A Role of Machine Learning Algorithms for Demand Based Netflix Recommendation System

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Keywords: Machine Learning, Collaborative Filtering, Content-based Filtering, SVD, Personalization, User Engagement, Streaming Platforms.

Abstract: The rise of streaming services, personalized content recommendation is one of the critical features enhancing user engagement and retention. This paper presents a comprehensive analysis of the Netflix recommendation system, which bases its predictions on machine learning and collaborative filtering from behavioural data about the viewers' preferences. It combines the two techniques into a hybrid approach to create personalized recommendations. It further honed the system using the technique of Singular Value Decomposition with enhanced accuracy for recommendations relevant to the viewer. This is realized by dynamism whereby it is possible to learn through the models that the viewers' tastes change over time by feature engineering and techniques based on deep learning. Hence, there is alignment with actual viewer preferences at the more precise level. This research demonstrates and depicts how these methodologies efficiently work toward improving viewer satisfaction, and therefore significantly contribute towards the competitive advantage of a company such as Netflix, within the very competitive streaming market. The study provides prime ideas and guidelines for progress into future advancement regarding the recommendation system in streaming platforms.

1 INTRODUCTION

In the streaming industry, one change in user experience due to machine learning is the Netflix recommendation system. This uses content-based filtering, collaborative filtering, and hybrid models to make recommendations tailored from large datasets of viewing tastes and habits. Recent research through deep learning algorithms helps in discovering complex usage patterns, and hence adaptation algorithms need to be continually updated based on the analysis for enhancing users' engagement and reducing attrition. In paper (More, Jadhav, et al., 2024) author proposed a hybrid model integrating the improved CBF and CF using CNNs. They also introduced Cascade Hybrid Filtering, which outperformed all baselines with an RMSE of 0.6325. Additional work in optimizing CNN feature extraction would support nuanced recommendations. In paper (Mali, Pawar, et al., 2023) authors combined CF with K- means clustering to reduce the computational cost of CF on large datasets, with RMSEs of 0.6354. It is a good example of how clustering may improve the precision of recommendations.

In paper (Mali, Mohanpurkar, et al., 2015) according to authors, the recommendation system of Netflix shapes user preferences through "taste communities" because it creates algorithmic taste-making. The authors of this paper focus on the cultural implications of tailoring content recommendations (Nalawade, Pattnaik, et al., 2004), for recommending content, Sharma et al. applied feature extraction from metadata; they also noted the

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Bhoye, T., Mane, A., Navale, V., Mohapatra, S., Chitalkar, S., Borate, V. and Mali, Y.
A Role of Machine Learning Algorithms for Demand Based Netflix Recommendation System.
DOI: 10.5220/0013589500004664

In *Proceedings of the 3rd International Conference on Futuristic Technology (INCOFT 2025) - Volume 2*, pages 212-220
ISBN: 978-989-758-763-4

importance of data visualization in raising user engagement (Patil, Zurange, et al., 2024). To deal with the data sparsity problem, in paper (Modi, Modi, et al., 2024) authors devised a co-clustering algorithm that proved to have accuracy gain of 7.91% as compared to classical CF.

In handling the missing data modalities, Agrawal et al. proposed a meta-learning approach which utilizes a Graph Attention Network. This resulted in greatly reducing the RMSE of multi-modal recommendation systems. In paper (Mehta, Chougule, et al., 2024) the methodology used significantly improved Movie Lens datasets that address the temporal aspect for dynamic user preferences on the matrix factorization model (Shimpi, Balinge, et al., 2024). The Figure 1. Shows the Flowchart of recommendation system.

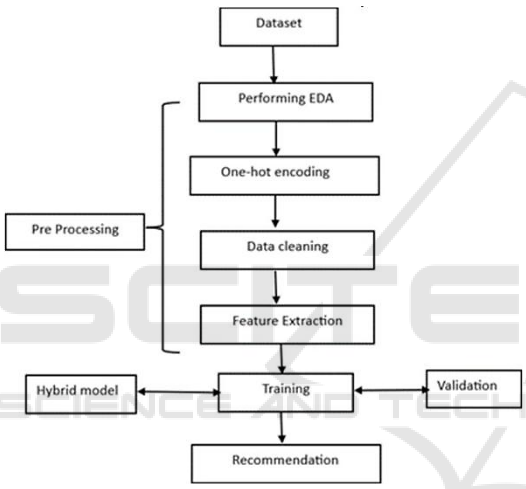

Figure 1: Flow Diagram for Recommendation System.

