PREDICTING EFFECTIVE ARGUMENTS THROUGH STUDENT RESPONSE

A Project Report in partial fulfillment of the degree

Bachelor of Technology

in

Electronics & Communication Engineering/Computer Science & Engineering

By

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CERTIFICATE

This is to certify that the Project Report entitled "Fake news detection using NLP" is a record of bonafide work carried out by the student(s) Irukulla Apoorva, T. PhaniPriya, M.Sneha bearing Roll No(s) 19K41A0599, 19K41A05B6, 19K41A04G6 during the academic year 2022-2023 in partial fulfillment of the award of the degree of ***Bachelor of Technology*** in **Electronics & Communication/Computer Science Engineering** by the Jawaharlal Nehru Technological University, Hyderabad.

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ABSTRACT

The current education system did not put much emphasis in persuasive writing, which may hinder critical thinking development of the students. The task is to build an argument grading system. The purpose of the study is to develop a grading system by predicting effective arguments through student responses which can grade students' response based on three factors in user writing as effective, adequate, or ineffective. The proposed system is evaluated using datasets from Kaggle. The accuracy of model and obtained results show an agreement with user' grading. This gives us an indication that the model can be deployed for response of students' writing, thereby leading to reduction in time, efforts and cost for evaluating an essay.

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1. INTRODUCTION:

The assessment plays a significant role in measuring the learning ability of the student. The education system is changing its shift to online-mode, like conducting computer-based exams and automatic evaluation. It is a crucial application related to the education domain, which uses natural language processing (NLP) and Machine Learning techniques. The evaluation of responses is impossible with simple programming languages and simple techniques like pattern matching and language processing. Here the problem is for a single question, we will get more responses from students with a different explanation. So, we need to evaluate all the answers concerning the question. Response scoring is a computer-based assessment system that automatically scores or grades the student responses by considering appropriate features. These systems use natural language processing (NLP) techniques that focus on style and content to obtain the score of an essay. The vast majority of the essay scoring systems in the 1990s followed traditional approaches like pattern matching and a statistical-based approach. Since the last decade, there response grading systems started using regression-based and natural language processing techniques

2. LITERATURE REVIEW

S.No	Published date	Author	Title	Methodology	Article ID	accuracy	Link
1	30-Jun-2020	Masaki Uto, Masaki Okano	Automated essay scoring using response theory	CNN-LSTM, BERT	9783030	0.88	https://link.springer.com/chapter/10.1007/978-3-030-52237-7_44
2	Nov-2022	Kshitij Gupta	Data Augmentation for automated Essay scoring	RNN,LSTM,BERT,RoBERTa	364689774		https://www.researchgate.net/publication/364689774_Data_Augmentation_for_Automated_Essay_Scoring_using_Transformer_Models
3	23-Sep-2021	Suresh kumar Sanampudi	An automated essay scoring system	CNN-LSTM	10462021		https://link.springer.com/article/10.1007/s10462-021-10068-2
4	18-Sep-2019	Christopher Ormerod	Language models and Automated Essay Scoring	BOW& LSTM, BERT& XLNet	190909482		https://arxiv.org/abs/1909.09482
5	8-May-2022	Yongjie Wang, Chuan Wang	Use of bert for automated essay scoring	BERT	220503835		https://arxiv.org/abs/2205.03835
6	10-Dec-2018	Guoxi Liang, Dongwon Jeong	Essay Scoring using Nural networks	CNN and RNN(LSTM)	329378585		https://www.researchgate.net/publication/329378585_Automated_Essay_Scoring_A_Siamese_Bidirectional_LSTM_Neural_Network_Architecture

7	11-April-2022	Jumoke Eluwa, Shade O Kuyore	Essay scoring Model Based on Gated Recurrent unit Technique	TF(Term frequency),LSTM,GRU(gated recurrent unit)	360440446	0.53	https://www.researchgate.net/publication/360440446_Essay_Scoring_Model_Based_on_Gated_Recurrent_Unit_Technique
8	5-May-2016	Kaveh Taghipour, Hwee Tou Ng	A Neural Approach to Automated Essay Scoring	GRU,LSTM	305748202		https://www.researchgate.net/publication/305748202_A_Neural_Approach_to_Automated_Essay_Scoring
9	1-Jun-2021	Majidi Beseiso, Omar A.Alzubi	A Novel automated essay scoring approach	Bi-LSTM, RoBert	101007	0.87	https://link.springer.com/article/10.1007/s12528-021-09283-1
10	2019	Farah Nadeem, Huy Nguyen	Automated essay scoring using Discourse-Aware Neural Models	RNN,LSTM	W19-4450	0.86	https://aclanthology.org/W19-4450.pdf

