Representation of the Temporal Ego-networks through Graph Evolution Rules: a Tool for Web3 Applications

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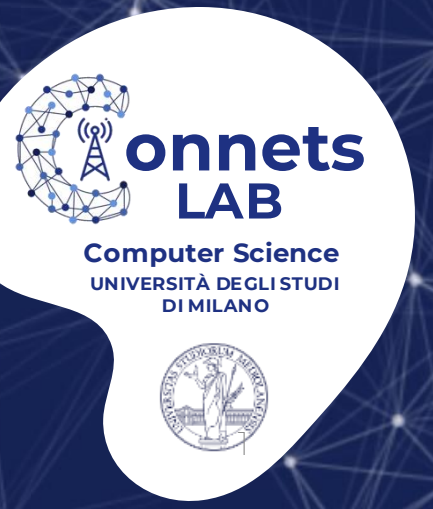
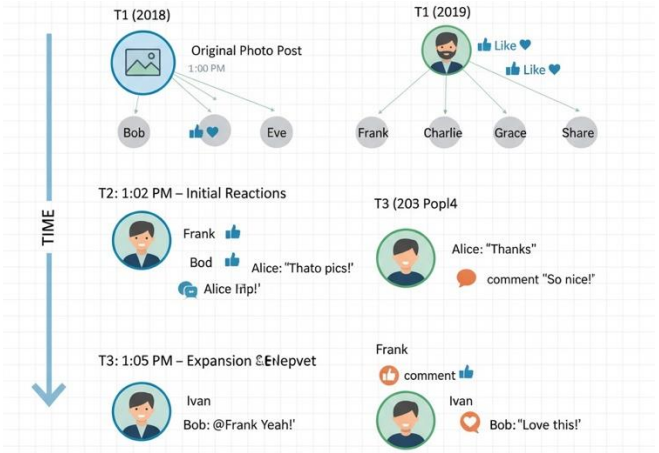
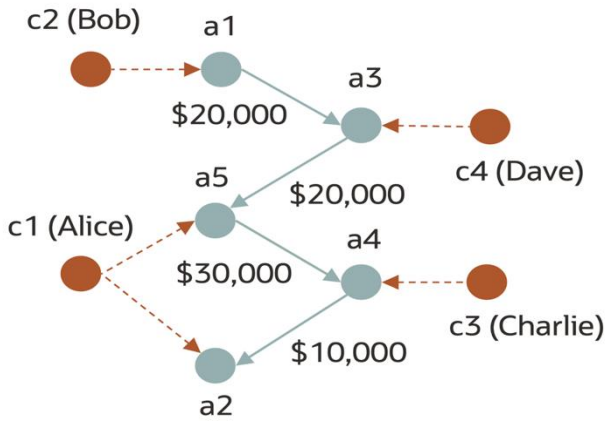


Temporal Networks for Modern Web Paradigms





- **Temporal dynamics** reveals mechanisms driving network changes → Applications: anomaly detection, role discovery, prediction and forecasting future state
- **Growth mechanisms** for comprehend socio-techno systems:
  - Understanding of dynamics of network growth by a unique parameterized mechanism (Preferential Attachment, Copying mode, Triadic closure)
  - No specific assumptions but focus on small substructure (graphlets | temporal motifs) but on the overall network

Node representation based on temporal subgraphs

Our perspective: **node-level temporal patterns**

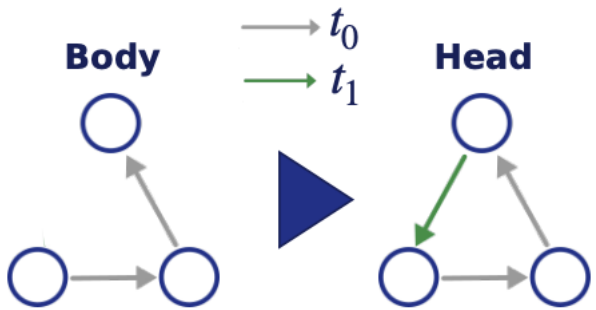
- Recurring patterns and behaviors of single nodes
- Node representation for identification of behavioral patterns at population level

Recent advancements in node vectorial representation leverage frequent subgraphs, motifs, and graphlets

