DU PROMPTING AU FINE-TUNING

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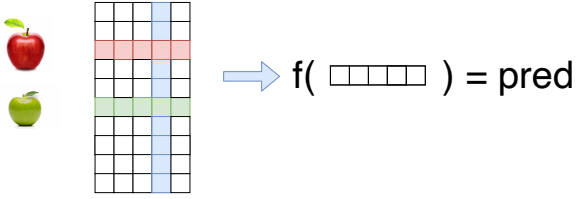
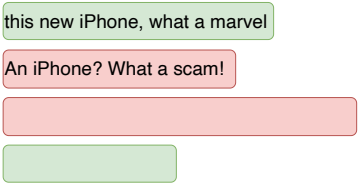
Textual data

From tabular data to text

- Tabular data
  - Fixed dimension
  - Continuous values



- Textual data
  - Variable length
  - Discrete values

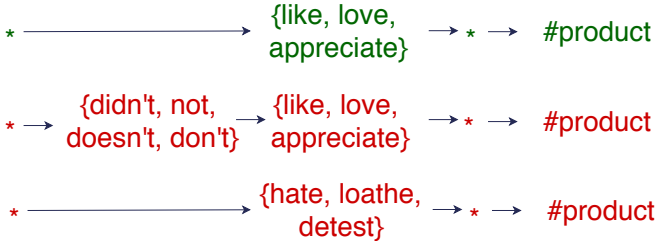


AI + Textual Data: Natural Language Processing (NLP)

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

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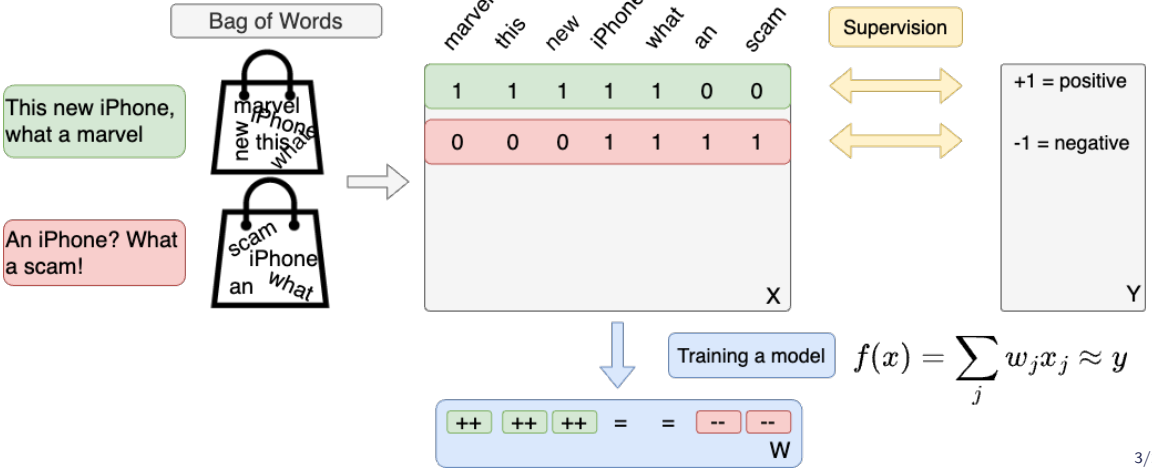
Machine Learning [1990-2015]



AI + Textual Data: Natural Language Processing (NLP)

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Linguistics [1960-2010]

- Requires expert knowledge
- Rule extraction ⇔ very clean data

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

Machine Learning [1990-2015]

- Little expert knowledge needed
- Statistical extraction ⇔ robust to noisy data

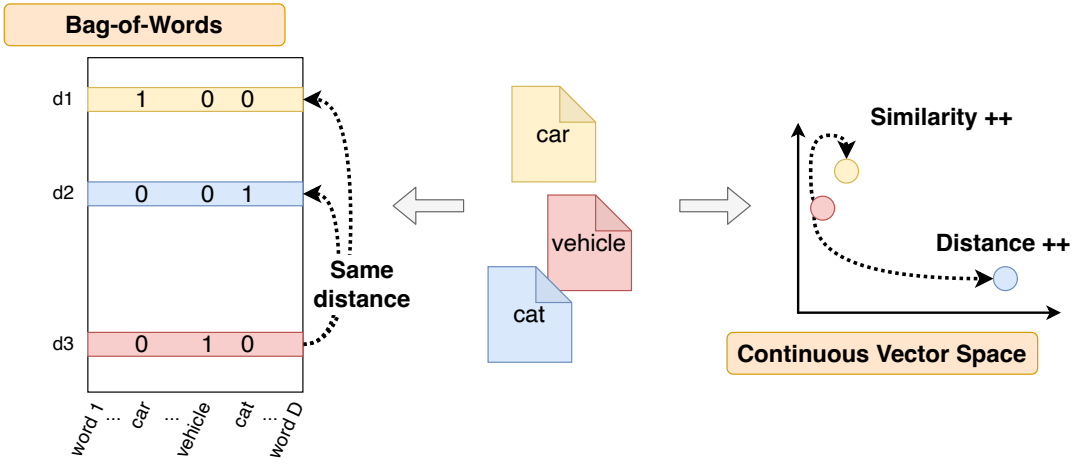
≈ Less interpretable system
− Lower precision
\+ Better recall

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]

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I adopted a stray cat from the shelter last week.
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The black cat stealthily crept through the dark alley.
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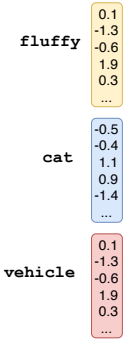
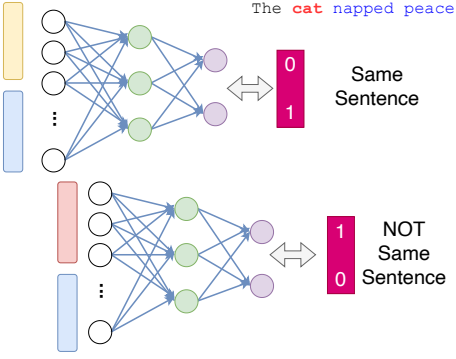
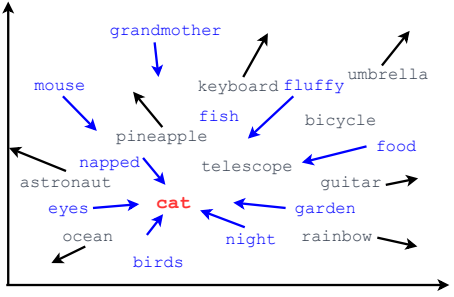
My grandmother has a collection of porcelain cat figurines.
The cat napped peacefully in the warm sunlight.







