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소셜 네트워크 데이터베이스를 이용한 퍼지 결정 기반의 추천 채널 시스템

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요 약

사용자는 일반적으로 멀티미디어 소셜 서비스로부터 다른 사람들과 같은 결과를 제공받는다. 따라서 소셜 네트워크 안에 개인의 어려운 문제를 해결하기 위해 본 논문에서는 의사 결정 시스템 구축을 사용자의 활동, 사용자의 기분과 소셜 네트워크를 통한 사용자의 친구 관계 정보를 활용하는 방법을 제안한다. 사용자의 현재 기분 상태에 따라 시스템은 사용자에게 가장 적합한 영상을 유추한다. 이 시스템은 사용자가 이용하는 소셜 네트워크 데이터베이스에서 추출한 추천 방법의 집합을 측정하고, 가중치에 따라 모호한 값이 각각의 방법에 할당한다. 본 논문에 시스템에서는 퍼지 수집 솔루션을 찾아서 하위 집합들로 방법들을 분류하고, 가장 적절한 방법을 선택하기 위해 퍼지로직을 기반으로 상기 하위 집합을 결정한다. 마지막으로, YouTube API와 다양한 영상을 이용하여 시뮬레이션 실험을 진행하였다. 이 실험에서 채널 추천 시스템은 사용자 특성에 맞는 적절한 결과를 보여주며, 이것은 여러 사용자의 평가에 기반하는 현재 유튜브 보다 더 좋은 만족감을 준다.

키워드 : 퍼지 의사 결정, 추천 시스템, 소셜 네트워크, 개인 서비스

Fuzzy Decision Making-based Recommendation Channel System using the Social Network Database

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Abstract

A user usually gets the same suggesting results as everyone else in most of the multimedia social services, nowadays. To address the challenging problem of personalization in the social network, we propose a method which exploits user's activities, user's moods, and user's friend relationships from the social network to build a decision-making system. Depending on a current state of the user's mood, this system infers the most appropriated video for the user. In the system, the user evaluates a set of the given recommendation methods which extract from the user's database social network and assigns a vague value to each method by a weight. Then, we find the fuzzy collection solution for the system and classify the set of methods into subsets, and order the subsets based on its local dominance to choose the best appropriate method. Finally, we conduct an experiment using the YouTube API with a lot of video types. The experiment result shows that the channel recommendation system appropriately affords the user's character, it is more satisfying than the current YouTube based on an evaluation of several users.

Keywords : Fuzzy decision making, Recommendation system, Social network, Personalization service

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1. Introduction

Since the strong growth of the Internet, people are being connected closer to others beyond the national border. As in the real life, they gather in a virtual place on the internet. Many companies involved to build those Social Networking Services (SNS) to serve people who share similar interests, activities, backgrounds or real-life connections [1]. It has taken the role of a platform on which people pursue an increasing amount of activities that they have usually only done in the real-world. In such way, the social television technology has emerged recently. Millions of people now share their TV experience with other viewers on social media such as Twitter and Facebook using smartphones and tablets. The field has attracted significant investment from established media and technology companies. The market is also seeing numerous tie-ups between broadcasters and social networking players such as Twitter and Facebook. The rise of one technology does not always mean the end of another as the analysis in [2], it can also create new many emerging and exciting marketing and advertising opportunities.

Much of the investment in the earlier years of social TV went into standalone social TV application. In [3, 4, 5], the authors proposed the Internet Protocol Television (IPTV) customized social TV platform in which they use Hadoop MapReduce and analyze the words which users were looking for and recommended through the SNS, TV channel to recommend a channel to the user. The analysis is based on users' customized TV with a smartphone application, it works efficiently as the user's desire. However, their algorithm only focuses on a specific aspect of channel recommendation by the population of that channel or video. Thus, it lacks personalization and usually serve for everyone. Many recommendation systems [6, 7] have proposed to assist people effectively filter out the pieces of information that are most appropriate in the information overload nowadays.