In paper (Ingale, Wankar, et al., 2024) authors have combined data for Netflix and Amazon Prime using the analytics of big data and the enhancement in terms of cross-platform movie recommendations are done on the grounds of providing platform-specific suggestions. The flowchart illustrates how a recommendation system is built by the process. A set of dataset and exploratory data analysis determine the trend and abnormality in data. Feature extraction selects those important features to model the data. Data cleaning manages missing values, and it uses one-hot encoding on categorical data before processing. Before training the model for trend, validation is performed for the processed data. The hybrid model uses a variety of recommendation strategies in a high accuracy level. It delivers recommendations through the trained model to the users.

1.1 Singular Value Decomposition (SVD)

From Figure 2 SVD is one of the major benefits is the simplification of some data that help in improving the prediction accuracy, especially reducing the number of features of the complex information that Netflix collects. Of course, such information usually includes, but is not restricted to, user interactions, preferences, and content attributes. SVD makes it possible to support personalized recommendations that are more closely related to the interests of each individual user by identifying latent factors that stand in for the hidden user interests and content features.

SVD also addresses the sparse data problem faced by Netflix, which basically means that most of the viewers haven't engaged with most of the content items available. Even for less active users, SVD guarantees strong recommendations by precisely predicting missing elements of the user-content matrix. This is possible because of the computational efficiency of SVD, enabling it to process very large volumes of data from Netflix's at just about virtually no computation cost, which also relates to an important requirement for real-time dynamic suggestions.

SVD Architecture is represented as in the Figure 2.

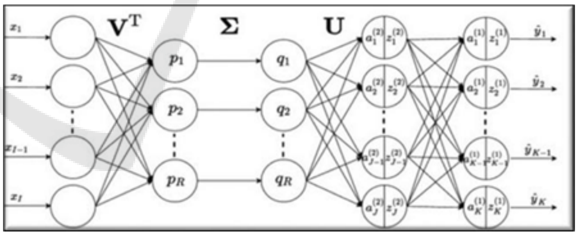

Figure 2: SVD Architecture.

2 RELATED WORK

In paper (More, Jadhav, et al., 2024) authors have suggested a hybrid approach using CNN that combines Collaborative Filtering (CF) with an improvement in Content- Based Filtering (CBF) to enhance the hybrid recommendations. In their "Cascade Hybrid Filtering" approach, the user-item interactions enable the first stage to continue through CF that begins recommending some movies based on those interactions, then continue the refinement by assessing how much those movies resemble, according to the contents in CBF. The performance of the approach was tested on MAE and RMSE metrics and it gave RMSE 0.6325 with an accuracy of 6 per over the baseline models.

In paper (Mali, Pawar, et al., 2023) authors proposed a Netflix recommendation system based on the combination of Collaborative Filtering and K-means clustering. Although CF is the most popular technique, the high computational cost in case of large datasets makes this algorithm inefficient. Therefore, authors used K-means clustering for grouping users with common interests before applying CF. They used Twitter data mainly to obtain user ratings; ratings were converted using Text Blob polarity scores. This combined model achieved the lower RMSE of 0.6354 in comparison to the individual CF methods.

In paper (Mali, Mohanpurkar, et al., 2015) authors have given recommendations on Netflix by overcoming the cold- start problem in a hybrid recommendation model based on the combination of Collaborative Filtering and Content-Based Filtering. Their system is making use of machine learning algorithms to compute user behaviour and content attributes, thereby bringing about a delicate balance between item-based and user-based recommendations.

In paper (Nalawade, Pattnaik, et al., 2004) auuthors analyses NRS, one of its parts includes critical questioning as to how it serves to central purpose constructing preferences in the vast range of users through “algorithmic taste-making”. In application of a reverse engineering of NRS, Pajkovic reveals how both methods of content-based filtering along with collaborative filtering amalgamate by putting users together to produce a form of ”taste communities,” which, while spreading out beyond national borders, stay coherent.

3 PROPOSED METHDOLOGY

3.1 Data Collection

The dataset utilized in this research was sourced from kaggle Netflix Recommendation System. The primary datasets include:

User Features
User ID: Every user is assigned a unique number, for example, user001.Age: The age of the user can be used while making the demographic analysis.
Gender: It can include the gender of the user while making the suggestions.
Material: It depends on the subscription model.

