An Overview of Social Network Analysis: Metrics, Tools and Applications

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Introduction

A social network is defined as a collection of social entities, such as individuals, groups, and organizations, connected by relational data with some interactions or relationships between them. Examples of such networks include friendship networks, follower networks, interaction networks, co-authorship networks, and spread networks (Tabassum et al., 2018). The two main components of any social network are entities and relationships (Scott, 2000). The combination of these two elements creates a social network. Entities may be individual people or collective actors, such as groups and organizations. Common examples of individual actors include students in a school, employees in a corporate firm, or members of a political organization. Collective actors could be companies, foundations, or political parties. Sometimes, networks consist of different types of entities, such as a healthcare system or an education system. A relationship is generally defined as a specific type of contact, connection, or bond between a pair of entities or a dyad (Wasserman & Faust, 2004). Relationships can be directed, where one actor initiates and the other receives (e.g., giving advice, selling), or undirected, where reciprocity occurs (e.g., chatting, collaborating). A relationship is not a characteristic of a single entity but is a common dyadic property that exists as long as both participants maintain it. The diverse relationships between individual and collective entities can represent network structures and explain their impacts. The specific type of relationship a researcher should measure depends on the research objectives. For example, a study on community networks will likely examine various neighborhood activities, whereas a study on banking networks will focus on financial transactions. Borgatti et al. (2009) classified the types of relationships in social networks. These classifications and examples related to them are presented in Table 1.

Table 1
Types of Relationships

Relationship Type	Example
Similarities	Being on the same team, attending the same school, same gender, similar hobbies
Relationships	Kinship, marriage, friendship

Interactions	Help, advice, recommendation
Flows	Information flow, personnel changes, international trade

Social networks are suitable subjects for both quantitative and qualitative studies as they contain both the structure and the content of social relationships (Coviello, 2005). The analytical approach used in studying social networks is Social Network Analysis. Social Network Analysis (SNA) is a powerful analytical method aimed at examining connections and interactions between individuals, groups, institutions, or devices to make inferences from these relationships (Edwards, 2010). SNA finds application not only in personal relationships and social circles but also in business, healthcare, education, biology, and many other fields. This analytical method provides data scientists, researchers, and analysts with a broad and versatile toolkit, enabling the understanding of complex network structures and the extraction of information from them.

The rapidly growing subset of social networks is social media. Applications like Instagram, Twitter, LinkedIn, and WeChat facilitate daily information exchange. A significant concern is how the vast, complex data generated by online social network users can be searched, retrieved, stored, shared, processed, and visualized. SNA has become a widely applied method in research to investigate networks of relationships at individual, organizational, and societal levels. With the popularization of social networking sites like Facebook, Twitter, and Instagram, and the development of automated data collection techniques, the demand for SNA has recently increased significantly.

Social network analysis, with its interdisciplinary approach, is used in various fields and is of considerable importance. It offers the opportunity to analyze the relationships between social entities and the significance of these relationships (Oliveira & Gama, 2012). It allows the identification of similarities and differences in relationships between entities within social networks (Somyürek & Güyer, 2020). It also enables the integration of relationships and attributes in data structures (DeJordy & Halgin, 2008). In social network analysis, the visual presentation of data allows the entire structure to be seen as a whole and provides insight into the dynamics and effectiveness of any network (Lewis, 2011).

Historical Development of Social Network Analysis (SNA)

Social network analysis is a method that has evolved over time with the integration of various disciplines and has become an important tool in modern social sciences today. Social network analysis (SNA) has been used for a long time to represent complex relationships between participants in social systems at all scales. It is summarized the historical development process of SNA in five main stages (Somyürek & Güyer, 2020) (Figure 1).

Figure 1
Historical Development of SNA
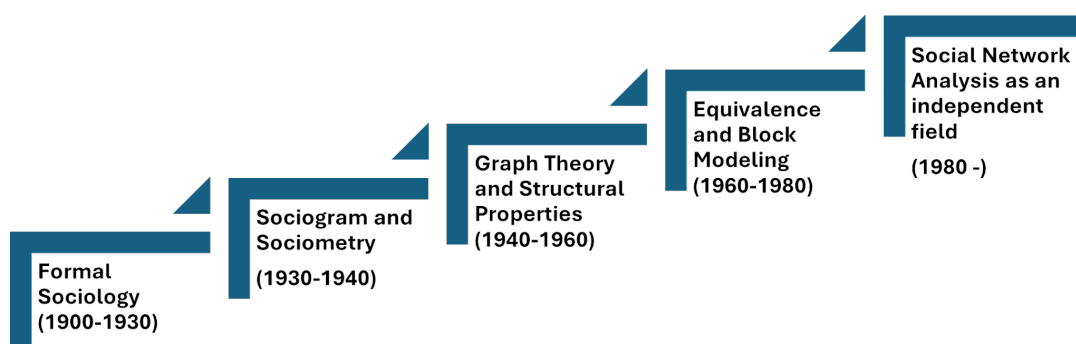
Formal Sociology (1900-1930)

- George Simmel laid the theoretical foundation of modern social network analysis by focusing on the formal analysis of social interactions.
- Simmel examined different patterns of relationships, such as dyadic and triadic interactions, and argued that sociology should focus on the forms of social relationships.

