Neighbourhood matching creates realistic surrogate temporal networks

Antonio Longa, Giulia Cencetti, Sune Lehmann, Andrea Passerini, Bruno Lepri

Who am I?

- Antonio Longa
- PhD student at the Fondazione Bruno Kessler and University of Trento (Italy).

Table of contents

Network:

A network **G** is a pair of sets **G**=(**N**,**E**). Where **N** is a set of nodes and **E** is a set of edges (couple of nodes).

Network:

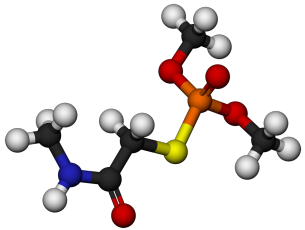
A network **G** is a pair of sets **G**=(**N**,**E**). Where **N** is a set of nodes and **E** is a set of edges (couple of nodes).

Social networks

Network:

A network **G** is a pair of sets **G**=(**N**,**E**). Where **N** is a set of nodes and **E** is a set of edges (couple of nodes).

Social networks

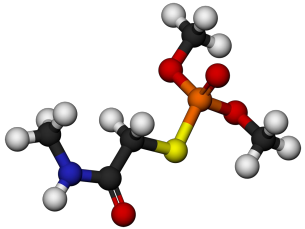


Moleculas

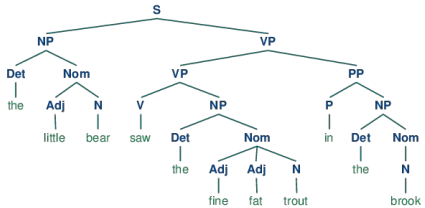
Network:

A network **G** is a pair of sets **G**=(**N**,**E**). Where **N** is a set of nodes and **E** is a set of edges (couple of nodes).

Social networks



Moleculas

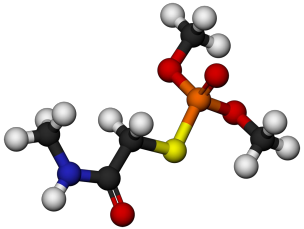


Sentence

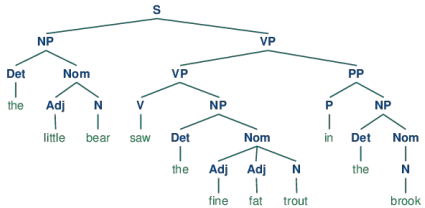
Network:

A network **G** is a pair of sets **G**=(**N**,**E**). Where **N** is a set of nodes and **E** is a set of edges (couple of nodes).

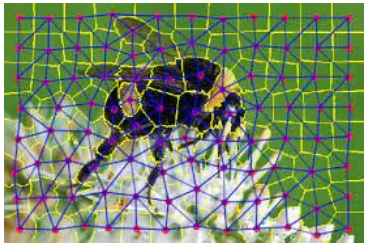
Social networks



Moleculas



Sentence



Images

Temporal network:

Many times networks are not enough to represent real world scenarios.

Interactions change over time...
Images could be videos...
Traffic on roads change...

So temporal networks solve this problem

Temporal network:

Many times networks are not enough to represent real world scenarios.

Interactions change over time...
Images could be videos...
Traffic on roads change...

So temporal networks solve this problem

We can represent temporal graphs as an **ordered sequence** of static graphs.

Temporal network:

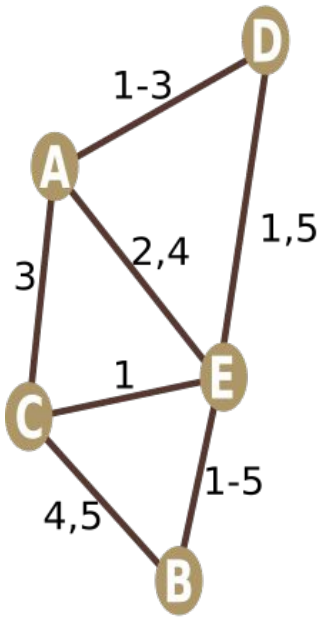
Many times networks are not enough to represent real world scenarios.

Interactions change over time...
Images could be videos...
Traffic on roads change...

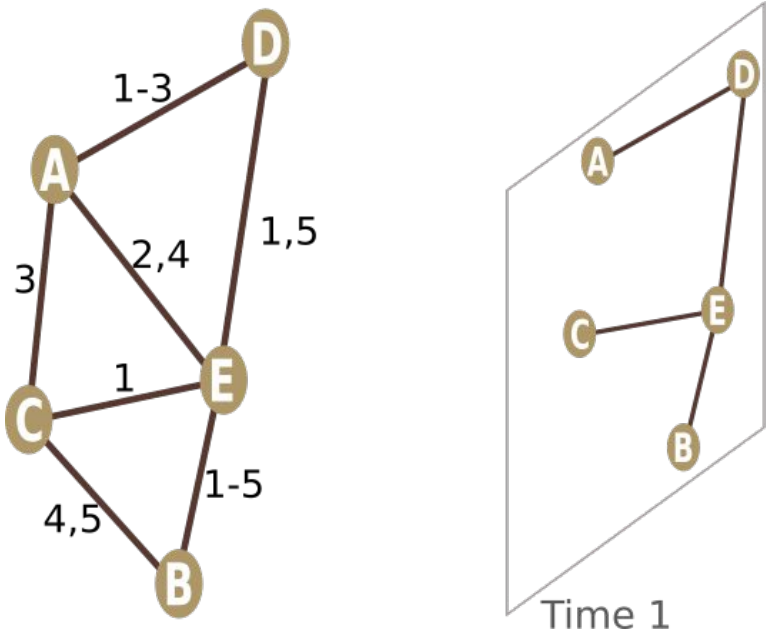
So temporal networks solve this problem

We can represent temporal graphs as an **ordered sequence** of static graphs.

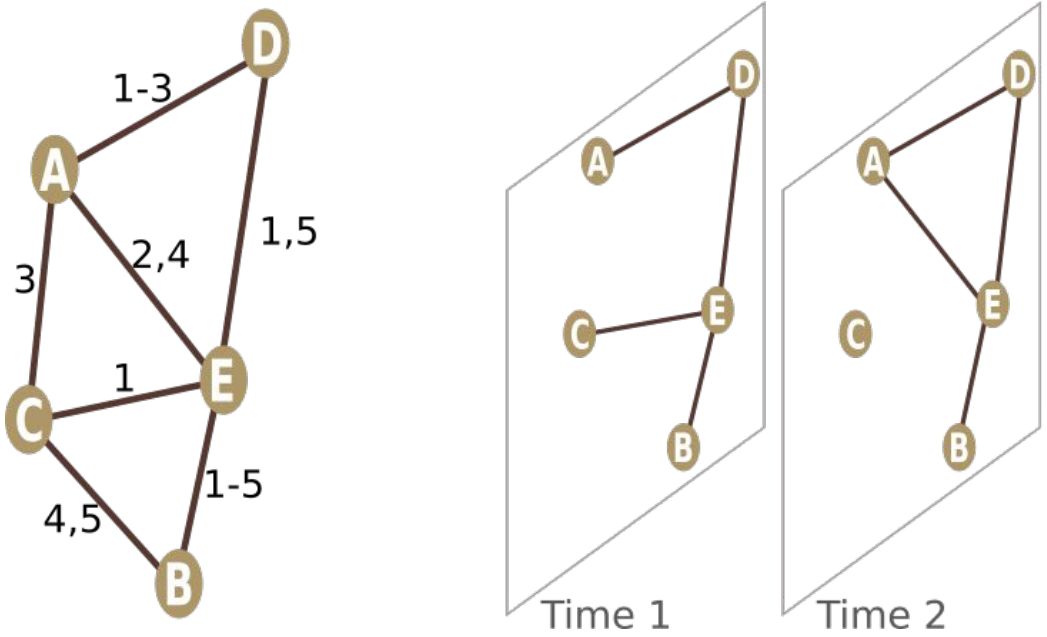
Neighbourhood matching creates realistic surrogate temporal networks



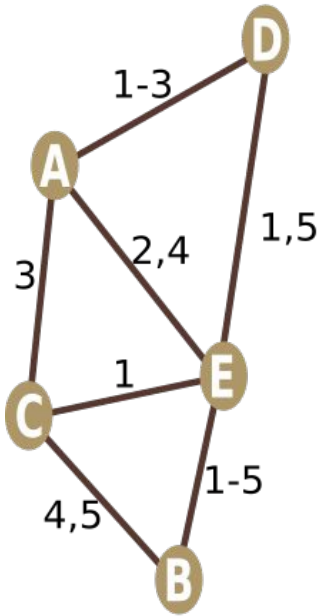
Neighbourhood matching creates realistic surrogate temporal networks

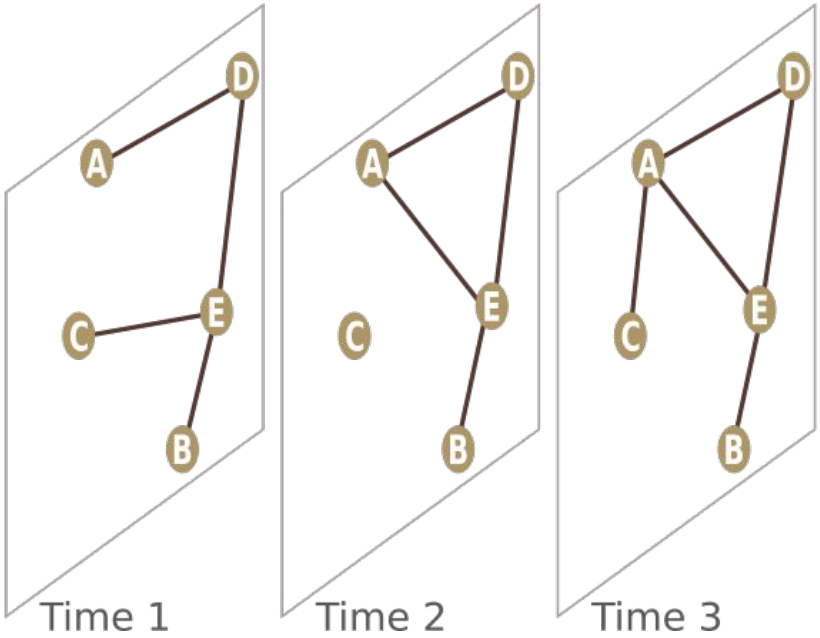


Neighbourhood matching creates realistic surrogate temporal networks

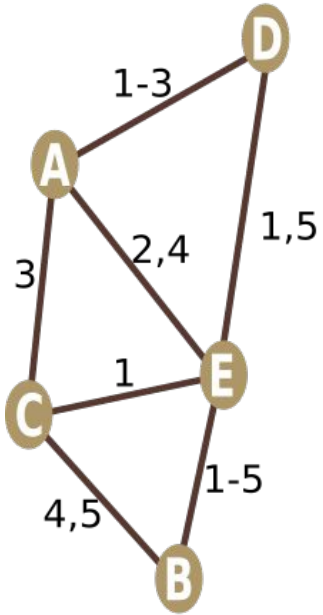


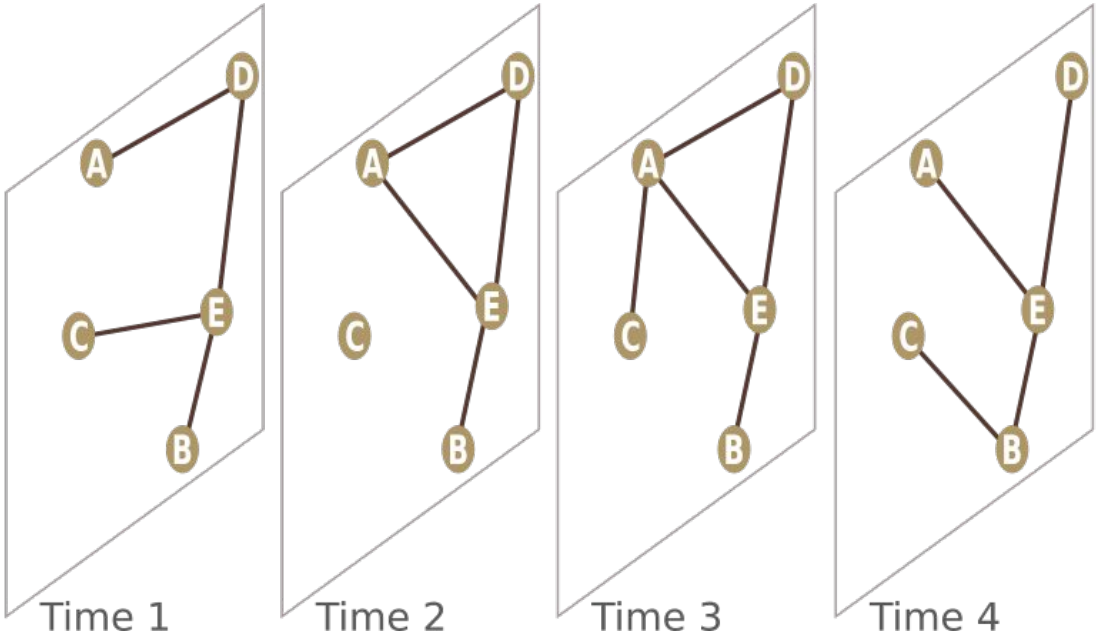
Neighbourhood matching creates realistic surrogate temporal networks





