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Movie Recommendation System Using Machine Learning

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A B S T R A C T

Nowadays, the recommendation system has made finding the things easy that we need. Movie recommendation systems aim at helping movie enthusiasts by suggesting what movie to watch without having to go through the long process of choosing from a large set of movies which go up to thousands and millions that is time consuming and confusing. In this article, our aim is to reduce the human effort by suggesting movies based on the user's interests. To handle such problems, we introduced a model combining both content-based and collaborative approach. It will give progressively explicit outcomes compared to different systems that are based on content-based approach. Content-based recommendation systems are constrained to people, these systems don't prescribe things out of the box, thus limiting your choice to explore more. Hence, we have focused on a system that resolves these issues.

Keywords: Movie recommendation, Rating, Genre, Recommender system, Collaborative filtering.

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1. Introduction

The evolution of technology brings us many advanced platforms such as Machine Learning, Deep Learning, Data Mining, the Internet of Things (IoT), etc. To satisfy the need of society, almost in each work, we use this technology. It has many real-life applications such as PowerShell [1], TP [2-4], IoT [5-12], Cloud Computing [13], Artificial Intelligence [14], Uncertainty [15-17], virtualization Environment [18], SPP [19-26], and so on. IT is the mode to store, fetch, communicate and utilize the information. So, all the organizations, industries and also every individual are using computer systems to preserve and share the information. As we probably are aware, the world is becoming quicker and everybody is moving towards accomplishing their objectives. Individuals need more time to go to the market and purchase things, not simply that, they don't have the opportunity to pick between things. What's more, this has prompted the innovation of recommendation systems [27, 28]. Recommendation systems have become well

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known nowadays, be it in the field of entertainment, education, etc. Earlier, the users needed to settle on choices on what books to purchase, what music to tune in to, what motion pictures to watch and so on. Commercial movie libraries effectively exceed 15 million films, which boundlessly exceeds the visual ability of any single individual. With a large number of motion pictures to browse, individuals now and then get overpowered. Therefore, an efficient recommendation system is necessary for the enthusiasm of both movie service providers and customers [29]. With the improvement of recommendation systems, the customers will have no agony in settling on choices and organizations can keep up their client gathering and draw in new clients by improving users' satisfaction [30, 31]. Additionally, nowadays the modern technologies like machine learning and deep learning also plays a vital role in the process flexible technologies for day to day operations. In this manuscript, we discuss about the recommendation by using machine learning. Now, we discuss a method that has been previously implemented.

1.1. KNN Algorithm

KNN algorithm is called the K nearest neighbor algorithm [32]. The center thought of this algorithm is if most of the k most comparable neighbors of the test in the component space have a place with a specific class, at that point the example is considered to have a place with this category. As appeared in ***Figure 1***, most of w's nearest neighbors have a place with the x class, w has a place with the X classification [33].

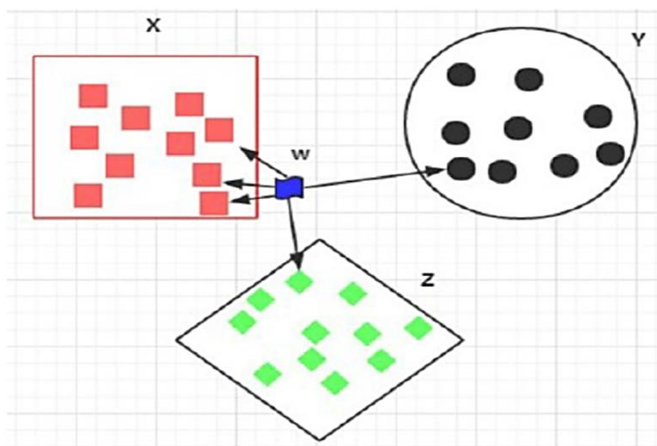

Figure 1. K nearest algorithm [33].

