False News Detection on Social Media

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ABSTRACT
Social media has become an important information platform where people consume and share news. However, it has also enabled the wide dissemination of false news, i.e., news posts published on social media that are verifiably false, causing significant negative effects on society. To help prevent further propagation of false news on social media, we set up this competition to motivate the development of automated real-time false news detection approaches. Specifically, this competition includes three subtasks: false-news text detection, false-news image detection, and false-news multi-modal detection, which aims to motivate participants to further explore the efficiency of multiple modalities in detecting false news and effective fusion approaches of multi-modal contents. To better support this competition, we also construct and release a multi-modal data repository about False News on Weibo Social platform(MCG-FNeWS) to help evaluate the performance of different approaches from participants.

1 INTRODUCTION
Social media, such as Twitter1 or Chinese Sina Weibo2, has become an important information platform where people acquire the latest news and express their opinions freely [1], [2]. However, the convenience and openness of social media have also promoted the proliferation of false news, i.e., news posts published on social media that are verifiably false, which not only disturbed the cyberspace order but also caused many detrimental effects on real-world events. For example, in India, dozens of innocent people were beaten to death by locals because of the false news about child trafficking that was widely spread on social media [3]. Thus, false news detection is a critical issue that needs to be addressed.

Some existing researches utilize the information generated in the news proliferation process, such as reviews, retweets and other relevant posts, to help detect false news [4], [5], [6], [7], but these contents can become available only after the news has been propagated on social networks for a while. However, according to statistics, false news spreads very quickly on social media, even six times faster than real news [8]. This further indicates that false news may have already been widely spread and caused many negative effects when enough relevant posts are generated. Therefore, to help prevent further propagation of false news on social media, we set up this competition to motivate the development of automated real-time false news detection approaches.

To effectively detect the false news from the news feed on social media in real time, the information we are looking at will mostly be the raw news content, which mainly includes text, images or videos, and publisher profile. Traditional false news detection researches based on news content usually focus on the textual content [9], [4], [10], from where they exploit some linguistic features to capture the differences of writing styles between false and real news. With the evolution of self-media news from text-based posts to multimedia posts with images or videos, false news usually utilize misrepresented or even tampered images to attract and mislead readers for rapid dissemination, which leads researchers to pay more attention to the visual content of false news [11], [12]. Considering that multiple modalities could provide cues for distinguishing false news, some works propose novel models to fuse features from different modalities to solve the challenging false news detection problem [13], [14], [15]. For this reason, we set up this competition to encourage participants to fully utilize the raw news content for false news detection, which consists of three subtasks: (a) false-news text detection, (b) false-news image detection, and (c) false-news multi-modal detection. Existing datasets about false news detection usually lack corresponding visual content [16], [4], [17], and the scale of multi-modal datasets in this field are limited [18], [19], [13]. Therefore, to better support this competition, we construct and publicize a multi-modal data repository about False News on Weibo Social platform(MCG-FNeWS), which is the largest multi-modal false news detection dataset, to help evaluate the performance of different approaches from participants. Besides, external knowledge is also helpful for determining the truthfulness of a particular claim in a real-time [20]. Thus, we also provide some resources which contain a large number of refutations about existing false news. We encourage participants to utilize the given external knowledge to help detect false news.

2 TASK OVERVIEW
The problem addressed in this competition is how to utilize the raw news content, mainly including the textual and visual content and publisher profile, to verify whether the given post is false or real in real-time. It has been proved that textual and visual content play important roles in detecting false news, thus we establish subtask A and subtask B to explore the efficiency of textual and visual modalities in detecting false news, respectively. Different modalities can not only mutually support but also be supplementary [21], but how to effectively process and relate information from different modalities is still a challenging problem. Subtask C aims to effectively fuse the information of different modalities to detect false news. In all the above subtasks, we encourage participants to fully utilize the external knowledge that we have given to help detect false news.

