LEARNER CENTERED NETWORK MODELS: A SURVEY

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ABSTRACT

The possibility of modeling and abstracting interaction has been the key driver in social network-based research as it facilitates, among other things, the generation of recommendations which is vital for most businesses. Being ubiquitous, learning activities also facilitate the formation of these networks. Thus, to gain insights into the evolution of activities and interactions that occur during learning events, it is important to understand these networks and their respective models. In this article, we present a survey of the representative methods employed in modeling various interactions observed in learner-centered networks. Finally, we comparatively analyze the respective models and identify which models perform better in respective cases.

KEYWORDS

Team Collaboration, Social network models, Interaction models.

1. INTRODUCTION

A social network generally arises in collaborations as a consequence of the dependencies, and interactions between actors, and their respective partners [1]. As the collaboration progresses, the behavior of participants tends to become interdependent. Hence, a variation in an actor's profile results in a corresponding change in the partner's profile. In the event that their interaction progresses over a period of time, a relationship is formed. This relationship is called a tie. A tie can be strong, weak, or at a later time broken. With the formation of ties, different forms of activities start taking place. These activities generate the interactions observed in social networks. A sample activity in a university setting could be a course project. Now, most course projects encourage group formation, have a start date, deadlines, and grades. Furthermore, this course project activity could be a subset of a semester task which consists of several course projects that eventually results in several collaborations among students, and in some cases, interaction with software tools, such as Moodle [2, 3], LearnDash [4] Blackboard [5, 6, 7] and the SQLValidator [8] etc. As a consequence of these activities, and accompanying interactions, different networks begin to emerge. Thus being able to gain insight into the evolution of these networks, interdependence among learners, and learning-related activities becomes immensely beneficial to students that make up these teams, instructors that supervise the students, and curriculum developers.

The goal of this survey article was to provide a comprehensive, and up-to-date classification of networks, and a range of possible interaction models that can be observed among learners in the course of learning-related interactions. We describe the main features, and structural characteristics of these networks and how learners interact within them. The remainder of this paper is organized as follows: Section 2 describes the essentials of social network interaction and introduces the learner-centered network interaction hierarchy. Section 3 describes the ego

DOI :10.5121/ijite.2022.11205

network and corresponding models. Furthermore, section 4 describes the duocentric network and corresponding models. Section 5 describes the triadic network and corresponding models while section 6 describes the scale-free network. In Section 7 we comparatively analyze the various models. Section 8 presents the summary and future work.

1.1. Contributions and article structure

Interaction modeling is an important topic that has high practical relevance in the area of social network analysis and beyond. This importance is linked to the viability of social networks and the multitude of insights one can gain from the unending interactions occurring within them. As part of our initial effort, we surveyed and reviewed several existing publications in the area of social network and interaction modeling found on Elsevier, JASTOR, ACM, Google Scholar, IEEE explorer etc. Our survey revealed the absence of a literature survey for learner-centered networks and associated models. Ergo, this survey article aims to provide researchers' desire to model group collaboration, readily useful social units with which groups can be classified. We also, describe associated models that readily give insight into group interaction dynamics, and the effects of collaboration. Compared to previous surveys related to learner network modeling, this survey:

- Introduces the learner network interaction hierarchy.
- Characterizes the various interaction modeling forms in learner-centered social networks.

Overall, we provide a comprehensive, and up-to-date classification of interaction models that assume interdependence. While there are stochastic interaction models, learner interactions, and partner choices are not random. Hence our focus will be on this class of models.

2. ESSENTIALS OF SOCIAL NETWORK INTERACTION

As Gupta et al. said: "The concept of randomness and coincidence will be obsolete when people finally define a formulation for patterned interaction between all things within the universe [9]." Hence, in this section, we present the essential attributes that constitute an interaction. In general, interaction is broadly social and constitutes situations where the behaviors of an individual are consciously reorganized, and influenced by the behaviors of another individual, and vice versa. These interactions and behaviors form the basis of a social structure, and therefore fundamental objects of social inquiry and analysis [10, 11, 12]. A social network platform acts as a new dimension to the traditional social interaction process. These interactions as observed in social networks are no different from the three-way handshake [13, 14, 15, 16, 17], i.e., the algorithm used by the Transmission Control Protocol to establish and terminate a connection on the internet. These sequences of processes are involved in establishing and terminating a connection with an entity in a network consisting of message exchanges. The most important part of these messages is the internet protocol addresses. Hence, an actor has to know the name, address, and possibly the location of an artifact or another actor that it wants to interact with. Also very important in the three-way handshake is the response from the destination. This response can either be an acceptance or a denial. As a consequence of this structure, the identity, availability, location, and integrity information of every participating element of interaction needs to be known and shared for any interaction to take place. The lack or absence of any of them will result in a communication breakdown. Based on this context, one can define interaction as a multi-path relationship between two or more nodes in order to achieve an objective. The essential components required for the formation of these multi-path relationships in a social network can be categorized into two groups: the network structures which are essentially graphs and the profile of a node [18].

In a graph, there are nodes that represent actors and for each node, there exists an interaction path between it and other nodes. These paths are called edges and they represent social connections such as friendship or project collaboration in the network. To get a better understanding, in the next subsection, we describe graphs and important properties.

2.1. Graphs

A graph, G is an ordered pair such that

$$G = (V(G),E(G)) \tag{1}$$

where V is a set, whose elements are called vertices or nodes

$$E \subseteq \{\{x, y\} | \ x, y \in V\langle x , y\rangle\} \tag{2}$$

and E, a set of edges which are unordered pairs [19].

