User-Characteristic Enhanced Model for Fake News Detection in Social Media

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Abstract. In recent years, social media has become an ideal channel for news consumption while it also contributes to the rapid dissemination of fake news out of easy access and low cost. Fake news has detrimental effects both on the society and individuals. Nowadays, fake news detection in social media has been widely explored. While most previous works focus on different network analysis, user profiles of individuals in the news-user network are proven to be useful yet ignored when analyzing the network structure. Therefore, in this paper, we aim to utilize user attributes to discover potential user connections in the friendship network with attributed network representation learning and reconstruct the news-user network to enhance the embeddings of news and users in the news propagation network, which effectively identify those users who tend to spread fake news. Finally, we propose a unified framework to learn news content and news-user network features respectively. Experimental results on two real-world datasets demonstrate the effectiveness of our proposed approach, which achieves the state-of-the-art performance.

Keywords: Fake News Detection, Social Media, User Profiling, Network Embedding.

1 Introduction

In recent years, social media has become an indispensable part of daily life in which people can actively create or exchange their own ideas about news. However, the easy access, low cost and non-certification of social media enable fake news to disseminate widely and rapidly because of malicious accounts. Fake news, aiming to mislead readers out of commercial or political purpose, denotes a type of falsified information and brings detrimental effects to individuals as well as the society. The uniqueness of fake news makes it difficult to distinguish whether it is true or not simply from news content even with human eyes. Up until now, several fact-checking websites have been deployed to confirm the news, but it is still hard to deal with all the news promptly. Besides, external information such as knowledge base or user social engagements can help alleviate the shortcoming of text features but it is along with in-complete data or unexpected noises. Therefore, detecting fake news in social media is an important yet extremely challenging task.

In most studies, detection of fake news is regarded as text categorization that relies on computational linguistics and natural language processing [1]. Network analysis [2] is also considered to be an ideal method combined with text features. A previous study [3] used a novel concept of believability for edge re-weighting with network embedding to enhance user representation. However, attributes of individuals in the social network are usually ignored when analyzing the network structure, which help find malicious accounts like social bots [4] or trolls. Research [5] has provided evidence that fake news is likely to be spread by non-human accounts with similar attributes and structure in the network. For example, social bots tend to connect with legitimate users instead of other bots. They try to act like a human with fewer words and fewer followers in social media, who contributes to the forward of fake news.

In this paper, we propose a unified framework by learning both news content and news-user network to solve the above problems. We firstly construct a news-user network and leverage accelerated attributed network embedding to learn user representations with user profiles from friendship network, which makes it possible to discover abnormal users due to the similar topological structure and profiles. Secondly, we reconstruct the news-user network by adding new user connections based on the similarity of above user vectors and enhance embeddings of news and users with DeepWalk. In this way, we can make user embedding close to news embedding through network representation learning. Finally, we joint news and user embeddings as network features and fusion with content via pipeline learning. Experimental results on two real-world datasets demonstrate that the proposed method significantly outperforms the state-of-the-art model.

The rest of paper is structured as follows. In Section 2, we provide a brief introduction of related work. Then, we demonstrate our proposed model in a detailed way in Section 3. Section 4 reports the experimental process and result analysis. Finally, we present the conclusion and future work in Section 5.

2 Related Work

In this section, we briefly review the related work of fake news detection, which is categorized into content-based, network-based and feature fusion methods.

Content-based Content refers to the body of news, including source, headline, text and image-video, which can reflect subtle differences. Castillo [6] et al. first made use of special character, emotive words and hashtags to identify fake news. Qazvinian [7] et al. added lexical patterns and part of speech to improve the above work. In most studies, LIWC features have been applied to identify the role of individual words in news classification, which have already been outlined by [8-9] from all proposed methods. In terms of writing style, Rubin [10] et al. transferred the method of deception detection to detect fake news for the first time, and used rhetorical structure to measure the coherence of news. However, existing textual features are generally insufficient for fake news detection because fake news tries to mock true news.

