What to watch next?

A recommendation System for Movie Ratings

Group 21

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Executive Summary

Recommendation engines remain in the forefront for various streaming platforms that suggest movies to their users based on their likes, dislikes and ratings. These recommendations typically speed up the searches and make it easier for users to access content they've always been interested in and to provide options that they would've never searched for. Designing effective recommendation systems is very crucial as it enhances engagement and retention of viewers. To create a recommendation system by predicting ratings for existing and new users, we've used collaborative and content-based filtering methods (through calculation approaches including distance, mean-centered and z-scored) for movies. Of the various approaches, it was clear that the user-user z-score approach resulted in the most accurate predictions. Subsequently, we calibrated filters on movies (genres and year of launch) to understand its impact on the accuracy of ratings. We tackled the problem of cold start for new customers by averaging the existing ratings of users, post categorizing and bucketing them on the basis of their demographics. Based on the accuracy of the predicted ratings, given that the data we dealt with was relatively small, we conclude that designing a recommendation system with the right resources will be worth the efforts & investment.

Introduction

Internet is a huge digital market these days, where users are presented with a number of options to choose from, which can sometimes get extremely confusing. Recommendation systems help solve this issue by processing large volumes of information that is dynamically generated, to provide users with personalized options. Providing recommendations to the users offers flexibility and personalized customer experience, attracts users, boosts engagement, retains customers by mapping them to their personalized preferences. A very common use case of recommender systems is in the streaming industry as given the plethora of options available, choosing the right movie to watch can be exhausting. Typically, there are two main types of recommendation engines, collaborative filtering focusing on user similarity and content-based filtering, focusing on item similarity, both having their own sets of pros and cons.

Problem Formulation

Typically, as most firms would, we address three types of use cases through our analysis, first - predict rating for movies for a group of existing users and compare it to the ratings that were provided originally, second - predict ratings for three new movies for the same group of existing users and third - predict ratings for three existing movies for three new customers. We utilize the accuracy of our predicted ratings when compared to the actual ratings as a measure to gauge if creating a recommender system is worth the investment for the firm. We have addressed the below questions:

- Scenario 1: Predict movie rating for existing users & movies- Aishwarya, Hanish, Harisha and Vivian for the movies Inception, Black Swan & Life of Pie (also compared to existing ratings)
- Scenario 2: Predict movie rating for existing users and new movies- Aishwarya, Hanish, Harisha and Vivian for the movies Winter's Bone, A Serious Man and Son of Soul
- Scenario 3: Predict movie ratings for new customers - Camille, Shachi, and Amy before
- Scenario 4: Predict movie ratings for new customers (same as above) after receiving the new info

Data Description

We have utilized two sets of data sources for analysis, first a list of 50 movie ratings for a batch of 98 MSBA 2023 students and second, a dataset with 50 movie ratings for 250 users chosen at random. All the ratings are ordinal and range from 1 to 5. We utilized some additional knowledge for these movies including the year of release, genre and for users including their demographics for analysis.

Model Development, Estimation, and Result

To predict user ratings in scenarios highlighted above, we looked at primarily two approaches: **Collaborative Filtering -** User rating for a movie is predicted based on the rating of other users for that movie in conjunction with similarity metric for these users. The assumption behind this approach is if User A and B agree on a rating for Movie 1, it is likely they agree on Movie 2 too **Content Based Filtering -** User Rating for a movie is predicted based on how the same user has rated other movies. We assume if Movies 1 & 2 have similar attributes, user A will rate these movies similarly.

We start with the case of predicting the rating of existing users on movies they have already rated (Scenario 1) using original data, mean centered and z-scored variations of both methods (Content vs collaborative) and check for which is more accurate.

We also experimented using some filters to only keep relevant movies to calibrate cosine similarities: *Filter 1 (F1)* segments given movies into various genres. We have chosen movies with genres - Action/War/Thriller and Drama for analysis. *Filter 2 (F2)* sieves the data based on the year of movie launch. We have chosen years which had more than 5 movies - 2009, 2010, 2012 and 2014 for analysis.