Another graph H is a sub-graph if

$$H \subseteq G \Leftarrow\Rightarrow V(G)| \wedge E(H) \subseteq E(G) \tag{3}$$

So, H is a sub-graph of G if and only if the vertex set of H is a subset of the vertex set of G and the edges set of H is a subset of the edges set of G. Fig. 1 shows a sample graph and a sub-graph. As can be seen from the two graphs, the vertices 1, 2, 3, 4, 5 and the corresponding edges of Graph B correspond to the vertices 1, 3, 4, 8, 5 and the corresponding edges in Graph A. Hence Graph B is a sub-graph of Graph A. These graphs can be either undirected or directed. For instance, Facebook's network structure can be described as an undirected graph since the friendship structure is bidirectional, i.e., Alice and Bob being friends is the same as Bob and Alice being friends. On the other hand, Twitter can be described with a directed graph, i.e., Alice can follow Bob without Bob following Alice.

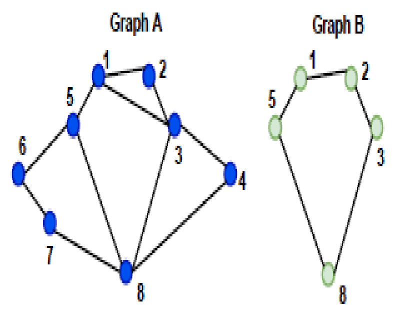


Figure 1. Graph and Subgraph

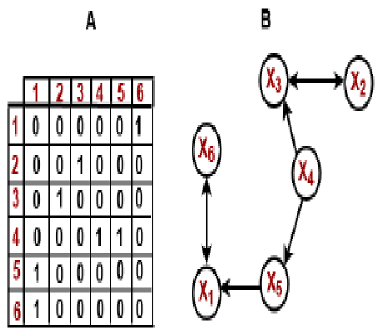


Figure 2. Sociogram with six nodes

Directed graphs or digraphs are a set of "nodes", and a set of directed "lines" or "edges" connecting pairs of nodes. We will denote the number of nodes in a digraph by "g", the group size. This type of graph is better represented with an (n*n) square matrix X^m, called the adjacency matrix. Given a directed interaction, involving a group of 6 nodes or individuals, the square matrix X^m, shown in Fig. 2 A, is used to represent the associated interactions. In X^m, $X^m{}_{ij}$ designates the status of the relationship between node *i* to node *j*. Using a binary representation, we indicate the presence of a tie with "1" and its absence thereof with a "0". After the establishment of a tie, the frequency of interaction can be indicated using ordinal numbers [20, 21]. Furthermore, in Fig. 2 B, the direction of the tie is represented using a sociogram. The arrowheads indicate the direction of the ties. An arrow pointing from node 5 to node 1 indicates a tie from Node 5 to Node 1. This is also seen through the sociomatrix $X^{m} = 1$ but $X^{m} = 0$. The profile information annotates the established paths with details that inform on the attributes of the node and neighbor nodes [22, 23, 24]. In the next subsection, we describe the node profile.

2.2. Node Profile

A profile describes the significant characteristics of the individual that is represented by a node. In social networks, these characteristics consist of information about interactions, behavior, connections, opinions, etc. They are modeled within a graph as labels associated with the node. So given a node or individual, the profile information is modeled as a set of labels:

$$L = \{l_1, \ldots, l_n\} \qquad (4)$$

These labels as identified in [1] come in several forms: demographic labels, such as age, gender, and location; labels that represent political or religious convictions; labels that encode activities, hobbies, and affiliations; and many other aspects that capture an individual's preferences [25, 26]. So in general as also observed in offline social networks, interaction occurs between individuals that have similar profiles, i.e. when the nodes have similar hobbies, attend the same lecture, have close convictions, etc. For network measures such as centrality, diversity, and density, please refer to [1, 27]. Given these interactions, 4 types of networks can be inferred: the dyad, the triad, and networks of arbitrary size. These networks form a hierarchy which we discuss in the next section.

2.3. Learner Centered Network Interaction Hierarchy

Within the scope of the considered interaction classes, i.e., ergodic, dyadic, and triadic interactions, etc., we observe that an interaction hierarchy can be inferred. This survey presents a classification of these hierarchies. Based on [1, 28, 29, 30], our hierarchy includes three main classes of networks or social units, namely dyadic networks, triadic networks, and networks of arbitrary size.

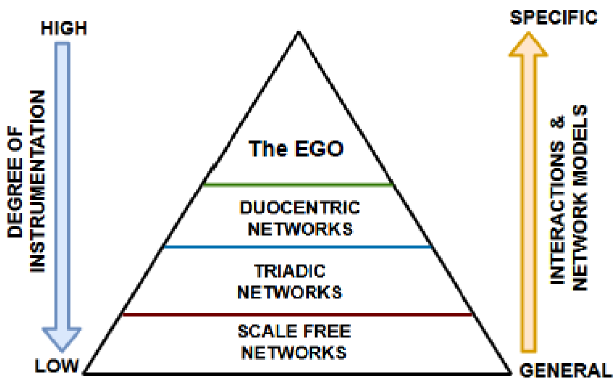


Figure 3. Learner Network Interaction Hierarchy

As illustrated in Fig. 3, these roughly form a hierarchy where networks of arbitrary size are the widest, i.e., most general type, whereas duocentric networks have the most specific domain. So as we move up the hierarchy, interactions become more restricted hence reducing the number of independently varying parameters in the interaction. This constrained degree of freedom allows for easy interaction modeling and instrumentation.

