# Disentangling the Growth of Blockchain-based Networks by Graph Evolution Rule Mining

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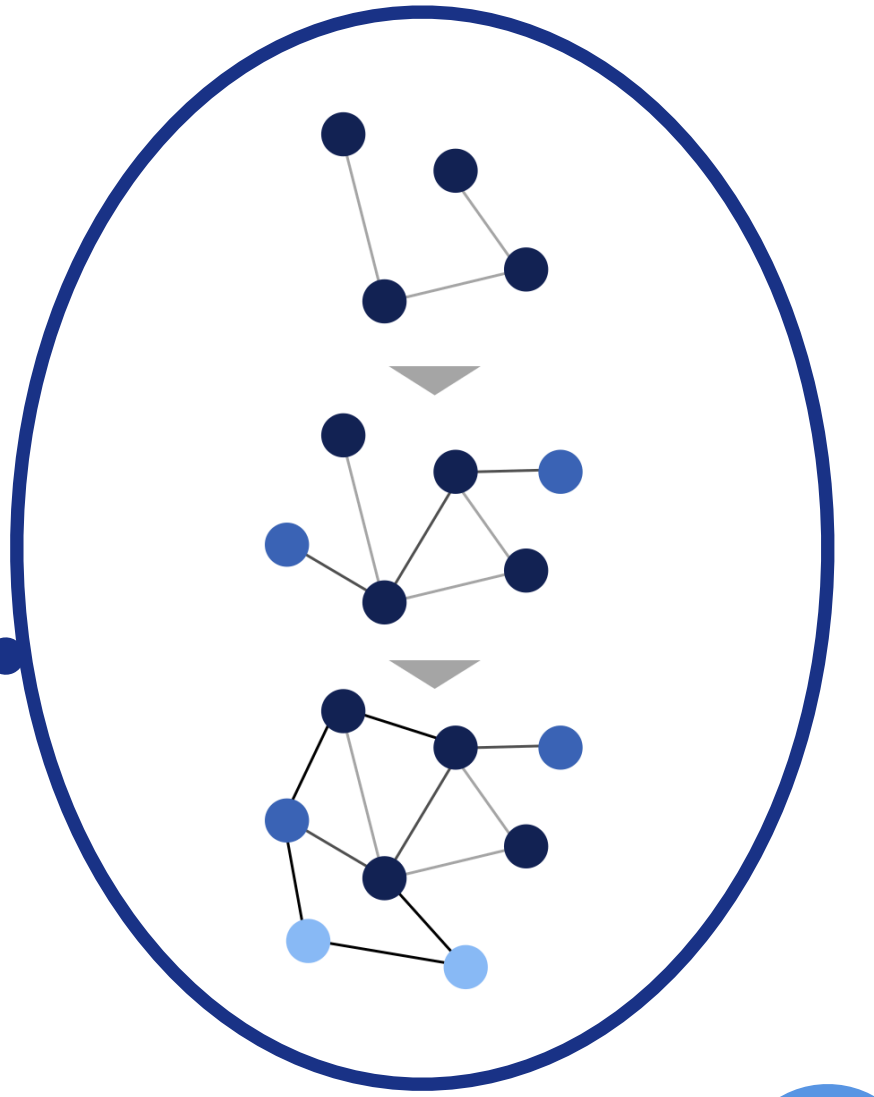
# Introduction

## KEY ELEMENTS


Web3

Network evolution



# Web3

## A PARADIGM FOR A DECENTRALISED WEB



**Web 2.0** - - - - - - → **Web3**

Over-centralization

Decentralization by blockchains

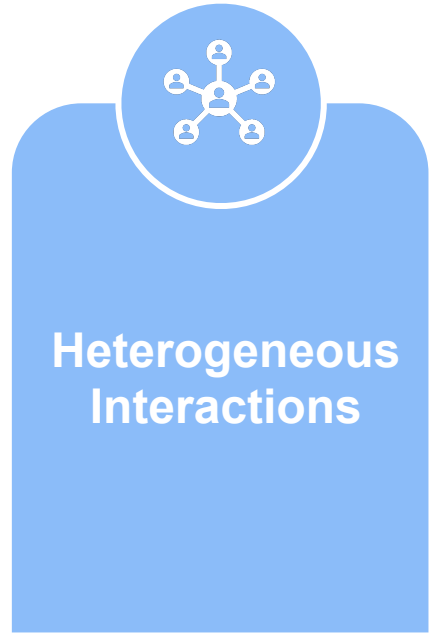
### Web3 services:

- Decentralized Finance (DeFi)
- Decentralied autonomous organisation (DAO)
- Non-fungible Token (NFT)
- Blockchain-based Online Social Network (BOSN)

