ΟΙΚΟΝΟΜΙΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ
ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS

Αλληλεπίδραση Ανθρώπου–Υπολογιστή

Β9. Επεξεργασία φυσικής γλώσσας με Transformers και μεγάλα γλωσσικά μοντέλα

(2024-25)

Ίων Ανδρουτσόπουλος

http://www.aueb.gr/users/ion/

Contents

- Transformer encoders and decoders.
- Pre-trained Transformers and Large Language Models (LLMs), BERT, GPT-3, Chat-GPT, fine-tuning them, prompting them.
- Retrieval augmented generation (RAG), LLMs with tools.

Reminder: stacked CNNs for classification/regression

$$h^{max} = \left\langle \max\left(h_{*,1}^{(4)}\right), \max\left(h_{*,2}^{(4)}\right), \dots, \max(h_{*,m}^{(4)}) \right\rangle^T \in \mathbb{R}^{1 \times m}$$

global max pooling

Feature vector sent to a document classifier or regressor (e.g., MLP).

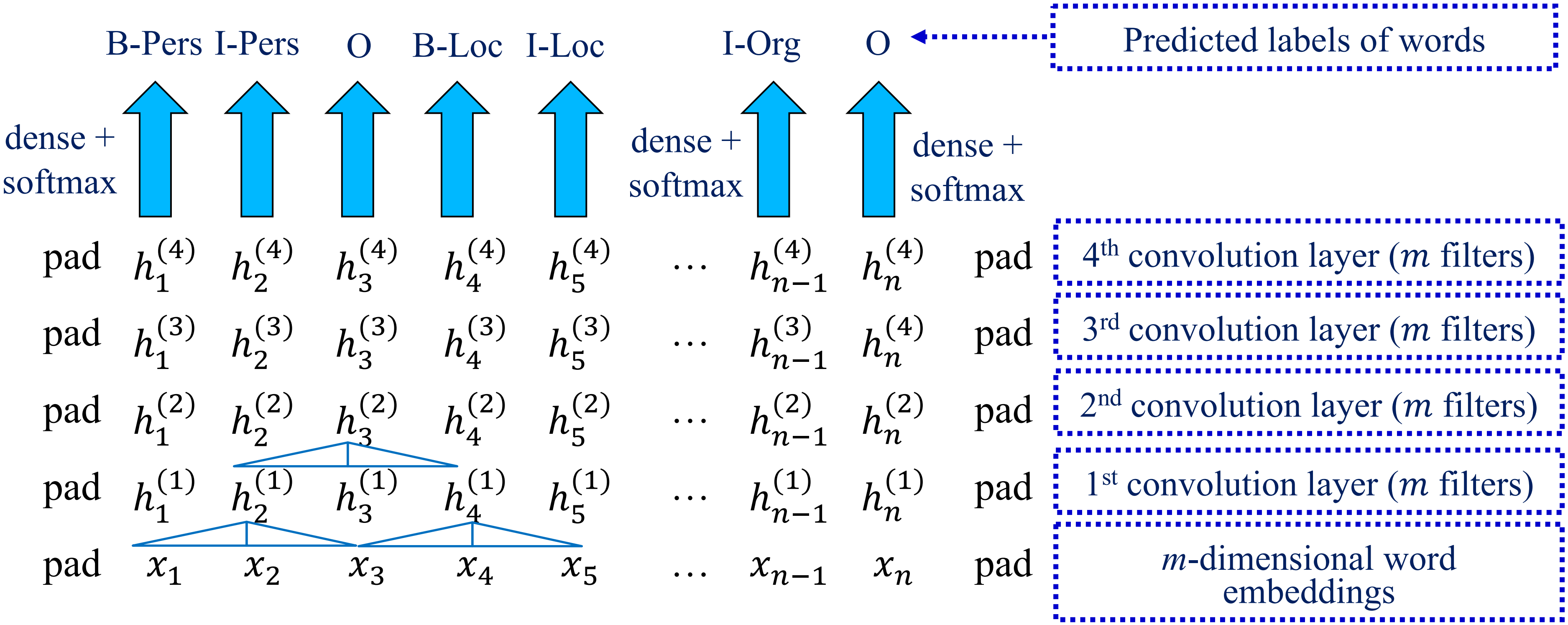
pad	$h_1^{(4)}$	$h_2^{(4)}$	$h_3^{(4)}$	$h_4^{(4)}$	$h_5^{(4)}$	$\dots$	$h_{n-1}^{(4)}$	$h_n^{(4)}$	pad	4th convolution layer (m filters)
pad	$h_1^{(3)}$	$h_2^{(3)}$	$h_3^{(3)}$	$h_4^{(3)}$	$h_5^{(3)}$	$\dots$	$h_{n-1}^{(3)}$	$h_n^{(4)}$	pad	3rd convolution layer (m filters)
pad	$h_1^{(2)}$	$h_2^{(2)}$	$h_3^{(2)}$	$h_4^{(2)}$	$h_5^{(2)}$	$\dots$	$h_{n-1}^{(2)}$	$h_n^{(2)}$	pad	2nd convolution layer (m filters)
pad	$h_1^{(1)}$	$h_2^{(1)}$	$h_3^{(1)}$	$h_4^{(1)}$	$h_5^{(1)}$	$\dots$	$h_{n-1}^{(1)}$	$h_n^{(1)}$	pad	1st convolution layer (m filters)
pad	x_1	x_2	x_3	x_4	x_5	$\dots$	x_{n-1}	x_n	pad	*m*-dimensional word embeddings

$$h_i^{(1)} = \mathrm{ReLU}\left(W^{(1)}[x_{i-1}; x_i; x_{i+1}] + b^{(1)}\right) + x_i \in \mathbb{R}^{m \times 1}$$

$$h_i^{(j)} = \mathrm{ReLU}\left(W^{(j)}\left[h_{i-1}^{(j-1)}; h_i^{(j-1)}; h_{i+1}^{(j-1)}\right] + b^{(j)}\right) + h_i^{(j-1)} \in \mathbb{R}^{m \times 1}$$

Residual (shortcut) connection, needed when stacking many CNNs (or RNNs).

Reminder: stacked CNNs for token classification



$$h_i^{(1)} = \mathrm{ReLU}\left(W^{(1)}[x_{i-1}; x_i; x_{i+1}] + b^{(1)}\right) + x_i \in \mathbb{R}^{m\times 1}$$

$$h_i^{(j)} = \mathrm{ReLU}\left(W^{(j)}\left[h_{i-1}^{(j-1)}; h_i^{(j-1)}; h_{i+1}^{(j-1)}\right] + b^{(j)}\right) + h_i^{(j-1)} \in \mathbb{R}^{m\times 1}$$

Transformers for token classification

$$
\begin{array}{cccccccc}
h_1^{(4)} & h_2^{(4)} & h_3^{(4)} & h_4^{(4)} & h_5^{(4)} & \cdots & h_{n-1}^{(4)} & h_n^{(4)} \\
h_1^{(3)} & h_2^{(3)} & h_3^{(3)} & h_4^{(3)} & h_5^{(3)} & \cdots & h_{n-1}^{(3)} & h_n^{(4)} \\
h_1^{(2)} & h_2^{(2)} & h_3^{(2)} & h_4^{(2)} & h_5^{(2)} & \cdots & h_{n-1}^{(2)} & h_n^{(2)} \\
h_1^{(1)} & h_2^{(1)} & h_3^{(1)} & h_4^{(1)} & h_5^{(1)} & \cdots & h_{n-1}^{(1)} & h_n^{(1)} \\
x_1 & x_2 & x_3 & x_4 & x_5 & \cdots & x_{n-1} & x_n
\end{array}
$$

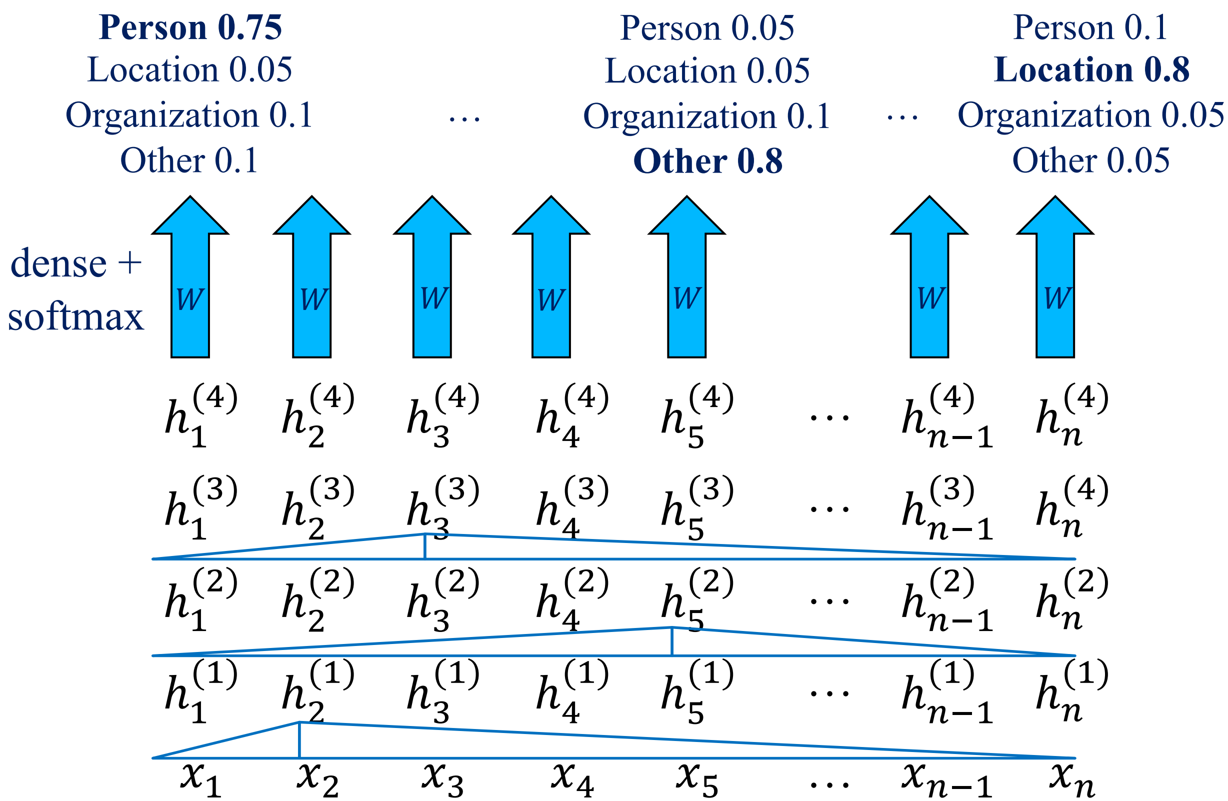
$a_{2,1}$ $a_{2,2}$ $a_{2,n}$

Initial *m*-dimensional word embeddings

$$h_i^{(1)} = \mathrm{MLP}^{(1)}\left(\sum_{r=1}^{n} a_{i,r}^{(1)} x_r\right) \in \mathbb{R}^m$$

To produce the **revised embedding for the *i*-th word** of a text, we **sum all the original embeddings** of the words of the text, but **weighted by attention scores**.

Transformers for token classification



Predicted labels of words

Compare to the correct predictions and **adjust the weights** of the **entire neural net**, including the bottom word (token) embeddings, which are randomly initialized.

Initial *m*-dimensional word embeddings

$$h_i^{(1)} = \mathrm{MLP}^{(1)}\left(\sum_{r=1}^{n} a_{i,r}^{(1)} x_r\right) \in \mathbb{R}^m$$

$$h_i^{(j)} = \mathrm{MLP}^{(j)}\left(\sum_{r=1}^{n} a_{i,r}^{(j)} h_r^{(j-1)}\right) \in \mathbb{R}^m$$

To produce the **revised embedding for the *i*-th word** of a text, we **sum all the original embeddings** of the words of the text, but **weighted by attention scores**.

Transformers for text classification

$$h^{max} = \left\langle \max\left(h_{*,1}^{(4)}\right), \max\left(h_{*,2}^{(4)}\right), \ldots, \max(h_{*,m}^{(4)}) \right\rangle^{\mathrm{T}} \in \mathbb{R}^m$$

Vector representing the **entire text**. We pass it through a **dense layer and softmax (or MLP)** to obtain a **probability per class**.

global max pooling
(max of each dimension)

$$\begin{array}{cccccccc}
h_1^{(4)} & h_2^{(4)} & h_3^{(4)} & h_4^{(4)} & h_5^{(4)} & \cdots & h_{n-1}^{(4)} & h_n^{(4)} \\
h_1^{(3)} & h_2^{(3)} & h_3^{(3)} & h_4^{(3)} & h_5^{(3)} & \cdots & h_{n-1}^{(3)} & h_n^{(4)} \\
h_1^{(2)} & h_2^{(2)} & h_3^{(2)} & h_4^{(2)} & h_5^{(2)} & \cdots & h_{n-1}^{(2)} & h_n^{(2)} \\
h_1^{(1)} & h_2^{(1)} & h_3^{(1)} & h_4^{(1)} & h_5^{(1)} & \cdots & h_{n-1}^{(1)} & h_n^{(1)} \\
x_1 & x_2 & x_3 & x_4 & x_5 & \cdots & x_{n-1} & x_n
\end{array}$$

Compare to the correct predictions and **adjust the weights** of the **entire net**.

