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NSEP: Early fake news detection via news semantic environment perception

Xiaochang Fang, Hongchen Wu *, Jing Jing, Yihong Meng, Bing Yu, Hongzhu Yu, Huaxiang Zhang

School of Information Science and Engineering, Shandong Normal University, Jinan, China

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ABSTRACT

The abundance of heavy data on social media enables users to share opinions freely, leading to the rapid spread of misleading content. However, existing fake news detection methods exaggerate the influence of public opinions, making it challenging to combat misinformation since its early spreading state. To tackle this issue, we propose a novel fake news detection framework through news semantic environment perception (NSEP) to identify fake news content. The NSEP framework consists of three major steps. First, NSEP divides the news semantic environment with time-constrained intervals into macro and micro semantic environments using an in-depth distinguisher module. Second, graph convolutional networks are applied to perceive the semantic inconsistencies between intrinsic news content and extrinsic post tokens in the macro semantic environment. Third, a micro semantic detection module guided by multihead attention and sparse attention is utilized to capture the semantic contradictions between news content and posts in the micro semantic environment, providing explicit evidence for determining the authenticity of fake news candidates. Empirical experiments conducted on real-world Chinese and English datasets show that the NSEP framework on Chinese datasets achieved as high as 86.8% accuracy, performing at most 14.1% higher accuracy than that of other state-of-the-art baseline methods and confirming that detecting news content through both micro and macro semantic environments is an effective methodology for alleviating early propagation of fake news. The findings also comprehensively indicate that both news items and posts are critical for the early debunking of fake news and in theories concerning information science.

1. Introduction

As the postpandemic era is congested with perplexing news text and baffled audiences with little knowledge and rash moods being immersed in the ersatz digital world, arguments have become a fertile hotbed of fake news disseminated across the open and interactive internet. Since sharing viewpoints after reading news online and making audiences follow gripping ideas have become a lucrative and contagious business, users are primed to spread news, and seamless internet connections propagate the content uncontrollably once it is shared. Currently, many scholars are committed to discovering effective methods, e.g., computational approaches for automatic fact-checking (Augenstein et al., 2019; Chung & Kim, 2021), identification of linguistic differences (Xue et al., 2021; Zhang et al., 2021), computing the trustworthiness of content producers (Dou, Shu, Xia, Yu, & Sun, 2021; Meel & Vishwakarma,

* Corresponding author.
E-mail address: wuhongchen@sdnu.edu.cn (H. Wu).

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2021; Qi, Cao, Yang, Guo, & Li, 2019; Song et al., 2019), etc., to keep false content in the news, such as clickbait, rumors, hoaxes, biased stories and so on (Jing, Wu, Sun, Fang, & Zhang, 2023; Samadi, Mousavian, & Momtazi, 2021; Wang et al., 2018), from spreading wider or longer (Liu, Liu, Tu, Li, & Li, 2022; Silva, Han, Luo, Karunasekera, & Leckie, 2021). However, due to the increasingly realistic writing styles and formats of false content, separating false content from an ocean of information by relying only on the main content of news is difficult. Scholars who explore alternative approaches are committed to accurately detecting fake news by exploring other auxiliary information, such as the external environment, comments, news transmission networks, external knowledge graphs and user profiles. Among them, the external environment is an important inspiration for news fabrication, as it represents the recent mainstream media views and public attention.

In 2016, the Pizzagate incident went from a rumor to gunfire in D.C. (Marsh & Yang, 2017). In 2019, the mob in Bangladesh lynched several people over child abduction rumours. In 2020, hundreds of people died because of the COVID-19 misinformation. The above events indicate that online fake news has caused serious offline harms, and social networks' omnipresence and ease of use have raised thedifficulty level of detection. As a result, fake news has brought devastation and threatened tremendous numbers of people in terms of their attitudes and actual behaviors, making the timely detection of fake news a critical need for maintaining a healthy online news ecosystem. By zooming out the event itself, one can observe as shown in Fig. 1, that fake news is often intended to catch the public's attention with unexpected and novel content to gain greater exposure and disseminate further. After paying close attention to the external environment, it is found that fake news is often semantically contradictory or unrelated to external environmental information.

In addition, the construction process of macro and micro semantic environments is depicted in Fig. 2. News in the micro semantic environment is defined as verified posts constructing strong event constraints with common linguistic components under common topics within time intervals, normally the inner relationship between fake news and posts in the micro environment is more explicitly demonstrated in semantic contradiction evidence. In contrast, news in the macro semantic environment consists of a larger amount of posts concerning current affairs that are derived from different public perspectives within time-constrained comprehensive semantic circumstances. For example, the micro semantic environment contains the official dogmatic text from the perspective of the Russo Ukrainian War, while the macro semantic environment can include broader and more diverse discussion environments such as online discussions, livelihood discussions, and live streams produces by internet celebrities through social networks. This provides semantic guidance for distinguishing between fake news and real news, and is also a new perspective for debunking any semantic inconsistencies or factual contradictions.

Therefore, a fake news detection framework based on news semantic environment perception (NSEP) is proposed to form early fake news detection techniques. This framework consists primarily of the following three scholarly steps. First, a micro- and macro semantic environment distinguisher module is applied to form an integrated news semantic environment for each possible fake news, and the news semantic environment is further divided into macro- and micro semantic environments according to their times and events. Second, a micro semantic detection module consisting of multihead attention and sparse attention is applied, which reduces the computational complexity and redundant information required to identify fake news with strengthened semantically contradictory features. Third, a macro semantic detection module including a graph convolutional network is applied to deeply identify semantic contradictions and inconsistencies between news content and the corresponding environment, and fused perceptual features are obtained to determine the authenticity of fake news candidates. The experimental results indicate that NSEP outperforms other state-of-the-art baselines with accuracies as high as 86.8% and 74.1% on two real-world Chinese and English datasets, respectively.

The main contributions are summarized as follows. 1) To our knowledge, NSEP is the first framework to achieve early fake news detection by perceiving the news semantic environment through deep neural networks. 2) A novel sparse attention mechanism is proposed to fully capture and perceive semantic contradictions between fake news items and selected posts in the micro semantic environment. In addition, sparse attention combines multihead attention to obtain more detailed auxiliary information for

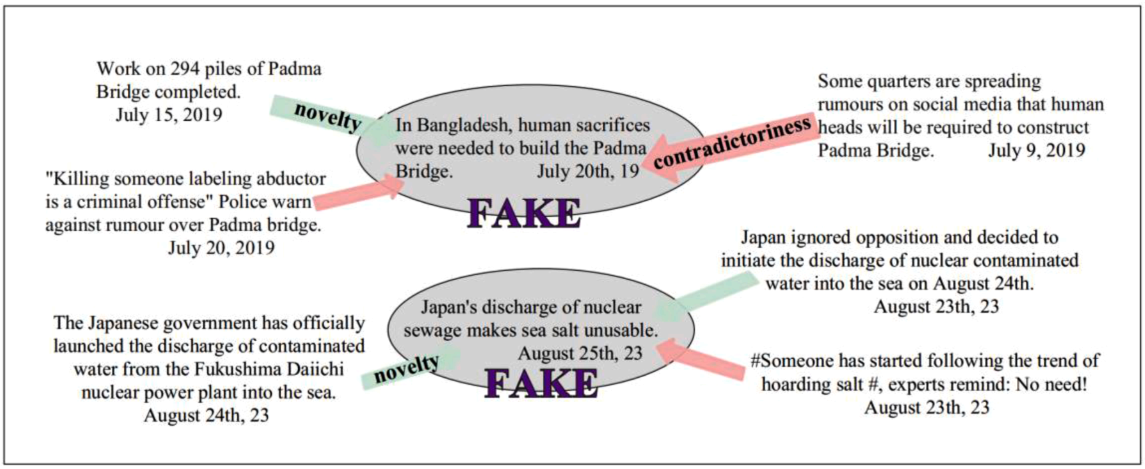

Fig. 1. Fake news can often be exposed based on its novelty and contradictions with the external environment.

