EE219 Project 3

Collaborative Filtering

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Introduction and Problem Statement

The increasing importance of the web as a medium for electronic and business transactions has served as a driving force for the development of recommender systems technology. An important catalyst in this regard is the ease with which the web enables users to provide feedback about their likes or dislikes. The basic idea of recommender systems is to utilize these user data to infer customer interests.

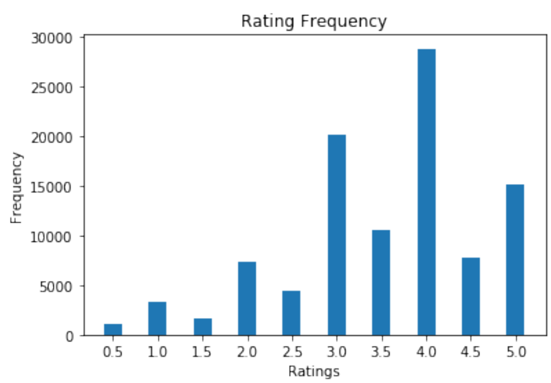
The basic models for recommender systems works with two kinds of data: User-Item interactions such as ratings and attribute information about the users and items such as textual profiles or relevant keywords. Models that use first type data are referred to as collaborative filtering methods, whereas models that use second type data are referred to as content based methods. This project is a recommendation system using collaborative filtering methods.

Solution

Problem 1

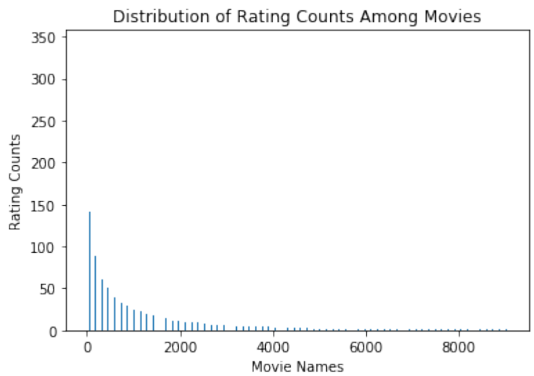
Available Ratings: 100004
Possible Ratings: 6083286
Sparsity: 0.016439

Problem 2

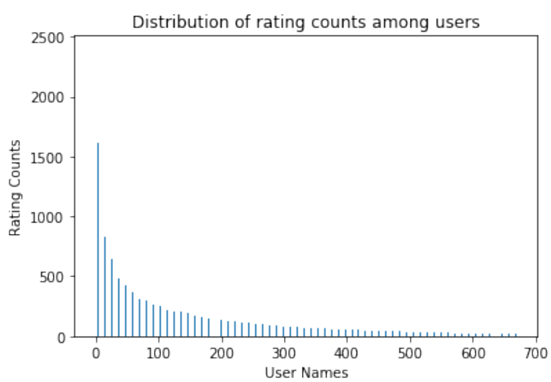


It can be concluded that most of ratings are in interval 3.0 - 5.0.
The rating with score 4 appears most frequent.
The rating with score 0.5 appears least frequent.

Problem 3



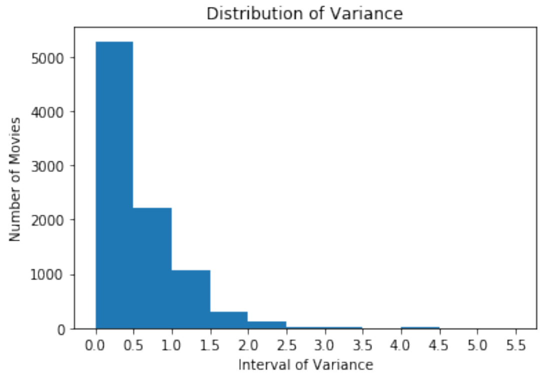
Problem 4



Problem 5

From the distribution of rating counts among users, we can observe that many people are most likely to have similar preferences to some kinds of movies, because for some specific sort of movies the rating counts are pretty high. This fact demonstrates that we can rate the movies collaboratively and recommend them to other users according to the same preferences.

Problem 6



It can be concluded that most of movie have variance in rating between 0.0 - 2.5.
Also, the number of movies that have a variance between 0.0 - 0.5 is largest.

Problem 7

the formula for μu in terms of Iu and ruk:

$$\mu_u = \frac{\sum_{k \in I_u} r_{uk}}{len(I_u)}$$

Problem 8

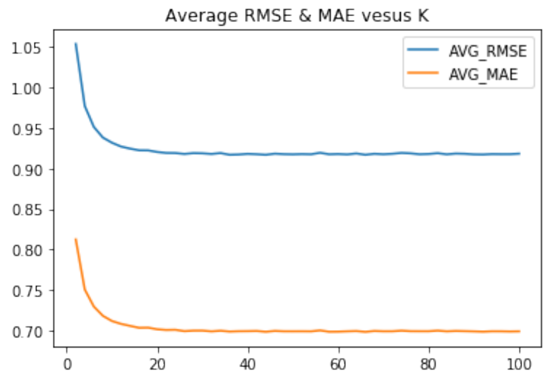
It means the indices of movies that both users have rated. Since Rating Matrix is sparse, it can be null if those two users rated completely different two sets of movies.

Problem 9

If users' ratings on all items are always at one extreme, then the absolute rates can not reflect the true rates of items. Therefore, relative rates should be used in this case.

Problem 10

The KNN-filter was used to predict the ratings of all movies in the dataset. The plot of different average RMSE & MAE for different number of neighbors (k) is shown below:

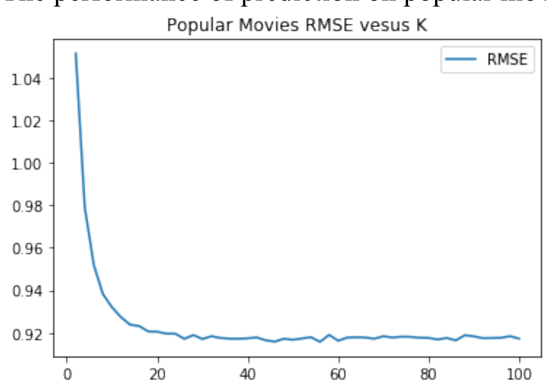


Problem 11

It can be concluded that the slopes of both AVG_RMSE and AVG_MAE approach to zero around k=25. The minimum k is about 25, where AVG_RMSE is about 0.925 and AVG_MAE is about 0.7.

