Information Processing and Management 60 (2023) 103146

Contents lists available at ScienceDirect

Information Processing and Management

journal homepage: www.elsevier.com/locate/infoproman

Multi-view co-attention network for fake news detection by modeling topic-specific user and news source credibility

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ARTICLE INFO

Original content: FakeNewsNet (Reference data)

Keywords:
Fake news detection
Echo-Chamber
Socio-Cognitive Bias
Partisan Bias
Topic-Specific Credibility
Knowledge Graph

ABSTRACT

The wide spread of fake news and its negative impacts on society has attracted a lot of attention to fake news detection. In existing fake news detection methods, particular attention has been paid to the credibility of the users sharing the news on social media, and the news sources based on their level of participation in fake news dissemination. However, these methods have ignored the important role of news topical perspectives (like political viewpoint) in users'/sources' decisions to share/publish the news. These decisions are associated with the viewpoints shared by the echo-chamber that the users belong to, i.e., users' Socio-Cognitive (SC) biases, and the news sources' partisan bias. Therefore, the credibility of users and news sources are varied in different topics according to the mentioned biases; which are completely ignored in current fake news detection studies. In this paper, we propose a Multi-View Co-Attention Network (MVCAN) that jointly models the latent topic-specific credibility of users and news sources for fake news detection. The key idea is to represent news articles, users, and news sources in a way that the topical viewpoints of news articles, SC biases of users which determines the users' viewpoints in sharing news, and the partisan bias of news sources are encoded as vectors. Then a novel variant of the Multi-Head Co-Attention (MHCA) mechanism is proposed to encode the joint interaction from different views, including news-source and news-user to implicitly model the credibility of users and the news sources based on their interaction in real and fake news spreading on the news topic. We conduct extensive experiments on two public datasets. The results show that MVCAN significantly outperforms other state-of-the-art methods and outperforms the best baselines by 3% on average in terms of F1 and Accuracy.

1. Introduction

With the popularity of social network platforms in recent years, the spread of fake news, i.e., news containing false information (Shu et al., 2017), has increased widely. Due to the negative effects caused by fake news dissemination in different areas, automatic detection of fake news has received much research attention in recent years. Fake news detection has been studied extensively from various aspects, including news content (Liu et al., 2021; Zhou et al., 2020), news propagation (Dou et al., 2021; Song et al., 2021), users stances toward the veracity of news (Davoudi et al., 2022) or other social network context such as user profile features (Shu & Wang, 2019). While particular attention has been paid to the user friendship community for fake news detection (Chandra et al., 2020;

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https://doi.org/10.1016/j.ipm.2022.103146
Received 12 June 2022; Received in revised form 25 October 2022; Accepted 30 October 2022

Nguyen et al., 2020; Shu et al., 2019), the topical aspect of online communities have received no attention. Recent social context-based methods have leveraged Graph Neural Networks (GNNs) to encode the underlying users' and publishers' credibility (Chandra et al., 2020; Nguyen et al., 2020; Yuan et al., 2020). Despite the success of recent GNN-based methods, most of them have modeled users' or publishers' credibility based on their participation in fake news dissemination, i.e., users and sources that interact with fake news are less credible (Chandra et al., 2020; Yuan et al., 2020). However, these methods ignored the important role of news topics in user-s'/news sources' decisions to share/publish the news, which are associated with the users' SC biases, i.e., the beliefs and opinions shared by social community members that the users belong to; and the news source partisan bias, i.e., the bias of the news media in how news on different topics are reported and covered to make a specific political party more attractive.

The way online users consume and share news are related to their viewpoints about the news topic (Dou et al., 2021; Etta et al., 2022). Due to the confirmation bias (Lord et al., 1979), online users prefer to consume news (even fake news) that is aligned with their beliefs while ignoring dissenting news (Vicario et al., 2019). For instance, according to the recent dataset of USA 2020 election fraud claims on Twitter (Abilov et al., 2021), users who agree with the electoral fraud would more likely share the news with a similar opinion, regardless of its truthfulness. In addition to the users' cognitive biases, the importance of social connections and peer influence on the user sharing behavior in the social network cannot be overlooked (Konc & Savin, 2019). According to confirmation bias, people are more likely to follow those who hold similar viewpoints, which leads to the formation of like-minded clusters of users, known as echo-chambers. Echo-chambers intensify users' SC biases that underlie user content sharing behavior and network structure. Echo-chambers and SC biases might affect users' factual beliefs about topics since congruent opinions are amplified and dissenting viewpoints are filtered out. Thus, the credibility of the user's shared content on different topics is impressed by his/her cognitive bias and the beliefs shared by the echo-chamber that he/she belongs to, which we refer to as the user's SC bias. The user's SC bias and his/her engagement in fake news spreading could show the potential topics that the user or his/her community is vulnerable to spreading misinformation about them, and therefore the user credibility on the topics.

In addition to users' SC biases, the partisan bias of news sources impacts the visibility of topics or entities in media coverage and the way news is reported (Hamborg et al., 2019; Shu et al., 2019). For example, the news source with right-wing partisan bias would more likely share the news that promotes Republican Party or news against Democratic Party. Therefore, entities mentioned in the news article and the partisan bias of the source that has published it could bring great information about news topical and political ideology. Additionally, there is a strong relationship between the factuality of a news source about a certain topic and its level of partisan bias, as news articles from extremely biased sources are less likely to be factual (Nakov et al., 2021). News articles about the same topics or entities from different news sources hold different stances and different veracity levels according to the news source partisanship and level of bias.

Different from previous research, in this paper, we propose the credibility of users and news sources at the topic-level based on the mentioned cognitive biases, and propose a novel method to jointly model the credibility for fake news detection. We refer to topic as fine-grained semantic information that includes the news topical viewpoints, i.e., both topic and perspective of the news article such as

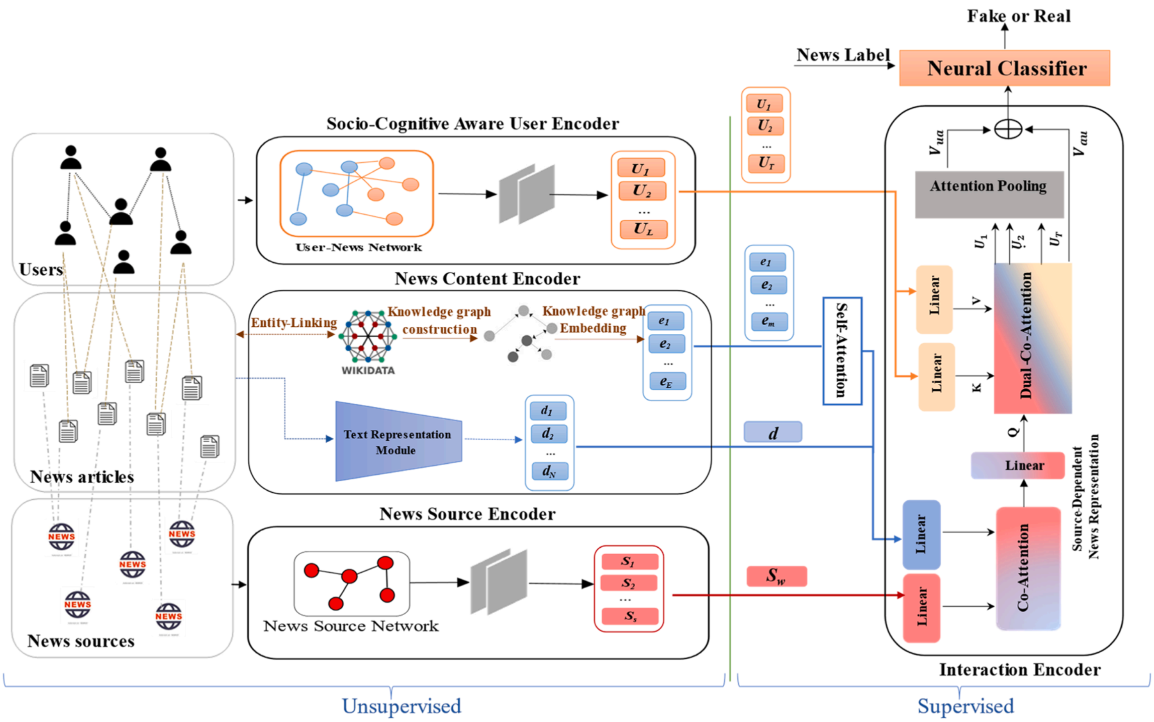

Fig. 1. The overall architecture of the proposed MVCAN framework for fake news detection.

news political leaning. We hypothesize that fake news might be detected by investigating the users and news sources concerned with the story according to their cognitive biases, and therefore their credibility on the news topic. For example, the probability of the anti-democratic news article, created by the news source with extreme right-wing bias and shared by users belonging to the low credible echo-chambers which have already shared some fake news against the Democratic Party, being fake is high.

