Recommendation Technique-based Government-to-Business Personalized e-Services

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Abstract— **One of the new directions in current e-government development is to provide personalized online services to citizens and businesses. Recommendation techniques can bring a possible solution for this issue. This study proposes a hybrid recommendation approach to provide personalized government to business (G2B) e-services. The approach integrates fuzzy sets-based semantic similarity and traditional item-based collaborative filtering methods to improve recommendation accuracy. A recommender system named Intelligent Business Partner Locator (IBPL) is designed to apply the proposed recommendation approach for supporting government agencies to recommend business partners.**

Keywords: Recommender Systems, Personalization, E-government, E-Services, Fuzzy sets, Collaborative Filtering.

I. INTRODUCTION

Web-based technologies offer governments more efficient and effective means than traditional physical channels to provide high quality online services to their citizens, businesses and other arms of government. Government online services, including those delivering government information to citizens and businesses, and enabling them to make online transactions, have been well-developed in the last few years [1]. In Australia, the use of e-government services has seen continual growth since 2004, with a corresponding decline in contact in person over the same period. This growth in government e-services has mainly been driven by the Internet, as Internet use has doubled from 2004 to 2008 [2].

There is growing evidence that businesses are positioned to make effective use of e-government; meanwhile, e-government is progressing faster for business services than for citizens. The European Commission Report states that the fully-online availability of public services for businesses is considerably higher than that for citizens and stands at 70% [3]. Government to Business (G2B) e-services involve information distributions, transactions and interactions with businesses in various aspects through e-government websites. For example, the Australian federal government (http://www.australia.gov.au/) provides services for business number (ABN) online application, tax return online application and AusTender publication of Australian business opportunities, annual procurement plans, multi-use lists and contracts awarded. The U.S. Commercial Service (http://www.buyusa.gov) offers valuable assistance to help American businesses export goods and services to markets worldwide. One of the services is to help businesses find and communicate with potential and current international business partners from many countries, according to their needs and requirements, in a short period of time. This study will focus on G2B e-services.

The amount of information available on the Web is overwhelming, and business users of e-government are constantly facing the problem of information overload. This increasing information overload could hinder government G2B e-service effectiveness. Obviously, the difficulties of locating the right information for the right users would increasingly affect loyalty to returning to those e-government websites. Web-based personalized e-service, otherwise known as 'e-service personalization techniques', aims to provide a solution for this problem. E-service personalization can be defined as the ability to use information technology to provide content and services to individuals based on their preferences and behaviors [4]. It can be seen as an evolution of the intentions-based approach and will be one of the next directions of government e-services [5].

Recommender systems, as one of the most popular implementations of e-service personalization techniques, have gained much attention and real-world developments in the past ten years [6]. Recommender systems apply knowledge discovery techniques to the problem of making personalized recommendations for information, products or services during a live interaction. These systems, especially the *k*-nearest neighbor collaborative filtering (CF)-based approaches, are achieving widespread success on the Web [7]. Various recommender systems have been extensively applied in e-commerce and e-business [8, 9], but their adoption in the context of e-government has received less attention. This study presents a recommender system design, named Intelligent Business Partner Locator (IBPL), which aims to help government effectively recommend the right business partners (e.g., international buyers, agents, distributors, and retailers) to individual businesses (e.g., exporters) based on their requirements, interests and business product categories. The proposed IBPL system integrates fuzzy sets-based semantic similarity and traditional item-based collaborative filtering methods for improving the accuracy of recommendations.

The rest of this paper is organized as follows. Section 2 presents the related works on e-government, personalized e-service and recommender systems. Section 3 describes a fuzzy semantic product relevance (FSPR) model and a hybrid recommendation approach which integrates the fuzzy sets-based semantic similarity with traditional item-based collaborative filtering methods. In Section 4, the design of the IBPL recommender system, which contains the proposed FSPR model and the hybrid recommendation approach, is presented. An illustrative example is given in Section 5 for explaining the working process of the IBPL recommender system. Finally, conclusions and future study are discussed in Section 6.

