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Detecting Fake News and Performing Quality Ranking of German Newspapers Using Machine Learning

Sandler Simone
Advanced Information Systems and Technology
University of Applied Sciences Upper Austria
Hagenberg im Mühlkreis, Austria
simone.sandler@fh-hagenberg.at

Krauss Oliver
Advanced Information Systems and Technology
University of Applied Sciences Upper Austria
Hagenberg im Mühlkreis, Austria
oliver.krauss@fh-hagenberg.at

Diesenreiter Clara
Advanced Information Systems and Technology
University of Applied Sciences Upper Austria
Hagenberg im Mühlkreis, Austria
clara.diesenreiter@fh-hagenberg.at

Stöckl Andreas
Digital Media Department
University of Applied Sciences Upper Austria
Hagenberg im Mühlkreis, Austria
andreas.stoeckl@fh-hagenberg.at

***Abstract*—Nowadays, news spread quickly, and it is not always clear to the reader whether an article is real or fake. Moreover, readers use only a few sources to read the news without knowing the quality of the source. This is due to a lack of up-to-date news or media rankings. Machine learning models can be used to automatically detect fake news. In this work, a Passive-Aggressive-Classifier, a Random-Forest, and an LSTM network are trained to distinguish between fake and non-fake (real) news. Moreover, these models are used to classify news sources according to the amount of possible Fake News they may spread. The models are tested on English and translated German articles. The best results for Fake News detection on English articles is reached with the Passive-Aggressive-Classifier. For automatic news ranking of translated German articles, Random-Forest provides the best result. The correlation of Random-Forest with an actual news ranking reached 0.68. This shows that automated classification can be extended to languages other than English, using this approach. In the future, other machine learning models and translators will be used to extend the approach.**

***Index Terms*—Fake News Detection, Machine Learning, News Quality, Natural Language Processing**

I. Introduction

In this work, machine learning is used to detect Fake News in English news articles and the same approach is used to rank articles translated from German in order to rank news sources. This shows a working approach to detect fake news in languages other than English.

In recent years, the term *Fake News* gained in popularly. According to Kalsnes et al. [1] the problem with fake news gained international interest especially with the American presidential election in 2016. Fake News often have a financial, political, or social motivation and can be used to manipulate opinions. Therefore, the need of solutions to counter *Fake News* rises.

One way to solve this problem is using a machine learning classifier that detects fake news automatically. These classifiers first need to be trained on labelled data, and then they can perform the task they are trained for. The reason why machine learning is important for fake news detection is, that fake news spread fast and a lot of data needs to be checked in order to detect them [2]. Labelled data exists in abundance for the English language, but is less common for other languages. Thus, an approach that can use models trained in English for other languages is necessary.

To detect Fake News, a machine learning model is trained on English news articles, as most available labelled information is provided in the English language. In order to evaluate if this work is extensible to other languages, articles from different languages are considered as well. For this, the model is evaluated on articles that are translated, using Google Translator [3]. For this work, the model is applied to translated German news articles. This result is further used to rank German news sources by their percentage of potentially Fake News articles. The data used to train the model is combined from different datasets that contain articles labelled into fake or trusted news, as well as datasets that contain articles from newspapers that are considered as trustworthy. In total, three different machine learning models (Passive-Aggressive-Classifier, Random-Forest and LSTM) are trained and evaluated.

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II. BACKGROUND

In Shue et al. [4] different approaches for Fake News detection on online texts are described. They state that possible features are not only from the news content itself (text, images, author, ...), but also from social context (by analyzing the user-driven social engagement). They also analyzed different datasets and came to the conclusion that most of them only provide information to extract linguistic features, which is also the case for the data used in this work.

When choosing the right machine learning model for a given task, a decision needs to be made concerning the tradeoff between power and interpretability of the model. This problem is described in detail in Ngie et al. [5]. They state that models like Neural-Networks, Support-Vector-Machines and Random-Forest are powerful, but have less interpretability. In comparison, Decision-Trees, Logistic-Regression and Linear-Regression are less powerful, but have a better interpretability. For the goal of this work, the quality of the results are more important than the interpretability of the model. Therefore, models with these properties were preferred in the selection.

The first model used is a Passive-Aggressive-Classifier (PAC) [6], which belongs to online learning algorithms. The model works by reacting passive on correct classifications and aggressive on misclassifications.

The second model is a Random-Forest (RF) [7]. This model belongs to ensemble learning methods and combines multiple decision trees into one model. For classification problems, the final output is the class which is predicted by the most trees.

The third and final model tested is a LSTM Network [8]. LSTM stands for Long Short-Term Memory, the model is a type of recurrent neural network. The specialty of the network is to use information over a long period of time and not only from the recent past.

