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DEVELOPMENT OF A NATIONAL TOURISM WEB PORTAL WITH ENRICHED RECOMMENDER: EMPIRICAL EVIDENCE

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ABSTRACT

The paper argues the importance of creating personalized recommender, particularly in small and tourism developing countries as Macedonia. Due to the fact that tourism emerged as one of the major industries in the world economy by benefiting various sectors, each country is interested in its development. Having in mind that increasing the number of tourists is significant source of income and economic growth, meeting their preferences is inevitable. In this respect, the paper makes an attempt to justify the necessity of designing national tourism portal in order to help the tourists to identify their holiday through a recommender. So, this empirical evidence reports on practical experience gained from a successful implementation of a collaborative filtering tourism recommendation system. Moreover, software module is developed which is capable of generating a personalized list of interesting items for all visitors of a national tourism web portal.

Key words: tourism, web portal, recommender, preferences.

1. INTRODUCTION

Tourism has emerged as one of the major industries in the world economy, by benefiting transportation, accommodation, catering and many other sectors. Thus, each country insists in developing it and making a profit from its variety of impacts. Moreover, everyone is interested in increasing the number of incoming visitors since it serves as a source of economic growth. In 2011, the tourism contributed almost US$ 6 trillion to the world global economy, or 9% of global gross domestic product (GDP), 100 million direct jobs and US$ 650 billion investments in tourism (WTTC, 2011a: 2).

Macedonia identified tourism as a mean for generating various micro and macro-economic. In this line, a National Strategy on Tourism Development 2009-2013 was prepared with a main vision: Macedonia to become famous travel and tourism destination in Europe based on cultural and natural heritage (Government of Macedonia, 2009: 3). Up-to-date, tourism in Macedonia has accomplished an average growth of 4.64% per year, which is higher than the average growth of the entire economy (3.12%). In this respect, the participation of tourism in the creation of the gross domestic product (GDP) has probably modest average of 1.7 % per year, but the impression is completely opposite when compared to the average for Central and Eastern Europe (CEE) of 1.6% (WTTC, 2009: 6). With regards to the participation of tourism employees in the total workforce in Macedonia, the national average is 3.1%, which is more than twice bigger than the average of the CEE being 1.4% in 2009 (WTTC, 2009: 6). The importance of tourism to national economy can be evaluated by the tourism inflows which in 2009 represented 26% of total inflows of services and 8% of exports of goods in Macedonia. In the same line, the tourism inflows were 20% higher than the foreign direct investments. Additionally, in the frames of services, tourism inflows were the second biggest item (just a little bit lower compared to the inflows of transport services), which is 1.3 times higher than the inflows of business services and 2.4 times larger than communication services inflows. Accordingly, the net tourism inflows in Macedonia have an average of 1% of GDP (Petrevska, 2010: 105-107). Such condition indicates high potential to increase the tourism effects in economic activity in Macedonia.

The forecasts regarding tourism development in Macedonia are very optimistic. Namely, according to the estimations by 2021 it is expected tourism contribution to the national GDP to reach 4.9% thus bringing revenue of US$200 million; the total contribution to employment including jobs indirectly supported by tourism industry is forecast to rise to 35 000 jobs (5.4%) and the investment in tourism is projected to reach the level of US$ 95 million representing 2.8% of total investment (WTTC, 2011b: 3). Consequently, Macedonia identified tourism as an industry which might contribute to: enhancing foreign export demand for domestic goods and services, generating foreign currency earnings, new employment opportunities within the country, repaying the foreign debt, increasing the national income etc.

However, attracting a bigger number of tourists is not a trouble-free process, particularly in times of ever-changing travel preferences. Despite the variety of options regarding tourist destination or attraction, tourists frequently are not capable to cope with such a huge volume of choice. Moreover, they need advice about where to go and what to see. In a tourism domain, recommendations may indicate cities to go to, places to visit, attractions to see, events to participate in, travel plans, road maps, options for hotels, air companies, etc. Such scope of work very often is not a trivial task. In this respect, recommenders assist tourists by facilitating personal selection and prevent them from being overwhelmed by a stream of superfluous data that are unrelated to their interest, location, and knowledge of a place. So, it is much easier for tourists to access the information they need thus resulting in shorter lead-time for bookings, making last-minute decisions and generally, tailoring their own packages from a suite of options.

