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A Pilot Study of Status Sharing and Guessing in Cacophony

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A Pilot Study of Status Sharing and Guessing in Cacophony

THESIS

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in Information and Computer Science

with concentration in Informatics

by

Shih-Chieh (Jeff) Lee

Thesis Committee,
Professor Donald J. Patterson, Chair
Professor Gillian Hayes
Professor Bill Tomlinson

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Abstract of the Thesis

A Pilot Study of Status Sharing and Guessing in Cacophony

By

Shih-Chieh (Jeff) Lee

Master of Science in Information and Computer Science

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University of California, Irvine, 2014

Professor Donald J. Patterson, Chair

The concept of the Internet of Things (IoT) has been thriving over the last couple years. As computing systems have become more ubiquitous due to the reduced prices of chips and sensors, the proliferation of mobile devices and sensors has created opportunities for context-aware applications. Previously, we have built Cacophony, a network of peer-to-peer nodes where each Cacophony node (C-Node) is capable of monitoring, reasoning about, and providing real-time prediction of a specified set of sensors in the wild. However, making meaning out of data from sensors and aggregating data from other C-Nodes can be difficult. A robust system is necessary for C-Nodes to deal with unavailable nodes and communicate with other online nodes in a peer-to-peer network.

In this thesis, I propose a new communication model for sensors on the basis of sociological theories. I have developed a group status system to examine people's mental process of building awareness of their friends' daily trends of life and have conducted two pilot studies to gain a deeper understanding of computer-mediated communication behaviors. In the pilot studies,

participants are required to report their statuses and guess their friends' via their smartphones every three hours from 9 A.M. to 9 P.M. Through follow-up semi-structured interviews with the participants, we uncover their rationale for the status they reported and their behaviors in computer-mediated communication by drawing on social exchange theory and social penetration theory. The results give new insights into communication behaviors between humans and help us establish a different communication model for C-Nodes, as human communication in a (social) network can provide a template for how C-Nodes interact in a peer-to-peer computer network.

1 Introduction

1.1 Cacophony project

With development in mobile devices, sensors, and embedded systems, computing systems have become more ubiquitous and provide advanced connectivity of devices and systems. Many of these embedded devices and sensors are connected to Internet services in order to manage and monitor data in real-time. In addition, “virtual” sensors can be created as software that monitors a certain set of real-time information online: for example, the mood of a city can be captured through geographic sentiment analysis derived from Twitter feeds (Kouloumpis, Wilson, & Moore, 2011). Although the interconnection of these objects, or the Internet of Things, has created increased opportunities for context-aware applications, it is difficult to manage the opportunities afforded by the scale of this trend.

Hence, Cacophony has been built to conquer these obstacles. Cacophony prediction nodes (C-Nodes) can be used by any application with access to the web. Creating a new C-Node involves three steps: (1) Developers and domain-knowledge experts, via a simple web UI, specify which sensor data they care about—possible sources of sensor data include stationary sensors, mobile sensors, and the real-time web. (2) The C-Node automatically aggregates data from the relevant sensors in real time using a next generation JXTA-based peer-to-peer network. (3) The C-Node uses the aggregated data to train a prediction model via the Weka machine learning library.

1.2 Challenges and Opportunities

While the Cacophony network has been designed and prototyped, there are still some inherent difficulties with no straightforward answer for discovering, fusing, and reasoning with data from a heterogeneous set of distributed sensors. In statistical machine learning, the sensor data is specified by domain exports before the predicting model is trained, but this is not feasible for the fast changing machine learning models that each model may refer to in the real-time Cacophony network. In Cacophony, each C-Node can communicate with each other, reducing duplication of effort and creating an effective use of computing and monitoring resources. After domain-knowledge experts specify which sensor data they care about, the configuration is malleable and subject to change, because the meaning of each sensor might subtly change over time. A communication model for C-Nodes is required to deal with fast changes and to handle unavailable sensors/C-Nodes.

When designing the technical architecture of Cacophony, we built an instant messenger on Android phones that use the same communication protocol and the same peer-to-peer network to examine the possibilities and analyze the performance of Cacophony. This inspired us that the way C-Nodes communicate with each other is similar to how humans act and communicate in a social network. Hence, we decided to discover how people communicate with each other in computer-mediated communication and to make meaning of a friend's or a stranger's status with limited information. We hypothesize that this result will help us establish a better protocol for C-Nodes.

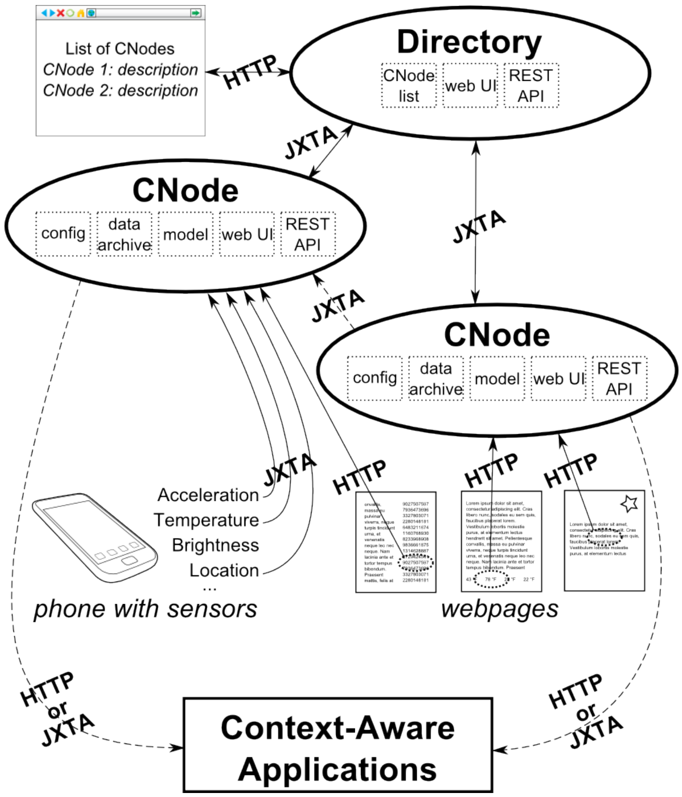

Figure 1. A diagram of the Cacophony network showing the flow of sensor data, predictions, and C-Node metadata[1].

