

Language Models:

The Hidden Secrets

Agenda

- 13:30 - 14:00** Intro to Deep Learning, LLM's and other buzzwords
- 14:00 - 14:30** Pretraining, Finetuning and RLHF (more buzzwords)
- 14:30 - 14:45** Break
- 14:45 - 15:15** Easley deploying your own LLM and make it do things for you
- 15:15 - 15:45** The secret sauce behind GPT-4



Yotam Nahum

Co-Founder & CTO
Samplead

- **Head of AI Dep. (Major)** – Israeli Air Force
- **Senior Researcher** – The Data Science Institute
- **Research fields & publications** – Social Networks, NLP, Recommendation Systems, Cryptography
- **IDC, Columbia University**



**What's the different between
Machine Learning and AI?**

BUZZWORDS

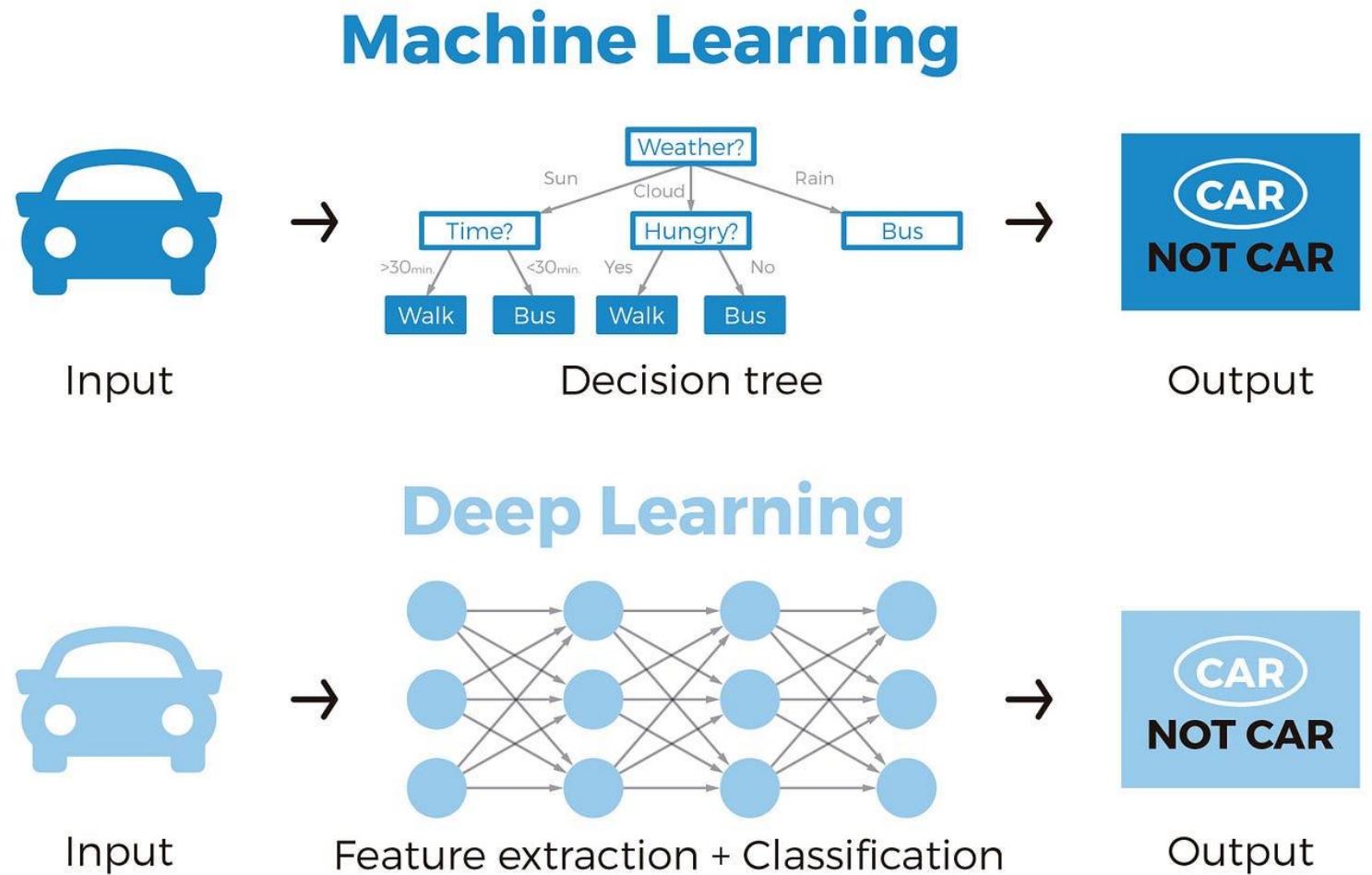


BUZZWORDS EVERYWHERE



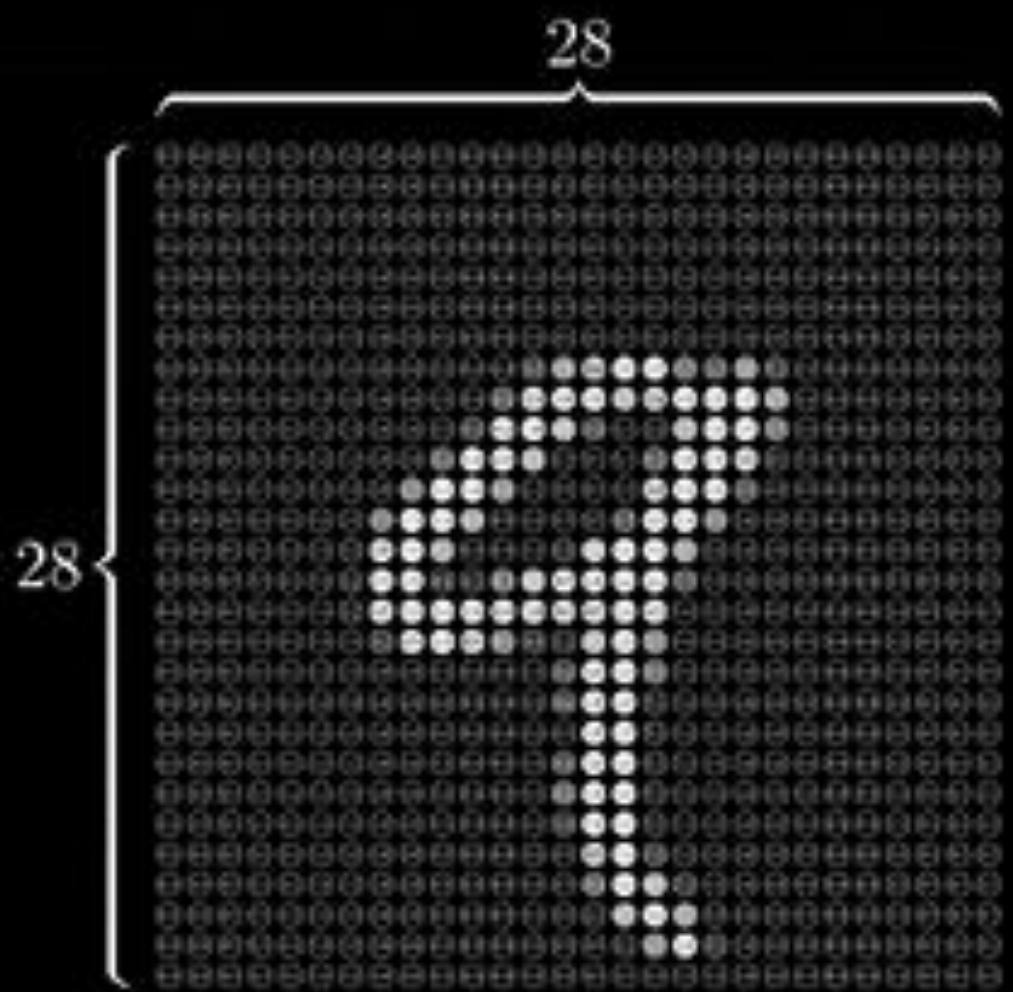
Intro to Deep Learning, LLM's, And other buzzwords

Machine Learning vs. Deep Learning



**So no more
feature engineering?**





$$28 \times 28 = 784$$



```
def generate_resource_report_prompt(question, research_summary):
    """Generates the resource report prompt for the given question and research summary.

    Args:
        question (str): The question to generate the resource report prompt for.
        research_summary (str): The research summary to generate the resource report prompt for.

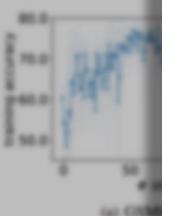
    Returns:
        str: The resource report prompt for the given question and research summary.
    """
    return f'"""{research_summary}""" Based on the above information, generate a bibliography
recommendation report for the following \
    f' question or topic: "{question}"'. The report should provide a detailed analysis of each
recommended resource,' \
    ' explaining how each source can contribute to finding answers to the research question.' \
    ' Focus on the relevance, reliability, and significance of each source.' \
    ' Ensure that the report is well-structured, informative, in-depth, and follows Markdown
syntax.' \
    ' Include relevant facts, figures, and numbers whenever available.' \
    ' The report should have a minimum length of 1,200 words.'
```

LARGE LANGUAGE MODELS AS OPTIMIZERS

Chengrun Yang^{*} Xuezhi Wang Yifeng Lu Hanxiao Liu
 Quan V. Le Denny Zhou Xinyun Chen^{*}
 (chengrun, xuezhiw, yifenglu)@google.com, 6.hanxiao@gmail.com
 (qvl, dennyzhou, xinyunchen)@google.com
 Google DeepMind * Equal contribution

ABSTRACT

Optimization is ubiquitous tools for various problems in real-world applications (OPB). A simple solution is to use optimizers, where each optimization step contains previously proposed solutions that are evaluated and adapted. We showcase OPB on how to prompt optimize LLMs to improve the task accuracy. We show that LLMs can be optimized by OPB up to 50% faster and by up to 50% more accurate.