Suppose that we have a set of video/channel type such as music, sports, gaming, history, adventure, drama, fantasy, etc. Traditionally, we choose a video that has larger viewer than others to suggest to the user. Sometimes, we choose a video that relating to the current watching video. These suggesting videos base above method might satisfy user requirements or if it does not fit user's desire. However, these methods do not base on user characteristic and user customization in general. Some others approach exploit user data warehouse by using data mining techniques for discovering patterns in large data sets. It involves database and data management aspects, data pre-processing, model and inference considerations, interestingness metrics, complexity considerations, post-processing of discovered structures, visualization, and online updating. In spite of that, the method can not decide the most appropriate corresponding to user aspiration, it also avoids the interaction between users in the social network. Therefore, by the meaning of social networking, we exploit completely both user and their friend relationship to get the best desirable user video/channel. First, we use data mining techniques to achieve a set of methods that fit the user mood. Secondly, we select a set of experts that are user and users' friends to evaluate the above methods by vague values. Thirdly, we solve those fuzzy relations and obtain the fuzzy collective solution by using group decision making in [9, 10] for clustering and sorting the methods. From that, we use the traditional technique on the most appropriate method in suggesting channel process.

In the next section, we will discuss some related research topics, such as a Fuzzy Collective Solution (FCS), the recent recommendation system, and its application. Furthermore, in section 3, an overview system describes an overall system architecture. Section 4 introduces two cluster algorithms and Linguistic Ordered Weighted Averaging (LOWA) operator. Finally, we demonstrate how the system suggests a channel appropriately in the experimental section.

2. Related Research

In applied mathematics, specifically in fuzzy logic, the fuzzy linguistic approach has been widely used for making assessments in a qualitative setting from a group of experts such as a video streaming research in [8]. It has been widely used in computational intelligence because of its ability to model linguistically expressed aggregation instructions. In [9, 10, 11], the authors put their works on the set of all alternatives and on the individual linguistic preference relations. Some choice processes are devoted to the model using consensus measures and LOWA operator. A multiple criteria group decision model in linguistic setting and some aggregation processes are also described. In addition, They proposed a model and new processes which allow incorporating human consistency in decision support systems.

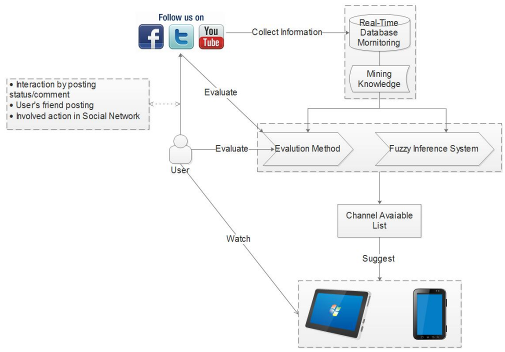
Nowadays, we are dealing with the problem of overloading information. Thus, to obtain knowledge from the big bunch of information, in [12], the authors proposed a trust-based recommendation system which, is an automated and distributed fashion, filters information for agents based on the agents' social network and trust relationship. In which, trust can be defined as the expectancy of an agent to be able to rely on some other agent's recommendations. The idea at the core of the model is that agents leverage their social network to reach information, and make use of trust relationships to filter information.

In addition, consumer electronic products cope with a decision of choosing a product that fits their budget as well as the usefulness of the product function. Therefore, depending on the sort of product, various personalized recommender systems can be built up to guide the consumers in a large product feature space. In [13], the authors proposed a fuzzy-based recommendation system for those less frequently purchased products, especially for consumer electronics. The proposed system aims to assist a consumer in navigating the product feature space in an interactive way in which the consumer has his own need in each feature dimension so that the customer can find the optimal products according to his personal preferences. Their results showed that the system can give sensible recommendations, and adapt to customers' up-to-date preferences.

