Enhanced Product Recommendations based on Seasonality and Demography in Ecommerce

2020 2nd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN) | 978-1-7281-8337-4/20/$31.00 ©2020 IEEE | DOI: 10.1109/ICACCCN51052.2020.9362760

Keerthika K
Department of CSE
Karpagam College of Engineering
Tamilnadu, India
kikeerthika@gmail.com

Saravanan T
Department of CSE
Galgotias College of Engg. & Tech.
Greater Noida, India
tsaravcse@gmail.com

***Abstract*—Today, the social network environments are trending to list the customers with the product recommendations. The social recommendations are generated by recommender system based on product ratings and comments. There has been number of work towards improving the accuracy of recommendations generated by recommender systems. These tend to make the system to narrow the suggestion of product variety. The system should get evolved to the trend of generating diversity of recommendation so that the customer can explore the wide variety of products. The diversity of user demographic in social network makes the recommendation system can be applied to introduce variety of product recommendation. The seasonality of product is emerging trend in recommendation system to actively seek out the right product at right time. The work focuses on investigating the efficiency of recommender system, in generating the diverse suggestions for E-commerce dataset.**

Keywords—recommender system, seasonality, demography, collaborative filtering, seasonal product

I. INTRODUCTION

In recent years, E commerce websites has been improved its profit margin with the help of recommender systems. A recommender system is a customized information filtering technology that can be used to predict the user interest to particular product or certain product will be liked by the customer. The recommender system mainly helps in improving user experience which in turn will impact the commercial sales in the website. There has been lot of study on improving the performance of recommender system. Much research has investigated application of it to various domains. However, improving the recommendation accuracy has made the recommender system to narrow in generating suggestions. This is known as portfolio effect – recommendations that are more similar to user's history of activities. But this do not always result in high user satisfaction. The recommender system should generate diversity to introduce new and relevant suggestions that gives new experience. In this work, a new approach is introduced to diversity recommendation by incorporating the user demographics and seasonality of products. Using these add on features as a kernel, it would introduce diverse recommendations. The seasonality related recommendations are given based on their past seasonal purchased records and demography.

II. APPROACHES

The recommender systems are classified into content based: the item recommendations are shown to the users based on their past preference and collaborative based: the users will receive item recommendation based on similarity of user with other people based on preferences or likes in past. The collaboration can be various methods like item based, user based, location based in social recommender systems. There is another approach called hybrid which is the combination of content-based and collaborative methods. Each of the recommendation techniques has its strength and weakness, therefore incorporating them in different ways, improves like performance with fewer drawbacks. Many recommender systems have shown efficient performance on incorporating hybrid approach in it. But this may lead to overspecialization. When the recommender system is built based on feature of content based filtering approach, the specific user would get recommendations that are similar to those products rated good already. The user rated the bag will be repeatedly suggested with the homogeneous alternatives of that product. Thus the diversity of recommendation is preferable in recommender system. For example, If the user have rated sweater he would be shown the similar products repeatedly. If the user have not rated the electronics he would never be suggested with kind of products.

A. Seasonal Product

The seasonal product is products that are highly desirable in a month or useless in the rest of months (Schafer et.al.2001). The products that are in demand or used generally during particular climatic season, festival or holiday season comes under seasonal product. The products are same way influenced with the seasonality are clothing cosmetics, movies, some electronic machines. Clothing like shrugs, sacks, demand is always high in winter than rest of the year. The movies or web series have high rating during winter season or vacation times then the rest of the year. This shows the influence of product purchase by the season. The recommender system which does not include product seasonal information may reduce user satisfaction on e-commerce site. When the recommender system is built tagging the seasonal product would help for its efficient performance. For Example, If the user have rated sweater already, which is the seasonal product, suggesting the homogeneous alternative set of sweater irrespective of season will lower the user experience. Tagging it as seasonal product would help the system to match its season to suggest. This shows that the seasonal products have high demand and low demand for certain duration of the year.

ISBN: 978-1-7281-8337-4/20/$31.00 ©2020 IEEE

B. *Demography of Users*

The data of user's demographics include their gender, age, location, likes and ratings. The demography is the information useful for business application to understand the customer favorites, which helps to engage the customers with their interests, especially in e-commerce websites. This can be used to introduce diversity of recommendations in combination with seasonality of products. Many works have studied about demographic recommender system which leverages the various personal attributes of the users or products. This kind of system would gather information of ratings and user demographics to investigate the similarity among the users to generate the recommendations.