Predicting effective arguments through student responses,[1] Automated essay scoring is the task of automatically assigning scores to essays as an alternative to human grading. DNN-AES models used for taraing on a large dataset of grading essay, this achieved state-of-the-art accuary.The Dnn-AES framework that integrates IRT models to deal within traing data. [2] Automated essay scoring is one of the most important problem in Natural Language Processing. It has been explored for a number of years, and it remains partially solved. Many works in the past have attempted to solve this problem by using RNNs, LSTMs, etc. This work examines the transformer models like BERT, RoBERTa. [3] Reviewed AES systems on six dimensions like dataset, NLP techniques, model building, grading models, evaluation, and effectiveness of the model. Feature extraction is with NLTK, WordVec, and GloVec NLP libraries; these libraries have many limitations while converting a sentence into vector form. [4] compare two powerful language models, BERT and XLNet, and describe all the layers and network architectures in these models. System lucidate the network architectures of BERT and XLNet using clear notation and compare the results with more traditional methods, such as bag of words (BOW) and long short term memory (LSTM) networks. [5] in the area of Automated Essay Scoring (AES), pre-trained models such as BERT have not been properly used to outperform other deep learning models such as LSTM. In this paper, we introduce a novel multi-scale essay representation for BERT that can be jointly learned and may be a new and effective choice for long-text tasks. [6] It helps reduce manual workload and speed up learning feedback. The model termed Siamese Bidirectional Long Short-Term Memory Architecture (SBLSTMA) can capture not only the semantic features in the essay but also the rating criteria information behind the essays. Here it use the SBLSTMA model for the task of AES and take the Automated Student Assessment Prize (ASAP) dataset as evaluation. [7] Deep learning algorithms such as Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) were used to learn the model with performance evaluation on metrics such as validation accuracy, training time, loss function, and Quadratic Weighted Kappa. MLP, LSTM, and GRU had average validation accuracy of 0.48, 0.537, and 0.511 respectively. GRU was shown to be the optimal classifier and was used in the development of the essay scoring model. [8] model is a long short-term memory neural network and is trained as a regression method. long short-term memory networks have been used to obtain parse trees by using a sequence-to-sequence model. [9] This paper presents a transformer-based neural network model for improved AES performance using Bi-LSTM and RoBERTa language model based on Kaggle's ASAP dataset.[10] a RNNs, particularly LSTMs, are good at representing text sequences, essays are longer structured documents and less well suited to an RNN representation.

3. DESIGN:

3.1 Requirement Specifications (S/W & H/W)

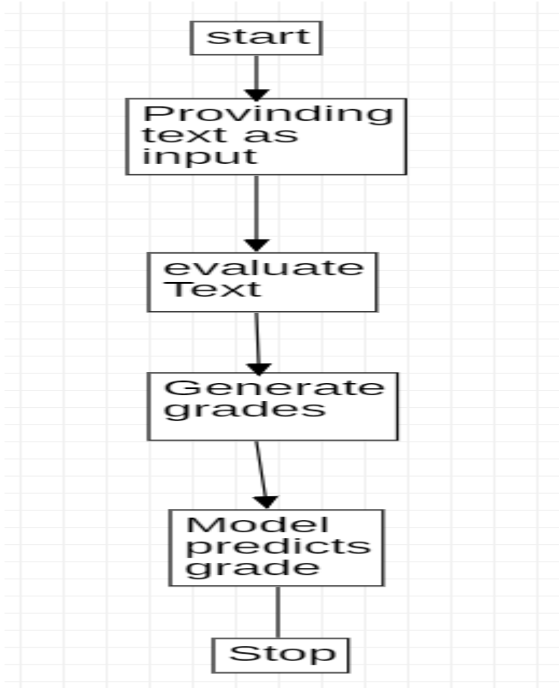
<u>Hardware Requirements</u>

- ✓ **System** : Processor Intel(R) Core (TM) i5-8265U CPU @ 1.60GHz, 1800 MHz, 4 Cores, 8 Logical Processors
- ✓ **RAM** : 8 GB
- ✓ **Hard Disk** : 557 GB
- ✓ **Input** : Keyboard and Mouse
- ✓ **Output** : PC

<u>Software Requirements</u>

- ✓ **OS** : Windows 10
- ✓ **Platform** : Google Colaboratory / Jupyter Notebook
- ✓ **Program Language** : Python

3.2 FLOW CHART



4. DATASET:

The dataset presented here contains argumentative essays written by U.S students in grades 6-12. These essays were annotated by expert raters for discourse elements commonly found in argumentative writing:

- Lead - an introduction that begins with a statistic, a quotation, a description, or some other device to grab the reader's attention and point toward the thesis
- Position - an opinion or conclusion on the main question
- Claim - a claim that supports the position
- Counterclaim - a claim that refutes another claim or gives an opposing reason to the position
- Rebuttal - a claim that refutes a counterclaim
- Evidence - ideas or examples that support claims, counterclaims, or rebuttals.
- Concluding Statement - a concluding statement that restates the claims

Your task is to predict the quality rating of each discourse element. Human readers rated each rhetorical or argumentative element, in order of increasing quality, as one of:

- Ineffective
- Adequate
- Effective

For more information on the annotation scheme and scoring rubric, please see: Argumentation Annotation Scheme and Descriptions.

