Temporal network MOTIFS

Antonio Longa
https://antoniolonga.github.io/

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NETWORK MOTIFS

NETWORK

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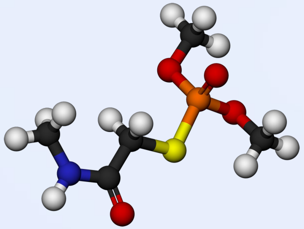

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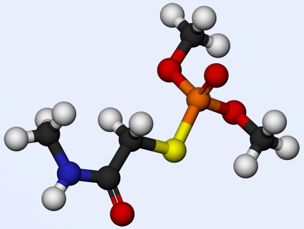

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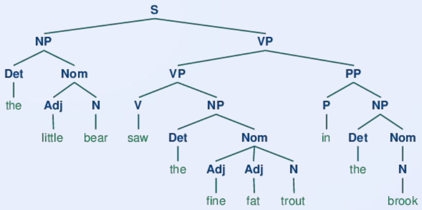

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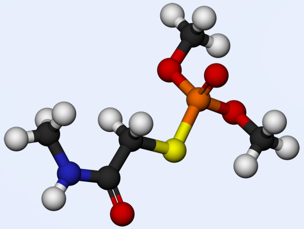

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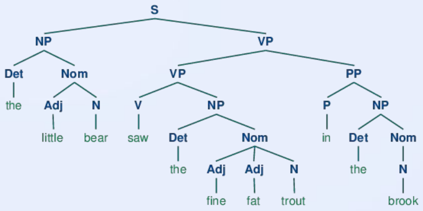

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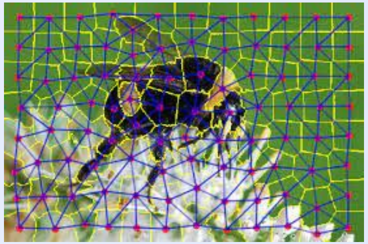


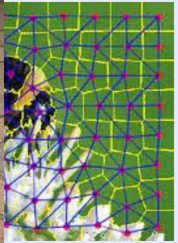
Images

Netw

A netw a

set of

Social netw



es

NETWORK

How can we study networks?

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Topology

Many properties:
Degree, clustering,
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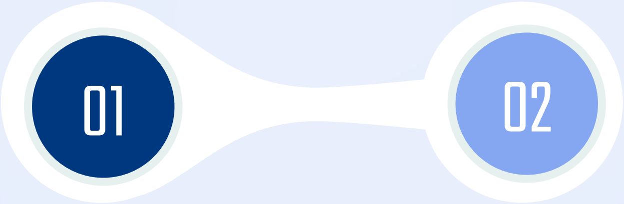

Dynamic simulations

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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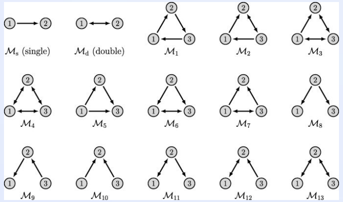

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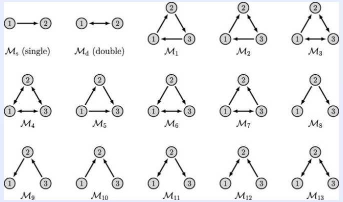

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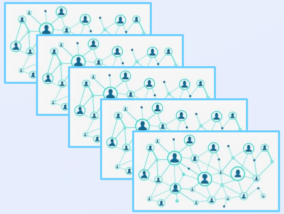

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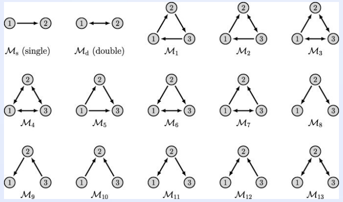

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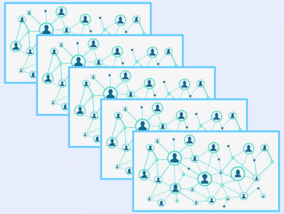

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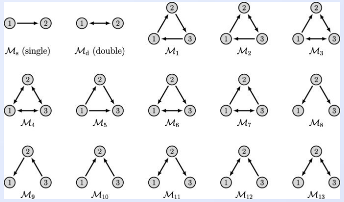

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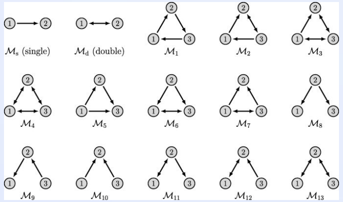

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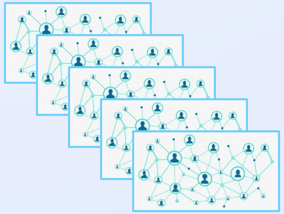

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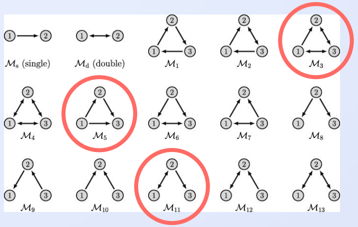

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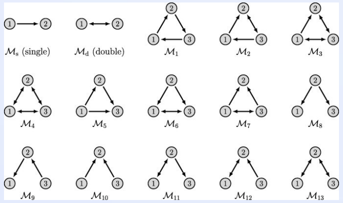

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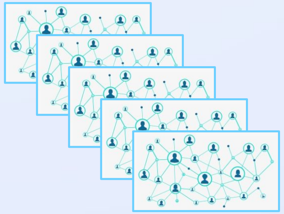

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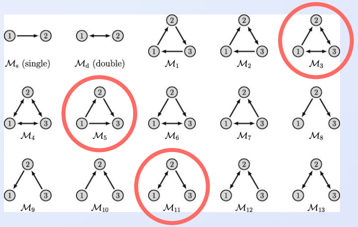

