Towards Fine-Grained Reasoning for Fake News Detection

Yiqiao Jin[1]*, **Xiting Wang**[2]†, **Ruichao Yang**[3], **Yizhou Sun**[1], **Wei Wang**[1], **Hao Liao**[4], **Xing Xie**[2]

[1] University of California, Los Angeles, [2] Microsoft Research Asia,
[3] Hong Kong Baptist University, [4] Shenzhen University
ahren2040@g.ucla.edu, {xitwan, xing.xie}@microsoft.com,
{yzsun, weiwang}@cs.ucla.edu, csrcyang@comp.hkbu.edu.hk, haoliao@szu.edu.cn

Abstract

The detection of fake news often requires sophisticated reasoning skills, such as logically combining information by considering word-level subtle clues. In this paper, we move towards fine-grained reasoning for fake news detection by better reflecting the logical processes of human thinking and enabling the modeling of subtle clues. In particular, we propose a fine-grained reasoning framework by following the human's information-processing model, introduce a mutual-reinforcement-based method for incorporating human knowledge about which evidence is more important, and design a prior-aware bi-channel kernel graph network to model subtle differences between pieces of evidence. Extensive experiments show that our model outperforms the state-of-the-art methods and demonstrate the explainability of our approach.

Introduction

The emergence of social media has transformed the way users exchange information online. People are no longer mere reviewers of information, but content creators and message spreaders. Consequently, it has become much easier for fake news to spread on the Internet. Since fake news can obscure the truth, undermine people's belief, and cause serious social impact (Brewer, Young, and Morreale 2013), detecting fake news has become increasingly important for a healthy and clean network environment (Shu et al. 2017).

Recently, neural models have been proposed to detect fake news in a data-driven manner (Pan et al. 2018; Dun et al. 2021). These works have shown the promise in leveraging big data for fake news detection. However, works that approach the task from the perspective of *reasoning* are still lacking. According to the literature on psychology, reasoning is the capability of *consciously applying logic* for truth seeking (Honderich 2005), and is typically considered as a distinguishing capacity of *humans* (Mercier and Sperber 2017). We observe that such ability is essential to improve the explainability and accuracy for fake news detection:

Explainability. Most existing works on fake news detection either do not provide explanations or enable explainability for a small part of the model (e.g., the attention layer).

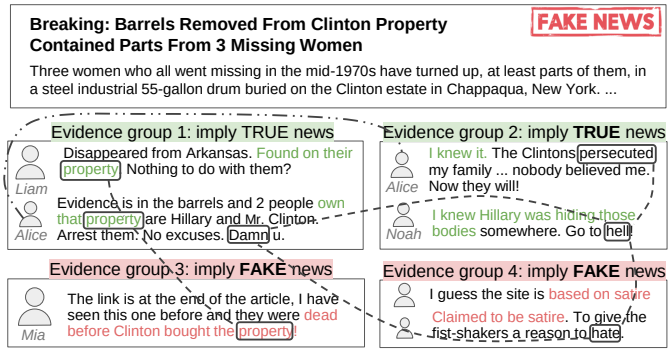

Figure 1: A motivating example of fine-grained reasoning for fake news detection.

The major part of the model (e.g. the overall workflow) remains obscure to humans. This prevents humans to better understand and trust the model, or steer the model for performance refinement.

Accuracy. When humans reason about the authenticity of a news article, they have the ability to perform *fine-grained* analysis for identifying subtle (e.g., word-level) clues, and can connect different types of clues (e.g., textual and social) to draw conclusions. An example is shown in Fig. 1. Although the four groups of evidence are semantically dissimilar, humans can logically connect them in terms of subtle clues such as the word "property", which leads to a much more confident conclusion about the article. For example, reasoning in terms of "property" reveals that the accusation of finding bodies in Clintons' property (evidence group 1) might be false, since the women were dead before the Clintons bought the property (evidence group 3). Reasoning with respect to "hate" suggests that users in groups 1 and 2 might post false messages because they hate the Clintons. The overlap between users in groups 1 and 2 further strengthens this suggestion. Existing methods lack such capability of fine-grained reasoning: they either do not model the interactions between different types of evidence or model them at a coarse-grained (e.g., sentence or post) level.

We aim to move towards using deep reasoning for fake news detection. The goal is to improve accuracy and explainability by 1) better reflecting the logical processes of human thinking and 2) enabling fine-grained modeling of subtle clues. In particular, we study three research questions:

- RQ1. Can the model be designed by following the hu-

*Work done during an internship at Microsoft Research Asia.
†Xiting Wang is the corresponding author.

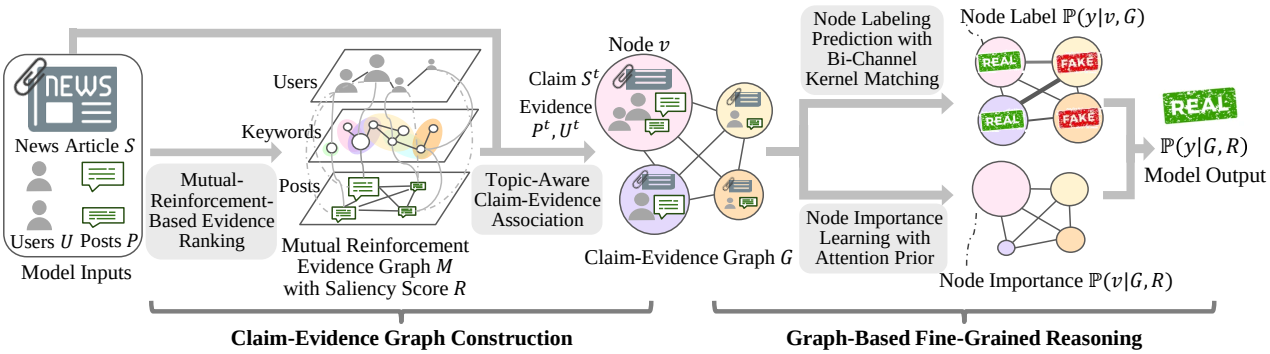

Figure 2: Our proposed *FinerFact* framework for fake news detection.

man's information-processing model (Lang 2000)?

- RQ2. Can human knowledge about which evidence (e.g., posts and users) is important be better incorporated?
- RQ3. How does one achieve fine-grained modeling of different types of subtle clues?

Specifically, we make the following contributions.