3.1.1 Features of the Content

Movie/Show ID: A unique number assigned to every title.
Title: The title of the film or the show. Genres are classifications that apply to the plot of a movie or the television show; among these are action, comedy, drama, science fiction, and many more (Mulani, Nandgaonkar, et al., 2024).
Description: It should be clear whether a user would want to read the information based on a brief overview or description of it (Sonawane, Mulani, et al., 2024).
Release Year: It gives the year that this content was released, which can therefore make one have a better idea of how old or new the content is (Mandale, Modi, et al., 2024).
Language: The main language used within the content is this one, which is information that may be a decision maker when determining what to watch (Sengupta, Nalawade, et al., 2024), (More, Khane, et al., 2024).
Cast: The females and actors who feature in the movie or TV program. Information about the actors in the movie help describe a user’s preferences (Wanaskar, Dangore, et al., 2024).
Director: Information about who directed the movie may affect whether or not to view it (More, Ramishte, et al., 2024).
Production Company: Company that produced the above stated film (Palkar, Jain, et al., 2024), (Dangore, Modi, et al., 2024).

3.1.2 User-to-User Communication

User Evaluation Features Rating at specific instance such as 1 to 5 stars and likes/dislike. This defines the list of movies or a series a viewer has seen, and this list for a viewer is termed the watch list (Dangore, Bhaturkar, et al., 2024), (More, Shinde, et al., 2024).
Viewing time: The number of hours, say 90 minutes, that a person spends viewing material (Vaidya, Dangore, et al., 2024).
Watchlist: Titles that a user has added to their watchlist but hasn’t watched (Sawardekar, Mulla, et al., 2025).

3.2 Data Pre-Processing

3.2.1 Data Cleaning & Missing Values

Netflix deals with the missing data about the user

Such as missing ratings for any content by imputation techniques or rejection of incomplete records (Modi, Mali, et al., 2024), (Bhongade, Dargad, et al., 2024).

3.2.2 Similarity Computation

The system identifies users similar to the target user. This is done by comparing their movie preferences or other data points (Mali, Yogesh., et al., 2023).

3.2.3 Prediction

A machine learning model uses the similarity information to make predictions about what movies the target user would likely enjoy (Kale, Hrushikesh, et al., 2024).

3.2.4 Recommendations

The model generates a list of recommended movies for the target user, based on the predictions made (Inamdar, Faizan, et al., 2024).

3.2.5 Normalization

The ratings obtained from the users may be normalized, such that it will be consistency in smoothness (Jagdale, Sudarshan, et al., 2020), (Modi, Mali, et al., 2024).

3.2.6 Data Transformation

Encoding User and item features: Netflix assigns numeric representations both to the users and content. The information regarding both user and item is encoded in a way so that all the categorical features like user demographics, genres of movies, among others convert into numerical vectors using techniques such as one-hot encoding (Mali, Sharma, et al., 2023).

Dimensionality Reduction: high dimensionality of the data is reduced using for example a technique like SVD or PCA(Modi, 2024). For instance, reducing ratings over thousands of movies to identify key the latent factor is the preference of users. The pre-processing steps are shown in Figure 3.

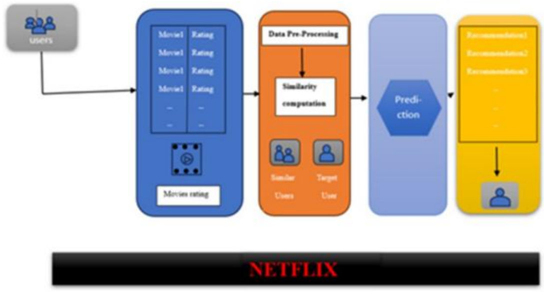

Figure 3: Flow diagram of Pre-processing data.

3.3 Encoding Categorical Variables

For ease of modelling, categorical variables within Netflix dataset have been label-encoded into numeric formats. The process of label encoding assigns a unique integer to each category so that machine learning algorithms can handle it easily. The categorical variables genre, content rating and subscription tier were encoded to differentiate the categories of different types of contents and levels of subscription made by users (Mali, and, Chapte, 2014).

3.4 Train-Test Split

To test the efficiency of the recommendation systems, the datasets were divided into training and testing sets. An 80:20 split of the dataset into training and testing was made to check the effectiveness of the recommendation system of Netflix (Asreddy, Shingade, et al., 2019).

3.5 Models Performed

3.5.1 Logistic Regression

The logistic regression can be used to predict the likelihood that a user will engage with or enjoy a particular show or movie. This approach involves framing the recommendation problem as a binary classification task: given a set of user, item, and interaction features, the model predicts the probability of a positive user response (like, watch, or high rating) (Pathak, Sakore, et al., 2019).