Sociogram and Sociometry (1930-1940)

- Jacob Levy Moreno developed the techniques of sociogram and sociometry to study interpersonal relationships in small groups.
- Sociograms provided a visual dimension to network analysis by graphically representing social ties within groups.

Graph Theory and Development of Structural Features (1940-1960)

- Heider's (1946) work on group dynamics and balance made significant contributions to SNA.
- Cartwright and Harary (1956) mathematically analyzed social relationships in terms of balance and group dynamics.
- Graph theory, with its structures of nodes and edges, enabled a better understanding of social relationships.
- Modeling positive and negative relationships allowed for the identification of structural features like density and clustering in social networks.

Equivalence and Block Modeling (1960-1980)

- Harrison White and his students defined social structures through roles and relationships.
- Granovetter (1983) demonstrated that weak ties could be more effective than strong ties, highlighting the functionality of social relationship networks.
- Block modeling was used to group structurally similar nodes and to determine the fundamental features of the network.

Social Network Analysis as an Independent Field (1980-Present)

- In the 1980s, SNA emerged as a distinct research field within social sciences.
- INSNA (International Network for Social Network Analysis) was established, the Sunbelt Conference was organized, and the journal *Social Networks* began publication.

SNA has since taken a more analytical approach, developing its methodologies, theoretical expressions, and software. Software like UCINET, Gephi, PAJEK, and R packages has been developed, broadening the application of SNA.

Graph and Metrics

Social networks are generally presented in 2 ways. The first one is graphs. Graphs are structures that visually share information about social networks. Mathematical operations cannot be processed indirectly with analysis. The other is matrices. Since matrices allow for computational operations, detailed information is shared by conducting butchered analyses (Streeter & Gillespie, 1992).

Social networks are typologically classified as directed-undirected and binary-valued. If there are arrows between the links in the representation of a network, it is defined as a directed network; if there are no arrows, it is defined as a non-directional social network

(Tunalı, 2016). The other is classified as valued and binary according to the value of the link. The first one is the type that expresses the presence or absence of the links between nodes as 0-1 expressed as binary. The other is the type where the numerical value of a link indicates the density, strength, frequency, or volume of connections between pairs of nodes. This type is called valued (Tunalı, 2016).

Centrality

Centrality is an essential metric that indicates which node has a critical position within the network. If an actor has a high centrality value, it shows that this actor holds a central position in the network (Bloch, Jackson & Tabaldi, 2023).

In calculating centrality, the nature of the relationship is considered. Centrality is calculated based on whether the relationship is directed, undirected, weighted, or unweighted. In undirected networks, the degree of a node is the number of connections that node has. In directed networks, incoming connections to the node are referred to as in-degree centrality, while outgoing connections are referred to as out-degree centrality. The sum of the in-degree and out-degree is the total degree of that node.

Degree Centrality

In a network graph, degree centrality is measured by the total amount of direct connections to other nodes. It indicates the level of outward connectivity. Higher values suggest greater connectivity, indicating how central the node is relative to other nodes in the network (Laghridat & Essalih, 2023). In-degree centrality is based on relationships initiated by other users towards a user, while out-degree centrality is based on relationships initiated by a user towards others. Degree centrality assumes that all neighbors in the network are equally important. What matters is the number of neighbors. However, in many cases, if a node is connected to powerful nodes, its importance increases.

For undirected networks:

- Degree Centrality = Node's degree (number of connections) / (N-1)

For directed networks, it is divided into in-degree and out-degree centrality:

- In-degree Centrality = Number of incoming connections to the node / (N-1)
- Out-degree Centrality = Number of outgoing connections from the node / (N-1)

Betweenness Centrality

Betweenness centrality is used to measure a node that plays an 'intermediary' role in a network (Marin & Wellman, 2011). If a node is located on the only path that other nodes need to traverse, such as communication, connection, transportation, or transaction, then this node must be important and is likely to have a high betweenness centrality.

The betweenness centrality CB(v) for a node in a non-directional network is calculated by the formula.

$$c_{betweeness}(v) = \sum_{s \neq t \neq v} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

$$c_{betweeness}(v) = \frac{c_{betweeness}(v)}{(N-1)x(N-2)/2}$$

- s and t: Other nodes (node pairs) in the network,

- σ_{st} : The total number of shortest paths between nodes s and t,
- $\sigma_{st}(i)$: The number of shortest paths between nodes s and t that pass through node i
- N: The total number of nodes in the network

Closeness centrality

Closeness centrality is a measure of the total distance of a node from other nodes, if the length of the shortest paths of node N to other nodes in the network is small, then node N has a high closeness centrality (Zamanitajeddin et al., 2024). It refers to the convenience and ease of connections between the node of focus and other nodes.