First, we design a **Fine-grained reasoning framework for Fake news detection** (**FinerFact**) by following the human's information-processing model (RQ1). This enables us to detect fake news by better reflecting the logical processes of human thinking, which enhances interpretability and provides the basis for incorporating human knowledge.

Second, we propose a **mutual-reinforcement-based method** for evidence ranking, which enables us to better incorporate prior human knowledge about which types of evidence are the most important (RQ2).

Finally, we design a **prior-aware bi-channel kernel graph network** to achieve fine-grained reasoning by modeling different types of subtle clues (RQ3). Our method improves accuracy, and provides explanations about the subtle clues identified, the most important claim-evidence groups, and the individual prediction scores given by each group.

Methodology

Problem Definition

Input. The inputs of our model are threefold. Each training sample consists of 1) a news article S to be verified; 2) a collection of online posts P for the news and the commenting/retweeting relationships between the posts; and 3) the online users U that publish the posts P.

Output. The output of our model is the predicted label of the news, which can be fake $(y = 1)$ or real $(y = 0)$.

Fine-Grained Reasoning Framework

We propose a *Fine-grained reasoning framework for Fake news detection* (*FinerFact*) by following the human's information-processing model (Lang 2000). Our framework consists of two major modules as shown in Fig. 2.

The first module, **claim-evidence graph construction**, corresponds to the *storage* sub-process of the human's information-processing model, in which people select the most important pieces of information and build their in-between associations to store them in the memory. As of fake news detection, it corresponds to the process in which people search for key information such as the major viewpoints, opinion leaders, and the most important posts, which enables them to get an idea about the key claims and their associated evidence (e.g., supported posts and users). This step is essential for filtering noise, organizing facts, and speeding up the fine-grained reasoning process at the later stage. It also enables us to incorporate human knowledge about which information is important.

The second module, **graph-based fine-grained reasoning**, corresponds to the *retrieval* sub-process of the human's information-processing model, in which people reactivate specific pieces of information based on their associations for decision making. In fake news detection, this module enables fine-grained modeling of evidential relations by considering subtle clues, such as the word "property", "hate", and the overlapping user in Fig. 1.

By designing the framework based on the human's information-processing model, the overall workflow of our method resembles the logical processes used by humans, and most of the intermediate results are understandable by ordinary users. This provides a good basis for users to trust the model and steer it by integrating human knowledge.

Claim-Evidence Graph Construction

Our graph construction method contains two parts: 1) **mutual-reinforcement-based evidence ranking**, which distinguishes important evidence from noise by incorporating human knowledge (filtering noise); and 2) **topic-aware claim-evidence association**, which follows journalists' knowledge about quality journalism (for Excellence in Journalism 2005) to extract the key claims and associate them with the corresponding evidence (organizing facts).

Mutual-Reinforcement-Based Evidence Ranking As a news article propagates on the Internet, it leaves many traces, e.g., posts about the news and users who support the news, which can all be considered as evidence for verifying the news. Such evidence typically has a large scale, and performing fine-grained reasoning by considering all evidence is quite difficult, if not impossible, due to limited GPU memory. To efficiently and accurately identify the most valuable evidence in an interpretable way, we propose ranking the evidence by integrating human knowledge. The human knowledge can be divided into two types based on whether it considers the inherent **attributes** (Lampos et al.

2014) of the evidence or its **topological** (Pasquinelli 2009) information. We observe that these two types of knowledge can be integrated in one framework and computed efficiently by using the mutual reinforcement mechanism (Duan et al. 2012). Specifically, our mutual-reinforcement-based evidence ranking consists of the following three steps.

Step 1: Attribute saliency computation. We compute the attribute saliency E based on the human knowledge summarized from the current literature. In particular, the attribute saliency e_{u_i} for a **user** u_i is computed by using the user impact index (Lampos et al. 2014):

$$e_{u_i} = \ln\left(\frac{(\phi_i^I+\theta_U)^2(\phi_i^L+\theta_U)}{\phi_i^O+\theta_U}\right) \quad (1)$$

where ϕ_i^I, ϕ_i^O, ϕ_i^L are u_i's follower count, friend count, and listed count, and θ_U is a smoothing constant added to ensure that the minimum saliency score is always positive. The attribute saliency e_{p_i} of each **post** p_i is computed based on its number of retweets C_i, considering that retweets rarely provide extra textual information and are usually regarded as votes to the original post (Chang et al. 2013). Specifically, $e_{p_i} = \ln(C_i + 1) + \theta_P$, where θ_P is a smoothing constant. The attribute saliency e_{k_i} of each **keyword** k_i is set to $\ln(\text{freq}(k_i) + 1) + \theta_K$, where $\text{freq}(k_i)$ is the term frequency of k_i with respect to the news article and the posts, and θ_K is a smoothing constant (Rousseau and Vazirgiannis 2013).

Step 2: Mutual reinforcement evidence graph building. As shown in Fig. 2, we build the mutual reinforcement evidence graph M so that it encodes both the relations within posts, users, or keywords, and the relations between them to enable the effective modeling of topological saliency. Mathematically, $M = \{A_{xy}|x, y \in \{P, U, K\}\}$ is a three-layer graph, where subscript indices P, U, K denote posts, users, and keywords, respectively, and A_{xy} is an affinity matrix that represents relations between items. We design the graph based on two considerations: 1) M should effectively encode diverse types of social interactions and 2) edges in M should reveal the mutual influence between items in terms of saliency. For example, constructing edges between users and their posts means that if a user is important, then his/her posts are important, and vice versa. Such human knowledge about which items should influence each other in terms of saliency can be effectively incorporated into the edge design. Based on these considerations, we construct M by using the cosine similarity between the term frequency vectors of the posts (A_{PP}), the commenting relationships between users (A_{UU}), the co-occurrence relationships between keywords (A_{KK}), the mentioning relationships that link a keyword to all the posts and users that mention it (A_{KP}, A_{KU}), and the authoring relationships that link a user to all the posts that s/he has published (A_{UP}). More details about the construction of M and how human knowledge is used are given in the supplement.

