Fake news detection problem

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Abstract

Everyday we accessing media outlets such as news blogs, social media feeds, and online newspapers. Yellow journalism have made it challenging to identify trustworthy news sources, thus increasing the need for computational tools able to provide insights into the reliability of online content.

I have conducted a set of learning experiments to build accurate fake news detector. Let me show accuracy I achieved.

https://github.com/Chawalar/Fake-news-detection.

1 Introduction

In recent years, due to the rapid development of online social media, more and more people tend to seek out and obtain news from it rather than from traditional media. It gives fake news a lot of chances to spread off. Compared with traditional suspicious information such as email spam and web spam, fake news has much worse societal impact, because fake news spreads faster and broadly. Traditional suspicious information often targets specific recipients and only produces a local impact. However, online fake news disseminates exponentially, affecting more people.

News disseminate online faster and easier through social media and online news sites. Large amounts of disinformation such as fake news, i.e., those news articles with intentionally false information, are produced online for a variety of purposes, ranged from financial to political gains. In our case we take fake news articles as an example of disinformation. The extensive spread of fake news may have severe negative impacts on individuals and society.

The recent proliferation of social media has significantly changed the way in which people acquire information. Often intentionally and verifiable false news stories could be spreaded virally on social media platforms even faster, because people rarely check the source of news when sharing a news article that sounds like truth. The spreading of fake news may bring lots of negative impacts, such as social panic and financial losses. Recent years have witnessed a numbers of high-impact fake news spreaded regarding terrorists plots and attacks, presidential elections, and various natural disasters. In many of these cases, even when correct information later appears and disseminates, the rapid spread of fake news can have devastating consequences. According to that, there is an urgent need of the development of automatic fake news detection algorithms which can detect fake news as early as possible to help to stop the viral spread of such news.

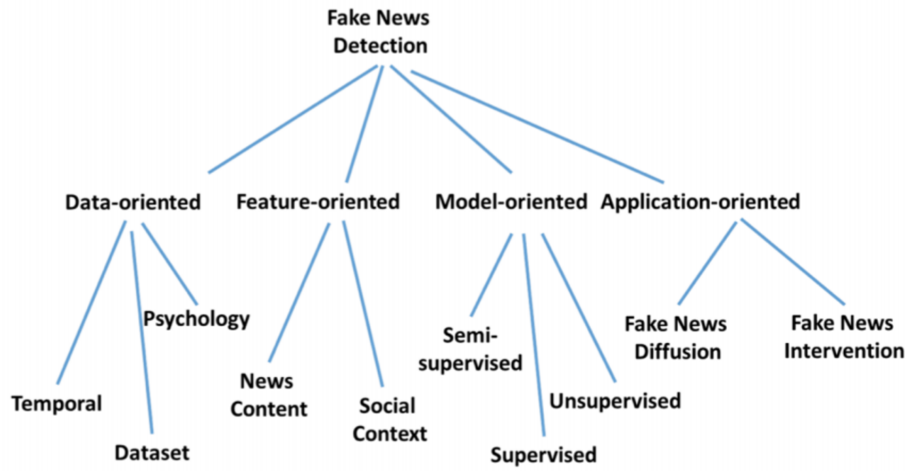

Figure 1: Different approaches to fake news detection.

2 Related Work

Fake news detection has been studied in several investigations. Conroy et al.[1] presented an overview of deception assessment approaches, including the major classes and the final goals of these approaches. They also investigated the problem using two approaches: (1) linguistic methods, in which the related language patterns were extracted and precisely analyzed from the news content for making decision about it, and (2) network approaches, in which the network parameters such as network queries and message metadata were deployed for decision making about new incoming news.

Ruchansky et al. [2] proposed an automated fake news detector, called CSI that consists of three modules: Capture, Score, and Integrate, which predicts by taking advantage of three features related to the incoming news: text, response, and source of it. The model includes three modules; the first one extracts the temporal representation of news articles, the second one represents and scores the behavior of the users, and the last module uses the outputs of the first two modules (i.e., the extracted representations of both users and articles) and use them for the classification. Their experiments demonstrated that CSI provides an improvement in terms of accuracy.

