An Ontology-based Personalized Retrieval Model Using Case Base Reasoning.

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An ontology-based personalized retrieval model using case base reasoning

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Abstract

A novel ontology-Based Personalized Retrieval model using the Case Base Reasoning (CBR) tool is designed and presented in this paper. The proposed approach is aimed at achieving a scalable and user friendly data retrieval system with high retrieval performance where search results are ranked based on user preferences. The proposed retrieval framework integrates the advantages of two methods, a content-based method (ontology) to represent data and a case-based method (CBR) to personalize the search process and to provide users with alternative documents recommendations. To analyze the performance of the proposed approach, computer experiments are carried out using recall-precision curve and average precision (AP) metric. The performance of our approach is then compared to a framework that uses the classic vector space model. Results clearly indicate the strength of the proposed approach as well as its ability to accurately retrieve pertinent information. The proposed approach is particularly promising in applicable related to city logistics, especially in the field of itinerary research for urban freight transport.

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Keywords: Case base reasoning, ontology, personalized search, information retrieval; query formulation.

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1. Introduction

The ontology domain is considered as a backbone of the semantic Web in the view that ontology domain can capture useful knowledge of domain via different heterogonous sources of data in order to facilitate information sharing and exchange.

An increasing number of recent information retrieval systems make use of ontologies to help the users clarify their information needs. Many ontology-based information retrieval systems and models have been proposed in the last decade. Dridi [1] presented an interesting review on IR techniques based on ontologies while in Tomassen [2] the author studied the application of ontologies to a large-scale IR system for web purposes.

Among the various works in the subject matter, we can mention: Guarino et al. [3] proposed the OntoSeek system. In this system Guarino et al. [3] used the ontology concept to formulate queries and improve the precision of the retrieved document. Guha et al. [4] improved the quality of information retrieved by augmenting the search results with related concepts in the ontology. Hyvnen et al. [5] suggested a semantic portal for museums, where a user can browse the collections with the help of the relations in the domain ontology. Kara et al. [6] proposed an ontology-based retrieval system using semantic indexation in the soccer domain. This system includes crawler a module, an automated information extraction, an ontology population module, an inferencing module and a keywords-based semantic query. In addition, domain ontologies have been used in many other applications, including image retrieval Fan et al. [7], video retrieval Erozel et al.[8], information extraction Kara et al. [6], Moreno et al.[9], in information science Bastinos and Krisper [10] , in medical domain Riano et al. [11].

Despite the array of applications of domain ontology in information retrieval, only few of them provide personalized services or applications. Among the existing works, we can mention: Vallet et al. [12] utilized an ontology based user model with contextual information to provide personalized multimedia content access. Middleton et al. [13] exploited an ontological approach to model users for recommending online academic research papers. Jiang and Tan [14] suggested ontology-based user model, called user ontology for providing personalized information service in the semantic Web. The proposed model uses tow concept: Taxonomic elations, and non-taxonomic relations to capture the user interest from a given domain ontology. Riano et al. [6] propose an ontology for the care of chronically ill patients and suggest two personalization process and a decision select tool. Shi and Setchi [15] proposed a knowledge-based framework integrating ontology-based personalized retrieval and reminiscence support. The aim of this system is to provide personalized information about user's live events according to his/her profile and background knowledge. Niarki and Kim [16] developed a new approach in personalization of itineraries search based on the combination of the AHP methods and the Ontology. Olivera et al. [17] defined an ontology in the field of public transport in order to generate personalized user interfaces for transportation interactive systems by model driving engineering.

One of the main drawbacks of the above mentioned approaches is the fact that the retrieval model may not detect easily user preferences or interests in the retrieving process. Few researchers tackled this challenging issue due to the lack of learning techniques. Another drawback is the re-ranking process for search results, which requires more explicit interaction with the users. To provide an efficient personalized retrieval results and improve the user satisfaction, we propose in this paper a new method of personalization based on the combination of domain ontology for information extraction from data sources and the CBR tools for learning and query formulation process. The rest of this paper is organized as follows. In section 2 we present our new approach. Application and results are represented in Section 3. Section 4 concludes this paper.

