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Mapping Human Networks

Jonathan Gips, Alex (Sandy) Pentland
Human Dynamics Group, The Media Lab, MIT
{jgips, sandy}@media.mit.edu

Abstract

We have developed a method of measuring user interest and affiliation for conference attendees, using behavioral data to collected by 'smart badges' worn by the attendees. These measures allow validation, refinement, and extension of on-line user profiles, improving the dissemination of conference information.

1. Introduction

A core problem in computer-assisted information dissemination is knowing what to share with whom. Two key dimensions in this decision are privacy and interest or relevance, and as a consequence elaborate methods of quantifying these variables have been developed. However most of these methods use precomputed user profiles, obtained either from on-line forms or data mining of personal data, making them inflexible, limiting effectiveness, and creating privacy and security difficulties.

Consequently it would be very helpful to have automatic, real-time methods of measuring interest and preferred privacy settings. Such automatic methods would allow:

- validation of data obtained by traditional means (e.g., the stored profiles say these two people don't know each other, but they are hanging out together).
- provide flexibility to adapt to new circumstances (e.g., the user has shown interest in all the wireless demos they have seen so far, despite the fact that their profile didn't indicate an interest in wireless).
- provide greater insight into user preferences (e.g., all the people who seem interested in the wireless demos also seem interested in VoIP).

To address this problem we have developed automatic detectors of *human interest* and *affiliation* that run on the UbER-Badge [8], an electronic conference badge. The detectors were developed and validated using data from two daylong conferences where attendees "bookmarked" each other and live demonstrations, thus indicating interest, while at the same time the badge recorded ambient audio and upper body motion.

This has allowed us to measure user `interest' and affiliation automatically and during the course of the conference, as will be described in the following sections. These measurements were then combined with profile data obtained from attendees via an on-line survey, and used to disseminate contact and demonstration information.

2. Background

Conferences are great networking events, and it seems natural to use badge-like devices to capture the attendees' networking activity and promote interesting new encounters. Consequently there have been many demonstrations of social support using badge-like or pocket-sized devices, some of which have matured into commercial products [3,4,11]. Below is a sample of the diverse projects in this field.

Active Badge. Perhaps the earliest and best known experiment was the Active Badge system [16], which used early RF tags to allowed a central system to track wearers information, allowing introductions, analysis, and structured recall of users interactions.

Figure 1. The UbER-Badge is worn around the neck and sits on the wearer's chest.

Meme Tag. The Meme tag used IR transceivers to match users on the basis of prerecorded questions. When users who were facing each other had similar answers to the questions, green LEDs would flash; if the answers were different then red LEDs would flash [2].

Hummingbird. The Hummingbird is a custom mobile RF device developed to alert people when they were in the same location in order to support collaboration and augment forms of traditional office communication mediums such as instant messaging and email [7].

Experience Ubicomp Project. Using inexpensive RFIDs with traditional conference badges, the Experience Ubicomp Project was able to link profiles describing many of the conference participants with their actual locations. When users would approach a tag reader and display, relevant 'talking points' would appear on the screen [10].

Social Net. Social Net is a project using RF-based devices to learn proximity patterns between people. When coupled with explicit information about a social network, the device is able to inform a mutual friend of two proximate people that an introduction may be appropriate [15].

Jabberwocky. Jabberwocky is a mobile phone application that performs repeated Bluetooth scans to develop a sense of an urban landscape. It was designed not as an introduction system, but rather to promote a sense of urban community [12].

Serendipity. Serendipity is a mobile phone application that performs repeated Bluetooth scans in order to introduce people to each other. When a scan shows an unfamiliar person nearby, a query is sent to a central server containing profiles of participating individuals; these profiles are similar to those stored in other social software programs such as Friendster and Match.com. When a match of interests is found, an introduction messages are sent [5].

3. Motivation for our system

One of the main limitations of these systems is that their notion of human interest is set either by answering a few questions before the interaction, or is simply built into the system design. This limits the range and flexibility of these systems, making them feel more like party games than serious networking tools.

The goal of our interest detector is to remove the restrictions imposed by use of preset questions and the requirement that users explicitly `bookmark' interesting people/events. Instead we want to measure interest directly from normal human behavior. With the affiliation classifier, we aim to infer relationships between subjects without any such explicit labels. A person should be able to pick up a badge, wear it, and have the system learn the group of people with whom he associates.

If we can achieve both of these goals, then we can begin to group people by the pattern of interests they display, and make introductions based on these patterns, without requiring users to answer preset questions or input new data during the networking event. By learning the affiliations between people, we gain a social network that can be used to further guide the introductions.

