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An Innovative Recommender System for Health Tourism in a Smart Digitalized World

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Abstract

The recommender systems process data for extracting information relevant to the user profile. In this study, we present an innovative recommender system aiming at matching health tourist preferences to health/tourism providers. It focuses on providing complete health tourism products, by matching the user profile to characteristics of both health and tourism service providers, in order that users receive the treatment they choose, in the right location, the right period, at the right cost. The proposed recommender system is implemented by applying a facility location problem which employs a parameter that controls the diversity of the recommendation list and thus the variety of the proposed results. It incorporates a database of cases, i.e., medical, wellness and tourism service providers. A case is described by a set of attributes such as medical service category, spa category, wellness category, cost, infrastructure, accreditations, communication languages, and so on. Users that have already acquired a health tourism package provide ratings for certain categories of attributes. A new user expresses her preferences in the form of a query and then the system tries to match this query to the cases that exist in the database. At first, the best possible cases are extracted, by applying a sorting procedure based on comparisons to the ideal one, i.e., that containing the best ratings for each attribute of the database. Then the facility location method is applied to provide the final recommended cases to the user that are both similar to the provided query and diverse to each other.

Keywords: *Recommender System, Health Tourism, Hotel Industry, Digital Marketing*

JEL Classification: M31, C44, C38

1. Introduction

Nowadays, the introduction of the Internet and the new opportunities that arise regarding e-business services frequently overwhelm users. Huge amounts of data are available to them, thus the processing procedure and the extraction of useful knowledge is difficult. Also, mass customization tends to replace mass marketing and personalized services are offered to users. Firms need a better understanding of customers' needs and preferences in order to offer personalized products or services.

Recommender systems (RS) can facilitate all these procedures. They are tools that can process the recorded data and based on users' preferences and needs that are explicitly acquired or predicted by the system, they can keep only the part of the data that is relevant to the user and suggest customized services (Lorenzi & Ricci, 2003). The firms with the use of RS can increase the volume of their sales, since they can offer products and services that satisfy customers' needs or they can suggest products and services that the user might not be able to find without this recommendation or might not imagine that he is in need of them. The current trend in RS is the diversity of the recommendation list, which means that the recommended products or services are similar to the query inserted by the user and diverse to each other. This leads to a variety of choices for the user.

In a common recommender system, users insert queries by selecting some attributes out of the offered ones and by giving values to them. In this way, they express their needs and preferences. Then, the RS tries to match the inserted query to the relevant items of the electronic database. In other cases, user profiling is exploited, where users are asked to classify themselves in one of the profiles provided by the system. In this case, implicit needs that have not been provided by the user may be guessed by the system (Ricci, Arslan, Mirzadeh, & Venturini, 2002).

The main purpose of this article is to present an innovative recommender system in the field of health tourism. This system aims at matching health tourist preferences and needs to health/tourism providers. It focuses on providing complete health tourism products, by matching user profile characteristics of both health and tourism service providers in order that users receive the treatment they choose, in the right location, the right period, at the right cost. It incorporates a database of cases, i.e. medical, wellness and tourism service providers. Usually, the contemporary databases contain huge amounts of data that have to be processed and thus recommender systems need fast and effective techniques since exact methods might be ineffective. In our case, we use a facility location problem – solved by a fast heuristic technique presented in Panteli, Boutsinas & Giannikos (2019) - in the recommendation process, which employs a parameter that controls the diversity of the recommendation list and thus the variety of the proposed results. Our general objective anywise, is to broaden the perspective of the techniques that can be used in the recommendation process.

2. Literature Review

Recommender Systems & Health Tourism

The Recommender Systems (RS) are software tools that collect data related to preferences and needs through the interaction of a user with a website or a web application and then organize and process them in order to keep only the relevant part of data and make personalized suggestions (Fesenmaier et al., 2003).

The basic components of RS are the items, the users and the transactions. The items are the recommended objects that are characterized by a series of attributes. The users interact with the system and they insert queries by giving values to the attributes. The system usually asks the users to provide basic information about preferences and needs and tries to offer a more customized experience. The interaction between the user and the RS is usually called a transaction. It contains log-like data that can help the recommendation algorithm to operate properly (Ricci, Rokach, & Shapira, 2011).