Closeness centrality is calculated according to the following formula.
N: Total number of nodes in the network,
d (v,u): The length of the shortest path between node v and the other node u.

$$c_{closeness}(v) = \frac{(N-1)}{\sum_{u \neq v} d(v,u)}$$

The normalized closeness centrality for an undirected network can be expressed as follows.

$$c'_{closeness}(v) = \frac{c_{closeness}(v)}{(N-1)}$$

Eigenvector Centrality

This metric is based on assigning a relative score to each node and measures how well-connected a given actor is with other well-connected actors (Codal & Coskun, 2016). The main focus of eigenvector centrality is that the power and status of an actor is recursively defined by the power and status of its alters. Alters is a term often used in the egocentric approach of social network analysis and refers to actors who are directly connected to a particular actor, called the ego. What is noteworthy in this centrality measure is that the centrality of an individual depends on the centrality of all its neighbors with a positive constant. An individual with a high centrality of neighbors will also have a high centrality.

Eigenvector centrality is a more detailed version of degree centrality. It assumes that not all links have the same importance, taking into account not only the quantity but especially the quality of these links.

The eigenvector centrality x_i for node i in a network is calculated by the following formula.

Eigenvector centrality: $x_i = \frac{1}{\lambda} \sum_{j \in N(i)} x_j$

x_i: Eigenvector centrality for node i.

λ: A constant scaling factor, eigenvalue

N(i): Neighbors of node i

x_j: The centrality of node j

This formula states that the centrality of each node is a function of the centralities of

its neighbors. The eigenvalue λ is usually chosen to be the largest eigenvalue and the eigenvector centrality values are solved to find the eigenvector corresponding to the largest eigenvalue of the network.

Pagerank Centrality

PageRank centrality is a special type of eigenvector centrality and is the ranking criterion of the popular search engine Google (Tunalı, 2016). The three different factors that determine the PageRank of a node are the number of incoming links, the link propensity of anchors, and the centrality of anchors (Gençer, 2023).

An Example of a Social Network on Centrality Values

Figure 2
A Sample Social Network Graph
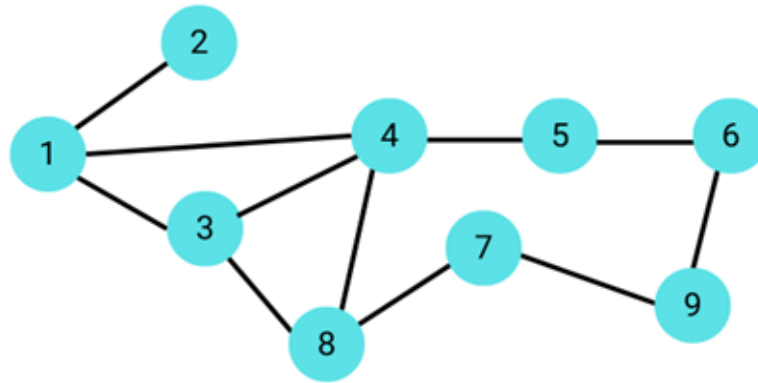
The edges representing the connections between nodes in the social network shown are listed as follows.

Edges: (1, 2); (1, 3); (1, 4); (3, 4); (3, 8); (4, 5); (4, 8); (5, 6); (6, 9); (7, 8); (7, 9)

Average Degree of the Network

First, it is calculated the degrees of the nodes in this network to calculate the average degree.

Degree of node 1: 3; Degree of node 2: 1; Degree of node 3: 3; Degree of node 4: 4; Degree of node 5: 2; Degree of node 6: 2; Degree of node 7: 3; Degree of node 8: 2; Degree of node 9: 2

Total degree of the nodes: 3 + 1 + 3 + 4 + 2 + 2 + 3 + 2 + 2 = 22

Since the total number of nodes is 9, the average degree is: 22 / 9 = 2.44

Table 2
Centrality Calculations for the Social Network in Figure 1

Node/ Actor	Degree Centrality	Closeness Centrality	Betweenness Centrality	Eigenvector Centrality	PageRank Centrality
1	0.375	0.471	0.250	0.408	0.135
2	0.125	0.333	0.000	0.143	0.055
3	0.375	0.533	0.095	0.480	0.127
4	**0.500**	**0.615**	**0.405**	**0.540**	**0.167**
5	0.250	0.500	0.202	0.231	0.094

6	0.250	0.421	0.095	0.118	0.099
7	0.250	0.444	0.155	0.185	0.095
8	0.375	0.533	0.262	0.422	0.129
9	0.250	0.381	0.071	0.106	0.099

Table 2 shows centrality calculations regarding Figure 1.