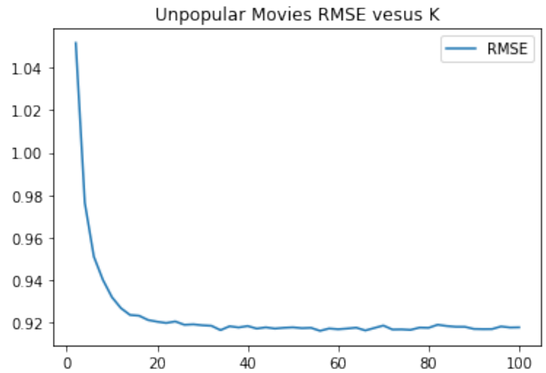
Problem 12

The performance of prediction on popular movies (more than 2 ratings) :



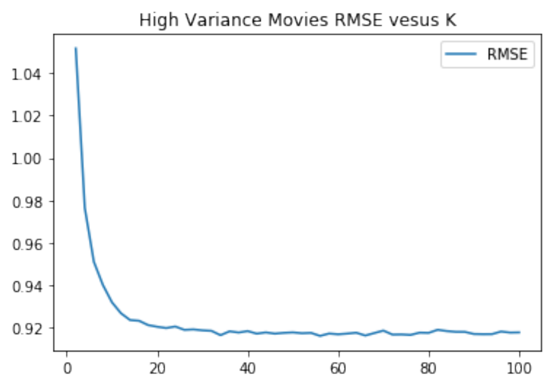
It can be concluded that the slopes of RMSE approach to zero around k=30.
The minimum k is about 30, where RMSE is about 0.92.

Problem 13



It can be concluded that the slopes of RMSE approach to zero around k=35.
The minimum k is about 35, where RMSE is about 0.92.

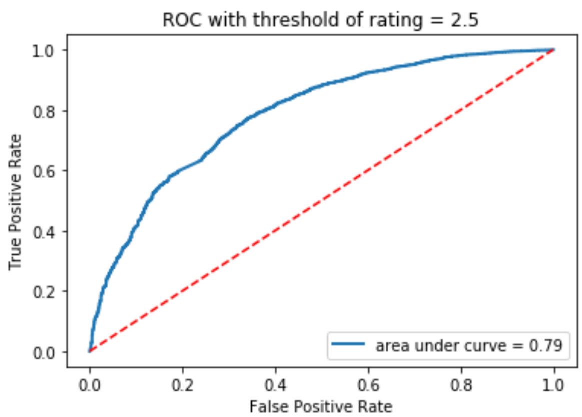
Problem 14

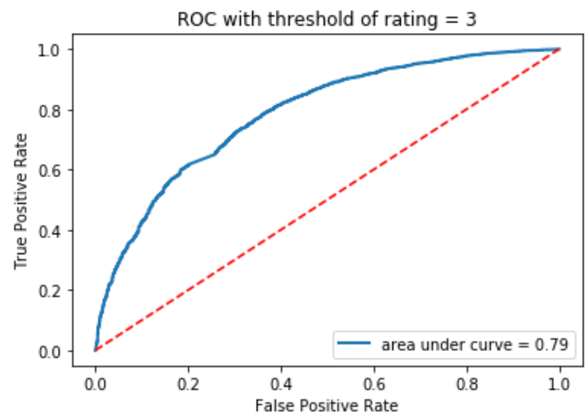


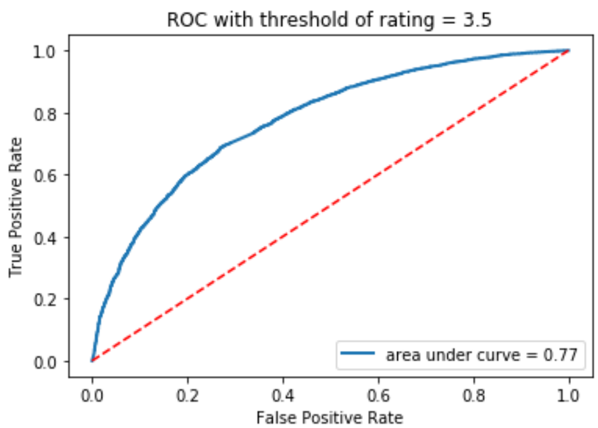
It can be concluded that the slopes of RMSE approach to zero around k=35.
The minimum k is about 35, where RMSE is about 0.92.

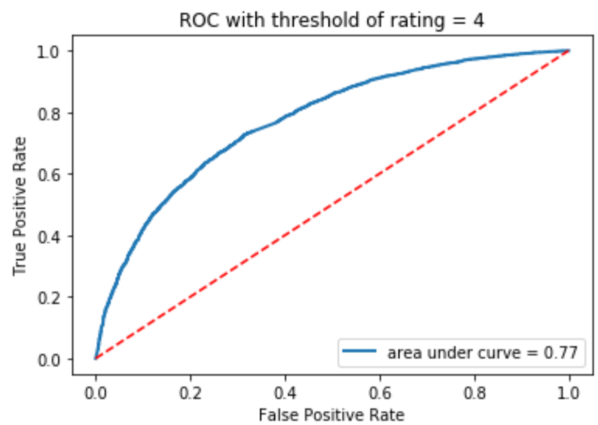
Problem 15

Below are ROC curves for the k-NN collaborative filter for threshold values [2.5, 3, 3.5, 4]. The area reported are [0.79, 0.79, 0.77, 0.77] respectively.









Problem 16

Yes. Equation 5 is a convex.

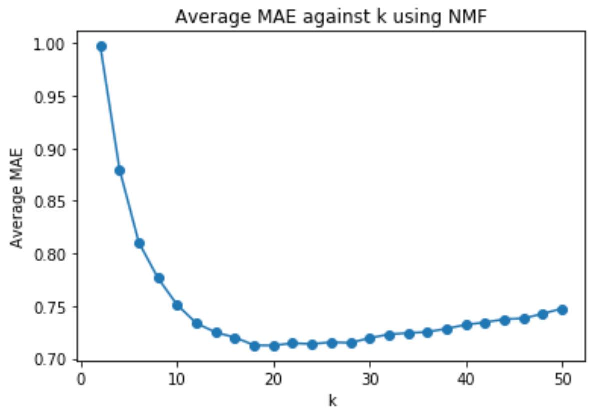
Let R' be a vector where contains all non-zero entry of rating matrix R with N * 1 where N is the number of non-zero entries in rating matrix R.