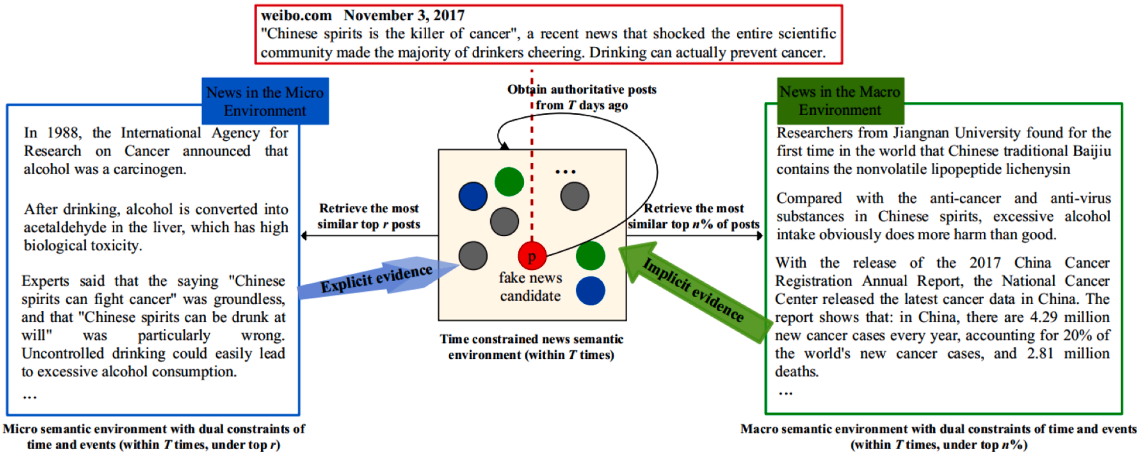

Fig. 2. The construction method and inconsistent example of news semantic environment, where the red node represents the news source, the blue nodes represent news in the micro semantic environment, and the green nodes represent news in the macro semantic environment. Explicit and implicit evidence can be found in both micro- and macro semantic environments to determine the authenticity of news.

determining whether a post is true or false. 3) Extensive experiments conducted on Chinese and English datasets show that NSEP outperforms other full baseline methods. The findings of this paper indicate that observing the relationship between a given news item and its news semantic environment can provide a new perspective for fake news detection.

Our research goal is to perceive the internal relationships between news items and their macro- and micro semantic environments. Two perceptual features are captured separately and combined by applying deep learning technology to better judge the authenticity of a news item. The main objectives are as follows:

- By effectively modeling macro- and micro semantic environments, sufficient groundwork is laid for the early detection of fake news.
- The macro semantic detection module is used to explore the potential impacts of posts in the macro semantic environment on fake news items, i.e., gather implicit evidence.
- The micro semantic detection module, composed of multihead attention and sparse attention, is used to gather explicit evidence from the micro semantic environment.

The remainder of this paper is organized as follows. In Section 2, related works regarding fake news detection methods are given. Section 3 elaborates on the framework architecture we proposed, including news semantic environment construction, news semantic environment perception and prediction. The experimental process, performance comparison and result evaluation can be found in Section 4. The discussion of our research is presented in Sections 5.

2. Related work

Fake news detection research has not yet determined how to quickly verify the authenticity of news on social media platforms. In (Bondielli & Marcelloni, 2019), fake news is defined as a piece of news produced by a counterfeiter to mislead readers, but the news can be confirmed fictional through other sources. The current detection methods generally focus on using the news itself, social context information, or knowledge sources to detect the authenticity of news and substantially progress toward fake news detection (Kumar & Geethakumari, 2014). Specifically, the current methods mainly debunk possible fake news by extracting writing styles and emotional features (Hamed, Ab Aziz, & Yaakub, 2023; Lv, Wang, & Shao, 2022; Mohawesh, Maqsood, & Althebyan, 2023; Samadi et al., 2021), exploring specific patterns between the news and the dissemination networks in depth (Cui et al., 2023; Kaliyar, Goswami, & Narang, 2021; Raponi, Khalifa, Oligeri, & Di Pietro, 2022; Sivasankari & Vadivu, 2021), and tapping into knowledge sources and social media profiles (Jiang, Liu, Zhao, Sun, & Zhang, 2022; Zrnec, Poženel, & Lavbič, 2022). Recent related literature has paid more attention to measuring the environments in which news is released and propagated (Sheng et al., 2022) and attempting to obtain early evidence for fake detection support. Most applied methods are categorized into nonsemantic news environment perception methods and semantic-aware news environment perception methods according to whether the news semantic environment information is considered during the detection procedure.

2.1. Nonsemantic news environment perception methods

Deep learning techniques are highly favored by researchers due to their ability to embed and extract inner states and feature correlations through neural network models. These techniques are widely applied in computer vision and natural language processing fields, including fake news detection. For instance, (Ma et al., 2016) conducted a pioneering work, applying deep learning to the detection of fake information. It modeled social context information as variable-length time sequences and used RNN to learn how the contextual features of Weibo posts changed over time. A new deep network paradigm was utilized to automatically extract discriminative high-level features. (Yu, Liu, Wu, Wang, & Tan, 2017) used a CNN to extract textual features and input the embedded vectors into a context-aware classifier. This approach enables the flexible extraction of the crucial features scattered throughout the input sequence and facilitates high-level interactions among the important features. With increasing amounts of information on online platforms in the forms of images and text, as well as the convenience of mobile photography and the widespread application of image modification software, (Qi et al., 2019) proposed a framework that combines both the physical and semantic features of images. They designed a CNN-based network to automatically capture the complex patterns of fake news images in the frequency domain. They also utilized a multi-branch CNN-RNN model to extract visual features at different semantic levels in the pixel domain. The framework then employs attention mechanisms to dynamically fuse the feature representations derived from the frequency domain and pixel domain, enabling effective image authenticity predictions. Xue (Xue et al., 2021) employed BERT and ResNet to model both textual and visual information and designed a visual tampering feature extraction module that was tasked with extracting visual physics and tampering features . Subsequently, the authenticity of the news was determined based on the consistency between the text and images, in addition to the tampering characteristics of the images. Wang adopted the idea of adversarial networks to propose an end-to-end framework named EANN, which learns shared features among all events by designing an event discriminator to detect fake news from unverified posts (Wang et al., 2018). Jing (Jing et al., 2023) proposed the MPFN model, which captures both deep and shallow news features from different levels by gradually fusing multimodal features jointly extracted by Swin Transformer, BERT, and Vgg19. A multimodal fake news detection framework was proposed to exploit its ability to extract hidden patterns from text using a hierarchical attention network and visual image features together with image captioning and forensic analysis, thus addressing multimedia data forgery issues (Meel & Vishwakarma, 2021). Other researchers (Popat, Mukherjee, Yates, & Weikum, 2018; Vo & Lee, 2021) have progressed toward effective detection by validating account profiles and knowledge graphs, which aggregate signals via external literary articles through hierarchical multihead attention networks to detect perceptual evidence. Gathering social context information is another debunking solution; for example, fusing emotional expressions both from text and social interactions can enable to further exploration of the internal differences between article contents and subsequent posts throughout news dissemination (Dou et al., 2021; Zhu et al., 2022). In summary, nonsemantic news environment perception methods mainly rely on feature embedding and fusion strategies during news propagation routes, but their classification performance may drop during the beginning stages since news contents in social interactions or contextual information are not sufficient for truth detection.

2.2. Semantic-aware news environment perception methods

Although nonsemantic news environment perception methods include various feature extraction and fusion strategies, most of them focus on the data-driven internal features in the news context while neglecting the external mainstream atmosphere representing public opinion, making it difficult to alleviate the early impact of false information on the dissemination path. Semantic-aware news environment perception methods are proposed as countermeasures for deeply investigating linguistic features to better address early detection requirements when very few checkable news candidates are available. Sheng (Sheng et al., 2022) designed popularity-oriented modules and novelty-oriented modules to extract useful signals for judging fake news, but these modules cannot efficiently capture the relationships between posts and the posting environment due to relatively weak expressive kernel power. Deep learning techniques, such as transformer (Vaswani et al., 2017) and graph convolutional networks, were proposed to capture any in-depth sequential features and internal connections in linguistic and graph data.

The attention mechanism is derived from the human visual system, which can help the model assign different weights to each part of the input, extract the representative information, and more accurately classify real and fake facts. Therefore, it is regarded as the core of the transformer, which has been widely applied in natural language processing (Brown et al., 2020; Devlin, Chang, Lee, & Toutanova, 2018) and computer vision (Carion et al., 2020; Zhai et al., 2022) since it was first proposed in 2017. However, Transformer have three major drawbacks in solving various tasks, namely high computational time and spatial complexity caused by self-attention, memory bottleneck caused by stacks of encoders/decoders, and step-by-step inferring caused by dynamic decoding. Many scholars have been committed to improving Transformer, and many new transformer-like models have emerged. For example, the LogSparse Transformer (Li et al., 2019), Longformer (Beltagy, Peters, & Cohan, 2020) using heuristic methods, and Reformer (Kitaev, Kaiser, & Levskaya, 2020) using locality-sensitive hashing self-attention all achieve reduced spatiotemporal complexity at the cost of performance losses. During the same period, Informer (Zhou et al., 2021) significantly reduced spatiotemporal complexity by proposing ProbSparse self-attention to replace inner product self-attention, designing distilling operation to significantly reduce the network size, and adopting generative style to directly predict the output, while achieving excellent performance in temporal sequence prediction tasks. Informer's core ProbSparse self-attention reduces the square level spatiotemporal complexity of traditional self-attention by observing the distribution of the inner product results between each query and randomly sampled keys, thereby finding the dominating queries based on the long tail distribution of the inner product results and effectively removing redundant information. In addition, graph structures widely used in social (Ji, Pan, Cambria, Marttinen, & Philip, 2021; Liu, Cheng, Xie, & Yu, 2022; Rezvanian & Meybodi, 2016; Zhang, Lin, Xu, & Wang, 2021) and transportation networks (Han et al., 2020; Song, Lin, Guo, & Wan, 2020) can also represent differences among written features through spatial relationships between fake news items and posts in the environment. Therefore, applying a graph convolutional network may be a promising solution, and on this basis, our work proposes two core modules. The micro semantic detection module combines sparse attention with multihead attention to improve the generalization ability and reduce the computational complexity of the model, while the macro semantic detection module utilizes a graph convolutional network to extract implicit evidence for detecting fake news. Overall, our work involves deep learning innovations and architecture advancements, which are used to perceive semantic inconsistencies and factual contradictions to detect fake news in the early stages, which is a major limitation of the traditional fake debunking literature.

