Obama was born on August 4, 1961, making him 61 years old as of February 2, 2023.

Stability/predictability

- Difficult to bound a behavior
- Impossible to predict good/bad answers

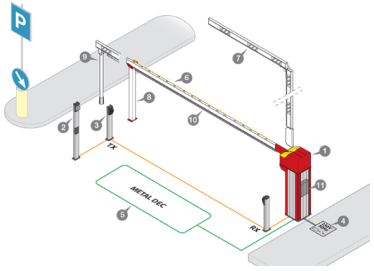
$\Rightarrow$ Little/no use in video games

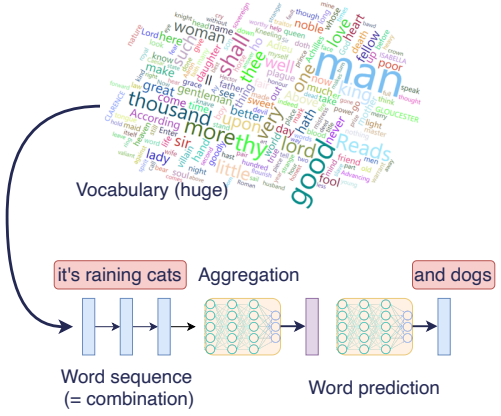
V how old is obama?

As of 2021, Barack Obama was born on August 4, 1961, so he is 60 years old.

V and today?

Stability, explainability... And complexity





- Simple system
- Exhaustive testing of inputs/outputs
- **Predictable** & **explainable**

- Large dimension
- Complex non-linear combinations
- **Non-predictable** & **non-explainable**

Stability, explainability... And complexity

Interpretability *vs* Post-hoc Explanation

Neural networks = **non-interpretable** (almost always)

too many combinations to anticipate

Neural networks = **explainable a posteriori** (almost always)

[Uber Accident, 2018]

- Simple system
- Exhaustive testing of inputs/outputs
- **Predictable** & **explainable**

- Large dimension
- Complex non-linear combinations
- **Non-predictable** & **non-explainable**

Transparency

- Model weights (*open-weight*)... $\Rightarrow$ but not just the weights
- Training data (*BLOOM*) + distribution + instructions
- Learning techniques
- Evaluation

Foundation Model Transparency Index Scores by Major Dimensions of Transparency, 2023

Source: 2023 Foundation Model Transparency Index

Major Dimensions of Transparency	Meta Llama 2	BigScience BLOOMZ	OpenAI GPT-4	stability.ai Stable Diffusion 2	Google PaLM 2	ANTHROPIC Claude 2	cohere Command	AI21labs Jurassic-2	Inflection Inflection-1	amazon Titan Text	Average
Data	40%	60%	20%	40%	20%	0%	20%	0%	0%	0%	20%
Labor	29%	86%	14%	14%	0%	29%	0%	0%	0%	0%	17%
Compute	57%	14%	14%	57%	14%	0%	14%	0%	0%	0%	17%
Methods	75%	100%	50%	100%	75%	75%	0%	0%	0%	0%	48%
Model Basics	100%	100%	50%	83%	67%	67%	50%	33%	50%	33%	63%
Model Access	100%	100%	67%	100%	33%	33%	67%	33%	0%	33%	57%
Capabilities	60%	80%	100%	40%	80%	80%	60%	60%	40%	20%	62%
Risks	57%	0%	57%	14%	29%	29%	29%	29%	0%	0%	24%
Mitigations	60%	0%	60%	0%	40%	40%	20%	0%	20%	20%	26%
Distribution	71%	71%	57%	71%	71%	57%	57%	43%	43%	43%	59%
Usage Policy	40%	20%	80%	40%	60%	60%	40%	20%	60%	20%	44%
Feedback	33%	33%	33%	33%	33%	33%	33%	33%	33%	0%	30%
Impact	14%	14%	14%	14%	14%	0%	14%	14%	14%	0%	11%
Average	**57%**	**52%**	**47%**	**47%**	**41%**	**39%**	**31%**	**20%**	**20%**	**13%**	

https://crfm.stanford.edu/fmti/May-2024/index.html

(Main) Risks derived from ML & LLM

Typology of AI Risks in NLP (L. Weidinger)

Discrimination, exclusion and toxicity

Harms that arise from the language model producing discriminatory and exclusionary speech.

Information hazards

Harms that arise from the language model leaking or inferring true sensitive information.

Misinformation harms

Harms that arise from the language model producing false or misleading information.

Malicious uses

Harms that arise from actors using the language model to intentionally cause harm.

Human-computer interaction harms

Harms that arise from users overly trusting the language model, or treating it as human-like.

Automation, access and environmental harms

Harms that arise from environmental or downstream economic impacts of the language model.

Access to Information

- Access to dangerous/forbidden information
  - +Personal data
  - Right to digital oblivion
- Information authorities
  - Nature: unconsciously, image = truth
  - Source: newspapers, social media, ...
  - Volume: number of variants, citations (pagerank)
- Text generation: harassment...
- Risk of anthropomorphizing the algorithm
  - Distinguishing human from machine

Machine Learning & Bias

Mustache, Triangular Ears, Fur Texture

Cat

Over 40 years old, white, clean-shaven, suit

Senior Executive

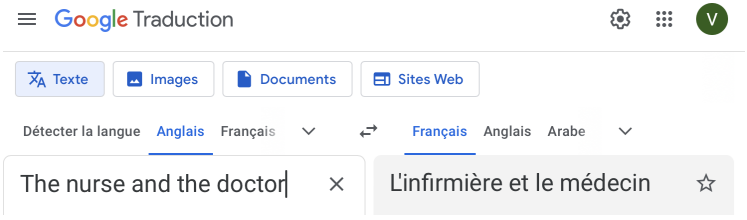
Bias in the data ⇒ bias in the responses

Machine learning is based on extracting statistical biases...