Network-based Researches in this direction mainly focus on two aspects, user characteristics and group characteristics (social network or diffusion network). Castillo [6] et al. utilized user attributes such as age and number of followers/followees on twitter while Yang [11] et al. carried out similar experiments on Weibo platform. Jin [12] et al. learnt users' potential stance and conflict opinions from user comments by building a topic model. In order to extract temporal features from user comments, Ma [13] et al. took advantage of recurrent neural network while Chen [14] et al. added an attention mechanism to better distinguish effective features. In terms of network analysis, Zhang [15] et al. constructed a heterogeneous network with author, news and topic as nodes and combined with text features while a model [16] consisting of RNN and CNN was used to mine the global and local changes of user characteristics in the diffusion path respectively. Typically, Ma [17] et al. developed a kernel-based propagation tree and compare the similarity of rumor propagation tree in structure to obtain higher-order models for distinguishing different rumor types.

Feature fusion Due to the limitation of one source data, researchers have begun to explore how to combine different sources of features. Wang [18] provided a public benchmark dataset LIAR for fake news detection and then tried to combine content with metadata as feature input. Karim [19] et al. made further research on constructing an end-to-end model integrating feature extraction, multi-source fusion and automatic detection to capture the relationship between different data sources. Besides, Natali [20] built three modules called "Capture", "Score" and "Integrate" to fusion news texts, user comments and news sources effectively. Shu [21] studied the relationship between readers, news and writers through matrix decomposition, and made a breakthrough in the experimental result. Yang [22] et al. made innovative use of the image in news, who proposed a model Ti-CNN that integrates text and image, and confirmed the effectiveness of image in identifying fake news.

In this paper, we build a fusion framework that joints news representations learning from news content and news-user network respectively. Different from previous methods, our model focus on the characteristic of users engaged in fake news by taking advantage of network embedding to learn user representation in friendship network with user attributes and then reconstruct the news-user network with new relationships of similar users.

3 Model

In this section, we present the details of user-characteristic enhanced model UCEM, a unified framework by learning news textual content and news-user network respectively (Fig 1). We regard the news as a source user and construct a homogeneous network consisting of news propagation and user friendship network, the reason for which is that it enables mutual improvements of embeddings between users and news when learning the constructed network. Taking user profiles into consideration, we first utilize AANE to learn user embeddings in friendship network and discover the potential connections between users especially robot users. Then, a reconstructed news-user network is leveraged to learn news and user representations that are subsequently concatenated as input. By unifying news content and news-user network embeddings, our model detects the original news is fake or not. The detailed implement of sub-models will be presented in Section 3.1-3.3.