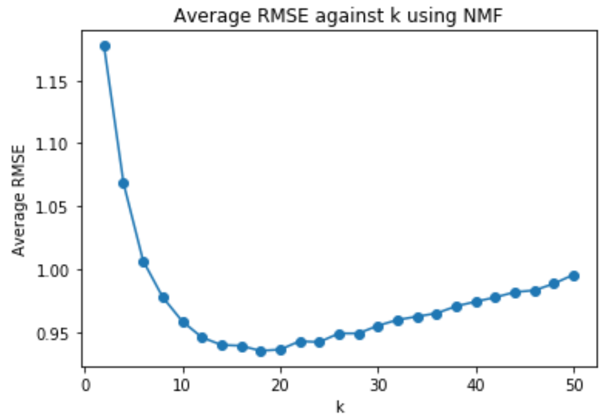
Let V' be a vector which contains [V11 ... Vnk] with the size nk*1.

Since U is fixed, U' can be factored as a vector which contains the coefficients of V' with size N*nk.

Then, the problem becomes min||R'-U'V'||^2 and this is a least square problem and R' and U' are known and V' is unknown.

Problem 17



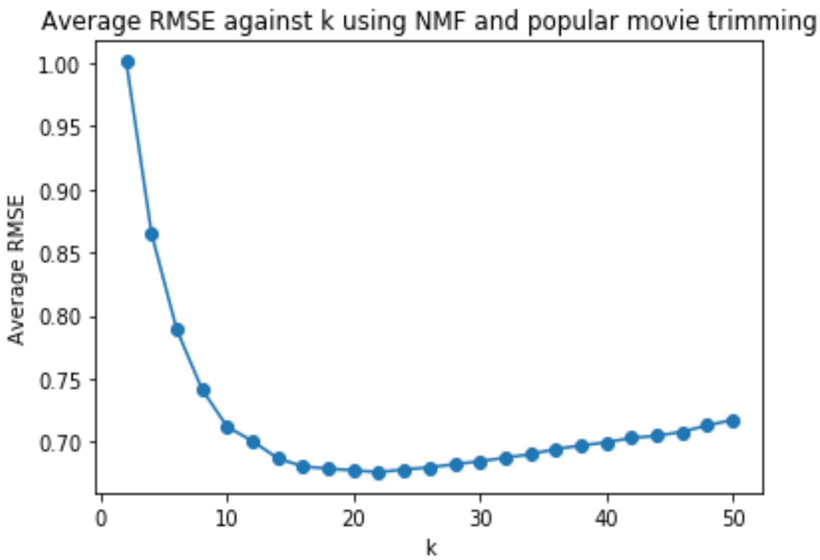


Minimum average MAE is 0.712406724893 and optimal k is 20.
Minimum average RMSE is 0.935021873173 and optimal k is 18.
Both figures above have U shape plot of average error when number of latent factors becomes larger. The reason of large error when k is too small or too large is that latent factors fail to correctly reflect the internal relationship between two groups of data (in this case users and movies). When k reaches a value where minimum error happens, the number of latent factors can match the number of internal relationship of two groups of data.

Problem 18

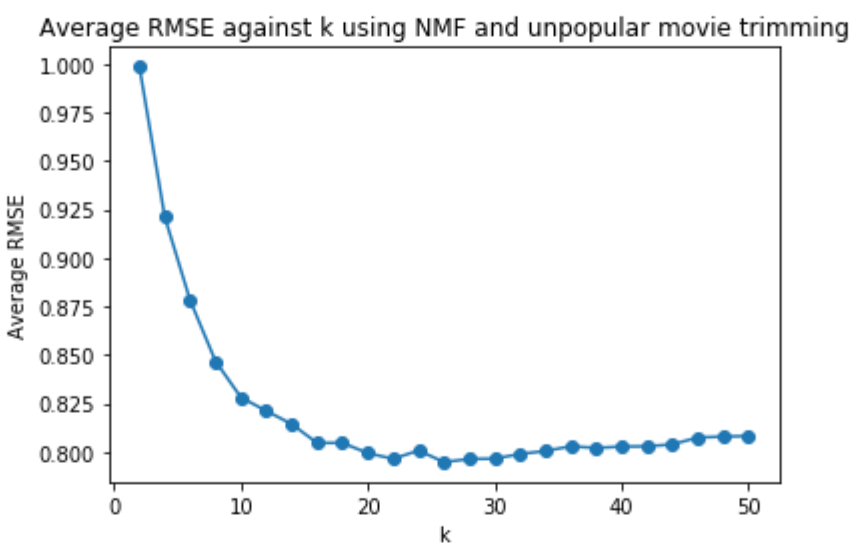
When k = 18, minimum average MAE is 0.713850751067.
When k = 18, minimum average RMSE is 0.935598311477.
The number of genres is 18. If including no genre, the number is 19. The optimal number of latent factors k, 18, is equal to the true number of genres.

Problem 19



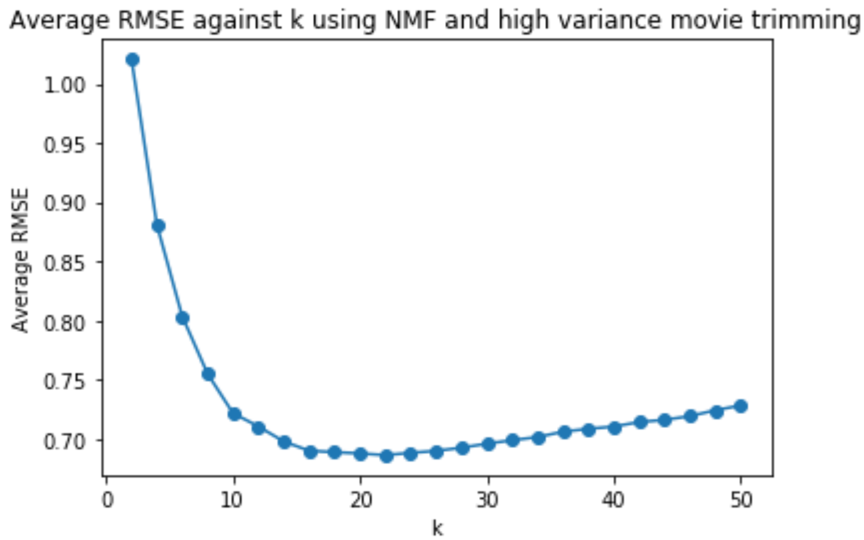
Minimum average rmse is 0.676283784209.