The motivation behind these systems is to eliminate or reduce the information overload. In fact, users are overwhelmed by the massive volume of data since the Internet became a part of every aspect of their everyday life. The RS are effective tools that can help them filter the abundant part of data and extract only the part that is relevant to their needs and preferences. Recommender systems organize the data in order to be processed by effective heuristic algorithms that operate within these systems and they provide precise and appropriate results based on users' queries.

The recommendation process is divided in the information collection phase, where data about the user are collected, in the learning phase where a learning algorithm is used in order to extract the useful knowledge from the previous phase and in the recommendation/forecast phase where the suggestion of relevant objects to the user's preferences takes place (Núñez-Valdéz et al., 2012). However, the "feedback" of the recommendation process is quite important and the RS must incorporate techniques that collect the biggest possible amount of information by the users and advanced processing techniques that evaluate and exploit the feedback in order to make more accurate and useful recommendations.

The RS were used initially in the process of internet document search. However, the evolution of the Internet and the wide spread of new multimedia technologies, encouraged the development of RS and their applications can now be found in a wider range of services. Today they are present in many domains such as the entertainment, the tourism, the health-care, the education, the web search, the e-commerce and so on. In fields where personalization is necessary, RS play an important role. For example, the interactive digital television contains an electronic personal guide that informs the user when a program, that the user might be interested in, is broadcasted. Another personalized service is the advertising that is shown to the users based on their internet search history or based on their known preferences. RS, by predicting content that the user might like or find interesting, not only assist users in the decision making process but also help the businesses to improve their revenues through cross-selling and long tail marketing, which distinguishes the “hit” products which means the products that sell well, the most popular ones from the rest (Celma, 2010).

Recommender systems are divided into some basic categories. Collaborative Filtering (CF) recommender systems are almost the most popular nowadays. They consist of databases with preferences of users regarding various items expressed by ratings. Usually, there is a triple of a user, an item and a rating. A rating matrix, most of the times a sparse one, shows pairs of users and items, where the user has either rated or not the corresponding item. The pairs of users and items that do not contain a rating are unknown values of the matrix. As a result, in these cases, the recommender system tries, as a first step, to predict the preference of a user regarding an item and as a second step, recommend a list with items that have the highest predicted preferences. Therefore, collaborative filtering (CF) bases its predictions and recommendations on the ratings or the behavior of other users of the system. The basic concept of CF is that if users’ preferences about a range of items coincide, then it is highly possible that these users may agree in other items as well, so the system recommends items that the user has not tried yet, but other users with similar preferences have already selected. The CF systems relate users and items with the use of two different methods, the neighborhood approach and the latent factor models.

In contrast to CF recommender systems which find similar users to a given one and propose items that these other users with similar preferences liked in the past, content-based (CB) recommender systems focus on the discovery of items that present high levels of similarity to the items that a given user has liked in the past (Balabanovic & Shoham, 1997). In fact, CB systems adopt approaches that analyze a set of items’ characteristics that the user has rated in the past and they try to create a profile with the preferences of the user based on the objects’ attributes that have already been rated by the user. In this way, they try to propose interesting items to the user, which means items that contain characteristics that match the corresponding ones of the user’s profile. There are many problems related to this type of systems. They do not have a specific technique for finding something that is not expected. Usually, the systems that incorporate CB methods do not suggest novel items. In contrast, the recommended items are highly associated to the user’s profile which means that they present high similarity to the items that the user has already evaluated in the past. Thus, this type of recommendation leads to overspecialization which means that the RS by trying to find items similar to the ones that the user has already preferred, they eventually propose the same group of items (Adams, Benett & Tomasic, 2007). Finally, the basic problem of CB systems derive from the fact that in new users, the ratings are inadequate and as a result, the systems cannot produce accurate recommendations. CF faces as well the cold-start problem. This means that since CF require data about the purchasing history and the rating experience of users in order to make a recommendation, in cases where such kind of data is unavailable or limited, the result is poor.

Both categories of recommender systems are not highly effective to domains where the product is customized, its description is complex, it is not regularly bought and thus sufficient ratings do not exist. These two categories of RS need domain knowledge and sufficient ratings from either the purchase history of the user or of her “neighbors” in order to effectively discover interesting items for the user. Such examples of products or services can be found in the real estate sector, in the financial and tourism domain and so on (Aggarwal, 2016).

