6312 – Natural Language Processing
Final Project Report
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1.0 Introduction

COVID-19 is a serious global infectious disease outbreak. It is part of a family of viruses called coronaviruses that infect both animals and people caused by the SARS-CoV-2 virus. This one originated in China at the end of 2019, in the city of Wuhan, which has 11 million residents.

1.1 Problem Statement

Long before COVID-19 was identified, a lot of people struggle to believe information when it comes to public health due to various reasons. Maybe a good way to handle this is to make more scientific information available to readers. Therefore, I imagined having a question-and-answer application model where anyone can ask questions related to COVID-19 and a simple summarized answer is returned citing scientific research. By adopting this method, it saves people the time of having to look through entire internet websites and streamline it down to covid-19 articles providing summarized answers and pointing to the articles where these answers were obtained from.

2.0 Dataset Overview

The dataset that we will use is sourced via Kaggle and was put together by the white house and some of the leading research groups. The dataset is 16 GB of text data consisting of csv and json files. It is a resource of over 134,000 scholarly articles, including over 60,000 with full text, about COVID-19, SARS-CoV-2, and related coronaviruses. The dataset also has web links to the full text of each article by uses the doi number. One of the most important files on this data is the metadata which has the following columns:
cord_uid, sha, source_x, title, doi, pmcid, pubmed_id, license, abstract, publish_time, authors, journal, mag_id, who_covidence_id, arxiv_id, pdf_json_files, pmc_json_files, url, s2_id

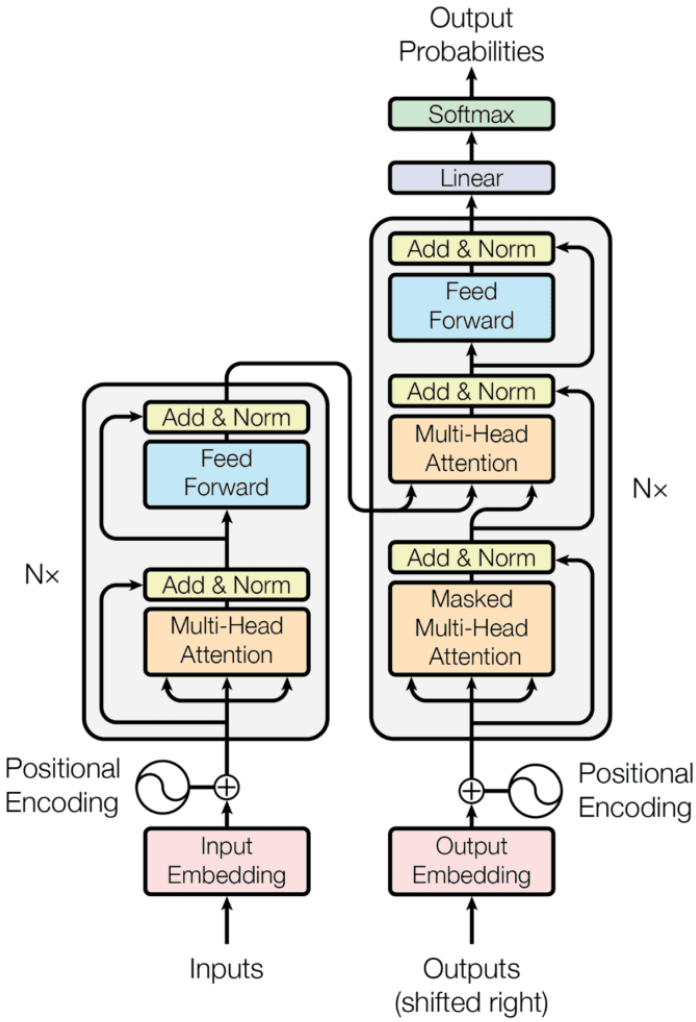
3.0 Text Preprocessing

As discussed above the dataset is very large. Training a model on that data will be computationally expensive. A better option was to streamline the dataset by using the meta data and only selecting the most important fields like title, doi, authors, abstract etc.
In order to generate the dataset for model training, I loaded the metadata csv file into a pandas data frame and ran an iterator. On each iteration, I got the doi number and appended it to the doi URL and sent a web request to return the webpage containing the article. I used beautiful soup to extract the text from the webpage and appended it to a new column labelled body text.

