A Context-Aware Music Recommendation System Using Fuzzy Bayesian Networks with Utility Theory

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Abstract. As the World Wide Web becomes a large source of digital music, the music recommendation system has got a great demand. There are several music recommendation systems for both commercial and academic areas, which deal with the user preference as fixed. However, since the music preferred by a user may change depending on the contexts, the conventional systems have inherent problems. This paper proposes a context-aware music recommendation system (CA-MRS) that exploits the fuzzy system, Bayesian networks and the utility theory in order to recommend appropriate music with respect to the context. We have analyzed the recommendation process and performed a subjective test to show the usefulness of the proposed system.

Keywords: context-awareness, music recommendation system, fuzzy system, Bayesian networks, utility theory.

1 Introduction

Information recommendation has become an important research area since the first papers on collaborative filtering published in the 1990s [1]. Extensive work has been done in both industry and academia on developing new approaches on recommendation systems over the last decades [2]. Recently, the interests have been increased due to the abundance of practical applications such as recommendation system of books, CDs, and other products at Amazon.com, and movies by MovieLens.

Music recommendation is also an area where this recommendation system is required. As the World Wide Web becomes the source and distribution channels of diverse digital music, a large amount of music is accessible to people. In this situation, music recommendation gets required for each person since it becomes a difficult and time-consuming job to search and change the music whenever he wants to.

There is already a commercial product like iTunes by Apple Computer even though they have used simple rules described by the users [3]. Previously, H. Chen and A. Chen presented the music recommendation system for website, and Kuo and Shan proposed a personalized music filtering system considering user preference [4]. These studies considered the user preference fixed in their recommendation models. However, a user's preference on music changes according to the context. It varies so dynamically that the recommendation system should consider this information.

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This paper proposes a context-aware music recommendation system (CA-MRS) using the fuzzy Bayesian networks and utility theory. CA-MRS exploits the fuzzy system to deal with diverse source information, Bayesian networks to infer the context, and the utility theory to consider the user preference by context. In experiments, CA-MRS with the proposed method provides better recommendations than the original Bayesian networks.

2 Related Works

2.1 Music Recommendation

Generally, there are two approaches for the recommendation system: content-based and collaborative recommendations [2]. The former analyzes the content of objects that user has preferred in the past and recommends the one with relevant content. The latter recommends objects that the user group of similar preference has liked.

Cano *et al.* presented the MusicSurfer in order to provide the content-based music recommendation. They extracted descriptions related to instrumentation, rhythm and harmony from music signal using similarity metrics [5]. H. Chen and A. Chen presented the music recommendation system for website. They clustered the music data and user interests in order to provide collaborative music recommendation. Kuo and Shan proposed a personalized music filtering system which learned the user preference by mining the melody patterns from users' music access behavior [4]. These studies did not consider the user preference which changed by the context. The proposed system, CA-MRS, attempts to work out this problem by reflecting the context sensitively using fuzzy Bayesian networks with utility theory.

2.2 Context Inference Using Bayesian Networks

Dey defined context as any information that can be used to characterize the situation of an entity such as a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves [6]. Context is an important factor when one provides services such as music recommendation to the users since user preferences to a service (music in this work) could vary due to context where the user is. There have been many studies on context inference [7, 8].

Bayesian networks (BNs), which constitute a probabilistic framework for reasoning under uncertainty in recent years, have been representative models to deal with context inference [7]. Korpipaa *et al.* in VTT used naïve BNs to learn the contexts of a mobile device user [7], and Horvitz *et al.* in Microsoft research presented the notification system that sense and reason about human attention under uncertainty using BNs [8]. However, context inference using BNs has a limitation that it cannot deal with the diverse information effectively. Since BNs require the discrete input, the loss of information might happen and it cannot reflect the context appropriately. This limitation has been overcome by utilizing the fuzzy system.

