Language Technology

Chapter 17: Transformers: Encoder-Decoder and Decoder

Pierre Nugues

Pierre.Nugues@cs.lth.se

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Machine Translation

Process of translating automatically a text from a source language into a target language

Started after the 2nd world war to translate documents from Russian to English

Early working systems from French to English in Canada

Renewed huge interest with the advent of the web

Google claims it has more than 500m users daily worldwide, with 103 languages.

Massive progress permitted by the encoder-decoder networks

Corpora for Machine Translation

Initial ideas in machine translation: use bilingual dictionaries and formalize grammatical rules to transfer them from a source language to a target language.

Statistical machine translation:

1. Use very large bilingual corpora;
2. Align the sentences or phrases, and
3. Given a sentence in the source language, find the matching sentence in the target language.

Pioneered at IBM on French and English with Bayesian statistics.

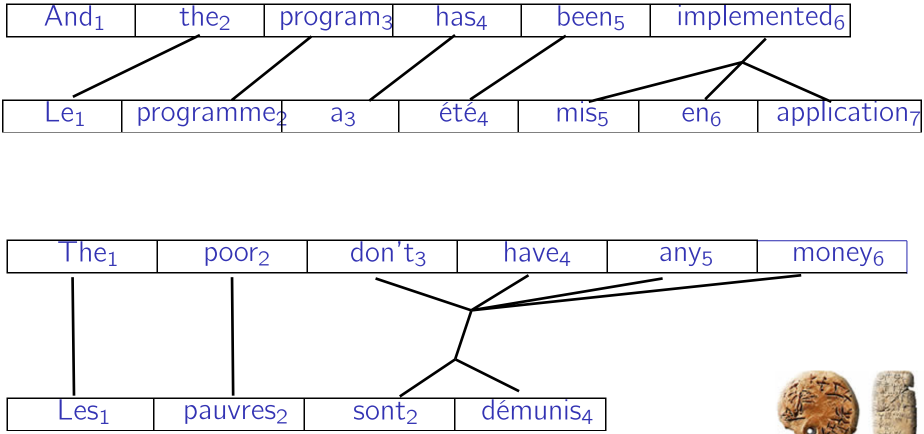
As of today, the encoder-decoder architecture is dominant

Parallel Corpora (Swiss Federal Law)

German	French	Italian
Art. 35 Milchtransport	**Art. 35 Transport du lait**	**Art. 35 Trasporto del latte**
1 Die Milch ist schonend und hygienisch in den Verarbeitungsbetrieb zu transportieren. Das Transportfahrzeug ist stets sauber zu halten. Zusammen mit der Milch dürfen keine Tiere und milchfremde Gegenstände transportiert werden, welche die Qualität der Milch beeinträchtigen können.	1 Le lait doit être transporté jusqu'à l'entreprise de transformation avec ménagement et conformément aux normes d'hygiène. Le véhicule de transport doit être toujours propre. Il ne doit transporter avec le lait aucun animal ou objet susceptible d'en altérer la qualité.	1 Il latte va trasportato verso l'azienda di trasformazione in modo accurato e igienico. Il veicolo adibito al trasporto va mantenuto pulito. Con il latte non possono essere trasportati animali e oggetti estranei, che potrebbero pregiudicarne la qualità.

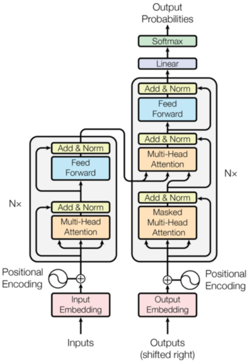
Alignment (Brown et al. 1993)

Canadian Hansard



Transformers: The Encoder-Decoder

Transformers were originally developed for machine translation
Initial language pairs were: English-French, English-German, and the reverse



The input corresponds to words in the source language (say English) and the output in the target language (French or German).

Generation

The transformer consists of an encoder and a decoder.