To this end, we build a fake news detection framework, MVCAN, which consists of 5 components as shown in Fig. 1: (1) News Content Encoder: Knowledge entities mentioned in news articles play an important role in expressing the topical perspectives (such as political viewpoints) of the news articles. To consider topical relatedness among entities and thus the news articles, we leverage an external Knowledge Graph (KG) for news content encoding. (2) Socio-Cognitive Aware User Encoder: In this component, we propose a user-news heterogeneous graph by considering users' shared news and significant friendship connections (that lead to the creation of echo-chamber) to model the user's belief in content sharing, which encoded using GNN. (3) News Source Encoder: A GNN based encoder to learn news source partisan bias and level of their bias by encoding the news source graph that is constructed by defining edges between similar sources based on their audience homophily. (4) Interaction Encoder: We proposed a variant of the MHCA mechanism (Vaswani et al., 2017) to encode the joint interaction among the three mentioned components to represent the latent credibility of users and sources on news topics. The co-attention is implemented hierarchically to encode the joint interaction from different views. First, between the news vector and its news source vector to model the topical and political ideology of the news article and then between resulted news vector and user vectors. (5) A neural classifier to predict the news veracity label. The first three components are unsupervised; therefore, they can be used for other tasks as well. The experimental results on two real-world datasets show the success of our proposed method in modeling user and news source credibility, and the effectiveness of the interaction between the news topic, source partisan bias, and user's SC bias in verifying the authenticity of the news. Our main contributions in this paper are summarized as follows:

- To the best of our knowledge, we are the first to define topic-specific user and source credibility based on their cognitive biases and use them for fake news detection.
- We develop three novel representation components to encode news topical viewpoints, users' SC biases, and news sources' partisan bias.
- A principled approach is applied to model the joint interaction among topics, users, and news sources to encode topic-specific users' and news sources' credibility jointly for fake news detection.
- Experimental results illustrate that the MVCAN outperforms seven state-of-the-art baselines, including different types of fake news detection methods.

2. Related works

2.1. Fake news detection

Extensive research has been conducted on the detection of fake news. Fake news detection methods can be divided into two general categories: content-based and social-context-based methods. Content-based approaches aim at detecting fake news by extracting features manually from news textual content (Zhou et al., 2020) or different deep language models with hierarchical attention architecture (Shu et al., 2019) for explaining the fake part of the news, Transformer network and BERT (Rai et al., 2022). Multimodal approaches have been also developed to exploit both visual and textual features using various fusion strategies such as attention mechanism (Wu et al., 2021) or the similarity of image and text (Zhou et al., 2020). Recently, multi-domain fake news detection models (Nan et al., 2021; Zhu et al., 2022) have been proposed to design specialized model that works effectively in multiple domains. However, previous works (Shu et al., 2019) showed that it is difficult to identify news veracity by considering only the news content as fake news content is often very similar to real news.

Social-context-based methods exploit various social contexts of news such as users' stances about the veracity of news (Dungs et al., 2018; Poddar et al., 2018), emotions of news social comments (Zhang et al., 2021), or the interaction between users. The user interactions can be modeled in different types of graphs to help fake news detection. For instance, a range of studies has modeled the news propagation patterns by considering various user representations (Chen et al., 2022; Dou et al., 2021; Ni et al., 2021; Silva et al., 2021). Other graph-based models have obtained social context-based news representation by modeling underlying users and source interaction with the news. FANG (Nguyen et al., 2020) have modeled users from their friendship network in addition to their stances on fake news dissemination, i.e., the users who support fake news have similar representation. The news representation in FANG has been obtained from news content, user engagement pattern, and news-source relations, which assigns news from similar sources to similar vectors. The tri-relationship fake news detection framework (Shu et al., 2019) has also modeled users from users' friendship relationships and obtained user credibility levels from the size of the community around the user with the intuition that low-credible users are more likely to interact with one another and form large clusters. These methods consider the interaction between news, news sources, and users, i.e., users and sources that interact with fake news are more likely to produce and spread false information. However, the majority of users and news sources engaged in both fake and real news. These methods ignore the importance of news topic and its correlation with the news source and users' cognitive biases. Different from these studies, our method models the topic-level user and source credibility associated with their viewpoints and biases for fake news detection.

2.2. Knowledge graph

KG is a semantic network that represents relationships between real entities such as people, places, events, etc. Within a KG, nodes are associated to the entities, and directed edges describe their relations which are often named triples and represented as *(h,r,t)*, with *h* representing the head entity, *t* representing the tail entity, and *r* representing the relation linking the head and the tail entities. KG is widely used for entity linking (Shen et al., 2015) which is beneficial for many tasks. The KG as additional information and entity linking has been used successfully in many tasks such as language representation (Liu et al., 2020) by injecting domain-specific knowledge into the model, text classification (Ostendorff et al., 2019) that combined text representations with KG embedding, and recommender systems (Liu et al., 2020; Wang et al., 2018) to discover latent knowledge-level connections among news using KG embedding for better encoding users' favorite news topics. Recently, KG has been used for fake news detection to better represent news content. DTN (Liu et al., 2021) modeled the extracted triples from news content using both word2vec (Mikolov et al., 2013) and pre-trained KG embedding as news representation for fake news detection. KAN (Dun et al., 2021) combined news content with linked entities representation vector obtained from word2vec. However, the relationship between entities is not considered in this study. Inspired by the recommender systems (Liu et al., 2020; Wang et al., 2018), in this paper, we use KG for modeling news topical (and also political) relations.

2.3. News media partisan bias detection

Partisan or political bias detection, i.e., predicting left, center, or right bias, is an important and challenging task. The news article's political ideology is usually obtained from the news media that has published it (Nakov et al., 2021). In addition, news media bias is important in detecting the factuality of news articles, e.g., extremely biased media tends to perform poorly in factual reporting. Many news media bias detection methods have analyzed the text of news articles they have published using linguistic features (Baly et al., 2018; Horne et al., 2018) or different deep neural models (Baly et al., 2019; 2020). Subsequent methods have tried to enhance the news media bias detection by utilizing additional information, such as an external political knowledge graph of contemporary U.S. politics for political perspective detection (Feng et al., 2021), political entity mentions in text that is encoded using the Wikipedia2Vec method (Li & Goldwasser, 2021), and social connections of users interacting with the news media, with the intuition that the news articles that shared by the similar user might have similar partisan bias, and users who shared a lot of similar news have similar political viewpoints (Li & Goldwasser, 2019; 2021). Despite a range of studies on news sources' partisan bias detection, the connection between the level of news sources' partisan bias and their factuality in publishing news on different topics has not been investigated yet. Our study connects these two lines of study.

3. Problem statement

Formally, consider $A = \{a_1, a_2, \ldots, a_n\}$ be the set of n news articles, $S = \{s_1, s_2, \ldots, s_s\}$ be the set of news media sources that have published these news articles, and $U = \{u_1, u_2, \ldots, u_L\}$ be the set of L users who have shared these news articles on social media. Our first objective is to represent news articles, users, and news sources in a way that:

- Each news article $a_i \in A$ is represented as a vector $V_{a_i} \in R^D$ encoding its topical viewpoints.
- Each user $u_j \in U$ is modeled as a vector $V_{u_j} \in R^C$ representing the user's SC bias. In other words, users with similar SC biases, i.e., users belonging to the same echo-chamber with the same beliefs, are represented close to each other in the embedding space.
- Each $s_w \in S$ is represented as a vector $V_{s_w} \in R^F$ characterizing the partisan bias of the news media. In other words, sources with similar partisan bias are represented to nearby vectors in the embedding space.

We address the fake news detection task as a binary classification. Hence, each news article is either real $(y = 0)$ or fake $(y = 1)$. Given a news source s_w publishing a news article a_i and T users $U_{a_i} = \{u_{i1}, u_{i2}, \ldots, u_{iT}\}$ sharing that article on social media, our final objective is to learn a function $F : V_{a_i} \times V_{U_{ij}}^{j=1\ldots T} \times V_{s_w} \rightarrow y$, with $F(.)$ modeling the joint interaction among news items to model the credibility of the users and the news sources based on their interaction in real or fake news spreading on the topic of a target news article. In this way, a source obtains credibility by generating credible news articles in the news topical domain associated with its partisan bias, which is spread on social media by credible users of that domain. Users attain credibility by spreading true articles about the topic and interacting with other credible users. Similarly, the likelihood of a news article being real increases if it is generated and spread by credible sources and users in the news topical domain.

