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A service recommendation algorithm based on similarity evaluation and collaborative filtering

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Abstract. Aiming at issues, like information inaccuracy and more new information in the web service recommendation algorithm and unsatisfactory effect and the higher computation complexity of the traditional accurate algorithm, SOA system of web service recommendation based on multi-criteria decision-making and similarity evaluation has been put forward. The innovation points are as follows: including firstly establishing the service evaluation system based on SOA structure of hierarchy on the basis of the characteristics of analysis process of the multi-criteria decision-making to solve the defects of AHP method; secondly increasing the more scientificity of decision-making of web service with weighted time-varying multi-criteria similarity evaluation algorithm and in the deep consideration of criteria weight of each period under the combination of weighted time-varying process; finally verifying the superiority of the proposed algorithm in the accuracy and quality of web service recommendation with the experiment of the web service recommendation data set on the Yahoo domain.

Key words. Multi-criteria decision-making, Similarity evaluation, Web service, SOA sys-tem
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1. Overview

The web service decision-making methods commonly used are AHP (Analytic Hierarchy Process), such as the fuzzy priority method proposed in the Literature [1], the improved project risk evaluation of fuzzy analytic hierarchy process based on hierarchical structure raised in the Literature [2] and the application of evaluation index system based on FAH to the virtual maintenance training evaluation based on FAHP (Fuzzy Analytic Hierarchy Process) presented in the Literature [3], etc.

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However, the AHP algorithm also has disadvantages[4, 5]: including (1) poor expansion of the program, (2) relatively few quantitative data and poor reliability, (3) large volume of data and uncertain weight under the excessive evaluation indexes and (4) comparatively complicated accurate representation of characteristics, etc. Especially when the AHP algorithm is available to web service recommendation, the excessively high computational complexity is presented.

In the recent years, scholars have put forward SOA [6] (Service-oriented Architecture), and such structure is an architectural style of applications of integration services, and these services are provided by different service providers and play key roles in SOA. Services can be atomic or comprehensive services. In the comprehensive service, the function of a single service depends on another atomic service. Service combination has become the decision-making problem for service selection, and is a new kind of service which is called as compound service [7, 8]. For example, with regard to factors of SOA structure affecting the reliability confirmed in the Literature [9], three main factors affecting the overall system reliability have been proposed with industry review; four factors of SOA structure, including reusability, application to business file configuration, component dependency and application complexity analysis, have been presented in the Literature [10], and based on SOA framework, the communication and service monitoring methods have been raised in the Literature [11], so that such method is available in the service under failure for the effective command execution. However, in the above literatures, the similarity between services is not taken into account when the application of SOA structure, and the experimental subjects used all are accurate data, which is not suitable for the qualitative evaluation and application, while the web service is characterized by a large number of qualitative evaluation elements. Therefore, the effect of web service recommendation directly with SOA framework is not ideal. Simultaneously, when the web service decision is made in the above literatures, the multi-criteria problem [3] is not considered, and it is not consistent with the real situation. Although the multi-criteria decision-making is available to the most of existing web services (for example, the web service recommendation process based on SMIcloud framework is designed in the Literature [12], in which the attribute quality of web service has been firstly successfully evaluated on the basis of SMI system, and the web service has been rated with AHP method; the web service recognition program which has obtained the title of the optimum matching system of web service is presented in the Literature [13], and the web service evaluation system under complete AHP framework is designed in the Literature [14], so as to the effective evaluation on web service), such literatures are not designed for SOA system when considering the multi-criteria decision-making.

2. Criterion fuzzification

The fuzzy number can be expressed as the number of uncertain forms, and simultaneously as the function called the membership. This membership function is indicated between 0 and 1. The triangular fuzzy number can be defined as triplet state (a_1, a_2, a_3), which is shown as Fig.1, and the corresponding membership function is [15]:

$$\mu_A(x) = \begin{cases} \dfrac{(x-a_1)}{(a_2-a_1)}, a_1 \leq x \leq a_2 \\ 0, \quad otherwise \\ \dfrac{(a_3-x)}{(a_3-a_2)}, a_2 \leq x \leq a_3 \end{cases} \tag{1}$$

Where, a_1, a_2, a_3 is called as the lower limit, while the possible value and the upper limit can be denoted as (l, m, u).

