

ROBIN:

(ROBUSTNESS IN NETWORK)

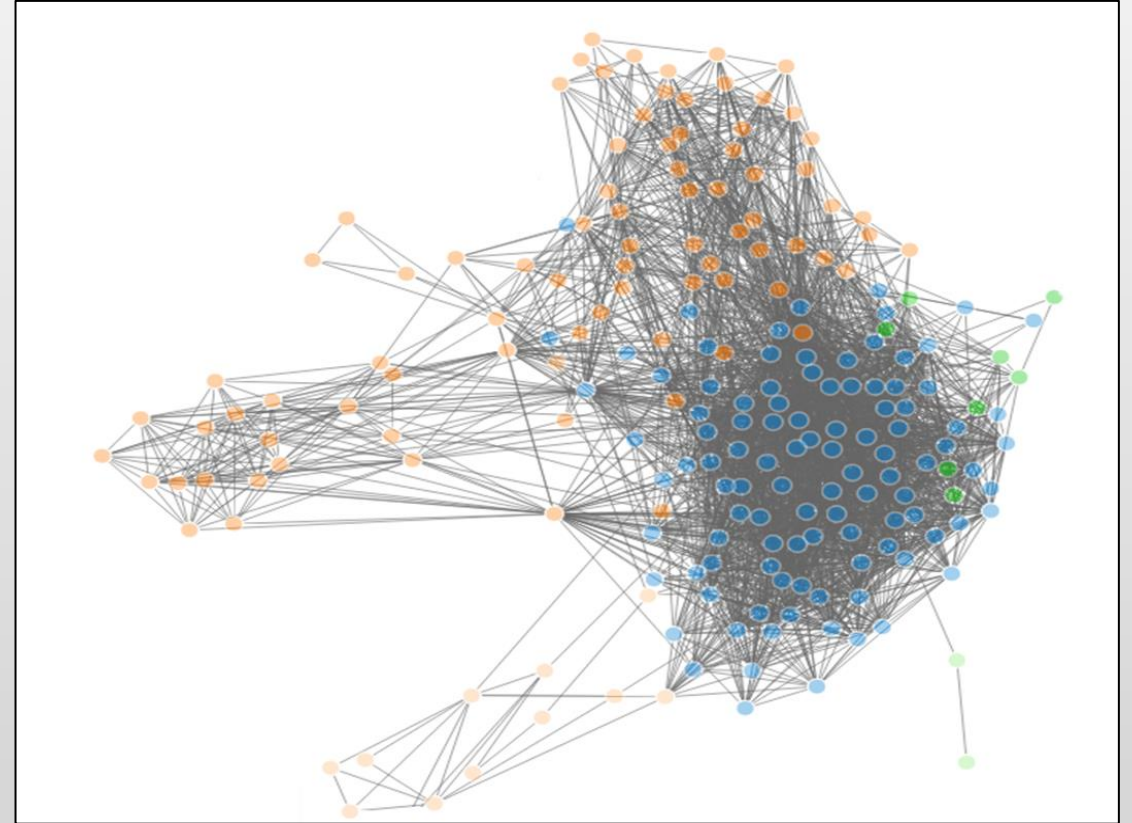
AN R PACKAGE FOR VALIDATION OF
COMMUNITY ROBUSTNESS

Valeria Policastro

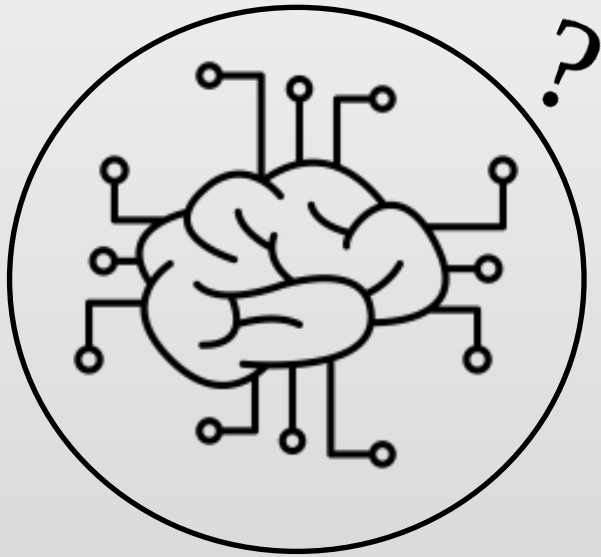
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COMMUNITY DETECTION

- ❖ One of the most relevant features of graphs representing real systems is their **community structure**
- ❖ How can we say that is statistically robust?



ROBUSTNESS



Are the detected communities significant or are they a result of chance only due to the positions of edges in the network?

ROBIN: (ROBustness In Network)



❖ An R package that gives a statistical answer to the ***validation of the community structure*** by looking at the robustness of the network

*Carissimo A., Cutillo L., De Feis I., Validation of community robustness
Computational Statistics and Data Analysis 2017*

ROBUSTNESS AGAINST RANDOM PERTURBATION



- ❖ If a partition is significant, it will be recovered even if the structure of the graph is modified

❖ **ROBIN** gives the possibility to analyze community detection in all different aspects:

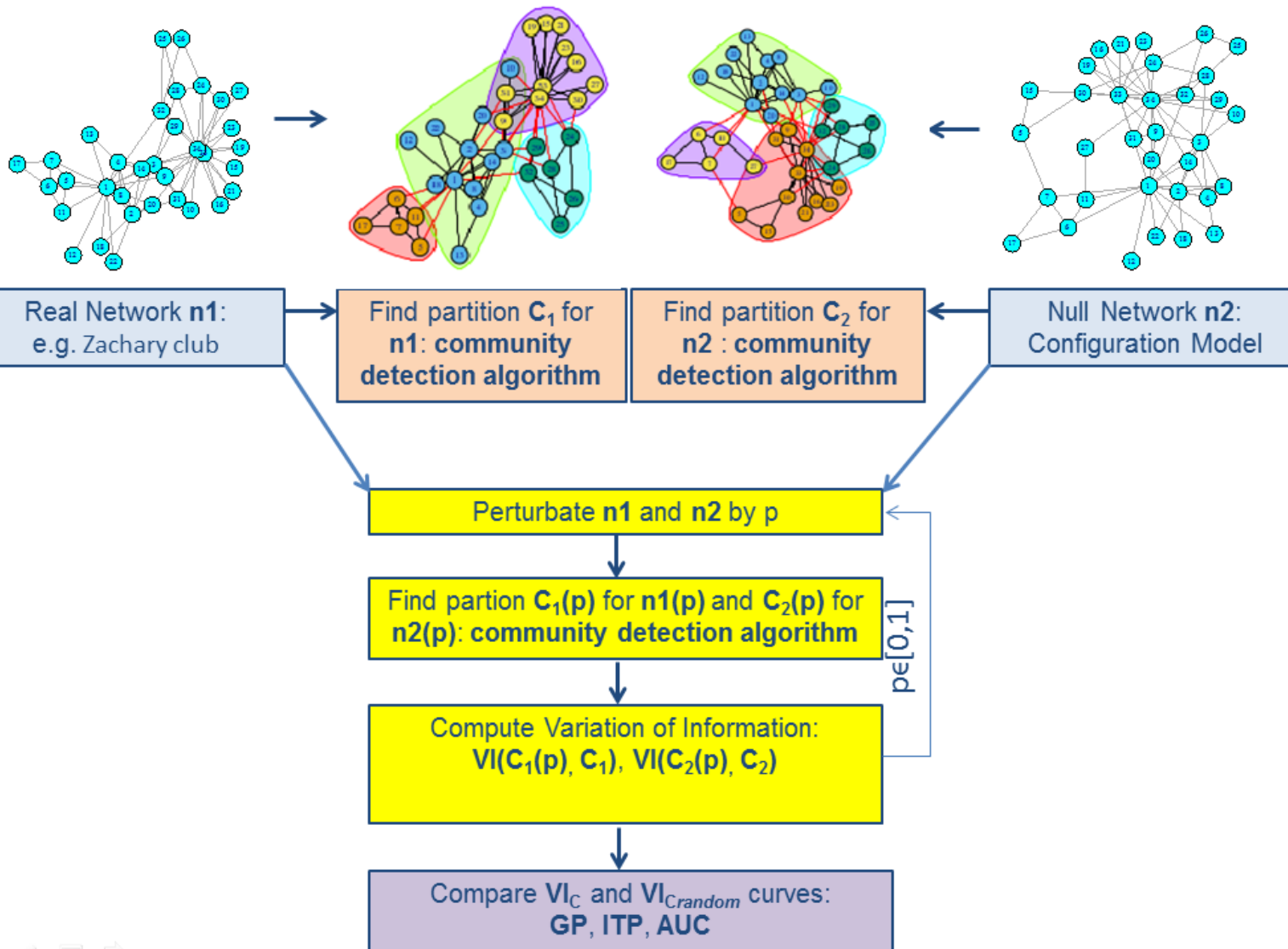
- ✓ Community detection algorithms
- ✓ Validation of the community structure
- ✓ Comparison of different community algorithms
- ✓ Graphical interactive representation of 3D networks

A decorative header banner featuring a complex network graph with numerous nodes and edges, rendered in a light blue color against a dark background. The word "PROCEDURE" is centered in white, uppercase letters.

