A Tourist Recommendation System: A Study Case in Mexico

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Abstract. The present work deals with implementing tourist recommendation systems designed to predict the user preferences about a place or tourist activity in Mexico. Three recommendation systems have been proposed: two based on collaborative filtering (user and items) and the other based on demographic issues. To this aim, a corpus has been built by collecting 2,263 ratings from TripAdvisor.com about eighteen tourist places in Mexico. Experimental results show that the demographic-based recommendation system outperforms those based on collaborative filtering, obtaining a mean absolute error of 0.67 and a mean square error of 1.2980. These results also show significant improvement over a majority class baseline based on a sizeable unbalanced corpus.

Keywords: Tourist recommendation system · Collaborative-based filtering · Demographic-based filtering

1 Introduction

Tourism in Mexico has a significant impact on the economy due to its multiplier effects in the generation of added value and employment [13]. Only in 2019, the tourism industry contributed 17.2% of gross domestic product (GDP) in Mexico [7], obtaining sixth place in the international tourism ranking [18]. In terms of economic income, tourism in Mexico represents approximately 22.5 billion dollars per year [21]. Recently, the economic impact generated by the SARS-CoV-2 coronavirus pandemic has repercussions that may extend into the medium term [2,6,23]. Despite this, digital technologies have allowed a reorientation of the social, cultural, and economic models related to the tourism proposals that would alleviate such impact.

Currently, many technologies allow and achieve the scope of tourism at all its levels (transport, restaurants, hotels, events, among others). However, a large number of web pages and online services specialized in tourism usually drown relevant results to informational "noise" that can hinder the best touristic options

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according to the user preference [8]. One of the technologies that optimize the selection process for suitable tourist places based on the user profile is the recommendation system. A tourist recommendation system seeks to predict a 'score' or preference that users have regarding tourism options, aiming to match tourist attractions with user needs [1].

The main objective of this work is to generate baselines for future researches related to tourist recommendation systems specialized in Spanish-speaking countries, especially in Mexico. With this in mind, three recommendation systems have been proposed. Two of them are based on collaborative filtering, while the other one considers demographic issues. For this aim, a new corpus was built, consisting of 2,263 opinions and ratings about eighteen touristic attractions from the state of Nayarit, Mexico. To the best of our knowledge, this is the first corpus of touristic opinions in Spanish that includes ratings about places in Mexico intended for the training and evaluating of tourist recommendation systems.

The rest of the paper is organized as follows. In Sect. 2, related works on tourist recommendation systems are mentioned. In Sect. 3, the proposed methodology and the database that was built are described. In Sect. 4, the results achieved are described. Finally, in Sect. 5, the conclusions reached in this work and the proposed future work are listed.

2 Related Work

Nowadays, some works in the scientific literature deal with the application of recommendation systems in the tourism domain [10,16,25]. These works are commonly categorized according to three well-known recommendation techniques: content-based filtering, collaborative filtering, and hybrid recommendation systems [25].

In content-based filtering, a user receives recommendations of similar items to the ones the user favored in the past. For the decision-making process, different content factors can be considered from the tourists' preferences [10]. For example, Binucci et al. [4] designed a content analyzer for a content-based travel recommendation system. They use geographical data provided by a set of points of interest (POI) to indicate how much a POI is relevant for a set of possible topics of interest. On the other hand, Vu et al. [22] obtain tourist dining preferences based on restaurant review websites. They use text processing techniques to analyze tourists' preferences concerning dining activities (cuisines, dishes, meals, and restaurant features). Shen et al. [20] use location-based social networks to offer tourists the most relevant and personalized local venue recommendations. However, content-based filtering is not a suitable approach when there is an absence of prior user data to make decisions. Under this perspective, collaborative filtering can offer early data based on user similarities [24].

In collaborative filtering, a user receives recommendations of items establishing relations with people that have similar tastes, or choices preferred in the past. Recent examples of recommendation systems using the collaborative approach are [3,14]. Al-Ghobari et al. [3] proposes a tourist recommendation system that integrates the preferences of users and their geographical information to generate personalized and location-aware recommendations. They used a k-Nearest Neighbor item-based collaborative filtering for this purpose. Their solution aimed to develop a mobile application that uses the service of Google to provides suggestions based on nearby popular attractions. Kuanr et al. [14] present a tourist recommendation system that store the opinions of local users about their preferences on food and purchase. Their system uses the stored information by finding similar users to any querying user and providing him recommendations of the sites with good food and products available on those sites.