III. Proposed Work

The seasonality product recommendation alone will not improve user satisfaction. Some users may have sacks even when it is not winter because the product may found to cheap. Therefore, the customer need to be categorized so that the system will able to recommend seasonal product to the particular user or not. To support the categorization, the demography of user is add-on feature given to recommender system. The proposed work on recommender system improvisation would involve in the following

1. Distinguishing the seasonal product
2. Identifying user relation with seasonality.
3. Analyze the impact of seasonal product in generating recommendation.

A. *Algorithm to distinguish seasonal product*

SeasonalDependency (topN, months)
for all pi ⟵ topN
do
if si > = MPV
then
if MR (pi, month) < TR
then
RemovefromList (topN, pi)

Minimum purchase value (MPV): This defines the number of minimum purchase done for the particular product to distinguish or predict whether it is a seasonal product or not. This helps to find when a product has high or low demand duration. Example: Product like mouse which is purchased by the user in December which has only few purchase value within the last 12 months should be taken out of seasonal product.

Product threshold ratio (TR): This defines for which months a product should be removed from recommendation list. Example: Sacks would be removed from seasonal product during may if the purchase ratio of it is below minimum threshold.

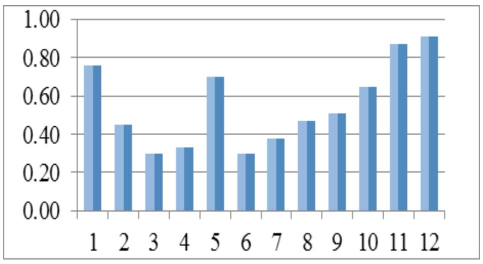

Fig. 1. Product Threshold Ratio throughout the year

p_i denotes product ($p_{1,2,\ldots,n}$).The input parameters are topN which has products generated by standard recommender system. The other parameter is month which values from 1 to 12, to find topN product in each month. The algorithm check that minimum purchase value is equal or greater than the number of products ordered.MR is the sub function that finds the month ratio. If the product has the value less than the minimum threshold ratio, then the other sub function RemovefromList will remove the particular product from the standard recommendation list of topN products. Fig 1 , shows the product ratio variation over the month. It shows the impact of seasonality impact on the rating of the product.

B. *Identifying user relation with seasonality*

The user rating history is used to identify user relation with seasonal product. For each seasonal product, the rating given is plotted according to month. This helps to view the scaled value ranges from 0 to 1 when user rated the movie in each month. The average of this rated value gives the user relation with seasonal product. If many of scaled values are close to one, it shows that user is very much related to seasonality products (always buying winter clothing in November) Table 1. Shows the average of user rating for the seasonal products is close to 1 which shows that the user has high interest on seasonality product and do purchase those products in particular season.

TABLE I. User relation with seasonality

Sherlin		
Jerkins	Sacks	Umbrella
0.8	0.73	0.94
Average :0.82		

3.3. *Performance metrics to analyze the impact*

The commonly used evaluation metrics are precision and recall. Precision is the ratio of recommended seasonal products out of all standard recommendations. Recall is the ratio of items recommended out of all possible relevant items.

$$Precision = \frac{\{seasonal\ \ products\} \cap \{standard\ recommendations\}}{\{standard\ recommendations\}}$$

$$Recall = \frac{\{seasonal\ \ products\} \cap \{standard\ recommendations\}}{\{all\ seasonal\ products\}}$$

The diverse recommender systems are expected to result with low precision and recall. If the introduction of diverse is more, then the precision and recall will show poor results. This was observed by Zielger et.al [2]. Fall out is the metric which refers to the proportion of non-relevant items recommended out of all possible non-relevant items.

$$Fallout = \frac{\{nonrelevent\ products\} \cap \{standard\ recommendations\}}{\{non-relevent\ products\}}$$

As the diversity increases the fall out will definitely increase as it measures the proportion of non-relevant recommendations. Intra List similarity defined by Zeigler.et.al [2] can also be used as a measure to capture the average value of similarity between each item and user rated as positive preference on seasonal product.

IV. Discussion And Conclusion

Recommender systems are generally evaluated through precision and recall. But to evaluate the accuracy in diversity of recommendation, fall out is used which helps to find how they may differ from standard recommendations. However, the best measurement for diversity is user satisfaction. Creating live experiment of recommender system helps to study the usefulness of diversity recommendation using seasonality and user demographic to improve lesser satisfaction in E-commerce social environment. The hybrid strategy has the ability to solve the cold-start problem for the new users. It has been noted that rating data set used has the user rating of thousands of products .The use who rate the product may not end up with purchase of that products. This is the case in movie, ecommerce websites. The feasibility of this approach to diversity is validated with study on MovieLens dataset.

The metrics available for evaluating diversity is also discussed which would helps in better understanding of user needs to improve recommender systems. The work shows how seasonal products are to be dealt to generate recommendation and also the impact of user relation with the seasonality.