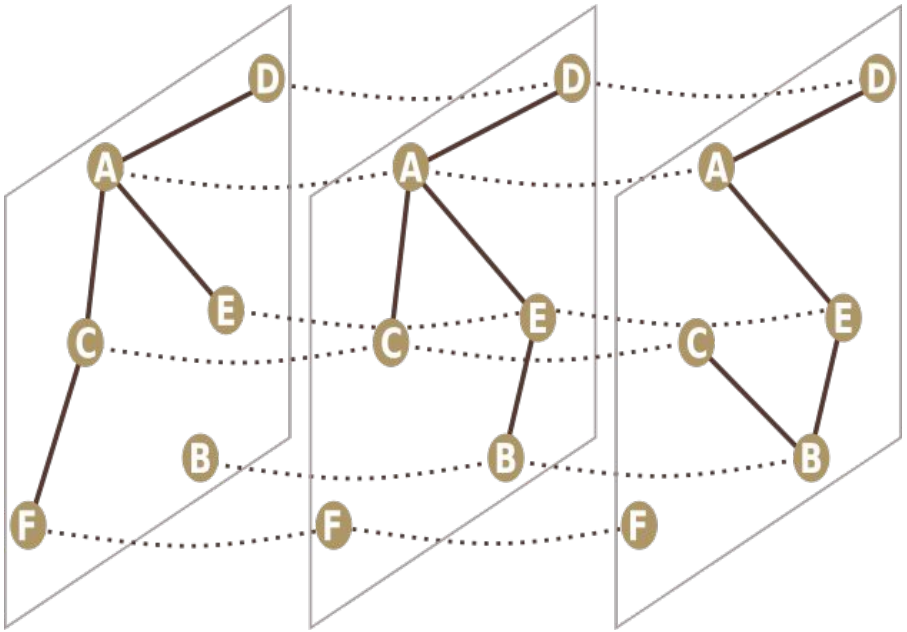
Neighbourhood matching creates realistic surrogate temporal networks



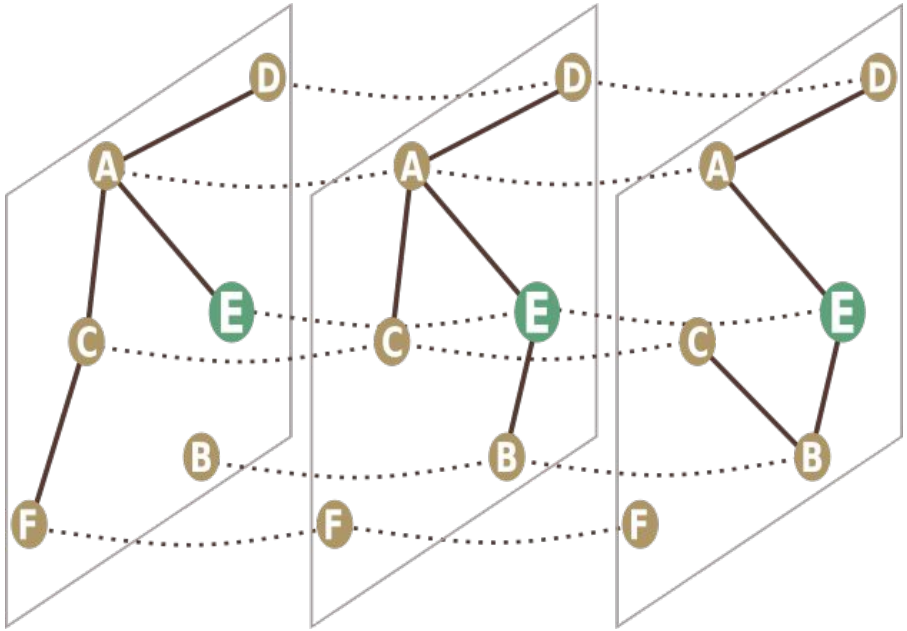


ETN

k = 2

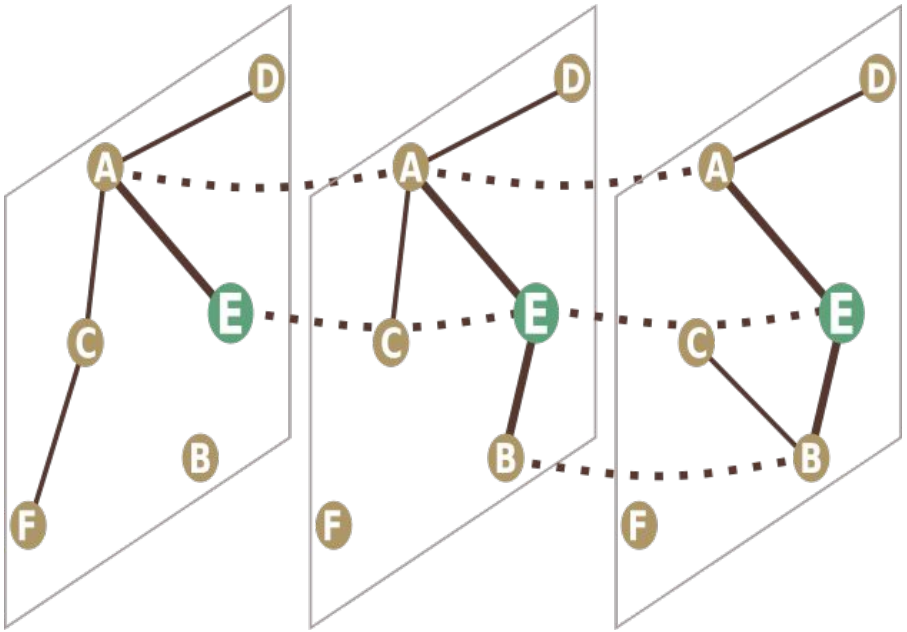


ETN



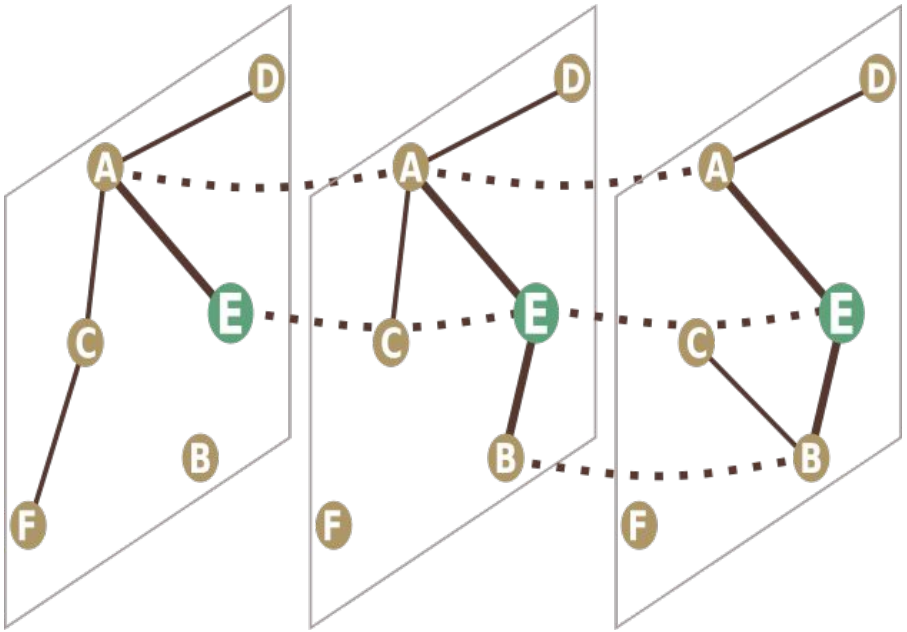
k = 2
ego node = E

ETN



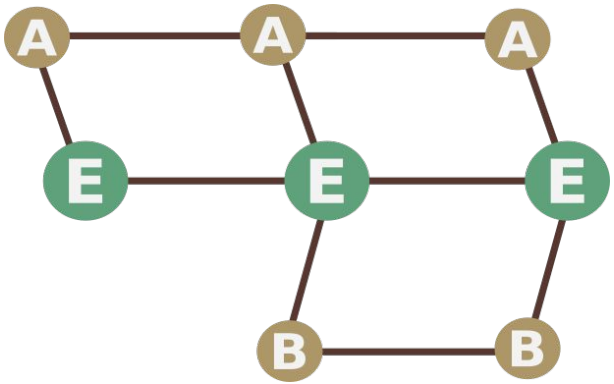
k = 2
ego node = E

ETN

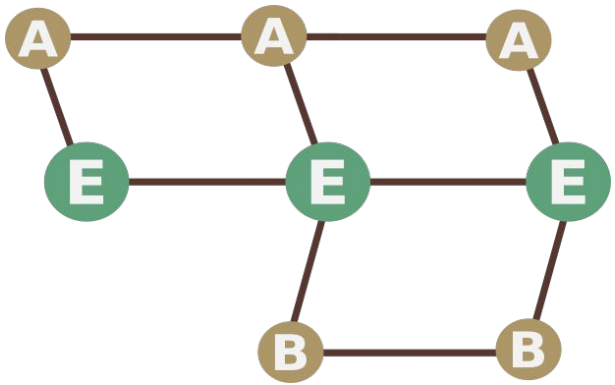


k = 2
ego node = E

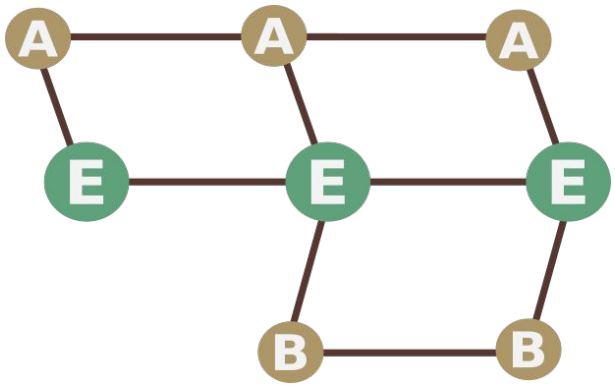
ETN



Egocentric Temporal Neighbourhood Signature (ETNS)



Egocentric Temporal Neighbourhood Signature (ETNS)

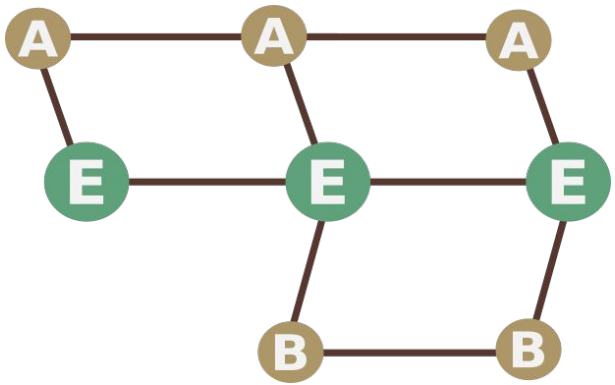


NODE ENCODING

A → 111

B → 011

Egocentric Temporal Neighbourhood Signature (ETNS)