Problem 20



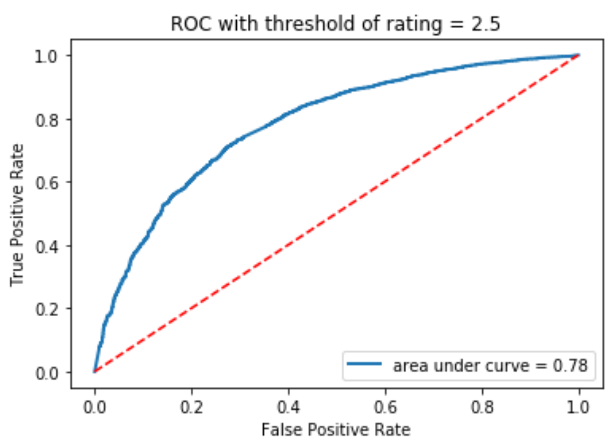
Minimum average rmse is 0.794827623088. After removing popular movies' ratings, it is clear to see that the prediction error becomes larger. This is because the unpopular movies tend to be unpopular in both train set and test set. The prediction of ratings of unpopular rating lacks information from ground truth rating matrix.

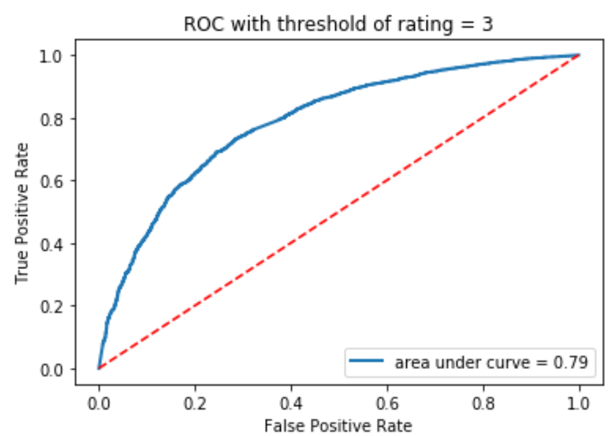
Problem 21

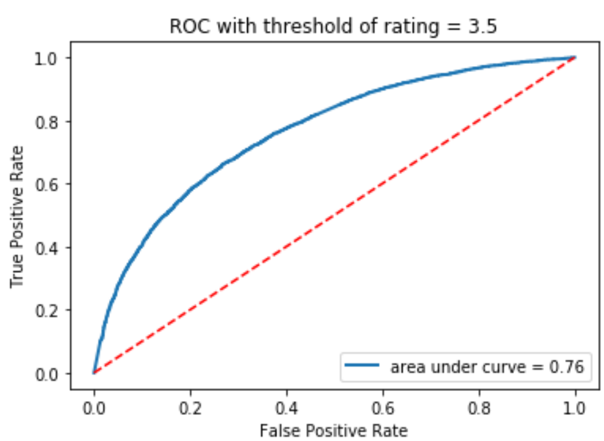


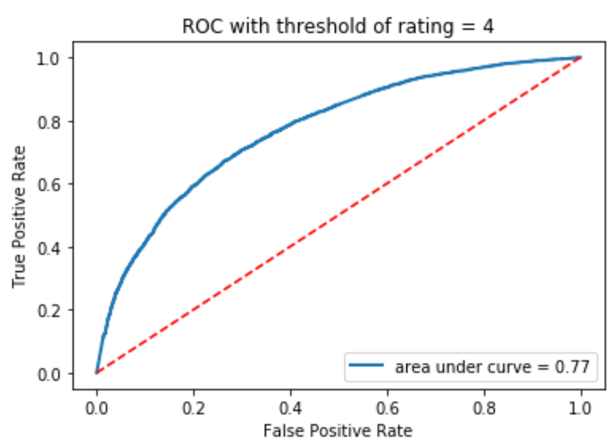
Minimum average rmse is 0.686406804386

Problem 22









It is clear to see that the area under ROC curve becomes smaller when preference threshold is too small or too large.

Problem 23

Column 0
Drama|Mystery|Romance
Action|Comedy|Crime|Fantasy
Comedy|Documentary
Drama|War
Children|Comedy
Action|Adventure|Sci-Fi|War|IMAX
Thriller
Comedy|Western
Action|Adventure|Sci-Fi|IMAX
Drama

Column 1
Comedy|Documentary
Adventure|Animation
Musical
Comedy|Romance
Drama|Fantasy|Horror
Comedy
Drama|Sci-Fi
Drama
Adventure|Drama|Sci-Fi
Drama|Romance

Column 2
Adventure|Drama|Fantasy|Romance
Action|Adventure|Drama|Thriller
Action|War
Action|Crime|Thriller
Comedy
Comedy|Drama|Romance
Comedy
Comedy|Mystery|Thriller
Drama
Comedy

Column 3
Drama
Comedy|Crime
Comedy|Drama
Documentary|Drama
Action
Drama|Thriller
Adventure|Children
Drama|Romance
Comedy
Drama

Column 4
Comedy|Crime|Mystery|Thriller
Action|Comedy
Documentary
Action|Adventure|Sci-Fi|Thriller
Comedy|Drama
Drama|Romance
Children|Comedy|Musical|Romance
Comedy
Documentary
Comedy|Romance

Column 5
Action|Crime|Drama|Mystery|Thriller
Comedy|Crime|Drama
Horror
Action|Sci-Fi|Thriller|IMAX
Horror|Sci-Fi
Comedy|Drama
Action|Adventure|Fantasy|IMAX
Action|Adventure|Sci-Fi|IMAX
Action|Adventure|Comedy
Drama|Romance|Thriller

Column 6
Crime|Horror|Mystery|Thriller
Adventure|Comedy|Thriller
Adventure|Children
Action|Sci-Fi
Drama|Mystery|Thriller
Horror
Comedy|Drama|Romance
Crime|Drama
Comedy|Horror
Horror

