User-Based Collaborative Filtering Multi-criteria Recommender System Based on Interaction Between Criteria, Criteria Set with Choquet Integral

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Abstract. The exploitation of knowledge in stored data is one of the current research trends. The increasing of the need of users about searching information, the consulting system is special attented by researchers. Many decision-making solutions for multi-criteria recommender model have been proposed. However, with the intrinsic of the data, the latent values of the interaction relationship, the dominance between the criteria always changes the results of decision-making to advise users. When we take enought these values, decision-making becomes more efficient. In this paper, we propose a new approach to building a decision model for a user-based multi-criteria filtering system with Choquet integration. The operation is also based on the capacity function of a criterion, a set of criteria. The effect of decision making is the degree of interaction between the criteria in the data. This model is also based on traditional techniques and integrates some our new methods. We tested and evaluated the proposed model on the multirecsys tool we built. The standard datasets is used to test. We compare results with some the same existing models. Through experimentation, we saw that the proposed model is quite effective and reliable. It can be applied well in many appropriate systems, contributing to improving the deficiencies and the limitations of the current recommendation.

Keywords: Recommender · multi-criteria · user-based · interaction · Choquet

1 Introduction

Recommender systems [1] are growing and having an important role in our lives. It helps users find information quickly according to their references. There are many different consulting models that service different requirements. Depending on the characteristics of each system, we can apply the appropriate model. Many decision-making solutions can be based on historical factors, habits, popularity, correlation… in stored data. Today, many decision-making models have not attended much to the hidden values in data.

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In other hand, searching knowledge that exists and is reflected in the data to make better recommendations for users. One of the solutions for that goal is applying Choquet integration to calculate the interaction values in the data. The multi-criteria recommender system [2, 3, 5, 17–20] is the most research choice today because user's preferences are always diverse and data is increased more, so it is necessary to consider on many criteria to make a more effective decision. Many operations have been applied to decision making for multi-criteria recommender model [2, 16, 19] but has'n been considered to the interaction between criteria and sets of criteria each other.

In this article, we propose a new approach to build user-based collaborative filtering multi-criteria recommender system based on interaction between criteria, criteria set with Choquet integration. A capacity function is applied to perform fuzzy measurements in the applicable data for calculations. The criteria and set of criteria are calculated about the level of interaction in the decision-making operation but there is a limit on the number of criteria sets. We build the model only make with at most 3 criteria because based on the ability of the empirical tool, the model could not calculate all sets of criteria in the system. Three standard data sets were applied to experiment the model are: MovieLense, MSWeb and Jester5k, this data set has different nature.

2 Multi-criteria Decision

2.1 Multi-criteria Decision Model

We build the model with matrix $\mathrm{M}(\mathrm{x} \times \mathrm{y})$ consists of x rows $\mathrm{r}_1, \mathrm{r}_2, \ldots, \mathrm{r}_\mathrm{x}$ and y columns $\mathrm{c}_1, \mathrm{c}_2, \ldots, \mathrm{c}_\mathrm{y}$. Each row of $\mathrm{r}_\mathrm{i}(\mathrm{i} : 1..\mathrm{x})$ with each column of $\mathrm{c}_\mathrm{q}(\mathrm{j} : 1..\mathrm{y})$ is determined the value $\mathrm{r}_{\mathrm{ij}} = (\mathrm{r}_\mathrm{i}, \mathrm{c}_\mathrm{j})$ as Table 1. A criterion is defined be a row or a column. Call sets: $\mathrm{R} = \{\mathrm{r}_1, \mathrm{r}_2, \ldots, \mathrm{r}_\mathrm{x}\}$ and $\mathrm{C} = \{\mathrm{c}_1, \mathrm{c}_2, \ldots, \mathrm{c}_\mathrm{y}\}$, define a function $\hat{\mathrm{r}} : \mathcal{F}(\mathrm{RxC}) \rightarrow \mathbb{R}$ determines values $\hat{\mathrm{r}}_\mathrm{i}$ on M from set R and C.

