Longitudinal methods to analyse networked learning

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Abstract

We learn from others by example, through observation, or simply by combining known concepts to yield new concepts. While doing so, we inherently connect to one another (*connectivism*). Learners are interconnected by learning relationships ('X learns from Y'), but also by shared interests, similar actions, or shared resources. When these connections are aggregated, they form a learning network, and the act of participating in that network is called networked learning.

Networked learning can be analysed using social network analysis (SNA). SNA can detect structural characteristics of the network, communities or clusters, but also underlying characteristics of network actors (learners). In networked learning research, SNA is used in four ways: visualisation, analysis, simulation and intervention. However, the majority of approaches focuses merely on the visualisation and analysis of the network, rather than simulation and intervention, which can be of great value to networked learning research. Intervention has already taken off in the form of learning analytics (dashboards), and the actions that result from them. Simulation, however, may reveal the underlying mechanism that should be the main driver for intervention.

Learning network simulation can be used to predict networking behaviour by modelling the influence independent variables (e.g. actor characteristics) have on the dependent variable (e.g. network size). In such a case, one way to analyse a learning network is to use existing longitudinal network data to estimate a model that explains that influential behaviour. Simulation parameters vary along a range to create several combinations of input parameters, and are subsequently simulated numerous times (also known as Monte Carlo simulation) to yield a model that explains the behaviour of the dependent variable in terms of the explanatory variables. Other approaches use multilevel or regression analyses to create a model that explains the dynamic nature of the network.

The current paper shows the ways in which longitudinal network analysis can be used. That is, we provide examples of research questions, and how they can be addressed by longitudinal network analysis. Also, we supply practical guidelines to collecting data for analysis in an off-the-shelf program like RSiena. We include five data types that can be used as explanatory variables: constant actor variables, dynamic actor variables, constant dyadic variables, dynamic dyadic variables, and composition change indicators.

Keywords

Social networks, longitudinal network analysis, social network analysis, networked learning, dynamic network analysis

Introduction

Networked Learning and Social Network Analysis

Learning takes place everywhere, at any time. We learn from others by combining other people's concepts and knowledge with our own concepts and knowledge to derive new knowledge (Bruner, 1966). We learn from others by example (Bandura, 1977), or by observation (Vygotsky, 1978) and we try to exhibit similar behaviour. And as we learn in such a social manner, we try to create order in the information chaos that has only been increasing since the advent of the Internet (Siemens, 2005). Therefore, Siemens (2005) coined the term *connectivism*, to denote the fact that everything we do is connected. Concepts, ideas, and knowledge are connected through, for instance, semantic relationships. Concepts and ideas can relate to individuals, groups, or even communities (of practice, Lave & Wenger, 1991). People are connected through, for example, friendship or learning relationships. Whether we want it or not, we and our surroundings are interconnected into what

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Rainie & Wellman (2012) call a social operating system. That is, we form a social network, and if this network is used for learning, it is called a *learning network*. The learning actions we engage in while being a network actor, is called *networked learning*. This definition is closely in line with Jones, Ferreday, and Hogdson's (2008). Other definitions assume the use of ICT (Steeples and Jones, 2002), or a learning environment to foster "didactic flexibility" (Sloep et al., 2012). However, this particular definition does not exclude learning without ICT, nor does it exclude learning that takes place offline.

Recent initiatives have tried to make learners aware of their network neighbourhood by visualising their contacts (Schreurs & De Laat, 2012; Dawson, 2010; Heo, Lim, & Kim, 2010) and the concepts that drive their conversations (Schreurs, Teplovs, Ferguson, De Laat, & Buckingham Shum, 2013). The underlying technology that is used is called *social network analysis* (SNA). SNA is a means to analysing a graph (learning network) that contains nodes (learners) and the relationships ('X learns from Y') between these nodes. It uses mathematical calculations to derive information about nodes (e.g. one's power with respect to others (Sie, Bitter-Rijpkema, & Sloep, 2011)), about communities (e.g. individuals that share the same interest), or the social network itself (e.g. does a network revolve around a few individuals?).

SNA originates from psychology and anthropology, where it was initially used to capture group dynamics (Moreno, 1934; Mayo, 1945) and structural balance in sentiment towards others (Heider, Cartwright & Harary, 1977). Later on, mathematicians such as Erdös, Bollobás and Renyí (Bollobás & Erdös, 1976; Erdös & Renyí, 1977) laid further foundations for the more formal analysis of social networks. Common SNA metrics include:

- *density*: the actual relationships formed, divided by the total number of relationships possible
- *degree centrality*: the number of links that a network actor has. Often a distinction is made between incoming relationships (indegree) and outgoing relationships (outdegree)
- *betweenness centrality*: the extent to which a particular network actor is in-between other network actors. That is, the number of times one is on the shortest path between any two network actors.

