A Web Platform and a Context Aware Recommender System for Active Sport Events

Achilleas Achilleos[1], Andreas Konstantinides[1], Rafael Alexandrou[1], Christos Markides[1], Effie Zikouli[2] and George A. Papadopoulos[3]

[1]Frederick Research Center, 7 Filokyprou Street, CY-1036, Nicosia, Cyprus
{com.aa, com.ca, st008390, com.mc}@frederick.ac.cy
[2]SportsTraveler76 Ltd., 46 Nikolaou Ioannou Street, CY-1036, Nicosia, Cyprus
e.zikouli@sportstraveler76.com
[3]University of Cyprus, Department of Computer Science, CY-2109, Nicosia, Cyprus
george@cs.ucy.ac.cy

Abstract. Customer recommendations have proved to boost sales, increase customer satisfaction and improve user experience, making recommender systems an important tool for businesses. While recommendations of items such as products or movies, when browsing online, are heavily examined and several recommendation algorithms and systems are developed, still recommendation systems for events present unique challenges. This becomes even more challenging when recommending active sport events to users, due to inherent restrictions and limitations. This paper presents a context aware recommender system developed and integrated to the ST76 web platform, which enables for the first time, to the best of our knowledge, to provide recommendations of users that are more likely to participate in an upcoming active sport event. Also, we showcase the importance of the ST76 platform and recommender system for sports tourism, through the analysis of the economic impact of an active sport event hosted on the platform.

Keywords: Active Sport Events • Context Aware • Economic Impact • Recommender Systems • Sports Tourism • Web Platforms

1 Introduction

Nowadays, end-users have a wide variety of choices to select from and this applies to online store products to buy (e.g., Amazon, eBay), movies and TV shows to watch (e.g., Netflix), restaurants to visit (e.g., TripAdvisor), as well as events to attend. Information systems have a major role to play in terms of “understanding” what customers like in order to help them in their choices, while at the same time increase sales. In fact, due to the huge variety of high-quality items at competitive pricing, businesses need to provide personalised and customer tailored information services to the user. Therefore, information systems help to acquire quickly information from the end-user and meet customers demands in real-time, otherwise there is a direct risk to lose customers [1].

A key subset of information systems is recommender systems (RS), which aim to address the information overload problem faced by customers. These software systems aim to extract information about users, which will allow offering personalised recommendations to the users. Existing research works have demonstrated that recommendations increase sales [2, 3] and customer satisfaction [2], while at the same time can improve user experience [4]. In particular, two distinct categories of recommender systems can be identified from the literature. These are “traditional” RS and context aware recommender systems (CARS). In contrast to “traditional” RS, CARS are designed to incorporate context information (e.g., location, season, time, companion) [5], in order to increase recommendation accuracy [2, 5]. CARS are adopted in this work due to the fact that they provide increased accuracy and because they offer solutions to the unique challenges faced by event-based recommender systems.

RS and CARS have been developed and used extensively in the last two decades to provide solutions in different domains, e.g., web stores, movies, restaurants. While several systems have been developed and widely used in these domains, event-based RS, as aforesaid, present unique development challenges due to the volatile nature of the recommendation items (i.e., events). In fact, RS applied in all domains typically face the cold start problem (i.e., no/limited data at the start), while event-based RS unique constraints are: 1) temporal nature: events are once off, 2) location bound: usually they are not repeated at the same location and 3) time sensitive: happen at a specific time.

This paper focuses on a specific type of events, which refer to active sport events, and presents a web platform and a CARS based on historical context data that can support the organisation and management of these events. Different research works have been performed for event recommendations such as social based event RS and mobile and context-aware event RS. Finally, the key differentiating point of this paper is that it proposes for the first time, to the best of our knowledge, to shift the perspective of recommendations from "a current user to many events" to "a given event recommended to a subset of interested users". The work presented in this paper delivers a commercial platform and CARS for the first time, which enables the delivery of recommendations for active sport events. Also, it examines and presents the economic impact that active sport events can have for sports tourism and the economy of the country in general.

The paper is structured as follows. Section 2 presents the theory and related work on existing web platforms for sport events management. It also presents the theory behind “traditional” RS and CARS, as well as defines related research work on generic RS and RS and CARS for events. The ST76 platform and recommender system are presented in Sect. 3, while the economic impact analysis of an international active sport event is performed in Sect. 4. The final Sect. 5 defines the conclusions and future work.

2 Background Information and Related Work

Sports tourism is becoming increasingly important and can help a tourist destination to differentiate from the norm. In the editorial note “The Growing Recognition of Sport Tourism” [6], the authors clearly state that: “Sport tourism includes travel to participate in a passive (e.g., sports events and sports museums) or active (e.g., scuba diving, cycling, golf) sport event, and it may involve instances where either sport or tourism are the dominant activity or reason for travel.” In related research work [7], the nature and evolution of active sport tourism is portrayed. The following subsections present web platforms for sport events management, as well as existing work on RS for events.