2. Novel ontology-based personalized information retrieval approach

In this section we present a new personalized information retrieval approach for a particular domain which is logistics transportation filed. We assume the availability of a corpus of text or data, represented by domain concepts (instances or classes) from ontology. We start by extracting and systematically listing all the instances, which may reflect a concept or relationship in the ontology. By mapping the listed instances into ontology and inference, we obtain our structured knowledge base. In our search model, knowledge base rather than corpus is the final search space. Finally, the query is processed against the indexed knowledge base using keyword search interface. The overall system's architecture is illustrated in Fig.1. Personalization based on user preferences is performed by the CBR approach.

CBR, is one of the learning approaches for Artificial Intelligence (AI) Chan [18] that has been drawing the attention of researchers in recent years. CBR is used to solve a new problem by remembering a previous similar situation and by reusing information and knowledge of that situation Aamodt and Plaza [19]. The benefits of using the CBR approach is to provide a more convenient retrieving process in information retrieval system in order to reach conclusions and give recommendations based on knowledge from previous cases and experiences (pervious queries).

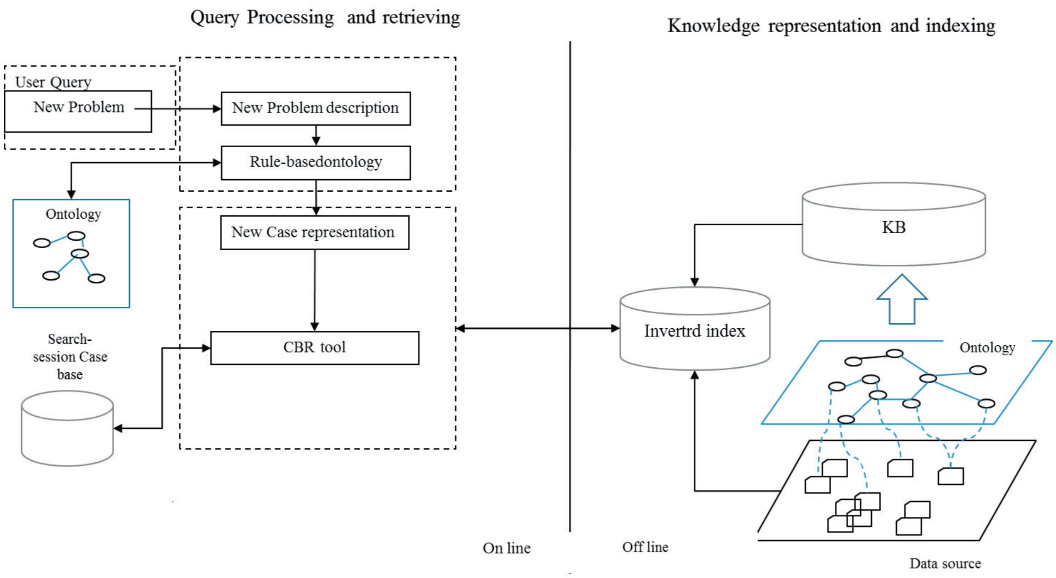

Fig.1 Overall diagram of the system

2.1. Knowledge representation

This step consists on the knowledge acquisition which relies on (semi-) automatic methods to transform un-structured, semi-structured and structured data source into instance data. In order to acquire knowledge, we adopted ontology population technique. This last, deals with the task of identifying new instances belonging to concepts in a given ontology and enriches knowledge bases using the identified instances and their semantic relationships Sánchez et al. [20]. Ontology population is high cost processes that require major engineering efforts and human intervention; it starts by the selection of instances and their mappings to ontology. In our approach, the mapping process was performed semi-automatically using *OWLExporter* proposed by Witte et al. [21] and the intervention of domain specialist. The inference module extracts additional information from retrieved instances using axioms defined in the ontology (Table.1). This feature was built in the ontology in order to formulate the instance-level.

Table1. Example of axioms from GenLog Ontology

Axioms
Carrier has_activity some Loading
Carrier has_ressource some Driver
Carrier has_ressource some Road_freight_vehicle
Receiver has_objective some Other_nuisance_reduction Shipper has_objective someTransport_cost_reduction

2.2. Document Indexing

Indexing is the process of converting a given document into a format that facilitates the retrieval task. The underlying structure of our indexing is based on the inverted index that has been widely for text-query evaluation. In fact, the Inverted index allows on one hand to optimize scalability and in other hand to provide high performance retrieval Culpeper and Moffat [22]. Our index works by maintaining a lists of concepts from the knowledge base, called a vocabulary. For each concept in the vocabulary, the index contains an inverted list, which records an identifier for all documents in which instances of this concept exists. Weights are computed automatically by an adaptation of the TF-IDF algorithm proposed by Sánchez et al. [20], based on the frequency of occurrence of the instances in each document. More specifically, the weight w_I of an instance I for a document d is computed as:

$$w_I = \frac{freq_{I,d}}{\max_J freq_{J,d}} * \log \frac{N}{n_I} \tag{1}$$

Where $freq_{I,d}$ is the number of occurrences in d of the keywords attached to I, $max_J\, freq_{J,d}$ is the frequency of the most repeated instance in d, n_I is the number of documents which contain I, and N is the set of all documents in the knowledge base.

