Mobile Music Personalization at Work

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Abstract. Although personalization is a widely used technology in e-commerce it has not yet gained the importance it should have in m-commerce. With the availability of mobile services operating on huge content sets (e.g. audio archives) the need for personalization rises. In this paper we present the current state of a music personalization system designed to improve a large mobile music portal.

1 INTRODUCTION

Distributing music is currently a very hot topic in e- and especially in m-commerce. Many portals offering music (e.g. amazon.com) try to improve their service by providing personalization for better supporting the user in finding and buying the appropriate music items.

While most available systems are based on some recommending algorithms the approach of SAT is not to tackle personalization as a data-mining and/or user modelling problem, but viewing it in a broader context where the optimization of the users' needs as well as the requirements of the operators are in focus.

The system (Adaptive Personalization) presented in this paper is part of a large international mobile music platform (http://www.ericsson-mediasuite.com) and is currently online in Europe, Asia and the USA.

2 THE CONCEPT

The 'Adaptive Personalization System' of SAT is a hybrid, self adapting recommendation system, combining the advantages of social/collaborative and item based filtering approaches. The cornerstones of this concept are

- a highly sophisticated, multi dimensional profile system, combining model-based and behaviour based approaches,
- a well defined set of recommendation strategies, based on data-mining and artificial intelligence algorithms,
- self-adapting or 'learning' behaviour, based on *instance based learning* and data mining algorithms
- support of user generated content

2.1 Adaptive Profile Systems

2.1.1 Modelling the User

User needs can be distinguished in well and ill defined ones. Well defined needs are needs the user is explicit about, for instance preferred genres or artists. Ill defined needs are needs where the user does not know exactly what he/she is looking for and is far from being able to define them. Furthermore, users are normally not isolated during the usage of personalization systems, and user behaviour has a certain effect on the community employing the system.

These effects can be very multifarious, ranging from deliberate interactions like the placement of ratings or recommendations to indirectly shaping the sample data to which learning algorithms are applied. These considerations led to a multi- layer model where each user is represented by a profile consisting of three different views:

- self assessment
- system observations
- community assessment (assessment of others)

Each view is implemented by a feature vector, as shown in figure 1, which represents the basis for a user profile in the *Adaptive Personalization* approach. The decision, which views are used and which attributes (features) model a given view, depends on the kind of application and problem domain. For example, within the mentioned online music portal the *community assessment* view is (still) not in use.

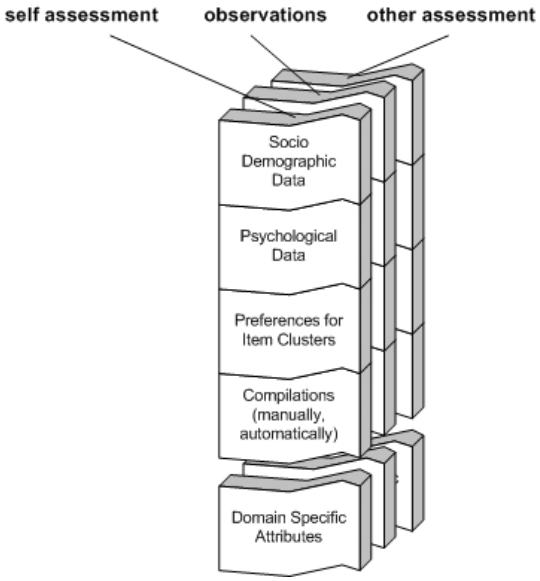

Figure 1. Structure of User Profile

This complex model, combining knowledge- and behaviour-based approaches, forms the basis on which a wide range of needs can be served. The information of the self-portrait can be used to satisfy the 'obvious' needs - even (and especially important) when this description is somewhat 'idealized'. The sub profile created and automatically refined through the observations view is used to identify and satisfy behaviour-based needs.

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2.1.2 *Modelling the Items*

The affiliation of items to certain clusters is also modelled along three different views (see figure 2).

- the assessment of the domain expert
- the assessment of the (user) community
- cluster affiliations calculated by appropriate classifier systems, if available.

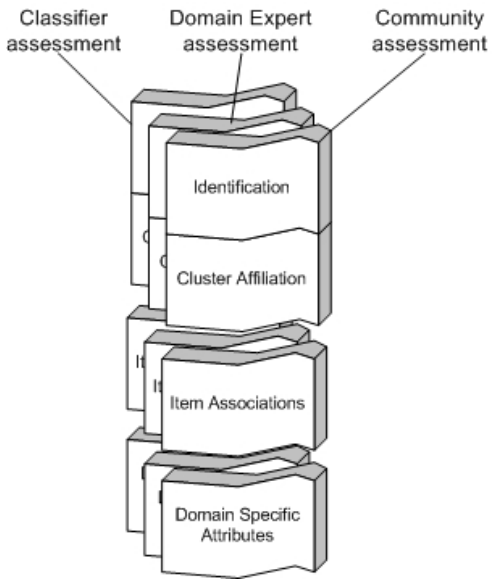

Figure 2. Structure of Item Profile

The assessment of the domain expert often represents the opinion of the content owner, while the community view reflects how the content is seen by the consumers/users. By providing both views the content owner gets an important feedback, and a better explanation model can be provided for the user concerning the recommended items. The classifier assessment can be seen as an extension of the domain expert view, where 'third party' information is used to refine the item profile. In the context of our online system an audio classifier is used, based on Music Information Retrieval methods.

Beside genres we also support music clustering according to mood and situation like music for 'First Love', etc.

