A Semantic-based Recommender System Using A Simulated Annealing Algorithm

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***Abstract*— A recommender system based on semantic web technologies and on an adaptive hypermedia architecture is shown in this paper. The system uses a stochastic algorithm to provide recommendations to users. The paper presents the system architecture based on the semantic Web technologies and explains a simulated annealing algorithm performing the recommendations. A mobile application for the tourism domain proving the feasibility of this system is described at the end of the paper, some benchmarks are presented. In this application, the recommendations are defined as combinations of tourism products, which are linked to each other. The paper is mainly focused on the architecture and the recommendation process of the system.**

Keywords - ***Semantic based recommender system, adaptive hypermedia system, simulated annealing algorithm, tourist travel.***

I. INTRODUCTION

These last years, the number of customer relationship management (CRM) implementations has increased enormously. CRM systems aim at allowing organizations to provide fast and efficient user-focused services. A CRM system uses client related information or knowledge to provide relevant products or services to clients [1]. The increasing use of digital technologies by customers, and particularly the Web and mobile devices, is changing what is possible and what is expected in terms of customer management. CRM evolved from business processes such as the need to improve the client retention by the effective management of customer relationships [2].

Our project aims to facilitate tourists for the definition of a complete journey on the region Côte d'Or in Burgundy, France from a database composed of more than 4 thousand geo-localized tourism products. Today, searching and finding relevant tourism products related to a user profile is tedious. Consequently, a recommendation system has been defined. The use of personalized recommender systems [3] [4] [5] to assist customers in the selection of products is becoming more and more popular and wide-spread. Most of the recommender systems is based on algorithms computing recommendations using methods like collaborative filtering [6] [7], content-based classifier [8] [9] and hybrids of these two techniques [10] [11] [12].

Recommender systems suggest information sources and products to users based on learning from examples of their likes and dislikes [4]. A typical recommender system has three steps: 1/ Users provide examples of their tastes. These can be explicit, like demanding ratings of specific items, or implicit, like analyzing his browsing behavior. 2/ A user profile is computed using the information from the first step. It is a representation of the user's likes and dislikes; 3/The system computes recommendations using these user profiles.

Content-based (CB) and collaborative filtering (CF) methods are two of the main approaches used to form recommendations. Hybrid techniques integrating these two different approaches have also been proposed. The CB method has been based on the textual filtering model described in [13]. Generally, in CB systems, the user profile is inferred automatically from documents' content that the user has seen and rated. The profiles and domain documents are then used as input of a classification algorithm. The documents which are similar (in content) to the user profile are considered interesting and are recommended to the user.

CF systems [6] [7] are an alternative to CB systems. The basic idea is to go beyond the experience of an individual user profile and instead to use the experiences of a population or community of users. These systems are designed with the assumption that a good way to find interesting content is to find people with similar tastes and to propose items they like. Typically, each user is associated to a set of nearest-neighbor users, comparing profiles' information. With this method, objects recommendations are based on similarities of users rather than the similarities of objects.

Both CF and CB systems have strengths and weaknesses. In CF systems, the main problem is that the new objects with no rate cannot be recommended. CB systems suffer from deficiencies in the way of selecting items for recommendation. Indeed, the objects are recommended if the user has seen and liked similar objects in the past. Consequently, a variety of hybrid systems have recently been developed: 1/ Some use other users' ratings as additional features in a CB system [10]. 2/ Some use CB methods for the creation of bots producing additional data for "pseudo-users". These data are combined with real users' data using CF methods [12]. 3/ Others use CB predictions to "fill out" the probable user-items' ratings in order to allow CF techniques to produce more accurate recommendations [11].

We have developed a CB system inspired by Adaptive Hypermedia systems. Adaptive hypermedia systems are hypermedia systems (websites, e-learning platforms, etc.) with adaptive behavior to provide adaptive content, presentation and navigation to users, based on their knowledge, preferences, goals, etc. The purpose of the proposed system is to find the best combination of individuals from a domain ontology that fit to the user interest and we propose the use a simulated annealing algorithm to do this. The first part explains what an adaptive

 ISBN: 978-1-61208-104-5

hypermedia system is. It is also shown in this part how adaptive hypermedia systems are positioned relative to recommender systems. Then, a part describes the architecture, the properties and the recommendation process of the proposed recommender system applied to tourism domain. The next part shows a utilization example for a touristic journey proposition and the final one gives some benchmark of the application.