Below are key insights from this Scenario 1 analysis from various approaches (details in Appendix I):

Movie	Black Swan				Inception				Life of Pie			
Approach	Actual	W/O Filter	F1	F2	Actual	Filter	F1	F2	Actual	W/O Filter	F1	F2
Aishwarya	4	4	4	4	4	4	4	4	5	5	5	4
Harisha	5	5	5	4	4	4	4	4	5	5	5	4
Hanish	4	5	5	5	5	4	4	5	-	4	5	5
Meng-Wei (Vivian)	-	4	5	4	5	5	5	5	4	4	5	4

- Mean Scored and Z scored approaches were more accurate than gave the best results. This is in line to our understanding that these approaches normalize data and eliminate bias.
- Also, accuracy of the predictions hasn't improved much with these movie filters, and we believe that is because of fewer data points used for the comparison
- Hanish has given generous ratings than other users in our predictions

Based on the previous calculation, we continue to Scenario 2 and apply mean-centered, and z-score approaches to predict movie ratings on *Winter's Bone, A Serious Man, and Son of Soul*. Because we do not have ratings on these movies on the class survey, we utilized the DBMI data. We followed collaborative filtering, content-based filtering for predicting the user ratings and also trying variations using the same movie filters discussed above. We have displayed the results from Collaborative Filtering below as we expect this to have better predictions based on the results from 1a (others covered in appendix II).

Movie	Winter's Bone			A Serious Man			Son of Soul		
Approach	W/O Filter	F1	F2	W/O Filter	F1	F2	W/O Filter	F1	F2
Aishwarya	4	4	4	4	4	4	5	4	4
Harisha	4	4	4	4	4	4	5	4	4
Hanish	5	5	5	4	4	5	3	4	4
Meng-Wei (Vivian)	5	5	5	5	4	5	4	4	4

Results from Scenario 2

Scenario 3 and 4 where there is less to almost no information to predict the ratings are referred to as the 'Cold Start' problem. They pose challenges as there are no user preferences available for recommendation systems to operate with. We have discussed a few methods below to fill for the unavailable data and predict ratings for Camile, Shachi and Amy (new users).

3A (baseline approach): Average Rating of all other users for a movie. For our prediction, we are using the average rating of all users which include 98 users from our class and 250 anonymous user data.

3B (refined approach I): For our prediction, Amy, Shachi and Camile were divided into categories based on age, gender and their average rating was used for each user along with the IMDB data.

3C (refined approach II): Instead of user ratings use user demographics to find similarities between users. This is based on the underlying assumption that users of the same age, gender, location like similar types of movies on average. (Can be followed when demographic info is available)

In **scenario (#4)**, when a user starts interacting or provides some ratings, the recommendation system can use this information to get more personalized recommendations or better predictions for those users using **collaborative filtering (4A)** & **content-based filtering (4B)** as mentioned above. Additionally, since the data is sparse it can also be reinforced with customer demographics for better similarity comparison (Can be followed when demographic info is available) [Details for prediction available in Appendix III & IV]

Movie	Avatar				The Wolf of Wall Street				Inception			
Approach	3A	3B	4A	4B	3A	3B	4A	4B	3A	3B	4A	4B
Camile	4	4	3	3	4	4	3	3	4	4	4	3
Shachi	4	4	4	4	4	4	4	5	4	4	4	4
Amy	4	4	3	3	4	4	3	3	4	4	4	3

Results from Scenario 3 and Scenario 4

Upon comparing the results from approaches followed in Scenario 3 and 4, we could easily identify how user ratings in scenario 4 helped provide more reliable predictions. We can say this due to 2 reasons - firstly, the 3A and 3B have similar ratings to all users with no differentiation but 4a and 4b were able to differentiate between users. Secondly, based on the known ratings we expected Shachi to have a higher rating than Amy and Camile, which can be seen in approach 4A and 4B. Out of these 4A is preferred because of the better accuracy of this approach in Scenario 1 (final predictions highlighted in box).

