Belief Reasoning Recommendation

Mashing up Web Information Fusion and FOAF.

Shijun Li
Wuhan University, Wuhan,China
shjli@whu.edu.cn

Yunlu Zhang, Ming Xie, and Hao Sun
Wuhan University, Wuhan,China
{zhang.yunlu850527, wolfgangtse, huruyizhenfeng}@gmail.com

***ABSTRACT*—This paper mashes up Web Information Fusion and FOAF (Friend of a Friend) to design a belief reasoning recommendation system for user service. Belief reasoning recommendation user service takes into account the spatial and temporal information of the process of user services, and it analysis the relationships between the users and information publisher based on their FOAF profiles. BRRUS uses Markov chain Monte Carlo algorithm to improve the confidence level of cold-start users on virtual social networks who have not registered in BRRUS. This work also proposes an algorithm for particular expert user's detection from the training datasets according to spatial and temporal queries that users submitted. These theoretical findings are supported by experiments on several test collections and compared with another classic recommendation system Taste, which makes users more satisfactory than other recommendation system.**

***Index Terms*—web information fusion, FOAF, belief reasoning, trusted graph, expert user detection, spatial and temporal**

I. INTRODUCTION

FOAF (Friend of a Friend) has come out of laboratories into engineering practice. It describes the relationship between internet users and things about them (interests, work conditions, reading books) with RDF/XML with FOAF vocabulary and RDF syntax. This social services application provides much more possibilities relationship management for users. FOAF research can help business quickly and accurately achieve the search intentions of their users for how to share resources on the Internet. Yahoo!, Microsoft, Amazon and Apple, etc. use existing FOAF standards or extend of FOAF property to obtain commercial profits.

For FOAF, a basic research question is to extract the user's basic information to analyze users' characteristics and interaction between them. There are a large number of research articles in this area, but it is not enough to merely consider the basic information for reusing the semantic features and relationship among the users.

Firstly, Traditional methods cannot effectively use the excessive users' data on the Internet, for the hugeness of users' connections relationship and the dispersion of data. Secondly, the ways FOAF uses to identify user mailbox according to their email boxes are unsteadily, for users may change or abandon a foregoing mailbox or use different mailbox for different purposes. In some situation one mailbox may belongs to more than one user.

This model increases ontology description and sets up reasoning rules for multiply users' data source infusing according to their personal FOAF information. By the means of mining the trust relationship amongst the internet users to mine expert level users using ontology reasoner is another important issue in our model. The model is suitable for any cases require both spatial and temporal condition and cooperative action amongst users to personalize serve a particular user. This paper takes the athletic sports as an example for referring to spatial and temporal information and teamwork amongst users at the same. We use the classical belief network as a theoretical foundation for recommend potential interesting contestants for users. The prototype sets up on the computers which users log on to analysis the location on the basis of IP address, then it takes the spatial and temporal information of a users' submitted query as inputted parameters to recommend the qualified court. The data stream of the model is as shown in Fig.1.

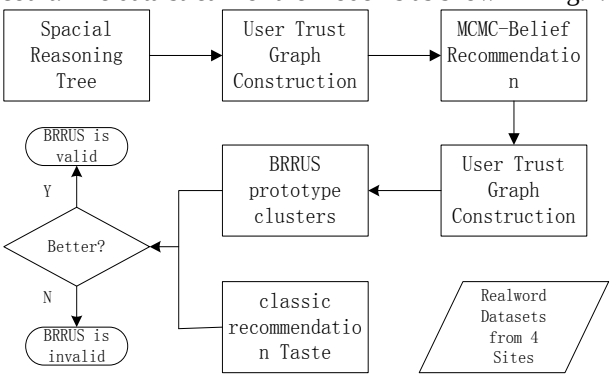

Figure 1. Data Stream

II. RELATED WORK

A. Spatial and Temporal Analysis

PIMO[1], SUPER[2] , SL[3] and P^2[4], which support complex personalized user information query, achieve lightweight integration of virtual desktop personal information, support for user's complex and

doi:10.4304/jcp.5.12.1885-1892

personalized information query, such as "give me John March 's presentation in proceeding of Paris this year". PIMO rewrites queries with alternative rules and wildcard. It selects the data sets in relevant areas: the calendar items, meeting records, publications, the users' FOAF profiles, and telephone conference. SUPER integrates multiple data sources (Google Calendar, FOAF, mobile phones, RUPO (the shopping list described by Retail User Profile Ontology) to analyze the user's purchasing behavior to recommend. The system is suited for memory-based query such as "During the time between X and Y, How many users participate in the same event as what if do in the system ".P^2collects multi information services and merge them into a shared personal space, uses the P^2 rules to create a new user file after accessing to FOAF file data of users on multiple platforms. After registering the service, the user can enjoy the personalized recommendation in the P^2 environment without the constraints of time and space.