There is reason to believe that we can make good estimates of peoples' interest level and affiliation from sensor data *without* requiring explicit interaction. In Malcolm Gladwell's popular book, *Blink*, he describes the surprising power of "thin-slicing," defined as "the ability of our unconscious to find patterns in situations and people based on very narrow 'slices' of experience" [6, p. 23]. Gladwell writes, "there are…lots of situations where careful attention to the details of a very thin slice, even for no more than a second or two, can tell us an awful lot" [6, p. 47].

Gladwell's observations reflect decades of research in social psychology, and the term "thin slice" comes from a frequently cited study by Nalani Ambady and Robert Rosenthal [1]. They have shown that observers can accurately classify human attitudes (such as interest) from non-verbal behavior using observations as short as six seconds! The accuracy of such thin slice classifications are typically around 70%, corresponding to a correlation between observer prediction and measured response of about r=0.40.

Our initial experiments using a range of motion and sound features indicate that it is possible for computers to duplicate this human perceptual ability [9,13]. We therefore set out to measure human interest levels and affiliations using the sensors and computation capacity of our badge platform.

We created the interest detector described in this paper by using the bookmarks recorded by the

UbER-badges as labels for the sensor data. Individual models were created for both badge-to-badge and badge-to-demonstration encounters.

Our affiliation detector draws upon company names as ground truth for its learning. The classifier infers dyadic affiliation based on observations of face-to-face encounter duration as well as correlations in badge motions over time.

The interest classifiers can run in real-time on the badge microprocessor alone, allowing classification of user interest during the course of the event. The affiliation classifier runs in real-time mostly on the badge, but requires using the badges' RF link to a PC server in order to compare results between badges.

4. System description

The UbER-Badge [8] is a conference-style badge that enables the development of wearable applications that scale up to hundreds of people in a single event. The badge includes electronic components to sense information about the wearer's context, display both private and public messages, and communicate with other badges both in face-to-face encounters and over distance. In particular, the badge includes audio and two-axis acceleration sensors, together with a short-range, forward-oriented IR transceiver.

In the fall of 2004, we collected a day's worth of data from a sponsor meeting at the MIT Media Lab. One hundred and thirteen sponsors wore the UbER-Badge throughout the course of the conference, which ran for approximately eight hours. In addition to deploying UbER-Badges, infrared (IR) beacons called Squirts were positioned at seventy-six project demonstrations. Sponsors were instructed to press a button on their badges when they encountered either another badge wearer or a Squirt demonstration that they desired to "bookmark". They were told that after the conference bookmarks would be downloaded from the badges and reported to the originating bookmarkers, facilitating further contact and deeper exploration of personal interests.

We collected a second dataset during the spring of 2005 sponsor meeting. At this conference, eighty-four sponsors bookmarked each other and ninety-three demonstrations in the same manner as in the fall.

4.1. Sensors

Our detectors continuously sample the accelerometer and microphone. Accelerometer readings are taken at 100 Hz, and an average sample for each of the two dimensions (ACC_X, ACC_Y) is computed and recorded every twenty-five samples (4 Hz).

Microphone readings are taken at a rate of 8 KHz and averaged every eight readings yielding a down-sampled rate of 1 KHz. These averaged readings are used to create two different samples with different characteristics. The first measurement is the average amplitude (AUD_{AMP}), and we calculate it by accumulating the absolute value of the averaged readings and dividing the sum by the frame size. The second measurement is the average difference between the 1 KHz averaged readings (AUD_{DIF}). Similar to the average amplitude, we accumulate the differences between successive averaged readings and divide by the frame size. The frame size for our experiment was 256 samples producing a final audio feature sampling rate of 3.91 Hz.

The UbER-Badge contains a 2 MB dataflash for nonvolatile storage. The aforementioned sampling rates produce an upper bound of about 13.5 hours of recording time before the badge fills up.

4.2. Interaction

Both the UbER-Badge and Squirt transmit IR packets with unique identifiers at regular intervals of about a second. These packets are received at up to six meters away within an unobstructed conical field of view of approximately ninety degrees. As a badge wearer walks around, his or her badge may encounter other badges and Squirts. If a badge sees one or more badges at any given time, it displays a shifting pattern of blue LEDs that indicate to the parties that the badge recognizes the current encounter. An encounter with a Squirt is not displayed on the badge but rather triggers an LED on the Squirt, which is affixed to a point of interest. During our event, Squirts were attached to placards associated with demonstrations.

