Professional Certificate in Social Media Research Methods (United Kingdom)

Network Analysis and Visualization

Adjacency Matrix – A square matrix used to represent connections between nodes in a network, where rows and columns correspond to actors and cell values indicate the presence (1) or absence (0) of a tie. Related terms: edge list, graph. Example: In a Twitter retweet network, the matrix shows which users retweeted whom. Practical application: Enables computation of centrality measures using matrix algebra. Challenges: Large matrices become memory-intensive for big social media datasets.

Betweenness Centrality – A metric that quantifies how often a node lies on the shortest paths between other pairs of nodes, indicating its role as a bridge or broker. Related terms: bridge, structural hole. Example: A user who frequently shares content between disparate hashtag communities will have high betweenness. Practical application: Identifying influencers who can disseminate information across clusters. Challenges: Sensitive to network size and may be skewed by noisy ties.

Cliques – Subsets of nodes where every member is directly connected to every other member, forming a fully connected subgraph. Related terms: complete graph, cohesive subgroup. Example: A group of Instagram users who all follow each other forms a clique. Practical application: Detecting tightly-knit communities for targeted marketing. Challenges: Real-world social media networks rarely contain large cliques; detection algorithms may miss near-cliques.

Community Detection – The process of partitioning a network into groups of nodes with denser internal connections than external ones. Related terms: modularity, cluster. Example: Using the Louvain algorithm on a Facebook friendship graph to reveal hobby-based communities. Practical application: Segmenting audiences for personalized content strategies. Challenges: Choice of algorithm influences results; overlapping communities can be hard to capture.

Degree Centrality – The count of direct ties a node has; in directed networks, distinguished as indegree (incoming ties) and outdegree (outgoing ties). Related terms: hub, popularity. Example: A Twitter user with many followers has high indegree; a prolific retweeter has high outdegree. Practical application: Quickly spotting highly active or visible users. Challenges: Does not consider tie strength or network position beyond immediate neighbors.

Dyadic Tie – A relationship between two actors, the fundamental unit of a network. Related terms: edge, pairwise interaction. Example: A private message exchange between two LinkedIn members constitutes a dyadic tie. Practical application: Analyzing reciprocity or balance in communication. Challenges: Aggregating dyadic data into higher-order structures can obscure individual nuances.

Edge Weight – A numeric value assigned to a tie that reflects its strength, frequency, or intensity. Related terms: weighted network, tie strength. Example: Number of comments a user makes on another's posts can be used as weight. Practical application: Differentiating casual followers from engaged collaborators. Challenges: Determining appropriate weighting schemes; missing data may bias results.

Egocentric Network – A network centered on a single focal node (the ego) and all nodes directly connected to it (alters), plus the ties among those alters. Related terms: personal network, ego-centric analysis. Example: Mapping a brand manager's connections on Twitter to assess influence reach. Practical application: Profiling individual users' social capital. Challenges: Limited view of global structure; privacy restrictions may block alter-alter data.

Edge List – A simple two-column table where each row records a source node and a target node, optionally with a weight. Related terms: adjacency matrix, graph representation. Example: Exporting a Reddit comment reply network as an edge list for import into Gephi. Practical application: Easy data exchange between software tools. Challenges: Large edge lists can become unwieldy; duplicate edges need handling.

Eigenvector Centrality – A measure that assigns higher scores to nodes connected to other highly central nodes, capturing influence through indirect ties. Related terms: Google PageRank, spectral analysis. Example: A user who is followed by other popular users will score high on eigenvector centrality. Practical application: Ranking accounts for recommendation algorithms. Challenges: Requires connected networks; may be dominated by a few hubs.

Force-Directed Layout – A visualisation algorithm that treats nodes as repelling particles and edges as springs, positioning the network to reveal clusters organically. Related terms: Fruchterman-Reingold, spring-embedder. Example: Visualising a TikTok collaboration network where popular creators pull related users together. Practical application: Intuitive exploratory maps for presentations. Challenges: Layout can be unstable for very large networks; results may vary between runs.

Graph Density – The proportion of actual ties to all possible ties in a network, ranging from 0 (no ties) to 1 (complete graph). Related terms: connectivity, sparsity. Example: A niche forum with many reciprocal friendships may exhibit high density. Practical application: Assessing overall cohesion of a social platform. Challenges: Density alone can be misleading; larger networks naturally have lower density.

