Hybrid user modelling algorithms for tourism providers

Abstract

Currently, tourism providers build tourist models by collecting some specific pieces of information and then combining the knowledge they have about the groups to which current tourists belong. This paper presents the BaliaTour user modelling and recommender system, which combines several techniques and methodologies in order to enhance the modelling process when scarce of data about an individual tourist is available. The core of the model is based on the predictions made over stereotypes as a initial characterization of the user profile. The modelling is further refined and enhanced by the combination of explicit preferences and ratings provided by the user. As a result, the proposed approach takes advantage of every information piece known about tourists in tourism ecosystems. The main advantage of BaliaTour is to minimize the main drawbacks of each of the existing user modelling techniques to obtain a user model.

Keywords: Hybrid user model; stereotypes; explicit preferences; tourism entity.

1 Introduction

Information and Communication Technologies (ICT) have enabled tourists to access and search reliable and accurate information as well as to make online bookings, plan trips and make other purchases themselves. However, the number of choices has increased so dramatically that tourists are overwhelmed with information and can not find what they are looking for. To cope with this problem, Travel Recommender Systems (TRS) personalize the interaction for each individual tourist, capturing or inferring the needs of that user. Such information is the basis of a user model, which can be defined as a description of a persona including the most representative characteristics about him or her.

To be successful, a user modelling system must provide techniques to process the recorded information and build a model for a particular user. This implies a well-structured arrangement of the user data and the inference processes. If a user model is very complex, the way of collecting the required information could be very cumbersome. Furthermore, it does not make sense to record information about a user which has no use, although nearly every piece of information helps to describe the model of the user.

This paper presents the BaliaTour user modelling and recommender system, which combines several techniques and methodologies in order to enhance the user modelling process when only few data about an individual tourist is available. The core of the model is based on the predictions made over stereotypes as an initial characterization of the user profile. The modelling is further refined and enhanced by the combination of explicit preferences and ratings about tourism services and experiences provided by the user. As a result, the proposed approach combines every information piece known about tourists in tourism ecosystems.

This paper is organized as follows. First, Section 2 presents a brief state of the art where several definitions and classifications about user modelling techniques are described, including examples related to the tourism sector.

Section 3 describes the BaliaTour user modelling and recommender system, including a general overview of its architecture, the user modelling approach and a brief description of the recommender system. The final Section presents some conclusions and future work.

2 State of the art

User modelling research has been fostered by the need of many software application areas to automatically adapt to their customers. Since tourism is closely connected to interests and preferences of the user, many of the technological applications developed in this field aim at providing personalized experiences. Personalization means that the system should know about each user on the basis of his/her interests, skills and previous experiences. Thus, applications should make assumptions about the user which may be relevant to personalize the behaviour of the system to the user.

Although the first traces related to user models research appeared in the late 70's, there is currently no standard definition for user models. Generally speaking, the term "user model" can be used to describe a wide variety of knowledge about people (Rich, 1983). A de facto definition made by Wahlster and Kobsa (1989) states that a user model is "a knowledge source in a natural-language dialog system which contains explicit assumptions on all aspect of user that may be relevant to the dialog behaviour of the system". Three important dimensions that characterize user models have been identified by Rich (1979):

- One model of a single, canonical user which is necessarily uncertain but can represent users who have not usually interacted with the system vs. a collection of models of individual users.
- Models specified explicitly vs. models inferred by the system on the basis of the behaviour of the user. For explicit models to be generated, users have to answer a large number of questions before they can interact with the system. Thus, implicit user modelling has been considered less intrusive than explicit one, although not so accurate.
- Long-term user models which represent demographics or general interests of the user vs. short-term user models that are suitable for a specific session or task.

First, the proposed BaliaTour user model combines a canonical user model based on stereotypes with models for individual users to refine tourism services and experiences personalization. Secondly, BaliaTour includes explicit preferences defined by tourists to also improve the accuracy of the personalization. Finally, BaliaTour uses long-term user models which are enhanced by the interaction with the system.

