FONCTIONNEMENT DES MODÈLES DE LANGUE EXPLOITATION SUR DONNÉES ALIMENTAIRES

Lundi 29 septembre 2025
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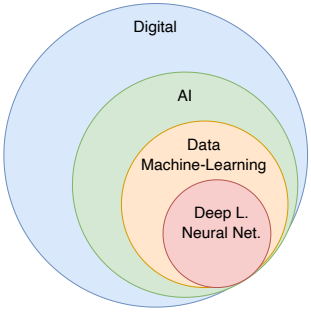
Vincent Guigue
https://vguigue.github.io

Introduction

Artificial Intelligence & 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

AI: computer programs that engage in tasks which are, for now, performed more satisfactorily by human beings because they require high-level mental processes.

Marvin Lee Minsky, 1956

N-AI (Narrow Artificial Intelligence), dedicated to a single task

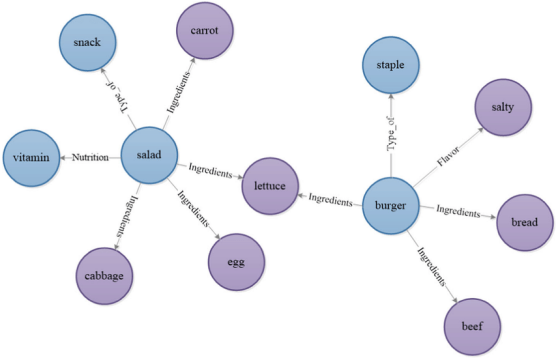
$\neq$ **G-AI (General AI)**, which replaces humans in complex systems.

Andrew Ng, 2015

The Ingredients of Machine-Learning

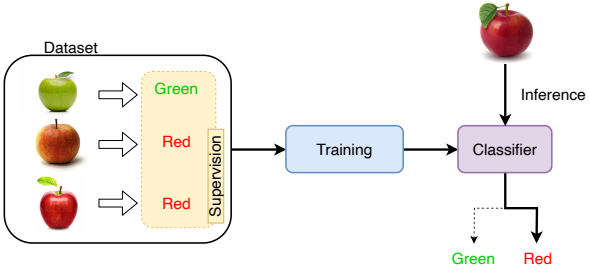
Machine-Learning vs Expert Knowledge

Modeling Expert Knowledge



A relationship extraction method for domain knowledge graph construction, Yu et al. 2020

Machine Learning

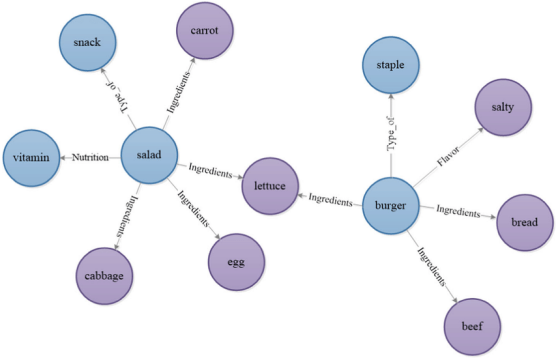


Different behaviors:

different strengths and weaknesses, different costs & requirements

Machine-Learning vs Expert Knowledge

Modeling Expert Knowledge



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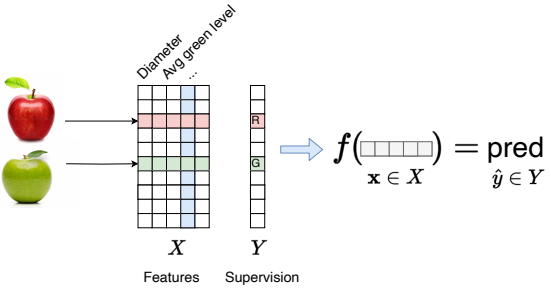


Different behaviors:

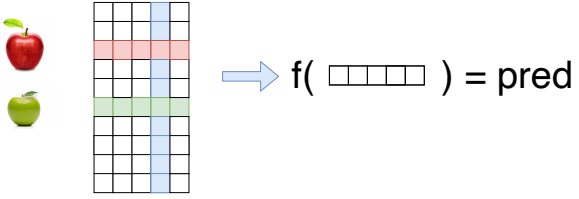
different strengths and weaknesses, different costs & requirements

Deep learning & Representation Learning

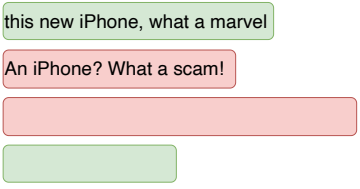
[Application to textual data]

From tabular data to text

- Tabular data
  - Fixed dimension
  - Continuous values



- Textual data
  - Variable length
  - Discrete values

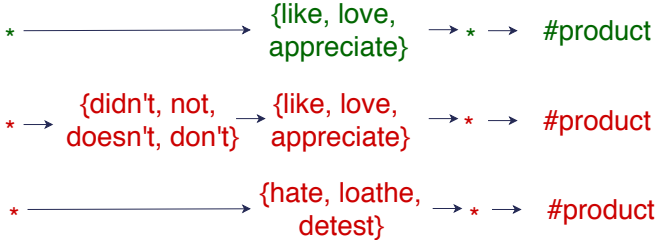


AI + Textual Data: Natural Language Processing (NLP)

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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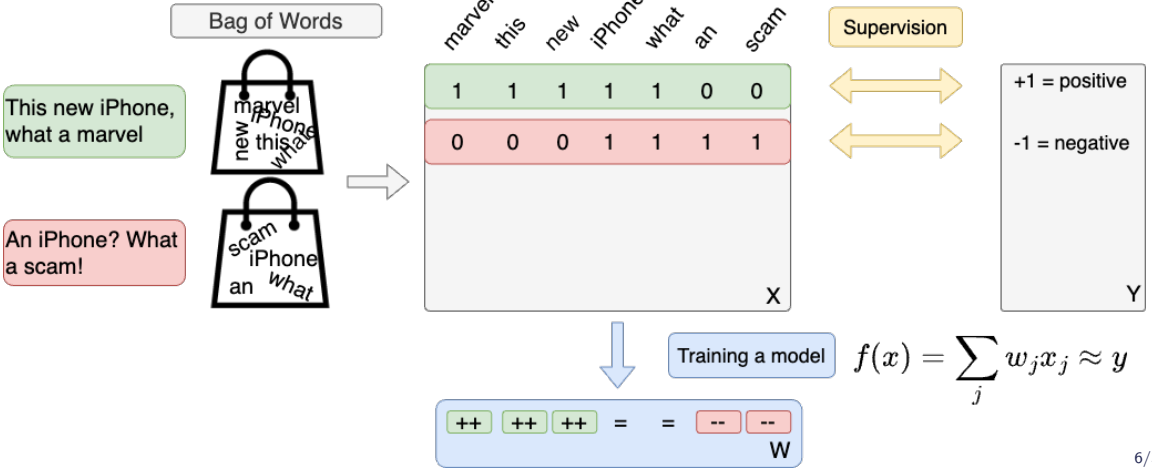
Machine Learning [1990-2015]



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

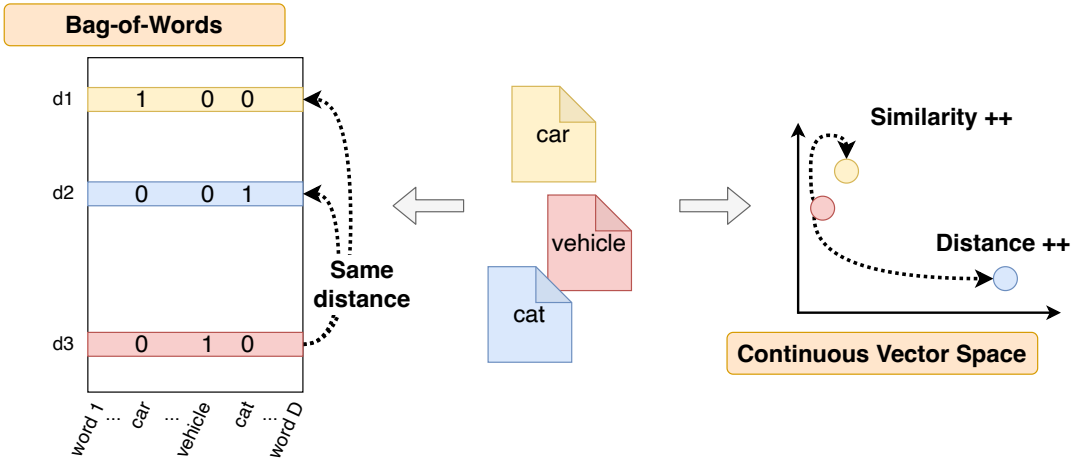
$\approx$ Less interpretable system
− Lower precision
\+ Better recall

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]

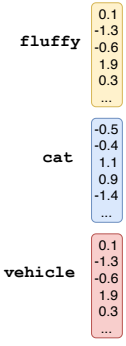


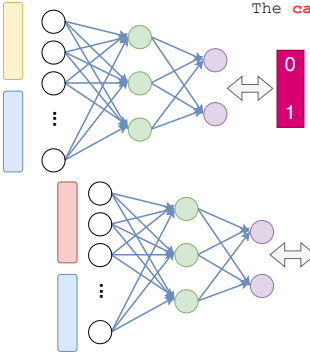
LeCun, Y., Bengio, Y., Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.

