IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Personality Aware Product Recommendation System (RECCOKART)

Mr.Nale Rajesh*, Mr.Ganesh Bobade, Mr.Khomane Rohit **,Mr.Raviraj Mane**,Mr.Patil Umesh****

*(AssistantProfessor, Information Technology, SVPM's College of Engineering Malegaon (bk), Baramati Email: rajesh.nale@gmail.com)

**(UG Students, Information Technology, SVPM's College of Engineering Malegaon(bk), Baramati)

Abstract:

Any modern social networking or online retail platform must have a recommendation system. A product recommendation is basically a filtering system that seeks to predict and show the items that a user would like to purchase. It may not be entirely accurate, but if it shows you what you like then it is doing its job right. As a typical illustration of a legacy recommendation system, the product recommendation system has two significant drawbacks: recommendation repetition and unpredictability about new items (cold start). Because the older recommendation algorithms only use the user's previous purchasing history when making recommendations, these limitations exist. The cold start and recommendation redundancy may be lessened by incorporating the user's social attributes, such as personality traits and areas of interest. In light of this, we present Meta-Interest, a personality- aware product recommendation system built on user interest mining and metapath discovery. The suggested method incorporates the user's personality qualities to forecast his or her themes of interest and to link the user's personality facets with the relevant things, making it personality-aware from two perspectives. The suggested system was evaluated against current recommendation techniques, including session- based and deep-learning-based systems. According to experimental findings, the suggested strategy can improve the recommendation system's memory and precision, particularly in cold-start conditions.

Keywords:; social networks; social computing; user interest mining; user modeling personality computing; product recommendation; recommendation system.

1.INTRODUCTION

A product recommendation is basically a filtering system that seeks to predict and show the items that a user would like to purchase.The product recommendation system as a typical example of the legacy recommendation systems suffers from two major drawbacks:recommendation redundancy and unpredictability concerning new items (coldstart). These limitations take place because the legacy recommendation systems rely only on the users previous buying behaviour to recommend new items. In personality- aware recommendation system, the similarity between the users is computing based on their personality trait similarity or using a hybrid personality-rating similarity measurement, and the resulting set of neighbors are similar in terms of personality traits to the studied user.

AimofProject

The aim of a recommender system is to estimate the utility of a set of objects belonging to a given domain,starting from the information available about users and objects.

1.1 Motivation

To Motivate the users Product recommendation engines analyze data about shoppers to learn exactly what types of products and offerings interest them. Based on search behavior and product preferences, they serve up contextually relevant offers and product options that appeal to individual shoppers — and help drive sales.

1.3 ProjectObjectives

The objective of Personality aware product recommendation system is to provide recommendation based on recorded information on the users buying similarity. Increase performance while working with huge data. Provide 24x7 access system.

1.4Application

A product recommendation is basically a filtering system that seeks to predict and show the items that a user would like to purchase. It may not be entirely accurate, but if it shows you what you like then it is doing its job right.

2.LITERATURESURVEY

Reference No: 1.

Title: Study of E-commerce recommender system based on Big data Publication: Oxbridge college, kunning university Author: Xuesong Zhao Summary: In this paper they In this era of web, they have a huge amount of information overloaded over Internet. It becomes a big task for the user to get the relevant 1 information. To some extent, the problem is being solved by the search engines, but they do not provide the personalization of data.Recommender system algorithms are widely used in e-commerce to provide personalized and more accurate recommendations to online users and enhance the sales and user stickiness of e-commerce. This study aims to build a product recommendation system on ecommerce platform according to user needs.

Reference No: 2

Title: Collaborative Filtering for Recommender Systems Publication: 2014 Second International Conference on Advanced Cloud and Big Data Author: Michael D. Ekstrand, John T. Riedl and Joseph A. Konstan Summary: The report also highlights the discussion of the types of the recommender systems as general and types of CF such as; memory based, model based and hybrid model. In addition, this report discusses how to choose an appropriate type of CF. The evaluation methods of the CF systems are also provided throughout the paper However, there are several limitations for the memory-based CF techniques, such as the fact that the similarity values are based on common items and therefore are unreliable when data are sparse and the common items are therefore few. To achieve better prediction performance and overcome shortcomings of memory-based CF algorithms, model-based CF approaches have been investigated.