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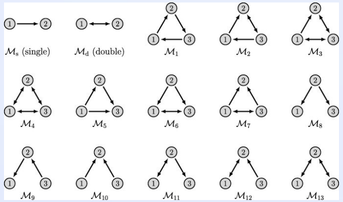

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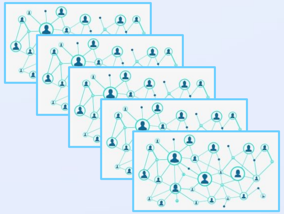

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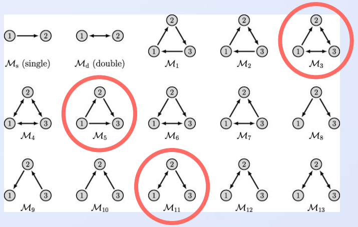

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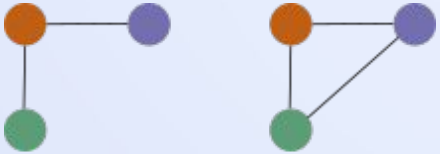

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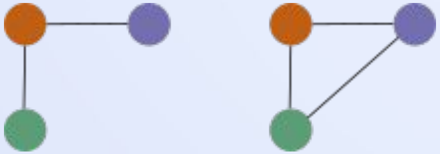

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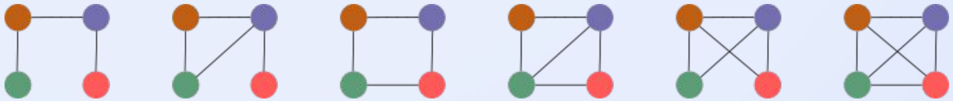

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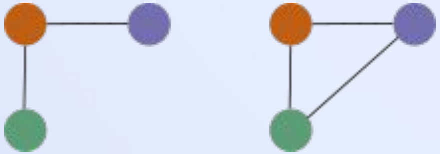

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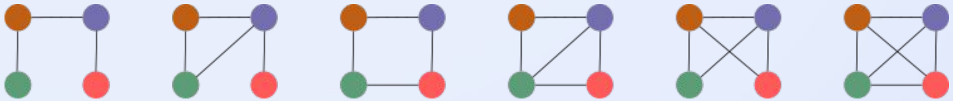

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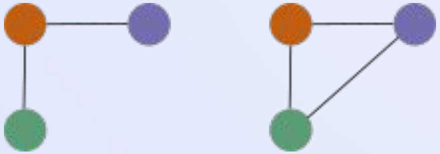

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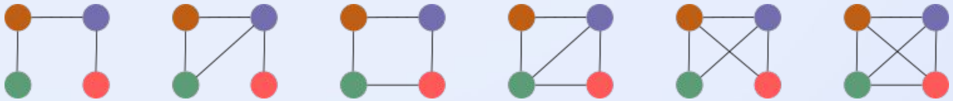

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Computational expensive

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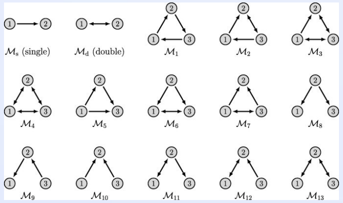

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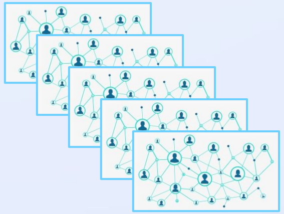

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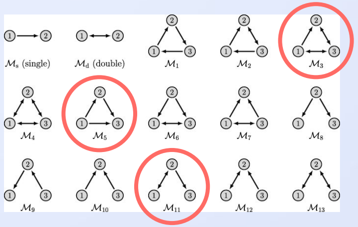

Network motifs

Temporal network motifs

02

TEMPORAL NETWORK MOTIFS

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

So temporal networks solve this problem.

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Temporal network:

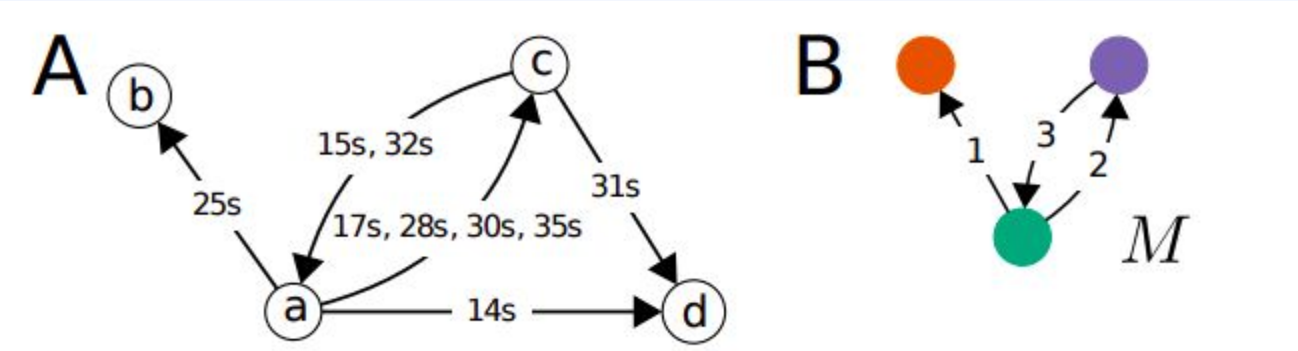
1) **Edges** → interactions among peoples
2) **Nodes** → users in social networks
3) **Attributes** → enemies can become friends