Another type of RS can be more effective in this kind of products. They are called Knowledge – Based (KB) recommender systems. They exploit knowledge related to users and items in order to produce a recommendation. In fact, this type of systems try to find items that satisfy the users' preferences and needs. The KB systems, which are more interactive, ask the customers to explicitly define their requirements and as a result, the user guides and controls the recommendation process. They are more effective than CF and CB in cases where it is difficult to obtain ratings for an item due to the complexity of the product domain. Also, they are proved to be more accurate in cases where the ratings of the products are time-sensitive such as computers. Another difference between the three categories is related to the kind of input data. In CF and CB historical data are used whereas in KB systems the users, based on their preferences, specify their requirements.

KB systems can be divided into two subcategories, the constraint based and the case based recommender systems. On the one side, in constraint based RS, users specify requirements or constraints about the attributes of the items. Also, rules are used that are related to the specific domain that the items belong to and constitute the domain specific knowledge. On the other side, in case based recommender systems, the user specifies her requirements in the form of a query and similarity metrics are used in order to retrieve cases similar to the query. The similarity metrics that are used are selected according to the domain under observation and they constitute the domain knowledge. Due to the fact that each of the aforementioned categories of recommender systems (CF, CB and KB) present disadvantages, hybrid recommender systems that combine techniques of more than one categories of RS are developed. In this way, these hybrid systems can exploit the benefits of each category and avoid the corresponding drawbacks.

The algorithm that will be chosen in the recommendation process depends on the application domain of the RS (Montaner, López, & De La Rosa, 2003) and the type of the available data that have to be processed. Recommender systems employ different kind of techniques in order to exploit the available data and extract useful information by taking into account the preferences and needs of the users. In this way, RS can provide more reliable results and personalized suggestions. Currently, the RS use data mining techniques in order to analyze huge amounts of data that the contemporary databases contain. Data mining techniques aim either at the building of a "model" that takes as input huge amounts of data, tries to present them in a summarized and more convenient form and usually makes predictions or at the pattern detection where structures and unusual features in data are discovered in a local level (Hand & Adams, 2015).

Such techniques might be association rule mining, decision tree, k-nearest neighbor, link analysis, neural network, regression, clustering and other heuristic methods. Clustering techniques are usually incorporated in RS because they are thought to reduce dimensionality – i.e. reduce the number of operations - and thus, increase efficiency. However, clustering has to be carefully adapted in order not to compromise accuracy in the effort of improving efficiency.

In our study, an innovative recommender system is used in health tourism. The tendency to health tourism started when people tried to find cheaper alternatives to cosmetic procedures. However, currently people choose to undergo more important surgeries in regions that charge lower prices. Many definitions exist about health tourism. At first, we refer to health tourism when a tourism facility tries to attract tourists by offering at the same time health-care and tourism services. Also, it is considered as the aggregate relationships and events related to travel and accommodation of tourists, whose main objective is to maintain or improve their health (Mueller & Kaufmann, 2001). The International Union of Tourist Organizations defines health tourism as "the provision of health facilities utilizing the natural resources of the country and more specifically mineral water and climate (IUTO, 1973, Health Tourism, Geneva: United Nations). This definition has been further enriched in the following years and has been stated that it refers to the process of receiving medical services in a leisure setting away from home (Goeldner, 1989) or else, the process of travelling outside the country of residence in order to receive medical treatment. Travelers visit health tourism resorts in order not only to receive a medical treatment of an ailment but to relax and rest as well, for beauty care, nutrition and healthy diet, meditation, mental and spiritual renewal, recreational activities, sports and so on (Smith & Kelly, 2006). The treatments may vary from vital procedures such as heart surgeries, hip resurfacings to less important such as dental and wellness treatments (Reddy, York, & Brannon, 2010). Typical examples of this concept are the cruise lines that offer health tourism services or the therapeutic landscapes.

Usually, an important factor that encourages pe-ople to health tourism is the poor health care system of their countries. Long waiting lists in operations cause people to go abroad to seek medical care. This fact in combination with the high medical cost in some countries motivate people to seek abroad for lower-cost options and thus, contributes to the development of health tourism.

Health tourism from the supply-side has been proven as an efficient alternative solution to increase the profits in areas where the tourism demand is seasonal. Health tourism is thought to have been discovered by the hotel industry in cooperation with the healthcare and medical providers.

In the past, related analysis of health tourism data proved that the corresponding resorts in that field did not advertise properly the offered services. According to the specific motives of the health tourists, the health tourism market is divided into some market segments. For example, if the primary motive for travel abroad is health in a different climate or context, or wellness activities in combination with health activities or medical treatment along with leisure activities and so on.