In the next sections, we will describe the important features of each network in the interaction hierarchy and the respective models associated with them.

3. Duocentric Networks

In the following, we briefly describe duocentric networks, a network that facilitates dyadic interactions. Given a directed network, we define a duocentric network as a sub-network consisting of a pair of nodes and their associated ties [31, 32]. This pair of nodes are called dyads, the fundamental unit of interpersonal relations [31, 33, 34, 35]. The duocentric network is used when a pair of egos is central to a research problem. The main characteristic of this network is that it is bounded around a pair of egos while ignoring the ties among the respective alters [27].

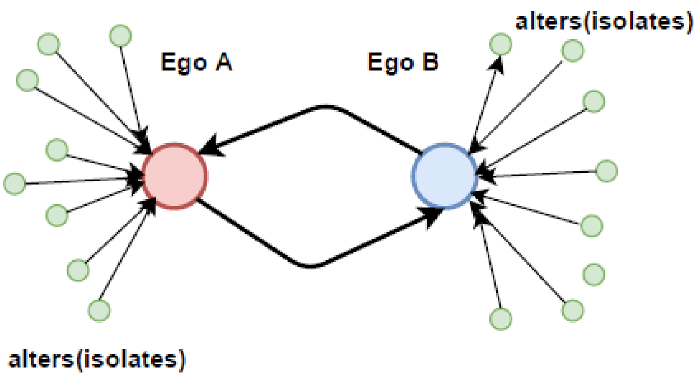


Figure 4. Duocentric network

In the analysis of a duocentric network, it is important to verify whether the two selected egos, singular individuals, are from the same class or category, i.e., whether they can be are precisely distinguished from one another as a function of some variable that can be used to differentiate them [36, 37, 38]. So if a research objective is to gain insight into on performance of male and female students in a programming language course, gender will topically be treated as a distinguishing variable.

The students can further be distinguished by roles, i.e, if the respective course project is to be done by groups of students, and roles are designated within the groups. Apart from dyads being distinguishable, it is important to know if they are exchangeable. for exchangeable dyads, there are no relevant variables or roles by which the egos in the dyads can be consistently distinguished (e.g., same-sex friendships).

The following are the characteristics of a duocentric network as shown in Fig. 4:

- Primary actors, Ego A and Ego B, must be central and expressed as egos.
- Other actors are classified as alters per the ego model.
- No relationships are captured among alters.

- Actors who only interact with one ego are classified as isolates.
- Interaction and dependence are shown by arrow direction.

The interactions that occur in duocentric networks are not random. They are characterized as within-dyad dependencies. These dependencies are both bounded and influenced by the commonalities, and similarities shared by the network nodes in question. In the next subsection, non-independence, the property that gives insight into the shared dependencies found in duocentric networks is described.

3.1. Non-Independence

When dependencies exist between pairs of attributes belonging to nodes in dyadic interactions (e.g, a male and a female student that belong to the same project group in a university course), the attributes of these two individuals or nodes are then more similar to one another than other nodes, (i.e. other students in the same course in other groups). For the dyad, other students, and instructors that constitute the main network are called isolates. An isolate that is a structural hole influence the interaction dynamics within a duocentric network [39]. These two nodes are said to exhibit the non-independence property [40]. This non-independence feature captures the commonalities shared by two sides of a dyad [41, 42].

3.2. Dyadic Data Analysis

The primary objective of duocentric network analysis is the formulation of mathematical models that explain the non-independence property. For this, two types of variables, i.e. exogenous and endogenous variables are used. Exogenous variables, depicted as ”X” in the models, are independent variables. They appear only as explanatory variables, and their values are determined outside the model. Endogenous Variables on the other hand are dependent variables. They will be depicted as ”Y” in the models. They are caused by one or more variables in a model. Also, an endogenous variable may cause another endogenous variable in a model [43, 44, 45]. Furthermore, a structural equation model is defined for each endogenous variable. These structural equation models are multiple equation regression models representing assumed causal relationships among several variables, some of which may affect each other mutually [45]. Using these variables, three different models that produce non-independence in a duocentric network setting, the Social Relations Model, the actor-partner model, mutual influence model, and common fate model will be described in the next sub-sub sections

3.2.1. Actor-Partner Interdependence Model

In the actor–partner model, non-independence is hypothesized to occur as a result of pre existing attributes of each partner, which affects both his or her interaction behavior, and also the interaction behavior of his or her partner [46, 40, 47]. For each partner as shown in Fig. 5, there exist endogenous variables and exogenous variables. The “X_i” as previously described, represent pre existing attributes or predispositions that the two actors bring to the interaction that may shape their interaction behaviors depicted by the ”Y_j”. Thus, in a class project consisting of dyadic groups, a neglectful behavior of a group member may result in a poor performance for every group member.

$$Y_1 = aX_1 + bX_2 + E_1 \qquad (5)$$

$$Y_2 = bX_1 + aX_2 + E_2 \qquad (6)$$

In Fig. 5, ‘a’ and ‘b’ represents the paths and is equal across the two members of the interacting pair, ‘c’ represents the error variances, ‘d’ represent the variances of the exogenous variables, ‘e’ represents the covariance of the exogenous variables X1 and X2, and ‘f’ represents the covariance of the errors or disturbances E1 and E2.