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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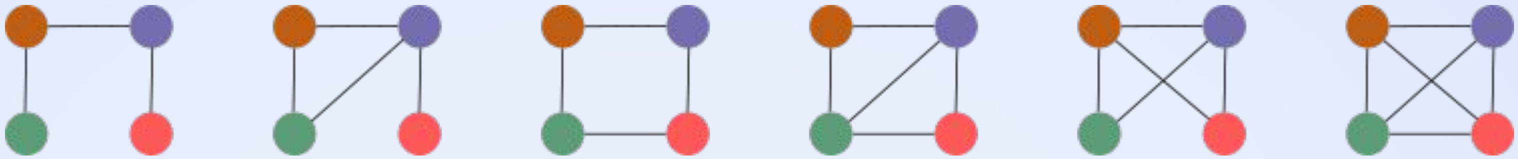

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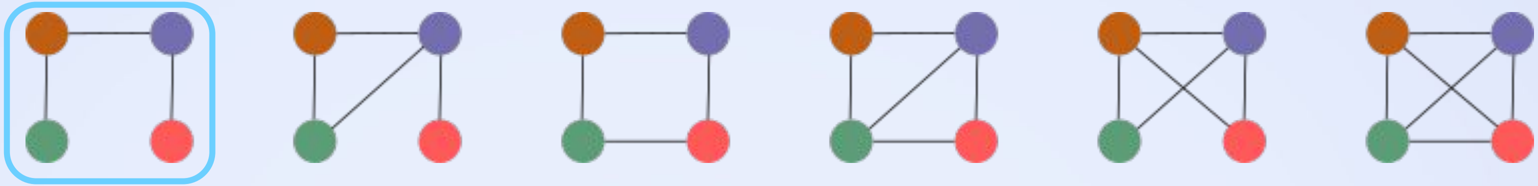
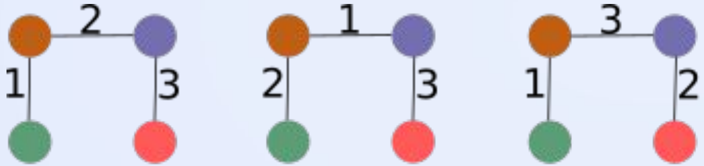


Temporal network



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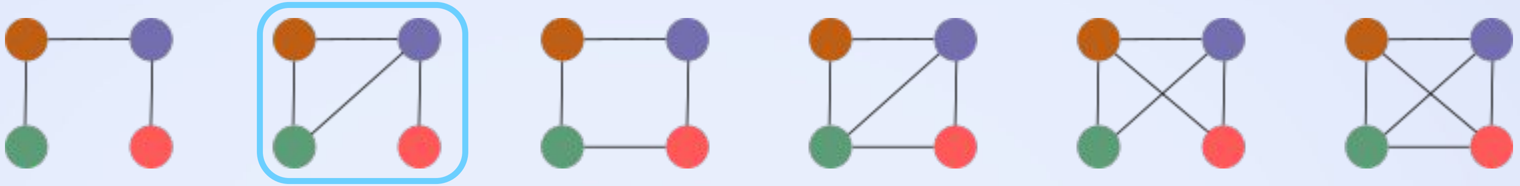

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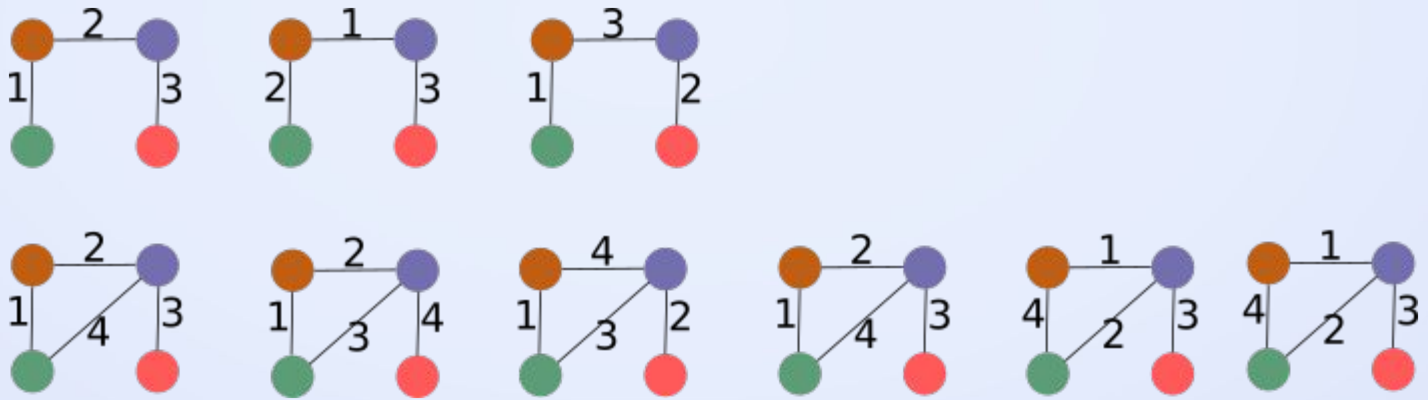

A lot of more

TEMPORAL NETWORK MOTIFS

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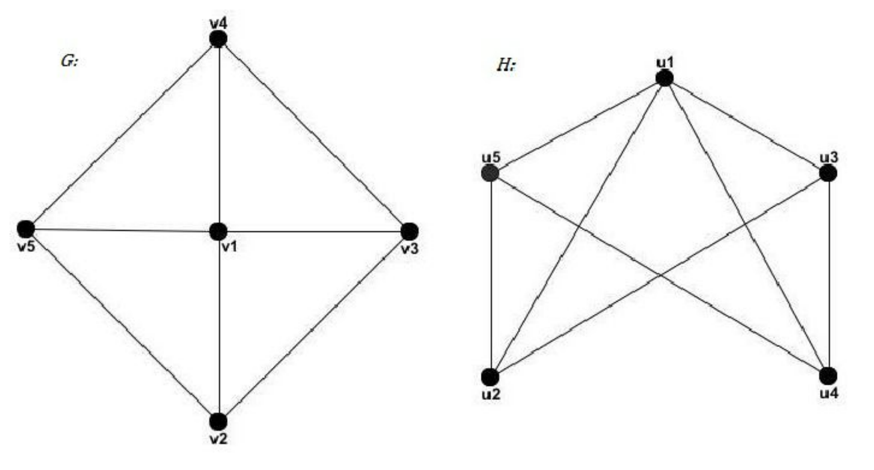


