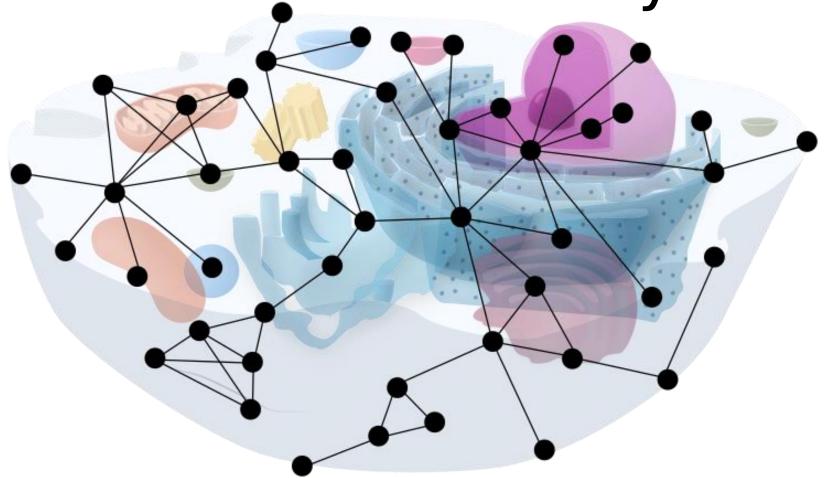
Networks Across Biological Scales: From molecules to

Ecosystems



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University of Würzburg
Germany

Outline agenda

- Biological networks are ubiquitous
- Basic component of a network
- Constructing and modeling networks
- Network motifs
- Multilayer networks
- Introduction of Knowledge graph
- Thoughtful experiment of networks
- Application of knowledge graph

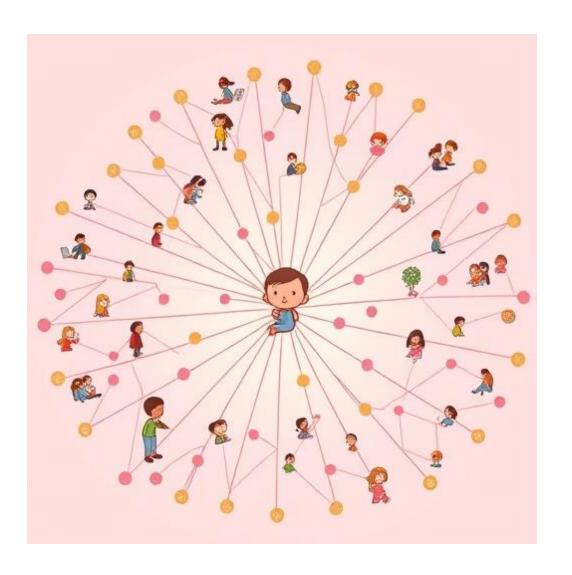
Scan me to download the presentation and the codes



Social networks

Prompt

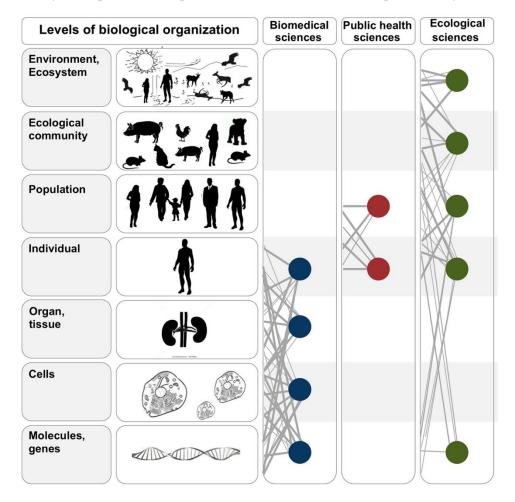
Create a cartoon-style illustration showing the evolution of a person's social network from infancy to adulthood. Start with a baby in the center who first connects with their parents and siblings. As the child grows, add connections to extended family (grandparents, aunts, uncles), followed by friends from school, teachers, and neighbors. Then, show young adult connections branching out to university friends, mentors, and colleagues. Make the network web grow larger and more interconnected with each stage of life, symbolizing social expansion



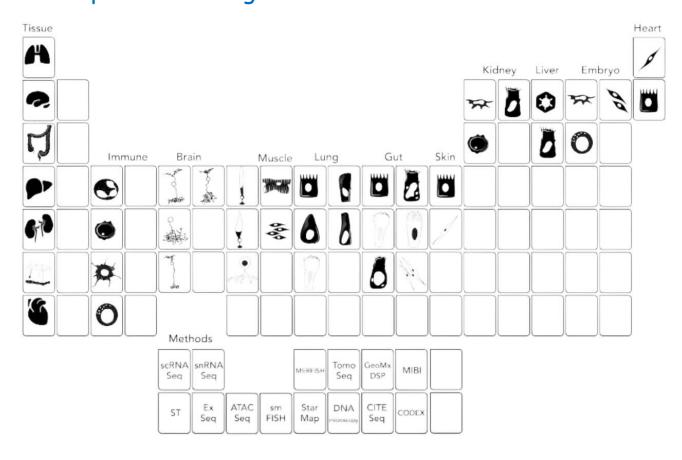
https://deepai.org/machine-learning-model/text2img