3. Methodology

In this study, a fake news detection framework based on semantic-aware news environment perception is proposed to concentrate on authenticity judgments involving text processing management in news contents and post contexts in macro and micro environments, as shown in Fig. 3. The NSEP framework consists of three parts, i.e., news semantic environment construction, news semantic environment perception, and prediction. Demonstrated on the left side of Fig. 3, each target post p, represented as a red node, and its surrounding news items set E, represented as other nodes, form a semantic-aware news environment that is further divided into micro- and macro news semantic environments denoted as E^{mac} and E^{min}. Afterward, in the news semantic environment perception procedure, the micro semantic detection module and the macro semantic detection module are used to evaluate the relationships between posts and the micro semantic environment and between posts and the macro semantic environment. A multilayer perceptron is also applied to adjust the inner dimensions to better extract micro- and macro semantic environment perception features, denoted as F and G, respectively. F and G are also referred to as explicit and implicit evidence, operating in the upper and lower concatenations illustrated in the middle part of Fig. 3. Finally, the perceived features are handled in the prediction procedure to determine whether the given post is true or false. The following sections separately describe each of the above modules in detail.

3.1. Micro- and macro semantic environment distinguisher module

The construction of the news semantic environment contains the release of both mainstream media and fake news candidates. Through dividing the environment into macro- and micro environments, the internal relationships between the target posts and the semantic context are further explored. Let $E = \{v_1, v_2, \dots v_m\}$ represent the set of comprehensive news semantic environment published by authoritative media within a time length T before the release of post p. A verified news article v_i is released in ascending order before the target post p. To eliminate irrelevant noise data in the subsequent evaluation through event constraints, a similarity set is proposed between the post p and the news items E in the news semantic environment based on cosine similarity. Fake news attempting to exaggerate and undermine often uses exaggeration and subjective language to increase the degree of novelty in its reporting to attract readers, while true news accurately and fairly reports events based on objective facts, providing reliable information. The BERT model effectively captures and reflects the aforementioned semantic features through its unique word vectors and sentence encoding capabilities, and a GCN has a strong ability to handle the complex relationships between nodes. We visualize the posts and news items represented by BERT in the macro environment as graph nodes, and use a GCN to learn feature representation between nodes. By comparing the node features between different environments, we deeply mine and determine the specific semantic patterns between environments. As such, the n news items in the news semantic environment E with the highest semantic similarity to the k-th post p are regarded as the macro semantic environment for post candidates, denoted as $E^{mac} = \{v_1^k, v_2^k, \dots, v_j^k\}$, where n is a percentage and j represents the number of news items in the macro semantic environment, which is equal to the n% of the number of news items m in the news semantic environment. Therefore, the value of j is different for each target post. Because an important inspiration for fabricating fake news is to attract public attention through novelty, the raised momentum could lead followers' opinion trend with wider audience ranges and longer exposure times. As a result, genuine news demonstrates a high semantic-relevant level with the target post in the micro semantic environment, while fake news tends to be labeled as an abnormal outlier through clustering and similarity computing processes. Specifically, the micro semantic environment is constructed where relevant news items demonstrate the same themes as the target post. The top-r news items that most resemble the authoritative article in E are chosen to build a micro semantic environment, denoted as $E^{mic} = \{v_1^k, v_2^k, \dots, v_r^k\}$. Specifically, the distance-based Wasserstein K-means algorithm, as shown in Eq. (1), is adopted to

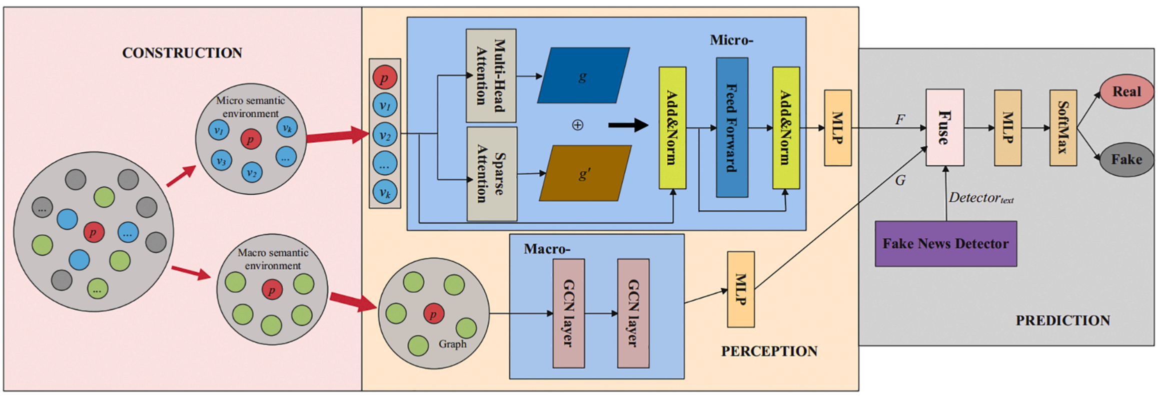

Fig. 3. The architecture of our NSEP framework is divided into three stages: construction, perception, and prediction. The red, green, and blue entities represent the fake content candidates and the news items in the macro- and micro semantic environments, respectively.

cluster the comprehensive news semantic environment and obtain $\mathscr{K}$ groups, so these groups cover $\mathscr{K}$ shared themes. Specifically, the greedy algorithm proceeds in an iterative manner as shown in Eq. (2). Given an initial cluster membership estimate $G_1^{(1)},\ldots,G_{\mathscr{K}}^{(1)}$, one assigns each probability measure represented by fine-tuned BERT $v_1,\ldots,v_m$ based on minimizing the averaged squared W_2 distances to all current members in every cluster, leading to an updated cluster membership estimate.

$$\min_{G_1,\cdots,G_{\mathscr{K}}}\left\{\sum_{\mathscr{k}=1}^{\mathscr{K}}\frac{1}{|G_{\mathscr{K}}|}\sum_{i,j\in G_{\mathscr{k}}}W_2^2\left(v_i,v_j\right):\cup^{\mathscr{K}}{}_{\mathscr{k}=1}G_{\mathscr{k}}=[m]\right\} \tag{1}$$

$$G_{\mathscr{k}}^{(t+1)}=\left\{i\in[m]:\frac{1}{\left|G_{\mathscr{k}}^{(t)}\right|}\sum_{s\in G_{\mathscr{k}}^{(t)}}W_2^2(v_i,v_s)\leqslant\frac{1}{\left|G_j^{(t)}\right|}\sum_{s\in G_j^{(t)}}W_2^2(v_i,v_s),\ \forall j\in[\mathscr{K}]\right\} \tag{2}$$

$$s(p,v_i)=\frac{p\cdot v_i}{||p||^2+||v_i||^2-p\cdot v_i} \tag{3}$$

Where $|G_{\mathscr{k}}^{(t)}|$ denotes the cardinality of cluster $G_{\mathscr{k}}^{(t)}$. $\bigcup$ denotes the disjoint union operation, and $[m]=\{1,\ldots,\ m\}$. Mean-pooling is applied to each cluster obtained in the result, which yields common thematic features for each cluster. Subsequently, the cluster that is most relevant to the target post is selected. Then, similarity calculation is performed between the target post p and news items within the selected cluster. Finally, r news items are chosen to construct the micro semantic environment.

3.2. Perception of news semantic environment

3.2.1. Macro semantic detection module

News in the macro semantic environment refers to a large number of current event posts derived from different public perspectives within a comprehensive news semantic environment under time constraints. The macro semantic environment can include broader and more diverse discussion platforms, such as online forums, livelihood discussions, and live streams provided by internet celebrities. Therefore, graph convolutional networks are introduced to recognize semantic patterns and extract implicit evidence to better detect misinformation. Specifically, posts and news items in the macro semantic environment are treated as nodes on the graph, initialized as $h_p^0=p$ and $h_{v_i}^0=v_i$, respectively, and the similarity score between posts and news items is denoted as the weight of edges between nodes on the graph. After updating and aggregating adjacent nodes on the graph, implicit evidence, also known as macro semantic environment perception features, can be obtained from the node vector of the post to determine whether the post is fake or genuine. The relevant formulas for calculating update and aggregation operations are as follows:

$$h_p^l=\sigma\left(W_V\sum_{v\in E^{mac}}s(p,v)\frac{h_v^{l-1}}{|E^{mac}|}+W_Ph_p^{l-1}\right) \tag{4}$$

$$h_{v_i}^l=\sigma\left(W_V\sum_{v\in E^{mac}}s(v_i,v)\frac{h_v^{l-1}}{|E^{mac}|}+W_Ph_{v_i}^{l-1}\right) \tag{5}$$

where h_p^l represents the feature vector obtained when the post node p is in the l layer because each news node changes synchronously in the GCN, and $h_{v_i}^l$ represents the feature vector of other news nodes v_i in the l layer. L represents the number of layers of GCN, W_V and W_P represent the parameters of the graph convolutional network, and σ represents the sigmoid function, where $|E^{mac}|$ represents the number of news articles in the macro semantic environments. The feature vector h_p^L at the L-layer post node is input into the fully connected layer to adjust to the appropriate dimension and obtain the macro semantic environment perception feature G. The graph convolutional network is applied to explore implicit evidence between our observed posts and news articles in the macro semantic environment and prepare for future predictions.

