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KAGN: Attentiveness driven by knowledge Also used for social media rumor detection are graph convolutional networks.

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Abstract
Given how quickly online and social media platforms are developing, rumours have drawn a lot of attention. The public at large, the government, and social media companies are becoming increasingly concerned about the automatic identification of rumour from posts. While neglecting knowledge entities and concepts concealed within the article that aid in rumour detection, the majority of current approaches concentrate on the language and semantic components of postings' content. In this paper, we propose a unique end-to-end attention and graph-based neural network model (KAGN) that detects rumour by incorporating external knowledge from the knowledge graphs. This model aims to overcome these limitations. In particular, we locate entity mentions in the post's content and connect them to entities and ideas in the knowledge graphs, which serve as a means of addressing the sparse and confusing semantics of the post.

Keywords*: social media, Graph convolutional networks, knowledge graphs, attention, and rumor detection*

I. Introduction

Social media websites have also fostered a variety of rumor, many of which contain misrepresented or even forged content in order to mislead readers and spread quickly. For example, over the last 2 years, social media networks in various countries have been inundated with various rumor about COVID-19. Therefore, in order to maintain social harmony it is highly crucial to detect rumor on these platforms and also regulate themto ensure that the users receive genuine information. The traditional automatic rumor detection methods were based on various handcrafted linguistic(feature engineering) and semantic features for differentiating between posts documents [1, 2]. With the advent of big data and deep learning, we have seen a shift toward deep-level features. Various deep neural models such as CNN [3], Bi-LSTM [4] and the graph based method [5] are proposed and greatly improve the detection performances. Even though existing deep neural networks approaches have been successfully used to capture high-level syntax and semantic feature representations of posts content, these approaches do not take into account the external knowledge that is commonly used to judge the authenticity of posts.

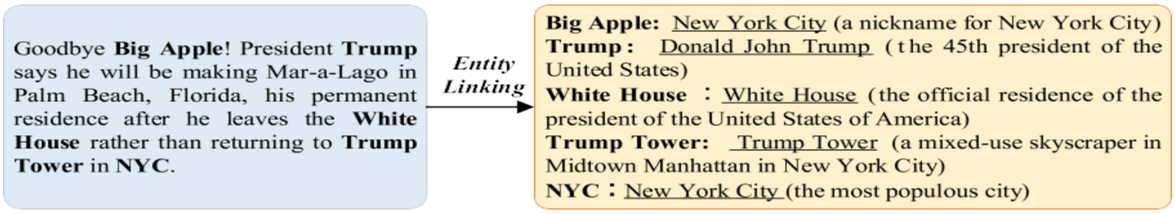

Fig. 1 An illustration for entity linking. Entity mentions detected from text are in boldface; By entity linking and disambiguation, the entity mentions are mapped to correct entities which are underlined

Generally, posts contents contain many mentions of entities which condense information. A named entity is an individual such as a person, organization, location, or event. A mention is a piece of text that refers to an entity. A named entity could possibly denote different entity mentions because a named entity may have multiple textual forms, such as its aliases, abbreviations and alternate spellings. [6] As seen in Fig. 1, a post contains the following ambiguous entity mentions: “Big Apple”, “Trump”, “White House”, “Trump Tower”, and “NYC”. When reading the text, one realizes that “Trump” is a person, “Big Apple”, “White House”, “Trump Tower” and “NYC” are geographical locations, and that “Trump” and “Donald Trump" refer to the same person, “Trump” and “Trump” are references to the entity “Donald Trump”.