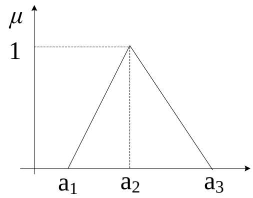

Fig. 1. Triangular membership function

Set $A = (a_1, a_2, a_3)$ and $B = (b_1, b_2, b_3)$ as two triangular fuzzy numbers, and the basic arithmetic operation process is:

Inversion operation

$$A - 1 = (\frac{1}{a_3}, \frac{1}{a_2}, \frac{1}{a_1}) \,. \tag{2}$$

Supplement operation:

$$A + B = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \,. \tag{3}$$

Subtraction operation:

$$A - B = (a_1 - b_3, a_2 + b_2, a_3 + b_1) \,. \tag{4}$$

Scalar multiplication:

$$\begin{cases} \forall k > 0, k \in R, kA = (ka_1, ka_2, ka_3) \\ \forall k < 0, k \in R, kA = (ka_3, ka_2, ka_1) \end{cases} \tag{5}$$

Multiplication:

$$AB = (a_1 b_1, a_2 b_2, a_3 b_3) \,. \tag{6}$$

Division:

$$\frac{A}{B} = (\frac{a_1}{b_3}, \frac{a_2}{b_2}, \frac{a_3}{b_l}) \,. \tag{7}$$

For the pairwise comparison of quantitative evaluation, the triangular fuzzy number $\bar{x}$ can be defined, as shown in Table 1, in which, $1 \leq x \leq 9$.

The decision-making problem generally includes several alternatives, and it can be expressed as $A_i\,(i = 1, 2, 3, \cdots, n)$; the criterion set is $C_j\,(j = 1, 2, \cdots, m)$; the performance rate is x_{ij} where $i = 1, 2, \cdots, n$ and $j = 1, 2, \cdots, m$, which indicates the performance of each item under the consideration of the criterion C_j decision matrix.

Table 1. Qualitative evaluation of fuzzy number

Fuzzy number	Membership function
$\bar{1}$	(1,1,3)
$\bar{x}$	$(x-2, x, x+2)$, $x = 3, 5, 7$
$\bar{9}$	(7,9,11)

3. web service recommendation process

As previously mentioned, in the web service recommendation process, with the evaluation criteria, like working load and service redundancy computation of the server, reusability and fault, etc., the criterion superposition mode simply used easily leads to the assimilation of criterion features, and is not conductive to the reasonable combination recommendation of web service. Therefore, the multi-criteria evaluation method based on the similarity is used to give consideration to influences of several criterions on web service recommendation and make the web service recommendation process more reasonable.

3.1. Steps of similarity evaluation

The specific steps of similarity evaluation include:

Step 1: the fuzzy judgment matrix described in Table 1 is multiplied by the weight matrix (W) or multiplied by the standard option (C_j):

$$C_j \ or \ W = \begin{bmatrix} \bar{a}_{11} & \bar{a}_{12} & \cdots & \bar{a}_{1k} \\ \bar{a}_{21} & \bar{a}_{22} & \cdots & \bar{a}_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \bar{a}_{k1} & \bar{a}_{k2} & \cdots & \bar{a}_{kk} \end{bmatrix}. \tag{8}$$

Where,

$$\bar{a}_{ls} = \begin{cases} \bar{1}, \bar{3}, \bar{5}, \bar{9}, l < s \\ 1, l = s, l, s = 1, 2, \cdots, k \\ 1/\bar{a}_{sl}, l > s \end{cases} \tag{9}$$

Step 2: decision matrix (X) and weight vector (W) can be calculated as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}, \tag{10}$$

$$W = (w_1, w_2, \cdots, w_m)\,, \tag{11}$$

Where,

$$x_{ij} or w_j = \frac{\sum_{s=l}^{k} \bar{a}_{ls}}{\sum_{l=1}^{k} \sum_{s=1}^{k} \bar{a}_{ls}}\,. \tag{12}$$

Where, $i = 1, 2, \cdots, n$, $j = 1, 2, \cdots, m$ and $k = m$ or n; x_{ij} and w_j are fuzzy weights of criterion C_j in consideration of fuzzy performance of criterion C_j and overall goals.