Step 3: Iterative saliency propagation. We then compute the saliency R based on the mutual reinforcement mechanism (Duan et al. 2012). In particular, we treat the attribute saliency E as a prior and integrate it with the saliency propagation process on M:

$$R^{(i+1)} = d\tilde{A}R^{(i)} + (1-d)E \quad (2)$$

$$\hat{A} = \begin{bmatrix} \beta_{PP}A_{PP} & \beta_{KP}A_{KP} & \beta_{UP}A_{UP} \\ \beta_{PK}A_{PK} & \beta_{KK}A_{KK} & \beta_{UK}A_{UK} \\ \beta_{PU}A_{PU} & \beta_{KU}A_{KU} & \beta_{UU}A_{UU} \end{bmatrix}, R^{(i)} = \begin{bmatrix} R_P^{(i)} \\ R_K^{(i)} \\ R_U^{(i)} \end{bmatrix}, E = \begin{bmatrix} E_P \\ E_K \\ E_U \end{bmatrix}$$

where $R^{(i)}$ is the joint ranking score vector in the i-th iteration, $\tilde{A}$ is the normalized affinity matrix derived from $\hat{A}$, and β_{xy} is a balancing weight to adjust the interaction strength among posts, keywords, and users.

Interpretability and efficiency. The designed method is highly interpretable and steerable, since each type of saliency can be easily explained to and controlled by human users. According to Eq. (2), a piece of evidence (e.g., a supported user) is important if it has a large attribute saliency (e.g., has many followers) and is connected with other salient evidence (e.g., writes a salient post). Other types of human knowledge can also be easily integrated by slightly modifying the equation. Our method is also efficient. In practice, ranking 240,000 posts, users, and keywords takes 620 seconds. Without evidence ranking, performing fine-grained reasoning on the same data causes the out of memory issue on NVIDIA Tesla V100.

Topic-Aware Claim-Evidence Association Given the saliency scores R, a straightforward way for constructing the claim-evidence graph is to select the pieces of evidence with the largest saliency scores. However, this method may easily obscure the truth by focusing only on one aspect of the story. For example, the news article in Fig. 1 may be dominated by posts related to evidence group 1, which are posted deliberately by users who hate the Clintons. To disclose the truth, we need to observe all four evidence groups closely. This echoes the journalists' knowledge about quality journalism (for Excellence in Journalism 2005), which states that a high-quality news article should cover multiple viewpoints to reveal two or more sides of the story. Motivated by this insight, we propose a topic-aware method, which consists of the following steps.

Step 1: Topic modeling. A typical solution to mine major viewpoints in a text corpus is topic modeling. In the scenario of fake news detection, the text corpus consists of each post and news sentence. We then utilize LDA (Blei, Ng, and Jordan 2003) to mine the topics, which summarizes the main viewpoints and serve as a bridge between the claims in the news sentences and the keywords in the evidence graph M:

- Each topic t is represented by a distribution of keywords $\mathbb{P}(k_i|t)$ in M. For each topic t, its top N_K keywords K^t are the ones that have the largest $\mathbb{P}(k_i|t)$.
- Each news sentence s_i is represented by a distribution of topics $\mathbb{P}(t|s_i)$. Given a topic t, we can extract its top N_S sentences S^t that have the largest $\mathbb{P}(t|s_j^t)$.

Step 2: Key claim and evidence extraction. To extract the key claims and their associated evidence based on the topics, we first select the top N_T topics with the maximum aggregate saliency score $r_t = \sum_{k_i \in K^t} \mathbb{P}(k_i|t) r_{k_i}$, where K^t is the set of top keywords extracted in step 1, and r_{k_i} is the saliency score computed by using mutual-reinforcement-based evidence ranking. The topics that are selected in this way not only cover major viewpoints of the article, but are also related with the most salient evidence in M.

For each selected topic t, its corresponding claims are the top news sentences S^t extracted in step 1. The key evidence consists of two parts. The first part is the key posts in t. Given a set of posts that are connected to the keyword set K^t, we normalize the saliency score of each post in the set to obtain a probability distribution, and then sample a set P^t with N_P posts according to the distribution. Similarly, we sample a set U^t with N_U users that are relevant with t, and treat U^t as the second part of the evidence. Keywords are not considered as evidence because they are less useful for fine-grained reasoning when considered without the context. To model keywords more effectively, we treat the posts as ordered sequences of keywords in fine-grained reasoning.

Step 3: Graph construction. Finally, we build a claim-evidence graph G as shown in Fig. 2. In G, each node v is a tuple (t, S^t, P^t, U^t) that corresponds to a selected topic t, where S^t refers to the key claims and P^t, U^t form an evidence group shown in Fig. 1. Given all nodes V, a straightforward approach to construct G is to build edges between two nodes if the percentage of overlapping words is larger than a threshold (Zhong et al. 2020). However, this method may easily overlook important subtle clues, because 1) it is difficult to find an appropriate global threshold and 2) topics (or evidence groups) may be connected logically with different words (e.g., 'damn", "hate", and "hell" in Fig. 1). Based on this observation, we choose to build a fully connected graph and let the fine-grained reasoning module to decide whether subtle clues exist for a set of topics.

Fine-Grained Graph-based Reasoning

After constructing the claim-evidence graph G, we model subtle clues and effectively leverage them for prediction through fine-grained graph-based reasoning. Our method is based on the Kernel Graph Attention Network (KGAT) (Liu et al. 2020). We choose this method because it can effectively model subtle differences between statements and propagate the learned information on the graph. However, KGAT cannot be directly applied on our claim-evidence graph, because it handles only textual inputs and cannot integrate the learned saliency R, which incorporates human knowledge about which evidence is important. To solve these issues, we propose a Prior-Aware Bi-Channel KGAT that extends KGAT to 1) simultaneously model subtle clues from both textual (posts) and social (users) inputs with two connected channels; and 2) integrating existing knowledge about important evidence with attention priors. Mathematically, the final prediction $\mathbb{P}(y|G,R)$ is obtained by combining individual node-level predictions:

$$\mathbb{P}(y \mid G, R) = \sum_{v \in G} \underbrace{\mathbb{P}(y \mid v, G)}_{\text{Node label prediction}} \underbrace{\mathbb{P}(v \mid G, R)}_{\text{Node importance learning}} \tag{3}$$

This formulation provides explainability for individual prediction scores that each node (or claim-evidence group) gives and importance of the nodes for the final prediction. Since we do not have node-level annotations for label prediction or importance, we learn them automatically with:

- **Node label prediction with bi-channel kernel matching**, which accurately computes $\mathbb{P}(y|v,G)$ by integrating different types of subtle clues from the whole graph;
- **Node importance learning with attention priors**, which effectively models $\mathbb{P}(v|G,R)$ by integrating the evidence saliency R as attention priors.