Tacchini et al. [3] introduced a new approach which tries to decide if a news is fake or not based on the users that interacted with and/or liked it. They proposed two classification methods. The first method deploys a logistic regression 3 model and takes the user interaction into account as the features. The second one is a novel adaptation of the Boolean label crowdsourcing techniques. The experiments showed that both approaches achieved high accuracy and proved that considering the users who interact with the news is an important feature for making a decision about that news.

Prez-Rosas et al. [4] introduced two new datasets that are related to seven different domains, and instead of short statements containing fake news information, their datasets contain actual news excerpts. They deployed a linear support vector machine classifier and showed that linguistic features such as lexical, syntactic, and semantic level features are beneficial to distinguish between fake and genuine news. The results showed that the performance of the developed system is comparable to that of humans in this area.

Wang [5] provided a novel dataset, called LIAR, consisting of 12,836 labeled short statements. The instances in this dataset are chosen from more natural contexts such as Facebook posts, tweets, political debates, etc. They proposed neural network architecture for taking advantage of text and metadata together. The model consists of a Convolutional Neural Network (CNN) for feature extraction from the text and a Bi-directional Long Short Term Memory (BiLSTM) network for feature extraction from the meta-data and feeds the concatenation of these two features into a fully connected softmax layer for making the final decision about the related news. They showed that the combination of metadata with text leads to significant improvements in terms of accuracy.

Long et al. [6] proved that incorporating speaker profiles into an attention-based LSTM model can improve the performance of a fake news detector. They claim speaker profiles can contribute to the model in two different ways. First, including them in the attention model. Second, considering them as additional input data. They used party affiliation, speaker location, title, and credit history as speaker profiles, and they show this metadata can increase the accuracy of the classifier on the LIAR dataset.

Ahmed et al. [7] presented a new dataset for fake news detection, called ISOT. This dataset was entirely collected from real-world sources. They used 4 n-gram models and six machine learning techniques for fake news detection on the ISOT dataset. They achieved the best performance by using TF-IDF as the feature extractor and linear support vector machine as the classifier.

Wang et al. [8] proposed an end-to-end framework called event adversarial neural network, which is able to extract event-invariant multi-modal features. This model has three main components: the multi-modal feature extractor, the fake news detector, and the event discriminator. The first component uses CNN as its core module. For the second component, a fully connected layer with softmax activation is deployed to predict if the news is fake or not. As the last component, two fully connected layers are used, which aims at classifying the news into one of K events based on the first component representations.

Tschiatschek et al. [9] developed a tractable Bayesian algorithm called Detective, which provides a balance between selecting news that directly maximizes the objective value and selecting news that aids toward learning user's flagging accuracy. They claim the primary goal of their works is to minimize the spread of false information and to reduce the number of users who have seen the fake news before it becomes blocked. Their experiments show that Detective is very competitive against the fictitious algorithm OPT, an algorithm that knows the true users parameters, and is robust in applying flags even in a setting where the majority of users are adversarial.

References

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3 Model Description

In my approach I used machine learning algorithms to get baselines, then I used main model named BERT to get best accuracy score.

For the baseline models were used: Passive Aggressive Classifier, Naive Bayes, Logistic Regression, Random Forest, XGBoost, with different methods of text prepossessing and TF-IDF transformation. This classic machine learning algorithms show basic accuracy score I achieved on fake news classification task. Then I used main model (BERT) to get even more accuracy.