Regarding the hybrid recommendation systems, they combine both content-based and collaborative filtering to issue recommendations. For example, Fararni et al. [8] propose a hybrid architecture and a conceptual framework based on big data technologies, artificial intelligence, and operational research. Other research works, like those reviewed in [25], also use hybrid approaches by using linked open data (a concept as the data is shared and built based on semantic web, linked data, and open data) in the tourist domain.

3 Methodology

This study is conducted using two phases: data collection and the design of the recommendation systems, which are described below.

3.1 Data Collection

In order to achieve the proposed goals, a corpus was built by collecting tourism reviews in Spanish and overall ratings of about eighteen domestic tourist places or attractions in the state of Nayarit, Mexico.[1] Data were collected from TripAdvisor.com, a website with user-generated content that captures aspects of travel experiences. A web crawler was used to gather the information via the following two software tools: Selenium WebDriver and Python Selenium [17]. A total of 2,263 online reviews and ratings performed by 2,033 users were collected from May 2012 to January 2021. Each of these ratings consists on a five-point Likert-type scale [15]: 1 (terrible), 2 (poor), 3 (average), 4 (very good) and 5 (excellent). Table 1 shows the distribution of corpus instances according to their rating.

The eighteen tourist places were selected considering eight tourism types based on the purpose for travel: sun and beach, cultural, adventure, religious, natural, gastronomic, ecotourism, and shopping. Table 2 shows the typology of tourism used for these places.

In addition to the reviews and ratings, information about each of the 2,033 users was also obtained via a web crawler. However, manual processing was required to gather the gender of the users and a brief opinion on the rated places. There are no empty fields in the corpus instances, in such a way that if a user did not have any of them, the user and its ratings are omitted. Finally, the username was changed to an ID preserving the privacy of the opinions. Table 3 shows the user information consisting of eight fields.

[1] https://sites.google.com/cicese.edu.mx/rest-mex-2021/corpus-request.

Table 1. Distribution of corpus instances according to their rating.

Rating	Number of instances
1	65
2	77
3	239
4	653
5	1229

Table 2. Typology of tourism destinations.

Tourist places	Types of tourism destinations
Bahia de Matanchen	Sun and beach
Playa Los Muertos	Sun and beach
Bucerias Art Walk	Cultural, shopping
Centro Historico de Tepic	Cultural, religious
Galerias Vallarta	Shopping
Isla de Coral	Sun and beach, ecotourism
Islas Marietas	Sun and beach, adventure, ecotourism
Manantial La Tovara	Sun and beach, adventure, ecotourism
Mercado del Pueblo Sayulita	Gastronomic
Mexcaltitan	Natural
Playa Destiladeras	Sun and beach
Playa El Anclote	Sun and beach
Playa Los Ayala	Sun and beach
Splash Water Park	Adventure, shopping
The Jazz Foundation	Cultural
Isla Isabel	Sun and beach, ecotourism
Cerro de la Contaduria	Cultural, adventure
Santuario de Cocodrilos El Cora	Ecotourism

Additionally, a history of opinions of some of the 2,033 users was also collected. This history of opinions consists of comments and observations that each of these users made about the tourist places he/she visited (non-necessarily those listed in Table 2). Table 4 shows the fields of the history of opinions.

Finally, the set of instances in the corpus was split into the following two groups: a training sample consisting of 1,582 randomly selected ratings and a test sample containing 681 randomly selected instances for performance measurement. The split of the corpus instances was made in a stratified K-fold validation based on the distribution of Table 1. Therefore 70% for each rating was ensured for the training sample and 30% for the test sample.

Table 3. User information in the corpus.

