Fake News Spreader Detection on Twitter using Character N-Grams
Notebook for PAN at CLEF 2020

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Abstract The authors of fake news often use facts from verified news sources and mix them with misinformation to create confusion and provoke unrest among the readers. The spread of fake news can thereby have serious implications on our society. They can sway political elections, push down the stock price or crush reputations of corporations or public figures. Several websites have taken on the mission of checking rumors and allegations, but are often not fast enough to check the content of all the news being disseminated. Especially social media websites have offered an easy platform for the fast propagation of information. Towards limiting fake news from being propagated among social media users, the task of this year’s PAN 2020 challenge lays the focus on the fake news spreaders. The aim of the task is to determine whether it is possible to discriminate authors that have shared fake news in the past from those that have never done it. In this notebook, we describe our profiling system for the fake news detection task on Twitter. For this, we conduct different feature extraction techniques and learning experiments from a multilingual perspective, namely English and Spanish. Our final submitted systems use character n-grams as features in combination with a linear SVM for English and Logistic Regression for the Spanish language. Our submitted models achieve an overall accuracy of 73% and 79% on the English and Spanish official test set, respectively. Our experiments show that it is difficult to differentiate solidly fake news spreaders on Twitter from users who share credible information leaving room for further investigations. Our model ranked 3rd out of 72 competitors.

Keywords: Author Profiling, Fake News Spreader, Fake News Detection, Deception Detection, Social Media, Twitter

1 Dataset and Corpus Analysis

To train our system, we used the PAN 2020 author profiling corpus\textsuperscript{1} proposed by Rangel et al. \cite{rangel2019author}. The corpus consists of 300 English (EN) and Spanish (ES) Twitter user accounts each. The tweets of every Twitter user are stored in an XML file containing 100

\textsuperscript{1} https://zenodo.org/record/3692319#.XrlnomgzZaQ
tweets per author. Every tweet is stored in a `<document>` XML tag. The tweets were manually collected and fact-checked. The dataset is balanced which means the data refers to an equal distribution of class instances. Half of the documents per language folder are authors that have been identified sharing fake news. The other half are texts from credible users. Table 1 shows excerpts from the data. Every author received an alphanumeric author-ID which is stored in a separate text file together with the corresponding class affiliation. For training and testing, we split the data in the ratio 70/30. The gold-standard can only be accessed through the TIRA [7] evaluation platform provided by the PAN organizers. The results are hidden for the participants.

Table 1. English (EN) and Spanish (ES) excerpts from the PAN 2020 Twitter “Fake News Spreader” data.

| EN and ES True News Tweets | EN and ES Fake News Tweets |
|---------------------------|---------------------------|
| “RT #USER#: Best dunk of the contest no doubt “Jay-Z Must Give Beyonce $5 Million Per about it. Aaron Gordon robbed again #URL#” Child They Have Together Due to Crazy Prenupâ¿URL#” | “RT #USER#: Sure would be an interesting day “RT #USER# #USER# When Obama was tap-to read a book that examines Trumpâ¿s obsession my phones in October, just prior to Election with the king-like powers of his officâ¿tion!” “A Data-Driven Approach Aims to Help Cities “Why Trump lies, and why you should care - Recover After Earthquakes #URL#” The Boston Globe #URL#” |
| “Javier CAñamara ya es el lÃder mÃ¡s val- “Dictadura pura y dura toma tasas y todos feli-orado de los espaÃ±oles por delante de Pe- cies #URL#” dro SÃ¡nchez, segÃ¼n una encuesta #URL# #URL#” | “Me gusta la foto. Una foto con variedad, diver- “GANAR DINERO AHORA ES FACIL â§ sidad. Me da la impresion que con mÃ¡s son- Google te paga 15 dÃ¡lares por contestar en-cuestas que otras. #URL#” “Navidad en RD: son 3 dÃ­as gozando, luego “Ortega Smith: “VOX expulsarÃ¡ de EspaÃ±a a 362 llorando y deseando mal a los demÃ¡s. De- todos los inmigrantes ilegales” #URL#” jen su hipocresÃ¡n!” |

As can be seen in Table[1], the Twitter specific tokens hashtags, URLs and user mentions were replaced by the providers with the following placeholders: #HASHTAG#; #URL# and #USER#. Prior to the feature engineering, we analyzed the distribution of different tokens. Additionally, we determined the sentiment of each tweet (positive, negative, or neutral) using TextBlob[2]. For recognizing the named entities (NER), we used the Python library spaCy. Table[2] shows some key insights for both languages.

