# Scalable Partitioning of Large Complex Networks

#### Luce le Gorrec

UK IC Postodoctoral Research Fellow

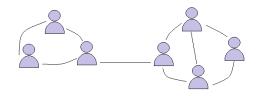
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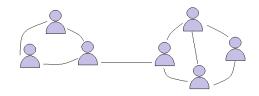
Glasgow, United Kingdom



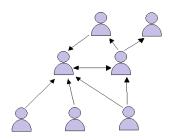
**Graph** (or network): entities (nodes) connected by relations (edges).





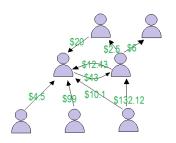






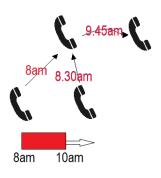
E.g. Who-follows-who network.



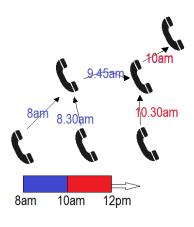


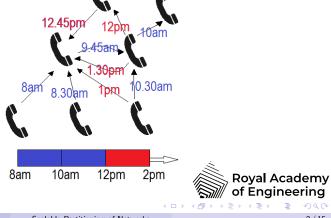
E.g. Money transfer network.



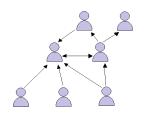








**Graph** (or network): entities (nodes) connected by relations (edges). Different kinds of graphs: directed, weighted, evolving...

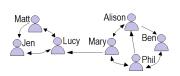


⇒ Our study case : directed, unweighted, static.

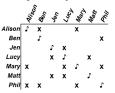


What: A partition of nodes with high (low) density of edges within (between) the groups: a **community structure**.





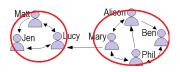
#### Its Adjacency Matrix



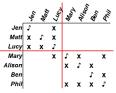


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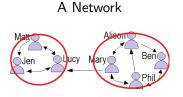
#### A Network



#### Its Adjacency Matrix



What: A partition of nodes with high (low) density of edges within (between) the groups: a **community structure**.



Its Adjacency Matrix



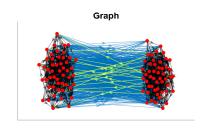
### Why:

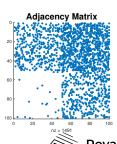
- Data analysis: Users spreading terrorist propaganda on Twitter[1].
- Numerical efficiency: Analysis of a hundred-million-node network[2].



How: Partitioning a graph: NP-hard:

- But for undirected graphs: Efficient, simple and well-established heuristic (Louvain [3], Metis [4], ...).
- For directed graphs: Nothing as simple or well-established ([5]).
- $\Rightarrow$  "forgetting" edge directions to get undirected networks (suboptimal).





Recent works [6,7,8] focus on motifs to partition directed networks.

Motif: A small induced subgraph of a certain kind.

Looking for motifs  ${\mathcal M}$ 

in a graph



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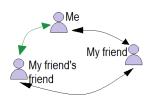
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#### Motifs express complex notions in networks:

Friends of my friends are my friends:







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Motif: A small induced subgraph of a certain kind.

#### Motifs express complex notions in networks:

Cooperative propagation of information:



Transmitters



Receivers



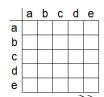
An application of motifs: an undirected network induced from a directed one:

Looking for motifs \_\_\_\_\_ in the graph





provides the graph:





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provides the graph:



	а	b	С	d	е
а		1	1		
a b	1		1		
c d	1	1			
d					
е					

An application of motifs: an undirected network induced from a directed one:

Looking for motifs \_\_\_\_\_ in the graph





provides the graph:



	а	b	С	d	е
а		1	2		1
a b	1		1		
c d	2	1			1
d					
е	1		1		



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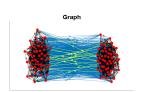
whose adjacency matrix is:

	а	b	С	d	е
а		1	2		1
b	1		2	1	
С	2	2		1	1
d		1	1		
е	1		1		

 $\implies$  the **Benson Graph** of the initial network [6].



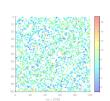
# Motifs and Benson Graphs





Adjacency Matrix of the Benson graph of motif:





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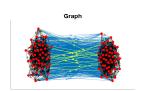


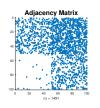






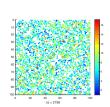
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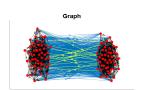


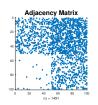




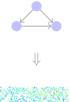


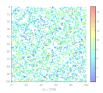
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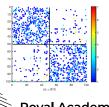




Adjacency Matrix of the Benson graph of motif:









# Which motif(s) should we use?

#### Assessing a motif significance:

- With inferred knowledge.
- What if no available knowledge?



