Network analysis of protein interaction data: an introduction

This course provides an introduction to the theory and concepts of network analysis. It explores some of the features of protein-protein interaction networks and their implications for biology. Finally, the course discusses the tools and strategies that can be used to build and analyse biological networks.

Learning objectives:
Network analysis in biology

Biological systems are often represented as networks which are complex sets of binary interactions or relations between different entities. Essentially, every biological entity has interactions with other biological entities, from the molecular to the ecosystem level, providing us with the opportunity to model biology using many different types of networks such as ecological, neurological, metabolic or molecular interaction networks (Figure 1).

The data explosion that originated in the -omics era of biological research necessitated the development of more systemic approaches to data analysis and a move away from the single gene/protein perspective. Systems biology aims to understand biological entities at the systemic level, analysing them not only as individual components, but also as interacting systems and their emergent properties. Related to this is network biology which allows the representation and analysis of biological systems using tools derived from graph theory.
Introduction to graph theory

Biological network analysis historically originated from the tools and concepts of social network analysis and the application of graph theory to the social sciences.

Wikipedia (1 [2]) defines graph theory as:

“[…] the study of graphs, mathematical structures used to model pairwise relations between objects. A graph in this context is made up of vertices, nodes, or points which are connected by edges, arcs, or lines”.

In practical terms, it is the set of abstract concepts and methods that can be used to visualise and analyse networks.
The history of graph theory

Graph theory and the idea of topology was first described by the Swiss mathematician Leonard Euler as applied to the problem of the seven bridges of Königsberg. Königsberg consisted of four islands connected by seven bridges (Figure 2). No one had ever found a path that visited all four islands and crossed each of the seven bridges only once. Naturally, people assumed that no such path existed, but there was no mathematical proof of this.

Euler showed that, to solve the problem, only the relations between the land masses are relevant, not the shape or actual distances on the map. These relationships can be represented in the form of a graph where the land masses are the nodes and the bridges are the edges of the graph. Euler used this graph and its topological features to prove that the path did not exist.

Euler’s formulation of this problem provided the basis of a whole area of mathematics and it is the foundation of all the tools and concepts we will explore in this course.

You can read more about Euler’s solution to this problem on [Wikipedia](https://en.wikipedia.org/wiki/Seven_Bridges_of_K%C3%B6nigsberg) (2).

Let’s learn a bit more about graph theory and the main concepts we will use in this course.

**Graph theory: graph types and edge properties**

Networks can represent many different types of data. The nodes represent different entities (e.g. proteins or genes in biological networks), and edges convey information about the links between the nodes. First we will concentrate on the edges. Depending on the nature of underlying edge information, different types of analysis can be performed. For this reason, it is useful to highlight the main types of edges that can be found in a network (Figure 3).

**Types of network edges**

**Undirected edges**

This type of edge is found in protein-protein interaction networks (PPINs). The relationship between the nodes is a simple connection, without a given ‘flow’ implied, since the evidence behind the relationship only tells us that A binds B.

**Directed edges**

This is the kind of connection found, for example, in metabolic or gene regulation [5] networks. There is a clear flow.
of signal implied and the network can be organised hierarchically.

**Weighted edges**

Directed or undirected edges can also have weight or a quantitative value associated with them. This is used to depict concepts such as reliability of an interaction, the quantitative expression change that a gene induces over another or even how closely related two genes are in terms of sequence similarity. Edges can also be weighted by their centrality values or several other topological parameters.

![Figure 3 The main types of edges found in a network.](image)

**Graph theory: adjacency matrices**

Every network can be expressed mathematically in the form of an adjacency matrix (Figure 4). In these matrices the rows and columns are assigned to the nodes in the network and the presence of an edge is symbolised by a numerical value. By using the matrix representation of the network we can calculate network properties such as degree, and other centralities by applying basic concepts from linear algebra (see later in the course).
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Figure 4 Graphs by edge type and their adjacency matrices.

A network with undirected, unweighted edges will be represented by a symmetric matrix containing only the values 1 and 0 to represent the presence and absence of connections, respectively.

Directed and weighted networks can make use of different numerical values in the matrix to express these more complex relationships. The sign of the values, for example, is sometimes used to indicate stimulation or inhibition.

Graph theory: network topology

Graphs have some properties that are very useful when unravelling the information that they contain. It is important to realise that the purpose of any type of network analysis is to work with the complexity of the network to extract meaningful information that you would not have if the individual components were examined separately.

Network properties, and particularly topological properties, can help us identify relevant sub-structures within a network.

Topology is the way in which the nodes and edges are arranged within a network. Topological properties can apply to the network as a whole or to individual nodes and edges. Some of the most used topological properties and concepts are:

Degree
Figure 5 The degree of a network.

The degree is the number of edges that connect to a node. It is a fundamental parameter that influences other characteristics, such as the centrality of a node. The degree distribution of all nodes in the network helps define whether a network is scale-free or not, as we will see later. In the figure, the degree of each node is indicated and reflected in its size and colour. Directed network nodes have two values for degree: out-degree for those edges coming out of the node and in-degree for those edges coming into the node.

**Shortest paths**
Figure 6 Shortest paths.

Shortest paths, or the shortest distance between any two nodes, is used to model how information flows. This is especially relevant in many biological networks. In the figure, the shortest path between nodes A and B is highlighted and takes five steps.