(a) GSM8K

Source	Instruction	Acc
<i>Baselines</i>		
(Kojima et al., 2022)	Let's think step by step.	71.8
(Zhou et al., 2022b)	Let's work this out in a step by step way to be sure we have the right answer. (empty string)	58.8 34.0
<i>Ours</i>		
PaLM 2-L-IT	Take a deep breath and work on this problem step-by-step.	80.2
PaLM 2-L	Break this down.	79.9
gpt-3.5-turbo	A little bit of arithmetic and a logical approach will help us quickly arrive at the solution to this problem.	78.5
gpt-4	Let's combine our numerical command and clear thinking to quickly and accurately decipher the answer.	74.5

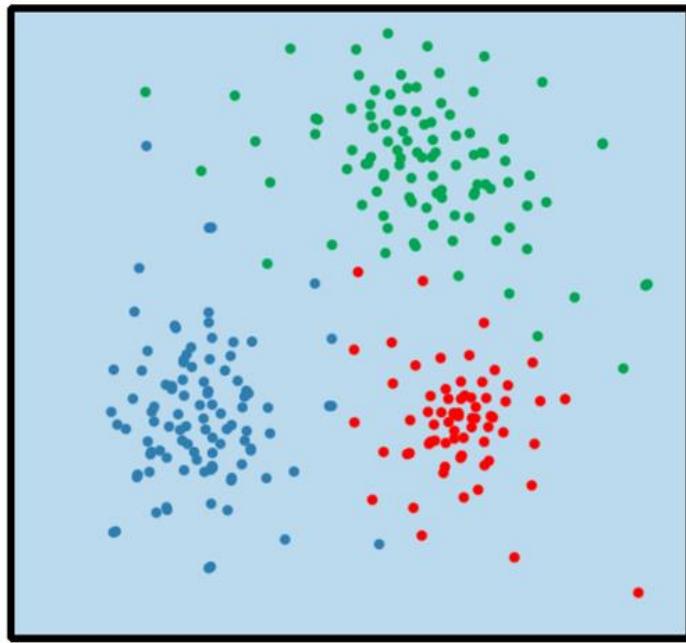
Figure 1: Prompt optimization on GSM8K (Cobbe et al., 2022) and BBB movie recommendation. The optimization on GSM8K has pre-trained PaLM 2-L as the scorer and the instruction-tuned PaLM 2-L (denoted PaLM 2-L-IT) as the optimizer; the optimization on BBB movie recommendation has LLaMA-0.1.0 as the scorer and PaLM 2-L-IT as the optimizer. See Section 2 for more details on experimental setup.

Table 1: Top instructions with the highest GSM8K zero-shot test accuracies from prompt optimization with different optimizer LLMs. All results use the pre-trained PaLM 2-L as the scorer.

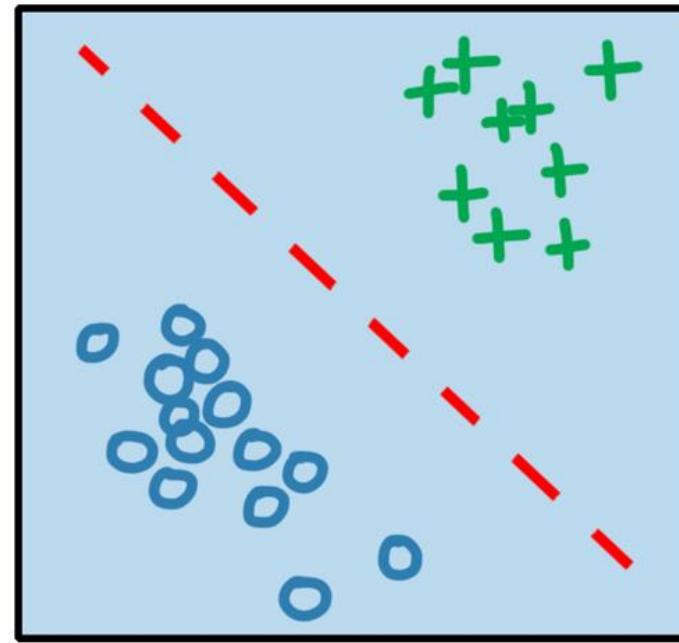
Source	Instruction	Acc
<i>Baselines</i>		
(Kojima et al., 2022)	Let's think step by step.	71.8
(Zhou et al., 2022b)	Let's work this out in a step by step way to be sure we have the right answer. (empty string)	58.8 34.0
<i>Ours</i>		
PaLM 2-L-IT	Take a deep breath and work on this problem step-by-step.	80.2
PaLM 2-L	Break this down.	79.9
gpt-3.5-turbo	A little bit of arithmetic and a logical approach will help us quickly arrive at the solution to this problem.	78.5
gpt-4	Let's combine our numerical command and clear thinking to quickly and accurately decipher the answer.	74.5

