NATURAL LANGUAGE PROCESSING

CSE4022

PROJECT REPORT

PROJECT TITLE-

Using Transformers and Recurrent Neural Network
(Bi- LSTM and Bi-GRU) to Identify Clickbaits.

TEAM MEMBERS- (Group 13)

1. Soumyaraj Roy , 19BCE0200
2. Kaustubh Dwivedi, 19BCE0249
3. Rebello Nishma Avalon, 19BCE0253
4. Debangsu Sarkar, 19BCE0902

1. ABSTRACT-

Clickbait is a widespread problem that troubles online readers and misleads the readers to an irrelevant site. Currently, detection of clickbait on tweets remains a challenging task.

In this project, we propose to build a Clickbait Detector using Bidirectional Encoder Representations from Transformers (BERT), which can effectively identify click-baits using the latest developments in advanced training methods like BERT and Longformer and using Recurrent Neural Networks (Bi. - LSTM and Bi-GRU) with a parallel model structure.

Our model will support end-to-end training without incorporating any manual features and achieve efficient results. We will approach this task as a regression problem in our two parallel baseline models for benchmarking with previous models. The model will take the post title and the linked content as input and will output a clickbait score in the range of [0, 1] with 0 indicating non-clickbait and 1 indicating clickbait.

By training on a large twitter posts corpus with annotations of their ‘click-baitness’ on a scale of [0, 1], we expect our model to be capable of capturing clickbait patterns in the headline and the content.

2. INTRODUCTION-

Clickbait refers to a certain kind of headline that attracts people to click but gives something uncorrelated in that link. The motivation behind clickbaiting is to boost site traffic (and therefore, advertisement revenue) by exploiting the curious nature of human readers. The clickbait technique works by dangling a hyperlink with enticing headlines to lure people into clicking; and then redirect them to the publishers' own websites which are uncorrelated to the headline.

The discrepancy between the headline and the destination content wastes online readers significant amount of time on contents of which they have no interest. To address this problem, we propose Click-BERT*: (Clickbait Detector with Bidirectional Encoder Representations from Transformers), which could effectively identify clickbaits utilizing state-of-the-arrt pre-training methods and self-attentive network. We approach this task as a regression problem in our two parallel baseline models for benchmarking with previous models. The model takes the post title and the linked content as input and will output a clickbait score in the range of [0, 1] with 0 indicating non-clickbait and 1 indicating clickbait. By training on a large twitter posts corpus with annotations of their 'clickbaitness' on a scale of [0, 1], we expect our model to be capable of capturing clickbait patterns in the headline and the content.

Main challenges of the clickbait detection problems lies-

in how well our model capture the meaning and correlation of the input headline/content (which differs greatly in length) and how properly the followed analysis gets performed. And our main contributions include:

1. We applies advanced pre-trained models BERT and Longformer to extract sequence (headline/content) embedding to form a better understanding of the headline and the content.

2. We proposes a parallel model structure to integrate both prediction of whether the headline is luring people to click and prediction of whether the headline is related with the content into final judgement.

3. LITERATURE REVIEW

S. No.	Paper Title & Details	Method/Algorithm	Challenges	Observations
1.	Clickbait Detection in YouTube Videos. Authors- Ruchira Gothankar, Fabio Di Troia, Mark Stamp. Year- 2021	The authors performed clickbait detection experiments are based on a set of labeled videos. The problem is formulated as a binary classification problem where for each video a machine learning algorithm classifies it is clickbait or non-clickbait. The information from multiple sources (e.g., title, description, comments) are combined and fed to the classification model. The performance is evaluated and analyzed by multiple measures, specifically, precision, recall and the F-score. BERT, Word2Vec, and DistilBERT were used for word embeddings	They confirmed that the accuracy of the models could be increased by adding more features. For future work, more features have to be included and also DocToVec embeddings could be considered.	Multiple classification techniques were considered, including logistic regression, random forest, and MLP, and we employed Word2Vec, BERT, and DistilBERT as language models. The best accuracy was achieved using an MLP classifier based on BERT embeddings which is 94.5 %, but a the more lightweight DistilBERT performed almost same.
2.	exBAKE: Automatic Fake News Detection Model Based on Bidirectional Encoder Representations from Transformers (BERT). Authors- Heejung Jwa , Dongsuk Oh, Kinam Park, Jang Mook Kang and Heuiseok Lim.	In this paper, the authors focus on data-driven automatic fake news detection methods. First they apply the Bidirectional Encoder Representations from Transformers model (BERT) model to detect fake news by analyzing the relationship between the headline and the body text of news. To further improve performance, additional	They experiment with various cases of fake news detection tasks using the pre-trained BERT model proposed in this study. They only analyzed the relationship between the headline and the body text of an article. But, Further experimentation is needed to apply data from other fake news detection tasks to	They determine that the deep-contextualizing nature of BERT is best suited for this task and improves the 0.14 F-score over older state-of-the-art models