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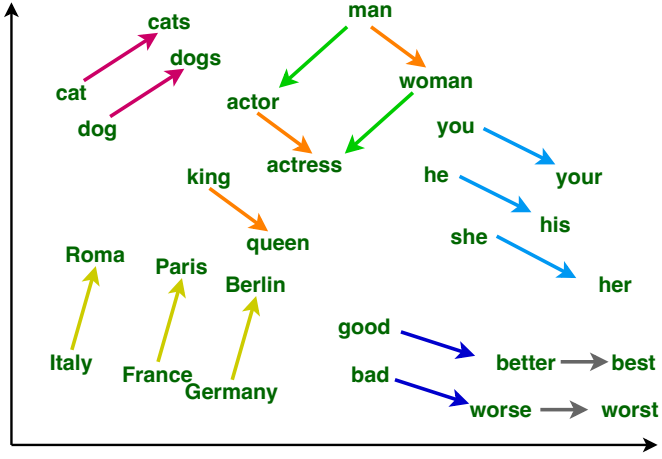


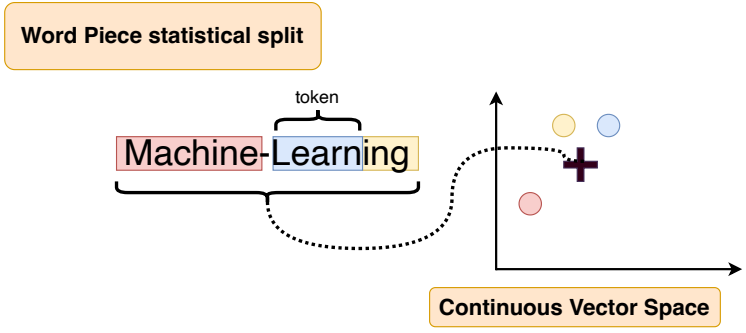
- Semantic Space:
  similar meanings
  $\Leftrightarrow$
  close positions
- Structured Space:
  grammatical regularities,
  basic knowledge, ...

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

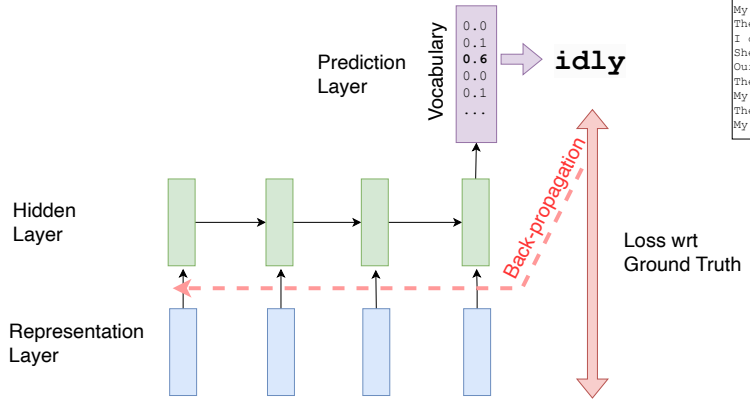


- Representation of unknown words
- Adaptation to technical domains
- Resistance to spelling errors

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

Use-Case: Machine Translation

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

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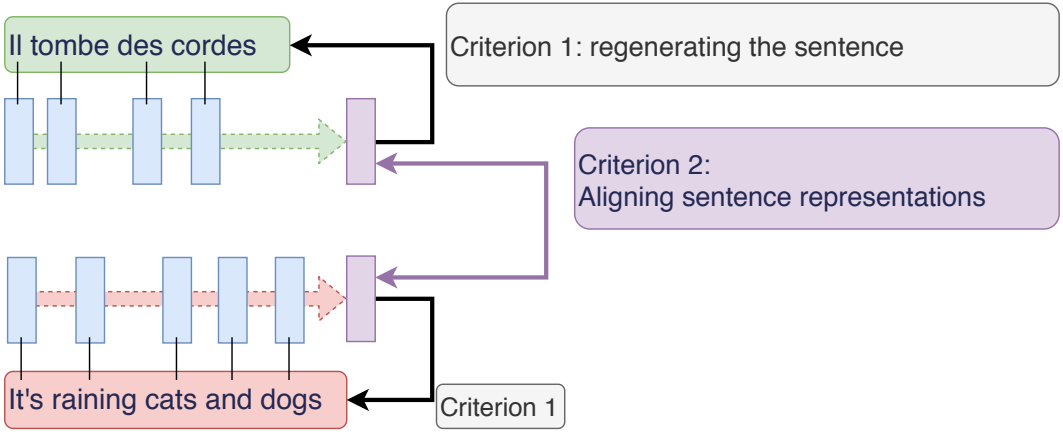

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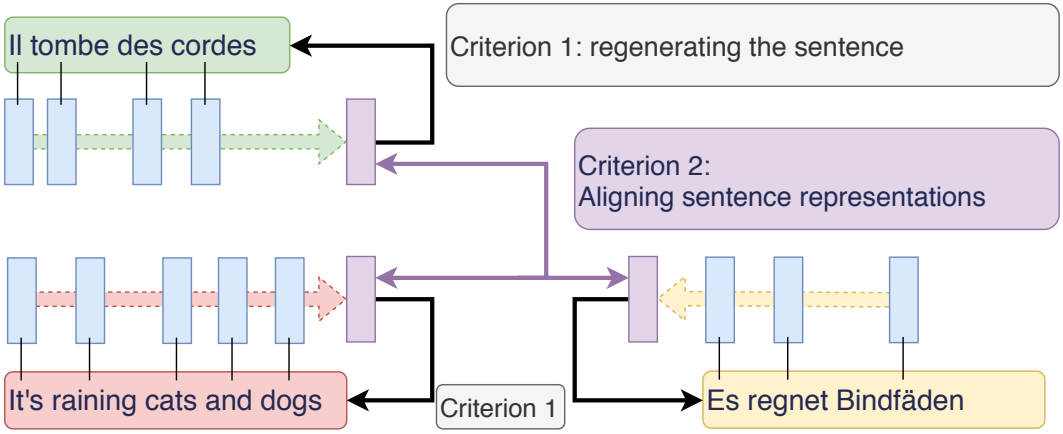
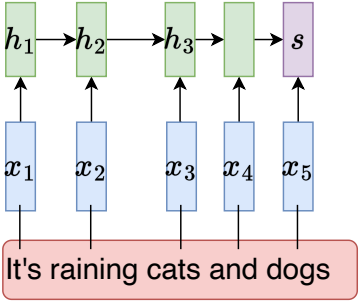


Beyond word-for-word translation, multilingual representation of sentences

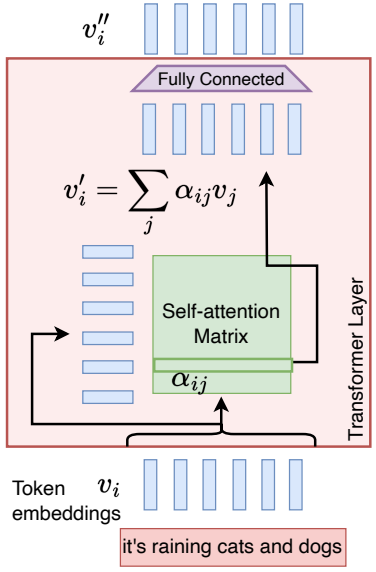
Transformer architecture: state-of-the-art aggregation

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

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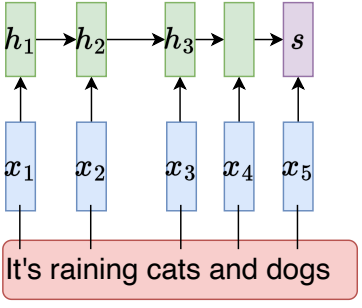

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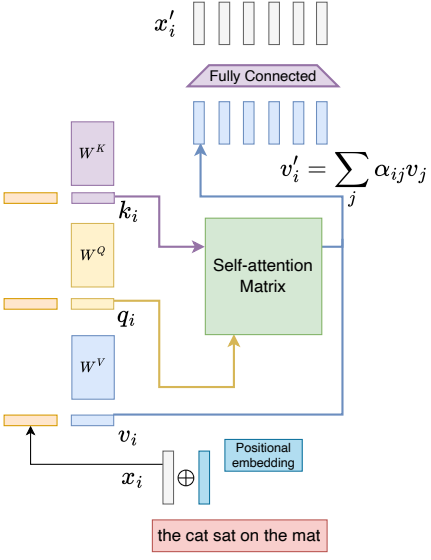