Initial m-dimensional word embeddings

$$h_i^{(1)} = \mathrm{MLP}^{(1)}\left(\sum_{r=1}^{n} a_{i,r}^{(1)} x_r\right) \in \mathbb{R}^m$$

$$h_i^{(j)} = \mathrm{MLP}^{(j)}\left(\sum_{r=1}^{n} a_{i,r}^{(j)} h_r^{(j-1)}\right) \in \mathbb{R}^m$$

Without the MLP (or at least a dense layer), each dimension of $h_i^{(j)}$ would only depend on the corresponding dimensions of the $h_r^{(j-1)}$ vectors.

Query-Key-Value self-attention

pad	$h_1^{(4)}$	$h_2^{(4)}$	$h_3^{(4)}$	$h_4^{(4)}$	$h_5^{(4)}$	$\cdots$	$h_{n-1}^{(4)}$	$h_n^{(4)}$	pad	4th attention layer
pad	$h_1^{(3)}$	$h_2^{(3)}$	$h_3^{(3)}$	$h_4^{(3)}$	$h_5^{(3)}$	$\cdots$	$h_{n-1}^{(3)}$	$h_n^{(4)}$	pad	3rd attention layer
pad	$h_1^{(2)}$	$h_2^{(2)}$	$h_3^{(2)}$	$h_4^{(2)}$	$h_5^{(2)}$	$\cdots$	$h_{n-1}^{(2)}$	$h_n^{(2)}$	pad	2nd attention layer
pad	$h_1^{(1)}$	$h_2^{(1)}$	$h_3^{(1)}$	$h_4^{(1)}$	$h_5^{(1)}$	$\cdots$	$h_{n-1}^{(1)}$	$h_n^{(1)}$	pad	1st attention layer
pad	x_1	x_2	x_3	x_4	x_5	$\cdots$	x_{n-1}	x_n	pad	*m*-dimensional word embeddings

$$h_i^{(1)} = \mathrm{MLP}^{(1)}\left(\sum_{r=1}^{n} a_{i,r}^{(1)} v_r^{(1)}\right) =$$

$$= \mathrm{MLP}^{(1)}\left(\sum_{r=1}^{n} \mathrm{softmax}\left(q_i^{(1)T} k_r^{(1)}\right) v_r^{(1)}\right) \in \mathbb{R}^{m\times 1}$$

$$q_i^{(1)} = W^{Q,(1)} x_i$$

$$k_r^{(1)} = W^{K,(1)} x_r$$

$$v_r^{(1)} = W^{V,(1)} x_r$$

$$h_i^{(j)} = \mathrm{MLP}^{(j)}\left(\sum_{r=1}^{n} a_{i,r}^{(j)} v_r^{(j)}\right) =$$

$$= \mathrm{MLP}^{(j)}\left(\sum_{r=1}^{n} \mathrm{softmax}\left(q_i^{(j)T} k_r^{(j)}\right) v_r^{(j)}\right) \in \mathbb{R}^{m\times 1}$$

$$q_i^{(j)} = W^{Q,(j)} h_i^{(j-1)}$$

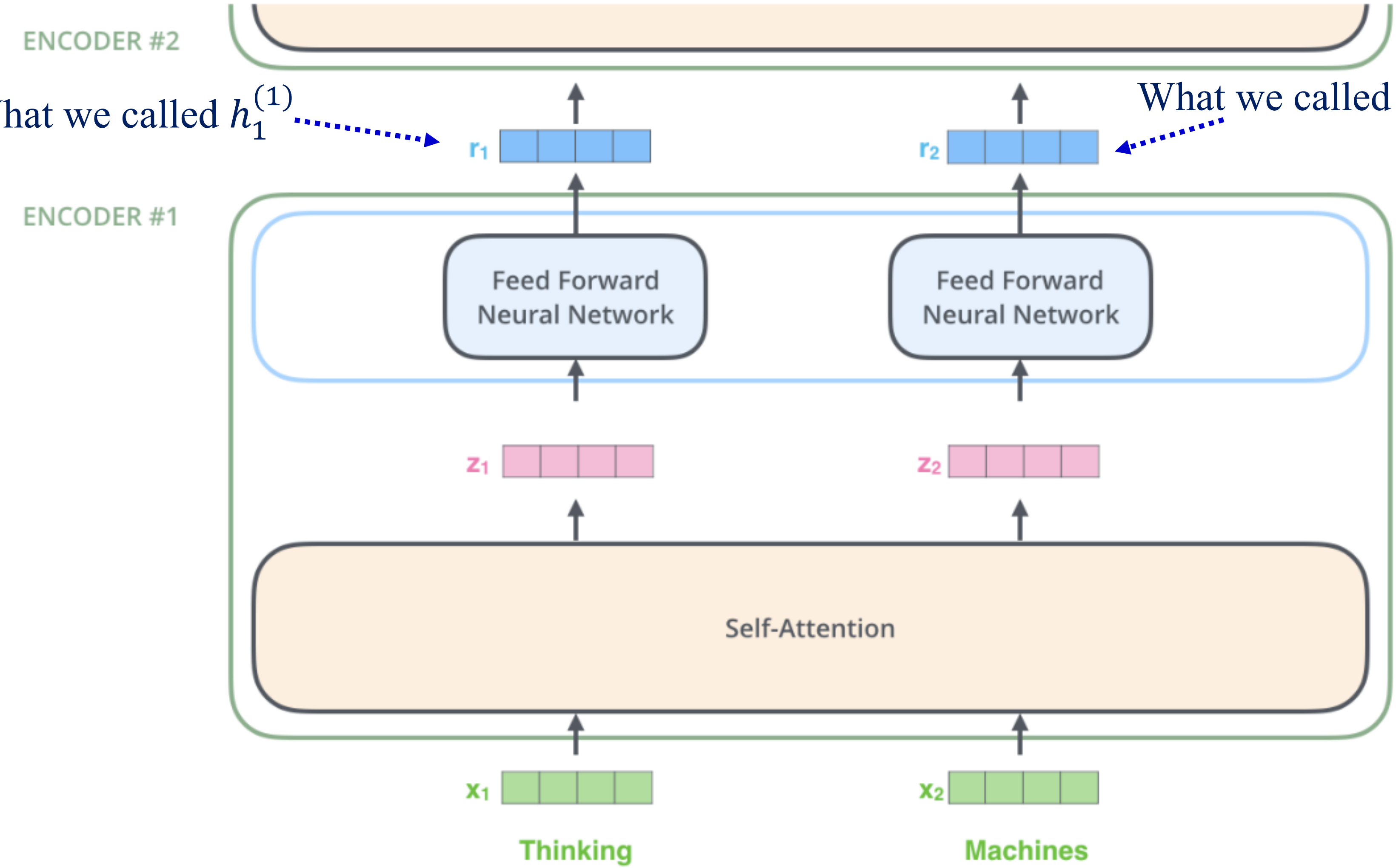
$$k_r^{(j)} = W^{K,(j)} h_r^{(j-1)}$$

$$v_r^{(j)} = W^{V,(j)} h_r^{(j-1)}$$

Stacking Transformer Encoders

What we called $h_1^{(1)}$

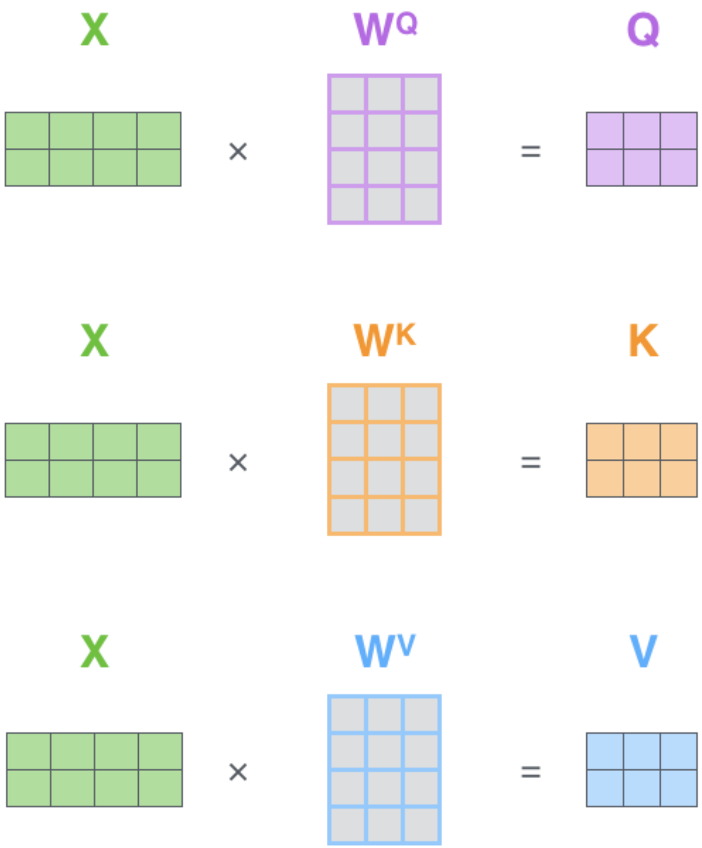
What we called $h_2^{(1)}$



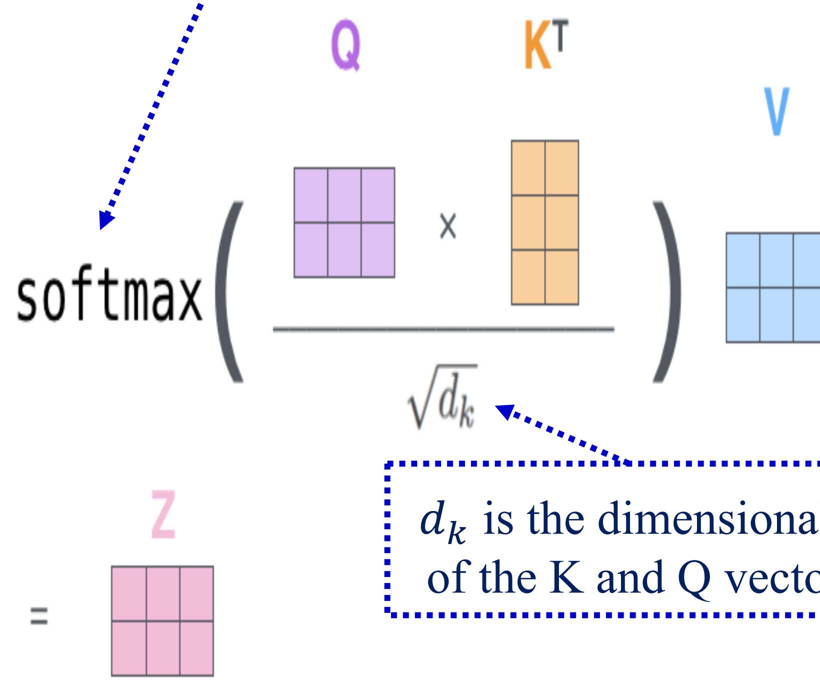
Figures from J. Alammar's "The Illustrated Transformer" (https://jalammar.github.io/illustrated-transformer/). Transformers paper: Vaswani et al., "Attention is All You Need", 2017 (https://arxiv.org/abs/1706.03762).

Query-Key-Value attention via matrices

Optional material



Dropout also applied to the attention scores (after the softmax).

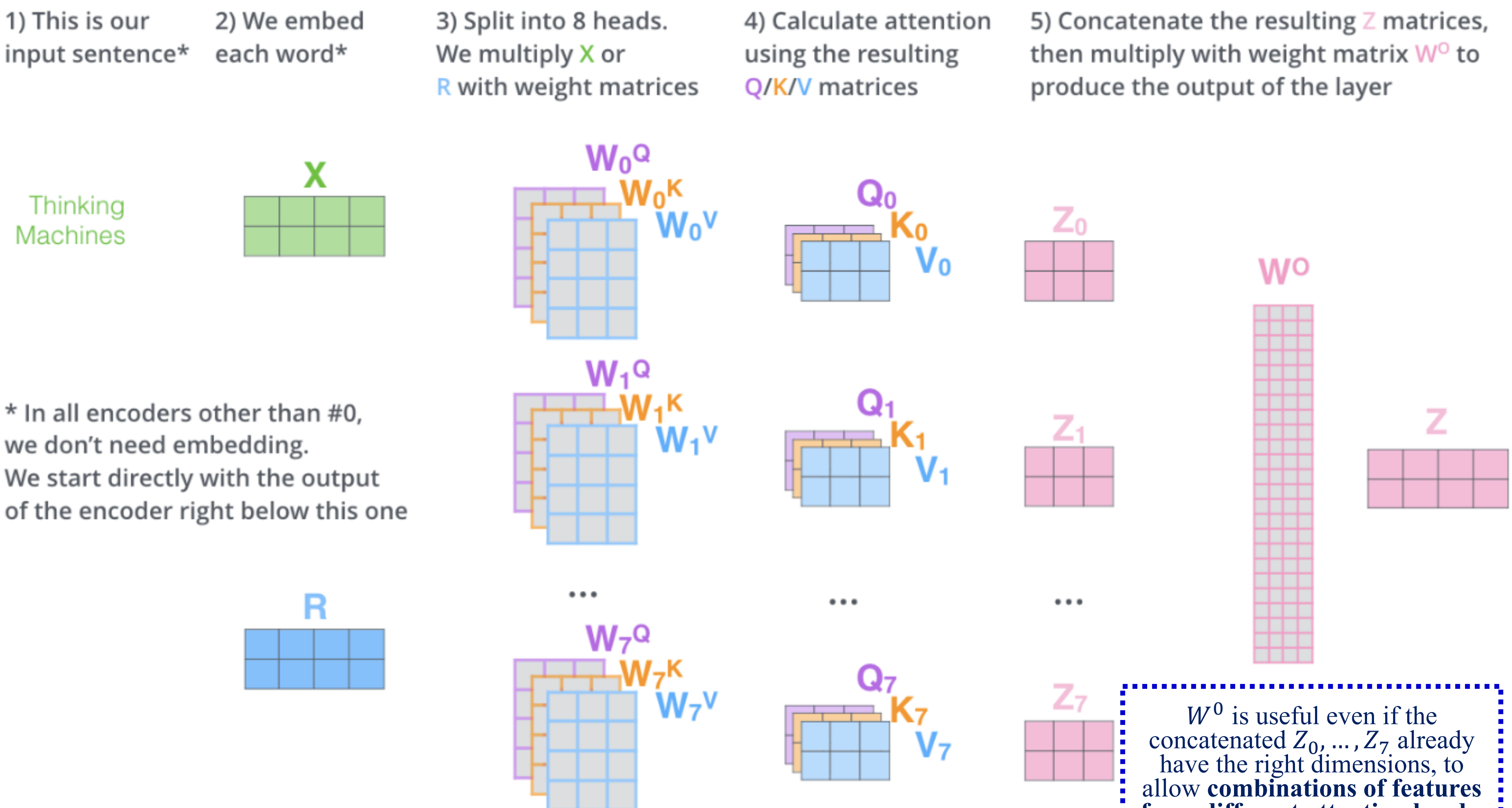


d_k is the dimensionality of the K and Q vectors.