The work reveled that recommending the seasonal product in their desirable season to the user with high degree of seasonality will highly improve the user satisfaction; especially in e-commerce application. The great advantage of the approach is that it can be easily incorporated in exiting recommender system.

The future plan is to evaluate the overall performance of diversity with seasonal approach in terms of product coverage, serendipity in other domains.

References

[1] Sheth, S. K., Bell, J. S., Arora, N., & Kaiser, G.E., Towards diversity in recommendations using social networks", Columbia University Academic Commons, 2011.

[2] C.N. Ziegler, S. M. McNee, J. A. Konstan, and G. Lausen. "Improving recommendation lists through topic diversification", In Proceedings of the 14th international conference on World Wide Web, WWW '05, , New York, NY, USA, pp. 22-32,2005.

[3] J. Wei, J. He, K. Chen, Y. Zhou, and Z. Tang, "Collaborative filtering and deep learning based recommendation system for cold start items," Expert Syst. Appl., vol. 69, pp. 29–39, 2017.

[4] D. Shankar, S. Narumanchi, H. A. Ananya, P. Kompalli, and K. Chaudhury, "Deep Learning based Large Scale Visual Recommendation and Search for E-Commerce," arXivrepr.arXiv1703.02344,2017.

[5] G. Adomavicius and A. Tuzhilin, "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions," IEEE Trans. Knowl. Data Eng., vol. 17, no.6, pp. 734–749, 2005.

[6] Y. Wang, S. C.-F. Chan, and G. Ngai, "Applicability of demographic recommender system to tourist attractions: A case study on trip advisor," in Proceedings of the 2012 IEEE/WIC/ACM International Joint Conferences on Web Intelligence and Intelligent Agent Technology-Volume 03, pp 97–101, 2012.

[7] C.N.Zielger, "Taxonomy Driven Filtering," in Social Web Artifacts for Boosting Recommenders, Springer, pp.23-45,2013.

[8] Radas, S., and Shugan, S. M. "Seasonal marketing and timing new product introductions" in Journal of Marketing Research vol.35(3) pp.296–315,1998.

[9] [9] GroupLens Research Group. Movie lens data sets.http://grouplens.org/node/12.

[10] P.Symeonidis, E.Tiakas, and Y.Manolopoulos, "Product recommendation and rating prediction based on multi-modal social networks," in Proc. 5th ACM Conf. Recommender Syst., pp. 61–68, 2011.

[11] R.McLauglin and J.Herlocher, "A collaborative filtering algorithm and evaluation metric that accurately model the user experience," in Proc. 27th Annu. Int.ACM SIGIR Conf. Res. Development Information Retrieval, pp. 329–336, 2004.

[12] Kawasaki, Y. 2006. A structural time series model facilitating flexible seasonality. In Proceedings of the Conference on Seasonality, Seasonal Adjustment and Their Implications for Short-term Analysis and Forecasting.98Linden, G.; Smith, B.; and York, J.Amazon.com recommendations. IEEE Internet Computing 3: pp.76–80,2003.

[13] Poo, Danny, Brian Chng, and Jie-Mein Goh. "A hybrid approach for user profiling." In System Sciences, 2003, Proceedings of the 36th Annual Hawaii International Conference on, pp. 9-13, 2003.

[14] I. Fernández-Tobias, P. Tomeo, I. Cantador, T. Di Noia, and E.Di Sciascio, "Accuracy and diversity in cross-domain recommendations for cold-start users with positive-only feedback," in Proceedings of the 10th ACM conference on Recommender Systems, pp. 119–122, 2016.

B.Mahalakshmi , K.Keerthika "Effective Generation of Location-Sensitive Recommendations in Social Network Environments using Enhanced SSU Approach", in International Journal of Advanced Research in Management, Architecture, Technology & Engineering, Vol 2 ,pp 210-213,2016.

AUTHORS

Dr.T.Saravanan graduated from Selvam College of Technology, Anna University, Chennai with a B.E degree in Computer Science and Engineering. He has an M.E degree in Network Engineering from Anna University Regional Center, Coimbatore, India, and he had completed Ph.D. degree in the department of Information and Communication Engineering at Anna University, Chennai, India. He had published several SCI and Scopus papers. His research interests include Computer Networks, Fuzzy logic and Wireless Sensor Networks.

K. Keerthika graduated from Vidhya Vikas College of Engineering, Anna University, Chennai with B.E in the field of Computer Science and Engineering. She has completed her M.E in the field of Computer Science and Engineering from K.S.R College of Technology, Anna University, Chennai. She has published her work in several journal and conferences. Her research interests include Data analytics, Artificial Intelligence, Social area networks.