**Scale-free networks**
Figure 7 Scale-free networks.

In scale-free networks most of the nodes are connected to a low number of neighbours and there are a small number of high-degree nodes (hubs) that provide high connectivity to the network. In the figure, hubs are highlighted in orange.

**Transitivity**
Transitivity relates to the presence of tightly interconnected nodes in the network called clusters or communities. These are groups of nodes that are more internally connected than they are with the rest of the network. These groups are also called topological clusters and are highlighted in the figure.

Centralities
Figure 9 Centralities.

As we will see later, there are different flavours of centrality, each representing different concepts. Centrality can be measured for nodes and for edges and gives an estimation on how important that node/edge is for the connectivity or the information flow of the network. The degree of a node has a direct influence on many centrality measures, most prominently on the ‘degree centrality’. Its significance is reduced in more sophisticated types of centrality measures, for example, betweenness centrality. In the figure, the most central nodes (according to their betweenness centrality) are highlighted in warm colours and the node size reflects its degree.

Types of biological networks

Biological networks

Different types of information can be represented in the shape of networks in order to model the cell (Figure 10). The meaning of the nodes and edges used in a network representation depends on the type of data used to build the network and this should be taken into account when analysing it.
Figure 10 Types of biological interactions that can be represented by networks (Adapted with permission from slides by Dr. Natas?a Prz?ulj, Imperial College, London).

Different types of data will also produce different general network characteristics in terms of connectivity, complexity and structure, where edges and nodes potentially convey multiple layers of information.

Some of the most common types of biological networks are:

1. Protein-protein interaction networks
2. Metabolic networks
3. Genetic interaction networks
4. Gene / transcriptional regulatory networks
5. Cell signalling networks

**Protein-protein interaction networks.**
Figure 11 A protein-protein interaction network.

- Represent the physical relationships between proteins. They are central to practically every process that takes place in the cell.
- Proteins are represented as nodes that are linked by undirected edges.
- We will look at protein-protein interaction networks in more detail later in the course.

Metabolic networks
Figure 12 A metabolic network.

- Represent the biochemical reactions that allow an organism to grow, reproduce, respond to the environment and maintain its structure.
- Metabolites and enzymes take the role of nodes and the reactions describing their transformations are represented as directed edges.
- Edges can represent the direction of the metabolic flow or regulatory effects of a specific reaction.

Genetic interaction networks
Figure 13 A genetic interaction network.

- Genetic interaction is the synergistic phenomenon where the phenotype\(^6\) resulting from simultaneous mutations in two or more genes is significantly different from the phenotype that would result from adding the effects of the individual mutations.
- Represent a functional relationship between different genes, rather than a physical one.
- Genes are represented as nodes and their relationships as edges. Depending on the type of evidence behind the interaction, directionality can be inferred for the edges.

**Gene / transcriptional regulatory networks**
Figure 14 A gene / transcriptional regulatory networks.

- Genes and transcription factors are represented as nodes, while the relationship between them is depicted by different types of directional edges.
- Regulatory RNAs and other mechanisms can also form part of this type of network.
- Usually generated via databases representing consensus knowledge of gene regulation [5] (e.g. Reactome [8] or KEGG), although large-scale experimental datasets are increasingly available.

**Cell signalling networks**
Figure 15 A cell signalling network.

- Cell signalling is the communication system that controls cellular activities.
- Signalling pathways represent the ordered sequences of events and model the information flow within the cell.
- Gene regulation networks can be considered as a sub-type of cell signalling networks, focusing on a specific signalling event which is often the final stage of a signalling cascade.
- Elements in the pathway (e.g. proteins, nucleic acids, metabolites) are represented as nodes and the flow of information is represented by directed edges.
- Are systematically represented by two types of resources:
  - **Pathway databases** (also known as ‘process description’ resources) such as Reactome [9], KEGG [10] or Wikipathways [11]. These aim to provide a formal representation of the current scientific consensus on cell signalling pathways. They are generated by manual curation [12] and organise the information in the form of reactions, with substrates and products being affected by the action of catalysers. This information must be converted according to specific rules in order to be represented as a network. Some information loss can occur during this process.
  - **Reaction network databases** (also known as ‘activity flow’ resources) such as Signor [13], SignaLink [14] or SPIKE [15]. These aim to capture known binary relationships in cell signalling, such as activation, phosphorylation, etc. They are generally manually curated, but not always. In contrast with the pathway databases, they are already graphs in the mathematical sense and require no transformation in order to be represented as a network.

**The sources of data underlying biological networks**

It is important to emphasise that significant challenges arise not only from the sheer size of the dataset used, but also due to the fact that biological datasets are inherently noisy and incomplete. Often, different types of evidence will not overlap or will be contradictory. The way the data was obtained is an important aspect to consider here, with the information typically coming from the following sources:

- **Manual curation of scientific literature**: Scientific curators or domain experts evaluate existing published evidence and store it in a database. This provides high-quality, well represented information, but curation is an expensive and time consuming task and the size of the datasets is limited by these factors.
High-throughput datasets: Some experimental approaches can generate large amounts of data, such as large-scale PPI datasets generated via yeast two-hybrid or affinity purification plus mass spectrometry identification. They provide large, systematically produced datasets but the information suffers the inherent biases of the chosen technique and they vary in quality.