User modelling aims at providing information about knowledge, goals or preferences of a user to application systems that try to adapt their behaviour to the individual characteristics of users (Pohl, 1996). Many research efforts have been put on the way information required for a specific model can be best collected or extracted from the user.

A limiting factor towards the building of a complete user model is the large number of characteristics or properties of the model. Several techniques are available to acquire the specific information required.

One of the oldest and simplest approaches to user modelling is classifying users into stereotypes (Rich, 1979; Rich, 1989). A stereotype is a collection of frequently occurring characteristics of users. This technique is useful when there is no further information available about the user. New users are categorized and classified into a stereotype according to their initial user model characteristics. The small amount of initial information is used to infer a large number of default assumptions.

If a system should cope with stereotypes effectively, it needs two types of information. It must know about the stereotypes themselves- the collection of characteristics or facets. A user is characterized by a set of facets, each of them containing a value. Although they depend on the domain and purpose of the system, the age, sex or type of tourism could be some facets of a tourist stereotype. Furthermore, a system using stereotypes should also know about a set of triggers, or events which determine that a particular stereotype is appropriate for a user.

For instance, INTRIGUE (Ardissono *et al*, 2003) provides personalized recommendations of tourist attractions to heterogeneous groups. Group user profiles are defined on the basis of the stereotypical knowledge about the typical tourist classes. The generated stereotypes are mainly characterized by socio-demographic information and preferences over the features of the tourist attractions. Furthermore, TravelPlanner (Chin and Porage, 2001) combines stereotypes with a multi-criteria decision making theory to evaluate the available travelling opportunities and proposes the one that fits best the needs and preferences of the user. Finally, Yang and Marques (2005) proposed a framework called UMT for modelling user profiles based on user transactional data which has been applied to a hotel network. BaliaTour also uses stereotypes to initialize the user model, mapping them to individual tourist models.

Another simple approach for user modelling is to explicitly ask users for information about their preferences using questionnaires and tests based on choice of answers, tick boxes or rating on scales. This method is very effective to get information, although the proper number of questions should be found to get the optimum amount of information from these questions without disturbing the user. Systems that only use this technique take the representations of the characteristics provided by the user as the corresponding elements in the user model. For example, Kramer, Modsching and ten Hagen (2006) have implemented an itinerary recommender system that matches user preferences collected by the mobile device to extract interesting categories for users.

As the previous technique has several limitations (long forms, tell or write the truth, non-willingness to provide data), many modelling systems attempt to infer implicit knowledge about the users by observing their interactions with the system, recording them and discovering patterns from the collected data. In this case, the corresponding elements in the user model are estimated by the system though machine learning techniques.

A wide variety of techniques coming from the areas of Machine Learning, Data Mining and Information Retrieval have been used for user modelling. Examples include Bayesian Networks, decision trees, association rules or Case-based Reasoning. As an example, Zheng *et al* (2011) have implemented a personalized friend and location recommender for geographical information systems (GIS) on the Web. The system uses real visits to a location as implicit ratings of that location.

Regarding explicit and implicit user modelling techniques in the tourism sector, Kabassi (2010) includes a detailed categorization of user modelling systems on the basis of the method of information acquisition. For example, Entrée (Burke, 2000) explicitly asks users about their preferences to recommend restaurants. Other guides such as PTA (Coyle and Cunningham, 2003), GUIDE (Cheverst *et al*, 2000) or INTRIGUE (Ardissono *et al*, 2003) learn about preferences of a customer implicitly through different sources.

The more properties of a user that can be modelled, the better personalization can be achieved. However, overloading users with explicit modelling may make them impatient. On the other hand, if all information was modelled implicitly, users may not trust the system and feel that they cannot control the modelling processing.

The main advantage of BaliaTour is to minimize the main drawbacks of each of the existing user modelling techniques to obtain a user model. User profiles are only partially based on stereotypes, which avoids the bias of the tourism expert. At the same time, the limited need of explicit user preferences reduces the extra burden to tourists. Finally, as tourists can rate tourism services and experiences, the user model is enhanced with this overall knowledge.

