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PRODUCT RECOMMENDATION FOR USER REVIEWS IN ONLINE BIG DATA ANALYSIS USING MACHINE LEARNING TECHNIQUE

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ABSTRACT

Because recommendation systems are applicable to several of business domains, they have achieved great popularity recently. Recommendation is a problem of information filtering using some criteria that decides an item's usefulness for a particular user. Many websites provide accommodation information and reviews. For a very large dataset review, model requires to recommend correct data in such a way so that it can retrieve necessary data very fast. Real-time recommendation systems are become fairly easy to implement because to evolutions in big data processing technologies. This paper presents, Product Recommendation for User Reviews in Online Big Data Analysis Using Machine Learning Technique. Support Vector Machine (SVM) is used in this paper as machine learning classification. The Amazon product dataset, which includes reviews and product ratings, are used for the experiments. Big data combined with SVM is utilized in the online recommendation phase to determine which item is most relevant to the new item. Recall, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and other evaluated parameters are utilized to assess the performance of the recommendation system. The result shows effectiveness of described model than other existing models.

Keywords: Recommendation system, Machine Learning, Big data, SVM, RMSE, MAE.

I. INTRODUCTION

The advancement in digital technology, especially after the introduction of smart phones, had exploded data online tremendously. Social site like face book and twitter are significant sources of data generation. The exponential growth in e-commerce industry has provided the users with a wide variety of products to choose from. E-commerce websites are modern day departmental stores with wide range of products. Recommender systems play the role of sales-person who would understand customers' requirements and suggest products to them. Today almost all e-commerce websites use recommender systems to help its users enhanced user experiences by providing suggestions which the user might like [1]. The success of any recommender system depends on whether it can continuously provide its users with products. With advancement in data acquisition and reduced costs of data storage,various types of user's activity and feedbacks can be recorded easily. In recent years, various recommendation algorithms have been developed, like content-based, collaborative filtering, matrix factorization and domain specific systems like case-based, contextual recommender systems. Locationbased systems have also been applied to enhance social networking services [2].

With such an expeditious growth in this trade, sophisticated algorithms are used by the companies to identify the transaction pattern of its consumers in order to ameliorate the experience of the user[3]. Among shopping sites, there is huge competition in presenting their products, discount offer and the buying experience they given to users. All these promotions and discounts are depending on analytics and business research done by professionals inside and outside of different firms. Consumer reviews and product rating are the main parameters that companies used in the e-commerce sites in order to strategize the analysis. These reviews provide a crucial role in users to decide about buying an item or not. Thus, examining consumer feedbacks help shopping companies and manufacturers who can identify specific areas of improvement in their products[4].

Online shopping is becoming popular day by day because of the low cost, effective logistic systems, and variety. These days, recommender systems are crucial towards millions of users globally in many domains, providing they receive personalized recommendations. News, books, movies, and many other products were between those that are recommended, all of which are proposed accordance on the tastes and preferences of individual users.

Recommender system use many types of data about user's activities and behaviors in their recommendation mechanism, in order to provide more accurate recommendations that fit user's requirements.

Big data is more in the national economy and the use of marketing. With the development of mobile Internet and intelligent cloud technology, big data has begun to affect more and more business. That is to be able to more effectively on the supply chain, product development, online drainage guide, thereby enhancing the efficiency of the operation of the platform[5]. Big data development is become the technological backbone of e-commerce cross-border and business innovation. The boundaries separating traditional trade enterprises from e-commerce cross-border enterprise were blurring in the context of big data, and data has become the connecting factor that significantly driving every player in the entire trade industry. Huge amounts of data can be professionally analyzed and processed by big data technology, which can also be used to extract useful information from redundant big data through processing data. This allows for the accurate segmentation of the global e-commerce cross border market, the tracking of distribution as well as logistics, with the realization of the analysis of market demand, the optimization of product category design, and the realization of standardized analysis of product packaging [6].

Software tools and techniques that make recommendation system for products that would be useful to the user are called recommendation systems [7]. It has been demonstrated that recommendation system are valuable tools for assisting user in deal with the overload of choice and provide appropriate recommendations to them. Recommender System (RS) are widely established as a crucial solution for helping customers navigates the wide range of options while also keeping them engage and satisfy with personalized information. The idea behind RS is the easy observation that people fallow recommendation from other users. Before decide to buy a product, for example, user will read product reviews. In a similar character, prospective employees are desired to provide strong reference letters to employers [8]. Because there is so much content available on a given platform, it can be expanding for consumers to choose from the large number of items, leading to the problem of information overloaded. Whether it's the next song to listen to, the next movie to watch, the next news story to read, or the next job application to submit, the suggestion or recommendation is really about a decision making process.