# Web3

## DATA IN A DECENTRALISED CONTEXT



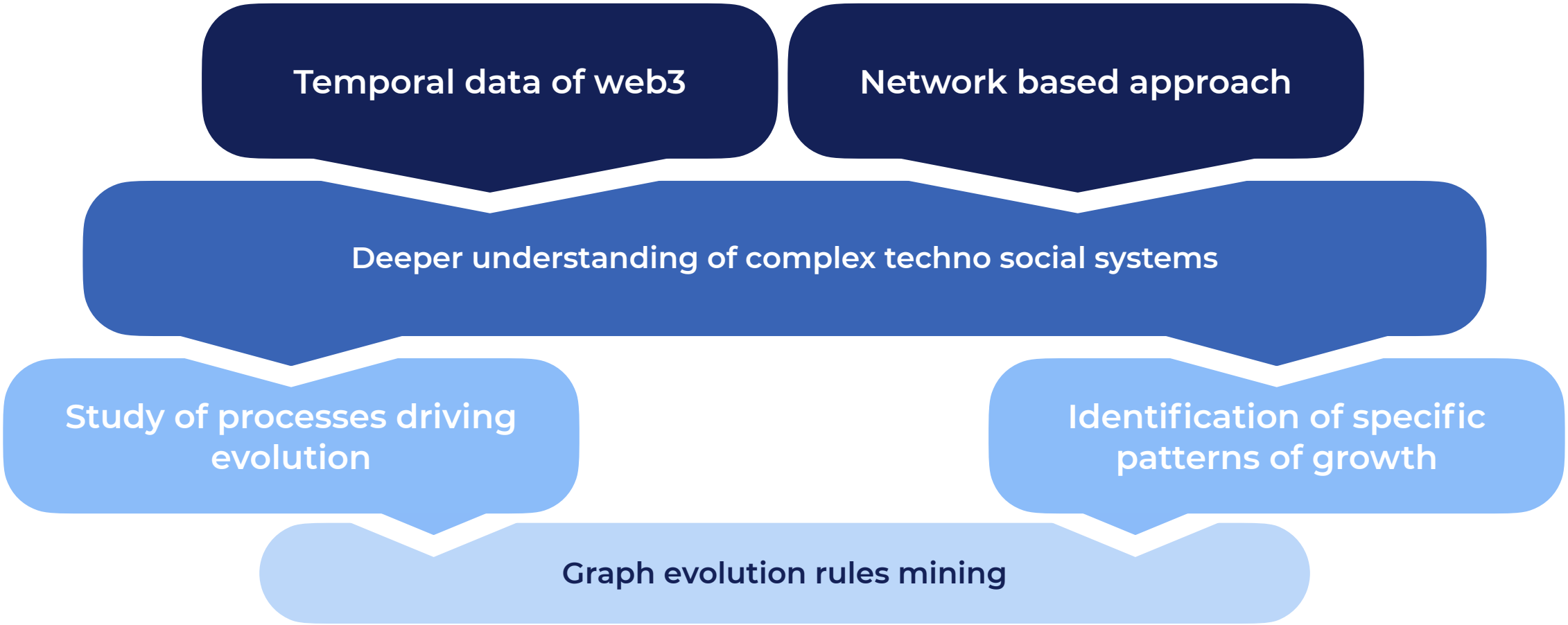




Interconnected human behaviour layers

In-depth analysis of users' traits

# Network evolution

## IN THE WEB3 CONTEXT



# Background

## WEB3 PLATFORMS

### Blockchain-Based Online Social Networks (BOSN)

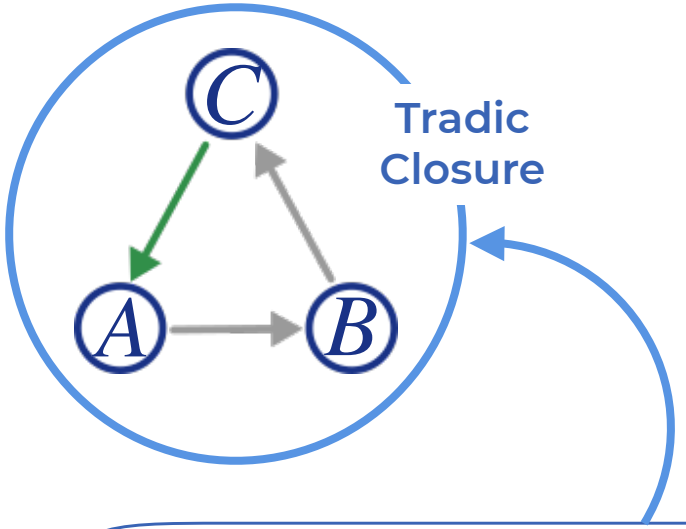
- Share the social media and micro-blogging platform concepts
- A Cryptocurrency system is involved in both social and financial operations
- A reward system promotes high quality content

### Non-Fungible Tokens (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

# Background

## GRAPH EVOLUTION RULES (GER)




Several models, mechanisms and measures have been proposed to describe the network growth

**BUT**

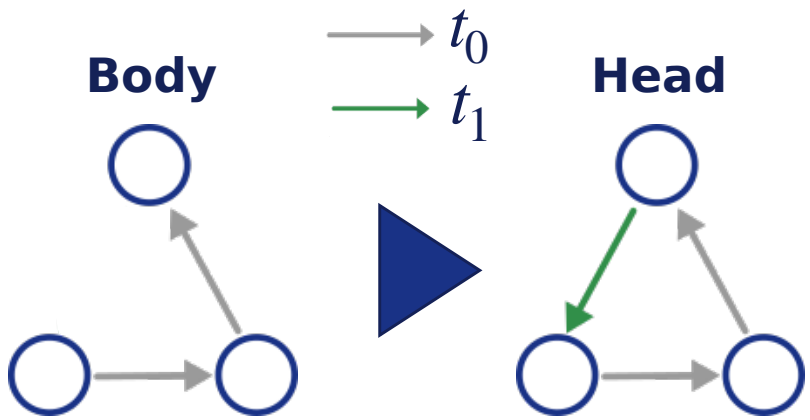
- They assume that the growth is guided by a single parameterized mechanism
- Identifying which mechanism plays a more important role is challenging