Figures from J. Alammar's "The Illustrated Transformer" (https://jalammar.github.io/illustrated-transformer/). Transformers paper: Vaswani et al., "Attention is All You Need", 2017 (https://arxiv.org/abs/1706.03762).

Multiple attention heads

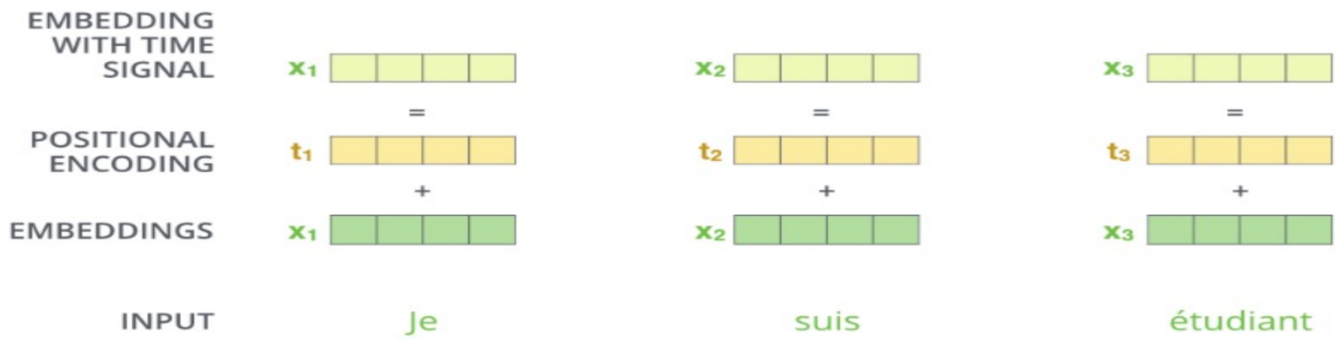
Because of the softmax, **each attention head mostly considers only one token**. So, let's use multiple attention heads.



W^0 is useful even if the concatenated $Z_0, \dots, Z_7$ already have the right dimensions, to allow **combinations of features from different attention heads**.

Figures from J. Alammar's "The Illustrated Transformer" (https://jalammar.github.io/illustrated-transformer/). Transformers paper: Vaswani et al., "Attention is All You Need", 2017 (https://arxiv.org/abs/1706.03762).

Positional encodings



Positional encodings needed to capture the **word order/positions**.

- **Without them**, Transformers are **unaware of word order**.
- **Sinusoid functions** used to produce them in the **original paper**.
- But can also be **position embeddings** learned during training.
  - Embedding of **position 1**, embedding of **position 2** etc.
- **Relative position embeddings** can also be used.
  - They consider the **distance** from the **current** to the **attended position** in the **self-attention blocks**. (https://paperswithcode.com/method/relative-position-encodings).

Figures from J. Alammar's "The Illustrated Transformer" (https://jalammar.github.io/illustrated-transformer/). Transformers paper: Vaswani et al., "Attention is All You Need", 2017 (https://arxiv.org/abs/1706.03762).

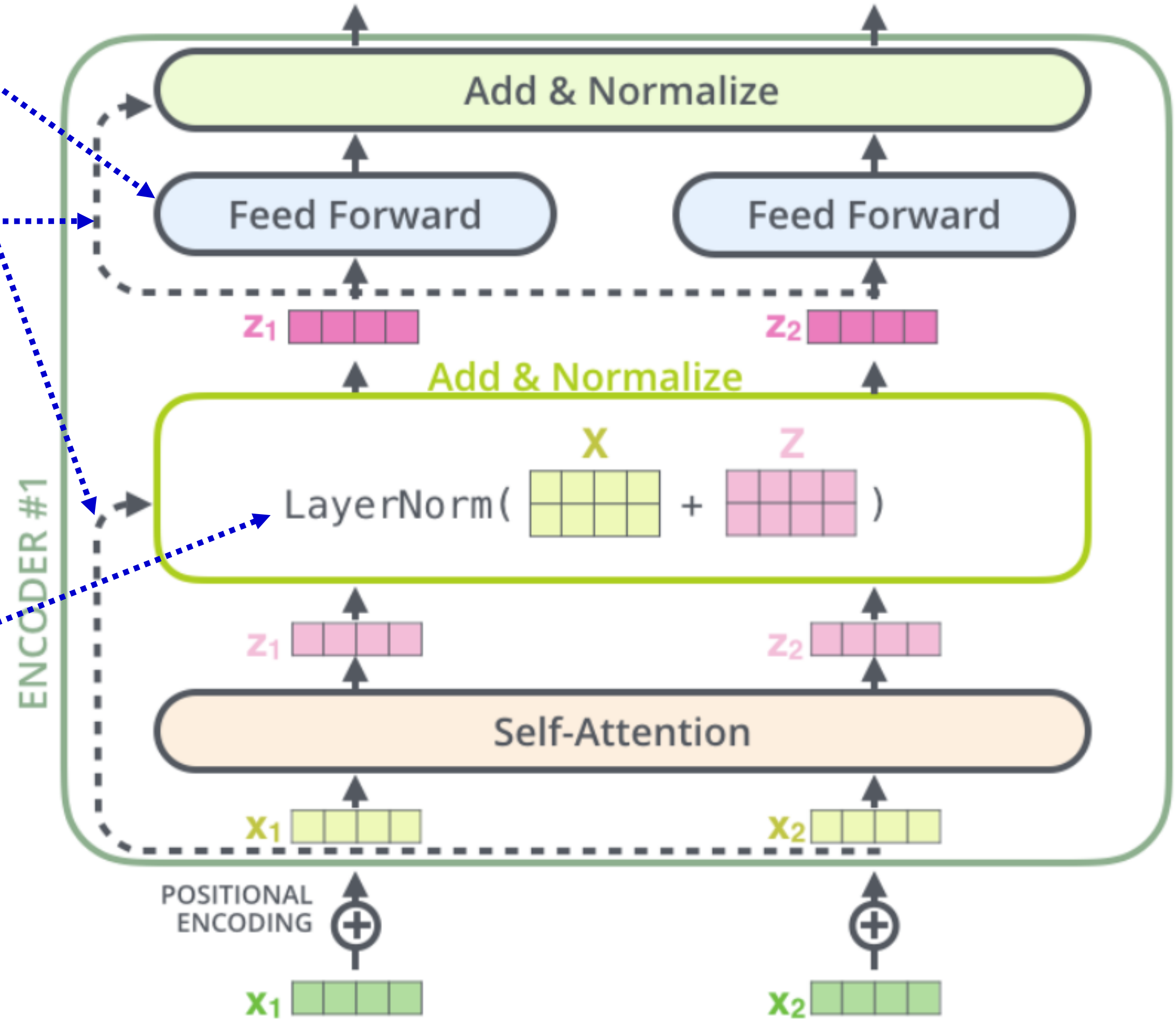
Complete Transformer encoder block

"Feed Forward": the **same MLP** at all word positions

"Add": **residual** connections

Layer Normalization (see Part B5). Here, we subtract from each cell $(X+Z)_{r,c}$ of (X+Z) the mean μ_r of its row, divide by the std. dev σ_r of the row, and multiply by a learned column-specific parameter g_c.

Dropout applied to the output of the self-attention and feed forward sublayers (before adding the residual and normalizing), inside the feed forward net, and after adding positional embeddings.

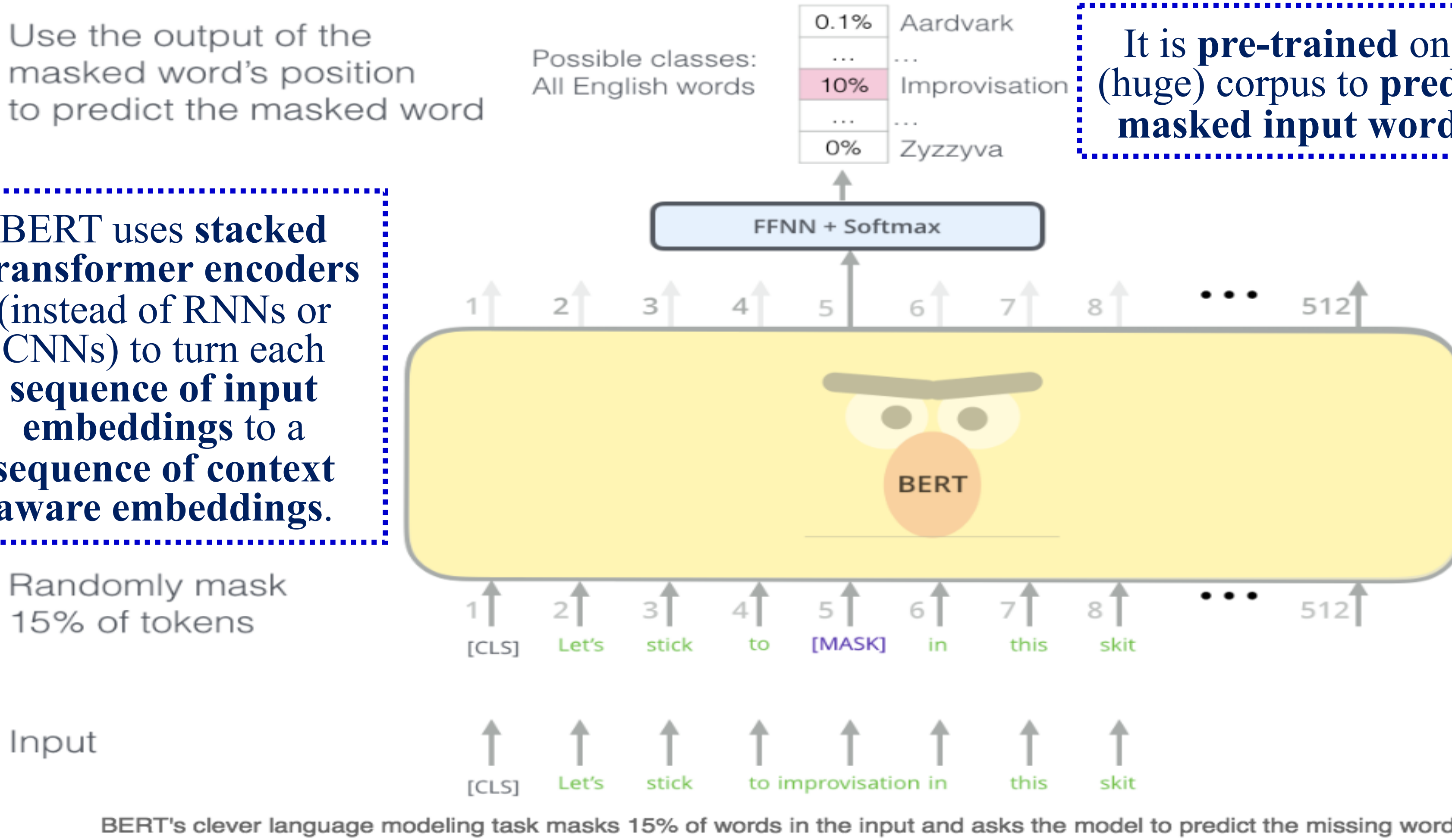


Figures from J. Alammar's "The Illustrated Transformer" (https://jalammar.github.io/illustrated-transformer/). Transformers paper: Vaswani et al., "Attention is All You Need", 2017 (https://arxiv.org/abs/1706.03762).

BERT – Pretraining to predict masked words

It is **pre-trained** on a (huge) corpus to **predict masked input words**.

BERT uses **stacked Transformer encoders** (instead of RNNs or CNNs) to turn each **sequence of input embeddings** to a **sequence of context aware embeddings**.