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[1] The diagram is depicted by John Brock in "A Peer-to-peer Machine Learning Layer for the Internet of Things". Unpublished manuscript.

1.3 Study Objectives

The goal of this thesis is to gain a deeper understanding of how human participants share their statuses and establish awareness of others' activities in order to help propose new design insights for C-Nodes and Cacophony more broadly. The results of the pilot studies conducted in this thesis will be a foundation of "group status" experiments for examining how human participants make meaning of sensor data.

1.4 Research Questions

The previous sections suggest that human communication behaviors can be utilized as a template for C-Nodes, and the way humans establish awareness can be used to theorize how C-Nodes could make meaning of a set of sensor information. The investigation for communication behaviors via the group status system is the starting point for research in this thesis. My research questions includes:

1) What factors do people consider when they share their activities?

2) How do people guess their friends' statuses or activities? What is the difference between closed friends, acquaintances, and strangers whom people establish awareness of?

3) How can we apply the results to the communication model for C-Nodes?

1.5 Contribution

Driven by the trend of the Internet of Things, the amount of available online sensors has increased rapidly with the development of mobile devices. This thesis focuses on the construction of an experimental system for research in message sharing/guessing and awareness, and takes a close look at two pilot studies conducted as a foundation for conducting a more complicated experiment in the future. Drawing on social exchange theory and social penetration theory, we propose a communication framework for C-Nodes. This thesis makes the following contributions:

First, a peer-to-peer instant messaging client application as a proof of concept of a next generation JXTA-based peer-to-peer network on Android devices.

Second, a group status system that is designed and built to conduct various status sharing/guessing research in either client-server or peer-to-peer architecture.

Finally, an analysis of insights of participants' status sharing/guessing behaviors by conducting a pilot study of group status setting behavior and positioning them against theories.

2 Related work

The previous section underlines the difficulties of the Cacophony project and the opportunities of how we can utilize an experimental system to reveal human communication behaviors as a template for C-Nodes. Recent work in HCI, UbiComp and CSCW has explored and discussed the issue of context-aware applications and activity recognition.

2.1 Context-Aware Application

Context-aware computing is one of the main properties that distinguish the field of ubiquitous computing from other disciplines. It has received much attention with the paradigm shift from desktop to mobile devices, which has brought technologies from relatively stable and predictable office environments into the “wild”. With the trend of the Internet of Things (National Intelligence Council, 2008), the main idea of Weiser’s vision (Weiser, 1991) – calm technology – seems possible to be achieved in the near future. To reach the goal of calm technology, a ubiquitous computing system should be context-aware to inform without demanding users’ focus or attention, and to make the computer like a quiet and invisible servant, which could realize and extend users’ unconscious needs (Weiser & Brown, 1995). Hence, improving the computer’s access to context could enhance human-computer interaction, especially in mobile computing or ubiquitous computing. By collecting implicit context and information, the system should be able to adapt itself to context, take full advantage of the context, and respond to users’ need or action.

Before realizing the need for context, the system should understand what context is. As Dourish (2004) states, Context “keeps to the periphery and slips away when one attempts to define it”, because it is “a form of information” but not information itself. Besides, context and activity are different and separable. The computer may gather the context of the user’s environment. As Dourish (2004) explained, “ The context describes features of the environment within which the activity takes place, but which are separate from the activity itself.” User’s activity would change some factors in the surroundings (and context), although describing an appropriate name for an activity is at least as difficult as figuring out what an appropriate context is because the name participants pick is highly dependent on the relationship between the "namer" and the "audience". Therefore, in order to establish a context-aware application, a ubiquitous computing system has to collect a wide variety of context from the environment, the content, or even the activity itself.

Mobile devices are often equipped with various sensors, such as GPS, accelerometers, ambient light sensors, and noise sensors. This can help us develop more in situ activity recognition systems in various settings (Baek, Lee, Lim, & Huh, 2005; Favela et al., 2007). However, many existing activity recognition studies have focused on single user activities. People usually perform activities in a group since we live in social groups. In this thesis, we refer to such activities as group statuses. The existing user activity frameworks focused on single user’s activity recognition so they might not be able to deal well with group statuses. Hirano & Maekawa (2013) gave an example of the limitation of single user activity recognition frameworks:

> “Assume that a user is attending a meeting and is taking notes: When we perform single user activity recognition focusing only on the user, we may be able to determine that she is taking notes. However, we cannot know that she is attending a meeting solely from her sensor data. “

By developing group activity recognition framework, we can not only strengthen the ability of context-aware application for providing better services but also enhance the recognition accuracy of single activity recognition.

2.2 The Nomatic System

Nomatic*IM (Patterson, Ding, & Noack, 2006) is a machine learning recommendation system for placing predicted activities into an instant messenger (IM) custom status (in lieu of "Available" or "Away"). It recommends a status update when it detects there is a significant context change, such as a change in a user's location. Users have the option to accept the recommendation or reject it and compose their own status update. Nomatic* IM records user decisions in both cases and uses this data as the ground truth for training machine learning models. In this thesis, the application will be built on the basis of the concept of Nomatic* IM in order to collect sensor data and shared statuses.

Nomatic*Viz (Ding & Patterson, 2009) is a situated large display placed in the community space that shows people's status messages to complement Nomatic*IM. Nomatic*IM can suggest user's status messages based on contexts categorized from various built-in sensors such as Wi-Fi access points, battery charging status and ambient light. The Nomatic*Viz display shows status messages including location, activity and mood information; it could provide straightforward information of individuals as a whole community. The community here can be considered as complete work group at the same workplace, so everyone in the same workplace could be aware of what others are doing and what they have done as entire community behavior. The visualization of status messages of a community can support more lightweight and peripheral awareness of group activities, promote active engagement through data interpretation and then make individual work more visible.

