Estimating People Perception of Intimacy in Daily Life from Context Data Collected with Their Mobile Phone

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ABSTRACT
Nowadays, personal context is extensively used in personalized mobile services. However, gathering this kind of information may compromise the privacy of the user. Moreover, the number of services that collect and share the personal context with others is growing. Yet, the users are not able to easily control what information is shared and with whom. An important step towards this goal is to understand how and when the user wants to *share* his personal context. The literature suggests that the willingness to disclose personal information depends on the level of *intimacy* perceived in given contexts. In this paper we show how the MDC data enabled us to estimate the level of intimacy of the user in a given contexts of his/her daily life.

Categories and Subject Descriptors
K.4.1 [**Computers and Society**]: Public Policy Issues – *privacy, human safety*.

General Terms
Algorithms, Design, Experimentation, Human Factors, Theory.

Keywords
intimacy, privacy, mobile application, context sharing.

1. INTRODUCTION
The rise of so-called People-Centric Sensing [2][3], in which people are involved in the collection of sensor data using their mobile devices, requires protection of the user's privacy. The question remains, how to know what type of data are people willing to have gathered, interpreted, and then shared. Usually, predefined classes of privacy bound the freedom of the configuration and the end-user must conform to them. However, our proposal is to allow privacy policies to evolve over time by learning users' preferences from their mobile usage.

Towards this end, we start to explore how to leverage the users' perception of intimacy to automate the sharing of information. But, how does the intimacy relate to privacy? According to Gerstein [4] one important point for intimacy, especially in intimate relationships, is the exclusive sharing of personal information to selected individuals [5][6]. More specifically Gerstein [4] says that, an intimate relationships cannot exist if there is no privacy and an *unwanted observer* can degrade or destroy intimacy. The long-term goal of our research aims at facilitating the mobile user not to share selected personal context information to unwanted observers. In this paper we present a first step in this direction. Thanks to the Mobile Data Challenge[1] (MDC) data [1] we devised a preliminary approach to analyze raw data collected from several users using their smartphones in their daily life. In Section 2 we present the analysis of the MDC data, the assumptions we made and the basic algorithm used to derive the users' level of intimacy in particular intervals of time. In Section 3 we provide the most interesting results derived from the MDC data and an overall view over the intimacy levels derived for the whole set of study participants. In Section 4 we conclude upon the conducted research.

2. FROM RAW DATA TO INTIMACY
2.1 Raw Data Exploration
The MDC dataset has been collected as described in [1]. We have acquired access to approximately 1 year of data as collected by 38 selected participants, as described in details in further sections of this paper. We started our research by a literature study and a high level analysis of the raw MDC data to understand which features were best suited to describe the intimacy perception of the users (*c.f.*, Section 2.2). For example, firstly we confirmed that Bluetooth data (periodical scans of surrounding Bluetooth devices) is a good indicator to have an estimation of the immediate crowd around the user (*i.e.*, ~10m circle) and the possible relations between people [7–9]. The results show that only two participants of the study may be strongly related (*e.g.*, be a couple), and that the majority of them have some frequently-encountered, but unknown to the study, devices logged in their scan data. The second example of important data is the phone ring status (*e.g.*, normal, ascending, silent). For each user we computed the overall percentage of all phone's ring status during each hour of the day. We found out that all users follow a precise ring pattern similar for every hour. In Figure 1 we show the percentage of each ring state of user P9, for the full day over the whole study (note that 'ring-once' option is present, but never used by any user). All the other users follow the same behavior, but with different distribution of probabilities. This result can suggest that users react to particular situations by changing their ring status and that these situations are almost uniformly distributed over the whole time of the data collection.

Pervasive'12, June 18-22, 2012, Newcastle, UK.