II. Related Works

This section first reviews the concepts of personalized e-services in the e-government field. It then analyses current recommendation techniques and their applications.

A. E-Government and Personalized E-Services

Governments worldwide are increasingly using the Internet to provide more effective and efficient public services to their citizens and businesses [4]. However, the current solution of e-government services is mainly a 'one size fits all' service which cannot satisfy the increasing service requirements of individual users. As a new direction of e-government, personalized e-services are highly demanding. Literature shows three main types of personalized e-service applications:

1) Adaptive website: This is defined as the process of modifying the content and structure of websites according to individual users' preferences. Zotos, Stamou, Tzeko and Kozanidis [10] proposed a novel website customization model that personalizes the site's contents and structure according to a particular user's needs by learning from the user's interests which are identified and described through the user's website navigation records.

2) Personalized search: This tailors the search results according to each user's personal needs. Ma, Pant and Sheng [11] suggested a personalized mapping framework that automatically maps a set of known user interests onto a group of categories in the open directory project, which therefore categorizes and personalizes search results according to a user's interests.

3) Recommender system: This is defined as "personalized information filtering technology used to either predict whether a particular user will like a particular item (prediction problem) or to identify a set of N items that will be of interest to a certain user (top-N recommendation problem)" [12].

Personalized e-services offered by e-Government aim to achieve a high level of government online service integration and support flexible, user-friendly, precise, targeted and non-baffling online services to both citizens and business users. Several researchers have explored possible ways to develop personalized government e-services. For example, Grandi et al. [13] presented the design of ontology-based personalized techniques to the choice and execution of e-government web services. They also implemented a personalized system to support citizen efficient and personalized access to multi-version resources in an e-government scenario by using semantic web techniques and an ontology-based user-profiling approach. The authors Guo and Lu [5] proposed a personalized recommender system which can handle one-and-only item recommendation issues and can be applied in G2B online services for recommending suitable exhibitions to individual business users. Furthermore, Pasquale et al. [14] proposed a personalized multi-agent system which is capable of suggesting the most interesting government services to citizens by taking into account both their preferences and the capabilities of the devices. However, compared with e-commerce and e-business, current e-government service developments are still lacking effective, automatic, flexible, intelligent and efficient personalization facilities, and there is relatively little research effort on applying personalization techniques in the context of e-government services [5, 13, 14].

B. Recommender Systems

Recommender systems attempt to predict some items of services or products that a user may be interested in. Various recommendation systems have been developed and many explicit and implicit data collection methods have been used in recommender systems [4]. In general, recommender systems are classified by the recommendation approaches or algorithms used [12]. From the literature, there are four typical classes of recommendation approaches as follows:

1) Collaborative Filtering (CF)-based: CF is probably the most familiar and widely adopted recommendation technique. It has been used in many different e-service applications such as e-commerce, e-learning, e-tourism, and so on. It operates upon the assumption that users who have exhibited similar behavior in the past can serve as recommenders for each other on unobserved data items [6]. It contains user-based and item-based approaches. The item-based approach looks into the set of items the target user has rated and computes how similar they are to the target item *i* and then selects k most similar items to the user. Once the most similar items are found, the prediction is then computed by taking the target user's ratings on these similar items. However, the widespread use of CF-based recommendation methods has exposed two major limitations. The first is related to sparsity. The sparse user-item problem occurs if the number of ratings obtained is very small compared to the number of ratings that need to be predicted. As a result, a recommender system becomes unable to locate successful neighbors and generates a weak recommendation. The second is related to scalability. The CF-based recommendation algorithms require calculations to find the neighborhood, which grow linearly with both the number of users and the number of items. Thus, as users and resources increase, the system's performance tends to decrease to some extent [4, 6].

2) Content-based (CB): The CB approach mainly relies on the content and relevant profiles to generate personalized recommendations. The basic principle of the CB approach is that it learns users' preferences based on product (item) features to generate a recommendation [6]. It often compares contents and user profiles in order to recommend items which are similar to those a given user liked in the past.