4. MVCAN framework

In this section, we describe the proposed MVCAN framework in detail. As shown in Fig. 1, MVCAN consists of 5 components: (1) News content encoder, (2) Socio-cognitive aware user representation, (3) News source representation, (4) Interaction encoder (5) Fake news detector. The details of each component are described in the following subsections.

4.1. News content encoder

News textual contents commonly comprise many knowledge entities that play an important role in expressing the topic, and also the perspective of the news article like its political leanings. The entities in the same topical or political concepts might be of interest to the users belonging to the same echo-chamber. For instance, as shown in Fig. 2[1], two illustrated news pieces are about the same political party since "Clinton" and "Nancy Pelosi" connect to common entity nodes which most of them are connected to the Democratic Party. Therefore, these two news pieces might share by the users of the same echo-chamber with a high probability according to their SC biases.

To consider the topical and political relatedness between entities and thus the news articles, we leverage external KG (which is Wikidata in our study). We exploit the news entities' representations from KG embedding in addition to the partisan bias of the news source, to model the topical and political ideology of news articles. We will describe it as a source-dependent news document representation in Section 4.4.

KG Construction. First, knowledge entities within all news contents are recognized and linked to their relevant entities in Wikidata using TAGME (Ferragina & Scaiella, 2010) entity linking tool[2]. To extract relevant relations between recognized news entities, we additionally search the 2-hop neighbors of each news entity in Wikidata. Within the search, if it finds another entity in our news entity set, we add their common one-hop neighbor to our news entity set. Next, all relation links between entities are extracted from Wikidata to create our knowledge graph $\mathscr{KG}$. To clarify it more, we extract all triples from Wikidata whose head and tail are in the identified news entity set as our KG.

KG Embedding. Different KG-embedding methods such as TransE (Bordes et al., 2013), RotateE (Sun et al., 2019), and CopmlEx (Trouillon et al., 2016) could be used to generate an embedding vector for each entity. We use TransE, which is trained on our constructed KG to generate embedding vectors $v_{e_i} \in R^{d}$ for entity e_i in the graph. In TransE, the relations and entities are represented in the same embedding space and for any triple *(h,r,t)* the relation r is regarded as a translation vector between entity vectors, i.e., $\overrightarrow{h} + \overrightarrow{r} = \overrightarrow{t}$, resulting in a short distance between the entity vectors ($\overrightarrow{h}$ and $\overrightarrow{t}$) that are connected by relation *r*. While TransE generates structure-based representations, motivated by the studies in KG-based recommender systems (Wang et al., 2018, 2019), for each entity we exploit its one-hop neighbors' embedding vectors as its context for better encoding the position of entities and the KG structure.

Entity Representation. N_{e_i} denotes the set of entities in the immediate tail neighborhood of the entity e_i in the graph $\mathscr{KG}$ where:

$$N_{e_i} = \{e|(e_i, r, e) \in \mathscr{KG}\}. \tag{1}$$

The context embedding $\overline{v_{e_i}}$ for entity e_i is produced by averaging the entity vectors in N_{e_i}:

$$\overline{v_{e_i}} = \frac{1}{|N_{e_i}|} \sum_{e \in N_{e_i}} v_e. \tag{2}$$

For each entity e_i , the entity embedding vector v'_{e_i} is obtained from the concatenation of its vector with its context embedding vector:

$$v' e_i = v_{e_i} \oplus \overline{v_{e_i}}, \tag{3}$$

where $\oplus$ shows the concatenation operator.

News Content Encoder. Consider a news article a_i containing m entities with representation vectors $E_{a_i} = \{v'_{e_1}, v'_{e_2}, \ldots, v'_{e_m}\}$. The document representation vector of a news article a_i is V_{d_i} which is generated using pre-trained BERT embedding (Devlin et al., 2019). We expand the news document representation V_{d_i} with its entity vectors E_{a_i} (obtained from equation 3), to assign such news with similar topical viewpoints to nearby vectors in the embedding space. To get a fixed-length entity vector for all news, for each news article a_i, we aggregate all representation vectors of entities in E_{a_i} via a self-attention layer which is shown in Fig. 3, and the news entity vector V_{e_i} is obtained. We remove the subscript *i* in the following content for simplicity. The news vector V_a is defined as the concatenation of the news document vector V_d and its news entity vector V_e as follows:

$$V_a = V_d \oplus V_e . \tag{4}$$

4.2. Socio-cognitive aware user encoder

The purpose of the user encoder is to represent users based on their SC biases. To combine the social and cognitive perspectives of users, we consider both user-user and user-news relationships as a heterogeneous graph to generate user representation. Furthermore, we rely on the content of news articles shared by users to infer the user's ideology and topical preferences.

Graph Construction. To fulfill the idea, we propose a user-news heterogeneous graph *G= {N, E}* where *N* is the node set including two kinds of nodes: user nodes $N_u = \{N_{u_j} | u_j \in \{u_1, u_2, \ldots, u_l\}\}$ and news nodes $N_n = \{N_{a_i} | a_i \in \{a_1, a_2, \ldots, a_n\}\}$. *E* denotes the edge set including two sets of edges: user-user relationships obtained from algorithm 1 and user-news relationships which show sharing actions

[1] The upper and lower news pieces were published by yournewswire.com and Thelastlineofdefense.org, respectively.

[2] We used TAGME API wrapper for python: https://github.com/marcocor/tagme-python

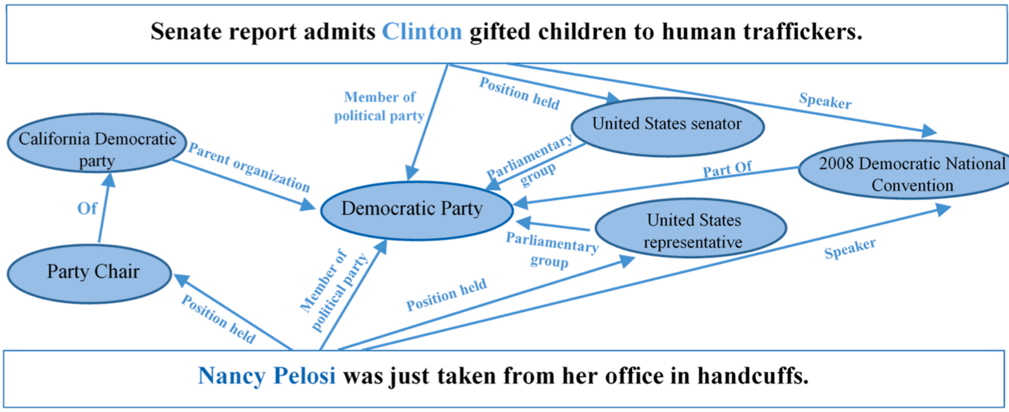

Fig. 2. Illustration of political relatedness among two pieces of news.

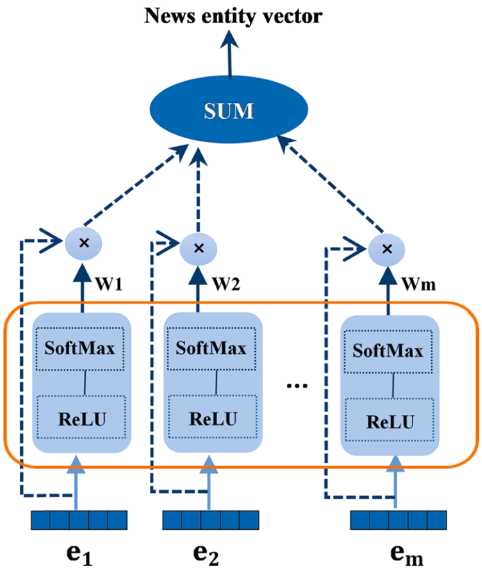

Fig. 3. Self-attention layer architecture.

Algorithm 1
User-user relationship construction.

Input: user-news bipartite graph G, Friendship adjacency matrix F, alpha=0.1, n: number of news nodes, l: number of user nodes
Output: user-user adjacency matrix U
M← zero matrix $\in R^{l\times l}$
For each user *A* and news *J* in G **do**:
  IF user *A* shared news *J* **do**:
    $m_{AJ} = 1$
  Else:
    $m_{AJ} = 0$
End
For each user pair (*A*,*B*) in G **do**:
  $V_{AB} \leftarrow \sum_{J\in\{n_1,n_2,\cdots,n_n\}} m_{AJ}.m_{BJ}$
  $F(V^*_{AB}) \leftarrow$ *The probability distribution of the values* V^*_{AB} *under the BICM null model.*
  $p - value(V_{AB}) = \sum_{V^*_{AB}\geq V_{AB}} F(V^*_{AB})$
  IF $p - value(V_{AB}) < alpha$ **do**:
    M[*A*][*B*]=1
End
U=M.F (dot product)

of the news articles by the users. For each news, we include those users who just share the news article without any comment which shows that these users agree with the news article's viewpoint.