⇒ Fighting bias = manually adjusting the algorithm

Machine Learning & Bias

Sterreotypes from *Pleated Jeans*



- Gender choice
- Skin color
- Posture
- ...

Bias in the data ⇒ bias in the responses

Machine learning is based on extracting statistical biases...

⇒ Fighting bias = manually adjusting the algorithm

Bias Correction & Editorial Line

Bias Correction:

- Selection of specific data, rebalancing
- Censorship of certain information
- Censorship of algorithm results

⇒ Editorial work... Done by whom?

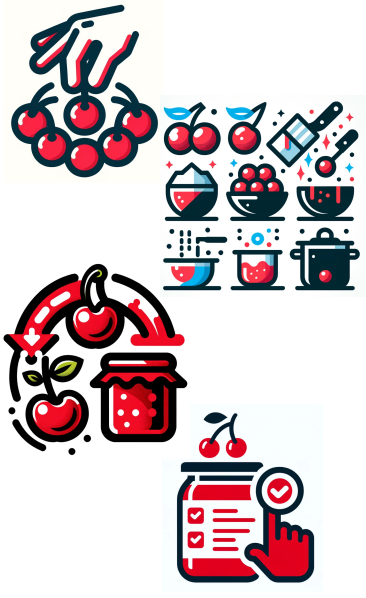
- Domain experts / specifications
- Engineers, during algorithm design
- Ethics group, during result validation
- Communication group / user response

⇒ What legitimacy? What transparency? What effectiveness?

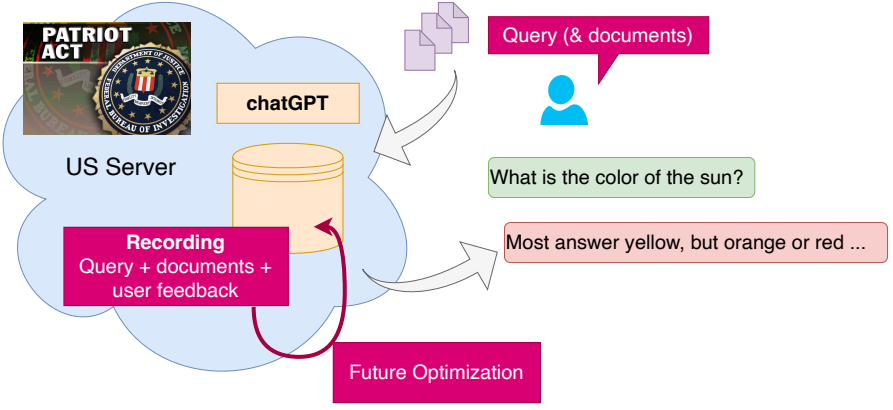
Machine learning is never neutral

1. Data selection
   - Sources, balance, filtering
2. Data transformation
   - Information selection, combination
3. Prior knowledge
   - Balance, loss, a priori, operator choices...
4. Output filtering
   - Post processing

$\Rightarrow$ Choices that influence algorithm results



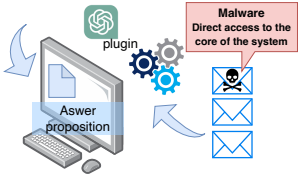
Data Leak(s)

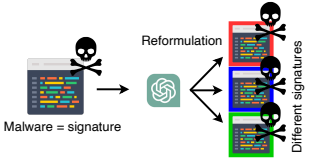


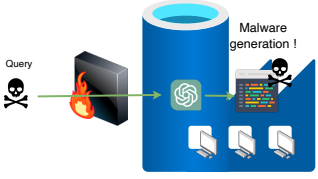
- Transfer of sensitive data
- Exploitation of data by OpenAI (or others)
- Data leakage in future models

Security Issues

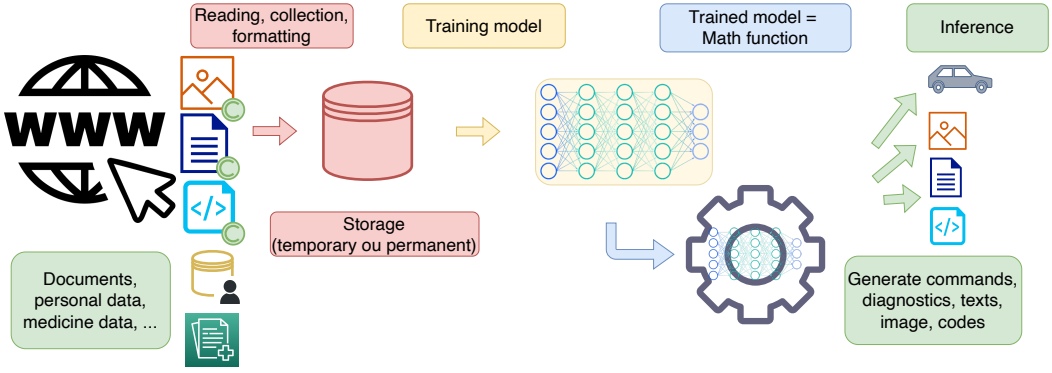
- Plug-ins ⇒ Often significant security vulnerabilities for users
  - Email access / transfer of sensitive information etc...
- Management issues for companies
  - Securing (very) large files
- Increased opportunities for malware signatures
  - ≈ software rephrasing
- New problems!
  - Direct malware generation







Legal Risks/Questions



Copyright and database law

Right to collect, right to copy, consent

Right to use data in an algorithm **Optout**

Model = emanation of data?