It was stated in the literature that there are at least two possible segmentation aspects of the health tourism market, health and income. As for the health segment, marketing campaigns could target people with minor ailments such as high cholesterol, anorexia, dental, dermatological, infertility problems and so on. Furthermore, marketing campaigns could target people who would like to maintain their youth and their external appearance through cosmetic surgeries, spa treatments, holistic medicine approaches, leisure activities for an active everyday life and so on. As for the income segment, hotels or spa resorts might target high – income people that are able to spend much money for the luxurious offered health services or middle-class people who can afford medium level prices (Goodrich, 1994).

Nowadays, user's feedback data combined with log data from websites leads to a more efficient segmentation of users based on similar preferences, needs and ways of acting. Hospitality marketers diversify their marketing plans by targeting health tourists since health tourism seems a profitable sector. In fact, there are facilities that integrate wellness or alternative medical therapies with the conventional medicine. Therefore, health tourists may have an operation but at the same time they may receive treatment or recuperation in a more pampering, pleasant and refreshing form. For example, these hotel-like or spa-like facilities might offer not only general surgeries, but also massages, aromatherapy, facial services and so on.

Searching for tourism related information and services is a quite attractive web activity and many web sites incorporate contemporary technology and tools in order to support the traveler in the decision making process of the selection of a tourism destination or a tourism related service (Katsoni, 2011). Users frequently search in web sites for information such as mostly visited places, sightseeing, weather conditions, flights, hotels, transport, currency, restaurants and so on.

Travel and tourism related services contain much information and thus the corresponding industry is the primary sector for the application of electronic commerce (Werthner, 2002). Smart applications like the recommender systems assist users in the process of making a decision about tourism related activities. Moreover, when the tourism industry tries to analyze consumer-related data, it is necessary to perform data pre-processing in order then to conduct efficient data mining. Recommender systems assist in this process as well (Cooley et al. 1997).

In the tourism domain usually case-based recommender systems are used since their operational efficiency gets improved over time by learning from past interactions and by updating their case bases with new experience. In fact, these systems focus on the reuse of experience, which is modeled as a case. They also exploit the explicit feedback that users give about their experience regarding the services that they received. New problems are solved by transferring and adapting solutions that were used for similar problems in the past. Actually, in the retrieval step the system receives a problem specification (in the form of a query), searches through the case base, scores each case for similarity to the query, and selects the highest-scoring case(s), which are the subject of subsequent processing steps (Bridge, Göker, McGinty, & Smyth, 2005). The similarity measure that is used in order to score the matching of the case to the query is extremely important and depends on the type of data and other factors.

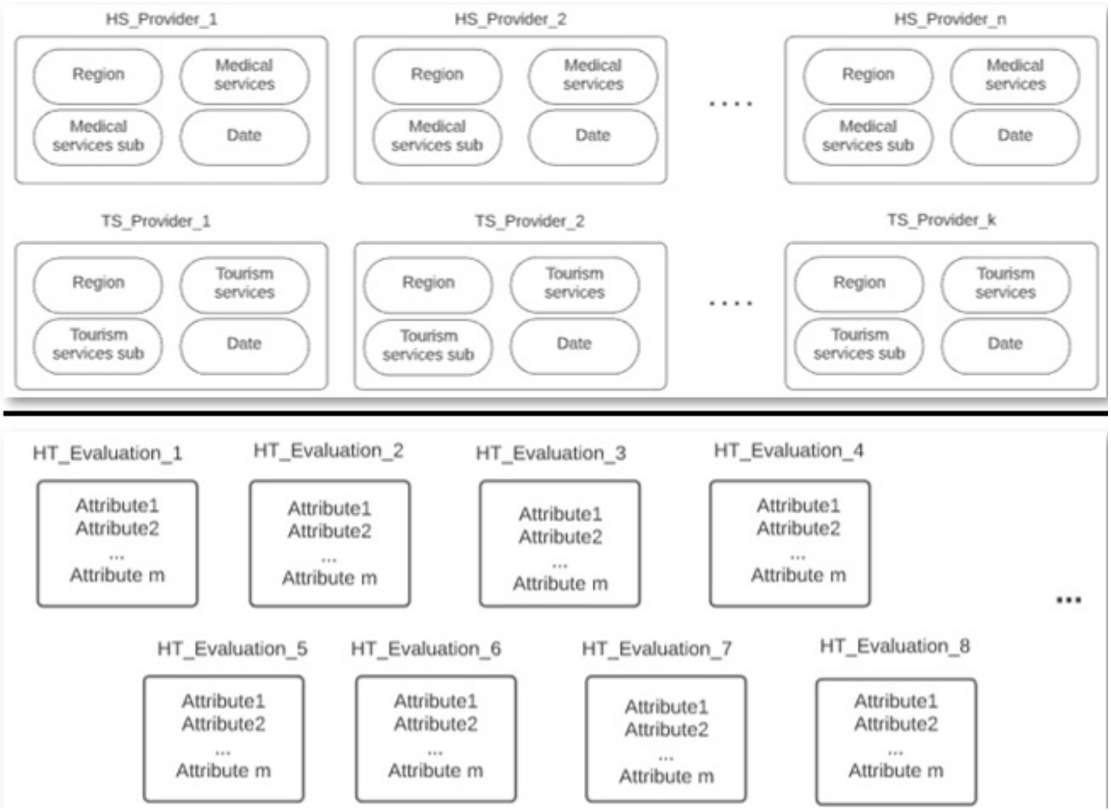
The efficiency of a case based RS depends on the similarity metric that is adopted and on the critiquing method. Similarity metrics have to be selected in an appropriate way in order that relevant results are obtained and meaningful items are retrieved in response to the target query. The type of data related to the attributes of the cases play a significant role in the selection of the right metric. Critiquing methods allow the interactive exploration of the available data and the result is usually the exclusion from further examination of the search results of cases that are considered as irrelevant.

