Exploring the temporal nature of online interactions

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Dynamic social relations and interactions

There is a growing requirement to develop analysis techniques for dynamic relations

- Social networks are inherently dynamic: actors repeatedly create ties and break up others (Brandes, Lerner & Snijders, 2009)
- A social network is formed by “regular exchange connections that actors consider important to their activity” (Quintane, Pattison, Robbins & Mol, 2013)
- Consideration of the temporal and sequential nature of social interactions enables the investigation of network dynamics and volatile network structures
Time in social network analysis

The context for this research is information transmission over social networks as a result of time-stamped communications and what this reveals about the social interaction processes in a network.

- Most existing research in social network analysis does not take time into account
  - Cross-sectional datasets and static theories (interactions over time are aggregated into weighted relational ties)
- Exceptions include longitudinal analyses (e.g. SIENA) and Relational Event Models
  - How do networks evolve or change?
  - How are ties created or dissolved?
  - What is the effect of past interaction history on tie creation processes
- But what about the sequence of interactions?
Relational structures: Static vs. Dynamic

Recent development of an algebraic approach for the analysis of dynamic relations in social networks allows explicit representation of time-ordered flows in dynamic networks (Kontoleon, Falzon & Pattison, 2013)

- **Static networks** describe relationships that are universally present or absent
  - e.g., parenthood, marriage, friendship

- **Dynamic networks** have edge “weights” given by the interval or set of intervals over which interactions occur,
  - e.g., short-term partnerships, transactions

Time-stamped data provides opportunities to re-construct the unfolding of coordination processes over time and to model explicitly the duration and path-lengths of specific sequences of exchanges.
Motivation for modelling time order

The temporal order of interactions has implications for

- **The propagation of information, ideas, resources over social networks:**
  - The order of interactions in a sequence is a necessary consideration for tracking propagation
  - Useful measures include: time-ordered paths, reachability, betweenness, source node sets and target node sets

- **The communication processes among individuals and groups**
  - Closure and reciprocal structures in dynamic networks enable a study of coordination processes and information exchange patterns
  - The sequence of communications traces different brokerage patterns
Reachability - order matters
Reachability - order matters
Reachability – activity over time (Email communications)

Node 118 - Level 2 - Week 6; reports to 80; Boss of lots...
Comparing activity of different individuals
Comparing activity over different weeks
Reachability (phone call data)

- 575 mobile phone calls among 45 callers over a 10-day trial.
- Reachability is calculated for three values of $\delta$ using a generalised Gauss-Seidel algorithm adapted for dynamic networks.
- As the number of potential paths increases so does the reachability of each node.
Case study: Reachability (phone call data)

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### Reachability graph for various values of $\delta$

<table>
<thead>
<tr>
<th>$\delta$</th>
<th>Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>6 hrs</td>
<td>0.2237</td>
</tr>
<tr>
<td>24 hrs</td>
<td>0.4612</td>
</tr>
<tr>
<td>194 hrs</td>
<td>0.6321</td>
</tr>
<tr>
<td>Ignoring time</td>
<td>0.8444</td>
</tr>
</tbody>
</table>
Sequential patterns and other features of time-ordered networks

**Example: transitive triads**

In traditional **social network analysis** the following interaction pattern is a **transitive triad** (i.e. A→B→C; A→C):

But if we consider time order ...

- **Social Network Analysis (SNA)** provides a theoretical framework for exploring the emergence of social phenomena from local structures and interactions (Pattison & Robins, 2004)
- **Dynamic network analysis** can be described as the temporal counter to classical SNA
- It allows us to represent aspects of structural processes as specific measures on dynamic networks (Spiro, Acton, Butts, 2013)
When do two or more sequential interactions form a path?

- Different types of flows have different characteristics (Borgatti, 2005) and this needs to be considered in network path constructions.
- We therefore define a decay variable $\delta$ which represents a possible time lag or decay factor, after which the substance being transmitted loses its potency.
  - $\delta$ is specified by the type and medium of transmission.
  - It represents the maximum time period at which a transfer may occur.
  - Speedy transmissions, e.g. hot gossip, are modelled by setting $\delta$ to be very small.

Three interactions form a triad if the second one occurs within $\delta$ of the first one being transmitted, and the third arrives within $\delta$ of the second.
Case study: exploring communication processes in an organisation

Research objective: To provide more granularity to our understanding of the temporal aspects of the process of triadic closure in an organization communication network

- Importance of triads as building blocks of network structure
- The process of triadic closure is fundamental in the explanation of network dynamics.

Transitive triads: referrals, coordination based on hierarchy

Cyclic triads: generalized information exchange, coordination based on peer adjustment
Data

• Organisation
  • Formal structure organised along functional areas but workflow is centred on clients and projects
  • Email is primarily used for work-related matters; regular sharing of electronic documents that are task-sensitive
• Actor attributes:
  • Hierarchical position
  • Gender
  • Department
  • Reporting lines

Email
• Email communications activity records between the 129 employees of a digital advertising agency during 8 months: 600k e-mails in total
• Kept only e-mail sent to 4 recipients or less (Kossinets & Watts): 2926 dyads
• Time stamped, we know the exact time at which each e-mail was sent, by whom and to whom (anonymised)
Measuring time in sequences of transactions

Duration

Closing time

Time

For this data set, we have set $\delta$ to be 24 hours (i.e. 86400 seconds) based on sensitivity analyses.
How long do (transitive, cyclic) triads take to Form?

Duration of Cycles and Transitive Triads - Density Function

Proportion of Structures

Duration (hours)

Density Function

Cycles
Transitive Triads
Does exchange frequency affect closing speed?

**Average Closing Time and Duration of Transitive Triads Over Entire Study**

- Duration: $y = -20.742x + 28756$
- Closing: $y = -10.221x + 14315$
Using brokerage roles (Fernandez and Gould, 1989)

Coordinator

Representative

Gatekeeper

Itinerant Broker

Liaison
Brokerage Roles

Duration for Brokerage Roles of Triads

- Coordinator
- Representative
- Gatekeeper
- Itinerant Broker
- Liaison

Time (seconds)

- Cycle - Duration
- TTriad - Duration
Brokerage Roles

Closing Time for Brokerage Roles of Triads

- Coordinator
- Representative
- Gatekeeper
- Itinerant Broker
- Liaison

- Cycle - Closing
- TTriad - Closing
Analysis of online networks

How can we understand the dynamics of information exchange among networked users?

- Twitter messages are a dynamic stream of events
- Twitter users form dynamic connections through mentions, replies and re-tweeting
- Can we identify structures in these networks using these techniques?
- Can we apply social network theory to the highly dynamic networks generated by social media exchanges?
Understanding Twitter networks: a collaborative project with the University of Melbourne

Can we identify structure among hashtags and Twitter users?

Over time, do we see changes in users, hashtags and their structures?

Twitter data: A bi-partite network of users (blue nodes) and associated hashtags (red nodes)
Understanding Twitter Discussion Threads

Information flows

By whom, where and when do they originate?

How far do they travel?

Can they be controlled or manipulated?

What can we learn from the paths they trace?