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## **Delivering Personalized Information: What You Get Is What You Want**

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**Abstract:** The information age has brought with it massive amounts of data and the promise of being able to access any information when needed. However, the tools to help us navigate through this maze of information are not well developed. Users are faced with a significant information overload problem as they become more and more frustrated by their inability to locate the right information at the right time. Personalized recommendation systems have been forwarded as a potential solution. These systems customize themselves to their respective user by learning about their user's preferences and process, select and display information accordingly. In this paper we survey some of the principal personalization techniques in the context of a number of case-studies.

### **1. The Need for Personalization**

As information becomes abundant, humans are confronted with more difficult decisions for how to access, navigate through and select available options. The sheer number of alternatives often makes a wise choice impossible without some intelligent computational assistance. The term *information overload* has become almost synonymous with the Internet. In response to this need, there have been increased efforts to design and implement intelligent aides for filtering web sites (e.g., Pazzani, Muramatsu, and Billsus (1996)), news stories (e.g., Lang (1995)), TV listing (Smyth and Cotter, (1999, 2000), Cotter and Smyth (2000a&b)) and other information sources. A related line of research and development has led to *recommendation systems* (e.g. Burke, Hammond, and Young (1996), Resnick and Varian (1997), Burke (1999)), which are not limited to filtering information but can be used for any task that requires choice among a large set of predefined items. Given a large set of items and a description of the user's needs, recommendation systems present to the user a small set of the items that are suited to these requirements.

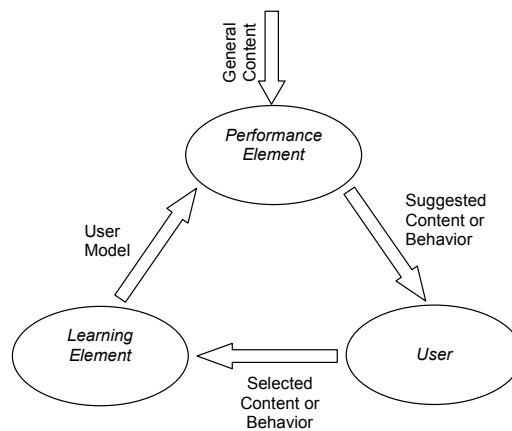
Society, on the other hand, is getting more complex and diversified. The differences in personal preferences, social and educational backgrounds and private or professional interests are increasing, and tools to access information are becoming

ubiquitous. This causes the need for intelligent systems that process, filter and display available information in a manner suitable for the characteristics and desires of each of these individuals. The ‘one result fits all’ approach to item selection delivered by standard recommendation systems does not satisfy this need. Research on personalization has led to the development of systems that adapt themselves to the characteristics of their user: *user adaptive* or *personalized systems* (e.g. Rich (1979), Langley (1997), Ardissono, Barbero, Goy, and Petrone (1999), Ferrario, Waters and Smyth (2000), McGinty and Smyth (2000), Fiechter and Rogers (2000)).

## 2. Personalized Systems

Raw data usually does not change based on the individual processing it. However, the resulting information and the manner in which it is presented can be influenced by personal differences. A computer system should ultimately be sophisticated enough to take individual variations in preferences, goals, and backgrounds into account and generate, select, and present personalized information.

Personalized systems obtain user preferences through interactions with users, summarize these preferences in a user model and utilize this model to adapt themselves to generate customized information or behavior (see Fig. 1). They deliver customized information in the manner that is most desirable for the current user, thereby increasing the quality of both the interaction and the generated result.



**Figure 1:** Personalization Cycle

### 2.1. Problem Analysis and Representation Engineering

The first step in the development of a personalized system is to analyze the general task to be performed and the information available about the content and the user. Based on this knowledge, decisions regarding the level at which personalization can be applied and the approach to be used can be made.

Personal preferences can have an effect at the *data processing level*, the *information filtering level*, and the *interaction and information presentation level*. On the data processing level, the algorithms used on a data set can be varied in accordance with the user's preferences. During information filtering, the results of the data processing algorithms can be screened based on the preferences of the user and subjectively irrelevant choices can be eliminated. The presentation of the information as well as the interaction with the user is also subject to personal preferences and needs. While some users may prefer a mostly textual description of the information, others may choose to have the content delivered in a graphical manner. The user preferences also permit to streamline the interaction by eliminating choices that can be derived from the user model.