The Cambridge Dictionary defines the word credibility as ”the fact that someone can be believed or trusted”. [9] In the context of newspapers, credibility can be seen as the trustworthiness of the paper. For this work, the quality of a newspaper is defined by its trustworthiness or credibility, measured by the percentage of potentially Fake News they contain.

In [10] the quality of traditional and social media is discussed. They found out that the trust in traditional news sources like TV, radio and newspapers is higher than in new media, like online news and social media news.

How to measure and define news quality is also discussed in Bachmann et al. [11]. They defined multiple criteria for measuring newspaper quality which are: Relevance (focus on general and social issues), Contextualization (reporting of longer-term developments), Professionalism (objectivity, source transparency and credibility) and Diversity (content diversity and geographical diversity).

Fake news is similar to satirical news. The detection of both can be made with the same classifier if it is trained on the right data. Stöckl [12] trained a classifier that is specialized on detecting this type of news in German newspapers. As classifier, logistic regression and Support Vector Machines are used. Thereby, an accuracy of 0.98 is reached on the test dataset and 0.88 when testing on data from publishers that are not in the training set.

III. METHODS

This section describes the methods used for the classification of the articles into *fake* or *no fake*. Because of the lack of labeled German news articles, the model is trained on English articles. Afterwards, the model is applied on translated articles. Three different models are tested, a Passive-Aggressive-Classifier (PAC), a Random-Forest (RF) and a LSTM-Network.

A. Preprocessing

The following steps are performed in order to clean the articles:

Lower casing all upper characters are transformed into their corresponding lower ones
e.g. Fake-News-Detection is important! →
fake-news-detection is important!

Replacing possible word separators The Following characters are replaced by a whitespace: ”/(){}\[]|@,;-”
e.g. fake-news-detection is important! →
fake news detection is important!

Removing all special characters Only characters that are in the English alphabet, plus-sign, underscore and the hash-symbol are kept.
e.g. fake news detection is important! →
fake news detection is important

Stop word removal The stop words from NLTK [13] are used.
e.g. fake news detection is important →
fake news detection important

B. Feature Extraction

The feature extraction for the Random-Forest and the Passive-Aggressive-Classifier is made with a TF-IDF vectorizer. [14], via which the texts are transformed into a feature matrix. Each word inside the text corpus is transformed into a feature. The values are calculated using the TD-IDF score. TD-IDF stands for *Term frequency–inverse document frequency* and weights terms high that often occur in one text, but rare in a collection of texts [15]. For the LSTM model, the feature extraction is made using the Keras tokenizer. [16] This tokenizer transforms each text into a sequence of integers.

C. Training and Testing

For training, multiple datasets are combined:

Misinformation & Fake News text dataset 79k [17] This dataset contains around 79,000 news articles. Whereas the *True* articles are from newspapers, like the New York Times or the Washington Post. The *Fake* articles are from websites or other datasets containing *Fake News* and misinformation.

REAL and FAKE news dataset. [18] This dataset contains 6,256 news articles that are labeled as fake or real.

Fake News Detection [19] This dataset contains around, 20,000 labeled news articles.

BBC News [20] This dataset contains around, 5,000 from BBC. With only the previous datasets, the classes have an imbalance towards fake news. Therefore, this dataset containing only non-fake articles is added.

Guardian News Dataset [21] This dataset contains articles from the guardian. 3,000 out of the 50,000 articles are used in order to balance out the classes of the other datasets.

All these datasets combined contain 114,438 entries, split into 57,464 real and 57,219 fake news articles. From these datasets, only the article content and the labels are used.

Before training, 0.33 percent of the data is separated for testing. The rest is used for training and validating each of the three models.

The Passive-Aggressive-Classifier reached an accuracy of 0.96, the Random-Forest 0.77 and the LSTM 0.93. For the Passive-Aggressive-Classifier and the Random-Forest the implementation from sklearn [14] is used.

The Passive-Aggressive-Classifier reached the best results when using the squared hinge loss function and the Random-Forest with a max depth of 1,000, minimal samples per leaf nodes of 200 and a sample size for bootstrapping of 0.5.

The LSTM contains 3 layers and is trained using Keras [16]. Whereas the LSTM layer of the model has 32 dimensions and a dropout rate of 0.2. The middle layer is a dense layer with 16 nodes, a ReLU activation function and again a dropout rate of 0.2. The last layer only has one node that uses a sigmoid activation function. If the article is fake, the node has a value above 0.5 and otherwise below. Figure 1 shows the confusion matrices of these models.