Computational predictions: Many methods use existing experimental evidence as their basis and aim to predict unexplored relationships between biological entities. For example, protein interactions in humans can be used to predict a similar interactions in mice if there are close enough orthologues in this organism. They provide a tool to broaden and even refine the space of experimentally derived interactions, but the datasets produced are understandably noisier than with the previous sources.

Literature text-mining: Multiple algorithms are used to computationally extract systematically represented relationships from the published literature. As with the previous case, although they can greatly increase the coverage of the data, natural language processing [16] is a tricky business and the results tend to be rather noisy.

Protein-protein interaction networks

Protein-protein interactions (PPIs) are essential to almost every process in a cell, so understanding PPIs is crucial for understanding cell physiology in normal and disease states. It is also essential in drug development, since drugs can affect PPIs. Protein-protein interaction networks (PPIN) are mathematical representations of the physical contacts between proteins in the cell. These contacts:

- are specific;
- occur between defined binding regions in the proteins; and
- have a particular biological meaning (i.e., they serve a specific function).

PPI information can represent both transient and stable interactions:

- Stable interactions are formed in protein complexes (e.g. ribosome, haemoglobin).
- Transient interactions are brief interactions that modify or carry a protein, leading to further change (e.g. protein kinases, nuclear pore importins). They constitute the most dynamic part of the interactome.

Knowledge of PPIs can be used to:

- assign putative roles to uncharacterised proteins;
- add fine-grained detail about the steps within a signalling pathway; or
- characterise the relationships between proteins that form multi-molecular complexes such as the proteasome.

The interactome

The interactome is the totality of PPIs that happen in a cell, an organism or a specific biological context. The development of large-scale PPI screening techniques, especially high-throughput affinity purification combined with mass-spectrometry and the yeast two-hybrid assay, has caused an explosion in the amount of PPI data and the construction of ever more complex and complete interactomes (Figure 16). This experimental evidence is complemented by the availability of PPI prediction algorithms. A lot of this information is available through molecular interaction databases such as IntAct [17].
Figure 16  Yeast (left) and human (right) interactomes obtained using the yeast-two hybrid method. Images reprinted by permission from Macmillan Publishers Ltd: Jeong et al. Nature 2001. 411 (3) and Rual et al. Nature 2005: 437 (4).

It is important to emphasise once more the limitations of available PPI data. Our current knowledge of the interactome is both incomplete and noisy. PPI detection methods have limitations as to how many truly physiological interactions they can detect and they all find false positives and negatives.

To learn more about PPIs in general and the IntAct database in particular take our free online courses:

Protein Interactions and their importance [18]

IntAct: The molecular interactions database at EMBL-EBI: webinar [19]

IntAct: Molecular interactions at EMBL-EBI [20]

On the next few pages we will take a look at some of the properties of protein-protein interaction networks and the implications of these properties for biology.

Properties of PPINs: small world effect

Protein-protein interaction networks show a small world effect meaning that there is great connectivity between proteins (Figure 17). In other words, it can be said that the network’s diameter (the maximum number of steps separating any two nodes) is small, no matter how big the network is. This usually means that any two nodes are separated by less than six steps, more or less, reflecting the now widely popularised “six degrees of separation [21]” theory used in social sciences.
Figure 17 The small world effect.

This level of connectivity has important biological consequences, since it allows for an efficient and quick flow of signals within the network. However, it also poses an interesting question: if the network is so tightly connected, why don’t perturbations in a single gene or protein have dramatic consequences for the network?

Biological systems are extremely robust and can cope with a relatively high amount of perturbations in single genes/proteins. In order to explain how can this happen, we need to have a look at another fundamental property of PPINs: they are scale-free networks.

Properties of PPINs: scale-free networks

Protein-protein interaction networks are scale-free networks (Figure 18A). The majority of nodes (proteins) in scale-free networks have only a few connections to other nodes, whereas some nodes (hubs) are connected to many other nodes in the network.
The number of connections each node has is called its degree. If we represent the degree distribution of a scale-free network in a logarithmic scale, we can see how it fits with a line (they fit a power-law), having a small number of nodes with high degree (the hubs) and a large number of nodes with a low degree (Figure 18B).

Scale-free networks can be built following the preferential attachment model, also known as the ‘rich get richer’ principle. This principle simply states that scale-free networks can be built by adding edges that are preferentially attached to those nodes with a highest degree ([2]). This building principle provides a self-organising mechanism for the generation and expansion of this type of network.

The scale-free nature of protein-protein interaction networks gives them a number of important features:

- **Stability**
  - If failures occur at random, and the vast majority of proteins are those with a small degree of connectivity, the likelihood that a hub would be affected is small.
  - If a hub-failure occurs, the network will generally not lose its connectedness, due to the remaining hubs.

- **Invariant to changes of scale**
  - No matter how many nodes or edges the network has, its properties remain stable.
  - The presence of hubs is what allows for the small-world effect to be present regardless of the size of the network.

- **Vulnerable to targeted attack**
  - If we lose a few major hubs from the network, the network is turned into a set of rather isolated graphs.
  - Hubs are enriched with essential/lethal genes. For example, many cancer-linked proteins are hub proteins (e.g. the tumour suppressor protein p53).