- Neural Temporal Walks (NeurTWs): structural,tree traversal properties along with time constraints to capture dynamic ➔ temporal nodes through representative motifs.
- Non-neural approaches:
  - Hulovatyy et al.: vectorial representation of nodes using dynamic **graphlets** → network decomposition into smaller segments to characterize node behavior over time.
  - Longa et al.: egocentric perspective = track the evolution of node neighborhoods across temporal layers and condense them into **egocentric temporal motifs** (ETMs)

Node representation based on GER

Temporal Ego-network viewpoint rooted in Graph Evolution Rules – GER



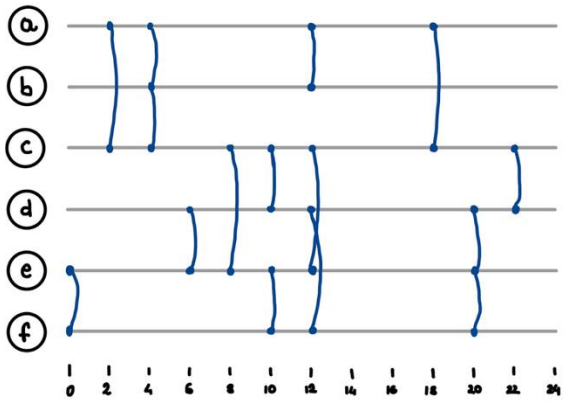
Discover frequent local changes s.t. subgraphs matching the body have evolved into the head

Why? Mechanism driving interactions in ego-networks more explicit and easily readable

Methodology

Temporal network $G = (V, E)$

- V users in the system
- $E = \{(u, v, t) | t \in T, (u, v) \in V \times V\}$ set of timestamped directed links
  - Repeated interactions or unique interactions