3.5.2 SVM

The Support Vector Machines (SVM) can be used for the task of categorization or to make a prediction [16] about user engagement, view preferences, or churn risks during the analysis of behaviour for users on Netflix (Jagdale, Khandre, et al., 2021).

3.5.3 Random Forest

Random Forest is an ensemble learning technique, which is efficient in analysing user behaviour and forecasting what content a user might like in a Netflix recommendation engine (Mali, Sawant, et al., 2023).

3.5.4 Singular Value Decomposition (SVD)

It is one of the most useful techniques for developing dimensional reduction and latent factor discovery to influence user choices in recommendation systems like Netflix.

3.5.5 Decision Tree

A more-beloved, if perhaps more interpretable, machine learning technique is called decision [16] trees. They work by building a model that, given a variety of input features-things like user demographics and content qualities-will predict the value of a target variable, say user ratings or preferences, as Netflix and all sorts of recommendation systems do.

3.5.6 Naive Bayes

Naıve Bayes can be applied in a Netflix recommendation system by predicting user preferences for movies or TV shows based on demographic characteristics and viewing history.

3.5.7 Xg Boost

For supervised learning tasks, such as recommendation systems like Netflix, XGBoost is the most popular and effective gradient boosting method implementation. Its sturdiness against overfitting and capacity to handle huge datasets make it very successful.

3.5.8 Cascade Hybrid Model

In complex systems especially, as in Netflix, this hybrid approach may increase the user's level of satisfaction and engagement through multiple models with their unique advantages but their unique disadvantages limitations.

3.5.9 Neural Network

Neural networks make it possible to provide highly customized recommendations by simulating connections between users and content.

3.5.10 K-Nearest Neighbors

The KNN algorithm is a very simple yet powerful collaborative filtering tool that Netflix and other recommendation systems use to present content to users based on their tastes.

4 RESULTS AND DISCUSSION

This resulted in an accuracy of 68.74% and a Root Mean Square Error of 0.4560. User preference, to an extent can be derived through this algorithm; however the idea should further be augmented with its application to get closer more accurate predictions. KNN vs. Gradient Boosting Classifier. Gradually, the Gradient Boosting Classifier outsmarted the KNN with an absolute accuracy of 74.65% with the least RMSE value of 0.4207 as compared to the overall prediction. With an RMSE of 0.2826, and with the highest accuracy of 90.66%, Cascade Hybrid was amazing, showing its capabilities to be able to produce relevant suggestions.

The clear winner on this one would be the Singular Value Decomposition because it had the highest accuracy at 94.34% and had the smallest RMSE value at 0.2580. What this result reveals is that SVD could really depict the user preference accurately. SVM performed quite well with an accuracy of 75.80% and an RMSE of 0.4108, although it is still behind models like SVD and Cascade Hybrid. Decision Tree seems to be less useful in this situation with an accuracy of 64.70% and comparatively high RMSE at 0.5942. With an accuracy of 74.20% and an RMSE of 0.4229, Random Forest established that recommendations made were nearly accurate enough. With the neural network, an accuracy of 73.81% with an RMSE of 0.5099 showed user preferences that can improve. With the Naive Bayes approach, a moderate capacity for prediction had an accuracy of 75.03% and an RMSE of 0.4997.

On the contrary, SVD performed excellently, yielding an unbelievable accuracy of 94.34% and a reduced RMSE of 0.2580. Such high accuracy proves that this is a very successful relevance-based recommender system as well.

Table 1: Performance Comparison of Recommendation Models.

Model	RMSE	Accuracy (%)
KNN	0.4560	68.74
Gradient Boosting Classifier	0.4207	74.65
Cascade Hybrid	0.2826	90.66
SVD	0.2580	94.34
SVM	0.4108	75.80
Decision Tree	0.5942	64.70
Random Forest	0.4229	74.20
Neural Network	0.5099	73.81
Naive Bayes	0.4997	75.03
Logistic Regression	0.4787	77.09
XG Boost	0.5048	74.52

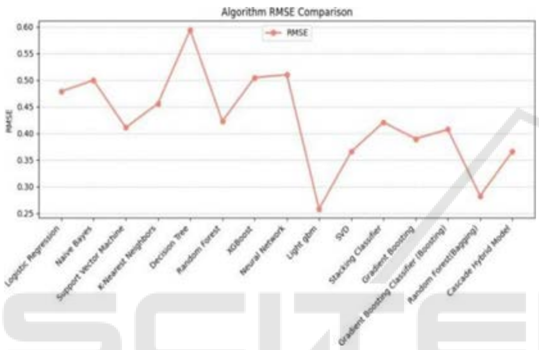

Figure 4: RMSE for different models.