B. User Cooperation

Ref.[5] stressed the necessary of using simple and clear semantics data format to build a global information system (such as fully distributed community network) and to build a metadata makes it important to realize the simple and friendly editable tools (foaf-a-matic) for Semantic Web. Even using the FOAF-a-matic tool, the publish and update the FOAF file is presently tedious manual work for users, so [6] proposed OKKAM-based FOAF-O-matic to improve the FOAF-a-matic, OKKAM can integrate multiple data sources to deal with the unique identification of users; the "O" underlined integrity of OKKAM on FOAF file.

The academic research is one import field to establish the cooperation among strange users by FOAF. TrustMail[7] creates a trusted network to analyze that of consumer, to enhance the security of e-mail by presenting the sender's trust degree in email inbox. Rig.[8] used wireless devices (such as mobile phones, portable computers) and FOAF file to analyze the multi-behavior user relationship, like recommending the nearest user by determining the spatial location of the wireless devices, and expanse the FOAF properties <foaf : basedNear> to search a group of potential users. [9] put forward the insufficiency impartiality of FOAF for the quality of self-described at the same of pointed out the importance of FOAF as a method to analysis social network.SemoRA [10] digs and analysis of academic researchers information in different web data sources and FOAF files to analyze relationship between researchers, which is conducive to the establishment of the cooperation of researchers.

C. Trust Management

Moleskiing.it [11] makes the ski mountaineering safer by the matrix of credibility according to the user's FOAF: seeAlso links including the rating of other users' trust. Moleskiing.it integrates others web information form relevant web sites and the trust degree from 1 to 10.Reference [12] used RDF expansion named map (Named Graphs) in the field of web publishing to ensure the credibility of information sources, provides the trust-based framework in semantic Web. The anytime, anywhere share and access resources with more natural way makes the access control to resources to be the key question, José Bringel Filho proposed [13], which based on the access control model of context (identity, location (indoor/outdoor), FOAF files, events, real-time (time) , time control. etc.) makes the access control solution to the frequent-changing and unpredictable users, resources and environment. Coarse-grained privacy policy of government's and the relatively low sensitivity of individual citizens decrease data security. Reference [14] proposed citizen privacy protection solution in e-government PPP, which used the FOAF to describe the relationship among citizens' information and other information resources in detail. D-FOAF [15] and LOAF [16] used distributed user foaf file and the computing user distance to identify the user identity and manage user access rights. Ref.[17] [18] used the FOAF to analyze the role relationship between users (classmates, colleagues, teachers and students, project leaders and staff, etc.), allowing users to publish an attached social network-based access control lists, after receiving the request information to access, the application determines whether to authorize the requestor to read the content published according to the access control lists . Wei Shi [19] extended some attributes of FOAF(such as the incredible user), added some constraints on the BPEL, strengthened BPEL to extract RBAC (Role Based Access Control, Role-Based Access Control) model, which can prevent the illegal affairs business acts. FOAF content can be obtained only by business enterprises, which ensures the user's privacy.

The traditional information integration technology is not suitable for web environment because of the distributed, dynamic, uncontrollable and unstructured information data. Web information Fusion integrates a large number of information on the web at its own characteristics to provide new information services and firm theories and technical support, such as decision-making based on the web [20].

III. BELIEF REASONING RECOMMENDATION

This paper chooses indispensable properties for our model from existing FOAF vocabulary (http:// xmlns.com/foaf/0.1/) shown as Table 1,and Example 1 is an example of the parts of users' FOAF owl information There are two knowledge reasoning subclasses in belief reasoning recommendation ontology model: spatial/temporal and friends.

TABLE I. FOAF PROPERTY FOR REASONING

Basics	Personal	Groups
Person	knows	Project
DateOfBirth	interest	Group
name	basednear	member
nick	workInfo	
homepage	publications	

Example 1

```
<foaf:Person>
<foaf:nick>crsch</foaf:nick>
```

```
<foaf:dateOfBirth>1984-03-19</foaf:dateOfBirth>
<foaf:knows>
   <foaf:Person>
   <foaf:nick>deriva</foaf:nick>rdfs:seeAlso
   rdf:resource="http://deriva.deadjournal.com/data/foaf"/>
   <foaf:interest dc:title="d"
   rdf:resource="http://www.facebook.com/interests.?int=d"/>
   </foaf:Person>
</foaf:knows>
<foaf:interest dc:title="a"
 rdf:resource="http://wwwfacebook.com/interests.?int=a"/>
</foaf:Person>
```

A. Spatial Reasoning

DEFINITION 1 (Space Model). We analyze the location and time information of users start the model to get the available set of courts nearby. Let $C=\{C_1,C_2,...,C_{10}\}$ be the set of sorting courts recommended. Let $L(j)=\{l_{j1},l_{j2},...,l_{j10}\}$ be the set of information about top-10 enterprise that around the court Cj (1≤j≤10)in a given threshold. Let $W(j)$ ={ cloudy, Rain, …} be the set of weather at the specific time, l_{jk} includes the number of employers and enterprise character.