Step 3: fuzzy evaluation matrix Z is the overall performance of each criterion and all options, and it can be multiplied by the weight vector to obtain the decision-making matrix:

$$Z = \begin{bmatrix} w_1x_{11} & w_2x_{12} & \cdots & w_mx_{1m} \\ w_1x_{21} & w_2x_{22} & \cdots & w_mx_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ w_1x_{n1} & w_2x_{n2} & \cdots & w_mx_{nm} \end{bmatrix}. \tag{13}$$

Step 4: seek the interval performance matrix with α cutting method of the performance matrix, where $0 \le \alpha \le 1$:

$$Z_\alpha = \begin{bmatrix} [z_{11l}^{\alpha}, z_{11r}^{\alpha}] & [z_{12l}^{\alpha}, z_{12r}^{\alpha}] & \cdots & [z_{1ml}^{\alpha}, z_{1mr}^{\alpha}] \\ [z_{21l}^{\alpha}, z_{21r}^{\alpha}] & [z_{22l}^{\alpha}, z_{22r}^{\alpha}] & \cdots & [z_{2ml}^{\alpha}, z_{2mr}^{\alpha}] \\ \vdots & \vdots & \ddots & \vdots \\ [z_{n1l}^{\alpha}, z_{n1r}^{\alpha}] & [z_{n2l}^{\alpha}, z_{n2r}^{\alpha}] & \cdots & [z_{nml}^{\alpha}, z_{nmr}^{\alpha}] \end{bmatrix}. \tag{14}$$

Where,

$$\begin{cases} \alpha_l = [\alpha \cdot (m - l)] + l\,, \\ \alpha_r = u - [\alpha \cdot (u - m)]\;, \end{cases} \tag{15}$$

Step 5: calculate the brittle matrix with the optimistic index λ

$$Z_\alpha^{\lambda'} = \begin{bmatrix} z_{11\alpha}^{\lambda'} & z_{12\alpha}^{\lambda'} & \cdots & z_{1m\alpha}^{\lambda'} \\ z_{21\alpha}^{\lambda'} & z_{22\alpha}^{\lambda'} & \cdots & z_{2m\alpha}^{\lambda'} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1\alpha}^{\lambda'} & z_{n2\alpha}^{\lambda'} & \cdots & z_{nm\alpha}^{\lambda'} \end{bmatrix}. \tag{16}$$

Where, $0 \le \lambda \le 1$, $z_{ij\alpha}^{\lambda'} = \lambda z_{ijr}^{\alpha} + (1 - \lambda)\, z_{ijl}^{\alpha}$. For λ is the fixed value, it can be expressed as $\lambda = 1$, $\lambda = 0.5$ and $\lambda = 0$. Therefore, all values could be used by the decision maker to present views of optimism, gentleness or sadness. In the following examples, calculate the brittle matrix with $\lambda = 0.5$.

Step 6: apply the standardized method to the brittle matrix, and the normalized performance matrix could be obtained:

$$Z_{\alpha}^{\lambda}=\begin{bmatrix} z_{11\alpha}^{\lambda} & z_{12\alpha}^{\lambda} & \cdots & z_{1m\alpha}^{\lambda} \\ z_{21\alpha}^{\lambda} & z_{22\alpha}^{\lambda} & \cdots & z_{2m\alpha}^{\lambda} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1\alpha}^{\lambda} & z_{n2\alpha}^{\lambda} & \cdots & z_{nm\alpha}^{\lambda} \end{bmatrix}. \tag{17}$$

Where,

$$z_{ij\alpha}^{\lambda}=\frac{z_{ij\alpha}^{\lambda'}}{\sqrt{\sum_{i=1}^{n}\left(z_{ij\alpha}^{\lambda'}\right)^2}}. \tag{18}$$