The health tourism recommender system of our study is a case based system and focuses on the patients and tourists and tries to offer them health and touristic services according to their preferences and needs. In that way, it matches patients and tourists to health and touristic units in order that they receive the treatment they choose.

3. Health Tourism Recommender System

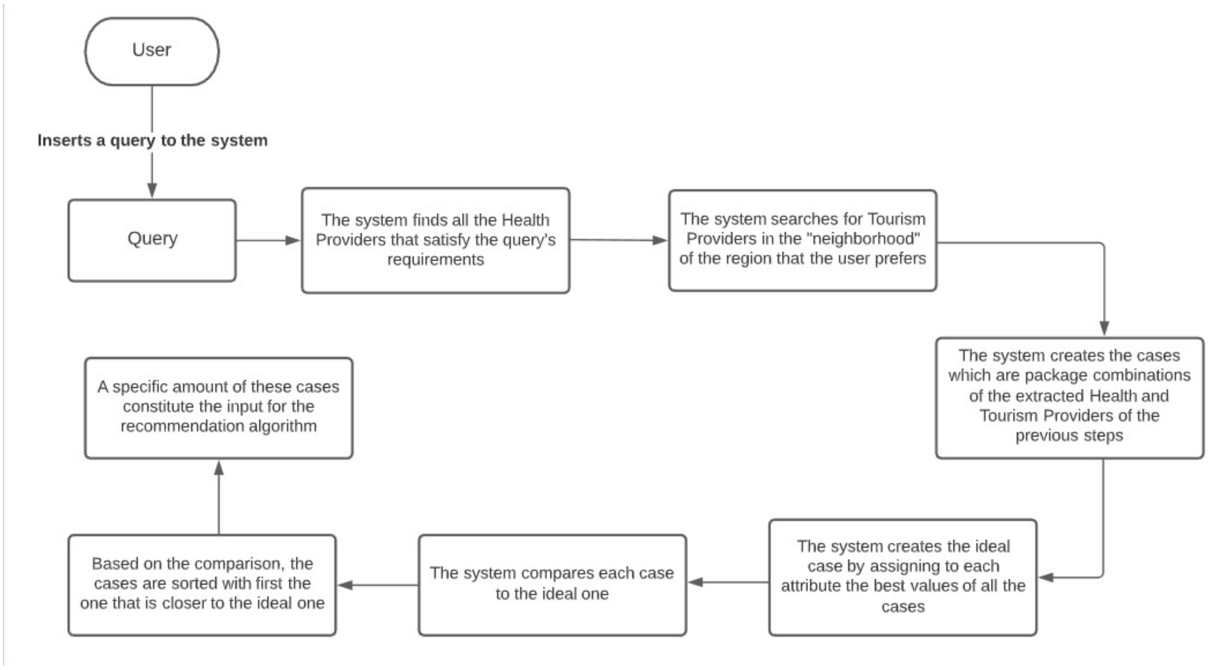
The recommender system of our study consists of a case base which contains information about the health (HS_Provider) and tourism (TS_Provider) service providers such as location, medical service category and subcategory, tourism service category and subcategory, dates that the facilities are available for services and so on. Moreover, it contains ratings from users (HT_Evaluation), who have already acquired a health tourism package. In fact, the users evaluate the provided services according to their experience. For example, the medical cost, the quality of medical services, the infrastructure quality, the accommodation quality, the medical staff's responsiveness and so on. Figure 1 represents the Case Base of the health tourism recommender system.

