CAPTURING IMMEDIATE INTERESTS IN AMBIENT INTELLIGENCE ENVIRONMENTS

Anton Nijholt
University of Twente, Faculty EWI
PO Box 217, 7500 AE Enschede, the Netherlands
anijholt@ewi.utwente.nl

ABSTRACT

We investigate how to capture the interests of users in Ambient Intelligence (AmI) environments. The goal is to design environments that anticipate the users' goals based on the users' profiles and domain knowledge. Recommender systems for AmI environments can structure their recommendations based on the goals the users have. We discuss (our) research on structuring recommendations and investigate the capturing of user interests in AmI environments. For the latter we look at possibilities to capture the user's interests from sensors in the environment.

KEYWORDS

Recommender systems, user profiles, ambient intelligence.

1. INTRODUCTION

People have interests. There are long-term interests, guided for instance by ambitions and moral standards, there are medium term interests, most likely derived from the long-term interests and there are short-term or immediate interests. The short term or immediate interests of a person tell us what he or she prefers to do and to experience right now, the next hour or a longer period of time, where the length of the period also depends on the particular context, that is, is it a short holiday period, a working day, a museum visit, a TV evening, a weekend or just a free afternoon during a working week? In this paper we look at short term goals (needs, immediate interests) of people and how we can recommend them what to do in order to achieve these goals.

We will look at these short term goals and immediate interests using two types of knowledge. First of all, knowledge about the domain, that is, knowledge about possible immediate interests and goals that people usually have in a particular situation. For example, assuming that a decision to watch TV has already been made, do we want to see programs that we expect to be watched by our friends too, so we can talk about them tomorrow, do we want to see programs that keep us up to date on events in the world, do we want to see a program that makes us forget about all our daily sorrows, et cetera. Similar choices can be presented to someone visiting a museum (which section of the museum do want to visit, what will be the order of visits, etc.), someone looking for an evening of entertainment, someone looking for a restaurant and, as a further example, someone who has to decide what to cook this evening. A system that helps the user to make decisions should know which domain is being addressed and it should have knowledge about this domain. While sometimes it may be the case that the domain is explicitly chosen by a user (for example, by consulting an electronic program guide), in other cases such a system can provide the user with decision making support by being aware (through sensing and interpreting) of the user's context. Obviously, when the user is performing a certain task while asking for or proactively being provided by recommendations, then knowledge about this task can also help in providing appropriate suggestions.

The second type of knowledge is knowledge about the user. There are many ways to acquire such knowledge. Simply asking what features of potential products or services are important for the user at a particular moment is a possibility. Using questionnaires that more indirectly try to gather information about a user's preferences or characteristics are another possibility. It is also possible to learn about the user's characteristics (personality, customs, preferences, etc.) and their relation to the user's decisions in certain situations. Machine learning techniques can help to learn from a user's interaction history and all other information that is electronically available (e.g., email contents or webpage visits). Even more indirectly are attempts to gather information about user' s characteristics and user's immediate interests as they can be obtained, possibly in addition to the previously mentioned ways, through sensing and interpreting the behavior of a user. Clearly, then again, as mentioned above when we discussed the detection of the context of a user, we enter the research area of ambient intelligence (ubiquitous computing and social and intelligent interfaces). These Ambient Intelligence (AmI) environments are expected to be attentive and pro-active. They can be home environments, but they can also be office environments or public spaces where people obtain support that helps them to perform particular tasks or where knowledge about the particular user is used to adapt the environment in accordance with the user's preferences. Sensors to detect characteristics of a particular user include cameras, microphones, location and activity sensors and biometrical sensors.

Research in AmI and pervasive computing aims at creating environments where such sensors are embedded in the environment and where user behavior is interpreted in order to provide support to the user. Assuming the existence of such environments, how can we conclude immediate short term interests of a person in a particular context (physical environment, task to perform, leisure activity to be chosen) and how do we suggest possibilities (products, services, activities, etc.) to satisfy these interests? Obviously, no clear-cut answer can be given to such a general question. Nevertheless it is useful to investigate how current research interests and research results in designing smart environments can help to answer this question. Our investigations are also guided by the results of our experiments with so-called recommender systems [Setten et al., 2006], where we investigated how users of electronic TV program guides prefer to see the presentation of recommendations.