Algorithm 1：Location Reasoning Tree

1. Mapping the computer terminal IP address to spatial information and setting Ki as the root keyword set , i is initialized to 1
2. Secondary development of GoogleEarth , set Ki as search keyword ;
3. Extracting the text of current search page, structuring the hierarchical tree;
4. Weighting the edges between parent nodes and child nodes, presenting the spatial distance between the keyword and search results. as shown in Fig. 2.
5. Searching the information of surrounding business by taking the child node as a keyword set Ki +1 if the threshold value reach the required one, then exit the level tree structure, otherwise returns to step 3
6. Storing the node information into user local database.

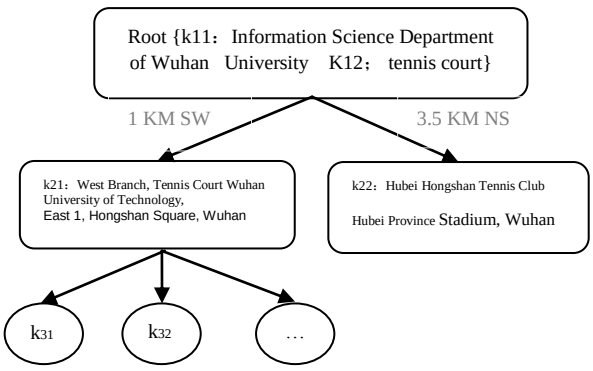

Figure 2. The search hierarchy tree

B. User Reasoning

We analyze the users' relationship graph with approximate reasoning and collaborative workers with severe reasoning after simplify the relationship graph. And by the way of 'subsumption check' and 'consistency check' the reasoning algorithm can accomplish the 'Individual' and 'Realization' for individual user.

DEFINITION 2 ULM (User logliner Model) is used to analyze the relative weight of various factors, which impact of customer relationship. The main parameters of ULM's are shown as formula 1 below. There are five classified variables in ULM, and the meanings of them are shown as follows.

1nterest (I: 2 grades); Job (J: 7 grades); Level (L: 5 grades); Years (Y: 3 grades); Gender (G: 2 grades)

μ : presents the average effect of the global property;

μ_i^I : The effect of property i in set I the time;

μ_{ij}^{IJ} : Interaction (association) property of I and J;

μ_{ijklm}^{IJLYG} : interactive effects of all the five properties

$$\log \mu_{ijklm}^{IJKLM} = \mu + \mu_i^I + ... + \mu_{ij}^{IJ} + ... + \mu_{ijl}^{IJL} ... + \mu_{ijly}^{IJLY} + ... + \mu_{ijklm}^{IJLYG} \quad (1)$$

Automatic select the significant effective items through reversing elimination and setting maximum counts of selection and the significant level standards of deleted effective items. After 23 screening procedure we have build the best model and output each parameter of effective items in the final model. Table 2 is the initial screening procedure. Finally we normalize the weight of each variable to <I: 0.03; J: 0.3; L: 0.3; Y: 0.07; G: 0.3>

TABLE II. SATURATED MODEL TO SHOW THE OBS COUNT, EXP COUNT, RESIDUAL AND STD RESID OF EACH VARIABLE

Factor	I	Y	I	J	M	OBS	EXP	Residual	Std
Code 1	1	1	1	1	1	55.5	55.5	.00	.00
Code 2	1	2	1	1	1	17.5	17.5	.00	.00

DEFINITION 3 (User Trust Graph).For each user u, we build a trusted graph UTG(u)=(V(u),E(u)) using ULM, the steps are shown as follows:

Step1: User classification

Class :(c_1, c_2, ... ,c_m),

The feature space of class X = (I, J, L, Y, G),

User sample u_x, classification feature x = (i, j, l, y, g),

Then the probability of sample u_x belongs to class c_y :

$$P(c_y \mid u_x) \propto \prod_{x_i \in u_x} \omega_i P(c_y \mid x_i) \quad (2)$$

u_x : User's FOAF information to be classified

c_y : Category to be classified.

x_i : Current factor of user's FOAF information

ω_i : The ULM weighting factor of current x_i .

Step2: Similarity of inter-class

1. Mutual Information

$$sim(u_a,u_b) = \sum_{i \in ULM} P(u_a^i,u_b^i)\log(\frac{P(u_a^i,u_b^i)}{P_1(u_a^i)P_2(u_b^i)}) \quad (3)$$

$u_a^{(i)}$: The i factor of user u_a ULM information.

$u_b^{(i)}$: The i factor of user u_b ULM information.

2. Build user u_a similarity row vector

$$a_i = (sim(u_a^i, u_b^i), sim(u_a^i, u_c^i), sim(u_a^i, u_d^i), ...) \quad (4)$$

$$Score(u_a, ULM, ux) = \sum_{i \in ULM} a_{i(u_a, u_x)} \quad (5)$$

$$where\{x \mid x \in USER\}$$

3. $Normalize(Score) \in [0,1]$
4. Turn $Normalize(Score)$ into binary representation
5. Build users' similarity cube as $U \times ULM \times U$, and $< u_a, nlm_{ab}, u_b >$ indicates the binary $Normalize(Score)$ value of user u_a with u_b
6. Build edge weight among users according to the values of nodes in $U \times ULM \times U$

Set six maximum similar vector friendships for each user (k=6), then choosing six friends for each friend with the same way, in them not including the users pointing to that. For each node of UTG interact with only a few other nodes directly, it is beneficial to design the reasoning process according to codes of condition dependent sentence sets. As being shown below, graph node consists of two data fields (user name, whether has been traversed), and two pointers tracts (one points to the parent node, the other points to the sibling nodes).

