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Context-aware Question and Answering for Community-based Learning

Irina Diaconita, Christoph Rensing, Stephan Tittel

Multimedia Communications Lab
Technische Universität Darmstadt
Rundeturmstr. 10
64283 Darmstadt
[firstname.surname]@kom.tu-darmstadt.de

Abstract: Together with the rapid change and evolution in many fields comes also the problem of keeping up with this evolution and acquiring the necessary competences and knowledge to successfully complete work tasks. Community-based informal learning in the workplace is a widespread possibility to acquire knowledge, in which collaboration between colleagues plays an essential role, both in the form of documented knowledge artifacts and as concrete questions asked between colleagues. The challenge is to find colleagues who have the necessary experience to help and are available at the given time, without putting the whole counseling load on the shoulders of the same few people. In this paper we describe an innovative solution for context-aware question and answering handling as part of a wider application supporting community-based learning in consideration for mobile workers.

1 Introduction

The complexity of many fields nowadays, coupled with the rapid pace of change, make it impossible for anyone to be an expert in a whole area or over a long time period. Employees have to learn continuously considering the need of their job. In addition to a scheduled form of learning employees acquire knowledge and competences quite often on the job, in particular by cooperating with colleagues or observing the behaviour of colleagues. This kind of knowledge acquisition describes a type of community-based learning or also social learning [BA08].

In general these kinds of problems and challenges are often encountered by workers who have to deal mainly with problem solving tasks, like car technicians as far as our project is concerned. For them the aspect of the limited time frame for solving a task is particularly important, such as repairing a broken car on the highway. Therefore, in such a situation, not only colleague support is essential, but also having a short response time, which leads us to another essential aspect, namely finding available colleagues. Simply checking one by one takes a lot of time and might be infeasible for larger companies, while also disturbing the unavailable employees.

With these challenges in mind, we propose a module that offers context-aware handling of questions related to ad-hoc knowledge needs, based on the priority level of the query, while minimizing the disruption level within the community. Our module is an extension to a learning platform supporting community-based learning, which, besides the question and answering module, consists of a learning repository, containing learning resources as well as quality proven pairs of questions and answers. Users of the learning platform are all car technicians and car mechanics master craftsmen employed by two of the companies involved in our project and spread across 21 different locations.

2 Related work

While, to the best of our knowledge, there is no research regarding context-aware question answering communities, but still mobile context and activity detection is a popular and growing field. It includes different types of devices, from worn sensors to smartphones and various other mobile devices, most of the with medical applications or aimed at elderly people supervision and help and emergency situations management. Most research regarding activity recognition focuses on location [Lia06], accelerometer data or aims to build a framework to combine various sensor readings.

While location data offer important clues regarding a person's activity, or regarding whether he or she is traveling or not, accelerometer data has a good accuracy in determining physical activities. [BI04] using more worn accelerometers determine various activities, from basic ones like sitting, walking and running, to more complex activities like reading, bicycling, working on the computer or eating. As worn sensors are not a particularly comfortable solution for the user, activity detection using only the accelerometer integrated within a smartphone is more practical. [KSS03, BGC09] and [KWM11] have used this method to detect various physical activities like climbing up and downstairs, sitting, standing, walking, running or falling.

Other directions in activity recognition include building platforms that take into account multiple types of sensor readings and use various types of machine learning algorithms, from supervised learning algorithms, like decision trees [BI04, STC+09], Bayesian classifiers [KMK+03] or both of them [LHP+07] to semi-supervised learning algorithms [CBC+08].

3 Context-aware Question and Answering Handling

3.1 Functionalities of the Question and Answering module

We propose a design concept of a community-based context-aware learning platform to which users can connect in case they have learning needs using their smartphones and, if the repository queries returns no useful hints, they can send questions to fellow platform users and through which they will also receive questions from other users.

This is specifically aimed at situations where a car technician would need to solve a specific problem and would either find no suitable information regarding it, or no material concise enough to be read and applied within the limited time frame allocated to the task or suitable for the understanding of the user. Therefore the question would be routed to available colleagues who received the lowest number of questions during the day, in order to minimize the disruption level.

The system automatically detects and keeps account at all moments of the availability status of the members of the community and checks permanently for context changes so that when a question arrives it is routed to a given number of available users. If these users don't answer the question in a certain amount of time, it will be routed to other users available at this new moment and the process will be repeated iteratively until the question is answered or all members of the community received it but didn't reply.

Furthermore, even though available, both the context of the car technician asking the question, which characterizes his situation, and the context of the colleague(s) answering him might not allow any communication means or might make a particular one optimum, like writing in a noisy environment and talking/listening while driving. For this reason, the communication means are decided based on the user information.

3.2 Context Detection

We define three kinds of user context: the sensor data that includes readings of the values of different parameters of the environment (like location, time, noise level, user movements, acceleration etc.), the raw context information which associates meanings to each sensor reading (like associating a set of GPS coordinates with a building or a certain set of accelerometer readings with the user walking at a fast pace) and the inferred user situation. Furthermore, each situation is classified as being busy or not and interruptible or not. As the user's activity is what defines his availability in this case, we will consider his situation equivalent to his activity and in what follows use the two terms interchangeably.