Recommendation and Managerial Implications

Recommendation engines add value to movie streaming and many other business platforms that hold customers as their primary business goal. Apart from contributing to retaining customers and better user experience, recommendation engines also boost revenue and encourage more engagement with their products. Ecommerce & mobile websites use recommendation engines to generate product suggestions, to send targeted emails to customers which helps to offer dynamic buying opportunities for their customers with wavering preferences and needs. Moreover, when a user comes to the checkout page of the shopping platform, a recommendation system will make suggestions to an additional assortment of products likely to be sold together so that they can be an add-on to the cart. Additionally, recommendation systems also open the advertisement channel as recommendation systems can display preferred products (e.g., Google Search) first (based on advertising amount) similar to the idea of shelf space and size in retail stores. These ways help the recommendation system solve assortment issues. For generating better results, it would help to have a more elaborate dataset with a comprehensive collection of information on the various customers preferences, their gender, age and other demographic details.

Maximizing user time spent on a streaming platform and maximizing the accuracy of movie predictions based on individual interests can be two objective value functions that can be used to refine the recommendation process. By building an efficient system, we get customers to spend more time on the platform thus increasing their familiarity ensuring customers return to the platform. It will also reduce the customers path to choosing the right product by recommending them a suitable option [2].

Conclusion

Recommendation engines appear everywhere, and many companies want to build out the most accurate recommendation system in order to increase the revenue, enhance customer retention and improve the reputation. Especially, customers now emphasize on personalization and are fed with multiple and various resources, so it will be a huge challenge but also a great advantage to figure out the best fit for each customer. However, setting up a recommendation system takes much time and effort and may be engaged in privacy issues, so companies should cautiously consider the design of these systems.

References

[1] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2853093

[2] https://research.aimultiple.com/recommendation-system/

[3] https://www.imdb.com/

Appendix - I

Question 1

Movie / Base		Black Swan		Inception		Life of Pie	
		Mean	Z-score	Mean	Z-score	Mean	Z-score
Aishwarya	**User-User**	5	4	4	4	5	5
	Item-Item	4	4	4	4	4	4
Harisha	**User-User**	5	5	4	4	5	5
	Item-Item	4	4	4	4	4	4
Hanish	**User-User**	5	5	4	4	4	4
	Item-Item	5	5	5	4	4	4
Meng-Wei (Vivian)	**User-User**	4	4	5	5	4	4
	Item-Item	4	4	5	4	4	4

<u>Approach 1: User User Mean Centered</u>

Vivian

Vivian	Predicted Rating		OG Rating
Inception	**4.69**	**5.00**	5
Life of Pie	**3.80**	**4.00**	4
Black Swan	**3.98**	**4.00**	No original Rating to compare

Hanish

Hanish	Predicted Rating		OG Rating
Inception	**4.28**	**4.00**	5
Life of Pie	**4.42**	**4.00**	No rating
Black Swan	**4.61**	**5.00**	4

Harisha

Harisha	Predicted Rating		OG Rating
Inception	**4.11**	**4.00**	4
Life of Pie	**5.02**	**5.00**	5
Black Swan	**5.01**	**5.00**	5

Aishwarya

Aishwarya	Predicted Rating		OG Rating
Inception	4.03	4.00	4
Life of Pie	5.20	5.00	5
Black Swan	4.67	5.00	4

Approach 2: User User z scored

Vivian

Vivian	Predicted Rating		
Inception	4.54	5.00	5
Life of Pie	4.08	4.00	4
Black Swan	4.17	4.00	No original Rating to compare

