A novel hybrid feature combination method for enhanced movie recommendations with user resemblance and attitude mining

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Abstract
Most movie recommendation methods use hard-clustering and simple collaborative filtering techniques in order to achieve their end results. However, these methods tend to overlook crucial aspects of both users and items. When these methods hard cluster a movie item into a cluster, they turn a blind eye to the fact that the item also exhibits some properties of another cluster’s items. Recommender systems facilitate users and relevant things expeditiously supported their requests and historic communications with alternative customers. Recommendation systems are a crucial portion of signifying things particularly in streaming amenities. For streaming motion-picture show services like Netflix, recommendation methods are vital for serving to users notice fresh movies to get pleasure from. However, massive amounts of information will turn out restrictions in recommendations due to accuracy as a result of diversity and meagerness problems. Our work proposes a unique hybrid technique that mixes collaborative filtering and characteristics of demographic filtering technique to point the close users, and associate against one another. This technique has been established over associate in tending analysis of the way to cut back the blunders in grading estimates supported users’ earlier communications that ends up in improved prediction accuracy in among completely different algorithms. Additionally, a feature combination technique is utilized that progresses the expectation accuracy and to check our method, using MovieLens 1M dataset, we contended an offline assessment, already available assessment tactics, and compared the same with the output factors to support authenticating the proposed procedure.

Keywords Movie-recommender system · Collaborative filtering · Demographic filtering · Hybrid recommendation

1 Introduction
In this day and age, E-commerce assumes an essential part. Numerous industries have been utilizing E-commerce for quite a while now, for example, film industries, online book stores, online market, and numerous others. The rise of OTT stages that give occupations to numerous entertainers, chiefs, and makers and gives a quality substance for the watchers is all conceivable due to E-commerce. Particularly, in the current situation because of COVID-19, its ubiquity has soar and the online business sectors are developing significantly. Here, recommendation frameworks come into picture, and they are utilized by E-commerce organizations broadly to improve the experience of clients and increment deals. Among incredible online stages like Amazon, Netflix, Flipkart, and numerous others, the proposal frameworks are among the most investigated ideas.

The essential thought of suggestion frameworks is to prescribe items to the client. It very well may be founded on the past buy history or fame and metadata of an item or it very well may be founded on client experiences of different clients with comparable tastes or interests. Proposal systems, similar to the name recommends, are utilized to make suggestions. Rigorously talking, recommender situation utilizes three kinds of separating techniques: (i) content-based, (ii) collaborative, and (iii) hybrid (a mix of the two) ([8]). Content-based sifting utilizes thing properties to discover through which things are comparative and consequently prescribes things like the one being referred to. Communitarian filtering, which is likewise the most utilized of the three, utilizes similitudes between both the clients and the things to help make expectations. In the process, a “client thing” lattice is created which is basically a score of the express input given to various films by a
(typically) unique number of clients. This lattice is of the inadequate assortment. This sparsity is because of two principal reasons: (a) clients cannot in any way shape or form observe each film in the network and (b) in some cases even subsequent to watching a film, client essentially declines to give an express input (rating). These appraisals in the client thing framework are misused in short-sighted collaborative filtering frameworks to make proposals. Since these appraisals are fundamental, their nonattendance makes a significant migraine for a basic collaborative filtering (CF) framework and it is this sparsity that has prompted specialists utilizing strategies other than evaluations to extricate data about motion pictures. Analysts have proposed strategies that separate data from utilizing verifiable input (if a client watched a film, whether or not a rating was given or not) to extricating data from visual sources like film banners and still to endless others [11].

Suggestion frameworks frequently utilize shared channels or substance-based channels, alongside different projects, for example, data-based projects. Synergistic separating strategies structure a strategy for the client’s previous inclinations and close choices made by different clients [6, 17]. Nonetheless, broad development with measures of clients with possessions leads to a sparsity concern in CF methods while utilized all alone. Hence, we have built up a technique that utilizes the two evaluations and segment data, by consolidating segment credits with client thing rating CF to take care of the issue of information sparsity. (2) This strategy permits us to productively compute similitudes in an enormous dataset without already computed or early usage. (3) We have assessed our technique utilizing a genuine dataset and notable assessments and measurements and shown that it is both pragmatic and viable.