The analysis and design of the representation and information content of the items and the user models is done during representation engineering. Depending on the domain and problem formulation, item representations can be unstructured (e.g. emails, news stories), semi-structured (e.g. Web-Sites), structured (e.g. restaurants, hotels), or with varying structure (e.g. routes, schedules). The representation of the user model can have the same characteristics.

Apart from the issues related to the structural representation of the items and the user model, the semantics of the attributes utilized in each description have a governing effect on the system as well. Both the item and user description can be atomic (just an identification number), independent (directly measurable and modifiable), or dependent (can be modified or measured only by means of the independent attributes, cf. Göker (1999)). While the ingredients of a meal might be considered independent attributes, the resulting dish and its characteristics (gourmet, fast-food) are dependent. The combination of these descriptions spans the field of possible systems and determines the approach that can be used in personalization.

## **2.2. Designing the Learning Element for Generating User Models**

User models can represent stereotypical users or individuals, they can be handcrafted or learned (from questionnaires, ratings, or usage traces), and they can contain information about previously selected items, preferences regarding item characteristics, or properties of the users themselves (c.f. Rich (1979)). These approaches are complementary but developers usually choose one of them to create their user model.

In terms of actually acquiring user models we can broadly distinguish between two basic approaches. The *direct-feedback* approach places the burden on the user by soliciting preference information directly. One standard approach is to ask the user to complete a preferences form by classifying or weighting their interests using a range of interest categories. The problem with this approach is that users are usually put off by the need to complete long questionnaires before they can even begin to enjoy a given service. In response, another form of direct-feedback encourages the user to provide feedback as they use a particular service, and on an on-going basis. An example of such a system is PTV, a system that generates personalized TV listings (see the paper by Smyth & Cotter elsewhere in this issue).

The second, and no doubt more interesting, approach to acquiring user models is to derive user preferences *unobtrusively*, by mining the interactions with the user. Examples of such systems are CASPER, a personalized online recruitment service (section 3.1) and the Adaptive Place Advisor, a system for generating personalized destination advice (section 3.2).

### **2.3. Designing the Performance Element, Utilizing the User Model**

Ultimately personalization techniques are all about how one can utilize a learned user profile in order to identify and present (*recommend*) relevant information to the right user at the right time. In general two broad strategies have emerged. The *content-based* approach (c.f. Pazzani et.al. (1996), Lang (1995)) seeks to recommend similar items to the items that a user has liked in the past. In contrast, the *collaborative approach* seeks to select items for a given user that similar users have also liked (c.f. Konstan, Miller, Maltz et. al. (1997), Billsus and Pazzani (1998), Smyth & Cotter (1999, 2000)).

Content-based recommendation has its roots in information retrieval (IR) and case-based reasoning (CBR) research (Watson, (1997), Aamodt and Plaza, (1994)). The success of the content-based method relies on an ability to accurately represent recommendable items in terms of a suitable set of content features, and to represent user profile information in terms of a similar feature set. It is then a matter of ranking items for recommendation according to their similarity with a given user profile. The downside of content-based recommendation methods is that this content description requirement can be problematic and time consuming. Another problem is that a user profile effectively delimits a region of the item-space from which all future recommendations will be drawn. Therefore, future recommendations will display limited diversity. This is particularly problematic for new users since their recommendations will be based on the very limited set of items represented in their immature profiles.

Collaborative recommendation (also known as collaborative filtering) techniques represent a recent alternative to the more traditional content-based strategies (Balabanovic and Shoham (1997), Billsus and Pazzani (1998), Goldberg, Nicols, Oki and Terry (1992), Maltz and Ehrlich (1995)). The basic idea is to move beyond the experience of an individual user profile, and instead to draw on the experiences of a population or community of users. Collaborative recommendation techniques look for correlations between users in terms of their ratings assigned to items in a user profile. The users that display the strongest rating correlation to the target user act as “recommendation partners”, and items that occur in their profiles (but not in the target user profile) can be recommended to the target user. In this way items are recommended on the basis of user similarity rather than item similarity.

Since explicit content representations are not needed during recommendation the knowledge-engineering problem associated with content-based methods is relieved. More importantly perhaps, as the available user-base grows so too can the quality of recommendations made by the collaborative strategy. By identifying closely correlated recommendation partners collaborative techniques can suggest items whose relevance to a target user is not limited to a small set of similar items.

