

Sem-Fit: A semantic based expert system to provide recommendations in the tourism domain



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ABSTRACT

The hotel industry is one of the leading stakeholders in the tourism sector. In order to reduce the traveler's cost of seeking accommodations, enforce the return ratio efficiency of guest rooms and enhance total operating performance, evaluating and selecting a suitable hotel location has become one of the most critical issues for the hotel industry. In this scenario, recommender services are increasingly emerging which employ intelligent agents and artificial intelligence to "cut through" unlimited information and obtain personalized solutions. Taking this assumption into account, this paper presents Sem Fit, a semantic hotel recommendation expert system, based on the consumer's experience about recommendation provided by the system. Sem Fit uses the consumer's experience point of view in order to apply fuzzy logic techniques to relating customer and hotel characteristics, represented by means of domain ontologies and affect grids. After receiving a recommendation, the customer provides a valuation about the recommendation generated by the system. Based on these valuations, the rules of the system are updated in order to adjust the new recommendations to past user experiences. To test the validity of Sem Fit, the validation accomplished includes the interaction of the customer with the system and then the results are compared with the expert recommendation for each customer profile. Moreover, the values of precision and recall and *F1* have been calculated, based on three points of view, to measure the degree of relevance of the recommendations of the fuzzy system, showing that the system recommendations are on the same level as an expert in the domain.

1. Introduction

Tourism is one of the most powerful industries worldwide. With roughly 11% of the world's total employment or GDP, tourism is often presented as the first global industry, and Europe is by far the first tourist continent (Longhi, 2007). The World Tourism Organization (2006) predicts that by 2020, tourist arrivals around the world will increase by over 200%. Because tourism is an information intensive business, there are opportunities to apply information technology (IT) to support tourism and tourists (Watson, Akselsen, Monod, & Pitt, 2004), and, pursuing these opportunities, the tourism industry is leading eCommerce applications (Werthner & Ricci, 2004) and one of the fastest growing segments of eCom

merce (Cao & Schniederjans, 2006). Not in vain, to be able to compete in an increasingly competitive and globalized market, companies need to be provided with new strategies that allow them to confront successfully the environment challenges (Acosta & Febles, 2010). Developments in search engines, carrying capacity and speed of networks, have influenced the number of travelers around the world that use technologies for planning and experiencing their travels (Buhalis & Law, 2008). Thus, according to Kenteris, Gavalas, and Economou (2009), the convergence of IT and communications technologies and the rapid evolution of the Internet have been some of the most influential factors in tourism that have changed travelers' behavior. Indeed the Internet is currently the primary source of tourist destination information for travelers (Chiu, Yueh, Leung, & Hung, 2009). Buhalis (1998) pointed out that the use of the Internet in the tourism industry provides access to a large number of people, as well as offering the opportunity to develop closer relationships with customers. ICTs have radically changed the efficiency and effectiveness of tourism organisations, the way that businesses are conducted in the marketplace, as well as how consumers interact with organisations (Buhalis, 2003). And in a highly competitive environment,

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according to Luo, Feng, and Cai (2004), tourists who searched on the Internet tended to spend more at their destinations as compared to those who consult other information sources.

The hotel industry is one of the leading stakeholders in the tourism sector. In order to reduce travelers' cost of seeking accommodations, enforce the return ratio efficiency of guest rooms and enhance total operating performance, evaluating and selecting a suitable hotel location has become one of the most critical issues for the hotel industry (Chou, Hsu, & Chen, 2008). Service quality in hotels can be regarded as a composite measure of various attributes, including tangible attributes but also intangible/subjective attributes (safety, quietness, ...) (Benítez, Martín, & Román, 2007). Consumers' judgments towards a service depend basically on the strength of their beliefs or expectations about various features or attributes associated with the service and the weight of attributes (Engel, Blackwell, & Miniard, 1995). And, since online travelers are enthusiastic about meeting other travelers who have similar attitudes, interests and way of life (Wang, Yu, & Fesenmaier, 2002), there is a strong connection between travelers' judgments and hotel recommendations. In this scenario, recommender services are increasingly emerging that employ intelligent agents and artificial intelligence to "cut through" unlimited information and obtain personalized solutions (Ricci & Werthner, 2006). Recommender systems are commonly defined as applications that e-commerce sites exploit to suggest products and provide consumers with information to facilitate their decision making processes (Niininen, Buhalis, & March, 2007). How to deliver relevant information to both potential and existing customers has become an important task for the hospitality industry (Xian, Kim, Hu, & Fesenmaier, 2007), which, in many cases, is based on artificial intelligence techniques (Schiaffino & Amandi, 2009). Destination recommendation systems are mostly fed with subjective information provided by the tourism industry itself (Goosen, Meeuwssen, Franke, & Kuyper, 2009), but most of the relevant information for recommendation should come from customers. Indeed, according to Klein (1998), travel products in general are arguably "experience goods" in that full information on certain attributes cannot be known without direct experience.

Taking this assumption into account, this paper presents Sem Fit, a semantic hotel recommendation expert system, based on the consumer's experience about the recommendation provided by the system. The proposed expert system uses the consumer's experience point of view in order to apply fuzzy logic techniques to relating customer and hotel characteristics. Hotel characteristics are represented by means of a domain ontology. After receiving a recommendation, the customer provides a valuation about the recommendation generated by the system. Based on the customer's valuations, the rules of the system are updated in order to adjust the new recommendations to the past user experiences.

