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REVIEW

Survey on Fake Information Generation, Dissemination and Detection

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Abstract — The current booming development of the Internet has put the public in an era of information overload, in which false information is mixed and spread unscrupulously. This phenomenon has seriously disturbed the social network order. Thus, a substantial amount of research is beginning to be devoted to the effective management of fake information. We analyze the abnormal characteristics of fake information from its mechanism of generation and dissemination. In view of different exceptional features, we systematically sort out and evaluate the existing studies on false content detection. The commonly used public datasets, metrics, and performance are categorized and compared, hoping to provide a basis and guidance for related research. The study found that the current active social platforms show different novelty. The future direction should point to mining platform features of multi-domain sources, multi-data forms, and multi-language heterogeneity to provide more valuable clues for fake information.
Keywords — Fake information, Abnormal characteristics, Detection methods, Public datasets.
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I. Introduction

Fake information is false or misleading information [1]. With limited attention, fake information can increase our workload and bias our understanding of something important. The false content is diverse and includes false or misleading news stories, hoaxes, conspiracy theories, click-bait headlines, and junk science. Some researchers refer to the above various types of unverifiable information as fake information [2]. Fake information usually spreads virally [3], and faster and more widely than real information [4].

Currently, the rapid development of online media has attracted many users, while it has also provided favorable conditions for fake information proliferation. Due to the self-media's low threshold and lack of regulation, it is difficult to guarantee the quality of disseminated content. On the other hand, the breeding of false public opinions seriously interferes with the audience's discernment and choice of helpful information. Moreover, fake information not only damages the image of individuals, the interests of companies, and the credibility of the government, but also can even disrupt the regular order of society and cause the social panic. Similar to advertising campaigns, underground markets can reap enormous financial benefits from spreading misinformation. Fake information also may contain strong political motives [5] and even threaten democracies. It has been confirmed that disinformation does cause real harm in the health and financial spheres. For example, since the COVID-19 epidemic, comments on "specific drugs" and vaccination policies have brought a terrible social and market impact; Social bots [6] spread false news indiscriminately during the 2016 US presidential election, disrupting political election campaigns. The expansion of fake information has been listed by the World Economic Forum as one of the main threats to global society [7]. Therefore, the discrimination of fake information has become a hot issue in media communication research.

To make the network platform play a good role in information sharing and guide rational public opinion, we need to conduct an in-depth summary of the generation and dissemination mechanism of fake information, the manifestation of abnormal characteristics, etc. It explores better means from existing detection technology to resist

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false content. This article reviews and analyses the sources of fake information and its diffusion patterns in the process of generation and propagation. We identify its abnormal characteristics and outline the key technologies and methods of detection currently. By generalizing the strengths and weaknesses of existing technologies, the references and next steps for further research are provided. It is of great practical and scientific significance.

II. Mechanisms for the Generation and Dissemination of Fake Information

Fake information is produced by propaganda for a definite purpose. We first analyze the generation mechanism of fake information. It is mainly composed of both intrinsic motives and external environmental conditions. 1) Intrinsic subjective motivation is the decisive factor. Thanks to competition from curiosity-seeking media or individuals. They deliberately distort the facts to improve circulation, ratings, and notability. Of course, it also contains a few unintentional interpretations. The circulation of information makes the authenticity unintentionally distorted and confused. 2) The external environment refers to the communication characteristics of the current social media platform. The platform allows messages to expand and spread widely through such interactive behaviors as forwarding and liking. Thus, for the interests of the economic and political, the underground market of public opinion manipulation is extremely active, such as organized and premeditated political and military activities, entertainment news, social machine accounts, etc.

In fact, the algorithm designed for the platform is mainly to provide help to netizens, which collects and recommends interesting content to users. However, the algorithm pays more attention to attracting users through the behavior of automatic forwarding without verifying the credibility of the message. In particular, personalized recommendation services, promotion based on background knowledge and social user connections all make false information more acceptable. Those works usually combine knowledge graph technology in social networks to create and disseminate false information [8], [9].

The spread of fake information benefits from the openness and interactivity of the current social media platform. In addition to algorithmic recommendations in the platform, theories of cognitive and social psychology, such as "gossip psychology", also show that people are vulnerable to the spread of fake information. At present, the research on false information communication models majorly adopts methods in the field of psychology and network science, focusing on selective exposure and epidemic models [10], etc. This qualitative analysis method has a guiding significance for the research on information communication process, but they ignore the quantitative research on the crucial factors in dissemination.