It is important to note that, given the current limited coverage levels and variable quality of interaction data,
the observed scale-free topology of existing protein-protein interaction networks cannot be confidently extrapolated to complete interactomes. In fact, some works have been questioning how well biological networks fit the scale-free power law distribution (6 [2]).

Properties of PPINs: transitivity

Another crucial characteristic of PPINs is their modularity. The transitivity or clustering coefficient of a network is a measure of the tendency of the nodes to cluster together. High transitivity means that the network contains communities or groups of nodes that are densely connected internally. Following an analogy from the social sciences, “the friends of my friends are my friends”. In biological networks, finding these communities is very important, because they can reflect functional modules and protein complexes (Figure 19).

![Figure 19](image)

**Figure 19** Topological clusters reflecting biological function. Clusters are highlighted within dashed-line squares: I – Proteasomal machinery; II - translation-related protein cluster, containing several ribosomal proteins; III – energy production-related cluster, containing several mitochondrial ATPases. Image reproduced with permission of the authors of Hsia et al. Int J Mol Sci. 2015: 16. (7 [2]).

A module is an exchangeable functional unit. They are self-contained components of a system with well-defined interfaces with other components. The defining feature of a module is that its intrinsic functional properties do not change when it is placed in a different context. Modules help reduce the complexity of biological networks by giving us a set of reducible, functional units that can be studied as an integrated entity. Topological study of PPINs can help detect and define these modules.

Protein complexes can be considered a type of module in which proteins are interacting with each other in a stable manner, maintaining a more or less fixed configuration in time and space. They represent multi-protein machineries with specific functions. A broader type of functional module does not require the proteins to be stably bound to each other as long as its intrinsic functional properties do not change when placed in another context.

The study of modules is also useful when defining intermodular interactions and proteins. These are the edges/nodes that link different communities within a network. They can act as switches or high-level modulators.
that, for example, mediate cross-talk between different complexes or pathways.

We will talk more in detail about the search for modules in PPINs in a further section. Now let's talk about the main strategies that can be used to analyse PPINs.

**Building and analysing PPINs**

Now that we know a bit about graph theory and protein-protein interaction networks, we can look at the steps, strategies and tools used to build and analyse these networks (Figure 20).

![Figure 20](image.png)

**Figure 20** A potential workflow for building and analysing protein-protein interaction networks.

First, we will briefly introduce various software packages or programmatic methods used to build and analyse networks. Next we talk about sources from which you can obtain PPI data and discuss several ways of analysing the data of which topological analysis of centralities and community-finding approaches are common strategies. Finally, we look at ways in which additional data can be added to understand the biological context of the network.
Network representation and analysis tools

There are a variety of tools that can be used to obtain, integrate and analyse PPI data to understand its biological context. Let’s have a brief look at some of them.

Cytoscape

Cytoscape [22] is one of the most popular network analysis tools. It is an open-source, Java-based, multi-platform desktop application that is widely used for network representation, integration and analysis. It was originally designed for the analysis of biological networks, which remains as its main application, but can also be used for general purpose network analysis.

![Cytoscape](image)

Figure 21 Cytoscape is a popular tool for network analysis.

Advantages

Cytoscape apps

- One of the main reasons for its popularity is the large variety of apps (almost 300 at the time we wrote this course) that provide further, specific functionality to the core distribution of Cytoscape. This provides great flexibility, making the tool adaptable to multiple types of analysis in various domains of knowledge.
- For PPI network analysis there are specific apps for community search, (for example MCODE [23], clusterMaker2 [24], JActiveModules [25]) or to perform Gene Set Enrichment Analysis (BiNGO [26], ClueGO [27], EnrichmentMap [28]).
- Some Cytoscape apps will only work with a specific version of the core distribution of Cytoscape. It is important to check that you have the right version for the type of analysis you need to run.

Automation

- Cytoscape tasks can be automated through command-line arguments, although the number of features you can access this way is still limited.

Limitations

- It is quite demanding in terms of computing resources when it comes to large-scale networks and it reaches a limit of what it can handle once networks become too large (hundreds of thousands of nodes and edges).
Non-programmatic options for large networks

A non-programmatic option for handling large networks is Gephi [29]. Gephi is capable of dealing with hundreds of thousands of nodes, and millions of edges, albeit processing and especially drawing of such nets requires massive computer power.

![Gephi](image)

Figure 22 Gephi is a non-programmatic tool for analysing large networks.

The benefits of Gephi are that it is open source, multi-platform, and has a wide range of advanced network-related algorithms (often not found anywhere else) in the form of plugins. The one disadvantage is the lack of any capability for processing specifically biological information. It is a general network tool, and should be treated as such and used for enumerating, statistics, and visualisation.

Programmatic solutions

Programmatic solutions for large scale network analysis include packages such as igraph [31] (for R, Python and C) or NetworkX [32] (for Python). These are scripting packages that have much lower demand on your computer resources and are more amenable for automated tasks. This means they can be easily implemented as part of larger bioinformatics analysis pipelines. For example, the R implementation of igraph is often used hand-in-hand with other biostatistics packages available through this language.

![igraph and NetworkX](image)

Figure 23 igraph and NetworkX are programmatic solutions for large scale network analysis.

Sources of PPI data

The first step in performing PPI analysis is, of course, to build a network. There are different sources of PPI data (Figure 24) that can be used to do this and it is important to be aware of their advantages and disadvantages.