2 Related work

Ahuja et al. [1] proposed a paper where a recommendation scheme is envisioned extracting the KNN algorithms and K-means approach. The client is approached to give the subtleties as information. The client provides details such as userid, sex, and age. In the processing module, the pandas module splits the statistics roughly the customer and movies to distinct dfs. The K-means module is built to display a data edge presenting movie genre. WCSS finds the right no. of clusters. Pearson’s correlation similarity and regularization model computes the relation by means of the matrix. The KNN model uses KNN forecasts for film rating to ascertain with the assistance of the comparability and UC grid.

In Indira and Kavithadevi [7] and in this work (NPCA-HAC), the dataset is pre-processed to get rid of outliers. Afterwards, the tactic of feature selection is administered along with the principal component analysis (PCA) method. The chosen features are then grouped together using K-means and HAC. The clustered groups are ranked by the use of a trust ranking algorithm. This paper shows a loss of data due to dimensionality reduction within the clustering method used. There is a trade-off between prediction performance and scalability. At curbing the complications such as data sparsity, high computation complexity and over specification are brought about due to approaches such as collaborative filtering. The proposed model suggests developing a combination model which will be able to produce a real-time item best suited for the users. Final classification of the recommendation list is obtained by the MP neuron model. The proposed model, however, does not address scalability. The novel item-centered scheme uses CF and CBF methodologies and recommends objects based on emotions. Emotion extraction is done from reviews and comments particular to an item. Extracted emotions help generate item-item similarity. However, the model does not take the problem of scalability and high computation time into account. The technique of exploring and creating the movie through considering movie forms of customers. Closeness between users is measured by rating of movies supported by users and users with the same preferences are clubbed. RNN is applied to find out movie patterns of comparable user clusters and also to analyze and producing movies. However, the restrictions of the system include increase in computational time because the dataset increases, longer sequences in RNN result in poor prediction accuracy, and therefore the methodology is complex to implement. In Roy et al. [13] and in this paper, 3 approaches are used: simple K, content-based, and CF approach. The methodology used is machine learning. For the simple recommender system, IMDB’s formula for weighted rating is used to formulate the chart. The other two approaches are executed accordingly. Performance decreases with sparsity, new user problem, and computational efficiency decreases with increasing dataset. In Liang et al. and in this paper, item-based collaborative filtering is applied since it is proved to be one step ahead than user-based CF on analysis and data processing complexity. The content of items and feature vectors are used to better the working performance. The user personalization information is collected through a sign-up system. The data from the experiment is used to find the closeness between users. Towards the end of the experiment, the adjacency matrix of user closeness is formulated. The purpose of the matrix is to club the profiles into various clusters calculated through the k-clique method. Finally, various clusters of the users are displayed. The computational time for k-clique methods is high, implemented a CF algorithm, KM-Slope-VU, which requires partitioning of users using K-means, in accordance to attributes of users’ profile, thereafter, each cluster is assigned an opinion leader which is calculated using the mean rating of the items. Since, a single opinion leader is calculated as a representative of each cluster, loss of information of each cluster is inevitable, and hence, the precision of the proposed algorithm is lower. The two novel methods, i.e., SRCF and SRWCF,