The research finds that fake information has unique network structure characteristics in the propagation path. Shao [2] built the Hoaxy system to collect and track fake news. It effectively identifies the relationship between critical nodes and competitive propagation based on the k-core decomposition of the information network. For the propagation process, Liu *et al.* [11] proposed a detection model for classifying fake information propagation paths. Based on communication behavior modeling, Jin *et al.* [12] tracked the propagation path of fake information and identified the key disseminators. According to the structural differences of networks, Reference [13] revealed the fake information communication mechanism from the structure of social networks.

Besides, it is also a vital technology to suppress the spread of fake information by controlling the highly centralized nodes in the propagation network. Hence, extensive studies have been conducted on the subjects that publish false content, namely, the identification of social natural persons and social bots. A social robot is manipulated on a social platform to promote the rampant dissemination and spread of false information through the characteristics of opinion leaders. According to the investigation, social bots usually use a lot of repeated publicity, hijacking topic hashtags, inserting comments and discussions, and other strategies to spread fake information. Social robots rely on their numerous fans to initiate and expand their dissemination through following, replying, mentioning, liking, etc. They show apparent abnormal characteristics. Just like "super disseminators" in virus spread, they push a message thousands of times, share a high proportion, and have many fans. The keywords of fake information will be mentioned repeatedly so the frequency of fake words will increase suddenly. Therefore, given the user characteristics and the abnormal characteristics of the spreading process, the current strategy of social bot identification has achieved effective results in curbing the generation and spread of fake information. It is mainly divided into based on features [14] and graph theory [15]. In the face of the diversity of sources of fake information, the detection of social bots alone cannot completely achieve effective containment of fake information. Hence, many researchers devote themselves to the characteristics of fake information, which improve recognition accuracy and comprehensiveness.

III. Fake Information Detection Method

Countermeasures against fake information mainly include accurate identification and real-time monitoring of false content. The connection among fake information is weak, and there is almost no correlation in the space-time sequence. Therefore, in the work of false detection, existing researchers focus on the feature extraction of content, including its information attribute, communication process, effect, etc. They propose detection and analysis models with different dimensions such as false content identification, abnormal user detection, and abnormal feature discovery. So that timely discover false news and implement blocking restrictions, disinformation, and other operations. The prominent characteristics of the current fake information and the classification of its detection methods are summarized in Figure 1.

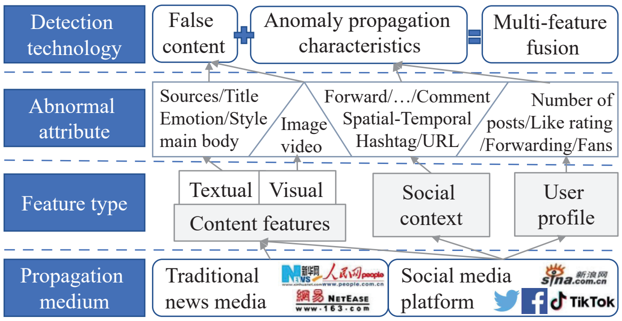

Figure 1 Generation platform, abnormal characteristics, and detection method classification of fake information.

The propagation medium is necessary for the existence of disinformation, which can be divided into traditional news media and social platforms. According to the characteristics of information release and dissemination on diverse platforms, different cause features are regarded as clues to identify fake information. Detection models or algorithms are designed based on abnormal characteristics. For classic news media platforms, misinformation is mainly reflected in content features, including source, title, body, and other text types [16], [17] and visual features, such as pictures and videos [18], [19]. The detection method is usually the knowledge-based [20] or the style-based of display [17], [21], which is verified manually by experts and crowdsourcing. However, with the prevalence of social media, social platforms have become a hotbed for the proliferation of fake information. Compared with traditional news media, social platforms provide users with more flexible and free interactive space. In addition to the content characteristics, it also reflects the social environment and communication process characteristics of fake information. They include the temporal [22] and spatial characteristics, topic hashtags, and the emotions [23]. Social and user [24] also include the network structure [25], the volume of forwarding, liking, propagation trajectory, and social behavior characteristics, etc. The rich attribute information brings convenience for detection and tracking. With the help of current machine learning and data mining technologies, the detection methods mainly focus on content, social, user abnormal feature discovery [12], [26], and multi-attribute fusion detection methods. In the specific empirical research, most studies have obvious application limitations. This section provides a detailed summary of each type of approach.