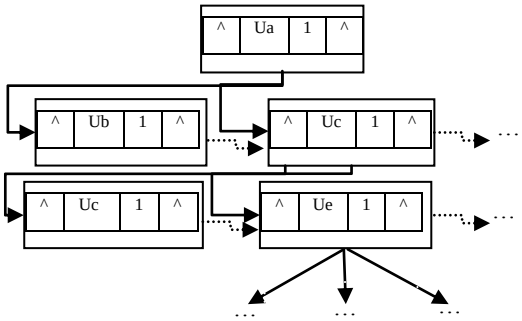

Figure 3. Part of User Trust Graph

C. Belief Recommendation

Problem Description 1: The probability of successful activity when the temporal and special conditions satisfied with the aid of user recommendation UserFree (UF), Success(S), CourtFree (CF)

Enumerate reasoning:

$$\begin{aligned} P(S \mid CF, UF) &= P(S, CF, UF) \\ &= \sum upP(S, UP, CF, UF) \quad (6) \\ &= P(S) \sum upP(UP) P(CF \mid UP) P(UF \mid UP) \end{aligned}$$

Problem Description 2: Given the activity has carried out, the problem is to evaluate the probability of helps from BRRUS users' profiles by approximation reasoning

Algorithm2: MCMC-Belief Recommendation

Input: e ={S, CF}; Z= {UP}; X= (UF)

Output: P(X | e)

1. Local variables: N[X],
2. Query vector of variables X, the initial value is 0
3. Z (non-evidence variable set in utgn)
4. X (current state of UF in utgn)
5. Use random value of variables Z to initialize x;
6. For j = 1 to N dp
7. N(x) ← N(x) + 1;
8. For each Zi in Z do
9. MB (Zi) is the Markov coverage of Zi
10. Sample the value of Zi according to P(Zi |mb(Zi));
11. Return Normalize(N[X])

D. Expert Recognition

In this section, the "expert recognizant" means the experts, who can give a specifically advices to user when he/she needs, will be recognized. For example, the expert, who is applicable to meet the need of user, is good in reputation of respective field. The system is designed to encourage the expert to give advice to user. We are focus on how to mine the expert in the user graph. Based on the set of users' FOAF profiles and UTG, we use the HMM (Hidden Markov Model) algorithm to recommend the top k experts to user. Given there are online community posts set T, FOAF profile set F and user interest clique set UIC.

PROBLEM DEFINITION 4(HMM Estimation Problem).

Given HMM parameters and observation sequence (user's FOAF profile lists), the way of quickly find the output probability of each recommend expert is based on their input probability.

HMM expert recognition Model: N, M, A, B, Π:

N(states 7): UIC 1, UIC 2…UIC 7(user interest clique)

M(exported symbols10:E1, E 2…E 10(Expert)

A(state-transition matrix): Upper triangular matrix according to K,T,U A={a_{ij}}

B(observation events for each state): 7*10 matrix according to K,T,U B={bj(k)} k=W_i

$$A = \begin{bmatrix} a_{11}, a_{12}, ..., a_{17} \\ 0, a_{22}, ..., a_{27} \\ 0, 0, ..., ... \\ 0, 0, ..., 0, a_{77} \end{bmatrix}, B = \begin{bmatrix} b_{11}, b_{12}, ..., b_{10} \\ b_{21}, b_{22}, ..., b_{20} \\ ..., ..., ..., ... \\ b_{71}, b_{72}, ..., b_{70} \end{bmatrix}$$

Algorithm3 :offline train: Parameter computing

Input: online community set T, FOAF profile set F

Output: E HMM model parameters for a specific user

1 extracts T, F text feature

2 Analysis V_j Properties in each of state W_i

3 Analysis transition probability of user's W_i

4 Forward and backward algorithm P (Otrain|λ):

$$P(O \mid \lambda) = \sum_{i=1}^{N} \alpha_t(i) \beta_t(i) = \sum_{i=1}^{N} \alpha_T(i), 1 \le t \le T-1 \quad (8)$$

5 Parameters iteration using Baum-Welch revaluation, to get HMM training model parameters

$$\overline{\pi_i} = \xi_1(i) \tag{9}$$

$$\bar{a}_{ij} = \sum_{t=1}^{T-1} \xi_t(i,j) / \sum_{t=1}^{T-1} \xi_t(i) \tag{10}$$

$$\bar{b}_{jk} = \sum_{\substack{t=1 \\ O_t = V_k}}^{T} \xi_t(j) / \sum_{t=1}^{T} \xi_t(j) \tag{11}$$

Algorithm4 :online prediction： Learning Problem

Input: Users interested in model parameters hmm <A,B,λ> user queries as single O

Output: sorted experts E1, E 2…E 10

Function [prob,q] = viterbi(hmm, O)