Reference No: 3

Title:Content-Based Filtering: Techniques and Applications Publication: 2017 International Conference on Communication, Control, Computing and Electronics Engineering (ICCCCEE) Author: Khartoum, Sudan Summary: Besides collaborative filtering, content-based filtering is another important class of recommender systems. Content-based recommender systems make recommendations by analysing the content of textual information and finding regularities in the content. The major difference between CF and content-based recommender systems is that CF only uses the user-item ratings data to make predictions and recommendations, while content-based recommender systems rely on the features of users and items for predictions. Both content-based recommender systems and CF systems have limitations. While CF systems do not explicitly incorporate feature information, content-based systems do not necessarily incorporate the information in preference similarity across individuals. collaborative filtering models which are based on assumption that people like things similar to other things they like, and things that are liked by other people with similar taste.

Reference No: 4

Title: Automatiic Personality Recognition of Authors using Big Five Factor model Publication: Jacques Author: k. Pramodh, Y. Vijayalata Summary: The paper focuses on an approach developed to recognize the personality of the author by evaluating their writings. The score for each of the Big-Five personality traits is computed programmatically.

3.SYSTEMARCHITECTURE:

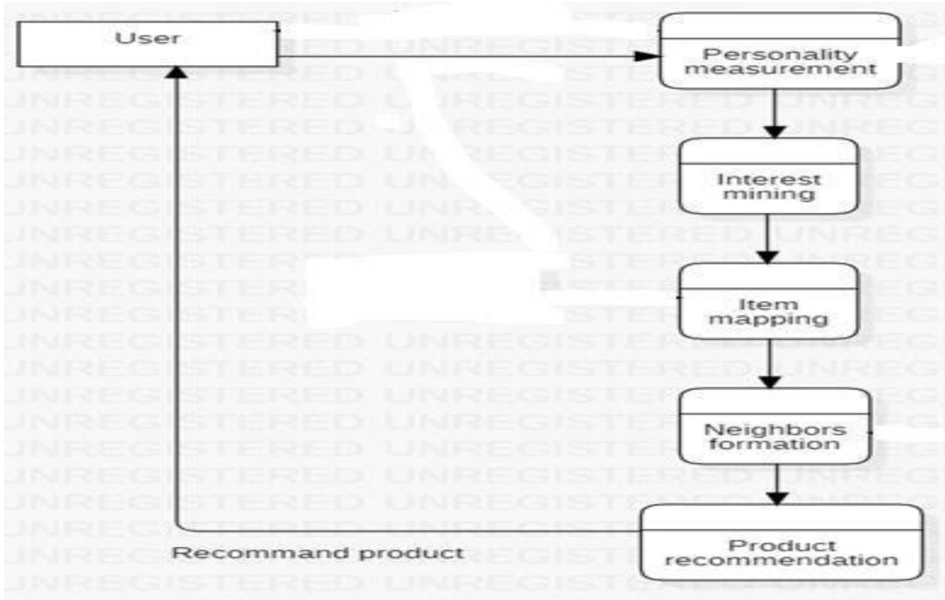
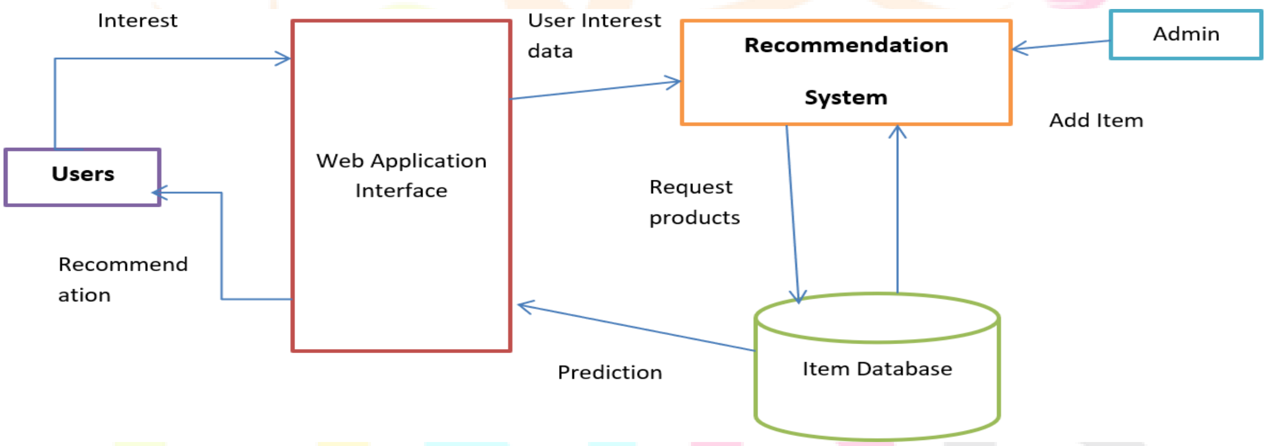


Fig. Meta-interest recommendations process.