1. False content identification

Identification based on false content facilitates early detection of false information. The presentation forms of fake information include text, images, video, and other multi-modal data. In the generation and transmission, fake information is usually displayed and forwarded with plenty of repeated contents, forming a dense structural cluster. The frequency of critical false words has the characteristics of burst and surge. Therefore, the method of fake content identification can realize the timely discovery by processing and mining different modal data, such as analyzing false word frequency and image semantics using topic models and neural networks.

They extract features from the text, image, and multi-modal data sources to obtain representations. Then, the statistical methods, traditional machine learning, and neural network models are utilized to select and learn features. Finally, machine learning algorithms i.e., deep learning frameworks or support vector machine (SVM) are adopted to classify and predict the true and false messages. The overall detection process of fake information is generally shown in Figure 2.

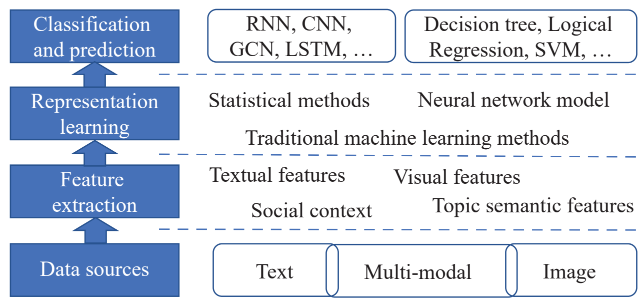

Figure 2 The overall detection process of fake information

1) Detection based on text content

Detecting text content applies to traditional news platforms and social media. This method focuses on the presentation form of text content and the learning of features, including the language and structure features of the text. Based on natural language processing technology, it is taking text features as modeling objects to mine the different granularity of text. It can be divided into two representation methods oriented to explicit features and implicit features to identify false text content.

The fake information detection method based on text field features is a technology that counts the number of sudden high-frequency false words or writing style, etc. Przybyla [27] detects false content based on styles features. Shojaee *et al.* [28] analyzed text writing style based on lexical and used naive Bayesian and sequential minimal optimization classifiers to identify false comments. Horne *et al.* [29] constructed text style features, complexity features, and psychological features to propose a fake information detection model based on a SVM. Dhamani *et al.* [30] built a coupling network based on CNN and LSTM to learn emoticons, slang, spelling errors, etc. to detect fake information. Reference [31] manually constructed the combined feature set of N-grams, punctuation, psycholinguistics, and other word levels of the text, and trained the SVM model to detect fake information. These methods check fake news based on text writing style and language characteristics. They have achieved good results to a certain extent, but it is limited by constantly updated network terms and new types of fake information. They are hard to learn and update the model dynamically.

The fake information detection method based on text-hidden features is to mine more semantic information by introducing deep feature representation learning technologies. In recent years, deep learning technology has shown superior performance in feature representation. In terms of fake text content detection, it can improve detection accuracy by deep learning models mining implicit text features. Relevant research mainly adopts the recurrent neural network (RNN) [32], convolutional neural network (CNN) [33], [34], generation adversarial network (GAN) [35], BERT model [36], etc. Reference [37] captured the hidden representation of text and significantly improved the effect of fake information detection. Other studies combined different depth network models to build detection algorithms, which can better identify fake information. Wang [21] used CNN and Bi-LSTM to integrate word embedding and detected fake information. Volkova *et al.* [38] combined CNN and LSTM to fuse text language clues and word embedding to evaluate the authenticity of the information. Yu *et al.* [39] learned paragraph-embedded representation based on the CNN model to extract advanced text features of information. Agrawal *et al.* [40] constructed a hybrid model by combining the benefit of blockchain with an intelligent deep learning model to reinforce robustness and accuracy in combating fake news's hurdle. Liu *et al.* [41] proposed a fake information detection method based on a layered attention mechanism combining CNN and Bi-LSTM.