2.1 Web Platforms for Sport Events Management

At a national level, there are several information websites[1] that promote the island of Cyprus and enable tourists to identify "things to do", available activities, hotels, etc. Over the last years these websites are complemented by fully-fledged web booking platforms[2], which enable booking hotels, flights or packages and are used mainly by Cypriot and Greek tourists. The only dedicated information website for sports tourism[3] is produced as an effort of a sports fan. Still the events available is rather limited (August 30, 2018 – 9 events: 5 running, 3 sailing,1 cycling, July 2, 2020 – 1 event: running), providing basic information about a sport event and with no registration and booking solutions.

The most popular national web platform for events[4] has an explicit category related to sports and offers a search functionality for a specific event category, city as well as other parameters. Yet again, a limited number (2-3) of sport events are available, which reveals both the lack of coverage of sport events and the limited number of sport events. Moreover, basic information is provided and links to other pages in order to register.

Finally, at a national level, individual sporting activities, such as three recurring marathons taking place in Cyprus, are promoted and added by the organizers in international websites or web platforms. These systems are dedicated to a specific type of sport[5], while offering only information and instructions on how to buy tickets.

There are several international websites or web platforms that promote passive sport tourism and offer tours and travel packages for sports fans that mainly travel to watch an event. For instance, Sports Traveler[6] features sporting events such as NBA matches, Wimbledon matches, etc., and continues to create tours and travel packages with guaranteed premium tickets, top-quality lodging, transportation, and VIP hospitality access. Similar web platforms[7] exist, a major thing in USA, while when it comes to Europe, it contains mostly football matches, GP and events such as World Championships and Cups (football, Rugby, etc.). These passive sport event management platforms provide packages that include tickets, accommodation and transportation including flights.

On the other hand, Worlds Marathons[5] is a major active sports tourism web platform that specializes only on marathon races. It contains more than 4000 races all over the world, and it's a leader for this kind of sporting activity. The website provides all the information uploaded by the organizer. The user can register and pay for the race. There are additional websites promoting active sport tourism, but all of them have limitations such as covering only specific sport types, registering only for the race without paying,

---

[1] Cyprus Tourism Portals: http://www.visitcyprus.com, http://www.heartcyprus.com/.

[2] Web-based Holidays Booking Platforms: https://www.pamediakopes.gr/cy/, https://www.topkinisis.com.

[3] Sports Tourism Website: www.runbis.com.

[4] Cyprus Events Website: https://www.cyprusevents.net/

[5] Worlds Marathons: http://www.worldsmarathons.com/

[6] Sports Traveler: https://www.sportstraveler.net/

[7] Sport Event Websites or Web Platforms: http://www.roadtrips.com/, http://www.sportstravelandtours.com/, http://www.sportstraveltours.com/, http://www.globalsports.travel/ and https://gulliverstravel.co.uk

or paying only for the tickets of the race. For instance, Field Sports Travel[8] promotes and supports only fishing, shooting and cricket activity sports.

2.2 Recommender Systems for Events

Recommender systems focusing on events of all kinds offer users a way to easily identify events that they may enjoy. RS for events face explicit challenges. Firstly, events are available to recommend and then they disappear when they are over. Also, if we consider that two events are rarely the same, or at least rarely they take place at the same location, recommendations become harder. Also, events take place at a specific time. Moreover, users' experiences play a role in what events they enjoy and as users grow and mature so does their taste and preferences. Finally, due to the key differences between events (e.g., location), it is more challenging to make recommendations.

In [8], a social-based RS is described as a way to solve these issues. To do so, location is considered as a means of determining the best event to attend. Two datasets were used, regarding the Greater Boston Area, with the first one containing location estimates of one million mobile phone users and the second containing big social events in the same area. Based on the first dataset users' homes could be determined, as well as where they usually go. Recommendations of events were made starting from simple approaches and then trying more complex ones: (i) Most popular, (ii) Closest to users, (iii) Most popular based on where users live, (iv) A calculated score of popular social events in particular home regions that were not popular in other regions, (v) k-nearest locations based on event popularity and (vi) k-nearest events based on events similarity.

In [9], another approach is using social media (i.e., Facebook), to determine event recommendations based on the preferences of a single user and a group of users. It considers that an event is more likely to be attended by a group of friends and attempts to make recommendations that fit all needs. Friends are clustered based on the number of common friends they have on Facebook. Then it considers the Facebook photo tags, which are more personal, the age of the photo and the number of people tagged in the photo to determine the closest friends of the user. Recommendations are the product of the following steps: 1) Events in a specific time period, price range and geographical area are selected. 2) Recommendations for each user and each member of the group are determined. 3) If the recommendation is based on a single user's preferences a group of friends is created for each recommended event that could enjoy the event with the user. If the recommendation is based on a group's preferences a list of events that satisfy everyone will be recommended. 4) To add serendipity, the recommended events are selected by highest rating and uniformly by other classes of events that are not be very accurate but may present an interest for the user which could not be predicted.

