Deep Learning for Natural Language Processing

Lecture 12 – Contemporary LLMs: Prompting and in-context learning

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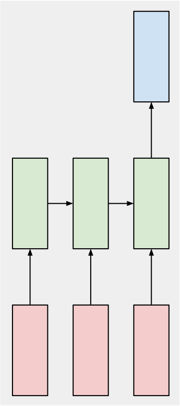
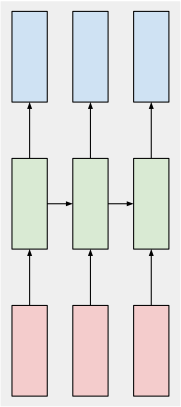
Recap

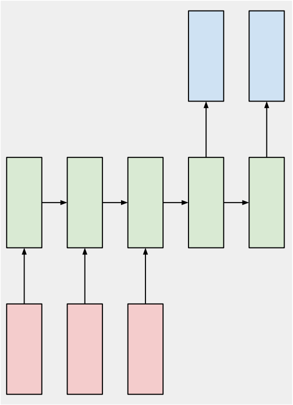
Overview of NLP task types



(a) Seq. classification



(b) Seq. labeling



(c) Sequence-to-sequence

Sequence classification

We want to categorize an input text (or some relation between multiple texts)

- Tasks: sentiment analysis, news article categorization, natural language inference,...
- Input: sequence of tokens $\{x_i\}_{i=1}^n$
- Output: class $y \in \boldsymbol{Y}$
  1. We **embed** the input tokens $\{\boldsymbol{x}_i\}_{i=1}^n \rightarrow \{\boldsymbol{e}_i\}_{i=1}^n$; $\boldsymbol{e}_i \in \mathbb{R}^{d_e}$
  2. We **encode** the input sequence into a **fixed size representation** by using a RNN or Transformer network $\{\boldsymbol{e}_i\}_{i=1}^n \rightarrow \boldsymbol{s}$; $\boldsymbol{s} \in \mathbb{R}^{d_m}$
  3. We feed the sequence representation into a **classification network** (decoder head) $\boldsymbol{s} \rightarrow \hat{\boldsymbol{y}}$; $\boldsymbol{y} \in \mathbb{R}^k$

Sequence labeling

We want to categorize each token from the input sequence

- **Tasks**: part-of-speech tagging, named entity recognition,...
- **Input**: sequence of tokens $\{x_i\}_{i=1}^n$
- **Output**: sequence of labels $\{y_i\}_{i=1}^n \ ; \ y_i \in \boldsymbol{Y}$
    1. We **embed** the input tokens $\{\boldsymbol{x}_i\}_{i=1}^n \rightarrow \{\boldsymbol{e}_i\}_{i=1}^n \ ; \ \boldsymbol{e}_i \in \mathbb{R}^{d_e}$
    2. We **encode** the input sequence using a RNN or Transformer network $\{\boldsymbol{e}_i\}_{i=1}^n \rightarrow \{\boldsymbol{s}_i\}_{i=1}^n \ ; \ \boldsymbol{s}_i \in \mathbb{R}^{d_m}$
    3. We feed **each token** representation into a **classification network** (decoder head) $\{\boldsymbol{s}_i\}_{i=1}^n \rightarrow \{\hat{\boldsymbol{y}}_i\}_{i=1}^n \ ; \ \hat{\boldsymbol{y}}_i \in \mathbb{R}^k$

Sequence to Sequence

Based on an input sequence, we want to **generate** the corresponding output sequence

- **Tasks**: machine translation, text summarization,...
- **Input**: sequence of tokens $\{x_i\}_{i=1}^n$
- **Output**: sequence of **tokens** $\{y_i\}_{i=1}^n$; $y_i \in \boldsymbol{Y}$
  1. We **embed** the input tokens $\{\boldsymbol{x}_i\}_{i=1}^n \rightarrow \{\boldsymbol{e}_i\}_{i=1}^n; \qquad e_i \in \mathbb{R}^{d_e}$
  2. We **encode** the input sequence by using a RNN or Transformer network $\{\boldsymbol{e}_i\}_{i=1}^n \rightarrow \{\boldsymbol{s}_i\}_{i=1}^n$; $\boldsymbol{s}_i \in \mathbb{R}^{d_m}$
  3. We **decode** the output sequence based on the encoded input sequence...
     - 3.1 **Encoder-decoder**: ...with a **different** RNN or Transformer **network**
     - 3.2 **Encoder-only**: ...with the **same network**