1 extraction new text feature

2 Initial probability Π and transition probabilities A

3 Best match path calculation: According to the probability and transition probability sequence

4 Viterbi：

$$\delta_t(j) = \max_{1 \le i \le N}[\delta_{t-1}(i)a_{ij}]b_j(o_t), \quad 2 \le t \le T, 1 \le j \le N \tag{12}$$

$$\psi_t(j) = \arg\max_{1 \le i \le N}[\delta_{t-1}(i)a_{ij}], \quad 2 \le t \le T, 1 \le j \le N \tag{13}$$

$$P^* = \max_{1 \le i \le N} \delta_T(i) \qquad q_T^* = \arg\max_{1 \le t \le N} \delta_T(i) \tag{14}$$

5 Calculate log probability: prob

6 sort R by prob

7 return R (set of Output probability P (O|M))

In the system, the text feature of online community set T, FOAF profile set F are not difficult to extracted when the total amount of the user data is in a small or middle scale such as 10,000 or less online user. However, the situation will become extremely emergence when the number of users is exceed 12,000, especially the real-time update or modify is required. As a result, the algorithm of HMM model is significant in time complexity. Beside, some computing procedures should be integrated in the modeling to improve the performance of the expert recognition.

When solving the problems of outputting the sorted experts E1, E 2…E 10 by inputting the Users interested in model parameters hmm <A,B,λ> user queries as single O, we can optimize model parameters [1,2,3,4,5,6,7,8], an adjustment of the parameters of the model is done. The Baum-Welch is used as mentioned in the previous section of this chapter. The adjustment of the model parameters should be done in a way that maximizes the probability of the model having generated the observation sequence.

$$\lambda^* = \arg\max_{\lambda}[P(O \mid \lambda)] \tag{15}$$

The ξ variable is calculated for every interest in the training session. This is used with the γ variable which is also calculated for every interest in the training session. It means that we have two (number of experts * samples per interest large) γ matrix. The following equation is used.

$$\zeta_t(i,j) = \alpha_t(i)a_{ij}b_j(o_{t+1})\hat{\beta}_{t+1}(j) / \sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_t(i)a_{ij}b_j(o_{t+1})\hat{\beta}_{t+1}(j) \tag{16}$$

$$\gamma_t(i) = \hat{\alpha}_t(i)\hat{\beta}_t(i) / \sum_{i=1}^{N}\hat{\alpha}_t(i)\hat{\beta}_t(i) \tag{17}$$

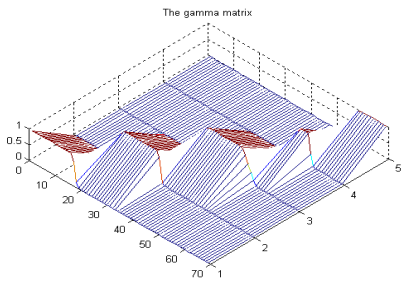

Figure 4. The Gamma Matrix

Note that there are no difference in using the scaled α and β due to the dependency of time and not of state.

IV. EXPERIMENTAL DESIGN

The purpose of this study was to determine if the BRRUS prototype could produce better clusters than the classic recommendation system Taste (http: //taste. sourceforge.net/) and to determine if users were more satisfied with the results from the new framework. We argued that, besides the huge efficiency gain, the proposed BRRUS algorithm is at least equally effective as compared to the classic Taste algorithm. That is, we hypothesized that BRRUS≥ Taste in terms of the three levels of reasoning effectiveness as stated in the research questions

A. Methodology

The methodology employed for this study was a within subject study of 40 students in our laboratory. Each subject performed two of the four tasks on the BRRUS system and the other two on the Taste method. Combinations of task order and system order were randomly assigned to the subjects. Through cross validation, we made sure that half of the subjects completed each task with the BRRUS system and the other half completed the same task with Taste.

There are more than 50 students in our institute of Web from different grades. We choose 40 of them from each grade. The subjects were asked to complete a demographic questionnaire which identified their age, sex, year in school, computer experience, Web searching experience. The average age of the subjects in this study was 24 years of age, with 40% of the subjects are undergraduate career, the other 50% are master candidate and the remaining 10% are doctor candidate. 70 % of the subjects were female and 30% of the subjects were male. The majority of the subjects indicated that they were experienced with computers and Web searching. Subjects were unaware of which algorithm they were using and additionally unaware of the fact that they were comparing two systems.

B. Dataset

There are two datasets used in our tasks. One is was a modified version of the Entree Chicago Recommendation Data and Syskill and Webert Web Page Ratings used for simulations. The former database

contains a record of user interactions with the Entree Chicago restaurant recommendation system. This is an interactive system that recommends restaurants to the user based on factors such as cuisine, price, style, and atmosphere, etc. or based on similarity to a restaurant in another city (e.g. find me a restaurant similar to the Patina in Los Angeles). The user can then provide feedback such as finding a nicer or less expensive restaurant. The later database contains the HTML source of web pages plus the ratings of a single user on these web pages. The web pages are on four separate subjects (Bands- recording artists; Goats; Sheep; and Biomedical).The other collection used for this study are from "http://km.aifb.kit.edu/projects/btc-2010/" The major part of the dataset was crawled during March/April 2010 based on datasets provided by Falcon-S, Sindice, Swoogle, SWSE, and Watson using the MultiCrawler/SWSE framework.

