Fake news: an algorithmic perspective on fact-checking

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Abstract

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1 Introduction

The ability to broadcast information on a large scale has been in the hands of large publishing organizations in the pre-Internet era, but nowadays everyone can share news via social media [7]. This introduces risks on validity and authenticity of news, as social media and digital platforms can speed up the spread of falsehoods without much effort from the author [5].

As a matter of fact, 63% of adults in the United States prefer to read their news on the Internet. Young adults take the lead: 76% of adults between the ages 18 and 49 get their primary news consumption via the web, compared to just 43% for adults of 50 years and older [12]. As time passes by, social media is slowly becoming the primary source of news for more and more people.

The main danger of this development is that human perception is often skewed with regards to objectivity of facts. Naïve realism let consumers of news belief that their perception is right, while other's perceptions are uninformed. Furthermore, confirmation bias results in consumers preferring information that confirms beliefs they already have [17]. This makes consumers vulnerable for the spread of misinformation or fake news.

According to the European Commission, *"disinformation - or fake news - consists of verifiably false or misleading information that is created, presented and disseminated for economic gain or to intentionally deceive the public, and may cause public harm"* [5]. The answer to the problem of fake news as of recently has been to manually fact-check statements on validity, but, as Shu et al. underlines, one of the downsides to this approach is that fake news typically relates to newly emerging, time-critical events. This means the real news may not be fully verified by proper knowledge bases due to a lack of contradicting claims [17]. An automated approach would both help in solving the problem of human subjectivity and the speed at which false information is spread in the current news spreading landscape.

Natural language processing has been in rapid development over the past years. With the releases of OpenAI's GPT-2 model in February of this year and Google's BERT in the autumn of 2018, state-of-the-art pre-trained textual embedding techniques have shown promising results on various classification tasks [13][6]. Although fake news classification has been attempted before [19][9], performance has been rather low. However, these new pre-trained textual embeddings have not yet been used in the fight against disinformation.

This thesis is focussed on the following research question: *what is the performance of combinations of pre-trained embedding techniques with machine learning algorithms when classifying fake news?* This main question will be answered through the results of the following subquestions:

RQ1 Which way of pooling vectors to a fixed length works best for classifying fake news?

RQ2 At what padding sequence length do neural networks hold the highest accuracy when classifying fake news?

RQ3 How well do neural network classification architectures classify fake news compared to non-neural classification algorithms?

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2 Related Work

2.1 Automatic fake news detection

There have been several attempts in the past to create classifiers for automatic detection of lies and fake news. Wang used both linear and neural classifiers to classify statements from the Liar dataset into 6 possible gradations of truthfulness. Furthermore, he added speaker metadata to improve the result of his classifications [19].

From the same dataset, Khurana extracted linguistic features such as n-grams, sentiment, number of capital letters and POS tags to classify the data into 3 labels instead of the original 6 labels. For classification, she used a set of non-neural classifiers [9].

The British factchecking organization Full Fact has developed an architecture that is able to monitor and factcheck statements from the British Parliament and major media outlets in the United Kingdom. It can automatically factcheck the accuracy of statistical claims, for example [3]. For detecting factual claims from texts, the organization uses InferSent, which is a way of transfer learning that has been proved to perform well for the use case of Full Fact [10].

Various tools with regards to fake news detection are also available. Faker Fact is a tool which can classify texts into a set of categories ranging from satire to agenda-driven, the former identifying humorous intent, the later identifying manipulation [1]. Hoaxy, on the other hand, allows for the visualization of unverified claims through Twitter networks [15].

2.2 Pooling

Linear classifiers need data in a two-dimensional shape to be able to perform calculations. In the case of raw text data, sentences in the dataset have variable word lengths, resulting in a different vector length when turning the text into a vector representation. To turn the vector representations into a uniform length, we can either cut off the vectors at a fixed length (*padding*), or we can perform calculations to reduce the length of the vectors (*pooling*).

In computer vision, feature pooling is used to reduce noise in data. The goal of this step is to transform joint feature representations into a new, more usable one that preserves important information while discarding irrelevant details. Pooling techniques such as max pooling and average pooling perform mathematical operations to reduce several numbers into one [4]. In the case of transforming the shape of the data, we can reduce vectors to the smallest vector in the dataset to create a uniform shape.

Scherer et al. compared performance of two pooling operations on a convolutional neural network architecture. The first pooling method extracted maximums and the second one was primarily based on working with averages. They have shown that a max pooling operation is vastly superior for capturing invariances in image-like data [14].

Shen et al. noted that in text classification, only a small number of key words contribute to the final prediction. As a result, simple pooling operations are surprisingly effective for representing documents [16]. Lai et al., Hu et al. and Zhang et al. use a max pooling layer in a (recurrent) convolutional neural network for identifying key features in text classification [11][8][21]. In the case of text classification, max pooling strategies seem to be the most popular.