Although these two works focused on individual status updates and how to label an individual activity or context, the concept of status and machine learning in Nomatic*IM and the concept of community in Nomatic*Viz both provides a foundation of this thesis.

2.3 Group Activity Recognition

Single user activity recognition usually collects data from physical sensors such as body-worn acceleration sensors and position sensors on a mobile phone (Maekawa & Watanabe, 2011). As Maekawa & Watanabe (2011) states, in order to conduct group activity recognition, some sensor-based studies recognize the single activity first and then construct a vector of the recognition results; others simply construct a vector of features extracted from collected sensor data. These types of group activity recognition frameworks are not adaptable to changes in the number of users.

Gu et al. (2009) states "group activity is not necessarily the same as the sum of the activities of the individuals in it." Gordon et al. (2012) further explained, "This implies that the activity or context of a group is a function of the activity or context of each individual in the group, in the same way that the context or activity of a single user is a function of sensor measurements." A pre-defined model or a machine learning model is required in order to select and deal with multiple sensor data. The source of sensor data can range from physical sensors in the wild to personal wearable sensors. However, the data collected from wearable sensors on multiple users cannot be used to form the group context without data aggregation. Despite data aggregation, a previous study showed that group activity recognition could be conducted on data at different levels of context abstraction (Sigg et al. 2011). The lower abstraction level contains more information, like a stream of values direct from sensor measurements, but it requires more energy for transmitting this data. On the other hand, the higher abstraction level contains context labels (e.g. meeting) and it takes less cost to communicate, but it contains less information about the ground truth (Sigg et al. 2011). However, these abstraction levels are not connected without appropriate interpretation. One of the goals in this study is to fill the gap between these levels by presenting collected sensor data at a high abstraction level in order to examine how Mechanical Turkers comprehend high level context.

3 Materials and Methods

I have developed an Android smartphone application in order to have people report their ground truth activities and to collect sensor data from their smartphones' built-in sensors. We need these data in order to perform activity recognition. After collecting self-reported activities and sensor data, we used Amazon Mechanical Turk, a crowdsourcing platform, to have people who are independent of participants' groups summarize the group statuses. Semi-structured interviews with participants who use the application were conducted after the experiments. In this section, technical details of the system and experiment protocols are described.

3.1 The Systems

A peer-to-peer instant messenger (IM) client has been developed as a preliminary investigation into the development of the research agenda and a proof of concept of Cacophony's next generation JXTA peer-to-peer network working on Android devices (Figure 2). I explored different types of interface design in order to reflect what happens when people chat on a peer-to-peer network – the message is being sent only when the receiver and the sender are both online. This instant messenger client had inspired us that how humans communicate in a peer-to-peer network is similar to C-Nodes communication. Hence, I developed a group status application that enables participants to share and guess statuses in order to observe how individual nodes would interact with each other.

The group status system contains three units: 1) an Android application for collecting participants' activities and sensor data, 2) a server for aggregating and storing information and raw data into a database from participants, and 3) a crowdsourcing analyzer that can parse the data from the database and submit human intelligence tasks (HITs) to Amazon Mechanical Turk. The architecture is shown as Figure 3.

During the pilot study, the participants were required to report what they were doing and guess what their friends might be doing through the Android application (Figure 4). When the application uploads collected information and sensor data, it retrieves the answers from the participant's friends at the same time, so the participant can see whether their friends' answers match their current activity or not. Uploaded data is stored in a database on the Google App Engine for retrospective analysis. The crowdsourced tasks are conducted after the end of the pilot study in order to lower the risk of accidentally leaking participants' information in real-time.

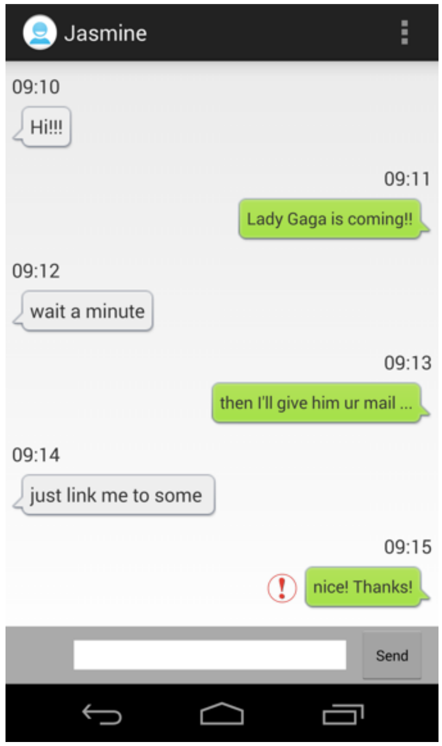

Figure 2. The screenshots of the peer-to-peer IM client for a preliminary investigation.

