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Customer Relationship Management for Better Insights with Descriptive Analytics

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Abstract

The Customer Relationship Management (CRM) dashboard with analytics capabilities may be useful for businesses desire to understand consumer behaviour and gain competitive advantages. This user-friendly dashboard allows organizations to efficiently collect and evaluate important data, including customer interactions, purchase histories, and demographics. By leveraging various visualization techniques, such as histogram, bar charts, line charts, and heatmaps, the CRM dashboard displays statistics, enabling businesses to understand more about customer journeys, patterns, and behavioural trends. The integrated recommender system on the CRM dashboard is also crucial. Based on their historical interactions and buying behaviours, this system recommends tailored products or services to customers, enhancing engagement and ultimately increasing sales. The methodology used in this research is structured based on a standard data analytics procedure. The methods used to gather and evaluate the data are described in the data gathering and analysis. It contains details on the data gathering, the steps used to clean and prepare the data, and the statistical or analytical

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techniques employed to evaluate the data. As a result, machine learning simulations may be made using the data to demonstrate the effectiveness of the CRM dashboard. The CRM dashboard with analytics capabilities provides a comprehensive solution for businesses wishing to manage and study customer data and interactions owing to its user-friendly interface, visualizations, and recommender system.

Keywords: Business intelligence, Data visualization, Customer relationship management dashboard, Descriptive analytics, Recommender system

1. INTRODUCTION

Enhancing customer satisfaction and successfully managing customer relationships are important goals for organizations in the competitive business environment of today. By guiding consumers in choosing the best goods and services based on their tastes and requirements, recommender systems play a significant role in helping to achieve these aims. With so many recommender systems techniques available, it is necessary to weigh the advantages and disadvantages of each strategy in order to choose the one that will maximize customer happiness and enhance a company's Customer Relationship Management (CRM) procedures.

Organizations may better understand consumer behaviour, preferences, and requirements thanks to descriptive analytics, which offers useful insights into customer data. Organizations may identify patterns and trends in consumer interactions, communication, and purchasing behaviour by utilizing descriptive analytics approaches, such as data analysis and visualization. This research will examine how better client and organizational communication may support CRM through the use of descriptive analytics. Organizations may better satisfy consumer expectations by adjusting their CRM strategy by analyzing and understanding the data collected from numerous touchpoints.

There are many different recommender system types [1, 2], that may be applied to enhance CRM procedures. Among the most popular Recommender System (RS) solutions are collaborative filtering, content-based filtering, and hybrid approaches. In-depth analysis of various RSs' advantages and disadvantages, as well as an assessment of their efficiency in raising customer happiness and optimizing CRM, will be covered in this project. Organizations may decide which kind to use in their CRM system to give personalized and pertinent suggestions to clients by examining the effectiveness and applicability of various RS techniques.

By using descriptive analytics, a dashboard for CRM that will accurately reflect what has happened in a company and how it relates to earlier similar periods can be generated [3]. In addition, utilizing the most effective RS strategies can enhance client interactions within a business and precisely determine the accuracy of anticipating an item. In addition, by examining historical data, descriptive analytics will be used to understand better how changes within a company have evolved. Visualization techniques, such as graphs and charts, can be employed to represent the descriptive analytics results better [4, 5].

This study seeks to address these concerns in order to offer insightful analysis and suggestions for businesses looking to raise client happiness, improve CRM procedures, and ultimately increase client loyalty. Organizations may make data-driven choices to enhance customer experiences, spur business growth, and gain a competitive edge in today's changing market by doing a thorough examination of descriptive analytics.

The contributions of the paper are as follows:

1) Exploration on the existing CRM technologies, recommender system and machine learning.

2) Design and implementation of CRM dashboard with analytics and visualization features to provide insight on the data.

2. LITERATURE REVIEW

2.1 Related Work on Customer Relationship Management

Khodakarami and Chan [6], emphasize the CRM process's primary goal of acquiring customers, understanding them, offering services, and meeting their needs. There are three types of operational CRM systems: customer support, sales, and marketing. Analytical CRM systems help firms understand customer behavior, while collaborative CRM systems connect and communicate with customers through various channels. Pilar et al. [7], utilized big data from CRM information systems to identify client profiles in the hotel industry. They utilized map-reduce techniques to efficiently handle statistical descriptions, proportion tests, and bootstrap resampling, simplifying detailed reports and increasing customer satisfaction. Saha et al. [8], studied analytical CRM and found supervised learning techniques, division trees, Naive Bayes, structural equation modeling, and hypothesis testing as effective statistical analysis methods. Lamrhari et al. [9], developed a social CRM analytic framework for customer retention, acquisition, and conversion. They used data from social media sites and used topic modeling, sentiment analysis, and fuzzy-kanoo classification. Random Forest outperformed other machine learning techniques in customer classification and clustering.