1.1.1. Calculating the similarity

This similarity value is going to play an eminent role in the collaborative filtering technique to select trustworthy users from the given set of users [8]. Hence, they give us a method to increase or decrease the significance of a particular user or item. At present, we are using adjusted cosine similarity for calculation of similar items, as shown in ***Eq. (1)***.

$$AC(l,k)=\frac{\sum_{U\in u_{lk}}\left(r_{u_l}-\overline{r}_u\right)\left(r_{u_k}-\overline{r}_u\right)}{\sqrt{\sum_{U\in u_{lk}}\left(r_{u_l}-\overline{r}_u\right)^2\sum_{U\in u_{lk}}\left(r_{u_k}-\overline{r}_u\right)^2}}. \quad \textbf{(1)}$$

Where in this, r_{u_l} represents the rating of the user to the item *l*. r_{u_k} represents the user's rating to item k, $\overline{r}_u$ indicates the average ratings.

1.1.2. Choosing a neighborhood

In this technique, the neighbors that we are going to use as a part of prediction also makes an influence on the recommendations that are going to be generated. Consequently, this determination of neighbors must be accomplished more cautiously to not influence the nature of suggestions created. Hence, we will be choosing the most related neighbors who have the highest match compared to others. So, this value must be chosen more delicately.

1.1.3. Predicting undetermined ratings

In this for the user, to whom we want to predict those movies for which he hasn't rated, should be predicted using similar weights that are calculated in the previous steps.

2. Literature Review

Kumar et al. [29] proposed MOVREC, a movie recommendation system based on collaborative filtering approaches. Collaborative filtering takes the data from all the users and based on that generates recommendations. A hybrid system has been presented by Virk et al. [30]. This system combines both collaborative and content-based method. De Campos et al. [34] also made an analysis of both the traditional recommendation techniques. As both of these techniques have certain setbacks, he proposed another system which is a combination of Bayesian network and collaborative technique. Kużelewska [35] proposed clustering as an approach to handle the recommendations. Two methods for clustering were analyzed: Centroid-based solution and memory-based methods. The result was that accurate recommendations were generated. Chiru et al. [27] proposed Movie Recommender, a system that uses the user's history in order to generate recommendations. Sharma and Maan [36] in their paper analyzed various techniques used for recommendations, collaborative, hybrid and content-based recommendations. Also, it describes the pros and cons of these approaches. Li and Yamada [37] proposed an inductive learning algorithm. Here a tree had been built which shows the user recommendation. Some of the major contribution in recommendation system is discussed in ***Table 1***.

Table 1. Literature review of recommendation systems.

Authors	Year	Descriptions
Scharf & Alley [38]	1993	The authors proposed a flexible multicomponent rate recommendation system to predict the optimum rate of fertilizer for winter wheat.
Basu et al. [39]	1998	The authors proposed an approach to the recommendation that can exploit both ratings and content information.
Sarwar et al. [40]	2001	The authors proposed various techniques for computing item-item similarities.
Bomhardt [41]	2004	The author proposed an approach for a personal recommendation of news.
Manikrao & Prabhakar [42]	2005	The authors presented the design of a dynamic web selection framework.
Von Reischach et al. [43]	2009	The authors proposed a rating concept that allows users to generate rating criteria.
Choi et al. [44]	2012	The authors proposed approaches for integrating various techniques for improving the recommendation quality.

Table 2 discussed the contribution of filtering techniques for different purposes.

Table 2. Literature review of filtering techniques.

Authors	Year	Descriptions
Goldberg et al. [45]	1992	The authors introduced the collaborative filtering technique.
Herlocker et al. [46]	1997	Authors applied filtering techniques to Usenet news.
Miyahara & Pazzani [47]	2000	The authors introduced an approach to calculate the similarity between a user from negative ratings to positive ratings separately.
Hofmann [48]	2004	The author introduced a new-family of model-based algorithms.
Dabov et al. [49]	2008	The authors proposed an image restoration technique using collaborative filtering.
Pennock et al. [50]	2013	The authors proposed various approaches for filtering by personality diagnosis.
Liu et al. [51]	2014	The authors introduced a new method to provide an accurate recommendation.

One undertaking from the above discussions is that recommendations systems have gained vital name and recognition among researches because of their frequent look in varied and widespread applications within the fields of various branches of science and technology.

