Crowdsourcing Situated & Subjective Knowledge for Decision Support

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Abstract
In this paper we present a study on crowdsourcing subjective knowledge. We introduce a mobile app that was built for this purpose, and compare results from two datasets collected using the app. One dataset was collected during a workshop and the other one during a one-week long field trial. We present interview findings on mobile knowledge collection. Further, we discuss the types of information that should optimally be collected on the go, and show how our data analysis supports the qualitative findings. This work directly continues our earlier efforts on creating a platform that encapsulates wisdom of the crowd for decision support.

Author Keywords
Mobile Crowdsourcing; Wisdom of the Crowd; Crowdsourcing; Decision Support; Android; Smartphones.

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

Introduction
Earlier, we introduced a crowd-based Decision Support System (DSS) called *AnswerBot* [7]. Our DSS offers decision support on practically any arbitrary problem based on the classic theory of *wisdom of the crowd*

[12]. Our goal is to make AnswerBot a platform where any visitor can easily contribute to a number of problems being investigated at the time. At the same time, the platform can offer real-time decision support on each problem.

The initial experiments proved the feasibility of our DSS concept, as well as its ability to provide trustworthy decision support [7] as long as the data (wisdom) collection is done appropriately. In this paper we continue exploring the data collection procedure and introduce *AnswerBot Mobile*, an Android application encapsulating key functionality of the online version of AnswerBot. In particular, we explore why – if at all – it is important to facilitate easy mobile data collection. The findings we present are based on an initial workshop, a field trial that lasted for 7 days, and concluding 1-on-1 interviews with 12 participants.

Related Work

Wisdom of the crowd refers to the aggregated opinions of a crowd and relies on mathematical aggregation methods [10]. While its earliest mentions can be traced back to Aristotle, the work by Sir Francis Galton in 1907 on a weight-judging contest of a fat ox at a farmer's fair is widely acknowledged as the first academic investigation of the concept [5]. In our case, we merely revitalize this age-old concept into modern settings by using mobile crowdsourcing to collect the "audience opinions", or wisdom of the crowd, for a given problem.

Decision Support Systems is a discipline of information systems that assist in making decisions [1]. While DSSs lack a single accepted definition [2,11], Finlay defines a DSS as broadly as "*a computer-based system that aids the process of decision making*" [4]. Conceptually, DSSs consist of three main components: the knowledge base, the model, and the user interface [2]. The knowledge base stores data relevant to the problem. The model formulates a decision based on the knowledge base contents. Finally, the user interface enables users to build the models (input data), and obtain decision support by adjusting configuration parameters.

One goal in our work is to replace the costly process of harvesting input from multiple sources to populate knowledge bases [3]. To this end, recent work suggests that crowdsourcing using both situated and mobile technologies together with appropriately designed incentives can help in reaching large numbers of individuals both affordably and rapidly [6,8,9].

AnswerBot Mobile

AnswerBot Mobile is implemented as a native Android application that uses the online counterpart's (introduced in [7]) APIs to offer identical functionality for mobile users. AnswerBot practically breaks down any question (e.g. "*Where should I go for holiday?")* into potential answers ({Finland, Hawaii, Argentina, …}) and criteria ({Expensive, Good nightlife, Safe, …}), and builds a model of how well each criterion describes each of the answers.

AnswerBot Mobile users can contribute to the underlying knowledge bases of any available questions in the system by i) adding potential answers (we use the term *option* in official contexts, although *answer* is more explanatory towards end users and is thus used in the user interface), ii) adding potential criteria, and iii) donating their own subjective knowledge to the

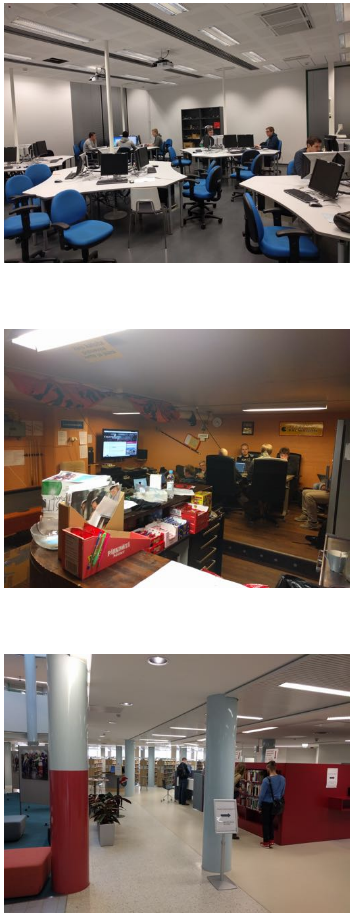

Figure 1: Three of the locations used in our study.

available option-criteria pairs. Each criterion and option can be accompanied by an additional description to further clarify its meaning. Rating of the pairs is implemented using a slider input element (scale from 1 to 100) – identical to the online version. Mobile users can also receive decision support on the questions, but here we focus on the data collection part, *i.e.* donating knowledge to the available option-criterion pairs. The mobile user interfaces for all the mentioned functionalities are depicted in Figure 2.

