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An Improved Collaborative User Product Recommendation System Using Computational Intelligence with Association Rules

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Abstract:

In order to address the issue of information overload, recommendation systems have grown in popularity in recent years. They do this by presenting users with the most relevant products from a vast quantity of data. Online collaborative product recommendations aim to help people find their favorite products by identifying exactly identical neighbors between persons or products based on their shared ratings in the past. However, with the rapidly growing number of items and users, neighbor selection becomes more challenging due to the scant data. This research proposes a hybrid model-based product recommendation system that divides transformed user space using the improved Apriori algorithms. In order to densely classify products, it uses the principle component analysis data reduction technique, which may also lessen the computational complexity of intelligent product recommendations. When compared to the current methods, the experiment findings show that the suggested strategy may produce more dependable and customized product recommendations in addition to offering excellent accuracy performance.

Keywords: Product Recommendation, Collaborative filtering, Apriori algorithm, K-means, Computational Intelligence, Recommendation System.

1. Introduction

Over the past ten years, the amount of information available has increased explosively due to the internet's rapid expansion. One of the majority fashionable uses for information filtering is recommendation systems, which has materialized as a useful method for addressing the issue of information overload. Product recommender systems display products that are for sale on websites, in emails, on mobile apps, and on any screen that is linked, including kiosks and other Internet of things devices. Recommendations, one of the most widely employed strategies by merchants, direct customers to products they are probably interested in, speeding up their search and facilitating a more efficient discovery process.

These days, merchants frequently stock thousands, even millions, of products, making it challenging for clientele to discover exactly what they're looking intended for. Additionally, brands can facilitate the easy discovery of relevant products for customers based on their affinities, trends, interests, and behavior through tailored recommendations, ultimately increasing sales, upsells, cross-sells, cart sizes, and average order values.

A product recommender system is the technology that suggests which products to present to users interacting with a brand's digital properties. It is powered by machine learning. Recommendation algorithms excavate customer, manufactured goods, and appropriate data (both on-site and offline), powered by several algorithmic decisions, to provide each user with a customized experience.

Enhancing the process of discovery, this aids consumers in finding the products they seek and occasionally, things they aren't even aware they are seeking for. By doing this, companies may gain greater insight into the distinct interests and preferences of each user, improving real-time performance and long-term testing roadmaps at the same time.

Recommendations offer important information and the chance to learn more about a client in order to satisfy them, create value, and strengthen the bond between them and a business. There are also three main tiers in terms of the strategies underlying each of them:

- **Global recommendation strategies**
- **Contextual recommendation strategies**
- **Personalized recommendation strategies**

Global recommendation strategies: These tactics are typically the simplest to put into practice; they simply show the most popular, trending, or frequently bought products in a recommendation widget to any user, known or unknown.

Contextual recommendation strategies: These techniques make recommendations to customers based on the context of the product, taking into account factors like color, style, category it belongs in, and how often it is bought alongside other products.

Personalized recommendation strategies: The most advanced layer, personalized strategies, takes into account not just the context but also the real-time actions of users. To provide suitable recommendations for each user individually, they take into account the context of the product and the user data that is currently available. This implies that a brand needs access to customer behavioral data, including purchase narration, affinity, clack, add-to-carts, and supplementary, in order to implement them successfully.

Section one of this research paper provides a quick review of recommendation systems. A recommendation system has been applied to a number of active research projects listed in the second section. Part three included a full discussion of the suggested methodology, the proposed model's operation, and the comparative metrics. The fourth section addresses the argument and recommendations with some of the current approaches in these recommendation systems. The fifth and final section, the conclusion, addresses the potential and expectations of recommendations and extends to future study information.

2. Review of Related Literature

Based on the core concepts included into their operations, the current approaches are categorized into groups. The concept presented by the involved authors, the experimental methodology, and the performance evaluation standards are emphasized. The researchers' claims are also mentioned. The shortcomings that have been discovered are emphasized together with our findings from the extensive literature review.

The authors' work is essential for comparing various AI-based product recommendation systems, an essential first step before addressing related issues. After conducting a literature analysis, I have implemented a system that makes product recommendations to consumers. The tool makes suggestions for products based on the preferences of a certain user. I have used machine learning techniques to collect data on objects and users. The proposed approach creates a connection between the products and the consumers [7].