Event-based social networks (EBSNs) enable users to create, promote and share upcoming events of any kind with other users. The sheer volume of events available in social networks creates the usual problem of information overload. RS are a natural solution to this problem. The cold start problem is though faced, while events published in social networks are usually short-lived, planned in the future and having limited to

[8] Field Sports Travel: http://www.fieldsportstravel.com/

no trace of historical data. In [10], the authors propose a CARS to overcome these issues, by exploiting content-based information based on the events' description, collaborative information derived from users' RSVPs, social information based on group memberships, location information based on the users' geographical preferences and temporal information derived from the users' time preferences. The authors perform experiments using a large crawl of Meetup.com, which demonstrates the effectiveness of their contextual approach in comparison to existing social based RS for events.

In another work [11], the authors highlight the benefits and challenges of mobile and context-aware event recommender systems. The paper introduces the basics and related work covering the most important requirements for developing event RS, proposes a hybrid algorithm and develops an Android application for context-aware event recommendations. The two-week user study performed by the authors shows clear benefits and accurate recommendations, while the authors based on the findings of their study they outline future challenges related to event-based recommendations.

The work in [12], outlines the first and only research attempt dedicated to sport events and in particular to the World Cup. The authors propose an Ontology-based hybrid system for recommendation of events. The system collects data from various Internet sources (i.e., Mashup), applies Natural Language Processing and Unsupervised Clustering to process raw data, adds semantics to the processed data and to adhere to the defined ontology, in order to provide recommendations based on smart content-based filtering and social-network-based user profiles for sport events. Empirical results by applying the framework to the past World Cup show promising applications.

2.3 Beyond State of the Art

Context can offer a new perspective on what events users enjoy, since it allows taking into consideration context parameters such as when (e.g., season) and with whom (e.g., solo,) they enjoy the events. Therefore, CARS is particularly important for two reasons: 1) the motives of sports tourists when participating in different sports are not at all identical and 2) addressing the cold start problem. In order to design and develop a CARS, context information was gathered explicitly with the use of a questionnaire. The CARS developed in this work is the first attempt, to the best of our knowledge, to provide recommendations of active sport events. It does not display recommended sport events when the user is browsing on the ST76 web platform, due to the fact that there are limited events listed on the platform (i.e., no information overload). Instead recommendations are delivered when the administrator adds a new sport event. In fact, based on the parameters of the new event the administrator will receive recommendations of the top-N users that are more likely to be interested to participate in this event.

3 SportsTraveler76

3.1 The Web Platform

ST76 is the first commercial platform, to the best of our knowledge, that offers the complete set of services for online management and booking of active sport events. The web platform offers to the administrator the capability to manage sport events through the backend. Figure 1 shows on the left pane the entire set of features offered to the administrator of the platform, who apart from managing active sport events, is also able to manage users, manage newsletter clients, etc.

The administrator when creating an event is able to select one of the following event modes: 1) Only tickets – customers are only able to purchase tickets for participating in the races of the event, 2) Only package (hotel) – enables customer to book only hotels for a specific event and 3) Tickets and package (hotel) – enables a customer to book a combined ticket and hotel package price. The first and third mode are the popular options when creating an event using the platform.

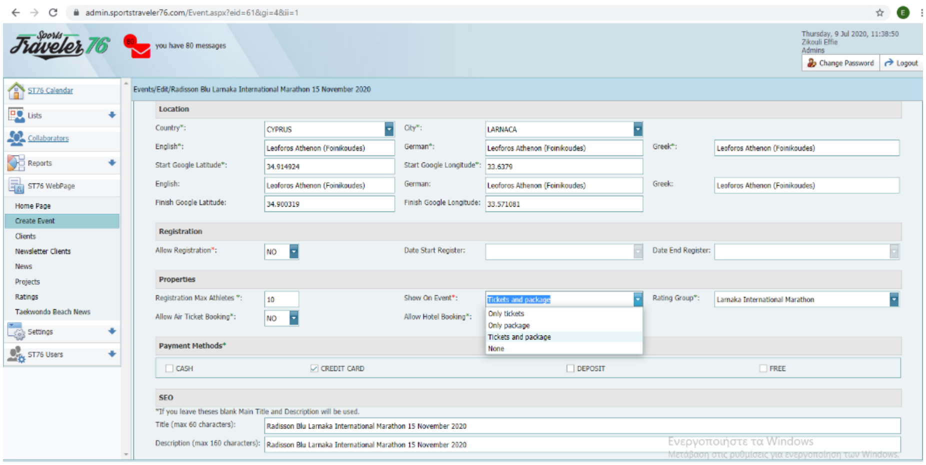

Fig. 1. ST76 Web Platform – Backend

Figure 2 illustrates the end-user view when an event is published, where the customer is able to purchase a ticket or a package based on the type of the active sport event. For instance, in the case the customer selects a package (ticket and hotel) then the user follows a page-by-page wizard where he/she needs to select the number of rooms, the number of athletes, enter each athlete details and finalise the purchase using Six Payment services. Finally, the platform allows creating an event where the hotel and flight ticket can be purchased by company's external collaborators (e.g., travel agency) with the help of iFrames [13] that are integrated in the process flow of the customer registration and purchase wizard.