The paper consists of five sections and is structured as follows. Section 2 reviews the relevant literature. Section 3 discusses the main features of Sem Fit including the conceptual model, algorithm and architecture. Section 4 describes the evaluation of the tool performed including a description of the sample, the method, results and discussion. Finally, the paper ends with a discussion of research findings, limitations and concluding remarks.

2. Background

It is a widely recognized fact that information and decision making have become the foundation for the world economy (Wang, 2008). Among many enterprise assets, knowledge is treated as a critical driving force for attaining enterprise performance goals because knowledge facilitates better business decision

making in a timely fashion (Han & Park, 2009). And due to the importance of tourism, recommender systems and decision support systems for tourism have been a field of study since the very beginnings of artificial intelligence.

A recommender system can provide a set of solutions that best fit the user, depending on different factors concerning the user, the objective or the context where it is applied. Such systems can reduce search efforts (Liang, Lai, & Ku, 2006) and provide valuable information to assist consumers' decision making process (Ricci, 2002) in order to solve the problem of information overload (Kuo, Chen, & Liang, 2009). Adomavicius and Tuzhilin (2005) provide a survey of recommender systems as well as describe various limitations of current recommendation methods, and discuss possible extensions that can improve recommendation capabilities and make recommender systems applicable to an even broader range of applications.

Due to the importance of tourism, many efforts had been devoted to recommender systems for tourism (e.g. Castillo et al., 2008; Loh, Lorenzi, Saldana, & Licthnow, 2004; Ricci & Nguyen, 2007; Wallace, Maglogiannis, Karpouzis, Kormentzas, & Kollias, 2003), often based on artificial intelligence techniques, as was predicted in the early nineties by Crouch (1991): intelligent agents (e.g. Aciar, Serarols Tarres, Royo Vela, & De la Rosa i Esteva, 2007; Schiaffino & Amandi, 2009), fuzzy approaches (e.g. Lenar & Sobecki, 2007; Ngai & Wat, 2003), Bayesian networks (e.g. Huang & Bian, 2009; Jiang, Shang, & Liu, 2009), to cite just a few.

Nor is the field of using semantics in tourism new. Fodor and Werthner (2004) presented Harmonise, a project that deals with business integration in tourism using ontologies for mediation. The SATINE project by Dogac et al. (2004) describes how to deploy semantically enriched travel Web services and how to exploit semantics through Web service registries. Niemann, Mochol, and Tolkendorf (2008) propose how to enhance hotel search with Semantic Web Technologies. Jakkilinki, Georgievski, and Sharda (2007) proposed an ontology based e-Tourism Planner AuSTO that enables users to create an itinerary in one single application by this intelligent tool that builds on semantic web technologies. The LA_DMS project (Kanellopoulos, 2008) provides semantic based information for tourism destinations by combining the P2P paradigm with semantic web technologies.

In the specific field of using semantics to provide better information for tourists there have been relevant and recent efforts in the literature. For example, García Crespo et al. (2009) proposed a semantically enriched recommendation platform for tourists on route, later expanded to Destination Management Organizations (García Crespo, Colomo Palacios, Gómez Berbís, Chamizo, & Rivera, 2010a). Lee, Chang, and Wang (2009) used ontologies to provide recommendation in the context of the city of Tainan (Taiwan). Finally, and in the most similar contribution to the literature, Huang and Bian (2009) integrated Bayesian networks and semantics to provide personalized recommendations for tourist attractions over the Internet.

According to Huang and Bian (2009), there are two challenges in developing a system for personalized recommendations for tourism. One is the integration of heterogeneous online travel information. The other is the semantic matching of tourist attractions with travelers' preferences. Taking into account that all information will be given to the system by the users using this means, the challenge of Sem Fit will be the semantic matching between attractions and preferences. To do so, Sem Fit will use the fuzzy logic paradigm in order to express the relationship between the hotel characteristics and the customer preferences. The Sem Fit's fuzzy engine will recalculate this fuzzy relationships based on the customer feeling about previous recommendations, allowing the automatic adaptation of the recommender system to the customers' preferences.

3. Sem-Fit: fundamentals and internals

Usually experts and customers express their knowledge and preferences in the form of imprecise terms such as “young” or “near”. The fuzzy logic paradigm allows the representation of these imprecise terms in order to implement intelligent systems. Based on this paradigm, Sem Fit allows the representation of fuzzy variables in order to describe hotels and customers. Later on, Sem Fit uses these variables to perform recommendations. This section is structured as follows. First, an explanation on the fuzzy logic paradigm is given. Secondly, the process of capturing fuzzy knowledge in hotel recommendation is depicted. Later on, the recommendation process is defined and explained. Fourth, the customer feeling capturing procedure is portrayed. Finally, Sem Fit architecture and implementation is shown.

3.1. Fuzzy logic paradigm

The fuzzy sets theory provides a framework for the representation of the uncertainty of many aspects of human knowledge (Zadeh, 1965). Classic sets theory establishes that the elements of the universe may belong to a set or may not belong to that set. Then, given the set of odd numbers:

$$U = \{1, 2, 3, 4, 5, \dots\},$$

we can affirm that “3” belongs to such a set. We can also affirm that the number “21” belongs to the set of numbers greater than 7, but number 3 does not belong to such a set. The membership function for a given set can be depicted as shown in Fig. 1. When the element belongs to the set, the function takes the value 1, and when the element does not belong to the set, the function takes the value 0.