PROCEDURE

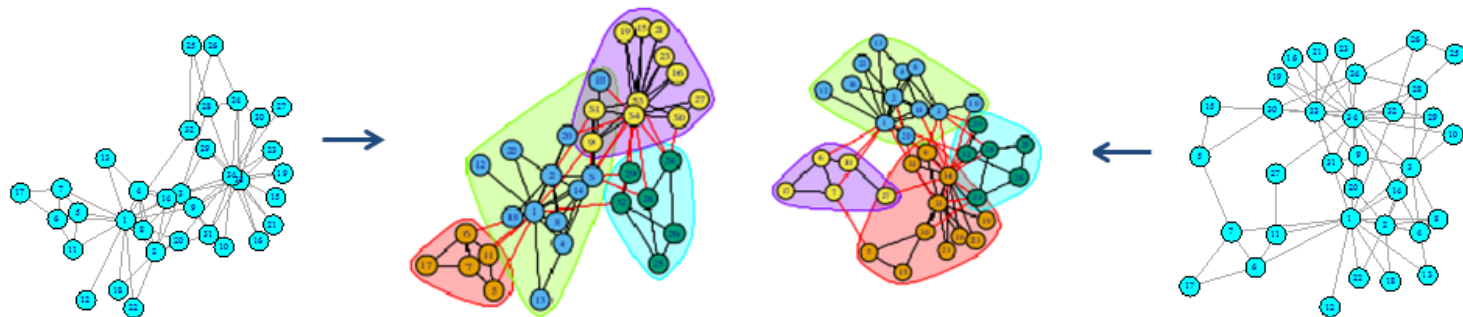
- ❖ Given a **community detection method** and a **network** of interest ROBIN analyses the stability of the partitions
- ❖ It implements a **perturbation strategy** and a **null model** to build a procedure based on **Variation of Information**

ROBIN WORKFLOW



1. Given a network, find a partition C with some algorithm
2. Perturb the network to create a new network, find the partition C' for the perturbed network, compare C and C' computing the Variation of Information VI
3. Repeat this calculation for different perturbation levels p

ROBIN WORKFLOW



Real Network $n1$:
e.g. Zachary club

Find partition C_1 for
 $n1$: community
detection algorithm

Find partition C_2 for
 $n2$: community
detection algorithm

Null Network $n2$:
Configuration Model

Perturbate $n1$ and $n2$ by p

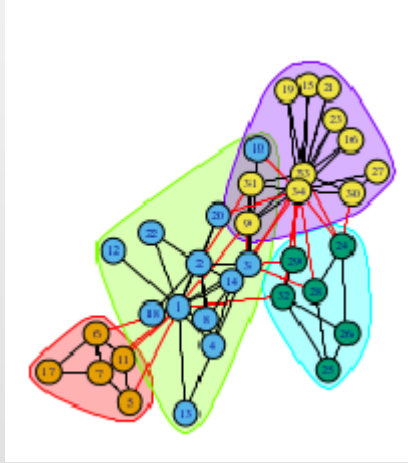
Find partition $C_1(p)$ for $n1(p)$ and $C_2(p)$ for
 $n2(p)$: community detection algorithm

Compute Variation of Information:
 $VI(C_1(p), C_1), VI(C_2(p), C_2)$

Compare VI_C and $VI_{C_{random}}$ curves:
GP, ITP, AUC

4. Perform 2. and 3. on a random graph (*null model*)
5. Compare the curves obtained plotting the average VI versus p of the original and the null model

ROBIN PERTURBATION STRATEGY



- ❖ The perturbed network has the same number of vertices and edges as the original unperturbed network

$$p \in [0, 1]$$

$p=0$ The original unperturbed graph

$p=1$ The maximal perturbation level (*random graph*)

ROBIN PERTURBATION STRATEGY

- ❖ **Rewire algorithm:** chooses two arbitrary edges in each step (e.g. (a,b) and (c,d)) and substitutes them with (a,d) and (c,b) if they do not already exist in the graph
- ❖ **keeping_degseq:** preserving the original graph's degree distribution

rewireComplete(graph, number)

ROBIN PERTURBATION STRATEGY

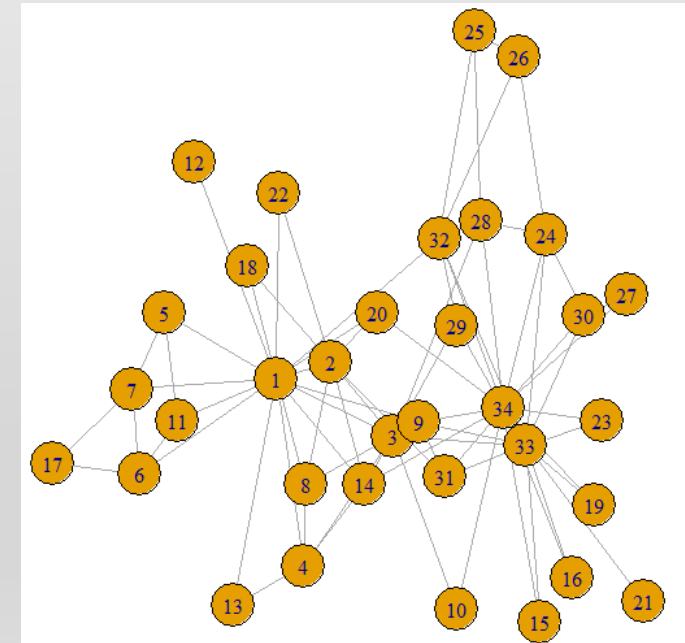
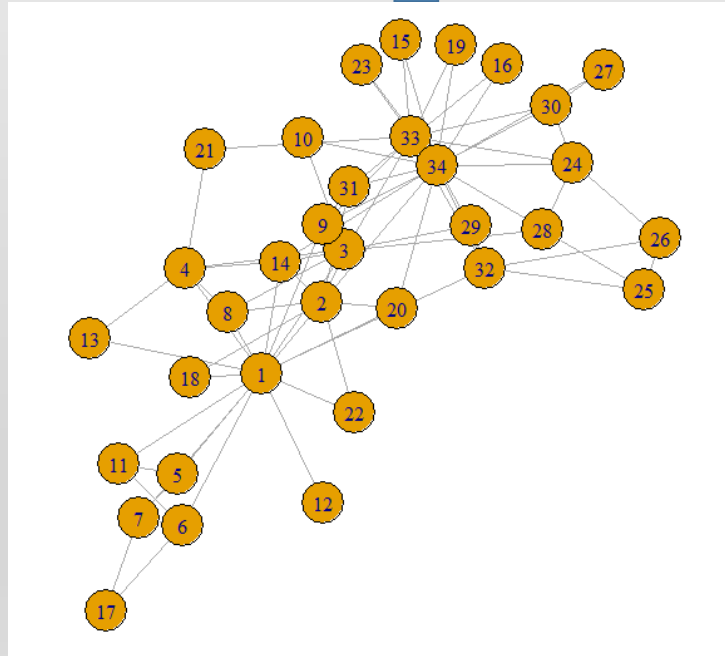
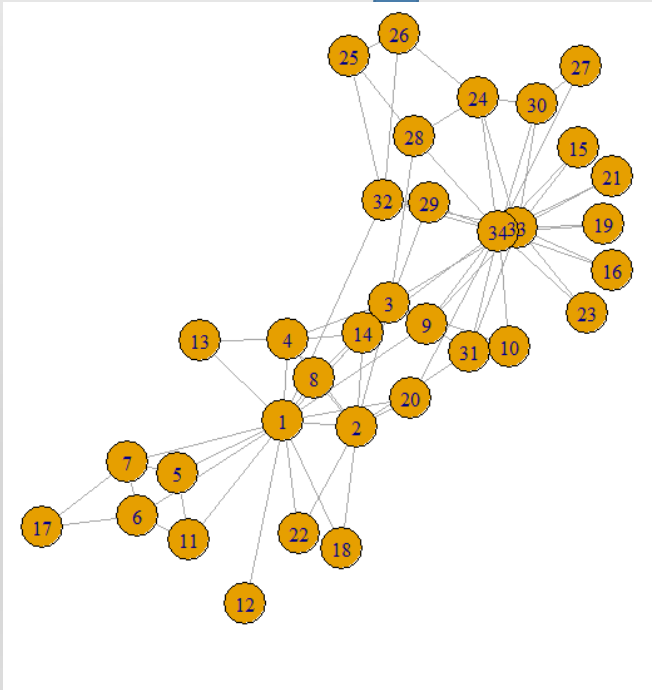
I° level of p

5%

Remove edges rewired

II° level of p

5%



...until is all perturbed

ROBIN PERTURBATION STRATEGY

Generates 20 levels of p

- ❖ For each different level it generates 10 perturbed graph. Then, from each of the obtained graphs, it generates other 10 graphs rewiring 1% of edges each time

Result: 100 graphs for each level !!!