Users can receive recommendations from a variety of recommender systems based on their interests. Recommendation systems are utilized in a number of applications, likely e-commerce, healthcare, and markets. The major intention of the author is to demonstrate different challenges with the techniques used to provide recommendations. The objective is to use historical sales data to investigate and create recommendation systems. It goes over the concepts of shared filtering, relationship rules for commendation systems, content-based filtering, and mixture representation suggestion.

Three methods are utilized for product suggestion: the Apriori algorithm, the numerous prototype augmentation algorithms, and the popularity manufactured goods commendation algorithm. The suggested recommendation methodology produces strong recommendation outcomes, which boost sales and market response. It also recommends certain products to prospective customers. The research atmosphere for grocery shop commendation systems is described in this study. According to the observed recommendation models, consumer analysis is not necessary for popular product recommendation. Because of its quicker execution time than the Apriori model, FP Growth outperforms other models that compare customer behavior. This study offered a highly applicable and useful business transformation scenario that aids companies facing similar situations in altering their business strategies [8].

Consumers today are presented with a wider range of goods and information than ever before. This results in a growing diversity of consumer demands, making it more difficult for a retail establishment to offer the appropriate products in accordance with consumer preferences. Recommender systems are a tool for overcoming this difficulty; by offering products that meet consumers' requirements and expectations, it is feasible to satisfy existing clientele while drawing in new ones.

However, the effectiveness and caliber of recommendations are diminished by the enormous quantity of transactional databases that are characteristic of retail businesses. To overcome these challenges, a hybrid recommendation system that blends data mining and content-based collaborative filtering approaches is presented in this study. The recommendation system uses customer lifetime value to begin obtaining similar customer groups. Subsequently, an association rules mining technique is employed, which is predicated on comparable purchasing baskets of clients belonging to the same group, during a designated timeframe, to furnish more proactive and tailored customer product recommendations.

A chain of perfumeries' worth of data was used to test the algorithm. The experimental findings demonstrate that the suggested algorithm can raise the value of sales without sacrificing suggestion accuracy when compared to a basic recommendation (based just on customers' previous purchases) [9].

The use of product recommendations, or recommendation systems, is becoming more and more commonplace. Product suggestions are a kind of e-commerce customization where products are constantly made for a user on a website, app, or email based on information such user traits, browsing patterns, or situational context. This creates a customized shopping experience. The recommendation system that forecasts or suggests products based on user preferences. A variety of e-commerce websites employ product suggestion systems these days.

The website that eliminates needs for customers to visit actual stores, in order to buy and sell goods, services, and digital items. An organization can handle orders, payments, shipping & logistics, and customer support using an e-commerce website. There are many various platforms that offer recommendations. For music, there is Spotify; for movies, Netflix; for videos, YouTube; for play stores (different categories), and so on. A variety of filtering techniques and algorithms were employed in the product recommendation process in order to match products to the user's likeness. The current state of machine learning techniques (MLT) that were applied to product recommendations was covered in this study. By using these methods, the algorithm is able to forecast or suggest goods based on the user's likeness and information. [10].

Due to the mounting attractiveness of the internet, personalization tendency, and the embryonic behaviors of PC clients, commendation systems are efficient instruments for transmission online contented. While contemporary commendation systems are exceptional at providing precise recommendations, they have a quantity of drawbacks and involvedness, together with sparsity, cold start, scalability, and other concerns.

Because there are so many different approaches available, choosing one to utilize when developing application-focused recommender systems can be challenging. Furthermore, every technique has a unique set of benefits, drawbacks, and features, which creates additional issues that need to be resolved. With an importance on an assortment of applications such as books, movies, products, etc., this revision attempts to conduct a systematic assessment of numerous modern advances in the field of commendation systems.

The different uses for each recommender system are first examined. Next, an algorithmic analysis of different recommender systems is carried out, and a taxonomy that takes into consideration the different elements needed to create an efficient recommender system is framed. Furthermore, each contribution's performance metrics, simulation platform, and collected datasets are assessed and documented. Lastly, in order to assist future researchers in creating an effective recommender system, this review highlights the gaps and difficulties in the contemporary situation of research in this vicinity [11].