1. The encoder builds a representation of an input sequence, $(x_1, x_2, \ldots, x_n)$ called the memory, M,

$$\text{encoder}(x_1, x_2, \ldots, x_n) = M;$$

2. The decoder uses M and a start symbol `<s>` as first input. The decoder generates a new output and concatenates it until it generates a stop symbol, `</s>`:

$$\begin{aligned}
\text{decoder}(M, \texttt{<s>}) &= y'_1, \\
\text{decoder}(M, \texttt{<s>}, y'_1) &= y'_2, \\
\text{decoder}(M, \texttt{<s>}, y'_1, y'_2) &= y'_3, \\
&\ldots \\
\text{decoder}(M, \texttt{<s>}, y'_1, y'_2, \ldots, y'_{p-1}) &= y'_p, \\
\text{decoder}(M, \texttt{<s>}, y'_1, y'_2, \ldots, y'_{p-1}, y'_p) &= \texttt{</s>}.
\end{aligned}$$

Example

For two source and target sequences of characters in English and French:

```
Source: ('H', 'e', 'l', 'l, 'o')
Target: ('B', 'o', 'n', 'j', 'o', 'u', 'r')
```

We first encode *Hello*, the source sequence:

$$\text{encoder}(H, e, l, l, o) = M;$$

Using M and <s>, we decode the target sequence:

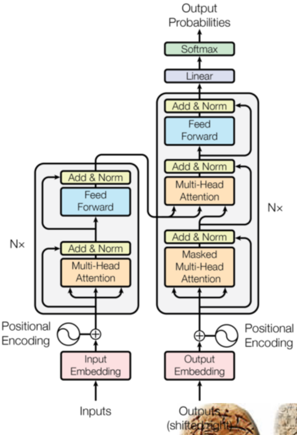
$$\begin{aligned}
\text{decoder}(M, \texttt{<s>}) &= B, \\
\text{decoder}(M, \texttt{<s>}, B) &= o, \\
&\ldots \\
\text{decoder}(M, \texttt{<s>}, B, o, n, j, o, u) &= r, \\
\text{decoder}(M, \texttt{<s>}, B, o, n, j, o, u, r) &= \texttt{</s>},
\end{aligned}$$

We would need a linear layer to map it to the character prediction

Decoder (I)

The right part of the initial transformer
Same components:

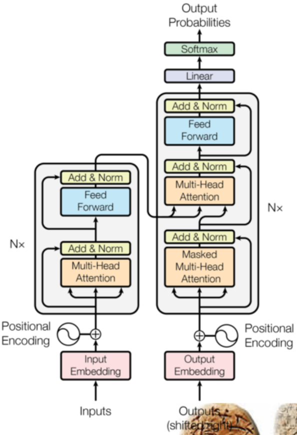
1. Attention
2. Add and norm
3. Feed-forward



Decoder (II)

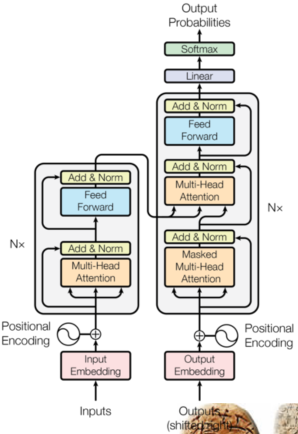
But:

1. Two attentions:
   1. **Masked** self-attention on the inputs
   2. **Cross-attention** with the encoded source
2. Second attention module: $Q = X_{\text{dec\_sublayer}}, K = Y_{\text{enc}}, V = Y_{\text{enc}}$;
3. The decoder predicts the input shifted by one (linear and softmax)



Transformer Embeddings

In Vaswani's paper, the input and output embeddings and the last linear module share the same matrix (weights)
Same with BERT in the pretraining step for the input embeddings and last linear layer.
See code: `https://github.com/google-research/bert/blob/master/run_pretraining.py#L240`)