Homophily – The tendency of actors to associate with others who share similar attributes (e.G., Age, interests, ideology). Related terms: assortative mixing, similarity bias. Example: Users who identify as vegan often cluster together in Instagram hashtag networks. Practical application: Predicting community formation and diffusion pathways. Challenges: Distinguishing homophily from influence (the "chicken-or-egg" problem).

Incidence Matrix – A rectangular matrix that records membership of nodes in edges (for bipartite networks), with rows representing nodes and columns representing ties. Related terms: bipartite graph, affiliation matrix. Example: Mapping users (rows) to the hashtags they use (columns) on Twitter. Practical application: Transforming two-mode data for projection onto a one-mode network. Challenges: Can become extremely sparse with many hashtags.

Influencer Identification – The process of locating users who have the capacity to affect opinions or behaviours across a network. Related terms: opinion leader, key actor. Example: Using a combination of degree, betweenness, and content virality metrics to flag emerging TikTok creators. Practical application: Influencer marketing campaign planning. Challenges: Influencer impact may be context-specific; algorithmic bias can overlook niche voices.

Isolates – Nodes with no ties to any other node in the network, effectively disconnected. Related terms: singleton, disconnected component. Example: A newly created Instagram account that has not followed anyone nor been followed. Practical application: Identifying dormant or brand-new users for onboarding strategies. Challenges: Isolates are often filtered out before analysis, potentially discarding early adopters.

Jaccard Similarity – A coefficient measuring the overlap between two sets, calculated as the size of the intersection divided by the size of the union. Related terms: binary similarity, co-occurrence. Example: Comparing the hashtag sets of two Twitter users to gauge similarity. Practical application: Recommending accounts with shared interests. Challenges: Sensitive to sparse data; may undervalue rare but meaningful overlaps.

K-Core Decomposition – A method that iteratively removes nodes with degree less than k, revealing a nested structure of increasingly cohesive subgraphs. Related terms: coreness, network backbone. Example: Extracting the 5-core of a Reddit comment network to focus on highly engaged participants. Practical application: Filtering noise and highlighting core communities. Challenges: Choice of k influences results; may discard peripheral yet strategic actors.

Latent Dirichlet Allocation (LDA) – A generative statistical model that discovers topics within text corpora by assigning words to latent topics. Related terms: topic modeling, semantic network. Example: Applying LDA to YouTube video titles to identify emerging content themes. Practical application: Linking thematic clusters to network communities for richer analysis. Challenges: Requires careful tuning of topic number; interpretability can be subjective.

Modularity – A scalar value ranging from –1 to 1 that measures the strength of division of a network into modules (communities); higher values indicate dense intra-community ties and sparse inter-community ties. Related terms: community detection, partition quality. Example: A modularity score of 0.42 For a Facebook group suggests well-defined subgroups. Practical application: Selecting optimal community partitions. Challenges: Resolution limit may merge small but meaningful communities.

Multimodal Network – A network comprising more than one type of node (e.G., Users, posts, hashtags) and possibly multiple edge types. Related terms: bipartite graph, heterogeneous network. Example: A Twitter network linking users to hashtags and URLs simultaneously. Practical application: Analyzing how content types mediate user interactions. Challenges: Visualization becomes complex; projection to single-mode may lose information.

Node Attribute – Any characteristic assigned to a node, such as demographic information, sentiment score, or account age. Related terms: metadata, node label. Example: Adding “verified” status to Twitter accounts as an attribute. Practical application: Enriching visualisations with colour-coded attributes for pattern spotting. Challenges: Missing or inaccurate attributes can bias interpretations.

Node Degree Distribution – The probability distribution of node degrees across a network, often visualised on a log-log plot to assess scale-free properties. Related terms: power law, degree variance. Example:

Observing a heavy-tailed distribution in a TikTok follower network. Practical application: Determining whether a few hubs dominate the system. Challenges: Statistical tests for power-law fit are nuanced; sampling bias can distort the distribution.

