

Outline

Motivation

- Transformers
 - Goals
 - Components

Applications



Motivation

Language translation

Next word prediction

- Downstream tasks
 - Sentiment analysis
 - Semantic search



Goals

- The goal of any language model is to transform a block of text into a sequence of vectors
 - One vector for each word/token
- We then use that sequence of vectors to do something else
 - Predict the next word
 - Classify a sentence
- We will use a transformer to do this!



- A transformer is a type of neural network
- First developed in 2017 (AIAYN)

- Just like word embedding neural networks, we will train on a large corpus of text
 - OpenAl uses 'web-scale' data
 - Use SGD to update parameters of the NN
 - Transformers are more powerful!



Transformers – Goals

- Contextual awareness
 - I don't like the sun. When I saw the <u>blue</u> sky, I felt <u>blue</u>.
- Learned relevance
- Speed
 - Every part of a transformer is parallelizable
 - Build bigger models and train them faster
 - OpenAl bought ~30,000 Nvidia gpus in 2022!



I asked chatGPT

- How do transformers work?
 - Transformers are a type of deep learning architecture introduced in the paper "Attention Is All You Need" by Vaswani et al. in 2017. They have since become a fundamental component in various natural language processing (NLP) tasks due to their efficiency in handling long-range dependencies and parallelization. Transformers are particularly renowned for their success in tasks such as machine translation, text generation, and sentiment analysis.
 - The key idea behind transformers is self-attention, a mechanism that allows the model to weigh the importance of different words in a sentence when processing each word. This way, the model can focus on relevant information and capture relationships between words that are crucial for understanding the context.



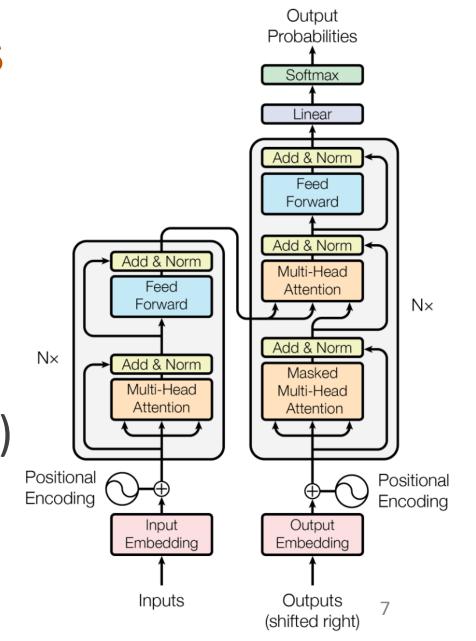
Transformers – Components

Embedding

Positional Encoding

Multi-Head Self Attention (MHSA)

Multi-Level Perceptron (MLP)





Embedding

- Convert input (text, images) to sequences of vectors
- Tokenization
 - Word, sub-word, character
 - I am learning about transformers.
 - [BOS], "I", "am", "learn", "##ing", "about", "transform", "##ers", ".", [EOS]
- Dictionary
- Convert each token in dictionary to vector
 - Explicit or implicit



Embedding

- We could start with the embeddings from word2vec or GloVe
- Take each token in the block of text's embeddings and feed them into the neural network
- Eventually, we may ask the transformer to modify the initial embedding for each word using SGD



Positional Encoding

- Transformer math is blind to the order that words appear
- Modify each vector in the sequence to represent its position
 - Additive
 - RoPE



Additive Positional Encoding

I like water.



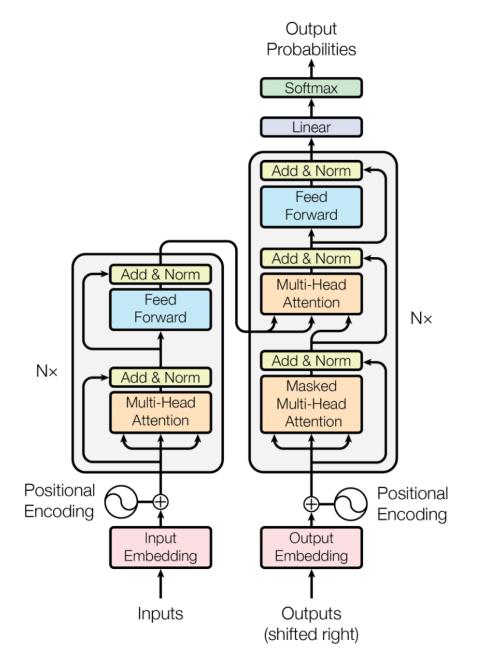
Rotary Positional Encoding

I like water.