In this section, we will present the theoretical framework of the proposed system. The purpose of Meta- Interest is to recommend the most relevant items by detecting the user's topical interests from its social networking data. Fig. 1 shows the general system framework of Meta-Interest. The recommendation process includes five steps. Step 1 is the personality traits' measurement, which can be obtained by asking the user to take a personality measurement questionnaire or using automatic personality recognition by analyzing the subject's social network data. The personality measurement phase is the only static part of the system, which isbecause personality traits have been proven to be relatively stable over time. Step 2 is mining the user's topicalinterests, including explicit and implicit interest mining. Explicit interest mining is performed by analyzing the text shared by the user in social networks in order to detect keywords that reflect its topical interests. Implicit interest mining involves a more complex analysis of the social network structure and other latent factors that may influence the user's topical interests. In Step 3, Meta-Interest matches the items with the corresponding topics. The matching is in the form of a many-to-many relationship that is to say that a topic might be related to many items. Similarly, an item might be related to more than one topic. In Step 4, the set of most similar users (neighbors) to the subject user is determined. In this context, Meta-Interest uses three similarity measures, personality similarity, viewing/buying/rating similarity, and common interest similarity. Finally, Step 5 is the item recommendation phase, and the recommendation is refined by updating theneighbors' set and the user's topical interest profile and topics–items matching.

Big-Five Personality Traits

The big five personality traits constitute a unique combination of an individual's behaviour, preferences and mannerisms. It can influence their friendships, relationships, hobbies and careers. Psychologists use objective tests and projective measures to break down an individual's personality into different components. Objective measures use self-reporting tests and tools, where an individual responds to a series of queries in a questionnaire. Projective measures use psychoanalytic theories that reveal inner aspects of an individual's personality. The big five tests or the five-factor model uses questionnaires and tests to rank the following five traits that can affect an individual's behavior and attributes:

Openness: If you score highly on openness, you are likely to prefer new, exciting situations. You value knowledge, and friends and family are likely to describe you as curious and intellectual.

Conscientiousness: If you're a conscientious person, you have a lot of self-discipline and exceed others' expectations. You have a strong focus and prefer order and planned activities over spontaneity.

Extroversion: Extroverts thrive in social situations. If you have a high score in extroversion, you are action- oriented and appreciate the opportunity to work with others.

Agreeableness: A high score in agreeableness shows that you're considerate, kind and sympathetic to others. As an agreeable person, friends and colleagues likely seek you out to participate in group activities since you're adept at compromise and helping others.

Neuroticism: Although this measure typically indicates anxiety and pessimism, some tests focus on low scores, which researchers call emotional stability. This measure can mean you have a more hopeful view of your circumstances.

Representation Model:

Let U = {u1, u2,..., un} be the set of users, T = {t1,t2,...,tm} the set of topics, and P = {p1, p2,..., pk} the set of all items. The system is modeled as a heterogenous graph that consists of three subgraphs G = (GU , GT , GP), GU =(Vu, Eu) is undirected graph where its node set Vu is the users set U, and the edges set Eu represents the similarity relationship between users. In addition to online behaviors similarity, such as posting and follower/followed similarities, the personality traits' similarity between users is also considered to compute the overall similarity between users. Similarly, the graphs GT = (Vt, Et) and GP = (Vp, Ep) represent the nodes and relationship between topics and items, respectively. The users' graph GU = (Vu, Eu) is constructed by measuring the similarity between its vertices. In this regard, we consider three types of similarities: topic interest similarity, product interest similarity, and personality traits' similarity, which we denote as SimT, SimI, and SimP, respectively.

3.1 ALGORITHM

Interest Mining:

The main advantage of our approach is that the proposed system makes use of the user's interests along with the user's personality information to optimize the accuracy of system recommendations and alleviate the cold-start effects. By analyzing the user's social network posted data, we can infer his/her topical interests. The task can be achieved by applying automatic topic extraction techniques.