Step 7: consider the positive ideal solution $A_{\alpha}^{\lambda^+}$ and the negative ideal solution $A_{\alpha}^{\lambda^-}$ of all criterions:

$$\begin{cases} A_{\alpha}^{\lambda^+} = \left(z_{1\alpha}^{\lambda^+}, z_{2\alpha}^{\lambda^+}, \cdots, z_{m\alpha}^{\lambda^+}\right) \\ A_{\alpha}^{\lambda^-} = \left(z_{1\alpha}^{\lambda^-}, z_{2\alpha}^{\lambda^-}, \cdots, z_{m\alpha}^{\lambda^-}\right) \end{cases} \tag{19}$$

In the formula,

$$\begin{cases} z_{j\alpha}^{\lambda^+} = \max\left(z_{1j\alpha}^{\lambda}, z_{2j\alpha}^{\lambda}, \cdots, z_{mj\alpha}^{\lambda}\right) \\ z_{j\alpha}^{\lambda^-} = \min\left(z_{1j\alpha}^{\lambda}, z_{2j\alpha}^{\lambda}, \cdots, z_{mj\alpha}^{\lambda}\right) \end{cases} \tag{20}$$

Step 8: find the distance between positive and negative ideal solutions. According to the formula of distances between two triangular fuzzy numbers, i.e. $A_1=(a_1,b_1,c_1)$ and $A_2=(a_2,b_2,c_2)$, proposed in the Literature [9], calculate:

$$d\left(A_1,A_2\right)=\sqrt{\frac{1}{3}\left[\left(a_1-a_2\right)^2+\left(b_1-b_2\right)^2+\left(c_1-c_2\right)^2\right]}.$$

$$\begin{cases} d_i^+ = \sum_{j=1}^{k} d\left(\tilde{v}_{ij}, \tilde{v}_j^+\right), i=1,2,\cdots m \\ d_i^- = \sum_{j=1}^{k} d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right), i=1,2,\cdots m \end{cases} \tag{21}$$

Step 9: calculate the close quotient (CC) of each alternative web service and sequence it; select the alternative web service mostly close the quotient.

$$CC_i=\frac{d_i^-}{d_i^+ + d_i^-}. \tag{22}$$

For the recommendation modes based on the similarity, the advantages are that the goal of web recommendation process is unnecessarily set and the non-objectivity and unfairness caused by human participation in the recommendation process will be reduced, and the fully automatic combination recommendation could be realized.

3.2. *Time variant of criterion weight*

In the web service recommendation process, the time attribute of service has the direct impact on the evaluation value recommended, and the earlier web service in our network guidance has the lower version or has been eliminated; therefore, in the web service recommendation process, we should try to select the web service mostly close to the current time as much as possible. To achieve the above purpose, this paper uses time-varying criterion weight, with the purpose of distinguishing different impacts of criterions of each period. If n weight periods are $t_1, t_2, \cdots, t_n$ respectively, the weighted time-varying logic attenuation progress corresponding to t_i is:

$$\omega_i = A + \frac{K - A}{\left(1 + e^{-B(\Delta t_i - M)}\right)^{0.5}} \,. \tag{23}$$

In the formula (23), Δt_i is the distance between the criterion period and the contrasted period. A, K, B, M are influence coefficients. A is the lower envelope line in the attenuation process; K is the upper envelope line in the attenuation process; B is influence coefficient on growth rate, and M is the maximum margin. When weight selection, set the weight closest to the relevant period as 1 and that furthest to such period as 0.4.

To make the web service decision results in all periods available, Boolean matrix is necessarily constructed:

$$U = \begin{array}{c} \\ S_1 \\ S_2 \\ \vdots \\ S_m \end{array} \begin{array}{c} \begin{array}{cccc} t_1 & t_2 & \cdots & t_n \end{array} \\ \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1n} \\ u_{21} & u_{22} & \cdots & u_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ u_{m1} & u_{m2} & \cdots & u_{mn} \end{bmatrix} \end{array} . \tag{24}$$

The matrix element u_{ij} shown in the formula (24) is the web service and its corresponding periods. If the web service S_i in the period t_j has the highest level among web services for the corresponding periods, $u_{ij} = 1$. The web of each array of matrix in corresponding period in the formula (24) could be output with service decision, and the matrix row represents the output of web service decision in all periods. Based on the above matrix, the output result R_i of fusion class corresponding to web service S_i is available.