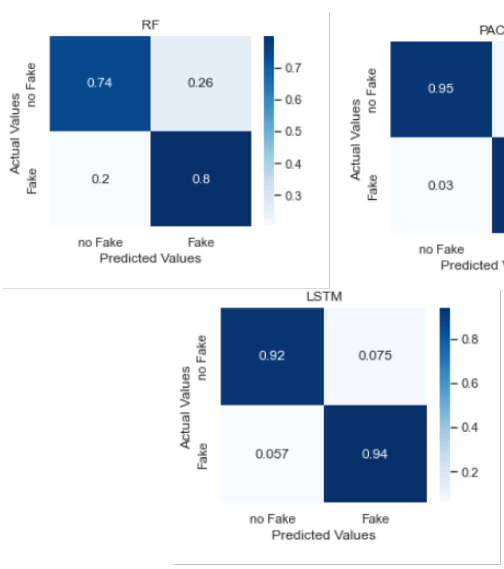

Fig. 1. Confusion matrix of the models. PAC performs best.

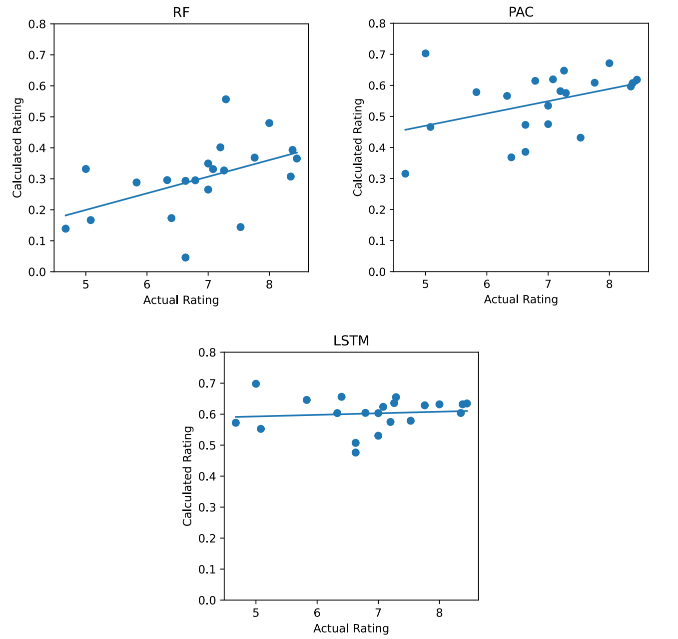

Fig. 2. Scatter plot of the rating from each model with the actual raiting.

D. *Prediction*

The final prediction is made using the German News Dataset [22]. This dataset contains 162,991 articles and their source. On order to apply the model on the articles, the texts are translated into English. For the translation, Google Translate is used, which has an accuracy of 97 percent when translating into English [23]. After that, the same preprocessing and feature extraction as described before is used. The classification result of the models is aggregated per news source. The sources than can be ranked according to the percentage of possible fake articles they have.

IV. Results

The goal of this work is to automatically rank German newspapers, by their amount of potential fake news article. Therefore, the calculated quality scores need to be compared to an existing media ranking.

In [24] German news sources are ranked by media experts according to their quality. For the ranking, each expert gave between 1 and 10 points to each news source. Afterwards, the sources are ranked according to their mean points. According to the report, *Spiegel*, *Die Zeit* and *Süddeutsche* are the best news sources. On the lower end of the ranking are *Express*, *BZ-Berlin* and *Bild*.

Figure 2 shows a comparison of the calculated media ratings from each model with the actual rating. The figure also include a regression line for each model. The line shows that the LSTM rankings and the actual rankings do not correlate, while RF and PAC do.

Figure 3 shows these ratings in more detail. The papers are ordered by the ranking found in the literature. Thus, a negative slope of the regression line indicates that the results of the model correlates with these ranks. The image shows that the results of the Passive-Aggressive-Classifier (PAC) and the Random-Forest (RF) correlates with the actual media ranking and that the LSTM does not.

To verify this result, two different correlation coefficients of our results with the media ranking are calculated. First, the Pearson coefficient is used to compare the quality values of the rankings. The Pearson coefficient measures the linear relationship of two variables, 1 indicates a perfect correlation, 0 no correlation and -1 a perfect negative correlation. Second, Spearman is used to compare the ranking of the Newspapers that result from these ratings. Spearman is used to compare rank values of two variables, again 1 indicates positive correlation and -1 a negative one. This coefficient is used because the goal of this work is to rank newspapers. In both cases, Random-Forest has the best results. The last column of the table contains the p-value of the Spearman correlation. In this case, a p-value under 0.05 indicates that the correlation is statistically significant. Therefore, the PAC and the RF can be used to rank Newspapers. Table I shows the calculated correlations.

V. Related Work

We compare ourselves with literature that also attempts to identify fake news. As our detection method is based on the wording, and not, for example, checking knowledge triplets, we only consider literature that attempts similar methods.