In terms of degree centrality, node 4 is in the most central position (0.500).

The node with the highest closeness centrality is node 4 (0.615), meaning that node 4 can reach other nodes in the network at shorter distances. Node A is positioned closest to the center, allowing it to connect with other nodes either directly or through short paths, which indicates that node 4 plays a key role in the information flow within the network. The node with the lowest closeness centrality is node 2 (0.000). This node is located at the most peripheral position in the network and must take longer paths to reach other nodes. The low closeness centrality of node 2 suggests that it is distant from the center of the network and participates less in information flow.

Betweenness centrality shows how much a node acts as a "bridge" between other nodes in the network. Calculations reveal that node 4 has the highest betweenness centrality value, at 0.405. According to these results, node 4 stands out as the most critical node on the shortest paths in the network. Node 2 has a betweenness centrality of zero, indicating that it does not act as a bridge between other nodes.

Eigenvector centrality is a measure based on how central a node's neighbors are. A node with high eigenvector centrality is more connected to central neighbors. Node 4, with the highest value, stands out as the most central node in the network, indicating that it is associated with neighbors who also hold highly central positions.

PageRank centrality calculates the importance of a node based on the centralities of the nodes that link to it. Originally used to rank web pages, this method is also widely used to identify influential nodes in networks. Node 4 has the highest PageRank value, indicating that it is in an important central position in the network. Node 2 has the lowest PageRank value, which suggests that its influence within the network is relatively low.

Local Clustering Coefficient

It is the ratio of the number of links between a node and its neighbors to the number of possible links they could have. In other words, it is a measure of the degree to which a node clusters with its neighbors.

The Local Clustering Coefficient indicates the probability that a node's neighbors will connect with each other. The value ranges from 0 to 1, with 1 indicating that all neighbors are connected.

The clustering coefficient C_i for a node i is calculated by the formula.

$$c_{cc(i)} = \frac{2x(number of triangles)}{dx(d-1)}$$

C_{cc} (i): local clustering coefficient for node i

d= Number of neighbors of the node

triangle= Number of available triangles

The local clustering coefficient of each node in an example social network of Figure 1 is calculated and presented in Table 3.

Table 3
Local Clustering Coefficient

Node	1	2	3	4	5	6	7	8	9
Local Clustering Coefficient	0.33	0.00	0.67	0.33	0.00	0.00	0.00	0.33	0.00

Node 3 has the highest clustering coefficient with a value of 0.667, indicating that its neighbors have strong ties to each other.

For nodes 2, 5, 6, 7, and 9, the clustering coefficient is 0, meaning that there are no connections between the neighbors of these nodes.

Whole Network Metrics

Size

The size of a network is determined by the number of actors in that network. When we consider a school as a social network, if both students and teachers play the role of actors, then all individuals will constitute the size of the network. When considering politics, the network size represents the number of people with whom an individual discusses political topics.

Average Degree

One of the metrics that defines the overall structure of a network based on degree is the average degree of all nodes in the network. This is calculated differently depending on whether the network is directed or undirected. Letting k_i be the degree of node i, the average degree of an undirected network with N nodes and E edges is calculated as follows:

$$\text{Average Degree} = \frac{1}{N}\sum_{i}^{n}k_i = \frac{2E}{N}$$

Density

The density of a network is equal to the total number of connections divided by the number of possible connections. The number of possible connections assumes that each person can have a connection with every other person. The normalized range varies from 0-1. It represents the extent of communication within the network. Higher numbers (above .03) indicate faster information diffusion and greater group cohesion (Aboelela et al., 2007).

The density of the network shown in Figure 1 is calculated as the number of available edges divided by the maximum number of possible edges.

The density of the network according to the formula density $= \dfrac{2xE}{Nx(N-1)}$

E= Number of edges; N = Number of nodes

In this network

Total number of nodes N=9

Number of sides E=11

The density is calculated as = (2x11) / 9 x (9-1) = 22 / 72 = 0.306. The density of this network corresponds to approximately 31%.

Centralization

Centralization is based on the extent to which the majority of links are connected to a small set of nodes (Scott, 2000). It indicates whether there is an asymmetry in the distribution of connections. It indicates the degree to which communication is centralized around a single agent or a small group. More centralized groups tend to be more hierarchical in nature.

To calculate the centralization value of an example social network plotted in Figure 1, the following steps are followed:

> 1.Degree Centrality is calculated.
> 2.Determine the Maximum Degree of Centrality.
> 3.Centralization Value: The sum of the differences between the degree centrality of all nodes and the highest degree centrality.

This sum is divided by the theoretical sum of differences that could have the highest degree centrality in the network.

- C_{maks}: The highest degree centrality (centrality of the node with the highest degree).

- C_i: Degree centralities of other nodes.

- The value in the denominator is used as the theoretical maximum centralization value.