For a given element, fuzzy sets theory proposes the use of intermediate degrees of membership to a set. In this way, if we consider the set of young people we can consider that a person who is 15 years old belongs to such a set with a degree of 1 (belongs), a person who is 30 years old belongs in some degree (for example 0.7) and a person who is 80 years old does not belong to this set (degree of 0). We can represent this membership function as depicted in Fig. 2.

Fuzzy sets provide a way for defining cases in which the membership to a given set is relative or the membership function is not defined at all, allowing the representation of imprecision or uncertainty. Imprecision and uncertainty modeling by means of fuzzy sets allows solving problems which cannot be solved by means

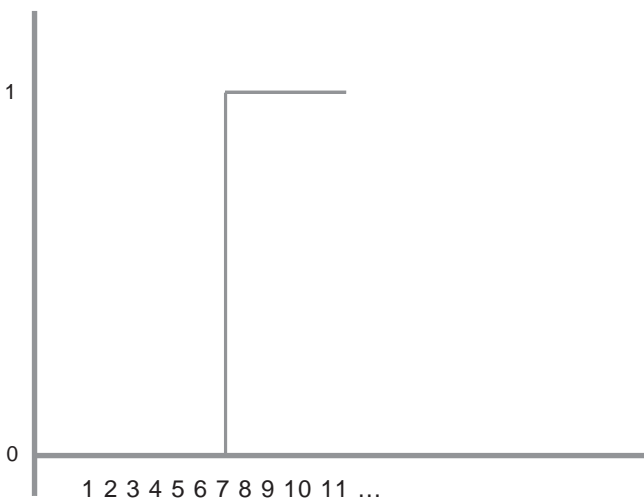


Fig. 1. Membership function for the set of numbers greater than 7.

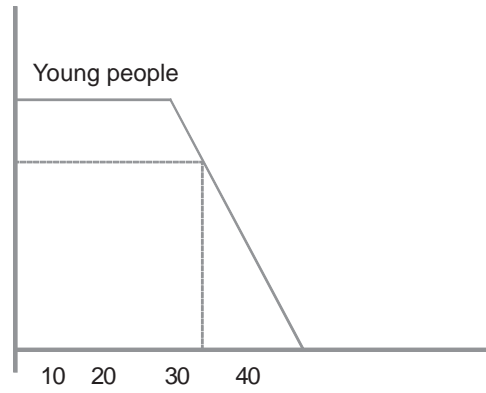


Fig. 2. Membership function for the fuzzy set “young people”.

of classic techniques. Some such domains are: classification problems, pattern recognition, signal processing, knowledge based systems or temporal reasoning.

Using this fuzzy theory, the purpose of Sem Fit is to offer hotel recommendations based on expert criterion. This expert criterion will be represented by means of fuzzy sets based on the affect grid (Russell, Weiss, & Mendelsohn, 1989). However, the customer preferences may be different from the expert point of view or may change as time goes by. For this reason it is necessary to update the fuzzy rules which represent the expert criterion using the customers’ feedback.

3.2. Capturing the fuzzy knowledge about hotel recommendation

Fig. 3 depicts the main elements in our proposal about capturing knowledge in hotel recommendations:

1. The semantic descriptions of the hotels.
2. The fuzzy relationship between the characteristics of the customers and the characteristics of the hotels.
3. The customer feeling about the recommendations.

The first step of the recommendation process consists of representation of knowledge about how the hotels are selected. This knowledge is expressed using fuzzy sets. In a first stage, the fuzzy sets are defined based on the expert knowledge. An expert defines by means of fuzzy sets the characteristics of the hotels and the characteristics of the customers. Some fuzzy sets defined are: luxury hotel, relaxing trip or young people.

After defining the fuzzy terms used by the expert to describe hotels and customers, the membership function is defined for each fuzzy set. This membership function allows for the transformation of the customer characteristics and the hotels characteristics into fuzzy values.

Studies of emotion and affect in human beings have an established history which originates in philosophy. As a result of this tradition, and using their own work as a basis (Russell, 1980), Russell et al. (1989) proposed a measure of affect which had a profound impact on the field of social psychology. They termed the measure the affect grid, a scale designed as a quick means of assessing affect along the dimensions of pleasure displeasure and arousal sleepiness on a 1-9 scale. The affect grid may prove to be the instrument of choice when subjects are called on to make affective judgments in rapid succession or to make a large number of judgments, especially when those judgments are to be aggregated (1989). Using this scale, researchers can collect emotion ratings from stress and tension to calm, relaxation or serenity, and

