Natural Language Processing and Transformers 🤖

March 8th, 2022

University of Toronto

Tutorial 8 CSC413/2516

The Big Picture

- Natural language (& speech) are central to human intelligence
- **N**atural **L**anguage **P**rocessing (**NLP**) attempts to capture some of this intelligence algorithmically and is of huge practical importance
  - machine translation, chatbots, automatic fact checking, …
- NLP has seen several transformative shifts in the last few years

Goals of this Tutorial

- Build basic NLP *literacy* by looking at **language models**
- Get up to date with recent developments
  - **BERT**, **GPT**, **S**elf-**S**upervised **L**earning (**SSL**)
- Know where to look if you're starting an NLP project
- *Will focus more on building intuition than math*

Language Models

Language Models

Language models (LMs) assign **probabilities** to sequences of words

- **Speech recognition**: $P(\textit{I will be back soonish}) > P(\textit{I will be bassoon dish})$
- **Spell checkers**: $P(\textit{There are two midterms}) > P(\textit{Their are two midterms})$
- **Machine translation**:

他 向 记者 介绍了 主要 内容

$P(\textit{He to reporters introduced main content}) \lt$

$P(\textit{He briefed reporters on the main contents of the statement}) \lt$

Anatomy of a Language Model

Is the product of the conditional probability of each word and its history (chain rule)

$$P(w_{1:n}) = \prod_{k=1}^{n} P(w_k|w_{<k})$$

The probability of a sequence of n words

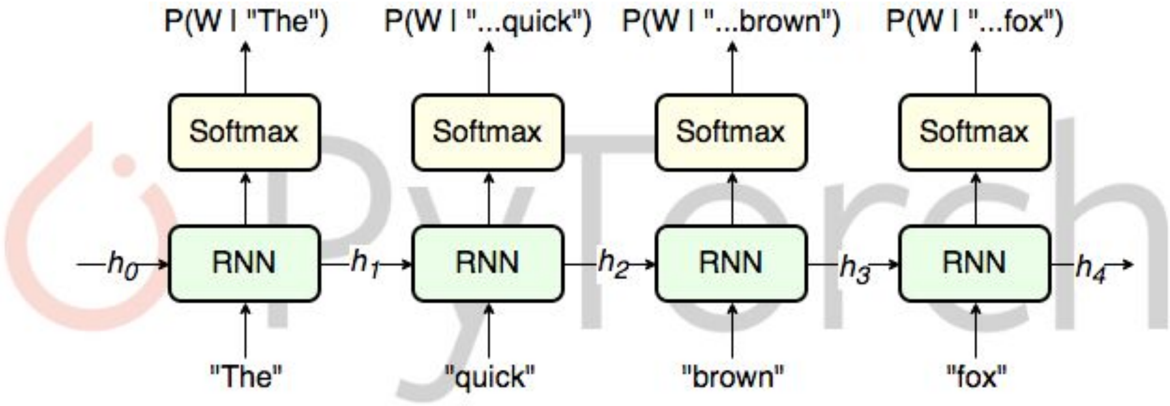
$$= \sum_{k=1}^{n} \log P(w_k|w_{<k})$$

How do we compute the conditional probability?

In practice, we take the log sum

Language Models

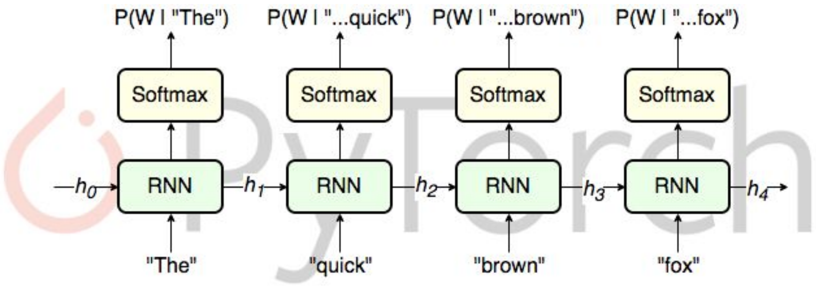
- We can use **recurrent** neural networks (RNNs)! E.g. LSTMS, GRUs
- Work well for variable length inputs, like sentences



Language Models

Recurrent neural networks have some shortcomings:

- Not parallelizable within training examples
- Difficult to optimize due to vanishing gradients
- Difficulty modelling long range dependencies