After a short introduction to recommender systems (section 2) and a report on experiments on the presentation and appreciation of recommendations (section 3), we try to embed what we learned from these experiments in an ambient intelligence framework (section 4). Hence, what is happening in AmI research right now and how can we capture useful information about a user's activities using ambient intelligence technologies? Obviously, with useful information we refer to detecting immediate interests of the user. We discuss how to combine the approaches we distinguish in recommender research and in AmI research in order to tackle research issues that address a user's goals and preferences in AmI environments. Section 5 and 6 are about user behavior and user profiles, and in section 7 we have some concluding remarks about our approach to collect and interpret immediate interests of a user.

2. RECOMMENDER SYSTEMS: AN INTRODUCTION

Recommender systems have been defined as systems that help users to identify interesting items from a large set of choices. Recommender systems "produce individualized recommendations as output or have the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options" [Burke, 2002]. Typical applications can be found on e-commerce web pages, that is, web pages that recommend which books to read (and buy), what music to download, which concerts to visit, which movies to see and which TV programs to choose [Setten et al., 2006]. In other applications the recommendations are on tourists' products, for example, travel booking support, how to travel, ski routes to choose from, which hotel to choose, and which restaurant to visit. Rather than one desktop PC web pages, this information should become displayed on mobile devices. There are many more examples of recommender applications. To name a few, recommendations that concern web pages to visit, what clothes to wear, recommendations on life style or on partner choice, which research papers to read, or which jokes to be presented with.

The two main approaches that are followed are social or collaborative filtering and content-based recommendation. Recommender systems are often identified with the first approach. This approach is based on collected user opinions rather than on features (or characteristics) of a product or service that is recommended. The profile of a current user is compared with previous users and items that have been selected by similar users in the past will be recommended to the active user. In the content-based approach a feature-based representation of the items that can be recommended is necessary. A profile of a user can be determined, for example by machine learning techniques from perceived interests, that is, from a user's implicit or explicit ratings of items. Hybrid recommender systems [Burke, 2002] use combinations of collaborative filtering and content-based filtering.

In [Burke, 2000] a more detailed distinction between recommender systems is provided. Because of the applications we want to investigate in section 4 of this paper we shortly summarize the main dimensions they distinguish. The first dimension is the data flowing into and out of these systems. For example, on the input side, a user's question, its navigation behavior, keywords and item attributes that are given by the user or derived from items being viewed, a purchase history and users' comments. On the output side we can have suggestions, predicted ratings, and ratings or reviews provided by other community members. The second dimension we want to mention is the recommendation method. Above we already distinguished between collaborative filtering and content-based recommendation. Obviously, there are other, less distinguished ways of recommendation. For example, a search engine can be considered as a recommender system that just lists everything in the database that matches the user's request without taking into account previously shown interests or the user's context. Companies can create their own lists of recommended items on their website or they can mention statistical summaries of community opinions. Yet another way of recommendation takes place when current interests of a user can be matched with associated items (e.g. the customer is interested in a record of the Beatles and the system makes the user aware of a recently published book about the Beatles). The third dimension from [Schafer, 2001] we want to summarize is the degree of personalization. A customer has a history of preferences, purchases and navigation. When this knowledge is used every customer can get different recommendations. The system is highly personalized. When this knowledge is not used, the system is non-personalized. In between are systems that provide recommendations based on the current interests of the user, that is, interests as they become clear from current navigation and selection. More interesting is persistent personalization. In this case the recommender system makes use of persistent attribute preferences in content-based recommendation or persistent user-to-user correlation in collaborative filtering.

When looking at current recommender systems several weaknesses need to be mentioned. Here we will not address the problems that are usually mentioned: the so-called 'cold start' problem in collaborative filtering, the recommender reliability problems, and attempts of shilling [Schafer, 2001]. Probably most relevant for our research purposes and related to the cold start problem and reliability is the so-called 'data sparsity' problem in collaborative filtering. This is the problem of having an insufficient number of rated items, not allowing the identification of users with similar interests and therefore no reliable recommendations can be made.

