A recommendation technique for cultural heritage hypermedial objects

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***Abstract*—The ever more widespread use of the Web for knowledge sharing has led to the creation of a wide spectrum of opportunities for employing shared information resources and, at the same time, a gradual increase in the technologies for making these resources available. In this scenario, it is important to define new methods and techniques that can support users' search activities and selection of the resources corresponding most closely to their needs. The work is situated in the context of research into recommendation methods for defining systems that can suggest to users what hypermedial resource best fits their specific requirements. The paper proposes a recommendation technique that can elicit relations existing within complex domains so as to be able to suggest semantically correlated hypermedial objects to users according to their requests.**

Recommender system; ontology; cultural heritage.

I. INTRODUCTION

The widespread use of the Web for knowledge sharing has led to the creation of a wide spectrum of opportunities for employing shared information resources and, at the same time, to a gradual increase in the technologies for making these resources available. Long ago, the introduction of the hypermedia paradigm serving to build information resources available on the Web posed the problem of determining the orientation and choice of navigational path best suited to the users' expectations and learning style. Although many different methodological and technological solutions have been reported in literature over the years, the information sharing culture that is now taking on so important a role has shifted the focus from the individual resource to the set of resources offered by the Web. In other words, nowadays users need to learn to navigate and orient their choices of resources among the myriad alternatives present on the Web.

In this scenario, it is essential to define new methods and techniques, integrated within technological solutions that can support users' search activities and selection of the resources corresponding most closely to their needs. The present work is situated in the context of research into recommendation methods for defining systems that can suggest to users what hypermedial resource best fits their specific requirements.

The applicative research context belongs within a regional project funded by the Apulia Region, named "Genomena: Cultural Non Tangible Heritage for Reconstructing the Historical Memory of the Territory". The project intends to improve and spread knowledge about our intangible cultural heritage [1].

Users of the system can therefore access hypermedial resources about intangible cultural heritage, classified as: Cultural Learning Object (CLO), if the resource is intended for students; Information Brochure (IB), if it advertises an event; Intangible Cultural Heritage card (ICH card), if it contains technical information about the event.

Moreover, since the information about a cultural event can be addressed to different types of people for different purposes, a number of problems arise as regards the best way to suggest the right cultural object in the best form to the user. In this article we present the Genomena system, the solution adopted in the project with the same name, illustrating the chosen knowledge-based recommendation technique.

II. THE RECOMMENDATION METHODS ANALYSIS

As stated by Robin Burke [2] the term "recommender system" describes the set of systems that produce individualized suggestions on the basis of internal computing or act as a personalized guiding system orienting the user among a wide range of possible options. Starting from the data the system works on, a distinction can be made between background data, in other words the data the system knows and manages before beginning the recommendation process, and input data, i.e. the information the user gives the system that is needed to process the suggestion. The background and input data are related to the recommendation algorithm that transforms these data into a suggestion. These three elements (background data, input data and algorithm) differentiate the various types of method, namely collaborative, demographic, content-based, utility-based, knowledge-based methods [4, 2].

The collaborative method aggregates the ratings and recommendations about the objects to be suggested according to similarities between users and their ratings; some examples are given in [5, 6]. The advantages of this method are: it can make "cross-genre" type suggestions, it is independent of the domain knowledge, and the suggestions provided will improve over time thanks to the presence of new feedback. On the down side, the system will have the ramp-up problem both as regards new items and new users, in other words, for the system a user with few ratings becomes difficult to categorize and so some problems can arise in suggesting new items and new users [2].

The demographic method classifies users according to their personal characteristics and processes suggestions based on the demographic class the user belongs to. The

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demographic method establishes correlations among people, like the collaborative method, but unlike the latter it works on personal data rather than the user's own assessments [7, 8]. This method is not subject to the ramp-up problem but its main problem is the difficulty in finding relevant demographic data since users are not very willing to insert their personal data. Moreover, the demographic system is not able either to provide explanations about the relations among the suggested items or to provide "cross-genre" suggestions.