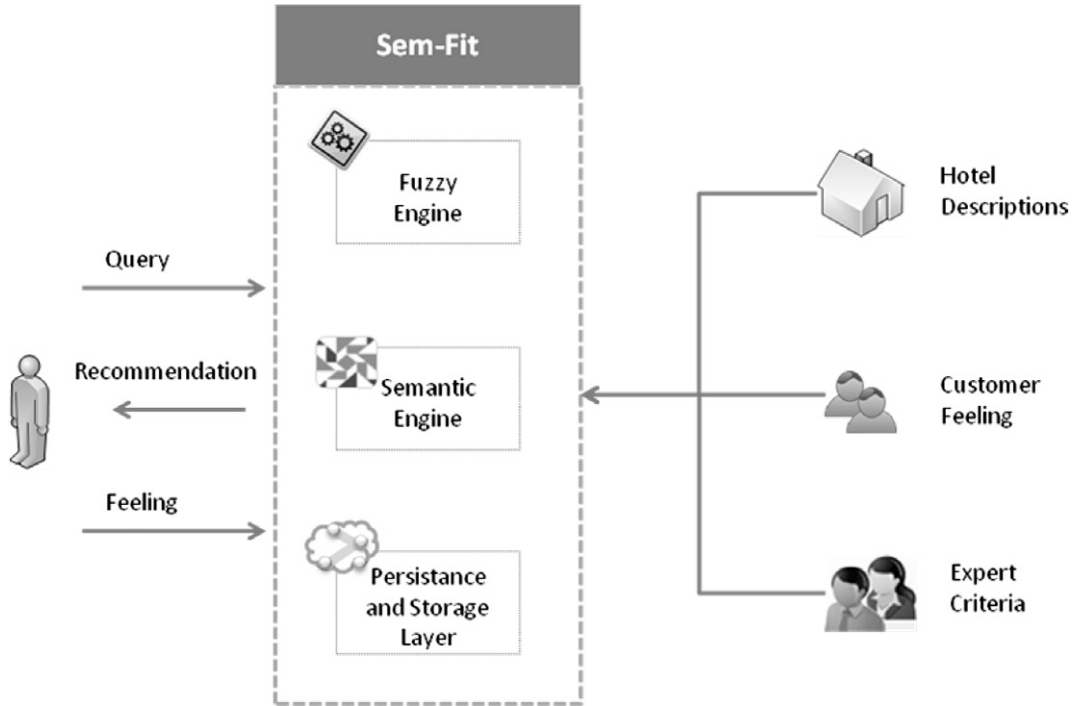


Fig. 3. System design.

from ecstasy, excitement and joy to depression, melancholy, sadness, and gloom.

According to the studies of these authors, the affect grid is potentially suitable for any study that requires judgments about affect of either a descriptive or a subjective kind. Based on the customer characteristics, the fuzzy system will estimate the customer's affect grid for each hotel characteristic. Then, the fuzzy sets for the representation of the customer characteristics are related with the concepts of the hotel ontology by means of the affect grid. In this way, the results of the fuzzy recommender can be translated into concepts of the hotel ontology in order to obtain the recommendation.

The measure of the affect grid will be translated to linguistic tags related to the hotel characteristics by means of semantic annotations based on the rules defined by the expert options. Such tags are adequate, very adequate, not adequate or never recommend. Each tag has a value related in order to rate each hotel based on the amount of positive or negative tags obtained from the fuzzy reasoning. Affect grid was previously employed by authors in previous works that combined semantic technologies with emotions (García Crespo, Colomo Palacios, Gómez Berbís, & García Sánchez, 2010b).

3.3. Recommendation process

The main steps of the recommendation process are depicted in Fig. 4.

The recommendation is primarily based on the customer characteristics. The steps of the reasoning process are:

1. Obtaining the customer characteristics. The customer provides the information about his personal situation, preferences, etc. The information required is established based on the expert criterion as mentioned in Section 3.1.
2. Fuzzification. The values provided by the customer are converted into the fuzzy sets defined by the expert to describe the customer characteristics. The fuzzy value for each variable is obtained by means of the membership function related to each fuzzy set.

3. Once the customer profile has been fuzzified, the fuzzy rules are evaluated obtaining the set of fuzzy values for the hotel characteristics, as well as its tag for defining the level of adequation based on the affect grid (Fig. 5).
4. The results obtained are defuzzified in order to obtain a set of concrete characteristics for the hotels.
5. With the defuzzified results, hotels with the obtained characteristics are retrieved based on the hotels ontology and the annotations.
6. Next the fuzzy recommendation system will calculate the weight of each hotel based on the values of the suitability obtained from the decision matrix.

The total weight can be configured in two modes, called "normal mode" and "sensible mode". The "normal" mode calculates the weight of the hotel as the summity of all the suitabilities:

$$P_{\text{product}} = \sum_{i=1}^n \sum_{j=1}^m W_{ij},$$

where W_{ij} is the defuzzified value of the association between the customer characteristic i and the hotel characteristic j .

The "sensible" mode calculates the weight of the hotel as the product of all the suitabilities.

$$P_{\text{product}} = \prod_{i=1}^n \prod_{j=1}^m W_{ij}.$$

The sensible mode allows greater differences between hotels, providing more differentiation between the recommendations.

7. The hotel which obtains the highest weight is the final recommendation, called "Star recommendation". Also a set of alternative recommendations, called "suggested hotels" will be shown.

These steps constitute the primary recommendation process. However, the expert criterion may not be adequate, because the customer tendencies can change. For this reason, the fuzzy relationships between the customer characteristics and the characteristics of the hotels must be dynamically recalculated based on the customer feeling.

