Smartphone usage in the wild: a large-scale analysis of applications and context

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ABSTRACT

This paper presents a large-scale analysis of contextualized smartphone usage in real life. We introduce two contextual variables that condition the use of smartphone applications, namely places and social context. Our study shows strong dependencies between phone usage and the two contextual cues, which are automatically extracted based on multiple built-in sensors available on the phone. By analyzing continuous data collected on a set of 77 participants from a European country over 9 months of actual usage, our framework automatically reveals key patterns of phone application usage that would traditionally be obtained through manual logging or questionnaire. Our findings contribute to the large-scale understanding of applications and context, bringing out design implications for interfaces on smartphones.

Categories and Subject Descriptors

H.5.m [**Information Interfaces and Presentation (e.g., HCI)**]: Miscellaneous

General Terms

Human Factors

1. INTRODUCTION

The short history of mobile phones has witnessed several stages, as phone adoption has increased rapidly across the globe. Today, several billion individuals carry these devices, becoming reachable almost anytime, anywhere. Mobile technology adoption has widespread social implications, ranging from western teenagers using mobile phones to exchange gifts [21], to economically challenged users leveraging the mobile phone to improve their livelihood [7].

A recent trend is associated with the rise of the smartphone - computationally powerful computing devices available to users across an increasingly wide range of prices [14]. Such devices have increased the functionalities available to users partly due to their large number of built-in sensors (GPS, Bluetooth, accelerometer, microphone, camera, etc). It is now commonplace to talk about an ecosystem of functions, applications, and services enabled by smartphones. End users are at the center of such an ecosystem, creating content with their devices, accessing content available through the mobile Internet, sharing it with their social networks.

The issues of multimodal interaction through mobile phones and context-aware mobile services are growing in importance. It has become key to understand how such devices are used, especially with the emergence of the App culture, where a multitude of mobile services and applications can be downloaded from the web and used on smartphones. Is it the case that smartphone usage is uniformly distributed across application types, or is there still a bias toward traditional communication means like voice calls and SMS? Given the multiple facets of these devices, it is also increasingly important to investigate how usage unfolds with respect to different types of contexts. In other words, to what extent does the selection of a given application depend on the physical or social context? Are certain applications independent of the type of environment where the phone is used? Addressing these questions is key for the design of successful mobile user experiences for smartphone users. In industry, the understanding of how these platforms are appropriated as part of everyday life could be leveraged across several layers of product design. From the user interface viewpoint, knowing which applications are relevant where and when could facilitate access to different functionalities. From the viewpoint of service discovery, it could be useful to know when a user is likely to be in need of specific information so that it can be offered at the right time. From the viewpoint of facilitating human communication, contextual insights could be used to modify specific phone features to make them more suitable to the given social and spatial situation.

When aiming to understand the impact of context on usage of mobile phones, traditional research techniques have focused on ethnographic observation [4] or quasi experiments on the field [18]. This paper, on the other hand, follows recent practices in mobile sensing [14] and adopts a large-scale approach, by analyzing rich data collected by the smartphones of a set of 77 participants from a European city over 9 months, where phones are carried around and used in a natural, unobtrusive manner in everyday life. Furthermore, we go beyond recent analyses of application usage patterns from automatically recorded logs [3, 6, 10] by introducing two contextual variables that condition the use of smartphone applications, namely semantic places and physical proximity. In our work, these two contextual cues are automatically extracted by exploiting multiple sensors available on the phones (GPS, GSM, Wifi, Bluetooth, and accelerometer). Our work examines the effects of individual as well as joint contextual cues on the use of communication, web, and media applications. Our study reveals a number of key patterns and shows that phone usage depends significantly on both location

ICMI'11, November 14–18, 2011, Alicante, Spain.

and social context. Furthermore, our findings directly suggest several smartphone design implications related to user needs.

The paper is organized as follows. Section 2 discusses related research. Sections 3, 4, 5 and 6 describe the data collection procedure, the resulting dataset, and the specific variables used in our study. Section 7 discusses the findings of the analysis. Section 8 discusses the implications of the results on features that could better address the contextual needs of smartphone users. Section 9 draws conclusions.

2. RELATED WORK

The existing works related to the understanding of mobile phone usage can be broadly categorized into those that have analyzed usage behavior through standard ethnographic and user studies (based on questionnaires, self-reports, diaries, and often conducted on small numbers of subjects), and recent studies that exploit the automatic recording and subsequent analysis of phone activity logs for larger populations and periods of time.

In the first category, early works on patterns of SMS usage include [12] and [11], in which users where asked to manually log their texting activity. Reid and Reid [20] studied differences of SMS and call usage preferences using questionnaire data. In a more recent example, Butt and Phillips presented a study on the relation between mobile phone usage and personality traits from the popular Big-Five model, using self-reports of weekly usage levels of calls, SMS, and a few applications including games and ringtones [5]. Recently, Barkhuus and Polichar [2] investigated how users adapt and adopt the different functions in smartphones based on interviews and daily diaries over 3 weeks from 21 users. Other studies have focused on other phone applications and mobility [4, 24].

