GPT-2 Based Meme Generator

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Abstract

This project explores the possibilities of deep learning mechanisms to create and improve the ways of social interaction in the 21st century. The main idea of the project is to prove that modern trained neural networks can synthesise entertainment data based on the input, embedded in an application that is easy to use by every user.

Literature Review

Introduction

GPT-2 introduces wide possibilities when it comes to human-like text synthesis. It is developed by OpenAI in February 2019 but the release to the public was postponed due to the apprehension that it could potentially be used to conduct malicious and harmful activities. The successor to the first GPT family member has been trained on a larger dataset and parameter count with around ten-fold growth. The reason behind choosing this exact neural network to produce this project lies in the philosophy followed by its creators. The aim was to take a new approach to the purpose of the system. The past neural networks "are better characterized as 'narrow experts' rather than 'competent generalists'" (Radford et al. 2019) and that was the main restraining factor. GPT neural network family uses transformer architecture with attention mechanism which allows faster training due to significantly increased parralelism (Vaswani et al. 2017). There are several advantages of using transformer neural networks to process text when compared to convolutional and recurrent neural networks (CNN and RNN). Transformers deal with sentences within a text as a whole and not word by word. Self attention is another advantage of transformers since it allows to relate different positions of a single sequence (sentence) to calculate a representation of it (Vaswani et al. 2017). And third major difference is positional embeddings. This concept allows the usage of fixed weights that encode information about a specific token in a sequence. Convolutional neural networks are very good at processing images and detecting patterns in them. Recurrent neural networks are mainly used in evolutionary robotics to deal with vision (Harvey et al. 1994).

Transformer Neural Networks

Transformer neural networks continue to gain more popularity among the other artificial intelligence systems for solving 'Natural Language Processing' problems. Before transformers gated recurrent units with added attention mechanism were mainly used to process natural language but transformers based on solely that attention mechanism has proven that they're more effiecient in solving particular problems (Vaswani et al. 2017). A vast amount of them used encoder-decoder structure in which the encoder maps an input sequence of symbol representation to a sequence of continious representation. Using that continious representation the decoder generates an output sequence. Also it uses the already generated output as an additional input in order to learn and generate more accurate output.

Encoder and decoder stacks consist of six identical layers. Every encoder layer has two sub-layers and every decoder layer has three sublayers. The first two sublayers of the decoder are similar to the encoder sublayers. The first is a multi-head self-attention mechanism and the second is a fully connected feed-forward network. The third layer of the decoder works with the output of the encoder by performing multi-head attention over it.

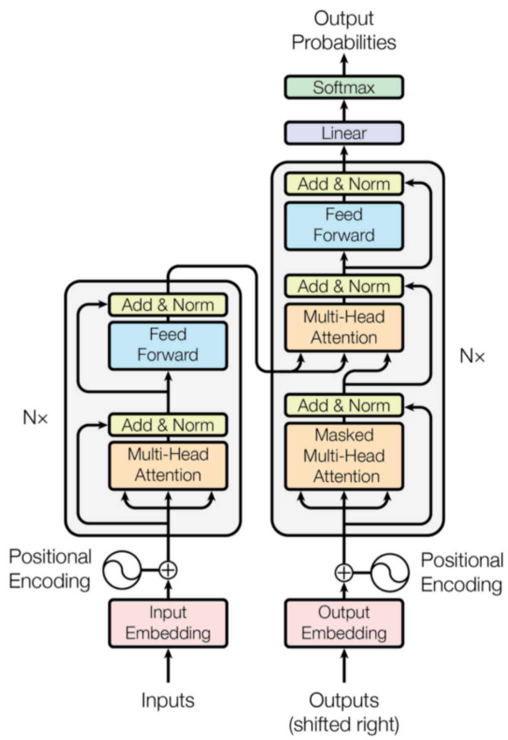

Figure 1: The Transformer - model architecture.

Since 2019 (release of GPT-2) a lot have changed in the field of transformers and as of November 2020 transformers are separated in different categories which different from each other in some aspects. Those categories are: Reformers, Linformers, Linear Transformers, Sinkhorn Transformers, Performers, Synthesizers, Sparse Transformers, and Longformers (Tay et al. 2020). Using this LRA benchmark the efficiency of different transformer models could be measured and this could give a better understanding how and in what areas they should be used. This testing suite is available in Python and is open-source so everyone could build upon it.

The suite developers pursued a goal of creating a suite for benchmarking having several important ideas in mind. Generality, Simplicity, Challenge, Long Inputs, Probing diverse aspects and accessibility of the suite. LRA Benchmark article depicts using a table of results for the comparison between different models. First test - Long 'ListOps' aims to test the parsing ability of the models and is a more complex version of the standard 'ListOps' task (Nangia & Bowman 2018). The best result is given by 'The Reformer'. Other conducted tests can be seen in the table provided in the research paper. The average score of 'Big Bird' is the highest, although it never showed best single result.

Applications of neural networks in entertainment

(Peirson & Tolunay 2018).

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