International Journal of Applied Engineering Research ISSN 0973-4562 Volume 14, Number 14 (2019) pp. 3274-3277
© Research India Publications. http://www.ripublication.com

A Survey on Recommender System

Koyel Datta Gupta

Maharaja Surajmal Institute of Technology
C4 Janakpuri, New Delhi 110058, India.

Abstract

Recommender systems have gained its importance because of the availability of enormous online information. In current time, deep learning has gained appreciable attention in many researches such as natural language processing, artificial intelligence due to high performance and great learning feature representations. The effect of deep learning is also persistent, lately showing its usefulness when put to retrieval of information and recommenders work which eventually have resulted in the flourish of deep learning approaches in recommender system. Hybrid approaches for designing recommender models have been gaining popularity in recent years. The paper aims in giving a comprehensive insight of recent research works on recommender systems.

Keywords: Recommender system, collaborative, content-based, hybrid technique

1. INTRODUCTION

The objective of any recommender systems is to enable consumers to find new items or services, such as books, music, restaurants or even people, based on information about the consumer, or the recommended item [1]. To enhance the experience for the consumer, personalization is an important policy. Recommender systems are useful to both consumer and service provider. The systems diminish the expenses related to finding and choosing items in an online environment. Recommender systems have improved the quality of decision making process. This plays a vital part in decision-making, aiding users to increase revenue [2] or lessen potential risk [3]. Recommender Systems are used in many web domains such as Twitter [4], Google [5], LinkedIn [6] and other e-commerce based websites. In online libraries, readers are supported by recommenders which allow them to proceed outside predefined searches. Therefore, there is a prerequisite of systems to practice proficient and precise recommendation techniques that will offer appropriate recommendations to consumers.

In an overall view, recommendations are constructed on the basis of consumer choices, user-item former dealings, item features and some other supplementary information such as sequential order. Recommendation models are mainly categorized as collaborative filtering, content-based and hybrid approach based recommender system based on the types of input data [7].

The research done on recommender system from various covering diverse perspectives has been analyzed and explained in this survey paper. The paper focuses to provide a view on the recent development in the area of recommender systems. The workdiscusses the challenges and problems, and discusses the new developments and forthcoming directions in this area. This paper is organized as follows: section 2 describes the terminologies important to understand the working principle of recommender systems and its overview. Section 3 presents the review work, and Section 4 discusses the conclusion and future scope pertinent in the present research works.

2. TEMINOLOGIES AND OVERVIEW OF RECOMMENDER SYSTEMS

It is important to understand the terminologies used in recommender systems and its working principle.

2.1 Important Terminologies and Overview of Recommender Systems

2.1.1 The Utility Matrix

In a recommender system there are two classes of entities, referred as users and items. Users usually have inclination for specific items, and these choices must be extracted out of the data. The data is denoted as a utility matrix, where each value denotes the preference of a consumer/user for an item covering all possible combination of user-item. Values are constituted from an ordered set, e.g., 1–10 representing the level of rating that the user has given for a specific item. The matrix is sparse, since the actual data about the user's preference for the item might not be known.

2.1.2 The Long Tail

The "long tail" phenomenon creates a need for recommendation systems. The limitation of physical resources can be overcome by online traders which has practically no limitation. Thus, an apparel store may have several hundred clothes but an e commerce apparel website offers thousands of clothes. The distinction between the physical and on-line services has been called the long tail phenomenon. In business, the term long tail is used to illustrate the trading tactic of marketing an appreciable quantity of unique items with comparatively lesser quantities traded of each (the "long tail")—usually in accumulation to retailing lesser popular items in large quantities (the "head"). In some cases an intermediate category may be included, referred as the body or middle or torso. The long-tail concept pushes on-line traders to recommend items to specific consumers.

2.2 Overview of Recommender Systems

Recommender systems are implemented using different technologies. The systems can be categorized into three classes.

i. Content-based systems are based on two significant set of information to recommend items. The first information is the details of the item and the second is the summary of the user's choices. On the basis of user's preferences, keywords are associated with items. These techniques suggest items that are similar to the users' past choices or the ones that have been examined in the present.

ii. Collaborative systems suggest items based on similarity measures between users and/or items. The items recommended to a user are those preferred by similar users.

iii. Hybrid Systems combines the benefits of both collaborative and content based systems and can minimize their restrictions [8]. The three major ways of merging collaborative and content based filtering methods into a hybrid system are as follows:

   a. Content-based and collaborative systems are implemented separately and the results are combined.
   b. The collaborative properties are utilized in content based method and vice versa.
   c. A combination model implemented combining both collaborative and content-based properties.