Because product suggestion systems give customers a better shopping experience, they are a significant component of the retail industry. Owing to the large selection of goods that shops offer, recommendation systems give the best method for showing clients the things that are pertinent to them by creating associations between products. However, it's also critical to comprehend the traits of consumers associated with various product linkages. Conventional methods for creating product recommendation systems use unsupervised consumer classification based on product ratings and association algorithms.

It is unclear, therefore, which client demographic traits are connected to which distinct product relationships. This work implements a hybrid coordination of machine learning relationship and clustering methods to display associations found in products together with individual customer profiles associated with these associations [12].

3. Methodology

A thorough examination or analysis of every research method is called methodology. Simply put, methods are actions or instruments used to choose study approaches. The investigation or study begins with the application of the methodology. Later on in the study and research process, methods are implemented and used.

3.1. Recommending Top Selling Items:

A user needs to be given recommendations for a number of best-selling comparable products when they attempt to purchase a product. Then, in order to make the greatest choice possible, the customer needs to understand the nuances of the best-selling products.

3.2. Recommending Top Purchased Items:

A pop-up window ought to show up when the consumer tries to buy the identical item they previously bought. Because doing something new might not provide them with enough satisfaction or stratification. If there is a review, the user will find the material beneficial in making a purchasing decision.

3.3. Enhanced Methodology Model

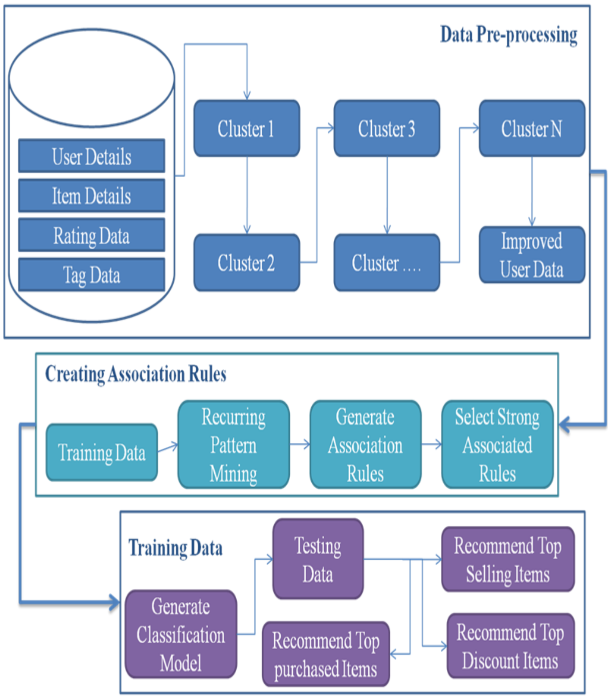

Figure.01 Architecture of Proposed Enhanced Model

3.4. Procedure for Enhanced Methodology Model

Step 1: Start the process

Step 2: Uk: User item set of size k

Step 3: Lk: frequent item set of size k

Step 4: L1 = {frequent items};

Step 5: for (k = 1; Lk !=∅; k++) do begin

Step 6: Uk+1 = Users generated from Lk;

Step 7: for each transaction t in database do

Step 8 increment the count of all Users in Uk+1 that are contained in t

Step 9: Lk+1 = Users in Uk+1 with min_support end

Step 10: return the value of transaction to database

Step 11: return ∪k Lk;

Step 12: End Process

3.5. Data Pre-processing

Following feature selection, the data is filtered to remove outliers and records with missing values. This is done since both missing and outlier values can lower the forecasting model's performance and result in erroneous forecasts.

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3.6. Creating Association Rules

In order to discover the most significant links, criterion support and confidence are used to search the data for frequent if-then patterns. This process creates association rules. The Support column shows the frequency of an item in the data. The number of times the if-then statement is proven to be true is indicated by confidence.

3.7. Training Data

The information used to educate an algorithm or machine learning replica to anticipate the result that user have designed his model to envisage is known as training information. Test information is utilized to gauge how well the algorithm the user using to educate the mechanism performs, including its accuracy and efficiency.

