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Towards Context Integration in Content Based Recommender System for Smart Tourism

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Abstract

Recommendation systems (RS) are now essential in various sectors of daily life, especially in tourism, where they assist tourists in making better choices about which points of interest (POIs) to visit. However, these RSs face a number of challenges, including the risk of a cold start when a new POI is taken into account, and the problem of tourist dissatisfaction with recommended POIs. To address these issues, we focused on Content-Based Recommendation Systems (CBRS) that mitigate the problem of data sparsity and integrate contextual information from tourists during their visits. In this paper, we refined tourist feedbacks using contextual variables like "time" and "companion" during the visit. Next, we implemented a CBRS using the vector representation of POIs with the Term Frequency/Inverse Term Frequency (TF/IDF) method to compute similarity between tourist profiles and POI characteristics. With this type of similarity, our system can run three variants of CBRS in parallel: the first ignores the tourist context, the second incorporates the "temporal context", and the third takes into account the "companion context". Finally, to compare these three recommendation variants, we used an online evaluation to calculate the Click Through Rate (CTR) metric. According to our initial experiments, the CBRS with the integration of temporal context outperforms the other two implemented RS.

Keywords: Recommender system; Content-based, context integration, Contextual pre-filtering, TF/IDF, Acceptation rat.

1. Introduction

With information overload, it is very hard for tourists to find the information that interests them. Similarly, tourism operators are also finding it difficult to promote their various travel offers. This is why many researchers and companies are developing recommendation systems (RS) to (1) help tourists find the points of interest (POIs) that are useful for them and (2) personalise the tourism products to be promoted by travel agencies.

Different techniques are used by RSs to formulate recommendations. The most popular are content-based recommendation methods and collaborative filtering methods. The latter use the scores provided by the user to evaluate an element. These scores are used to compute tourists' similarities [1]. Content-based methods work with information related to POIs (POI description, its categories or the keywords that characterise it) [2]. Both techniques are sensitive to the problems of cold start and data sparsity [3], which are linked to the dynamic nature of RSs (the addition of some new items, the arrival of a new user or the lack of feedback from a user on an item). Hybrid recommender systems are very effective in solving these problems, as they use the strengths of the other recommendations methods and generally give better results [4]. In contrast, CBRSs categorise new POIs based on their descriptions, while collaborative filtering recommender systems (CFRS) mandate at least one tourist's explicit evaluation of the added POI to involve them in the recommendation process. As a result, CBRS seems to better mitigate the sparsity and cold start problems. However, tourists' preferences may vary according to their contexts, such as the device used (PC or Smartphone), location, time, companion, etc. [5]. To solve these problems, we propose in this paper a modest approach that uses several CBRS and incorporates the evolving tourists' context. As a result, this approach offers tourists three different recommendation variants simultaneously and incrementally. The first variant relies solely on the content of POIs while disregarding the tourists' context. The second is a Context CBRS that incorporates the temporal context of the visit. The final variant is also a CBRS but specifically considers the context of the tourist's companion. In order to run these three recommendation variants in a parallel manner, we need to answer questions such as: (1) which tags should be used by the three CBRS variants. (2) What context variables should be included in the POI recommendation process? And (3), how should this process be evaluated?

To answer these questions, we developed an approach based on the annotation of POIs using tags (keywords). Then we adapted the TF/IDF method to our case of tourism recommendation by inferring the POI features and the tourist profile. Finally, we integrated the period of the day (time) and the companion as tourist context variables. These two variables are used to filter tourist feedbacks, keeping only those that correspond to the tourist's current situation. This enabled us to develop our three Context Aware Content Based Recommendation Systems (CACBRS). These systems will be evaluated by calculating the click-through rate (CTR) metric.

This paper is organised into five sections: Section 2 presents a synthesis of related works about contextual CBRS in the field of tourism. This section is also devoted to describe our contributions that concern the development of a context aware CBRS (CACBRS) prototype. Section 3 provides an elaboration of the results obtained from the experiments and their subsequent discussion. Finally, section 4 summarises the work achieved in this article and provides some perspectives for improving this work.