Solution is seen in personalization of the information delivery to each traveler, together with the travel history. Yet, the advanced tourist information systems must offer more than just relatively static information about sights and places. Over the past two decades Internet had an enormous impact on the tourism industry, specifically to the way how tourists search for information. A noteworthy transformation was made from just passive searching and surfing to creating content, collaborating and connecting. In this respect, the Web became the leading source of information particularly important in times of increased number of competitors in tourism market. The way out is detected in application of recommender as a promising way to differentiate a site from the competitors. So, user-generated content will gain in significance thus enabling developing more accurate recommender.

Generally, the contribution of this paper lies in the fact that it represents a pioneer research in Macedonia thus contributing to the successful implementation of the recommender, based on novel algorithms and methodology, in the national tourism industry.

2. LITERATURE REVIEW

One may argue the inevitable relationship between tourists and information. Moreover, it is a widely-recognized fact that information and decision-making have become the foundation for the world economy (Wang, 2008). Due to the importance of tourism, recommenders applied in tourism have been a field of study since the very beginnings of artificial intelligence.

2.1 Tourists' preferences and related work

It is more than obvious that whether a potential tourist will be interested in a certain item depends on the preferences. Although may sound fragile, but the vast majority of today's tourists know exactly what they are looking for. Yet, they are very demanding and have complex, multi-layered desires and needs. Today's so called "postmodern tourists" have specific interests and individual motives which results in tailored made tourist products according to their particular preferences. They are often high experienced in travelling and demand perfect tourism products rather than standardized ones. Consequently, they take much more active role in producing diversified tourism products with shorter life cycles enabled by increased usage of the information technology.

Many researchers were interested in identifying tourists' needs, expectations and behavior. In this respect, numerous papers discuss tourist roles in order to define their considerable variations. In mostly, the behavior is related to specific demographic and background characteristics emphasizing the life course as the leading component for investigating tourist role preferences. Yet, attention should be paid to a variety of social structures and processes, including psychological needs and lifecourse stage.

Cohen (1972) was one of the first sociologists who proposed a typology to conceptually clarify the term "tourist" by developing a four-fold typology. Based on that, Pearce (1982) identified specific behaviors thus enabling tying the evolutionary nature of tourist role preference and the psychological needs. Moreover he developed 15 different tourist types which allowed creation of several measurement scales. In this respect, the Tourist Roles Preference Scale (Yiannakis and Gibson, 1992) presents a comprehensive classification of leisure tourists. Additional work resulted in adding two more tourist types to the tourist categorization (Gibson and Yiannakis, 2002). Moreover, researchers focused on exploring the experience of tourists as well as the importance of the tourist experience for tourists (Yfantidou *et al.*, 2008).

2.2 Recommenders and related work

There is a large body of literature regarding the importance and effectiveness of applying the recommenders in tourism, travelling and hospitality. It is a matter of identifying a class of intelligent applications that offer recommendations to travelers, generally as a response to their queries. They mostly leverage in-built logical reasoning capability or algorithmic computational schemes to deliver their recommendation functionality. Consequently, the recommenders are an attempt to mathematically model and technically reproduce the process of recommendations in the real world.