The previous recommendation systems had certain gaps in them:

- As most of the users do not provide ratings, the rating matrix becomes very sparse.
- Over-specialization is the most common problem faced by content-based recommendation.
- Content-based recommendation systems always face the problem of a cold start.

Therefore, this motivates us to provide a new model for society:

- Improves sparsity by making rating as mandatory.
- The problem of over-specialization is resolved using neighborhood-based collaborative techniques.

3. Existing System

The reason behind this improvement is the popularity gained by organizations like Netflix whose primary objective is customer satisfaction. Before existence the recommendation system, individuals would physically choose movies to watch from movie libraries. They either had to read the user's reviews and based on the review they would select a movie or had to randomly select a movie. This procedure isn't feasible, as there is an enormous number of spectators with a unique preference for movies. Hence many recommendation systems have been developed over the past decade. These systems use different approaches like a collaborative approach [52], a content-based approach [53], a hybrid approach [54], etc. Taking a look at the behavior and history of different clients, based on their ratings, the system suggests to us what to watch without having to put effort into deciding what to watch. These recommendation systems are categorized into two types, i.e. collaborative filtering approach and content-based approach [55]. The collaborative approach combines the ratings of different users that have similar tastes and then recommends the movies whereas the content-based approach is limited to a single user, where the user’s past history and ratings are used for providing recommendations. There are a number of methodologies introduced to implement this recommendation system which includes various fields of Data Mining [56], Clustering [57] and Bayesian Network methodology [47].

3.1. Discussion of Existing Models

3.1.1. Matrix decomposition for recommendations

This methodology utilizes matrix decomposition. It is an effective algorithm on the grounds that normally when it comes to matrix decomposition, we don't give much importance to the items that are going to be in the columns and rows of the subsequent matrices [58]. But using this engine, we construct the vectors by the known scores and use them to anticipate unknown evaluations, as shown in ***Table 3***.

Table 3. Matrix decomposition of users and items.

User/Item	A	B	C	D
Jose		4		3
Ron	3		2	
Harry		5		2
John			4	

(a). Movies rating.

User	rating	
Jose	1.4	0.9
Ron	1.2	1
Harry	1.5	0.9
John	1.2	0.8

(b). Avg. rating of user.

Jose	Ron	Harry	John
1.4	1.3	0.9	1.2
0.8	1.1	2	0.8

(c). Avg. rating of item.

So here in ***Table 3***, after matrix decomposition we have a vector (1.4; 9) for Jose and vector (1.4; 8) for film A, now we can restore the grade from film A-Jose just by calculating the dot product of (1.4; 9) and (1.4; 8). As a result, we get 2.68 grade.

3.1.2. Clustering

The past proposal is fairly basic and is suitable for small systems. Until now, we considered recommendation as a supervised machine learning task. It's an ideal opportunity to apply unsupervised techniques to take care of the issue. Imagine we are building a massive recommendation system. The primary thought would we clustering [59].

However, independently, clustering is somewhat inefficient, on the grounds that what we do in reality is we recognize user groups and suggest every user in this group the same items [60]. At the point when we have enough information, it's ideal to utilize clustering as the initial step for contracting the selection of significant neighbors [61] in collaborative filtering algorithms [62]. It can likewise improve the performance of complex recommendation systems.

Each cluster would be appointed to particular preferences. Clients inside each cluster would get recommendations calculated at the cluster level [63].

3.1.3 Deep learning approach for recommendations

Over the most recent years, neural systems have made an immense jump in development. Today, they are applied in a wide scope of utilization and are step by step supplanting conventional ML strategies [64]. Without a doubt, it's an exceptionally challenging task to make recommendations for services like YouTube because of its huge scale and other external factors.

As indicated by the examination "Deep Neural Networks for YouTube Recommendations", the YouTube recommendation algorithm comprises of two neural networks: One for applicant generation and one for ranking.