The Study

As mentioned briefly in the introduction, our ultimate goal with AnswerBot Mobile is to explore aspects of mobile data collection to construct highly accurate knowledge bases. To this end, situated crowdsourcing – referring to either using fixed devices in the environment or using mobile devices in the correct spatiotemporal context [6] – has emerged as a promising means to collect high-quality data.

We recruited 12 participants (10 male, 2 female) from our campus by using a student mailing list. We first organized a joint 1-hour workshop to install AnswerBot Mobile from Google Play and to let participants familiarize themselves with the app. The workshop was followed by a 7-day long field trial where participants were requested to use the mobile client for a specified task around our university campus (see examples in Figure 1). Finally, the participants were sent an online survey, invited for a brief 1-on-1 interview and given their reward (a movie ticket).

For the workshop, we provided several questions in the system from our earlier experiments, and added two new questions that directly relate to our campus. The two new questions were "*How can I find information about University of Oulu courses?*" and "*What is a good place to study or work at our university campus?*" (Q1 and Q2, respectively). Q1 was added to the system merely for participants to come up with new criteria and options, donate knowledge to, and explore the functionality in general.

During the workshop, participants were encouraged to freely explore the client and to add options and criteria to the questions, or simply to think aloud to have one of the researchers add items. The participants were requested to provide one full round of subjective assessments for each option-criterion pair of Q2 (8 options, 6 criteria = 48 pairs) during the workshop. Q2 was also used for the 7-day field trial, or "homework", as we dubbed it. During the homework participants had to actually go to each of the option candidates (locations on our campus) and provide the same assessments there, in situ. To prove they actually went to the locations participants had to provide "selfies" from each location when coming back to the interview. The participants were also encouraged to make diary notes about what, or how, does it feel different when rating option-criteria pairs in situ at the location as opposed to doing the same at the workshop and thus physically away from the location. This is important, as the initial goal of this study was to start exploring factors behind mobile knowledge collection.