Hierarchy of biological organization, from molecules and genes to ecosystems

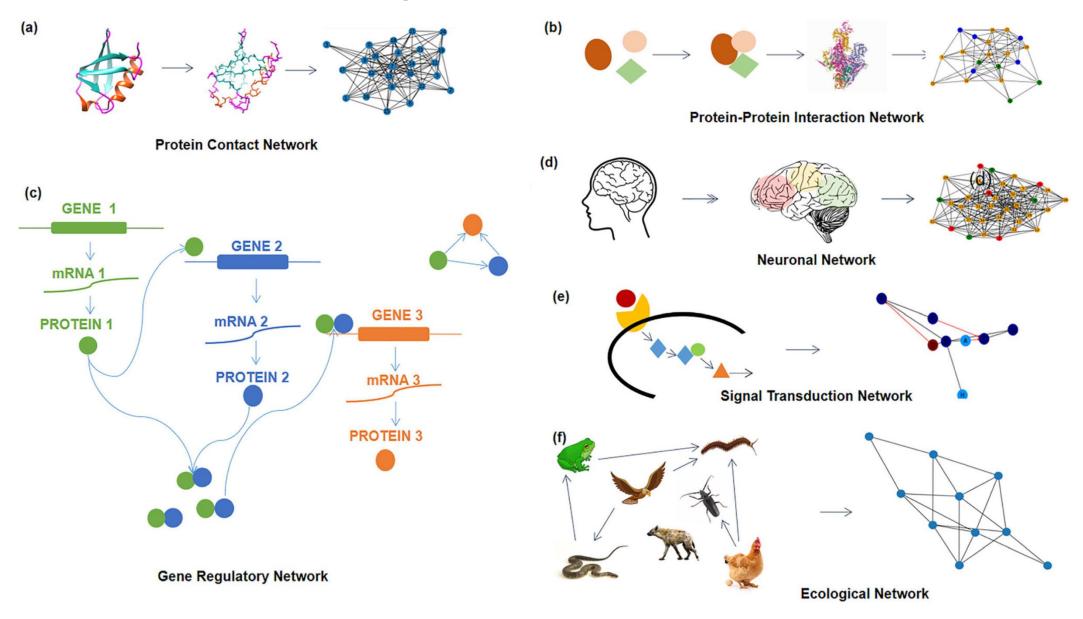
Concentrates on the structural and topological organization of biological systems



Focuses on the holistic understanding of biological systems, emphasizing how components interact to produce emergent behaviors

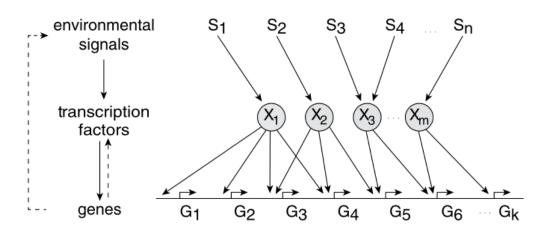


Types of Biological Network

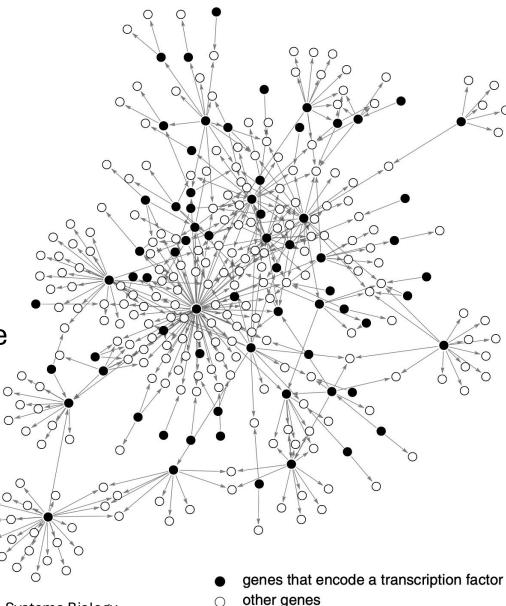


Cells are living machines

- Cells sense many different signals
 - Temperature and pressure
 - Damage
 - Signal from other cell
 - Nutrients and chemicals
- Cells respond to these signals by producing appropriate proteins
- These special protein called TF
- TF are designed to transit rapidly between active and inactive states

