Design of an Intelligent Cloud-based Car Radio and Music Player System

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Introduction

The traditional file or music recommendation mechanism often requires the user to provide detailed scores for each item. However, drivers will not be able to conduct these tedious procedures while driving. Therefore, special care needs to be taken when designing the feedback procedures for an intelligent car stereo system. In this paper, we use the preference record of users with similar backgrounds to predict a driver's favorite radio stations. The users only need to skip programs they dislike, and do not need to provide detailed feedback on the stations they like. Since radio programs have different schedules, the recommendations also take into account the time factor, which is to say that the system only recommends radio programs that are currently airing or available to the user. In addition, we have also personalized the recommendation mechanism to better meet the needs of different users. For music recommendations, on top of the recommendation mechanism used for radios, we also applied an artificial intelligence solution to learn the user's personal music preferences. It provides recommendations by studying the content of the songs.

Design Concept

In a car environment, drivers are naturally unable to provide ratings for a significant number of the radio stations or music items to which they listen. Therefore we use a method similar to the collaborative filtering method for radio or music recommendation. It has been observed that the selection of radio channels is related to the user's age, profession, education level and other personal background information. Additionally, it is difficult to extract feature values from radio content, which prevents us from using the content based filtering method to filter radio channels. Therefore, for a car radio recommendation system, we utilize the user's basic information to establish their clustering, and then employ the tracked listen records in each cluster to evaluate the suitability of radio channels for recommendation. For music recommendation, we also use the same clustering patterns and recommend songs to the user based on the preferences of other users in the cluster with similar preferences. The system design of the car radio and music recommendation system is shown in the Fig.1.

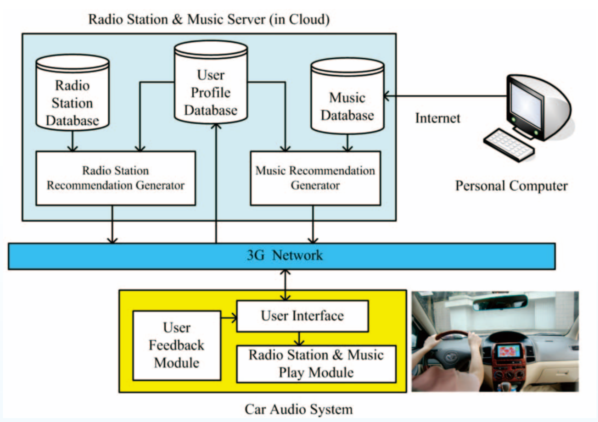

Fig. 1 Car radio and music recommendation system

Table 1 An example of a user's information

Attribute ID	Attribute	Value
A_1	Gender	Female
A_2	Age	30
A_3	NativeLanguage	Chinese
A_4	Residence	Taipei, Taiwan
A_5	Profession	Engineer
A_6	Education Level	Master

Table 2 An example of users' radio listen record

No.	User ID	Radio ID	Start Time	End Time	Date
1	A	R_1	AM08:00	AM 08:31	2012/6/1
2	B	R_1	PM 01:29	PM 02:35	2012/6/1
3	A	R_3	AM 08:31	AM 08:32	2012/6/1
4	A	R_2	AM 08:32	AM 09:30	2012/6/1
5	C	R_3	AM 08:30	AM 09:01	2012/6/2

Technical Development

According to our preliminary analysis of the radio listening behavior of general users, it is apparent that users of different ages listen to different radio stations. The user's education level also influences their radio listening behavior. Therefore, in designing the car radio recommendation mechanism, we took user's basic personal information and analyzed generalized user preferences for each attribute. Then we applied naïve *Bayesian prediction* method to predict user's preferences for the radio stations. In addition, since each attribute has a different impact on predicting user preferences, we adjusted the weight of each attribute according to user feedback, which improves the success rate of the recommendations.

When the system is used for the first time by the user, they are required to provide personal information. We collect the statistics of some of their attributes, with the most commonly used attributes being Gender, Age, Native Language, Residence, Profession, and Education Level. Table 1 shows a sample user. Since radio programs are time-dependent (e.g., a radio station might broadcast a news program at 8:00AM, and a music program at 8:30AM), we record data about every program that was listened to, and then calculate the number of times each program was listened to at a certain time. Table 2 shows an example.

