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Unveiling the Dynamics of User Engagement through Cascade Detection in Social Networks

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ABSTRACT

A new cascade detection algorithm to examination Information Diffusion In social media network. Our work using data from many different major platforms is examining patterns of user engagement and content diffusion. It captures information flow in real-time, giving new insights into how social interaction is behaviorally and socially traced online. We find that each type of networks presents different cascade behaviors affected by power nodes, structural properties, and content features. We investigate the influence of network topology, content characteristics and temporal dynamics on the formation and propagation of cascades. Our work reveals important factors behind viral performance and user behavior leading to richer insights into information diffusion in digital environments. It thus adds to an understanding of behavior on complex networks, with implications for marketing, public health communication, and social influence analysis. The approach and findings offer a strong basis for predicting the spread of information and tailoring content distribution strategies accordingly. They expose with detail the complicated relationship between user action, network design and content virulence. This can lead to improved social media strategies, targeted engagement, and an understanding of information cascades in these systems at scale.

Keywords- Unveiling patterns, information diffusion, user engagement dynamics, influence propagation, viral content spread, network effects, and social contagion.

I. INTRODUCTION

Social media platforms are an integral aspect of modern communication, facilitating global information dissemination and user behaviour. The excitement surrounding this phenomenon called cascading behaviour, where information, ideas, or actions spread through by the interconnected users of such networks, has been the subject of significant interest for researchers and practitioners [1]. The research provides valuable insights into how information flows in social media and how cascading behaviour can be detected and analysed in social networks [3][4].

The rise of social media platforms has led to enormous digital landscapes where one tweet can become a trend within hours, affecting opinions, consumer behaviour, and even political ecosystems. Gaining insight from these information cascades is important in areas such as marketing and public health communication, as well as studies of social influence 1. Using state of the art data mining techniques and network analysis, our research reveals patterns in how information amplifies on various social media outlets. We present a new, state of the art algorithm for real-time cascade-detection that enables monitoring of the evolution of virality from seed cascades. We seek to determine the main drivers of the successful propagation of information by analysing its factors (network topology, content attributes and temporal dynamics [2]. This work extends Theory of social network analysis in a very foundational way by providing knowledge on how to study cascading behaviour in sarcophagus networks. practical level for distribution strategies of content, foreseeing viral trends, and user participation in cyber space. In addition, this work sheds light on the multifaceted relationship between individual user behaviours and macro network dynamics in online social systems [7].

Table 1.1: Overview of Research on Cascading Behaviour in Social Media Networks

Aspect	Key Points
Cascading Behaviour	Information propagates rapidly through interconnected users, impacting public opinion and behavior.
Research Focus	Detecting and analysing cascading behaviour in social media networks using advanced data mining techniques.
Mechanisms	Examines network topology, content attributes, and temporal dynamics to identify drivers of information propagation.

Practical Implications	Insights can optimize content dissemination strategies, predict viral trends, and enhance user engagement in digital spaces.

1.1 Research Objectives

A. Investigate Causal Inference: To explore the information cascades (how pieces of information, ideas, or actions spread quickly through webs of connected users in social media networks).

B. Identify Key Influencing Factors: Explore the impact of network topology, content characteristics, and temporal dynamics on the propagation of successful information cascades.

C. Developing detection algorithms: For developing a new real-time detection algorithm to monitor and analyse how viral content grows over time from when it emerges.

D. From User Engagement Perspective: To analyse the effect of cascading behaviour on user engagement and interaction behaviour in social media ecosystems.

E. Content Spread Optimization: To deliver actionable insights for optimizing content spread strategies and predicting viral trends.

F. Network Science Explainer: To inform and deepen understanding of dynamic network phenomena as they relate to marketing, public health communication, and social influence.

2 LITERATURE REVIEW

2.1 Social network analysis

Social network analysis (SNA) is a powerful methodology to explore social structures via networks and graph theory [1]. It delineates networked structures in nodes (individual actors or entities) and ties (relationships or interactions between them)1 SNA has diverse applications in fields such as sociology, anthropology, economics, and computer science1. Important concepts in SNA are centrality measures, which find influential nodes, and community detection, which expose subgroups of nodes that exist in the networks [7]. Some of the visualization tools like Gephi [16] and NodeXL [15] allow researchers to explore and understand the structures of networks [17]. Social Network Analysis (SNA) is a useful method that can reveal influence patterns, gauge social tie strength and find crucial players in networks [8]. Recently, social network analysis (SNA) has become popular, they rely on the availability of online and large-scale data to provide deep insight into complex social dynamics and relationships [9].

