Advanced Engineering Forum *Online: 2011-09-09*
ISSN: 2234-991X, Vol. 1, pp 395-399
doi:10.4028/www.scientific.net/AEF.1.395

A Personalized Music Recommender based on Potential Preference Learning Dynamically

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Keywords: Multi-agent Recommender; potential needs; preference learning; filtering & ranking.

Abstract. An intelligent musical recommendation system for multi-users in network context is presented. The system is based on a comprehensive user profile described by feature-weight-like_degree-scene vectors. According different scenes, the system can filter the music that user may like in the internet, and form a music recommendation list which will be sent to the user. The Preference Learning Agent updates the users' profile dynamically based on explicit feedback or the hidden preference obtained from the users' behavior. The learning rate of like_degree, original like_degree and the weight of feature type are important for the improvement of the feature's learning efficiency. The recommendation system can capture the users' potential interest and the evolvement of preferences. Experiment results show that the algorithm can learn users' preferences effectively.

Introduction

User can obtain large abundance of information available in internet in 21 century. Therefore, this precipitates a need for an intelligent recommender to help consumers find personalized information. In recent years, recommendation technology is applied in a variety of fields, netnews recommender Grouplens[1], goods sale recommender ExpertClert[2], Music recommendation system Ringo[3], and so on.

An ideal personal music recommender can help user find music which meets the need of users according to corresponding scene users stay in. Thus, users can always in good mood. That is what modern people need.

According to the research, users' need include explicit needs and implicit needs [4]. Users' interests are changing over time, whereas users' preferences are changing by different moods and scenes. It is incomplete to acquire user preference only depending on filling out a form or updating the preference by users themselves. Only can intelligent musical recommendation system acquires users' explicit and implicit preference in different scenes, learns users' preferences dynamically and updates User Profile on time, users can get the music which they want quickly and accurately.

This paper presents a self-adaptive Preference Learning Agent in the network context. Firstly, recommendation system architecture is introduced. Secondly, a comprehensive User Profile described by feature-weight-like _ degree-scene vectors (FWLS) is presented. Thirdly, this paper shows the method that how to establish User Profile and update it dynamically according to explicit feedback and implicit feedback. Then, the music filtering and ranking strategy is proposed. Eventually, the experiment results prove the recommendation system's reliable. [1]

Personal Recommendation System

System Architecture

Fig.1 shows the architecture of the personal musical recommendation system. There are three parts for the system: Central Personal Server, Interaction Interface Agent, and Storage Device. Central Personal Server includes User Profile, Filtering Agent, Ranking Agent and Preference Learning Agent. User Profile includes lots of user profiles. Filtering Agent collects music metadata, and compares them with user profile and then finds the music user may like. Ranking Agent ranks several musical lists and selects music that most meet users' preferences according to different scenes and the filtering result, and sends them to Storage Device. The Storage Device stores music metadata according to corresponding scenes. When user inputs the scene, the Storage Device will filter the musical list in corresponding scene and sends them to Interaction Interface Agent. Interaction Interface Agent mainly is responsible for the interaction between user and musical device. On the one hand, Interaction Interface Agent can receive musical recommendation list according to the scene that user provides, and collect the users' explicit feedback and implicit feedback about the recommended music and then send the feedback to Preference Learning Agent. On the other hand, user can delete the dislike music through Interaction Interface Agent. Preference Learning Agent can form and update user profile according to the feedback which is provided by Interaction Interface Agent.