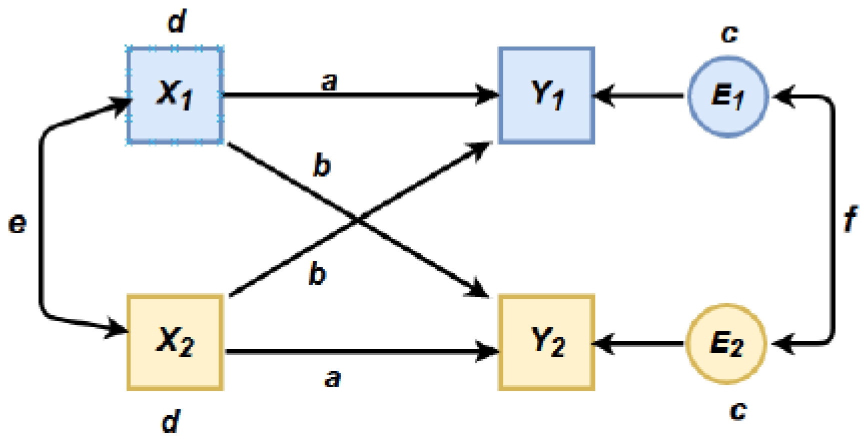


Figure 5. Actor Partner model [47]

The heart of the model are Paths a and b. Path a represents the actor effect, i.e., the effect of a person’s level of X on his or her level of Y. Path b represents the partner effect, i.e., the effect of a person’s level of X on his or her interaction partner’s level of Y [47] The structural equation model, and the multilevel modeling or hierarchical linear model are two modeling approaches applicable to analyzing the actor–partner interdependence model.

3.2.2. Mutual Influence Model

In the mutual influence model, a derivative of the actor-partner interdependence model shown in Fig. 6, interdependence is hypothesized to arise because the partners’ behaviors constitute a feedback loop [40, 47], whereby the Y’s reciprocally influence each other. For example, a learners satisfaction is influenced or affected by his/her partner’s ot team members satisfaction i.e, the commitment of one partner influences the commitment of the other.

Where ‘a’ and ‘b’ represents the paths and is equal across the two members of the interacting pair, ‘c’ represents the error variances, ‘d’ represent the variances of the exogenous variables ‘e’ represents the covariance of of the

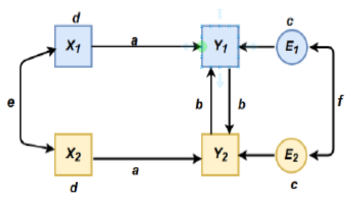


Figure 6. Mutual influence model [47]

$$Y_1 = aX_1 + bY_2 + E_1 \quad (7)$$

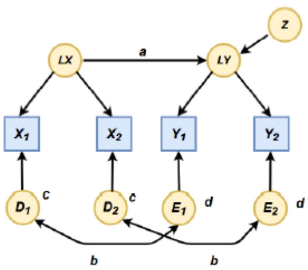
$$Y_2 = aX_1 + bY_1 + E_2 \quad (8)$$

exogenous variables X_2 and X_2, ‘f’ represents the covariance of the errors or disturbances E1 and E2. The heart of the model is the feedback loop represented by the reciprocal Paths b, and also Paths a, through which the X’s serve as instrumental variables [47].

3.2.3. Common Fate Model

In the common fate model, the partners' behaviors become non-independent owing that they are both impacted in the same way by influences at the dyad level. Latent variables in a statistical model are random variables that are not necessarily immeasurable. They are employed to represent features of interest in a model, that are not directly measurable or were not measured. They can also be used to construct estimators that are more efficient than those constructed from non-latent variable models. These shared situational or environmental pressures are conceived as dyad-level latent variables. They can also be used to construct estimators that are more efficient than those constructed from non-latent variable models [48]. In Fig. 7 two indicators, X_1, X_2, and Y_1, Y_2 are used to measure the latent variables. They reflect the scores of dyad member A and Member B (team member A and team member B) on the underlying latent construct [49, 47, 40, 50]. As shown in Fig. 7, one dyad-level latent variable, LX, influences another dyad-level latent variable, LY. This influence is indicated by the path "a" which indicates LX is directly affecting LY.

Using LX as an example, the variances and standard error of the between-dyad latent variables LX, LY, and Z are calculated as follows:



$$\mathbf{Var(LX)} = \frac{\mathbf{1}}{\mathbf{2}}\mathbf{Var(LX_{bd})} \quad (9)$$

$$\mathbf{SE} = \frac{\mathbf{1}}{\mathbf{2}}\mathbf{SE}_{\mathrm{Var(LX_{bd})}} \quad (10)$$

Figure 7. Common fate model [47, 49]

3.3. The Social Relations Model (SRM)

The SRM allows the number of individual under evaluation to scaled up to more than just two individuals. Thus given that six individuals are involved in an interaction, it is tenable that their characters' will influence or affect one another. Thus, their joint or dyadic, characteristics affect what happens between them. Hence they are interdependent on each other in as much as their relationship is concerned. To model this interdependence, the social relations model, a conceptual, and analytic approach to focus on the interdependence that exists in the relationships among individuals is employed. It analyzes the two-dimensional matrices of data representing interpersonal perceptions, affect, or behaviors elicited from their interaction via questioners [51, 52].