A recommendation system can be build in a several ways, with the approaches divided based on the requirements of the application. Although recommendation systems build in several types, they can mainly be categorized into three types: Content-based filtering, hybrid recommendation system, and collaborative filtering [9]. Let us have a look at each of these types. The idea of collaborative filtering is straightforward: based on user ratings; identify all the users whose, similar to the active user, have previously expressed similar preferences. Based on this information, predict the ratings of all unknown products that the user active has not yet rated but are being rated in their neighborhood, taking neighbor tastes or preferences into consider. In this case, the person serving recommendation from the system is the active user. The two categories of collaborative information filtering techniques are UBCF and IBCF [10]. In User Based Collaborative Filtering (UBCF), the recommendations are generated by considering the preferences in the users' neighborhood. Item Based Collaborative Filtering (IBCF) creating recommendations based on the items' neighborhood relative. We recommends non-rated goods that are similar to the items the active user has previously rated, in contrast to UBCF, which finds for similarities between items first [11].

Recommendations are made using the Content Based Fitering (CBF) method that works by comparing the detail of the property of the advertised property product with the advertisements that are often seen by users. In the other words, the CBF method looks for the similarities of recommended advertisements content like home or shop category, property status sold or rented, house size and others according to the previous advertisements viewed by the user [12]. Three main steps involved in a content-based filtering recommendation system: generates product content information; generate user profile and preferences based on product features; and generate recommendations and predicting a list of items the user might like. The product's representative features are extracted throughout the item-profile generation process. Data structured or unstructured can be included in this features.

The limitations of each of the above types gave rise to hybrid recommendation systems. Thus, hybrid recommender engines which combine content-based filtering and Collaborative Filtering have been created using several of strategies. Initially, the sum of the recommendation outcomes is obtained from each, and equal weights are assigned to each of these outcomes. Gradually, the weights are modified subsequent to an evaluation of the user response to the recommendations.

Real-time recommendation models can be generated with machine learning algorithms. In order to choose the best suitable channel for the viewer, the system assists in making a self-adapting real-time recommendation system [13]. The suggested system is made up of multiple main modules, each of which carries out different relevant tasks, like machine learning in the training module and real-time stream processing. Through the usage of machine learning techniques, prediction accuracy has improved, leading to the final convergence of an accurate recommendation system. The percentage of recommendation that viewers accept depends how accurate a recommendation system is.

The rest of the paper is organized as follows: the literature surveys were related in section II also the Product Recommendation for user reviews are describes in Section III. Section V of the paper concludes with the result analysis presented in Section IV.

II. LITERATURE SURVEY

M. Fu, Y. Liu, H. Qu, Z. Yi, L. Lu et. al. [14] proposes a novel deep learning technique that, first understanding the consumers and items, imitates an effective intelligent recommendation. The related pretrained representational vectors are taken as the neural networks' inputs during the prediction step, when a feed-forward neural network is used to model the interaction between the user and the item. To verify the effectiveness of the proposed method, a series of experiment based on two benchmark datasets are carried out. The outcome demonstrate that our model perform very comparably with state-of-the-art method on both datasets as well as significantly outperforms previous approaches that used feed-forward neural networks. D. Z. Rodríguez, W. V. Ruggiero, G. M. Schwartz, R.L. Rosa, et. al. [15] presents a Knowledge Based Recommendation System (KBRS) that include an emotional health monitoring system to detect user who may be potential psychological disturbances, specifically stress and depression. A bidirectional long short-term memory Recurrent Neural Networks (RNNs) and convolution neural networks are used to detection sentence that include depressive and stressful content. According to experimental data, the proposed KBRS received a rating of 94% from highly satisfied users, compared to a rating of 69% obtained by an RS that did not include ontologies or sentiment metric. D. Ayata, Y. Yaslan and M. E. Kamasak, et. al. [16] suggests a framework for emotion-based music recommendation which learn signal from wearable physiological sensors to obtain a user's emotion. The PPG and GSR signal data from 32 subjects were utilized to obtain experimental results utilizing the decision tree, support vector machine and k-nearest neighbor's algorithms, and random forest, with/without feature fusion. The comprehensive experiment results under real data confirm the accuracy of the proposed system for classifying emotions, which could be easily integrated into any recommendation engine.