Node Label Prediction with Bi-Channel Kernel Matching Given a node v, we predict the individual label it gives by aggregating subtle clues from the whole graph. To reason about subtle clues that are provided by both the textual and social (user) inputs, we design two interconnected channels. We will first introduce how each channel is designed when they are modeled *independently*, and then illustrate how the channels can be *fused* for prediction.

Text-based reasoning channel. We first derive an initial textual representation for node $v = (t, S^t, P^t, U^t)$ by concatenating the claims in S^t and evidential posts in P^t with token "[SEP]". The concatenated string is then encoded by using BERT (Devlin et al. 2019):

$$[\mathbf{h}_v^0, \mathbf{h}_v^1, ...\mathbf{h}_v^{N_v}] = \text{BERT}(S^t \oplus P^t), \quad \mathbf{z}_v = \mathbf{h}_v^0 \tag{4}$$

where $\mathbf{h}_v^i$ denotes the BERT embedding for the i-th token. $\mathbf{z}_v$, which corresponds to the embedding of the "[CLS]" token, is considered as the initial textual representation for v.

The fine-grained match features between nodes v and q can then be extracted by constructing a token-level translation matrix $L_{q,v}$. In $L_{q,v}$, each entry $l_{q,v}^{i,j} = \cos(\mathbf{h}_q^i, \mathbf{h}_v^j)$ is the cosine similarity between their token representations. For each token i in node q, we use Υ kernels to extract the kernel match features between the token and its neighbor v:

$$\Psi_\tau(L_{q,v}^i) = \log \textstyle\sum_j \exp(-\frac{(l_{q,v}^{i,j} - \mu_\tau)^2}{2\sigma_\tau^2}) \tag{5}$$

$$\vec{\Psi}(L_{q,v}^i) = \{\Psi_1(L_{q,v}^i), \ldots, \Psi_\Upsilon(L_{q,v}^i)\} \tag{6}$$

Each Ψ_τ is a Gaussian kernel that concentrates on the region defined by the mean similarity μ_τ and the standard deviation σ_τ. The kernel match feature $\vec{\Psi}$, which consists of Υ kernels, summarizes how similar the i-th token in q is to all tokens in v at different levels. Such soft-TF match features have been shown effective for fact verification (Liu et al. 2020). In our framework, they help identify subtle clues by comparing different claim-evidence groups (nodes). For example, in Fig. 1, the match features can help identify "hate" in group 4 (node q) by comparing it with all words in group 2 (node v). This neighbor-aware token selection is achieved by computing an attention score based on $\vec{\Psi}$:

$$\alpha_{q,v}^i = \text{softmax}_i(W_1 \vec{\Psi}(L_{q,v}^i) + b_1) \tag{7}$$

We can then compute the content to propagate from q to v:

$$\hat{\mathbf{z}}_{q,v} = \textstyle\sum_i \alpha_{q,v}^i \mathbf{h}_q^i \tag{8}$$

Note that by setting σ_τ to ∞, Eq. (8) degenerates to mean pooling, which assigns an equal weight to all tokens.

Given $\hat{\mathbf{z}}_{q,v}$ that contains the information to be propagated to v, we derive a final textual representation κ_v for v by attentively aggregating $\hat{\mathbf{z}}_{q,v}$ from all $q \in G$:

$$\kappa_v = (\textstyle\sum_{q \in G} \gamma_{q,v} \cdot \hat{\mathbf{z}}_{q,v}) \oplus \mathbf{z}_v \tag{9}$$

$$\gamma_{q,v} = \text{softmax}_q(\text{MLP}(\hat{\mathbf{z}}_{q,v} \oplus \mathbf{z}_v)) \tag{10}$$

The kernel-based textual representation κ_v aggregates fine-grained, token-level subtle clues from the whole graph, and can be used to reason about the authenticity of the news from the perspective of node v. Next, we introduce how to derive kernel-based user representations with a user channel, and how these two channels can be fused for final prediction.

User-based reasoning channel. The initial user representation $\mathbf{x}_v$ for node $v = (t, S^t, P^t, U^t)$ is derived by applying a graph neural network, APPNP (Klicpera, Bojchevski, and Günnemann 2018), on the mutual reinforcement evidence graph M. We choose APPNP because its efficient message-passing scheme enables it to scale to large graphs with hundreds of thousands of nodes. Specifically, for each user in U^t, we first obtain its feature embedding by using a look up layer, which encodes the main user attributes including the user's follower count, friend count, listed count, favourite count, status count, the number of words in the self description, as well as the account status about whether the user is verified or geo-enabled. We then use the message passing scheme of APPNP to aggregate the feature embeddings from the neighbor users in M. This results in an initial user representation $\mathbf{u}_v^i$ for each user, and max pooling is used to derive the initial user presentation $\mathbf{x}_v$ for node v:

$$[\mathbf{u}_v^0, ...\mathbf{u}_v^{\tilde{N}_v}] = \text{APPNP}(M), \;\; \mathbf{x}_v = \text{maxpool}(\mathbf{u}_v^0, ...\mathbf{u}_v^{\tilde{N}_v}) \quad (11)$$

We can then derive the kernel-based user representation $\tilde{\kappa}_v$ by using a kernel attention mechanism similar with that in the text-based reasoning channel:

$$\rho_{q,v}^i = \text{softmax}_i(W_2 \vec{\Psi}(\tilde{L}_{q,v}^i) + b_2) \quad (12)$$

$$\hat{\mathbf{x}}_{q,v} = \textstyle\sum_i \rho_{q,v}^i \mathbf{u}_q^i \quad (13)$$

$$\lambda_{q,v} = \text{softmax}_q(\text{MLP}(\hat{\mathbf{x}}_{q,v} \oplus \mathbf{x}_v)) \quad (14)$$

$$\tilde{\kappa}_v = (\textstyle\sum_q \lambda_{q,v} \cdot \hat{\mathbf{x}}_{q,v}) \oplus \mathbf{x}_v \quad (15)$$

where $\tilde{L}_{q,v}$ is a user-level translation matrix in which each entry is a cosine similarity score between two initial user representations. This formulation of $\tilde{\kappa}_v$ allows us to reason about the final prediction by considering user-based subtle clues, e.g., the overlap between users in Fig. 1.

