

Investigating Search Behavior and Performance using Personal and Social Context Signals

Dongho Choi
Rutgers, The State University of New Jersey
4 Huntington Street
New Brunswick, New Jersey 08901
United States
dongho.j.choi@rutgers.edu

Emerging trends in smart-phones and wearable devices provide us efficient way through we could observe and understand individuals' behavior and allow for the creation of a rich user behavioral profile. Through a user study, personal and contextual signals from participants' everyday lives were collected, while information search behavior was observed in a lab study. Preliminary analysis over data indicates that possibilities of relationship between social/geo-locational interaction between information search performance.

Keywords: Search behavior, Social context, Wearable devices

1. INTRODUCTION

Emerging technologies and relating devices help people find information and share their knowledge and experience with ease. In addition to the traditional desktop PC environment and smart-phones, diverse types of wearable devices are also quickly emerging as information devices/systems through which people search, produce, and share information. While smart-phones make easier ways to quickly seek information and communicate people, wearable devices tend to be focusing on personalized information, such as notification for pre-defined request and users' biophysical signals. More specifically, various types of sensor on these devices help us understand people's behavior in everyday lives from diverse aspects. Personal and social context information has become much approachable for researchers to study both individual and social behavior in details thanks to the devices and sensors. Interested in exploring signals from various types of sensors and/or devices, a user study was conducted aiming to investigate individual and collaborative search and the factors that relate to them.

2. BACKGROUND

An individual, the person who consumes and produces information, has several intrinsic characteristics, such as general behavioral style and personality, as well as preferences toward social relationship and physical activities. Multiple studies have acknowledged the effect of individual personality, demographic descriptors, and personal context in human information behavior (Burdick 1996). However, most studies had to focus on traits that could be easily observed (e.g. gender, ethnicity) or elicited in a short time in laboratory settings. In effect the human personal context was captured by observations made in short, unnatural settings, as recorded or reported by participants or the study conductor and had to contend with multiple challenges, including subjectivity in observation, recall/cognitive/socio-cognitive biases, and limited observation opportunities.

Meanwhile, collaboration is considered an activity where individual characteristics and social context work simultaneously in complicated manners. Multiple number of person who has different characteristics and background gather and work together to achieve common goal(s). And the basic assumption and/or expectation of collaboration is that through working together physically or timely, they obtain

improved outcomes both in quantitatively and qualitatively. Collaboration often involves working with information, such as collaborative search. Collaboratively searching for information can be found in many domains ranging from education (Hyldegård 2006) to health-care (Reddy and Jansen 2008). However, we lack of understanding when and how people working together could take the advantage of collaboration and the fruits; what kinds of combination of people benefits collaboration regarding their unique characteristics and contexts.

The emergence of mobile phones and sensors that people wear while undertaking activities of daily living is allowing researchers to create rich personalized models of human behavior in social, spatial, and temporal contexts and connect them to various types of outcomes. Singh et al. (2013) used social behavior that was measured through face-to-face interaction, phone call, and SMS use logs, to predict the spending behavior regarding visiting to diverse businesses and overspending. Mobile phone sensors are also used to develop context-aware systems that detects when individual is depressed and he/she requires assistance (Burns et al. 2011), and emotion sensing platform (Rachuri et al. 2010; Yano et al. 2012).

The research questions I have are as follows:

RQ1. To what extent, if any, do behaviors observable via mobile phones relate to information seeking behaviors when people work in individual and/or collaboration?

RQ2. To what extent, if any, do behaviors observable via wearable devices relate to collaborative search behavior?

RQ3. To what extent, if any, are personal signals and social signals different in terms of predicting the search performance?

3. STUDY

3.1. Session Flow

25 student participated in this study through three batches of session during Spring semester in 2015. The workflow of each session is described in Table 1. The participants were invited to a lab for the introduction during which required apps were installed on their phones and a wearable device was given to each of them. During the field study, participants were not asked to do anything specific except keeping the mobile app installed and wearing the device on their wrist on daily life with regular (automatic, in the background) syncing to the

3.2. Lab session

During the lab session, participants were asked to collect relevant information in an exploratory search task on the given topics. The first task (Task 1) was done individually with the topic of “data security, ” while the second task (Task 2) was done in pair randomly assigned with the topic of “health and wellness”.