II. ADAPTIVE HYPERMEDIA SYSTEMS

The research domain of adaptive hypermedia has been very prolific these 10 last years. Some systems [14] [15] [16] have been developed, giving principally solutions for e-Learning which is considered as the first application domain. Each system brings its own architecture and methods. Moreover, few attempts have been made to define reference models [17] [18] [19] [20] but without success because of being not enough generic to take account of the new trends and innovations. Nevertheless, most of the systems and models are based on a set of layers, also called models, which separate clearly the different tasks. Then, we can see that there are at least three models in common, necessary and sufficient to achieve adaptive hypermedia systems according to Brusilovsky [21]. It needs to primarily be a hypermedia system based on a domain. The domain model is a representation of the knowledge on a given subject the creator wants to deliver. It describes how the domain is organized and interconnected. The second model is called a user model which is a representation of the user within the system. It models all user information which may require the system to provide an adaptation. The last model is the adaptation model. It performs all the adaptive algorithms based on other models to provide an adaptation to the user. Beyond the use of domain, user and adaptation models, the trend is to use additional models like presentation, goals, context or other models. This allows to better identify the different performed tasks and to facilitate the construction of adaptive hypermedia systems. Nevertheless, there is no generic model integrating them for the moment.

Methods to model domain/user (adaptation principles are also described):

The **keywords vectors space** methods consider that each document and user profile is described by a set of weighted keywords vectors [22] [23] [24]. At the adaptation model, the weights are used to calculate the similarity degree between two vectors and then to propose relevant document to the user. The keywords representation is popular because of its simplicity and its efficiency. Nevertheless, the main drawback is that a lot of information is lost during the representation phase.

In **semantic networks**, each node represents a concept. Minio and Tasso [25] present a semantic networks based approach where each node contains a particular word of a corpus and arcs are created following the co-occurrences of the words from connected nodes into the documents. Each domain document is represented like that. In simple systems using only one semantic network to model the user, each node contains only one keyword. The keywords are extracted from pages which the user gives its taste. Then, they are treated to keep only the most relevant ones and are weighted in order to remove those with a weight lesser than a predefined threshold. The selected keywords are then added to the semantic network where each node represents a keyword and each arc their co-occurrence into the documents. With this method, it is possible to evaluate the relevance of a document compared to the user profile. Indeed, it suffices to construct a semantic network of a document and compare it to the semantic network of the user to classify it to interesting, uninteresting or indifferent documents.

Ontology approach is similar to the semantic network approach in the sense that both are represented using nodes and relations between nodes. Nevertheless, in concepts based profiles, nodes represent abstract subjects and not word or set of words. Moreover, links are not only co-occurrence relations between words, they have several significations. The use of ontology can keep a maximum of information. In QuickStep [26], the ontology is used for the research domain and has been created by domain experts. The ontology concepts are represented as vectors of article examples. The users' papers from their publication list are modeled as characteristic' vectors and are linked to concepts using the nearest neighbor algorithm. These concepts are then used to form a user profile. Each concept is weighted by the number of papers linked to it. Recommendations are then made from the correlations between the current interests of the user to topics and papers that are related to these topics. In [27] and [28], a predefined ontology is used to model the domain. User profiles are represented with a set of weighted concepts where weight represents the user's interest for a concept. Its interests are determined by analyzing its behavior.

Three types of adaptation have been highlighted in the researches on adaptive hypermedia systems: content, navigation and presentation adaptation. The content adaptation consists in hiding/showing or highlighting some information. The adaptation model makes the decision of which content has to be adapted and how to display it. The navigation adaptation consists in modifying the link structure suggesting links or forcing the user to follow a destination. There is URLs' adaptation or destinations adaptation. In the first, the adaptation model provides destination links to the presentation model; these links are displayed at the page generation. Whereas, in the second one, the adaptation model provides links without fixed destination to the presentation model; the destination is decided by the adaptation model when the link is accessed by the user. The presentation adaptation consists in insisting (or not) on the content parts or on the links. It consists also in adapting the preferences setting to the device or the page. The adaptation model process makes the decision of which content or links to insist in following the presentation context. Even if recommender systems are often differentiated from adaptive hypermedia systems, a lot of similarity between these two types of systems can be

 ISBN: 978-1-61208-104-5

highlighted. Indeed, the recommender systems provide recommendations using different algorithms, as it is done in the adaptation model. Moreover, we can see that they model also users' tastes and domain's items, as it is done in adaptive hypermedia systems with the user model and domain model. Nevertheless, recommender systems perform only adaptation of the content whereas adaptive hypermedia systems realize two more adaptation types. Following these observations, a recommendation system appears to be a constrained adaptive hypermedia system. Thus, it seems clear that recommender systems can be defined as a subset of adaptive hypermedia systems, whatever its type (CB or CF).