2.3 Padding

When padding a sequence, a list of sequences is transformed to a specific length. Sequences longer than the desired length will be truncated to fit the requirement, while sequences shorter than the desired length will be padded by a specified value [2]. To fill the sequences, a value of zero is often used. Hu et al. also use zero values for padding their sequences [8].

Apart from controlling the size of the feature dimension, padding has other uses as well. Simard et al. make use of sequence padding for convolutional neural networks to center feature units, and concluded it did not impact the performance of the classifier significantly [18]. Wen et al. apply padding to convolutional network models to prevent dimension loss [20].

2.4 Neural text classifiers versus linear text classifiers

3 Methodology

3.1 Description of the data

3.2 Charts

3.3 Methods

3.3.1 RQ1

3.3.2 RQ2

3.3.3 RQ3

4 Evaluation

4.1 RQ1

Which way of pooling vectors to a fixed length works best for classifying fake news?
The answer to this question will be given by comparing accuracy of a logistic regression with different pooling strategies (max, min, average).

4.2 RQ2

At what padding sequence length do neural networks hold the highest accuracy when classifying fake news?
The answer to this question will be given by comparing accuracy of a bidirectional LSTM architecture with variable padding lengths.

By comparing all embedding techniques, I plan on getting a peak padding length with the best overall performance shared by all embedding methods. At this moment, the optimal length averages at around a length of 22.

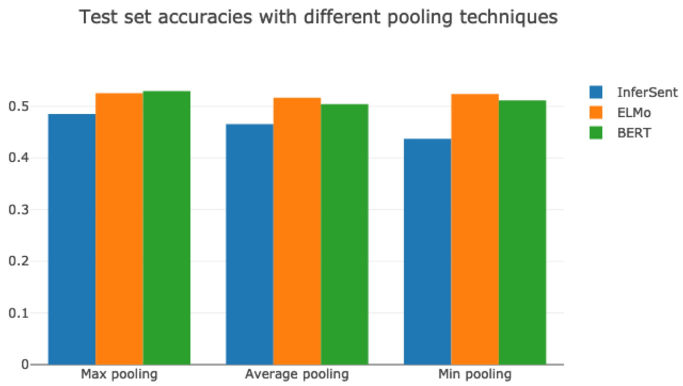

Figure 1: Comparing different pooling strategies.

4.3 RQ3

How well do neural network classification architectures classify fake news compared to non-neural classification algorithms?
The answer of this question will be given by comparing two linear classifiers with two neural classifiers.

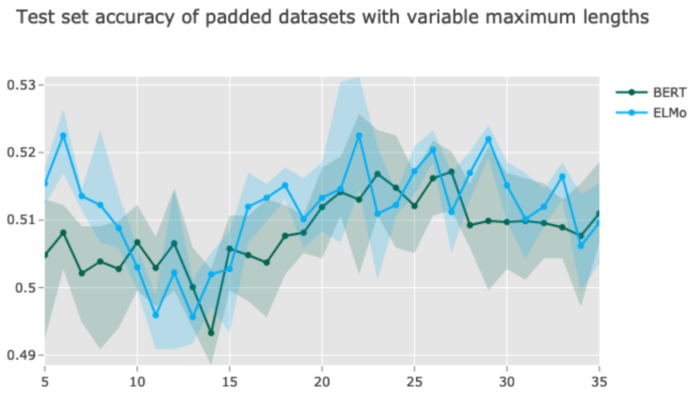

Figure 2: Comparing different maximum padding lengths.

5 Conclusions

5.1 Acknowledgements

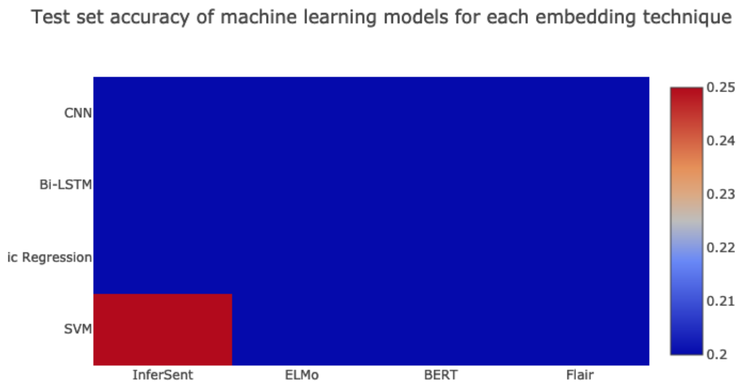

Figure 3: Comparing linear classifiers with neural classifiers.

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