Configuration Model :

- Able to preserve strongly heterogeneous degree distribution of the real network.
- It randomly assign edges between vertices with a given degree distribution.

graphRandom(graph)

VARIATION OF INFORMATION (VI)

- ❖ At each level of perturbation p ROBIN compares the partition obtained from the original graph with the partition obtained from the perturbed graph computing Variation of Information (**VI**)

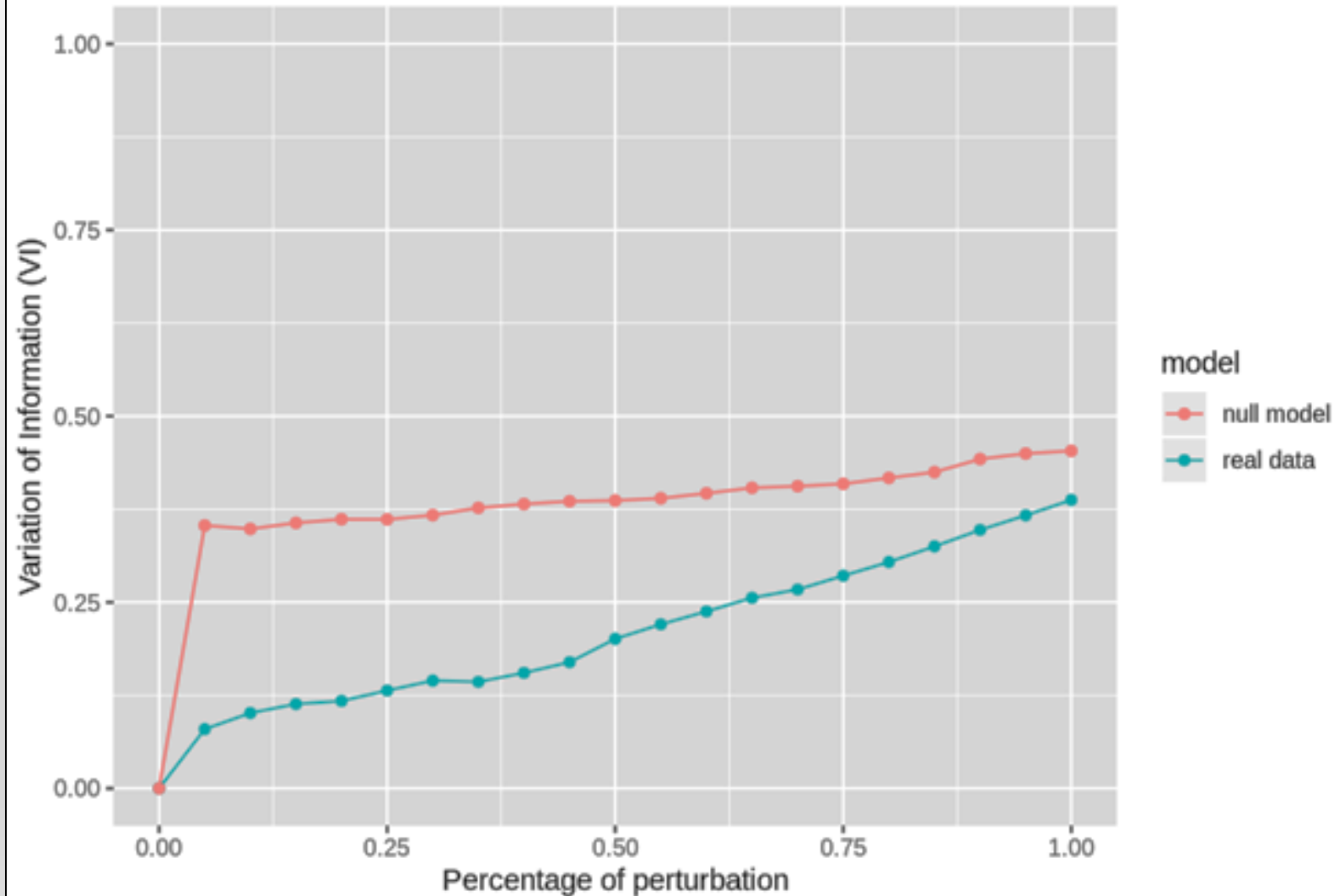
`compare(comReal, comR, method="vi")`

comReal = Community Real

ComR = Community Rewire at a specific level

VI AS FUNCTION OF AMOUNT OF PERTURBATION P

Robin plot



`plotRobin (graph,model1,model2, legend)`

model1= mean vi real data

model2= mean vi null model

***How can ROBIN
test the
differences
between the
two curves?***

A decorative header image featuring a complex network of blue lines and nodes on a black background, resembling a molecular structure or a data network.

ROBIN TESTS

❖ The percentage of perturbation as time points of two time series

Gaussian Process(GP)

❖ Functional data analysis

Interval Testing Procedure (ITP)

❖ Compare the area under the curves

AUC

GAUSSIAN PROCESS

❖ Are the two curves from the same process or not?



Gprege package: Gaussian Process Ranking and Estimation of Gene Expression time-series

```
callGp (ratio)
```

```
ratio= log2(viMean/viMeanRandom) for each level
```



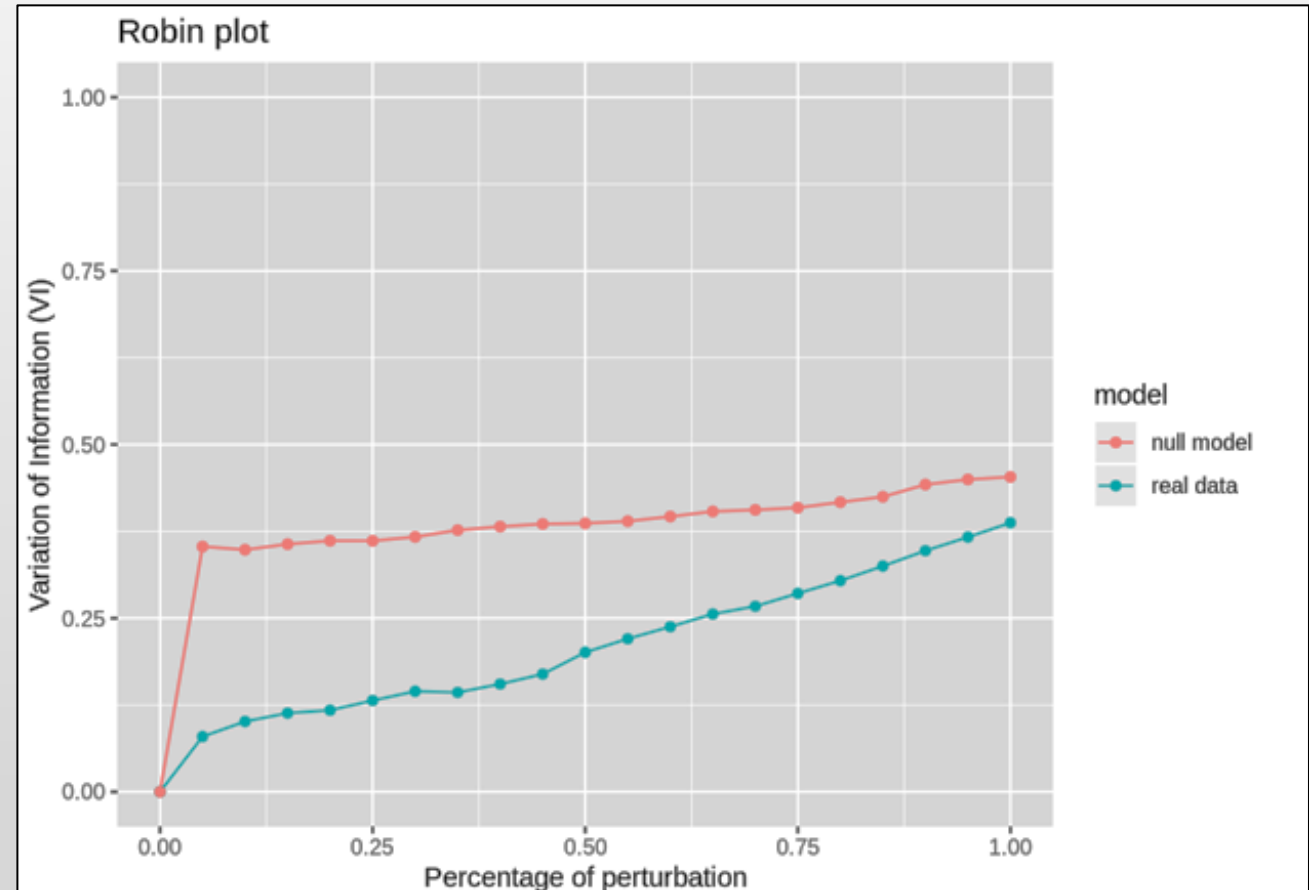
Bayes Factor: score based on the log-ratio of marginal likelihoods

```
bf=gpregeOutput$rankingScores[1]
```