BERT (Devlin et al., 2018), which stands for Bidirectional Encoder Representations from Transformers, is designed to pre-train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. BERT uses the ”masked language model” (MLM) pre-training objective, inspired by the Cloze task (Taylor, 1953). The masked language model randomly masks some of the tokens from the input, and the objective is to predict the masked word based on its context. In addition to the masked language model, BERT also uses a ”next sentence prediction” (NSP) task that jointly pre-trains text-pair representations. For the pre-training corpus (Devlin et al., 2018) use the BooksCorpus (800M words) and English Wikipedia (2,500M words). The self-attention mechanism in the Transformer allows BERT to model many downstream tasks — whether they involve single text or text pairs. For each task, the steps are: (1) simply plug in the task-specific inputs and outputs into BERT and (2) fine-tune all the parameters end-to-end.

With news articles classification task for finding fakes I wanted to understand problem deeper. I started with using machine learning methods for building fake news detector on my own data, that I collected from different sources, then I wanted to research this problem even deeper to bring existing solution on a brand new level.

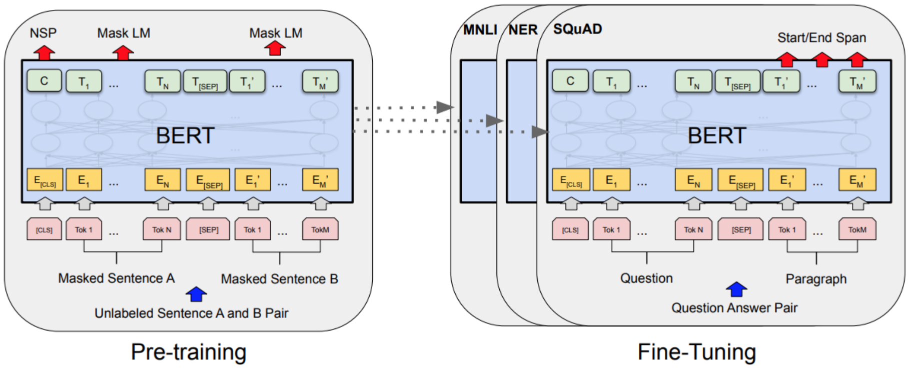


Figure 2: Overall pre-training and fine-tuning procedures for BERT. Apart from output layers, the same architectures are used in both pre-training and fine-tuning. The same pre-trained model parameters are used to initialize models for different down-stream tasks. During fine-tuning, all parameters are fine-tuned. [CLS] is a special symbol added in front of every input example, and [SEP] is a special separator token (e.g. separating questions/answers).

For experiments on fake news classification task I used pre-trained BERT by Hugging Face Transformers library and fine-tuned it on collected news articles dataset.

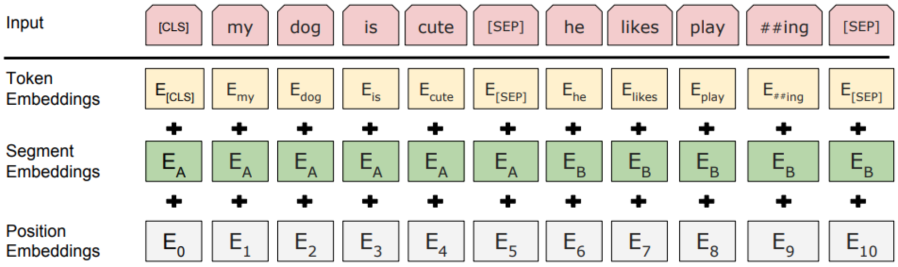


Figure 3: BERT input representation. The input embeddings are the sum of the token embeddings, the segmentation embeddings and the position embeddings.

Fine-tuning is straightforward since the selfattention mechanism in the Transformer allows BERT to model many downstream tasks— whether they involve single text or text pairs—by swapping out the appropriate inputs and outputs.

For classification tasks, the special [CLS] token is adding to the beginning of every sentence. This token has special significance. BERT consists of 12 Transformer layers. Each transformer takes in a list of token embeddings, and produces the same number of embeddings on the output.