4. Description of the Research Work

In the proposed model we use a pre channel before applying the K-mean algorithm. The credits used to learn detachment of each point from centroid are [65]:

- Genre
- Rating

Different characteristics have different loads [66]. In our assessment we have found that the most fitting suggestions that can be delivered should be established on the assessments provided for the movies by existing customers, right now have given more importance to the rating characteristic than various properties. For the user to get the recommendation he has to rate at least 6 movies. If he/she is a new user and has not rated any movies then he is expected to search for a random movie or any movie of his interest in the search box and rate at least 6 movies. Only then the movies will be recommended to him/her.

4.1. Problem Statement

This recommendation system recommends different movies to users. Since this system is based on a collaborative approach [67], it will give progressively explicit outcomes contrasted with different systems that are based on the content-based approach. Content-based recommendation systems are constrained to people, these systems don't prescribe things out of the box. These systems work on individual users' ratings, hence limiting your choice to explore more. While our system which is based on a collaborative approach computes the connection between different clients and relying upon their ratings, prescribes movies to others who have similar tastes, subsequently allowing users to explore more [68]. It is a web application that allows users to rate movies as well as recommends them appropriate movies based on other's ratings.

4.2. Solution Methodologies

This section contains a series of steps and the methodology of the proposed system. How the system is going to operate, and events that are going to occur is briefly explained in ***Table 4***. And with the help of a flowchart as shown in ***Figure 2***.

Table 4. Proposed methodology.

Steps	Descriptions
Step 1	First, a new user is provided with a screen that contains a search bar that allows him to search for a particular movie. If the user is an existing one, he will be provided a different screen.
Step 2	In this step, the user's local data, which is the movies he has previously watched and the ratings provided by him will be stored in a separate database.
Step 3	In this step, the user's local data, which is the movies he has previously watched and the ratings provided by him will be stored in a separate database.
Step 4	In this step, all the information about movies such as genre, abstract, the title will be stored in a "Movie data" database and all the other users' global ratings will be stored in a database called "User ratings".

Collaborative filtering works based on users that have similar tastes. In ***Table 5***, since users A and B have given similar ratings to 'Reggae' they both are considered users having similar likes and dislikes. A has rated 4 for 'Trance', so next time when user B requests for a recommendation, the system will recommend 'Trance' to B since user A has rated 4 to 'Trance'.

Table 5. Ratings based on collaborative filtering.

Genre/Users	EDM	Pop	Reggae	Trance
A	1		5	4
B	2	3	4	
C	4	5		2
D	2		4	5

4.2.1. Flowchart of the proposed system

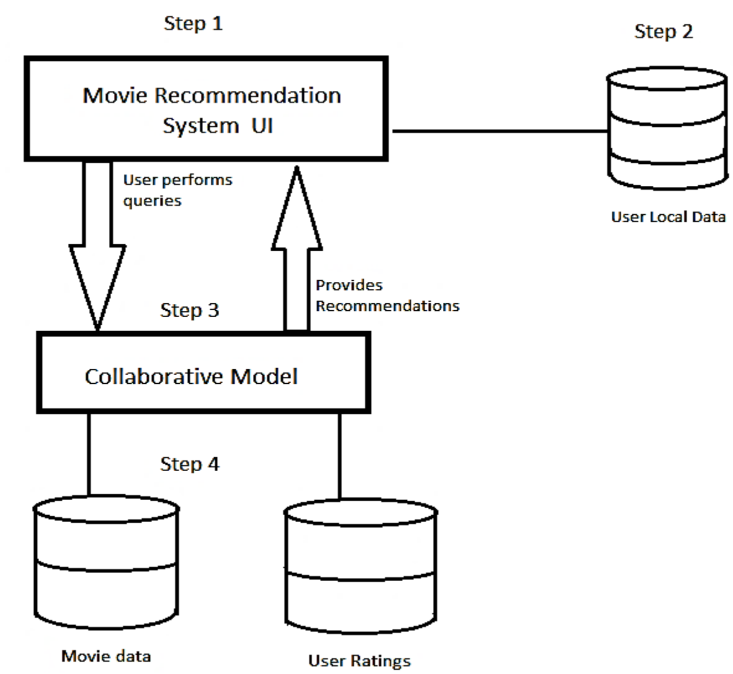

Figure 2. The architecture of movie recommendation system.

