UrduFake@FIRE2020: Shared Track on Fake News Identification in Urdu

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ABSTRACT
This paper gives the overview of the first shared task at FIRE 2020 on fake news detection in the Urdu language. This is a binary classification task in which the goal is to identify fake news using a dataset composed of 900 annotated news articles for training and 400 news articles for testing. The dataset contains news in five domains: (i) Health, (ii) Sports, (iii) Showbiz, (iv) Technology, and (v) Business. 42 teams from 6 different countries (India, China, Egypt, Germany, Pakistan, and the UK) registered for the task. 9 teams submitted their experimental results. The participants used various machine learning methods ranging from feature-based traditional machine learning to neural network techniques. The best performing system achieved an F-score value of 0.90, showing that the BERT-based approach outperforms other machine learning classifiers.

1 INTRODUCTION
Automatic detection of fake news is an essential task, because fake news are often presented to the global audience to sway its opinion. This variation of public opinion can be manipulated for various objectives such as a political campaign or induction to a war, etc. Although fake news causes excitement or fear and spurs action, however, the propagation of fake news brings devastating and havoc impact in our society. For example, BBC\(^1\) reported in a recent study that fake news had severe consequences for minority communities and some businesses in India. The study highlighted that some Muslims were victimized as responsible for spreading the coronavirus, and such fake news led the calls for an economic boycott of Muslim business. Likewise, in a different study, BBC\(^2\) reported that some Indian sites claimed a civil war had broken out in one of the biggest city of Pakistan, known as Karachi, which eventually turned out a fake news. Therefore, combating and controlling the speed of fake news propagation by automatic detection is a vital task to support vulnerable communities and maintain a trustworthy news ecosystem.

Automatic fake news detection task received the attention of many researchers, especially after the US 2016 presidential election, where fake news were widely used as a political instrument during the campaign. For example, recent overview papers reported scientific issues associated with fake news detection [3, 10]. This shared task is greatly inspired by three previous evaluation forums, PAN@CLEF 2020 [8], MediaEval\(^3\), and RumourEval [4]. Significant shared tasks in several languages, in particular for English\(^4,5\), Spanish\(^6\) and Arabic [9] were designed. Usually, the studies focus on the resource-rich languages, in terms of size of annotated datasets and availability of NLP tools, such as English [6], Spanish [7], German [11] and Chinese [5]. As the spread of fake news is still growing on the internet and digital media, therefore technological support to identify fake content is necessary for all languages, including low resource languages like Urdu.

\(^1\)https://www.bbc.com/news/world-asia-india-53165436  
\(^2\)https://www.bbc.com/news/world-asia-54649302  
\(^3\)https://multimediaeval.github.io/editions/2020/tasks/fakenews/  
\(^4\)http://www.fakenewschallenge.org/  
\(^5\)https://pan.webis.de/clef20/pan20-web/author-profiling.html  
\(^6\)https://pan.webis.de/clef20/pan20-web/author-profiling.html
This paper provides a brief description of the UrduFake track at FIRE 2020. The study [1] provides a detail explanation of the problem definition and the participating team systems and describes the dataset, which we created for the shared task and made available to the research community. There is a growing need for research on the classification of fake news. Specifically, supervised machine learning algorithms based on a set of annotated training examples (news articles) can help to detect fake news. Keeping this in mind, we organize the 1st competition to address the current challenges with fake news detection for a low resource language (Urdu language, in our case). This competition also aims to encourage further development of resources in the form of annotated datasets and different digital solutions to combat the spread of fake news on the Web and digital media platforms.

2 TASK DESCRIPTION

This is a binary classification task, when the goal is to assign a label (fake or real news) for given news articles written in the Urdu. In a different study [2], we presented the definition of fake news. The mathematical formulation of fake news article and fake news detection is as follows:

- “Fake News Article”: A fake news is a factually incorrect news article, which provides factually incorrect information with the intention to deceive a reader making him to believe it is true news.
- “Fake News Detection”: For a given news article (unannotated), call as α, where α ∈ N (α is a news article out of N news articles), an automatic fake news detection algorithm assigns a score S(α) ∈ [0, 1] indicating the extent to which S(α) is considered as fake news article. For instance, if S(α̂) > S(α), then it can be inferred that α̂ is more likely to be a fake news article. A threshold χ can be defined, such that the prediction function F : N → [not fake, fake] is:

\[
F(N) = \begin{cases} 
  \text{fake}, & \text{if } S(\alpha) \in \chi, \\
  \text{not fake}, & \text{otherwise}. 
\end{cases}
\]

3 DATA COLLECTION AND ANNOTATION

For this competition, we created a dataset for automatic fake news detection task in Urdu. This dataset contains news articles in five domains: (i) Business, (ii) Health, (iii) Showbiz (entertainment), (iv) Sports, and (v) Technology. This section briefly describes the collection procedure of real and fake news. The dataset is publicly available to use for academic research7.