Recap

Attention

Attention

Recall: problem of learning **long dependencies**

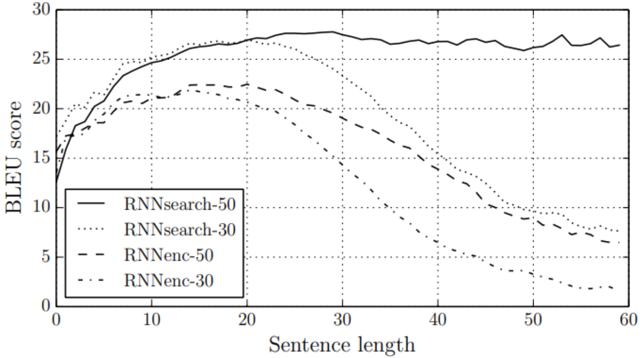


Figure from Bahdanau et al., 2014

Attention

The attention mechanism

Inputs: a **query** vector $\boldsymbol{q}$ and a sequence of **key** $\boldsymbol{K} = \{\boldsymbol{k}_i\}_{i=1}^{n}$ and **value** $\boldsymbol{V} = \{\boldsymbol{k}_i\}_{i=1}^{n}$ vectors.

Output: $\boldsymbol{a}$, a **weighted summary** of **value** vectors.

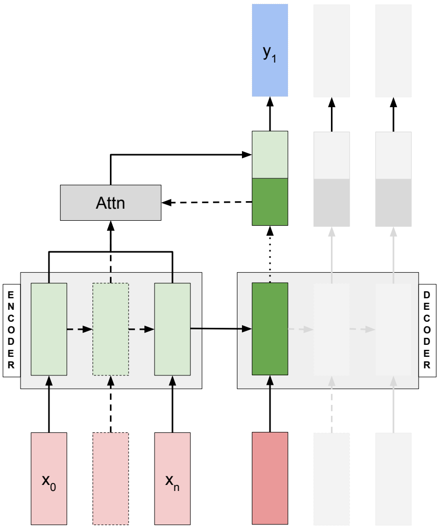
Query, values & keys are computed from neural network (RNN or Transformer) states.

$$\boldsymbol{a} = \sum_{i}^{n} \alpha_i \boldsymbol{v}_i \qquad\qquad \hat{\alpha}_i = f_{\text{attn}}(\boldsymbol{q}, \boldsymbol{k}_i) := \frac{\boldsymbol{q}^T \cdot \boldsymbol{k}_i}{\sqrt{d_m}}$$

Attention variants

- The **energy function**:
  1. (scaled) Dot product attention $\rightarrow \hat{\alpha}_i = \frac{\boldsymbol{q}^T \cdot \boldsymbol{k}_i}{\sqrt{d_k}}$
  2. Bahdanau (tanh) attention $\rightarrow \hat{\alpha}_i = \boldsymbol{W}_2 \text{tanh}(\boldsymbol{W}_1 [\boldsymbol{q} | \boldsymbol{k}_i])$
  3. Bilinear attention $\rightarrow \alpha_i = \boldsymbol{q}^T \boldsymbol{W} \boldsymbol{k}_i$
- **Parametrization**
  1. Use raw network hidden states
  2. Transform network hidden states (e.g. with a linear layer)
- **Direction**
  1. Self-attention (within encoder/decoder)
  2. Cross-attention (between encoder and decoder/two networks)