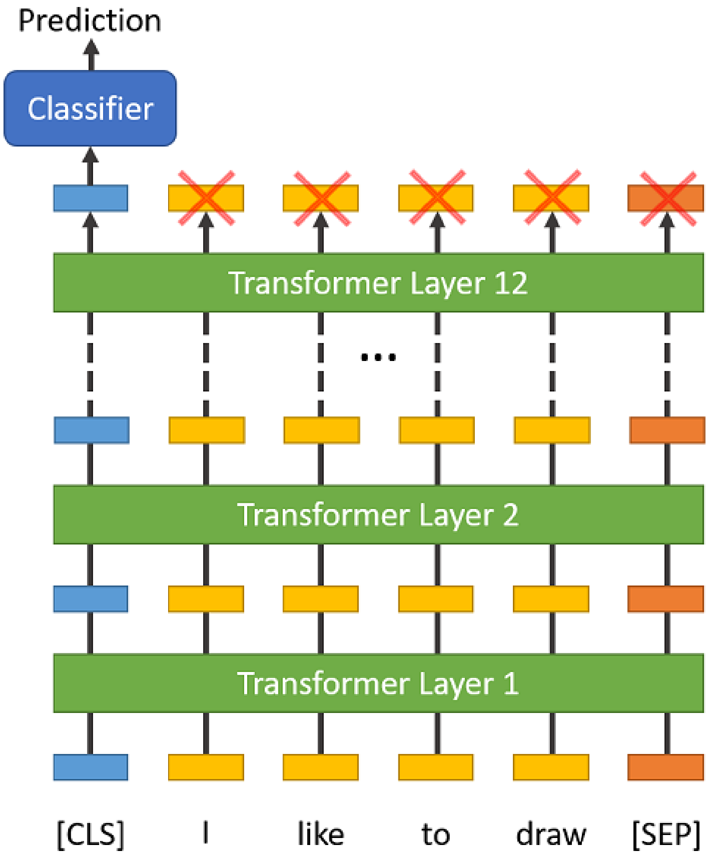


Figure 4: On the output of the final (12th) transformer, only the first embedding (corresponding to the [CLS] token) is used by the classifier. The first token of every sequence is always a special classification token ([CLS]). The final hidden state corresponding to this token is used as the aggregate sequence representation for classification tasks.

BERT has a maximum limit of tokens - 512. I used this limitation and set maximum to first 512 tokens. For else approaches may be used different way of choosing tokens from larger texts, but in my case it worked well.

4 Dataset

Data of news articles has been collected by web scraping of popular news sites. Solving the problem I have tested various of approaches to get information about fake news by myself. Reading and labeling all of the articles, checking facts by myself was really hard and time-consuming, and because of I worked on my alone I refused of this idea. I have checked hundreds of sites labeled like fake news or spam (most of them currently don‘t work) and finally found some of them, that were still working. I used this sources to scrap fake news articles for collected dataset. Eventually I worked with two datasets, political fake news and finance/business.

	Train	Valid	Test
Articles	5454	303	303
Vocabulary size		6060	

Table 1: Statistics political dataset, with balance classes, without duplicates articles.

Second dataset was scraped from 25 news sites, 5 from which were sites with fake news articles. This articles are classified as fakes. Scraped articles in dataset has web links, publishing date, title, text, author, and after preprocessing also label.

	Train	Valid	Test
Articles	4344	543	543
Vocabulary size		5430	

Table 2: Business/finance dataset with class imbalance, with preprocessing and without duplicates.

I iterate through each of news sites, getting the page and downloading article and some other information to json file, then preprocessing text.

5 Experiments

Overall I performed four sets of experiments. In the following sub-sections I describe and analyze them.

5.1 Metrics

The main chosen metric is accuracy, but for better understanding prediction process I also suggest to look at precision, recall and F1-score, it is important in our second dataset because of class imbalance.

Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations. One may think that, if we have high accuracy then our model is best. Yes, accuracy is a great measure but only when you have symmetric datasets where values of false positive and false negatives are almost same.

$$Accuracy = TP + TN/TP + FP + FN + TN,$$

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. High precision relates to the low false positive rate.

$$Precision = TP/TP + FP,$$

Recall is the ratio of correctly predicted positive observations to the all observations in actual class - real.

$$Recall = TP/TP + FN,$$

F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if you have an uneven class distribution. Accuracy works best if false positives and false negatives have similar cost. If the cost of false positives and false negatives are very different, it's better to look at both Precision and Recall.

$$F1Score = 2 * (Recall * Precision)/(Recall + Precision),$$

5.2 Experiment Setup

Starting point are those machine learning algorithms: Passive Aggressive Classifier, Naive Bayes, Logistic Regression, Random Forest, XGBoost, with text preprocessing and TF-IDF transformation.

Text preprocessing is always an important part. The list of methods I used for experiments: lower casing, removal of punctuation, removal of stopwords, removal frequent/rare words, steamming, removal url and HTML tags, chat words conversation, spelling correction.

After text preprocessing I split the data with 'train test split' method with test size = 0.2, then transform it with TF-IDF and trained my classifiers.

For second dataset with class imbalance can be used oversampling to get better results.

BERT model does preprocessing by bert tokenizer so usually we do not get benefits from standard preprocessing tips. It can be useful to pass through a contraction corrector to replace misspelled words with correction. Training parameters: max length 512, batch size 16, learning rate 2e-5, number of epochs 20. Without hyperparameters tuning.

5.3 Baselines

One of the best baseline for fake news classification task that I found was Logistic Regression over TF-IDF embedding and multinomial Naive Bayes as well as Passive Aggressive Classifier. It works fast and gets really fine results on classification task with text preprocessing.

6 Results

Machine learning algorithms parameters for baseline approach

- Passive Aggressive Classifier (max_iter = 50)
- Naive Bayes
- Logistic Regression (solver = saga, penalty = l1)
- Random Forest (n_estimators = 100)
- XGBoost

6.1 Political dataset

Accuracy of algorithms used with already preprocessed text and transformed to TF-IDF on political dataset:

Algorithms	Accuracy	Training time
Passive Aggressive Classifier	93.45 %	103ms
Naive Bayes	95.21 %	312ms
Logistic Regression	90.13 %	3.7s
Random Forest	89.98 %	2.05s
XGBoost	88.87 %	30.4s

This is a really good result. Then let's look at BERTs model. BERT pretrained model by Hugging Face fine-tuned on our political dataset with training parameters: max length 512, batch size 16, learning rate 2e-5, number of epochs 20.

