The Design Space of Ubiquitous Product Recommendation Systems

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ABSTRACT

Customer reviews and recommendations for products are provided by almost all e-business platforms, supporting consumers when shopping on the web. Mobile and ubiquitous computing provide extended means to sense input data for recommendations and to make recommendations available for consumers when shopping in traditional stores. This work contributes a comprehensive design space that outlines design options for product recommendation systems using mobile and ubiquitous technologies. A visual notation for the design space is proposed, based on which existing systems are categorized. Blank spaces are identified and concrete possible extensions are proposed by the example of an existing mobile product recommendation system. Finally, general options for future research on product recommendation systems using UbiComp technologies are discussed.

1. INTRODUCTION

When shopping, consumers often face a situation where not enough information is available to make an informed choice. If the benefit of searching for additional information is higher than the cost, they search for additional product information, sometimes relying on recommendations of others [33]. When relying on recommendations, the lack of personal experience with a product is inferred by experiences that others have made, by so called 'virtual experiences' [22].

Research has found out that those recommendations significantly influence the buying decision [38] [39] especially for so called experience products [21], i.e., products that are dominated by attributes that need to be experienced in order to be evaluated. Typical examples for experience products are wine, movies, and books. However, product recommendations do not only influence the buying decision. They are also a valuable tool for manufacturers and retailers [12]. These can make use of user-generated product recommendations for market research and advertisement purposes. The former allows companies to find out how their products are perceived in the market and take actions accordingly. The latter is relying on the fact that trusted referrals are said to be more influential than conventional advertisements [18], meaning that personal recommendations are a powerful marketing tool.

Before the era of information technology, virtual experiences used to be exchanged through word of mouth, recommendation letters, printed CD reviews, and the like. These have become digitized in the recent decade. Nowadays, recommendations are offered on the web as a part of the customer service of almost all e-commerce platforms (such as on Amazon.com). They are provided either in the form of customer reviews and ratings for a given product, or as recommendations of a specific product to a particular user, performed by so called recommender systems. Product recommendation systems usually come in the following shapes: in simple cases they act as a communication channel that is used to directly make available a recommendation to interested entities. More complex recommendation systems take recommendations as input and aggregate and target them to particular users. Sometimes the systems only aggregate entered recommendations, and in some cases recommender systems make matches between the users recommending and the users seeking recommendations. For this matching, the developers of the first recommender system, Tapestry [15], have coined the phrase 'collaborative filtering', and many others have adopted it. In this work, we will summarize all IT systems that aim at providing product recommendations as product recommendation systems.

Although product recommendations are currently predominantly a phenomenon of the Internet, there are first approaches that reach out into the real world. Keeping in mind the fact that people shop differently in the real world than in the web [11] [8], both research and practice[1] and have come up with mobile applications that interact with products through tag scans, and smart shopping carts making recommendations to shoppers at the point of sale [23].

We argue that these applications are yet only the beginning. UbiComp technologies in the form of sensors and ubiquitous information displays provide new possibilities of extended sensing, building a foundation for measuring product experiences implicitly and displaying recommendations to consumers when actually shopping.

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MUM 2009, November 22-25, 2009, Cambridge, UK.
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[1]Practical examples are 'Compare Everywhere' and 'ShopSavvy' , both finalists of the Google Android Developer Challenge, as well as the newer android apps 'Wine by the Bar', and 'Barcoo'.