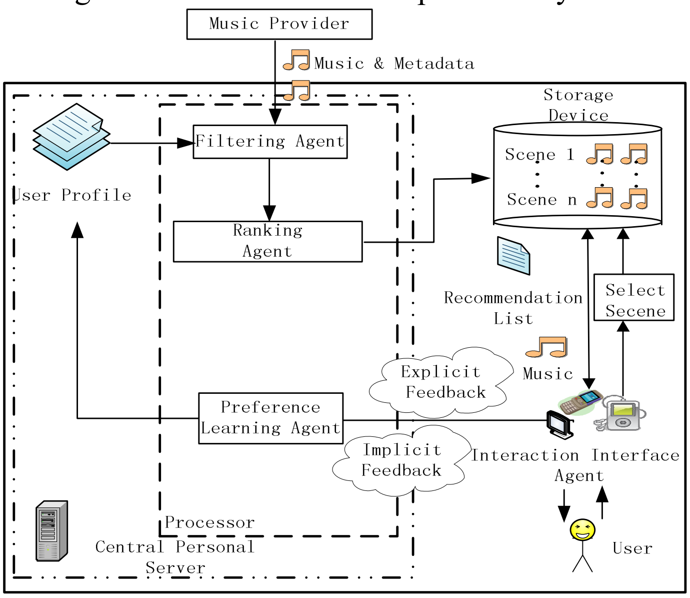

Fig. 1 Musical Recommendation System Architecture

In the Multi-Agent System (MAS), Knowledge Query and Manipulation Language (KQML) is a language that is designed to support interactions among intelligent software agents. There are a variety of protocol oriented performatives among KQML to support interactions among intelligent software agents. For example, the simplest protocol, namely, client / server protocol, one agent as a client request to another, then the server agent will one-off return the result data [5].

Preference Self-learning

To providing personal recommendation service for different users, there needs to obtain corresponding users' interest and to describe them in a structural form, according which the recommendation system can create preference model that reflects what user like. This process is called user modeling [6] [7].

The system updates User Profile according to user behavior to achieve the purpose of self-learning and improving the recommendation precision. The method of User Profile modeling includes explicit modeling and implicit modeling. Once user profile is initiated, it can be updated constantly according to explicit and implicit feedback to express user preference more accurately.

Preference Database-----FWLS User Profile.

The user profile in the musical recommendation system is based on vector space model (VSM). the system is based on a comprehensive user profile described by FWLS. FWLS User Profile can be represented by the vectors of 4-tuples:

$$P=\begin{bmatrix} P_{11},...,P_{1j},...,P_{1m} \\ \vdots \\ P_{j1},...,P_{ij},....,P_{im} \\ \vdots \\ P_{n1},...,P_{nj},....,P_{nm} \end{bmatrix}=\begin{bmatrix} (f_{11},w_{11},ld_{11},s_1),...(f_{1j},w_{1j},ld_{1j},s_1),...(f_{1m},w_{1m},ld_{1m},s_1) \\ \vdots \\ (f_{i1},w_{i1},ld_{i1},s_i),...(f_{ij},w_{ij},ld_{ij},s_i),....(f_{im},w_{im},ld_{im},s_i) \\ \vdots \\ (f_{n1},w_{n1},ld_{n1},s_n),...(f_{nj},w_{nj},ld_{nj},s_n),....(f_{nm},w_{nm},ld_{nm},s_n) \end{bmatrix} \tag{1}$$

Where m is the number of features in certain scene, n is the total number of scene, s_i represents the i-th scene, f_{ij} is the i-th feature in j-th scene. w_{ij} is the weight of feature type which feature f_{ij} belongs to, ld_{ij} is the like_degree of feature f_{ij}. Both w_{ij} and ld_{ij} range from 0 to 1.

For the purpose of interoperability, the musical metadata and user profile in the system are both represented by XML[8].

Preference Initiation.

User Profile can be initiated by explicit modeling and acquire explicit preferences. User can initiate User Profile in the modeling interface showed in Fig. 2. The other way of User Profile initiation is learned from feedback by Preference Learning Agent.

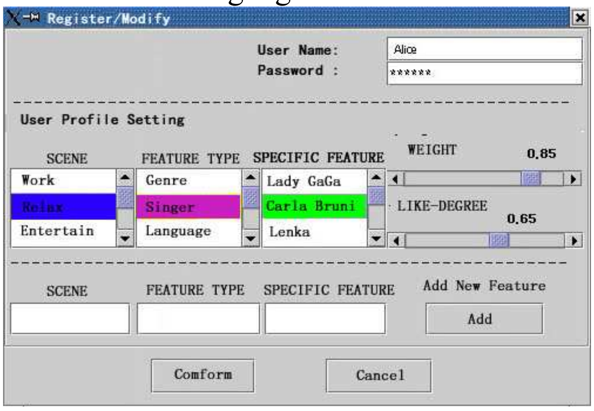

Fig. 2 Explicit Modeling

Preference Updating---Modeling based on Feedback.