When the user needs a radio recommendation at a certain point in time, we find the radio programs to which other similar users commonly listen. First, we retrieve the listen records of all users at that point of time. Take Table 2 as an example. Suppose that the user needs a recommendation at 08:30 AM. The fifth record from Table 2 will be retrieved, as user C listened to the radio at that time. But considering that users do not switch channel at exactly the same time, we extend the point of time to become a period of time, and all the records within that period will be retrieved. For example, for a period of 2 minutes, the third and fourth records should be retrieved as well. However, we can see that the duration of the third record is only one minute, so it is deemed an invalid record. Thus, only the fourth and fifth records are retrieved and further processed. The temporary table used to compute recommended radio programs in our example is shown as Table 3.

Table 3 An example of temporary table for Bayesian prediction

A_1	A_2	A_3	A_4	A_5	A_6	Radio ID
Female	30	Chinese	Taipei, Taiwan	Engineer	Master	R_2
Female	25	Chinese	Pingtung, Taiwan	Teacher	Master	R_3

Next, we use naïve Bayesian prediction to compute the maximum posterior probability of each radio program. The more people with similar backgrounds that have listened to the radio program, the higher the value it gets. The naïve Bayesian prediction works as follows [1]:

Each data sample is represented by a 6 dimensional feature vector, $X=(x_1, x_2, \ldots, x_6)$ depicting measurements made on the sample from user attributes, i.e., $A_1, A_2, \ldots, A_6$.

Suppose that there are m radio stations, $C_1, C_2, \ldots, C_m$, which depend on the kinds of Radio ID in the temporary table. Given a user's data sample X (i.e., the attributes in Table 1), the naïve Bayesian prediction can predict the maximum posterior probability $P(C_i|X)$ that user X will listen to the radio station Ci. The radio station C_i for which $P(C_i|X)$ is maximized is called the *maximum a posteriori* estimate. By Bayes theorem,

$$P(C_i \mid X) = \frac{P(X \mid C_i)P(C_i)}{P(X)} \qquad (1)$$

As $P(X)$ is constant for all radio station, only $P(X|C_i)P(C_i)$ need be computed. The radio station prior probabilities may be estimated by

$$P(C_i) = \frac{S_i}{S} \qquad (2)$$

Where S_i is the number of samples of radio station C_i in the temporary table and S is the total number of samples in the temporary table.

Moreover, in order to reduce computation overhead in evaluating $P(X|C_i)$, the naïve assumption of class conditional independence is made. Thus,

$$P(X \mid C_i) = \prod_{k=1}^{6} P(x_k \mid C_i) \qquad (3)$$

The probabilities $P(x_1|C_i), P(x_2|C_i), \ldots, P(x_6|C_i)$ can be computed from the samples in Table 3. If A_k is categorical (e.g., k=1, 3, 4, 5, 6 in Table 1) then:

$$P(x_k \mid C_i) = \frac{S_{ik}}{S_i} \qquad (4)$$

Where S_i is the number of samples of the radio station C_i in the temporary table and S_{ik} is the number of samples of radio station C_i having the value x_k for A_k. If A_k is continuous value (e.g., age attribute), the attribute is assumed to be Gaussian distribution, then:

$$_k \mid C_i) = g(x_k, u_{Ci}, \delta_{Ci}) = \frac{1}{\sqrt{2\pi}\,\delta_{Ci}} e^{-\frac{(x_k-u_{ci})^2}{2\delta_{Ci}^2}} \qquad (5)$$

Where $g(x_k, u_{ci}, \delta_{ci})$ is the normal density function for attribute A_k and u_{ci} and δ_{ci} are the mean and standard deviation, respectively, given the values for attribute A_k for the samples of radio station C_i in the temporary table.

After calculating the probability of each radio program, they are sorted in descending order of probability and sent to the user. Considering the need to ensure driving safety, a maximum of 10 candidate programs will be sent to the user's screen, from which the user can select the one she wants to listen to at that moment.

