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Portable Personality and its Personalization Algorithms: An Overview and Directions

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ABSTRACT

With the advances in ubiquitous computing, there is an increasing focus on personalization of user information especially in web-based applications and services. Currently those personalized user profiles are scattered, mostly stored for each individual service. Therefore, this prohibits the usage of those profiles in different environments such as other web-based services, shopping in local stores or sharing interests among people. The so-called Portable Personality focuses on the management and distribution of personalized profiles (in form of a digital personality representing the real-world user) through mobile devices. These portability aspects merge with the idea of cross-system personalization using a single generic user profile. We will briefly introduce some aspects related to profile representation and management with focus on attempts towards such a generic representation. The main discussion will be concentrated around profile portability and its effects on personalization especially towards cross-system support. We include different portable profile scenarios and their personalization methodologies. Furthermore, current personalization algorithms are considered with possible associations towards the presented portable scenarios. At the end, we reflect on existing challenges of current approaches in the field of portable personalization and try to provide some recommendations.

USER PROFILES AND THEIR MANAGEMENT

Personalization of any kind of information is evolving in a rapid manner especially for web-based applications and services whether in advertisement, search engines, online shopping, or social networks. Hence, the collection and application of personalized information is currently omnipresent. We understand personalization as tailoring and providing content and services to individuals and groups based on knowledge about their preferences and behavior. This can range from simple superficial factors such as custom ring-tones to the complex tailoring of the presentation of a shopping web site to a user's personal interests and their previous purchasing behavior. To make use of such information, a so-called 'personalized user profile' (UP) is to be generated preferably without user intervention. Such user profile may vary from a rather simple to complex representations depending on how much and what type of information is gathered and stored. A simple relation is pictured in Figure 1. An example what kind of information might be stored in a rather complex user profile is illustrated in Figure 2. (Note that in the annual personalization survey from www.choicestream.com in 2009, personalization and recommendations are well received and considered useful to make purchases. However, they also found that the quality of recommendations decreased to previous year 2008 as well as recommendations can widely vary depending on different retail categories.)

The general concept is to gather user-specific information about the user (profiling), to manage and store this information (content management), distribute it to consumer applications or services (profile distribution, portability), and finally extracting those pieces of information valuable to the consumer current needs (profile evaluation, personalization).

Current UPs are mainly used in web applications to personalize searches, advertisements and shopping recommendations such as music, movies, and books. Most of the time, the user has a different profile for every online shop, service, or website such as last.fm (http://www.last.fm – recommendations for music such as songs, videos and concerts) or FOAF (http://www.foaf-project.org/), which makes them mostly application-dependent. The project of OpenID (http://www.openid.net – supported by big players such as Google, Yahoo, Flickr, MySpace, Facebook, WordPress, AOL) tries to overcome this problem but it is more related to a single digital authentication identity across the Internet. Furthermore, the access and usage of those profiles is limited to a device connected to the Internet. This mainly means that, on the server-side, the user does not have much control over the information gathered about him or her and due to multiple profiles for different services, this leads to a fragmented personalization experience. Schuurmans (2004) already believed in the need for a cross-domain profile that is under control of the user. However, the recently started data portability project (http://www.dataportability.org) tries to develop a standard that allows users to gain control over their own data again.

Figure 1: **Complexity of user profiles**

Figure 2: **Information stored in a complex user profile**

Now imagine pushing this one step further, what happens if the user visits a local music, video, or book store? Its preferences about music, videos or books have not changed. Therefore, users should be able to carry around their own electronic UP in a portable manner instead of storing multiple UPs in a decentralized way for each website and interest. That shows, for this profile scenario, mobile devices such as phones and PDAs, which are nowadays so-called “smart” and multifunctional, provide an optimal platform for managing UPs in a single user-central place. Considering this, they can be easily distributed when necessary. However, portability does not solve the question how to manage the UP on the device itself. As in real life there is only one “you” combining all your associated interests, preferences, and behaviors. This should ideally also apply for automatically generated UPs so that there is only one single UP representing the entire user’s personalized information about its likes and dislikes as illustrated in Figure 2. Therefore, this could be seen more as a digital personality rather than a user profile.

Modeling such user behavior is a dynamic and eventually lifelong process. This arises some challenges in the procedure of user modeling on how to handle interoperability, scrutability, and privacy. Interoperability is the exchange of user profiles across various sources in a distributed environment. This can only be achieved by developing and adopting explicit and widely accepted protocols so to enable the discovery and exchange of user models, stored in various systems. Scrutability ensures control of the user over its own data how and what has been modeled. It further allows changing stereotypes and preferences and the way in which conclusions are inferred from these data. Also, privacy considerations should be taken into account such as the Minimization, Consent, Openness, Access, and Accuracy principles stated by Kobsa (2007, p.30). The process of acquiring this personalized information can range from manually entered to fully automatically generated data for various types of preferences. Hence, there is a necessity for methods and approaches to combine and merge multiple UPs into one single UP in a smart and efficient way.

Nowadays, there is vast number of services using their own UP type to store knowledge about users. Most commonly is to store all related user preferences for each single user individually (He, 2007; Chen, 2007; Amazon). The type of information gathered and stored will depend on the application, service and applied domain. Thus, single user preferences may contain just identity information (OpenID), one specific domain-dependent preference such as music (including songs, videos, and concerts see last.fm) or multiple preferences such as music and movies as in (Chen, 2007). Such profiles for users and domains can, of course, interconnect as seen in large online shops such as Amazon, where one user may have preferences in book, music, and movie domains. Yet another possibility is to represent the behavior and preferences of groups (Shtykh, 2009) or stereotypes (Castellano, 2007).

While combining different user information, the UP can be divided into static and dynamic parts as done by (Magoulas, 2006; Yu, 2005; Papadogiorgaki, 2008). On the one hand, the static part mainly includes all fixed activity or interest-independent user information, which does not change regularly, such as name and address. On the other hand, the dynamic part contains all the information and preferences about current activities and interests, which do evolve and need to be updated more frequently. Moreover, the dynamic part can further be split into short-term and long-term interests as done in (Papadogiorgaki, 2008; Park, 2009; Zhuhadar, 2009) where short-term profiles specify current interests which might change rather frequently and long-term profiles relate to more general interest which is also subject to change but slow and gradually over time. (Park, 2009) adds further differentiation between recent interests and most current interests to represent the UP according to recency, frequency and persistency. This also illustrates the different aspects of how to store certain parts of the user preferences. Short- and long-term profiles are one option; another is to either store them in different sub-profiles (Sutterer, 2007), personas (Gosh, 2007) or activities (Yu, 2005) as shown in Figure 3.

