Smartphone recommendation using popularity and collaborative filtering based models

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***Abstract*—The Smartphone Industry is an ever growing market. In 2021, the size of the global smartphone market was estimated at USD 457.18 billion. The market is anticipated to expand at a CAGR of 7.3% from 2022 to 2029, rising from USD 484.81 billion in 2022 to USD 792.51 billion. After China, India is the world's second-largest market for smartphones. In India, over 134 million smartphones were sold in 2017, and it is predicted that number will rise to almost 442 million by 2022. But with so many options available in the market, the question of which model is to be purchased, arises. The model proposed in our project will be trained with large datasets which can then suggest the perfect model with a given set of inputs without any hassle to search for hours on the internet in order to decide which phone is best suited to the customer in accordance with his/her needs. Therefore, Our smartphone's recommendation system is designed to create a system that can suggest the best suited smartphones based on the choices or behaviours of the consumers. In this paper, it should be assumed that "Users" and "Reviewers" are used interchangeably in this paper as we have assumed that the people who reviewed phones have also been a user of the phones.**

Keywords—Smartphones, Data Analysis, Dataset, AI, Recommendation System, Models

I. Introduction

A. Problem Statement

In the modern smartphone market, there are different factors which are crucial to the understanding of their functionality and appeal, such as the location, the screen size and the processor speed. With such information obtained, the question of how such information is used to construct a system that recommends smartphones in accordance with the needs of customers arises. Here, a recommendation system becomes a necessity. We are working on a dataset containing the different specifications and reviews of different phones in the current market so as to formulate any recommendation for the user.

B. Related Work

In the current world where there are a plethora of options when it comes to smartphones, customers find it hard to choose the smartphones that they think suits their needs the most. There also seems to be a lot of customers who aren't completely aware of what they actually need in their smartphones with respect to what they want out of them, and thus emerges the necessity to construct a model system that takes into account their needs and recommend the right smartphones to them without the hassle of getting into more research into different phone specs which may end up wasting more of the customers' time itself.

There have been numerous recommendation systems for smartphones developed in the past, some differ in the methods that they used for their systems, some in the efficiency and complexity and many other factors. In the next part, we will discuss some of the relevant works done in the past.

A mobile phone recommendation system with user centric voting approach [1]

A methodology based on user desire and voting was used to create a recommendation system for choosing mobile phones. To categorise mobile users based on their interests and to cluster mobile types based on the weights generated from the actual attributes associated with user voting, a model with user preferences and actual weights of various mobile phone variants was used. Potentially limiting the use of the well-liked k-means algorithm is the initial cluster centre selection. This research suggests a clustering process variant with improved cluster centres initialization as representatives. 1000 mobile phone users participated in a controlled experiment that led to the evolution of the recommendation system. A well-designed questionnaire was used to collect the data online. According to the analysis's findings, using the suggested system yields greater satisfaction than using benchmark systems based on equal weight.

To find the list of items that will appeal to a certain user's interest, collaborative filtering and content-based algorithms are applied. Personalised recommendation approaches are benefiting from the expansion of the Internet and e-commerce, but they are also up against obstacles brought on by information overload when it comes to accurately selecting products and services for clients. [2]

J.Nielson stated that in order to develop a useful and user-friendly interface, the analyst must first pay attention to understand what consumers do rather than what they say. A study on user interface design for the efficient implementation of recommendation systems was carried out by F.J. Martin [3]. The author concluded that an effective user interface is the most crucial element in the design and development of a recommendation system after carefully examining the study that was conducted. According to the author, this study shows that the user interface accounts for 50% of the whole user experience. According to Srivasthava. J. et al. [4], user interest and behaviour mining based on specifics of online usage has been used for a very long time.

By utilising a theoretical model of conceptions, C. Webber et al. [5] created a mechanism for modelling, assessing, and diagnosing the conceptions of various types of learners. For the objective of group decision-making, authors employed a variety of strategies based on the principles of voting theory. To smooth the unrated data details for individual users with respect to the clusters, G. Xue, et al. developed a collaborative system based on the conventional simple k-means clustering algorithm in their paper published in Nature Communications [6].

