PREDICTING EFFECTIVE ARGUMENTS THROUGH STUDENT RESPONSES

A Capstone project report
in partial fulfillment of the requirement for the award of the degree

BACHELOR OF TECHNOLOGY
in
COMPUTER SCIENCE & ENGINEERING
and
ELECTRONICS AND COMMUNICATION ENGINEERING
By

19K41A0599	IRUKULLA APOORVA
19K41A05B6	T.PHANI PRIYA
19K41A04G6	M .SNEHA

Under the guidance of

D. Ramesh Kumar

Assistant Professor, Department of CSE.

SR ENGINEERING COLLEGE

Ananthasagar, Warangal.

<u>**CERTIFICATE**</u>

This is to certify that this project entitled **“PREDICTING EFFECTIVE ARGUMENTS THROUGH STUDENT RESPONSES”** is the bonafide work carried out by **IRUKULLA APOORVA, T.PHANIPRYA, M.SNEHA,** bearing Roll No(s) 19K41A0599,19K41A05B6,19K41A04G6 as a Capstone project for the partial fulfillment to award the degree **BACHELOR OF TECHNOLOGY** in **COMPUTER SCIENCE & ENGINEERING /ELECTRICAL & ELECTRONICS ENGINEERING** during the academic year 2022-2023 under our guidance and Supervision.

Mr. D. RAMESH
Asst. Professor,
S R Engineering College,
Ananthasagar, Warangal

Dr.M. Sheshikala
Assoc. Prof. & HOD (CSE),
S R Engineering College,
Ananthasagar, Warangal

External Examiner

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.

Table of contents

INTRODUCTION

1.1 OVERVIEW

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.

1.2 RELATED WORK:

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. compared performance on three essay scoring tasks with different characteristics, contrasting results with a strong feature-based system.

1.3PRESENT WORK

In the proposed system we are using LSTM and Bert

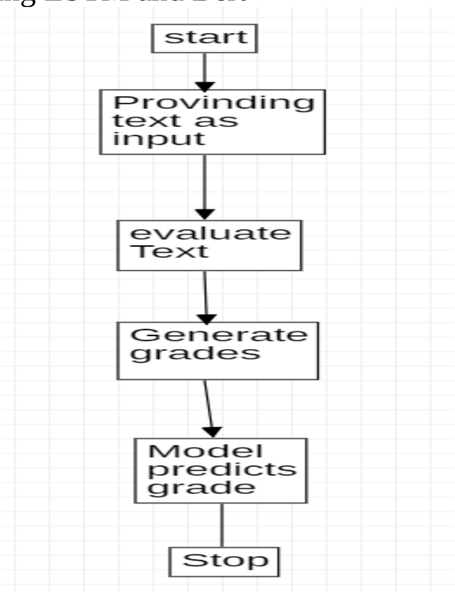


Fig: 1.1 *Overview of proposed system*

2. LITERATURE SURVEY

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

3.Design

3.1 REQUIREMENT SPECIFICATION(S/W & H/W)

Hardware Requirements

- ✓ **System** : Pentium 4, Intel Core i3, i5, i7 and 2GHz Minimum
- ✓ **RAM** : 4GB or above
- ✓ **Hard Disk** : 10GB or above
- ✓ **Input** : Keyboard and Mouse
- ✓ **Output** : Monitor or PC

Software Requirements

- ✓ **OS** : Windows 8 or Higher Versions
- ✓ **Platform** : Jupiter Notebook
- ✓ **Program Language** : Python

4. DATA-SET

Training.csv file

	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 v	Countercla	Adequate	
10	28a94d3e	007ACE74	Though pe	Concluding	Adequate	
11	d226f0636	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	6efd91022	00944C69	the enviro	Claim	Effective	
16	d6807f31c	00944C69	"Passeng	Evidence	Effective	
17	024f3edf0	00944C69	, adding th	Claim	Effective	

