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ADVANCED MULTI RECOMMENDER SYSTEM FOR ONLINE TOURISM USING AI METHODS

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ABSTRACT: Route schema is difficult to plan for tourist to demand pick points of interest (POI) in unknown areas that align with their preferences and limitations novel personalized method for POI route recommendation that employs contextual data. The research utilizes ambient intelligence technology to regulate the response visualized in serious game scenarios. The work uses the Multi-Criteria Recommender System (MCRS) to produce recommendations for selecting tourist destinations is reference for selecting scenario visualizations. Many researches is developed different kinds of recommendation system to solve number of tourism related problems. Important attributes of recommender systems are discussedmany design guidelines. Some widely recognised methodologies is examined. Lastly movie recommenders of the three most relevant domain movies, music, and e-commerce, are introduced. Machine learning algorithms is take in large datasets to generate personalized recommendations and continuously improve their effectiveness in corpora ting new data and user feedback.The recently introduced Weighted Extended Jaccard Similarity (WEJS). is employed for the first time within a recommender algorithm. We incorporate our algorithm within a realto available at Google Play, tour-planning mobile application for short-term visitors of the popular touristic. We propose a real-time recommendation system for tourism (R2Tour) that responds to changing situations in real timeto external factors and distance information and recommends customized tourist destinations according to the type of tourist. The values of precision and recall and F-measure are calculated and the results discussed in terms of improved accuracy and response time significantly better than the traditional approaches.

INDEX TERMS: Self preference, collaborative filtering; potential preferences; mixed recommendation; multi-objective optimization,Systems, Collaborative Filtering, Ontology, Hybrid Systems.

1. INTRODUCTION

Recommendation system is defined as an information filtering system that is used to recommend the users items based on their previous history or their preferences [1].With the advent of the information age data has become a decisive factor in the development of the industry, and any decision needs to rely on data to speak. In the face of massive data resources storing them in the cloud to form cloud data that is easy to manage is beneficial for users to access relevant information [2].A serious game in the tourism sector is a promotional medium for developers to introduce their tourist destination brand to increase tourist arrivals to tourist destinations [3]. Its implementation for tourism sector is increase players knowledge and travel experience as potential tourists. Conventional Collaborative Filtering (CF) methods provide suggestions relying on the travel habits of users who are acted in the same way as targeted tourists [4]. In real-world applicationsuser may differ implying to most contemporary symmetric techniques yield lower precise findings [5]. Travel planning and guidebook applications and tourism recommendation services which are tourism service tools for FIT to advantages such as improved customer experiences time and cost savings data analysis and marketing utilization [6]. Finally CB algorithm is combined with a Bayesian Inference component that is responsible for building a user model via a lightweight Bayesian elicitation process that asks the user to rate generic images [7]. Set of generic POI items corresponding to the user preferences captured by the Bayesian component are fed into the CB algorithm that eventually recommends the actual POIs is most similar to the constructed user model [8].In supervised machine learning techniques two types of data sets are required training dataset and test data set. An automatic classifier learns the classification factors of the document from the training set, and the accuracy in classification is evaluated using the test set[9].

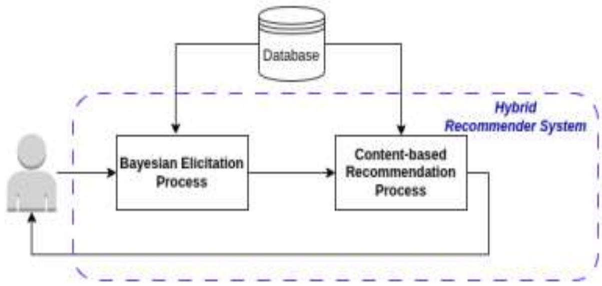

Figure1: The high-level structure of our content baed Recommender System

2. RELATED WORK

Tourism service tools include a CF method that recommends tourist destinations according to the relevance to tourists and a CB method that recommends tourist destinations to the relevance of tourist destinations [10]. As it is difficult to handle the size of the required data and the cold start problem research is being conducted to recommend tourist destinations based on tourism patterns using AI [11]. Introduction the cold-start problem refers to the inability of such algorithms to

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make recommendations and personalized relevant to users preferencesis lack of ratings in dealing with new users and items-torecommend this problem [12]. User-based collaborative filtering to recommendations based on the similarities many users while item-based collaborative filtering generates recommendations based on the similarities between items [13]. The findings of this analysis indicate that use preferences and various forms of heuristics were derived by the proposed model to find the total usefulness of the POI recommendation to the target user in the currentcontextual position [14].