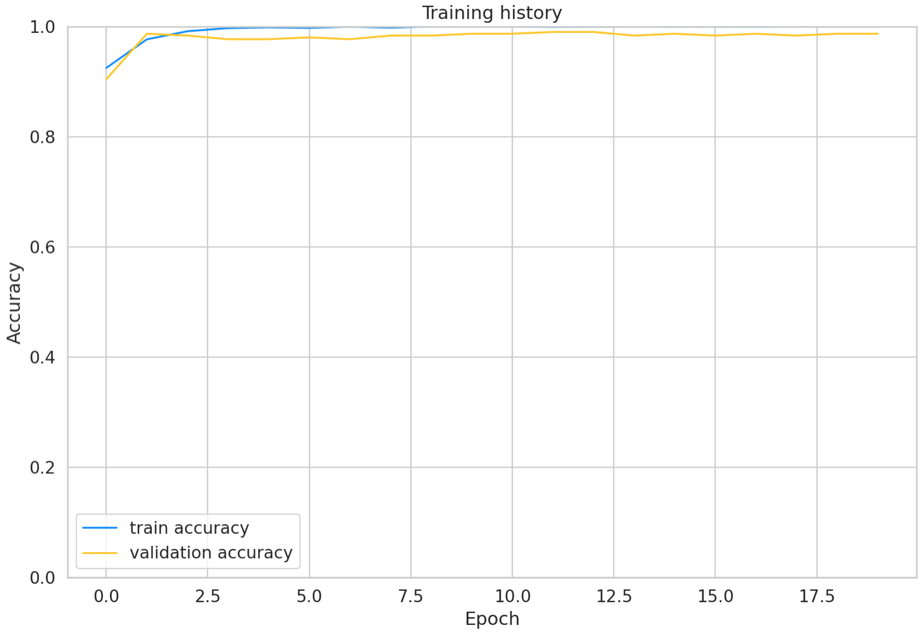
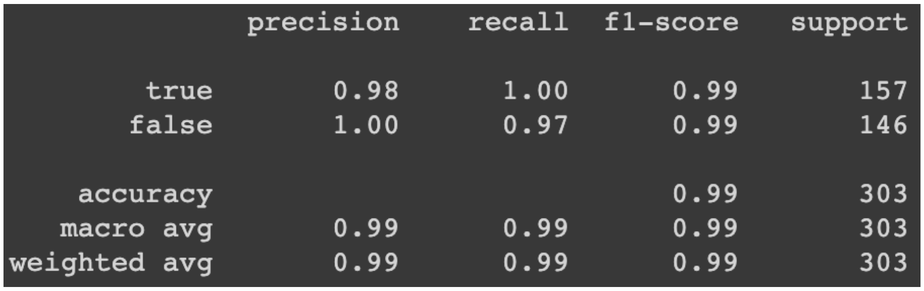


Figure 5: BERT training process.

Then look at metrics:



```
              precision    recall  f1-score   support

        true       0.98      1.00      0.99       157
       false       1.00      0.97      0.99       146

    accuracy                           0.99       303
   macro avg       0.99      0.99      0.99       303
weighted avg       0.99      0.99      0.99       303
```

Figure 6: BERT classification report.

This dataset with balanced classes, precision, recall and f1-score looks good. BERT achieved best score on this task in our models.

For better visualisation let's look at confusion matrix:

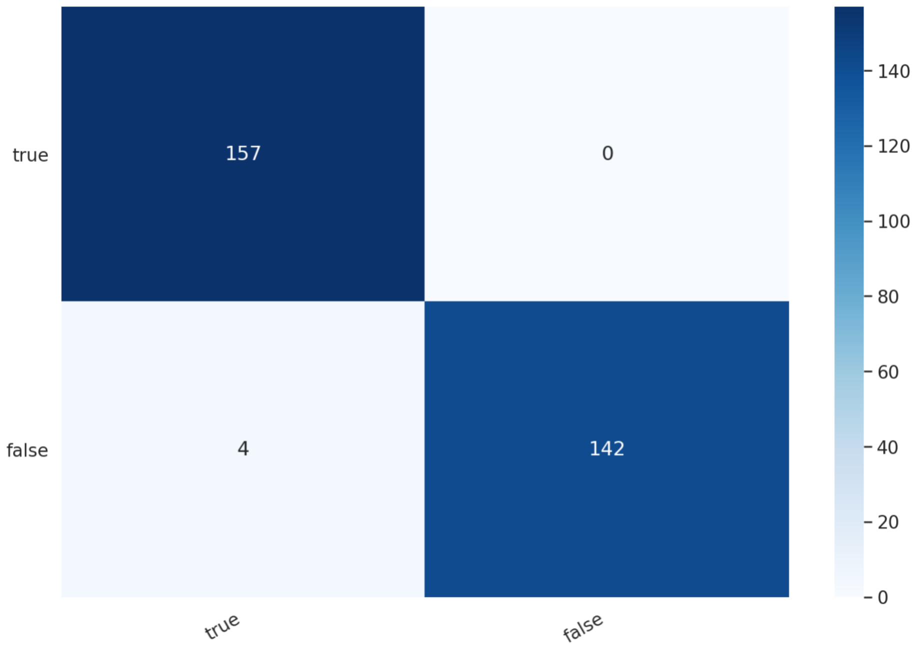


Figure 7: BERT confusion matrix.