2. Materials and methods

2.1. Related works

The basic idea of a CBRS is to recommend POIs that are similar to what the tourist has previously enjoyed [6].

However, there are various methods for item modelling, with the Vector Space Model (VSM) [7] being the most renowned. VSM extracts item keywords from their descriptions and assigns keyword weights using the TF-IDF method, which calculates the weight for each term based on its significance in a document. Simultaneously, it inversely weights these terms according to their frequency across the entire dataset. As a result, each item can be described using TF-IDF weights. The user's profile is inferred using a feature weight vector, indicating the user's interest in these features [6].

Using keywords to model this type of profile is a complex problem for many RSs. To solve this problem, there are two main approaches: the first relies on tourism experts to tag POIs [8], while the second gives tourists the opportunity to annotate each POI according to their views [9]. After tagging the POIs, the recommendation process can be carried out using the tags and keywords collected; this process suggests similar POIs to those previously enjoyed by the tourist. Then it establishes an ordered list of these POIs by calculating the similarity between the profile of a given tourist, represented by his preferences, and the set of characteristics of each POI. This calculation uses a vector representation of the characteristics of each POI and the profiles of each tourist.

To implement the POI prediction process, CBRSs use three distinct components [6]: (a) the content analyser to represent the POIs, (b) The profile learner, which gathers information reflecting the user's tendencies by building his profile [10] and (c) the filtering module, which recommends useful POIs calculated from the match between the POI description and the user's profile.

Traditional CBRS employs entries like <userId, itemId, givenRating> to make predictions of POI ratings. This type of system ignores information about the tourist's evaluation context, making the process of recommending POIs to unreliable and less accurate. To deal with this situation, CACBRSs use context information representing the state in which the tourist has rated a given POI using data records like <userId, itemID, context, givenRating>. Context can encompass information regarding the situation of a place, person, or object that holds relevance for the relationship between the user and the application [11]. Consequently, the tourist context may include the visit time, the tourist's position, network capacities (bandwidth, coverage, etc.), the type of tourist (alone, with a partner, or with the family), the weather, and so on. However, collecting contextual information generates a significant volume of data and poses problems when it comes to determining the most relevant rating for a given POI. To solve this problem, three types of visit history filtering can be used in the contextual POI recommendation process: (1) pre-filtering, (2) post-filtering, and (3) contextual modelling [12]. In pre-filtering, the current context information related to a tourist's experiences is employed to extract relevant evaluations before the beginning of the recommendation process. In contrast to this type of filtering, contextual post-filtering uses this information about a tourist's context to filter relevant predictions at the end of the POI recommendation process. Contextual modelling uses this same contextual information during the visit to refine the tourist's profile and deduce increasingly personalised recommendations [12].

In the field of tourism, it is not always possible to have a complete list of a tourist's preferences because these are constantly evolving and are closely linked to the actual context of the visit. Consequently, the three approaches described above quickly find their strengths. Consequently, the use of automatic inference of tourist profiles with contextual support would be more effective because it records and examines tourists' actions throughout their visit to obtain an objective opinion [2]. Based on this type of profile, CBRSs are able to recommend travel plans, travel packages, group choices and destinations (POIs) to discover [13]. In our article, we are interested in works that recommend POIs using the implicit tourists profiles calculated when they visit. These works use mobile applications because they allow tourists to check in using GPS locations and evaluations at the time of the visit.

According to the literature, content-based methods are more prevalent in tourism, due to their ability to restrict the POI search field by considering similarities between visitors and POIs. In the following, we have compared our approach to existing works in the tourism domain considering the (1) context variable employed, (2) the use of the interactive map, (3) the description of POIs with tags, and (4) the type of evaluation of the POI recommendation process (see Table 1). The existing works in the tourism works studied in this paper are as follow:

Malet is a mobile application for local tourism that uses APIs to provide recommendations for tourist attractions with the tourist's context integration: weather, location and time. This application encourages users to explore more places by providing relevant information and a map interface to visualise this contextual data. It also aims to enhance the tourist experience by using contextual information to provide personalised recommendations [14].

