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Tourism Recommender Systems: An Overview of Recommendation Approaches

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ABSTRACT
Recommender systems have become an active research topic during the last two decades, thus giving rise to several approaches and techniques. They have also become increasingly popular among practitioners and used in variety of areas including movies, news, books, research articles restaurants, garments, financial services, insurance, social tags and products in general. Tourism is an important sector for economic development and a potential application area of use of recommender systems. This paper presents an overview of existing recommender approaches used in tourism and discusses their relevance taking into account tourism context and specificities.

General Terms
Information systems, information retrieval; retrieval tasks and goals; recommender system

Keywords
Recommender systems; Tourism field; Content based; Collaborative based; Ontology Based; Hybrid Recommender System.

1. INTRODUCTION
Recommender Systems (RS) are computer based tools and techniques providing suggestions for items to be of use to a user [1] [2] [3]. They have become an important research field since the emergence of the first paper on collaborative filtering in the mid-1990s [4] [5] [6] [7]. RS have also become increasingly popular among practitioners because of the abundance of practical applications that help users to deal with information overload and provide them personalized recommendations, content, and services [8]. Indeed, RS are nowadays widely used in variety of areas including movies, news, books, research articles restaurants, garments, financial services, insurance, social tags and products in general.

The tourism field is one of the most potential application area of RS. On one side, from the point of view of tourism operators and service providers, employing RS could boost tourist flows and increase revenue by recommending, at the right moment and when they are at the appropriate location, suitable items to potential tourist consumers [9]. On the other side, from the tourists' point of view, RS could be a valuable help while preparing a trip or searching a service among many destinations, numerous attractions and activities. The use of RS could help tourists to save time and energy while searching for a trip and or services that match their preferences and interests [10] [11].

RS are based on fundamental components. The first is about data models, which describe items, and users the second component is related to algorithms, which apply specific methods, approaches and strategies, in order to recommend the most appropriate item to a targeted user. The quality of recommendations depends hugely on these two components.

The main issue encountered when building Tourism Recommender Systems (TRS) is, what approaches and which data models are the most suitable for a high quality recommendations.

This paper gives an overview of existing recommendation approaches and data models and discusses their relevance to the tourism field.

The paper is organized as follows. Next section gives an overview of recommendation approaches used in TRS. Section III is devoted to data models. The last section is dedicated to conclusions and perspectives.

2. TOURISM RECOMMENDER APPROACHES
RS are computer-based tools, which attempt to predict items out of large pool a user may highly likely be interested in, and to suggest him the best one. They also support systems helping users to find and/ or to make choices about items that matches their preferences and interests [12]. To achieve these tasks, RS rely on characteristics and attributes of both users and items as well as algorithms, which implement specific strategies and approaches, to generate a recommendation to a target user. They are also generally defined as a subclass of information filtering system that seek to predict the 'rating' or 'preference' that a user would give to an item, using a model built from the characteristics of an item and/or the user's social environment[13] [14] [15].

In the tourism field, recommender systems aim to match the characteristics of tourism and leisure resources or attractions with the user needs [16]. Unlike RS in other domains, TRS frequently combine multiple types of recommendation techniques for example SigTur/E-Destination [13] employs many recommendation techniques, such as the use of stereotypes (standard tourist segments), content-based and collaborative filtering techniques, personalized and ontology-based approaches. However, the special characteristics of tourism items generate continuous appearance of new problems and the need to develop new techniques [13]. In this work the methods used by TRS are classified in two categories: Classical approaches and Non Classical ones.

2.1 Classical approaches

Classical approaches use content-based filtering and collaborative filtering methods. Widely used and studied, collaborative filtering and content-based approaches constitute the base of the majority of RS and are domain independent.

2.1.1 Collaborative Filtering Approach

Collaborative filtering is based on the similarity between the users. This filtering recommends items appreciated by users who have previously made choices similar to those of the current user. Collaborative-filtering RS determines the utility of an item based on the feedback (ratings, likes ...) of similar users [12]. The idea here is not to focus specifically on the new item that would be likely appreciated by the user, but to look to which items have interested other users who are close to the current user [17]. Collaborative filtering technique start by building a database (user-item matrix) of preferences for items by users. Then it matches the items with the users based on the outcome of the similarity test between their profiles [18]. This approach is the most mature, the most common and the most referenced in literature [14]. It is the most implemented since it often gives good results, and does not require much data preparation to start with.

2.1.2 Content-Based Filtering Approach

Content-based RS are content oriented, which means the content of users interests and the content of the features of items play an essential role in the recommendation process [12]. RS using content-based filtering approach base their evaluations on ratings given by a user on a set of items [17]. Unlike collaborative filtering method, Content-based filtering determines which items are likely to be useful or interesting to a given user by analyzing the content or the descriptions of items.