Numerous researchers made efforts in their introducing. In this respect the need for developing intelligent recommenders which can provide a list of items that fulfill as many requirements as possible is elaborated (Mirzadeh *et al.*, 2004; McSherry, 2005; Jannach, 2006). Also, a recommender system dealing with a case-based reasoning is introduced in order to help the tourist in defining a travel plan (Ricci and Werthner, 2002; Wallace, 2003). However, as the most promising recommenders in the tourism domain are the knowledge-based and conversational approaches (Ricci *et al.*, 2002; Thomson *et al.*, 2004). Yet, some other variants of the content-based filtering and collaborative filtering are engaged for recommendation, like knowledge-filtering, constraint-based and casebased approaches (Kazienko and Kolodziejski, 2006; Ricci and Missier, 2004; Zanker *et al.*, 2008). In the same line, the recommenders based on a text mining techniques between a travel agent and a customer through a private Web chat may easily find an application (Loh *et al.*, 2004).

Due to the rapid expansion of tourism industry, the recommenders for tourism have attracted a lot of interest in academia. Additionally, we refer to some late research that brought more sophisticated outcomes, like: introducing a personalized tourist information provider as a combination of an event-based system and a location-based service applied to a mobile environment (Hinze *et al.*, 2009); investigation on sources and formats of online travel reviews and recommendations as a third-party opinions in assisting travelers in their decision making during the trip planning (Zhang *et al.*, 2009); findings regarding development of a web site in order to enable Internet users to locate their own preferred travel destinations according to their landscape preferences (Goossen *et al.*, 2009) and similar. Furthermore, the usage of the orienteering problem and its extensions to model the tourist trip planning problem was elaborated as efficient solution for number of practical planning problems (Vansteenwegen and Wouter, 2011). It is evidently that the research area is extending resulting in improving the dependability of recommendations by certain semantic representation of social attributes of destinations (Daramola *et al*., 2010). Moreover, most recommenders focus on selecting the destination from a few exceptions (Niaraki and Kim, 2009; Charou *et al.*, 2010).

3. METHODOLOGY

The main objective of the developed national tourism web portal which relies on an efficient and accurate personalized recommender is to support tourists visiting Macedonia by helping them to identify relevant tourist objects matching their personal interests.

To accomplish this objective, a several step methodology was developed. The first step foresees tourist and tourist objects profiling. The system uses tourist types taken from the scientific tourism literature to model the tourist personal profile. The tourist profile indicates the degree to which tourists identify themselves with the given types. Typically, individual tourist cannot be characterized by only one of these archetypes but has unique combination of these personalities, although to varying degrees. Thus, tourist types model the tourists' generic interests in an abstract form. Vectors are suited to model such tourist profile, whereby each dimension corresponds to a certain tourist type while the value indicates how much the tourist identifies him- or herself with the corresponding type.

Tourist profiling is a two-step process which involves creating the profile and then reviewing the profile to make any necessary adjustments. The initial tourist profile for each system user is created by the user himself during the process of registration, by determining the degree of membership to each of the tourist types. Considering the fact that the human preferences change over time due to various factors, the tourists might change their behavior too. To make the system capable to cope with these changes, we have enabled tourist profile adjustment. It is based on the ratings the tourist give for each tourist object that he visits after his journey and according to Eq. 1.

$$Uij_{t+1} = \frac{1}{2}(Uij_t + Rik_{t+1} * w * Okj) \tag{1}$$

where *Ui* represents the *i-th* user and $Ui \in U$, *U*- is the set of users registered to the system, Uij_t is the degree of membership in the moment *t* of the *i-th* user to the tourist type T_j and $Tj \in T$, T – is the set of tourist types according to literature (Gibson and Yiannakis, 2002). $Ok \in O$ represents the *k-th* object in the set of all objects *O* registered in the system, w-is the weighting factor and R_{ik} is the rating of the *k-th* tourist object given by *i-th* user.

Similarly, we may generate profiles for attractions and in the same way as the tourist profile is represented in form of a vector, every tourist object is modeled through a vector as well. Thereby, this vector describes in a quantitative way how much the object is related to the given types. For example, the famous monastery Saint Panteleimon in the city of Ohrid known as a birthplace for Cyrillic alphabet and used by Saint Clement for teaching the Cyrillic alphabet, might be highly relevant for sightseeing tourists but not for such kind of tourists that would like to do some risky activities.