3.8. Comparison Metrics:

3.8.1. Precision

A statistic called precision counts how many positive, accurate forecasts were made. As a result, precision determines the accuracy for the minority class. It is computed as follows: the ratio of accurately anticipated positive examples to the total number of predicted positive examples.

--(1)

3.8.2. Recall

A measure known as recall counts the number of accurate positive predictions among all possible positive predictions. Recall gives an indicator of missed positive predictions, in contrast to precision which only comments on the right positive predictions out of all positive predictions. Recall offers a sense of the positive class's coverage in this way.

--(2)

3.8.3. F-Score

Since classification accuracy is a single metric used to sum up model performance, it is commonly employed. Recall and precision can be combined into a single measure that accounts for both attributes, called the F-Measure. Recall or precision by themselves don't provide the complete picture. Either horrible precision with outstanding memory or excellent precision with bad recall are both possible.

A single score can be used to indicate both concerns using the F-measure. For a binary or multiclass classification task, precision and recall can be computed separately and then combined to get the F-Measure.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$ **--(3)**

4. Results and Discussions

Table 01 and Figure 02 compare the precision of the four distinct existing techniques, and the results indicate that the Enhanced Model performs better in the sparsity levels of 0–20, 20–40, 40–60, 60–80, and 80–100 than the other existing approaches.

Table.01. Precision Comparison

Data Sparcity	0 - 20	20 - 40	40 - 60	60 - 80	80 - 100
Basic CF	0.7012	0.6999	0.6756	0.6083	0.5978
PCA + KMeans	0.7525	0.7525	0.7422	0.7022	0.6556
TriFac	0.7214	0.7189	0.6978	0.6578	0.6078
FP-G	0.8177	0.8177	0.8077	0.7887	0.7787
Enhanced Model	0.8265	0.8267	0.8198	0.7982	0.7869

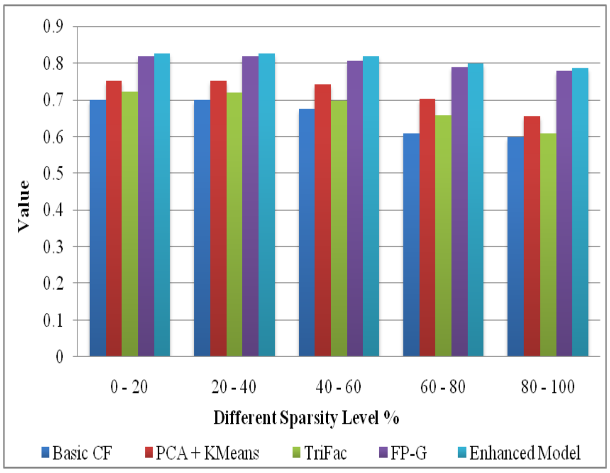

Figure.02. Precision Comparison

Table.02. Recall Comparison

Data Sparcity	0 - 20	20 - 40	40 - 60	60 - 80	80 - 100
Basic CF	0.6877	0.6755	0.6522	0.6066	0.5898
PCA + KMeans	0.7622	0.7622	0.7089	0.7001	0.7534
TriFac	0.7123	0.7033	0.6933	0.6733	0.6833
FP-G	0.8089	0.8089	0.7989	0.7702	0.7602
Enhanced Model	0.8129	0.8128	0.8055	0.7855	0.7725

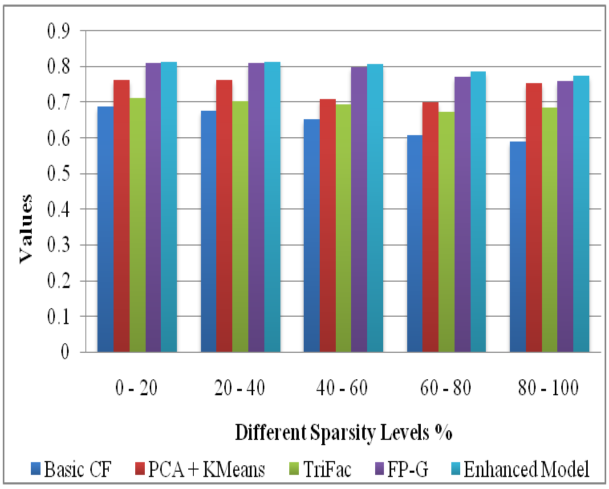

Figure.03. Recall Comparison

The recall comparison between the four distinct existing techniques is depicted in Table 02 and Figure 03, which demonstrates that the Enhanced Model outperforms the other existing methodologies in the sparsity levels of 0–20, 20–40, 40–60, 60–80, and 80–100.