3.2.2. Micro semantic detection module

The micro semantic environment is constructed by selecting the r news items that are most relevant to the target post p with the aim of capturing the semantic contradictions between the news content and the micro semantic environment. Convolutional neural networks extract local and global features through convolution operations. However, each convolution kernel can only extract features in a local region. In contrast, attention mechanisms assign different weights at different positions to better capture the correlation between inputs. The hidden state of an RNN is fixed and cannot be adaptively adjusted according to specific situations. On the other hand, attention mechanisms adjust the focus on relevant information based on the input characteristics through a learning process. Manually designed features, such as n-grams, usually require domain-specific knowledge and extensive experimentation to determine appropriate feature combinations, and cannot fully express the information contained in text. In addition, statistical-based feature representation methods, such as Bag-of-Words model, TF-IDF, and Gaussian kernel functions, cannot learn the complex correlations between representations derived from inputs. Therefore, attention mechanisms have non-linear modeling capabilities and can adaptively learn the complex relationships between inputs compared with traditional machine learning methods that use linear models and hand-crafted features to capture input correlations. Our input M is composed of the post p and the news items $\{v_1, v_2, \ldots, v_r\}$ in the micro semantic environment and can be expressed as $M \in R^{(r+1)\times d}$, where d represents the dimensionality of the news semantic vector obtained by BERT. Q, K and V are linear maps of M, and the weight coefficient corresponding to V is obtained by point multiplication of Q and K^T. After softmax normalization, the corresponding V is weighted and summed to obtain the final output Att of the self-attention mechanism. $\sqrt{d}$ here provides an adjustment to prevent the point multiplication result of Q and K^T from being too large, which would affect the weight distribution.

$$Att(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d}}\right)V \tag{6}$$

where $Q = M\times W_Q$, $K = M\times W_K$, $V = M\times W_V$, $W_Q \in R^{d\times d_q}$, $W_K \in R^{d\times d_k}$, and $W_V \in R^{d\times d_v}$. Here, $d_q = d_k = d_v$.

Multihead attention uses different weight matrices to linearly transform Q to obtain multiple queries. Each newly formed query requires different relevant key-value pairs, allowing the attention model to introduce more information into the context vector calculation. Accordingly, Q, K, and V are divided into H different subspaces by H different learnable linear maps. The query, key and value of the h-th head can be expressed as $Q_h = Q\times W_{Q,h}$, $K_h = K\times W_{K,h}$, and $V_h = V\times W_{V,h}$, respectively, where $W_{Q,h} \in R^{d_q\times\frac{d_q}{H}}$, $W_{K,h} \in R^{d_k\times\frac{d_k}{H}}$, and $W_{V,h} \in R^{d_v\times\frac{d_v}{H}}$. Self-attention operations are performed on each group of Q_h, K_h, V_h after linear projection to obtain:

$$Att_h(Q_h,K_h,V_h) = softmax\left(\frac{Q_hK_h^T}{\sqrt{\frac{d_k}{H}}}\right)V_h \tag{7}$$

Then, the output of the above H heads are concatenated and the output of the multihead attention after linear transformation is obtained, where $W \in R^{d_v\times d_v}$. The result of multihead attention in Fig. 3 is simplified as g:

$$MultiHead(Q,K,V) = concat(Att_1, Att_2, \ldots, Att_H)W \tag{8}$$

Compared to the ProbSparse self-attention described in Section 2.2, the proposed sparse attention has some subtle changes. In the traditional attention mechanism, as shown in Fig. 4(a), an attention matrix $A \in R^{(r+1)\times(r+1)}$ is obtained when the length of the input sequence is initialed as $r+1$. At this time, redundant items are contained in the attention matrix, which is not conducive to better method functioning. Therefore, sparse attention is proposed to address this issue while improving the generalization ability of the method. Specifically, point multiplication is performed between each query and some randomly selected keys, where the number of selected keys is w. Next, the activity level is calculated for each query using Eq. (9) and the most relevant items in the w queries are selected. Finally, w active queries and their corresponding keys form the sparse attention matrix $\widehat{A}$ are shown in Fig. 4(b), thereby reducing the impact of redundant terms on the framework. The corresponding calculations are as follows:

$$Ac(q_i,K) = max_j\left\{\frac{q_ik_j^T}{\sqrt{d}}\right\} - \frac{1}{w}\sum_{j=1}^{w}\frac{q_ik_j^T}{\sqrt{d}} \tag{9}$$

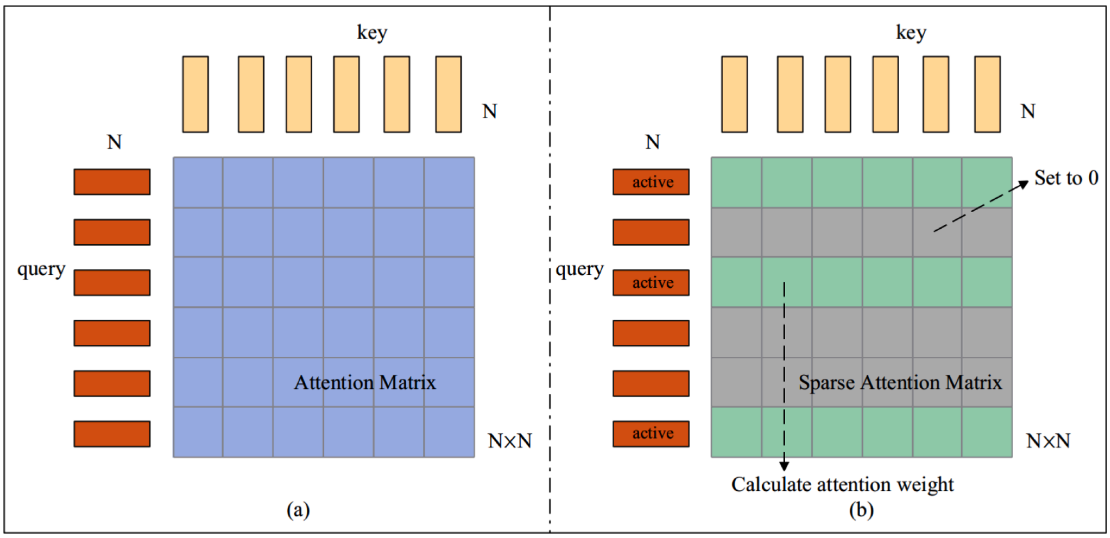

Fig. 4. Attention matrices derived from traditional attention and sparse attention.

$$Att^{'}(\widehat{Q},\widehat{K},\widehat{V}) = softmax(\widehat{A})V^{'} \tag{10}$$

$$SAN(Q^{'},K^{'},V^{'}) = Att^{'}W^{'} \tag{11}$$

where $\widehat{Q} = M \times W_Q{'}$, $\widehat{K} = M \times W_K{'}$, $\widehat{V} = M \times W_V{'}$, and similar to self-attention, $W^{'}$, $W_Q{'}$, $W_K{'}$, and $W_V{'}$ are mapping matrices. Here, the result of sparse attention as depicted in Fig. 3 is simplified as $g^{'}$.

g and $g^{'}$ have the same size. The corresponding elements are added to obtain preliminary perceptual features. This can be expressed as follows:

$$F_{pre}(M) = MultiHead(Q,\ K,\ V) + SAN(Q^{'},K^{'},V^{'}) \tag{12}$$

where Q, K, V, $Q^{'}$, $K^{'}$, and $V^{'}$ are obtained by the linear projection of M.

Further progress is made using (He, Zhang, Ren, & Sun, 2016) as a basis, as layers are inner-connected through a gradient-flowing network with residual, shortcut, and skip connections. The layer normalization technique, abbreviated as LayerNorm, further normalizes the results of the residual connection of the two layers. This operation is performed to encourage speed and stability during training since normalization can smoothly reduce the internal covariance shift.

In our work, the input sequence M represents a series of news items, while the i-th token in the input sequence is the i-th embedded news representation. The following calculations are completed:

$$X = LayerNorm\left(F_{pre}(M) + M\right) \tag{13}$$

$$F = LayerNorm(FFN(X) + X) \tag{14}$$

where M and F are the input of our micro semantic detection module and the final micro semantic environment perception features, respectively.

