International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Design and Development of Data-Driven Product Recommender Model for E-Commerce using Behavioral Analytics

[1]Dr. D. Srinivasa Kumar, [2]Dr. Kilaru Madhavi, *[3]Dr. Tenneti Ramprasad, [4]Dr. K. R. Sekhar, [5]Dr. Srinivasa Rao Dhanikonda, [6]Dr. CH Ravi

Submitted: 24/12/2023 **Revised**: 30/01/2024 **Accepted**: 06/02/2024

Abstract: Recommendations assist users in more precisely locating the information they require for a given sample. People all around the world have been drawn to E-Commerce-based businesses in recent years. The Recommendation Model (RM) is an important system in internet business that recommends products to consumers based on their previous actions. Furthermore, the RM is effectively employed by both corporate service suppliers and customers. Furthermore, because so much product information exists online, recommender systems are critical for analyzing the existence of items that should be offered to clients, which enhances customer decision-making by giving extensive knowledge about the product and saves the effort required. However, the complications are recognized and observed from various methodologies as per the literature. To maintain proper RM, the research needs to focus more on data collection and analysis that provide real-time support. Thus, the user behavior data and machine learning concepts are utilized for designing Data-Driven Product Recommender Model (DD-PRM). From the experimental results, it has been determined that the proposed DD-PRM outperforms than the exiting models.

Keywords: *Data-Driven, Recommender System, Behavioral Analytics, E-Commerce, Cross-domain Recommender System, Deep Neural Networks*

1. Introduction

E-commerce's fast expansion has altered the way customers purchase, providing exceptional ease and a wide choice of products at their hands. However, the multitude of options has resulted in information overload, making it increasingly difficult for people to choose things that truly resonate with them. This difficulty has fueled the creation of product recommender systems, which use modern technologies like data analytics and machine learning to deliver personalized suggestions [1].

Personalized product suggestions have the potential to significantly improve the entire shopping experience for users. Recommender systems can give personalized suggestions that adapt to individual necessities by determining user preferences, purchasing history, and browsing behavior. This degree of customization saves customers time while also increasing their level of involvement and pleasure with the e-commerce site. As a result, organizations may profit from increased client loyalty, revenues, and customer lifetime value.

Behavioral analytics emerged as an effective method for interpreting user behavior patterns and extracting appropriate information for recommendation systems. Behavioral analytics may give a complete perspective of user preferences and desires by analyzing user activities such as clicks, searches, purchases, and reviews [2-3]. This data-driven approach enables the creation of more accurate and effective recommendation models, as it captures real-time user behavior and adapts to evolving preferences.

The design and development of an effective data-driven product recommender model involve several crucial steps. Firstly, data collection is performed to gather relevant user data, including browsing history, purchase records, and demographic information. Next, data preprocessing techniques are applied to cleanse and transform the raw data into a usable format. Feature engineering is then employed to extract meaningful features that capture user preferences and behavior.

The deployment of data-driven product recommender systems has far-reaching implications for e-commerce platforms and users alike. By offering personalized recommendations, businesses can enhance customer satisfaction, increase conversion rates, and ultimately drive

[1]Professor, Department of Basic Sciences and Humanities, GMR Institute of Technology, Rajam,Vizianagaram (Dist), Andhra Pradesh, India, Pincode: 532127, Email: srinivasakumar.d@gmrit.edu.in
[2]Assistant Professor, Department of Humanities and Sciences, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, Telangana, India, Pincode: 500090, Email: madhavi.aditi@gmail.com
[3]Associate Professor, Department of Mathematics, Vasavi College of Engineering (A), Hyderabad, Telangana, India, Pincode: 500031. Email: ramprasad@staff.vce.ac.in
[4]Assistant Professor, Faculty of Mathematics, School of Technology, The Apollo University, Murukambattu, Chittoor, Andhra Pradesh, India, Pincode: 517127. Email: sekharkuppala_r@apollouniversity.edu.in
[5]Associate Professor, Department of IT, BVRIT HYDERABAD College of Engineering for Women, Hyderabad, Telangana, India, Pincode: 500090. Email: srinivasarao.dhanikonda@gmail.com
[6]Professor, Department of CSE, AVN Institute of Engineering and Technology, Ibrahimpatnam, Hyderabad, Telangana, India, Pincode: 501510. Email: ravi.chinapaga@gmail.com

revenue growth. Users, on the other hand, benefit from a more tailored shopping experience, saving time and effort in finding products that match their preferences [4-5].

While product recommender systems offer great potential, there are several challenges that need to be addressed during their design and development. One of the main challenges is the sparsity and noise in user data. In many cases, users may have limited historical data or may not provide explicit feedback, making it difficult to accurately capture their preferences. Another challenge is the scalability of the recommender system, as e-commerce platforms often handle a large number of users and products simultaneously. Efficient algorithms and infrastructure are required to process and analyze vast amounts of data in real-time. Additionally, addressing issues such as privacy concerns and ensuring transparency and fairness in recommendations are critical considerations in the development of recommender systems [6-7].

The design and development of data-driven product recommender models for e-commerce have witnessed significant advancements in recent years. Researchers and practitioners have explored various approaches and techniques to improve the accuracy, effectiveness, and personalization of recommendation systems. Here are some notable research developments in this field:

Deep Learning-based Recommender Systems:

Deep learning methods, especially neural networks, have been used to increase recommender system performance. These models have the ability to capture complicated patterns and relationships in user behavior data, resulting in more precise recommendations. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been used to model sequential and image-based data. Deep learning algorithms combined with classic collaborative filtering and content-based methods have demonstrated promising results in improving recommendation accuracy [8].

