Felix Becker



Natural Language

Transformers

Natural Language Processing and Transformers

Lecture Machine Learning vom 29-31.3.2023

Felix Becker

(material in collaboration with Lars Gabriel and Mario Stanke)

Institut für Mathematik und Informatik

Universität Greifswald

Felix Becker



Natural Langua

Transformers

What is Natural Language Processing (NLP)?

Process and analyze large amounts of natural human language data using computer programs (in the modern context: deep learning models).

The goal is to understand the contents of text, in particular understand the context of a word in its surrounding sentence(s).



Felix Becker



Natural Languag

Transformers

Some NLP problems

- Translation:
 - Input: "I love you."
 - Output: "Je t'aime."
- Text generation (example output generated by GPT-3):
 - Input: "Write a joke about machine learning."
 - Output: "Why did the machine learning model break up with its training data? Because it found a better fit!"
- Question answering (related to text generation):
 - Input: "Do I need my car in New York City?"
 - Output: "No. Please keep your car at home."
- Language understanding
- Text summary
- Speech recognition



Felix Recker



Natural Lan

Transformers

Token

The inputs to NLP models are sequences of tokens. A token is usually a word. There are also special tokens for specific purposes e.g. to mark the end of sentences.

Input: Friends, Romans, Countrymen, lend me your ears;				
Output: Friends	Romans	Countrymen	lend me	your ears

٠

There are details we omit here for simplicity e.g. how to tokenize words like o'neill, aren't or equivalence classing (e.g. anti-discriminatory and antidiscriminatory).

¹nlp.stanford.edu/IR-book/html/htmledition/tokenization-1.html

Felix Becker



Natural Langua

Transformers

Embedding

A high dimensional vector representing a specific sequence position (and potentially its context).

Sequence

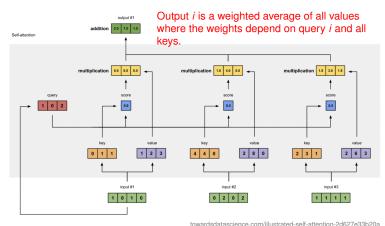
A series of tokens or embeddings in a spatial or temporal relationship.

Sequence-to-sequence model

Maps an input sequence of tokens to an output sequence. The sequences are not required to have the same length and no 1:1 token correspondence is assumed. Predicting a correct output length is responsibility of the model.

Transformers

Self-attention



Felix Becker

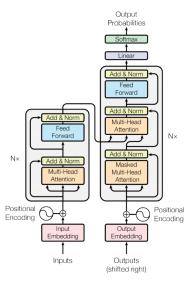


Natural Language Processing

Transformers

The transformer architecture

 Based on self-attention and cross-attention (attention between inputand output sequence)



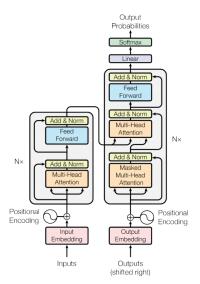
Felix Becker



Natural Language Processing

Transformers

- Based on self-attention and cross-attention (attention between inputand output sequence)
- Introduced in 2017 (Attention is all you need, Vaswani et al.)



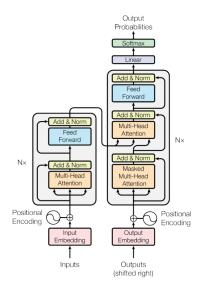
Felix Becker



Natural Language Processing

Transformers

- Based on self-attention and cross-attention (attention between inputand output sequence)
- Introduced in 2017 (Attention is all you need, Vaswani et al.)
- A transformer can consist of an encoder (left) and a decoder (right)



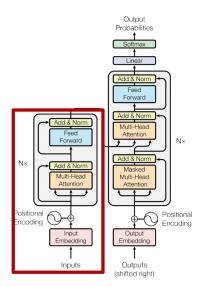
Felix Becker



Natural Language Processing

Transformers

- Based on self-attention and cross-attention (attention between inputand output sequence)
- Introduced in 2017 (Attention is all you need, Vaswani et al.)
- A transformer can consist of an encoder (left) and a decoder (right)
- Here, we will focus on the encoder

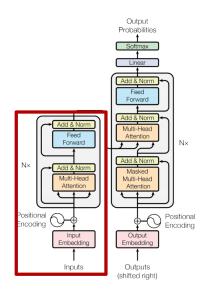




Natural Language Processing

Transformers

- Based on self-attention and cross-attention (attention between inputand output sequence)
- Introduced in 2017 (Attention is all you need, Vaswani et al.)
- A transformer can consist of an encoder (left) and a decoder (right)
- Here, we will focus on the encoder
- The encoders task is to learn a model of the input language (e.g. english or the "language" of protein sequences)

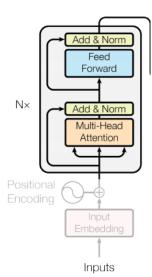


Natural Language Processing

Transformers

The transformer encoder

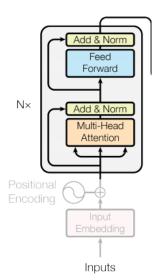
 Consumes a tensor of (embedded) input sequences and outputs a tensor with the same shape and updated embeddings