$$R_i = \sum_{j=1}^{n} \omega_j u_{ij} \,. \tag{25}$$

In the formula (25), ω_j is the criterion effect weight time-varying value. The above procedure is circularly conducted for all web services, and the rank of all web services for the whole period could be obtained. The above calculation process can be based on the matrix of the formula (24), and the product operation is done to column vector of weight.

$$\begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_m \end{bmatrix} = \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1n} \\ u_{21} & u_{22} & \cdots & u_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ u_{m1} & u_{m2} & \cdots & u_{mn} \end{bmatrix} \cdot \begin{bmatrix} \omega_1 \\ \omega_2 \\ \vdots \\ \omega_n \end{bmatrix}. \tag{26}$$

According to the result of the fusion class R from the formula (26), the web service S_k with the largest output R_k of class is selected as the final output of decision.

3.3. web services evaluation

When web service is sequenced, the criterion within duration is used for determination in the fusion process, and the time-varying weight is considered for analysis instead of mean of weighted criterion proposed in the Literature [10]. It can be used to implement the local extremum problem of web service sequence process and performance loss of information time variant. The web service sequence process designed includes:

Step 1: estimate the goal reliability with SOA system construction; divide the periods for continuous web service; the user uses the web service criterion C_j $(j = 1, 2, \cdots, n)$ for determination, and the web service of each period could extract information from the criterion base with decision-making module (which is shown as Fig.1). (**Period division)**

Step 2: querier sequences the importance of web service criterion $C_j(j = 1, 2, \cdots, n)$, and makes the web service decision based on the specific preference. The paper has proposed the adaptive time-varying selection mode of criterion weight, so as to simplify the selection process of the criterion C_j $(j = 1, 2, \cdots, n)$. Refer to Step 1 and Step 2 for details. (**Criterion selection)**

Step 3: construct the decision matrix in performance for criterions of all periods of web service; make the web service decision based on the weight criterion. For the period has non-crossing characteristic, the above sequence procedure may be circularly conducted at each period; then, the selection of web service performance of each period is shown as steps 3-7. (**Criterion sequence)**

Step4: according to different period, assign the time-varying weights, and based on the distance of periods, make the assignment. The weight reduction mode means gradual reduction from $1 \to 0.4$, and the criterion representing the proximal period is more important than that representing the longest period. The assignment based on weighted time-varying results performs the decision-making fusion for the optimal web service of each period. (**Weighted time-varying decision)**

On the basis of the above research, this paper gives a general framework of service sequence based on SOA, and such framework is designed based on fuzzy pairwise comparison and similarity calculation method and combined with the hierarchical results. All of these jobs are in a hierarchy, which is shown as Fig.2.