Self-reported data can be prone to errors, due to personal biases, recall limitations, etc., and therefore the feasibility of automatically capturing logs of mobile phone usage at large scale has generated a second, more recent body of work, where longitudinal analyses of phone application logs is collected by combining automatic collection of smartphone data and human-centric data analysis [14, 1]. This practice is becoming increasingly relevant for mobile phone manufacturers, operators, and service providers. Nokia has released brief findings related to phone usage patterns in the context of the Smartphone 360 effort [17]. One study involved over 500 users in three countries over three months, and reported that both the time spent on the phone and the frequency of usage of certain applications increased with respect to previous years. Nielsen Mobile has also disclosed summaries of their analysis on operator-based data from thousands of users, in particular about mobile web usage given basic demographics (age, gender, income level, country, and phone type) [16]. Zokem, whose work originated in academia [22], also analyzes mobile phone application logs, and has recently made some initial findings public [25]. Anderson et al. have applied "ethno-mining" techniques to understand use practices of a number of mobile devices, including laptops, netbooks, and phones [1]. A large-scale study of patterns of phone application usage using the time of the day as contextual anchor was recently presented [6]. In [10], a study on 255 users of Android and Windows Mobile smartphones, characterized usage in terms of energy consumption, traffic, time spend with the device, and applications. Statistics of popular apps, relations to basic demographics, and basic day/night patterns were reported. In all these cases, however, no usage analysis grounded on location and social proximity automatically estimated from sensor data has been presented, as we do here. Battestini et al. [3] presented a large-scale study of SMS usage, based on a population of 70 university students over four months who used a loggging software that also recorded the location where the SMS were received or sent, using a GSM cell positioning method. Unlike this work, our paper analyzes multiple phone applications (SMS included), with location anchors automatically estimated from multiple sensor data types (GPS, GSM, Wifi, motion), which results in higher accuracy in location estimation. In addition, we present an analysis of usage with a proxy for social context derived from Bluetooth.

3. DATA COLLECTION FRAMEWORK

Our data collection framework was based on a server-client architecture built around the Nokia N95 8GB smartphone. Phone usage was continuously collected using non-intrusive client software. Information pertaining to usage of apps and contextual information such as location and proximity was recorded. The client was programmed to start automatically at startup of the phone, run in the background and collect data on a 24/7 basis with the only restriction of having to recharge the phone once a day. In order to achieve sensing over a full day, the client was designed using a state-machine approach similar to [23], which results in a power-efficient adaptive sensing procedure. The client changes the sensors that are activated and the corresponding sampling rate at any given time according to the status of the state machine. This is key to be able to maintain all phone sensors active without draining the phone battery in a few hours (specially GPS sensing is power consumming). States are defined by the current readings of many of the phone sensors (GPS, GSM, WiFi, accelerometer, etc.). We omit the implementation details for space reasons. The recorded data is first stored in the phone local memory and then uploaded daily to a server via a user-defined WiFi connection. We used the following sources of usage data:

App logs. App logs consist of the usage events of all applications, including system apps, pre-installed apps like Camera or Calendar, and other user downloaded apps. Note that in the rest of the paper, we use the term “app” to denote all phone applications, and not only Ovi Store-like applications. Each time the user accesses an app, the client software captures the event and stores it together with the timestamp. Due to technical difficulties on capturing accurately the timestamp of close/switch events for some apps, we did not consider the usage duration and our analysis was focused on usage frequency.

Location data. The outdoor location information is obtained from the phone built-in GPS. For common visited places in a person’s daily life, it is also possible to locate the user based on WiFi access points (APs). The software client periodically scans for WiFi APs and maintains a list of known-location APs (based on the simultaneous availability of GPS). Each time the client observes a AP in the list of known-location WiFi APs, the GPS sensor is turned off and the client uses the recorded location of the AP. This technique helps saving phone battery and allows having location information in many indoor environments.

Bluetooth data. The smartphone scans nearby Bluetooth devices every 1-3 minutes, depending on the state of the client. The number of discovered nearby devices can be used as an approximate measure of the human density and the type of environment, and provides to some degree the social context of the user. Bluetooth has been used as a noisy, yet reasonable proxy for social context in ubiquitous computing [19, 9], although it clearly does not imply actual face-to-face interaction (e.g. a person can be detected as being proximate while being in a contiguous room).

4. FROM GEOGRAPHIC LOCATIONS TO SEMANTIC PLACES

While our client provides instantaneous physical location information, access to the semantic meaning of any given location would be useful in order to understand how people use the phone in different contexts. Semantic information would allow elaborate analyses to be performed on the behavioral differences between different kinds of places. For this purpose, we transformed the geographic location into a semantic place by following a two-step procedure: 1) automatic discovery of visited places and 2) human annotation of most visited places. Each step is summarized below.