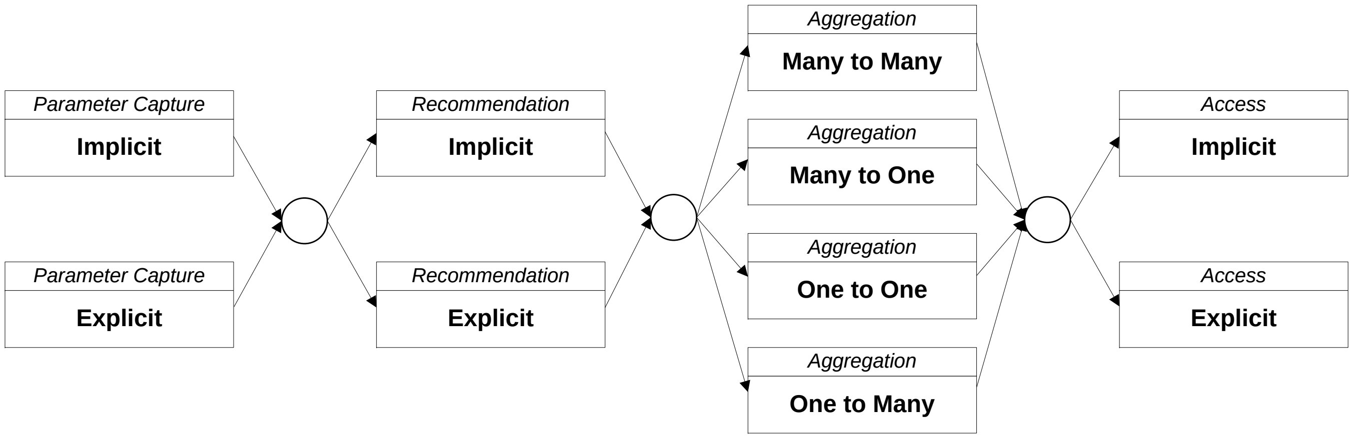

Figure 1. A visualization of the design space of product recommendations.

We study: How can product recommendation systems using UbiComp technologies be designed? What has already been researched? What are potential research directions?

For investigating these questions, this paper proceeds as follows. It spans a technical design space for product recommendation systems using UbiComp technologies (Section 2). Based on this, it validates the design space by filling it with web applications and UbiComp applications (Section 3). Having identified white spots in the design space, possible extensions for current systems are outlined by the example of APriori, a mobile product recommendation system (Section 4). Fourthly, it generalizes the extensions and comes up with guidelines for future research (Section 5). It closes with conclusions (Section 6).

2. DESIGN SPACE

This section spans the design space of product recommendation systems using UbiComp technologies. In this design space relevant design decisions are outlined and categorized.

In order to be electronically accessed by consumers when shopping, product recommendations are modeled in dedicated systems. We consider a product recommendation as a *value* that is assigned to the combination of a *user ID* and a *product ID*, for example using a data base table 'recommendations' with the columns *user ID*, *product ID*, and *value*. It is worthwhile mentioning that this value can be expressed as an absolute value of one specific product or as a relative value assigned to a product compared to other products. Also, a recommendation assigned to a particular product type, for example to a wine of a type and of a certain year, can also apply to some extent for other products in the same category, for example the same wine type of another year. The *value* assigned to a product in the process of generating a product recommendation is usually represented through one or several of the following options:

- Binary (e.g. 'I like the product' /'I don't like the product')
- Numeric (e.g. a rating on a five-stars Likert scale)
- Symbolic (e.g. an image 'thumbs up' /'thumbs down')
- Textual (e.g. a textual review of a product)
- Audio (e.g. a spoken product review)
- Visual (e.g. a video-recorded product review)

Following the sequential logic of generating, aggregating, and accessing product recommendations, we have chosen the following dimensions for the design space (see Figure 1): parameter capture, recommendation, aggregation, and access. The dimension 'parameter capture' classifies options for capturing the input data for recommendations (i.e. *product ID* and *user ID*). The dimension 'recommendation' shows how the value expressing a product experience can be assigned to a combination of a *product ID* and a *user ID*. Based on this, the dimension 'aggregation' outlines the options for aggregating and targeting the captured data, and the dimension on 'access' classifies ways of making product recommendations available to consumers.

It is certainly debatable what issues are important enough to be explicitly considered dimensions in the design space and one could argue in favor of adding more dimensions or removing some of the dimensions described below. We have taken the approach of modeling the process of recommending products on an abstract level and considering specifically the steps that can potentially be influenced by UbiComp technology. In the descriptions of each dimension below we will justify their existence. We build up on the work of [2], who have proposed a design space for web-based recommender algorithms, but have not considered context-sensitive data capture and user interfaces interacting with the real world.

2.1 Parameter Capture

Before a user can express a product experience through a product recommendation, the parameters, i.e. the product to be recommended and the identity of the recommending user need to be captured by a recommendation system. The *product ID* and the *user ID*, as defined above, can be captured either explicitly or implicitly. Capturing data explicitly means that the user interacts with the system specifically for the purpose of providing the system with the necessary data, implicitly in contrast means that the system captures the data while the user is interacting with the system for another purpose.

Why is this a relevant dimension? Because UbiComp technologies can provide extended means to capture data implicitly. Developers need to take a choice whether to capture data explicitly or implicitly, or a mix of both.

Explicit: A possibility to provide a recommendation system with the input parameters *product ID* and *user ID* is the explicit entry of these. In this case, the product's identity is captured through an explicit interaction of a user with the product, be it scanning a tag (for example a barcode or an RFID tag) or entering an identifier manually (for example typing in an EAN barcode another a product ID). In addition to the *product ID*, the user needs to provide the system with his own identity. This can also be done explicitly and implicitly. An explicit means to provide the system with the *user ID* is for example logging on to a mobile application with a user name and password.