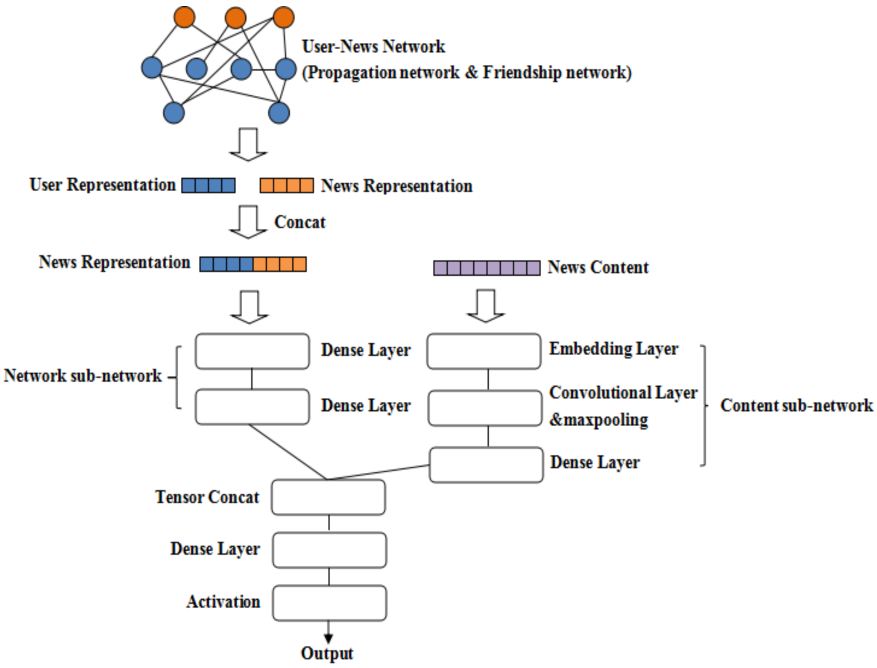

Fig. 1. Illustration of user-characteristic enhanced model for news classification

3.1 User attributed network learning based on AANE

Since social engagements are large-scale, we alleviate data sparsity by utilizing social proximity via network embedding. As science theories like homophily [23] and social influence [24] suggest, nodes' attributes are highly relevant to the network topological structure. AANE [25], namely accelerated attributed network embedding, gets better node representation by combing attribute proximity with network embedding, which develops a distributed optimization algorithm to decompose a complex problem into many sub-problems with low complexity.

Therefore, we utilize AANE to incorporate user profiles with user friendship network and get user embeddings. Given a set of users $U = \{u_1, u_2, \dots, u_n\}$ connected by a friendship network G associated with edge weights W and user profiles A, we aim to represent each user as a d-dimensional vector h_i where i denotes i^{th} user and get the final embedding representation H preserving the user proximity both in topological structure and user profiles. We treat it as an undirected network $G = (U, E, W)$ where E is a set of edges and weights are set to 1 or 0 if there is no connection between two users. Finally, we get embedding of each user after learning the friendship network with AANE, which is of great value for finding similar users.

3.2 Reconstruction for news-user topological network based on user similarity

In network representation learning, the first-order proximity indicates that two nodes are similar if there is a connection between them. In turn, if two nodes are similar, we can add a new relationship for them to make them closer in network structure. Similar users who tend to spread fake news may not follow each other, and malicious accounts present fewer connections in social networks. Motivated by this, we use cosine similarity to compute similarity for each user and add new user connection if the value is beyond the threshold ϵ that is set by experiment (Equation 1). H denotes the user embeddings from the above work where i denotes i^{th} user and j denotes j^{th} user.

$$\text{connection}(H_i, H_j) = \begin{cases} 1, \ if \ \epsilon < \cos(\theta) = \frac{H_i \cdot H_j}{\|H_i\| \|H_j\|} \leq 1 \\ 0, \ if \ \epsilon \geq \cos(\theta) = \frac{H_i \cdot H_j}{\|H_i\| \|H_j\|} \end{cases} \tag{1}$$

Based on the user similarity, we reconstruct the news-user network by adding new user connections. As we know, users in the spread of fake news and the way of propagation are different from true news. Network representation learning can help find those differences and show them both on news and user embeddings. In addition, malicious accounts are usually fewer-follower and fewer-word in social media. Thus, the new relationships of users enable to enhance embeddings about abnormal accounts and fake news. Specifically, we learn the news and user representations by employing DeepWalk [26], which samples a sequence of data with a random walk algorithm. We define the news-user network $G = (V, E)$ where V represents the nodes including users as well as news and E indicates the relationships between nodes like spreading or following. Besides, the weights of news-user edges are the number of reposting and the weights of user-user edges are set to be 0 or 1. The main idea of DeepWalk is updating node representation with SkipGram [29] by maximizing the co-occurrence likelihood of the nodes that come into view within a window using an independent assumption.