Dyadic - Covariance $$S_{gg'} : \frac{1}{2}\left(\frac{\frac{2\Sigma(\hat{g}_{ij}+\hat{g}_{ji})^2}{2}}{\left[\frac{(n-1)(n-2)}{2}\right]-1} - \frac{\Sigma(\hat{g}_{ij}-\hat{g}_{ji})^2}{(n-1)(n-2)}\right)$$

Actor - Partner Variance $$S^2_{ab} : \frac{\Sigma(\hat{a}_i\hat{b}_j)}{n-1} - \frac{S_{gg'}(n-1)}{n(n-2)} - \frac{S^2_g}{n(n-2)}$$

Actor Variance $$S^2_a : \frac{\Sigma\hat{a}_i^2}{n-1} - \frac{S^2_g(n-1)}{n(n-2)} - \frac{S_{gg'}}{n(n-2)}$$

Partner Variance $$S^2_b : \frac{\Sigma\hat{b}_i^2}{n-1} - \frac{S^2_g(n-1)}{n(n-2)} - \frac{S_{gg'}}{n(n-2)}$$

Figure 8. Associated Variances and Covariances

	1	2	3	4	5	6
1	--	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}
2	X_{21}	--	X_{23}	X_{24}	X_{25}	X_{26}
3	X_{31}	X_{32}	--	X_{34}	X_{35}	X_{36}
4	X_{41}	X_{42}	X_{43}	--	X_{45}	X_{46}
5	X_{51}	X_{52}	X_{53}	X_{54}	--	X_{56}
6	X_{61}	X_{62}	X_{63}	X_{64}	X_{65}	--

Figure 9. A two-dimensional matrix

Fig. 9 shows such a matrix. Here, X_{12} for example, represents scores derived from surveys on the extent that six student "*1*" perceives student "*2*" as knowledgeable with respect to a structured query language task. These scores can either be continuous or a dichotomous variable but it's common that these data consists of continuous scores. When using continuous scores in a survey, respondents receive a score for each survey question. These scores add up to a predefined total from which associated variances and covariances shown in Fig. 8 are derived. The variances and covariances facilitate the estimation of individual effects for a range of concepts as actor, partner, dyadic effects, etc. Actor effects for example are impartial assessments of an individual's behavior toward others, and partner effects refer to unbiased assessments of the ways in which an individual influences their partner [52, 51].

3.4. Discussion

As mentioned above, the interactions observed in duocentric networks are characterized by within-dyad dependencies. These dependencies are the fundamental building blocks for measuring interpersonal influence. As observed in the majority of the surveyed literature, the actor partner model is the most employed of the three discussed models. The actor partner model evaluates to which extent an actor's behavior or state is a consequence of his character or the character of his partner. It can be applied when dyad members are either distinguishable or exchangeable. The mutual influence model which is a variation of the actor-partner model omits partner effects. So for a group of two students working together for the first time on a course project, the mutual influence model does not take their individual effects into account. This omission of partner effects makes the implementation of the model difficult and further increases the possibility of erroneous estimates. The common fate model is an alternative to the actor-partner model in that the two egos are assumed not to influence each other. Rather, both are under the influence of either a shared situational, an environmental factor, or their dyadic personality [47, 50, 40].The social relations model is more in-depth, in that it requires elicitation and analysis of data representing interpersonal perception effects, or behaviors of all the participants, etc. It is mostly employed for large dyadic group studies. When a third node or individual joins a dyadic network, a triadic network is formed. This new network not only creates room for new forms of social relationships but also alters the interpersonal dynamics of the dyad. In the next section, we discuss the triadic network and associated model.

4. TRIADIC NETWORKS

Given a directed or an undirected network, a triadic network is a subnetwork consisting of any three nodes and their associated ties. These nodes take either a null or unconnected configuration, disconnected or connected pair configuration, and an open or closed configuration as shown in Fig. 10. Nodes in a triad are transitively associated with each other [28], and to determine their roles, we take the triad census,

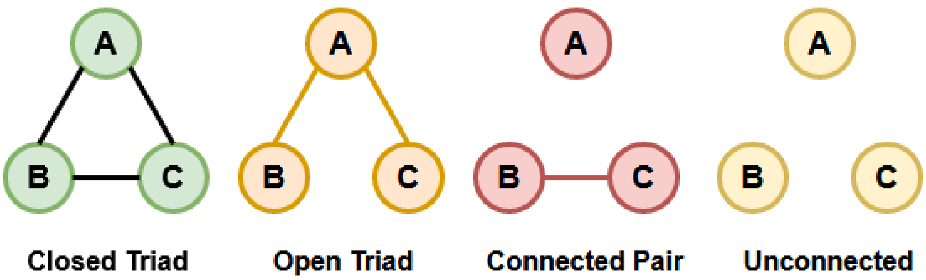


Figure 10. Triads [53, 54] shown in Fig. 10.

i.e., we count the number of the different triad variations it participated in. The relationship between these nodes can either be directed or undirected. For undirected relationships, the nodes can form closed, open, and unconnected relationships. The unconnected relationship can either be completely unconnected or a connected pair as shown in Fig 10.

The closed triad describes a cyclic relationship such that all nodes in the triad are connected, i.e., A—T—B, (A is tied to B), B—T—C, and A—T—C. For the open triad, interaction is mediated, i.e, a single node A mediates the relationship between node B and node C. So we have A—T—C, and A—T—B. Hence, information passes from A to B and then to C and back to A.