Note that this is a Code Competition, in which you will submit code that will be run against an unseen test set. The unseen test set comprises about 3,000 essays. A small public test sample has been provided for testing your submission notebooks.

This dataset is a subset of the dataset from the Feedback Prize - Evaluating Student Writing competition. You are welcome to make use of this earlier dataset, if you like.

Training Data

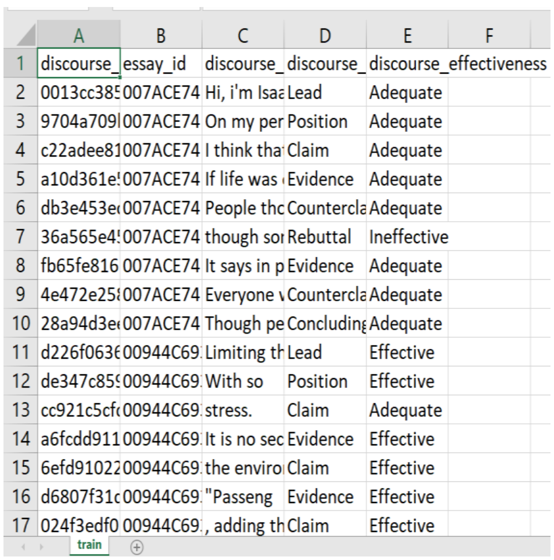
The training set consist of a `.csv` file containing the annotated discourse elements each essay, including the quality ratings, together with `.txt` files containing the full text of each essay. It is important to note that some parts of the essays will be unannotated (i.e., they do not fit into one of the classifications above) and they will lack a quality rating. We do not include the unannotated parts in train.csv.

- train.csv - Contains the annotated discourse elements for all essays in the test set.
    - `discourse_id` - ID code for discourse element
    - `essay_id` - ID code for essay response. This ID code corresponds to the name of the full-text file in the train/ folder.
    - `discourse_text` - Text of discourse element.
    - `discourse_type` - Class label of discourse element.
    - `discourse_type_num` - Enumerated class label of discourse element .
    - `discourse_effectiveness` - Quality rating of discourse element, the target.

Example Test Data

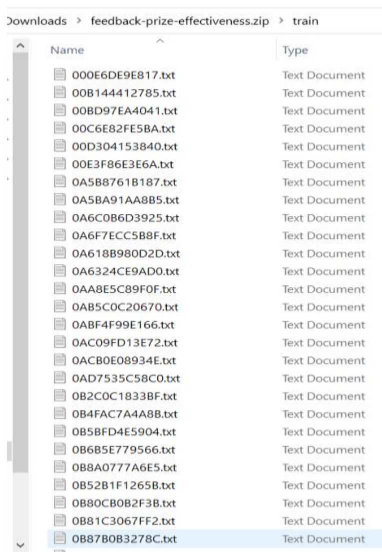
To help you author submission code, we include a few example instances selected from the test set. When you submit your notebook for scoring, this example data will be replaced by the actual test data, including the sample_submission.csv file.

- test/ - A folder containing an example essay from the test set. The actual test set comprises about 3,000 essays in a format similar to the training set essays. The test set essays are distinct from the training set essays.
- test.csv - Annotations for the test set essays, containing all of the fields of train.csv except the target, discourse_effectiveness.
- sample_submission.csv - A sample submission file in the correct format. See the Evaluation page for more details.

