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An Approach towards Deployable Hybrid Product Recommendation Systems for E-Commerce

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ABSTRACT

As India is moving fast towards digital economy, E-commerce industry has been on rise. Many platforms provide their customers with a shopping experience better than actual physical stores. Several E-commerce websites use different methods to improve the customer engagement and revenue. One such technique is the use of personalized recommendation systems, which uses customer's data like interests, purchase history, ratings to suggest new products, which they may like. Recommendation systems are used by E-commerce websites to suggest new products to their users. The products can be suggested based on the top merchants on the website, based on the interests of the user or based the past purchase pattern of the customer. Recommender systems are machine learning based systems that help users discover new products. Due to the recent pandemic situation of 2020 and 2021, many of the local retail stores have been trying to shift their business to online platforms such as dedicated websites or social media. The proposed methodology based on Machine Learning aims to enable local online retail business owners to enhance their customer engagement and revenue by providing users with personalized recommendations using past data using methods such as Collaborative Filtering, Popularity-based and Content-Based Filtering.

Keywords : E-commerce, Recommendation Systems (RS), Machine Learning, Personalized recommendations, Collaborative Filtering, Content Based Filtering, TF-IDF, Popularity Based Recommendation System, Stream-lit, TF-IDF, Pearson Correlation, Tokenization, PaaS.

I. INTRODUCTION

Every time we visit any shopping website, or a music or video streaming site, we are greeted with new products that we do not realize we want until we see them. Whenever we view a product or rate any previously bought product, the next time we visit the website, we are presented with products that are very similar to what we have previously bought or new products that other users with same taste have bought.

This is made possible using Machine Learning based recommendation systems that learn from our past behavior and predict or future behavior. These systems are used by almost every E-commerce giants to basically attract their customers back to them. Unlike traditional commerce that is carried out physically by a person to sell items and inform customers about new products, E-commerce and recommendation systems have made is easier for us to buy products as well as discover new ones.

These systems work by analysing our behaviour such as ratings and preferences and use these attributes to predict which products we may like. These systems are mostly built using two techniques called collaborative filtering and content based filtering. The collaborative filtering approach works by recommending products that other users have bought and the content based filtering method works by recommending products having similar attributes to the user's previous purchases. However, the cost of developing and deploying such systems is huge and certainly cannot be afforded by every local online business owner.

Collaborative filtering method comprises of two subtypes called user-user collaborative filtering and item-item collaborative filtering. The only requirement here is the availability of sufficient data. We also have to address the incomplete or unavailable data in our dataset as it can have a negative effect on the performance of the algorithm. The higher the similarity, the greater is the probability of the user liking that product.

However, the Content-Based Filtering approach works differently. It attempts to determine what an user's favourite aspect of an item is and then recommends items that present those aspects. The aspect can be anything like genre of a movie, colour of a clothing item. It then ranks similar products corresponding to their similarity scores and recommends the most similar products to the user. Another type of such system is the Popularity-Based Recommendation System. These type of systems works on the basis of popularity of an item. Any item, which is most popular and trending among the users, is directly recommended to the active user.

Instead of using either one of these methods to provide personalized recommendations to the users, combining all of these into a Hybrid Recommendation System is the best option. Using only either of the method such as collaborative filtering can give rise to an issue known as cold-start, where a new user cannot get any recommendations from the system due to lack of any previous data. In such cases, collaborative filtering paired with content-based filtering and/or popularity-based model can be the solution.

II. LITERATURE REVIEW

An exploratory research was conducted which applied and demonstrated the method of data mining with the help of association rule technique and item-based collaborative filtering. It was used in an approach for baseline recommender systems in e-commerce. It uses the review dataset from Amazon from the year 2018 and focuses on online shopping of phones and their accessories. [1]

Investigation of accuracy issues of implicit feedback in a RS was done and a system developed on hybrid Real Time Incremental Stochastic Gradient Descent was presented by combining Alternating Least Squares with Weight Regularization and SGD. This helped for faster updating of the matrix factorization model. [2]

The system uses dataset from Movie-Lens and constructs a matrix of users and ratings. It uses a deep learning approach to calculate the similarity between the items. It then uses matrix factorization to generate the recommendations. The method shows that, involvement with datasets can convey exactness better than traditional closest neighbor approach. [3]