Rahayu et al. [10], suggested to maintain customer loyalty, businesses must improve service to meet discerning customer needs. Their research aims to design and build a computerized system to manage transaction processes and identify superior features. The CRM system can help businesses acquire new customers and maintain existing ones. The system aids administrators in managing transactional operations, product management, flagship initiatives, and customer promotions, ensuring its validity throughout the implementation phase.

TABLE 1 depicts the summary of the related works in terms of the dataset and evaluation metrics employed. From the review, it is clear that the CRM is crucial for keeping customers happy and identifying the right new markets.

2.2 Related Work on Recommender System

To predict user preferences, recommender systems use statistical and artificial intelligence approaches [11]. Content-based, collaborative filtering, context-aware filtering, and hybrid techniques are just a few available methods. Each method has its advantages and limitations (see TABLE 2). In order

Table 1: Summary Of The Related Work

References	Dataset	Evaluation Metrics
[6], (2014)	A number of local organizations from different industries	Interviews, surveys, statistic
[7], (2018)	International hotel clients	Statistics
[8], (2021)	138 papers published between 1996 and 2021 in the area of analytical CRM	Case study
[9], (2021)	Real data on e-commerce	Case Study
[10], (2023)	E-commerce	Blackbox testing

to find patterns of preferences, collaborative filtering uses previous behavioural data from a user community. They employ linear techniques like matrix factorization and graph-based techniques as well as nonlinear techniques like deep neural networks.

Table 2: Type of Recommender System

Advantages	Disadvantages
1. Content-based	
The system recommends new items without ratings, avoids item cold-start problems, and manages recommendations based on intrinsic features, allowing users to choose items without sharing.	The system uses meta-data for limited content analysis and recommends similar items based on user consumption, resulting in overspecialization.
2. Collaborative Filtering	
User receives unexpected algorithm-generated recommendations, accurate system provides accurate information, even without profile information.	The system faces cold-start problems due to insufficient information about items and users, data sparsity problems due to insufficient data for items with less or no ratings, and scalability issues due to increasing user and item numbers.
3. Hybrid-based	
System enhances collaborative filtering and content-based recommender systems for more accurate item recommendations.	The system incurred high implementation expenses and is more complex than other recommender systems.

Several Machine Learning research were employed to classify and cluster the user preferences. Singal et al. [12], employed AdaBoost machine learning method. Additionally, Exenberger et al. [13], employed clustering, decision trees, and association rule mining. Lu et al. [14], employed a collaborative filtering technique called Difference Factor' K Nearest Neighbors (DF-KNN) by tuning on the difference factor's K-NN. Othayoth et al. [15], employed agglomerative clustering methods.

Karn et al. [16], found that sentimental analysis improves recommendation accuracy in social information. They proposed a hybrid recommendation model using a Hybrid Recommendation Model

(HRM) and hybrid sentimental analysis to address issues like cold-start and data sparsity. This method generates a preliminary recommendation list that is accurate in the context of e-Commerce.

Bellini et al. [17], observed that current marketing solutions often focus on popular items, losing focus on customer centricity and personality. They proposed a multi-clustering recommendation system for fashion retail shops, utilizing mining techniques to predict purchase behavior of newly acquired customers. The system has been validated in-store and online on a real dataset.

With the inclusion of a recommender system, the CRM will be able to anticipate market segments more precisely [18, 19].

3. PROPOSED FRAMEWORK

A prototype that performs the data cleaning, model training and evaluation tasks is proposed. The collaborative filtering will be showing the user which items have the highest ratings. For improved visualization, a GUI-based dashboard will also be created. The prototype's flowchart is depicted in FIGURE 1.

