Measuring user influence on temporal networks

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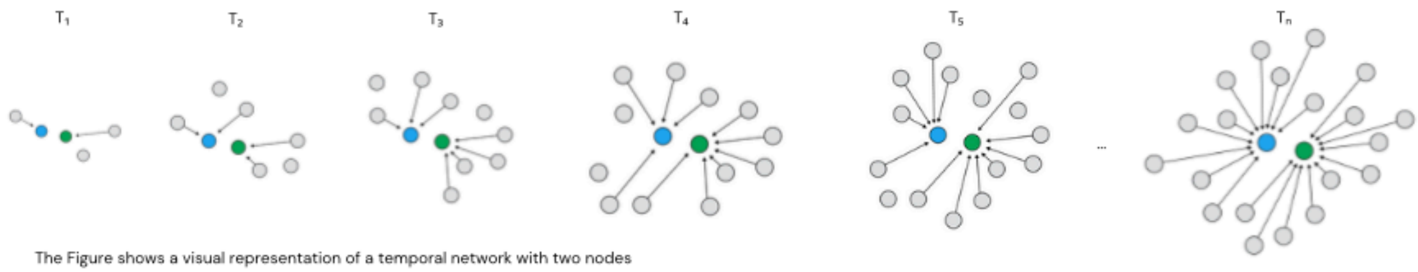
Introduction

Social media users establish communities to share opinions, influence others, and build a reputation for themselves over time. As a result, users' influence becomes a valuable asset. Influential users can determine trends, political opinions, and mis- information [1]. Prior work has provided multiple metrics to measure user influence based on their interactions, which can be modeled as social networks [2–6]. However, most of these studies focus mainly on the most recent users' interactions and do not consider the role of past interactions in users' influence. Analyzing static network metrics may only detect popular users after posting something that became viral, but they do not necessarily gain influence afterward. Understanding the role of past interactions is crucial nowadays since it can provide more information and insights about how these influential users emerge from their communities.

In this work, we study how users' influence can be measured by considering prior interactions and how they affect the most recent network. To comprehend users' influence amid their interactions, it is relevant to address two main factors: temporal analysis and graph centrality. The temporal analysis allows us to determine influence as the consequence of prior interactions and provides a perspective on how relevant users change over time. On the other hand, graph centrality allows us to rank users in the network according to their interactions, which can be a proxy for measuring their influence.



The Figure shows a visual representation of a temporal network with two nodes connecting with other nodes. While the green node and blue node have the same centrality in the current time Tn, their temporal centrality will differ when considering their prior interactions (i.e., $T_1, \ldots, T_{n-1}$).

Formulation

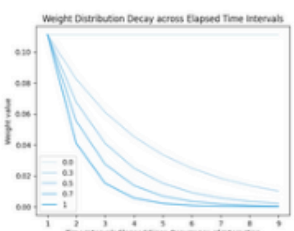
We define an evolving graph as a succession of directed weighted graphs over time. The evolving graph can be formulated as $G = (g^1, g^2, \ldots, g^n)$ with associated time labels $T = t_1, t_2, \ldots, t_n$. Each $g^t = (V, E^t)$ represents a graph with V users, and E labeled by a time t. We assume the set of V does not change over time. An interaction is an edge between users i and j ($i, j \in V$) at some time t. These interactions are affected by time, causing the presence or absence of an edge to vary across different time intervals. We represent interactions using the notation $E^t(i, j) \in E^t$.

Temporal analysis

Once two users interact, the influence of that interaction will tend to decay over time. Therefore, it is crucial to consider the elapsed time when representing the influence of that interaction. We implement geometrically weighted degree counts [8] to represent this. Given two users i and j from V , each weigth is defined as $w_{i,j}$ determined by:

$$w_{i,j} = \sum_{t=1}^{T_n} \frac{a_{ij} e^{-\alpha(T_n - t)}}{T_n}$$

where, aij is the adjacency value for the directed edge $E^t(i, j)$ and Tn is the time-interval of the most recent graph of G. We define α as the parameter that regulates the geometric rate of temporal decrease.



The Figure shows the value decay over time across elapsed time intervals for different values of α. As a result of influence interactions' decay over time.

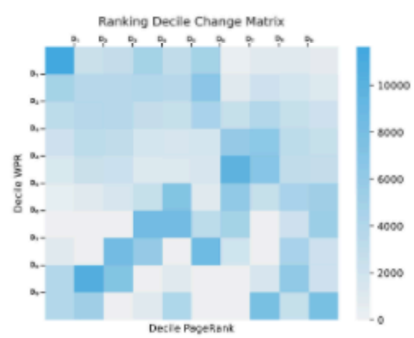
Centrality

To calculate users' centrality based on the evolving graph G, we implemented a temporal Weighted Page Rank (WPR) based on [7]. For each user *i* from *V*, we can calculate its WPR score as:

$$WPR(i) = \gamma \sum_{j \in V} \left(\theta \frac{w_{ji}}{s_j^{(out)}} + (1-\theta) \frac{a_{ji}}{d_j^{(out)}} \right) WPR(j) + \frac{(1-\gamma)}{|V|}$$

Results

We tested our metric WPR using data collected from Twitter. For this study, we used online interaction related to Gabriel Boric, the Chilean president. We collected data related to his presidential campaign in 2021. The data collection extends from September 23 to December 20, 2021. In total, we collected 6,530,536 interactions from 327,282 unique users. For this analysis, we created 10-day intervals from the studied period. As a result, we obtained nine temporal networks to analyze. Different intervals, such as days, weeks, or months, could be studied.



When comparing the evaluation of PageRank on T_n versus our metric WPR ranking. The figure illustrates the changes in deciles for users. A significant group remains in the first decile in both rankings. Many of them are close colleagues or work with the President. Others Users who ranked high PR scores (from the first to the fourth decile) now score low WPR scores, showing that many users were not in central positions of the network in previous interactions. We think this is a consequence of ephemeral but not meaningful influencers.

References

1. Zhang, Y., Chen, F., Lukito, J.: Network amplification of politicized information and misinformation about covid-19 by conservative media and partisan influencers on twitter. Political Communication 40(1), 24–47 (2023)
2. Riquelme, F., Gonz´alez-Cantergiani, P.: Measuring user influence on twitter: A survey. Information processing & management 52(5), 949–975 (2016)
3. Romero, D.M., Galuba, W., Asur, S., Huberman, B.A.: Influence and passivity in social media. In: Proceedings. of the 20th International Conference Companion on World Wide Web, pp. 113–114 (2011)
4. Bakshy, E., Hofman, J.M., Mason, W.A., Watts, D.J.: Everyone's an influencer: quantifying influence on twitter. In: Proceedings of the Fourth ACM International Conference on Web Search and Data Mining, pp. 65–74 (2011)
5. González-Bail'on, S., Borge-Holthoefer, J., Moreno, Y.: Broadcasters and hidden influentials in online protest diffusion. American behavioral scientist 57(7), 943–965 (2013)
6. Zengin Alp, Z., S¸ule G¨und¨uz O¨g˘ud¨uc¨u: Identifying topical influencers on twitter based on user behavior and network topology. Knowledge-Based Systems 141, 211–221 (2018). doi:10.1016/j.knosys.2017.11.021
7. Zhang, Panpan and Wang, Tiandong and Yan, Jun: PageRank centrality and algorithms for weighted, directed networks. Physica A: Statistical Mechanics and its Applications 586, 126438 (2022)
8. Snijders, T.A., Pattison, P.E., Robins, G.L., Handcock, M.S.: New specifications for exponential random graph models. Sociological methodology 36(1), 99–153 (2006)

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