Network Backbone – A reduced representation of a network that retains the most significant edges while discarding weaker, potentially noisy ties. Related terms: filtering, significance threshold. Example: Applying the disparity filter to a large Instagram comment network to expose the core interaction structure. Practical application: Simplifying visualisations for stakeholder reports. Challenges: Selecting appropriate thresholds; risk of eliminating meaningful low-frequency ties.

Network Centrality – A family of metrics that quantify the importance or influence of nodes based on their position within the network. Related terms: degree, betweenness, closeness. Example: Comparing centrality scores across different platforms to identify cross-platform influencers. Practical application: Prioritising outreach targets. Challenges: Different centralities capture different notions of importance; results can be contradictory.

Network Density – See graph density. (Duplicate entry for cross-reference.)

Network Visualization – The graphical representation of nodes and edges to facilitate interpretation of structural patterns, often using colours, sizes, and spatial layouts. Related terms: graph drawing, visual analytics. Example: A dynamic Sankey diagram showing flow of retweets over time. Practical application: Communicating findings to non-technical stakeholders. Challenges: Over-plotting, colour blindness considerations, and preserving data integrity.

Node Size Encoding – A visual design technique where the size of a node reflects a quantitative attribute, such as follower count or activity level. Related terms: visual encoding, glyph. Example: Larger circles for accounts with >100k followers in a Twitter network map. Practical application: Quickly spotting high-impact actors. Challenges: Scale selection can obscure mid-range values; overlapping nodes may hide details.

Node Colour Encoding – Using colour to represent categorical or continuous node attributes, enhancing pattern detection. Related terms: chromatic mapping, legend. Example: Blue nodes for “brand” accounts and orange for “consumer” accounts in an Instagram interaction graph. Practical application: Differentiating stakeholder groups. Challenges: Limited colour palettes; accessibility for colour-deficient viewers.

Node Positioning – The algorithmic determination of where nodes appear in a visual layout, influencing readability and interpretability. Related terms: layout algorithm, spatial arrangement. Example: Employing a hierarchical layout to display reply chains on Reddit. Practical application: Emphasising directionality in conversation flows. Challenges: Balancing aesthetic appeal with accurate representation of network topology.

PageRank – An algorithm originally developed by Google that assigns a probability distribution to nodes based on the likelihood of a random walk, effectively measuring prestige. Related terms: eigenvector centrality, link analysis. Example: Calculating PageRank scores for YouTube channels based on cross-linking videos. Practical application: Ranking content creators for recommendation engines. Challenges: Sensitive to dangling nodes and spam link farms; requires damping factor tuning.

Path Length – The number of edges traversed to move from one node to another; the average shortest path length summarises overall network compactness. Related terms: geodesic, small-world property. Example: An average path length of 4.2 In a Facebook friendship network suggests rapid information diffusion. Practical application: Estimating speed of viral spread. Challenges: Disconnected components complicate averaging; outliers can inflate values.

Peripheral Node – Nodes located on the outer fringes of a network, typically with low degree and limited influence. Related terms: leaf, outlier. Example: A user who follows many accounts but receives few mentions. Practical application: Identifying low-engagement users for re-engagement campaigns. Challenges: Peripheral status may be temporary; newly joined users often start as peripheral.

Power-Law Distribution – A functional relationship where the frequency of an event scales as a power of its size, commonly observed in degree distributions of social media networks. Related terms: scale-free network, heavy tail. Example: The number of followers per Twitter account follows a power-law with exponent ≈2.5. Practical application: Anticipating the impact of a few hubs on overall reach. Challenges: Empirical verification requires rigorous statistical testing; finite-size effects can mislead.

Projection (One-Mode) – The process of converting a bipartite network into a single-mode network by connecting nodes that share a common affiliation. Related terms: bipartite projection, co-occurrence network. Example: Projecting a user-hashtag bipartite graph onto users to create a hashtag-based similarity network. Practical application: Revealing implicit collaborations. Challenges: Projection can create artificial ties and inflate density.

Reciprocity – The proportion of mutual ties in a directed network, indicating the tendency for relationships to be bidirectional. Related terms: mutual tie, symmetry. Example: 68% Of follow relationships on a niche micro-blogging platform are reciprocal. Practical application: Assessing community cohesion and trust. Challenges: Reciprocity varies across platforms; high reciprocity may mask hierarchical structures.