		news data are gathered and used to pre-train this model.	BERT model, which will use additional news data in the pre-training phase.	
3.	Clickbait Headline Detection in Indonesian News Sites using Multilingual Bidirectional Encoder Representations from Transformers (M-BERT). Authors-Muhammad Noor Fakhruzzaman , Sa’idah Zahrotul Jannah, Ratih Ardiati Ningrum, Indah Fahmiyah. Year 2021.	This study contributes to show that Multilingual BERT, a state-of-the-art model is able to classify Indonesian clickbait headlines. By using BERT, the whole model looks simplified, using only a BERT layer and a hidden standard dense layer, finally topped with a sigmoid activated neuron, the classifier worked remarkably well with an average accuracy of 92%.	A further study is needed to evaluate the model versatility. Moreover, training a Neural Network with M-BERT took a lot of computing resource.	If efficiency is the priority, XGBoost can perform moderately well (80% avg.). The additional evaluation shows average accuracy of 0.83, precision of 0.82, recall of 0.83, and f1-score of 0.83
4.	Stop clickbait: Detecting and preventing clickbaits in online news media. Chakraborty, A., Paranjape, B., Kakarla, S. and Ganguly, N. IEEE	1. Authors did a definite phonetic investigation on the 15, 000 features both in the misleading content and non-misleading content, utilizing the Stanford CoreNLP tool. They examined how semantic and syntactic subtleties which are explicit to misleading content sources like Sentence Structure, Stop words, Determiners, Word N Grams, POS Tags. At last they characterized utilizing Feature selections like Word patterns, clickbait content language, N Gram features. At last they implement the classifier through a Browser extension.	1. Manually identify the clickbait articles from Clickbait-y sites, and to avoid false negatives we need multiple opinions as an article is a clickbait or not is a subjective opinion - We need to take majority vote. 2. Need to manually compiled a list of most commonly used bait phrases. 3. One issue about earlier works is that they either work on a single domain, or the fixed ruleset does not capture the nuances employed across different websites	1. Conventional non-clickbait headlines contain much larger proportion of proper nouns. 2. Clickbait headlines contain more adverbs and determiners There’s a lot of extreme positive or negative words in clickbait sites, called Hyperboles. 3. Informal Punctuations.

5.	Bert: Pre-training of deep bidirectional transformers for language understanding, J., Chang, M.W., Lee, K. and Toutanova, K., 2018	There are two steps in the BERT framework: pre-training and fine-tuning. During pre-training, the model is trained on unlabeled data over different pre-training tasks. For finetuning, the BERT model is first initialized with the pre-trained parameters, and all of the parameters are fine-tuned using labeled data from the downstream tasks. Each downstream task has separate fine-tuned models, even though they are initialized with the same pre-trained parameters	1. Deployment of BERT models in dynamic commercial environments often yields poor results. This is because commercial environments are usually dynamic, and contain continuous domain shifts (e.g. new themes, new vocabulary or new writing styles) between inference and training data, thus the challenge of dealing with dynamic cross-domain setups in which there is no labeled target-domain data, still remains. 2. BERT can be used only for answering questions from very short paragraphs and a lot of key issues need to be addressed. NLP as a general task is way too complex and has many more meanings and subtleties. BERT solves only a part of it but is certainly going to change entity Recognition models soon.	1. A distinctive feature of BERT is its unified architecture across different tasks. There is minimal difference between the pre-trained architecture and the final downstream architecture. 2. Recent empirical improvements due to transfer learning with language models have demonstrated that rich, unsupervised pre-training is an integral part of many language understanding systems. In particular, these results enable even low-resource tasks to benefit from deep unidirectional architectures. 3. To improve the training procedure, RoBERTa removes the Next Sentence Prediction (NSP) task from BERT’s pre-training and introduces dynamic masking so that the masked token changes during the training epochs. It was also trained on an order of magnitude more data than BERT, for a longer amount of time.

6.	Detecting and Categorization of Click Baits, INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT) NTASU – 2020 (Volume 09 – Issue 03). Sainath Patil, Mayur Koul, Harikrishan Chauhan, Prachi Patil, 2021.	The authors propose a completely unique approach considering all information found during a social media post. We train a bidirectional Long Short Term Memory(LSTM) with an attention mechanism to learn the extent to which a word contributes to the posts clickbait score in a differential manner. Sequence Followed: Data Collection, Word Embedding, Developing the Deep Learning Models.	1. The aforementioned Attention mechanism wasn't implemented into the paper, leading to us thinking that it might be hard to do so. 2. However, work done specifically for Twitter had to be expanded since clickbait was available throughout the Internet, and not just social networks. 3. Again, the definition of what a clickbait is and what isn't is vague and is an issue that needs to be discussed before approaching the required problem.	1. The primary instance of detecting clickbait across social media can be traced , hand-crafting linguistic features, including a reference dictionary of clickbait phrases, over a data set of crowdsourced tweets. 2. The features need to be more nuanced to avoid flagging non-clickbait articles.
7.	Unified Medical Language System resources improve sieve-based generation and BERT–based ranking for concept normalization 2020 Dongfang Xu ,1 Manoj Gopale,2 Jiacheng Zhang ,3 Kris Brown,4 Edmon Begoli,4 and Steven Bethard	Authors designed a sieve-based system over the training data, Unified Medical Language System (UMLS) preferred terms, and UMLS synonyms to generate a list of possible concepts for each mention.They then design a list-wise classifier based on the BERT neural network to rank the candidate concepts, integrating UMLS semantic types through a regularizer.	A major challenge is the unseen mentions and concepts: 50.76% (29.85%) of test mentions (concepts) were not seen in the training data. Systems that memorize the training data or rely on it to determine the space of output concepts will thus perform poorly. Also Lexical and grammatical variations are pervasive in such text, posing key challenges for data interoperability and the development of natural	Analysis of the model shows that prioritizing UMLS preferred terms yields better performance, that the UMLS semantic type regularize results in qualitatively better concept predictions, and that the model performs well even on concepts not seen during training.

