Project3_with_report

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1 EE219 Project 3

1.0.1 Team members:

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1.0.2 Required Packages:

python 3.6
numpy v1.14.0
scikit-learn v0.19.1
scipy v1.0.0
matplotlib v2.1.2
pandas v0.22.0
surprise v0.1
scikit-surprise v1.0.5

```
In [42]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt

         import logging
         import pickle
         import os
         from logging.config import fileConfig

         # create logger
         fileConfig('logging_config.ini')
         logger = logging.getLogger()
         logger.setLevel("WARNING")
         # logger.setLevel("INFO")
```

```
GET_DATA_FROM_FILES = True

# load data
r_data = pd.read_csv('data/ratings.csv', header=0, usecols=[0, 1, 2])
print(r_data.head())
R = r_data.pivot_table(index='userId', columns='movieId',
                       values='rating').values
print("(number of users, number of rated movies): ", R.shape)
```

```
   userId  movieId  rating
0       1       31     2.5
1       1     1029     3.0
2       1     1061     3.0
3       1     1129     2.0
4       1     1172     4.0
(number of users, number of rated movies):  (671, 9066)
```

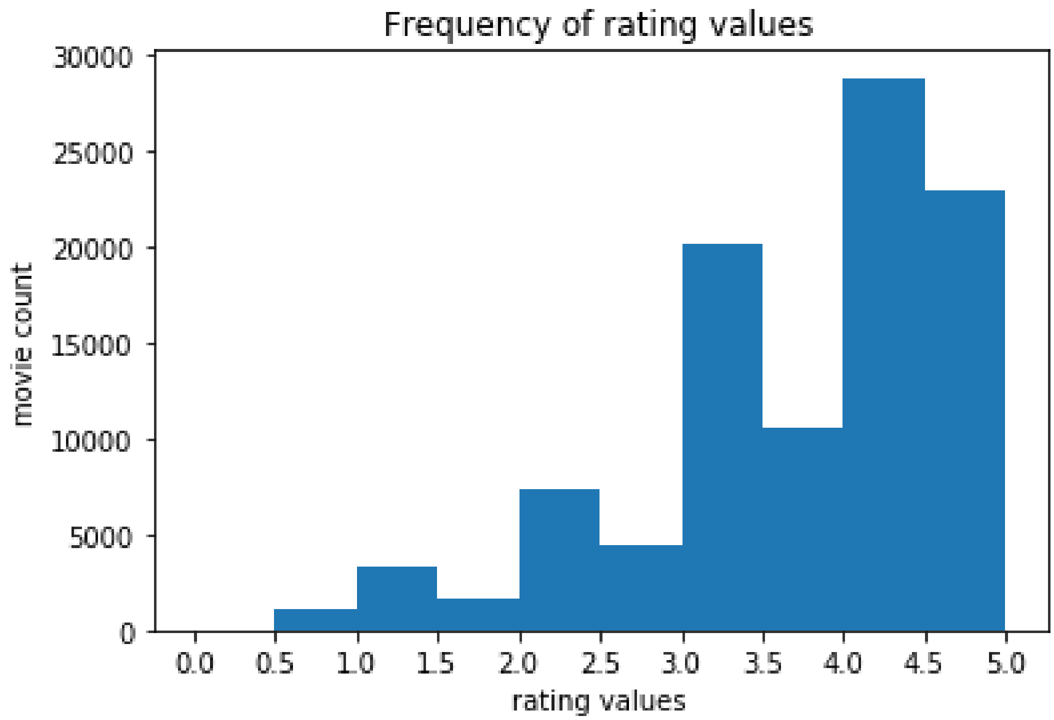
Question 1

```
In [43]: # Question 1
         user_count = R.shape[0]
         movie_count = R.shape[1]
         max_rating_count = user_count*movie_count
         rating_count = len(r_data.rating.tolist())
         sparsity = rating_count*1.0/max_rating_count
         print("Matrix sparsity = %0.4f" % sparsity)
```

```
Matrix sparsity = 0.0164
```