machine learning

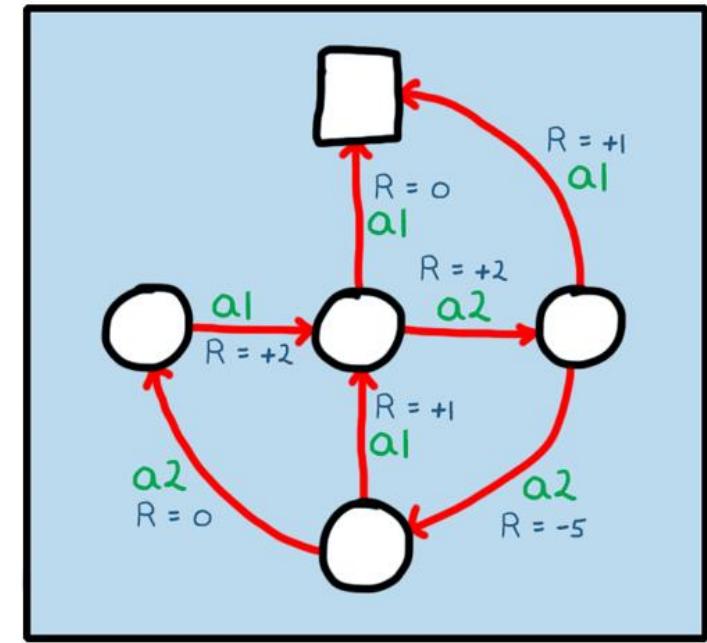
unsupervised
learning

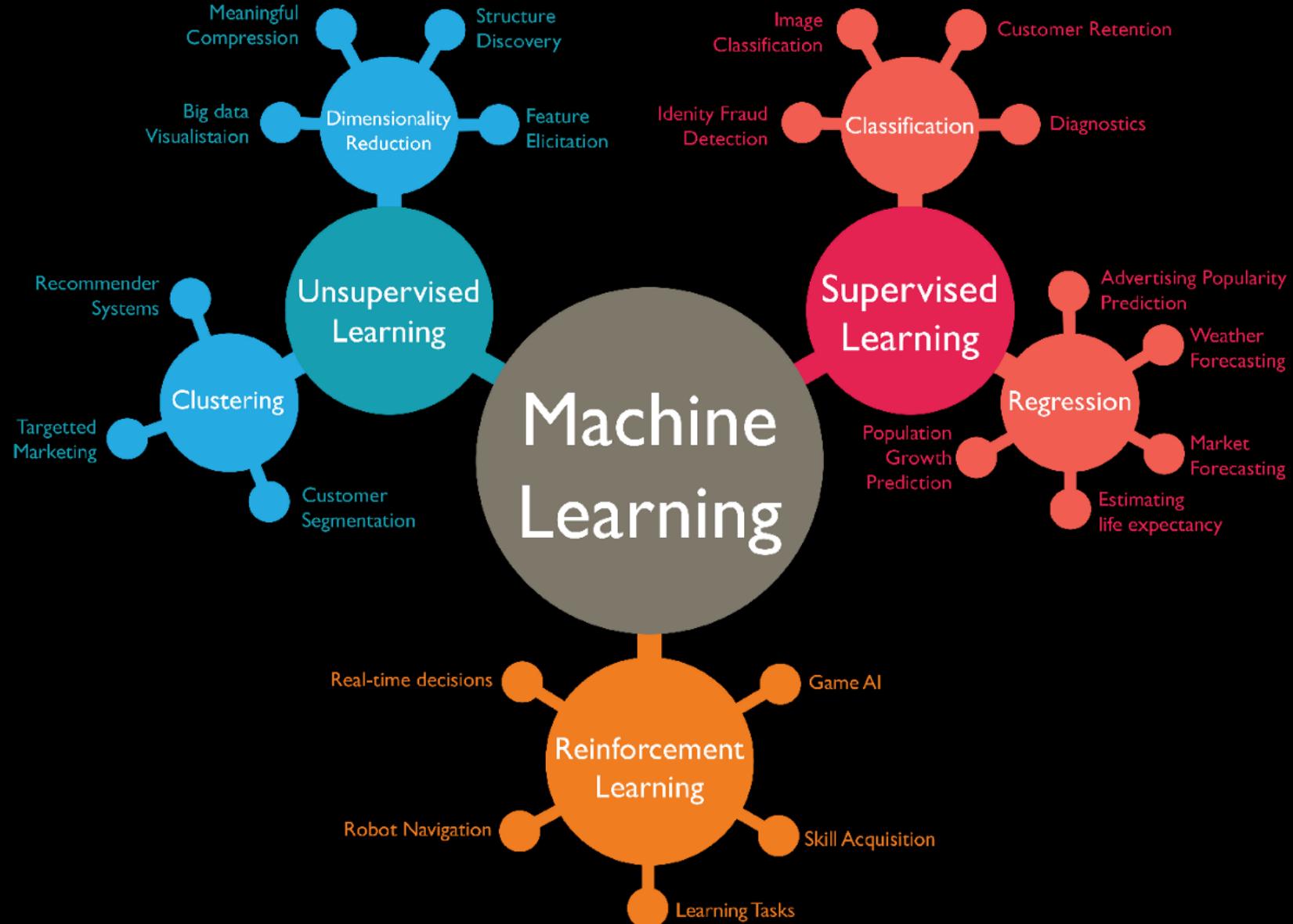


supervised
learning

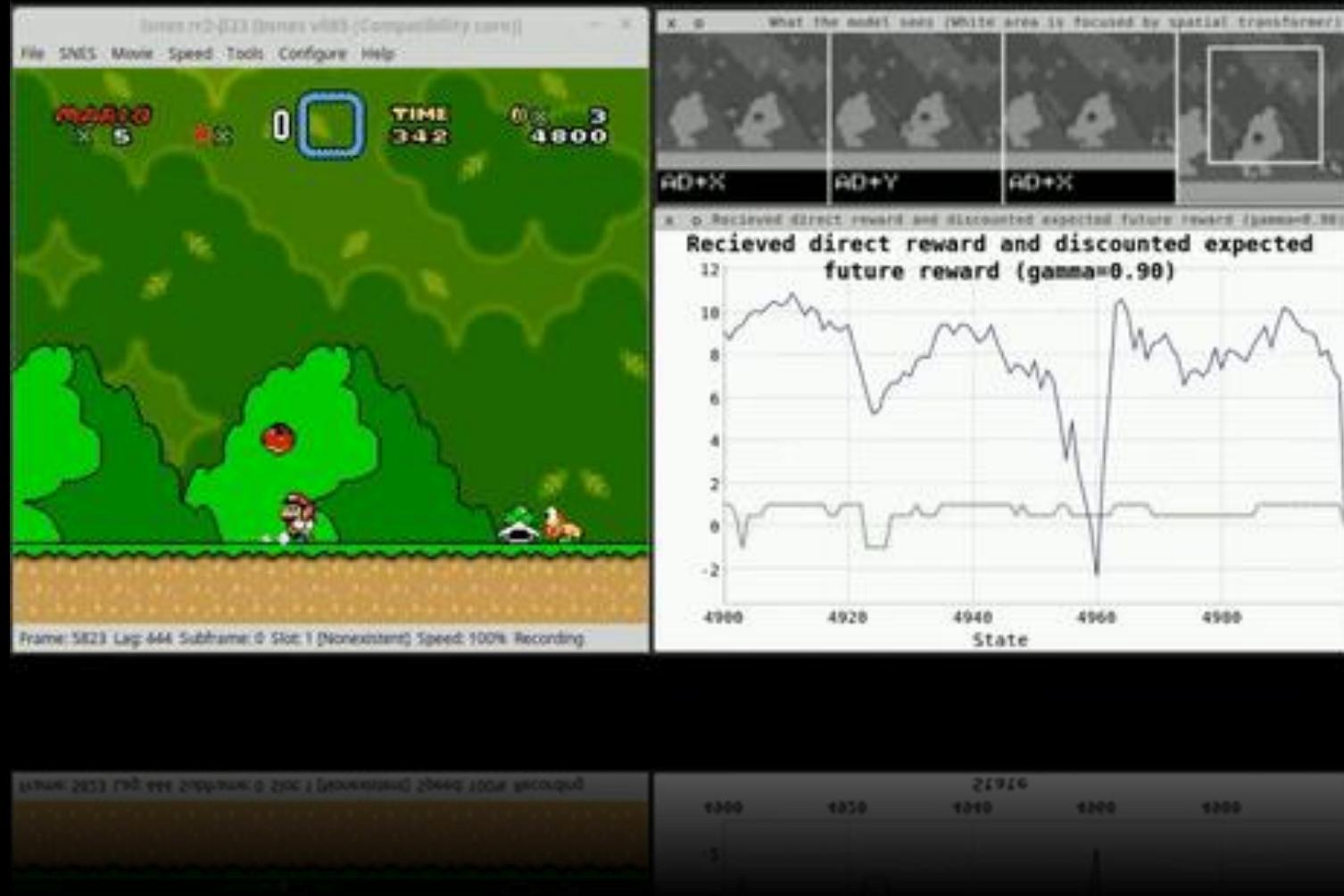


reinforcement
learning





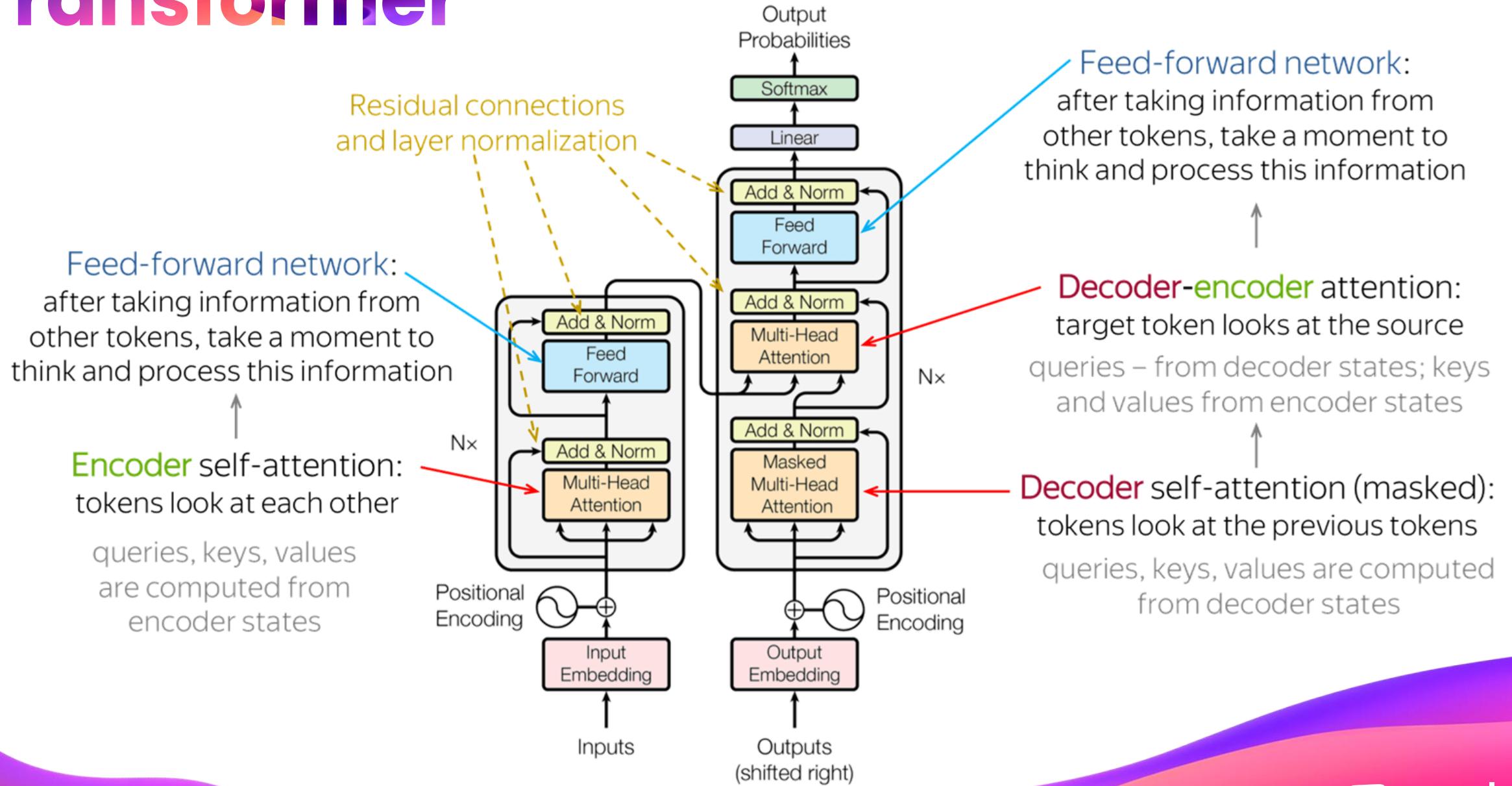
Reinforcement Learning



Language models

Language models

Transformer



Tokenization

```
3 tokenizer = AutoTokenizer.from_pretrained("bert-base-cased")
4 tokenized_text = tokenizer.tokenize(text)
5 print_tokenization_stats(text, tokenized_text, tokenizer)
```

original text: Using tokenizers is easy! And simple! OpenAI

tokenized text: ['Using', 'token', 'mizer', '005', 'is']

length: 14

vocabulary size: 28996

Byte-Pair Encoding (BPE)

```
1 from transformers import AutoTokenizer
```

tokenized_text = tokenizer.tokenize(text)

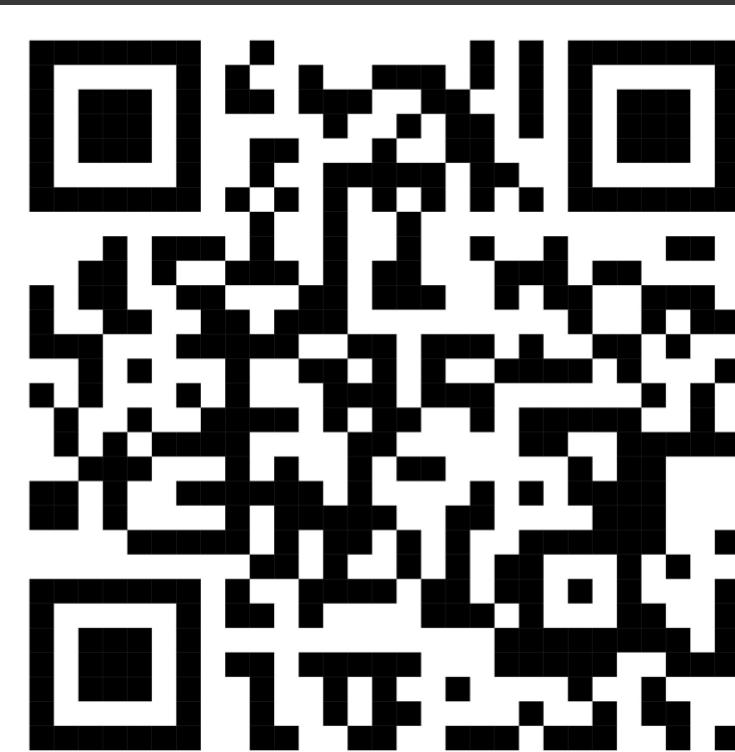
```
5 print_tokenization_stats(text, tokenize)
```

original text: Using tokenizers is easy! And simple! Go

tokenized text: ['Using', 'Gtoken', 'izers', 'Gis', 'Ge

length: 12

vocabulary size: 59257



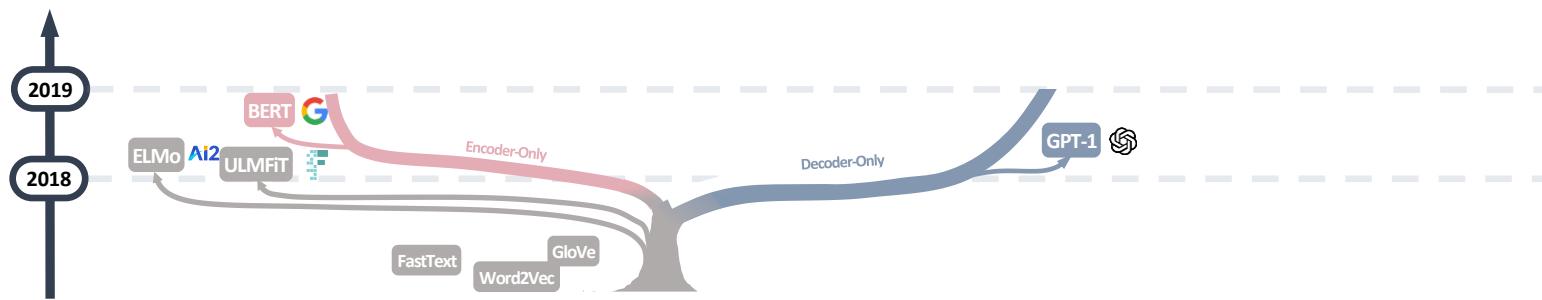
Sentence-piece tokenization

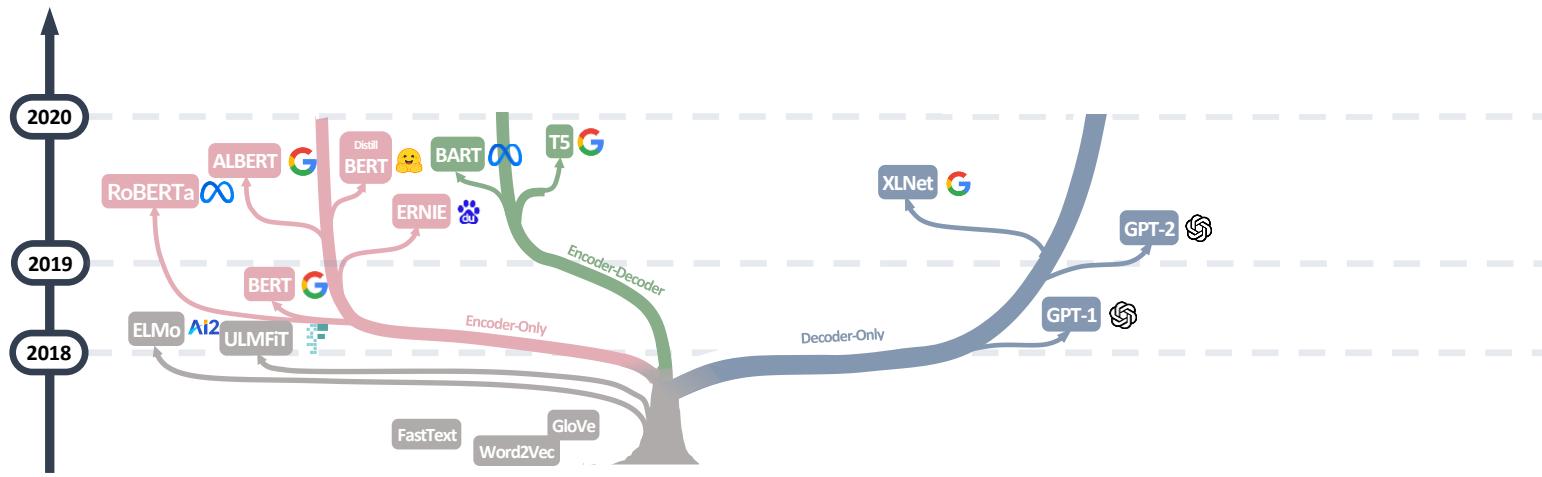
```
1 from transformers import AutoTokenizer
```

