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Cloud Service Selection With Fuzzy C-Means Artificial Immune Network Memory Classifier

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Abstract- **This paper addresses an cloud service selection model which supports to customize evaluation attributes dynamically. Using expanding the OWL-S Ontology, Cloud service QoS semantics is constructed. The weight of attribute is obtained by the objective and subjective synthetic approach. Based on fuzzy theory and artificial immune network, a new data classification method, named Fuzzy C-Means artificial immune network memory classifier (FCMAINMC), is put forward. According the algorithm, memory antibody collection in which characteristics of service are condensed is abstracted, and each service (antigen) that belongs to some type is also obtained. Using membership matrix and a hundred-mark way, evaluation result which reflects Web quality of service is obtain. The prototype is designed. It is applied to case evaluation fruitfully, and the experiment results are veracious and reliable as well as stable.**

Key words cloud service ; evaluation model ; Web ontology language for services(OWL-S); Fuzzy C-Means; artificial immune network;

1 INTRODUCTION

The available cloud services are added on a daily base, which means a larger selection space for service consumers. Even for a single functional requirement, there may be so many similar services to meet various customers' individual requirements. Evaluating these services based quality of Service (QoS) becomes an important factor to find out the satisfied service for users. cloud service evaluation model based Qos is to calculate service quality through a set of evaluation criteria.

Current research has proposed a variety of service quality evaluation model, but there are many problems. Firstly, in the evaluation criteria they lacked of public evaluation scale, and there is no considering of objective facts and subjective feelings. They have given evaluation model, but the evaluation of attributes which is meted the needs of different users and Qos bound aren't dynamically generated in the model. The models lack of adaptability and flexibility. Secondly, the weights of attributes based Qos are used to obtain the subjective mode, which will impact the accuracy of evaluation results. Finally, in the evaluation of the algorithm evaluation results are obtained by the weighted sum for evaluation attributes based Qos. However, some Web services attributes based Qos are fuzzy, and the weighted sum can't reflect this characteristic. In addition, fuzzy comprehensive evaluation is used in some model, but fuzzy matrix is obtained by subjective value of statistics and compare. That can't reflect the current characteristics of the candidate Web services accurately. As a result, it is necessary to put forward a new evaluation model of Web service based Qos.

In this paper, a new evaluation model of Web service based Qos is proposed. The concept and relations are described by Ontology Web Language (OWL) in the model. At the time of user accessing Web services, the functions of the service request put forward, and Qos constraints also advance at same time. The model can select automatically evaluation attributes from knowledge base that reflect function requirements, application area and Qos constraints. The evaluation tree is introduced. An objective and subjective synthetic approach to determine weigh is given. About algorithm in the evaluation, a new artificial immune network algorithm which is fuzzy c-means artificial immune network memory classifier (FCMAINMC) is proposed. It can implement generalization of classification to Web services (as a collection of antigen) which meet the user functionality and Qos constraint. According the algorithm, memory antibody collection in which characteristics of service are condensed is abstracted, and each service (antigen) that belongs to some type is also obtained. Degree of membership matrix is acquired by using fuzzy cluster, form which evaluation response to the merits of Web services is to obtain.

The evaluation model of Web service based Qos can be applied of engine of selection and composition of the Web services engine, and Web services engine management system, furthermore, it is applicable to components retrieval of non-Web services. Quality evaluation for candidates in other research areas also uses it.

2 ONTOLOGY-ORIENTED EVALUATION MODEL DESCRIPTION OF SEMANTIC CLOUD SERVICE BASED QOS

Evaluation attributes F = <Name, Description, Category, W> , where Name is the name of the property for

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the evaluation, Description is the property for a description of the information, and Category is evaluation category for attributes, and W ∈ [0,1] is evaluation the weight of property, that is, the importance of attribute evaluation in Qos. Evaluation attributes F is the extracted basic evaluation cell from Web service properties (including the evaluation properties of generic Web service, the evaluation properties of user's the field and user feedback evaluation properties of Web services).

Evaluation category C = <Sname, Set, W>, where Sname is name of evaluation category, Set= (e_1, e_2, ⋯, e_n | e_k is evaluation attribute or category,k=1,…,n)is a collection, and W ∈ [0,1] is the weight of evaluation category that represents with the importance of evaluation categories.