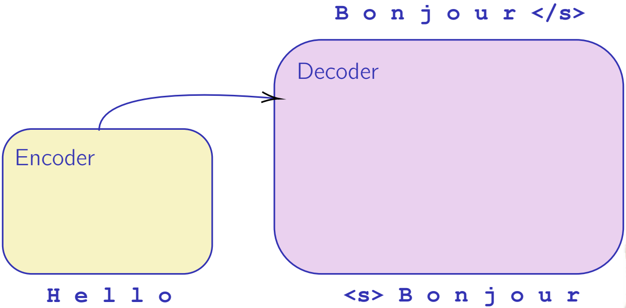


Prediction with Characters

Translation pairs: (Source sentence, Target sentence)

For instance: (Hello, Bonjour), here with characters

1. Encoder input: *H e l l o*
2. Decoder input: *B o n j o u r* and the encoded *H e l l o*
3. Decoder output: *B o n j o u r* shifted by one to the left
4. We align the decoder strings with `<s>` and `</s>`



Training and Inference Steps

1. Training step

			Target output:	B	o	n	j	o	u	r	</s>
		↱ Encoded source:	⟶	↑	↑	↑	↑	↑	↑	↑	↑
Source input:	H e l l o		Target input:	<s>	B	o	n	j	o	u	r

2. Inference:

			Target output:	B	...	
		↱ Encoded source:	⟶	↑		
Source input:	H e l l o		Target input:	<s>	B	...

Vaswani's Attention Scores

The attention scores are scaled and normalized by the softmax function.

$$\text{softmax}(\frac{QK^\intercal}{\sqrt{d_k}}),$$

	i	must	go	back	to	my	ship	and	to	my	crew
i	0.36	0.05	0.07	0.05	0.04	0.19	0.01	0.02	0.04	0.19	0.01
must	0.14	0.20	0.10	0.06	0.11	0.10	0.03	0.05	0.11	0.10	0.02
go	0.18	0.09	0.14	0.09	0.08	0.13	0.02	0.04	0.08	0.13	0.02
back	0.14	0.05	0.09	0.19	0.08	0.12	0.03	0.06	0.08	0.12	0.03
to	0.11	0.11	0.09	0.09	0.15	0.08	0.04	0.07	0.15	0.08	0.03
my	0.19	0.03	0.05	0.04	0.03	0.29	0.01	0.02	0.03	0.29	0.01
ship	0.03	0.03	0.03	0.04	0.05	0.03	0.55	0.03	0.05	0.03	0.13
and	0.10	0.08	0.07	0.10	0.12	0.09	0.04	0.15	0.12	0.09	0.04
to	0.11	0.11	0.09	0.09	0.15	0.08	0.04	0.07	0.15	0.08	0.03
my	0.19	0.03	0.05	0.04	0.03	0.29	0.01	0.02	0.03	0.29	0.01
crew	0.06	0.05	0.05	0.06	0.05	0.06	0.21	0.04	0.05	0.06	0.31

Attention

We use these scores to compute the attention.

$$\text{Attention}(Q, K, Q) = \text{softmax}(\frac{QK^\intercal}{\sqrt{d_k}})V,$$

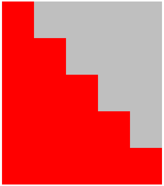
For *ship:*

```
attention_ship = (0.03 * embeddings_dict['i'] +
                  0.03 * embeddings_dict['must'] +
                  0.03 * embeddings_dict['go'] +
                  0.03 * embeddings_dict['back'] +
                  0.04 * embeddings_dict['to'] +
                  0.05 * embeddings_dict['my'] +
                  0.55 * embeddings_dict['ship'] +
                  0.03 * embeddings_dict['and'] +
                  0.05 * embeddings_dict['to'] +
                  0.03 * embeddings_dict['my'] +
                  0.13 * embeddings_dict['crew'])
```

where the *ship* vector received 13% of its value from *crew*
Is this possible in an autoregressive setting?

