Introto Agural Networks

BA865 – Mohannad Elhamod



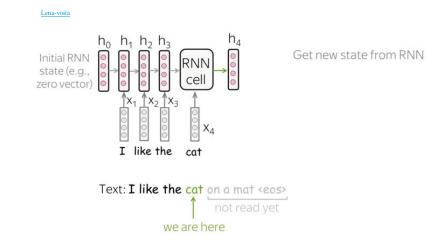
Transformers

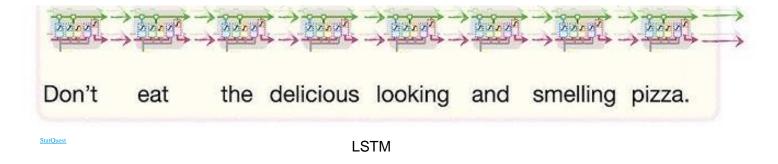


Last time on BA865...

Catastrophic forgetting...!

- We started with having one memorization path...
- There were some attempts to solve the issue by adding more paths (e.g., LSTM added long and short term paths).
- Still a struggle to learn long sequences...



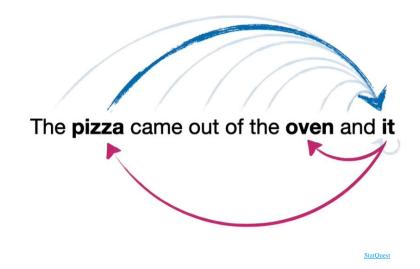




An Embedding Per Token?

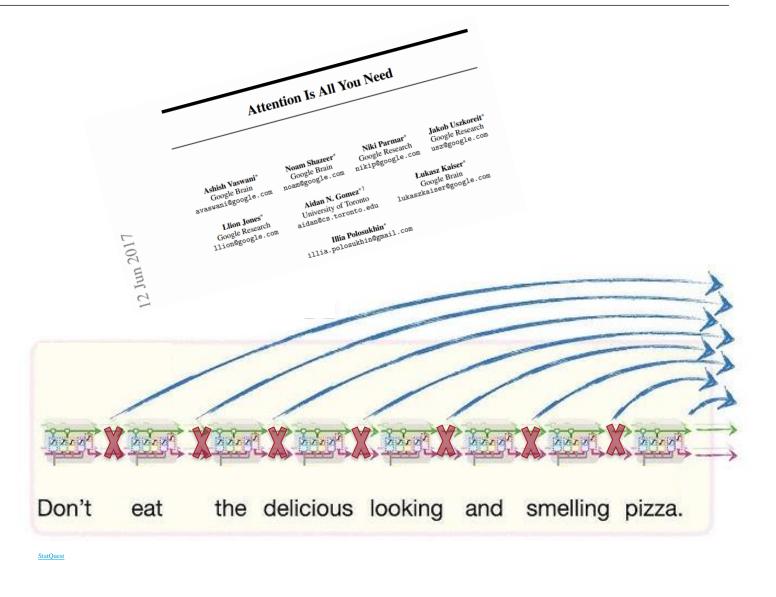
Instead of having embedding(s) that represent entire sequences, how about we...

- Learn different embeddings for different tokens.
- Learn the relationship(s) (or similarity) between these tokens to represent the sequence (e.g., the sentence).



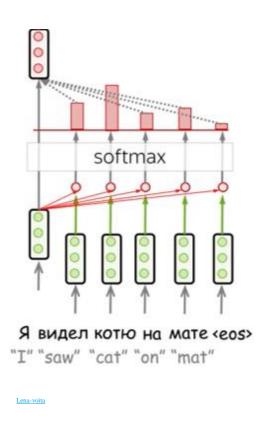


- So, let's not bother with memories that represent entire sequences anymore...
- We are only interested in the <u>attention</u> between tokens.



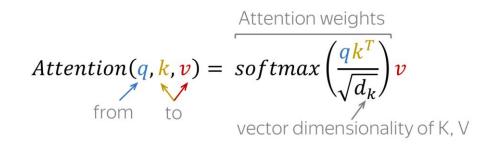


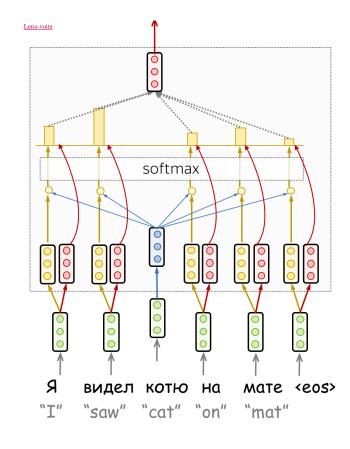
- How do we capture similarity?
 - Dot product (i.e., cosine similarity)
 - Based on the similarities between the tokens, we can create new embeddings!
 - How is this implemented?





- The objective is to learn more sophisticated embeddings that capture the semantics of the sentence.
 - Query: Source of attention (e.g., I am looking for an adjective)...
 - Key: Target of attention (e.g., I am your adjective)...
 - Their dot product gives the <u>attention scores</u>.
 - Value: used as an <u>embedding</u> weighted by these scores.







