

INTELLIGENT PRODUCT RECOMMENDATION SYSTEM USING MACHINE LEARNING

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Abstract—Presently a-days there are a lot of trends in online shopping. Almost all the products which are used in day-to-day life are accessible online, particularly groceries. This online shopping makes client simpler to buy their required products. Every individual can buy their required product at any time and anywhere. Suggestions are utilized to make crafted by the clients simpler and faster. This helps to diminish their significant time and endeavors. For this, the suggestions given to the customer should be exact and should be fast. And most importantly they should be non-irritable to the customers. In this undertaking on the web basic food item proposal framework, we will create a recommendation model which will recommend the products to the customer based on the reviews

Key Words: *Online shopping, grocery, recommendations, customers.*

I. INTRODUCTION

We individuals nowadays are hoping to finish our jobs fast and simply way not making any difference whether the assignment is enormous or little. To create our undertaking a piece simpler we can utilize advice or proposals. On the off chance that we are confounded to get some garments or hardware, we could require some help from others like a suggestion or any better proposals. Suggestions imply the pieces of advice which are given in light of an individual's decision or his/her past activities. Similarly, we can suggest an item through on the web or in a digitalized way by utilizing a Recommender Framework.

Recommender Framework:

The Recommender framework is a framework that is intended to suggest things in light of various factors. In basic terms, we can likewise characterize as it is separating technique that assists with suggesting related things because of the client's interest, and evaluations are given for the item. This framework can be utilized

in many fields, for example, shopping, book buying, motion pictures, and lodgings, and in numerous web-based sites. This makes our work simpler as it suggests the best and first-class things we need to pick. For the model, we want to purchase a cell phone with great elements. So we are looking through it in changed online sites to pick the best one. Here the recommender framework will assist us with picking it. It accumulates our inquiry history a gives us suggestions in light of it and further, it likewise suggests the connected things. For example, if we purchased a cell phone, it suggests headphones, a telephone case,

a screen watch, and so forth... By this, we can without much of a stretch look at the highlights and rating of the item and can pick the best which is likewise a period deliverer for this bustling world. Even though recommender frameworks are useful similarly they may bother once in a while. Like, we could get undesirable and pointless proposals and advertisements which are bothering us. To keep away from this we utilize two sorts of separating techniques.

In particular,

1. Collaborative Separating
2. Content-based Separating

These separating strategies are used to give just the looked and client-based proposals to the clients. These prompts keep away from disturbing promotions to the client.

Collective Filtration:

In order to recommend products to users with similar interests, collaborative filtering is used to cluster users who share similar characteristics and interests. This indicates that rather than recommending an item based on its features, we classify users into clusters of similar types and recommend each user based on the preferences of its cluster. For instance, there are three users: A, B, and C. User A is looking for movies in the fiction and comedy genres, user B is

looking for movies in the comedy genre, and user C is looking for movies in the fiction genre. Therefore, user B will receive recommendations based on A's search by comparing all of these data, and user C will also receive recommendations from A's search.

Collaborative filtering can be divided into two categories. They are,

1. Memory-based Cooperative Sifting.
2. Collaborative filtering based on models.

In this instance, memory-based collaborative filtering entails taking the weighted average ratings and locating users with cosine similarities. Simply put, uses the user's previous data and ranking to calculate the similarity between users or items. This method's primary goal is to describe the degree of similarity between users or objects and find uniform ratings to suggest hidden items.

There are two types of methods in it. For instance,

1. User-based Collaborative Filtering

In this approach, the same user with similar rankings for the same items is identified, and the user's order for the item to which the user is never linked is then highlighted.

2. Content-based filtering:

Item-based collaborative filtering

The goal of content-based separating calculations is to make recommendations based on what customers know. It is essential to include a significant number of products in the system because this design is all about contrasting product highlights with customers' advantages. Prior to developing a strategy to select the most desirable features for each customer, this should be the top priority. A possible combination of these two methods is possible. In the beginning, the client receives a list of highlights from which they can select the most captivating aspects. Additionally, the calculations comprise the client's conduct information and keep track of the variety of items selected by the stoner in the set of experiences.

