A Case Base Travel Advisory System for Personalization

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Abstract

Web personalization and one to one marketing have been introduced as strategy and marketing tools. By using historical and present information of customers, organization can learn, predicts customer's behavior and develop services to fit potential customers. There are two learning approaches using in this study. First, Personalization Learner by Group Properties is learning from all users in one group to find the group interests of travel information by using given data on user ages and genders. Second, Personalization Learner by User Behavior: user profile, user behaviors and trip features will be analyzed to find the unique interest of each web user. The results from this study reveal that it is possible to develop Personalization in a Travel Advisory System (PTAS). In this study, a Personalization in Travel Advisory System (PTAS) is introduced to manage traveling information for users. It provides the information that matches the users' interests. This system applies the Reinforcement learning to analyze, learn customer behaviors and recommended conditions to meet customer interests.

1. Introduction

At present information technology (IT) plays an important role in working environments, many organizations use IT as tool in making their business runs smoother and completing faster in the marker. In many industries, the internet and WWW have significant roles in business processes. Online business is more competitive than traditional one since there are plenty of low cost online stores offering products and services on the internet [6, 7]. Further, customer royalty for online business is low comparing to traditional market so that it is challenging for a company to attract new and keep customers in e-Commerce. Traditional marketing is not always successful on the Internet, and thus more specific online system such as one-to-one marketing should be helpful [5]. In order to be more competitive on the Internet marketing, it is compulsory to offer customers with products or services which match for each customer [1]. During the past few years online massive marketing by using a push technology and informative websites always containing a great deal of information have been introduced to users. The existing search engines do not allow users to find the relevant information easily. Due to these challenging, web personalization and one to one marketing have been introduced to the e-commerce business, including tourist sector, retail banking and finance and entertainments [8].

In order to build an interactive, personalized advisory system, background knowledge has to be excited from domain experts and formalized for the user. Moreover, the development of a highly-adaptive and maintainable user interface, which reflects the underlying personalization knowledge, can also be a challenging task due to the typically strong interdependencies between recommendation personalization and presentation logic. In this system, the specific e-tourism application is characterized as follows: about the possible questions have been modeled, out of which always only a personalized subset is asked in order to keep dialog lengths at a size which is acceptable by end users, about the same number of rules has been designed, which together with a specific relaxation rule for searching for suitable arrival and departure dates were sufficient to generate personalized recommendations. This system comprises a built-in logging component which can be configured to record the full history of interactions of each individual user, which means that the advisory traveling interactions are much more important types of information about the tourisms and their preferences can be obtained. One can, for instance, analyses whether there are typical customer profiles or combinations of services which are requested by customer profiles or combination of services which are requested by customers but are not part of any package. This additional knowledge could be subsequently used to adapt the range of offered services accordingly.

In this paper, we will first give an overview of a deployed application in the e-tourism domain. Section 2 subsequently illustrates on the system's architecture and the design of the Personalization in Travel Advisory System. Section 3 discusses the basic CBR problem solving techniques. In Section 4, we present recommender system to travelers with single travel item selection and complete travel item selection. After that the hierarchical structure of case model and session similarity computation are also explained. We conclude the discussion in Section 5.

2 Design of Personalization in Travel Advisory System

Recommender systems are commonly defined as applications that commerce sites exploit to suggest product and provide consumers with information to facilitate their decision-making process. They usually extract the knowledge required for a truly personalized advice, logging each single page visited and then analyzing this data with data mining techniques. These usually produces large databases, which are hard to manage, and where it is difficult to single out an expressive representation of which the user are trying to do, in which context, and which finally achieved. [8, 9]

In this system, users search for destination-related information such as point of interest, historical data, for products and services such as travel packages, flights and hotels. We illustrate the design of personalization in travel advisory system as illustrate as Figure 1.