TF-IDF i.e. Term Frequency and Inverse Document Frequency, which identifies the occurrence of a term in a document and the total number of documents containing the term respectively, can be used to generate product tags based on the product description. By doing so, the process becomes quite efficient and dynamic. [4]

Flipkart Product Recommendation System is built on Content Based, Collaborative Based and Hybrid Filtering Techniques to attain accurate recommendations. Content-based Filtering uses the history of purchase of the active user to evaluate proper recommendations. Collaborative Filtering is a prediction technique that does not depend on the domain. It matches the users, which have similar preferences. Collaborative Filtering is further classified into Item Based Filtering and User Based Filtering. [5]

Collaborative Filtering and Deep Learning based RS addresses the problem for CSS and ICS items. It uses the architecture SDAE which is based on deep learning. This system uses two types of methods: Collaborative Filtering is a prediction technique that looks for the users which have similar interests. Deep Learning uses datasets from reputed sources containing millions of reviews about a product. There are two classifications of feedbacks: Implicit Feedbacks and Explicit Feedbacks. Implicit Feedbacks are the indirect feedbacks taken from a user for example when a user watches a YouTube video. Most of new recommendation systems use implicit feedback. Explicit Feedbacks are the direct feedbacks taken from the user like the rating system for products on amazon's website. This System with these two techniques combined is effective to handle Cold Start Problem. [6]

The Book Recommender System has considered many several attributes like category of the book and content by applying techniques such as collaborative filtering to the ratings given by the other users. This recommender system also utilizes an association-based model to give accurate recommendations. It has offline recommendations so the performance is not affected. [7]

Automated Web Usage Data Mining and Recommendation System uses K-Nearest Neighbor (KNN) method because it is one of the simplest problem solving method. Unlike many existing data mining methods, it overcomes the problem of Scalability, reduces Error rate and provides more accurate and faster recommendations. The system has provided a base for Real-Time recommendation systems. It collects "click stream" and "matches" on active sessions from the users and compares them with dataset in the data mart to generate such accurate recommendations in real time. [8]

State of the Art Approach is categorized into four types of approaches. They are Content Based Filtering, Collaborative Based Filtering, Demographic Filtering and Hybrid Filtering. It also manifests the ranking (rating) of a Product. Ranking maximizes the user convenience. Thus, rank plays an important role in the recommendation systems. It ensures the optimal ordering of a group of items for the user. [9]

Recommender System Application Development analyzes traditional techniques fundamentally Content Based System, Collaborative System, Knowledge Based System and Hybrid Methods and also latest techniques like Fuzzy set based, Social Network based, Trust based, Content Awareness based and Group based. This system also introduces techniques such as E-Government recommender system, E-Business Recommender System, E-Commerce Recommender System, Tourism Recommender System, TV Program based

Recommender System and Group Activity Recommender System. [10]

Recommender System traverses through various prediction techniques and analyzes the characteristics and potential of these systems and guides the field of recommendation system in the proper direction. It explores the various phases of a recommender system like Information Gathering Phase, Explicit Feedback, Implicit Feedback, Hybrid Feedback, Learning Feedback, Prediction Phase, Weighted Hybridization, Switching Hybridization and Cascade Hybridization. In addition, this paper puts a light on Advantages and Limitations of these Hybridization techniques. The knowledge secured during this study helps the researchers to enhance the road map of State of the Art Recommendation systems. [11]

Product Recommendation System will require large quantity of data in order to arrive at the correct decision. The information, which is provided to the recommender system, must be persistent in nature. For the method, some sort of preset information is required. The recommender system gathers the information and calculates the decision in two possible ways by the use of Collaborative Filtering or by the use of Content Based Filtering. The collaborative filtering is the method of filtering for data among the multiple sources. On the other hand, Content Based Filtering will filter the data, which is going to be used within the system. Content filtering will be utilized here. The users have preferences for the certain items. The preferences of the users continuously change because of which recommendation system is created. [12]