Scale-Free Network – A network whose degree distribution follows a power-law, implying the presence of a few highly connected hubs and many low-degree nodes. Related terms: power-law, preferential attachment. Example: The follower network of a popular TikTok creator exhibits a scale-free pattern. Practical application: Designing robust diffusion strategies that target hubs. Challenges: Real networks often deviate from pure scale-free behavior; interventions may unintentionally reinforce inequality.

Sentiment Network – A network where edges are weighted by sentiment scores derived from textual interactions (positive, negative, neutral). Related terms: affect analysis, emotional tie. Example: Mapping sentiment-weighted replies among users discussing a brand on Twitter. Practical application: Monitoring brand health and identifying polarized sub-communities. Challenges: Sentiment detection errors can misclassify ties; sarcasm detection remains difficult.

Shortest Path – The minimum number of edges required to travel between two nodes; often computed using Dijkstra's algorithm for weighted graphs. Related terms: geodesic, path length. Example: The shortest path between two Instagram influencers may pass through a mutual collaborator. Practical application: Calculating influence spread potential. Challenges: In large sparse graphs, many node pairs are disconnected, requiring alternative approximations.

Social Capital – The aggregate of resources accessible to an actor through their network ties, encompassing bonding, bridging, and linking capital. Related terms: network resources, structural advantage. Example: A user with diverse cross-industry connections can leverage bridging capital for career moves. Practical application: Measuring the value of online networks for professional development. Challenges: Quantifying intangible benefits; disentangling capital from personal attributes.

Structural Hole – A gap between non-redundant contacts in a network; actors who span structural holes can act as brokers and gain competitive advantage. Related terms: brokerage, network bridging. Example: A content creator who connects two otherwise separate fandom communities fills a structural hole. Practical application: Identifying brokerage opportunities for marketing campaigns. Challenges: Detecting holes requires precise community delineation; dynamic networks may close holes quickly.

Subgraph – A subset of nodes and the edges connecting them, forming a smaller network within the larger graph. Related terms: induced subgraph, graph fragment. Example: Extracting the conversation subgraph around a specific hashtag on Reddit. Practical application: Focused analysis of topical discussions. Challenges: Selecting appropriate boundaries; risk of omitting peripheral context.

Temporal Network – A network where edges are time-stamped, allowing analysis of how connections evolve over time. Related terms: dynamic graph, time-slice. Example: Tracking retweet cascades minute-by-minute during a breaking news event. Practical application: Detecting early-stage viral trends. Challenges: Data volume grows rapidly; visualising temporal changes without overwhelming the viewer.

Triad Census – A count of the 16 possible types of three-node subgraphs (triads) in a directed network, useful for understanding local structural patterns. Related terms: motif analysis, graphlet. Example: High prevalence of transitive triads (A→B, B→C, A→C) indicates hierarchical communication. Practical application: Comparing organizational communication styles across platforms. Challenges: Computationally intensive for large networks; interpretation requires domain knowledge.

Undirected Graph – A network where edges have no orientation, implying mutual relationships. Related terms: symmetrical tie, bidirectional edge. Example: A friendship network on Facebook where “friend” is mutual. Practical application: Simplifying analysis when directionality is irrelevant. Challenges: Some platforms inherently encode direction (e.G., Follows) that may be lost if forced into undirected form.

Weighted Network – A graph where edges carry numeric values representing strength, frequency, or capacity. Related terms: edge weight, intensity. Example: Number of comments exchanged between two YouTube channels as weight. Practical application: Prioritising strong collaborations in partnership analysis. Challenges: Determining meaningful weight scales; dealing with zero-weight edges.

Visualization Dashboard – An interactive interface that combines network graphics with filters, metrics, and contextual information for real-time exploration. Related terms: BI tool, exploratory analytics. Example: A

Tableau dashboard displaying live Twitter conversation clusters with selectable date ranges. Practical application: Enabling stakeholders to drill down into specific segments without coding. Challenges: Performance constraints on large networks; ensuring consistent metric updates.