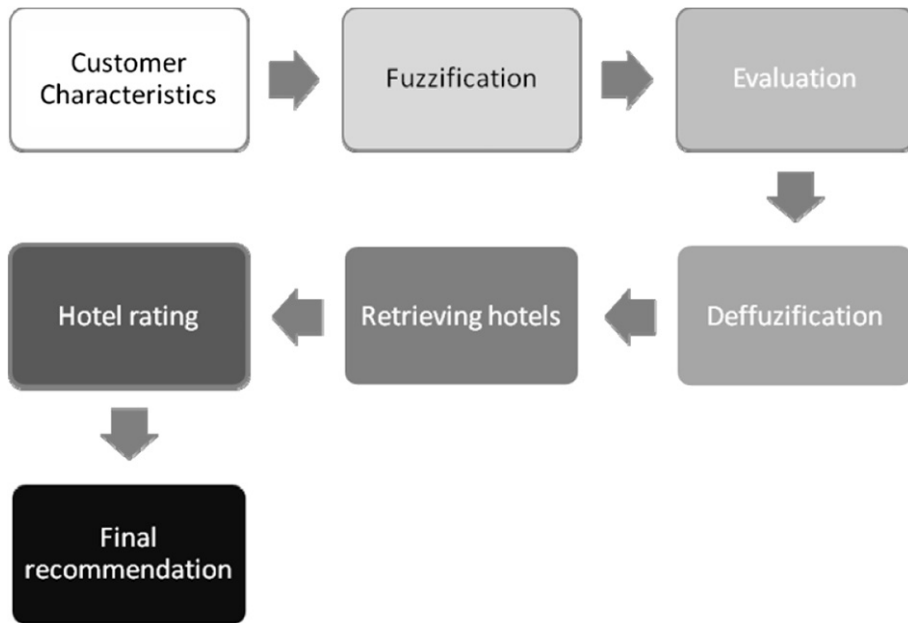


Fig. 4. Recommendation process.

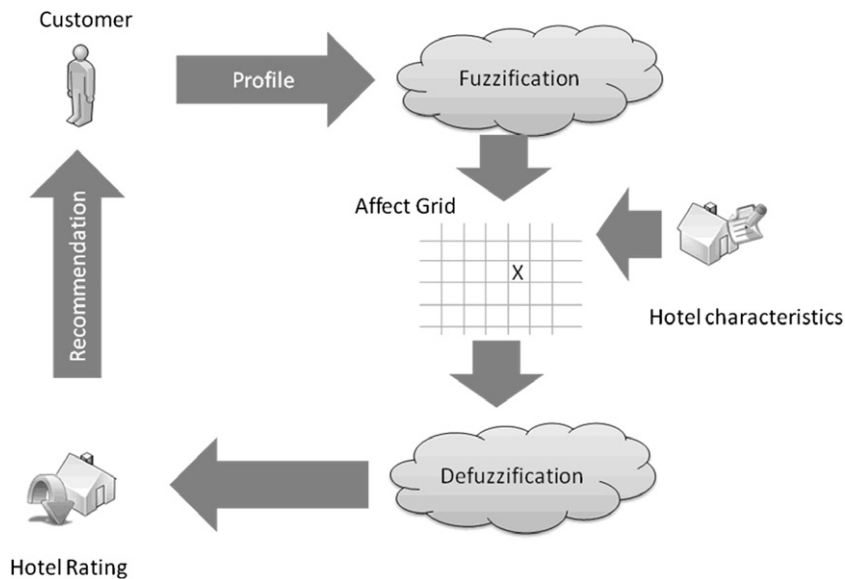


Fig. 5. Affect grid for hotel characteristics.

3.4. Capturing the customer feeling

As mentioned, the knowledge about the relationships between customer characteristics and hotel characteristics represented by means of the affect grid (Russell et al., 1989) has to be updated. There are two possibilities to update such values. On the one hand, the expert can update the values of the affect grid and, on the other hand, these values can be automatically updated by means of heuristics. The first option is the classic approach in which an expert updates the knowledge after studying the customer tendencies. The second option allows the automatic adaption of the recommender system based on the information acquired during the recommendation process. For this option it is necessary to take into account the level of agreement of the customer with the solution provided in order to make future recommendations. Such recom-

mendations have an effect in two ways: on the one hand they allow the correction of the initial criterion of the expert because the negative valuation by the customers may imply the need to redefine the initial affect grid. On the other hand, the feedback of the customer may be stored in order to adjust the criterion of the expert to the customer preferences.

For this reason, we propose the automatic reconfiguration of the fuzzy relationships using customer feedback. After receiving a recommendation the customer will rate his level of pleasure/displeasure about the characteristics of the recommendation received. The objective of this question is to obtain the first impression of the customer about the recommendation. The fact that the rating of the customer is about his feeling about the recommendation instead of his real experience is important. This is because the recommendation could be correct but the real experience of the

customer could be negative, due to external factors (bad weather, personal problems, illness, etc.).

The customer feelings are stored in the knowledge base. When the number of customer evaluations is greater than one hundred, the fuzzy system will evaluate the overall customer feelings based on fuzzy meta rules defined in order to determine when it will be necessary to update the affect grids. If the overall customer feeling is negative, then the affect grids related to the negative valued recommendations will be adjusted according to such meta rules. The updating process will be repeated every 100 customer valuations.

3.5. System architecture and implementation

Fig. 6 depicts a three layer scheme that represents the recommendation system architecture.