The recommendation system analyzes the information of user preference, and then updates User Profile. For the existed feature in the User Profile, the updating algorithm of the feature like degree is shown as follows:

$$ld'_{ij}=ld_{ij}+\alpha\times w'_{ij}\times\beta\times\varphi_{ij} \tag{2}$$

$$\beta=(T/T_r-\delta) \tag{3}$$

Where ld'_{ij} and w'_{ij} respectively represent the revised like_degree and the weight of feature type that feature f_{ij} belongs to, ld_{ij} and w_{ij} are the original like_degree and the weight of feature type that feature f_{ij} belongs to, α is learning speed and is used to control the learning speed. δ is the threshold of the ratio between user appreciation time T and the music time T_r, β represents the potential evaluated like degree about the listened music. φ_{ij} represents the influence degree of revised like degree to the change of user preference. If $T/T_r>\delta$, it means user like the music, then $\varphi_{ij}=ld_{ij}$, Preference Learning Agent can increase the like degree of feature f_{ij}; in contrast, If $T/T_r<\delta$, it means user dislike the music, then $\varphi_{ij}=1-ld_{ij}$, Preference Learning Agent can decrease the like degree of feature f_{ij}.

For the inexistent feature in User Profile, the relevant parameter an be revised as Follows:

In the first place, the weight of feature equals the weight of the feature type that the feature belongs to.

In the second place, the like_degree of the feature can be acquired as follows:

$$ld'_{ij} = \alpha \times w'_{ij} \times \beta \tag{4}$$

The control of User Profile size: User Profile should include and only include $m \times n$ features. According to the value of $(ld'_{ij} \times w'_{ij})$, the system selects the first $m \times n$ features and corresponding parameters to form User Profile.

Filtering Agent and Ranking Agent

When Filtering Agent compares musical metadata and User Profile, it can get the similarity of music and User Profile. Similar to User Profile, music C can be represented as follows:

$$C = \begin{bmatrix} C_{11},...,C_{1j},...,C_{1m} \\ \vdots \\ C_{i1},...,C_{ij},...,C_{im} \\ \vdots \\ C_{n1},...,C_{nj},...,C_{nm} \end{bmatrix} = \begin{bmatrix} (u_{11},v_{11},sc_1),...,(u_{1j},v_{1j},sc_1),...,(u_{1m},v_{1m},sc_1) \\ \vdots \\ (u_{i1},v_{i1},sc_i),...,(u_{ij},v_{ij},sc_i),...,(u_{im},v_{im},sc_i) \\ \vdots \\ (u_{n1},v_{n1},sc_n),...,(u_{ni},v_{ni},sc_n),...,(u_{nm},v_{nm},sc_n) \end{bmatrix} \tag{5}$$

Where u_{ij} is the weight of the feature type which feature f_{ij} belongs to, sc_i is the i-th scene, v_{ij} is the like degree of feature f_{ij}. If feature f_{ij} belongs to the metadata of the music, then (u_{ij}, v_{ij}) = (1, 1), otherwise (u_{ij}, v_{ij}) = (0, 0).

The similarity between music P and User Profile C is shown as follows:

$$\theta = sim(C,P) = \cos(C,P) = \frac{C \bullet P}{\| C \| \times \| P \|} \tag{6}$$

If the similarity value acquired by computation is larger than threshold θ, then the system consider the music meet the need of user.

Experiment

The experiment involves 100 different music. The 100 music are divided into 5 batches for testing whether the recommending result meets with the user's demand. Two parameters of Precision and Recall rate are used to evaluate the recommendation precision of the recommendation system: Precision = RMR/TMR, Recall rate= RMR/RMB. Where, TMR represents the total recommending music number, RMR is the total recommending music which meet with the user's interest, RMB is the total number of user interested music. In addition, the number of test music is 100; learning rate $\alpha = 0.2$; the rate threshold between listen time and music time $\delta = 0.8$, feature number $m = 10$; scene number $n = 4$; the similarity threshold of recommended music $\theta = 0.95$. There are 5 participants in the test. The scene when user log in the system is shown as follows.