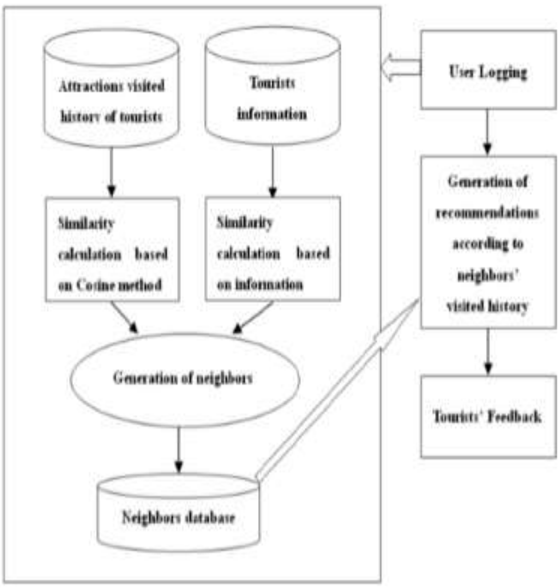

Figure2: Generation of recommendation

3. SYSTEM MODEL

System design isone of the objectives of research is to build a recommender system isproduce recommendations for selecting tourist destinations as a response from the ambient intelligence system to players according to their preferences [15]. We divide TDSG main parts to achieve this goal tourism destination recommender system (TDRS), data sharing system, and game visualization [16]. System model to build a recommender system to produce recommendations for selecting tourist destinations is response from the ambient intelligence system to players according to their preferences. Every data in the rating and preference database is from previous players and continue to grow with the assessment response from players who have used TDSG [17].

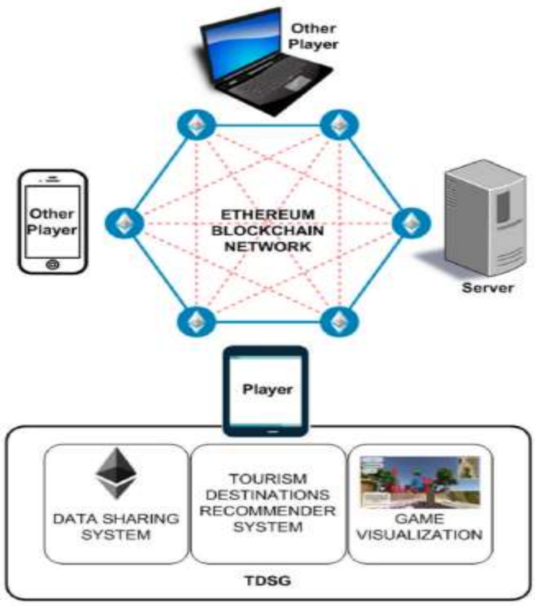

Figure3: TDSG in the ethereum block chain network

4. PROPOSED SYSTEM

Proposed System to recommender the uses to heterogeneous nature of data crawled in from World Wide Web (www). Data are obtained from the selected websites (data sources) containing the keywords present in the active user search query [18]. A web crawler was used to download the requested data and store the obtained data in a NoSQL database Cassandra for further processing [19].The system was tested with real time information. Number of were made using demo information, considering the variety of possibilities with different hotel types, airlines, cities, prices etc. to make it more challenging for the system.Every data in the rating and preference database is from previous players and continue to grow with the assessment response from players who have used TDSG. the system should ensure that players rating and preference data exchange goes well and safely [20].