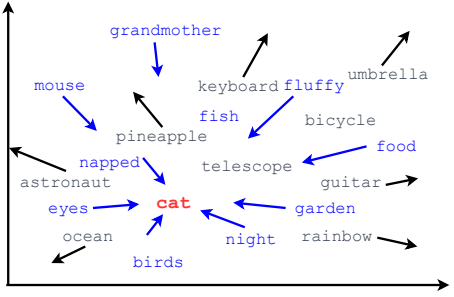
Deep/Representation Learning for Text Data

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.







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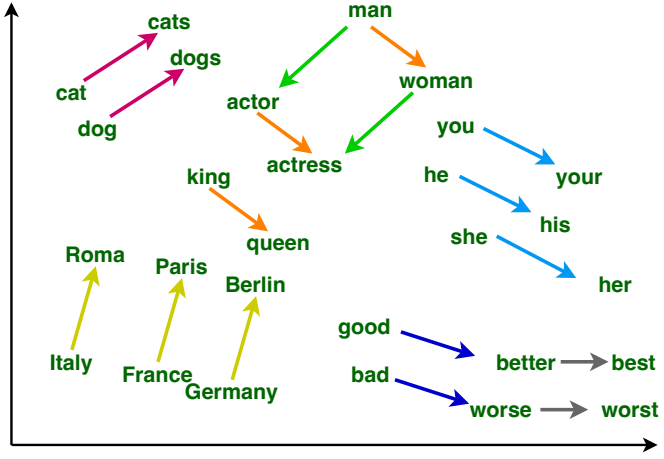


- Semantic Space:
  similar meanings
  $\Leftrightarrow$
  close positions
- Structured Space:
  grammatical regularities,
  basic knowledge, ...

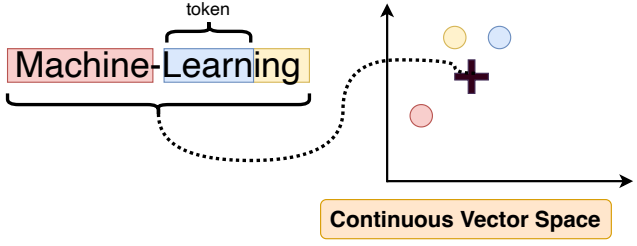
Distributed representations of words and phrases and their compositionality, Mikolov et al. NeurIPS 2013

Deep/Representation Learning for Text Data

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

From Words to Tokens

Word Piece statistical split

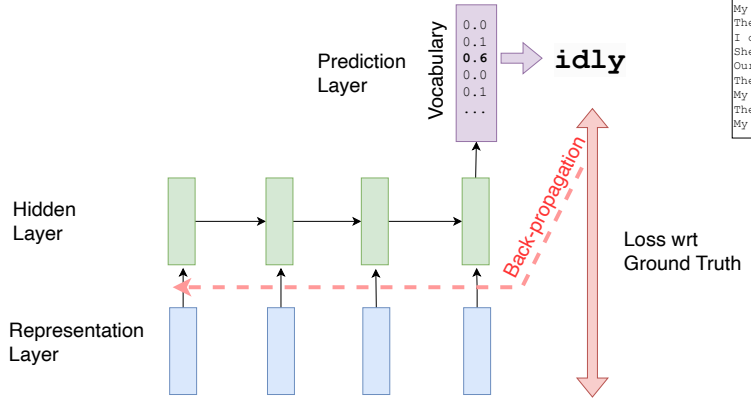


- Representation of unknown words
- Adaptation to technical domains
- Resistance to spelling errors

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



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My grandmother has a collection of porcelain cat figurines.

Corpus

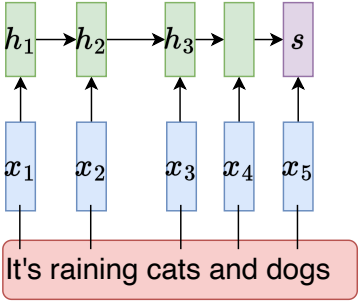
The fluffy cat napped lazily in the sunbeam.

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

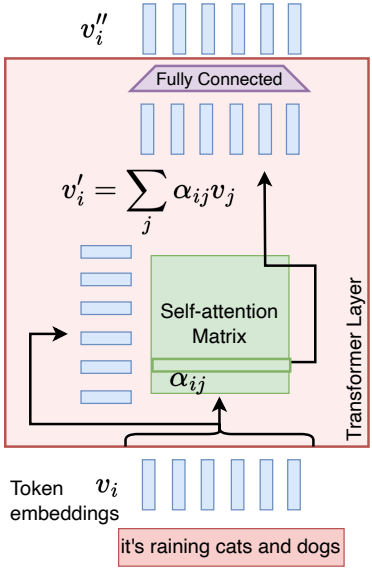
Transformer architecture: state-of-the-art aggregation

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

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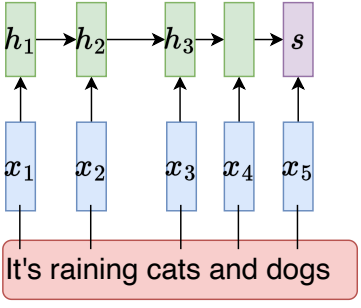

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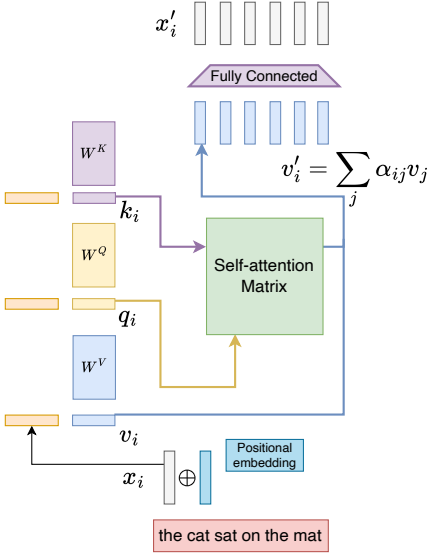

$$v_i' = \sum_j \alpha_{ij} v_j$$

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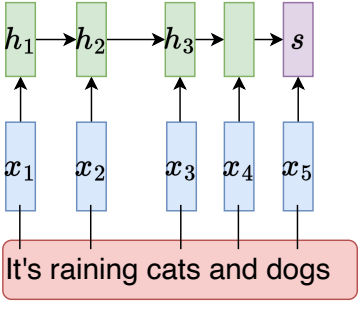
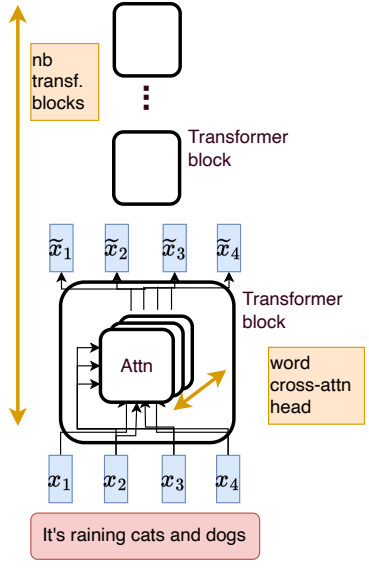


