NETWORK EVOLUTION IN THE WEB3 SCENARIO

March 27, 2025

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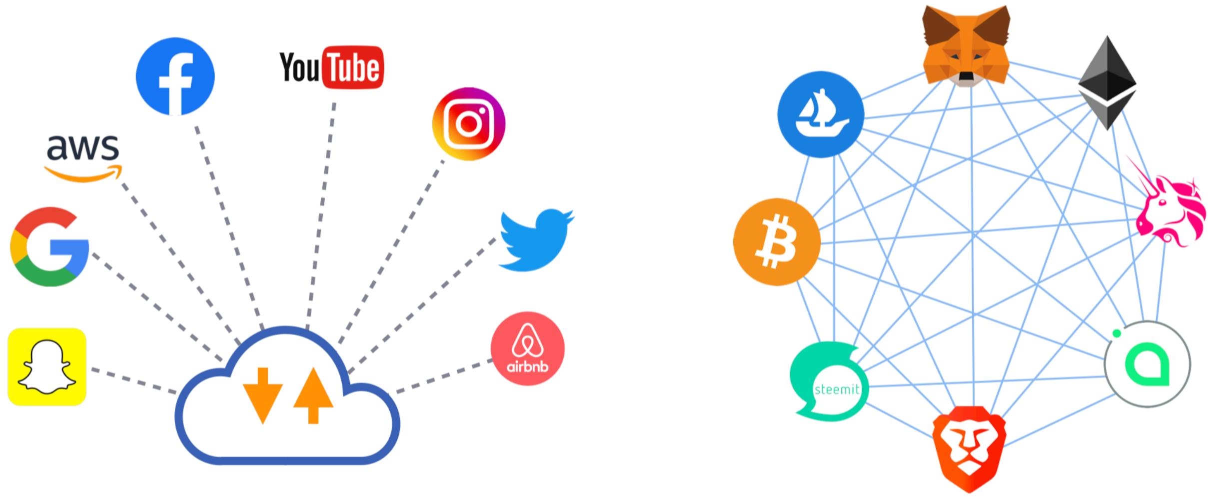
Tales on Data Science and Big Data

DATA SCIENCE
CINI NATIONAL LAB

NETWORK EVOLUTION IN THE WEB3 SCENARIO

The WEB3



Web 2.0

Over-centralization

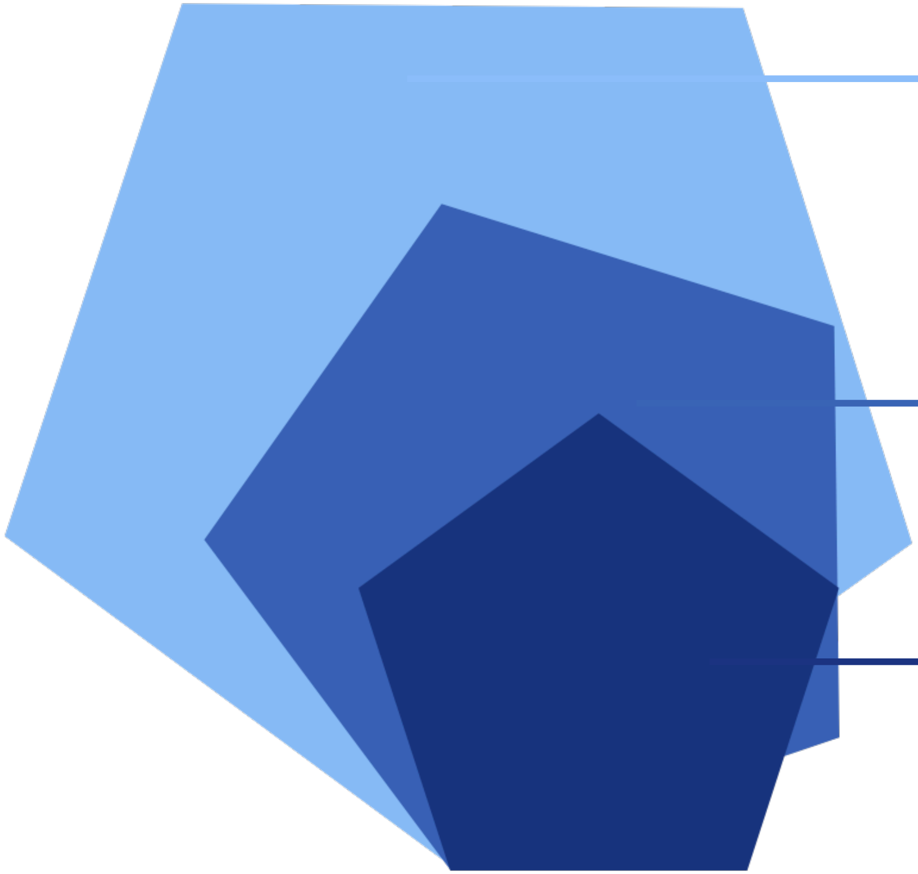
Web3

Decentralization by blockchains

Web3 data

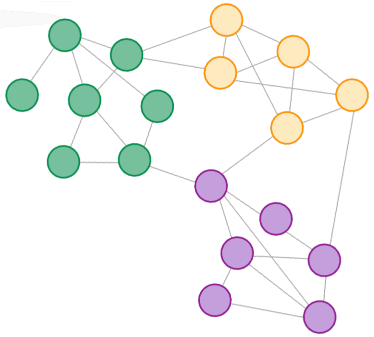
- Huge volume of high resolution data
- Available and affordable by API
- Timestamped and validated
- Heterogeneous interactions