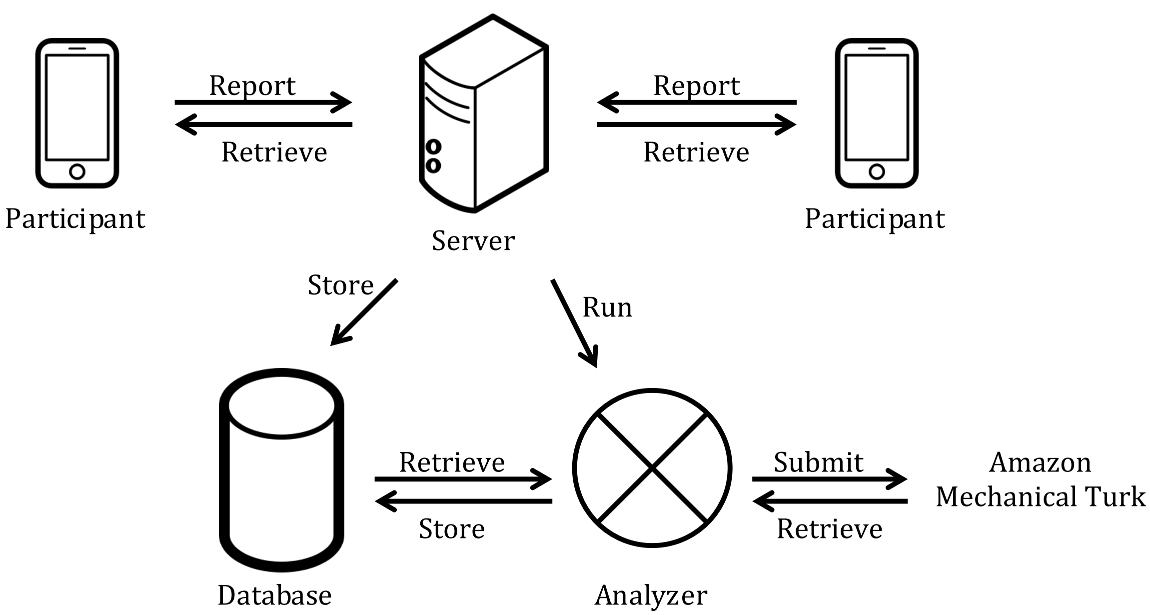

Figure 3. The architecture of the group status system.

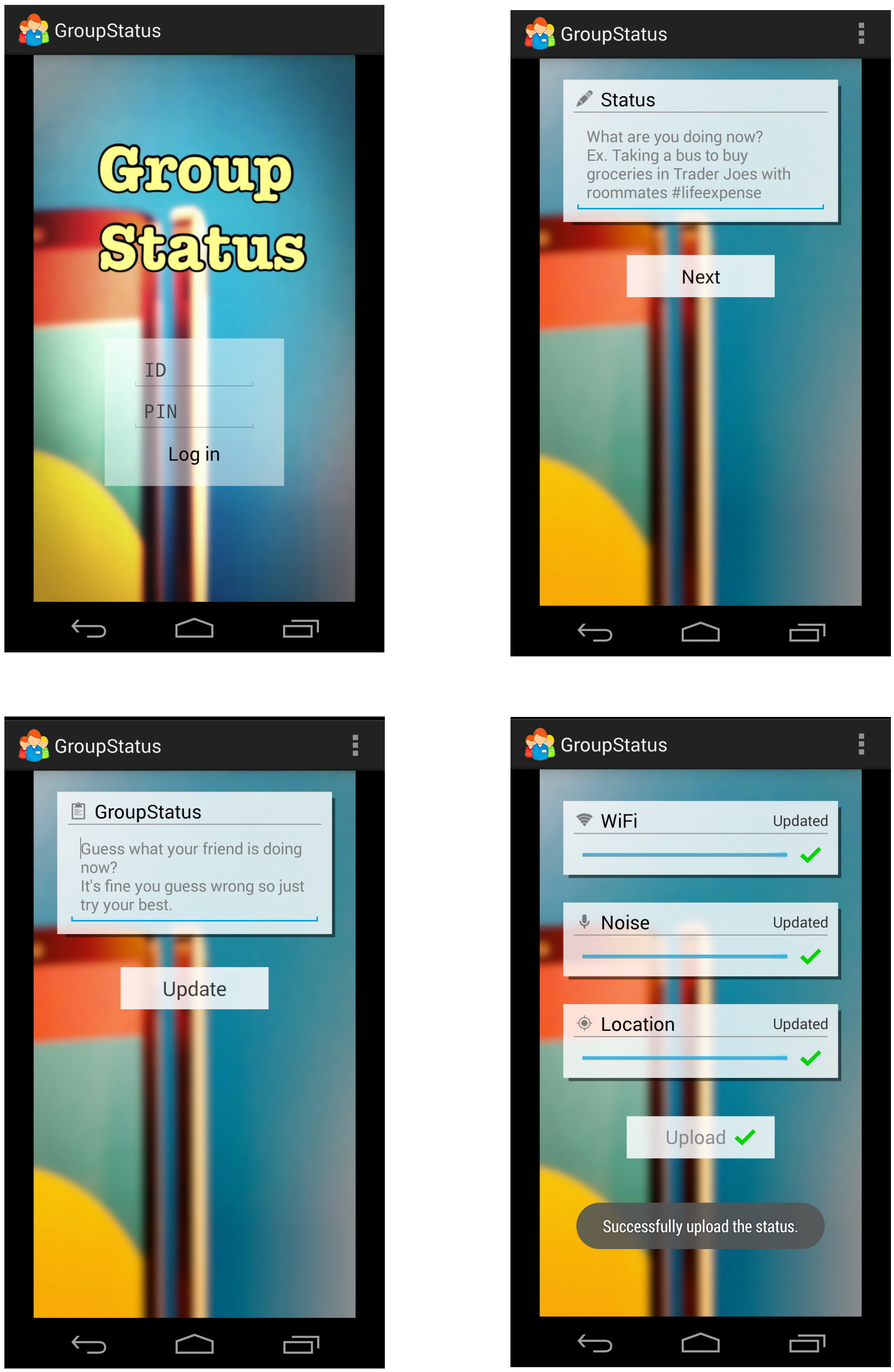

Figure 4. The screenshots of the Android application for the pilot study.

3.1.1 The User Flow of the Android Application

Each participant was given a pair of ID and PIN numbers to use to authenticate with the server. Once a participant logs in, the application receives some basic information about the pilot study, including the starting date and the ending date of the experiment and when the participants should use this application to report their statuses. Subsequently a reminder alarm is set up on the phone to facilitate status captures for the rest of the time in the pilot study.

When the notification alarm pops up, the user can easily click the notification to enter the application. As shown is figure 3, the participant will be asked to enter what he is doing, and then guess what his friends might be doing. While the participant is typing, the application collects data from built-in sensors for statistical machine learning, including 1) the location from built-in GPS, 2) detected Wi-Fi access points, and 3) the noise level in the user's environment.