Empirical Analysis of the Impact of Recommendation System interrogates a primary question that is the influence of these systems on sales. Considering the interaction between sales, recommendations, and the retail process, a robust model was developed that comprises of the indirect effect of recommendations on potential coexistence between sales and recommendations, and sales through retailer pricing, and an overall calculation of the strength of recommendations. During a survey on two online retailers, they came to the conclusion that the Recommendations have positive impact not only on sales but also on price of the product by providing the flexibility to adjust it. Analysis has revealed that recommendations have shown better results in increasing the sales even greater than customer feedback. [13]

A Literature Survey on Recommendations Systems based on Sentimental Analysis digs into various techniques such as the weighted algorithms, which are used to produce scores for multiple texts. The methodology of sentiment analysis covers the way for the advancement of recommender system on personal basis. Substantial research has been done on recommendation systems and they have been mainly divided into three categories: Collaborative filtering, Content Based and Context Based recommendation systems. The research shows the employment of Sentimental Analysis in developing of a more accurate Recommender System. [14]

Convolutional Neural Networks can also be used for recommender system. CNN is a type of neural network that is used for classification purposes. For collaborative filtering, user id and product id can be given as inputs to the network and can be used to extract features. These features are then assigned weights. CNNs include various applications including Soil Nutrients and Leaf Disease Detection. [15]

III.PROPOSED SYSTEM AND METHODOLOGY

The Proposed System uses a Hybrid Recommendation System composed of Collaborative Filtering, Content Based Filtering and Popularity Based Model. It consists of a Dataset, which contains product details and ratings. This dataset is then provided to the algorithms for processing and generating recommendations. The system can also be deployed on cloud with an UI for user experience. It can also be used by any online e-commerce platform with the help of any front-end web technology for improving their user experience and overall revenue. Whenever the user will search for any product, the product will be provided as a query to the recommendation system through the front-end UI. The system will process the query with the help of provided algorithms and top 10 recommendations will be generated by using each method. These recommendations will be given as output to the user. By adding recommendations, the level of convenience for the users will increase while shopping on online platforms. Users do not need search for all the products they want to purchase. Instead, the system can detect their purchase pattern, likes, dislikes, and provide potential suggestions that may be preferred by the user. An advertising section is also recommended which will select any random product from the dataset and recommend to the user. Product images are also provided which will increase overall attractiveness of the system. Each image will be fetched via cloud in real time by using the product id as image name so that search time is reduced. For demonstration purpose, the system is deployed on a cloud service using their open-source app framework using python. It provides User Interface elements like search box, widgets and containers that will provide input as well as display output from the system.