Cambridge Analytica

Clearview.ai

Reproductions of untraceable extracts

Usage regulation

Responsibility for errors

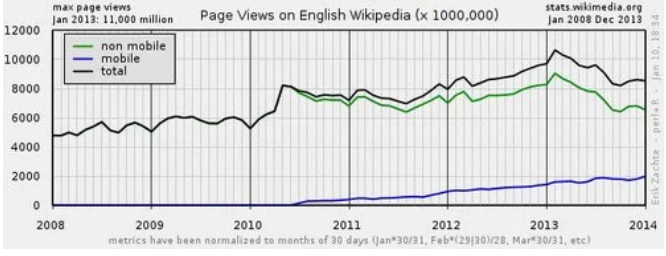
Economic Questions

- Funding/Advertising $\Leftrightarrow$ **visits** by internet users
- Google knowledge graph (2012) $\Rightarrow$ fewer visits, less revenue
- chatGPT = encoding web information... $\Rightarrow$ much fewer visits?

$\Rightarrow$ What **business model for information sources** with chatGPT?

Google's Knowledge Graph Boxes: killing Wikipedia?

by Gregory Kohs

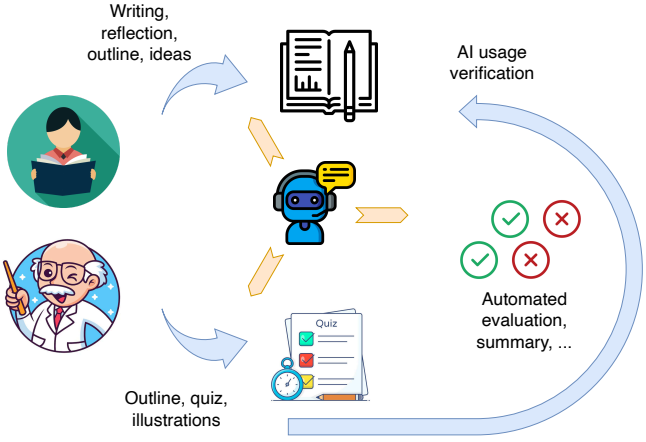


$\Rightarrow$ Who does **benefit from the feedback**? [StackOverFlow]

Risks of AI Generalization

AI everywhere =
loss of meaning?

- In the educational domain
- Transposition to HR
- To project-based funding systems



How to approach the ethics question?

Medicine

1. **Autonomy:** the patient must be able to make informed decisions.
2. **Beneficence:** obligation to do good, in the interest of patients.
3. **Non-maleficence:** avoid causing harm, assess risks and benefits.
4. **Justice:** fairness in the distribution of health resources and care.
5. **Confidentiality:** confidentiality of patient information.
6. **Truth and transparency:** provide honest, complete, and understandable information.
7. **Informed consent:** obtain the free and informed consent of patients.
8. **Respect for human dignity:** treat all patients with respect and dignity.

Artificial Intelligence

1. **Autonomy:** Humans control the process
2. **Beneficence:** including the environment?
3. **Non-maleficence:** Humans + environment / sustainability / malicious uses
4. **Justice:** access to AI and equal opportunities
5. **Confidentiality:** what about the Google/Facebook business model?
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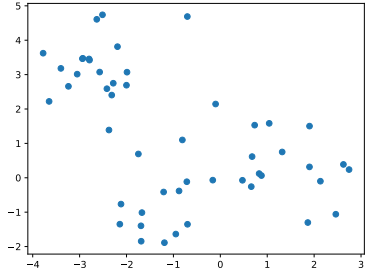
From Generative AI to Foundation Models

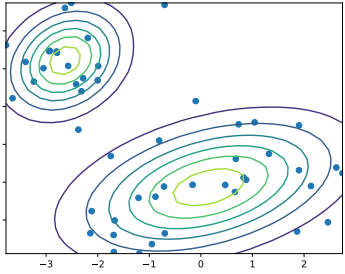
At the origin of statistical modeling

1. **Observing** data (and context)
2. **Modeling** = Choosing probabilistic model / bayesian network
3. **Optimize** parameters (Max. Likelihood, EM, BFGS, ...)
4. **Sampling** / Inference + Evaluate distances : existing *vs* sampled

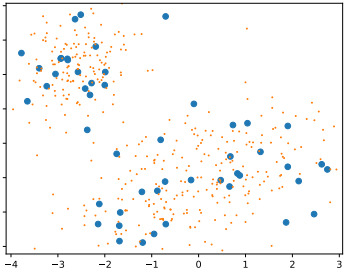
Observations



Modeling: choice+optim.