Channel fusion. We fuse the channels to better integrate information from the textual and social inputs. To this end, we first refine the node-level attention scores by aggregating the textual and user representations. Specifically, we replace $\gamma_{q,v}$ and $\lambda_{q,v}$ in Eqs. (10) and (14) with $\text{softmax}_q(\text{MLP}(\hat{\mathbf{z}}_{q,v} \oplus \mathbf{z}_v \oplus \hat{\mathbf{x}}_{q,v} \oplus \mathbf{x}_v))$. This allows us to combine both textual and social clues when reasoning about one node based on another node. For example, in Fig. 1, we may consider both words related to "hate" and the overlapping user when reasoning about evidence group 1 from the perspective of evidence group 2.

We then fuse the kernel-based textual and user representations to predict the label that node v gives:

$$\mathbb{P}(y \mid v, G) = \text{sigmoid}_v(W_5(\kappa_v) + W_6(\tilde{\kappa}_v) + b_5) \quad (16)$$

Node Importance Learning with Attention Priors Node importance decides which topic (node) should be considered more in detecting fake news. To better characterize the relative importance of each node with regard to the predicted label, we learn the probability $\mathbb{P}(v \mid G, R)$ by jointly consider its claims, evidence, and the evidence saliency R:

$$\mathbb{P}(v \mid G, R) = \text{softmax}_{v \in G}(\varphi(v) + \delta(v, R) + b_6) \quad (17)$$

$$\varphi(v) = W_7 \left[\text{average}_i(\vec{\Psi}(\hat{L}^i_{S^t, P^t}))\right] \quad (18)$$

$$\delta(v, R) = W_8 R_{P^t} + W_9 R_{U^t} + W_{10} R_{K^t} \quad (19)$$

where $\varphi(v)$ is the node ranking feature learned by comparing the claims with the evidence, and $\delta(v, R)$ is the attention prior used to encode the previously learned saliency score R, which embeds human knowledge about evidence significance. More specifically, $\varphi(v)$ is derived by using the kernel match feature $\vec{\Psi}(\hat{L}^i_{S^t, P^t})$, where $\hat{L}_{S^t, P^t}$ is a token-level translation matrix that measures the cosine similarities between tokens in the claims S^t and tokens in the supported posts P^t. The attention prior $\delta(v, R)$ is learned by combining the saliency scores R_{P^t}, R_{U^t}, and R_{K^t}, which correspond to the top posts, users, and keywords that are the most relevant with the topic t of the node v. W_8, W_9, W_{10} are non-negative weight vectors that enable us to re-weight each piece of evidence during fine-grained reasoning.

Joint Optimization Let $\|\Theta\|$ be the $L2$ norm of all model parameters. For each news article S, we compute the loss

$$\mathcal{L}_S = -y^* \log(\hat{p}) + (1 - y^*) \log(1 - \hat{p}) + \lambda_{reg} \|\Theta\|^2 \quad (20)$$

where y^* is its the ground-truth label, $\hat{p} = \mathbb{P}(y|G, R)$ is the probability learned based on Eq. (3), and λ_{reg} is the regularization coefficient. The parameters are then optimized jointly by minimizing $\sum_{S \in \mathcal{N}} \mathcal{L}_S$, where $\mathcal{N}$ consists of all the news articles in the training set.

Experiment

Experimental Setup

Dataset To evaluate the performance of *FinerFact*, we conduct experiments on two benchmark datasets, PolitiFact and GossipCop (Shu et al. 2020), which contain 815 and 7,612 news articles, and the social context information about the news, their labels provided by journalists and domain experts. We follow (Dun et al. 2021) to preprocess the data and conduct experiments. More details about dataset and the preprocessing steps are given in the supplement.

Baselines We compare our *FinerFact* method with eight baselines, which can be divided into two groups:

The first group (**G1**) is content-based methods, which leverage the textual or visual content of the news for fake news detection. G1 contains four baselines: **SVM** (Yang et al. 2012), **GRU-2** (Ma et al. 2016), **RFC** (Kwon et al. 2013), and **DTC** (Castillo, Mendoza, and Poblete 2011).

The second group (**G2**) consists of knowledge-aware methods that detect fake news by leveraging auxiliary knowledge such as knowledge graphs and social knowledge about the online posts. This group includes four methods: **B-TransE** (Pan et al. 2018), **KCNN** (Wang et al. 2018a), **GCAN** (Lu and Li 2020) and **KAN** (Dun et al. 2021).

Evaluation Criteria Our evaluation criteria include Precision (**Pre**), Recall (**Rec**), the **F1** score, Accuracy (**Acc**), and Area Under the ROC curve (**AUC**). We conduct 5-fold cross validation and the average performance is reported.

		PolitiFact					GossipCop				
		Pre	Rec	F1	Acc	AUC	Pre	Rec	F1	Acc	AUC
G1	SVM	0.7460	0.6826	0.6466	0.6694	0.6826	0.7493	0.6254	0.5955	0.6643	0.6253
	RFC	0.7470	0.7361	0.7362	0.7406	0.8074	0.7015	0.6707	0.6691	0.6918	0.7389
	DTC	0.7476	0.7454	0.7450	0.7486	0.7454	0.6921	0.6922	0.6919	0.6959	0.6929
	GRU-2	0.7083	0.7048	0.7041	0.7109	0.7896	0.7176	0.7079	0.7079	0.718	0.7516
G2	B-TransE	0.7739	0.7658	0.7641	0.7694	0.8340	0.7369	0.7330	0.7340	0.7394	0.7995
	KCNN	0.7852	0.7824	0.7804	0.7827	0.8488	0.7483	0.7422	0.7433	0.7491	0.8125
	GCAN	0.7945	0.8417	0.8345	0.8083	0.7992	0.7506	0.7574	0.7709	0.7439	0.8031
	KAN	0.8687	0.8499	0.8539	0.8586	0.9197	0.7764	0.7696	0.7713	0.7766	0.8435
Ours	FinerFact	**0.9196**	**0.9037**	**0.9172**	**0.9092**	**0.9384**	**0.8615**	**0.8779**	**0.8685**	**0.8320**	**0.8637**
	Impv.	+5.1%	+5.4%	+6.3%	+5.1%	+1.9%	+8.5%	+10.8%	+9.7%	+5.5%	+2.0%

Table 1: Performance comparison of *FinerFact* w.r.t. baselines. The best results are highlighted in **bold**.

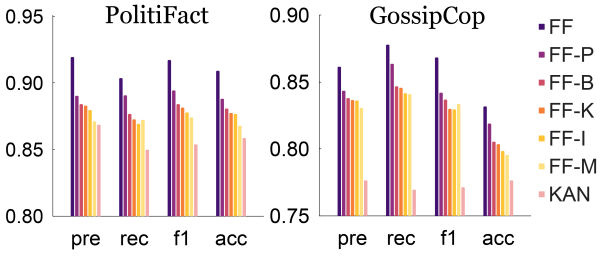

Figure 3: Results of the ablation study.