Context-Aware Recommendation:

Contextual information, such as time, location, and device, is increasingly being included in recommender systems in order to deliver more appropriate recommendations. Context-aware recommendation algorithms consider the user's context of the situation and tailor their recommendations appropriately. Consideration of the time of day or the user's present location, for example, might aid in personalizing suggestions for certain contexts, such as breakfast products in the morning or regional restaurants at lunchtime. Context-aware techniques have been shown to increase suggestion quality and user satisfaction [9].

Hybrid Recommender Systems:

Hybrid recommender systems combine multiple recommendation techniques to leverage their complementary strengths. Collaborative filtering and content-based filtering methods are often integrated to overcome their respective limitations. Hybrid approaches can provide more diverse and accurate recommendations by capturing both the user-item interactions and item attributes. Ensemble techniques, such as stacking and blending, have also been explored to combine predictions from different recommendation algorithms, resulting in improved recommendation performance [10].

Explainable Recommender Systems:

As recommendation systems become more pervasive, there is a growing need for transparency and explainability in the recommendations provided. Researchers have focused on developing explainable recommender systems that can provide understandable and interpretable explanations for the recommendations generated. Techniques such as rule-based approaches, feature importance analysis, and model-agnostic explanations have been explored to enhance the transparency of recommendation models. Explainable recommendations not only improve user trust and satisfaction but also enable users to make informed decisions.

Reinforcement Learning in Recommender Systems:

Reinforcement learning (RL) techniques have gained attention in the domain of recommendation systems. RL algorithms enable systems to learn and optimize recommendation policies through trial-and-error interactions with users. These models can dynamically adapt to changing user preferences and explore new recommendations while balancing the exploration-exploitation trade-off. RL-based recommender systems have shown promise in improving long-term user satisfaction and addressing the cold-start problem, where limited user data is available.

Sequential Recommendation:

Sequential recommendation aims to capture the temporal dynamics of user preferences and recommend items based on the sequence of user interactions. Recurrent neural networks (RNNs), particularly variants like long short-term memory (LSTM) and gated recurrent units (GRU), have been widely used to model sequential patterns in user behavior. Sequential recommendation techniques are particularly relevant for e-commerce platforms where user preferences evolve over time, enabling the generation of personalized and context-aware recommendations.

Privacy-Preserving Recommender Systems:

Addressing privacy concerns in recommender systems has become crucial. Researchers have focused on developing privacy-preserving recommendation approaches that can protect sensitive user information while maintaining recommendation accuracy. Techniques such as differential privacy, federated learning, and secure multiparty computation have been explored to ensure user privacy in the data-driven product recommender models.

These research developments demonstrate the continuous efforts to enhance the design and development of data-driven product recommender models for e-commerce. By incorporating advanced techniques, such as deep learning, context-awareness, hybridization, explainability, reinforcement learning, sequential recommendation, and privacy preservation, researchers strive to improve the accuracy, effectiveness, and user satisfaction of recommendation systems in the e-commerce domain. These advancements pave the way for more personalized, relevant, and trustworthy product recommendations in the rapidly evolving e-commerce landscape.

2. Related Works

Covington, P., et al. (2016) presented a deep learning-based recommendation system used by YouTube to provide personalized video recommendations [11]. The authors proposed a deep neural network architecture that leverages user behavior data, such as watch history and search queries, to generate accurate and diverse video recommendations. The authors focus on collaborative filtering techniques for implicit feedback datasets, where user preferences are inferred from user behavior rather than explicit ratings. The work explores matrix factorization methods and proposes algorithms to improve recommendation accuracy in the absence of explicit user feedback [12].

In [13] the authors provided an overview of context-aware recommender systems, which consider contextual information in the recommendation process. The authors categorize various contextual factors, such as time, location, and social context, and discuss the challenges and techniques employed in developing context-aware recommendation models. Burke, R. (2002) presents a comprehensive survey of hybrid recommender systems that combine multiple recommendation techniques. The paper discusses various hybridization strategies, such as weighted combination, switching, and feature combination, and provides insights into their strengths and limitations [14].

In [14] the authors explored explainable recommendation systems, which provide transparent explanations for the recommendations generated [15]. The authors review different approaches, including rule-based explanations, feature-based explanations, and post-hoc explanation techniques, and discuss their impact on user trust and satisfaction. Kang, W., et al. (2018) proposed a deep reinforcement learning framework for generating list-wise recommendations [16]. The model employs an actor-critic architecture to learn sequential interactions and optimize the recommendation policy. The work demonstrates the effectiveness of reinforcement learning techniques in improving long-term user satisfaction.

Hidasi, B., et al. (2015) are interested in sequential suggestion in e-commerce environments, where customer preferences change over time [17]. The authors propose GRU4Rec, a recurrent neural network-based model that records sequential patterns in user behaviour and delivers personalised suggestions. Shokri, R., and Shmatikov, V. (2009) study and analyse possible privacy threats in collaborative filtering-based recommendation systems [18]. The study addresses approaches for preserving user privacy while retaining recommendation accuracy, such as introducing noise, utilising secure multiparty computing, and applying differential privacy.

The authors of [19] suggested a personalised product recommendation algorithm for e-commerce that makes use of machine learning techniques. To create personalised suggestions, the authors investigate collaborative filtering, content-based filtering, and hybrid techniques. The study assesses the performance of several algorithms and offers insights into their usefulness in enhancing suggestion quality. Sarwar, B., and colleagues (2001) developed a hybrid recommender system for personalised product suggestions in e-commerce [20]. To increase suggestion accuracy, the authors mix collaborative filtering and content-based filtering algorithms. The study reveals how hybridization might produce more accurate and diversified suggestions.