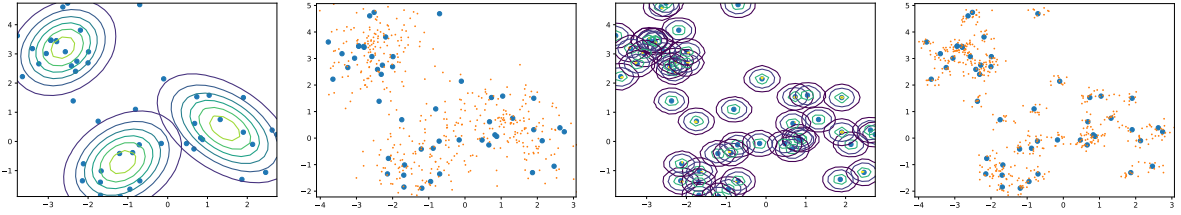
Sampling / eval.



At the origin of statistical modeling

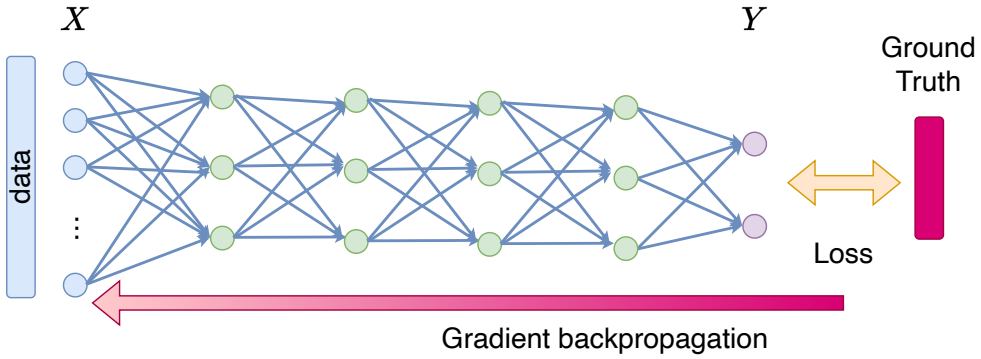
1. **Observing** data (and context)
2. **Modeling** = Choosing probabilistic model / bayesian network
3. **Optimize** parameters (Max. Likelihood, EM, BFGS, ...)
4. **Sampling** / Inference + Evaluate distances : existing *vs* sampled

Different modeling options / different traps



At the origin of deep learning

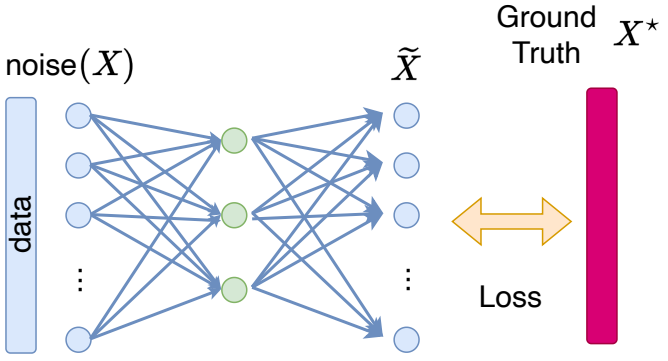
- Gradient vanishing issue in deep architecture



Gradient **weakening => vanishing**

At the origin of deep learning

- Gradient vanishing issue in deep architecture
- Auto-Encoder architecture / facing unsupervised dataset with NN

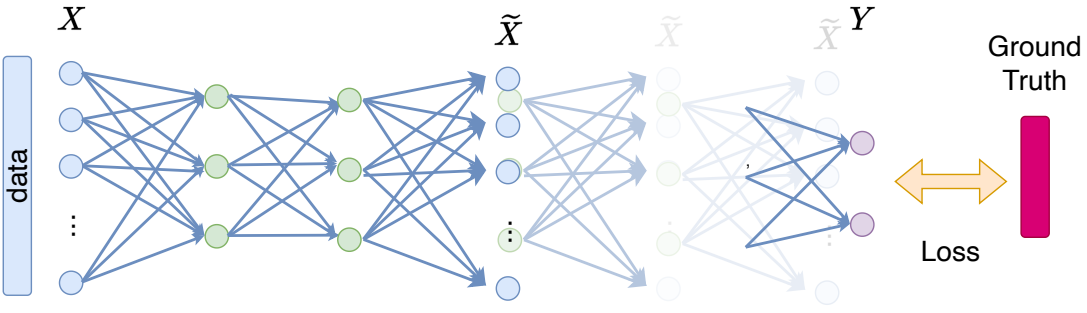


- Denoising
- Low dimensional representation learning (/ PCA, SVD)

Auto-association by multilayer perceptrons and singular value decomposition, Biological Cybernetics, 1988
H. Bourlard & Y. Kamp

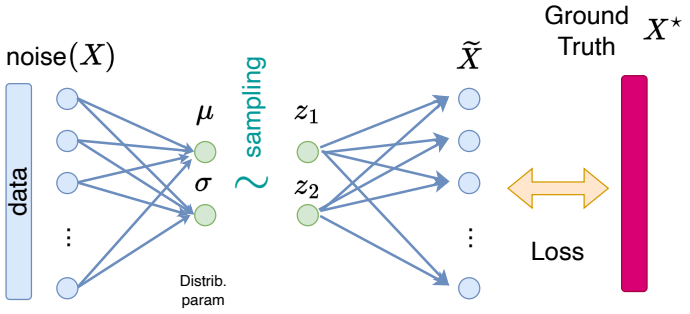
At the origin of deep learning

- Gradient vanishing issue in deep architecture
- Auto-Encoder architecture / facing unsupervised dataset with NN
- Stacked Denoising Auto-Encoder : iterative training / **pretraining**



The difficulty of training deep architectures and the effect of unsupervised pre-training, AIS, PMLR 2009
Erhan, D., Manzagol, P. A., Bengio, Y., Bengio, S., & Vincent, P.

