



NETWORK EVOLUTION

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*Based on the PhD thesis
of Alessia Galdeman and
Manuel Dileo*

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works visit

<https://connets.di.unimi.it/>



CONNETS LAB

UNIVERSITÀ DELL'ETNA
DIPARTIMENTO DI INFORMATICA

NETWORK SCIENCE



Sabrina Gaito
Head of the Lab

Multilayer Networks

Network Evolution

Temporal Networks

Cheick
Ba



Alessia
Galdeman



GNN
Manuel
Dileo



ARTIFICIAL INTELLIGENCE



Matteo Zignani

LLM

Alessandro
Cagiano



COMPUTER NETWORKS



Christian Quadri

Edge computing

Autonomous driving

Alberto
Bertонcini



NETWORK EVOLUTION

Every network exhibits a distinct **evolution signature** that shapes its peculiar structural and dynamical characteristics.

How to identify each network's distinctive evolutionary signature?

By defining and constructing a **network evolution profile**

a **concise yet comprehensive and explainable quantitative descriptor**

Able to capture the **mechanisms** underlying its evolution and temporal dynamics



The CONTEXT

- Past research mainly 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;



The CONTEXT

TEMPORAL
NETWORKS

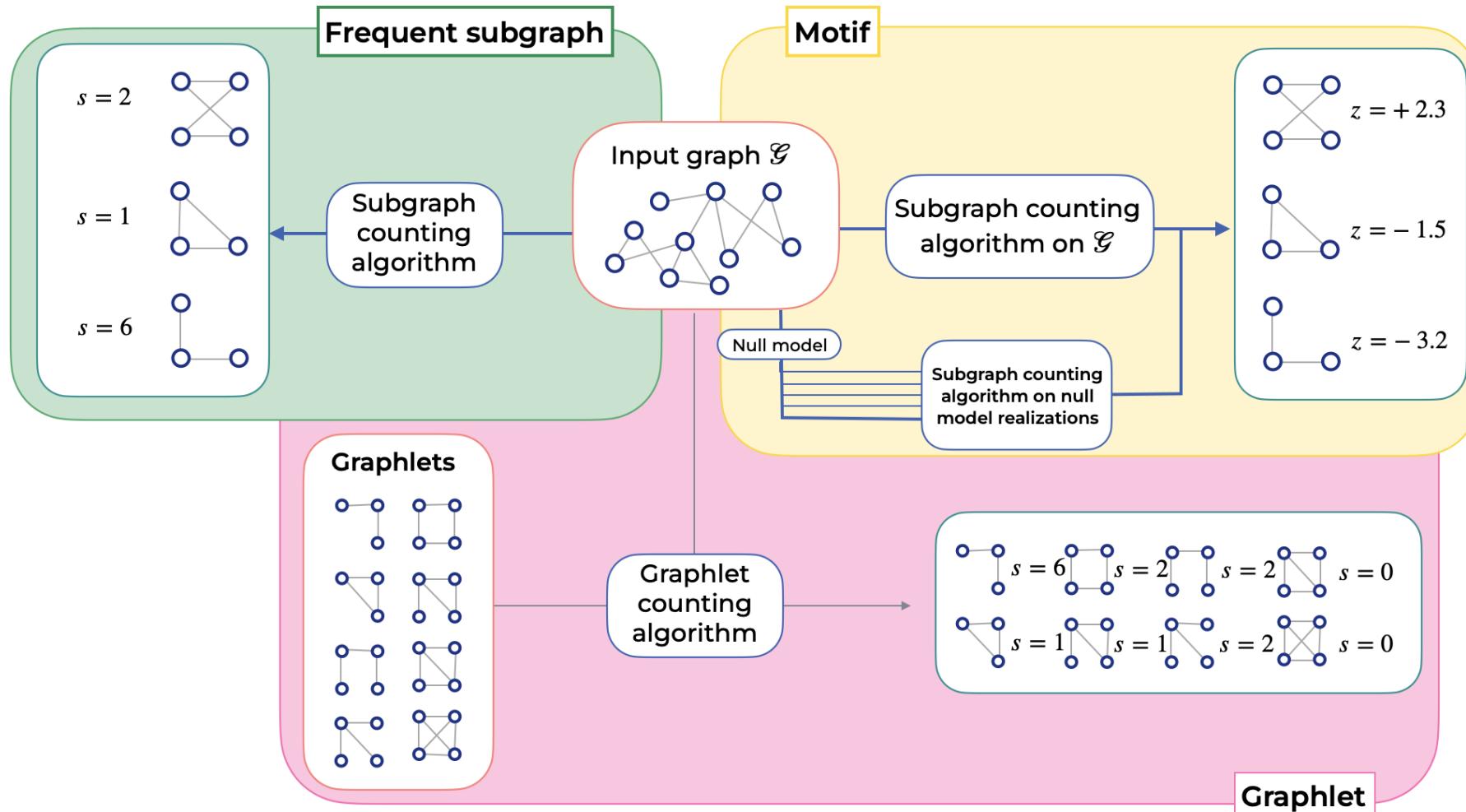


NETWORK
EVOLUTION

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

The CONTEXT

FREQUENT SUBGRAPH METHODS



Even if they are time-labelled

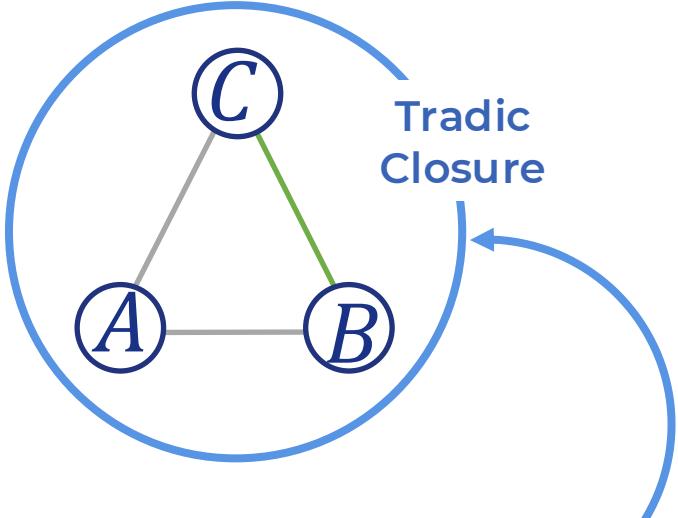
They do not really describe the evolution mechanisms

GRAPH EVOLUTION RULES

**DEFINITIONS, FORMALISMS, MINING ALGORITHMS,
AND VISUALIZATION**

Graph evolution rules

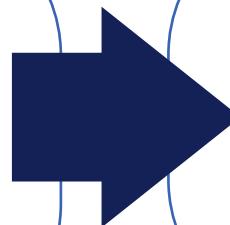
REASONS WHY



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

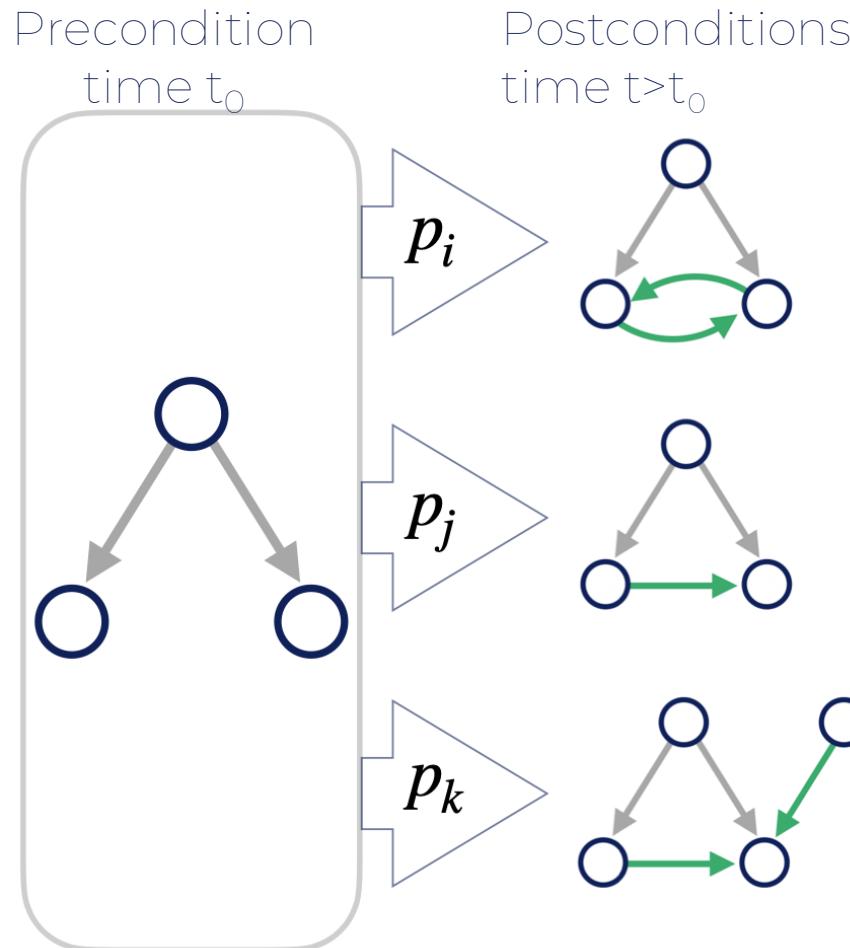
BUT

- 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 all evolutionary behaviors, while avoiding any a-priori mechanism

IDEA: Graph Evolution Rules



- Inspired by association rules in the data mining field, a GER consists of a precondition and a set of postconditions
- A subgraph matching the precondition evolve in the different postconditions with the associated probability