The authors in [15] present a tourism RS that provides personalised recommendations based on the user's preferences and contextual information that is represented by an ontological approach. This system uses a propagation activation technique to dynamically adapt recommendations to the user's profile, taking into account his preferences and contextual constraints.

Del *et al.* [16] propose a development framework to generate contextual recommendation for mobile users. This project proposes a generic recommendation architecture that is extensible and adaptable to the specific needs of different domains. This approach offers a demand-based recommendation module, this project cover pre-filtering, post-filtering, and contextual modelling paradigms.

Splsis is a web mapping application that uses semantic technologies (ontology) to recommend targeted offers to user groups based on their geographical context. It also integrates content-based recommendations, taking into account user preferences. This contextual approach enhances the user experience by providing relevant geographic information and personalised offers. This project improves user satisfaction by combining contextual aspects with content characteristics [17].

The "ReRex" application provides contextual POI recommendations to mobile users. Contextual information can be inferred, such as distance to POI, season, weather and time, or explicitly provided by the tourist, such as mood, budget, and means of transport. This application generates a list of POI recommendations, which are displayed in text format with a description or displayed on maps [18].

"LiveCities" uses geolocation to send personalised notifications to users, providing POI information and activity suggestions in real time based on the user's context. Notifications can include text, audio, video, or links to external sites. LiveCities aims to personalise the tourism experience by minimising device interactions based on user profile and geographical context to improve tourist satisfaction [19].

PSiS is designed for mobile devices. It recommends POIs using content-based filtering algorithms by integrating user information such as location and weather during the visit. The application requires a connection and thus offers personalised recommendations along the way [20].

In what follows, Table 1 classifies the applications mentioned above according to the parameters that characterise their use in the field of tourism.

Table 1
Context-based CBRS applications for tourism

Smart tourism CARS	Context integration	Evaluation type	Map interaction	Using POI tags
MAELT [14]	Time, Location, weather	Empiric evaluation	Yes	No
[15]	distance to POIs, time, and weather information	Empiric evaluation	Yes	Yes
[16]	User location, social media data	Empiric evaluation	Yes	Yes
SPLIS[17]	Time, Location, weather	user evaluation	Yes	Yes
ReRex[18]	Time, weather, companion	User evaluation	Yes	Yes
LiveCities[19]	Location, social	User Experience	Yes	No
PSiS[20]	Time , weather	Empiric evaluation	Yes	No
Our Approach	Time, companion	Online evaluation	Yes	Yes

The work mentioned above still faces several challenges, including issues like data sparsity and cold start problems. Hybrid recommendation systems, therefore, present an interesting solution for addressing these issues, especially within the tourism sector.

2.2. Contribution

Our objective was to develop a website prototype, which permit to assist a tourist in his discovery of Chlef city, thanks to personalised recommendations of POIs. Our prototype is based on hybrid RS that combines the results of three CBRSs launched in parallel during the tourist's visit: the first system does not take into account the tourist's context, while the 2nd and 3rd systems are based on pre-filtering of the "Companion" and "Time" contexts, respectively. Our contribution is composed by two parts: (1) pre-filtering with context and (2) content-based recommendation.

2.2.1. Pre-filtering with context

The context variables we have used are the "time" variable, which is a context variable obtained implicitly and the "companion" variable, which is obtained explicitly. The values of these context variables are described in Table 2.

Table 2
Context variables used for the tourist (user) profile.

Context Variables	Variable values	Variable tests	Context type
Time	Early Morning	01 :00 <= Time <=0 5:59	Inferred (implicit)
	Morning	06 :00 <= Time <=11 :59	
	Afternoon	12 :00 <= Time <=17 :59	
	Evening	18 :00 <= Time <=00 :59	
Companion	Alone, with family, with friend	Alone, with family, with friend	Declared (explicit)

The pre-filtering phase with context according to the "time" and "companion" variables is carried out using algorithm I below. We then run three RSs: (1) CBRS without context, (2) CBRS with the "time" context and (3) CBRS with the "companion" context. The results of these RSs can be combined by displaying them on a map that can be accessed on demand by any online tourist.