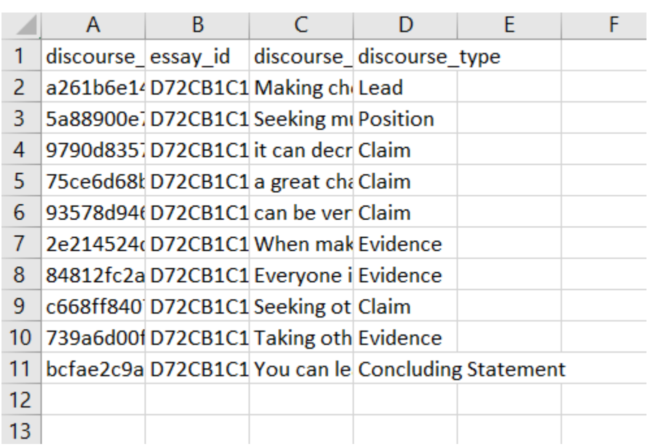


	A	B	C	D	E	F
1	discourse_	essay_id	discourse_	discourse_	discourse_effectiveness	
2	0013cc385	007ACE74	Hi, i'm Isaa	Lead	Adequate	
3	9704a709	007ACE74	On my per	Position	Adequate	
4	c22adee81	007ACE74	I think tha	Claim	Adequate	
5	a10d361e	007ACE74	If life was	Evidence	Adequate	
6	db3e453e	007ACE74	People thc	Countercla	Adequate	
7	36a565e4	007ACE74	though sor	Rebuttal	Ineffective	
8	fb65fe816	007ACE74	It says in p	Evidence	Adequate	
9	4e472e25	007ACE74	Everyone	Countercla	Adequate	
10	28a94d3e	007ACE74	Though pe	Concluding	Adequate	
11	d226f063	00944C69	Limiting th	Lead	Effective	
12	de347c85	00944C69	With so	Position	Effective	
13	cc921c5cf	00944C69	stress.	Claim	Adequate	
14	a6fcdd911	00944C69	It is no sec	Evidence	Effective	
15	6efd9102	00944C69	the enviro	Claim	Effective	
16	d6807f31c	00944C69	"Passeng	Evidence	Effective	
17	024f3edf0	00944C69	, adding th	Claim	Effective	

Training.csv



Training folder



	A	B	C	D	E	F
1	discourse_	essay_id	discourse_	discourse_type		
2	a261b6e1	D72CB1C1	Making ch	Lead		
3	5a88900e	D72CB1C1	Seeking m	Position		
4	9790d835	D72CB1C1	it can decr	Claim		
5	75ce6d68	D72CB1C1	a great ch	Claim		
6	93578d94	D72CB1C1	can be ver	Claim		
7	2e214524	D72CB1C1	When mak	Evidence		
8	84812fc2a	D72CB1C1	Everyone i	Evidence		
9	c668ff840	D72CB1C1	Seeking ot	Claim		
10	739a6d00	D72CB1C1	Taking oth	Evidence		
11	bcfae2c9a	D72CB1C1	You can le	Concluding Statement		
12						
13						

Testing.csv

5. DATA PREPROCESSING:

Removing stop words:

The words which are generally filtered out before processing a natural language are called stop words. These are actually the most common words in any language (like articles, prepositions, pronouns, conjunctions, etc) and does not add much information to the text. Examples of a few stop words in English are “the”, “a”, “an”, “so”, “what”. Stop words are available in abundance in any human language. By removing these words, we remove the low-level information from our text in order to give more focus to the important information. In order words, we can say that the removal of such words does not show any negative consequences on the model we train for our task. Removal of stop words definitely reduces the dataset size and thus reduces the training time due to the fewer number of tokens involved in the training. NLP is one of the most researched areas today and there have been many revolutionary developments in this field. NLP relies on advanced computational skills and developers across the world have created many different tools to handle human language. Out of so many libraries out there, a few are quite popular and help a lot in performing many different NLP tasks.

Tokenization:

Tokenization is the first step in any NLP pipeline. It has an important effect on the rest of your pipeline. A tokenizer breaks unstructured data and natural language text into chunks of information that can be considered as discrete elements. The token occurrences in a document can be used directly as a vector representing that document. This immediately turns an unstructured string (text document) into a numerical data structure suitable for machine learning. They can also be used directly by a computer to trigger useful actions and responses. Or they might be used in a machine learning pipeline as features that trigger more complex decisions or behavior.

punctuation removal:

The punctuation removal process will help to treat each text equally. For example, the word data and data! are treated equally after the process of removal of punctuations. We need to take care of the text while removing the punctuation because the contraction words will not have any meaning after the punctuation removal process. Such as ‘don’t’ will convert to ‘dont’ or ‘don t’ depending upon what you set in the parameter.We also need to be extra careful while choosing the list of punctuations that we want to exclude from the data depending upon the use cases. As string.punctuation in python contains these symbols !"#$%&\'()*+,-./:;?@[\\]^_{|}~`