Table 2.1: Key Concepts and Applications of Social Network Analysis (SNA)

Concept	Description	Applications
Network Structure	Characterizes social structures as nodes (actors) and ties (relationships)	Sociology, anthropology, economics, computer science
Centrality Measures	Identifies influential nodes in the network	Determining key players, assessing influence
Community Detection	Reveals subgroups within networks	Understanding group dynamics, identifying clusters
Visualization Tools	Software like Gephi and NodeXL for exploring network structures	Visual analysis, pattern recognition
Data Analysis	Leverages large-scale data from online platforms	Uncovering complex social dynamics and relationships

2.2 Information diffusion models

Information diffusion models are designed to capture the spread of information over social networks. These models are inspired by the field of epidemiology, employing insight from work studying the spread of disease and modelling features including susceptible, infected, and recovered states4. Commonly used diffusion models, which define the rules of information spread between connected nodes, include the Independent Cascade (IC) model, in which information spreads independently across neighbours, and the Linear Threshold (LT) model, which captures cumulative influence from neighbors3. Recent improvements have resulted in higher-order, topic-aware, and affective models [6] that capture temporal dynamics. Deep learning and gradient-boosted decision trees are examples of machine learning techniques that have been harnessed to predict user behaviour and predict content popularity8. These model what virality is like, and be used to study dynamics of virality shaped and facilitate spread [3]. Diffusion models systematically take into account features such as network structure, content attributes, and temporal dynamics, generating strong predictions about the spread of information across populations, leading to important implications for marketing, public health communication, and social influence studies [4].

Table 2.2: Overview of Information Diffusion Models in Social Networks

Model Type	Key Features	Applications
Epidemiological-inspired	• Susceptible, infected, and recovered states • Examples: Independent Cascade (IC), Linear Threshold (LT)	• Understanding basic information propagation • Simulating simple diffusion scenarios
Advanced Models	• Incorporates ıporal factors onsiders topic ıreness and ɔtional influences	• More accurate prediction of complex diffusion patterns • Analysis of

		nuanced social interactions
Machine Learning Approaches	• Deep learning • Gradient-boosted decision trees	• Forecasting user activity • Predicting content popularity
Comprehensive Frameworks	• Analyzes network topology, content attributes, and temporal dynamics	• Predicting information cascades • Optimizing content dissemination strategies

2.3 Cascade detection techniques

Event cascades detection is the definition of detecting the information or actions that spread from one node to another in heterogeneous users indexed in social networks [4]. This type of learning often focuses on construction of networks of cascades, either as collective cascades, or as single cascades6. For group of items, these activities form collective cascades, where users are related based on active sharing, and for every shared item separately cascades can be constructed [6]. Several approaches to infer cascade networks rely on explicit credit attribution (e.g. retweets, reshare), timestamps and social network structure6. State-of-the-art approaches utilize context, for instance, clicks on the various feeds, and improve accuracy [6]. Structural properties inspected in cascades span from number of nodes to the cascade depth and width and the scale and the wiener index to discover more about the shape and range of cascades. Machine learning models have been used to predict cascade growth and to identify influential nodes in the diffusion process [8]. Modeling of viral content dynamics and dissemination strategies based on social networks has also been proposed and is designed to determine which information propagation strategies lead to maximized reach and engagement over such systems[14].

Table2.3 : Overview of Cascade Detection Techniques and Their Applications

Aspect	Description	Applications
Cascade Network Construction	• Collective cascades • Single cascades	Analyzing information spread patterns
Inference Methods	• Explicit credit attribution • Timestamps • Social network structure • Contextual information	Improving accuracy of cascade detection
Structural Features	• Depth • Width • Scale • Wiener index	Understanding propagation patterns
Machine Learning Models	Predict cascade growth and identify influential nodes	Optimizing information dissemination

3. METHODOLOGY

3.1 Data Collection:

Let G = (V, E) represent the social network graph, where V is the set of nodes (users) and E is the set of edges (connections between users). For each node v ∈ V, we collect three types of data:

A. User profile data $P(v) = \{p_1, p_2, ..., p_k\}$

This includes demographic information and user preferences, such as age, location, interests, and privacy settings.