The **CONTEXT**

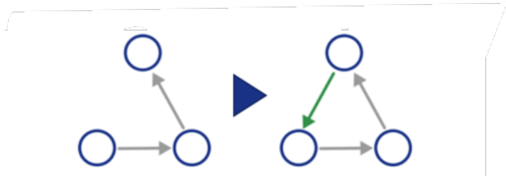


DATA AND NETWORK SCIENCE

GRAPH MINING



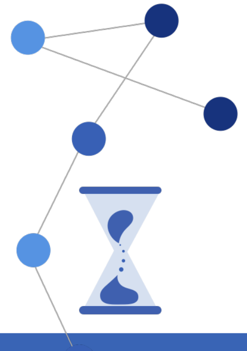
NETWORK EVOLUTION



The **CONTEXT**

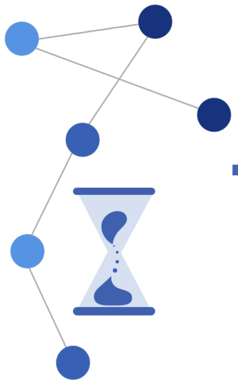
- Past research focused on **static networks**: developing theoretical frameworks, scalable algorithms, and deep knowledge of network structures;

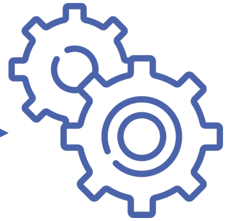
- In recent years researchers recognized the complexity and **time-varying nature** of large systems;

TEMPORAL  **NETWORKS**

The **CONTEXT**

TEMPORAL NETWORKS





NETWORK EVOLUTION

When studying **temporal networks,** we talk about **network evolution** if the focus is on the **mechanisms** that drives the **growth** of a network

TEMPORAL Networks

WEB3 data

Web3 platforms offer huge amounts of data with fine-grained temporal information

Blockchain-based online social networks

Social networks based on a reward-system for content creator and curators
Examples: Steemit, Hive, and Galxe

Non-fungible tokens

Networks of NFT trades on different markets
Examples: Cryptokitties, OpenSea, and Decentraland

Complementary currency

Exchange of a complementary currency through the blockchain technology. Examples: Sarafu, and Circle

Bitcoin / Stable coins

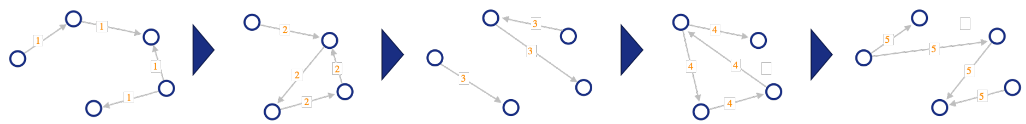
Understanding the evolution of Web3 networks is crucial for revealing emerging trends, potential vulnerabilities, and opportunities for growth in the rapidly evolving blockchain ecosystem