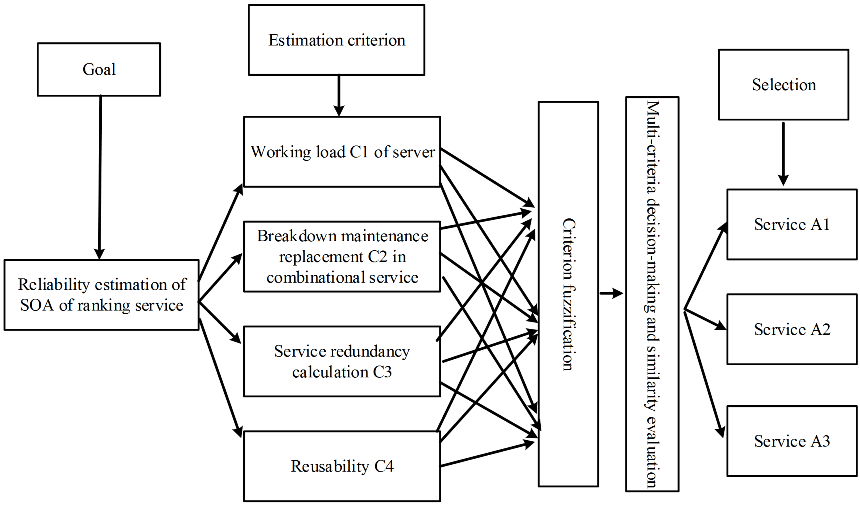

Fig. 2. Web service evaluation algorithm framework

4. Experimental analysis

The experimental subjects include 11 groups of web service sequence datasets [13] selected of yahoo website, and experimentally verify the recommendation of algorithm sequence. Select the probability under the comparison with sequence methods and via web service sequence methods [8] (JPMLC), logistic regression fine-gritted web service sequence method [14] (IBLR-ML), the steepest web service sequence optimization of RBF network [15] (SDRBF). Hardware setting and processor include: i7-6300HQ 3.5GHz; the internal memory refers to 16G ddr4-2400 GHz, and the simulation platform is Matlab2013a.

Table 2. Data information

S/N	Data set	T	C	DC(%)	MNC	RC(%)
1	Arts	452	26	44.48	11	19.23
2	Business	443	30	42.19	10	50.00
3	Computers	683	33	29.58	17	39.39
4	Education	553	33	33.47	7	57.58
5	Entertainment	639	21	29.29	9	28.57
6	Health	613	32	48.07	7	53.13
7	Recreation	611	22	30.18	13	18.18
8	Reference	796	33	13.76	5	51.52
9	Science	753	40	34.75	7	35.00
10	Social	1017	39	20.95	9	56.38
11	Society	646	27	41.87	13	25.93

Extract features of web service sequence datasets selected; reduce the dimensionality of web service dataset, and carry out the sequence service recommendation verification for 2% of texts or those with high frequency and deletion treatments for other data. The single text is formed in a vector form, and each vector dimension represents the frequency of appearance of the word in the text. The experimental dataset of each group contains 2500 groups of samples used for model training and 3500 groups of data for testing, and the mean of class number is set as 30. Refer to Table 1 for the rest parameters involved.

In the data information shown in Table 2, T is the number of item; C is the number of category; DC is the multi-class proportion of sample; MNC is the maximum of distribution of individual sample; RC is rarity proportion of class. Experimental data can be divided into 1500 groups of data sets, 1000 of which are used to build the classifier, while 500 of which are used for data testing. The adjustment parameters mainly include ϕ_{ini}, τ_1 and τ, and the remaining parameters include $n_{\max} \to \infty$, $\rho = 100$, $\alpha = 0.2$, $\eta = 0.8$ and $\tau_2 = 1/300$. The above parameters are set through the reference to relevant parameters recommended in the tag. In the practical application of web service sequence, these parameters have a smaller impact on the performance of the algorithm. The evaluation indexes are selected as follows:

Index 1: Hamming loss (hl) which represents the quantity of classification error of example d_j;

$$hl = \frac{1}{p} \sum_{j=1}^{p} \frac{1}{|C|} \left| P_j \Delta C_j \right|. \tag{27}$$

In the formula (27), $|C|$ is the quantity of class; Δ is the set symmetrical difference between class prediction P_j and class reasonability degree C_j. The sequence grade of class prediction is higher than the threshold value τ set.

Index 2: error rate (E_{error}) which is mainly to evaluate whether the highest class sequence of example d_j belongs to reasonable set C_j;

$$E_{error} = \frac{1}{p} \sum_{j=1}^{p} E_{error}^{j}. \tag{28}$$

$$E_{error}^{j} = \begin{cases} 0, & if \left[\arg\max_{c \in C} f\left(d_j, c\right) \in C_j \right] \\ 1, & otherwise \end{cases} \tag{29}$$

In the formula (29), $\left[\arg\max_{c \in C} f\left(d_j, c\right) \in C_j\right]$ outputs the highest sequence of class of example d_j;

Index 3: coverage rate (C_{cover}) which is mainly to evaluate the necessary reduction threshold value for class grade and guarantee that test example d_j belongs to all classes;

$$C_{cover} = \frac{1}{p} \sum_{j=1}^{p} \left(\max_{c \in C_j} r\left(d_j, c\right) - 1 \right). \tag{30}$$

In the formula (30), $\max_{c \in C_j} r\left(d_j, c\right)$ is maximum grade class set of test example d_j;