3. REVIEW WORK

The early phase of research on recommenders were based on collaborative filtering that prescribed music album and artist recommendations from social information [9] and news articles to users [10]. This trend was later shifted to find products or services based on contents such as movies, books, music, electronic merchandise etc. depending on reviews of different users on items

[11] [12] [13].

A Fab system proposed in [14] suggests web pages and it the suggestion is derived from representation of the content of web page using 100 most significant words. Similarly the most important 128 words are used to recommend documents in [15]. Bayesian classifier is used to estimate the probability of an item to be approved by the user. In [16], term frequency/inverse document frequency (TF-IDF) measure is used to find the significance of a keyword. The work presented in [36] builds the content based profile using Rocchio algorithm [17] where a method is used to calculate the average vector from respective content vectors. The work [18] offers good results in case an item has enumerated multiple features. In [19][20] content based recommender systems have been designed using adaptive filtering which classifies relevant documents by scanning the documents in an ordered way from a document collection. A threshold which signifies a certain degree of match is utilized to determine the relevance of a document to the user in [21]. The works in recommender systems mainly focusses on collaborative techniques. A work proposed in [22] discovers similar users having similar interests by applying statistical methods on entire user database. In [23] proposed a combination of collaborative and case based reasoning system (MIFA and RAA). The choices of an active user were predicted based on fractional information available about the user and the weights calculated from thereof is proposed in [24]. The work [25] used PCC (Pearson Correlation Coefficient) to evaluate the weights portraying the relation between the active user and other users. A tailored collaborative method was presented in [26] that combined user and item based concept and applied to web services by calculating the similarity. In [27] a user model was build which implemented demographic information and item combination features using genetic algorithms to search for a set of adjoining users having similar preferences. The work [28] presents an Association Cluster Filtering (ACF), which utilizes a ratings matrix to create clusters where users belonging to same cluster have similar preferences and users from different clusters have lesser common choices. Unknown rating is conceivable if an item in a cluster has multiple ratings associated to it and this is suitable for sparse dataset. A hybrid technique was proposed in [29] which club the features, demographic data and ratings of an item to provide a potential solution to the limitations of both collaborative and content based techniques. An approach presented in [30] adds the concept of temporal information to collaborative method which enhanced the performance and accuracy of the recommendations. An amalgamation of global data and item based values is used in [31] to provided better suggestions and was effective on sparse data. The proposed method portrayed an betterment over the Netflix's system for movie recommendations. Netflix also conducted a competition [32] to enhance the performance of its existing algorithm.

Recommendations can be provided using trust- based techniques as in [33] considering trusts between users. The trust is defined according to a connection to a friend or a following in any social network. Risk-aware recommendations presented in [34] are a subset of context-aware techniques and consider a context having critical facts, such as crucial user information and any incorrect suggestion might have critical impact on users. The examples of such risk-aware recommendation may include prescribing medicines or stock shares.

Neural Network Matrix Factorization (NNMF) [35] and Neural Collaborative Filtering (NCF) [36] are two proposals based on dual neural network to build 2-way relations between users and products and on matrix factorization which decomposes the rating matrix into low-dimensional user/item preference values. Multilayered Perceptron technique was applied in YouTube recommendation in [37].In [1] another MLP based model is presented for recommending makeup. In this research, two exactly similar MLPs are built for examples and expert rules respectively. Parameters of these two networks are modified regularly by reducing the differences between their outputs. It shows good result but lot of human intervention was required. Collaborative Metric Learning proposed in [38] substitutes the dot product of matric factorization with Euclidean distance and user and item preferences are learned through maximization ofthe distance between users and their disliked items and minimizing that between users and their liked items. In [39], a Deep Structured Semantic Model based on deep neural network is proposed. The model learns semantic depictions of entities in a common continuous semantic space and measuring their semantic similarities. This concept has also been used in information recovery area for top-n recommendation [40, 41]. A variant of variational auto-encoder (Multi-VAE and Multi-DAE) for recommendation is presented in [42] showing good results. It uses a Bayesian inference approach for parameters. Auto-encoder based Collaborative Filtering (ACF) technique is proposed in [43] and applies original partial perceived vectors.

4. CONCLUSION AND FUTURE WORK

The availability of practically limitless online information makes recommender system absolutely necessary. The research work carried in this direction has seen remarkable progress in the past few decades. However, the challenges in the field of recommender models still persist and there is plenty of scope for improvement. This work has focused on listing some important research in the field. Every year is witnessing large number of novel developing techniques and emerging recommenders. This study can provide readers a perception on recommenders. Future works can concentrate more potentials of applying deep learning, fuzzy based approaches and genetic algorithms in improving the precision of recommenders.