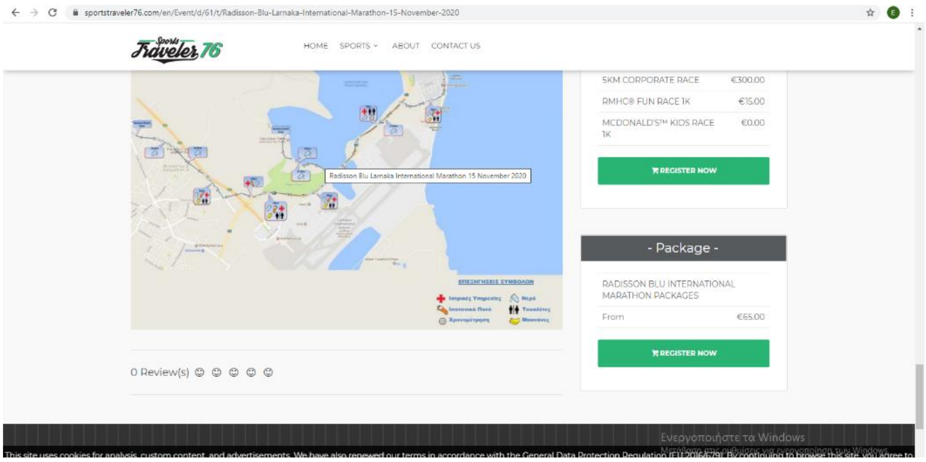

Fig. 2. ST76 Web Platform – Frontend

3.2 The Context Aware Recommender System

The definition and design of the recommendation algorithm and system solves the problem of providing recommendations of existing customers that more likely to be interested to attend the new event that is currently created and published. In this work, a CARS based on historical context data retrieved from a survey, has been designed and implemented for active sport events. The ST76 platform's programming framework (.NET framework) was used for the implementation of the frontend of the CARS system, while the CARS system was implemented as a Web API with the help of the Python programming language. In fact, the Python CARS implementation exposes a Web API through which the functionality of the RS can be invoked. In this way, straightforward integration is provided with the ST76 web platform.

System Model

The ST76 platform new feature is the ST76 recommender system (ST76_RS). It is a domain specific solution that aims at providing recommendations of users that are more likely to attend a specific type of event based on the similarity between users' contextual information and events' preferences. In particular, the ST76_RS is used as a Software as a Service (SaaS) to the ST76 web platform. The web service is hosted on the cloud (i.e., Windows Server) and is developed leveraging the .Net Core Framework, which ensures scalability, reliability, and reusability. Additionally, the recommendation algorithm with the K-Means machine learning algorithm, is developed on top of the scikit-learn python library, which ensures valid and efficient operation, as well as high performance; it is also hosted on the same server.

Figure 3 shows the ST76 Recommender System Model: consider a web platform $\boldsymbol{wp}$ (i.e., the SportsTraveler76 web platform) and a web service $\boldsymbol{ws}$ located on server $\boldsymbol{S}$. Consider a dataset D that contains contextual information of several users clustered into $\boldsymbol{C1} \dots \boldsymbol{Cn}$ clusters of users, where $\boldsymbol{Ci}$ is composed of users interested for similar events, using a K-means algorithm. Users contextual information include event type $\boldsymbol{t}$, event intensity $\boldsymbol{i}$, event season $\boldsymbol{s}$, user's companion $\boldsymbol{c}$ and participation's regional information $\boldsymbol{p}$ described by the tuple $\boldsymbol{CI}\,\{\boldsymbol{t}, \boldsymbol{i}, \boldsymbol{s}, \boldsymbol{c}, \boldsymbol{p}\}$. Additionally, consider a prediction model $\boldsymbol{m}$ stored on $\boldsymbol{S}$ that is able to predict which cluster of users $\boldsymbol{Ci}$ is more suitable to attend a new event $\boldsymbol{e}$, which is represented by the tuple $\boldsymbol{CIe}\,\{\boldsymbol{t}, \boldsymbol{i}, \boldsymbol{s}, \boldsymbol{c}, \boldsymbol{p}\}$. In this case, $\boldsymbol{wp}$ sends an HTTP Request to $\boldsymbol{ws}$ for a user recommendation based on $\boldsymbol{CIe}$ and $\boldsymbol{ws}$ responds back with a set of users $\boldsymbol{Su}$ that are most likely to attend event $\boldsymbol{e}$ based on their contextual information.