NODE ENCODING

A → 111

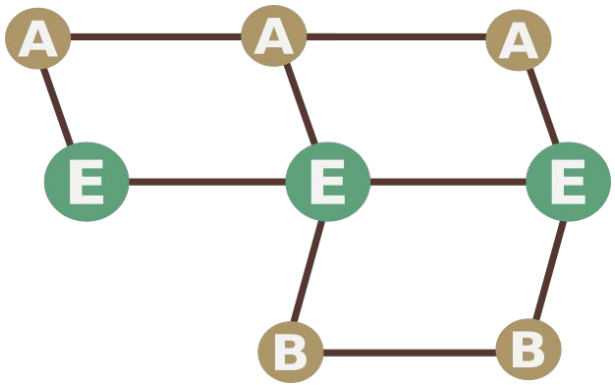
B → 011

SORTED NODE ENCODING

B A

011 111

Egocentric Temporal Neighbourhood Signature (ETNS)



NODE ENCODING

A → 111

B → 011

SORTED NODE ENCODING

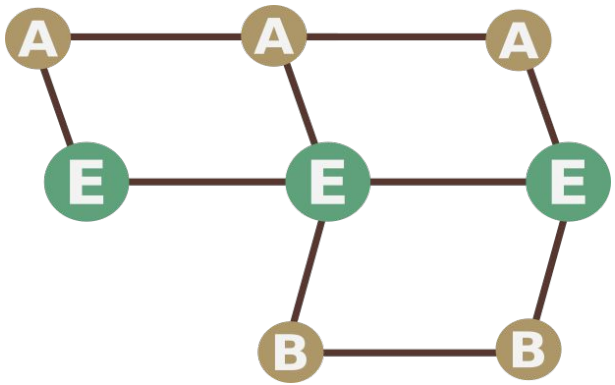
B A

011 111

Egocentric Temporal Neighbourhood Signature
ETNS

011 111

Egocentric Temporal Neighbourhood Signature (ETNS)



NODE ENCODING

A → 111

B → 011

SORTED NODE ENCODING

B A

011 111

Egocentric Temporal Neighbourhood Signature
ETNS

011 111

Complexity:

d = maximum degree of the graph

k = number of temporal snapshots - 1

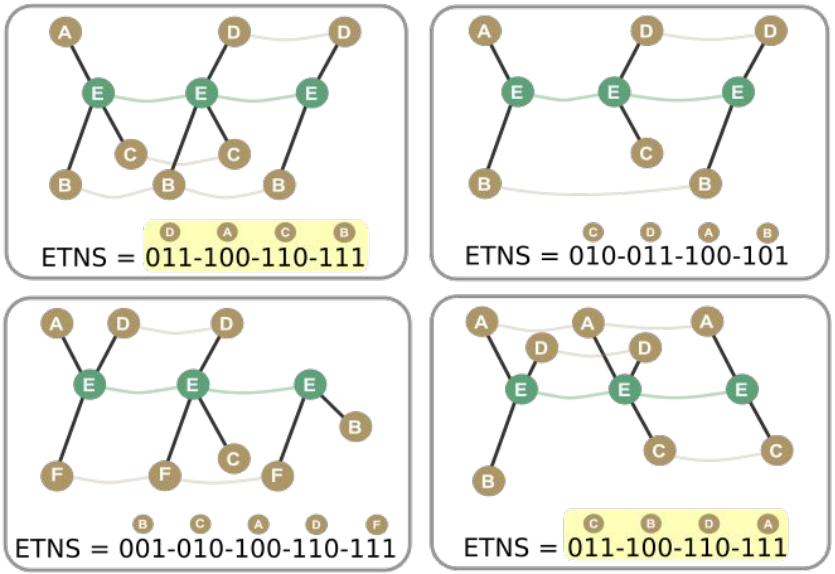
$$O(d^k \log d^k)$$

Springer Link

Open Access | Published: 12 November 2021

An efficient procedure for mining egocentric temporal motifs

Antonio Longa ✉, Giulia Cencetti, Bruno Lepri & Andrea Passerini

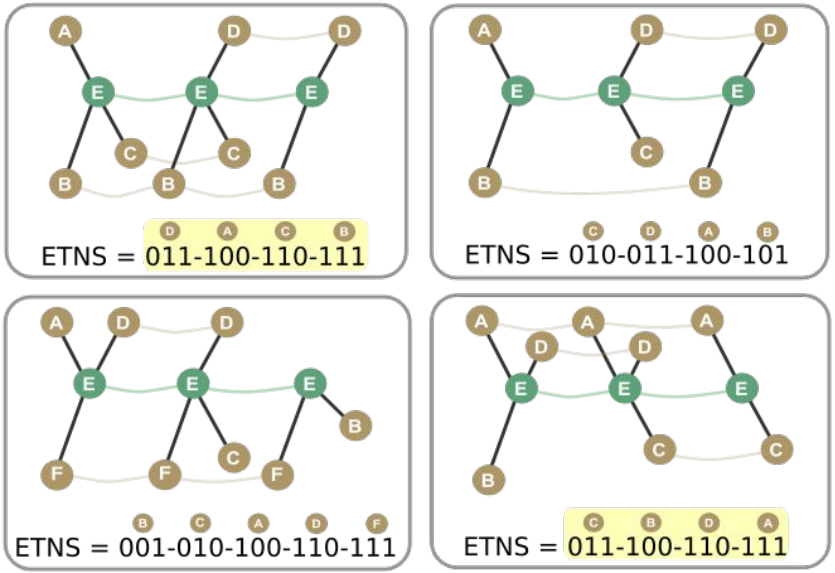


Springer Link

Open Access | Published: 12 November 2021

An efficient procedure for mining egocentric temporal motifs

Antonio Longa, Giulia Cencetti, Bruno Lepri & Andrea Passerini



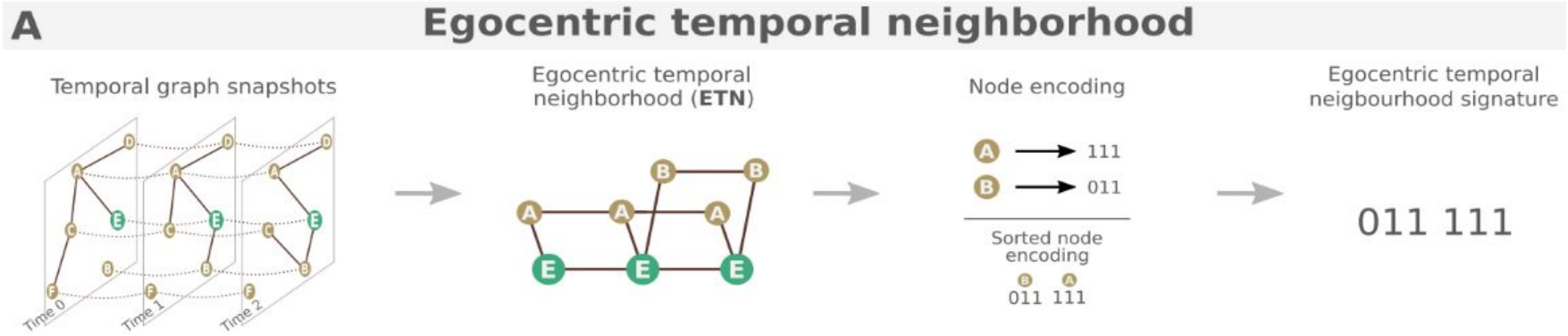
	Office	Hospital	High School 1	High School 2	High School 3	Primary School	University
Office	0	0.07	0.29	0.22	0.29	0.67	0.47
Hospital		0	0.29	0.22	0.30	0.66	0.45
High School 1			0	0.04	0.04	0.59	0.06
High School 2				0	0.02	0.61	0.13
High School 3					0	0.62	0.08
Primary School						0	0.62
University							0

Pairwise distance between different environments according to the most significant Egocentric Temporal Networks

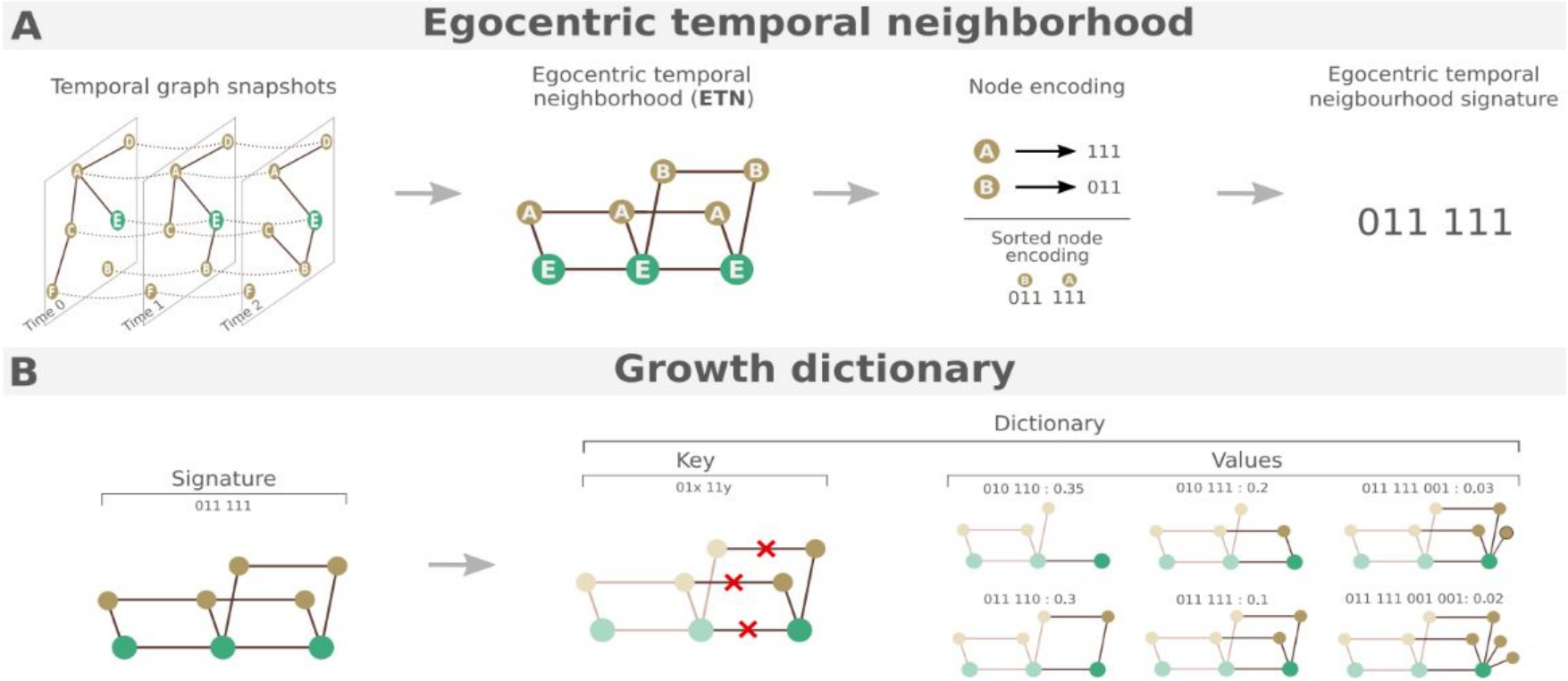
How to use ETN?

We can generate a new temporal network!