Column 7
Action
Drama
Animation
Thriller
Drama|Sci-Fi
Horror|Sci-Fi
Comedy|Horror|Sci-Fi
Horror
Comedy|Musical
Sci-Fi

Column 8
Comedy
Action|Comedy
Animation|Musical
Action|Adventure|Fantasy
Crime|Drama
Action|Sci-Fi
Adventure|Fantasy
Drama|Horror|Thriller
Drama
Drama|Romance

Column 9
Action|Drama|Thriller
Comedy
Crime|Drama|Mystery|Thriller
Drama|Horror|Mystery
Documentary|War
Comedy
Action|Comedy
Adventure|Comedy|Fantasy|Sci-Fi
Comedy|Drama
Action|Comedy

Column 10
Drama
Drama
Drama
Adventure|Children|Drama|Fantasy|IMAX
Drama
Crime|Drama
Action|Adventure|Sci-Fi
Drama
Action|Comedy|Crime
Comedy|Crime|Drama|Mystery|Romance

Column 11
Documentary
Children|Comedy
Drama
Action|Drama|Thriller
Drama|Mystery|Sci-Fi
Horror
Horror|Thriller
Comedy|Romance
Comedy
Documentary

Column 12
Drama|Romance
Crime|Drama|Thriller
Comedy|Crime|Musical
Comedy|Horror|Sci-Fi
Comedy|Romance
Adventure|Drama|Sci-Fi
Horror
Comedy|Drama
Crime|Drama|Mystery|Thriller
Horror|Thriller

Column 13
Comedy
Drama
Action|Comedy|Drama
Comedy
Fantasy|Horror
Children|Comedy
Action|Sci-Fi
Drama|Musical
Comedy|Drama|Romance
Drama

Column 14
Adventure|Drama|War|Western
Musical
Action|Sci-Fi
Adventure|Children|Drama
Comedy
Horror
Children|Comedy|Fantasy
Comedy|Romance
Horror|Thriller
Comedy

Column 15
Action|Adventure|Animation|
Crime|Fantasy
Comedy|Romance
Action|Comedy
Animation|Comedy|Musical
Comedy|Crime
Horror|Mystery|Thriller
Drama
Comedy
Comedy|Drama
Comedy|Romance

Column 16
Horror|Sci-Fi|Thriller
Drama
Comedy|Drama|Romance
Comedy
Action|Adventure|Comedy|Fa
ntasy
Comedy
Documentary
Adventure|Children|Fantasy
Comedy
Adventure|Animation|Childre
n|Sci-Fi|IMAX

Column 17
Comedy|Thriller
Adventure|Animation|Childre
n|Fantasy|Sci-Fi
Drama
Comedy
Animation|Children|Musical
Adventure|Drama
Drama|Horror|Mystery|Thrill
er
Comedy|Fantasy|Romance
Drama|Romance
Comedy|Western

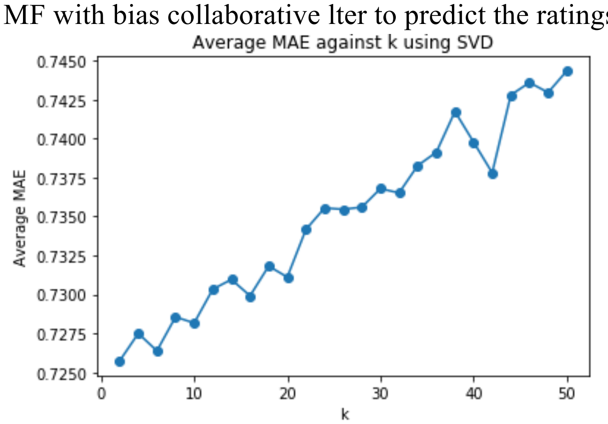
Column 18
Comedy|Drama
Horror
Comedy|Romance
Action|Drama|Thriller
Crime|Drama|Thriller
Comedy|Drama|Musical
Comedy|Drama
Horror|Sci-Fi
Comedy
Comedy|Drama

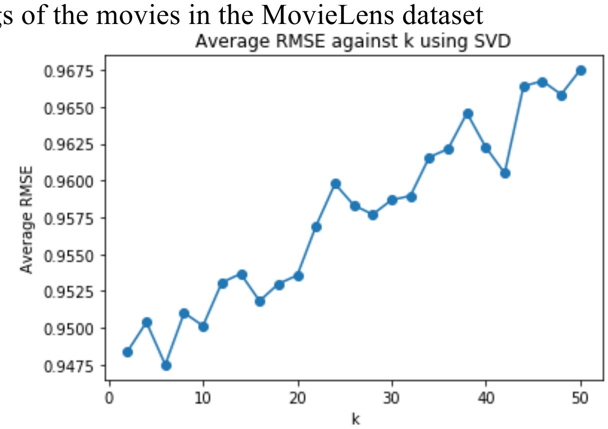
Column 19
Action
Comedy
Comedy|Fantasy|Musical|Romance
Comedy
Horror|Sci-Fi
Comedy|Romance
Action|Adventure|Animation|Crime|Fantasy
Adventure|Sci-Fi
Adventure|Children|Fantasy
Drama|Mystery|Romance

Viewing the genres of top 10 movies after sorting columns of item latent matrix V, we found that top 10 movies within a column tend to share the same set of genres. Since one movie can have multiple genres, even though they might not have one exactly the same genre, there still are internal relationships among them in terms of genres.

Problem 24

MF with bias collaborative lter to predict the ratings of the movies in the MovieLens dataset



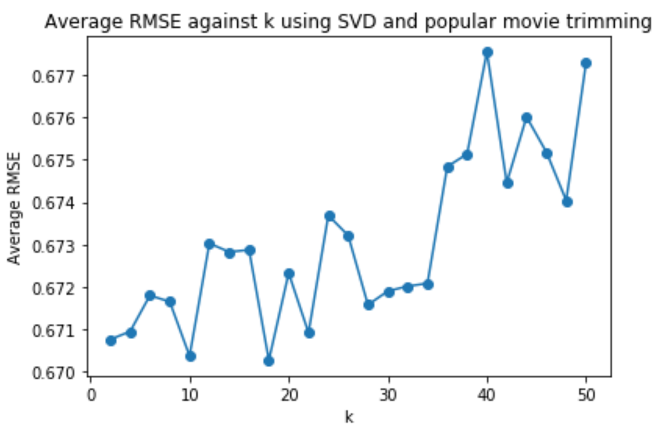


Problem 25

When k = 6, it gives the minimum average MAE which is 0.727182512535.
When k = 6, it gives the minimum average RMSE which is 0.948641321929.