3 CA-MRS Using Fuzzy Bayesian Networks and Utility Theory

Overall recommendation process in CA-MRS is as shown in Fig. 1. First, various information is obtained from sensors and internet. This information is pre-processed with the fuzzy system, where fuzzy membership vector is generated. It enters into fuzzy Bayesian network inference module, and FBN module infers context with the probability. Scoring module computes the final score of music in music database considering user preference by context, and then recommendation is conducted based on the final score. User preference can be stored by users.

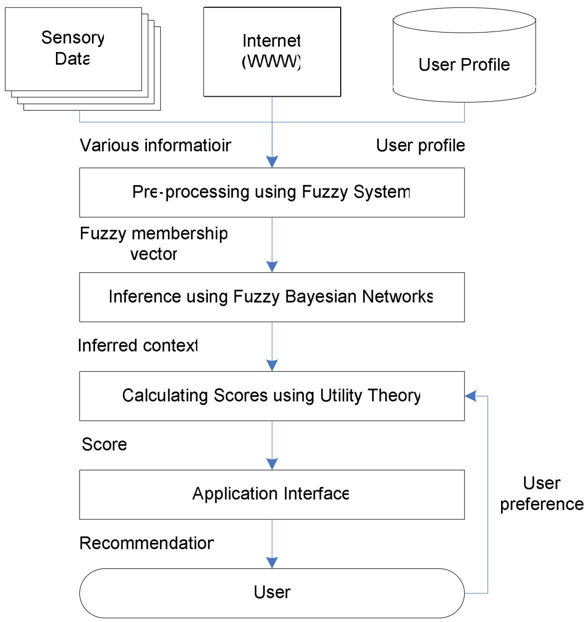


Fig. 1. The recommendation process in CA-MRS

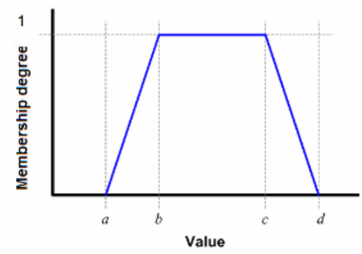
3.1 Data Pre-processing Using Fuzzy System

Since Bayesian networks require discrete data, they generally have disadvantages though they are promising tools for reasoning context. They cannot deal with various types of information effectively because discretization can lose information compared with the original one. Context inference module can use several types of sensor information. Some are continuous, and others are discrete. Besides, it is possible for one data to be categorized into several states at the same time. Usually, a state with the largest value is selected as its state, but this method has a problem when the value is near the criteria or the value belongs to several categories. We have used the fuzzy system for pre-processing step for Bayesian network inference since the fuzzy system is relevant in dealing with diverse information and uncertainty [9].

The input data are pre-processed so that they are represented as a fuzzy membership vector. If the membership degree of $state_k$ of an observed node is μ_{state_k}, fuzzy membership vector is defined as follows.

$$FMV_{node} = (\mu_{state_1}, \mu_{state_2}, \dots, \mu_{state_n}), k = 1,2,\dots,n \quad (1)$$

Here, the membership degree of each state is calculated considering the type of data. If the data are continuous values, pre-defined membership function is used. We have used the trapezoidal function, which is simple and widely used [10].



$$\mu_{state_k} = \begin{cases} 0, & x < a \\ \dfrac{x-a}{b-a}, & a \le x < b \\ 1, & b \le x < c \\ \dfrac{x-d}{c-d}, & c \le x < d \\ 0, & d \le x \end{cases}$$

Fig. 2. Trapezoidal fuzzy membership function

When the data are discrete, the membership degree of each state is calculated after normalization. If the membership degree of $state_k$ of an observed node is c_{state_k}, fuzzy membership vector is calculated as follows.

$$\mu_{state_k} = \frac{c_{state_k}}{\arg\max_{c_{state_k}}(k)}, k = 1,2,\dots,n \quad (2)$$

By pre-processing with this fuzzy system, the problems mentioned above are solved. For example, if current temperature is 27.9 degrees, we can represent this information as a fuzzy membership vector of (0, 0.65, 0.81), which means (cold, moderate, hot), using the pre-defined membership function. The data source and type information used in this paper is summarized in Table 1.