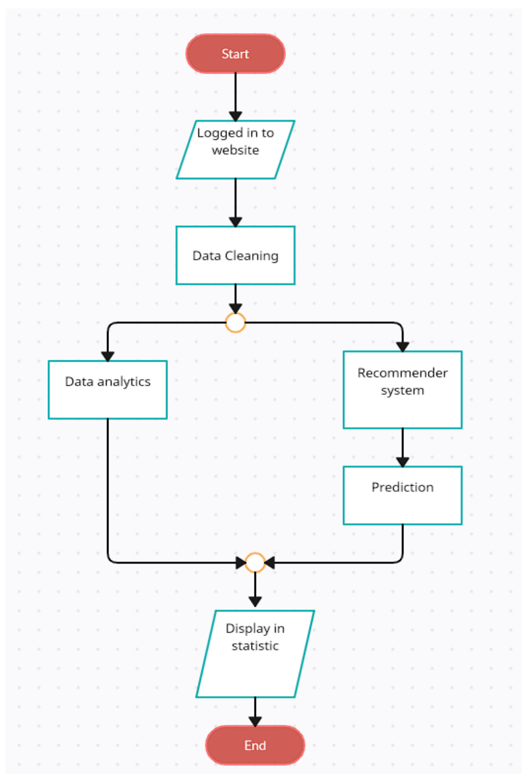

Figure 1: Proposed framework

3.1 The Dataset

The E-Commerce Market Insight Analysis for New Sellers dataset [20], was used to train the prototype's model. The creation of a recommendation system for the administrator, users, and customer is usually done using descriptive analysis. TABLE 3 shows some of the attributes of the dataset with its data type and description.

Table 3: The Dataset Description

Attribute	Type	Description
Title	object	Title for localized european countries. May be the same as title_orig if the seller did not offer a translation
Title_orig	object	Original English title of the product
Price	float64	Price you would pay to get the product
Retail_price	int64	Reference price for similar articles on the market, or in other stores/places. Used by the seller to indicate a regular value
Currency_buyer	object	Currency of the prices
Units_sold	int64	Number of units sold.
Uses_ad_boosts	int64	Whether the seller paid to boost his product within the platform
Rating	float64	Mean product rating
Rating_count	int64	Total number of ratings of the product
Rating_five_count	float64	Number of 5-star ratings
Rating_four_count	float64	Number of 4-star ratings
Rating_three_count	float64	Number of 3-star ratings
Rating_two_count	float64	Number of 2-star ratings
Rating_one_count	float64	Number of 1-star ratings
Badges_count	int64	Number of badges the product or the seller
Badges_local_product	int64	A badge that denotes the product is a local product. Conditions may vary (being produced locally, or something else)
Badge_fast_shipping	int64	Badge awarded when many buyers consistently gave good evaluations 1 means Yes, has the badge

3.2 The Prototype and Descriptive Analytics

Once the user or the merchant has logged onto the website, they are greeted on the main page. The top portion of their screen is where the admin, dashboard, user profile, logout, and other options are all shown.

FIGURE 2 shows the main page of the CRM dashboard that contains six charts: histogram, sales bar chart, rating stack bar chart, ad boost bar chart, badges bar chart and inventory bar chart. Insights into customer behaviour and purchase patterns may be gained from the first histogram, which shows the users' pricing and buying consistency. For example, several interpretations of what this histogram could show include the following. The histogram can display the pricing distribution for the goods or services that your clients have purchased. It may be used to determine the most typical price ranges as well as any outliers or notable price deviations. Understanding client preferences and developing price strategies may benefit from this knowledge. The histogram can reveal the regularity of a customer's purchases. It could show if clients tend to make purchases on an irregular basis or at regular intervals. This data can assist in identifying devoted consumers who make repeated purchases and may be targeted for loyalty initiatives or retention programmes.