The **STATE** of the **ART**

NETWORK EVOLUTION

Very few works on the evolution of networks

A lot of works focus on the analysis of the network changes snapshot by snapshot



BUT THE EVOLUTION MUST BE STUDIED THROUGH THE

MECHANISMS
DYNAMICS
PROCESSES

THAT ARE SHAPING THE NETWORK AS IT GROWS

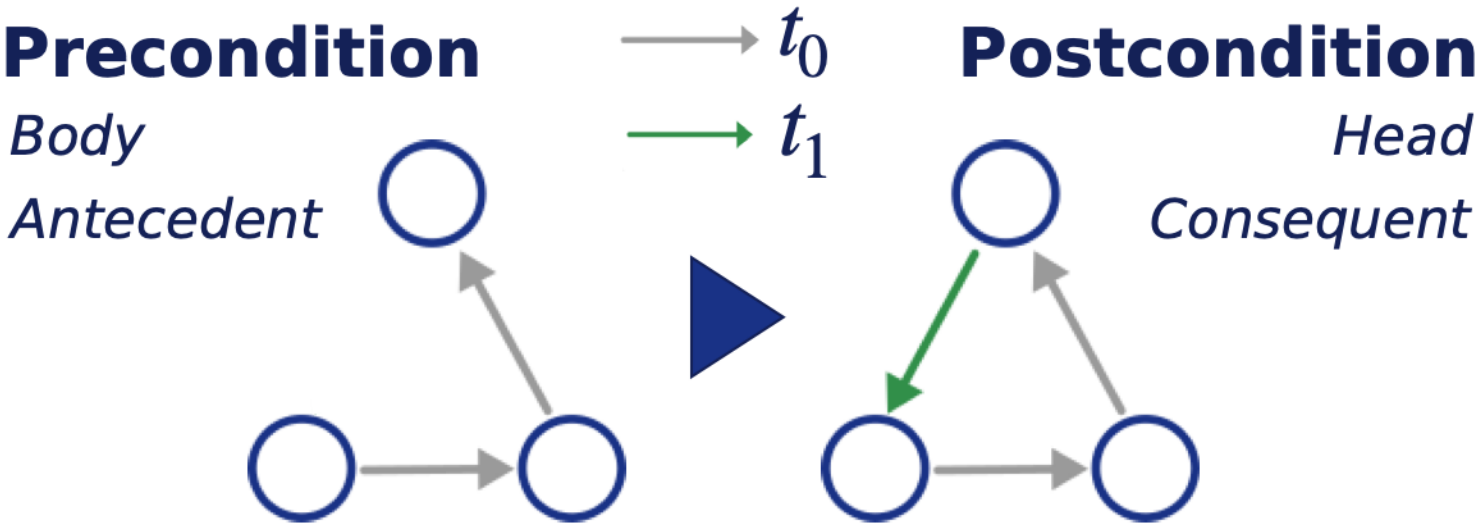
We need to extract

THE RULES OF EVOLUTION

to reveal the evolution of the network from a mesoscopic perspective

The Graph Evolution Rules

COMPOSITION AND MEANING



A rule matching (being isomorphic) to the precondition will probably (frequently) evolve into one matching the postcondition

The Graph Evolution Rules

EXISTING ALGORITHMS

There exists a few algorithms that propose similar approaches that differ mainly for:

Rules constraints

Type of graphs

Frequency counting measures

USEFUL but TRICKY

GERANIO

GEneral fRAmework for Network evolutIOn

GERANIO

Modeling FRAMEWORK
Unified framework to model evolving networks

NULL model
Find statistical significant rules

TULIP algorithm
New algorithm to mine general GER

Evolutionary PROFILE
Tool for immediate analysis of evolutionary behavior

CANONICAL coding
Assignment of unique codes to isomorphic rules

Available TOOLKIT
Tools available on GitHub to easily work with GER algorithms

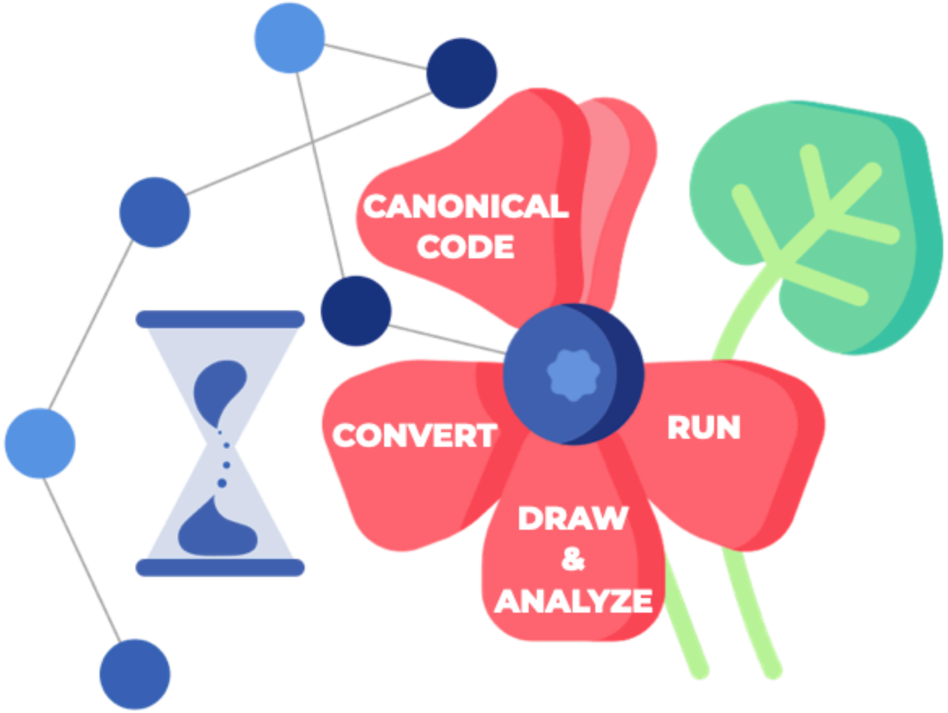
GERANIO

GEneral fRAmework for Network evolutIOn

Tools available on
GitHub to easily work
with GER algorithms

Available TOOLKIT

GitHub



https://github.com/alessiaatunimi/geranio

Web3
APPLICATIONS

Tool for immediate analysis of evolutionary behavior

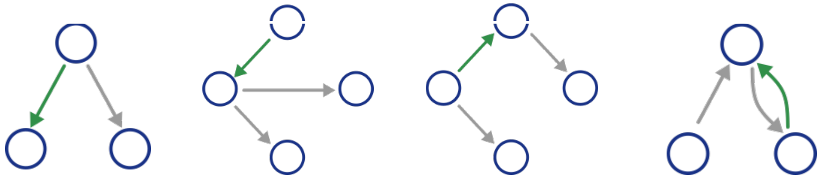
Evolutionary PROFILE

The **EVOLUTIONARY PROFILE**

WHY? To compare networks' evolutionary behavior easily

HOW? **Probability distribution** over rules' frequency, each position refers to a **specific rule**

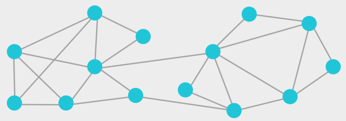
$$\begin{bmatrix} 0.01 & 0.64 & 0.27 & 0.08 \end{bmatrix}$$



The **EVOLUTIONARY PROFILE**

DIFFERENT LEVEL OF APPLICATION

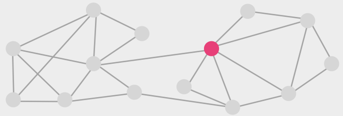
GRAPH



Evaluate evolutionary behavior for the whole graph

- **NFT transactions**
- **Blockchain-based Online social networks**

NODE



Compare the evolutionary behavior of each node's ego-network

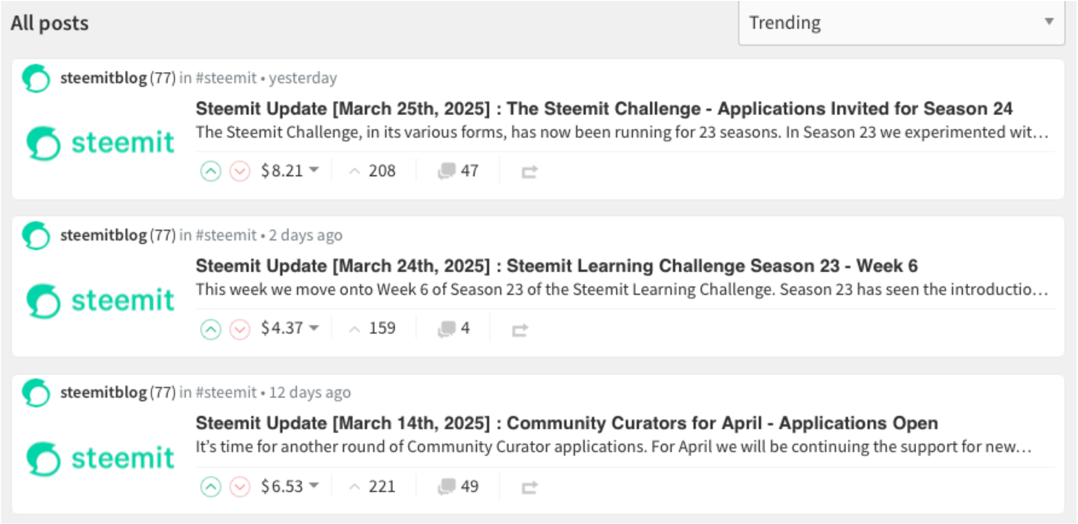
- **Complementary Currency network**

Graph **LEVEL**

CASE STUDIES

STEEMIT

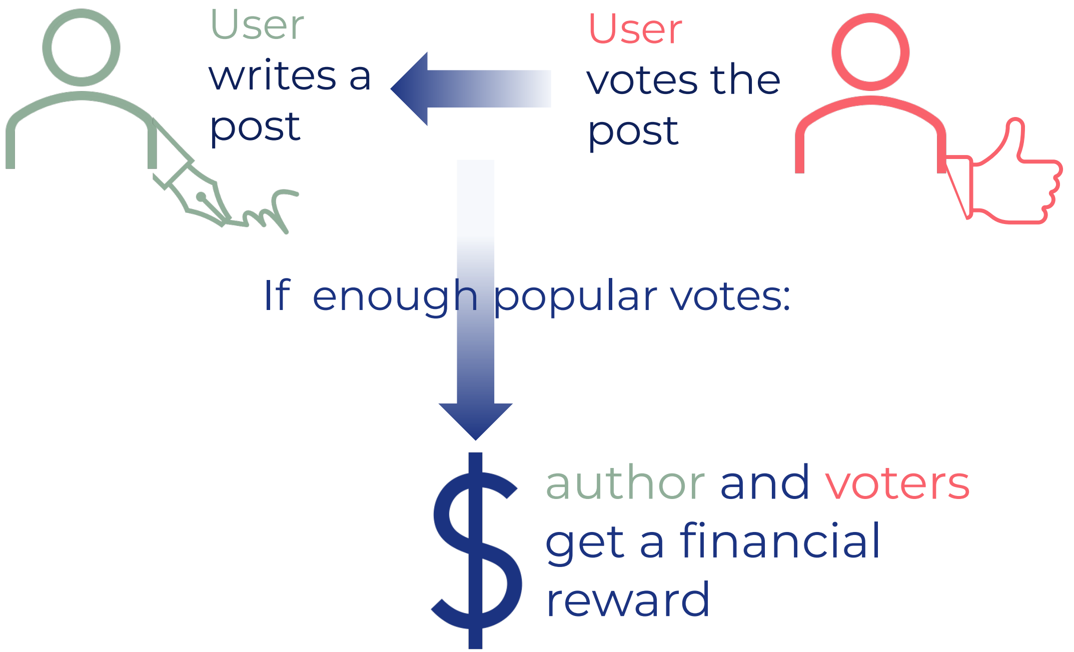
It is a blokchain-based social network with an encoded reward system