Recipe for generating a synthetic network

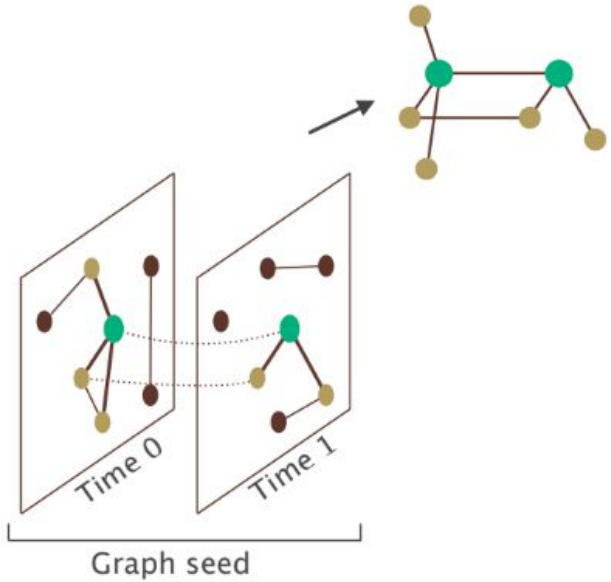


Recipe for generating a synthetic network

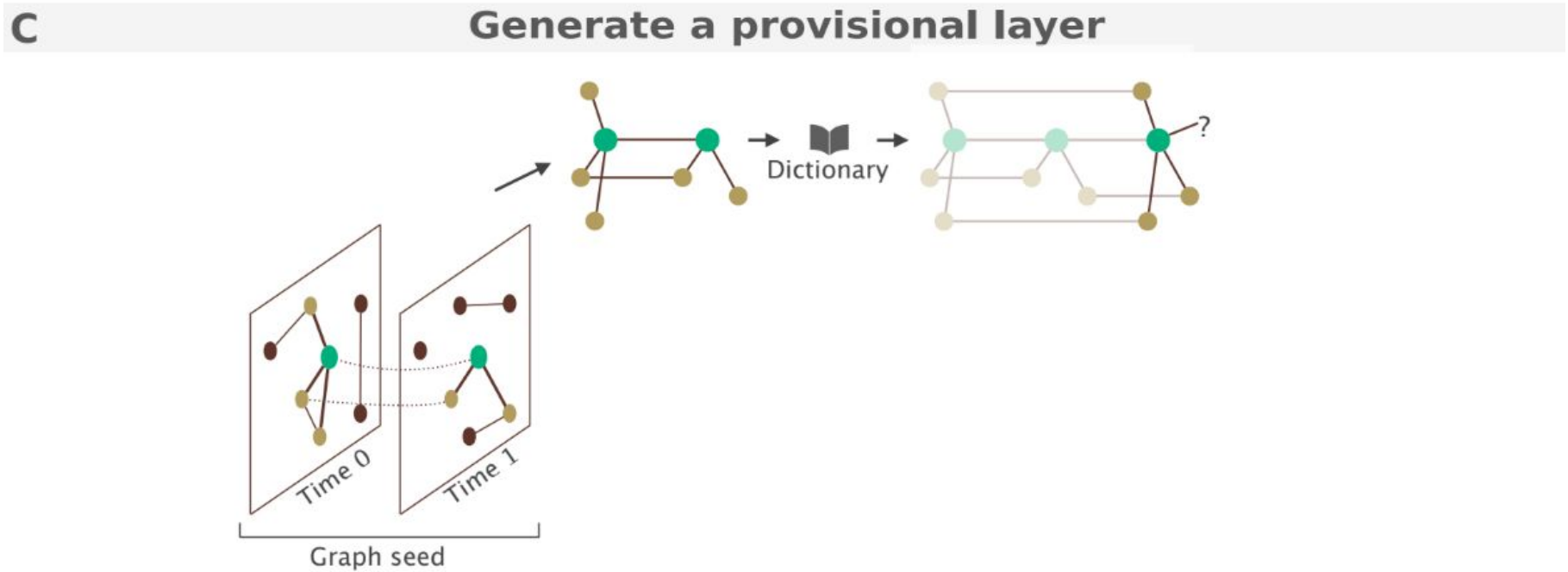


Recipe for generating a synthetic network

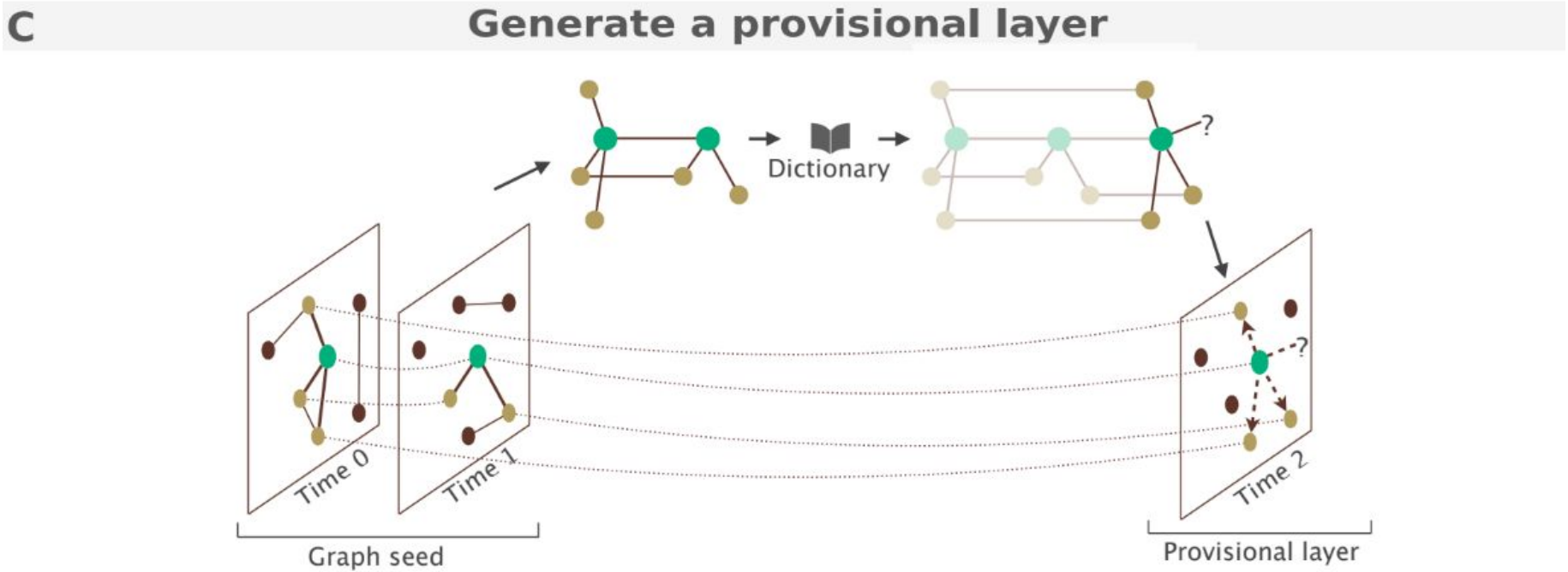
C **Generate a provisional layer**



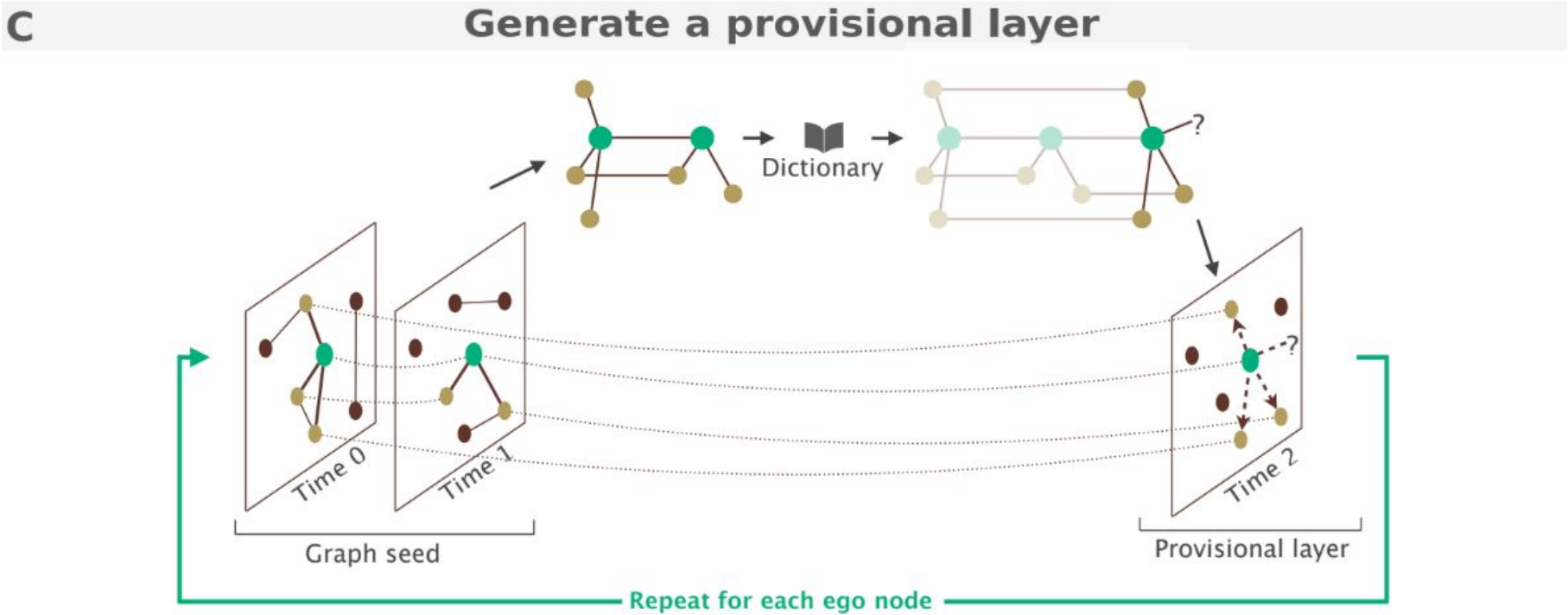
Recipe for generating a synthetic network



