An efficient procedure for mining egocentric temporal motifs

Antonio Longa, Giulia Cencetti, Bruno Lepri and Andrea Passerini

https://antoniolonga.github.io/

TABLE OF CONTENTS

01

NETWORK MOTIFS

NETWORK

Network:
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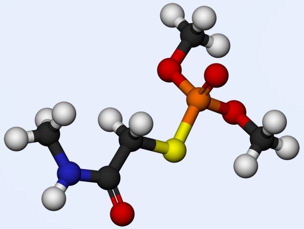

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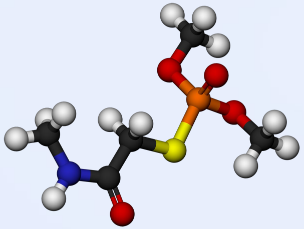

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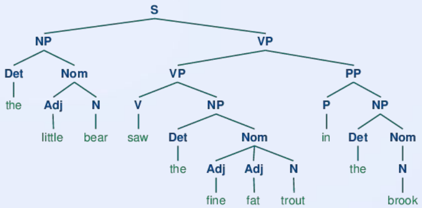

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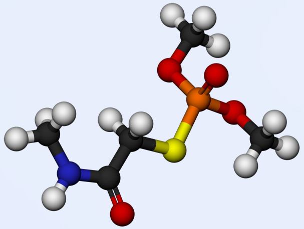

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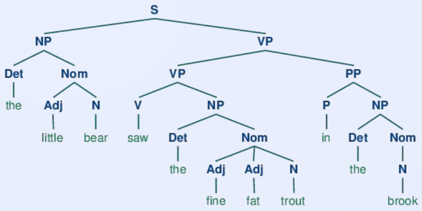

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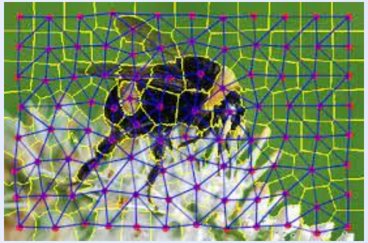

Images

NETWORK

How can we study networks?

01

Topology

Many properties:
Degree, clustering,
assortativity, connectivity,
...

02

Dynamic simulations

Simulate an epidemic in a network. (R0, infected individuals, ...)

NETWORK MOTIFS [1]

are **subgraphs**, that **appear** in an observed network **significantly more often** than in compatible randomized networks.

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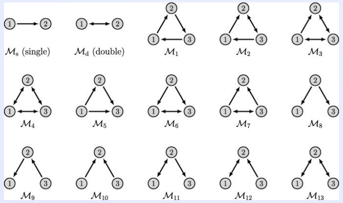

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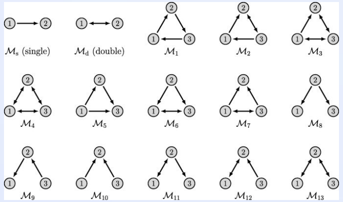

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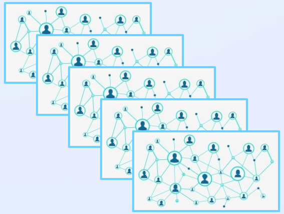

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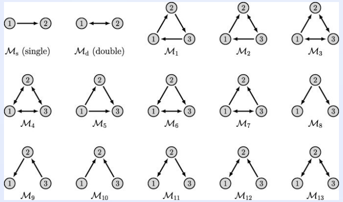

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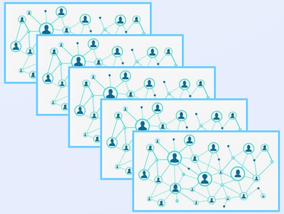

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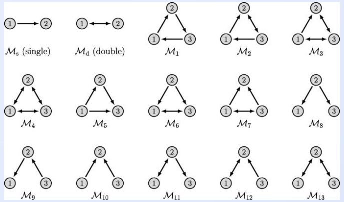

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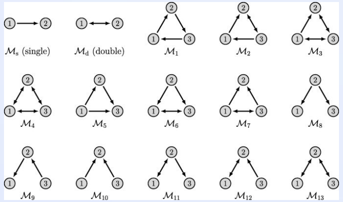

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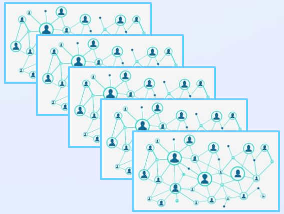

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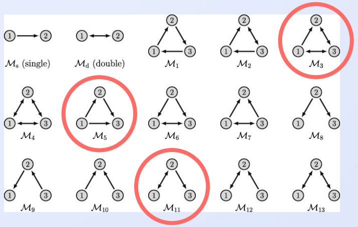

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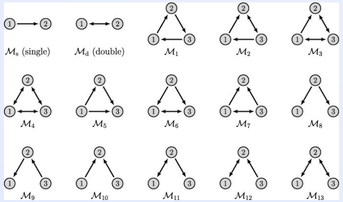

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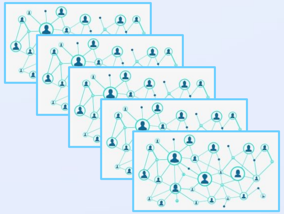

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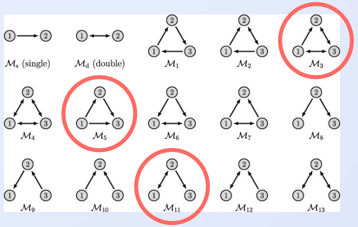

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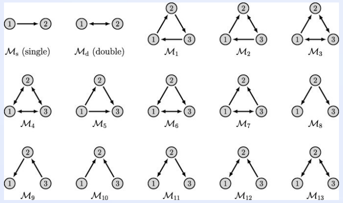

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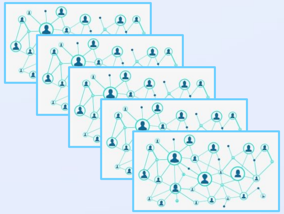

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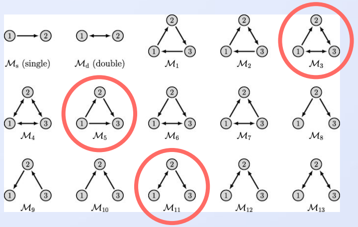

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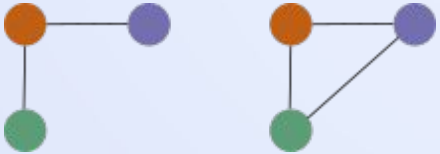

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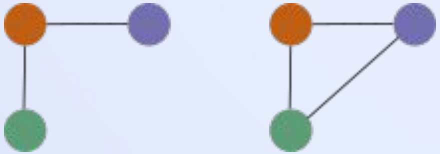

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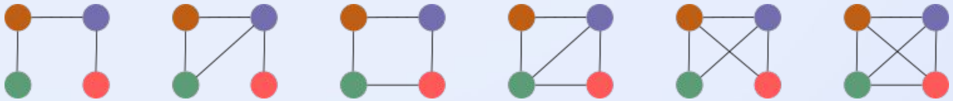