All posts | Trending

steemitblog (77) in #steemit • yesterday
steemit
Steemit Update [March 25th, 2025] : The Steemit Challenge - Applications Invited for Season 24
The Steemit Challenge, in its various forms, has now been running for 23 seasons. In Season 23 we experimented wit…
$8.21 208 47

steemitblog (77) in #steemit • 2 days ago
steemit
Steemit Update [March 24th, 2025] : Steemit Learning Challenge Season 23 - Week 6
This week we move onto Week 6 of Season 23 of the Steemit Learning Challenge. Season 23 has seen the introductio…
$4.37 159 4

steemitblog (77) in #steemit • 12 days ago
steemit
Steemit Update [March 14th, 2025] : Community Curators for April - Applications Open
It's time for another round of Community Curator applications. For April we will be continuing the support for new…
$6.53 221 49

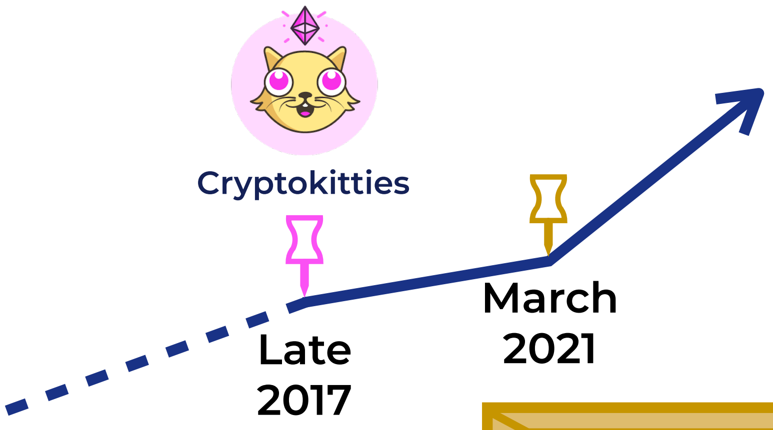


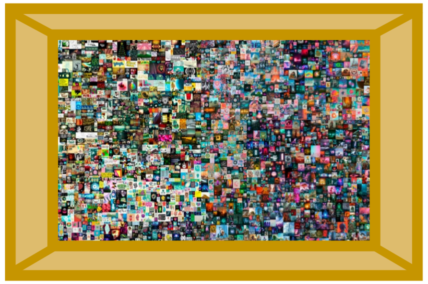
Graph **LEVEL**

CASE STUDIES

NFT

- Ensure a unique certificate of ownership
- Guarantee uniqueness and non-transferability
- Track down the complete history of ownership of an object and check the authenticity