Walktrap Algorithm – A community detection method that simulates random walks to find densely connected subgraphs, assuming that short random walks tend to stay within the same community. Related terms: random walk, modularity optimisation. Example: Applying Walktrap to an Instagram co-like network to uncover micro-communities. Practical application: Detecting emergent groups for targeted outreach. Challenges: Computational cost grows with network size; results can be sensitive to walk length parameter.

Weighted Degree (Strength) – The sum of edge weights attached to a node, reflecting total interaction intensity rather than simple tie count. Related terms: node strength, weighted centrality. Example: A user who exchanges many comments with a few contacts may have high strength despite low degree. Practical application: Identifying truly active participants. Challenges: Requires accurate weight attribution; outlier weights can dominate the metric.

Visualization Aesthetics – Design principles (colour contrast, spacing, font size) applied to network graphics to enhance comprehension and reduce cognitive load. Related terms: visual hierarchy, design ergonomics. Example: Using muted background tones and bright node colours to highlight key influencers. Practical application: Creating publication-ready figures. Challenges: Balancing aesthetic appeal with scientific accuracy; avoiding misrepresentation through visual exaggeration.

Zoomable Layout – An interactive visualisation feature that allows users to pan and zoom, facilitating inspection of both macro-level structures and micro-level details. Related terms: focus+context, pan-and-zoom. Example: A web-based D3.Js network map where analysts can zoom into a specific hashtag cluster. Practical application: Providing depth of analysis without cluttering the overview. Challenges: Rendering performance for very large graphs; maintaining label readability at different scales.

Zero-Inflated Model – A statistical approach that accounts for excess zero counts in network data, distinguishing between structural zeros (no possible tie) and sampling zeros (ties not observed). Related terms: hurdle model, count regression. Example: Modelling the number of retweets between user pairs where many pairs never interact. Practical application: Improving prediction accuracy for sparse interaction data. Challenges: Model selection and interpretation can be complex; requires sufficient data to estimate parameters.

Affiliation Network – A bipartite network linking actors to groups, events, or attributes (e.G., Users to hashtags, authors to journals). Related terms: bipartite graph, two-mode network. Example: Mapping Twitter users to the political hashtags they employ. Practical application: Understanding shared interests and coalition formation. Challenges: Projection to one-mode may introduce artificial ties; visual clutter in raw bipartite form.

Betweenness-Based Edge Removal – A technique that iteratively removes edges with highest betweenness to reveal community structure (also known as Girvan-Newman algorithm). Related terms: edge betweenness, community detection. Example: Applying the algorithm to a Facebook friendship graph to uncover nested social circles. Practical application: Hierarchical clustering for marketing segmentation. Challenges: Computationally intensive for large networks; results can be sensitive to initial edge weighting.

Cluster Coefficient – A measure of the degree to which nodes tend to cluster together; the local coefficient evaluates the proportion of a node's neighbours that are also connected. Related terms: transitivity, triadic closure. Example: High clustering among users discussing a niche hobby on Reddit. Practical application: Assessing network cohesiveness and potential for rapid diffusion. Challenges: Global clustering can mask local variations; directed networks require adapted definitions.

Community Size Distribution – The statistical distribution of the number of nodes per detected community, often used to assess the granularity of partitioning. Related terms: modularity, cluster analysis. Example: A power-law distribution of community sizes in a large Twitter conversation indicates many small niche groups and few large ones. Practical application: Allocating resources proportionally across community-based campaigns. Challenges: Community detection algorithm choice heavily influences size distribution.

Directed Graph – A network where edges have orientation, representing asymmetrical relationships such as follows, mentions, or citations. Related terms: arrow, asymmetric tie. Example: The follower network on Twitter where user A follows user B but not necessarily vice versa. Practical application: Modelling influence flow. Challenges: Many centrality measures need adaptation for directionality.

Dyad Census – A count of all possible dyadic configurations (mutual, asymmetric, null) in a directed network, providing a baseline for structural analysis. Related terms: reciprocity, dyadic tie. Example: In a corporate email network, 30% of dyads are mutual, 45% asymmetric, and 25% absent. Practical application: Benchmarking relational patterns against theoretical expectations. Challenges: Interpretation can be abstract without contextual grounding.