Language Models

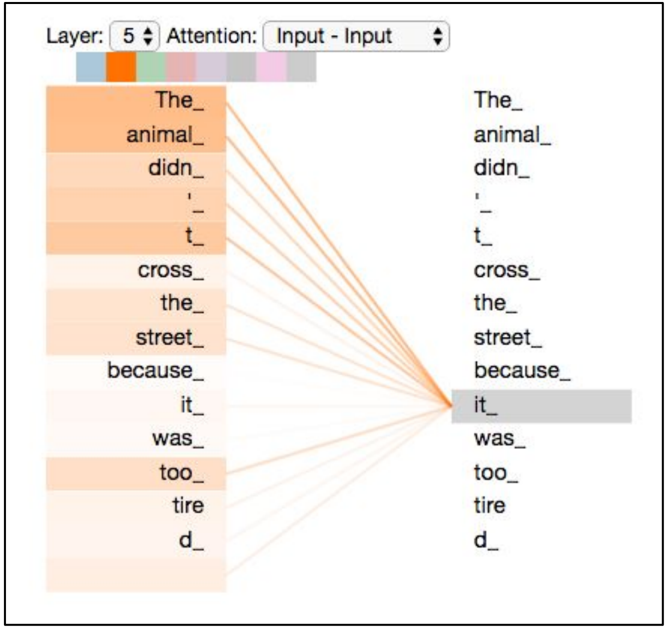
We'd like an architectural primitive that:

- Is parallelizable within training examples
  - Take advantage of accelerators like GPUs/TPUs
- Directly facilities interactions between tokens
  - To better model long range dependencies
- Attention to the rescue?

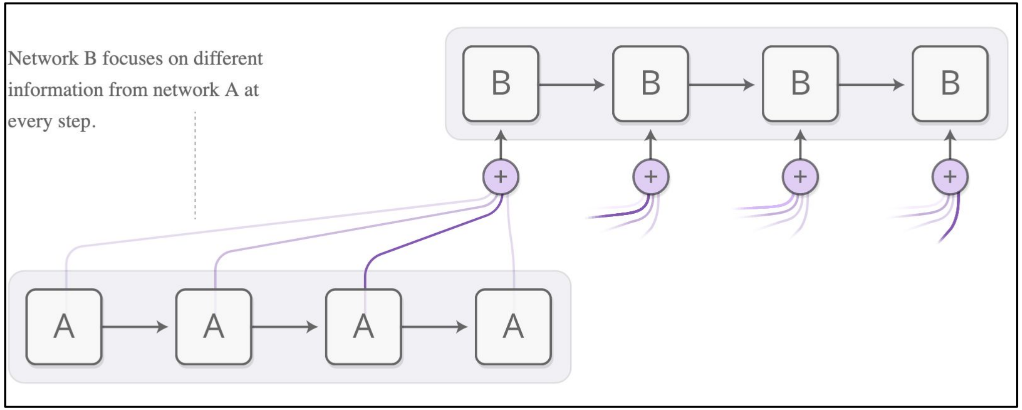
Attention

Attention

Self-attention



Cross-attention



https://jalammar.github.io/illustrated-transformer/
https://distill.pub/2016/augmented-rnns/

Attention

- Many flavours of attention have been proposed
- We will focus on the most common, (**scaled**) **dot-product** attention
- Scaled dot-product attention is the backbone of **transformers**
- Like any attention mechanism, we need to make two decisions:
    - How to compute similarity? → **dot-product**
    - How do we normalize the similarity score? → **softmax**

Scaled Dot-Product Attention

Similarity is simply the dot product between Q and K

Scaled dot-product attention takes three matrices as input

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

The output is simply a scaling of V

A softmax normalizes similarities → [0, 1]

Attention maps a query, Q and a set of key-value (K, V) pairs to an output. The output is **computed** as a **weighted sum** of the **values**, where the weight assigned to each value is computed by a **compatibility function** of the **query** with the **corresponding key**.

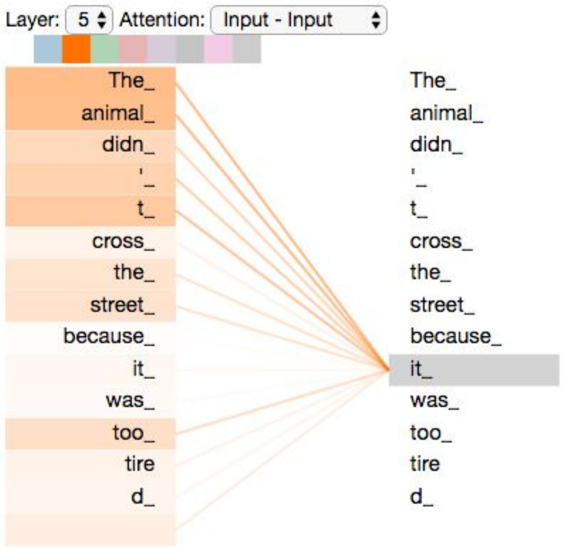
Vaswani, Ashish, et al. "Attention is all you need." Advances in neural information processing systems 30 (2017).