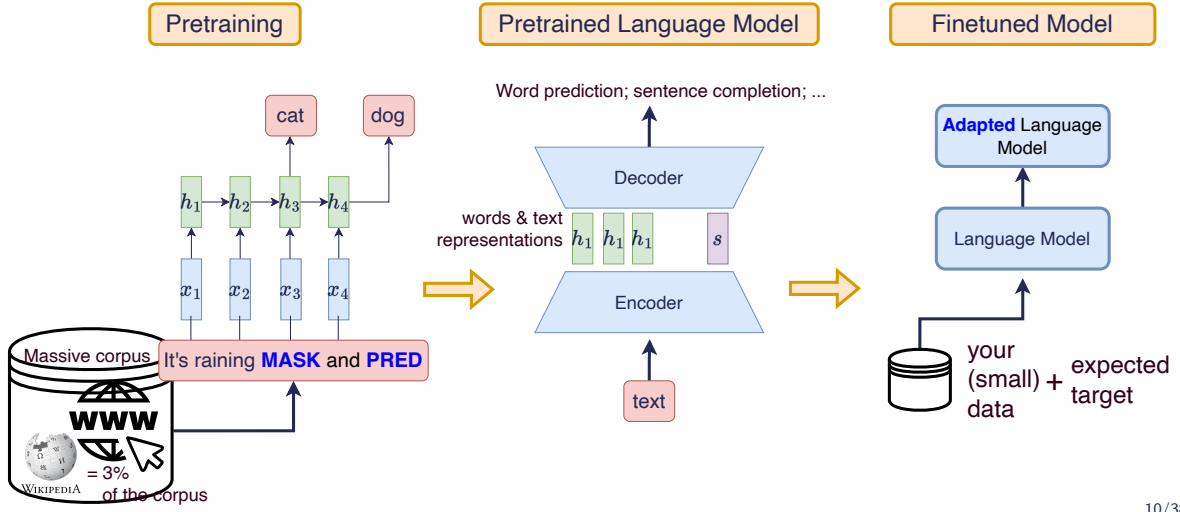
Transformer:



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

A new developpement paradigm since 2015

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



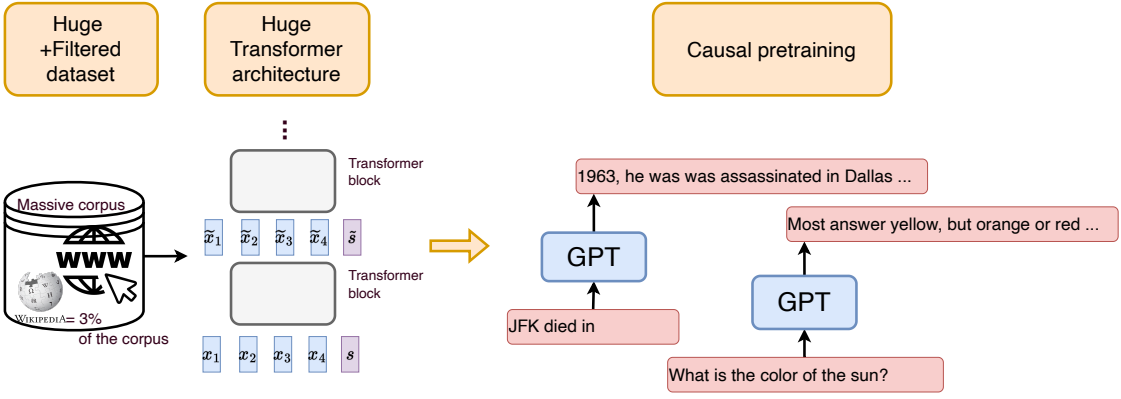
chatGPT

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)



- Grammatical skills: singular/plural agreement, tense concordance
- (Parametric) Knowledge: entities, names, dates, places

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

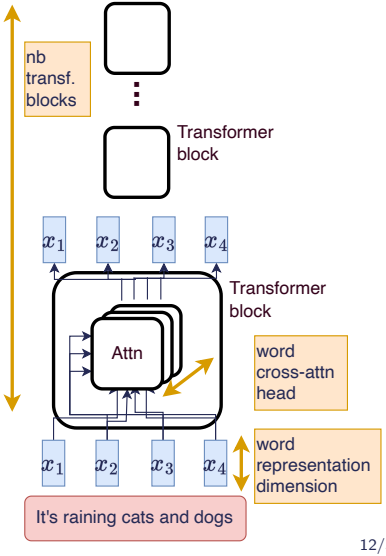
The Ingredients of chatGPT

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]

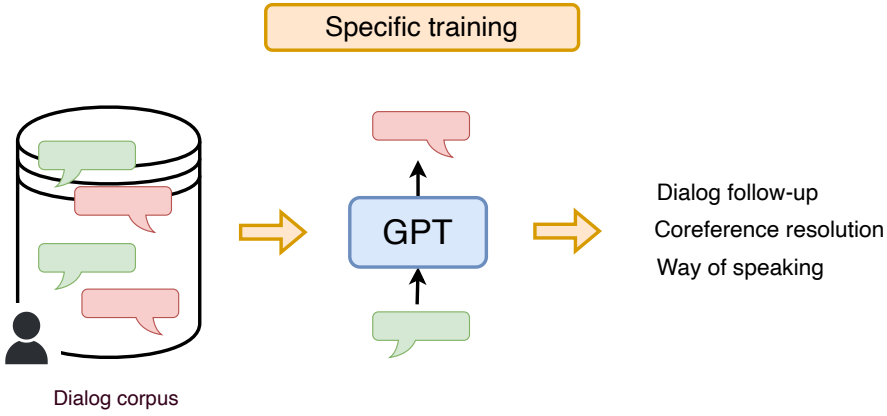
175 Billion parameters... What does it mean?

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



The Ingredients of chatGPT

2. Dialogue Tracking

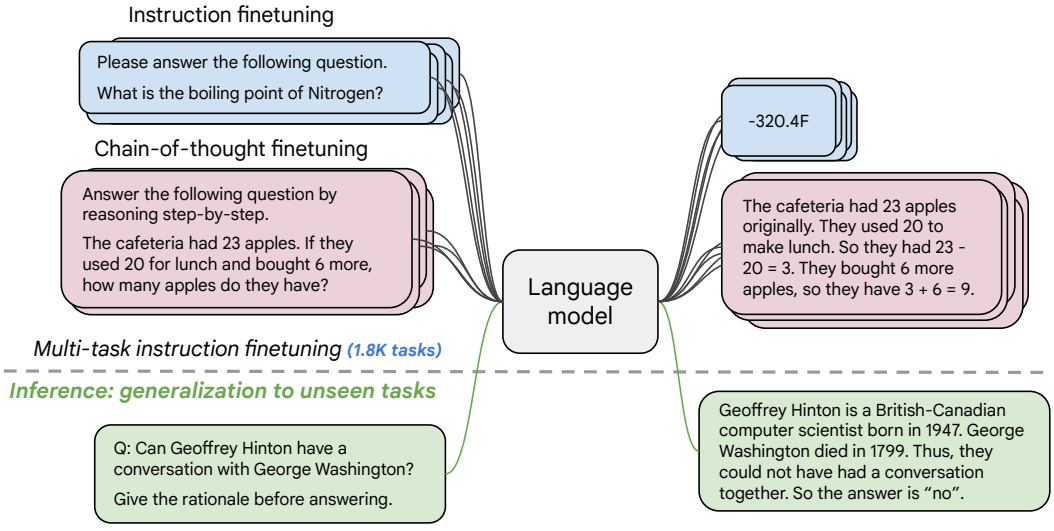


- **Very clean** data

Data generated/validated/ranked by humans

The Ingredients of chatGPT

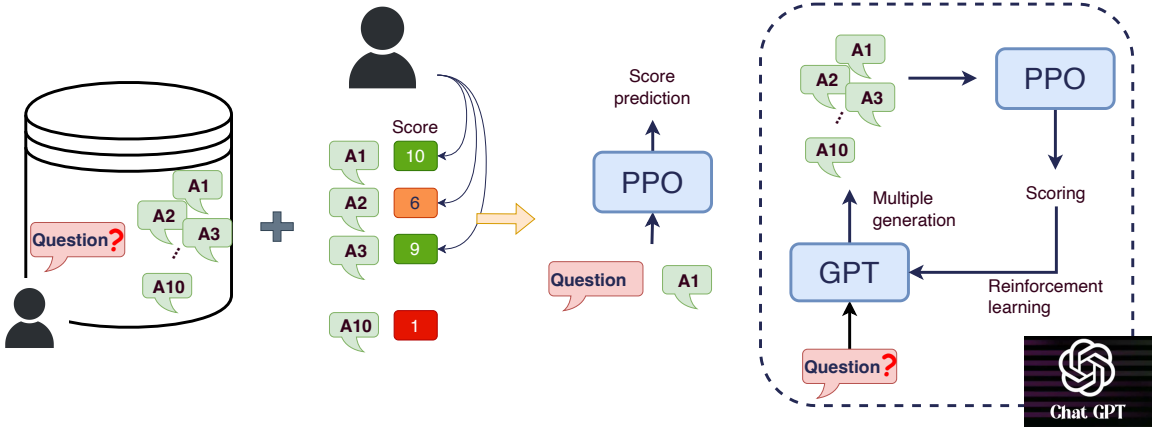
3. Fine-tuning on different (±) complex reasoning tasks



