An Ontology-based Approach for Personalized Itinerary Search

Hajer Baazaoui-Zghal *hajer.baazaouizghal@riadi.rnu.tn*
Riadi Laboratory/ ENSI/ Manouba University
Manouba,Tunisia

Ghada Besbes *ghada.besbes@gmail.com*
Riadi Laboratory/ ENSI/ Manouba University
Manouba,Tunisia

Abstract

Personalization plays an important role in information retrieval systems. In the field of transportation, and more specifically multimodal transportation, personalization represents an efficient way for travelers to find appropriate routes. Providing travelers with the relevant information to their needs and preferences is challenging for transportation systems.
In this paper, we propose an ontology-based approach for personalized itinerary search. Our proposal is based on modeling each user using an ontological fuzzy modular profile that incorporates a set of fuzzy modules representing several aspects of the user's description. The approach is applied in the transportation domain and integrates a new method of matching between the profile ontology and the domain ontology to obtain personalized responses for individual user profiles. Our proposal was implemented and evaluated. Obtained results show that personalization coupled with ontology matching enables an improvement of query reformulation.
Keywords: Information Retrieval, Personalization, Ontology, Ontology matching, Public transportation.

1. Introduction

With the rapid development and interconnection of multimodal transportation systems, suggesting adequate personalized itinerary for travelers has become increasingly challenging. This is compounded by the large amount of data required to maintain information on the various means of transportation, user profiles and changing routes. As such, personalization [?] has played a significant role in improving search results. If the user profile accurately represents the user's needs and preferences, the improved search process delivers personalized results.
Users express their needs through queries. An adequate analysis of that query coupled with the user profile reveals useful information regarding the user's demographic and, the context of the search to subsequently return useful and accurate results. It is important to note that search queries may be poorly expressed, ambiguous or imprecise. Therefore, the integration of fuzzy logic in the retrieval model in order to handle this kind of queries has proven to increase results relevancy [? ?]. In fact, ontologies [?] are efficient models to represent all shared and reusable resources in the web. However, crisp ontologies do not support uncertain information. Hence, fuzzy ontologies are designed to incorporate concepts that do not have precise and exact definitions. Generally, the process of building an ontology for a domain or a profile is expensive and time-consuming. Therefore, making smaller ontological modules appears to be a perfect solution to reduce building complexity. In addition, a single ontology may not sufficiently represent all shared resources in a domain or in a profile. Thus, ontology matching [?] allows search systems to retrieve the most relevant relations and matches between the shared resources of different ontologies.

In this paper, we propose an ontology-based approach for personalized itinerary search. Our motivation is to help travelers find the most suited itineraries based on their preferences. First, we model the user by an ontological fuzzy modular profile. Then, we propose a novel ontology matching process between the profile ontology, which is enriched by contextual data, and the transportation domain ontology which maximizes search results according to user profiles, hence improving the personalized search.
The remainder of this paper is organized as follows: Section 2 presents an overview of previous research on personalized itinerary search in multimodal transportation systems. Section 3 describes our method for personalized itinerary search based on the proposed fuzzy profile ontology and the transportation domain ontology. Section 4 presents and discusses the experimental results of our proposal. Finally, section 5 concludes with suggestions for future study.

2. Related Work

Different applications and systems have been proposed to assist the users during their trips. The aim of these works is to adapt the results' search to their preferences and profiles in a comfortable visual way [**?**]. Part of the proposed works are based on case-based reasoning to search for the itinerary that matches the users preferences, in order to predict users' behaviors by comparing preferences and interests with other users with the same preferences for a given search context [**? ?**].
Other works are based on the use of ontologies to ensure the personalization in the transportation search systems. In [**?**] the authors propose an ontology-based approach to represent interaction between the user's profile and the context of his search for collaborative learning. It aims to provide the appropriate recommendations according to the real needs of the user.
Several drawbacks related to itinerary search engines exist. On the one hand, the query is generally limited to the textual representation, meaning if the itinerary information does not fit correctly with the submitted query, the system asks the user to restart the search or it may provide irrelevant results. On the other hand, heterogeneous data from tremendous different sources of the transportation field must be represented in a formal way in order to establish a certain number of interlinks and relations between them. Since ontologies offer formal representations to the various aspects of knowledge, ontology matching [**?**] provides an efficient way to ensure communication between the heterogeneous ontologies.
In [**?**], the authors present contributions in the field of ontology matching, by presenting a matching system that aims to automatically discover the matches between two heterogeneous ontologies, through different techniques for calculating the similarities between their elements across three levels: terminological, structural and semantic. Also, The research work of [**?**] has one of the main contributions in the field of ontology alignment. The authors of this paper presented a new approach called YAM++ to improve ontology matches using techniques from different domains such as machine learning, information retrieval, and graph matching. The novelty of this work lies in the individual matchers as well as in their combinations.
The authors of [**?**] support another method of ontology matching that takes place in four major steps: 1) Manage semantics of domain ontologies within the knowledge base, 2) Produce different types of alignments, including equivalence, subclass, same as and alignments of instances, 3) Use similarities between two domain ontologies to improve equivalence and similar discoveries as alignments and 4) Based on the acquired alignments, deduce inferred alignments in order to guarantee the completeness of the corresponding results.