REFERENCES

[1] Alashkar, T., Jiang, S., Wang, S,. and Fu, Y., 2017, “Examples-Rules Guided Deep Neural Network for Makeup Recommendation,” Proc. 31st AAAI Conference on Artificial Intelligence, pp.941–947.

[2] Chen, M., Xu, Z., Weinberger, K., and Sha, F., 2012, “Marginalized Denoising Autoencoders for Domain Adaptation,” Proc. 29th International Conference on Machine Learning, pp. 767–774.

[3] Catherine, R., and Cohen, W., 2017, “Transnets: Learning to transform for recommendation,” Proc. 11th ACM Conference on Recommender Systems, pp. 288-296.

[4] Bai, B., Fan, Y., Tan, W., and Zhang, J., 2017, “DLTSR: A Deep Learning Framework for Recommendation of Long-tail Web Services,” IEEE Transactions on Services Computing pp.1-1.

[5] Donkers,T., Loepp, B., and Ziegler, J., 2017, “Sequential User-Based Recurrent Neural Network Recommendations,” Proc. 11th ACM Conference on Recommender Systems, pp.152–160.

[6] He, R., and McAuley, J., 2016, “VBPR: Visual Bayesian Personalized Ranking from Implicit Feedback,” Proc. 13th AAAI Conference on Artificial Intelligence, pp. 144–150.

[7] Adomavicius, G., and 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), pp. 734–749.

[8] Burke, R., 2007, Hybrid Web Recommender Systems, The Adaptive Web, Springer-Verlag, Berlin Heidelberg.

[9] Shardanand, U., and Maes, P., 1995, “ Social Information Filtering: Algorithms for Automating ‘Word of Mouth’,” Proc. SIGCHI Conference on Human Factors in Computing Systems, pp. 210-217.

[10] Resnick, P., Iakovou, N., Sushak, M., Bergstrom, P., and Riedl, J, 1994, “ GroupLens: An Open Architecture for Collaborative Filtering of Netnews,” Proc. Conference on Computer Supported Cooperative Work, pp. 175-186.

[11] Frias-Martinez, E., Chen, S. Y., and Liu, X., 2009, “Evaluation of a Personalized Digital Library Based on Cognitive Styles: Adaptivity vs. Adaptability,” International Journal of Information Management: The Journal for Information Professionals, 29(1), pp. 48–56.

[12] Frias-Martinez, E., Magoulas, G., Chen, S. Y., and Macredie, R, 2006, “Automated User Modeling for Personalized Digital Libraries,” International Journal of Information Management: The Journal for Information Professionals, 26(3), pp. 234–248.

[13] Kim, J. K., Kim, H. K., Oh, H. Y., and Ryu, Y. U., 2010, “A Group Recommendation System for Online Communities,” International Journal of Information Management, 30(3), pp. 212–219.

[14] Balabanovic, M., and Shoham, Y., 1997, “Fab: Content-Based, Collaborative Recommendation,” Comm. ACM, 40(3), pp. 66-72.

[15] Pazzani, M., and Billsus, D., 1997, “Learning and Revising User Profiles: The Identification of Interesting Web Sites,” Machine Learning, 27, pp. 313-331.

[16] Salton, G., 1989, Automatic Text Processing. Addison-Wesley.

[17] Rocchio, J.J., 1971, Relevance Feedback in Information Retrieval, SMART Retrieval System—Experiments in Automatic Document Processing, Prentice Hall, Chap. 14.

[18] Littlestone, N., and Warmuth, M., 1994, “The Weighted Majority Algorithm,” Information and Computation, 108(2), pp. 212- 261.

[19] Somlo, G., and Howe, A., 2001, “Adaptive Lightweight Text Filtering,” Proc. 4th International Conference on Advances in Intelligent Data Analysis, pp. 319-329.

[20] Zhang, Y., Callan, J., and Minka, T., 2002, “Novelty and Redundancy Detection in Adaptive Filtering,”