More weaknesses can be mentioned. One weakness is that recommender systems lack in giving explanations about their recommendations. This is a serious problem; users will not trust a recommender system when it can not explain its recommendations. In conversational recommender systems [Burke, 2000] the recommender's line of reasoning, that is, its explanation, becomes clear for the user during the interaction a user has with the system. It is interesting to see how current research on question-answering and dialogue systems [Hirschman et al., 2001] can possibly be combined with interactive recommender systems. The second weakness we want to mention is the lack of knowledge a recommender system has about its active user and the active user's context. We will address this issue in the next section of this paper. There we will assume that the recommender systems know about the interests of the user as they have become clear from previous choices. Three more viewpoints will be added. The first one concerns how to capture and interpret information from a user's context and the user's activities in order to make the user's profile as complete as possible, the second one concerns the question how to conclude a user's immediate interests from the captured data, and the third one concerns the question how to add information about the user's context and interests to the recommendation process.

3. RECOMMENDERS AND IMMEDIATE INTERESTS

3.1 Introduction

In [Setten et al., 2006] experiments are reported that aimed at investigating if the explicit mentioning in the recommender interface of a user's possibly immediate interests (rather than mentioning global characteristics or features) of items to be recommended is preferred by the user and really makes a difference when a user considers using a particular type of recommender system. In this section we recall these experiments since the results provide us insights and ideas about how to employ recommender systems in ambient intelligent environments.

What do we mean by immediate interests? Immediate interests are what the user wants to experience right now. The immediate interests are his or her immediate goals. How can we, or rather an AmI environment, know what a user's immediate interests are? As mentioned in [vanSetten et al., 2006], we can ask the user. In this case the burden is on the user, but is the user capable or willing to answer questions? This can not be expected. Users have difficulties to make their goals explicit and, moreover, are not necessarily in the mood to do so. When we want to ask the user we should be more than helpful and probably make suggestions that make the user aware of his or her immediate interests. Conversational recommender systems can certainly help to make clear what the user's interests are.

One viewpoint that should be mentioned here is that users do not always think in terms of goals but rather of gratifications. A goal may express what the user wants to achieve, while a gratification tells us about the sense of personal satisfaction that a user wants to experience [Katz, 1959; Severin et al., 2001].

The opposite of asking the user is to predict his or her immediate interests from what we know about the user, his or her behavior and the context in which we need to interpret our knowledge of the user and his or her behavior. Clearly, knowledge about tasks and global beliefs, desires, and goals of the user need to be taken into account. This is a rather ambitious research aim. It requires sensor-equipped environments that help in detecting and interpreting user behavior in a particular environment and it requires the interpretation of conscious and unconscious communication behavior of occupants of such smart environments. Sensors may include cameras and microphones, location and activity sensors, sensors that collect physiological information and sensors that collect and distinguish different forms of brain activity. Information collected by such sensors need to be fused and interpreted at a semantic and pragmatic level.

As mentioned, in the remainder of this section we will look at ways to provide a user with suggestions about possible goals in the domain or context in which he or she is present. Rather than provide a user with decisions, we prefer to provide the user with suggestions. These suggestions can take the form of possible and reasonable goals in the domain and the user has the opportunity to navigate, adjust, and refine the goal (or suggestion) space.

3.2 Presentation and Appreciation

In [Setten et al, 2006] experiments are reported in which various ways of presenting recommendations to a user are compared. In fact, in these experiments, recommendations consisted of presenting items that were thought to be of interest to the user. And, since the domain of recommendation was an electronic TV program guide, recommended items were TV programs. Hence, the recommendations were suggestions to view certain TV programs. These suggestions have to be presented to a user and the question that was addressed in this research was how different ways of presenting items (suggestions) account for differences in appreciation of the recommender system.