Multi-Headed Self Attention

- We now understand the input to transformer
- Next, these modified input embeddings are fed through a multi-headed self attention layer
- To understand this, we need to build up!





Attention

- Web search
 - Search term Query
 - Meta Data Key
 - Content of page Value
- How similar is the query to each key?
 - Cosine or dot-product similarity between query and keys
- Softmax



Attention

- Query: What types of trees grow in Texas?
- Keys:
 - Fishing, boats, dogs
 - Arborists, Austin, grass
 - Texas, music, motorcycles
- Dot-Product Similarities: -0.1, 0.9, 0.5
- Softmax: 0.18, 0.49, 0.33



Attention

Weighted average of values

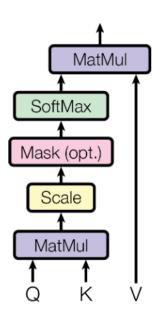
Pay more <u>attention</u> to the things that are similar!



Self Attention

- Set each embedded token to be the queries, keys, and values!
 - Get a new vector for each token!
- Before that...
 - Feed each embedding through 3 separate dense layers: for key, query, and value
 - Weights and biases of 3 layers are learned

Scaled Dot-Product Attention





Self Attention – Example

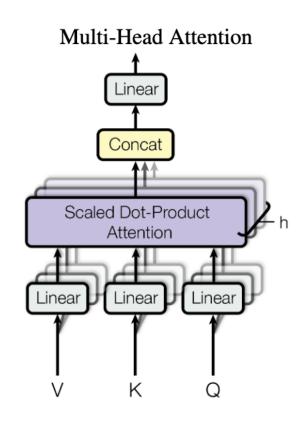
Attention is cool



Multi-Head Self Attention

- Self attention several times, using several query/key/value matrices
- Concatenate

 Feed all outputs through standard dense layer of MLP with ReLU activation



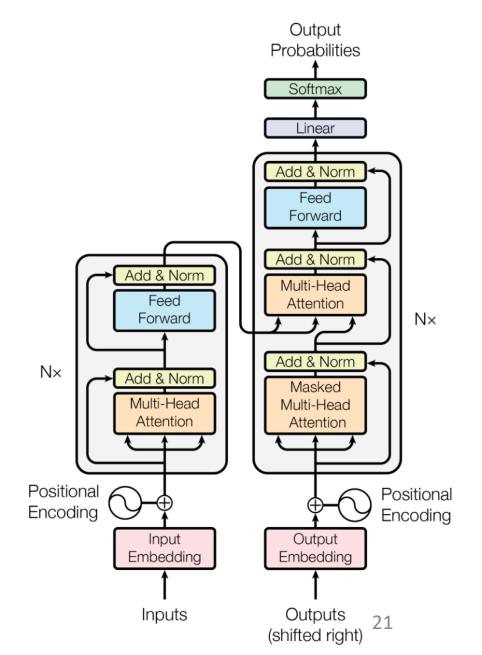


- Each token's embedding gets changed to something new from MHSA
- Take outputs, and feed them each through a dense layer
- Then feed that into a new MHSA layer with new query/key/value layers
- Stack several MHSA/Dense layers on top of each other!