Table 1. The initial setting of scenes

	Test1	Test 2	Test 3	Test 4	Test 5
User1	on the way home	learning	working	entertainment	learning
User2	learning	working	entertainment	on the way home	working
User3	working	on the way home	learning	working	entertainment
User4	entertainment	on the way home	entertainment	entertainment	learning
User5	learning	working	on the way home	learning	on the way home

The initiated User Profile only involves the explicit preference of users. There only exists normal potential change of user preference. Table 2 represents experiment results.

Table 2. Experiment result

Session	Average precision	Average Recall rate
Test 1	0.67	0.80
Test 2	0. 87	0.89
Test 3	0.68	0.80
Test 4	0.83	0.88
Test 5	0.90	1

The experiment result shows that the recommendation system can update user profile dynamically. User preference is changed slowly and potentially and the recommendation precision is improved steadily. This condition shows that the system can learn user preference intelligently according to user behavior. The improvement of the recommendation precision also indicates that it is hard to express all the preference in the process of initiated modeling in explicit way. Therefore, it is necessary for the system to analyze the recommended music and the behavior pattern of users to recommendation music, learn users' implicit preference and the potential change of the preference, and then the system can acquire user preference completely.

Conclusion

User preference includes explicit preference and explicit preference. Users can express their preference by explicit way. In the networking context, the paper proposes a model of self-learning Preference Learning Agent. The agent can mine the implicit preference to update User Profile according to explicit feedback and implicit feedback, then learn the implicit preference and the potential change of user preference. Experiment result shows the learning algorithm can learn user preference effectively.

This work sponsored by National 863 plans projects (2009AA043001), supported by Shanghai Education Committee Projects (J50604), supported by Ministry of Communications Research Project (2009-329-810-020&2009-353-312-190), supported by Shanghai Maritime University Research Project (20100130&20110019). supported by Shanghai Science & Technology Committee Research Project (09DZ2250400). supported by Innovation Program of Shanghai Municipal Education Commission (09YZ241)

References

[1] K. Kurapati, S. Gutta, D. Schaffer, J. Martino, J. Zimmerman, "A Multi-Agent TV Recommender". In Proceedings of the User Modeling 2001: Personalization in Future TV Workshop, Sonthofen, Germany, pp. 2001,458-463.

[2] H. Shimazu, "ExpertClerk: Navigating Shoppers' Buying Process with the Combination of Asking and Proposing", In Proceedings 17th International Joint Conference on Artificial Intelligence (IJCAI'01), USA, August 2001.

[3] Cotter, P., Smyth, B., "PTV: Personalised TV Guides". In Proceedings of the 12th Conference on Innovative Applications of Artificial Intelligence, IAAI 2000, Austin, Texas, 2000,pp. 287-295.

[4] White, R.W., Jose, J.M., Ruthven, I. , Comparing Implicit and Explicit Feedback Techniques for Web Retrieval: TREC-10 interactive track report. Proceedings of the Text Retrieval Conference (TREC 2001). Gaithersburg, Maryland, USA. 2001.

[5] Finin, T. Fritzson, R. McKay, D. McEntire, R., "KQML as an agent communication language", In Proceedings of the 3rd international conference on Information and knowledge management (CIKM'94), 1994,pp. 456-463.

[6] Xiaoping Yang, Bingyong Tang, Yuechan Song. Personal service review. Sci-Tech Information Development & Economy, 2006,16(12) 247, 310.

[7] Schmidt-Thieme, L.. "Compound classification models for recommender systems", Data Mining, Fifth IEEE International Conference on, 8(2005) 27-30.

[8] "XML Path Language (XPath) 2.0", http://www.w3.org/TR/xpath20/, Apr. 2002.