1https://twitter.com/
2https://weibo.com/
2.1 Subtask A – False-news text detection

Text is a major component of a news event, which is widely utilized by existing researches to verify the given news post is real or false. Many linguistic-based features have been widely studied to help to detect false news, but the underlying characteristics of false news have not been fully understood. Therefore, the aim of subtask A is to further explore the efficiency of text content in detecting false news. Success on this subtask will support the success of subtask C by providing effective features. The definition of subtask A is the following: Given a set of news posts \( X = \{x_1, x_2, \ldots, x_m\} \) and labels \( Y = \{y_1, y_2, \ldots, y_m\} \), the subtask requires participants to learn a classifier \( f \) that can utilize the corresponding text to classify whether a given post is false news \((y_i = 1)\) or real news \((y_i = 0)\), i.e., \( \hat{y}_i = f(x_i) \). Accordingly, we define false-news text as text in false news, and real-news text as text in real news. In practice, participants receive a list of text and are required to automatically predict, for each text, whether it is a false-news text or a real-news text.

2.2 Subtask B – False-news image detection

Visual cues have been shown to be an important manipulator for false news detection [22], [23]. However, very limited research has been done to exploit effective visual features, including traditional local and global features [24] and newly emerging deep network-based features [12], for the false news detection problem. Subtask B encourages the participants to put more attention on the visual content (images) to detect false news. Similarly, success of this subtask also promotes the success of subtask C. The definition of subtask B is the following: Given a set of news posts \( X = \{x_1, x_2, \ldots, x_m\} \), corresponding images \( I = \{i_1, i_2, \ldots, i_m\} \), and labels \( Y = \{y_1, y_2, \ldots, y_m\} \), learn a classifier \( f \) that can utilize the corresponding image to classify whether a given post is false news \((y_i = 1)\) or real news \((y_i = 0)\), i.e., \( \hat{y}_i = f(i_i) \). Accordingly, we define false-news image as attached image in false news, and real-news image as attached image in real news. In practice, participants receive a list of images and are required to automatically predict, for each image, whether it is a false-news image or a real-news image. Note that this subtask is different from tampered image detection because the tampered image is only a typical category of false-news image [12].

2.3 Subtask C – False-news multi-modal detection

This subtask aims at utilizing information from different modalities to effectively detect false news. Although there are already some studies focusing on fusing multi-modal information for false news detection, it is still a challenging problem which needs further investigation. For example, we can use the semantic alignment between image and text to explore the role of different modalities in false news detection, or utilize the technique of co-learning to tackle the problem of missing data. The definition of subtask C is the following: Given a set of news posts \( X = \{x_1, x_2, \ldots, x_m\} \), corresponding images \( I = \{i_1, i_2, \ldots, i_m\} \), publisher profile \( U = \{u_1, u_2, \ldots, u_m\} \), and labels \( Y = \{y_1, y_2, \ldots, y_m\} \), learn a classifier \( f \) that can utilize the corresponding text, image and publisher profile to classify whether a given post is false news \((y_i = 1)\) or real news \((y_i = 0)\), i.e., \( \hat{y}_i = f(x_i, i_i, u_i) \). Moreover, we refer to existing category lists from well-known debunking websites and finally summarize the following nine overarching topics: Society & Life, Disasters & Accidents, Health & Medicine, Education & Examinations, Science & Technology, Finance & Business, Culture & Sports & Entertainment, Politics and Military. For each post in the dataset, we also provide a topic tag which is manually labeled by its key objects of interest. In practice, participants receive a list of posts which include a text component, an associated images list, a user profile, and a topic tag, and are required to automatically predict, for each post, whether it is a false-news post or a real-news post.

In all cases, the competition asks participants to optionally return an explanation (which can be a text string, or indexes pointing to the given knowledge) that supports the verification decision. The explanation is not used for quantitative evaluation, but rather for gaining qualitative insights into the results.

3 DATA & RESOURCES

Training dataset: This is provided with ground truth and is used by participants to develop their approaches. It contains 38,471 news posts with 34,096 corresponding images, comprising 19,285 false-news posts with corresponding 13,635 false-news images, and 19,186 real-news posts with corresponding 20,461 real-news images.