Question 2

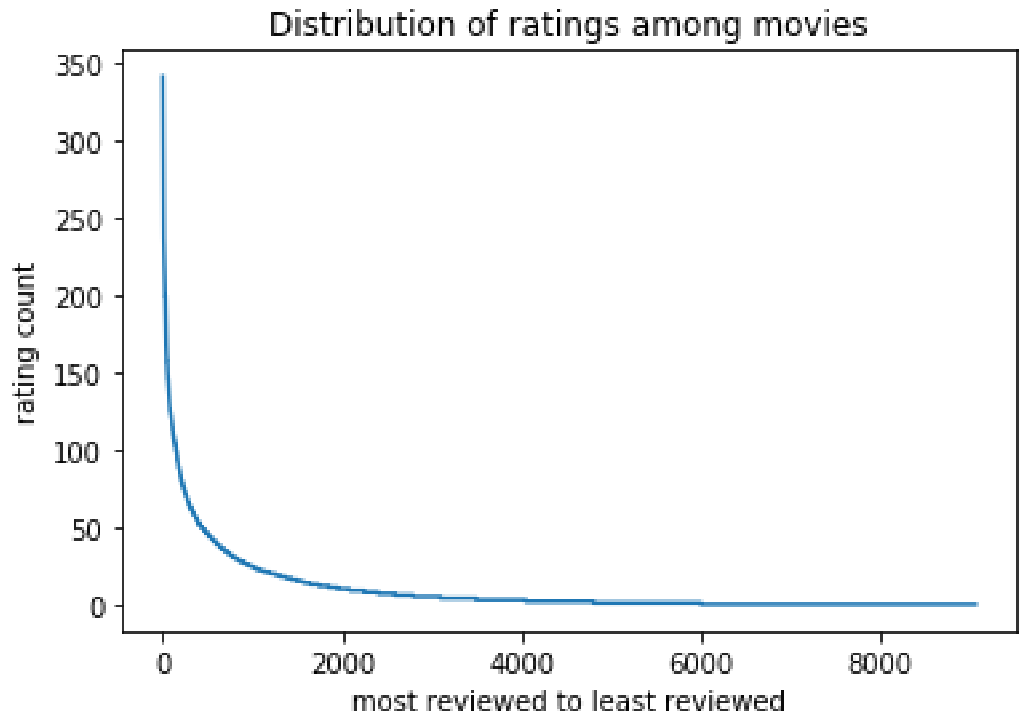
```
In [44]: # Question 2
         plt.figure()
         ax = plt.subplot(111)
         ratings = r_data.rating.tolist()
         xrange = np.arange(0, 5.5, 0.5)
         ax.hist(ratings, bins=xrange)
         ax.set_xticks(xrange)
         ax.set_title("Frequency of rating values")
         ax.set_xlabel("rating values")
         ax.set_ylabel("movie count")
         plt.show()
```



We binned the rating values into intervals of 0.5 and got the bar chart of frequency vs rating value. As shown on the graph, the rating value between 4.0 and 4.5 appear most frequently. An interesting pattern of the rating is that most of the users tend to give a rating value with tenths smaller than 5. Also, if we bin the rating value into intervals of 1, we could find that the higher rating values are, the more frequent they are. In other words, in this dataset, users tended to rate the movies high.