Table 1. Multi-criteria decision model

row/column	r_1	r_2	…	r_x
c_1	*5*	*1*	…	*3*
c_2	*3*	*3*	…	*5*
c_3	*3*	*4*	…	*1*
…	…	…	…	…
c_y	*2*	*3*	…	*4*
$\hat{\mathbf{r}}$	$\hat{\mathrm{r}}_1 = 63$	$\hat{\mathrm{r}}_2 = 38$	…	$\hat{\mathrm{r}}_\mathrm{x} = 45$

Example: $\widehat{\mathrm{r}_1} = (\mathrm{r}_1\mathrm{xC})$ is determined to be the sum of values $\{\mathrm{r}_{11}, \mathrm{r}_{12}, \ldots, \mathrm{r}_{1\mathrm{y}}\}$

$$\hat{\mathrm{r}}_1 = \mathcal{F}(\mathrm{r}_1 \times \mathrm{C}) = \sum_{\mathrm{j}=1}^{\mathrm{x}} \mathrm{r}_{1\mathrm{j}} = \mathcal{F}(\{5, 3, 3, \ldots, 2\}) = 63$$

R and C is called multi-criteria sets, $\hat{r}$ is called a multi-criteria decision function and this model is called the multi-criteria decision model [1][6][7].

2.2 Model Multiple-Criteria Model with Some Operations Are Used for Decision Making: Arithmetic Mean (AM), Geometric Mean (GM), Harmonic Mean (HM) and Ordered Weighted Averaging Operator (OWA)

Model have criteria: 3 columns and 4 rows, p: 1..3, q:1..4

AM: $\hat{r}_p\left(r_{p1}, r_{p2}, r_{p3}, r_{p4}\right) = \frac{1}{4}\sum_{q=1}^{4} r_{pq}$

GM: $\hat{r}_p\left(r_{p1}, r_{p2}, r_{p3}, r_{p4}\right) = \sqrt[4]{r_{p1} * r_{p2} * r_{p3} * r_{p4}}$

HM: $\hat{r}_p\left(r_{p1}, r_{p2}, r_{p3}, r_{p4}\right) = \frac{4}{\sum_{i=1}^{4}\left(\frac{1}{r_{pi}}\right)}$

OWA: $\hat{r}_p\left(r_{p1}, r_{p2}, r_{p3}, r_{p4}\right) = 1/4\sum_{\mathbf{j}=1}^{4} w_j * r_{pj}$ *(index on w and r).*

Table 2. Some Operations Are Used For Decision Making

row/column	r_1	r_2	r_3	w
c_1	5	1	3	1.5
c_2	3	3	5	2.4
c_3	3	4	2	1.3
c_4	2	3	4	4.2
$\hat{r}_{AM}$	3.25	2.75	3.5	
$\hat{r}_{GM}$	3.08	2.45	3.31	
$\hat{r}_{HM}$	2.92	2.08	3.12	
$\hat{r}_{OWA}$	8.82	7.45	9.43	

Decision-making is based on the interaction between criteria and sets of criteria.

2.3 Capacity Function

With set of values $R_p = \{r_{p1}, r_{p2}, r_{p3}, r_{p4}\}$, a capacity function μ 14 on $\hat{r}_p$ is function $\mu : \Re\left(R_p\right) \rightarrow [0, 1]$, with $\mu(\emptyset) = 0$, $\mu\left(R_p\right) = 1$. [8–13] With A and B are sets of criteria. $A, B \subseteq R_p$ *and* $A \subseteq B \Rightarrow \mu(A) \leq \mu(B)$. On set R_p, define a vectơ P with weights, $Q \subseteq R_p$, when μ defined as follow: $\mu(Q) = \sum_{a\in Q} P(a)$,

$$\sum_{i\in R_p} P(i) = 1, i \in R_p \quad (1)$$

The value of $\mu(Q)$ depend on the criteria in Q. C_1, C_2 are two criteria in Q. The value of $\mu(C_1, C_2)$ can get the value as follow:

or $\mu(C_1, C_2) = \mu(C_1) + \mu(C_2)$, or $\mu(C_1, C_2) > \mu(C_1) + \mu(C_2)$, or $\mu(C_1, C_2) < \mu(C_1) + \mu(C_2)$.