From the original corpus of documents, we removed all those documents which had no relevance assessments to build the simulation database. The remaining subset was classified to three data sets: the weather weatherset (4,842 tuples, and 6 keywords property), temporal and spatial reasoning sample Courtset (11,728 tuples and 5 keywords property) user FOAF profiles set FOAFset (4 Category properties and a keyword property, which probably includes 93,800 data records). The three data sets were manually constructed, mainly from some well-known portal site.

The experiment uses Protégé as the tool of ontology modeling and rules establishment, using Jena as the tool of reasoning and ontology information management, taking Graphiz as the tool of descriptive of relationship diagram between ontology class, using the QQwry database (version2010) as IP database, and with the help of JaHmm developing HMM algorithms in Eclipse. The detail experimental environment is shown as Table 3.

TABLE III. EXPERIENTIAL ENVIRONMENT

	Local Host	Extractor Host
CPU	2.8G	1.8G
MEMORY	2G	1G
OS	Windows Server2000's	Windows XP
PLATFORM	Eclipse 3.2.2	Eclipse 3.2.2
DEVELOP TOOL	Jena JaHmm Protégé	

V. RESULTS

Below we briefly discuss the efficiency of BRRUS and then focus on the effectiveness results from users study.

EVALUATION 1 Precision and Recall

The system effectiveness is measured in different ways. We use the two most frequent and basic measures for information retrieval effectiveness, which are precision and recall. In the experiment, firstly, we define some cases where the system returns a set of documents for a query. Then we extend these notions to ranked retrieval situations.

Precision $(\underline{P})$: fraction of retrieved documents relevant

$$\Pr ecision = \frac{\#(\text{relevant items retrived})}{\#(\text{retrieved items})} = P(relevant \mid retrieved)$$

Recall $(\underline{R})$: fraction of relevant documents retrieved

$$\operatorname{Re} call = \frac{\#(\text{relevant items retrived})}{\#(\text{relevant items})} = P(retrieved \mid relevant)$$

These evaluations can be made clear by examining the following contingency table:

Given:

	Relevant	Irrelevant
Retrieved	true positives (tp)	false positives (fp)
Not retrieved	false negatives (fn)	true negatives (tn)

Then:

$\underline{P}$	$\equiv$	$\mathrm{tp}/(\mathrm{tp}+\mathrm{fp})$
$\underline{R}$	$\equiv$	$\mathrm{tp}/(\mathrm{tp}+\mathrm{fn})$

Then the accuracy of BRRUS is shown as:

$$accuracy = (tp + tn)/(tp + fp + fn + tn)$$

In this experiment, there are two actual classes, relevant and irrelevant, and the information retrieval system can be thought of as a two-class classifier which attempts to label them as such. It retrieves the subset of documents which it believes to be relevant to get the precisely effectiveness measure

In almost all circumstances of the experiment, the data is extremely skewed: normally over 99.9% of the documents are in the irrelevant category. The system tuned to maximize accuracy can appear to perform well by simply deeming all documents irrelevant to all queries. There is a good reason why accuracy is not an appropriate measure for information retrieval problems.

We found it in the evaluation as following, even if the system is quite good, trying to label some documents as relevant will almost always lead to a high rate of false positives. However, labeling all documents as irrelevant is completely unsatisfying to an information retrieval system user. Users are always going to want to see some documents, and can be assumed to have a certain tolerance for seeing some false positives providing that they get some useful information. The measures of precision and recall concentrate the evaluation on the return of true positives, asking what percentage of the relevant documents has been found and how many false positives have also been returned.

The advantage of having the two numbers for precision and recall is that one is more important than the other in many circumstances. Typical web surfers would like every result on the first page to be relevant (high precision) but have not the slightest interest in knowing let alone looking at every document that is relevant. In contrast, various professional searchers such as paralegals and intelligence analysts are very concerned with trying to get as high recall as possible, and will tolerate fairly low precision results in order to get it. Individuals searching their hard disks are also often interested in high recall searches. Nevertheless, the two quantities clearly trade off against one another: you can always get a recall of 1 (but very low precision) by retrieving all documents for all queries. Recall is a non-

decreasing function of the number of documents retrieved. On the other hand, in a good system, precision usually decreases as the number of documents retrieved is increased. In general we want to get some amount of recall while tolerating only a certain percentage of false positives.