3. The Proposed Personalized Itinerary Search Approach

Our approach has two objectives. The first aims to build the modular user profile ontology using fuzzy logic. This is based on the user's queries and search history. The second objective is to match the profile ontology and the transportation domain ontology [**?**] to create personalized search engine results. The transportation domain ontology contains information about transportation modes and route in the city of Valenciennes, France. Our goal is to improve search results for itineraries by taking into account the travelers' needs and preferences.

Fig.**??** illustrates the four major components of our approach: (1) Query analysis which aims to decompose and understand the user's query using Babelnet and TreeTagger (2) Profile ontology update which aims to fuzzify the concepts and relations of the modules forming the profile then updating it by new fuzzy concepts (3) Ontology matching which aims to generate an XML matching file by interconnecting the ontological fuzzy modular profile and the transportation domain ontology in order to extract the linked entities between them (4) Query reformulation based on the keywords stored in the generated matching file which will be submitted to transportation domain ontology in order to respond to the user's query. The relevant extracted results from the ontology are then returned to the user.
The four components are detailed in the next subsections.

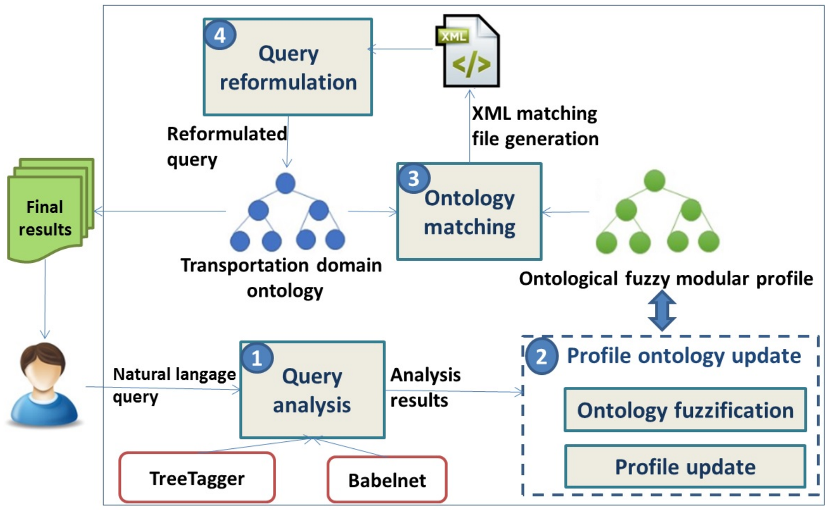

Figure 1. General architecture of the proposed approach.

3.1. Query analysis component

This component treats user data. Each user completes a user profile with personal information which also includes a set of submitted queries. We treat the query using three steps:

- Lexical analysis: removing the empty words and dividing the query into separate words to facilitate the calculation of similarities thereafter.
- Syntactic analysis: labeling the terms recovered after the lexical analysis to determine their grammatical natures using the Treetagger API[1]. This process considers only the root of the word. In this way, a search using any of the word's variants will lead to the same result.
- Semantic analysis: computing semantic similarity based on the BabelNet [2] lexical re-

[1]http: //www.cis.uni-muenchen.de/ schmid/tools/TreeTagger/
[2]http://babelnet.org/

source, by calculating the distance between the different words within the queries.

The aim of this component is to generate relevant concepts and relations from the user's query and its results will be integrated in the ontological profile during the next component.