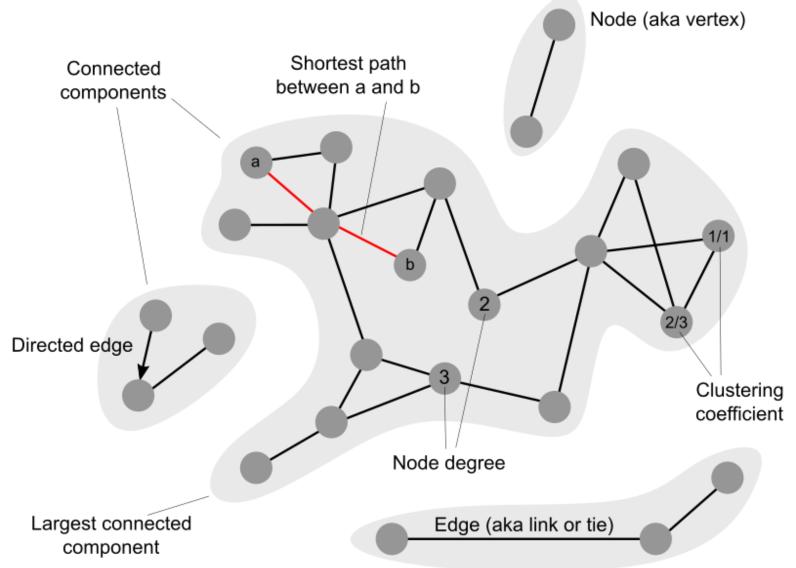


Transcription network



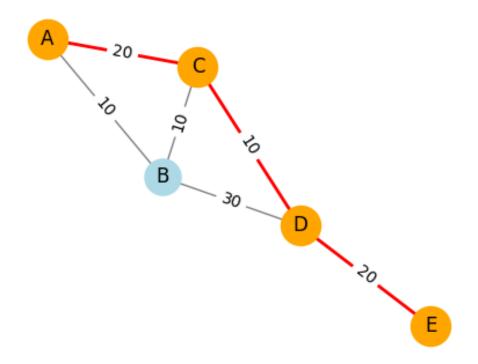
Uri Alon An Introduction to Systems Biology Design Principles of Biological Circuits-CRC Press

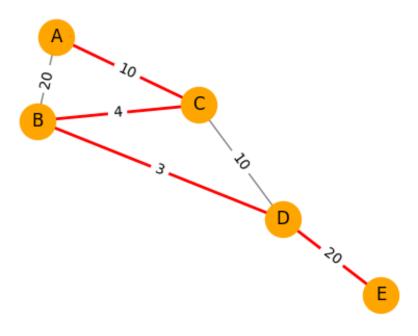
Properties of network



Shortest path in weighted graph

- Shortest Path: ['A', 'C', 'D', 'E']
- Shortest Path Length: 50





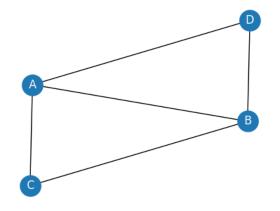
• Shortest Path:

• Shortest Path Length: 37

Centrality

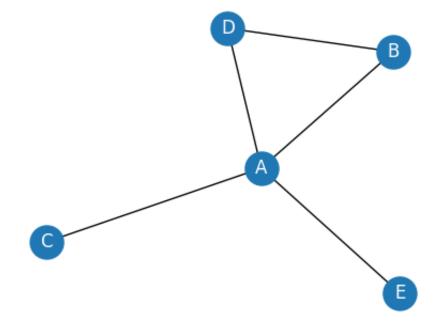
Degree: number of nearest neighbors / (n-1)

n is maximal possible degree {'A': 1.0, 'B': 1.0, 'C': 0.66, 'D': 0.66}



• Closeness: centrality of a node u is the reciprocal of the average shortest path distance to u over all (n-1) reachable nodes.

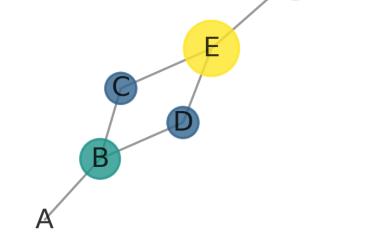
$$C(u)=rac{n-1}{\sum_{v=1}^{n-1}d(v,u)}$$



Betweeness Centrality

• Betweenness centrality of a node v is the sum of the fraction of all-pairs shortest paths that passes through v.

$$c_B(v) = \sum_{s,t \in V} rac{\sigma(s,t|v)}{\sigma(s,t)}$$



```
A = 0.0
```

$$B = 6.5$$

$$C = 4$$

$$D = 4$$

$$E = 12.5$$

$$F = 10$$

$$G = 0.0$$

$$H = 0.0$$

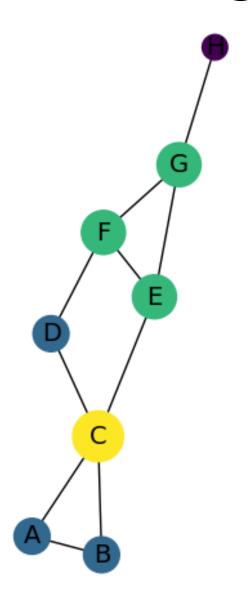
```
Node E = (AF+AG+AH+BF+BG+BH+

CF+CG+CH+DF+DG+DH+CD)

=(2/2+2/2+2/2+2/2+2/2+

1/1+1/1+1/1+1/1+1/1+1/2)
```

Clustering coefficient



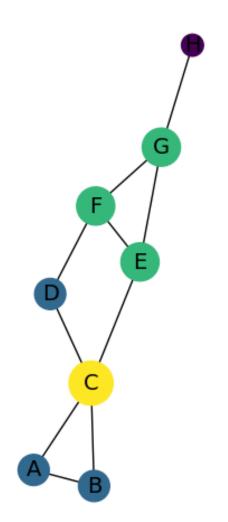
Clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together.

Neighbors of a given node are connected to each other.