[1] *This material was prepared for the Mobile Data Challenge 2012 (by Nokia) Workshop; June 18-19, 2012; Newcastle, UK. The copyright belongs to the authors of this paper.*

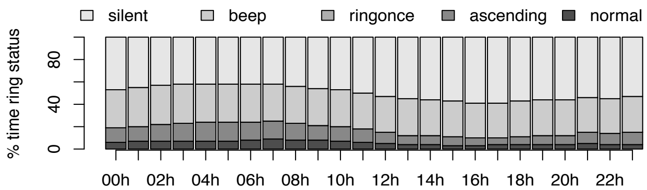

Figure 1: Phone's ring status (P9)

A third example of raw data used for deriving the intimacy level of mobile users is the analysis of the phone's charging status (*e.g.*, no charging, charging, and full). As presented in [10] from the resulting charging patterns we noticed that users have a predictable behavior on charging their phones. In particular they charge more often their phone during night and when the phone is fully charged, it stays for a long time attached to the power adapter. During the day, charging and full charged times are shorter. In addition to these three particular raw data examples, we investigated also other kind of data. Calls and SMS logs (essentially durations and relations) [5][7][8], GPS and WIFI traces (for a greedy indoor/outdoor recognition: available GPS implies outdoor, while WIFI implies indoor), and we split all the analyzed data above in working days and weekends to see if there were differences in the resulting patterns.

2.2 Features Selection

Given the result of the first raw data analysis and based on the concepts drawn from the literature about privacy and intimacy [4–6] we decided to select some specific features and split them in two categories: *observers* (for people) and *safe places* (for locations). For the *observers* category we chose all the features that can help us to identify if the user is surrounded by people and what is his relation with them. In the *safe places* we selected only features that can give us an indication about the user trust in the place he is in a given moment (*i.e.*, if he does feel secure).

For each feature we devised some assumptions upon raw data that helped us to decide which of them to use and in which category they are supposed to be. In the category of **observers** we have:

Bluetooth: the number of the devices around the user can reveal the (minimum[2]) number of people observing him. In addition using the overall appearance frequency of devices we can also derive the relation of the user with these observers.

Ring status: can represent the willingness of the user to share the events of the device with others. A silent status may indicate that the user is surrounded by people that he does not want to disturb or that are not supposed to know that he received a message, call, or similar. A normal status can represent the opposite.

Outgoing call: the duration of a call made by the user and the relation with the called person (based on the overall frequency of call exchanged between them) can give us a hint about how the user feels about speaking on the phone at that moment. If the user trusts the observers (or he is alone) he may feel more relaxed to call a family member or a friend and speak for long time.

Outgoing SMS: the concept is the same as for calls, but is reversed. If a user is exchanging many SMS with a family member or a friend it may indicate that is in company of people that are not supposed to know the content of the conversation or even that he is actually communicating.

[2] Assuming each device correspond to a person. There can be more people around than discovered devices.

Furthermore, for the **safe-places** we have the followings:

Charging status: can reveal if a user is in a trusted place. If the phone is charging it can indicate that the user is currently at home, office or in his car. In addition the full charged status for long time could tell us that the phone is left for long time attached to the charger and confirm that the place is really trusted.

Ring status: is the inverse of the ring status in the observers' category. This time is related to "how much" the user wants to be disturbed by external events. A silent status may indicate that the user is in a safe place and does not want any other to enter that place in any way, for example with a call.

Indoor/Outdoor: there is a high probability that if the user is outdoor, he may not be in a safe place.

2.3 Intimacy Estimation Algorithm

Recalling our goal of evaluating the intimacy level of a user, after the selection of the features, we attempt to combine them to obtain a single score representing the level of intimacy. Since we do not have the ground truth to evaluate the accuracy of our algorithm against, our primary idea is not to have an accurate way to devise the intimacy level, but to have an estimation of it, based on the assumptions we made. For this reason we chose to create a greedy algorithm that using a fixed score system combines all the features to obtain the final estimation of the intimacy level. The first step we made to be able to assess the intimacy level was to divide the raw data of each user in intervals of 10 minutes (in this way we can estimate the intimacy status 6 times per hour, and have enough raw data to process in each interval). Then we decided to fix the intimacy scale from 1 to 6, where 6 represents the highly intimate state (and would imply no context sharing) and 1 - no intimacy at all. This scale was chosen to have enough distinct intimacy levels and at the same time fit the scales of the single features presented before. Always keeping the two main categories, *i.e.*, *observers* and *safe places*, we defined the following rules to compute the level of intimacy for each feature in each time interval. For the **observers** category:

Bluetooth: we started by ranking all the different devices found by all the scans by their appearance frequency. The most frequent device is the first in the rank (most known observer) and the less frequent - the last. Then to each Bluetooth device found on the considered interval we assigned a weight between 0 and 1 depending on the position on the rank (0 for the first position). The inverted mapped sum of all these weights between 1 and 6 give us the level of intimacy for this feature, *i.e.*, the known observer is the most intimate.