Accuracy on test dataset: 0.9867, training time on Google Colaboratory: 3h 20min 37s with Tesla T4.

6.2 Business/finance dataset

Then I took second dataset with business/finance news articles and imbalanced classes.

Accuracy of algorithms used with already preprocessed text and transformed to TF-IDF on business/finance dataset:

Algorithms	Accuracy	Training time
Passive Aggressive Classifier	93.53 %	106ms
Naive Bayes	99.13 %	38.3ms
Logistic Regression	80.22 %	4.95s
Random Forest	91.0 %	1.99s
XGBoost	89.34 %	35.8s

As we can see from results with this algorithms, logistic regression accuracy drops, but naive bayes shows great result.

Then fine-tune our BERT pre-trained model on second dataset with training parameters: max length 512, batch size 16, learning rate 2e-5, number of epochs 20.

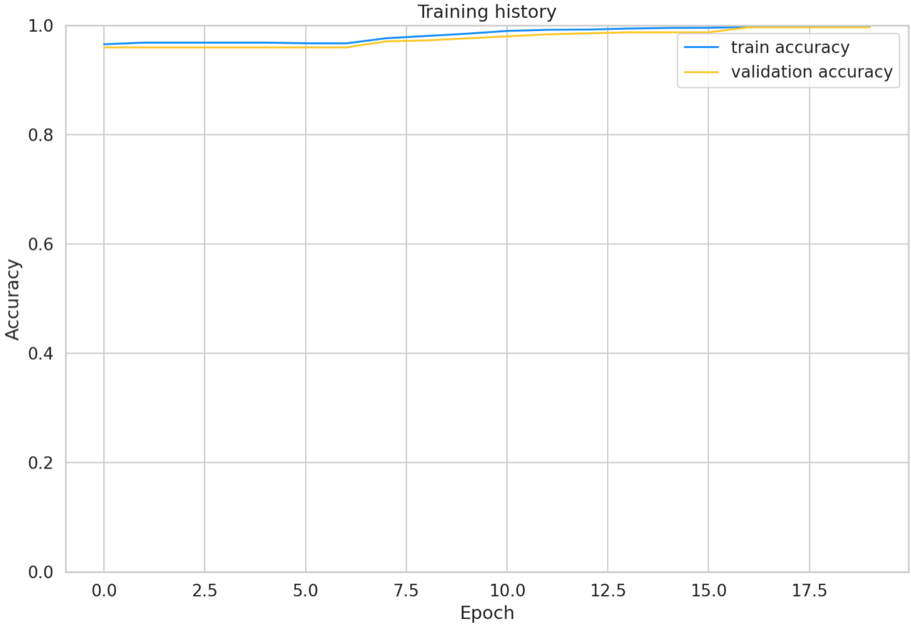
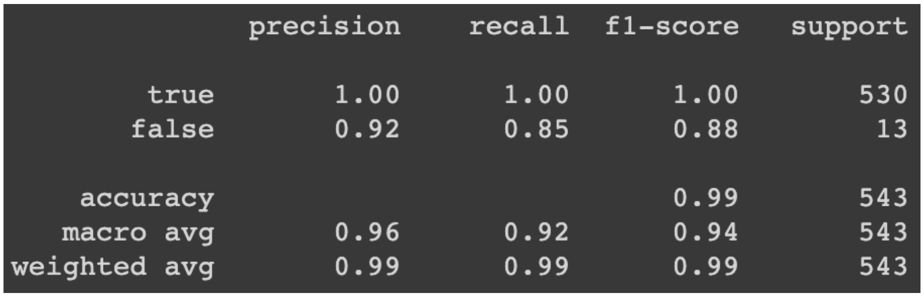


Figure 8: BERT training process.