GAUSSIAN PROCESS

Bayes_Factor 383.8757

K	dHart	bits	Strength of evidence
$< 10^0$	0	—	Negative (supports M_2)
10^0 to $10^{1/2}$	0 to 5	0 to 1.6	Barely worth mentioning
$10^{1/2}$ to 10^1	5 to 10	1.6 to 3.3	Substantial
10^1 to $10^{3/2}$	10 to 15	3.3 to 5.0	Strong
$10^{3/2}$ to 10^2	15 to 20	5.0 to 6.6	Very strong
$> 10^2$	> 20	> 6.6	Decisive



AUC

❖ Calculate the area under the curve with a spline approach



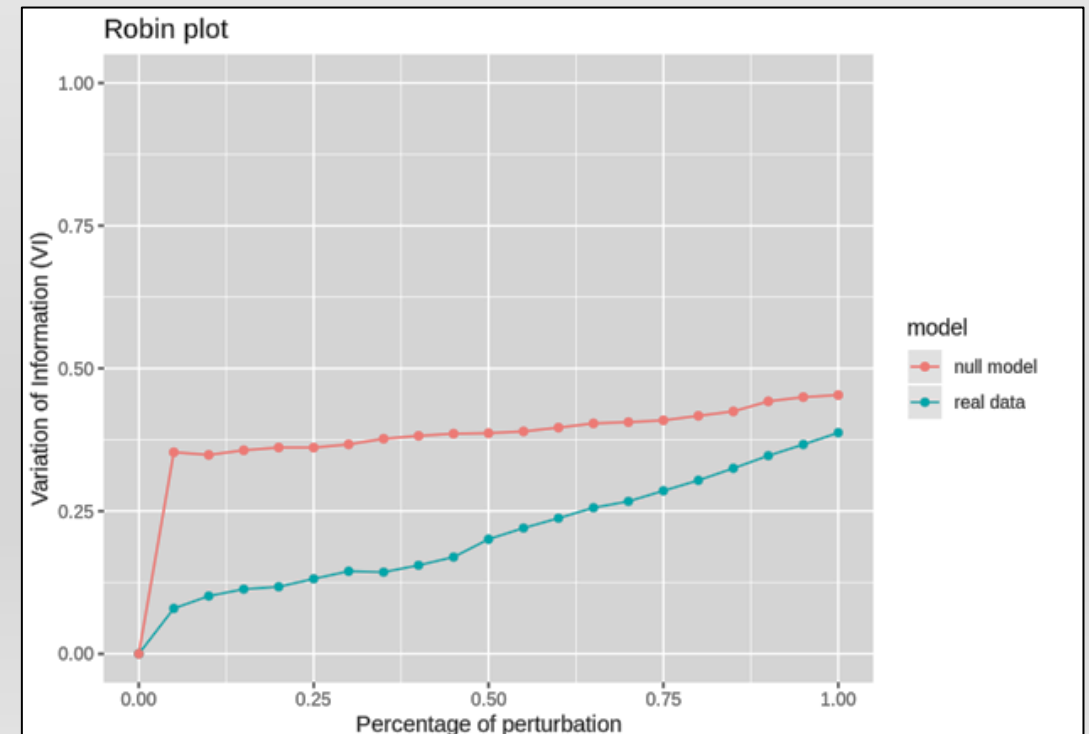
DescTools package: Tools for Descriptive Statistics

```
AUC(x=percPerturb, y=mvimmeanmodel1, method="spline")
```

Area Under the Curve:

Area1 0.2082588

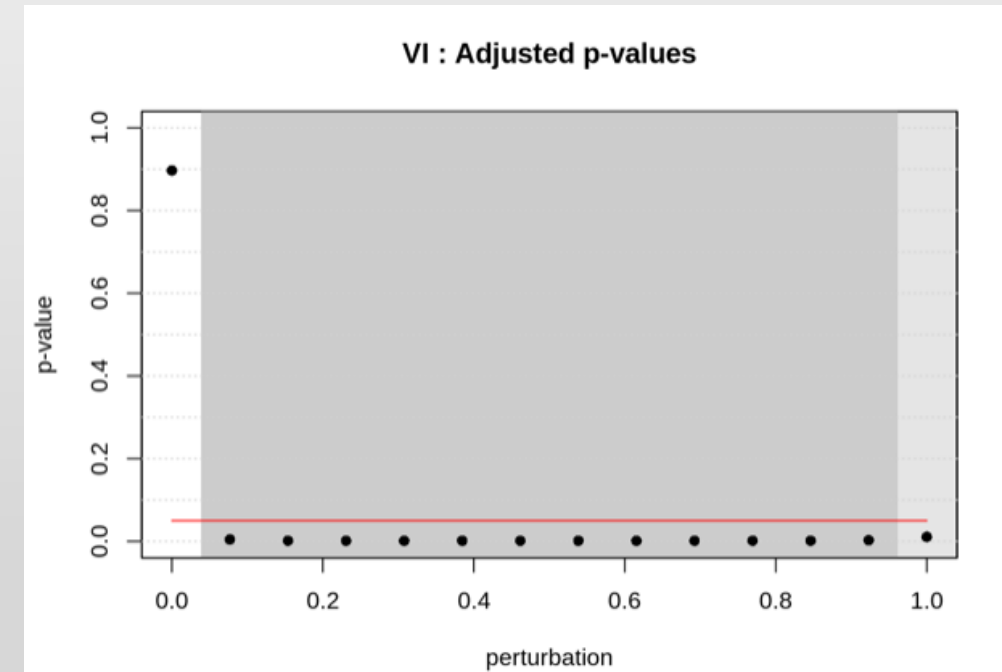
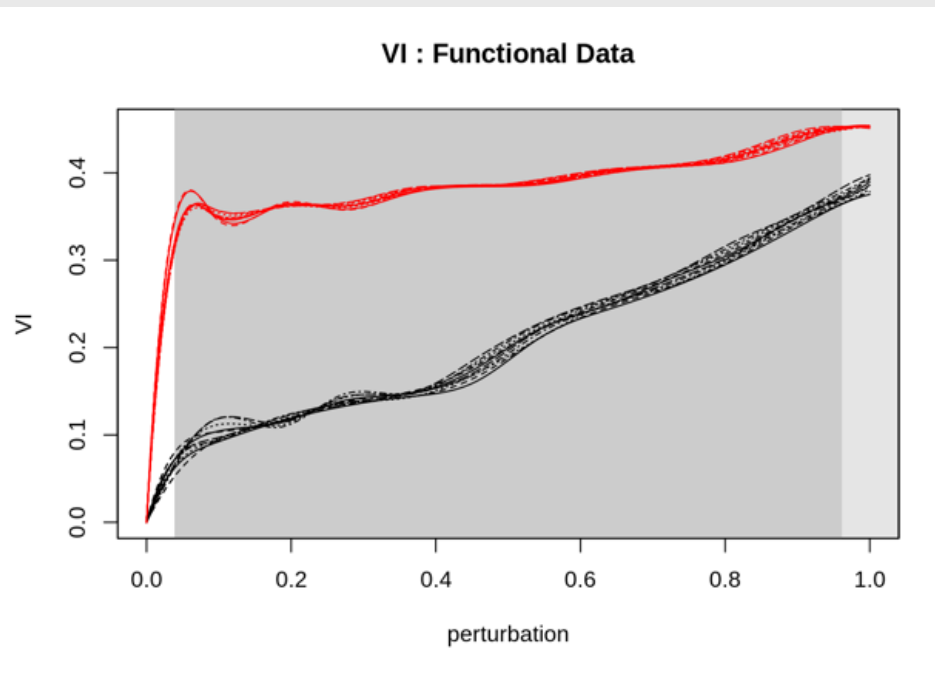
Area2 0.3840378



INTERVAL-WISE FUNCTIONAL TESTING PROCEDURE

- ❖ Provides an interval-wise non parametric functional testing able to point out specific differences

```
createITPSplineResult (graph, model1, model2)
```



The community structure found is statistically significant!!

IGRAPH COMMUNITY DETECTION ALGORITHMS

➤ Modularity

Fast greedy

Louvain

Optimal

Leading eigenvector

➤ Random walk

Walktrap

Infomap

➤ Node

Propagating labels

➤ Edges

Edge betweenness

Springlass

```
methodCommunity(graph, method, directed, weights, steps, spins, e.weights, v.weights, nb.trials)
```

HOW CAN WE SAY WHICH METHOD IS THE BEST?

❖ A procedure to compare different algorithms

To check which algorithm fits better your network!