Different classifiers for Fake News detection are used in Reis et al. [25]. They tested k-Nearest Neighbors, Naive Bayes, Random Forests, Support Vector Machine and XGBoost. Their best results were obtained with Random Forests and XGBoost. They reached an accuracy of 0.85 with Random-Forest, which is better than the performance of our Random-Forest (0.77). Our best model, the Passive-Aggressive-Classifier, with an accuracy of 0.96, is better than their best result which is XGBoost with an accuracy of 0.86.

Ruchansky et al. [26] solved the problem using their own Neural Network named CSI. It consists of multiple parts that are called capture, score and integrate. With this model, they reached an accuracy of 0.89 on the Twitter dataset and 0.95 on the Weibo dataset. Hence, their model offer similar results to our models.

Detecting fake news with a Support Vector Machine (SVM) is done by Stöckl [12]. The model reached an accuracy of 0.996, on the test set, and an accuracy of 0.88 on articles from publishers that are not part of the training set. Resulting in a higher accuracy than our models on their test set.

-	pearson	spearman	p-value (spearman)
PAC	0.41	0.43	0.04
RF	**0.54**	**0.68**	**0.0007**
LSTM	0.13	0.19	0.41

TABLE I: Correlation comparison of the three classifiers. Random-Forrest (marked in bold) performed best overall.

VI. Discussion and Outlook

During training and testing on the English texts, the LSTM model performed well (accuracy: 0.93), but on the translated ones the model has bad results (Pearson correlation: 0.13). The reason for that is probably because for LSTMs the context of a word is taken into account. Due to the translation, the grammar and meaning may be different from what a native speaker would write, and thus differ from the texts that were originally written in English. Therefore, the context of the words might be different in these texts. This is an important finding, as contextual models work well for detecting fake news, but seem to be unusable when translation is applied.

Random-Forest and Passive-Aggressive-Classifier are trained using TF-IDF weights. This might be the reason why they are less sensitive to translation errors compared to the LSTM. On the original English texts, Random-Forest had the lowest accuracy (0.77), but on the translated data the model lead to the bests results (Pearson correlation: 0.68). The reason for that is probably that the Random-Forest managed to build a more general model. This is possible because of the parameter setting of the model, to build pruned trees.

In the end, two of these models provided a ranking, that have a statistically significant correlation with the literature [24]. These are Random-Forest and Passive-Aggressive-Classifier. Therefore, these models can be used to rank newspapers.

In the future other language models, like BERT, Naive Bayes, XGBoost, GPT3 and BOOST, will be tested. A labeled German Fake news dataset will be used to further verify and test the models [27]. Furthermore, the translation of the texts could be improved by using DeepL [28] instead of Google Translator.

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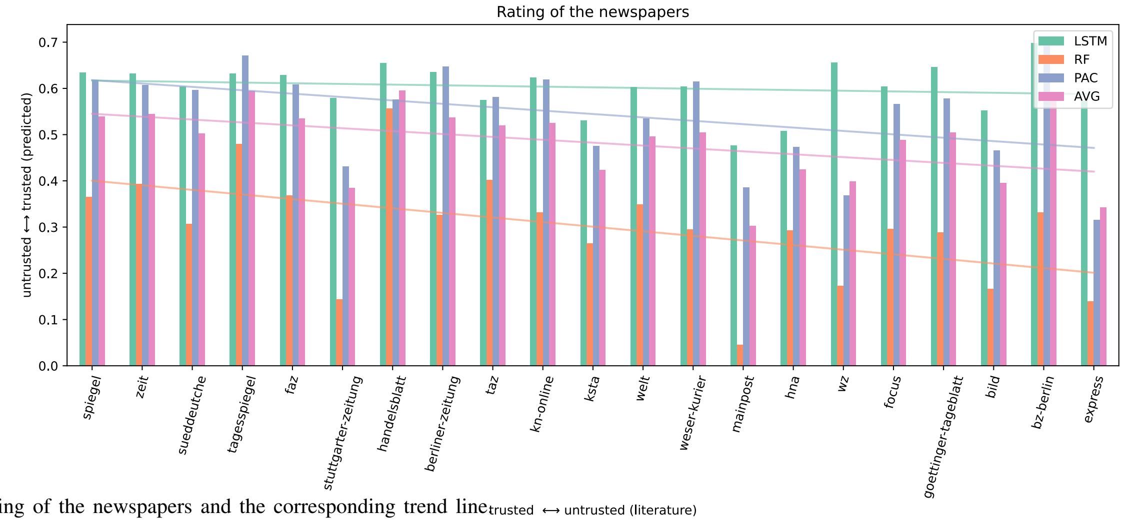

Fig. 3. Rating of the newspapers and the corresponding trend line

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