The observations of the corpus content were the following:

- Fake news spreaders:
  - mention other Twitter users less often (#USER#)

2 https://textblob.readthedocs.io/en/dev
3 e.g. “@Username”
Table 2. Feature distribution of the fake news (Fake) and true news (True) spreaders

| Features                | English   | Spanish   |   |   |
|-------------------------|-----------|-----------|---|---|
|                         | True      | Fake      | True | Fake |
| Unique Tokens           | 24,050    | 23,809    | 32,802 | 27,932 |
| Emojis Total            | 1,614     | 522       | 3,867 | 1,629 |
| Emojis Unique           | 325       | 145       | 603   | 301   |
| Neutral Tweets          | 6,857     | 7,061     | 14,228 | 14,261 |
| Positive Tweets         | 6,173     | 5,464     | 571   | 488   |
| Negative Tweets         | 1,970     | 2,475     | 201   | 251   |
| Uppercased Tokens Total | 38,519    | 32,467    | 36,388 | 30,177 |
| Uppercased Phrases Total| 861       | 1,019     | 406   | 953   |
| #URL# Token             | 16,565    | 17,018    | 10,887 | 13,900 |
| #HASHTAG# Token         | 6,739     | 4,715     | 5,905 | 1,580 |
| #USER# Token            | 5,628     | 2,279     | 10,668 | 5,949 |
| Retweets (RT)           | 2,383     | 1,158     | 4,289 | 1,977 |
| NER ORG                 | 8,340     | 7,299     | 2,617 | 2,595 |
| NER PERSON              | 7,742     | 9,801     | 4,845 | 5,573 |
| NER LOC                 | 188       | 222       | 5,337 | 5,214 |

- utilize fewer hashtags (#HASHTAG#).
- re-post fewer tweets (RT).
- share slightly more URLs (#URL#).
- Spanish speaking authors use more emojis than English speaking Twitter users.
- Half of the English tweets are based on factual information and most of the Spanish tweets (90%) are free of emotions.
- Fake news tend to be more often negative.
- Tweets of true news spreaders tend to be more often positive.
- By counting the named entities no significant difference between the classes could be established.
- Fake news spreaders tend to tweet slightly more often about other people.
- Uppercased tokens are shared equally by true news and fake news spreaders.
- Spanish fake news spreaders make more often use of capitalized phrases.

2 Preprocessing and Feature Extraction

The preprocessing pipeline was performed for both languages (EN and ES) basically. The steps for cleaning and structuring the data were performed as follows:

1. First, we extracted the text from the original XML document of each user and concatenated all 100 tweets to a single text.
2. White space between tokens were normalized to a single space.
3. URLs, hashtags and user mentions were left untouched as they are already replaced by placeholders by default.
4. Numbers and emojis were replaced by the placeholders #NUMBER# and #EMOJI#.
5. Irrelevant signs, e.g. “+,*/,” were deleted.
6. Sequences of repeated characters with a length greater than three were normalized to a maximum of two letters (e.g. “LOOOOOOOOL” to “LOOL”).
7. Words with less than three characters were ignored.
8. Stopwords were deleted by using the NLTK (Natural Language Toolkit) library\[^4\] for each language separately.
9. From the NLTK library we additionally used the TwitterTokenizer to tokenize the words. The tokenizer is suitable for Twitter and other casual speech that is often used in social networks. Additionally, TwitterTokenizer contains different regularization and normalization features. We made use of the lowercaser.