5. Implementation and Result Discussion

When the user presses the "Generate Recommendation" button it will recommend movies based on his previous ratings. If he is a new user and has not rated any movies then he is expected to search for a random movie or any movie of his interest in the "search" box and rate at least six movies. Only then the "Generate Recommendation" button will be enabled as shown in ***Figure 3***.

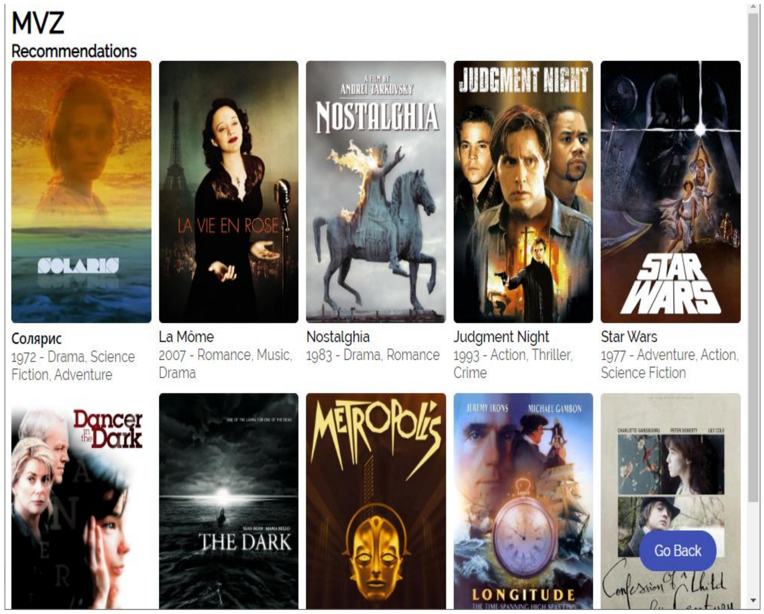

Figure 3. Home page.

Since the user is new and has not rated any movies he searches for the word 'Harry' in the search box and all the movies with words 'Harry' in them will appear on the screen as shown in ***Figure 4*** and ***Figure 5***.

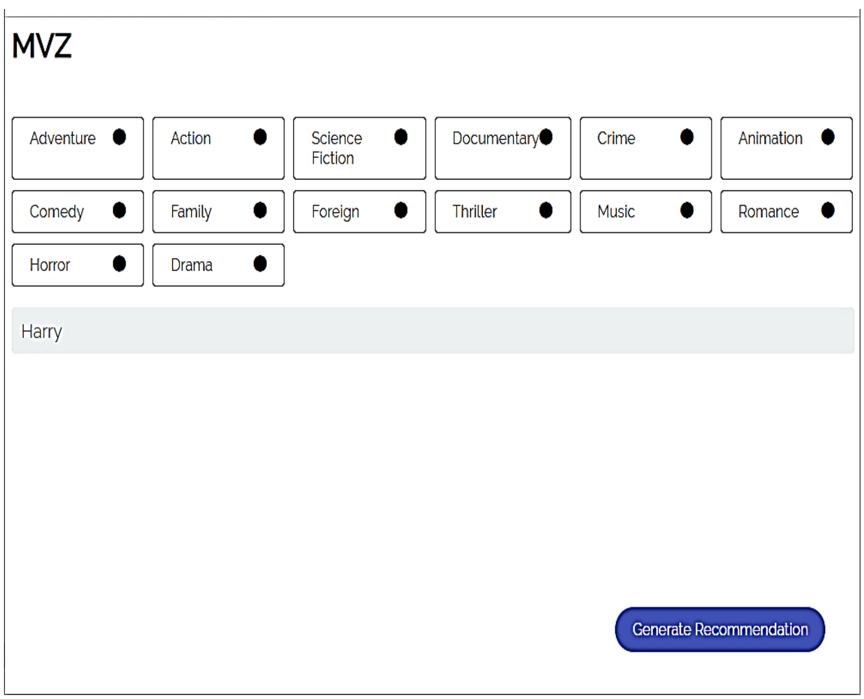

Figure 4. Search.