Are there different ways to present recommendations? Interesting items, in this case TV programs can be presented without any structuring, but there can also be a structuring based on channel (non-goal-oriented), based on genre (implicit goals), or based on explicit goals (gratifications). In the experiments these three viewpoint were combined with the parameters 'with predictions' and 'without predictions', where the predictions were obtained with a recommender system. In this particular domain user goals can be made explicit. These goals are not so much particular features or combinations of features of items (TV programs), but rather they tell us what a user wants to experience (to loose myself in a program, watch what my friends watch, mood improvement, etc.).

Before looking at the results, we should make clear what we mean by 'differences in appreciation' and how to measure them. For this we made use of a framework introduced by [Venkatesh, 2003], called the 'Unified Theory of Acceptance and Use of Technology'. This framework provides questionnaires with which to measure performance expectancy ("the degree to which an individual believes that using the system will help him or her attain gains in job performance"), effort expectancy "the degree of ease associated with the use of the system") and behavioral intention. The latter is assumed to provide the answer to the question how easy it is for users to find interesting items and hence it is used in the experiments where we compared various ways to present suggestions to the users to show differences in appreciation.

3.3 Goal-based Structuring

In the experiments it turned out that structuring items based on the user's explicit goals is the most important factor in evoking positive appreciation by the user. Goal-based structuring of items that should be suggested to a user helps the user to make his or her choices. Obviously, we looked at one particular domain, we made our choices about immediate interests in that particular domain and when we want to make a translation to other domains we should be extremely careful. Is it possible to identify immediate interests in a particular domain, does a recommender system allow presenting results according to these immediate interests, and does this structuring work as well as in the case of a TV program recommender?

Our aim in the next section is to investigate how our research results can be put into use in ambient intelligent environments. Clearly, in any environment users have goals and interests. And, although not always immediately clear, for any environment we can identify (or have the environment learn) potential interests of users or visitors of that particular environment with its particular characteristics, e.g. a home environment, an office environment, or an entertainment environment. Once these potential interests have been identified or learned, they can be used to structure recommendations presented to the occupants of the environment. The occupants can choose among the recommendations that are presented in the list that describes their interests as best as possible. Can we help the occupants of these environments even more, for example by using knowledge that has been obtained from the occupant (a user profile provided by the occupant and adapted and extended based on recordings of previous activities in the environment) and real-time capturing and interpreting of current activities in the environment? In the remainder of this paper we will look at possibilities to gather information about the interests of an occupant of a 'smart' environment. This can be done by asking the user, for example by asking to fill in questionnaires, but, this is a rather unnatural way to capture immediate interests. It is more interesting to derive them from automatic capturing and interpretation of his or her behavior and activities. These possibilities are investigated in the next section.

4. CAPTURING IMMEDIATE INTERESTS IN AMI

4.1 Introduction

In the previous section we discussed the presentation of suggestions what to do - or what to choose from - to a user of a recommender system. The underlying assumption is that a user does not think in terms of all kinds of features of items that contribute to reaching his or her immediate interests. Rather, the user wants to word the preferences in terms of immediate interests, and because in this case the domain is reasonably well-defined, it is possible to provide the user with a list of possible immediate interests to choose from.

We want to go from this website TV-recommendation domain to a situation where (1) the user's goals are not yet zoomed in to a particular application, and (2) the smart environment is able to capture verbal and nonverbal activities of the user, and (3) the smart environment is able to sense and understand the context in which these activities take place. That is, the user inhabits or visits an AmI environment and the environment is able to support the user's daily and other activities.