Node	# of neigh	# possible conne	clustering coef
Α	2	1	(1/1)=1
В	2	1	(1/1)=1
С	4	6	(1/6)=0.167
D	2	1	(0/1)=0
E	3	3	(1/3)=0.33
F	3	3	(1/3)=0.33
G	3	3	(1/3)=0.33
		Avg	coef. = 0.40

Let's have some fun with python programming to make our first graph

Adjacency matrix



	Α	В	С	D	Е	F	G	Н
Α		1	1					
В	1		1					
С	1	1		1	1			
D			1			1		
Ε			1			1	1	
F				1	1		1	
G					1	1		1
Н							1	

Network modularity

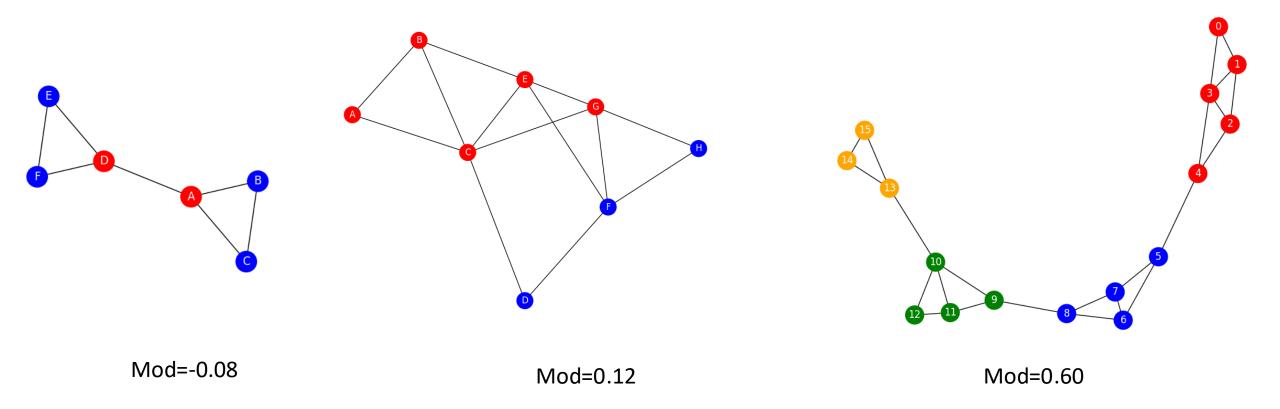
- Modularity measures the strength of division of a network into modules (also called clusters or communities).
- Values
 - closer to 1 indicate strong community structures.
 - near 0 indicate no significant community structure.
 - Negative values means worse-than-random divsions.

$$Q = rac{1}{2m} \sum_{ij} igg(A_{ij} - \gamma rac{k_i k_j}{2m} igg) \delta(c_i, c_j)$$

- m is the number of edges (or sum of all edge weights)
- A is adjacency matrix of graph G
 - k_i is the (weighted) degree of noid i
 - γ is the resolution parameter
 - $\delta(c_i, c_j)$ is 1 if i and j are in same cluster else 0.

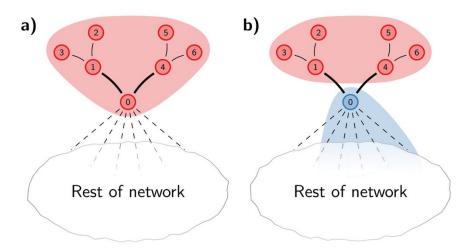
Examples

mod = nx.community.modularity(G,
nx.community.label_propagation_communities(G))



Application of modularity

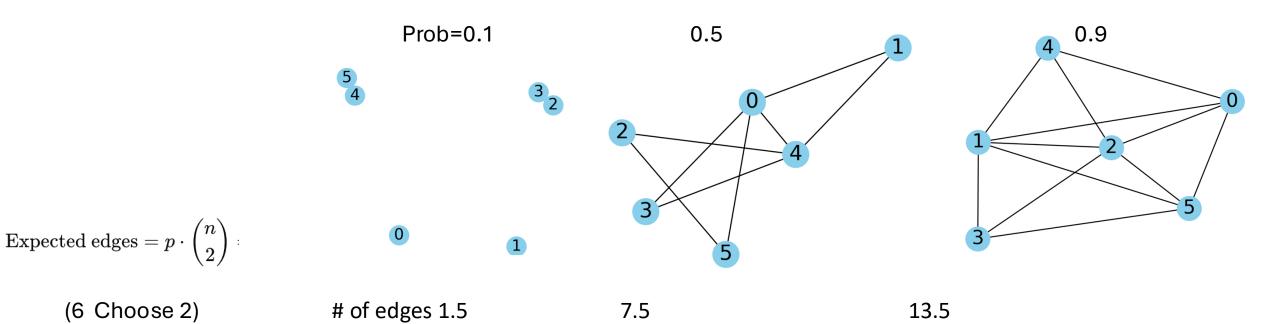
- Louvain clustering 2008
 - Start with a single partition where all nodes are in their own community
 - Iterat repeatedly
 - Local node movement: Move nodes to communities to maximize modularity
 - Network aggregation: Aggregate communities into new nodes within network
- Leiden clustering 2019
 - Faster and address an issue where communities may become internally disconnected but remain as one community



V. A. traag et al Scientific Reports 2019

Random graph

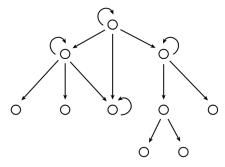
- A graph is constructed by connected nodes randomly.
- Each edge is included in the graph with probability p, independently from every other edge.
- Equivalently, the probability for generating each graph that n nodes and M edges is



Network motifs

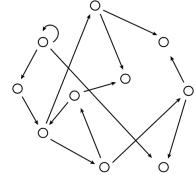
- A recurring patterns that occur in the real network significantly more often than in randomized networks with the same characteristics (number of nodes, number of edges) are called network motifs.
- Edges in the network motifs must be constantly selected in order to survive randomization forces in unexpected high amounts.