The content-based method is an evolution of information filtering techniques [3]. In content-based systems it is some elements of the objects themselves that are the features defining the objects of interest. The user interests profile is, therefore, learned on the basis of the characteristics present in the object rated by the user. This method is also known as "item-to-item correlation" [10]. A survey of content-based systems is present in [9]. Like the collaborative method, content-based user profiles are long term models that are updated when new evidence about the user preferences is obtained; this generates problems when users' interests change [4]. Moreover, this method also suffers from the ramp-up problem and is unable to provide "cross-genre" suggestions, so it is not suitable for domains where there are very similar items.

The utility-based method (like the knowledge-based method) does not try to build long term generalizations about users. By means of a utility function, it suggests the most suitable objects by comparing the user's needs with the set of possible options that can satisfy them. There are two advantages to this approach: it is not susceptible to the ramp-up problem and it can include different factors that can even be extraneous to the features set. However, it is up to the user to build the utility function, which slows down the interaction and, in addition, if the user's aims change, the utility function will have to be completely revised.

The knowledge-based method works by inferring the users' needs and preferences starting from the data available. This method is suited to occasional use because it is not based on comparisons of users ratings, it does not suffer from the ramp-up problem and, finally, it can provide suggestions within very wide knowledge fields.

On this basis, all the above described recommendation methods could be defined as knowledge-based, because they all make inferences using functional knowledge. In literature [11, 12], reasoning techniques based on first order logic have been used to implement knowledge-based recommender systems.

III. The Genomena System

The aim of the Genomena system is to gain a better understanding of past traditions, habits and customs that have been passed down the centuries and whose faint echoes are still perceivable even nowadays. The purpose of the system is to enhance and spread a knowledge of this intangible cultural heritage among the present-day inhabitants of the territory. The system implements three actions: supporting research into intangible cultural heritage to offer researchers in this sector advanced information tools that can help them to share and correlate their knowledge; spreading the culture to all those interested, from school-age children to senior citizens; promoting tourism. In each of these actions, the system provides personalized services aiming to respond to users' interests and to indicate further information that could widen their knowledge.

The innovative aspect of the recommendation technique defined in the context of this research and applied in the Genomena system is that it is not only able to respond very precisely to the requests of all different types of users but also to suggest references to other cultural topics related to the request either by their geographical vicinity or by the time period, or some other pre-established aspects. In addition, the system can indicate the type of correlation, making it easier for the user to understand whether the resource really does come into her/his field of interest or not. The need to choose the recommendation method best suited to the Genomena system led us to analyze the characteristics of each pure method. Our in-depth analysis led us to opt for the knowledge-based method because it is the most general and so poses the least constraints for defining the technique. Since it does not suffer from the ramp-up problem, it can also be browsed by occasional users who do not wish to register with the system. Moreover, it is the only method that is able to justify the choices made and relate the items to their semantic basis.

IV. Defining the Recommendation Technique

The organization of knowledge inside the Genomena system was the first problem that had to be faced when implementing the knowledge-based method. After a close study of the domain carried out in collaboration with experts on cultural heritage, we decided to structure the knowledge as factual, specific and general. Factual knowledge, represented in the database, describes the objects in the system: the ICH cards, CLOs and IBs. Specific knowledge, expressed in ontological form, serves to relate the factual knowledge to well circumscribed knowledge domains. For example, the ICH cards about the life of St. Nicholas are found in the context of the ontology of the Saint. The general knowledge is also expressed in ontological form and can place the factual and specific knowledge in context, thus representing, over a period of time spanning from the pre-Christian era to the present day, traditions, cultures, dominations and religions. The three knowledge forms are not directly linked but are correlated during the recommendation phase. The formalization of the data structure and knowledge inside the system and the way the knowledge is used to provide suggestions are described below.

A. Factual Knowledge

The scheme shown in Figure 1 illustrates how factual knowledge is organized. In the center, there is the ICH card with all the attributes defined by the ICCD (Central Institute for Cataloging and Documentation) standard. The CLOs and IBs, with their respective attributes, are all entities linked to the card.