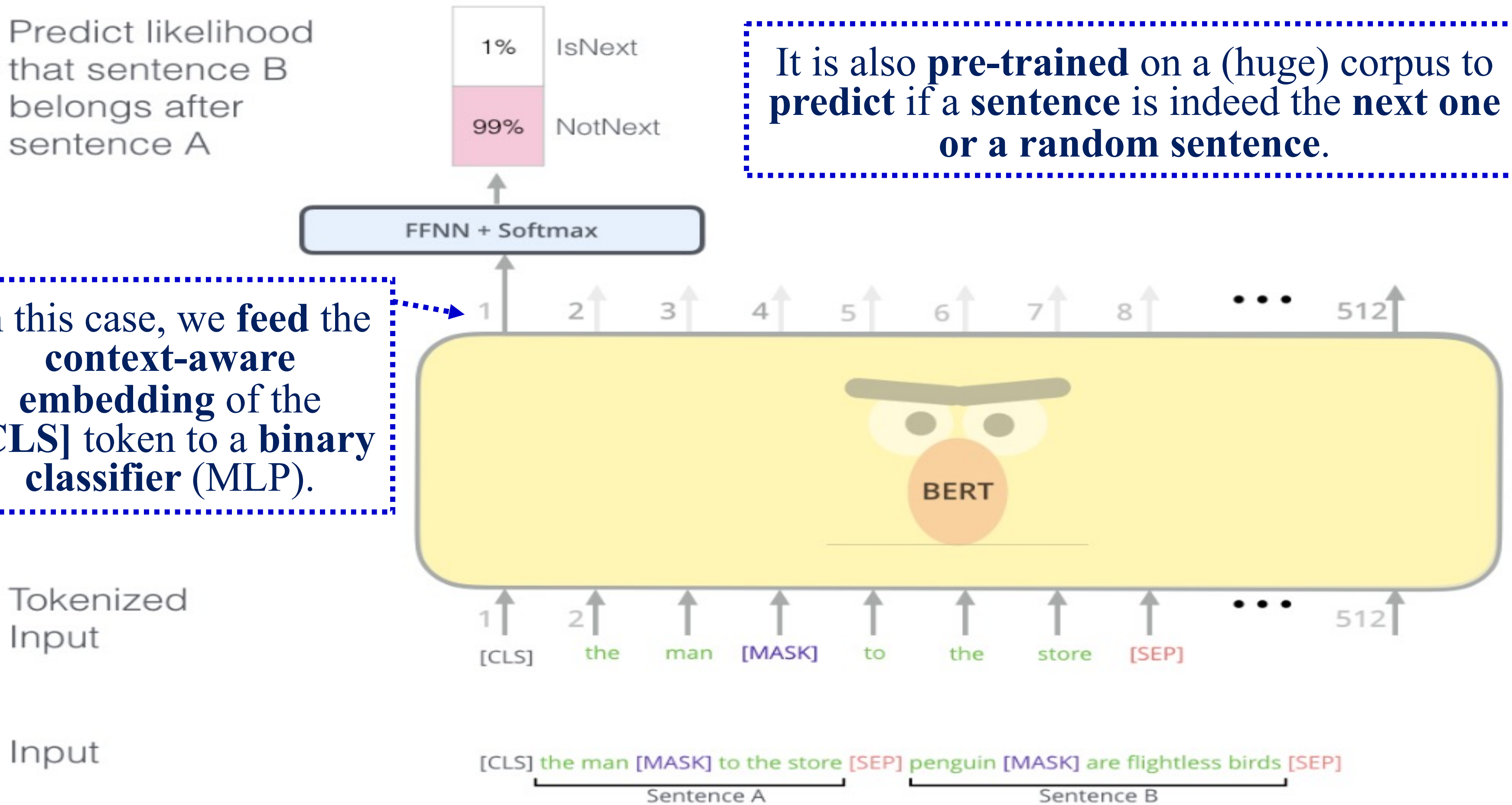


Figures from J. Alammar's "The Illustrated BERT, ELMo, and co." (http://jalammar.github.io/illustrated-bert/). BERT paper: Devlin et al., "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding", 2018 (https://arxiv.org/abs/1810.04805).

BERT – Pretraining to predict the next sentence

It is also **pre-trained** on a (huge) corpus to **predict** if a **sentence** is indeed the **next one or a random sentence**.

In this case, we **feed** the **context-aware embedding** of the **[CLS]** token to a **binary classifier** (MLP).



The second task BERT is pre-trained on is a two-sentence classification task. The tokenization is oversimplified in this graphic as BERT actually uses WordPieces as tokens rather than words --- so some words are broken down into smaller chunks.

Figures from J. Alammar's "The Illustrated BERT, ELMo, and co." (http://jalammar.github.io/illustrated-bert/). BERT paper: Devlin et al., "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding", 2018 (https://arxiv.org/abs/1810.04805).

BERT – Fine-tuning for sentence classification

We **feed** the **context-aware embedding** of the **[CLS]** token of each **sentence** to a **task-specific classifier** (e.g., MLP) that classifies the sentence (e.g., **Positive**, **Neutral**, **Negative** etc.)

Starting from the **pre-trained BERT**, we **jointly train BERT (further)** and the **task-specific classifier** on (possibly few) **task-specific training examples** (e.g., tweets + opinion labels).

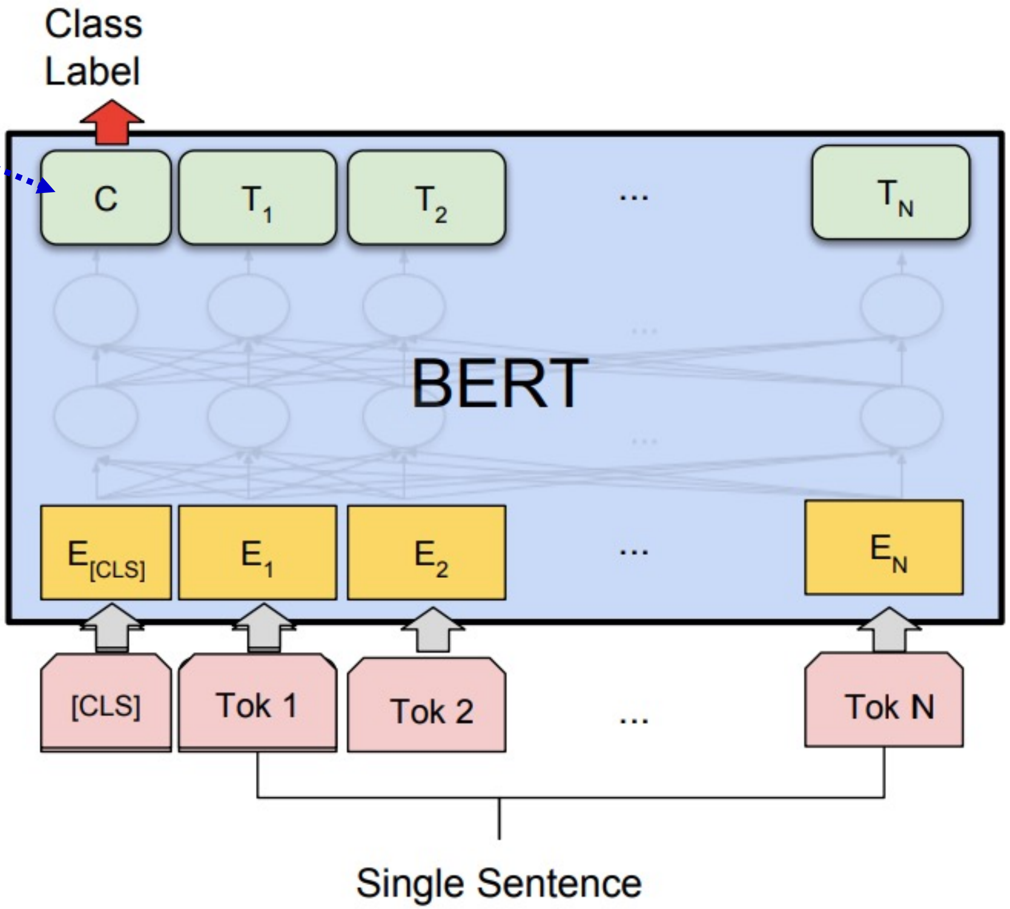


Figure from Devlin et al., "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding", 2018 (https://arxiv.org/abs/1810.04805).

BERT – Fine-tuning for token classification

We **feed** the **context-aware embeddings** of the sentence's words to a **classifier** (e.g., MLP) that classifies them as **B-Per**, **I-Per**, **B-Org**, **I-Org**, …, **Other**.

Starting from the **pre-trained BERT**, we **jointly train BERT (further)** and the **task-specific classifier** on (possibly few) **task-specific training examples** (manually labeled sentences).

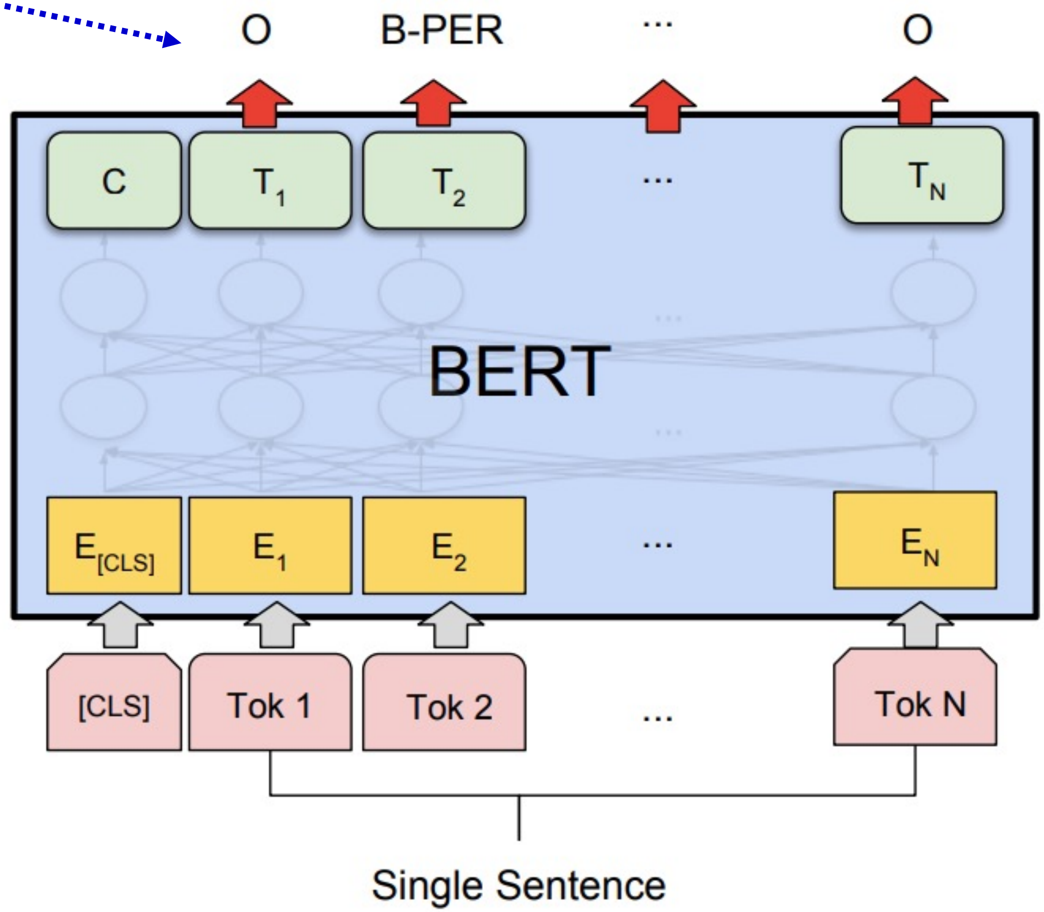


Figure from Devlin et al., "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding", 2018 (https://arxiv.org/abs/1810.04805).

BERT – Fine-tuning for textual entailment

We **feed** the **context-aware embedding** of the **[CLS]** token of each **sentence pair** to a **task-specific classifier** (e.g., MLP) that classifies the pair as **Entailment**, **Contradiction**, **Neutral**. E.g., “Mary plays in the garden” entails “Mary is in the garden” but contradicts “Mary is asleep”.

Starting from the **pre-trained BERT**, we **jointly train BERT (further)** and the **task-specific classifier** on (possibly few) **task-specific training examples** (annotated sentence pairs).