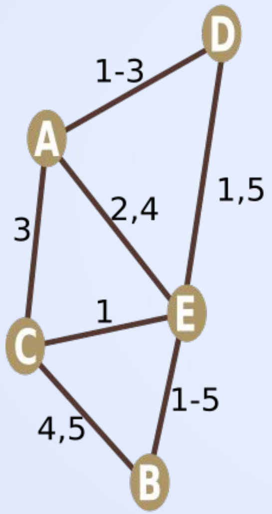
If the size of the sub graph is big, we have to compute an **isomorphism test.**
It requires lot of time!

Egocentric Temporal Motifs

03

EGOCENTRIC TEMPORAL MOTIFS

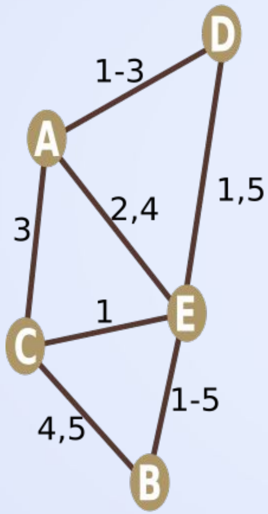
Temporal graph

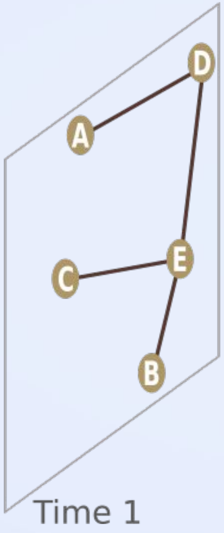


A. Longa, G. Cencetti, B. Lepri, and A. Passerini, “An efficient procedure for mining egocentric temporal motifs,” Data Mining and Knowledge Discovery, pp. 1–24, 2021.

EGOCENTRIC TEMPORAL MOTIFS

Temporal graph





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EGOCENTRIC TEMPORAL MOTIFS

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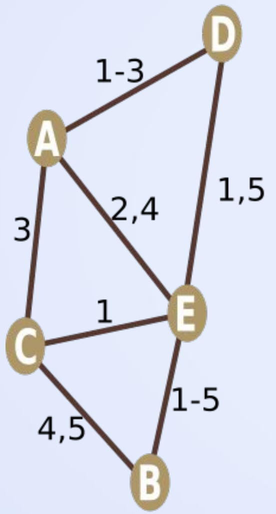

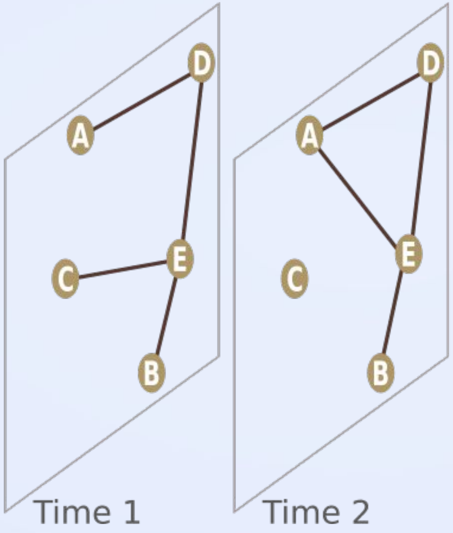

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EGOCENTRIC TEMPORAL MOTIFS

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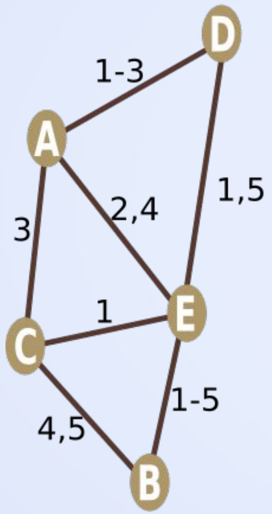