**Graph evolution rules mining** can detect evolutionary behaviors, while avoiding any a-priori mechanism

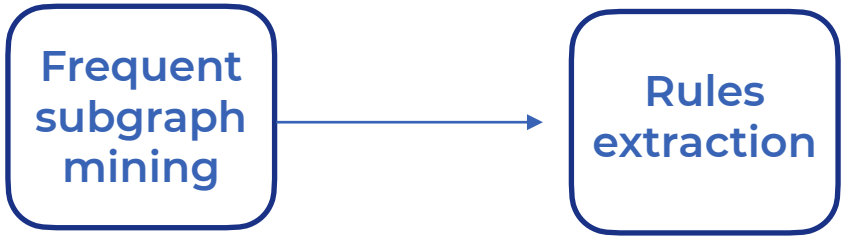
# Background

## GRAPH EVOLUTION RULES (GER)

- **Graph evolution rules mining** is a frequency-based pattern discovery method that allows discovering frequent local changes occurring repeatedly throughout the network evolution
- A **GER** is composed of a precondition (body) and a postcondition (head)




Generally, a GER mining algorithm consists in two phases:



# Methodology

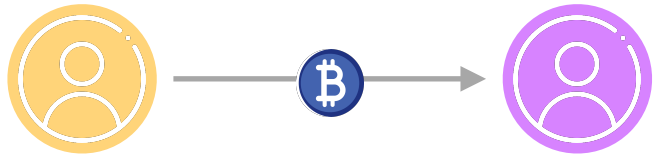
## PIPELINE

1 **Web 3 data** → 2 **Temporal Graph representation** → 3 **GER extraction** → 4 **GER profiles**

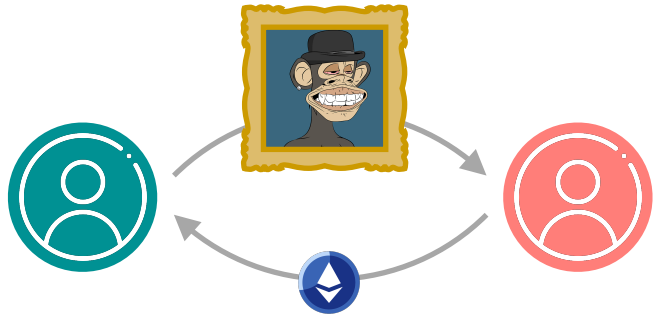
$$(u_1, u_2, t)$$
$$(u_3, u_2, t)$$
$$(u_1, u_4, t)$$
$$\vdots$$

Tuples recording that a source $u_i$ performed an operation towards a destination $u_j$ at timestamp $t$

Examples:



Yellow user transfers cryptocurrency to violet user

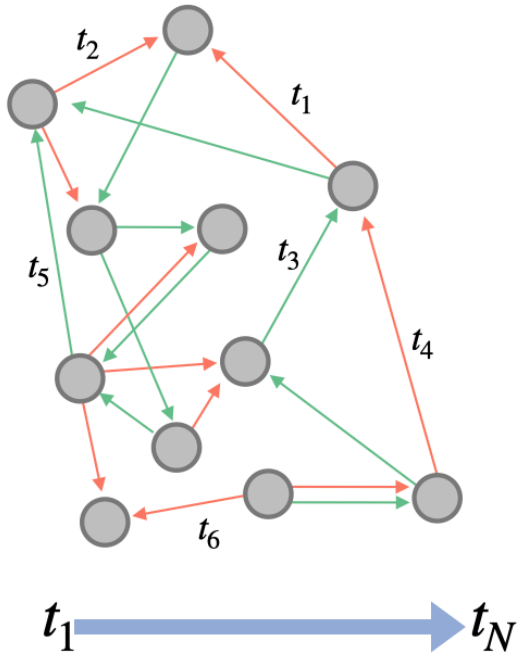


Green user sells a bored ape NFT to the salmon user

# Methodology

## PIPELINE

1 Web 3 data → 2 Temporal Graph representation → 3 GER extraction → 4 GER profiles




- Each transaction is translated into a directed link from source node $s$ to destination node $d$ with timestamp, or edge label, $t$
- The obtained temporal graph is modeled as a sequence of snapshots

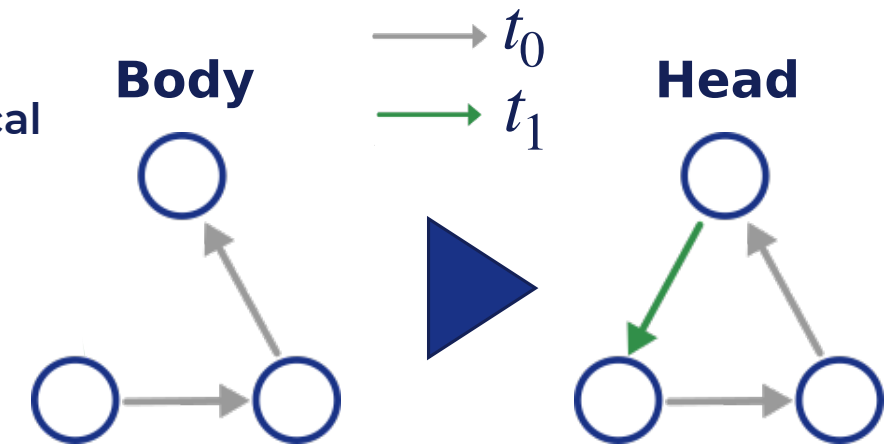
$$G_1 \rightarrow G_2 \rightarrow G_3 \rightarrow \ldots \rightarrow G_T$$

A snapshot includes edges with a single timestamp

# Methodology

## PIPELINE


- A graph evolution rule highlights frequent local changes occurring throughout the network evolution
- We use EvoMine[1] algorithm to obtain graph evolution rules with event support