3 BaliaTour User modelling and Recommender System

3.1 General architecture

The BaliaTour user modelling and recommender system for tourism entities aims at recommending services and experiences in real-time that best fit the preferences of tourists, taking into account their demographics and preferences; the profiling information of the experiences defined by the providers; information about stereotypes; and the ratings of previously consumed experiences. Figure 1 shows some important aspects of the system, including the data gathering (D), the algorithms related to the user modelling (UM) and the recommender system (R).

In order to standardize concepts, BaliaTour defines a tourism entity as the entity that provides tourism services and experiences. The entity can be composed of a single provider (a resort, a destination, a congress centre) or an ecosystem of providers (accommodation, transport and services).

3.2 User modelling

As stated by Pohl (1996), the main objectives of a user modelling system are the proper representation of the user model and the acquisition of assumptions about the user. Regarding the former, the BaliaTour user model defines the user preferences and ratings about tourism services and experiences, as well as the similarity values of each tourist with the remaining ones.

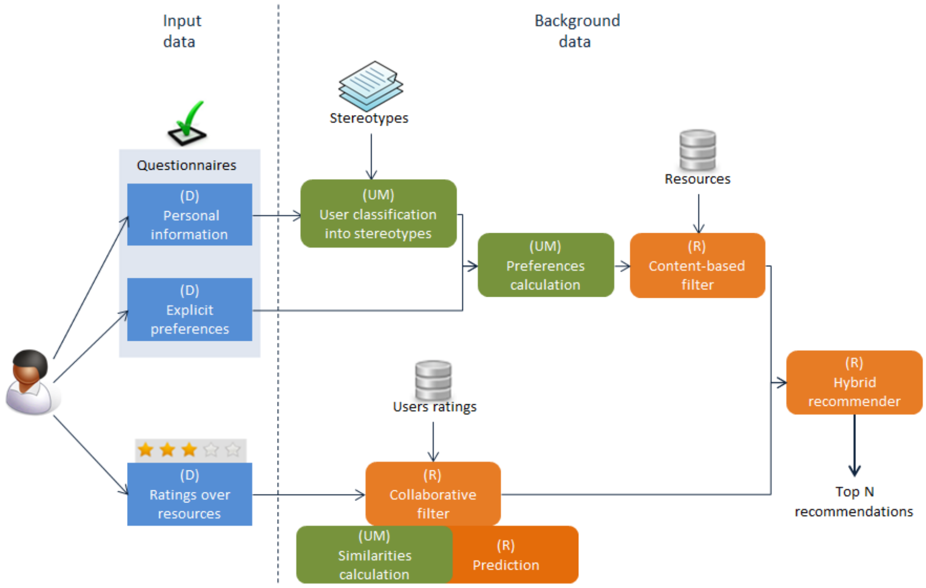

Fig. 1. Architecture of user modelling and recommender systems of BaliaTour.

Preferences are transformed into affinity with the metadata values of those services and experiences in a content-based process, while ratings and similarities are used in a collaborative process. The latter implies the collection of data to make assumptions about the user.

Input data to build the user model can be gradually gathered within the interaction between the tourism entity and the tourists. The BaliaTour input data consists of three main sources:

- Personal information or user characteristics, which include demographic data (i.e. nationality, age, gender), transportation means or duration of the stay (number of nights). These data are useful to infer personal interests when comparing them to already defined stereotypes.
- Explicit preferences of tourists related to one or more types of tourism services and experiences. Each tourism entity defines the preferences that best correlate to each of the services and experiences offered. For example, in the case of a resort, "gastronomy", "sport" or "shopping" could be some of such preferences. The preferences are represented on a discrete numerical scale which ranges from 0 to 100, with zero representing displeasure and 100 representing the best score.
- Ratings of the user about consumed services and experiences. They represent the starting point of the computation of similarities among users which are taken into account to recommend experiences to those users similar to the ones that liked those experiences in the past. Services and experiences are rated in a range between 1 and 5.