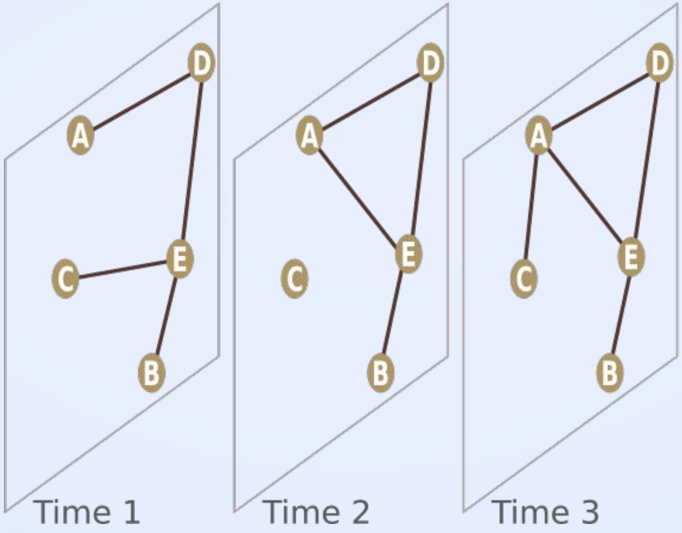

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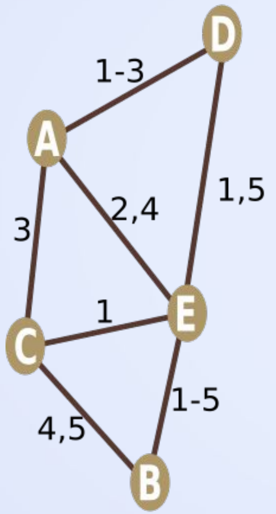
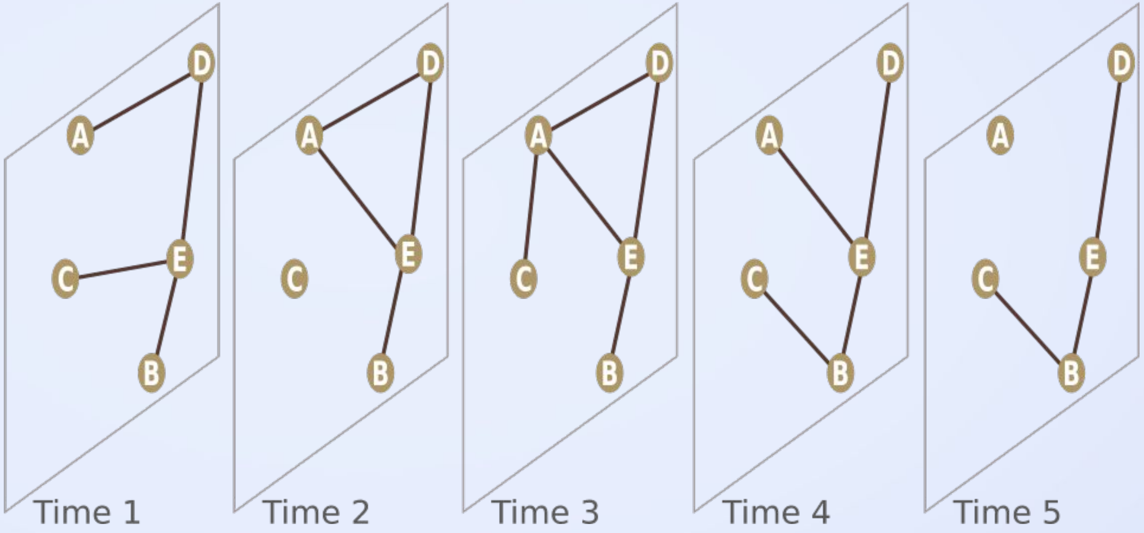


Temporal graph snapshots



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EGOCENTRIC TEMPORAL MOTIFS

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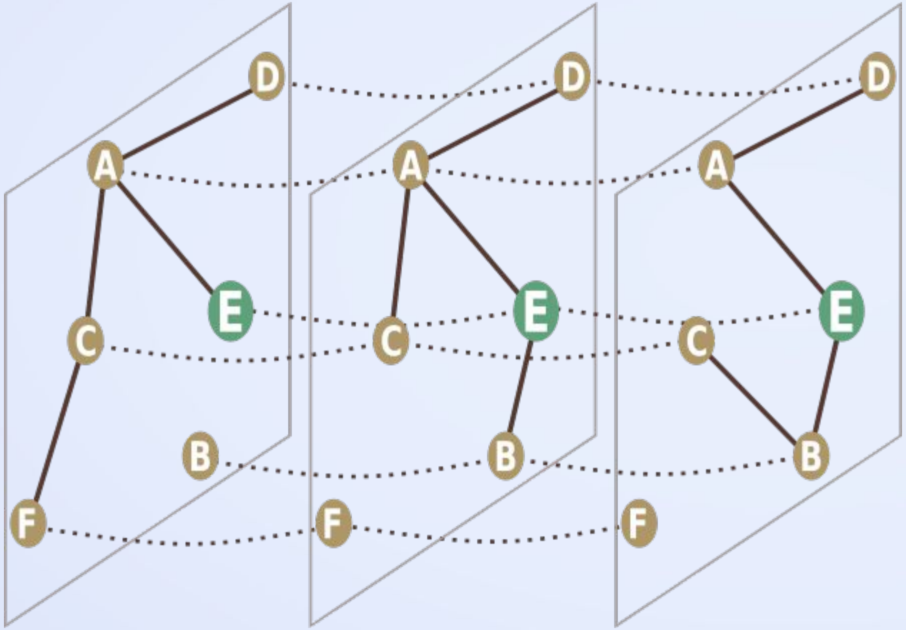
Decide and EGO Node = E



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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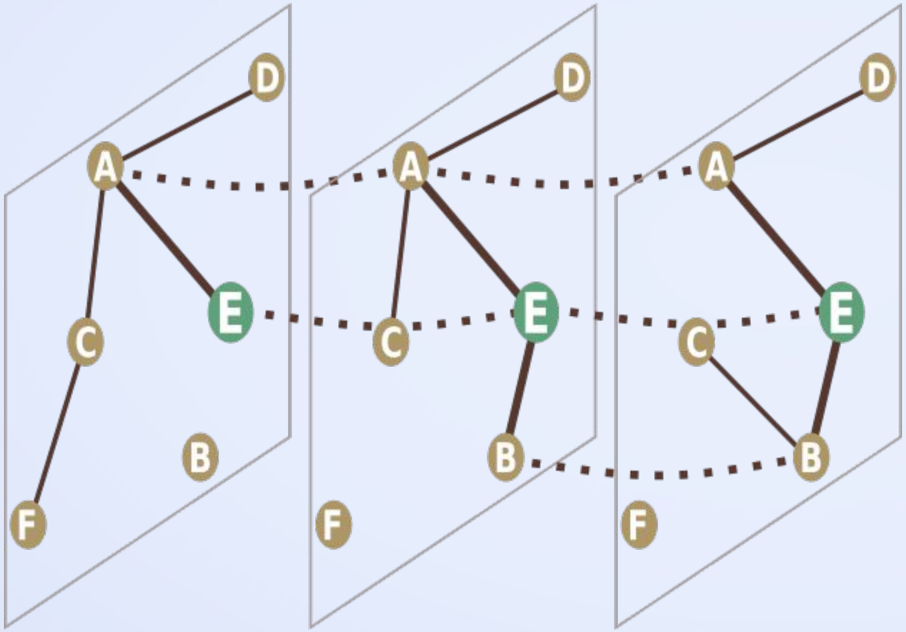