Most previous works (Chandra et al., 2020; Nguyen et al., 2020; Shu et al., 2019) have used friendship connections to model echo-chamber of users. However, a friendship relation might not always reflect agreement on various topics which is an important factor in the formation of echo-chambers. Therefore, to precisely model the partisan community, i.e., eco-chambers, we choose only significant friendship relations based on a statistical null model which analyzes the users' homophily in content sharing behavior. With this aim, we project the bipartite user-news graph on the user layer to obtain the monopartite user-user network using Bipartite Configuration Model (BiCM) (Saracco et al., 2015). More precisely, given any two user nodes A and B in a user-news bipartite network and the number of their common news neighbors V_{AB}, any two user nodes are linked if V_{AB} is determined to be statistically significant in comparison with a well-defined benchmark model, i.e., BiCM. The obtained user-user network from BiCM is then compared to the user friendship network, and the intersection (shared undirected edges) between these two networks is selected as a user-user relationship. Algorithm 1 shows the pseudo-code for the user-user relationship construction, which we implemented using the python implementation of BiCM[3].

To model the topical preferences of users' communities, the content of the news shared by the users is considered as well. We employ the pre-trained BERT model to encode the textual content of news articles and user topical preferences. Each news node is associated with a feature vector from the title text of the news article represented by the cased BERT-Large model. For each user node, all title vectors of the news articles shared by him/her are averaged to get the user's preference representation.

Graph Encoder. Next, we obtain the user representation using 2-layer GraphSAGE (Hamilton et al., 2017) as the graph encoder. The GraphSAGE is trained with an unsupervised loss function which preserves the proximity between nodes. In this way, the vectors of the users that are closely connected to each other and share similar news (belong to the same echo-chamber, and therefore have similar SC biases) are represented close to each other in the embedding space, while making the representations of users with different viewpoints from distinct echo-chambers to be very far apart. We minimize the following unsupervised loss function:

$$L = -\frac{1}{|\mathrm{V}|}\sum_{r\in G}\left(\sum_{v_p\in P_r}\log\left(\sigma\left(z_r^T z_{v_p}\right)\right) - \sum_{v_n\in N_r}\log\left(\sigma\left(-z_r^T z_{v_n}\right)\right)\right), \tag{5}$$

Where Z_r is an embedding vector of node r, P_r is a list of adjacent nodes to node r on a fixed-length random walk, N_r is a negative sampling set to r, V is the set of all nodes in the graph, and σ is the sigmoid function. The trained GraphSAGE is learned to generate embedding of any user $V_u \in \mathrm{R}^{\mathrm{C}}$ which assigns the user to implicit echo-chambers. By utilizing news content as a node feature, the topics to which the community and the user are more concerned are jointly modeled.

4.3. News source encoder

To encode the news source partisan bias, we first get the news sources' partisan bias from a comprehensive media bias and fact-checking website, MBFC[4]. However, the partisan bias label for many of the news sources does not exist. Therefore, to encode all news sources' partisan bias, we construct a graph to build similarity links to the seed sources with known partisan bias. A heterogeneous graph $G_s = (N_s, E_s)$ is constructed, where N_s denotes the node set consisting of the news sources in $S = \{s_1, s_2, \ldots, s_s\}$ and political party nodes *P= {right, center, left, extreme bias}*. E_s denotes the edge set containing source-source and source-political party edges. To measure the level of similarity between any two news sources, we exploit the level of similarity between their audience (social network users who have shared at least 3 news of that source) preferences in sharing news, i.e., how many of the audiences are shared between two news sources, and how many of the audiences are specific to each source. The intuition is that the more audience any two news sources have in common, the more similar those news sources are in terms of their viewpoint and partisan bias. Therefore, to compute audience homophily between two news sources, A and B, we use the ϕ correlation coefficient which is shown in Eq. 6, to consider the level of similarity between their audience preferences;

$$\phi(A,B) = \frac{nn_{AB} - n_A n_B}{\sqrt{n_A n_B (n-n_A)(n-n_B)}}, \tag{6}$$

where n_{AB} is the number of users who have shared news from both A and B, n_A is the number of users who have shared news from source A, n_B is the number of users who have shared news of source B, and n is the total number of users in our dataset. $\phi(A,B)$ shows the degree of similarity between A and B. Two source nodes, A and B, are connected if $\phi(A,B)$ is positive. The partisan bias labels in MBFC are classified into seven categories: extreme-left, left, left-center, least-biased, right-center, right and extreme-right. To consider the political side and level of media bias jointly, we consider four nodes for the political parties in a graph G_s and connect the source to political parties' nodes according to its label from the MBFC site. For example, if the source label is extreme-right, it is connected to both right and extreme bias nodes.

Each news source node is associated with the feature vector obtained from news articles covered by it. For each news source node, all of its published news articles are represented using the pre-trained BERT model and are averaged to build a news source node

[3] https://github.com/mat701/BiCM
[4] https://mediabiasfactcheck.com/

feature. For each political party node, the feature vectors of all its associated news source nodes are averaged and considered as a node feature. By encoding the proposed network using GraphSAGE (Hamilton et al., 2017), the idea is to assign sources with similar ideology and partisan bias to nearby vectors in the embedding space. GraphSAGE is trained with an unsupervised loss function similar to the user training phase in the previous section.

4.4. Interaction encoder

Given a news source s_w generating a news article a_i which contains m entities $\{e_1, e_2, \ldots, e_m\}$ and T users $U_{a_i} = \{u_{i1}, u_{i2}, \ldots, u_{iT}\}$ sharing that article on social media, our model considers their interactions to model the latent credibility of users and news sources on different news topics. We develop a co-attention mechanism which is the variation of multi-head attention from Transformer Network (Vaswani et al., 2017). The formula for calculation of the multi-head attention is as follows:

$$e = \frac{\mathrm{QK^T}}{\sqrt{\mathrm{d_k}}}, \tag{7}$$

$$\mathrm{Attention(K, Q, V) = SoftMax(e)V}, \tag{8}$$

$$\mathrm{MultiHead(K, Q, V) = concat(head_1, head_2, \ldots head_h)}, \tag{9}$$

$$\mathrm{head_i} = \left(\mathrm{KW_i^K, QW_i^Q, VW_i^V}\right), \tag{10}$$

where queries, keys, and values are encoded with the matrices Q, K, and V respectively; d_k is the dimension of keys, and h is the number of heads. e is the similarity score between Q and K obtained from dot product operation. The attention mechanism in Transformer Network was designed for alignment where the model wants to look at one word for translation. In this case, attention is a mean-field approximation of sampling from a categorical distribution over source word embedding vectors, and therefore the output of a softmax normalization is used to parameterize categorical distribution. Given that our purpose is to model the interaction between news as the query and users who have shared the news as the values to model topic-specific user credibility, and the credibility of users are mutually independent, we treat the alignment with the news embedding vector of a_i at the current timestamp as a collection of independent Bernoulli variables (as many as there are users in U_{a_i}), rather than a categorical distribution over all users in U_{a_i}. With this aim, we propose to use the sigmoid function rather than softmax for attention score normalization in our model.

The interaction component is implemented hierarchically: First, between the news article and its news source to obtain source-dependent news document representation, and its results are passed to the user-news dual-co-attention, which are described in detail below.

Source-Dependent News Document Representation (SNDR). First, we obtain source-dependent news document representation $V_{a_i s_w}$ for the news a_i, from topic-enriched news article vector V_{a_i} (from Section 4.1) and its source vector V_{s_w} (from Section 4.3). News about the same entities from different news sources hold different stances and viewpoints in addition to different factuality levels. Therefore, we consider the partisan bias of news sources in news document representation to precisely model the topical and political viewpoints of the news article in addition to the news source's topic-specific credibility.

Since we have only one news source vector for each news, the proposed attention using sigmoid normalization is used to model the news source credibility score, which is shown in Eq. 11. e_{as} is the similarity score (from Eq. 7) between V_{s_w} as the key, and V_{a_i} as the query. We omit subscriptions i and w for simplicity. Source-dependent news representation V_{as} is computed as Eq. 12:

$$\alpha_{as} = sigmoid(e_{as}), \tag{11}$$

$$\mathrm{V_{as}} = \mathrm{LN}\left(\mathrm{ReLU}\left(r_q + \alpha_{as}.v_s\right)\right), \tag{12}$$

where LN(.) is the layer normalization operator (Ba et al., 2016). r_q is a residual connection from the query. v_s is obtained from the linear transformation of V_{s_w} as value.