Ring status: in this case we simply assigned an intimacy score[3] between 1 and 6 to the different ring status accordingly to the assumptions made for this feature. We have 6 for *normal*, 4.32 for *ascending*, 2.66 for *beep*, and 1 for *silent*. In case of different states in the same interval, an average of the scores is taken.

Outgoing call: we ranked all the phone numbers found in the call log depending on the number of interaction the user had with each of them. First in the rank is the most contacted number (most intimate person). So each call's duration can be weighted by the importance of the called. For each interval, we summed all the weighted durations and map this sum to the interval 1 to 6 accordingly to the assumptions made for this feature.

[3] To equally distribute the 5 states of this feature over the 6 levels of intimacy.

Outgoing SMS: we ranked the phone numbers as for the calls. Each message found in the interval has a weight depending on its position in the rank. As for Bluetooth, we summed all these weights and mapped the result on a number between 1 and 6 to obtain the intimacy level of this feature.

The **safe-places** follow the same line of thinking:

Charging status: as done for ring status; in this case we just assigned an intimacy value depending on the state. When the phone was *no charging* we have 2, when *charging* 4, and when *fully charged* 6. In case of different charging situations in the same interval, an average of the scores is taken. In future we are thinking to weight each score depending on the time the phone is on that state (*e.g.*, more time spent on fully charged, more weight would be given).

Ring status: the procedure is similar to the same feature in the category of observers, but accordingly to the assumption of this feature, in the category of safe places the scale of intimacy states is inverted.

Indoor/Outdoor: this feature is just a simple binary 'yes'/'no' decision. If the user is indoor during the considered interval we give the score of 6, otherwise the score of 1. In case of a mix between outdoor and indoor in the same interval, the score is 3.

The algorithm completes by putting together all the scores for each category. It first computes an average of the scores for each time interval for the observers and then it does the same with the safe places. The final intimacy level for a given time spot is given by the average of the score of the two main categories. In this way all the features inside the categories and the two categories have the same weight to derive the intimacy level. It is important to remark that the proposed approach uses only the data of each user; no data is shared/crossed among them to perform the analysis. The motivation is that in the future such an algorithm may be implemented directly on the user's personal smartphone; not depending on the others' data, to preserve privacy.

3. RESULTS

To derive mobile users' intimacy level we used the MDC data collected by 38 different participants with different demographic attributes such as sex, occupation (*e.g.*, students, full time job, etc.), age range, etc. The data collected from the participants is not uniform. We have different starting and ending dates of the data gathering and non-uniform missing data across all the users (12% to 85% for the raw data used in this study). For clarity of this paper, we have selected a user that presents the most interesting results and who is among the ones with less missing data (P26, 15% missing data).

3.1 Observers and Safe Places

We analyzed the results for each feature independently, but for space reasons, in this paper we are going to present only details about their main categories. In Figure 2 we present the observers (left) and safe places (right) most frequent intimacy level per interval of the whole experiment for the selected participant (P26). We divided the data into the days of the week from Monday to Sunday and each day is divided in 144 intervals of 10 minutes. For observers, we can notice a particular intimacy level pattern. From Monday to Friday the level of intimacy is always reduced during working hours (around 7 am and 5 pm) and it is higher during nights and evenings. During the weekend the pattern is different. This can suggests that in weekends the user is more intimate or he tends to meet people that are more close to him like family members, best friends, etc. Instead, for safe places we observe a slightly different pattern. For all the weekdays the night hours and some part of working hours are more intimate than the rest of the day. Also in this case the pattern is a little bit different for the weekend, *i.e.*, when the person does not work. The time spent in places that can be considered less safe is more frequent than during the working week, where this behavior is more present just at the end of the day. We can also add, that from the intimacy level of the indoor/outdoor feature it is possible to see that during the weekend the user is more active outdoors, so he may be for more time in possibly less safe places. If we look to both categories at the same time we can say that they share some similarities that can indicate that our reasoning about intimacy may be right. Although the working place is somehow considered safer than home, the differences may not be necessary against our reasoning. For example during weekend afternoons and evenings, the person tends to be less intimate accordingly the safe places, but intimate accordingly to the observers. That can mean that she is in a not safe place (*e.g.*, a park), but she may be alone or with someone that is close to her.