W. Zhang et al. (2019) concentrated on the use of deep learning algorithms in personalised product recommendation [21]. The authors suggested a deep learning-based model that takes into account user behaviour, item properties, and contextual information. The study illustrates deep learning's advantage in capturing complicated patterns and enhancing suggestion accuracy.

S. Rendle (2012) investigated the application of factorization machines (FM) for personalised product recommendation [22]. Factorization machines are a versatile model that combines the benefits of matrix factorization with linear regression. The study shows how FM may capture both user-item interactions and item features for personalised suggestions.

Zhou, T., et al. (2020) proposed an ensemble learning approach for personalized product recommendation on e-commerce platforms [23]. The authors combine multiple recommendation algorithms, including collaborative filtering, content-based filtering, and association rule mining, to enhance recommendation accuracy. The study evaluates the performance of the ensemble model and demonstrates its effectiveness in improving recommendation quality.

Zhang, M., et al. (2020) addressed the privacy concerns in personalized product recommendation in e-commerce [24]. They proposed a privacy-preserving recommendation framework that incorporates secure multi-party computation and differential privacy techniques. The study demonstrates that privacy protection can be achieved without sacrificing recommendation accuracy.

3. Materials and Methods

Data-Driven Product Recommender Model for E-Commerce using Behavioral Analytics

The proposed approach is designed to improve on existing web mining-based product recommendation algorithms used in E-Commerce apps and services. A unique Data-Driven Product Recommender Model (DD-PRM) is designed in this article. The model comprehensively observes the various client behaviors and product popularity. Various indicators from online usage behaviors are examined to determine the essential qualities. Additionally, consumer browsing patterns and user actions are tracked to anticipate product interests in online purchases.

The assessments are based on a variety of aspects such as product range, quality, and so on. The navigation points of users are observed via online data mining in this case. Product popularity is calculated based on the assessments. Furthermore, the coefficient matrix is developed to offer user purchasing considerations. Second, product opinion measurements are analyzed based on user reviews or comments for each product. Weight Factor (WF) is produced from the aforementioned evaluations to deliver Product Recommendations to the consumer.

Factors in Data-Driven Behavioral Analysis

This section elaborates the elements that are observed and examined during the data-driven behavioral analysis process.

Web Data Analysis

The web usage data is gathered from the webserver access log and can be used as the model's first input. The log file is updated for each new entry on the web for product search or purchase. As a result, a wide range of consumers and their interests may be efficiently assessed using this.

Customer Behavior Analysis

Web data contains a wealth of information on customers, such as browsing data, user IP, protocol data, period, and resources, among other things. The received web usage data is pre-processed for effective analysis, and so the undesirable log files are removed from the weblog. In the proposed study, the customer IP and resource data are regarded as important aspects that must be addressed while framing the PRM.

Activity Score

A single user does not use or view the server's web resources. The pages are viewed by various individuals and will be assessed to determine the main activity. Furthermore, under this approach, the activity score is considered based on the number of times a consumer views a specific page. The Activity Score is calculated as follows in Equation 1.

$$Activity\ Score = \frac{Total\ Number\ of\ Visits}{Total\ times\ a\ web\ page\ visited\ by\ different\ users} \quad \ldots\ldots(1)$$

Current Search Data

In this case, the desired product is searched for by a specific user, which is utilized to determine the search data. Product reviews and media popularity are taken into account when calculating current user search statistics.

Product Reviews: In all commercial sites, a review column about the target product is supplied to assist purchasers.

Opinion Measure: Stanford Natural Language Processing is employed here to measure the opinions of user reviews, which contains the review statements for specific products and delivers a rating for each remark based on the user feelings. The word intensities in the review statements are used to calculate the opinion score.

Popularity Measure: In this case, the popularity metric is based on the ratings, likes, and other feedback given to a single product. It is computed as follows in Equation 2.

$$Popularity\ Measure = \frac{Total\ number\ of\ positive\ responses\ to\ the\ product}{Total\ number\ of\ responses} \ldots\ldots(2)$$

Range of Products: The item valuing is the essential angle assessed while conveying item ideas in light of the client's perspective while looking for an item. This is used to assess customers' purchasing habits.

Purchasing Pattern of Users: This is to analyze the list of products purchased by the users on the commercial website, which may significantly help in providing recommendations based on the user interests and requirements.

Co-efficient Matrix: The correlation coefficient (CE) between the product price and the purchase history of consumers is calculated here. The relevant formula is shown in the Equation 3.

$$CE = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}} \quad \ldots\ldots(3)$$

where 'x' denotes the item in the product list and 'y' denotes the price of the particular product.

Weight Factor Computation: The weight factor is calculated by taking into account the preceding computations. The goods are graded based on the WF for delivering online suggestions to users. The derivation is given in the form of an Equation 4.

$$WF = m_1 * A + m_2 * B + m_3 * C \ldots\ldots(4)$$

Where 'A' is the activity score, 'B' is the opinion score and 'C' denotes the popularity measure. Further, m_1, m_2 and m_3 are the normalized weight factors for equalizing the values from different measures, which can be given as 0 to 1.

The Product Recommendation Model is divided into three major components, as shown in Figure 1. The phases are as follows: Data-Driven Behavioral Analysis, Model Derivations and Product Recommendations.