Variational Auto-Encoder

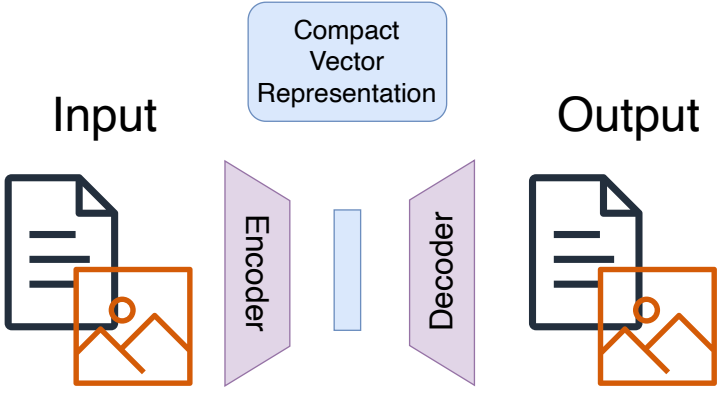


- a priori on the distribution
- Structuring of the latent space

Generative AI (for statisticians)

Auto-Encoding Variational Bayes, 2013
DP Kingma

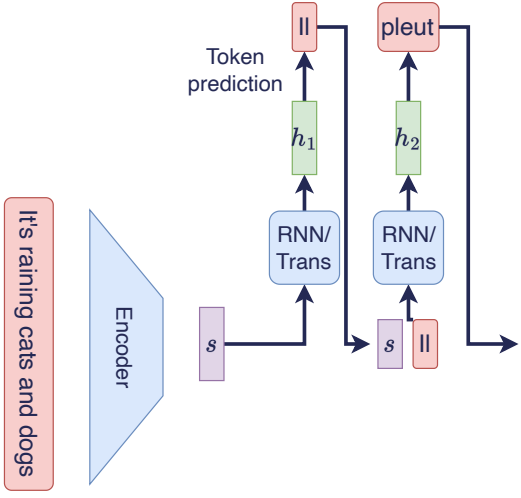
Different Forms of Generative AI



1. Encode an input = construct a vector
2. Decode a vector = *generate* an output

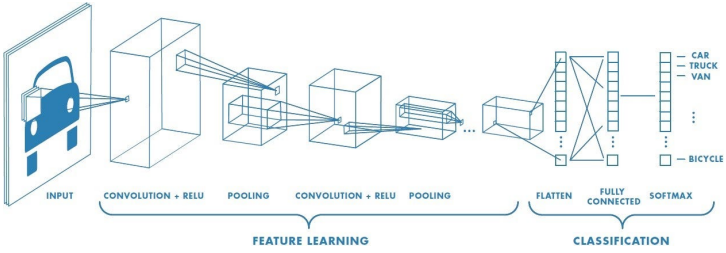
Different Media / Different Architectures

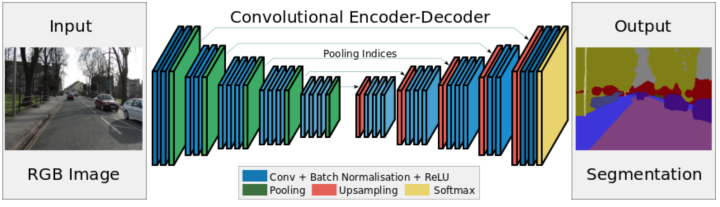
- Texts: classification problem



Different Media / Different Architectures

- Texts: classification problem
- Images: multivariate regression problem





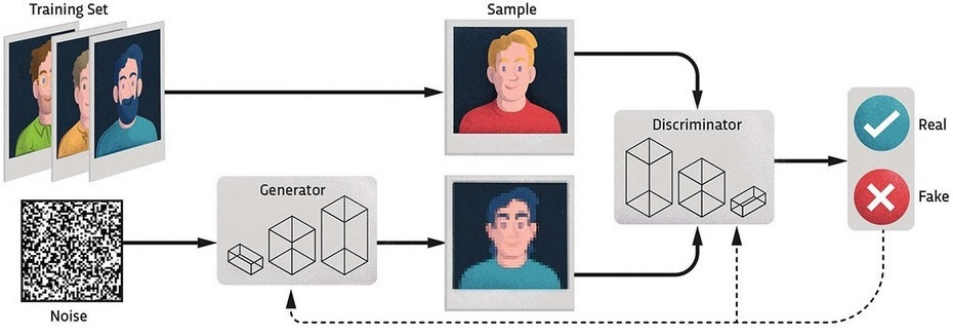
U-Net: Convolutional Networks for Biomedical Image Segmentation, MICCAI, 2015
Ronneberger et al.

NVidia Lab.