2.3 Query Processing and retrieving

In our system, the query execution returns a set of documents which describe real word itineraries. First, the system computes the similarity between the new query q and each document d, using the classic vector space IR model Eq. (2). Vectors q and d are constructed after assigning weights w_I during the indexing process and calculated according to Eq. (1).

$$Sim(q,d) = \frac{q.d}{|q|.|d|} \tag{2}$$

In order to retrieve relevant results, we propose a new approach based on CBR tool to provide users with alternative documents recommendations. The idea is to improve the retrieving process by reusing and learning from pervious search sessions to satisfy new queries of user. Our CBR system contains three steps: Case representation, Case retrieval and Case retain.

2.3.1 Case representation

In our paper a new case represent the new user query. The underlying concept in CBR is to store the pervious user's queries as a case and when a new user query is formulated the system uses the most relevant past stored cases or queries to resolve the new problem and then recommend more pertinent documents.

A given case is generally described by a problem and a solution McGinty and Wilson [23]. In our work, a problem consists of the description of a user need of information search (user query), it is defined by:

-An Ontological representation O^C (Table.2): a domain ontology which contains a set of concepts with its common properties strongly related by semantic relations used to identify the context of search.
-A Rules-based case representation: a set of SWRL rules is used to represent the new query and to personalize the search.
User query is analyzed based on textual and numerical instances which belong to different concepts and properties in O^C. Textual instances represent information about a given itinerary namely; the address of origin and destination, stockholders, directions, vehicles, customers....etc. However numerical instances represent the search criteria which are mainly stockholders objectives (Fuel consumption, transportation cost, emission reduction ...).

Table 2. Ontological representation of the user query

Keyword query	Ontology concepts	Ontology properties
Oringin/Destination	OWLClass_00000046661641579586 Annotations: rdfs:label "Shipper" OWLClass_00000046661637366480 Annotations: rdfs:label "Carrier" OWLClass_0000004666164059677 Annotations: rdfs:label "Receiver"	OWLObjectProperty_00000003714219380954 Annotations:rdfs:label "connect" OWLObjectProperty_00000043948583785090 Annotations: rdfs:label "origin" OWLObjectProperty_00000044016042214862 Annotations: rdfs:label "destination" OWLObjectProperty_00000045309184500823 Annotations: rdfs:label "ship_address
Vehicle Type	OWLClass_00000048681345885021 Annotations: rdfs:label" Road_freight_vehicle"	OWLObjectProperty_000000485818 Annotations: rdfs:label "has_resource"
Fuel concumption	OWLClass_00000017260945781935 Annotations: rdfs:label "Fossil_fuel_consumption_reduction"	OWLClass_00000022452118786605 Annotations: rdfs:label "Logistics_cost_reduction" OWLObjectProperty_00000049659148982342 Annotations: rdfs:label "has_objective"
Transportation cost	OWLClass_00000017260940625694 Annotations: rdfs:label "Transport_cost_reduction"	OWLClass_00000022452118786605 Annotations: rdfs:label "Logistics_cost_reduction" OWLObjectProperty_00000049659148982342 Annotations: rdfs:label "has_objective"
Emission Co2	OWLClass_00000017260944876793 Annotations: rdfs:label "Emission_reduction" ….	OWLClass_00000022452118786605 Annotations: rdfs:label "Logistics_cost_reduction" OWLObjectProperty_00000049659148982342 Annotations: rdfs:label "has_objective"

When a user submits a query in which the stakeholders like shipper (origin) and receiver (destination) has respectively an economic (Transportation cost) and environmental (Gaz emission) objectives and the type of vehicle chosen is a truck. Then, concepts with labels {“Carrier”, “Shipper”, “Receiver”,”Road_freight_vehicle”, “Transport_cost_reduction”, “Emission_reduction”} and properties with labels {“connect”, “origin”, “destination”, “has_objective”, “has_resource”} are selected from the City logistic ontology Nilesh et al. [24] ontology . Selected concepts are considered as attributes of the new case and the query terms are considered as instances. The new case is then formulated using a new SWRL rule (Example in Table.3).