Collaborative recommendation does suffer from a number of significant drawbacks however. Since collaborative recommendation techniques rely directly on the ratings of other users, it is not suitable for recommending new items or one-off items. This so-called latency problem is a serious limitation that may render a pure collaborative recommendation strategy inappropriate for a given application domain.

Collaborative recommendation can also prove to be unsatisfactory in dealing with what might be termed an unusual user. If a target profile contains only a small number of ratings or contains ratings for a set of items that nobody else has looked at, then it may not be possible to make a reliable recommendation using the collaborative technique.

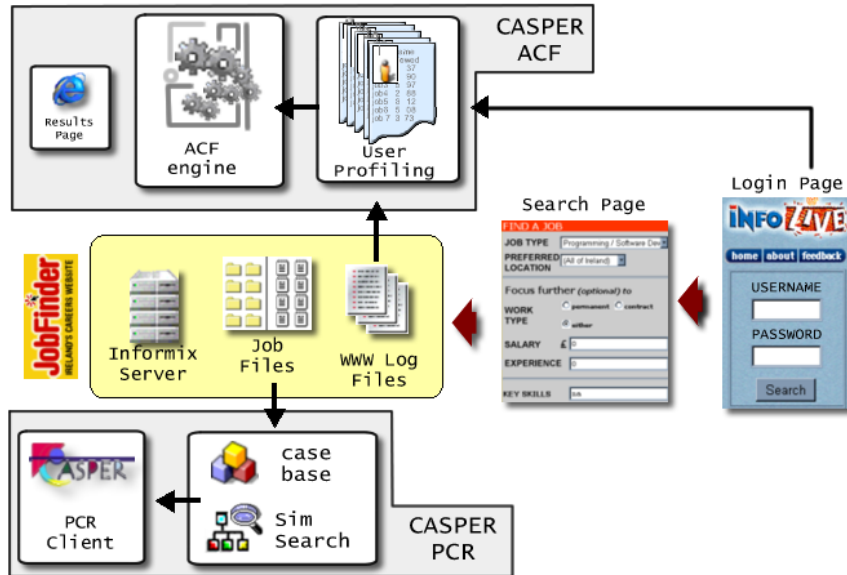
It should be clear from the discussion so far that, individually, the content-based and collaborative personalization methods suffer from a number of significant disadvantages. However, taken together, both techniques complement each other perfectly, each solving the problems of the other.

### **3. Sample Systems**

#### **3.1. CASPER – A Personalized Online Recruitment Service**

Online Recruitment services have proved to be one of the most successful and popular types of information service on the Internet. Typically these sites provide job seekers with a comprehensive database of categorized jobs, a dedicated search engine, and the ability to submit resumes and apply for jobs online. The award winning Irish site, JobFinder.ie is a good example of one such service.

However, like many traditional search engine services, JobFinder.ie suffers from two basic problems: 1) its reliance on exact-match database driven retrieval technology; 2) a lack of personalization. This is problematic because typically users are poor at constructing accurate search queries. For example, consider two users submitting the same query to JobFinder.ie, indicating that they are interested in software engineering jobs specializing in Java. Both of these users would receive the same results even though, implicitly, one user may be interested in Dublin based jobs while the other is willing to travel. The point is that these users have important preferences that are rarely made explicit in a search query.



**Figure 2.** The CASPER Architecture.

The CASPER project was established to investigate how the new generation of intelligent, personalized information retrieval technology could be used to improve the JobFinder.ie service. The CASPER architecture is shown in Figure 2 and is seen to consist of two new components, CASPER ACF and CASPER PCR, in addition to the existing JobFinder component.

CASPER PCR (*personalized case retrieval*) is designed to supplement the existing JobFinder search engine with a personalized, case-based reasoning search engine that is capable of selecting job-cases that not only match a user's query but that also match the user's past preferences. The PCR process is a two stage one. During stage one, a similarity-based retrieval process (operating on the server-side) selects the  $k$  most similar cases to the user query from the CASPER case-base (a structured version of the JobFinder database). During stage 2 these  $k$  cases are passed to the user's client where each case is classified with respect to previous job cases that the user has graded. Ultimately, cases that are strongly similar to jobs that the user has previously liked are preserved, while cases that are strongly similar to jobs that the user has disliked are eliminated. As such, the resulting cases are those that are not only similar to the user query but that also match the user's previous job preferences. One of the benefits of the PCR component, in addition to its ability to accurately personalize retrieval results, is that the personalization does not take place on the server-side – the personalization process and the user profile are stored and maintained on the client, improving security and satisfying many privacy concerns that a user may have.