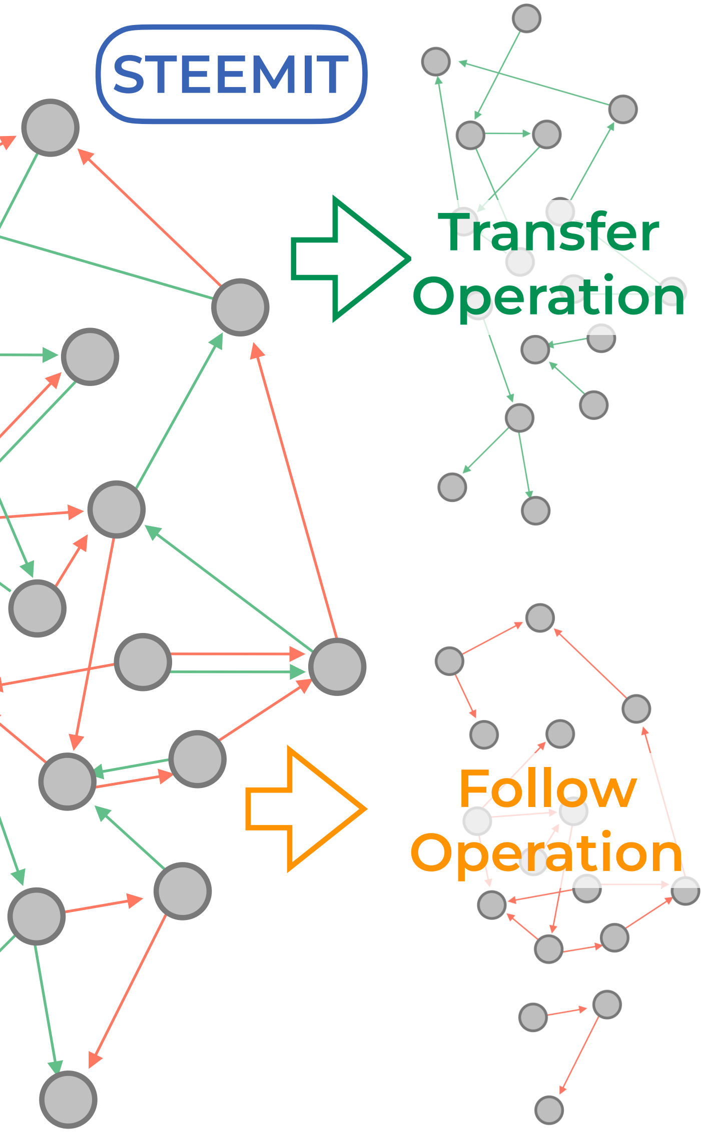




Everydays: the first 5000 days
Beeple

Graph **LEVEL**

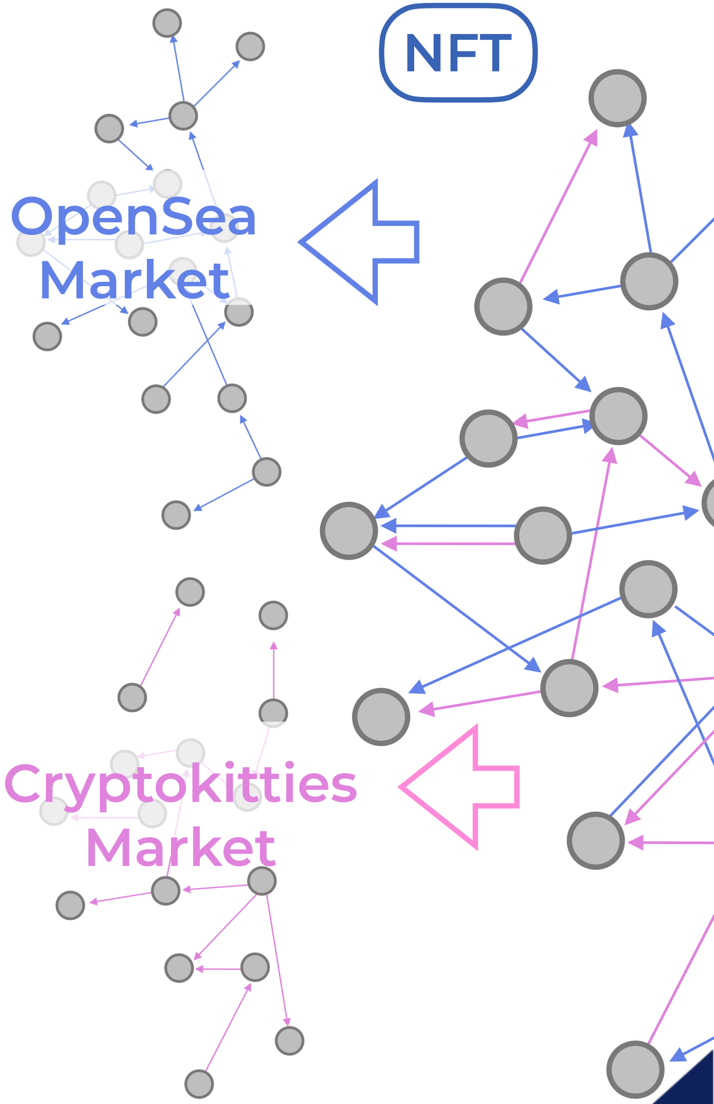
CASE STUDIES



Each operation is a tuple

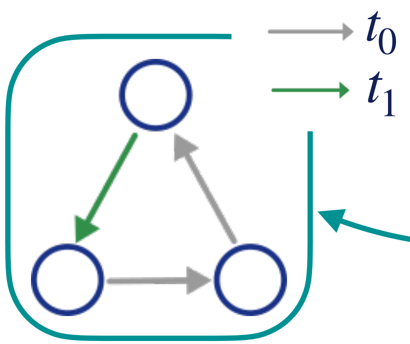
$$(u, v, t)$$

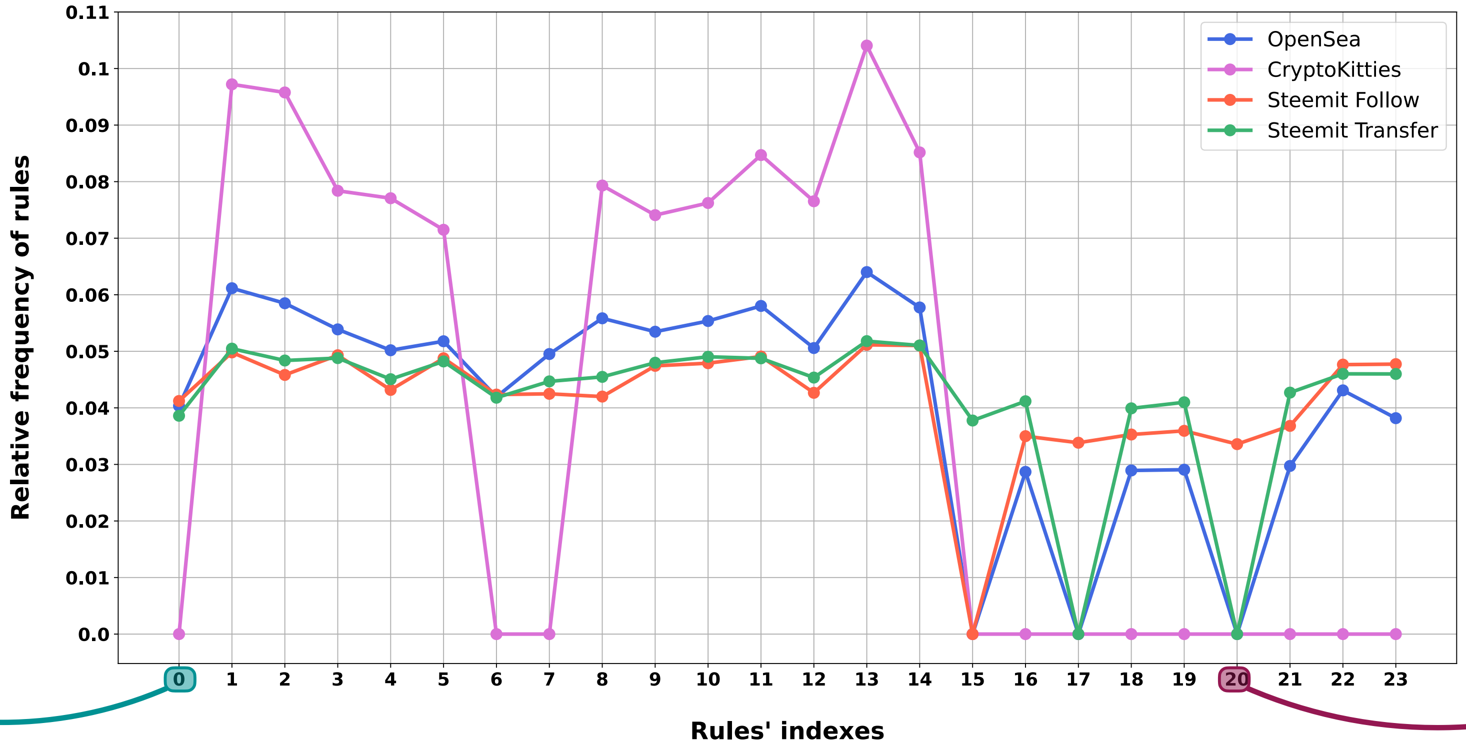
That record the operation from user u to user v at timestamp t



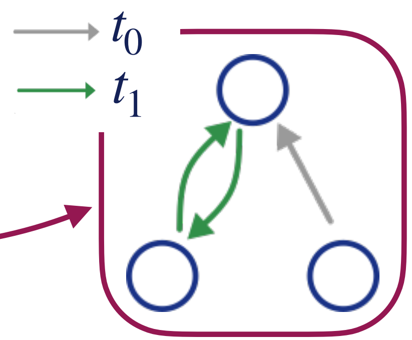
Graph **LEVEL**

Not in the frequent GER set for the cryptokitties market





Frequent only in Steemit follow (the only social network)



Both cases are explainable with the nature of the network itself

Node **LEVEL**

CASE STUDY

We applied our approach to **Sarafu**, a **complementary currency** platform with rich **temporal** data. It represents a contemporary human **complex system** because it was used for **humanitarian aid** during COVID-19

412 050 *Transactions* **BY** **40 343** *Users*

Jan20 → **Jun21**

How do single nodes evolve in this humanitarian context?

Node **LEVEL**

How to obtain node evolutionary profiles (NEPs) from nodes' ego network using the GER approach

1 Ego-networks

We first model the transactions into a **directed temporal network**. Then, we extract the **ego-network** for each node, corresponding to the subgraph induced by the nodes neighbors and itself.