Table 1. Data source and type for context inference

Data	Source	Data Type
Temperature	Temperature sensor	Continuous
Humidity	Humidity sensor	Continuous
Noise	Noise sensor (microphone)	Continuous
Illuminance	Illuminance sensor	Continuous
Current weather	Meteorological office website	Discrete
Weather forecast	Meteorological office website	Discrete
Gender	User profile	Discrete
Age	User profile	Continuous
Season	System information	Discrete
Time	System information	Continuous

3.2 Context Inference Using Fuzzy Bayesian Networks

There have been studies to combine the fuzzy system and Bayesian networks. Yang proposed fuzzy Bayesian approach that estimates the density function from the conditional probabilities of the fuzzy-supported values in order to use continuous value in Bayesian framework. Pan and Liu proposed fuzzy Bayesian network and inference algorithm using virtual nodes and Gaussian functions [11]. However, these methods have constraints where observed information should be only one and membership degree sum should be one [11]. Our proposed model includes simple and effective fuzzy Bayesian network without those constraints.

The fuzzy Bayesian networks presented in this paper are extensions of original Bayesian networks. When fuzzy membership vectors are input, fuzzy Bayesian network inference is performed using Eq. (3).

$$\begin{aligned}\text{Fuzzy Evidence} &= FMV_{node_1} \times FMV_{node_2} \times \cdots \times FMV_{node_n} \\ &= (\mu_{s_1}, \mu_{s_2}, \ldots) \times (\mu'_{s_1}, \mu'_{s_2}, \ldots) \times \cdots \\ &= ((\mu_{s_1} \times \mu'_{s_1} \times \cdots), (\mu_{s_2} \times \mu'_{s_2} \times \cdots), \cdots)\end{aligned} \tag{3}$$

Finally, the probability of state s_k^{target} is calculated as follows:

$$P(x_{target} = s_k^{target} \mid \text{Fuzzy Evidence}) = \sum_{\forall E_r} \frac{P(x_{target} = s_k^{target} \mid E_r)\mu_{E_r}(e)}{\sum_{\forall E_r} \mu_{E_r}(e)} \tag{4}$$

where $P(x_{target} = s_k^{target} \mid E_r)$ can be calculated by general Bayesian network inference.

3.3 Application of Utility Theory

After fuzzy Bayesian networks infer the context, the final score of the music is calculated based on user preference by this context. User preference is input by the users and it is represented as a combination of attribute and state of music. Table 2 shows the attributes of music and their possible states, and Table 3 provides an example of user preference.

Table 2. Attribute and states of music

Attribute		States
Genre		Rock, Ballad, Jazz, Dance, Classic
Tempo		Fast, A Little Fast, Moderate, A Little Slow, Slow
Mood	Cheerful – Depressing	Cheerful, A Little Cheerful, Normal, A Little Depressing, Depressing
	Relaxing – Exciting	Relaxing, A Little Relaxing, Normal, A Little Exciting, Exciting
	Disturbing – Comforting	Disturbing, A Little Disturbing, Normal, A Little Comforting, Comforting

Table 3. An example of user preference

	$u^{depressing}$	$u^{content}$	$u^{exuberant}$	$u^{anxious/frantic}$
Genre::Rock	4	3	2	3
Genre::Ballad	2	5	4	1
Genre::Jazz	4	3	4	1
Genre::Dance	3	5	5	2
Genre::Classic	1	2	3	2
Tempo::Fast	4	3	3	2
Tempo::Moderate	2	4	4	2
Tempo::Slow	3	2	5	4
Mood1::Cheerful	1	5	4	1
Mood1::Normal	3	3	2	1
Mood1::Depressing	5	1	2	3
Mood2::Relaxing	2	2	4	3
Mood2::Normal	4	3	4	4
Mood2::Exciting	2	4	2	3
Mood3::Disturbing	2	1	2	3
Mood3::Normal	3	4	4	2
Mood3::Comforting	3	5	4	1