Hybrid Recommendation System:

A mixture suggestion framework is a unique kind of proposal framework that can be considered as the blend of the substance and cooperative sifting strategy. It joins more than one technique, model, or system in various ways to accomplish improved results. There is a wide number of approaches, calculations, and strategies that are utilized to foster a proposed framework. There are two well-known strategies utilized for separating the proposals, content-based and cooperative separating. These strategies face the issue when there isn't an adequate number of information to get familiar with the connection between the client and things. In such cases, the third kind of approach is

utilized to assemble the proposal frameworks named Cross breed Suggestion Framework. This approach survives the limits of both strategies. Consolidating cooperative and content-based sifting together may help in defeating the deficiency we are looking at utilizing them independently and can be more compelling now and again. Half-breed recommender framework approaches can be executed in different ways like by utilizing content also, cooperative-based strategies to create expectations independently and afterward joining the forecast or we can simply add the capacities of cooperative-based techniques to a substance-based approach as well as the other way around.

II. LITERATURE REVIEW

1. David Robert Stockli, Hamid Khobzi, "Recommendation systems and convergence of online reviews: The type of product network matters", Decision Support Systems, Elsevier, 2021.

That's what the creator said, this paper looks at the relationship between item networks created by proposal frameworks and the item evaluations by an assembly of the items. That implies it looks at whether the kind of item networks are related to the combination of communicated feelings for items in an item network diversely or not and the information is gathered from a significant Swiss online business stage. Here in this paper, they utilized the cooperative sifting model to suggest the items. The eventual outcomes are they thought about the assembly and dissimilarity items and suggested the most comparative products to the client.

Meng, McCreadie, "Variational Bayesian representation learning for grocery recommendation", Journal 24, pg.no: 347-369, Springer, 2021.

The author of this work discusses how existing grocery recommendation systems only represent each user and item as a single deterministic point in a continuous space with a low dimension, which limits the expressiveness of their embeddings and yields poor results. As a result, they suggested a variational Bayesian Context Aware Representation (VBCAR) model as a technique used for recommending groceries. By utilizing the information about the contents of baskets, this model makes use of historical user data and interactions. As a result, it displays information about the overall performance of recommendations, the impact of various item-side information kinds, and feature visualization.

[3] An Overview of Recommendation Methods and Its Applications in Healthcare, W. Yue, Z. Wang, J. Zhang, and X. Liu, IEEE/CAA Journal of Automatica Sinica, vol. 8, no. 4, p. 701-717, April 2021.

According to the author, as there is more information available online, recommendation systems are being used in a wide range of industries. The purpose of this study is to describe several

recommendation techniques, such as collaborative filtering, content-based filtering, and hybrid techniques. In contrast to content-based filtering, the CF will offer suggestions after cooperatively analyzing a significant amount of user activity data. As CF simply uses user behavior data and ignores item content information, it is not constrained by content limitations.

[4]. Online grocery shopping in Thailand: Customer acceptance and usage behavior, Fabian Driediger and Veera Bhatiasevi, *Journal of Retailing and Consumer Services*, Elsevier, 2019.

The author of this essay examines the adoption and usage patterns of online grocery shopping in Thailand. To better understand the characteristics and the amount to which they contribute to the acceptance or rejection of online grocery shopping, it suggests an extension of the technology acceptance model that takes into account subjective norm, visibility, perceived risk, and perceived enjoyment. This study employed partial least squares structural equation modeling (PLS-SEM). A constructed and distributed the planned research model to 450 persons in the Bangkok area, and 263 legitimate responses were given back to the researcher. The outcomes foresaw the user's conduct.

[5]. "Product-Seeded and Basket-Seeded Suggestions for Small-Scale Retailers," 2017 Elsevier, M. Kaminskis, D. Bridge, and F. Foping.