Recipe for generating a synthetic network

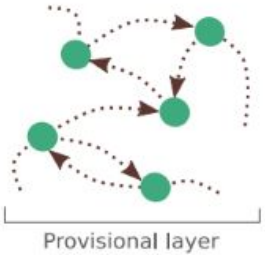


Recipe for generating a synthetic network

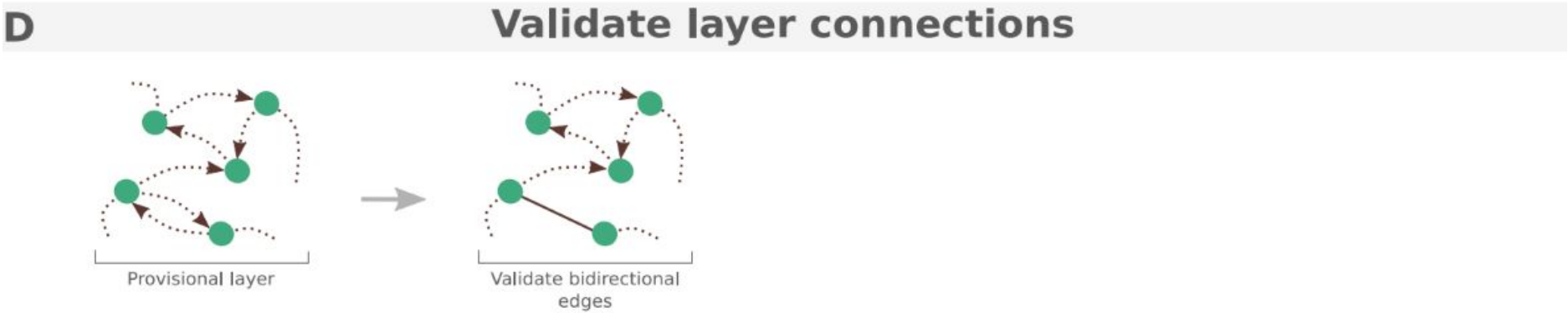


Recipe for generating a synthetic network

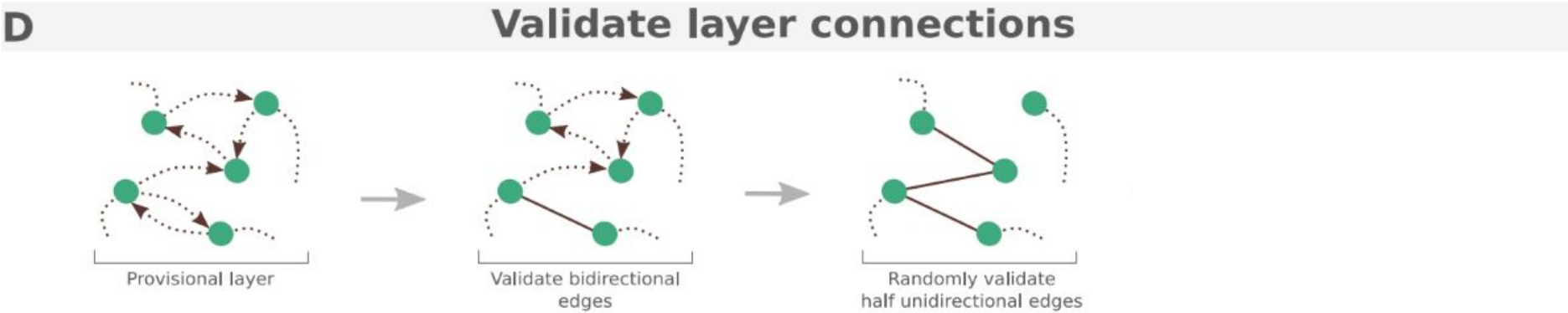
D **Validate layer connections**



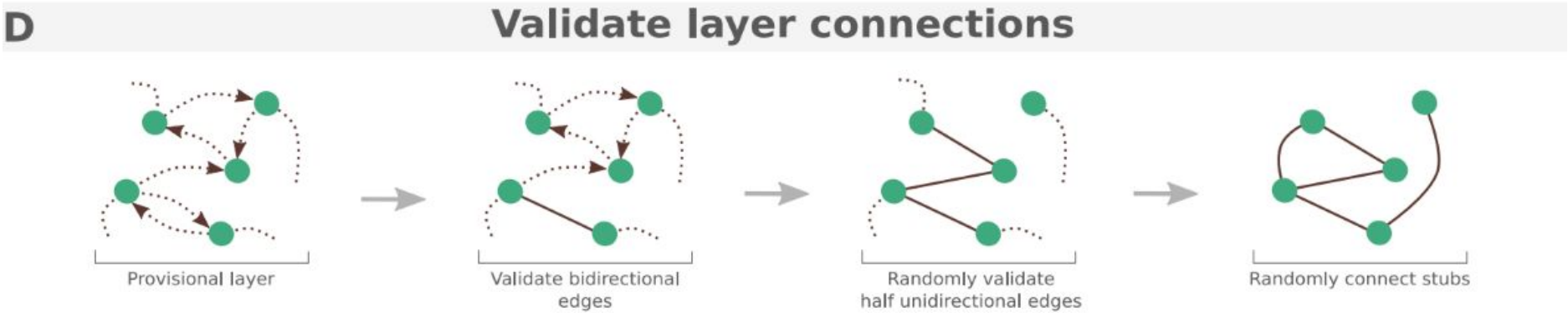
Recipe for generating a synthetic network



Recipe for generating a synthetic network



Recipe for generating a synthetic network



Competitors

STM (Structural Temporal Modeling), based on temporal motifs.

[Purohit, Holder, Chin. Temporal graph generation based on a distribution of temporal motifs. Proceedings of the 14th International Workshop on Mining and Learning with *Graphs*, volume 7, 2018.]

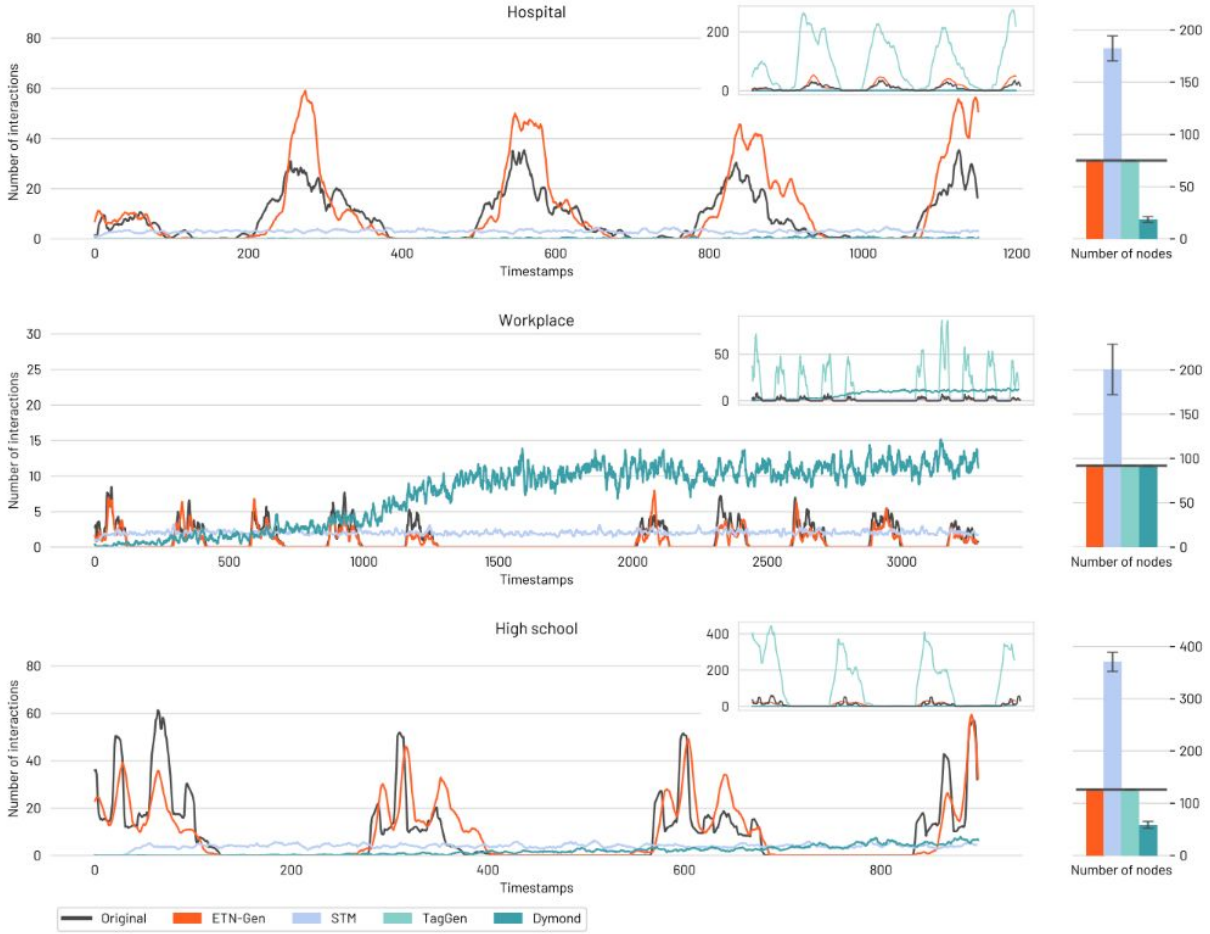
TagGen, based on deep learning.

[Zhou, Zheng, Han, He. A data-driven graph generative model for temporal interaction networks. *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 401–411, 2020.]

Dymond (DYnamic MOtif-NoDes Network Generative Model), based on temporal motifs.

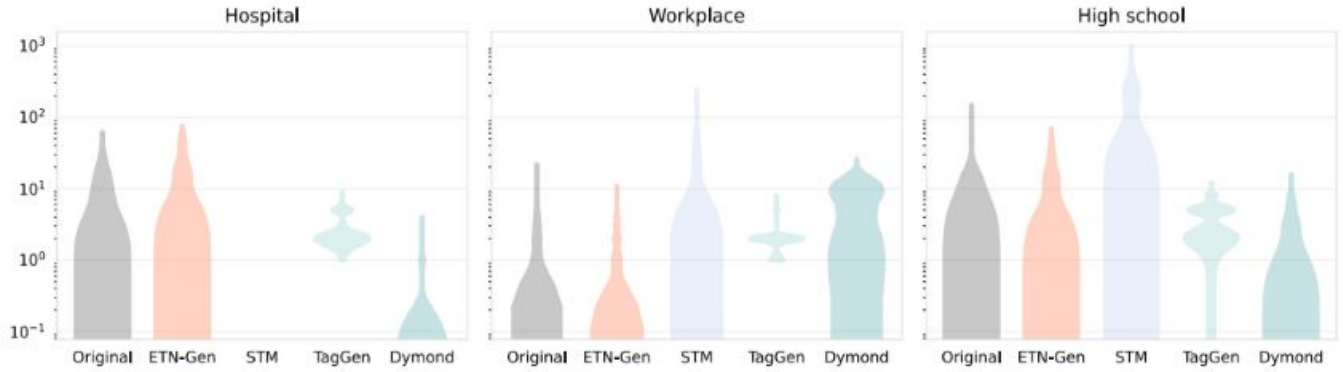
[Zeno, La Fond, Neville. Dymond: Dynamic motif-nodes network generative model. *Proceedings of the Web Conference 2021*, 718–729, 2021.]