Figure 3: Sub-profile example of user profile representations

The idea of profiles is obviously not new, and various profile types, management approaches and initiatives exist such as 3GPP Generic User Profile (3GPP:GUP - http://www.3gpp.org), Composite Capabilities / Preference Profiles (CC/PP - http://www.w3.org/Mobile/CCPP/), and Open Mobile Alliance - User Agent Profile (OMA:UAProf - http://www.openmobilealliance.org). Yet due to their network relations, they are not really relevant for user modeling linked to portable personalities. However, over the past years, research has increasingly focused on personalization and representation of user preferences and interests in a compact and efficient but extendable and machine readable form.

An earlier approach was made by the European Telecommunications Standards Institute (ETSI) Specialist Task Force (STF) 265 to describe a standard on user profile management. Their finished document on "User Profile Management", ETSI (2005), proposed that further work in this area is necessary to produce standardized user profile components that will help to provide the optimum user experience. People have been working on it since to achieve such an experience.

Probably one of the oldest and simplest form of information representation is the Vector-Space model, where UP is a vector containing representative keywords or terms with associate weights. It is still widely used (Castellano, 2007; Zhou, 2007; Yu, 2006) due to its simple nature.

Currently the most popular method in relation with the semantic web is the application of ontologies. An ontology can be defined as a formal representation of a set of concepts within a domain that provides a shared vocabulary, which can be used to model this domain including the type of objects and/or concepts that exist as well as their properties and relations among each other. In the context of user profiles, ontologies can represent and organize user information, their context and relationships more accurately especially considering the necessity of dynamic preference and interest changes. Furthermore, it offers an easy expandability by merging, expanding, and combining parts of existing ontologies into new ones.

There are mainly two-forms for ontology representations also relevant for UPs, domain- and foundation ontology. In domain ontology, the user preferences are commonly described in form of an interest hierarchy directly related and based on the observed user behavior (Kim, 2003; Zhou, 2006; Anand, 2007; Sendhilkumar, 2008; Nakatauji, 2009). In foundation ontology, a model is described which unities common objects that are generally applicable across a wide range of domain ontologies. Therefore, it normally provides a core glossary to describe common objects in a set of domains.

Over the years, a few attempts such as (Golemati, 2007), SOUPA (Chen, 2004), UPOS (Sutterer, 2008), GUMO (Heckmann, 2005) have been made to define such a standard mainly in the form of foundation (or upper) ontologies by employing modular structures which are extendable by referencing existing ontologies or vocabularies for particular concepts such as beliefs, desires, intentions, time, space, events, user profiles, and actions. A general idea of the structure is visualized in Figure 4. Considering this, the key goal is to focus on the basic user model dimensions and leave the general world knowledge to existing ontologies such as SUMO (http://www.ontologyportal.org/) and UBISWORLD (http://www.ubisworld.org/).

SOUPA was a first step in the right direction. Anyway, the authors of (Villalonga, 2009) think that it lacks consideration of users' needs and support of mobile services and applications. Too overcome these limitations, a Mobile Ontology (http://ontology.ist-spice.org/) as part of the IST project SPICE was introduced. They extend the SOUPA approach by linking subontologies through a minimal core ontology from which all the sub-ontologies inherit. Already crucial sub-ontologies are defined but it is clearly anticipated that further sub-ontologies will be defined to cover the mobile domain more comprehensively.

Figure 4: Upper ontology separated into core and extension ontologies

A recent framework, which follows the GUMO approach building upon the notion of subject-predicate-object statements, is the Grapple User Modeling Framework (GUMF) by (Abel, 2009). It specifies a common structure and language to provide user preferences, user observations, and user model representations within the modeling infrastructure. GUMF aims to support various systems and integration of new kinds of statements and derivation rules within the user model format.

However, in recent years, there has been an initiative named Attention Profiling Markup Language (APML - http://www.apml.org) which allows users to share their own personal Attention Profiles. The goal is to combine all types of Attention Data (blogs, browsing, music, photos, social networking) into a portable file format which then describes user preferences ranked by interest. These Attention Profiles are stored in such a way that computers and web-based services are able to handle and process them. APML has not been widely adopted yet but is regarded as a step in the right direction. The two most famous web site applying APML are probably Digg (http://www.digg.com) and BBC (http://www.bbc.co.uk/blogs/radiolabs/). At Digg, the generated Attention Profile is based on the categories a user was interested the most over the past 30 days. At the BBC, their Radio Labs Pop service started in 2008 to allow users to export APML files based on their radio listening behavior.

In (Niederée, 2004) an ontology-based unified user context model (UUCM) is presented which describes the relevant dimensions of the user and its working context(s). This approach uses the metaphor of a context passport that accompanies users on their travel through the information space. UUCM is developed concerning cross-system and cross-service application enabling improved support for multistep information activities. Other earlier or recent approaches such as Description Logic (Sinner, 2004), concept lattice (He, 2007; Kwon, 2009) or tag clouds (Pessemier, 2009) a valid research efforts but might not make it to widely accepted standards for user modeling.

We can see that there have been many approaches to describe UPs and their data. So far, there is no standard yet which defines a general or generic user profile which stores any type of interest or preference that can be used across systems and where the user is in full control over its data.

Management

Before being able to use an UP and its represented user knowledge, this information has to be acquired and probably maintained first. Obviously, this part of information acquisition and management is not a simple task and there exist various methods and techniques to handle them. We will mention and focus on some more current approaches of the past few years. For information regarding general and earlier approaches we refer to the additional reading material.

Generally, there are three major information acquisition methods for user profiles, which could be ranked by user interaction. Firstly, there is, of course, the manual way where the user provides its information directly; usually done in form of a brief questionnaire or survey. This might be acceptable for basic information rather than complex interest. However, the user will get bored and annoyed when she or he has to provide the same or similar data again for different services. Therefore ideally, this should be done only once such as OpenID for logins. Secondly, the information can be gathered from explicit data either in the form of documents such as web pages or feedback. Here, the user provides data, which represent his interests, but the actual extraction is done automatically (He, 2007). Thus, it could be seen as a semi-automatic technique. Finally, implicit methods focus on the automatic acquisition of user information by observing, imitating, and recording user's behavior. However, it is not uncommon to combine explicit and implicit methods as done by (Zhou, 2007) and (Padadogiorgaki, 2008).

Over the past years, researchers have introduced various information acquisition methods using a variety of data to gather from. The most common one nowadays is the Internet especially the World Wide Web by using server-side (Sugiyama, 2004; Castellano, 2007; Papadogiorgaki, 2008) and client-side methods (Sendhilkumar, 2008). However, client-side acquisition became more popular by using web-browsing behavior related to page visits, time spent, and page length (Kim, 2003) or direct browser actions such as bookmarking, saving, printing as importance feedback (Sendhilkumar, 2008). Others (Chen, 2007) have also included private data such as calendar, schedule, email information or applied meta-data and tags while bookmarking (Michlmayr, 2007). A non-web approach of preference acquisition is used by (Reymann, 2007), where the way a user listens to its music on the computer is used to generate a music profile, which can be stored on a mobile phone for further use. This is extendable to other preferences as well.