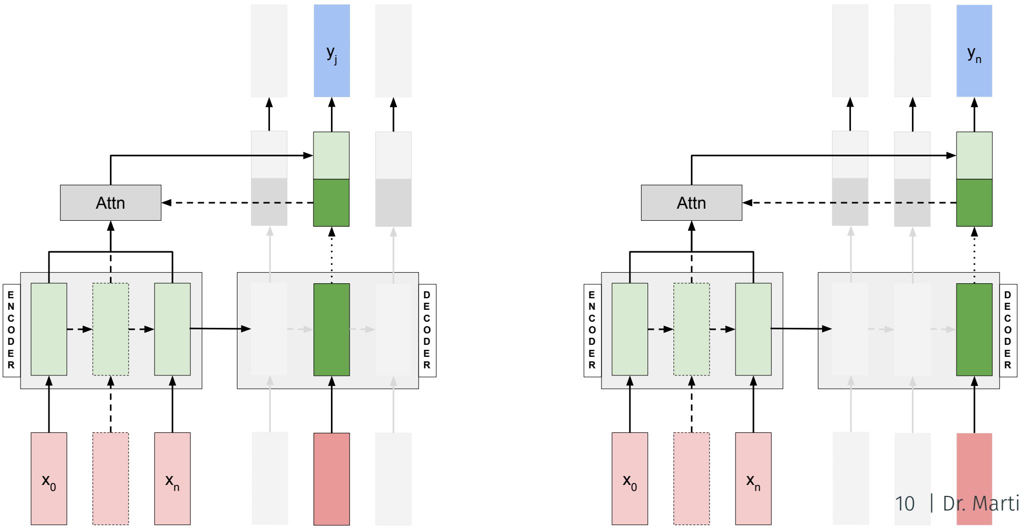
Attention in encoder-decoder RNNs



Encoder-decoder attention:

- We want to obtain information relevant for **current decoder state** from the encoder states
- We **concatenate** the attention output a to the current decoder state prior to prediction

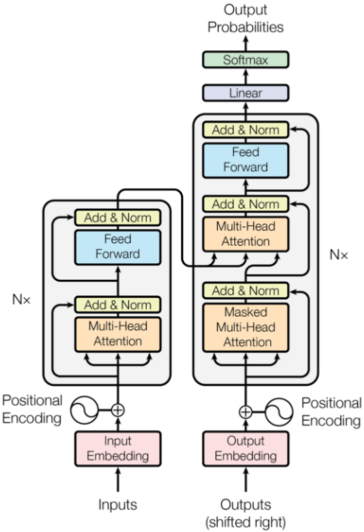
Attention in encoder-decoder RNNs



Recap

Transformers

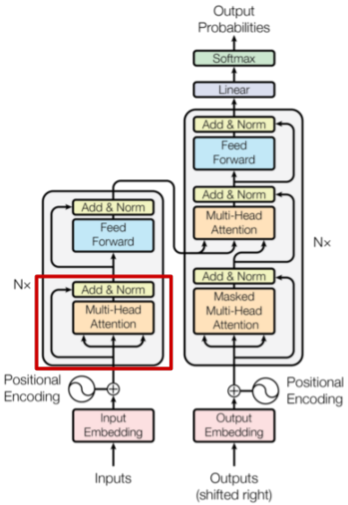
Transformers



Fully attention-based model for NLP

- Self-attention → contextualization
- Positional embeddings → word order
- Byte-pair encodings → open vocabulary
- Residual connections
- Multi-head attention

Transformers



Fully attention-based model for NLP

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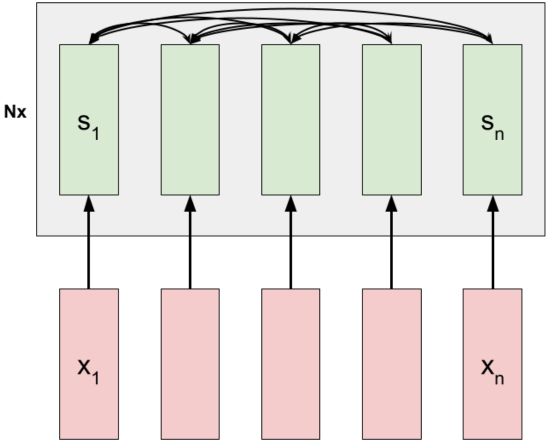
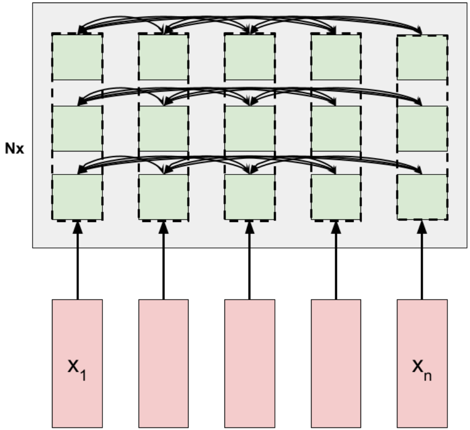
Attention in Transformers



- Each token representation **simultaneously** attends to *all other* tokens in the sequence
  - Except when we want to **mask out** some tokens
- What about **multi-head** attention?