6. METHODOLOGY:

After Data pre-processing we are going to perform word embedding using

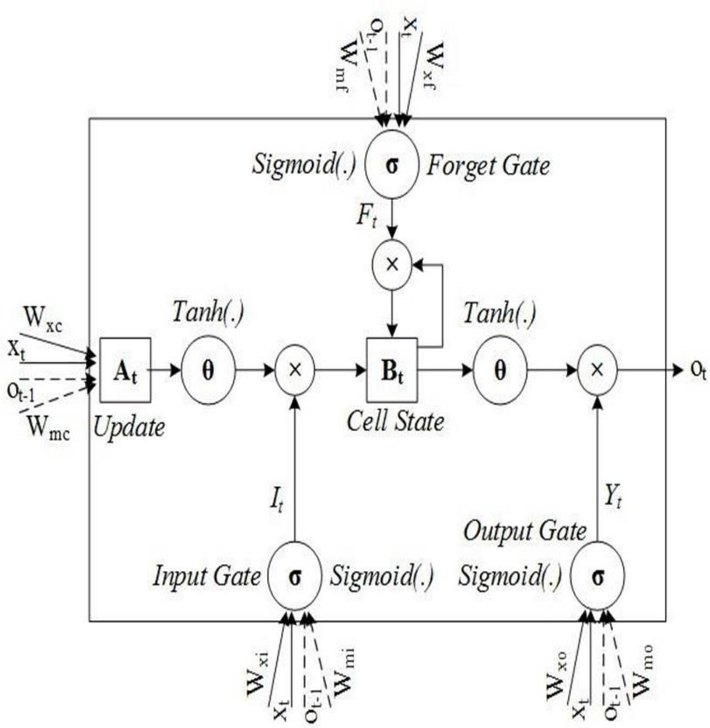
6.1 LSTM

LSTM (Long Short-Term Memory) network is a type of RNN (Recurrent Neural Network) that is widely used for learning sequential data prediction problems. As every other neural network LSTM also has some layers which help it to learn and recognize the pattern for better performance. The basic operation of LSTM can be considered to hold the required information and discard the information which is not required or useful for further prediction.

The Architecture of LSTM

A simple LSTM network consists of the following components.

- Forget gate
- Input gate.
- Output gate



6.2) BERT

We can use BERT for problems which needs Language understanding:

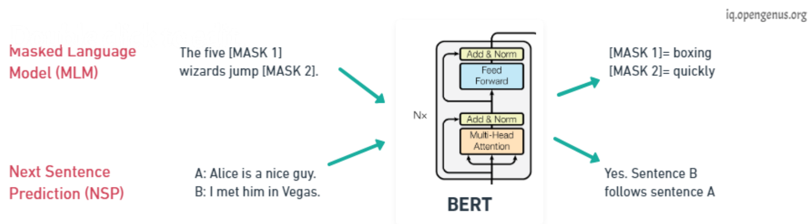
- Neural Machine Translation
- Sentiment Analysis
- Question Answering
- Text summarization

These problems can be solved by **BERT Training phases** which are:

1. **Pretain** BERT to understand language and context.
2. **Fine tune** BERT to learn how to solve a specific task.

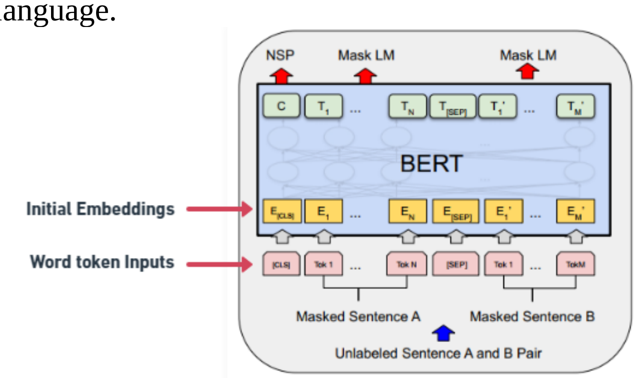
. Pre-training

The goal of pre training is to make BERT learn *what is language and what is context*? BERT learns language by training on two Unsupervised tasks simultaneously, they are **Mass Language Modeling (MLM)** and **Next Sentence Prediction (NSP)**.



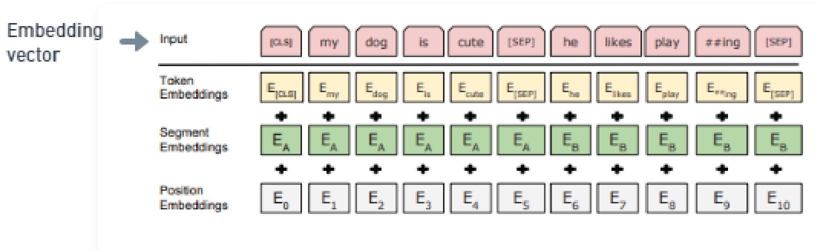
For **Mass Language Modeling**, BERT takes in a sentence with random words filled with masks. The goal is to output these masked tokens and this is kind of like fill in the blanks it helps BERT understand a bi-directional context within a sentence.

In the case of **Next Sentence Prediction**, BERT takes in two sentences and it determines if the second sentence actually follows the first, in kind of like a binary classification problem. This helps BERT understand context across different sentences themselves and using both of these together BERT gets a good understanding of language.

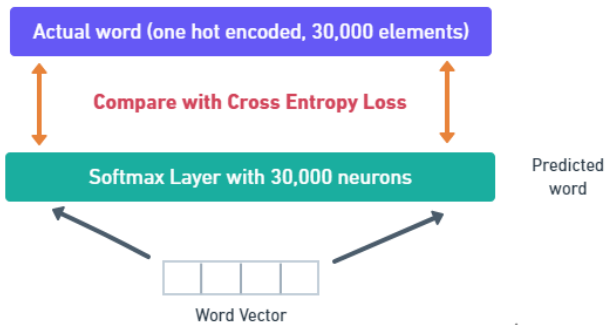


During BERT pre-training the training is done on Mass Language Modeling and Next Sentence Prediction. In practice both of these problems are trained simultaneously, the input is a set of two sentences with some of the words being **masked** (each token is a word) and convert each of these words into **embeddings** using **pre-trained embeddings**. On the output side **C is the binary output for the next sentence prediction** so it would output 1 if sentence B follows sentence A in context and 0 if sentence B doesn't follow sentence A. Each of the **T's here are word vectors that correspond to the outputs for the mass language model problem**, so the number of word vectors that is input is the same as the number of word vectors that we got as output.