The degrees of each node in the network were calculated earlier.

- Node degrees: 3,1,3,4,2,2,3,2,2

- Highest degree: $C_{maks}=4$

Calculation of centralization

> 1.Find the differences between C_{max} - C_i for each node.

Table 4
Calculation of Centralization

$c_{maks}-c_i$	$c_{maks}-c_1$	$c_{maks}-c_2$	$c_{maks}-c_3$	$c_{maks}-c_4$	$c_{maks}-c_5$	$c_{maks}-c_6$	$c_{maks}-c_7$	$c_{maks}-c_8$	$c_{maks}-c_9$
Difference	4-3	4-1	4-3	4-4	4-2	4-2	4-3	4-2	4-2
Result	1	3	1	0	2	2	1	2	2
Total					14				

> 2.Calculate the theoretical maximum difference sum. In this case, the theoretical maximum difference occurs when the degree centrality of all nodes except the most central node is zero.

$$maks \sum (C_{maks} - C_i) = (N-1)xC_{maks} = 8 \times 4 = 32$$

3.Centralization=14/32=0.438

The centralization value of this network is 0.438.

Reciprocity

It is defined as the calculation of whether the connections between nodes are reciprocal, i.e. bidirectional. This metric, calculated in directed networks, is the ratio of the number of node pairs in the network to the number of all possible node pairs. The expression "follow to follow", which is frequently used in social media, refers to the reciprocity metric (Cheng et al., 2011).

SNA Software Tools

Tools for social network analysis are predominantly used for constructing networks, visualizing and manipulating network structures, conducting qualitative and quantitative/ statistical analyses, detecting communities, and performing predictive analysis. Despite the availability of many tools, the most widely used ones include Pajek, Gephi, UCInet, NodeXL, R libraries, and NetworkX (Oliveria & Gama, 2011):

- **Pajek**: A free tool designed for analyzing and visualizing large-scale networks.
- **Gephi**: An open-source platform for network manipulation and exploration, featuring a three-dimensional render engine for displaying networks that evolve in real-time.
- **UCInet**: A commercial tool for social network analysis, which uses Pajek and NETDRAW for visualization. It is particularly well-suited for statistical and matrix-based analyses.
- **NodeXL**: A free add-in for Microsoft Excel, providing an accessible, user-friendly way to explore and visualize networks without requiring programming knowledge. However, it is not ideal for analyzing large networks.
- **R libraries** (e.g., igraph, sna, tnet, statnet): Free packages within the R environment, offering a comprehensive set of tools, including a large array of algorithms for community detection, longitudinal network analysis, and two-mode network analysis, with effective two- and three-dimensional visualization options.

NodeXL

NodeXL is mainly used for analyzing networks. It is mostly implemented as an add-in to Microsoft Excel. With the collection of network data, NodeXL provides quick statistics and reporting for people who can use the basic features of Microsoft Excel to analyze network data. NodeXL is a highly effective tool for analyzing and visualizing a social network. In addition to visualizing the entire network in the form of a graph, it can also draw graphs of different social network properties such as Proximity Centrality, Betweenness Centrality, Vertex Degree, Vertex PageRank, etc. Together with Nodexl, it enables network analysis by collecting data from social media platforms such as Twitter, Facebook, YouTube, and Flickr. In addition, topics that are on the agenda on Twitter can be analyzed and analyzed.

The analysis process with NodeXL generally consists of the following steps.

- Importing data

- Data preparation

- Grouping with clustering

- Calculating metrics

- Time series analysis

- Text analysis

- Identifying the Most Important Elements of the Network

- Visualizing the network

GEPHI

GEPHI is an open-source, independent software for visual and network analysis. The primary benefit of utilizing GEPHI for network research is its capability to handle extensive data sets or networks. The GEPHI program possesses certain drawbacks. Occasionally, the response time for a little task or procedure is excessively prolonged. For instance, accessing a file requires considerable time. Given that GEPHI is independent open-source software, it offers numerous functionalities. GEPHI is capable of importing data from text files (TXT), spreadsheets (CSV), and databases. GEPHI is capable of receiving information from various other social network analysis tools. GEPHI facilitates the straightforward graphical representation of a network. GEPHI is capable of producing network graphs and visual representations.

UCINet and Netdraw

UCINet is a menu-based application for social network analysis (Wu & Duan, 2015). UCINet is independent software. In UCINet, all data are represented as matrices. UCINet accepts two categories of input and produces two categories of output. The input comprises input parameters and datasets, whilst the output consists of output text and datasets. The spreadsheet editor is utilized for modifying, inputting new data, and converting UCINet data to Excel or SPSS formats. The UCINet spreadsheet accommodates tiny networks. For extensive datasets, multiple data formats are provided, accessible through an editor known as the dl editor.