3.2. Profile ontology update component

This component is based mainly on two parts: 1) The fuzzifcation of the concepts and relations by computing the membership values, and 2) The update of the profile ontology by adding new concepts and relations retrieved from the user's query.

The user profile ontology is modular and represented by two ontological modules:

- "UserProfile" module which describes the personal data of a user and contains classes such as gender, address, search history, user request etc.

- "UserPreference" which represents the user's preferences and, if required, accommodations for certain disabilities. This module contains classes such as cognitive issues, physical issues, language preference, restaurant preference etc.

We illustrate in Fig.**??** the module "UserProfile" and in Fig.**??** the module "UserPreference".

The two modules are manually built, and, initially, they do not contain any specific information. Each new user is required, using a form, to fill the ontology with personal data. The next updates are automatic and completely transparent to users.

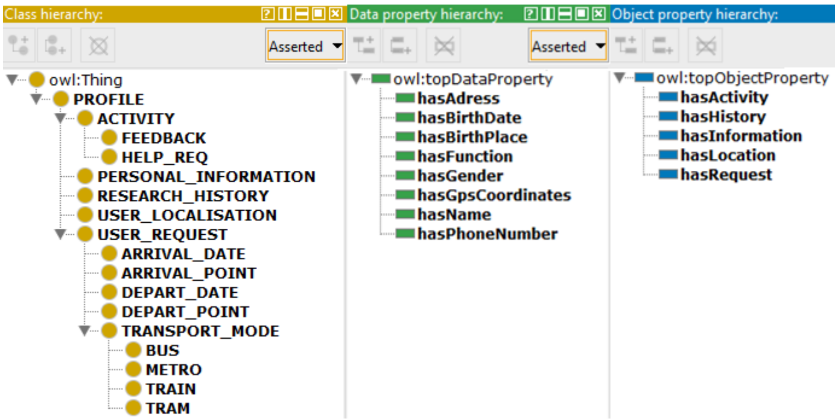

Figure 2. UserProfile ontological module.

Ontology fuzzification

Our fuzzification method for the profile ontology is based on two major steps.

- **Extraction of fuzzy concepts.** Our method focuses on fuzzy concepts from user queries that carry uncertain knowledge. Therefore, the characterization of a fuzzy concept is based on linguistic variables. Our proposed fuzzification method automatically defines fuzzy concepts from the ones extracted in the previous component by exploiting the BabelNet lexical resource for parsing. BabelNet groups words from different languages into synonym sets named Babel synsets containing all nouns, verbs, adjectives, and adverbs with the same semantics.

  Since fuzzy concepts represent imprecision and uncertainty, only groups of nouns, adjectives and adverbs are used in our proposal to generate these latter. For example, the

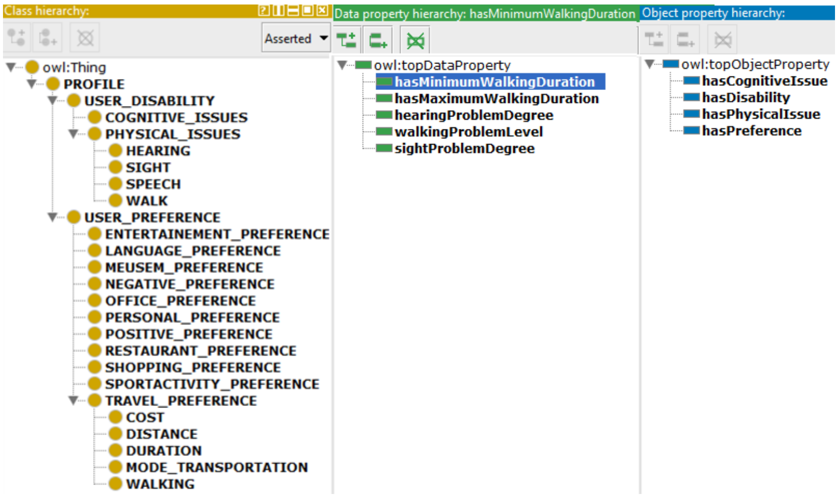

Figure 3. UserPreference ontological module.

concept "age" is considered fuzzy and the possible fuzzy values include "young", "adult" and "elderly". The fuzzy concept extraction algorithm takes as input all concepts of the user query and checks all of them. It delivers as output the list of concepts considered as fuzzy.