There are various ways an environment can provide support. Importantly, providing support can be regulated by laws and professional codes of conduct of designers of smart environments. Providing support can also be regulated by owners and those that have been appointed as being responsible for the maintenance of the environments. Moreover, the inhabitants or visitors can have profiles known by the environment or detected from wearables that include their preferences for obtaining particular modes of support. Embedded in these observations, smart support can be 'hard-coded' (if someone approaches a door the environment checks access admission), can be reactive (there needs to be an explicit request from the user or a command requiring feedback of the environment), or pro-active (there is a continuous monitoring of the user and based on this monitoring the environment predicts and anticipates the user's next actions and wishes; anticipating means making changes to the environment that suit the user or inhabitant, or to start a dialogue in order to suggest, discuss or negotiate changes to the environment). Whatever mode or combination of modes is made available, the environment needs knowledge about its inhabitant or visitor. In the next subsections we look at ways to provide the environment with knowledge about its occupants. In section 4.2 we look at user profiles that provide demographic information about the user, information about interests, and information that can be obtained from texts that are related to the user (e.g. web pages, blogs, email exchanges, other information available on the web). Moreover, in section 4.3 we look at the use of questionnaires or more implicit ways of extracting knowledge from a user by embedding questions in task and context related interaction; for example, in question-answering systems, natural language dialogue systems, or chatbot conversations. In section 5 we consider the capturing of the characteristics of a particular user by looking at his or her behavior. That is, how can cameras, microphones and other sensors capture characteristics of the occupant of a smart environment that can help to determine his or her emotions, moods, preferences and interests? Obviously, in order to do so, our environments need to be equipped with all kinds of sensors: cameras, microphones, location and proximity sensors, pressure, tactile and haptic sensors, et cetera.

4.2 Designing, Learning and Adapting a User's Profile

Our assumption is that users in AmI environments can be identified. They can make their identity known to the system by explicit interaction (for example, log-in using a password, wearing an identity tag, using a fingerprint to get access to the location, or by letting the environment make an attempt to recognize the user from his or her face or other biometrical and physiological information. If we can identify the user, we can make a match between this identity and information available in its user profile. This user profile can contain demographic information about the user (e.g., age, gender, affiliation, interests), information obtained from previous interactions in the environment or from other electronically available resources (emails communications, web searches, home pages, blogs, etc.). The user profile can be continuously adapted because of new information made available by the user (not necessarily with the aim to have its profile updated). That is, new information can become available through, for example, new entries in a blog, new searches for information, or new contacts in the user's address book. Depending on the available ways an AmI environment can perceive the user's activities, other user characteristics can become part of a user profile or can help to interpret a profile in a particular situation.

4.3 Ask the User

In order to learn about the user, his or her personality, his or her 'human values' and attitudes, questionnaires have been designed. Obviously, there is no need to ask the user of an AmI environment about his or her preferences, immediate interests, values, personality characteristics, lifestyle, etc., when we don't know how to adapt the interface (including the use of interaction and presentation modalities) to this knowledge. In [Pervin et al., 2001] it is remarked that "Personality represents those characteristics of the person that account for consistent patterns of feeling, thinking, and behaving." Clearly, in face-to-face interaction, our interaction behavior does not only depend on our own personality, but also on the personality characteristics that we try to derive from the behavior of our partner in the interaction and that we attribute to our interaction partner or to the profile we made up from already previously available information about our interaction partner.

Questionnaires that aim to measure personality are well-known. They depend on models of personality theory (trait theory, personal construct theory, psychodynamic theory, etc.). Personality is often expressed in five dimensions (Big Five: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) and most tests to assess one's personality are in terms of these dimensions. In educational environments it is not unusual to take into account personality characteristics and associated questionnaires in order to match learning styles with tutoring strategies, and the display of feedback. Using a user's scores on the above mentioned dimensions in order to adapt an AmI environment is however a still unexplored area of AmI research. Clearly, when we know that a particular user has a high score on curiosity, creativity and untraditional (high scores on Openness), we can make use of that. Similarly, as an other example, it also helps if we know that a user is cynical, rude and uncooperative (low scores on Agreeableness).