UCINet employs Netdraw to facilitate network visualization. Netdraw facilitates various layouts for visualization objectives. These encompass isolates, components, subgroups, and centrality metrics. It also offers functionalities such as node restoration, color scheme adjustment, property visibility toggling, and node size modification, among others.

PAJEK

PAJEK is a software application designed for the visualization and analysis of extensive social networks. It is adequate to calculate most centrality measurements. Furthermore, functions that require many applications can be stored for subsequent re-analysis. PAJEK supports fundamental operations such as subnetwork extraction, identification of linked components (strong, weak, connected), determination of shortest pathways, calculation of maximum flow, centrality assessment (closeness, betweenness, degree, etc.), fragment search, and community detection. The findings generated by PAJEK can be further analyzed with R programming and SPSS. PAJEK accommodates bimodal networks, temporal networks (networks that evolve over time), acyclic and multi-associative networks (many interactions established among the same vertices), and signed networks (networks with both negative and positive connections). PAJEK additionally facilitates text-mining algorithms for the investigation of social networks (Majeed et al, 2020).

NetworkX

NetworkX is a powerful Python library for graph and network analysis. It is used to model and analyze graph structures such as social networks, biological networks, route optimization, connectivity analysis and many more. It allows you to analyze nodes and edges in network or graph structures. It is advantageous for research and applications where new metrics or algorithms need to be developed. Various types of graphs (directed, undirected, weighted, etc.) can be easily calculated with NetworkX. It supports reading and writing data from various formats (e.g. GraphML, GML, Pajek). Together with Matplotlib and other visualization libraries, graph structures can be visualized. In summary, NetworkX is a popular tool for both simple and complex network analysis.

R Programming and Packages

The R programming language has many libraries for analyzing social networks. One

of these libraries is the igraph package. igraph is a fast, efficient, constantly updated, and highly preferred package. Other packages such as sna, tidygraph, and network have a large user base, especially among those interested in statistical network modeling (Gençer, 2023).

Social Network Visualizer

Social Network Visualizer (SocNetV) is a cross-platform, user-friendly free software application for social network analysis and visualization. With SocNetV, the following operations can be performed.

- Draw social networks with a few clicks on a virtual canvas, upload domain data from a file in a supported format (GraphML, GraphViz, Adjacency, EdgeList, GML, Pajek, UCINET, etc.), or browse the internet to create a social network of connected web pages.

- Organize actors and ties through point-and-click, graphs and social network properties that can be analyzed.

- Generate HTML reports.

- Standard graph and network fit metrics such as density, diameter, geodesics and distances, connectivity, eccentricity, clustering coefficient, reciprocity, etc.

VOSviewer and Bibliometrix

The 2 tools used for bibliometric analysis are VOSviwer and Bibliometrix. They are used to process and analyze data extracted from databases such as Scopus or Web of Science. They allow for analysis based on keywords in articles or on the relationships established through authors. Bibliometrix is an R package with a programmable structure (Gencer, 2023).

SNA in Higher Education

Social Network Analysis (SNA) in higher education enables the analysis of relationships and interactions between students, academics, and other stakeholders through network structures. With this method, information flow, collaboration, interaction patterns, and internal dynamics in higher education institutions are analyzed and patterns are revealed. Examples of social network analysis in higher education are listed below.

Examining Student Interactions

Academic achievement and social relationships: How students build social networks inside and outside the classroom can have an impact on their success. The SNA can be used to identify which groups students are more active in and the relationship between academic performance and social interaction.

Improving learning environments: Network structures of interactions in group work, project teams or online platforms (e.g. LMS) are analyzed. It can be revealed which students remain isolated or which groups collaborate more. For example, by analyzing the frequency with which students help each other or share information in the classroom, academic support mechanisms can be better shaped.

Examining Academic and Interdisciplinary Collaboration

Publication and project collaborations: Networks of articles and projects produced by academics together are analyzed. It is revealed which academics play central roles and how interdisciplinary collaborations are shaped.

Strengthening research networks: Areas of intra- or inter-institutional collaboration can be identified and incentives can be given to units that do not have strong ties. For example, by mapping the collaboration network of faculty members in a faculty, joint research projects can be proposed for academics who remain disconnected or isolated.

Analyzing Online Learning Environments

Learning analytics: Students' interactions with each other or with instructors through the LMS (Learning Management System) are analyzed. Student engagement can be increased by analyzing forums, discussion groups, and messaging networks.

Identify students at risk of failure: Isolated students can be identified in advance and counseling and support services can be provided.

Analysis of Management, Leadership, and Organization Networks

Internal decision-making processes: More effective governance can be achieved by analyzing the collaboration and communication structures between administrators, and academic and administrative units.

Leadership and information flow: It can be determined which administrators or academic units are central in information and decision flow, thus optimizing institutional processes.

Alumni tracking systems: Examine how alumni interact through job and career networks. Collaborating with alumni can contribute to the university's career network.

Mentoring networks: By establishing links between alumni and students, students can receive career guidance from alumni.