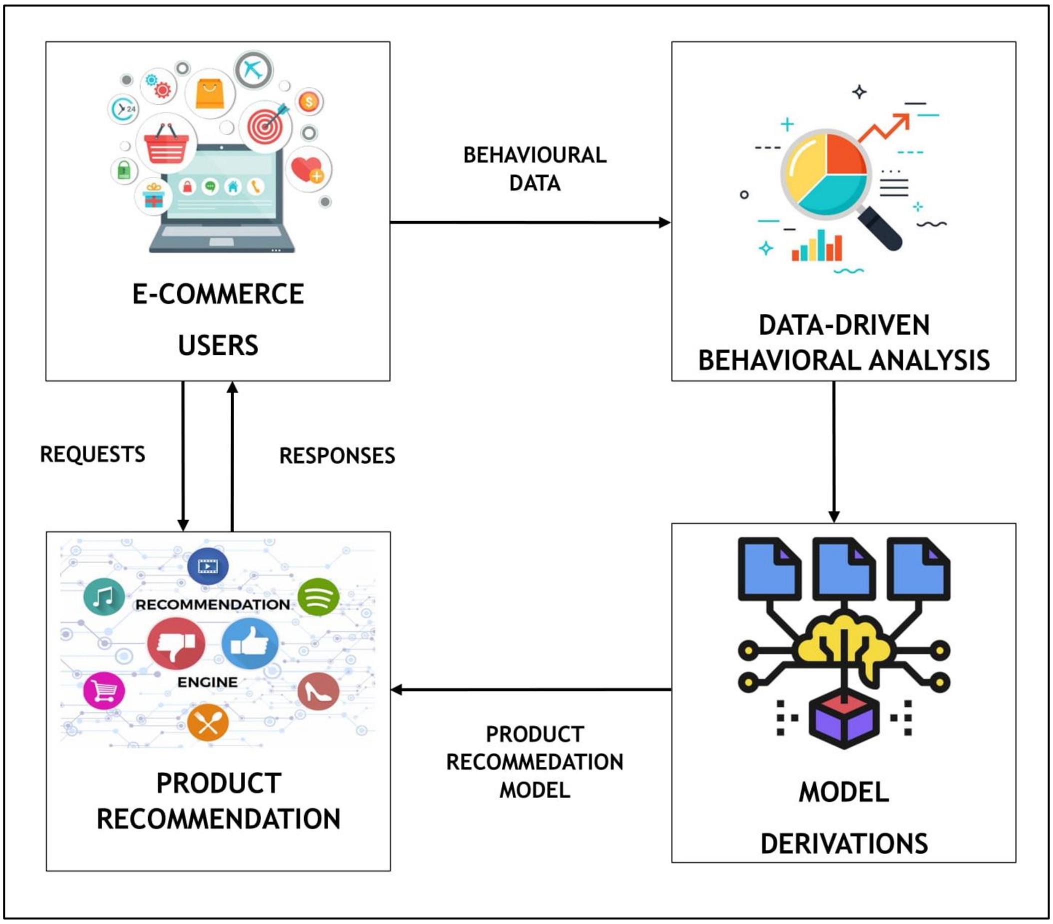

Fig 1. General Architecture of Data-Driven Product Recommender Model

The initial behavior logs analysis module analyses user behaviors based on search history, purchase history, and product ratings, much as it did in the previous section. The coefficient matrix and Weight factors are assessed in model derivations based on user records on online purchases and product search history.

Furthermore, the collaborative filtering approach is applied here to provide the best product suggestions. The matrix M(a,b) is constructed using the WFs calculated for products, where 'a' signifies the number of users and 'b' specifies the number of goods. The weight factor of customer C_i for the product P_j is denoted by matrix (a, b) member w_{ij}. Equation 5 shows the matrix format based on the weight variables that were established.

$$\begin{pmatrix} Customer & P_1 & P_2 & \ldots & P_n \\ C_1 & w_{11} & w_{12} & \ldots & w_{1n} \\ C_2 & w_{21} & w_{22} & \ldots & w_{2n} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ C_n & w_{n1} & w_{n2} & \ldots & w_{nn} \end{pmatrix} \ldots\ldots(5)$$

Furthermore, the Customer Similarity (CS) is calculated using the Equation 6,

$$CS(i,j) = \cos(\vec{i},\vec{j}) = \frac{\vec{i}.\vec{j}}{\|\vec{i}\|.\|\vec{j}\|} \ldots\ldots(6)$$

And, the optimization problem can be effectively determined with the following Equation 7

$$\min_{C,P} \pi(D,C,P) + \delta w(C,P) \ldots\ldots(7)$$

Here, 'D' is the data matrix and $X = CP^T$, denotes the low-grade approximation. Furthermore, when the matrix completion issue is regarded to be performing supervised learning-based model training, the loss function is specified as in Equation 8. The smallest square inaccuracy is provided as

$$\min_{C,P} \sum_{(i,j\in\varphi)} \left(d_{i,j} - C_i P_j^t\right)^2 + \delta\left(\| C_i \|^2 + \| P_j \|^2\right) \quad \ldots\ldots (8)$$

Where the non-zero elements in the matrix 'D' are mentioned with index factor as 'φ'. The optimized goal function is also given, along with the formulation of the maximum matrix function.

$$F(C,P,\mu) = \sum_{(i,j\in\varphi)} \sum_{r=1}^{R-1} Z\left(t_{i,j}^r\left(\sigma_{i,r} - C_i P_j^t + \frac{\delta}{2}\left(\| C_i \|^2{}_F + \| P_j \|^2{}_F\right)\right)\right) \quad \ldots\ldots (9)$$

where,

$$t_{i,j=}^r \begin{cases} 1 & if\ r \geq d_{i,j} \\ -1 & Otherwise \end{cases}$$

where, $\| C_i \|^2{}_F + \| P_j \|^2{}_F$ denotes the Frobenius Norm and, '$\sigma_{i,r}$'represents the rank of the i[th] customer. Then, the optimal recommendation function is given as,

$$RF(t) = \begin{cases} 0, & if\ t \geq 1 \\ \frac{(1-t)^2}{2}, & if\ t \in (0,1) \\ 0.5 - t, & otherwise \end{cases} \quad \ldots\ldots (10)$$