'Real' network



N=10 nodes A=14 arrows N_{self}=4 self-arrows

Randomized network (Erdos - Renyi)

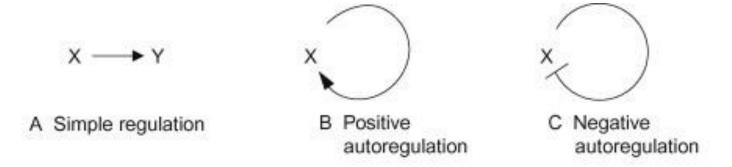


N=10 nodes A=14 arrows N_{self}=1 self-arrow

Autoregulation is a network motif

- Regulation of a gene by its own gene product is known as autogenous control, or autoregulation.
- Is autoregulation significantly more frequent in the real network than at random?
- Probability of connecting to itself: $p_{self} = 1/N$
- If E edges are placed at random to form the random network, the average number of self-arrows is

$$\langle N_{self} \rangle_{rand} = E p_{self} = E / N$$



Autoregulation example

Real Path length

	Α	В	С
Α	0	1	2
В	2	0	1
С	1	2	0

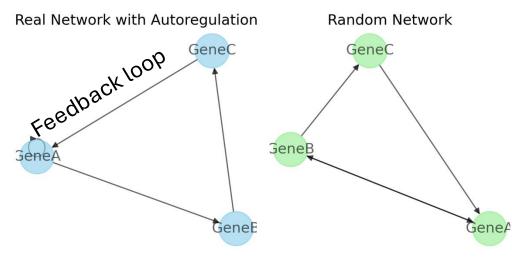
Radom Path length

	Α	В	С
Α	0	1	2
В	1	0	1
С	1	2	0

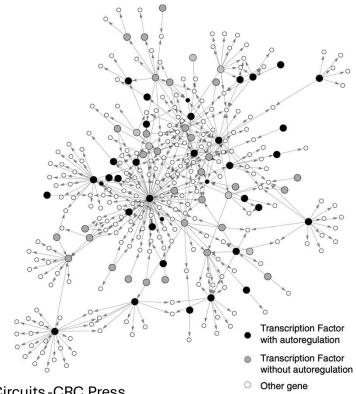
- In the E. coli transcription network
 N = 424 and E = 519
- In random network with the same N and E would give the number of self-arrows

$$< N_{self} >_{rand} = E / N = 1.22$$

 The real network has 40 self-arrows, which exceeds the random networks



Clustering Coefficient: 1.0



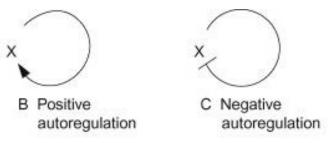
Regulation slows/speed the response

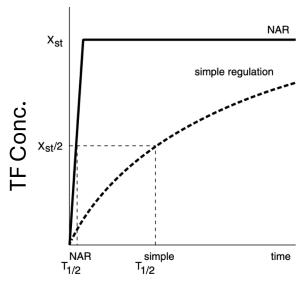
Positive regulation

- Slows response time: Positive feedback often reinforces itself, leading to a delay before reaching a steady state.
- Bistability: Positive feedback can create two stable states (e.g., ON or OFF), enabling decision-making processes in cells

Negative Regulation

- Speeds response time: Negative feedback counteracts changes quickly, stabilizing the system and making it more responsive to fluctuations.
- Reduces Variability: Negative feedback ensures a steadystate concentration of molecules like proteins, reducing differences across cells in a population.

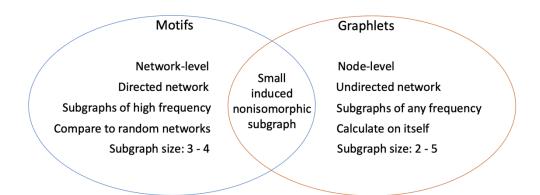




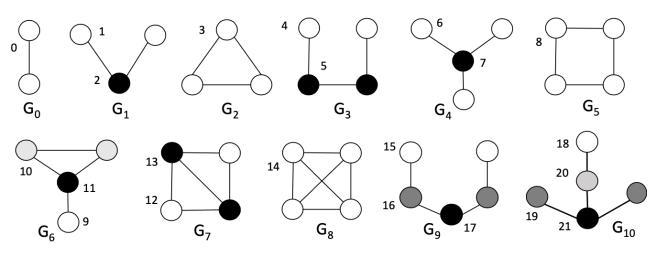
Response Time

Occurrence of network motifs

Motif	Designation	Type of network
	3-node feed-forward loop	Gene regulation network Neural network Electronic circuits (forward logic chips)
	3-chain	Food webs
	3-node feedback loop	Gene regulation network Neural network Electronic circuits (forward logic chips)
	Bi-fan	Gene regulation network Neural network Electronic circuits (forward logic chips) Electronic circuits II
	Bi-parallel	Neural network Food webs Electronic circuits (forward logic chips)
	4-node feedback loop	Electronic circuits II



Occurrence of graphlets



Orbits: Specific positions a node occupies within a graphlet, considering the symmetry of the graphlet. Nodes in symmetric positions are part of the same orbit.