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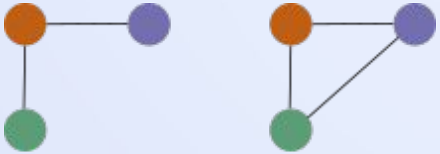

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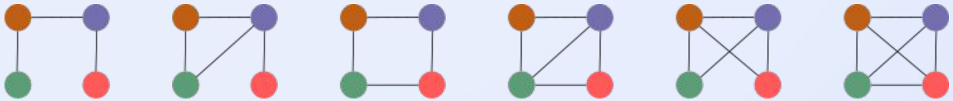

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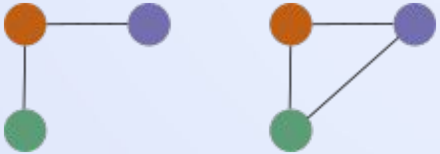

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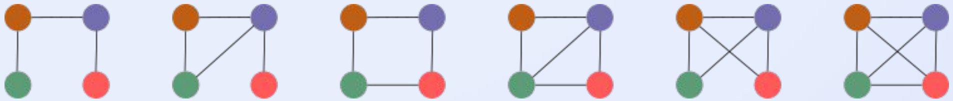

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Computational expensive

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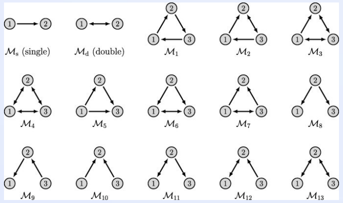

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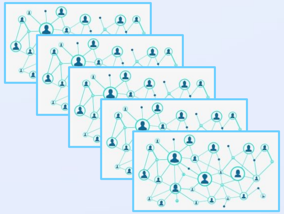

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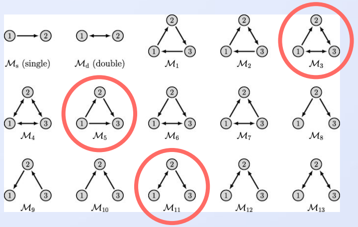

Network motifs

Temporal network motifs

02

TEMPORAL NETWORK MOTIFS

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 MOTIFS

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Interactions change over time...
Images could be videos...
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So temporal networks solve this problem.

Temporal network:

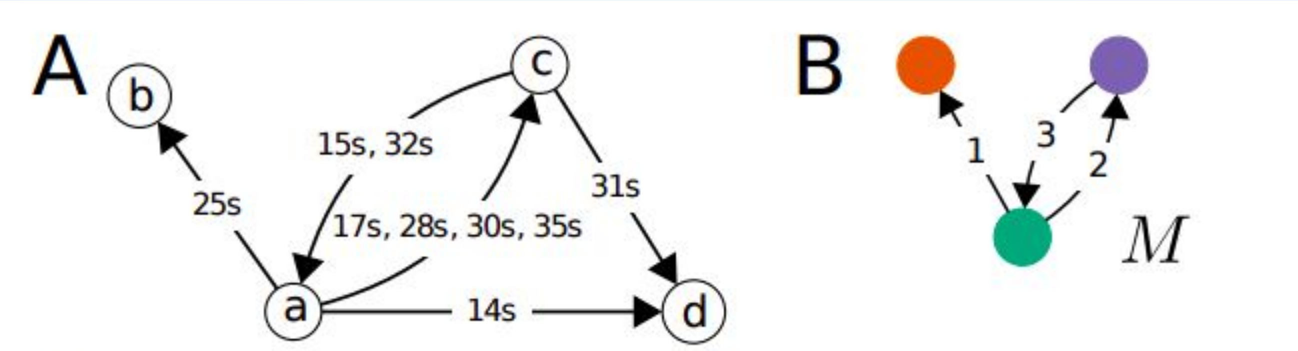
1) **Edges** → interactions among peoples
2) **Nodes** → users in social networks
3) **Attributes** → enemies can become friends

TEMPORAL NETWORK MOTIFS

Obviously, even temporal network has motifs.

Temporal network

Temporal network motifs



Paranjape, Ashwin, Austin R. Benson, and Jure Leskovec. "Motifs in temporal networks." *Proceedings of the tenth ACM international conference on web search and data mining*. 2017.

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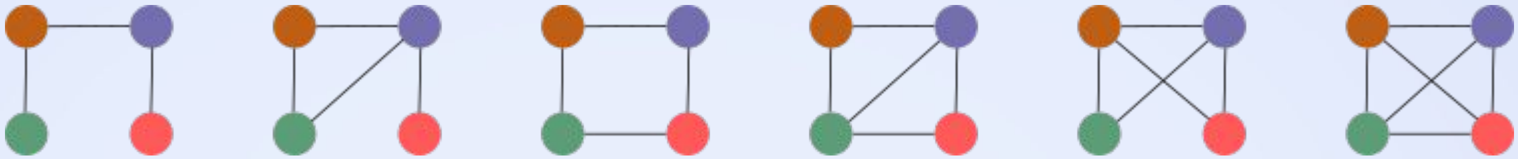

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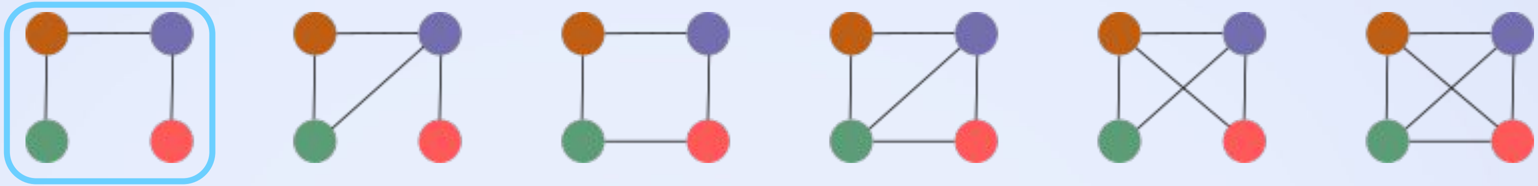

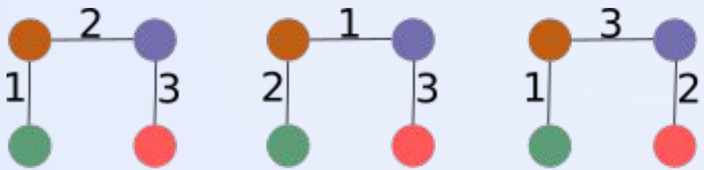

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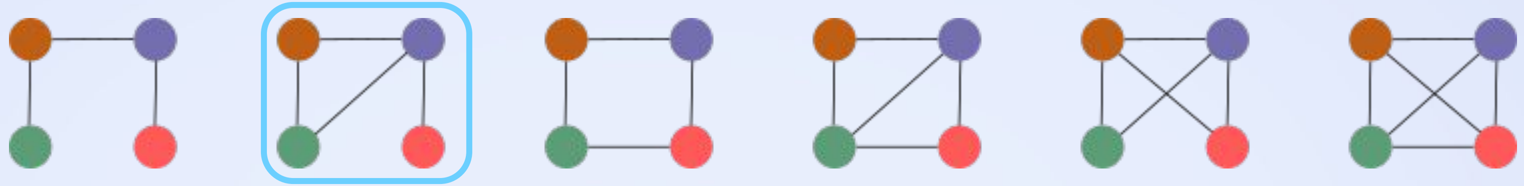