- **Calculation of the membership degree.** According to [?], the membership function defines a fuzzy set. Thus, to represent previously-determined fuzzy concepts, the appropriate membership function must be selected to calculate the degree of membership. For the annotation of fuzzy concepts in our profile ontology, we used the representation using OWL2 proposed by [?]. We compute the membership degrees by applying the membership functions such as: Linear function, trapezoidal function, triangular function, etc. on the range of linguistic variable values. For example, for the fuzzy concept "young person", the calculation of its membership value depends on the membership function associated with the linguistic variable "age". Consider that the function associated with the datatype "age" is the left-shoulder function, the degree of membership of the concept is calculated as follows:

$$\mu_A(x) = \begin{cases} 1 \; if \; x \leq \; a \\ \dfrac{b-x}{b-a} \; if \; a \; < \; x \; < \; b \\ 0 \; if \; x \; \geq \; b \end{cases} \tag{1}$$

With x: the value of the linguistic variable and [a, b]: the limits of x. So, for example, if a traveler is 23 years old, with [a, b]=[20,40]: the range of possible values of "young person" then the membership degree will be equal to μ_A(age: 20,40)=μ_A(age = 23) = $\dfrac{40-23}{40-20} = 0.85$

Profile update

This component extends the ontological modules of the profile by adding new concepts and relations created each time the same user enters a new query. For the example query: "when does transport-mode-15 departs from EAUBONNE?"
The update of the profile ontology following the input query is as follows: "Transport-mode-15" will be an instance of the "transportation-mode" concept and "Eaubonne" will be an instance of the "departure-point" concept.

3.3. Ontology matching component

In this section, we present the matching process between the profile ontology and the transportation domain ontology to identify the set of matches needed to enrich the user request and improve search results. Fig.**??** shows the detailed ontology matching process.

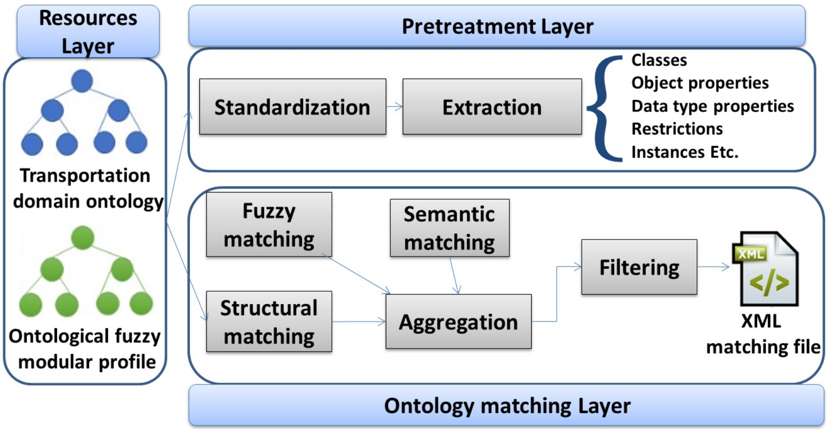

Figure 4. The proposed ontology matching process.

- The first layer is the "resources layer". It contains the two ontologies representing the input of the proposed ontology matching system.

- The second layer is the pretreatment layer that standardizes input ontologies to facilitate matching. In our approach, both ontologies are described in OWL format. The first step is the standardization phase, which removes punctuation marks, special characters, spaces, stop words, and URL links from the ontology and resources URIs. The second step extracts the ontology components: classes, datatype properties, object properties, restrictions, axioms, instances, etc. in order to deliver the most precise alignments.

- The third layer describes our ontology matching process, it uses a fuzzy, semantic, and structural alignment. Our process aims to find the degree of similarity between each pair of entities of the two input ontologies. After computing the similarity between the different ontologies' elements, the values are aggregated to a single match-value between each pair of elements. Not all matches are considered, only the most relevant are selected by applying the Minimum Cost Flow (MCF) and represented as the output of our system by a personalized XML file containing the matching entities and the match values between them.