Most content-based recommendation systems identify items similar to those that a given user has appreciated. This approach is based on the similarity between the different objects: the objects are recommended to users based on their feedback on similar objects [15].

2.1.3 Discussion

The methods exposed above certainely provide good recommendations, however they suffer from many limits in the and can't be extended as shown in the table 1 , and because of specificities of TRS, among which difficulties of representing the tourism and travel items .

Table1. limits of classical appoarches

approach	limits
Collaborative Filtering	the shortage of information about the items, the scalability and cold start
Content-Based Filtering	Need of big amount of information about users and items. Overspecialization, cold start, and scalability

Tourism items have specificities that affect deeply the quality of recommendation based on classical approaches. For example, when a tourist appreciate a monument or a museum during a trip it does not mean he will want to see it again. However using content-based methods only, the system will suggest to him when he returns a second time to the same place the same type of monuments, while he maybe will be more interested in items he did not discover during last trip.

Another example which, Is it appropriate to suggest visiting a place or enjoying an activity while the place or the activity are planned in his tourist circuit, or while he has just visited them few days before?

Moreover, collaborative filtering methods alone are more difficult to satisfy the tourist needs, when matching users' trips is nearly impossible, two people experiencing the same trip the same travel duration, the same place of interests, the same experience, the same transportation mode is very hard to come by [19].

Given the above examples, it appears that taking into account the specificities of tourist domain is very important to improve the quality of TRS. Tourism domain needs to consider multiple factors such as time, space, whether, location, distance between two sites, roads, history of tourist trips, etc. in order to make an accurate recommendation, therefore new technics should be developed and implemented in order to enhance the quality of TRS.

2.2 Non classical approaches

Non-Classical approaches include personalized recommendation, ontology-based recommendation and context-aware recommendation.

2.2.1 Personalized Approaches

Personalized means fitting the goals, preferences and abilities of the user [20]. Personalized RS aim to provide users with items based on their personal interests and preferences, by employing all the knowledge available on them explicitly or implicitly [21] [22]. Explicit data may be given by the user in different ways, for instance whenever he specifies his cultural interests by filling in a form. Implicit interests can be inferred by the system through the analysis of the behavior of the user.

Personalized recommendation approaches in TRS aim to void information overload and offer only relevant information to the tourist [11], they recommend a list of tourism items matching personal preferences and take note of tourist experiences [23]. This is the aspect where personalized recommendation approaches demonstrate their importance and enhance the quality of recommendations, since they consider each user having unique, special characteristics and its own experiences.

2.2.2 Context-aware approaches

Context has been studied across different research disciplines including computer and organizational sciences [16]. This is one among multiple definitions given to the term "context" in the literature: "Context is any information that can be used to characterize the situation of an entity. An entity is a persona, place, or object that is considered relevant to the interaction between a user and an application (including the user and the application themselves)" [24].

Recommendation systems are called context-aware when they use the context in its calculation to predict items likely to interest the user [11].

Context is considered as one of the most important factors while presenting recommendation to a tourist. Thus, it is important to consider several context elements such as Geo-localization, which is the most used in the context-aware RS, time, which will give better recommendations and allow tourists to enjoy a pleasant visit and to appreciate recommended items [18]. RS based on context-aware methods, are proactive; they present to users the needed recommendation whenever, wherever without any user explicit demand. Proactive recommendation systems retrieve large quantities of documents, decide what information is likely to be relevant to users' needs, and suggest this information without an explicit user request [25].

Nowadays, mobile and numerous smart devices connected to internet, called connected “things”, are widely available and used. These devices are able to capture and to provide many information that could enrich the current context as well as its variations. However, this aspect is the most challenging part in these type of RS; since it demand the definition of which context element is relevant to the recommendation, and which one provide more accuracy [11].

2.2.3 Ontology Based Appraoche:

Ontologies are recently initiated tools for structuring knowledge. According to Gruber [26], ontology is defined as an explicit formal specification of terms of a domain and relations among them; they provide an abstract view of an application domain. Ontologies form the core of the Semantic Web play an important role to facilitate semantic integration of heterogeneous data. Ontologies have been intensively used in many domains such as semantic web, heterogeneous systems integration [27] [28] and recently [29] in RS.

Ontology based RS incorporate semantic knowledge and semantic information related to both user and item profiles; they achieve this by using ontologies in order to improve recommendation’s quality [12] [30]. They also use ontologies to gather user data profiles available in heterogeneous sources, such social applications. [13] [33] [25] [31].