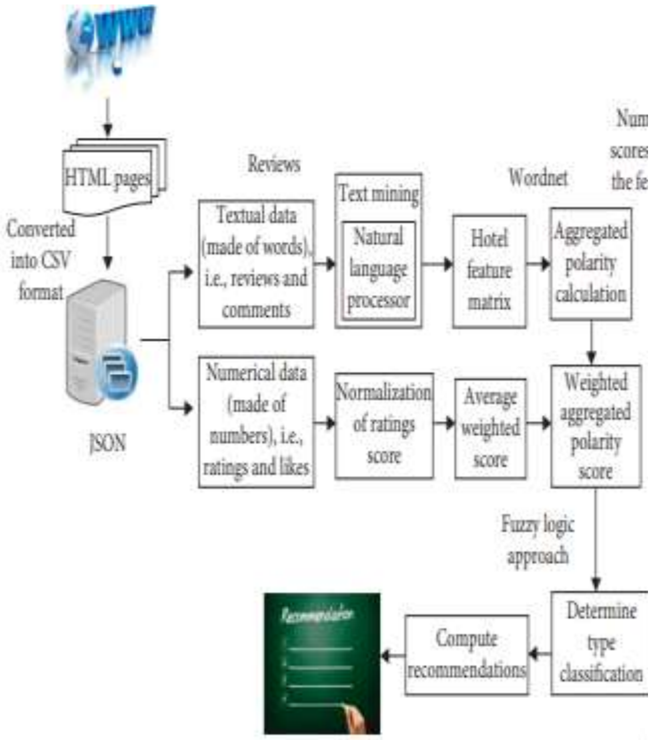

Figure4: Proposed System Recommendation

1. **Content-Based Recommender Component**

The content-based (CB) component of our A.I As mentioned in the introduction this component makes use of two main sub-components and hierarchy similarity measure-based sub-component [21]. The POIs' database stores our hierarchy andit represented with values ranging from 1 to 10, reflecting the extent to which each feature characterizes the POI in question.Process executed by our algorithm is the construction of the user profile we use two different components namely the Generic Images and Build User Profile components. Ninety (90) generic images isalso stored in our database and are each related to a specific category of POIs [22]. We utilize in our algorithm is asymmetricalarbitrary number of children per node and all branches may have different length [23]. Generic POIs and actual POIs are inserted as leaves in the tree structure lying under its layer that contains nodes corresponding to the different POI categories.

Algorithm Weights Generation of the user profile

1: profileu ← user profile vector

2: POIs ← all POIs with their 56 features

3: counters ← count vector of length stating to zero

4: for each POI in POIs do

5: character POI ← first features of POI

6: characteristicsPOI ← last features of POI

7: if cosines (pro fileu, character POI) ≥ 0 then

8: for each f in characteristics POIdo

9: if vf 6= ∅ then

10: counters' ← counters + 1

11: weights Profileu ← normalize (counters)

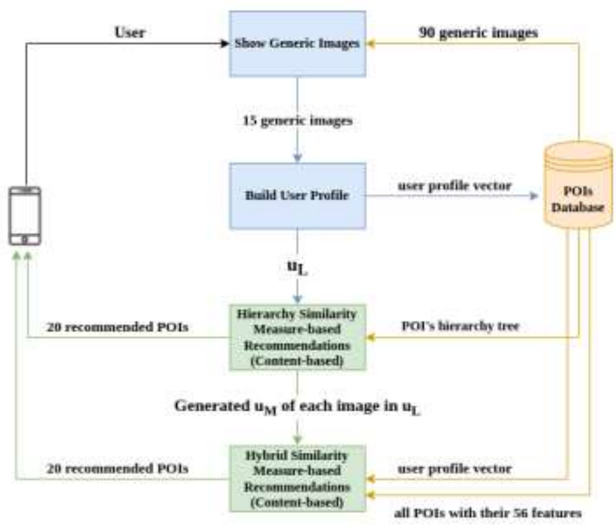

Figure5: The algorithmic engine of the CB Recommender

2. **Self-Preference Model (SPM):**

The Self Preference Model (SPM) is built basis on CBRto intuitively reflect the user's own interests and total construction process to the text features is obtained by pre-processing the user browsing history using a vector space model to represent the text featuresis within time factor to adjust the text modeland finally obtaining the user own preference model [24].In the text pre-processing stage special characters such as emoticons and face characterise removed and then the text is divided into sequences of word order using the word different technique. To avoid excessive word sequences that increase the computational effort meaningless word sequences such as conjunctions auxiliaries and stop words used screened out of the feature word sequences while verbs nouns and adjectives is retained in the word sequences [25]. Representation of text features is a key technique in CBR where key content features is used to represent text information and build a text model.