Implicit: The input parameters for generating recommendations can also be captured while a user is interacting with a product for another purpose. A scenario for capturing the product implicitly may be a consumer buying a product (see [26]), or the return and repair of a product. In collaboration with retailers this data, for example captured through customer loyalty cards, can possibly be used for recommendations. Another typical scenario of implicit data capture on the web is the capture of data when a user is browsing product descriptions such as on Amazon, or scanning products in the shop with a mobile phone in the frames of another application (e.g. when assessing the carbon footprint of a product). Capturing the *user ID* implicitly may either be performed while capturing the *product ID* (e.g. when paying a product using a loyalty card, credit card, etc.) or captured separately (e.g. using the SIM card data of a mobile phone as user data).

Options: Explicit vs. Implicit

2.2 Recommendation

No matter whether *product ID* and *user ID* have been captured explicitly or implicitly, the *value* of the product recommendation can be generated explicitly or implicitly. Although the parameters might have been captured for example during purchase of a product, a user might still assign a *value* explicitly. This does not account for the other way around: the case that someone captures parameters explicitly for recommendation, but the recommendation (entry of the value) is performed implicitly, seems unrealistic. Generally it needs to be considered that capturing a *value* explicitly requires more cognitive effort. However, the advantage of capturing a recommendation explicitly is that it can be more accurate, since mistakenly implied recommendations can be avoided.

It is important to understand that this step is independent of entering *product ID* and *user ID*, meaning that mixes of explicit and implicit capture of the parameters and actual recommendation, possibly applying UbiComp technology to only one part of the two, can make sense.

Explicit: If the recommendation is captured explicitly, a user decides on a subjective *value* that expresses his experience with a product and enters the *value* into the system. Examples are typing a product review on a computer's keyboard or recording a video using a mobile phone. The system might remind users to explicitly perform a recommendation a certain time after they have bought a product. It is worth mentioning that, in the same way as data of other scenarios is used for generating recommendations, recommendations made by users explicitly might implicitly also be used for other scenarios. The privacy of the generating user is obviously critical in this case. Possible implicit use cases of product recommendations could be in the areas of market research and advertising.

Implicit: In case only the *product ID* and the *user ID* were captured, the system has to generate a product recommendation implicitly. A system calculates or infers the value of a given product entity based on other interactions of a user with the system. An example is if a user buys a product several times. Then the system could infer that the user likes the product. For example if someone buys a wine several times, the system could infer that he likes the wine. Or if a user returns a product the day after he has bought it and buys another product of the same category, the system could infer that the user did not like the product he bought first. The main motivation for using implicit ratings is that it removes the cost to the evaluator of examining and rating the item [31]. However, if made implicitly, the recommendations might not be as precise and reliable as explicitly generated recommendations.

It is also possible that the data used for the generation of product recommendations is entered both explicitly and implicitly. For example the web radio station last.fm monitors the music files a user has stored in his private music collection ('scrobbling') and uses this information implicitly to suggest songs, but also allows the user additionally to explicitly provide feedback to songs through 'blocking' or 'loving' them.

Options: Explicit vs. Implicit

2.3 Aggregation

For a given product, there might exist too many *values* or more general, too much captured data to be accessed. It is a usual procedure to aggregate recommendations and make them available for only a selected audience. For the aggregation of product recommendations according to users the following options exist: a recommendation of one particular user is targeted at specifically one other user (including himself) (one to one), a recommendation of one particular user is targeted at many users (one to many), recommendations of many users are aggregated towards one specific user (many to one), or recommendations of many users are targeted to many users (many to many). We have built up in this classification on several works on recommendation algorithms, for example on [41], who provided a state of the art analysis in this domain.

Why is this a relevant dimension? Independently of UbiComp technology, recommendations of relevant others like friends of family members are said to be more valuable than recommendations of random users [18], meaning that the origin of a recommendation influences its effectiveness. Also, recommendations that are targeted towards one particular user, taking into account his individuality are followed in a greater proportion than general recommendations [39].

Many to Many: Performing this aggregation the values of many unspecified users (for example ratings) might be aggregated (e.g. averaged) for a certain product (so called *item-based filtering*) and made available to many other unspecified users. Another option is that the values of many users are not aggregated at all (e.g. textual product reviews) and made available as they are for many users. As the recommendation is not created specifically for a user in this case, the receiving user needs to do the cognitive step of determining whether a recommendation matches his needs.