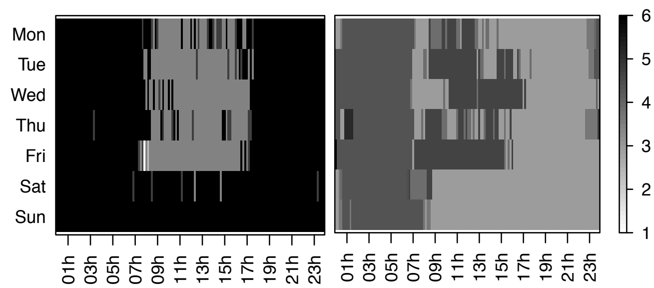

Figure 2: Observers (left) and Safe Places (right)(P26)

3.2 Intimacy Levels

Always considering participant 26, in Figure 3 we show his overall most frequent intimacy level per interval (combination of observers and safe places as explained in the algorithm) during a week. Also in this case is possible to recognize a pattern that reflects the ones depicted when discussing the two main categories alone. Weekdays are similar, but different from weekend. The higher level of intimacy is always during evenings and nights except for Friday and Saturday nights, that seem to be shifted. This can suggest us that P26 uses to go out and be more social on those nights.

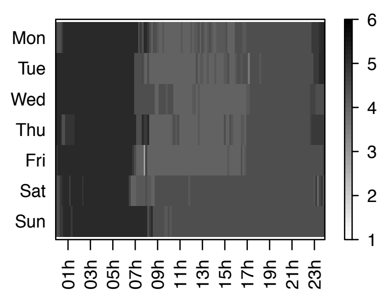

Figure 3: Intimacy Levels (P26)

Figure 4 presents the probability of participant 26 to be in a given intimacy level (considering missing data as well) for the seven days of the week. To categorize the data in 7 distinct categories (intimacy levels plus not available data) we rounded the outcome of our algorithm to the closest integer. From the graph we can see

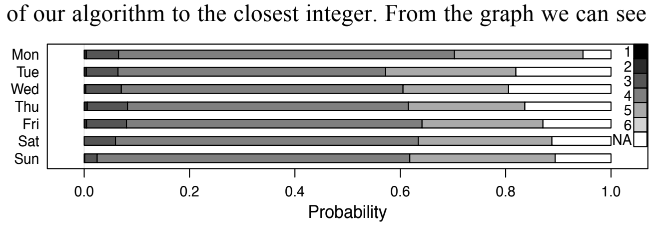

Figure 4: Intimacy Levels Probabilities (P26)

that this person is most of the time around the 4^{th} and 5^{th} level of intimacy. She tends to be more social at the end of the week (and thus less intimate) and on Sunday she prefers to spend more time alone or with a closer person (and thus to be intimate). Based on data for Monday we make the assumption that if the majority of the missing data for the rest of the week would be present, the probability to be in intimacy level 4 may increase. Another important fact to depict from the graph is that we do not have many situations of absolute intimacy or not intimacy at all (no probability for levels 6 and 1). In order to have such levels of intimacy the user would need to be in extreme situations either with a lot of not known people to reach level 1 (*e.g.*, an opera) or, to get level 6, all the features at once would need to correspond to an intimate case (really unlikely to happen given our assumptions).

3.3 Demographic Analysis

With the help of Figure 5 we want to discuss our analysis considering all the MDC participants. From a survey filled by 29 of them (out of 38) we have demographic information that may help us to connect specific intimacy level patterns to population.