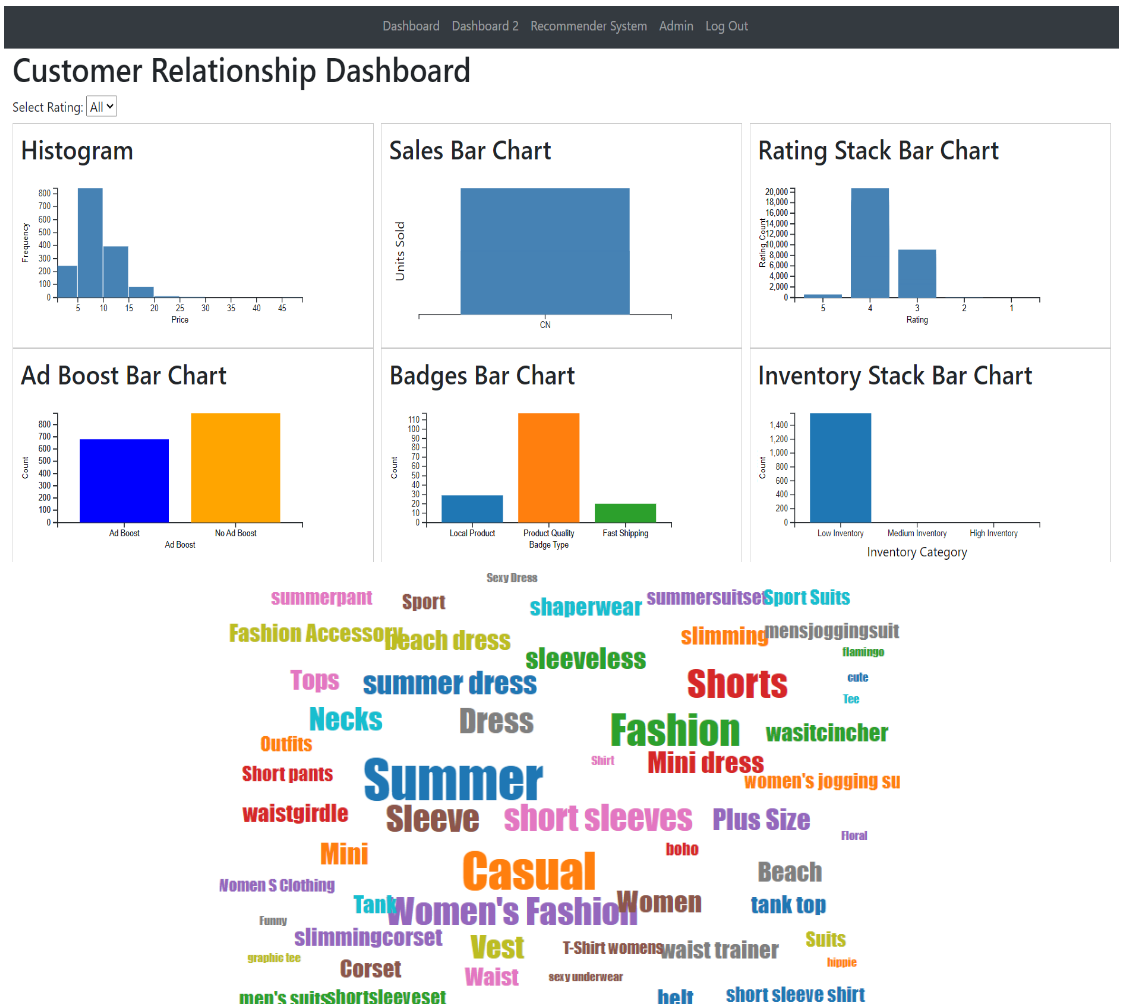

Figure 2: CRM dashboard for User

An effective visual representation that can be added to a CRM dashboard to illustrate the most common tags or phrases among clients is a word cloud. The frequency or prominence of various tags or phrases used by consumers is visually represented by a word cloud. Words that are more prevalent or regularly linked to consumer interactions, purchases, or reviews appear larger and bolder in the word cloud. This enables companies to find the most popular and pertinent tags fast being used by clients. The word cloud reveals information about client preferences, passions, and the terminology they employ when describing goods or services. Companies may identify the subjects or features that appeal to customers by examining the most popular tags, which will help you to better match your marketing strategy and product offers. Using this information, companies may target consumer preferences and increase sales by emphasising well-liked tags in advertising or product descriptions.

FIGURE 3 shows the dashboard for the admin, which allows them to view the merchants dashboard and ratings. The admin can gain insight of their information and rating. A cart orders chart is a bar chart that displays merchant names and calculates the total number of cart orders, providing insights into the performance and contribution of different sellers. It helps companies assess the efficiency and financial success of buyer-seller alliances, identify high-performing merchants, and prioritize collaborations. The chart also helps manage connections with vendors, identifying retailers who consistently or rapidly increase order volumes, and addressing problems or planning measures to improve merchant performance.