Figure 1.
Representation of the Case Base of the Health Tourism Recommender System



The following figure (Fig.2) describes the data flow in the system. A user inserts a query which specifies her needs and preferences in the form of values in specific attributes. The system processes this type of information and applies a matching procedure. It selects those *health providers* that 1) offer services which belong to the category and subcategory that the user has selected in her query, 2) are located in the "neighborhood" of the location that the user has stated and 3) are available during the time period that the user has mentioned. It should be mentioned that the "neighborhood" expands the specific location that the user selects to a greater radius i.e. to a larger region around the location stated by the user. Then, the system searches for *tourism providers* in this "neighborhood" in order to create all possible package combinations. In fact, a package combination offers health services by a health provider based on the requirements of the user's query in combination with tourism services offered by a tourism provider in the same "neighborhood" of the health provider. In this way, it creates the available "cases", the package combinations. Moreover, by taking into consideration the ratings that exist in the Case Base and the requirements of the user's query, the system creates an ideal case that contains the best values for all the attributes that exist in the case base. Each case is compared to the ideal one and a sorting procedure is the next step. After these steps, the system employs a recommendation method that is analyzed in Panteli & Boutsinas (2019) utilizing association rule mining (Fayyad et al. 1996, Boutsinas et al. 2008).

Figure 2.
Representation of the Data Flow in the Health Tourism Recommender System



Nowadays, the trend in recommender systems is to provide diverse results. This derives from the fact that when a recommendation list does not contain a satisfying level of diversity, if the user does not like a top-ranked result, it is usual that she may not like the other results as well, since they are all quite similar to each other. The adopted method in the innovative health tourism recommender systems focuses on the diversity of the recommendation list which is a major challenge in contemporary recommender systems since it contributes to the solution of the over-fitting problem.

In fact, diversity provides important value and leads to the user's satisfaction. Bradley & Smyth (2001) defined the diversity in the process of recommendation as the opposite of similarity. The items that are suggested to the target user have to be similar to the inserted query in order to be close to the requirements of the user, but at the same time diverse to each other since users may get bored or unsatisfied after receiving many recommended objects that present a high level of similarity to each other (Hurley & Zhang, 2011). Usually, users cannot express their needs and preferences in a detailed way or they might not imagine exactly what they want or what options do exist but might be open to explore new and diverse directions. As a result, a list with cases that constitute the same exact match with a more implicit query might be ineffective, whereas a more diverse recommendation list that provides a variety of cases might be more useful to the user because of the existence of alternative options. However, the most common problem when the diversity and the similarity of the recommendation list are studied, is the trade-off between these two measures since they have an almost reverse relationship. When the overall diversity between the objects of the recommendation list is high, this might lead to a lower similarity ratio of each recommended object to the query.

In our application, we incorporate a specific facility location problem to the recommendation process, the multiple p-median problem (MPMP) which contains a parameter that has been proven in our previous work (Panteli A. & Boutsinas B., 2019) that plays the role of the regulator of the similarity – diversity tradeoff. The value of this parameter in combination with the size of the recommendation list, can affect the similarity to diversity ratio. This parameter refers to the alternatives that are recommended to the user by a recommender system and how these alternatives satisfy the requirements of the user.

Therefore, the health tourism system recommends some possible health and tourism providers that satisfy the requirements of the user and have the best ratings. At the same time, the recommended cases except from satisfying the user's requirements i.e. being similar to the query inserted by the user, are diverse to each other in order that alternative choices are offered. The facility location problem can be solved by a heuristic technique since the health tourism database contains large volumes of data and exact techniques might be ineffective.

Consider the following example that describes the operation of the health tourism recommender system in a simple way. Given that the case base consists of only 100 available health and tourism providers, a user inserts a query and defines her preferences.