The relationship between three components, namely place, purpose, and time, was proposed by Pinyapang, S., and Kato, T. [7]. They also condensed the fundamental guidelines for critical data analysis and the algorithms for query processing. The surveys of mobile recommender systems conducted by T. Harzov et al. [8] included several examples and overviews of the most crucial methods, functions, and computational models. Recommended systems, according to Jyodeep Das et al. [9], are a subclass of information filtering systems that are extremely helpful to customers in their decision-making process by proposing objects that the customers may prefer.

According to E. Ephrati and J. Rosenschein [10], the ideas and rules of voting theory have been successfully applied in many fields for a long time in multi-agent systems with regard to collective decision making that maximises the welfare of individuals. Voting theory is extremely helpful in recommendation engines that maximise the preferences of the client. Utilising an iterative clustering technique that takes advantage of the connections between users and objects, X. Jiang et al. [11] effectively constructed a cluster-based collaborative filtering system.

J. Herocker and M. O' Connov [12] tested a number of clustering techniques to divide the item set based on user voting information. The design, implementation, and assessment of an intelligent based recommendation system have been provided by Deng-Neng Chen et al. and are highly helpful for users to choose appropriate mobile phone models based on their unique customer votes or preferences. The effectiveness and utility of a developed intelligent web-based recommendation system were empirically assessed.

Authors in [13] developed a traditional personalised recommender system that can learn about the capabilities of mobile phones and provide customised offering services to potential clients. In their work, triangular fuzzy numbers with fuzzy near compactness are used to technically convey consumer preferences and product features. In light of these similarities, the best items to meet the needs were suggested.

II. METHODOLOGY

The obtained dataset is prepared and cleaned. We load, merge and perform basic analysis on the dataset. We perform certain modifications such as data cleaning, imputation and rounding-off. We then perform the data split. After that, we perform in-depth analysis of the data. Based on the popularity model, we recommend the top 5 mobile phones. We then implement the collaborative filtering based models that includes SVD, kNNWithMeans_Item based and kNNWithMeans_User based. We then proceed to analyse the RMSE value and make the necessary comparisons. We examine the average ratings for test users and then recommend top 5 products for test users. We cross check the results with the cross_validation techniques. We discuss the results and some business scenarios where we should use popularity based recommendation systems and CF based recommendation systems. We finally look into some other possible methods which can further improve the recommendation for different users.

III. DATA PREPROCESSING

A. *Import Libraries*

Some of the libraries that were used for this project include pandas, numpy, surprise, etc.

B. *Data preparation and basic cleaning*

Except score and score_max (which are of float type) all other features are of object type.
feature date should be of datetype.
Also, score, score_max, extract and author: columns seem to have Null values.

Thus, multiple similar names, with different details exist in the product list. For eg:
Huawei P8lite zwart / 16 GB and
Huawei P8 Lite Smartphone, Display 5" IPS, Processore Octa-Core 1.5 GHz, Memoria Interna da 16 GB, 2 GB RAM, Fotocamera 13 MP, monoSIM, Android 5.0, Bianco [Italia] are exactly the same models.
Another observation is that 'phone_url' column also contains the phone name and model information. Let's check what extra information is present in 'product column'.

Extra information is generally:

phone memory: 8Gb/16GB/32GB etc
phone colour: Marble white, Blue, Red etc
carrier: AT&T, Verizon etc
Another observation is that these specifications are not present in all the product names, for eg: there is no-way available to differentiate between the 2 products below:
'Samsung Galaxy S III Cellular Phone' and
'Samsung Galaxy S III SPH-L710 - 16GB - Marble White (Sprint) Smartphone'

Thus differentiating information is not the same in all the product details. Also, the goal is to recommend a phone not the carrier. and other specs like colour etc are of low importance in recommendation. The only consistent differentiating information in all the product names is the 'phone manufacturer and model number', which can also be extracted from the 'phone_url' column.