The use of an adaptive hypermedia architecture for the creation of recommender systems is interesting because we can clearly define the tasks associated with each part of the application, and it gives the opportunity to evolve the system adding modules and/or other types of adaptation without difficult modifications of parts already implemented. For instance, a CB recommender system could be improved with features of CF systems, adding a group model where clusters of users can be defined. For the creation of our CB recommender system, we base on adaptive hypermedia architecture. Beyond the use of the three main ones (domain, user and adaptation model), a goal model has been added. It allows the modeling of users' goals. A description of the architecture is explained in the following part.

III. THE PROPOSED RECOMMENDER SYSTEM

This part describes, first, the architecture of the proposed recommender system. Then, the recommendation process is explained, it is based on a simulated annealing algorithm. It is followed by an overview of the implementation for the tourism application.

A. Architecture

The proposed recommendation system is based on a set of layers (models). It consists of a user model, a domain model, an adaptation model and a goal model. This modeling allows a clear separation between the tasks. The domain model defines the whole domain knowledge. It consists of sets of domain concepts and relations between concepts. Generally, the concepts index the contents or the pages in order to be provided to the user. The most appropriate structure we have chosen for this modeling is the ontology. Actually, it facilitates the creation of complex structures. It allows also the inferences and this structure is portable thanks to the standardized OWL language. The ontology concepts are populated by individuals representing instances of these concepts which can be provided to the user.

The goal model is an overlay model on the domain model. Actually, it consists of a set of goal concepts that bring together individuals of the domain model. A goal concept is a set of domain model individuals, knowing that different goal concepts can group same individuals. A goal is defined by an SWRL rule allowing the selection of the individuals which verifies the rule.

The user model aims at modeling the user into the system. In the present case, it is composed of two parts. The first part is based on the goal model which is based, by definition, on the domain model. This part is called overlay part on the domain or domain dependant part, or even dynamic part because it is very changeable. Instead, the second part is called static part; it is a domain independent part. The user model is composed of a set of goals concepts, selected using the user behavior and <attribute-value> pairs for data such as date of birth, gender, etc. With the dynamic part, we have an idea of the user interests on domain individuals. Actually, when an individual appears into more than one goal concept selected by the user, then this individual is considered more important for the user. Thus, we can induce interest weights on the domain individuals related to the selected goal concepts. Moreover, we can propagate these weights to the entire domain model using the links into the domain ontology.

The adaptation model is considered as the core of the system, the adaptive algorithms are carry out in this level. The recommendations provided to the user are formulated as a combination of individuals from the domain model, according its user model. The problem consists in finding the optimal combination of individuals from the domain model constrained by a user model. Browsing all the possible combinations to find the best one is not possible in a short time, consequently, we propose the use of a stochastic algorithm called simulated annealing in order to find a combination which is close to the best one in a short time. Simulated annealing [29] is an optimization technique particularly well suited to overcoming the multiple minima problem. Unlike gradient-descent methods, simulated annealing can cross barriers between minima and thus can explore a greater volume of the parameter space to find better models in deeper minima.

This algorithm is used to minimize an energy function defining the relevance of a combination according to a user model. This energy depends mainly on the interest weights deduced from the user dynamic part on the domain individuals. But, depending on the type of application, more parameters can be taken into account. For instance, we can use geographic parameters for an application which aims to provide a nearby restaurant corresponding to the user requirements and coordinates. Moreover, constraints can be defined in the ontology between individuals or/and concepts. For instance, a medical application which provides a combination of medicines has to indicate in the ontology when one medicine cannot be given with another one, so that the application cannot generate a bad combination.

B. Recommendation process

The recommender system aims at providing a combination of individuals from the ontology. This part presents how this recommendation is undertaken.

In order to solve the problem of providing the best combination of individuals from the domain model, we propose the use of a stochastic algorithm called simulated annealing for its resolution. Actually, this kind of algorithms allows to find a solution that approaches the best (or is the best) in a very short time. The simulated annealing is inspired from a method used in the steel industry. To obtain a metal with a perfect structure crystal type (fundamental state corresponding to the minimum internal energy), the process is as follow: after bringing the material to liquid, the temperature is lowered to solidification state. If the decrease of temperature is very sudden, a "glass" is obtained, feature of the technique of "hardening". On the contrary, if it is very gradual, allowing time for atoms to reach statistical equilibrium, it will tend toward more regular structures, to finish in the ground state: the "crystal", characterizing the system freeze. If this lower of temperature is not slow enough, defects could appear. Then, it would be necessary to correct them by heating the material again slightly to allow atoms to regain freedom of movement and facilitating a possible rearrangement toward a more stable structure.