Problem 26

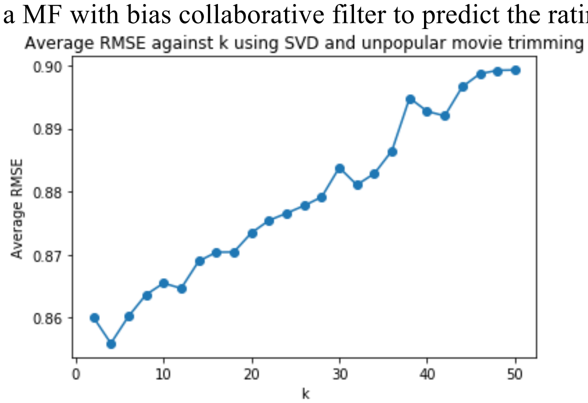
a MF with bias collaborative filter to predict the ratings of the movies in the popular movie trimmed test set.



Minimum average rmse is 0.670272206435 at around k = 18.

Problem 27

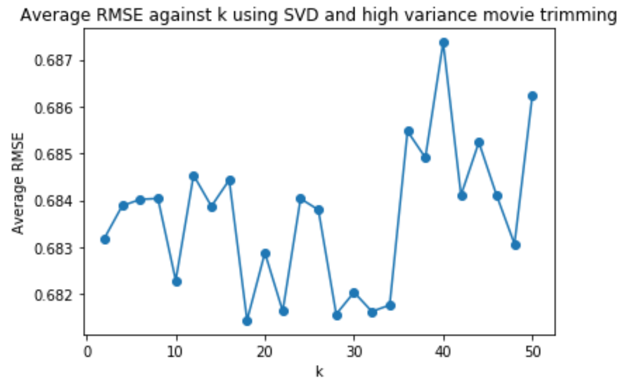
a MF with bias collaborative filter to predict the ratings of the movies in the unpopular movie trimmed test set.



Minimum average rmse is 0.855906892249 at around k = 4.

Problem 28

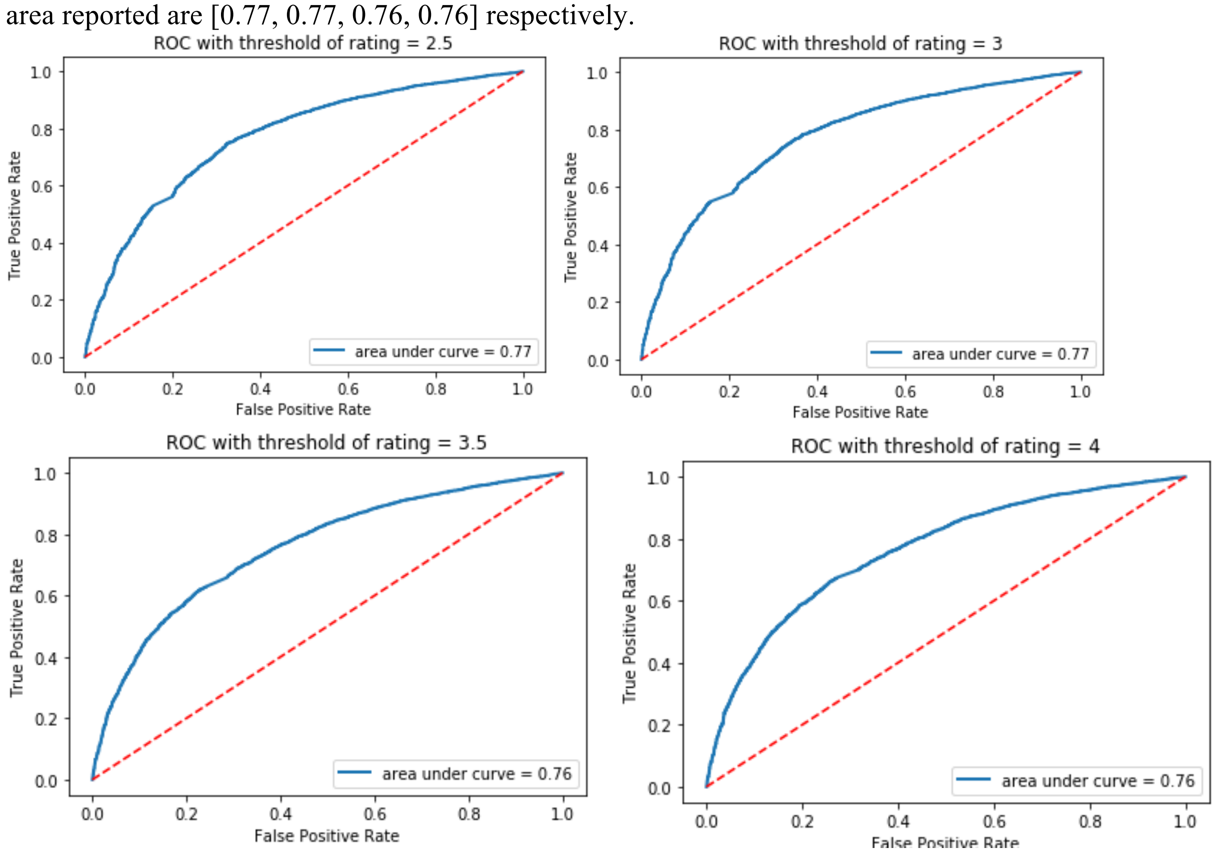
a MF with bias collaborative filter to predict the ratings of the movies in the high variance movie trimmed test set.



Minimum average rmse is 0.681440108235 at around k = 18.

Problem 29

Below are ROC curves for theMF with bias collaborative filter for threshold values [2.5, 3, 3.5, 4]. The area reported are [0.77, 0.77, 0.76, 0.76] respectively.



