AN ONTOLOGY-BASED APPROACH TO PROVIDE PERSONALIZED RECOMMENDATIONS USING A STOCHASTIC ALGORITHM

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Abstract: The use of personalized recommender systems to assist users in the selection of products is becoming more and more popular and wide-spread. The purpose of a recommender system is to provide the most suitable items from an knowledge base, according the user knowledge, tastes, interests, ... These items are generally proposed as ordered lists. In this article, we propose to combine works from adaptive hypermedia systems, semantic web and combinatory to create a new kind of recommender systems suggesting combinations of items corresponding to the user.

1 INTRODUCTION

In the first years after its creation, Web was the same for everybody. Websites was presenting the same information and the same links to each visitor, without taking into account their goals and their knowledge.

Given the important growth of the number of available information, the diversity of users and the complexity of Web applications, researchers started to question the "one-size-fits-all" approach. Therefore researches have emerged to answer these problems, to propose a Web where the appearance, the behaviour, the resources would be ideally adapted to each individual. This Web would offer a different experience to each user. This Web is called the Adaptive Web.

A first step to reach the Adaptive Web is to reason on local adaptation problems.

This adaptation to users is currently widely found into the so-called domain of recommender systems (Tintarev and Masthoff, 2007) (Mcsherry, 2005). These systems have the role to provide recommendations to users. This domain has become important since the mid-year 90. It is yet a big domain of research due to its richness in terms of problem to solve, and given the great number of possible applications to deal with information overload and provide adaptive recommendations. Recommender systems allow companies to filter information, and then to recommend products to their customers, according their preferences. Recommending products or services can consolidate relations between the seller and the customer, and thus, enhance the benefits (Zhang and Jiao, 2007). Many systems developed as TrustWalker (Jamali and Ester, 2009) emphasize the current interest of recommendation.

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 developed basing on the textual filtering model described in (Oard, 1997). 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 (Goldberg, 1992) 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

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propose items they like. Typically, each user is associated to a set of nearest-neighbour users, comparing profiles' information. With this method, objects are recommended basing 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:

- Some use other users' ratings as additional features in a CB system.
- 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.
- Others use CB predictions to "fill out" the probable user-items' ratings in order to allow CF techniques to produce more accurate recommendations.

In this paper, we propose a content-based recommender system. Its architecture is inspired from adaptive hypermedia researches. Unlike most recommender systems which provide a list of items to users, we suggest to generate combinations of items corresponding to them. A first part will explain what an adaptive hypermedia system is. Then, our proposition is presented. The final part shows a application to tourism domain.

2 ADAPTIVE HYPERMEDIA SYSTEMS

The research domain of adaptive hypermedia has been very prolific these 10 last years. Some systems (Cristea and Mooij, 2003) (Henze, 2000) 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 (De Bra et al., 1999) (Hendrix and Cristea, 2008) 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 Brusilovsky (Brusilovsky, 2001). 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):

- Keywords vectors: A popular method to represent domain and user model used by a lot of systems is the keywords vectors space representation (Liberman, 1995) (Kamba et al., 2007). This method considers that each document and user profile is described by a set of weighted keywords vectors. 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.
- Semantic networks: In semantic networks, each node represents a concept. Minio and Tasso (Minio and Tasso, 1996) 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: This 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 (Middleton at al., 2002), 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 modelled as characteristic' vectors and are linked to concepts using the nearest neighbour 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 (Cantador and Castells, 2006) and (Sieg et al., 2007), 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 behaviour.

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 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 modelling of users' goals. A description of the proposition is explained in the following part.

3 PROPOSITION

This section describes the architecture of the proposed recommender system based on an adaptive hypermedia architecture. This system aims to generate a combination of necessary items for the purpose of the application according the items types