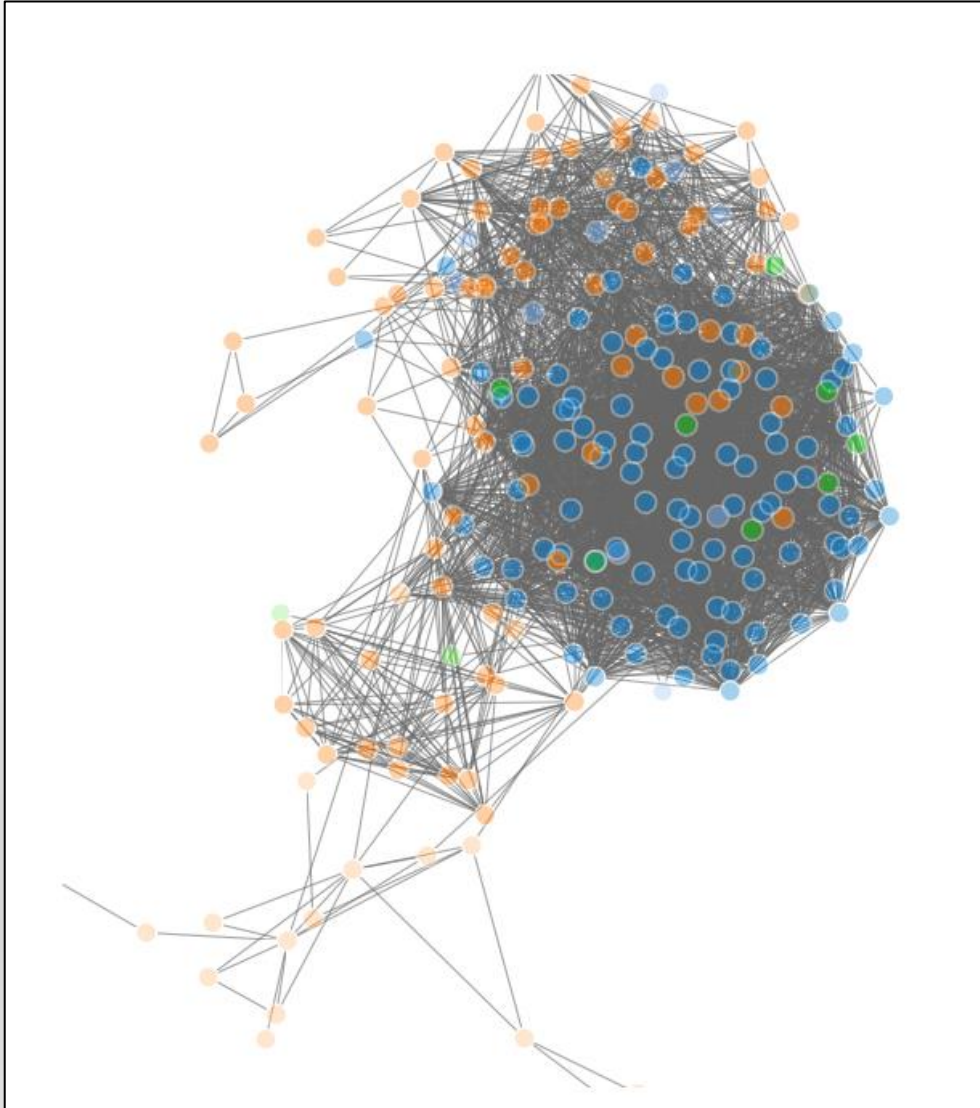
```
comparison(graph,graphRandom,method1,method2)
```

❖ At each perturbation level the procedure calculates the **VI** for both methods

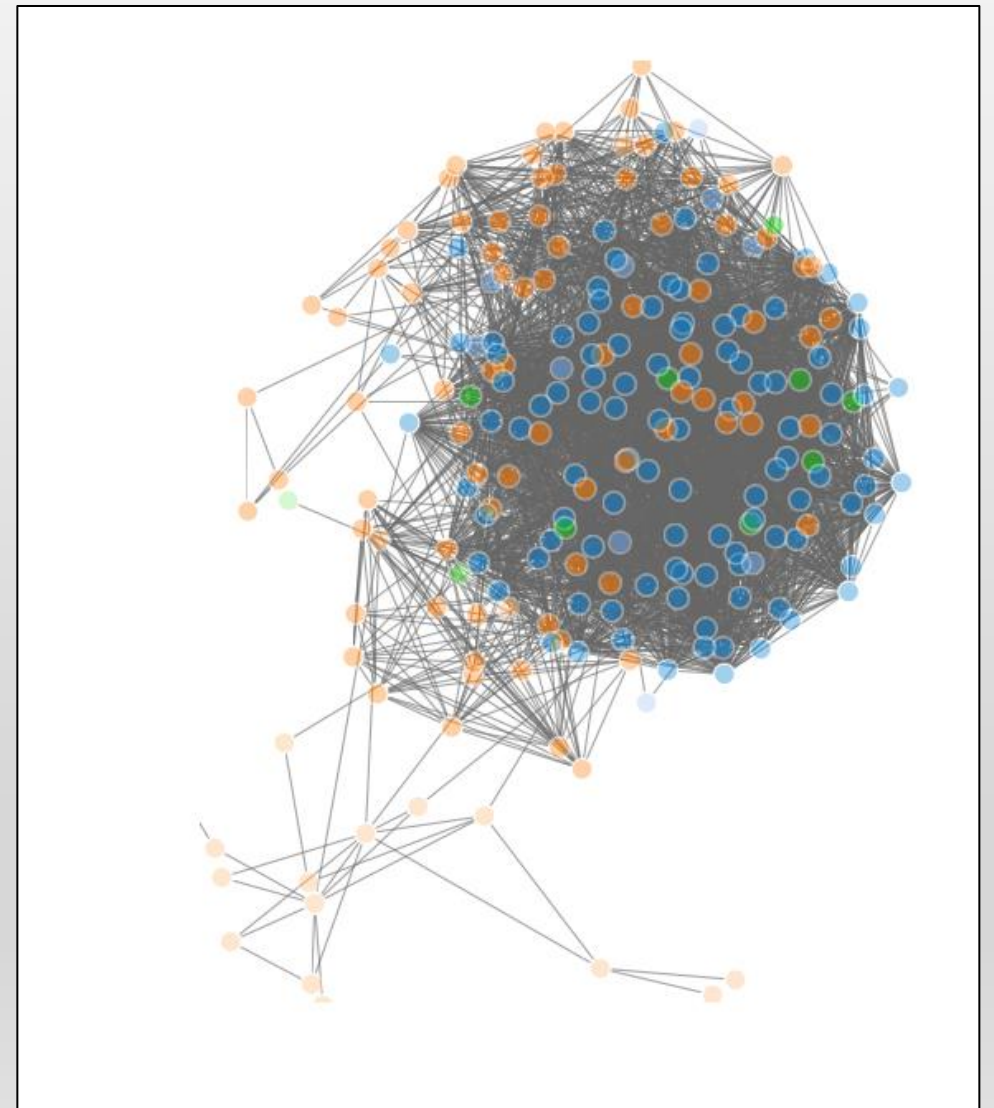
```
compare(comr1, comReal1, method="vi") for the first method  
compare(comr2, comReal2, method="vi") for the second method
```

HOW CAN WE SAY WHICH METHOD IS THE BEST?

