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Early-Stage Rumor Detection in Online Social Networks Using Hybrid Temporal–Graph Deep Learning Models

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Abstract

The widespread use of online social networks has transformed the way information is created and shared, while simultaneously increasing the circulation of unverified and misleading content. Detecting rumors at an early stage is particularly difficult because only limited textual and structural signals are available shortly after an event emerges. This paper presents a hybrid temporal–graph deep learning approach for early-stage rumor detection. The proposed framework jointly learns representations from post content, short-term temporal behavior, and partial diffusion structures observed during the initial phase of information spread. By fusing temporal sequence modeling with graph-based representation learning, the model captures complementary cues that are often overlooked by single-view approaches. Experimental results on benchmark Twitter datasets show that the proposed method achieves superior performance compared to existing baselines under early observation settings, confirming its effectiveness for timely rumor identification.

Index Terms— ***Rumor detection, early-stage analysis, online social networks, information diffusion, temporal modeling, graph neural networks.***

Introduction

Online social networks (OSNs) have become a primary medium for information exchange, enabling users to rapidly publish and consume content. Alongside these benefits, OSNs also facilitate the rapid spread of rumors—information whose accuracy has not been verified at the time of dissemination. Once such content begins to spread, it can influence public opinion, create panic, or undermine trust in online information.

A key challenge in rumor analysis is timely detection. Many existing approaches depend on rich propagation patterns or long-term interaction histories, which are typically unavailable during the early stages of an event. Consequently, detection often occurs only after the rumor has already diffused widely. This limitation highlights the need for early-stage rumor detection

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methods that can operate under sparse and incomplete data conditions.

Deep learning techniques have recently been applied to rumor detection with notable success. However, models that focus exclusively on textual content or solely on network structure often fail to capture the full dynamics of early rumor spread. In early stages, textual narratives evolve rapidly, while even partial interaction graphs can reveal meaningful patterns of user engagement. This work is motivated by the observation that combining these perspectives can lead to more robust early detection.

In this paper, we propose a hybrid temporal–graph learning framework that integrates short-term temporal modeling of post sequences with graph-based representation learning over partial diffusion networks. The main contributions of this work are threefold: (i) a unified framework designed specifically for early-stage rumor detection, (ii) a principled fusion strategy for combining temporal and structural features, and (iii) an extensive experimental evaluation demonstrating improved performance under limited observation windows.

Related Work

Research on rumor detection in online social networks has evolved from traditional feature-based methods to advanced representation learning techniques. Early studies primarily relied on manually designed linguistic, statistical, and user-based features combined with conventional classifiers. Although these approaches provided initial insights, their performance was highly dependent on feature quality and domain specificity.

With the emergence of deep learning, neural architectures began to dominate rumor detection research. Text-focused models such as CNNs and recurrent networks demonstrated improved capability in learning semantic patterns directly from raw content. Temporal extensions of these models further captured how discussions evolve over time. Despite these advances, content-only approaches often struggle during early stages, when limited posts are available.

To address structural aspects of information diffusion, graph-based methods have been proposed to model user interactions and propagation patterns. Graph neural networks and attention-based models effectively capture relational dependencies among users. However, many of these methods assume access to complete diffusion graphs, which restricts their applicability for early- stage analysis.

More recent studies have explored hybrid strategies that combine textual, temporal, and structural information. While these approaches report performance gains, most are evaluated under full or near-complete diffusion settings. In contrast, the present work focuses explicitly on early-stage rumor detection, emphasizing partial observations and proposing a unified temporal– graph learning framework tailored to this challenging scenario.

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Proposed Methodology

A. Problem Formulation

An online social network is represented as a graph $G = (V, E)$, where V denotes the set of users and E represents interaction edges such as retweets or replies. Each post p_i is associated with textual content x_i and a timestamp t_i.

Given an event-related post set $P = \{p_1, p_2, \ldots, pn\}$ observed within an early time window T_e, the objective is to learn a function:

$$f(P, G_{T_e}) \longrightarrow y, \qquad y \in \{0,1\}$$

where $y = 1$ denotes a rumor and $y = 0$ denotes non-rumor, and G_{T_e} represents the partial diffusion graph observed within T_e.