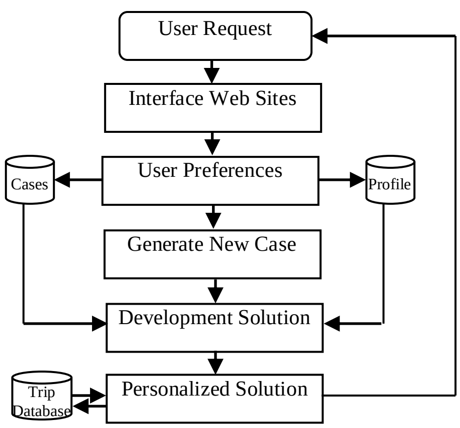

Figure 1: System Design of the Personalization in Travel Advisory System

Tourisms products and services typically have complex structures, where the final recommended item is an aggregation of more elementary components. This can either comprise a prepackaged offer or can be obtained by selecting travel components (items) such as location to visit, accommodations, attractions and services. The recommendation methodology must support the implementation of advanced search functions that are still perceived by the user as conventional, and simple to use, as in form-based information search engines. This would make the methodology simple to integrate into existing systems. A recommender system, exploiting the methodology, must provide a range of query-forms: for elementary products and services and for predefined combinations (e.g., a complete travel package).

In this system, user preference, generate new case and development solution are the three main stages. In user preference, the user can select the "Travel Wish" and "Item Wish" using single travel item selection or complete travel item selection. Depending on the user's inputs, the system generate new case by using CBR. In the development solution, the system is accumulated the current case with the set of cases by using similarity measure.

3. CBR Learning Cycle

The CBR problem-solving cycle is universally recognized as the basic common denominator of all CBR approaches and is summarized in Figure 2 and discussed more fully below.

(i) Retrieve: Given a problem description, retrieve a set of cases stored in the case base, whose problems are evaluated as similar. A similarity metric is used to compare the problem component of the new case being built with the problem description of the cases in the base. Indexes, case base partitions, case clusters or other similar tools can be used to speed up this stage.

(ii)Reuse: The retrieved cases are reused to build the solution. This stage could be very simple, e.g., only extract the 'solution' component from one retrieved case, or much more complex, e.g., to integrate all the solutions extracted from the retrieved cases to build a new candidate solution.

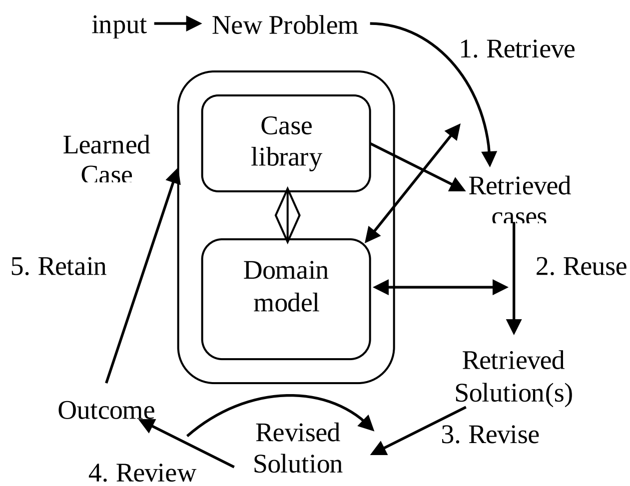

Figure 2: A View of the Case-Based Problem Solving Cycle

(iii)Revise: The solution is then adapted to fit the specific constraint of the current situation. For instance, a reused therapy for a patient suffering disease must be adapted to the current patient (e.g., considering differences in the weight or age of the two patients).

(iv)Review: The constructed solution is evaluated applying it (or simulating the application) to the current problem. If a failure is detected, backtracking to a previous stage might be necessary. The 'reuse', 'revise' and 'review' stages are also called case adaptation.

(v)Retain: The new case is possibly added to the case base. Not all the cases built following this process must be added to the case base. There could be poorly evaluated cases or cases to similar to previous situations, and therefore not bringing new knowledge.

4. Recommender System to Travelers

In the tourism context, the use of recommender systems becomes especially interesting as there are many different destinations on the hand and on the other hand many different kinds of activities for travelers at those places. This situation leaves the person in the planning process of a trip confronted with an enormous amount of possible combinations of locations and activities. Hence, travelers need help filtering these possibilities. Therefore, tourists usually take advice from travel agents. These recommendations are restricted by the human factor. Because of this, the complex requirements of the customer cannot be fully met and decisions often become too dependent on the specific agent. A recommender system is supposed to aid the process of filtering and evaluating different options for the individual customer [4]. Altogether recommender systems in tourism can be classified as an intermediary between customer and travel agency. Recommender systems in tourism have difficulties matching the specific needs of a user, because the needs might be different from the specific individual approach a user has on the system.