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

The Ingredients of chatGPT

4. Instructions + answer ranking



- Database created by humans
- Response improvement

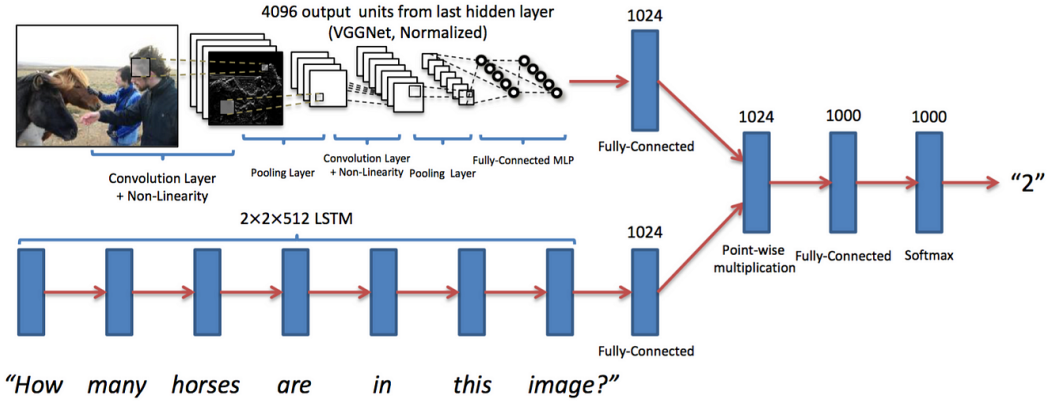
- ... Also a way to avoid critical topics = censorship

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

GPT4 & Multimodality

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

The example of VQA: visual question answering

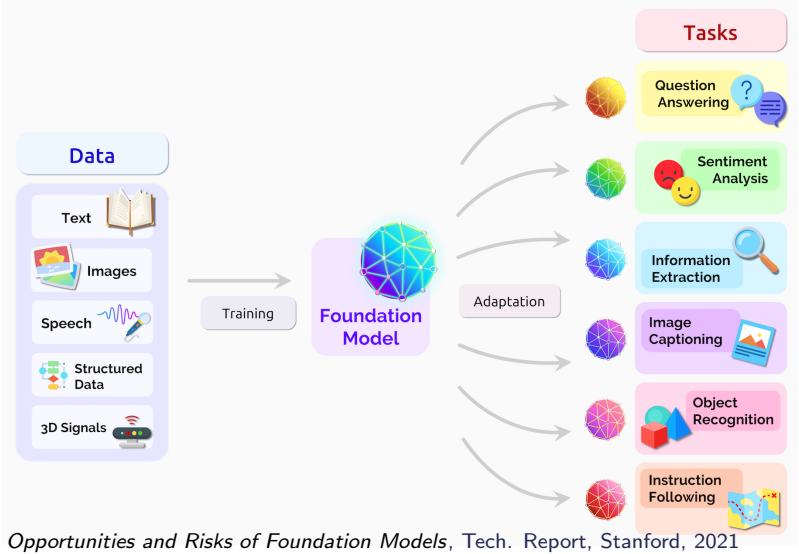


$\Rightarrow$ Backpropagate the error $\Rightarrow$ modify word representations + image analysis

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

Towards Larger Foundation Models?

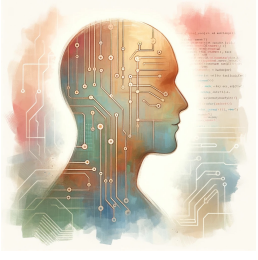
- Let the modalities enrich each other

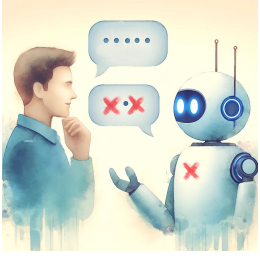


On the Opportunities and Risks of Foundation Models, Tech. Report, Stanford, 2021
Bommasani et al.

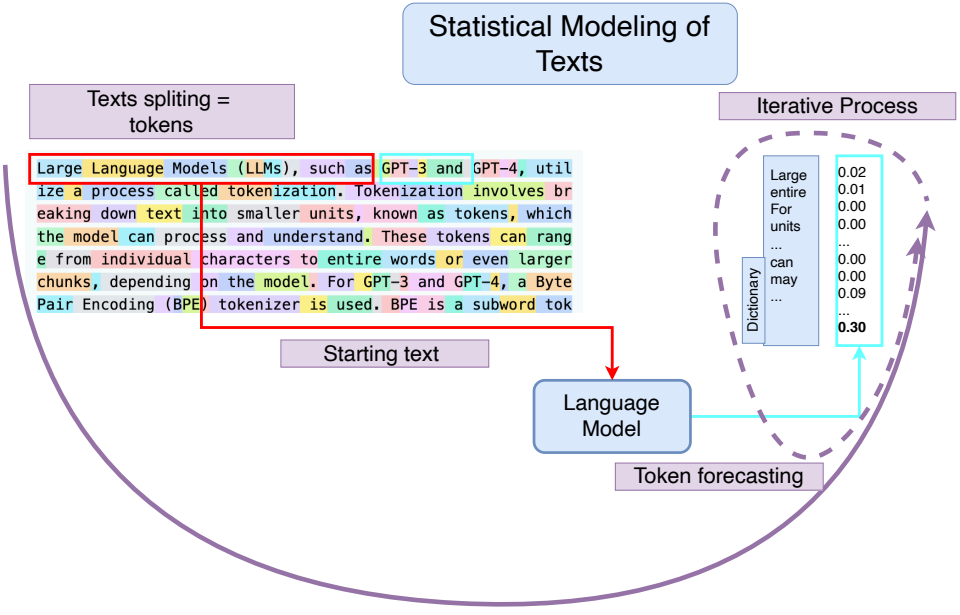
Why So Much Controversy?

- 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?





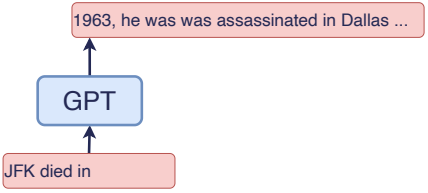
At the end of the day



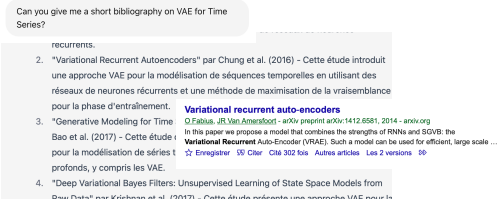
Machine Learning Limits

chatGPT and the relationship with truth

1. **Likelyhood** = 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



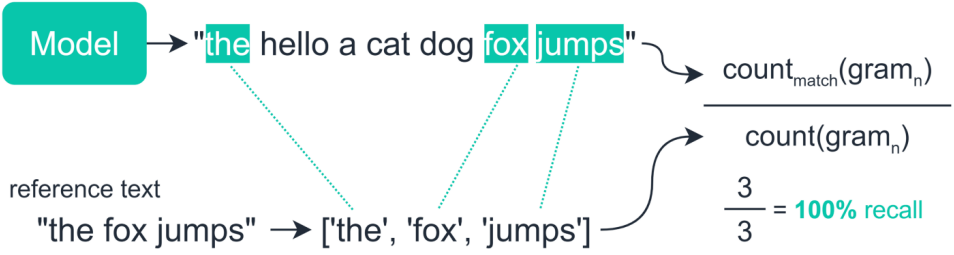
Example: producing a bibliography



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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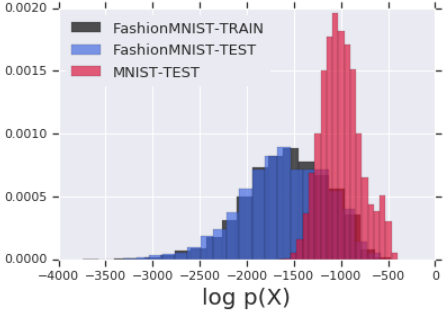

Plausibility

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

⇒ Little/no use in video games

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
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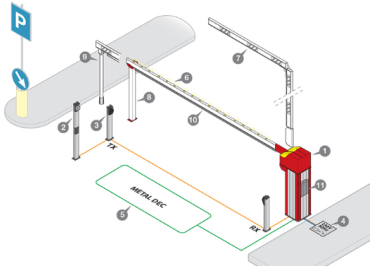
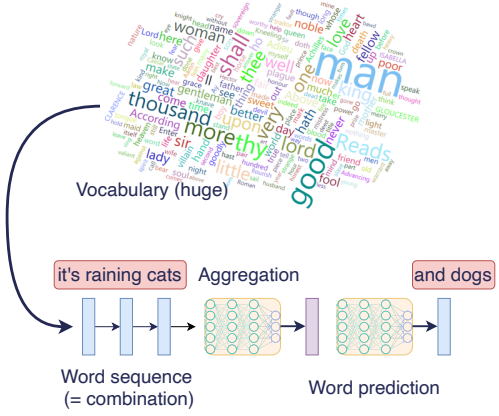
V how old is obama?