Directed relationships constitute an isomorphism. An isomorphism is a structure-preserving mapping between two structures of the same type that can be reversed by an inverse mapping [56, 57, 58], and owing to that two subgraphs are isomorphic if they are identical [1], a dyad that is neither asymmetrical nor mutual is null as shown in the sociomatrix in Fig. 11. Thus we have the first dyad variation, the null dyad. The second isomorphism, is invariant to a transformation, such as reflection hence it is not possible to distinguish between the two different forms i.e. B(i → j), and C(j → i) of asymmetric dyadic relations. The mutual dyad relationship, denoted by $i \Leftrightarrow j$ between actor i, and actor j comes into play when i → j and j → i in the dyad [55, 59]. Thus, the mutual dyadic relation between

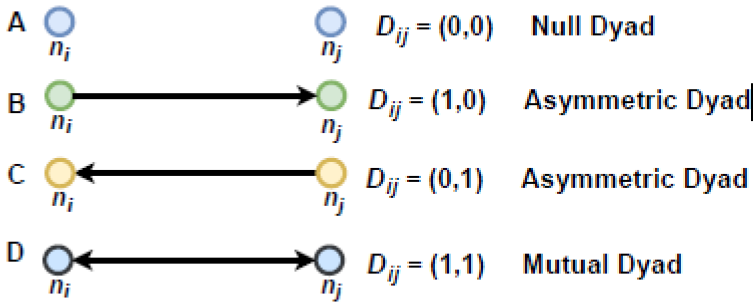


Figure 11. Dyadic isomorphism [55]

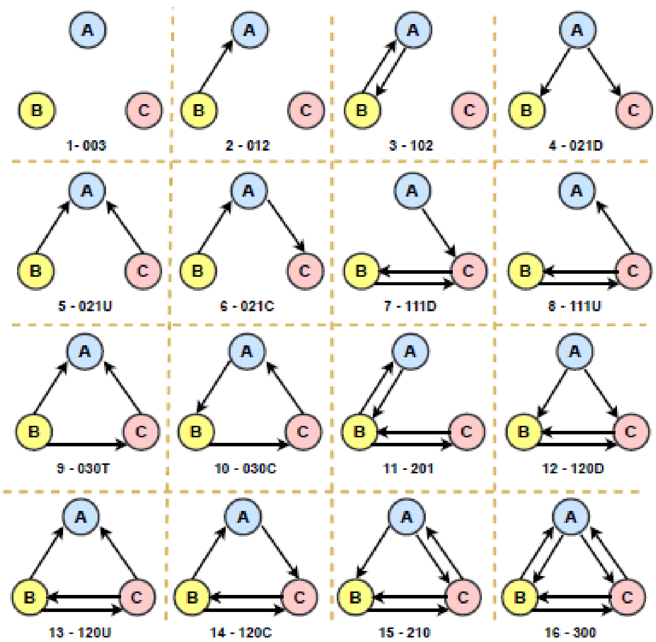


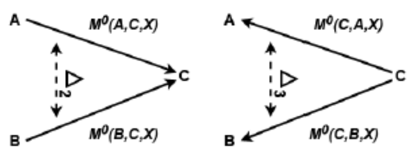
Figure 12. Directed triad relationship configurations [53, 54]

actor I and actor j is represented by D_{ij} = (1, 1) as shown in Fig. 11. Thus for directed triad relationships, there exists $g3$, distinct 3-subgraphs formed by selecting each of the possible subsets of the 3 respective nodes, and their corresponding ties. This results in 16 isomorphism classes as shown in Fig. 12. Letter: U indicates Up, and D signifies Down, C indicates Cyclical and T signifies transitive (i.e., having 2 paths that lead to the same endpoint). The variation denoted with 120D has 1 mutual, 2 asymmetric, 0 null dyads, and the down orientation. In this manner, the triads 1-3 depict an unconnected relationship, triads 4-8, and 11 depict variations of structural holes, and triads 9, 10, and 12-16 are variations of closed triads. The relationship between nodes in directed triad relationships eventually becomes a closure. Triadic closure, also known as transitivity or clustering, refers to tie formation in open triads, which closes over time [60, 61, 62, 63, 64]. So for two individuals with a common acquaintance, there is a high likelihood of a tie forming between them via the social influence of their common acquaintance [61, 65, 66, 67]. Triadic closure not only occurs in stand-alone triads but also in triads within large groups and entire networks. Thus, as one mutual connection increases the likelihood of tie formation between two individuals, multiple mutual connections increase the probability for even more connections [61, 68]. To measure the presence of triadic closure, we employ the clustering coefficient measure, which is a measure of the degree to which nodes in a graph tend to cluster together [69, 70]. In the next subsection, we describe the mutual modeling and triadic relations model.

4.1. Mutual Modelling

Mutual modeling is a bidirectional approach employed in both dyadic, and triadic interaction modelling [71]. Given a task involving three actors, A, B, and C, A builds a model of B, and C, and B builds a model of A, and C and C builds a model of B and A. This is represented using the notation M(C, A, X) which denotes "C knows that A knows X". As the non-independence assumption is in play, C's model of what A knows includes what C knows about A. So, if A states "C thinks I am proficient in programming", A then builds a second-level model: M(A, C,

M(C, A, Programming - Skill)). Furthermore, M^o(C, A, X) represents the degree of accuracy of the model. So, for the accuracy of what A, B, C models about each other, we have 6 models as shown in Fig. 13



$\mathcal{M}^o(\text{A, B}, \mathcal{X})$, $\mathcal{M}^o(\text{B, A}, \mathcal{X})$, $\mathcal{M}^o(\text{A, C}, \mathcal{X})$,
$\mathcal{M}^o(\text{C, A}, \mathcal{X})$, $\mathcal{M}^o(\text{C, B}, \mathcal{X})$, $\mathcal{M}^o(\text{B, C}, \mathcal{X})$,

