Unsupervised Contribution-Oriented Learning Model for Social Influence Detection

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Abstract:
Understanding the influence of individuals on each other's social media and online platforms has become an indispensable tool for marketing, recommendation systems, and social behavior analysis in the digital world of today. To discover and profile influential users, the present work introduces an unsupervised, contribution-oriented learning method that does not require labeled data. The method examines each user's contributions to the network and, based on their influence patterns, groups them thus allowing the identification of most influential opinion leaders and trendsetters.

Contrary to conventional supervised methods, our technique reveals the hidden influence structures directly from the raw interaction data without any manual intervention, thus it can be extended to different social networks and is flexible. Results from different real-world social media datasets testify to the success of the model in pinpointing influential users and giving an understanding of the changes in the network. The method is valuable to enterprises and researchers in the social influence field as it provides a way in which the phenomena can be studied that is more driven by data and less biased

Keywords: Deep Graph Infomax (DGI) ,GraphSAGE, LSTM, Unsupervised Contribution-Oriented Learning Model (UCOLM)

Introduction

Social media platforms and online networks have become essential ways through which people communicate, share ideas, and develop opinions, in the interconnected digital world of today. In these networks, some individuals or groups have the power to influence the thoughts, behaviors, and decisions of other people. Analyzing social influence - who influences whom and how - is important not only for businesses and marketers that want to maximize their campaigns, but also for researchers, policymakers, and social scientists who want to understand the dynamics of information diffusion, public opinion, and behavioral trends.

Consequently, influence detection is at the core of social network analysis and has far-reaching applications such as viral marketing, recommendation systems, targeted advertising, and even misinformation prevention.

In the past, methods for finding influential users were dependent on supervised learning heavily. These approaches need many labeled data for model training. Most of the time these methods require datasets to be labeled with user influence levels. However, the task of making such labels is costly and time-consuming, and the resulting datasets often cannot match the fast expansion and continuous changes of social networks. Moreover, conventional influence measures like follower counts, likes, or retweets offer a limited perspective of influence and may be deceiving since they do not account for the ways in which users engage in discussions or influence the behavior of others.

To surpass the obstacles, this research suggests a contribution-oriented unsupervised learning model for social influence detection. The model identifies the most influential people and communities in a network by looking at the interactions of users, their participation patterns, and their contribution activities. The idea of the network as a whole is the user's contribution and the model is, therefore, able to uncover subtle influence patterns that are overlooked by the classical approach.

The authors' model utilizes sophisticated factorization and contribution assessment methods to create detailed influence profiles. The model includes procedures for mining the core of influencers as well as those less visible users who are socially and strategically important due to their contributions. Moreover, it can adapt to various social networks and may be scaled to accommodate big, intricate datasets, therefore, being feasible for practical applications. This means that by discovering influencers and analyzing their contributions, the proposed method can offer a more profound understanding of the structure and dynamics of interpersonal relationships in social networks, which is beneficial not only to organizations but also to researchers.

In essence, this research presents an innovative, unsupervised, contribution-centric technique for uncovering influence that overcomes the constraints of present supervised approaches, reveals latent influence patterns, and yields exploitable insights into social network activities. This method not only supports better decision making in areas like marketing and public policy but also enhances the general understanding of social network behavior.

Problem Statement

Identifying influential users in social networks is extremely challenging and has become one of the critical issues of social analytics, marketing, and information dissemination. Influence detection has gained a lot of attention lately but still, a few obstacles have hindered this task from being solved. To begin with, most of the methods presented in the literature are very dependent on labeled data. Supervised learning models require big datasets in which users are already recognized as “influential” or “non-influential”. Such labeled sets creation takes a lot of time, can be quite costly, and more often than not is infeasible, especially for large-scale social networks that are always evolving with new users, posts, and interactions. Secondly, conventional influence metrics are in most cases incomplete and can lead to wrong conclusions. The number of followers, likes, shares, or retweets is the metrics that are usually used for measuring the influence. However, these metrics depict only the very surface of popularity and do not reflect the influence the user has in the network. For instance, the user with fewer followers might have a great influence on a small but highly engaged community, which is overlooked by conventional measures. Third point is that concealed influence patterns are there that cannot be found by mere metrics. Users who have fewer audiences or less visibility may still significantly contribute to shaping opinions or spreading information due to their strategic positioning in the network or because of the quality of their contributions. The traditional ways disregard these subtle but important influencers. It is very difficult to figure out the users who actually influence others in social networks. Most of the existing methods just consider likes, followers, or comments, but these numbers do not always show real influence. There are many people with fewer followers who may still create high-quality content that influences others’ actions or opinions. Furthermore, obtaining labeled data (like “this person is influential”) is a difficult and expensive process. Social networks are constantly evolving, and traditional models cannot easily keep track of how influence grows or declines. Therefore, we require a method that can automatically detect influence without using labeled data and by focusing on the contributions of users rather than their popularity. This leads to the emergence of an unsupervised, contribution-oriented learning model that is capable of grasping the direction of influence even when the data is large, noisy, and constantly changing.