Hanish

Hanish	Predicted Rating		OG Rating
Inception	4.28	4.00	5
Life of Pie	4.42	4.00	No rating
Black Swan	4.61	5.00	4

Harisha

Harisha	Predicted Rating		Original Rating
Inception	4.24	4.00	4
Life of Pie	4.74	5.00	5
Black Swan	4.73	5.00	5

Aishwarya

Aishwarya	Predicted Rating		OG Rating
Inception	3.99	4.00	4
Life of Pie	4.77	5.00	5
Black Swan	4.42	4.00	4

Approach 3: Item Item Mean Centered

Black Swan

Black Swan	Predicted Rating		OG Rating
Harisha	4.33	4	5
Aishwarya	4.33	4	4
Hanish	4.58	5	4
Vivian	4.46	4	0

Inception

Inception	Predicted Rating		OG Rating
Harisha	4.47	4	4
Aishwarya	4.43	4	4
Hanish	4.69	5	5
Vivian	4.61	5	5

Life of Pie

Life of Pie	Predicted Rating		OG Rating
Harisha	4.15	4	5
Aishwarya	4.14	4	5
Hanish	4.42	4	0
Vivian	4.34	4	4

Approach 4: Item Item z scored

Black Swan

Black Swan	Predicted Rating		OG Rating
Harisha	4.33	4	5
Aishwarya	4.33	4	4
Hanish	4.58	5	4
Vivian	4.46	4	0

Inception

Inception	Predicted Rating		OG Rating
Harisha	4.42	4	4
Aishwarya	4.42	4	4
Hanish	4.42	4	5
Vivian	4.42	4	5

Life of Pie

Life of Pie	Predicted Rating		OG Rating
Harisha	4.15	4	5
Aishwarya	4.14	4	5
Hanish	4.38	4	0
Vivian	4.31	4	4

Filter 1 by User User z scored - Launched Year (Partial information)

Movie	Year
[The Social Network]	2010
[A Prophet]	2009
[Amour]	2012
[The King's Speech]	2010
[La La Land]	2016
[Boyhood]	2014
[Inception]	2010
[A Separation]	2011
[The Artist]	2011
[The White Ribbon]	2009
[Zero Dark Thirty]	2012
[Avatar]	2009
[Spotlight]	2015
[Precious]	2009
[The Tree of Life]	2011
[12 Years a Slave]	2013
[Blue is the Warmest Colour]	2013
[Son of Saul]	2015
[Up in the Air]	2009
[Inglourious Basterds]	2009
[Mad Max: Fury Road]	2015
[Moonlight]	2016
[Birdman]	2014

Vivian

Vivian	Predicted Rating		OG Rating
Inception	4.57	5.00	5
Life of Pie	4.65	5.00	4
Black Swan	5.41	5.00	No original Rating to compare

Harisha

Harisha	Predicted Rating		Original Rating
Inception	4.24	4.00	4
Life of Pie	4.74	5.00	5
Black Swan	5.56	6.00	5

Aishwarya

Aishwarya	Predicted Rating		OG Rating
Inception	4.21	4.00	4
Life of Pie	4.52	5.00	5
Black Swan	4.06	4.00	4

Hanish

Hanish	Predicted Rating		OG Rating
Inception	4.49	4.00	5
Life of Pie	4.61	5.00	No rating
Black Swan	4.56	5.00	4

Filter 2 by User User z scored - Movie Genres (Partial information)

Genre	Movie
Drama	[The Social Network]
Drama	[A Prophet]
Drama	[Amour]
Drama	[The King's Speech]
Musical	[La La Land]
Coming of age	[Boyhood]
Action/War/Thriller	[Inception]
Mystery	[A Separation]
Romance	[The Artist]
Mystery	[The White Ribbon]
Action/War/Thriller	[Zero Dark Thirty]
Sci/Fi	[Avatar]
Drama	[Spotlight]
Drama	[Precious]
Drama	[The Tree of Life]
History	[12 Years a Slave]
Romance	[Blue is the Warmest Colour]
Action/War/Thriller	[Son of Saul]
Romance	[Up in the Air]
Action/War/Thriller	[Inglourious Basterds]
Action/War/Thriller	[Mad Max: Fury Road]
Drama	[Moonlight]
Comedy	[Birdman]