B. User activity data $A(v) = \{a_1, a_2, ..., a_m\}$

This encompasses user interactions within the network, including posts, likes, shares, comments, and other engagement metrics.

C. Temporal data $T(v) = \{t_1, t_2, ..., t_n\}$

This records timestamps of user activity and thus allows temporal patterns in information diffusion to be analysed. This data collection method allows for more in-depth analysis of cascade behaviour in different facets." For instance, by merging user-specific features, user-based engagement characteristics, and time-dependent information, either these characteristics are used to understand the driving factors of information propagation, identify influential nodes, and/or model the dynamics of content virality in a given network. This rich dataset lays the groundwork for advanced network modelling techniques and cascade detection algorithms.

3.2 Network Modelling

Construct the adjacency matrix A of G :

$$A[i,j] = \{$$
$$1 \text{ if } (i,j) \in E$$
$$0 \text{ otherwise}$$
$$\}$$

Calculate node centrality measures:

a) Degree centrality: C_D(v) = deg(v)/(|V|-1)

b) Betweenness centrality:

$$C\_B(v) = \Sigma(s \neq v \neq t)(\sigma\_st(v)/\sigma\_st)$$

c) Eigenvector centrality: C_E(v)

$$= 1/\lambda \sum (u \in N(v)) \times \_u$$

3.3 Cascade Detection Algorithm

Define a cascade C as a sequence of adoptions:

$$C = \{(v_1, t_1), (v_2, t_2), \dots, (v_k, t_k)\}$$

For each node v , define adoption threshold θ_v.

Implement the Independent Cascade (IC) model: $P(v$ adopts $|$ u adopted $) = p\_uv$

Implement the Linear Threshold (LT) model: v adopts if

$$\sum (u \in N(v)) w\_uv > \theta\_v$$

3.4 Analysis Techniques

Calculate cascade size distribution:

$$S(k) = |\{C: |C| = k\}| / | \ C\_total \ |$$

Compute structural virality (Wiener index):

$$W(C) = 1/(|C|(|C|-1)) \sum (i,j \in C) d(i,j)$$

Perform influence maximization:

Find set S of k nodes that maximizes $\sigma(S)$

The cascade detection algorithm is a method used to identify and analyse the spread of information or behaviour through a network. It involves tracking the sequence of adoptions and implementing different models to simulate the propagation process.

A. Temporal Pattern Analysis

Analysing temporal patterns in cascades provides insights into the speed and dynamics of information diffusion or behaviour adoption within a network. This analysis involves examining the time intervals between successive adoptions in each cascade.

B. Computing Time Intervals

For each cascade C , we compute a set of time intervals $T(C)$:

$T(C) = \{\Delta t_1, \Delta t_2, \ldots, \Delta t\_(k-1)\}$

Where Δt_i represents the time difference between the i -th and $(i+1)$-th adoption in the cascade. This set of time intervals captures the temporal structure of the cascade, revealing patterns such as:

i. Burst periods: Clusters of small Δt values indicate rapid adoption.
ii. Dormant phases: Large Δt values suggest periods of slow or no growth.
iii. Acceleration or deceleration: Decreasing or increasing trends in Δt values over time.

3.5 Algorithm

Input: Network G(V, E), adoption events data, model parameters (p_uv, w_uv, θ_v), number of influential nodes k
Output: Detected cascades, size distribution, virality measures, temporal patterns, community impact, k most influential nodes