Example with three criteria: C_1, C_2, C_3 and $\mu(C_1) = 0.28$, $\mu(C_2) = 0.32$, $\mu(C_3) = 0.47$. To subsets: $\mu(C_1, C_2) = 0.45$, $\mu(C_1, C_3) = 0.89$, $\mu(C_2, C_3) = 0.65$, $\mu(C_1, C_2, C_3) = 1$

2.4 Choquet Fuzzy Integral

With capacity function μ, the Choquet fuzzy integeal [10] C based on μ of $R_p = \{r_{p1}, r_{p2}, r_{p3}, r_{p4}, r_{pm}\}$ is defined by function $\Gamma : R_p \to \Re^+$, $\mu(A)$ is fuzzy measure on subset A, $\mu(R_p)$ is fuzzy measure of R_p. Choquet integral is one of the operations that show clearly about the interactive relationship between criteria:

$$C(\Gamma) = \sum_{q=1}^{m} \left(\Gamma(r_{pq}) - \Gamma(r_{p(q-1)})\right)\mu(A_{pq}) \tag{2}$$

where $A_{pq} = \{r_{pq}, r_{p(q+1)}, \ldots, r_{pm}\} \in R_p$ is set of k criteria, with $k = m - p + 1$: satisfying the conditions: $0 \geq \Gamma(r_{p1}) \geq \cdots \geq \Gamma(r_{pm}) \geq 1 and \Gamma(r_{p0}) = 0$

Example 1: a set of criteria: $\{A, B, C\}$ with the values: $x_A \geq x_B \geq x_C$, the item's aggregated score is calculated based on the Choquet fuzzy integral:

$$C(x_A, x_B, x_C) = x_C * \mu(A, B, C) + (x_B - x_C) * \mu(A, B) + (x_A - x_B) * \mu(A)$$

With $x_A = 5, x_B = 3, x_C = 1$, $\mu(0) = 0$, $\mu(A, B, C) = 1$, $\mu(A) = 0.4$, $\mu(B) = 0.8$, $\mu(C) = 0.7$, $\mu(A, B) = 0.9$. Then $C(x_A, x_B, x_C) = 3.6$.

The capacity function of the criteria set depends on the capacity function of each criterion and the interaction value of criteria. With set of two criteria:

$$\mu(r_{pi}, r_{pj}) = \mu(r_{pi}) + \mu(r_{pj}) + I(r_{pi}, r_{pj})$$

where $I(r_{pi}, r_{pj})$ is call: the interaction value between r_{pi} and r_{pj}, $I(r_{pi}, r_{pj})$ in [-1,1]. When two criteria r_{pi}, r_{pj} are in larger set $B = A \cup \{r_{pi}, r_{pj}\}$ with m criteria:

$$I(r_{pi}, r_{pj}) = \sum\nolimits_{A \in I \backslash \{r_{pi}, r_{pj}\}} \frac{(m - |A| - 2)|A|!}{m!} [\mu(A \cup \{r_{pi}, r_{pj}\}) - (\mu(A \cup \{r_{pi}\}) + \mu(A \cup \{r_{pj}\})) + \mu(A)]$$

Thus, with each set of criteria $A \in \{(r_{p1}, r_{p2}, \ldots, r_{pm})\}$, the capacity function of A can determine as follow:

$$\mu(A) = \sum_{r_{pi} \in A} \mu(r_{pi}) + I, with\, I > 0\, or\, I < 0, \tag{3}$$

$if\, \mu(A) > 1 then \mu(A) = 1$, I is sum of the interaction value of subsets in A.

3 Proposed Model

3.1 Rating Matrix

The model uses the above rating matrix to represent a list of users who rate data items through rows and columns. Items that are not rated will have a value of "?". Here, u_a is the consulted user (Table 3).

Table 3. Data model with Rating matrix

	i_1	i_2	…	i_x	…	i_y	…	i_n
u_1	?	4	…	3	…	?	…	3
u_2	3	4	…	2	…	5	…	4
…	…	…	…	…	…	…	…	…
u_m	5	3	…	4	…	5	…	?
u_a	?	3	…	?	…	?	…	4
$\hat{\boldsymbol{r}}$	?	-	…	?	…	?	…	-

3.2 Similarity

The model uers k nearest neighbors (kNN) [15] to value the similarity (or distance) between u_q (q:1..m) ua is accorded by measures Pearson. The Pearson measure [23] between two items are u_x and u_y is defined:

$$\boldsymbol{sim_{pearson}(u_x, u_y)} = \frac{\sum_{i\in I_{u_x,u_y}} (r_{u_x i} - \bar{r}_{u_x})(r_{u_y i} - \bar{r}_{u_y})}{\sqrt{\sum_{i\in I_{u_x,u_y}} (r_{u_x i} - \bar{r}_{u_x})^2}\sqrt{\sum_{i\in I_{u_x,u_y}} (r_{u_y i} - \bar{r}_{u_y})^2}} \tag{4}$$

I_u is the set of data items evaluated by u_x, $\bar{r}_{u_x}$ is the average rating evaluation of u_x on all data items, $\bar{r}_{u_y}$ is the average rating evaluation of u_y on all data items. Then, the distance between two users is (1-r).