Motifs

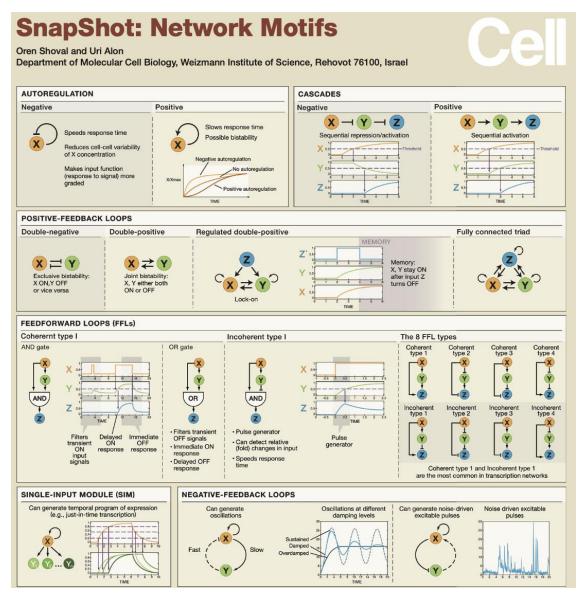
Network-level
Directed network
Subgraphs of high frequency
Compare to random networks
Subgraph size: 3 - 4

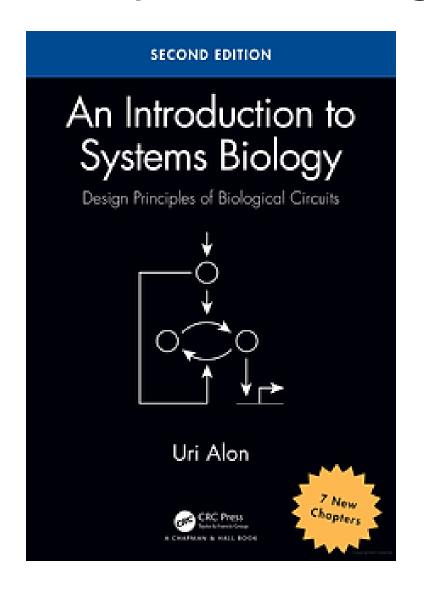
Small induced nonisomorphic subgraph

Graphlets

Node-level
Undirected network
Subgraphs of any frequency
Calculate on itself
Subgraph size: 2 - 5

Resources: Motif connections to systems biology





Oren Shoval and Uri Alon, Cell 2010

Let's have some fun with python programming to find motifs

Multilayer networks

- Multilayer networks provide the framework to capture the complexity typical of systems of systems.
- It enable the analysis of biophysical, social and human-made networks from an integrated perspective.
- Layered structure of multilayer networks is responsible for phenomena that cannot be observed from the analysis of subsystems in isolation or from their aggregation, such as emergent mesoscale organization.

Network B Supernetwork Laver B Layer B Layer A Layer A

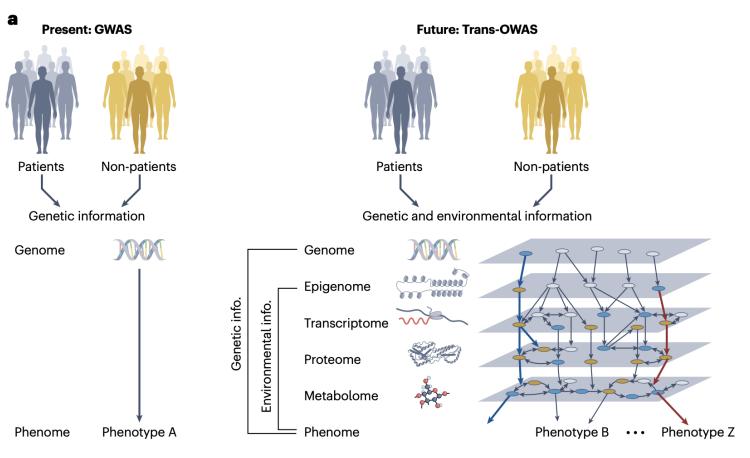
Manlio De Domenico "More is different in real-world multilayer networks" Nat Phys 2023

A network of two network A multiplex network systems A and B

of two layers A and B

An interconnected network of two layers A and B

Multilayer networks

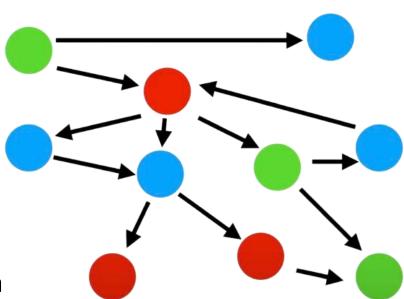


- Genetic information collected from healthy and unhealthy groups is generally used to capture information about macroscopic effects, such as a disease.
- Multi-omics makes available richer datasets that can be integrated within a multilayer network, where layers also encode interactions at the scale of the transcriptome, the proteome and the metabolome

Manlio De Domenico "More is different in realworld multilayer networks" Nat Phys 2023 Genome-wide association studies (GWAS)
Openness weighted association studies (OWAS)

Knowledge graph

- A knowledge graph is knowledge base that is a graph and represents facts about the world.
- What is a knowledge base?
 - A knowledge base is a technology used to store complex structured and unstructured information.
 - A collection of knowledge expressed using some formal knowledge representation language.
 - A store of information or data that is available to draw on.
 - The underlying set of facts, assumptions, and rules which a computer system has available to solve a problem.
- What is a graph?