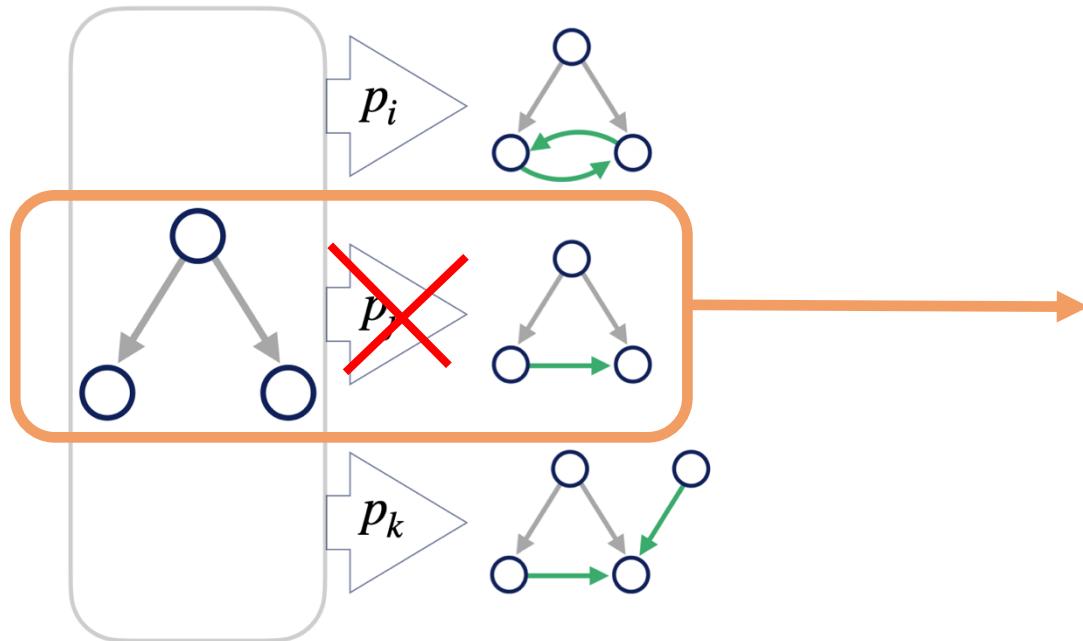
The PITFALLS of GERs

Very few works propose algorithm to find GERs

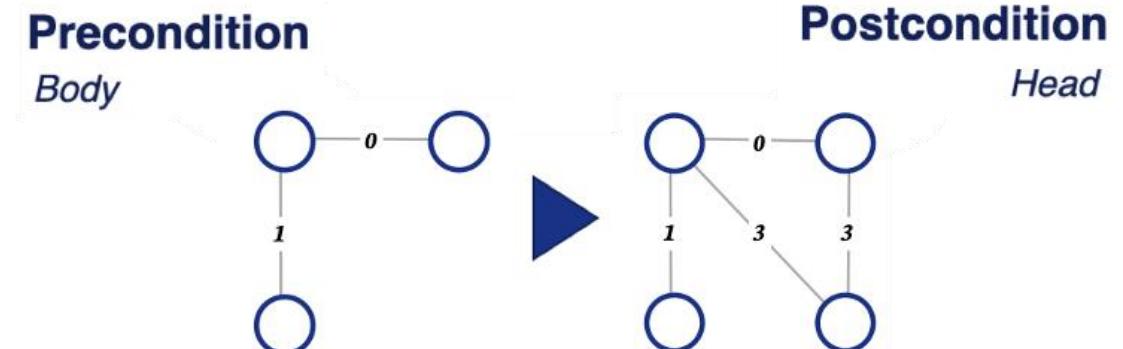
&

They all find stand-alone (independent) rules

GENERAL
GRAPH EVOLUTION RULES

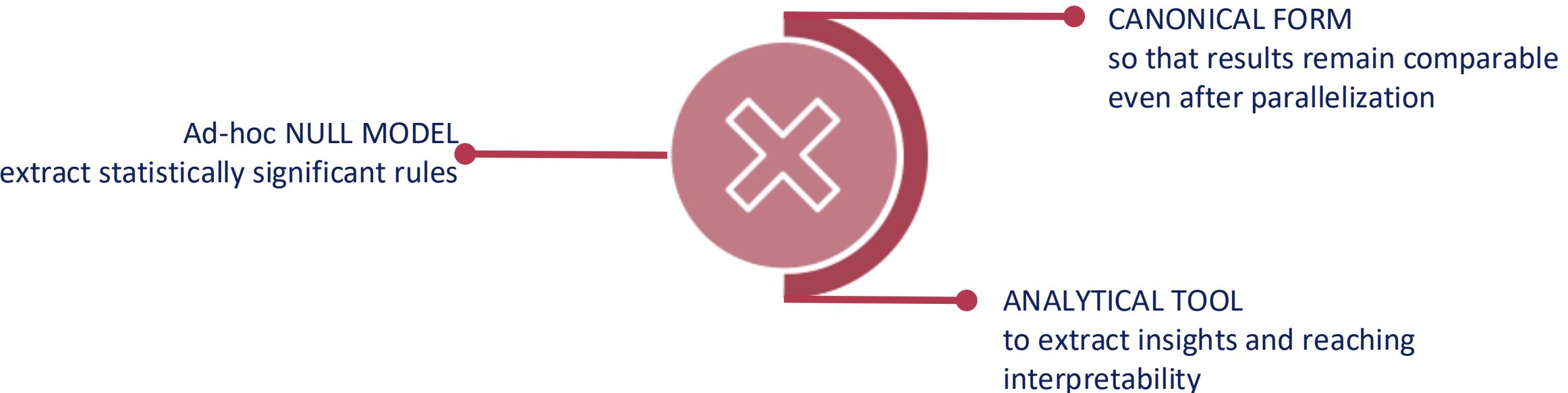


STAND ALONE
RULES



The PITFALLS of GERs

Existing stand-alone algorithms lacks of:



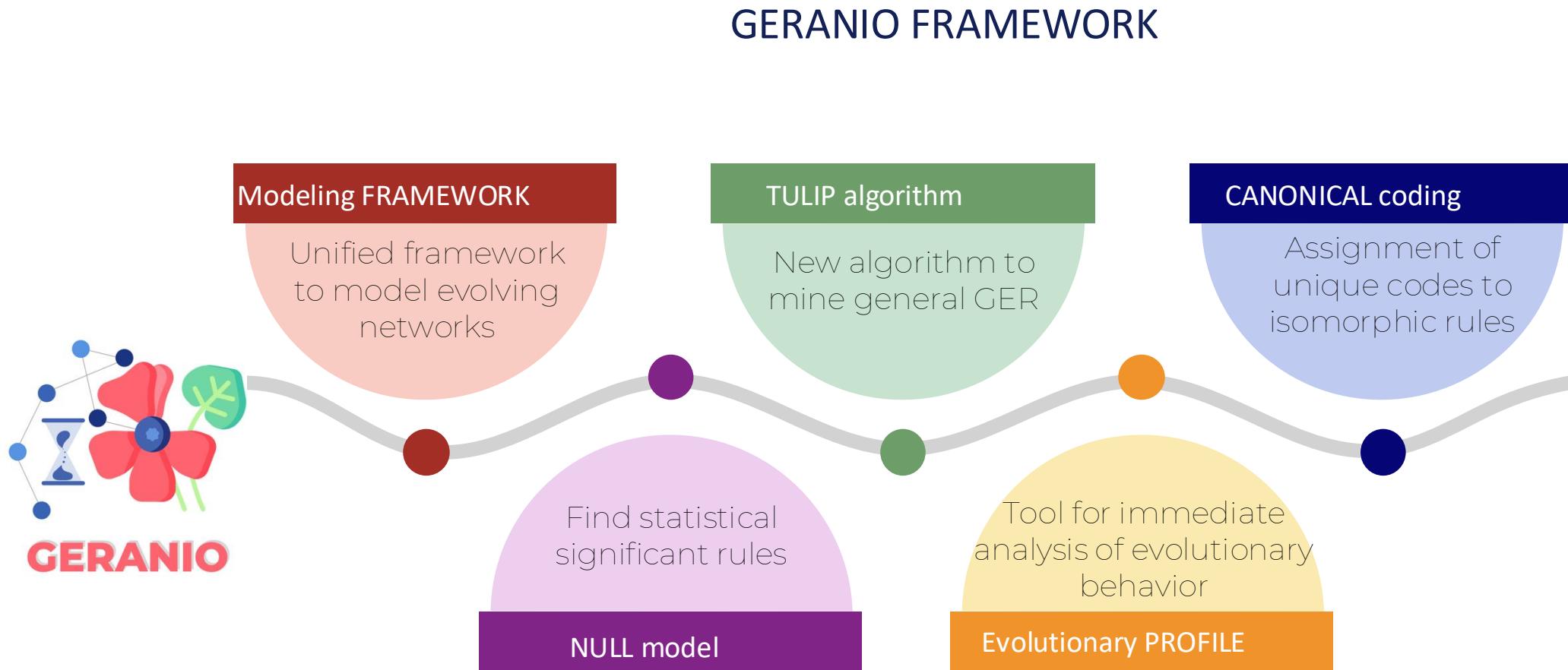
No algorithms for general graph evolution rules

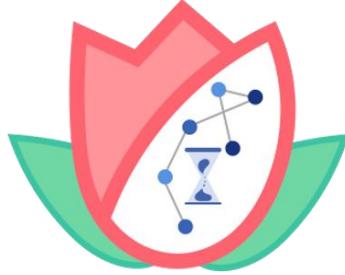
Methodological FRAMEWORK for Network Evolution Profile