			language processing (NLP) techniques.	
8.	A transformer based approach for fighting COVID-19 fake news 2021 S.M. Sadiq-Ur-Rahman Shifath1, Mohammad Faiyaz Khan2, and Md. Saiful Islam3	Authors performed experiments primarily on traditional language models such as Bidirectional LSTM(Bi-LSTM) with attention, 1 dimensional CNN(1D-CNN), Hierarchical Attention Networks(HAN), Recurrent convolutional Neural Networks(RCNN), and Multichannel CNN with Attention(AMCNN) on the competition dataset. We also experiment with transformer-based pre-trained models like BERT and RoBERTa.	Authors tested different hyper-parameters like the number of layers, number of units in a layer, learning rate, weight decay, dropouts, normalization, etc. within a feasible range which was a very difficult job, also they faced resource limitation for experimenting with larger models.	Authors have presented our overall workflow for the fake news detection task. They have conducted a number of experiments and provided a comprehensive solution based on modified transformers with additional layers and An ensemble classifier.
9.	A Comparative Analysis Of Classifiers Used For Detection of Clickbait In News Headlines. Aaryaman Bajaj , Himanshi Nimesh , Raghav Sareen , Dinesh Kumar Vishwakarma. Proceedings of the Fifth International Conference on Intelligent Computing and Control Systems (ICICCS 2021).	The authors compare the performance of different classifiers in detecting the clickbait headlines of news articles by performing the extraction of new features from a multi-source dataset. Random Forest classifier yields a better accuracy than Naïve Bayes and Logistic Regression models in identifying headlines disseminating misleading information.	New clickbait formats are added each year, and many new methods can be incorporated into the model, to further improve accuracy. There is a high degree of similarity between the evaluation performance of the proposed model and other existing models.	They obtained scores on applying the various methods. We got the best results from Random Forests. Random Forest accuracy 0.891.

10.	BERT, XLNet or RoBERTa: The Best Transfer Learning Model to Detect Clickbaits 2021 Authors : PRABODA RAJAPAKSHA , (Student Member, IEEE), REZA FARAHBAKHSH , (Member, IEEE), AND NOEL CRESPI, (Member, IEEE)	:Based on the author’s knowledge, this is the first attempt to adapt Transfer Learning to classify Clickbaits in social media. In this work they have fine-tuned BERT, XLNet and RoBERTa models by integrating novel configuration changes into their default architectures such as model expansion, pruning and data augmentation strategies. Authors have used three fine-tuning approaches, namely; model generalization, expansion and pruning. The analysis has shown that pruning performed better than model expansion. In the expansion, the best result is achieved when we generated the output from hidden states without directly using pooled output (the default model output).	There is no significant performance improvement when each model expanded by adding an extra RNN layer(s). Apart from that, we experimented with another labelled clickbait dataset (Kaggle clickbait challenge) to explore the performance of our fine-tuned models under different scenarios.	The results shown that, RoBERTa outperformed the BERT and XLNet in many experiments mainly when we fine-tuned the model using hidden outputs to generate the output vector without using the pooled output and adding a non-linear layer at the end. This model architecture is considered to be the best performed model in our experiments.

4. PROBLEM STATEMENT-

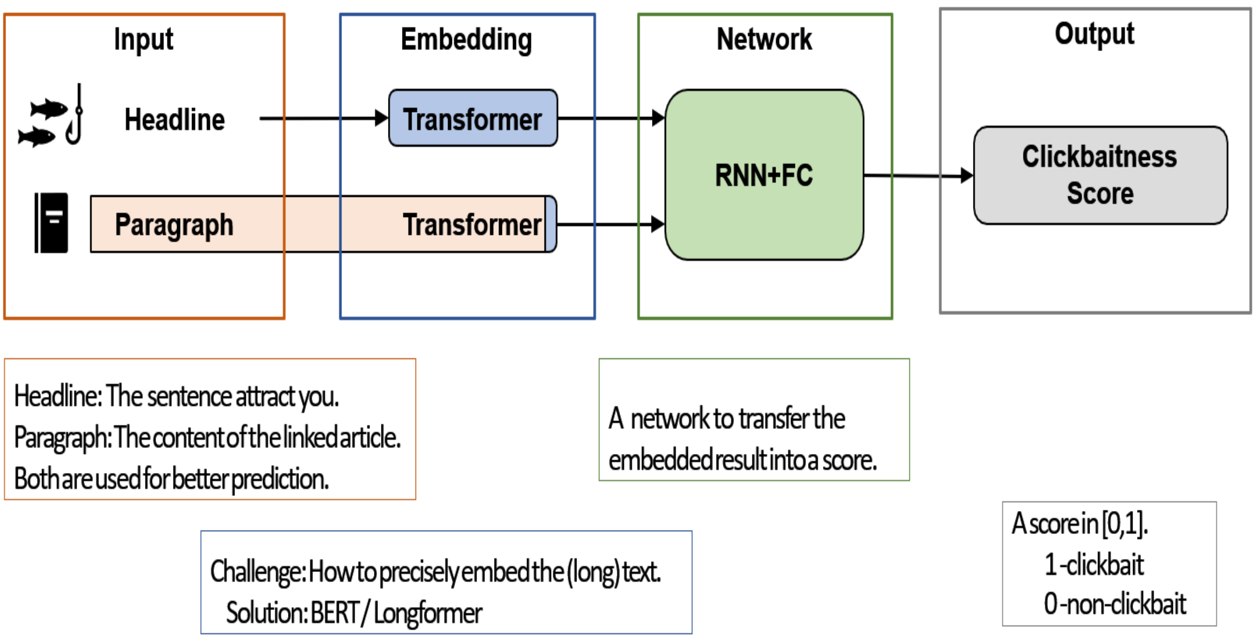
Clickbait refers to a certain kind of headline that attracts people to click but gives something uncorrelated in that Link. The motivation behind click-baiting is to boost site traffic (and therefore, advertisement revenue) by exploiting the curious nature of human readers.