Table.03. F-Score Comparison

Data Sparcity	0 - 20	20 - 40	40 - 60	60 - 80	80 - 100
Basic CF	0.6943	0.6874	0.6312	0.6074	0.5937
PCA + KMeans	0.7573	0.7573	0.7478	0.7055	0.6771
TriFac	0.7168	0.711	0.6955	0.6655	0.6433
FP-G	0.8099	0.8099	0.8032	0.7793	0.7693
Enhanced Model	0.8185	0.8187	0.8155	0.7897	0.7792

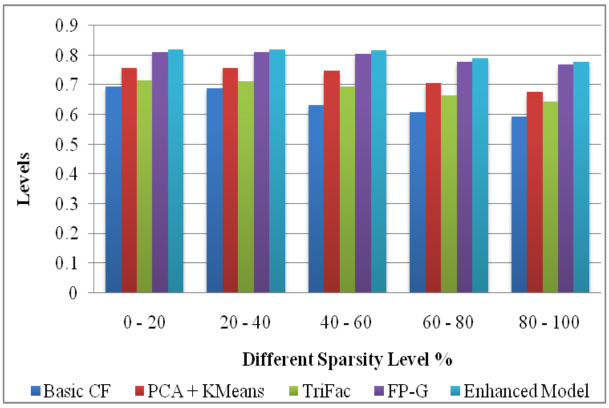

Figure.04. F-Score Comparison

Table 03 and Figure 04 present a comparison of the F-Scores of the four distinct existing techniques. The results indicate that the Enhanced Model outperforms the other approaches in the sparsity levels of 0–20, 20–40, 40–60, 60–80, and 80–100.

To assess the suggested procedures, two techniques were chosen from the literature review. The trial's findings demonstrate that the FP-G approach improves recommendation accuracy in terms of F-score, precision, and recall. Other CF-based methods are contrasted with the FP-G method.

The existing work on the PCA + K means strategy uses dimensionality reduction techniques like PCA to solve the problem of data sparsity and anticipates the unknown preference using K-Means clustering approaches. Using association rules and pattern analysis, it forecasts the user's unknown choice. The TriFac model, based on the probabilistic matrix factorization approach, determines correlations between user, item, rating, and tag that are associated with latent variables. When an object has numerous tags linked to it, the overlapping issue cannot be resolved by this method.

Even with its limitations (limited suggestions; for example), the FP-G method works well for both overlapping criteria and items with multiple tags. By providing the most suggestions to the customers, the Enhanced Model will surpass the minimal suggestions and increase user satisfaction. The findings indicate that it is critical to fully explore the underlying pattern knowledge in addition to relying user choice on rating scores.

5. Conclusion and Future Enhancement

In this study, the research section created an enhanced model based on a hybrid model that combines a clustering method and dimensional reduction technique to give product recommendations. Choosing a "like-minded" neighborhood based on shared ratings is a crucial step in producing high-quality movie suggestions in an environment with scant data.

This study optimizes the K-means technique to cluster similar users using Apriori algorithms. When compared to the current clustering-based CFs, the experimental evaluation of the suggested approach demonstrated its ability to provide high prediction accuracy and more dependable movie suggestions for users' preferences based on the product dataset. Regarding the cold-start issue, the experiment also showed that the suggested method may produce accurate movie ratings estimates for first-time users through conventional movie recommendation systems. Recommendation algorithms are often developed and improved to provide recommendations based on popular products. That shouldn't be the only application, though. Variety is essential since repeat clients could grow bored with the same old offerings. As a result, products and judgments based on products may be subject to greater precision.

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