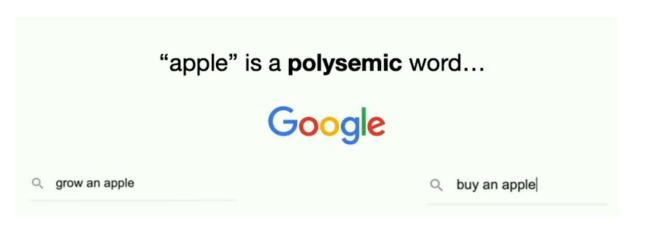
Evolution of Google search algorithm

- PageRank 1998: The order of search results returned by Google is based on this.
- Knowledge Graph 2012: Added semantic search by organizing information into entities and relationships, providing direct answers and improving contextual understanding.
- RankBrain 2015: Integrated machine learning to interpret user intent, handling queries never seen before.
- BERT 2019: Leveraged deep learning to understand the nuances of natural language, particularly context in search queries.

A Knowledge Graph is a data set that is:

- Structured in the form of a specific data structure.
- Normalised consisting of small units, such as vertices and edges.
- Connected defined by the possibly distant connections between objects.
- Explicit created purposefully with an intended meaning.
- Declarative meaningful in itself, independent of a particular implementation or algorithm.
- Annotated enriched with contextual information to record additional details and meta-data.
- Non-hierarchical more than just a tree-structure.
- Large millions rather than hundreds of elements.

Biological molecule is also context dependent



... whose particular meaning is resolved via sentence context Google grow an apple Q buy an apple grow an apple tree buy an apple watch grow an apple tree from seed buy an apple gift card grow an apple tree in a pot buy an apple tv grow an apple tree indoors

Knowledge graph in precision medicine

- Developing personalized diagnostic strategies and targeted treatments requires a deep understanding of disease biology and the ability to dissect the relationship between molecular and genetic factors and their phenotypic consequences.
- Such knowledge is fragmented across publications, non- standardized repositories, databases and evolving ontologies describing various scales of biological organization between genotypes and clinical phenotypes.
- Knowledge graph
 - Drug repurpose
 - Clinical trial optimization
 - Patient Stratification

Existing knowledge graph in biomedical

It connects molecular, genetic, phenotypic, and drug-related information, enabling analyses like drug-disease interactions, disease mechanisms, and therapeutic predictions.

Drugs Exposures

BP CC

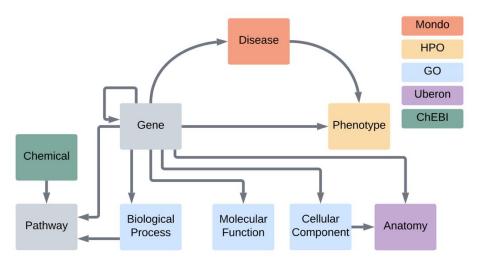
MF

Genes

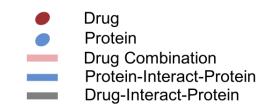
Phenotypes

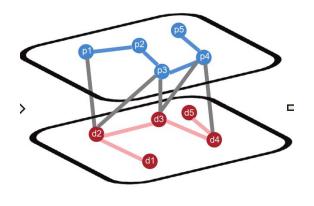
Anatomical regions

It is a translational research platform that integrates and analyzes genetic, phenotypic, and disease data across species using open ontologies, semantic data models, and knowledge graphs, enabling applications like variant prioritization, deep phenotyping, and patient profile matching.



Predict Drug combination therapies (DCBs) for infectious diseases





PrimeKG: Payal Chandak et al

Scientific Data 2023

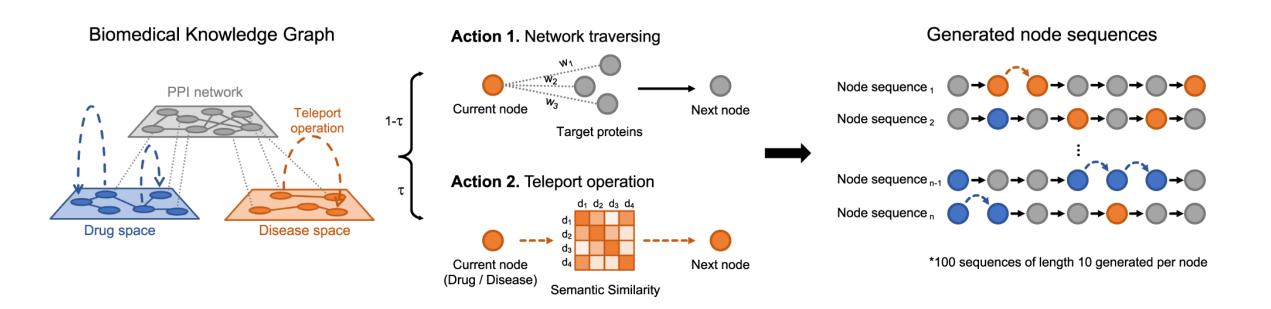
Monarch: Tim E. Putman et al

NAR 2024

Qing Ye et al Cell Reports 2023

Biomedical knowledge graph for drug repurposing

DREAMwalk map drugs and diseases into a unified embedding space, improving prediction of drug-disease associations.