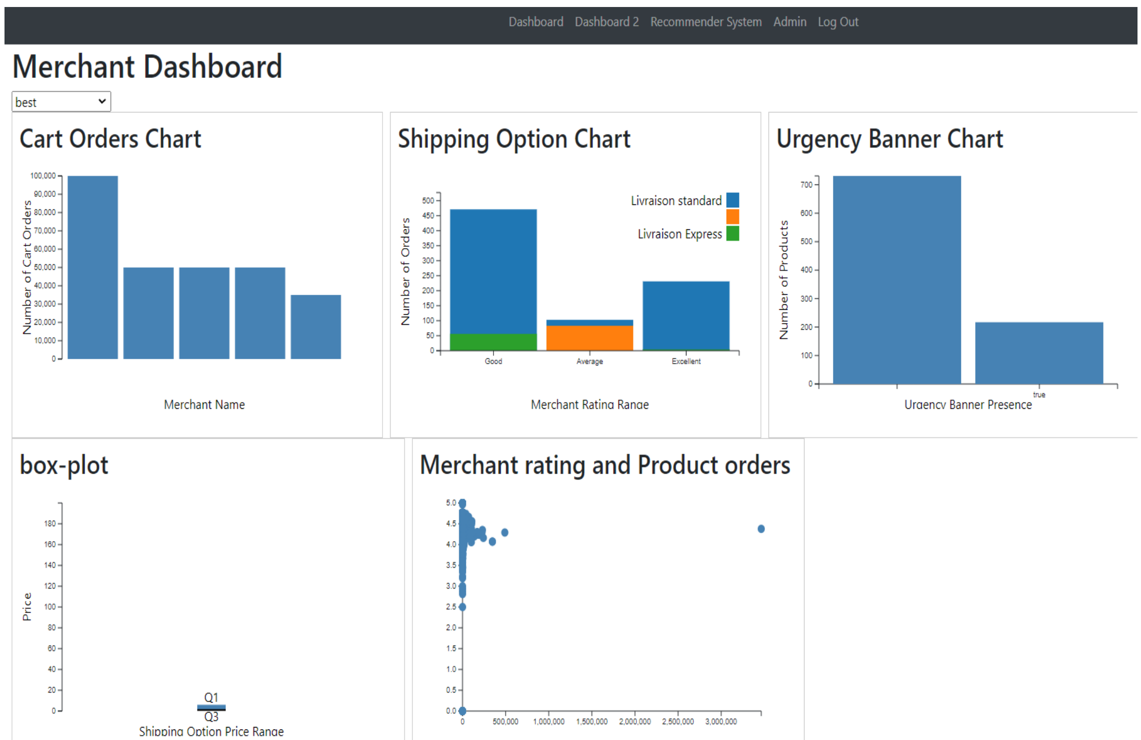

Figure 3: Dashboard with Analytical Features for Admin

The next chart is the shipping chart. The shipping chart categorizes data into three groups: "Excellent" for merchant ratings greater than 4.5, "Good" for ratings between 4.0 and 4.5, and "Average" for ratings below 4.0. This data can be used to assess merchant performance, make decisions on partnership formation, resource allocation, and management, and integrate the study of merchant ratings with shipping alternatives to understand their impact on client satisfaction and business performance.

The box plot is a chart that visually represents the distribution and variability of shipping prices. It displays the lowest, maximum, median, and quartiles of the data, allowing companies to identify potential outliers or skewness. This information helps companies understand the cost structure for shipping alternatives and compare costs for different options. The box plot also helps companies make informed decisions on price tactics, such as choosing competitive shipping costs or identifying cost-saving opportunities. It also helps companies match shipping choices to customer preferences and optimize pricing to increase perceived value by analyzing customer behavior and order patterns.

The last chart is merchant rating and product orders. It reveals the relationship between merchant ratings and product orders, providing valuable insights for companies. It allows them to analyze the distribution of merchants and their associated order volumes. High-performing retailers, such as those with positive reviews and high orders, can be identified. The graph also helps in determining the trend of higher-rated merchants, allowing companies to understand how consumer behavior and purchase decisions are influenced by merchant ratings.

3.3 Collaborative Filtering Recommender System

After the dataset has been cleaned, the collaborative filtering recommender system is chosen and ready to be fitted into the dataset. Collaborative filtering systems employ user behaviour to recommend alternative products. Typically, they can be either user- or item-based. An item-based strategy is typically preferred over a user-based one. User-based approaches are typically harder to scale since users tend to change than item-based approaches, which may frequently be computed offline and provided without the need for continuing retraining.

Matrix factorization is used in collaborative filtering to determine the relationship among the entities of items and users. It operates in such a way to multiplying two different types of entities to produce latent features. We would like to forecast user ratings of store items using the input of user ratings so that users can receive recommendations based on the prediction.