analyze the entries by users that are not rated, which as a result would curb data sparsity, by using already present. Devi and Parthasarathy [5] suggest to produce references to customers for objects liked by them. In order to address the issues of cold start, scalability, and synonymy, the paper uses a hybrid model approach. The engineering of feature stage selects properties based on the relevance and creates new attributes. In the Bayesian module, the data is applied and a model is trained. In the algorithm, the values $X=\{x_1, x_2, \ldots, x_n\}$ are used to predict the values $y_i$ using the Bayesian module. The method follows an algorithm which takes various user properties such as age, gender, and occupation, producing rating as output. Singla et al. [14] present a movie recommendation following a content-based approach. It uses approaches like oc2Vec and tfidf. It uses properties such as movie idea, ratings, and values for ratings of film from the matrix. Scalability can cause high computational time in this method release year to find similarity between movies and generate a recommendation. Movie plots are used as a foundation to evaluate movie s scores. The model embeds movie plot into a multidimensional area while also keeping relationships among words. The approach does not consider the quality of items. Movie plots often lack keywords. In order to tackle the problem, data such as movie rating, origin of release, and release year were considered. Each movie in the training set has utmost 3 genres. Some genres are common, and for each pair of movies, cosine similarity is used to calculate the similarity between them and an AI approach to produce a collaborative filtering model, which predicts movie ratings for a user based on ratings from other users. The paper uses AI to predict ratings for new movies. To evaluate the accuracy of the AI approach, the model uses collaborative filtering techniques: KNN and matrix factorization. The results show that the recommendation system outperforms a neighborhood system in terms of RMSE on ratings and in a survey in which users judge between recommend from both systems. Murali et al. [9] build a recommender system that proposes the set of factors used for building a technique which incorporates data, rating-supported users, and cosine similarity. Then ratings are made for users which can be determined by the amount of ratings. Cosine similarity is used to sort the result. The paper proposes a paper recommender system using the collaborative model to recommend a user paper, in their domain and support the similar entity found from others, which can help in removing time-consuming searches. We use CS to find the similarity between the choice of consumer with the opposite customer interest which comes under the same category. Nakhli et al. [10] propose a paper that uses a view approach to find movies for consumers. The best model is determined and used in the system. IOM is used to escalate the performance of the systems. Reddy et al. [12] show the effect of ignoring movies that have not gotten an average rating. The model of the movie of the user is done after taking into account all the different movies, then the predictions of the movies of the user are done after neglecting movies that have not gotten an average rating, and the predictions are compared with the predictions when all the movies are taken. Pearson’s correlation coefficient is used to compute similarities among the data values of the dataset for all movies in consideration. Collaborative filtering is used to predict the user ratings for the movies. The same process is followed to compute the predictions for the movies that have always got rating over half the rating scale. Irajian and Taheri [23] propose a framework that accepts different inputs from system and user community’s feedbacks. For solidifying the deep learning of the model for getting and ranking items, it uses AI tools to improve the qualities of recommendation. Users and items are mapped to a space, leading to a representation of user and item. The problem is viewed as a classification technique. Back propagation is used to train the framework. Wu et al. [15] describe the use of a recommender system via two collaborative models. The paper analyses the commonality between entities to build a system, using user and item collaborative model techniques. Explicit rating is users rating the item on some scale of measurement. For each user, we find the number of NN, then use between users’ ratings is found using PCS [18]. Items focus on the commonality between the item likes lead of the users. For recommendation, the item similar to the target is recommended [19].