Different Media / Different Architectures

- Texts: classification problem
- Images: multivariate regression problem

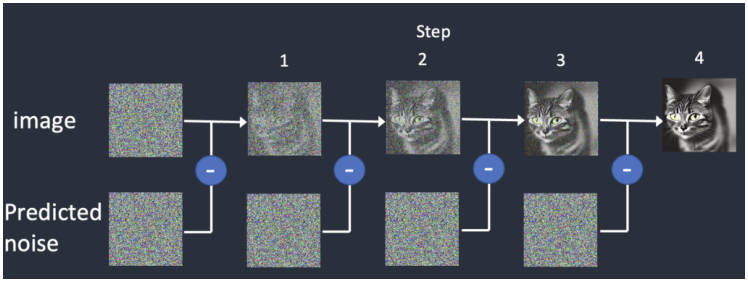
Generative Adversarial Networks (GAN): detecting generated samples

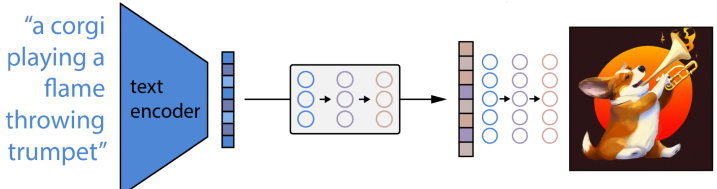


Generative Adversarial Nets, NeurIPS 2014
Goodfellow et al.

Different Media / Different Architectures

- Texts: classification problem
- Images: multivariate regression problem
- Physical processes





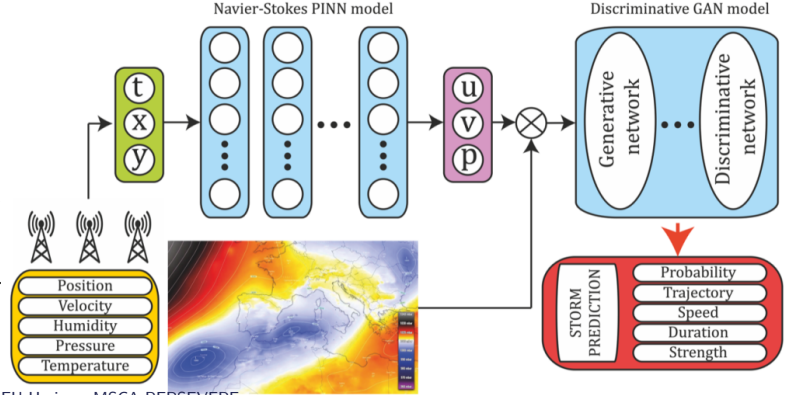
Denoising Diffusion Probabilisti Models, NeurIPS, 2020
Ho, J., Jain, A., & Abbeel, P.

Hierarchical Text-Conditional Image Generation with CLIP Latents, arXiv, 2022
Ramesh et al.

Different Media / Different Architectures

- Texts: classification problem
- Images: multivariate regression problem
- Physical processes
- Complex structures / 3D / graphs: sequential problem
- Mix mechanistic and *data-driven* approaches

e.g. Model differential equations in a neural network

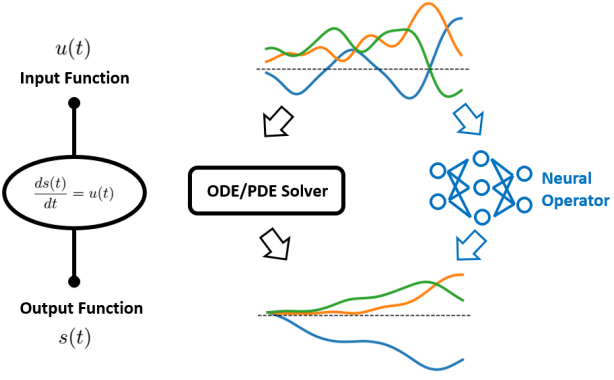


Neural ordinary differential eq tions, NeurIPS, 2018
Chen et al.

Physics-informed neural networ
J. Comp. Physics, 2019
Raissi et al.

Different Media / Different Architectures

- Texts: classification problem
- Images: multivariate regression problem
- Physical processes
- Complex structures / 3D / graphs: sequential problem

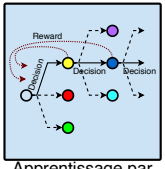


Data + Models :

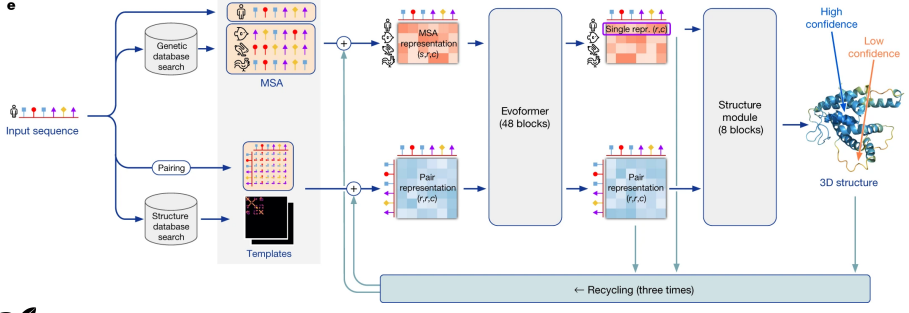
- PDE, neural ODE
- Simulation approximations
- Residual Models
- Hybrid Complex Systems