Another kind of implicit information is contained in the structural relationship of the text. Different logical structures such as words, phrases, sentences, and paragraphs can reflect diverse semantic information, which can excavate more implicit features of texts. The existing research can be divided into a tree-based and a graph-based structure. Zhou *et al.* [42] used a text rhetorical structure tree to extract text features. Uppal *et al.* [43] used the bidirectional GRU network to learn sentence representation and detect fake information. Other, the graph structure contains more relational information. It introduced GCN to integrate sentence embedding through the max-pooling layer, which generated text representation and detected fake information. Wang *et al.* [44] proposed a fake information early detection model Sem-Seq4FD based on the global semantic interaction structure, local adjacent order structure, and global order structure between sentences. We classify the above false text detection methods based on the learning of explicit and implicit levels, as shown in Table 1.

2) Detection based on visual features

In addition to text, fake information also contains visual features that are more likely to attract attention, such as pictures and videos. In the existing research, images have been widely used in the detection of fake information and played a central role [45], [21]. In fake information detection for visual features, images are usually used as supplementary data for text to provide more clues for detection. As the images attached to the fake information tend to focus on attracting the public's attention, their clarity is not high. The consistency score between the image and text is low, and the meaning discrepancy between the image and text is more serious. Therefore, the main direction of fake information detection research is to carry out image definition analysis [19], image and text consistency analysis [46], etc. These methods generally extract critical information such as Spatio-temporal attributes and users from published information to evaluate the degree of information matching. Reference [47] used the image2text model to convert visual into textual features, and mapped them into the same vector space through a full-connection layer to compare the similarity between visual information and text information. Reference [48] adopt BERT to model text information and ResNet to model visual representation. It calculated the similarity between them and determined whether the image and text are consistent.

Table 1 Classification of false text detection methods

Type	Reference	Identifying objects	Classify model
Explicit level	[30]–[32]	Writing style	Naive Bayesian, SVM, CNN, LSTM
	[33]–[35]	Linguistic feature	
Implicit level	[36]–[45]	Hidden representation	RNN, CNN, BERT, LSTM, Attention, etc.
	[46]–[48]	Structure feature	

Due to the development of the current short, adaptable, and fast platform, the capture and collection of images, videos, and other information are more convenient for users, so the visual presentation form of fake information can also reflect false content to a certain extent. To mine the information in the visual features, researchers build a deep neural network to extract complex image representations and then accurately identify the fake information [49]. Qi *et al.* [50] proposed a false image discriminator based on a multi-domain visual neural network. They extracted spatial and frequency domain features and designed a framework including a frequency domain module, pixel domain module, and fusion module to learn visual representation. Xue *et al.* [48] introduced an error level analysis algorithm and CNN to judge the authenticity of pictures at the physical level.

2. Abnormal characteristics identification

1) User-oriented detection method

The spread of fake information is usually carried out by users with the characteristics of social opinion leaders, such as social bots. Therefore, in addition to the noteworthy characteristics of the content information with the detection target, the user's abnormal behavior is also a valuable source of finding fake news. Because the users who spread fake information have the characteristics of malicious diffusion and repeated release, there have been related works on fake news identification based on the features of users, including the registration information (gender, age, personal data) and the social information. Such as attention (i.e., number of fans), number of published messages, number of retweets, and mentions (i.e., the total times of users are mentioned in the form of @ by other users) [25]. Some researchers construct user profiles for detection [51]. The comparative analysis of user explicit and implicit characteristics revealed that some user profiles are helpful to discover fake information. In recent years, with the emergence of many social media platforms and social bots, researchers devoted themselves into identify social bots to find propagation characteristics and patterns of fake information [3].

In view of the rapid development of deep learning and other technologies, based user feature depth representation and learning are effective detection methods. Reference [52] constructed a GCAN model to obtain the user embedding the by using user profile as the initialization information of the nodes in the graph. Finally, false news is detected by using user information. Jiang *et al.* [53] modeled the news dissemination network and the user social network as a heterogeneous graph and then modeled the node information through the heterogeneous graph neural network. They spliced the news information and user information together for fake news detection. The user sending history [54] is used to identify the user's credibility as an internal cause, while the news dissemination is used as an external cause. The internal and external causes are utilized to jointly detect false news.