Finally, we concatenate the average of user embeddings for each news, where *n* denotes the number of users who spread the news, with news embedding as the network feature input, shown as follows.

$$V_{users} = \frac{1}{n} \times \sum_{i}^{n} V_{u_i} \tag{2}$$

$$V_{network} = V_{users} \oplus V_{news} \tag{3}$$

3.3 Fusion framework of network and content learning

"Late fusion" is a useful technique that boosts performance in most studies [27], so we incorporate the news content and news-user network features via a "late fusion", which allows for a neural network to learn a combined representation of multiple input streams. In order to make different features effective for classification, we develop a neural network architecture to lean them respectively via pipeline.

The content sub-network consists of an embedding layer and a convolutional layer followed by a max-pooling layer capturing the n-gram information of text, which has already been proven useful in research [30]. Each news is represented as a series of words $\{x_1, x_2, \ldots, x_n\}$ and the input is the concatenation of each word (Equation 4). Then the convolutional layer produces a feature map c generated from a window of words $x_{i:i+h-1}$ with three different sizes of filters w_k as Equation 5 and 6 shows.

$$x_{input} = x_1 \oplus x_2 \oplus \ldots \oplus x_n \tag{4}$$

$$c_i^k = f(w_k \cdot x_{i:i+h-1} + b) \tag{5}$$

$$c^k = \left[c_1^k, c_2^k, \ldots, c_{n-h+1}^k\right] \tag{6}$$

Besides, the network sub-network is built by a shallow perceptron with two dense layers (Equation 7) where l_1 or l_2 denotes the layers and the output is $a_{network}$. Finally, both features will be concatenated to predict the result. They are first fed into a fully-connected layer and then updated by a binary cross-entropy loss function as Equation 8 and 9 shows.

$$a_{network} = relu(W_{l2} \cdot (W_{l1} \cdot V_{network} + b_{l1}) + b_{l2}) \tag{7}$$

$$M = relu(W \cdot (a_{network} \oplus a_{content}) + b) \tag{8}$$

$$\text{loss} = -\sum_{i=1}^{n} \hat{y}_i \ log y_i + (1 - \hat{y}_i) \log(1 - \hat{y}_i) \tag{9}$$

4 Experiments

4.1 Datasets

In this work, we use publicly available datasets called FakeNewsNet[1] provided by Shu [28]. FakeNewsNet is a combination of two small datasets collected from two fact-checking platforms, namely PolitiFact[2] and BuzzFeed[3]. Both datasets include, for each news, the text content of the news and social contextual information like user content and user followee/follower for relevant users who posted/spread the news on Twitter. After cleaning the data, the detailed statistics are shown in Table 1.

Table 1. The statistics of datasets

Platform	BuzzFeed	PolitiFact
# Candidate news	182	238
# True news	91	120

[1] https://github.com/KaiDMML/FakeNewsNet
[2] https://www.politifact.com/subjects/
[3] https://www.buzzfeed.com/

# Fake news	91	118
# Users	15257	23865
# Engagements	25240	36680
# Social links	634750	574744

4.2 Experiment settings

For content sub-network, we initialize the embedding layer with pre-trained word2vec [29] embeddings of 256 dimensions and the word excluded in word2vec is set to a uniform distribution between [-0.25, 0.25]. Besides, we adopt DeepWalk to learn news and user embedding of 128 dimensions from the reconstructed news-user network as the feature input, which is trained by two dense layers with 50 units and 100 units respectively. Meanwhile, the mini-batch is fixed to 16. Finally, we train our model using Adam optimization with a learning rate of 0.001. In order to make the result more persuasive, we use early stopping mechanism and evaluate them using 5-fold validation. The metrics we use to evaluate the performance of all models are common in related areas, namely precision, recall and F1.

4.3 Baselines

In order to make comparison with previous methods, we choose the proposed framework using features like only content, network or combination of them as follows:

RST+SVM [10] RST is a style-based method using the theory of rhetorical structure to measure the coherence of news.