Edge Bundling – A visual technique that groups adjacent edges together into bundles to reduce visual clutter in dense networks. Related terms: visual simplification, flow map. Example: Bundling retweet edges that share common source nodes in a large Twitter graph. Practical application: Clarifying major information pathways in presentations. Challenges: Over-bundling may hide important individual connections; algorithm choice affects aesthetics.

Exponential Random Graph Model (ERGM) – A statistical framework for modelling the probability of observed network structures based on local configurations (e.G., Edges, triangles). Related terms: network inference, logit model. Example: Using ERGM to test whether homophily on political orientation explains Facebook friendship patterns. Practical application: Hypothesis testing about underlying social processes. Challenges: Model degeneracy, computational intensity, and need for careful specification.

Force-Atlas 2 – An advanced force-directed layout algorithm that improves speed and stability for large networks, often used in Gephi. Related terms: force-directed layout, graph drawing. Example: Visualising a 100k-node Instagram interaction network with Force-Atlas 2 to reveal community clusters. Practical application: Rapid prototyping of exploratory maps. Challenges: Requires parameter tuning (gravity, scaling) to avoid node overlap.

Graph Sampling – Techniques for selecting a representative subset of nodes and edges from a large network to reduce computational load while preserving structural properties. Related terms: snowball sampling, node sampling. Example: Random walk sampling of a YouTube comment network to create a manageable analysis dataset. Practical application: Enabling analysis of massive platforms within limited hardware resources. Challenges: Sampling bias can distort centrality and community metrics.

Homophily Index – A quantitative measure (often Pearson's r or assortativity coefficient) that captures the degree of similarity among connected nodes. Related terms: assortativity, similarity bias. Example: An assortativity coefficient of 0.42 For age in a TikTok follower network indicates moderate age-based homophily. Practical application: Predicting future link formation based on shared attributes. Challenges: Requires accurate attribute data; mixed-type attributes complicate calculation.

Influence Propagation Model – Computational models (e.G., Independent Cascade, Linear Threshold) that simulate how ideas, behaviours, or information spread through a network. Related terms: diffusion, viral dynamics. Example: Using the Independent Cascade model to estimate the reach of a brand hashtag campaign on Twitter. Practical application: Optimising seed selection for maximal spread. Challenges: Parameter estimation is difficult; real-world diffusion often deviates from idealised assumptions.

Katz Centrality – An extension of eigenvector centrality that adds a constant attenuation factor, allowing influence to flow through longer paths while diminishing impact. Related terms: attenuation factor, path-based centrality. Example: A user who is not directly connected to many hubs but is two steps away may have higher Katz centrality than degree alone suggests. Practical application: Identifying indirect influencers. Challenges: Choice of attenuation parameter influences results; may over-emphasise distant ties.

Label Propagation Algorithm (LPA) – A fast, heuristic community detection method where each node adopts the most frequent label among its neighbours iteratively until convergence. Related terms: community detection, unsupervised clustering. Example: Applying LPA to a large Reddit comment network to quickly obtain provisional communities. Practical application: Rapid segmentation for exploratory analysis. Challenges: Results can be unstable; algorithm may merge small but distinct groups.

Latent Space Model – A statistical approach that embeds nodes in an unobserved multidimensional space, assuming tie probability decreases with distance in that space. Related terms: network embedding, probabilistic model. Example: Modeling friendship formation on a university social platform as a function of latent similarity. Practical application: Predicting future connections and visualising hidden dimensions. Challenges: Model fitting can be computationally demanding; interpretation of latent dimensions may be ambiguous.

Link Prediction – The task of forecasting which non-existent edges are likely to appear in the future, using similarity scores, machine learning, or probabilistic models. Related terms: edge recommendation, future tie. Example: Predicting which Instagram users will follow each other based on common hashtags and interaction history. Practical application: Recommender systems for social platforms. Challenges: Imbalanced data (far more non-edges than edges); evaluation requires temporal hold-out sets.

Modularity Optimisation – A family of algorithms (e.G., Louvain, Leiden) that iteratively improve the modularity score to find high-quality community partitions. Related terms: community detection, graph clustering. Example: Using Leiden to refine an initial Louvain partition of a Facebook group network, achieving higher modularity and more stable communities. Practical application: Robust community identification for targeted messaging. Challenges: Modularity suffers from a resolution limit, potentially overlooking small but meaningful groups.