Phone	**Number of ratings**
Samsung galaxy s iii	17093
Apple iphone 5s	16379
Samsung galaxy s6	16145
Samsung galaxy s5	16085
Samsung galaxy s7 edge	15917
Motorola moto g	14476

Samsung galaxy s7 789999	13488
Samsung i9500 galaxy s iv	13161
Huawei p8 lite	12629
Lenovo vibe k4 note	9662

Table 1: Distribution of number of ratings as per item (Clipped at 10)

Users	Number of ratings
Amazon Customer	76978
NaN	63202
Cliente Amazon	19304
e-bit	8663
Client d'Amazon	7716
Amazon Kunde	4750
Anonymous	2750
Einer Kundin	2610
Einem Kundin	1898
unknown	1738

Table 2: Distribution of number of ratings as per user (Clipped at 10)

Following observations are made:
Most active user is 'Amazon customer'
'Anonymous' and 'unknown' users are those whose names are not known. Thus we can use this to impute blank values in 'author' column
Many names are similar but in different languages like 'Amazon customer' and 'Cliente Amazon'. Let's search for these first and clean up the differences due to language.

Names like 'einer Kundin', 'einem Kunden','Anonymous' and 'unknown' can be interpreted in the same way i.e. an 'unknown customer'. Let's replace these names too.

Users	Number of ratings
Amazon Customer	76978
NaN	63202
Cliente Amazon	19304
Anonymous	10457
e-bit	8663
Client d'Amazon	7716
Amazon Kunde	4750
(unrecognised characters)	1071
David	1016
(unrecognised characters)	904

Table 3: Distribution of number of ratings as per user (Clipped at 10) after aggregating all the anonymous users into "Anonymous"

IV. DATA ANALYSIS

The Result of the extraction of the top few phones with the most number of ratings is shown below in Table 4.

Phone	Number of ratings
Samsung galaxy s5	11429
Samsung galaxy s6	11046
Motorola moto g	10382
Samsung galaxy s7 edge	10359
Iphone 5s	10281

Table 4: Result for most rated features and products

Extracting the rating value given the most number of times:

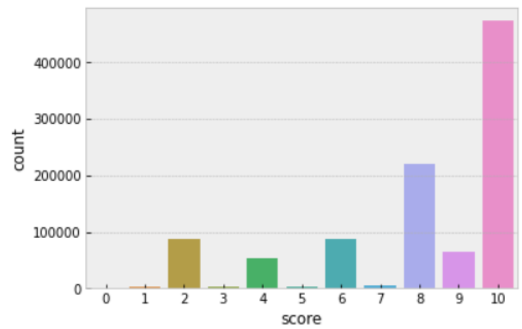

Fig 1: Bar chart of distribution of scores among all ratings

Extracting the list the top 10 reviewers that have given the most 10/10 ratings along with the total times they gave a 10/10 rating:

Users	Number of ratings

Amazon Customer	1530
Cliente Amazon	519
Amazon Kunde	422
Client d'Amazon	301
David	292
Alex	274
Daniel	258
Marco	229
Chris	228
Micheal	210

Table 5: Result for top 10 users that gave the most 10/10 ratings

Extracting the top few reviewers that have given the most number of reviews in total:

Users	**Number of ratings**
Amazon Customer	4816
Cliente Amazon	1663
Amazon Kunde	1179
Client d'Amazon	975
David	558

Table 6: Result for the users with the highest number of reviews

Extracting the list of products which have over 50 ratings as well as have reviewers who have also given over 50 ratings:

Number of authors who gave >50 ratings	**805**
Number of products with >50 ratings	**2496**

(a)

	Reviewer	**Product**	**Score**
66	James	Samsung galaxy s8	10
161	Paul	Samsung galaxy s8	10
167	Robert	Samsung galaxy s8	10
179	Michelle	Samsung galaxy s8	10
225	Andrew	Samsung galaxy s8	10

(b)

Table 7: (a) Authors and products who have given/received 50+ ratings (b) Result of extracting reviewers who have given 50+ ratings as well as have given a review on a product that has 50+ ratings along with the score given

The first part extracts the list and number of reviewers with over 50 ratings. The second part extracts the list and number of phones with over 50 ratings. Utilising the info from these 2 parts, we are able to extract products with over 50 reviews as well as have reviewers with over 50 reviewers.