Queries, Keys and What?

These will change depending on how the attention mechanism is used

- In **self**-attention, Q == K == V
- *Updating the representation of each token based on the other tokens in the sequence*

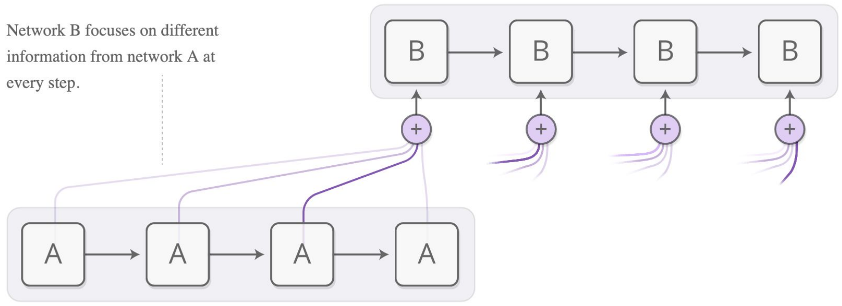
$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$



Queries, Keys and What?

These will change depending on how the attention mechanism is used

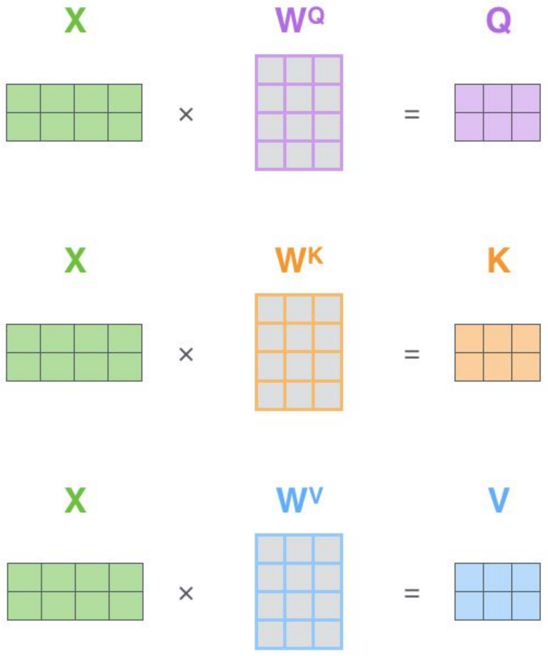
- In **cross**-attention, K == V and come from the encoder. Q comes from the decoder.
- *The decoder "focuses" on certain tokens in the encoders output*



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

Residuals: Projections

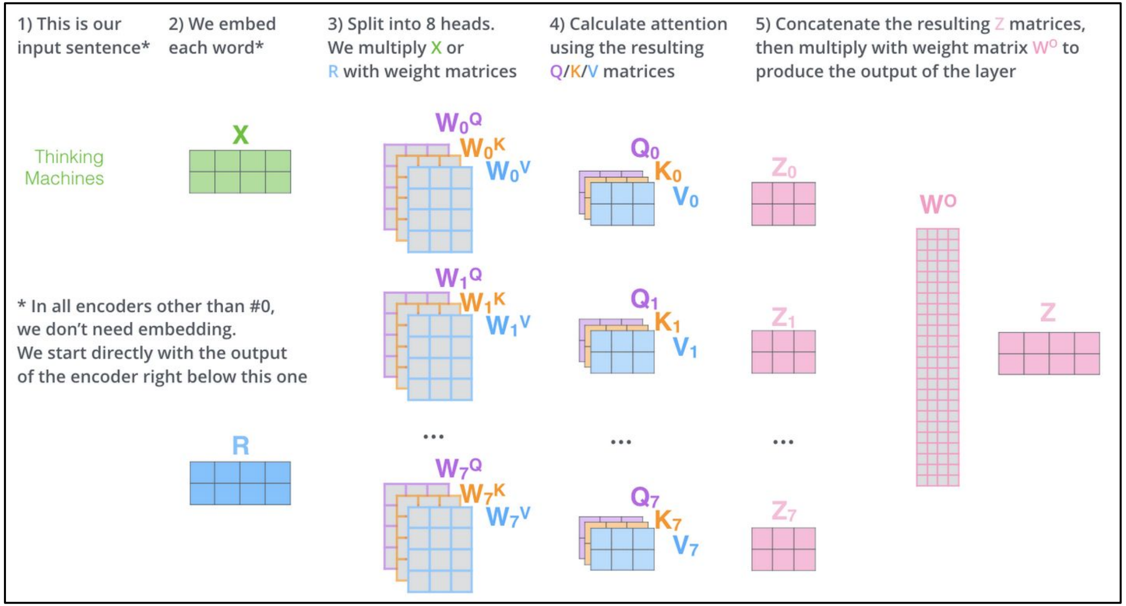
- Q, K & V are *projections* of embedded tokens
- If this is a multi-layered network (e.g. a transformer), they are outputs of the previous layer