Table 3. An example of a SWRL Rule

SWRL Rule#	Definition
Transport_cost_reduction(?t), Emission_reduction(?o), Carrier(?c), Receiver(?e), Shipper(?s), Road_freight_vehicle(?r), Itinerary_pattern(?p), has_ressource(?c, ?r), ,has_objective(?s, ?t), has_objective(?e, ?o)-> Shipper_receiver_pattern(?i)	Shipper receiver case : The case where the shipper and the receiver have objectives in the same itinerary

The solution is a new formulated query based on similar cases which may be retrieved from the search session case base. We associate for each case, two vectors of weighted instances (Text_vector and Numerical_vector) in order to obtain the most relevant cases.

- Text_features: (T) This vector is used to represent concepts with textual instances. This vector is the n-uple$((w^t_1\ I^t_1)\ (w^t_2\ I^t_2)\ldots\ (w^t_n\ I^t_n))$ where $I^t_i \in O^C$. w^t_j represents the weight of all terms referring the the textual instances of concepts in case Ca_i which belongs the ontological representation O^C.
- Numerical_features: (N) This vector is used to represent concepts with numerical instances. This vector is the n-uple $((w_1\ I^n_1)\ (w_2\ I^n_2)\ldots\ (w_m\ I^n_m))$ where $I^n_j \in O^C$. w_j represents the weight of all terms referring the numerical instances of concepts in Ca_i which belongs the ontological representation O^C.

The weighting procedure is discussed in section (2.3.2).

2.3.2 Case Retrieving

In the retrieving phase, we use two methods to compute case similarities; textual instance matching and numerical instance matching. Given two cases Ca_{mem} and Ca_{new} as input, instance matching is defined as the process of comparing set of instances I_p (p=1,…, m) which belong respectively to concepts $C^{mem}{}_p$ (p=1,…, m) and an instance I_q which belong respectively to concept $C^{new}{}_q$(q=1,…, n) , with a mapping between their matching assertions.

- Textual instance matching

In each case, textual instance weight w^n is computed automatically using TF-IDF algorithm Slaton [25]. Textual instance matching is then computed using cosine formula of T_{mem} and T_{new} which belong respectively to textuel_feature vectors of Ca_{mem} and Ca_{new}:

$$sim(T_{mem}, T_{new}) = \frac{T_{mem} . T_{new}}{|T_{mem}| . |T_{new}|} \quad (3)$$

- Numerical instance matching

This stage is carried out in two steps. In the first step, we calculate the local similarity between numerical instances (search criteria) by choosing from several measurements Zhang and Zhang [26].We adapted the following local similarity measure:

$$sim(I_i^n, I_j^n) = 1 - \frac{\left|I_i - I_j\right|}{I_i^{n(\max)} - I_j^{n(\min)}} \quad (4)$$

Where I^n_i is the i^{th} numerical instance of the new case Ca_{new}. The I^n_j is the j^{th} numerical instance of the case in memory Ca_{mem} and $I_i^{n(\max)}, I_j^{n(\min)}$ are the maximum and minimum values between all the search criteria cases (including the target case). The second step entails calculating overall similarity for search criteria by using the weights associated with each numerical instance as shown in Eq. (4).

$$Sim(N_{mem}, N_{new}) = \frac{\sum_{i=1}^{m}(sim(I_i^n, I_j^n)W_i}{\sum_{i=1}^{n} W_i} \quad (5)$$

Where N_{new} and N_{mem} belong respectively to numerical_feature vectors of Ca_{mem} and Ca_{new}, m is the number of numerical instances of each case and $\sum_{i=1}^{m} W_i$ the summation weights of m numerical instances in each case.

In our approach, the weights of numerical instances W_i is calculated using the Analytic Hierarchy Process (AHP) method Saaty [27]. The AHP approach can deal with both quantitative and qualitative criteria. The details of this method of weight aggregation are reported in Bouhana et al. [28]

Finally, we calculate the global similarities Eq (5) for case matching which consists in combining textual similarity measures with numerical similarity measures.

$$Sim\ glob\ (Ca_{new}, Ca_{mem}) = sim\ (average\ textual + sim_{gnum} average\ num)*\alpha$$

With α a coefficient of normalization α∈ [0.1]

$$Sim\ glob\ (Ca_{new}, C_{mem}) = \{ \mathrm{sim}(T_{mem}, T_{new}) = \frac{T_{mem} . T_{new}}{|T_{mem}| . |T_{new}|} + Sim(N_{mem}, N_{new}) = \frac{\sum_{i=1}^{m}(sim(I_i^n, I_j^n)W_i}{\sum_{i=1}^{n} W_i} \}*\alpha \quad (6)$$

Finally, the case having the biggest global similarity with the new case will be selected.