Algorithm1 RSPersCBContextPref (LPOI, RatPOI, User Id)

Input: LPOI: list of POI's
N1, N2, N3: The number of POI returned by each RS.
RatPOI: Rating values given by user for POI's
UserId:Id ot he active user
Output: Rec_POI: Recommendation results with POI's and id RS that recommend this POI.
1: C1_Ctxt_Comp = Retrieve Companion context
2: C2_Ctxt_Time = Retrieve Time context
3: Pref_RuPOI2 = Pre-filtering (RatPOI , C1_Ctxt_Comp) ;
4: Pref_RuPOI3 = Pre-filtering (RatPOI , C2_Ctxt_Time) ;
5: R1 = **Rec_TFIDF_Cosin** (LPOI, RatPOI, UserId, N1)
6: R2 = **Rec_TFIDF_Cosin** (LPOI, Pref_RuPOI2, User Id, N2)
7: R3 = **Rec_TFIDF_Cosin** (LPOI, Pref_RuPOI3, User Id, N3)
8: Rec_POI=Concatenate(R1, RS1, R2, RS2, R3, RS3)
9 : **Return** Rec_POI

2.2.2. Content-based recommendation

To implement our system, we follow the steps outlined below: (a) Data selection, (b) Data encoding, and (c) Content recommendation.

2.2.2.1. Data selection

In this step, we determine the data sets to be used by our system to provide POI recommendation. We have selected the most significant POI for nomadic tourists, based on markers previously established by tourist operators in the region we are exploring. We used UML language to describe the data structure about User, POI, tags and feedback (see Figure 1).

The Feedback class contains context information in the form of two context variables: "time" and "companion".

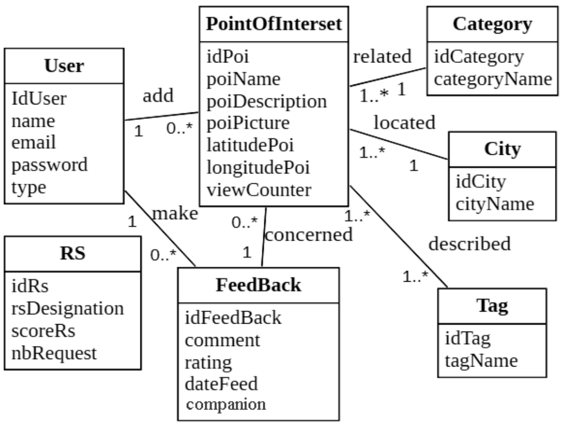

Figure 1: Class diagram modelling the data in our system

2.2.2.2. Data encoding

We used the encoding technique (TF-IDF) to represent our data in the form of feature vectors. TF-IDF expresses the calculation of the importance of a term in a document compared to a collection of documents. This technique favours frequent terms in a document while penalising frequent terms in the collection as a whole, thus making it possible to find key terms specific to a document.

This concept is used by document search methods and in our case of content-based POI recommendation, we will be looking at the importance of keywords (terms) in the description of POIs (documents). TF is the occurrence rate of the term ti inside the POIj description. With stop-words discarded, the higher the frequency of the term "ti" within the description of a POI, the greater its perceived relevance to that particular POI. TF is defined by formula (1).

$$TF(t_i,POI_j)=\frac{NC\ (t_i,POI_j)}{NT\ (POI_j)} \qquad (1)$$

With:

NC (t_i, POI_j)*:* The occurrence number of the term *"ti"* in the POI_j description.
NT (POI_j)*:* The number of terms in the description of the POI_j.