4.1 Single Travel Item Selection

The single travel item selection helps users with a lot of experience to navigate efficiently through the potentially enormous amount of available information. By selecting a product the user is giving the system information on his preferences so that the system can calculate whatever products he or she might be interested on the next stage of the decision process.

The user first provides his general needs and constraints for the single travel in his mind ("Hotel Wish or Places Wish"). For example, he may be interested in a suitable place. The system accepts this input as the (partially defined) problem specification, and filters out from the case base that nearly matches this wish. For example, a hotel near town center, sport facilities, and beach.

Having these items of inputs, the system retrieves from a set of case sessions (i.e., recommendation sessions) that are most similar to the current one. To select the items that best match to the user's wishes, the system gives personalized weight to the item features. This collection, called Reference Set, is dynamically computed, i.e., each time a recommendation function is called, a new contextual Reference Set is retrieved, matching all the user wishes accumulated at the stage of recommendation. Figure 3 shows the single travel item selection in the Personalization in a Travel Advisory system.

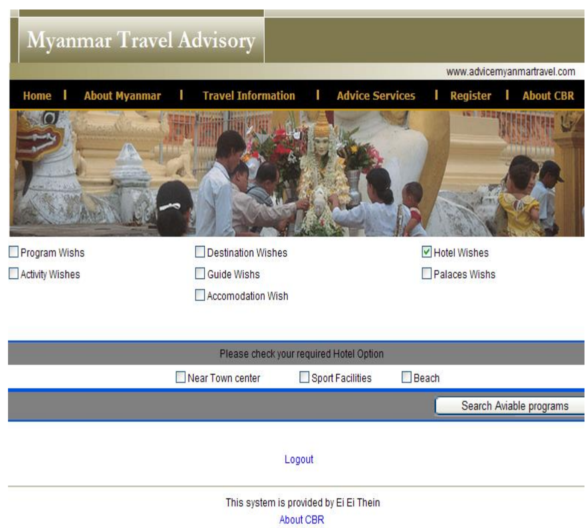

Figure 3: Single Travel Item in the PTA System

4.2 Complete Travel Selection

Another way is the complete travel selection. This approach is presenting personalized bundles of available products to a complete travel plan. The recommender system uses information collected from other users that have constructed their travels in comparable sessions to build and recommend a personalized plan.

The complete travel recommendation function provides the user with an already aggregated set of travel items. Here the user may specify destination wishes, guide wishes for language, accommodation wish, and hotel wishes. For instance, the system understands that Air Conditioning (AC), TV and Heater are important features for this user in Accommodation Wishes that he can be specified these items and the system will recommend. Such knowledge is gathered from the Reference Set, and this is the main point where we exploit the experienced recommendation sessions for this type of recommendations. In response, the system generates the Reference Set as above in the Single Travel Item recommendation, but now a selection of these cases is shown to the user as travel templates. The cases in the Reference Set are used to generate bundles of travel items appropriate to the user. Figure 4 shows complete travel item selection in the Personalization in a Travel Advisory system.