L. Qi, et. al. [17] presents a recommendation method according to Structural Balance Theory, or SBT-Rec. In the concrete of (I) user-based recommendation, here first appear the user's target "enemy"; afterwards, hence determine the user's target "possible friends" in accordance with the structural balance theory's "enemy's enemy is a friend" rule, and now suggested to the target user the product items that the "possible friends" of target users prefer. (II) In a similar manner, we establish the "possibly similar product items" for the product objects that the target user has preferred and purchase based on structural balance theory and recommend them to the target user. Lastly, a series of experiments deployed on the MovieLens-1M dataset validate the feasibility of SBT-Rec.

W. Chen, et. al. [18] describes a big-data supported prediction system and online mining for personalized job or candidate recommendations. In order to effectively analyze large-volume items at the cluster level and so lessen the computational load, a tree-based technique is introduced. Considering the dynamic property of Professional Social Networks (PSNs), our model can adapt to the growing dataset and enable accurate recommendations for the constant incessant of new members in real time. Finally, extensive experiments are conducted to verify our algorithm's outstanding performance in comparison to other existing algorithms in validate.

X. Zhang, et. al. [19] studies on issue systematically and suggests using a hybrid multilabel Convolution Neural Network with a Support Vector Machine (mCNN-SVM) technique to capture the intrinsic as well as complex relationships between location and clothing attributes. Our suggested approach outperforms several another techniques by over 29.41% -9.59 in terms of the map when ranking clothing by appropriateness for travel destinations, moreover outperforms various baselines by over 10.52 -16.38% in terms of the map for clothing item recognition according to experiment conduct on three datasets fashion also a benchmark journey outfit dataset. Lastly, exciting case studies demonstrates the effectiveness of our method.

S. Deng, X. Wu, Z. Wu, L. Huang, and G. Xu, et. al. in an attempts towards determinates the initialization within Matrix Factorization (MF) for trust-aware social recommendations,[20]. makes use of deep learning. It is proposed towards adopt a two-phase recommendation process that utilizes deep learning for initialization also synthesize interests of user along with their trust friends through the impact of the community effect to generate recommendations. Here perform extensive experiments on real-world social network data to show the accuracy as well as efficiency of now suggested comparison to other state-of-the-art methods. L. Guo, B. Jin, R. Yu, C. Yao, C. Sun and D. Huang, et. al. [21] focuses on the use of high-performance multi-label classification methods for 5G communication-related medical advice. For multi-label classification, we propose two label selection approaches: frequency-based sampling and clustering-based sampling. Therefore perform experiments using real-world data sets. When compared to baselines, the experimental findings demonstrate that our techniques achieve the state-of-the-art performance. In addition, we develop ours proposed methods to create a doctor recommendation system mobile application.

J. Chen, K. Li, Z. Tang, K. Bilal and K. Li, et. al. In order to predicts the waiting time for each treatment task for a patient, [22]. Proposed the Patient Treatment Time Prediction (PTTP) algorithm. To generate a patient treatment time model for every task, here employ realistic patient data from many hospitals. The Hospital Queuing-Recommendation (HQR) algorithm predicts with calculates an effective as well as convenient treatment plan that is suggested for the patient. To accomplish the above objectives, therefore leverage a cloud implementation by apache spark-based cloud implementation at the national supercomputing center in changsha. Our proposed model for recommending an appropriate treatment is effective and applicable, as shown by extensive experimental and simulation findings. Guimarães R., Rodrı´guez D. Z., Gerais M., Rosa R. L., Bressan G., Paulo S., et al. [23] determines the polarity of sentence taken from social network by utilizing polarity of adverbs. The solution is apply in a recommendation system, which uses sentences taken from social network and evaluated as having negative polarity to send user positive messages.