3.1.2 Amazon Mechanical Turk

Amazon Mechanical Turk (AMT), the crowdsourcing platform in the study, started in 2005 as a service to "crowd source" labor-intensive tasks and has recently become popular among HCI researchers as a source of human computation (Buhrmester, Kwang, & Gosling, 2011). There are more than 400,000 workers registered according to Amazon (Ross, Irani, Silberman, Zaldivar, & Tomlinson, 2010). Because of its huge population of people who are interested in participating in web-based tasks at their own convenience in exchange for money, the crowdsourcing service can provide near real-time feedbacks for labeling or annotating sensor data (Zhao, Sukthankar, &

Sukthankar, 2011) or novel activities that are not recognizable to a system (Lasecki, Song, Kautz, & Bigham, 2013). In this study, we will go one step further and explore the possibilities of human computation of observing information from multiple sources.

Reported activities were stored and cleaned up for duplicate uploads and spelling errors before submitting to AMT. In this study, we hope Turkers, who have the ability to summarize the vague information as human beings, can correctly guess what the participant is doing given certain degree of contexts. The results can be a foundation for informing future group status experiments. Here is an example of human intelligence tasks (HITs) posted on AMT (All options are retrieved from the participant's reported activities.):

> Please choose an option that best describes what this person is doing at 3:00 PM this afternoon given the following description of him:
>
> "A foreign student who just graduated from a grad school and is looking for a job now."
>
> Options:
>
> - Playing guitar
> - Watching a movie
> - Watching NBA
> - Took a nap and just woke up

.

3.2 The Experimental Procedure

This is an observational study of an activity recognition system in conjunction with a crowdsourcing service. The experiment is designed to collect raw sensor data and status updates through the following procedures:

1. **Recruitment**: We recruited 8 study participants through email advertisements to publicly available mailing lists and advertisements on websites of sports clubs, student association, and sports teams in order to ensure they had been familiar with one another before the experiment.

2. **Screening**: An online screening survey was provided to interested individuals within the same club or sports team. Eight individuals who passed the automated screening were reviewed by our research team and invited to come to an enrollment interview. Our automated screening identified adults over 18 who own an Android smartphone and who were willing to report their activities 5 times per day for less than 1 week. Our research team will schedule enrollment interviews with eligible participants based on scheduling availability, resource availability, and a desire to maintain a rough gender balance in our participants.

3. **Entrance interview and setup**: We met interested individuals in person in the LUCI lab on the UCI main campus for a short enrollment interview. This interview entailed describing the study in person and obtaining written consent. The entrance interview lasted no more than 30 minutes and was audio-recorded. Once enrolled, we installed an

application on their Android smartphone and provided necessary training in how the application works.

4. **Data collection**: Data collection has lasted up to 3 days. During this phase, participants used their smartphones as usual, and the Android mobile application still ran on their smartphone in the background. The application prompted the participant to describe whatever activity he was currently performing every three hours from 9 A.M. to 9 P.M. This information was transmitted back to our secure server for retrospective analysis later.

5. **Crowdsourcing task**: After the data collection phase, we organized the collected statuses and the qualified sensor data as a timeline page and created human intelligence tasks on Amazon Mechanical Turk. Turkers followed our guidelines and guessed what the participant was doing at the specified time.

6. **Exit interview**: After Turkers summarizing group statuses, we met with participants one more time in the LUCI lab on the UCI main campus. During this session, we conducted a short exit survey and a semi-structured interview. The interview was audio-recorded and transcribed. The application was removed from the user's phone. Each participant was provided with an anonymous ID number that can be used to delete his or her data in the future if desired.

3.3 Pilot Study

Four groups were recruited for the pilot studies. There were two group members in each group, and they were all asked to report their activity and guess what their group member is doing five times per day. The first group had conducted the experiment for 1 day; the other three groups had conducted for 2-3 days. After they had finished the experiment, we conducted semi-structured interviews with participants in order to find out how people are aware of their friends' activities (Table 1). No compensation has been made for this study.

Table 1. The basic information of some pilot study groups in the study

	Group 1	Group 2
Number of participants	2	2
Profession	New grads	1 year grad students
Experiment period (day)	2	2
Experiment time	While looking for jobs	In finals week
Interview style	Individual interview	Group Interview

	Group 3	Group 4
Number of participants	2	2
Profession	New grads	New grads
Experiment period (day)	3	3
Experiment time	While looking for jobs	While doing internships
Interview style	Individual interview	Individual interview

4 Results

In this thesis, we have recruited four groups, two group members in each group; conducted 10 days of experiment data in total (Table 1). Although two participants kept using the application after the end of the experiment for several days, these data were not stored for retrospective analysis. During the experiments, there are 94 statuses collected from four groups; among collected statuses, 5 statuses are duplicates. 10 statuses were chosen as the ground truth for Human Intelligence Tasks (HITs); other statuses were used for options. 10 HITs were submitted to Amazon Mechanical Turk; there were 300 Mechanical Turk interactions in total.

This section focuses on the results we discovered and concluded from the semi-structured interviews conducted after the experiments. During the interview, we reviewed the status history of their experiment group with participants, asked them to score reported status, and discussed how they reported their activities and how they guessed others'. With transcription and analysis of the interviews, we tried to answer two research questions:

1) What factors do people consider when they share their activities?

2) How do people guess their friends' statuses or activities?

The first question is about the thinking process of posting statuses via the application. Participants were asked to explain their choice of the posted message in terms of their ground truth activities and other participants' guesses. This question could help us understand the attributes of statuses researchers received via the application. The second question can be answered by comparing participants' guesses with their friends' ground truth activities. The results of the comparison are reviewed and discussed with participants in order to have them talk about their mental process of being asked to guess others' activities. By answering this question, we can try to reveal the process of establishing awareness of their friends. Here we list major factors affecting how our participants post and guess statuses.

