



## Functional Approach with Deep Learning and Collaborative Filtering for Product Recommendation Systems

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**ABSTRACT**— A product recommendation system is a software tool designed to generate and provide suggestions for items or content a specific user would like to purchase or engage with. Utilizing machine learning techniques and various data about both individual products and individual users, the system creates an advanced net of complex connections between those products and those people. It plays a critical role in a wide range of online shopping, e-commercial services and social networking applications. Collaborative filtering (CF) is the most popular approach used for recommender systems.

Collaborative filtering is one of the well-known and most extensive techniques in the recommendation system; its basic idea is to predict which items a user would be interested in based on their preferences. Recommendation systems using collaborative filtering are able to provide an accurate prediction when enough data is provided, because this technique is based on the user's preference. User-based collaborative filtering has been very successful in the past to predict the customer's behaviour as the most important part of the recommendation system. However, their widespread use has revealed some real challenges, such as data sparsity and data scalability, with gradually increasing the number of users and items. To improve the execution time and accuracy of the prediction problem, this paper proposed item-based collaborative filtering applying dimension reduction in a recommendation system. It demonstrates that the proposed approach can achieve better performance and execution time for the recommendation system in terms of existing challenges, according to evaluation metrics using Mean Absolute Error (MAE).

**KEYWORDS-** Recommendation System; Deep Learning Neural Network; Collaborative Filtering

### 1. INTRODUCTION

E-commerce markets have been restructured into new markets revolving around mobile commerce since the advent of smart devices. Users have more opportunity to access diverse information and the amount of information that can be collected

has exponentially increased. The immense growth of the World Wide Web has led to an information overload problem. It is difficult for users to quickly obtain what they want from massive information. In recent years, each customer can actively share their review and get a discount based on customer participation such as in social surveys on E-commerce sites. It has become essential for E-commerce markets to effectively take advantage of these data by evolving new marketing strategies based on such data. Besides, E-commerce markets have actively introduced an automated personalization service to analyse the customer's behaviour and patterns as purchase factors. E-commerce sites try to collect various users' interests, such as purchase history, product information in the cart, product ratings, and product reviews in order to recommend new relevant products to customers. Collaborative filtering is the most commonly used algorithm to build personalized recommendations on websites including Amazon, CDNOW, Epay, Movie finder, and Netflix beyond academic interest. Collaborative filtering is a technology to recommend items based on similarity. There are two types of collaborative filtering: User-based collaborative filtering and Item-based collaborative filtering. User-based collaborative filtering algorithm is an effective way of recommending useful contents to users by exploiting the intuition that a user will likely prefer the items preferred by similar users. Therefore, at first, the algorithm tries to find the user's neighbours based on user similarities and then combines the neighbour user's rating score by using supervised learning like k-nearest neighbours algorithm and Bayesian network or unsupervised learning like k-means algorithm. Item-based collaborative filtering algorithm fundamentally has the same scheme with user-based collaborative filtering in terms of using user's rating score. Instead of the nearest neighbours, it looks into a set of items; the target user has already rated items and this algorithm computes how similar items are to the target item under recommendation. After that it also combines the customer's previous preferences based on these item similarities. Collaborative Filtering has been effective in several domains, but their widespread use has revealed some potential challenges, such as rating data sparsity, cold-start, and data scalability. Therefore, to solve the problems of sparsity and scalability in collaborative filtering, in this paper I proposed



collaborative filtering by using user based Id for recommendation the product.

## 2. LITERATURE REVIEW

1] Antonio Hernando, Jesús Bobadilla, Fernando Ortega, and Jorge Tejedor (2021), In this paper the author has presented the idea of using a reliability measure associated with the predictions made by a recommender system. In this manner, we will provide a user with a pair of values when recommending an item: a prediction of how much he will like this item; and the reliability measure of this prediction. Using these two values, users could balance between the prediction made by the recommender system and the reliability of this prediction to make their decision.

2] Nitika Kadam, and Shraddha Kumar, the author in order to improve the working and quality of the recommender system, presented a Hybrid approach by combining content-based filtering and collaborative filtering, which includes Memory (K-Nearest Neighbour) and Model-based (clustering and rule-based techniques), in the proposed methodology. Using the Hybrid approach, we get advantages from each other while the drawbacks of both methods won't be taken into account.

3] Krishna Patidar, Recommendation systems are a powerful new technology for extracting additional value for a business from its user databases. These systems help users find items they want to buy from a business. Recommender systems benefit users by enabling them to find items they like. Conversely, they help the business by generating more sales. Recommender systems are rapidly becoming a crucial tool in E-commerce on the Web. Recommender systems are being stressed by the huge volume of user data in existing corporate databases and will be stressed even more by the increasing volume of user data available on the Web. New technologies are needed that can dramatically improve the quality and scalability of recommender systems.