Different Media / Different Architectures

- Texts: classification problem
- Images: multivariate regression problem
- Physical processes
- Complex structures / 3D / graphs: sequential problem
  - Reinforcement learning: action/reward



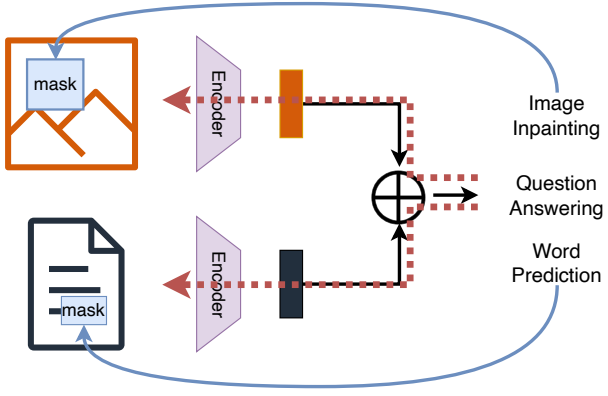
Apprentissage par renforcement



Highly accurate protein structure prediction with AlphaFold, Nature, 2021
Jumper et al.

Multi-Modality

- Construction of multimodal representation spaces = *grounding*
- Image ⇒ Text: *Captioning, Visual Question Answering*
- Text ⇒ Image: *mid-journey, dall-e, ...*

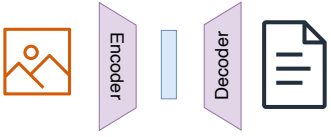


Alignment of representation spaces

Word	*Teraword*	*Knext*
Spoke	11,577,917	372,042
Laughed	3,904,519	179,395
Murdered	2,843,529	16,890
Inhaled	984,613	5,617
Breathed	725,034	41,215

Multi-Modality

- Construction of multimodal representation spaces = *grounding*
- Image ⇒ Text: *Captioning*, *Visual Question Answering*
- Text ⇒ Image: *mid-journey*, *dall-e*, ...



Show and Tell: image captioning open sourced in TensorFlow, Chris Shallue , Google Research, 2016

Multi-Modality

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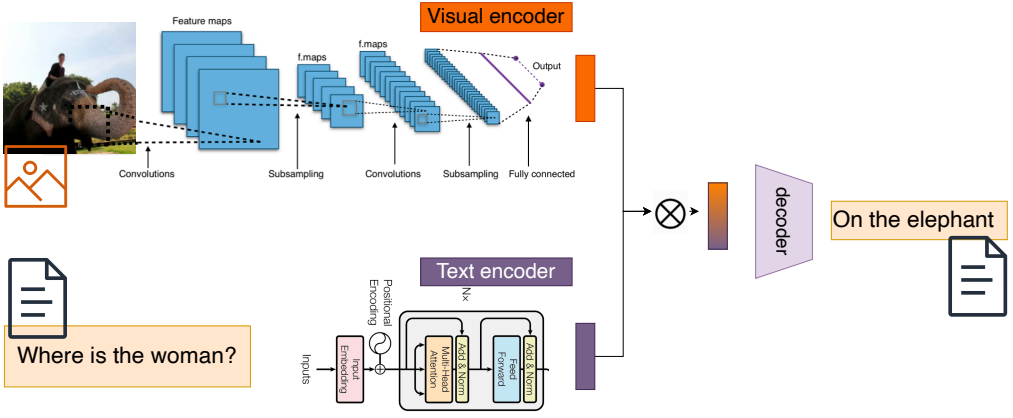
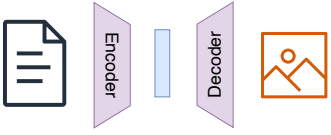


Vqa: Visual question answering, ICCV, 2015
Antol et al.

Multi-Modality

- Construction of multimodal representation spaces = *grounding*
- Image ⇒ Text: *Captioning, Visual Question Answering*
- Text ⇒ Image: *mid-journey, dall-e, ...*



TEXT DESCRIPTION

An astronaut Teddy bears A bowl of soup

riding a horse lounging in a tropical resort in space playing basketball with cats in space

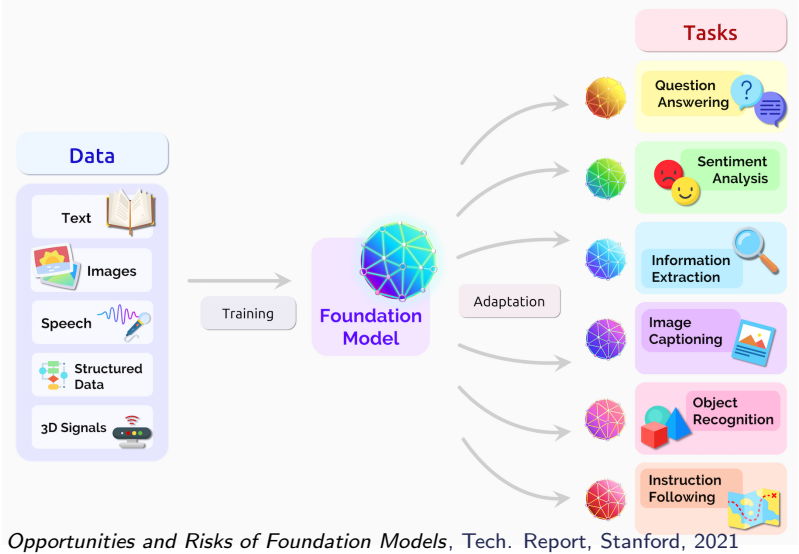
in a photorealistic style in the style of Andy Warhol as a pencil drawing

→

DALL·E 2

Towards Larger Foundation Models?