3) Knowledge-based (KB): The KB recommendation approaches attempt to suggest objects based on inferences about a user's needs and preferences. A KB recommendation system uses knowledge bases in relevant to users and items to generate recommendations [15]. For example, Prasad [8] presented a knowledge-based product recommendation system, RecommendEx, for e-commerce purposes. The system used case-based reasoning plan recognition approaches and automated collaborative filtering approaches in its applications.

4) Hybrid-based: Hybrid recommender systems combine two or more recommendation approaches to gain better performance with fewer of the drawbacks of any individual one. Thus the goal of a hybrid recommender system is to overcome the shortcomings of the individual recommender techniques. Many hybrid recommender systems have been developed in different ways [15], such as the combination of the CF and CB approaches.

C. Recommender systems with fuzzy logic techniques

Recommendations to online users are often made under incomplete and uncertain information. The similarity between items or between users is naturally with fuzziness. Fuzzy set theory lends itself well to handle the fuzziness and uncertain issues in the recommendation problems [16]. Recent research efforts have indicated that fuzzy sets, fuzzy logic and fuzzy relations are potentially within the domain of recommender systems [16-18]. For example, Chen and Duh [17] developed a personalized intelligent tutoring system based on the proposed fuzzy item response theory, which is capable of recommending courseware with suitable difficulty levels for learners according to a learner's uncertain responses. Cornelis, Lu, Guo and Zhang [16] developed a conceptual framework for recommending one-and-only items using fuzzy logic techniques to overcome the limitations of existing recommendation techniques in an uncertain information processing and matching. Furthermore, Leung, Chan and Chung [18] proposed the use of the fuzzy association rules to solve the sharp boundary problem, which was associated with the CF approach as major drawback.

However, with the complexity of e-services in a G2B framework, there is a need to develop new recommendation techniques to deal with semantic features and attributes of various e-services in the G2B field.

III. A Hybrid Recommendation Approach

This section first proposes a fuzzy semantic product relevance (FSPR) model. It then presents a hybrid recommendation approach which applies fuzzy numbers to deal with the semantic similarity issue in order to generate recommendations of business partners. The approach is described by four main steps.

A. A Fuzzy Semantic Product Relevance Model

In principle, semantic information about an item consists of the attributes of the item, the relationship of the item to other items, and other meta-information [4]. Usually, attributes describe different types of distinguishing features of an item, and provide the opportunity to capture details about the item [19]. On the other hand, product taxonomy plays an important role in presenting online information and a business type. It is used for identifying similar products and grouping them together, by specifying the level of aggregation provided by market managers or domain experts [4, 5]. In this study, by combining the semantic similarity and product taxonomy approaches, we propose the FSPR model to conduct the semantic-based product relevance analysis.

Unlike comparing two books or two movies in online shopping systems, we cannot compare two business partners simply based on their names. We will consider the similarity between two business partners based on exporters' preferences. We will also consider their product taxonomy to calculate their similarity. As both interests and relevance are subjective opinions, they are often expressed by linguistic terms by business users or experts. Therefore, two sets of linguistic terms will be used in the proposed recommendation approach.

The first linguistic term set is {*Strongly Interested, More Interested, Interested, Less Interested, Not Interested*}, as shown in Table I, to represent the interest/preference degree of a user to an item. In our example, a linguistic term expresses an exporter's interest/preference degree for a business partner. Another set of linguistic terms *{Strongly Related, More Related, Related, Less Related, Not Related}* is the relevance degree of a partner's products to a target product category as shown in Table II. A business partner may have many kinds of products, and each particular type of product has a relevance degree to a product category which can be expressed by an appropriate linguistic term. As these linguistic terms will be handled by fuzzy numbers, we call it fuzzy semantic product relevance (FSPR). Fig. 1 shows an example of the FSPR model. It presents the relevance degrees between a product category (Electronics) and two business companies (Apple Inc and Nortel Networks) with their products' subcategories (audio, computers, portable devices, and networking).