As demonstrated in Eq. (15), d_f represents the hidden layer dimensions of the feed-forward network, while a row vector is applied in a position-wise manner:

$$FFN(x) = \max(0,\ xW_1 + b_1)W_2 + b_2 \tag{15}$$

where $W_1 \in R^{d \times d_f}$ and $W_2 \in R^{d_f \times d}$. The final output of LayerNorm is given below:

$$LayerNorm(x) = \alpha \odot \frac{x-\mu}{\sqrt{\sigma^2+\varepsilon}} + b \tag{16}$$

where $\odot$ represents the elementwise multiplication operator, μ and σ denote the average and standard deviation, respectively, the gain α and the bias b are two evolving parameters in the training process, and the constant ε is utilized to stabilize the output. Generally, sparse attention was proposed on the basis of an improved version of Transformer, i.e., Informer. In sparse attention, active queries found through the query activity calculation equation shall be paid with higher attention, since high attention scores indicate the evident representatives of the semantic contradiction features between posts and news in the macro environment. The method of combining multihead attention and sparse attention is proposed in the micro semantic detection module, aiming to fully capture the semantic contradictions mentioned in a complementary manner.

3.3. Prediction

After the macro semantic environment perception feature G and the micro semantic environment feature F are obtained, the two feature vectors with the output of the original detector are concatenated to further determine the authenticity of the target post. The concatenated vector is input into MLP and softmax to obtain the final prediction $\widehat{y}$.

$$\widehat{y} = softmax(MLP(F \oplus G \oplus Detector_{text})) \tag{17}$$

Our objective is to determine whether any post is false news, so we minimize the cross-entropy loss function during training.

$$\mathscr{L}(\theta) = -ylog(\widehat{y}) - (1-y)\log(1-\widehat{y}) \tag{18}$$

where θ is all the parameters of the proposed NSEP, and $y \in \{0,\ 1\}$ represents the ground-truth label of the target post p.

4. Experiments

This section demonstrates the performance comparison between the proposed NSEP and other state-of-the-art baseline methods on two real-world datasets consisting of English and Chinese articles with commented posts. The ablation experiment is also given to validate the componential contributions of NSEP with a detailed training process and parameters.

4.1. Datasets

Using the existing datasets as a basis, (Sheng et al., 2022) built Chinese and English datasets that included the news environment information of the same period. Table 1 shows the statistical details of the two datasets. Datasets can be found in https://forms.office.com/r/Tr6FMGQJt0.

The Chinese dataset includes integrated posts from 2010 to 2021 (Ma et al., 2016; Sheng, Cao, Zhang, Li, & Zhong, 2021; Song et al., 2019; Zhang et al., 2021). We crawled 583,208 news items from microblog accounts opened by six well-known Chinese mainstream media sources to build a news environment for the posts.

The English dataset consists of news articles posted from 2014 to 2018 (Augenstein et al., 2019; Kochkina, Liakata, & Zubiaga, 2018; Shaar, Babulkov, Da San Martino, & Nakov, 2020). Accordingly, to build a news environment for the posts, 1003,646 headlines from 2014 to 2018 were obtained from three well-known English media sources, namely, Huffington Post, National Public Radio and Daily Mail.

4.2. Experimental setting

Accuracy, macF1, F1 score, precision, and recall are adopted as evaluation metrics in this experiment. First, accuracy represents the proportion of correctly predicted samples by the model and is the most intuitive metric. However, when a class distribution imbalance is present, i.e., when there is a significant difference between the numbers of true news items and fake news items, accuracy may underestimate the tested model's performance. Second, precision and recall are two important metrics for binary classification problems. Precision measures the model's ability to correctly predict positive instances, while recall measures the model's ability to identify all positive instances. Third, F1 score is the harmonic mean of precision and recall, providing a more comprehensive model performance evaluation in cases with classification imbalance. Therefore, using these metrics as evaluation criteria for binary classification tasks allows us to gain a comprehensive understanding of the model's performance and assess its performance from different aspects. In this paper, the semantic feature of news is a 768-dimensional vector obtained by BERT. The time length T for building the news environment is set to 72 h. The ratio n in the micro- and macro semantic environment distinguisher module is set to 0.5, and the number of layers of GCN in the subsequent perception process is 2. In addition, the $\mathscr{K}$ in the clustering algorithm is set to 8, aiming to encompass eight major types of news: political news, social news, economic news, cultural news, ecological environment news, technology news, sports news, and entertainment news. The dimensional value of the feature vector after perceiving the macro and micro semantic environments is set to 128. The learning rate and batch size are set to 1e-05 and 6, respectively. In GCN, to avoid overfitting, dropout is set to 0.2. The Adam optimizer is also applied to better select the parameters.

4.3. Baselines

To verify whether the NSEP framework can improve the performance of the original detectors, the obtained joint news semantic environment perception features are applied to several representative fake news detectors to observe performance changes. For early detection purposes, the selected detectors do not involve social context information.

Bi-LSTM (Graves & Schmidhuber, 2005), an updated variant of the LSTM model, is applied to efficiently encode posts and precisely extract article features. This is a nonsemantic news environment perception method.

As a neural network based on an event adversarial mechanism, EANN (Wang et al., 2018) guides the model to learn event-independent multimodal features by introducing event classifiers. The text variant of the original EANN, which is a nonsemantic news environment perception method, is used.

BERT (Devlin et al., 2018): BERT is a large-scale pretraining model that can be applied to various downstream tasks of NLP. We fine-tune the model to apply it to our tasks. It is fine-tuned to better adapt it to fake news detection tasks. This is a nonsemantic news environment perception method.

BERT-EMO (Zhang et al., 2021): This fuses a series of emotional features with BERT encoded features for classification. The publisher emotion version is used in our experiment. This is a nonsemantic news environment perception method.

DeClarE (Popat et al., 2018): To embed the semantics of evidence and obtain the representation of the claim, BiLSTMs with average pooling are utilized. Subsequently, an attention mechanism is employed between the claim and each word in the evidence to generate the final representation that is aware of the claim. This is a nonsemantic news environment perception method.

MAC (Vo & Lee, 2021): This model combines multihead word-level attention and multihead document-level attention and proposes a nonsemantic news environment perception method of using a hierarchical multihead attention network to fact-check textual claims,

Table 1
Statistics of the datasets.

Dataset	Chinese			English		
	Train	Val	Test	Train	Val	Test
#Real	8787	5131	5625	1976	656	661
#Fake	8992	4923	5608	1924	638	628
Total	17,779	10,054	11,233	3900	1294	1289
#News Items		583,208			1003,646	

which helps to describe fake news at the word level and evidence level.

In addition, an advanced semantic-aware news environment perception method is selected as the baseline method to determine whether NSEP can comparatively capture enough evidence to support fake news detection.

NEP (Sheng et al., 2022): This is currently the only method to enhance fake news detection by utilizing news environment information. This method uses Gaussian kernel pooling to convert the similarity list constructed by posts and news items into a fixed-length kernel output to assist in detecting fake news. This framework is applied to all the detectors mentioned above, and the degree of performance improvement is observed.

4.4. Performance comparison

Effectiveness of perceived features. To verify the effectiveness of the features obtained by each module in NSEP, we feed macro semantic environment perception feature F, micro semantic environment perception feature G, and joint feature $F \oplus G$ into several layers of simple MLP. The experimental results obtained on the Chinese and English datasets are shown in Table 2.

The experimental results in Table 2 show that using only the feature information of a single module for fake news detection can achieve good prediction results. In addition, using the joint features can further improve detection performance, with an accuracy improvement of at least 5.3% and 1.3% compared to using single features in Chinese and English datasets, respectively. This indicates that the perceptual features obtained by the two modules are complementary, and it is reasonable to enhance fake news detectors by exploring the interrelationships between posts and the environment.

Effectiveness of NSEP. The following experiments are conducted to determine whether the NSEP framework can improve the performance of the model in fake news detection. We use the currently popular BERT as a fake news detector along with perceptual features with detector features to distinguish false news, denoting this method as BERT+NSEP. The results of a comparion between BERT+NSEP and various detectors are shown in Table 3.

First, NSEP+BERT outperforms various single detectors on both datasets under all metrics. This indicates that our NSEP framework can effectively improve fake news detection; that is, considering environmental perception features can effectively improve the detection level. Second, BERT and BERT-Emo have better experimental results than the other baseline methods that focus on the post itself, so pretrained BERT can better learn text features and represent the semantic features of news. Finally, NSEP+BERT improves the accuracy metric by 8.7% and 2.3% compared to MAC on both datasets, indicating that capturing the semantic differences between posts and environments more effectively improves false news detection performance than using external knowledge. In addition, the experimental results further indicate that NSEP can correctly distinguish many fake news and reduce false positives and negative impacts, which helps to improve the performance of the NSEP model.