Based on the user preference, the score of each music for a certain attribute is calculated with fuzzy evidence of current context as shown in Eq. (5).

$$Score_{attribute_i} = \sum_{\forall Mood_k} P(Mood_k \mid FuzzyEvidence) \times u_{attribute_i}^{Mood_k} \tag{5}$$

Subsequently, the scores of all music in DB are calculated based on this score. When an attribute saved in DB is $attribute_i$, the recommendation score of $music_k$ is as follows.

$$RecommendationScore_{music_k} = \sum_{\forall attribute_i} Score_{attribute_i} \tag{6}$$

Using these scores, the top n music are selected for recommendation.

4 Experimental Results

We have analyzed the recommendation process and conducted the subjective test so as to show the usefulness of CA-MRS. As analyzing the recommendation process, we have compared the fuzzy Bayesian networks and original Bayesian networks, and also compared the model with the utility theory and the model without one. After that, we have confirmed that user satisfaction increased when CA-MRS was used with the subjective test.

4.1 Analyses of Recommendation Process

1) Experimental Environment

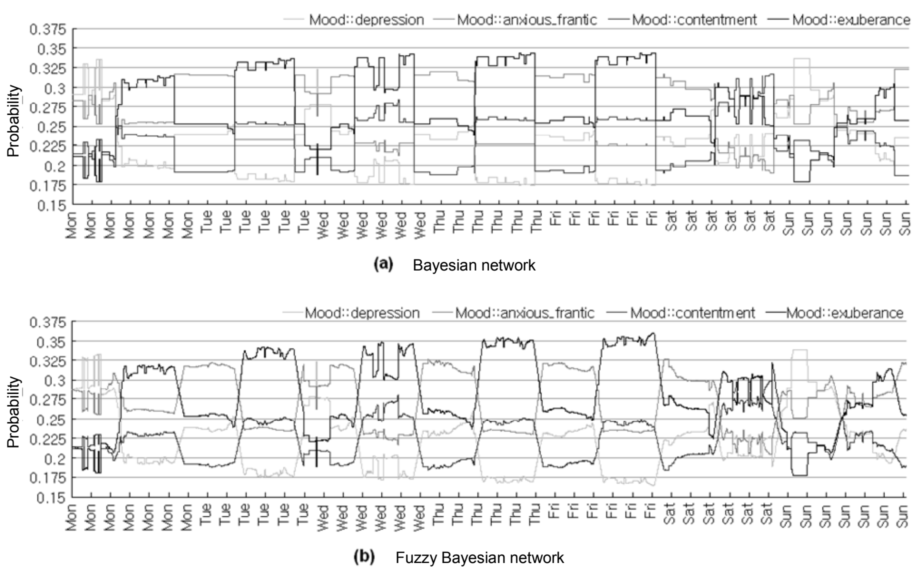
CA-MRS was implemented in Windows XP platform with MFC, and a desktop PC with Pentium IV 2.4GHz CPU was used. In total, 322 music pieces have been collected from music streaming web site [12]. Information on music is also obtained from the same web site, but tempo and mood are set by hand after listening to music.

Data for experiments were created as follows. Weather information was collected from Meteorological Office website during one week [13]. Illumination was generated considering sunrise and sunset time, and noise was generated randomly. The user was a man of 24-years old. Situations in data proceeded from Monday to Sunday with one minute interval, and the total number of situations is 9,803. Music recommendation has been also performed at the same period.