To use this model, domain experts can first define semantic relevance degrees related to the electronics category, for example, to businesses according to their product taxonomy. When an exporter wants to find a business partner with an indicated product category, the FSPR model can help find potential businesses which have relevant products to the category given by the exporter. In the context of our research, the use of linguistic terms also allows domain experts distributed in different locations to participate in the activity through the Web to provide semantic product relevance by defining the relevance weights of each product to its category/subcategories.

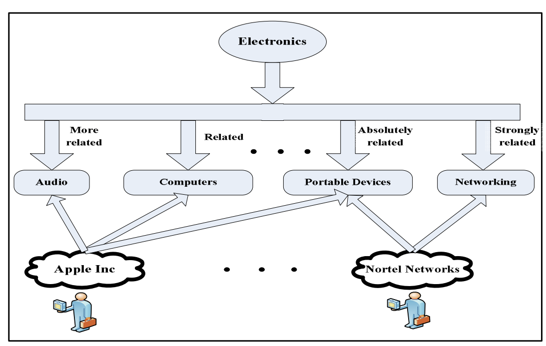

Figure 1. An example of FSPR model

Since these two sets of linguistic terms reflect the uncertainty, inaccuracy and fuzziness of humans, fuzzy numbers (see Tables I and II) are suitable techniques to be directly applied to deal with them [20].

TABLE I. LINGUISTIC TERMS AND RELATED FUZZY NUMBERS FOR EXPORTERS' INTEREST DEGREES TO A PARTNER

Linguistic term	Fuzzy numbers
Strongly Interested (SI)	a_1
More Interested (MI)	a_2
Interested (IN)	a_3
Less Interested (LI)	a_4
Not Interested (NI)	a_5

TABLE II. LINGUISTIC TERMS AND RELATED FUZZY NUMBERS FOR RELEVANCE DEGREES TO A PRODUCT TYPE

Linguistic term	Fuzzy numbers
Strongly Related (SR)	b_1
More Related (MR)	b_2
Related (R)	b_3
Less Related (LR)	b_4
Not Related (NR)	b_5

Now we give definitions of the fuzzy numbers used in Tables I and II.

Let $F(R)$ be the set of all fuzzy numbers. By the decomposition theorem of fuzzy set [21], we have

$$a = \bigcup_{\lambda \in (0,1]} \lambda [a_\lambda^-, a_\lambda^+], \quad \text{and} \quad b = \bigcup_{\lambda \in (0,1]} \lambda [b_\lambda^-, b_\lambda^+],$$

For example, as shown in Fig. 2,

$$a_1 = \bigcup_{\lambda \in [0,1]} \lambda [0, \frac{1-\lambda}{4}], a_3 = \bigcup_{\lambda \in [0,1]} \lambda [\frac{1+\lambda}{4}, \frac{2-\lambda}{4}], a_5 = \bigcup_{\lambda \in [0,1]} \lambda [\frac{3+\lambda}{4}, 1].$$

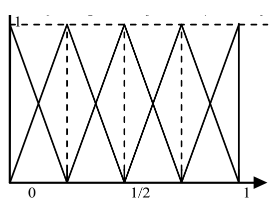

Figure 2. Example of fuzzy numbers

For any $a, b \in F(R)$, we define

$$a + b = \bigcup_{\lambda \in (0,1]} \lambda [a_\lambda^L + b_\lambda^L, a_\lambda^R + b_\lambda^R],$$

$$a \times b = \bigcup_{\lambda \in (0,1]} \lambda [a_\lambda^L \times b_\lambda^L, a_\lambda^R \times b_\lambda^R].$$

These definitions of fuzzy numbers will be used in a linguistic term similarity calculation in the proposed hybrid recommendation approach.

B. Recommendation Approach Description

The item-based CF approach first analyzes the user-item matrix to identify similarity relationships between different items. It then uses these relationships to indirectly compute recommendations for users. These items can be products, information, or in our case, business partners, and the users are exporters. The proposed approach looks into business partners and finally selects *k* most suitable ones to an active exporter by fuzzy similarity-based prediction.