Validation dataset: This is provided with ground truth and is used by participants to evaluate their approaches. It contains 4,000 news posts with 3,837 corresponding images, comprising 2,000 false-news posts with corresponding 1,760 false-news images, and 2,000 real-news posts with corresponding 2,077 real-news images.

Testing dataset: This is provided without ground truth and is used by organizers to compare the performance of participants’ approaches. It contains 3,902 news posts with 3,957 corresponding images.

In all datasets, the text of false news and real news are used to develop subtask A, images are used to develop subtask B, and all given data are for subtask C.

The data for all datasets are publicly available. The false-news posts are crawled from May 2012 to November 2018 and verified by the official Weibo Community Management Center, which usually serves as a reputable source to collect false-news posts on Weibo platform in literature [4], [13], [25], [26]. The real-news posts are collected during the same period as false news from Weibo. To explore the underlying characteristics of false-news posts in addition to superficial linguistics features, we crawl some real-news posts which have the similar linguistic style with false-news posts as negative samples. Specifically, following the method in [27], we discover false-news linguistics patterns like "is it real/false?" in false-news posts via text mining, and then crawl a large set of matched posts from the live stream of Weibo. For each post, we extract the keywords as the seed to crawl corresponding posts. After removing the duplicated posts, we obtain a candidate set of real-news posts, which are further manually verified by cross-checking.

https://www.biendata.com/competition/falsenews/data/
https://service.account.weibo.com/
online sources (articles and blogs), producing a real-news set. Finally, we sample the real-news posts to keep the balance of false-news and real-news posts. To alleviate the impact of events [14], we select real-news posts that belong to the same or similar events with false-news posts. In the preprocessing stage, we manually remove some meaningless statistical clues from the text.

We also provide a debunking repository which contains 37,877 refutations about existing false news. We crawl these refutations from multiple reputable debunking Weibo accounts and web articles. These refutations are crawled from September 2012 to August 2019. We encourage participants to utilize these refutations to help the detection of false news, but we do not promise that all false news in the competition dataset has corresponding refutations in this debunking repository.

4 EVALUATION
Overall, all the above subtasks are interested in the accuracy with which an automatic method can distinguish between false news and real news. Hence, given the testing set of labeled instances and a set of predicted labels (included in the submitted runs) for these instances, the classic measures (i.e., Precision P, Recall R, and F1-score) are used to quantify the classification performance, where the target class is the class of false news. Since the two classes (false news/real news) are represented in a relatively balanced way in the testing set, these measures are good proxies of the classifier accuracy.

5 BASELINES
In this section, we provide some baselines of the three subtasks for reference, which are shown in Table 1. For each subtask, we deploy some basic and state-of-the-art baselines on given datasets. Note that we don’t focus on searching the best hyper-parameters of these model, thus the given baselines are not the best results of corresponding models.

- **Subtask A**: For subtask A, we introduce four basic models including LSTM [28], GRU [29], TextCNN [30] and Bert [31], which are widely used in many NLP applications. In detail, we adopt the implementation of Bert in [32]. According to Table 1, Bert is slightly better than other models in accuracy.

- **Subtask B**: VGG [33] is widely used as a feature extractor in existing studies about multi-modal fake news detection [13], [14], [15], thus we implement pre-trained and fine-tuned VGG19 as baselines of subtask B. Also, we implement the state-of-the-art method utilizing visual content to detect false news MVNN [12], which is much better than other baselines in subtask B.

- **Subtask C**: For subtask C, we introduce three baselines including early and late fusion and attention based fusion models has made a classification decision. More intuitively, attention based fusion models have made a classification decision.