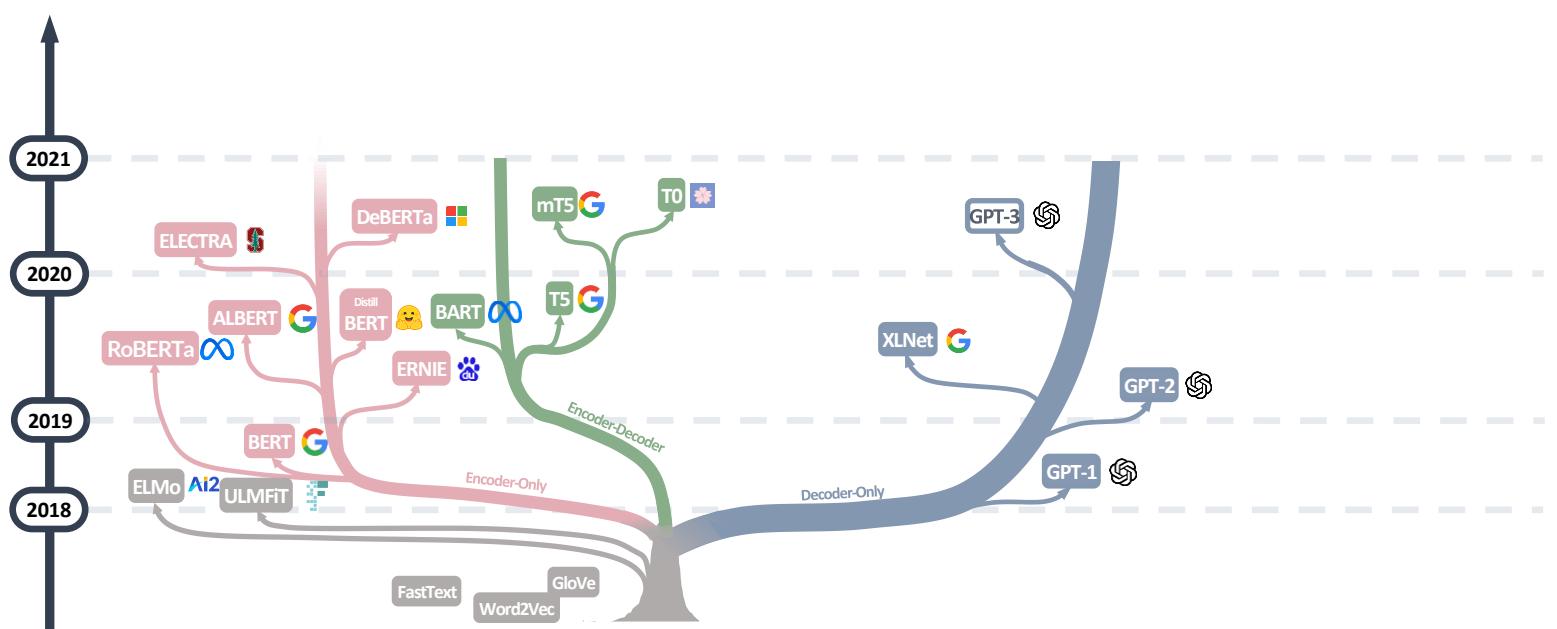


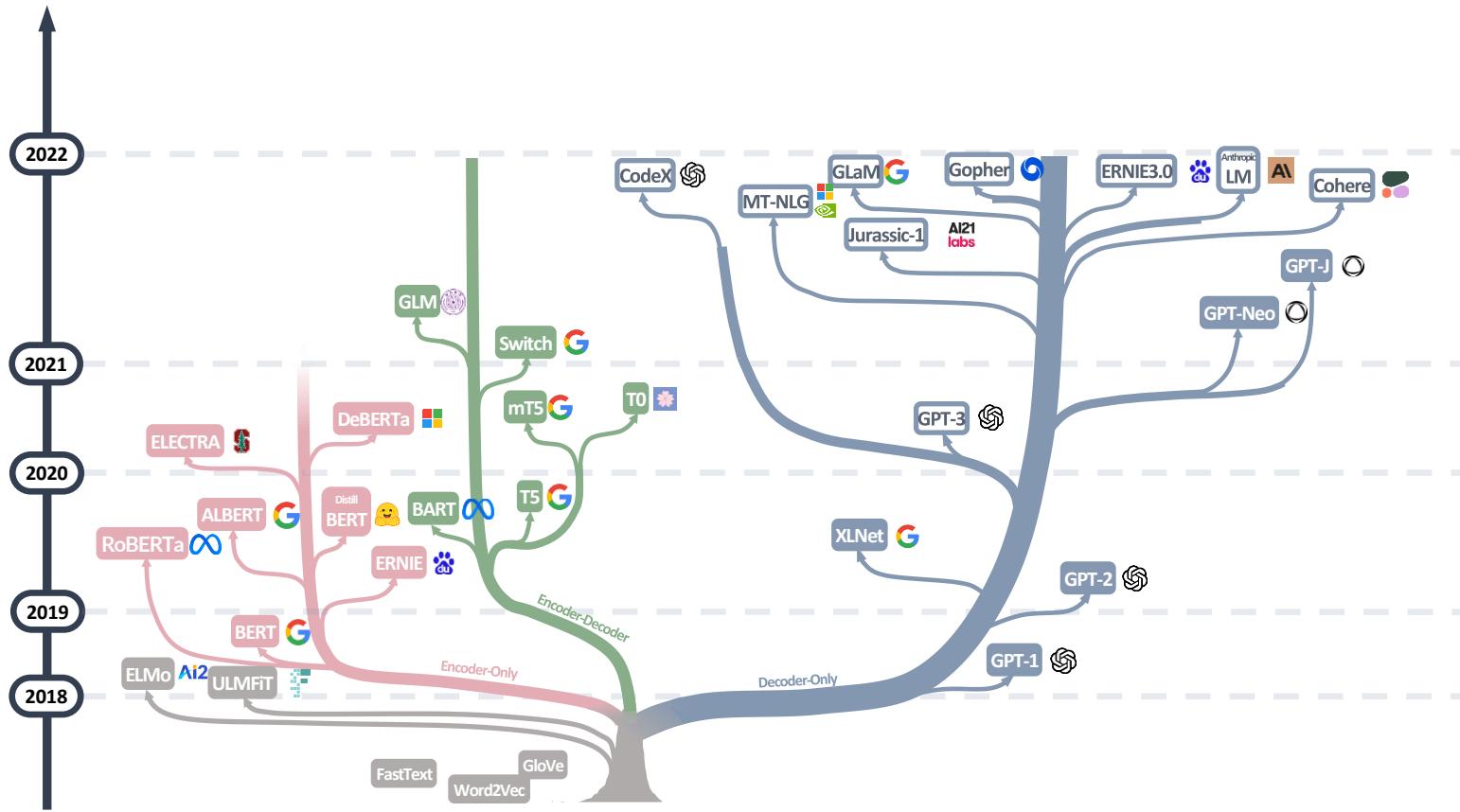
FastText
Word2Vec
GloVe

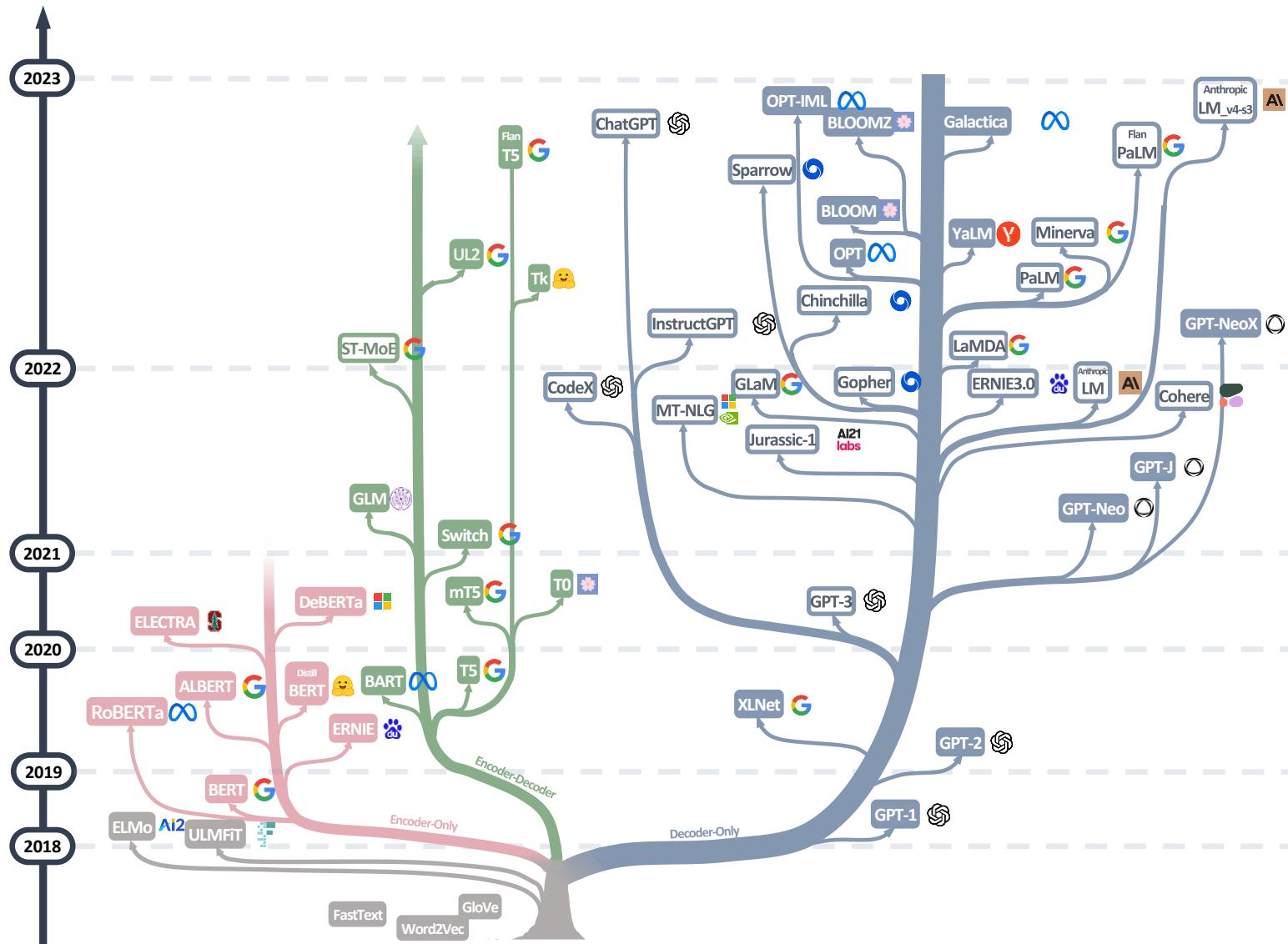


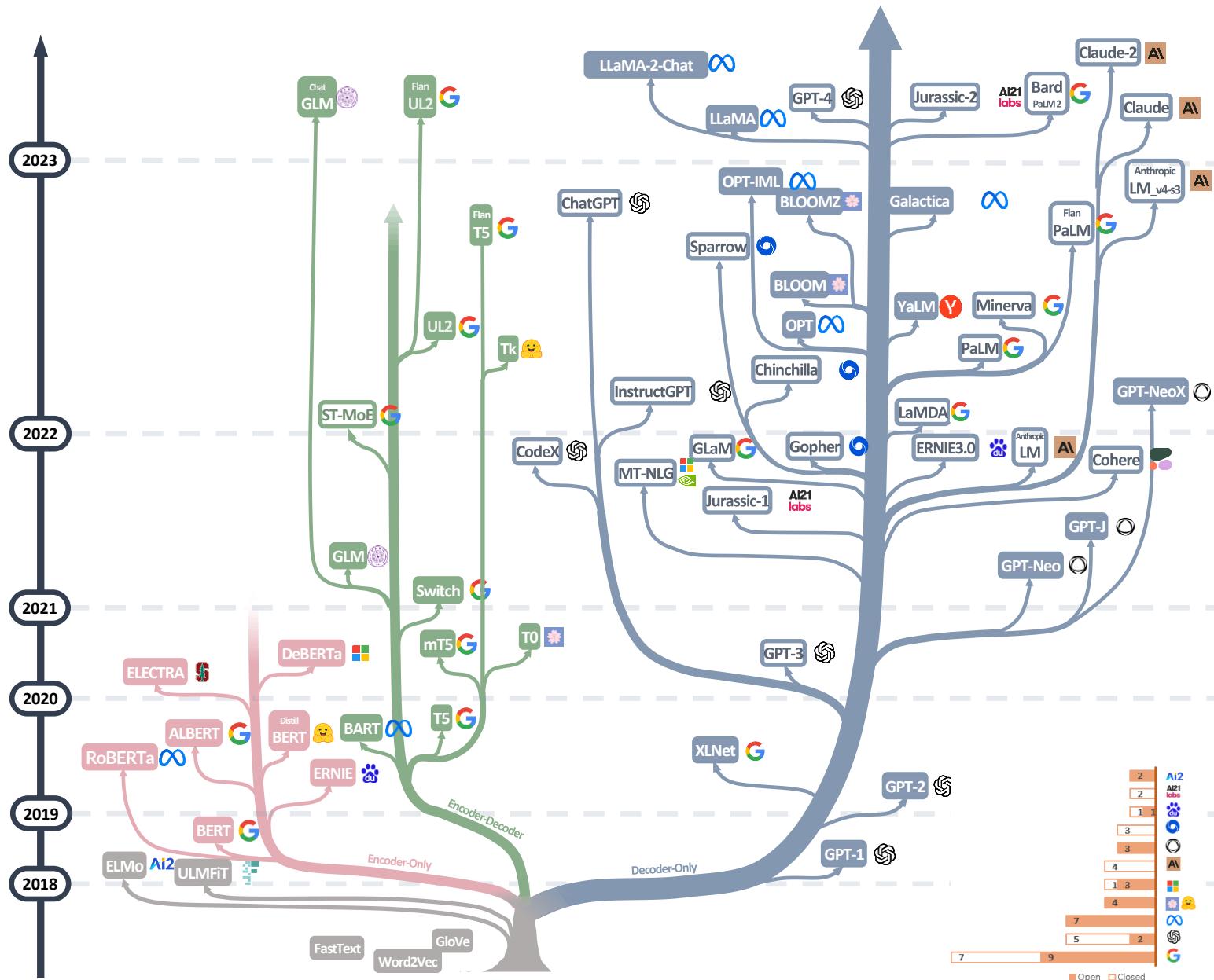










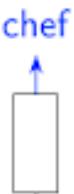