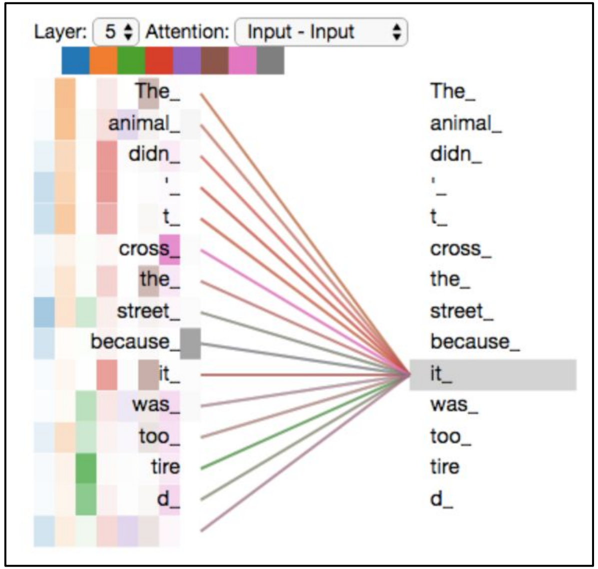


https://jalammar.github.io/illustrated-transformer/

Residuals: The Beast with Many Heads

Usually, we use **multi-head** scaled dot-product attention





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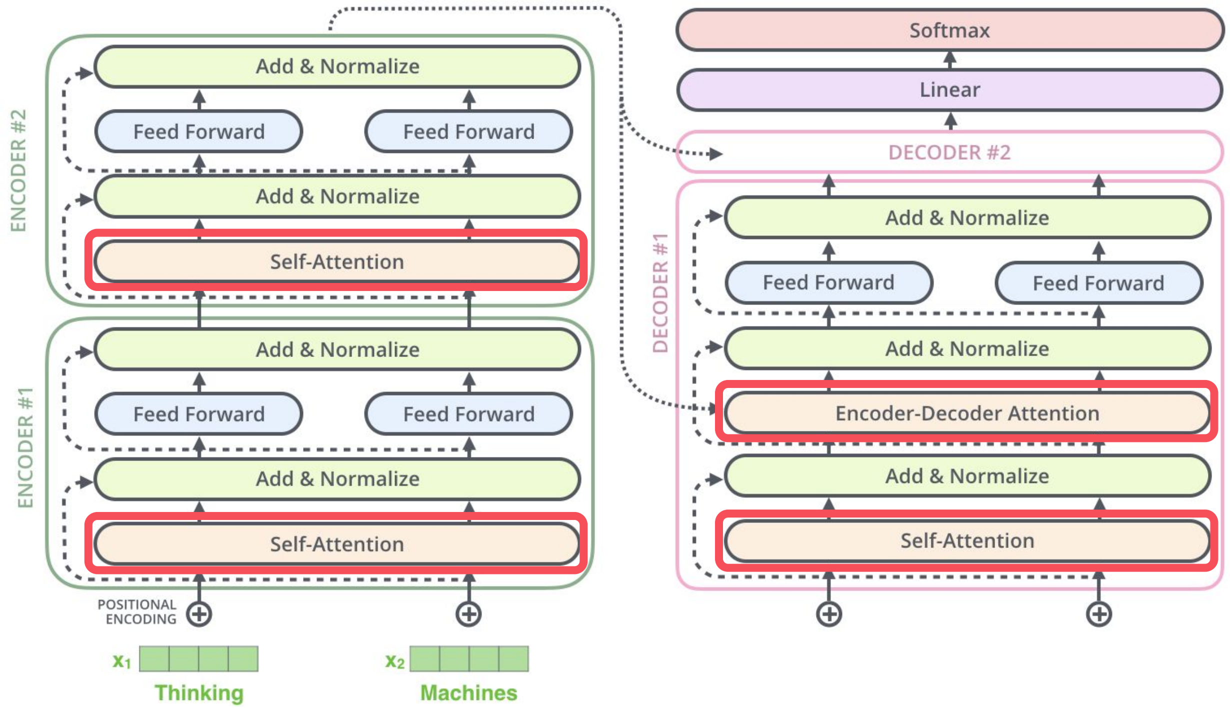
Transformers (covered in lecture)