LIWC+SVM In traditional methods, LIWC is widely used for extracting linguistics features. In our experiment, we use features of 90 dimensions obtained from LIWC as input with SVM classifier.

Castillo [6] This method extract features from user profiles and user friendship network that is added the credibility score of users in [21] to ensure fair comparison.

RST + Castillo This method combines features obtained from RST and Castillo.

LIWC + Castillo This method combines features obtained from LIWC and Castillo.

TriFN [21] This method combines news and social engagements through modeling tri-relationship between publisher, news and readers. The SVM classifier is applied for classification.

4.4 Experimental result and analysis

We report the experimental result and the comparison is shown in Table 2.

Table 2. Result of models for fake news detection on FakeNewsNet

	BuzzFeed			PolitiFact		
	precision	**recall**	**F1**	**precision**	**recall**	**F1**
RST+SVM	0.610	0.561	0.555	0.571	0.533	0.544

LIWC+SVM	0.655	0.628	0.623	0.637	0.667	0.615
Castillo	0.747	0.783	0.756	0.779	0.791	0.783
RST + Castillo	0.758	0.784	0.789	0.812	0.792	0.793
LIWC + Castillo	0.791	0.834	0.802	0.821	0.767	0.813
TriFN	0.864	0.893	0.870	0.878	0.893	0.880
UCEM	**0.895**	**0.955**	**0.888**	**0.932**	**0.944**	**0.929**

We observe that baselines considering purely news contents achieve a lower F1 than other methods. In addition, methods considering both news content and social engagements can boost the performance. It is noticeable that our model UCEM increases by approximately 2% and 4% in terms of F1 compared with the best model. The possible reason is that our model unifies two features via "late fusion" for classification and improves the news-user network using user characteristics based on network embedding. Our model is different from TriFN that utilizes matrix analysis on tri-relationship for the reason that we aim to reconstruct the news-user network, which effectively improves the capability to identify fake news.

Analysis based on news content.

We mainly focus on features extracted from news content using different classifiers. We aim to compare the traditional method and deep learning models CNN and Bi-LSTM. Due to overfitting, the Bi-LSTM did not perform well with a lot of parameters as Table 3 shows and leveraging CNN to train with word2vec embeddings (static mode) performs better especially on PolitiFact datasets, considered to be a part of the unified framework.

Table 3. Result of news classification based on news content

	BuzzFeed			**PolitiFact**		
	precision	**recall**	**F1**	**precision**	**recall**	**F1**
LIWC+SVM	0.655	0.628	0.623	0.637	0.667	0.615
CNN (rand)	0.616	0.486	0.502	0.748	0.855	0.771
CNN (static)	0.658	0.807	**0.698**	0.818	0.812	**0.821**
CNN (nonstatic)	0.731	0.635	0.657	0.801	0.762	0.780
Bi-LSTM	0.478	0.801	0.523	0.513	0.830	0.625

Analysis based on the news-user network.

We analyze different network embedding methods based on the news-user network and the reconstructed news-user network improved by user characteristics. We first explore the user content (Fig 2) and user relationship (Fig 3) on two datasets.

We note that zero-word, zero-followee and zero-follower users can also be seen in both datasets. The above analysis confirms the idea of malicious or useless accounts that exist in the propagation of news. In the meanwhile, research [5] also find that users who spread fake news have fewer followers and more followees on both datasets and it verifies our hypothesis.