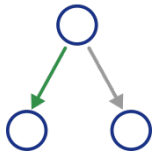


# Methodology

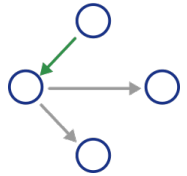
## PIPELINE

1 Web 3 data → 2 Temporal Graph representation → 3 GER extraction → 4 GER profiles

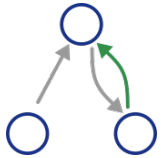
$\sigma = 6071$



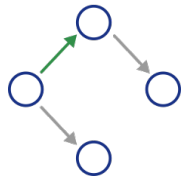
$\sigma = 74403$



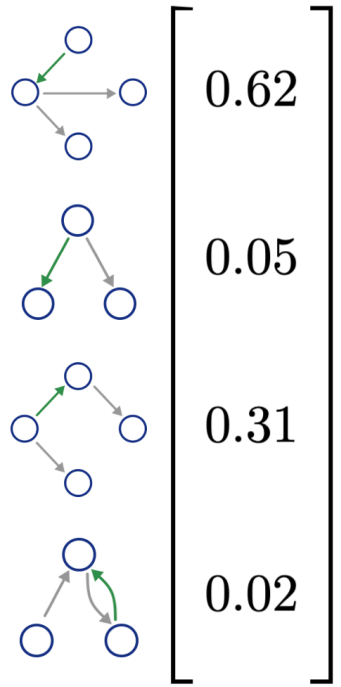
$\sigma = 2405$



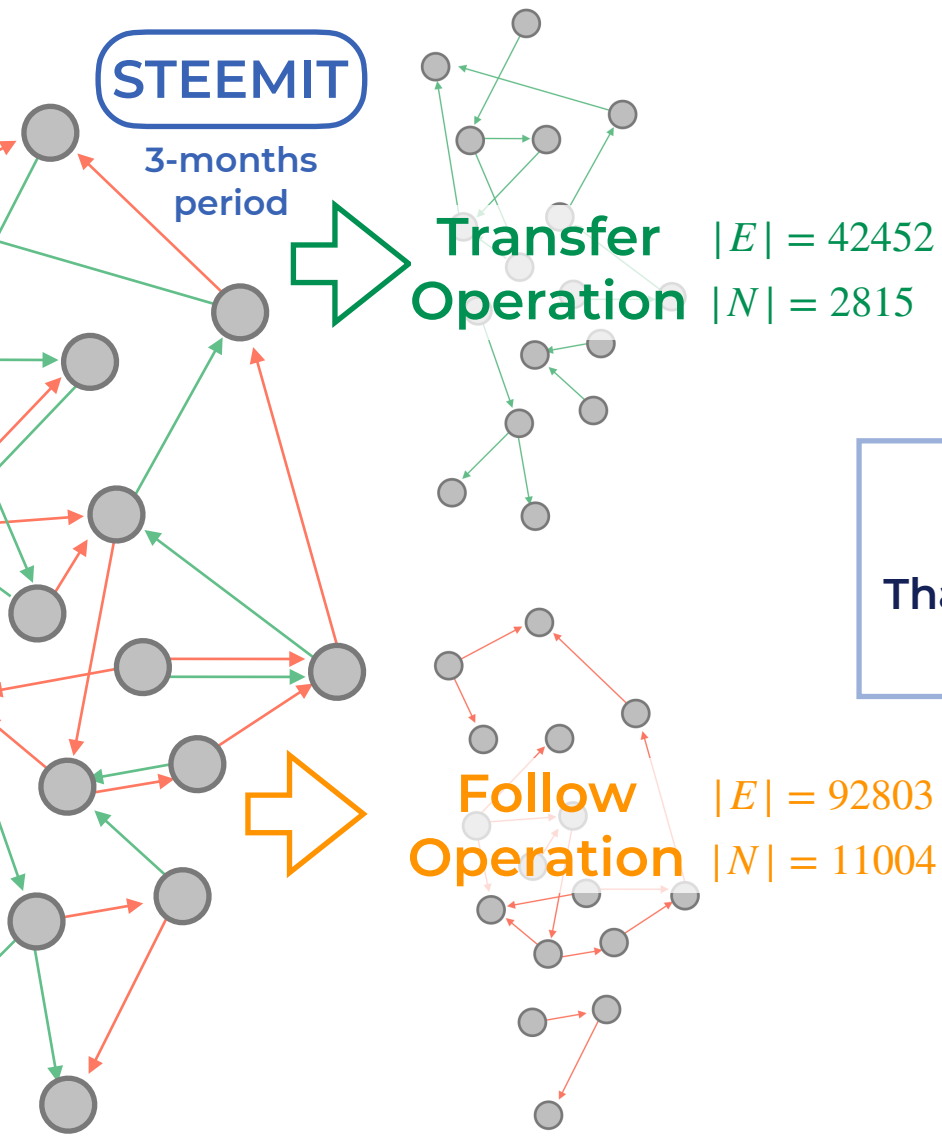
$\sigma = 37204$



- GER profiles show the distribution over types of evolution rules for a given dynamic graph
- Comparing the GER profiles for different graphs it is possible to find similar evolutionary behaviors