State-of-art in SNA for Networked Learning

Sie et al (2013) provide an overview of how SNA is currently applied in research. They distinguish four types of SNA applications of SNA used (with increasing complexity):

1 *visualisation*: showing networks of nodes (learners) which are interconnected through edges (learning relationships) (De Laat, Schreurs & Sie, 2014); Schreurs, Teplovs, Ferguson, De Laat, & Buckingham Shum, 2013; Sie, Van Engelen, Bitter-Rijpkema, & Sloep, in press)

2 *analysis*: data about network relationships can be analysed (De Laat, 2002; Haythornthwaite & De Laat, 2012) using measures such as density (Meijs & De Laat, 2012; Moolenaar, Sleegers, & Daly, 2012), degree (Meijs & De Laat, 2012) and betweenness (Sie, Drachsler, Bitter-Rijpkema, & Sloep, 2012b)

3 *simulation*: network models can be simulated to predict future network behaviour. Networks can be simulated using stochastic models (Van de Bunt, Van Duijn, & Snijders, 1999; Lomi, Snijders, Steglich, & Torló, 2011) but also using multi-agent simulation models (Koper, 2005; Nadolski, Van den Berg,, Berlanga, Drachsler, & Hummel, 2006; Sie, Bitter-Rijpkema, & Sloep, in press). The former tries to model the influence independent variables such as personal characteristics have on a dependent variable such as network density or centralisation. The latter tries to model behaviour on a micro level (e.g. 'agents' represent network actors), to study network behaviour on the macro level

4 *intervention*: SNA is used to actually intervene in real-world settings (Dawson, Bakharia, & Heathcote, 2010; Sie et al., in press). Some SNA metrics require a considerable amount of computational power, which makes it difficult to deliver real-time feedback on network actions, which is often needed in learning settings. Also, the computational load of SNA metrics may inhibit scalability of the intervening software program.

Problems

Sie et al. (2013) pinpoint a number of problems with the current state-of-art research in social network analysis for learning. Two of these problems are of special interest to the readers of the current paper:

- Current initiatives merely use social network data to analyse and visualise network behaviour. The vast majority of studies does not employ simulation techniques to explain or extrapolate behaviour, nor is social network analysis used to intervene in real-world settings.
- Learning is an ongoing process, and a 'snapshot' of learning behaviour may only reflect a temporary state of the learning network. De Laat (2002) suggests that research initiatives take into account the changing behaviour of learners and stress the importance of timeline analysis.

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It must be noted that some studies in the field of networked learning do try to explain network behaviour. For instance, Van Engelen (2012) computed the correlation between the betweenness centrality of individuals in a co-author network, and their H-index. Also, Macfadyen and Dawson (2010) used correlation analysis and multiple regression to study the predictability of student networking behaviour on their final grade, which yielded a model with 33% explanatory power. Yet, Macfadyen and Dawson merely tested the extent to which the target variable (final grade) could be explained by the predictor variables (networking behaviour), but by no means does multiple regression explain the effect of variables on the target variable (Constantine, 2012).

Another complicated factor of using SNA is that these results as well as SNA visualizations can be used to actively inform networked learners and use these results to make them reflect time and again about how these network structures impact and influence their learning (De Laat, Schreurs & Sie, 2014). Finally we must be cautious in general with applying this kind of SNA in the domain of learning. SNA is generally used to understand for example how information flows through network structures or to understand communication patterns in studying peer-to-peer networks, but this does not mean that this kind of research can be elevated to networked learning research, simply because it is not always clear what makes a learning tie (Haythornthwaite & De Laat, 2012) and to what extend these learning ties impact learning. Hypothetically one can learn much more from a distant relation approached only once (cf. the strength of weak ties), than from close relations with whom one interacts on a daily basis. In terms of SNA, it remains difficult to interpret learning ties based on quantifying the amount of information that is being shared (e.g. is this really learning?), the frequency by which one has been approached (impact of learning) as well as how these connections change over time (difficulty maintaining meaningful learning ties over time). Longitudinal network analysis may be able to answer such questions, for instance, one could map the strength of learning ties (weak vs. strong) and how they change over time, to the amount of information shared over time. Similarly, one could overcome the other difficulties by explaining how learners' comprehension is influenced by networking behaviour, and how persistent learning ties are.