User-News Dual-Co-Attention (UNDCA). The dual MHCA is used for user and news interaction modeling. We determine two vectors of attention coefficients for news and users as shown in Eqs. 13 and 14, respectively:

$$\alpha_{q_{ij}} = sigmoid\left({e_{ij}}^T\right), \tag{13}$$

$$\alpha_{v_{ij}} = sigmoid\left(e_{ij}\right), \tag{14}$$

e_{ij} is the similarity score between $V_{u_j}(u_j \in U_{a_i})$ as the key and $V_{a_i s_w}$ as the query. The attention score $\alpha_{q_{ij}}$ determines the credibility of user u_j in news a_i. If user u_j is part of the community which has already shared fake news in the news a_i topical domain, he gets a high score if a_i is fake (low credibility). A user (community) who has shared real news in the news a_i topical domain gets a high score if a_i is real (high credibility). $\alpha_{v_{ij}}$ models user u_j's (and also its community) credibility for certain semantics of news a_i. User-dependent news representation $V_{a_i u} \in R^{d_{nu}}$ and news-dependent user representation $V_{u_j a_i} \in R^{d_{un}}$ are shown in Eqs. 15 and 16, respectively:

$$V_{a_i u} = \mathrm{LN}\left(\mathrm{RelU}\left(r_{q_i} + \sum_{j=1}^{T} \alpha_{q_{ij}} v_j\right)\right), \tag{15}$$

$$V_{u_j a_i} = \mathrm{LN}\left(\mathrm{ReLU}\left(r_{v_j} + \alpha_{v_{ij}} q_i\right)\right),\ j = 1, 2, \ldots, T \tag{16}$$

$V_{a_i u}$ encodes news using users' topic-specific credibility. Value vector v_j (value=key=V_{u_j} for $u_j \in U_{a_i}$), and q_i obtained from the value and query linear transformation, respectively. r_{q_i} and r_{v_j} are residual connections from query and value, respectively. To aggregate all users' representation $V_{u_j a_i}$ ($u_j \in U_{a_i}$) for news article a_i as V_{ua_i}, the masked attention pooling layer is used as follows:

$$h_{u_j a_i} = ReLU\left(WV_{u_j a_i} + b\right), \tag{17}$$

$$\beta_{ij} = \frac{\exp\left(h_{u_j a_i}\right)}{\sum_{z=1}^{T} h_{u_z a_i}}, \tag{18}$$

$$V_{ua_i} = \sum_{j=1}^{T} \beta_{ij} V_{u_j a_i}\ . \tag{19}$$

4.5. Fake news detection

To predict whether a news article a_i is fake or real, we integrate the outputs of the interaction component $V_{a_i u}$ and V_{ua_i} and predict the probability of the news article being fake or real with the following objective function:

$$\widehat{y} = softmax\left(W_f[V_{a_i u} \oplus V_{ua_i}] + b_f\right), \tag{20}$$

with $\widehat{y} = [\widehat{y}_0, \widehat{y}_1]$ where $\widehat{y}_0$ is the predicted probability of the news article being real and $\widehat{y}_1$ is the predicted probability of news being fake. $b_f \in R^{1 \times 2}$ is the bias vector. The model is trained by minimizing the cross-entropy loss function as follows:

$$\mathscr{L}(\theta) = -ylog(\widehat{y}_1) - (1 - y)\log(1 - \widehat{y}_1), \tag{21}$$

where $y \in \{0, 1\}$ is the ground-truth label, and θ determines the entire parameters of the model.

5. Experiments

In this section, we first introduce the datasets used in our experiments. Then, we present the conducted experiments to evaluate the effectiveness of the MVCAN framework by seeking answers to the following questions:

- **Q1**. Can MVCAN improve the performance of fake news detection by considering the interaction between news, sources' partisan bias, and users' SC biases?
- **Q2**. How effective are news entities, news source partisan bias, users' SC biases, and our proposed interaction component in improving the detection performance of MVCAN?
- **Q3**. How effective is our proposed edge filtering method in the representation of echo-chambers for fake news detection?
- **Q4**. How does our proposed source encoder improve news article representation and fake news detection?
- **Q5**. Is our hypothesis about the impact of users' SC biases on their credibility in different topics true?

5.1. Datasets

We utilize two publicly available datasets from FakeNewsNet (Shu et al., 2020) repository that were collected from two fact-checking websites: PolitiFact[5], which contains political news; and GossipCop[6], which includes fact-checked news about celebrities; as well as the related social context from Twitter, i.e., the tweets that cited the news articles, and users who have shared them. We keep users who have engaged at least in sharing two news from the dataset. To eliminate the impact of repeated users in news veracity identification, users who have shared more than ten news, and more than 85% of their shared news pieces are false, or all of their shared news pieces are true, are omitted from the datasets. The intuition is that they likely are bots or malicious users (shared a lot of fake news), or the account belongs to a news agency (shared a lot of true news). These users cause a bias in news veracity prediction as the model learns that all news from these users is true or false. Therefore, they are omitted from both datasets to remove the bias of the model to fake news spreader detection rather than fake news detection. The detailed statistics of the datasets are shown in Table 1.

[5] https://www.politifact.com/
[6] https://www.gossipcop.com/

Table 1
The statistics of datasets.

Platform	PolitiFact	GossipCop
#True News	252	2864
#Fake News	286	2132
#Users	79973	70205
#sources	327	395

The statistics of the constructed knowledge graph in Section 4.1, the user-news graph in Section 4.2, and the news sources graph in Section 4.3 for our two datasets are shown in Table 2.

5.2. Experimental settings

Similar to classification problems in related areas, we use Accuracy, Precision, Recall, and F1 scores as performance evaluation metrics. We perform 5-fold cross-validation three times and report the average results. All models are trained for a maximum of 100 epochs using Adam optimization. The initial learning rate is set to 0.1 and a 0.1 decay rate every ten steps. To avoid overfitting, early stopping is done in a way that the training will stop if the model performance does not increase for ten consecutive epochs.

We implement all models using PyTorch and all GNN models using the Deep Graph library (DGL) package (Wang et al., 2019). We grid-search over the different values of the parameters for respective model components and choose the best setting based on the F1 score on the test set, as follows:

- KG Embedding: entity embedding dimension=100, negative sample size=256, batch size=1024, learning rate=0.25, max epoch=10000.
- User-news Graph: user embedding dimension=300, number of layers=2, negative sample size=10, batch size=200000, learning rate=0.01, max epoch=250
- News Source Graph: news source embedding dimension=300, number of layers=2, negative sample size=10, batch size=5000, learning rate=0.01, max epoch= 250
- Interaction component: source-news hidden dimension=300, user-news co-attention hidden dimension=300.

5.3. Baselines

We compare MVCAN with several state-of-the-art baselines for fake news detection:

- **KAN** (Dun et al., 2021). A content-based method that fuses knowledge entities representation with news content representation (both obtained from Word2vec) using the transformer network.
- **GCN-FN**(Monti et al., 2019). This method is the first one that uses GCN to encode the fusion of users' social connections, retweet network, user profile features, and tweet contents for fake news detection.
- **Bi-GCN** (Bian et al., 2020). This model utilizes bi-directional GCN to learn both the structures and patterns of fake news propagation. The nodes' features are TF-IDF representations of tweet content.
- **SAFER** (Chandra et al., 2020). This method concatenates user representation and news content representation for detecting fake news. For user representation, their friendship connections and shared news are modeled as a heterogeneous graph. The news content is encoded using RoBERTa (Y. Liu et al., 2019).
- **FANG** (Nguyen et al., 2020). A GNN-based fake news detection that encodes a heterogenous graph of news, users, and sources. Three losses: 1) proximity loss, 2) stance loss, and 3) fake news detection loss, are optimized simultaneously in this model.
- **GNN-CL** (Han et al., 2021). This method encodes the retweet graph without considering the content of the news to detect fake news from different propagation patterns between fake and real news.
- **UPFD** (Dou et al., 2021). A propagation-based fake news detection method that uses users' historical posts as user news consumption preferences. The user preference is represented using a pre-trained BERT model, and it is used as a node feature in the user retweet graph.
- **BERT+MLP**. We consider another baseline that uses only the news content encoded by BERT as the input of MLP.