Skip Connections

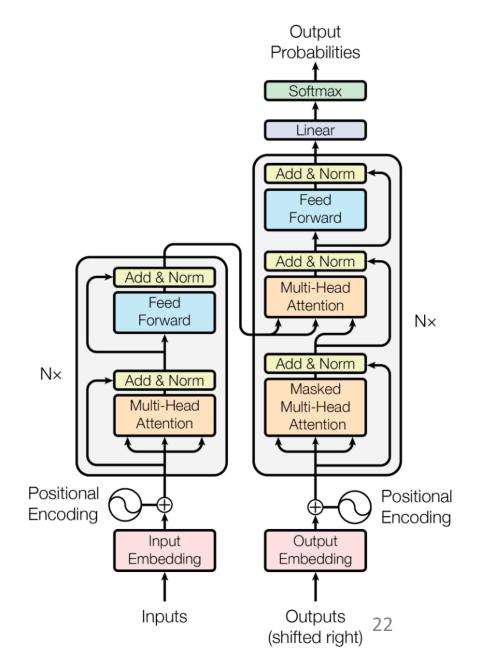
Masking





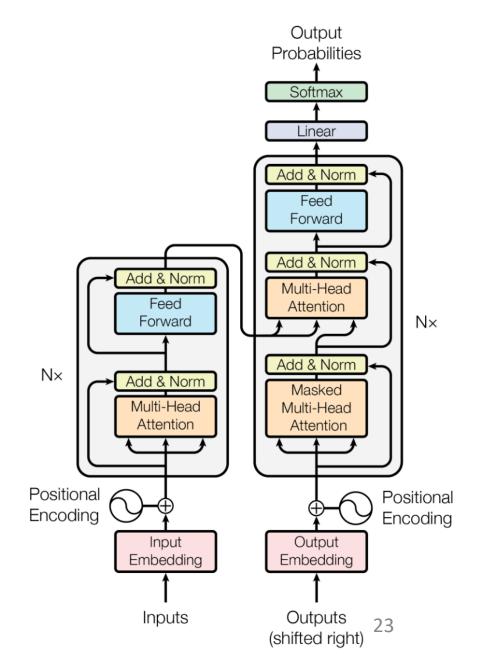
Encoder

Decoder



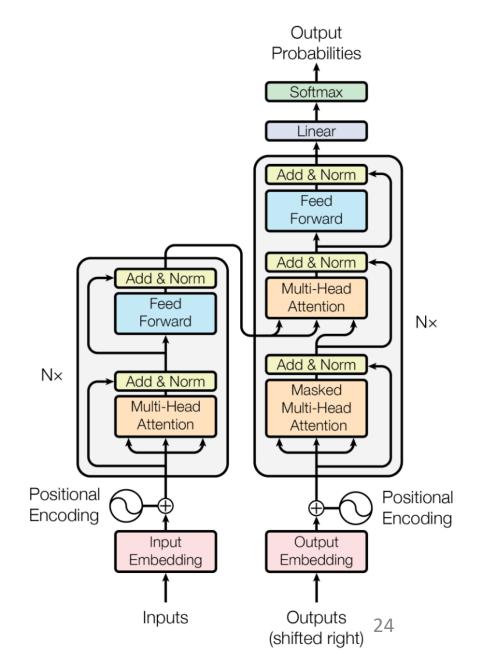


Encoder / Decoder





- Encoder only
 - BERT





BERT Applications

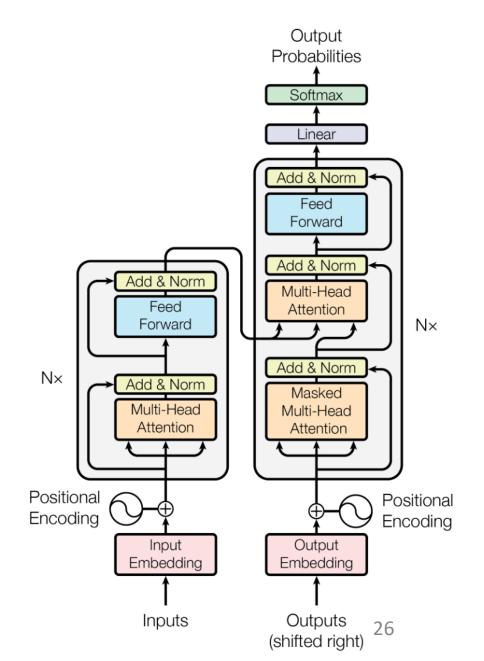
Sentiment Analysis

Text Classification

Semantic Search



- Decoder only
 - GPT





GPT

- Next word prediction with just a decoder
 - 1. Create a block of text
 - 2. Input the block of text to decoder
 - 3. Predict probabilities of next word
 - 4. Randomly pick one of those words and append it to block of text
 - 5. Go back to 2, until the chosen word is [EOS]



Training

- Feed block of text to the transformer
- It sequentially predicts the probabilities of every possible next word after each word
- Compare predicted probabilities to true next word
- Stochastic gradient descent

I like to go to the beach.



Fine Tuning

- Most models are pre-trained over a LONG time
- They are trained using a broad corpus of text
- You may have a task tailored to a specific text
 - Repair manuals for tractors
- You can fine tune a model using your corpus of specific text
 - You'll get better results for your task



Why Transformers?

- Recall goals
 - Contextual Awareness
 - Learned Relevance
- Multi-Head Self Attention achieves both of these
- LSTM models relevance sequentially
- Transformers let this be learned!



Applications

Language translation (AIAYN)

Supervised learning (BERT)

Text Generation (GPT)



Software

TensorFlow / Torch (2015/2016)

- Hugging Face
 - Transformers package
 - Hub



New Advances

- Multi-modal transformers
 - Personalized text to speech
 - Text to images
 - Speech to text
 - Text to videos

GANs



Summary

- Transformers are a powerful class of neural networks
- Transformers use a special type of layer called multiheaded self attention
- Transformers are trained using HUGE data sets
- There are many applications of Transformers