The first assumption of the BaliaTour system about the user states that if a tourist belongs to a category, then he/she may have similar characteristics and behaviours to other tourists in that category under a determined set of circumstances. Therefore, if a tourist is found to belong to a stereotype, it is possible to estimate his/her preferences.

Existing stereotype-based approaches in the literature are generally based on empirical observations (sales, analysis of user data, etc). Their main drawback is the work needed to build and fill appropriate stereotypes. Moreover, it is important to remark that the obtained conclusions could be uncertain. The BaliaTour platform enables each tourism entity to define its own stereotypes on the basis of their knowledge about previous tourists. In order to cluster tourists into stereotypes, the following steps have been taken in the BaliaTour platform.

An initial set of stereotypes was created for a tourism entity by exploiting existing information about tourist profiles and preferences from large query campaigns conducted by the Basque Government. These studies enabled specifying 47 stereotypes for the BaliaTour platform, such as Italian tourists, German tourists in the Basque Country, wellness tourism or urban tourism.

In parallel, the facets for each stereotype have been defined. These properties must be observable and measurable. It is compulsory to differentiate among the selected properties in order to ask tourists about them. The defined facets for BaliaTour are the age, sex and nationality of the tourist; the type of tourism (business, congress, general, …) and the way of travelling (alone, family, group).

The correct definition of the stereotypes took into account two main aspects. On the one hand, stereotypes are consistent with the considered facets. For instance, the "German tourist" stereotype must have Germany as the input variable for the "Origin" facet. On the other hand, tourism entities are responsible for the appropriate weighting of each preference in the stereotype. For example, the assumption that people belonging to the "German tourist in the Basque Country" stereotype like going to restaurants is represented with a high weight of the "Gastronomy" value of that stereotype for that preference.

Once the stereotypes have been defined, questionnaires to classify tourists into stereotypes were designed. Questions are related to the list of defined BaliaTour facets, so that each tourist can be classified into one stereotype. In order to make it more efficient and attractive for tourists, questionnaires have a fixed number of questions with predefined answers just to be clicked. Four questionnaires have been designed for the BaliaTour platform depending on the type of tourism (general tourism, business tourism, trade fairs or exhibitions). In some application scenarios (for example, accommodation), there is no need to design questionnaires, as the required data can be easily obtained at the registration.

Once this process is completed, BaliaTour is capable of classifying tourists into stereotypes. The platform compares the answers to questionnaires with the expected values of the facets for each stereotype on the basis of the k-Nearest Neighbour algorithm. This algorithm retrieves the k instances more similar to the data that has to be classified. The closest instance is the stereotype assigned to the tourist. A user associated with the stereotype inherits all stereotype preferences automatically.

In such a way, the user model of the tourist is initialized with the values of the preferences associated to that stereotype. BaliaTour uses the implementation of the algorithm by the Weka library (http://www.cs.waikato.ac.nz/ml/weka [September 6,2012]), which includes a collection of automatic learning algorithms for Data Mining.

Secondly, the BaliaTour platform acquires the explicit user preferences related to the services and experiences available at the tourism entity. BaliaTour displays those preferences through an intuitive interface in order to be selected by tourists. The platform stores the user explicit preferences that have an important weight in order to generate recommendations. The information collection (both questionnaires for stereotypes and explicit preferences) has been unified into a single process when tourists register at the tourism entity.

After the explicit interaction with the tourist, the platform calculates the preferences of a tourist, weighting between the preferences assigned to his/her stereotype and those explicitly selected by the user. Such weighting solves several limitations. Firstly, the output of the system can use one alternative (stereotype or explicit preferences) in cases where information is scarce. Secondly, when possible, the approach not only takes into account the explicit preferences, as they have been calculated on the subjective rating of only one user, but it is also based on the collective thinking represented by the stereotypes.

The algorithm tries to reduce the possible bias of the selection of several explicit preferences by odd users. Thus, a correction factor calculated from the typical deviation of the weights of the preferences has been applied. This means that if there are not important variations among explicit preferences, it can be concluded that the user has not properly determined the preferences. Thus, a larger weight is given to the stereotypes.