Many to One: People are individual and like different products. There are algorithms catering to this fact, taking implicitly and/or explicitly captured recommendations of dedicated users and targeting recommendations at other users with similar user profiles. This procedure is frequently referred to as *collaborative filtering*. In contrast, *content-based filtering* (see below) only relies of the past behavior of the user a recommendation is targeted to. There are also *hybrid approaches*, following both methods to make a recommendation.

One to One: These are approaches where either one particular user who knows a lot about a certain product type and/or a lot about a certain peer user (e.g. for example a friend) recommends a certain product to this one peer user. An example is the classical word of mouth, where one consumer tells another consumer about an experience with a product orally. Another approach where history data of the targeted user himself (either captured explicitly or implicitly) is used to predict a recommendation for the user himself are called *content-based filtering* algorithms. These take recommendations that a user has stored explicitly or implicitly in the system in order to propose new products to the user. Yet another approach for one on one recommendations are so called electronic shopping lists. It is possible that a particular user makes a recommendation only to himself, in order to not forget a product choice he has made and has been happy with. Typical examples on the web are electronic shopping lists (explicitly entered data) and automatically stored electronic shopping carts when logging out before purchasing that are used for recommendations (implicitly entered data) on Amazon.

One to Many: In this case the recommendation of a particularly relevant user is made available to many interested users. Examples are test reports of a particular consumer organization, or a wine expert sharing his experience with a certain wine with his friends through a social network. The Facebook application LivingSocial.com is so far the most popular of these social-network-based recommendation systems. It allows users to explicitly select products they like and explicitly review these, and share these reviews with friends on social network platforms such as Facebook. But there are also Facebook applications that capture product recommendations implicitly and make them available to friends [25]: so called social ads. Facebook has tested the implicit capture of transactions with the ticket site 'Fandango' and shared these transactions as recommendations with other users on the news feed of the user who did the transaction. In this and similar cases privacy is an important issue. History indicates that consumers do not want to share product recommendations attributed to their name with random other users.

Options: Many to Many, Many to One, One to One, One to Many

2.4 Access

Having generated and published product recommendations, the recommendations need to be accessed by the users they are targeted for. The accessing of recommendations can be performed either explicitly or implicitly, depending on whether a consumer is actively searching for additional information for a product of a certain type, or is only attentive towards information of a certain product type.

Why is this important? Because UbiComp technologies provide new possibilities to allow consumers to access recommendations at the point of sale either explicitly or implicitly.

If a user accesses recommendations explicitly, he is interested in a certain product category (e.g. a ranking of all digital cameras) or maybe even more specifically in a product of a type. This means that information aggregated towards this product (see above: item-based filtering etc.) needs to be implemented. If the recommendation is accessed implicitly, the user is not yet focused on a particular product, meaning that the recommendation should not have been aggregated over many products, but rather be targeted towards the user.

Explicit: Possible ways to access product recommendations explicitly are using one's mobile phone during shopping, or accessing them actively while shopping on the web. Recent developments have drawn our attention also to augmented reality. There have been approaches to project product recommendations to the products themselves [30].

Implicit: Also, product recommendations might be accessed in the frames of reading a magazine or during any other activity, for example in the form of advertisements while you are watching your favorite TV show. An example using ambient technology is using light spots of different colors to highlight items implicitly when a certain user comes in the vicinity of certain items. For example, if a user approaches a wine shelf, its identity could be recognized automatically, and the best rated wines could be highlighted with green lights, and worse ones with red lights.

Options: Explicit vs. Implicit

3. APPLICATIONS

In the above section we have categorized how product recommendation systems can be designed in a design space. In the following we validate the design space. To do so, we give an overview of existing applications and assign them to options in the design space. The first subsection gives an overview of applications that are applied in practice already, the second subsection describes applications that have been researched in the Mobile and UbiComp domain in recent years. Obviously, there has been research on recommendations in other domains as well (e.g. recommender algorithms, consumer research). However, we focus on listing applications where recommendations are reaching out into the real world, in order to identify white spots in the design space and list possible extensions in the UbiComp domain accordingly.

3.1 Practice

Recommendation systems using ubiquitous computing technology yet do not exist in practice. Many online retailers however, for example Amazon.com, cover the complete design space with their recommendation systems. They capture parameters and recommendations explicitly (e.g. users entering product reviews) and implicitly (e.g. using earlier transactions of users as an input for recommender systems), offer means to add products to a personal shopping cart (one to one) recommend products directly with friends per mouse click (one to many), use data from other users to generate recommendations targeted at a specific user in form of collaborative filtering algorithms (many to one) and allow product-specific textual reviews of anybody for anybody (many to many). The reviews are accessed implicitly while browsing (e.g. the feature 'who bought this also bought that') and explicitly when specifically interested in information about a certain product (reviews and ratings).