2.2 Recommendation Strategies

Another key factor is to support the right set of recommendation strategies the user is expecting from an intelligent system. The SAT approach provides a set of 'need based' strategies, as proposed in several papers of the research community e.g. [5], [3], [4].

1. Reminder recommendations
2. 'More like this' recommendations
3. Recommend new/'hot' items
4. 'Broaden my horizon' recommendations
5. Show me, what 'similar' users do or like (e.g. view or buy)

Reminder recommendations should help the user not to forget or oversee those items that he/she has earlier put on a digital shopping list, but not yet bought.

'More-like-this' recommendations - probably the most common ones - should help the user to find similar items. In our context similarity is defined on the basis of genre affiliation and an external calculated 'sounding similar' [1], [2] relation, with the latter being calculated offline.

'Hot-Item-recommendation' should support the user to be up-to-date within the range of his/her preferences. These recommendations help to satisfy community needs, where a user wants to be best informed within his/her social environment.

'Broaden my Horizon' is a very important recommendation strategy, because it supports the user to explore his/her taste and it helps to sharpen or verify the user's profile.

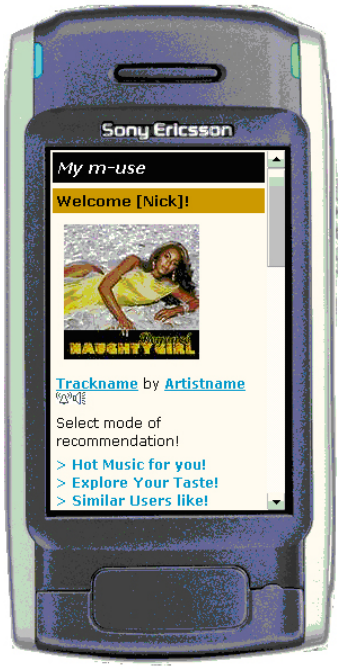

Figure 3. Recommendation strategies

Figure 3 demonstrates a page where three of the mentioned recommendation strategies are shown in the context of a given track.

2.3 Self Adapting Capability

The self adapting or 'learning' behaviour of the personalization system of SAT is realized by using data mining and instance based learning algorithms. This 'learning behaviour' is realized on three different levels

1. The individual level, where profiles of users are permanently refined based on implicit (e.g. navigation observation) and explicit feedback (e.g. ratings, buying behaviour). For frequent users, the quality of the profile will increase over time.
2. The collaborative level, where the community ratings of items improve the recommendation quality as well as the refinement of profiles leads to the improvement of the 'similarity' relation (e.g. 'items similar users like').
3. The statistical level, where data mining algorithms are applied (e.g. association rules) to generate new recommendations. Because these algorithms operate on data based on user-behaviour

(e.g. shopping history, compilations of favoured items) the quality will improve over time.

2.4 User Generated Content

Feeding portals regularly with interesting and engaging content is a very challenging (and of course expensive) task for operators. So we decided to involve users in that process by encouraging them to post affiliations of items (including personally compiled collections like play lists) to mood and situation clusters. Figure 4 demonstrates a use case, where the user can assign a track to a predefined cluster (music for 'First Love'). For handheld devices only one choice of a cluster is presented, which can be either accepted ('YES') or rejected ('NO'). When accessing the music portal on the WEB (via PC), all clusters are presented and the user may assign a track to several clusters.

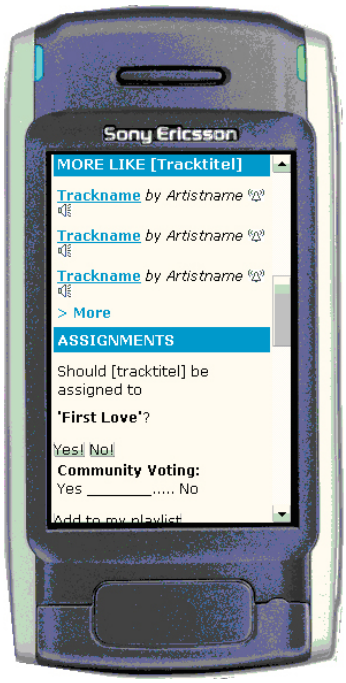

Figure 4. Assigning a track to a cluster

3 DEMONSTRATION

During the demonstration of our system we will explain how the concepts mentioned above were realized for the handheld as well as for desktop clients. Furthermore at the time of the workshop first results concerning user acceptance will be available.

ACKNOWLEDGEMENTS

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REFERENCES

[1] J.-J. Aucouturier and F. Pachet, 'Improving timbre similarity: How high is the sky?', *Journal of Negative Results in Speech and Audio Sciences 1(1)*, (2004).

[2] E. Gstrein and al. et, 'Polynomial preconditioners for Conjugate Gradient calculations', *In Fifth Open Workshop on MUSICNETWORK: Integration of Music in Multimedia Applications, Vienna, Austria*, (2005).

[3] R. Sinha and K. Swearingen, 'Comparing recommendations made by online systems and friends', *Proceedings of the DELOS-NSF Workshop on Personalization and Recommender Systems in Digital Libraries*, (2001).

[4] K. Swearingen and R. Sinha, 'An hci perspective on recommender systems', *In ACM SIGIR 2001 Workshop on Recommender Systems, New Orleans, Lousiana*, (2001).

[5] K. Swearingen and R. Sinha, 'Interaction design for recommender systems', *In Designing Interactive Systems (DIS 2002)*, (2002).