The first layer corresponds to the user interface. There are two different elements in the user interface layer. On the one hand, the administrator GUI allows the administrator to define the fuzzy rules that represent knowledge about hotel recommendation. The administrator GUI consists of a web based application to allow the definition of the fuzzy sets as well as the membership function for each fuzzy set. This application also allows the easy matching between customer characteristics and hotel characteristics by means of the affect grid. On the other hand, the GUI recommendation allows the customers to obtain intelligent recommendations about hotels. The GUI recommendation consists of a web questionnaire in which the customer answers a set of questions proposed by the expert. Such questions determine the customer profile in order to determine the most suitable hotel. After the questions have been answered, the fuzzy engine evaluates the rules, and the most suitable hotel

is shown to the customer. Optionally, a list of less suitable hotels can be displayed. After the recommendation, the customer provides his degree of pleasure/displeasure about the recommendation received. This information will be used by the fuzzy engine for reconfiguring the fuzzy relationships between the customer characteristics and the hotel characteristics.

The second layer represents the business logic. This layer contains the fuzzy engine and the semantic engine. The fuzzy engine will evaluate the fuzzy rules defined by the expert in order to determine the most suitable hotel characteristics for a given customer profile based on the affect grid. As mentioned, the fuzzy knowledge is defined by means of the GUI administrator. Once the hotel characteristics have been determined, the fuzzy engine retrieves the hotels with these characteristics by means of the semantic engine. The semantic engine, based on the Jena Framework (Reynolds, 2006), will manage the hotels ontology and will provide the set of hotels with the characteristics determined by the fuzzy engine. Besides the recommendations, the fuzzy engine will recalculate the fuzzy affect grid based on the customer feedback. The fuzzy recalculation has been implemented as a daemon in the web server. Such a daemon monitors customer feedback, recalculates the fuzzy relationships between characteristics when the customer evaluation is significant and updates the affect grids according to such customer feedback.

Finally, the persistence layer stores the knowledge about the hotel recommendation. As mentioned, on the one hand, the hotel ontology defines the relevant characteristics of each hotel. The concepts of the hotel ontology (Fig. 7) describe the category of each hotel based on stars, the room characteristics, the special equipment of the hotel, etc. This ontology also describes special activities related to the hotel based on the season. All this information

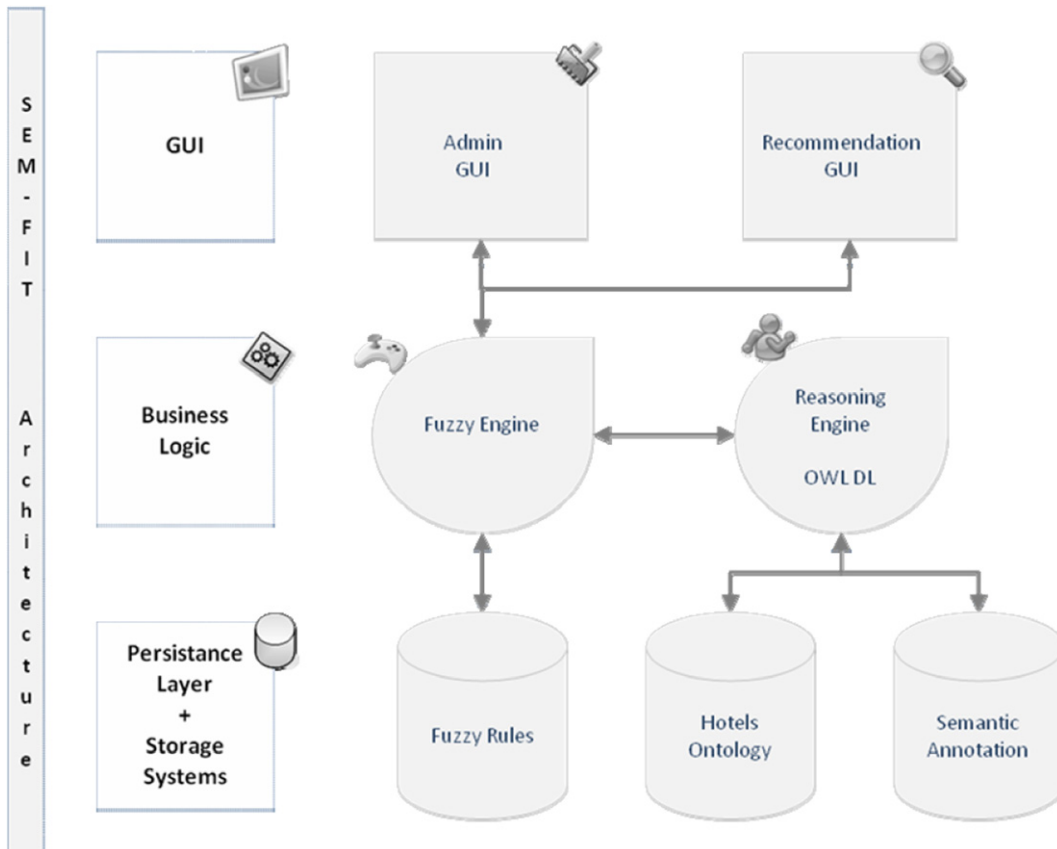


Fig. 6. System architecture.



Fig. 7. Partial view of the hotels ontology.

is used to describe the hotels available in the system. The hotels ontology has been defined using the Ontology Web Language (OWL) (Bechhofer et al., 2004). The OWL language has three variants: OWL Lite, OWL DL and OWL Full. OWL Lite provides a small set of features, while OWL DL is more expressive than OWL Lite providing decidability based on description logics. OWL Full allows full expressivity but decidability is not warranted. For this reason, we have used OWL DL for the ontology definition. The storage and ontology reasoning has been developed based on the Jena framework. Besides the ontology specific storage, a database stores the information about the fuzzy sets and the fuzzy relationships with the ontology. On the other hand, the customer characteristics and their relationships with the hotel characteristics are represented by means of fuzzy sets and fuzzy relationships by means of affect grids and are stored in a database.