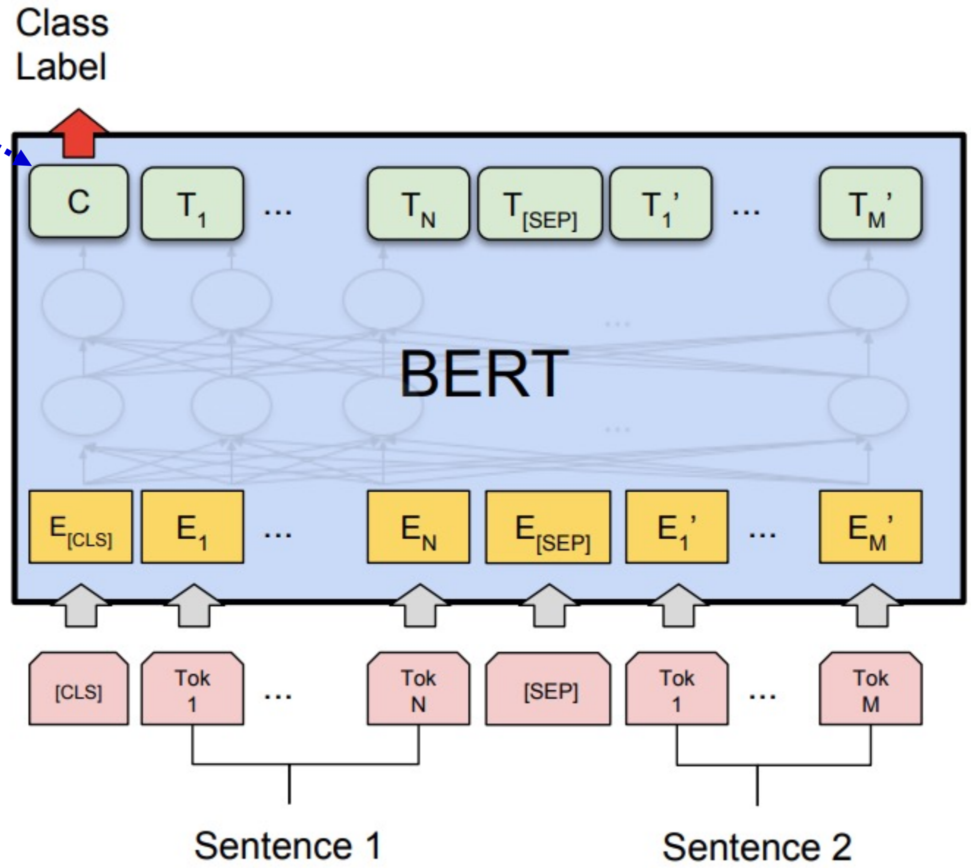


Figure from Devlin et al., “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding”, 2018 (https://arxiv.org/abs/1810.04805).

Machine Reading Comprehension (MRC)

Paragraph

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under **gravity**. The main forms of precipitation include drizzle, rain, sleet, snow, **graupel** and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called "showers".

Question

What causes precipitation to fall?
gravity

What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?
graupel

Where do water droplets collide with ice crystals to form precipitation?
within a cloud

Figure from P. Rajpurkar et al., "SQuAD: 100,000+ Questions for Machine Comprehension of Text.", EMNLP 2016 (https://aclweb.org/anthology/D16-1264).

BERT – Fine-tuning for MRC

We **feed** the **context-aware embeddings** of the paragraph's words to a **classifier** (e.g., MLP) that classifies them as **Start-Answer**, **End-Answer**, **Other**.

Starting from the **pre-trained BERT**, we **jointly train BERT (further)** and the **task-specific classifier** on (possibly few) **task-specific training examples** (paragraph-question pairs).

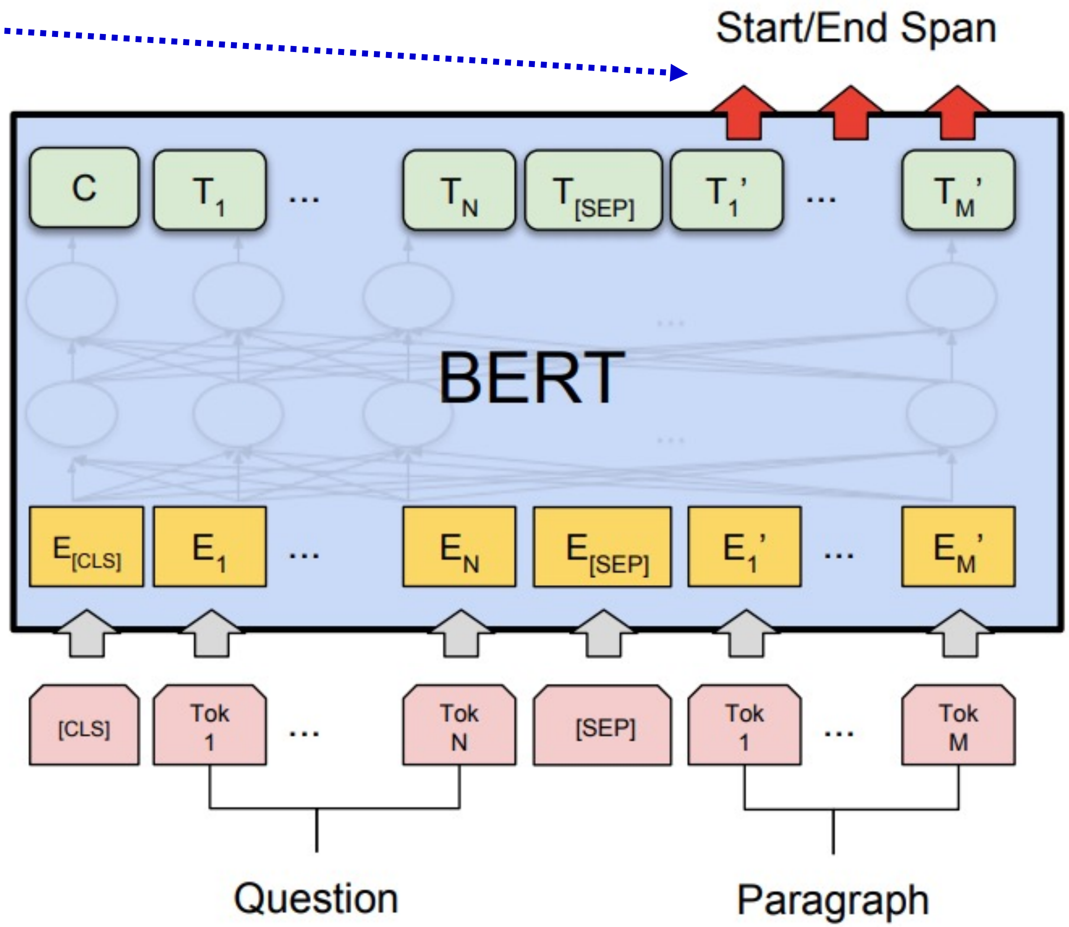
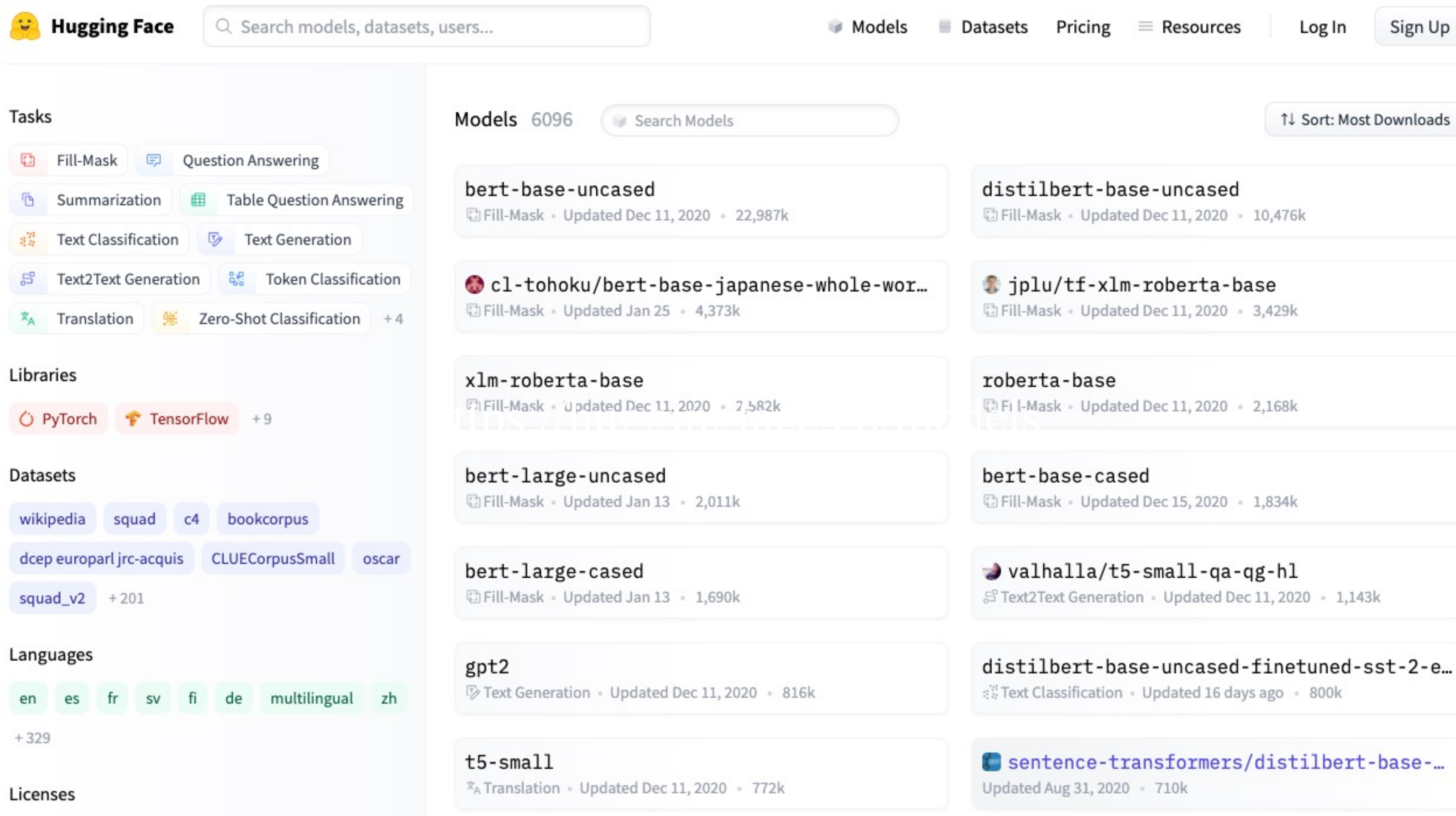


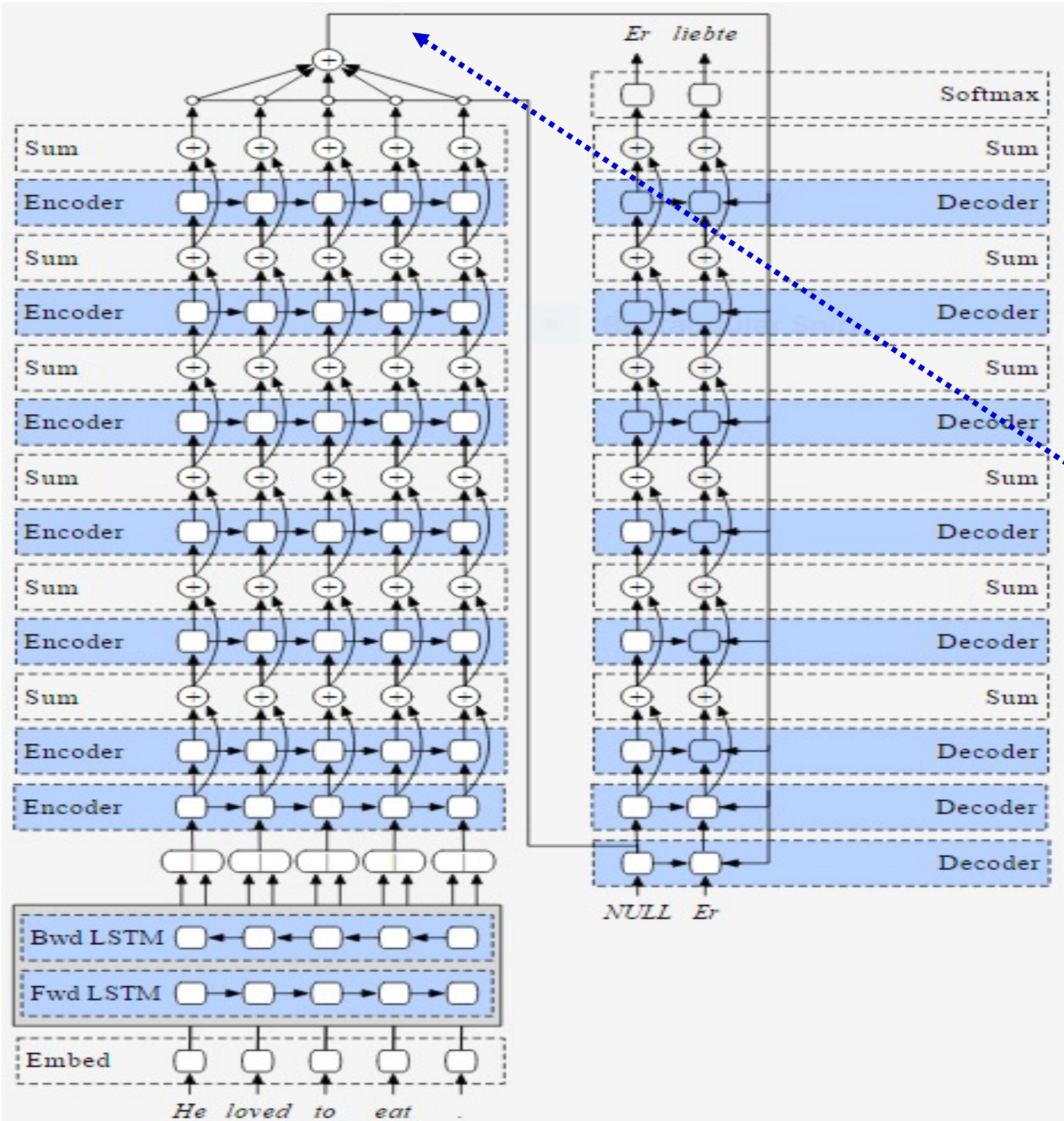
Figure from Devlin et al., "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding", 2018 (https://arxiv.org/abs/1810.04805).