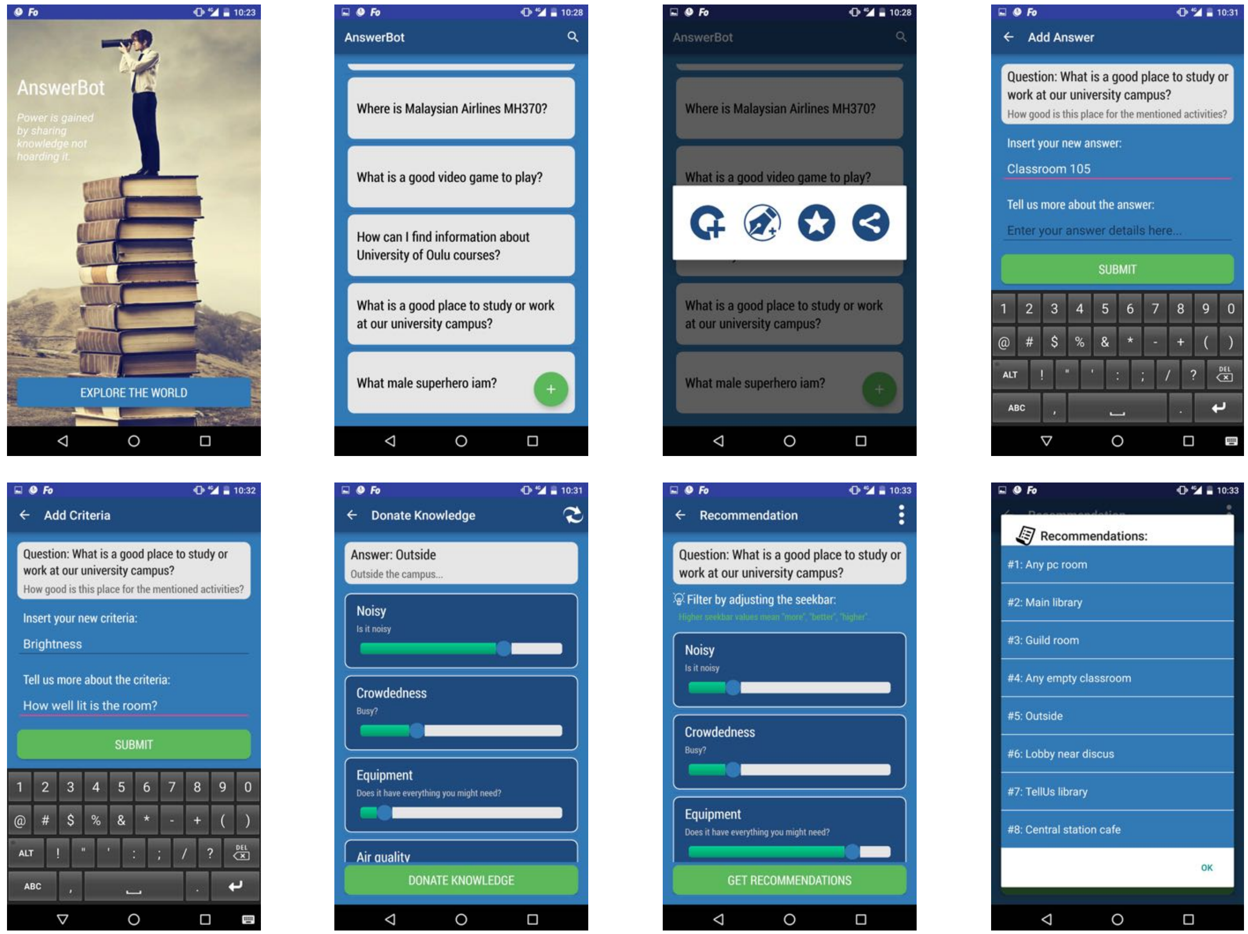

Figure 2: AnswerBot Mobile screenshots. Top row from left: the application start screen, list of already available questions in the system, a menu that appears by long-clicking an item to interact with the item content, and a screen to add new answers to a question. Bottom row from left: a screen to add new criteria to a question, a screen for donating knowledge to the system, a decision support interface where the users first decides the desired optimal criteria, and decision support presented as a list of best-matching options available in the knowledge base.

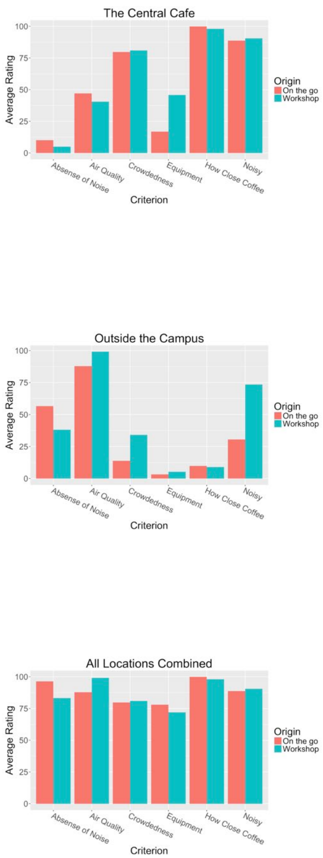

Figure 3: Assessments of The Central café, Outside the Campus, and all locations combined in both conditions (on the go and workshop).

Analysis and Results

Table 1 lists the results of the options and criteria collection during the workshop. Each criterion and option was also accompanied by a small description as well, as can be seen in Figure 2 (bottom row, three leftmost screenshots).

	Options	Criteria
Q1	- Weboodi	- How fast to find info
	- University staff	- Up-to-date info
	- Ask professor	- Reliability of info
	- University website	- Available to everyone
	- Ask friends	
Q2	- Tellus library	- Absence of noise
	- Guild room	- Noisy
	- Central café	- Crowdedness
	- Outside the campus	- Equipment level
	- An empty classroom	- Air quality
	- Any PC room	- Coffee found nearby
	- Discus lobby	
	- Main library	

Table 1: Options and criteria the participants bootstrapped during the workshop for the two campus-related questions.

The maximum amount of ratings for Q2's available option-criterion pairs is 576 (6*8*12). During the homework we collected 436 ratings (75.7% of maximum). We analyse the effect of origin context (workshop or on the go) on the ratings. Examples can be seen in Figure 3. For each option-criterion pair we consider all ratings by all participants together. Pairwise comparisons revealed that the origin context affect the ratings in 5 cases ($p < .05$). For instance, equipment level was found significantly lower in the Central café when rating on the go than when rating at the workshop. Another example is when assessing general noisiness, outside the campus was found to be significantly less noisy than anticipated during the workshop. Noise in particular surprised many individual participants in the main library. While the difference between all library noise ratings from both origins is not significant, four individual participants expressed during the interviews that it was much noisier than anticipated: "*I expected the library to be much less noisy actually, and then when going there it was full of people and just noise*" or "*library certainly noisier than expected*".

Interview comments in general tend to support the need for mobile data collection methods: "*things like location or nearest services are easy to rate beforehand, but things like quietness or air quality are hard to remember afterwards*" or "*need to expand the available set of criteria definitely on the spot, could not think of some obvious criteria in the meeting room*".

Discussion and Conclusions

In our earlier work we have extensively discussed crowdsourcing subjective knowledge for decision support [7]. Here we set to explore whether it is beneficial to provide a dedicated mobile means for the data collection. Ultimately, the verdict is unclear, although we did collect evidence in favour of mobile data collection solutions. If the topic for what knowledge is being collected for is familiar to the users, an online version might suffice. However, sometimes the correct context significantly changes the collective perception on a specific assessment criterion, and thus proves the preconceptions about a given matter wrong. Another example of the benefits of a situated assessment is when the characteristics of a location change over time. By using situated assessment, it is possible to have a more nuanced decision support system (e.g., noisy in the morning, not noisy in the afternoon) that can be challenging to gather using online an online mechanism. Further, two participants indicated in the interviews that it is difficult to come up with all the imaginable criteria do describe a location unless actually being there.

Our ongoing and future work on mobile knowledge collection focuses on collecting situated knowledge on different city regions.

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