In the developed system a manual process to link the given tourist types to appropriate tourist objects is proposed. Therefore, for each of the tourist objects, the degree of relationship to each of the tourist types is specified by domain experts. In order to prevent information overload of the tourist and provide only relevant information, the system should recommend a subset of tourist objects according to the personal experiences individual tourist desire and those he/she prefer to avoid. This in turn might lead to an increase of the tourist's satisfaction of experiencing a relaxed sightseeing trip.

According to this, the next step of the proposed methodology aims to match tourist profiles against the set of tourist objects on the basis of tourist types, thus producing a ranked list of objects for each given tourist and reducing the set of objects. If a tourist profile matches the characteristics of an object, this object should be recommended to the respective tourist. Therefore, the matchmaking algorithm has to examine whether they share similar structures. The more similarities they have in common, the more contributes the tourist object to the tourist’s satisfaction and therefore should be ranked higher.

To estimate the similarity degree between tourist profiles and tourist objects, the system contains a special module based on a vector-based matchmaking function, whereby a given profile and each tourist object constitute vectors and are compared in a vector space model. A common method to obtain the similarity is to measure the cosine angle between two vectors. If the vector space is non-orthogonal, kernel based algorithms can be applied to measure the similarity in such a space. The dimensions of the vector space model correspond to selected tourists types found in scientific tourism literature (Gibson and Yiannakis, 2002), such that each distinct tourist type (e.g., adventure or cultural type) represents one dimension in that space. The implemented matchmaking function has the following form (Eq. 2):

$$SIM_{\cos}(Ui, Oj) = \frac{\sum_{k=1}^{N} Ui_k \cdot Oj_k}{\sqrt{\sum_{k=1}^{N} {Ui_k}^2}\sqrt{\sum_{k=1}^{N} {Oj_k}^2}} \qquad (2)$$

where Ui_k is the degree of membership of the *i-th* user to the tourist type T_k, Oj_k is the degree of membership of the *j-th* tourist object to the tourist type T_k, and N is the number of tourist types. According to the previous equation, the degree of similarity between tourist profiles and tourist objects will be calculated. Tourist objects will be ordered by the value of the matchmaking function for a given user, and only those objects that have positive value for this function will be considered for recommendation:

$$Oi_{rec} = \{Oj, where\ SIM_{\cos}(Ui, Oj) > 0\} \tag{3}$$

Considering the five point Likert scale for rating the objects, to each object in the constructed set, a recommendation mark will be assigned (Eq. 3).

$$Ri_{rec} = \{R(Oj) = 5 * SIM_{\cos}(Ui, Oj),\ \forall Oj \in Oi_{rec}\} \tag{4}$$

In our methodology, we have considered another very important fact related with the behavior of the people planning a vacation or trip. In everyday life, while planning a vacation or trip, people also rely on recommendations from reference letters, news reports, general surveys, travel guides, and so forth. In addition, they desire personal advice from other people with similar preferences or people they trust. In fact, over 80% of travelers participating in a TripAdvisor.com survey agree that "reading other travelers' online reviews increases confidence in decisions, makes it easier to imagine what a place would be like, helps reduce risk/uncertainty, makes it easier to reach decisions, and helps with planning pleasure trips more efficiently" (Gretzel, 2007).

Experimental findings show that there exists a significant correlation between the trust expressed by the users and their similarity based on the recommendations they made in the system; the more similar two people are, the greater the trust between them (Ziegler and Golbeck, 2006). Similarity can be interpreted in several ways such as similarity in interests or ratings or opinions. Different methodologies can be used to calculate the similarity between the users in the system.