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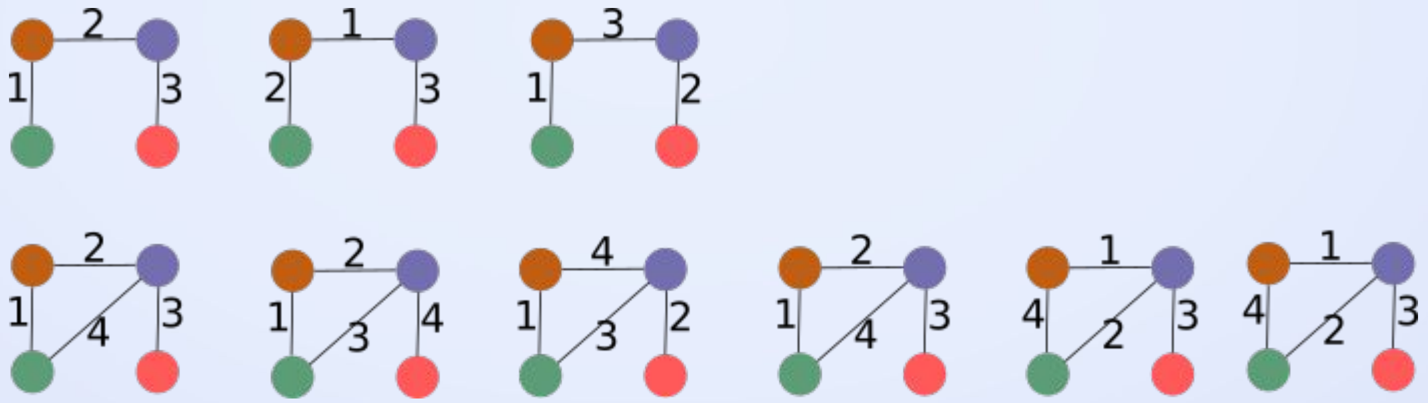

A lot of more

TEMPORAL NETWORK MOTIFS

The **time** required to **count** motifs in **temporal network** is **higher** due to the **complexity** introduced by the **temporal** dimension.

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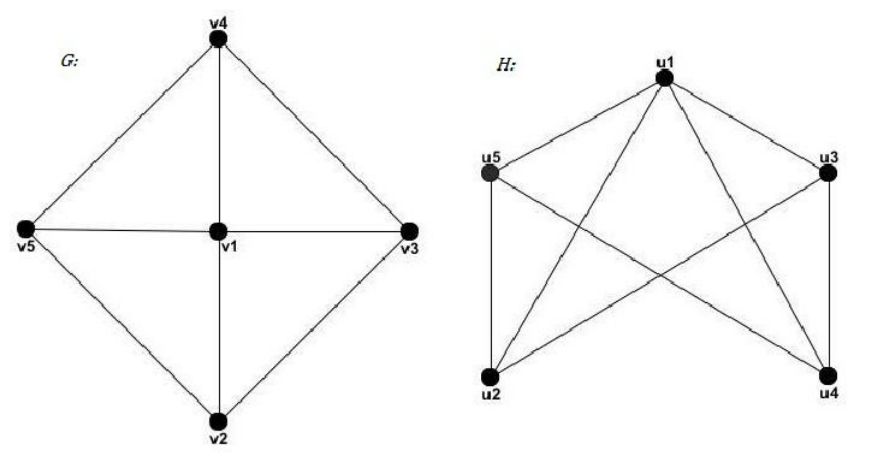


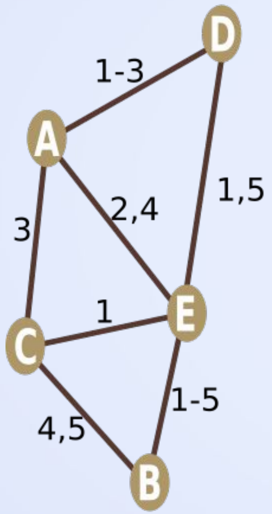
If the size of the sub graph is big, we have to compute an **isomorphism test.**
It requires lot of time!

Egocentric Temporal Motifs

03

EGOCENTRIC TEMPORAL MOTIFS

Temporal graph



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EGOCENTRIC TEMPORAL MOTIFS

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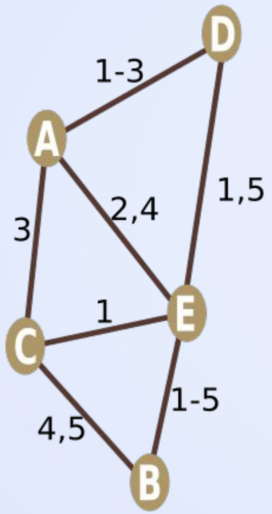

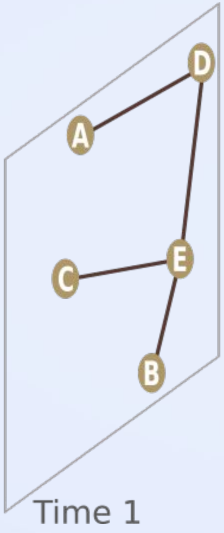

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EGOCENTRIC TEMPORAL MOTIFS

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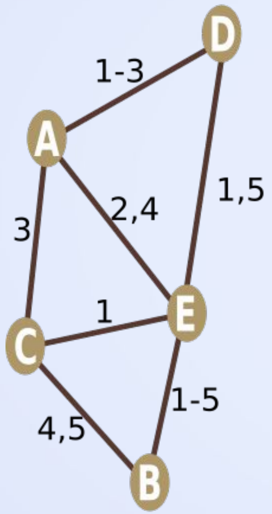

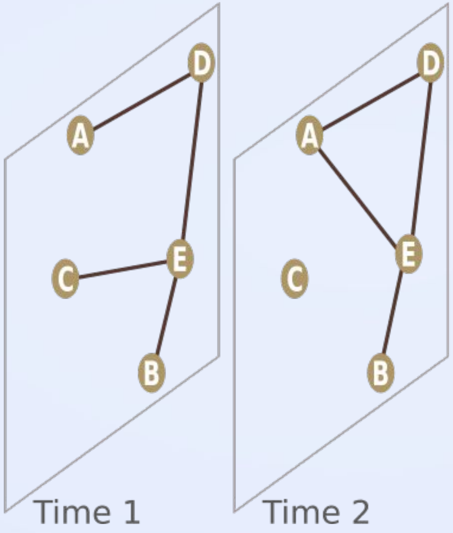

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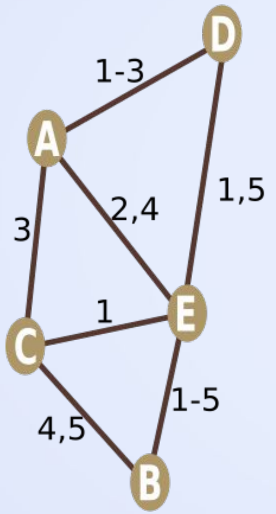