B. Temporal Representation Learning

Textual content is first embedded using a contextual encoder. Let h_i denote the embedding of post p_i. A temporal encoder (B_LSTM/Transformer) models the sequence:

$$H_t = TemporalEncoder(h_1, h_2, \quad , h_n)$$

where H_t captures early temporal dynamics of information diffusion.

C. Graph-Based Representation Learning

Node representations are updated using a Graph Neural Network (GNN) according to the following formulation:

$$H_g^{(l+1)} = \sigma(\tilde{A} H_g^{(l)} W^{(l)})$$

where $\tilde{A}$ denotes the normalized adjacency matrix of the partial diffusion graph, $W^{(l)}$ represents trainable weight parameters at layer l, and $\sigma(\cdot)$ is a non-linear activation function.

This update mechanism enables the model to capture early structural patterns and user influence characteristics, even under incomplete diffusion conditions.

D. Temporal–Graph Fusion

To jointly exploit temporal and structural information, temporal and graph-based representations are fused using an attention-inspired weighted mechanism. Let H_t denote the temporal representation learned from the sequence modeling component and H_g denote the graph-based representation obtained from the GNN module. The fused representation is computed as:

$$H_f = \alpha H_t + (1 - \alpha) H_g$$

where $\alpha \in [0,1]$ controls the relative contribution of temporal and structural features. The fused representation H_f is subsequently fed into a soft max classifier to generate the final prediction.

Experimental Setup and Datasets

Datasets

Experiments are conducted on benchmark datasets including Twitter15, Twitter16, and PHEME. These datasets contain labeled rumor and non-rumor events with associated posts, timestamps, and interaction networks.

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Baselines

The proposed model is compared with traditional machine learning classifiers, deep learning- based text models (CNN, LSTM), and recent graph-based rumor detection methods.

Evaluation Metrics

Performance is evaluated using Accuracy, Precision, Recall, and F1-score, with a focus on early-stage observation windows.

Results and Discussion

The experimental findings demonstrate the effectiveness of the proposed hybrid framework for early-stage rumor detection. As reported in Table I, text-based models such as SVM and CNN show limited performance when only early posts are available, indicating that lexical cues alone are insufficient under sparse conditions.

Table I

Performance Comparison on Twitter Datasets (Early-Stage Detection)

Model	Accuracy	Precision	Recall	F1-score
SVM (Text)	0.78	0.76	0.74	0.75
CNN	0.81	0.80	0.78	0.79
LSTM	0.83	0.82	0.80	0.81
GNN	0.84	0.83	0.82	0.82
Proposed Temporal – Graph Model	**0.88**	**0.87**	**0.86**	**0.86**

Temporal sequence models, including LSTM-based approaches, improve detection accuracy by capturing short-term evolution patterns in user-generated content. Graph-based models further enhance performance by exploiting early interaction structures among users, even when the diffusion graph is incomplete. The proposed temporal–graph fusion model consistently outperforms all baseline methods across accuracy, precision, recall, and F1-score metrics.

These results indicate that temporal dynamics and partial network structure provide complementary information for early rumor detection. Temporal modeling reflects how narratives develop shortly after an event emerges, while graph representations capture early engagement and influence patterns. Their integration leads to more discriminative representations and improved detection reliability in early-stage scenarios.

Conclusion and Future Work

This paper proposed a unified deep learning approach that integrates temporal modeling with graph-based analysis to enable early detection of rumors in online social networks. By simultaneously capturing semantic information from text, short-term temporal patterns, and incomplete diffusion topology, the framework overcomes the dependence of many existing techniques on fully observed propagation processes. As a result, effective rumor identification can be achieved even when only limited spread information is available.

Experimental results on standard benchmark datasets show that the proposed

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model consistently surpasses state-of-the-art baseline methods, particularly under early observation scenarios. These outcomes demonstrate that the joint exploitation of temporal dynamics and network structural features leads to more reliable and discriminative representations for prompt rumor detection.

Future work will focus on extending the framework to multimodal environments by integrating visual and auditory signals, as well as designing adaptive and scalable solutions suitable for real- time deployment on large-scale social media platforms.

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