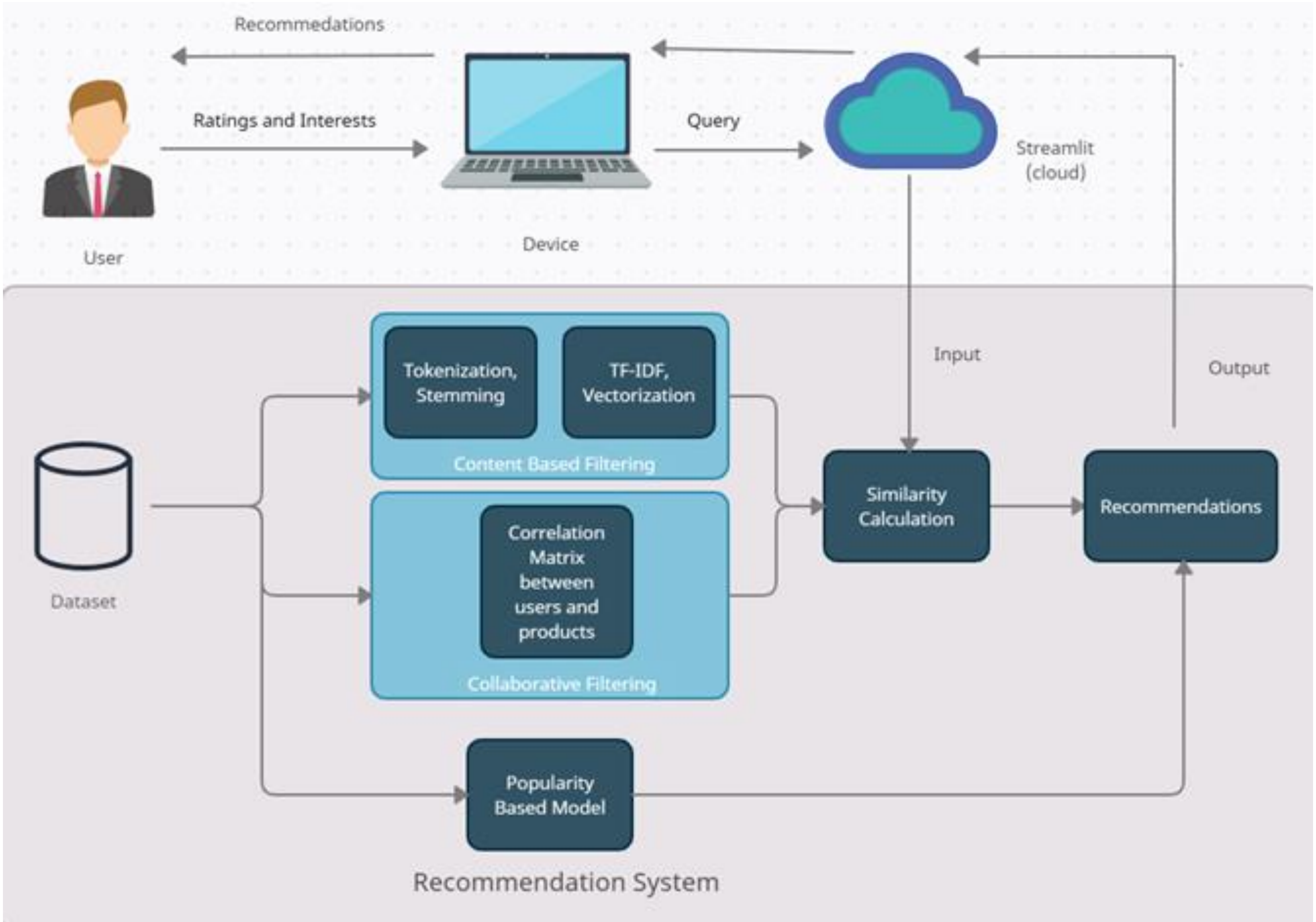


Fig 1: System Architecture

Initially, the data was scrapped from various e-commerce websites using a Python Script. It consists of Product Name, Image URL, Category and Average Rating for over 3000 products.

id	product_url	image_url	name	category	rating	no. of ratings
10001	https://www	https://m.n	The Sinful Sil	books	4.2	155
10002	https://www	https://m.n	The Dogfight	books	4.4	10
10003	https://www	https://m.n	Harry Potter	books	4.7	34786
10004	https://www	https://m.n	The Complet	books	4.5	11986
10005	https://www	https://m.n	The Silent Pa	books	4.5	82530
10006	https://www	https://m.n	Harry Potter	books	4.7	28520
10007	https://www	https://m.n	Harry Potter	books	4.7	21254
10008	https://www	https://m.n	Harry Potter	books	4.7	17678
10009	https://www	https://m.n	Harry Potter	books	4.7	18862
10010	https://www	https://m.n	Harry Potter	books	4.7	24060
10011	https://www	https://m.n	The Tower of	books	4.8	12341
10012	https://www	https://m.n	Secret of the	books	5	1

Fig 2: Dataset of product details.

Collaborative Filtering:

Collaborative Filtering systems make recommendation of an item to a user based on ratings provided by other users. User based collaborative filtering method is used to recommend the items to a user that he/she might like based on the ratings given to that item by the other users who have similar interests with the active user. A custom dataset was made with 30 users and their ratings for all 3000+ products.

	The Sinful	The Dogfi	Harry Pott	The Comp	The Silent	Harry Pott
user1	3.7	4.6	4.2	2.7	3.8	3.7
user2	1	2.3	3	2.9	3.1	2.8
user3	4.4	1.7	1.9	3.8	2	4.6
user4	4.3	2.8	1.1	1.8	3.6	4.5
user5	4.1	3.2	3	4.5	4.8	3.8
user6	3.2	1.7	3.6	3.6	4.4	2.8
user7	2.7	4.7	1.9	4.8	1.5	1.9
user8	2.5	3.2	4	4.2	2.4	4.3
user9	3.8	2.6	4.2	4	2.2	2.8
user10	1.9	1.3	1.7	4.6	1.1	2.7

Fig 3: Dataset of ratings of multiple users.