The fuzzy matching

In our system, we have defined the fuzzy similarity SF(CO_1, CO_2) between a concept of the first ontology having a set of properties (P_1O_1, P_2O_1, ..., P_nO_1) and a concept of the second ontology which also has properties (P_1O_2, P_2O_2, ..., P_nO_2). These concepts can be fuzzy or not fuzzy (in which case, the membership value equals 1). We measure the fuzzy similarity SF between the concepts and properties of two ontologies in the following way:

$$SF(CO_1, CO_2) = \frac{\sum_{i=1}^{n} SP(P_iO_1, P_iO_2)}{n} \quad (2)$$

Where: CO_1: a concept from the first ontology, CO_2: a concept from the second ontology.
SP represents the similarity between two concepts properties and it is computed as follows:

$$SP(P_iO_1, P_iO_2) = \frac{1}{1 + DF(P_iO_1, P_iO_2)} \tag{3}$$

Where: P_iO_1: the concept's properties from the first ontology, P_iO_2: the concept's properties from the second ontology.
DF is the fuzzy Euclidean distance between two properties from the two ontologies, DF is defined as follows:

$$DF(P_iO_1, P_iO_2) = \sqrt{\sum_{i=1}^{n} (\mu_{P_iO_1}(x_i) + \mu_{P_iO_2}(x_i))^2} \tag{4}$$

Where: $\mu_{P_iO_1}(x_i)$: the membership value of the property from the first ontology and $\mu_{P_iO_2}(x_i)$: the membership value of the property from the second ontology.
Then, we calculate the similarity score between one concept of the profile ontology and each concept of the transportation domain ontology, and we retain the concept having the maximum score.

The semantic matching

For the semantic matching, we have used the BabelNet lexical resource that provides multilingual lexicons, which are interconnected with a huge amount of semantic relations. Due to the diversity of sets and semantic relations that BabelNet provides, we can move towards a similarity measure based on the similarity calculation between sets such as Jaccard index [**?**]. Thus, we chose to compute the similarity according to the sets of synonyms and categories related to an entity. The final Ind_{sem} result will be the average of two indices, defined between two entities e_1 and e_2 as follows:

$$SM(e_1, e_2) = \frac{\sum(Ind_{syn}(e_1, e_2) + Ind_{cat}(e_1, e_2))}{2} \tag{5}$$

With Ind_{syn} and Ind_{cat} between two entities e_1 and e_2 are computed as follows:

$$Ind_{syn}(e_1, e_2) = \frac{syn(e_1) \cap syn(e_2)}{syn(e_1) \cup syn(e_2)} \tag{6}$$

$$Ind_{cat}(e_1, e_2) = \frac{cat(e_1) \cap cat(e_2)}{cat(e_1) \cup cat(e_2)} \tag{7}$$

The structural matching

At this level, we are interested in the hierarchical structure of ontologies. Ontologies are easily assimilated to concept graphs whose nodes are the ontology concepts and the edges are the relations between the concepts. The Similarity Flooding algorithm [**?**] shows the structure of the ontologies, which makes it possible to record the alignments between the nodes and their neighborhoods based on the fixed point calculation method. This measure is computed by the Levenshtein distance [**?**].

Aggregation of similarities

After calculating the fuzzy, the semantic and the structural similarities; (SF), (SM) and (SS), we use a method of aggregating of the obtained values to return one match value between two ontology elements. Thus, the average is taken for the final calculation of the similarities as follows:

$$Sim(e_1, e_2) = \frac{\sum(SF(e_1, e_2) + SM(e_1, e_2) + SS(e_1, e_2))}{3} \quad (8)$$

To extract alignments, we apply the Minimum Cost Flow (MCF) to highlight only the most accurate matches to be stored in an XML matching file which contains the entity of the first ontology, the entity of the second ontology and the match value between them.

3.4. The Query Reformulation Component

This component enriches the search engine entries by using both ontologies: the profile ontology and the transportation domain ontology. To increase the amount of semantic information, we have added more specific concepts extracted from the list of matches of the two ontologies (stored in the matching file). Unlike the traditional enrichment methods that rely only on the concepts from the domain ontology, our enrichment method is based on the matching between the profile ontology and the domain ontology to support the personalization approach and improve the search process according to user needs and preferences in the public transportation domain. This refinement increases the number of specific concepts to question the domain ontology and hence, increases precision. For the same query example: "when does transport-mode-15 departs from EAUBONNE?: After treatment, the key concepts that will be candidates for the formulation of the sparql query are: "transport-mode-15", "depart", "EAUBONNE". But, the concept "depart" does not appear in the generated list of matches. So, we replace it with a concept related to it semantically and belongs to the list of matches which is "departure-time". The reformulation of the query in Sparql is:

```
" SELECT  ?departure_point ?transport_mode ?departure_time
      "+"  WHERE {"+
      "?r, ns:departure_point ?departure_point." +
      "?r, ns:transport_mode ?transport_mode." +
      "?r, ns:departure_time ?departure_time." +
      FILTER (?departure_point= 'EAUBONNE' &&
      ?transport_mode= 'transport_mode_15')." + "}";
```