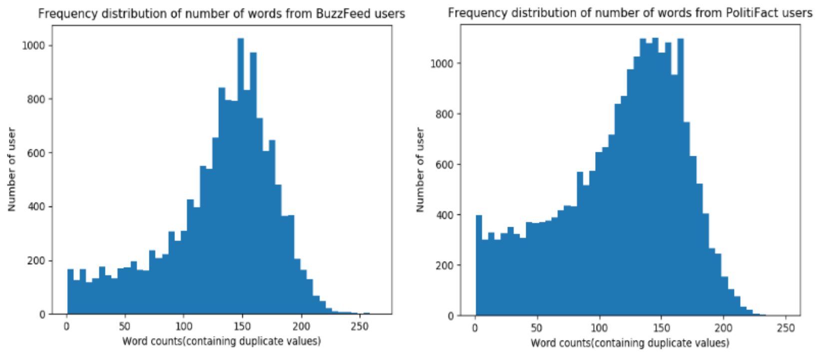

Fig. 2. Distributions of number of words in user content

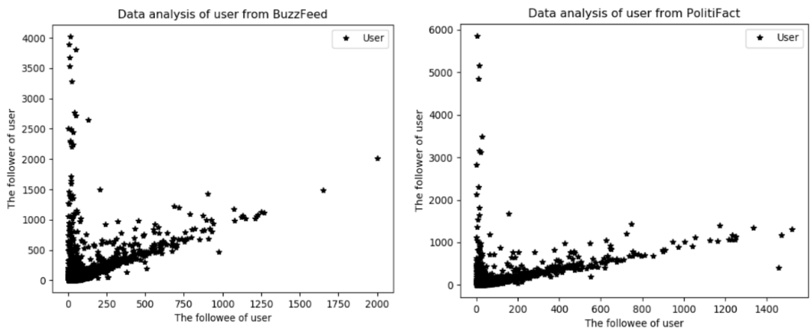

Fig. 3. Data analysis of user relationship

Subsequently, we carry out experiments on the news-user network using traditional models DeepWalk, LINE, node2vec and the reconstructed network based on AANE with the best threshold. The classifier is perceptron with two dense layers. The result is shown in Table 4. It is noticeable that using AANE to discover potential connections of users and learn the reconstructed news-user network from DeepWalk can get a better result. The news-user network consists of friendship network and propagation network where we treat the news as a source user, so it is like radial-shape for each node. Therefore, the possible explanation for the result is that Node2vec tend to learn node-centric information while LINE leverage the 2^{nd}-proximity to improve representation, so DeepWalk is more suitable for the reconstructed network learning.

Table 4. Result of news classification based on news-user network

	BuzzFeed			PolitiFact		
	precision	**recall**	**F1**	**precision**	**recall**	**F1**
DeepWalk	0.824	0.720	0.798	0.916	0.912	0.915
Node2vec	0.813	0.755	0.797	0.878	0.859	0.872
LINE	0.824	0.787	0.797	0.861	0.877	0.859
AANE+Node2vec	0.833	0.833	0.833	0.813	0.761	0.809

AANE+LINE	0.778	0.833	0.789	0.896	0.841	0.894
AANE+DeepWalk	0.874	0.811	**0.861**	0.924	0.915	**0.920**

Effect of threshold.

In the process of reconstruction, the threshold of similarity is a significant parameter. We employ different thresholds using AANE + DeepWalk for comparison as Table 5.

Table 5. Result of news classification on news-user network using different threshold

	BuzzFeed			PolitiFact		
Threshold ϵ	**precision**	**recall**	**F1**	**precision**	**recall**	**F1**
0.90	0.824	0.730	0.800	0.886	0.876	0.883
0.95	0.874	0.811	**0.861**	0.895	0.882	0.894
0.96	0.847	0.766	0.829	0.899	0.868	0.898
0.97	0.814	0.768	0.803	0.924	0.915	**0.920**
0.98	0.808	0.744	0.791	0.861	0.839	0.855

The threshold is different when BuzzFeed or PolitiFact datasets get the best result. After analyzing the reason, we find that the number of users in PolitiFact is more than that in BuzzFeed and it contributes to a different range of new user connections. The main idea of reconstruction is to discover extremely similar users while threshold less than 0.90 leads to a huge number of similar users that are not useful for network learning because of the lower F1 and F1 for different thresholds is in form of normal distribution. We also visualize the users in new connections by sampling randomly (Fig 4). Most of them are zero-follower users that are reasonable to the research [5].