A correlation matrix was created of these 30 users and their ratings using Pearson Correlation Method. Correlation Matrix is used to show correlation coefficient between variables.

A correlation coefficient tells us about the strength of relationship between two variables.

Pearson's Correlation (R):

Pearson's Correlation measures the linear correlation between two variables. It is the ratio of covariance and product of standard deviation of two variables. It is normalized such that the result lies between -1 and 1.

1 indicates a strong positive relationship, -1 indicates a strong negative relationship and 0 indicates no relationship at all.

R is calculated by:

$$\frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \qquad (1)$$

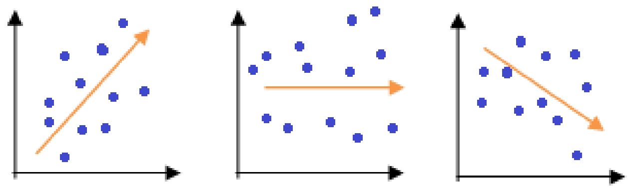
r = correlation coefficient

x_i = values of the x-variable in a sample

$\bar{x}$ = mean of the values of the x-variable

y_i = values of the y-variable in a sample

$\bar{y}$ = mean of the values of the y-variable



R=0.7 (Positive) R=0 (No relation) R=-0.7(Negative)

Fig 4: Pearson's Correlation

Some assumptions in Pearson's Correlation state that the data should be derived from random samples. Both variables should be normally distributed. There should be Homoscedasticity. Extreme outliers can influence the Pearson Correlation.

1.000000	-0.202986	0.297035	-0.246014	0.350297	0.502616	-0.317886	0.209504
-0.202986	1.000000	-0.258349	0.413646	-0.167450	-0.303099	0.348028	-0.038566
0.297035	-0.258349	1.000000	-0.172422	0.272461	0.085108	-0.307514	0.225707
-0.246014	0.413646	-0.172422	1.000000	-0.392915	-0.257852	0.143188	0.080774
0.350297	-0.167450	0.272461	-0.392915	1.000000	0.245710	-0.114100	-0.081144

Fig 5: Correlation Matrix

After calculating Correlation coefficients, the product, which is selected and rated by the user, is then given as query to the matrix and top similar items with highest score are recommended. Similarity can be calculated by using cosine distance.

$$\cos(\theta) = \frac{A.B}{\|A.B\|} = \frac{\sum_{i=1}^{n} A_i \,.B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\ \sqrt{\sum_{i=1}^{n} B_i^2}} \qquad (2)$$

A function is created for passing the query item for calculating the similarity between the active user and other users with similar rating. This returns a list of top similar products, which were similarly rated by other users.

```
(['I KALL K48 Premium Keypad Mobile (1.8 Inch, 1500 mAh Battery) (Green)',
  'Something I Never Told You Shravya Bhinder',
  'Nokia 3310 Dual SIM Feature Phone with MP3 Player, Wireless FM Radio and Rear Camera',
  'The Magnificent Seven (2016)',
  "U.S. POLO ASSN. Men's Regular Button Down Shirt New-ZU",
  'Olicoop Green Stuffed Olives, 450g, Pack of 2, Produced in Spain',
  "CAVALLO by Linen Club Men's Checkered Regular Fit Casual Shirt",
  'Usha Racer 1200MM Ultra High Speed 400RPM Ceiling Fan Brown W/O REG',
  "Amazon Brand - Symbol Men's Regular Fit Casual Shirt",
  "itel A23 Pro Jio (Lake Blue, 1GB RAM, 8 GB Storage, 5'' Bright Display) (L5006C)"],
```

Fig 6 : Recommendations using Collaborative Filtering

Content Based Filtering:

Content Based Filtering is a technique based on description of the item and the user's preferences. This method is suited when enough information is provided about the item and recommends items that have similar properties. The TF-IDF vectorizer can be used in this approach. TF stands for Term Frequency i.e. the number of times a term 't' occurs in a given document 'd'. It is given by:

$$TF(t,d) = \frac{Number\ of\ occurrences\ of\ t\ in\ d}{total\ number\ of\ words\ in\ d} \quad (3)$$