Comparison between NSEP and the baseline framework. To determine whether NSEP can capture sufficient evidence to support fake news detection, NSEP and NEP are used with various detectors. The experimental results of these uses are shown in Table 4.

The experimental results on the Chinese and English datasets are shown in Table 4, and the following three points can be observed. First, overall the support of the NSEP framework has improved almost all performances to varying degrees. Second, the performance on the Chinese dataset is improved more greatly than that on the English dataset. This is because environmental items in the English datasets are sourced from news headlines, making it relatively difficult to capture semantic contradictions and inconsistencies between posts and the environment. Finally, the support of NSEP for MAC detectors results in an increase in accuracy metrics on both datasets by 4.7% and 1.4%, respectively, compared to the baseline method without the NSEP framework shown in Table 3. This may indicate that the role of the perceived features and external knowledge features in terms of improving detection performance is complementary. In summary, the above experimental findings demonstrate that NSEP can capture sufficient evidence to support fake news detection.

4.5. Ablation study

Two ablation experimental groups are established to verify the effectiveness of micro and macro semantic detection modules in improving NSEP performance.

(w/o) Mac semantic detection module: The above evaluation indicators accuracy, macF1 and F1 value of each classification result are still used, and the macro semantic detection module is removed to observe the impact on the performance of the method. The detector model here uses BERT.

(w/o) Mic semantic detection module: Here, the micro semantic detection module is removed to observe the impact on the

Table 2
Experimental results of individual and joint features of two modules in NSEP.

Dataset	Feature	Acc	macF1	Fake news			Real news		
				Precision	Recall	F1	Precision	Recall	F1
Chinese	Mac semantic environment feature	0.688	0.669	0.681	0.517	0.588	0.729	0.774	0.751
	Mic semantic environment feature	0.688	0.660	0.605	0.525	0.562	0.740	0.775	0.757
	Joint feature	**0.741**	**0.727**	**0.689**	**0.641**	**0.664**	**0.787**	**0.791**	**0.789**
English	Mac semantic environment feature	0.665	0.665	0.687	0.643	0.664	0.641	**0.694**	0.666
	Mic semantic environment feature	0.679	0.679	**0.707**	0.661	0.683	0.669	0.681	0.675
	Joint feature	**0.692**	**0.692**	0.669	**0.711**	**0.689**	**0.740**	0.655	**0.695**

Table 3
The performance comparison between NSEP and various detectors, with the detectors in the NSEP framework using the representative BERT.

Dataset	Model	Acc	macF1	Fake news			Real news		
				Precision	Recall	F1	Precision	Recall	F1
Chinese	Bi-LSTM	0.727	0.713	0.751	0.576	0.652	0.714	0.847	0.775
	EANN	0.732	0.718	**0.848**	0.536	0.657	0.656	**0.962**	0.780
	BERT	0.792	0.785	0.781	0.710	0.744	0.799	0.853	0.825
	BERT-Emo	0.812	0.807	0.783	0.769	0.776	0.804	0.875	0.838
	DeClare	0.764	0.758	0.761	0.683	0.720	0.786	0.804	0.795
	MAC	0.755	0.751	0.728	0.706	0.717	0.695	0.899	0.784
	BERT+NSEP(ours)	**0.842**	**0.840**	0.827	**0.821**	**0.824**	**0.845**	0.867	**0.856**
English	Bi-LSTM	0.705	0.704	0.700	0.678	0.689	0.693	0.747	0.719
	EANN	0.700	0.699	0.707	0.661	0.683	0.688	0.742	0.714
	BERT	0.709	0.709	0.706	0.696	0.701	0.707	0.725	0.716
	BERT-Emo	0.718	0.718	0.715	**0.723**	**0.719**	0.721	0.715	0.718
	DeClare	0.714	0.714	0.725	0.694	0.709	0.658	**0.790**	0.718
	MAC	0.706	0.705	**0.734**	0.684	0.708	0.646	0.769	0.702
	BERT+NSEP(ours)	**0.729**	**0.729**	0.720	0.714	0.717	**0.729**	0.751	**0.740**

Table 4
Performance comparison of NSEP and the baseline framework on various fake news detectors.

Dataset	Model	Acc	macF1	Fake news			Real news		
				Precision	Recall	F1	Precision	Recall	F1
Chinese	Bi-LSTM+NEP	0.776	0.771	0.864	0.646	0.739	0.721	0.906	0.803
	EANN+NEP	0.776	0.770	0.786	0.687	0.733	0.731	0.901	0.807
	BERT+NEP	0.810	0.805	0.724	0.720	0.722	0.831	0.843	0.837
	BERT-Emo+NEP	0.831	0.829	0.761	0.861	0.808	0.863	0.837	0.850
	DeClarE+NEP	0.800	0.797	0.754	0.793	0.773	0.844	0.801	0.822
	MAC+NEP	0.764	0.760	0.768	0.699	0.732	0.768	0.811	0.789
	Bi-LSTM+NSEP	0.789	0.780	0.775	0.701	0.736	0.788	0.863	0.824
	EANN+NSEP	0.799	0.793	0.833	0.699	0.760	0.726	0.960	0.827
	BERT+NSEP	0.842	0.840	0.830	0.818	0.824	0.841	0.872	0.856
	BERT-Emo+NSEP	0.868	0.857	0.875	0.813	0.843	0.845	0.897	0.870
	DeClarE+NSEP	0.832	0.832	0.964	0.720	0.825	0.740	0.968	0.839
	MAC+NSEP	0.802	0.800	0.807	0.760	0.783	0.766	0.875	0.817
English	Bi-LSTM+NEP	0.718	0.718	0.740	0.701	0.720	0.664	0.778	0.716
	EANN+NEP	0.722	0.722	0.686	0.763	0.722	0.699	0.746	0.722
	BERT+NEP	0.718	0.718	0.737	0.704	0.720	0.698	0.733	0.715
	BERT-Emo+NEP	0.728	0.728	0.745	0.712	0.728	0.694	0.767	0.728
	DeClarE+NEP	0.717	0.716	0.697	0.740	0.718	0.703	0.726	0.714
	MAC+NEP	0.716	0.716	0.778	0.664	0.716	0.667	0.773	0.716
	Bi-LSTM+NSEP	0.720	0.725	0.728	0.720	0.724	0.729	0.723	0.726
	EANN+NSEP	0.725	0.722	0.710	0.692	0.700	0.741	0.755	0.748
	BERT+NSEP	0.729	0.729	0.713	0.721	0.717	0.744	0.736	0.740
	BERT-Emo+NSEP	0.741	0.732	0.706	0.728	0.717	0.755	0.737	0.746
	DeClarE+NSEP	0.723	0.723	0.773	0.667	0.716	0.649	0.835	0.730
	MAC+NSEP	0.720	0.720	0.739	0.698	0.718	0.767	0.682	0.722

performance of the method, and everything else remains the same as above.

The results of ablation experiments conducted on the two datasets are shown in Table 5. Adding the macro and micro semantic detection modules to the Chinese dataset can improve accuracy indicators by 2.5% and 0.8%, respectively. Adding the macro and micro semantic detection modules to the English dataset can improve accuracy indicators by 0.6% and 1.0%, respectively. At the same time, NSEP outperforms the variant methods in all experimental indicators. The above results indicate that the various modules of the NSEP framework are essential to the performance of the framework.

Table 5
Performance comparison of the NSEP and its variants. The best result is in boldface.

Model	Chinese				English			
	Acc	macF1	F1fake	F1real	Acc	macF1	F1fake	F1real
BERT+NSEP w/o Mac-	0.817	0.815	0.794	0.836	0.723	0.723	0.712	0.733
BERT+NSEP w/o Mic-	0.834	0.832	0.820	0.843	0.719	0.715	0.709	0.719
BERT+NSEP	**0.842**	**0.840**	**0.824**	**0.856**	**0.729**	**0.729**	**0.717**	**0.740**

4.6. Effectiveness of micro semantic detection module

In order to clarify the effectiveness of the designed micro semantic detection module, we conduct experiments on four experimental groups on the Chinese dataset and find that the experimental results support our hypothesis. The detailed experimental results are shown in Table 6.

Group A, multihead attention. This group only uses multihead attention in the micro semantic detection module, with the number of heads initialed as 12. Because the original method performs best when the number of heads is 12.

Group B, multihead sparse attention. This group only uses multihead sparse attention in the micro semantic detection module, with the same number of heads as group A, with a value of 12.

Group C, multihead sparse attention + self-attention. This group combines 12 heads sparse attention and self-attention in the same way as they are applied in this article to perform a more comprehensive contrast experiment.

Group D, multihead attention + sparse attention (our method). This group adopts sparse attention and 12 head attention.