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

V and today?

Explainability... And complexity





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

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

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]

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Transparency : open source / open weight

- Can I modify it? — Adaptation
- What training data was used? — Data contamination / skills
- What editorial stance / censorship is involved? — Access to information
- Why this answer? — Explainability / interpretability

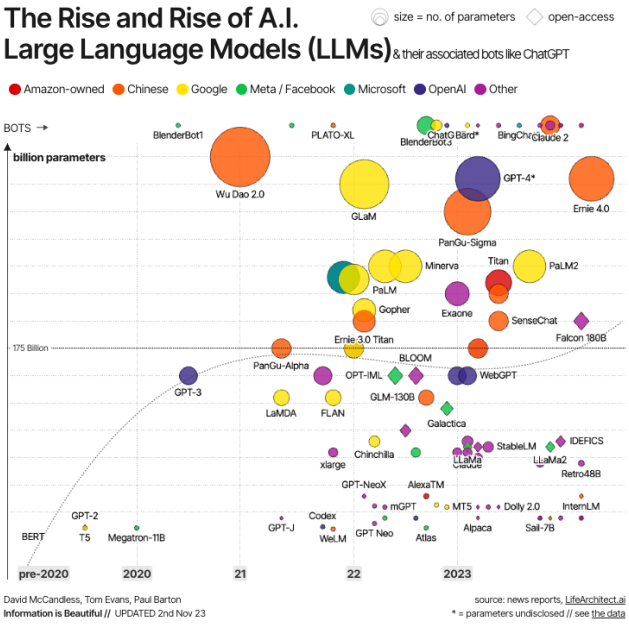
Foundation Model Transparency Index Scores by Major Dimensions of Transparency, 2023

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

Costs / Frugality



Parameters

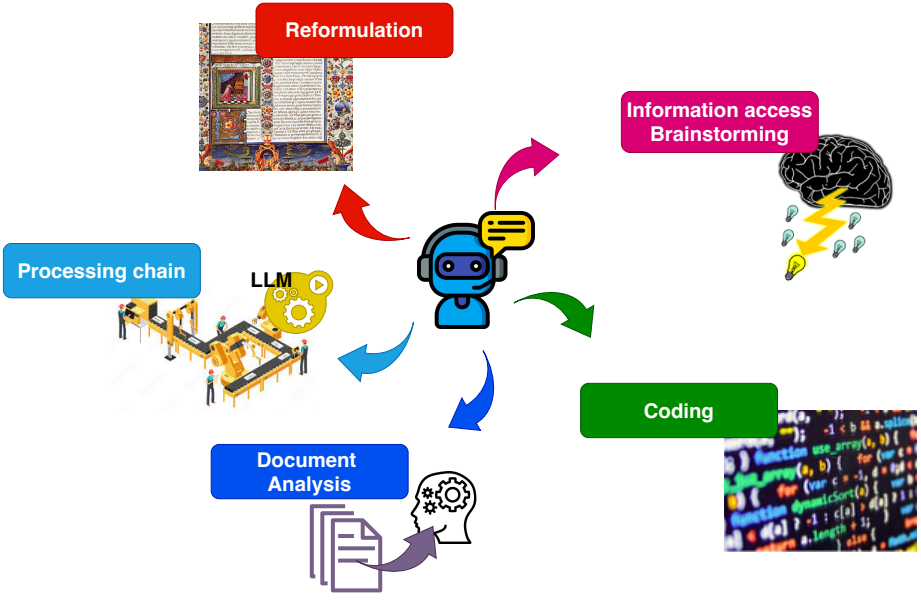
1998	LeNet-5	= 0.06M
2011	Senna	= 7.3M
2012	AlexNet	= 60M
2017	Transformer	= 65M / 210M
2018	ELMo	= 94M
2018	BERT	= 110M / 340M
2019	GPT2	= 1,500M
2020	GPT3	= 175,000M
2025	Llama-4	= 2,000,000M

Everything beyond the LLM's capabilities/training

- Simple calculations (multiplication, division)
- Generating *n*-syllable animal names (in progress)
- Playing chess
- Follow (complex) causal reasoning
- ...

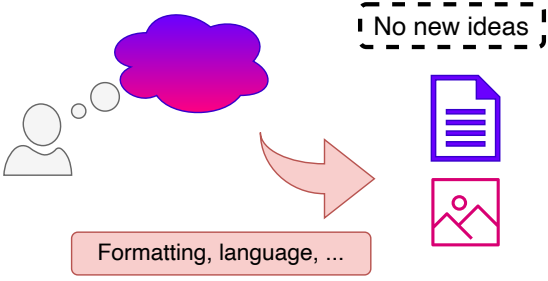
Large Language Models Uses [in nutrition research]

Key uses in 5 pictures



(1) Formatting information

A fantastic tool for **formatting**



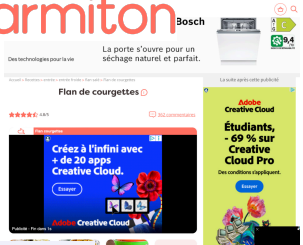
- Personal assistant
  - Standard letters, recommendation letters, cover letters, termination letters
  - Translations
- Meeting reports
  - Formatting notes
- Writing scientific articles
  - Writing ideas, in French, in English

$\Rightarrow$ No new information, just writting, cleaning up, ...

(1) Nutrition use : Input standardization (?)

⇒ opportunity to fuse heterogeneous information

marmiton



Food.

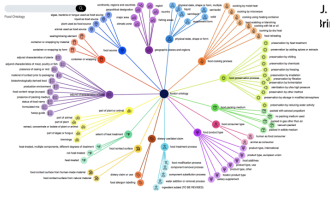
INCA2 Individual national study of food consumption in France Database

anses
agence nationale de sécurité sanitaire alimentation, environnement, travail

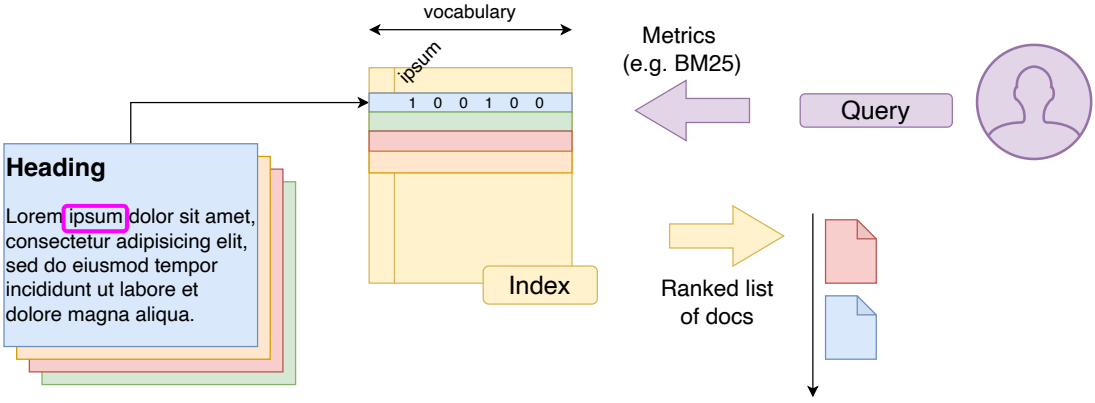
ARTICLE OPEN

FoodOn: a harmonized food ontology traceability, quality control and data ir

J. Griffiths[2,8], Gurinder S. Gosal[1], Pier L. Buttigieg[3], Ro Irinkman[2] and William W. L. Hsiao[1,2,7]



(1) Chat & RAG : a new way to access information



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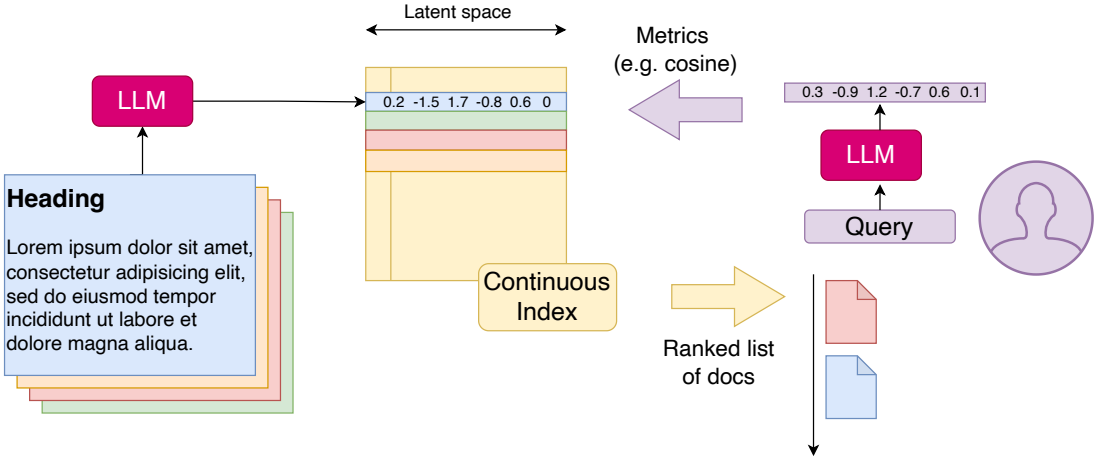