4. Experimental Evaluation

The proposed approach has been implemented using JAVA programming language and the proposed query reformulation process was integrated. In order to evaluate our approach, we conducted a series of experiments that compare the performance of the system and the results' improvement thanks to the personalization. The evaluation measures adapted in the experimental study are based on precision and recall. Below are five ontology matching scenarios which highlight the difference between the results obtained in each scenario.

4.1. Experimental Setup

We aim to evaluate the impact of fuzzy, semantic and structural ontology matching process on the query reformulation improvement. The used data for the experimentation and the evaluation were composed of: a transportation domain ontology developed by [**?**], a fuzzy modular profile ontology and users' queries. We considered a set of 30 queries in the transportation domain and 3 users. To evaluate our proposal, we tested five scenarios; in scenario 1 and 2 we combine different matchers and in scenario 3, 4 and 5 we use just one matcher. This choice of scenarios aims to validate the benefit of the hybridization of three matchers by comparison to one or two matchers only. The tested scenarios are:

- Scenario 1: a query reformulation based on list of matches from a hybridization of a fuzzy, semantic and structural matching which is the ontology matching process that we propose, namely ***Sc1***.
- Scenario 2: a query reformulation based on a list of matches from a hybridization of semantic and structural matching. This scenario deploys the same algorithms as the first scenario on the semantic and the structural level only, namely ***Sc2***.
- Scenario 3: a query reformulation based on a list of matches from a fuzzy ontology matching based on the fuzzy Euclidean distance, namely ***Sc3***.
- Scenario 4: a query reformulation based on a list of matches from a semantic ontology matching based on our proposed semantic similarity measure, namely ***Sc4***.
- Scenario 5: a query reformulation based on a list of matches from a structural ontology matching based on the Similarity Flooding algorithm, namely ***Sc5***.

In order to measure the information search effectiveness, we used the following as evaluation metrics:

- The precision which is defined in terms of a set of retrieved documents (e.g. the list of documents produced for a given query) and a set of relevant documents (e.g. the list of all documents that are relevant for a given query).
- The recall which is the ratio of relevant instances that are retrieved. Recall is determined by dividing relevant retrieved documents by relevant documents which is not enough because of the need to measure the number of irrelevant documents, too. Therefore we present the precision-recall chart.

4.2. Evaluation Results

According to the illustrated results by Fig.**??**, we find that the ontology matching process affects search engine responses.

On the one hand, the first scenario, which represents our approach, outperforms the rest in terms of precision and recall. Hence, query personalization based on the proposed hybridization of fuzzy, semantic and structural matching processes delivers best results. To verify these results, the second scenario (hybridization of semantic and structural matching processes) was executed and showed declined results compared to the first scenario and better results compared to the rest which use only one matcher. In conclusion, the hybridization of matching levels improves the personalized results.

On the other hand, the third scenario (fuzzy matching) gave better results compared to the fourth and the fifth scenarios (semantic and structural matchings, respectively). This is explained by the fact that assigning membership values for fuzzy concepts in the user profile offers an understanding to the user's preferences and background. In fact, knowing the degree of preference of the user in regards to different concepts (such as transportation modes, museums, sport activities etc.) as well as the degree and nature of potential disabilities improves personalized results. The fourth scenario outperforms the fifth, and this is explained by the quality of the proposed profile ontology and the fact that this latter is modular. In fact, modular ontologies are used to offer structured representation of the profile in different modules which allows the independence yet the correlation between the attributes that represent the users' needs.

