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Comparison of Techniques used for Detecting Cascade Behavior on Social Media Networks

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Abstract:

This study systematically reviews and compares techniques for detecting cascade behavior in social media networks, emphasizing their underlying modeling paradigms. We categorize these into five main approaches: feature-based methods, deep learning methods (including Graph Neural Networks), real-time diffusion analysis methods, point process-based methods (particularly Hawkes processes), and hybrid methods. Feature-based techniques, while enabling popularity prediction, are limited by their reliance on domain expertise for feature engineering and static representations. Deep learning methods offer advantages in learning latent representations and capturing complex structural and sequential information without extensive feature engineering, but often face challenges with interpretability, computational cost, and handling imbalanced data. Real-time diffusion analysis excels in processing high-velocity data streams for immediate insights into unfolding cascades, crucial for rapid response applications, yet struggles with the inherent noise and complexity of real-world social data. Point process-based methods, especially Hawkes processes, are highly effective for modeling inter-dependent events over continuous time and capturing the "rich get richer" phenomenon in diffusion, although they can be limited by strong assumptions and difficulties in exploiting long-term dependencies. Hybrid methods combine the strengths of these individual techniques, enhancing accuracy and robustness by fusing complementary information modalities. The findings indicate an evolution towards deep learning integrations, such as Hawkes process-based networks and graph representation learning, promising improved handling of temporal dynamics and more precise predictions. Future research should prioritize scalable hybrid architectures incorporating continuous-time dynamic graph neural networks to enhance real-time cascade detection while maintaining interpretability and developing multi-task learning frameworks for comprehensive prediction and influence estimation.

Keywords: Cascade Behaviour, Social Media Networks, Cascade detection techniques, Comparison.

Introduction

The proliferation of online social media platforms has revolutionized information dissemination, enabling rapid and widespread sharing of content, ideas, and behaviors. This phenomenon has given rise to “cascade behavior,” where information or actions propagate through a network of connected individuals. The individuals are connecting through social ties, thereby forming the structural backbone for the emergence and propagation of cascade behavior in social media networks [1], [2]. A cascade effect in social networks refers to the sequential activation or adoption of an item (e.g., a piece of information, a trend, or a behavior) by individuals, where each adoption is influenced by previous adoptions within the network . This can be conceptualized as a directed graph where nodes represent users and edges represent relationships, with activation spreading from one user to their inactive neighbors [3]. Such cascades are often represented as rooted, directed, time-stamped trees that record the spread of a single diffusion event [4]. Information cascades are characterized by their temporal evolution, where the state of nodes changes over time from inactive to activated (e.g., retweeting a message) [5]. The structure of these cascades, which can include loops and reciprocal edges, provides valuable insights into the diffusion process [6]. These diffusion processes are ubiquitous in self-organized social systems, facilitating news propagation, the dissemination of innovative technologies, and even the spread of epidemics. The generation of cascade effects in social media is a complex interplay of various endogenous and exogenous factors. A fundamental mechanism involves users sharing content with their contacts, leading to a multiplicative spread that can reach a vast number of people, often distant from the original source [7]. This user-driven re-sharing can be triggered by social influence, where individuals are motivated by the actions of their peers, or by external influences such as burst events [8]. Some cascades exhibit a “broadcast” pattern, where a single node accounts for a large portion of the diffusion, akin to a breadth-first search. In contrast, “viral” cascades are driven by word-of-mouth mechanisms, resembling a depth-first search, where each node contributes a smaller fraction to the overall spread [9]. Factors such as the content’s novelty, emotional appeal, and the characteristics of the spreading users (e.g., follower count, past engagement) significantly influence the likelihood and extent of a cascade [10], [11], [12]. The “diffusion protocols”—the social exchanges that enable information transmission—also play a crucial role in how cascades grow. These protocols can range from simple reshares to more complex interactions, with the effort required to participate impacting a cascade’s growth [13]. Network structure, along with nodal activity, has been shown to influence the cascade threshold and the spreading capacity of social media [14].

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Detecting cascade behavior in social networks is critical for a broad range of real-world applications and holds significant importance in understanding online dynamics [8]. One primary application is the early detection of rumors and misinformation. Identifying viral rumors allows for crisis management and the implementation of mitigation strategies to prevent their widespread impact, especially when the information is false [15]. This is particularly relevant in scenarios like pandemics, where misinformation can hinder effective public health responses and cause widespread confusion [16]. Beyond mitigating negative impacts, cascade detection is vital for influence prediction, enabling the evaluation of information strategies and identification of content likely to achieve significant user engagement. This has direct applications in viral marketing and advertising, where understanding what makes content go viral can inform campaign design [8], [12]. Moreover, analyzing cascade patterns can provide insights into behavioral patterns and the propagation of ideas, which is valuable for areas like humanitarian efforts and public policy [12], [17]. The ability to predict cascade outcomes, such as their size and reach, can help in identifying hot information, optimizing resource allocation, and even minimizing destructive cascades or keeping them within specified ranges [6], [13], [18], [19]. The increasing scale and speed of information diffusion on social media make cascade prediction and detection an essential tool for navigating the complexities of the digital information landscape [4].