Algorithm 1 Interest_mining
Input ux,sx, Fx Output Ix 1: if (sx > CS) then
2: Semantic_Annotation(sx)
3: Topics_Extraction(sx)
4: else
5: for f ∈ Fx do
6: Ix ← Ix ∪{Personality_facet_topics(f)} 7: end for
8: end if

The pseudocode shown in Algorithm 1 presents the steps of Interest Mining.

Item Mapping:

After populating the topics public space using ODP ontology categories, the items are matched with these topics. Each item is associated with one or more topics and, subsequently, recommended for users that have these topics within their topical interests. With newly added items that have not been viewed by any user, the item is directly associated with the corresponding topic category in ODP ontology, whereas items that have passed the cold-start phase are associated with the interest of those that are related to the personality facets that are shared among the users who bought this item.

Algorithm 2 Item_mapping
Input pz,Upz Output Ipz 1: if (views(pz)>CS) then 2: Ipz ← OPD_Topics(pz) 3: else
4: for f ∈ Fx and ux ∈Upz do
5: if (|uy, f ∈ Fy|> |Upz| 2) then
6: Ipz ← Ipz ∪{Personality_facet_topics(f)} 7: end if
8: end for
9: end if

The pseudocode shown in Algorithm 2 presents the steps of Item Mapping.

Meta Path Discovery:

After building the users–topics–items heterogeneous graph G = (GU , GT , GP) that incorporates the users, topics, and items subgraphs and their interrelationships. At this stage, the objective is to predict for a given user the N-most recommended items that match his/her topical interests and previous buying/viewing behaviors. Predicting the users' recommended items is formulated as a graph-based link prediction problem.

Algorithm 3 DiscoverMetaPaths
Input us,lmax,ε Output FNL 1: VIST←Ø
2: P ←Ø
3: FNL←Ø
4: for i =1 tolmax do
5: if (i =1) then
6: VIST← VIST∪{us}
7: for NGB∈ us do
8: P ← P ∪{us → NGB}
9: VIST← VIST∪{NGB}
10: end for
11: else
12: TEMP←Ø
13: for CURN ∈ P do 14: NODE← pc[i]
15: if (NODE=item) and (wpc >ε) then 16: FNL← FNL∪{pc}
17: end if
18: if (NODE−VIST =Ø) then

for NGB∈ NODE−VIST do
TEMP← TEMP∪{CURN → NGB}
VIST← VIST∪{NGB}
end for
end if
P ← P −CURN
end for
P ← TEMP
end if
end for

The pseudocode shown in Algorithm 3 presents the steps of metapath discovery.

Algorithm 4 Recommend Products

Input us,ls Output R
R ←Ø
if (CS(us)) then
for t ∈ Is do
PR← Product_interest(t)
R ← R∪ PR
end for
else
P = DiscoverMetaPath(us)
IP= InterestPaths(P)
FP= FriendPaths(P)
CP=ContentPaths(P)
RecPaths = TopNPaths(IP∩ FP ∩ CP, FP ∩ CP,CP ∩ IP)
for Path∈ RecPaths do
PR← Path[lastnode]
R ← R∪ PR
end for
end if

The pseudocode shown in Algorithm 4 presents the steps of Product Recommendation.

3.2 User And Admin Interface Design:-

Figure : Admin Side.

Figure : User Side.