Attention in Transformers



1. We **split** each token representation into h equally sized chunks
2. We **independently** perform scaled dot-product self-attention for each set of chunks
   - Intuition: multiple **aspects** of similarity between tokens

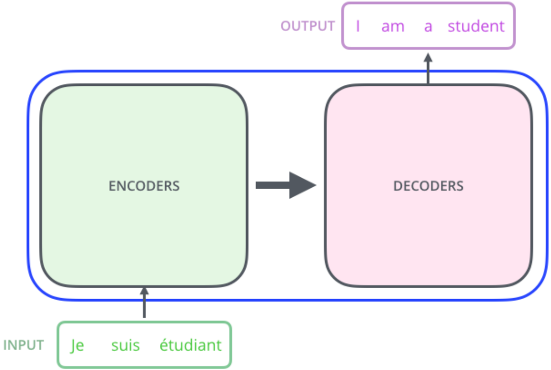
Transformer for machine translation

We studied the Transformer encoder-decoder for machine translation

Image source: The illustrated Transformer

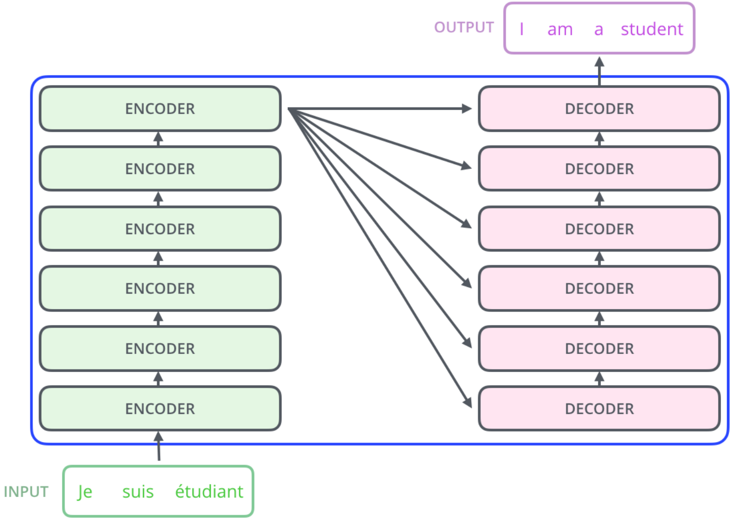
The model is built of stacked encoder and decoder blocks

Transformer encoder-decoder



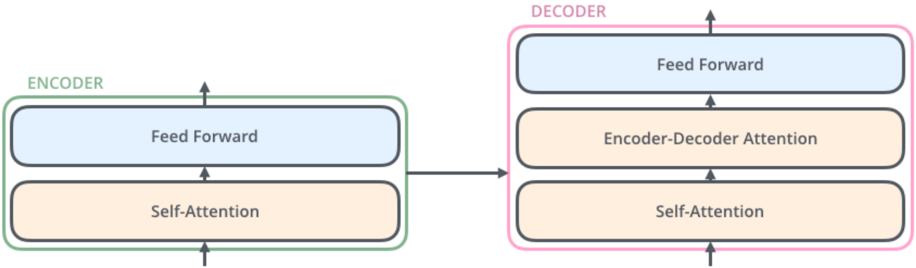
The encoder and decoder are made of stacked **encoder** and **decoder blocks**

Transformer encoder-decoder

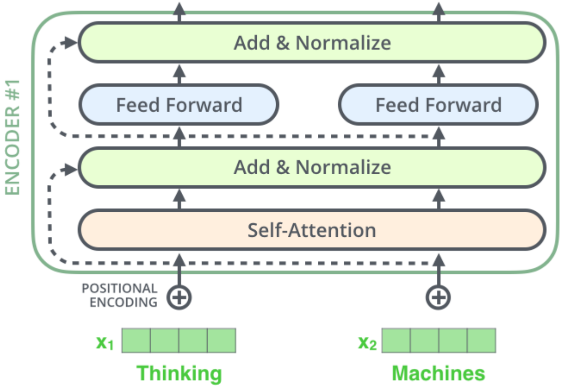


Transformer encoder and decoder block

The encoder and decoder blocks are different – the decoder block has an additional **encoder-decoder attention** (cross-attention) layer