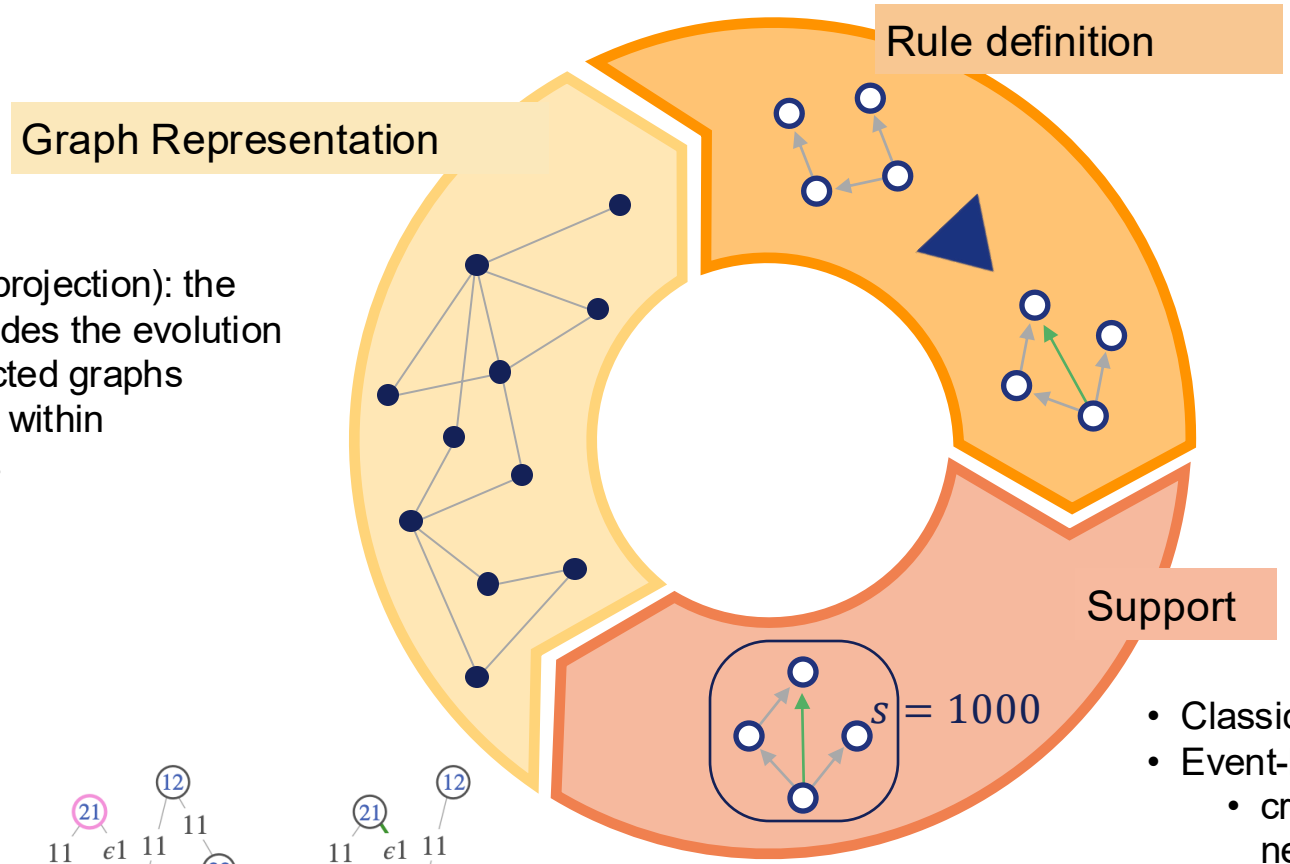


Ego-network of u: temporal subgraph induced by u's neighborhood:

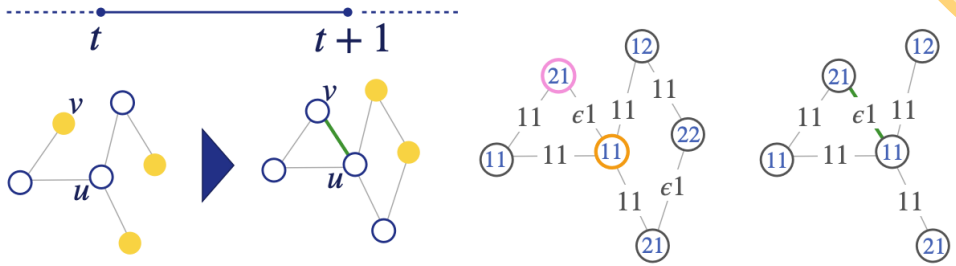
- $V_u = u \cup \Gamma(u)$ and $E_u = \{(v, w, t) | (v, w, t) \in E, v, w \in V_u\}$
- Small temporal subgraph for each node → parallelization of node-centric analysis

Methodology – EvoMine for GER Discovery

- Union Graph (Evolving projection): the label on the edges encodes the evolution
- For directed and undirected graphs
- The evolution is tracked within consecutive timestamps



- The only timestamps on the edges are t_0, t_1
- The body (pattern without the edges with t_1 timestamp) must have the same nodes as the head
- From body to head something must change, labels or edges
- The union graph of the rule must be connected



- Classical MIB support +
- Event-based support:
  - creates event graphs: subgraphs including the neighborhood of each event (edge insertion, node relabeling and so on)
  - count the event graphs in which a rule appears

Methodology – Network Evolutionary Profile

Idea: distribution of measures based on static and/or temporal subgraphs used for encapsulating node's signature

- Graphlet Degree Vector and dynamic graphlet degree vector

Node Evolutionary Profile – NEP - of node u = GER distribution for the temporal ego-network $S(u)$:

$$\mathrm{NEP}(u)_i = \frac{\sigma_{event}(r_i)}{\sum_{j=1}^{n} \sigma_{event}(r_j)}$$

where $\sigma_{event} r_i$ is the event-based support of the rule r_i and n is the number of GERs on the whole set of nodes

➔ signature of the evolution of the u's ego-network

Dataset – Sarafu (Web3 platform)

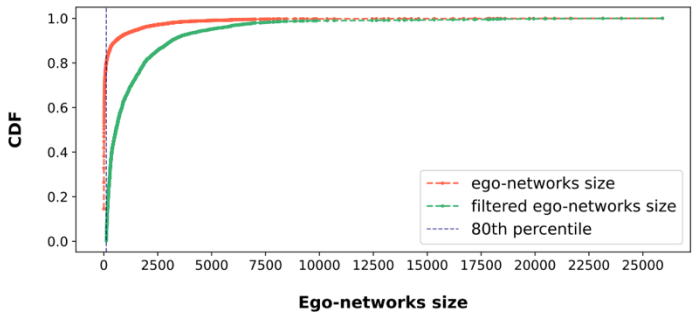
Sarafu: Web3 platform based on digital complementary currency token developed by the Grassroots Economics (GE) foundation

- Payments via mobile phones by transferring Sarafu tokens to other registered users ➔ humanitarian-aid project for local economies