2.2.3 Case Retain

When a new case occurs it is compared to set known solutions. The most similar and relevant solutions are retrieved. The solution of retrieved case is then adapted. The revised solutions are then retained temporarily. And then, when the suggested solutions are actually applied the solution outcomes for the current solution can be evaluated.

Finally the new problem description (new case) and its solution is retained as a new case in the search session Case Base in order to help the user's to find the right solution for future search. We conducted experiments to evaluate the performance our retrieved model. The experiments are presented in the following section.

3. Computer experiments and results

We are testing our techniques on a corpus of documents from the Paris open data [†]web site. The KB was created using City logistic ontology Nilesh et al. [26]. Initially, our KB includes a set of extracted instances which rely on 4480 documents in text format and the search session case base includes 20 cases. The first evaluation is done using recall curve and on the basis of a rating of document relevance. Fig. 4 illustrates the performance of our techniques (VSM/GS) on the query *Q* compared to the results obtained with only VSM. Here, we mean by VSM, obtained results using only the classic vector space model and without learning phase (CBR). However, we mean by (VSM/GSM), obtained results using CBR tool (recommendation).

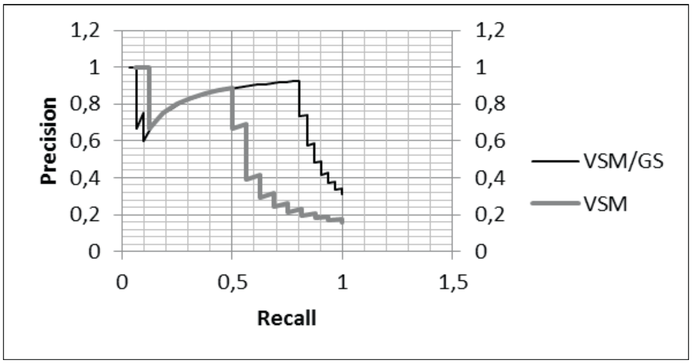

Fig. 4.Precision recall curve of *Q*= "go from Rue Saint Denis to Rue Galvani" with search criteria: Time less than 30 mn, Vehicle type is truck, Fuel consumption less than 0.270, Emission co2 less than 500 co2/km and Transportation cost less than 50 euro

For the same query we have computed the average precision value for VSM and (VSM/GS). Results are presented in Table.4. The second column depicts the original results of VSM. The third column lists the obtained results using (VSM/GS).

Table 4. Average Precision using VSM and VSM/GS

Documents	Precision (VSM)	Precision (VSM/GS)
15 docs	0,694	0,777(+8,3%)
25 docs	0,419	0,910(+49,1%)
30 docs	0,344	0,862(+51,8%)
35 docs	0,294	0,735(44,1%)
40 docs	0,282	0,666(+38,4%)
45 docs	0,252	0,590(+33,8%)
50 docs	0,244	0,552(+30,8%)
Average Precision	0,158	0,318(+16%)

† http://opendata.paris.fr/opendata/

Based on the above results, we can conclude that our initial experiments are showing promising results by high rate of precision using the (VSM/GS). More extensive testing is needed (and actually under way at the time of this writing), in order to complete and extend these first observations.

4. Conclusion

In this paper, a novel personalized retrieval framework was proposed to achieve a scalable and user friendly data retrieval system with high retrieval performance. The proposed personalized retrieval framework integrates the advantages of the ontology in data and user preferences representation while using the CBR technology as a learning technique to improve the efficiencies of our IR system.

The proposed method was tested using Precision-recall curve an average precision metric. Experimental results showed that these methods are efficient and promising. Since using the CBR models for personalized information retrieval, there are many opportunities for future works in this field implementing suitable tools for other steps of the CBR method, such as: an expert systems for dealing with the adaptation phase or the integration of the Fuzzy AHP tool with the CBR technique to accurately solve the problem of personalized information retrieval in uncertain environments.

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