Automatic place discovering. The data collection client on the phone recorded the location of the user in a continuous fashion. From these traces, we first extracted stay points which are time-stamped, small circular regions in which user stays for at least 10 minutes. These stay points were then clustered into meaningful places (or location anchors) with the maximum size of a cluster being limited to 250m, using a grid clustering algorithm recently proposed [15]. The output of the algorithm produces a personalized list of places for each user that are visited over the whole sensing period along with the timestamps when they were visited (see Section 5). Note that location sensing sometimes fails and thus not all locations can be detected, and also that many initially detected user locations do not give rise to the discovery of a place, either because users were on the move (e.g. on a train), or because they did not stay long enough in those regions.

Semi-automatic place labeling. The algorithm produces a diary of visited places that make geographic, but not semantic, sense. To provide semantics for places, the participants were required to fill in an online survey at the end of the experiment. Each participant was presented with a set of eight automatically chosen places. Five of the eight places were the most frequently visited locations of the user, across the entire experiment period. Places such as user's home and office typically ended up on the top five list. In order to also illuminate the semantics of less frequently used places, three of them were randomly chosen from the lowest tenth percentile (in terms of time spent) of the place list of the given individual. These eight places were then presented to the respondent in a random order, one by one. Each place represented by a rectangle whose size was determined by the grid clustering algorithm. For each place, a separate web page was generated, displaying the location on a map as a rectangle. The respondent then had to label the place by using a set of 22 mutually exclusive predefined labels. These labels were subsequently mapped to the following 11 labels: *Home, Work, Friend-Home, Friend-Work, Restaurant, Sport, Transport, Holiday, Shopping, Relaxing and Other*. The set of locations consists of 10 explicit categories and a special category called "Other" which includes both unlabeled places and labeled places that does not belong to any of the ten mentioned categories. "Friend" denotes both relatives or friends of the participant. All discovered places are static by construction, and the "Transport" category corresponds to transportation-related places such as train or metro station, bus stop, etc.

5. LARGE-SCALE DATA

Our analysis was conducted on the data from the Lausanne data collection campaign [13]. We use a subset of data consisting of 77 volunteer users who were given the smartphone and the cost for the mobile phone plan during the data collection period. The phone plan used by the volunteers includes the data plan (1GB/month) so that people are expected to use the web. The population is mainly composed of middle class individuals who are university students or professionals. Of them, 63% used public transportation, 27% used a car, and 7% used both. Figure 1 shows the composition of the studied population in terms of age and gender. All participants previously owned a mobile phone, although most of them were not familiar with the N95 before the study. Users used their smartphone as their only mobile phone. The data was collected between October 2009 and June 2010. All users filled out consent forms to have their data recorded and agreed to participate in the place labeling survey. There were roughly 8.6 million location entries and about 6.2 million of non-empty Bluetooth readings during the recording period. Among 7156 discovered places, 616 of them were annotated by participants, covering 95% of the total time people spent in detected places.

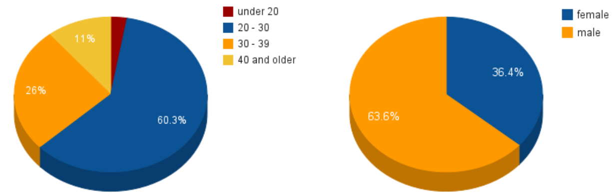

Figure 1: Age and gender of the studied population.

SMS and Voice Call	The two primary applications of mobile phone.
Web	Available web browsers. We consider both native the smartphone browser and user-installed browsers (e.g. Opera Mobile).
Multimedia	A group of multimedia applications including music players, video players, and image viewer.
Clock	The native application for setting the alarm and adjusting time.
Camera	The native application for taking photos and recording video.
Email	We consider both native the e-mail client and mobile Gmail.
Calendar	The native calendar app.
Voice chat	A set of messenger clients including Fring, Skype, and "Internet tel."
Maps	Apps access GPS and get user location. Both native map and Google map are studied.
Sport Tracker	Nokia app to track user route, speed and timings while engaging in sports.
Visual Radio	Interactive radio with FM radio over a data connection for graphics and text.

Table 1: Selected apps.

6. SELECTED APPS FOR THE STUDY

As stated earlier, we investigate the use of both native and installed apps during the data collection period. Among hundreds of applications found in the data, we selected a subset of the most popular ones for this study, listed in Table 1.

Figure 2 shows the total number of uses of each app in decreasing order. As can be seen, Voice Call and SMS are the most used applications followed by Web and Multimedia. On average, people accessed SMS 11.2 times per day and had 5.7 phone calls per day. For other applications, the usage frequency was relatively low, suggesting that relatively few participants used these apps actively. To clarify this, in Figure 3, we show the percentage of people who are interested in these applications (trying them at least once) and the percentage of people who accept them (using the app more than 10 times). As can be seen, the first six applications are used at least 10 times by almost all users which reflects the need for these apps and their acceptance. Calendar and Maps are also interesting for most users, but the percentage of actual users is slightly lower (around 70-75%). For other apps, the percentage of people who use them

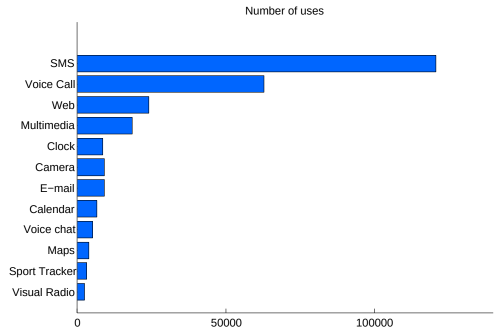

Figure 2: Number of events for each application.