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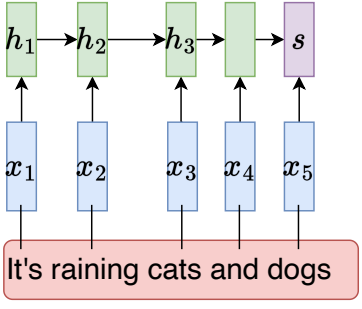

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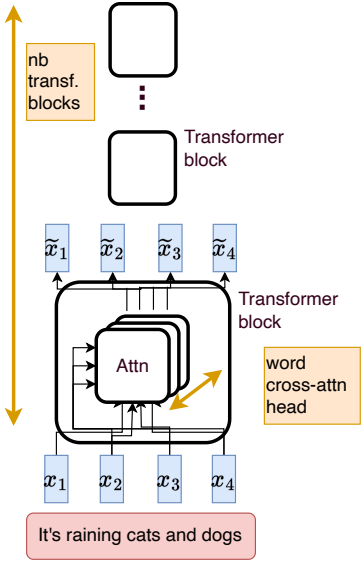

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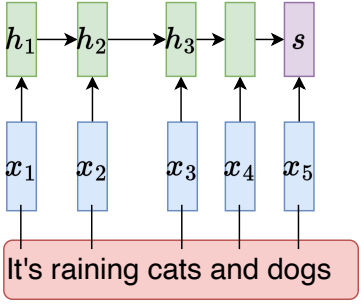

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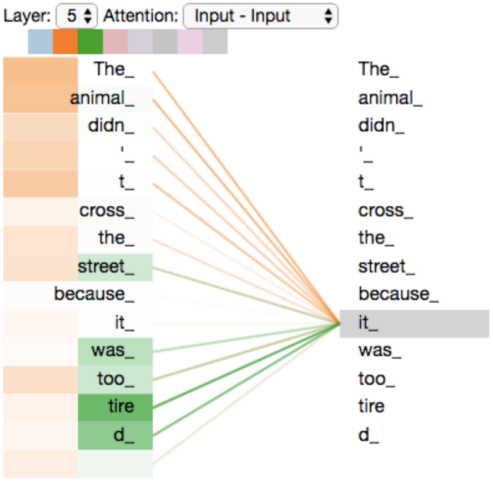

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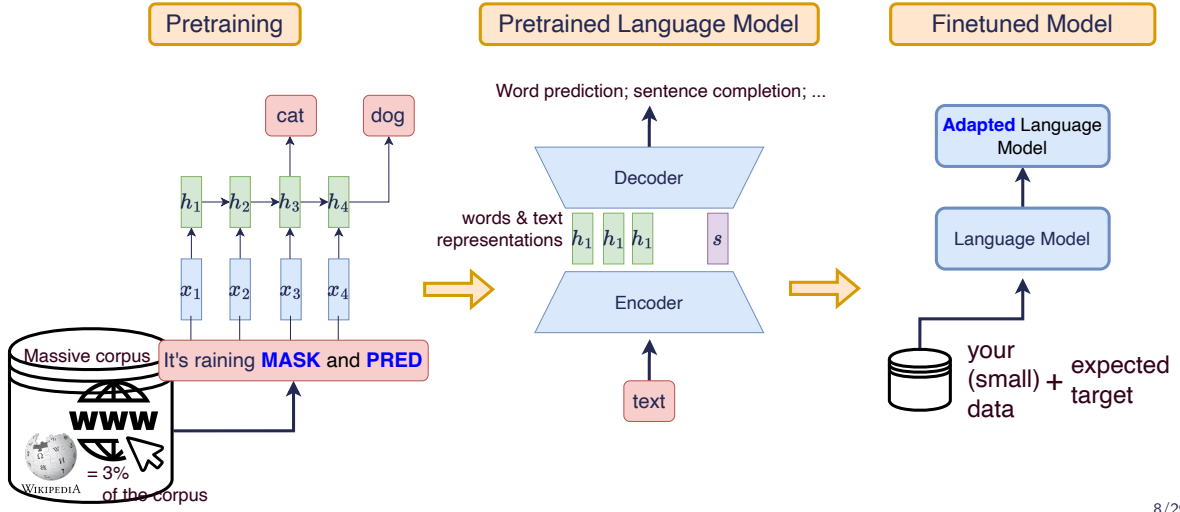
A new developpement paradigm since 2015

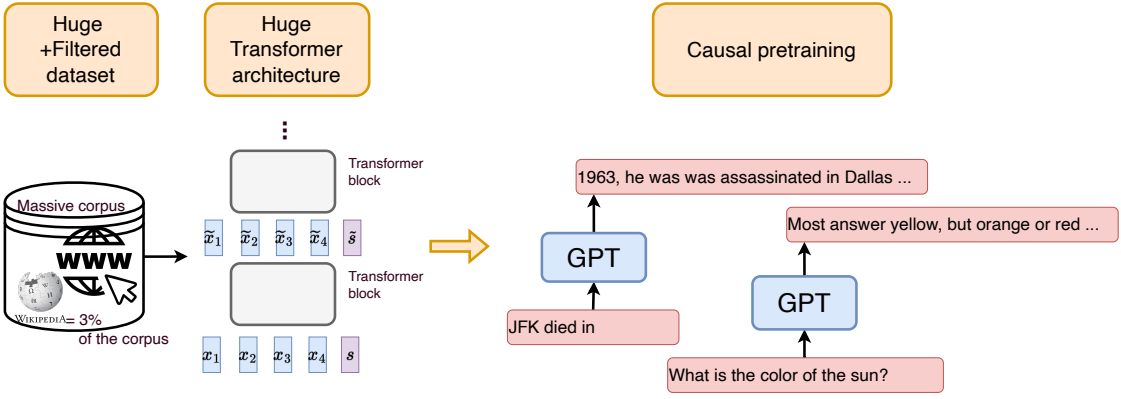
- Huge dataset + huge archi. $\Rightarrow$ unreasonable training cost
- Pre-trained architecture + 0-shot / finetuning



Generative AI & finetuning

The genAI wave

- *Causal* architecture / generating relevant answers

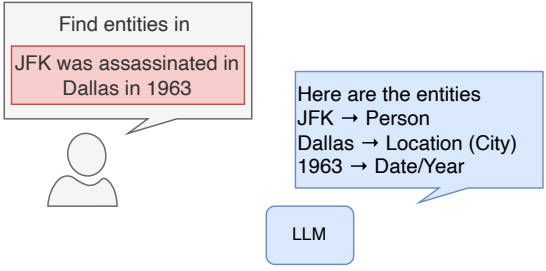


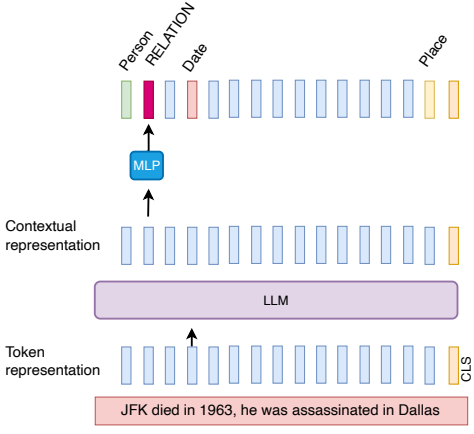
- Grammatical skills: singular/plural agreement, tense concordance
- Knowledges: entities, names, dates, places

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

A revolution in NLP: new formulation, new(?) metrics

- input = text... output = text also !!!