GERANIO

Main CONTRIBUTIONS



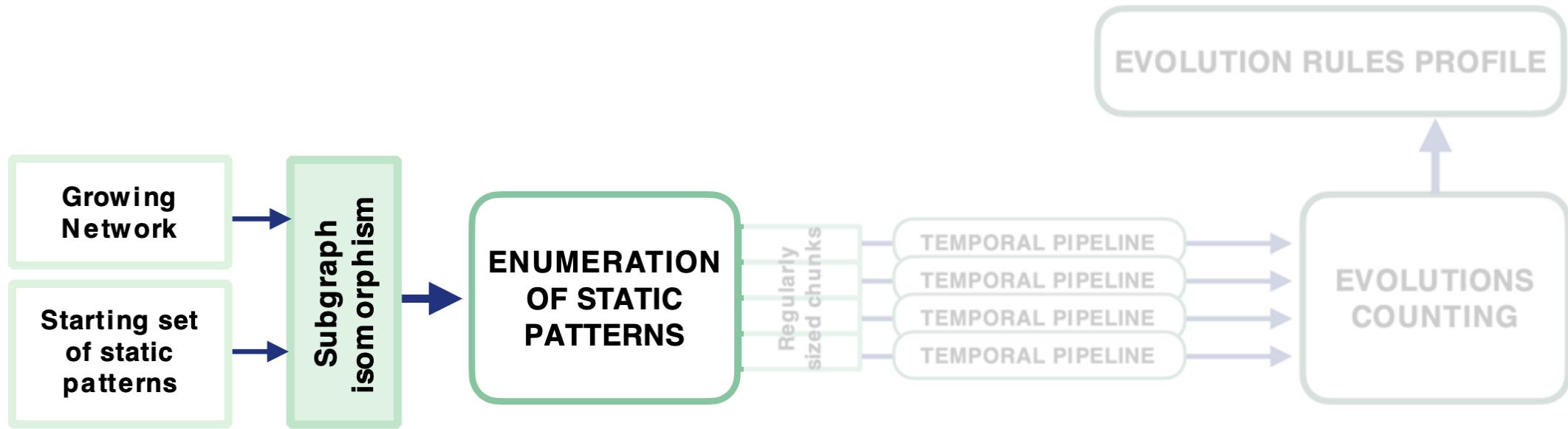


The TULIP ALGORITHM

TEMPORAL SUBGRAPHS FOR EVOLUTIONARY PROFILING

The PIPELINE

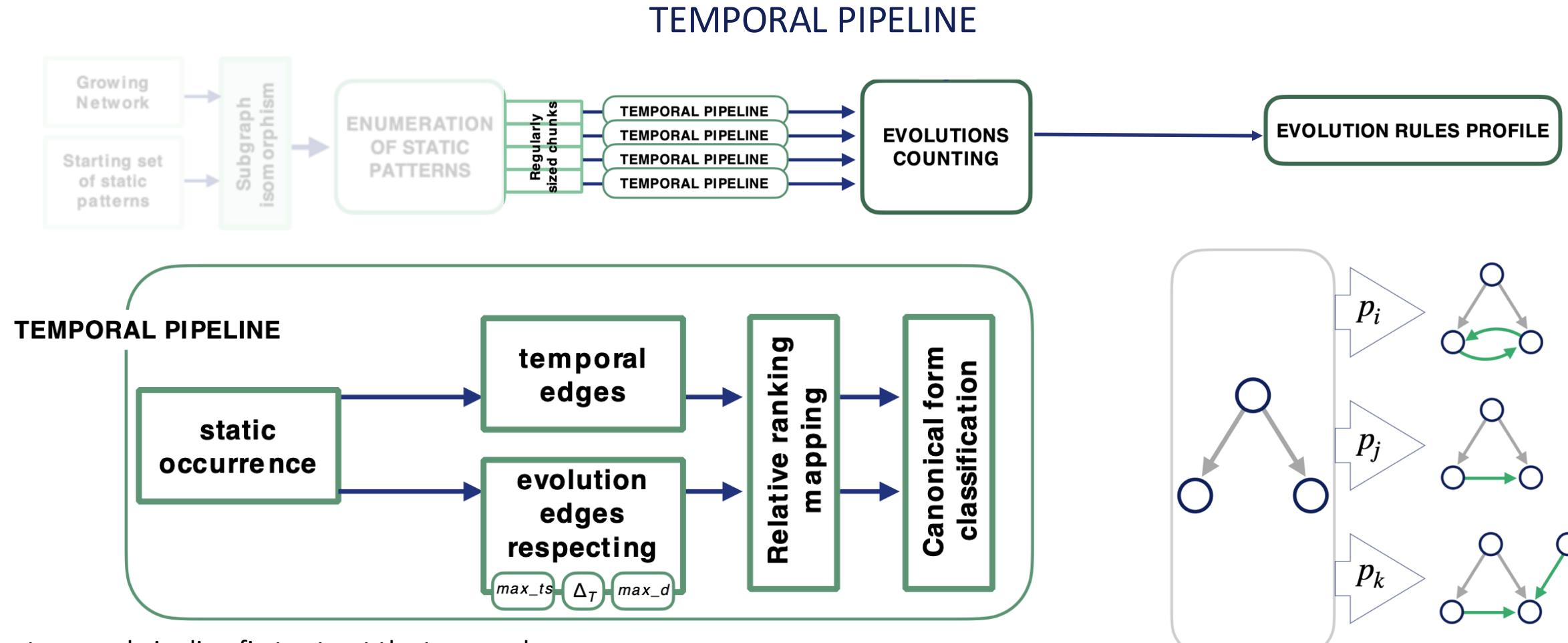
ENUMERATION OF PATTERNS



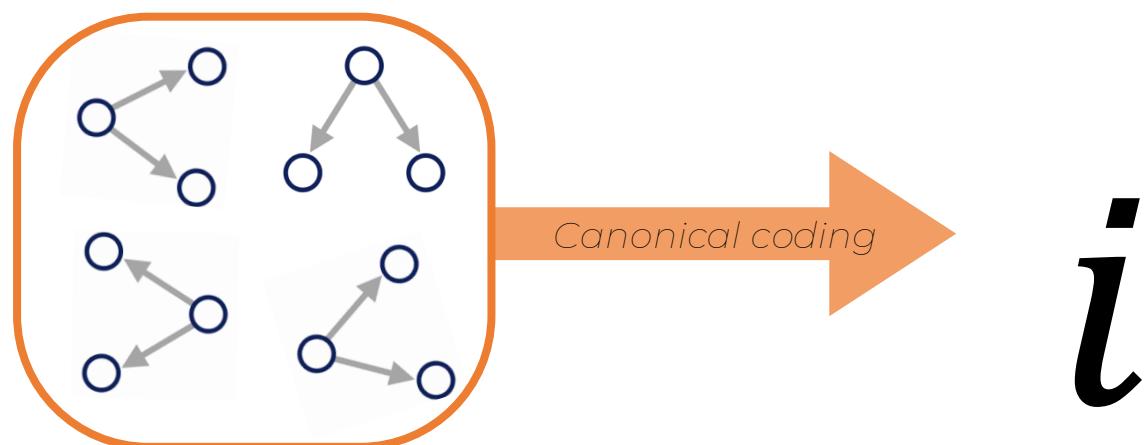
Graph mining is already a complex task, and temporal graph mining comes with additional constraints.

The idea for the tulip algorithm is to enumerate static patterns, and then extract the temporal information from edges that we know exists.

The PIPELINE



The CANONICAL CODING



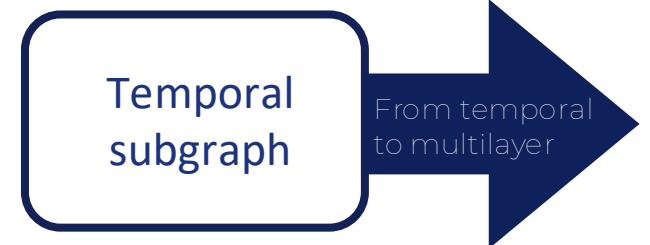
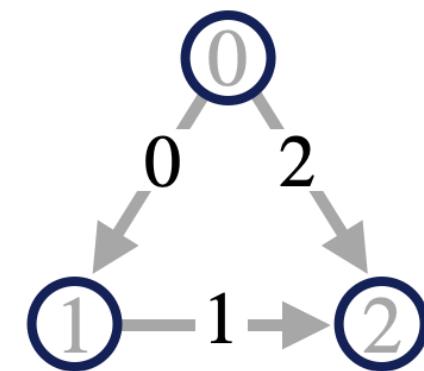
Obtain a unique code for
all isomorphic subgraphs

The CANONICAL FORM

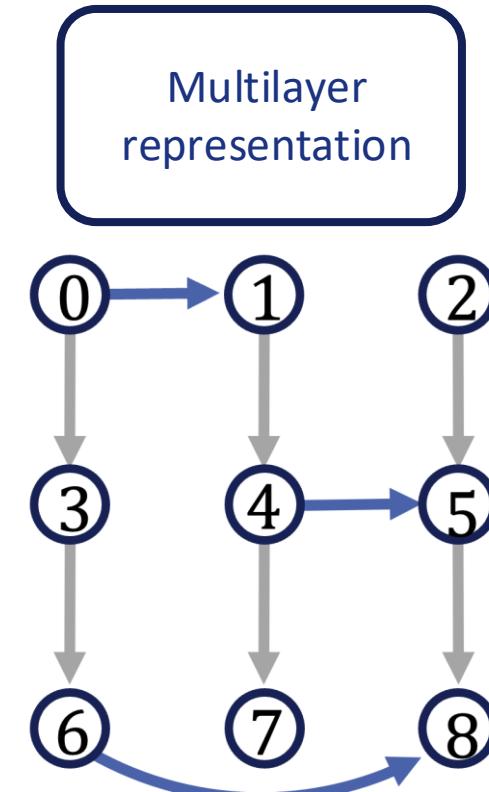
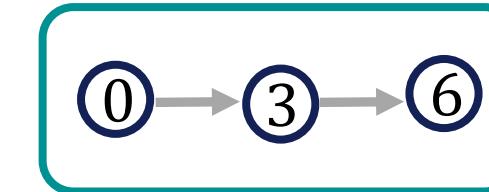
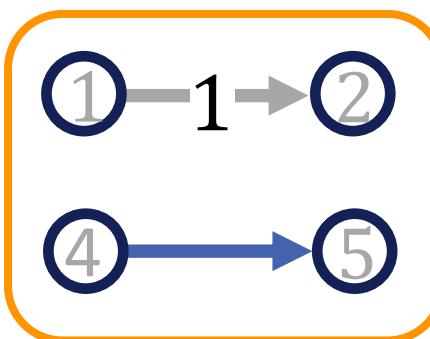
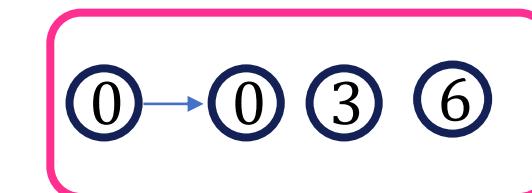
THE PIPELINE