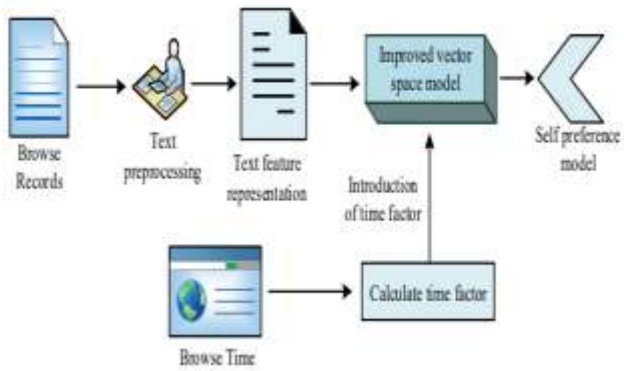

Figure6: Construction process of self-preference model

5. METHODS FOR RECOMMENDER SYSTEM

There are various methods in which recommendation systems are modelled. Domain usage and attributes present in them play a key role in determining the method of choice [26].

A. Social Information Based Recommender Systems.

In the authors discuss the recommendations based on two types of information: social-based information and content-based information. Their goal is to create a recommendation system is social and content-based information. The frame the problem as one classification instead of artefact rating thus departing from the conventional social-filtering method

B. Clustering Based Recommender Systems.

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Uses clustering to produce outputs arequickly to meet the real-world demands of large-scale e-commerce. A basic collaborative filtering algorithm of nearest neighbours using Pearson's correlation is used as the standard measure to compare against a clustering neighbourhood formation algorithm namely the bisecting K-means algorithm [27].

C. Classification and Regression Based Recommender Systems.

Uses a linear regression component combined with a matrix factorisation component to identify a final rating for each item pertaining to the user. The linear regression block LASSO uses the tags derived from the item poster and parameters corresponding to that item to estimate the user rating value

D. Matrix Factorisation

Matrix factorisation is recommender systems to capability of recognising implicit relationships and features many users and items by decomposing the user-item matrix with rating values. Joint matrix factorisation can be used to combine a regular matrix factorisation method with movie similarity within a certain mood context. An objective function concurrently factorises the two matrices and a gradient descent optimisation is applied to the objective function to minimise it.

E. Artificial Intelligence and Recommender Systems.

Propose a solution to tackle over-generalisation by deep neural networks with embedding's which results in less relevant items using wide and deep learning. They present a model to amalgamate the advantages of memorisation and generalisation with jointly trained wide linear models and deep neural networks. Memorisation is the learning of frequent number of items or features in the past in the data. In contrastgeneralisations takenew combinations that have never occurred in the past and are not already available in the data.

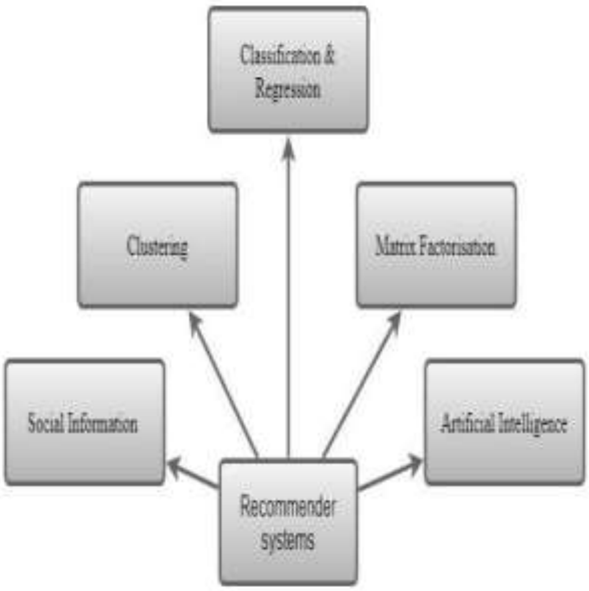

Figure7: Recommender system methods

6. RESULT AND DISCUSSION

This section describes the results of experiments and testing of several system parts including blockchain-based data sharing is recommendation systems and in game systems. This subsection discusses the collection and preparation of datasets is used as a reference in generating recommendations. This study uses tourist destinations total city.

The city is one of the tourist development areas with many exciting tourist destinations.