J. Zahálka, S. Rudinac and M. Worring, et. al. [24] proposed City Melange, a content-based venue explorer that is interactive and multimodal. The data collection integrates general multimedia sharing platform like Picasa or Flickr with location-based social networks like Foursquare. Similar users are determines and preferences of the interacting user's are learned through linear SVM model. Experiments show that even in the early phase of interaction, therefore content-based approach outperforms the user-activity-based as well as popular vote baselines, as well as can recommend off-the-beaten-track venues under aficionado's also mainstream venue to mainstream users. It is demonstrated that City Melange is a well-performing venues exploration approach. W. Dou, X. Zhang S. Meng, J. Chen, et. al. [25] proposed a Keyword-Aware Service Recommendation method, named KASR, to address the above challenges. Users' indicate their preferences and keywords, with a user-based collaborative filtering algorithm are adapted to generating appropriate recommendations. KASR is implementing using the Map Reduce parallel processing paradigm on Hadoop, a widely-adopted distributed computing platform; towards enhance its scalability as well as efficiency in big data environment. Lastly, an extensive of experiments is conduct on real-world data sets, and the outcomes show that KASR significantly improve existing approaches in conditions of scalability and accuracy for service recommender systems.

III.PRODUCT RECOMMENDATION

The block diagram of Product Recommendation for User Reviews in Online Big Data Analysis Using Machine Learning Technique is represented in below Fig. 1.

The information from Amazon product dataset was utilized. User's feedbacks for 24 different product categories, including digital music, office products, musical instruments, Amazon videos, and automotives reviews, are integrated in the dataset. The ratings, reviewer ID, reviews text, product ID, helpfulness timestamp and votes were between the features that are present in the dataset. Each user and item in the 5-core dataset has at least 5 reviews and ratings that is a subset of the Amazon product dataset. There are ratings and user review in this dataset. Huge amount of data can be professionally analyze and processed by big data technology, which also has the ability to extract valuable information from redundant big data through data processing. These allow for accurate market segmentation and realize analysis for the global crossborder e-commerce market.

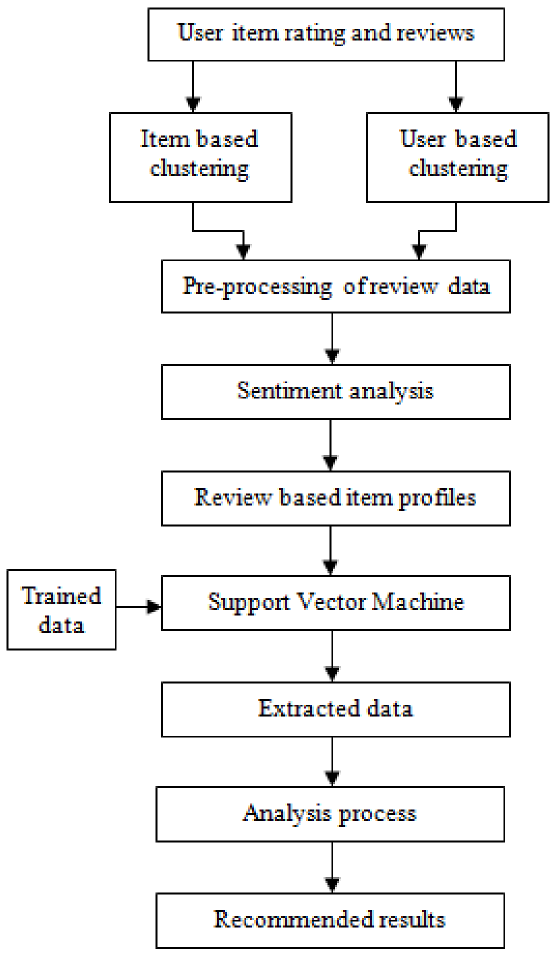

Fig. 1: Block Diagram of Product Recommendation for User Reviews

The first processes involve pre-processing the data to remove any irrelevant entries from users; only information related to the recommendation process is collected. Tokenization and stopwords elimination are two natural language processing techniques used in the pre-processing of review raw text. Tokenization is the process of dividing the text review into discrete phases, or token that could be used as individual identity for additional analysis. After tokenization, stopwords removed to obtain only the keywords that include insightful user comments and eliminate any unnecessary items.

A user-based approach compute neighbors (a set of user have similar activity histories) by calculating the user similarity, after which it produces predictions. When employing used based clustering, users are clusters based on the similar ratings and preferences. Fallowing user clustering, the opinion from each cluster is used to estimate unknown ratings for target user or what things they would like and dislike.

The item-based approaches generate prediction by compute the similarity between the set of objects that the user have rated with other items. The items in these clustering methods are grouped according to user's similar ratings. After the items are clustered, the aggregate opinion of each item in the cluster is used for the prediction task for the target items.