IDF is a metric used to assess the significance of a term based on its rarity within a collection of documents (POIs). The less common a term is within the collection, the higher its IDF value, signifying its greater importance in information retrieval (POI). This is because it can effectively distinguish between various documents (POIs). The IDF is calculated using formula (2) as follows:

$$IDF(t_i)=log\,\frac{N(POI)}{Nb(t_i)} \qquad (2)$$

With:
N (*POI*)*:* The total number of POIs in the dataset.
Nb (t_i)*:* The number of occurrences of the term *"t_i"* in all POIs descriptions.

The TF-IDF is computed using Formula 3 [21]. A higher TF-IDF value indicates that the term "ti" is more relevant in the description of POIj.

$$TF-IDF(t_i,POI_j) = TF(t_i,POI_j) \times IDF(t_i) \qquad (3)$$

Where
$TF(t_i,POI_j)$ is defined by the formula (1).
$IDF(t_i)$ is defined by the formula (2).

In content-based recommendation, we compute TF/IDF values for each POI. Afterward, we measure the similarity between two POIs vectors, denoted as $P = (p_1,p_2,\ldots,p_m)$, and $Q = (q_1,q_2,\ldots,q_m)$, using their TF/IDF values. In the literature, various similarity measures exist, such as Pearson's coefficient, Euclidean, Jaccard and cosine similarity. In our scenario, we have opted for cosine similarity, which is defined by formula (4) as follows:

$$Cosine\ sim\ (P,Q)=\frac{\sum_{i=1}^{m} p_i\, q_i}{\sqrt{\sum_{i=1}^{m} p_i^2}\sqrt{\sum_{i=1}^{m} q_i^2}} \qquad (4)$$

2.2.2.3. Content recommendation

Once we have computed the probabilities of selecting a set of POIs given by similarity-based methods for the current tourist, the next step is to proceed with the POI features and the tourist profile computation. For this reason, we calculate the prediction of the POI not yet visited by choosing the one with the profile most similar to the profile of the current tourist. Below, we explain the algorithm 2 used to generate content-based recommendations for an active tourist using his notes pre-filtered by the "time" or "companion" context.

Algorithm2 Rec_TFIDF_Cosin (LPOI, RuPOI, UserId,N)

Input:
LPOI: POI's list
RuPOI: POI's rating given by the active user.
UserId: The active user Id
N: The number of POI returned by RS.
Output: L_Rec_POI: Recommendation results with POI's id
1: Df_POI= read LPOI // binary format of tags for all POIs
// Df_POI (POIId | tag1| tag2|….|tag_m) with binary value 0 or 1
2: TF_IDF_matrix = calculate TF-IDF for all POIs According to (3)
// TF_IDF_matrix format (POIId | Tag1| ….|Tag_m) with TF-IDF values
3: Cosin_Sim_Matrix = calculate POI cosine sim with TF_IDF_matrix values according to (4)
// Cosin_Sim_Matrix (POIId1 | POIId2| ….| $POIId_n$) with Cosine values
4: Df_User_Rating = read RuPOI
5: Add column ['Weight'] to Df_User_Rating matrix.
// Df_User_Rating (POIID, Rating,Weight)
6: **For each** row of Df_User_Rating
7: Df_User_Weight = Df_User_Rating /5
8: **End For**
9:TF-IDFUserVisitedPOI = from TF_IDF_matrix get TF-IDF of POI rated by the active user.
10: User_profile = TF-IDFUserVisitedPOI **dot** Df_User_Weight
// User_profile format (Tag1|….|Tag_m) with TF-IDF value
11: TF-IDFUserNotVisitedPOI = from TF_IDF_matrix get TF-IDF of POI's not yet visited by the user with UserId
// **dot** is the product function of two vectors
12: L_Sim_POI = Cosin_sim(TF-IDF_UserNotPOIVisited, User_profile)
// L_Sim_POI format (POIId, CosinSim)
13 : L_Rec_POI = Descending sorting (L_Sim_POI,N)

The Rec_TFIDF_Cosin algorithm is used to generate contextualised tourist profiles that change from one context to another. For example, the profile of an early-morning tourist differs from that of an evening tourist.