Vivian

Vivian	Predicted Rating				
Inception	4.52	5.00	5		
Life of Pie	4.49	4.00	4		
Black Swan	4.46	4.00	No original Rating to compare		

Harisha

Harisha	Predicted Rating		Original Rating
Inception	4.25	4.00	4
Life of Pie	4.32	4.00	5
Black Swan	4.30	4.00	5

Aishwarya

Aishwarya	Predicted Rating		OG Rating
Inception	4.11	4.00	4
Life of Pie	4.04	4.00	5
Black Swan	3.81	4.00	4

Hanish

Hanish	Predicted Rating		OG Rating
Inception	4.81	5.00	5
Life of Pie	4.96	5.00	No rating
Black Swan	5.03	5.00	4

Appendix - II

Question 2

Movie / Base		Winter's Bone		A Serious Man		Son of Soul	
		Mean	Z-score	Mean	Z-score	Mean	Z-score
Aishwarya	**User-User**	4	4	4	4	5	5
	Item-Item	3	3	3	3	3	3
Harisha	**User-User**	4	4	4	4	5	5
	Item-Item	3	3	3	3	3	3
Hanish	**User-User**	5	5	4	4	3	3
	Item-Item	3	3	3	3	3	3
Meng-Wei (Vivian)	**User-User**	5	5	5	5	4	4
	Item-Item	3	3	3	3	3	3

Approach 1: User User Mean Centered

	Aishwarya	
Winter's Bone	3.84028733	4
A Serious Man	3.90718231	4
Son of Saul	4.74873782	5

	Hanish	
Winter's Bone	5.08044989	5
A Serious Man	4.01251452	4
Son of Saul	3.47874829	3

	Harisha	
Winter's Bone	4.26410275	4
A Serious Man	4.14343856	4
Son of Saul	4.67495018	5

	Meng-Wei (Vivian)	
Winter's Bone	4.89501852	5
A Serious Man	4.67269342	5
Son of Saul	4.14014912	4

Approach 2: User User z scored

	Aishwarya	
Winter's Bone	3.86094469	4
A Serious Man	3.84478273	4
Son of Saul	4.59112876	5

	Hanish	
Winter's Bone	5.22298938	5
A Serious Man	4.15554263	4
Son of Saul	3.49160522	3

	Harisha	
Winter's Bone	4.30627989	4
A Serious Man	4.1893487	4
Son of Saul	4.59117356	5

	Meng-Wei (Vivian)	
Winter's Bone	4.67286549	5
A Serious Man	4.59291846	5
Son of Saul	4.19039753	4

Approach 3: Item Item Mean Centered

User	Winter's Bone	
Aishwarya	2.7864856	3
Harisha	2.8085361	3
Hanish	3.00082	3
Meng-Wei	2.8658879	3

User	Son of Saul	
Aishwarya	3.3058063	3
Harisha	3.3151901	3
Hanish	3.4054544	3
Meng-Wei	3.3430061	3

User	A Serious Man	
Aishwarya	2.6812185	3
Harisha	2.7250712	3
Hanish	2.8906193	3
Meng-Wei	2.7836093	3

Approach 4: Item Item z scored

User	Winter's Bone	
Aishwarya	2.8073903	3
Harisha	2.8307457	3
Hanish	3.0752124	3
Meng-Wei	2.9274928	3

User	Son of Saul	
Aishwarya	3.3236066	3
Harisha	3.3343585	3
Hanish	3.4213847	3
Meng-Wei	3.3727442	3

User	A Serious Man	
Aishwarya	2.6913491	3
Harisha	2.7356792	3
Hanish	2.9272111	3
Meng-Wei	2.827898	3