Table 1: Baselines for Three Subtasks

| Method       | Accuracy | Precision | Recall | F1    |
|--------------|----------|-----------|--------|-------|
| LSTM         | 0.864    | 0.891     | 0.829  | 0.859 |
| GRU          | 0.857    | 0.911     | 0.784  | 0.843 |
| TextCNN      | 0.851    | 0.953     | 0.732  | 0.828 |
| Bert         | 0.867    | 0.916     | 0.799  | 0.854 |
| Pre-trained VGG19 | 0.728    | 0.729     | 0.622  | 0.671 |
| Fine-tuned VGG19 | 0.759    | 0.791     | 0.607  | 0.687 |
| MVNN         | 0.805    | 0.804     | 0.743  | 0.772 |
| Early Fusion | 0.876    | 0.916     | 0.837  | 0.875 |
| Late Fusion  | 0.846    | 0.935     | 0.757  | 0.836 |
| atTrNN       | 0.852    | 0.871     | 0.820  | 0.845 |

6 CONCLUSION
With the popularity of multi-modal content in social media, incorporating the information of different modalities to detect false news is a critical task in the current media landscape. This competition about false news detection set up three subtasks to encourage participants to fully explore the efficiency of different modalities and effective fusion methods. This competition also leaves behind a benchmark dataset of ten thousands of false news and real news, which will help beginners of this research domain to quickly get started and evaluate their systems.

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REFERENCES

[1] Timothy I. Murphy. News use across social media platforms. 2018. https://www.journalism.org/2018/09/10/news-use-across-social-media-platforms-2018/. Accessed September 10, 2018.

[2] A research report about china internet news market 2016. http://www.cnic.cn/hlwfx3j/hlwzxbg/mthg/201701/d20170111_66401.htm. Accessed January 11, 2017.

[3] Annie Gowen. As mob lynchings fueled by whatsapp messages sweep india, authorities struggle to combat fake news. https://www.washingtonpost.com/world/asia-pacific/as-mob-lynchings-fueled-by-whatsapp-sweep-india/2018/07/02/683a1578-7bba-11e8-ac4e-421ef7165923.html. Accessed July 2, 2018.

[4] Jing Ma, Wei Gao, Prasenjit Mitra, Sejoong Kwon, Bernard J Jansen, Kam-Fai Wong, and Meeyoung Cha. Detecting rumors from microblogs with recurrent neural networks. In IJCAI, pages 3818–3824, 2016.

[5] Han Guo, Juan Cao, Yan Zhang, Junho Guo, and Jintao Li. Rumor detection with hierarchical social attention network. In Proceedings of the 27th ACM International Conference on Information and Knowledge Management, pages 943–951. ACM, 2018.

[6] Kai Shu, Limeng Cui, Suhang Wang, Dongwen Lee, and Huan Liu. defending: Explainable fake news detection. 2019.

[7] Chuan Guo, Juan Cao, Xueyao Zhang, Kai Shu, and Miao Yu. Exploiting emotions for fake news detection on social media. 2019.

[8] Soroush Vosoughi, Deb Roy, and Sinan Aral. The spread of true and false news online. Science, 356(6380):1146–1151, 2018.