DF stands for Document Frequency, which measures the number of occurrences of the term 't' in the entire set or 'corpus' of documents. It is given by:

$$DF(t) = occurrence\ of\ t\ in\ N\ documents \quad (4)$$

IDF stands for Inverse Document Frequency, which measures the informativeness of the term 't'. It basically tests how relevant a term is and we get the weight of that term. The IDF of a term is the number of documents 'd' in the entire set separated by the number of times the term occurs.

$$IDF(t) = \log(\frac{N}{DF(t)}) \qquad (5)$$

Where, N = Number of documents containing t.
DF(t) = Document frequency of a term t

For implementing this approach, the attributes item description and category are merged together and cleaned by removing numbers, punctuations and extra spaces. Each sentence is tokenized which divides strings into a lists of substrings. A stop words list is used which is provided by NLTK library which contains all the common English language words like 'the', 'an' etc. which need to be removed. The last step in pre-processing is Stemming. This converts a word into its root or base word. For Example, 'dancing' becomes 'dance'. In this way, tags are generated for each item in the dataset.

```
0                     [sinful, silence, abir, mukherjee]
1               [dogfight, lone, peacekeeper, suyog, ketkar]
2               [harry, potter, philosopher, stone, rowling]
3          [complete, novels, sherlock, holmes, arthur, c...
4          [silent, patient, record, breaking, multimilli...
                                 ...
2892        [kall, keypad, mobile, inch, big, battery, blue]
2893       [tecno, pova, energy, blue, ram, storage, mah,...
2894       [lava, max, big, screen, big, battery, stroked...
2895       [kall, triple, sim, multimedia, keypad, mobile...
2896       [nokia, dual, sim, feature, phone, player, wir...
```

Fig 7: Generated Tags

These tags are then vectorized using CountVectorizer. It is used to convert text into vectors w.r.t their frequency in the document. It creates a matrix in which each word and its frequency is given. Using these vectors a similarity matrix is created using cosine similarity to find out distance of a product with every other product in the dataset.

```
array([[1.        , 0.18257419, 0.18257419, ..., 0.        , 0.        ,
        0.        ],
       [0.18257419, 1.        , 0.16666667, ..., 0.        , 0.        ,
        0.        ],
       [0.18257419, 0.16666667, 1.        , ..., 0.        , 0.        ,
        0.        ],
       ...,
       [0.        , 0.        , 0.        , ..., 1.        , 0.20044593,
        0.19364917],
       [0.        , 0.        , 0.        , ..., 0.20044593, 1.        ,
        0.34503278],
       [0.        , 0.        , 0.        , ..., 0.19364917, 0.34503278,
        1.        ]])
```

Fig 8: Similarity matrix of products

A function is then created for calculating distance of the query product with other products and top similar products are appended and recommended.

```
recommend('Harry Potter and the Chamber of Secrets J.K. Rowling')
```

```
Harry Potter and the Chamber of Secrets: Illustrated Edition J.K. Rowling
Harry Potter and the Goblet of Fire J.K. Rowling
Harry Potter and the Philosopher's Stone J.K. Rowling
Harry Potter and the Prisoner of Azkaban J.K. Rowling
Harry Potter and the Order of the Phoenix J.K. Rowling
Harry Potter and the Deathly Hallows J.K. Rowling
Harry Potter: The Complete Collection (1-7) J.K. Rowling
Harry Potter and the Half-Blood Prince J.K. Rowling
Harry Potter and the Goblet of Fire: Illustrated Edition J.K. Rowling
Harry Potter and the Goblet of Fire  Gryffindor Edition J.K. Rowling
```

Fig 9: Content Based Recommendations

Popularity Based Model:

Since the dataset contains number of ratings for each products as well, we can sort them according to the number of ratings in highest order and get the top rated products, which will be considered popular among all the users. Top 500 products are chosen and out of these, a random sample of 10 is chosen at each runtime.

id	name	category	no. of ratings
12913	Samsung Galaxy M31 (Ocean Blue, 8GB RAM, 128GB...	mobile phones	280653
12884	Samsung Galaxy M21 2021 Edition (Charcoal Blac...	mobile phones	204672
12842	Samsung Galaxy M21 2021 Edition (Arctic Blue, ...	mobile phones	204672
13129	Samsung Galaxy M21 (Raven Black, 4GB RAM, 64GB...	mobile phones	204672
12876	Redmi 9A Sport (Carbon Black, 2GB RAM, 32GB St...	mobile phones	140296
13125	Redmi 9A Sport (Coral Green, 3GB RAM, 32GB Sto...	mobile phones	140296
12833	Redmi 9A Sport (Metallic Blue, 2GB RAM, 32GB S...	mobile phones	140296