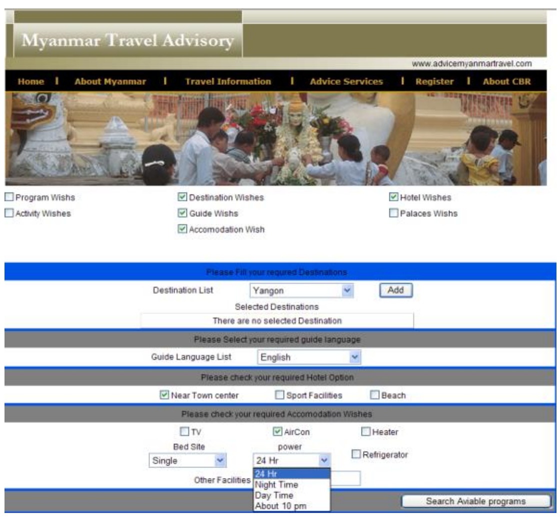

Figure 4: Complete Travel Item in the PTA System

4.3 Hierarchical Structure of Case Model

To develop conversational recommenda--tion systems in which the interaction between the system and the user becomes more efficient over time due to the system's adjustments to the preferences of the user. Our system is adapts its behavior on the information filtering level and, by changing the order of the operators in the conservation, the information presentation level. To efficiently provide the users with the solution that matches their needs best, it is necessary to acquire and model the preferences of the users.

A user may have preferences about: specific items, the relative importance of an attribute, values for an attribute, the combination of certain attribute-value pairs and the delivery of the suggested items and values. Item preferences manifest themselves in the user having a bias for or against a certain item, independent of its characteristics (item preferences). The preferences regarding an attribute represent the relative important a user places on the attribute while selecting an item. Item preferences are derived by observing how often a certain item was suggested again after a certain time has passed. The items, attributes, values and combination preferences relate to the suitability of items in general. The case is modeled in a hierarchical tree of components and sub-components. A case is decomposed into: travel wishes, travel bag, user, navigation history and reward. Figure 5 illustrates an example of a case.

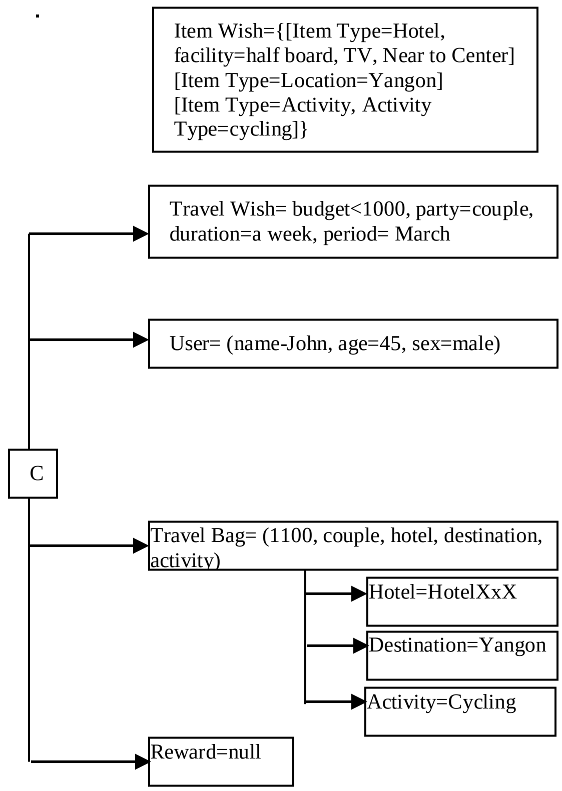

Figure 5: An Example of a Case

- Case (c) :A case c = (*tw.tb*,*u*,*r*) model a complete recommendation session, where *tw* (travel wish), *tb* (travel bag), *u* (user), and *r* (reward) are its sub-components.
- User (*u*): This block carries the user-specific data for registered users, and is modeled as a simple features vector. For non-registered users, all these data will remain null.
- Travel Wish (*tw*): This will carry the users' constraints (and needs) about the travel in his mind. Travel wish consists of constraints over the travel features

that are specified by the user during this interaction with the system.

- Item Wish: This will carry more specific data about travel items. While travel wish contains constraints about the whole travel plan, item wish consists of item-specific feature-value pairs provided by the user. For sake of simplicity, we will assume here that there are three types of items, hotel, destination and activity), mentioned as type 1, type 2 and type 3 respectively.