Decoder Masking

Masking is used in the training step of a decoder
We use an upper triangular matrix $U_{-\infty}$ to prevent a look ahead
We just replace the gray cells with -10^9 and keep the original values of the red cells



$$\text{MaskedAttention}(Q, K, V, U_{-\infty}) = \text{softmax}\left(\frac{QK^\intercal}{\sqrt{d_k}} + U_{-\infty}\right)V.$$

After Masking

The attention scores after masking.

	i	must	go	back	to	my	ship	and	to	my	crew
i	1.00	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
must	0.42	0.58	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
go	0.44	0.22	0.35	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
back	0.29	0.11	0.19	0.40	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
to	0.20	0.20	0.16	0.17	0.27	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
my	0.30	0.05	0.08	0.07	0.04	0.45	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ship	0.04	0.04	0.04	0.05	0.06	0.05	0.73	**0.00**	**0.00**	**0.00**	**0.00**
and	0.14	0.10	0.09	0.13	0.16	0.12	0.05	0.21	**0.00**	**0.00**	**0.00**
to	0.12	0.12	0.10	0.11	0.16	0.10	0.04	0.08	0.16	**0.00**	**0.00**
my	0.20	0.03	0.05	0.05	0.03	0.29	0.01	0.02	0.03	0.29	**0.00**
crew	0.06	0.05	0.05	0.06	0.05	0.06	0.21	0.04	0.05	0.06	0.31

Code Example

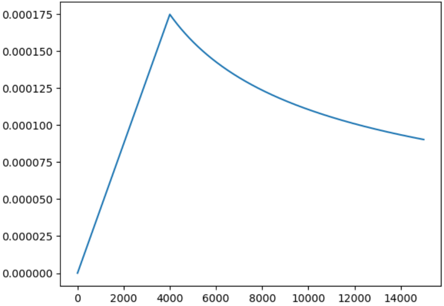
Experiments:

- Jupyter Notebook: `17_01_masked_attention.ipynb`
- 6th laboratory on machine translation

Learning Rate

The lab uses a constant learning rate as in all the other labs

Vaswani et al. (2017) used a variable rate:



$$\text{lrate} = d_{model}^{-0.5} \cdot \min(\text{step\_num}^{-0.5}, \text{step\_num} \cdot \text{warmup\_steps}^{-1.5})$$

where

$$\text{warmup\_steps} = 4000$$

Label Smoothing

True labels and predictions:

- Truth: $(0, 0, 1, 0)$
- Prediction: $(0.1, 0.2, 0.4, 0.3)$

Cross-entropy loss so far:

$$-(0 \cdot \log 0.1 + 0 \cdot \log 0.2 + 1 \cdot \log 0.4 + 0 \cdot \log 0.3) = -\log 0.4$$

Label smoothing: we dedicate a small amount to the wrong predictions:

$$(1-\epsilon)\mathbf{e}_i + \frac{\epsilon}{N_{\text{subwords}} - 1} \sum_{j=1, j \neq i}^{N_{\text{subwords}}} \mathbf{e}_j,$$

Cross-entropy loss with $\epsilon = 0.1$:

$$-(\frac{0.1}{3} \cdot \log 0.1 + \frac{0.1}{3} \cdot \log 0.2 + 0.9 \cdot \log 0.4 + \frac{0.1}{3} \cdot \log 0.3)$$

Beam Search

In the lab, you will use a greedy decoding: You keep the highest prediction

A beam search uses the N highest predictions at each step

You rank the prediction sequences (the paths) with the probability product

N is called the beam diameter

PyTorch Decoders

PyTorch has a class to create an decoder layer (https://pytorch.org/docs/stable/generated/torch.nn.TransformerDecoderLayer.html):

```
decoder_layer = nn.TransformerDecoderLayer(d_model, nheads)
dec_layer_output = decoder_layer(input, memory)
```

and another to create a stack of N layers (https://pytorch.org/docs/stable/generated/torch.nn.TransformerDecoder.html):