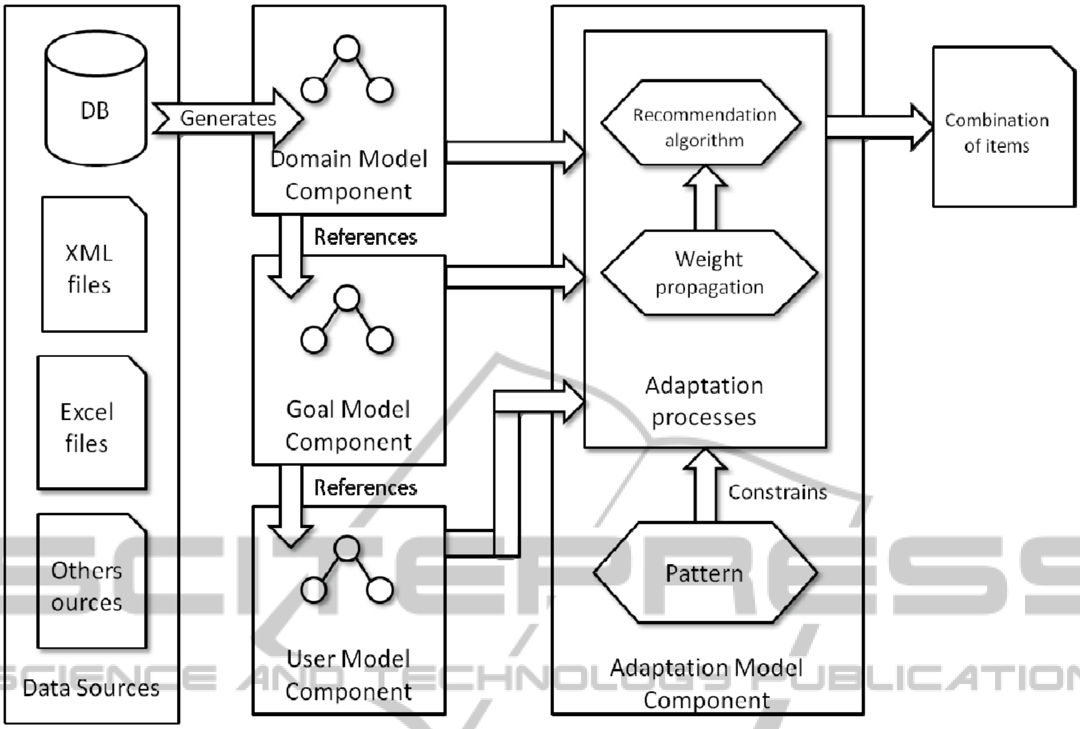

Figure 1: The components of the architecture.

and constraints (semantics, localization, ...). An item is a piece of information provided by the information system transformed into the recommender system. The architecture of the system is composed of four components: The domain model component, the goal model component, the user model component, the adaptation model component (Figure. 1).

3.1 The Domain Model Component

To fully express the knowledge of a domain, the domain model component uses an OWL ontology. An item will be an individual of this domain ontology which is generated from data provided by data sources like relational databases, XML documents, Excel files, etc. Actually, the ontology is enriched by the schema of the data sources and populated by the data of the sources. This construction is carried out using expert's knowledge. Three steps have been identified to achieve this goal. The first step consists in using the database as a starting point for the basis of the domain ontology. The second step consists in enriching this basic ontology by domain experts adding new axioms usually not present in the data source. Usually, this process comprises the addition of semantic links between concepts which are often unqualified in the relational schema. Moreover, the hierarchical structure of concepts is refined with the help of professionals. The last step consists in populating the ontology with instances selected from the data source.

The ontology creation process is partly manual and automatic. The first step and the second step require the investment of domain experts. The third step is automatic and, fortunately, it is the only one that is brought to be repeated regularly to update the data of the ontology. The structural part of the ontology which is set up by the first two steps will not often be changed.

3.2 The Goal Model Component

Our objective is to use the domain ontology within a specific user-centered application. In this context, an adjustment of the ontology must be made to adapt it to the usage and, especially, to the user modeling. Hence, the domain ontology is enriched with goal concepts. These concepts define the user possible objectives into the system.

A goal concept is composed of first order logic rules. A rule makes a link between individuals of the ontology and the related goal. Each rule has a weight representing the importance of it within a goal concept.

For example, we could have the goal "culturalActivity " defined by the weighted rules:

- (Cinema(x) ^ haveCulturalAspect(x,y) -> culturalActivity (x), 5)
- (Theater(x) ^ haveCulturalAspect(x,y) -> culturalActivity (x), 9)
- (Museum(x) ^ haveCulturalAspect(x,y) -> culturalActivity (x), 10)

The set of the goal concepts is called the goal model.