3. Results and Discussion

We implemented this system using SQL Lite and the Django Framework. Tourist profiles and features of POIs are characterised by tags that have been expertly defined within the field of tourism. Tourists have the choice to recommend their own tags to improve the current ones. Our site recommends POIs using a content-based approach with TF/IDF encoding in three scenarios: (1) POIs from CBRS that ignore the tourist context, (2) POIs from CBRS that include the "time" context and (3) POIs from CBRS that include the "companion" context.

Then, the choices of POIs made by the tourist during his journey, as well as his comments and evaluations, will be recorded by our system. These informations help to enrich our site and improve the quality of future recommendations. Tourists and tourist guides can update the descriptive tags of POIs.

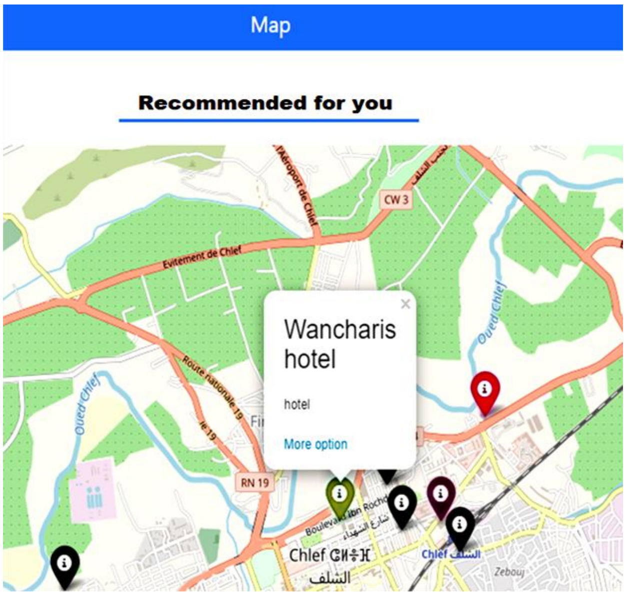

Figure2: POI recommendations results displayed on Map

To test this tool, we invited 30 tourists to visit Chlef city described by 50 POIs. This test phase was carried out over a period of two months. Then, to evaluate the performance of our tool, we carried out an online evaluation of our three approaches, as shown in Figure 2.

This approach uses the click-through rate (CTR) because this parameter is widely used in online evaluations of RSs [22]. In our case, we calculated the CTR using formula 5 below:

$$CTR=\frac{Nb\_Accepted\ \_Rec}{Nb\_Displayed\ \_Rec} \quad (5)$$

Where:

*Nb*_Accepted_Rec is the number of POI recommendations accepted by the tourist.

*Nb*_Displayed _Rec is the number of POI recommendations visible to the tourist.

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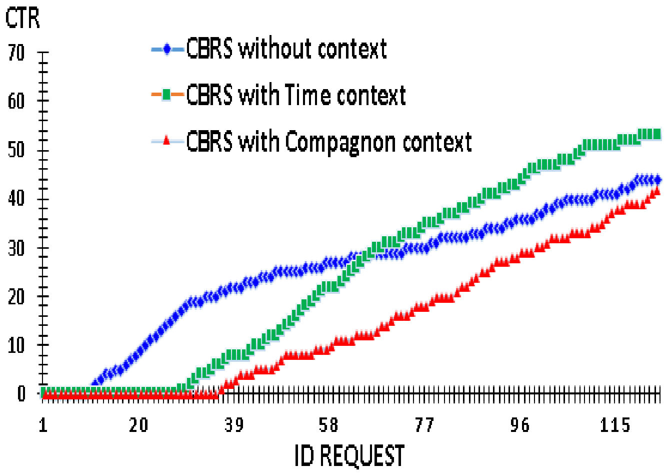

Figure 3: Online evaluation results by CTR metric

Figure 3 above illustrates the results of the CTR metric to compare the three CBRSs that we implemented. From these results, we observe that the cold start problem affects all three systems until query 14, when the CBRS without context starts to give acceptable recommendations for tourists. On the other hand, the CBRS with time context (respectively, CBRS with companion context) gives acceptable recommendations from query 27 (respectively query 35). Figure 3 also shows, using the CTR metric, that CBRS with TF-IDF and time context integration outperforms the two other RSs from query 63 onwards.