train

Train folder

Downloads › feedback-prize-effectiveness.zip › train

Name	Type
000E6DE9E817.txt	Text Document
00B144412785.txt	Text Document
00BD97EA4041.txt	Text Document
00C6E82FE5BA.txt	Text Document
00D304153840.txt	Text Document
00E3F86E3E6A.txt	Text Document
0A5B8761B187.txt	Text Document
0A5BA91AA8B5.txt	Text Document
0A6C0B6D3925.txt	Text Document
0A6F7ECC5B8F.txt	Text Document
0A618B980D2D.txt	Text Document
0A6324CE9AD0.txt	Text Document
0AA8E5C89F0F.txt	Text Document
0AB5C0C20670.txt	Text Document
0ABF4F99E166.txt	Text Document
0AC09FD13E72.txt	Text Document
0ACB0E08934E.txt	Text Document
0AD7535C58C0.txt	Text Document
0B2C0C1833BF.txt	Text Document
0B4FAC7A4A8B.txt	Text Document
0B5BFD4E5904.txt	Text Document
0B6B5E779566.txt	Text Document
0B8A0777A6E5.txt	Text Document
0B52B1F1265B.txt	Text Document
0B80CB0B2F3B.txt	Text Document
0B81C3067FF2.txt	Text Document
0B87B0B3278C.txt	Text Document

Testing.csv

	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						

5. Pre-processing

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:

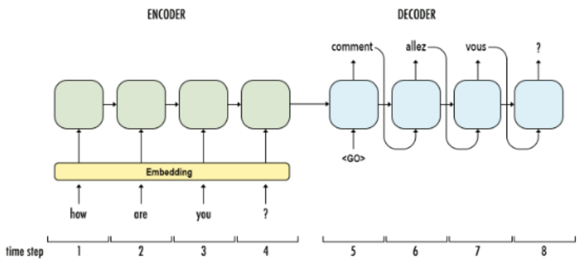
Tokenization is the first step in any NLP pipeline. It has an important effect on the rest of your pipeline. A tokenizer breaks unstructured data and natural language text into chunks of information that can be considered as discrete elements. The token occurrences in a document can be used directly 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

1) LSTM Model

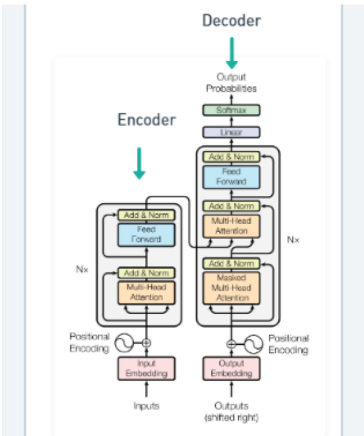


Initially LSTM networks had been used to solve the Natural Language Translation problem but they had a few problems. LSTM networks are-

- Slow to train. Words are passed in sequentially and are generated sequentially it can take a significant number of timesteps for the neural net to learn.
- It's not really the best of capturing the true meaning of words, even bi-directional LSTMS are not. Because even here they are technically learning left to right and right to left context separately and then concatenating them so the true context is lost.

Transformer Architecture

This is the transformer neural network architecture that was initially created to solve the problem of language translation.

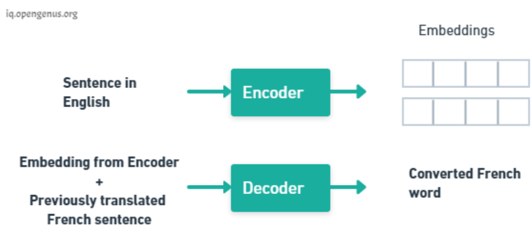


Transformer architecture addresses some of the drawback of LSTM:-

- They are faster as words can be processed simultaneously.
- The context of words is better learned as they can learn context from both directions simultaneously.

Transformer Flow

Now let's see the transformer in action. Say we want to train this architecture to convert English to French.



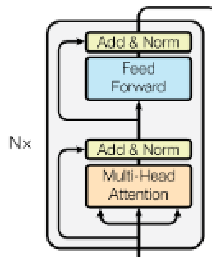
The transformer consists of two key components an Encoder and a Decoder.

The Encoder takes the English words simultaneously and it generates embeddings for every word simultaneously these embeddings are vectors that encapsulate the meaning of the word, similar words have closer numbers in their vectors. The Decoder takes these embeddings from the Encoder and the previously generated words of the translated French sentence and then it uses them to generate the next French word and we keep generating the French translation one word at a time until the end of sentence is reached.