Attributes	**Query inserted by the user**
Preferred Region	Patras
Preferred Medical Service Category	Wellness Tourism
Preferred Medical Service Subcategory	Cosmetic Surgery
Preferred Dates	9/8-12/8

The system tries to match the inserted by the user query to the health providers that exist in the Case Base. As a result, it tries to find the health providers in the neighborhood of the specified by the user region (Patras) that offer cosmetic surgery services and are available for the dates specified by the user. The neighborhood of the specified region can be calculated by a common distance measure.

At the same time, the system tries to find the tourism providers that exist in this neighborhood in order to create all possible package combinations. As a result, the cases are package combinations of health and tourism providers that are located in the neighborhood of Patras and offer the services requested by the user in the specific dates.

After the creation of all the possible cases (package combinations) that contain the corresponding ratings, the system creates the ideal case. The ideal case consists of the best ratings for each of the attributes that are included in the package combinations.

Given the ideal case, the system compares each of the available package combinations to the ideal case. In a real Case Base with many available providers, this step would end up with a large number of comparisons. Then, the system sorts these cases starting from the ones who are the most close to the ideal case and selects a specific number of them that are used as the input of the recommendation algorithm that is based on the MPMP, as stated before. This problem takes as an input a data matrix that contains the distances between the ratings of the cases and these of the ideal case. Given a specific threshold that depends on the nature of the input data, a binary matrix is created that shows if a package combination is appropriate for the recommendation list. Then the system, by the solution procedure of the multiple p-median problem (MPMP) tries to end up with p recommended cases (package combinations). The value of p is defined initially according to the system's requirements. This problem also incorporates a parameter *mc* that states how many cases out of p have to match the ideal case's values. According to the size of the recommendation set i.e. the value of p and the value of the *mc* parameter, as it has been already proven in Panteli & Boutsinas (2019), the similarity to diversity ratio takes different values. As a result, the *mc* parameter in combination with the size of the recommendation set constitute a regulator for the trade-off between similarity and diversity measures. The metrics that are used in order to calculate the diversity and the similarity ratios can be found in Smyth & McClave (2001).

In the end, the system by taking into consideration the fact that the diversity of the recommendation list is a current need, it creates the final set of recommender cases to the user. The user after her experience, provides her personal evaluation and in this way the Case Base is updated with more cases.

4. Conclusions

In this paper we presented the operational procedure of a recommender system that aims at matching the preferences of the health tourists to health and tourism providers. Actually, this system's innovative character derives from the fact that provides package combinations of medical and tourism providers. The user asks for medical services and the system tries to satisfy these needs in combination with tourism services from providers in the neighborhood of the region that the user prefers. These package combinations consist of ratings regarding some attributes. The ratings are recorded by users that have already received the corresponding medical and tourism services from these providers. The package combinations constitute the cases of the Case Base that are then processed by a facility location based method. In fact, the multiple p-median problem from the facility location field is employed in the recommendation procedure. This problem incorporates a parameter that plays the role of the regulator of the similarity and diversity tradeoff among the objects of the recommendation list. As a result, the proposed health tourism recommender system suggests health tourism package combinations according to the needs and preferences of the user and based on the experiences of other users that have provided the corresponding ratings regarding the received services. These package combinations, since the multiple p-median problem is employed, present satisfactory levels of diversity between them in order that the user selects from a variety of alternative choices.

References

Adams, J. M., Bennett, P. N., & Tomasic, A. (2007). Combining Personalized Agents to Improve Content-Based Recommendations. Pittsburgh: Language Technologies Institute, Carnegie Mellon University.

Aggarwal C.C. (2016) Knowledge-Based Recommender Systems. In: Recommender Systems. Springer, Cham.

Balabanović, M., & Shoham, Y. (1997). Fab: content-based, collaborative recommendation. Communications of the ACM, 40(3), 66-72.

Basu, C., Hirsh, H., & Cohen, W. (1998, July). Recommendation as classification: Using social and content-based information in recommendation. In Aaai/iaai (pp. 714-720).

Boutsinas, B., Siotos C. & Gerolymatos, A. (2008). Distributed mining of association rules based on reducing the support threshold, International Journal on Artificial Intelligence Tools, World Scientific Publishing Company, 17(6), 1109-1129.