Dataset: transaction network from January 2020 to June 2021

- 412,050 token transactions ***(source, destination, timestamp, amount)***
- 40,343 users
- Timestamp down to milliseconds ➔ aggregation of timestamps into a **daily granularity**

  - Reduce the sparsity of the temporal network snapshots



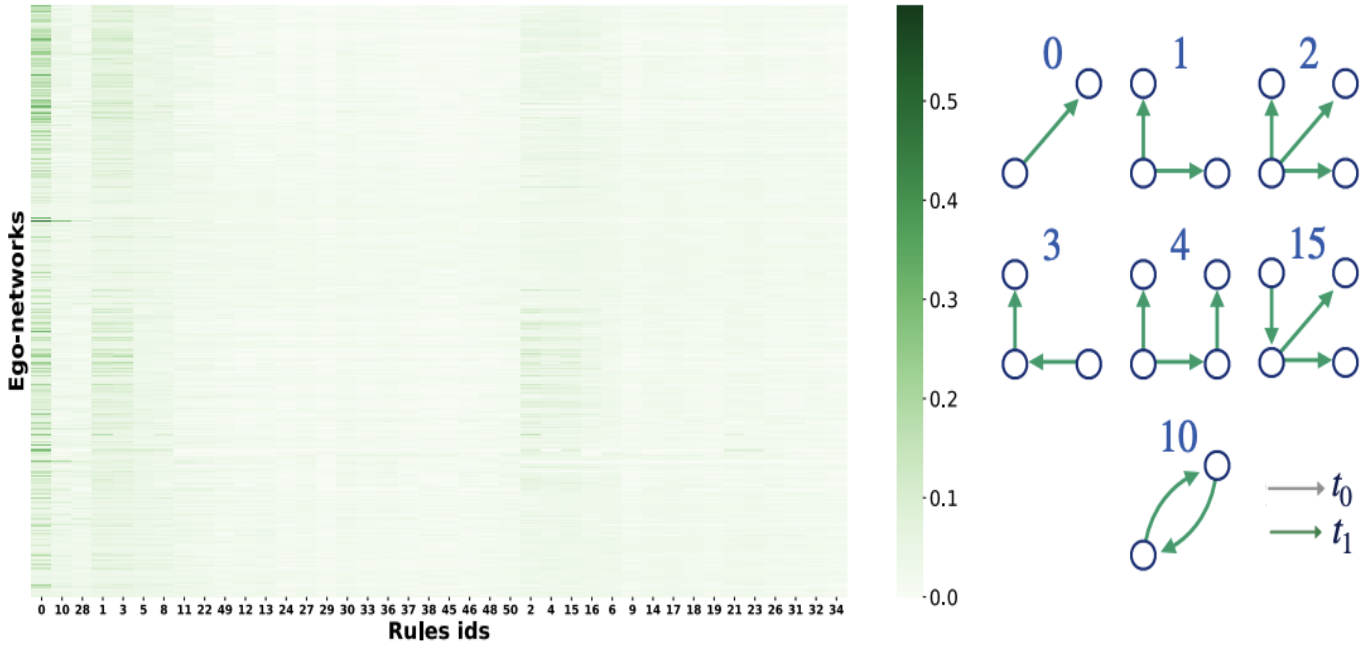
Most significant accounts in Sarafu for transaction activities:

- Filtering on consecutive snapshot criterion
- Filtering on activity

Number of accounts: 3207

Results (1)

RQ: Which are the main mechanism driving the evolution of nodes' ego-networks?



Most common GERs:

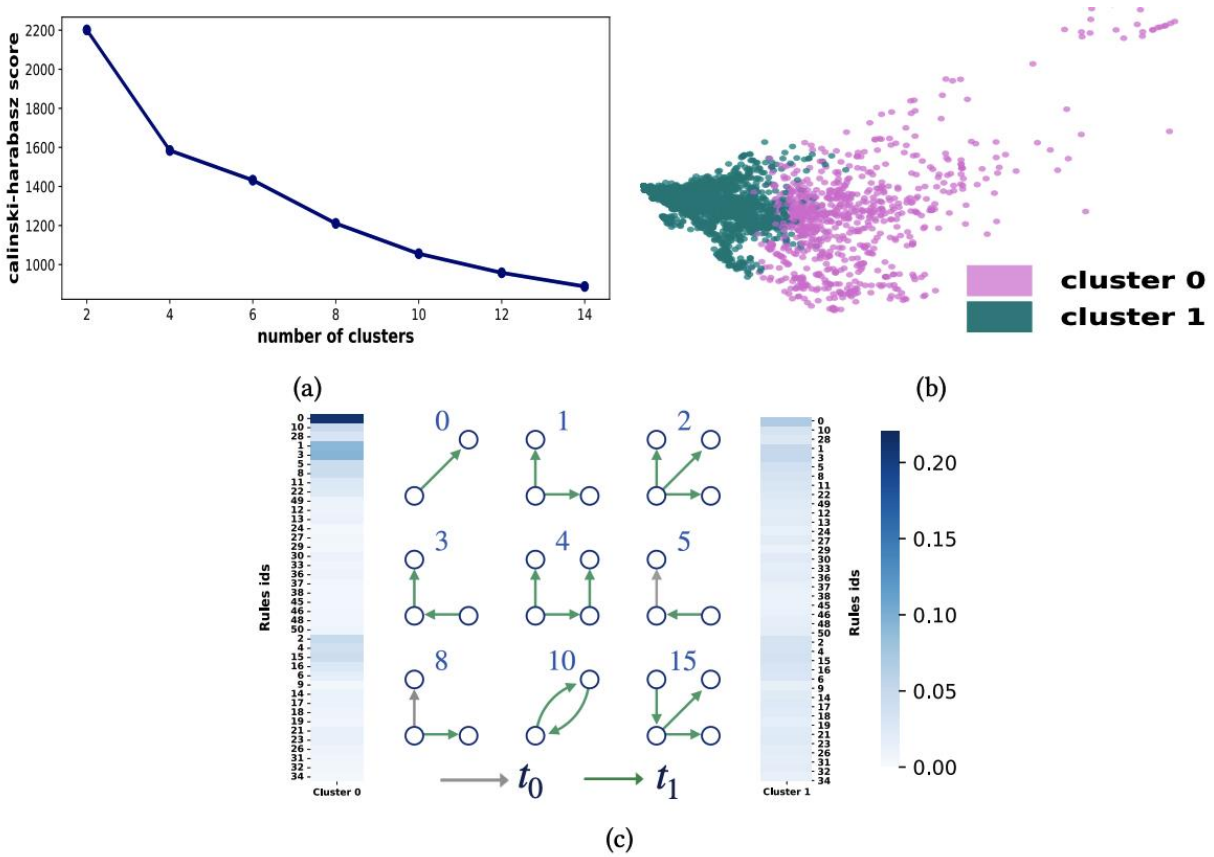
- **star**- or **chain**-like expansions starting from an empty precondition,
- transactions becoming **reciprocal** in just one day.
  - The reciprocal rule represent a distinctive trait of the Sarafu → it mirrors the cooperation in local communities ➔ cooperative behavior actualizes in only a day.

Skewed distribution of GERs ➔ reduce the dimensionality of NEPs: most of the information remains.

Certain level of variability but a few **representative traits** are identifiable

Results (2)

RQ: Are there classes that may represent dynamic traits of ego-networks' evolution?



- Dimensionality reduction by PCA on NEP matrix (40 → 24)
- Agglomerative clustering (Ward as the linkage strategy → less sensitive to noise)
  - CH scores analysis → k= 2.

There are **two main traits** of the dynamics of the transactions occurring within ego-networks

First trait: dynamics driven by star- and chain-like without a precondition

Second trait: dynamics more homogeneous leading to the same kind of expansion rules.

GERs are the same but frequencies are different

Conclusions

- Representation of nodes through **Node Evolutionary Profiles (NEPs)** based on Graph Evolution Rules (GERs)
- Application to the **Sarafu transaction network**, revealing two main evolutionary traits of ego-networks.
- Identification of **recurring growth patterns** (star- and chain-like expansions, rapid reciprocity) that highlight cooperative dynamics.
- Potential of NEPs for **behavioral analysis** and **node segmentation** in temporal networks and Web3 contexts

- **Future work (1):** extend the methodology to larger datasets and different domains
- **Future work (2):** integrate NEPs into **machine learning pipelines** for forecasting and anomaly detection

Thanks for your attention

Some icons and illustrations are from freepik@flaticons and Storyset