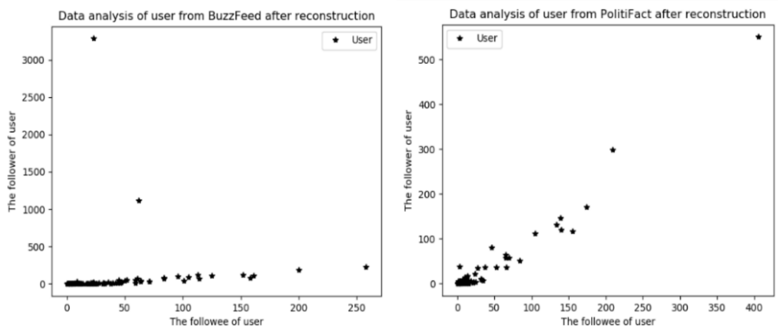

Fig. 4. Data analysis of new user relationship

5 Conclusion

In this paper, we deeply analyze the characteristics of user in the propagation of news and reconstruct the news-user network. We observe that our model can effectively identify accounts tending to spread fake news in social media. Furthermore, we built a novel user-characteristic enhanced model that jointly learn news textual content and news-user network information to identify the types of news. Experimental results show that our model performs better than models using the same datasets.

In future work, we may focus on how to utilize user comments to improve the whole network. Besides, a complete and large-scale dataset including content, user profile, user comment, social engagement and so on would like to be collected for further research.

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References

1. Potthast, M., Kiesel, J., Reinartz, K., Bevendorff, J., Stein, B.: A Stylometric Inquiry into Hyperpartisan and Fake News. (2017).
2. Shu, K., Bernard, H.R., Liu, H.: Studying Fake News via Network Analysis: Detection and Mitigation. In: Emerging Research Challenges and Opportunities in Computational Social Network Analysis and Mining. pp. 43-65 (2018).
3. Rath, B., Gao, W., Ma, J., Srivastava, J.: From retweet to believability: Utilizing trust to identify rumor spreaders on Twitter. In: Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining. pp. 179-186 (2017).
4. Ferrara, E., Varol, O., Davis, C., Menczer, F., Flammini, A.: The rise of social bots. Communications of the ACM59(7), 96–104 (2016).
5. Shu, K., Wang, S., Liu, H.: Understanding User Profiles on Social Media for Fake News Detection. In: 2018 IEEE Conference on Multimedia Information Processing and Retrieval. pp.430–435 (2018).
6. Castillo, C., Mendoza, M., Poblete, B.: Information credibility on twitter. In: Proceedings of the 20th international conference on World wide web. pp.675-684 (2011).
7. Qazvinian, V., Emily, R., Dragomir, R.R., Qiaozhu, M.: Rumor has it: Identifying Misinformation in Microblogs. In: Proceedings of the Conference on Empirical Methods in Natural Language Processing. pp. 1589–1599 (2011).
8. Conroy, N.J., Rubin, V.L., Chen, Y.: Automatic deception detection: Methods for finding fake news. Association for Information Science and Technology52(1), 1–4 (2015).
9. Heydari, A., Tavakoli, M.A., Salim, N., Heydari, Z.: Detection of review spam: A survey. Expert Systems with Applications42(7), 3634-3642. (2015).
10. Rubin, V.L., Conroy, N.J., Chen, Y.: Towards News Verification: Deception Detection Methods for News Discourse. In: Hawaii International Conference on System Sciences. pp. 5–8 (2015).
11. Yang, F., Liu, Y., Yu, X., Yang, M.: Automatic detection of rumor on Sina Weibo. In: Proceedings of the ACM SIGKDD Workshop on Mining Data Semantics - MDS ’12. pp. 1–7. (2012).
12. Jin, Z., Cao, J., Zhang, Y., Luo, J.: News Verification by Exploiting Conflicting Social Viewpoints in Microblogs. In: Thirtieth AAAI Conference on Artificial Intelligence. pp. 2972–2978 (2016).