Longitudinal Network Analysis

Longitudinal network analysis (Kossinets & Watts, 2006; Lomi et al., 2011; Opsahl & Hogan, 2011; Snijders, 2004; Van de Bunt et al., 1999) can be used to compute statistical inference. In other words, longitudinal network analysis can compute the effect of independent variables on a dependent variable. Longitudinal network analysis is based on a repeated measures methodology, that is to say, network characteristics (and optionally personal characteristics) are computed at two or more time points (Snijders, 2004) to compute the effect of independent variables (e.g. network density, actor betweenness centrality) on the dependent variable (e.g. network centralization). However, one must make sure that the longitudinal effects are not the result of confounding environmental variables (Cohen-Cole & Fletcher, 2008).

Roughly two types of analyses can be distinguished for longitudinal network data. First, we have regression and multilevel analyses that try to discover models that can explain the behaviour of the dependent variable (Fowler & Christakis, 2008). Second, we have simulation models such as *stochastic actor-oriented models* (SAOM)(Snijders, 2010; Van de Bunt et al., 1999) and *Bayesian blockmodels* (Rodríguez, 2012) that try to estimate a model through simulation. They often assume a *Markov Chain*, which means that transitions are made between network states. This entails that the network continuously evolves, yet the observations occur as 'snapshots' at specific time points. In other words, learning networks continuously evolve, but we collect data only at discrete time points, with several weeks in-between, for instance.

To estimate the effect of independent variables, often a *Monte Carlo* simulation is used to estimate a model of independent variables and their effect on the dependent variable. For example, consider a network of learners, and gender, age, and personality as independent variables, and network density as dependent variable. This could tell us to what extent knowledge is spread among a learning network, and how this can be explained in terms of the actor's characteristics. The Monte Carlo simulation will try to approximate a model – or formula that takes into account the gender, age and personality of all learners – that can predict the network density at a later time point. This model is very complex, and contains errors in the first instance, that is, it incorrectly predicts the network size. By continuously simulating and adapting the model (using several variable ranges), the model's error is reduced, until it converges to a model that correctly describes the dynamics of the network size.

The type of analysis greatly depends on the research question at hand. Lubbers et al. (2010) distinguish five types of research questions for personal networks (Table 1) and propose to use appropriate (variations on) analyses. The data and the research question may impose problems, such as the lack of independence between observations, which is the case for personal (ego) networks (Lubbers et al., 2010). A bypass may be the exclusion of the ego from the network, since the ego is "by definition tied to the alters" (Lubbers et al., 2010). In SNA, 'alters' are a common way to denote one's contacts.

Table 1. Research questions and corresponding analyses

research question	method of analysis	sample research question
1. Persistence of ties across time	multilevel analysis (Ünlüsoy, De Haan, Leander, & Volker, 2013; Van Duijn, Van Busschbach, & Snijders, 1999) or logistic (hierarchical) regression analysis (Feld, Suitor, & Hoegh, 2007; O'Malley & Christakis, 2011)	Does reciprocity influence the persistence of learning ties?
2. Changes in characteristics of persistent ties (dyad covariates)	multilevel regression analysis (Van Duijn et al., 1999)	How can the strength of a learning tie (dependent variable) be explained by the personality of the learners (independent variables) that are interconnected by the tie?
3. Changes in the size of the network over time	multiple linear regression (Bickart, Hollenbeck, Barrett, & Dickenson, 2012)	To what extent do average tie strength and centralization (independent variables) affect the size of the network (dependent variable)?
4. Changes in the composition of the network	multiple linear regression, quadratic assignment regression (Butts, 2008; Conti & Doreian, 2010; Lewis, Kauffmann, Gonzalez, Wimmer, Christakis, 2008)	Can the learning network at time point 2 be explained by underlying structural characteristics of the network at time point 1?
5. Persistence of relationships among alters	stochastic actor-oriented models (Snijders, 2001; Steglich, Snijders, & West, 2006)	Can the learning network's density be explained by actors' personality?

Suggestions for data collection

How does one commence with the collection of longitudinal network data? First of all, longitudinal network data uses repeated measures of network behaviour. In other words, networking behaviour should be measured at two or more time points. This puts forward several logistic requirements, such as bringing together your sample at least twice for the repeated measures.

For example, imagine a simple learning network at time point t = 1, in which Albert learns from Brenda, and Brenda learns from Charles. This can be denoted by a network that consists of three nodes Albert, Brenda and Charles, with a directed edge from Albert to Brenda, and a directed edge from Brenda to Charles (Figure 1a). We specifically use directed edges, since 'learning from' is a unidirectional relationship; Albert can learn from Brenda, but this does not imply that Brenda learns from Charles. At t = 2, say two weeks later, things have changed. Brenda now also learned from Albert. This can be denoted by an evolved network that has an additional directed edge from Brenda to Albert (Figure 1b).