3.3 Determining the Capacity Function of Criteria, a Set of Criteria

(a) Determining $\mu(u_q)$ of each user u_q, $q : 1..m$ in system is a potential weight of each u_q, it is the ratio between the number of the user's rating values (# "?") for item of m users.

$$\mu(u_q) = \frac{count(rating(u_q, i_p)\#"?")}{m} \tag{5}$$

(b) Determined $\mu(A)$ of each subset A, $A \subseteq U$, U is a set of all users, with steps:

- First, $\mu'(u_i),\ u_i \in A = [\mu(u_i)/\sum_{j=1}^{s}\mu(u_j)$, with s is number of u_i in A.
- Determined

$$\mu(A) = sum(\mu'(u_i)), u_i \in A \tag{6}$$

This value $\mu(A)$ based on μ' and it responds with formula 3. However, the level of interaction in the system is not high.

3.4 Recommendation Model

With a data table as Table 2, a user u_a, is recommended user. A column is used for determining the capacity functions $\mu(u_q)$, $q : 1..m$. At each rating value of $u_a foritems =$ "?", we determined the values $\hat{r}_p$, $p : 1..n$ (Fig. 1, 2, 3, 4, 5, 6, 7).

Table 4. Proposed model.

	i_1	i_2	…	i_8	…	i_{52}	…	i_n	μ
u_1	?	1	…	5	…	?	…	1	
u_2	2	3	…	4	…	2	…	2	0.34
…	…	…	…	…	…	…	…	…	…
u_x	5	2	…	2	…	4	…	5	0.25
…			…		…		…	…	…
U_y	3	4	…	0	…	3	…	1	0.12
…	…	…	…	…	...	…	…	…	…
u_m	3	?	…	4	…	4	…	?	
u_a	3	?	…	?	…	?	...	3	
$\hat{r}$	**-**	**3.04**	**…**	**2.16**	**…**	**1.2**	**…**	**-**	

3.5 Identify Results of Recommender System

(1) First, determine the similarity between the user u_a and each user in the data (formula 4). The results are as Table 4,.
(2) Next, determining the capacity function of each user μ (formula 5) in the system. we take the similarity values of kNN (k highest values) to calculate μ by at each $i_{\mathrm{p}}, : 1..n$ with each $u_{\mathrm{k}}, : 1..kNN$.
(3) Next, we calculate the values $\hat{r}_p$ at $r_{pk}\#?$, k : 1..kNN (formula 2,6) at the values of $u_a = ?$. $\hat{r}_p$ values are ranked in descending order, selecting highest values: i_2 and i_8; $\hat{r}_2 = 3.04 and \hat{r}_8 = 2.16$.

3.6 Evaluation Recommendations

Method used to evaluate model is the Receiver Operating Characteristic (ROC) [4, 16, 17]. Evaluation for two systems can compare the size of the area under the ROC-curve, where a bigger area indicates better performance. Four values contain the true-false positives/negatives, as follows: True Positives (TP): and False Positives (FP). False Negatives (FN) and True Negatives (TN). True Positive Rate TPR = TP/(TP + FN). False Positive Rate FPR = FP/(FP + TN).

$$Precision(L) = \frac{1}{|U|}\sum_{u \in U} |L(u) \cap T(u)|/|L(u)|$$

$$Recall(L) = \frac{1}{|U|}\sum_{u \in U} |L(u) \cap T(u)|/|T(u)|$$

U is set of users. $L(u_a)$ get items that u_a want to chose. $I = I_{test} \cup I_{train}$, $T(u) \subset I_u \cap I_{test}$. I_u is item set that u_a has chosen

4 Experiment

4.1 Data Sets

Experimentation use three datasets: MovieLens100K, MSWeb, Jester5k are integrated in recommenderlab [14].

4.2 Tools

The model was experimented by multirecsys tool which we built, developed and installed applications on R [www.r-project.org].