4.3. Alignment Results Discussion

The generated matching file size is very important. Therefore, we present only some alignment results to show the differences between evaluation scenarios. For example, "office-preference"

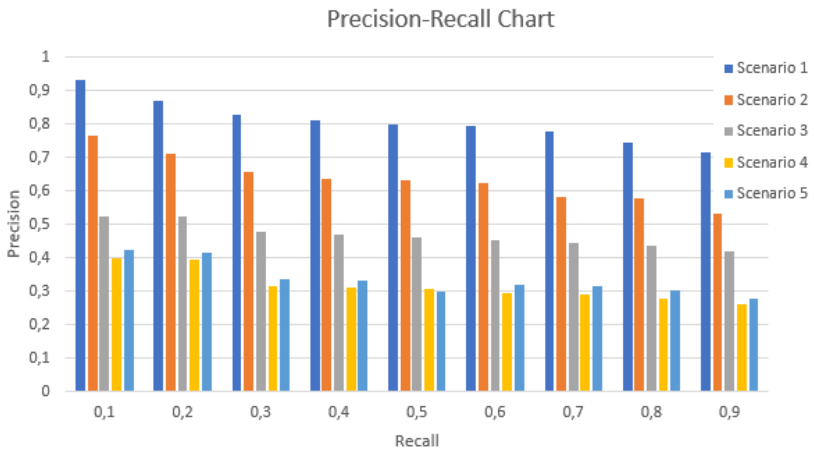

Figure 5. Precision-Recall chart.

and "duration" represent concepts of the profile ontology and "bank", "waiting-room", and "tram" represent concepts of domain ontology. The table below represents the match values of each pair of concepts according to the different evaluation scenarios.

Table 1. Alignments by different scenarios.

Sc1	office-preference	duration
bank	0.923	0.856
waiting-room	0.722	0.933
tram	0.000	0.752
Sc2	office-preference	duration
bank	0.725	0.788
waiting-room	0.666	0.755
tram	0.000	0.833
Sc3	office-preference	duration
bank	0.687	0.588
waiting-room	0.644	0.690
tram	0.822	0.521
Sc4	office-preference	duration
bank	0.701	0.000
waiting-room	0.463	0.428
tram	0.000	0.694
Sc5	office-preference	duration
bank	0.308	0.384
waiting-room	0.527	0.477
tram	0.123	0.206

The table's results show that the first two scenarios (Sc1 and Sc2) are close in results and they both highlight the link between the concepts "waiting-room" and "duration" and indicate that the concepts "tram" and "office-preference" have no similarity.
According to Sc3, the concepts "office-preference" and "tram" have the highest match value. The obtained result mainly depends on the membership values calculated between the fuzzy concepts. This result may be explained by the fact that the user would like to go to work by "tram" every day, and subsequently the membership value between the work place and the transportation mean is important.

According to Sc4, the concepts "office-preference" and "bank" have the highest match value. In fact, at a semantic level, the match value between the two concepts is very reasonable because they are not synonymous but they belong to the same semantic category "office". A bank may be an office preference specified by the user.
According to Sc5, the concepts "office-preference" and "waiting-room" have the highest match value. This value mainly depends on the distance between two concepts in the ontology hierarchy.

5. Conclusion and Future Works

This paper presents a new service for personalized itinerary search based on fuzzy modular ontologies. Our approach is based primarily on the personalization of results in order to adapt them to the user's real needs and preferences. As a conclusion, the main contributions proposed in our work:

- The personalization of search results: A fuzzy modular user profile is proposed in order to capture the user's preferences as well as personal information. Relying on the proposed profile takes advantage of the user information in order to propose adapted results (personal information, user localization, special needs, travel preferences etc.)

- The semantic and fuzzy representation of the user profile: the fuzzy aspect deals with the inaccuracy and uncertainty of some information and represents temporary relations that user research history may contain. The fuzzy ontology is a model that expresses more accurately the user needs and interests which are increasing and changing over time. Our goal is to bring our profile ontology closer to the modeled profile of human perception in the real world to improve the route search and the system's performance.

- The modular representation of the user profile: it's an ontology composed of ontological modules that vary in size and semantics but belong to the same profile. The proposed modules represent different dimensions of each user profile to form an interconnected network of inter-module connectors to maximize the modular ontology's closeness to representing the user. The modular representation is scalable; with the aim that it would be adaptable in other fields of application. This feature allows modification, expansion of ontology modules due to the evolution and dynamicity of user's data as well as the ability to reuse existing ontology modules.

- The fuzzy, semantic and structural ontology matching: this ontology matching process allows the interconnection of the profile ontology and the transportation domain ontology in an automatic way to identify most relevant matches between their different entities and relations.