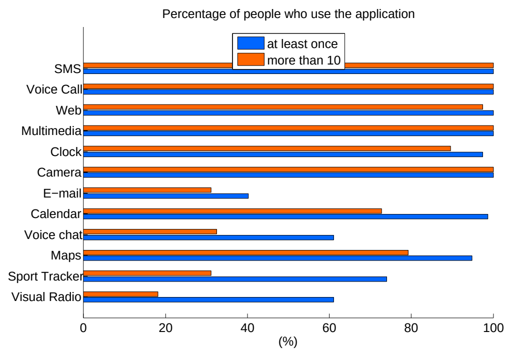

Figure 3: Percentage of active users for each apps.

more than 10 times is relatively low (less than 30%) and there are big differences between the number of users who try them and the number of users who actually use them. An interesting exception is the case of E-mail, where people who tried it once are likely to continue using it. Note that, while having less than half of number of users of Calendar or Maps, the number of uses of E-mail is high, which reflects the fact that E-mail is frequently used.

7. FINDINGS

7.1 App usage vs location

In this section, we study phone usage patterns with respect to user location. Figure 4 reports the aggregated time of stay in each semantic location for all users without counting night time (0-6am). Note that the stay time is plotted in log-scale since it varies significantly depending on the location category. For instance, the total time people stay at home (without night time) is twice the time people spend at work. Among labeled locations, places for Relaxing (e.g. Park) has the lowest staying time with about 14 hours (accumulated from 25 visits). Note also that the 'Other' catch-all category does correspond to the third most used label.

Table 2 reports the number of usage events occurring in each place. Notice that the number of events is strongly correlated with the total time people spent in each place (Pearson correlation $r = 0.44, p < 0.001$). The top 4 most popular places (Home,Work,Friend-Home,Other) cover 96.7% of all location-detected usage events. In order to study how people use the phone in each context, we introduce the notion of *hourly usage frequency* (huf), defined as follows for application i and location j:

$$huf(i, j) = \frac{number\ of\ events\ for\ application\ i}{total\ staying\ time\ in\ hours\ in\ location\ j}$$

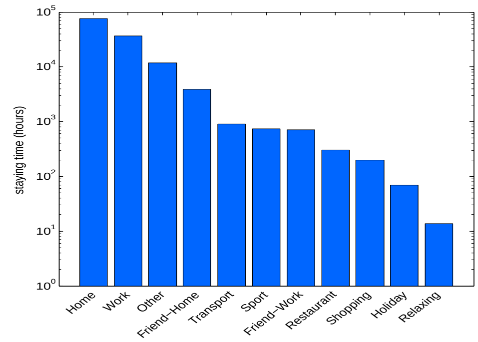

Figure 4: Staying time in each place category (in hours) and plotted in log scale.

	Home	Work	Friend-Home	Friend-Work	Restaurant	Sport	Transport	Holiday	Shopping	Relaxing	Other
SMS	31696	18706	2427	516	159	685	301	6	42	2	8756
Voice Call	13701	10708	1295	217	83	189	515	10	64	7	4721
Web	3783	3041	1157	12	58	57	460	30	39	4	1850
Multimedia	4808	2451	242	38	6	19	157	15	16	4	1043
Clock	4473	319	203	11	4	10	57	1	2	0	182
Camera	1532	759	113	34	9	19	67	56	17	0	1091
E-mail	2171	1481	393	0	13	137	7	3	0	0	729
Calendar	1177	961	121	9	12	36	123	0	4	0	1093
Voice chat	1390	475	133	3	0	68	7	24	1	0	208
Maps	560	283	53	2	12	16	10	5	1	1	423
Sport Tracker	706	423	86	0	0	32	3	0	0	0	175
Visual Radio	700	496	2	0	0	4	1	0	0	0	91

Table 2: Number of events occured in each place during the data collection period.