In what follows we'll present the typical job-related activities and contexts for car technicians and the relevant environment parameters associated to them, together with the ways these parameters can be used to discriminate between various situations and the means to acquire them.

Unless the user is on vacation, activity detectable using his calendar, or having the regular legal days off, his routine that would be relevant for use would include his commute to and from work and the activities he carries out during the work hours. Of course, the application could be expanded to detect activities and forward questions even during the user's free time, but this could be seen as either an intrusion of privacy or extension of working hours. The main activities a car technician could carry out during his job would be repairing a car in the garage or on the street, driving to or from a broken car, looking up information or documenting a difficult case, studying, attending a meeting or simply taking a break.

User location is an essential context parameter, as a lot of activities are bound or determined by specific location. Location can tell us if he is traveling or not, or which company room he is in, but in most cases it has to be correlated with other environment elements in order to infer the user activity.

Another aspect to take into account is the position of a user's colleagues, as being alone in the meeting room for instance would make it clear there is no meeting taking place.

Time helps differentiate mainly between similar activities that could be carried out either in the free time or during the office hours, like traveling, but also to increase or decrease likeliness for various activities. For instance, if someone is staying for two hours in the repairment room, it's unlikely he's not repairing a car, even though other environment parameters might suggest the opposite. In the context of repairing a car, the noise level could also be a clear indicator of the mechanic's activity.

Gyroscopes and accelerometers integrated in smartphones also offer very important insight, as a person's walking pace or frequent change of position could suggest a specific type of activity, or at least the fact that he is actually engaged in some sort of activity.

An example of a user activity and the means to detect it can be seen in Table 1.

General activity	Activity details	Sensors and environment parameters	Detection methods
travelling	driving from/to work	GPS position time periodic stops or lack thereof	changing GPS position before/after working hours no regular stops and slightly higher speed
	driving to solve a task		changing GPS position during working hours
	using public transportation means to get to/from work		changing GPS position before/after working hours regular stops and slightly lower speed

Table 1: A sample activity of a technician and the relevant smartphone sensor readings for detecting it

We label each of the user activities as interruptible or not and the user in the given situation as busy or not. This distinction is necessary for the case a question didn't get an answer even though it was rerouted a few times. When the question is sent for the first time, only users who are not busy are considered, however for the next rounds also busy but interruptible users would be considered, as the delay with which the answer is received is essential .

We also personalize the communication applications used based on user preferences and activities. An user could prefer sending a SMS over using the app for a user who is driving a car, it would be more appropriate to use voice mail to receive questions and send answers.

4 Implementation and projected evaluation

Our application has two main sides, the client and the server side. On the client side, which is a smartphone app, there are two main modules, the Sensor Data Collector, which gathers the data (including location, noise level, accelerometer and gyroscope data) and sends it to a communication bus and the Question and Answering app itself, which allows the user to send and receive questions in various formats (app, SMS, voice mail). The client application also gives the user the possibility to register, set up a profile and preferences (like preferred communication means or times and activities he does or does not want to be disturbed).

The Situation Detection Module listens to the bus and use collected raw context information to infer users situation. By this if the readings of the sensor fusion module show only a negligible change in the GPS coordinates of the user, the user's situation is not recalculated.The Situation Detection Module classifies activities using a set of rules/various machine learning algorithms/decision trees built based on an initial set of inputs, where users manually annotated some of their activities. The detected activities get their availability and interruptibility levels based on the set of rules previously presented in Figure 2. This module sends on startup the availability and interruptibility statuses of all users to the Learning Module and afterwards just sends updates (as events) when user's situations change.

The concept has been developed in an intensive cooperation with different representatives from four companies (two car dealers, one manufacturer with own garages and an auditing agency responsible for technical tests). We analyzed the different roles involved in the presented scenario and the representatives from the four companies described the desirable functionalities in form of user stories. Based on a analysis of the user stories we designed a first version of the overall concept, described in the previous sections, which has been discussed with the partners during a workshop and has been modified based on the workshop results. Therefore the design concept has been evaluated by future users. We plan a step by step introduction of the overall learning platform starting with the question and answering application, as the application partners give special priority to the informal communication and the mutual assistance between the workers.

5 Conclusion and future work

In this paper we described an application supporting community-based learning aimed at mobile workers. Its focus is on the automatic detection of context, specifically of the activity of a mobile worker and on the usage of this information for the selection of available coworkers to help with answering a question as well as for the selection of the communication means. Our overall concept proposes on the one hand side to use additional kinds of context information and other context-sensitive application modules which shall part of the community-based learning application.

Our architecture is extensible. To integrate new sources for context information we only have to train our context detection module. So new application modules can get information about the context from the Situation Detection Module.

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