The CASPER ACF (*automated collaborative filtering*) component provides a query-less recommendation facility to deliver personalized daily job recommendations to individual users based on user profiles that have been mined from the JobFinder.ie server logs. Very briefly, CASPER ACF constructs user

profiles by inferring user interests from their browsing patterns, noting the click-through and read-time activity associated with specific jobs. A cluster-based collaborative filtering strategy is then able to compile a short-list of job recommendations from a user's virtual community on a regular basis.

In summary then, CASPER provides a personalization layer for the JobFinder.ie online recruitment portal, allowing users to benefit from a more relevant recruitment service that is tuned to their particular recruitment needs and preferences. The interested reader is referred to Bradley et al, (2000) and Rafter et al. (2000a&b) for further information.

### 3.2. The Adaptive Place Advisor

The *Adaptive Place Advisor* (Göker and Thompson (2000)) is a user adaptive, conversational recommendation system designed to help users decide on a destination, specifically a restaurant.

The selection of destinations is viewed as an interactive, conversational process, with the advisory system inquiring about desired item characteristics and the human responding. Rather than using the ranked list approach typical for searches on the internet, the system mimics an interaction between an advisor and an inquirer. A typical interaction with the Adaptive Place Advisor takes the following form:

*Inquirer:* Where do you think I should eat tonight?  
*Advisor:* Well, what type of cuisine would you like?  
*Inquirer:* What types are there?  
*Advisor:* Some examples are Chinese, Indian, and Mediterranean.  
*Inquirer:* Oh, maybe Indian.  
*Advisor:* What quality rating would you like?  
*Inquirer:* I don't care, as long as it's cheap.  
*Advisor:* How do you want to pay?  
*Inquirer:* No, I think I'd like Chinese instead.  
*Advisor:* Okay, we'll switch to Chinese food. What city do you prefer?  
*Inquirer:* How about Berkeley?  
*Advisor:* I know three cheap Chinese restaurants in Berkeley. One is the Long Life Vegi House on 2129 University Avenue. Does that sound alright?  
*Inquirer:* Sure, that sounds fine.

Such dialogues seem better for recommendations that must be delivered by speech rather than visually. They also seem ideal, independent of modality, for tasks like destination selection or help-desk applications (c.f. Aha and Breslow (1997), Göker and Roth-Berghofer (1999)), in which the user needs to converge on at most a few items.

The conversation with the user, similar to constraint satisfaction, will ultimately direct the system to a suitable solution. However, such a conversation can become very tiring and the quality of the returned result may not be acceptable for each user. Just as interactions with a friend who knows your concerns can be more directed and produce better results than those with a stranger, dialogues with the Adaptive Place Advisor become more efficient and effective over time. The goal for user modeling in the Adaptive Place Advisor is to improve the subjective quality of both the results and

the dialogue process. The system is built on a case-based paradigm and utilizes traces of the interaction with the user to adapt its similarity calculation, thereby personalizing the retrieval and the conversation.

The user model contains preferences regarding items, attributes, values, value combinations, and diversification and is acquired during the conversation. The system enhances the user's explicit requirements with the user model and retrieves suitable items from a case-base. If the number of items found by the system is unsuitable (too high, too low) the next attribute to be constrained or relaxed is selected based on the information gain associated with the attributes. Using an information gain measure in conjunction with user dependent similarity calculation ensures that the most suitable restaurant is found with a minimal number of questions.

#### 4. Summary

We live in a world of information but suffer from the lack of tools to properly search, select and display the right information at the right time and in the right manner. However, recently a potential solution has emerged in the guise of personalized recommendation systems. These systems combine user profiling and information filtering techniques to learn automatically about the user's preferences and customize themselves to process, filter and display information accordingly.

In this paper we have examined the various issues facing designers of personalized recommendation systems, the steps that have to be taken while developing them, and the techniques that are commonly employed for acquiring and utilizing user profiles. Finally we have outlined three successful recommendation systems from the Digital TV, recruitment and destination selection domains.

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