Index 4: goal sequence loss (C_{rloss}) which is mainly to evaluate the sequence grade of class on $\langle c_k, c_l \rangle$ example d_j;

$$C_{rloss} = \frac{1}{p} \sum_{j=1}^{p} \frac{|\{(c_k, c_l)\,|f(d_j, c_k) \le f(d_j, c_l)\}|}{|C_j| \cdot |\bar{C}_j|}. \tag{31}$$

In the formula (31), $(c_k, c_l) \in C_j \times \bar{C}_j$, and $\bar{C}_j$ is the supplementary set of class of C_j;

Index 5: sequence accuracy (C_{avep}) which is mainly to evaluate the sequence accuracy of example d_j;

$$C_{avep} = \frac{1}{p} \sum_{j=1}^{p} \frac{1}{|C_j|} \sum_{k=1}^{|C_j|} N_{precis}^{j}(R_{jk}). \tag{32}$$

In the formula (32), R_{jk} is the distance of location k from the goal with the highest level. For the examples d_j and $c_i \in C_j$, $N_{precis}^{j}(R_{jk})$ is the relative numbers of R_{jk} class.

In the above indexes, except for sequence accuracy, the smaller the index is, the better the sequence effect of web service becomes. The optimum of sequence is $hl = E_{error} = C_{cover} = C_{rloss} = 0$ and $C_{avep} = 1$. Contrasting indexes are shown as figures 3-7.

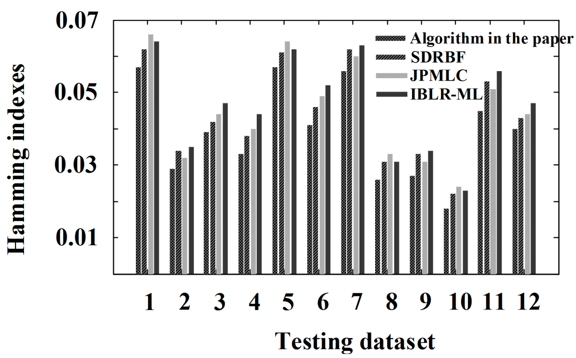

Fig. 3. Hamming indexes [s.n]

Figure 3 shows the comparison among Hamming index data of the selected verification algorithms. The smaller the index value is, the better the result becomes in the sequence process. Numbers of the x axis shown in Fig. 3 are respectively corresponding to numbers of experimental datasets shown in Table 1, and the number of 12 represents the mean of indexes of the algorithm, while the numbers of x axis shown in figures 4-7 have the same meaning. It can be seen that in terms of Hamming web service sequence index, the performance of the algorithm in the paper is more superior than that of another three contrasting algorithms (i.e. JPMLC, IBLR-ML and SDRBF). Hamming web service sequence index of SDRBF algorithm is better than that of another two algorithms, and it occupies the second place, while the indexes of another two algorithms are close to each other, and both have advantages.

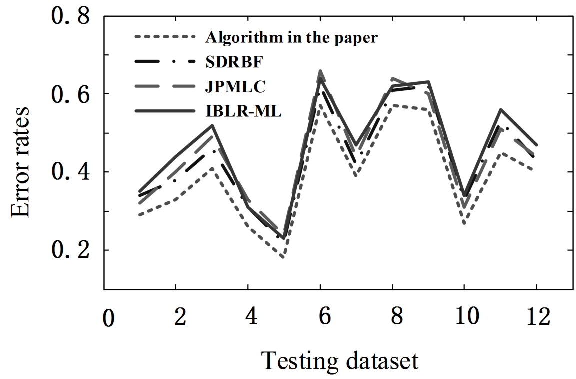

Fig. 4. Error rates [s.n]

Fig. 4 shows the comparison among error rate indexes of JPMLC, IBLR-ML, SDRBF and algorithm in the paper. From the contrasting data, it can be seen that the error rate index of the algorithm in the paper is better than that of the three contrasting algorithms. The error rate indexes of the three contrasting algorithms are very close to each other, and all have advantages.