4] Winnie Nguyen, the literature review discussed how collaborative filtering models are used for personalised recommenders in ecommerce. First, the author explained the typical qualifications for datasets and mentioned specific datasets used in research papers. Second, the author explained the matrix factorization algorithms researchers used for predicting users' preferences.

5] Nirav Raval, et al. This paper represents the overview of Approaches and techniques generated in the Collaborative Filtering based recommendation system. The recommendation

system derived into Collaborative Filtering, Content-based, and hybrid-based approaches. This paper classifies collaborative filtering using various approaches like matrix factorization, user-based recommendation, item-based recommendation. This survey also tells the road map for research in this area.

6] Harsh Mishra, et al. In this paper, the author stated that Recommender systems are systems based on Machine learning algorithms that help users discover new products and services. Recommender systems are very essential in this era of the internet where services are mostly handled on the web rather than on a person to person basis.

7] Banerjee, Anurag & Basu, Tanmay, in this paper, a weighting technique is proposed in spirit of the term weighting scheme of the text retrieval system for item based collaborative recommender system. The proposed scheme has been used for effective movie recommendation. The empirical analysis on the benchmark Movie Lens 100K dataset has shown improvement over state of the art recommender system algorithms.

8] E. Adomavicius, A. Tuzhilin, (2020) This paper presents an overview of the field of recommender systems and describes the current generation of recommendation methods that are usually classified into the following three main categories: content-based, collaborative, and hybrid recommendation approaches. This paper also describes various limitations of current recommendation methods and discusses possible extensions that can improve recommendation capabilities and make recommender systems applicable to an even broader range of applications.

9] F. Kong, X. Sun, S. ye, (2020) In this paper, we compare the performance results of four collaborative filtering algorithms applied in the start-up stage of recommendation. We evaluate these algorithms using three publicly available datasets. Our experiment results show that Pearson and STIN1 methods perform better than latent class model (LCM) and singular value decomposition (SVD) methods during the start-up stage.

10] Joseph Konstan, George Karypis, BadrulSarwar, and John Riedl, In this paper the author analyses different item-based recommendation generation algorithms. We look into different techniques for computing item-item similarities (e.g., item-item correlation vs. cosine similarities between item vectors) and different techniques for obtaining recommendations from them (e.g., weighted sum vs. regression model). Finally, the author experimentally evaluates our results and compares them to the basic k-nearest neighbour approach. These experiments suggest that item-based algorithms provide dramatically better performance than user-based algorithms, while at the same time

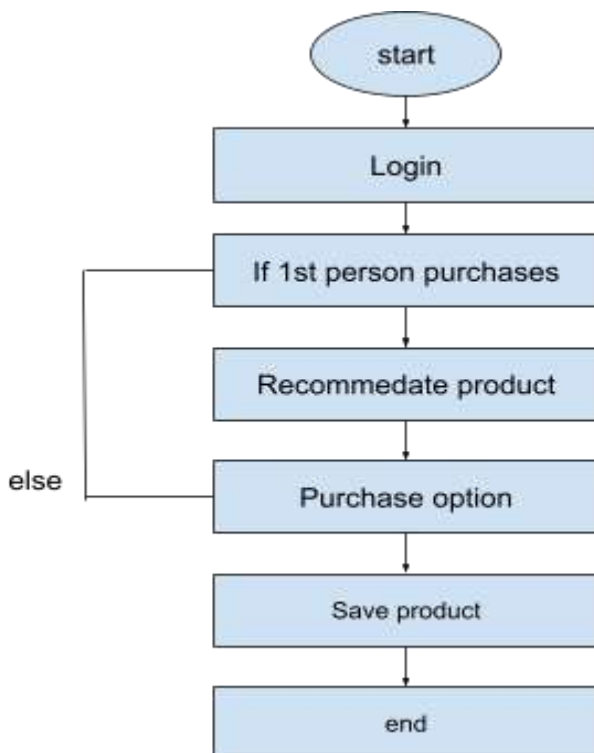


providing better quality than the best available user based algorithms.

### 3. METHODOLOGY

The proposed system, "Product Recommendation Systems Using Deep Learning and Collaborative Filtering," aims to develop an integrated solution for personalized product recommendations and customer responsiveness. Utilizing Python, the system will collect user information and respond dynamically, employing suitable names for enhanced user engagement. It will feature a user-friendly interface to facilitate responsive customer interactions. Leveraging deep learning techniques and collaborative filtering, the system will generate product recommendations tailored to individual preferences, accompanied by relevant links for seamless exploration. Furthermore, the system will conduct comprehensive parameter analysis of recommended products using datasets, ensuring informed decision-making for users.