This technique works by dangling a hyperlink with enticing headlines to lure people into clicking; and then redirect them to the publishers' own websites which are uncorrelated to the headline.

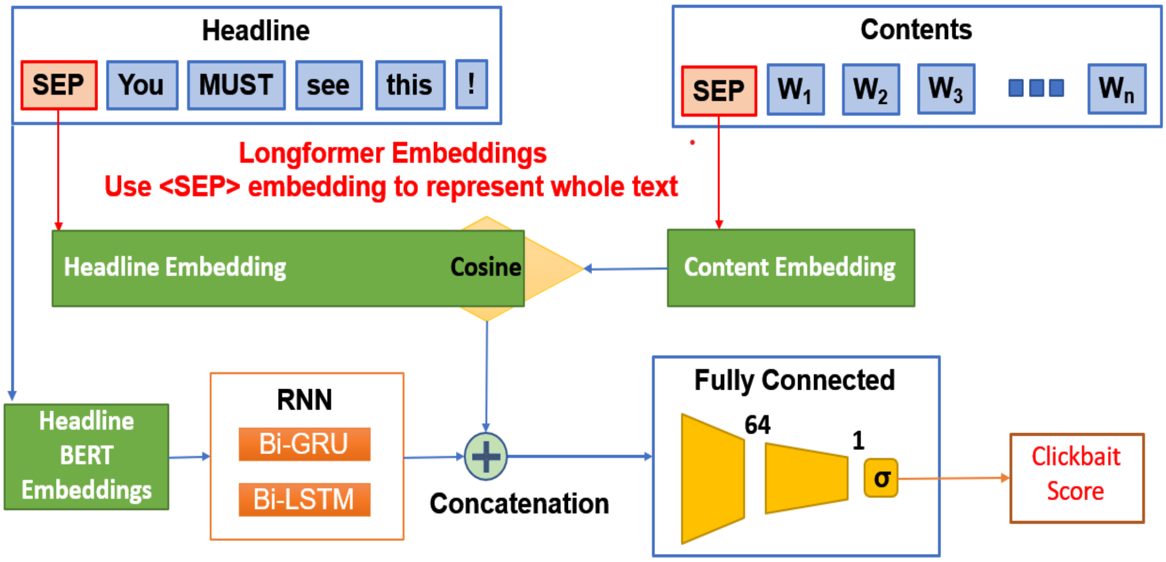
The discrepancy between the headline and the destination content wastes online readers significant amount of time on contents of which they have no interest.

To address this problem, we propose a Clickbait Detector with Bidirectional Encoder Representations from transformers which could effectively identify clickbait.

4.1 ARCHITECTURE DIAGRAM



4.2 FLOW DIAGRAM



4.3 PSEUDO CODE

Step1 : Load the webis dataset corpus : both instances.jsonl (containing clickbaits title and texts) and truth.jsonl (having truth values of clickbaits). The training data will have 19538 values.

Step2 : The next step is to do Bert Embedding. For it we will download and load the BERT. Bert Tokenizer and Bert Model from transformers. Bert_uncased (uncased means that the text has been lowercased before WordPiece tokenization).

Step3 : In our data cleaning process, we also decided it would be beneficial to exclude data that come with annotation (or label) of low confidence. The raw clickbait scores ('truth Mean' label) are in a range of [0, 1], as an average of 5 scores coming from 5 annotators, and we decided to exclude tweets with a mean clickbait score that deviate no more than 0.2 from 0.5, or in the range of [0.3, 0.7]. These annotations shows little confidence to be distinguished as either clickbait or not, and might confuse our model. After the cleaning process, we obtained a total of 12963 valid examples from training set.

Step 4 : We divide the dataset into a training set of 11663 tweets and a validation set of 1300 tweets. We use the validation set for preliminary performance evaluation and model selection and we report our results on the final test set.

Step 5 : Then we process by patches in the group of 800 until all the patches are complete. We save them using torch files to our directory.

5. EXPERIMENTS AND RESULTS

5.1 DATASET

Webis-Clickbait-17 Dataset (19538 Tweets)

Link-

https://zenodo.org/record/5530410#.YjIb5XpBxhF

5.1.1 METHODOLOGY WITH DATASET

We perform experiments on the Webis 17 dataset. comprises a total of 38,517 Twitter posts from 27 major US news publisher. They had been curated into various levels of their clickbait nature. These tweets contained the title and text of the article and included supplementary information such as target description, target keywords and linked images. The data set is already split into train set (19,538 posts with 4761 being clickbaits and 14,777 non-clickbaits) and test set (18,979 posts).

All posts were annotated on a 4-point scale [not click baiting (0.0), slightly click baiting (0.33), considerably click baiting (0.66), heavily click baiting (1.0)] by five annotators from Amazon Mechanical Turk. A total of 9,276 posts are considered clickbait by most annotators.

ERT and Longformer with Parallel Structure-

We build up our final model on top of the two baseline models. The first baseline model captures the relation between the headline and the contents. The second baseline model focuses on interpreting the headline. Under the clickbait definition outlined in our introduction section, both aspects should be taken into consideration when deciding whether a tweet is a clickbait or not. Therefore, we arrange the two models in a parallel structure, and concatenate the outputs from both. In doing so, we essentially attain an ensemble of the two baseline models. Finally, the outputs are again mapped by a fully connected layer, activated by the Sigmoid function to get the clickbait score. To overcome the input length restriction of the BERT model, we changed the encoding layer in the second baseline model into Longformer, which performs well on long texts. Here, we only tried both Bi-LSTM in the recurrent neural network block since the previous test result shows the performance difference between Bi-LSTM and Bi-GRU is trivial