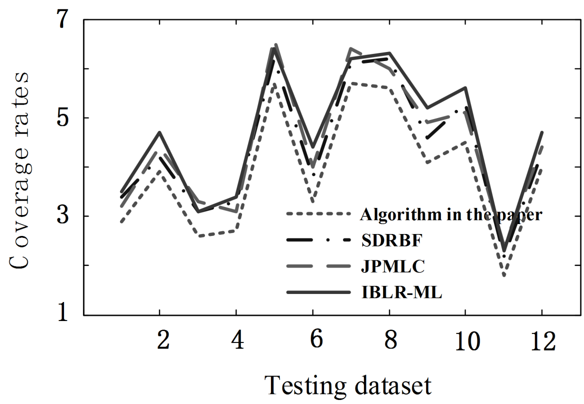

Fig. 5. Coverage rates [s.n]

Fig. 5 shows the comparison among coverage rates of JPMLC, IBLR-ML, SDRBF and the algorithm in the paper. Such index possibly presents the necessary reduction value of sequence threshold value, and the smaller the value is, the better the sequence performance of the algorithm becomes. From the curve in the Fig.5, it can be seen that the coverage effect of the algorithm in the paper is better than that of the three contrasting algorithms (i.e. JPMLC, IBLR-ML and SDRBF).

Fig. 6 shows the comparison among sequence losses of JPMLC, IBLR-ML, SDRBF and the algorithm in the paper. The smaller the index value is, the better the performance of the algorithm becomes. From the contrasting data shown

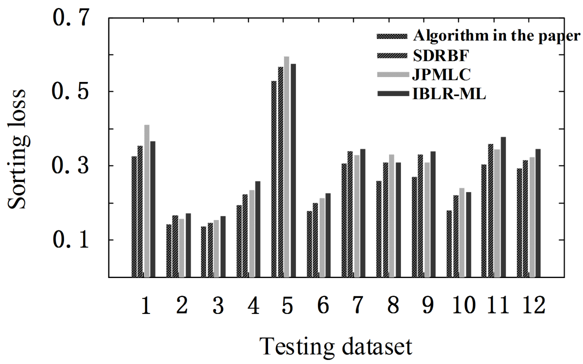

Fig. 6. Sequence losses [s.n]

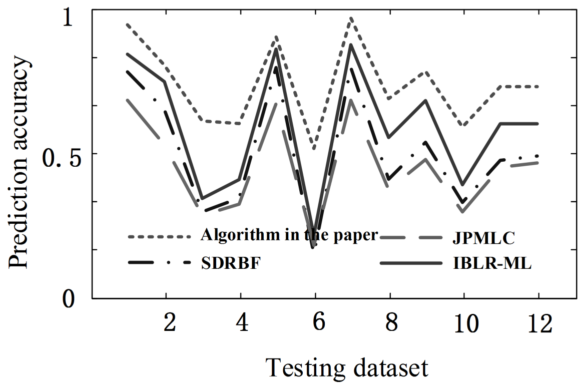

Fig. 7. Sequence accuracies [s.n]

in Fig.6, it can be seen that the algorithm in the paper is superior to contrasting methods selected in terms of performance.

Fig.7 shows the comparison among sequence accuracies of JPMLC, IBLR-ML, SDRBF and the algorithm in the paper. From the contrasting data shown in Fig. 7, it can be known that the algorithm in this paper is better than the contrasting methods selected in terms of prediction accuracy index.

Table 3. Running time

Data set	SDRBF	IBLR-ML	JPMLC	Algorithm in the paper
Computing time (s)				
Yahoo	42.32	37.54	12.39	13.47

From the contrasting data on running time in Table 3, it can be seen that the algorithm in the paper is superior to three contrasting methods (i.e.JPMLC, IBLR-ML and SDRBF) in terms of index of running time, and it indicates that the proposed method has the better execution efficiency.

5. Conclusion

SOA system of the web service recommendation based on multi-criteria decision-making and similarity evaluation has been proposed, which solves the problem that the web service decision-making process is not ideal. On the basis of characteristics of multi-criteria decision-making analysis process, the service evaluation system based on SOA structure of hierarchy has been constructed, and the time-varying weighted multi-criteria similarity evaluation method is proposed. With the experiment of Yahoo domain name and web service recommendation data set, the advantages of the proposed algorithm are verified in recommendation accuracy and quality.

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