Let $C=\{c_1, c_2, \ldots c_N\}$, $N>1$, be a given set of possible business partners, and $E=\{e_1, e_2, \ldots e_M\}$, $M>1$ be a given set of exporters, $P=\{p_1, p_2, \ldots p_T\}$, $T>1$ be a set of target products of exporters. The proposed approach generates recommendations to each exporter through the following four steps.

Step1: Calculate *CF fuzzy similarity* between partners

The step first builds a user-item (exporter-partner) rating matrix by collecting exporters' interests to possible business partners. Let $a_{m,p}$ represent the rating (interest degree) of an exporter e_m on a partner c_p, $a_{m,p} \in$ {*Strongly Interested, More Interested, Interested, Less Interested, Not Interested*}. The exporter-partner rating matrix is $(a_{m,p})_{M*N}$.

This step then computes the item-based CF fuzzy similarity between any partners c_p and c_q, $p, q=1, 2, \ldots N$. The Pearson correlation coefficient is used here as a similarity measure since the previous research has shown its superiority in performance over others [6]. We denote the *CF fuzzy similarity* between two business partners (c_p and c_q) by

$$S_{CF}(c_p,c_q)= \frac{\sum_{m=1}^{M}\int_0^1 \frac{1}{2}\left[(a_{m,p_\lambda}^- - \bar{a}_{p_\lambda}^-)\times(a_{m,q_\lambda}^- - \bar{a}_{q_\lambda}^-)+(a_{m,p_\lambda}^+ - \bar{a}_{p_\lambda}^+)\times(a_{m,q_\lambda}^+ - \bar{a}_{q_\lambda}^+)\right]d\lambda}{\sqrt{\sum_{m=1}^{M}\left(\int_0^1 \frac{1}{2}\left[(a_{m,p_\lambda}^- - \bar{a}_{p_\lambda}^-)+(a_{m,p_\lambda}^+ - \bar{a}_{p_\lambda}^+)\right]d\lambda\right)^2} \times \sqrt{\sum_{m=1}^{M}\left(\int_0^1 \frac{1}{2}\left[(a_{m,q_\lambda}^- - \bar{a}_{q_\lambda}^-)+(a_{m,q_\lambda}^+ - \bar{a}_{q_\lambda}^+)\right]d\lambda\right)^2}} \quad (1)$$

where a_{m,p_λ} and a_{m,q_λ} represent the ratings of exporter e_m on partners c_p and c_q under λ-cut respectively, $a_{p_\lambda}^-$ and $a_{q_\lambda}^+$ are the left-end and right-end of λ-cut respectively, $\bar{a}_{p_\lambda}$ and $\bar{a}_{q_\lambda}$ are the average rating of the *M* exporters on c_p, c_q respectively.

Step 2: Calculate *semantic fuzzy similarity* between partners

In general, semantic similarity [19] refers to the similarity between two concepts or items. The semantic similarity in this step represents the degree of semantic relevance between the types of two business partners. Unlike comparing two books, we cannot obtain type similarity between two businesses through comparing their names. We need to test the type similarity between two businesses through comparing the relevance of their product categories or subcategories to the target product category required by the exporter.

According to the FSPR model shown in Fig. 1, both the relevant degrees of categories on the products of a business partner and the product taxonomy tree are taken into consideration. This step first determines a category for a particular product or sub-category given by an exporter using a product taxonomy tree. For example, when an exporter gives a product 'Computer', a category 'Electronic' is determined by a product taxonomy tree. It then uses the relevance degrees, *{Strongly Related, More Related, Related, Less Related, Not Related}* of the category to the products of partners as the relevance degrees of the given product or subcategory to these partners' products.