2) Anomaly feature-oriented detection method

The abnormal characteristics of fake information include social context, forwarding, number of comments, time release, sentiment, social attributes, network structure, and other unexpected and abnormal phenomena during propagation. Among them, emotion is an important feature that resonates with the public. Emotional mining based on messages, comments, and other aspects is beneficial to target fake information. Thus, the existing research on emotional abnormalities is the main channel to finding false statements. Ajao *et al.* [55] constructed an emotional attribute to calculate the ratio of negative and positive words in news content that help detect fake information. Guo *et al.* [56] proposed a dual emotion fusion model based on text content and comment. They designed three gates for feature fusion at different levels and introduced GAN to enhance the robustness of the model. Zhang *et al.* [57] combined text emotion, user emotion, and emotion difference into a dual emotion feature model to detect fake information. Li *et al.* [58] proposed a recognition model based on BERT and Bi-LSTM from the perspective of emotion analysis.

In order to mine the potential semantic information, some researchers focus on social context and improve the message content feature representation [59], [60]. Ma *et al.* [32] introduced the RNN model to capture the changes in social context characteristics of relevant messages over time. At the time of message release, the same fake information is usually aggregated. Therefore, Chen *et al.* [61] added an attention mechanism to RNN to selectively extract time representation and further discovered the false information. Bian *et al.* [62] adopt Bi-GCN to mine the propagation and dispersion patterns of fake news top-down and bottom-up to find them.

3. Multi-feature fusion detection method

1) Multi-modal oriented approach

Since the diversity and diversification of information platforms, the content of fake information tends to be with abundant pictures and accompanying content, which provides more clues and data support for anomaly detection. Combining text, images, and other multi-modal data to detect fake information is one of the current research focuses. To solve the problem of multi-modal fusion, some researchers have proposed different deep learning frameworks, which map multi-modal data to a consistent semantic space.

The first method concatenates multi-modal features. Reference [63] used VGG19 and BERT to extract visual and textual information respectively, and then spliced the two together. Reference [64] employed VGG and XLNET to extract visual and text features, which input the two into the classifier to discover false news. Meng *et al.* [65] proposed a multi-modal depth fusion model based on text and image information. The above methods are spliced or added, resulting in redundant modal information and unable to exploit the advantages of different modes.

The second method is to design an auxiliary task model after splicing two modal features to better understand multi-modal semantics. After splicing different modal information, Reference [34] designed an event identification auxiliary task in the EANN model. The event discriminator takes the fusion multi-modal data as the input and outputs the event category. Reference [66] encoded the visual and text information of the news through an encoder, and reconstructed them through a decoder. It better integrated the multi-modal information of the news through the reconstruction task.

The third method introduces an attention mechanism to enhance information fusion between modes. Jin *et al.* [67] used LSTM to extract text and VGG to learn visual features. Then, they introduced the attention mechanism between modes to enhance the information understanding and obtained better results. Song *et al.* [68] selectively extracted information related to the target mode from the source data, which used the cross-modal attentional residual network. In addition, References [69], [70] designed a double-layer co-attention of image and text information, and enhanced the information representation.

2) Multi-attribute fusion oriented approach

The above methods improve the effect of fake information detection to a certain extent, but only from the perspective of text or images. The information utilization and detection performance are low. Hence, researchers began to pay attention to more false clues. They combine more multi-attribute features to conduct unified measurement and jointly build a recognition model to improve detection accuracy and precision.

The fake information detection technology integrating external knowledge and facts can better learn the characteristics of false content under the guidance of external information. The attention mechanism integrates visual features and external knowledge information into the text representation, which helps the model better understand the news content and achieve false news classification [71]. Reference [72] used the pre-trained fact-checking model to re-find the factual evidence in the external knowledge corpus. To introduce more abundant semantic information, KAN [73] model used the corresponding entity context information in the knowledge graph. The news text, entity, and entity context information are fused by using the designed multi-head attention method to obtain semantic-rich news text modeling, which has achieved good results for false news classification.

It is the current research hotspot to carry out detection in combination with anomaly propagation characteristics in the context of fake information [74]. Reference [75] proposed a hybrid depth model, which fully extracts available features by integrating text, user, feedback, and propagation path, and then more accurately detects false information. Qazvinian *et al.* [23] added special symbols, URLs, hashtags, and other statistical features in tweets to the feature set and used model validation. Ruchansky *et al.* [76] proposed a CSI approach. The C module uses LSTM to mine text features and user features. The S module scores users and the I module splices the output vectors of the C module and S module. It inputs these elements into the fully-connection layer and predicts test data. Reference [77] proposed a fake information detection method based on attention mechanism multi-feature fusion. It integrated text and emotional features into a false information recognizer and event classifier.