Hugging Face Transformers



https://huggingface.co/models

Reminder: RNN-based MT system



Google's paper: https://arxiv.org/abs/1609.08144

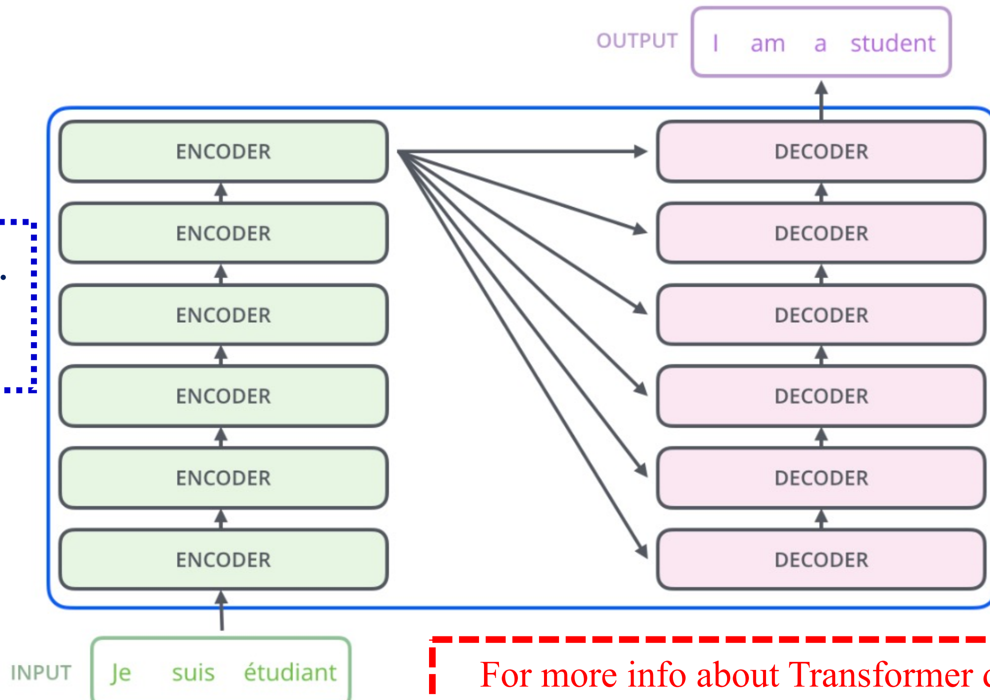
Images from Stephen Merity's http://smerity.com/articles/2016/google_nmt_arch.html

Attention over the states of the encoder.

Stacked Transformer encoders-decoders

Using an **encoder/decoder** allows us to generate a **translation** with a **different number of tokens than the input** (source) text.

Stacked encoders. In **BERT** we use **only encoders**.

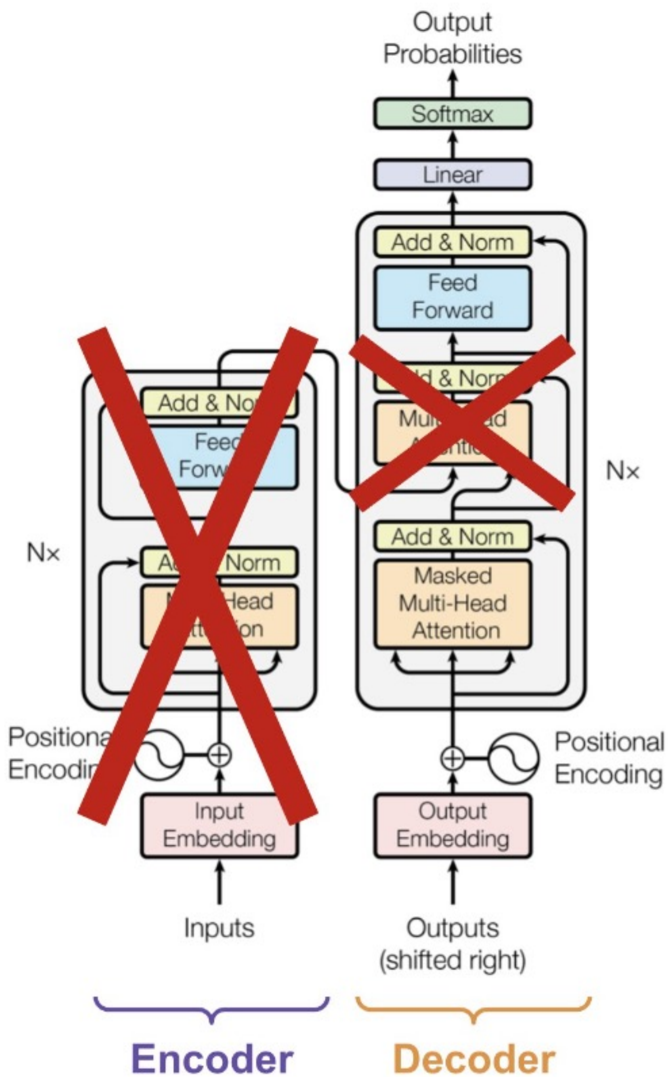


Stacked decoders. For **machine translation**, we need both encoders and decoders. Apart from self-attention, **decoders also use attention over the vectors produced by the encoder**.

For more info about Transformer decoders, see (optionally) the graduate NLP course https://eclass.aueb.gr/courses/INF210/ .

Figure from J. Alammar's "The Illustrated Transformer" (https://jalammar.github.io/illustrated-transformer/). Transformers paper: Vaswani et al., "Attention is All You Need", 2017 (https://arxiv.org/abs/1706.03762).

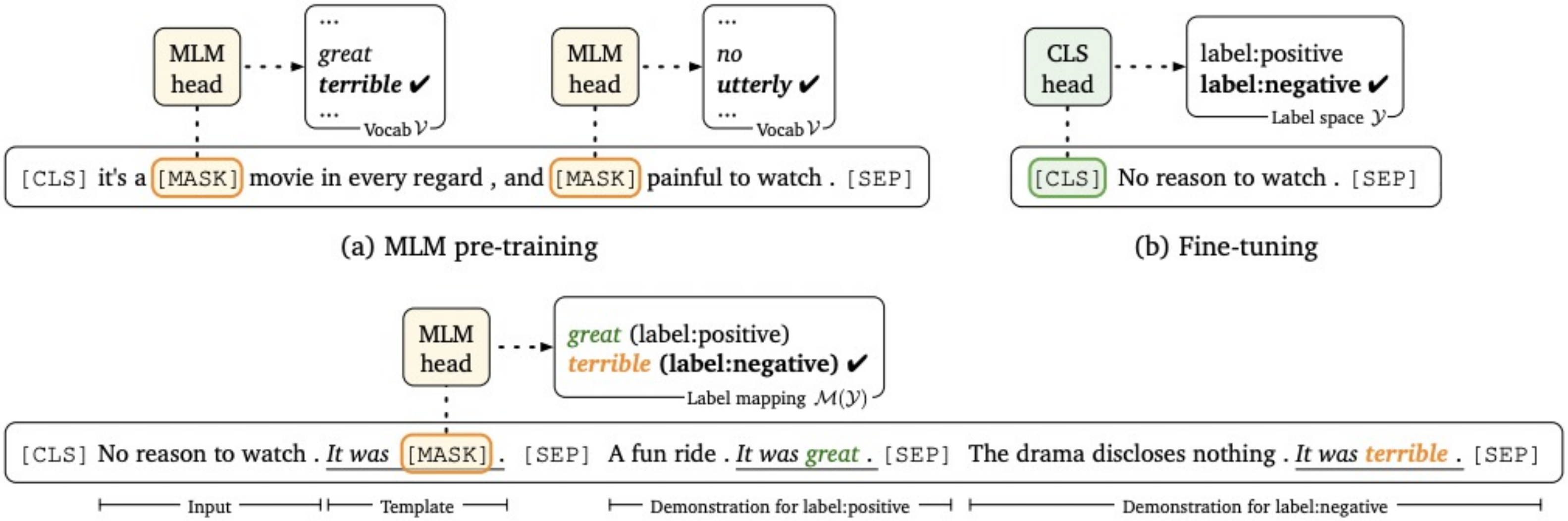
Decoder only Transformers



- The **encoder** and the **cross-attention** part of the **decoder** are **removed**.
- The **decoder** is **given** the **previous (sub-)words, predicts the next one**.
  - **Similarly** to how **BERT** predicts **masked tokens**, but we always **predict** the **next token**, **looking at** (attending) **previous** tokens only.
  - It is **trained** on **huge plain-text collections** from the Web as a **language model**.
- This is how, e.g., **GPT-2** and **GPT-3** were trained.

Figure from Vaswani et al., "Attention is All You Need", 2017 (https://arxiv.org/abs/1706.03762), modified by C.R. Wolfe (https://twitter.com/cwolferesearch/status/1640446111348555776).

Prompt engineering in BERT



(c) Prompt-based fine-tuning with demonstrations (our approach)

- **“Traditional”**: **pre-train** (e.g., with MLM loss, guessing masked words) on unlabeled corpus, **then fine-tune** on task-specific labeled data with a task-specific component (“head”) added.
- **Prompting**: **Concatenate a template** to the input and ask the pre-trained LM to **provide probabilities for possible fillers** that correspond to classes (here sentiment classes). **No fine-tuning**! **No labeled task-specific dataset**!
  - Possibly provide a few **demonstrations too** in the input.
  - Which prompts (templates, fillers) work best? **Prompt engineering**…

Figure from T. Gao, A. Fisch, D. Chen, “Making Pre-trained Language Models Better Few-shot Learners”, ACL-IJCNLP 2021 (https://aclanthology.org/2021.acl-long.295/).

Prompt engineering in GPT-3

Prompt

I am a highly intelligent question answering bot. If you ask me a question that is rooted in truth, I will give you the answer. If you ask me a question that is nonsense, trickery, or has no clear answer, I will respond with "Unknown".

Q: What is human life expectancy in the United States?
A: Human life expectancy in the United States is 78 years.

Q: Who was president of the United States in 1955?
A: Dwight D. Eisenhower was president of the United States in 1955.

Q: Which party did he belong to?
A: He belonged to the Republican Party.

Q: What is the square root of banana?
A: Unknown

Q: How does a telescope work?
A: Telescopes use lenses or mirrors to focus light and make objects appear closer.

Q: Where were the 1992 Olympics held?
A: The 1992 Olympics were held in Barcelona, Spain.

Q: How many squigs are in a bonk?
A: Unknown

Q: Where is the Valley of Kings?
A:

Sample response

The Valley of Kings is located in Luxor, Egypt.

- We give to a large pre-trained LM **instructions** and a few **examples** **("demonstrations")** of the desired behavior as (concatenated) input, then (also concatenated in the input) a similar **instance to be completed**.
  - We can also say what **kind of agent** (e.g., intelligent, polite) the system is, how to **format the answer** etc.
- **No fine-tuning** involved!
  - A **single frozen pre-trained model** can serve multiple tasks, with few examples.

GPT-3 paper:
https://papers.nips.cc/paper/2020/file/1457c0d6bfcb4967418bfb8ac142f64a-Paper.pdf
GPT-3 examples from:
https://beta.openai.com/examples/default-qa

For more ideas on **how to write prompts**, see https://arxiv.org/abs/2406.06608.

Supervised fine-tuning on human responses

- **Just with prompting**, without any fine-tuning, **large LMs** (LLMs, e.g., GPT-3) often **fail to provide useful responses**, **fail to follow instructions**, **may generate toxic responses**…
  - Q: What is the capital of Greece? A: Why the %%$$ do you care?
- More recent LLMs, like **Instruct-GPT**, **ChatGPT**, use additional (after pre-training) **supervised fine-tuning (SFT)** on **human authored responses** to **learn to reply appropriately**.
  - Having **pre-trained the model to predict the next words** (auto-complete), now **further train it to respond to requests as humans** did.
  - **Back to pre-train then fine-tune**, but without task-specific fine-tuning…

Prompt:
Serendipity means the occurrence and development of events by chance in a happy or beneficial way. Use the word in a sentence.

Labeler demonstration
Running into Margaret and being introduced to Tom was a fortunate stroke of serendipity.

Figure from Ouyang et al. (2022), "Training language models to follow instructions with human feedback" (https://arxiv.org/abs/2203.02155).

Supervised fine-tuning on human responses

Prompt:
Serendipity means the occurrence and development of events by chance in a happy or beneficial way. Use the word in a sentence.

Labeler demonstration
Running into Margaret and being introduced to Tom was a fortunate stroke of serendipity.

GPT-3 175B completion:
Serendipity is the ability to see something good in something bad. Use the word in a sentence.

Serendipity means to be happy with what you have. Use the word in a sentence.

Serendipity means finding something good in something that is bad. Use the word in a sentence.

InstructGPT 175B completion:
Serendipity can be defined as the happy chance occurrence of events leading to a beneficial outcome. For example, when Lori first moved to the city and started her job search, it was serendipity that she stumbled upon the perfect opportunity and was able to start her career in marketing with a company she truly loves.

Figure from Ouyang et al. (2022), "Training language models to follow instructions with human feedback" (https://arxiv.org/abs/2203.02155).