As one of the most prevailing and efficient techniques to build a recommender, collaborative filtering (CF) implements the idea for automating the process of "word-of-mouth" by which people recommend items to one another. It uses the known preferences of a group of users who have shown similar behavior in the past to make recommendations of the unknown preferences for other users. CF is facing many challenges, among which the ability to deal with highly sparse data and to scale with the increasing numbers of users and items, are the most important in order to make satisfactory recommendations in a short time period. Sparsity of ratings data is the major reason causing poor recommendation quality. The sparsity problem occurs when available ratings data is rare and insufficient for identifying the similar neighbors. This problem is often very significant when the system is in its early stages. On the other hand, when numbers of existing users and items grow tremendously, traditional CF algorithms will suffer serious scalability problems, with computational resources grown nonlinearly and going beyond practical or acceptable levels.

To reduce the dimensionality of data and avoid the strict matching of attributes in similarity computation the cloud-model CF approach has been adopted. It is constructing the user's global preference based on his perceptions, opinions and tastes, which are subjective, imprecise, and vague (Palanivel and Siavkumar, 2010), and it seems to be an appropriate paradigm to handle the uncertainty and fuzziness on user preference.

The main goal of the cloud model CF is to construct the global preference for each user by calculating a triple of three digital characteristics $\vec{V} = (\mathrm{Ex}, \mathrm{En}, \mathrm{He})$. The expected value Ex represents the typical value of user ratings, that is, the average of user ratings. The entropy En represents the uncertainty distribution of user preference, which is measured by the deviation degree from the average rating. The hyper-entropy He is a measure of the uncertainty of the entropy En, which is measured by the deviation degree from the normal distribution. Given a set of ratings data for a user u_i, $r_{u_i} = r_u = (r_{u,1}, r_{u,2}, ..., r_{u,n})$, the three characteristics can be defined as (Zhang *et al.*, 2009):

$$
\begin{aligned}
Ex &= \frac{1}{n}\sum_{i=1}^{n} r_{u,i} \\
En &= \sqrt{\frac{\pi}{2}} \times \frac{1}{n}\sum_{i=1}^{n} |r_{u,i} - Ex| \\
He &= \sqrt{S^2 - \frac{1}{3}En^2}, \, where \, S = \frac{1}{n-1}\sum_{i=1}^{n}(r_{u,i} - Ex)^2
\end{aligned}
\tag{5}
$$

The *k* similar (neighbor) users, for an active user are selected based on the cloud model similarities between the active user and the users that already rated the object $Oj \in Oi_{rec}$. A likeness similarity method based on cloud model using the cosine measure was proposed in Zhang et al., 2009. Given two cloud models in terms of the characteristic vectors $\vec{V}_u = (\mathrm{Ex}_u, \mathrm{En}_u, \mathrm{He}_u)$ and $\vec{V}_v = (\mathrm{Ex}_v, \mathrm{En}_v, \mathrm{He}_v)$, the similarity between them are defined as

$$sim(u,v) = \cos(\vec{V_u}, \vec{V_v}) = \frac{Ex_u Ex_v + En_u En_v + He_u He_v}{\sqrt{{Ex_u}^2 + {En_u}^2 + {He_u}^2}\sqrt{{Ex_v}^2 + {En_v}^2 + {He_v}^2}} \tag{6}$$

The recommendation function based on the cloud model is defined as:

$$R_{u,j} = \bar{r}_u + \frac{\sum_{v \in N(u)} (r_{v,j} - \bar{r}_v) \times sim(u,v)}{\sum_{v \in N(u)} sim(u,v)} \tag{7}$$

where *N(u)* is the *k* most similar users to active user *u* and r_u and r_v are the average rating of user *u* and *v*, respectively. The value of rating $r_{v,j}$ is weighted by the similarity of user *v* to user *u*; the more similar the two users are, the more weight $r_{v,j}$ will have in the computation of the recommendation function .