4.3 Scenario 1: Experiment the Model and Compare It with Some Existing Models

In this scenario, we test the proposed model UBCF_Choquet on three datasets: Movielens100K (non-binary dataset), MSWeb (binary dataset) that are two too sparse datasets and Jester5k which is too thick dataset. Using them shows the recommendation results and the existing models (UBCF, IBCF, Random, SVD, Pupular) [2][5]. Each model, we chose five items to recommend for tow users and show ROC-curve and Precision/Recall of each model on three datasets with kNN = 7, the result of the model as follow: On Movilense:

	941	942
[1,]	"Star Wars (1977)"	"Return of the Jedi (1983)"
[2,]	"English Patient, The (1996)"	"Godfather, The (1972)"
[3,]	"Casablanca (1942)"	"Independence Day (ID4) (1996)"
[4,]	"Scream (1996)"	"Men in Black (1997)"
[5,]	"Fargo (1996)"	"Courage Under Fire (1996)"

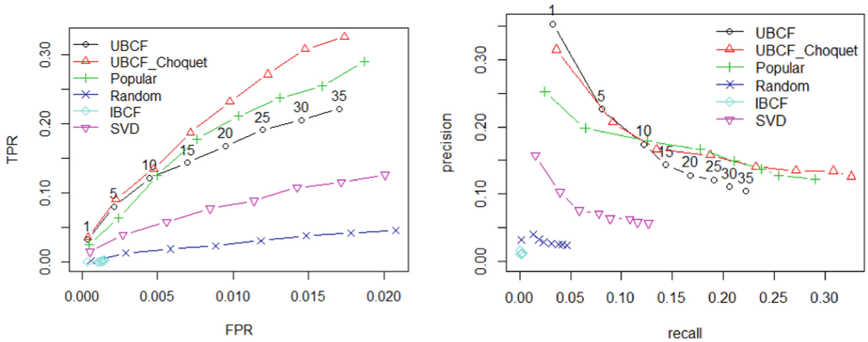

Fig. 1. Roc-curve and Precision/Recall with kNN = 7 on Movielense

	1	2
[1,]	"Knowledge Base"	"isapi"
[2,]	"Microsoft.com Search"	"Microsoft.com Search"
[3,]	"MS Office Development"	"Free Downloads"
[4,]	"Products"	"Visual Basic Support"
[5,]	"Internet Explorer"	"NT Workstation Support"

On MSWeb:

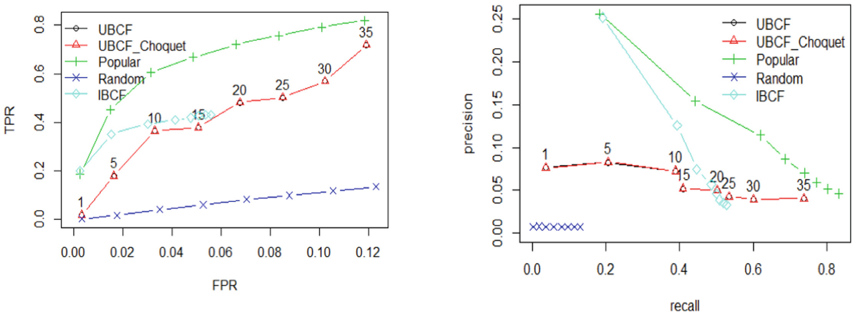

Fig. 2. Roc-curve and Precision/Recall with kNN = 7 on MSWeb.

$u3270 : "j27" "j69" "j38" "j47" "j93"
$u15348: "j76" "j92" "j97" "j93" "j74"

On Jester5k"