Founded in February 2005, YouTube has quickly grown to be the world's most popular video site. Millions of users make the service grow up in the data storage with lots of videos. Thus, personalized recommendations are a key method for information retrieval and content discovery in such the information rich environment. Hence, in [14] proposed a recommendation system, which delivers personalized sets of videos to signed in users based on their previous activity on the YouTube site. In the results, they found that co-visitation based recommendation performs at 207% of the baseline Most Viewed page when averaged over the entire period, while Top Favorited and Top Rated perform at similar levels or below the Most Viewed baseline.

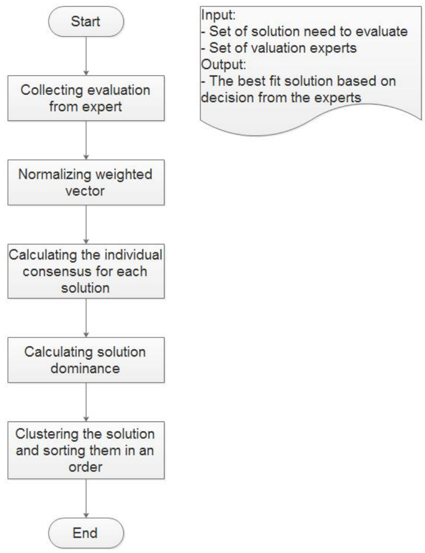
3. System Architecture

(Figure 1) An interaction between user and the recommendation system



In this section, we propose a recommendation channel system which uses the data mining technique and decision-making with a classification algorithm to assist user achieves their desired channels corresponding to their moods and friend's suggestion. The system determines the recommendation channel in real-time so that it can serve user at any time. In Figure 1, the user is in the center of the system who interacts with three main components. First, the social network acts as the place where the user posts their feeling by a status or comment on their friends' actions in daily life. Secondly, the real-time database monitoring system stores user's information which gets from the user via the social network and analyses the user's routine and favorite. By doing this way, we achieve a set of user-based recommendation methods. Thirdly, the user assesses an affected weight of friends' evaluations by assigning a weight which is a real number, they also estimate the recommended methods with vague values which describe the probability of the involving method uses for suggesting channel, such as Certain, Extremely_likely, Most_likely, Meaningful_chance, It_may, Small_chance, Very_slow_chance, Extremely_unlikely, and Impossible or we can abbreviate these fuzzy variables as $F=\{f_1,f_2,f_3,f_4,f_5,f_6,f_7,f_8,f_9\}$. Then, the suggesting channel later displays the result in mobile application or IPTV service [6].

(Figure 2) Clustering algorithm using LOWA



4. LOWA Operator in Clustering Analysis Algorithm

In this section, we put our work in a glance aspect of LOWA and its application in decision classification. In [10] defined that, given a vector $A=\{a_1,a_2,\ldots,a_n\}$ is a set of labels to be aggregated. Given $W=\{w_1,w_2,\ldots,w_n\}$ is a weighting vector, $w_i>0, \forall\ i\in(1,n)$, and $\sum_i w_i=1$. The LOWA operator is defined as a combination of vector A with weighted W, $Low:(A,W)\rightarrow F$ as follows formula:

$$\mathrm{Low}(A,W)=C^n\{w_i,b_i,i=1,\ldots,n\} \quad (1)$$

$$=\{(w_1,a_1),(1-w_1,Low(a',w'))\},$$

$a' = \{a_{i_{n-1}}, ..., a_{i_1}\}$, $w' = [w'_{i_1}, w'_{i_2}, ..., w'_{i_{n-1}}]$, and $w'_j = w_j/(1-w_{i_n})$, $a_{i_{n-1}} > ... > a_{i_1}$, and C is a combination of any two fuzzy variable values (f_i, f_j), $i > j$, $w_j > 0, w_i > 0, w_i + w_j = 1$,

$$C\{(w_j, f_j), (w_i, f_i)\} = f_k \quad (2)$$

where $k = i + \mathrm{round}(\mathrm{w_j} \times (\mathrm{j} - \mathrm{i}))$. Now we apply the operator in clustering the set of solutions.