Algorithm: Data-Driven Product Recommender Model

Data-Driven Behavioral Analysis Phase

1. Gathering of Web Usage Data

2. Calculate the Activity Score of Users using

$$Activity\ Score = \frac{Total\ Number\ of\ Visits}{Total\ times\ a\ web\ page\ visited\ by\ different\ users}$$

3. Determine the Current Search Data, Product Reviews, Opinion and Measure

4. Compute the Popularity Measure using

$$Popularity\ Measure = \frac{Total\ number\ of\ positive\ responses\ to\ the\ product}{Total\ number\ of\ responses}$$

5. Calculate the Correlation Coefficient of Product Price and Purchase History using

$$CE = \frac{\sum_{i=1}^n (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^n (x_i - \overline{x})^2}\sqrt{\sum_{i=1}^n (y_i - \overline{y})^2}}$$

6. Compute the Weight Factor using

$$WF = m_1 * A + m_2 * B + m_3 * C$$

Model Derivation Phase

1. Construct the Matrix using Weight Factors as

$$\begin{pmatrix} Customer & P_1 & P_2 & \ldots & P_n \\ C_1 & w_{11} & w_{12} & \ldots & w_{1n} \\ C_2 & w_{21} & w_{22} & \ldots & w_{2n} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ C_n & w_{n1} & w_{n2} & \ldots & w_{nn} \end{pmatrix}$$

2. Calculate the Customer Similarity using

$$CS(i,j) = \cos(\vec{i},\vec{j}) = \frac{\vec{i}.\vec{j}}{\| \vec{i} \|.\| \vec{j} \|}$$

3. Optimize the Data Matrix using

$$\min_{C,P} \pi(D,C,P) + \delta w(C,P)$$

4. Compute the Loss Function using

$$\min_{C,P} \sum_{(i,j\in\varphi)} \left(d_{i,j} - C_i P_j^t\right)^2 + \delta\left(\| C_i \|^2 + \| P_j \|^2\right)$$

5. Optimize the Goal Function using Maximum Matrix Function

$$F(C,P,\mu) = \sum_{(i,j\in\varphi)} \sum_{r=1}^{R-1} Z\left(t_{i,j}^{r}\left(\sigma_{i,r} - C_i P_j^t + \frac{\delta}{2}\left(\| C_i \|^2{}_F + \| P_j \|^2{}_F\right)\right)\right)$$

Product Recommendation Phase

1. Determine the Optimal Product Recommendations using

$$RF(t) = \begin{cases} 0, & if\ t \geq 1 \\ \frac{(1-t)^2}{2}, & if\ t \in (0,1) \\ 0.5 - t, & otherwise \end{cases}$$

Experimental Results and Discussion

The following part compares the results of the proposed recommender system with the existing recommender systems to showcase the superiority of the proposed system.

Performance Evaluation Metrics

Using standard measures, the proposed approach is compared to established recommendation systems. These measures are Precision, Recall, F-Measure, Mean Absolute Error (MAE), Space Complexity and, Processing Time. The following formulas are used to calculate these metrics:

Precision Measure: Precision Measure is characterized as the extent of reasonable outcomes among the total number of anticipated outcomes. This is determined to assess the model's efficacy. The higher the rate of accuracy, the fewer the false positives, and the formula is as follows:

$$Precision\ Measure\ (PM) = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: The recall rate denotes the number of relevant outcomes that are incorrectly determined. The greater the rate of recall value, the fewer the false-negative findings, and the formula is as follows:

$$Recall\ Rate\ (RR) = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Space Complexity: The collected web data is kept in the main memory for suitable model execution, which requires enough space, which may be assessed as the space complexity. The following formula is used in computations to determine storage effectiveness.

$$Memory\ Used = Total\ Mem - Free\ Mem$$

F-Measure: It is calculated using the as per Equations (3.10) and (3.11) data, and the formula is shown below.

$$F - Measure = 2 \times \frac{PM \times RR}{PM + RR}$$

Mean Absolute Error: MAE is computed for measuring the appropriate error rate between the determined and actual rates. This is to find the accurateness of the model as in Equation (3.14).

$$MAE = \frac{\sum_{i=1}^{n}(a_i - b_i)}{N}$$

where 'a_i' is the determined rate and 'b_i' is the actual rate.

4. Results and Discussion

For model computations and evaluations, the data from two standard datasets such Netflix Dataset and Amazon Review Dataset. The Netflix dataset comprises over 100,000, 000 ratings for 18000 pieces of content submitted by over 500, 000 individuals. Furthermore, the Amazon review dataset contains a massive number of product reviews. In particular, 120 users are selected for evaluations and outcome analysis in this trial. Customer and product data such as age, gender, most interesting category, product quality, discount, and feedback are all taken into account when making suggestions. The findings are compared to current models such as Cross-domain Recommender System (CDRS), Reinforcement Learning (RL), Variational Autoencoders (VAE), Generative Adversarial Networks (GAN) and, Deep Neural Networks (DNN).

Table 1 and Figure 2 portray the precision measures of the proposed and existing models. The figure shows that the proposed DD-PRM gives a higher rate of precision measure, which means fewer false-positive values. This analysis demonstrates that the proposed model performs better by presenting the user with relevant product recommendations.