It should be understandable that just any cluster of acquired data does not provide meaningful user information or make a UP what so ever. Hence, the underlying hidden information out of that data chaos needs to be unraveled first and related to user's interests to generate meaningful UPs. Eventually managing and maintaining UPs by evolving and updating them due to interest changes is a key component following the initial data acquisition and UP generation. We describe some general ideas by presenting the concepts assuming they could also be applied to any other domain.

A popular and effective method is the use of clustering schemes such as fuzzy, hierarchical and conceptual clustering. (Castellano, 2007) used fuzzy clustering to combine similar interests of multiple users into groups and (Han, 2009) combines fuzzy clustering techniques with optimization techniques to construct ontology-based user profiles (FCOU). (Kim, 2003) implicitly learnt a user interest hierarchy based on user behavior where hierarchical clustering algorithm groups words (topics) into a hierarchy. This is an analogous approach as to build a subject taxonomy for a book catalog in a library and then assigning books to the taxonomy. A more current scheme of hierarchical clustering is used in (Nasraoui, 2008). They employed a hierarchical version of an Unsupervised Niche Clustering (H-UNC) that used a Genetic Algorithm to evolve a population of candidate solutions through generations of competition and reproduction. Another web document clustering approach is presented in (Godoy, 2006), named Web Document Conceptual Clustering (WebDCC). It carried out incremental, unsupervised concept learning to generate user profiles as conceptual hierarchies.

Non-clustering approaches have been explored as well. Formal Concept Analysis (FCA) employed by (He, 2007; Kwon, 2009) describes a lattice which consists of concepts and their weights that express how much that concept supports a certain topic. Their assumption for the weight calculation is: The more similar a concept is with other concepts in the lattice, the more the concept supports the topic. (Magoulas, 2006) illustrated another approach, where a Fuzzy Analytic Network (FAN) process is employed seeing user preference extraction as a multi-attribute decision making problem.

(Marghny, 2006) focused on an adaptive system for learning the user profile, the dynamics and the rate of change of the user interests. This technique employed genetic algorithm for adapting to the user interest relying on user feedback. In (Sieg, 2007), a Spreading Activation algorithm is used to incrementally update the interest score of the ontological user profiles concepts. As the user interacts with the system by selecting or viewing new documents, the user profile is updated and the annotations for existing concepts are modified. The approach of personalized news content in (Papadogiorgaki, 2008) focused on a two-level learning process, which is employed on a mobile device side to automatically update the general and specific profile models. It involved the use of machine learning (ML) algorithms applied to the implicit and explicit user feedback. As ML algorithms they used a weight adaptation depending on whether the user selects or ignores news items. (Zhuhadar, 2009) also employed ML techniques to detect user convergence within a lower-level semantic UP gathers. A higher-level semantic representation keeping track of the user's general interests is used to detect shifts in the user activities which are then used to automatically update the overall user profiles.

USER PROFILE AND PERSONALIZATION

Once the UP is generated and in a state of future updates and evolution, it can be used for its sole purpose to customize services by making product or service recommendations personalized to a particular user based on its UP interests and preferences. This personalization is achieved by personalization algorithms also called recommendation approaches. Parts of this work in the next chapters are based on an earlier work by (Uhlmann, 2008) and are updated with new current personalization approaches and concepts regarding profile portability and cross-system profiling.

They can be classified into three main categories: content-based, collaborative, and hybrid recommendation system. Considering content-based ones the user will be recommended items similar to the ones the user preferred in the past. However, there are three general drawbacks of such system. Firstly, since only the content is analyzed it depends on the associated features related to the items the system recommends. Secondly, there is the challenge of overspecialization because the system can essentially only recommend items that score highly against an UP and, therefore, the user is limited to being recommended items that are similar to those already rated, used or bought. Finally, the biggest issue is the so-called new user problem. How does recommendation work when a new user enters the system? The challenge is the new user has to rate sufficient items before such a content-based recommendation system can really understand the user's preferences and present the user with reliable recommendations. Therefore, a new user, having very few ratings, would not be able to get accurate recommendations.

In a collaborative recommendation system the user will be recommended items that people with similar tastes and preferences liked in the past. Obviously, this is not problem free either and one can also identify three drawbacks. First, there is the same new user problem, where the system must first learn the user's preferences from the ratings that the user provides, in order to make reasonable recommendations. Second, there is also a new item problem. Since new items are added to such recommendation system on a regular basis, the system will not be able to recommend the new item until many users have rated it. This is due to recommendations on just user preferences. And thirdly, we have the so-called sparsity which depends on the availability of a critical mass of users. When having items only rated by a few users or users with a rather unusual taste compared to the mass, it will lead to rather rare or poor recommendations by the system. The authors of (Rafter, 2009) have explored the characteristics within collaborative predictions and one major implication regarding their observations is the importance of developing new algorithms that offer prediction improvements on extreme ratings because users need to receive reliable recommendations containing items they strongly like and avoiding items they strongly dislike.

To use the advantages but overcome certain drawbacks of the content-based and collaborative recommendation systems, hybrid approaches combine both methods to make better recommendations.

There are, however, different ways to combine them into a hybrid system.

1. Implementing collaborative and content-based methods separately and combining their predictions
2. Incorporating some content-based characteristics into a collaborative approach
3. Incorporating some collaborative characteristics into a content-based approach
4. Constructing a general unifying model that incorporates both

Regardless of the type of recommendation approach or system, it is important in personalization to avoid the problem of so-called tunnel vision. This principally means to focus too much on the main and most dominant user's interest and preferences. This may narrow down exploration or in other words, the importance of serendipity providing recommendations outside of the main user's interest space. It is essential to also "discover" new topics which might interest the user based on its current preferences. One option in that direction could be to present all found choices and highlight recommendations. Now the user can still explore the newly generated information space and might find something interesting but unrelated to current preferences and interests while browsing the results.

So far, there has been no superior recommendations approach. Even though hybrid systems have shown high potential to make good recommendations, the underlying techniques and algorithms are still mostly dependent on the applications or task at hand.

Most of the personalization techniques are related to information acquisition of user's web behavior or computer interaction. Thus, this means that the application of the constructed UPs is mainly limited to the web or computer. To overcome this limitation, the focus has been shifted towards portable profiles. This shift is confirmed by an evaluation of user expectations in (Brugnoli, 2005) where the most popular idea among participants was the possibility of using a so-called "Simplicity Card" containing user profile and personal data in conjunction with a mobile phone. Most participants saw it as a "Personal ID" and as a kind of an extension of themselves. On scenario to achieve portability is by mobile devices, which are able to store the profile data on the medium itself. Nowadays, mobile devices such as phones, PDAs or handhelds are often used to store UPs (Bartolomeo, 2006; Ghosh, 2007; Papadogiorgaki, 2008). Other device-like approaches including smart cards (Potonniee, 2002) or flash drives (Liffick, 2007) have been investigated as well. To extend the mobile only scenario, distributed UPs (Ghosh, 2007; Papadogiorgaki, 2008) are introduced by keeping service-related profile information on the service side besides the mobile device profile part. Of course, there is also the option of a centralized scenario where the UP is kept completely on a server and obtained on request (Ankolekar, 2006). Note that many user profile approaches mention application of mobile and portable devices but they never state how the exchange and usage of the profile is actually carried out or performed. There have been different approaches investigated to achieve portability.