After the Twitter texts were preprocessed, we tested different vectorization techniques with manual hyperparameter tuning, and by employing scikit-learn’s grid search function. The hyperparameters were tuned separately for English and Spanish, but the features we used were mainly language-independent which means that the same set of features can be used in multi-language domains. The selected features were presented in Section\[^1\](e.g. counts of tokens or named entities). The only language dependant feature we experimented with was the sentiment polarity calculated separately for every tweet (whether it is positive, negative, or neutral). Besides the handcrafted features, we also experimented with automatically learned features i.e. term frequency distribution (tf) and character and word n-grams. Additionally, we made use of Feature Union\[^5\] to experiment with feature concatenation. To convert the tokens to a numerical matrix in order to build a vector for each language, we made use of:

1. Scikit-learn’s term frequency-inverse document frequency (TF-IDF)
2. GloVe\[^6\] (Global Vectors for Word Representation) word vectors pre-trained on Twitter data as well as custom trained word2vec\[^7\] word embeddings
3. Scikit-learn’s Count Vectorizer

All tested features and their representations are summarized in Table 3.

**Table 3.** Features, vectorization techniques and model hyperparameters used for training purposes

| Features       | Vectorizer     | Hyperparameters / ranges          |
|----------------|----------------|-----------------------------------|
| Tokens         | Word Embeddings | n-gram_range: [1;3],[2;7],[3;7]    |
| Token n-grams  | TF-IDF         | min_df: 1,2,3                      |
| Character n-grams | Count Vectorizer | max_features: [1,000;50,000]      |

\[^4\] http://www.nltk.org/
\[^5\] https://scikit-learn.org/stable/modules/generated/sklearn.pipeline.FeatureUnion.html
\[^6\] https://nlp.stanford.edu/projects/glove
\[^7\] https://radimrehurek.com/gensim/models/word2vec.html
3 Methodology

We defined the author profiling task as a binary problem predicting whether a tweet was composed by a fake news spreader or a reliable Twitter user. For each language (EN and ES) a separate classification model was trained. As mentioned before, for training and testing, we split the data in the ratio 70/30. We tested different features, vectorization techniques and dimensionality sizes in combination with a Support Vector Machine (SVM) and Logistic Regression of which we report the best performed ones. For the final SVM, we used a linear kernel with default hyperparameter values. Logistic Regression was also trained by utilizing default hyperparameter values.

The performance of the fake news spreader author profiling task was ranked by accuracy. Table 4 shows the scores for our final system performed on the official PAN 2020 test set on the TIRA platform. Accuracy scores were calculated individually for each language by discriminating between the two classes. Each model was trained on 70% of the training data. Hyperparameters were tuned on the remaining 30% split. As the data set is hidden, the four confusion matrix values (TP, TN, FP and FN) and other metrics like Precision and Recall cannot be provided. Therefore, we display these classification results and accuracy scores which we achieved on the 30% test dataset (see Table 4). The highest accuracy in English was obtained using SVM with TF-IDF weighted character n-grams with range [1;3] and top 3,000 features. In Spanish, the best results were achieved using Logistic Regression employing a feature union of TF-IDF weighted character n-grams with range [1;3] and top 5,000 features and a vector consisting of character n-gram counts with range [3;7] and top 50,000 features. The submitted models achieve an overall accuracy of 73% and 79% on the English and Spanish corpus, respectively.

Table 4. Accuracy (Acc.) scores of the final submitted systems on the official PAN 2020 test dataset on Tira

| Model                  | Features                                      | Language | Acc. |
|------------------------|-----------------------------------------------|----------|------|
| SVM                    | TF-IDF char n-grams [1;3] 3,000 features      | EN       | 0.73 |
|                        | Feature union TF-IDF char n-grams [1;3]       |          |      |
| Logistic Regression    | 5,000 features and                            | ES       | 0.79 |
|                        | char n-gram counts [3;7] 50,000 features      |          |      |

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8 https://scikit-learn.org/stable/modules/generated/sklearn.svm.LinearSVC.html
9 https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html
Table 5. Evaluation results on the test split of the submitted systems for every language (EN and ES) with the metrics Precision (P), Recall (R), Accuracy (Acc.) and $F_1$-Score.

| Model              | Features                                      | Language |  |  |  |  |  |  |
|--------------------|-----------------------------------------------|----------|---|---|---|---|---|
| SVM                | TF-IDF char n-grams [1;3] 3,000 features     | EN       | 35| 35| 10| 10| 0.78|
|                    | Feature union TF-IDF char n-grams [1;3]      | ES       | 42| 36| 9 | 3 | 0.92|
| Logistic Regression| 5,000 features and char n-gram counts [3;7] 50,000 features |          | 0.80| 0.80| 0.86| 0.87|

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