Improved error performance from lower values of RMSE is represented by Figure 4, Algorithm RMSE Comparison. Figure 5 represents Algorithm Accuracy Comparison on how well each algorithm really performs and higher values indicate a better predicted result. In turn, they reflect trade-offs between accuracy and RMSE in revealing those discrepancies between algorithms that represent effectiveness Fig. 4 and Fig. 5.

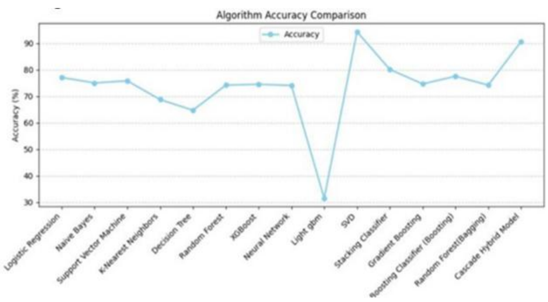

Figure 5: Accuracy for different models.

The scatter diagram in Fig. 6, represents the data onto two dimensions and showing the result of a K-means clustering experiment on a data set. The x-axis is "PCA Component 1," and the y-axis is "PCA Component 2," which is the original multi-dimensional data projected onto two principal components to view it.

5 CONCLUSION

In this research, we developed a Netflix recommendation system model using the Netflix Recommendation System dataset. Different forms of suggestion on Netflix had shown how well such complex algorithms work to enhance user experience as well as increase viewer engagement, which ultimately boosts retention rates and revenue growth.

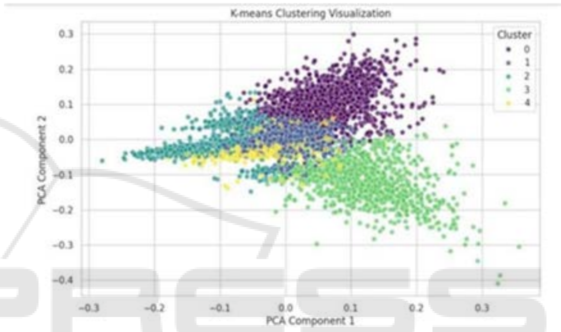

Figure 6: Scatter plot that visualizes the results of a K-means clustering.

The SVD model alone is proven to be accurate and efficient in its application on the dataset of Netflix so well, as it may go in mitigating problems associated with bespoke content recommendation. Results of this research are consequential for trends of the entertainment industry, as well as building more advanced recommendation systems responding dynamically to changes in the user's preference.

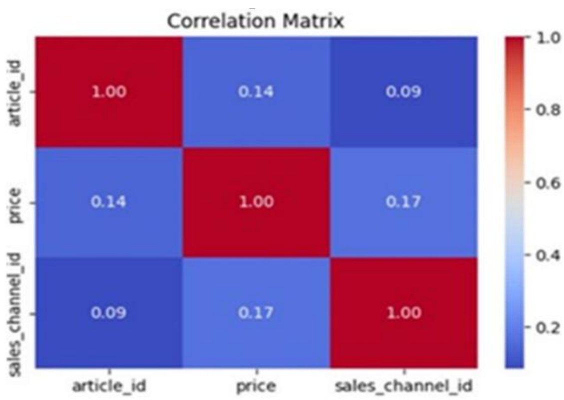

Figure 7: Visual representation of Confusion Matrix.

Future research in this direction is expected to extend beyond these conventional approaches and include new machine learning techniques, such as deep learning and reinforcement learning, in order to increase recommendation prediction accuracy and real-time adaptability further in diverse streaming environments, such as that of Netflix. The following advanced technologies include:

5.1 Context-Aware Suggestions

Through context-aware algorithms, depending upon the present situations of the users, it can change suggestions related to the location and time in addition to considering the device type. It may increase user engagement when proper suggestions are brought up at a particular moment in time.

5.2 Multi-Modal Learning

Quality can be improved of recommendations by researching multi-modal learning strategies that will combine information from many sources, including but not limited to text evaluation, photos, and videos.

5.3 Ethical AI

The future research is related to the moral concern of the recommendation algorithm in Netflix, such as bias detection and minimization, ensuring fairness, and also promotion of transparency in the algorithmic decision- making. XAI methodologies can very well explain the recommendations. This will increase user enjoyment and satisfaction.

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