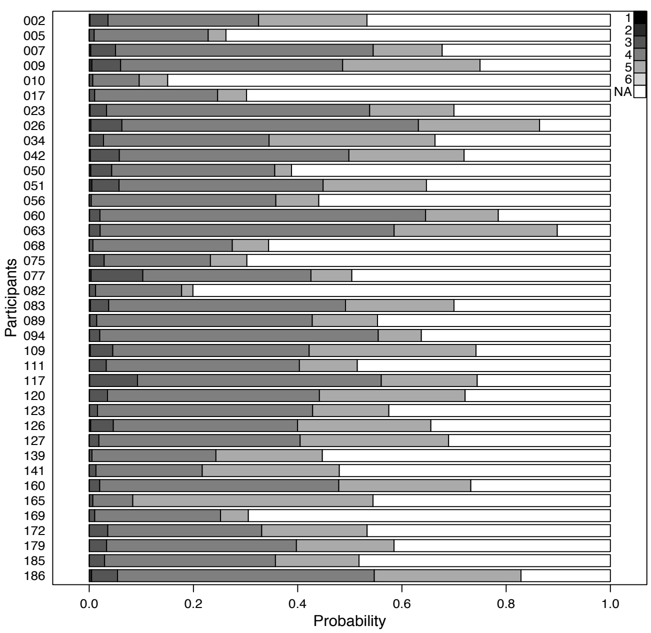

Figure 5: Intimacy Levels Probabilities for All Users

In general from the graph is evident that for the majority of the people under analysis the quantity of missing data is greater than the probability to be in a given intimacy state. In addition we can say that most of the users tend to be around the 4^{th} and 5^{th} level of intimacy. This fact can reveal that we tend to stay alone or with people that we trust most of the time (trend is confirmed by results presented in [12]). The users gender shows that female seem to be less intimate, but we have only 8 females in the whole group, hence our conclusion is drawn with care. In each age range there are heterogeneous behaviors and the distribution of the people is not uniform enough to make further assumptions. The occupation of the participants does not seem to be correlated with the level of intimacy. In each category (students, full/part time workers, etc.) there are no evidences of similar intimacy patterns. We have some indications, as may be expected, that people that use public transportation to go to work are less intimate than the one using the car, bike or walk. Also in this case the number of answers and the distribution are not enough to be certain about this phenomenon. We wanted to investigate more the correlation between our results and survey data about relationships and time spent with trusted people, but given the distribution of the answers seen so far we cannot derive statistically significant results. A less general study with pre-selected participants would be more representative to have meaningful results.

4. DISCUSSION

In this section we firstly discuss the validity of the results of our study, and particularly the limitations stemming from assumptions employed in our approach. Secondly, we discuss the role of ground truth and possible ways of acquiring it. Furthermore, we discuss possible application areas of our research.

4.1 Study Assumptions & Limitations

To develop our approach identifying the intimacy state of the study participants, we employed several assumptions on how to interpret the data. In this section we discuss these assumptions and ponder on possible inaccuracies that can influence the outcome of our research. We are going to list them as they are presented in Section 2.2. As done previously, we start by the category of the **observers**. There are following limitations of our assumptions.

Bluetooth: it is possible that there were many people around the study participants, but they do not have the Bluetooth activated (or even did not have a smartphone at all). In this case the quantification of the level of intimacy can be inaccurate. Our approach might show that the user is more intimate than in reality. Another problem related to this assumption is the existence of fix devices (*i.e.*, printers) with Bluetooth capabilities. These devices can be interpreted as people (owners of mobile phones) that we encounter often and so simulate people that are highly intimate with the study participant. As a future work, we recommend the analysis of the MAC address of the Bluetooth devices. The prefix of the MAC address can give a hint about the kind of device being considered. In this way one can filter out the undesired ones, before to proceed with the Bluetooth data analysis.

Ring status: the problem with this assumption is that generally people change their ring status accordingly to the situation they are in. We assumed that the majority of people do so, but this may not always be true. Depending on the cultural context or just personal behavior (*i.e.*, people that have always the ring tone on vibrate) “the rules” can change and for example it may not be considered impolite to have the phone’s ringer volume set at maximum during a meeting, lecture or just in a open space office. For these people there would be no difference between being in a crowded tram (where we would hypothesize the ring is ON) and being in a meeting (ring is OFF). This matter can result in inaccuracies in our results, because we are not anymore able to distinguish these kinds of situations from each other.

Outgoing call and SMS: these assumptions are based on two events, namely performing a call and sending SMS, that for the overall considered time may be infrequent and irregular. The occurrence of these events can help us to improve the accuracy of the intimacy assessment given some specific time interval, where these events are present, but the absence of such events do not provide any information. In addition, given their infrequent distribution, one needs to have at disposal a long trace of events, in order to indicate accurately, which are the most frequent numbers called or texted. This implies collection of data from the user for longer periods of time to understand his behavior.

Furthermore, for the **safe-places** we discuss the following assumptions.