Let $b_{t_p,p} = \frac{\sum_{1}^{S_p} D_{t_p,i}}{5 \times S_p}$ represent the semantic relevance rating of the tth target product on pth partner c_p, where S_p is the number of products of the pth partner related to the target product of the exporter, $D_{t_p,i}$ is the tth target product's relevance degree on ith product of the pth partner. We then have a product-partner semantic relevance matrix $(b_{t_p,i})_{T*N}$, where T is the number of target products of exporters, N is the number of business partners $C=\{c_1, c_2, \ldots c_N\}$. The fuzzy semantic similarity measure $S_{Sem}(c_p,c_q)$, for partners c_p and c_q, is then computed using the standard vector-based cosine similarity [6]:

$$S_{Sem}(c_p,c_q) = \frac{\sum_{t=1}^{T}\int_0^1 \frac{1}{2}\left(b_{t,p_\lambda}^{-} \times b_{t,q_\lambda}^{-} + b_{t,p_\lambda}^{+} \times b_{t,q_\lambda}^{+}\right) d\lambda}{\sqrt{\sum_{t=1}^{T}\int_0^1 \frac{1}{2}\left({b_{t,p_\lambda}^{-}}^2 + {b_{t,p_\lambda}^{+}}^2\right) d\lambda}\sqrt{\sum_{t=1}^{T}\int_0^1 \frac{1}{2}\left({b_{t,q_\lambda}^{-}}^2 + {b_{t,q_\lambda}^{+}}^2\right) d\lambda}} \quad (2)$$

where b_{t,p_λ} and b_{t,q_λ} represent the semantic relevance rating of the tth target product of an exporter on possible business partners c_p and c_q under a fuzzy λ-cut respectively.

Step 3: Integrate the item-based CF fuzzy similarity with the semantic fuzzy similarity

In this step, we integrate the two similarities to get *TotalSim*(c_p, c_q) through their linear combination:

$$TotalSim\,(c_p,c_q) = \beta * S_{CF}(c_p,c_q) + (1-\beta) * S_{Sem}(c_p,c_q), \quad (3)$$

where β is a semantic combination parameter specifying the weight of similarity in the integrated measure. Finding an appropriate value for β is usually highly dependent on the characteristics of the data used. We can choose a proper value by performing sensitivity analysis for particular data sets.

Step 4: Generating prediction values for recommendation

The most important step in a recommendation approach is to generate predictions. Once we isolate the set of most similar items we will look into the target exporters' ratings. This approach will compute the prediction on a partner c_p for an exporter e by computing the sum of the ratings given by the export on the items similar to c_p. Each rating is weighted by the corresponding similarity *TotalSim*(c_p, c_q) between partners c_p and c_q. The predicted rating value (PV) is calculated by

$$PV_{e,p} = \frac{\sum_{q=1}^{v}(a_{e,q} \times TotalSim\,(c_p,c_q))}{\sum_{q=1}^{v} TotalSim\,(c_p,c_q)}, \quad (4)$$

where $a_{e,p}$ denotes the rating value of the active exporter e on partner c_q, v is the number of its similar partners. Finally, for the active exporter, a prediction value vector with v business partners' prediction values is obtained and top K ($K<=v$) prediction values are selected. The corresponding potential business partners of the K prediction values constitute a recommendation list to the exporter.

IV. An Intelligent Business Partner Locator Recommender System

This recommendation approach is applied in the design of a recommender system prototype named Intelligent Business Partner Locator (IBPL). This recommender system can suggest relevant potential business partners to individual exporters. The framework of the IBPL recommender system is shown in Fig. 3. It constitutes of three main components:

1) Data Collector: Involves the collection of business user preference and businesses profile information;

2) DB Builder: Involves the development of three databases: product relevance database, businesses profile database and users' ratings database;

3) Recommendation Engine: Generates a recommendation list of potential business partners to individual exporters according to their product types and preferences. It consists of three parts:

a) Item-based CF fuzzy similarity analyzer: to calculate exporter-partner matrix and then use these ratings to find all similar businesses based on exporters' preferences.

b) Semantic similarity analyzer: to use the FSPR model to extract the semantically similar business partners.

c) Recommendation generator: to offer prediction rating values of similar businesses based on integrating the two similarity measures and then generate top-k partners for recommending to the exporter.