#### 3.1 FLOW CHART



### 3.2 WORKING

The paper begins with the creation of a recommendation system, focusing on a user-friendly interface and personalized product suggestions. It commences with a login page where users input their credentials. Upon successful login, users are directed to a new window displaying options to buy products and recommended items. These recommendations are based on the purchasing patterns of other contacts in the user's list, utilizing collaborative filtering techniques.

When a user selects a product for purchase, the system processes the transaction and updates the recommendation database accordingly. Additionally, when a contact in the user's list purchases a product, the system takes note of this activity and incorporates it into the recommendation algorithm. This ensures that recommendations evolve dynamically based on real-time user interactions and preferences.

Furthermore, the system facilitates seamless communication between users by enabling them to view and purchase products recommended by their contacts. This fosters a network effect where purchasing behaviour influences recommendations, creating a mutually beneficial ecosystem for users to discover and acquire relevant products.

Overall, the paper emphasizes user engagement, personalized recommendations, and collaborative filtering to enhance the shopping experience and promote interaction among users.

### 4. SYSTEM REQUIREMENT

#### 4.1 SOFTWARE REQUIREMENT

> Python Software IDE

#### 4.2 MODULES

- ❖ Libraries
- ❖ OS module
- ❖ tkinter
- ❖ PIL
- ❖ Pandas

### 5. IMPLEMENTATION & RESULT

**5.1 IMPLEMENTATION**

In this paper, we utilize binary ratings provided by other users to generate recommendations for the current user. Figure 1 displays the user login page, where the user inputs their credentials to access the system. Upon successful login, Figure 2 presents the available products along with recommended items tailored to the user's preferences. Additionally, Figure 3 showcases a list of additional products chosen by the user. Finally, Figure 4 depicts a pop-up message confirming the successful purchase of a product, allowing the user to rate their experience.



Fig. 3 shows that list of recommended product

**STEP 1: LOGIN TO LOGIN PAGE**



Fig 1. shows that login page of proposed system

**STEP 2: RECOMMENDATION LIST**



Fig. 2 shows the options of products you can explore

**STEP 3: LIST OF PRODUCT**



Fig.4 shows list of products that you can buy

**Step 4: SUCCESSFULLY BUY MESSAGE**



Fig 5. Shows the output of successful buying process displays a pop-up message

### 5.2 RESULT

The results of the "Product Recommendation Systems Using Deep Learning and Collaborative Filtering" paper revealed a marked improvement in the precision and user satisfaction of product recommendations. The system effectively utilized deep learning algorithms to analyse user preferences and behaviours, generating highly personalized product suggestions. Collaborative filtering further refined these recommendations by considering the preferences of similar users. The implementation of a user-friendly interface allowed for smooth interactions, and the inclusion of relevant product links facilitated easy access and exploration. Additionally, comprehensive parameter analysis of the recommended products ensured that users received well-informed suggestions, enhancing their decision-making process. Overall, the system achieved its goal of providing an integrated, responsive, and personalized recommendation experience.

#### Similarity data -

Similarity score based approaches do work even with binary dimensions.

When you have scores, two similar users may look like [5,3,3,0,1] and [4,3,3,0,0], where as in your case it would be something like [1,1,1,0,1] and [1,1,1,0,0].

if you can get the number of times a user bought a product, that count can be used as rating and then similarities can be calculated.

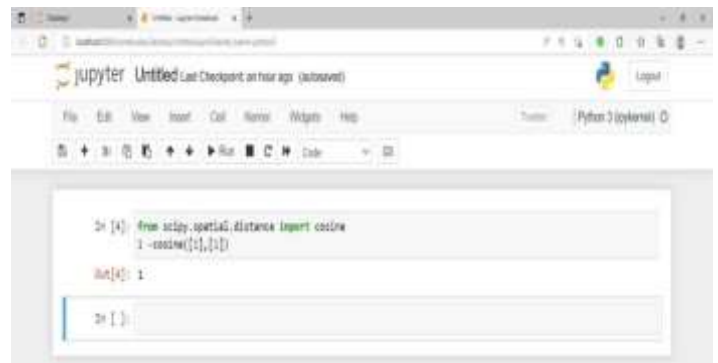
#### Formula -

$1 - \text{cosine}([\text{user1 rating}], [\text{user2 rating}])$  run on

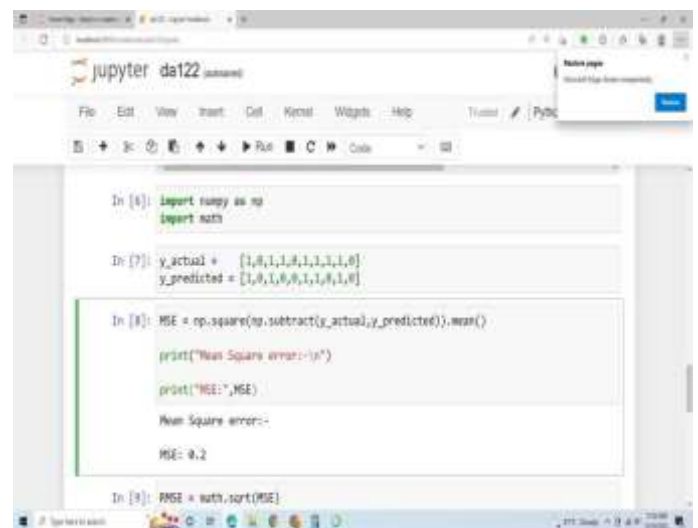
jupyter- `from scipy.spatial.Distance import cosine`