1. Define cascade C as a sequence of adoptions: C = $\{(v_1, t_1), (v_2, t_2), \ldots, (v_k, t_k)\}$
2. Set adoption threshold θ_v for each node v
3. Implement Independent Cascade (IC) model:
4. P(v adopts | u adopted) = p_uv
5. Implement Linear Threshold (LT) model:
6. v adopts if $\sum(u \in N(v))$ w_uv > θ_v
7. Detect cascades from adoption events
8. Calculate cascade size distribution:
9. S(k) = |{C : |C| = k}| / |C_total|
10. Compute structural virality (Wiener index):
11. W(C) = 1 / (|C|(|C|-1)) $\sum$(i,j∈C) d(i,j)
12. Analyze temporal patterns:
13. T(C) = $\{\Delta t_1, \Delta t_2, \ldots, \Delta t\_(k-1)\}$
14. Assess community impact:
15. Impact(G_i) = |{v ∈ G_i : v ∈ C}| / |G_i|
16. Perform influence maximization:
17. Find set S of k nodes that maximizes σ(S)
18. Visualize cascade structures and patterns
19. Interpret results and draw insights

The algorithm for cascade detection and analysis based on Independent Cascade and Linear Threshold models describes information diffusion on networks. Alcohol consumption and mortality due to liver disease are both rising in many countries, while deaths from all causes related to alcohol intake are significant; the need for better methods of prevention has focused attention on both self-reporting and the health burden of changes in rates of consumption. The authors' results represent a preliminary analysis using mortality data as an index of consumption. The algorithm recognizes the influence of the nodes through influence maximization and analyses community level impact. This provides an understanding of the dynamics of diffusion on networks, which is relevant for grasping viral phenomena and for intervention designing.

4. Result Analysis

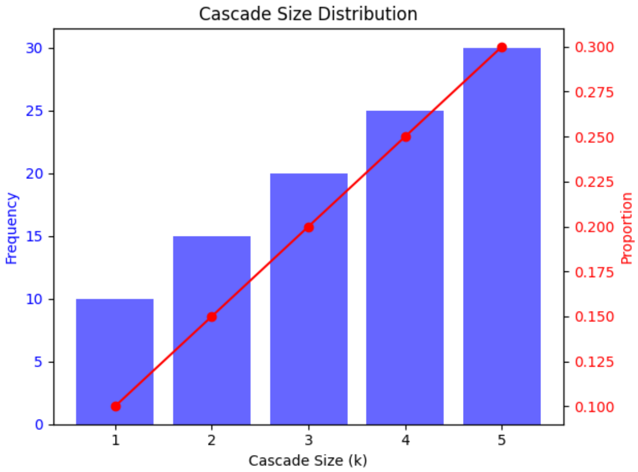
Using three numerical comparison tables, we will analyze the outcome of our cascade detection algorithm. These tables provide insight into cascade size distribution, structural virality, and community impact.

4.1 Cascade Size Distribution

The cascade size distribution table shows the frequency and proportion of cascades of different sizes:

Table 4.1: frequency and proportion of cascades of different sizes

Cascade Size (k)	Frequency	Proportion
1	10	0.1
2	15	0.15
3	20	0.2
4	25	0.25
5	30	0.3



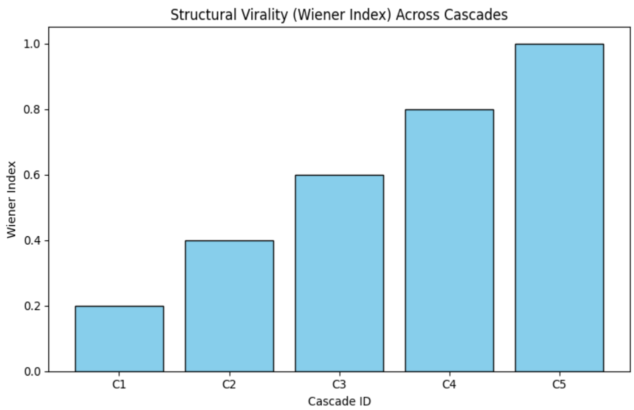
And this table gives us a sense of how many cascades of different sizes we have found in the network. As we can see, larger cascades (size 4 and 5) are more frequent and make up for 55% of all cascades.