Sentiment analysis offers a numerical representation of customer opinion of the product. It extracts useful information from reviews using a various natural language processing techniques and text mining. Textual data is classified by sentiment analyzer using a variety benchmark dictionary that contain a pre-established set of terms that indicate positive, neutral and negative emotions. Compound values representing the user's sentiment towards the products are produced by the sentiment intensity analyzer using the token derived from the data text.

Based on the sentiment score derived from the reviews, user and item profile were constructed. The user's preferences are determined from the reviews they have provided. Users that have similar activity histories were consider as neighbors, also one neighbor's activity can be found there. Review-based user profiles provides a precise through description consumer opinion because user rating on an integral scale, and while individual users' rating habits may range greatly, reviews give a clear indication of what users think of the product. User review of the item can include descriptions of the user's experience with the product; its good features, any challenges or drawbacks faced during use, or any similar experience.

The system's recommendation to the user is its most crucial feature. The user profile analysis is taken into consideration when designing the recommendation process. Real-time recommendation models can be generating with machine learning algorithms. A significant problem with model prediction process is the scarcity of beginning data for training. The machine learning libraries Support Vector Machine (SVM) algorithm is used by the system. Every active user in the system goes through the training process.

Support Vector Machine (SVM) for classification can be seen as the application of perceptron. When classification problem is linearly separable, a hyperplane that makes two categories of separable data more close to the plane are set up usually the plane is called optimal separation hyperplane. This technique creates an apparent gap between the instances that belong to different classes by mapping the examples in space. The examples are represented as points in space using an SVM. The same area is then used for new examples. These new example are categorized according to whose side they belong to in this space. New data set is linearly separable in feature space, thus the classification in higher dimensional space is completed.

Weighting product reviews derived from both explicit and implicit feedback is part of the analysis. Every product review arises is collected and processed. The recommendation process is carried out in real time by combining big data tasks with machine learning. The method of assessing various input type might improve the recommendation's correctness.

IV. RESULT ANALYSIS

The Amazon product dataset was used for the experiments. There are 24 product categories in the dataset that a customer of Amazon.com has reviewed. A subset of the dataset, consisting of five categories Amazon instant videos, digital music, automotives, and office products & musical instruments was utilized. Recommendations were generated using machine learning and big data technologies with sentiment analysis provided by users to products. The dataset was dividing between train and test data in order to provide evaluation predictions for every user. Thirty percent of the samples are in the test data, and seventy percent of the sample was in the train data. System performance is assessed using evolution parameter like Mean Absolute Error (MAE) and Root Mean

Squared Error (RMSE) over the collected dataset. Table 1 show the comparative performance analysis of product recommendation system based on SVM with Big data and Logistic Regression (LR) for several cluster sizes.

The Root Mean Squared Error (RMSE) between the user-provided actual ratings and the predicted ratings, or R_Predict and R_Actual, is determined.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(R_{Predict} - R_{Actual})^2} \ldots\ldots(1)$$

Mean Absolute Error (MAE) is a measure of the average size of the mistakes in a collection of predictions, without taking their direction into account. It is measured as the average absolute difference between the predicted values and the actual values and is utilized to assess the efficiency of a model.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}(R_{Predict} - R_{Actual}) \ldots\ldots(2)$$

Table 1: Comparative Analysis

Classification model used for recommendation system	Cluster size	RMSE	MAE
SVM	400	0.83	0.61
	500	0.85	0.63
	600	0.87	0.67
LR	400	1.5	0.9
	500	1.6	0.92
	600	1.7	0.98