The cased BERT-Large model is used for content embedding in MVCAN and all other baselines for fair comparison. For all baseline models, except KAN, the implementation codes are available[7] and we just run the codes and trained the models for our datasets. For KAN, we implemented the codes according to the paper descriptions and train the model for our datasets. FANG considered four user-news stance relations: neutral support, negative support, deny, and report. However, as our datasets contain posts with only supportive stances, we have just one stance relation for FANG. For fair comparison, the same feature vectors (using the Cased BERT-Large model)

[7] GCN-FN, Bi-GCN, GNN-CL, UPFD can be find in https://github.com/safe-graph/GNN-FakeNews. SAFER : https://github.com/shaanchandra/SAFER, and FANG: https://github.com/nguyenvanhoang7398/FANG

Table 2
Statistics of the knowledge graph, user-news graph, and news sources graph for two datasets.

Dataset	Knowledge Graph			User Graph		Source Graph	
	#entities	#relations	#triples	#nodes	#edged	#nodes	#edges
Gossip	582425	575	1392547	75201	2621677	399	28193
PolitiFact	882409	660	2087388	80511	8098129	331	7483

as MVCAN are considered for user, news, and source nodes in FANG rather than TF.IDF which is used in the original paper.

5.4. Experimental results and analysis

To answer Q1 and evaluate the effectiveness of MVCAN in fake news detection, we make comparisons with the current state-of-the-art fake news detection methods. The experimental results and the confusion matrix of MVCAN on the two datasets are shown in Table 3 and Fig. 4, respectively. The differences between the experimental results of the original papers which used FakeNewsNet and our results are that each paper has used different subsets of the PolitiFact and GossipCop according to their models. We have described our data selection in Section 5.1. From the results, we can make the following conclusions:

- Compared with all baselines, MVCAN achieves the best performance in terms of Precision, Recall, Accuracy, and F1 on both PolitiFact and GossipCop data. Paired T-test with $p<0.05$ indicates that the improvement is statistically significant compared with the other baselines. This shows the effectiveness of the interaction between the news topic, source partisan bias, and the user's SC bias in verifying the authenticity of the news. MVCAN outperforms the best GossipCop baseline, i.e., UPFD, for around 2%, and the best PolitiFact baseline, i.e., GCN-FN, for around 4% in terms of F1 score.
- The experimental results show the effectiveness of utilizing social contexts in fake news detection. However, the results of GNN-CL, which only uses a news propagation graph without news content, show that news content and social contexts are complementary to each other; and our proposed interaction method between news content and social context was able to impose important information for fake news detection.
- As can be seen from the results, KAN, which incorporates news entities in news content representation, could not perform well in detecting fake news. This method just improves news content representation by using news entities while the news about different entities could be true or false. This result shows that news entities alone are not important in news veracity identification and suggests the importance of our hypothesis in considering the correlation between user/source ideology and news entities.

5.5. Ablation study

To answer Q2, in this subsection, we conduct a series of experiments to investigate the effectiveness of the key components on MVCAN. Five variants of MVCAN are defined by omitting some components from the MVCAN:

- **MVCAN\E**: We eliminate the knowledge entity representations from the news content encoder. Therefore, we just use the news document vector for news content representation.
- **MVCAN\S**: The source encoder component is eliminated from the MVCAN. The output of the news content encoder is directly fed to the UNDCA module.
- **MVCAN\U**: It is the variant of MVCAN without considering the user encoder component. The output of the SNDR module is considered as the input of fake news detection.
- **MVCAN\US**: In this variant, we eliminate both user and source encoder components from MVCAN. Only the content of news is considered for fake news detection.

Table 3
Performance comparison of our model and the baselines. Stars denote statistically significant under the t-test for $p\leq 0.05$.

Model		PolitiFact				GossipCop			
		Precision	Recall	F1	Accuracy	Precision	Recall	F1	Accuracy
News Content	BERT+MLP	0.8361	0.8822	0.8569	0.8400	0.6980	0.6943	0.6948	0.7375
	KAN	0.8162	0.8561	0.8354	0.8207	0.7057	0.7344	0.7168	0.7532
News Content +Social Context	GCN-FN	0.8977	0.8406	0.8688	0.8681	0.9578	0.9607	0.9590	0.9590
	Bi-GCN	0.8715	0.7867	0.8318	0.8326	0.9267	0.8971	0.9123	0.9127
	GNN-CL	0.7477	0.7541	0.7499	0.7909	0.9083	0.9705	0.9356	0.9360
	SAFER	0.8679	0.8632	0.8655	0.8610	0.9509	0.9301	0.9404	0.9409
	FANG	0.8651	0.8770	0.8530	0.8609	0.9589	0.9586	0.9581	0.9590
	UPFD	0.8579	0.8750	0.8648	0.8550	0.9650	0.9629	0.9637	0.9638
	MVCAN	**0.9201***	**0.9170***	**0.9176***	**0.9127***	**0.9789***	**0.9887***	**0.9835***	**0.9859***

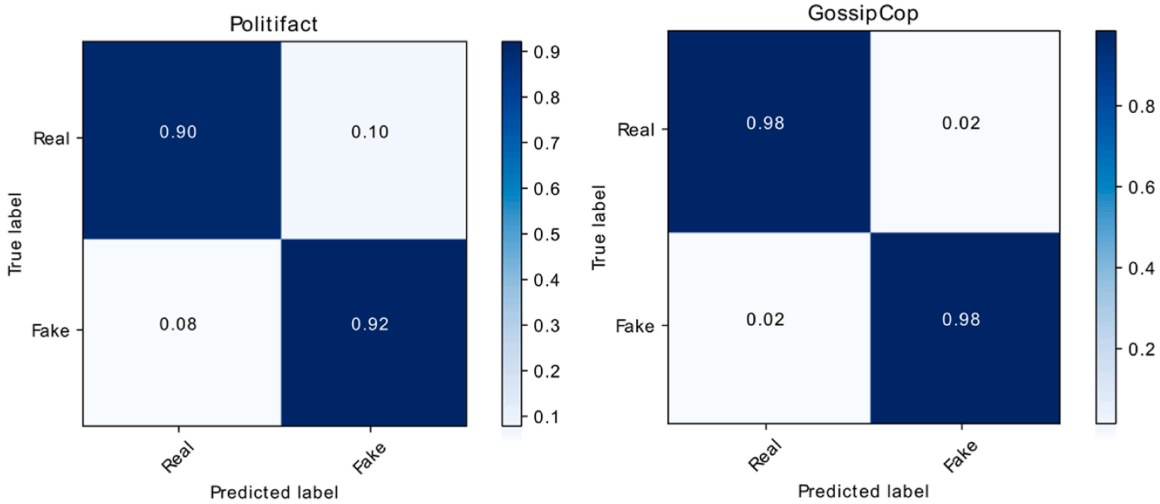

Fig. 4. The normalized confusion matrix of MVCAN for PolitiFact and GossipCop datasets.

- **MVCAN\INT**: In this variant, we eliminate the interaction component. The outputs of the content, user, and source encoder components are concatenated simply as the input for fake news detection (The user vectors and entity vectors which interact in each news are first averaged).

The five variants are evaluated using 5-fold cross-validation, and the results are shown in Fig. 5. It is observed that:

- By comparing the results of MVCAN and MVCAN\E, we find out that the F1 score is reduced by 3.6% and 2.6% for PolitiFact and GossipCop datasets, respectively. The results show the importance of entities in news content representation, especially in political news, where entities are associated with political parties.
- For MVCAN\S, the F1 score dropped by 3.66% and 2.2% for the PolitiFact and GossipCop datasets, respectively. The results show the effectiveness of our proposed news source encoder not only in political fake news detection but also in other domains such as entertainment stories from the GossipCop dataset. The effect of news sources in our model is analyzed in more detail in Section 5.7.
- A similar result for MVCAN\U is observed. The results show that the user component is more important than the other components for the GossipCop dataset, which removal reduced the performance of the model by around 20% in terms of F1.
- For MVCAN\US, F1 dropped by 6.8% and 26.8% for the PolitiFact and the GossipCop datasets, respectively. The result is worse than MVCAN\S and MVCAN\U and suggests that components of the source and user encoders are complementary to each other. The result also shows the effective role of the social contexts in detecting fake news as fake news textual content is usually similar to real news textual content. Especially in the GossipCop dataset, the contents of both real and fake news are very similar, and hence, social context largely improves the model performance.