We then extract the list of unique reviewers and the list of unique products as per the dataset.

Extracting the top rated products in accordance with the mean of their ratings:

Phone	**Rating Count**	**Mean Rating**
Nokia 8270	2	10.0
Htc sprint ppc 6700	2	10.0
Alcatel ot e805	2	10.0
Verykool s505	5	10.0
Samsung i700	4	10.0
Samsung t419	2	10.0
Motorola e680i	2	10.0
Inew v1	2	10.0
Lg b2000	2	10.0
Verykool t742	8	10.0

Table 8: Result for top 10 products with the highest mean ratings

The mean rating is calculated for each product, and in accordance with the new mean rating, these records are ordered to bring the top rated products first. Here, the first 10 records are shown.

Constructing a scatter plot that visualises the mean ratings against the number of ratings for the top rated 50 phones:

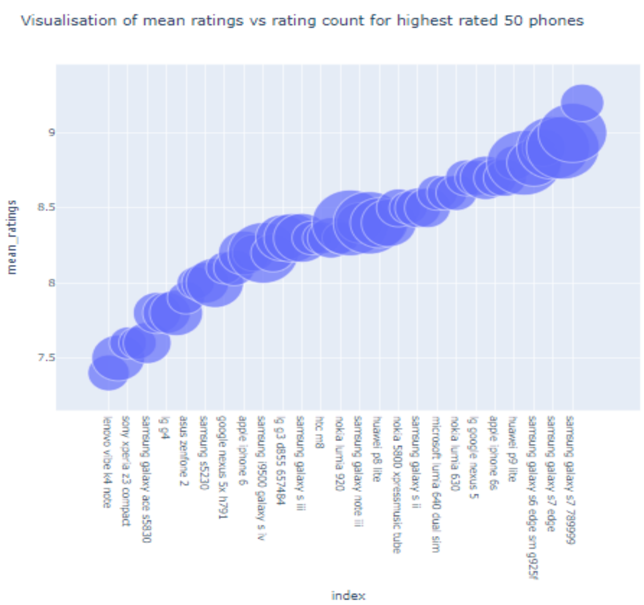

Fig 2: Visualisation of mean ratings vs. rating count for the highest rated 50 smartphones

V. POPULARITY BASED MODEL

Popularity based recommendation systems are the kind of recommendation system that bases choices on factors like popularity and/or current trends. These algorithms look up the products or movies that are most in demand or well-liked by users and then immediately suggest those. For instance, if a product is frequently purchased by the majority of users, the system will learn that it is the most popular, and it will recommend that product to any new users who have just joined up, increasing the likelihood that they will also buy it. It doesn't have cold start issues, so it can make product recommendations for a variety of different filters right away. The past information about the user is not required.The architecture of the popularity based model is shown below:

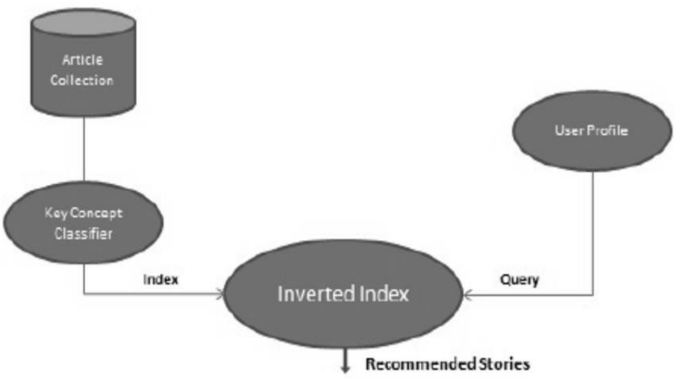

Fig 3: Visualisation of mean ratings vs. rating count for the highest rated 50 smartphones

(Jonnalagedda, Nirmal & Gauch, Susan. (2013). Personalized News Recommendation Using Twitter. 21-25. 10.1109/WI-IAT.2013.144.)