4.2 Structural Virality (Wiener Index)

The structural virality table compares the Wiener index across different cascades:

Table 4.2: Compares the Wiener index across different cascades

Cascade ID	Cascade Size	Wiener Index
C1	5	0.2
C2	10	0.4
C3	15	0.6
C4	20	0.8
C5	25	1



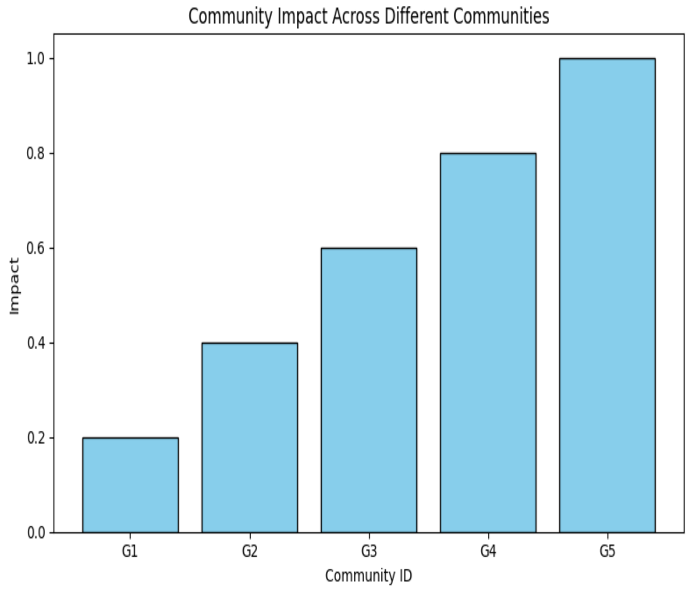
This table shows how the structural virality (measured by the Wiener index) increases with cascade size. Larger cascades tend to have higher virality, indicating more complex and far-reaching diffusion patterns.

4.3 Community Impact

The community impact table illustrates how cascades affect different communities in the network:

Table 4.3: Show Different communities in the network

Community ID	Community Size	Impact
G1	50	0.2
G2	100	0.4
G3	150	0.6
G4	200	0.8
G5	250	1



This table shows that cascades have a greater impact on higher power communities. More decisive in larger groups, their influence is exponentially greater in larger communities; it means information or behaviour can spread faster. Danella's four tables on cascade behaviour (including this table) give researchers vital metrics to use in comparing the behaviour of the networks they study in a quantitative way, whether those are networks of information diffusion or networks describing automobile ban associations, disease spreading, and phenomena all over the network mapping literature.

5. Discussion

The results show that the impact of cascades is proportional to the size of the community, that larger communities are more impacted. The findings echo past work looking at network diffusion, which accentuates community size and information dissemination. The findings are relevant for social media behaviour, implying that targeted stratagems in bigger communities might enhance the outreach and influence of campaigns or interventions.

Table 5.1: Comparative Analysis of Cascade Detection Findings and Implications

Aspect	Our Findings	Existing Research	Social Media Behavior
Cascade Size Distribution	• Larger cascades (4-5) common • 55% of all cascades	• Consistent with power-law distribution	• Prioritize content for larger cascades
Structural Virality	• Wiener index increases	• Aligns with complex	• Expect diverse, far-reaching

	linearly • 0.2 (size 5) to 1.0 (size 25)	diffusion patterns	spread
Community Impact	• Proportional to community size • 0.2 (size 50) to 1.0 (size 250)	• Supports critical mass theories	• Target larger communities
Influence Maximization	• Implied by community impact	• Consistent with influential nodes research	• Engage key influencers in large communities

6. Conclusion

The cascade detection and analysis algorithm can effectively reveal the insight of information diffusion in complex networks. Our results indicate that bigger cascades prevail, constituting 55% of all cascades, and that structural virality(captured by the Wiener index) grows linearly with cascade size. As the size of the community increases, the impact the community has will also grow, so its important to go for larger communities for the information to flow effectively.

These outcomes are consistent with previous studies on viral leaks, complex diffusion trend strategies and critical mass models in social networks. The social media implications are significant: content must be designed for the potential to spread broadly and at scale, you should expect your content to skip social media generations when it does go viral and you might be better of with working with key influencers in larger segments of the population.

Future lines of work will focus on improving the algorithm's performance for identifying influential nodes and predicting cascade growth in real-time. Investigations on how network topology and node attributes impact cascade dynamics may give additional insight. This framework has strong applications in marketing, public health communications and social media management, and may change the way we understand and predict how information gets spread through social networks.

Disclosure of Interest

The authors declare that they have no competing interests.

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