The terms “Big Apple” and “NYC” refer to the same entity “New York City”. The knowledge-level based judgments and connections help determine the believability of posts. However, the entities and concepts linked with mentions cannot be recognized and comprehended immediately from the content of the posts. As a result, the incorporation of external knowledge is critical for detecting rumor. A knowledge graph is a multi-relational graph, consisting of nodes representing entities and edges representing relationships of various types. On the one hand, the introduction of the knowledge graphs can ensure that each mention in the posts corresponds to the appropriate entity in the knowledge graphs, eliminating the noise caused by ambiguous entity mentions. In addition, knowledge graphs can provide connection information between entities and concepts, which facilitates learning knowledge that is not explicitly stated in the posts text but relevant for rumor detection. Compared to paragraphs or documents, posts made by users on social platforms do not have sufficient contextual information and suffer from limited word count and incomplete semantics, which leads to semantic ambiguity in posts and poses a significant challenge for short text classification. To resolve this issue, we extract the set of entities and the set of entity-related concepts from the knowledge base(KBs) to enrich the semantics of the text, but some improper entities and concepts are easily introduced due to the ambiguity of entities or the noise in KBs.

We therefore propose to use an attention mechanism to inject knowledge into the text in a hierarchical manner, i.e. injecting conceptual knowledge into entities first, and then entities into the text, as a way to filter useful knowledge. Most of the current work does not consider the implicit connections between knowledge, which may be useful for classification. Therefore, we consider the use of graph structures to establish long-range semantic relations between knowledge, i.e. Knowledge share within a sentence on the one hand, and between different posts in the corpus on the other. Specifically, we propose a Knowledge-Powered Attention and Graph Neural Networks (KAGN) for rumor detection by combining the textual information and knowledge concepts into a unifed deep model. To fully utilize external knowledge, we first identify entity mentions in the post contents and then obtain corresponding entities via external knowledge graphs such as Wikidata [7], Probase [8], Freebase [9], and YAGO [10]. Ten, as supplementary information, we extract the concepts of each entity. (2)To facilitate the fusion of knowledge, we perform feature extraction from both local and global perspectives.

From the local perspective, we calculated the weight distribution of each concept to the same entity using the attention mechanism to consider the granularity of concepts and the relative importance of concepts. Furthermore, taking into account the different contribution of each entities to the posts text, we designed the attention mechanism to determine the semantic similarity between the text and entities. Taking a global view, we built a heterogeneous graph with nodes representing posts, entities, and concepts, and used graph convolutional neural networks to focus on long-range interconnectedness knowledge. (3)Finally, post text representations incorporating entity and knowledge concepts are fed into fully connected layers to predict the authenticity of posts. The major contributions of this paper are summarized as follows:

• We propose a novel end-to-end unifed deep model called KAGN incorporating entities and concepts information derived from knowledge graphs for detecting rumor.

• KAGN utilizes attention mechanisms to hierarchically and effectively inject external entity and conceptual knowledge into the text, and employs graph convolutional networks to mine long-range semantic connections within and between texts, jointly modeling text and knowledge information from both local and global perspectives.

• We conduct extensive experiments on four standard datasets for rumor detection.

The results show that KAGN outperforms or is comparable to the state-of-art methods, and the ablation study has demonstrated that KAGN is effective in rumor detection analysis. Related works In this section, we briefly review the work related to the proposed model. We mainly focus on the following topics: rumor detection, knowledge graphs, attention mechanism, graph neural network.

Rumor detection Social-based rumor detection Social environment for posts contains an abundance of information, such as the interaction patterns of the users, the dissemination patterns, and the credibility of the posts. Ma et al. [11] propose a kernel-based method to capture high-order patterns of microblog posts diffusion with propagation trees, which provide valuable clues on how a post is diffused and developed over time. Liu et al. [12] modeled the propagation path as multivariate time series, and applied both recurrent and convolutional networks to capture the variations of user characteristics along the propagation path. Wu et al. [13] proposed a random walk graph kernel to model the propagation trees of messages to improve rumor detection. Sitaula et al. [14] analyzed the history of association between authors and rumor, as well as the number of authors of posts to detect rumor on the internet. Content-based rumor detection A large number of researchers have looked for important clues to distinguish rumor from credible posts through semantic, style and knowledge graphs of posts content. Various deep models, such as the architecture of LSTM [15], graph convolutional network [16], gated

GNN [17], generative adversarial network (GAN) [18], deep convolutional neural network [19], event adversarial network [20], and hybrid convolutional neural network [21] are used to extract potential textual and visual features of posts content. Approaches based on knowledge graphs have also been investigated for rumor detection. [22] Propose a Knowledge-driven Multimodal Graph Convolutional Network (KMGCN) to jointly model the semantic representations of textual information, knowledge concepts and visual information for fake news detection.