5.1.2 OUTPUT

0 - Setup

In [1]:
```
import pandas as pd
import numpy as np
import os

import warnings
warnings.filterwarnings('ignore')

dir = 'C:\\Users\\kaust\\Desktop\\Click-BERT-main\\clickbait17-validation-170630\\'
```

In [2]:
```
dir
```

Out[2]:
```
'C:\\Users\\kaust\\Desktop\\Click-BERT-main\\clickbait17-validation-170630\\'
```

In [3]:
```
# !pip install transformers
# !pip install tensorflow
# !pip install torch
```

In [4]:
```
from transformers import pipeline;
print(pipeline('sentiment-analysis')('we love NLP'))
```

```
No model was supplied, defaulted to distilbert-base-uncased-finetuned-sst-2-english (https://huggingface.co/distilbert-base-unc
ased-finetuned-sst-2-english)
```

```
[{'label': 'POSITIVE', 'score': 0.9997754693031311}]
```

1 - Data Corpus

- data = 19538

In [17]:
```
class Webis17:
    '''
    self.corpus: (post, text, truthMean)
    '''
    def __init__(self, path):
        self.train_file = path + 'instances.jsonl'
        self.truth_file = path + 'truth.jsonl'
        df_train = pd.read_json(self.train_file, lines=True)
        df_truth = pd.read_json(self.truth_file, lines=True)
        self.size = df_train.shape[0]

        truth_id, truth_mean = list(df_truth['id']), list(df_truth['truthMean'])
        truth_dict = {truth_id[i]:truth_mean[i] for i in range(self.size)}
        train_id, train_post, train_text = list(df_train['id']), list(df_train['postText']), list(df_train['targetParagraphs'])
        self.corpus = [(train_post[i][0], ' '.join(para for para in train_text[i]), truth_dict[train_id[i]]) for i in range(self.

#       print(self.corpus[:10])
```

In [18]:
```
# web17 = Webis17('./data/clickbait17/')
dir = 'C:\\Users\\kaust\\Desktop\\Click-BERT-main\\clickbait17-validation-170630\\'
web17 = Webis17(dir)
num_data = len(web17.corpus)
print(num_data)
```

```
19538
```

In [19]:
```
print(web17.corpus[0])
```

```
('UK's response to modern slavery leaving victims destitute while abusers go free', 'Thousands of modern slavery victims have\x
a0not come forward, while others who have chosen to report their enslavers have ended up destitute as a result of insufficient
support, say\xa0MPs "Inexcusable" failures in the UK's system for dealing with modern slavery are\xa0leaving victims reduced to
destitution while their abusers go free because they are not adequately supported to testify against them, an alarming report h
```

2 - Dataset Preprocessing - BERT Embedding

Download BERT

In [8]:
```
from torch.utils.data import TensorDataset, DataLoader
from transformers import BertTokenizer, BertModel

bert_tokenizer = BertTokenizer.from_pretrained("bert-base-uncased")
bert_model = BertModel.from_pretrained("bert-base-uncased")

bert_tokenizer.save_pretrained(dir+'bert-base-uncased')
bert_model.save_pretrained(dir+'bert-base-uncased')

# it turns out that bert has limited token length of 512
```

```
Some weights of the model checkpoint at bert-base-uncased were not used when initializing BertModel: ['cls.predictions.bias',
'cls.predictions.transform.dense.bias', 'cls.predictions.decoder.weight', 'cls.seq_relationship.bias', 'cls.predictions.transfo
rm.LayerNorm.weight', 'cls.predictions.transform.LayerNorm.bias', 'cls.predictions.transform.dense.weight', 'cls.seq_relationsh
ip.weight']
- This IS expected if you are initializing BertModel from the checkpoint of a model trained on another task or with another arc
hitecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing BertModel from the checkpoint of a model that you expect to be exactly identical
(initializing a BertForSequenceClassification model from a BertForSequenceClassification model).
```

Load BERT

In [21]:
```
## load from files & tokenizer analysis

from torch.utils.data import TensorDataset, DataLoader
from transformers import BertTokenizer, BertModel

bert_tokenizer = BertTokenizer.from_pretrained(dir+'bert-base-uncased')
bert_model = BertModel.from_pretrained(dir+'bert-base-uncased')
```

data profiling

In [22]:
```
## extract data
import torch
title_all = [data[0] for data in web17.corpus]
content_all = [data[1] for data in web17.corpus]
score_all = torch.tensor([data[2] for data in web17.corpus], requires_grad=True)
```

In [23]:
```
score_all
torch.save(score_all, dir+'/scores.pt')
```

In [24]:
```
# title profiling

title_all_tokenized_raw = bert_tokenizer(title_all,return_token_type_ids=False, return_attention_mask=False)['input_ids']
print(max([len(lst) for lst in title_all_tokenized_raw ]))
print(f"Average # of tokens = {np.mean([len(lst) for lst in title_all_tokenized_raw])}")
print(f"max # of tokens = {max([len(lst) for lst in title_all_tokenized_raw])}")
print(f"ID of title with max # of tokens = {np.argmax([len(lst) for lst in title_all_tokenized_raw ])}")
print("---the title---")
print(title_all[np.argmax([len(lst) for lst in title_all_tokenized_raw ])])
print("---the title---")
```

```
104
Average # of tokens = 17.628058143105743
max # of tokens = 104
ID of title with max # of tokens = 16508
---the title---
................
................
................
................
................
................
Okay, then...
---the title---
```

In [25]:
```
# content profiling
content_all_tokenized_raw = bert_tokenizer(content_all,return_token_type_ids=False, return_attention_mask=False)['input_ids']
print(f"Average # of tokens = {np.mean([len(lst) for lst in content_all_tokenized_raw])}")
```

```
Token indices sequence length is longer than the specified maximum sequence length for this model (1467 > 512). Running this se
quence through the model will result in indexing errors
```

```
Average # of tokens = 791.2599037772546
```