3.3. Evaluation

In order to measure and evaluate the participants’ information searching behaviors, and compare the differences between those from individual tasks and collaborative tasks, the study adopted a subsets of evaluation measures suggested in Shah (2014) and Shah et al. (2015). A brief description of the framework is presented in Table 2.

4. RESULTS AND DISCUSSION

In this session, results of preliminary correlation analysis between the variables in Table 2 are presented.

4.1. Individual Search Performance

Regarding data collected through mobile app, two features show correlation with some of search performance. The *number of SMS* has positive relationship with *Unique Relevant Coverage*, while *Distinct Location* also has positive relationship with *Unique Coverage*.

The variable of *Number of SMS* shows the extent to which a person interacts with other individuals through mobile texts. Higher value of this variable means a person frequently sends and receives text messages to and from other people no matter who they are. In the meantime, higher value of *Unique Relevant Coverage* indicates that a person visited relatively much number of relevant Web pages during the search task. More specifically, when considering the term “unique,” the person might have distinct and unique criteria for relevancy. When it comes to the exploratory search, the tendency also infers that an individual who sends/receives relatively higher number of messages per day tends to understand and learn the topic differently from others who does not.

One additional interesting finding is the positive relation between *Unique Coverage* and *Distinct Location*. The variable of *Distinct Location* measures that the total number of distinct locations during a day, captured by different cell tower IDs and/or GPS data. This information does not necessarily

Table 1: Session Workflow.

Session	Procedure	Description
Field Session	Introduction	Introduce the study, install required apps and sync the wearable device with a dedicated app.
	Field task	Have participants keep using wearable devices in everyday lives and apps on the phone, collecting their individual and social context data.
	Survey	In the middle of the field session period, ask about their behavioral style, social capital, and information behavior.
Lab Session	Introduction	Introduce the lab session and information-seeking tasks the participants will be given.
	Lab task 1	Exploratory search task-1. Includes pre-survey and post-survey.
	Lab task 2	Exploratory search task-2. Includes pre-survey and post-survey.
	Wrap-up	Wrap-up study and (optional) interview.

for activities or commuting. No matter what the purposes of movement, the result indicate that a person who moves more tends to visit Web pages that have not visited by other participants. This brings us an interesting question: "Does geolocal movement affect information exposure to an individual and affect again toward the way of thinking and understanding?"

4.2. Collaborative Search Performance

Among the features extracted signals, we found relationship between the dissimilarity in the number of SMS counterparts and the synergy effect. This means that the more participants are different with regard to the social activities that are measured how many people they are keeping to talk with, the less synergy effect they have when working together. Though it is not significant enough, we can see the negative relationship between distinct users for SMS and the ratio of increased Coverage. However, if we selected sample with negative synergy effect, the relationship is much stronger and significant.

An another aspect of SMS usage, the number of SMS that an individual sends and receives per day, shows a relationship with the synergy effect on *Relevant Coverage* in collaboration ($N = 12, R^2 = .344, p = .045$). This implies that if members in a pair have substantial difference of the extent of using SMS, they tend to have less synergy effect regarding information relevancy.

Seeing the data, even with very limited number of samples, we came up with an interesting question: "Do the large differences in the values of the same feature from the collaborators matter? Or does the minimum value of each feature among the collaborators matter more for group synergy?" This question is inspired by the "Liebig's Law of Minimum (Odum et al. 1971)," which is originally a concept applied to plant or crop growth. It was found that increasing the amount of plentiful nutrients did

not cause the increasing plant growth and the yield. Likewise, we suspected even if one participant in a team has incredible potential in terms of productivity and efficiency in the task, the results might not be productive as expected, when the other one cannot support him/her very well.

4.3. Limitations and Future Work

There are some limitations on this study. For example, we need to consider the changing techniques and applications people use for chatting, instead of using the conventional simple text messaging. We can easily name a couple of popular chatting applications for smart-phones, which have been replacing texts. The way of using those apps maybe a lot different from the collected data in this study. If we could use a method through which observing interpersonal communication over smart-phones, we can conduct much different kinds of experiments and analysis.