The authors of [23] introduced a KGs(Knowledge Base) for fact checking claims by collecting data from popular fact-checking websites and exploring additional information from DBpedia. Furthermore, researchers have proposed interpretable methods for detecting rumor using KGs [24]. Knowledge graphs Google officially released the Knowledge Graphs in 2012 [25]. A knowledge graph is a large-scale semantic network that generates new knowledge by acquiring information and integrating it into a knowledge base and then reasoning about it, which contains a large amount of entities, attributes, and semantic information between entities. Knowledge graphs have been widely used in risk control anti-fraud, credit auditing, accurate advertising delivery, search engines, personalized recommendation systems and question and answer systems [26–28]. Knowledge graphs generally use triples to record and store entity relationships, and the hidden attributes of entities and their relationships with other entities can be mined through knowledge graphs embedding learning, and the knowledge graphs triples are represented as low-dimensional vectors [29].

A named entity is an individual, such as a person's name, a place name, or an organization's name. An entity mention is a name string that appears in the text to refer to the entity. To extract named entities from text, two main tasks are involved: named entity recognition tries to find every fragment of text that mentions a named entity. Named entity linking is divided into candidate entity generation, which is based on retrieving the knowledge base to get all the eponymous entities to form a candidate entity set, and candidate entity disambiguation, which is a method to find the target entity from the candidate entity set that matches the current context.

Attention mechanism

Bahdanau et al. [30] first used an attention mechanism in a machine translation task, which was mainly based on the Encoder-Decoder framework, where the attention mechanism weighted the source sentence features to focus on those that were important for the current translation and ignored those that were not. Yang et al. [31] proposed a hierarchical attention mechanism, which introduced an attention mechanism at the word level to get important sentence features and introducing an attention mechanism to get important document features at the sentence level to achieve document classification. The Transformer model proposed by Google Vaswani et al. [32] is an automatic translation model, which proposes a self-attention mechanism approach, which is one of the representative approaches in the development of attention mechanism. Wu et al. [33] combine word embedding with contextual embedding of words captured using a self-attentive mechanism, and then capture semantic features by convolutional neural networks for text classification. Liu et al. [34] proposed to use an attention mechanism to assign different weights to the information output from the hidden layer of the bidirectional LSTM to obtain local features and global semantics of phrases to improve the classification accuracy. Ma et al. [35] proposed a Global–Local Mutual Attention (GLMA) model for the text classification problem, which introduces a mutual attention mechanism for mutual learning between local semantic features and global long-term dependencies. Guo et al. [36] proposed a multi-scale self-attentive mechanism model where the self-attentive mechanism is introduced into the multi-scale structure to extract different scale features of the text. In addition, the multi-head self-attention mechanism in Transformer idea is also combined with multi-scale to let each head extract different scale information of the text.

Graph neural networks

Yao et al. [37] were the first to apply graph convolution to text classification tasks, and proposed the TextGCN model to construct a corpus-level graph for the entire dataset using words and text as nodes, and to learn both word representation and text representation using standard graph convolutional networks. Liu et al. [38] proposed a tensor graph neural network model for coordinating and integrating multi-graph heterogeneous information, constructing a text graph tensor to describe semantic, syntactic, and sequential contextual information, and then performing intra-graph and inter-graph propagation on the text graph tensor. Hu et al. [39] introduced a two-layer attention structure in a heterogeneous graph neural network to obtain key in-formation at different granularity levels and reduce the influence of noisy information. Zhang et al. [40] proposed TextING to construct a text-level edge weight matrix and use Gated Graph Neural Network (GGNN) to update the word node representation in the message passing phase. Gianni's et al.[41] proposed MPAD, which introduces a text node in the construction of the text-level graph and establishes a connection with all words to obtain global statistics, and puts the word representation through a self-attention mechanism to obtain a temporary text representation in the read-out phase, and performs a join operation with the updated representation of the text node in the graph as the final text representation for classification.