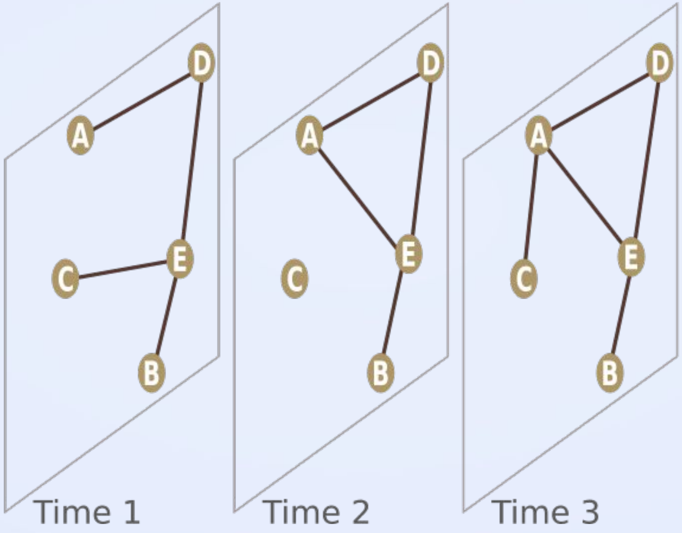

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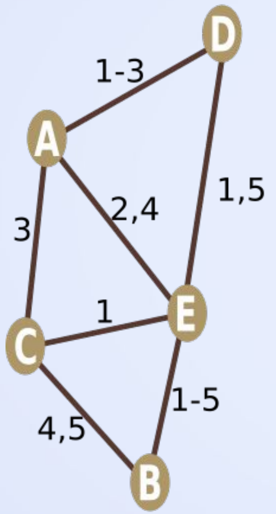
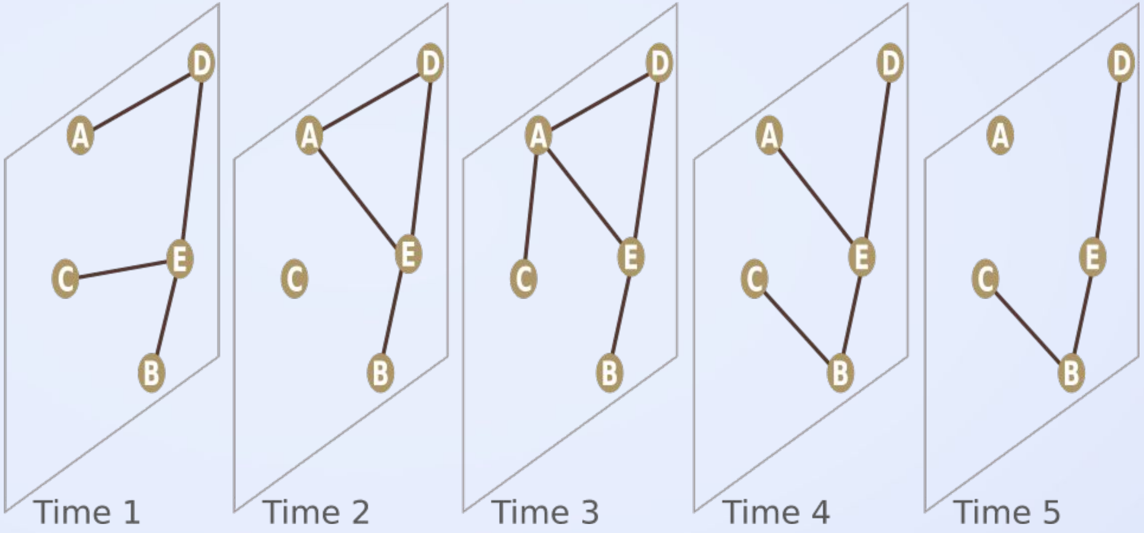


Temporal graph snapshots



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EGOCENTRIC TEMPORAL MOTIFS

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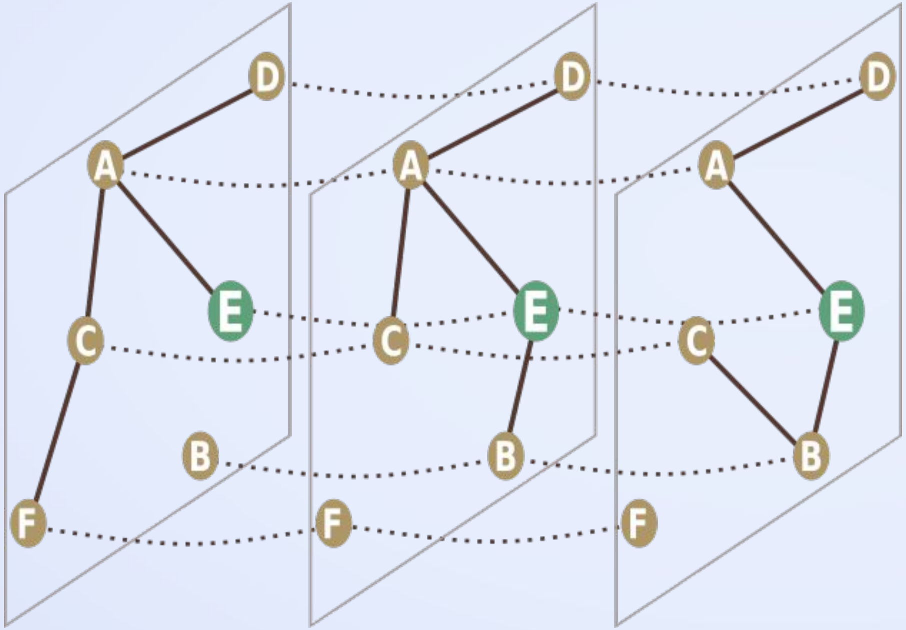