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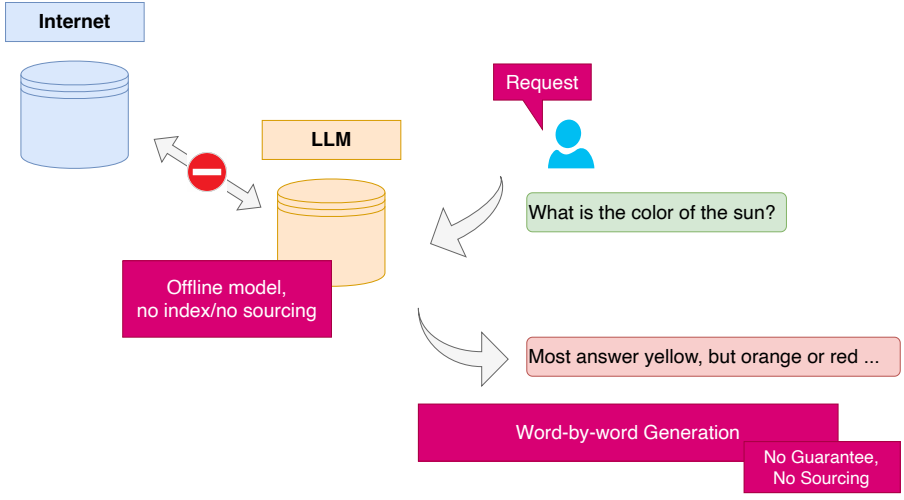

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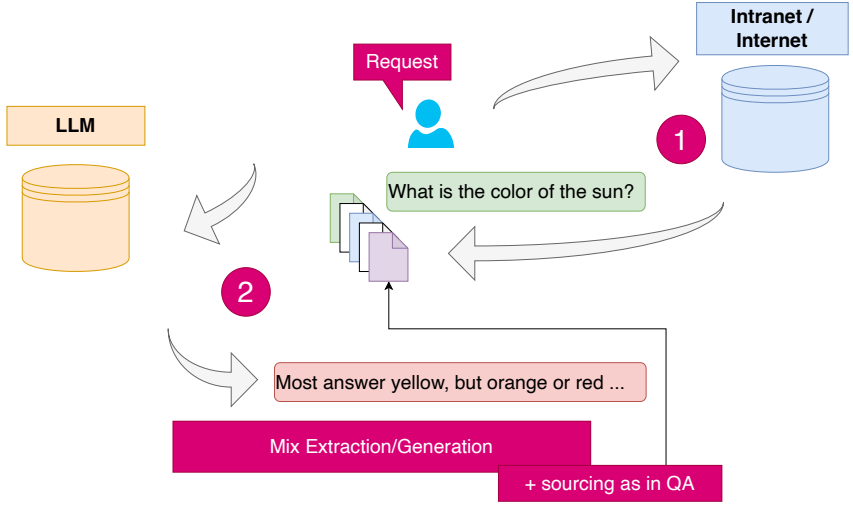


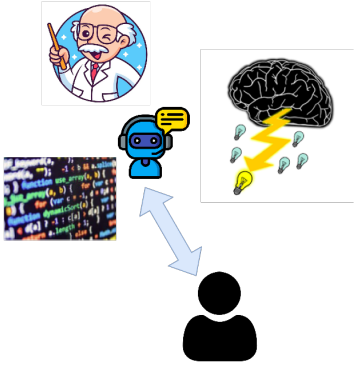
⇒ A way to build a *reliable* chatbot to advise users?

- Parametric memory *vs* Information Retrieval : opposite objectives?

(2) Brainstorming / Course Planning / Statistics Review

- **Find** inspiration [writer's block syndrome]
- **Organize** ideas quickly
- **Avoid omissions** / increase confidency
- **Search** in a targeted way, adapted to one's needs

⇒ Impressive answers, sometimes incomplete or partially incorrect... But often useful

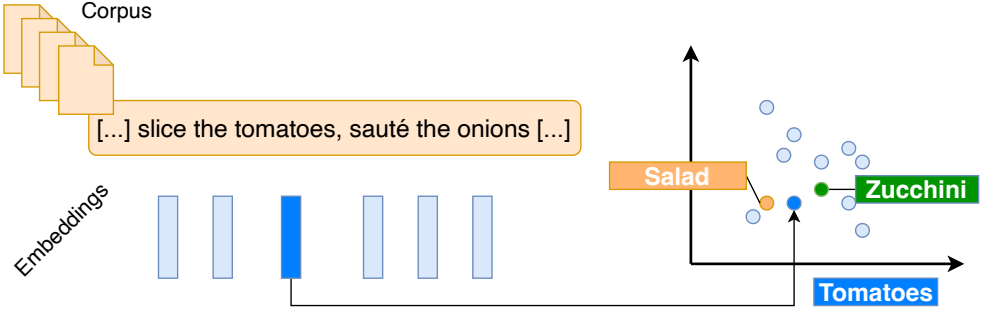


3 reference articles on the use of transformers in recommendation systems
What is the purpose of the log-normal Poisson law?
Propose 10 sections for a course on Transformers in AI

- In which areas are LLMs reliable?
- What are the risks for primary information sources?
- What societal risks for information?

(2) Internal knowledge exploitation for nutrition

- Brainstorming in the kitchen: which application for cooking?
- Ingredient substitution... At every scale: Ingredient, Food, Dish



(2) Internal knowledge exploitation for nutrition

- Brainstorming in the kitchen: which application for cooking?
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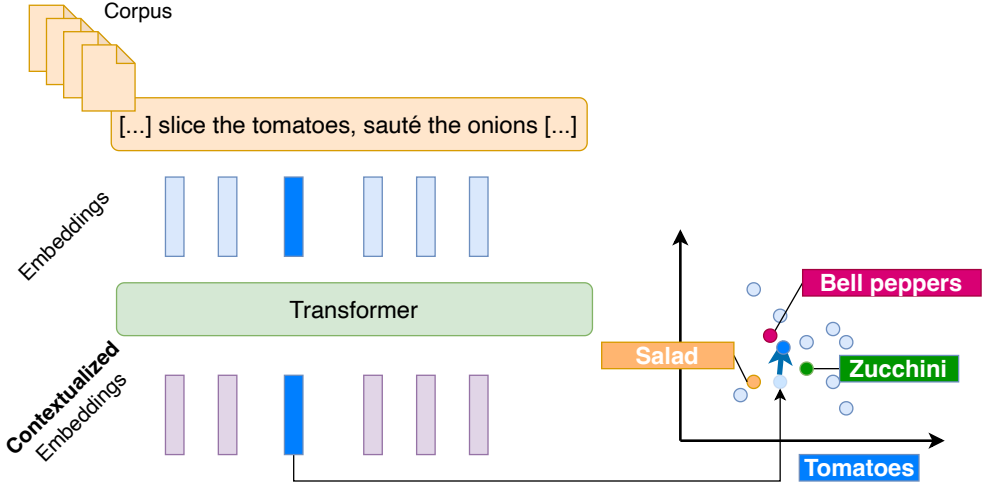
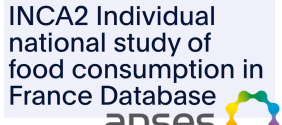
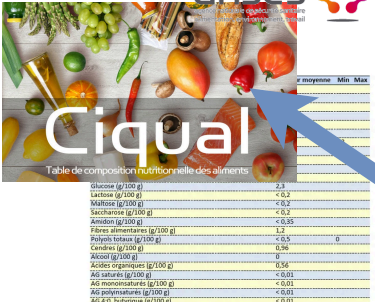
- ++ Upgrade by contextualization



(2) Internal knowledge exploitation for nutrition

- Brainstorming in the kitchen: which application for cooking?
- Ingredient substitution... At every scale: Ingredient, Food, Dish
- ++ Upgrade by contextualization
- Interoperability and ontologies