First, given solutions set S and experts $E = \{e_1, e_2, \cdots, e_n\}$. Each expert assigns their valuation for each solution as $e_k : S \rightarrow F$, . $k = 1, ..., n$.

Secondly, from vector weighted W which assigns to each expert, we normalize the vector by $w'_i = w_i / w_M, w_M = \sum_i w_i$.

Thirdly, we calculate total Individual Consensus (IC) for each solution s_i which is the consensus when a group of experts evaluates the solution s_i by the following formula,

$$IC(i)[f_t] = \sum_k \{w'_k : e_k(s_i) = f_t\} \quad (3)$$

Fourthly, Calculating the dominance of each solution a_i by using LOWA operator,

$$E(i) = Low(S, U(i)), \quad (4)$$

where $U(i) = [u_t, ..., u_1]$, $u_t = IC(i)(f_t)$, for every $t, f_t \in F$.

Fifthly, clustering the solution set A by using $\{E(i) : s_i \in S\}$. We get a set of classes $Y_1, Y_2, ..., Y_T$, $Y_t = \{s_i : E(i) = f_t\}$ which can be an empty set, $f_t \in F$ and $S = \cup_t Y_t$. Then, we sort the set Y_t into an order as follows:

$$Y_t < Y_{t'} \text{ if } t < t'. \quad (5)$$

The algorithm is depicted in Figure 2 with five steps, input parameters, and output result.

By defining a fuzzy collective solution, we extend the above algorithm in another way in which experts compare one solution with each other. Later on, we solve fuzzy equation constraints to cluster those solutions into clusters and select the best appropriate solution which was depicted in Figure 3.

First, we redefine the individual consensus as a calculation of a pair solution,

$$IC(i,j)[f_t] = \sum_k \{w'_k : e_k(s_i, s_j) = f_t\}. \quad (6)$$

The fuzzy collective solution is a fuzzy set which determines in a set $F = \{f_1, ..., f_n\}$ is defined as,

$$FCS = (\mu_{FCS}(s_1)/s_1, \mu_{FCS}(s_2)/s_2, ..., \mu_{FCS}(s_n)/s_n), \quad (7)$$

where $\mu_{FCS}(s_i) = Low(S, W(i))$, $W(i) = \{w_1, w_2, ..., w_n\}$, for each $k \in [1, n]$, $w_k = \frac{1}{n-1}\{\#: \mathrm{E(i,j)} = \mathrm{s_k}, \mathrm{j} \neq \mathrm{i}\}$, in which, # describes the number of time that the condition satisfies. $E(i,j)$ is the relative dominance of a pair of solution calculates by,

$$E(i,j) = Low(S, U), \quad (8)$$

where $U = \{u_1, ..., u_n\}$, for each $k \in [1, n]$, and $u_k = IC(i,j)[f_t], k = 1, ..., n$.

The algorithm has six steps as follows:

Step 1: given a set of solutions A, we name a set S to collect evaluating from a set of experts $E = \{e_1, e_2, \cdots, e_m\}$. Each expert assigns their valuation for each solution as $e_k : S \times S \rightarrow F$ by considering a pair of solutions.

Step 2: from vector weighted W which assigns to each expert, we normalize the vector by $w'_i = w_i / w_M, w_M = \sum_i w_i$.

Step 3: we calculate total IC for a pair of solution (s_i, s_j) which is the consensus when a group of experts evaluates the pair with vague value f_i by equation (6).

Step 4: Calculating the dominance of the solution pair (s_i, s_j) by using LOWA operator which was given in (8).