The author of this paper considers small-scale retail as a venue product recommendation. websites, Product recommendations are a common practice in e-commerce and have been proven to increase both product sales and consumer happiness. For creating suggestions based on a single seed product, or "Product seeded recommendation," they used two techniques: association rules and text-based similarity. The findings indicate that the placement of suggestions is crucial since users are more likely to click on them if they are prominently displayed on a website and less likely to do so if they must scroll to find them. Gradients (HOG) characteristics (SVM). Swathy S. Pillai developed a.

III. METHODOLOGY

Dissimilar to content-based sifting, which recommends just comparative items or area explicit items, cooperative separating suggestion frameworks permit clients to track down comparable items and bounce (or change) to other categories of items in light of similitudes with different clients and items. For this situation, we investigate 3 distinct ways of utilizing cooperative-based sifting.

1. The principal technique recommends items that different clients like to a particular client because they rated a particular item Basically, it finds clients that

evaluated an item like the particular client and returns the top items different clients loved.

2. The subsequent technique predicts what items a client might like because of past rating history and the rating history of different clients. This strategy isn't well defined for the rating of one item like the first strategy.

3. The third strategy predicts items like a particular item by finding the closest neighbors to that item. This technique is great for clients who might need to buy items in groups. Testing the proposal frameworks to see what items they return.

The dataset that is utilized has 5,813,109 all-out audits/appraisals from 3,649,861 one-of-a-kind clients that audit 11,502 extraordinary items that are in the classes of auto, computerized music, toys, music, cameras, video DVD, devices, computerized Digital book, child, instruments, books, watches, advanced video download, video, versatile applications, outside, home improvement, PC, computer games, yard and nursery, sports, gadgets, remote, home diversion, kitchen, office items, home, wellbeing, and individual care and shoes.

In web-based grocery recommendation, it will suggest the main 5 items given the client's interests.

The informational collection contains 18 sections that contain unnecessary information so at first, we need to drop the items which are having under 100 audits. Even though we lost approximately 75,000 special items, the majority of them were the single acquisition of similar things with various item ids. This would cause a lot of superfluous commotion in our examination and demonstrating stages.

Presently we need to drop the missing columns since the dataset comprises of enormous measure of information so we can drop the columns which are having missing information.

Presently this is preprocessed information and this information is utilized for additional examination.

In the wake of preprocessing the information, we are bringing in required modules chiefly the shock module which has a wide assortment of calculations. Through shock, we might cross-approve, train-test-split, foresee, find closest neighbors, tune calculations, perform framework look, and so forth

From the beginning, here the calculations utilized are:

1. Normal Predictor: Calculation foreseeing an irregular rating given the dispersion of the preparation set, which is thought to be typical.
2. KNNBasic: An essential cooperative separating calculation.
3. KNNMeans: An essential cooperative separating calculation, considering the mean evaluations of Each user.
4. SVD: The well-known SVD calculation, as promoted by Simon Funk during the Netflix Prize. When baselines are not utilized, this is comparable to Probabilistic Framework Factorization.
5. SVDpp: The SVD++ calculation, an expansion of SVD considering understood evaluations.

IV. RESULTS

Name	Type	Size	Value
algorithm	prediction_algorithms.knns.KNNWithMeans	1	KNNWithMeans object of surprise.prediction_algorithms.knns module
all_algos_cv	list	4	[('test_rmse':Numpy array, 'test_mae':Numpy array, 'fit_time':(...), '...
basic_popularity_model	DataFrame	(281, 2)	Column names: Score, prod_rating_count
benchmark	list	5	[Series, Series, Series, Series, Series]
columns_count	int	1	10
computational_time	float	1	0.0249959468041553
cv_results	DataFrame	(4, 5)	Column names: Model, RMSE, MAE, Fit Time, Test Time
dataset	DataFrame	(569454, 5)	Column names: Id, ProductId, UserId, ProfileName, Score
find_recom	list	5	[15, 121, 55, 230, 344]
grocery_dataset	DataFrame	(5699, 7)	Column names: Id, ProductId, UserId, ProfileName, Score, users_counts, ...
i	int	1	344
k	int	1	3
knm_param_grid	dict	3	{'bsl_options':{'method':['...'], 'reg':['...']}, 'k':[15, 20, 25, 30, 40, ...]}
knmBasic_cv	dict	4	{'test_rmse':Numpy array, 'test_mae':Numpy array, 'fit_time':(0.0305029 ...}
knmBasic_cv_results	DataFrame	(1, 5)	Column names: Model, RMSE, MAE, Fit Time, Test Time