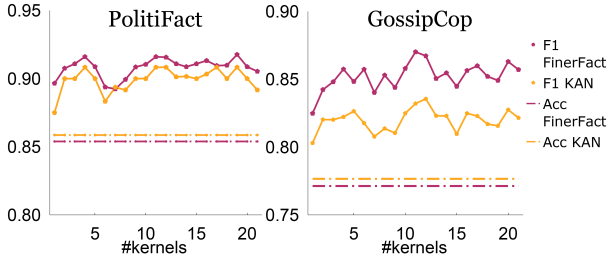

Figure 4: Sensitivity analysis w.r.t. the number of kernels.

Implementation Details To choose the number of topics, we conducted a grid search within the range [2, 10] and picked the number that results in the smallest perplexity. BERT is fine-tuned during training. A more comprehensive description about the implementation details, experimental setup, and evaluation for topic quality are in the supplement.

Overall Performance

Table 1 compares our method *FinerFact* with the baselines. As shown in the table, *FinerFact* consistently outperforms the baseline in both datasets. For example, *FinerFact* performs better than the most competitive baseline *KAN* by 6.3%, 5.1% on PolitiFact and 9.7%, 5.5% on GossipCop, respectively, in terms of the F1-score and accuracy. This demonstrates the effectiveness of our fine-grained reasoning framework, which enables the model to make predictions by identifying and connecting different types of subtle clues. Meanwhile, comparing with *GCAN*, which models the interactions between the textual content and social information with co-attention, *FinerFact* increases F1 by 8.3%, 9.8% on the two datasets. This implies that our kernel-attention-based approach can better model the interactions between news articles and evidence. We also observe that methods that incorporate external knowledge (**G2**) generally perform better than content-based methods (**G1**). This illustrates the usefulness of external knowledge in fake news detection.

Ablation Study and Sensitivity Analysis

We conduct the ablation study by implementing five variants of our method: 1) **FF-P** removes the attention prior $\delta(v, R)$ when learning node importance; 2) **FF-B** eliminates bi-channel reasoning by removing the user-based reasoning channel; 3) **FF-K** replaces the kernel-based representation learning with a GNN-based aggregation scheme, i.e., replacing $\hat{\mathbf{z}}_{q,v}$ and $\hat{\mathbf{x}}_{q,v}$ with $\mathbf{z}_q$ and $\mathbf{x}_q$ in Eqs. (9)(15); 4) **FF-I** excludes node importance learning and assigns an equal weight to every node; 5) **FF-M** eliminates mutual-reinforcement-based evidence ranking, and selects the evidence for each topic t by random sampling. The ablation study results in Fig. 3 show that removing each component leads to a decrease in model performance, which demonstrates the effectiveness of our major components. A result of **FF-T**, which replaces our pretrained text encoder with that of KAN, can be found in the supplement.

We then conduct a sensitivity analysis of *FinerFact* by changing the number of kernels τ. Fig. 4 shows that *FinerFact* consistently outperforms the state-of-art baseline *KAN* with varying numbers of kernels, which demonstrates the robustness of our method. In addition, the performance is the best when using around 11 kernels. Using more kernels does not necessarily lead to better performance due to overfitting.

Case Study

In addition to improving accuracy, our method also enables humans to understand most parts in the reasoning workflow. In this case study, we illustrate how *FinerFact* reasons about the authenticity of a news story, which is about FBI lawyer Lisa Page disclosing that she was instructed to cover-up China's hacks of the DNC server. *FinerFact* successfully identifies that the news is fake, with a detailed explanation about the salient evidence, subtle clues, and the prediction scores for each viewpoint.

Identifying salient evidence. As shown in Fig. 5(a), *FinerFact* identifies meaningful and relevant keywords that be-

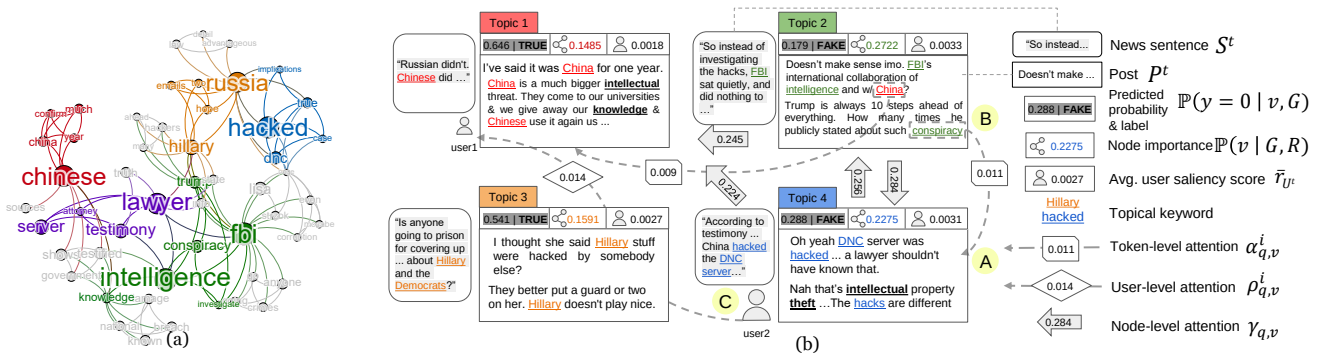

Figure 5: Reasoning with *FinerFact*: (a) the keyword layer of the mutual reinforcement graph M, with saliency R indicated by the font size; (b) fine-grained reasoning over the claim-evidence graph G. Each color encodes a topic.

long to diverse topics. For each topic t, we can further understand its key evidence by observing its salient posts P^t and average user saliency $\bar{r}_{U^t}$. As shown in Fig. 5(b), users of topic 1 support the news because of their political stance (consider China as a threat) and are generally not credible opinion leaders (small $\bar{r}_{U^t}$). In contrast, users of topic 4, who question that the news is fake with more objective reasons, e.g., it is unlikely that an outsider lawyer knows about the server hack (Fig. 5A), receive more attention (larger $\bar{r}_{U^t}$).