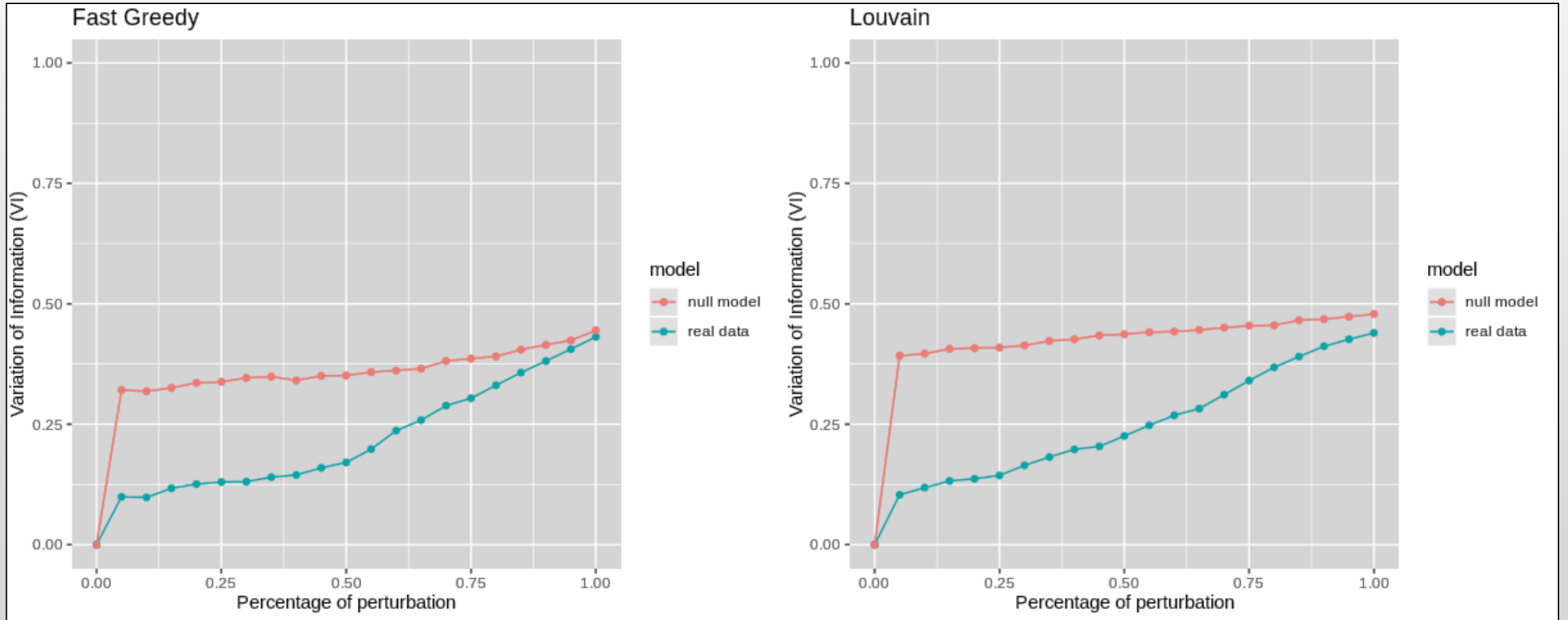
➤ Fast greedy



➤ Louvain



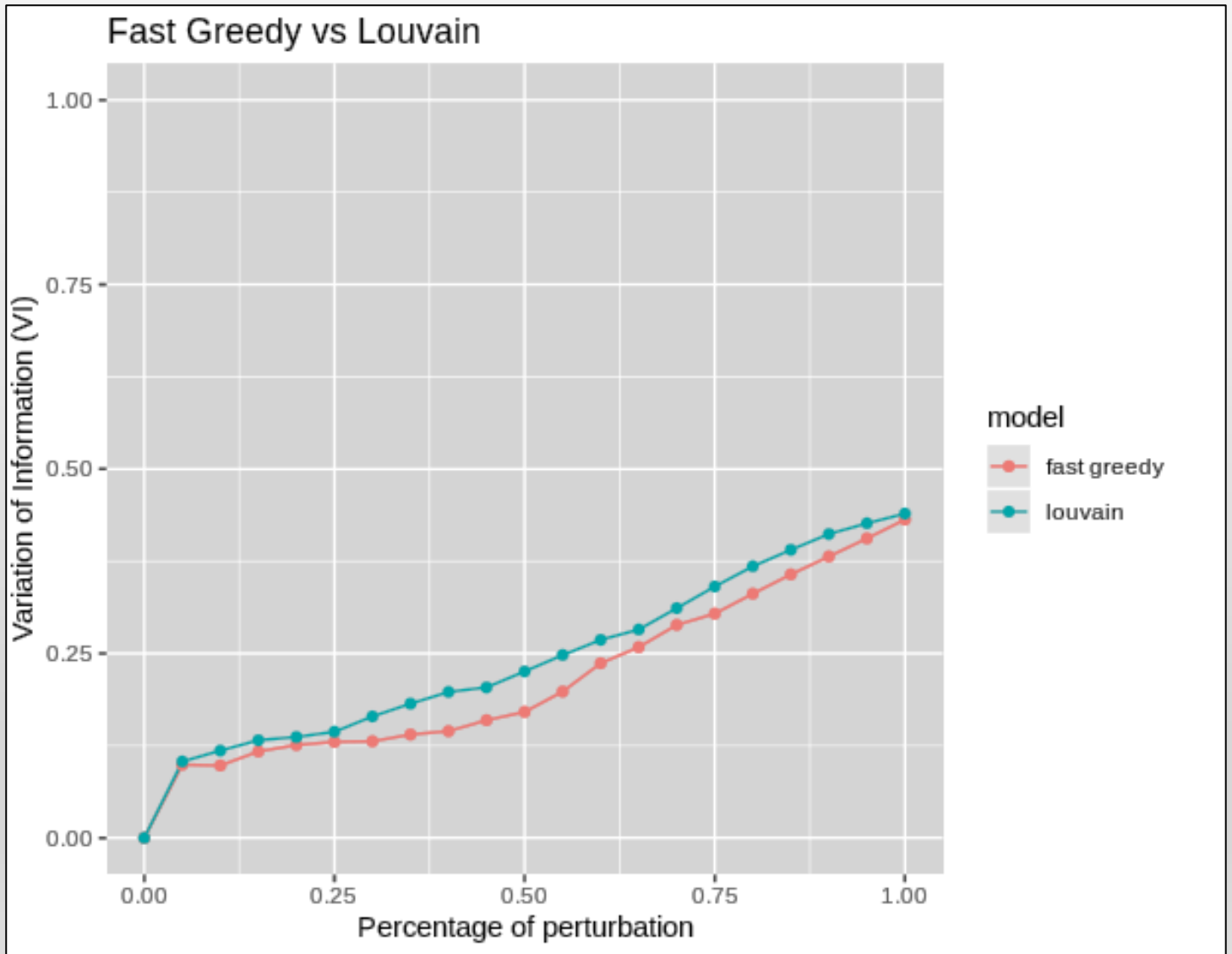
VI CURVES



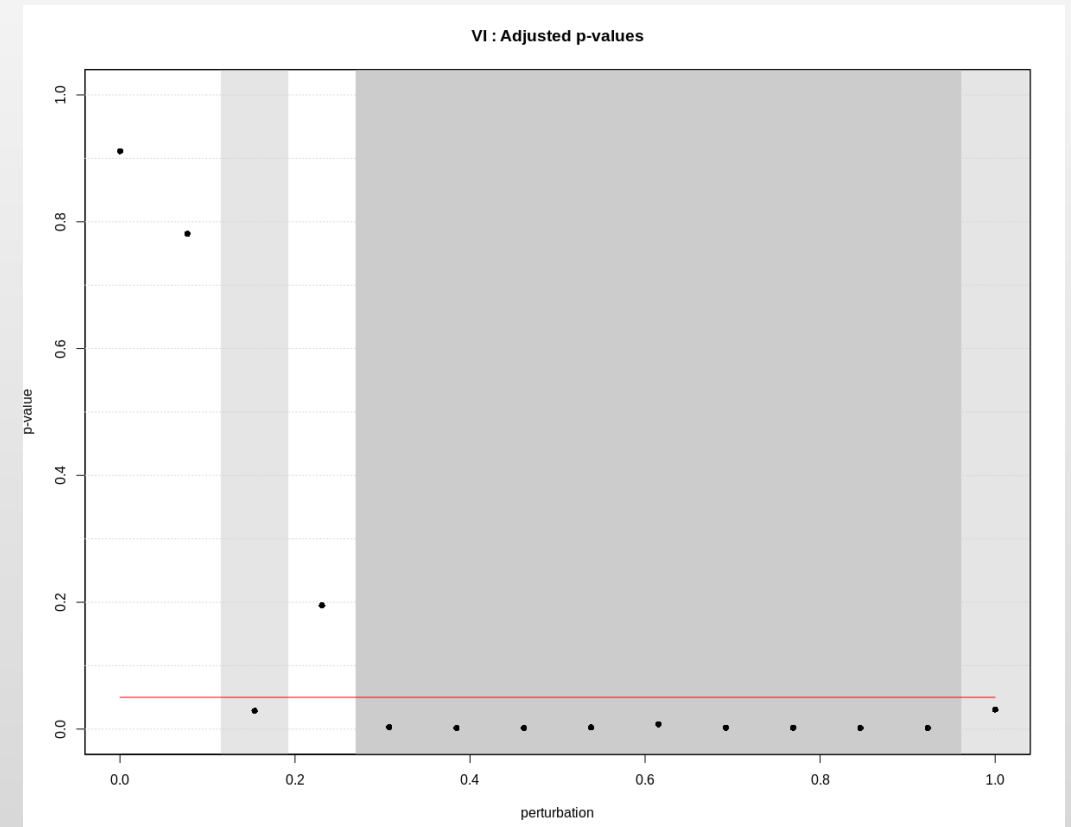
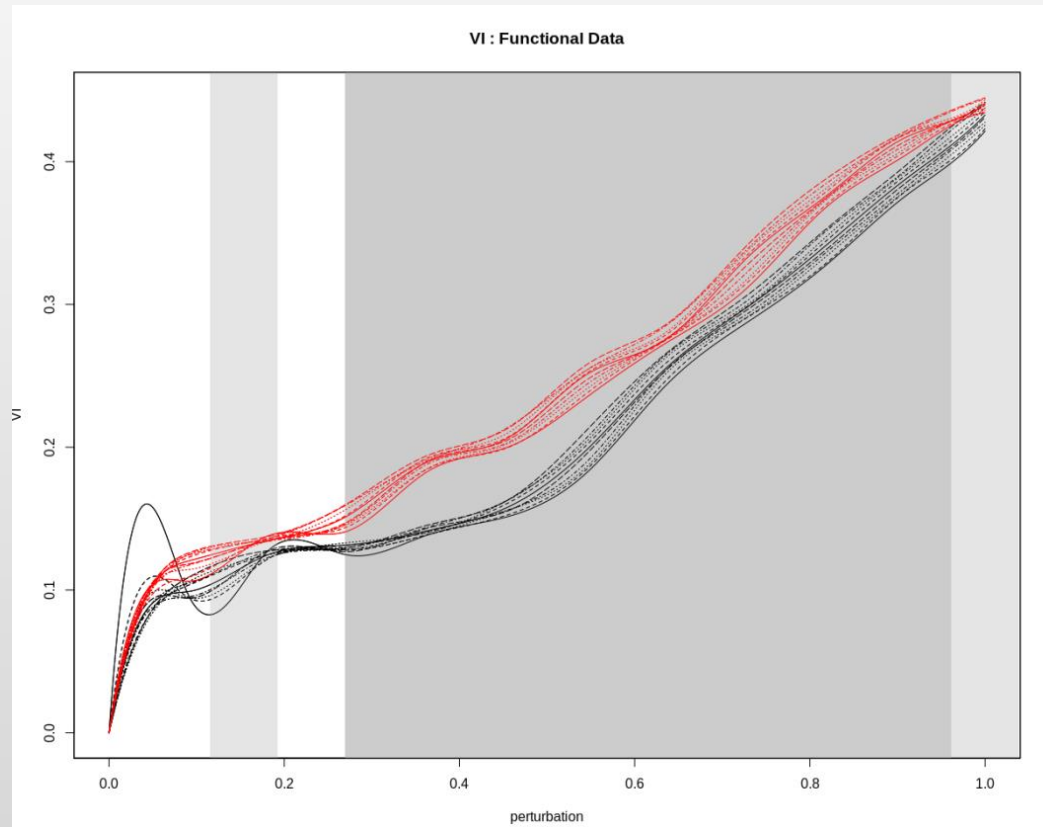
plotRobinCompare(graph, legend, legend1vs2, title1, title2, title1vs2)