Field	Description	Data type
ID	The user ID for each recommendation	Text
Gender	The tourist's gender	[Male, Female]
Place	The tourist place that the tourist is recommended to visit	Text
Location	The place of origin of the tourist (the central, northeast, northwest, west, and southeast regions refer to the regions of Mexico)	Text
Date	Date the recommendation was issued	Date
Type	Type of trip that the tourist would do	[Family, Friends, Alone, Couple, Business]
Rating	The rating represented the level of satisfaction that the tourist will have when going to the recommended place	[1, 2, 3, 4, 5]
Comment	The comment that the tourist granted	Text

Table 4. History of opinions of the users

Field	Description	Data type
Comment	The comment that the user granted (unknown = blank comment)	Text
Rating	The level of satisfaction that the user had regarding an specific place	[1, 2, 3, 4, 5]
Place	The place a user visited (this place can be from anywhere in the world, not necessarily from Mexico)	Text
Location	The place of origin of the user (the central, northeast, northwest, west, and southeast regions refer to the regions of Mexico)	Text
Overall rating	The overall rating that a place has on the TripAdvisor.com site	[1..5]

In the following subsections, the models used for generating recommendations of tourist places are described.

3.2 Collaborative-Based Filtering

Collaborative-based filtering (CF) is a common technique to determine similarity decisions in recommendation systems. CF seeks to predict items for a target user (for whom the recommendation is aimed) using data of other similar users or items. While the user-based approach finds the users who share the same rating patterns with the target user, the item-based approach looks into the set of items the target user has rated and computes how similar they are.

In this work, CF is used applying both user-based and item-based approaches to recommend tourist places. The recommendation models under these approaches are built using the well-known k-Nearest Neighbors (KNN) algorithm or some of its variants. The KNN-type algorithms allow providing recommendations by aggregating the ratings of the closest k neighbors. In particular, the present work uses the algorithm of KNN with means [11], which takes into account the mean rating of each user as well as the mean of k neighbors. Since there is a low number of items compared to the users, different parameters of k were used. The user-based approach was applied with the following values of $k = 10, 20, 25, 30, 35$. These values were chosen following the work of Ghazanfar et al. [9], where they evaluated the optimal value of k from 0 to 100 and computed the mean absolute error for various models of recommendation systems. On the other hand, for the item-based approach, the values of k were $1, 3, 5, 7, 9$. Since there are only 18 items (or tourist destinations), the size of k is limited from 1 to 18 for this approach.

The KNN user-based and item-based approaches were implemented by using the Surprise library[2] which is a Python Scikit for recommendation systems. This library offers a range of recommendation system algorithms, including such variations of KNN and different similarity indexes at ease. Surprise library was also used to compute the following four steps: (1) building the user-item rating matrix, (2) computation of similarity matrix, and (3) compute rating predictions and identify recommendations.

Building the User-Item Rating Matrix. The user-item rating matrix consists of the ratings given by users to items (the tourist places). It relies on the similarities between given user ratings to predict a target user's ratings on particular items. Table 5 shows an example of the user-item rating matrix. In this table, the columns correspond to the tourist places while the rows to the users. The intersection between them is the rating that a user gives to a specific tourist place.

Table 5. Example of the user-item rating matrix.

	Islas Marietas	Manantial La Tovara	Sayulita	...	Mexcaltitan
user_1		5		...	
user_2	3			...	4
user_3		3		...	5
⋮	⋮	⋮	⋮	⋮	⋮
user_n	4		5	...	

Computation of Similarity Matrix. The similarity matrix consists of weights that represents the relation between two elements (users or items). The higher the weight value, the firm of the relation between them. In this work, the

[2] https://surprise.readthedocs.io/en/stable.

cosine similarity between all pairs of elements (users or items) was computed to generate the weight values. Let U_{ij} be the set of all users that have rated both items i and j in the recommendation system, and let I_{uv} be the set of items rated by both users u and v. The rating of user u for item i is denoted as r_{ui}.

Equation (1) express the cosine similarity between users u and v, while Eq. (2) describes the similarity between items i and j. Table 6 shows an example of similarity matrix for users.

$$sim(u,v) = \frac{\sum_{i \in I_{uv}} r_{ui} \cdot r_{vi}}{\sqrt{\sum_{i \in I_{uv}} r_{ui}^2} \cdot \sqrt{\sum_{i \in I_{uv}} r_{vi}^2}} \tag{1}$$

$$sim(i,j) = \frac{\sum_{u \in U_{ij}} r_{ui} \cdot r_{uj}}{\sqrt{\sum_{u \in U_{ij}} r_{ui}^2} \cdot \sqrt{\sum_{u \in U_{ij}} r_{uj}^2}} \tag{2}$$

Table 6. Example of similarity matrix for the users-based approach.