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The Payoff

Table 1: Maximum path lengths, per-layer complexity and minimum number of sequential operations for different layer types. n is the sequence length, d is the representation dimension, k is the kernel size of convolutions and r the size of the neighborhood in restricted self-attention.

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(log_k(n))$
Self-Attention (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

Vaswani, Ashish, et al. "Attention is all you need." Advances in neural information processing systems 30 (2017).

Before we move on...

- LMs assign **probabilities to sequences** and are the "workhorse" of NLP
- Typically implemented with RNNs; being replaced with **Transformers**
- **Multi**-head **scaled** dot-product attention the backbone of Transformers
    - Allows us to learn long range dependencies and parallelize computation within training examples
- *How do we train Transformers as language models?*

Pretrained Language Models & Self-Supervised Learning

Wishlist

- We want to train transformers as LMs
  - Learn general properties of language that can be transferred to **downstream** tasks
- Ideally, we could train LMs using unlabeled text
  - Leverage unsupervised or **S**elf-**S**upervised **L**earning (**SSL**)
- (At least) two paradigms have emerged
  - **G**enerative **P**retrained **T**ransformer (**GPT**)
    - Next-token prediction, decoder only transformer
  - **B**idirectional **E**ncoder **R**epresentations from **T**ransformers (**BERT**)
    - Masked language modelling, encoder only transformer

Generative Pretrained Transformer (GPT)

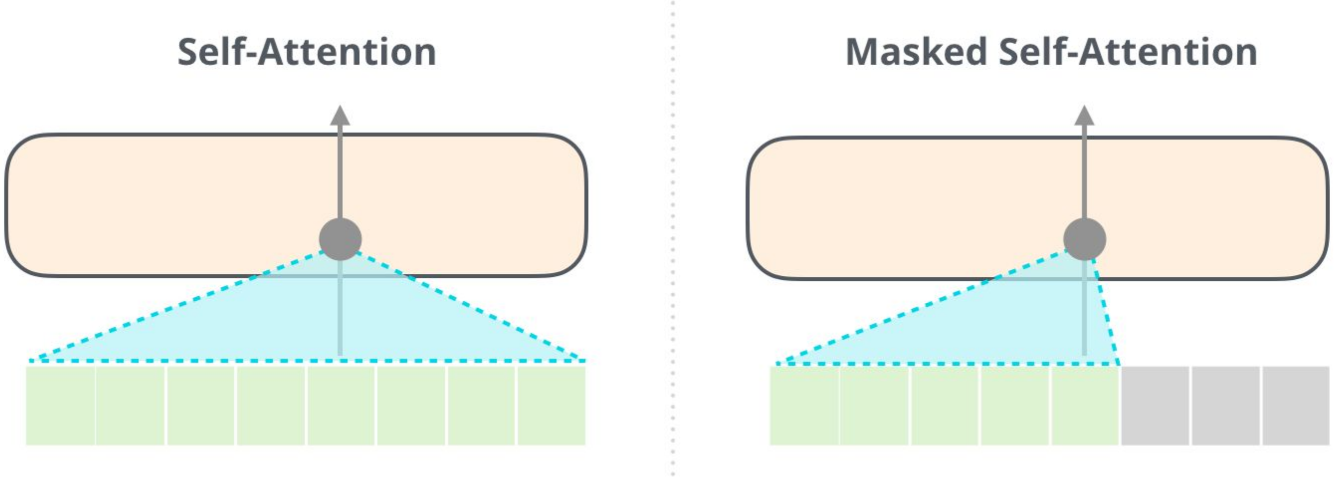
- **GPT** is a *decoder only* transformer pretrained on huge amounts of text
- The latest version, GPT-3 is trained on 45TB of unlabelled text
- The (pre)training objective is simply to predict the next token
- For this, we will need to slightly tweak the self-attention...

Radford, Alec, et al. "Improving language understanding by generative pre-training." (2018).