Reasoning with subtle clues. The token-level and user-level attention scores $\alpha^i_{q,v}$ and $\rho^i_{q,v}$ reveal the subtle clues *FinerFact* detects. For example, in topic 2, the words with the largest $\alpha^i_{2,1}$ and $\alpha^i_{2,4}$ are "china" and "conspiracy". These clues are meaningful and interesting: the statement about "china" being unlikely to collaborate with FBI in topic 2 decreases the credibility of the posts in topic 1, and relating "conspiracy" with topic 4 (about "hacking") enables us to understand that the news may be fake because such a hacking conspiracy is likely to be made up by people who like to talk about it (Fig. 5B). Topics 1 and 4 are also related: user 2, who has the largest $\rho^i_{4,1}$, questions users in topic 1 by commenting on them, and points out that China's problem in terms of intellectual property does not mean that Chinese will hack the server (Fig. 5C).

Prediction for each viewpoint. Based on the subtle clues, *FinerFact* makes prediction for each node. Our method understands that evidence from groups 1 and 3 imply that the news is true ($\mathbb{P}(y = 0|v, G) > 0.5$) and that the evidence from groups 2 and 4 imply that the news is fake ($\mathbb{P}(y = 0|v, G) < 0.5$). It assigns a low probability score that is close to 0.5 to group 1 by propagating the information from groups 2 and 4 to group 1 (large $\gamma_{q,v}$). It also assigns a small node importance $\mathbb{P}(v|G, R)$ to group 1. This is reasonable, since group 1 has a low user saliency $\bar{r}_{U^t}$, which can be modeled by using the attention prior. While the users in group 3 are considered salient according to the mutual reinforcement graph, we find that they are not talking about whether the article is true, but are instead drifting towards criticizing Hillary. Our model successfully identifies this and assigns a low node importance to topic 3.

Steering the model. *FinerFact* also provides opportunities for users to steer and refine the model. For example, we may integrate *FinerFact* with the method proposed by Liu et al. (2015) to enable interactive refinement of evidence ranking. Please refer to the supplement for more details.

Related Works

Methods for fake news detection can be divided into two main categories: content-based and knowledge-aware.

Content-based methods mainly utilize the textual or visual content from the news article and related posts for news verification (Yang et al. 2012; Afroz, Brennan, and Greenstadt 2012; Kwon et al. 2013; Przybyla 2020; Ma et al. 2016; Zellers et al. 2019; Qi et al. 2019; Gupta et al. 2013; Jin et al. 2016b; Kaliyar, Goswami, and Narang 2021). These methods enable the detection of fake news at an early stage (Wei et al. 2021; Pelrine, Danovitch, and Rabbany 2021). However, their performance is limited as they ignore auxiliary knowledge for news verification.

Knowledge-aware methods leverage auxiliary knowledge for news verification (Ruchansky, Seo, and Liu 2017; Wang et al. 2018b; Shu et al. 2019; Jin et al. 2016a; Ma, Gao, and Wong 2018; Cho et al. 2014; Wang et al. 2018a).

These methods typically utilize external knowledge about entity relationships (Dun et al. 2021; Pan et al. 2018; Silva et al. 2021; Hu et al. 2021) or social knowledge about online posts (Lu and Li 2020; Nguyen et al. 2020; Khoo et al. 2020; Bian et al. 2020) for fake news detection. While existing methods have demonstrated the usefulness of heterogeneous social relations and external information (Yuan et al. 2019), they either do not model the interactions between the news content and different types of knowledge data, or model them at a coarse-grained (e.g., sentence or post) level, which limits their performance.We tackle this issue by proposing a prior-aware bi-channel kernel graph network, which enables fine-grained reasoning and improves detection accuracy.

Conclusion

We propose *FinerFact*, a fine-grained reasoning framework for explainable fake news detection. We devise a mutual-reinforcement-based method for efficient evidence ranking and a prior-aware bi-channel kernel graph network for fine-grained reasoning on multiple groups of evidence. Experimental results show the effectiveness of our method.

References

Afroz, S.; Brennan, M.; and Greenstadt, R. 2012. Detecting hoaxes, frauds, and deception in writing style online. In *2012 IEEE Symposium on Security and Privacy*, 461–475. IEEE.

Bian, T.; Xiao, X.; Xu, T.; Zhao, P.; Huang, W.; Rong, Y.; and Huang, J. 2020. Rumor detection on social media with bi-directional graph convolutional networks. In *AAAI*, volume 34, 549–556.

Blei, D. M.; Ng, A. Y.; and Jordan, M. I. 2003. Latent dirichlet allocation. *JMLR*, 3: 993–1022.

Brewer, P. R.; Young, D. G.; and Morreale, M. 2013. The impact of real news about "fake news": Intertextual processes and political satire. *International Journal of Public Opinion Research*, 25(3): 323–343.

Castillo, C.; Mendoza, M.; and Poblete, B. 2011. Information credibility on twitter. In *WWW*, 675–684.

Chang, Y.; Wang, X.; Mei, Q.; and Liu, Y. 2013. Towards twitter context summarization with user influence models. In *WSDM*, 527–536.

Cho, K.; van Merriënboer, B.; Bahdanau, D.; and Bengio, Y. 2014. On the Properties of Neural Machine Translation: Encoder–Decoder Approaches. In *Proceedings of SSST-8, Eighth Workshop on Syntax, Semantics and Structure in Statistical Translation*, 103–111.

Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *NAACL*, 4171–4186.

Duan, Y.; Chen, Z.; Wei, F.; Zhou, M.; and Shum, H. Y. 2012. Twitter topic summarization by ranking tweets using social influence and content quality. In *COLING*, 763–780.

Dun, Y.; Tu, K.; Chen, C.; Hou, C.; and Yuan, X. 2021. KAN: Knowledge-aware Attention Network for Fake News Detection. In *AAAI*, volume 35, 81–89.

for Excellence in Journalism. 2005. The State of the News Media 2005.

Gupta, A.; Lamba, H.; Kumaraguru, P.; and Joshi, A. 2013. Faking sandy: characterizing and identifying fake images on twitter during hurricane sandy. In *WWW*, 729–736.

Honderich, T. 2005. *The Oxford companion to philosophy*. OUP Oxford.

Hu, L.; Yang, T.; Zhang, L.; Zhong, W.; Tang, D.; Shi, C.; Duan, N.; and Zhou, M. 2021. Compare to The Knowledge: Graph Neural Fake News Detection with External Knowledge. In *ACL-IJCNLP*.

Jin, Z.; Cao, J.; Zhang, Y.; and Luo, J. 2016a. News verification by exploiting conflicting social viewpoints in microblogs. In *AAAI*, volume 30.