Using popularity based model we tried to figure out most popular phones amongst users, if we consider data from the most popular phones amongst the most frequent users, we are finding that samsung e1120 with score of 10 and rating count of 4, zte v987 with score of 10 and rating count of 4, lenovo p700i , also score of 10 but has rating count of 2, lg kf700 again with score of 10 and rating count of 4 and 5th one is motorola mpx200, with perfect score of 10 and that of rating 2, but if we consider the original data (excluding 'Anonymous' users), Top 5 recommendations for the products are: verykool t742 with score of 10 and rating count of 8, supersonic sc 150 with score of 10 and rating count of 6, verykool s505, vodafone smart 4 power, mitsubishi trium mondo are other 3 products with rating counts of 5, 5, 4 respectively

	Scores	**rating_counts**
product		
samsung e1120	10.0	4
zte v987	10.0	4
lenovo p700i	10.0	2
lg kf700	10.0	2
motorola mpx200	10.0	3

Table 9: Using the data from the most popular phones amongst the most frequent users

	Scores	**rating_counts**
product		
verykool t742	10.0	8
supersonic sc 150	10.0	6
verykool s505	10.0	5

vodafone smart 4 power	10.0	5
mitsubishi trium mondo	10.0	4

Table 10: if we consider the original data (excluding 'Anonymous' users)

VI. COLLABORATIVE FILTERING BASED MODEL

Collaborative filtering approach builds a model from a user's past behaviours (items previously purchased or selected and/or numerical ratings given to those items) as well as similar decisions made by other users. This model is then used to predict items (or ratings for items) that the user may have an interest in as compared to Content based approach where they utilise a series of discrete characteristics of an item in order to recommend additional items with similar properties. Predicting a user's rating based on their reviews of other movies and the overall ratings of other users is an example of collaborative filtering. It is common practice to employ this idea when recommending books, articles, software, and a variety of other products. There are two types of collaborative filtering:

1. User-User-based similarity/Collaborative Filtering:
   User-user collaborative filtering is a type of recommendation technique that seeks out comparable users based on the products users have previously enjoyed or positively interacted with.

2. Item-Item-based similarity/Collaborative Filtering:
   Here, we investigate the connection between the two things (the user who bought Y, also bought Z). With the help of the ratings the user has provided for the other goods, we locate the missing rating.

The architecture of a collaborative filtering based model is as shown:

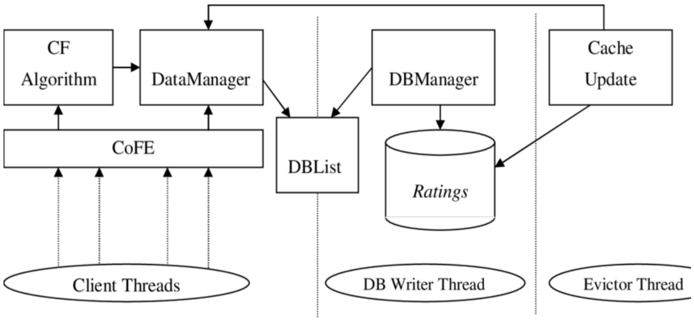

Fig 4: Lowd, Daniel & Godde, Olivier & Mclaughlin, Matthew & Nong, Shuzhen & Wang, Yun & Herlocker, Jon. (2004). Challenges and Solutions for Synthesis of Knowledge Regarding Collaborative Filtering Algorithms.