The proposed approach faces several cases, depending on whether the user has answered or not the questionnaire and the explicit preferences, as shown in Table 1. In each case, the most appropriate algorithm is selected. All algorithms are based on the same approach, giving more weight to the preferences directly selected by the user (α = 0.9) than the ones defined in the stereotype (β = 0.1). Figure 2 displays the pseudo-code for the proposed algorithm.

Table 1. Defined cases for the proposed approach.

<table>
<tr><td colspan="2"></td><td colspan="2">Has the user answered the questionnaire about the preferences?</td></tr>
<tr><td colspan="2"></td><td>NO</td><td>YES</td></tr>
<tr><td rowspan="2">Does the user have an assigned stereotype?</td><td>NO</td><td>Algorithm 1
No explicit preferences and no stereotype</td><td>Algorithm 2
Explicit preferences and no stereotype</td></tr>
<tr><td>YES</td><td>Algorithm 3
No explicit preferences and stereotype</td><td>Algorithm 4
Explicit preferences and stereotype</td></tr>
</table>

When there is no stereotype assigned to the user and the preferences have not been rated, algorithm number 1 calculates the value of each preference $w'_{u,p}$ as the weighted sum of the default value for all the explicit preferences w^{o}_{p} and the assigned value of a preference due to all the stereotypes $\overline{w}_{p\_s}$.

$$w'_{up} = \alpha * w^{o}_{p} + \beta * \overline{w}_{p\_s} \quad (1)$$

Algorithm number 2 is applied when the user has no assigned stereotype and has rated at least one of the preferences. In this case, a correction factor sep_u related to the explicit preferences of the user u is applied, which takes into account the similarity among all his/her punctuations. If the similarity is high (small standard deviation), less importance is given to those punctuations and more importance is given to the collective value assigned to the preference related to the stereotypes.

$$w'_{up} = (\alpha - sep_u) * w_{up} + (\beta + sep_u) * \overline{w}_{p\_s} \quad (2)$$

It calculates the weight about the preferences defined by a tourist entity for a user u

Data: u: active user

Result: W'_u: set of computed weights of the user u about all the preferences

P: set of all the preferences p defined by the tourist entity

$hasEP_u$: 1 if the user u has defined at least one explicit preference or 0, otherwise

$hasS_u$: 1 if the user u has been classified into one stereotype or 0, otherwise

w_{up}: weight about the preference p explicitly assigned by the user u

w_{sp}: weight about the preference p assigned to the stereotype s by the tourist entity

w'_{up}: computed weight about the preference p assigned to the user u

w^0_p: default weight for the preference p assigned by the tourist entity

$\overline{w}_{p\_s}$: default weight for each preference p according to stereotypes

sep_u: similarity value over the explicit preferences of the user u

begin

- **for** $p \in P$ **do**
  - **if** $hasS_u = 0$ **and** $hasEP_u = 0$ **then**
    - $w'_{up} \longleftarrow applyAlgorithm1(w^0_p, \overline{w}_{p\_s})$
  - **else if** $hasS_u = 0$ **and** $hasEP_u = 1$ **then**
    - $w'_{up} \longleftarrow applyAlgorithm2(w_{up}, \overline{w}_{p\_s}, sep_u)$
  - **else if** $hasS_u = 1$ **and** $hasEP_u = 0$ **then**
    - $w'_{up} \longleftarrow applyAlgorithm3(w^0_p, w_{sp})$
  - **else if** $hasS_u = 1$ **and** $hasEP_u = 1$ **then**
    - $w'_{up} \longleftarrow applyAlgorithm4(w_{up}, w_{sp}, sep_u)$
  - $W'_u \longleftarrow w'_{up}$

Fig. 2. Algorithm for calculating user preferences.