Bradley, K., & Smyth, B. (2001). Improving recommendation diversity. In Proceedings of the Twelfth Irish Conference on Artificial Intelligence and Cognitive Science, Maynooth, Ireland (pp. 85-94).

Bridge, D., Göker, M. H., McGinty, L., & Smyth, B. (2005). Case-based recommender systems. The Knowledge Engineering Review, 20(3), 315-320.

Celma, Ò. (2010). The long tail in recommender systems. In Music Recommendation and Discovery (pp. 87-107). Springer, Berlin, Heidelberg.

Cooley, R., Mobasher, B., & Srivastava, J. (1997, November). Web mining: Information and pattern discovery on the world wide web. In Proceedings ninth IEEE international conference on tools with artificial intelligence (pp. 558-567). IEEE.

Fayyad, U.M., Piatetsky-Shapiro, G., & Smyth, P. (1996). Advances in Knowledge Discovery and Data Mining. AAAI Press/MIT Press.

Fesenmaier, D. R., Ricci, F., Schaumlechner, E., Wöber, K., & Zanella, C. (2003, January). DIETORECS: Travel advisory for multiple decision styles. In ENTER (pp. 232-241).

Goeldner, C. (1989). 39th congress AIEST: English workshop summary. Revue de Tourisme, 44(4), 6-7.

Goodrich, J. N. (1994). Health tourism: A new positioning strategy for tourist destinations. Journal of International Consumer Marketing, 6(3-4), 227-238.

Hand, D.J. and Adams, N.M. (2015). Data Mining. In Wiley StatsRef: Statistics Reference Online (eds N. Balakrishnan, T. Colton, B. Everitt, W. Piegorsch, F. Ruggeri and J.L. Teugels).

Hurley, N., & Zhang, M. (2011). Novelty and diversity in top-n recommendation--analysis and evaluation. ACM Transactions on Internet Technology (TOIT), 10(4), 1-30.

International Union of Tourism Organisations (IUTO) (1973). Health Tourism. Geneva: United Nations.

Katsoni V., (2011). The Role of ICTs in Regional Tourist Development. Regional Science Inquiry Journal, 3(2).

Lorenzi, F., & Ricci, F. (2003, August). Case-based recommender systems: A unifying view. In IJCAI Workshop on Intelligent Techniques for Web Personalization (pp. 89-113). Springer, Berlin, Heidelberg.

Montaner, M., López, B., & De La Rosa, J. L. (2003). A taxonomy of recommender agents on the internet. Artificial intelligence review, 19(4), 285-330.

Mueller, H., & Kaufmann, E. L. (2001). Wellness tourism: Market analysis of a special health tourism segment and implications for the hotel industry. Journal of vacation marketing, 7(1), 5-17.

Núñez-Valdéz, E. R., Lovelle, J. M. C., Martínez, O. S., García-Díaz, V., De Pablos, P. O., & Marín, C. E. M. (2012). Implicit feedback techniques on recommender systems applied to electronic books. Computers in Human Behavior, 28(4), 1186-1193.

Panteli, A., & Boutsinas, B. (2019, July). Improvement of similarity-diversity trade-off in recommender systems based on a facility location model. In 2019 10th International Conference on Information, Intelligence, Systems and Applications (IISA) (pp. 1-7). IEEE.

Panteli, A., Boutsinas, B., & Giannikos, I. (2019). On solving the multiple p-median problem based on biclustering. Operational Research, 1-25.

Reddy, S. G., York, V. K., & Brannon, L. A. (2010). Travel for treatment: students' perspective on medical tourism. International Journal of Tourism Research, 12(5), 510-522.

Ricci, F., Arslan, B., Mirzadeh, N., & Venturini, A. (2002, September). ITR: a case-based travel advisory system. In European Conference on Case-Based Reasoning (pp. 613-627). Springer, Berlin, Heidelberg.

Ricci, F., Rokach, L., & Shapira, B. (2011). Introduction to recommender systems handbook. In Recommender systems handbook (pp. 1-35). Springer, Boston, MA.

Smith, M., & Kelly, C. (2006). Wellness tourism. Tourism Recreation Research, 31(1), 1-4.

Smyth, B., & McClave, P. (2001, July). Similarity vs. diversity. In International conference on case-based reasoning (pp. 347-361). Springer, Berlin, Heidelberg.

Werthner, H. (2003, August). Intelligent systems in travel and tourism. In IJCAI (Vol. 3, pp. 1620-1625).