Encoders

the chef cooked the meal

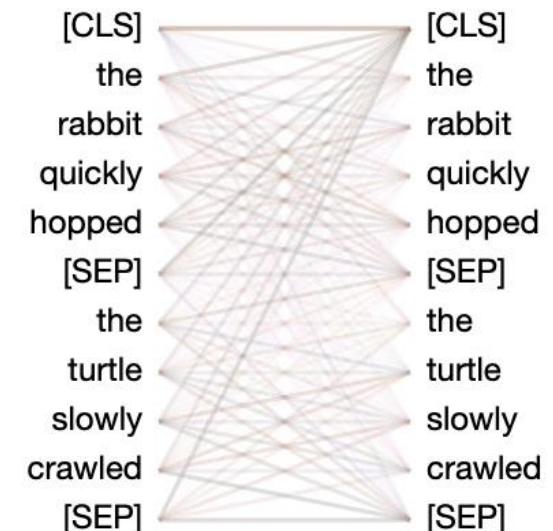
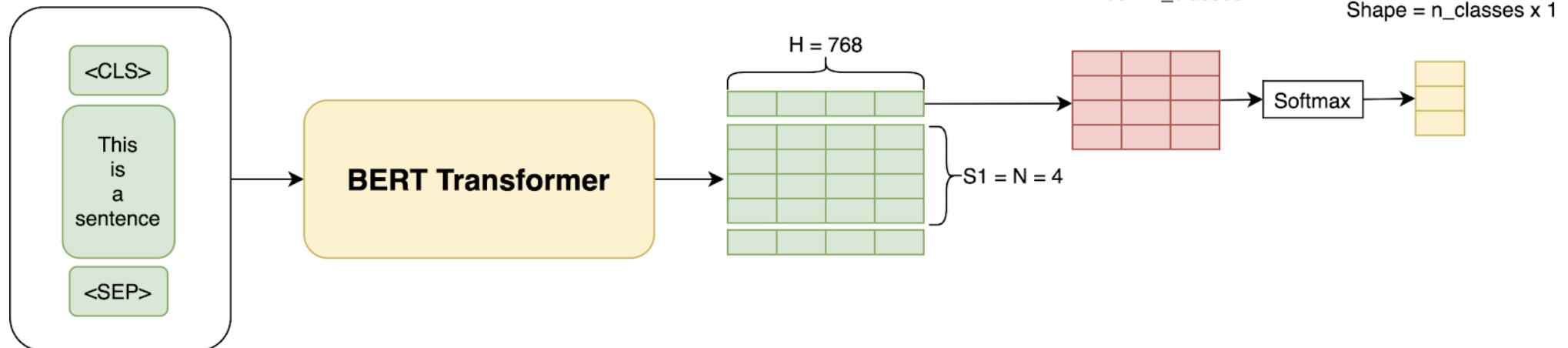
Decoders

chef
the

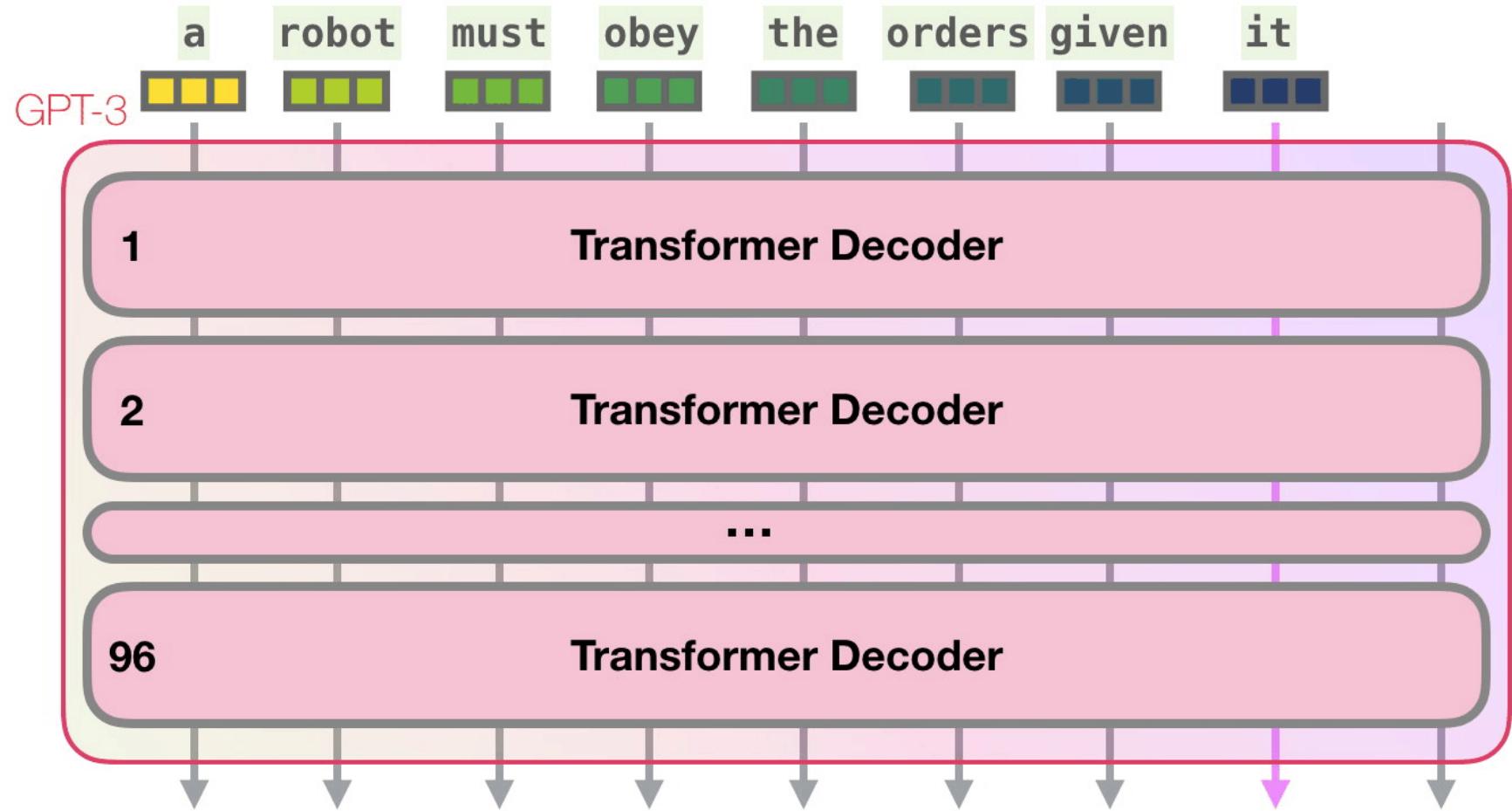


```
graph TD; A["the"] --> B["chef"]
```