IV. Public Dataset and Metrics Statistics

1. Public datasets

In the works on fake information generation and dissemination, they are evaluated on different network models by means of simulation. We summarize and compare the common network models in the experimental evaluation, as shown in Table 2.

Table 2 Network models for fake information dissemination

Related works	Network model
[78]	Random network; Small-world network; Scale-free network; Regular network
[10]	Random network; Scale-free network; Real social network—Facebook
[4], [79]	Scale-free network
[2], [14], [80]	Real social network—Twitter
[81], [82]	Real social network—Facebook
[83]	Generated social network data

With the continuous improvement of the security of social platforms, access to the personal privacy data of users is strictly restricted. According to the survey, the research data on fake information detection mainly comes from Sina, Twitter, Facebook, etc. The experimental dataset used in the current research is collated and analyzed. Table 3 reveals the source of the dataset [84], the data characteristics [85], etc. It provides a reference for subsequent researchers to select more appropriate data to verify the model.

Table 3 Statistics on public datasets for fake information detection

Dataset	Platform	#News	#Fake	Text	Visual	User	Context	Data sources
Weibo [68], [33]	Sina	9528	4749	✓	✓	✓	✓	https://www.dropbox.com/s/7ewzdrbelpmrnxu/rumdetect2017.zip?dl=0
Weibo21 [86]	Sina	9128	4488	✓	✓	–	✓	https://github.com/kennqiang/MDFEND-Weibo21
Twitter [87]	Twitter	15821	9596	✓	✓	✓	✓	https://github.com/MKLab-ITI/image-verification-corpus/tree/master/mediaeval2015
FakeNewsNet [88]	Twitter	201921	6480	✓	✓	✓	✓	https://github.com/KaiDMML/FakeNewsNet
CREDBANK [89]	Twitter	60 million	$\sim$ 24%	✓	–	✓	✓	http://compsocial.github.io/CREDBANK-data/
BuzzFeedNews [17]	Facebook	1627	–	✓	–	–	–	https://github.com/BuzzFeedNews/2016-10-facebook-factcheck/tree/master/data
BuzzFace [90]	Facebook	2263	–	✓	–	–	✓	https://github.com/gsantia/BuzzFace
FacebookHoax	Facebook	15500	6780	✓	–	✓	✓	https://github.com/gabll/some-like-it-hoax

Note: "✓" denotes the corresponding characteristics used in the literature. "–" indicates that the relevant feature is not used in the literature. The columns 3 and 4 indicate the total number of news and false information.

The datasets usually are crawled by designated keywords or events. They use authoritative systems or experts to make false and true judgments and to label information. Weibo dataset [67] is formed by real information collected from China authoritative information sources, and fake information obtained through the official rumor-dispelling system of microblogs. Twitter dataset [86] uses keywords and hashtags to retrieve specific events with the help of Topsy and Twitter APIs. Manual verification by cross-checking online sources (articles and blogs).

2. Evaluation index

Fake information detection is a classification task. The designed algorithm and model distinguish the authenticity of the message, which labels the true or false for the dataset. Generally, the evaluation indicators include precision (P), recall (R), F1-score, accuracy (Acc), mean average precision (MAP), and detection efficiency, etc. They evaluate the performance of the detection method. The higher the values of top-5 indicators are, the better the detection algorithm is, and the higher the recognition rate of fake information is.

We investigate some literature and summarized the common metrics, detection object, datasets, and performance comparison as shown in Table 4. It can be seen from the statistical results that the more commonly used indicators are P, R, F1, and Acc. The phenomenon shows that the current detection technology pays more attention to recognition accuracy. The main datasets include Twitter and Sina Weibo, which are the most popular social media at home and abroad.