Thank you

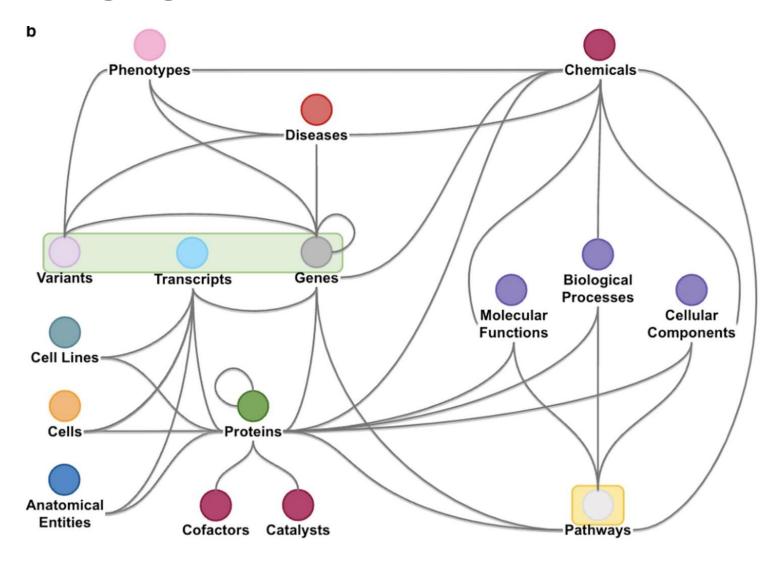
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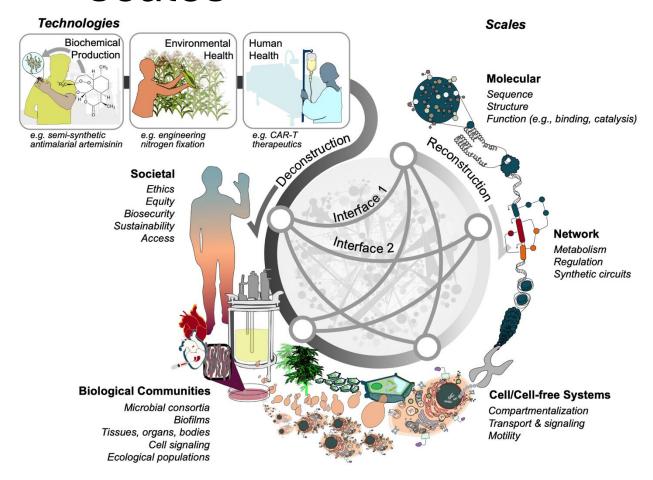
Famous algorithms related to graphs

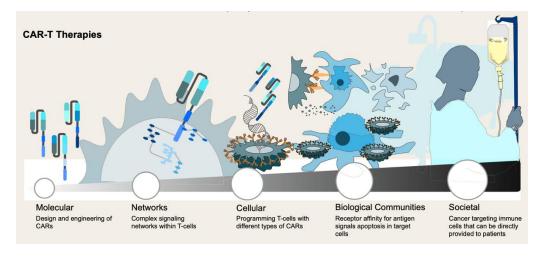
- Dijkstra's (shortest path problem)
- PageRank
- Leiden community detection
- Kd-tree
- Random Forest
- Causal
- Markov clustering
- Search

Knowledge graph of a disease



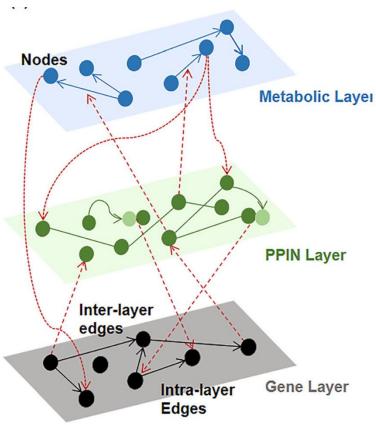
Deconstructing synthetic technologies across scales





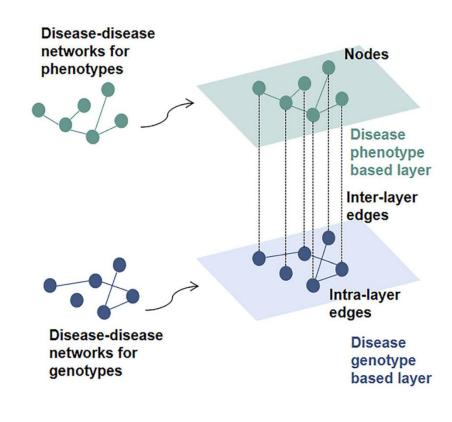
Multilayer network exa

An interdependent network of gene regulation and metabolism comprising three layers



Edges represent the inter-layer connections such as activation, repression, and catalysis.

Disease network



Disease connected by symptoms

Connections between diseases.

Diseases connected by common genes