Essentially, you can obtain PPI data from:

- **Your own experimental work**, where you can choose how the data is represented and stored.

- **A primary PPI database**. These databases extract PPIs from the experimental evidence reported in the literature using a manual curation process. They are the primary providers of PPI data and they can
represent a great deal of detail about interactions, depending on the database.

- **A metadatabase or a predictive database.** These resources bring together the information provided by different primary databases and provide a unified representation of the data to the user. Predictive databases go beyond that and use the experimentally produced datasets to computationally predict interactions in unexplored areas of the interactome [35]. Predictive databases provide a way of broadening or refining the space of experimentally derived interactions, but the datasets produced are noisier than those from other sources.

![Figure 24 Sources of PPI data and challenges when building a PPIN.](image)

A more detailed overview of PPI databases can be found in this section of our introductory course on protein interactions [36].

It will often be necessary to integrate PPI data from multiple sources as no database has a full representation of all the PPI evidence available. This creates some interesting challenges because different databases use different identifiers and contain different types of data.

In order to avoid redundancies and inconsistencies, it is important to understand the differences between the different databases in terms of:

i) The type of data and metadata [37] they include. For example, some databases will give you only experimentally-derived data and others will also include predictions. Similarly, the level of detail given about the experimental setup varies between databases.

ii) The identifiers used by the database. Different databases make different choices in this regard, so sometimes you may have to map different types of identifiers for data integration.

The creation of the IMEx [38] consortium, enforcing the use of common representation standards and
Assessing reliability and measuring confidence

An important concern in network analysis is whether the interaction network can be trusted to represent a “real” biological interaction. Given the noise inherent in current interactome information, it is important to be stringent when evaluating the protein-protein interaction data we use in our analysis. It is important to take into account that interactome coverage is also incomplete and patchy, so we will not always have the luxury of filtering out less reliable evidence.

There are many different methods for ascertaining reliability and giving a measure of confidence. Some strategies make use of:

- **Contextual biological information** regarding the proteins or molecules involved in the interaction. For example, overlapping co-expression patterns ([8](#), [9](#)).
- **Count how many times a given interaction has been reported in the literature**, as a measure of experimental orthogonal validation. This is a popular and straightforward approach and there are more elaborate variations of this strategy, such as Mlscore (see boxed text).
- **Aggregated methods** that use a number of different strategies and integrate them in a single score, such as **INTscore** ([40](#)).

### The Mlscore method

Mlscore is a method for assessing the reliability of protein-protein interaction data based on the use of standards ([11](#)). Mlscore gives an estimation of confidence weighting on all available evidence for an interacting pair of proteins. The method allows weighting of evidence provided by different sources, provided the data is represented following the standards created by the IMEx consortium.

As shown in Figure 25, the method weights the:

- number of publications;
- detection method;
- interaction evidence type.

Different interaction detection methods and interaction types have different weights, assigned by a group of expert curators. These parameters are aggregated for each interacting pair and then normalised, giving a quantitative measure of how much experimental evidence there is behind a given interaction.
Figure 25 The Mlscore normalised score calculates a composite score for an interaction based on the number of publications reporting the interaction, the reported interaction detection methods and interaction types. Reprinted from Villaveces et al. Merging and scoring molecular interactions utilising existing community standards: tools, use-cases and a case study. Database (Oxford), 2015 (11 [2]). By permission of Oxford University Press.

Now let's have a look at some strategies we can use to extract information from a network.

**Topological PPIN analysis**

Analysing the topological features of a network is a useful way of identifying relevant participants and substructures that may be of biological significance. There are many different strategies that can be used to do this (Figure 26). In this section we focus on centrality analysis and topological clustering, although there are other strategies such as the search for shortest paths or motifs that are more often applied to networks with directionality and will not be covered here.
Figure 26 Common structural analysis strategies for PPINs.

**Centrality analysis**

Centrality gives an estimation on how important a node or edge is for the connectivity or the information flow of the network (Figure 27). It is a useful parameter in signalling networks and it is often used when trying to find drug targets.

Centrality analysis in PPINs usually aims to answer the following question:

*Which protein is the most important and why?*

Edge centrality can also be analysed, but this is less common and the concepts can easily be translated from the node-based centralities, so we will focus on the latter in this section.
Figure 27 Node centrality represented in a network. Bigger, redder nodes have higher centrality values in this representation.

The definition of ‘central’ varies with the context or purpose of our analysis. Centrality can be measured using different metrics and criteria:

- **Degree of the nodes**

  The degree of the nodes can be used as a rough estimate of centrality. As we saw earlier, nodes with a high degree (hubs) are key in maintaining some characteristics of scale-free networks such as their robustness and the small-world effect. However, this is a local measure since it does not take into account the rest of the network and the importance we give to its value depends strongly on the network’s size.

- **Global centrality measures**

  Global centrality measures take into account the whole of the network. They are relative measurements that
provide a normalised value that is independent of network size. There are many different types of global centrality measures, each addressing a slightly different definition of centrality. Two of the most widely used global centrality measures are **closeness** and **betweenness** centralities, which we will address in more detail in the following sections.