Based on various surveys, we found that many researchers are not focused in a novel hybrid feature combination method for enhanced movie recommendations with user resemblance and attitude mining techniques. After analyzing several literatures, it was found that many researchers were not focusing on the resemblance-based data mining approach. The usage of the Top-K ranking algorithm in the research work for selecting the best and optimal features is very low. The performance improvement must be revealed by the proposed method along with the comparative analysis report, which helps to ensure the effectiveness of algorithm. This approach is novel and generates the best results when compared to previous work. The disadvantages of the previous research works are understood clearly from this literature study and hence suitable computational techniques are to be developed and justified with performance metrics.

3 Proposed method

In this part, the proposed strategy is characterized that consolidates CF and DF. The primary thought of the technique, which is not found in different works in the writing, is to have a mixture proposal approach that can be effortlessly utilized for the assessment of various classifiers to recognize which classifier performs better when segment information is coordinated into the suggestion cycle [20]. The sparsity issue is a
significant test for recommender frameworks as far as creating the correct proposals for the correct clients. This issue has been additionally extended because of the development of things accessible and of clients with few evaluations and little client data. This prompts trouble in discovering likeness between two clients. In this part, we propose how an element mix crossover approach takes care of the sparsity issue and decreases the mistake rate through utilizing two classifiers. It joins coordinating with user demographic attributes with their rating CF technique as demonstrated in Fig. 1.

3.1 Rating prediction and Top-K ranking

In the wake of positioning the accumulated loads, the top \( n \) clients with the most elevated loads are chosen as neighbors who partake in the rating forecast. Furthermore, as per the forecast evaluations in numerous thing classes, things with the most elevated rating esteems are chosen to structure the Top-K suggestion applicant list. Evaluations are anticipated as [3]:

\[
P_{u,i} = \frac{\sum_{v \in u} W(u,v) \times (R_{u,i} - \bar{R}_u)}{\sum_{v \in u} W(u,v)}
\]

(1)

3.1.1 Top-K ranking

The customary suggestion list utilizes rating esteems to rank things. Given the trouble of distinguishing the likely interests of clients, its goal is essentially to expand proposal precision. In this way, a variety factor is acquainted with change the extent of things with high variety. The anticipated evaluations of the Top-K things in the applicant slope may surpass the normal appraisals of clients. Condition [4] analyzes the likenesses among the \([1-\alpha]R \cup \emptyset\) things and the upper \(\alpha R\) things as given in Eq. (1). The one with the most reduced similitude will be chosen to be a substitution thing.

\[
\min_{i \in [0, \alpha R], j \in [(1-\alpha)R, \emptyset]} \left( \frac{N_i - N_j}{M_i - M_j} \right)
\]

(2)

Here, in Eq. (2), the rating esteems are \( N_i \) and \( N_j \) given by client \( u \) for possessions \( i \) and \( j \), separately, and ubiquity of possessions \( i \) and \( j \), are \( M_i \) and \( M_j \) separately. For the proposed calculation through an unmistakable comprehension, the itemized paces of the strategy are specified in Fig. 2.

4 Results and discussion

4.1 Experiments and analysis of results

To assess the presentation of the DBTS technique with notable proposal models, we contrast the strategy in this paper and other conventional calculations. The focal point of the proposed calculation is to create a rundown of Top-K proposals, so precision and recall can be utilized as far as exactness. The pointers that incorporate customized variety (PD) and total variety (AD) are utilized in variety.

4.2 Dataset

To evaluate the proposed technique, the MovieLens dataset was operated, it being gathered from Kaggle site that empowers clients to offer input and offer thoughts with others. Clients rate motion pictures on a scale from 0.1 to 5. A great appraising worth addresses a high inclination for a thing. The dataset contains 36,447 assessments given by 1705 customers for 1941 movies. The rating network has a thickness of 1.54%. A customer who accepts another customer is implied by an assessment of 1 in the trust cross section. Something different, a customer is shown by an assessment of 0 in the trust grid. The trust system fuses 1547 trust relations among 1426 customers. The trust matrix has a thickness of 0.52%. Fivefold cross endorsement was used to parcel the dataset.

4.3 Feature selection

The determination of applicable ascribes is finished by the cycle of highlight choice. The choice of highlight is performed with the utilization of guideline segment examination (PCA) calculation. The information is the pre-handled information. On applying the rule segment examination, the mean is found by perusing the document variable. At that point, the covariance is recognized from which the Eigen esteems. The Boolean capacity is utilized to discover the translate values. At last, the component information is accomplished by the utilization of this calculation.
4.4 Evaluation metrics

4.4.1 Accuracy

We utilize the notable measurements of precision and recall to assess the exactness of the calculation. Precision, the idea acquired from data recovery [2], is characterized as

\[
\text{Precision} = \frac{TP}{TP + FP}
\]

(3)

where TP implies genuine positive, signifying the effectively ordered positive models; FP implies bogus positive, indicating mistakenly grouped positive models. Accuracy typically diminishes as the length of the suggestion list increments. A high accuracy esteem shows that numerous clients are keen on the suggested things [21]. Review estimates the odds that a pertinent thing is chosen for suggestion.