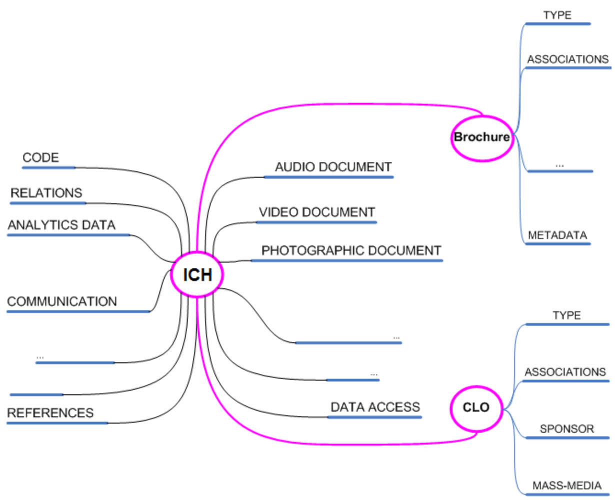

Figure 1. Organization of the data in the DB.

This type of organization makes it possible to concentrate the domain knowledge inside the ICH cards. In this way, the recommendation algorithm can work on all the objects, taking into account only the ICH cards, that are the objects containing the richest quantity of historical information, since they have been defined and inserted by the experts in the field. In this way the system can respond using the same semantic relations regardless of whether the object suggested is an ICH card, a CLO or an IB. The user profiling system will have the task of defining, among correlated objects, which ones are best suited to the user profile.

B. Specific and General Knowledge

The difference between specific and general knowledge only affects the knowledge domain, but in any case the same representation method was adopted. In both cases, in fact, it was necessary to represent the objects, with their properties and relations, together with the events in their space-time context (where and when). To represent the objects, the ontological approach was adopted, using the OWL language. Instead, the space-time representation posed a challenge. For example, how should a religious cult that was celebrated in different regions at different times be represented? How should figures of authority, like the king of a nation, be represented bearing in mind that although the political figure is always the same, the "king of France", is a different person at different periods of time? The problem was faced and solved by means of the calculation of events.

1) The OWL ontology: experts with a deep knowledge of cultural heritage were involved in drawing up the ontology. First of all, it was considered necessary to identify the needs the knowledge was intended to supply. Then, after having collected the knowledge needed to satisfy this requirement, the vocabulary of functions, predicates and constants was defined. In this phase, the concepts (or classes) to be represented and the relations among the classes were defined. After determining the instances of the classes, the defined ontology was populated.

2) The event calculus: is a refinement of the situation calculus [13]. The latter technique is used to represent knowledge describing the state of a predicate according to when a particular action occurred. Situation calculus is useful when the actions are short lasting, or in any case of short duration for the purposes of the chosen representation method. Instead, when actions last longer and may cause overlaps, it is better to use the calculation of events, according to which a flow predicate is true, at a point in time, if it was triggered by an event that occurred at some point in the past and was not terminated by any other event [13]. Using this technique, it is possible to generalize the concept of an event as a space-time portion rather than just as an event in time. A set of functions, predicates and rules was thus defined, on which the space-time reasoning was based. The table I shows a meaningful selection of operators among those defined.

TABLE I. OPERATORS DEFINED TO CALCULATE THE EVENTS

Operator	Explanation
Occurrence(e,t)	Predicate indicates that event e occurred at time t
In(e1, e2)	Predicate indicates spatial projection of an event inside another space e.g. In(Rome, Italy)
Location(e)	Function denoting the smallest place that completely covers event e. E.g. Location(relicX)=ChurchY
Start ()	Function indicating the first moment of time of the event
End ()	Function indicating the end of the event
Consecutive(i,j) ⇔ Time(End(i)) = Time(Start(j))	Rule establishing that two events are consecutive if the second one starts at the moment when the first one ends

These predicates and functions allowed us to define the relations highlighting analogies among fragments of knowledge. There are three different types: time, space and concept. To illustrate the logic used, we analyze the following example of a time relation.