One of the earlier approaches is the “Digital Aura” (Ferscha, 2004) which considered profile portability, handling and storing in a mobile device. Those profiles would be exchanged and compared via Bluetooth when the devices are in close vicinity of each other. Another Bluetooth-based approach is presented in (Bartolomeo, 2006) where a UP stored on a mobile or portable device was inspired by 3GPP:GUP to create a Simplicity User Profile (SUP). The SUP data are viewed and edited on the device itself and the profile is intended to adapt services, applications and networks.

In (Potonniee, 2002) a smart-card approach is introduced and demonstrated on an example in the context of interactive TV where collaborative personalization is realized on server side and the individual personalization on smart card side. Anyway, the introduced approach is generically applicable to any application. However, it can be seen as a disadvantage to store the UP on a smart-card since that means there is always a need to have a smart-card reader at hand whenever one wants to used its profile.

The BlueCard approach in (Ghosh, 2007) uses again Bluetooth enabled mobile devices. These devices use the OBEX Object Push Profile standard (OPP) which is amongst the most widely implemented Bluetooth specifications on mobile phones. Thus, this allows for the transfer of high-level objects between devices. For storing profile information they employ the vCard format (VCF) natively supported by all OPP devices. A VCF object is a structured collection of properties that may include not only information usually found on a business card such as names, addresses, telephone numbers but also other types of information describing resources such as audio, graphical objects or geo-positioning data. So in the proposed BlueCard approach, they create a new BlueCard on the mobile devices whenever a new service is been used otherwise an already existing BlueCard is used for authentication. The main idea is to use the BlueCard to assert general preferences and information about the user, which can then be combined with service-specific user profiles that are maintained at the service end. This approach was demonstrated as an implementation on the HP Labs Retail Store Assistant kiosk.

So far, most user modeling and profiling approaches were specific to the task at hand. However, the ultimate goal of this process should be to separate user modeling from applications to make gathered information reusable across applications. An approach in support of cross-system personalization is investigated and presented in (Niederée, 2004) and (Mehta, 2005, 2006, 2007). The Unified User Context Model (UUCM – context passport) provides a basis for the realization of cross-system and cross-service personalization approaches that enable the exchange and reuse of user profiles scattered across multiple systems. The interaction between the user and the information system (IS) using the context passport can be summarized as follows. The user presents its context passport to an IS. The IS can then interpret the user’s requirements and activities supported. The relevant context-of-use is extracted and activities are “transformed” according to that context-of-use. Now the IS can perform the supported activities based on information derived from the context passport. The user interaction feedback from the IS is used to update the context passport and keep it up to date.

For such a cross-system personalization approach, it is assumed that the user context-meta model is publicly available as a shared ontology. All participating systems rely on (and need access) to this model. The exchange of such information requires a negotiation between activities that an IS can perform and those activities that the user context outlines.

Hence, cross-system personalization needs to address

1) broader user models that can cope with the variety in user modeling,

2) handling heterogeneous personalization systems and approaches, and
3) giving more control to the user,

which are all related to a generic UP idea.

A quite interesting cross-service approach (Reymann, 2007) with extensions and applications (Bruns, 2007; Lugmayr, 2009) is the Portable Personality (P^2) Project. The main idea is to carry a XML-based UP (representing more like a digital personality) on a mobile device which can then be used to personalize services. They introduce a framework which provides a platform for cross-service interchange of personal context information based on any generic metadata type. This framework architecture is designed for mining, enriching, and exchanging XML-based personal profiles between arbitrary multimedia services to allow

– integration of multiple service specific metadata formats into one P^2 profile,

– exchange of metadata across devices and services to accomplish a seamless service and getting rid of all the single services,

– and support of sophisticated mining and personalization algorithms to gather and evaluate personal profiles.

The ultimate goal of P^2 is to handle a portable personality profile rather than a common user profile as mainly used today.

The overall framework is divided into four main parts, namely P^2 Provider, P^2 Service, AmbiNET, and P^2 Consumer. The P^2 Provider is responsible to gather metadata from all types of sources. However, within the framework it is not specified how this is done and, thus, is up to the Provider to apply appropriate algorithms for acquiring such metadata. The P^2 Services are responsible to manage and merge the context metadata into a personal context profile acquired by the various Providers. AmbiNET is the communication component within the framework allowing information being exchanged through various technologies such as Bluetooth, IP-networks, Internet, Infrared, or Wi-Fi according to availability. P^2 Consumers provide the actually personalization based on the obtained personality profile. As for Providers, the framework does not specify how this is can or has to be achieved. It is up to the application on the Consumer side to implement a suitable personalization algorithm. Within their framework, a mobile device is only seen as a carrier of the UP between different application services. An interconnection between the different parts is shown in Figure 5.

Within their framework they developed a so-called personality profile life cycle including stages such as Aggregate, Carry, Use, and Enrich. A more detailed description regarding this life cycle and the actual distribution of profiles between different entities can be read in (Lugmayr, 2009, p.192-193) and (Bruns, 2007, p.36-38). Considering their sample scenarios described in (Lugmayr, 2009, p.195-198), this is one of the first approaches taking into account automatically PC-generated UPs in traditional shopping context.

Figure 5: P^2 AmbiNET interconnection between different applications

Supporting the idea of portable profiles, there is a common tendency nowadays to have distributed profiles (Ghosh, 2006; Papadogiorgaki, 2008) where different parts or profiles are stored on the mobile device and on a server or service-side. This is mainly to separate general and service specific information from each other. For example in Papadogiorgaki, 2008) a detailed user profile (short-term interest) for the news domain is maintained on client, a mobile device. Long-term interest, however, are stored on server side. They do not explicitly mention anything about moving profiles between different devices (e.g. mobile - PC) but say that it is easily applicable / extendable to other platforms.

As mentioned earlier, most UPs are stored on the server-/service side, which, obviously, limits portability if the UP is tied to the service or server it is stored on. However, if there would exist a centralized UP, using its Unified Resource Identifier (URI) might provide the desired portability while keeping the server-sided approach. This idea has been employed by (Ankolekar, 2006), where the HTTP GET method was extended by a parameter containing the URI of the user's FOAF profile. A more generic approach based on this could be a portable profile on a mobile device which just contains a centralized URI pointing to the actual profile that is acquired from the used service up on request.

CROSS-SYSTEM PROFILE PORTABILITY

Personalization and profile portability efforts so far have been mainly service or application dependent. Cross-system approaches such as UUCM and P^2 are attempts to bring light to the jungle of proprietary and application dependent personalization by providing ideas for independent and generic frameworks.