RESULTS

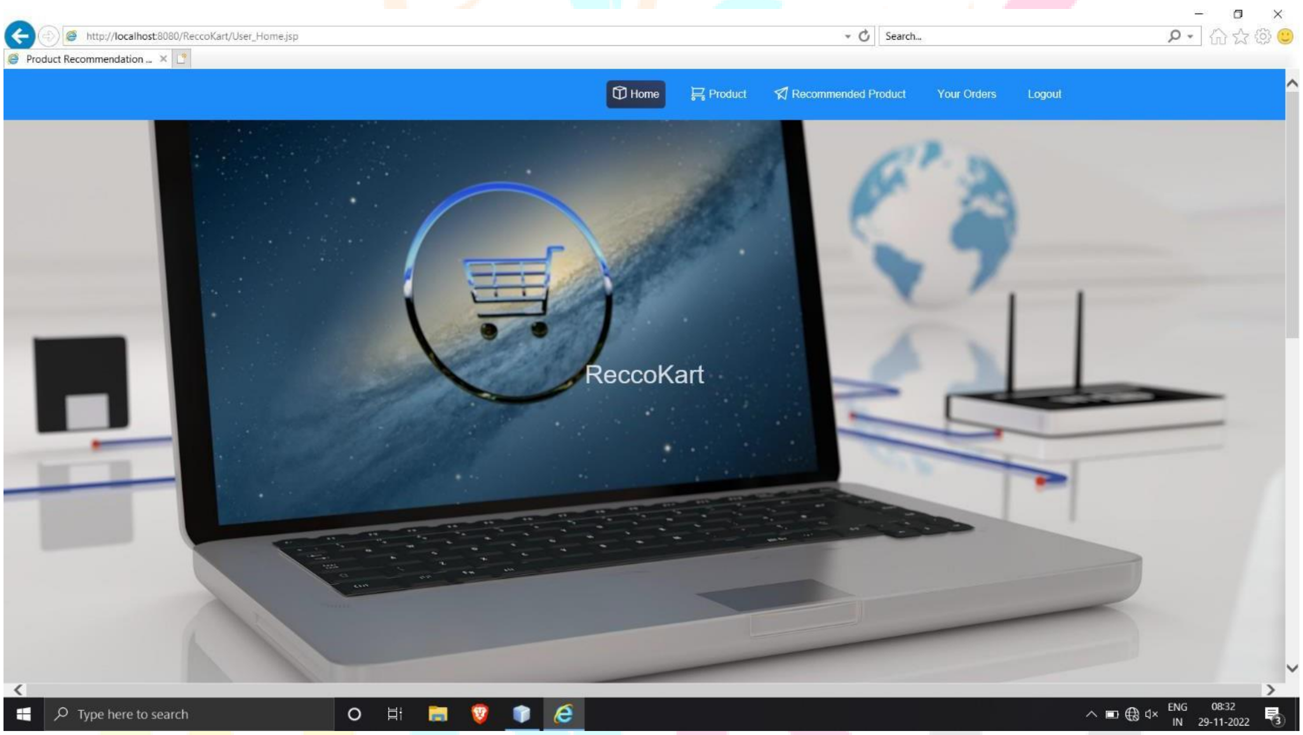
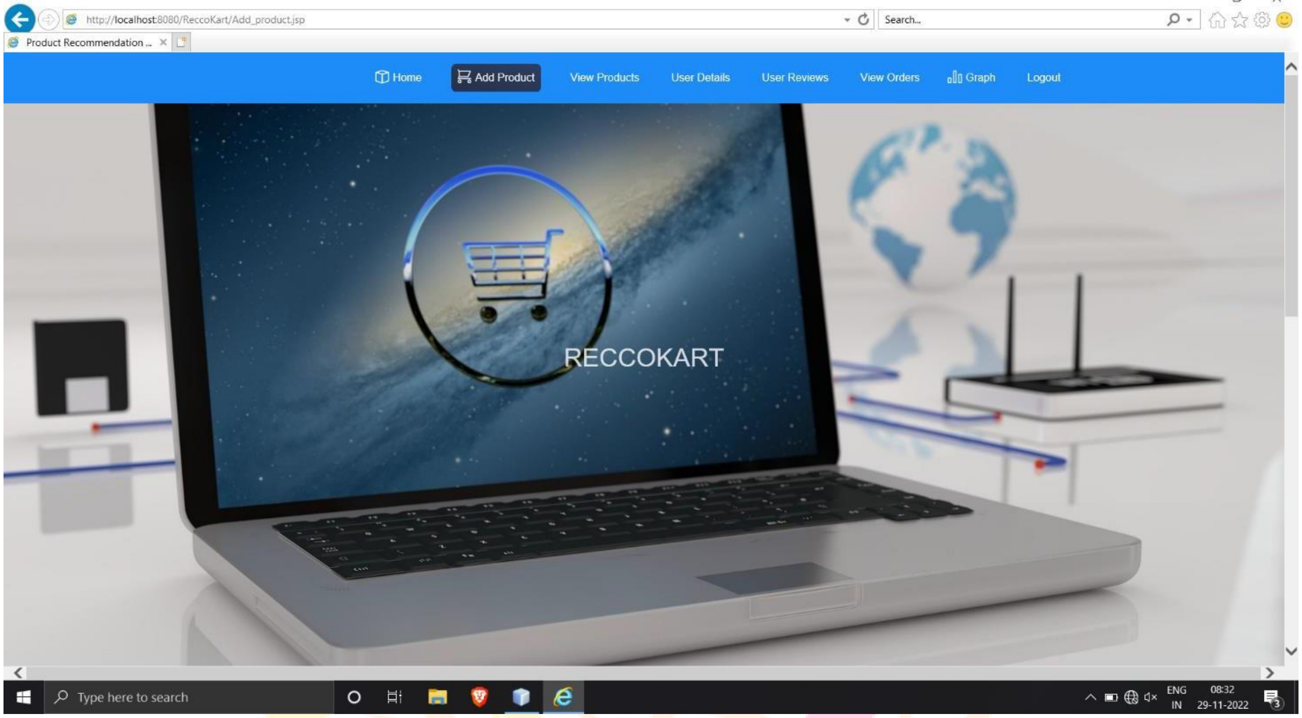