In [26]:
```
print(f"max # of tokens = {max([len(lst) for lst in content_all_tokenized_raw])}")
```

```
max # of tokens = 43357
```

extract embeddings & divide train/val/test set

Raw

In [27]:
```
# All embeddings
title_all_tokenized = bert_tokenizer(title_all, padding=True,truncation=True,max_length=20, return_token_type_ids=False, return_a
print(title_all_tokenized.shape)
print(title_all_tokenized)
torch.save(title_all_tokenized, dir+'titles_tokens.pt')
```

```
torch.Size([19538, 20])
tensor([[  101,  2866,  1521,  ...,  2489,   102,     0],
        [  101,  2023,  2003,  ...,     0,     0,     0],
        [  101,  1996,  1000,  ...,  1996,  2047,   102],
        ...,
        [  101,  2413,  2015,  ...,  2112,  1997,   102],
        [  101,  2821,  5076,  ...,     0,     0,     0],
        [  101,  2957, 11011,  ...,     0,     0,     0]])
```

In [28]:
```
train_size = 700
val_size = 100
outputs = bert_model(title_all_tokenized[:(train_size+val_size), :])
title_all_embed = outputs[0]  # The last hidden-state is the first element of the output tuple
print(title_all_embed.shape) # batchsize x # tokens of sent x embed_dim
```

```
torch.Size([800, 20, 768])
```

Process by patches

In [31]:
```
import torch
title_all_tokenized = torch.load(dir+'titles_tokens.pt')
print(title_all_tokenized.shape)
```

```
torch.Size([19538, 20])
```

In [32]:
```
import gc

num_data = 19538
extract_size = 800
for i in range(num_data//800):
    outputs = bert_model(title_all_tokenized[(extract_size*i):(extract_size*(i+1)), :])
    title_all_embed = outputs[0]  # The last hidden-state is the first element of the output tuple
    print(title_all_embed.shape) # batchsize x # tokens of sent x embed_dim
    print(f"From size {str(extract_size*i)} to {str(extract_size*(i+1))}")
    # save Data
    torch.save(title_all_embed, dir+'/titles_'+str(extract_size*i)+'_'+str(extract_size*(i+1)))
    del outputs
    del title_all_embed
    gc.collect()
```

```
torch.Size([800, 20, 768])
From size 0 to 800
torch.Size([800, 20, 768])
From size 800 to 1600
torch.Size([800, 20, 768])
From size 1600 to 2400
torch.Size([800, 20, 768])
From size 2400 to 3200
torch.Size([800, 20, 768])
From size 3200 to 4000
torch.Size([800, 20, 768])
From size 4000 to 4800
```

In [21]:
```
# last portion

num_patchs = num_data//extract_size
outputs = bert_model(title_all_tokenized[(extract_size*num_patchs):, :])
title_all_embed = outputs[0]  # The last hidden-state is the first element of the output tuple
print(title_all_embed.shape) # batchsize x # tokens of sent x embed_dim
print(f"From size {str(extract_size*num_patchs)} to {str(num_data)}")
# save Data
torch.save(title_all_embed, dir+'/titles_'+str(extract_size*num_patchs)+'_'+str(num_data))

del outputs
del title_all_embed
gc.collect()
```

```
torch.Size([163, 20, 768])
From size 12800 to 12963
```

Out[21]: 0

Combine

In [22]:
```
Xt = torch.zeros(num_data, 20, 768)
for i in range(num_data//800):
    # curr_Xt = torch.load(dir+'/titles_'+str(extract_size*i)+'_'+str(extract_size*(i+1)))
    Xt[extract_size*i:extract_size*(i+1), :,: ] = torch.load(dir+'/titles_'+str(extract_size*i)+'_'+str(extract_size*(i+1)))
Xt[extract_size*num_patchs:,:,:] = torch.load(dir+'/titles_'+str(extract_size*num_patchs)+'_'+str(num_data))

print(Xt.shape)
# print(Xt[-10:,:,:])
```

```
torch.Size([12963, 20, 768])
```

In [23]:
```
torch.save(Xt, dir+'/titles_all.pt')
```

All (20 tokens)

In [24]:
```
# load data
import torch
from torch.utils.data import TensorDataset, DataLoader

dir = 'C:\\Users\\kaust\\Desktop\\NLP_Project\\Data\\'
Xt_all = torch.load(dir+'titles_all.pt')
yt_all = torch.load(dir+'scores.pt')
print(Xt_all.shape)
print(yt_all.shape)

num_data = Xt_all.shape[0]
train_size = 10000
val_size = 2000
test_size = num_data - train_size - val_size
batch_size = 64
train_set = TensorDataset(Xt_all[:train_size,:,:], yt_all[:train_size])
val_set = TensorDataset(Xt_all[train_size:train_size+val_size,:,:], yt_all[train_size:train_size+val_size])
test_set = TensorDataset(Xt_all[train_size+val_size:,:,:], yt_all[train_size+val_size:])

train_dataloader = DataLoader(train_set, batch_size=batch_size)
val_dataloader = DataLoader(val_set, batch_size=batch_size)
test_dataloader = DataLoader(test_set, batch_size=batch_size)
```

```
torch.Size([12963, 20, 768])
torch.Size([12963])
```

Only [CLS]