At the collection phase, thousands of news articles were crawled from multiple national and reliable international mainstream media agencies. To collect news articles from numerous online sources, a Python library Newspaper\(^8\) was used as a web scraper to extract and curate the content of news articles from multiple national and international newspaper web pages. This library automatically discards irrelevant information such as HTML tags, author’s name, location of the publisher, noisy texts and images, and advertisements.

7https://github.com/UrduFake/urdufake2020eval.git
8https://newspaper.readthedocs.io/en/latest/

- Real News Collection for Training and Testing Sets:

  To manually collect and annotate news articles as a real news article, numerous articles were retrieved from various national and international mainstream news channels from January 2018 to December 2018. The list of the news agencies used to crawl real news and the procedure of verification for news authenticity is described in [2]. A news article qualifies to be a real news only if it is published in a reliable newspaper and information such as place of the event, image, and date can be verified through prominent news agencies. We read the complete news article to check whether a news article correlates with the title and its content before annotation. Similarly, the same procedure was followed to collect and annotate the real news articles for the testing dataset. Nonetheless, all the news for the testing dataset were retrieved from January 2019 to June 2020.

- Professional Crowdsourcing to Collect Fake News for Testing and Training Sets:

  The collection and annotation of fake news articles, which correspond to the real news articles is a difficult task. Therefore, we used professional journalist services from various news agencies in Pakistan (Dawn news, Express news, etc.). They were asked to write fake news stories that correspond to the original real news articles. The journalists wrote fake news for both training and testing datasets. This approach is similar to fake news dataset development for English language [6], where the authors as well adopted professional crowdsourcing to collect fake news.

Table 1 describes the distribution of the news articles in the dataset.

|        | Real News | Fake News | Total |
|--------|-----------|-----------|-------|
| Train  | 500       | 400       | 900   |
| Test   | 250       | 150       | 400   |
| Total  | 750       | 550       | 1300  |

4 EVALUATION METRICS

In this shared task, the task is to classify a news article as either fake or real news article. Initially, to develop and train automatic fake news detection systems, we released the training dataset for the participants. In the next stage, the test dataset was released to test and evaluate the performance of the system. Each participating team could submit only 3 different runs for evaluation.

The submitted systems were evaluated by comparing the labels predicted by the participants’ classifiers and the ground truth labels. For quantifying the classification performance, we employed the commonly used evaluation metrics: Precision (P), Recall (R), Accuracy, and two F1-scores (F1-score for each class and F1-macro). The F1-score has many variants like weighted F1, F1-macro or F1-micro. We calculated F1real to predict the label of the “real” class,
F1 fake to predict the label of the “fake” class out of all news, and F1-macro.

Fake news detection classification task suffers from class imbalance. The distribution of class labels is often unbalanced in datasets, which also happens in our case (i.e., we have more real news than fake news articles). Therefore, to accommodate the skew towards the real class, which dominates (it has more samples than the fake news class), we used the macro-averaged F1-macro, which is the average of F1 real and F1 fake. F1-macro does not use weights for the aggregation. However, F1-macro penalizes when a system does not perform well for the minority classes. Although weighted-F1 is calculated independently for each class, but when the weighted-F1 of both classes is summed up, it gives more weight to the majority class. Therefore, we only report F1-macro.

5 BASELINE SYSTEMS

We provided three baseline systems with the goal that their performance could serve as reference points for qualitative evaluation of the submissions’ placement in the ranking. First, we provided the Random Baseline as the most basic and trivial baseline, which is expected to be ranked at the bottom with a more massive gap from the participating systems. Second, we provided the most traditional baseline: bag of words (BoW) model. It uses words as features and then apply a machine learning classifier. In this baseline, we used binary weighting scheme (i.e., a feature is present or not) with Logistic Regression classifier. For the third baseline, we provided the results of character bi-gram with tf-idf weighting scheme using Logistic Regression classifier, which achieved surprisingly good results. In addition, for the last two baselines, we tried five weighting schemes (tf-idf, logent, norm, binary, relative frequency) [2] along with various classifiers such as Logistic Regression, SVM, Adaboost, Decision Tree, Random Forest, and Naive Bayes (we got the best results with Logistic Regression).

6 OVERVIEW OF THE SUBMITTED APPROACHES

This section gives a brief overview of the systems submitted to this competition. 42 teams registered for participation, from which 9 teams submitted their runs. Registered participants were from 6 different countries (India, Pakistan, China, Egypt, Germany, and the UK). Participation of different teams from multiple countries confirms the importance of this task. The team members came from various types of organizations: universities, research centres, and industry. Table 2 describes the submitted approaches.