What makes Transformer conceptually stronger than LSTM cell is that we can physically see a separation in tasks. The Encoder learns What is English and its grammar? and What is context? The Decoder learns how do English words relate to French words. Separately they both have some underlying understanding of language and it's because of this understanding that we can pick apart this architecture and build systems that understand language.

We stack the decoders and we get the GPT (Generative Pre-training) transformer architecture, conversely if we stack just the encoders we get BERT a bi-directional encoder representation from transformer.

2)BERT



BERT

We can use BERT for problems which needs Language understanding:

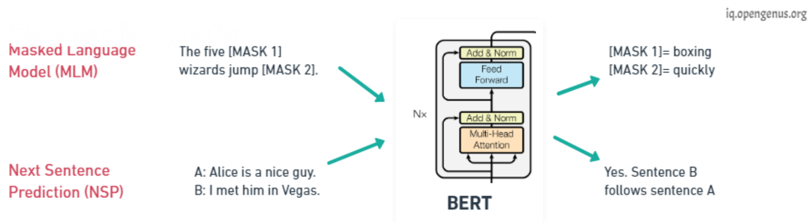
- Neural Machine Translation
- Sentiment Analysis
- Question Answering
- Text summarization

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.

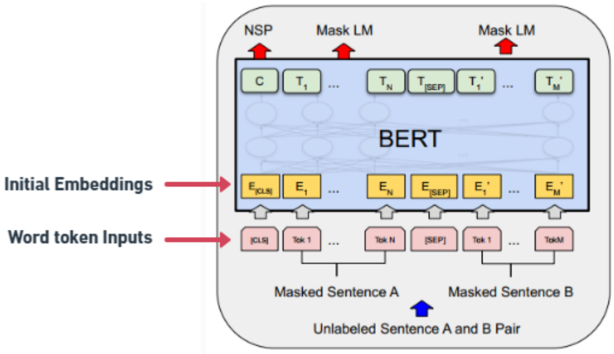
1. Pre-training

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).



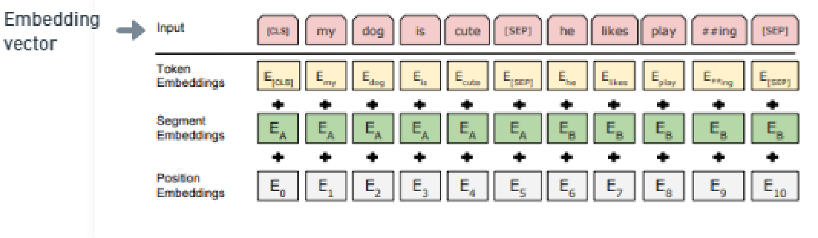
For Mass Language Modeling, BERT takes in a sentence with random words filled with masks. The goal is to output these masked tokens and this is kind of like fill in the blanks it helps BERT understand a bi-directional context within a sentence.

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.

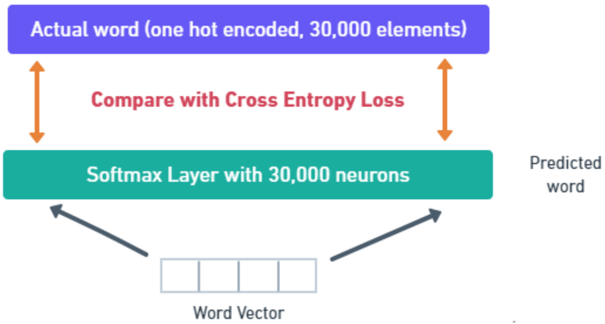


During BERT pre-training the training is done on Mass Language Modeling and Next Sentence Prediction. In practice both of these problems are trained simultaneously, the input is a set of two sentences with some of the words being masked (each token is a word) and convert each of these words into embeddings 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.