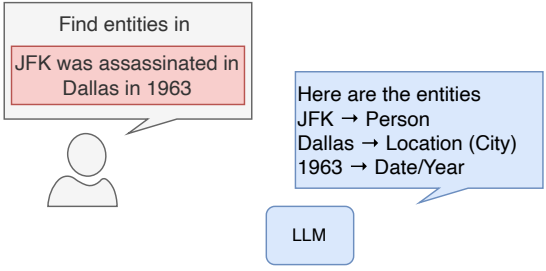




- How to evaluation Entity location?
- What about rephrasing?
- Over detection

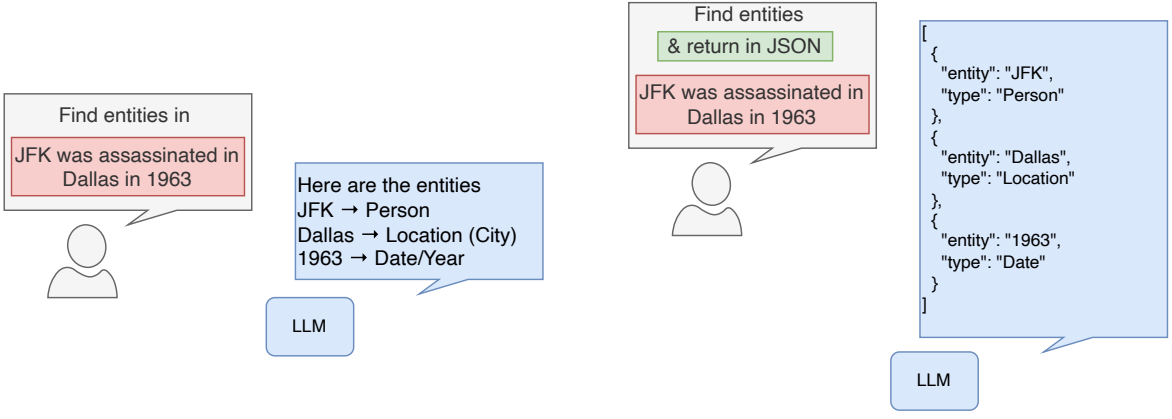
JFK PERSON was assassinated in Dallas GPE in 1963 DATE

Formating constraints



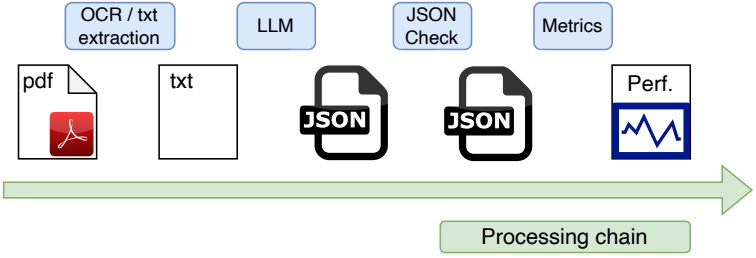
- Prompt optimization: role, task, categories, examples, ...

Formating constraints



- Prompt optimization: role, task, categories, examples, ...
- Adding constraints ⇒ processing chain
- Forcing the system to return JSON... **and only JSON**

Processing chain

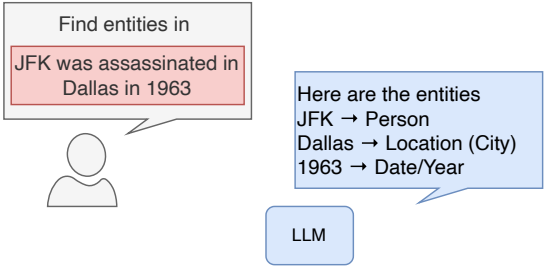


- Famous framework = langchain
- Challenge: all components should be replacable
- OCR : pypdf, tesseract...
- LLM : ollama, HuggingFace, GPT, ...
- JSON : regex, LLM constraint, multiple queries
- Metrics

Zero-shot

Zero-shot

Exploiting a model on a task... (almost) without training



- Is the task really new?
  - to be efficient, LLM are trained on multiple instructions
  - Risk of data contamination
- Which performance to expect?

1st optimization step: Prompting

Prompting = the way to ask a question ⇒ impact on the performance

You are an information extraction system. Your task is to read an English news article and extract named entities of the following types:

- **PERSON**: names of individual people
- **LOCATION**: geographical entities such as cities, countries, landmarks
- **ORGANIZATION**: companies, institutions, government bodies, media outlets, NGOs, etc.
- **DATE**: explicit calendar dates or temporal expressions (e.g., "January 5, 2023", "last Monday")

Return the results in **JSON format** with the following structure:

json Copier le code

```
{
  "PERSON": ["..."],
  "LOCATION": ["..."],
  "ORGANIZATION": ["..."],
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}
```

If a category has no entities, return an empty list. Do not include duplicates.

Text to analyze:

1st optimization step: Prompting

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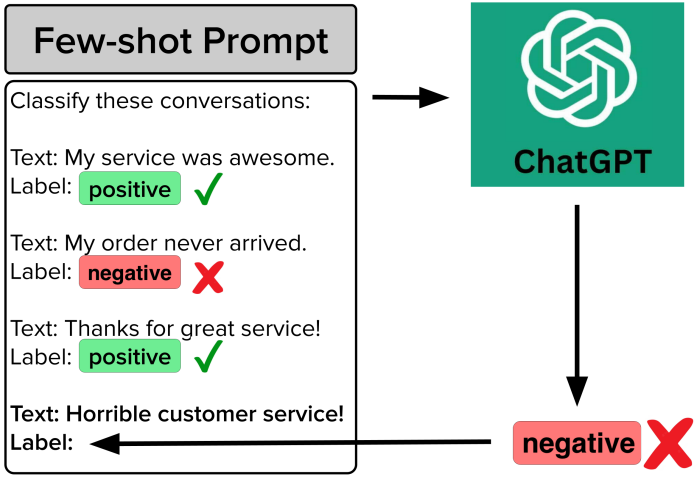
ROLE
TASK
Class DEF
Format
Supp.

If a category has no entities, return an empty list. Do not include duplicates.

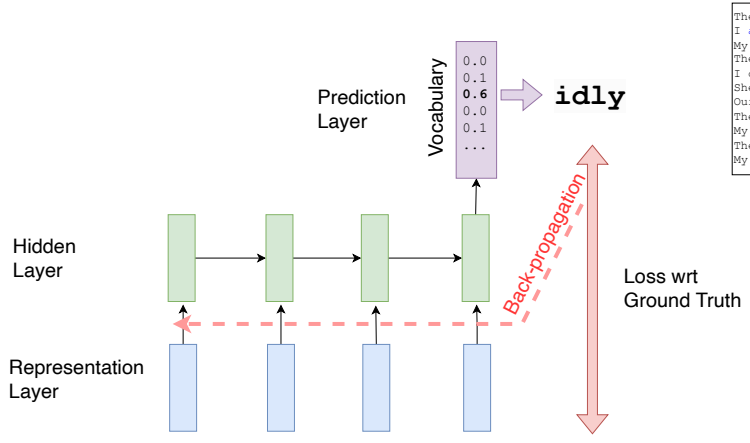
Few-shot learning (no optimization yet!)