EVALUATION 2 F measure

Besides, a single measure that trades off precision versus recall is the F measure, which is the weighted harmonic mean of precision and recall:

$$F = 1/\alpha\frac{1}{p} + (1-\alpha)\frac{1}{R} = \frac{(\beta^2+1)PR}{\beta^2 P + R} \text{ where } \beta^2 = \frac{1-\alpha}{\alpha}, \alpha \in [0,1]$$

thus $\beta^2 \in [0,\infty]$. The default balanced F measure equally weights precision and recall, which means making $\alpha = 1/2$ or $\beta = 1$. It is commonly written as F_1, which is short for $F_{\beta=1}$, even though the formulation in terms of α more transparently exhibits the F measure as a weighted harmonic mean. When using $\beta = 1$, the formula on the right simplifies to: $F_{\beta=1} = 2PR / P + R$

However, using an even weighting is not the only choice. Values of $\beta < 1$ emphasize precision, while values of $\beta > 1$ emphasize recall. For example, a value of $\beta = 3$ or $\beta = 5$ might be used if recall is to be emphasized. Recall, precision, and the F measure are inherently measures between 0 and 1, but they are also very commonly written as percentages, on a scale between 0 and 100.

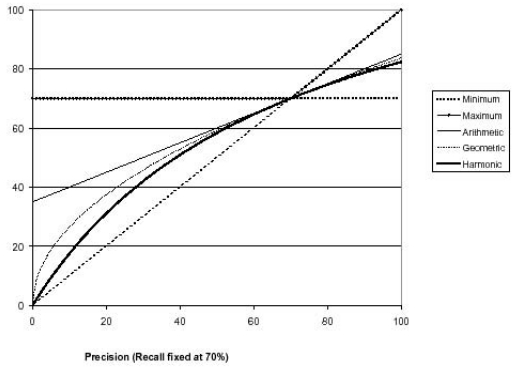

Figure 5. Harmonic Mean

Fig.5 compares the harmonic mean to other means. The graph shows a slice through the calculation of various means of precision and recall for the fixed recall value of 70%. The harmonic mean is always less than either the arithmetic or geometric mean, and is often quite close to the minimum of the two numbers. When the precision is also 70%, all the measures coincide. Table 4 and Fig.6 show maximum and threshold of different precision, recall and F-measure of the system.

TABLE IV. THE EVALUATION VALUES OF THE SYSTEM

	Threshold	Precision	Recall	F-measure
Max	0.85	0.81	0.61	0.69
Threshold	0.85	0.54	0.56	0.68

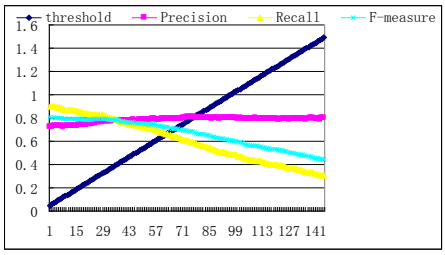

Figure 6. The diagram of performance of the system

As can be seen in Fig.7, the evaluation values of precision, in Fig.8 recall and in Fig.9 F-measure are improved after using the FOAF system. However, the precision is not satisfied comparing with the value of maximum situation.

We use a harmonic mean rather than the simpler average (arithmetic mean). Recall that we can always get 100% recall by just returning all documents, and therefore we can always get a 50% arithmetic mean by the same process. This strongly suggests that the arithmetic mean is an unsuitable measure to use. In contrast, if we assume that 1 document in 10,000 is relevant to the query, the harmonic mean score of this strategy is 0.02%. The harmonic mean is always less than or equal to the arithmetic mean and the geometric mean. When the values of two numbers differ greatly, the harmonic mean is closer to their minimum than to their arithmetic mean; see Fig.7.

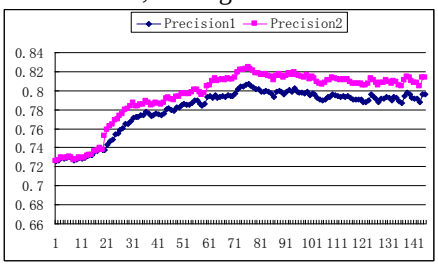

Figure 7. The Precision after using the system

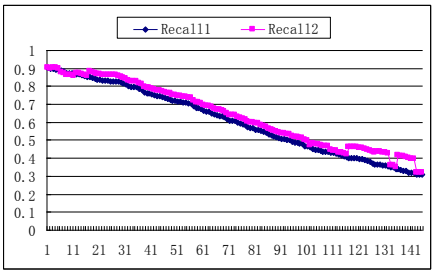

Figure 8. The Recall after using the system

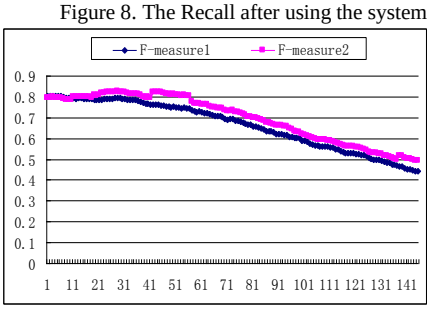

Figure 9. The F-measure after using the system

VI. CONCLUSIONS AND DISSCUSSION

This proposed model combines ontology with existing research and establishes the rule of information

integration, bases on the user information and ontology reasoning engine supplied by the clear FOAF (Friend of a Friend) to analyze the trust relationship among users and proceeding the experts discovery. The model is applicable to any personalized service, which contains the scenarios of temporal, spatial and user relationship. The model uses the classical trust network as the reasoning theory base of recommendation model. and takes sports (involved in spatial and temporal information and user relations) as a model case. The Model is stored in the user's local host, which is based on the user's geographical location and the system running time to recommend the possible free surrounding sites; recommend may be spatial and temporal consistent friends according to the user relations.