Evaluation tree T is made of root node, internal node and leaf node. Root node is defined R. Internal node is evaluation category C. Leaf node is evaluation attributes F.

Dynamic evaluation of the generated tree: ① Evaluation attributes is determined by evaluated Web service. Evaluation attributes come from knowledge base, in which evaluation attributes is represented by F, and they are associated with C. Evaluators can add F and C to knowledge base according to their own needs. ② Evaluation tree is generated with bottom-up method. Leaf nodes come from knowledge base of evaluation attribute. Internal nodes are obtained from Category in evaluation attributes F. Children of evaluation category C (Internal node) are each element in the Set, and in addition to the root node the other nodes have only one parent node. ③ The objective and subjective synthetic approach to determine weigh is used . Thus, to sum up three points which we have just indicated, evaluations tree with weight is generated that is evaluation index system of the Web service based Qos.

Evaluation model of Web service based Qos M = <T, SI, DT, ER, P>, here T is evaluation tree. SI is examples for evaluation services. DT is a data vector, and each data in the vector is value of evaluation attribute. ER is output of evaluation model. P is constraint relation between the concepts in evaluation model.

3 EVALUATION ALGORITHM OF CLOUD SERVICE BASED QOS

3.1 The objective and subjective synthetic approach for weigh of evaluation attribute

Weight should reflect user's concern degree of different evaluation attribute. To calculate weight accurately, Subjective feelings and objective facts should be considered. Furthermore, the objective and subjective synthetic approach is proposed to determine weight.

Let w_i represent weight of evaluation attribute F_i, $w_i \in w=(w_1,w_2,\ldots,w_m)'$, $\sum_{i=1}^{m} w_i = 1, w_i \geq 0 . i=1,2,\cdots,m$

Let SI represent examples for evaluation services.

Let B represent standard form of evaluation attribute value matrix for Web service example. $B=[b_{ij}]_{n\times m}$.

$$b_j^* = \max\{b_{1j}, b_{2j}, \cdots, b_{nj}\}$$

Let D represent comparison matrices of evaluation attribute value. $D=[d_{ij}]_{m\times m}$, and d_{ij} is important degree compared evaluation attribute F_i with F_j. $d_{ij} >0$, $d_{ij}=1/ d_{ji}$, $d_{ij} \approx w_i/w_j$

In order to calculate weight, we structure the mathematical model as follows.

$$\begin{cases} \min f_1 = \sum_{i=1}^{m}\sum_{j=1}^{m}(d_{ij}w_j - w_i)^2 \\ \min f_2 = \sum_{k=1}^{n}\sum_{j=1}^{m}(b_j^* - b_{kj})^2 w_j^2 \\ subject \quad to \sum_{j=1}^{m} w_j = 1, w_j \geq 0, j = 1,2,\ldots,m \end{cases} \tag{1}$$

In order to solve the model to be translated into multi-objective programming as follows:

$$\begin{cases} \min f_3 = \alpha\sum_{i=1}^{m}\sum_{j=1}^{m}(d_{ij}w_j - w_i)^2 + \beta\sum_{k=1}^{n}\sum_{j=1}^{m}(b_j^* - b_{kj})^2 w_j^2 \\ subject \quad to \sum_{j=1}^{m} w_j = 1, w_j \geq 0, j = 1,2,\ldots,m \end{cases} \tag{2}$$

M do not consider the weight of the non-negative constraints, structural Lagrange function:

Non-negative constraints of weight aren't consided, structural Lagrange function:

$$L = \alpha\sum_{i=1}^{m}\sum_{j=1}^{m}(d_{ij}w_j - w_i)^2 + \beta\sum_{k=1}^{n}\sum_{j=1}^{m}(b_j^* - b_{kj})^2 w_j^2 + 2\lambda(\sum_{j=1}^{m} w_j - 1) \tag{3}$$

Here λ is Lagrange coefficient.