As mentioned before portability requires a carrier generally a mobile device to carry the profile around between different application services. For this reason, portable personalization can be divided and classified into three main scenarios regarding where and how the profile is stored and where the actual recommendation process takes place. We refer to them as: mobile device side, distributed between mobile and service provider, and centralized. We will describe the ideas behind them including drawbacks and advantages. Then we review some current personalization and recommendation system approaches and investigate their applications with respect to the described scenarios.

A. **distributed scenario** : Mobile Device (MD) – Service Provider (SP)

Here parts of the UP are stored on the user's mobile device and the service provider end. This can be further divided into three sub-scenarios depending on what information is stored where and how it is used.

1. MD (general) – SP (specific)

In this scenario, the mobile device stores the static and/or general preferences of the user whereas the SP creates a specific profile. The use case scenario could be seen as follows.
A user uses a particular service (offered by an SP) the very first time. S/he can use its portable UP for a first initialization. After using the service, the SP gathered some more specific user interests and preferences based on the user's interaction and behavior. After the user made use of this service several times, the SP learns and adapts a specific UP started from the general mobile UP part. The main personalization would be carried out on the SP side where the specific UP information of the users can be utilized to provide detailed recommendations. However, one major drawback of such system is when the user interacts with another similar or different service (online or high-street shops), this generated specific UP stays with that particular SP and is not moved to the mobile device. Therefore, using a new service from a different SP, the procedure to learn and adapt to the user's interests starts again from the general UP obtained from the MD. An application for such a scenario is mainly authentication purposes and to provide some information to an SP so as to avoid a cold-start with no information about the user what so ever.

2. MD (specific) – SP (general)

The vice versa scenario is when the MD stores the specific UP and the SP just keeps a record of the general main interests. Since all user information is stored on the MD, the actual recommendation system would be embedded into the device itself. This is a particular case where the MD is actively used with the service not just carrying the UP. When a user interacts with a service providing its specific UP, the service would extract and generate general information from it and stores a general UP on its side. Accessing the service with the MD again means the SP would provide new content related to the user's general interest and on the mobile device side the recommendation system would personalize (rank) the information according to the specific user interests available there. A clear advantage over scenario *A1* is that when the user goes to another SP the specific UP is stored on the MD and therefore controlled by the user. Thus, all the information is always available to the user. Anyway, there are some issues with this scenario. First, if the SP would be able to obtain a specific UP it would probably use it to provide a better service for the user. Because, obviously, just using general information to do some pre-selection or pre-filtering on the service side is not an efficient approach. However, users might prefer this as a security and privacy alternative. Furthermore, the recommendation system on the SP side would not be able to exploit its full power by just utilizing user's general interest. Recommendations would probably lack accuracy, innovation, and serendipity.

3. MD (general, specific) – SP (general, specific)

This could be seen as an extension to scenario *A2* where the service side also keeps a specific UP. Besides overcoming limitations of scenario *A2*, this further introduces some other issues. Here we have the assumption that the SP UP can be stored on the mobile side. Otherwise it would be a combination of scenarios *A1* and *A2*. If both sides are able to exchange their UPs then either the user ends up with various service profiles on its MD or more challenging a mechanism is needed to merge and update the SP UP and MD UP. Obviously, the same procedure is needed in the other direction of UP exchange when the MD UP is provided to the SP. Now the SP must also be able to merge or update the service UP based on the MD version which may has changed since the last time to avoid storing redundant information. If no merging or updating procedure is in place, the system would treat the user and its MD UP as a first time user appearance which is similar to the cold-start problem in *A1* and it would, of course, add a certain level of complexity overhead. However, note that depending on the merging and updating procedure this might be a favorable approach. Furthermore, a generic or standardized UP would be highly beneficial for such a scenario, which does not exist yet; same goes for the universal merging procedure, which kind of relies on a generic (standardized) UP.

B. **mobile device side** : MD (general, specific) – SP (none)

In this particular case the entire UP would be kept on the MD of the user and the service would not use or store any user information. This can be seen as a special case of *A3* regarding the cold-start challenge. However, as mention before in scenario *A2* it is highly unlikely that a service would not use specific user information given to it to improve service. Therefore, such service system would probably not be used even though it would be favorable from a privacy point of view.

C. **centralized** : third-party storage

This is a very special scenario of a portable UP. The idea would be to store and maintain a UP at a central point on a network-based server. Now the MD would just contain a reference to the UP server location. When using a service the MD and SP would exchange this URI information and the SP would be able to obtain the UP from that particular location. There would be, of course, privacy and security challenges with such an approach especially adding a new third-party into this process which we do not want to discuss here. However, there are two basic options. First, the SP is only allowed to access the UP as long as the user uses the service. This, however, would suffer from similar issues as scenario *A3*. The second option could be that the service is granted longtime access. The advantage would be that the SP is able to obtain the UP even though the user does not currently use the service. This may be used to periodically check for UP changes, feed them to the recommendation system and update recommendations. In either option it would require a procedure on the SP side to update and merge local changes back to the central UP. Such an approach would combine advantages from *A3* regarding service recommendation as well as the portability factor similar to having the specific UP stored on the MD. Further, every SP would be allowed to access and update one single UP. This has, however, the need of a unified or standardized profile representation. Also the merging procedure to handle updates of interest (long/short term) needs to be specified and employed by each SP.

Note that scenarios *A* and *C* can be locally combined within an SP domain (such as an SP with multiple online representations or high-street shops / branches). This means the UP would be centralized within the local domain of the SP providing up-to-date UPs in each branch, which is certainly employed by major companies.

The aforementioned P^2 framework can be considered as an *A3* scenario where both sides, MD and SP, hold specific UPs which are exchanged, merged and updated. Here, the merging and updating procedure on the SP side handles the different metadata acquired from different sources. SPs are in charge of gathering the needed data and personalize the service according to the UP. Results are fed back to the MD where the user can browse the recommendations provided by the SP. Quite obviously, the profile exchange and merging is the most important part within in this P^2 framework and personalization is done on the fly after obtaining the new profile due to merging. This might be highly complex for large content or services with a huge number of users (if a collaborative or hybrid approach is employed). However, within the P^2 framework scenario, time might be not that critical since UP synchronization is done automatically after first time usage of a particular SP.

Anyway, complexity could be reduced by just using the obtained UP updates during merging for new suggestions. This would be applicable since the rest of the UP is still the same and, thus, recommendations would be kept up-to-date by the SP. Then, existing and new recommendations just need to be merged for up-to-date user recommendations based on the previous SP UP and the newly provided MD UP.

A description of a scenario *A1* approach is given by (Ghosh, 2007). They capture and maintain models of user profiles using semantic web technologies by aggregating and sharing distributed fragments of user profile information spread over multiple services introducing the Semantic User Profile management framework (SUPER). It supports the combination of portable user profiles on a mobile phone or PDA and service profiles. This enables the user to assert general preferences and information about themselves on the mobile device, which can then be combined with service (application, domain)-specific user profiles that are maintained at the service end. Furthermore, they integrate calendar and FOAF information from the user to make recommendations. They mainly use it at retail kiosk locations for identification and then getting a list of offers customize based on their service profile. The applied scenario could easily be swapped with other services providing their specific customizations and recommendations.