Using the matrix factorization approach, the first step is partitioning a large user-item rating matrix into two smaller matrices, a user matrix and an item matrix. To approximate the large rating matrix as the union of two low-rank matrices (each row of which represents a user and each row a single item in the user matrix, matrix factorization is used). By factoring the rating matrix into these two smaller matrices, the recommender system can gain latent representations of users and things, which it can subsequently use to produce customized recommendations.

On the other hand, KNN is a machine learning system that identifies groups of people with similar preferences and makes predictions based on the average rating of the top k neighbours. KNN is a good starting point for developing recommender systems and a suitable model to use for implementing item-based collaborative filtering. KNN is often a sluggish, non-parametric learning technique. In order to draw conclusions about recent samples, it makes use of a database where the data points are divided into clusters. KNN depends on item feature similarity rather than making any assumptions about the underlying data distribution. KNN calculates the "distance" between the target product and each other product in its database before concluding a product. After ranking its distances, it returns the top K nearest neighbour products as the most similar product suggestions. The MAE and RMSE criteria are then used to evaluate the discrepancy between the predicted and actual rating. The scores for both assessment criteria are gathered to determine if a model performs better.

FIGURE 4 shows the recommender for the selected item. The user needs to input the product title that they want and select the correct dataset. It displays the top 10 of the product with the highest rating similar to the selected item.

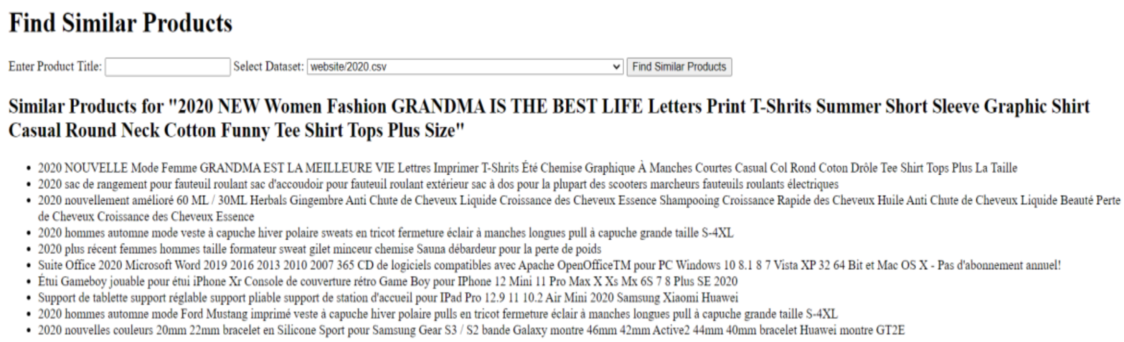

Figure 4: Recommendation for the Selected Item

3.4 Evaluation Metrics

A recommender system's objective is typically to predict a user's rating or preference for a certain item. The precision of the predictions made by the recommender system can be evaluated using the MAE. On the other hand, the RMSE calculates the expected and actual values discrepancy. It is calculated using the square root of the mean of the squared discrepancies between the expected and actual values. In regression issues, it is frequently employed as a model performance indicator.

The predictor system's predictions are more accurate when the RMSE value is lower and less accurate when the RMSE value is greater. Because it is sensitive to differences in significant mistakes, the RMSE is often used. TABLE 4 displays the outcome of the item-based collaborate technique implemented.

Table 4: Evaluation Results

Technique	**MAE score**	**RMSE score**
Item Based Collaborative Filtering	0.2953	0.4552

The scores are rounded to four decimal places in the table, which displays the MAE and RMSE scores produced via item-based collaborative filtering. The MAE and RMSE score indicate how far the anticipated ratings deviate on average from the actual ratings, which can vary from 1 to 5.

4. CONCLUSION AND FUTURE WORK

This paper has made considerable headway in understanding and analyzing the dataset, adding a collaborative filtering recommender system, grasping the CRM industry and its obstacles and potential, preparing the data, and producing a prototype visually representing the results. These actions will improve knowledge of consumers' requirements, preferences, and behaviour, promoting customer satisfaction and essential to the success of the CRM website.

In our future work, we will put strong emphasize on enhancing the visualization to make it more user-friendly and detailed analysis. As a consequence, stakeholders will be able to quickly interact with the simulation findings and comprehend how the CRM website affects consumer satisfaction. In addition, it may entail experimenting with various measures for evaluation or improving the algorithm used to produce suggestions for the recommender system. We will also present the comparative results for proving the authenticity of the model.

5. ACKNOWLEDGMENT

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