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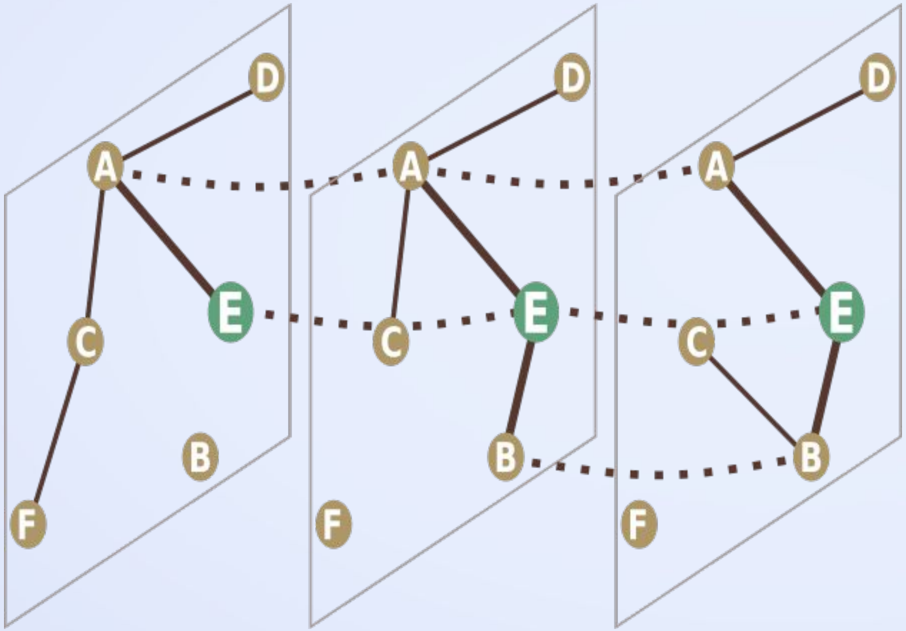

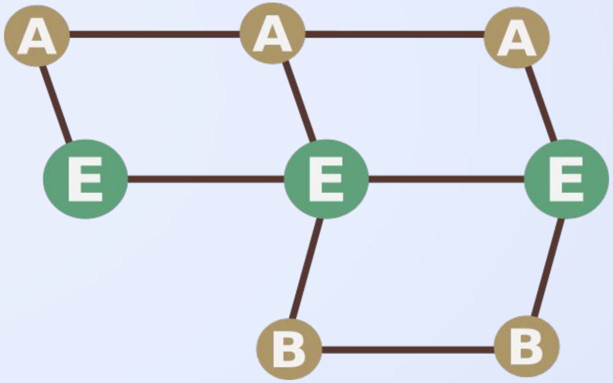

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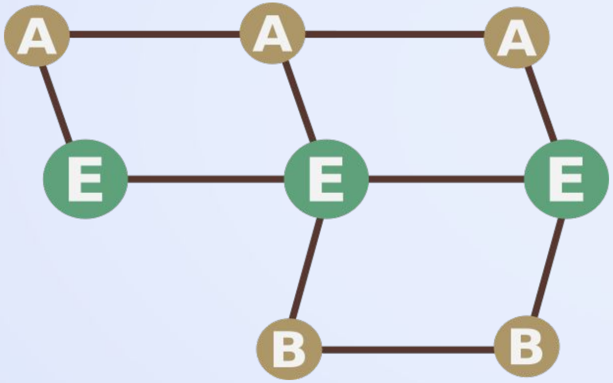

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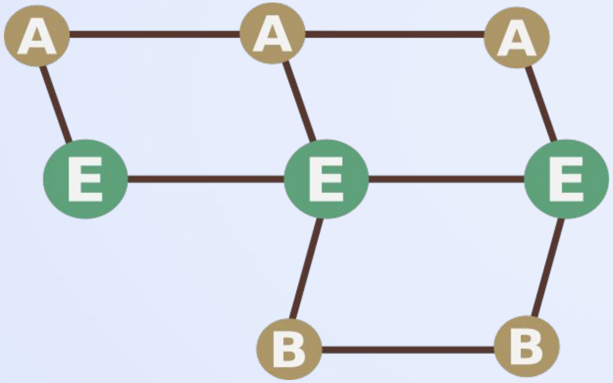
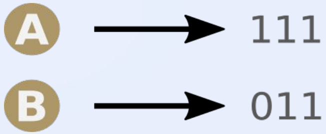


NODE ENCODING



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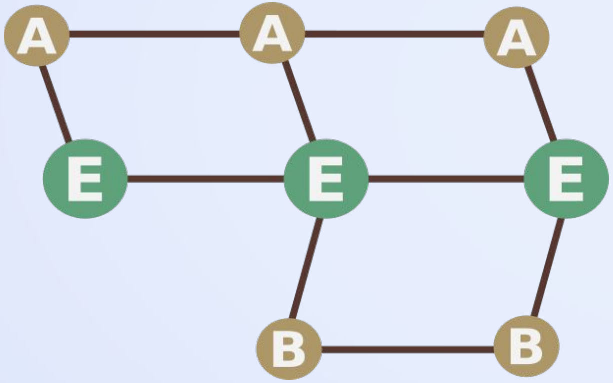