The vice versa option is presented in (Papadogiorgaki, 2008), where a distributed client-server user profile for personalized news delivery to mobile users consists of two separate models: long-term interests are stored in a skeleton profile on the server and the short-term interests in a detailed profile on the mobile device. The available content is initially filtered on the server to derive a list of recommended items in the general preferred categories, while the matching of detailed user preferences in the mobile device results in displaying items in a ranked order. This is a representation of an *A2* scenario and it is assumed that other retail services may be applied instead of the news domain.

Similarly to P^2, (Ghosh, 2007) and (Papadogiorgaki, 2008) can be considered generic representations of their kind using portable UPs and, therefore, independent of personalization and recommendation approaches. Hence, we want to present some current personalization algorithms which could be employed in the aforementioned scenarios and illustrated possible benefits and drawbacks when applied to the mobile or service side.

One simple form of UP representation is tag clouds (Pessemier, 2009). This is a content-based algorithm that recommends user-generated content with the aid of generally available metadata such as tags and categories. The recommendation algorithm will predict the rating that a user will give to a content item which contains a set of tags. To accomplish this task, the recommender will compare the set of tags T, with each of the tag clouds of the user profile one after the other. Based on these comparisons an obtain similarity value will indicate how the user previously evaluated content items with tags of T. This is used as a basis to predict the personal rating for the particular content item. Due to infrequent occurrence of tags a correction factor derived from the user profile is applied. This personalized correction factor gives less frequent or new tags a fair chance to get into the user profile, which will lead to more varied and novel recommendations for the end user.

An interesting hybrid approach (for music recommendation) is presented in (Yoshii, 2006). The method integrates both rating and content data by using a Bayesian network called a three-way aspect model, where a set of latent variables describe substantial preferences. The latent variables represent user preferences; each latent variable conceptually corresponds to a genre, and a set of proportions of the genres reflects a musical taste of each user. A visual representation of the relations in this model is pictured in Figure 6. A possible explanation of this model is that a user (stochastically) chooses a genre according to his or her preference, and then the genre stochastically "generates" pieces and polyphonic timbres. The collaborative part tries to predict unknown rating scores of a target user for musical pieces that have not been rated by the particular user considering someone else's scores of those pieces whereas the content-based part ranks musical pieces on the basis of music-content similarity by representing user preferences in the music-content space. They are able to achieve high recommendation accuracy and rich artist variety as well as solving the challenge of finding items with low or no ratings.

Figure 6: Bayesian three-way model

Another hybrid recommendation approach (Yu, 2006) uses content-based, Bayesian-classifier, and rule-based methods. They introduce a system that can handle three context categories for mobile usage - user situation context, user media preference, and media terminal's capability. At first, a content-based approach is used to measure the similarity between a media item and the preference context. Then, Naïve Bayes classifier approach is applied to calculate the probability of the item belonging to the situation context. Finally, a weighted linear combination of these two sub-scores is calculated to get the overall score. Now, all media items are ranked according to the scores achieved through these three steps and they choose the highest score or three highest-scored items for user's choices. At the end, a rule-based approach determines the appropriate form of the item to be presented in, given the capability context. Overall the system takes 3D input (MediaItem × UserPreference × Terminal-Capability) and recommends 2D output (Modality × Score). Here, Modality represents the final recommended format for a multimedia item—video, image, or text and Score represents the degree of user interest in the recommended item.

The authors of (Nakatsuji, 2009) explore the domain of Japanese music blogs to make recommendations based on ontology similarity between a user and other users. Their key goal is to detect so-called "innovative topics". At the beginning user-interest ontologies are generated to allow the construction of UPs as a hierarchy of classes. Details about that process can be read in (Nakatsuji, 2009, pp.109-111). Next, a user group *GU* is created which has a high similarity to a particular user *u*. *GU* is obtained by measuring the similarity between user interests. The "innovative topics" for user u are then detected by determining a suitable size of *GU* and analyzing the ontologies within *GU*. This suitable size is obtained by using a heuristic threshold to derive *X* users who have a high similarity with user *u*. The ontologies of user *u* and *X* are compared where also a parameter of innovations is defined indicated by the number of hops needed to get from different instances of an ontology of *X* to a class of user *u*. At the end, recommendations are based on ontology instances unknown to user u but well-known to the *X* users determined earlier. Note that determining the most suitable size of *GU* is very important for detecting attractive and innovative instances. Too small the innovations might be too close to the user own interest. Too large, on the other hand, the innovations might be too far off as a good recommendation related to the user interests.

Novel recommendations are not easy to predicate. Therefore, (Zhang, 2009) partitions the user profile into clusters of similar items and the recommendations are in a list of items matching well with each cluster rather than fitting the entire user profile. In order to achieve this, the user profile is first partitioned into subgroups. The strategy is only applied to user profiles sufficiently large enough. Possible partitioning strategies aka clustering are Extreme clustering (one item per cluster, all items in a single cluster), Graph partitioning, K-Means and Modularity maximization. By applying a dimension reduction strategy such as Singular Value Decomposition before clustering the items the contrast in their similarity values can be enhanced, and thereby improving the clustering results. After partitioning, the recommendations are then made by matching items to those pertained subgroups. Now the recommendations obtained for each subgroup are aggregated to form the final retrieval set.

A current large-scale collaborative approach (Das, 2007), however, uses a linear model to combine different algorithms to generate personalized recommendations for users of Google News. They apply a mix of memory based and model based algorithms. As part of model-based approaches, two probabilistic clustering techniques namely MinHashing (MH) and Probabilistic Latent Semantic Indexing (PSLI) are used to model the relationship among users and news items. MH is a probabilistic clustering method that assigns a pair of users to the same cluster with probability proportional to the overlap between the set of items that these users have voted for. PLSI is employed to perform collaborative filtering. It models and learns the relationship between users and items by modeling the joint distribution of users and items as a mixture distribution. A memory based method for recommending items makes use of covisitation instances, where covisitation is defined as an event in which two stories are clicked by the same user within a certain time span. Thus, recommendations for a particular user can be generated by considering the union of all stories that have been clicked by the members of the clusters that this user belongs to and the set of stories that have been covisited with the set of stories in the user's click history. For this reason, only stories from this union will get nonzero score, and therefore are sufficient candidate stories for recommendation.

Another large scale recommendation system is introduced by (Chu, 2009) based on a feature-based machine learning approach. Data are recorded in multidimensional format with at least three kinds of objects: user · content · temporal context (timestamp). Considering all features in the user and content profiles, a family of predictive bilinear models is employed to discover pattern affinities between heterogeneous features. A set of weight coefficients is introduced to capture the pairwise associations between user and content features. The parametric model is optimized by fitting observed interactive feedback which reveals the correlations between user patterns and content features. In general, the proposed framework is generic and flexible for other personalized tasks. The bilinear model provides a linear projection from the users' preferences onto the item characteristics. This will provide a user score indication composed of three parts:

1. long-term personal preferences on content features learnt from historical activities;
2. dynamic characteristics, such as temporal popularity over the whole user population, i.e. item quality;
3. the tradeoff between static personal preferences and article item.