4. Evaluation

The subsequent section describes the empirical evaluation of the project. The final aim of this study is to work out if Sem Fit serves as a valid recommendation system in a controlled environment.

4.1. Research design

Once the system has been developed and trained, it is necessary to prove the validity of our proposal; we must prove that the star recommendations provided by the system are accepted by the customers. In case of disagreement with the star recommendation, it is of interest to know if the customer found a valid alternative in the list of suggested hotels. Additionally, given a set of customer profiles we have evaluated the similarity between the recommendations provided by the fuzzy system and the recommendations provided by four experts in hotel recommendations. By means of this experiment we have evaluated the accuracy of the fuzzy system comparing its recommendations to the recommendations of human experts. In case of disagreement between the expert criteria and the fuzzy system's star recommendation, it is of interest to know if the expert recommendation is included in the list of suggested hotels. Finally, comparison between the expert recommendation and the selection of the customer has been performed in order to validate the expert criterion.

Precision, recall and F_1 will be used in order to measure the degree of relevance of the recommendations of the system. This technique has been employed based on two points of view: on the one hand, it is used to measure customer agreement with the recommendation received and, on the other hand, to measure the agreement between the system results and the expert recommendations. As mentioned, this technique has been also employed to measure customer agreement with the expert's recommendation. These measures had been used before to measure recommendations in semantic systems (e.g. García Crespo, Colomo Palacios, Gómez Berbís, & Ruiz Mezcuca, 2010c, García Crespo, Rodríguez, Mencke, Gómez Berbís, & Colomo Palacios, 2010d, Paniagua Martín, García Crespo, Colomo Palacios, & Ruiz Mezcuca, 2011). Precision, recall and F_1 measures are defined as follows:

$$\text{precision} = \frac{\text{CorrectHotelsFound}}{\text{TotalHotelsFound}},$$

$$\text{recall} = \frac{\text{CorrectHotelsFound}}{\text{TotalCorrectHotels}},$$

$$F_1 = \frac{2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}}.$$

The correct hotels will be determined by the expert criteria or the customer depending on the test. The following subsections describe the experimentation carried out and the results obtained.

4.2. Sample

In order to determine the validity of the proposed approach, the designed evaluation was carried out. A set of 50 students (37 male and 13 female) in their final year of the Computer Science degree program at Universidad Carlos III de Madrid accessed the system in order to obtain a recommendation for their spring break. The system was trained with information on 10 hotels in Mallorca (Spain) based on the knowledge of an expert from a travel agency. With the results obtained from the system, each student selected the start preference or, in case of disagreement, one of the alternative recommendations provided or an empty alternative.

Four experts in the travel domain recommend a hotel for each student in order to compare the recommendation of the system with the expert criteria. Recommendation generated by the fuzzy system was also compared with the expert recommendations in order to measure the validity of the star and alternative recommendations.

4.3. Results

The experimentation was carried out in two separated tests that will be analyzed in the next subsections.

4.3.1. Test 1. Comparison between the system results and the expert recommendation

Table 1 summarizes the precision and recall and F_1 values obtained by means of the comparison between the expert recommendations and the results provided by the fuzzy system. This comparison has been divided into two stages. In the first stage, we have compared the star recommendation of the system with the expert recommendation. The star recommendation consists of a single recommendation (the top rated hotel for the customer characteristics) provided by the fuzzy system for each customer, and the expert recommendation is also a single recommendation suggested by the expert for each customer. The precision of the fuzzy system is 0.58. The value of recall is the same as precision because the number of returned categories is the same as the number

Table 1
Comparison between system and expert recommendations.

	Precision	Recall	F1
Star recommendation vs. expert recommendation	0.58	0.58	0.58
Overall system suggestions vs. expert recommendation	0.19	0.96	0.32

of valid categories. We consider this value a promising result because more than 50% of the recommendations of the system are the same as the expert, and there is only one possible result.

On the other hand, the fuzzy system provides a set of four alternatives for the star recommendation. We have compared the overall results of the system (five results, star recommendation and four suggested hotels) with the suggestion of the expert. In this scenario we have obtained a precision of 0.192, less than the 0.58 obtained for the star recommendation. It is logical consequence because the number of returned values is greater (5 for each customer vs. only one star recommendation) and the number of correct values (recommendations of the expert) is the same. However the recall value achieves the value of 0.96. It means that in 96% of the cases the fuzzy system includes the recommendation of the expert in the set of results returned (either as star or suggested recommendation). It is a good result because the system is capable of providing an expert recommendation in the set of suggestions in almost all of the cases.

4.3.2. Test 2. Comparison between the customer selection and the suggestions of both system and expert

Test 1 compared the results of the system with the suggestions of the expert. But, are the expert suggestions a good basis? In order to answer this question, Test 2 compares the recommendations of the expert with the selection of the customer. Table 2 shows the precision, recall and F1 values obtained in this test. The precision value is 0.76, and the recall value is the same. It means that the 76% of expert recommendations are accepted by the customer.