OpenAI

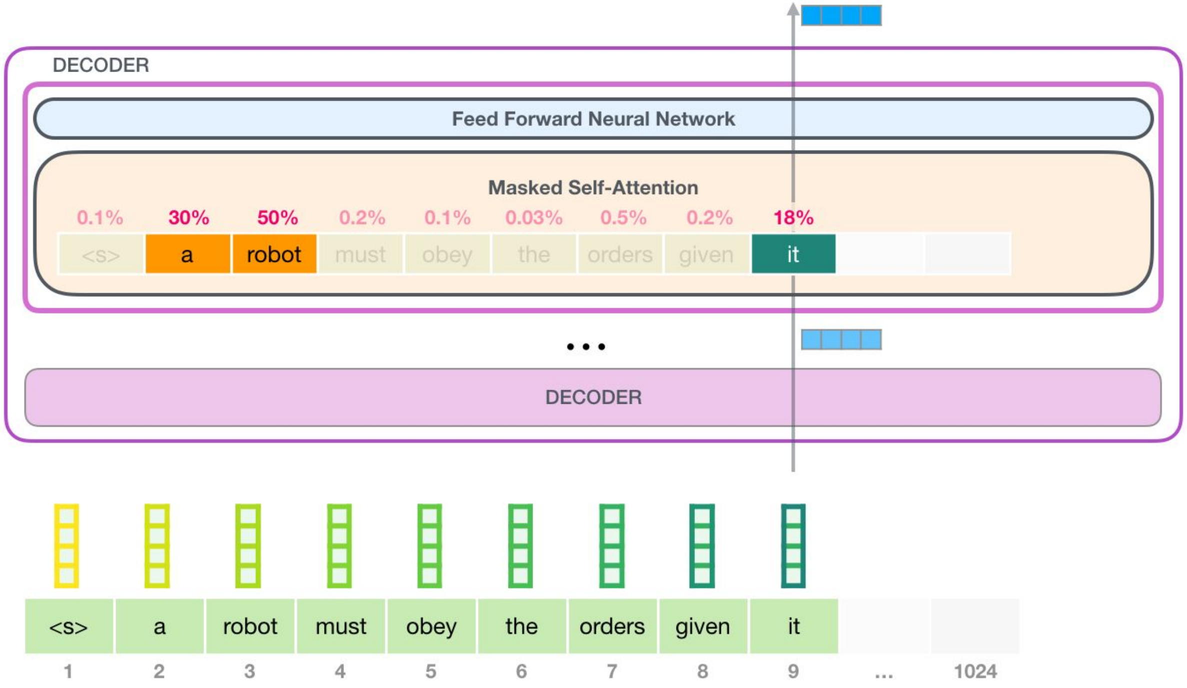
Masked Self-Attention

Future timesteps are **masked** to prevent decoder from "peaking"



https://jalammar.github.io/illustrated-gpt2/

Next Token Prediction



https://jalammar.github.io/illustrated-gpt2/

Generative Pretrained Transformer (GPT)

Once pretrained, GPT can be used for any "text in, text out" task

Mood to color

Transformation | Generation

Turn a text description into a color.

Prompt

The CSS code for a color like a blue sky at dusk:

background-color: #

Sample response

B2CED1

SQL request

Transformation | Generation | Translation

Create simple SQL queries.

Prompt

Create a SQL request to find all users who live in California and have over 1000 credits:

Sample response

```
SELECT * FROM users WHERE state='CA' AND credits > 1000;
```

https://beta.openai.com/examples

Generative Pretrained Transformer (GPT)

Once pretrained, GPT can be used for any "text in, text out" task

Grammar correction

Transformation Generation

Corrects sentences into standard English.

Prompt

Correct this to standard English:

She no went to the market.

Sample response

She didn't go to the market.

English to other languages

Transformation Generation

Translates English text into French, Spanish and Japanese.

Prompt

Translate this into 1. French, 2. Spanish and 3. Japanese:

What rooms do you have available?

1.

Sample response

Quels sont les chambres disponibles?
2. ¿Cuáles son las habitaciones disponibles?
3. 何室がありますか?