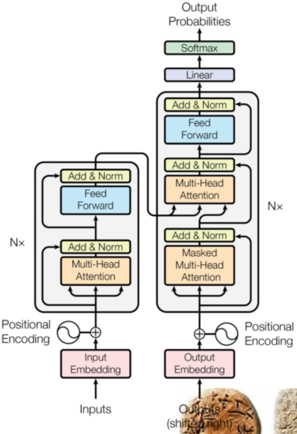
```
decoder = nn.TransformerDecoder(decoder_layer, num_layers)
```

```
decoder = nn.TransformerEncoder(decoder_layer, 6)
dec_output = decoder(input, memory)
```

Autoregressive Models

Reference papers:

1. *Improving Language Understanding by Generative Pre-Training* by Radford et al. (2018)
   Link: `https://s3-us-west-2.amazonaws.com/openai-assets/research-covers/language-unsupervised/language_understanding_paper.pdf`
2. *Language Models are Unsupervised Multitask Learners* by Radford et al. (2018) Links:
   `https://d4mucfpksywv.cloudfront.net/better-language-models/language-models.pdf`
   `https://github.com/openai/gpt-2`



Transformer Decoder Training (I)

Pretrained as an autoregressive language model:

$$P(\mathbf{x}) = \prod_{i=1}^{n} P(x_i | x_1, \ldots, x_{i-1}).$$

Fine-tuning applications in the initial paper

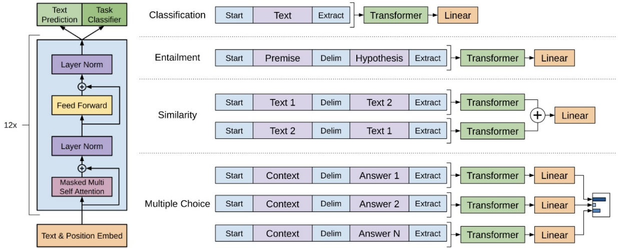


Figure 1: **(left)** Transformer architecture and training objectives used in this work. **(right)** Input transformations for fine-tuning on different tasks. We convert all structured inputs into token sequences to be processed by our pre-trained model, followed by a linear+softmax layer.

Note there is no cross-attention

Transformer Decoder Training (II)

The second system is pretrained using the same objective function and a more general formulation:

$$P(\text{output}|\text{input})$$

Large corpora encapsulate more knowledge, such as examples of tasks:

$$P(\text{output}|\text{input}, \text{task})$$

Training examples in the second paper:

- translate to French, English text, French text;
- answer the question, document, question, answer

Prompts

Zero-shot

Task description	Translate English to French:
Prompt	cheese ⇒

One-shot

Task description	Translate English to French:
Example	sea otter ⇒ loutre de mer
Prompt	cheese ⇒

Few-shot

Task description	Translate English to French:
Example	sea otter ⇒ loutre de mer
Example	peppermint ⇒ menthe poivrée
Example	plush giraffe ⇒ girafe en peluche
Prompt	cheese ⇒

Prompt Engineering

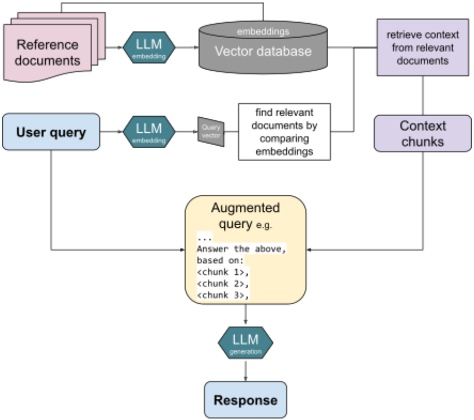
Many techniques to write prompts
Follow the ones recommended by the language model
See for instance the guides by Hugging Face:

- On prompting: `https://huggingface.co/docs/transformers/main/en/tasks/prompting`
- Leaderboard `https://huggingface.co/spaces/open-llm-leaderboard/open_llm_leaderboard`

Why does it work? Two explanations:

- `https://x.com/fchollet/status/1709242747293511939`
- `https://arxiv.org/pdf/2212.07677`

Retrieval Augmented Generation



Credit: Wikipedia, Retrieval-augmented_generation

Fine-Tuning Chat Decoders

Many large systems like chatGPT do not disclose their models.