Neighbourhood matching creates realistic surrogate temporal networks

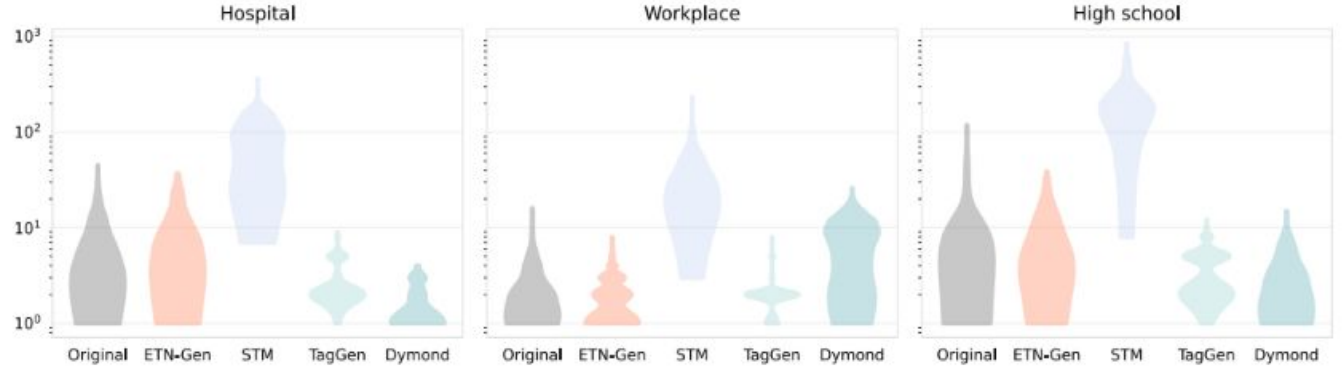


Neighbourhood matching creates realistic surrogate temporal networks

Number of interactions

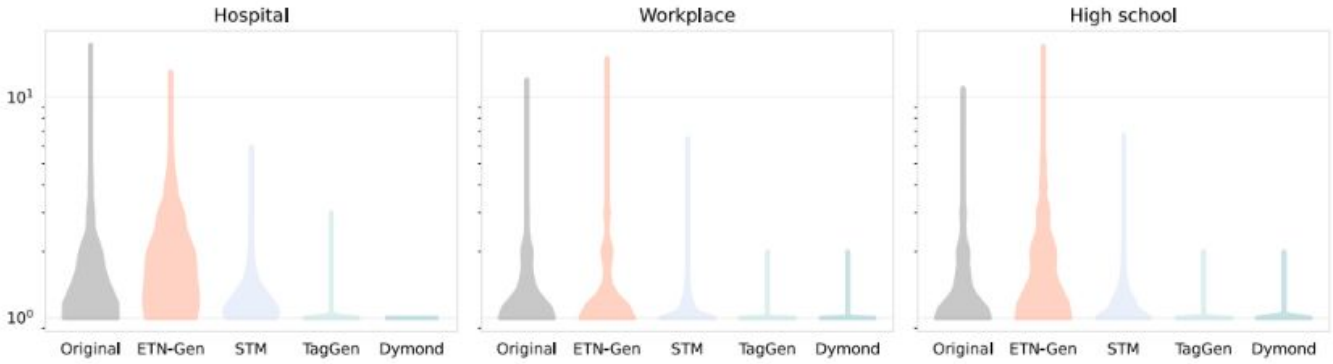


New conversations

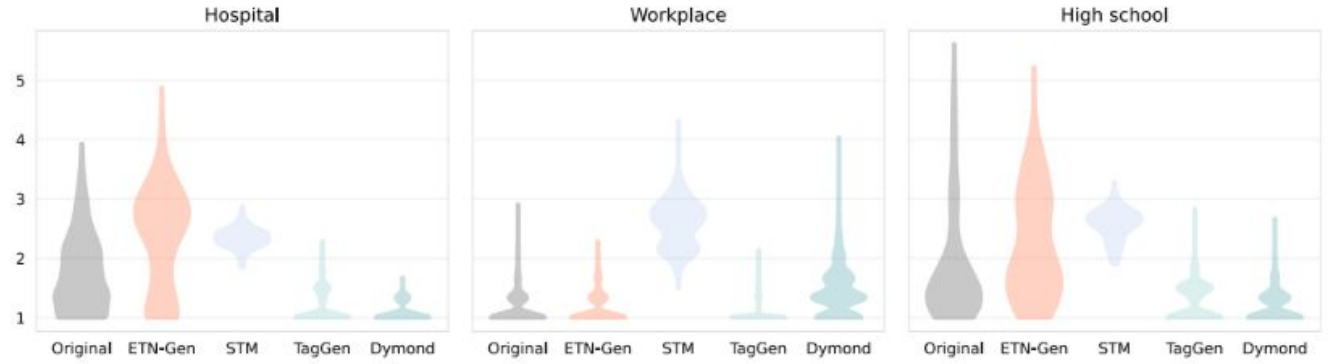


Neighbourhood matching creates realistic surrogate temporal networks

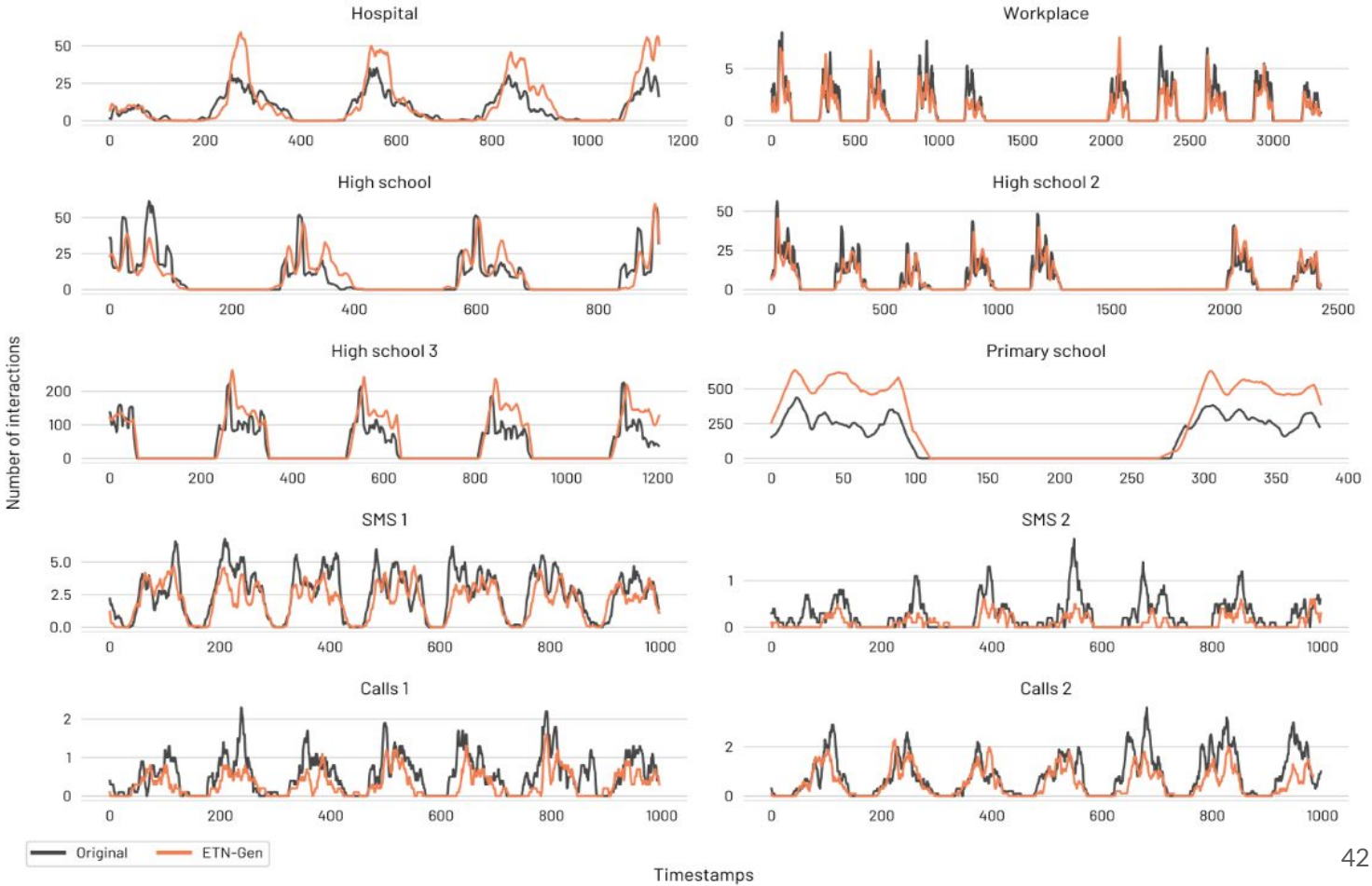
Duration



Average shortest path on static layers

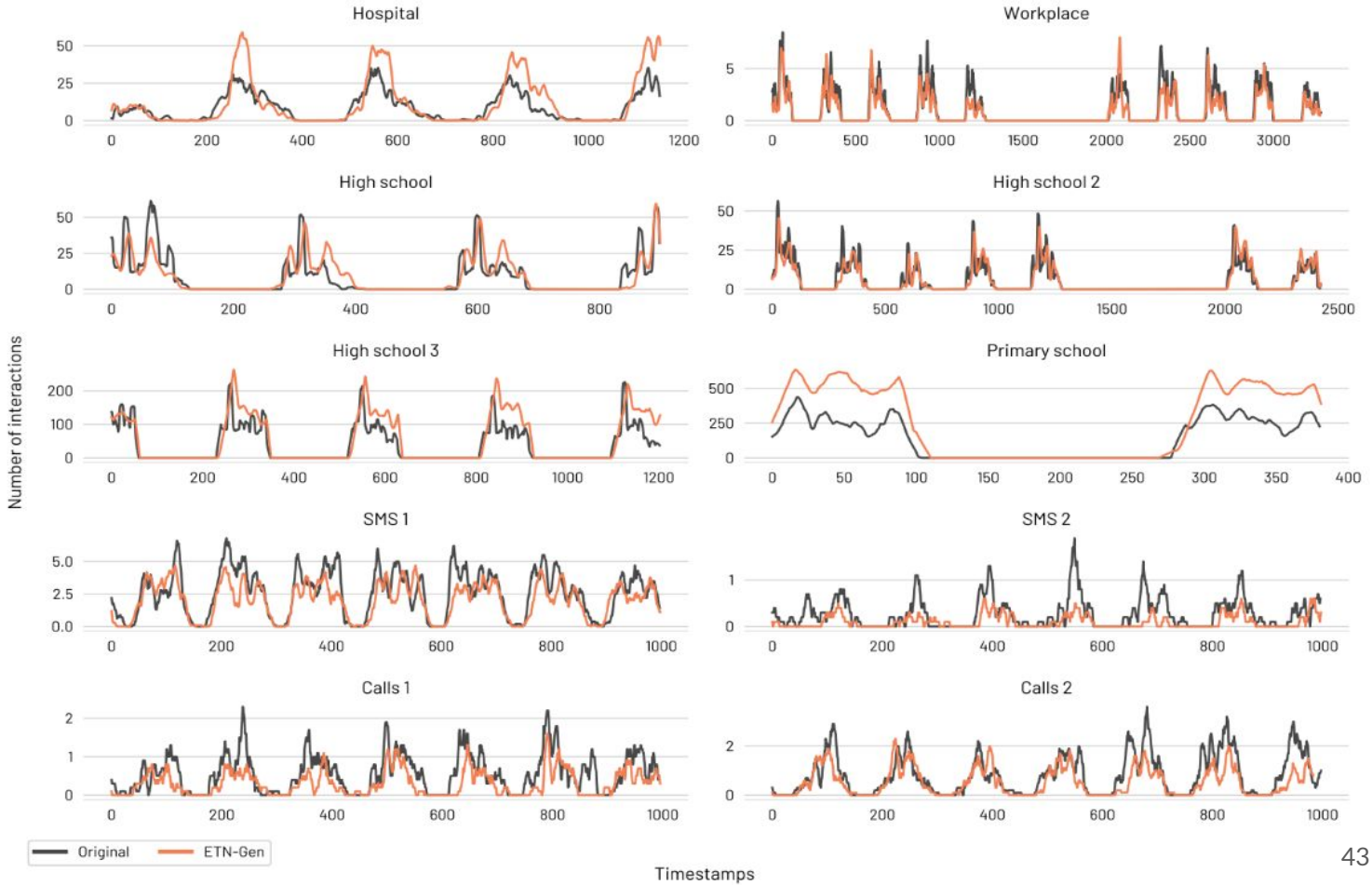


Results


Hospital
Workplace
High school
High school 2
High school 3
Primary school
SMS 1
SMS 2
Calls 1
Calls 2
Number of interactions
Original
ETN-Gen
Timestamps

Results

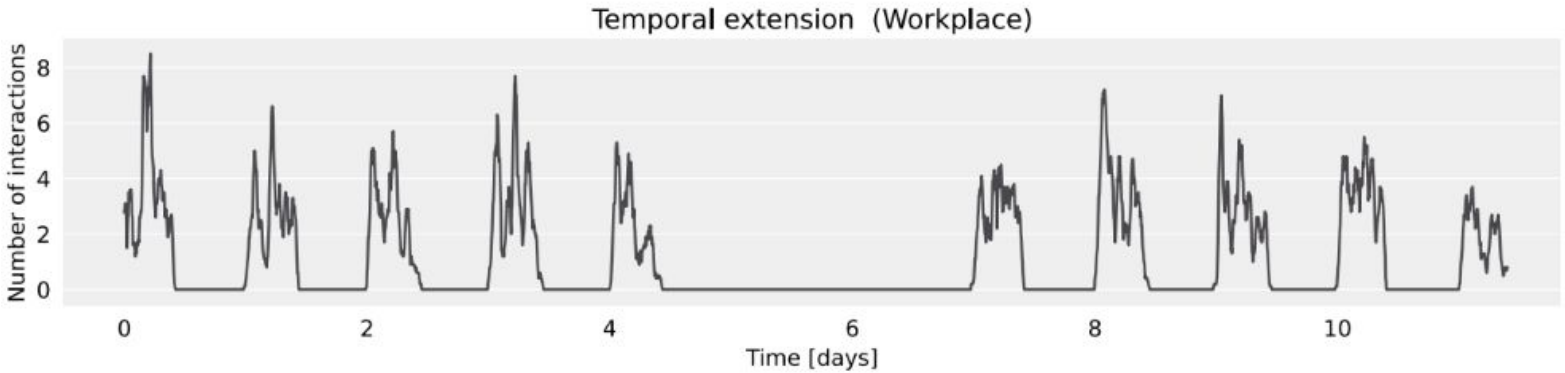
competitors?