On the input side, how are we going to generate embeddings from the word token inputs?



The initial embedding is constructed from three vectors, the **token embeddings** are the pre-trained embeddings; the main paper uses **word-pieces embeddings** that have a vocabulary of 30,000 tokens. The **segment embeddings** is basically the sentence number that is encoded into a vector and the **position embeddings** is the position of a word within that sentence that is encoded into a vector. Adding these three vectors together we get an embedding vector that we use as input to BERT. The **segment and position embeddings are required for temporal ordering** since all these vectors are fed in simultaneously into BERT and language models need this ordering preserved.



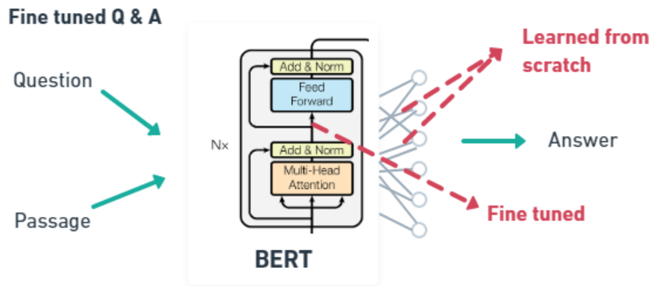
The output is a binary value **C** and a bunch of word vectors but with training we need to minimize a loss. So two key details to note here all of these word vectors have the same size and all of these word vectors are generated simultaneously, we need to take each word vector pass it into a fully connected layered output with the same number of neurons equal to the number of tokens in the vocabulary so that would be an **output layer corresponding to 30,000 neurons in this case and we would apply a softmax activation**. This way we would convert a word vector to a distribution and the **actual label of this distribution would be a one hot encoded vector** for the actual word and so we **compare these two distributions and then train the network using the cross entropy loss**.

But note that the output has all the words even though those inputs weren't masked at all. The loss though only considers the prediction of the masked words and it ignores all the other words that are output by the network this is done to ensure that **more focus is given to predicting [MASK]ed values** so that it gets them correct and it increases context awareness.

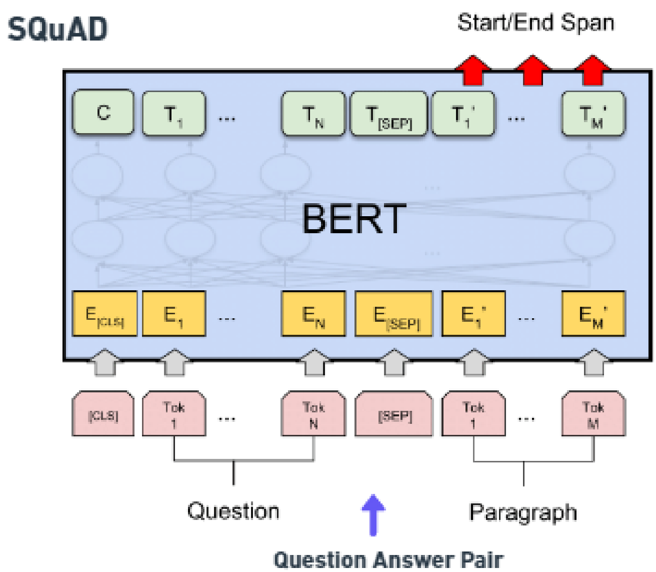
Once training is complete BERT has some notion of language as it's a language model.

2. Fine-tuning

We can now further train BERT on very specific NLP tasks for example let's *take question answering*, all we need to do is replace the fully connected output layers of the network with a fresh set of output layers that can basically output the answer to the question we want.



Then supervised training can be performed using a question answering dataset it won't take long since it's only the output parameters that are *learned from scratch*, the rest of the model parameters are just slightly *fine-tuned* and as a result training time is fast. This can be done for any NLP problem that is replace the output layers and then train with a specific dataset.



Now on the fine tuning phase, if we wanted to perform question-answering we would **train the model by modifying the inputs and the output layer**. We **pass in the question followed by a passage containing the answer as inputs** and in the **output layer we would output Start and the End words** that encapsulate the answer assuming that the answer is within the same span of text.