Let $\partial L / \partial w_h, h = 1,2,\ldots,m$, and combine constraints $\sum_{i=1}^{m} w_i = 1$. m +1 equation is represented with matrix form as follows:

$$\begin{bmatrix} Z & e \\ e' & 0 \end{bmatrix}\begin{bmatrix} w \\ \lambda \end{bmatrix} = \begin{bmatrix} O \\ I \end{bmatrix} \tag{4}$$

Let $Z=[Z_{ij}]_{m\times m}$, w=(w1,w2,…,wm)',e=(1,1,…,1)',O=(0,0,…,0)',

Z elements form as follows:

$$z_{kj} = -\alpha(d_{kj} + d_{jk}) \qquad k \neq j; k, j = 1,2,\ldots,m \tag{5}$$

$$z_{kk} = \alpha(\sum_{i=1}^{m} d_{ik}^2 + m - 2) + \beta\sum_{i=1}^{n}(b_k^* - b_{ik})^2 \qquad k = 1,2,\ldots,m \tag{6}$$

Solving equations, available: $AG = \{< Ag_1, v_1 >, < Ag_2, v_2 >, \cdots, < Ag_I, v_T\}', AG \in \Re^I$ $Ag_i = (Ag_{i1}, Ag_{i2} \cdots, Ag_{iL})$

$$w^* = Z^{-1}e / e'Z^{-1}e \tag{7}$$

$$\lambda = -\frac{1}{e^{'}Z^{-1}e}$$

Here w^* is weight which is solved by the objective and subjective synthetic approach.

3.2 Fuzzy C-Means artificial immune network memory classifier (FCMAINMC)

3.2.1 Classification mechanism

Classification of data mining is a very important task, used widely in the current commerce. The purpose of classification is to propose a classifier.Data item in the database can be mapped to a particular category with classifier. Memory cells to the datas are made by immune memory mechanism of artificial immune network.Finding implied classifier of datas is called artificial immune network memory classifier. Its structure is divided into two stages of the process that is tainning and testing. In the training stage, accurate description or model of mapping between AG_1 and M is emerged according analyzing training set AG_1. In the testing stage, the test data set AG_2 is classified by description or model .

3.2.2 Fuzzy c-means artificial immune network memory classifier (FCMAINMC)

In traditional artificial immune network there are many problems as follow: Firstly, the initial antibody is generated randomly for lack of application of prior knowledge. Secondly, attribute values are normalized in the range of [0,1], which can not only require additional spending but also lose of information. Euclidean distance is primary metric of affinity, but affinity of using Euclidean distance doesn't take into consideration the weigh of evaluation attributes.Thirdly, the object of classification is approximation of original data but not original data set. Doing like that cann't obtain each antigen category.

In this paper,a new classifier based on aritificial innune network is proposed,which is fuzzy c-means artificial immune network memory classifier(FCMAINMC). It can use priori knowledge to establish initial antibody set. Weight of evaluation attribute is taken into account in affinity calculation.The classifier achieves high concentration of antibody and antigen category.

Parametric definition:

Let AG represent set of antigen Ag. I is antigen spatial amplitude.T is number of category.L is number of evaluation attribute.

Let M represent set of memory antibody, and m_i is set of memory antibody for current.

Let Af_k represent affinity set of antigen Ag_k and current M.

Let N represent number of initial antibody.

δ_{sd} is the lower threshold of antibody in limitation network.

Let $\xi\%$ represent selecting rate clone.

Let n represent number of selected clone memory cells.

Let C_r represent clone speed.

Let G represent Iteration time.

Let V represent set of category.

AG is divided into two parts, AG_1andAG_2. They meet the following conditions, $AG_1 \cap AG_2 = \Phi$，$AG_1 \cup AG_2 = AG$。

In addition to better explain the algorithm, some parameters of the calculation of the definition and description is given:

(1) calculation of affinity

Affinity between antigen Ag_i and antibody Ab_j is:

$$af(Ag_i, Ab_j) = \sum_{k=1}^{L} w * match(Ag_{ik}, Ab_{jk}) \quad (8)$$

Here w is weight of Ag_i，and match（Ag_{ik}，Ab_{jk}）is degree of match of evaluation attribution value between Ag_{ik} and Ab_{jk}.