Recall = \frac{TP}{TP + FN}

(4)

where FN is the bogus negative, meaning the inaccurately ordered negative models. The recall esteem normally increments as the length of proposal list increments. \(F\)-measure is a weighted normal of precision and recall and equally mirrors the exhibition of proposal.

\[
F\text{-Measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]

(5)

4.4.2 Diversity metric

Past works have commonly utilized two rules to assess suggestion variety [16]. To start with, customized variety (PD) is utilized to portray the difference between any two things in the proposal list. As the variety of the suggested things expands, the likelihood of clients discovering things of interest increments. The PD is characterized as

\[
PD = \frac{1}{|U|} \sum_{u \in U} \left(1 - \frac{\sum_{i \neq j, (u) \in I} (1 - \text{sim}(i, j))}{\frac{1}{2} |L(u)|(|L(u)|-1)} \right)
\]

(6)

Also, total variety (AD) is estimated by the absolute number of novel things suggested for all clients. A high AD esteem guarantees that more things can be seen by clients of a RS. The AD is characterized as

\[
AD = \frac{\sum_{u \in U} |L(u)|}{|I|}
\]

(7)

The proposed strategy hopes to refine total variety by taking in any event \(N\) things approach per ubiquity bunch. It is then treating every suggestion list as a substance to create a repositioned usage of long-tail items which is improved alongside the nature of proposals made to the user without significantly influencing the precision of the system, utilizing a worldly repositioning method.
4.5 Comparisons of different fusion ratios

In the proposed calculation, we change the combination proportion as the boundary. The combination proportion takes various qualities; suggested results are additionally extraordinary.

For each set of preliminaries, we underscore on different occasions and take the ordinary worth. Figure 7 shows that the proposed approach has higher exactness contrasted with others. Figure 8 shows that the proposed calculation accomplishes the most elevated variety contrasted with different calculations.

The proposals of conventional methodologies are exceptionally one-sided towards mainstream things, which massively restricted their variety execution [22]. The UCF has lower variety in light of the fact that, as the quantity of suggested things expands, UCF just considers client inclinations with respect to famous things. Hence, customized variety and total variety are diminished. The proposed approach utilizes a variety factor to change the extent of re-positioned things, which at the same time improves total variety and customized variety.

We set Top-k = 100, portrayal picking up installing measurement is 200, and the combination proportion scale from (0:10) to (10:0) addresses from completely utilizing the semantics for suggestion to completely utilizing community sifting for proposal. Figures 3, 4, and 5 are recall bend, precision bend, and F-measure bend, individually.

The RMSE values for all conventional methodologies are contrasted and the proposed calculation. Among these, the proposed approach has the most elevated precision as it acquired least RMSE esteem. The RMSE relies upon the significant degree of the noticed qualities and essentially change starting with one application then onto the next. The comparison of RMSE values for all the approaches is shown in Figs. 6, 7, and 8.

5 Conclusion

In this paper, we proposed a closeness model dependent on the crossover method that blends CF with the attributes of demographic separating procedure to point the closest clients, and look at against each other. The proposed closeness model can
choose various neighbors which have higher comparability with the objective client for each unique objective thing and consider the semantic similitude. The proposed novel hybrid recommender approach uses similitude of users in an idle point space alongside their rating cover-based comparability to refine neighborhood development, improving nature of proposals. Our exact assessments demonstrate that the proposed approach altogether outflanks standard user-based CF and item-based CF and is appropriate for recommender spaces with logical information in text structure, portraying things being suggested. The proposed strategy was approved through a progression of examinations dependent on a genuine world dataset. The approval results demonstrate that the proposed approach viably improves both the total variety and the character variety of proposals while keeping up high exactness.

Declarations

Conflict of interest The authors declare no competing interests

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