The simulated annealing algorithm used into the adaptation model is based on this principle. At the beginning, the algorithm chooses an initial random combination of individuals following a given pattern (for instance, a combination consisting of a hotel, two restaurants and two activities). This combination has an energy E_0, called the initial energy, which represents the quality of a combination. The lower the energy is, the better the combination is. A variable T, called temperature, decreases in increments over time. At each level of temperature is tested a number of elementary random changes on the current combination. A cost d_f is associated to each modification; it is defined as the difference between the combination's energy after the modification and the one before. A negative cost signifies the current combination has a lesser energy than the previous one (thus better by definition), it is then kept. Conversely, a positive cost represents a "bad" change. Nevertheless, it can be kept according a given probability (acceptance rate t_a) depending on the temperature and the cost. The higher the temperature is, the higher the probability is. Thus, over time, the number of changes allowed decreases as the temperature decreases, until no longer accepting any changes. Finally, the system is said frozen, and the current combination becomes the final combination to be presented to the user. The acceptance rate is defined in (1) where T_k is the temperature at the level k, $k \in$ N.

$$t_a = e^{-\frac{d_f}{T_k}} \qquad (1)$$

$$T_0 = \frac{d_{fmean}}{\ln \frac{1}{t_a}} \qquad (2)$$

An initial temperature T_0 is computed using this formula and setting the values of the acceptance rate and the cost. The initial acceptance rate is defined arbitrarily and the cost is set calculating the average cost by performing multiple changes on random combinations. Thus, the initial temperature is presented in (2) where d_{fmean} is the average cost of the modifications.

The temperature decrease is achieved through a geometric decay at each level:

$$T_k = g(T_{k-1}) = coef \times T_{k-1} = coef^k \times T_0 \qquad (3)$$

where k is the current level and $0<coef<1$.

The relevance of a combination is determined by an energy function. The quality of the final combination, given by the simulated annealing algorithm, depends a lot on the definition of this energy. This function is highly dependent on the type of application. For instance, in a tourism application, the individuals and user coordinates could be taken into account, whereas these data are useless in a medical application. Nevertheless, the energy function is based, in all cases, on the user interests deduced from its dynamic part.

The dynamic part is constituted of goals determined by the user clicks on icons which are linked to goals. Thus, each time a user clicks on an icon, the related goal is added to the dynamic part of its user model. To deduce the user's interest weights on the ontology individuals, an algorithm of weight propagation uses the fact that each goal is a set of rules including individuals from the domain model. Thus, each time an individual is selected by a rule, its weight is incremented. Therefore, this weighting allows the demarcation of some individuals, giving an idea of the user interests. With this modeling, after few user clicks on icons, the system can quickly provide a combination of domain individuals that matches its interests. According the definition, this type of recommender system is a CB system. Nevertheless, it is also possible to base on group of users to have the benefits of CF systems. It just needs to add a group model to the system. The next part shows an application of this modeling for a tourism application which is currently in development.

C. Tourism implementation

This modeling is being applied to the tourism domain in the region of Côte-d'Or in France for the company Côte-d'Or Tourisme. The aim is to create a tourism application that should provide a combination of tourism products from Côte-d'Or according to a user profile. At the beginning, a domain ontology has been created with all the concepts and the individuals related to the application domain. This ontology was supplied from a database composed of more than 3000 tourism products. Then, a goal model has been defined using goal concepts like "Week end", "Going out with friends", "with a baby", etc. This knowledge was generated from the specialists of the domain represented by people working for the company Côte-d'Or Tourisme.

 ISBN: 978-1-61208-104-5

An empirical pattern is defined to determine what kind of combination the adaptation model has to return. The energy function which gives the relevance of a combination is based on the interest weights and the coordinates of the tourism products, because it is not relevant to propose an activity in the morning and a restaurant for lunch with a distance of more than 50 kilometers. The traveling time required to reach the restaurant after the activity ending is inappropriate.

A variance threshold needs to be set in order to define the maximum preferred variance between the individuals coordinates. This variance characterized the value dispersion regarding the average, in this case the threshold. The subsets in this pattern are possible. For instance, we can define a pattern like “Accommodation, Restaurant1, Activity, Restaurant2” in which “Accomodation and Restaurant1” are the first subset, and “Activity and Restaurant2” the second subset. In addition, a variance threshold is defined for each one. Thereby, the system can use more complex patterns for the combinations.