Three findings are demonstrated in the experimental results given by Table 6. First, Group A achieves better performance compared to Group B because multihead sparse attention reduces the computational complexity and inevitably losses some key dependency information captured from the input. Second, it is possible that self-attention fills in some of the information missed by multihead sparse attention, and the results of Group C outperform the method that only uses multihead sparse attention. Third, we observe that the combination of multihead attention and sparse attention can achieve the best performance, indicating that our method can more fully capture the differences between fake news candidates and the micro semantic environment than the other experimental group methods. The excellent results are achieved due to the sparse attention that eliminates the influence of redundant information by actively searching for active queries, which could be a new research perspective of reconciling the tension between fake news detection and heavy traffic data through model optimization.

4.7. Parameter analysis

In this subsection, the impacts of different parameter settings on our framework are discussed. When observing the effects of specific parameters on the performance of NSEP, the non-specified parameters remained unchanged, and their parameter values are set to the same as the original method. To show the experimental results more succinctly, the experiment is conducted on the Chinese dataset, and accuracy and macF1 are used as our measurement indicators.

Effects of time length T in micro- and macro semantic environment distinguisher module. In this subsection, we discuss how the time length T required in the construction phase of the news semantic environment effects the performance of the proposed framework. Specifically, the time length T is set to [12, 24, 36, 48, 60, 72, 84, 96] with intervals of 12 h. The experimental results are shown in Table 7. The performance of the NSEP first increases and then decreases with increasing time length T, with optimum performance when T=72. It is believed that this occurs because the news scale extracted when T is too small is not enough to verify the authenticity of the news; however, when T is too large, some noise news is introduced, affecting the performance of the NSEP.

Effects of the ratio n in the micro- and macro semantic environment distinguisher module. In this subsection, we discuss what ratio n is needed in the construction of the macro semantic environment to make our NSEP work best. To set the parameter range in all directions, the ratio n is increased from 0.3 to 0.7 in intervals of 0.2. The results obtained are shown in Table 8. This method performs best when half of the news semantic environment is selected as the macro semantic environment. This is why n is set equal to 0.5.

Effects of the number of r in the micro- and macro semantic environment distinguisher module. Here, we discuss the optimum value of r in the construction of the micro semantic environment when NSEP works best. To set the parameter range in all directions, the value of r in the Chinese dataset ranges from 10 to 50. Too low/high value of r may lead to insufficient semantic differences/redundant information, causing sharp decline in genuine and fake detection performance. Furthermore, news headlines (plus short descriptions if any) from the Huffington Post, NPR, and Daily Mail are used as substitutes for news tweets containing too little semantic information due to Twitter's restriction. As a result, a larger value of r is needed to guarantee the performance of fake news detection. The specific experimental results are shown in Fig. 5, verifying that the performance curves obtained on both datasets have the same trend. On the Chinese dataset, the performance reaches its peak when r equals 25, and on the English dataset, the performance reaches its peak when r equals 60. It also indicates that by selecting a reasonable number of news items related to authoritative articles, NSEP can be helped to maximize its performance. We also study the optimal r value on Chinese and English datasets and aim to reveal the impact of this parameter in different language environments. This difference may be due to differences in language characteristics and datasets. As a language with higher semantic density and complexity, Chinese may convey more

Table 6
Contrast experiment of four experimental groups in micro semantic detection module, where the detector used is a representative BERT. The best result is in boldface.

Group	Acc	macF1	F1fake	F1real
A	0.832	0.832	0.825	0.839
B	0.824	0.823	0.810	0.837
C	0.829	0.830	0.826	0.834
D	0.842	0.840	0.824	0.856

Table 7
The experimental results for different time lengths T. The detector used is a representative BERT.

# of T	12	24	36	48	60	72	84	96
Acc	0.776	0.799	0.819	0.826	0.829	0.842	0.833	0.831
macF1	0.748	0.795	0.818	0.822	0.829	0.840	0.831	0.829

Table 8
The experimental results of different ratios n. The detector used is a representative BERT.

# of n	0.3	0.5	0.7
Acc	0.837	0.842	0.840
macF1	0.835	0.840	0.839

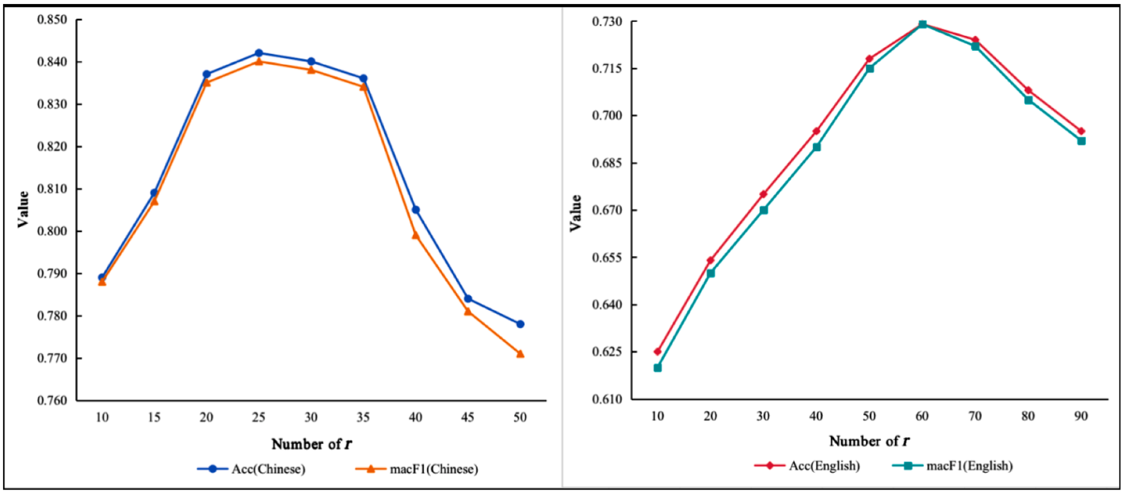

Fig. 5. The experimental results of different r on Chinese and English datasets.

information in the same number of characters compared to English. Conversely, English is often characterized by longer sentences and numerous modifiers, meaning that a higher value of r may be more appropriate for capturing additional contextual information in those cases. In summary, our experimental research shows that the r value has a significant impact on the experimental results.

Effects of the number of heads. In this subsection, we discuss the impact of the number of heads of multihead attention on the performance of our method is studied. The experimental results are shown in Fig. 6. The number of different heads impacts our

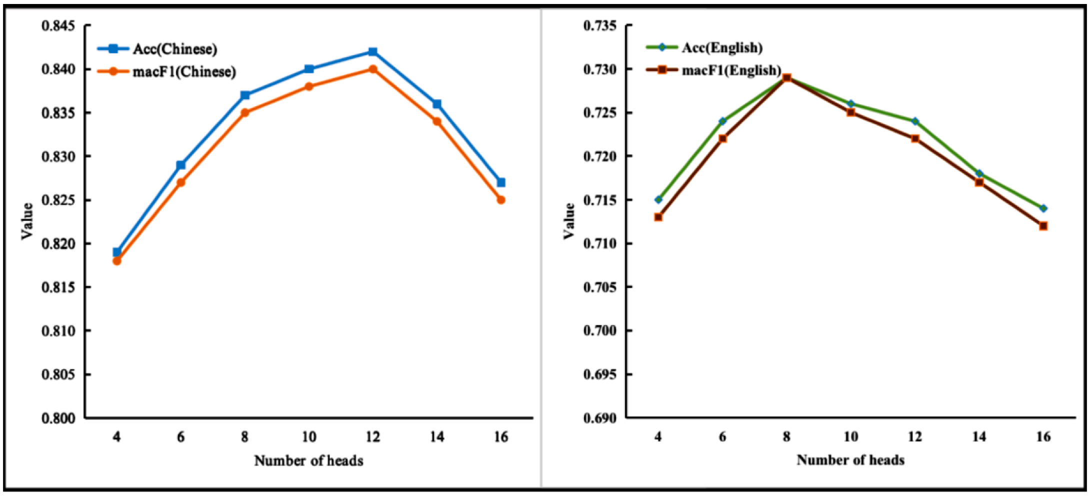

Fig. 6. The experimental results of different heads on Chinese and English datasets. The detector used is a representative BERT.

framework differently on Chinese and English datasets. The method performs best when the number of heads is equal to 12 for the Chinese datasets and 8 for the English datasets. Too many or too few heads are not conducive to the expression of NSEP performance. (Michel, Levy, & Neubig, 2019) showed that more heads do not necessarily have a good impact because some of the heads are redundant and affect the generalization ability of NSEP. However, too few heads are not conducive to feature information expression. Therefore, our framework can be better developed with an appropriate number of attention heads and the support of SAN.

4.8. Factor analysis

In this section, we discuss why incorporating news environment features can significantly improve the performance of fake news detection from the following aspects. First, the success of NSEP stems from our meticulous observation of semantic inconsistencies and contradictions between fake news candidates and the news environment. This relationship information is extracted and fake news is jointly detected with the basic model. The extracted relational information, namely, perceptual features, can be combined with complementary features obtained from the basic model to assist in the detection of fake news. Second, various parameters are accurately selected to maximize the effectiveness of NSEP. For example, the experimental results for time length T values [12, 24, 36, 48, 60, 72, 84, 96] are observed, and the optimal performance of NSEP is obtained when T=72. The parameter values, such as the ratio n used in the macro environment and the number of GCN layers L, are kept the same. Third, the last important reason that fake news detection is significantly improved is that the graph convolutional network and attention mechanism play a significant role in obtaining perceptual features. In particular, GCN captures neighbor information through cascaded layers, mining out information that the machine considers important. In addition, the attention mechanism, due to its excellent performance in exploring correlations, is the best choice for micro semantic detection modules applied to this framework.

