

# Rumour detection and analysis of Tweets

## COMP90042 - Natural Language Processing Project Report

### Abstract

This document contains the report for the COMP90042 Natural Language Processing project. The following report explores the topic of automatic rumour detection in Twitter, it is also accompanied by an analysis section. The automatic rumour detection section explores multiple state of the art techniques for text classification, one model explored is a simpler model which does not take the tree structure into consideration whereas the more complex one does.

### 1 Introduction

Automatic Rumour detection is a difficult topic.

### 2 Strategy

The strategy used to obtain the best model was simply to do some quick, lost cost experiments to establish a baseline for accuracy. There were 4 models that were explored briefly at this stage of the project. The four models explored were a simple feed forward neural network, a convolutional neural network, a random forests classifier and a naive bayes classifier. The text preprocessing done was handled by spaCy (Honribal et al., 2020) alone. In addition to these 4 models, Facebook's FastText (Joulin et al., 2016) program/library was used for text classification to quickly determine the best accuracy obtainable with their system. The accuracy scores for these simple models are listed below.

Table 1: Accuracies for some ML models

Accuracies				
ANN	CNN	RF	NB	FT
FAIL	%67.67	%70.08	-	%80.31

Please note that the simple feed forward neural network was not able to be trained due to a OOM

exception, even when using a 8 node GPU cluster, it was clearly evident that the model needed to be simplified and this lead to convolutional neural networks being explored.

### 2.1 Preprocessing for simple models

### 3 BERT

Multiple attempts were made to a develop a BERT (Devlin et al., 2019) based classification model, two of the three attempts were failures, however the final model achieved near state of the art performance on the test dataset.

#### 3.1 Attempt One

The initial attempt at training BERT was performed on a complex model. The model was passed through multiple

#### 3.2 Attempt Two

#### 3.3 Attempt Three

##### 3.3.1 Determinging token length

In BERT , there is a max token length of the pre-trained models of 512 tokens. This obviously presents a challenge for us, especially considering that some of the space available needs to be used for the special tokens. There are solutions to this problem such as Longformer and Big Bird which are designed for large documents, but they introduce more training time.

In order to determine if Big Bird or Longformer should be used, a simple visualisation was used to asses the amount of entries that fit under the BERT imposed limit of 512 tokens.

As seen from Fig. 1, the token length can be capped at 512 and we should still preserve the discourse captured in the set of tweets.

use synonym

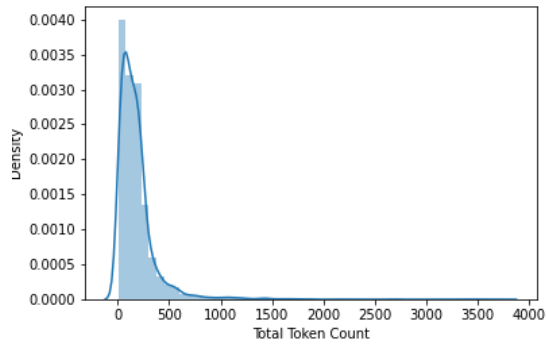


Figure 1: Distribution plot of combined token lengths

## References

- Ipek Baris, Lukas Schmelzeisen, and Steffen Staab. 2019. [Clearumor at semeval-2019 task 7: Convolutioning elmo against rumors](#). *Proceedings of the 13th International Workshop on Semantic Evaluation*.
- Jodie Burchell. [Using vader to handle sentiment analysis with social media text](#).
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. [BERT: Pre-training of deep bidirectional transformers for language understanding](#). In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.
- Matt Gardner, Joel Grus, Mark Neumann, Oyvind Tafjord, Pradeep Dasigi, Nelson F. Liu, Matthew Peters, Michael Schmitz, and Luke S. Zettlemoyer. 2017. [Allennlp: A deep semantic natural language processing platform](#).
- Matthew Honnibal, Ines Montani, Sofie Van Landeghem, and Adriane Boyd. 2020. [spaCy: Industrial-strength Natural Language Processing in Python](#). Zenodo.
- Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. 2016. Bag of tricks for efficient text classification. *arXiv preprint arXiv:1607.01759*.
- Jing Ma, Wei Gao, and Kam-Fai Wong. 2018. [Rumor detection on twitter with tree-structured recursive neural networks](#). *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*.