ACKNOWLEDGMENTS

The work is supported by the Fundamental Research Funds for the Central Universities (Wuhan University.China) (Grant No. 20102110101000101).

REFERENCES

[1] R. Stecher , C. Niederée , "Wildcards for Lightweight Information Integration in Virtual Desktops," CIKM'08, October 26–30, 2008, Napa Valley, California, USA.

[2] R. Ghosh, M. Dekhil, "Mashups for Semantic User Profiles," WWW 2008, April 21--25, 2008, Beijing, China.

[3] M. M. Tuffield, "The Semantic Logger: Supporting Service Building from Personal Context," CARPE'06, October 28, 2006, Santa Barbara, California, USA.

[4] S. Reymann, D. S. Alves, Artur Lugmayr, "Personalized Social Networking: an Applied Scenario in a Portable Personality Environment," MindTrek 2008, October 7–9, 2008, Tampere, Finland.

[5] D. Konopnicki , O. Shmueli, "Database-Inspired Search," Proceedings of the 31st VLDB Conference, Trondheim, Norway, 2005.

[6] S Bortoli, H Stoermer, P Bouquet, H Wache, "Foaf-O-Matic - Solving the Identity Problem in the FOAF Network," 4th Italian Semantic Web Workshop SEMANTIC WEB APPLICATIONS AND PERSPECTIVES (SWAP 2007) Bari, December 18-20, 2007 Proceedings.

[7] J. Golbeck and J. Hendler, "Reputation network analysis for email filtering," In Proceedings of the First Conference on Email and Anti-Spam, 2004.

[8] S. Ben Mokhtar, L. Capra, "From Pervasive To Social Computing: Algorithms and Deployments," ICPS'09, July 13–17, 2009, London, United Kingdom.

[9] M. Hamasaki,Y. Matsuo, "An Integrated Method for Social Network Extractio," WWW 2006, May 23–26, 2006, Edinburgh, Scotland.

[10] S. Adnan, A. Tahir, A. Basharat,"Semantic Agent Oriented Architecture for Researcher Profiling and Association (SemoRA)," 2009 IEEE DOI 10.1109/WI-IAT.2009.349.

[11] P. Avesani, P. Massa, and R. Tiella, "Moleskiing it: a trust-aware recommender system for ski mountaineering," International Journal for Infonomics, 2005.

[12] J. J. Carroll, C. Bizer, "Named Graphs, Provenance and Trust," WWW 2005, Chiba, Japan.

[13] J. Bringel Filho, H. Martin, "A Generalized Context-based Access Control Model for Pervasive Environments," ACM SPRINGL '09, 2009. Seattle, WA, USA.

[14] J. Warner , "Soon Ae Chun A Citizen Privacy Protection Model for E-Government Mashup Services," The Proceedings of the 9th Annual International Digital Government Research Conference.

[15] S. Ryszard Kruk, S. Grzonkowski, A. Gzella, "D-FOAF: Distributed Identity Management with Access Rights Delegation Social Networks as a Mean to Delegate Trust," ASWC 2006, LNCS 4185, pp. 140–154, 2006.

[16] T. Akahoshi, M. Okamoto, M. Shimomura and N. Komatsu, "Improving the Safety and Practicality of Authorization Technology Using LOAF," DIM'09, November 13, 2009, Chicago, Illinois, USA.

[17] J. Mori, T. ugiyama, "Real-world Oriented Information Sharing Using Social Networks," GROUP'05, November 6-9, 2005, Sanibel Island, Florida, USA.

[18] Y. Matsuo, J. Mori, "POLYPHONET: An Advanced Social Network Extraction System from the Web," WWW 2006, Edinburgh, Scotland.

[19] W. Shi, J. Wu, Y. Li, Z. H. Wu, "Using Improved FOAF to Enhance BPEL-extracted RBAC Capability," 2007 IEEE/WIC/ACM International Conference on Web Intelligence.

[20] J. T. Yao, "An introduction to Web-based support systems," Journal of Intelligent Systems 17 (1-3) (2008) 267-281.

Shijun Li, Hunan, China, 1964
Professor, Wuhan University,
Bachelor: mathematics Beijing Normal University 1987
Master: Computer School of Wuhan University, Wuhan, China, 1998
Docter: Computer school of Wuhan University,Wuhan,China,2001
Visiting scholar: Computer department of Carleton University, Canada, 2003

Yunlu Zhang, Henan, China, 1985
Bachelor: e-Business Engineering, PLA Information Engineer University, 2007
Master: computer application, Wuhan University, Wuhan, China, 2009
First-year PhD student:computer application Wuhan University, Wuhan, China, 2009