Proc. 25th Annual International ACM SIGIR Conference, pp. 81-88.
[21] Robertson, S., and Walker, S., 2000, “Threshold Setting in Adaptive Filtering,” Journal of Documentation, 56, pp. 312-331.
[22] Sarwar, B. M., Karypis, G., Konstan, J. A., and Riedl, J., 2001, “Item Based Collaborative Filtering Recommendation Algorithms,” in Proc. 10th International Conference on World Wide Web, pp. 285–295.
[23] Zhuo, G., Sun, J., and Yu, X., 2007, “A Framework for Multi-Type Recommendations”, Proc. 8th International Conference on Fuzzy Systems and Knowledge Discovery, pp. 1884-1887.
[24] Breese, J. S., Heckerman, D., and Kadie, C., 1998, “Empirical Analysis of Predictive Algorithms for Collaborative Filtering,” In Proc. 14th Annual Conference on Uncertainty in Artificial Intelligence, pp. 43-52.
[25] Konstan, J. A., Miller, B. N., Maltz, D., Herlocker, J. L., Gordon, L. R., and Riedl, J., 1997, “GroupLens: Applying Collaborative Filtering to Usenet News” Comm. ACM, 40(3) , pp.77-87.
[26] Jiang, Y., Liu, J., Tang, M., and Liu, X.F., 2011, “An Effective Web Service Recommendation Method based on Personalized Collaborative Filtering”, Proc. IEEE International Conference on Web Services, pp. 211-218.
[27] Wang, Q., Yuan, X., and Sun, M., 2010, “Collaborative Filtering Recommendation Algorithm based on Hybrid User Model”, Proc. 7th International Conference on Fuzzy Systems and Knowledge Discovery, pp. 1985-1990.
[28] Huang, C., and Yin, J., 2010, “Effective Association Clusters Filtering to Cold-Start Recommendations”, Proc. 7th International Conference on Fuzzy Systems and Knowledge Discovery, pp. 2461-2464.
[29] Ghazanfar, M.A., and Prugel-Bennett, A., 2010, “A Scalable, Accurate Hybrid Recommender System,” Proc. 3rd International Conference on Knowledge Discovery and Data Mining, pp.94-98.
[30] He, L., and Wu, F., 2009, “A Time-context-based Collaborative Filtering Algorithm”, Proc. IEEE International Conference on Granular Computing, pp. 209-213.
[31] Almosallam, I.A., and Shang, Y., 2008, “A New Adaptive Framework for Collaborative Filtering Prediction,” IEEE Congress on Evolutionary Computation, pp. 2725-2733.
[32] Bennett, J., Lanning, S., 2007, “The Netflix Prize,” Proc. KDD Cup and Workshop, pp.51-52.
[33] O'Donovan, J., and Smyth, B., 2005, “Trust in recommender systems,” Proc. 10th International Conference on Intelligent User Interfaces, pp. 167-174.
[34] Bouneffouf, D., Bouzeghoub, A., and Ganarski, A. L., 2013, Risk-Aware Recommender Systems, Neural Information Processing,Springer Berlin Heidelberg, pp. 57-65.
[35] Dziugaite, G.K., and Roy, D.M., 2015, “Neural Network Matrix Factorization,” arXiv 103 preprint arXiv:1511.06443, 2015.
[36] He, X., Liao, L., Zhang, H., Nie, L, Y., Hu, X., and Chua, T-S., 2017 “Neural Collaborative Filtering,” Proc. 26th International Conference on World Wide Web, pp. 173–182.
[37] Covington, P., Adams, J., and Sargin, E., 2016, “Deep Neural Networks for YouTube Recommendations,” Proc. 10th ACM Conference on Recommender Systems, pp. 191–198.
[38] Hsieh, C-K., Yang, L., Cui, Y., Lin, T-Y., Belongie, S., and Estrin, D., 2017, “Collaborative metric learning,” Proc. 26th International Conference on World Wide Web, pp.193–201.
[39] Huang, P-S., He, X., Gao, J., Deng, L., Acero, A., and Heck, L., 2013, “Learning Deep Structured Semantic Models for Web Search using Click through Data,” Proc. 22nd ACM International Conference on Information & Knowledge Management, pp. 2333–2338.
[40] Elkahky, A.M., Song, Y., and He, X., 2015, “A Multi-View Deep Learning Approach for Cross Domain User Modeling in Recommendation Systems,” Proc. 24th International Conference on World Wide Web, pp. 278–288.
[41] Xu, Z., Chen, C., Lukasiewicz, T., Miao, Y., and Meng, X., 2016, “Tag-Aware Personalized Recommendation using a Deep-Semantic Similarity Model with Negative Sampling,” Proc. 25th ACM International on Conference on Information and Knowledge Management, pp. 1921–1924.
[42] Liang, D., Krishnan, R. G., Hoffman, M.D., and Jebara, T., 2018, “Variational Autoencoders for Collaborative Filtering,” Proc. World Wide Web Conference, pp. 689-698.
[43] Ouyang, Y., Liu, W., Rong, W., and Xiong, Z., 2014, “Autoencoder-Based Collaborative Fitering,” 21st International conference on Neural Information Processing, pp. 284-291.