Give (input $\Leftrightarrow$ output) on few examples to guide the extraction



Finetuning of genAI

Most generative finetuning = train to generate the ground truth



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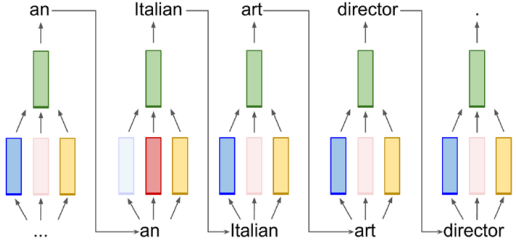
Corpus

The fluffy cat napped lazily in the sunbeam.

Faithfulness optimization : At the token level[1]

Name	Giuseppe Mariani
Occupation	Art director
Years active	1952 - 1992

Giuseppe Mariani was an **Italian** art director.

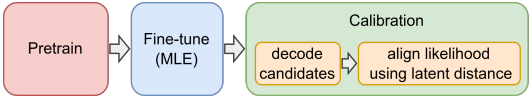


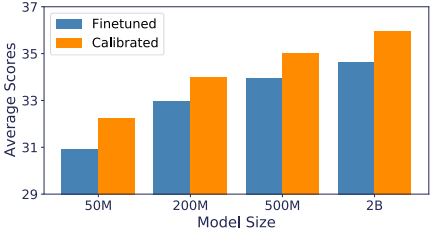
- Require annotation at the token level
- Multi-branch decoder ⇒ find the good balance (fluency, faithfulness, ...)

[1] Rebuffel et al, Data Mining and Knowledge Discovery 2022.
Controlling hallucinations at word level in data-to-text generation.

Faithfulness opti as a post-processing step[3]

- Calibrating the likelihood in the beam-search procedure





- Conditional PMI Decoding[2]: detecting hazard (entropy) + shifting proba

$$\text{score}\left(y \mid \mathbf{y}_{<t}, \mathbf{x}\right) = \log p\left(y \mid \mathbf{y}_{<t}, \mathbf{x}\right) - \lambda \cdot \mathbb{1}_{\{\mathrm{H}(p(\cdot \mid \mathbf{y}_{<t}, \mathbf{x})) \geq \tau\}} \cdot \log p\left(y \mid \mathbf{y}_{<t}\right)$$

[2] van der Poel et al.; EMNLP 2022
Mutual Information Alleviates Hallucinations in Abstractive Summarization

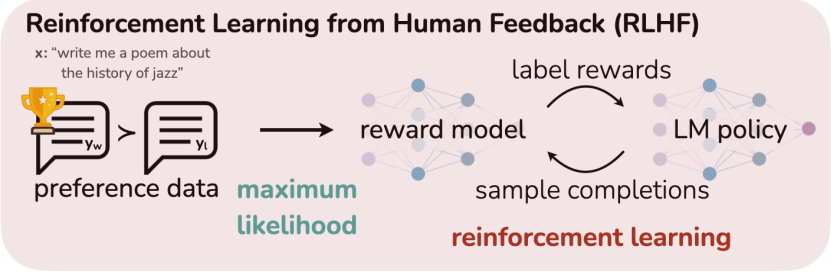
[3] Zhao et al.; ICLR 2023
Calibrating Sequence likelihood Improves Conditional Language Generation

Let's optimize preferences ! [PPO[4]]

(Major) assumption

We have hallucinated *vs* proper sentences in a data-to-text framework

Since instructGPT... We use PPO (Proximal Policy Optimization)



[4]Schulman et al. arXiv 2017. Proximal Policy Optimization Algorithms

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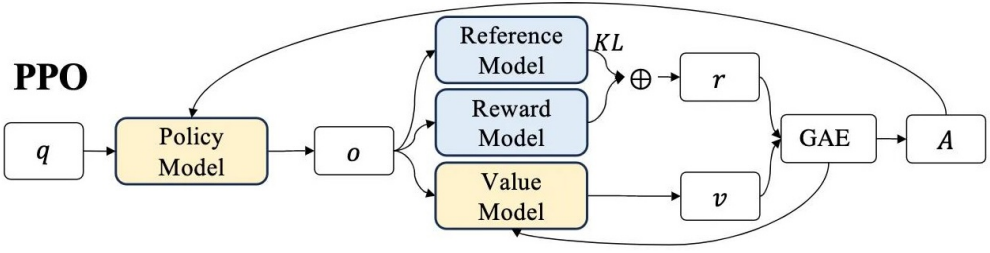
Since instructGPT... We use PPO (Proximal Policy Optimization)



[4]Schulman et al. arXiv 2017. Proximal Policy Optimization Algorithms

Let's optimize preferences ! [PPO[4]]

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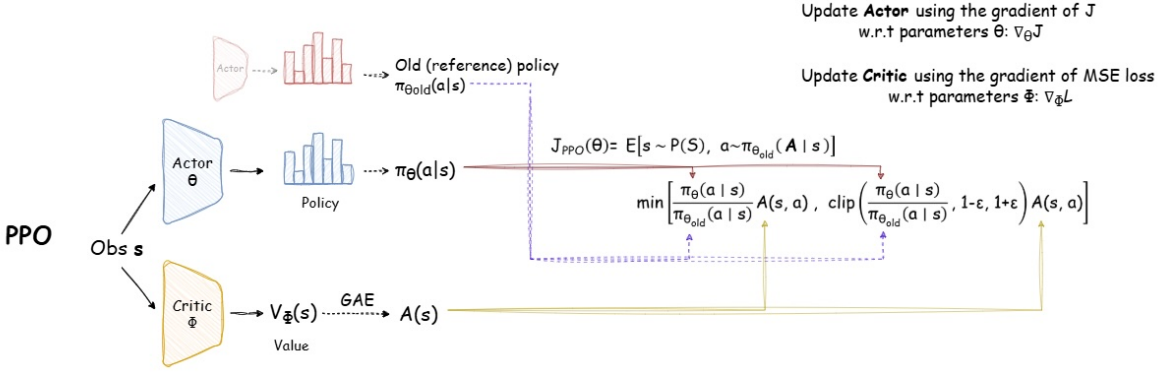

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Let's optimize preferences ! [PPO[4]]

(Major) assumption

We have hallucinated *vs* proper sentences in a data-to-text framework

Since instructGPT... We use PPO (Proximal Policy Optimization)

- 4 models to load in memory (π_θ, π_0, V)
- 2 models with gradients ($\pi_\theta, V/A$)
- Intensive sampling $\propto \pi_\theta(y_t \mid y_{<t})$
- Instable procedure (cf regul. terms)

[4] Schulman et al. arXiv 2017. Proximal Policy Optimization Algorithms

Let's optimize preferences ! [PPO[4]]

(Major) assumption

We have hallucinated *vs* proper sentences in a data-to-text framework

Since instructGPT... We use PPO (Proximal Policy Optimization)

```
(Données humaines)
      |
Comparaisons ↴
     Train Reward Model r_ϕ

      ↓
Prompts → LLM (π_θ) → Réponses
                      ↓
               Eval avec r_ϕ
                      ↓
             Recompense + KL + Avantage
                      ↓
             PPO update π_θ ← π_θ + Δθ
```

