



## Introduction to Network Science Introduction to Network Biology

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## **Network Science**

- Start 21th century
- Roots on graph theory
- In the context of data production and computer sciences
- closely linked to the study of complex systems



G={V, E}





# Macromolecules do not act isolated, but interact with each other to perform their functions



Molecular interactions: Protein-Protein Protein-DNA Protein-RNA Protein-Lipid

Transient, stable, obligatory ...



- Global/collective behaviour cannot be deduced from the knowledge on the components
- Phenotype does not emerge from isolated biological molecules but from their interactions



## Part 1: Building Biological Networks

- From literature, knowledge, curation
- From large-scale interaction experiments
- From inference from large-scale omics data



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# Building biological networks from literature, knowledge, curation

#### **b** Activity flows



#### c Process descriptions



#### Le Novère et al. Nature Review Genetics. 2015

#### Activity flow / Gene Regulatory Networks / Influence Graphs

**Signalling networks** 



#### Gene Regulatory networks



**Metabolic Cycle** 



2 types of nodes : enzymes & substrates, reaction directional or bidirectional

Nature Reviews | Genetics



# Building biological networks from literature, knowledge, curation

**b** Activity flows



#### c Process descriptions



# => pathway databases => mathematical modelling



#### pathway databases: Reactome





#### pathway databases: Kegg







#### pathway databases

**Pathways** 



~250 000 edges

Curated networks



# Building biological networks from literature, knowledge, curation

**b** Activity flows



#### c Process descriptions



# => pathway databases => mathematical modelling



Variables



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# Experimental interaction screenings

- Protein-protein interactions
- Protein-DNA interactions
- Protein-RNA interactions
- •
- => Small-scale / Large-scale







B. One fusion protein only (Gal4-BD + Bait) - no transcription



C. One fusion protein only (Gal4-AD + Prey) - no transcription



D. Two fusion proteins with interacting Bait and Prey

By Anna - Own work, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=2890233

#### Interactomes: protein-protein interactions



#### Set of detected protein-protein interactions

Physical interactions, but physiological interactions?

Interactomes are devoid of spatiotemporal information



#### **Interactomes: Pull-Down**





# False-negatives and "sparse networks"

#### Interaction space (to be discovered)



Interactions discovered by method 1

Interactions discovered by method 2



#### **Interaction databases**

#### Multi-organisms: DIP (dip.doe-mbi.ucla.edu) IntAct (www.ebi.ac.uk/intact) MINT (mint.bio.uniroma2.it/mint)

BioGRID (www.thebiogrid.org) BIND (www.blueprint.org)



International Molecular Exchange Consortium



## **PSICQUIC** portal

EMBL-EBI				Services Research Training About us	٩				
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Input Form Browse Help					🗪 Feedback				
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1,832 binary interactions found for search term BRCA2									
<ul> <li>APID Interactomes@</li> <li>BindingDB@-0</li> <li>DIP-IMEx@</li> <li>GeneMANIA@</li> <li>GeneMANIA@</li> <li>GeneMANIA@</li> <li>InnateDB@-0</li> <li>IRefIndex@</li> <li>IRefIndex@</li> <li>Spike@</li> <li>ZINC@</li> </ul>	Solution       Solution         Solut	Image: Control of the control of th	Second state       BIND@         DIP@       DIP@         Second state       EBI-GOA-nonIntAct@-65         Second state       EBI-GOA-nonIntAct@-65         Second state       Interoporc@         Interoporc@       Interoporc@         Second state       Eeactome-Fis@-29         Second state       VirHostNet@	Status of the service ONLINE OFFLINE WARNING: Time out FRROR: Unexpected Error 1,832 selected interactions Cluster this query					



## Part 1: Building Biological Networks

- From literature, knowledge, curation
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## **Network inference from -omics**

- Inferring/learning regulatory interactions from gene expression data (time-series, perturbation experiments)
- Famous methods: WGCNA, GENIE3
- Now on single-cells

Greenfield A, Madar A, Ostrer H, Bonneau R (2010) DREAM4: Combining Genetic and Dynamic Information to Identify Biological Networks and Dynamical Models. PLoS ONE 5(10): e13397.

Saint-Antoine, M. M. & Singh, A. Network inference in systems biology: recent developments, challenges, and applications. *Current Opinion in Biotechnology* **63**, 89–98 (2020).

Algorithm Class	Temporal Data Required?	Directionality	Advantages	Disadvantages	Examples
Correlation	No	Undirected	<ul> <li>Fast, scalable</li> <li>Detection of feed-forward loops, fan-ins, and fan-outs</li> </ul>	<ul> <li>Possibly</li> <li>over-simplistic</li> <li>False positives for</li> <li>cascades</li> </ul>	WGCNA [13] PGCNA [14]
Regression	No	Directed	Good overall accuracy	<ul> <li>Bad detection of feed-forward loops, fan-ins, and fan-outs</li> </ul>	TIGRESS [15], GENIE3 [16], bLARS [17]
Bayesian - Simple	No	Directed	Performance on small networks	<ul> <li>Performance on large networks.</li> <li>Inability to detect cycles</li> </ul>	[19,20]
Bayesian - Dynamic	Yes	Directed	<ul> <li>Performance on small networks</li> <li>Detection of cycles and self-edges</li> </ul>	Performance on large networks.	[21]
Information Theory	No	Undirected (at least in simplest form)	Detection of feed-forward loops, fan-ins, and fan-outs     Similar to correlation methods, with better accuracy	False positives for cascades	ARACNE [25], CLR [26], MRNET [27], PIDC [28]
Phixer	No	Directed	Parsimonious output due to pruning step.	Possible loss of overal accuracy due to pruning step (this can be removed if the user chooses)	[31]