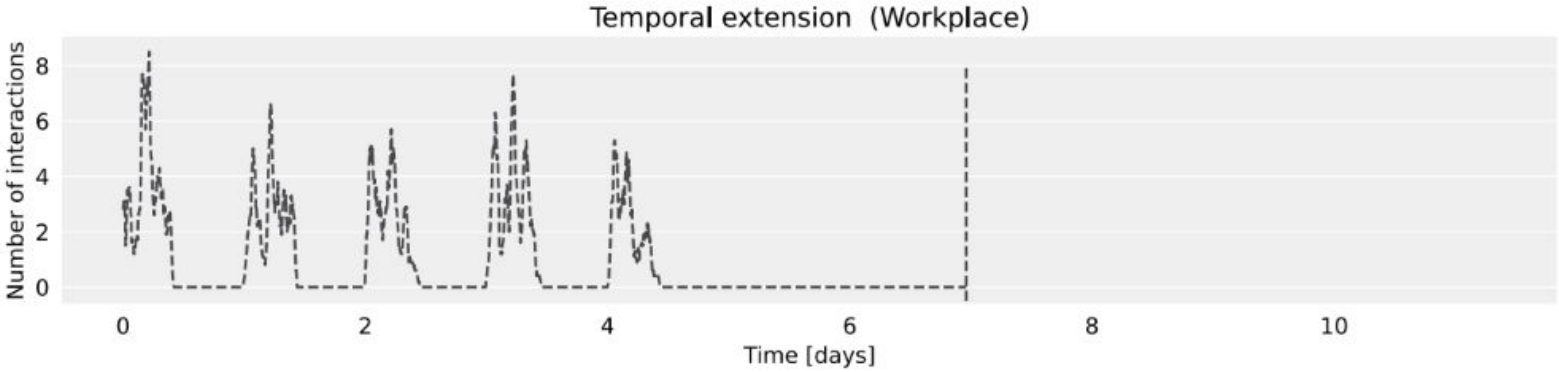
Execution Time

	Hospital	Workplace	High School
ETN-gen	$17s$	$52s$	$22s$
Dymond	$3.6 \times 10^4 s$	$1.4 \times 10^3 s$	$3.2 \times 10^5 s$
STM	$1.4 \times 10^3 s$	$9.6 \times 10^2 s$	$1.6 \times 10^3 s$
TagGen	$2.7 \times 10^4 s$	$8.7 \times 10^3 s$	$2.4 \times 10^4 s$