The independent web platform Epinions.com, in contrast, has focused on product reviews between peer customers (many to many).

Another interesting approach has been taken recently by LivingSocial.com. They have specialized on product recommendations, integrated with the social network Facebook, and cover almost the complete design space as well. While logged on to Facebook, users can keep track of what they like, receive recommendations based on their own collection based on content-based filtering (both one to one), and interestingly, share recommendations with selected friends (one to one/one to many) easily through Facebook. The friends in turn receive a trusted referral from a friend.

3.2 Research

Research on ubiquitous computing has come up with a number of recommendation systems reaching out in the real world. Many of the works are related to mobile phones and have been performed under the terms m-commerce [47]

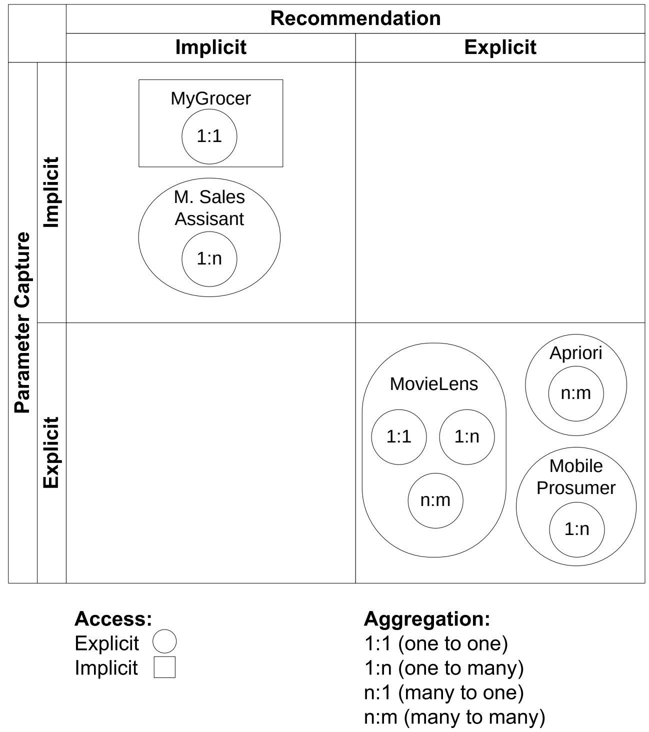

Figure 2. Existing UbiComp systems in the design space.

and mobile shopping assistance [24] [3]. In addition, there have been a number of mobile applications focusing on price comparison [6] [13] instead of product recommendations. This is somewhat similar to recommending products, although the seller is actually compared based on the criterion 'price'.

Also, there are a remarkable number of UbiComp applications that have investigated recommendations for other entities than products. For example, there have been numerous works on recommending tourist attractions. Some have developed mobile context-aware tourist guides like CyberGuide [1], COMPASS [43], and Magitti [5], others have evaluated the user interfaces of such systems [10] [4]. Also, there have been more general recommendation algorithms for mobile devices [16]. These focus on finding similar users in the vicinity in mobile peer to peer networks [29] for sharing files and general information like web links [42] and music [19] on the go. An example is the PILGRIM [7] system. A possible reason why product recommendations on mobile phones have been researched predominantly in the very recent past is certainly the emergence of mobile phones that in the meantime can easily interact with products by reading barcodes and RFID tags, and enable high speed Internet connections.

In the following we will have a closer look at mobile and UbiComp product recommendation applications and categorize them according to the design space defined earlier in this paper (see Table 2). By showing how the existing applications fit into the design space, we validate the selected dimensions.

MyGROCER [23]: MyGrocer is a ubiquitous shopping system. It allows businesses to support consumers in the whole shopping process (B2C). The concept of MyGrocer is built around three scenarios: (i) an in-store scenario, where consumers access relevant product information (like recommendations targeted to them specifically) through a smart shopping cart, (ii) an on-the-move scenario where consumers can edit their shopping list using a mobile phone, (iii) and smart-home scenario, where RFID readers in the kitchen detect when a consumer is running out of certain goods and puts these on a shopping list. Where is MyGrocer settled in the design space? MyGrocer captures the parameters implicitly by sensing out of stocks in the kitchen and whenever a consumer buys something. A recommendation is both made explicitly (shopping list) and implicitly (recommender system). The aggregation of recommendations is made 'one to one' through a wish list a user creates for himself, and a content-based filtering algorithm that uses the history of purchases to make recommendations. The user accesses recommendations implicitly in through a display mounted on a smart shopping cart when shopping.