Problem 30 – 33:

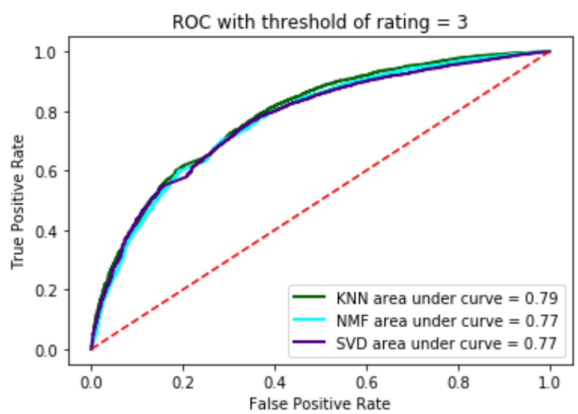
From problem 30 to 33, RMSE is calculated based on different dataset of movies. RMSE is 0.922 for the entire movie data. The value of RMSE is similar to the entire movie dataset for popular movies and high variance movie. However, the RMSE is very small comparing to the other three values.

	MovieLens	Popular Movies	Unpopular Movies	High Variance Movies
RMSE	0.922	0.916	0.563	0.916

Table: RMSE for different dataset of movies

Problem 34:

ROC curves (threshold = 3) for the k-NN, NNMF, and MF with bias based collaborative filters.



According to the figure shown above, the three kinds of filters demonstrate an almost same performance at threshold = 3, because they have almost the same ROC curve and the area. But we should notice that, KNN collaborative filter has about 2% larger area than the other two filters. Thus, we can say that KNN collaborative filter has better performance than the other two.

Problem 35:

Precision is the fraction of relevant elements over retrieved elements. For instance, precision in this case is the fraction of the recommended movies intersected with movies liked by target use r over recommended movies

Recall is the fraction of relevant elements over total amount of elements. For instance, precisio n in this case is the fraction of the recommended movies intersected with movies liked by targe t user over all the movies liked by target user

Problem 36:

As the recommended items t increases, the precision for KNN filtering method decreases. In contrast, the recall increases as t increases. The plot of precision vs recall decreases as t increases. They are almost monotonic curves.

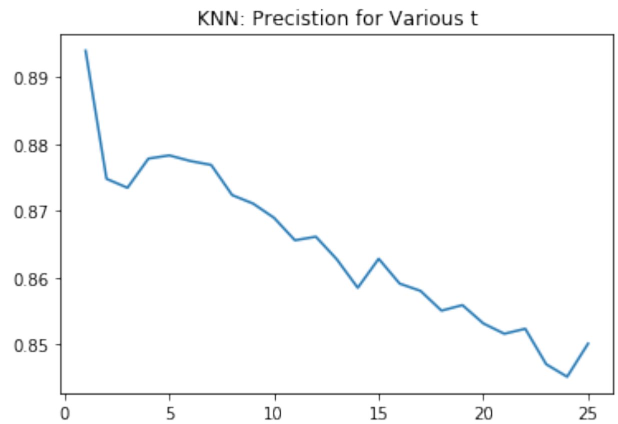


Figure: Precision for KNN

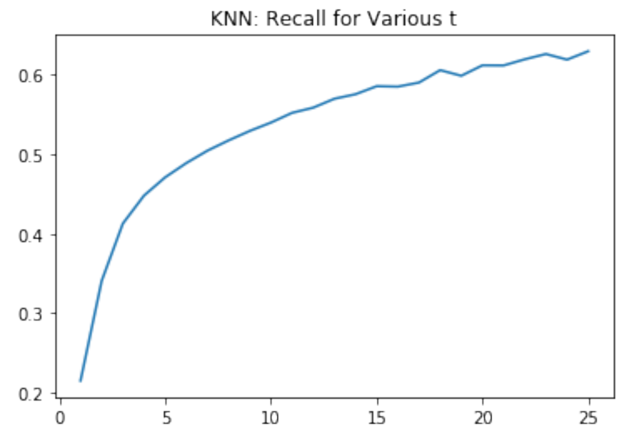


Figure: Recall for KNN

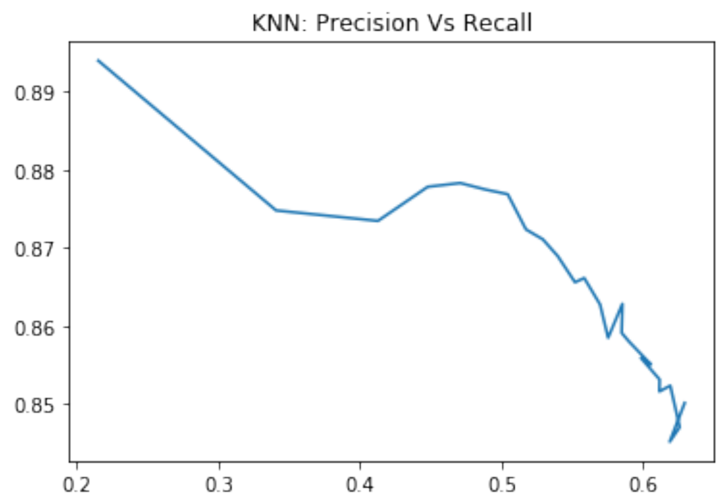


Figure: Precision Vs Recall for KNN

Problem 37

As the recommended items t increases, the precision for NMF filtering method decreases. In contrast, the recall increases as t increases. The plot of precision vs recall decreases as t increases. They are almost monotonic curves.