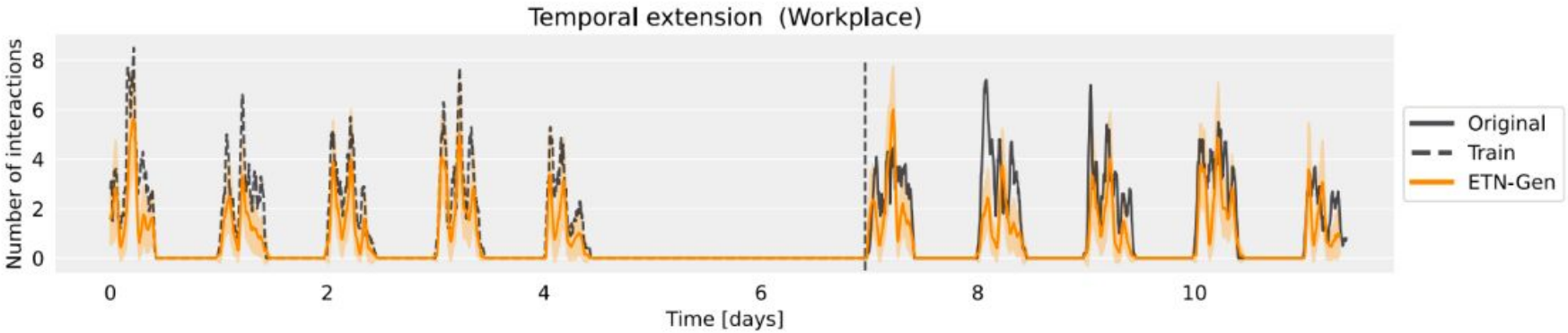
Temporal extension & Size expansion



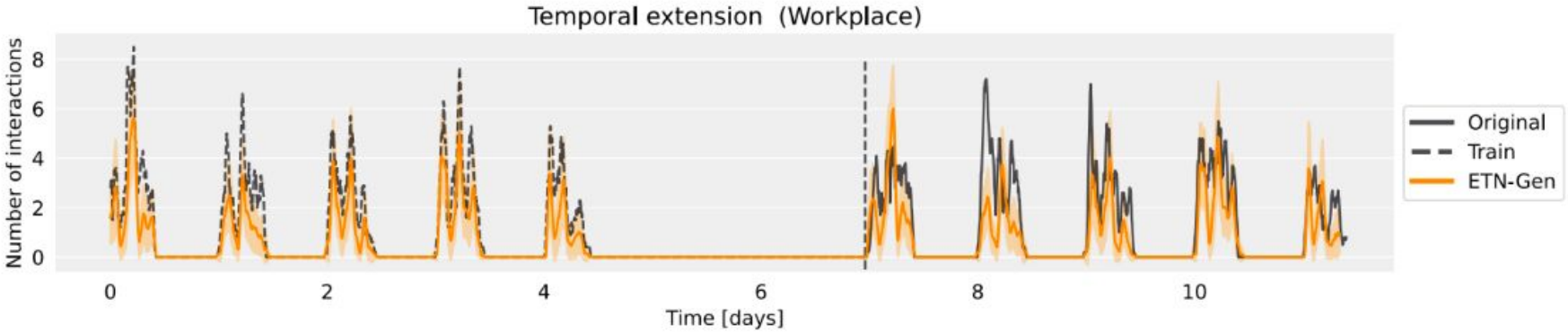
Temporal extension & Size expansion

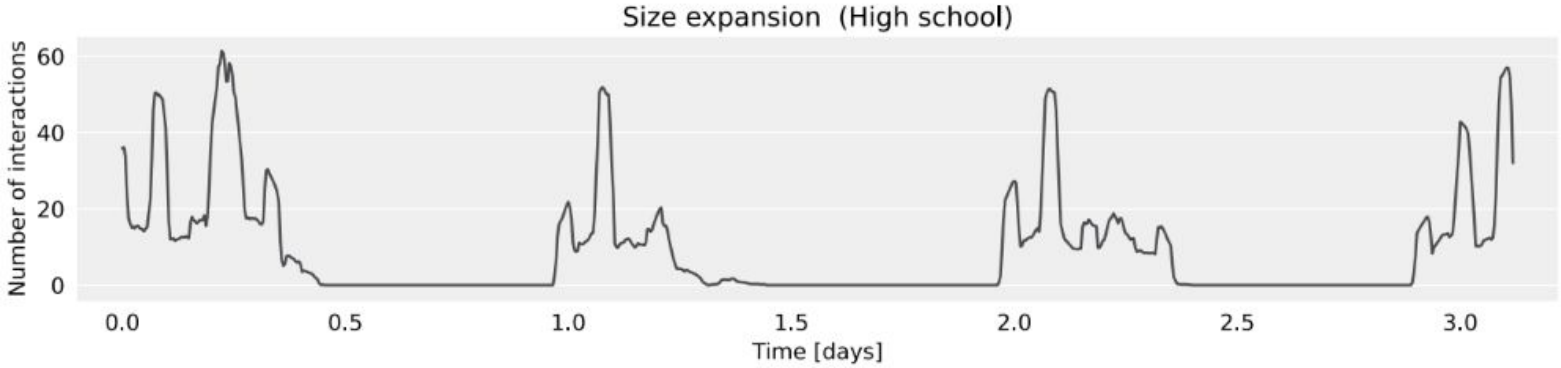


Temporal extension & Size expansion

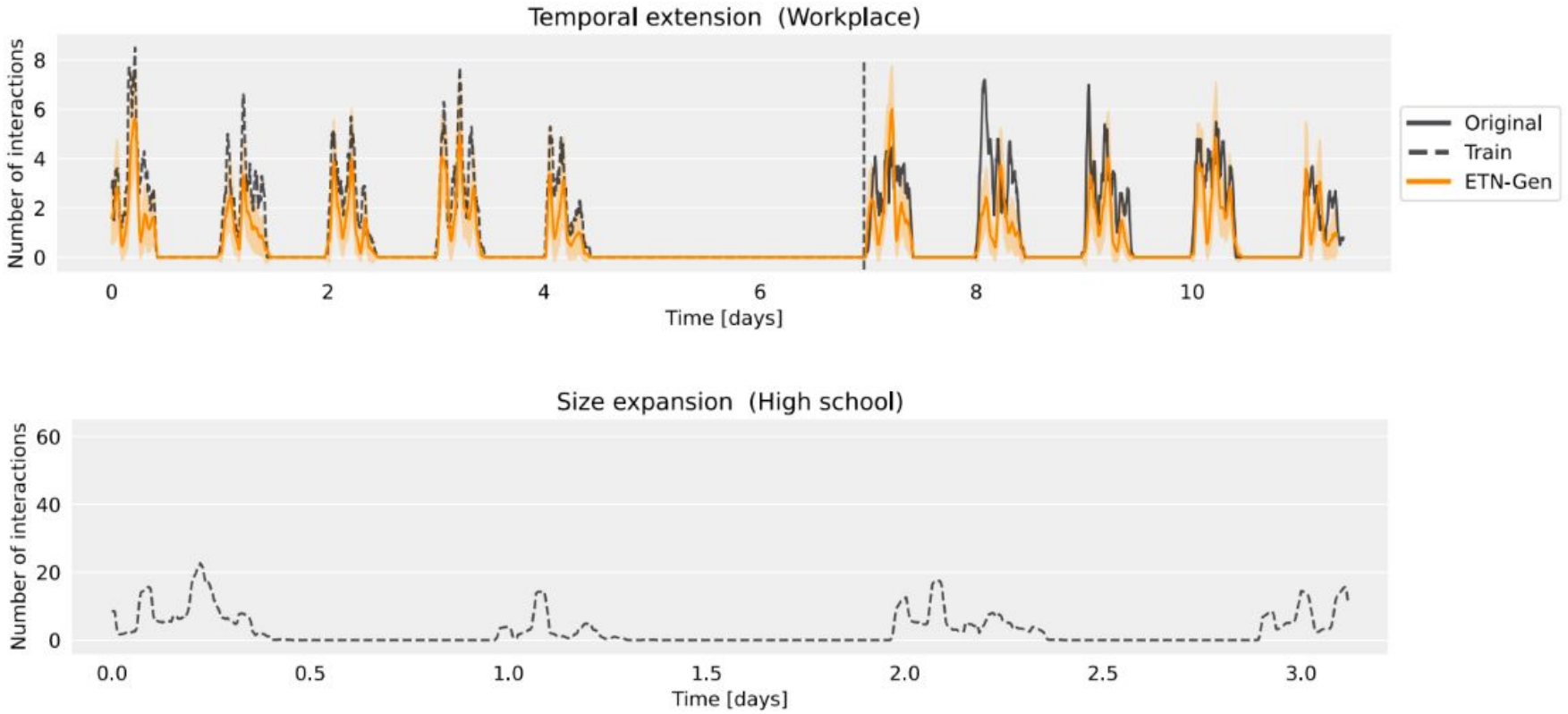


Temporal extension & Size expansion

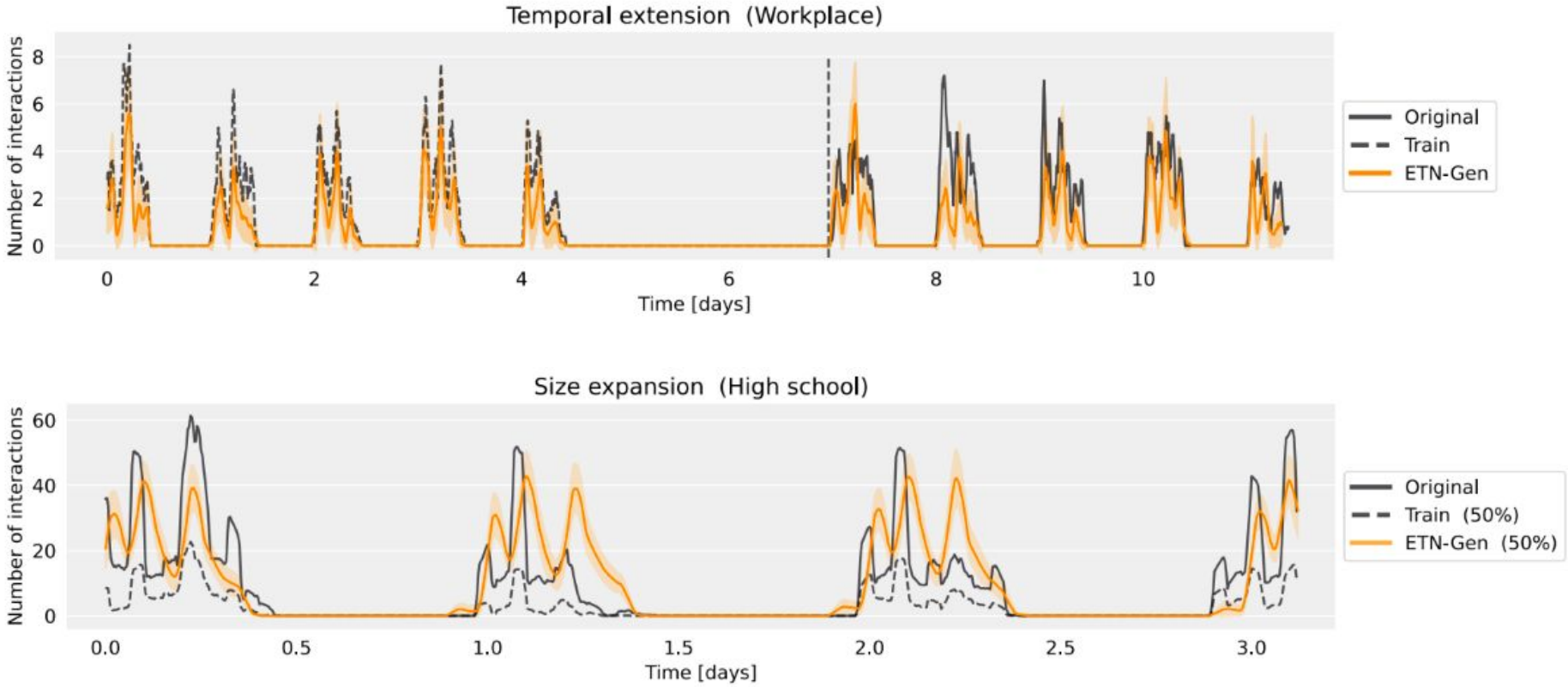




Temporal extension & Size expansion



Temporal extension & Size expansion



Thank you

Do you have any questions?

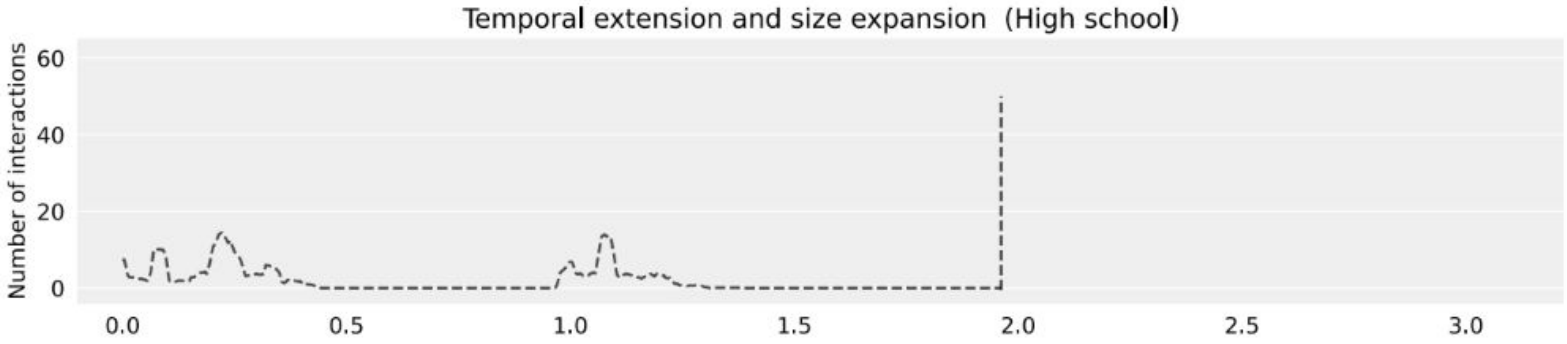
CODE: https://github.com/AntonioLonga/ETNgen

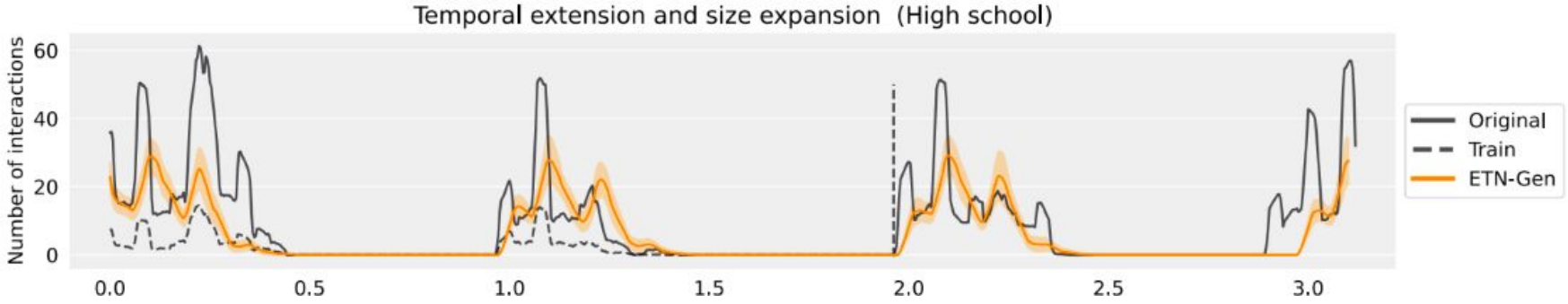

alonga@fbk.eu


AntonioLonga94

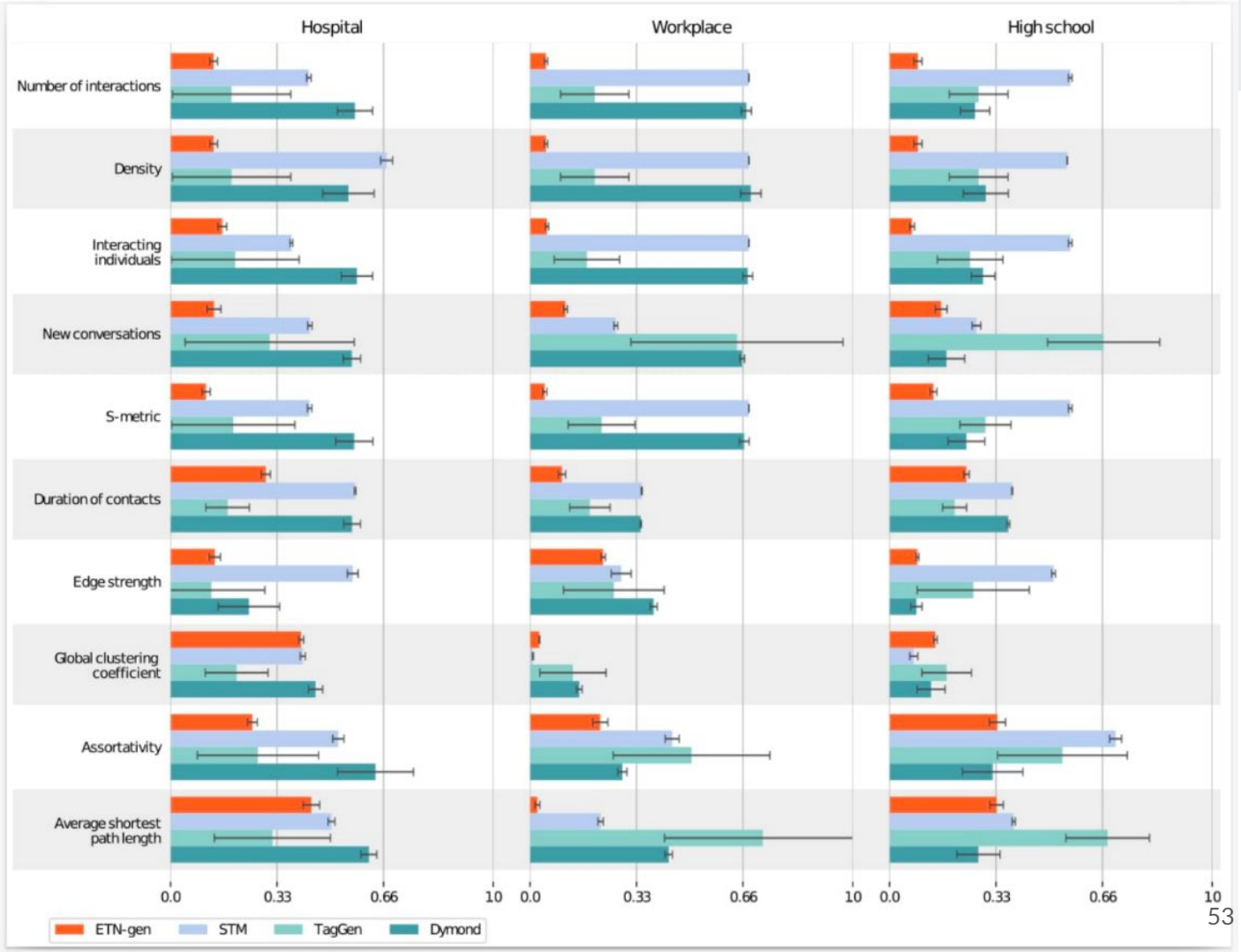

antoniolonga.github.io/

Temporal extension & Size expansion

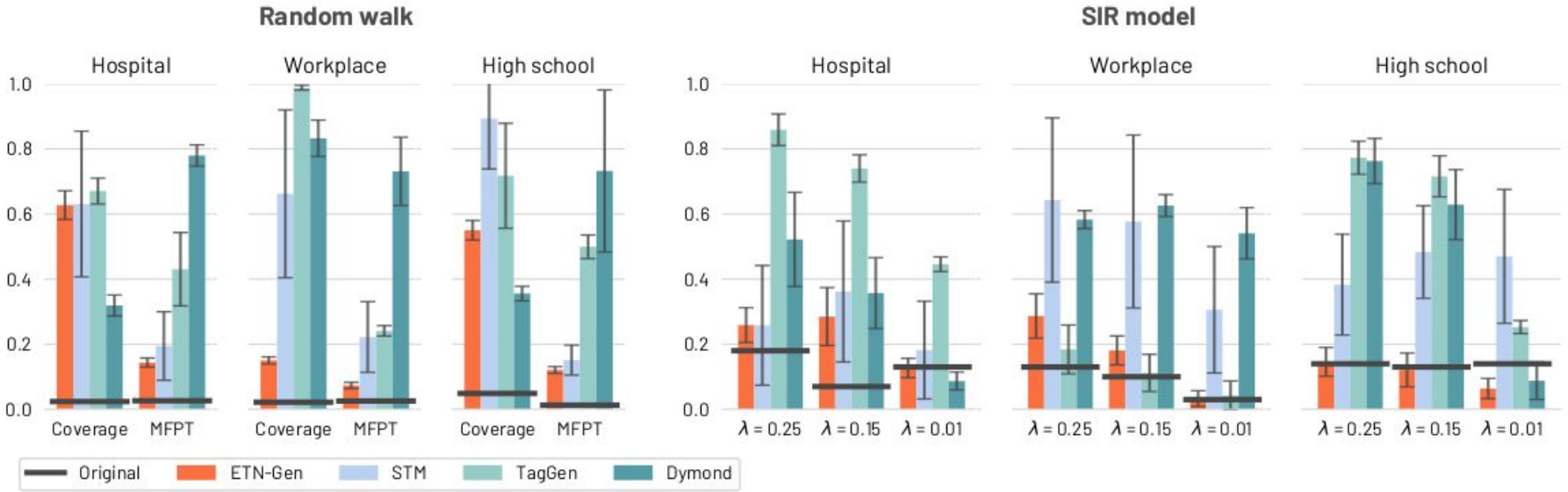




Topology


Hospital
Workplace
High school
Number of interactions
Density
Interacting individuals
New conversations
S-metric
Duration of contacts
Edge strength
Global clustering coefficient
Assortativity
Average shortest path length
0.0
0.33
0.66
1.0
ETN-gen
STM
TagGen
Dymond

Dynamic


Random walk
SIR model
Hospital
Workplace
High school
Hospital
Workplace
High school
1.0
0.8
0.6
0.4
0.2
0.0
Coverage
MFPT
λ = 0.25
λ = 0.15
λ = 0.01
Original
ETN-Gen
STM
TagGen
Dymond