MovieLens [28]: The paper of Miller, Konstan, and Riedl is a classic of mobile shopping assistance. The system called MovieLens Unplugged (MLU) supports consumers when browsing for movies in their video rental store. The work focuses on the technical realization of the mobile application, which was not straight forward at the time. The system has been deployed and tested on four different mobile devices (cell phone, web phone, PDA, wireless PDA) and, remarkably, provides a voice interface for accessing recommendation. It captures the input parameters explicitly: users log onto the application and interact with the phone through a voice interface. Also, the recommendations are made explicitly: on a scale from one to five and through textual reviews. The aggregation of the recommendations is performed 'one to one' through a personal wish list, 'many to many' in the form of item-based product ratings and reviews that are made by any user and available for any user, and through 'one to many' recommendations that allow specific users to share recommendations with a selected group of friends.

Mobile Sales Assistant [34]: The mobile sales assistant is a mobile shopping assistant that allows consumers to access additional retailer-offered product information when shopping. The mobile phone interacts with tagged products through NFC, a mobile phone technology that allows reading RFID tags. Parameter capture and recommendation are both made implicitly, since the data that is displayed (product descriptions, advertisements) is imported from the existing system landscape of the retailer and not entered specifically for the purpose of recommendation. The aggregation is of the type 'one to many' since one specific source (the retailer) provides information to a large number of recipients (consumers). These access the recommendations explicitly by scanning a product from a mobile phone application.

Mobile Prosumer [35]: The Mobile Prosumer is a mobile shopping assistant that interacts with products through scanning NFC tags. It assumes that all products will be tagged with RFID (NFC) tags once (see above). Based on scanning the tag with a mobile phone as a trigger, the a user receives a detailed product description, direct recommendations from friends, expert recommendations, and an order form. The work is one of the most recent approaches and has been evaluated extensively. Both parameters and actual recommendations are captured explicitly by the users. Recommendations can be provided by either random users or experts. The recommendations are aggregated 'one to many': either a dedicated friend or an expert performs a product review and makes it available to a broad audience. Consumers access recommendations by scanning an NFC tag from a mobile application.

APriori [45] [44]: APriori is a product recommendation system that interacts with tagged products through NFC, a mobile phone technology that allows reading RFID tags (see above). Users receive ratings of random other users upon scanning of a tag. The system proposes the approach to use self-defined rating criteria instead of long textual reviews in order to cater for the limited input and display modalities that mobile devices still face. Users enter recommendations on their mobile phone on the go. For this, they capture the input parameters explicitly by scanning the NFC tag of a product from a mobile phone application and typing in a rating on a scale from one to five (recommendation: explicit). The aggregation is many to many, since the ratings of many random users are averaged and provided to many other random users. These access the ratings explicitly scanning a tagged product from a mobile phone application.

4. CASE STUDY: APRIORI

Filling the design space with applications from the UbiComp domain (see section 3) indicates that research on porting product recommendations into the real world has focused on making product recommendations to consumers shopping in real shops with their mobile phone. Although we believe that there is much more to ubiquitous product recommendations than porting product recommendations to mobile phones, we have selected one of the above mobile systems and performed a white spot analysis, and proposed extensions. This decision is based on the tendencies, that mobile phones are considered the next step in applying UbiComp technology in our everyday life. Of the above systems we have selected APriori, since it is the only of the above approaches that is a pure mobile recommendation system, meaning that, unlike the other systems discussed, it completely focuses on product recommendations. In the following we describe APriori in some more detail and outline how APriori could be extended into several directions of the design space defined above.

Apriori is a product recommendation system for mobile phones. APriori has been applied to olive oil and wine as products to be recommended. Let us assume that a consumer is standing in front of the shelf and is overwhelmed by the choice of wine bottles he is offered. Triggered by scanning a tagged product (NFC RFID tag) with his mobile phone, an application allows the user to access and create recommendations for exactly this product. Having scanned a product, a consumer receives ratings that other consumers have entered for this product on his mobile phone, displayed as an average rating of all other consumers on a one to five stars scale. He can zoom in, meaning that he can look at specific criteria, such as the headache factor, and receive ratings for this criterion specifically. Also, based on the scanned product, a ranking of all products in the product category is provided and displayed.

The conceptual novelty of APriori is in its so-called dynamic criteria. Users can define the criteria for which they rate the actual products. This makes recommendations easy to access and also easy to enter on mobile phones. For example for olive oil, a consumer could add the criterion 'solubility' if he thinks it is necessary, and rate a specific olive oil upon this criterion. Based on these criteria, users express the experience they have had in APriori only on a 5-star-Likert rating scale.