Natural Language Processing

Transformers

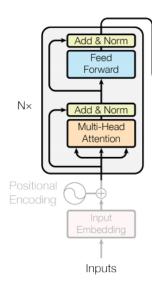
- Consumes a tensor of (embedded) input sequences and outputs a tensor with the same shape and updated embeddings
- First step: Self attention makes each embedding (in parallel) aware of all other embeddings



Natural Language Processing

Transformers

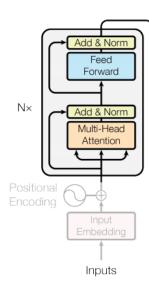
- Consumes a tensor of (embedded) input sequences and outputs a tensor with the same shape and updated embeddings
- First step: Self attention makes each embedding (in parallel) aware of all other embeddings
- Second step: Update the embeddings independently with a neural network usually larger than the embeddings itself



Natural Language

Processing **Transformers**

- Consumes a tensor of (embedded) input sequences and outputs a tensor with the same shape and updated embeddings
- First step: Self attention makes each embedding (in parallel) aware of all other embeddings
- Second step: Update the embeddings independently with a neural network usually larger than the embeddings itself
- These steps can be repeated several times



Felix Becker

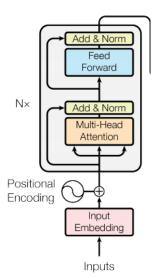


Natural Language Processing

Transformers

The transformer encoder

 Input Embedding replaces tokens with high dimensional embeddings



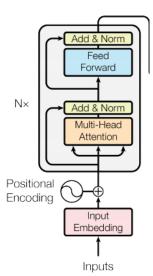
Felix Becker



Natural Language Processing

Transformers

- Input Embedding replaces tokens with high dimensional embeddings
- A Positional Encoding adds spatial/temporal information (without it the transformer is invariant to the ordering of the input tokens)

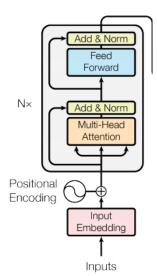




Natural Language Processing

Transformers

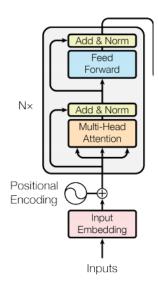
- Input Embedding replaces tokens with high dimensional embeddings
- A Positional Encoding adds spatial/temporal information (without it the transformer is invariant to the ordering of the input tokens)
- Multi-Head Attention is a more complicated form of self-attention, where multiple heads allow to attention to different subspaces of the sequence in parallel.



Natural Language Processing

Transformers

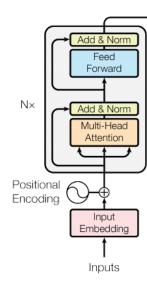
- Input Embedding replaces tokens with high dimensional embeddings
- A Positional Encoding adds spatial/temporal information (without it the transformer is invariant to the ordering of the input tokens)
- Multi-Head Attention is a more complicated form of self-attention, where multiple heads allow to attention to different subspaces of the sequence in parallel.
- Feed Forward is a neural network that is applied position-wise to the embedded sequences



Natural Language Processing

Transformers

- Input Embedding replaces tokens with high dimensional embeddings
- A Positional Encoding adds spatial/temporal information (without it the transformer is invariant to the ordering of the input tokens)
- Multi-Head Attention is a more complicated form of self-attention, where multiple heads allow to attention to different subspaces of the sequence in parallel.
- Feed Forward is a neural network that is applied position-wise to the embedded sequences
- Add and Norm means we introduce so called skip-connections and Layer Normalization (details omitted)



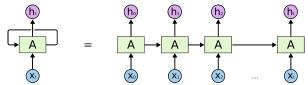
Felix Becker



Natural Language Processing Transformers

Comparison to recurrent neural networks (RNNs)

- RNNs lost popularity since the Transformer
- usually slower (because sequential, not parallel) and can not capture long-range interactions as good as attention can



2



3

²colah.github.io/posts/2015-08-Understanding-LSTMs

³ai.googleblog.com/2017/08/transformer-novel-neural-network.html

Natural Language

Processing

Fine-tuning



4

- Pre-train a large model on a general dataset (like Wikipedia)
- Reuse the weights as initialization for further training on more specific datasets (e.g. movie reviews) to solve more specific tasks
- The fine-tuning step is usually much faster than the pre-training
- A single pre-trained model can be reused many times

⁴www.ruder.io/recent-advances-Im-fine-tuning/



Natural Language Processing

Transforme

Masked language modeling





- Mask a percentage of the input tokens (i.e. the model receives a special MASK token instead of the actual token)
- Unsupervised (or sometimes called semi-supervised) training of a model with the goal to fill the gaps correctly using the cross-entropy loss function
- Can train models on large amounts of text from the internet without requiring any labeling