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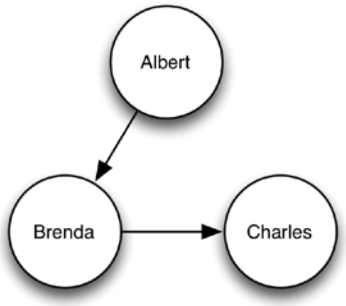

Fig 1a. Network at time point *t* = 1

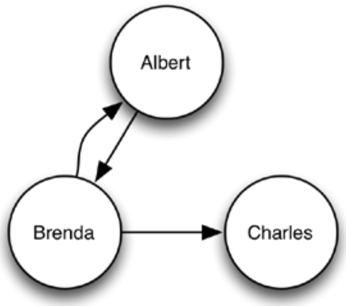

Fig 1b. Network at time point *t* = 2

Now we have a network with two states in which the second state comprises a change in the network, that is, Brenda started to learn from Albert.

What should be measured? Naturally, one needs to aggregate (learning) relationships to construct a network. Such a network consist of nodes, and typically directed edges (‘X learns from Y’). The edges may have a certain value between zero and five, to denote their strength, rather than a dichotomous value that represents whether or not a relationships is present. Also, the network is measured at distinct time points, so for each learning relationship, one needs to note down the particular time point.

Furthermore, to conduct longitudinal network analysis, one or more explanatory or independent variables, and one dependent variable should be measured. Independent variables may be of five types (adapted from Ripley, Snijders, & Steglich, 2013):

- constant actor variables, such as gender, age, personality,
- dynamic actor variables, such as betweenness, degree, or closeness centrality,
- constant dyadic variables, such as the tie type,
- dynamic dyadic variables, such as the tie strength, which may increase or decrease over time,
- composition change indicators that denote how many actors have joined or left the network.

The dependent variable may be a network-level measure, such as density or centralization, but also an actor variable, such as an actor’s degree centrality.

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What format should one use for import in analysis software? With respect to the format in which data should be published: this (naturally) depends on the type of software that you use, if at all. For instance, RSiena, a package for the R Statistics program, allows for comma-separated (CSV) files. A CSV file typically calls for one tie per row. A row consists of a sender ID, a receiver ID, the tie strength, and the time point (called a 'wave' in RSiena). As one may notice, a two-dimensional sender-receiver matrix will not suffice, since the tie strength and wave number requires a matrix of at least one extra dimension. For the network shown in Figure 1, we use the following CSV text to denote the change in the network:

senderID, receiverID, strength, wave
Albert, Brenda, 1, 1
Brenda, Charles, 1, 1
Albert, Brenda, 1, 2
Brenda, Charles, 1, 2
Brenda, Albert, 1, 2

As one can see, wave 2 includes the relationships {Albert, Brenda} and {Brenda, Charles} that were formed in wave 1, plus the additional relationship {Brenda, Albert}. If we were to exclude the relationships from wave 1, this would mean the learning relationships had come to an end in wave 2.

Conclusion

In this paper we addressed an emerging development in SNA, which concerns dynamic, longitudinal network analysis. These kinds of measurements will help to understand why and how networks change and what are the driving factors behind them. In the area of networked learning these questions are also emerging and simple techniques such a visualizing a network at time point t=1, t=2, and t=3 do not suffice anymore. This paper provides the kind of techniques and data collections that are needed to provide a more solid and structured approach to analyse the dynamics of networked learning, and its underlying principles. This type of research is interested in explaining the factors that contribute to the changing structure and nature of learning ties. Longitudinal methods can be used to provide definitive answers to the question whether and how networked learning can be effective.

Longitudinal network analysis will help us to better evaluate interventions in networked learning, or even networked learning as an intervention. Longitudinal network analysis approximates models that explain the effect that, for instance, actors' characteristics have on the learning outcome of networked learners. Such information can be used to predict the effectiveness of a future intervention in networked learning, such as promoting the formation of strong, rather than weak learning ties, or the other way around. Such process-oriented research will be of great help producing the 'before and after' picture and analyse the contributing factors to the change observed. In this paper we have introduced some of them and addressed the kind of research that becomes available. This kind of research will help us to improve design of social learning networks, understand which roles can facilitate and improve networked learning and it will help to improve networked learning literacies and outcomes in general.

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