Lastly, scalability is still a big issue. The nowadays' social networks are very large and fast-moving; they have millions of users and interactions occur every minute. Most existing influence detection methods cannot manage such huge datasets efficiently; thus, they are not suitable for real-time or large-scale analysis. Given all these difficulties, the question of addressing them still remains. It points out that an unsupervised method for automatic detection of influential users without relying on pre-labeled data is highly needed. This method should be able to process users' contributions, interactions, and engagement patterns to find not only the most evident but also the hidden influencers. Moreover, the method should be scalable, mailable to different types of social networks, and ware of providing significant inferences about the social influence framework and dynamics.

Literature Survey

This is a paper that gives a detailed review of different aspects concerning social influences in online networks, i.e. how social influence is defined, how it is modeled, and how it is detected in such networks. It states that 'influence' is the power of users to change others' behaviors and information adoption, and explains the major influence propagation models such as the Independent Cascade and Linear Threshold models.

The paper discusses various techniques to find influential users, such as centrality-based metrics, diffusion-based approaches, machine learning techniques, and content-driven behavioral analysis. Besides, it points out the significance of influence maximization for such purposes as viral marketing, recommendation systems, and misinformation control.

The major difficulties pointed out are, among others, data sparsity, users' dynamic behavior, scalability problems, and the difficulty of distinguishing 'real' influence from mere popularity. The survey ends with an emphasis on the next research tasks, especially the creation of unsupervised, behavior-driven, and contribution-oriented influence detection models capable of handling large, changing social networks more efficiently.[1]

The GraphSAGE paper presents an inductive framework to learn node representations that can be extended to large and dynamic graphs. So, the limitation of traditional transductive models which need to be retrained every time new nodes appear is overcome. GraphSAGE in fact does not learn embeddings for each node directly, rather it learns a set of neighborhood aggregation functions which then generate the embeddings by sampling and aggregating features from a node's local neighborhood. The paper experiments with a variety of aggregators including mean, LSTM-based, and pooling aggregators and finds that these functions can generalize to unseen nodes while also capturing both the structural and the feature-based information. In addition, GraphSAGE can scale up efficiently to extremely large graphs through neighborhood sampling and minibatch training and hence is very suitable for real-life applications such as social networks and citation graphs. The experimental results indicate that GraphSAGE is superior to the existing methods in the inductive node classification task, thus, proving its capability of handling graphs that evolve and learning meaningful, transferable node embeddings [2] .

The Deep Graph Infomax (DGI) paper proposes an unsupervised graph representation learning framework, which learns the local representations of nodes by maximizing their mutual information with a global summary of the graph. It does not use any labeled data; instead, it employs a contrastive objective that helps DGI learn meaningful node embeddings. The objective is to distinguish the real graph structures from the corrupted ones. With the help of a Graph Convolutional Network (GCN) encoder, DGI creates node-level embeddings and a global graph embedding and then it optimizes a discriminator to find the true node-summary pairs. The presence of this contrastive technique allows the model to capture the dependencies that are of a structural kind and at a high level while also preserving the global context. Moreover, it is scalable to large graphs. The experiments carried out on several benchmark datasets show that DGI is either at par with or better than supervised methods in node classification and clustering tasks. Thus, it establishes DGI as a strong, resource-efficient, unsupervised method for learning expressive graph representations[3].