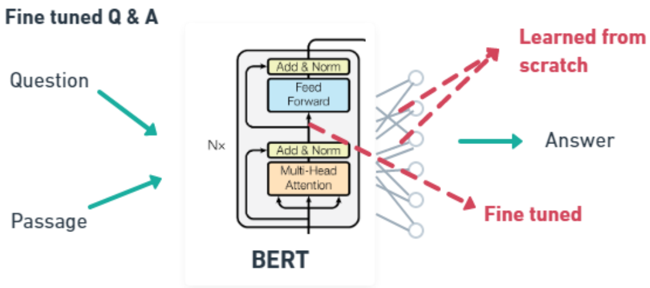
The output is a binary value C and a bunch of word vectors but with training we need to minimize a loss. So two key details to note here all of these word vectors have the same size and all of these word vectors are generated simultaneously, we need to take each word vector pass it into a fully connected 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.

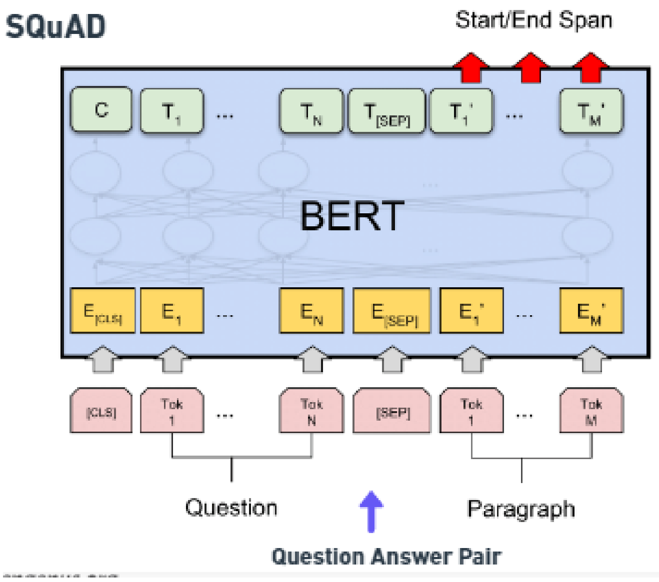
Once training is complete BERT has some notion of language as it's a language model.

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.

Code:

```
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.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

```
def gen_freq(text):
    #will store all the words in list
    words_list = []

    #Loop over all the words and extract word from list
    for word in text.split():
        words_list.extend(word)

    #Generate word frequencies using value counts in word_list
    word_freq = pd.Series(words_list).value_counts()

    #print top 100 words
    word_freq[:100]

    return word_freq
```

```
freq = gen_freq(data.discourse_text.str)
freq
```

```
the            77217
to             57242
a              38013
and            36578
of             33395
                ...
cluping            1
clup               1
leasat             1
coumputer's        1
someones'          1
Length: 53022, dtype: int64
```

```
from nltk.corpus import stopwords
stop_word_list = stopwords.words('english')
from nltk.tokenize import word_tokenize,sent_tokenize
from nltk.tokenize.toktok import ToktokTokenizer
```

```
tokenizer=ToktokTokenizer()
```

```
def remove_stopwords(text, is_lower_case=False):
    tokens = tokenizer.tokenize(text)
    tokens = [token.strip() for token in tokens]
    if is_lower_case:
        filtered_tokens = [token for token in tokens if token not in stop_word_list]
    else:
```

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(data,label,test_size = 0.2, random_state = 42)
```

```
from tensorflow.keras.preprocessing.text import Tokenizer

tokenizer = Tokenizer(num_words = 15000)
tokenizer.fit_on_texts(data)
#tokenizer.word_index
```

```
x_train_tokens = tokenizer.texts_to_sequences(x_train)
x_test_tokens = tokenizer.texts_to_sequences(x_test)
```

```
#Then we take the word count of each of our sentences in our data and create a list.
num_tokens = [len(tokens) for tokens in x_train_tokens + x_test_tokens]
num_tokens = np.array(num_tokens)
```

```
#Here, when setting the number of tokens, a number is determined by taking into account the variability around the average.
max_tokens = np.mean(num_tokens) + 2 * np.std(num_tokens)
max_tokens = int(max_tokens)
max_tokens
```

```
68
```

```
#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
```

```
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
_________________________________________________________________
```

7.Results

```
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.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