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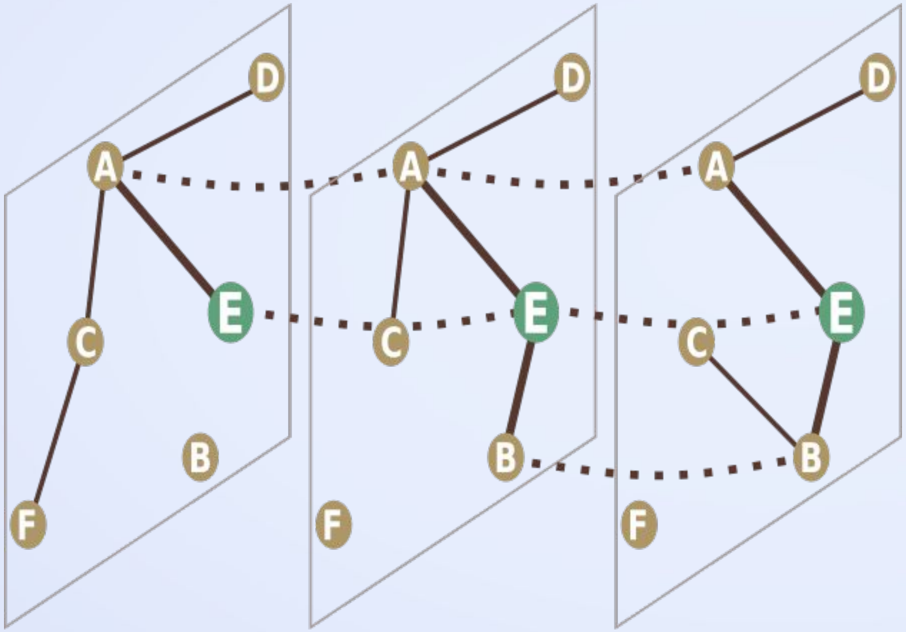
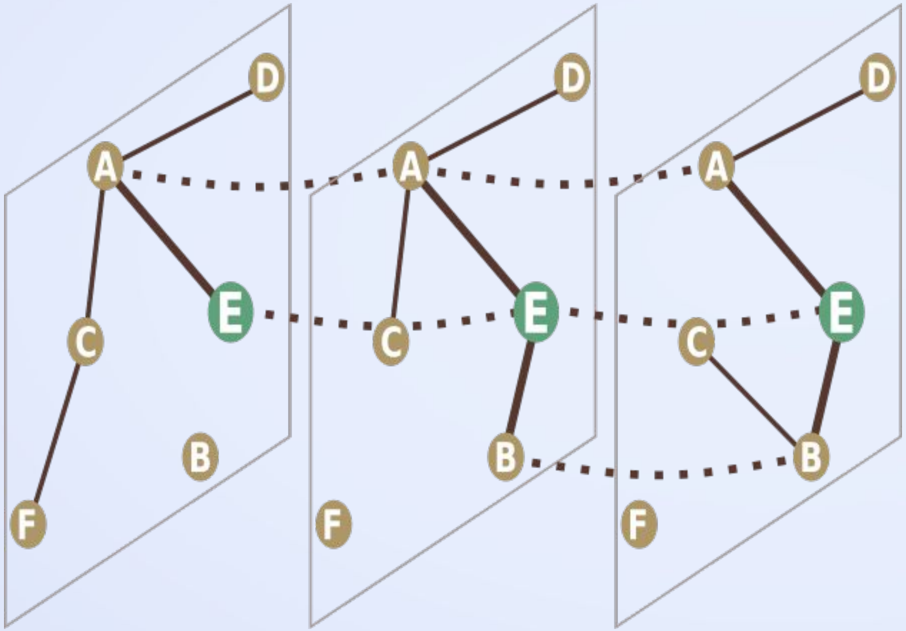


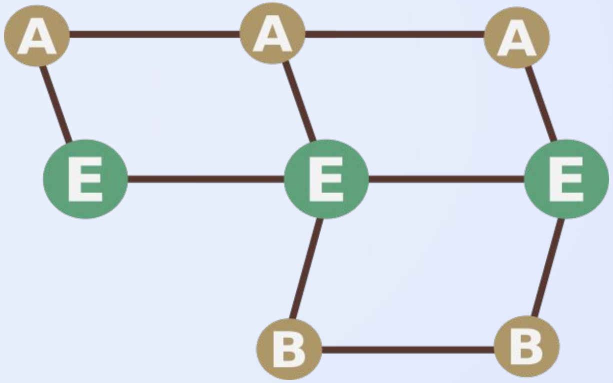
A. Longa, G. Cencetti, B. Lepri, and A. Passerini, "An efficient procedure for mining egocentric temporal motifs," Data Mining and Knowledge Discovery, pp. 1–24, 2021.

EGOCENTRIC TEMPORAL MOTIFS

K = 2

Decide and EGO Node = E





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EGOCENTRIC TEMPORAL MOTIFS

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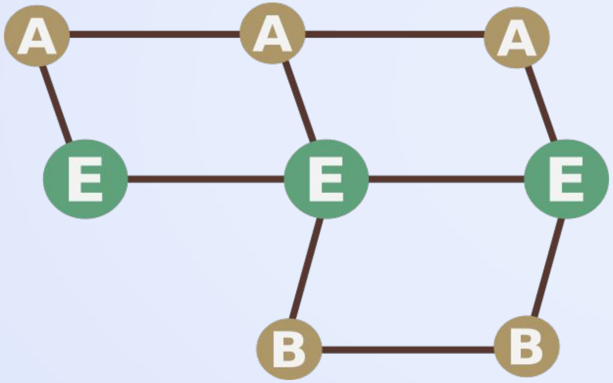

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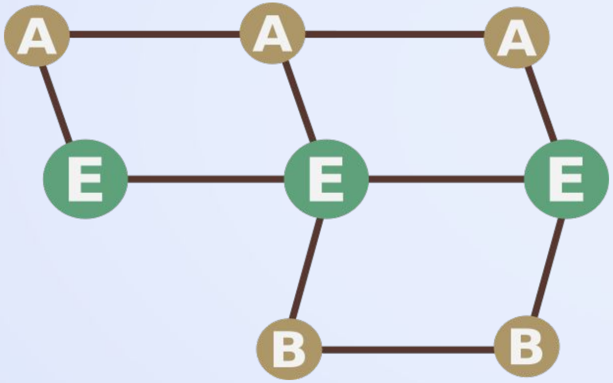
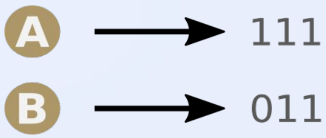


NODE ENCODING



A. Longa, G. Cencetti, B. Lepri, and A. Passerini, “An efficient procedure for mining egocentric temporal motifs,” Data Mining and Knowledge Discovery, pp. 1–24, 2021.

EGOCENTRIC TEMPORAL MOTIFS

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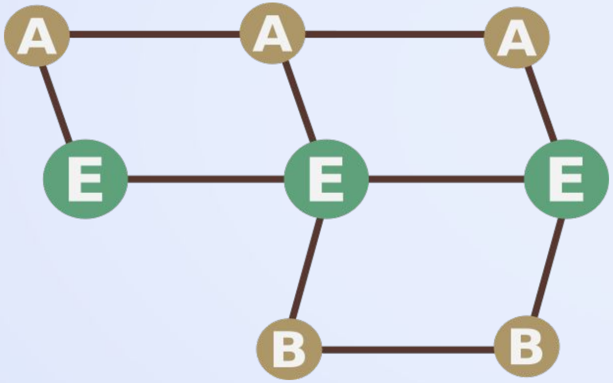

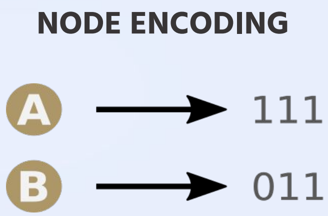

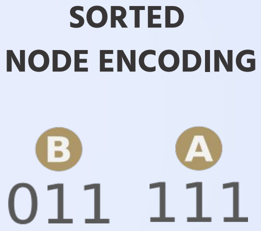

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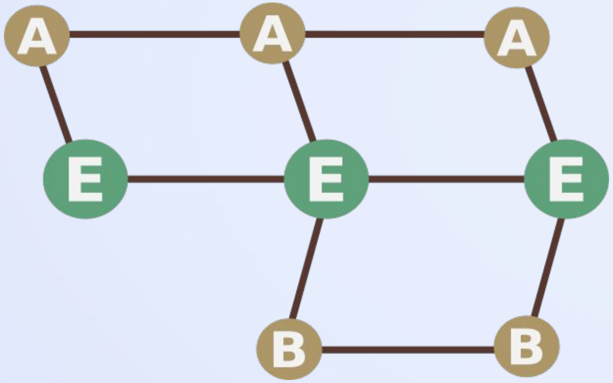


NODE ENCODING

A → 111
B → 011

SORTED
NODE ENCODING

B A
011 111

Egocentric Temporal Neighbourhood Signature
ETNS

011 111

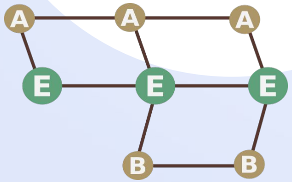
A. Longa, G. Cencetti, B. Lepri, and A. Passerini, “An efficient procedure for mining egocentric temporal motifs,” Data Mining and Knowledge Discovery, pp. 1–24, 2021.