Encoders

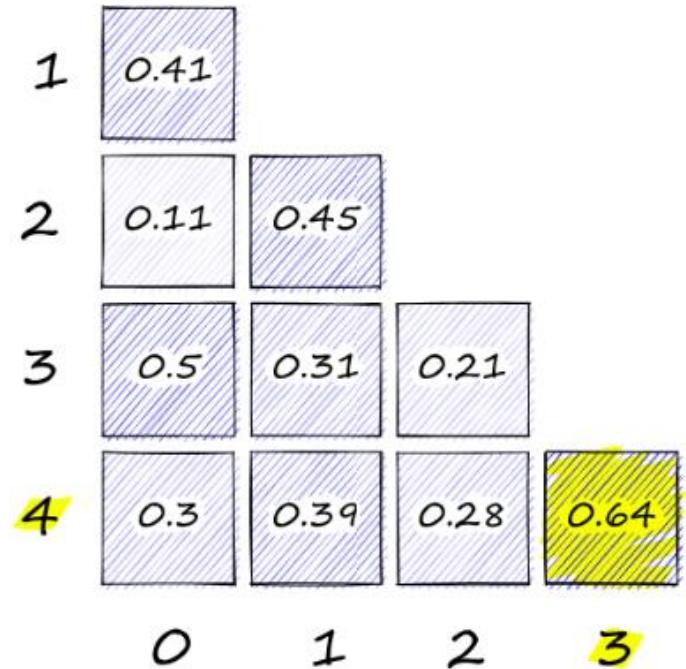


Decoders

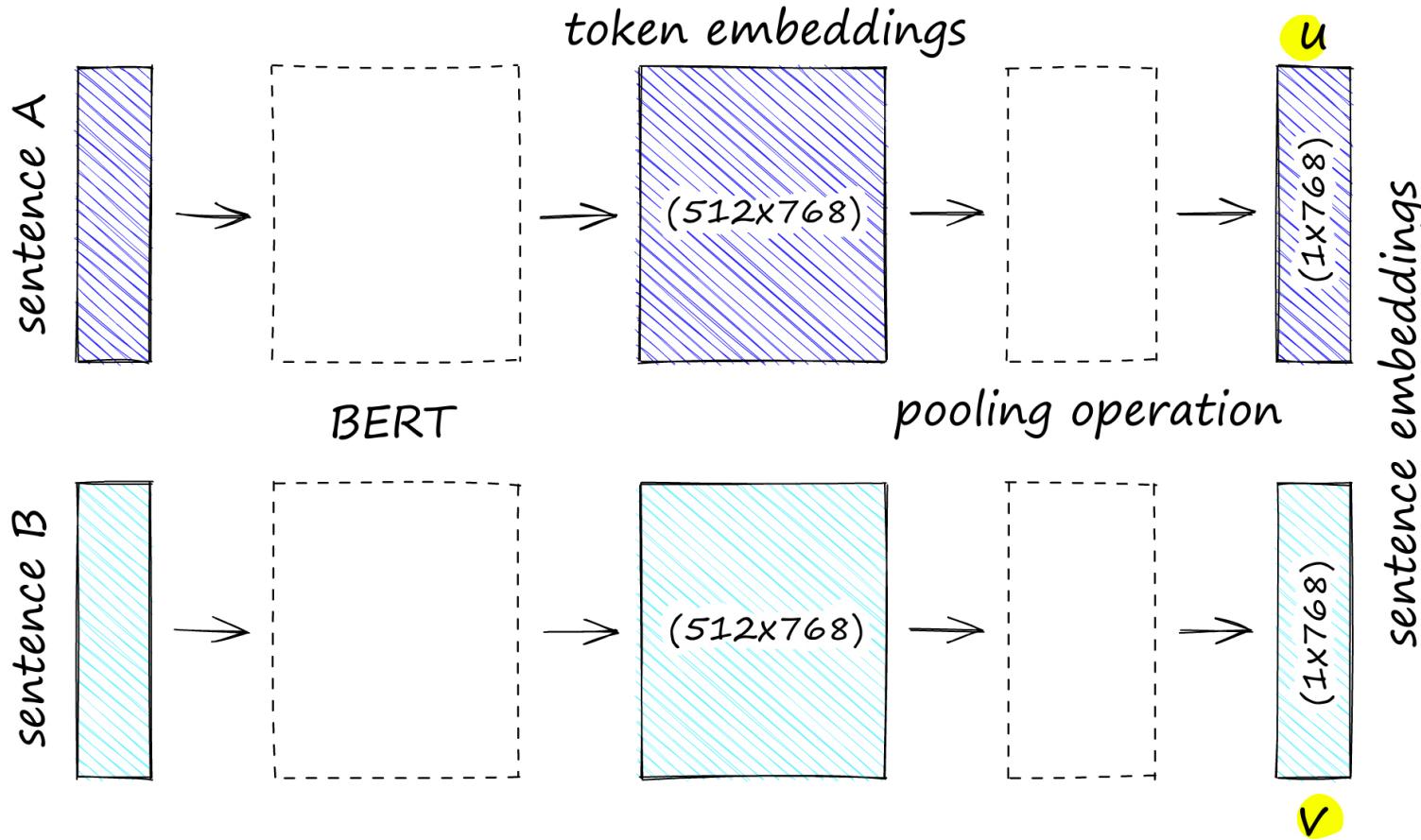


Metric Learning & Semantic Similarity

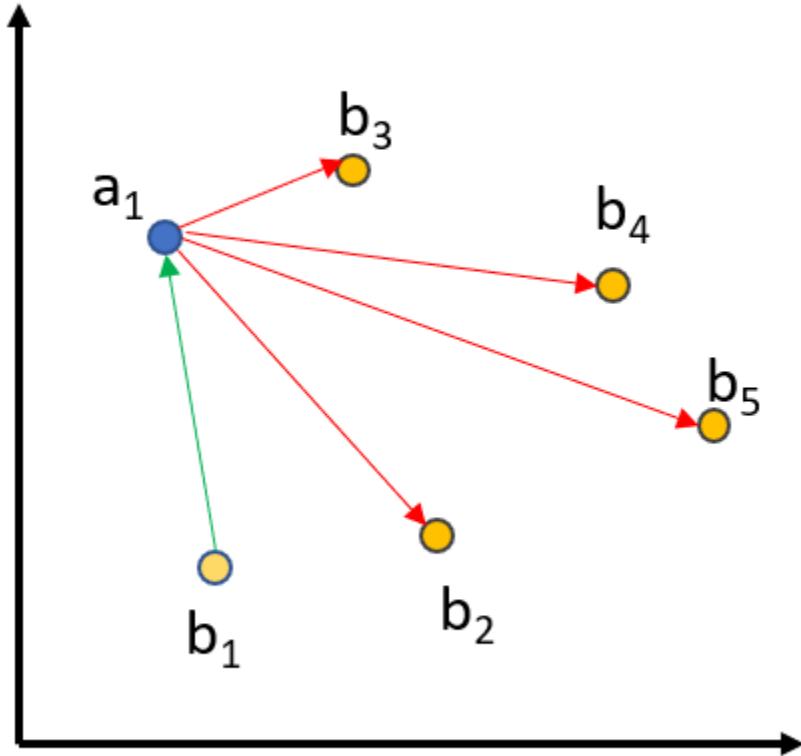
Index	Sentence
0	the fifty mannequin heads floating in the pool kind of freaked them out
1	she swore she just saw her sushi move
2	he embraced his new life as an eggplant
3	my dentist tells me that chewing bricks is very bad for your teeth
4	the dental specialist recommended an immediate stop to flossing with construction materials



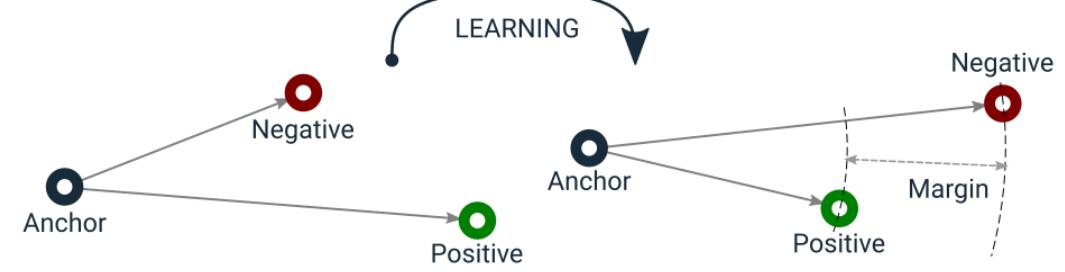
Metric Learning & Semantic Similarity



Metric Learning & Semantic Similarity



Multiple Negatives
Ranking Loss



Triplet Loss



Pretraining, Finetuning and RLHF

(more buzzwords)

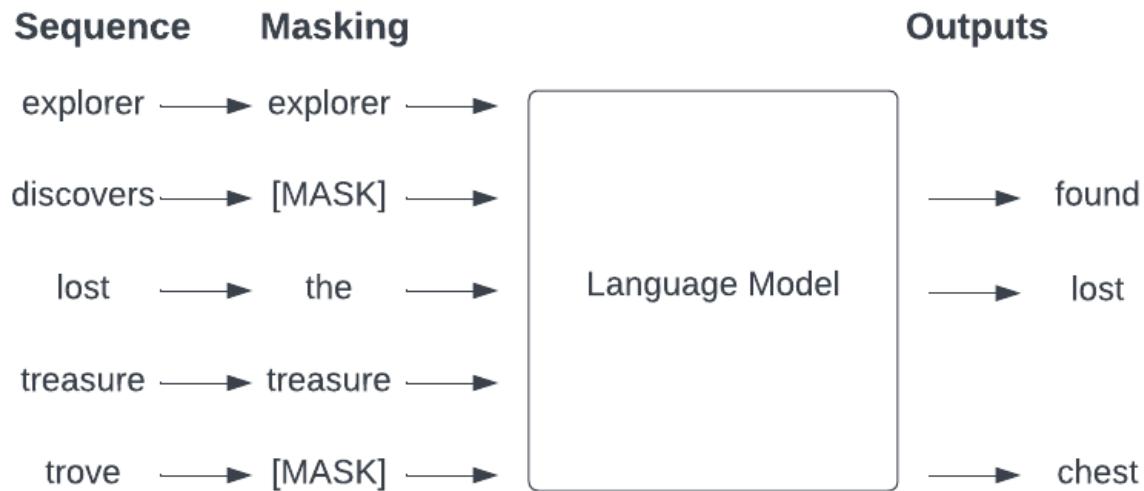
Methods

- ◆ **Pretraining**
- ◆ **Finetuning**
- ◆ Reinforcement Learning from Human Feedback (**RLHF**)