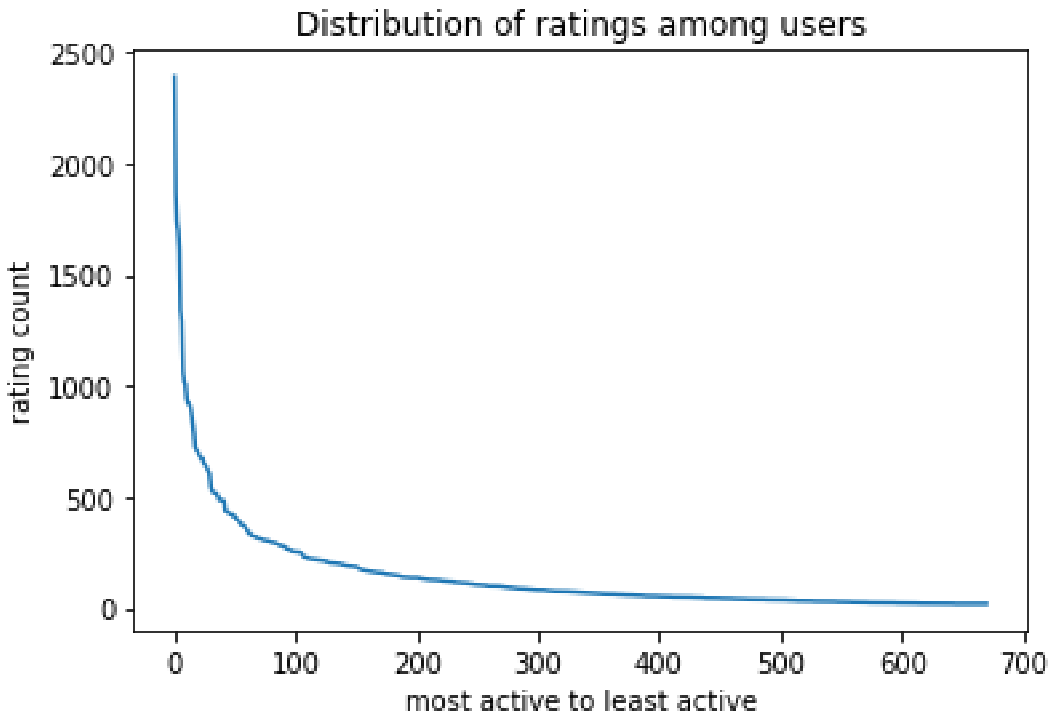
Question 3

```
In [45]: # Question 3
         plt.figure()
         movie_rating_count = np.count_nonzero(~np.isnan(R), axis=0)
         sorted_mrc = sorted(movie_rating_count, reverse=True)
         ax = plt.subplot(111)
         ax.plot(range(len(movie_rating_count)), sorted_mrc, '-')
         ax.set_title("Distribution of ratings among movies")
         ax.set_xlabel("most reviewed to least reviewed")
         ax.set_ylabel("rating count")
         plt.show()
```



Question 4

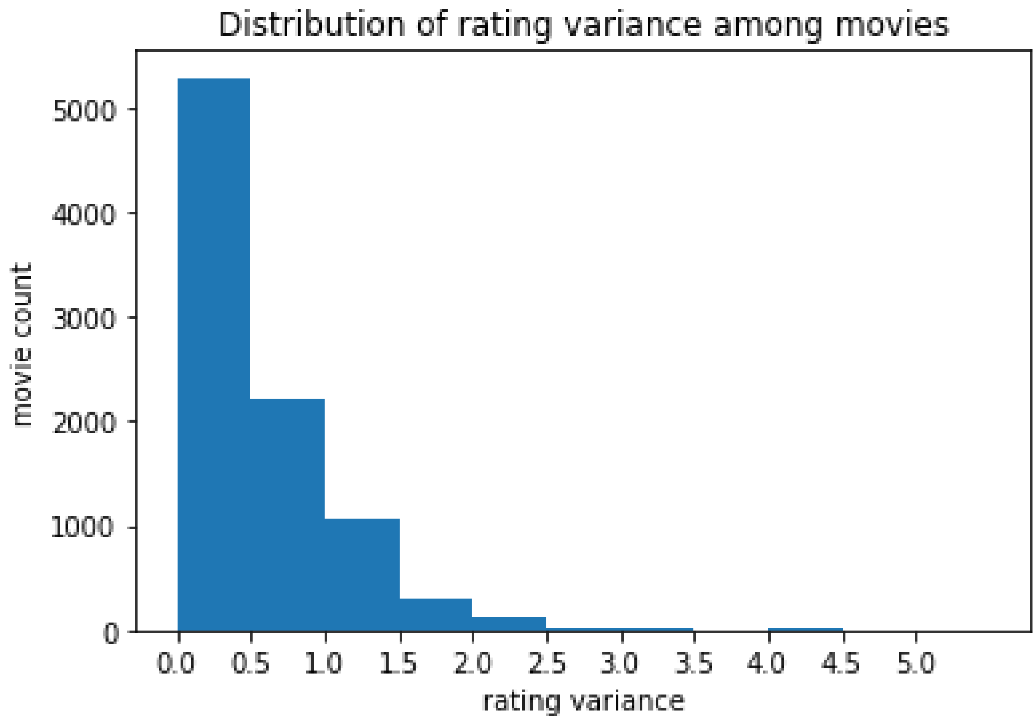
```
In [46]: # Question 4
         plt.figure()
         user_rating_count = np.count_nonzero(~np.isnan(R), axis=1)
         sorted_urc = sorted(user_rating_count, reverse=True)
         ax = plt.subplot(111)
         ax.plot(range(len(user_rating_count)), sorted_urc, '-')
         ax.set_title("Distribution of ratings among users")
         ax.set_xlabel("most active to least active")
         ax.set_ylabel("rating count")
         plt.show()
```



