Stance Detection & Fake News NLG Proposal

Anonymous ACL submission

1 Introduction

The term *Fake News* has gained popularity following the 2016 United States presidential election and the vote for the United Kingdom to exit the European Union (Rose, 2017)(Kucharski, 2016). Fake News refers to articles that meet poor journalistic standards, and contain incorrect or misleading information. It's suggested that these articles, and their tendency to be shared on social media had discernible effect on the events of the USA election, and Brexit (Allcott and Gentzkow, 2017).

Determining whether or not a news article is fake is difficult. A Stanford study shows students from middle school through college have difficulty distinguishing real news articles from advertisements (Wineburg et al., 2016). As a a result, attempts have been made to automate the detection of fake or misleading news articles (Conroy et al., 2015)

The purpose of this research is to apply natural language processing and machine learning techniques to analyzing the validity of news articles. In particular, we will begin by following the outline presented by Fake News Challenge (Challenge).

The *stance* of a text is the attitude it expresses towards a particular target (Augenstein et al., 2016). The first step of the Fake News challenge is to categorize the stance of the body against the stance of the heading of the article. The Fake News Challenge organization provides an implementation, which we will use as our baseline.

2 Previous Work

2.1 Data Requirements

Rubin et. al. showed data used to investigate rumors and deception need to have the following characteristics. There must be both truthful and deceptive news within the data set, the format must be accessible, the data must be verifiable, and there must exist data points of comparable lengths and writing styles(Rubin et al., 2015).

2.2 Stance Detection

In Emergent: a Novel Data Set for Stance Classification (Ferreira and Vlachos, 2016), stance detection was used to classify claims in relation to news articles in the Emergent data set. Headlines could be classified as either for, against or observing a claim, where observing a claim merely mentions the claim without giving a stance. A logical regression classifier was used to classify stances.

A headline of a news article and an associated claim were considered. Certain features were extracted, considering first the headline alone and then the headline and claim together. Headline features were extracted using the bag of words representation, as well as whether the headline ended in a question mark. Features for the distance from the root word to any refuting words (e.g deny) and any reporting words (e.g claim, presumably) were also added.

When a headline and a claim were considered together, for each word pairing between the claim and the headline an edge created and assigned a score. If the stems of the words are identical, it is given the max score. If the words are paraphrases, which is determined using the Paraphrase Database (PPDB) (Ferreira and Vlachos, 2016),

they are given the maximum paraphrase score. If neither they are given the minimum score. The Kuhn-Munkres algorithm was run on the graph. Features were added for negating words and subject-to-verb objects. Vectors were used for comparing the claims to headlines, looking at the cosine similarity of the subject-to-verb objects.

Using the headline and headline-claim methods, two overlap thresholds were defined, minimum for and maximum against. If the overlap is higher than the minimum for threshold it is labelled for, if it is less than the maximum against it is labelled against. If it hits neither threshold it is labelled observing. An accuracy of 73% was achieved on the Emergent test data set using this method. This method was challenged though in detecting observing stances, due to the similarities between the headlines and the claims when a headline is observing. This lead to a mislabelling of the observing claims as for claims.

Other work done on stance detection includes Stance Detection with Bidirectional Conditional Encoding (Augenstein et al., 2016). This paper looked at the stances of tweets, given sparse training data or where the target is not explicitly mentioned in the text. Two baselines were used, in a manner of treating stance detection as sentence level sentiment analysis. One was implemented using a Support Vector Machine Classifier and the other with long-short term memory network (LSTM). LSTM was found to work best and was used for most of the encodings.

Initially, the text and targets were independently encoded as a k-dimensional dense vector space, using two different LSTM networks. The model learned target-independent representation for the tweets and relied on the nonlinear projection layer to incorporate the target in the stance prediction (Augenstein et al., 2016).

For conditional encoding, first the target was encoded as a fixed length vector using one LSTM. The tweet was then encoded using another LSTM with its initial state with a representation of the target. This encoding was then adapted to use bidirectional conditional encoding. One encoding was achieved by reading the target and the tweet from left-to-right, and then another by reading them from right-to-left. This allowed for target dependant representation where the context on either side is considered.

To deal with the small amount of training data, unsupervised pretraining was used, by initialized word embeddings used in the LSTM with a trained word vector model. These embeddings were only used for initialization and were optimized with further training. The paper found that conditional encoding was well suited for learning how to fit a targets with generalized encodings and that bidirectional encoding performed best overall, especially where the target was not explicitly mentioned in the tweet.

3 Deception Detection

Research by Conroy et. al. deals with the concept of automatic fake news detection using natural language processing. This is described as categorizing news on a spectrum based on their level of certainty as well as their veracity (the intention to mislead). The automatic detection of fake news is centered around predicting the chances that any news item is intentionally misleading and deceptive based on the content of the news item. According to the research, the two main approaches currently being used are linguistic methods and network methods. Both of these methods make use of machine learning on their training data set (Conroy et al., 2015).

3.0.1 Linguistic methods

These methods utilize knowledge of speech patterns that are able to identify truthfulness and deception more accurately than most humans. Under this approach, a basic way that text is analyzed is considering all words in a block of text as equally significant units. Using natural language processing, this technique would be implemented using *n-grams* to analyze word frequencies and find indicators of deception. This method might also involve tagging the lexical cues of words (also called shallow syntax) or frequencies of words which can uncover linguistic patterns of deception. The techniques under this approach rely heavily on the analysis of the usage of language. They also work very well when combined with other approaches (Conroy et al.,

2015).

3.0.2 Network methods

These methods make use of a network of associated information (like metadata) to predict the level of veracity of the content. It is also pointed out that the use of networks of data can provide a means to check the validity of a news item due to the presence of findable truths in the network. This involves making queries on existing knowledge to measure the truthfulness of new news items (Conroy et al., 2015).

The conclusion drawn was that both methods are very accurate in classifying news items. This gives rise to the use of a hybrid methods that takes into account both approaches to automating fake news detection. Such hybrid methods would have a linguistics-based analysis process that takes into account lexical analysis. It would also be able to perform efficiently in place of a strictly linguistic or network based approach. These techniques should be created with the intent of complementing the processes performed by a researcher in detecting fake news, as opposed to replacing them (Conroy et al., 2015).

4 Proposed Approach

References

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