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Measuring knowledge and experience in two mode temporal networks

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ABSTRACT

Two mode social network data consisting of actors attending events is a common type of social network data. For these kinds of data it is also common to have additional information about the timing or sequence of the events. We call data of this type two-mode temporal data. We explore the idea that actors attending events gain information from the event in two ways. Firstly the event itself may provide information or training; secondly, as co-attendees interact, they may pass on skills or information they have gleaned from other events. We propose a method of measuring these gains and demonstrate its usefulness using the classic Southern Women Data and a covert network dataset.

1. Introduction

In this paper we examine how information flows through a network as a result of interactions at events. In particular, we consider how information learnt at events is spread to other actors at subsequent events. In so doing we propose a measure that serves as an index of what an actor has gained – directly and indirectly – from the events that they have attended. A consequence of this approach is that we only consider two mode data consisting of actors and events in which we know the order that the events occurred.

The proposed measure will be derived via a particular data representation, namely the bi-dynamic line-graph (BDLG), that represents individual affiliations over time as overlapping person-specific trajectories (Broccatelli et al., 2016)[1]. Let V= {i, j, k. . ..} be a set of actors and E = {e1, e2, . . . em} be a set of events which are arranged in time order, that is event ek occurs after event ej if j < k. Then a time stamped 2-mode network has the form G (V∪E, A) where A is the set of unordered pairs or edges of the form {i,ek} in which i ε V and ek ε E and indicates that actor i attended event ek. This would look exactly like a standard two-mode dataset except we now have an event attribute that tells us the order in which the events took place.

Informally a BDLG representation has the edges of the time-stamped 2-mode network at its vertices and two types of edges. The first type is undirected and connects actors that were at the same event. This means that each event will be represented by a clique connecting the actor-event nodes for that event. The second type is directed and shows the trajectory of an actor through different events. Formally a BDLG representation has as its *vertices* the edges of G, where an edge labelled iek of the BDLG corresponds to the edge {i, ek} in G. It has two types of ties, reciprocal ties and directed ties. A reciprocal tie {iex, jex} occurs when two actors i and j attended the same event ex. A directed tie (iex, iez) is where z is the smallest z > x such that i attended ez. The directed edge shows the next event, ez, i attended after attending event ex. Consider, for example, the BDLG shown in Fig. 1 representing individuals attending several events over time.

To ensure a clear identification of participants in events, nodes are labelled by a number and an alphabetic letter 'e' followed by a number so that (5,e3) would mean that actor 5 attended event e3. The numbers, e.g. 1,2,3. . ., identify individuals whereas the alphabetic letters 'e' followed by a number refer to events. If an individual participated in succeeding events, there are as many nodes involving that individual as the number of events in which the individual took part, and these nodes are sequentially connected by a directed arc. For example, the node referring to individual 2 participating at event 1 (2,e1) has an outgoing tie only toward the node referring to individual 2 participating at event 2 (2,e2) and from this, only

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[1] Dr Wouter Spekkink developed a tool that transforms two-mode data into BDLG. The tool can be downloaded from here: http://www.wouterspekkink.org/software/2017/03/10/bi-dynamic-line-graphs.html.

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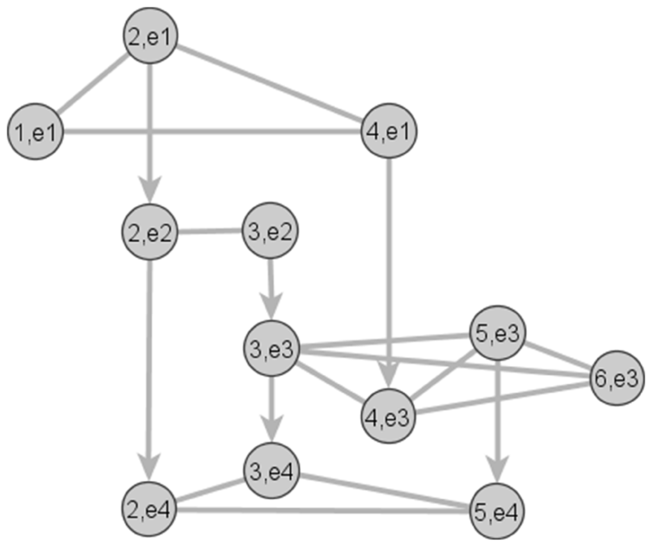

Fig. 1. A simple Bi-Dynamic Line-Graph. Events are vertically ordered with the first event at the top and the last at the bottom.

an outgoing tie toward the node referring to individual 2 participating at event 4 (2,e4). If individual 2 was also attending event 3, another outgoing tie starting from 2,e2 and finishing in 2,e3 would be present. Therefore, each node can only have a directed tie to (from)its following (preceding) event.