# Dataset



**STEEMIT**

3-months period

**Transfer Operation**

$|E| = 42452$

$|N| = 2815$

**Follow Operation**

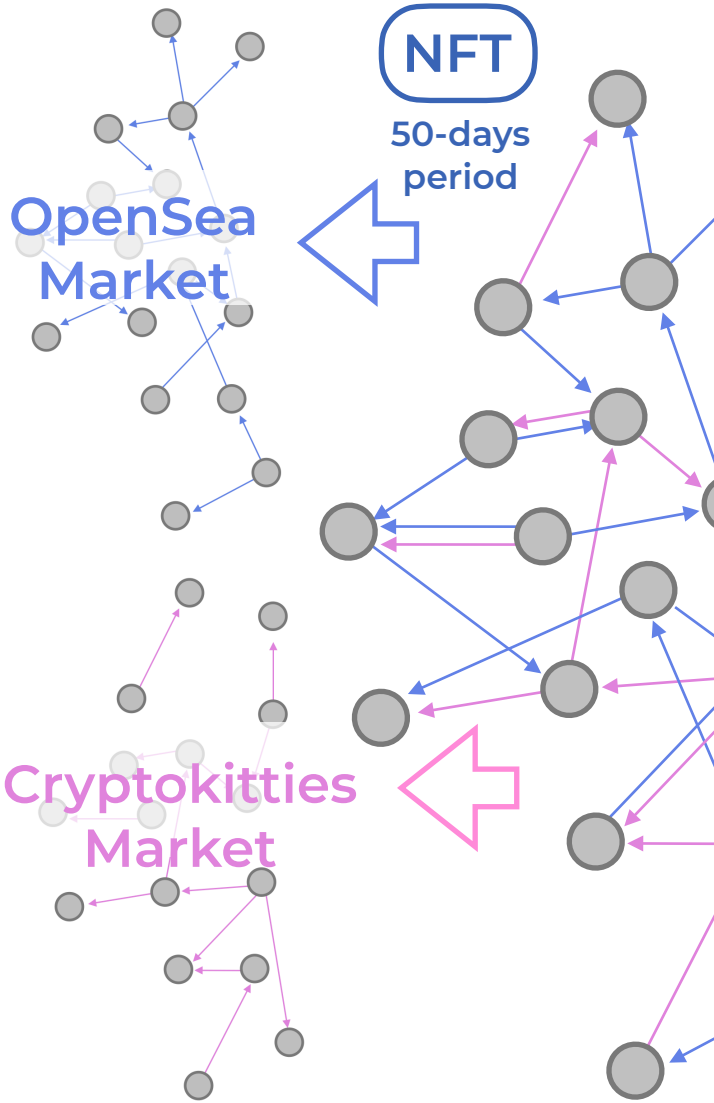
$|E| = 92803$

$|N| = 11004$

Each operation is a tuple

$(u, v, t)$

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



**NFT**

50-days period

**OpenSea Market**

$|E| = 23251$

$|N| = 4870$

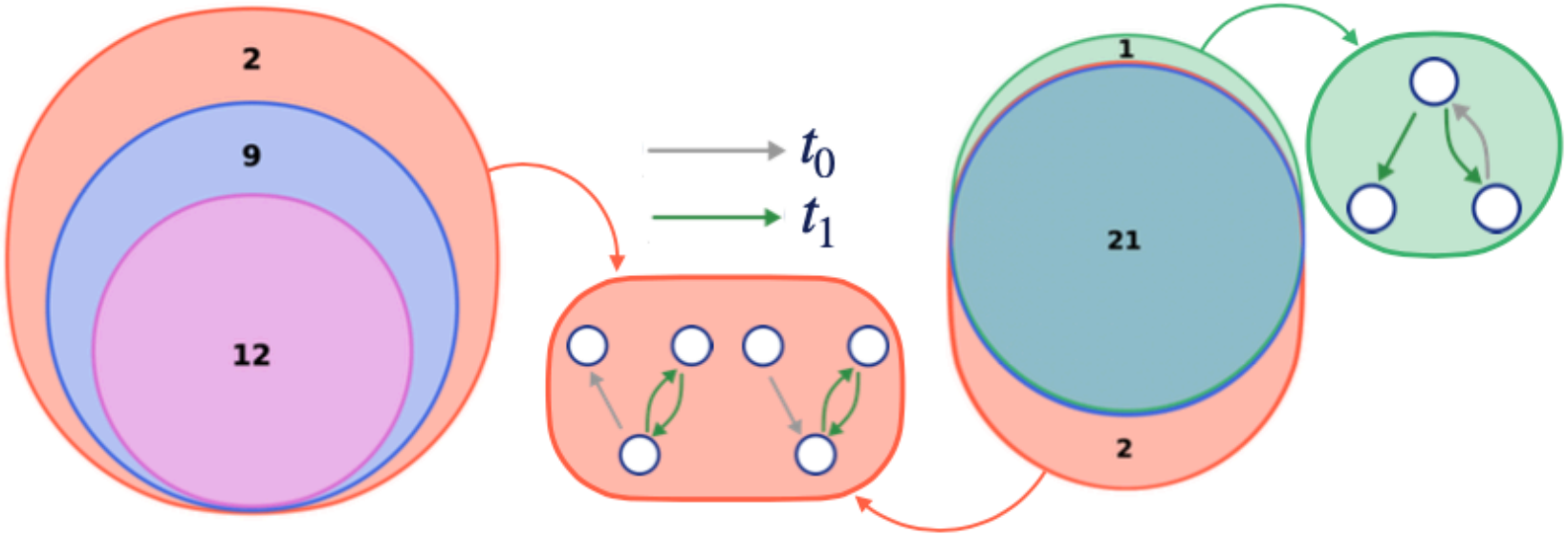
**Cryptokitties Market**

$|E| = 255947$

$|N| = 58906$

# Results

# Quantitative




| Number of rules | Dataset |
|---|---|
| 21 | NFT OpenSea |
| 12 | NFT Cryptokitties |
| 23 | Steemit Follow |
| 22 | Steemit Transfer |