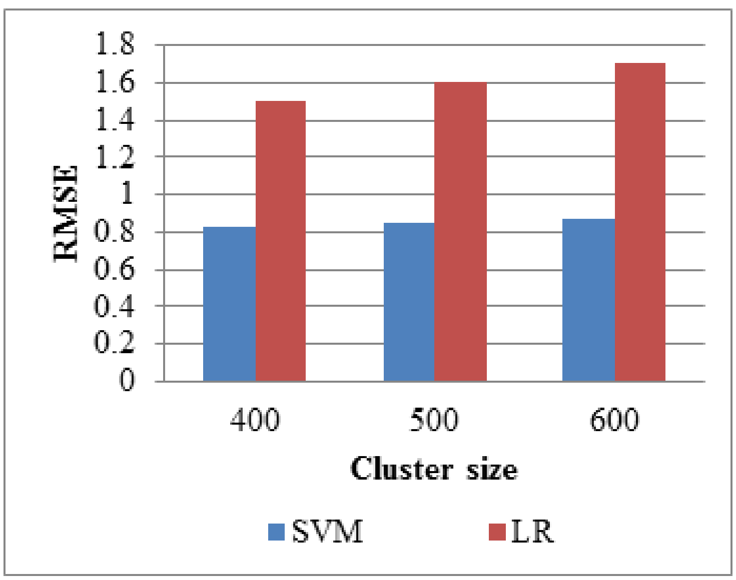

Fig. 2: Comparison In Terms of 'Rmse'

Fig. 2 shows the performance analysis of different classifiers with different cluster sizes in terms of RMSE. Fig. 3 show the performance analysis of multiple classifiers with different cluster sizes in terms of MAE.

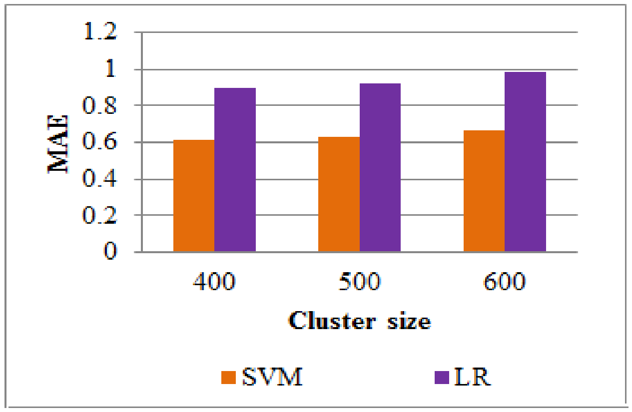

Fig. 3: Comparison in Terms of 'Mae'

Both MAE and RMSE values of described product recommendation system based on SVM classification are low compare to other classification which explain the effectiveness of describe model. Recall score was another tool here utilized to evaluate capacity of each product category's predictions performed. The ratio of true positives towards the total of true positives and false negatives is called as the recall score. False Negative (FN) is relevant items which were not recommended to the consumer, while True Positives (TP) is appropriate items that were recommended towards the user. Fig. 4 shows the comparative graphical representation for Recall parameter.

$$\text{Recall} = \frac{TP}{TP + FN} \dots (3)$$

Table 2: Performance Analysis with Recall Parameter

Classification model	Recall
SVM	91
LR	75

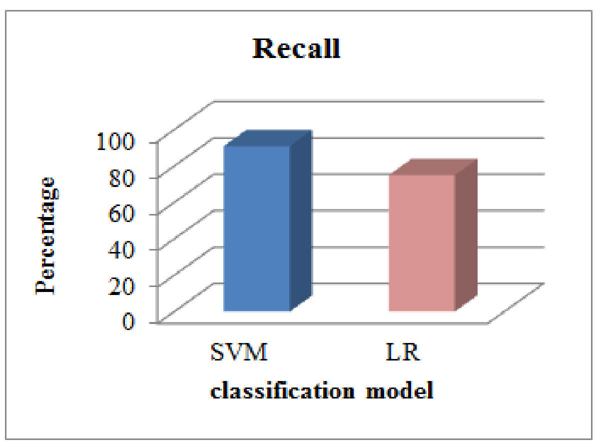

Fig. 4: Performance Analysis with Recall Parameter

Using the described Product Recommendation, a rise during the recall score with a reduce into the MAE as well as RMSE scores are seen for User Reviews in Online Big Data Analysis Using Machine Learning Technique compared to the other machine learning (LR) model.

V. CONCLUSION

In this paper, Product Recommendation for User Reviews in Online Big Data Analysis Using Machine Learning Technique is described. For more than ten years, recommendation system research and development has been vibrant field. Recommendation system is applicable in variety of business domains like recommending vacations, restaurants, therapy, movies, music, etc. Support Vector Machine (SVM) is used in this paper as machine learning classification. The Amazon product dataset, that include review and product ratings, are used for experiments. Recall, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), with other evolution parameters are used to assess the efficiency of the recommendation system. Using the described Product recommendation, a rise in the recall scores are observed for User Reviews in Online Big Data Analysis Using Machine Learning Technique compared to the other machine learning (LR) model.

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