In graph theory, two nodes connected by a line are said to be adjacent to one another. Since in the BDLG representation there are two different sets of ties – reciprocal and directed – the adjacency concept assumes a slightly different meaning depending upon the case. In the first case, two nodes are adjacent if linked by a reciprocal link, representing two individuals participating at the same event. In the second case, two nodes are adjacent when a directed link connects the same actor joining in different events. Directed lines, as a consequence, specify the sequence of events with arrows pointing towards a progressive time development, starting from the first and finishing with the last event. While reciprocal ties capture joint attendance at events, directed ties follow the person-specific participation in events over time.

2. Knowledge and experience

We start by observing that actors attending events gain some knowledge from the event. The event could be an explicitly informational or training event, in which case it is clear that attendance has meant that participants have gained some new information. Alternatively the event could be an activity or a game in which case the experience gained by participating will also contribute to knowledge. We shall call the information gained by an actor from attending a "network event experience" or simply "experience" for short. We use the term "network experience" to emphasize we are only looking at information gained from participating in the event.

There is a second opportunity for actors to gain information from an event. We shall assume at an event actors exchange information with other actors at the same event. Part of what they exchange is network experience they have from previous events they have attended. As a consequence an actor who did not attend an event may gain information from another actor who was at the event, i.e., their network experience, when they both meet at a later event. Even if both actors attended both events they still may gain additional information about the earlier event from each other when they meet at a subsequent event. We shall call information that an actor gains from other actors who attended a previous event "network knowledge". Again we use the term network knowledge to emphasize we are only looking at knowledge gained from network activity and not any external knowledge an actor may bring. To summarize experience is gained at an event from the event itself, once this is passed on it becomes knowledge to the receiver. When considering any transfer of experience we shall call it knowledge.

Our interest is in developing a purely structural measure which tries to capture the opportunity for actors in a network to gain information by directly experiencing an event and by learning from other actors who attended other events. Although we do not use the term this could be seen as a centrality type measure. The presented new measure clearly differs from well-known measures of centrality in a number of ways. Primarily, the proposed measure is innovative because it specifically applies to two-mode temporal networks, rather than using the one-mode projections of a two-mode matrix. By using the BDLG as a starting point, in fact, original two-mode networks are represented in a manner that directly focuses on both modes composing the affiliation network, e.g. individuals and events. The importance of this dual focus, widely discussed in the literature (Breiger, 1974; Faust, 1997; Diani, 2015; Everett, 2016) calls for new centrality measures that simultaneously combine the dependence of individuals and events and vice versa. This new measure does this since it jointly considers the effect of both network entities, that is actors and events, in determining network knowledge and experience of individual actors.

3. Towards an algorithm: assumptions behind this new measure

Through face-to-face and hands-on experiences individuals interact and in so doing tend to share information and skills. Here, shared participation is intended as a social mechanism that explains how people learn, gain experience, and adopt practical knowledge to perform their tasks. By collaborating with each other through face-to-face interactions, individuals who already possess certain skills and knowledge pass these to other participants. In this way, people can consolidate their abilities and gather new practical knowledge to be potentially used in future tasks during each activity/event they attended. From a modeling perspective, these social dynamics require a model that captures the importance of past relationships and past attendance to events and is also able to simultaneously examine hands-on experiences and face-to-face interactions as channels of knowledge transmission. Starting from the bi-dynamic line-graph representation, the proposed measure captures both these mechanisms and quantifies the amount of practical knowledge individuals acquire through these two channels.

In the following section, we outline the assumptions for the individuals and events which will form the basis of the knowledge and experience measure. These assumptions are important for defining a measure that rules out other potential measures that would result in unrealistic or absurd consequences.

- Network *boundaries*: we are only concerned with knowledge and experience generated and transmitted within a specified set of actors. Clearly there is potential for actors to bring in additional knowledge from outside the set but that is not what we intend to measure.

  Referring to individuals, it is formally assumed that:
- *Individuals who attend an event have a unique experience*. Different individuals attending the same event and undertaking activities learn different things based on their previous experience and abilities. As a consequence two individuals who attend the same event and meet again later at a different event can exchange additional information about the first event that adds to their network knowledge. This condition can easily be relaxed or modified if it is deemed unrealistic or too restrictive.