2) Experiments and Analyses

Fig. 3 shows the probability change of 'Mood' node in BN. Two graphs provide the similar tendency, but they are different when the probabilities are changed. Probability by BN shows a sudden change, but that by FBN shows a gradual change. Since the data are continuous values, they usually change gradually: The model with FBN infers more realistic context from data. Fig. 4 shows the change of recommendation score in attribute 'Genre'. The result is similar to Fig. 3. When using context inferred by FBN (See Fig. 4. (b)), the score changes gradually, but that with context inferred by original BN does not.

Fig. 5 compares the number of changed music in top 30 recommended ones at every time point. When using fuzzy Bayesian network, they changed more often and the number is smaller when they are changed. Considering gradual change of actual context, it reflects the context more nicely.



(a) Bayesian network

(b) Fuzzy Bayesian network

Fig. 3. Probability change comparison of 'Mood' node in Bayesian networks

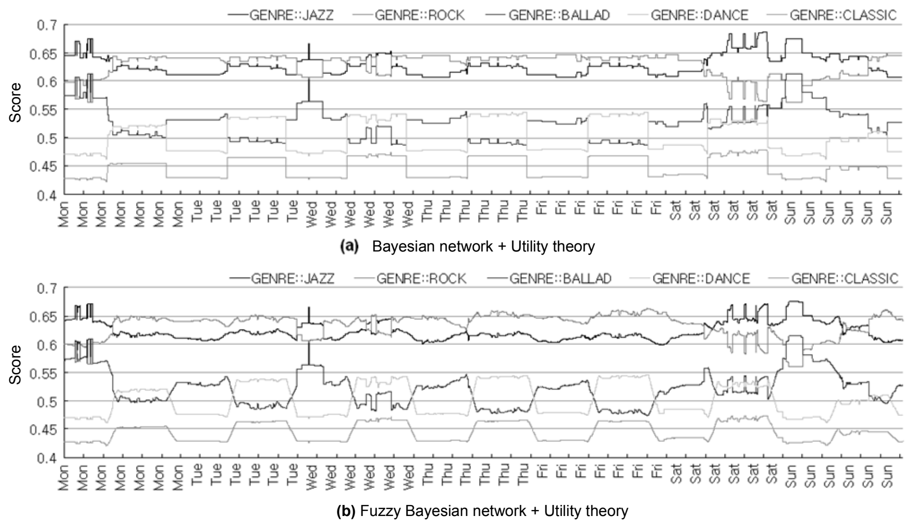


Fig. 4. Score change comparison in music attribute ‘Genre’

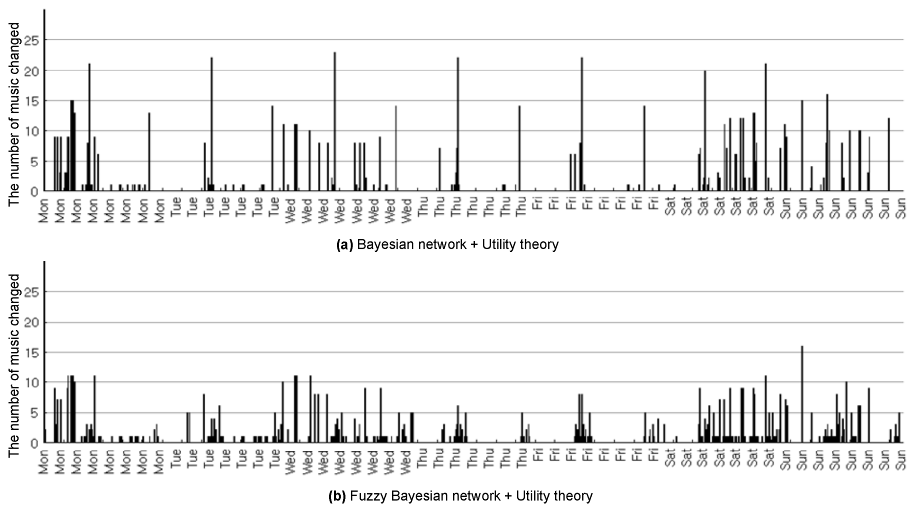


Fig. 5. Comparison of the number of changed music in top 30 recommended

4.2 Subjective Test

In order to test the satisfaction degree of the user, we have used Sheffe’s paired comparison [14]. It prevents subjects from evaluating the object too subjectively by requesting them to compare the object relatively.