The total recommendation function for a given tourist object (O_j), is calculated using a weighted average of the functions (Eq. 2 and Eq. 7).

$$Frec_{i,j} = \frac{w_1 * SIM_{\cos}(u_i, Oj) + w_2 * R_{u_i,j}}{w_1 + w_2} \tag{8}$$

According to the value of the total recommendation functions the objects will be ordered and further classified into five categories (Eq. 9).

$$Cat_{i,j} = \left\{ \begin{array}{c} k = 1, \forall Oj \in Oi_{rec} \wedge 0 \le Frec_{i,j} \le 0.2 \\ k = 2, \forall Oj \in Oi_{rec} \wedge 0.2 < Frec_{i,j} \le 0.4 \\ k = 3, \forall Oj \in Oi_{rec} \wedge 0.4 < Frec_{i,j} \le 0.6 \\ k = 4, \forall Oj \in Oi_{rec} \wedge 0.6 < Frec_{i,j} \le 0.8 \\ k = 5, \forall Oj \in Oi_{rec} \wedge 0.8 < Frec_{i,j} \le 1 \end{array} \right\} \tag{9}$$

4. WEB PORTAL DESIGN

The developed national tourism web portal is structured in the form of a social network. Our portal is a significant improvement on existing travel websites and provides tourists with a customized, unique, and enriching travel experience. It incorporates some standard plugins typical for social networks like Facebook. But, it advances the concept by including custom plugins, like the recommended objects plugin which is the core of the portal. It is using the Google Map of Macedonia to visualize static tourist objects (object that are not temporary, like churches, museums, archeology localities, etc.) and dynamic objects (object that have limited time duration, like events, expositions, etc.). They are displayed on the map according to their geographical location. Moreover, they are geographically grouped into municipalities.

Municipalities are recommended to the user in the form of circles as displayed on the map (Figure 1). The size of the circle indicates the user's affinity for the municipality; therefore, a large circle indicates a municipality with many tourist objects with high recommendation marks i.e. that match the user profile. By displaying the user's affinity through the size dimension of the circle, users can easily observe which municipalities would be of most interest to them.

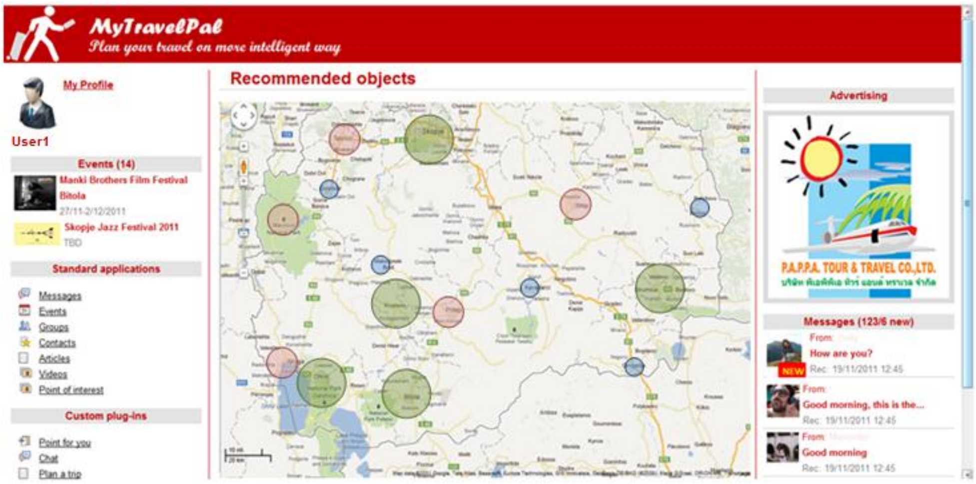

Figure 1. Recommended municipalities

The tourist objects are displayed as icons in the location of the correspondent object as shown in Figure 2.