Policy Development and Performance Measurement

Department and program performance: Strategic plans can be created by examining inter-departmental collaboration networks. In addition, according to the network structures, it is determined which departments need more collaboration.

Innovation and entrepreneurship ecosystems: By analyzing the university's innovation centers and entrepreneurship networks, the ecosystem can be made to work more effectively.

As a result, social network analysis provides a better understanding of the relationships between students, academics, and management structures in higher education. In this way, it is possible to optimize information flow, increase collaboration, and support academic success.

Conclusion and Future Trends

This paper provides a comprehensive overview of the basic principles and objectives of Social Network Analysis (SNA) methods and their applicability to different types of networks. Various SNA metrics and related tasks are described with respect to the different structures of networks. Nowadays, the discovery of network structures in the data generated by many applications and the quality of the information extracted from these networks is increasing the popularity of network analysis. One of the main reasons for this increased interest is the analysis requirements arising from the ever-growing and more complex amount of data. At this point, effectively processing, managing, and extracting meaningful results from large volumes of data flowing at high speed is one of today's most important challenges. Especially with the proliferation of new technologies such as Web 2.0, Internet of Things (IoT), and Industry 4.0, the need for network analysis increases and analysis processes become more demanding and challenging. Therefore, the development of innovative methods that can cope with high volumes of data in network analysis stands out as one of the most current and critical requirements in this field.

Current trends in social network analysis are changing rapidly in line with technological and social developments. Interest and application areas of social network analysis are expanding in areas such as artificial intelligence, data privacy, community analysis, sentiment analysis and language processing, ethical issues, location-based social network analysis, micro-impact analysis, Multilayer Network analysis, disinformation detection, and decentralized networks. These trends indicate that in the future, SNA will become

more effective and have more diverse use cases in both academic and commercial applications.

It is also expected that the popularity of SNA will continue to grow, attracting more researchers to the field and pushing an increasing number of companies to incorporate SNA methods into their business processes and expand their use as strategic tools.

Sample Social Network Analyses

Example 1

Scenario: Let's examine how metrics (degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, local clustering coefficient, density and centralization) are calculated based on students' relationships in a social network of 10 students.

Students: A, B, C, D, E, F, G, H, I, J

Assume that friendship relationships are formed as follows.

- A: B, C, D
- B: A, E
- C: A, D, F
- D: A, C, G
- E: B, H
- F: C, I
- G: D, J
- H: E
- I: F, J
- J: G, I

In the sociomatrix formed according to this network of relationships, each row and column represents an individual. The corresponding cell indicates whether the individuals are connected to each other. It is coded 1 if there is a connection and 0 if there is no connection. The sociomatrix created for individuals whose names are coded as A, B, C, D, E, F, G, H, I, and J is given in Table 5.

Table 5
Relationship Matrix

	A	B	C	D	E	F	G	H	I	J
A	0	1	1	1	0	0	0	0	0	0
B	1	0	0	0	1	0	0	0	0	0
C	1	0	0	1	0	1	0	0	0	0
D	1	0	1	0	0	0	1	0	0	0
E	0	1	0	0	0	0	0	1	0	0
F	0	0	1	0	0	0	0	0	1	0
G	0	0	0	1	0	0	0	0	0	1
H	0	0	0	0	1	0	0	0	0	0
I	0	0	0	0	0	1	0	0	0	1
J	0	0	0	0	0	0	1	0	1	0

The following table shows the formulas for the degrees and the calculated centrality values of each node and the local clustering coefficient.

Table 6
Metric Calculations for Example Network

Node	Degree Centrality	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality	Clustering Coefficient
Formula	$C_{degree} = \dfrac{DegreeofNode}{N}$	$c_{betweeness}(v) = \displaystyle\sum_{s \neq t \neq v} \dfrac{\sigma_{st}(v)}{\sigma_{st}}$ $c_{betweeness}(v) = \dfrac{c_{betweeness}(v)}{(N-1)x(N-2)/2}$	$c_{closeness}(v) = \dfrac{(N-1)}{\sum_{u \neq v} d(v,u)}$ $c'_{closeness}(v) = \dfrac{c_{closeness}(v)}{(N-1)}$	$x_i = \dfrac{1}{\lambda} \displaystyle\sum_{j \in N(i)} x_j$	$c_{cc(i)} = \dfrac{2x(numberoftriangles)}{dx(d-1)}$
A	0.33	0.5	0.50	0.49	0.33
B	0.22	0.39	0.41	0.24	0.00
C	0.33	0.28	0.47	0.49	0.33
D	0.33	0.28	0.47	0.49	0.33
E	0.22	0.22	0.32	0.11	0.00
F	0.22	0.17	0.39	0.27	0.00
G	0.22	0.17	0.39	0.27	0.00
H	0.11	0.00	0.25	0.044	0.00
I	0.22	0.06	0.33	0.17	0.00
J	0.22	0.06	0.33	0.17	0.00

The results for the 3 metrics that interpret the whole network (average degree, density and centralization) are as follows.