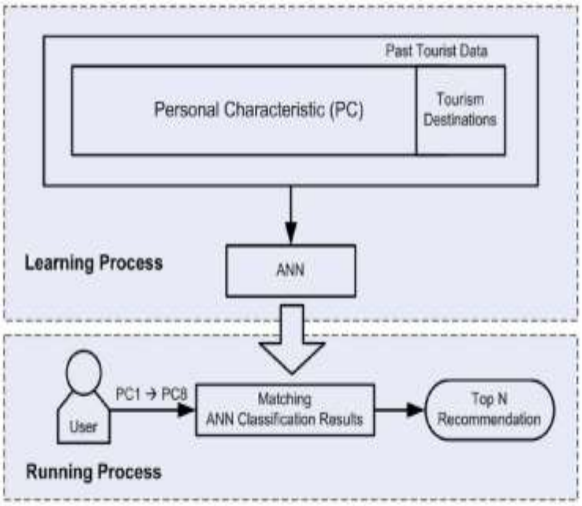

Figure8: An ANN-based recommender system

Blockchain as a platform to implement decentralized data sharing in developing TDSG in the Unity game engine the first process in the Ethereal blockchain setup is to create a wallet to accommodate the smart contract tokens needed to process data transactions on this TDSG.We program the Smart Contract algorithm in Solidity language compiled to manage the flow of data sharing in TDSG this research uses PUN which utilizes a central server of Photon Network.

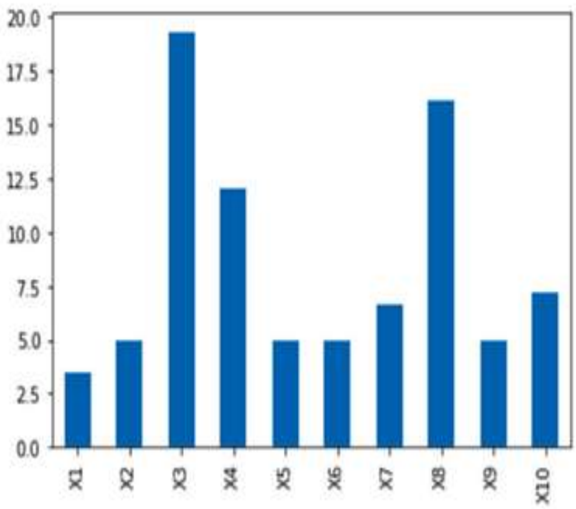

Figure9: Feature selection results using chi-square

7. CONCLUSION AND FUTURE WORK

Novel CF recommendation model is proposed number of handle heterogeneous data such as textual reviews, ranks, votes, and video views in a big data. The CBCF model combines the advantages of the two models is effectively improve its recommendation performance. The performance of CBCF-NNIA algorithm is analysed from the diversity and accuracy of recommendation results.We paid attention especially to RS in tourism with specifying travel details and sources of information used during the stages of the process. The proposed recommendation system is travellers select the best tourist attraction clustering methods is implemented the system is group items or users together based on the distances between them either to generate the final list of closest item recommendations create neighbourhoods of similar and trustworthy user classification algorithms for the system to learn user will like a particular item. In addition this model is improved by incorporating user opinions extracted from their comments on social media bidirectional encoder representations from transformer (BERT) to find more suitable sequential trips.

8. REFERENCES

[1] 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

[2] H. Liu, J. He, T. Wang, W. Song, and X. Du, "Combining user preferences and user opinions for accurate recommendation," Electronic Commerce Research and Applications, vol. 12, no. 1, pp. 14–23, 2013.

[3] M. Ibrahim and I. Bajwa, "Design and application of a multivariant expert system using Apache Hadoop framework," Sustainability, vol. 10, no. 11, p. 4280, 2018.

[4] J. J. Zhang and Z. Mao, "Image of all hotel scales on travel blogs: its impact on customer loyalty," Journal of Hospitality Marketing and Management, vol. 21, no. 2, pp. 113–131, 2012.

[5] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," Computer, vol. 42, no. 8, 2009.

[6] M.-Y. Hsieh, W.-K.Chou, and K.-C. Li, "Building a mobile movie recommendation service by user rating and APP usage with linked data on Hadoop," Multimedia Tools and Applications, vol. 76, no. 3, pp. 3383–3401, 2017.