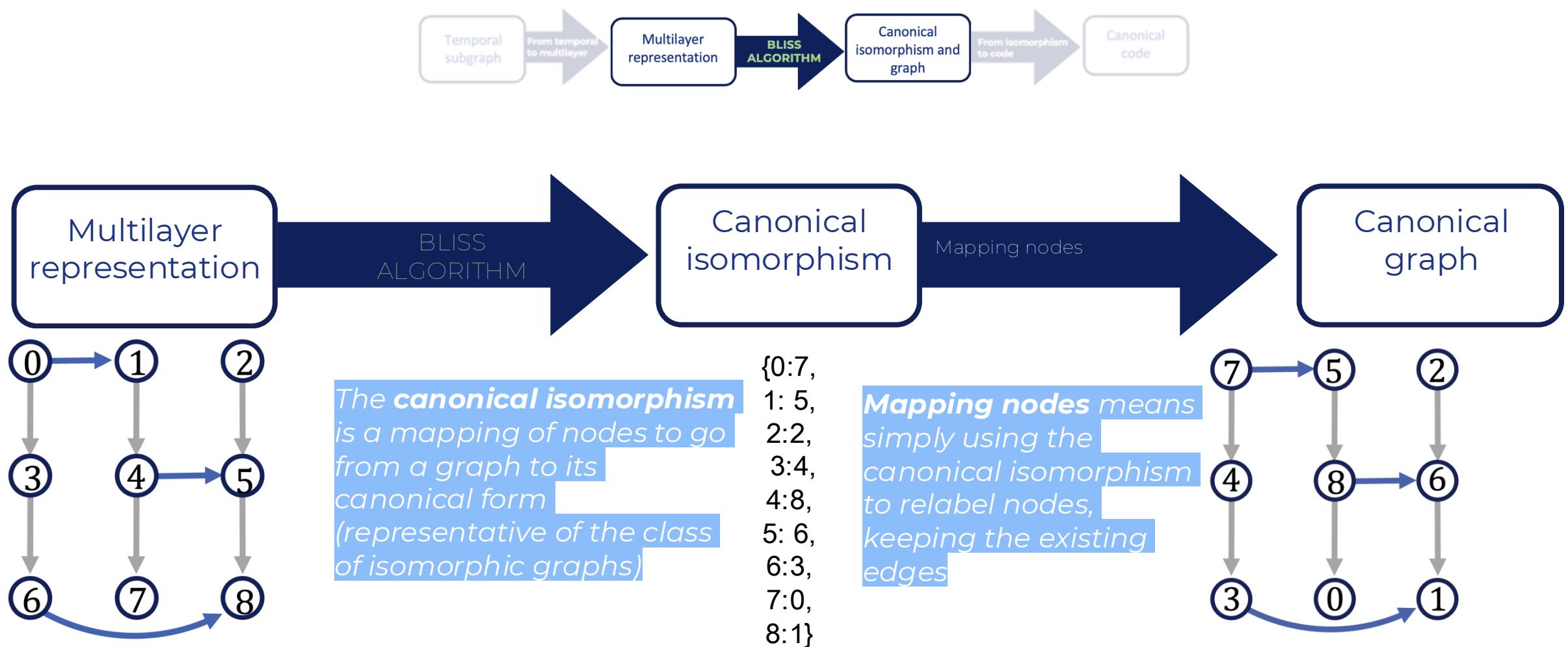
The CANONICAL FORM



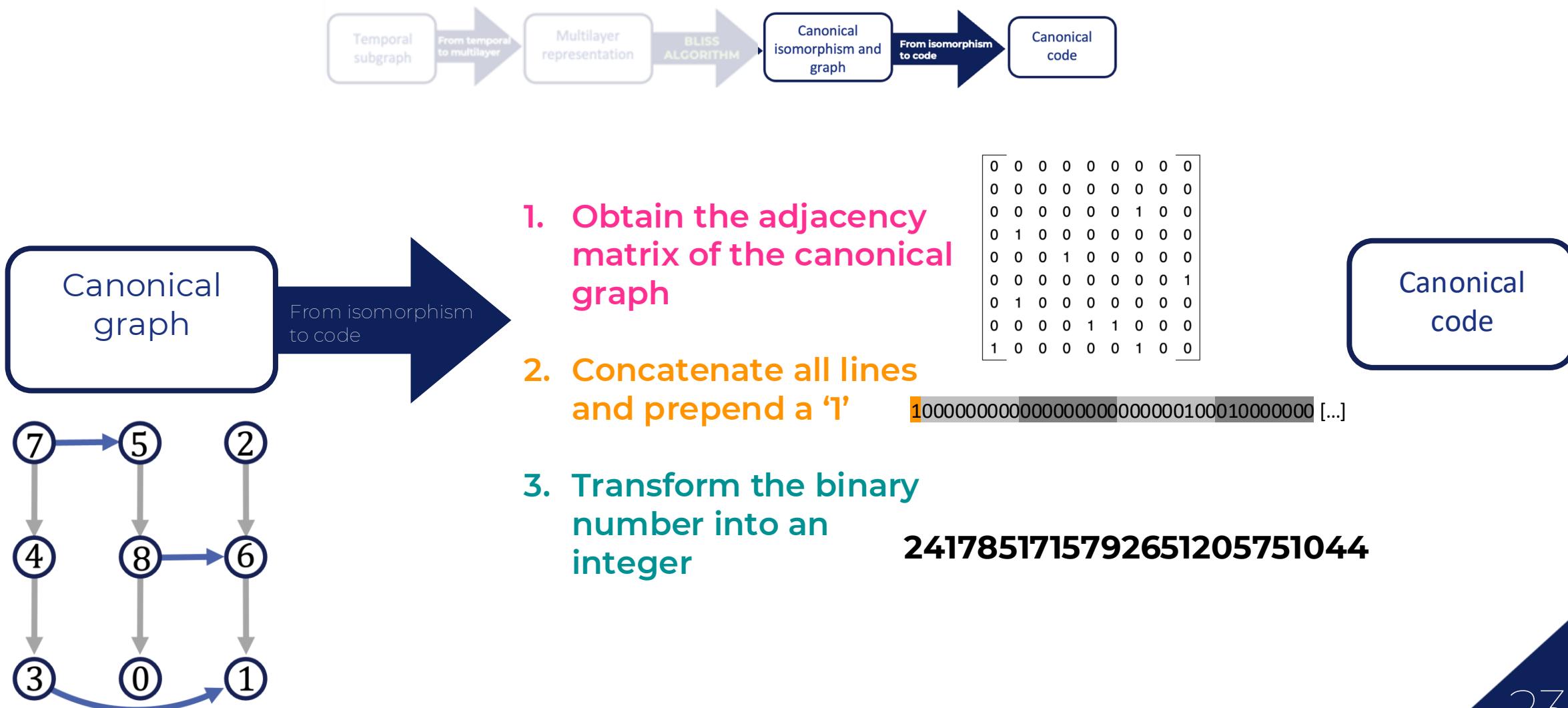
1. Duplicate nodes t times, where $t = \text{number of timestamps}$
2. Remap temporal edges in the correct “layer”
3. Insert pillar edges to ensure the temporal order of the multilayer representation