Fig 1:Attributes&Datatypes

- Presently we need to check the root mean square errors(RMSE) values. The calculation with the Highest RMSE esteem is the best.
- The accompanying table contains the calculations with their related RMSE values.
- By seeing the above table we can say that the SVD calculation is the best since it has the most note-worthy RMSE esteem.
- We will presently take an irregular example of 10000 evaluations, albeit all items aren't addressed in the test, and we will tune our calculation to the 10000 evaluations to check whether we can get a superior RMSE score for the entire dataset.
- In doing this we split the dataset arbitrarily to prepare and test, then burden and fit the information.
- We can see that the SVD approach gives preferred RMSE over some other methodologies. In the wake of affirming that our calculation is SVD calculation, we will anticipate client star evaluations for items and we will see the best forecasts and most exceedingly terrible expectations.
- Presently we will see the main 10 suggestions for five client ids.
- Presently we are assessing the items suggestions for a client utilizing accuracy and review. We can see that the tested expectations have genuinely high accuracy scores and review scores.
- Presently we are a structure of a suggested framework. In this proposal framework, we do not just prescribe the items like a given item, however, we show what item class the prescribed item is.

Name	Type	Size	Value
knmBasic_cv_results	DataFrame	(1, 5)	Column names: Model, RMSE, MAE, Fit Time, Test Time
knmBasic_described	DataFrame	(8, 4)	Column names: test_rmse, test_mae, fit_time, test_time
knmBasic_of	DataFrame	(5, 4)	Column names: test_rmse, test_mae, fit_time, test_time
knmBasic_gs	model_selection.search.GridSearchCV	1	GridSearchCV object of surprise.model_selection.search module
knmBasic_model	prediction_algorithms.knns.KNNBasic	1	KNNBasic object of surprise.prediction_algorithms.knns module
knmeans_gs	model_selection.search.GridSearchCV	1	GridSearchCV object of surprise.model_selection.search module
knmeans_cv	dict	4	{'test_rmse':Numpy array, 'test_mae':Numpy array, 'fit_time':(0.024557 ...}
knmeans_cv_results	DataFrame	(1, 5)	Column names: Model, RMSE, MAE, Fit Time, Test Time
knmeans_cv_described	DataFrame	(8, 4)	Column names: test_rmse, test_mae, fit_time, test_time
knmeans_cv_of	DataFrame	(5, 4)	Column names: test_rmse, test_mae, fit_time, test_time
knmeans_cv_model	prediction_algorithms.knns.KNNWithMeans	1	KNNWithMeans object of surprise.prediction_algorithms.knns module
mae_cv	list	4	[0.5462, 0.5827, 0.6229, 0.6388]
panda_data	DataFrame	(5699, 4)	Column names: ProductId, UserId, ProfileName, Score
panda_data_grouped	DataFrame	(281, 2)	Column names: ProductId, score
panda_data_sort	DataFrame	(281, 3)	Column names: ProductId, score, Rank