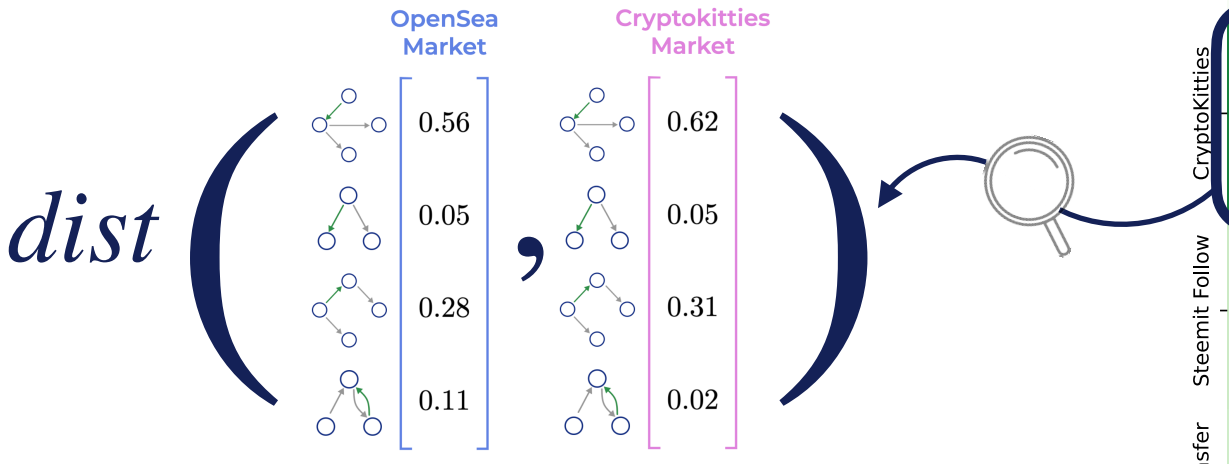
Steemit follow rules' set includes all open sea's and cryptokitties' rules

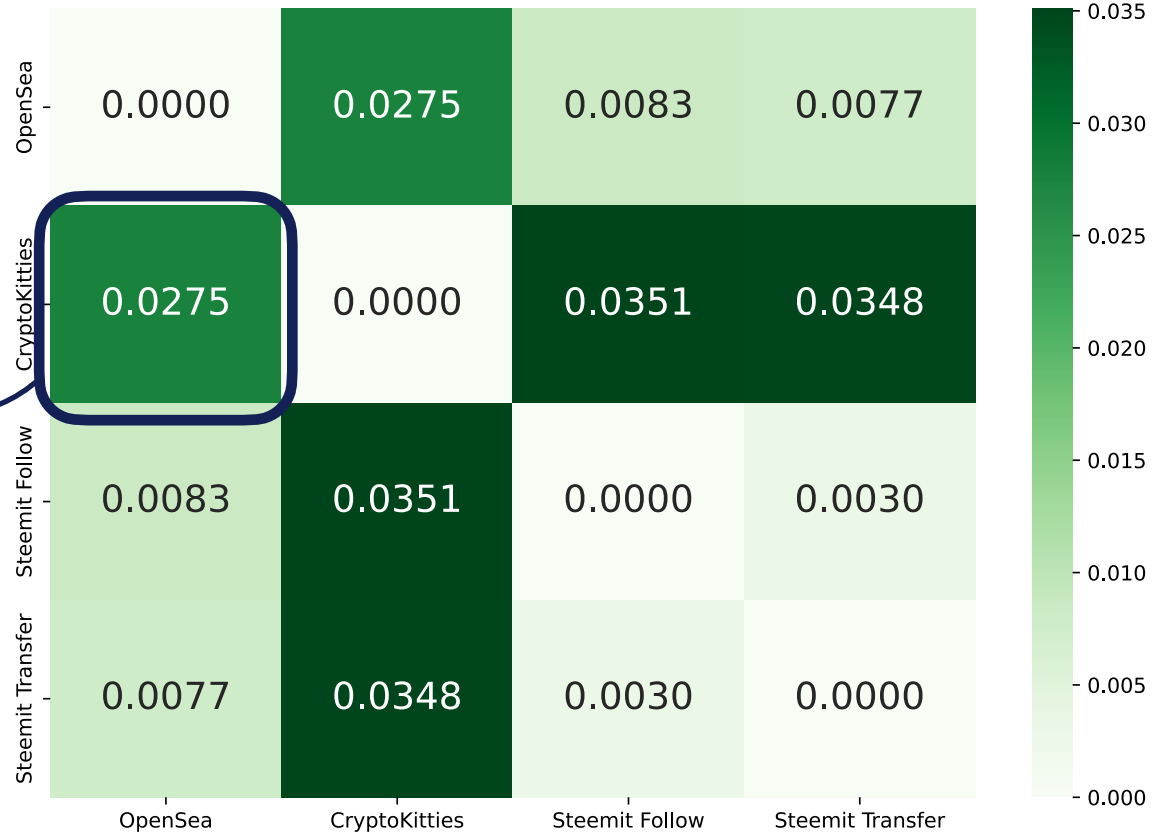
Steemit transfer's set present a rule not seen in other sets

# GER profiles

## WASSERSTEIN DISTANCE

We compute the Wasserstein distance between GER profiles to measure the difference in the evolutionary behaviour