Now this user score indicator needs to be related to different types of interactions. This is done by employing likelihood functions over Gaussian distribution. Thus, the posterior distribution of the weight coefficients is determined by a maximum-a-posteriori (MAP) estimation employing a gradient-descent method. MAP estimate is then applied to new user-item pairs predicting the indicator user score.

A concept lattice has been applied in (Kwon, 2009) for the shopping-retail domain using sales data and user-item ratings with weather and location ontology. Their proposed profile lattice is constructed by a data matrix which is first normalized and then digitized to binary format (*threshold* implies sensitivity of occurrence). A node in the lattice can then be translated into an IF-THEN rule and a choice of recommendation is done by generating strong and weak rules by simply varying the *threshold* value for matrix digitization. Using the lattice, the recommender system can suggest a specific service according to the user dynamic profiles.

From these algorithms and approaches it can be seen that hybrid recommendations are most common combining content and user information. Most of them are already employed in a server-side scenario related to the Internet. Therefore, applications on service provider sides should be straightforward with no to minor adaptations. Instead of logging into the service via a PC, accessing would be realized by a mobile device and at the same time user profiles are exchanged (merging and updating done, if necessary). The obviously easiest approach would be to send the MD UP to the SP and the SP sends its recommendations back to the MD where the user can browse them. This has the advantage of utilizing the immense computer-power available on the SP side for their recommendations especially for large-scale system with huge content- and user group information such as in (Dias, 2007; Chu, 2009). Furthermore, changes in the system can now be quickly integrated into the recommendation algorithm / system to update existing structures and / or profiles.

The ideas of “innovative topics” by (Nakatsuji, 2009) also falls into these SP side scenarios since it heavily relies on data from other users combined into similar user / interest groups. Due to the large amount of users needed to work reliably, constant changes and updates directly affect the user groups and their combined group profile representation.

Generally, simpler and smaller-scale algorithms such as tag clouds (Pessemier, 2009) and concept lattice (Kwon, 2009) could also be employed on the mobile device with a few limitations. For the tag clouds approach an option might be to only send small chunks of information (new or updated information after last visit) matching general interests and detailed recommendations can be made on the mobile using the specific UP. In this case the algorithm would predict ratings for the new information and ranks them accordingly. Watching or purchasing a recommended item would update the weights in the tag cloud accordingly. For the concept lattice, the idea would be similar. Since the lattice is generated from a data matrix due to thresholding, the data matrix could be transferred to the MD where the thresholding is applied by user interaction. Recommendations are achieved by varying the threshold. In both cases, obtaining the necessary data from the SP would be part of accessing the service.

One can argue recommendations directly on the mobile device would be feasible as well. This is probably true since MDs become more advanced in their computational power and unlimited data transfers are quite common nowadays. However, for large-scale and / or commercial systems this approach is probably not realizable since we believe the amount of data would be too huge and computational power (not even considering effects on power consumption) not enough to use complex hybrid recommendation algorithms. However, in small-scale scenarios where a mobile application shares content only among (personal) friends (not strangers), the aforementioned approaches by (Yoshii, 2006; Yu, 2006; Pessemier, 2009; Kwon, 2009) may be applicable due to the smaller amount of content as well as the rather limited number of further user input.

Profile Merging

An essential part of any mobile and service recommendation system or framework is the ability to efficiently sync, merge and update different existing profile versions on MD and / or SP side. Thus, the growth of UPs for different people and services have encouraged researchers to explore options to merge multiple UPs of a single person or a single SP-specific UP of multiple persons into a so-called common audience profile. A still existing challenge is, however, gathering information from multiple sources and representing the personal content in form of these unknown source structures.

An earlier approach related to user profiling and profile management in a smart home is presented in (Salem, 2004). Their issue of merging multiple profiles is related to the processing of profiles when multiple users are using or being present in an aware environment. Therefore merging profiles of multiple users is needed to relate each user to the environment and ensure a cohesive response. Profile merging is used by the environment to either

1. modify and influence the environment response to the users,
2. to concurrently respond to the users,
3. or to direct an environment request to the users.

The first case happens when there is neither a conflict of resources nor a conflict of interest. The second case occurs when there is a divergence of resources such as sharing a facility or service. Best example is probably the TV at home. Finally the third case is for situations when there is a conflict of interest when some user(s) want to have influence over other user(s). The merging technique is based on the statistical analysis of vector distribution in the meta-data space. It is a combination of Boolean Logic, a Vector-Space model and a probabilistic model.

In (Yu, 2006), a TV program recommendation scheme is implemented where the user profile merging algorithm combines individual profiles to form a common user profile that reflects most and consistent preferences of the group. Therefore, the merging strategy is based on total distance minimization and is as follows. The user profiles are formed into vectors of features and weights. Based on the features, a lexicon is constructed. Then the universal vector for each user profile is generated by thresholding the feature weights. From these universal vectors features are selected using total distance minimization. After normalizing the weights, the target weights can be calculated to generate the common user profile. They results showed that the approach works best for homogeneous groups whereas heterogeneous group results were not satisfactory, which, of course, would be the more interesting scenario. A disadvantage of this method is that the profiles are stored on the TV set and people have to log on via an interface to activate and use their profile.

A portable solution is presented in (Reymann, 2008) as part of their P^2 framework (Reymann, 2007) where UPs on mobile devices can be exchanged with TV-sets or set-top boxes via Bluetooth and then construct a common audience profile. They require that UPs are represented in XML format extended with specific P^2 attributes such as p2:merge, which is used for merging items but does not change the existing structure. It is checked if all values of all defined identifiers and their location within the structure are equal. After that the child elements of the item can be merged by individual merging strategies. After merging, based on the performed decisions of the audience the existing profile can be updated on the P^2 provider, in this case the TV equipment. Additionally, individual profile updates are distributed to each mobile phone of the audience. So far they are able to merge content of multiple sources embedded in the same namespace specification into one XML representation whereas merging of personal content originating from two different namespaces is not supported. Those two techniques could also be applied to other multimedia domains. The result is a collection of multiple namespaces holding personal content of multiple profiling sources. More inside into the procedure is provided by (Reymann, 2008).