13. Ma, J., Gao, W., Mitra, P., Kwon, S., Jansen, B.J., Wong, K.F., Cha, M.: Detecting rumors from microblogs with recurrent neural networks. In: IJCAI International Joint Conference on Artificial Intelligence. pp. 3818–3824 (2016).
14. Chen, T., Li, X., Yin, H., Zhang, J.: Call attention to rumors: Deep attention based recurrent neural networks for early rumor detection. In: Pacific-Asia Conference on Knowledge Discovery and Data Mining. pp. 40-52 (2018).
15. Zhang, J., Cui, L., Fu, Y., Gouza, F.B.: Fake News Detection with Deep Diffusive Network Model. (2018).
16. Liu, Y., Wu, Y.B.: Early Detection of Fake News on Social Media Through Propagation Path Classification with Recurrent and Convolutional Networks. In: Thirty-Second AAAI Conference on Artificial Intelligence. pp. 354–361 (2018).
17. Ma, J., Gao, W., Wong, K.: Detect Rumors in Microblog Posts Using Propagation Structure via Kernel Learning. In: Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics. pp.708–717 (2016).
18. Wang, W.Y.: “Liar, Liar Pants on Fire”: A New Benchmark Dataset for Fake News Detection. (2017).
19. Karimi, H., Roy, P., Saba-Sadiya, S., Tang, J.: Multi-Source Multi-Class Fake News Detection. In: Proceedings of the 27th International Conference on Computational Linguistics. pp. 1546–1557 (2018).
20. Ruchansky, N., Seo, S., Liu, Y.: CSI: A Hybrid Deep Model for Fake News Detection. In: Proceedings of the 2017 ACM on Conference on Information and Knowledge Management - CIKM ’17. pp. 797–806 (2017).
21. Shu, K., Wang, S., Liu, H.: Beyond News Contents: The Role of Social Context for Fake News Detection. In: Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining. pp. 312-320 (2017).
22. Yang, Y., Zheng, L., Zhang, J., Cui, Q., Li, Z., Yu, P.S.: TI-CNN: Convolutional Neural Networks for Fake News Detection. (2018).
23. McPherson, M., Smith-Lovin, L., Cook, J.M.: Birds of a Feather: Homophily in Social Networks. Annual review of sociology27(1), 415–444 (2002).
24. Tsur, O., Rappoport, A.: What’s in a hashtag?: content based prediction of the spread of ideas in microblogging communities. In: Proceedings of the fifth ACM international conference on Web search and data mining - WSDM’12. pp. 643(2012).
25. Huang, X., Li, J., Hu, X.: Accelerated Attributed Network Embedding. In: Proceedings of the 2017 SIAM international conference on data mining. pp. 633-641 (2017).
26. Perozzi, B., Al-Rfou, R., Skiena, S.: DeepWalk: Online Learning of Social Representations Bryan. In: Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining - KDD ’14. pp. 701–710 (2014).
27. Volkova, S., Shaffer, K., Jang, J.Y., Hodas, N.: Separating Facts from Fiction: Linguistic Models to Classify Suspicious and Trusted News Posts on Twitter. In: Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics. pp. 647–653 (2017).
28. Shu, K., Mahudeswaran, D., Wang, S., Lee, D., Liu, H.: FakeNewsNet: A Data Repository with News Content, Social Context and Spatial temporal Information for Studying Fake News on Social Media. (2018).
29. Mikolov, T., Chen, K., Corrado, G., Dean, J.: Efficient Estimation of Word Representations in Vector Space. (2013).
30. Yu, F., Liu, Q., Wu, S., Wang, L., Tan, T.: A convolutional approach for misinformation identification. (2017).