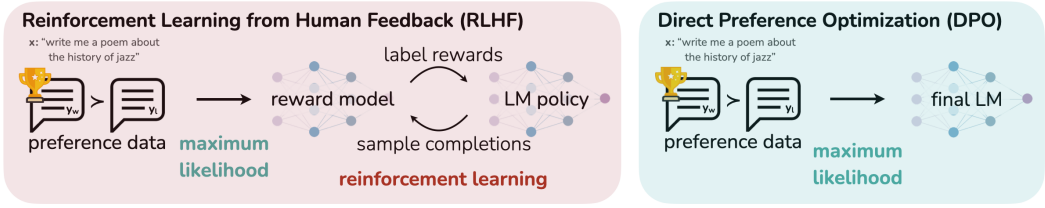
$$L^{\text{CLIP}}(\theta) = -\mathbb{E}\left[\min\left(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\varepsilon, 1+\varepsilon)\hat{A}_t\right)\right]$$

Reward:

$$r_t(\theta) = \beta \log \frac{\pi_\theta\left(y_t \mid y_{<t}\right)}{\pi_0\left(y_t \mid y_{<t}\right)}$$

[4] Schulman et al. arXiv 2017. Proximal Policy Optimization Algorithms

Simplifying the procedure [DPO[5]]



Same reward:

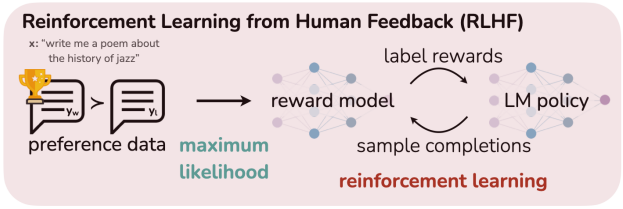
$$\hat{r}_\theta(x, y) = \beta \log \frac{\pi_\theta\left(y_t \mid y_{<t}\right)}{\pi_0\left(y_t \mid y_{<t}\right)}$$

Different cost:

$$\mathcal{L}_{\mathrm{DPO}}\left(\pi_\theta; \pi_{\mathrm{ref}}\right) = -\mathbb{E}_{(y_{t+}, y_{t-}, y_{<t},) \sim \mathcal{D}}\left[\log \sigma\left(\beta \log \frac{\pi_\theta\left(y_{t+} \mid y_{<t}\right)}{\pi_0\left(y_{t+} \mid y_{<t}\right)} - \beta \log \frac{\pi_\theta\left(y_{t-} \mid y_{<t}\right)}{\pi_0\left(y_{t-} \mid y_{<t}\right)}\right)\right]$$

[5] Rafailov et al., NeurIPS 2023.
Direct Preference Optimization: Your Language Model is Secretly a Reward Model

Simplifying the procedure [DPO[5]]



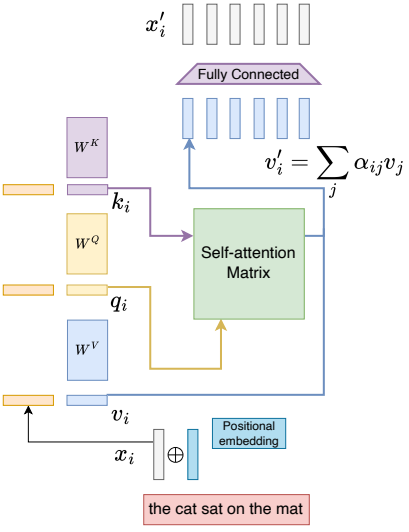
- 2 models to load in memory (π_θ, π_0)
- 1 models with gradients (π_θ)
- Intensive sampling but $\propto \pi_0(y_t \mid y_{<t}) \Rightarrow$ enable precomputing
- Classical (=stable) likelihood optimization

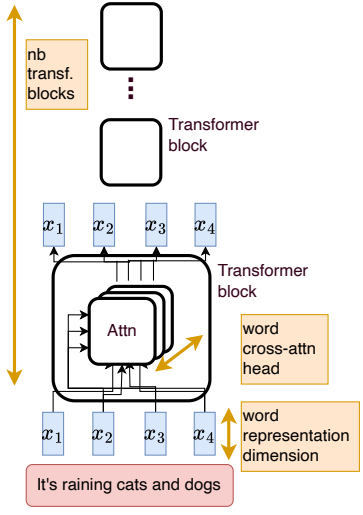
[5] Rafailov et al., NeurIPS 2023.
Direct Preference Optimization: Your Language Model is Secretly a Reward Model