In [25]:
```
# load data
from torch.utils.data import TensorDataset, DataLoader

dir = 'C:\\Users\\kaust\\Desktop\\NLP_Project\\Data\\'
Xt_all = torch.load(dir+'/titles_all.pt')
yt_all = torch.load(dir+'/scores.pt')
print(Xt_all.shape)
print(yt_all.shape)

num_data = Xt_all.shape[0]
train_size = 10000
val_size = 2000
test_size = num_data - train_size - val_size
batch_size = 64
train_set = TensorDataset(Xt_all[:train_size,0,:], yt_all[:train_size])
val_set = TensorDataset(Xt_all[train_size:train_size+val_size,0,:], yt_all[train_size:train_size+val_size])
test_set = TensorDataset(Xt_all[train_size+val_size:,0,:], yt_all[train_size+val_size:])

train_dataloader = DataLoader(train_set, batch_size=batch_size)
val_dataloader = DataLoader(val_set, batch_size=batch_size)
test_dataloader = DataLoader(test_set, batch_size=batch_size)
```

```
torch.Size([12963, 20, 768])
torch.Size([12963])
```

4 - Model 1 - Simple LSTM

Model Architecture

In [26]:
```
import torch
import torch.nn as nn
import numpy as np

class LSTM(nn.Module):
    def __init__(self, batch_size, num_tokens, embed_dim, hidden_dim,  n_layers = 1, dropout = 0.0):
        super(LSTM, self).__init__()
        self.hidden_dim = hidden_dim
        self.n_layers = n_layers
        self.lstm=nn.LSTM(embed_dim, hidden_dim, n_layers, batch_first=True, dropout=dropout, bidirectional=True)
        self.flatten = nn.Flatten(1)
        # self.fc1=nn.Linear(num_tokens*hidden_dim, 64)
        # self.fc1=nn.Linear(num_tokens*hidden_dim, 1)
        # take CLS token, birection
        self.fc1=nn.Linear(2*hidden_dim, 64)

        self.fc2=nn.Linear(64, 1)

    def forward(self, x, hidden):
        '''
            x: batch_size x num_tokens x embed_dim
        '''
        # take CLS token
        # print(x[:,0,:].unsqueeze(1).shape)
        lstm_out, hidden = self.lstm(x.unsqueeze(1), hidden) # batch_size x 1 x (2*hidden_dim)

        # flat = self.flatten(lstm_out)
        flat = lstm_out.squeeze() # batch_size x hidden_dim

        out1 = self.fc1(flat) # batch_size x 64
        out2 = self.fc2(torch.relu(out1)) # batch_size x 1
        out = torch.sigmoid(out2)

        # # single layer
        # out = torch.sigmoid(out1)
        return out, hidden

    def init_hidden(self, batch_size):
        weight = next(self.parameters()).data
        # birections -> *2
        hidden = (weight.new(self.n_layers*2, batch_size, self.hidden_dim).zero_().to(device),
                  weight.new(self.n_layers*2, batch_size, self.hidden_dim).zero_().to(device))
        return hidden

def init_weights(m):
    '''
    Initialize weights
    '''
    if isinstance(m, nn.Linear):
        torch.nn.init.xavier_uniform_(m.weight)
        m.bias.data.fill_(0.0)
```

Hyperparamters

In [28]:
```
hidden_dim = 10 # num of tokens is typically 20
_ , num_tokens, embed_dim = Xt_all.shape
# dropout = 0.0
dropout = 0.2

model = LSTM(batch_size, num_tokens, embed_dim, hidden_dim, n_layers=2, dropout = dropout).to(device)
loss_fn = nn.MSELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=3e-4)

from torch.optim.lr_scheduler import ReduceLROnPlateau # learning rate scheduler
lr_scheduler = ReduceLROnPlateau(optimizer, 'min', factor=0.25, patience=0, threshold=0.05,min_lr=3e-5, verbose=True)

model.apply(init_weights)
```

Out[28]:
```
LSTM(
  (lstm): LSTM(768, 10, num_layers=2, batch_first=True, dropout=0.2, bidirectional=True)
  (flatten): Flatten(start_dim=1, end_dim=-1)
  (fc1): Linear(in_features=20, out_features=64, bias=True)
  (fc2): Linear(in_features=64, out_features=1, bias=True)
)
```

Training

In [29]:

```
from sklearn.metrics import f1_score
from scipy.stats import pearsonr

### Training ###
def train(train_dataloader, y_truth, model, loss_fn, optimizer, mute = False):
    model.train()

    size = len(train_dataloader.dataset)

    y_pred_train = []
    for batch, (X, y) in enumerate(train_dataloader):
        hidden = model.init_hidden(X.shape[0])
        X, y = X.to(device), y.to(device)

        optimizer.zero_grad()

        # Compute prediction error
        pred, hidden = model(X, hidden)
        y_pred_train.extend(pred.squeeze().cpu())
        loss = loss_fn(pred.squeeze(), y)
        # Backpropagation

        loss.backward()
        optimizer.step()

        if batch % 20 == 0:
            loss, current = loss.item(), batch * len(X)
            if not mute:
                print(f"Training loss: {loss:>7f}  [{current:>5d}/{size:>5d}]")

    y_pred_train = torch.tensor(y_pred_train, dtype=float)
    performance = loss_fn(y_pred_train, y_truth)
    clf_performance = ((y_pred_train>0.5)==(y_truth>0.5)).float().mean()

    if not mute:
        print(f"Training Loss: {performance}")
        print(f"Training Classifier Accuracy: {clf_performance}")
    return y_pred_train
```