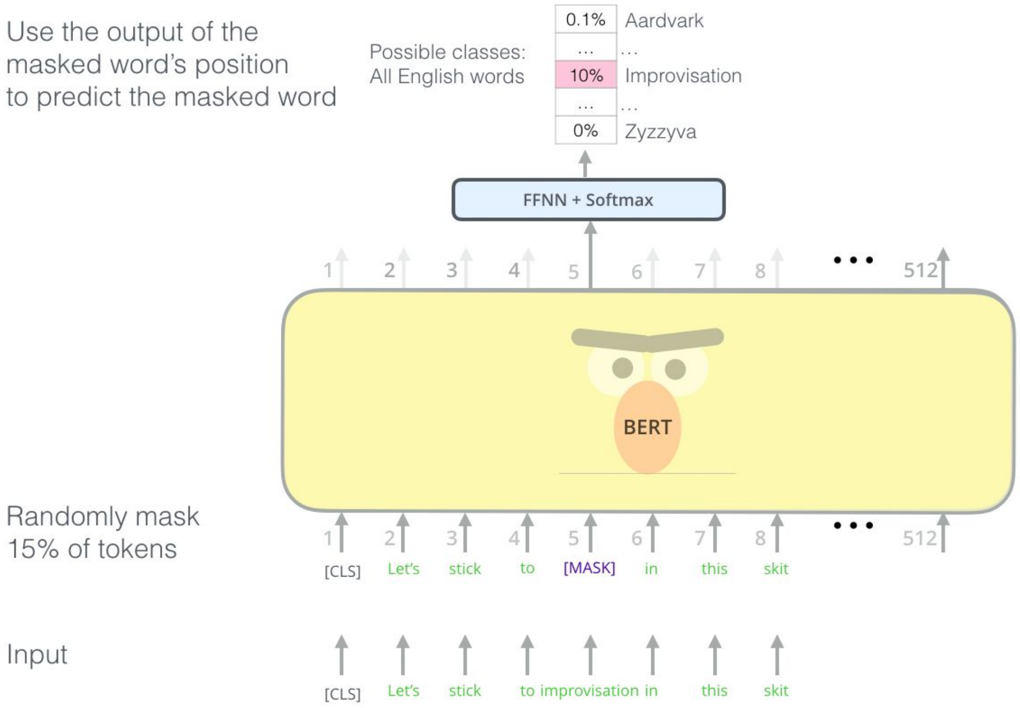
https://beta.openai.com/examples

Bidirectional Encoder Representations from Transformers (BERT)

- GPT is a **unidirectional** LM, incorporating context from *previous* tokens
- This is likely sub-optimal for many token- or sentence-level tasks
- BERT proposes a **bidirectional** LM based on a transformer encoder
- BERT is pretrained with two self-supervised objectives:
  - **M**asked **L**anguage **M**odelling (**MLM**)
  - **N**ext **S**entence **P**rediction (**NSP**)

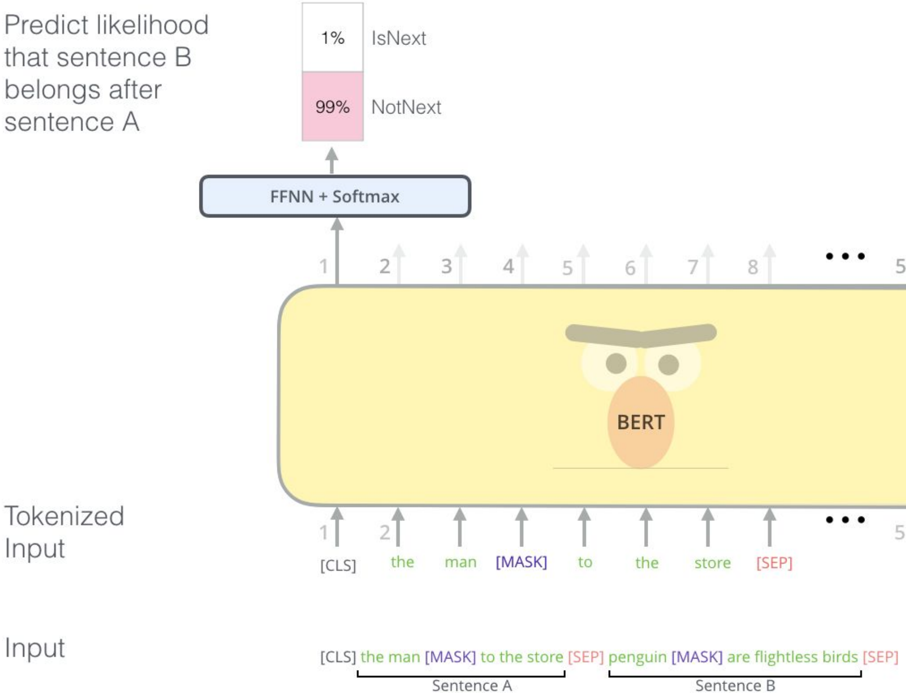
Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805 (2018).