A. Collaborative filtering model using SVD

The SVD is employed as a collaborative filtering mechanism in the recommender system. Each row in the matrix symbolises a user, and each column a piece of merchandise. The ratings that users provide to goods make up the matrix's components. We rearrange columns for SVD and split the data into training and testing patterns. Top 2 values from testset:
('Luca', 'samsung galaxy core plus', 10.0)
('Andre', 'asus zenfone 2 ze551ml', 10.0)

To get top_n recommendations for each user, we First map the predictions to each user then sort the predictions for each user and retrieve the n highest ones.
('Luca', 'samsung galaxy core plus', 10.0)
('Andre', 'asus zenfone 2 ze551ml', 10.0)
We can clearly see the top 2 phones both form test data and training data comes out to be the same but with RMSE value of 2.9677.

B. CF model using kNNWithMeans_Item based

To implement an item based collaborative filtering, KNN is a perfect go-to model and also a very good baseline for recommender system development. It uses a database in which the data points are separated into several clusters to make inference for new samples.In item based collaborative filtering as well we are getting the same phone samsung galaxy core plus and asus zenfone 2 ze551m but with RMSE Score of 2.8640.

C. CF model using kNNWithMeans_User based

Item based approach is usually preferred over user-based approach. User-based approach is often harder to scale because of the dynamic nature of users, whereas items usually don't change much, and item based approach often can be computed offline and served without constantly re-training. But even we used the user based model and found that samsung galaxy core plus and asus zenfone 2 ze551m are the top 2 results of User based collaborative filtering model, but with RMSE Score of 2.9002.

2.9002, 2.8640, 2.9677 are the rmse values of user based, item based and svd, the item based collaborative filtering has the lowest rise value, therefore we can say that item based collaborative filtering is a great fit, and we used this for our further analysis as well

VII. RMSE VALUE AND COMPARISON

Root Mean Square Error (RMSE) is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are; RMSE is a measure of how spread out these residuals are. In other words, it tells you how concentrated the data is around the line of best fit. Root mean square error is commonly used in climatology, forecasting, and regression analysis to verify experimental results

RMSE is a popular formula to measure the error rate of a regression model. However, it can only be compared between models whose errors are measured in the same units in the graph. Comparison of RMSE scores from different collaborative algorithms is shown in the graph below.

Actually the RMSE scores are shown in the graph. Best RMSE score is given by knn .This is a total item based on product and product ratings . These comparison show prediction of error recommendation in our project .this can be useful to get good error less recommendation to the user

Graph shows how much error is producing in the rmse value. Here knn i rmse is better performing compared with both svd and knn_u because errors occurrence

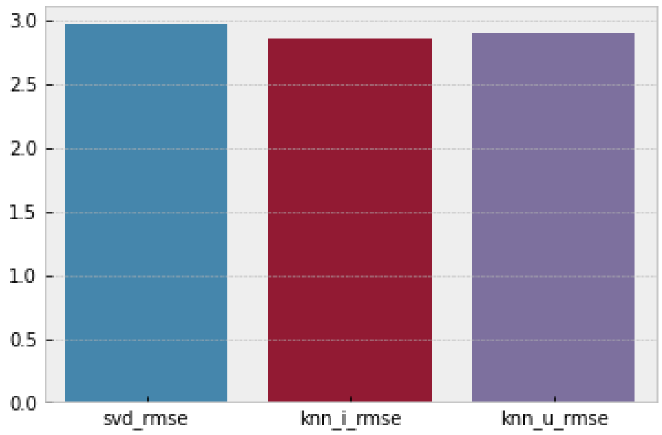

Fig 5: Comparison between the RMSE values of SVD, KNN (item based) and KNN (user based)

The best RMSE score is given by knn (Item based), so we are using it for further analysis.

VIII. AVERAGE RATINGS

According to the three algorithms we will get prediction and rating ,average error prediction. Then it will be generalised by the ratings and it will be represented by rmse value . By these average ratings we will be getting closer values of errors and that will be given as output in the system.