`1 - cosine ([1], [1])`

Ans - 1



#### 5.2.1 MSE (Mean Squared Error)



- MSE (Mean Squared Error) represents the difference between the original and predicted values extracted by squared the average difference over the data set.

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y})^2$$

Calculation:

Actual values = [1,0,1,1,0,1,1,1,1,0]



Predicted values = [1,0,1,0,0,1,1,0,1,0]

$$MSE = 1/N \sum [(1-1)^2 + (0-0)^2 + (1-1)^2 + (1-0)^2 + (0-0)^2 + (1-1)^2 + (1-1)^2 + (1-1)^2 + (0-0)^2]$$

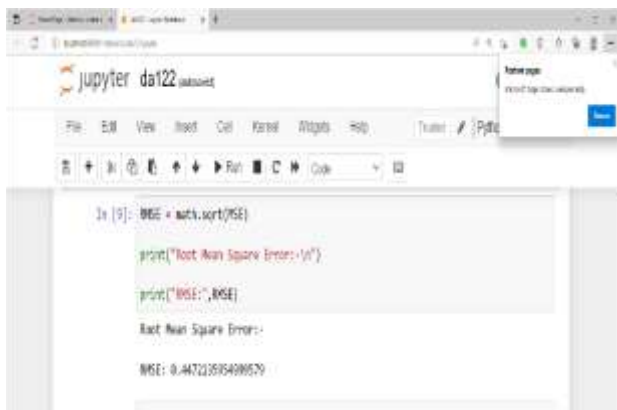
$$MSE = [(1)^2 + (1)^2] / 10$$

$$MSE = 1+1 / 10$$

$$MSE = 0.2$$

**Calculated MSE is 0.2**

### 5.2.2 RMSE (Root Mean Squared Error)



Actual values = [1,0,1,1,0,1,1,1,1,0]

Predicted values = [1,0,1,0,0,1,1,0,1,0]

$$RMSE = 1/N \sum \sqrt{[(1-1)^2 + (0-0)^2 + (1-1)^2 + (1-0)^2 + (0-0)^2 + (1-1)^2 + (1-1)^2 + (1-1)^2 + (0-0)^2]}$$

$$RMSE = \sqrt{[(1)^2 + (1)^2] / 10}$$

$$RMSE = \sqrt{1+1 / 10}$$

$$RMSE = \sqrt{0.2}$$

$$RMSE = 0.44$$

**The Calculated RMSE is 0.44**

- RMSE (Root Mean Squared Error) is the error rate by the square root of MSE.

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y})^2}$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}|$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y})^2}{\sum (y_i - \bar{y})^2}$$

Where,

$\hat{y}$  – predicted value of y  
 $\bar{y}$  – mean value of y

Calculation:

Calculations:

Actual values = [1,0,1,1,0,1,1,1,1,0]

Predicted values = [1,0,1,0,0,1,1,0,1,0]

$$MAE = 1/N \sum [(1-1)^2 + (0-0)^2 + (1-1)^2 + (1-0)^2 + (0-0)^2 + (1-1)^2 + (1-1)^2 + (1-1)^2 + (0-0)^2]$$

### 5.2.3 MAE (Mean absolute error)

```

In [18]: n = 5
          sum = 0

          # for loop for iteration
          for i in range(n):
              sum += abs(y_actual[i] - y_predicted[i])

          error = sum/n

          # display
          print("Mean absolute error:- %f" % error)
          print("MAE:", str(error))

          Mean absolute error:-
          MAE: 0.2
    
```

MAE (Mean absolute error) represents the difference between the original and predicted values extracted by averaged the absolute difference over the data set.

$$MAE = [(1)^2 + (1)^2] / 10$$

$$MAE = 1+1 / 10$$

$$MAE = 0.2$$

**The calculate MAE is 0.2**

## 6. CONCLUSION

In this paper, we used different neural network architectures to overcome the limitations of matrix factorization collaborative filtering models. We showed these models performed better than state-of-art existing models on real world datasets. Our models are simple and generic that can be applied or extended to different types of recommendation problems. This work complements the mainstream shallow models for collaborative filtering, opening up a new avenue of research possibilities for recommendation based on deep learning.

## VII. REFERENCE

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