4.1 The Logic of Posting a Status

4.1.1 Privacy

Some participants said that they would not share personal activities in their statuses. Although the statuses they wrote in this study are only available to other participants in the same experiment group and to the researchers, they still understand reported statuses to be public. One participant said that the degree of details in statuses depends on "how familiar we are". Furthermore, the other participant gives an example explaining how he defines privacy in terms of familiarity with the acquaintance – "A prospective student asked me whether I had found an internship or not. I said yes but I wouldn't actively tell him what I am going to do for internship." Privacy is mostly the first answer we received when we asked participants what is the first thing they consider when posting or changing the status. The results of the interviews show that participants in this study are used to be aware of sharing their activities and information with regards to privacy.

On the other hand, some participants might be more willing to share personal information in this study than on social media. In the experiment description, participants are told to report their current activity and guess others', which is marked as the goal of this study. A participant said that he is willing to report a status with more personal details, because he knew one of the researchers and he realized that his statuses would not be leaked. Although this might be the case of justifying themselves in shared reasons as well, it is almost certain that the receivers always matter regardless of their identities (either the friends or the researchers).

4.1.2 Feedback

Participants expect to receive feedback when they share statuses. They asked whether our Android application would provide feedbacks like others' guesses or the status history when they were first introduced to the application. The direct feedbacks from their friends during the pilot study make a difference, because we got a request from a participant to keep using the application with her friends after the pilot study.

We found that participants would subconsciously choose the activity that might get more feedbacks. For instance, they prefer to share a more evocative status by writing down a more specific activity. One participant said, "When I said 'I am watching NBA finals', I hope my friends would think 'yeah, this guy is watching the game 2 as well.'" The participant would choose an either more specific or more general status in order to gain as much attention as possible. Here are two types of statuses that we found in the study:

1) More general (and shared with a larger group of people)

A participant likes to share a more general status (like "relaxing") rather than a specific one (like "chatting on FB"). This type of status is less specific but more general – more understandable to most people. For instance, writing down "chatting on FB" might not get the participant more feedback than "relaxing", because the former can't provide significantly more hints for other people to give feedback. Sharing a status in an unfocused or imprecise way makes it more understandable to most receivers, because people can interpret the status in their own ways without specific contexts.

2) More specific (but shared with a smaller group of people)

Another participant likes to share a more specific status (like "watching NBA Finals") rather than a general one (like "watching TV"). This type of statuses is more specific but more evocative to some of the participant's friends who are watching NBA as well, so the participants think they would get more feedbacks by arousing further discussion.

Sharing a detailed status in a specified field narrows down the potential receivers who understand the status but raises the possibility of getting feedbacks from them. The depth of a shared status depends on a degree of intimacy, which means how open and close the participants can become with other group members despite their anxiety over self-disclosure.

4.1.3 Significance

On the other hand, another participant said, "I won't say any details if they are not important for me, like watching NBA Finals is important, but watching the talk show is not. … Because NBA Finals only happens once a year." The more the participant cares about the activity, the more he would like to share details. Currently we still don't know the relationship of importance and detail when the participants post their statuses.

Participants would like to share fewer details if they think the activity they write down is unimportant to them. A participant mentioned that he often shares undetailed statuses. For instance, relaxing might implies either listening to music, surfing on the Internet, or taking a nap. "It is too trivial to explain", said the participant when he was asked why he didn't exactly say what he had been doing. For this type of activities, people like to write statuses down in a non-trivial way that allows for many possibilities, if the time it takes to construct a status and post it is much larger than the importance of the revealing details. The results show that these statuses are usually broad topics or the activities that is not related to the group identity shared by the participant and the receivers.

4.2 The Logic of Guessing a Status

There are two major factors when people are guessing their friend's activity; they are both time-dependent. The first is based on a general schedule shared by a group of people. The second is based on personal habits on a basis of a personalized schedule. A general schedule means that the schedule is shared with others who have the same identity and it can be revealed to anyone. It can be a gym class schedule for tennis players, an academic schedule for students, or NBA finals schedule for basketball fans. On the other hand, a personal habit represents a regular practice that is more private and would only be revealed to closed friends. It can be a schedule of the dance class in the gym that you want to try, irregular mealtime or, a schedule of the class that you are most likely to skip.

4.2.1 General Schedule

Most reported statuses are time-dependent. “Time” is always the first answer we got when we ask the participants “why did you guess this?” Many responses starts like “It’s 12 o’clock, so I assume …” because time is the most obvious difference between statuses. Participants start guessing from daily routines or schedules in general, but the shared (academic) schedule might be considered at the same time. A participant said he usually starts thinking with daily routines. In one round, he could guess either “studying for the final” or “having lunch”, but he finally chose the former. He said, “I have considered two possible answers, but I would like to guess the more important one (studying for the final).” In this case, his final guess depends on which corresponds to his friend’s schedule better at the specific time, daily routines or academic schedule.

Table 2. A section of the status history

Timestamp	Participant A’s guess	Timestamp	Participant B’ status
15:01	Sleep	15:45	Took a nap and just wake up
21:01	Playing guitar	21:03	Just took a shower and sitting in front of computer now

This strategy does not guarantee the right answer. For example, a participant who has practiced this strategy in two different scenarios only guessed it right one time, as Table 2. Participant A recalled, “I remember he always takes a nap on Sunday afternoon, so I guessed so.” To participant A, sleeping is part of participant B’s weekly routine, and playing guitar is part of participant B’s daily routine. As participant A said “He usually plays guitar at night, so I guessed so.” However, participant B said he is simply relaxing rather than playing guitar at that time.

(The reason why he didn't specify what he is actually doing is because "it is too trivial to explain".)

Overall, guessing others' activities based on time and schedule is a simple and easy strategy that works if participants don't have a significant or rare event in the near future.

4.2.2 Personal Habits

Close friends know each other very well and they are aware of each other, especially some habits. We list a section of participant C and participant D's status history as an example of how people use their awareness of other's habits to guess.