Multi-Level Graph – A hierarchical representation where nodes are aggregated into higher-level meta-nodes, facilitating analysis at different scales. Related terms: graph abstraction, coarse-graining. Example: Collapsing individual Twitter users into country-level nodes to study cross-national information flow. Practical application: Managing complexity in global campaign monitoring. Challenges: Aggregation choices affect observed patterns; loss of individual-level detail.

Network Motif – Recurring, statistically significant subgraph patterns (e.G., Feed-forward loops) that may indicate functional building blocks of the network. Related terms: graphlet, triad census. Example: Over-representation of triadic closure motifs in a LinkedIn endorsement network suggests trust building. Practical application: Identifying structural signatures of collaborative behaviour. Challenges: Motif detection is computationally intensive; significance testing requires appropriate null models.

Node Attribute Mapping – The process of visually linking node attributes (e.G., Gender, sentiment) to visual properties such as colour, shape, or size. Related terms: visual encoding, glyph design. Example: Mapping sentiment polarity to node colour (green for positive, red for negative) in a brand discussion network. Practical application: Immediate visual assessment of sentiment clusters. Challenges: Over-encoding can cause visual overload; color choices must consider accessibility.

Path Dependency – The concept that the sequence of ties formed influences future network evolution, often leading to entrenched structures. Related terms: historical contingency, network growth. Example: Early adopters of a hashtag become central hubs, shaping later diffusion pathways. Practical application: Timing interventions to exploit or disrupt established pathways. Challenges: Requires longitudinal data; causality can be difficult to establish.

Power-Law Exponent – The parameter (often denoted α) that characterises the steepness of a power-law distribution; lower values indicate heavier tails. Related terms: scale-free network, degree distribution. Example: An exponent of 2.1 For a YouTube subscriber network signifies a very skewed distribution with extreme hubs. Practical application: Anticipating resource allocation for influencer outreach. Challenges: Accurate estimation demands large samples; small-sample noise can distort exponent.

Reciprocal Tie Strength – The combined weight of mutual interactions between two nodes, reflecting balanced engagement. Related terms: mutual intensity, bidirectional weight. Example: Two collaborators who comment equally on each other’s posts exhibit high reciprocal tie strength. Practical application: Identifying stable partnerships for co-creation projects. Challenges: Asymmetric platforms may lack explicit reciprocity data; weighting decisions affect results.

Scale-Up Visualization – Techniques for rendering very large networks (millions of nodes) using level-of-detail, aggregation, or GPU acceleration. Related terms: big-graph visualisation, hierarchical rendering. Example: Visualising the full Twitter follower graph using WebGL-based tools that cluster nodes on-the-fly. Practical application: Providing macro-level overview to executives. Challenges: Maintaining interactivity, avoiding loss of critical detail.

Semantic Network – A network where nodes represent concepts or terms and edges denote semantic relationships (e.G., Synonymy, co-occurrence). Related terms: concept map, knowledge graph. Example: Building a semantic network from hashtags to uncover thematic clusters in a Twitter conversation. Practical application: Content categorisation and trend detection. Challenges: Requires robust NLP pipelines; polysemy can create ambiguous links.

Shannon Entropy (Network) – A measure of the amount of information or disorder present in a network's degree distribution or attribute distribution. Related terms: information theory, complexity. Example: High entropy in a Facebook friend network suggests diverse connectivity patterns. Practical application: Comparing structural diversity across platforms. Challenges: Interpretation varies with network size; entropy alone does not indicate specific structural features.

Sociogram – A visual diagram representing social relationships, traditionally used in qualitative research to map interpersonal ties. Related terms: network diagram, graphical representation. Example: Hand-drawn sociogram of a focus group illustrating who interacts with whom. Practical application: Communicating relational findings to non-technical audiences. Challenges: Manual creation limits scalability; may oversimplify complex digital interactions.

Structural Equivalence – The condition where two nodes have identical patterns of ties to all other nodes, implying they occupy similar positions in the network. Related terms: role similarity, automorphic equivalence. Example: Two brand accounts that follow the same set of influencers and are followed by the same set of users. Practical application: Grouping actors for role-based analysis.