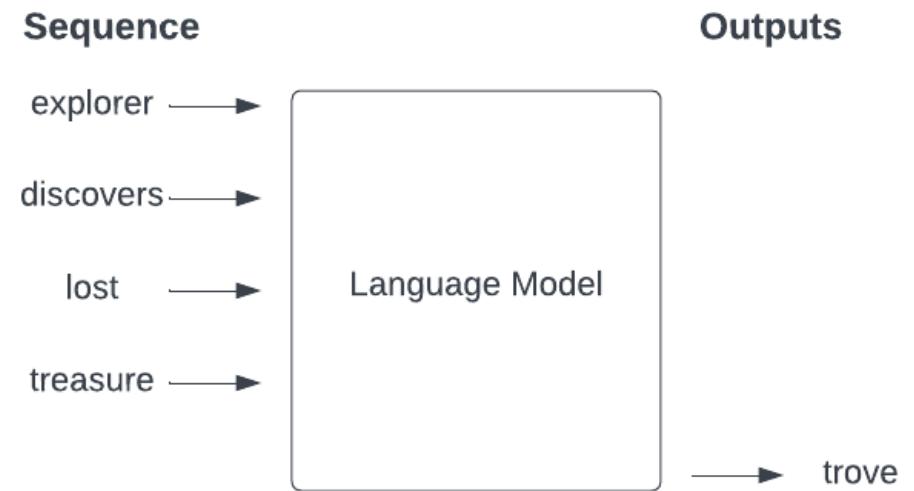
Pretraining

Pretraining objectives

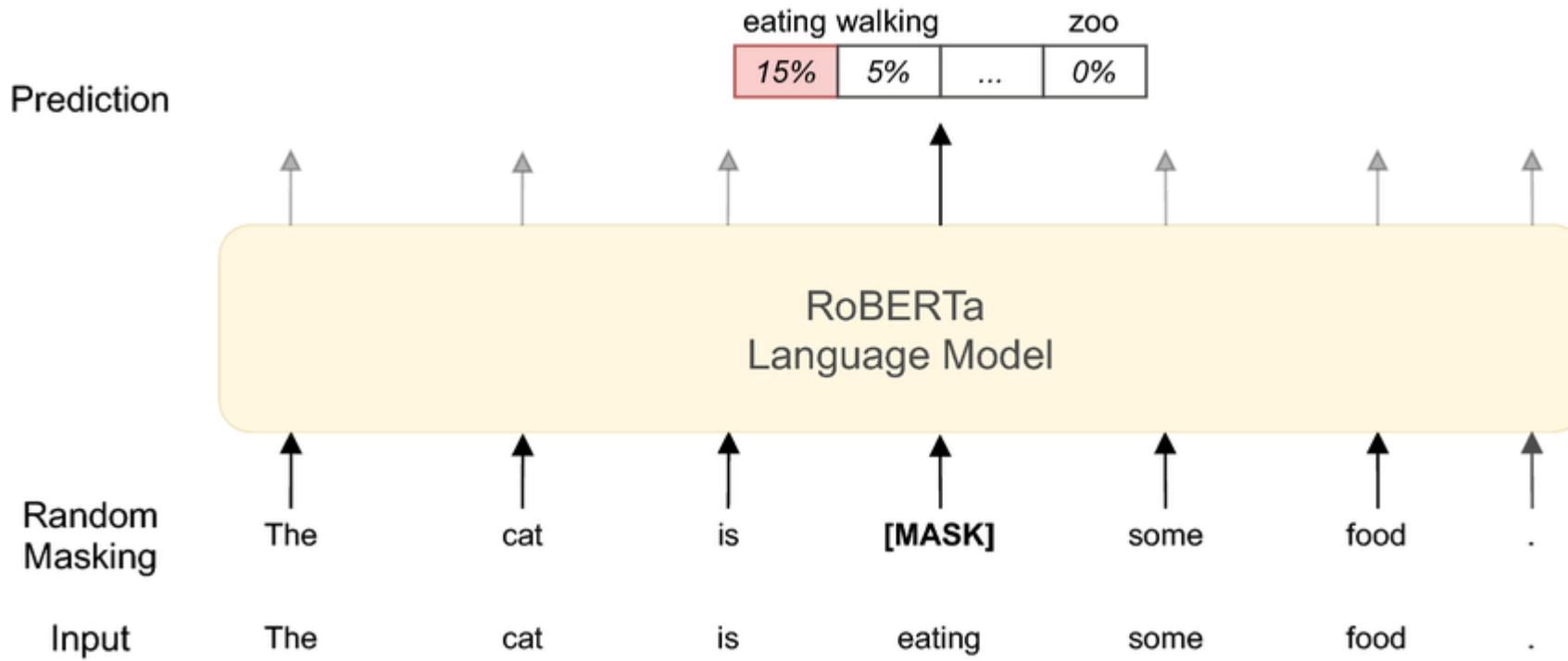
Encoders



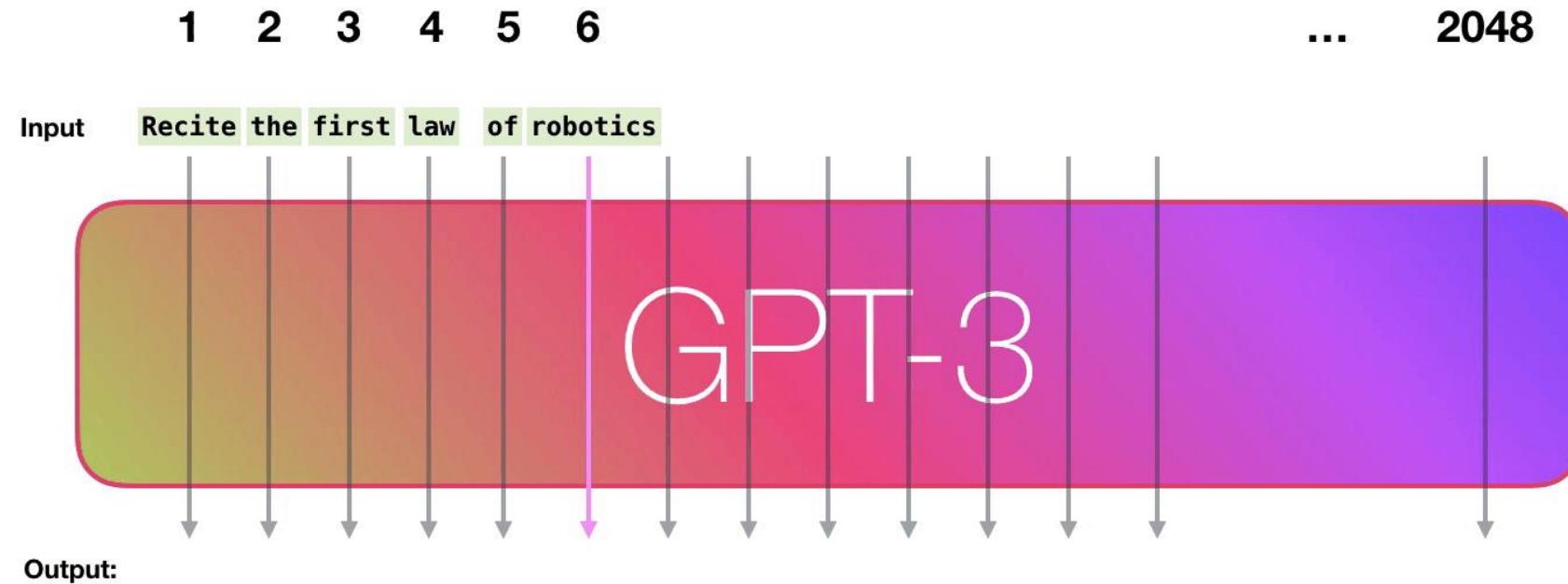
Decoders



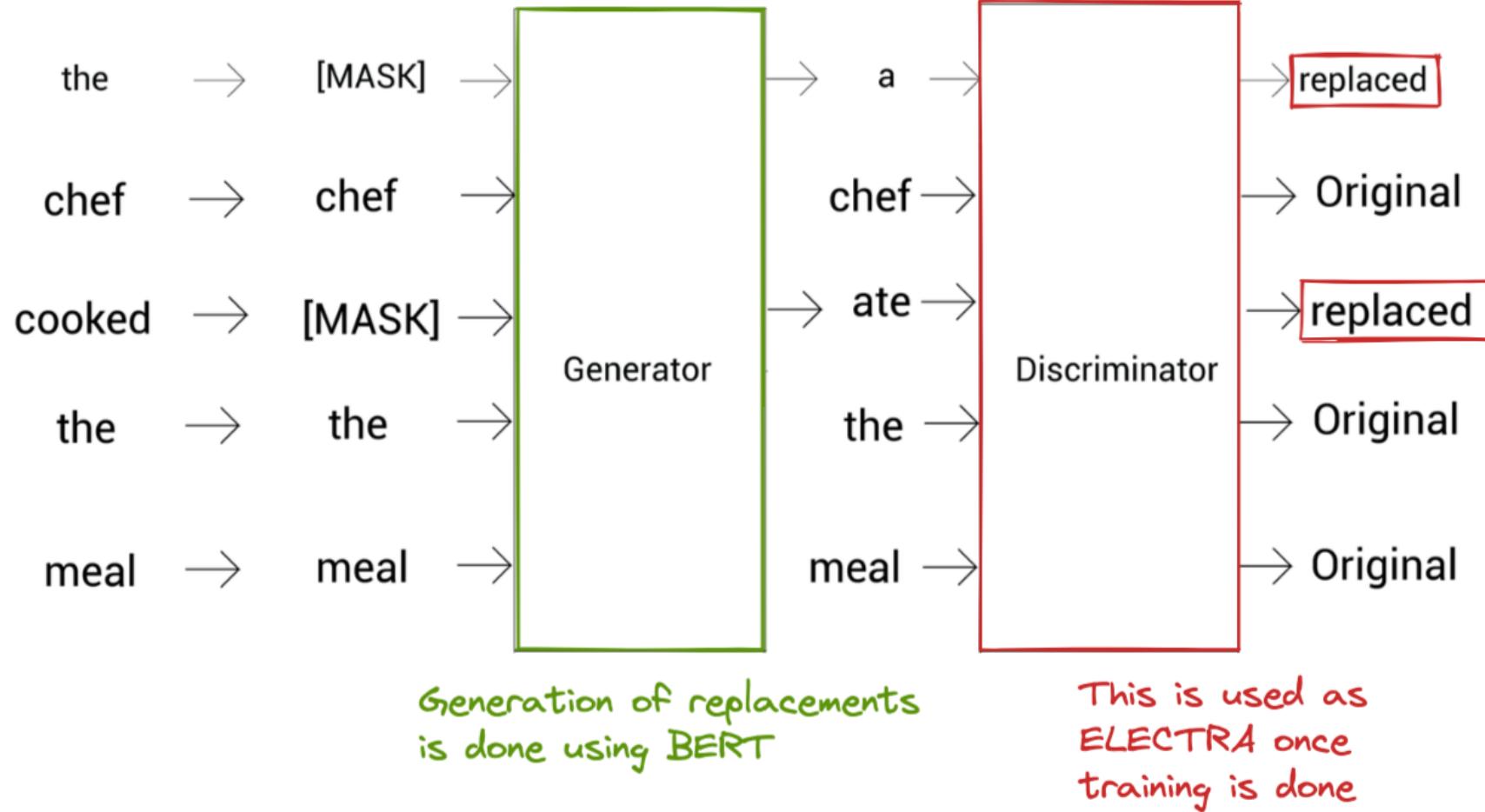
Masked Language Modelling (CLM)