Fig 10: Popular Recommendations

IV. DEPLOYMENT

Streamlit, an open-source application framework was used to deploy the hybrid recommendation system. It has several elements like search-box, which allows searching for products. Containers, which can be used to display and hold elements. Spinners, which are similar to loading screens that can be displayed during the time of processing. It also provides PaaS based cloud service to deploy applications. This framework allowed us to demonstrate the working of all of the three recommendation algorithms.

V. RESULTS

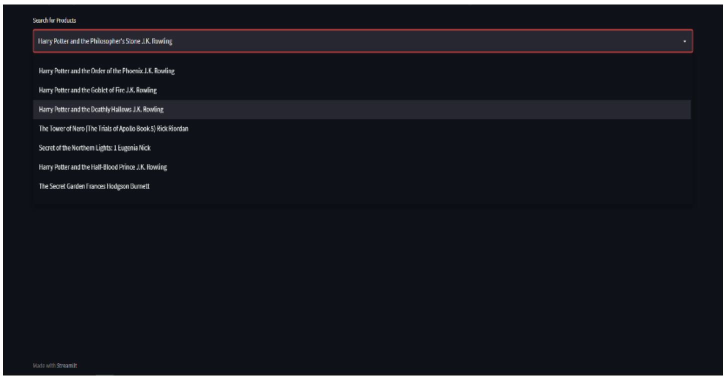


Fig 11: Search for Products

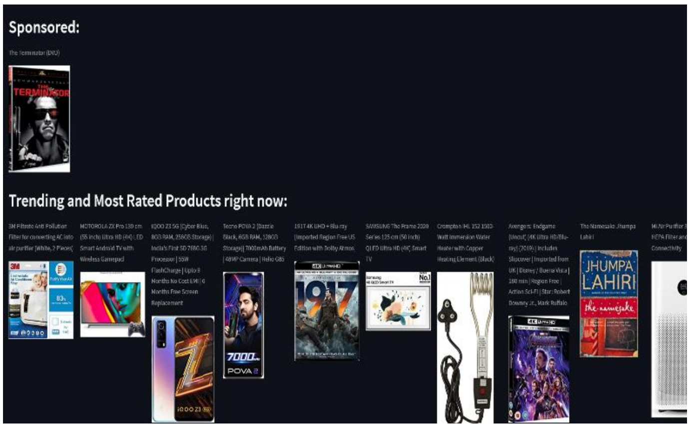


Fig 12: Advertising and Popularity Based Recommendations

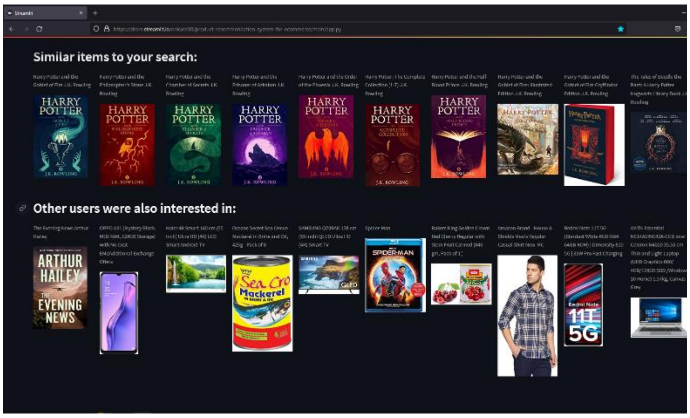


Fig 13: Content Based and Collaborative Filtering

VI. CONCLUSION

We are able to build and deploy a hybrid recommendation system comprising of three different algorithms, which provide accurate recommendations the user based on their preferences. This system shall be made completely free to use and deploy to anyone who wishes to add it to their system. This methodology shall allow local online retail business owners to directly deploy the recommendation system into their existing system thus generating more revenue and attracting more customers.

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