ARTICLE OPEN

FoodOn: a harmonized food ontology traceability, quality control and data ir

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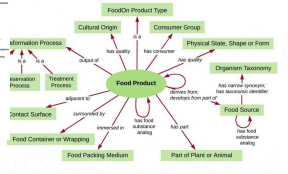


Multilingual alignment

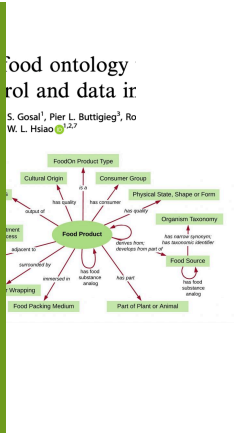
(2) Internal knowledge exploitation for nutrition

- Brainstorming in the kitchen: which application for cooking?
- Ingredient substitution... At every scale: Ingredient, Food, Dish
- ++ Upgrade by contextualization
- Interoperability and ontologies

A new alignment method based on FoodOn as pivot ontology

Patrice Buche, Julien Cufi, Liliana Ibanescu, Alrick Oudot, Magalie weber

12/10/2021



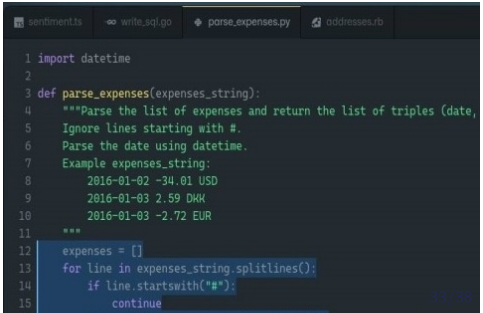
(3) Coding: Different Tools, Different Levels

- Providing solutions to exercises
- Learning to code or getting back into it
  - New languages, new approaches (ML?)
  - Benefit from explanations...

    But how to handle mistakes?
- Help with a library [*getting started*]
- Faster coding

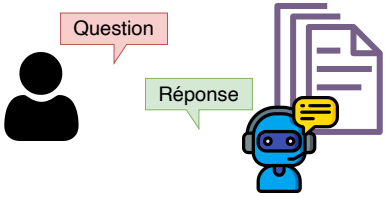
- What about copyrights?
  - What impact on future code processing?
- How to adapt teaching methods?
- How many calls are needed for code completion?

  What about the carbon footprint?
- What is the risk of error propagation?



(4) Document Analysis

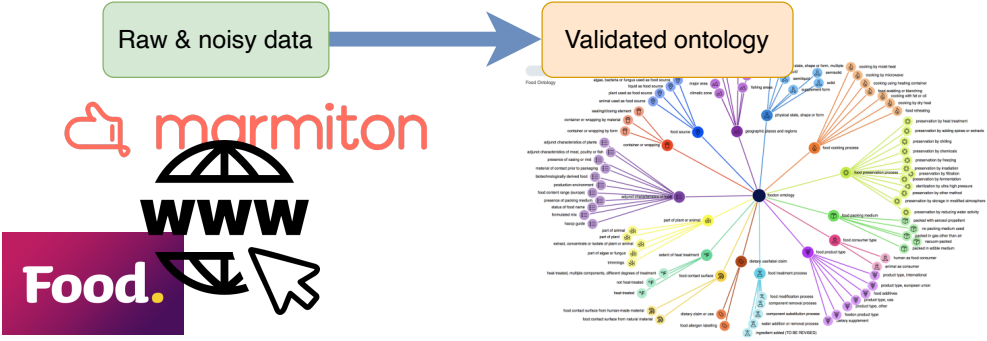
- Summarizing documents / articles
- Dialoguing with a document database
- Assistance in writing reviews
- FAQs, internal support services within companies
- Technology watch
- Generating quizzes from lecture notes



- Will articles still be read in the future?
  - Should we make our articles NotebookLM-proof?
- How to save time while remaining honest and ethical?

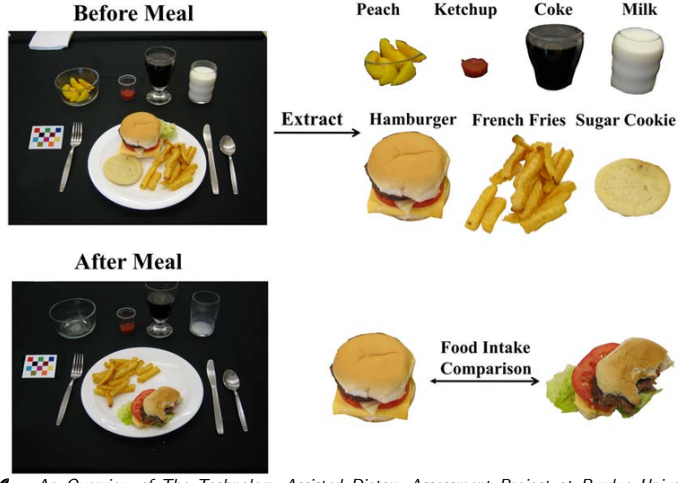
(4) Information Extraction in Nutrition

- Ontology building (mostly textual data)



(4) Information Extraction in Nutrition

- Ontology building (mostly textual data)
- Image analysis

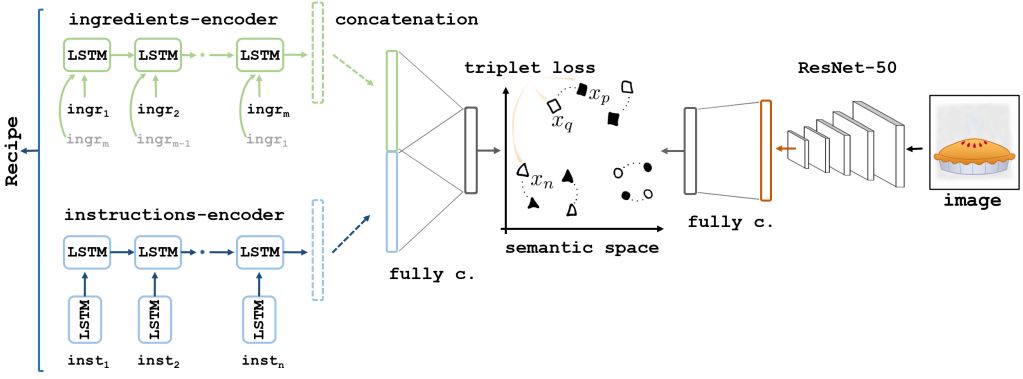


- Food recognition
- Segmentation
- Estimation of quantities

An Overview of The Technology Assisted Dietary Assessment Project at Purdue University., Khanna et al. , 2010

(4) Information Extraction in Nutrition

- Ontology building (mostly textual data)
- Image analysis
- Multimodal analysis + algorithmic process



Images & Recipes: Retrieval in the cooking context, SIGIR 2018
Carvalho et al.

(4) Information Extraction in Nutrition

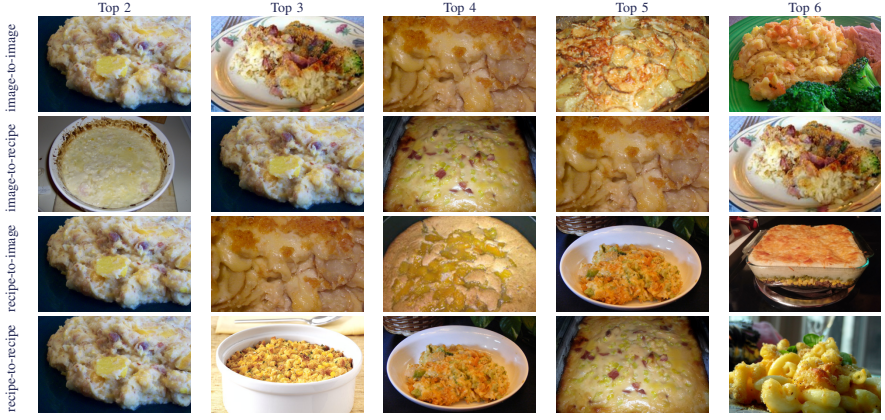
- Ontology building (mostly textual data)
- Image analysis
- Multimodal analysis + algorithmic process

	ingr (ingredients)	instr (cooking instructions)	image
Pizza	1) *pizza dough* 2) *hummus* 3) *arugula* 4) *cherry / grape tomatoes* 5) *pitted greek olives* 6) *crumbled feta cheese*	1) *Cut the dough into two 8-ounce sized pieces.* 2) *Roll the ends under to create round balls.* 3) *Then using a well-floured rolling pin, roll the dough out into 12-inch circles.* 4) *Place the dough circles on sheets of parchment paper.*	
Pecan Pie	1) *unsalted butter* 2) *eggs* 3) *condensed milk* 4) *sugar* 5) *vanilla extract* 6) *chopped pecans* 7) *chocolate chips*	1) *Preheat the oven to 375 degrees F.* 2) *In a large bowl, whisk together the melted butter and eggs until combined.* 3) *Whisk in the sweetened condensed milk, sugar, vanilla, pecans, chocolate chips, butterscotch chips, and coconut.*	

Images & Recipes: Retrieval in the cooking context, SIGIR 2018
Carvalho et al.

