Movie Recommendation System

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Abstract

When it comes to entertainment and the programs we watch, we are like kids in a candy store. With the growth of online streaming, there are so many choices for movies and shows that are available at our fingertips. Recommendation systems have become a common feature in many e-commerce sites including streaming services such as Netflix or YouTube. Users interact with these systems to have more personalized experiences and to explore new content. Recommendation systems are based on different algorithms and filtering methods, such as collaborative filtering and content-based filtering. They factor in different sources of information to provide recommendations for users. This project implements a movie recommendation system.

Background

In today's digital world, consumers have many choices. Whether you are browsing the web, shopping for items, or watching online content, you have likely interacted with a recommendation system. Recommendation systems suggest items that may be of interest to you. For example, when you are shopping for a smartphone, an e-commerce site may suggest compatible accessories such as a case or headset that you may want to include in your purchase. If you have watched content on Netflix or YouTube, both applications have items in queue to watch next.

The designs for recommendation systems mimic how people would choose candy in a candy store. Individuals would rely on current knowledge, preferences, or past experience, such as which candy they tried and liked or did not like. Additionally, people make decisions based on input from others around them such as family and friends.

There are many approaches in the design of recommendation systems. One common approach is collaborative filtering. Collaborative filtering makes recommendations based on patterns of ratings or usage. Another approach is content-based filtering where a system determines what a user would like by analyzing information describing the item while factoring in the user's preferences. Other approaches for recommendations systems combine different aspects to form a hybrid approach.

Problem Statement

Consumers of online content are constantly looking for entertainment options. It is important that movie recommendation systems work well so that customers are satisfied with the movies that they watch. Many of us have probably wasted time cycling through movies and watching the beginning parts only to stop and choose another movie. A movie recommendation system that works well leads to many satisfied customers who feel that there are endless movies to watch. They become loyal to a business who become dependent on the services that are provided.

This project will analyze movies and reviews data and propose a movie recommendation system. It will investigate the different approaches that are used by recommendation systems. This project will address various questions.

1. What data was available and how was it used in the recommendation system?
2. What limitations or problems existed because of the data?
3. How do the different approaches of recommendation systems work?
4. What are the benefits versus the disadvantages the approaches?
5. Does one approach perform better than the others?
6. Is there a better approach that can be created?

7. How does your recommendation system work?
8. What was the output/recommendations given?
9. What issues did you face?
10. What improvements can you make to your implementation?

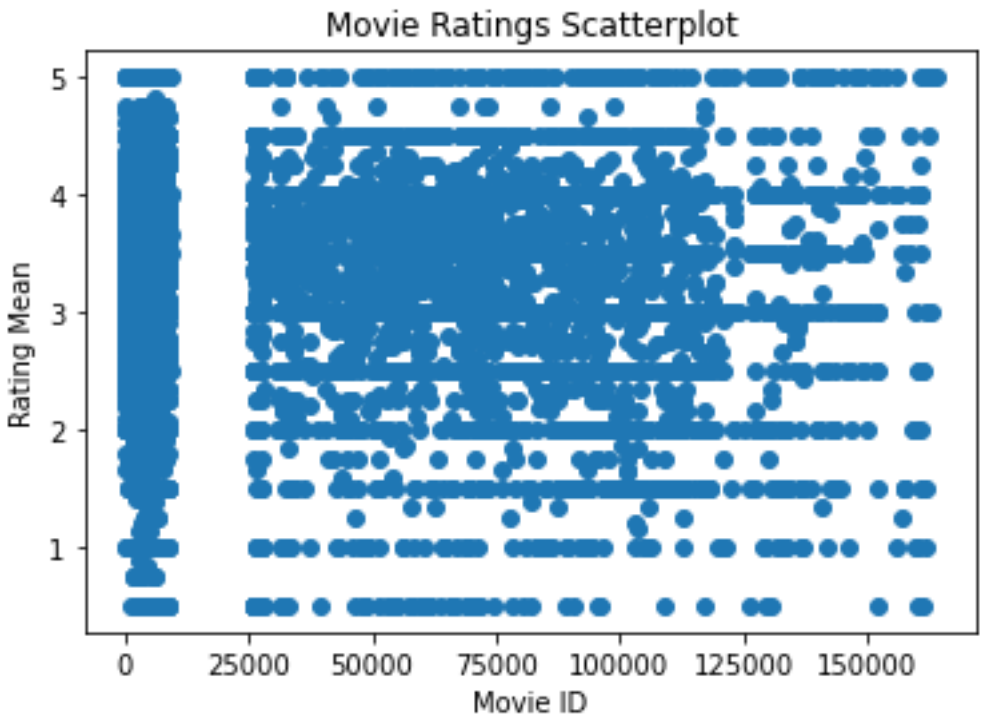
Data Understanding

The dataset for this project is The Movies Dataset found on Kaggle- https://www.kaggle.com/rounakbanik/the-movies-dataset. This dataset contains metadata for the Full MovieLens Dataset (https://grouplens.org/datasets/movielens/latest/), which contains over 45,000 movies and over 26 million ratings from more than 270,000 users. The Movies Dataset contains seven csv files of data out of which two files are subset data files.

Methods

Exploratory data analysis was done to understand the data that was available for the recommendation engine. There were no issues with missing or null data in the data set. However, relevant data for movies were found in multiple tables, and keys that joined the different tables were in different formats. Therefore, the process of joining the tables is a more tedious process that has yet to be done. For now, movies are identified by their associated ID's but will be matched up with corresponding titles by the final draft.

One approach for the recommendation system is to recommend the top movies with the highest rating. One problem with this approach is that the dataset has over 45,000 movies, and even the smaller dataset is still relatively large with over 9k movies. The scatterplot below of movies with their rating mean is not very valuable because of the large data.



To narrow the amount of data, we look to set a minimum threshold for the number of reviews. This will prevent movies with only a few reviews and high rating mean from being the first to be recommended as we can see many movies with the highest rating (5) with only 1 review.

	movieId	rating	count
0	163949	5	1
208	1933	5	1
215	26150	5	1
214	26094	5	1
213	1859	5	2
212	25852	5	1
211	7564	5	1
210	25801	5	1
209	8955	5	1
207	8699	5	1
217	1819	5	1
206	8675	5	1
205	8261	5	1
204	8254	5	1
203	8240	5	1
202	8208	5	1
201	8123	5	1
200	8121	5	1
216	26151	5	1
218	26422	5	1
198	7773	5	1
228	6033	5	1
235	5301	5	1
234	5264	5	1
233	5244	5	1

We can see other movies with many reviews and relatively high ratings but not the topmost rating.

	movieId	rating	count
1208	356	4.05425	341
800	296	4.25617	324
669	318	4.48714	311
1055	593	4.13816	304
932	260	4.22165	291
3162	480	3.7062	274
974	2571	4.1834	259
2543	1	3.87247	247
768	527	4.30328	244
1271	589	4.00633	237
919	1196	4.23291	234
2312	110	3.94518	228
1265	1270	4.01549	226
799	608	4.2567	224
973	1198	4.19318	220
915	2858	4.23636	220
4549	780	3.48394	218
1206	1210	4.05991	217
3254	588	3.67442	215
2291	457	3.95305	213
3138	590	3.71782	202
983	2959	4.17822	202

Another approach we want to investigate in this project is to evaluate the patterns of the reviews of certain users. If we can detect a pattern where a user is giving high reviews for certain sets of movies, then we can factor this method in improving the recommendation system. This work is still pending.

Results and Conclusion

Acknowledgements

References

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