[9] Carlos Castillo, Marcelo Mendoza, and Barbara Poblete. Information credibility on twitter. In Proceedings of the 20th international conference on World wide web, pages 675–684. ACM, 2011.
[10] Jing Ma, Wei Gao, and Kam-Fai Wong. Detect rumors on twitter by promoting information campaigns with generative adversarial learning. 2019.
[11] Zhiwei Jin, Juan Cao, Yongdong Zhang, Jianshu Zhou, and Qi Tian. Novel visual and statistical image features for microblogs news verification. IEEE transactions on multimedia, 19(3):598–608, 2017.
[12] Peng Qi, Juan Cao, Tianyin Yang, Junbo Guo, and Jintao Li. Exploiting multi-domain visual information for fake news detection. In 19th IEEE International Conference on Data Mining. IEEE, 2019.
[13] Zhiwei Jin, Juan Cao, Han Guo, Yongdong Zhang, and Jiebo Luo. Multimodal fusion with recurrent neural networks for rumor detection on microblogs. In Proceedings of the 2017 ACM on Multimedia Conference, pages 795–816. ACM, 2017.
[14] Yaqing Wang, Fenglong Ma, Zhiwei Jin, Ye Yuan, Guangxu Sun, Kishlay Jha, Lu Su, and Jing Gao. Eann: Event adversarial neural networks for multi-modal fake news detection. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pages 849–857. ACM, 2018.
[15] Khattar Dhruv, Goud Japal Singh, Gupta Manish, and Varma Vasudeva. Mvae: Multimodal variational autoencoder for fake news detection. In Proceedings of the 2019 World Wide Web Conference. ACM, 2019.
[16] Xiaomo Liu, Armineh Nourbakhsh, Quanzhi Li, Rui Fang, and Sameena Shah. Real-time rumor debunking on twitter. In Proceedings of the 24th ACM International on Conference on Information and Knowledge Management, pages 1867–1870. ACM, 2015.
[17] Kai Shu, Deepak Mahudeswaran, Suhang Wang, Dongwon Lee, and Huan Liu. Fakenewsnet: A data repository with news content, social context and dynamic information for studying fake news on social media. arXiv preprint arXiv:1809.01286, 2018.
[18] Christina Boididou, Katerina Andreadou, Symeon Papadopoulos, Duc-Tien Dang-Nguyen, Giulia Boato, Michael Riegler, Yiannis Kompatziaris, et al. Verifying multimedia use at mediaeval 2015. In MediaEval, 2015.
[19] Christina Boididou, Katerina Andreadou, Symeon Papadopoulos, Duc-Tien Dang-Nguyen, Giulia Boato, Michael Riegler, Stuart E. Middleton, Yiannis Kompatziaris, et al. Verifying multimedia use at mediaeval 2016. In MediaEval, 2016.
[20] Shu Kai, Suhang Wang, Amy Shiva, Jiliang Tang, and Huan Liu. Fake news detection on social media: A data mining perspective. Acm Sigkdd Explorations Newsletter, 19(1), 2017.
[21] Tadas Baltrukaitis, Chaitanya Ahuja, and Louise-Phillippe Morency. Multimodal machine learning: A survey and taxonomy. IEEE Transactions on Pattern Analysis and Machine Intelligence, 41(2):423–443, 2018.
[22] Aditi Gupta, Hemank Lamba, Ponnurangam Kumaraguru, and Anupam Joshi. Faking sandy: characterizing and identifying fake images on twitter during hurricane sandy. In Proceedings of the 22nd international conference on World Wide Web, pages 729–736. ACM, 2013.
[23] Peter Bae Brandtzaeg, Marika Lüders, Jochen Spangenberg, Linda Rath-Wiggins, and Asbjørn Folstad. Emerging journalistic verification practices concerning social media. Journalism Practice, 10(3):323–342, 2016.
[24] Dongping Tian et al. A review on image feature extraction and representation techniques. International Journal of Multimedia and Ubiquitous Engineering, 8(4):385–396, 2013.
[25] Yahui Liu, Xiaolong Jin, Huwei Shen, and Xueqi Cheng. Do rumors diffuse differently from non-rumors? a systematically empirical analysis in sina weibo for rumor identification. In Pacific-Asia Conference on Knowledge Discovery and Data Mining, pages 407–420. Springer, 2017.
[26] Zilong Zhao, Jichang Zhao, Yukie Sano, Ott Levy, Hideki Takayasu, Misako Takayasu, Daqing Li, and Shlomo Havlin. Fake news propagate differently from real news even at early stages of spreading. arXiv preprint arXiv:1803.03443, 2018.
[27] Zhiwei Jin, Juan Cao, Jiebo Luo, and Yongdong Zhang. Image credibility analysis with effective domain transferred deep networks. arXiv preprint arXiv:1611.05328, 2016.
[28] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. Neural computation, 9(8):1735–1780, 1997.
[29] Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555, 2014.
[30] Yoon Kim. Convolutional neural networks for sentence classification. arXiv preprint arXiv:1408.5882, 2014.
[31] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805, 2018.
[32] Implementation of bert that could load official pre-trained models for feature extraction and prediction. https://github.com/CyberZHG/keras-bert.
[33] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014.