	User_1	User_2	User_3	...	User_n
User_1	–	0	0.61	...	0
User_2	0	–	0.45	...	0.4
User_3	0.61	0.45	–	...	0
⋮	⋮	⋮	⋮	⋮	⋮
User_n	0	0.4	0	...	–

Computing Rating Predictions and Identifying Recommendations. The rating prediction is computed considering the mean rating of each user. Let μ_u the mean rating of each user u (or μ_i if the prediction is computed using the item-based approach). The rating prediction $\hat{r}_{ui}$ for user u about item i is expressed in Eq. (3) under the user-based approach and in Eq. (4) under the item-based approach. In these equations, $N_i^k(u)$ denotes the set of k neighbors of u that have rated the item i.

$$\hat{r}_{ui} = \mu_u + \frac{\sum_{v \in N_i^k(u)} sim(u,v) \cdot (r_{vi} - \mu_v)}{\sum_{v \in N_i^k(u)} sim(u,v)} \tag{3}$$

$$\hat{r}_{ui} = \mu_i + \frac{\sum_{j \in N_u^k(i)} sim(i,j) \cdot (r_{uj} - \mu_j)}{\sum_{j \in N_u^k(i)} sim(i,j)} \tag{4}$$

3.3 Demographic-Based Filtering

Demographic-based filtering (DF) categorizes users or items based on their attributes and performs a recommendation based on such demographic categorizations. In the present work, a recommendation model using DF was generated by using the following user information: gender, location, and the type of trip that the tourist did. These fields (described in Table 3) comprised the feature vector for each user instance. Table 7 shows an example of the set of features that characterizes the demographic information on users. Regarding the tourist place instances, each of them consists of a binary feature representation of the typology of tourism destinations (see Table 2). For this binary representation, 0's and 1's indicate whether or not the tourist place fits one or more types of tourism destinations. In order to build the recommendation models, we used the following machine learning algorithms implemented in Python Scikit-Learn: the KNN for $k = 10, 20, 25, 30, 35$, random forest (RF), and neural networks (NN).

Table 7. Demographic information on the users who rated a tourist place.

ID	Gender	Location	Type
User_1	Male	Argentina	Business
User_2	Female	West region of Mexico	Family
User_3	Female	Central region of Mexico	Alone
⋮	⋮	⋮	⋮
User_n	Male	USA	Friends

4 Experimental Results

Experiments were conducted to evaluate the performance of the three proposed recommendation models. The experiments were carried on Google Colab, a free cloud-based service of a Jupyter notebook[3]. The performance of the models was evaluated by using the following error measures:

- Mean absolute error (MAE). It measures the average magnitude of the absolute value differences between the true and the predicted rating [5].
- Mean squared error (MSE). It evaluates the quality of the recommendation models to make predictions computing the average of the squared difference of the predicted ratings.
- Root mean squared error (RMSE). It evaluates the accuracy of the predicted ratings penalizing disproportionately large errors [12].

To use different metrics that allow evaluating other aspects of the recommendation models, the values were transformed from reals to integers through rounding. Thus, the original regression problem was converted to a classification problem considering five classes: 1 (bad), 2 (bad), 3 (fair), 4 (very good), and 5 (excellent). In particular, we use the following two types of statistical measures:

[3] https://colab.research.google.com.

- Accuracy. It measures the percentage of cases in which the recommendation model was correct.
- F1-score. It represents the harmonic mean between precision and recall

See [19] to get more details about the metrics for evaluation of the recommendation models.

A majority class baseline was used as the reference value for the experiments. This value is computed by selecting rating 5 as the default response, which corresponds to a 54.1854% of accuracy (see Table 8). Notice that approximately 30% of the corpus instances have a rating equals to 4 while the remaining rating (from 1 to 3) represents almost the 20%.

Table 8. Results for a majority class baseline.

MAE	MSE	RMSE	Accuracy	F1-score
0.72246	1.49779	1.22384	0.54185	0.14057

Table 9 shows the performance of the CF model under the user-based approach. The result with the lowest error measures and the highest accuracy is when $k = 10$. This is not the case for the F1-score and Accuracy measure, where the highest value results when $k = 25$. Notice that there is no significant difference concerning the remaining results. Regarding the majority class baseline, this approach obtains lower MSE and RMSE values; however, it does not outperform the rest of the metrics.