In addition, a study is conducted to verify the feasibility of the method. First, 200 samples are randomly selected for an independent sample T test, including 100 real news items and 100 false news items. For each sample, three news items from the macro environment and three news items from the micro environment are randomly selected to manually verify the authenticity of the target news. Second, five undergraduate students are selected to rate news items in both micro and macro environments, with the score set of each news item within the [0, 5] range. Scoring is based on to what extent the news item can prove the authenticity of the target post; that is, the higher the score, the greater extent to which the news item can prove the authenticity of the target news. The scores of three news items in the micro environment and three news items in the macro environment are added together to obtain manually measured micro confidence scores and macro confidence scores, with scores being within [0, 15]. To avoid subjective influence from individual students, we averaged the micro and macro confidence scores obtained by five students to obtain the final micro and macro confidence scores. Finally, the obtained data are used for independent sample T tests to compare the macro and micro confidence scores of true and false news. The conclusions are as follows. The S–W test is applied to the micro confidence score and the macro confidence score, and the significance P-values are 0.083 and 0.669, respectively, both of which are greater than 0.05. Therefore, the two groups of values are not significant horizontally, meeting the normal distribution. The results of the homogeneity of variance test show that the significance P-values for the micro and macro confidence scores are 0.094 and 0.892, respectively, not showing significance at this level. Therefore, the original hypothesis cannot be rejected, and the data satisfies the homogeneity of variance. Next, as shown in Table 9, the mean values of true and false news on micro confidence scores are 11.231 and 6.907, and the mean values on macro confidence scores are 9.525 and 6.496, respectively. The P value results of both significance results are less than 0.01, indicating significant differences in confidence scores between true and false news at both the micro and macro levels. This shows that it is the right choice for exploring the micro and macro semantic perception features to assist in identifying fake news candidates.

Then, binary logistic regression is performed on the data to explore whether there is a clear and simple relationship between the dependent variable, namely, true or false news, and the independent variable, namely, micro and macro confidence scores. We obtained a significance of 0.722 for the Hosmer-Lemeshow test, indicating that the equation obtained has a good degree of fit. The prediction accuracy percentage of the classification table shown in Table 10 can reach 0.81, which is a good result, indicating that simple environmental information can better assist in the detection of fake news and further supporting our speculation that micro and macro semantic perception features can more fully determine fake news.

5. Implications

Through observing Chinese and English datasets, it is found that the incubation and spread of fake news are largely influenced by its environment. Specifically, posts often have inextricable relationships with news items in a semantically similar macro semantic environment. We believe that useful information can be obtained from this implicit relationship to determine whether a post is true or false. Second, there is also a certain relationship between post and news items in a micro semantic environment with the same topic as the post, and this relationship is mutually exclusive. Because when detecting the authenticity of posts, the events related to these posts have been mentioned and reported by some authoritative media, but these reports have not attracted the attention of our audience. Thus, two major issues arise in our work, namely, whether NSEP can mine the post-environment relationship and whether using this relationship feature can further improve the performance of fake news detection. Through the above performance comparison and some experiments, it can be concluded that perceiving news semantic environment information can improve the performance of fake news detection, and further prove that post-environment characteristics contribute to the improvement of NSEP performance.

To further validate our claim, a qualitative analysis is conducted on NSEP. Three false news items that were not detected by (Sheng et al., 2022) are selected, and the authenticity of fake news candidates is verified using BERT+NSEP and attach confidence scores. It is found that our method can accurately identify fake post candidates and then randomly select two news items from the micro and macro

Table 9
Comparison of differences in micro and macro confidence scores between true and fake news.

Variable name	Variable value	Mean±Std.Deviation	t	P
macro confidence scores	real news	9.525±1.084	19.375	***
	fake news	6.496±1.127		
micro confidence scores	real news	11.231±1.748	18.716	***
	fake news	6.907±1.511		

*** Note: represents a significance level of 1%.

Table 10
The classification table in binary logistic regression, where 0 indicates that the news is real and 1 indicates that the news is fake.

	0(predictive value)	1(predictive value)	Correct percentage
0(measured value)	78	22	0.78
1(measured value)	16	84	0.84
Overall percentage			0.81

news semantic environments, as shown in Fig. 7. Two observations are discussed. First, the division of the macro and micro semantic environments is in line with our assumption, which is conducive to obtaining accurate perceptual features in the future. Second, our method can more accurately determine the authenticity of posts with high confidence, indicating the effectiveness of our method. In summary, all posts are constructed into a news semantic environment, and the inherent advantages of graph convolutional networks and attention mechanisms are used to perceive sufficient post-environment features to support early detection of fake news.

Conclusion

This paper provides a fake news detection framework that perceives the news semantic environment. The main purpose of fake news produced and spread by lawbreakers is to win the attention of the audience and achieve their own goals. Indeed, fake news usually breeds in the environment in which it resides, and useful information can be obtained from the news semantic environment to determine whether a news item is fake news. Therefore, the proposed framework aims to observe the news semantic environment of post candidates and assist in predicting the authenticity of posts through the environment construction, perception, and prediction stages. The experimental results show that our method is more effective than and superior to all other baseline methods.

The method of detecting fake news through news semantic environment perception still faces challenges and needs to be further investigated. Currently, fake news on the internet is often spread in multimodal form as pictures and text, but thus far, no dataset

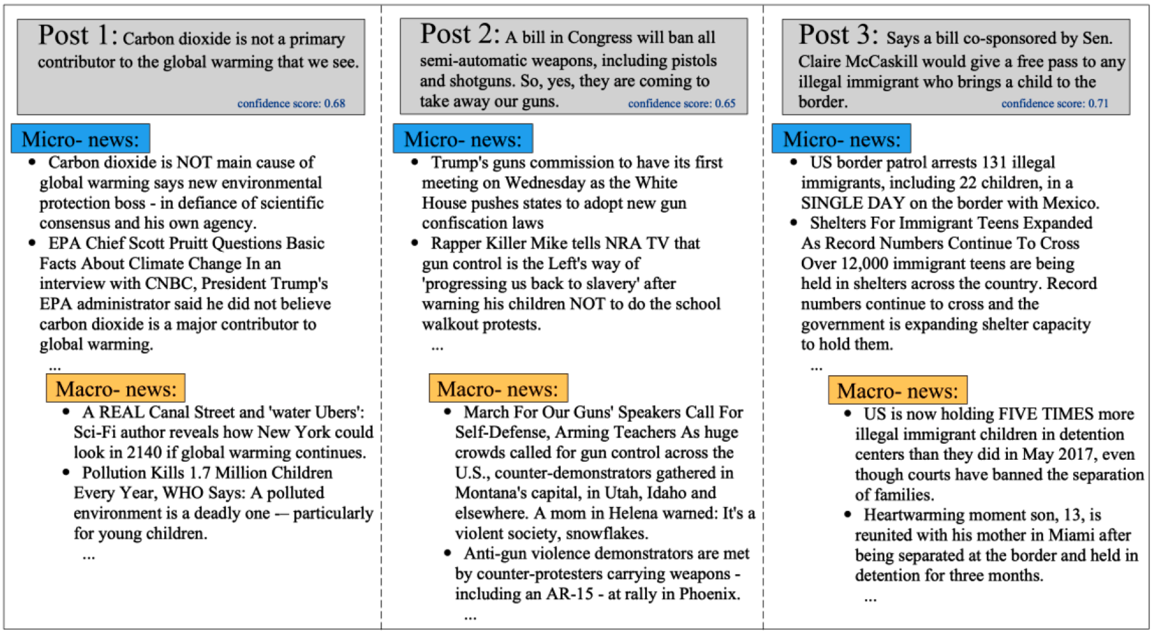

Fig. 7. Three fake news case on English datasets, which are missed by BERT+NEP but detected after using our BERT+NSEP. The news items of macro- and micro semantic environment and confidence scores are shown at figure.

contains environmental information in the form of pictures and text. Therefore, our future research will focus on building a multimodal dataset for exploring news semantic environment information and further investigating the relationship between posts and the environment to judge the truth of news more accurately.

CRediT authorship contribution statement

Xiaochang Fang: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft. **Hongchen Wu:** Data curation, Project administration, Funding acquisition, Writing – review & editing. **Jing Jing:** Methodology, Software, Validation. **Yihong Meng:** Software, Visualization, Resources. **Bing Yu:** Software, Validation, Writing – review & editing. **Hongzhu Yu:** Software, Validation, Writing – review & editing. **Huaxiang Zhang:** Supervision, Project administration.

Data availability

Data will be made available on request.

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