Table 1. Precision Rate of Existing and Proposed DD-PRM Recommender Systems

Models	**Number of Users**					
	20	**40**	**60**	**80**	**100**	**120**
CDRS	84	80	83	85	75	72
RL	86	79	86	83	80	86
VAE	82	70	82	80	70	82
GAN	74	68	71	78	72	68
DNN	88	91	92	91	93	91
Proposed DD-PRM	96	95	96	96	95	95

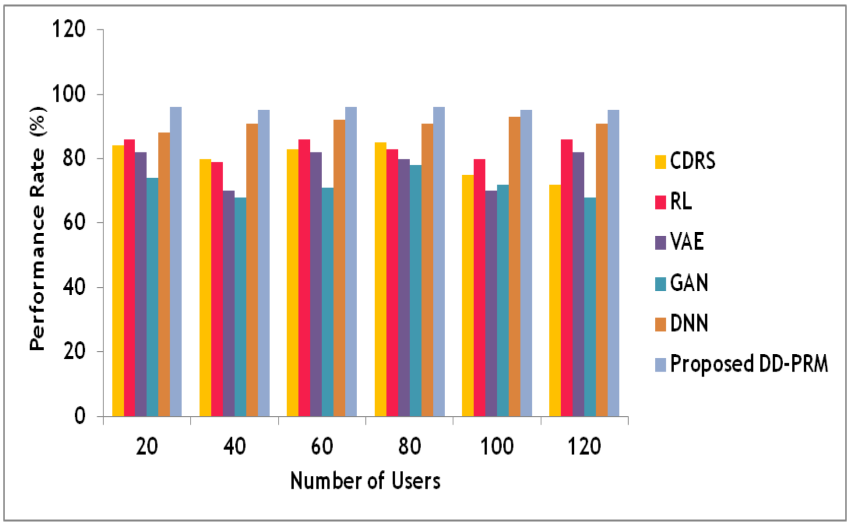

Fig 2. Performance analysis of existing and proposed recommender systems with respect to precision rate under various user's scenario

Table 2 and Figure 3 portray the recall rate of the proposed and existing models. The figure shows that the proposed DD-PRM gives a higher rate of recall rate, which means fewer false-negative values. This analysis demonstrates that the proposed model performs better than the existing models.

Table 2. Recall Rate of Existing and Proposed DD-PRM Recommender Systems

Models	**Number of Users**					
	20	**40**	**60**	**80**	**100**	**120**
CDRS	85	84	80	75	88	95
RL	81	77	68	69	86	93
VAE	84	84	80	72	83	94
GAN	86	81	78	79	82	91
DNN	76	78	68	73	84	92
Proposed DD-PRM	73	84	80	69	79	93

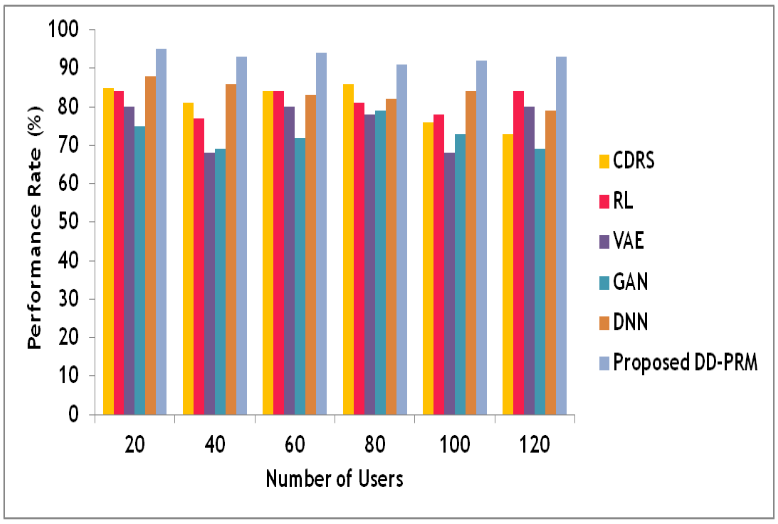

Fig 3. Performance analysis of existing and proposed recommender systems with respect to recall rate under various user's scenario

Because the model processes the vast amount of weblog data, the memory consumption rate of the proposed model is assessed. Unwanted data are deleted from the retrieved weblog through effective processing in the proposed technique. Table 3 and Figure 4 depict the findings and demonstrate that the suggested approach requires less system memory than existing models.

Table 3. Space Complexity of Existing and Proposed DD-PRM Recommender Systems

Models	Space Complexity (Bytes)
CDRS	3500
RL	2850
VAE	2790
GAN	2550
DNN	1880
Proposed DD-PRM	1240