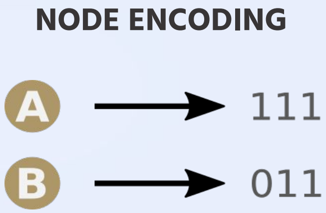

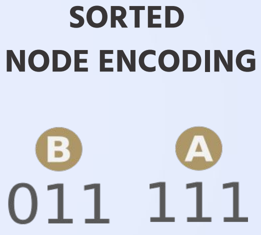

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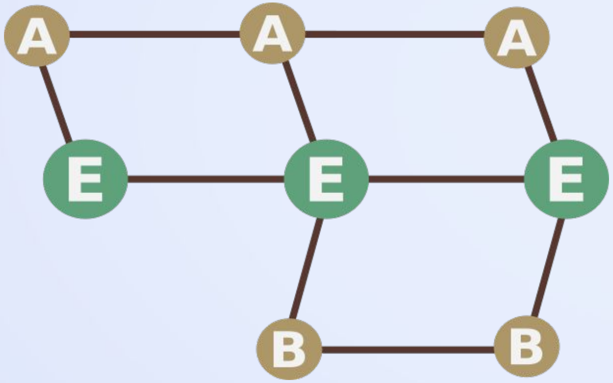
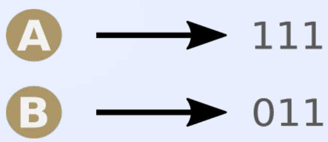
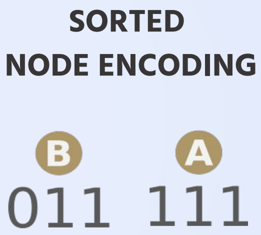






Egocentric Temporal Neighbourhood Signature
ETNS

011 111

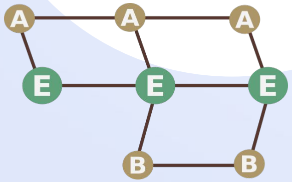
A. Longa, G. Cencetti, B. Lepri, and A. Passerini, “An efficient procedure for mining egocentric temporal motifs,” Data Mining and Knowledge Discovery, pp. 1–24, 2021.

IN SHORT

01

ETN

Egocentric
Temporal
Neighbourhood.
(a sub structure)



IN SHORT

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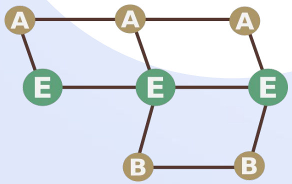

02

ETNS

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

011 111

IN SHORT

01

ETN

Egocentric
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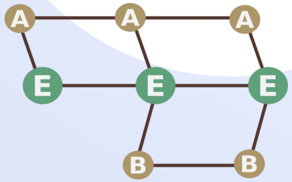

02

ETNS

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

011 111

03

Fast way to compute if two
sub structures are identical

IN SHORT

01

ETN

Egocentric
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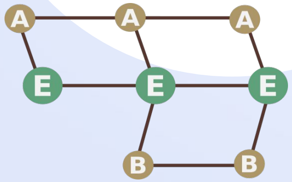

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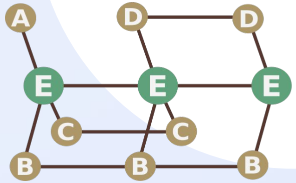

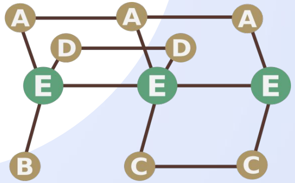

IN SHORT

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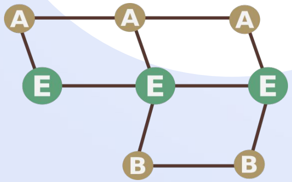

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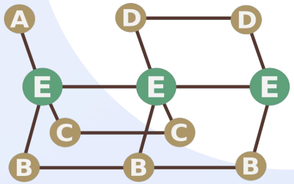
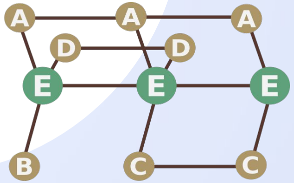


011 100 110 111



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

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Input graphs

APPLICATIONS

COMPUTE DISTANCES

Cosine similarity

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Input graphs

APPLICATIONS

COMPUTE DISTANCES

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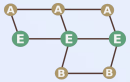
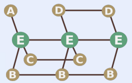
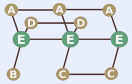
Input graphs

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

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Workplace and
Hospital are similar

COMPUTE DISTANCES

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Workplace and
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High Schools are
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COMPUTE DISTANCES

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Workplace and Hospital are similar

High Schools are similar

Primary school is different from all the networks

COMPUTE DISTANCES

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Quite similar to High Schools