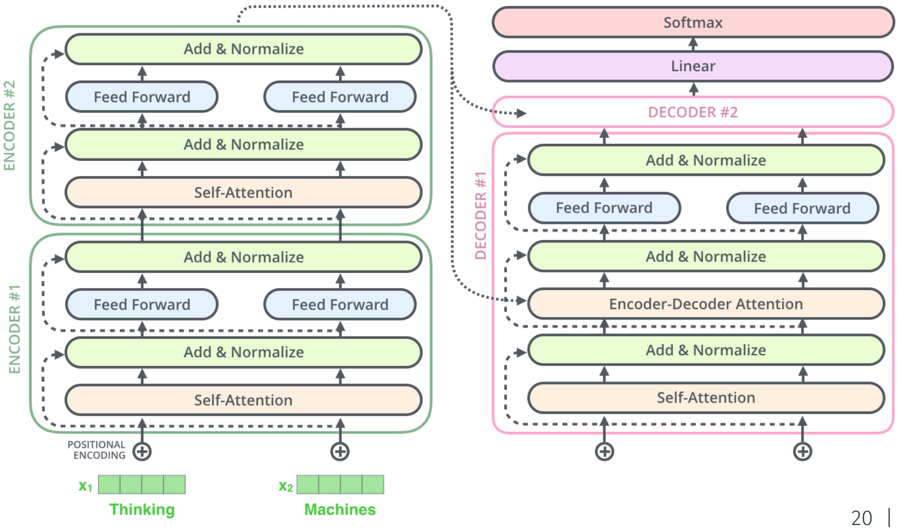
Transformer encoder block



Each Transformer encoder block consists of:

1. Self-attention: **contextualize** representations
2. **Residual** connection + **normalization**
3. **Feed-forward** layer (1 hidden layer NN)
4. **Residual** connection + **normalization**