First, four situations are provided to subjects as shown in Table 4. We have requested answers from 10 college students who often listen to music. For each situation, subjects listen to 10 music pieces selected at random and 10 music pieces recommended by CA-MRS. After listening to all music, subjects evaluate them considering context. Score has 7 degrees from -3 (First recommended music is better) to 3 (Second recommended music is better). The order was not known to subjects.

Table 4. Situations with similar context for experiment

Situation	Context	Collected information
1	End of November, rainy Monday morning	Late fall, Monday, 9 a.m., 4.8 degree C, 82.7% humidity, 500lux, 50Db, Rainy
2	Mid-August, sunny Saturday afternoon	Summer, Saturday, 3 p.m., 30.5 degree C, 65% humidity, 550lux, 65Db, Sunny
3	Early April, cloudy Wednesday evening	Spring, Wednesday, 7 p.m., 16.6 degree C, 40% humidity, 200lux, 65Db, Cloudy
4	End of January, Sunday night with moon	Winter, Sunday, 11 p.m., -7.3 degree C, 57% humidity, 50lux, 30Db, Sunny

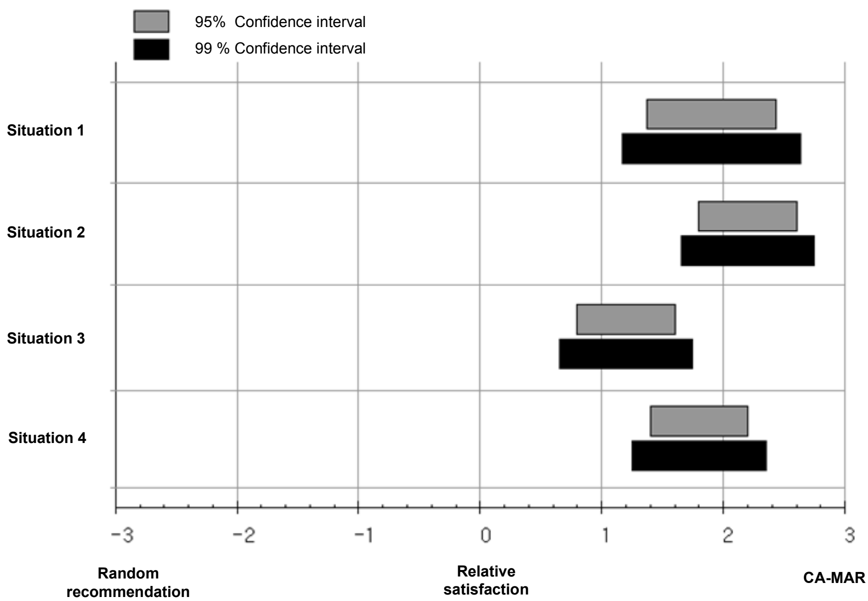


Fig. 6. Probability changes by temperature in case of using original BN

Fig. 6 shows the users satisfaction degree analyzed statistically. It means the recommended music by CA-MAR is better because the confidence intervals do not include 0, and they are closer to 3 for all situations.

5 Conclusion and Future Works

This paper proposes a context-aware music recommendation system using fuzzy Bayesian networks. CA-MRS provides music recommendation considering the sensitive change of context as combining the fuzzy system, Bayesian networks, and the utility theory. In experiments, we have confirmed the usefulness of CA-MRS by analyzing the recommendation process and performing subjective test.

As future works, it is required to determine the user preference with respect to context automatically, and it is also interesting to apply CA-MRS to mobile devices so that the recommendation service can be provided in more dynamic environment with more diverse information.

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