7. RESULTS:

Our project gave out the accuracy of 72%

The output labels are the predictions if the data sample is real or not.

```
import tokenizer
```

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats


from tensorflow.python.keras.models import Sequential
from tensorflow.python.keras.layers import Dense, Embedding,LSTM
from tensorflow.keras.preprocessing.text import Tokenizer
from keras.optimizers import Adam
from keras.layers import Dropout
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.python.keras.models import load_model
from sklearn.model_selection import train_test_split

import re
import nltk
nltk.download("stopwords")
from nltk.corpus import stopwords
nltk.download('punkt')

import warnings
warnings.filterwarnings("ignore")
```

```
[ ] data=data.drop(['discourse_id','essay_id'],axis='columns')
    data.head()
```

	discourse_text	discourse_type	discourse_effectiveness
0	Hi, i'm Isaac, i'm going to be writing about h...	Lead	Adequate
1	On my perspective, I think that the face is a ...	Position	Adequate
2	I think that the face is a natural landform be...	Claim	Adequate
3	If life was on Mars, we would know by now. The...	Evidence	Adequate
4	People thought that the face was formed by ali...	Counterclaim	Adequate

```
[ ] data.shape

(36765, 3)

[ ] data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36765 entries, 0 to 36764
Data columns (total 3 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   discourse_text           36765 non-null  object
 1   discourse_type           36765 non-null  object
 2   discourse_effectiveness  36765 non-null  object
```

```
data.describe()
```

	discourse_text	discourse_type	discourse_effectiveness
count	36765	36765	36765
unique	36691	7	3
top	Summer projects should be student-designed	Evidence	Adequate
freq	14	12105	20977

```
new_label = {"discourse_effectiveness": {"Ineffective": 0, "Adequate": 1, "Effective": 2}}
data = data.replace(new_label)
data = data.rename(columns = {"discourse_effectiveness": "label"})
data.head()
```

	discourse_text	discourse_type	label
0	Hi, i'm Isaac, i'm going to be writing about h...	Lead	1
1	On my perspective, I think that the face is a ...	Position	1
2	I think that the face is a natural landform be...	Claim	1
3	If life was on Mars, we would know by now. The...	Evidence	1
4	People thought that the face was formed by ali...	Counterclaim	1

```
#data is adjusted according to the number of tokens specified
x_train_pad = pad_sequences(x_train_tokens, maxlen=max_tokens)
x_test_pad = pad_sequences(x_test_tokens, maxlen=max_tokens)
x_train_pad.shape
```

```
(29412, 68)
```

```
idx = tokenizer.word_index
inverse_map = dict(zip(idx.values(), idx.keys()))

def return_to_sentence(tokens):
    words = [inverse_map[token] for token in tokens if token!=0]
    text = ' '.join(words)
    return text
```

```
#normal comment
print(return_to_sentence(x_train_pad[9]))
```

```
shows nasa trying keep sercet head mouth eyes noes ears mars trying put type effort get deeper situation even assummed normal planet nobody lived unusal head poped nowhere planet mars
```

```
#token equivalent of comment
print(x_train_pad[9])
```

```
[    0     0     0     0     0     0     0     0     0     0     0     0
     0     0     0     0     0     0     0     0     0     0     0     0
     0     0     0     0     0     0     0     0     0     0     0     0
     0     0   235   129   190    93 10420   768   842   512 10421  6179
```

- LSTM model results

```
from tensorflow.python.keras.optimizer_v2.rmsprop import RMSProp
model = Sequential()

embedding_size = 50

model.add(Embedding(input_dim=15000,output_dim=embedding_size,input_length=max_tokens,name='embedding_layer'))

model.add(LSTM(units=16, return_sequences=True))
model.add(Dropout(0.1))

model.add(LSTM(units=8, return_sequences=True))
model.add(Dropout(0.1))

model.add(LSTM(units=4))
model.add(Dropout(0.1))

model.add(Dense(1, activation='relu'))

optimizer = RMSProp()

model.compile(loss='mean_squared_error',optimizer=optimizer,metrics=['accuracy'])
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_layer (Embedding)  (None, 68, 50)            750000
```

```
[ ] model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_layer (Embedding)  (None, 68, 50)            750000
_________________________________________________________________
lstm (LSTM)                  (None, 68, 16)            4288
_________________________________________________________________
module_wrapper (ModuleWrappe (None, 68, 16)            0
_________________________________________________________________
lstm_1 (LSTM)                (None, 68, 8)             800
_________________________________________________________________
module_wrapper_1 (ModuleWrap (None, 68, 8)             0
_________________________________________________________________
lstm_2 (LSTM)                (None, 4)                 208
_________________________________________________________________
module_wrapper_2 (ModuleWrap (None, 4)                 0
_________________________________________________________________
dense (Dense)                (None, 1)                 5
=================================================================
Total params: 755,301
Trainable params: 755,301
Non-trainable params: 0
_________________________________________________________________
```

ACCURACY

LSTM