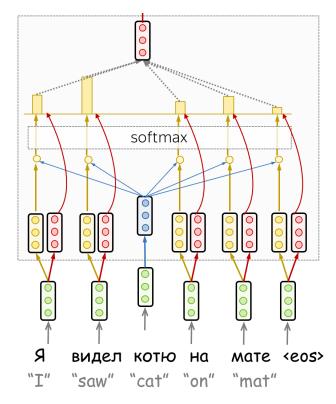
- How are these key, value, and query calculated?
- This is called an "attention head".



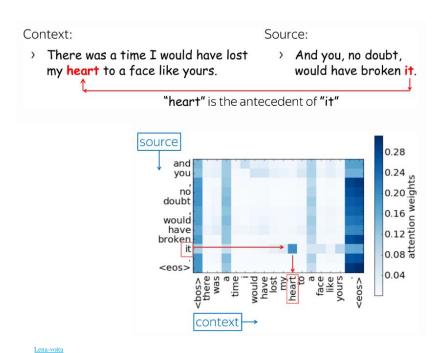
$$\left[\begin{array}{c} W_{K} \end{array} \right] \times \begin{array}{c} \circ \\ \circ \\ \circ \end{array} = \begin{array}{c} \circ \\ \circ \\ \circ \end{array}$$

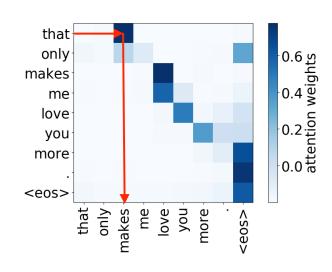
$$\left[\begin{array}{c} W_{V} \end{array} \right] \times \begin{array}{c} \circ \\ \circ \\ \circ \end{array} = \begin{array}{c} \circ \\ \circ \\ \circ \end{array}$$

Lena-voita

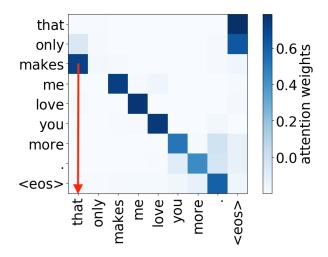


Examples





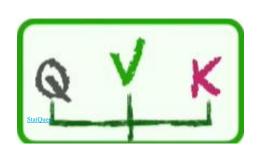
Subject -> verb



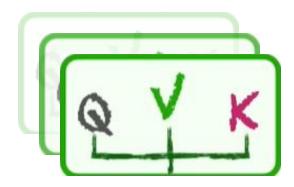
Verb -> subject



- If one head can learn some relationship in the sequence...
- multiple heads can learn multiple relationships.



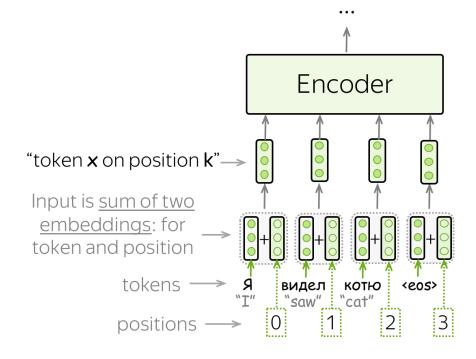




Multi-head attention



- Note that the word embeddings are now learned as part of model training.
- Since the order of tokens in the sequence matters, we add a "positional encoding" to the word embedding.

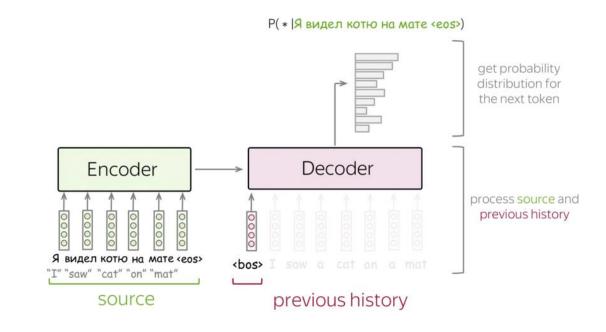


Lena-voita



Attention in an Encoder-Decoder Framework

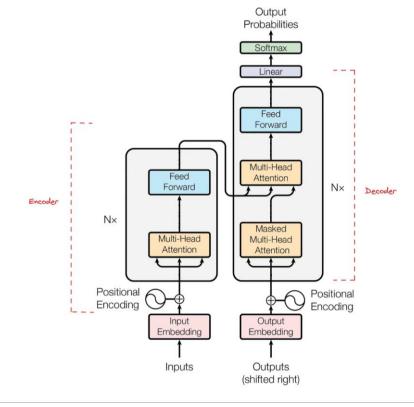
- One can think of the attention head(s) as the layer(s) in an encoder.
- Instead of having an embedding of the entire sequence (e.g., RNN), now we have an embedding per token.
- A decoder can be learned to do other tasks (e.g., translation, text-to-audio, etc.).