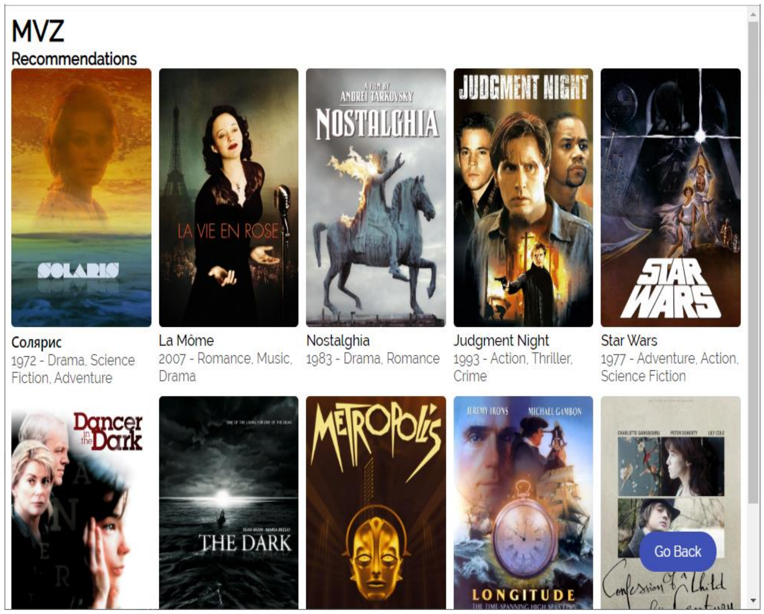

Figure 5. Search result.

The user then rates these movies according to his likes as shown in the ***Figure 6***. The user is expected to rate at least six movies in order to get recommendations. Once he rates six or more movies, the 'Generate Recommendations' button will be enabled until then the button remains disabled.

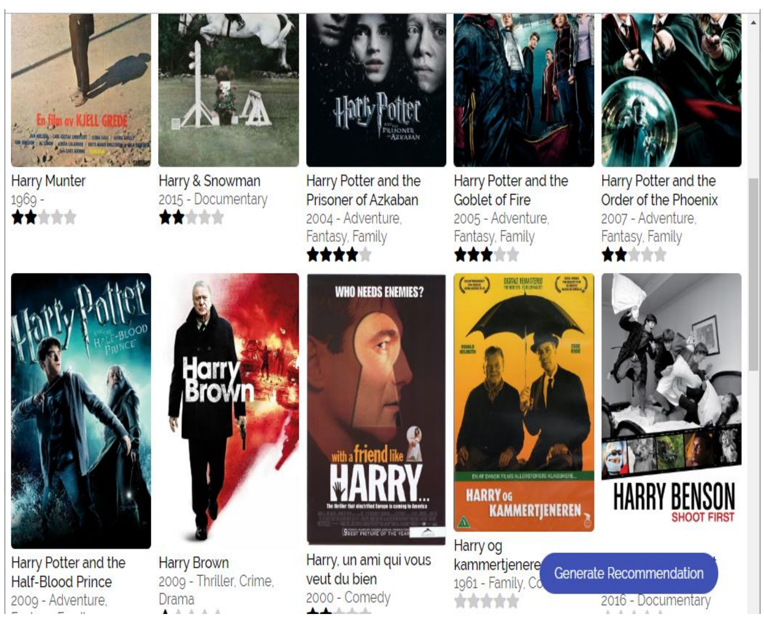

Figure 6. Rating page.

6. Conclusion

This recommendation system recommends different movies to users. Since this system is based on a collaborative approach, it will give progressively explicit outcomes contrasted with different systems that are based on the content-based approach. Content-based recommendation systems are constrained to people, these systems don't prescribe things out of the box. These systems work on individual users' ratings, hence limiting your choice to explore more. While our system which is based on a collaborative approach computes the connection between different clients and relying upon their ratings, prescribes movies to others who have similar tastes, subsequently allowing users to explore more. It is a web application that allows users to rate movies as well as recommends them appropriate movies based on other's ratings.

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