3.3 The User Model Component

From there, we have an ontology oriented to a particular application by a set of goal concepts. We have now to model the user within the system in order to offer an adapted environment. The user is modeled in two distinct parts. The first one concerns the characteristics that are independent of the domain, also called the static part. This may be the age, size, gender, etc. They are simply modeled using <attribute, value> vectors. The second part represents the user features directly related to the domain. It consists of goal concepts, representing the goals of the user with weights which allow the position of a discriminating index in terms of preferences. This part is said dynamic and is an overlay on the domain model. Together, these two parts represent the user model and the instantiation of this model represents a profile of a user.
For instance, a user profile can be: User1 (<age, 20>, <gender, male>, …) (<physicalActivity,5>, <culturalActivity,1>, …)

3.4 The Adaption Model Component

This component is responsible to provide a combination of items regarding the domain ontology. This set of item is adapted to the user profile which is an instance of the user model. In order to enclose the solution to provide, a pattern of combination is defined. The pattern constrains the elements to be returned to the user by filtering to the type, the number, the item order or the geolocalisation for example.
Using the goals weights into the user profile and the weighted connections between the individuals and goal concepts, the weights are combined linearly to be propagated to the individuals.

For instance, if a goal is weighted of 3 in a profile and is constituted of two rules with the respective weights 5 and 1, then the individuals linked to the goal by these rules receive the respective weights $15(3 \times 5)$ and $3(3 \times 1)$ which can be cumulated if individuals are associated to the two goals at once.

This weight propagation into the ontology is not done with the whole ontology. Indeed, it is not necessary to weight individuals which cannot be involved in the final solution. Only individuals that instantiate a concept from the domain model specified into the pattern of combination are weighted. In other words, the individuals which the type (the concept) is not reflected in the pattern are not weighted. Thus, we have a subset of weighted individuals from the domain ontology. We now wish to find a "good" combination of these individuals depending on the pattern. The notion of quality of a combination is defined by one or more relevance functions that will take into account the individual weights and other attributes (geographic coordinates, volume, etc.).

For example, we could have this pattern < (Activity, Activity, Activity, Activity), 1km > which constrains the combination to have 4 activities in a neighborhood of 1km.

The purpose consists then in optimizing the relevance function, in order to find the optimal solution. Searching an optimal solution means browsing the set of possible solutions and returns the best one. However, the number of possible solutions grows very rapidly according to the number of individuals, and it becomes quickly impossible to find the best solution in a reasonable time. Thus, to resolve this problem, a stochastic algorithm is used. This latter takes as input all the weighted individuals and the pattern of combination to provide. This algorithm will return “good” items approaching the best one. However, the results will depend on the type of the used stochastic algorithm which optimize the time for real-time application. Finally, the user is offered a combination of items supposed to correspond to their profile. The adaptation model is composed of all these processes.

4 TOURISM APPLICATION

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 4000 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.

An empirical pattern is defined to determine what kind of combination the adaptation model has to return. The relevance function giving 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. Subsets in this pattern are possible. For instance, we can define a pattern like “Accommodation, Restaurant1, Activity, Restaurant2” in which “Hotel 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:

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

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:

$$weight(C)=\frac{1}{N}\sum_{i=0}^{N-1}C_{iweight} \qquad (2)$$

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

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

$$Energy(C)=\frac{1}{weight(C)}\times\left(E\left(\frac{\mathrm{var}(C)}{Threshold_C}\right)+\sum_{j=0}^{L-1}E\left(\frac{\mathrm{var}(G_{Cj})}{Threshold_{G_{Cj}}}\right)\right) \qquad (3)$$

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.

Then, a stochastic algorithm is performed. We use a simulated annealing algorithm (Kirkpatrick et al., 1983) which try to optimise the relevance function, so that it can provide a combination of tourism products matching the user interests and with close coordinates.

5 BENCHMARK

Some tests of the algorithm for the generation of combinations have been done on a set of four thousand tourism products. 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. For example, 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 relevance function with a lesser cost (in terms of time) than calculating the optimal solution.

6 CONCLUSIONS

This paper presents a new content based recommender system. The idea consists in taking advantages of the semantic Web technologies, the properties of adaptive hypermedia systems, and in combining them with combinatory algorithms in order to provide recommendations, adapted combinations of items. 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. It is possible by adding a group model into the architecture. Thus, the recommender system would become a hybrid recommender system.

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