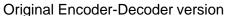


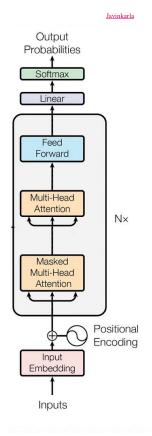


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The Transformer is Born!







GPT (Decoder only) version



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The Transformer is Born!

Model	Examples	Tasks
Encoder	ALBERT, BERT, DistilBERT, ELECTRA, ROBERTa	Sentence classification, named entity recognition, extractive question answering
Decoder	CTRL, GPT, GPT-2, Transformer XL	Text generation
Encoder- decoder	BART, T5, Marian, mBART	Summarization, translation, generative question answering

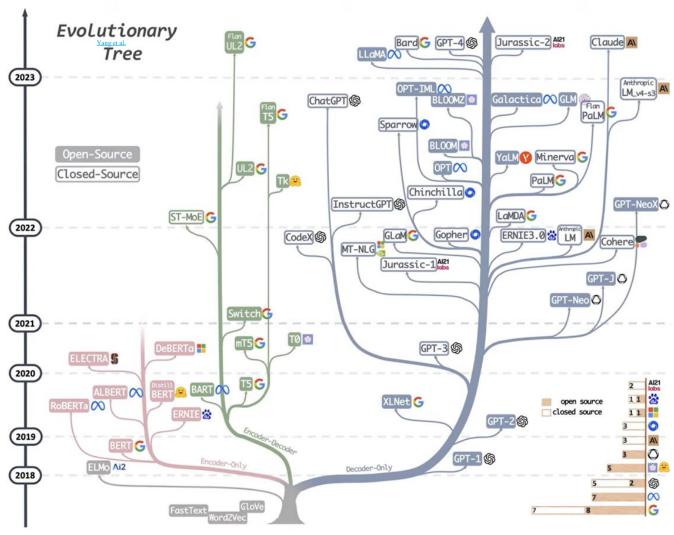


<u>Javinkara</u>

Why so many?

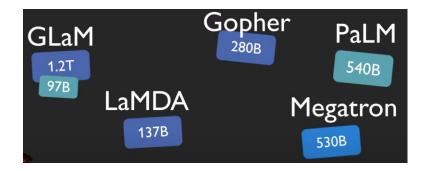
Where do the differences come from?

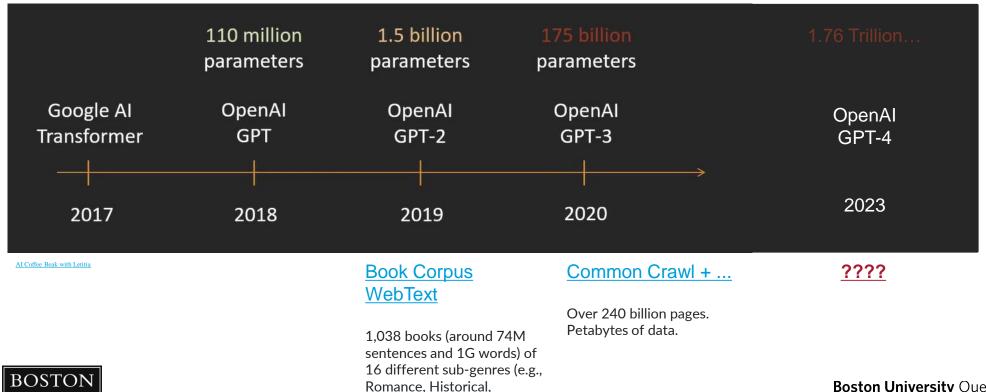
- Data.
- Model type and size.
- Hyperparameters (context size, embedding size,...).
- Training process (the cost function, fine-tuning, human feedback, etc.).





The GPT evolution...

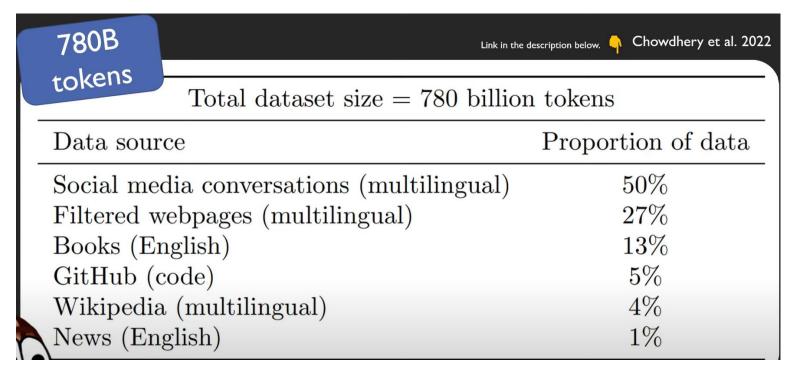




Adventure, etc.)



The GPT evolution...





Al Coffee Beak with Letitia

Different model sizes









117M Parameters

345M Parameters

762M Parameters

1,542M Parameters

Jay Alamma