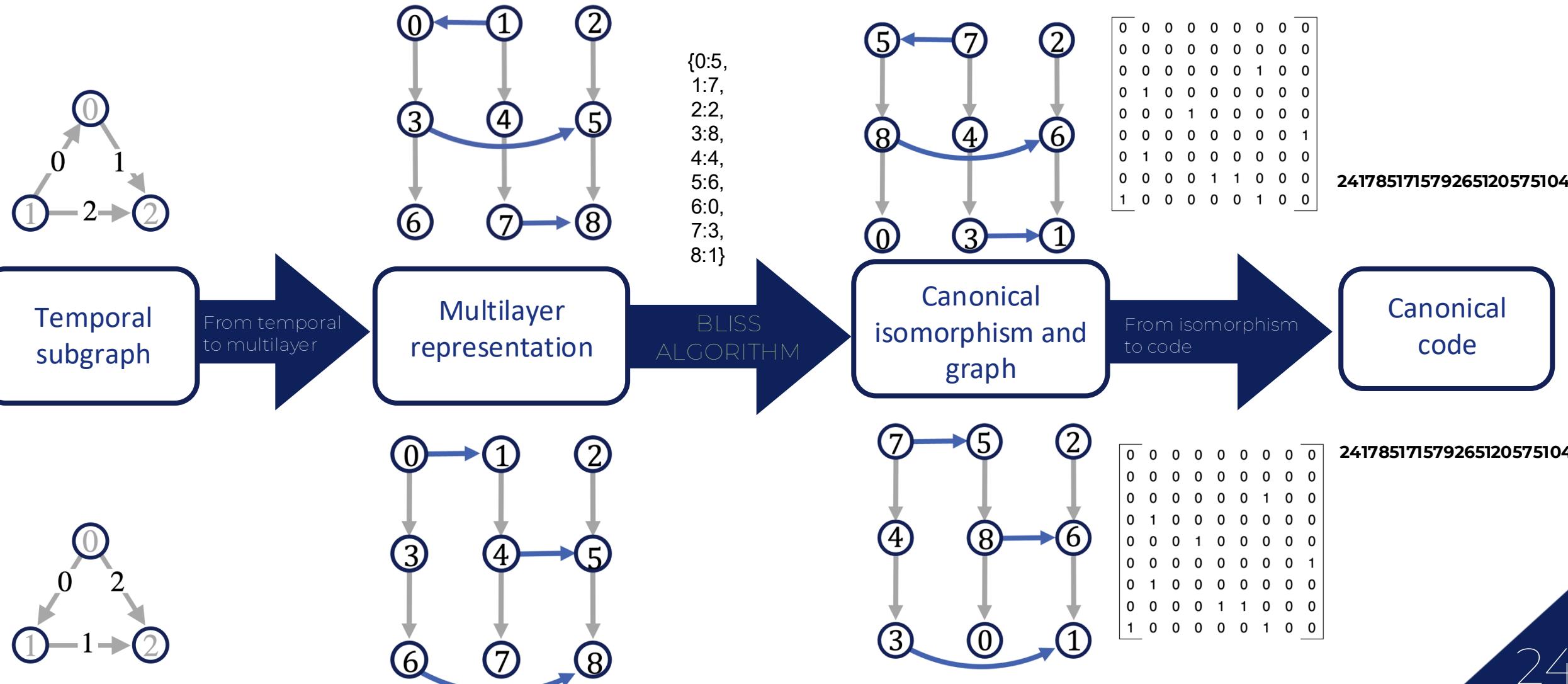
The CANONICAL FORM



The CANONICAL FORM



The CANONICAL FORM

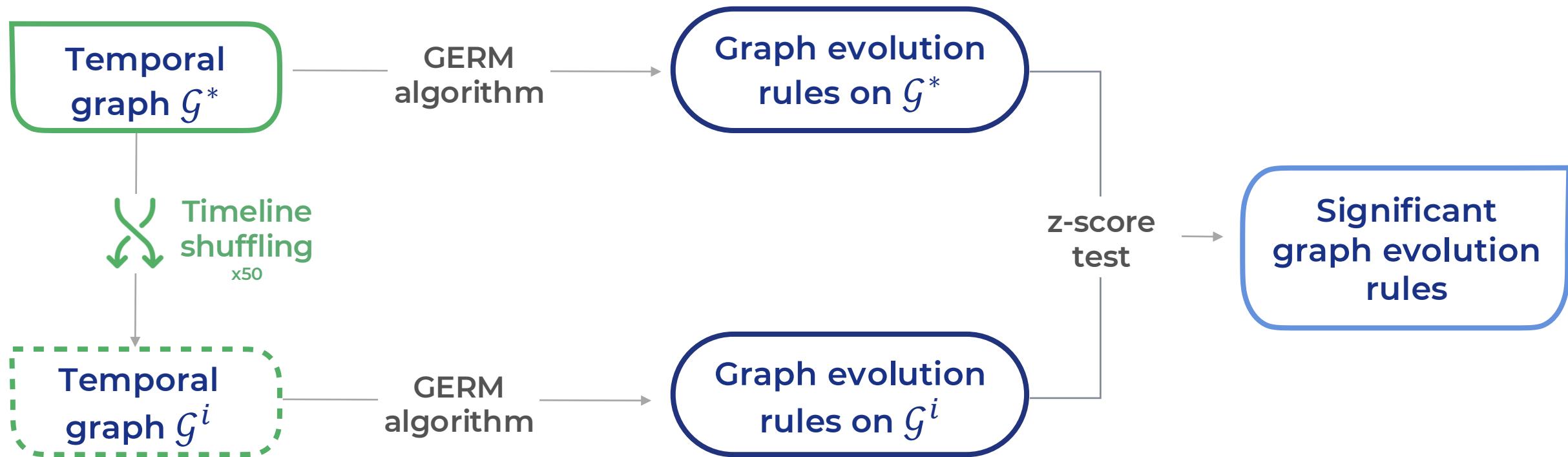


The **NULL MODEL**

WHY?

To evaluate the statistical significance of rules
and therefore find GERs that characterize the
evolution of a specific network

The PIPELINE



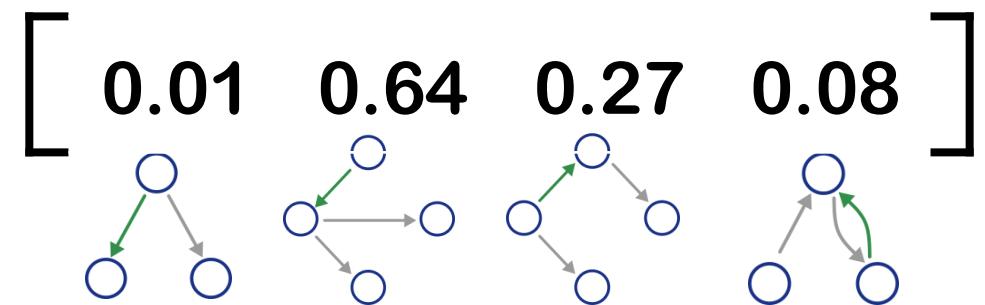
The EVOLUTIONARY PROFILE

WHY?

- To compare networks evolutionary behavior easily
- It represents the final output of the framework

HOW?

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



The **EVOLUTIONARY PROFILE**

Every network has its own **evolution signature**

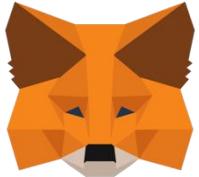
We capture it through an interpretable, quantitative fingerprint

the **network evolution profile**,

a **compact, complete, and explainable** representation

that encodes all the key mechanisms driving

the network's evolution and growth over time.



Some APPLICATIONS



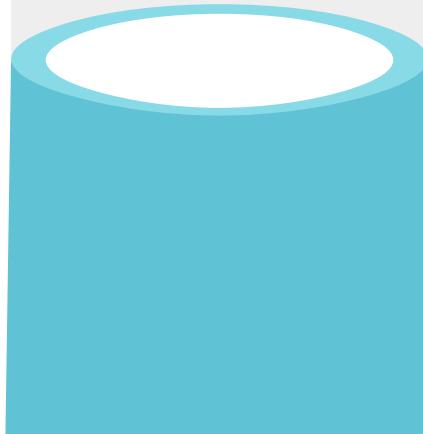
The EVOLUTIONARY PROFILE

DIFFERENT LEVEL OF APPLICATION

GRAPH



Evaluate evolutionary behavior for the whole graph



COMMUNITY



Consider the evolutionary behavior of each community



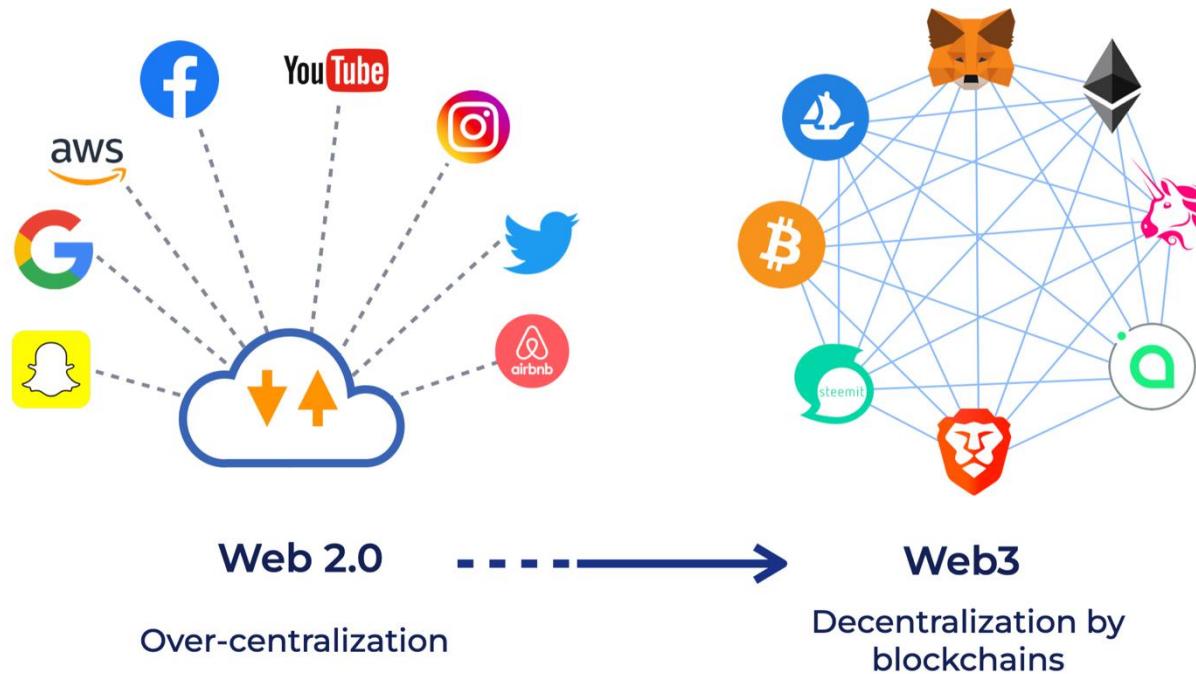
NODE



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



Temporal data: the WEB3



Web3 data

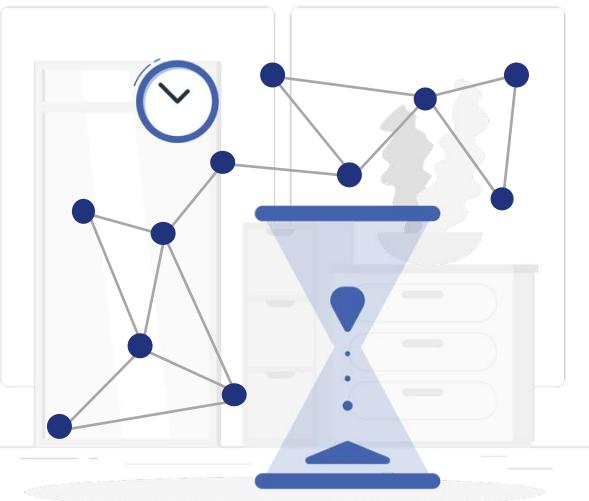
- Huge volume of high resolution data
- Available and affordable by API
- Timestamped and validated
- Heterogeneous interactions

Research
Question

Are Web3 platforms really different from web2 networks?