Many other questionnaires exist. Apart from personality we can look at questionnaires that measure intelligence and emotional intelligence. Moreover there are questionnaires that aim to measure the values a user has. A good example is the so-called Human Values Scale [Schwartz, 2003] and in particular how it is used in the context of recommender systems [Guzman et al., 2005]. There are also questionnaires that aim at extracting information that is more directly related to educational, game, and entertainment situations [Douse et al., 1993]. Hence, we can look at decision-making style questionnaires where thoroughness, control, hesitancy, social resistance, perfectionism, idealism and instinctiveness are among the issues that are assessed, and we can look at questionnaires where we can look at an inhabitant's willingness to empathize with other (virtual or real) personality characters in the environment (e.g. the empathy questionnaire [Davis, 1983]). There are, of course, more task-related questionnaires. PACES ((Physical Activity Enjoyment Scale) allows the measuring of enjoyment in physical exercises [Kendzierski et al., 1991]. Measurements of experiences is also the aim of the the Intrinsic Motivation Inventory (IMI) [Ryan, 1982]. Although knowledge about participants obtained from such scales can help to increase the quality of user profiles, it is of course more interesting to turn these explicit self-report questionnaries into implicit sensor observations aiming to obtain similar information in real-time.

Summarizing, to answer the question who is going to interact in our AmI environment, we can look at demographic information that has been collected, information about the user that can be generated from 'external' sources (email content and communication, web page visits, Skype, device use, etc.), information about the context (what behavior can be expected), and information that can be obtained from filled-in forms and questionnaires that tell us about intelligence, personality, emotional intelligence, and more specialized questionnaires that help us to anticipate interaction styles, and decision making behavior.

5. LEARNING FROM USER BEHAVIOR IN AMI

Although information about the AmI inhabitant can be obtained through questionnaires, as mentioned in the previous section, this is a rather unnatural way and we can not expect that people are willing to spend time before starting to use the environment. Obviously, a user profile, including scores on all kinds of questionnaires can have been obtained in advance and can be made use of in other environments too.

There are also possibilities to obtain information about the user by hiding the questionnaires in a playful interaction with the user. For example, in [Bodewitz, 2004] an attempt is made to score personality by means of an informal conversation where elements of the traditional questionnaires are merged into the conversation by the computer. Interesting is also the approach in [Rentfrow et al., 2003], where music preferences are correlated with personality dimensions. Hence, "You are what you listen to." These authors put their approach in a framework correlating personality dimensions and behavior that occurs in everyday life, and, as they mention, "music is a ubiquitous social phenomenon."

In AmI environments we have the technology to capture human behavior in everyday life. Hence, we can either assume that a particular user or visitor of our AmI environment already carries a user profile that has been generated from the user's behavior in the past, or we can assume that during a possibly playful interaction with the environment a profile can be obtained and can be used by the environment to adapt to the user's characteristics (for example, personality, preferences, mood and capabilities).

What can we learn about the user when we can observe his or her behavior during some period of time? What can we learn from behavioral information captured by sensors? In [Ambady et al., 1992] results are reported from short observations of expressive behavior. Observations include the assessment of relationships, distinguishing anxious and depressed people from normal people, predicting a judges' expectations for a trial outcome, determining political views of television newscasters, et cetera. Personality judgments from 'thin slices of behavior' are also discussed in [Borkenau et al., 2004].

An example where real-time behavioral analysis is done by a computer can be found in [Bechinie, 2003]. In that approach a participant is invited to dance in front of a video camera for about 30 seconds. At the end of this period a personality profile for the earlier mentioned Big Five personality traits will be generated.

6. USER PROFILES, INTERESTS AND TASKS

From the previous sections it has become clear that demographic information and information about preferences of the user can be made available to the AmI environment. Moreover, additional information can be obtained from the way an inhabitant of the AmI environment behaves and interacts. Approaches to collect such information have been mentioned in the previous sections. Our next source of knowledge is the particular domain and functions related to that particular domain. It will be useful to distinguish possible goals in AmI environments (kitchen, dining room, study, etc.), anticipate and detect the user's actions and relate them to common-sense goals in the particular environment.

7. CONCLUSION

We discussed a framework in which we can consider further development of recommender systems in AmI environments. We emphasized the importance of immediate interests (goals) of a user in structuring recommendations and we discussed ways to extract knowledge from a user's behavior in order to obtain a profile that can help us in structuring interests. In future research we need to distinguish domains in AmI environments where we can structure goals, as we did for the program guide recommender, and where we can match common-sense goals with interests of the user. And, further steps need to be taken in order to have automatic prediction of possible goals based on the user's actions and activities in the AmI environment.

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