Then look at metrics:


```
              precision    recall  f1-score   support

        true       1.00      1.00      1.00       530
       false       0.92      0.85      0.88        13

    accuracy                           0.99       543
   macro avg       0.96      0.92      0.94       543
weighted avg       0.99      0.99      0.99       543
```

Figure 9: BERT classification report.

In dataset with imbalanced classes precision, recall and f1-score slightly dropped. BERT also achieved best score on this task in our models.

For better visualisation let's look at confusion matrix:

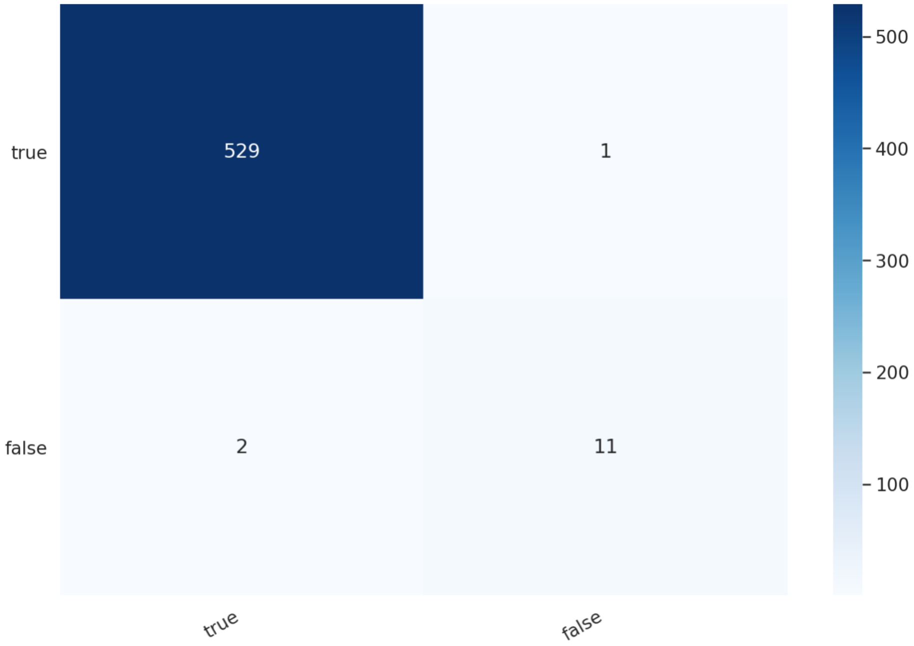


Figure 10: BERT confusion matrix.

Accuracy on test dataset: 0.9944, training time on Google Colaboratory: 1h 18min 37s with Tesla P100.

7 Conclusion

In this article, we have researched problem of fake news classification. We have analysed how traditional machine learning algorithms works on two different datasets, the second was imbalanced. Results were improved by using BERT model fine-tuned on collected datasets.

This approaches for fake news classification task looks good. Of course we can always do better, for example by scraping more articles, hyperparameters tuning, using oversampling, data augmentation technique, like SMOTE. But I prefer to dig at this problem deeper to get some tips for future work.

Main idea of this project is understanding of fake news classification problem, not just getting highest accuracy on one dataset, however, classification task on datasets were doing well. Article with fake or truthful news could be written by using proper narration style so that this type of article may be analyzed wrong. So that well written fake news article with lots of facts, dates, names and other information could be classified as real news. That is why detecting fake news according to only writing style of article is incorrect.

There are a lot of nuances in human language. It is determining a single statement to mark as true or false. There is no database of what's true or false indeed. If article is true or false when there are true facts as well as false facts? I want to share thoughts for future work, for creating a system for fake news classification for all topics.

Here are some of them:

- Title classification for clickbaits
- Author classification with rating database
- Newspaper resource classification on media bias
- Images classification on fake or true
- Fact cheking on database with facts

For all of this should be collected big databases with actual information. Also this information needs to be labeled and this is a lot of work. But only merging of this methods can help to solve a problem like fake news classification in wide comprehension.