  Mathematically, we represent the travel wish as $tw = (gw, iw_1, iw_2, iw_3)$, where gw, iw_1, iw_2, iw_3 are all symbolic or numeric valued vectors. For example, in Figure 5, we have:

- gw = [budget<1000, party = couple, duration = a week, period = March]
- iw_1 = [type = Hotel, catering = half-board, TV = true, near to =center]
- $iw2$ = [type = Destination, city = Yangon]
- iw_3 = [type = Activity, cycling = true, altitude > 800]

This refers to a travel bag which is suitable for a couple with budget limited to 1000 Kyat. More specifically, he is looking for a hotel with half-board catering service and TV equipment, near to a city center in Yangon, where he can practice some cycling activity.

- TravelBag(*tb*): TravelBag is acomplexd at a structure that collects together the items (sub-components) selected during a case session. It is represented in a tree-like hierarchical way, denoted $tb = (gd, d_1, d_2, d_3)$. *gd* is a vector that describes general properties of the travel bag. For instance, as in Figure 5, *gd* = (1100 couple, hotel, destination, activity) is a travel bag constructed, for a couple, the budget required for this travel is about 1100 Euros, and includes tree types of item. $d_1 = [d_1, d_2, \ldots], (1<=i<=3)$ denotes the items(s) of type i in the bag, d_i stands for the description of the j^{th} item of type i in the travel bag.
- Reward(r): Reward is a sequence of rates provided by the user for each item in the travel bag. More precisely $r=(gr, [r_{11}, r_{12}, \ldots], [r_{21}, r_{22}, \ldots], \ldots)$, where r_{11} is the rate for the first item of type 1, r_{12} is the rate for the second where r_{21} is the rate for the first item of type 2, etc. *gr* is the general rate for the whole travel bag computed as a composite average of rates of items.

4.4 Reference Set and Similarity

To retrieve the Reference Set, we compute the similarity between the current case and those in the case base. This similarity-based retrieval is applied after a logical (context dependent) filter has been enforced [3]. For instance, if the destination has been provided as input, only cases in the selected destination will be included in the reference set.

Given two cases $c=(tw,tb,u,s,r)$ and $c'=(tw', tb', u', s', r')$, the case similarity is computed as follow:

$$Sim(c,c') = \frac{1}{5}(w_w Sim(tw,tw') + w_b Sim(tb,tb') + w_{wb} Sim((tw,tb') + w_u Sim(u,u') + w_r \operatorname{Re} w(r')) \quad [1]$$

where $w_w, w_b, w_{wb}, w_u, w_r$ (real numbers between 0 and 1) are the weights that are used to balance the relative components importance in case similarity computation.

Note that the "cross" similarity between the travel wishes of c and the travel bag of c' is typically used when a new case c is going to be built. At that point, the system must match the wishes of c with the bag of c', not only the user wishes that were at the base of c'. This is motivated by the observation that there is always a mismatch between the explicit user wishes and the selected items. This is due both to psycological inconsistencies between desires and real actions, and the approximation brought by the CBR problem solving approach. Moreover, the term $Rew(r')$ does not represent any comparison between cases, but takes into account the importance of the retrieved case. The motivation here is to consider first those highly rated (i.e., successful) travel bag, so having better rate makes that case more important. In this way, the Equation 1 makes more similar a case that has been rated highly by the user that built the case.

For each of the sub-similarities in Equation 1, a different similarity measure is needed. If we consider, for the sake of the simplicity, tw and tw' to be two subsets $tw=\{w_1, \ldots\ldots, w_M\}$ and $tw'=\{w'_1, \ldots\ldots, w'_M\}$ of a space W (space of wishes, i.e. constraints over feature spaces), and we assume there is a definition of similarity in W, i.e., $Sim(w,w')$ is know a positive real number between

0 and 1, for all $w, w' \in W$, then we define two auxiliary similarities:

$$Sim_l(tw, tw') = \frac{1}{M} \sum_{i=1}^{M} \max_{j=1}^{N} Sim(w_i, w_j), \quad [2]$$

$$Sim_r(tw, tw') = \frac{1}{M} \sum_{j=1}^{N} \max_{i=1}^{M} (w_i, w_j) \quad [3]$$

where, for instance, $Sim_1(tw, tw')$ gives the average similarity of the elements in *tw* when they are matched with the best element in *tw'*, i.e., for each w_i is considered the element in *tw'* that gives maximal similarity. [2] Then the final similarity is computed as follows:

$$Sim(tw, tw') = \min\{ Sim_l(tw, tw'), Sim(tw, tw') \} \quad [4]$$

In Figure 6, we show the reference set of the similarity measure for the recommendation system.