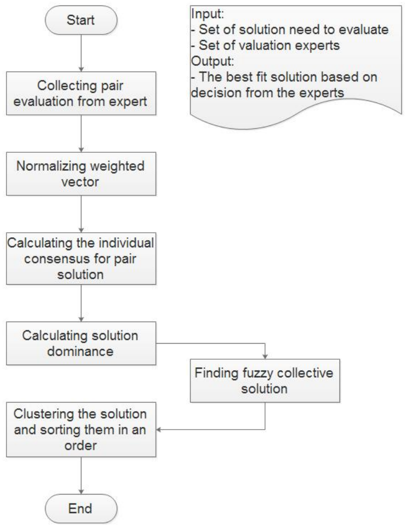
Step 5: Finding the fuzzy collective solution by using equation (7).

Step 6: Clustering the solution set S by using $\{\mu_{FCS}(s_i) : s_i \subset S\}$. We get a set of classes $Y_1, Y_2, ..., Y_T$, $Y_t = \{s_i : \mu_{FCS}(s_i) = s_t\}$ which can be an empty set, $s_t \in S$ and $S = \cup_t s_t$. Then, we sort the set Y_t into an order as in (5).

5. Decision Making-based Recommendation Channel

This research mainly focuses on fuzzy decision making for suggesting appropriate channel based on user's characteristic. Thus, we avoid describing the mining process in order to gain user routine and the relationship between user and friends. Suppose that we have a set of the users' friends with depth relationship so that they can assist the user to suggest the best channel since they know him indeed. Therefore, we assign the set of experts is $E = \{e_1, e_2, ..., e_m\}$ which includes user itself names as e_1 and his friends are labeled as $\{e_2, ..., e_m\}$. Hence, the user entrusts the valuation task to the friends and itself by a weighted which is $W = \{w_1, w_2, ..., w_m\}$ corresponding to the expert. In addition, the set of vague values which the experts use to evaluate a solution have defined as $F = \{f_1, f_2, f_3, f_4, f_5, f_6, f_7, f_8, f_9\}$. Finally, suppose that we have a list of methods to evaluate the appropriated channel such as a method suggests the channel bases on user's interesting feature channel as music, sports, gaming, history, adventure, drama, fantasy, etc. For example, a method suggests channel bases on the type of day such as the independence day, the children's day, international labor day or even weekend, etc. A suggesting channel method bases on the user's mood which they have exposed in the SNS, etc. A method bases on the popularity of the video/channel.

(Figure 3) Clustering algorithm using LOWA with pair solution



Our goal is to find the best solution based on the evaluation from the experts. Then, we use that method for suggesting the most appropriate channel. Aiming to demonstrate how the method works, we put our work on a determination of the interesting feature channel, we name $S = \{s_1, s_2, s_3, s_4\}$ is music, sports, gaming, movie channel type perspectively. Additionally, we select three friends of the user and user himself in the set of experts $E = \{e_1, e_2, e_3, e_4\}$, the user also evaluates the expert by the weight $W = \{w_1, w_2, w_3, w_4\}$ correspondingly.

6. Simulation experiments

(Figure 4) Evaluation of experts in channel suggestion methods

$$e_1 = \begin{bmatrix} IM & C & C & EU \\ SC & IM & ML & MC \\ EU & VLC & IM & ML \\ C & SC & VLC & IM \end{bmatrix} e_2 = \begin{bmatrix} IM & C & EL & MC \\ VLC & IM & EL & SC \\ I & EU & IM & ML \\ SC & C & EU & IM \end{bmatrix}$$

$$e_3 = \begin{bmatrix} IM & EL & EL & C \\ SC & IM & ML & EL \\ VLC & I & IM & SC \\ EU & VLC & C & IM \end{bmatrix} e_4 = \begin{bmatrix} IM & EU & EU & VLC \\ MC & IM & C & EL \\ ML & VLC & IM & I \\ EL & EU & EL & IM \end{bmatrix}$$