Question 5 As shown in the graph of question 3, the number of ratings drops significantly as the frequency decreased. Most of the movies in the datasets were rated only a few times, and about 4000 movies received nearly no ratings. We can conclude that most of the users are only interested in a small subset of the movies, and they don't even care about rating the rest movies.

Question 6

```
In [47]: # Question 6
         plt.figure()
         ax = plt.subplot(111)
         movie_var = np.nanvar(R, axis=0)
         var_range = np.arange(min(movie_var), max(movie_var)+0.5, 0.5)
         ax.hist(movie_var, bins=var_range)
         ax.set_xticks(xrange)
         ax.set_title("Distribution of rating variance among movies")
         ax.set_xlabel("rating variance")
         ax.set_ylabel("movie count")
         plt.show()
```



The variance of the ratings on each movie is computed and shown in the graph. Among the 9066 rated movies, more than 5000 movies were rated with similar values (variance 0.0-0.5), and as the variance increased, movie count decreased. In general, the movie count vs rating variance is normally distributed.

Question 7 I_u : Set of item indices for which ratings have been specifed by user u
I_v : Set of item indices for which ratings have been specifed by user v
μ_u : Mean rating for user u computed using her specifed ratings
r_{uk} : Rating of user u for item k

$$\mu_u = \frac{\sum_{i \in I_u} r_{ui}}{\mid I_u \mid}$$

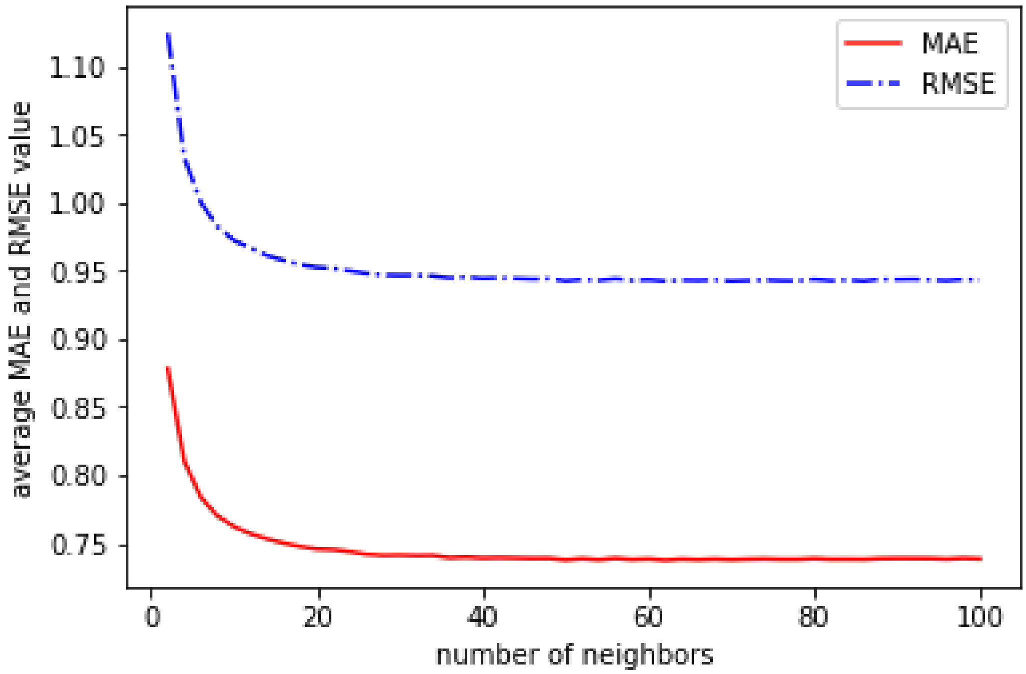
Question 8 $I_u \cap I_v$ represents the indices of movies that are rated by both user u and user v. It's possible that this intersection be the empty set ($\emptyset$), given the sparsity of the matrix. It happens when user u has not rated any movie that user v has.