Temporal networks

CHALLENGES AND DATA SOURCES



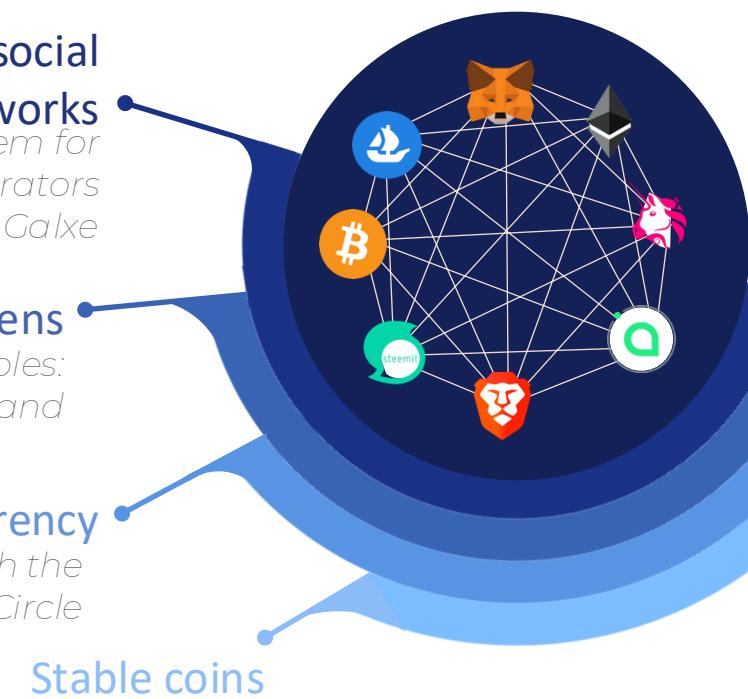
- An interesting but yet not fully explored field, mainly due to the lack of temporal data
- Thanks to the web3 development, we have enough data to develop solid temporal methodologies

WEB3 data

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



UC-social

Messages on a social network at UC Irvine college

N 2k | E 20k

Messages

Stack Overflow

Answers-to-questions interactions on the Stack Exchange website

N 2M | E 13.5M

Comments

Enron

Email communication records among Enron employees

N 32k | E 107k

Email

Bitcoin Alpha

Expression of trust on the Bitcoin Alpha platform

N 3.6k | E 22.6k

Trust

Sarafu

Complementary currency exchange within the Sarafu project

N 40k | E 143k

Financial

Cryptokitties

NFT exchanges on the Cryptokitties marketplace

N 100k | E 725k

NFT

Opensea

NFT exchanges on the Opensea marketplace

N 214k | E 962k

NFT

Vote

Voting to posts or comment

N 758k
E 109M MultiE 590M

Transfer

Cryptocurrency exchange on the Blockchain-based social network
Steemit

N 474k
E 4M MultiE 59.4M



Follow

Cryptocurrency exchange on the Blockchain-based social network
Steemit

N 1.4M
E 117M MultiE 136M

Comment

Comments on Steemit to posts or other comments (Reddit like)

N 625k
E 20M MultiE 70M

Citation

Citation network from the Digital Bibliography & Library Project (DBLP)

N 12k | E 47.6k



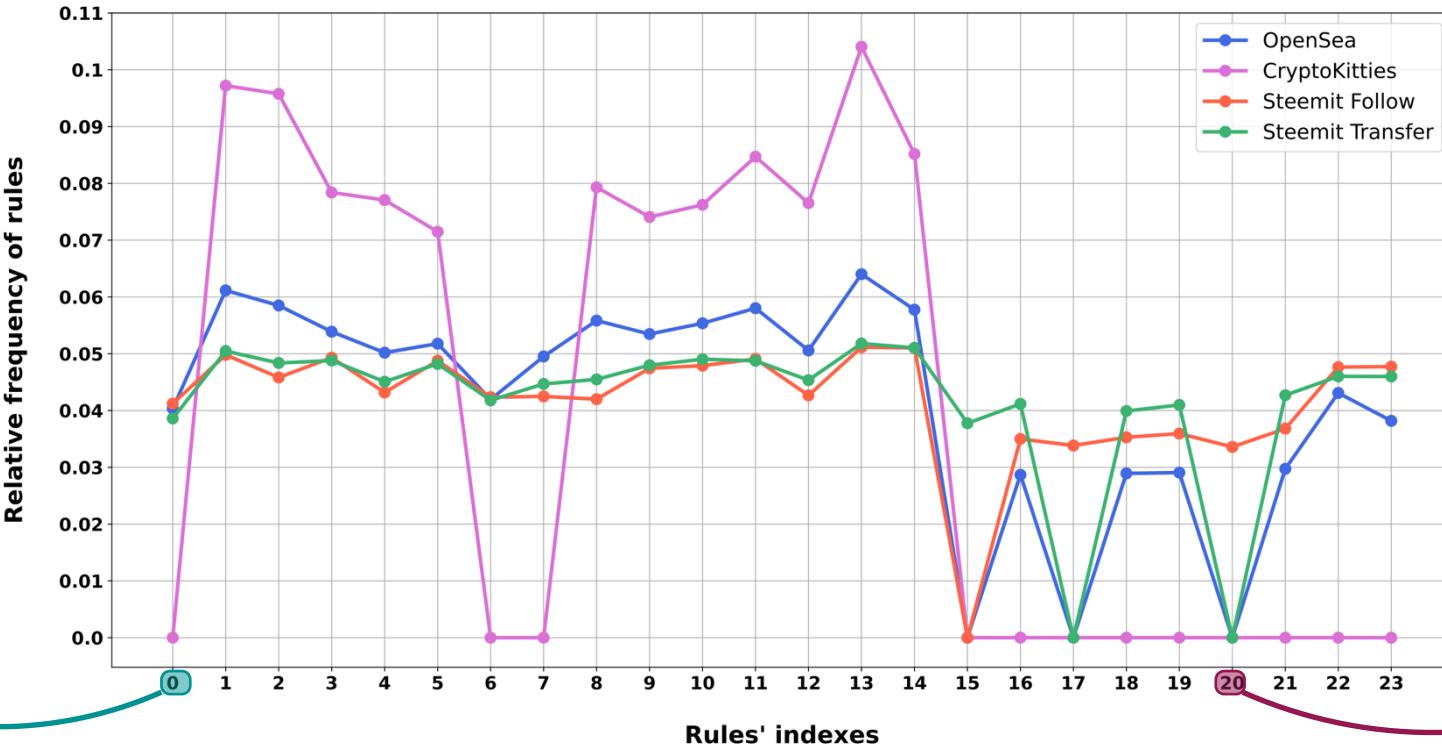
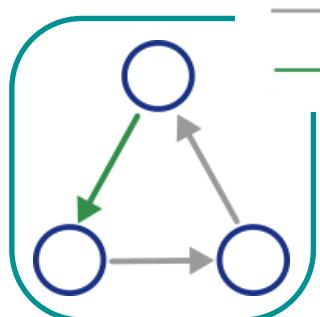
Collaboration

Co-authorship network from the Digital Bibliography & Library Project (DBLP)

N 129k | E 277k

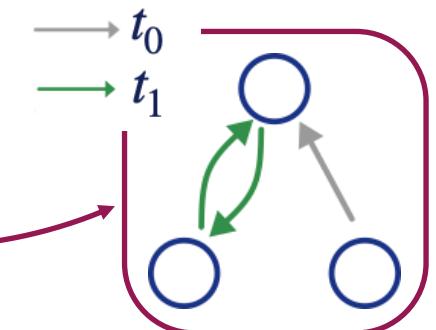
Graph LEVEL

Not in the frequent GER set for the cryptokitties market



Both cases are explainable with the nature of the network itself

Frequent only in Steemit follow (the only social network)



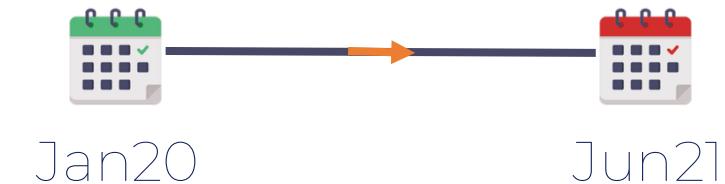
Node LEVEL

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



How do single nodes evolve in this humanitarian context?

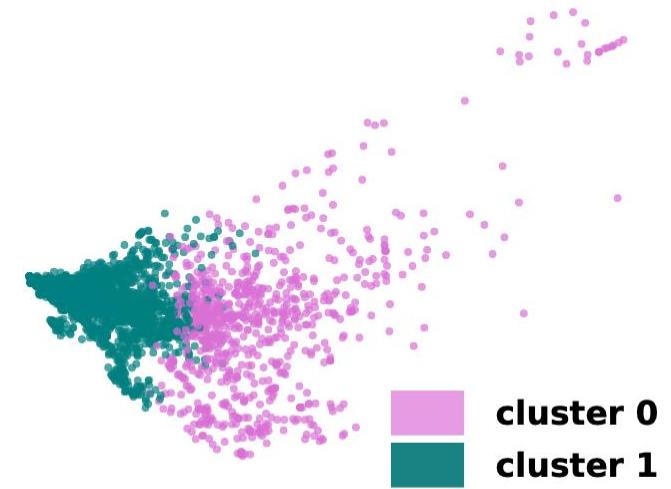
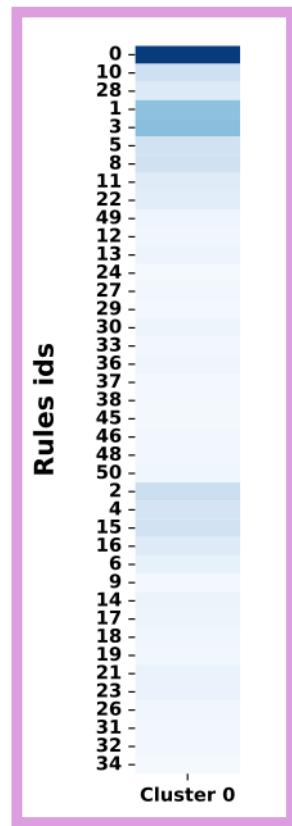
Node LEVEL