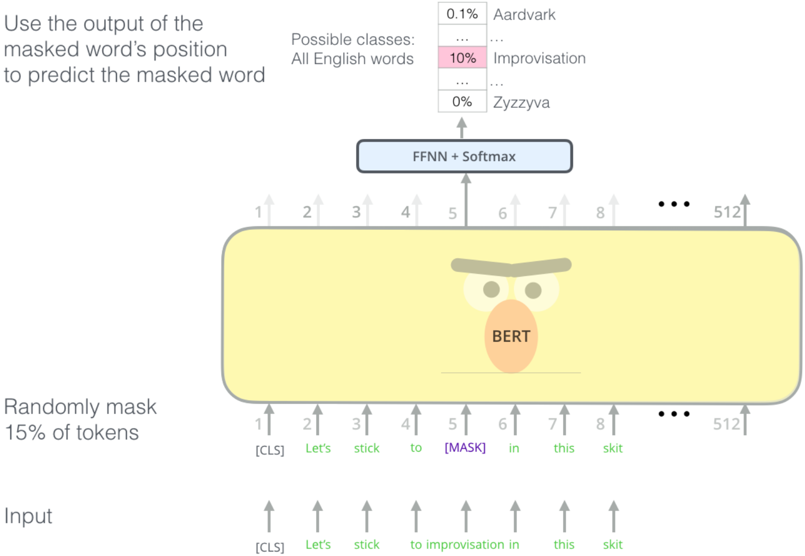
Recap: Transformer encoder-decoder



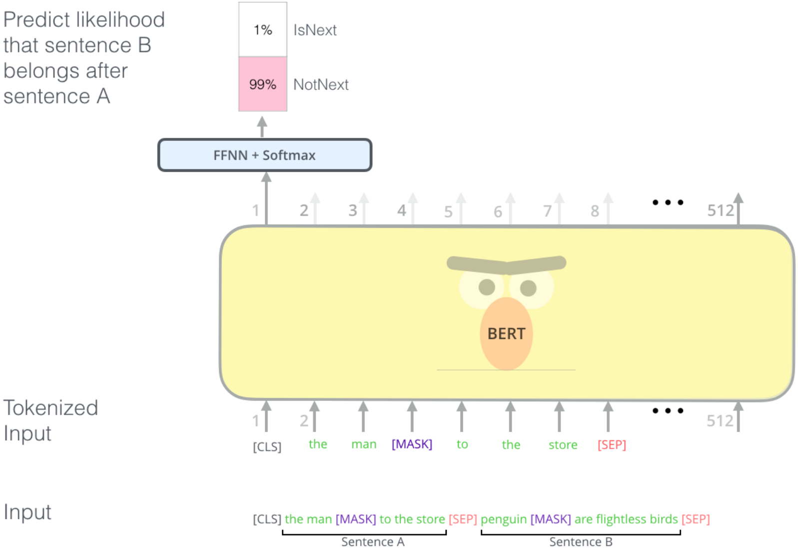
Recap

BERT

BERT: masked language modeling (MLM) [Image source]



BERT: next sentence prediction (NSP) [Image source]



BERT: summary

BERT is a **pretrained language model (PLM)**

- Through a (masked) language modeling pretraining task, the model has learned to recognize high level **patterns of language** and apply them for the task of **text reconstruction**
- Text reconstruction is, however, **rarely useful** in isolation
- In practice: use the PLM as a **starting point** (a very good initialization) for **fine-tuning** (additional training) for another task

Using BERT for NLP tasks

Fine-tuning is the procedure where we start from a base **pretrained** model and adapt its internal representations to our task.

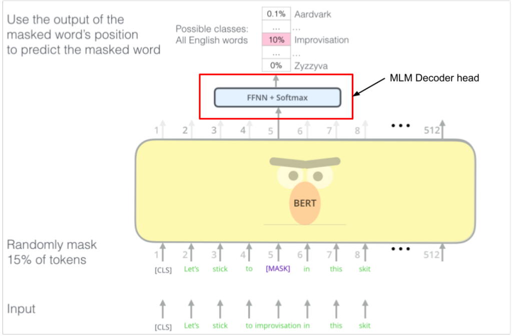
Fine-tuning variants:

1. **Vanilla fine-tuning**: add a **decoder head** to the model, then:
   1.1 Train **only** the decoder head;
   1.2 Train **progressively** more layers: first the decoder head, then also the last layer, then also the second to last ...;
   1.3 Train the **entire network** at the same time, maybe with **different learning rates** per layer.
2. **Adapters**: additional randomly initialized layers inserted inside the transformer layers
3. **Prompting** & **in-context learning**: future lectures

Using BERT for NLP tasks

What exactly are **decoder heads**?

Randomly initialized additional layers (usually linear) added **on top** of the pretrained model which **perform the downstream task**.



Using BERT: single sequence classification

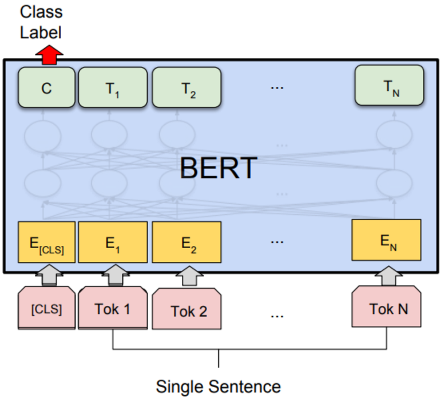


Image from BERT paper

For single **sequence** classification:

1. Add a randomly initialized **task decoder head** to the model
2. **Encode** the sequence along with the [CLS] special token
3. Use the **[CLS]** representation as input to decoder head

Alternatives to using CLS?

- Averaging over **token representations**
- ... from the **last four layers**

Recap

Pretraining tasks for PLMs

Variants of (unsupervised) pretraining tasks

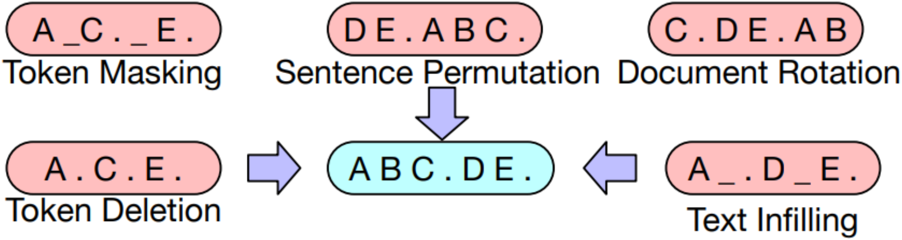


Image from BART paper

Variants of (unsupervised) pretraining tasks

- **Language modeling**
- **Token masking**: MLM
- **Token deletion**: masking, but **completely removes tokens** from input – model needs to determine where a token is missing
- **Text infilling**: masking, but **multiple** tokens are replaced with a **single** [MASK] token at the same time
- **Sentence permutation**: input **permuted sentence**, reconstruct correct word order (*linearization*)
- **Document rotation**: document is rotated so that it starts from a **random token**. The model has to determine the actual start of the document.