[7] R. Burke, "Hybrid recommender systems: survey and experiments," User Modeling and User-Adapted Interaction, vol. 12, no. 4, pp. 331–370, 2002.

[8] P. Lops, M. De Gemmis, and G. Semeraro, "Content-based recommender systems: state of the art and trends," in Recommender Systems Handbook, pp. 73–105, Springer, Boston, MA, USA, 2011

[9] F. Nafis, K. Al Fararni, B. Aghoutane, A. Yahyaouy, J. Riffi, A. Sabri. "Hybrid recommender system for tourism based on big data and AI: A conceptual framework." Big Data Mining and Analytics, vol. 4(1), pp. 47-55. 2021.

[10] P. Pirasteh, M. R. Bouguelia, K. C. Santosh, "Personalized recommendation: an enhanced hybrid collaborative filtering." Advances in Computational Intelligence, vol. 1(4), pp. 1-8, 2021.

[11] Z. Hu, Y. Lan, Z. Zhang, X. Cai, "A many-objective particle swarm optimization algorithm based on multiple criteria for hybrid recommendation system." KSII Transactions on Internet and Information Systems (TIIS), vol. 15(2), pp. 442-460, 2021

[12] GessFathan, TeguhBharataAdji, and RidiFerdiana."Impact of matrix factorization and regularization hyperparameter on a recommender system for movies". In: International Conference on Electrical Engineering, Computer Science and Informatics (EECSI) 2018-October (Oct. 2018), pp. 113–116.

[13] Shaowei Wang et al. "EnTagRec ++: An enhanced tag recommendation system for software information sites". In: Empirical Software Engineering 23 (2 Apr. 2018), pp. 800–832.

[14] Jiawei Chen et al. "Fast Adaptively Weighted Matrix Factorization for

Recommendation with Implicit Feedback". In: Proceedings of the AAAI Conference on Artificial Intelligence 34 (04 Apr. 2020), pp. 3470–3477.

[15] Mohd Abdul Hameed et al. "Collaborative Filtering Based Recommendation System: A survey". In: Article in International Journal on Computer Science and Engineering (2012).

[16] "Offline A/B testing for recommender systems". In: WSDM 2018 - Proceedings of the 11th ACM International Conference on Web Search and Data Mining 2018-Febuary (Feb. 2018), pp. 198– 206.

[17] Zeng B, Gerritsen R. What do we know about social media in tourism? A review. Tourism ManagePerspect.2014;10:27–36.

[18] Huang J-H, Peng K-H. Fuzzy rasch model in TOPSIS: A new approach for generating fuzzy num-bers to assess the competitiveness of the tourism industries in asian countries. Tourism Manage.2012;33(2):456–465.

[19] F. Benzi, F. Cabitza, D. Fogli, Gamification techniques for rule management in ambient intelligence, in: European Conference on Ambient Intelligence, 2015, pp. 353–356, https://doi.org/10.1145/2909132.2926083.

[20] A. Nijholt, D. Reidsma, R. Poppe, Games and Entertainment in Ambient Intelligence Environments, first ed., Elsevier Inc..

[21] W. Looi, M. Dhaliwal, R. Alhajj, J. Rokne, Recommender system for items in DOTa 2, IEEE Trans. Games 11 (4) (2019) 396–404,

[22] M. Hassan, M. Hamada, Enhancing Learning Objects Recommendation Using Multi-Criteria Recommender Systems," Proceedings of 2016 IEEE International Conference on Teaching, Assessment and Learning for Engineering, 2017,

[23] S. Malik, A. Rana, M. Bansal, A survey of recommendation systems, Inf. Resour.Manag. J. 33 (4) (2020) 53–73.

[24] J. Borr` as, A. Moreno, A. Valls, Intelligent tourism recommender systems: a survey, Expert Syst. Appl. 41 (16) (2014) 7370–7389.

[25] M.V. Gopalachari, DBT recommender: improved trustworthiness of ratings through de-biasing tendency of users, Int. J. Intellig. Eng. Sys. 11 (2) (2018) 85–92,.

[26] M. Hamada, N.B. Odu, M. Hassan, A Fuzzy-Based Approach for Modelling Preferences of Users in Multi-Criteria Recommender Systems," Proceedings - 2018