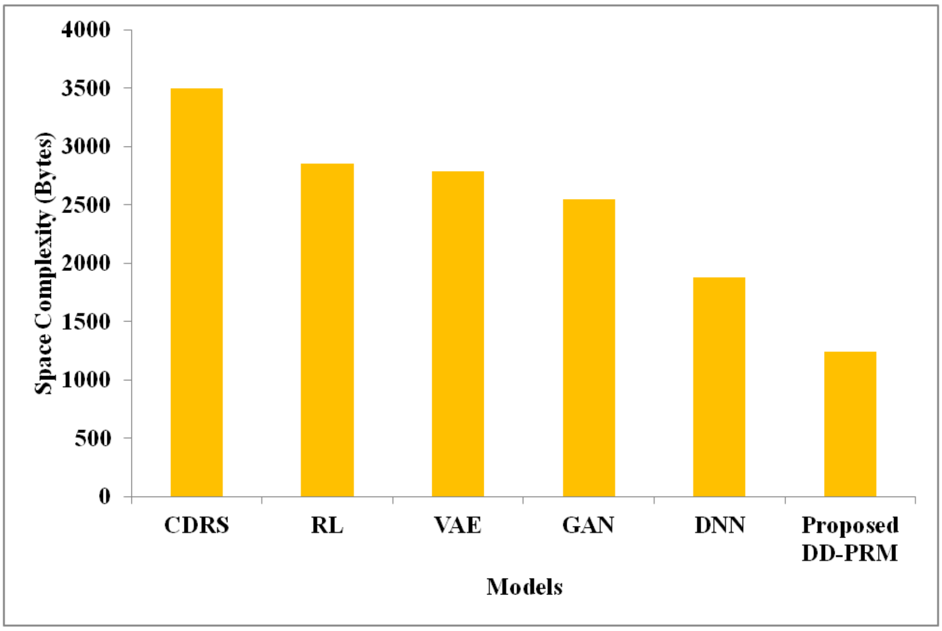

Fig 4. Performance analysis of existing and proposed recommender systems with respect to space complexity

The suggested model's error rate should be low when it is designed to deliver relevant product suggestions to clients online. According to the results in Figure 5 the error rate of DD-PRM model is less error than the existing models. Therefore, it can be inferred that the proposed algorithm successfully analyzes all client behaviors for giving optimum and appropriate product suggestions.

Table 4. Error Rate of Existing and Proposed DD-PRM Recommender Systems

Models	Number of Users					
	20	**40**	**60**	**80**	**100**	**120**
CDRS	63	62	61	59	63	65
RL	56	52	53	56	56	57
VAE	74	70	70	69	76	77
GAN	68	67	67	65	65	66
DNN	45	44	44	43	44	41
Proposed DD-PRM	30	29	29	28	27	29

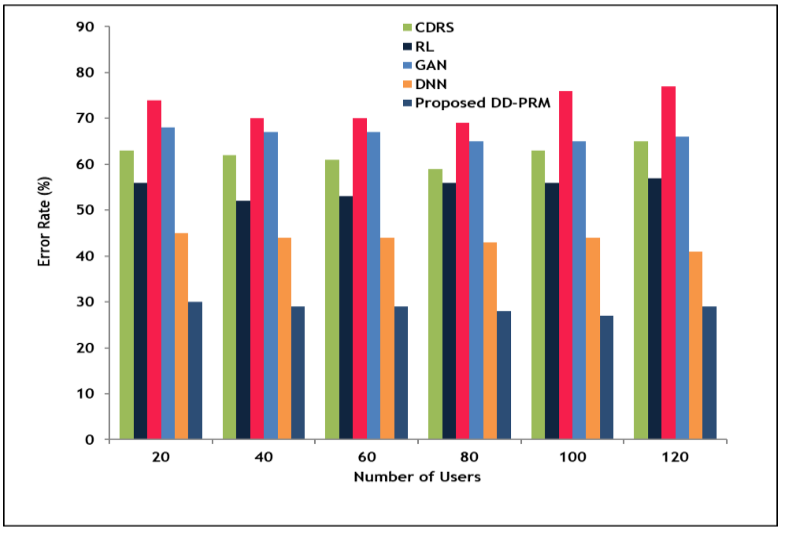

Fig 5. Performance analysis of existing and proposed recommender systems with respect to error rate under various user's scenario

Further, the time factor is very significant to analyze the model efficiency. The processing time for providing product recommendations has been evaluated and the results are presented in Table 5 and Figure 6. By the analysis, it is evidenced that the proposed DD-PRM executes faster than the existing models.

Table 5. Processing Time of Existing and Proposed DD-PRM Recommender Systems

Models	Number of Users					
	20	**40**	**60**	**80**	**100**	**120**
CDRS	40	41	40	44	47	47
RL	38	40	39	40	39	40
VAE	35	35	36	37	37	35
GAN	29	34	30	30	33	32
DNN	37	38	39	36	35	39
Proposed DD-PRM	25	20	23	24	25	22

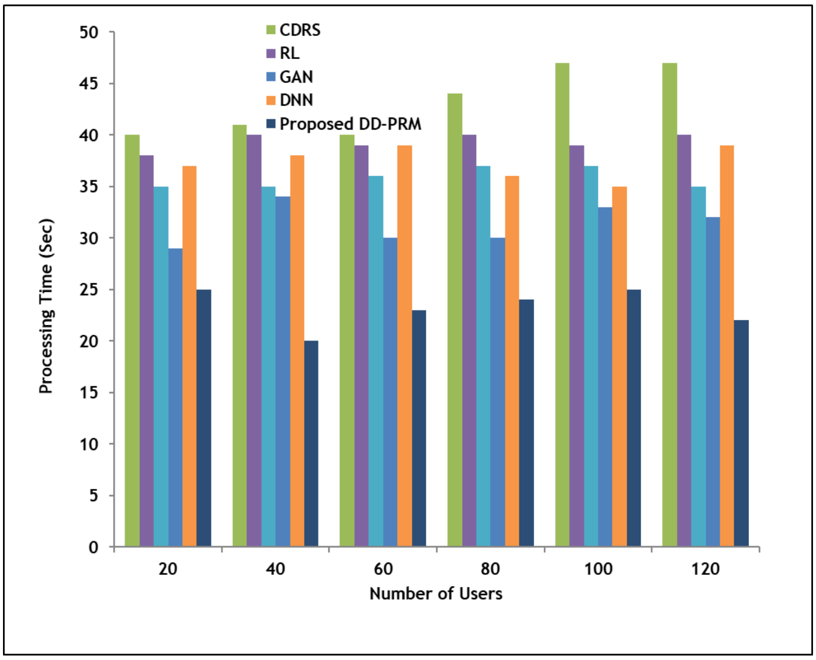

Fig 6. Performance analysis of existing and proposed recommender systems with respect to error rate under various user's scenario