Average Degree

Average Degree = $\dfrac{(2xE)}{N}$ = (2x11)/10 =2.2

The average degree of this network is calculated as 2.2. This means that each node in the network has 2.2 links on average.

Density

The density of a network is calculated as the ratio of the number of available edges to the maximum possible number of edges between all nodes in the network.

$$D = \frac{2E}{(Nx(N-1))}$$

E: Number of available edges in the network => E=11

N: Number of nodes in the network => N=10

D= (2*11) / (10*9) = 0.244

The density of this network is calculated to be approximately 0.244. This means that about 24% of the node pairs in the network are directly connected by an edge.

Centralization

The centralization value of the network is a measure of the centrality differences of the nodes in the network and is calculated by the formula.

Centralization = $C = \dfrac{\sum_{i=1}^{N}(c_{maks} - c_i)}{(N-1)x(N-2)}$

C: Network centralization value

C_{maks}: Degree centrality of the node with the highest degree

C_i: Degree centrality of each node

N: Number of nodes (N=10)

$C_{maks} = 3$

Table 7
(C_{maks} - C_i) Values

	A	B	C	D	E	F	G	H	I	J
C_i	3	2	3	3	2	2	2	1	2	2
C_{maks} - C_i	0	1	0	0	1	1	1	2	1	1

Sum of C_{maks} and C_i differences = 0+1+0+0+1+1+1+2+1+1 = 8

Centralization = C = 8/ (9X8) = 0.11

The centralization value of this network is calculated to be approximately 0.111 or 11.1%. This value indicates that the degree of centralization of the network is quite low and that a central structure between nodes is not very obvious.

Example 2

Let's create a graph of the image for the nodes whose connections are given in Table 8.

Now let us examine the neighborhood matrix (sociomatrix) to show the relationships of the nodes. The number 1 in the cells where the rows and columns intersect indicates that there is a relationship for the intersecting nodes, while the number 0 indicates that there is no relationship.

Table 8
Sociomatrix

	A	B	C	D	E	F	G	H	I
A	0	1	1	0	0	0	0	0	0
B	1	0	1	0	0	0	0	0	0
C	1	1	0	1	1	0	0	0	0
D	0	0	1	0	1	1	1	0	0
E	0	0	1	1	0	1	1	0	0
F	0	0	0	1	1	0	1	1	0
G	0	0	0	1	1	1	0	1	0
H	0	0	0	0	0	1	1	0	1
I	0	0	0	0	0	0	0	1	0

For example, when node C is examined, it will be seen that it is related to nodes A, B, D and E.

In order to create this matrix in UCINET program, click on Data>Data Editors>Excel Matrix Editor and in the editor opened by clicking on Data>Data Editors>Excel Matrix Editor, the values seen above should be entered in the rows, columns and cells and saved as Ucinet files (*.##h) as foldername. To create the social network in UCINET program using this matrix, click on Visualize>NetDraw menu and select the previously saved foldername.##h file by clicking the Open button in the NetDraw window. Below is the graph of the network formed according to the connections in the given matrix.

Figure 3

Graph Structure for the Sociomatrix is Given in Table 8
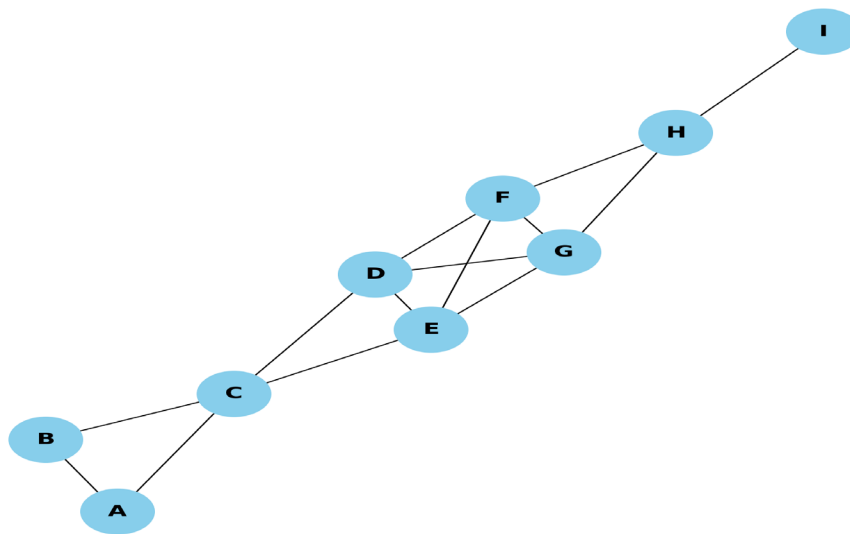
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