The impact of each attribute is different for different people. For example, some people share more characteristics with people of the same age, but are less similar to people of the same profession. Therefore when we collect feedback from the user we must adjust the weight of each attribute. The Formula (3) is modified as follows.

$$P(X \mid C_i) = \prod_{k=1}^{6} w_i P(x_k \mid C_i) \qquad (6)$$

Where $w_1+w_2+\ldots+w_6=1$. At the beginning we do not have the user's feedback, so it is assumed that every attribute has the same importance, i.e. $w_1=w_2=\ldots=w_6=1/6$. The prediction method with adjusted weight is called *weighted Bayesian prediction.*

Consider the hypothetical scenario in which a radio program is ranked first by the system, and that the user accepts that recommendation. This acceptance means that the recommendation is successful. However, if another radio program is ranked fifth by the system yet it is still selected by the user, it means that the program should be ranked first. Thus the weights in our probability calculation formula would need to be adjusted. Given that it is not convenient to rate each recommended radio while driving, we only account for the selected program, which has to be listened to for a sufficient period of time before it is considered to be a valid selection.

For a certain user, if the selected program is s, the original ranking based on the weighted probability formula is $R(s|W)$, where $W=\langle w_1,w_2,\ldots,w_d\rangle$ (i.e., in this system d=6), then the difference is $R(s|W)$-1. After T times of selections, the difference between the user's ideal ranking and the real ranking is

$$Dif(User, W, T) = \sum_{k=1}^{T} R(s_k \mid W) - T \qquad (7)$$

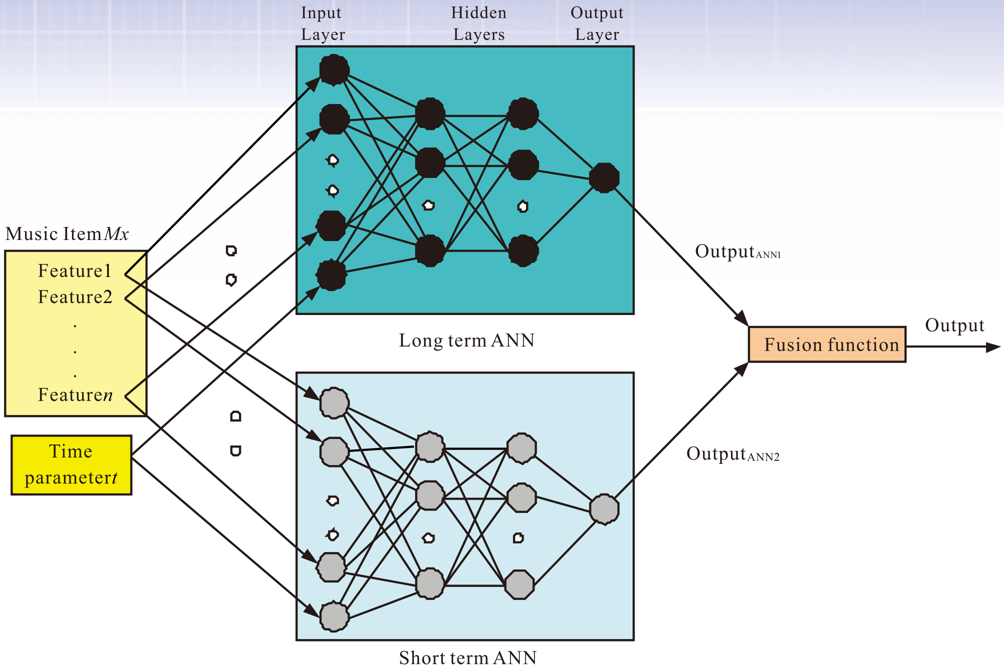

Fig. 3 The structure of the mixed artificial neural networks [3]

Therefore we need to adjust W to minimize Formula 7, which is defined as the following.

$$W' = \arg\min_{W} Dif(User, W, T) \qquad (8)$$

Every user has her own weight of W, meaning that the system provides a personalized radio recommendation service. If it is discovered by the user or the system's feedback processing that the recommendation success rate is too low, above W value adjustment process is initiated. In addition, in order to avoid the risk of the recommended radio programs becoming too concentrated on the often-listened ones; we also provide a random selection option to the users. But if the randomly selected radio program is not in the recommendation list, we will not be able to calculate the difference value. Therefore it will be not recorded for weight adjustment. We employ a genetic algorithm to establish the near optimal figures for the weight values. [2].