Back to the Encoders

BERT : 2018 milestone

- Efficient transformer architecture





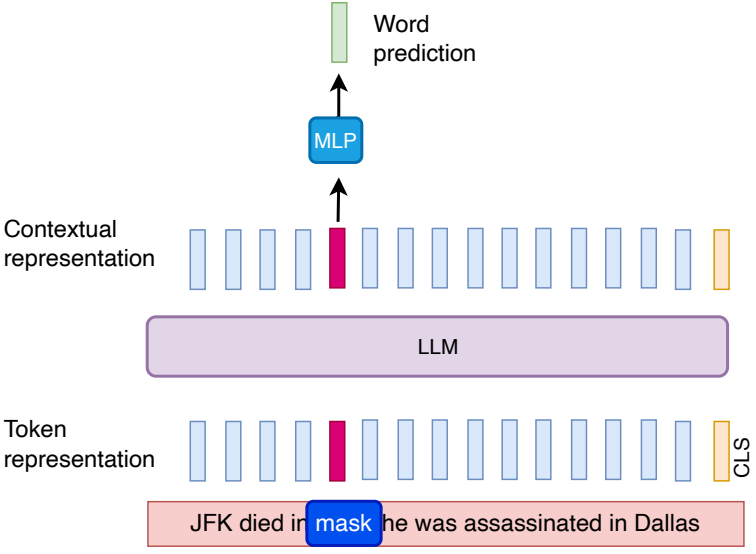
Several sizes

Nice implementation / pretraining

HuggingFace Integration

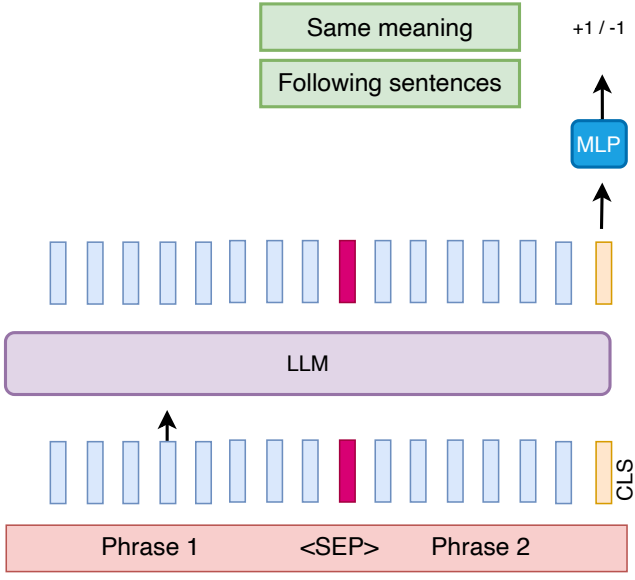
BERT Pre-training

- Masking words



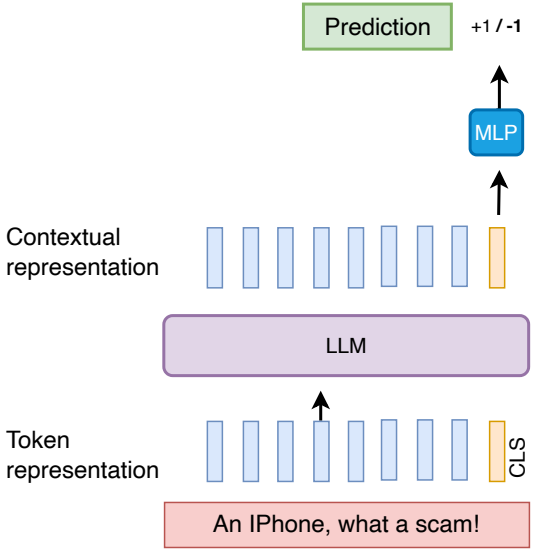
BERT Pre-training

- Predicting coherent / successive sentences



Then tackling various tasks

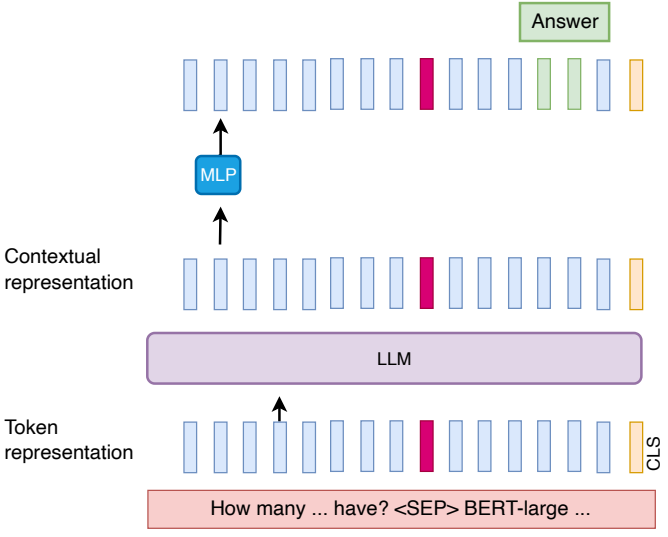
- Opinion mining



Then tackling various tasks

- Question Answering
- Often couple with Info Retrieval

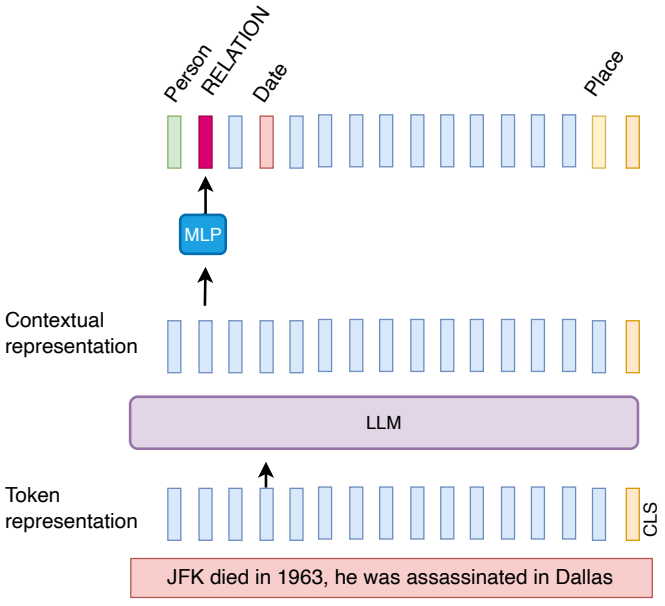
$\Rightarrow$ finding short passages to analyse



Then tackling various tasks

- Information extraction
- Named Entity recognition
- Relation extraction

  ... but on which word ??



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- Information extraction
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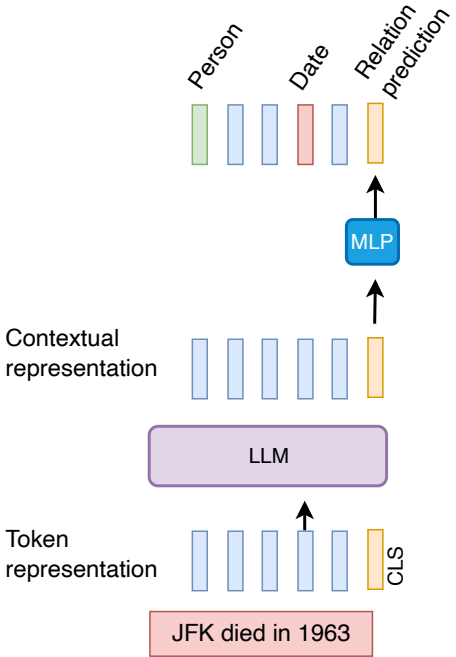
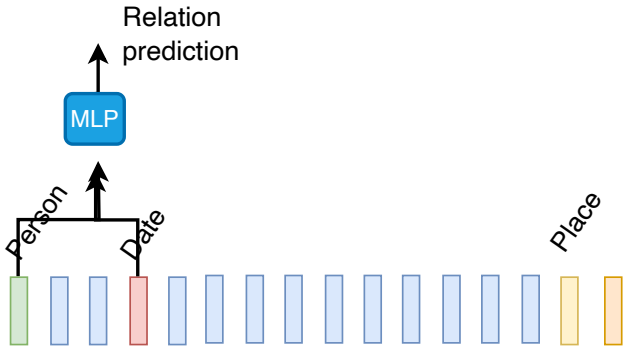
  ... but on which word ??
- Hyp : unique relation in the sentence



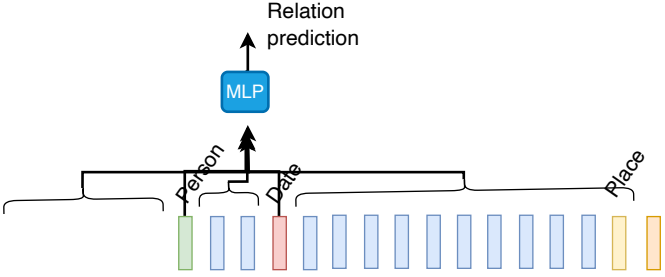
Then tackling various tasks

- Information extraction
- Named Entity recognition
- Relation extraction
  ... but on which word ??
- Hyp : unique relation in the sentence
- Between entities + all couple tested



Then tackling various tasks

- Information extraction
- Named Entity recognition
- Relation extraction
  ... but on which word ??
- Hyp : unique relation in the sentence
- Between entities + all couple tested
- Piecewise representation (PCNN)



Efficient Tuning

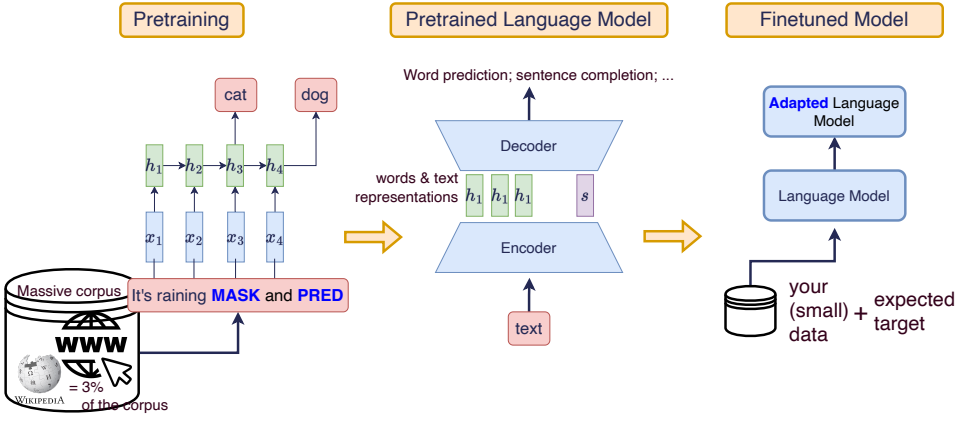
Once the pretraining done

How to update/upgrade a model for a specific domain/task?