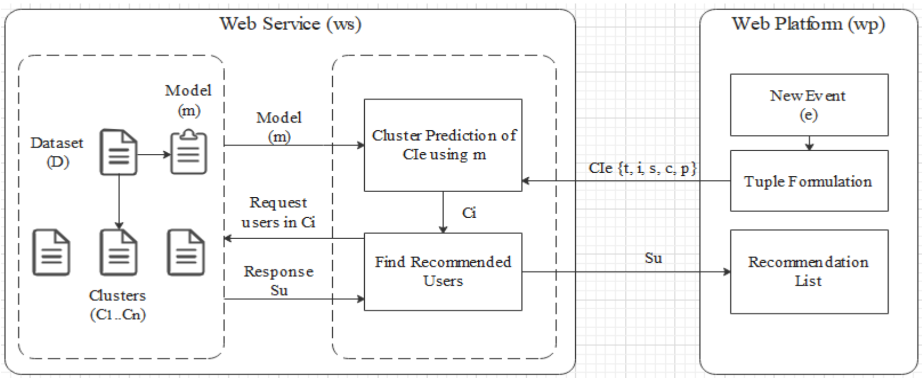

Fig. 3. ST76 – CARS System Model

The CARS Algorithm

The ST76_RS algorithmic part is composed of two phases:

i. In the **offline or clustering phase**, the dataset is clustered using the K-Means machine learning algorithm [14]. Each cluster consists of user-related entries that include users' contextual information which refers to specific type of events; Thus, each cluster represents one or more events along with the users that are most likely to attend or have already attended the specific event(s) based on their contextual information. Thus, a prediction model representing the clusters of users and their contextual information is generated using the Joblib python library and stored on a central server.[9]

ii. In the **online or recommendation phase**, the prediction model of the previous phase (i) is used to predict the cluster with users that their preferences and contextual information matches the profile of a new event.

[9] Joblib Python Library: https://joblib.readthedocs.io/

The Dataset

Finally, in order to provide accurate user recommendations to specific events a proper dataset is needed. In the absence of any existing dataset suitable for our needs, we generated our own ST76 dataset by collecting domain specific data from users' contextual information. In particular, the dataset formulated is a result of 68 users answering a Google Forms questionnaire[10], formulated in a way to obtain users' contextual information. The questionnaire was defined in such a way in order for participants to specify their answers including choices (e.g., user attends trails, marathons) and ratings (e.g., with 5/5 for trails, 3/5 for marathons) for those choices. The different answers, provided by each participant, produced a resulting dataset of approximately 2 thousand entries, with each entry providing contextual information of a user to a specific event type.

Contextual information includes information regarding:

1) the type of event (t) $(Official, Leisure, Domestic, Charity)$,
2) the intensity of the event (i) $(Scale\ 1 - 5)$,
3) the season event is scheduled (s) $(Autumn, Winter, Spring, Summer)$,
4) the user's companion (c) $(Solo, +1, Family, Team/Friends)$, and
5) the event's locality (p) $(National, European, International)$.

As explained above, each user may have multiple entries into the dataset and each entry describes contextual information about a specific event type, which the user has attended presenting a different user's profile perspective. More information on the ST76 platform and recommender system is out of the main context of this paper, but interested readers can refer to project's system specification deliverable[11]. The main contribution of this paper is the examination and analysis of the economic impact of active sport events, through the international active sport (swimming) event that is presented in the following case study.

Evaluation

For the evaluation of the clustering recommendation system a cosine similarity metric was used in order to measure the similarity between and within clusters. The cosine similarity is defined as follows:

$$sim(A, B) = \frac{A \cdot B}{\|A\| \times \|B\|} \qquad (1)$$

where A, B are two multi-dimensional vectors representing the attribute values of an item. In particular, the similarity between clusters is defined by the cosine similarity between the cluster centers vectors, where low similarity describes the dissimilarity between clusters.

[10] ST76_RS Questionnaire: https://forms.gle/d8Ah7VbeJLuQA3689 (EN version + 19 offline responses), https://forms.gle/6NTYjk8FXuDbBDxcA (GR version)

[11] System Specification Deliverable: http://mdl.frederick.ac.cy/SportsTraveler76/Main/Results

Also, the similarity within clusters as the average similarity between all vectors included in a cluster compared to cluster centre vector, and is defined as follows:

$$IntraSim(C_i) = \frac{\sum_{n=1}^{m} \mathrm{sim}(C_{\mathrm{n}}^{i}, \mathrm{V}_{\mathrm{c_i}})}{\mathrm{m}} \qquad (2)$$

where C_i is the corresponding cluster, C_{n}^{i} is represents each vector in C_i, $\mathrm{V}_{\mathrm{c_i}}$ is the vector representing the cluster center, and m is the number of vectors in the cluster.

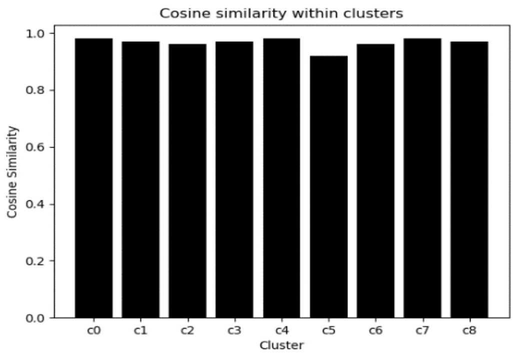

Fig. 4. Cosine Similarity within Clusters

As part of the evaluation, two experimental studies have been performed in order to examine the recommendation system's accuracy and reliability. In particular, both experiments reveal information regarding similarities between and within clusters, respectively. High similarity within clusters and low similarity between clusters reveal that any recommended cluster will ensure high accuracy in terms of recommended items within the recommended cluster.