Since the accuracy of the recommendation is relative to the information available on the user profile and the items described characteristics, the use of the semantic approach [19]enhance the quality of the RS. Especially the use of ontologies makes it possible to keep as much information as possible from multiple and heterogeneous sources [32].

Many ontologies have recently been developed to represent and reason about tourism domain knowledge [13]. MONDECA is an example of ontology built on tourism concepts given by World Tourism Organization. MONDECA, the concepts given are object profiling, tourism packages, multimedia content related to tourism and description of archeological objects along with other concepts.

2.2.4 Discussion:

Non-classical approaches would give adequate recommendations in which the current context and a good knowledge of the tourist and item profiles are available.

For example, a TRS using Non-classical approaches could avoid suggesting at 11:30 am the menu of a restaurant, located just near the hotel where the tourist stays, while the tourist has chosen all-inclusive formula. However, such recommendation will be appropriate if the tourist is far from his hotel.

Another example is the tourist who stays in a cheap hotel, a TRS based on Non-classical approaches could avoid suggesting him items from a high street store.

Non-classical approaches will undoubtedly improve TRS quality; however, the challenge is to define methods and techniques of selecting relevant information collected in real time and react immediately to the speedy variations of the context of the tourist. In other words, high quality TRS needs developing a specific data model for both tourist items and tourist profile, before choosing a recommendation strategy.

The next section is devoted to the issue of data models for TRS.

3. DATA MODELS FOR TRS

Since RS are information-processing tools, the data available on both items and users are primordial to build efficient recommendation systems. Data is mainly about items to suggest and system users in order to construct solid profiles for users and items.

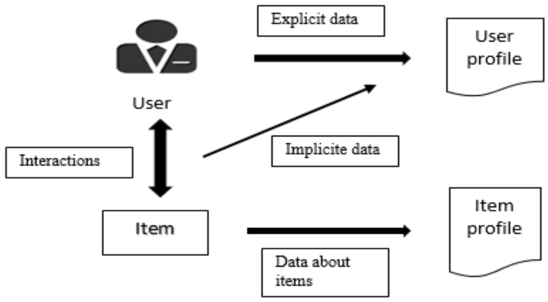

Fig1.profiling of users and items in RS

3.1 User’s data

RS exploit a big amount of data about users collected from numerous sources in order to create and maintain their profiles; this is a key element to build a relevant recommendation. The user profile store any potentially useful data on a user for Recommendation process [32]. Among the numerous user’s data, the user profile may contain demographic characteristics, personal preferences and interests [33]. The quality of the data collected play undoubtedly a starring role in the quality of recommendation. The profile of a user is generally composed of two main parts, one is domain independent and the other depends on the domain [13]. The first part contains usually the demographic characteristics of the user age, gender, status, etc., which can help the system build a generic recommendation. but, to reach a successful personalized recommendation the second part of the profile take an in-depth look in the whereabouts of the user according to the specified domain of the recommendation (in this case tourism: his location, the destinations, itinerary, travel budget etc.). Recommender systems implement a three-step process to build the user profile and keep it updated; the three steps are:

- *Data collection:*

It exists two types of data collected and stored in the user profile, explicit and implicit Data. Explicit data are Information that the user explicitly entered via forms to the RS, for example, the user name, its gender, profession, birthdate or by explicit feedback such as ratings [34]. Explicit data are also available in many different sources such as social media, tourism operators’ databases, mailing boxes etc. These data has to be processed and cleaned before incorporating them in the user profile. Implicit data is determined by analysing user behaviour and the actions he performs during his interaction with the RS, the implicit feedback are examples of implicit data that must be incorporated in the user profile.

- *User Profile Construction*

This step incorporates all the data extracted from the feedback and structure it according to the profile representation to shape the initial profile [35].

- *User profile update*

In order to keep the recommender accuracy, the changes of the user's interests and preferences as time goes on must be taken onto account to add new interests and forget the old ones[13] [32][35].

The knowledge about user's preferences and interests is the stepping-stone to create any type of recommender system, but the user for TRS are tourists who express complex and multi-layered need and interests [36], and hope for efficiency and diversity. In this light defining, a specific model for users of TRS which contain irrelevant data to tourism such user context [37] (his location, time, weather etc.) or the user travel history is a necessity.

3.2 Item's data

"Items are the objects that are recommended. Items may be characterized by their complexity and their value or utility" [38], the items recommended to the users are represented by a set of features, also called attributes or properties [39].