The proposal has been implemented and several scenarios have been tested. The results show an improvement in the returned results in terms of precision and recall. The obtained results show the impact of the fuzzification and matching on the user query reformulation based not only on the domain ontology but also on the profile ontology in order to ensure expressivity of user request and its adaptation to his real needs and interests.

Improvements can be introduced in order to enhance the effectiveness of the proposed approach. In fact, this latter lacks a reasoning over the user information stored in the ontology which could offer more understanding of the user's needs.

Our future work will focus on extending the ontological modules of the profile ontology with other modules such as: a social module and a cognitive-behavioral module as well as offering more support to the users with disabilities and special needs by adapting CBR (Case-Based Reasoning) techniques [**?**].

References

1. H. Baazaoui-Zghal and H. Ben Ghezala. (2014) "A fuzzy-ontology-driven method for a personalized query reformulation," IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Beijing, 2014, pp. 1640–1647.
2. F. Bacha, H. Mnasser, K. Marçal de Oliveira and M. Abed. (2013) "Transportation ontology definition and application for the content personalization of user interfaces". *Expert Systems with Applications*, Vol. 40, num. 8 pp. 3145–3159.
3. N. Ben Mustapha, H. Baazaoui Zghal, M. Aufaure and H. Ben Ghezala. (2010) "Enhancing semantic search using case-based modular ontology". *SAC 2010*, pp. 1438–1439.
4. G. Besbes and H. Baazaoui Zghal. (2016) "Fuzzy ontology-based Medical Information Retrieval". *FUZZ-IEEE 2016*, pp. 178–185.
5. F. Bobillo and U. Straccia. (2011) "Fuzzy ontology representation using OWL2". *International Journal of Approximate Reasoning*, Vol 52, num. 7, pp. 1073–1094.
6. A. Essayeh and M. Abed. (2015) "Towards ontology matching based system through terminological, structural and semantic level". *KES 2015*, Singapore, 7-9 September 2015 pp. 403–412.
7. A. Essayeh, H.Baazaoui Zghal and M.Abed. (2017) "An Ontology Driven Framework for Personalized Itinerary Visualization". *21st International Conference Information Visualisation, IV 2017, 152–157*.
8. J. Euzenat and P. Shvaiko. (2007) "Ontology matching".Springer-Verlag, Berlin, Heidelberg.
9. A. Fareedi and A. Ghazawneh (2018) "An Ontology Approach for Knowledge Acquisition and Development of Health Information System (HIS)". *International Conference on Information Systems Development (ISD2018) Proceedings*. Lund, Sweden.
10. F. Gargouri, H. Mnasser and M. Abed. (2014) "Performance of system based on two ontologies in order to supply personalised information". *J. Business Performance and Supply Chain Modelling, Vol. 6, Nos. 3/4*.
11. R. Haldar and D. Mukhopadhyay. (2011) "Levenshtein Distance Technique in Dictionary Lookup Methods : An Improved Approach". *CoRR*,abs/1101.1232.
12. X. Hu, Z. Feng, S. Chen, K. Huang, J. Li and M. Zhou (2017) "Accurate Identification of Ontology Alignments at Different Granularity Levels". *IEEE Access*, Vol. 5, pp. 105–120.
13. V. Luna, R. Quintero, M. Torres, M. Moreno Ibarra, G. Guzmn and I. Escamilla. (2016) "An ontology-based approach for representing the interaction process between user profile and its context for collaborative learning environments". *Computers in Human Behavior*.
14. S. Melnik, H. Garcia-Molina and E. Rahm. (2002) "Similarity Flooding: A Versatile Graph Matching Algorithm and its Application to Schema Matching". *Proceedings 18th International Conference on Data Engineering*, San Jose, CA, USA, pp. 117–128.
15. D. Ngo and Z. Bellahsene. (2016) "Overview of YAM++ (not) Yet Another Matcher for ontology alignment task". *Web Semantics: Science, Services and Agents on the World Wide Web*, Vol. 41, pp. 30–49.
16. R. Real and J. M. Vargas. (1996) "The Probabilistic Basis of Jaccard's Index of Similarity".*Systematic Biology*, Vol. 45, Issue 3, 1 September 1996, pp. 380–385.
17. L. ZADEH. (1965) "Fuzzy Sets" *Information Control*, Vol.8 pp. 338–353.