- **Other measures of centrality**

More complex measures of centrality can be defined depending on the specific method used to calculate it. For example, centralities are often calculated using ‘random walks’ where random nodes are chosen as a starting point and the ‘time’ or ‘speed’ needed to reach other nodes in the network is calculated. This can be combined with the weights assigned to nodes or edges in the graph to influence the centrality calculation derived from other features. This is the method used by the Google PageRank algorithm to assign weight to each webpage (12 [2]).

Note that centrality parameters can also be calculated taking the directionality of edges into account which can cause slight changes their definitions. Since we are focusing on PPINs, we will consider edges to be undirected in this section.

**Closeness centrality**

**Closeness centrality** is a useful measure that estimates how fast the flow of information would be through a given node to other nodes.

Closeness centrality measures how short the shortest paths are from node $i$ to all nodes. It is usually expressed as the normalised inverse of the sum of the topological distances in the graph (see equation at the top of Figure 28). This sum is also known as the farness of the nodes. Sometimes closeness centrality is also expressed simply as the inverse the farness (13 [2], 14 [2]). In the example shown on the bottom half of the figure, you can see the distances matrix for the graph on the left and the calculations to get the closeness centrality on the right. Node $B$ is the most central node according to these parameters.

\[
CC(i) = \frac{N - 1}{\sum_{j \neq i} d(i, j)}
\]

where

- $i \neq j$;
- $d_{ij}$ is the length of the shortest path between nodes $i$ and $j$ in the network;
- $N$ is the number of nodes.

\[
\text{farness} = \sum_{j=1}^{n} d(i, j)
\]

\[
CC(i) = \frac{N - 1}{\sum_{j} d(i, j)}
\]

- Node $B$ is the most central node according to these parameters.
Figure 28 Calculating the closeness centrality of nodes in a graph.

Betweenness centrality

Betweenness centrality is based on communication flow. Nodes with a high betweenness centrality are interesting because they lie on communication paths and can control information flow. These nodes can represent important proteins in signalling pathways and can form targets for drug discovery. By combining this data with interference analysis we can simulate targeted attacks on protein-protein interaction networks and predict which proteins are better drug candidates, for example see Yu, et al 2007 (15 [2]).

The calculation of betweenness centrality is not standardised and there are many ways solve it. It is basically defined as the number of shortest paths in the graph that pass through the node divided by the total number of shortest paths.

Betweenness centrality measures how often a node occurs on all shortest paths between two nodes. Hence, the betweenness of a node $N$ is calculated considering couples of nodes ($v_1$, $v_2$) and counting the number of shortest paths linking those two nodes, which pass through node $N$. Next the value is related to the total number of shortest paths linking $v_1$ and $v_2$.

\[
C_B(n_i) = \sum_{j<k} g_{jk}(n_i) / g_{jk}
\]

Where $g_{jk}$ = the number of geodesics (shortest paths) connecting $jk$, and $g_{k}(n_j)$ = the number that node $i$ is on.

Figure 29 Betweenness centrality.

To give a more intuitive example, in the graph from Figure 29, either node $B$ or node $C$ can be removed and there will still be paths leading to node $E$. Node $D$, however, is quite central, since it is required for any path leading to node $E$. You can think of this graph as a city map and our analysis is telling us that $D$ is the cross roads where traffic jams are more likely to occur. Betweenness centrality can in fact be used in city planning and there are studies aiming to optimise city transport based on this and related metrics (16 [2]).

Clustering analysis

Looking for communities in a network is a nice strategy for reducing network complexity and extracting functional modules (e.g. protein complexes) that reflect the biology of the network. There are several terms that are commonly used when talking about clustering analysis (Figure 30):
**Community / Cluster**

A general, catch-all term that can be defined as a group of nodes that are more connected within themselves than with the rest of the network. The precise definition for a community will depend on the method or algorithm used to define it. When talking about PPINs, communities fall into two categories: functional modules and protein complexes.

**Module**

In biology, modules are exchangeable functional units in which the nodes (proteins) do not have to be interacting in the same time or space. The most important characteristic of a module is that its intrinsic functional properties do not change when it is placed in a different context.

**Complex**

A complex is a group of proteins that interact with each other at the same time and in the same space, forming relatively stable multi-protein machinery. You can use the [Complex Portal][44] to explore known macromolecular complexes in a number of model organisms.

**Clique**

A subset of nodes in which every node is connected with every other member of the clique. A maximal clique is a clique that cannot be extended by adding an additional node not previously included in the clique. There are

[Figure 30](#) Some concepts in network community analysis. (Network communities figure from [Wikimedia commons][41] by j_ham3 and used under Creative Commons Attribution-Share Alike 3.0 Unported license. Haemoglobin 3D structure from [PDBe][42] and complex diagram from [IntAct][43]).
several different types of cliques and they can be used as the basis of algorithms that use topological criteria to look for communities.

**Motif**

Motifs are statistically over-represented sub-graphs in a network. They correspond with a pattern of connections that generates a characteristic dynamical response (e.g. a negative feedback loop). They are less important for the type of networks this tutorial is devoted to, but are quite useful in directed networks.

When exploring a PPIN for clusters, the goal is often to find functional modules or protein complexes that execute defined biological functions. There are many different methods that can help us find clusters and we will briefly introduce some of them in this section.

**Clustering analysis methods I**

In this section we will focus on methods that exclusively use the topology of the network to find closely-connected components. This is generally known in graph theory as 'community detection methods'. No assumptions are made about the internal structure of these communities, we are just looking at high-density regions.