Travel items are especially known to be of high level of complexity since they englobe both products and services. In fact, the large span and the variety of touristic items challenge the developers of TRS: from lodging (hotels perspectives), to food and beverage sector, to tourism attractions (sightseeing, shopping, entertainment, gaming, culture and recreation) all those heterogeneous items must be modeled, and represented in the TRS's databases. Furthermore, travel and tourism items are intangible, such as flight experiences, a visit to a museum and much more, which render the representation of items more challenging. A RS ultimate goal is to offer pertinent suggestions to users, and in order to attain this objective item's data collection and representation is an essential matter, and to provide more success rate the use of semantic representation and ontologies is preferred.

3.3 Discussion

Efficiency and quality of TRS depend highly of the quality of the user model adapted to the system. Choosing model increase the accuracy of the recommendation list generated and airing the real need of the users.

Tourism domain faces the same challenges as well as other domains in this field of researches, such as the adequacy of data and the noise within that data. However, tourism has also his own specific challenges: the context. The context (time, weather, geolocation, past history of visits...) plays a big role in determining the importance of an item and the ranking of this item in the recommendation list.

For instance, TRS should not suggest to a user of the system to visit a museum before its opening hours or after its closing hours. In addition, a qualified TRS cannot offer to a tourist to visit a club while he is in a visit for a conference, or advice him to visit a site or landscape he has already visited in a previous vacation.

Therefore, researchers need to construct a data model that incorporates these features and englobes the maximum factors that affect the preferences and the interests of the users. Consequently, a user model and item model for TRS must represent the characteristics of tourism domain by incorporating the context of the tourist and tourism objects.

4. CONCLUSION

The explosive growth and variety of information available on the Web and the rapid introduction of new e-business services (buying products, product comparison, auction, etc.) frequently overwhelmed users, leading them to make poor decisions. And In the face of the information overload and the fastidious task of preparing a trip, recommender systems bring more easiness in accessing information about travel destinations and tourist attraction. To achieve such results, multiples types of recommendation methods are used to offer the best suggestion of a trip tailored to the user's preferences and interests.

In this paper, some of the approaches used to produce tourism recommender systems were overviewed. Firstly the classical approaches used generally in recommender system, mainly divided in two categories: content-based filtering methods and collaborative filtering methods. Secondly, the new approaches, which integrate, personalized recommendation, the context and the semantic knowledge about the users and items. In addition, the steps to build a user profile within a recommender system to identify the items matching their preferences were presented.

Planning a trip is a complex decision process taking in account all the variables on tourism items and users, recommendation approaches need more involvement and more use of all the features of the items for example the opening and closing times of the attractions, or the time needed to go from one point of interest to another. More importantly, the user's characteristics his experiences, his behavior and his interactions on social media are to be taken in each steps of recommendation building. Therefore, to catch user needs and generate a satisfying recommendation especially in tourism domain is a hard work, and for better results will be more interested in data models in future work in order to have a better understanding of the tourism and travel items.

In the future works, the focus will be in determining a classification of tourism and travel items using their features, and to create a model user that can help catch all the user characteristics and interests using ontologies and semantic technologies.

5. REFERENCES

[1] Mahmood, T., Ricci, F.: Improving recommender systems with adaptive conversational strategies. In: C. Cattuto, G. Ruffo, F. Menczer (eds.) Hypertext, pp. 73–82. ACM (2009)

[2] Resnick, P., Varian, H.R.: Recommender systems. Communications of the ACM 40(3), 56–58 (1997)

[3] Burke, R.: Hybrid web recommender systems. In: The AdaptiveWeb, pp. 377–408. Springer Berlin / Heidelberg (2007)

[4] Deuk Hee Park, Hyea Kyeong Kim et. Al., "A Review and Classification of Recommender Systems Research", in IPEDR vol. 5 2011, International conference on Social science and humanity, Singapore 2011.

[5] Herlocker, J.L., and Konstan, J.A. "content-Independent Task-Focused Recommendation", IEEE Internet Computing, Vol. 5, 2001,pp. 40-47.

[6] Resnick, P., Iakovou, N., Sushak, M ., Bergstrom, P. and Riedl, J."GroupLens An Open Architecture for Collaborative Filtering of Netnews," Computer Supported Cooperative Work Conf, 1994.