The wearer may bookmark these encounters by pressing the button on the badge inwards (Figure 2). Pressing the bookmark button results in an animated check mark appearing on the target's badge. Squirts that receive bookmarks flash a red LED for feedback. The duration and end point of these encounters, as well as the occurrence of a bookmark event, are recorded to the badge's dataflash.

5. Training data set

The fall sponsor meeting resulted in a data set that included data from 113 badges and 76 Squirts. Unfortunately, due to a combination of hardware and software problems, a sizeable (but random) part of the full sensor data was lost.

We corrected these problems for the spring meeting and successfully collected data from 84 badges and 93 Squirts – 78 of which encountered badges. Figure 3 shows plots of the accelerometer and audio signals over the course of the day. The three vertical troughs of low activity represent periods when badge wearers were attending presentations in the auditorium.

5.1 Sample size

Figure 2. The person in the middle is bookmarking the person on the right.

After validating the data, we isolated sections of the sensor data that pertained to the badge-to-badge encounters (`badge encounters') and the badge-to-demo encounters (`Squirt encounters'). Within each of these categories, we further divided segments into two groups: 1) those that received bookmarks and 2) those that did not. This resulted in the dataset shown in Table 1.

5.2 Features

Using this sensor and interaction data, we created a 15 dimensional feature vector for every encounter.

The average amplitude (AUD_{AMP}) and average difference (AUD_{DIF}) samples were subtracted to create a third audio measurement (AUD_{SUB}). For each encounter, the means ($\mu_{AUD_{AMP}}, \mu_{AUD_{DIF}}, \mu_{AUD_{SUB}}$) and standard deviations ($\sigma_{AUD_{AMP}}, \sigma_{AUD_{DIF}}, \sigma_{AUD_{SUB}}$) of these measurements were used as audio features.

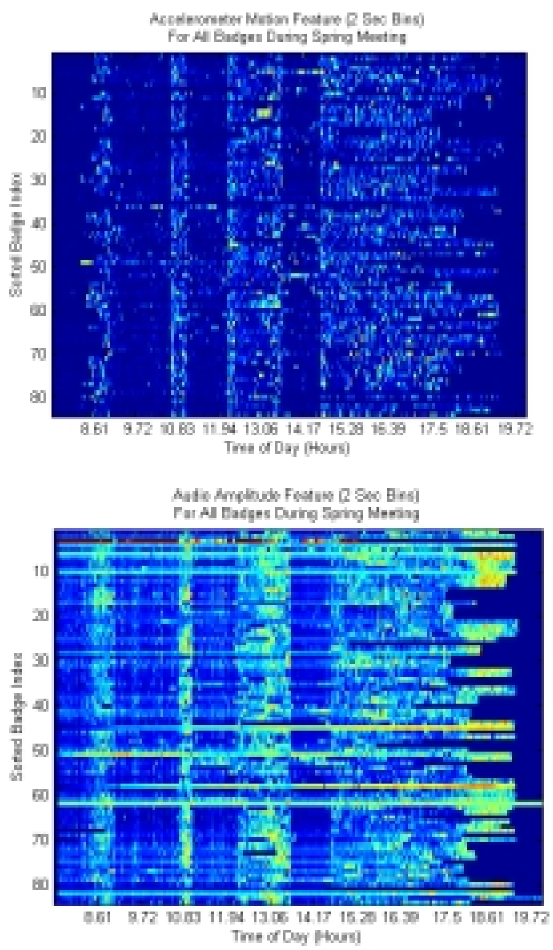

Figure 3. Two features created from the accelerometer and audio signals, respectively, are shown binned over two second intervals.

In a similar manner to the audio measurements, the accelerometer measurements (ACC_X, ACC_Y) were subtracted to create a third accelerometer measurement (ACC_{SUB}). For each encounter, the means ($\mu_{ACC_X}, \mu_{ACC_Y}, \mu_{ACC_{SUB}}$) and standard deviations ($\sigma_{ACC_X}, \sigma_{ACC_Y}, \sigma_{ACC_{SUB}}$) of these measurements were used as audio features.

The remaining three features were derived from the IR data and represented the number of encounters that occurred during the encounter (IR_{COUNT}), the sum of the lengths of all the encounters that occurred during the encounter (IR_{SUM}), and the length of the specific encounter being considered (IR_{LEN}).

In addition to the per-encounter features, we created a symmetric adjacency matrix that contains the sums of the durations that each dyad of badges spends within IR range of each other. These sums were accumulated for the course of the entire spring event.