Variants of (supervised) pretraining tasks

We can also use **supervised data** – from various datasets

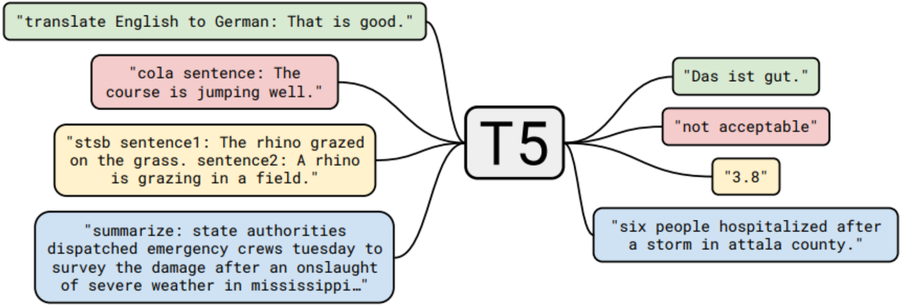
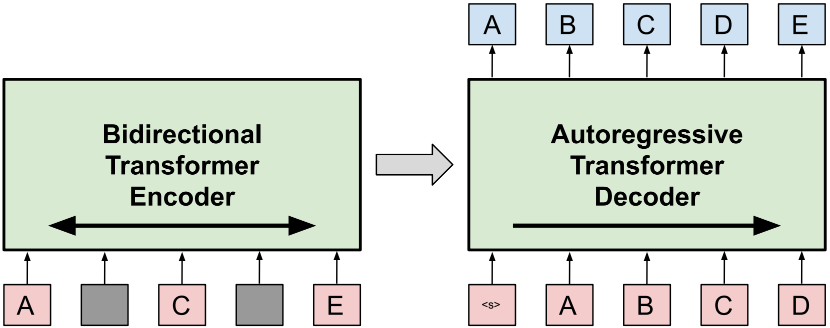


Image from T5 paper

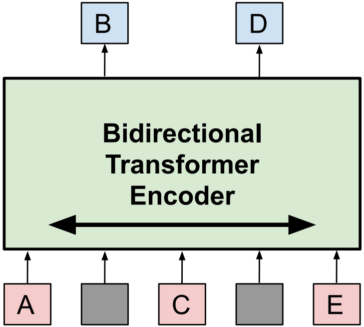
Recap

Types of Transformer Architectures

Encoder-Decoder Transformer

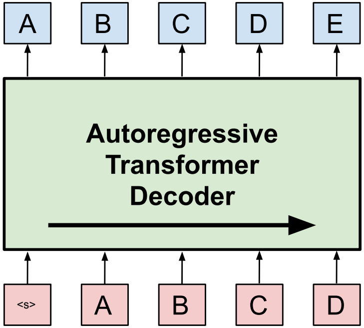


Bidirectional Encoder-only Transformer



- Efficient encoding ✔️
- Versatile base for downstream tasks ✔️
- Can’t **really** generate text ❌

Autoregressive Decoder-only Transformer



An **autoregressive** (causal) language model uses **past** values of a time series to predict future values.

- Didn't we decide not to use these because they were inefficient?