[7] Shardanand, U., Maes, P. "Social Information Filtering: Algorithms for Automating 'Word of Mouth", Conf. Human Factors in Computing Systems, 1995

[8] Gediminas Adomavicius, Alexander Tuzhilin Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions

[9] Walter Carrer-Neto, Maria Luisa Hernandez-Alcaraz, Rafael Valencia-Garcia , Francisco Garcia-Sanchez X Social knowledge-based recommender system. Application to the movies domain. 2012

[10] A.Moreno, L.Sebastiá and P.Vansteenwegen Recommender Systems in Tourism 2015

[11] Kevin Meehan, Tom Lunney, Kevin Curran, Aiden McCaughey 2013 Context-Aware Intelligent Recommendation System for Tourism

[12] Dalia Sulieman. Systèmes de recommandation sociaux et sémantiques 2014

[13] Moreno, A., Valls, A., Isern, D., Marin, L., & Borràs, J. (2013). SigTur/e-destination: Ontology-based personalized recommendation of tourism and leisure activities. Engineering Applications of Artificial Intelligence, 26, 633–651

[14] Charif Alcheikh Haydar Les systèmes de recommandation base de confiance, thèse de doctorat 2014

[15] Jonathan Loudec Stratégies de Bandit pour les Systèmes de Recommandation thèse doctorale 2016

[16] Context-Aware recommender systems Gediminas Adomavicius, Alexander Tuzhilin in F. Ricci, et al. (Ed.), Recommender Systems Handbook, 2011, pp. 217–253.

[17] Daniar Asanov Algorithms and Methods in Recommender Systems 2011

[18] Jonathan Loudec Stratégies de Bandit pour les Systèmes de Recommandation thèse doctorale 2016

[19] Francesco Ricci Travel Recommender Systems IEEE INTELLIGENT SYSTEMS 2002.

[20] Anind K. Dey and Gregory D. AbowdTowards a Better Understanding of Context and Context-Awareness 2000

[21] Janet Rajeswari , Shanmugasundaram Hariharan Personalized Search Recommender System: State of Art, Experimental Results and Investigations on Tourist Interests and Preferences 2016

[22] Liliana Ardissono Intrigue: Personalized recommendation of tourist attractions for desktop and handset devices applied artificial intelligence Special Issue on Artificial Intelligence for Cultural Heritage and Digital Libraries 17(8-9), pp. 687-714, 2003

[23] Ilhem Boussaid Personnalisation de l'information et gestion des profils utilisateurs : une approche fondée sur les ontologies thèse doctorale 2005

[24] Imen Akermi, Mohand Boughanem, Rim Faiz Une approche de recommandation proactive dans un environnement mobile 2016

[25] Marie-Françoise Canut, Sirinya On-at, André Péninou, Florence Sèdes Enrichissement du profil utilisateur à partir de son réseau social dans un contexte dynamique : application d'une méthode de pondération temporelle 2013

[26] Thomas Robert GRUBER, Gregory OLSEN, An ontology for enginering mathematics. In Proceedings of the 4th International Conference on Principles of Knowledge Representation and Reasonning. MorganKauffmann,1994

[27] Bouchra Aadil, Abderrahim Ait Wakrime, Larbi Kzaz, Abderrahim Sekkaki Ontological approach for Data WareHouse design 2015

[28] Larbi Kzaz, Hicham Elasri, Abderrahim Sekkaki An ontology-based method for semantic integration of business components 2011

[29] Nikola Minić, Angelina Njeguš, Jelena Tulić Ceballos The Impact of Web 3.0 Technologies on tourism information systems 2014

[30] Dieudonné Tchuente, André Peninou, Marie-Francoise Canut, Nadine Baptiste-Jessel, Florence Sesdes Modélisation du processus de développement des profils utilisateurs dans les systèmes d'information 2010

[31] Victor Codina and Luigi Ceccaroni Taking Advantage of Semantics in Recommendation Systems 2010

[32] Romain Picot-Clémente Une architecture générique de Systèmes de recommandation de combinaison d'items. Application au domaine du tourisme Mémoire de Thèse 2012

[33] Malak Al-Hassan, Haiyan Lu , Jie Lu A semantic enhanced hybrid recommendation approach: A case study of e-Government tourism service recommendation system 2015

[34] Gao, M., Liu, K., & Wu, Z. (2010). Personalization in web computing and informatics: Theories, techniques, applications, and future research. Information Systems Frontiers, 12, 607–629.

[35] Miquel Montaner, Beatriz Lopez And Joseph Louis De Larosa 2003 A Taxonomy Of Recommender Agents On The Internet

[36] Tobias Berka and Manuela Plößnig Designing Recommender Systems for Tourism

[37] Annika Hinze and Saijai Junmanee Travel Recommendations in a Mobile Tourist Information System

[38] Lior Rokach, Bracha Shapira Introduction to Recommender System Handbook Francesco Ricci, 2010.

[39] Pasquale Lops, Marco de Gemmis and Giovanni Semeraro Content-based Recommender Systems: State of the Art and Trends 2010.