Table 3. A section of the status history

Timestamp	Participant C's guess	Timestamp	Participant D' status
12:22	Taking a nap	12:46	Eating lunch and watching TBBT
22:45	Playing basketball	23:01	Playing basketball

Timestamp	Participant D's guess	Timestamp	Participant C' status
09:01	Sleep	09:00	Taking a bath
23:01	Eat junk food	22:45	Eating In-n-out

"[Participant D] is used to take a nap before the exam", said by participant C as a legitimate reason for guessing participant D's activity before the exam at that afternoon. Although the answer is not correct, it is pretty close because participant D said he was ready to take a nap after he had finished lunch. Another close answer is participant C's activity at 9:00. He said he had just woken up before he reported that status. Participant D told us that participant C usually goes to bed three hours later than him, but participant C said he had to wake up earlier for the exam at that afternoon.

Using this habit strategy can help people hit the target exactly. As participant C said, "Although I was not sure (when exactly he plays basketball), I thought he is most likely to play basketball at that time because he had just finished the exam or project." The habit strategy can help people narrow down the range easily and guess it right. Participant D said, "It is a good time to eat junk food, as a motivation for studying. Instead of that, I also thought he might be watching movie while eating junk food."

4.2.3 Interaction

The major reason why our participants can guess it right is their interaction with each other. "He would have asked me if he wanted to go out for dinner. He didn't ask my friend or me, so I assume he might be doing some errands." Participant S said that they have a Facebook group, which includes participants of his experiment group. Their interaction influences how the participant conducts simple time/schedule strategy to guesses others' activities. As we mentioned before in the last two sections, people start guessing other's activity with daily routines or habits. Participant S said, "Chatting is part of the daily routines, and usually I would guess routine stuff when you ask me what he or she is doing. If he is doing laundry, I might not be able to guess it. Basically I would guess what he usually does, because it is Sunday. If I have to guess in weekdays, I might guess something different, like preparing for an interview or looking for a job.” Because they are close friends and hang out a lot, participant S would alter his strategy of guessing. “If I didn’t hear any news from him at morning, I would guess he is still sleeping; if I didn’t hear anything from him at afternoon, I would guess he is busying doing something, like coding; at night, I would guess he is chatting on Facebook or something. In a nutshell, our conversation on Facebook affects my judgment.” Chatting on Facebook or in person gives people the context of future schedule and changes their strategy of guessing others’ activities.

Like direct interaction (e.g. Chatting), indirect interaction also matters. Indirect interaction means you get information about someone’s status through a mutual friend. Usually people use time/schedule strategy to guess someone who is not familiar. A participant said he would guess randomly but based on time, like finals week or dinnertime. However, indirect interaction can help them establish awareness of someone. When being asked how he would guess what his acquaintance is doing, a participant said, “I don’t know him very well. …… I might guess based on what I hear from our mutual friends or Facebook invitations.” Indirect interaction provides the contexts of others. One important mutual friend can provide more details than ten normal mutual friends. The familiarity with the person you are going to guess doesn’t matter as long as you have a mutual friend who is familiar with him.

4.3 Mechanical Turk

The results of tasks posted on Amazon Mechanical Turk demonstrate how strangers may guess given basic information of the participants. By comparing the result from the Mechanical Turk and the result between participants, it shows that there is no significant difference between acquaintances and the Turkers. Without having frequent interaction, they both use “general schedule" strategy, especially at the mealtime. Aside from the mealtimes, Turkers' answers generally distribute among available options.

The results from the Mechanical Turk also show that the degree of the reveal of participant's basic information doesn't affect the Turkers' answers. Since all the options come from the statuses uploaded by the same participant, the Turkers have no reference to distinguish between options based on limited information they have.

5 Discussion

Different logics of participants' behaviors are presented in the previous section. By drawing on existing theories, we analyzed the results from the semi-structured interviews and attempted to see how they aligned. The following discussion unveils the way our data supports those models.

5.1 Social Exchange Theory

Homans (1958) defined social exchange as "the exchange of activity, tangible or intangible, and more or less rewarding or costly, between at least two persons". Social exchange theory suggests a simplified model that people make rational decisions based on the net worth of costs and rewards. I assume that the action of sharing a status is a way of managing the relationship between the participant and other group members because it takes time and efforts to construct and post a status. According to social exchange theory, people would share more statuses and devote more into the relationship and be more likely to share statuses among friends only if the net worth were positive.

When explaining the logic of posting a status by social exchange theory, costs are defined as the factors that keep the participants away from posting a detailed status and revealing more personal feeling or information. The factors which are considered as costs include privacy, as the degree of self-disclosure to friends, and how much effort it takes to construct and post a status Rewards are defined as the factors that facilitate the quality and the quantity of shared statuses, and the factors which are considered as rewards include feedbacks and self-satisfaction.

The interviews show that there is no clear logical mind process of posting a status when participants rationalize their concerns in posting a status, but they do consider the trade-off between costs and rewards at some point before they click the share button.

5.2 Social Penetration Theory

Social penetration theory (Irwin & Dalmas A., 1973) suggests an onion analogy of interpersonal communication where the layers of the onion represents how much a person would like to reveal oneself to others with the progress of relationships. There are four stages in a continuous development of the relationship: orientation stage, exploratory affective stage, affective stage, and stable stage (Figure 5).