Suppose an ICH card related to a Saint's day has been retrieved, and other events occurring on the same day need to be suggested. For this purpose, two different types of time relations are considered, firstly those happening on exactly the same day (simultaneous events); the second pointing out things that happened at the same time in the past (concomitant events). For example, on the 6^{th} December of each year, the celebrations of Saint Nicholas are held in Bari. The relation retrieving simultaneous events suggests other cultural events occurring in the same period. The relation retrieving concomitant events suggests events like the ancient winter celebration that used to be held centuries ago, on the 6^{th} December. The added value obtained during the database query is that it is not necessary to define the concept contemporaneous in a rigid manner, as it normally is. Two events x and y are defined as contemporaneous if Start(x) and Start(y) occur within a period of five days or Start(y) and End(x) occur within a period of five days or End(x) and End(y) occur within the same five-day period or Start(x) and, although far from their respective Start(y) and

End(y), occur within the time interval of the Start(y) or End(y) of y or vice versa. Formally:

$$
\begin{aligned}
&Contemporaneous(x,y) :- \\
&(Days(\,|Time(Start\,(x)) - Time(Start\,(y))|\,) < 5) \vee \\
&(Days(\,|Time(Start\,(y)) - Time(End(x))|\,) < 5) \vee \\
&(Days(|Time(End(x)) - Time(End(y))|) < 5) \vee \ldots
\end{aligned}
$$

where:

- Time(x) reports (in GMT) when event x occurs
- Days(x) transforms the numerical value resulting from the function Time(x) into a day of the week

Using the same logic any type of relation between two or more ICH cards can be defined. We report an example of a rule that allows two different objects of religious art to be correlated.

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PertinentArt(Y,X) :-
  property(F,X,expressionof), not(isa(F,festa)),
 property(F,Y,expressionof)), property(X,Y,expressionof).
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C. Calculation of the Suggestion

The defined knowledge representation is used by the system to suggest information related to the user request.

The proposed recommendation technique consists of three essential phases: semantic enhancement of the string inserted by the user, aiming to complete the results set; search and selection of the ICH card, to exclude results with little affinity with the user's request; suggestion of other results correlated to those requested.

1) Semantic enhancement: the research string inserted by the user is broken down into single words; each word is analyzed and, on the basis of MultiWordNet lexical data [14], words like articles, prepositions and adverbs are eliminated, because these are not generally important to the search.

After the string has been purged from the lexical standpoint it is enhanced by synonyms taken from the MultiWordNet database and for each word, both singular and plural are considered, thus building vector Q that will be used to define the database query. Suppose the user has inserted the search string "Saint Nicholas' celebration". The resulting vector is defined as follows:

$$Q := \begin{bmatrix} [celebration, celebrations, festival, festivals] \\ [St, Saint, Saints, S., SS.] \\ [Nicola, Nicolò, Niccolò] \end{bmatrix}$$

Of course MultiWordNet is used in Italian; in this paper the search string and the vector Q have been translated into English.

2) Search and selection of the ICH card: vector Q is the input to the algorithm to retrieve the objects searched for, according to which the correlated topics will be calculated. To understand how the algorithm works, the following data structures are defined: $B:=[b_1,\ b_2,\ \ldots,\ b_l]$ vector of the objects present in the database; $C:=[c_1,\ c_2,\ldots,c_j]$ vector of the relevant search fields in the database; $P:=\ [p_1,\ p_2,\ldots,\ p_j]$ vector of the weights on the vector fields C.

$$Q := \begin{bmatrix} [q_{1,1}, q_{1,2}, \ldots, q_{1,p}] \\ [q_{2,1}, q_{2,2}, \ldots, q_{2,p}] \\ \ldots \\ [q_{w,1}, q_{w,2}, \ldots, q_{w,p}] \end{bmatrix}$$

It is important to note that, if there is not the same number of synonyms for each word, zero is added in the rows in order to build the matrix Q.

