Graph evolution rules for node temporal behavior representation

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Abstract

Studying real-world dynamic networks and their evolution is crucial for understanding the complex systems that govern various domains, from social interactions to financial transactions. The evolution of these networks provides insights into the underlying mechanisms driving their changes, which can be pivotal for applications such as node segmentation, prediction of future states, and role discovery. Among the various approaches to studying network evolution, graph evolution rules (GERs) stand out since they produce human-readable outcomes without requiring any pre-assumptions about the underlying evolutionary mechanisms. In this work, we leverage GER to derive evolutionary node profiles (NEPs), capturing the distinct patterns of how nodes change over time within the network. These profiles allow us to identify groups of accounts characterized by similar evolution rules, revealing common interaction patterns. As a case study, we apply our approach to Sarafu, a complementary currency platform with rich temporal data, representing a contemporary human complex system that integrates humanitarian aid, collaboration, and financial aspects. Our findings suggest the effectiveness of using graph evolution rules in real-world dynamic networks, showcasing their potential to enhance our understanding of the node-level dynamics of complex systems.

Keywords

Graph evolution rules, Network evolution, Temporal Networks, Complementary currency network

1. Introduction

Studying real-world dynamic networks and their evolution is crucial for understanding the complex systems that govern various domains, from social interactions to financial transactions. The evolution of these networks provides insights into the underlying mechanisms driving their changes, which can be pivotal for applications such as node segmentation, prediction of future states, and role discovery. Traditionally, models, mechanisms, and metrics have been introduced to interpret how dynamic networks grow and evolve, often assuming that their growth is governed by a unique parameterized mechanism. To address this limitation, graph evolution rules (GERs) have emerged as a promising frequency-based method [1, 2, 3] for analyzing network evolution. Firstly introduced by Berlingerio *et al.* [4], they stand out since they produce human-readable outcomes without requiring any pre-assumptions about the underlying evolutionary mechanisms.

Figure 1 shows a graphical representation of a graph evolution rule (GER). Inspired by the concept of association rule, a GER has a body (precondition) and a head (postcondition), indicating that a subgraph matching the body often evolves into the head.

In this work, we leverage GER to derive evolutionary node profiles (NEPs), capturing the distinct patterns of how nodes change over time within the network. These profiles allow us to identify groups of accounts characterized by similar evolution rules, revealing common interaction patterns. As a case study, we apply our approach to Sarafu, a complementary currency platform with rich temporal data, representing a contemporary human complex system that integrates humanitarian aid, collaboration,

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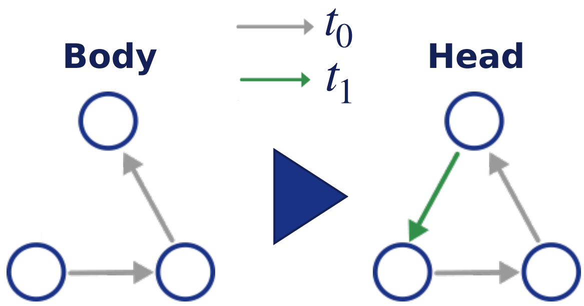

Figure 1: Example of graph evolution rule.

and financial aspects. By analyzing Sarafu's network using our GER-based method, we identify two distinct evolutionary traits, uncovering significant behaviors that contribute to the platform's operation. Our findings suggest the effectiveness of using graph evolution rules in real-world dynamic networks, showcasing their potential to enhance our understanding of the node-level dynamics of complex systems.

2. Methodology

From a node-centric perspective, our main aim is to represent nodes based on the mechanisms that characterize the evolution of the interactions surrounding them. The methodology to get this kind of representation is based on **two main tasks**: *a)* the extraction of the ego-networks from the overall temporal network describing the system, i.e. interactions surrounding every single node; and *b)* the identification of the mechanisms/rules driving the evolution of each ego-network through the computation of the graph evolution rules. We first model the set of interactions or transactions among the members of a networked system as a *temporal network* $\mathcal{G} = (V, E)$. While V is the set of users in the system, E is the set of timestamped directed links (u, v, t), with $(u, v) \in V \times V$. Each link corresponds to an interaction/transaction from node u to user v that occurs at time t. To accomplish the **first task**, we extract the temporal ego-network from the temporal graph $\mathcal{G}$. For each node u, its ego-network $S(u) = (V_u, E_u)$ corresponds to the temporal subgraph induced by u's neighborhood, including u itself. To deal with the **second task**, i.e. identifying the graph evolution rules characterizing a temporal ego-network of a node, we rely on the EvoMine algorithm [5] since it offers a richer set of link/node events for rule extraction, including edge deletion and the relabeling of nodes and edges. Moreover, the EvoMine approach based on consecutive snapshots is suitable for temporal networks based on interaction/transaction data, where a link can appear and disappear many times. In applying the EvoMine algorithm on the ego-networks, we implement some parallelization strategies to scale our method. We parallelize node-level computations and process timestamp pairs independently. To maintain consistency across parallel executions, we integrate an isomorphism check for unique pattern identification [6]. We also selectively process only timestamp pairs with link insertion events. These approaches significantly improve efficiency while preserving result accuracy and comparability. Finally, we propose a profile of the node evolutionary behavior that captures the distinct patterns of how nodes change over time within the network. We denote the vector representation as *Node Evolutionary Profile - NEP* and it represents the distribution of the graph evolution rules for the ego-network $S(u)$ of the node u. The construction of the node evolutionary profile is based on the graph evolution rules and their supports computed by EvoMine on each ego-network $S(u)$; while a vector representation common to all nodes is supported by the unique and common identifiers for rules based on canonical form.