Given that only limited number of features were used, we want to see more different aspects of the collected data. We are expecting to see more diverse perspectives toward the data through visualization and deep analysis with additional aspects, such as diversity, loyalty, regularity and so on.

5. CONCLUSION

Personal and social contextual signals were collected through smart-phone app and wearable device, while information search behavior was monitored during exploratory search tasks. Preliminary analysis over the extracted features from the raw data indicates several interesting points. Regarding individual task, *the number of SMS* has positive relationship with *Unique Relevant Coverage*, and *Distinct Location* has a positive relationship with *Unique Coverage*. When it comes to the collaborative task, social interaction (SMS usage) via phones

Table 2: Variables used in Analysis

Data Source	Features	Description
Wearable Device	Steps	The average number of steps per day of a user during the field study
	Minutes of Sedentary	Average minutes of being sedentary per day recognized by the wearable device
	Minutes of Very Active	Average minutes of being very active per day recognized by the wearable device
	Minutes of Sleep	Average minutes of being asleep per day recognized by the wearable device
Mobile App	Total Call Time	Average minutes of total call time per day
	Number of Calls	Average number of call per day
	Number of SMS	Average number of SMS sent/received per day
	Distinct User (Call)	Average number of distinct caller/receiver per day
	Distinct User (SMS)	Average number of distinct sender/receiver for SMS usage per day
	Distinct Location	Average number of distinct location per day, captured by the app using the number of cell tower around and GPS data
Searching Task	Coverage	The total number of distinct Web documents visited by a participant
	Unique Coverage	The total number of Web documents visited only by one participant
	Relevant Coverage	The total number of distinct relevant Web documents visited by a participant
	Unique Relevant Coverage	The total number of distinct relevant Web documents visited only by one participant
	Distinct Queries	The number of distinct queries that were submitted to search engines by participant

effect of collaboration. Also, our results implies that the difference between collaborators matter with regard to social interaction, while minimum extent of physical activity relate to the outcomes.

ACKNOWLEDGEMENT

I thank ELIAS (Evaluating Information Access Systems) ESF Research Networking Programme for the awarded scholarship for participating in ESSIR 2015 and the FDIA Symposium.

REFERENCES

Burdick, T. A. (1996), 'Success and Diversity in Information Seeking: Gender and the Information Search Styles Model.', *School Library Media Quarterly* **25**(1), 19–26.

Burns, M. N., Begale, M., Duffecy, J., Gergle, D., Karr, C. J., Giangrande, E. and Mohr, D. C. (2011), 'Harnessing context sensing to develop a mobile intervention for depression.', *Journal of medical Internet research* **13**(3), e55.

Hyldegård, J. (2006), 'Collaborative information behaviour—exploring kuhlthaus information search process model in a group-based educational setting', *Information Processing & Management* **42**(1), 276–298.

Odum, E. P., Odum, H. T. and Andrews, J. (1971), *Fundamentals of ecology*, Vol. 3, Saunders Philadelphia.

Rachuri, K. K., Musolesi, M., Mascolo, C., Rentfrow, P. J., Longworth, C. and Aucinas, A. (2010), 'EmotionSense', *Proceedings of the 12th ACM international conference on Ubiquitous computing - Ubicomp '10* p. 281.

Reddy, M. C. and Jansen, B. J. (2008), 'A model for understanding collaborative information behavior in context: A study of two healthcare teams', *Information Processing & Management* **44**(1), 256–273.

Shah, C. (2014), 'Evaluating collaborative information seeking - synthesis, suggestions, and structure', *Journal of Information Science* **40**(4), 460–475.

Shah, C., Hendahewa, C. and González-ibáñez, R. (2015), 'Two's Company, But Threes No Crowd: Evaluating Exploratory Web Search for Individuals and Teams', *Journal of Information Science* **Sep**.

Singh, V., Freeman, L., Lepri, B. and Pentland, A. (2013), 'Classifying spending behavior using socio-mobile data', *HUMAN* **2**(2), pp–99.

Yano, K., Lyubomirsky, S. and Chancellor, J. (2012), 'Sensing happiness', *IEEE Spectrum* **49**(12), 32–37.