  (RNNs)

- Yes, but…
  1. Hardware has improved
  2. Autoregressive models are *really* good at generating text

Recap

Prompting

Prompt-tuning MLMs

So far, we have **fine-tuned** masked language models

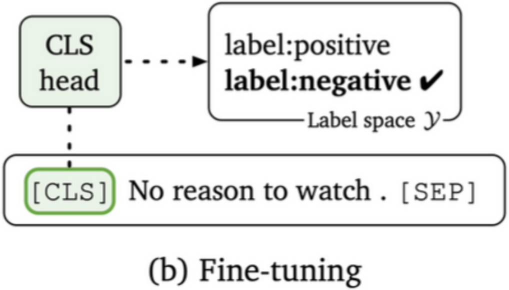
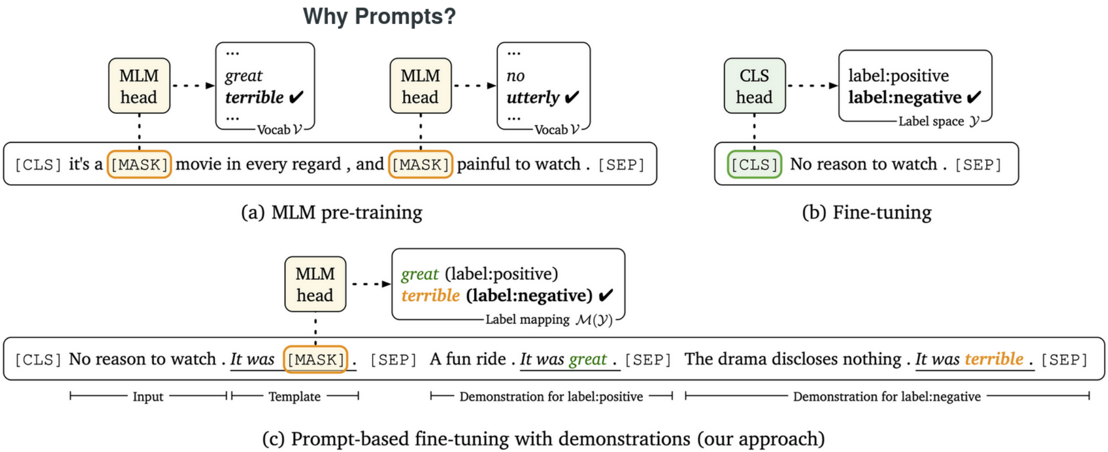


Figure from The Gradient

Is there an **easier way** to adapt encoder-only PLMs such as BERT to downstream tasks?

Prompt-tuning MLMs



Prompt-tuning MLMs

We transform the target task (e.g. sentiment analysis) to **masked language modeling**.

1. Choose the prompt and word/token used for each label
   - Choice of label token **important**
   - Template design also **important**
2. Demonstrate task through a few samples
   - Usually through **fine-tuning** (training the model)
3. **No new parameters needed** to perform task!

In-context learning

When we **don't fine-tune** the base model on prompt samples but provide **demonstrations** within the prompt, this is called **in-context learning**.

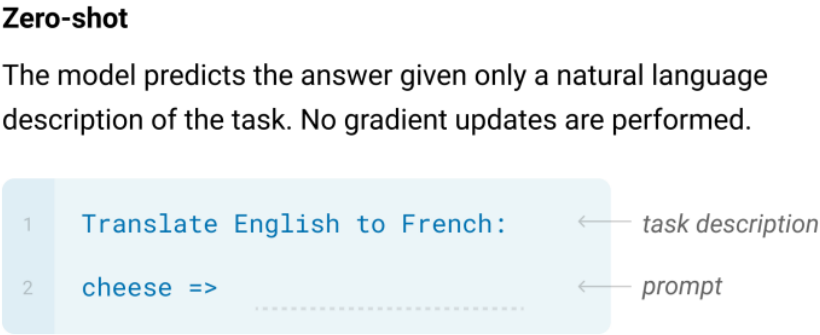


Image from GPT3 paper

Prompting

A prompt is a piece of text inserted in the input examples, so that the original task **can be formulated as** a (masked) **language modeling** problem.

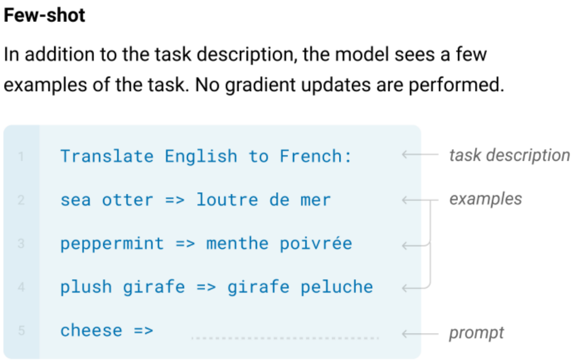


Image from GPT3 paper

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