From matrix Q a logical expression is derived where AND contains the data in the lines and OR the data in the columns. In the example:

$$Q^{\text{log.expr.}} = (q_{1,1} \vee q_{1,2} \vee \ldots \vee q_{1,p}) \wedge \ldots \wedge (q_{w,1} \vee q_{w,2} \vee \ldots \vee q_{w,p})$$

The logical expression $Q^{\text{log.expr}}$ is assessed to establish what object in the database contains, in the relevant fields, the words contained in the string inserted by the user. For each element in the matrix $M_{(t,u)}$ the function $Val(Q^{log.expr},\ c_t,\ b_u)$ returns 1 if the conditions imposed by the logical expression $Q^{\text{log.expr}}$ are satisfied in the relevant field c_t of the object b_u and 0 if they are not (where $1 \leq t \leq l$ and $1 \leq u \leq j$).

$$M = \begin{bmatrix} val(Q^{\text{log.expr}}, c_1, b_1) & \ldots & val(Q^{\text{log.expr}}, c_j, b_1) \\ \ldots & \ldots & \ldots \\ val(Q^{\text{log.expr}}, c_1, b_l) & \ldots & val(Q^{\text{log.expr}}, c_j, b_l) \end{bmatrix}$$

Matrix M containing the results of assessment of the function $Val(Q^{log.expr},\ c_t,\ b_u)$ is multiplied by vector P containing the weights assigned to the fields of vector C generating vector R.

$$R = \begin{bmatrix} val(Q^{\text{log.expr}}, c_1, b_1) & \ldots & val(Q^{\text{log.expr}}, c_j, b_1) \\ \ldots & \ldots & \ldots \\ val(Q^{\text{log.expr}}, c_1, b_l) & \ldots & val(Q^{\text{log.expr}}, c_j, b_l) \end{bmatrix} \times \begin{bmatrix} p_1 \\ \ldots \\ p_j \end{bmatrix}$$

R indicates for each element R_i by $1 \leq i \leq j$, the pertinence of each ICH card b_i according to the string inserted.

The results matrix *MRes* (jx2) is created, assigning each R_i with $1 \leq i \leq j$ the code of the relative ICH card.

$$M\,\mathrm{Re}s = \begin{bmatrix} \begin{bmatrix} p_1 \\ \ldots \\ p_j \end{bmatrix} \begin{bmatrix} \text{cod. ICHcard } \alpha \\ \ldots \\ \text{cod. ICHcard } \eta \end{bmatrix} \end{bmatrix}$$

MRes is ordered in increasing order of p_i $1 \leq i \leq j$, creating the list of results. The first n ICH cards in the list are presented in order of their relevance to the user's requirement. Note that vectors C and P and the number of ICH cards presented to the user are parameters to be provided as input for the algorithm.

3) Suggestion of ICH cards related to user requests: starting from the results presented to the user, the correlation to other ICH cards is calculated. The information on the ICH cards found, together with the specific and general knowledge, partly coded in Prolog and partly in OWL (as shown in table II), generates the knowledge base on which the correlations among the topics are calculated. The concepts, instances and properties of the ontology (OWL) have to be formalized in declarative language: in particular, the hierarchical representation of the concepts and the properties of the ontology are stated as rules, while the instances are inserted in the knowledge base in the form of facts. After creating the knowledge base, the goals for determining the ICH cards to be suggested were defined. In order to simplify the goals, during the building of the database, the correlation rules among the instances of the ontology were defined.