	Average value by svd_RMSE	Average value by knn_i_RMSE	Average value by knn_u_RMSE
Average Prediction for test users	7.800217805179583	7.760249631382037	7.787064696309136
Average rating by test users	7.800217805179583	7.850823647462162	7.850823647462162
Average prediction error for test users	2.304408782991	2.252437466152	2.253572244741

Table 10: Average prediction, rating and prediction error for test users for the various methods

IX.FINDINGS AND INFERENCES

Most widely used phone (ranked 10 by the largest number of users):
* Overall: verykool t742
* Amongst top users: samsung e1120

The overall statistics is heavily weighted in favour of "Amazon customers" from various nations. This might possibly be the case because "Amazon" is the largest phone trader in the world. Although it should have utilised authentic "user" names from Amazon. The majority of authors have given a rating of "10" or "8." The RMSEs of knn_i (item-based) and knn_u (user-based) are comparable.

X. IMPLEMENTATION

We recommend the top 5 products for the test users by using the following code:

```
> top_5 = get_top_n(knn_i_pred,5)

> print('Top 5 recommendations for all test users are: \n')

> for key,value in top_5.items(): print(key,'-> ',value,'\n')
```

We have implemented the GUI for the above built smartphone recommendation system using Flask and display the recommendations in the form of slides.

XI. RESULTS AND DISCUSSION

We have evaluated the results based on cross validation techniques. The mean svd cv score is 2.95. The mean knn_i_cv score is 2.86. The mean knn_u_cv score: 2.89. We perform the comparison of RMSE scores(mean cv) from different collaborative algorithms. We obtain the following graph as output:

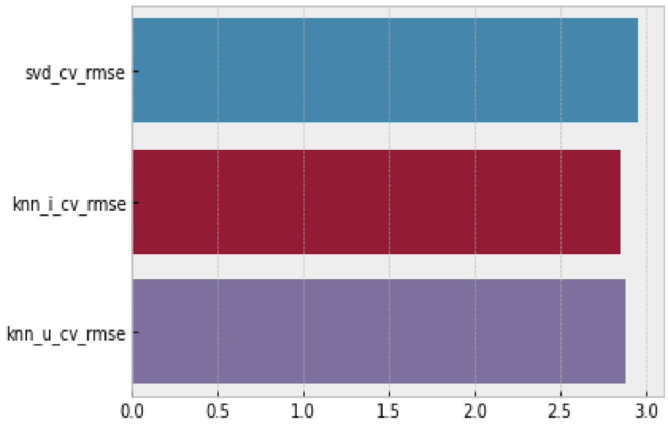

Fig 6: Comparison between the RMSE (mean cv) values of SVD, KNN (item based) and KNN (user based)

As a result, knn i is performing better on the CV as well. Popularity-based recommendation systems can be helpful in a variety of circumstances, including: when neither the user nor the items have any data, when it is necessary to display the most popular goods across various categories in addition to tailored results, such as on a music website or app, the most popular punjabi songs or English songs trendiest style in western or traditional clothing, most popular vacation packages are those for honeymoons, bike vacations, Himalayan adventures, etc. When user history or item data is available, collaborative filtering can be effective in situations like providing the user with personalised recommendations. Examples include: Personalised movie suggestions from streaming services like Netflix, Amazon Prime, and YouTube, among others.

XII. APPLICATION

The availability of product information including daily prices, specifications, rumours, trends, and review-based ratings using web mining present at a single platform thanks to the rise of e-commerce platforms aids people in making wise judgments while purchasing the goods. Users may easily assess prices, product and feature reviews, trends, and specifications-based rating using the suggested system's single platform. To save the user time and effort, the suggested solution also offers specification-based sentiment analysis on evaluations in real-time for every product.

Ultimately, a recommendation system that gives reviews was developed by fusing web crawling, web scraping, and machine learning algorithms.analytics from top online retailers assist the buyer in making decisions and facilitating online shopping. The results of the studies demonstrated the effectiveness of our strategy and encouraged more research in this area.