The cascade behaviour on social networks is detected by employing a variety of techniques, and each technique represents a distinct approach to modeling and identifying the propagation patterns of information diffusion across social networks. its essential to screen these techniques systematically to assess their efficacy, scalability, and applicability across diverse social media contexts, thereby enabling informed selection for specific detection scenarios.The present study was conducted to provide a comprehensive comparison of techniques employed for detecting cascade behavior on social media networks, with a particular emphasis on the role of diffusion protocols and multi-scale graph-based approaches in capturing diverse propagation patterns.

Objectives of Study

The present study was conducted under following objectives;

i. To examine the existing techniques for detecting cascade behavior in social networks.

ii. To categorize the cascade detection techniques based on their underlying modeling paradigms, such as feature-based, graph neural network-driven, and real-time diffusion analysis approaches.

iii. To provide the weakness of each technique in terms of computational efficiency, handling of temporal dynamics, and robustness to sparse network data.

Research Methodology

This study employs a secondary data-based research methodology, specifically a systematic literature review, to provide a comprehensive comparison of techniques utilized for detecting cascade behavior on social media networks. The initial phase involved a comprehensive literature search across multiple academic databases to identify relevant studies focusing on cascade detection techniques in social media. Key databases included, but were not limited to, IEEE Xplore, ScienceDirect, Springer, ACM Digital Library, and Scopus, chosen for their extensive coverage of computer science, information systems, and social science research [20], [21], [22].

A carefully constructed search string was utilized, combining keywords and Boolean operators to maximize the retrieval of pertinent studies. The core keywords encompassed terms such as "information cascade,""cascade detection,""cascade prediction,""social media,""social networks,""diffusion models,""propagation,""algorithms,""techniques," and "comparison." The search was further refined by prioritizing recent publications to ensure currency, and restricting results to peer-reviewed journal articles and conference proceedings published in English[22]. Backward snowballing, wherein references from existing systematic reviews and highly cited papers were examined, was also employed to identify additional relevant primary studies.
To ensure the relevance and quality of the selected literature, specific inclusion and exclusion criteria were applied during the screening process:

- **Inclusion Criteria**:
    a) Studies presenting novel techniques or comparative analyses for detecting, predicting, or modeling information cascades in social media or online networks.
    b) Papers discussing the theoretical underpinnings, empirical evaluations, or practical applications of such techniques.
    c) Studies published in peer-reviewed journals, reputable conference proceedings, or as comprehensive survey articles (e.g., [8]).
    d) Research clearly defining the methodology, datasets used, and evaluation metrics for cascade detection or prediction.
- **Exclusion Criteria**:
    a) Studies not directly related to cascade behavior or social media.
    b) Short papers, editorials, opinion pieces, or master's/doctoral theses (unless they were subsequently published in a peer-reviewed venue).
    c) Studies primarily focused on general social network analysis without specific emphasis on cascade detection or prediction [23], [24].
    d) Duplicate publications.

From each selected study, relevant information was systematically extracted and recorded. This included:

a) **Bibliographic Details**: Author(s), year of publication, title, and venue.

b) **Cascade Detection/Prediction Technique**: Name, type (e.g., feature-driven, point process-based, deep learning-based), and underlying model [3].
c) **Problem Addressed**: Specific aspect of cascade behavior the technique aims to solve (e.g., early detection, size prediction, source identification).
d) **Dataset Characteristics**: Type of social media platform, size, and nature of the data (e.g., text, images, temporal information).
e) **Evaluation Metrics**: Performance indicators used to assess the technique (e.g., accuracy, precision, recall, F1-score, AUC).
f) **Key Findings**: Main results, advantages, and contributions of the technique.
g) **Limitations**: Identified shortcomings, challenges, and areas for improvement.
h) **Comparative Aspects**: If the paper included a comparison with other techniques, the details of that comparison.

The extracted data underwent a rigorous analysis and synthesis process to fulfill the objectives of this chapter. A thematic analysis approach was employed to categorize and group similar techniques, identifying common themes, methodologies, and challenges [25]. A comparative analysis was then performed across the identified techniques, evaluating their efficacy, scalability, computational complexity, and applicability across diverse social media contexts and cascade types [26], [27], [28]. This involved assessing strengths and weaknesses, underlying assumptions, and suitability for different application scenarios (e.g., misinformation detection, trend prediction) [23], [29].