Table 4 Comparison of metrics, object, datasets, and performance for fake information detection

<table>
<tr><th>Metrics</th><th>Related works</th><th>Results</th><th>Detection objects</th><th>Datasets</th></tr>
<tr><td>Acc</td><td>[27]</td><td>0.884</td><td>Style</td><td>PolitiFact</td></tr>
<tr><td>F1, Acc</td><td>[62]</td><td>0.913/0.922</td><td>Text, Propagation</td><td>Twitter, Sina Weibo</td></tr>
<tr><td rowspan="2">P, R, F1</td><td>[1]</td><td>0,778/0,799/0,769</td><td>Text</td><td>Twitter</td></tr>
<tr><td>[46]</td><td>0.833/0.823/0.857</td><td rowspan="2">Multi-modal</td><td rowspan="6">Sina Weibo</td></tr>
<tr><td rowspan="16">P, R, F1, Acc</td><td>[50]</td><td>0.896/0.898/0.897/0.891</td></tr>
<tr><td>[12]</td><td>0.786/0.933/0.853/0.84</td><td>Network structure</td></tr>
<tr><td rowspan="2">[24], [26]</td><td>0.763/0.925/0.836/0.786</td><td rowspan="2">Propagation</td></tr>
<tr><td>0.553/0.752/0.664/0.87</td></tr>
<tr><td>[19]</td><td>0.855/0.808/0.831/0.836</td><td>Image</td></tr>
<tr><td>[32]</td><td>0.863/0.953/0.906/0.895</td><td>Comment, Context</td><td rowspan="6">Twitter, Sina Weibo</td></tr>
<tr><td rowspan="4">[34], [66], [67], [69]</td><td>0.834/0.725/0.774/0.771</td><td rowspan="4">Muti-modal</td></tr>
<tr><td>0.827/0.744/0.783/0.784</td></tr>
<tr><td>0.821/0.65/0.726/0.735</td></tr>
<tr><td>0.901/0.827/0.456/0.854</td></tr>
<tr><td>[39]</td><td>0.832/0.896/0.863/0.855</td><td rowspan="2">Text</td></tr>
<tr><td rowspan="2">[32], [33]</td><td>0.978/0.951/0.964/0.966</td><td rowspan="4">Twitter</td></tr>
<tr><td>0.808/0.844/0.825/0.822</td><td rowspan="2">Text, Social context</td></tr>
<tr><td>[52]</td><td>0.793/0.796/0.792/0.893</td></tr>
<tr><td>[23]</td><td>0.944/0.906/0.925/0.935</td><td>Text, Network, Social context</td></tr>
<tr><td>[47]</td><td>0.889/0.903/0.896/0.874</td><td>Muti-modal</td><td>PolitiFact</td></tr>
</table>

V. Challenges and Prospects

In recent years, the emerging short video and live broadcasts have become the main places for people to entertain and obtain information. In order to attract traffic and increase popularity, many voices, images, and texts show brilliant splendor and intricate. The existing fake information detection technology is no longer fully applicable. The detection and identification of fake information are confronted with complex environmental factors due to the diversity of platforms and information presentation forms. We demand to conduct comprehensive and all-round research on false news from multi-domain sources, multi-data forms, multi-language heterogeneity.

1) According to the domain content orientation of information on different platforms, specific knowledge can be learned and represented by combining cross-domain information. We need to increase the accumulation of fixed terms and expert knowledge in real-time and build a cross-domain knowledge base to support the comprehensive identification of false content. Relying on knowledge graph technology to construct and introduce prior knowledge will help identify false information.

2) The research on image recognition technology inclined to the vision needs to be enhanced. The temporal content of visual data is captured in video data, and then combined with social attributes to mine the text content in the interactive comments to further detect fake news.

3) The acquisition and representation of audio data is an important means to be urgently integrated into false content detection. Through voice conversion, it can assist in the content extraction of visual information.

4) With the openness and sharing of media platforms,

new forms of multi-lingualism are also the development trend of current popular media platforms. Therefore, cross-language fusion technology is also the research direction of fake information detection.

The growing prosperity of social media platforms has provided a hotbed for the proliferation of fake information. In order to better block and intercept false news and avoid the social panic and impact it causes, firstly, government departments need to educate and monitor the conscious behaviors of internet users. People's ability to recognize false information needs to be strengthened, which can restrain the large-scale unconfirmed proliferation behavior. Secondly, legal sanctions should be imposed on individuals and organizations that intentionally publicize false and terrorist information. Let the platform conduct preliminary screening and discriminate, and quickly and timely contain them from the source. Finally, combined with scientific researchers in different fields as natural science and humanities, we analyzed and judged the propagation and promotion rules of false content to achieve accurate monitoring.

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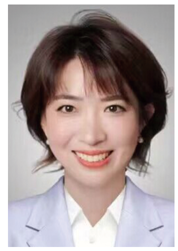

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