The variance of a combination is defined as follow:

$$\operatorname{var}(C) = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1}\left(\left(C_{ix} - \frac{1}{N}\sum_{i=0}^{N-1}C_{ix}\right)^2 + \left(C_{iy} - \frac{1}{N}\sum_{i=0}^{N-1}C_{iy}\right)^2\right)^2} \quad (4)$$

where C is a combination, N the number of elements into the combination, C_i the ith element of the combination, and C_{ix} and C_{iy} the x and y coordinates of the ith element.

The weight of a combination is defined as follow:

$$weight(C) = \frac{1}{N}\sum_{i=0}^{N-1} C_{iweight} \quad (5)$$

where $C_{iweight}$ is the weight of the ith element.

Using the variance and the weight function, the energy of a combination is:

$$Energy(C) = \frac{1}{weight(C)} \times E\left(\frac{\operatorname{var}(C)}{Threshold_C}\right) \times \prod_{j=0}^{L-1} E\left(\frac{\operatorname{var}(G_{Cj})}{Threshold_{G_{Cj}}}\right) \quad (6)$$

where $E(X)$ is the integer part of X, $Threshold_C$ is the variance threshold of the geographic coordinates for the combination C, $Threshold_{G_{Cj}}$ is the variance threshold of the geographic coordinates for the jth subset of C, and L the number avec subsets. Thus, the system performs the simulated annealing algorithm using this energy function and a user profile, so that it can provide a combination of tourism products matching its interests and close coordinates. The result of the algorithm gives a combination of close products with high weights. The next part shows an example of a touristic journey provided by this implementation. An interface has been developed for iPhone.

IV. AN UTILIZATION EXAMPLE

An interface for this tourism implementation has been developed for iPhone. This part explains briefly the utilization of this application. The user is first invited to define his profile by giving his stay duration and by clicking on goal icons in order to inform on its interests. Moreover, the geographic coordinates of the user can be used or specific geographic coordinates can be specified for a preferred area. Nevertheless, if no area is given, the area will be the entire region of Côte-d’Or. Tourism products can be also selected and a complete stay will be generated relevantly according these selections. After this step, the adaptation process is performed using the simulated annealing algorithm and the system provides a combination of tourism offers, corresponding to the user's profile, in a carousel. If the solution does not satisfy the user, he is able to demand a new generation, keeping some elements if wanted. Thus, the system takes the kept elements into account to provide a new combination. This new solution is generated by fixing the kept elements into the combination. Thus, only the others elements of the combination are modified during the process of researching the best combination. The kept elements are only considered for the energy computations. A benchmark is presented in the next part to show the relevance of the simulated annealing algorithm.

V. BENCHMARK

Some tests of the algorithm for the generation of combinations have been done on a set of three thousand tourism products. We did comparisons between the energy of random combinations, the energy of the solutions found by the algorithm and the energy of the optimal combination. The solutions given by the simulated annealing algorithm are closed or equal to the optimal solution in terms of energy. In these tests, the average time required for the generation of a combination of six products was around 3 seconds. But, this time depends on the different parameters (temperature decrease rate, the number of iteration per level of temperature) necessary to perform the simulated annealing algorithm. The faster is the temperature decrease and the lower is the number of iterations, the faster is the generation, but the worse is the resulting combination. In any case, this time is better than the time required to find the best combination by browsing all the possibilities. For example, in our test, finding the best combination needed around 3 hours against 3 seconds using the simulated annealing algorithm. These times are only given to have orders of magnitude, more tests need to be performed to have exacts results and to prove the interest of our proposition. Nevertheless, given these few results, the algorithm seems to give a relevant solution according a predefined energy function with a lesser cost (in terms of time) than calculating the optimal solution.

VI. CONCLUSION

In this article, we presented a new content based recommender system in order to improve the customer relationship management in e-tourism. The idea consists to take advantages of the semantic Web technologies, the properties of adaptive hypermedia systems, and to combine them with combinatory algorithms in order to create a recommender system. The simulated annealing algorithm is used in order to solve the problem of the polynomial time search required to generate a combination of tourism products. It gives a solution which approaches the best solution in a short time. The few results seem to be good considering the time required to obtain them and comparing to the best solutions. Nevertheless, for the future, we need to make more tests and benchmarks to quantify more precisely the relevance of our system. Moreover, we could improve the quality of the propositions by taking into account some group of users as it is done in collaborative filtering recommender systems. This is possible by adding a group model into the architecture. Thus, the recommender system would become a hybrid recommender system.

ACKNOWLEDGMENT

This research is done in collaboration with Côte-d'Or Tourisme, a company which aims to promote tourism in its region. The authors would like to thank Quentin Collin and Erwan Privat for their help.

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