Figure 4 presents the results of the first experimental study, that dealt with revealing information regarding the similarity within clusters. As seen in the same figure, every cluster reaches cosine similarity levels above 0.9. This ensures that the items within each cluster are highly similar and any cluster recommended will ensure high recommendation accuracy.

During the second experimental study, we evaluated the low similarity or high dissimilarity between all combination of clusters in order to ensure that the clustering process managed to cluster our data in dissimilar clusters. In particular, Table 1 presents the cosine similarities between all clusters' centres. The results show similarity levels between clusters in a range of 0.66 – 0.83. Given that the dataset used is a rather small dataset, the similarity between clusters can be classified as acceptable and the results reveal satisfying discrimination between the clusters. This ensures the reliability of the clustering process as well as acceptable levels of accuracy on cluster recommendations.

Table 1. Similarity between clusters

	C0	C1	C2	C3	C4	C5	C6	C7	C8
C0	1	0.78	0.76	0.76	0.77	0.73	0.78	0.78	0.81
C1	0.78	1	0.71	0.83	0.71	0.79	0.71	0.69	0.77
C2	0.76	0.71	1	0.7	0.67	0.77	0.73	0.75	0.75
C3	0.76	0.83	0.7	1	0.76	0.69	0.68	0.76	0.68
C4	0.77	0.71	0.67	0.76	1	0.73	0.69	0.72	0.73
C5	0.73	0.79	0.77	0.69	0.73	1	0.81	0.69	0.66
C6	0.78	0.71	0.73	0.68	0.69	0.81	1	0.76	0.73
C7	0.78	0.69	0.75	0.76	0.72	0.69	0.76	1	0.75
C8	0.81	0.77	0.75	0.68	0.73	0.66	0.73	0.75	1

Demonstration

The survey web form of the ST76 platform (see Fig. 5 and Fig. 6) allows new users to complete and submit the static context and profile data that are stored in the database of the platform using the CARS system's implemented Web Services. In fact, the user completes the first section of the form in order to give the required consent. As soon as the user gives the email and clicks Yes to consent, then the section 2 of the form is enabled (see Fig. 6). The user completes then the different questions and submits the profile data that are stored using the CARS Web Services in the database, while a Web Service generates the static context data that are also stored in the database that are to be used to create the clusters and generate the recommendations when required.

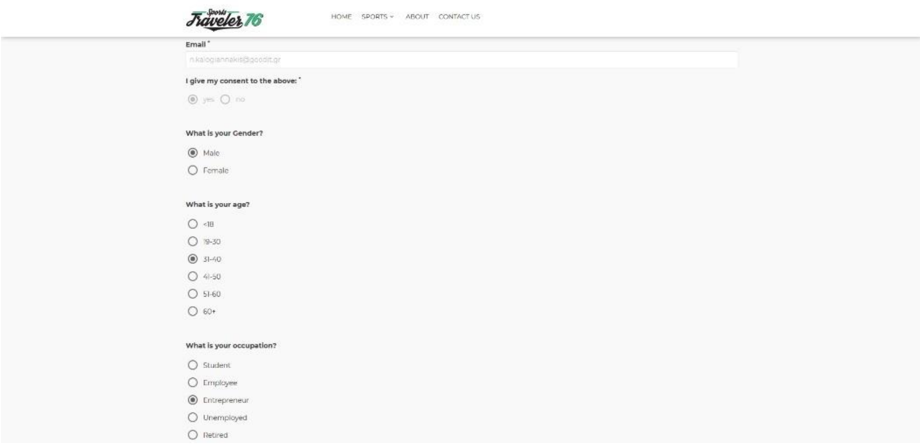

Fig. 5. The survey web form – section 1 – Survey.aspx

The new data records are stored in the database using the Web Services (i.e., Web APIs) provided by the recommender system. A conditional check is performed each time that validates if more than 10 new users have been added in the database, which kicks off the clustering process using the Python scripts that formulate the new clusters, in order to get the updated recommendations, when required by the manager, on the basis of all the information available in the dataset.