Algorithm number 3 is used when the user has not rated any preferences but there is an associated stereotype. In this case, the default value of all the explicit preferences is used as the first term of the sum and the value w_{sp} of the preference for the assigned stereotype for the second term.

$$w'_{up} = \alpha * \mathrm{w}^{\mathrm{o}}_{\mathrm{p}} + \beta * w_{sp} \qquad (3)$$

Finally, algorithm number 4 can be applied to every user that has a stereotype and has rated the corresponding preferences. In this case, the weight of the calculated preference is the weighted sum of the weights of the explicit user preference and that related to the assigned stereotype, applying the corrective factor related to the similarity of explicit preferences.

$$w'_{up} = (\alpha - sep_u) * w_{up} + (\beta + sep_u) * w_{sp} \qquad (4)$$

The final step of the BaliaTour user modelling system is related to the calculation of the similarities of the user with regard to other users on the basis of the ratings of tourism services and experiences. Tourists are able to rate all the services and experiences offered by the tourist entity after having experienced them, only selecting a number of "stars" between one and five. Although ratings are mainly included within the Travel Recommender Systems concept in the literature, the proposed BaliaTour model includes the ratings to enhance the user model.

The BaliaTour methodology follows a memory-based approach with off-line processing for a more efficient similarity calculation. Thus, the neighbourhood and the prediction generation are separated. The objective is to pre-compute the all-to-all user similarities so that the recommendation engine can retrieve the required similarity values more quickly.

For each particular user (or active user), similarity with the rest of the users is computed using Pearson's correlation which corresponds to the cosine of users' deviation from the mean rating. Pearson correlation ranges from 1.0 for users with perfect agreement to -1.0 for perfect disagreement users.

3.3 BaliaTour recommendation system

Recommender systems have been classified into Content-based (CB) versus Collaborative Filtering systems (CF). The former estimates the relevance of an item based on the preferences of the user towards the metadata values of that item. Thus, objects are defined by their associated metadata values. CB filtering systems recommend items similar to those that the user liked (i.e. positively rated) in the past or others with features that best satisfy the user preferences stored in the user profile.

On the other hand, the later generates recommendations based on the opinions (ratings) of other people. For each target user, these algorithms attempt to discover a neighbourhood of users with the strongest correlation on the basis of previous ratings. Scores for unseen items are then predicted in the basis of the ratings given to them within the neighbourhood. Thus, while the first approach focuses on the metadata of the items, the second one generates recommendations only on the rating basis.

Due to the strengths and limitations of both approaches, the BaliaTour platform has implemented a hybrid recommendation algorithm, where recommendations are based on a weighted average of both techniques. In this case, the values calculated on the basis of both techniques are consistent in the range [1,5]. In order to achieve this consistency, similarity values achieved from the CB technique in the range [0,1] are escalated into the [1,5] range.

Regarding the recommendation process, the CB system makes a prediction $p\_cb_{u,r}$ for an active user u about a tourism experience r. Then, the corresponding prediction $p\_cf_{u,r}$ is obtained from the CF system. In the case of BaliaTour, both predictions are equally weighted ($\gamma=0.5$) when making a recommendation.

$$p_{u,r} = \gamma * p\_cb_{u,r} + (1-\gamma) * p\_cf_{u,r} \qquad (5)$$

4 Conclusions

User modelling is a clear consequence of the need for personalization. It aims at providing a user model about the knowledge, goals and preferences of a user to systems that try to adapt their behaviour to those preferences. There are several approaches to classify the properties of a user model. The more relevant characteristics describing the user that are included in the user model, the more accurate and useful is the personalization provided.

The BaliaTour algorithm combines several information sources about tourists in order to build a proper representation of their user model. All these information sources are known by tourists at a tourism entity who participate actively in answering questionnaires, defining their interests and rating services and experiences. Tourists can perform one, some or all of these actions in a progressive way. Once the user model has been generated, it can be applied to personalized applications, such as a Travel Recommender System to suggest personalize tourism services and experiences about a destination.