2 GERs

We identify graph evolution rules using the **EvoMine** algorithm [3]. Thanks to the snapshot-based internal representation is suitable for transaction data and it also allows **parallelization** on consecutive snapshots.

3 NEPs

Thanks to a **canonical categorization** of rules [4], results are consistent across parallel executions. This allows to build the profile of the node evolutionary behavior, called **Node Evolutionary Profile** (NEP), that represents the the distribution of the GER frequency for the node's ego-network

4 Groups

We developed a clustering pipeline to identify distinct classes representing dynamic traits of ego-network evolution. First, we apply **PCA** for dimensionality reduction, then we used **hierarchical clustering** on the NEPs to identify groups with similar evolutionary traits

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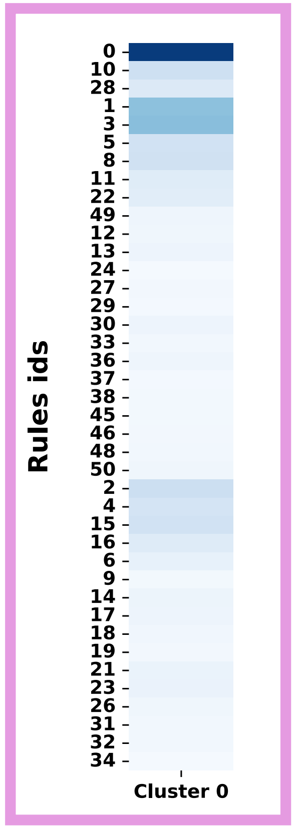
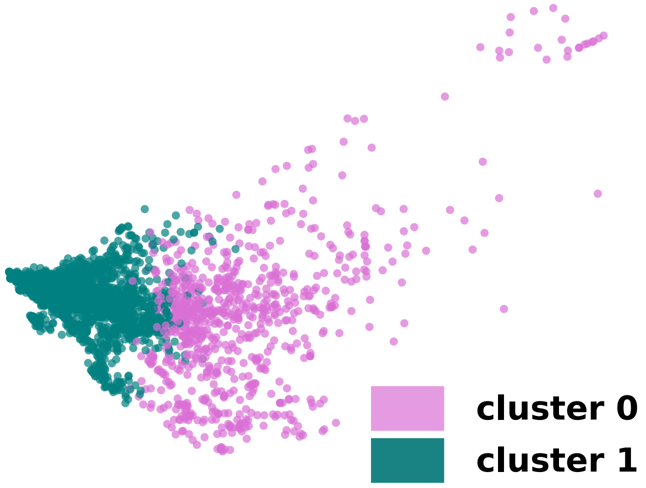
Node **LEVEL**

3 207

Ego Networks with consecutive timestamps and at least 116 edges

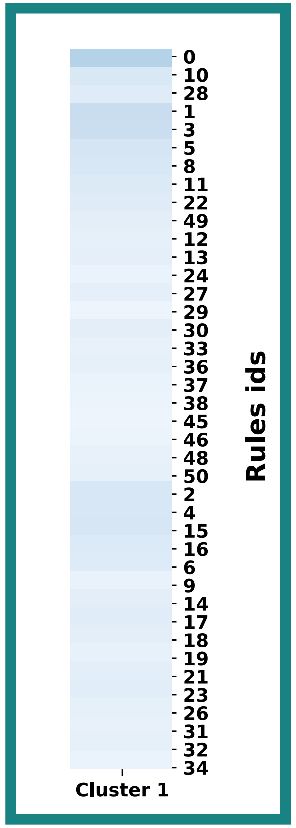
40 **distinct graph evolution rules found**





2 **distinct evolutionary behaviors**

- One group of users whose evolutionary behavior is dominated by single-link expansion
- Other group with homogeneous evolutionary behavior over expansion rules

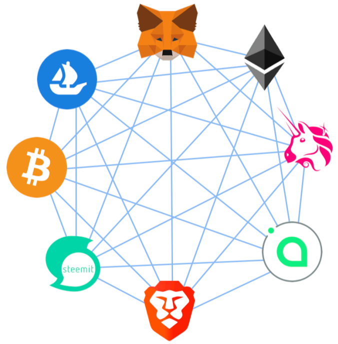


In **CONCLUSION**

GERANIO

Comprehensive **framework** for **modeling, mining,** and **analyzing**, the evolutionary **rules** governing network dynamics.

Applied the framework to different networks, including **innovative big data** sources like the web3, to find **evolutionary features** on these network new for the literature



Future RESEARCH

NETWORK GENERATION

Use rules to generate synthetic networks

AI INTEGRATION

Integrates the AI in the rule ming phase or use the evolutionary profile in AI tasks

SHOCK EVENTS

Use evolutionary profiles to detect shock events or change point

USER STRATEGIES

Study the evolution of a network from a user-perspective, analyzing the behavior

References

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THANKS

for you attention

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