Causal Language Modelling (CLM)



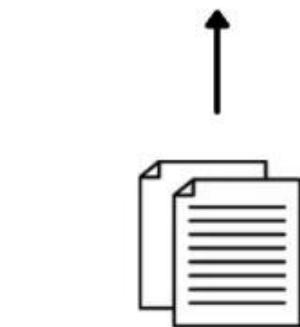
Replaced Token Detection (RTD)



Finetuning

Pre-Training

(Computationally Expensive)



Large
Unlabeled Corpus

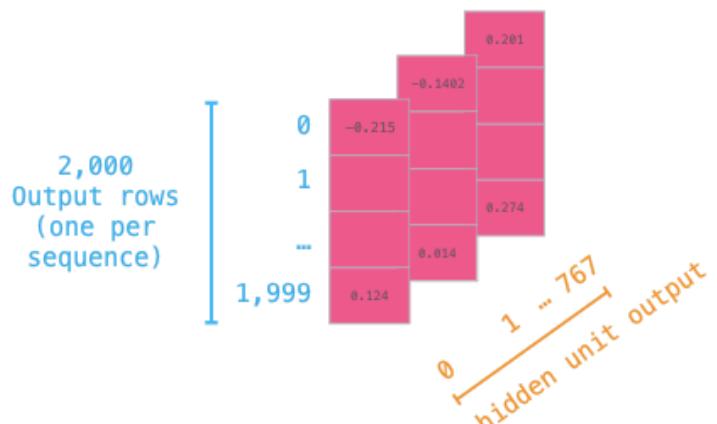
Fine-Tuning

(Cheaper)



Small
Labeled Corpus

Classification



Is the same as

A 2D matrix diagram representing sentence embeddings and labels. The vertical axis is labeled "2,000 Output rows (one per sequence)" with ticks at 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, ..., 1,999. The horizontal axis is labeled "Sentence Embeddings" with ticks at 0, 1, ..., 767, and "label" with ticks at 1, 0, 1. The matrix cells are colored pink and contain numerical values. A blue bracket on the left indicates the range from 1,999 to 0. An orange arrow points diagonally across the matrix, labeled "hidden unit output".

	0	1	...	767	label
0	-0.215	-0.1402	...	0.201	1
1	-0.215	-0.1402	...	0.201	1
2	-0.215	-0.1402	...	0.201	1
3	-0.215	-0.1402	...	0.201	1
4	-0.215	-0.1402	...	0.201	1
5	-0.215	-0.1402	...	0.201	1
6	-0.215	-0.1402	...	0.201	1
7	-0.215	-0.1402	...	0.201	1
8	-0.215	-0.1402	...	0.201	1
9	-0.215	-0.1402	...	0.201	1
...
1,999	0.124	0.014	...	0.274	1

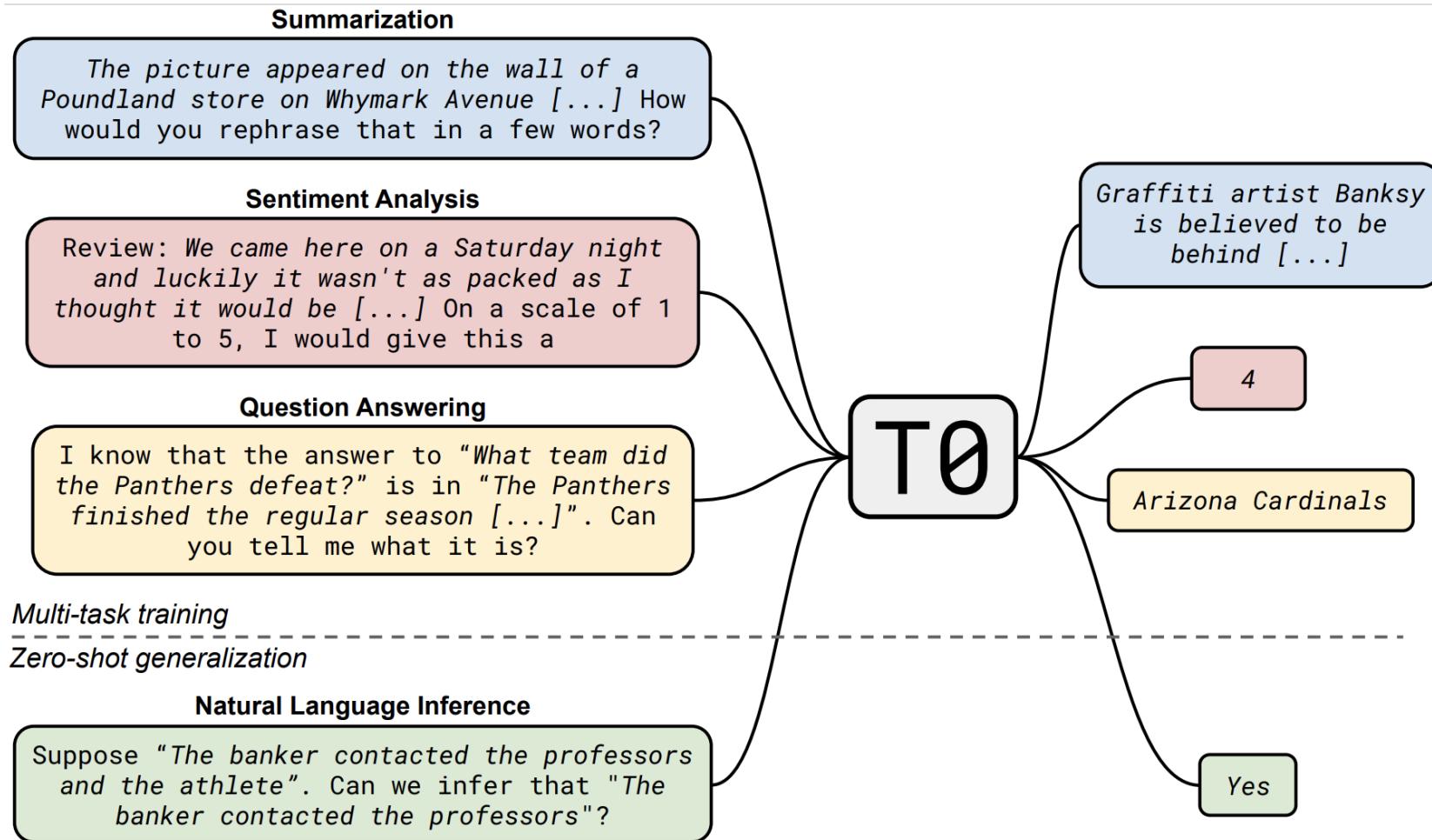
Translation

Can you me help this sentence to translate
↑ ↑ ↑ ↑ ↑ ↑ ↑
Kannst du mir helfen diesen Satz zu uebersetzen ?

Can you help me to translate this sentence
↑ ↑ ~~me to translate this sentence~~
Kannst du mir helfen diesen Satz zu uebersetzen ?

Generation?

Multi-Task



RLHF

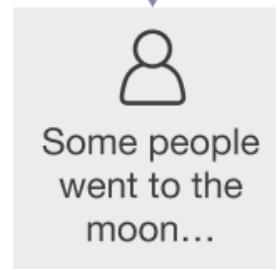
Reinforcement Learning from
Human Feedback

Step 1: Collect demonstration data and train a supervised policy.

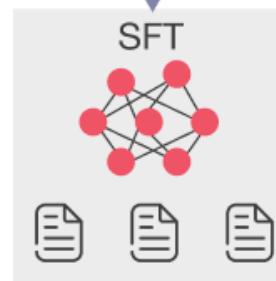
A prompt is sampled from our prompt dataset.



A labeler demonstrates the desired output behavior.

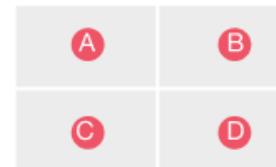


This data is used to fine-tune GPT-3 with supervised learning.



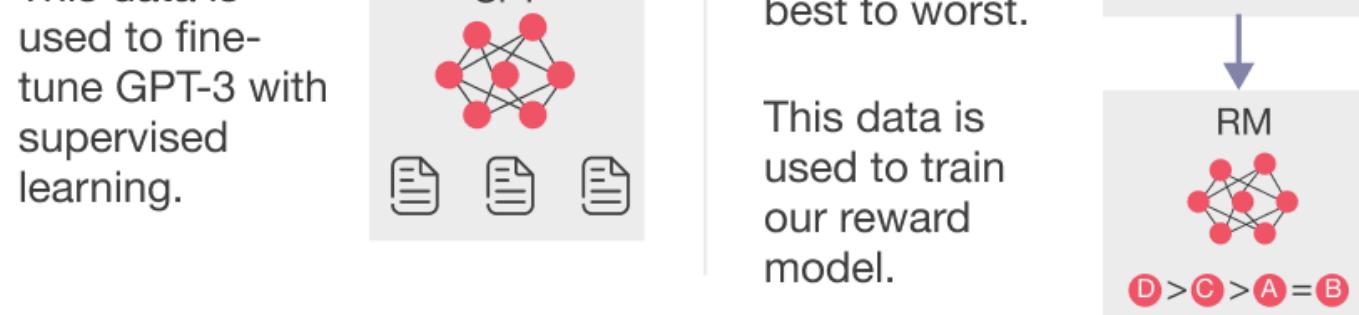
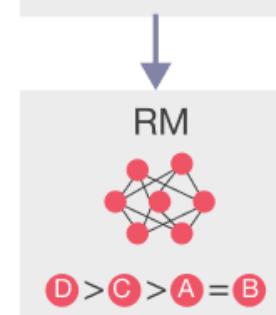
Step 2: Collect comparison data, and train a reward model.

A prompt and several model outputs are sampled.



A labeler ranks the output from best to worst.

This data is used to train our reward model.

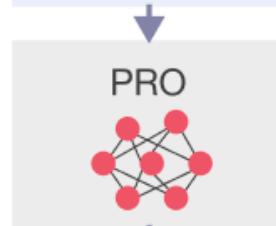


Step 3: Optimize a policy against the reward model using reinforcement learning.

A new prompt is sampled from the dataset.



The policy generates an output.



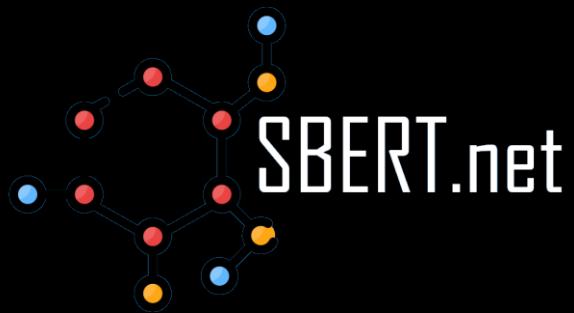
The reward model calculates the reward for an output



The reward is used to update the policy using PPO.

r_k

Code



Tutorials & Courses





Easley
deploy
your own
LLM

Inference

- ◆ **Serverless**
- ◆ **GPU/CPU**



**Amazon
SageMaker**



**Hugging Face
Inference**

Let's Train!