Table 2: Approaches used by the participating systems.

| System/Team Name | Feature Type | Feature Weighting Scheme | Classifying algorithm | NB-based |
|------------------|--------------|--------------------------|-----------------------|----------|
| BERT 4EVER       | context embedding BERT | BERT | CharRNN-Becona | No |
| BoW (baseline)   | char bi-grams, trigrams | TF-IDF | Logistic Regression | No |
| CANDLES           | word uni-grams, bi-grams | Binary | Logistic Regression | No |
| CNLP-NITS         | N/A | embedding, char embeddings | Dense Neural Network | Yes |
| CNLP-bi            | char bi-grams | TF-IDF | XNNet pre-trained model | Yes |
| SSNCSE_NLP        | n-grams | embedding, word embeddings | ULMfiT model | Yes |
| SSNCSE-MLP        | char n-grams | THDE (Unif, word trees), Bi-Adaboost, MLP, SVM | Yes |

7 RESULTS AND DISCUSSION

Table 3 describes the results of the best runs of the submitted systems.

The participating team (BERT4EVER) achieved the best F1-macro, Accuracy, as well as P fake (recall), F1 fake, and P real (precision) scores. However, the baseline approach with character bi-grams and Logistic Regression achieved the second position in the shared task with just 1.1% difference in F1 macro from BERT, which is quite an unexpected result. Explanation of this fact is a question for further research.

At this moment, it is hard to judge whether any of these approaches is ready to be applied “in the wild”. While the results of F1 real and F1 fake over 0.9 shown by the winning BERT 4EVER system are impressively high, the modest size of the provided training and testing dataset cannot guarantee the same performance on an arbitrary text input. To ensure the scalability of the presented approaches, more multifaceted research at a larger scale is needed. We see that one of the paths is a community-driven effort towards the increase of available resources and datasets in the Urdu language.

8 CONCLUSION

This competition was aimed at supporting and encouraging researchers working in different NLP domains to develop robust technology to tackle and minimize the propagation of fake content in Urdu on the web. Note that Urdu is a low-resource language, i.e., no significant datasets or NLP tools are available. We presented the dataset for fake news detection for Urdu news articles, which contains 1,300 news. Real news were obtained from reliable sources and verified manually, while fake news were written by professional journalists following specific instructions. We described the approaches presented for this shared task. Some approaches were based on non-neural networks while other approaches were based on neural networks. The best results were obtained by the approach based on BERT. In future, we plan to make our corpus larger and more robust. In addition, it will be interesting to try transfer learning approaches, e.g., train a system to detect fake news on Spanish or English and then test it on Urdu.

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Table 3: Participants’ best run scores.

| Team names           | Fake Class | Real Class |  |  |  |  |  |
|----------------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|
|                      | Precision  | Recall     | F1         | Precision  | Recall     | F1         |            |            |            |            |            |
| BERT 4EVER           | 0.890      | 0.860      | 0.874      | 0.918      | 0.936      | 0.926      | 0.900      | 0.908      |
| Character bi-gram (baseline) | 0.833      | 0.900      | 0.863      | 0.936      | 0.892      | 0.913      | 0.889      | 0.895      |
| CNLP-NITS            | 0.836      | 0.713      | 0.769      | 0.842      | 0.916      | 0.877      | 0.823      | 0.840      |
| NITP-AI-NLP          | 0.890      | 0.593      | 0.712      | 0.797      | 0.956      | 0.869      | 0.791      | 0.820      |
| Chanchal-Suman       | 0.881      | 0.593      | 0.709      | 0.796      | 0.952      | 0.867      | 0.788      | 0.818      |
| BoW (baseline)       | 0.722      | 0.746      | 0.734      | 0.845      | 0.828      | 0.836      | 0.785      | 0.798      |
| SSNNLP               | 0.709      | 0.733      | 0.721      | 0.837      | 0.820      | 0.828      | 0.774      | 0.787      |
| MUCS                 | 0.783      | 0.627      | 0.696      | 0.800      | 0.896      | 0.845      | 0.770      | 0.795      |
| CoDTeEM, NUST        | 0.771      | 0.607      | 0.679      | 0.791      | 0.892      | 0.838      | 0.758      | 0.785      |
| Rana Abdul Rehman    | 0.422      | 0.433      | 0.427      | 0.654      | 0.644      | 0.649      | 0.538      | 0.565      |
| Random (baseline)    | 0.373      | 0.420      | 0.395      | 0.623      | 0.576      | 0.599      | 0.497      | 0.517      |
| Cyber Pilots         | 0.377      | 0.533      | 0.441      | 0.628      | 0.472      | 0.538      | 0.490      | 0.495      |

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