<Table 1> Individual Consensus for pair solutions

IC	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9
(1,1)	0	0	0	0	1.0	0	0	0	0
(1,2)	0	0	0	0.5	0	0	0.3	0.05	0.15
(1,3)	0	0.3	0	0	0	0	0	0.2	0.5
(1,4)	0.3	0.5	0	0	0	0.05	0	0.15	0
(2,1)	0	0	0.05	0.65	0	0.3	0	0	0
(2,2)	0	0	0	0	1.0	0	0	0	0
(2,3)	0	0	0	0.5	0	0	0.15	0.05	0.3
(2,4)	0	0	0	0.05	0	0.5	0	0.45	0
(3,1)	0	0.5	0	0	0	0	0.3	0.05	0.15
(3,2)	0	0.05	0.45	0	0	0	0	0.5	0
(3,3)	0	0	0	0	1.0	0	0	0	0
(3,4)	0.3	0	0	0.15	0	0	0.05	0.5	0
(4,1)	0	0.15	0	0.05	0	0	0	0.3	0.5
(4,2)	0	0.3	0	0	0	0	0	0.15	0.55
(4,3)	0	0.05	0.5	0	0	0	0.3	0	0.15
(4,4)	0	0	0	0	1.0	0	0	0	0

<Table 2> Dominance of solution

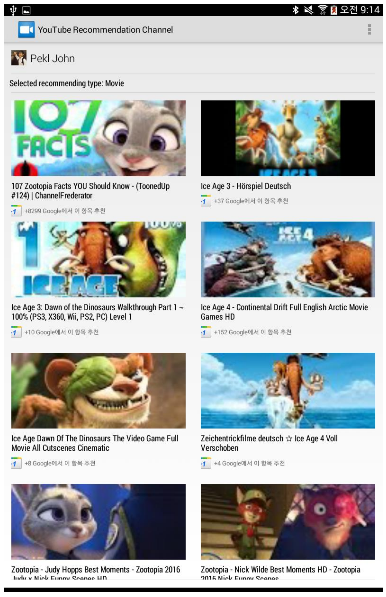
DS	s_1	s_2	s_3	s_4
s_1	IM	MC	ML	VLC
s_2	IM	IM	MC	ML
s_3	IM	MC	IM	MC
s_4	EL	ML	IM	IM

In this section, we implement the second algorithm, in which user assigns the weight $W = (0.5, 03, 0.05, 0.15)$ for each expert including themselves by comparing one recommended method with others, we achieve the evaluation matrixes in Figure 4, then we get the result of Individual Consensus (IC) for pairs of solution which are shown in Table 1, the local dominance is depicted in Table 2, the fuzzy collective solution is shown in Table 3.

<Table 3> Fuzzy Collective Solution

FCS	s_1	s_2	s_3	s_4
	IM	MC	MC	ML

(Figure 5) The demonstration for the recommended channel algorithm



From the result, we yield the best solution s_4 with maximum value in the set F is ML which is the most recommendation which experts tend to use in the recommendation system.

In the experiment, we yielded the appropriate recommendation according to user mood and friends' suggestion is the channel movie type. Hence, we perform traditional method on the movie type where the video has mostly visited.

By using YouTube API, we established a social account with YouTube channel and display the most certain recommended video to a playlist which is shown in Figure 5. We have tested the application for five persons and got a positive satisfaction on the suggesting algorithm.

7. Simulation experiments

In this paper, we have proposed the suggesting channel method which exploits user's characteristics and friends' relationship in the social network. Depending on the relationship, the user assigns the weight on their friends that are an expression on how the friend's evaluation method effects on the final suggestion result. In addition, the clustering fuzzy algorithm also used for achieving the final result of the users' evaluations. The simulation result showed that the method improved the quality of service of serving user than the traditional method which straightly used the most commonly visited video and offers these suggestions without knowing any type of user characteristics. Finally, we will expand the research in the future in detail of data mining techniques, exploit completely user customized, and reduce the usage of traditional method in a customized user system with an application which integrates social interactions.

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