The challenge of merging different UPs of the same person has been tackled by (Morikawa, 2004) and (Yu, 2005). In (Morikawa, 2004), the system uses two major parts Profile Collectors (PCs) and Profile Aggregator (PA). PCs acquire and handle various profiles from different sources such as location information, web behavior, and purchase history. The PA aggregates those various profiles from diverse PCs and manages them as a *Personalized Profile*. They assume that a user's home server can provide that functionality and data are synchronized periodically. The aggregation process updates the *Personalized Profile* based on a Resource Description Framework (RDF) triple model and a constructing template. They also assume XML profile data, which is transformed into an RDF based input profile by style reformatting. Then the *Personalized Profile* is updated via a personalized profile update module, which provides functions for adding triples, updating literal values, and unifying the same representation of triples. They applied the system to a shopping list and purchase history scenario.

The approach by (Yu, 2005) proposes an activity-based profile modeling approach. In this model, the complete user profile is created based on one or many activity profiles. During merging each attribute in the complete profile gets an annotation to indicate what activity it is associated with, when and where it should be used, what other attributes are highly related within the same activity. Now whenever the user sends a query, one activity profile is dynamically created by retrieving the corresponding attributes from the complete profile using the annotations.

The GUMF (Abel, 2009) uses a novel approach, which they call User Pipes that allows user profile reasoning by mashing up different user profile data streams in RDF or RSS-format by applying Semantic Web Pipes (http://pipes.deri.org/) or Yahoo Pipes (http://pipes.yahoo.com). Basically, multiple data stream can be combined with other data streams to derive new user profile information. An example may be combining profile information obtained from a search query session with data from profile interests to find out whether the user's preferences and search activities are thematically similar mashed up information with other RSS feeds from the Web. The benefit of the user pipe approach is that they result in user profile streams that can again be used by other profile reasoners, which allows for flexible and extensible user profile reasoning. The critical point of this approach is the immensely huge amount of RSS data on the Web that could slow down the processing of a pipe. Therefore, future work is to investigate options of caching strategies (e.g. precompute pipes regularly and deliver the cached results).

As with the personalization algorithm, due to the use of ontology profiles merging can be approached by ontology merging and adapting techniques including consistency checks among ontologies for applied context and tags (Thiagarajan, 2008). However, since domain ontologies represent concepts in very specific ways, they are not compatible most of the time. Thus, when a system relies on a domain ontology it often needs to merge the domain ontology into a more general representation. This is a challenge especially for the ontology designer since different ontologies in the same domain can also arise as a result of different perceptions of the domain based on cultural background, education, ideology, or because of a different representation language. Right now, merging ontologies that are not developed from a common foundation ontology is mostly a manual process. However, domain ontologies that use the same foundation ontology can be merged automatically. Current studies on generalized ontology merging techniques are still largely theoretical.

Challenges and Recommendations

Up to now, most services deal with personalization in their own way by employing own user profile representations and recommendation systems. The introduction of APML to describe user preferences and interests in a common language is one step in the direction of making user profiles available to other services. This leads to what can be seen as the biggest challenge for cross-service personalization: the lack of standardized generic form of UP representation. An approach to overcome issues from a non-profile perspective is the P^2 framework providing means to handle information from multiple sources by a common portable metadata repository. Another challenge rising from such generic profile is the tendency to gather more information from different non-related sources which are then to be combined into a single complex representation of a user (digital personality). So far this concept of such a complex UP is just theory where focus has been on attempts to handle and structure the data in a meaningful way. However, no practical implementation has been realized yet. The next stage would be, of course, to find mechanisms to update and merge such profile representations in an efficient manner. Furthermore, since such profile consists of various information, which is interconnected to certain extend, inference methods are applicable to enrich the profile based on existing information. Such a generic UP representation would be the ideal long-term vision for cross-system personalization. Anyway, an intermediate solution could be the P^2 approach were service providers have their own form of profile representation but there is a generic UP so different services could exchange UPs. APML might be worth investigating in that sense.

However, such generic yet complex UPs are just one step. Considering this, personalization approaches need to be able to sync, merge, and update such UPs and extract relevant information for their service. Here, partitioning the UP might be one solution as proposed by (Zhang, 2009) but instead of doing it based on algorithms, this could be done during the data gathering stage and profile updating and synchronization. This is, again, related to how to handle and represent these UPs properly. Furthermore, most personalization approaches are already employed on service sides today but so far they did not have to consider users providing a detailed profile upon their arrival (first service usage). Hence, service providers and their recommendation systems have to adapt to such scenarios where fast (or instant) personalization and recommendation is required based on detailed user data. Possible options might be to either always use the profile provided by the user since this will be the most current one for recommendations or sync an existing and the user provided profile and perform the recommendation service just on changes between the two profile versions.

Note that when talking about personalization, user profiles, and especially the combination of these two across multiple systems rises many issues and challenges related to security and privacy. We have not discussed anything related to that but want to mention that these are important points to be considered when going down that road. (Cranor, 2003) discusses privacy risks associated with personalization and describes a number of approaches to personalization system design that can reduce these risks. Furthermore, privacy and security concerns are supported by the second part of the 2009 personalization survey from www.choicestream.com where the majority of people are concerned about their data being share to services they do not know about and that their data might not be secure on any service. The security concern would probably grow further considering the portability aspect among different systems . Furthermore, this would also have an influence on the fact that many people actually do not want every service to know everything about them. Yet another important fact that needs to be considered in cross-system personalization.

CONCLUSIONS

With the growth of technology and its related services, personalization becomes more important and anticipated whether it is for web searches, music taste or (online) shopping. User profiles have been used before but nowadays there is more required. They should include semantic content and context as well as being adaptive and evolvable using short- and long-term preferences of any type; in short the long-term vision is a digital representation of a real-world personality. The application of ontologies and their related techniques seem to provide a promising direction towards that vision. To acquire and manage those user profiles, various approaches have been proposed but it is hard to compare their performance due to different data the user knowledge is gathered from and the different domains these techniques are applied to. However, the portability aspect of user profiles has been picked up by the (research) community especially considering the current trend of mobile devices. At the moment, the distributed client-server profile model shows potential to combine user expectations and service needs, and should be further investigated. Therefore, recommendation approaches ought to look also into the area of distributed profiling and simultaneously considering the application of multiple profile domains. First steps are directed towards cross-system personalization utilizing a single user profile representation but it is just the beginning and more efforts and focus needs to be invested in that direction; and not just from the technical point of view but also considering privacy and security issues as well as psychological and ethological aspects. The closely related issue of merging user profiles has not caught much attention either yet. Current techniques are rather simple and more advance methods are required to push the personalized user profile towards a new portable personality experience.

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KEY TERMS & DEFINITIONS

User profile – electronic representation within in a system of an user's preferences, interests and behavior accumulated by system interaction; user for personalization and recommendations

Digital personality – digital representation of a real-world user by a complex user profile which integrates every information of the user

Portable personality – portable form of the digital personality which can be carried around (e.g. mobile device) to personalize each and every used service

Personalization – an action by utilizing an user's profile to adapt a system or service to the user's preferences

Recommendation system – a system mainly consisting of algorithms and techniques to evaluate user profiles for personalization

Cross-System personalization – combining portable personality and personalization by using user information gathered by a system A on another system B to obtain personalization without going through the information accumulation process of system B again