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#### Assessing a motif significance:

- With inferred knowledge.
- What if no available knowledge?
- Statistical significance (ZScore) [9]: 'Significant motifs appear more often than "by chance".'
  A network G, a motif M, a sequence of random networks {H<sub>1</sub>,..., H<sub>k</sub>}:

$$\textit{ZScore}(\mathcal{M}) = \frac{\# \mathsf{motifs} \ \mathcal{M} \ \mathsf{in} \ \mathit{G} - \mathit{mean}(\# \mathsf{motifs} \ \mathcal{M} \ \mathsf{in} \ \mathit{H}_i)}{(\mathit{std}(\# \mathsf{motifs} \ \mathcal{M} \ \mathsf{in} \ \mathit{H}_i) + \varepsilon)}.$$

Expensive, no consensus about random model.



# Which motif(s) should we use?

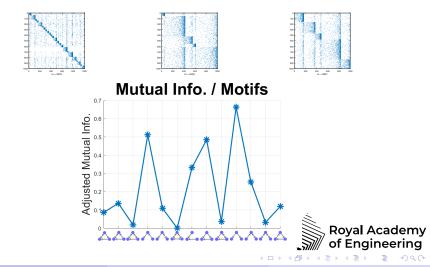
#### Assessing a motif significance:

- With inferred knowledge.
- What if no available knowledge?
- Statistical significance (ZScore) [9]: 'Significant motifs appear more often than "by chance".'
- X Expensive, no consensus about random model.
- Our proposal : Assess the **discriminatory capacity of motifs on a dataset**: a measure ( $\gamma$ -score) derived from a feature selection process based on Principal Component Analysis. (A preprint submitted).



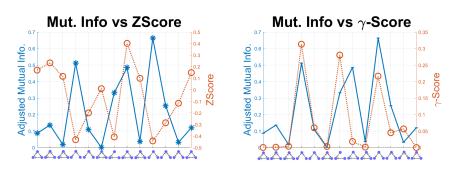
# Which motif(s) should we use? Work in progress

Detecting communities in modular networks [10] using Louvain applied on the Benson graphs.



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Detecting communities in modular networks [10] using Louvain applied on the Benson graphs.



 $\implies$  Motifs with highest  $\gamma$ -score  $\sim$  Motifs with highest Adj. Mut. Info. Royal Academy of Engineering

# Which motif(s) should we use? TO DO

- Expand the preliminary study to confirm/dismiss the correlation high  $\gamma$ -score/well-detected blocks.
- Focus on local community detection: different motifs may help to detect different communities [11].



# Building the Benson Graphs

- Naive: Whole decomposition of the network (finding all the Benson graphs): FanMod [12].
- Prohibitive complexity.
- Some efficient techniques exist [6].
- For certain kinds of motifs only.
- We have derived generic formulas to directly compute the Benson adjacency matrices of 3- and 4-node motifs.



# Building the Benson Graphs: Our formulas

Two observations: A graph G with n nodes, A of dim  $n \times n$  its adjacency matrix.

Observation 1: 3 matrices B, U, N of dim  $n \times n$  based on A s.t.:

- $B(i,j) = 1 \iff (i) \leftrightarrow (j)$  in G.
- $U(i,j) = 1 \iff (i) \rightarrow (j)$  in G.
- $N(i,j) = 1 \iff (i)$  (j) in G.

Observation 2: Given 2 nodes i, j in G, number of x s.t.



 $(i \longleftrightarrow j)$  and  $i \to x \leftarrow j$ B(i,j)  $\times \sum_{x=1}^{n} U(i,x).U(x,j)$ 

# Building the Benson Graphs: TO DO

- We are working on an efficient implementation of our formulas.
- Extension to larger motifs?



### Take Home Messages

- Partitioning directed networks: not as "simple" as for undirected case.
- Motifs express complex notions in networks .
- The Benson Graph provides an undirected representation of the network.
- Without other knowledge,  $\gamma$ -score seems to provide good indication about which motifs used to partition the graph.
- With linear algebra, the Benson adjacency matrix can be directly built for 3-and 4-node motifs.



### Thank you for your attention

Some codes and the slides are available on github.com/luleg/

#### **Bibliography**

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