Recognizing Expertise

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Introduction

A difficult issue with understanding face-to-face interactions is the lack of context information. Badge-like wearable sensors, for instance, can now tell us who talks to whom, but the context of these interactions (work? social?) likely trumps any content or conversational dynamics information.

Previously, most experiments to assess face-to-face communication networks have aggregated all interaction and behavioral information without differentiating by context. In this paper we detail a study where we have automatic annotations of work context information. We find that this leads to different indications of effective social structure in corporate contexts, showing that behavior during tasks drives the predictive strength of aggregated data.

Background

Expertise

At its core, what is expertise? Informally, we believe that someone is an expert when, for a particular type of question, that person will have the best answer.

The context of interactions with these experts is extremely important. If one of Warren Buffet's friends is talking to him in the gym, chances are they are not discussing the stock market. To recognize expertise, then, it is important to recognize the context of interactions as well.

In the context of this paper, we define expertise as *the centrality of an individual in the social network formed by examining only interactions that occur during work*. This definition is similar to those presented in (Barahona & Pentland, 2006), (Ibarra & Andrews, 1993), (Pujol, Sanguesa, & Delgado, 2002), and so is line with previous work. Here we define centrality as betweenness centrality, although we did not find any difference in predictive ability when we used other network position-based centrality measures.

Sociometric Badges

In order to recognize expertise, we first need to sense the underlying interactions that are occurring in the workplace. For this purpose we have created a wearable *Sociometric* badge that has advanced sensing, processing, and feedback capabilities. With regards to our work here the badges can recognize face-to-face interactions using an infra-red (IR) transceiver and a microphone and detect motion using a 3-axis accelerometer. This platform is described in detail in (Olguin Olguin, 2007).

Experiment

We deployed our Sociometric badge platform for a period of one month (20 working days) at a Chicago-area data server configuration firm that consisted of 28 employees, with 23 participating in the study. Each employee was instructed to wear a Sociometric badge every day from the moment they arrived at work until they left their office.

Task Structure and Productivity Data

Salesman in the field request a computer system configuration, which is automatically assigned a difficulty (basic, complex, or advanced, in ascending order of difficulty) based on the configuration characteristics. Employees in the department we studied are then assigned a configuration task in a first come first served fashion, which may require them to use a computer aided design program in order to satisfy the customer's needs. The employee submits the completed configuration back to the salesman, and the employee is placed at the back of the queue for task assignment. The exact start and end time of each task is also logged.

In our final dataset we have 170 basic tasks, 16 complex tasks, and 34 advanced tasks. In our analysis we only consider basic tasks, although we note that both complex and advanced tasks exhibited similar trends with the basic tasks.

We used (negative) completion time as our measure of productivity, since shorter completion times are more desirable, and in this organization employees are rewarded based on their throughput.

Methods

Recognizing Interactions

We are able to recognize face-to-face interactions by combining IR and microphone information. When two individuals are standing facing each other, there is an IR detection. Combining this with speaking information allows us to determine that the people were actually in a conversation. This method is elaborated in (Waber, Olguin Olguin, Kim, & Pentland, 2008).

Measuring Expertise

In this study we contextualize the interactions by differentiating circumstances where employees are working from those when they are not. We then look at the centrality of each person during work to measure expertise. We use the maximum expertise value of all interaction partners to measure the expertise that was accessed, although this had extremely high correlations with both the summed expertise values and average expertise values ($r = 0.93$, $p < 0.0001$ and $r = 0.82$, $p < 0.0001$, respectively).

Results

In our task level analysis, we wanted to discover if interacting with higher level experts enhanced or hampered completion rate. We controlled for behavioral and productivity differences by dividing all variables by their averages at the individual level, and we only examined tasks where people interacted with others ($n = 35$). In this case, interacting with higher level experts had a high *negative* correlation with productivity ($r = -0.67$, $p < 0.0001$).

The most likely explanation for this result is that people were assigned a task that was beyond their skill level, and therefore they had to talk to other employees with greater knowledge, and the people that are most likely to have that knowledge are those who are central.

Combining this measure of expertise accessed during a task with the standard deviation of movement energy, which we found to be predictive of productivity in a previous analysis of this data (Waber, Olguin Olguin, Kim, & Pentland, 2008), we performed a multi-linear regression. The results of this regression are shown in table 1 below. This model had extremely high predictive power with $r = 0.81$.

Manuscript Status

We have prepared a completed manuscript of this work with additional background details and experimental results. We hope to add late breaking research that uses these results to create organizational feedback mechanisms, which involve analyzing and visualizing behavioral data in real time to effect behavior change. We are planning to deploy this system in a study in the coming weeks.

Total Model: r = -0.81, F = 22.65, p < 0.0001		
Feature	β	p
Intercept	0.31	0.16
Movement σ	-0.29	0.002
Expertise	-0.81	<0.0001

Table 1. Productivity prediction using behavioral features, with the regression coefficients for each feature and their significance.

References

Barahona, J. C., and Pentland, A. (2006). Advice and Influence: The Flow of Advice and the Diffusion of Innovation. *The XXVI International Sunbelt Social Network Converence.* Vancouver, British Columbia, Canada.

Ibarra, H., and Andrews, S. B. (1993). Power, Social Influence, and Sense Making: Effects of Network Centrality and Proximity on Employee Perceptions. *Administrative Science Quarterly* , 277-303.

Olguin Olguin, D. (2007). *Sociometric Badges: Wearable Techonology for Measuring Human Behavior.* Cambridge, MA USA: Massachusetts Institute of Technology.

Pujol, J. M., Sanguesa, R., and Delgado, J. (2002). Extracting Reputation in Multi Agent Systems. *Proceedings of the first international joint conference on Autonomous agents and multiagent systems: part 1* (pp. 467-474). Bologna, Italy: ACM.

Waber, B. N., Olguin Olguin, D., Kim, T., and Pentland, A. (2008). Understanding Organizational Behavior with Wearable Sensing Technology. *Acadmey of Mangement Annual Conference.* Anaheim, CA, USA.