4. Conclusion

We have explored in this article, the possibility of adapting the TF-IDF technique for POIs suggesting at the CBRS level. We have also highlighted the contribution of context to improve the quality of the tourist experience, while ensuring that the problems associated with data sparsity and cold start are properly mitigated. Then, we focused on the contribution of our tool to assist the tourists during touristic visits on Chlef city sites. Finally, we used the CTR as an indicator to assess satisfaction with the use of our system by real tourists.

According to the results of our experiment, CBRS based on TF-IDF with the "time" context integration gives better results than the other two recommendations approaches.

In the future, we propose to continue the experimentation campaigns to build a rich data set that will make it possible to exploit the contribution of context to improve tourist satisfaction. We also propose to create other systems that (1) integrate the time and companion contexts at the same time and to take into account other context variables such as the distance between POIs. We also suggest to use (1) the post-filtering context technique and (2) the context modelling method in CBRS process. Finally, we try to create a new CBRS with Latent Dirichlet Allocation (LDA) technique [23] and to develop a system that helps tourists in choosing the most pertinent tags according to their areas of interest.

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Conflicts of interest

The authors declare no conflict of interest.

References

[1] Candillier, L., Jack, K., Fessant, F., & Meyer, F. (2009). State-of-the-art recommender systems. In Collaborative and Social Information Retrieval and Access: Techniques for Improved User Modeling (pp. 1-22). IGI Global.

[2] Pazzani, M. J., & Billsus, D. (2007). Content-based recommendation systems. In The adaptive web: methods and strategies of web personalization (pp. 325-341). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-72079-9_10

[3] Schein, A. I., Popescul, A., Ungar, L. H., & Pennock, D. M. (2002, August). Methods and metrics for cold-start recommendations. In Proceedings of the 25th annual international ACM SIGIR conference on Research and development in information retrieval (pp. 253-260). https://doi.org/10.1145/564376.564421

[4] Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE transactions on knowledge and data engineering*, 17(6), 734-749. https://pages.stern.nyu.edu/~atuzhili/pdf/TKDE-Paper-as-Printed.pdf (Accessed on 12/02/2024)

[5] Van Setten, M., Pokraev, S., & Koolwaaij, J. (2004). Context-aware recommendations in the mobile tourist application COMPASS. In Adaptive Hypermedia and Adaptive Web-Based Systems: Third International Conference, AH 2004, Eindhoven, The Netherlands, August 23-26, 2004. Proceedings 3 (pp. 235-244). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-27780-4_27

[6] Lops, P., De Gemmis, M., & Semeraro, G. (2011). Content-based recommender systems: State of the art and trends. Recommender systems handbook, 73-105. https://doi.org/10.1007/978-0-387-85820-3_3

[7] Baeza-Yates, R., & Ribeiro-Neto, B. (1999). Modern information retrieval (Vol. 463, No. 1999). New York: ACM press. https://web.cs.ucla.edu/~miodrag/cs259-security/baeza-yates99modern.pdf (Accessed on 18/02/2024)

[8] Song, Y., Zhuang, Z., Li, H., Zhao, Q., Li, J., Lee, W. C., & Giles, C. L. (2008, July). Real-time automatic tag recommendation. In Proceedings of the 31st annual international ACM SIGIR conference on Research and development in information retrieval (pp. 515-522). https://doi.org/10.1145/1390334.1390423

[9] Sen, S., Vig, J., & Riedl, J. (2009, April). Tagommenders: connecting users to items through tags. In Proceedings of the 18th international conference on World Wide Web (pp. 671-680). https://doi.org/10.1145/1526709.1526800

[10] Mitchell, T. M. (1997). Machine learning, McGraw-Hill, New York, 1997. Epbook: https://archive.org/details/machinelearning0000mitc/page/n3/mode/2up