Filter 1 by User User z scored - Launched Year

	Aishwarya	
Winter's Bone	4.17109385	4
A Serious Man	3.85734893	4
Son of Saul	4.29640183	4

	Hanish	
Winter's Bone	4.60176105	5
A Serious Man	4.47422638	4
Son of Saul	4.32124397	4

	Harisha	
Winter's Bone	4.34691097	4
A Serious Man	4.27505645	4
Son of Saul	4.41646851	4

	Meng-Wei (Vivian)	
Winter's Bone	4.67825466	5
A Serious Man	4.48814475	4
Son of Saul	4.45873708	4

Filter 2 by User User z scored - Movie Genres

	Aishwarya	
Winter's Bone	4.15408753	4
A Serious Man	3.78770609	4
Son of Saul	4.3579261	4

	Hanish	
Winter's Bone	4.66679819	5
A Serious Man	4.58480783	5
Son of Saul	4.4022877	4

	Harisha	
Winter's Bone	4.33422959	4
A Serious Man	4.24190788	4
Son of Saul	4.39829571	4

	Meng-Wei (Vivian)	
Winter's Bone	4.60868491	5
A Serious Man	4.56403234	5
Son of Saul	4.32417553	4

Appendix - III

Question 3

Approach 3A

Movie	Average of all Users (250 DBMI + 98 survey results)	Camile	Shachi	Amy
Inception	4.490384615	4.49038	4.49038	4.490384615
Avatar	4.015151515	4.01515	4.01515	4.015151515
The Wolf of Wall Street	4.116838488	4.11684	4.11684	4.116838488

Approach 3B

User Categorization

User	Gender	Age Bucket
Camile	Female	18-29
Amy	Female	30-45
Shachi	Female	30-45

Average Rating for each Bucket (out of 10)

	Male				Female			
Movie	<18	18-29	30-44	45+	<18	18-29	30-44	45+
Inception	9.1	9	8.8	8.2	8.9	8.8	8.7	8.2
Avatar	7.9	7.7	7.9	7.9	7.5	7.7	7.9	7.9
The Wolf of Wall Street	8.6	8.5	8.2	7.8	7.6	7.9	7.8	7.5

After dividing the user ratings from IMDB by 2

Predicted User Ratings

Movie	Camile	Shachi	Amy
Inception	4.4	4.35	4.35
Avatar	3.75	3.95	3.95
The Wolf of Wall Street	3.95	3.4	3.4

Appendix - IV

Question 4

Collaborative Filtering

Original Value Approach

Movie	Camile	Shachi	Amy
Inception	4.416	4.418	4.401
Avatar	3.907	3.906	3.906
The Wolf of Wall Street	4.058	4.065	4.0584

Mean Centered Approach

Movie	Camile	Shachi	Amy
Inception	2.471	4.164	3.089
Avatar	2.516	4.214	3.131
The Wolf of Wall Street	2.508	4.253	3.103

Z Score Approach

Movie	Camile	Shachi	Amy
Inception	2.512	4.191	3.111
Avatar	2.547	4.243	3.104
The Wolf of Wall Street	2.561	4.243	3.101

Content Based Filtering (Preferred because of more data points for comparison)

Original Value Approach

Movie	Camile	Shachi	Amy
Inception	2.945	4.169	3.126
Avatar	2.94	4.16	3.124
The Wolf of Wall Street	2.94	4.172	3.128

Mean Centered Approach

Movie	Camile	Shachi	Amy
Inception	3.558	4.71	3.854
Avatar	3.004	4.182	3.116
The Wolf of Wall Street	3.164	4.59	3.33

Z Score Approach

Movie	Camile	Shachi	Amy
Inception	3.671	4.623	3.925
Avatar	2.956	4.13	3.068
The Wolf of Wall Street	3.2	4.5	3.347