The second stage of the Test 2 consisted of the comparison between the system result and the final customer selection. In this stage we consider separately, on the one hand, only the star recommendation and, on the other hand, the star recommendation plus the alternative suggestions.

Precision and recall and F1 values for test 2 are presented in Table 3. The first row shows the comparison between the star recommendation and the customer selection. In this case, the precision value is 0.48. It means that the star recommendation of the system is the customer selection in the 48% of the cases. The value of recall is the same because the valid values are the same as the amount of values considered.

The second row of Table 3 presents the comparison between the overall results of the system (star recommendation plus 4 suggestions) and the final customer selection. As in Test 1, the precision value is smaller because the number of suggestions is greater, but the recall value is 0.96. It means that in 96% of the cases, the system offers a star recommendation or an alternative suggestion that satisfies the customer.

4.4. Discussion

After the interaction of the customer with the system, the results were compared with the expert recommendation for each customer profile. We found that 24 customers found the star recommendation provided by the fuzzy system suitable and 48 customers found a recommendation included in the star and suggested hotels suitable. Only two customers did not find a suitable recommendation. On the other hand, we found that 29 star recommendations coincide with the expert recommendation, and 48 expert recommendations were included in the sum of the star recommendations with the suggested recommendations. We can conclude that the sum of suggested and star recommendations provides an accurate set of recommendations in which the customer can find a hotel. The system recommendations fit with the expert recommendation taking into account star and suggested hotels. Finally the expert recommendation coincides with the customer selection in 38 cases. However, the sum of star and suggested hotels of the fuzzy systems obtain better results than the expert recommendation.

As shown in the previous subsection, the values of precision and recall and F1 have been calculated based on three points of view. Test 1 measured the similarity between the system recommendations and the expert recommendations. If we only take into account the star recommendation, both precision and recall values for the system recommendation in this scenario are 0.58. It means that 58% of the system star recommendations coincide with the expert recommendation. As mentioned, it is an acceptable margin because there is only one valid value (the expert recommendation which is highly subjective) and the system only offers one star recommendation. However, if we include in the study the four alternative suggestions of the system we can see that the precision decreases because the number of categories found is greater and the correct value is only one, but the recall value is 0.96. It is an excellent result because in 96% of the cases the system offers the expert recommendation. It means that the system recommendations are on the same level as an expert in the domain and the customer can express his feelings in the same way that he does with the expert.

Test 2 studies, on the one hand, the results of the expert vs. customer selection. In this case, the precision and recall values obtained are 0.76. We can see that the expert obtains better results with only one recommendation. This is natural, because the expert can take into account more parameters such as the corporal expression of the customer, non verbal behavior) in order to provide a recommendation. It is a good value, because the expert provides 3 good recommendations out of 4 recommendations. It also means that the knowledge represented in the fuzzy system is accurate. On the other hand, Test 2 compared the star recommendation of the system with the customer selection. In this case, the precision value was 0.48. It means that the star recommendation is accepted by the customer in 48% of the cases. However, when we add the additional suggestions of the system, the precision is smaller because the number of suggestions is greater and the number of correct values is only one (the customer selection), but the recall is 0.96. It is an excellent result because it means that the customer finds a suitable recommendation in 96% of the cases. It is a high rate of positive recommendations considering that the selection of a hotel is a highly subjective decision. Cao and Li (2007) obtain an average recall of 83.82% for recommendations of 15 laptops in all 138 laptops for seven different customers; however in Cao and Li's study the customer can select more than one recommendation. Zenebe and Norcio (2009) present a comparative study of several techniques for recommending systems obtaining a recall of 38% for the fuzzy set theoretical method in a highly subjective domain such as movies selection. Zenebe and Norcio's experiment includes a large number of customers and movies, and it is natural that the recall value was smaller. In our case of study the number of customers and products are smaller. Based on the obtained results, the proposed system is able to estimate customers' feelings based on their profile and is capable of offering a set of

Table 2
Comparison between expert recommendation and customer selection.

	Precision	Recall	F1
Expert recommendation vs. customer selection	0.76	0.76	0.76

Table 3
Comparison between system recommendation and customer selection.

	Precision	Recall	F1
Star recommendation vs. customer selection	0.48	0.48	0.48
Overall system suggestions vs. customer selection	0.19	0.96	0.32

recommendations that will be accepted most of the time. Future research may include a larger number of hotels and customers in order to measure the scalability of the proposed system.

5. Conclusions and future work

We have presented Sem Fit, a semantic hotel recommendation expert system, based on consumers' experience about the recommendation provided by the system. The proposed expert system uses the consumers' experience point of view in order to apply fuzzy logic techniques to relate customers and hotels characteristics, represented by means of domain ontologies and affect grids. After receiving a recommendation, the customer provides a valuation about the recommendation generated by the system. Based on the customers' valuations, the rules of the system are updated in order to adjust the new recommendations to the past user experiences. The validation accomplished shows that the sum of star and suggested hotels of the fuzzy systems obtains better results than the expert recommendation. Moreover, the values of precision and recall and *F1* reveal that the Sem Fit recommendations are on the same level as an expert in the domain and the customer will be able to express his feelings in the same way that he does with the expert.

As an extension of this paper, the knowledge base could be improved including more products, such as suitable destinies or associated services. Furthermore, other ways of collecting data on customer feeling about a recommendation with greater accuracy and clarity could be studied.

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