The main advantage of the proposed BaliaTour user model algorithm is the different nature and extent of the data used, adapting to several possible situations in a tourist scenario. First, the use of stereotypes is a partial solution in the initialization of the preferences of the user model, improving the cold start problem. As stereotypes include different facets (for example, origin, age or gender) defined by the tourism entity, tourists can be classified into one stereotype after answering a questionnaire. The main advantage of stereotypes is that they draw many assumptions about tourists based on very little input. Once a stereotype is activated, its associated preferences are transferred into the user model of the individual tourist.

If the user model were only based on these preferences from stereotypes, all tourists within the same stereotype would be represented by the same user model and thus, obtain the same recommendations. Therefore, explicit preferences of the users are also taken into account to refine personalization. In order to overcome discrepancies, preferences for each tourist are calculated as a weighting between the preferences assigned to his/her stereotype and those explicitly selected by the user.

Finally, users usually assign ratings to tourism services and experiences on the basis of a defined scale. This evaluation feedback represents a further source of information which helps building user models on the basis of similarities among tourists. Although these similarities represent valuable information for the recommender process, they could be also valuable to enlarge and refine the user model. When data is scarce about the user, his/her user model could be inferred from the models of users with similar ratings.

Future work on the BaliaTour user modeling and recommender system will include the extension of the user model in order to include implicit preferences, such as those inferred by the location or the context. For instance, the inclusion of location information from Bluetooth devices (bracelets, SmartPhones) carried by tourists at the tourism entity will be used to infer further preferences from the services and experiences consumed.

References

Rich, E. (1983). Users are individuals; individualizing user models. *International Journal of Man-Machine Studies* 18: 199-214.

Wahlster, W., & Kobsa, A. (1989). User Models in Dialog Systems. In A. Kobsa & W. Wahlster (eds.), *User Models in Dialog Systems*. Heidelberg: Springer.

Rich, E. (1979). User Modeling via Stereotypes. Cognitive Science 3 (4): 329–354.

Rich, E. (1989). *Stereotypes and User Modeling*. In: A. Kobsa and W. Wahlster: 1989, User Models in Dialog Systems, Heidelberg: Springer Verlag.

Pohl, W. (1996). Learning about the User- User Modeling and Machine Learning. In: Proc. ICML'96 Workshop Machine Learning meets Human-Computer Interaction, pp. 29-40.

Ardissono, L., Goy, A., Petrone, G., Signan, M. & Torasso, P. (2003). Intrigue: personalized recommendation of tourism attractions for desktop and handset devices. *Applied Artificial Intelligence* 17 (8–9): 687–714.

Chin, D. & Porage, A. (2001). Acquiring user preferences for product customization. In: Bauer, M., Gmytrasiewicz, P., Vassileva, J. (Eds.), *Proceedings of the 8th International Conference on User Modeling*, LNAI, vol. 2109, pp. 95–104.

Yang, Y. & Marques, N.C. (2005). User group profile modeling based on user transactional data for personalized systems. *Lecture Notes in Computer Science*, LNCS 3808, 337–347.

Kabassi, K. (2010). Personalizing recommendations for tourists. *Telematics and Informatics* 27(1): 51-66.

Burke, R. (2000). Knowledge-based recommender systems. *Encyclopedia of Library and Information Systems* 69 (32).

Coyle, L. & Cunningham, P. (2003). Exploiting re-ranking information in a case-based personal travel assistant. In: *Proceedings of the 5th International Conference on Case-based Reasoning*.

Cheverst, K., Davies, N., Mitchell, K., Friday, A. & Efstratiou, C. (2000). Developing a context-aware electronic tourist guide: Some issues and experiences. In: *Proc. of CHI'00*, Netherlands, pp. 17–24.

Kramer, R., Modsching, M., & ten Hagen, K. (2006). Field study on methods for elicitation of preferences using a mobile digital assistant for a dynamic tour guide. *ACM Symposiumon Applied Computing*. New York, USA, ACM Press.

Zheng, Y., Lizhu, Z., Zhengxin, M., Xing, X. & Wei-Ying. M. (2011). Recommending Friends and Locations Based on Individual Location History. *ACM Transactions on the Web* 5(1): 1–44.