As priorities can vary over time, we aim to incorporate an analysis of reviews' timeline to our future work. Additionally, the user's present location must be carefully compared to their previous location history and any associated user interests. This will make it easier to create a recommender system that users will like.

XIII. LIMITATIONS

The popularity based recommendation systems are not personalised. Every other user would receive the identical kinds of goods or movies that are entirely based on popularity from the system. For collaborative filtering, There must be sufficient users to locate a match. CF and Content-based matching hybrid techniques are frequently used to address such cold start issues. Even though there are many users and several things that should be frequently suggested, issues with user and rating matrix sparsity can occur, making it difficult to identify users who have rated the same item. the difficulty in making recommendations to the user because of sparsity issues.

XIV. FUTURE SCOPE AND CONCLUSION

We have successfully built a recommendation system such that most well-liked and tailored mobile phones are suggested to a user by using collaborative filtering and popularity-based methods. We have built an efficient smartphone recommendation system model that will be able to recommend the top 5 products for the test users through a well developed GUI made for users so that they can easily access the information. In addition to popularity and collaborative filtering, hybrid recommendation techniques such as the content+collaborative method, demographic, utility-based, and knowledge-based recommendation systems can also be utilised. This can be undertaken in the future to improve our recommendation system and provide more efficient and accurate results.

REFERENCES

[1] Mr. Y. Subba Reddy and Prof. P. Govindarajul., (February 2018). “A mobile phone recommendation system with user centric voting approach”, IJCSNS International Journal of Computer Science and Network Security, VOL.18 No.2

[2] Chen, Daniel; Mocker, Martin; Preston, David S.; and Teubner, Alexander. (2010). "Information Systems,Strategy:Reconceptualization, Measurement, and Implications," MIS Quarterly, (34: 2) (pp.233-259).

[3] J. Martin, (2009). "Top 10 lessons learned developing, deploying, and operating real-world recommender systems", ACM Recsys.

[4] Ting-Peng Liang, Paul J. H. Hu, Y. R. Kuo, D. N. Chen. “80. A Web-Based Recommendation System for Mobile Phone Selection”, 11th Pacific-Asia Conference on Information Systems.

[5] C. Webber, S. Pesty, and N. Balacheff. (ECAI 2002). “A multi-agent and emergent approach to learner modelling,” in Proceedings of the 15th European Conference on Artificial Intelligence, pp. 98–102.

[6] Xue, C. Lin, Q. Yang, G. Xi, H. Zeng, Y. Yu, and Z. Chen. (2005). “Scalable collaborative filtering using cluster-based smoothing,” in Proceedings of the 28th annual International ACM SIGIR Conference on Research and Development in Information Retrieval, (pp. 114–121).

[7] Pinyapong, S., Kato, T. (2004). Query processing algorithms for time, place, purpose and personal profile sensitive mobile recommendation. International Conference on Cyberworlds, (pp. 423–430, IEEE) .

[8] Horozov, T., Narasimhan, N., Vasudevan, V. (2006). Using location for personalised poi recommendations in mobile environments. In: International Symposium on Applications and the Internet, SAINT 2006, (p. 6).

[9] N. Chin, (2001). "Empirical Evaluation of User Models and UserAdapted Systems", User Modeling and User-Adapted Interaction.

[10] Ephrati and J. Rosenschein, (1993). “Multi-agent planning as a dynamic search for social consensus,” in Proceedings of the 13th International Joint Conference on Artificial Intelligent, (pp. 423–429).

[11] Jiang, W. Song, and W. Feng. (2006). “Optimizing collaborative filtering by interpolating the individual and group behaviors,” in APWeb, (pp.568–578).

[12] O'Connor and J. Herlocker. (1999). "Clustering items for collaborative filtering," in Proceedings of the ACM SIGIR Workshop on RecommenderSystems.

[13] A. Ojokoh, M. O. Omisore, O. W. Samuel and U. I. Eno. (2015). "Archetypal Personalized Recommender System for Mobile Phone Users", Research Methods: Concepts, Methodologies, Tools, and Applications, (pp. 20).