Masked Language Modelling (MLM)



https://jalammar.github.io/illustrated-bert/

Next Sentence Prediction (NSP)



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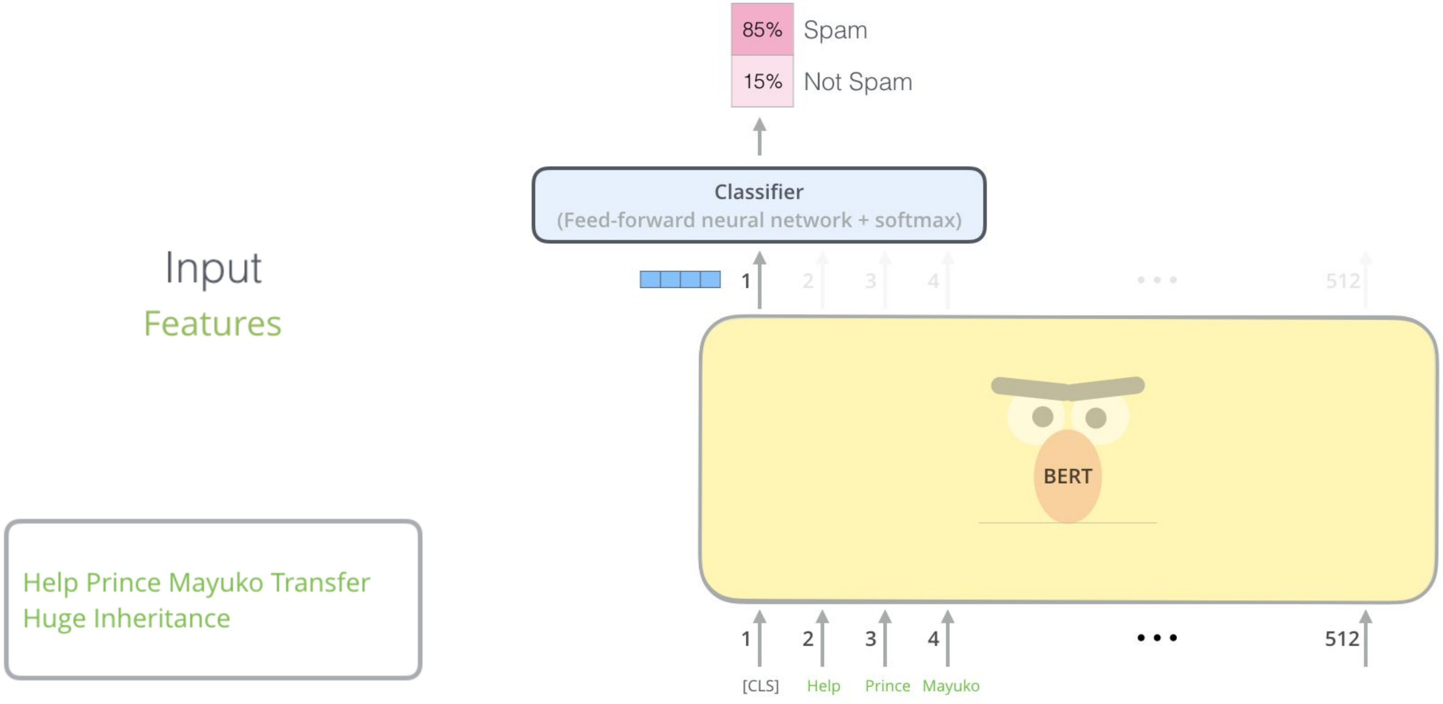
Fine-tuning BERT

- BERT has learned rich representations which encode **syntax** & **semantics**
  - We can take advantage of this for "downstream" tasks via using **fine-tuning**
- Add & initialize a new layer on top of BERTs outputs
  - Use **supervised learning** to tune all parameters
- Because BERT is pretrained, fine-tuning is typically cheap
  - 3-4 epochs on 100s or 1000s of labelled examples
  - Typically takes a few hours to fine-tune on GPU(s)
- Many, if not most, SOTA methods in NLP incorporate BERT-like models

Fine-tuning BERT



https://jalammar.github.io/illustrated-bert/

Resources

- For pretrained models and datasets, try HuggingFace
- For NLP specific machine learning library, try AllenNLP
- For a great free textbook, try Speech and Language Processing
- For a great MOOC, try Sequence Models (free with UofT Coursera)
- For great blog posts illustrating these concepts, try https://jalammar.github.io/

Thank you for your attention! (get it?)

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