Charging status: the assumption that when a person is charging her phone she is in a trusted place can be inaccurate. For example, in case if she is traveling in a plane, a train or in a long bus trip, where the electricity plug is available. Nowadays all these means of transportation offer the possibility to have a power source at a disposal. In these cases, using our approach we may conclude that the user is intimate, but in reality he is not. Furthermore as the Figure 2, right side (safe-places) shows, we consider the fact of being in an office as intimate too. The intimacy perception is subjective and for example working in an open space office may be considered somehow intimate for some people and not at all for others. The challenge in interpretation of the data arises from the fact, that both categories of people can charge their phone at work. For the people in the second group our assumption is wrong and it will decrease the accuracy of our algorithm.

Ring status: these assumption is closely related to the one made for the *observers* category. The same kind of observations can be made for this category where we assume *safe-places* and not *observers*. Also in this case we can say that a user may be at home alone, in a high intimacy state, but his phone's ring tone can be ON and phone's ringer volume set at maximum.

Indoor/Outdoor: the subjective perception plays an important role in this assumption. We assumed that if the participant is outdoor, most likely he is not in a safe-place. The challenge in interpretation of the data arises from the fact that some people may consider to be alone on a bench in a park or in a tent in the forest, as being in a safe place. In this case our algorithm recognizes an outdoor environment and therefore it can conclude that the users are not intimate.

4.2 Ground Truth and Experience Sampling

The validation of our assumptions and so of the accuracy of overall results of our algorithm it is not possible given that we do not have any ground truth from the data provided for the MDC challenge. This situation posed some limits not only on the verification of the existing assumptions, but also for further exploration of the data. More assumptions are made without a check of their validity more likely is to lead to significant inaccuracies in the final output. For these reasons we chose to limit the exploration space to the ones proposed in this paper.

In a future work, with experiments and a data collection targeting more precisely the given objective of estimating people intimacy, we will introduce Experience Sampling Method (ESM) to collect the needed ground truth. ESM will be deployed in a form of a short questionnaire appearing automatically on a user phone along his daily life activities, and asking him to label his current context with respect to his/her feeling of intimacy. With the help of periodical and random EMS logs on the user phone, we may be able to have a better understanding of the phenomenon of intimacy in different daily life contexts and start to validate our preliminary assumptions. Once we have a solid base we can start to explore other categories of data that may help us to refine the algorithm.

4.3 Applications

As we stated in the introduction, the main scope of our research is to estimate people intimacy to automatically detect when information about the users' context can be automatically collected and shared. Once accurate, this concept can be applied in developing applications in several domains. They may range from another data campaign similar to the one done for the MDC data [1] where the data would be collected respecting the level of intimacy of participants, via social applications (*i.e.*, messengers, social networking applications and etc.) where the status of the user and his relevant details are displayed and shared accordingly to the level of intimacy, to development of applications that, along the user preferences, automatically control how events and notifications to the users (receiving a message, a call, an email, a request for approval *etc.*) are handled by his/her smartphone or other devices in the environment, for example assuming that when the user is intimate the alerts shall be less intrusive (*e.g.*, just a notification without sound).

5. CONCLUSIONS

In this paper we presented our initial approach to the analysis of the concept of intimacy in privacy management for context sharing by mobile phone users. We devise a simple method to derive intimacy from daily life context data acquired on mobile phone and we have presented its preliminary results. Although we do not have sufficient information to confirm the accuracy of results of our analysis (no ground truth available and the initial participants' survey is not fully applicable), we have some first hints from the patterns of intimacy levels and from our personal experience. In addition, we found some supporting material from the specialized literature (*e.g.*, [12]) that confirm some of our conclusions, but we do not have yet the necessary knowledge in the field to assess the validity of the conclusions. In order to obtain more significant results, our current research involves setting up a dedicated experiment, following the MDC approach, and involving a pre-selected set of mobile Android OS participants and involving ESM deployment for ground truth availability. This first research results can help us to have a more clear view of which variables and confounding factors need to be investigated in the future experiments, to reach our final goal, namely to automate privacy management in people-centric sensing using accurate intimacy information.

6. ACKNOWLEDGMENTS

Our thanks to Nokia for this challenge and for the data that we used to experiment our thoughts, and the founding from WayFiS (AAL-2010-3-014) and MyGuardian (AAL-2011-4) European projects.

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