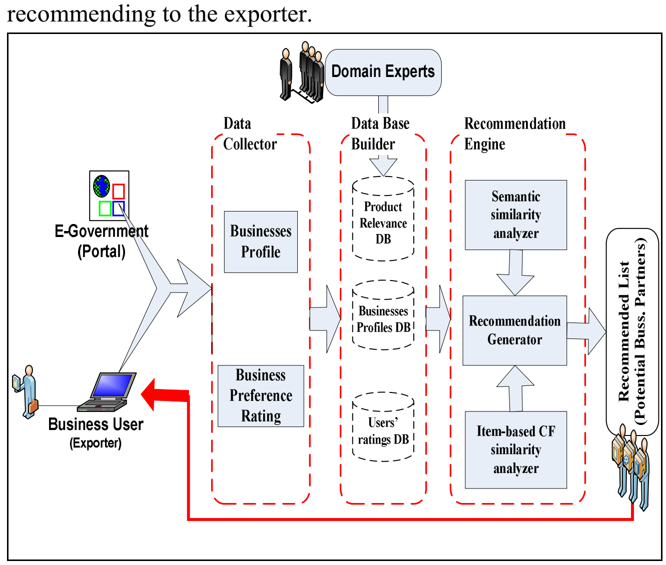

Figure 3. The IBPL System Framework

V. An Illustrative Scenario

In this section, we briefly present a simple recommendation scenario to illustrate the applicability of the proposed approach in supporting exporters to find relevant business partners. This scenario is envisioned in the context of the online services of the Australian e-government portal business.gov.au, which offers businesses convenient access to all government information and services. In this context, the business.gov.au portal is going to host a web-based directory of businesses that offers diverse products and services. The users of the web portal will be able to register their businesses online and complete a rating form beside their business profile before using the recommendation service. The FSPR model can therefore be built.

Based on the proposed approach, a sample of an exporter-partner rating matrix $(a_{m,p})_{M*N}$ is shown in Table III, where there are 3 exporters and 5 potential partners. The missing data is presented as 'null' and calculated as 0 in the method. First, in order to obtain the CF fuzzy similarity matrix $S_{CF}(c_p, c_q)$ $_{5*5}$ and the semantic fuzzy similarity matrix $S_{Sem}(c_p, c_q)$ $_{5*5}$, similarity of each pair of partners is calculated by using (1) and (2) respectively. Then, by giving a proper weight, for example let $\beta = 0.5$, the $TotalSim(c_p, c_q)_{5*5}$ can be obtained based on (3). Finally, the prediction value of each potential partner for each exporter can be calculated by (4), as shown in Table IV. Therefore, for an exporter e_1, for example, the top-2 most recommended partners are c_3 ($PV_{e1,c3} = 0.88$) and c_1 ($PV_{e1,c1} = 0.85$).

TABLE III. Exporter-Partner rating matrix

	c_1	c_2	c_3	c_4	c_5
e_1	Srongly Interested	Not Interested	Null	Interested	More Interested
e_2	More Interested	Srongly Interested	More Interested	More Interested	Less Interested
e_3	Interested	Null	Interested	Srongly Interested	Srongly Interested

TABLE IV. Exporter-Partner Prediction Value Matrix

	c_1	c_2	c_3	c_4	c_5
e_1	0.85	0.34	0.88	0.7	0.67
e_2	0.5	0.76	0.77	0.65	0.59
e_3	0.54	0.65	0.53	0.87	0.96

VI. Conclusion and Future Work

This study proposes a hybrid personalized recommendation approach to support exporters seeking business partners in e-government to business online services. The approach integrates the item-based CF approach with semantic similarity analysis techniques. This approach has been applied in the design of a recommender system prototype called IBPL. This system can recommend relevant business partners to individual exporters, and therefore will reduce the time, cost and risk of businesses involved in entering international markets. Further study will concentrate on the implementation of the IBPL system and the evaluation the proposed approach.