IN SHORT

01

ETN

Egocentric
Temporal
Neighbourhood.
(a sub structure)

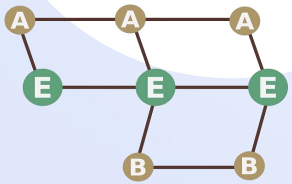


IN SHORT

01

ETN

Egocentric
Temporal
Neighbourhood.
(a sub structure)



02

ETNS

Egocentric Temporal
Neighbourhood Signature.
(a string representing a sub
structure)

011 111

IN SHORT

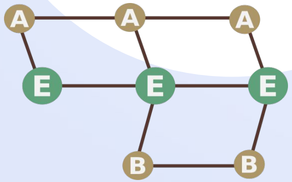
03

Fast way to compute if two sub structures are identical

01

ETN

Egocentric Temporal Neighbourhood.
(a sub structure)



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ETNS

Egocentric Temporal Neighbourhood Signature.
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011 111

IN SHORT

01

ETN

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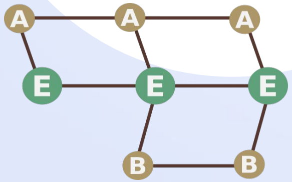

02

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Egocentric Temporal
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03

Fast way to compute if two
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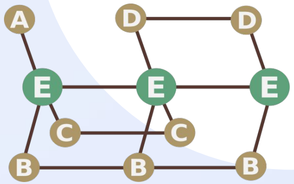
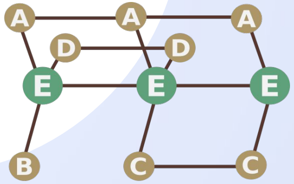


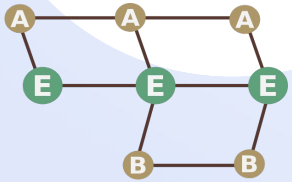


IN SHORT

01

ETN

Egocentric Temporal Neighbourhood. (a sub structure)



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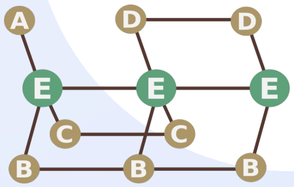
Egocentric Temporal Neighbourhood Signature. (a string representing a sub structure)

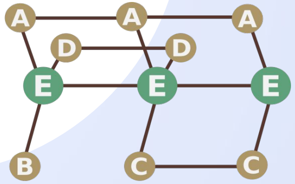
011 111

03

Fast way to compute if two sub structures are identical



011 100 110 111



011 100 110 111

Egocentric temporal motifs

Procedure

1) Count all possible **egocentric** substructure of a given network.
2) Generate networks similar to the input one.
3) **Count all possible ego substructure in the generated networks**
4) Check for those **egocentric** substructure that are:
    1. Over-represented
    2. Minimum deviation
    3. Minimum frequency
5) Those egocentric structure are the EGOCENTRIC TEMPORAL MOTIFS

Now it is fast

04

APPLICATIONS

Cool! How can we use those structures?

APPLICATIONS

COMPUTE DISTANCES

APPLICATIONS

COMPUTE DISTANCES

$$dist_M(\mathcal{G}_1, \mathcal{G}_2) = 1 - \frac{EMB_M(\mathcal{G}_1) \cdot EMB_M(\mathcal{G}_2)}{||EMB_M(\mathcal{G}_1)|| \; ||EMB_M(\mathcal{G}_2)||}$$

APPLICATIONS

COMPUTE DISTANCES

$$dist_M\boxed{(\mathcal{G}_1, \mathcal{G}_2)} = 1 - \frac{EMB_M(\mathcal{G}_1) \cdot EMB_M(\mathcal{G}_2)}{||EMB_M(\mathcal{G}_1)||\ ||EMB_M(\mathcal{G}_2)||}$$

Input graphs

APPLICATIONS

COMPUTE DISTANCES

Cosine similarity

$$dist_M\boxed{(\mathcal{G}_1, \mathcal{G}_2)} = 1 - \boxed{\frac{EMB_M(\mathcal{G}_1) \cdot EMB_M(\mathcal{G}_2)}{||EMB_M(\mathcal{G}_1)|| \; ||EMB_M(\mathcal{G}_2)||}}$$

Input graphs

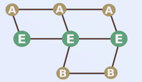
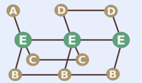
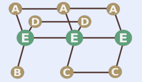
APPLICATIONS

COMPUTE DISTANCES

Cosine similarity

$$dist_M\boxed{(\mathcal{G}_1, \mathcal{G}_2)} = 1 - \boxed{\frac{\boxed{EMB_M(\mathcal{G}_1)} \cdot EMB_M(\mathcal{G}_2)}{||EMB_M(\mathcal{G}_1)||\ ||EMB_M(\mathcal{G}_2)||}}$$

Input graphs

ETM			
Counts	11561	35815	85112

COMPUTE DISTANCES

RESULTS

Sociopatter data, face to face interactions

Workplace
Hospital
High School 11
High School 12
High School 13
Primary school
University

COMPUTE DISTANCES

RESULTS

				ETMM-DIST			
	VS13	LH10	HS11	HS12	HS13	PS	DTU
Workplace	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 11			0	0.04	0.04	0.59	0.06
High School 12				0	0.02	0.61	0.13
High School 13					0	0.62	0.08
Primary school						0	0.62
University							0

COMPUTE DISTANCES
RESULTS

				ETMM-DIST			
	VS13	LH10	HS11	HS12	HS13	PS	DTU
Workplace	0	0.07	0.29	0.22	0.29	0.67	0.47
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Workplace and
Hospital are similar

COMPUTE DISTANCES

RESULTS

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University							0

Workplace and Hospital are similar

High Schools are similar

COMPUTE DISTANCES

RESULTS

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Primary school						0	0.62
University							0

Workplace and Hospital are similar

High Schools are similar

Primary school is different from all the networks

COMPUTE DISTANCES
RESULTS

				ETMM-DIST			
	VS13	LH10	HS11	HS12	HS13	PS	DTU
Workplace	0	0.07	0.29	0.22	0.29	0.67	0.47
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High School 13					0	0.62	0.08
Primary school						0	0.62
University							0