Table 9. Performance of the CF model under the user-based approach.

k value	MAE	MSE	RMSE	Accuracy	F1-score
10	**0.79083**	**1.07988**	**1.03917**	0.32599	0.13035
20	0.79374	1.0937	1.0458	0.32452	0.12993
25	0.79348	1.09309	1.04551	**0.32745**	**0.13188**
30	0.79354	1.09302	1.04548	0.32599	0.13091
35	0.79359	1.09314	1.04553	0.32599	0.13091

Table 10 shows the performance of the CF model under the item-based approach. The result with the lowest error measures and the highest accuracy is when $k = 9$. For the F1-score measure, the highest value was obtained when $k = 1$. Similar to the CF model under the user-based approach, there is no significant difference concerning the remaining results. In addition, this approach also obtains lower MSE and RMSE values than those of the majority class baseline, but it does not outperform the rest of the metrics.

Table 10. Performance of the CF model under the item-based approach.

k value	MAE	MSE	RMSE	Accuracy	F1-score
1	0.79588	1.11894	1.0578	0.32599	**0.13167**
3	0.78267	1.07929	1.03889	0.32892	0.12528
5	0.79882	1.11894	1.0578	0.32158	0.12819
7	0.79735	1.11747	1.05711	0.32305	0.12969
9	**0.78120**	**1.07489**	**1.036768**	**0.328928**	0.12517

Finally, Table 11 shows the performance of the DF models trained by the machine learning algorithms: random forest (RF), neural networks (NN) and KNN with $k = 10, 20, 25, 30, 35$ (see Sect. 3.3). All DF models outperform the majority class baseline in all the used evaluation metrics (although lower MSE and RMSE values are obtained with the CF models). The overall best result is obtained for the DF model trained by RF.

Table 11. Performance results for the demographic system

Model	MAE	MSE	RMSE	Accuracy	F1-score
KNN 10	0.69456	1.33186	1.15406	0.51982	0.19155
KNN 20	0.70778	1.39207	1.17986	0.52569	0.18355
KNN 25	0.70044	1.37885	1.17424	0.53010	0.18286
KNN 30	0.69603	1.36857	1.16986	0.53303	0.18070
KNN 35	0.68428	1.3392	1.15724	0.53597	0.18438
RF	**0.66666**	**1.29809**	**1.13933**	**0.54478**	**0.20378**
NN	0.68428	1.3392	1.15724	0.54185	0.17582

5 Conclusions and Future Work

In this work, three recommendation models were proposed: two based on collaborative filtering (user and items) and the other based on demographic issues. These methods serve as baselines for future work on recommendation systems for sites in Mexico. A corpus was built, collecting tourism reviews in Spanish and overall tourist places in Nayarit, Mexico. This is the first corpus, as far as the authors are aware of, which includes ratings about places in Mexico intended for tourist recommendation systems. Experimental results show that the demographic-based filtering approach outperforms a majority class baseline (used as a reference). This is not the case for the collaborative-based filtering (users and items) approaches, although they obtained the lower overall MSE and RMSE values.

As future work, it would be interesting to explore other recommendation approaches such as context-based models or others using deep learning and natural language processing.