Fig 2:Algorithms included in this project

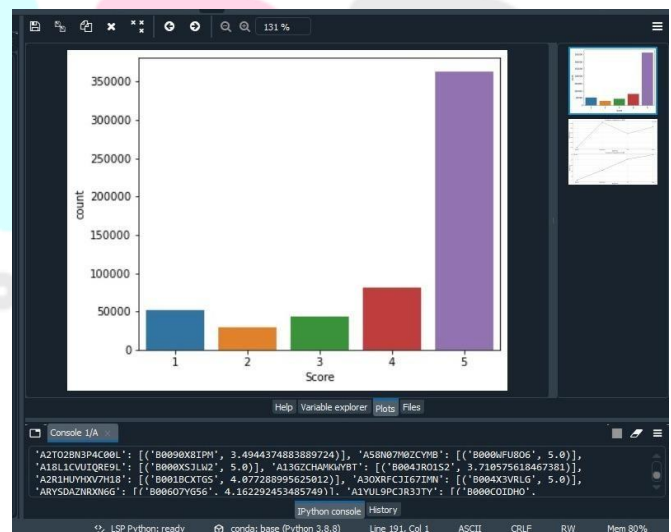


Fig 3: Plotting score for algorithms

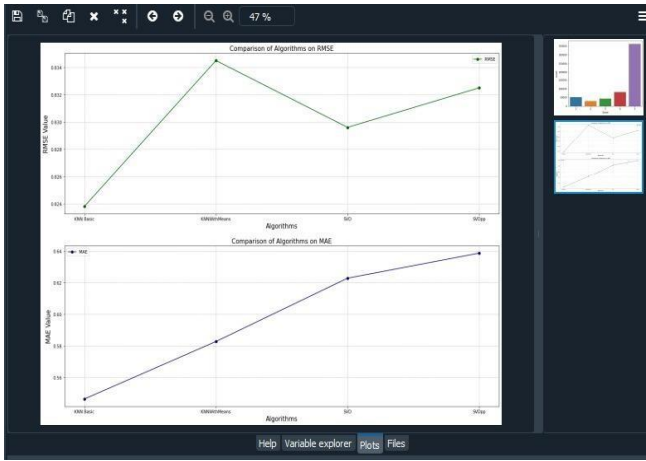


Fig 4: Comparison of algorithms on RMSE&MAE

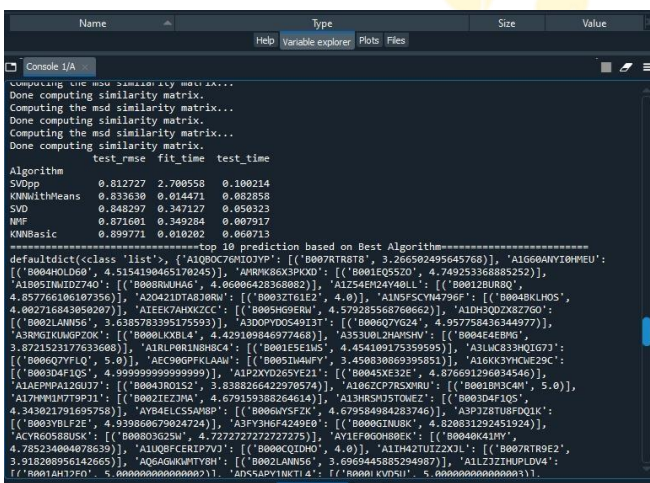


Fig 5: RMSE Values

V. CONCLUSION

- The future degree is:
- Here we have utilized 10000 appraisals because of the computational burden on the PC. So in the future,
- we would like to deal with preparing the total dataset.
- In this, we investigated 3 unique ways of utilizing cooperative-based separating:
- The main technique proposes items that different clients like to a particular client in light of their rating of an explicit item. It finds clients that evaluated an item like the particular client and returns the top items different clients enjoyed. This technique was utilized as a prologue to proposal frameworks with a

straightforward, worked without any preparation, recommender that didn't integrate genuine preparation of models or forecast techniques.

- The subsequent technique predicts what items a client might like given past rating history and the rating history of different clients. This strategy isn't intended for the rating of one item like the first technique. It is an evaluation-based technique that predicts the normal evaluations a client would give an item furthermore, positions the most noteworthy anticipated appraised items for that client. Tragically this strategy needed to utilize a test of the full dataset to prepare.
- The third strategy predicts items like a particular item by finding the closest neighbors to that item. This technique is great for clients who might need to buy items as packs.

VII. ACKNOWLEDGEMENT

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