APriori has been evaluated in several user studies: In a formative survey, the general acceptance of APriori was tested [44]. An additional web survey conducted in the frames of [46] evaluated what products people would rather buy in the web and what products they would rather buy in traditional supermarkets. In addition, the survey provided insights to the questions of what information people base their buying decision on and what they would be willing to pay for this information on a mobile phone when actually shopping. Also, an experiment evaluating several product identification techniques on mobile phones (e.g. barcode recognition, RFID tag scan, manual entry) was conducted based on APriori [46].

Having structured the possibilities for designing product recommendation systems in the above design space, we see the following concrete extensions for APriori and similar systems (see Figure 3):

Parameter Capture and Recommendation: Certainly, a valuable extension is to mix implicit and explicit parameter capture. For example, the parameters could be captured by a consumer using his mobile phone to receive recommendations, and implicitly used as input for a user profile that is then used to generate a recommendation implicitly (see (1)). Also, the data used when paying with loyalty cards or paying by mobile phone could provide our recommendation system with product ID and user ID (implicit parameter capture). These could be used to ask the user with some delay to enter a recommendation for the product he bought explicitly (see (2)). A third option that is not very likely is that a consumer scans several products he is interested in to explicitly build a profile for implicit recommendations, but does not enter a recommendation explicitly (see (3)). A general possible extension for explicit recommendations is to allow users to generate multi-media reviews. Our experience has shown that people are rather reluctant to enter longer textual reviews on mobile phones so far. This could change in the future with better text entry possibilities. However, also audio reviews and video reviews might be considered as an easy means to provide deep insights into a product experience.

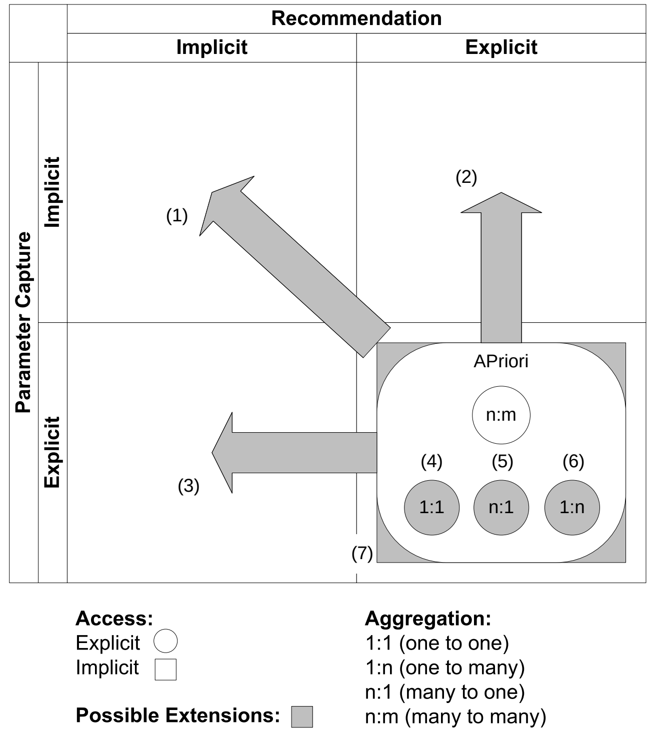

Figure 3. Possible extensions for APriori.

Aggregation: Independent from UbiComp technology, we see great value in integrating social networks and product recommendations. Already existing modeling of friendship relations could be used to enable trusted recommendations which provide a high value to consumers. A consumer could concretely recommend a product to one particular friend (one to one, see (4)) or to a selected group of friends (one to many, see (5)). Also, a feature to remind oneself of the own taste (for example for wine) is something worth considering. Our evaluations of APriori have shown that people actually forget what they have bought and liked, and that keeping track of their own taste could help them in future buying decisions. The system has so far strongly focused on rather basic, community-based recommendation features (item-centric many-to-many sharing of ratings). There is certainly value in utilizing more extensive recommendation algorithms than the ones we do today. Mobile phones provide means to discover similar users in the vicinity, which could enable extended collaborative filtering (many to one, see (6)) on mobile phones.

Access: Another possible extension is making use of different ways of accessing product recommendations. While access to recommendation in APriori is provided explicitly through mobile phones today, it is possible for the future to display recommendations also on in-store displays, smart shopping carts and the like, making them available implicitly to users (see (7)).