VI CURVES

```
plotRobinCompare(graph,  
legend=c("real data", "null model"),  
legend1vs2=c("fast greedy",  
"louvain"),  
title1="Fast Greedy",  
title2="Louvain",  
title1vs2="Fast Greedy vs Louvain")
```



ITP, GP and AUC



Bayes_Factor 120.642

Area1 0.2151066 Area2 0.2442918

```
robinTest(graph, model1, model2, ratio, legend)
```

REPRESENTATIONS

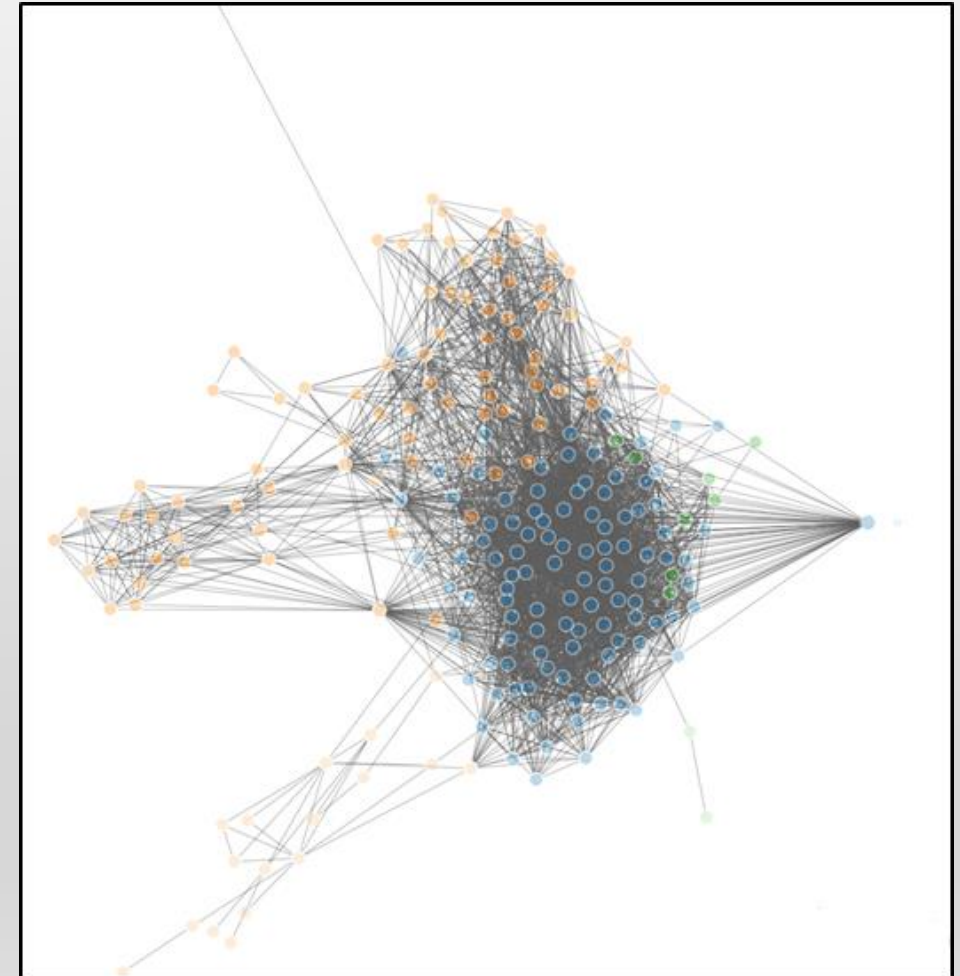
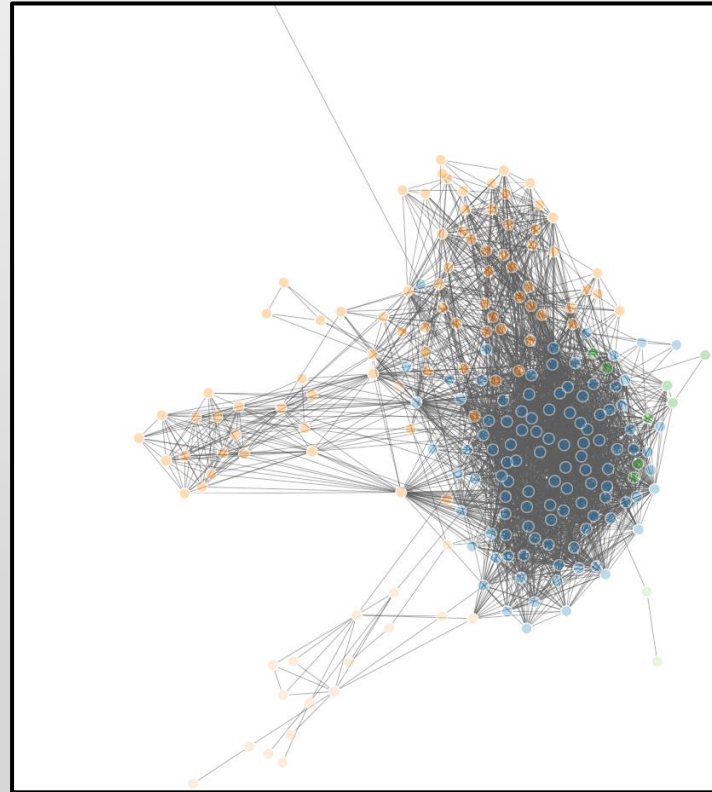
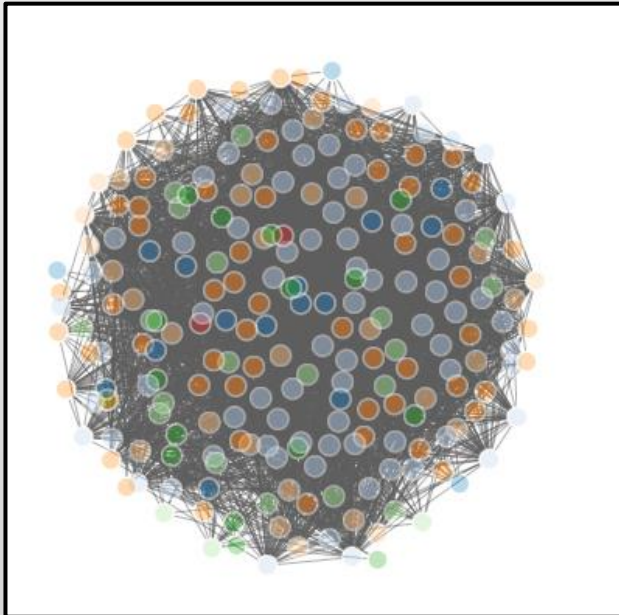
`plotCommunity(graph,method)`

➤ Fast greedy method

❖ Graph communities

❖ 3D

❖ Interactive



ROBIN (ROBustness In Network)

- ✓ ***Community detection algorithms***
- ✓ ***Validation of the community structure***
- ✓ ***Comparison of different community algorithms***
- ✓ ***Graphical interactive representation of 3D networks***

A decorative header image featuring a complex network graph with numerous nodes and edges, rendered in a light blue color against a dark background. The word "FUTURE" is centered in white, bold, uppercase letters.