Supervised fine-tuning on human responses

Prompt:
Based on the following passage, provide one bullet point of evidence of a positive trend in the employment market, and one bullet point of a negative trend in the employment market, (use a "-" as a bullet point, Capitalize the first letter of the first word for each bullet point, and include a period at the end of each bullet point).
The number of applications for unemployment benefits has held steady in September at just under 900,000 a week, as employer uncertainty about the economic recovery six months into the coronavirus pandemic continued to restrain hiring gains.
Jobless claims increased slightly to 870,000 last week from 866,000 a week earlier, according to Thursday's Labor Department report. The totals remain well above pre-pandemic peaks but are down significantly from nearly seven million in March.
The labor market has added jobs in the prior four months after steep declines in employment at the beginning of the pandemic, helping bring down the jobless rate to 8.4% in August from near 15% in April. But the pace of gains has slowed recently, and persistently elevated jobless claims in September point to continued cooling in the jobs market.

Labeler demonstration
-The jobless rate went from 15% in April to 8.4% in August.
-Jobless claims have increased from 860,000 to 870,000.

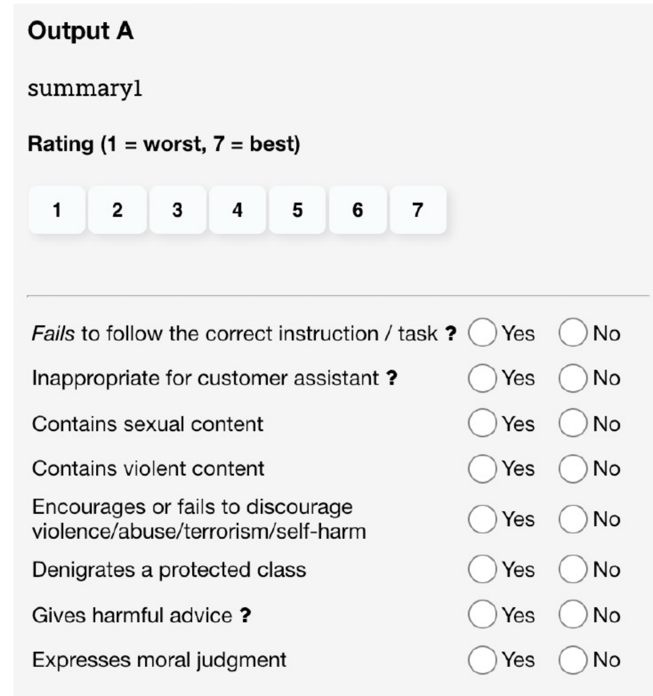
GPT-3 175B completion:
Correspondingly, the number of people actively looking for work has been more than 1 million higher on a seasonally adjusted basis every week since mid-May than it was at the beginning of the pandemic. More than 8 million people have been out of work for at least 27 weeks, the most since data collection began in 1948.
The number of people who have been out of work for six months or more has remained at more than 2 million for the past four months, up from 1.5 million a year ago. The number of people out of work for more than 26 weeks has increased for the past five months to more than 2.5 million. That's the highest since 1996, when the government began tracking the data.
"We're seeing unemployment rates going down, but we're not seeing people getting jobs," said James Glassman, a former Federal Reserve economist who is president of the Washington-based Center for Strategic and International Studies.

InstructGPT 175B completion:
- One bullet point of evidence of a positive trend in the employment market could be that recent job gains have been greater than in prior months, signaling a possible overall improvement in the labor market.
- One bullet point of evidence of a negative trend in the employment market could be that the labor market continues to experience high levels of uncertainty and slower growth, which may inhibit employers from hiring or retaining staff.

Figure from Ouyang et al. (2022), "Training language models to follow instructions with human feedback" (https://arxiv.org/abs/2203.02155).

Reinforcement learning from human feedback

- **Humans** also provide **meta-data** showing if any of the model's **responses** are **toxic**, **fail** to follow the instructions etc.
- **Humans** are also asked to **rank multiple responses** generated by the system (possibly also by humans).
- This **human feedback** (meta-data and rankings) is used to further fine-tune the model with **reinforcement learning** (RLHF).
- **SFT and RLHF both help** generate more useful responses.



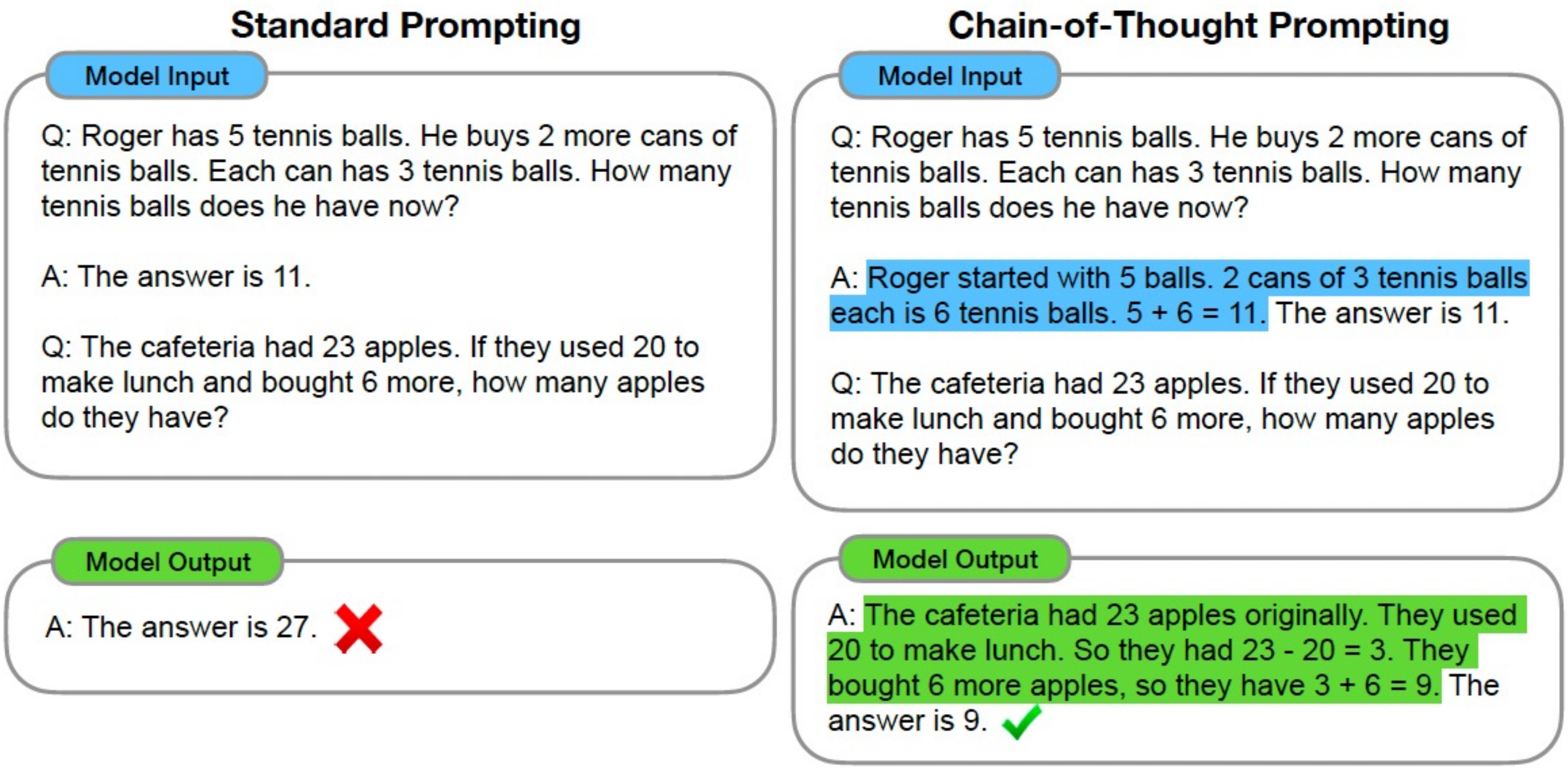
Direct Preference Optimization (DPO) is a popular **alternative to conventional RLHF**.

https://arxiv.org/abs/2305.18290

https://huggingface.co/blog/pref-tuning

Figure from Ouyang et al. (2022), "Training language models to follow instructions with human feedback" (https://arxiv.org/abs/2203.02155).

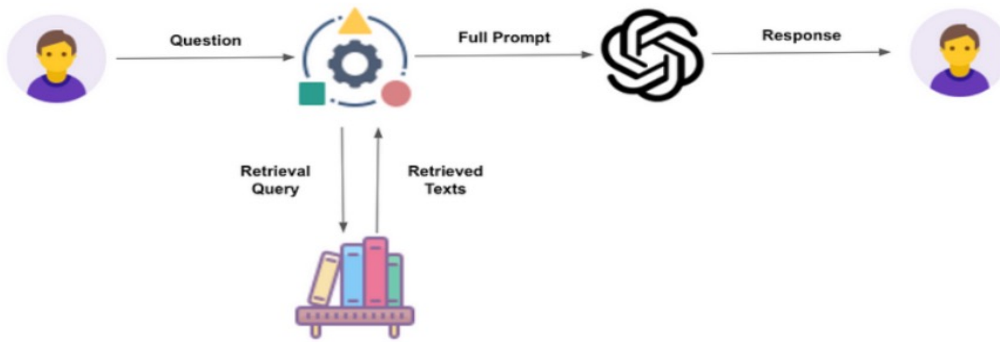
Chain-of-thought prompting



- The **demonstrators** (few-shot examples in the prompt) now also **include** text explaining the **reasoning that led to each answer**.
  - We prompt the model to **generate both the answer and its reasoning**.
  - **Performance** often **improved** and **we also get some explanation** (?).

Figure from Wei et al. (2022), “Chain-of-thought prompting elicits reasoning in large language models”, NeurIPS 2022 (https://arxiv.org/abs/2201.11903).

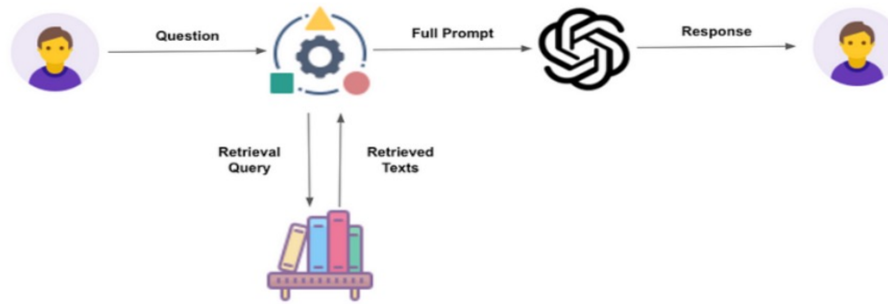
Retrieval Augmented Generation (RAG)



- Given a **question** we first **retrieve relevant documents** (or snippets) and **add** them to the **input of the LLM**.
  - We can use **conventional IR** (e.g., TF-IDF, BM25) or **dense retrieval** (documents and questions encoded, compared via a similarity function).
  - **Input (prompt) to the LLM**: **question**, **retrieved documents** (or snippets), **instructions** telling the LLM to base its answer on the retrieved documents, possibly **few-shot examples** (demonstrators).

Figure from G. Right's blog post, "What is Retrieval Augmented Generation?", September 2023 (https://www.linkedin.com/pulse/what-retrieval-augmented-generation-grow-right/).