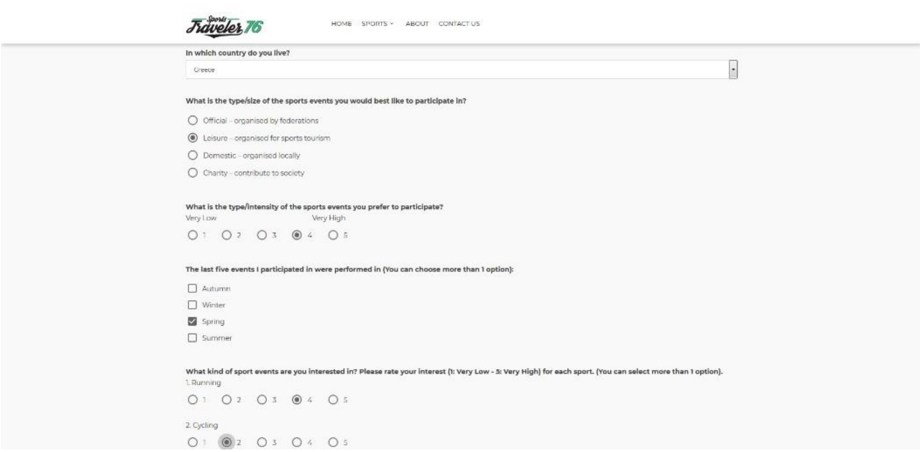

Fig. 6. The survey web form – section 2 – Survey.aspx

In order for the ST76 platform manager and organiser of the new event to get the recommendations of users that are more probable to be interested in the active sport event, the manager needs to complete the following web form by selecting the attributes that best characterise the upcoming event and click Generate to get the list of recommended users by invoking the appropriate service of the CARS system. Note that since during the project the survey was conducted for research purposes the participants that answered the questionnaire had the choice to opt out from providing their email. This was done in order to get as many participants as possible, in order to avoid the cold start problem when developing and testing the recommender system. This is the reason why some of the recommended customers in Fig. 7 are shown with a fake email (e.g., drbpopovic@gmail.com), while the emails of the research survey participants that did provide their emails, are crossed out in this deliverable for confidentiality reasons.

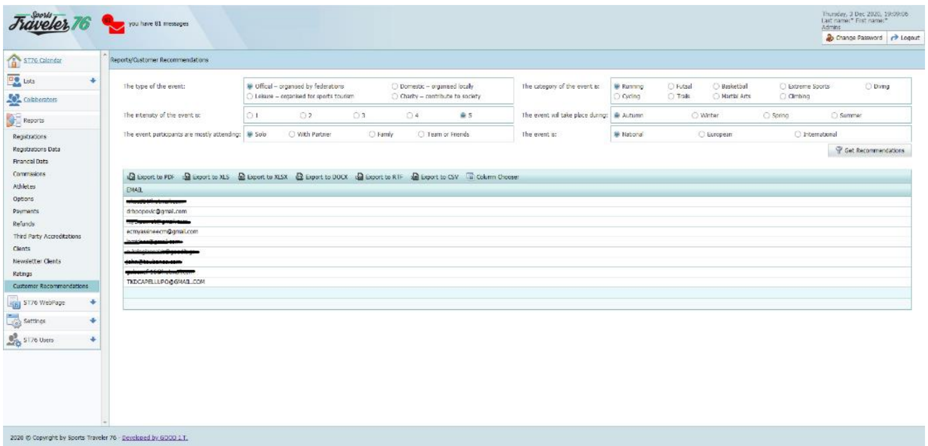

Fig. 7. The recommendations web form – Recommendations.aspx

The company can choose to clear the profile and context data of the users that have not provided their emails during the research survey, and since now the email is required by the company in order to complete the survey on the ST76 web platform, the recommender system will continue to work as expected providing the emails of all recommended customers.

3 SportsTraveler76 Case Study

The web platform and recommender system were designed and developed in order to support the organisation and management of active sport events. Complementing the technical contribution of this paper, the economic impact analysis of a sport event is presented. OceanMan is the first international active sport swimming event organized in Cyprus. It attracted 512 active participants (79 from Cyprus), while the 433 international participants arrived from 29 countries.

International visitors are the drivers of economic impact. Hence, only international visitors were considered in the calculation of the economic impact. To estimate the average accommodation cost we rely on rudimentary statistical analysis of questionnaire data. Because most of the responses are given in intervals (i.e. the respondents state whether they have stayed in Limassol between 2 and 4 nights or whether they have spent a sum between €200-300, etc) we calculate per-person averages using the mean of grouped data formulated as:

$$Mean\ (Grouped\ Data) = \frac{\sum(Interval\ Midpoint\ x\ Frequency)}{\sum(Frequency)} \quad (3)$$

Based on the data collected from the survey the IMPLAN Input-Output model was applied to calculate the economic impact of the event. In the case of accommodation cost we calculate the average per-person number of nights spent in Limassol and obtain an average cost per night from 2 online travel agencies, namely booking.com and budgetyourtrip.com. Based on these sources we set an average cost per night equal to €75. Finally, to estimate the economic impact of the entire event we apply the sample ($N = 51$) means of each spending category to the population of visitors ($N = 433$). In fact, based on their responses we estimated their expenditure patterns in the three NACE (Nomenclature of Economic Activities) categories shown in Table 1. This includes accommodation, food and beverages, excursions, transportation and retail shopping.