TABLE II. PREDICATES FROM OWL TO PROLOG

OWL	Prolog	Example
Class	class(x)	class(cathedral).
Subclass	isa(I, y) :- isa(I, x). y superclass x class, I individual.	isa(I, church) :- isa(I, cathedral).
Symmetric Properties	property(I1, I2, k) :- property(I2, I1, k). where k is the name of the property, I1 and I2 the relative individuals.	property(a, b, eSinDi) :- property(b, a, eSinDi) "If a is synonymous of b then b is synonymous of a"
Transitive Properties	property(I1, I3, k) :- property(I1, I2, k), property(I2, I3, k). where k is the name of the property, I1, I2 and I3 the related individuals.	property(a, c, friend) :- property(a, b, friend), property(b, c, friend). "If a is synonymous of b and b is synonymous of c then a is synonymous of c"

Thanks to this process, legible and relatively simple goals were obtained. Moreover, with this system it was possible to combine various types of relations (e.g. contemporary, neighboring events) so as to be able to choose the best ICH cards related to the user's request. Thus, "Concomitant Events" returns ICH cards corresponding to events occurring on the same date, regardless of the year, as the event referred in card x. For this reason, the system displays card y if it corresponds to an event held on the same date as the event referred in card x. For example if the card x is related to St. Nicholas' celebration day, held in Bari in December, the system will select the St. Nicholas religious icon exhibition, held in the same period in Molfetta cathedral (Molfetta is a city near Bari). Formally:

:-found(Rank,CodX),
ontologic_object(CodX,X),
concomitant(X,Y),
not(isa(Y,aggregation_event)),
ontologic_object(CodY,Y).

where

- found(Rank,CodX) indicates in the database the card identified by code CodX with rank (p_i in the described algorithm) "Rank".
- ontologic_object (CodX,X) indicates that card CodX is associated with instance X of the ontology
- concomitant(X,Y) indicates that events X and Y are concomitant
- not(isa(Y, aggregation_event)) indicates that Y is not an aggregation type event otherwise the concomitance would be obvious
- ontologic_object(CodY,Y) indicates that the card CodY is associated with instance Y in the ontology

The results found during the inferential process link two or more concepts in the ontology. These links may lead on to references to ICH cards or may not. In the first case, with a simple query of the DB, all the objects (CLOs, IBs and ICH cards) referred to the relative ICH card, resulting from the described process (in section VI-C-2), will be shown. All the objects found are presented to the user as suggestions. In the second case, a text suggestion is generated, in other words a string of text that suggests a conceptual relation because it is present in the ontology, but cannot provide further detail due to the lack of specific data in the DB. The output of the Genomena system is further processed on the basis of the final user type, presenting CLOs, ICH cards, IBs or points for further reflection.

V. CONCLUSIONS AND FUTURE DEVELOPMENTS

The present work proposes a recommendation technique that can elicit relations existing within complex domains, so as to be able to suggest semantically correlated objects (CLOs, IBs, ICH cards) in the context of the Genomena project to users according to their requests. Since the technique is derived from the knowledge–based method, it does not suffer from the ramp-up problem as regards either new items or new users. In other words, regardless of the rate of growth of the set of items the suggestions supplied are equally reliable. This is because the system does not rely on relevance feedback to calculate the suggestion and so maintains a constant quality even when employed by occasional users not registered in the system. Another strong point of the proposed technique is its transferability to environments like e-commerce or e-learning, in which it is important to be able to acquire suggestions linked to the specific domain and also to orient the research both vertically (supplying ever more specific suggestions in the same field) and horizontally (supplying less specific suggestions in different fields).

Application of this technique inside the Genomena system revealed some weak points. The computing complexity means that the operations for calculating the suggestions take quite a time. The critical points were seen to be the semantic enhancement phase (section IV-C-1) and the inference phase (section IV-C-3). As regards the former, we estimated that in the Genomena project semantic enhancement takes up about 20% of the total time needed to conclude the recommendation process. Since the process is based on searches in the MultiWordNet lexical database, that is one of the most complete, this point cannot currently be improved. Instead, as regards the times taken up by the inference phase, these are strictly linked to the Prolog interpreter, that makes an exhaustive search of the space delineating the states. For this reason, the more complex the knowledge base the longer the processing times. Our study data revealed that this process takes up about 55% of the total time needed to carry out the recommendation process.

To overcome this problem, we are now studying two different solutions: the implementation of meta-interpreters that employ informed searches, so as to restrict the possible solutions space, or alternatively the formulation of very specific goals that can simplify and speed up the inference process.

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