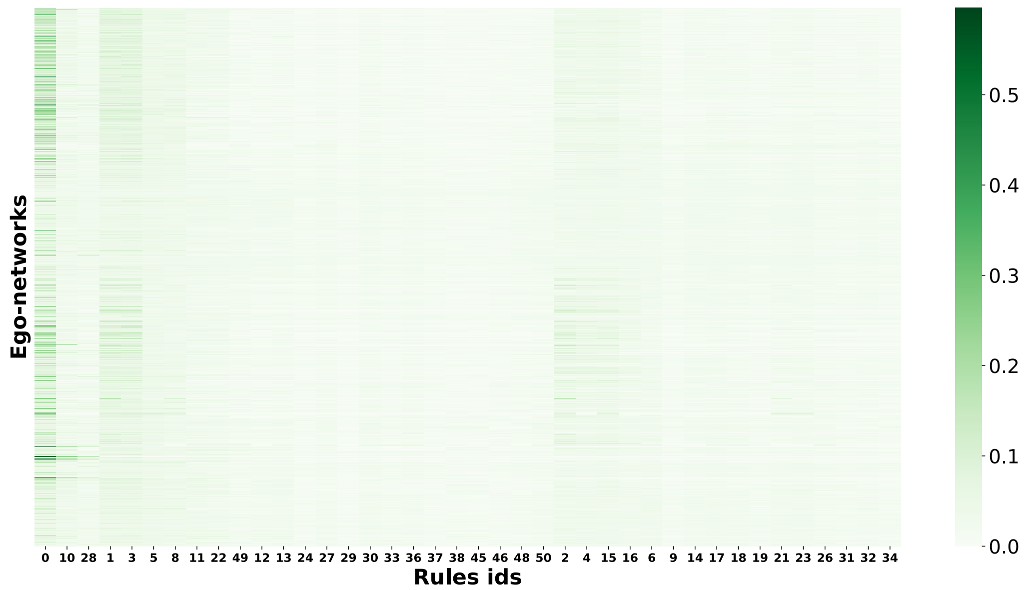

Figure 2: NEPs. Visualization as a heatmap of the matrix obtained by stacking all the NEPs. Rows represent ego-networks, columns show graph evolution rules ordered by increasing complexity (node count, size, timestamp count). Color intensity indicates rule frequency.

3. Dataset

Our work on node temporal behavioral representation using graph evolution rules considers as a case study a transaction network in the Web3 landscape: the Sarafu network[7, 8]. Sarafu, developed by Grassroots Economics[1], facilitates mobile payments and was used for humanitarian aid during COVID-19. Our dataset spans January 2020 to June 2021, containing 412,050 transactions among 40,343 users. It includes transaction details (anonymized IDs, token amounts, timestamps) and user attributes (business type, location, account type). We aggregate daily timestamps for feasibility. The Sarafu dataset, representing a complex system of humanitarian aid and financial transactions [9, 10], is ideal for applying our dynamic graph evolution rules approach to capture and characterize temporal behavioral patterns in this unique transaction network.

4. Results

We applied our methodology to the Sarafu transaction network, analyzing 40343 ego-networks. This number was reduced to 16030 after filtering for consecutive interactions (only ego-networks that show interactions with and among their neighbors in consecutive timestamps). To ensure sufficient data for meaningful behavioral analysis, we focused on ego-networks with at least 116 interactions (80^{th} percentile of the size distribution), resulting in 3207 ego-networks for detailed study. Using the EvoMine algorithm, we set a minimum support of 1 and a maximum of three edges per pattern, using event-based support. This process identified 40 distinct graph evolution patterns, which correspond to the dimensions of the node evolutionary profiles (NEPs). We collected all NEPs into a matrix, visualized as a heatmap (Figure 2) where rows represent ego-networks and columns indicate graph evolution rule IDs. From a column-wise inspection, we observe that in general, only a limited set of graph evolution rules characterizes the dynamics of the transactions in ego-networks. Indeed, there is concentration of frequency in rules 0, 1, 2, 3, 4, 10 and 15, with the first rule (0) being the most frequent for many ego-networks. The analysis of NEPs has pointed out two principal observations that are fundamental for showcasing how NEPs can be exploited for data discovery tasks: *i)* only a few GERs are frequent in NEPs; and *ii)* NEPs are varied but with a limited level of variability. Based on these observations, we

[1]https://www.grassrootseconomics.org/pages/about-us.html

developed a clustering pipeline to identify distinct classes representing dynamic traits of ego-network evolution in Sarafu. We first applied Principal Component Analysis (PCA) for dimensionality reduction, preserving most of the information in the NEP matrix. Then, we used hierarchical clustering on the transformed NEPs to identify groups with similar evolutionary traits. This process revealed two main groups of accounts: one dominated by single-link expansion over other star- and chain-like expansions, and another with a more homogeneous distribution among the same expansion rules.

5. Conclusion

We introduced a method using subgraph-based evolution rules to represent ego-network dynamics, enabling detailed analysis of temporal node behaviors. Applied to the Sarafu transaction network, our Node Evolutionary Profiles (NEPs) revealed two main interaction traits: one dominated by single-link expansion and another with more balanced expansion types. This approach effectively uncovers behavioral patterns in complex networks, supporting applications like distinguishing user behaviors in financial networks and enhancing understanding of interaction dynamics.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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