The user questions input is in two forms, the text and speech. The text is directly passed to the transformer model without any preprocessing, but the speech is recorded and written to a .wav file and the google translate interpreter is used to convert the .wav file to text and then it is passed to the transformer model.

4.0 Transformer Model

The transformer model is a neural network that learns context and meaning by tracking relationships in sequential data such as the words in sentences. These models apply self-attention mathematical techniques, to detect subtle ways even distant data elements in a series influence and depend on each other (https://machinelearningmastery.com/the-transformer-model/).



The Transformer consist of an encoder-decoder structure.The task of the encoder is to map an input sequence to a sequence of continuous representations, which is then fed into a decoder

while that of the decoder is to receive the output of the encoder together with the decoder output at the previous time step, to generate an output sequence.

4.1 Encoder

The encoder first sublayer implements a multi-head self-attention mechanism which implements h heads that receive a linearly projected version of the queries, keys, and values each, to produce h outputs in parallel that are then used to generate a result and the second sublayer is a fully connected feed-forward network, consisting of two linear transformations with Rectified Linear Unit (ReLU) activation in between.

4.2 Decoder

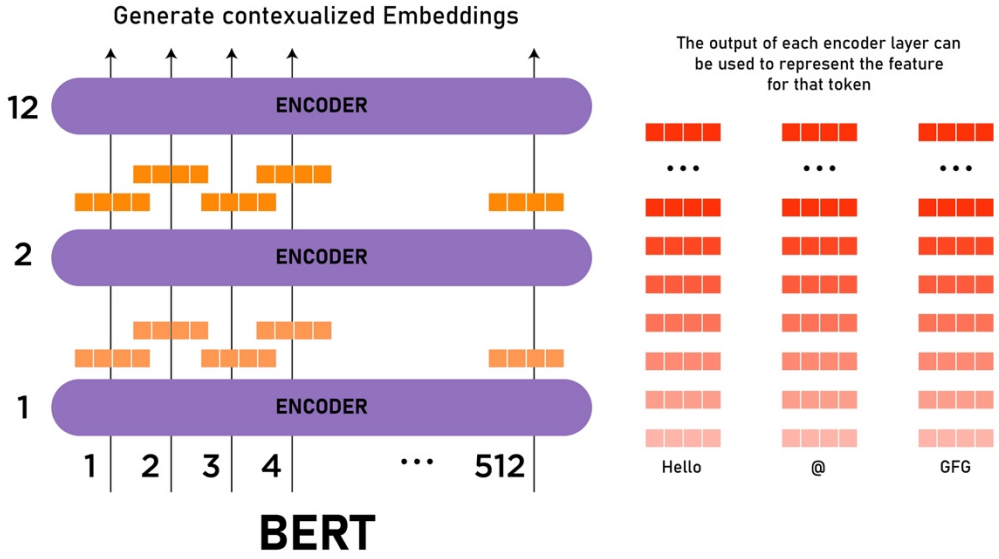
The decoder has three sublayers where the first sublayer receives the previous output of the decoder stack, augments it with positional information, and implements multi-head self-attention over it. The decoder is designed to only attend to preceding words. Hence, the prediction for a word at position i, can only depend on the known outputs for the preceding words in the sequence. In the multi-head attention mechanism is achieved by introducing a mask over the values produced by the scaled multiplication of matrices A and B. The second layer implements a multi-head self-attention mechanism which receives the queries from the previous decoder sublayer, and the keys and values from the output of the encoder. This allows the decoder to attend to all the words in the input sequence. Lastly, the third layer implements a fully connected feed-forward network.
Furthermore, the three sublayers in the decoder also have skip connections around them which are also succeeded by a normalization layer and positional encodings are also added to the input embeddings of the decoder.
In summary the Transformer model runs in the following processes:

1. Each word forming an input sequence is transformed into a n-model-dimensional embedding vector.
2. Each embedding vector representing an input word is augmented by summing it to a positional encoding vector of the same d_{model} length, hence introducing positional information into the input.
3. The augmented embedding vectors are fed into the encoder block.
4. The decoder receives as input its own predicted output word at time-step, t–1
5. The input to the decoder is also augmented by positional encoding, in the same manner as this is done on the encoder side.
6. The augmented decoder input is fed into the decoder block explained above and masking is applied in the first sublayer to stop the decoder from attending to succeeding words and at the second sublayer, the decoder also receives the output of the encoder, which allows the decoder to attend to all the words in the input sequence.

7. The output of the decoder finally passes through a fully connected layer, followed by a softmax layer to generate a prediction for the next word of the output sequence.

4.3 Bert Pretrained Model

BERT (Bidirectional Encoder Representations from Transformers) is a recent paper published by researchers at Google AI Language. It has caused a stir in the Machine Learning community by presenting state-of-the-art results in a wide variety of NLP tasks such as Question Answering, Natural Language Inference etc.



BERT is a transformers model pretrained on a large corpus of English data in a self-supervised mechanism. It was pretrained on the raw texts only with an automatic process to generate inputs and labels from those texts. BERT is basically a stack of Encoder architecture. BERT has 12 layers in the Encoder stack. It contains 512 hidden units and 8 attention heads. BERT contains 110M parameters (https://www.geeksforgeeks.org/explanation-of-bert-model-nlp/).

Bert was trained to achieve two objectives:

- Masked language modeling (MLM): This involved taking a sentence, the model randomly masks 15% of the words in the input then run the entire masked sentence through the model and must predict the masked words. It allows the model to learn a bidirectional representation of the sentence.
- Next sentence prediction (NSP): The models concatenate two masked sentences as inputs during pretraining. Sometimes they correspond to sentences that were next to each other

in the original text, sometimes not. The model then must predict if the two sentences were following each other or not.

BERT makes use of Transformer, an attention mechanism that learns contextual relations between words in a text. In its base form, a transformer model includes two separate mechanisms — an encoder that reads the text input and a decoder that produces a prediction for the task. Since BERT's goal is to generate a language model, only the encoder mechanism is necessary.
As opposed to directional models, which read the text input sequentially, either left-to-right or right-to-left, the Transformer encoder reads the entire sequence of words at once. BERT is considered bidirectional and a lot of times non-directional. This characteristic allows the model to learn the context of a word based on all its surroundings i.e., left, and right of the word.

5.0 Experimental Setup

To start training using the transformer models, I loaded the following into the main class.

1. From the data preprocessing, the generate dataset is loaded.
2. The bert-base-cased tokenizer is loaded
3. The facebook/bart-large-cnn summarizer is loaded
4. The bert-base-cased huggingface transformer model.

After loading the models, the articles are vectorized using the TF-IDF vectorizer while using the cosine similarity to read through the title, abstract and text of the articles and get the top n most articles related to that question based on the similarity score.
After retrieving the articles, then a batch size is created based on the length of the body text and the max length of tokens. A loop is run on the batch size and the question and the body text for the row in the iterator is passed to the transformer model. The question and body text and batch encoded with special tokens and padding, and tensor inputs are generated for the model. The input is passed into the transformer model. The model returns start logits and end logits which are used to determine the most likely beginning and ending of the answers are also generated based on the argmax score.
The answers are returned based on the start score and the answer text is now retrieved using the model decoder. For each of the generated answer, the text is passed to the summarizer model and limited to only 100 words to make it as simple as possible for users to read and understand.

6.0 Results

In order to arrive at the final results, we achieved several results from data preprocessing to model training.
During data preprocessing, when a user selects the speech input, the recorder starts and uses the system default microphone to record the question. The question is saved as a .wav file.
During translation to text, the .wav file is broken down to chunks for every 60 seconds.
During program execution, the bert-cased transformer model is loaded and written to the output folder if the model does not exist in the directory. The files written are config.json and the model.bin.
When the program performs TF-IDF cosine similarity and the model analysis the question, a dataframe of answers ranked by start score is generated and exported as anwers.csv.
For example, the question "Are there any drugs for Covid-19?" and below is a answers dataframe.