Yes, if we upgrade it!

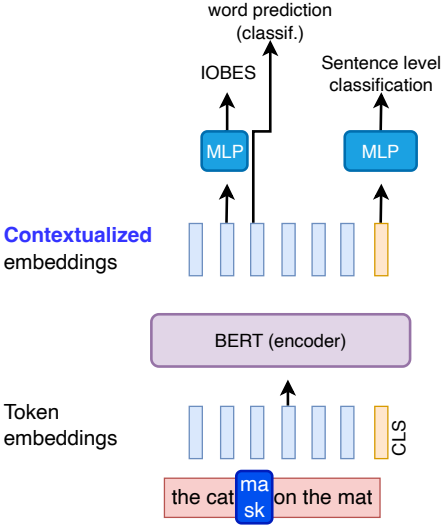
$\Rightarrow$ (Relatively) cheap update

$\Rightarrow$ Few data required



Refining the encoder

- Assuming we have textual data & supervision ⇒ optimizing the models



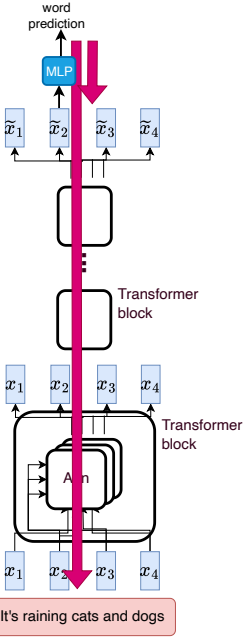
1. Supervision: X: texts; Y: targets; ($+$ W: parameters)
2. Finetuning: refining W s.t. $f_W(X) \approx Y$

May a **small** model become more efficient than a **big** LLM through refinement?

How to make the refinement process cheap?

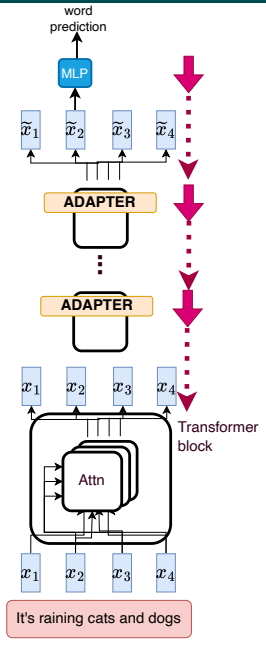
Efficient Tuning

- Limiting the number of epoch
  - Running on few data
- Only optimize the last layer



Efficient Tuning: main strategies

1. Adapter
2. Prompt Tuning
3. Low Rank Adaptation



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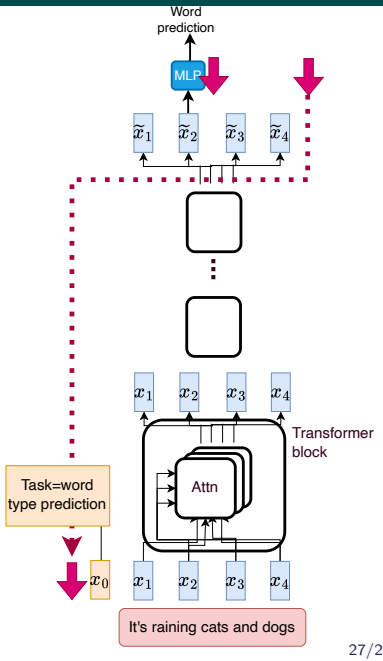

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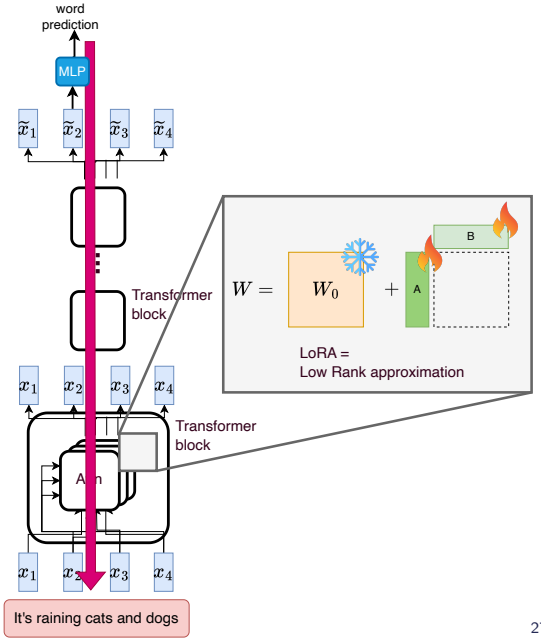
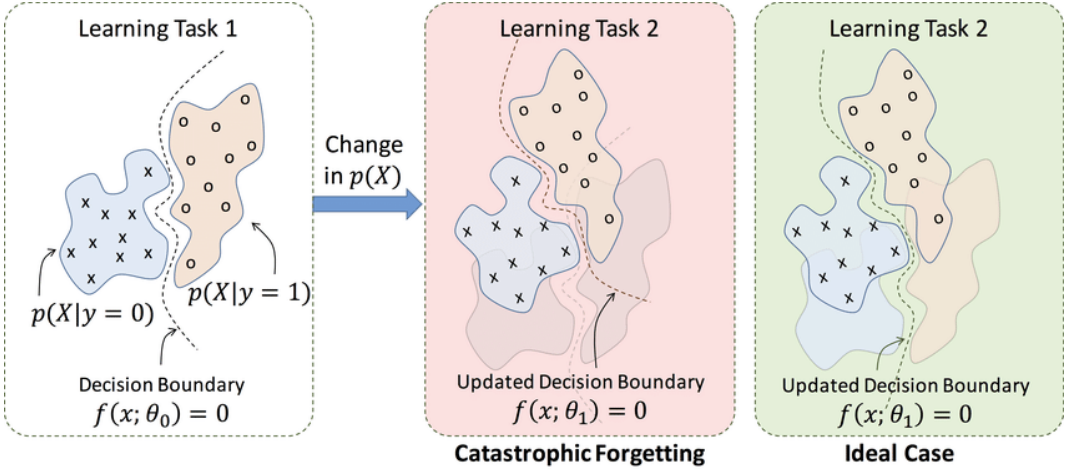


Catastrophic forgetting

Learning new skills... Forgetting the bases?



Conclusion

Generative AI : new opportunities at a cost

- **LLM cost** >> encoders (>> CRF / trad. ML >> classical lexical rules)
  - Paying for extraction *or* for development?
- New formulations ⇒ new metrics ⇒ **how to evaluate properly?**
- Above which threshold the systems are **useful**? Autonomously useful?
- What about a system that would be able to extract *statements*?

Transformer le texte suivant en une liste de statements élémentaires:

Des drones non identifiés ont été observés au-dessus de la plus grande base militaire du Danemark vendredi soir, a annoncé la police, après plusieurs survols d'aéroports cette semaine dans le pays nordique.

Voici une décomposition en statements élémentaires :

1. Des drones non identifiés ont été observés.
2. L'observation a eu lieu au-dessus de la plus grande base militaire du Danemark.
3. L'observation a eu lieu vendredi soir.
4. La police a annoncé cette observation.
5. Des survols d'aéroports ont eu lieu cette semaine.
6. Les survols d'aéroports ont eu lieu dans le Danemark.
7. Le Danemark est un pays nordique.