Results

The present review presents a systematic categorization of cascade detection techniques based on their underlying modeling paradigms, such as feature-based, graph neural network-driven, and real-time diffusion analysis approaches. In the following subsections the major techniques used for detecting cascade behavior in social media networks are described.

4.1. Techniques used for detection of cascade behaviour in social networks.

4.1.1. Feature Based Methods

Feature-based methods operate by extracting specific, hand-crafted features from raw data associated with information cascades. These features can include structural properties of the cascade graph, temporal attributes (such as publication and observation times), characteristics of users, content features, and network topology [2], [3], [30], [31]. Once extracted, these features are then input into conventional machine learning models, including regression models, regression trees, or Support Vector Machines, to perform tasks such as popularity prediction [32]. A primary limitation of this approach is its heavy reliance on domain expertise for effective feature engineering, which can restrict the generalizability of learned features to new or evolving contexts. Moreover, these methods often employ static feature representations, which struggle to fully capture the inherently dynamic nature of information cascades [3], [8], [30].

4.1.2. Deep Learning Methods

Deep learning methods represent a powerful paradigm for modeling and predicting information cascades, offering an alternative to traditional approaches by reducing the need for extensive feature engineering [33], [34]. Graph Neural Networks are particularly prominent within this category, effectively leveraging and learning from the structural information embedded within social graphs [35], [36], [37]. GNN-based models can integrate various node attributes, including user profiles and complex structural features, directly from cascade graphs, thereby capturing both the structural and sequential aspects of propagation paths [16], [38], [39], [40]. Beyond GNNs, deep learning also encompasses other architectures such as recurrent neural networks for modeling sequential cascade data [8], and topological recurrent neural networks designed to handle dynamic directed acyclic graphs to better represent cascade structures [41]. These methods enable the learning of latent representations and can integrate diverse data modalities, including text and network structures, in an end-to-end fashion for cascade prediction [33], [42].

4.2.3. Real-time Diffusion Analysis Methods

Real-time diffusion analysis methods are designed to detect and track cascade behavior as it unfolds within social media streams. These approaches often utilize continuous-time diffusion models or stream data mining techniques to analyze temporal irregularities and the dynamic states of users and cascades [2], [43], [44], [45], [46]. The primary objective is to provide early detection of significant events or emerging trends, such as identifying “bursty” keywords or monitoring the lifecycle of information propagation [44]. Techniques in this category are specifically engineered to handle high-velocity data streams, offering immediate insights into cascade evolution. This capability is crucial for applications demanding rapid responses, including real-time event detection, influence maximization on dynamic social streams, and monitoring viral content [43], [47], [48], [49], [50], [51], [52].

4.2.4. Point Process-based Methods

Point process-based methods, especially those employing Hawkes processes, are critical for modeling discrete, inter-dependent events over continuous time, making them highly suitable for understanding information cascades in social media [53], [54], [55]. Hawkes processes are characterized as self-exciting point processes, where the occurrence of a past event increases the likelihood of future events [56], [57]. This self-exciting property effectively captures the “rich get richer” phenomenon frequently observed in information diffusion, where early adoptions stimulate subsequent ones [54]. These models are employed to predict the final size of a cascade, estimate parameters for social influence, and infer the probability of an inactive node becoming activated [31], [58], [59]. Advanced variations include Network Hawkes processes, which integrate user connection strengths, and dynamic Hawkes process models that capture the evolving states of communities influencing diffusion processes [59], [60]. These methods are particularly effective for accurately modeling the temporal burstiness of events and their intricate interdependencies [59].

4.2.5. Hybrid Methods

Hybrid methods combine components from various modeling paradigms to harness their individual strengths and address their respective limitations, ultimately leading to more robust and accurate cascade detection and prediction. For example, some hybrid models integrate traditional machine learning classifiers with ensemble techniques like bagging and boosting to enhance anomaly detection in social networks [61]. Other approaches merge point process-based generative models with deep learning architectures, allowing for the integration of diverse features (e.g., content, network structure, exogenous signals) with sophisticated temporal modeling capabilities [62], [63]. Multi-modal hybrid frameworks can integrate distinct information sources such as fundamental cascade sequences, user social graphs, and sub-cascade graphs, often leveraging transformers or other deep learning models to effectively fuse these disparate clues and improve predictive performance. This integrated approach facilitates a more comprehensive understanding of the cascading process by simultaneously considering structural, temporal, and content-based information [19].