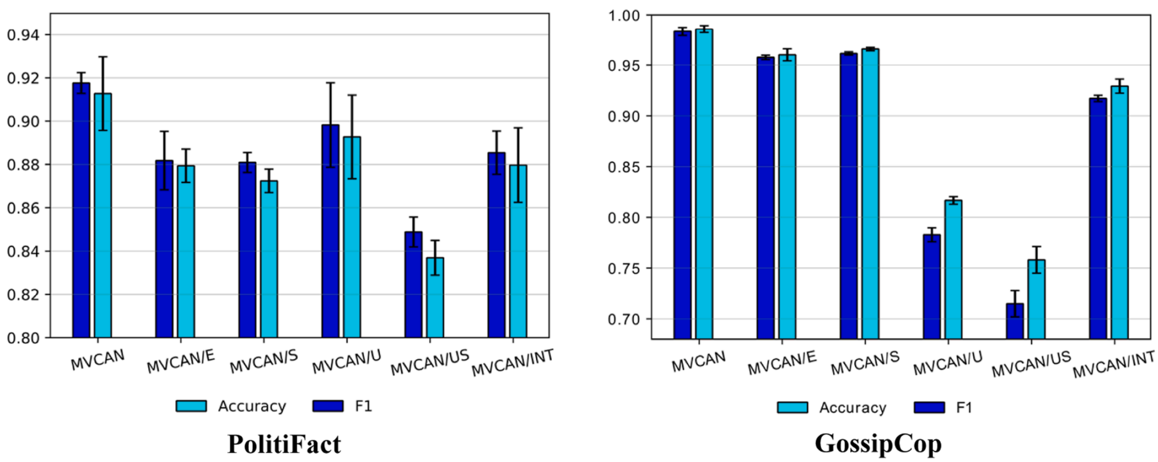

Fig. 5. Ablation Study on the PolitiFact and GossipCop datasets.

- By eliminating the interaction component, the performances dropped by 3.2% and 6.63% in terms of F1 for the PolitiFact and the GossipCop datasets, respectively. It shows the importance of modeling the correlation between the user's SC bias and news topic and also between the news source's partisan bias and news topic in fake news detection.

5.6. Effect of BiCM in user representation

To answer Q3, we investigate the impact of BiCM on the construction of a statistically significant user-user relationship for echo-chamber modeling. Some experiments are conducted by considering all friendship relations in the proposed user-news graph without using BiCM for edge filtering, in addition to considering different significance levels (α) in BiCM to obtain the optimum value for α. Fig. 6 shows the obtained results for the PolitiFact and the GossipCop datasets. As can be seen from Fig. 6, by considering all friendship edges in the user encoder, F1 is decreased by 3.2% and 2.7% for the GossipCop and the PolitiFact datasets, respectively, in comparison to F1 with an optimum value of α. This result shows the importance of using BiCM in filtering the non-significant friendship edges for user representation and echo-chamber modeling. Additionally, the proposed method for edge filtering not only improves the performance of the model, but also reduces the computation time by reducing the graph size. For instance, the total number of edges in the user-news graph is 2,621,677 in the GossipCop dataset, which is reduced to 352,779 after filtering.

5.7. News Source Representation analysis

To answer Q4, in order to investigate the role of news sources in news representation, we select some news examples from the PolitiFact dataset in four categories: pro-democratic, anti-democratic, pro-republican, and anti-republican news. News document representation from the News Content Encoder component and Interaction component (source-dependent news document representation) are compared in Fig. 7 using the Sklearn t-SNE (Maaten & Hinton, 2008) tool. Fig. 7 (a) and (b) illustrate the news about the Republican Party, and Fig. 7 (c) and (d) contain the news about the Democratic Party. It can be seen from Fig. 7 that pro-republican and also anti-democratic news pieces are mostly published from the news sources with right bias, and anti-republican and pro-democratic news pieces are mostly created by news sources with left-wing bias. The news pieces in Fig. 7 (a) and (b) are all fake. As it is shown in this figure, our proposed news representation can model news stance about entities quite well by considering the source of news. In Fig. s 7 (c) and (d), all anti-democratic news is fake, and all pro-democrat news is real. It can be seen that the source-dependent fake anti-democratic and true pro-democratic news representations are distributed closely while they are well separated from each other in the latent space. In addition, the representation of sources with unknown bias (sources without direct political labels) in Fig. 7 (c) and (d), which are modeled by our source news encoder component, show the effectiveness of our proposed source representation from political leaning of the news that they have published.

The above discussion demonstrates the effectiveness of our proposed news source encoder in political news representation and fake news detection. To evaluate the effectiveness of the news source encoder in other domains, we investigate the impact of the news source encoder in detecting fake news of the GossipCop dataset that contains entertainment news about celebrities. As shown in the ablation study, the elimination of the source encoder in MVCAN\S degrades the performance of MVCAN not only in the PolitiFact dataset but also in the GossipCop dataset. The news source encoder represents sources from the similarity of their audiences in order to represent sources with similar viewpoints to nearby vectors in the embedding space. In addition, four extra political party nodes, i.e., {right, center, left, extreme bias} are considered to model news sources' partisan bias as well. The partisan bias labels exist for 159 sources from 395 sources in GossipCop and 172 sources of 327 sources in PolitiFact. To evaluate the effectiveness of partisan bias nodes in the news source graph, we omit four political party nodes, i.e., {right, center, left, extreme bias} from the graph and then encode the graph of news sources to obtain their embedding. MVCAN\P is the variation of MVCAN obtained after eliminating partisan bias nodes from the news source encoder. As shown in Table 4, the partisan bias labels are not important in detecting GossipCop fake news. However, the source encoder obtained only from the similarity of news sources' audiences is effective in GossipCop fake news detection as eliminating the news source encoder degrades the performance of the model in MVCAN\S. The comparison of MVCAN and

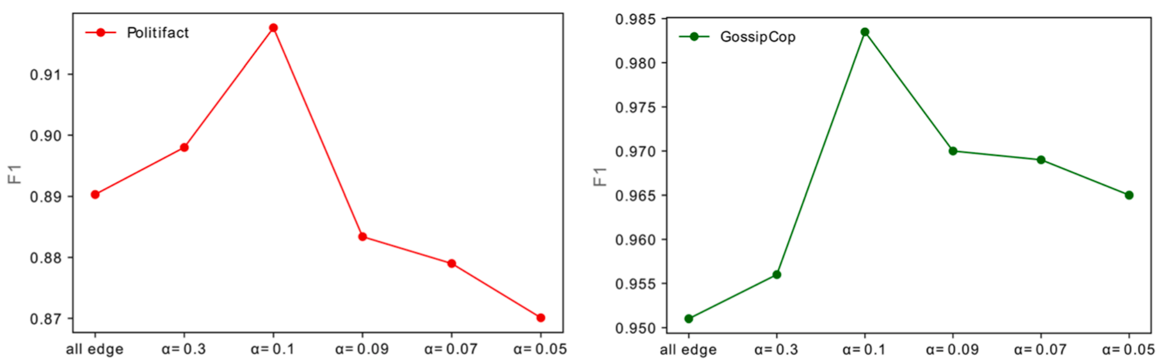

Fig. 6. The comparison of F1 score for models with all friendship edges (without edge filtering) and different significance levels (α) in BiCM. The optimum value of significance level is 0.1 for both datasets.