It is important to note that finding the best community structure is algorithmically extremely complex and is only possible for very small networks. For this reason, many approximation methods, often addressing different scenarios, have been developed. There are too many to cover in this course. Some examples include:

- **Clique-percolation method** [45]
- **Markov Clustering Algorithm (MCL)** [46]
- **Fuzzy C-Means** [47]
- **Affinity Propagation** [48]
- **Chinese Whispers Clustering** [49]
- **Label Propagation Clustering** [50]

We will briefly introduce two of the most popular methods used to analyse protein interaction networks: **Newman-Girvan fast greedy algorithm** and the **MCODE algorithm**.

Another way to address the search for communities within a network is to use a combination of the topology of the network and some external property, such as protein expression values, as an additional layer defining communities. A good example of this popular method is the **jActiveModules app** [25] for Cytoscape [17 [2]]. This app "[…] searches a molecular interaction network to find expression activated sub-networks. Such sub-networks are connected regions of a network that show significant changes in expression over particular subsets of conditions" [18 [2]]. In essence, connected regions within a network with differential expression can be identified using this tool.

**Clustering analysis methods II**

**Newman-Girvan fast greedy algorithm**

- Developed for the study of networks in general, with a special focus on social and biological networks (19 [2]).

- Identifies communities by using the edge betweenness centrality measure. Edges that connect different
communities have higher centrality values, since a larger proportion of shortest paths will pass through them.

- To define communities it uses the edge betweenness centrality scores to rank the edges of the network, then removes the most central edges and then re-calculates the betweenness scores until no edges are left. Edges affected by the removal are deemed to be part of the same community.

- Can be considered a ‘naïve’ approach that will define communities even when they are only marginally more connected than the rest of the network.

![Figure 31](image)

**Figure 31** Communities defined using Newman-Girvan and MCODE.

**MCODE algorithm**

- Developed to find protein complexes in PPI networks ([20](#)).

- Can be considered to be more stringent than the Newman-Girvan algorithm, since it aims to find only those sub networks that are very highly interconnected, representing relatively stable, multi-protein complexes that function as a single entity in time and space.

- The parameters of the algorithm can be adjusted to make it less stringent, so that a looser definition of a community is used.

- The algorithm uses a three-stage process:

1. Weighting: a higher score is given to those nodes whose neighbours are more interconnected.
2. Molecular complex prediction: starting with the highest-weighted node (seed), recursively move out, adding nodes to the complex that are above a given threshold.

3. Post-processing: applies filters to improve the cluster quality (haircut and fluff).

It is important to note that when we speak about 'stringency' we are talking about how interconnected the nodes within a sub-network must be in order to be considered a separate community. This changes depending on the biological question underlying the analysis. It is not the same to look for stable protein complexes, such as the proteasome, as it is to look for functional sub-modules representing a specific step in a signalling pathway.

**Annotation enrichment analysis**

There are many different approaches that can be used to understand the biological context of protein-protein interaction networks. **Annotation enrichment analysis** is one of the most popular methods. Although it is not strictly speaking a network analysis tool, it is often used in combination with topological network analysis.

There are different varieties of this type of analysis, but in its most basic form, annotation enrichment analysis uses gene/protein annotations provided by knowledge-bases such as Gene Ontology [51] (GO) or Reactome [8] to infer which annotations are over-represented in a list of genes/proteins that can be taken from a network (Figure 32). Essentially, annotation tools perform some type of statistical test (usually a hypergeometric test, often also a binomial test) that tries to answer the following question:

"When sampling $X$ proteins (test set) out of $N$ proteins (reference set; graph or annotation), what is the probability that $x$, or more, of these proteins belong to a functional category $C$ shared by $n$ of the $N$ proteins in the reference set."\(^{(21)}\) [2]

The result of this test provides us with a list of terms that describe the list/network, or rather a part of it, as a whole.
Figure 32 Annotation enrichment analysis using GO and Reactome in a network.

This type of analysis is most frequently performed using GO [52] annotation as a reference, but tools such as the Cytoscape apps BioNGO [26] and ClueGO [27] can also manage other annotation databases such as Reactome [9] and KEGG [10]. This is a widely used technique that helps characterise the network as a whole or sub-sets of it, such as inter-connected communities found through topological clustering analysis.

More complex versions of this technique can factor in continuous variables such as expression fold change. The GSEA [53] tool is a good example of a more advanced technique that makes use of similar basic concepts. A slightly old but very thorough overview of different tools of this family and the advantages and limitations of their different approaches can be found in Huang da et al 2009 (22 [2]).

To learn more about annotation and Reactome pathways have a look at these Train online courses:

- UniProt-GOA: Quick tour [54]
- GO: Quick tour [55]
- Reactome: Exploring and analysing biological pathways [56]

Limitations of annotation enrichment

Annotation
The main limitations of annotation enrichment come from the annotations themselves. Certain areas of biology are more thoroughly annotated and better described than others, with more detail and more accurate terms for well-known processes. For example, at the level of the proteins, more "popular" proteins are better annotated. This introduces a certain bias into the statistical analysis.