If evaluation attribute is the type of property, let

$$match(Ag_{ik}, Ab_{jk}) = \begin{cases} 0 & Ag_{ik} \neq Ab_{jk} \\ 1 & Ag_{ik} = Ab_{jk} \end{cases} \quad (9)$$

If evaluation attribute is the value of property, let

$$match(Ag_{ik}, Ab_{jk}) = 1 - \frac{|Ag_{ik} - Ab_{jk}|}{\sqrt{Ag^2{}_{ik} + Ab^2{}_{jk}}}$$

(2) calculation of threshold

$$\delta_s = c \times \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{k=i+1}^{n} \frac{1}{af(Ab_i, Ab_k)} \quad (10)$$

Here c is in range of（0，1），ans n is antibody number of current network.

$$\delta_d = \delta_s + s \times \frac{1}{n} \sum_{j=1}^{n} \min{}_{i=1}^{n} (\frac{1}{af(Ab_i, Ab_j}) \quad (11)$$

Here s is in range of [5,20].

(3) calculation of clone number

$$Nc = \left\lfloor C_r * \frac{1}{af(Ag_i, Ab_j)} \right\rfloor \quad (12)$$

(4) Rule of clone variation

$$m_j^{'} = m_j + \alpha_k \max[0,1)(Ag_j - m_j), j = 1,....L \quad (13)$$

Let $\alpha_k \propto 1/af(Ag_i, Ab_j); k = 1,..., N_c$,and $\max[0,1)$ represent random variable of uniform distribution from 0 to 1。

The FCMAINMC algorithm is summarized in the pseudo code presented below.

Input: AG, N, $\xi\%$,n, Cr, G。

Output: V, Updated AG in the types, M

Step1: Initialization: Let $AG_1 = \{<Ag_1, v>, <Ag_2, v>, \cdots, <Ag_I, v>\}', AG \in \Re^I$ .Take N which is number of initial antibody as the number of the clustering class. Fuzzy C-Means algorithm is implemented to AG1. Initial antibody set M is N cluster centers that is gotten from Fuzzy C-Means.

Step2: If the stopping condition is not satisfied, do the following operation:

(1)For each $Ag_i \in AG_1$:

①Pattern recognition and match: Calculate affinity by Eqns.(8) .Select n antibodies of highest affinity and same type in M as m_i.

②Clone operator：Every memory antibody of m_i is cloned, and clone number comes from Eqns.(12).

③Variation: Variation of every memory antibody of m_i is followed rule of Eqns.(13). Uniform mutation makes variation memory antibody away from the original location, thus it enable the memory antibodies distributed in the data space uniformly. It play the role of center of mass. That is more favorable effect on the classification.

④Clonal selection and affinity maturation: Recalculate affinity of Ag_i and cells of clone and Variation, and select $\xi\%$ cells of highest affinity as memory antibodies of Ag_i. Calculate δ_d according to Eqns.(11). Clear memory antibodies of m_i whose affinity is larger than δ_d .Calculate affinity among memory antibodies of current m_i, and Calculate δ_s according to Eqns.(10). Clear memory antibodies of m_i whose affinity is smaller than δ_s .

⑤Classification: Update v_K as type domain of m_i and Ag_i if the type domain of m_i is the initial type, or else make the type domain of Ag_i the same as m_i.

⑥M=[M，mi]

（2）Update δ_s according to current M, Clear memory antibodies of M whose affinity is smaller than δ_s .

Step3: Classification to AG_2 is implemented by using M. Majority voting mechanism of KNN is used.

3.3 Evaluation Result

Through the algorithm described in the 3.2 section memory antibody collection M which is characteristics of the enrichment for Web services is obtained. Characteristics of evaluation attribute value of same type in m is counted. The type code according to statistics is adjusted so that the best Web service is expressed by v_1, and so on. At the same time, the type adjusted of AG is same as the type of M. Using Eqns.(14) we can obtain membership matrix of every Web service.

$$U = [u_{ij}]_{l\times|V|} = \left[\frac{1}{\sum_{k=1}^{|v|} \left[\frac{\bar{d}_{ij}}{\bar{d}_{kj}} \right]^{\frac{2}{m-1}}} \right]_{L\times|V|} \tag{14}$$

$$\bar{d}_{ij} = \frac{1}{\bar{D}_{ij}}$$

Where $\bar{D}_{ij}$ is average of Euclidean distance between Ag_j and memory antibody of v_i, $|V|$ is number of type, and m is weight index in range of $[1,\infty)$

Namely, using a hundred-mark approach can obtain evaluation score of every antigen (Web service) .For example, $|V|$ =5,score vector is $B = (90,80,70,60,50)$,and the final score matrix of all antigens is $\text{Evaluation score} = \mathrm{B} \circ \mathrm{U}$.