The training procedure:

- Uses an autoregressive pretrained decoder model
- Fined-tuned on instructions with the format: Instruction, Input, Output

Large companies often apply supervised fine-tuning, see
`https://arxiv.org/pdf/2307.09288.pdf`

Instructions could be tedious to write though

No unique solution: Rapidly developing field

Self-Instruct

We follow self-instruct from Wang et al. (2023) to minimize human effort:

- Starts with a seed of human-written instructions: less than 200. `https://github.com/yizhongw/self-instruct/blob/main/data/seed_tasks.jsonl`
- The model generates more output from the seed instructions. The autogenerated instructions amount to 50k

Fine-tuning using the

> *concatenat[ion of] the instruction and instance input as a prompt and train the model to generate the instance output in a standard supervised way.*

From Wang et al. (2023) (`https://arxiv.org/pdf/2212.10560.pdf`, `https://github.com/yizhongw/self-instruct`)

Seed Instructions

{"id": "seed_task_0",
"name": "breakfast_suggestion",
"instruction": "Is there anything I can eat for a breakfast that doesn't include eggs, yet includes protein, and has roughly 700-1000 calories?",
"instances": [
{"input": "",
"output": "Yes, you can have 1 oatmeal banana protein shake and 4 strips of bacon. The oatmeal banana protein shake may contain 1/2 cup oatmeal, 60 grams whey protein powder, 1/2 medium banana, 1tbsp flaxseed oil and 1/2 cup watter, totalling about 550 calories. The 4 strips of bacon contains about 200 calories."}],
"is_classification": false}

Self-Instruct

Self-instruct from Wang et al. (2023) (https://arxiv.org/pdf/2212.10560.pdf

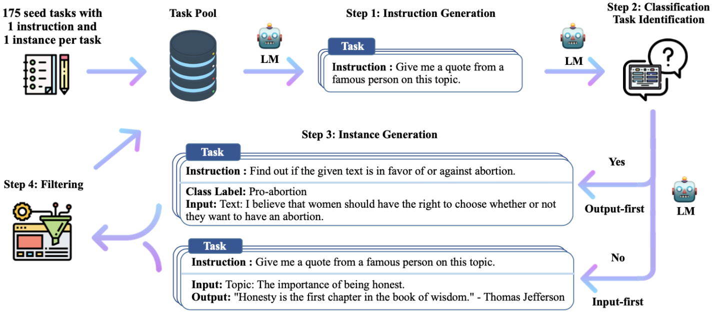


Figure 2: A high-level overview of SELF-INSTRUCT. The process starts with a small seed set of tasks as the task pool. Random tasks are sampled from the task pool, and used to prompt an off-the-shelf LM to generate both new instructions and corresponding instances, followed by filtering low-quality or similar generations, and then added back to the initial repository of tasks. The resulting data can be used for the instruction tuning of the language model itself later to follow instructions better. Tasks shown in the figure are generated by GPT3.

Alpaca

Alpaca is another example:
https://crfm.stanford.edu/2023/03/13/alpaca.html

- Uses Llama and Llama 2 as autoregressive pretrained decoder model
- Fined-tuned on instructions with the format: Instruction, Input, Output

Corpus Choice

The corpus selection is very important in the quality of answers.

1. Usually starts a large sample of web pages; see LLama and LLama 2 `https://arxiv.org/pdf/2302.13971.pdf`
2. Deduplicates the pages (`https://aclanthology.org/2020.lrec-1.494.pdf`)
3. Computes the proximity with wikipedia and discard distant pages
4. Computes the perplexity with a wikipedia model and discard too simple and too complex sentences