5.3 Normalization and data quality

Two types of preprocessing were performed on the measurements that are used in the feature vectors. First, the sensor data recorded to dataflash ($ACC_X, ACC_Y, AUD_{AMP}, AUD_{DIF}$) was normalized on a per badge basis. This allowed variation in badge hardware to be controlled. Second, the encounter data from the IR was propagated between all badges, to minimize the possibility of an incorrectly labeled encounter in the training dataset.

We also verified that the act of making a bookmark was not skewing the accelerometer features by testing our model on the badge-to-badge encounters that received bookmarks. These badges did not need to be handled in order to receive a bookmark and showed a similar classification distribution to the bookmarked encounters.

6. Analysis

The qualitative differences between the nature of ‘interest’ and ‘affiliation’ led us to consider two different types of features for the detectors. We consider interest to be a quality of a given conversation or encounter. One person may have an interesting discussion with another followed by an uninteresting encounter. Contrastingly, the affiliation between two people transcends the characteristics of an isolated encounter and depends more directly on the longer-term relationship.

	Bookmarked	**Non-Bookmarked**
Badge Encounter	311 (102+209)	3703 (464+3281)
Squirt Encounter	320 (33+287)	400 (42+358)

Table 1. The data set size for badge-to-badge (`badge’) and badge-to-demo (`Squirt’) encounters. Total number in each category is sum of fall and spring conference totals.

6.1. Interest detection

We analyzed the encounter data set with the goal of creating two classifiers: one that would predict bookmarking of badge-to-badge (badge) encounters and another that would predict bookmarking of badge-to-Squirt (Squirt) encounters.

6.1.1. Bookmark correlation. We found strong correlations between the features and an encounter being bookmarked for both the badge and Squirt encounters. Badge encounters showed a significant correlation between accelerometer features and bookmarks, primarily in the standard deviation features.

Squirt encounters showed a very different set of correlations. Audio features exhibited a negative correlation with receiving a bookmark but accelerometers showed no significant correlation at all.

6.1.2. Regression. Using the fall dataset as training data, we picked two separate sets of features from the original set of fifteen encounter features for badge and Squirt encounters. These sets represented the features that had the highest correlations with their respective outcomes – badge or Squirt bookmarks. We then constructed one predictor function for each set of features using a quadratic classifier. Cross-validation was performed using a 5-fold, “leave-twenty-percent-out” method, and decision boundaries were selected such that the difference between classification accuracy for the bookmarked and non-bookmarked encounters was minimized.

Using the six highest ranked badge encounter features ($\sigma_{ACCx}, \sigma_{ACCY}, \mu_{AUDAMP}, \sigma_{AUDAMP} \mu_{AUDDIF}, \sigma_{AUDSUB}$), our quadratic model has a cross-validation accuracy of 82.9% on the fall data. Applying this same model to the spring data yielded a testing accuracy of 74.6%.

For the Squirt encounters, we used a linear regression on the combined fall and spring datasets due to smaller sample sizes. The performance of the top five Squirt encounter features ($\sigma_{ACCSUB}, \sigma_{AUDAMP}, \sigma_{AUDDIF}, \mu_{AUDSUB}, \sigma_{AUDSUB}$) was almost as good with a cross-validation accuracy of 78.3% across fall and spring datasets. Figure 4 shows the classification distributions for both classifiers combining fall and spring datasets.

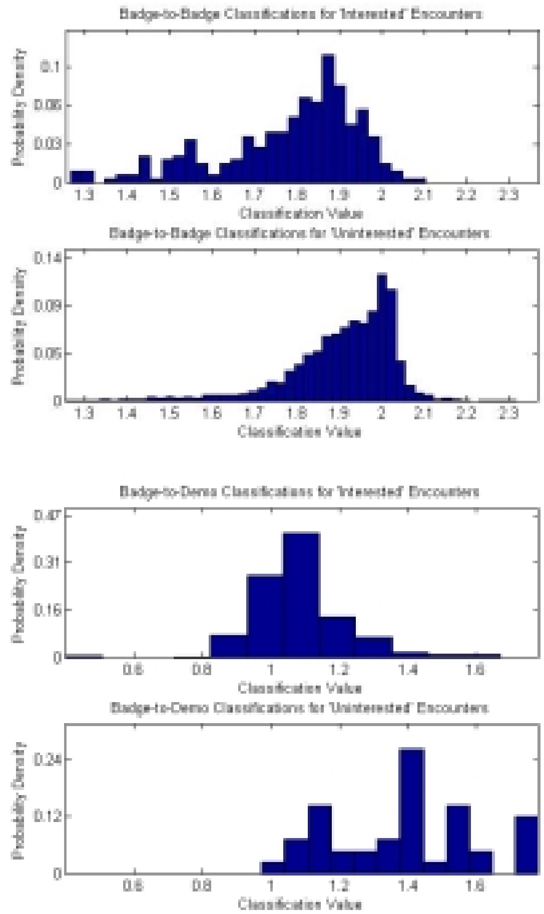

Figure 4. Performance of interest detectors are shown for badge-to-badge (top) and badge-to-demo (bottom) encounters.