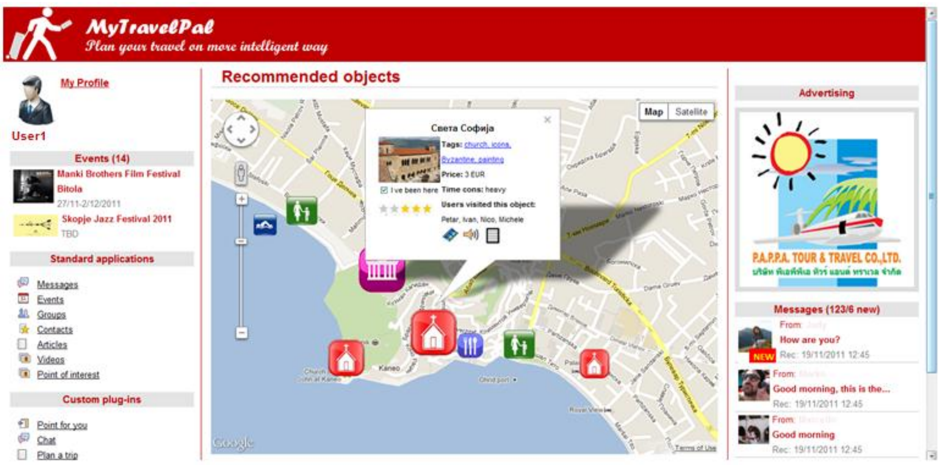

Figure 2. Recommended tourist objects

The image of the icon indicates the type of tourist objects such as a museum, church, or restaurant. The size indicates how closely the object meets the user’s interests. Each attraction also has an information window as displayed in Figure 2. The information window usually includes the name and picture of the attraction, an icon of an umbrella indicating that the attraction is accessible in the rain, and tags. Additionally, it displays a general idea of the time consumption of the attraction, friends who have visited the attraction, and an option to view narratives in either video, audio, or text format. Through this window, the user can also rate the object. This operation is recommended to be done after visiting the object and according to the personal experience and satisfaction. The goal of this operation is two-fold: to help updating the user profile, and to make the process of recommendation more accurate.

5. SYSTEM EVALUATION

We use dataset from proprietary database collected by the mixed research group composed of researchers from the Faculties of Computer Science and Tourism at the “Goce Delcev” University. It contains 56320 ratings from 483 users for 818 tourist objects. Each user has rated at least 30 objects, and each object has been rated at least once.

In order to measure recommendation accuracy more precisely we used information-retrieval classification metrics, which evaluate the capacity of the recommender system in suggesting a list of appropriate objects to the user. With such metrics it is possible to measure the probability that the recommender system takes a correct or incorrect decision about the user interest for an item. When using classification metrics, we can distinguish among four different kinds of recommendations (Table 1).

Table 1. Classification of the possible result of a recommendation of an object to a user

	Recommended	Non recommended
Interesting	True-positive (TP)	False-negative (FN)
Uninteresting	False-positive (FP)	True-negative (TN)

If the system suggests an interesting tourist object to the user we have a true positive (TP), otherwise the object is uninteresting and we have a false positive (FP). If the system does not suggest an interesting tourist object we have a false negative (FN). If the system does not suggest an object uninteresting for the user, we have a true negative (TN). The most popular classification accuracy metrics are the recall and the precision. These metrics can be calculated by counting the number of test object that fall into each cell in the Table 1 and according to the Eq. 10 and Eq. 11.

$$\mathrm{Precision} = \frac{TP}{TP + FP} \tag{10}$$

$$\mathrm{Recall}(True\,Positive\,Rate) = \frac{TP}{TP + FN} \tag{11}$$

Recall measures the percentage of interesting objects suggested to the users, with respect to the total number of interesting objects, while precision measures the percentage of interesting objects suggested to the users, with respect to the total number of suggested objects. In order to understand the global quality of a recommender system, we may combine recall and precision by means of the F-measure

$$F - measure = \frac{2 \cdot recall \cdot precision}{recall + precision} \tag{12}$$

In evaluating the quality of the recommendation, we use these metrics. To evaluate the system a methodology which uses the k-fold and the leave-one-out together with classification metrics recall and precision was used. According to the k-fold, users in the dataset are partitioned into k parts: k-1 parts represent the and are used to construct the model, the remaining part represents the testing set. The model created with the k-1 partitions is tested on the remaining partition by means of the following algorithm:

Step 1: One user in the testing set is selected (the active user).