[11] Abowd, G. D., Dey, A. K., Brown, P. J., Davies, N., Smith, M., & Steggles, P. (1999). Towards a better understanding of context and context-awareness. In Handheld and Ubiquitous Computing: First International Symposium, HUC'99 Karlsruhe, Germany, September 27-29, 1999 Proceedings 1 (pp. 304-307). Springer Berlin Heidelberg. https://sites.cc.gatech.edu/fce/contexttoolkit/chiws/Dey.pdf

[12] Adomavicius, G., Sankaranarayanan, R., Sen, S., & Tuzhilin, A. (2005). Incorporating contextual information in recommender systems using a multidimensional approach. ACM Transactions on Information systems (TOIS), 23(1), 103-145. https://doi.org/10.1145/1055709.1055714

[13] Bentaleb, A., El Bouzekri El Idrissi, Y., & Ait Lahcen, A. (2021). A review on content based recommender systems in tourism. In International Conference on Digital Technologies and Applications (pp. 527-541). Springer, Cham. https://doi.org/10.1007/978-3-030-73882-2_48

[14] Silva, C. A., Toasa, R., Guevara, J., Martinez, H. D., & Vargas, J. (2018). Mobile application to encourage local tourism with context-aware computing. In Proceedings of the International Conference on Information Technology & Systems (ICITS 2018) (pp. 796-803). Springer International Publishing.

[15] Bahramian, Z., Ali Abbaspour, R., & Claramunt, C. (2017). A context-aware tourism recommender system based on a spreading activation method. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 42, 333-339. https://doi.org/10.5194/isprs-archives-XLII-4-W4-333-2017

[16] M. del Carmen Rodríguez-Hernández, M., & Ilarri, S. (2016). Pull-based recommendations in mobile environments. Computer Standards & Interfaces, 44, 185-204. https://doi.org/10.1016/j.csi.2015.08.002

[17] Viktoratos, I., Tsadiras, A., & Bassiliades, N. (2015). A context-aware web-mapping system for group-targeted offers using semantic technologies. Expert Systems with Applications, 42(9), 4443-4459. https://doi.org/10.1016/j.eswa.2015.01.039

[18] Baltrunas, L., Ludwig, B., Peer, S., & Ricci, F. (2011). Context-aware places of interest recommendations for mobile users. In Design, User Experience, and Usability. Theory, Methods, Tools and Practice: First International Conference, DUXU 2011, Held as Part of HCI International 2011, Orlando, FL, USA, July 9-14, 2011, Proceedings, Part I 1 (pp. 531-540). Springer Berlin Heidelberg.

[19] Martin, D., Alzua, A., & Lamsfus, C. (2011). A contextual geofencing mobile tourism service. In Information and communication technologies in tourism 2011 (pp. 191-202). Springer, Vienna.

[20] Anacleto, R., Figueiredo, L., Luz, N., Almeida, A., & Novais, P. (2011). Recommendation and planning through mobile devices in tourism context. In Ambient Intelligence-Software and Applications: 2nd International Symposium on Ambient

Intelligence (ISAmI 2011) (pp. 133-140). Springer Berlin Heidelberg.

[21] Zhang, W., Yoshida, T., & Tang, X. (2011). A comparative study of TF* IDF, LSI and multi-words for text classification. Expert systems with applications, 38(3), 2758-2765. https://doi.org/10.1016/j.eswa.2010.08.066

[22] Beel, J., Genzmehr, M., Langer, S., Nürnberger, A., & Gipp, B. (2013, October). A comparative analysis of offline and online evaluations and discussion of research paper recommender system evaluation. In Proceedings of the international workshop on reproducibility and replication in recommender systems evaluation (pp. 7-14). https://doi.org/10.1145/2532508.2532511

[23] Uto, M., Louvigné, S., Kato, Y., Ishii, T., & Miyazawa, Y. (2017). Diverse reports recommendation system based on latent Dirichlet allocation. Behaviormetrika, 44, 425-444. https://doi.org/10.1007/s41237-017-0027-7
Erratum to: Behaviormetrika
https://doi.org/10.1007/s41237-017-0029-5