	Home	Work	Friend-Home	Friend-Work	Restaurant	Sport	Transport	Holiday	Shopping	Relaxing	Other	Avg.
SMS	0.41	**0.51**	0.63	0.72	0.52	0.93	**0.33**	**0.09**	0.21	0.15	**0.75**	0.48
Voice Call	0.18	**0.29**	0.34	0.30	0.27	0.26	**0.57**	**0.14**	**0.33**	0.51	**0.40**	0.24
Web	0.05	**0.09**	0.30	0.02	0.19	0.09	**0.52**	0.43	0.22	0.29	**0.16**	0.08
Multimedia	0.06	0.07	0.06	0.05	0.02	**0.03**	0.17	0.22	0.08	0.29	**0.09**	0.07
Clock	**0.07**	**0.01**	0.06	**0.02**	**0.01**	**0.01**	0.07	**0.01**	**0.04**	0.00	**0.02**	0.05
Camera	0.02	0.02	0.03	0.05	0.03	0.03	0.07	0.81	0.09	0.00	**0.09**	0.03
E-mail	0.09	0.11	0.17	0.00	0.10	0.32	**0.07**	0.06	0.00	0.00	**0.20**	0.11
Calendar	0.02	0.04	**0.04**	0.04	0.05	0.07	0.15	0.00	**0.03**	0.00	0.11	0.04
Voice chat	0.06	0.05	0.05	0.04	0.00	0.23	**0.05**	0.35	0.06	0.00	0.05	0.06
Maps	0.01	**0.01**	0.01	**0.01**	0.06	0.03	0.04	0.07	0.01	0.07	**0.05**	0.01
Sport Tracker	0.03	0.04	0.04	0.00	0.00	0.10	0.04	0.00	0.00	0.00	0.05	0.03
Visual Radio	0.06	0.05	**0.00**	0.00	0.00	**0.04**	0.01	0.00	0.00	0.00	0.05	0.05

Table 3: Hourly usage frequency (huf) for each app in each semantic place.

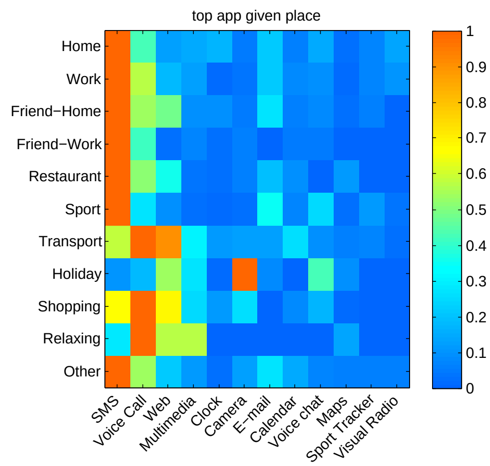

Figure 5: Top apps at a given place are highlighted in each row. A unity value (red) corresponds to the most frequently used app given a place.

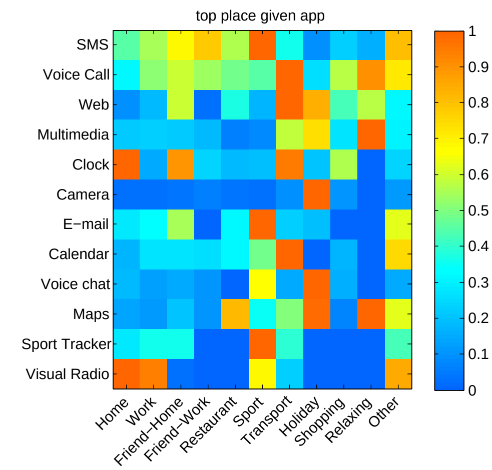

Figure 6: Top places for a given application are highlighted in each row. A unity value (red) corresponds to the place where the app is used the most.

which characterizes how frequently people use an application in a specific context. To have a practical meaning, for each app we only consider data from the set of active users of that app (i.e. those using the app more than 10 times). Table 3 reports the hourly usage frequency for each app at each place. For reference purposes, we also report the hourly usage frequency for each app averaged over all place (Avg.). For instance, we can see that the use of Voice Call at Work (0.29) is above average (0.24) but Clock usage at Work (0.01) is below average (0.05).

It is important to look at the generalization of the observations in Table 3 and to verify whether the observations have occurred by chance. For instance, if there are only a few people going to a sport center and they happened to be very active SMS users, then one can not draw the conclusion that all people use SMS a lot at the sport center. We conducted a statistical significance test by splitting data by user, and performed T-tests for the 2 hypotheses that the usage frequency of an app at a given location is above (respectively, below) the global average. Statistically significant cases ($p < 0.05$) are highlighted in bold in Table 3. As can be seen, having very low support in terms of active users and labeled locations, we do not have statistically significant results for Relaxing place and for Sport Tracker.

Visualizing apps that are used the most at a given place. Figure 5 highlights the top applications at each place by showing the app usage frequencies normalized by the maximum value over applications. The top applications are highlighted in each row with value close to 1. It is not surprising to notice that SMS and Voice Call are the top applications in most locations. However, while SMS is highly used in many indoor locations, people seem to prefer the use of Voice Call in moving contexts such as waiting at train or metro station (Transport category), or while shopping or relaxing in the park. This is a very interesting pattern of place-based communication preferences. At Friend-Home, Web and E-mail join SMS and Voice Call in the list of top apps. Finally, when on holidays people have a preference for the camera.