Testing

```python
### Testing ###
def test(val_dataloader, y_truth, model, loss_fn, lr_scheduler, mute = False, mode = 0):
    '''
    mode = 0: validation when training (lr_scheduler)
    mode = 1: validation
    mode = 2: test
    '''
    hidden_val = model.init_hidden(batch_size)
    model.eval()

    y_pred_val = []
    for batch, (X, y) in enumerate(val_dataloader):
        hidden_val = model.init_hidden(X.shape[0])
        X, y = X.to(device), y.to(device)

        pred, hidden_val = model(X, hidden_val)
        y_pred_val.extend(pred.squeeze().cpu())

    y_pred_val = torch.tensor(y_pred_val, dtype=float)
    performance = loss_fn(y_pred_val, y_truth)
    if mode == 0:
        lr_scheduler.step(performance)
    clf_performance = ((y_pred_val>0.5)==(y_truth>0.5)).float().mean()

    f1_performance = f1_score((y_pred_val>0.5).float().numpy(), (y_truth>0.5).float().numpy())
    p_performance = pearsonr(y_pred_val.detach().numpy(), y_truth.detach().numpy())[0]
    if not mute:
        if mode == 2:
            print(f"Test Loss: {performance}")
            print(f"Test Accuracy: {clf_performance}")
            print(f"Test F1 Score: {f1_performance}")
            print(f"Test Pearson Coefficient: {p_performance}")
        else:
            print(f"Validation Loss: {performance}")
            print(f"Validation Accuracy: {clf_performance}")
            print(f"Validation F1 Score: {f1_performance}")
            print(f"Test Pearson Coefficient: {p_performance}")

    return performance
```

Ongoing

In [30]:
```
## Training & validation

### ESTIMATED TIME: 2
# num * 20 * 768 -> 1 min per batch -> 2 hr per epoch
# CLS -> num * 1 * 768, hidden = 10, bidirectional -> 8 min per epoch
###


epochs = 5
model.train()

best_val_performance = 1.0 # any number works
for t in range(epochs):
    print(f"Epoch {t+1}\n-------------------------------")
    train(train_dataloader, yt_all[:train_size], model, loss_fn, optimizer)
    val_performance = test(val_dataloader, yt_all[train_size:train_size+val_size], model, loss_fn, lr_scheduler)

    if val_performance < best_val_performance:
        best_val_performance = val_performance
        print(f'NEW BEST MODEL! Performance: {best_val_performance}')
        torch.save(model, dir+'/best_model')
print("Done!")
```

```
Epoch 1
-------------------------------
Training loss: 0.130494  [    0/10000]
Training loss: 0.120505  [ 1280/10000]
Training loss: 0.098896  [ 2560/10000]
Training loss: 0.072008  [ 3840/10000]
Training loss: 0.075095  [ 5120/10000]
Training loss: 0.059128  [ 6400/10000]
Training loss: 0.065695  [ 7680/10000]
Training loss: 0.046549  [ 8960/10000]
Training Loss: 0.07642852594365278
Training Classifier Accuracy: 0.8353999853134155
Validation Loss: 0.0462958023445965
Validation Accuracy: 0.9020000100135803
Validation F1 Score: 0.6
Test Pearson Coefficient: 0.6695715744944148
NEW BEST MODEL! Performance: 0.0462958023445965
Epoch 2
-------------------------------
Training loss: 0.044389  [    0/10000]
Training loss: 0.041818  [ 1280/10000]
Training loss: 0.047358  [ 2560/10000]
Training loss: 0.041306  [ 3840/10000]
Training loss: 0.033113  [ 5120/10000]
Training loss: 0.039051  [ 6400/10000]
Training loss: 0.032798  [ 7680/10000]
Training loss: 0.023674  [ 8960/10000]
Training Loss: 0.03807899840006584
Training Classifier Accuracy: 0.9101999998092651
Validation Loss: 0.03325891615124802
Validation Accuracy: 0.9175000190734863
Validation F1 Score: 0.728171334431631
Test Pearson Coefficient: 0.7501662041118375
NEW BEST MODEL! Performance: 0.03325891615124802
```

In [31]:
```
#CLS, num * 1 * 768, hidden = 10, bidirectional -> 8 min per epoch
torch.save(model, dir+'model_CLS_10_bi')
```

In [32]:
```
import torch

dir = "C:\\Users\\kaust\\Desktop\\NLP_Project\\Data\\"

hidden_dim = 10 # num of tokens is typically 20
_ , num_tokens, embed_dim = Xt_all.shape
# dropout = 0.0
dropout = 0.2

model = LSTM(batch_size, num_tokens, embed_dim, hidden_dim, n_layers=2, dropout = dropout).to(device)
model = torch.load(dir+'/best_model')

loss_fn = nn.MSELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=3e-4)

from torch.optim.lr_scheduler import ReduceLROnPlateau # learning rate scheduler
lr_scheduler = ReduceLROnPlateau(optimizer, 'min', factor=0.25, patience=0, threshold=0.05,min_lr=3e-5, verbose=True)
```

In [33]:
```
_ = test(val_dataloader, yt_all[train_size:train_size+val_size], model, loss_fn, lr_scheduler, mode = 1)
_ = test(test_dataloader, yt_all[train_size+val_size:], model, loss_fn, lr_scheduler, mode = 2)
```

```
Validation Loss: 0.03325891615124802
Validation Accuracy: 0.9175000190734863
Validation F1 Score: 0.728171334431631
Test Pearson Coefficient: 0.7501662041118375
Test Loss: 0.03108036533118153
Test Accuracy: 0.9262720942497253
Test F1 Score: 0.7526132404181185
Test Pearson Coefficient: 0.7712170394031064
```

6. CONCLUSION

In this project, we proposed to build a Clickbait Detector with Bidirectional Encoder Representations from Transformers. It could be trained from end-to-end without involving any manual feature engineering. It will effectively identify clickbaits and non-clickbaits with high accuracy.

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