FUTURE

- ❖ To use a different clustering stability measure
- ❖ To compare the performance of different measures for community structure comparison
- ❖ To test if the differences of the different methods are only due to the degree distribution of the network or are influenced by other factors

BIBLIOGRAPHY

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- Alfredo A. Kalaitzis and Neil D. Lawrence. A simple approach to ranking differentially expressed gene expression time courses through gaussian process regression. BMC Bioinformatics, 12(180), 2011
- Mc Auley, J., Leskovec, J., 2012. Learning to Discover Social Circles in Ego Networks. NIPS. pp. 548–556
- Meilă M.,2007. Comparing clusterings-an information based distance. J. Multivariate Anal.98,873-895
- Bender,E.A., Canfield,E.R., 1978. The asymptotic number of labelled graphs with given degree sequences. J.Combin. Theory A24, 296–307
- Pini A.,Vantini S.,2016.The interval testing procedure: A general framework for inference in functional data analysis. Biometrics



Thanks for the attention!

MODULARITY

- ❖ A network with **strong** community structure has **high** modularity
- ❖ **Q is not sufficient**, not all networks with high modularity have strong community structure

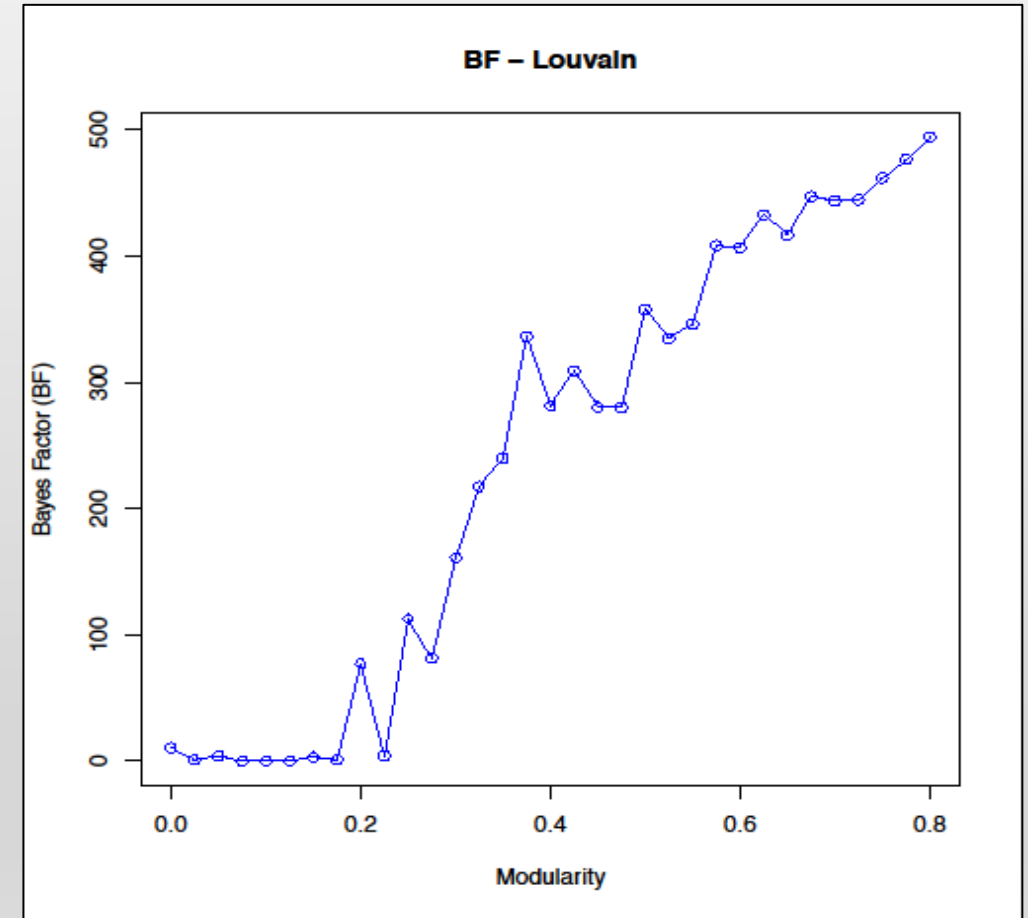
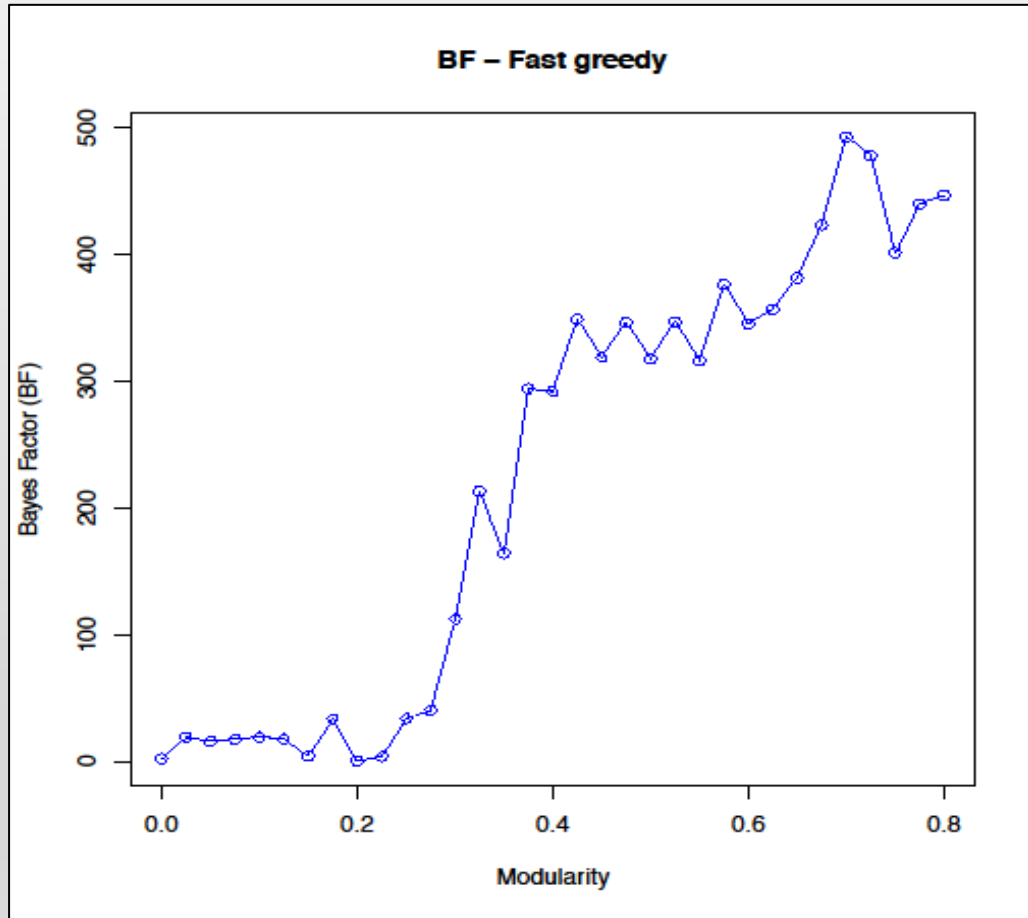
A decorative header image featuring a complex network graph with numerous nodes and edges, rendered in a blue and white color scheme against a dark background. The word "SIMULATION" is centered in white capital letters.

SIMULATION

- ❖ We used a literature model that generates undirected, simple and connected graphs with prescribed degree sequences and a specified level of community structure
- ❖ We constructed networks with 2000 nodes, 10 communities, an average degree equal to 10 at different value of modularity Q

SIMULATION STUDY

❖ Null models with different modularity



VARIATION OF INFORMATION (VI)

- ❖ At each level of perturbation p we compared the partition obtained from the original with the partition obtained from the perturbed graph computing Variation of Information (**VI**)

$$VI(C,C')=H(C|C') + H(C'|C)$$

- $0 \leq VI(C,C') \leq 2\log K$
- C and C' are two generic partitions
- K is the number of clusters

GAUSSIAN PROCESS

- ❖ Are the two curves from the same process or not?
- ❖ The hypothesis testing problem can be reformulated over the perturbation interval $[0,1]$ as:

$$H_0 : \log_2 \frac{Vlc(x)}{Vlc_{random}(x)} \sim \mathcal{GP}(0, k(x, x'))$$

$$H_1 : \log_2 \frac{Vlc(x)}{Vlc_{random}(x)} \sim \mathcal{GP}(m(x), k(x, x'))$$

Bayes Factor is approximated with a log-ratio of marginal likelihoods of two GPs, each one representing the hypothesis of differential (the profile has a significant underlying signal) and non differential expression (there is no underlying signal in the profile, just random noise).

1. **Basis Expansion:** functional data are projected on a functional basis (i.e. Fourier or B-splines expansion);
2. **Interval-Wise Testing:** statistical tests are performed on each interval of basis coefficients;
3. **Multiple Correction:** for each component of the basis expansion, an adjusted p-value is computed from the p-values of the tests performed in the previous step.

A decorative header bar with a black background and a complex network of glowing blue lines and nodes, resembling a molecular or digital structure.

ACKNOWLEDGMENT

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