Fig 1 : User Home Page

Description: In the figure 1 Homepage , there are 2 modules ,one is user and other is admin. Admin Loginwith the authorized



user id and password.

Fig.2 Admin Page

Description: In the figure 2, After successful login the admin can add Domain, add Products, Viewall Recommended posts, View all user reviews, View Post's rank results view user's search history and view all recommended Posts.

4.CONCLUSION

In this paper, we propose a personality-aware product recommendation system based on interest mining and meta route discovery, which predicts the user's wants and the related objects. The suggestion of products is calculated by examining the user's subject interests and then recommending the goods related to those interests. The proposed system is personality-aware in two ways: first, it uses the user's personality features to forecast his interests in topics; and second, it links the user's personality facets with the things that are connected with those facets. The suggested approach outperforms state-of-the-art systems in terms of precision and recall, particularly during the cold-start phase for new items and users, as per experimental results. However, Meta-Interest could be improved in different aspects.

5.REFERENCES

[1] http://link. springer.com/10.1007/s11257-018-9207-8

[2] G. Piao and J. G. Breslin, "Inferring user interests in microblogging social networks: A survey," User Model. User-Adapted Interact., vol. 28, no. 3, pp. 277–329, Aug. 2018. [Online]. Available: http://link. springer.com/10.1007/s11257-018-9207-8

[3] A. Vinciarelli and G. Mohammadi, "A survey of personality computing," IEEE Trans. Affect. Comput., vol. 5, no. 3, pp. 273–291, Jul. 2014. [Online]. Available: http://ieeexplore.ieee.org/ document/6834774/

[4] V. Martínez, F. Berzal, and J.-C. Cubero, "A survey of link prediction in complex networks," ACM Comput. Surv., vol. 49, no. 4, pp. 1–33, Feb. 2017.

[5] H.-C. Yang and Z.-R. Huang, "Mining personality traits from social messages for game recommender systems," Knowl.-Based Syst., vol. 165, pp. 157–168, Feb. 2019. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S095070511830577X

[6] W. Wu, L. Chen, and Y. Zhao, "Personalizing recommendation diversity based on user personality," User Model. User-Adapted Interact., vol. 28, no. 3, pp. 237–276, Aug. 2018.

6.BIBILIOGRAPHY

[1]G. Piao and J. G. Breslin, "Inferring user interests in microblogging social networks: A survey," User Model. User-Adapted Interact., *vol. 28.*

[2] Vinciarelli and G. Mohammadi, "A survey of personality computing," IEEE Trans. Affect. Comput., *vol. 5, no. 3, pp. 273–291, Jul. 2014.*[Online]. Avail- able: http://ieeexplore.ieee.org/ document/6834774/.

[3]L. Sebastia, I. Garc ´ıa, E. Onaindia, and C. Guzman Alvarez, ´e-Tourism: A tourist recommendation and planning application, International Journal on Artificial Intelligence Tools, vol. 18, no. 5, pp. 717–738, 2009.

[4]F. Ricci, L. Rokach, and B. Shapira, Introduction to recommender systems handbook, in Recommender Systems Handbook, F. Ricci, L. Rokach, B. Shapira, and P. Kantor, eds. Boston, MA, USA: Springer, 2011, pp. 1–35.

[5]G. Adomavicius and A. Tuzhilin, Toward the next generation of recommender systems: A survey of the stateof-the-art and possible extensions, IEEE Trans- actions on Knowledge and Data Engineering, vol. 17, no. 6, pp. 734– 749.