5. Conclusion

The proposed DD-PRM model incorporates various components of behavioral analysis, including web data analysis, customer behavior analysis, current search data, product reviews, range of products, purchasing patterns, and co-efficient matrix computation. The weight factor is analyzed and applied to the collaborative filtering approach based on those parameters. The weight factors for different people and items are derived using the derivations, and the suggestions are provided to the user. The DD-PRM for e-commerce improves the recommendation accuracy, effectiveness, and user satisfaction. From the experimental results it can be concluded that the proposed DD-PRM model performed better than the existing models. With further advancements and refinement, data-driven recommender models have the potential to revolutionize the e-commerce industry by delivering highly targeted and satisfying shopping experiences for users.

References

[1] Harsh Khatter and Anil K Ahlawat, "An intelligent personalized web blog searching technique using fuzzy-based feedback recurrent neural network", Soft Comput, vol. 24, pp. 9321-9333, 2020.

[2] Zhijun Zhang, Gongwen Xu and Pengfei Zhang, "Research on E- Commerce Platform-Based Personalized Recommendation Algorithm", Applied Computational Intelligence and Soft Computing, vol. 2016, pp. 1-6.

[3] Karthick, G. S., & Pankajavalli, P. B. (2023). Chronic obstructive pulmonary disease prediction using Internet of things-spiro system and fuzzy-based quantum neural network classifier. Theoretical Computer Science, 941, 55-76.

[4] Z. Fayyaz, M. Ebrahimian, D. Nawara, A. Ibrahim and R. Kashef, "Recommendation Systems: Algorithms Challenges Metrics and Business Opportunities", Applied Sciences, vol. 10, no. 21, pp. 7748, Nov. 2020.

[5] Karthick, G. S., & Pankajavalli, P. B. (2020). A review on human healthcare internet of things: a technical perspective. SN Computer Science, 1(4), 198.

[6] Hyunwoo Hwangbo, Yang Sok Kim and Kyung Jin Cha, "Recommendation system development for fashion retail e-commerce", Electronic Commerce Research and Applications, vol. 28, no. 2018, pp. 94-10.

[7] Karthick, G. S., & Pankajavalli, P. B. (2020). Architecting IoT based healthcare systems using machine learning algorithms: cloud-oriented healthcare model, streaming data analytics architecture, and case study. In Incorporating the Internet of Things in Healthcare Applications and Wearable Devices (pp. 40-66). IGI Global.

[8] G. Dubey, S. Kumar and P. Navaney, "Extended Opinion Lexicon and ML based Sentiment Analysis of tweets: A novel Approach towards Accurate Classifier", International Journal of Computational Vision and Robotics (IJCVR) Inderscience Publishers, vol. 10, no. 6, pp. 505-521, 2020.

[9] H Khatter and AK Ahlawat, "An Algorithmic approach for recommendation systems for web blogs

and microblogs", Journal of Xi'an Shiyou University Natural Science Edition, vol. 16, no. 9, pp. 347-350.
[10] Covington, P., et al. "Deep Neural Networks for YouTube Recommendations." Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, 2016.
[11] Hu, Y., Koren, Y., & Volinsky, C. "Collaborative Filtering for Implicit Feedback Datasets." IEEE International Conference on Data Mining. IEEE, 2008.
[12] Adomavicius, G., & Tuzhilin, A. "Context-Aware Recommender Systems: A Literature Survey and Classification." ACM Transactions on Interactive Intelligent Systems (TiiS) 5.4 (2011): Article 19.
[13] Burke, R. "Hybrid Recommender Systems: Survey and Experiments." User Modeling and User-Adapted Interaction 12.4 (2002): 331-370.
[14] Chen, L., et al. "Explainable Recommendation: A Survey and New Perspectives." arXiv preprint arXiv:2006.11269 (2020).
[15] Kang, W., et al. "Deep Reinforcement Learning for List-wise Recommendations." Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 2018.
[16] Hidasi, B., et al. "Session-based Recommendations with Recurrent Neural Networks." Proceedings of the 4th International Conference on Learning Representations (ICLR). 2015.
[17] Shokri, R., & Shmatikov, V. "Privacy-Preserving Collaborative Filtering: Attacks and Countermeasures." Proceedings of the 24th Annual International Conference on Machine Learning. ACM, 2009.
[18] Deshpande, M., et al. "Personalized Product Recommendation Using Machine Learning Techniques." International Journal of Computer Science and Information Technologies 10.3 (2019): 1006-1011.
[19] Sarwar, B., et al. "Hybrid Personalized Recommendation in E-commerce." Proceedings of the 2001 ACM Conference on Recommender Systems. ACM, 2001.
[20] Zhang, W., et al. "Deep Learning for Personalized Product Recommendation in E-commerce." Proceedings of the 33rd AAAI Conference on Artificial Intelligence. AAAI Press, 2019.
[21] Rendle, S. "Factorization Machines for Personalized Product Recommendation in E-commerce." Proceedings of the 26th Annual Conference on Neural Information Processing Systems (NIPS). 2012.
[22] Zhou, T., et al. "Personalized Product Recommendation on E-commerce Platforms: An Ensemble Learning Approach." Expert Systems with Applications 155 (2020): 113378.
[23] Zhang, M., et al. "Privacy-Preserving Personalized Recommendation in E-commerce." Proceedings of the 2020 IEEE International Conference on Big Data (Big Data). IEEE, 2020.