Visualizing places where apps are used the most. We continue the analysis by investigating frequency of use of the applications across different locations. Figure 6 illustrates the top places for an app by showing the usage frequency normalized by the maximum value in each row. First very interestingly, besides the Clock and Radio, none of the apps get used the most at Home or at Work (in terms of usage frequency). This indicates that mobile usage is directed towards other place than Home or Work. The use of Web is highest at transportation-related places such as bus stop or train station. In such contexts, the Internet is likely to be used for reading news, looking for information or killing time. People also surf the Web a lot during Holiday time, at a Friend's Home, and at Relaxing places like the park, which reflects the fact that for these places, smartphones replace computers as the primary web access device. A related app to Web is Email, which is similar to the Web in that it is frequently used in locations Friend-Home and Holiday. The main difference is that people are not likely to check email at transportation-related places, but they use email at frequently visited places such as the sport center. Calendar, in contrast, gets used the most in Transport places, and much less so at Work. This might be due to the fact that people rely on other devices at Work (desktop or laptops) to see their calendar in office hours. For other apps, the highlighted places are also meaningful. For instance, Multimedia is highly used at outdoor places such as Relaxing, Holiday, and Transport places. The Clock gets used at Home, Friend-Home and Transport. Maps is highly used during Holidays, at Restaurants and Relaxing places, which are often "first time visit" places. Sport Tracker, unsuprisingly, is used the most at Sport places.

Correlation between common places and app usage. The amount of time that people spend in different locations can tell us about the user's lifestyle [8]. In this section, we examine the relation between user lifestyle and app usage by studying the correlation between the proportion of time that people spend in each place and the app usage frequency. Table 4 reports Pearson correlation between these two types of variables for cases that are statistically significant ($p < 0.05$ or less). We can see that people who spent more time at Friend-Home also used Voice Call and Web more. This might correspond to people who are in a relationship, who called their significant other frequently, and used the phone to surf the net from their friend's place.

The second finding is related to people who spent more time waiting at transportation related locations. Given that these users travel often, they might use Web and Multimedia both while waiting and during the trip. Note however that in our study we do not infer what happens when people are actually moving, as we only consider (static) places. Clock and Camera usage also have significant correlation values with the time spent at transport-related

Location	App	Correlation
Friend-Home	Voice Call	0.26*
Friend-Home	Web	0.26*
Transportation	Web	0.26*
Transportation	Multimedia	0.27*
Transportation	Clock	0.52***
Transportation	Camera	0.51***
Holiday	Multimedia	0.24*
Holiday	Camera	0.28*
Holiday	Voice chat	0.36**
Holiday	Visual Radio	0.23*
Other	Calendar	0.42***

$^{*}\ p < 0.05,\ ^{**}\ p < 0.01,\ ^{***}\ p < 0.001$

Table 4: Correlation between the percentage of time people spent in each location and the app usage frequency.

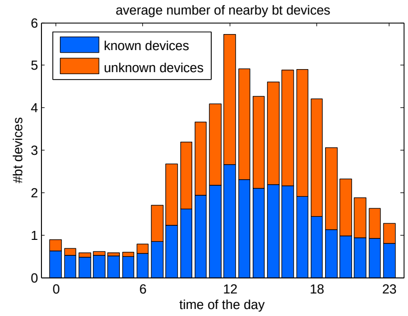

Figure 7: Number of nearby Bluetooth devices during the day.

locations. The use of the camera could be explained by people passing time while waiting. The use of clock id also intuitive, as users might consult the clock while waiting, e.g. in case of delays, etc. As a third finding, people who spent long time on holidays are likely to use Multimedia, Camera, and Voice Chat, which matches the analysis of phone usage wrt. location shown in Figure 5. Last but not least, there is a strong correlation between people who spent a lot of time in other location categories and the use of Calendar. As Other corresponds to a multitude of places corresponding to short or infrequent visits, one can think of these users as dynamic people for whom Calendar is a useful app when on the move.

7.2 App usage vs Bluetooth density

Using the Bluetooth sensor, one can make a coarse estimate of human density around the user. While some BT devices correspond to devices other than phones (e.g. laptops, netbooks), these devices themselves are mobile and carried by people. A high number of nearby Bluetooth devices likely means that there are many people around the user, such as a public place, a working place, or a large meeting. We refer to Bluetooth density as a rough proxy for social context (e.g. being alone or in a small or large group).

Figure 7 shows the average number of nearby Bluetooth devices to our population's phones on different times of the day, separating them into known (i.e., devices that have been previously observed at least on 5 different days) and unknown devices. Not surprisingly, there are few nearby Bluetooth devices during sleeping time (0-6am), and they are known Bluetooth devices in most cases. Office hours are the most active times, and the number of known devices seems to be somewhat proportional to the number of unknown devices. In the evening, the number of known devices tends to stabilize while the number of unknown devices gradually decreases. An explanation is that users are likely to be nearby the same people (relative or friend in proximity or neighbors across walls) in the evening, and the probability that they go out depends on the time.

We also study the usage frequency of the set of selected apps with respect to the social context proxy given by Bluetooth. Figure 8 shows different trends for usage frequency when the number of nearby Bluetooth devices increases. Again, we performed T-tests on the data splitted by user for the hypotheses that the usage frequency of a given app at high Bluetooth density places is above (or below) the usage frequency at low Bluetooth density places. Interestingly, we observe an statistically significant increase in app usage frequency when the Bluetooth density is high for SMS ($p = 0.03$), VoiceCall ($p = 0.0004$), and Web ($p = 0.008$). For instance, the use of Voice Call and Web at high Bluetooth density places is 50% higher than when people's phones do not detect any nearby Bluetooth device. In contrast, Clock has generally low use in high density Bluetooth environments, which matches our location analysis where people were found to use Clock highly at home and friends' home. Finally, a different pattern is observed in E-mail usage, where people are more likely to check email at either low Bluetooth density places or very high Bluetooth density places, which could resemble the "being alone" (no nearby BT devices) and "being in a class" (many nearby BT devices) situations. For the other investigated apps, there are no significant dependencies between app usage frequency and Bluetooth density.