```
def remove_stopwords(text, is_lower_case=False):
    tokens = tokenizer.tokenize(text)
    tokens = [token.strip() for token in tokens]
    if is_lower_case:
        filtered_tokens = [token for token in tokens if token not in stop_word_list]
    else:
        filtered_tokens = [token for token in tokens if token.lower() not in stop_word_list]
    filtered_text = ' '.join(filtered_tokens)
    return filtered_text
#Apply function on review column
data['discourse_text']= data['discourse_text'].apply(remove_stopwords)
```

```
import re
#clearing punctuation & unnecessary marks
data['discourse_text'] = data['discourse_text'].apply(lambda x: re.sub('[,\.!?:()"]', '', x))
data['discourse_text'] = data['discourse_text'].apply(lambda x: re.sub('[^a-zA-Z"]', ' ', x))

#capitalization to lowercase
data['discourse_text'] = data['discourse_text'].apply(lambda x: x.lower())

#cleaning extra spaces
data['discourse_text'] = data['discourse_text'].apply(lambda x: x.strip())
```

```
history = model.fit(x_train_pad, y_train, validation_split=0.3, epochs=90, batch_size=100, shuffle=True, verbose = 1)

Epoch 1/90
206/206 [==============================] - 44s 174ms/step - loss: 0.4908 - accuracy: 0.5333 - val_loss: 0.3318 - val_accuracy: 0.5697
Epoch 2/90
206/206 [==============================] - 37s 182ms/step - loss: 0.3427 - accuracy: 0.5742 - val_loss: 0.3197 - val_accuracy: 0.5699
Epoch 3/90
206/206 [==============================] - 35s 170ms/step - loss: 0.3154 - accuracy: 0.5790 - val_loss: 0.3208 - val_accuracy: 0.5641
Epoch 4/90
206/206 [==============================] - 35s 167ms/step - loss: 0.2960 - accuracy: 0.5851 - val_loss: 0.3181 - val_accuracy: 0.5650
Epoch 5/90
206/206 [==============================] - 35s 171ms/step - loss: 0.2788 - accuracy: 0.5906 - val_loss: 0.3265 - val_accuracy: 0.5614
Epoch 6/90
206/206 [==============================] - 34s 167ms/step - loss: 0.2628 - accuracy: 0.6000 - val_loss: 0.3239 - val_accuracy: 0.5672
Epoch 7/90
206/206 [==============================] - 35s 170ms/step - loss: 0.2502 - accuracy: 0.6067 - val_loss: 0.3363 - val_accuracy: 0.5617
Epoch 8/90
206/206 [==============================] - 35s 171ms/step - loss: 0.2405 - accuracy: 0.6122 - val_loss: 0.3489 - val_accuracy: 0.5507
Epoch 9/90
206/206 [==============================] - 35s 168ms/step - loss: 0.2283 - accuracy: 0.6190 - val_loss: 0.3451 - val_accuracy: 0.5626
Epoch 10/90
206/206 [==============================] - 34s 167ms/step - loss: 0.2162 - accuracy: 0.6250 - val_loss: 0.3541 - val_accuracy: 0.5572
Epoch 11/90
206/206 [==============================] - 36s 174ms/step - loss: 0.2057 - accuracy: 0.6297 - val_loss: 0.3495 - val_accuracy: 0.5622
Epoch 12/90
206/206 [==============================] - 35s 171ms/step - loss: 0.1976 - accuracy: 0.6356 - val_loss: 0.3560 - val_accuracy: 0.5595
Epoch 13/90
206/206 [==============================] - 36s 177ms/step - loss: 0.1895 - accuracy: 0.6390 - val_loss: 0.3763 - val_accuracy: 0.5563
Epoch 14/90
206/206 [==============================] - 35s 168ms/step - loss: 0.1803 - accuracy: 0.6437 - val_loss: 0.3668 - val_accuracy: 0.5519
```