The Regional Purchase Coefficient (RPC) allows measuring the true economic impact of tourist spending, e.g., when attending an event [15]. In particular, the international visitors that have attended the event purchase goods and services from local businesses. This is in fact, money coming from outside the community that stimulate the region, since tourism is linked with the other sectors of the local economy. Note that some of the spending leaves the community, which is the reason why local purchasing is calculated at the RPC of 65% [15]. Hence, as illustrated in Table 2, *the direct expenditure of international visitors is calculated at € 365,551.92, while local purchasing is calculated at € 237,608.75 that reflects money that stay within the local community.*

Table 2. Estimated expenditure by international visitors

Description	Direct Expenditure	(%)	Local Purchasing
Accommodation & Food	€ 202,621.79	55.43%	€ 131,704.00
Transportation	€ 111,025.64	30.37%	€ 72,167.00
Trade (Wholesale and Retail)	€ 51,904.49	14.20%	€ 33,738.00
TOTAL	€ 365,551.92		€ 237,608.75

4 Conclusions

Recommendations provide benefits to both the seller and the buyer by recommending the most likely items for which the user may be interested. Several RS have been proposed for various domains (e.g., e-commerce, movies) and demonstrated the benefits they provide. Still, research work on RS for events has been scarce, mostly exploiting social networks, and in many cases event-based RS continue to present unique challenges. In this work, a commercial platform and RS have been proposed, based on the historical context dataset explicitly gathered from customers, in order to avoid the cold-start problem and other event-related challenges (e.g., events commonly happen once). The RS evaluation confirmed the accuracy of the recommendations, while at the same time this paper briefly presents the economic benefits brought on by active sport events.

Acknowledgements

The work presented in this manuscript is performed based on the research funding received from the European Regional Development Fund and the Research Promotion Foundation of Cyprus as part of the Research in Startups SportsTraveler76 project (START-UPS/0618/0049–RESTART 2016–2020).

References

1. Adomavicius, G., Sankaranarayanan, R., Sen, S., Tuzhilin, A.: Incorporating contextual information in recommender systems using a multidimensional approach. ACM Transactions on Information Systems (TOIS), vol. 23 103–145 (2005).
2. Ricci, F., Rokach, L., Shapira, B., Kantor, P. B. Recommender Systems Handbook, 1st ed. New York, NY, USA: Springer-Verlag New York, Inc. (2010).
3. Walter, F. E., Battiston, S., Yildirim, M., Schweitzer, F. Moving recommender systems from on-line commerce to retail stores. Inf Syst E-Bus Manage, 10:367–393 (2012).
4. Hu, Y., Koren, Y., Volinsky, C. Collaborative Filtering for Implicit Feedback Datasets. In Proc. of the 8th IEEE International Conference on Data Mining, pp. 263–272 (2008).
5. Adomavicius, G., Tuzhilin, A. Context-Aware Recommender Systems. In: Ricci F., Rokach L., Shapira B., Kantor P. (eds) Recommender Systems Handbook. Springer, Boston, MA, pp. 217-253 (2011).
6. Ritchie, B., Adair, D. Sport Tourism: Interrelationships, Impacts and Issues. Clevedon, UK; Buffalo US, Channel View Publications (2004).
7. Gibson, H. J., Lamont, M., Kennelly, M., Buning, R., J. Introduction to the Special Issue Active Sport Tourism. Journal of Sport & Tourism, 22 (2), pp. 83-91, DOI: 10.1080/14775085.2018.1466350 (2018).

8. Quercia, Daniele, et al. Recommending social events from mobile phone location data. IEEE international conference on data mining. IEEE (2010).
9. Pessemier De T., et al. Social recommendations for events, CEUR workshop Proceedings. Vol. 1066 (2013).
10. Macedo, A. Q., Marinho L. B., and Santos R.L.T. 2015. Context-Aware Event Recommendation in Event-based Social Networks. In Proceedings of the 9th ACM Conference on Recommender Systems (RecSys '15). Association for Computing Machinery, New York, NY, USA, 123–130. DOI: https://doi.org/10.1145/2792838.2800187 (2015).
11. Herzog, D., Wörndl, W. Mobile and Context-Aware Event Recommender Systems. In: Monfort V., Krempels KH., Majchrzak T., Traverso P. (eds) Web Information Systems and Technologies. WEBIST 2016. Lecture Notes in Business Information Processing, vol 292. Springer, Cham. https://doi.org/10.1007/978-3-319-66468-2_8 (2017).
12. Nguyen Q., Huynh L.N.T., Le T.P., Chung T. (2019) Ontology-Based Recommender System for Sport Events. In: Lee S., Ismail R., Choo H. (eds) Proceedings of the 13th International Conference on Ubiquitous Information Management and Communication (IMCOM). Advances in Intelligent Systems and Computing, vol 935. Springer, Cham. https://doi.org/10.1007/978-3-030-19063-7_69 (2019).
13. World Wide Web Consortium (W3C). HTML Living Standard, The iFrame element. Accessed: Jul. 22, 2020. [Online]. Available: https://html.spec.whatwg.org/#the-iframe-element.
14. Forgy, E. W. Cluster analysis of multivariate data: efficiency versus interpretability of classifications. Biometrics, 768–769 (1965).
15. Stynes, D. J. Economic Impact of Tourism: A Handbook for Tourism Professionals. Urbana, IL: University of Illinois, Tourism Research Laboratory (1997).