Understanding Dynamic Interactions

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ABSTRACT

We outline some recent mathematical and computational ideas that deal with dynamic patterns of connectivity in digital communication. Typical examples are email, voice mail and on-line interactions. This new branch of network science addresses issues such as: where is the best place *and time* to start a rumour, which players have the ability to *exploit the dynamic structure most effectively* and how will the network evolution *respond to external stimulus*? In a new experiment we apply dynamic centrality measures to an email data set involving Enron employees. This reveals how an individual's ability to communicate across the dynamic network correlates with their position in the company hierarchy.

Categories and Subject Descriptors

J.4 [**SOCIAL AND BEHAVIORAL SCIENCES**]: Sociology—*communication network measures*

General Terms

MANAGEMENT, HUMAN FACTORS, MEASUREMENT, THEORY

1. BACKGROUND

Network science has emerged as an excellent tool for understanding the patterns of connectivity that arise in natural and engineered systems [8]. However, when applying traditional concepts from the field of social network analysis, it is easy to overlook the fact that many emerging network data sets are dynamic—the links appear and disappear over time [5]. For example, email, voice calls and on-line socializing produce structures that continually evolve. The arrow of time raises many interesting issues. Consider the case where A interacts with B today and B interacts with C tomorrow. Because of the timing of the interactions, news, or infection, may pass from A to C, but not from C to A. So models and algorithms that aim to describe or extract information from dynamic networks must respect the time dependency of the links.

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The mathematical sciences can contribute at two distinct levels. First, models that encapsulate possible 'laws of motion' can be devised. This allows hypotheses to be tested and 'what-if' scenarios to be simulated—in particular, various types of external intervention could be investigated that correspond, for example, to targetted advertising campaigns, malware attacks or breakdown of infrastructure. Second, for a given evolving network, data anaysis techniques specifically designed for the dynamic setting can be applied in order to extract information. For example, we may wish to rank individuals in terms of their importance or profitability.

2. MATHEMATICAL MODELS

Social scientists have empirically observed a *triad closure* effect, where new friendships tend to develop between individuals who currently have friends in common [2]. A mathematical model using this mechanism has recently been formulated and calibrated against real data [3], and an interesting bistability phenomenon was established, where small (microscopic) intervention at the start of the network evolution can have large (macroscopic) effects on the long time behaviour of the system.

Another trait observed by researchers in human dynamics is that certain players may 'punch above their weight' in the sense that their connections are especially timely and influential. Huffaker [6] discovered *on-line leaders* who "trigger feedback" and "spark conversations," and Gleave et al. [1] identified *discussion catalysts* who are "responsible for the majority of messages that initiate long threads." This idea of a hierarchy between players that affects the network dynamics was used in [7] as the basis for a new mathematical model.

3. DYNAMIC CENTRALITY MEASURES

As a means to extract useful information from large dynamic network data, the concepts of *broadcast centrality* and *receive centrality* were defined in [4]. Broadcast centrality measures how effectively an individual can transmit information (or disease) across the dynamic connectivity structure. Depending on the context, good broadcasters would be effective at spreading news, computer viruses, or disease. On the other hand, receive centrality quantifies how much bandwith can be accumulated by an individual, and good receivers are strong candidates for learning about the latest

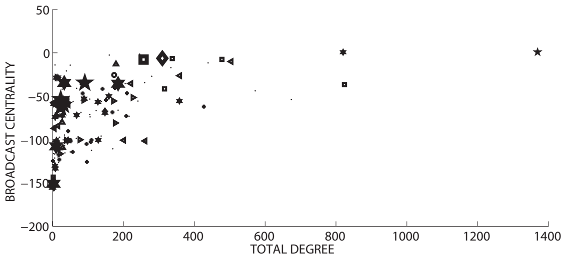

Figure 1: Enron email data: Horizontal axis measures the total email activity for each individual, and the vertical axis measures their ability to broadcast information in the dynamic setting. Symbols indicate position in the company.

rumours or becoming infected. We note that the empirical observations that we quoted above from [1] and [6] are relevant here—these effects depend not only on the *overall quantity* of a person's interactions, but also on their *timing*.

In Figure 1 we show computations on an email data set involving 151 employees of Enron over a period of 1138 days [4]. For each employee, the horizontal axis measures the total number of emails sent, without taking account of their timing or direction. The vertical axis shows the broadcast centrality, which is specifically designed to quantify effectiveness in this dynamic setting. We see that for a given amount of activity (total degree), individuals can span a wide range of effectiveness (broadcast centrality). Some people make more effective use of their bandwidth than others.

Similarly, Figure 2 shows total email activity against receive centrality for each employee.

This data set has the extremely attractive feature that, in many cases, the position of the employee within the Enron hierarchy is known. In the two figures we have used symbols to indicate job satus. Due to space limitations, the details are not given here. In the accompanying presentation, if time permits, we will describe this additional semantic information and show how it can be used to (a) add value to the data analysis and (b) test hypotheses about the nature of the interactions. In particular, we will address questions such as

- who are the on-line leaders/discussion catalysts, and where do these individuals lie within the company's hierarchy?
- do on-line leaders/discussion catalysts prefer to interact with each other, or do they typically avoid each other and cultivate their own set of followers?
- do the dynamic receiver results allow us postulate an analogue of on-line leaders/discussion catalysts in terms of receiving information?
- does job status correlate with the level of dynamic centrality in terms of broadcasting and/or receiving?

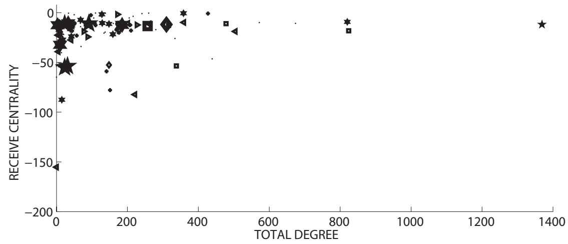

Figure 2: Enron email data: Horizontal axis measures the total email activity for each individual, and the vertical axis measures their ability to receive information in the dynamic setting. Symbols indicate position in the company.

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