After the model generates the answer, a summarizer is used to simplify the answer.

	title	source_x	authors	url	publish_time	doi	start_score	end_score	summarized_answer
996	A prospect on the use of antiviral drugs to control local outbreaks of COVID-19	medrxiv	Andrea Torneri; Pieter Jules Karel Libin; Joris Vanderlocht; Anne-Mieke Vandamme; Johan Neyts; Niel Hens	https://doi.org/10.1101/2020.03.19.20038182	2020-03-20	10.1101/2020.03.19.20038182	162	356	The methodology we propose will be key to avoid a second peak, especially given the limited depletion of susceptibles . Individuals are initially susceptible (S) and once infected, they enter the exposed class (E) The on the notion of infectious contact processes. 5 First, contacts between individuals are generated. When such contacts are generated between susceptible and infectious

									people, these can result in an infection event .
1014	Repurposing Therapeutics for COVID-19: Rapid Prediction of Commercially available drugs through Machine Learning and Docking	medrxiv	Sovesh Mahapatra; Prathul Nath; Manisha Chatterjee; Neeladrisingha Das; Deepjyoti Kalita; Partha Roy; Soumitra Satapathi	https://doi.org/10.1101/2020.04.05.20054254	2020-04-07	10.1101/2020.04.05.20054254	6	428	The recent outbreak of novel coronavirus disease is now considered to be a pandemic threat to the global population . This could potentially bring major challenges to global healthcare and disastrous effect on the global economy if the virus is not contained within a few months . The common symptoms include cough, fever, shortness of breath, fatigue etc . Efforts are ongoing on war footing to find the effective drug and vaccine to treat this pandemic .
208	Molecular mechanism of action of repurposed drugs and traditional Chinese medicine used for the	medrxiv	Fui Fui Lem; Fernandes Opook; Dexter Lee Jiunn Herng; Chin Su Na; Fahcina P Lawson; Chee Fong Tyng	https://doi.org/10.1101/2020.04.10.20060376	2020-04-14	10.1101/2020.04.10.20060376	6	26	In December 2019, a novel type of novel type will be released in December 2019 . The novel is set to be published in the U.S. National Geographic Geographic Geographic Adventure .

	treatment of patients infected with COVID-19: A systematic review								The book is published in New York City, New York, on December 19, 2019 .

From the table above, the answer is appended to each article that has a high similarity score. The answers are obtained using the start and end logit positions and summarized for simplicity. Based on the results and the fact i am using a question answering model, it was difficult to have an evaluation metric for the answers generated. This is also a concern because sometimes the answers might be wrong as seen when testing. A better strategy might be to have a score threshold and any answer below that threshold might be considered wrong.

7.0 Code

All the code was written in python. I used a repository system, segmenting each function to a class and function, making the code clean and reusable.

Lines of code written: 327 Lines
Percentage of code from the internet: 27.489 %

8.0 Conclusion

The use of transformer models has provided very great results efficiently. One benefit of using the transformer model is due to the multi-head attention mechanism that gives the network the ability to pass through multiple words simultaneously. The reason I selected bert is because it can be pre-trained on a massive corpus of unlabeled data, and then fine-tuned to a task for which you have a limited amount of data. This allows BERT to provide significantly higher performance than models that are only able to leverage a small task-specific dataset.

9.0 Citations

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4. https://huggingface.co/docs/transformers/tasks/summarization

5. https://www.gavi.org/vaccineswork/what-is-covid-19-and-how-does-it-spread?gclid=CjwKCAjw9e6SBhB2EiwA5myr9vipbbHCxlKWGmVhvNYuWIPNexzxpJGhBC2WGjOOhnwaWcVAaGiJjhoCUoMQAvD_BwE
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