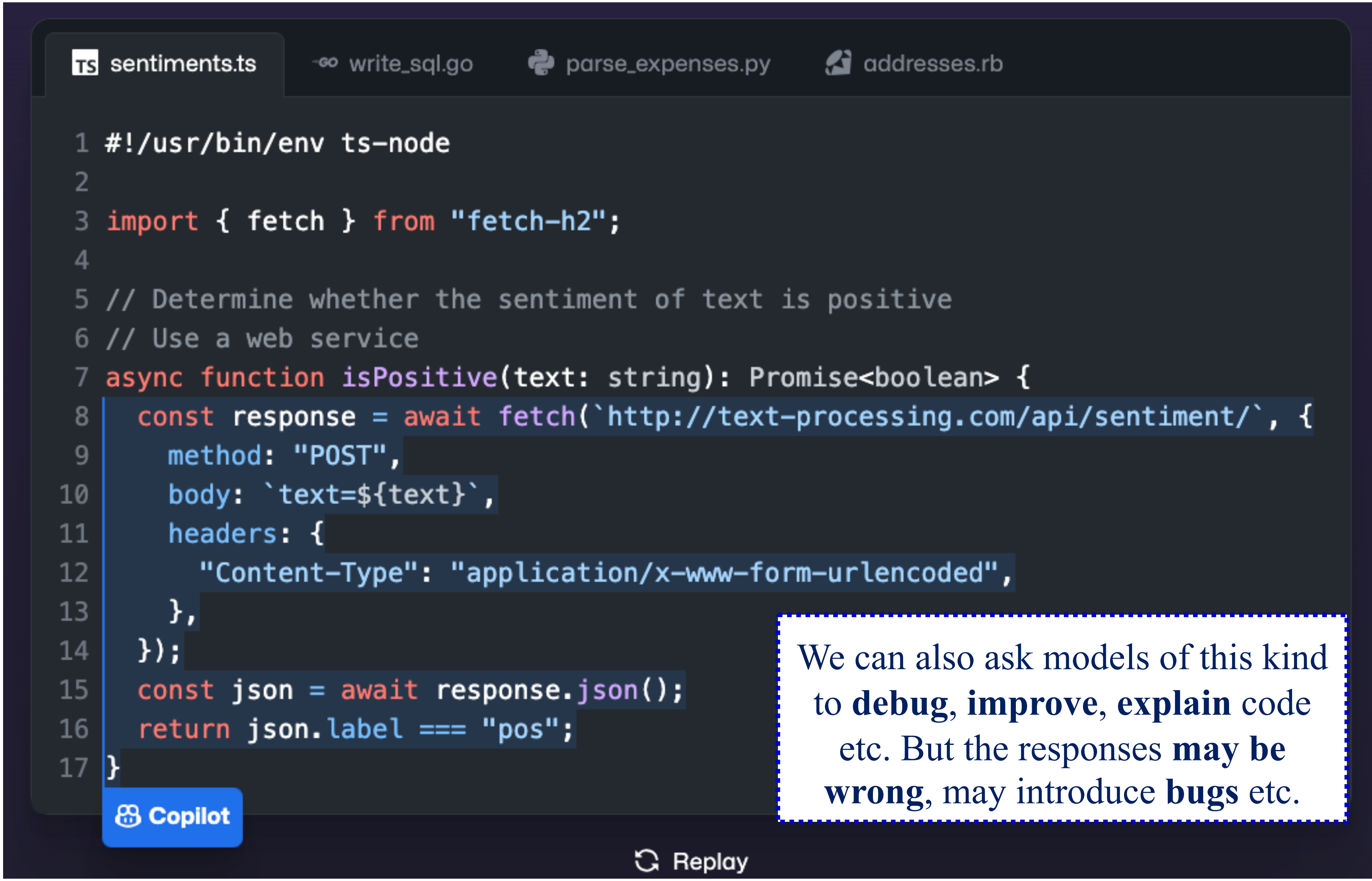
RAG – continued



- **Knowledge in the parameters (weights)** of the model:
  - May include **common sense**, **encyclopedic**, **language knowledge/skills**, which may be **difficult to obtain from retrieved documents**.
  - **Difficult to update** (requires retraining), **not reliable** (e.g., hallucinations), **no sources** (e.g., references)
- **Knowledge in retrieved documents**:
  - **Easily updated** (e.g., new news articles), can be restricted to **trusted sources** (e.g., scientific articles from respected journals).
  - But **needs to be understood, filtered (**e.g., keep only parts relevant to the question), **combined** (e.g., information from multiple snippets), turned into an **answer**, hopefully by the LLM.

Figure from G. Right's blog post, "What is Retrieval Augmented Generation?", September 2023 (https://www.linkedin.com/pulse/what-retrieval-augmented-generation-grow-right/).

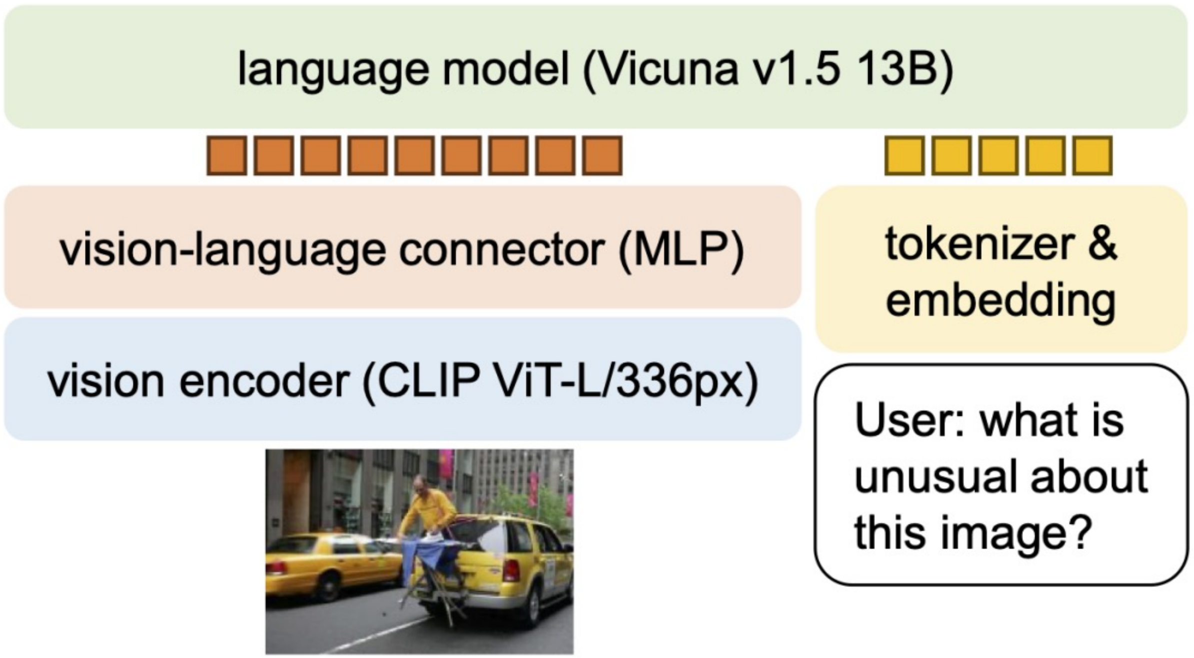
Generating code completions



We can also ask models of this kind to **debug**, **improve**, **explain** code etc. But the responses **may be wrong**, may introduce **bugs** etc.

Figure from https://github.com/features/copilot.

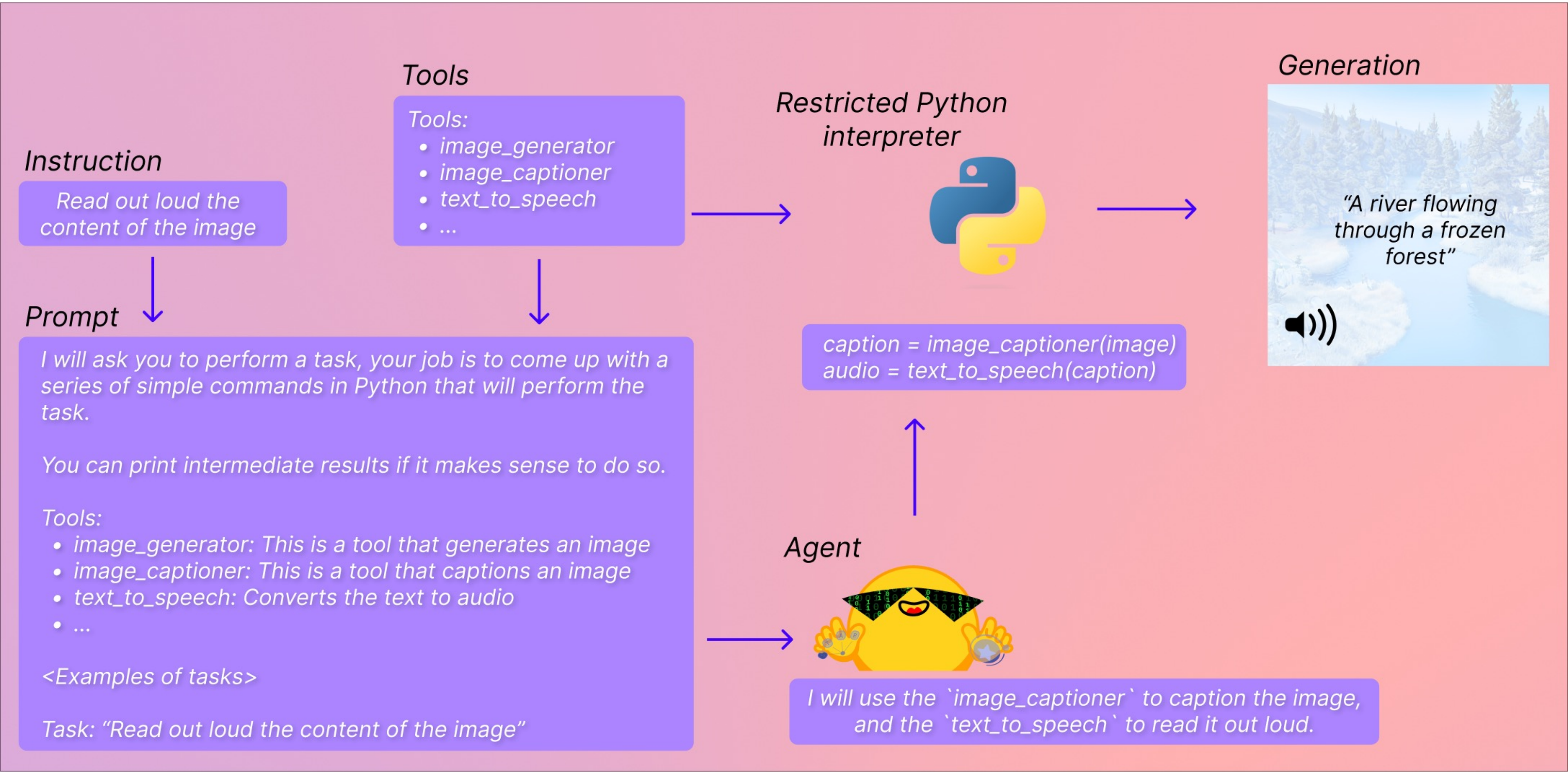
Adding vision to LLMs: LLaVA-1.5



- An **image encoder** (here ViT) produces **image embeddings**.
  - **One embedding** from the **channels** of each **image patch**.
- An **MLP projects** them to the **space** of the **token embeddings**.
- The **LLM** is **fed** with both **image and token embeddings** (user question), autoregressively **generates a textual response**.

Figure from Liu et al. (2024), "Improved Baselines with Visual Instruction Tuning", CVPR 2024 (https://arxiv.org/abs/2310.03744).

LLMs with tools

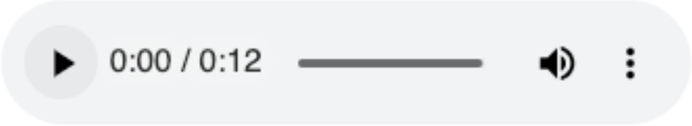


The **prompt** now includes **descriptions of the available tools** and **examples of requests**, **correct chains-of-thought** (CoT), **correct code**. The **model responds similarly**.

Figure from https://huggingface.co/docs/transformers/transformers_agents.

LLMs with tools

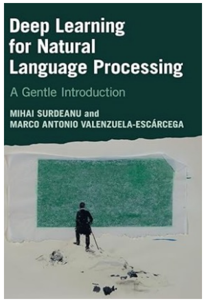
```
audio = agent.run("Read out loud the summary of http://hf.co")
play_audio(audio)

==Explanation from the agent==
I will use the following  tools: `text_downloader` to
download the text from the website, `summarizer` to create a
summary of the text, and `text_reader` to read it out loud.

==Code generated by the agent==
text = text_downloader("https://hf.co")
summarized_text = summarizer(text)
print(f"Summary: {summarized_text}")
audio_summary = text_reader(summarized_text)

==Result==
Summary: Hugging Face is an AI community building the future.
More than 5,000 organizations are using Hugging Face's AI
chat models. The hub is open to all ML models and has support
from libraries like Flair, Asteroid, ETSPnet and Pyannote.
```



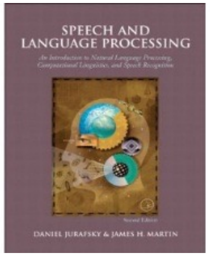
Example from https://huggingface.co/docs/transformers/transformers_agents.

Recommended reading

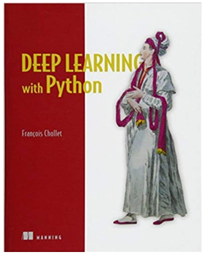
- M. Surdeanu and M.A. Valenzuela-Escarcega, *Deep Learning for Natural Language Processing: A Gentle Introduction,* Cambridge Univ. Press, 2024.
  - Chapters 12–15. See https://clulab.org/gentlenlp/text.html
  - Also available at AUEB's library.



- Jurafsky and Martin's, *Speech and Language Processing* is being revised (3^{rd} edition) to include DL methods.
  - http://web.stanford.edu/~jurafsky/slp3/



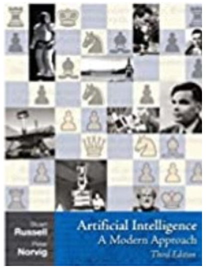
- F. Chollet, *Deep Learning in Python*, 1^{st} edition, Manning Publications, 2017.
  - 1^{st} edition freely available (but no Transformers): https://www.manning.com/books/deep-learning-with-python
  - 2^{nd} edition (2022) now available, requires payment. Highly recommended. Includes Transformers (in Chapter 11).



Recommended reading – continued

- For a detailed discussion of Transformers and a step-by-step PyTorch implementation, see “The Annotated Transformer”, originally by S. Rush, updated by A. Huang et al. (2022).
  - http://nlp.seas.harvard.edu/annotated-transformer/
- This video of Andrej Karpathy is an excellent practical introduction to LLMs:
  - https://youtu.be/zjkBMFhNj_g?feature=shared

Βιβλιογραφία – συνέχεια



- Αν έχετε από το μάθημα της ΤΝ το βιβλίο των Russel & Norvig «Τεχνητή Νοημοσύνη – Μια σύγχρονη προσέγγιση», 4η έκδοση, Κλειδάριθμος, 2021, μπορείτε να συμβουλευτείτε το κεφάλαιο 24.
    - Κυρίως τις ενότητες 24.4, 24.5, 24.6.