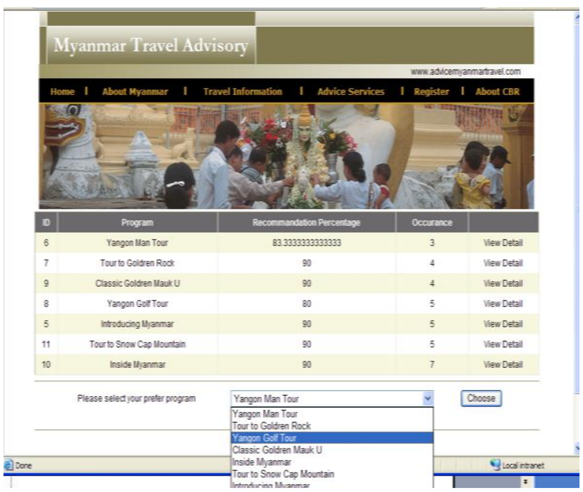

Figure 6: Reference Set with Similarity in the PTA System

5. Conclusions

The main result of our approach is a comprehensive middleware for issuing personalized recommendation to a leisure traveler in identifying and aggregating elementary services or activities to be consumed. It is based on the principal that suggestion effectiveness relies on a combination of factors like: appropriate destination modeling; data retrieval and filtering with both sharp and approximate matching; scoring using personal preferences that can be derived from a base of previous cases.

Moreover, the recommendation system, which is based on that middleware, should help to better understand the user needs and behavior, and will clarify the possible mismatch between offered destination packages and user's wishes. Besides, the case base of Travel Plans, which is an output of the user interaction with the system, will enable additional advanced functions: Travel Plan composition with Travel Advisory contained in other similar Travel Plans or tourist support during the travel (e-commerce).

References

[1] A.W. David, "The Omnipresence of Case Based Reasoning in Science and Application, Knowledge Based Systems", 11(5-6):261{273, 1998.

[2] B. Arslan and F. Ricci, "Case Base Session Modeling and Personalization in Travel Advisory System", eCommerce and Tourism Research Laboratory, Italy.

[3] R. Bergmann and A. Stahl, "Similarity Measures for Object-Oriented Case Representations*", In B. Smyth and P. Cunningham, Editors, Advances in Case Based Reasoning*, volume 1488 of Lecture Notes in Computer Science, pages 25-36, Springer, 1998.

[4] R. Burke, "Encyclopedia of Library and Information Science", volume 69, Chapter Knowledge-based Recommender Systems. Marcel Dekker, 2000.

[5] R. Cooley, "Web Usage Mining: Discovery and Application of Interesting Patterns from Web Data", Ph.D thesis, University of Minnesota, 2000.

[6] P. Cunningham, R. Bergmann, S. Schmitt, R. Traphner, S. Breen, and B. Smyth. "Websell: Intelligent Sales Assistants for the World Wide Web", *In R. Weber and C.G.von Wangenheim, editors, Procs. of the Workshop Programme at the Fourth International Conference on Case-Based Reasoning*, 2001.

[7] M. Doyle and P. Cunningham. "A Dynamic Approach to Reducing Dialog in On-line Decision Guides", *In Advances in case-based reasoning: 5th European workshop, EWCBR-2000, Trento, Italy, September 6-9, 2000*: proceedings. Springer, 2000.

[8] M. H. GÄoker and C. A. Thomson, "Personalized Conversational Case-based Recommendation.", *In Advances in case-based reasoning: 5th European work-shop, EWCBR-2000*, Trento, Italy, September 6{9, 2000: proceedings, pages 99-111. Springer, 2000.

[9] K. Grabler and A. H. Zins. "Vacation Trip Decision Styles as Basis for an Automated Recommendation System: Lessons from Observational Studies", *In Proceedings of the ENTER 2002 Conference, Innsbruck, Austria, January 22-25 2002*, Springer, Verlag.