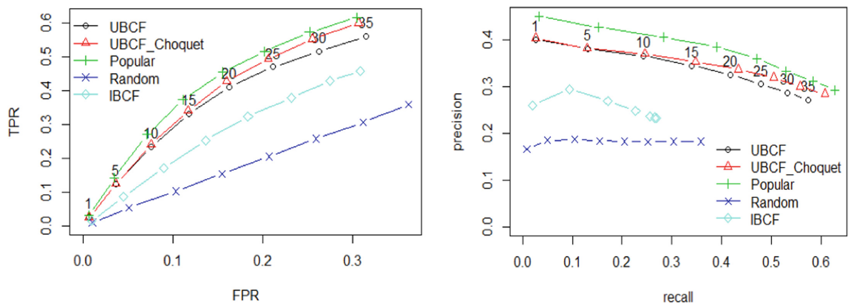

Fig. 3. Roc-curve and Precision/Recall with kNN = 7 on Jester5k

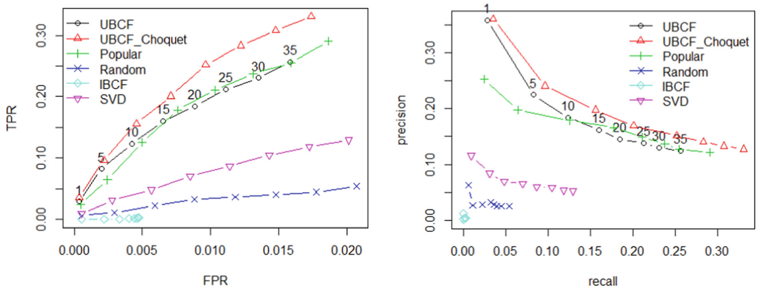

Fig. 4. Roc-curve and Precision/Recall with kNN = 15

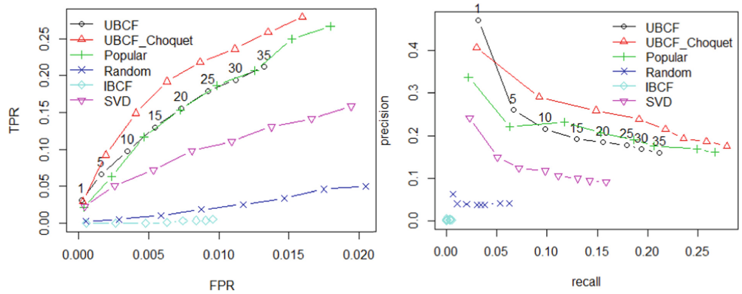

Fig. 5. Roc-curve and Precision/Recall with kNN = 25

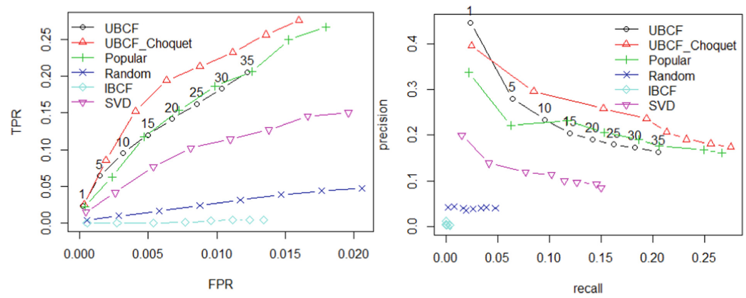

Fig. 6. Roc-curve and Precision/Recall with kNN = 35

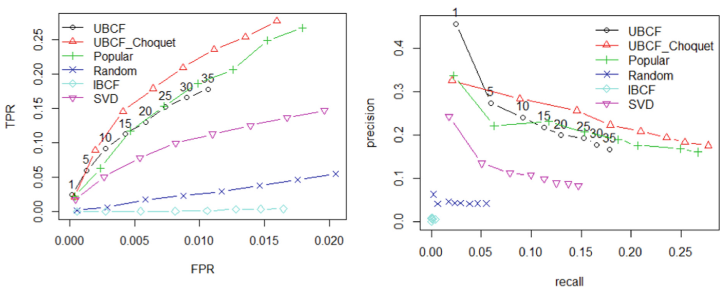

Fig. 7. Roc-curve and Precision/Recall with kNN = 45

4.4 Scenario 2: With Different kNN Values.

4.5 Discussion

The exploitation of the interaction relationships of criteria, sets of criteria for decision making is essential. However, to make effective decisions, we need to fully account for these interactive relationships. In the implementation process, we encountered certain difficulties when the complex exploded without a better solution. We will try to continue to improve in the future. We found that, with three empirical datasets, the proposed model gave rather good results. Especially with sparse or "long tail" datasets, the proposed model gets better consultation results.

5 Conclusions

There are many decision-making solutions for the consulting system. Models often use average operations to calculate values. In this model, we use the Choquet fuzzy integral to calculate for decision making. Data always contains interactive relationships. The average operation ignores these interaction values, so it is not possible to fully evaluate the resonance of the criteria. However, we have only calculated the resonance value of a set of 2 criteria, 3 criteria. Due to the current conditions, we cannot calculate sets that have more criteria. Therefore, the model has not promoted the effect of operations well yet. However, the proposed model is always responsive well, can be applied in many different datasets and contributes to improving the deficiencies of the current consulting system[1].

Acknowledgment. We built this model based on traditional consulting models but there are some changes in the solution. We also exploit and develop on the recommender lab tool package that researchers have developed.

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