6.2. Affiliation detection

We analyzed the encounter data set with the goal of determining what behaviors were useful predictors of affiliation. We found two factors, which can be used independently or in combination.

6.2.1. Cumulative time. Cumulative time spent face-to-face with someone as measured by IR encounters has a medium correlation with whether two people are affiliated or not (r=0.4681,p<0.001). Using this feature alone, a simple threshold model will achieve 88.7% accuracy in determining whether two people are in the same company or not.

6.2.2. Influence. We could also determine affiliations from correlations in wearer activity. To accomplish this we employed the influence model, a partially coupled Hidden Markov Model that can be used to learn "influence values" across multiple chains [14]. We modeled each badge as a Markov chain with two hidden states (moving, not moving) whose observations were accelerometer motion features. Using expectation maximization, we learned the parameters of this model, including the influence values. We found the influence values across two badges correlate with being from the same company (r=0.3981,p<0.001), producing 69.28% prediction accuracy.

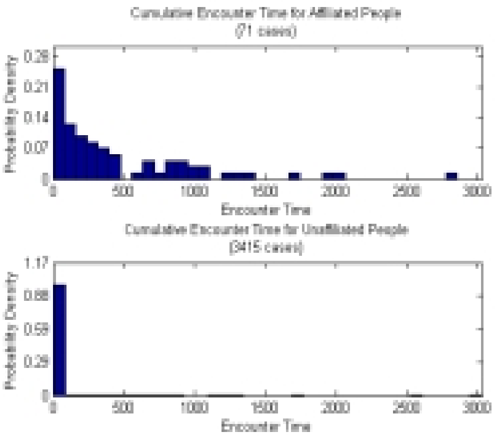

Figure 5. Histograms of the total amount of time that affiliated and unaffiliated dyads of people spend face-to-face with each other.

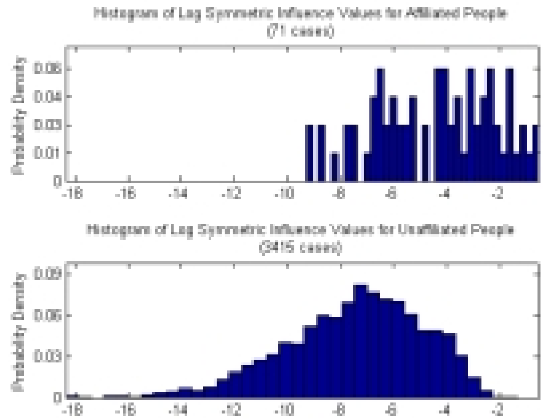

Figure 6. Histograms of log influence values for affiliated and unaffiliated dyads of people.

6.2.3. Combined predictor. Combining the cumulative time and influence predictors using a simple polynomial regression model produces a predictor with a cross-validation accuracy of 92.7%.

7. Discussion and future work

The intuition behind these results is fairly simple. One might expect that animated conversations are more likely to result in being bookmarked. The standard deviations of the accelerometer provide measurements of how much the badge moved around during an encounter, and, indeed, we found that these features play a substantial role in the badge encounter classifier (note that one must be careful to exclude motion due to the bookmarking itself). Similarly, one might expect that demonstrations where people are paying close attention will tend to be quieter, as there will be fewer other simultaneous discussions.

Similarly, two people with the same affiliation probably already know each other, and hence are more likely to spend time walking together among the various exhibits. People who explore the demonstrations together will have correlated patterns of activity.

8. Conclusion

Our analysis shows that we can automatically generate bookmarks that approximate the decisions made by UbER-Badge wearers with 80% accuracy, without taking into account personal characteristics, history, or other prior knowledge. Similarly, we can infer affiliations of the wearers with greater than 90% accuracy, again without prior knowledge.

The classification models that produce this accuracy have straightforward implementations, which make a real-time, interest classifier implementation possible on the UbER-Badge. This capability allows validation of stored profile data obtained by traditional means such as on-line registration surveys, provides flexibility to adapt to new circumstances by adapting the profiles based on user behavior, and provides greater insight into user preferences. Informal survey of the attendees who used our systems showed that the combination of these automatically generated assessments with on-line survey data collected at registration time could substantially improve the users' experience over that obtained using on-line survey data alone.

9. Acknowledgments

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