Step 2: One rated tourist object (the test object) is removed from the profile of the active user.

Step 3: An order list of recommended tourist objects is generated.

Step 4: If the test item is in the top-3 categories (according to the Eq. 9) of recommended objects, either the true positive or false positive counter is incremented, depending whether the user liked or disliked the test item.

We considered two distinct user groups. The group A contained all users who have rated 30-60 objects (the few raters user group), while group B contained all users who have rated 61-100 objects (the moderate raters user group). Step 1 of the proposed algorithm was repeated for all the users in both groups. Steps 2-4 are repeated for all the objects rated by the active user. In order to understand if a user likes or dislikes a rated tourist object, we suppose that an object is interesting for the user if it satisfies two conditions (Eq. 13).

$$Rate_{i,j} \geq 3 \wedge Rate_{i,j} \geq \overline{Rate_i} \tag{13}$$

where $Rate_{i,j}$ is the rate given by the user i for the tourist object j and $\overline{Rate_i}$ is the mean of ratings for user i. The first constraint reflects the absolute meaning of the rating scale, while the second the user bias. If a rating does not satisfy conditions given by Eq.13 we assume the item is not interesting for the user. Once computed recall and precision, we synthesize them with the f-measure, as defined in (Eq. 12).

Upon the conducted evaluation the results for system precision, recall and f-measure were averaged for each of the groups, and they are given in Table 2.

Table 2. Average values for recommendation system precision, recall and f-measure

Group	Precision (%)	Recall (%)	F-measure (%)
Group A	75.14	79.18	77,11
Group B	81.74	85.32	83.49

According to the obtained results, the developed national tourism web portal with its collaborative recommender system seems to be robust as it achieves good results in both scenarios (users with few and moderate ratings). It also accomplishes a good trade-off between precision and recall, a basic requirement for all recommendation systems. The experimental results show that the proposed approach can provide satisfactory performance even in a sparse dataset.

6. CONCLUSION

The designed national tourism portal in its initial phase resulted in accurate recommendations and guidelines for tourists and travelers in the line of identifying an ideal trip and holiday. In this respect, it must be noted that tourism is defined as one of the most economically-oriented industries in the world due to the fact that enhances and strengthens national economies. Moreover, the development of such software module contributes generally to increasing the awareness of tourist destination that is capable of fulfilling travelers' preferences, and respectfully in raising net tourism income.

The outcomes of this study complement the forecasts for tourism demand in Macedonia in terms of foreign tourists. Namely, according to the double-exponential smoothing model it is expected by 2014 to have an increase of nearly 40% of foreign tourists (Petrevska, 2011). This optimistic view is supplemented additionally with the fact that the number of user ratings is permanently increasing by 15% monthly growth rate. Supportive and not surprising is another fact that we have observed. Specifically, we noted an upward trend of web portal users. Accordingly, all these points lead us to a positive general conclusion referring tourism income in Macedonia. The average tourism consumption of $ 62 per day (WTTC, 2010) will note an increase of only half a dollar, which may be misinterpreted as insignificantly to the national economy. However, on long-term horizon based on these projections the tourism contribution to the gross domestic product may note an increase of more than 1%.

Additionally, it is worth noticing that the travel and tourism economy in the country incorporates broad spectrum of tourism-oriented activities and results with multiplicative impacts. With regards to the multiplier effects of tourism in Macedonia, it is calculated to 4, meaning that every dollar generated as direct tourism income results in four dollars of the global income including the direct and indirect income as well (WTTC, 2010).

The successful implementation of the national web portal (named "MyTravelPal") is in the line of supporting the national economy through improvement of tourism supply in more qualitative manner. Due to the fact that this portal indicates the motives, preferences and reasons for traveling to Macedonia, it may be of high importance to all key-tourism actors in the process of identifying measures and implementing activities necessary for creating comprehensive tourism policy.

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