7.3 App usage vs joint location and BT density

The analysis showed relevant patterns of phone app usage based on location information or based on Bluetooth density. We now consider a richer context by combining both of them. In order to have large enough support for each joint location-Bluetooth density category, we use a more compact set of 5 place labels: {*Home*, *Work*, *Friend Home* , *Other Indoor* and *Other Outdoor*} by merging the place categories previously used. Figure 9 shows the stay time in each joint location-Bluetooth context, where the most popular joint context is at Home without nearby BT device and the least one (184 hours in total) is the case of observing at least 8 nearby Bluetooth devices at home of a friend or a relative. As can be seen, people observe relatively few Bluetooth nearby devices in all places other than work. On the contrary, phones are likely to observe many nearby Bluetooth devices at work. This obviously is often a result not only of people carrying phones, but also laptops, netbooks, etc.

The app usage frequency in each location-Bluetooth density context is shown in Figure 10. Note that unlike Figure 5 and Figure 6, we do not need any normalization here because each app is plotted separately, and the raw hourly usage frequencies are shown. Note that to stress the differences in usage frequency in different contexts, we use different scales in these plots. For Voice and SMS, we see that people are likely to communicate with others when they are outdoors, especially when there are high number of nearby Bluetooth devices. This can be as high as 1 SMS per hour and 1 phone call every two hours on average. This is an interesting result, that could relate both to the high density of European cities and the associated lifestyle of people (spending time at coffee shops and bars, commuting or public transport). Some apps are highly used when the Bluetooth density is low in outdoor environments, including Multimedia, Camera and Map. This is likely to correspond to the case when people are in natural environment (e.g. mountains). Web has the highest frequency when people are at a friend's home and some nearby devices are detected. This is a somewhat puzzling finding.

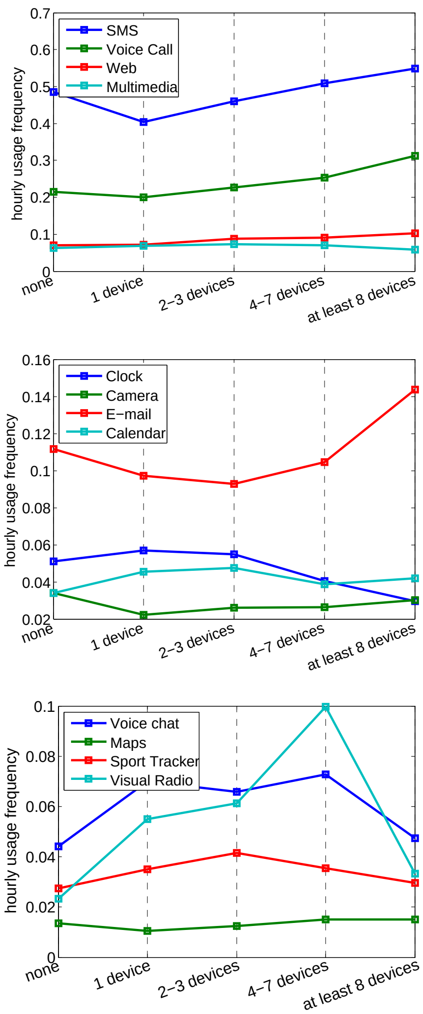

Figure 8: Usage vs Bluetooth density.

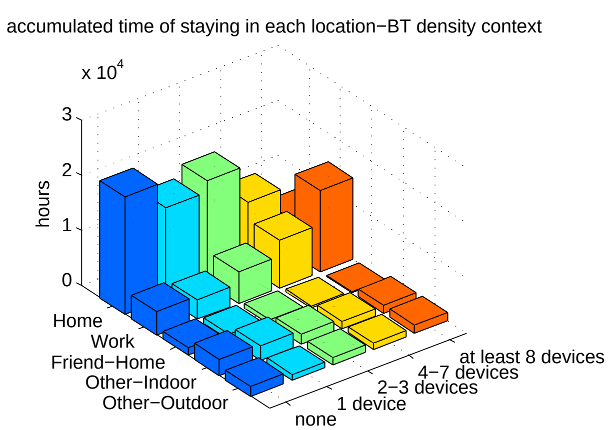

Figure 9: Accumulated time of each context (in hour unit).