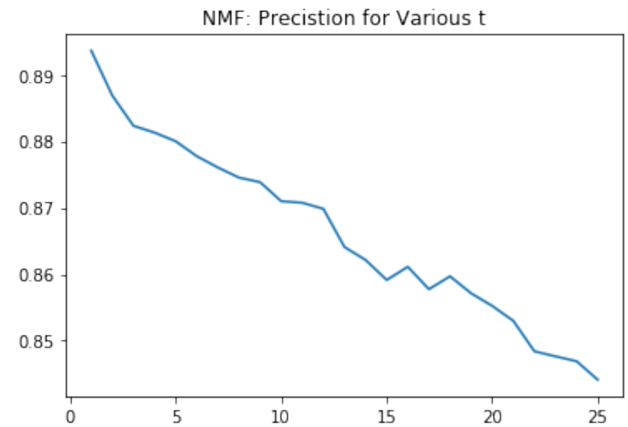


Figure: Precision for NMF

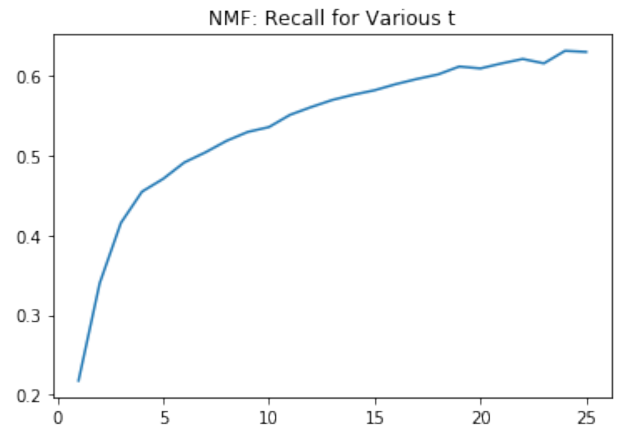


Figure: Recall for NMF

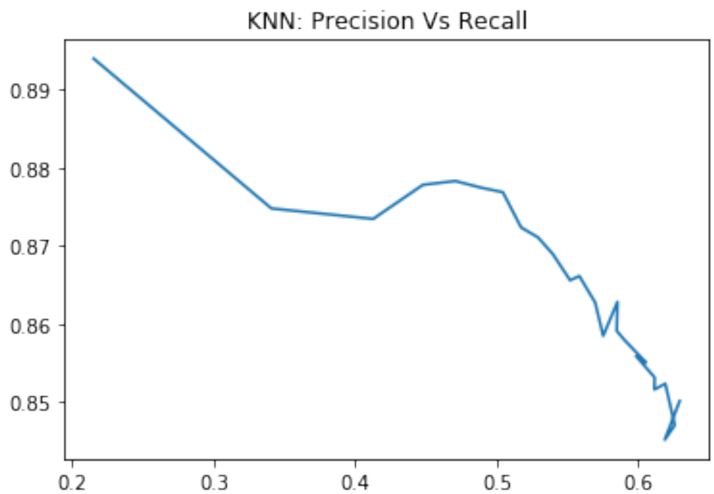
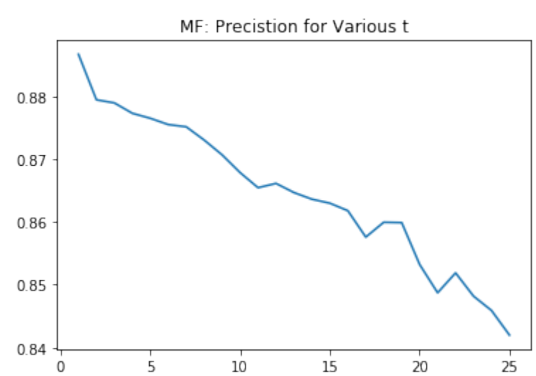


Figure: Precision Vs Recall for NMF

Problem 38

As the recommended items t increases, the precision for MF filtering method decreases. In contrast, the recall increases as t increases. The plot of precision vs recall decreases as t increases. They are almost monotonic curves.



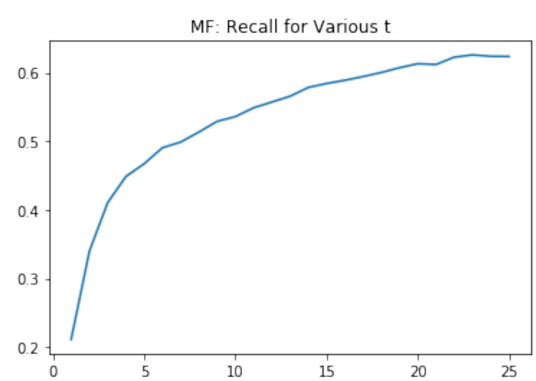


Figure: Precision for MF   Figure: Recall for MF

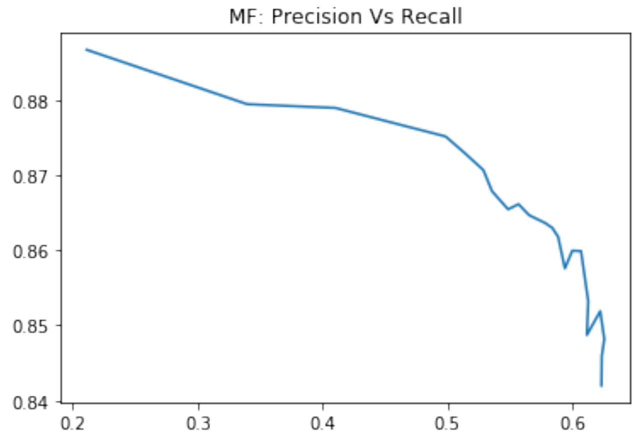


Figure: Precision Vs Recall for MF

Problem 39:

The precision for NMF is slightly greater than that of the other two filtering predictions. In addition, the shape of prediction vs recall for MF is smoother than the shape of KNN.

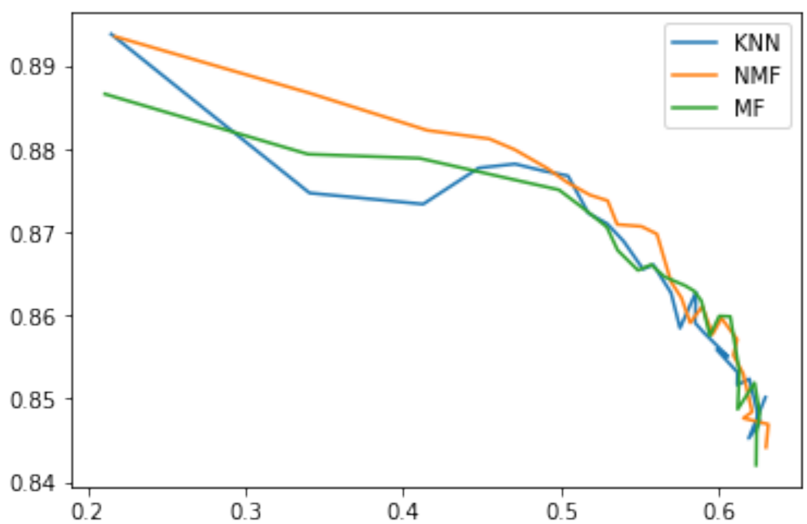


Figure: Precision Vs Recall among KNN, NMF, and MF