Quite similar to High Schools

COMPUTE DISTANCES

RESULTS

				ETMM-DIST			
	VS13	LH10	HS11	HS12	HS13	PS	DTU
Workplace	0	0.07	0.29	0.22	0.29	0.67	0.47
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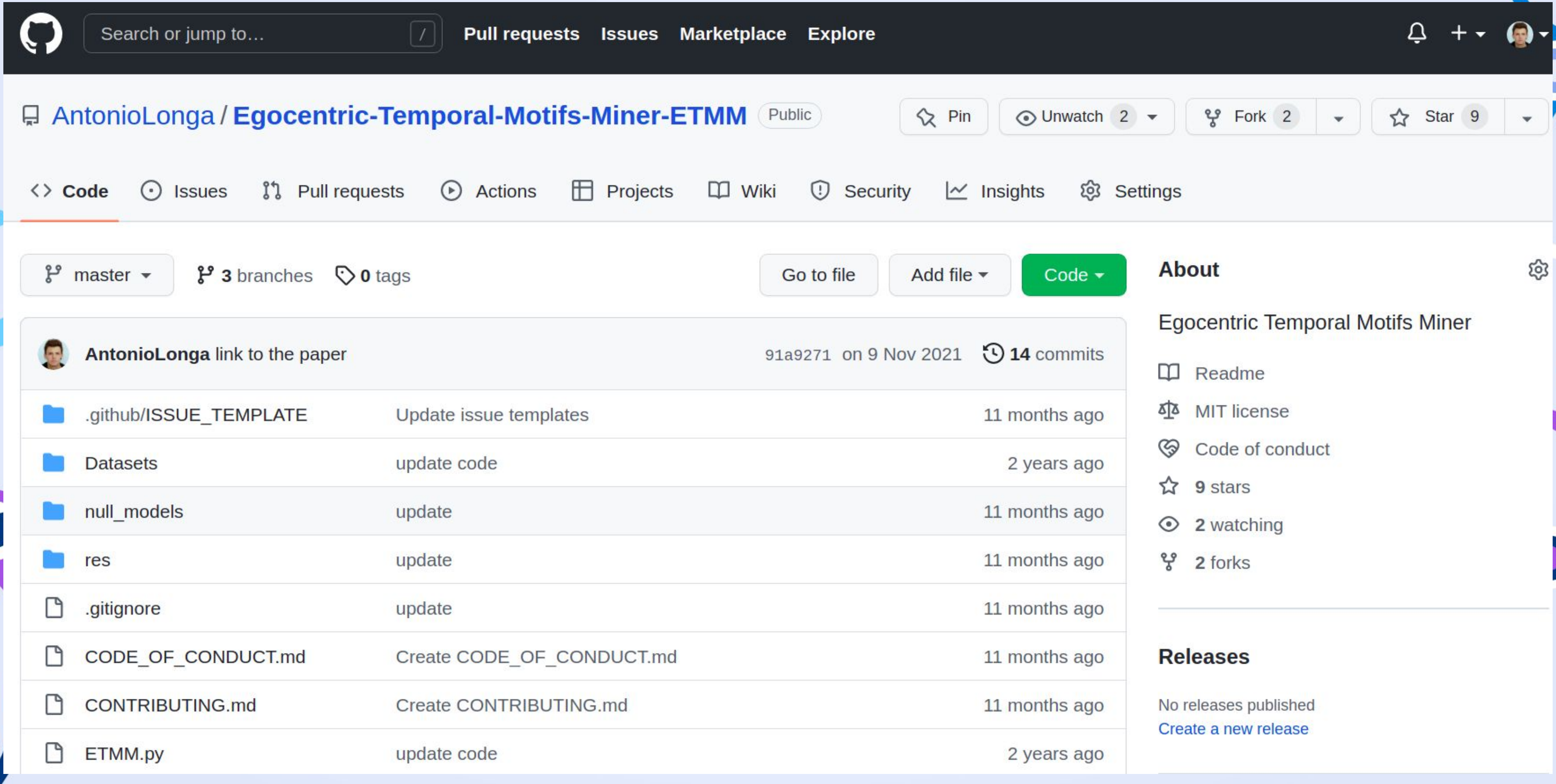
Primary school						0	0.62
University							0

Quite similar to High Schools

Different from primary school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Datasets
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2 years ago
null_models
update
11 months ago
res
update
11 months ago
.gitignore
update
11 months ago
CODE_OF_CONDUCT.md
Create CODE_OF_CONDUCT.md
11 months ago
CONTRIBUTING.md
Create CONTRIBUTING.md
11 months ago
ETMM.py
update code
2 years ago
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05

Future directions

ETN as building block for temporal network generation

Neighborhood matching creates realistic surrogate temporal networks

Antonio Longa[1,2] Giulia Cencetti[1], Sune Lehmann[3,4], Andrea Passerini[2] and Bruno Lepri[1*]

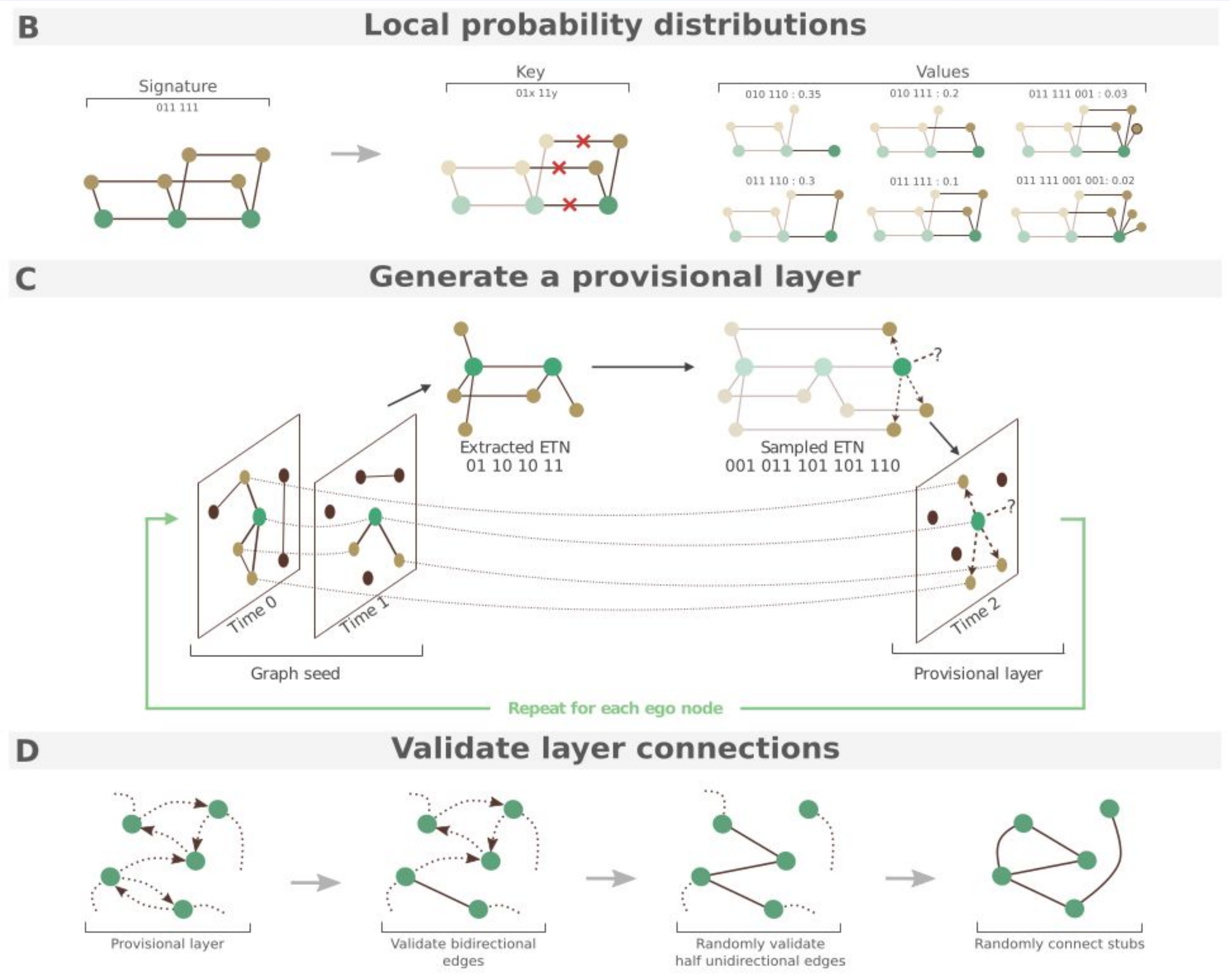
[1]Fondazione Bruno Kessler, Trento, Italy