3 207

Ego Networks with
consecutive timestamps
and at least 116 edges

40

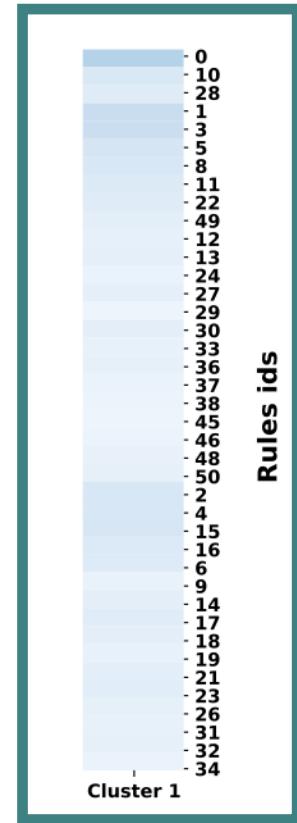
distinct graph
evolution rules
found



2

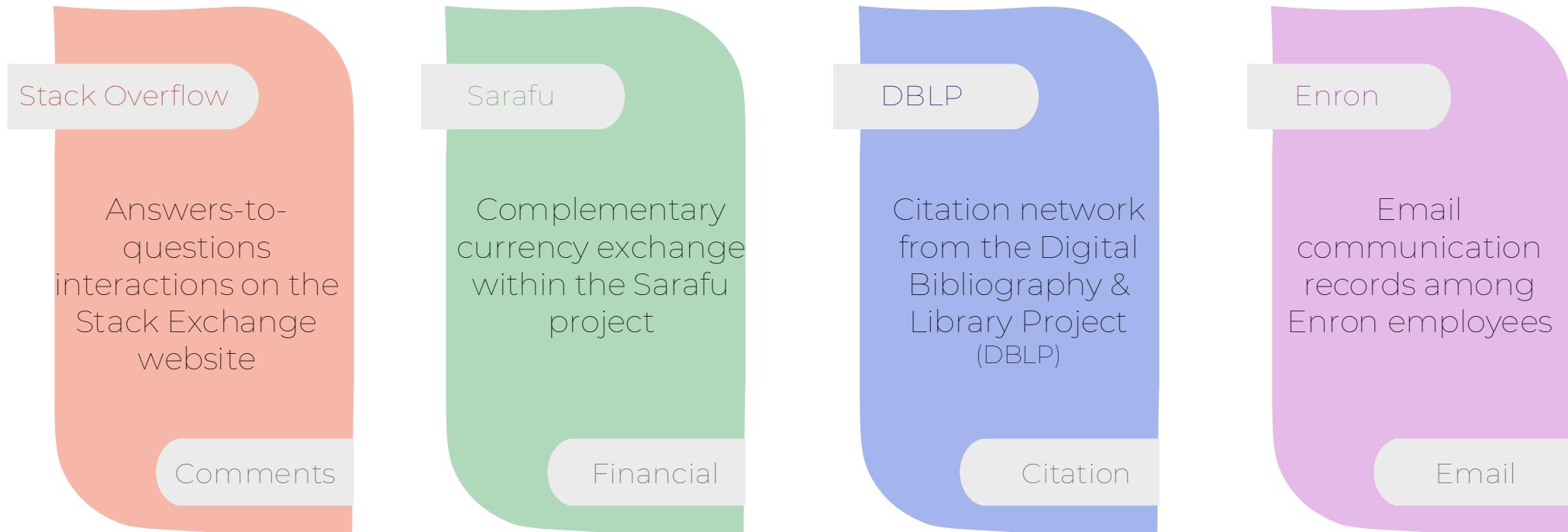
distinct
evolutionary
behaviors

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



Community LEVEL

CASE STUDIES

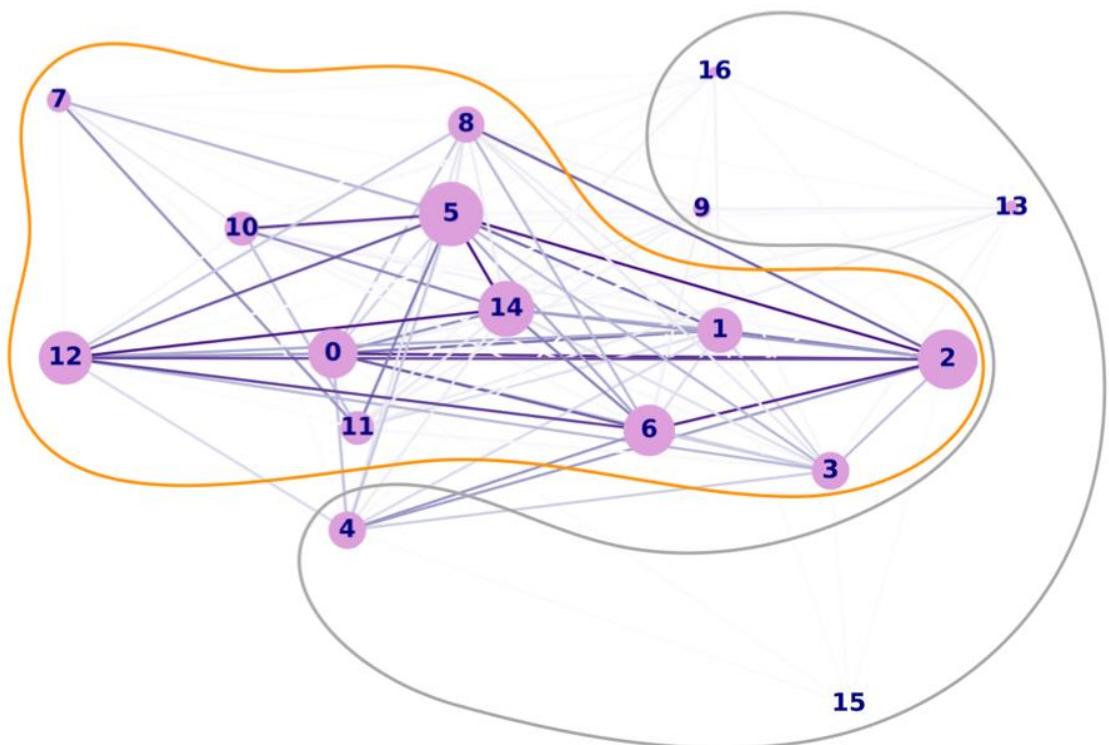


Do close communities also share similar evolutionary profile?

Community LEVEL

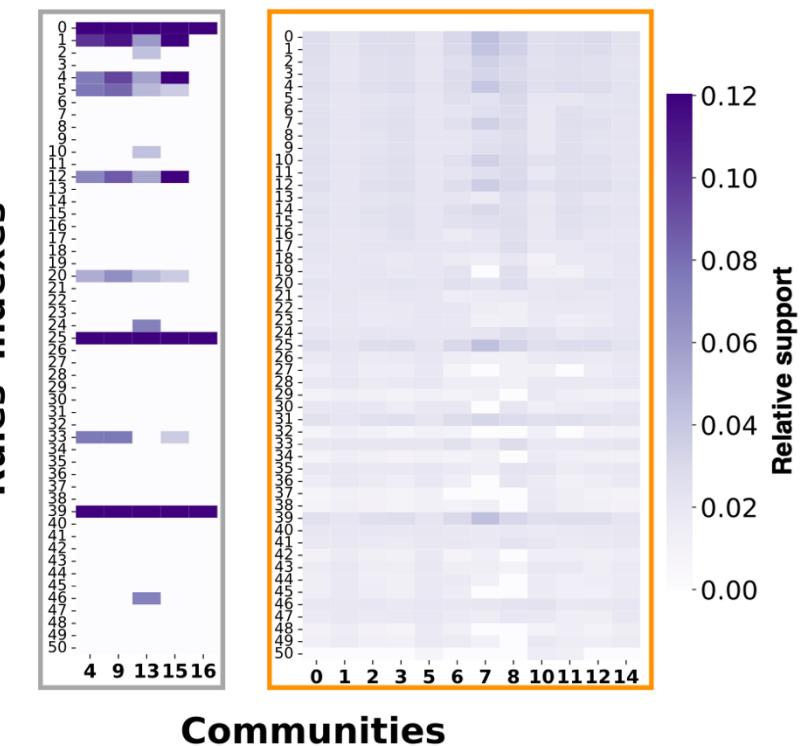
ENRON EXAMPLE

The community graph, where each node represents a community, so a group of nodes, and links between communities are weighted based on the number of edges between them in the original graph.



The position of the communities in the graph relates with the evolutionary profile

The evolutionary profiles represented as an heat map, each column is a evolutionary profile and rows are rules.



Two groups of profiles that correspond to the more central group of connected communities and the more isolated one.



Tulip GER

CASE STUDIES

UC-social

Messages on a social network at UC Irvine college

Messages

Sarafu

Complementary currency exchange within the Sarafu project

Financial

Steemit

Cryptocurrency exchange on the Blockchain-based social network

Steemit

Financial

Cryptokitties

NFT exchanges on the Cryptokitties marketplace

NFT

Bitcoin Alpha

Expression of trust on the Bitcoin Alpha platform

Trust

FUTURE RESEARCH: NETWORK SCIENCE MEETS AI IN GRAPH EVOLUTION RULES

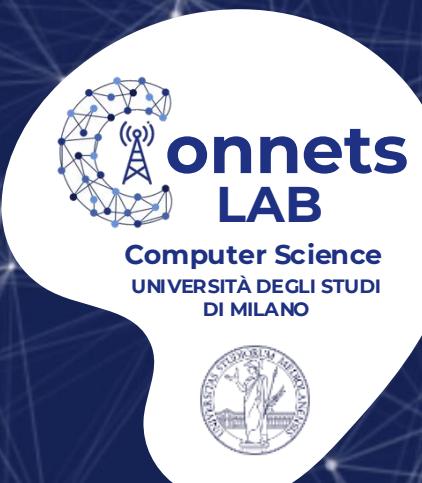


Machine learning general frameworks for temporal heterogeneous graphs: predictive methods, interpretability, applications, benchmarks

PhD Thesis: Manuel Dileo

Supervisor: Matteo Zignani

Co-supervisor: Sabrina Gaito



ML on Temporal Heterogeneous Networks

CHALLENGES

Predictive methods: Lack of an unified framework to handle temporal, heterogeneous, and multimodal information on graphs.