(4) Information Extraction in Nutrition

- Ontology building (mostly textual data)
- Image analysis
- Multimodal analysis + algorithmic process

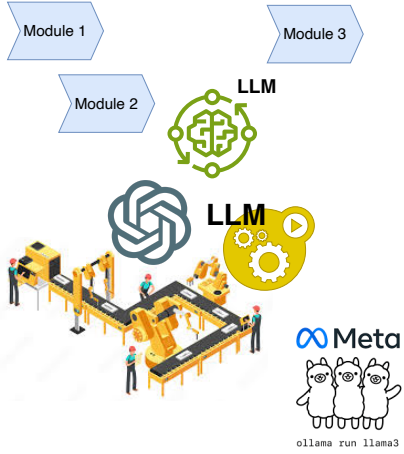


Images & Recipes: Retrieval in the cooking context, SIGIR 2018
Carvalho et al.

(5) LLM in a Production Pipeline / Agentic AI

- Run LLM locally
- Extract knowledge
- Sort documents / generate summaries
- Generate examples to train a model
  [Teacher/student - distillation]
- Generate variants of examples ↗↗ increase dataset size
  [Data augmentation]

⇒ Integrate the LLM into a processing pipeline
= little/less supervision = **Agentic AI**



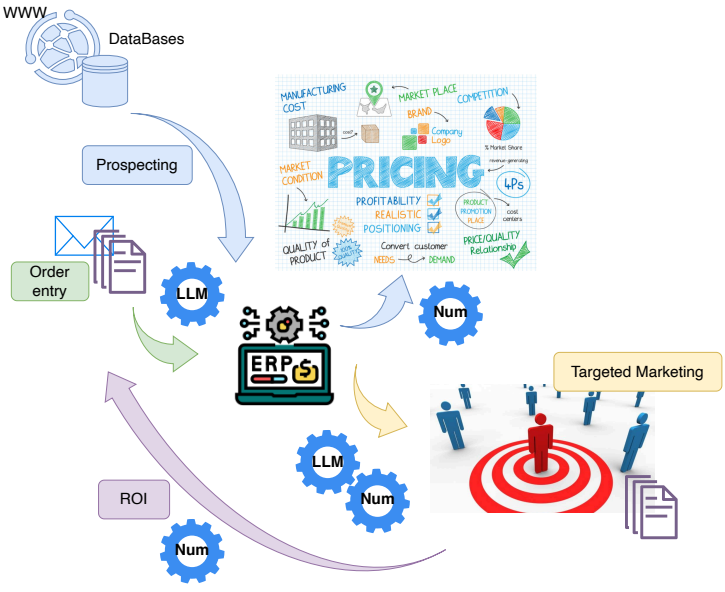
- Can I train models on generated data?
- How much does it cost? ($ + CO_2) Need for GPUs?
- How good are open-weight models?

(5) LLM in a Production Pipeline / Agentic AI

- Run LLM
- Extract kn
- Sort docu
- Generate e
- Generate v dataset siz

⇒ Integrate t =

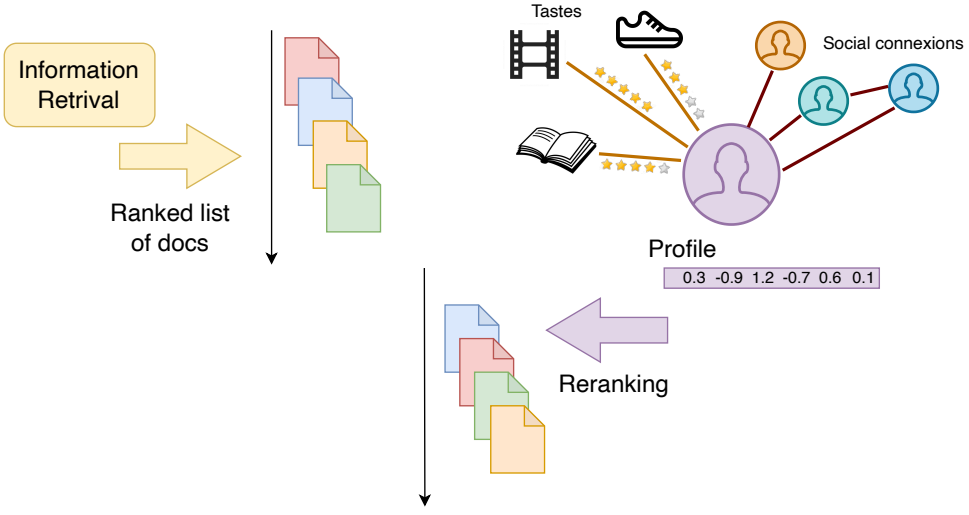
- Can I t
- How m
- How go



Module 3

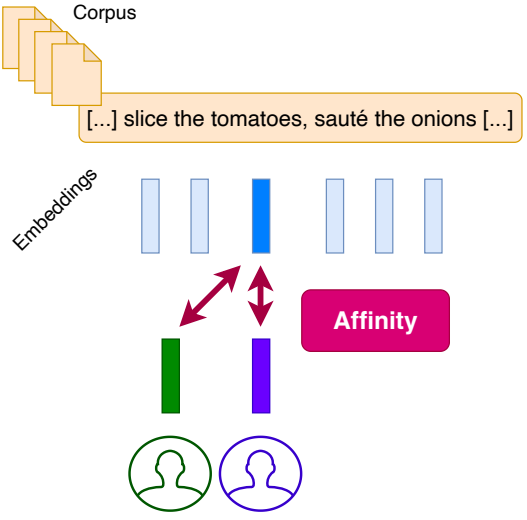
(5) What about Recommender System in Nutrition?

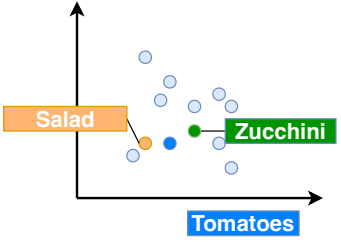
Profiling is roughly everywhere in Information Retrieval



(5) What about Recommender System in Nutrition?

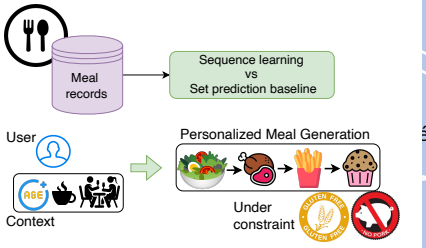
Opportunities in nutrition : modeling user preferences

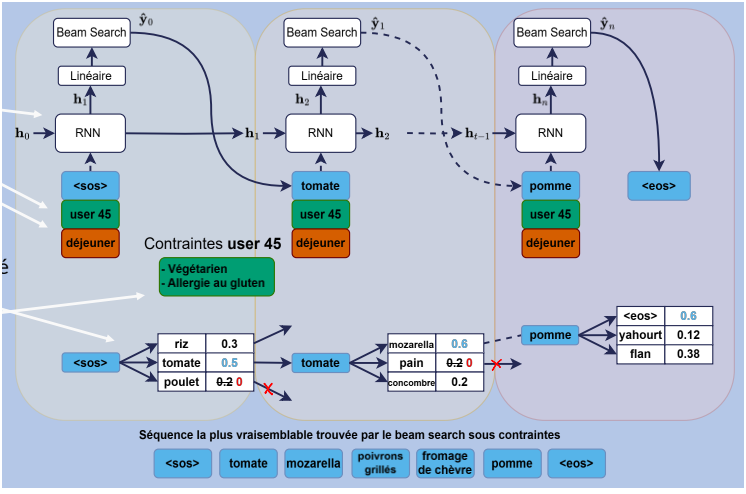




(5) What about Recommender System in Nutrition?

Building consistent proposals... With expert constraints





Génération séquentielle prenant en compte des informations contextuelles en nutrition , CAp 2025
Combeau et al.

Conclusion

New tools for new opportunities

LLMs offer new perspectives in nutrition:

- A natural and convenient interface for users
  - enabling dialogue, plate analysis, and personalized advice
- Accessible on multiple devices, from computers to smartphones and smart kitchens (Alexa, Google Assistant, ...)
- A means to unify and connect existing nutritional resources
- A powerful tool to extract and structure knowledge $\Rightarrow$ enrich databases
- A modular component for next-generation recommender systems