5. DISCUSSION

The design space defined above has shown the various different ways of implementing product recommendation functionality. Section 4 has shown the specific extensions the design space suggests for mobile product recommendation systems. In this section we want to give more general guidelines for recommendation systems supporting real-world shopping scenarios, not solely focused on mobile devices. We explicitly disregard specific recommendation and filtering algorithms and focus on the potential of making product recommendations ubiquitous. We discuss three aspects in which we see extensions for current recommendations systems: implicit data capture, incorporation of social trust and pervasiveness of recommendations.

Implicit Data Capture: Whereas online shops are aware of each interaction of their web-visitors, traditional retailers have less means for surveillance. However, data about interactions of consumers with product would also help traditional retailers, not only as an input for recommendation systems. There is benefit in capturing this interaction between consumer and product in an implicit way [9], i.e. sensed from 'an action, performed by the user that is not primarily aimed to interact with a computerized system but which such a system understands as input' [37]. That means, the user interacts with physical items in a natural way, e.g. touching them, lifting them, putting them into the shopping cart, and the recommendation system extracts the product's identity from these actions. Technologies of choice could be RFID or sensitive foam technology [27], as mid- to long-term future visions of retail[2] suggest. Rather short-term options for this implicit parameter capture are, as mentioned above, interactions where users place an item under a barcode scanner to find out about price or to add item to basket for self-checkout[3]. The captured parameters can then be used as an input to provide a recommendation. A third option remains the explicit capture of parameters. An analysis of current mobile reader technologies c be found here [46]. Concerning the generation of the recommendation itself, again implicit mechanisms could be applied, such as measuring attention of consumers [32] to derive recommendation values. Another rather explicit approach to generate a recommendation is to detect the most appropriate moment for interruption [20] in order to explicitly ask the user for feedback or the creation of a recommendation. Overall, implicit interaction seems a promising approach but still requires infrastructures and technologies which are not fully available yet. In addition, explicit generation is considered more reliable since the danger of drawing wrong conclusions from a captured context is not given.

Incorporation of Social Trust: As mentioned, the most trusted source for recommendations are people we share a relationship with and people we know well. This is leveraged by many service companies offering some discount to you if you recommend their service to your friends because then these companies can benefit from your reputation in your social network. Social web platforms allow the utilization of social relationships for various applications, e.g. to get know to friends of your friends, but also can represent a new backbone of trust concerning recommendations from users from the known environment. Especially interesting here is that personal recommendations and experiences with products are not only limited to direct friends but also can 'hop' throughout the network but still can be rooted back to their origin. Thus, personal recommendations are not just one-to-one anymore but become one-to-many limited to people part of a social network. Another option enabled through current mobile technologies is to leverage the expertise and communalities of people in the vicinity, e.g. using Bluetooth technology for telling the user about a person standing in the next row being an expert in SLR camera and thus expanding the range of social contacts towards knowledgeable, collocated consumers [14].

Pervasiveness of Recommendations: Although wearable computing technologies have been discussed as viable for augmenting the real world with additional information and services for a while already, these technologies have never been adopted by the broad public. In contrast, mobile phones with increasing capabilities concerning screens, input facilities and computing power have become an interesting platform for a variety of product-related services such as recommendation systems, as shown in section 3 and 4. Furthermore, product recommendation could be offered by neutral third parties in contrast to shopping guides embedded in stationary displays [40] or shopping carts. Nota bene, in both cases the infrastructure would be owned by the supermarket, implying that a recommendation system would have to be related to the supermarket in some way and possibly lose its identity. As technology develops, pleasing forms of embedding recommendations into the work-flow of shopping have to be found, be it vibro-tactile alerts [36], virtual avatars [17], voice, or displays on mobile devices.

6. CONCLUSIONS

Product ratings and customer reviews of products are standard practices for web-based shopping, supporting the buying decision of consumers through valuable independent information. When shopping in traditional stores, access to this type of information can be at least equally important. Currently, many different approaches in the field of mobile and ubiquitous computing are explored. This paper provides a comprehensive design space for product recommendations in the ubiquitous computing domain. We discuss implicit and explicit options for capturing the parameters for product recommendations, options for actually expressing product experiences (implicit vs. explicit), ways of aggregating product recommendations, and how access to products recommendations can be offered. The paper also offers a visual notation for the design space that allows categorizing existing and envisioned systems. Using the mobile product recommendation system Apriori as an example, and extensions filling the white spots in the design space are proposed. Finally, general guidelines for recommendation systems based

[2] http://www.future-store.org

[3] e.g. http://www.coop.ch/passabene

on mobile and ubiquitous computing technologies are discussed.

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