Current Opinion in Biotechnology

data

Interactome(s)









# Part2: What's next ? => Network Analysis Network metrics / Network algorithms

# How to use large-scale biological networks ?

**Global approaches** 

#### Local approaches



- mathematical modelling
- "guilt by association"

- Topological features
- Network analysis algorithms

# Local approach: identification of a new gene involved in breast cancer



Nodes correspond to proteins, edges to interactions identified by different experimental techniques

Functional associations (n)

- Expression profiling similarity (20)
- Similar gene deficiency phenotype (2)
- Y2H binary protein interaction (32)
- Protein co-AP (13)
- Protein co-IP (11)
- Biochemical interaction (1)

Pujana et al. 2007

# How to use large-scale biological networks ?

**Global approaches** 

#### Local approaches



- mathematical modelling
- "guilt by association"

- Topological features
- Network analysis algorithms





.....

#### **Degree distribution**







#### Power-law distribution



#### **Biological interpretation?**

- Growth with preferential attachement ("rich get richer") => create "hubs"
- Robust to random attack, sensitive to targeted attacks



## Network topological structure : Small-world property





(a) Random network

(b) Scale-free network

• Milgram, 6 degrees of separation



## **Metrics on graphs**

- N nodes, V edges
- Network size
- Adjacency matrix
- Degree, degree distribution
- Path, shortest path, distances
- Connectivity, clustering coefficient
- Betweenness
- Motifs

NETWORK MEASURES							
Degree/ connectivity (k)	Clustering coefficient/ interconnectivity (C)	Assortativity/average nearest neighbor's connectivity (NC)	Shortest path (SP) between two nodes	Betweenness/ centrality (B)			
$k_{A}$ =Nb of edges through A=5	$C_{A} = \frac{Actual links between A's}{\frac{neighbors (black)}{Possible links between A's}}$ $C_{A} = \frac{C_{A}}{\frac{Possible links between A's}{Possible links between A's}}$ $C_{A} = n_{A} / [k_{A}(k_{A}-1)/2]$ $= 2 / [4x(4-1)/2] = 0.333$	$NC_{A} = (k_{B} + k_{C} + k_{D} + k_{E} + k_{J})/5$ = (5+2+2+3+1)/5=2.6	F J E K SP <sub>FH</sub> =(F,D,A,B,H)=4	$B_{4}=Fraction of SPs passing through A = 0.090$			

#### Gavin, Cell



#### "Edge Betweenness"

#### Number of shortest paths running through an edge = "bottleneck"



#### "Node Betweenness"



#### Number of shortest paths running through a node = "bottleneck"



Biological interpretation ? Correlation with gene essentiality, gene involvement in diseases, importance in flux transmission ...

# Clustering coefficient / modularity



# Actual links between neighbours / Possible links between neighbours



## Algorithms for Network Analysis

- Clustering
- Exploration with Random Walk with Restart
- Integration of expression data to find active modules

## **Network Analysis - Clustering**

impacts

#### From molecular to modular cell biology

Leland H. Hartwell, John J. Hopfield, Stanislas Leibler and Andrew W. Murray

Functional module / community / cluster / class : discrete function Modules can be isolated or connected Groups of proteins involved in a common cellular function





Inspired from P. Aloy, ECCB 2014



## Network Exploration: Random Walk with Restart

# The Random Walk with Restart algorithm



# The Random Walk with Restart algorithm



# The Random Walk with Restart algorithm



# The Random Walk with Restart algorithm Seed Gene/Protein

Adapted from http://slideplayer.com/slide/5223771/





- Local exploration
- Proximity/pertinence score

wrt the seed







- Local exploration
- Proximity/pertinence score

wrt the seed(s)





- Local exploration
- Proximity/pertinence score wrt the seed(s)
- Guilt-by association







- Local exploration
- Proximity/pertinence score wrt the seed(s)
- Guilt-by association



#### Random Walk with Restart on Multiplex Networks (RWR-M)





- Walk one layer
- Jump across layers
- Gene/Protein Seed(s)

Pathways







# Integrating expression data and networks: finding active modules

Interactomes are devoid of spatiotemporal information

# **RNA-seq transcriptomics analyses**

RNA-seq transcriptomics data

#### Identify significant DE mRNAs

Patient - Control Exact\_Test





# Active module identification



Patient - Control Exact Test

A2M

Algorithms: Greedy searches (PinnacleZ), Simulated Annealing (jActiveModules), Genetic Algorithms (COSINE) (Ideker et al. 2002, Chuang et al. 2007, Ma et al. 2011, Ozisik et al. 2017...)



- Few methods consider the density of interactions
- Methods are using only one (usually protein-protein) interaction networks

=> We propose a **Multi-Objective Genetic Algorithm** to identify active modules from Multiplex Networks

#### Elva Novoa

#### **2 objectives to maximize**



#### 2 objectives to maximize



TEK

A2M

SCARA5

## **Multi-Objectives Genetic Algorithm**





# Multi-objective Genetic Algorithm to find Active Modules in Multiplex Biological Networks



## **Multi-Objectives Genetic Algorithm**





# Multi-objective Genetic Algorithm to find Active Modules in Multiplex Biological Networks

#### M@GAMUN



Novoa et al. BioRxiv, 2020 Bioconductor <u>https://github.com/elvanov/MOGAMUN</u>