Jin, Z.; Cao, J.; Zhang, Y.; Zhou, J.; and Tian, Q. 2016b. Novel visual and statistical image features for microblogs news verification. *IEEE Transactions on Multimedia*, 19(3): 598–608.

Kaliyar, R. K.; Goswami, A.; and Narang, P. 2021. FakeBERT: Fake news detection in social media with a BERT-based deep learning approach. *Multimedia Tools and Applications*, 80(8): 11765–11788.

Khoo, L. M. S.; Chieu, H. L.; Qian, Z.; and Jiang, J. 2020. Interpretable rumor detection in microblogs by attending to user interactions. In *AAAI*, volume 34, 8783–8790.

Klicpera, J.; Bojchevski, A.; and Günnemann, S. 2018. Predict then Propagate: Graph Neural Networks Meet Personalized PageRank. In *International Conference on Learning Representations*.

Kwon, S.; Cha, M.; Jung, K.; Chen, W.; and Wang, Y. 2013. Prominent features of rumor propagation in online social media. In *ICDM*, 1103–1108. IEEE.

Lampos, V.; Aletras, N.; Preoţiuc-Pietro, D.; and Cohn, T. 2014. Predicting and characterising user impact on Twitter. In *EACL*, 405–413.

Lang, A. 2000. The limited capacity model of mediated message processing. *Journal of Communication*, 50(1): 46–70.

Liu, M.; Liu, S.; Zhu, X.; Liao, Q.; Wei, F.; and Pan, S. 2015. An uncertainty-aware approach for exploratory microblog retrieval. *IEEE Transactions on Visualization and Computer Graphics*, 22(1): 250–259.

Liu, Z.; Xiong, C.; Sun, M.; and Liu, Z. 2020. Fine-grained Fact Verification with Kernel Graph Attention Network. In *ACL*, 7342–7351.

Lu, Y.-J.; and Li, C.-T. 2020. GCAN: Graph-aware Co-Attention Networks for Explainable Fake News Detection on Social Media. In *ACL*, 505–514.

Ma, J.; Gao, W.; Mitra, P.; Kwon, S.; Jansen, B. J.; Wong, K.-F.; and Cha, M. 2016. Detecting rumors from microblogs with recurrent neural networks.

Ma, J.; Gao, W.; and Wong, K.-F. 2018. Rumor Detection on Twitter with Tree-structured Recursive Neural Networks. In *ACL*, 1980–1989.

Mercier, H.; and Sperber, D. 2017. *The enigma of reason*. Harvard University Press.

Nguyen, V.-H.; Sugiyama, K.; Nakov, P.; and Kan, M.-Y. 2020. Fang: Leveraging social context for fake news detection using graph representation. In *CIKM*, 1165–1174.

Pan, J. Z.; Pavlova, S.; Li, C.; Li, N.; Li, Y.; and Liu, J. 2018. Content based fake news detection using knowledge graphs. In *ISWC*, 669–683. Springer.

Pasquinelli, M. 2009. Google's PageRank algorithm: A diagram of cognitive capitalism and the rentier of the common intellect. *Deep search: The politics of search beyond Google*, 152–162.

Pelrine, K.; Danovitch, J.; and Rabbany, R. 2021. The Surprising Performance of Simple Baselines for Misinformation Detection. In *WWW*, 3432–3441.

Przybyla, P. 2020. Capturing the style of fake news. In *AAAI*, volume 34, 490–497.

Qi, P.; Cao, J.; Yang, T.; Guo, J.; and Li, J. 2019. Exploiting multi-domain visual information for fake news detection. In *ICDM*, 518–527. IEEE.

Rousseau, F.; and Vazirgiannis, M. 2013. Graph-of-word and TW-IDF: new approach to ad hoc IR. In *CIKM*, 59–68.

Ruchansky, N.; Seo, S.; and Liu, Y. 2017. Csi: A hybrid deep model for fake news detection. In *CIKM*, 797–806.

Shu, K.; Cui, L.; Wang, S.; Lee, D.; and Liu, H. 2019. defend: Explainable fake news detection. In *KDD*, 395–405.

Shu, K.; Mahudeswaran, D.; Wang, S.; Lee, D.; and Liu, H. 2020. Fakenewsnet: A data repository with news content, social context, and spatiotemporal information for studying fake news on social media. *Big data*, 8(3): 171–188.

Shu, K.; Sliva, A.; Wang, S.; Tang, J.; and Liu, H. 2017. Fake news detection on social media: A data mining perspective. *ACM SIGKDD explorations newsletter*, 19(1): 22–36.

Silva, A.; Luo, L.; Karunasekera, S.; and Leckie, C. 2021. Embracing Domain Differences in Fake News: Cross-domain Fake News Detection using Multi-modal Data. In *AAAI*, volume 35, 557–565.

Wang, H.; Zhang, F.; Xie, X.; and Guo, M. 2018a. DKN: Deep knowledge-aware network for news recommendation. In *WWW*, 1835–1844.

Wang, Y.; Ma, F.; Jin, Z.; Yuan, Y.; Xun, G.; Jha, K.; Su, L.; and Gao, J. 2018b. EANN: Event adversarial neural networks for multi-modal fake news detection. In *KDD*, 849–857.

Wei, L.; Hu, D.; Zhou, W.; Yue, Z.; and Hu, S. 2021. Towards Propagation Uncertainty: Edge-enhanced Bayesian Graph Convolutional Networks for Rumor Detection. In *ACL-IJCNLP*, 3845–3854.

Yang, F.; Liu, Y.; Yu, X.; and Yang, M. 2012. Automatic detection of rumor on sina weibo. In *Proceedings of the ACM SIGKDD workshop on mining data semantics*, 1–7.

Yuan, C.; Ma, Q.; Zhou, W.; Han, J.; and Hu, S. 2019. Jointly embedding the local and global relations of heterogeneous graph for rumor detection. In *ICDM*, 796–805. IEEE.

Zellers, R.; Holtzman, A.; Rashkin, H.; Bisk, Y.; Farhadi, A.; Roesner, F.; and Choi, Y. 2019. Defending Against Neural Fake News. In *NeurIPS*.

Zhong, W.; Xu, J.; Tang, D.; Xu, Z.; Duan, N.; Zhou, M.; Wang, J.; and Yin, J. 2020. Reasoning Over Semantic-Level Graph for Fact Checking. In *ACL*, 6170–6180.