Figure 13. Mutual modelling in a triadic interaction [71]

4.2. Mutual Modelling (TRM)

The triadic relations model extends the logic of the social relations model, section 3.3, to the analysis of data cubes. It takes into account the characteristics of the perceiver, actor, and partner, as well as their combinations all resulting in seven variances, and 16 covariance estimates. Given a situation in which what to deduce if an actor A agrees against partner B according to partner C, the tiadic relations model assumes that the perceiver's insight is comprised of eight components as shown below:

$$\mathbf{X_{ijk} = M + a_i + b_j + c_k + ab_{ij} + ac_{ik} + ac_{ik} + bc_{jk} + abc_{ijk}} \quad (11)$$

where M is the mean perception within the group, a_i is the group's perception of actor i's aggressiveness, b_j is the group's perception of partner j's victimization, c_k is the perception perceiver k has of aggression (among peers in general), ab_{ij} is the group's perception of actor i's aggressiveness toward partner j, ac_{ik} is the perception subject k has of actor i's aggression toward others, bc_{jk} is the perception subject k has of partner j's victimization by others, and abc_{ijk} is the specific perception k has of actor i's aggression toward partner j [52]. Having derived these components, the individual level variances, dyad variances, and triad level variances are calculated, and further estimations are derived from them.

4.3. Discussion

Triads are less reliant on the particular behaviors of their immediate participants for their structure, and property. As such, commitment in triadic relationships is bounded by achieving a goal. Such a goal can be the achievement of success in a course project. Given this goal, mutual modeling for triadic interactions consists of models of what the participants know about each other with respect to the goal of the relationship. This makes it suitable for modeling learner networks. The triadic relations model, on the other hand, allows for the study of multiple individuals, and dyadic processes simultaneously. Furthermore, the TRM can be employed in studying three dyadic processes simultaneously. More importantly, the TRM allows one to analyze the overlap among dyadic processes, for instance, whether an individual's behavior toward a peer is associated with that peer's perception of the individual. Despite requiring more computation than mutual modeling, TRM gives more insight into factors that affect the dynamics of triadic collaboration [72].

While there are other models employed in triadic interaction modeling as observed in our literature survey, most of them incorporate stochastic assumptions which violate the non-independence assumption.

5. NETWORKS OF ARBITRARY SIZE

Social capital is an efficacy derived from collaborative connections between individuals which results in the accomplishment of goals [73]. For example, a group with high trustworthiness and skill for a specified task is able to accomplish much more than a comparable group with the same level of skill and no trust. As such, the structural importance of an individual or node in a network or social unit is affected by its centrality with respect to the flow of social capital. Thus, the formation of new ties, choice of partners, and the evolution of the above-discussed networks are mainly driven by homophily and directed by preferential attachment [74, 75]. In consequence, the growth or evolution of dyadic, and triad networks into networks of arbitrary sizes follow a pattern observed in systems that produce power-law distributions. These systems are described as scale-free. The scale-free networks will be described in the next subsection.

5.1. Scale-Free Networks

The term scale-free is a mathematical expression used to describe the power-law characteristics of a probability distribution. The most basic model capable of producing a power-law degree distribution is the Barabasi-Albert (BA)´ model [76, 77]. At each time step in Barabasi-Albert's model, once a new node is created, it is connected to existing´ nodes in conformity with "preferential attachment" principle. Thus given a scale-free network, the probability $P(K)$ of a node having K links follows a power law with degree exponent γ as shown in equation 12

$$P(K) \propto K_{\gamma} \qquad (12)$$

Furthermore, results from the study of Hein *et al* [78] in which the internet was mapped, shows that the majority of the pages or nodes had few links while few pages had a large number of links. This is illustrated in Fig. 14.A. The logarithmic plot of the distribution of the edges is further shown in Fig. 14.B, which reveals the power-law characteristics of the distribution [79, 78]. This power-law characteristic, explains why in a network, a large number of nodes have very few connections, and a small number of nodes, structural holes, have a very high degree [77].

In all, driven by preferential attachment the previously discussed networks continuously grow as shown in Fig. 15, thus scale-free. Of the scale-free network shown in Fig. 15. Two of the main features of learner-centered networks that mirror the scale-free characteristics are:

- Continuous evolution. In the course of university enrollment, a student starts as an ego, and with each passing semester, new relationships are formed with other students in the same study. Also owing that there are inter-faculty courses, relationships also form between students of different faculties. In all, a learner's networks continue to evolve beyond the individual learning period [78].

- Preferential attachments. This is a typical feature of offline networks. New associations or nodes prefer to attach to structural holes or nodes close to structural holes. As a result of this preference in tie formation, structural holes, their support cliques, affinity group members, and sympathy group members record more interactions. This leads to the formation of a few highly connected hubs [78].