```
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

```
Untitled17.ipynb > from tensorflow.python.keras.optimizer_v2.rmsprop import RMSProp
+ Code  + Markdown | Run All  Clear Outputs of All Cells  Restart | ...    base (Python 3.9.7)

 tf_distil_bert_model_2 (TFDist  TFBaseModelOutput(l  66362880   ['input_ids[0][0]',
 ilBertModel)                   ast_hidden_state=(N               'attention_mask[0][0]']
                                one, 69, 768),
                                 hidden_states=None
                                , attentions=None)

 tf.__operators__.getitem_5 (Sl  (None, 768)          0          ['tf_distil_bert_model_2[2][0]']
 icingOpLambda)

 dense_10 (Dense)               (None, 512)          393728     ['tf.__operators__.getitem_5[0][0
                                                                 ]']

 dropout_65 (Dropout)           (None, 512)          0          ['dense_10[0][0]']

 dense_11 (Dense)               (None, 3)            1539       ['dropout_65[0][0]']

...
736/736 [==============================] - 869s 1s/step - loss: 1.0986 - accuracy: 0.1754
Train score: [1.0986171960830688, 0.17535807192325592]
184/184 [==============================] - 203s 1s/step - loss: 1.0986 - accuracy: 0.1792
Validation score: [1.0986136198043823, 0.17916029691696167]
```

```
----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]
```

7. Conclusion

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%

8. References

[1] Uto, M., Okano, M. (2020). Robust Neural Automated Essay Scoring Using Item Response Theory. In: Bittencourt, I., Cukurova, M., Muldner, K., Luckin, R., Millán, E. (eds) Artificial Intelligence in Education. AIED 2020. Lecture Notes in Computer Science(), vol 12163. Springer, Cham. https://doi.org/10.1007/978-3-030-52237-7_44 https://link.springer.com/chapter/10.1007/978-3-030-52237-7_44

[2] Z. Chen and Y. Zhou, "Research on Automatic Essay Scoring of Composition Based on CNN and OR," *2019 2nd International Conference on Artificial Intelligence and Big Data (ICAIBD)*, 2019, pp. 13-18, doi: 10.1109/ICAIBD.2019.8837007.

[3] Ramesh, D., Sanampudi, S.K. An automated essay scoring systems: a systematic literature review. Artif Intell Rev 55, 2495–2527 (2022). https://doi.org/10.1007/s10462-021-10068-2 https://link.springer.com/article/10.1007/s10462-021-10068-2

[4] Christopher Ormerod(Septem,2019), "Language models and Automated Essay Scoring", **arXiv:1909.09482** (cs). https://arxiv.org/abs/1909.09482

[5] Yongjie Wang, Chuan Wang (May,2022). "Use of bert for automated essay scoring", **arXiv:2205.03835** (cs). https://arxiv.org/abs/2205.03835

[6] Guoxi Liang, Dongwon Jeong (2018). "Essay scoring using Neural networks", DOI:10.3390/sym10120682. https://www.researchgate.net/publication/329378585_Automated_Essay_Scoring_A_Siamese_Bidirectional_LSTM_Neural_Network_Architecture

[7] Jumoke Eluwa, Shade O Kuyore (April,2022) . "Essay scoring Model Based on Gated Recurrent unit Technique", DOI:10.32628/IJSRSET229257 https://www.researchgate.net/publication/360440446_Essay_Scoring_Model_Based_on_Gated_Recurrent_Unit_Technique

[8] JOUR,Eluwa, Jumoke,Kuyoro, Shade,O., Awodele,A., Ajayi,2022/04/30,323330"Essay Scoring Model Based on Gated Recurrent Unit Technique",10.32628/IJSRSET229257,International Journal of Scientific Research in Science, Engineering and Technology, https://www.researchgate.net/publication/360440446_Essay_Scoring_Model_Based_on_Gated_Recurrent_Unit_Technique/citation/download

[9] Beseiso, M., Alzubi, O.A. & Rashaideh, H. A novel automated essay scoring approach for reliable higher educational assessments. J Comput High Educ 33, 727–746 (2021). https://doi.org/10.1007/s12528-021-09283-1 https://link.springer.com/article/10.1007/s12528-021-09283-1

[10] Farah Nadeem, Huy Nguyen, Yang Liu, and Mari Ostendorf. 2019. Automated Essay Scoring with Discourse-Aware Neural Models. In Proceedings of the Fourteenth Workshop on Innovative Use of NLP for Building Educational Applications, pages 484–493, Florence, Italy. Association for Computational Linguistics. https://aclanthology.org/W19-4450/