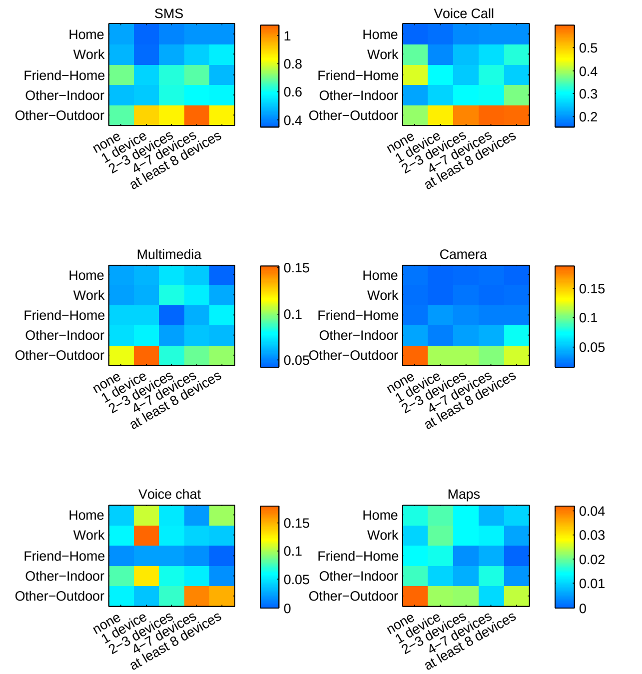

Figure 10: Hourly usage frequency for each app in each location-BT context.

8. DESIGN IMPLICATIONS OF CONTEXTUAL PHONE USAGE

The data-driven analysis revealed that the smartphone was used in a differential manner across various types of spatial and proximity contexts. Two design implications of this context-dependent behavior are highlighted in this section: supporting synchronous communication and context-dependent offering of functionality.

Supporting synchronous communication. Differences were observed between SMS and voice call usage. The former was associated with stable and stationary locations, such as one's home, the home of friends, and work. The latter stood out in nomadic contexts such as the park, bus stop, or shopping center. Such locations are likely to be associated with a certain degree of user movement and a relatively short duration of stay. The nomadic contexts may hence be associated with a need to exercise micro-coordination, i.e., fixing meetings and coordinating actions with members of one's social network. The fact that the calendar was used the most at places related to transportation also points in this direction. Choosing a voice call over SMS in these types of situations can be indicative of a preference for synchronous communication to handle coordination related activities. To satisfy this kind of preference, a design requirement emerges, namely ensuring that the device supports coordination and synchronous communication. Examples of such features could include communicating the current location of members of the social network to the user, prompting for a fast response from the recipient of a message, and providing a shared digital space for parties in need of coordinating with one another.

Context-dependent offering of functionality. Some locations were associated with using the phone in a multitasking way. Moreover, different patterns of multitasking emerged. Being at a friend's home or a restaurant triggered the use of voice call, SMS as well as browser. Being in a park was associated with making voice calls, browsing the web, and viewing images. Holiday-related location was the most distinctive context with respect to the use of browser, maps, camera, and voice chat. How can such differences in the preferred phone functionality be taken into account in the design of mobile interfaces and devices? A differential set of applications and functionality could be brought forth in the phone UI based on the context the user is in at any given time. This could be achieved through adaptive UI techniques. However, further research is needed across a range of topics. First, the generality of the effects reported here should be investigated using a larger, and more geographically diverse population. Given our current mobile sensing techniques, as demonstrated here, this goal seems feasible within certain scales. Second, motivational factors behind the contextual usage should be studied in order to reliably understand what makes users disposed to using the phone in certain ways given particular contexts. This is an area where our data-driven work would be complemented by ethnographic methods. Third, the ability to generate adaptive features that are user-friendly and intuitive is a design challenge requiring significant future research.

9. CONCLUSIONS

We presented a large-scale study of smartphone usage conditioned on two key contextual cues (location and proximity) automatically estimated from phone sensors. We found intuitive patterns of usage that help understanding how people use their phone. On a general level, the overarching conclusion is that recognizing aspects related to physical and social context could be an important ability in a device, so as to facilitate the extent to which relevant content is provided to the user in any given situation. The area touched by the paper, is complex, however, necessitating further research to be done. The current study was implemented with a relatively outdated phone (given the fast pace of smartphone technology), in terms of both the user interface and the applications available to the users, and with a population sample which is not generalizable to the general population. These aspects point to the importance of replicating the method using a larger sample, ideally spanning multiple cultures. The degree to which the user interface affects the usage, beyond the contexts themselves, seems to play a key role but remains to be quantified at large-scale. Furthermore, the study of phone usage while people are actually moving (e.g. on public transport) was not addressed here. Despite the limitations, the fact that contextual factors were indeed found to affect the use of the phone is a relevant finding and shows that the method chosen for the study is promising.

Several of the findings are non-surprising given the regularity of daily life, and the fact that we explicitly set out to study the main trends of our population, rather than the existence of any anomalies of deviations from the trend. As future work, we plan to examine the issue of anomalies. In terms of design, creating relevant contextual adaptations to user interfaces, without increasing their complexity, remains a significant challenge to study.

Acknowledgments

We thank Raul Montoliu (University of Castellon) for code for place extraction and Juha K. Laurila (NRC) for valuable discussions. This work was funded by Nokia Research Center Lausanne (NRC) through the LS-CONTEXT project.

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