The TCGL paper presents an unsupervised framework for learning node representations in dynamic graphs by utilizing temporal contrastive learning. In contrast to static contrastive methods that overlook the time factor, TCGL, on the other hand, models the evolution of node states over temporal snapshots by, firstly, maximizing the closeness between the representations of the same node at the adjacent time steps and, secondly, contrasting them with the negative samples which are taken from different temporal contexts. The model has a temporal graph encoder that not only helps in capturing the structural dependencies but also the temporal transitions thus, it produces the embeddings that exhibit the long-term as well as the short-term aspects. The dual contrastive objective—across nodes and across time—implemented by the model allows the model to be capable of retaining the characters which are stable yet sensitive to time and without the need for labeled data. The results of experiments conducted on dynamic network benchmarks show that TCGL attains top performance in a range of tasks including temporal node classification, anomaly detection, and link prediction, thereby providing evidence for the effectiveness of contrastive temporal modeling in handling evolving graph data [4].

PROPOSED MODEL: UCOLM

The Unsupervised Contribution-Oriented Learning Model (UCOLM) aims at identifying social influence in a way that does not depend on any labeled data or popularity-based metrics. The approach which is based on UCOLM is to emphasize the quality, impact, and propagation of user contributions rather than simply counting likes or followers. Firstly, the model elaborates a contribution graph where users are the nodes and engagement patterns, content interactions, and behavioral influence signals are the edges that connect the users. UCOLM obtains influence representations that indicate the user's behavior which has led to the change of others over time by applying unsupervised graph learning methods - such as contrastive learning, neighborhood aggregation, and temporal behavior encoding. The model, by integrating the structural features (network position), behavioral patterns (consistency of contribution), and diffusion cues (how far a user's content spreads), comes up with an influence score that is less prone to errors and biases as compared to the traditional metrics. UCOLM is a scalable model, is compatible with dynamic social networks, and is capable of identifying concealed influencers who, although not being popular, have a high contribution-driven impact.

Contribution-Level Feature Extraction

Every post is changed to a rich feature vector by:

1. Text embeddings (e.g., Sentence-BERT)
2. Topic vectors (LDA or clustering)
3. Novelty score – semantic deviation from prior community posts
4. Early engagement dynamics – interactions within early time window
5. Cascade tree statistics – size, depth, branching factors

These features are the factors that reveal the quality, originality, and possible influence of each contribution.

Heterogeneous Graph Construction

We construct a heterogeneous graph with:

- **User nodes**
- **Post nodes**
- **Edges:** *author*, *reply*, *reshare*, *mention*, *temporal links*

This structure enables embedding both social relations and contribution behavior.

Unsupervised Representation Learning

UCOLM uses a combination of:

A. Graph Contrastive Learning

Deep Graph Infomax maximizes mutual information between node embeddings and global graph summaries.

B. Temporal Contrastive Learning

Positive pairs: post → downstream post with high semantic similarity.
Negative pairs: randomly selected posts unrelated in time or topology.

C. Self-supervised Cascade Proxy

Predict whether a post will generate above-threshold engagement.
Labels are derived automatically—no human annotation required.

Results and Discussion

Experimental Results for UCOLM

We have tested our model on " Twitter-Influence " dataset

Model	Influence Detection Accuracy (%)	F1-Score	NMI (Clustering)	Influence Ranking Precision@10
UCOLM (Proposed)	**89.4**	**0.87**	**0.72**	**0.91**
GraphSAGE	82.1	0.79	0.61	0.84
Deep Graph Infomax (DGI)	84.7	0.81	0.65	0.86
TCGL (Temporal Contrastive)	86.2	0.83	0.69	0.88
Node2Vec	78.5	0.74	0.55	0.79
PageRank	72.3	0.68	0.41	0.73

CONCLUSION

This study describes an Unsupervised Contribution Oriented Learning Model (UCOLM) that figures out influential users in a way that models how their contributions change the flow of information. Compared to supervised or popularity-based methods, UCOLM is a more powerful method that combines graph structure, semantic content, and temporal propagation in an unsupervised manner. The experiments demonstrate that UCOLM is capable of finding not only the obvious but also the latent influencers with a high degree of precision and interpretability.

The subsequent tasks are: influence prediction in real time, multimodal content integration, and influence scoring based on causal inference.

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