COMPUTE DISTANCES

RESULTS

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University							0

Quite similar to High Schools

Different from primary school

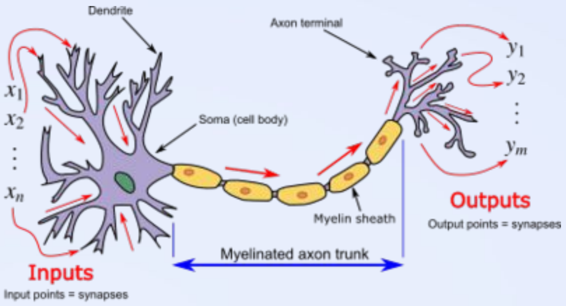
05

Future directions

APPLICATIONS

COMPUTE DISTANCES

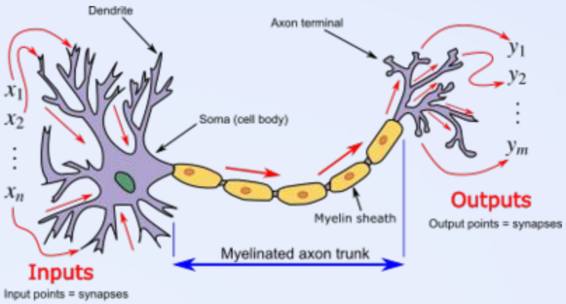
BIOLOGICAL NEURONS

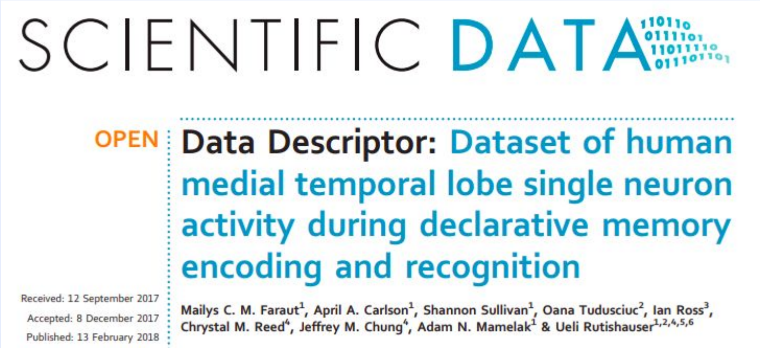


APPLICATIONS

COMPUTE DISTANCES

BIOLOGICAL NEURONS





SCIENTIFIC DATA

OPEN **Data Descriptor: Dataset of human medial temporal lobe single neuron activity during declarative memory encoding and recognition**

Received: 12 September 2017
Accepted: 8 December 2017
Published: 13 February 2018

Mailys C. M. Faraut[1], April A. Carlson[1], Shannon Sullivan[1], Oana Tudusciuc[2], Ian Ross[3], Chrystal M. Reed[4], Jeffrey M. Chung[4], Adam N. Mamelak[1] & Ueli Rutishauser[1,2,4,5,6]

- Neurons activation in human amygdala and hippocampus.
- Recognition memory task with pictures

APPLICATIONS

COMPUTE DISTANCES

BIOLOGICAL NEURONS

PROTEOME (protein interactions)

APPLICATIONS

COMPUTE DISTANCES

BIOLOGICAL NEURONS

PROTEOME (protein interactions)

INTERACTOME (molecular interactions)

APPLICATIONS

COMPUTE DISTANCES

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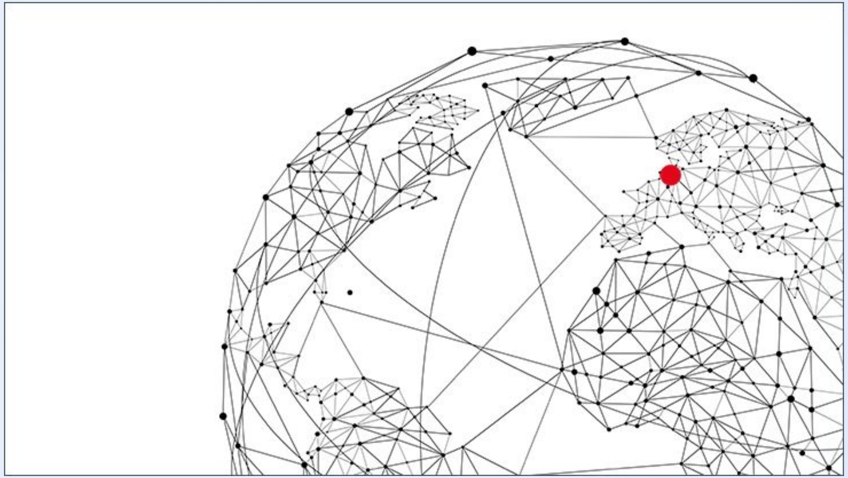
EPIDEMICS



APPLICATIONS

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BIOLOGICAL NEURONS

PROTEOME (protein interactions)

INTERACTOME (molecular interactions)

EPIDEMICS

AGING

APPLICATIONS

COMPUTE DISTANCES

BIOLOGICAL NEURONS

PROTEOME (protein interactions)

INTERACTOME (molecular interactions)

EPIDEMICS

AGING

METABOLIC NETWORK

APPLICATIONS

COMPUTE DISTANCES

BIOLOGICAL NEURONS

PROTEOME (protein interactions)

INTERACTOME (molecular interactions)

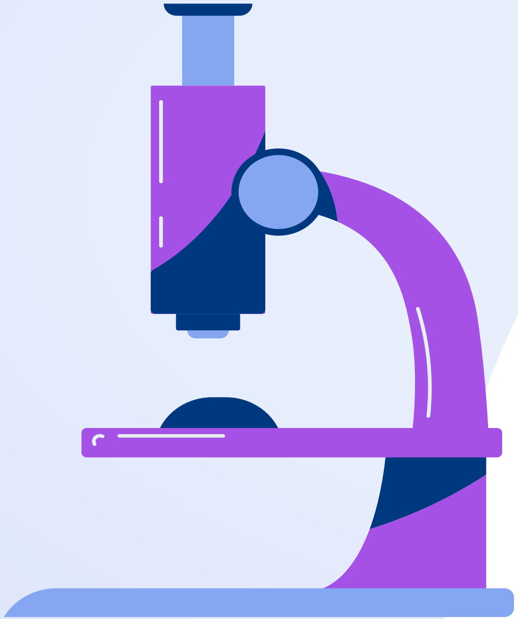
EPIDEMICS

AGING

METABOLIC NETWORK

……………..

IN BRIEF



- We show the importance of Temporal networks
- Motifs in temporal networks
- Egocentric temporal motifs
- Fast way to mine it
- Possible applications

THANKS

Do you have any questions?

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