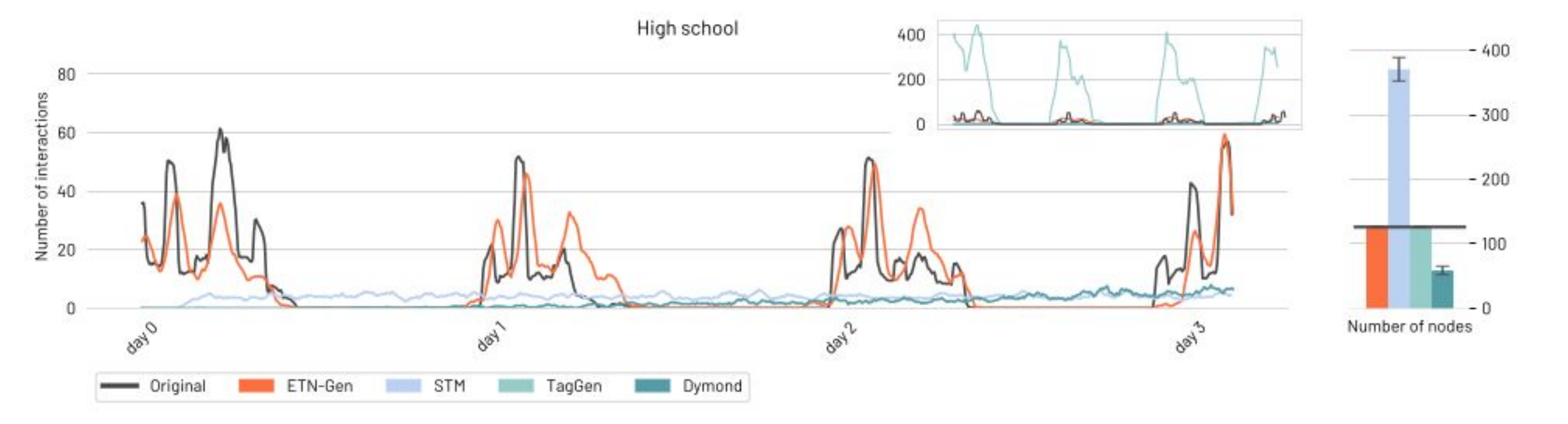
[1]University of Trento, Trento, Italy

[1]Tecnical University of Denmark, Kongens Lyngby, Denmark

[2]Copenhagen Center for Social Data Science, Copenhagen, Denmark

ETN as building block for temporal network generation




High school
Number of interactions
80
60
40
20
0
day 0
day 1
day 2
day 3
400
200
0
400
300
200
100
0
Number of nodes
Original
ETN-Gen
STM
TagGen
Dymond

THANKS

Do you have any questions?

alonga@fbk.eu
https://antoniolonga.github.io/

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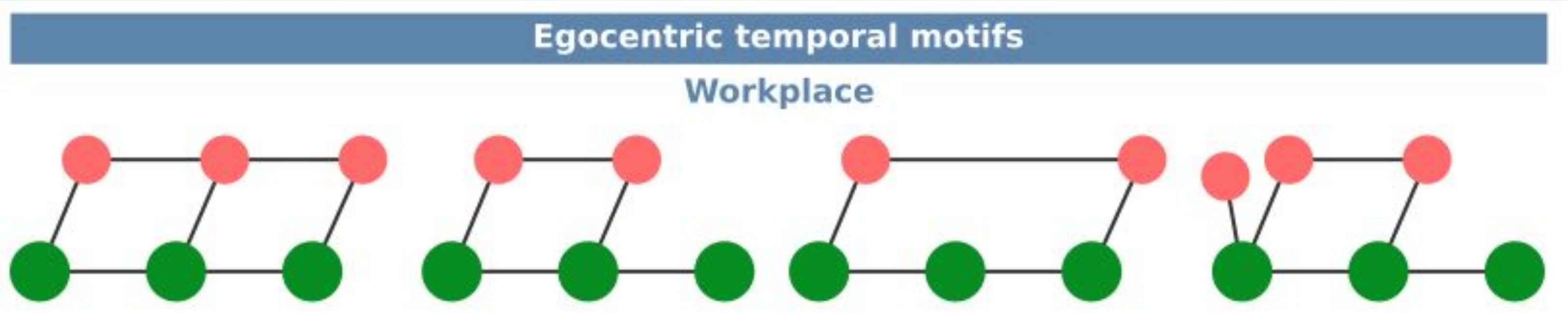
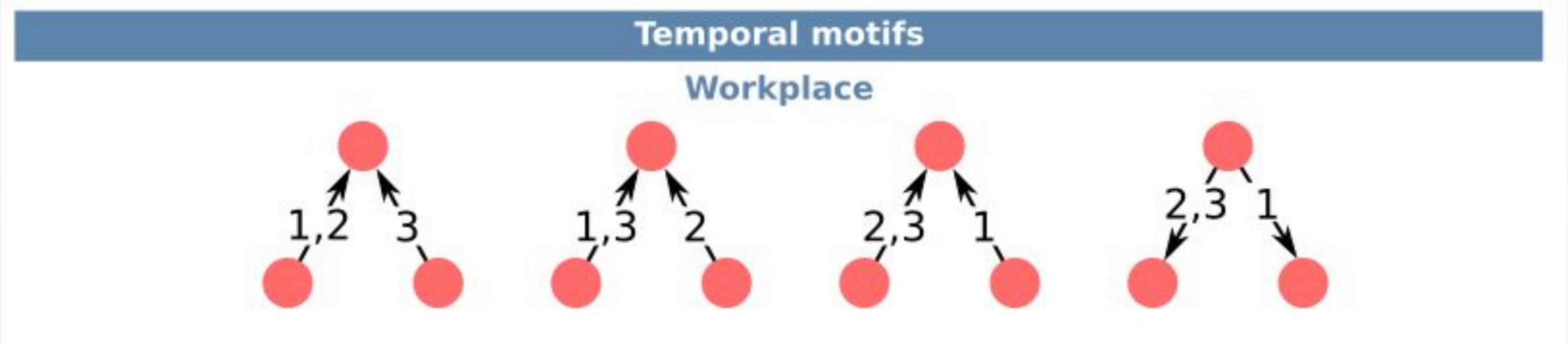
WORKPLACE



Egocentric temporal motifs
Workplace



Temporal motifs
Workplace
1,2
3
1,3
2
2,3
1
2,3
1