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References

1. Adomavicius, G., Tuzhilin, A.: Context-aware recommender systems. In: Ricci, F., Rokach, L., Shapira, B., Kantor, P.B. (eds.) Recommender Systems Handbook, pp. 217–253. Springer, Boston, MA (2011). https://doi.org/10.1007/978-0-387-85820-3_7
2. Aguirre Quezada, J.P.: Caída del turismo por la covid-19. desafío para méxico y experiencias internacionales. In: Instituto Belisario Dominguez, **186**, 1–13. Senado de la republica (2020)
3. Al-Ghobari, M., Muneer, A., Fati, S.M.: Location-aware personalized traveler recommender system (lapta) using collaborative filtering KNN. Comput. Mater. Continu. **68** (2021)
4. Binucci, C., De Luca, F., Di Giacomo, E., Liotta, G., Montecchiani, F.: Designing the content analyzer of a travel recommender system. Expert Syst. Appl. **87**, 199–208 (2017)
5. Chai, T., Draxler, R.R.: Root mean square error (RMSE) or mean absolute error (MAE)? - arguments against avoiding RMSE in the literature. Geosci. Mod. Dev. **7**(3), 1247–1250 (2014). https://doi.org/10.5194/gmd-7-1247-2014
6. EFE, A.: Estimas caida del 10% en el pib turistico de mexico (2020). https://www.efe.com/efe/america/mexico/estiman-caida-del-10-en-el-pib-tu-ristico-de-mexico/50000545-4233506
7. El economista (2019). https://www.eleconomista.com.mx/empresas/Sector-de-viajes-y-turismo-crecio-mas-que-el-PIB-20190301-0003.html
8. Fararni, K.A., Nafis, F., Aghoutane, B., Yahyaouy, A., Riffi, J., Sabri, A.: Hybrid recommender system for tourism based on big data and AI: a conceptual framework. Big Data Min. Anal. **4**(1), 47–55 (2021). https://doi.org/10.26599/BDMA.2020.9020015
9. Ghazanfar, M.A., Prugel-Bennett, A.: A scalable, accurate hybrid recommender system. In: 2010 Third International Conference on Knowledge Discovery and Data Mining, pp. 94–98. IEEE (2010)
10. Hamid, R.A., et al.: How smart is e-tourism? a systematic review of smart tourism recommendation system applying data management. Comput. Sci. Rev. **39**, 100337 (2021). https://doi.org/10.1016/j.cosrev.2020.100337
11. Hedlund, J., Nilsson Tengstrand, E.: A comparison between different recommender system approaches for a book and an author recommender system (2020)
12. Herlocker, J.L., Konstan, J.A., Terveen, L.G., Riedl, J.T.: Evaluating collaborative filtering recommender systems. ACM Trans. Inf. Syst. **22**(1), 5–53 (2004). https://doi.org/10.1145/963770.963772
13. INEGI: Estadísticas a propósito del día mundial del turismo (2019). https://www.inegi.org.mx/contenidos/saladeprensa/aproposito/2019/turismo2019_Nal.pdf
14. Kuanr, M., Mohanty, S.N.: Location-based personalised recommendation systems for the tourists in India. Int. J. Bus. Intell. Data Min. **17**(3), 377–392 (2020)

15. Likert, R.: A technique for the measurement of attitudes. Arch. Psychol. **140**, 55 (1932)
16. Ranjith, S., Paul, P.V.: A survey on recent recommendation systems for the tourism industry. In: Accelerating Knowledge Sharing, Creativity, and Innovation Through Business Tourism, pp. 205–237. IGI Global (2020)
17. Salunke, S.S.: Selenium Webdriver in Python: Learn with Examples, vol. 70. CreateSpace Independent Publishing Platform, USA (2014)
18. SECTUR: Ranking mundial de turismo internacional (2018). https://www.datatur.sectur.gob.mx/SitePages/RankingOMT.aspx
19. Shani, G., Gunawardana, A.: Evaluating Recommendation Systems, pp. 257–297. Springer, US, Boston, MA (2011). https://doi.org/10.1007/978-0-387-85820-3_8
20. Shen, J., Deng, C., Gao, X.: Attraction recommendation: towards personalized tourism via collective intelligence. Neurocomputing **173**, 789–798 (2016)
21. UNWTO: Unwto world tourism barometer and statistical annex, UNWTO World Tourism Barometer **18**(1), 1–48 (2020)
22. Vu, H.Q., Li, G., Law, R., Zhang, Y.: Exploring tourist dining preferences based on restaurant reviews. J. Travel Res. **58**(1), 149–167 (2019)
23. Welle, D.: El impacto al turismo arrastrará a la economía mexicana. (2020). https://www.dw.com/es/el-impacto-al-turismo-arrastra-a-la-econom%C3%ADa-mexicana/a-53137428
24. Xiong, H., Zhou, Y., Hu, C., Wei, X., Li, L.: A novel recommendation algorithm frame for tourist spots based on multi-clustering bipartite graphs. In: 2017 IEEE 2nd International Conference on Cloud Computing and Big Data Analysis (ICCCBDA), pp. 276–282. IEEE (2017)
25. Yochum, P., Chang, L., Gu, T., Zhu, M.: Linked open data in location-based recommendation system on tourism domain: a survey. IEEE Access **8**, 16409–16439 (2020). https://doi.org/10.1109/ACCESS.2020.2967120