Interpretability: Lack of proper baselines, which makes difficult to argue that we are making progress. Lack of explainability methods and benchmarks.

Datasets and applications: Lack of standard benchmarks, scarcity of datasets across diverse domains (mainly event networks).

DIFTHE: A discrete-time deep learning framework for temporal heterogeneous networks forecasting

Key idea: design the computation over temporal heterogeneous graphs with several modules

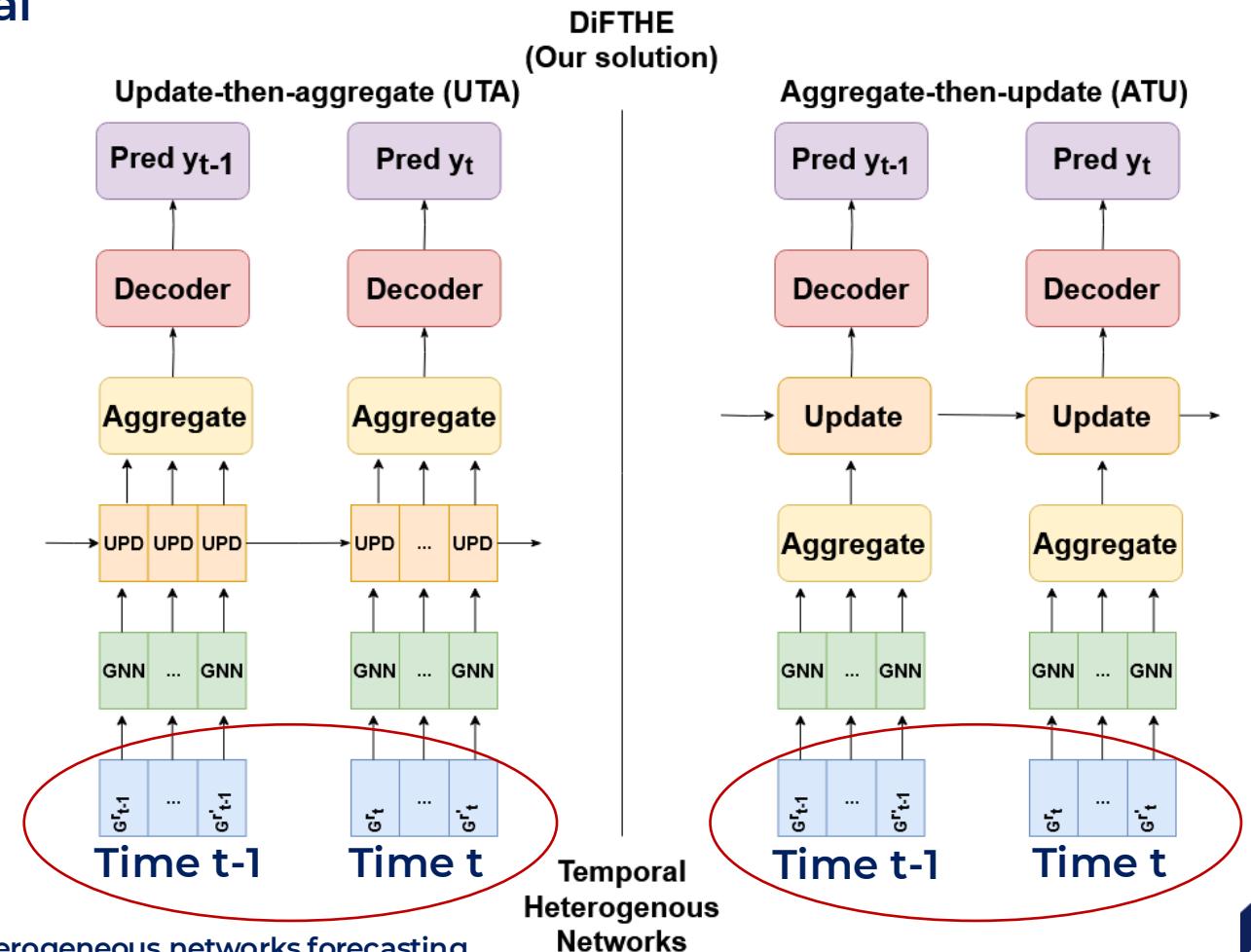
Decoder: solves a downstream task (e.g. link prediction, node classification)

Semantic aggregation: aggregates the embeddings over different relation types

Temporal update: Receives in input past and current node embeddings and produce new current node embeddings

Topology: A GNN for each relation type

Input: heterogeneous graph snapshots



Future Research: ML Integration

Integrating GER in GNN

NETWORK
GENERATION

Heterogeneous
temporal graphs

Learning GER in
heterogeneous
temporal graphs

Difthe framework

GER EMBEDDING

Explainability

Anomaly detection

Integrating GER in
anomaly detection ML
algorithim

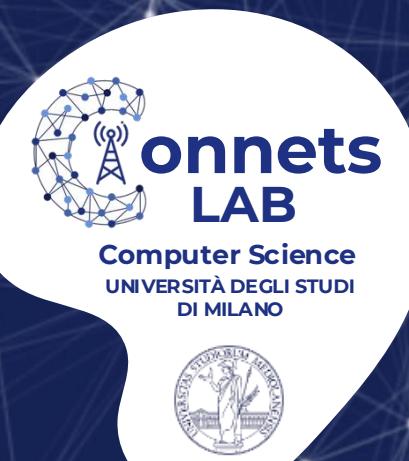
Use rules to
generate
synthetic networks

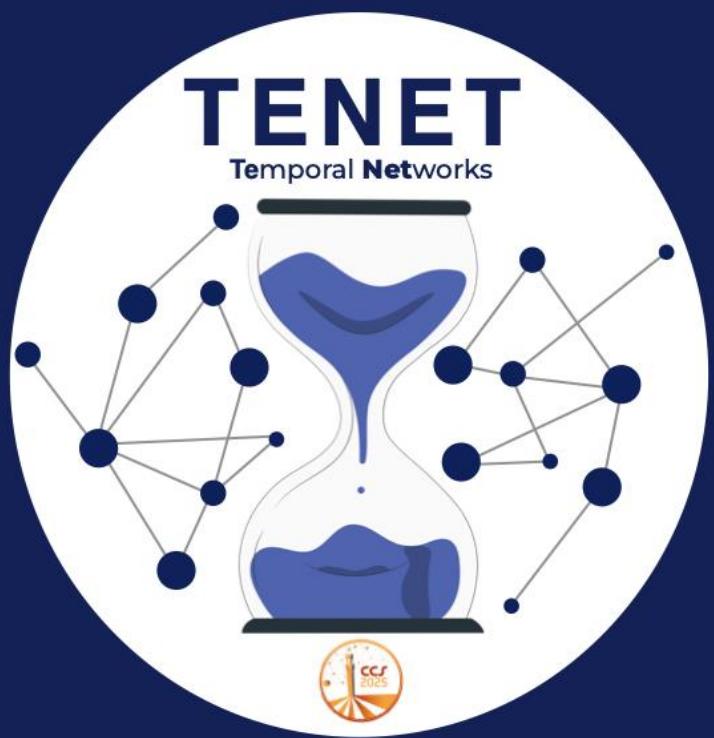
Some recent initiatives

On

Temporal/Evolutionary

Networks





Submissions
deadline:
2nd March



Satellite in conjunction with

***International School and
Conference on Network Science
2026***

**June 1-5, 2026
Boston (US)**

CCS25 <https://sites.google.com/view/tenet-ccs25/home>

-Netsci25 <https://netsci2025.github.io>

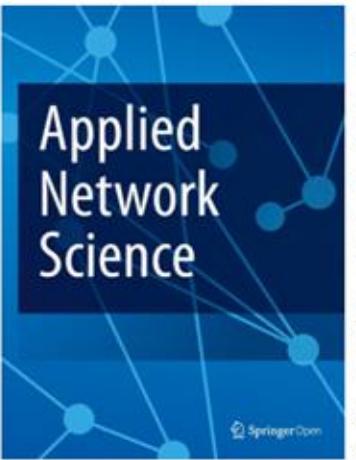


Consider submitting your work here!



Call for Papers

Evolution of Networks



The study of network evolution represents a critical frontier in understanding complex systems across diverse domains, from social networks and biological systems to financial and transport networks. As networks constantly adapt and transform over time, understanding their evolutionary patterns and underlying mechanisms has become increasingly crucial for both theoretical advancement and practical applications. This topical collection seeks contributions that explore the dynamic nature of networks from multiple perspectives. We encourage interdisciplinary approaches that bridge multiple domains or methodologies, as well as both theoretical contributions and applied research that advance our understanding of network evolution. The peer-review process will begin as soon as submissions are received, not after the submission deadline, ensuring timely feedback.

Springer.com

Applied Network Science



NETS-AI

The convergence of Networks Science and AI

HONAI 2025: Higher-Order Networks meets AI @ NetSci25 //

[https://hons-web.github.io/online/index.html //](https://hons-web.github.io/online/index.html)

Network Science meets AI

Special session of the 33th European Symposium on Artificial Neural Networks,
Computational Intelligence and Machine Learning (ESANN)

<https://sites.google.com/view/esann-netsai/home>

Special issue on Applied Network Science: **Bridging Network Science and AI**

<https://link.springer.com/collections/hafcebgfci>



THANKS FOR YOUR ATTENTION