- Let the modalities enrich each other



On the Opportunities and Risks of Foundation Models, Tech. Report, Stanford, 2021
Bommasani et al.

Conclusion

The main challenges of multimodality

- New applications
  - at the interface between text, image, music, voice, ...
- Performance improvement
  - Better encoding, disambiguation, context encoding
- Explainability (through dialogue)
  - IoT / RecSys / Intelligent Vehicle / ...

Dall-e

Conclusion

Tools and Questions

New tools:

- New ways to handle existing problems
- Address new problems
- ... But obviously, it doesn't always work!
- AI often makes mistakes (assistant *vs* replacement)

Learning to use an AI system

- AI not suited for many problems
- AI = part of the problem (+interface, usage, acceptance...)

Maturity of Tools & Environments

(More) mature tools

- **Environments**: Jupyter, Visual Studio Code, ...
- **Machine Learning** `Scikit-Learn`: blocks to assemble
  - Training: 1 week
  - Project completion: few hours to few days
- **Deep Learning** `pytorch, tensorflow`: building blocks... but more complex
  - Training: 2-5 weeks
  - Project completion: few days to few months
  - Mandatory for text and image

- A data project = 10 or 100 times less time / 2005
- Developing a project is **accessible to non-computer scientists**

Levels of Access to Artificial Intelligence

1. User via an interface: *chatGPT*
   - Some training is still required (2-4h)
2. Using Python libraries
   - Basics on protocols
   - Standard processing chains
   - Training: 1 week-3 months (ML/DL)
3. Tool developer
   - Adapt tools to a specific case
   - Integrate business constraints
   - Build hybrid systems (mechanistic/symbolic)
   - Mix text and images
   - Training: $\geq$ 1 year

Digital Sovereignty: the Entire Chain

Pre-trained model construction

Data Mastery
- Collection/balance
- Cleaning

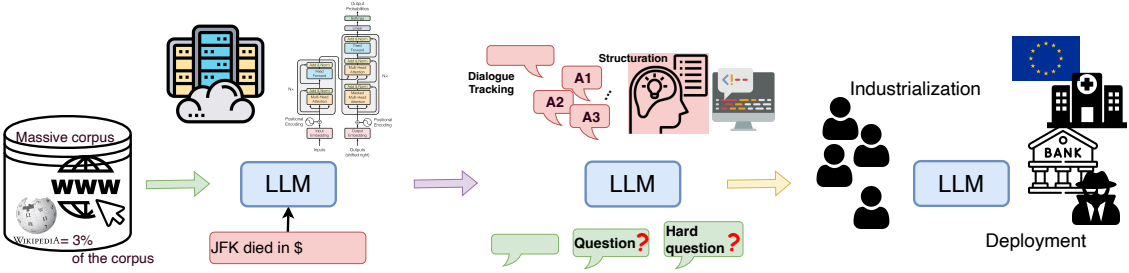
Training
- Computation power (x1000 GPU)
- Architecture ML

Model Fine-Tuning

Data Mastery & Construction
- Human interactions +++
- Dataset cost
- Domain adaptation

Model exploitation

Optimization / Cost reduction
- MLOps skills
- Local deployment



A Multitude of Professions

Data architect / manager
- Data management & hardware devices (storage, network, …)

Data Engineer
- Update & Query on the data

Data Analyst
- Data visualization (chart, indicators, …)
- Statistical trends

Prompt Engineer
- Query on LM/foundation models with "prompts"

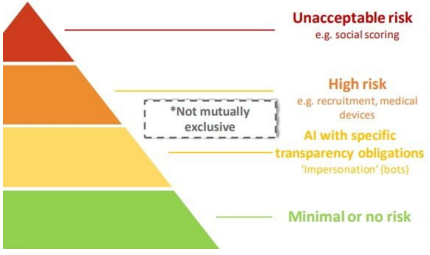
Data Scientist
- Query the data / critical selection & balance
- Algorithm development / adaptation / evaluation
- Advanced data visualization

MLOps Engineer
- Algorithm optimization
- Industrialize software solutions

+ **DPO** :
Data Protection Officer

Factors of Acceptability for Generative AI

1. **Utilitarianism**:
   - Performance (acceptance factor of chatGPT)
   - Reliability / Self-assessment
2. **Non-dangerousness**:
   - Bias / Correction
   - Transparency (editorial line, human/machine confusion)
   - Reliable Implementation
   - Sovereignty (?)
   - Regulation (AI act)
     - Avoid dangerous applications
3. **Know-how**:
   - Training (usage/development)



chatGPT: A Simple Step

- Training & Tuning Costs

  4-5 Million Euros / training $\Rightarrow$ chatGPT is **poorly trained**!

- Data Efficiency

  chatGPT $>$ 1000x a human's lifetime reading

- Identify Entities, Cite Sources

  Anchoring responses in knowledge bases
  Anchoring responses in sources

- Multiplication of initiatives: GPT, LaMBDA, PaLM, BARD, BLOOM, Gopher, Megatron, OPT, Ernie, Galactica...
- Public involvement,
  impact on information access