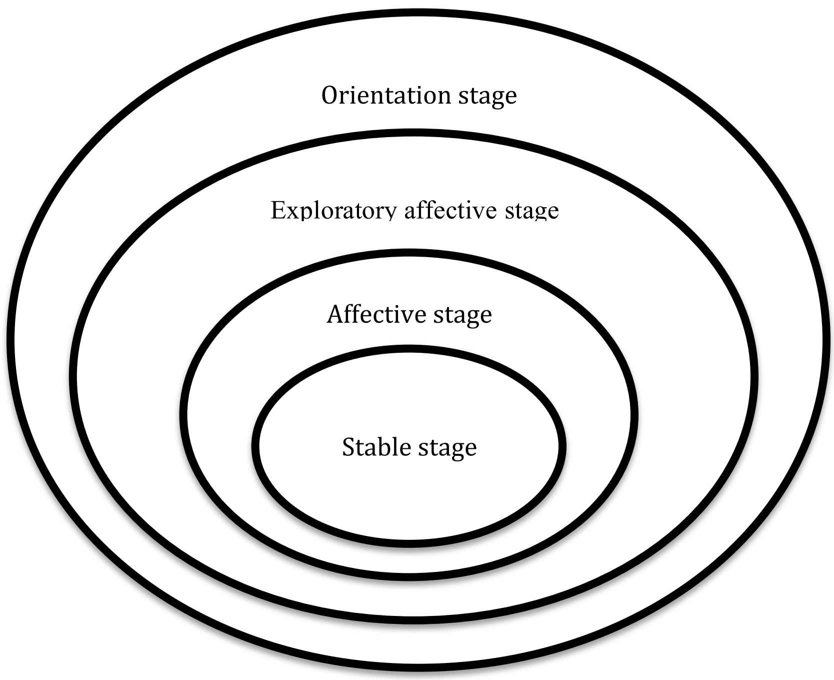

Figure 5. The onion metaphor of social penetration theory (Irwin & Dalmas A., 1973)

The orientation stage is the first stage when people meet others for the first time and reveal harmless information according to social norms, like biographical data or preference in food and music. The exploratory affective stage is where people start to express personal attitudes about topics. The affective stage is where people start to use inside idioms and jokes and share private and personal experience. The stable stage happens when the relationship is stable when people are willing to share personal thoughts, beliefs, values, and the emotional reactions.

Table 3. The onion metaphor of social exchange theory corresponding to the factors of the logic of guessing a status.

Factors of the logic of guessing a status	Stages of the onion metaphor
General schedule	Orientation stage
Personal habits	(Exploratory) affective stage
Interaction	Stable stage

The logic of guessing a status can be explained by the onion metaphor of social exchange theory as Table 3. As mentioned before, general schedule is the first guess coming to people's minds and is how people guess the status of someone they are not familiar with. This exactly corresponds to the orientation stage in social penetration theory. On the orientation stage, people start revealing personal information, which usually represents their identities, like age, race, or occupation. The revealed information helps people establish awareness in terms of certain identities. General schedule is still a fast and easy way to guess friends' statuses, even when the relationship has reached affective stage or stable stage, because the orientation stage contains the most breadth of areas in an individual's life.

When a relationship is in exploratory affective stage or affective stage, they start to know their friends' private behaviors, schedules, and habits. This corresponds to the time-based personal habits factor in the logic of guessing a status. The more deeply the participants know each other than acquaintances, the more they start to know the other person's private or personal schedule.

The stable stage is the final stage in the relationship, and it exposes the core of the individual's personality. In this stage, people interact with each other frequently and establish collective memory; they can predict how the other person will react to certain types of information. The assumption can explain the results in the study. The participants who both said their relationship is very closed had a better performance in the study, as they can guess right about the other participant's status very precisely, which wasn't achieved by the "normal friends" group in the pilot studies. For instance, when participant J reported at 10:30 PM as "eating in n out", his friend in the pilot study group, participant M, guessed J might be "eating fast food". Participant M explained, "I knew him very well, and I thought it was a perfect timing for him to eat something at late night after an exam." Participant M's rational shows how their closed relationship provides him with the awareness of participant J. This awareness needs frequent interaction to maintain, because even a close relationship might fade out over time.

Social penetration theory provides a general model of relationships that help us explain the results of the pilot studies. Furthermore, the theory can help us propose a behavior model for C-Nodes.

5.3 Reflective Thinking Process

Some statuses took no effort to be constructed and posted, but some did. A participant said that he sometimes pondered over the choice of activity included in a status because of the pilot study. Another participant said that he did think before typing their statuses and other's in some cases. This shows that participants sometimes walk through an actual internal process of constructing a status. In this section, we try to infer this process from the transcription of the interviews. When participants are in the thinking process of constructing a status, they might be considering the relationships between the researchers and the participants.

When the participant is asked to write down a status, they take the audience into consideration. If he is asked to report what he is doing, the audience consists of the researchers in the presence of the application. “The medium is the message”, proposed by Marshall McLuhan, means that “the form of a medium embeds itself in the message, creating a symbiotic relationship by which the medium influences how the message is perceived.” (McLuhan, 1964) This applies when the participants report their messages through the application. When the participant is reminded by the pop up notification and types the statuses in the application in the pilot study, they are aware of the fact that the status is shared with the researchers. The Android application developed by the researchers is the medium here in this study. The relationship between the researchers and the participants play an important role because of the interruption in the participant’s real life caused by the application. Since the regular interruptions remind the participants to report their statuses, the application itself is the message as the reminder that makes people reflect on how the audience would interpret what he is doing and conclude a status based on the relationship between the participants and the researchers.

6 Conclusions

In this thesis, I have built a system for message sharing and I conducted pilot studies in order to gain a deeper understanding of group status inference. Through semi-structured interviews, I found factors that people consider when they share their activities and explain these factors by drawing on social exchange theory and social penetration theory. Besides, we also realize how people establish awareness of others in a group and how they guess their friends’ statuses. This can help us design the architecture of Cacophony in the future. The results from Amazon Mechanical Turk shows that it is hard for strangers to guess a participant's current status in terms of his group identify. This will be a foundation of the group status experiment in the future.

Human activity recognition has the potential to provide real-time and task-relevant information in pervasive and ubiquitous computing systems. In fact, being able to recognize a person's current activity accurately is a key component for successful context-aware services. Despite the interest in individual activity recognition, there has not been extensive research published on group activity recognition. The concept of group activity can be defined as a shared status among members of the group, or group status. With the knowledge we acquired in this thesis, we can conduct the group status experiment by extending the amount of group members in the future. By exploiting the relationship between each individual in a group, we can go beyond recognizing the actions of individuals and reveal what group status means to group members. This will help us discover how people establish a group status and help us develop how C-Nodes can make meaning of semantic data.

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