The traditional music recommendation methods usually need an extensive history of user feedback to achieve a satisfactory recommendation performance. For example, the collaborative filtering method often records user song ratings and then recommends songs listened to by other similar users. However, as driving conditions are not appropriate for a significant history of accurate rating feedback, we designed two new mechanisms for music recommendation.

The first method is similar to the radio recommendation method discussed above. It uses the attributes from a user's basic information to find similar users' listen records, from which it is able to provide music recommendations. There are some essential differences between music and radio programs. Music is not time-dependent, while radio programs are. Users can listen to music at any time. Furthermore, the options available for music selection are far greater than that of radio programs. There may be a large number of songs that do not get recommended, resulting in less diversified recommendations.

Similar to the radio recommendation method, we first record the music listening history of every user. Considering that it is not easy to give ratings during driving, we regard a song as accepted by the user if it is played completely. Otherwise, it is considered not liked by the user or not appropriate during driving. Next, the Bayesian prediction method is applied to calculate the predicted probability of each class being selected by the user. Since there might be a lot of songs in each class, a random song from each candidate class will be presented to the user. Similarly to the previous method, we also record if the songs are played completely, to serve as evidence for adjusting the weights of the attributes. In addition, if a Music ID is used as the class, after being played several times it will be excluded from the temporary table in order to avoid recommending the same songs every time.

In this collaborative filtering mechanism, the recommended songs are the ones often listened to by the same group of users. By adjusting the weights of the attributes, we can also provide a personalized service (i.e. weighted Bayesian prediction).

The second method belongs to the content based filtering method. It was observed that people have different music preferences when they drive at different time. For examples, when a parent is driving their children to school in the morning, they prefer music that is suitable for, or loved by, children. Later, when they are driving to work, they choose music that they like themselves. Since this pattern is highly correlated to time, we adopt our previous method to provide this service [3].

In this method, we use artificial neural networks to learn the user's habits and preferences. In order to reduce the server load on artificial neural networks computation, we design a mixed artificial neural network that includes two networks. The design is shown in Fig. 3.

Technological Competitiveness

With the rapid development of the Internet and digital technology, digital music and Internet radio stations have come to attract increasing investment from various sources. Through the Internet, users are able to listen to music and radio stations without geographical limitations. The Internet also provides users more options in their music and radio station choices. The technology developments in this field allow for improvements in car audio systems. However, across all relevant studies, the question of how best to recommend radio or music choices to users remains an important topic in the research area of digital music and radio. Therefore, in this paper, we try to improve these recommendations by recording user behavior and analyzing the music preferences of users with similar background information. This is different to traditional recommendation mechanisms as we simplify the feedback procedure for users. In addition, by adjusting the weight in the formula calculating the recommendations, we are able to provide personalized recommendations. This would better satisfy the needs of different types of users. Through experimental results we prove that our recommendation mechanism has significantly helped the users to select radio stations and music.

R&D Result

Since the hardware requirements for this smart car stereo system are most likely to be realized through the use of tablet computers, in this experiment we use a tablet with the Android operation system as the client side platform for the cloud-based car audio system. All music files, their associated features, radio programs and user profiles are stored on the server. The calculations for radio and music recommendations are also conducted on the server. The client side provides the interface for the user to select radio stations and music as well as handling data transmissions and the playing of the music itself. The simulated car audio system is shown in Fig. 4.

Acknowledges

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(a)

(b)

(c)

Fig. 4 (a) The simulated car audio system is shown in 2012 Taipei International Invention Show & Technomart (Golden award) (b) Prototype in car (c) User interface