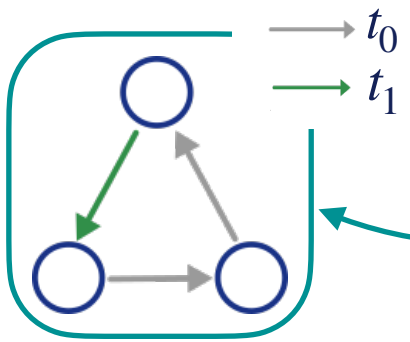



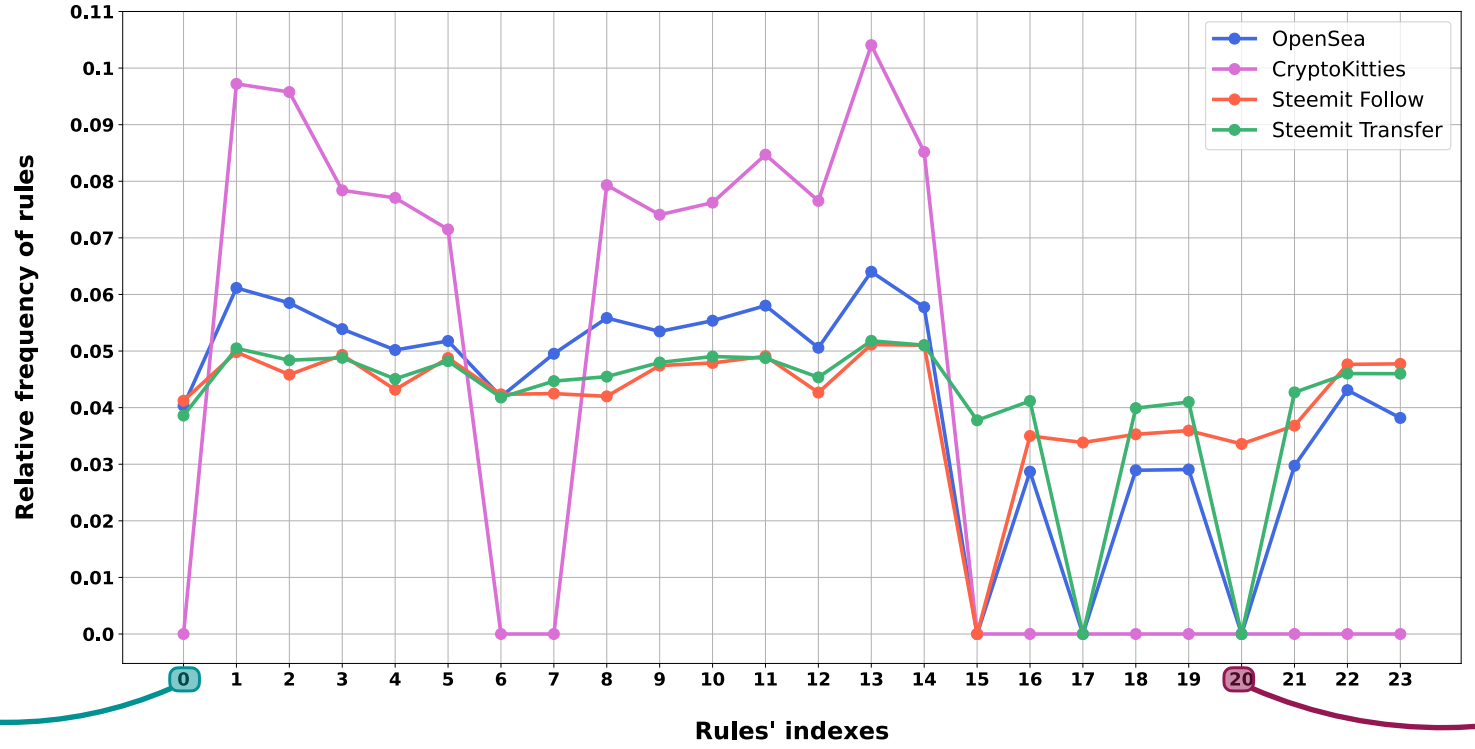

- Results suggest that the distribution over the different kinds of rules is rather homogeneous
- The cryptokitties network is the one that differs the most