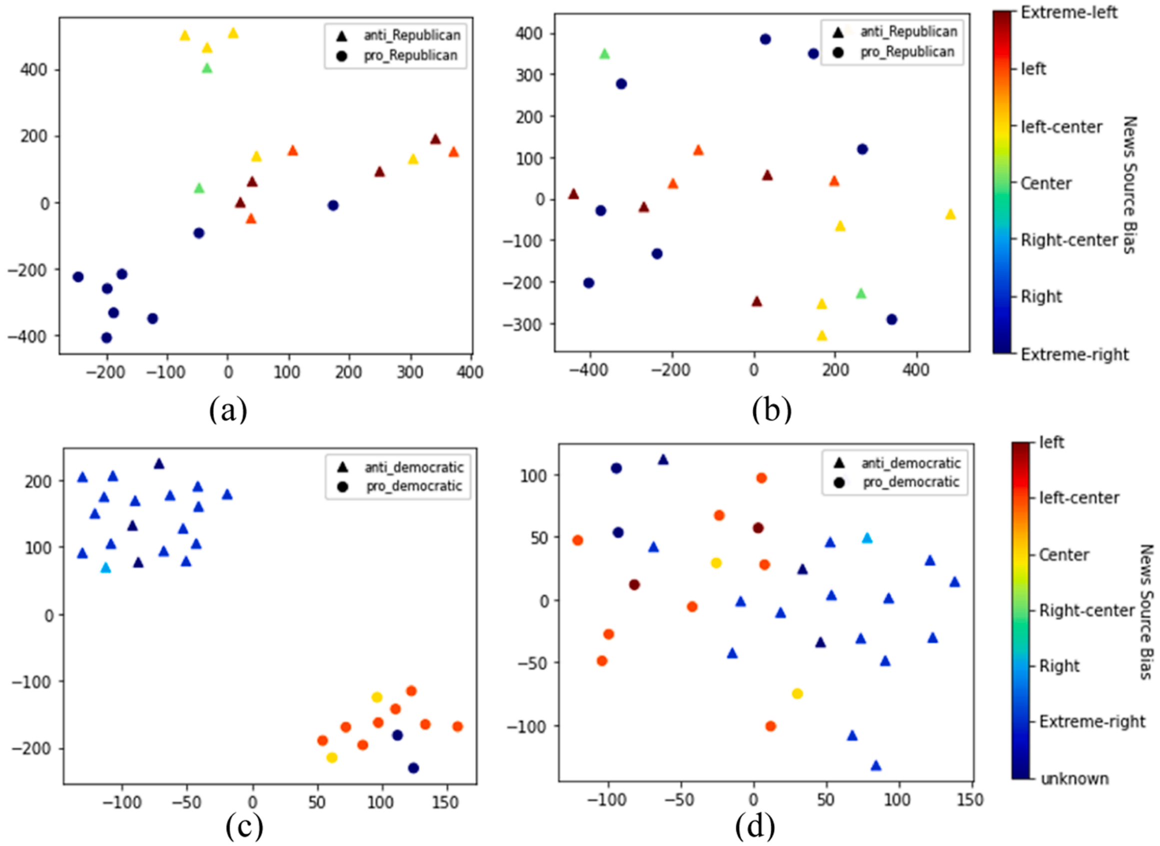

Fig. 7. Comparison of 2D t-SNE news representation for the sampled news about Republican Party (a, b) and Democratic Party (c and d). News representation in figures a and c are obtained from the SNDR module and b and d are obtained from News Content Encoder component.

Table 4
The performance comparison of MVCAN, MVCAN\P, and MVCAN\S.

Dataset	MVCAN		MVCAN\P		MVCAN\S	
	Accuracy	F1	Accuracy	F1	Accuracy	F1
PolitiFact	0.9176	0.9127	0.8901	0.8989	0.8724	0.8809
GossipCop	0.9835	0.9859	0.9790	0.9822	0.9659	0.9615

MVCAN\P for the PolitiFact dataset shows the efficiency of news source partisan bias in detecting fake news in the political domain. Overall, the results show the effectiveness of audience homophily in modeling the similarity between news sources in their viewpoints and the kinds of news they shared and thus for fake news detection in different domains.

5.8. *Topic-specific user credibility analysis*

The user-news co-attention assigns relative weights to the users who share the target news (the weights are between 0 and 1). For fake news, a user with lower credibility in news topics gets a higher attention score, and for real news, the more credible users get higher scores. To answer Q5 and check our hypothesis that users' SC biases have an impact on their credibility on different topics, we select some fake news examples from the PolitiFact dataset with related entities for analysis. As shown in Fig. 8, two topics from fake news are selected: n_1 to n_5 are examples of news against the Democratic Party, which contain different entities in this party, such as Obama, Clinton, and Nancy Pelosi. n_6 to n_8 are news examples that contain entities with Islamism political ideology. We first cluster the user representations from a socio-cognitive aware user encoder using K-means clustering with Euclidian distance. The optimum number of clusters using the elbow method for the PolitiFact dataset is 150. For the selected news in Fig. 8, users with attention scores higher than zero are selected, and their clusters are identified. The score of each cluster for each news is considered as the sum of the attention scores of the users in that cluster who share the news. The attention scores of 14 clusters that interact with selected news are shown in Fig. 8. As shown in this figure, the users in cluster C_1 have low credibility in their shared news about Democratic Party. C_2 and C_9 are more concerned about Islamic ideology and have low credibility in Islamic-related news. Users in C_6 are active users who spread

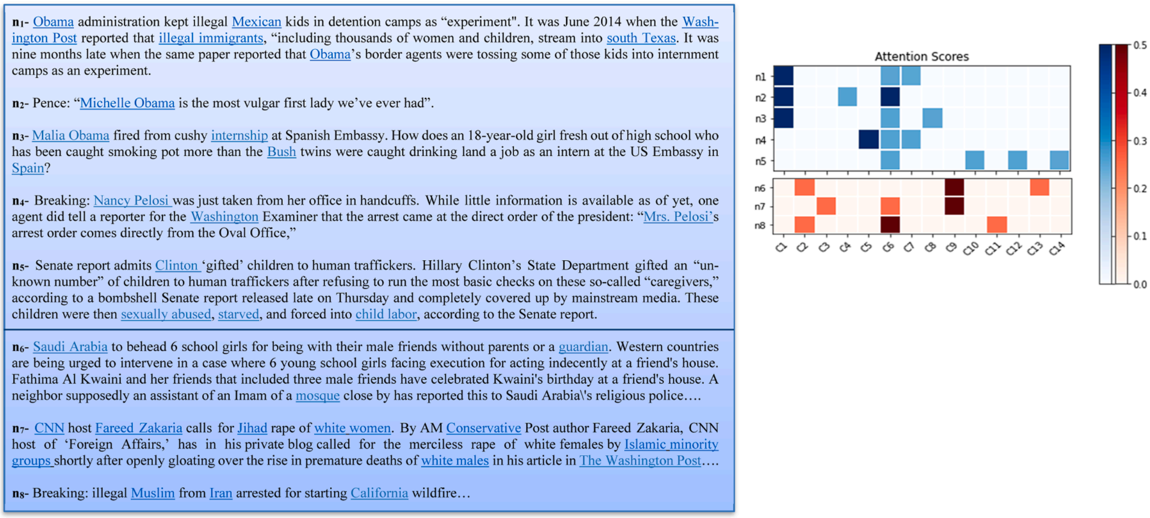

Fig. 8. News examples against the Democratic Party (n_1 to n_5) and news examples about the Islamic entities (n_6 to n_8) and their associated 14 user clusters (C_1 to C_{14}) attention score (right figure).

the news on different topics with low credibility. Therefore, as shown in Fig. 8, there is a clear correlation between users' SC biases and the topics that they are vulnerable to spreading fake news about them.

6. Discussion and conclusion

We propose a fake news detection framework that exploits the credibility of users and news sources interacting with the news for news veracity identification. Different from previous research, we propose the credibility of users and news sources at the topic-level based on their cognitive biases and propose a novel method to jointly model the credibility using a variant of the MHCA. The results show the effectiveness of the interaction between the news topic, source partisan bias, and user's SC bias in verifying the authenticity of the news. Also noteworthy, the proposed model could be applied to the tasks of news source factuality prediction, news political ideology detection, and user credibility prediction.

In addition, we propose a novel heterogeneous graph to model users' SC biases according to the echo-chambers they belong to. Most previous works (Chandra et al., 2020; Nguyen et al., 2020; Shu et al., 2019) have used friendship connections to model echo-chamber of users; however, friendship connections might not always reflect like-minded users. Unlike these studies, we utilize BiCM and content sharing behavior of users to model echo-chambers more accurately and the experimental results show the success of our method.

Moreover, our analysis shows the effectiveness of audience homophily in modeling partisan bias similarity between news sources. In addition, the results show the effectiveness of our idea of using the knowledge entities in addition to the news source partisan bias for modeling topical and political ideology of news articles which is an important and challenging task (Feng et al., 2021).

At last, the findings of this study provide validations for related psychological theories in journalism, i.e., there is a correlation between the level of partisan bias of the news source and the veracity level of its published news articles (Gentzkow et al., 2015; Shu et al., 2019), and between users' SC biases and their online news sharing behaviors (Shu et al., 2019).

For future work, we seek to enhance our model by employing multi-task learning for solving multiple tasks of news article political ideology detection, news source partisan bias and factuality prediction, fake news detection, and echo-chamber detection simultaneously.

CRediT authorship contribution statement

Parisa Bazmi: Conceptualization, Methodology, Software, Validation, Investigation, Writing – original draft, Visualization. **Masoud Asadpour:** Conceptualization, Data curation, Writing – review & editing, Supervision. **Azadeh Shakery:** Conceptualization, Validation, Writing – review & editing, Supervision.

Data Availability

We have shared the link to used data at the Attach File step.
FakeNewsNet (Reference data) (GitHub)

Acknowledgments

This research was in part supported by a grant from the School of Computer Science, Institute for Research in Fundamental Sciences, IPM (No. CS1400-4-237).

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