4.2. Comparison of techniques used for detection of cascade behaviour in social networks.

Table-1 shows the comparison of deep learning, real-time diffusion, point process-based, and hybrid techniques for cascade detection on the basis of description, mechanism, strength and weakness.This comparative analysis reveals that while individual techniques excel in specific dimensions—such as the temporal fidelity of point process-based methods or the structural capture of deep learning approaches—hybrid methods predominantly mitigate their collective drawbacks by fusing complementary modalities, though they introduce complexities in integration and computational overhead [3], [39], [69]. Future research directions should prioritize scalable hybrid architectures that incorporate continuous-time dynamic graph neural networks to enhance real-time cascade detection while preserving interpretability [3], [19], [70]. Additionally, advancements in multi-task learning frameworks that simultaneously optimize cascade prediction and user classification could further elevate detection efficacy by integrating spatiotemporal data fusion [3]. Such frameworks could also leverage foundational large language models to capture universal propagation patterns and variability in user behaviors, thereby improving generalization across diverse social media platforms [71].

Conclusion

The present study aims to provide a comprehensive comparison of cascade detection techniques on social media networks, highlighting their strengths, limitations, and potential for hybrid advancements to inform future methodological developments. The study used secondary data for the justifications of the framed objectives. The study has identified five major techniques which are used for detection cascade behaviour in social networks, they include; feature-based models, deep learning architectures, real-time diffusion analysis, point

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process-based approaches, and hybrid methods, each offering distinct advantages in capturing structural, temporal, and content-driven aspects of cascade propagation. Nevertheless, the evolution toward deep learning integrations, such as Hawkes process-based networks and graph representation learning, promises enhanced handling of temporal dynamics and cascade uncertainties, fostering more precise predictions of information popularity than other models. The author has revealed that there is a need to prioritize scalable hybrid architectures that incorporate continuous-time dynamic graph neural networks to enhance real-time cascade detection while preserving interpretability. Furthermore, the results confirm that there is a need for multi-task learning frameworks that jointly optimize cascade prediction, user influence estimation, and content virality assessment to bolster robustness against evolving disinformation dynamics on social media platforms.

Table-1: Shows the comparison of techniques used for detection of cascade behaviour in social networks

Technique Category	Description & Mechanisms	Strengths
Feature Based Methods	Extract specific, hand-crafted features (structural, temporal, user, content, network topology [2], [3], [30], [31]) which are then fed into conventional machine learning models (e.g., regression, SVM) to perform tasks such as popularity prediction [32].	Enables popularity prediction [32].
Deep Learning Methods	Employs deep neural networks, especially Graph Neural Networks [35], [36], [37], to learn latent representations from social graphs, integrating node attributes and complex structural features to capture structural and sequential propagation aspects [16], [38], [39], [40]. Includes RNNs and topological recurrent neural networks for dynamic graphs [8], [41].	Reduces the need for extensive feature engineering [33], [34]; effectively leverages and learns from graph structural information [35], [36], [37]; captures both structural and sequential aspects of propagation paths [16], [38], [39], [40]; enables learning of latent representations and integrates diverse data modalities in an end-to-end fashion for cascade prediction [33], [42].

Real-time Diffusion Analysis Methods	Utilizes continuous-time diffusion models or stream data mining techniques to detect and track cascade behavior as it unfolds within social media streams, analyzing temporal irregularities and dynamic states of users and cascades [2], [43], [44], [45], [46]. Aims for early detection of significant events or emerging trends [44].	Specifically engineered to handle high-velocity data streams, offering immediate insights into cascade evolution [43], [47], [48], [49], [50], [51], [52]; crucial for applications demanding rapid responses like real-time event detection and viral content monitoring [43], [47], [48], [49], [50], [51], [52].
Point Process-based Methods	Models discrete, inter-dependent events over continuous time using point processes, primarily Hawkes processes [53], [54], [55]. These self-exciting processes capture how past events increase the likelihood of future ones [56], [57].	Highly suitable for understanding information cascades [53], [54], [55]; effectively captures the “rich get richer” phenomenon [54]; predicts final cascade size, estimates social influence parameters, and infers user activation probability [31], [58], [59]; accurately models temporal burstiness and intricate interdependencies of events [59]; provides interpretable models of underlying diffusion mechanisms [67].
Hybrid Methods	Combines components from various modeling paradigms to leverage individual strengths and address respective limitations for more robust and accurate cascade detection and prediction. Integrates elements like traditional ML classifiers with ensemble techniques [61] or point process generative models with deep learning architectures [62], [63].	Aims for more robust and accurate cascade detection and prediction by harnessing individual strengths and addressing limitations [61], [62], [63]; enhances anomaly detection in social networks [61]; integrates diverse features with sophisticated temporal modeling capabilities [62], [63]; facilitates a more comprehensive understanding of the cascading process by simultaneously considering structural, temporal, and content-based information [19]; can improve predictive performance by

		fusing distinct information sources [19].

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