It is also important to note that GO terms can be assigned either by a human curator [57] who performs careful, manual annotation [58] or by computational approaches that use the basis of manual annotation to infer which terms would properly describe uncharted gene products. They use a number of different criteria that always refer to annotated gene products, such as sequence or structural similarity or phylogenetic closeness. The importance of the computationally derived annotations is quite significant, since they account for roughly 99% of the annotations that can be found in GO.

Simplifying the interpretation of annotation enrichment results

Another limitation of annotation enrichment is the complexity and detail of annotation associated with large gene or protein sets. This happens because resources such as Reactome and, especially, GO can be very complex and detailed in their annotation leading to the generation of overwhelmingly complicated networks of inter-related and similar terms. There are several ways to try and unravel this complexity.

The simplest approach is to use simplified ontologies. Many tools offer this option and use ontologies where fine detailed terms are removed and assigned to broader, more general parent terms. In GO, these simplified ontologies are called GOslims [59].

Other tools, such as the Cytoscape apps BINGO or ClueGO, represent the results as a network of terms, where directed edges represent term relationships as defined in the ontology [60] used. This allows tools from graph theory to be used to reorganise the layout of the network to uncover communities inside these terms networks which helps to simplify the output. BINGO only provides the network view, so other tools are required to further simplify the analysis. ClueGO makes use of network analysis tools and Cohen's kappa coefficient [61] to offer a simplified view of the results, grouping terms by similarity and offering much more interpretable results.

Finally, there are tools that are specifically devoted to simplifying the task of interpreting annotation enrichment results. The Cytoscape EnrichmentMap [62] app is a very good example. It can use the output from some of the most popular annotation enrichment tools, such as DAVID [63], BINGO [26], g:Profiler [64] or the more sophisticated GSEA [65], and render it in the shape of clustered networks. The tool applies clustering and automatic layout techniques to overlap similar gene sets and provide a simplified representation of annotation enrichment results. It is especially useful when comparing results obtained from different sets, for example, those representing two different conditions.

In summary, it is important to know the limitations of the annotation resource you are using to perform this type of analysis. It is also important to be aware of the inherent complexity of the results. Network analysis techniques can help simplify the interpretation of these results.

Summary

Biological networks

- Network biology makes use of the tools provided by graph theory to represent and analyse complex biological systems.

- There are several types of biological networks: genetic, metabolic, cell signalling etc. This course focuses on protein-protein interaction networks (PPINs), but the concepts and tools presented can be used in other networks too.
Networks are represented by nodes and edges. Nodes represent different entities (e.g. genes or proteins) and edges convey information about how the nodes are linked.

Protein-protein interaction networks

- PPINs have a number of characteristics, mainly:
  - **Small-world effect**: Network diameter is usually small (~ 6 steps), no matter how big the network is.
  - **Scale-free**: A small number of nodes (hubs) are lot more connected than the average node.
  - **Transitivity**: The networks contain communities of nodes that are more connected internally than they are to the rest of the network.

Analysing PPINs

- Several tools are available for PPIN analysis. For example, Cytoscape [22], igraph [31], Gephi [29], NetworkX [32].

- When building a PPIN it is important to be aware of the type and quality of the data used. Confidence scoring tools such as MIscore can help select the best characterised interactions.

- Two of the most used topological methods to analyse PPINs are:
  - **Centrality analysis**: Which identifies the most important nodes in a network, using different ways to calculate centrality.
  - **Community detection**: Which aims to find heavily inter-connected components that may represent protein complexes and machineries

- **Annotation enrichment analysis** is a complementary tool often used when analysing PPINs. It uses resources such as the Gene Ontology (GO) or Reactome to infer which annotations are over-represented in a list of genes or proteins. It can produce complex results that can be further simplified using network analysis tools.

Quiz: Check your learning

- Questions: 12
- Attempts allowed: Unlimited
- Available: Always
- Pass rate: 75%
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  - [IntAct: Molecular interactions at EMBL-EBI](#) [20]
  - [Complex Portal: Quick tour](#) [66]

- **Annotation and Reactome pathways**
  - [UniProt-GOA: Quick tour](#) [54]
  - [GO: Quick tour](#) [55]
  - [Reactome: Exploring and analysing biological pathways](#) [56]

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Matt Rogon completed his MSc in Molecular Biology at the University of Gdansk, Poland. After working for 3 years as an editor for an online education publishing house he switched his focus to Bioinformatics (MRes at Glasgow University, UK) and followed up with a PhD in Systems Biology at the German Cancer Research Center (DKFZ) and the University of Heidelberg, Germany. After a short postdoc he joined EMBL in 2013. He is coordinating the EMBL Centre for Biomolecular Network Analysis with a focus on consulting, project support, and teaching in the field of Network Biology and data integration.

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I am interested on disentangling the complexity of biological systems at different levels, generating data-driven hypotheses to explore the fundamental basis of disease, development, variability and evolution. My PhD research in Florencio Pazos’s group at CNB-CSIC focused on improving computational methods for predicting protein-protein interactions based on coevolution. These methods are founded on the idea that interacting or functionally related proteins tend to adapt to each other during the evolutionary process. As part of my post-doctoral research in the Beltrao group, I study the dynamics, specificity and functional relevance of post-translational modifications. Thanks to the rapidly growing volumes of proteomic data in recent years, the comparative analysis of genome-wide modification sites can provide deeper insights into the specificity and evolution of the regulatory mechanisms of protein activity.
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