4 SIMULATION

Architecture of system is based on J2EE, MySQL acts as storage and retrieval engine of ontology data. Experimental environment is as follows: Intel P4 3.0 GHz, 1GB RAM, Windows 2000 SP4, TOMCAT, 100 Mb/s. Buying book Online is experimented in the paper.

(1) Evaluation tree with weight

The architecture of evaluation tree with weight is shown in Fig.1.

(2) Fuzzy c-means artificial immune network memory classifier

Input: AG, N, $\xi\%$,n, C_r, G。

Here AG is 60 candidate Web services, and N=20, $\xi\% = 0.1$,n=4, C_r=10, G=5

Output: V, Updated AG in the types, M.

Here V is set of $\{v_1,v_2,v_3\}$. AG is Updated in the types where v_1 type is 13 Web services ,. v_2 type is 32 Web services, v_3 type is 15 Web services. M is as follows:

$$M = \begin{bmatrix} 32 & 5 & 5 & 100 & 2.2 & 0.12 & 1 & v_1 \\ 43 & 3 & 2 & 48 & 6.4 & 0.38 & 1 & v_2 \\ 46 & 3 & 3 & 52 & 5.1 & 0.35 & 0 & v_2 \\ 33 & 4 & 5 & 86 & 1.9 & 0.22 & 1 & v_1 \\ 55 & 2 & 2 & 22 & 8.7 & 0.68 & 1 & v_3 \\ 41 & 3 & 1 & 66 & 4.3 & 0.33 & 1 & v_2 \\ 39 & 3 & 3 & 80 & 5.2 & 0.51 & 0 & v_2 \\ 50 & 2 & 3 & 31 & 6.9 & 0.73 & 0 & v_3 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

From M we can find that $v_1$is the best type with good user needs , superior performance and high reliability, and v_2 is inferior to v_1, with the worst v_3.

(3) Evaluation Result

From U we can find Web service Ag_1 is subordination to v_1.

$$U = \left[u_{ij}\right]_{60\times3} = \begin{bmatrix} 0.4823796 & 0.3287672 & 0.1888532 \\ 0.3472289 & 0.4645421 & 0.1882290 \\ 0.3046888 & 0.4667485 & 0.2285627 \\ 0.1514619 & 0.2540733 & 0.5944648 \\ 0.5529410 & 0.2862607 & 0.1607984 \\ \vdots & \vdots & \vdots \end{bmatrix}$$

$$\text{Evaluation score} = \mathrm{B} \circ \mathrm{U} = (90,70,50) \circ U$$

5 CONCLUSION

A service evaluation model based QoS is set up. The evaluation algorithm is introduced. We also set up evaluation system The solution in this paper provides stronger QoS based supports to Web service based dynamic business collaboration. Our future research work will be focused on QoS based service process monitoring, QoS context based process management decision support and QoS based process improvement.

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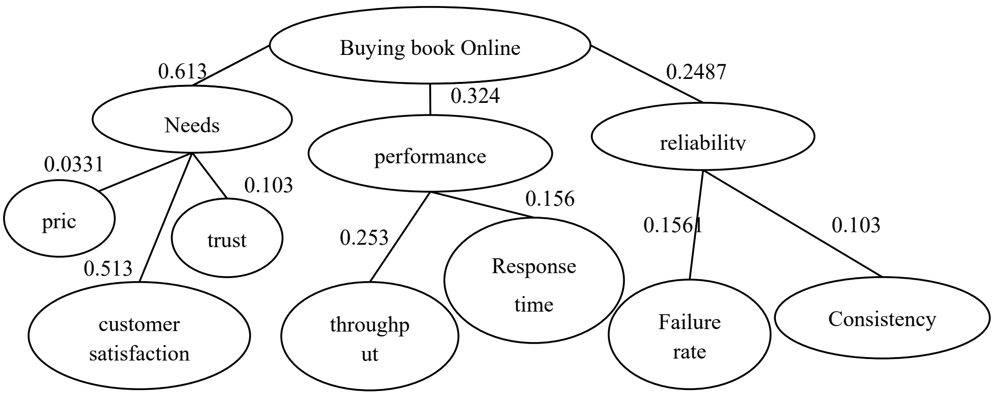

Fig.1 The architecture of evaluation tree with weight