References

[1] D. Evans and D. C. Yen, "E-Government: Evolving relationship of citizens and government, domestic, and international development," Government Information Quarterly, vol. 23, pp. 207-235, 2006.

[2] AGIMO, "Australians' use and satisfaction with e-government services," 2008.

[3] P. Wauters, M. Nijskens, and J. Tiebout, "The user challenge: Benchmarking the supply of online public services–7th Measurement," 2007.

[4] X. Guo, "Personalized Government online services with recommendation techniques," in Faculty of Engineering and Information Technology. vol. PhD: University of Technology Sydney, 2006.

[5] X. Guo and J. Lu, "Intelligent e-government services with personalized recommendation techniques: Research Articles," Int. J. Intell. Syst., vol. 22, pp. 401-417, 2007.

[6] G. Adomavicius and A. Tuzhilin, "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions," IEEE Trans. on Knowl. and Data Eng., vol. 17, pp. 734-749, 2005.

[7] B. Sarwar, G. Karypis, J. Konstan, and J. Reidl, "Item-based collaborative filtering recommendation algorithms," in Proceedings of the 10th International Conference on World Wide Web, 2001, pp. 285-295.

[8] B. Prasad, "A knowledge-based product recommendation system for e-commerce," International Journal, vol. 1, pp. 18-36, 2007.

[9] K. Wei, J. Huang, and S. Fu, "A survey of e-commerce recommender systems," in International Conference on Service Systems and Service Management, 2007, pp. 1-5.

[10] N. Zotos, S. Stamou, P. Tzekou, and L. Kozanidis, "Adaptive web site customization," iMetadata and Semantics, 2009, pp. 353-363.

[11] Z. Ma, G. Pant, and O. R. L. Sheng, "Interest-based personalized search," ACM Transactions on Information Systems (TOIS), vol. 25, 2007.

[12] N. Manouselis and C. Costopoulou, "Analysis and classification of multi-criteria recommender systems," World Wide Web, vol. 10, pp. 415-441, 2007.

[13] F. Grandi, F. Mandreoli, R. Martoglia, E. Ronchetti, M. Scalas, and P. Tiberio, "Semantic web techniques for personalization of eGovernment services," Advances in Conceptual Modeling - Theory and Practice, 2006, pp. 435-444.

[14] M. Pasquale De, Q. Giovanni, U. Domenico, and T. Giorgio, "A multi-agent system for the management of e-Government services," in Proceedings of the IEEE/WIC/ACM International Conference on Intelligent Agent Technology, 2005, pp. 718-724.

[15] R. Burke, "Hybrid web recommender systems," The Adaptive Web, 2007, pp. 377-408.

[16] C. Cornelis, J. Lu, X. Guo, and G. Zhang, "One-and-only item recommendation with fuzzy logic techniques," Information Sciences, vol. 177, pp. 4906-4921, 2007.

[17] C.-M. Chen and L.-J. Duh, "Personalized web-based tutoring system based on fuzzy item response theory," Expert Syst. Appl., vol. 34, pp. 2298-2315, 2008.

[18] C. W. Leung, S. C. Chan, and F. Chung, "A collaborative filtering framework based on fuzzy association rules and multiple-level similarity," Knowledge and Information Systems, vol. 10, pp. 357-381, 2006.

[19] P. Resnik, "Using information content to evaluate semantic similarity in a taxonomy," in Proceedings of the 14th International Joint Conference on Artificial Intelligence, Montreal, Canada, 1995, pp. 448-453.

[20] J. Lu, D. Ruan, and G. Zhang, "Fuzzy set techniques in e-Service applications," Fuzzy Sets and Their Extensions: Representation, Aggregation and Models, 2008, pp. 553-566.

[21] E. E. Kerre, "Introduction to the basic principles of fuzzy set theory and some of its applications", Communication & Cognition Ghent, Belgium, 1991.