# GER profiles

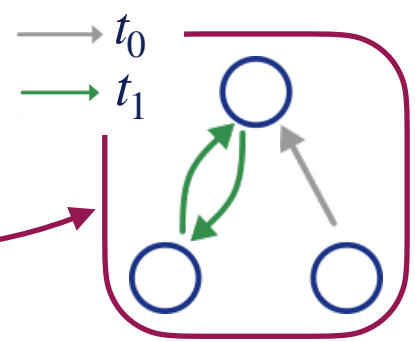
## DISCUSSION

Not in the frequent GER set for the cryptokitties market



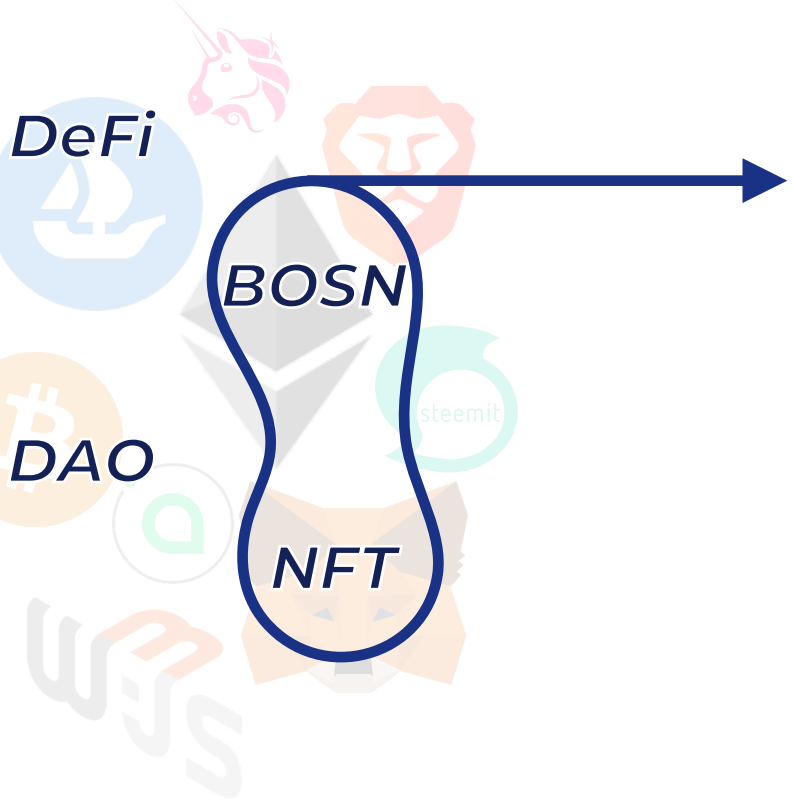




Frequent only in Steemit follow (the only social network)




Both cases are explainable with the nature of the network itself

# Conclusions

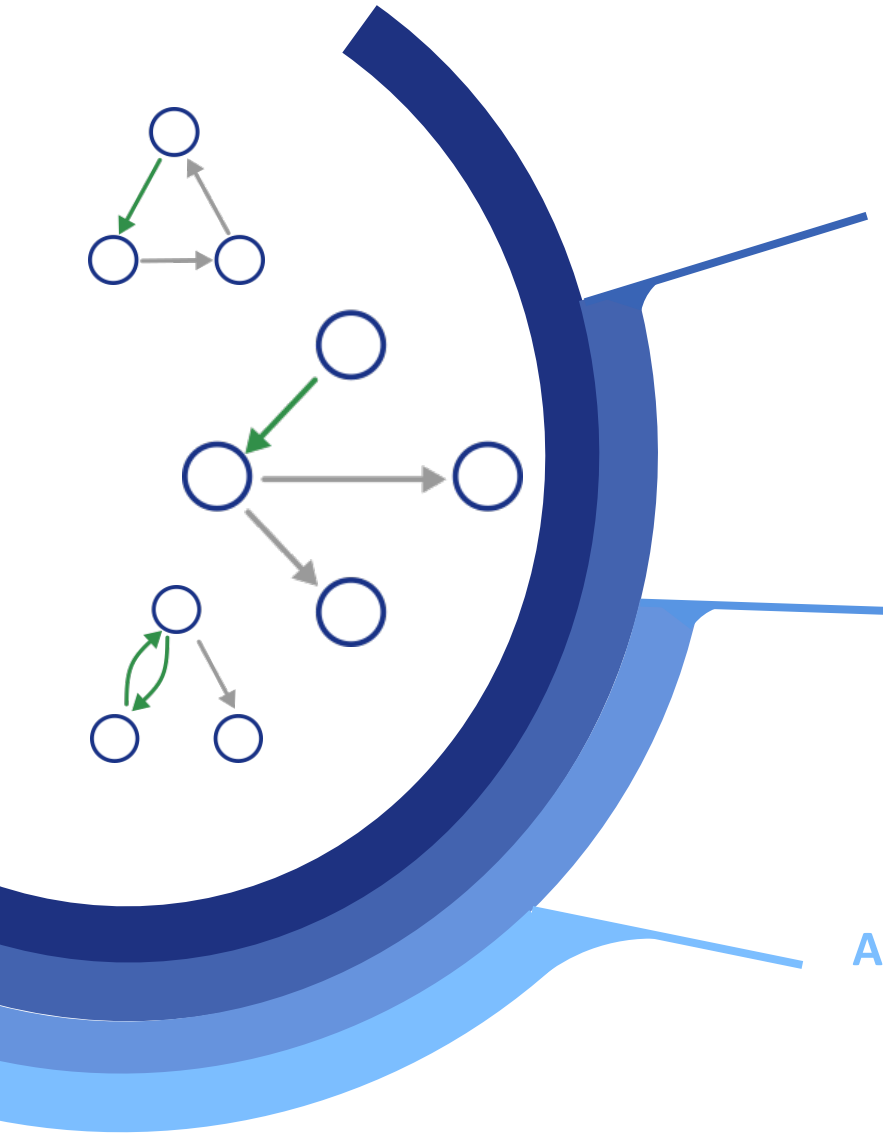



1. Web3 data modeled as temporal networks
2. Graph evolution rule mining
3. GER profile to compare the evolution of different networks

We identify:

- rules that are common to every platform,
- some evolution mechanisms strictly related to the nature of the single platform

# Future works



**Performance**

Improve the performance of the state-of-the-art algorithms

**Significance**

Evaluate statistically the significance of the rules, for example though the introduction of a null model

**Application**

More complete characterization of the growth of Web3 platforms

# Thanks for your attention

# References

[1] *E. Scharwa¨chter, E. Mu¨ller, J. Donges, M. Hassani, and T. Seidl, "Detecting change processes in dynamic networks by frequent graph evolution rule mining," in 2016 IEEE 16th International Conference on Data Mining (ICDM). IEEE, 2016, pp. 1191–1196.*