```
206/206 [==============================] - 35s 168ms/step - loss: 0.0503 - accuracy: 0.7180 - val_loss: 0.5103 - val_accuracy: 0.5222
Epoch 77/90
206/206 [==============================] - 35s 168ms/step - loss: 0.0496 - accuracy: 0.7188 - val_loss: 0.5182 - val_accuracy: 0.5171
Epoch 78/90
206/206 [==============================] - 35s 169ms/step - loss: 0.0502 - accuracy: 0.7183 - val_loss: 0.5140 - val_accuracy: 0.5266
Epoch 79/90
206/206 [==============================] - 36s 177ms/step - loss: 0.0506 - accuracy: 0.7185 - val_loss: 0.5192 - val_accuracy: 0.5233
Epoch 80/90
206/206 [==============================] - 36s 173ms/step - loss: 0.0492 - accuracy: 0.7188 - val_loss: 0.5145 - val_accuracy: 0.5249
Epoch 81/90
206/206 [==============================] - 35s 169ms/step - loss: 0.0466 - accuracy: 0.7210 - val_loss: 0.5205 - val_accuracy: 0.5240
Epoch 82/90
206/206 [==============================] - 35s 169ms/step - loss: 0.0488 - accuracy: 0.7197 - val_loss: 0.5253 - val_accuracy: 0.5226
Epoch 83/90
206/206 [==============================] - 35s 168ms/step - loss: 0.0486 - accuracy: 0.7205 - val_loss: 0.5016 - val_accuracy: 0.5288
Epoch 84/90
206/206 [==============================] - 34s 167ms/step - loss: 0.0459 - accuracy: 0.7228 - val_loss: 0.5239 - val_accuracy: 0.5236
Epoch 85/90
206/206 [==============================] - 35s 169ms/step - loss: 0.0460 - accuracy: 0.7222 - val_loss: 0.5136 - val_accuracy: 0.5290
Epoch 86/90
206/206 [==============================] - 35s 169ms/step - loss: 0.0455 - accuracy: 0.7226 - val_loss: 0.5160 - val_accuracy: 0.5245
Epoch 87/90
206/206 [==============================] - 35s 171ms/step - loss: 0.0451 - accuracy: 0.7227 - val_loss: 0.5211 - val_accuracy: 0.5237
Epoch 88/90
206/206 [==============================] - 36s 174ms/step - loss: 0.0457 - accuracy: 0.7208 - val_loss: 0.5156 - val_accuracy: 0.5308
Epoch 89/90
206/206 [==============================] - 35s 170ms/step - loss: 0.0450 - accuracy: 0.7227 - val_loss: 0.5082 - val_accuracy: 0.5345
Epoch 90/90
206/206 [==============================] - 35s 170ms/step - loss: 0.0443 - accuracy: 0.7235 - val_loss: 0.5140 - val_accuracy: 0.5332
```

```
result = model.evaluate(x_test_pad, y_test)
```

```
230/230 [==============================] - 5s 20ms/step - loss: 0.4988 - accuracy: 0.5473
```

Bert

```
----Building the model----
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_ids (InputLayer)         [(None, 69)]         0           []

 attention_mask (InputLayer)    [(None, 69)]         0           []

 tf_distil_bert_model (TFDistil  TFBaseModelOutput(l  66362880   ['input_ids[0][0]',
 BertModel)                     ast_hidden_state=(N               'attention_mask[0][0]']
                                one, 69, 768),
                                 hidden_states=None
                                , attentions=None)

 tf.__operators__.getitem (Slic  (None, 768)         0           ['tf_distil_bert_model[0][0]']
 ingOpLambda)

 dense (Dense)                  (None, 512)          393728      ['tf.__operators__.getitem[0][0]'
                                                                 ]

 dropout_22 (Dropout)           (None, 512)          0           ['dense[0][0]']

 dense_1 (Dense)                (None, 3)            1539        ['dropout_22[0][0]']

==================================================================================================
Total params: 66,758,147
Trainable params: 66,758,147
Non-trainable params: 0
__________________________________________________________________________________________________
Epoch 1/2
197/197 [==============================] - 9068s 46s/step - loss: 1.2493 - accuracy: 0.5454 - val_loss: 0.8683 - val_accuracy: 0.6062
Epoch 2/2
197/197 [==============================] - 9061s 46s/step - loss: 0.9203 - accuracy: 0.5947 - val_loss: 0.9293 - val_accuracy: 0.6072
197/197 [==============================] - 2627s 13s/step - loss: 0.9269 - accuracy: 0.6132
Train score: [0.9268680214881897, 0.6131582260131836]
50/50 [==============================] - 657s 13s/step - loss: 0.9293 - accuracy: 0.6072
Validation score: [0.9293137788772583, 0.6071732044219971]
```

8. CONCLUSION:

To conclude, our project Student responses became a standard evaluation criterion in several fields like secondary education, academics, software recruitment's etc. As there are huge number of applicants or participants, it’s a hurdle for human evaluators to assess each response and predict it. It will kill huge amount of time and delay the process. Student Responses are collections of sentences and paragraphs that are useful to analyze the “effective”, “adequate”, or “ineffective” based on some parameters. Here used models are LSTM and Bert, between them lstm has good accuary of 0.72%

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