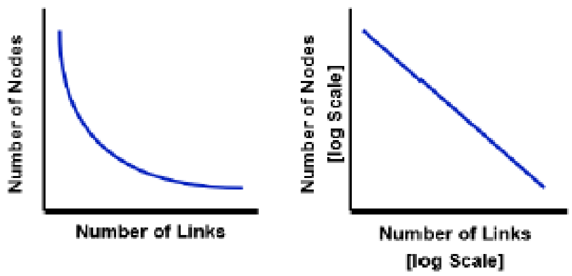


Figure 14. Power law distribution of node linkages [80]

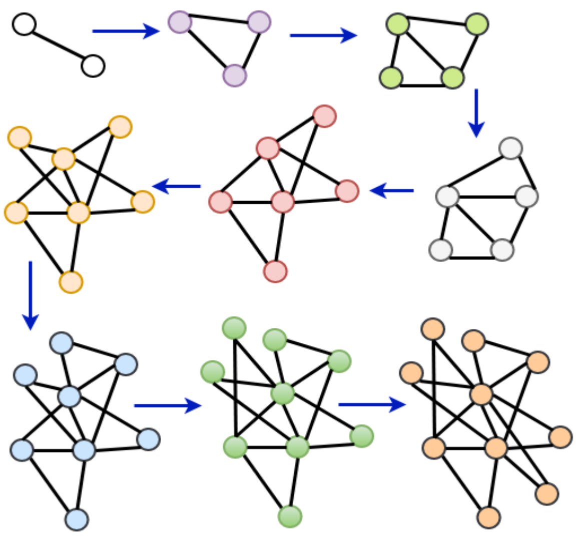


Figure 15. Evolution of a scale-free network as a consequence of transitive relationships

Fig. 15 shows a description of how scale-free networks evolve over a period of time, starting from a duocentric network. Some examples of scale-free networks are shown in Table 1.

Table 1. Examples of Scale-Free Networks [80]

Network	Nodes	Links
Internet	Routers	Optical and other physical connections
Protein regulatory network	Proteins that help to regulate a cell's activities	Interactions among proteins
Research Collaborations	Scientists	Co-authorship of papers
World Wide Web	Web pages	URLs

6. Comparative Analysis

The basic assumption that associates the models described in previous Sections with each other is the non independence assumption, which assumes that tie formation between individuals is not random. Based on this parent assumption, the following assumptions, and concepts,

- Distinguishability, which asserts that members of a social network are distinguishable if they differ on a dimension that is of factual relevance to the purpose of the investigation. For example, in an analysis examining instructor-student relation, the instructor, and student are typically interpreted as distinguishable because they play different roles in the interaction, one as an instructor in a lecture and the other as a student. Furthermore, members of a social network can be distinguished based on inherent variables such as age, sex, empirical scores, etc.

Table 2. Comparison of the considered network models

	Associated Models						
Criterion	Dunbar model	Actor Partner model	Mutual influence model	Common fate model	Mutual Model	SRM	TRM
Assumption of Distinguishability	0	X	X	X	0	X	X
Assumption of Homophily	0	X	X	X	X	X	X
Assumption of Network closure	-	-	0	-	X	X	X
Bidirectional Influence	-	0	0	0	X	X	X
Assumption of Transitivity	-	0	0	0	X	X	X
Assumption of Centrality	X	-	-	-	-	-	-
Legend: x = implements concept; o = partially implements concept; - = does not implement concept							

Table 3. Comparison of the considered network structures

Learner Networks			
Criterion	Duocentric	Triadic	Networks of Arbitrary Size
Instrumentation Level	Medium	Medium	low
Interaction with Alters	restricted	restricted	restricted
Network Size	2	3	unrestricted
Reciprocity	High	Medium	Medium

- Homophily, a predisposition for individuals to associate with other individuals they perceive via choice or external induction like culture, behavior, etc, to be similar to them. Thus contacts among similar people occur at a higher rate than among dissimilar people.
- Network closure, which describes networks in which nodes are highly connected to each other thus fostering trust, cooperative, and collaborative behaviors among nodes in the network.
- Centrality which indicates or measures the importance or position of an actor in a network. Thus, a structural hole is central with respect to its immediate local network.
- Bidirectional influence which are effects that are observed in dyadic and triadic relationships when partner effects from network members are present and statistically significant.
- Transitivity is the tendency that two actors who are connected to a third-party preferentially establish a mutual relationship in the course of time.

etc., are used in Table 2 to comparatively distinguish between the models based on which features and assumptions they embody. Table 3 further differentiates the networks in Fig. 3 based on their level of instrumentation, network size, actor interaction with alters, and reciprocity. Overall, the mutual model, and triad relations model while being feature-rich is suited for triads although they can be adapted for dyads. The mutual influence model is a derivative of the actor partner model which is specially fitted for dyadic networks. It can also be extended to triads, in which case six models are required, and a cumulative effect is derived by comparing all the individual effects. The common fate model, also a derivative of the actor partner model allows one to take into account, latent variables as individual behaviors, and emotions that affect how they interact. Calculating the variances, and covariances in the social relations model can sometimes be complicated and lead to errors, but they offer detailed insights into individual behaviors, and how they affect interaction. Also using this method, group structures are not a requirement.

SUMMARY AND FUTURE WORK

The goal of this survey article was to provide a comprehensive, and up-to-date classification of networks, and a range of possible interaction models that can be observed among learners in the course of learning-related interactions. We introduced the main features and structural characteristics of these networks and how learners interact within them. Having introduced the related models and their basic characteristics, we comparatively analyzed them. Taken together, we highlighted – from the conducted literature survey - the most relevant information and sufficient references to follow up on any of the above-mentioned models and networks. However, interaction models constitute a large, interdisciplinary area of research that is reasonably developed. Therefore, our survey analysis is by no means all-encompassing. Furthermore, as mentioned above, we solely focused on interaction models that assume interdependence. Future work could on the one hand widen the scope by addressing further aspects of learner-based interactions, and on the other hand focus on going deeper into specific subareas as skill acquisition, and effective collaboration strategies. Nevertheless, we hope that our article contributes to a better understanding of current learner-centered interaction models, and provide starting points for future research.

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