The proposed method

In this section, we mainly introduce the proposed Knowledge-Powered Attention and Graph Neural Networks (KAGN) in detail. We first describe the problem definition, and then, we introduce the overall framework of KAGN. The details of the proposed model are shown in the following sections.

Knowledge distillation

Background knowledge derived from a real-word knowledge graphs can be used to supplement the semantic representation of short post texts. Furthermore, the conceptual information extracted from entities can be used to provide additional evidence to aid in the detection of rumor. Tis module's specific goal is to retrieve relevant knowledge from knowledge graphs. We hope to find a concept set CE relevant to a given post text. The knowledge distillation process consists of two steps in Fig. 3. Given the short text content of posts, many entity

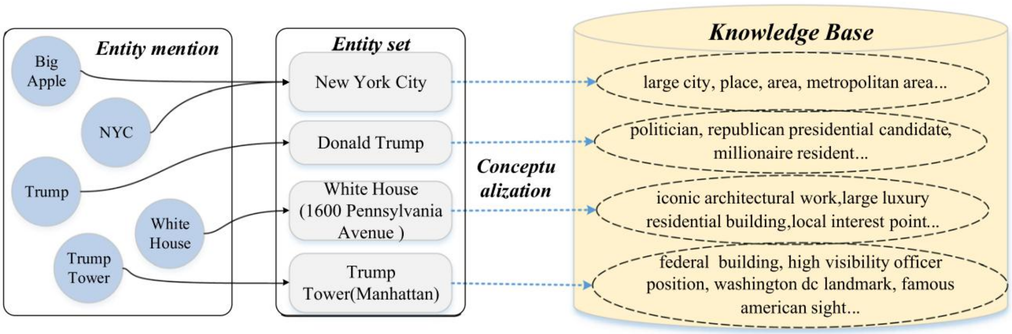

Fig. 3 An illustration for entity conceptualization. Conceptual knowledge extracted from a knowledge base for each entity are shown via a dashed arrow line and oval

Knowledge attention encoder

Knowledge encoder Prior knowledge obtained from external knowledge base provides richer information and reduces ambiguity caused by entity mentions in posts. Given a piece of post, entities and entity-related concepts in the post can help to improve performance of rumor detection.

Limitation

According to the above experimental results and discussions, our KAGN performs well for rumor detection tasks. However, since the proposed method takes advantage of knowledge from the external knowledge base, one limitation of our method is that the performance of KAGN is influenced by the accuracy of external entity linking tools and knowledge bases, which is beyond our control. Furthermore, KAGN is more applicable to text with obvious entity mention.. Therefore, we can only rely on the the word features of texts in our method for classification. However, from the analysis in the knowledge of text has an important contribution to the proposed method. Therefore, our method may be limited in predicting the authenticity of the news evoked by texts without obvious entities.

II. Conclusion and future work

KAGN is proposed in this paper as a method to detect rumor, which incorporates entities and concepts from an external knowledge base to complement the semantic representation of the short text of posts. When we incorporate entities and concepts into the representation of the text, we are able to make better use of external knowledge information because we have used an attention mechanism. In addition, we use graph convolutional neural networks to construct graphs containing post texts, entities, and concepts to obtain associative features among knowledge. The experimental results on four publicly datasets demonstrate the effectiveness of the proposed model and that the performance of the model can be effectively improved by introducing external knowledge. In the future, we intend to investigate the combination of multimodal data (e.g. Images) and external knowledge for the detection of fake message.

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