Question 9 By doing mean centering, we are able to decrease the multicollinearity between a single users' rating and its corresponding effects. For instance, if we encounter multiple users who rate all items highly, our predicted rating will be greatly affect by this. However, with mean centering, this problem is resovled.

Question 10

In [48]:
```
import surprise
from surprise import Dataset
from surprise.model_selection import cross_validate
data = Dataset.load_builtin('ml-100k')

k_lst = range(2,101,2)

sim_options = {'name': 'pearson'}
rmse_lst=[]
mae_lst=[]

if GET_DATA_FROM_FILES and os.path.isfile("./rmse_lst.pkl")\
                    and os.path.isfile("./mae_lst.pkl"):
    logging.info("Loading rmse_lst and mae_lst.")
    rmse_lst = pickle.load(open("./rmse_lst.pkl", "rb"))
    mae_lst = pickle.load(open("./mae_lst.pkl", "rb"))
else:
    for k in k_lst:
        algo = surprise.prediction_algorithms.knns.KNNWithMeans(k=k, sim_options=sim_o
        result = cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=10)
        rmse_lst.append(np.mean(result['test_rmse']))
        mae_lst.append(np.mean(result['test_mae']))

    pickle.dump(rmse_lst, open("./rmse_lst.pkl", "wb"))
    pickle.dump(mae_lst, open("./mae_lst.pkl", "wb"))
```

In [49]:
```
l1, = plt.plot(k_lst, mae_lst, 'r-', label='MAE')
l2, = plt.plot(k_lst, rmse_lst, 'b-.', label='RMSE')
plt.xlabel('number of neighbors')
plt.ylabel('average MAE and RMSE value')
plt.legend(handles=[l1, l2])
plt.show()
```



Question 11 The minimum k is about **12**. MAE converges to **0.74** and RMSE converges to **0.94**.

Question 12,13,14

```
In [50]: from surprise import accuracy
         from surprise import Reader
         from surprise.model_selection import KFold

In [51]: def trim_popular(testset):
             trimmed = []
             mat = np.array(testset, dtype=[('u', int), ('m', int), ('r', float)])
             mat.sort(order='m')
             counter = 0
             lastm = mat[0][1]
             for u, m, r in mat:
                 if m != lastm:
                     if counter <= 2:
                         for i in range(counter):
                             trimmed.pop(-1)

                     counter = 0
                     lastm = m

                 counter += 1
```

```
                trimmed.append((u, m, r))

        if counter <= 2:
            for i in range(counter):
                trimmed.pop(-1)

        return trimmed
```

```
In [52]: def trim_unpopular(testset):
             trimmed = []
             mat = np.array(testset, dtype=[('u', int), ('m', int), ('r', float)])
             mat.sort(order='m')
             counter = 0
             lastm = mat[0][1]
             for u, m, r in mat:
                 if m != lastm:
                     if counter > 2:
                         for i in range(counter):
                             trimmed.pop(-1)

                     counter = 0
                     lastm = m

                 counter += 1
                 trimmed.append((u, m, r))

             if counter > 2:
                 for i in range(counter):
                     trimmed.pop(-1)

             return trimmed
```

```
In [53]: def trim_highvar(testset):
             trimmed = []
             mat = np.array(testset, dtype=[('u', int), ('m', int), ('r', float)])
             mat.sort(order='m')
             counter = 0
             temp_r = []
             lastm = mat[0][1]
             for u, m, r in mat:
                 if m != lastm:
                     if counter < 5 or np.var(temp_r) < 2:
                         for i in range(counter):
                             trimmed.pop(-1)

                     counter = 0
                     temp_r = []
                     lastm = m
```

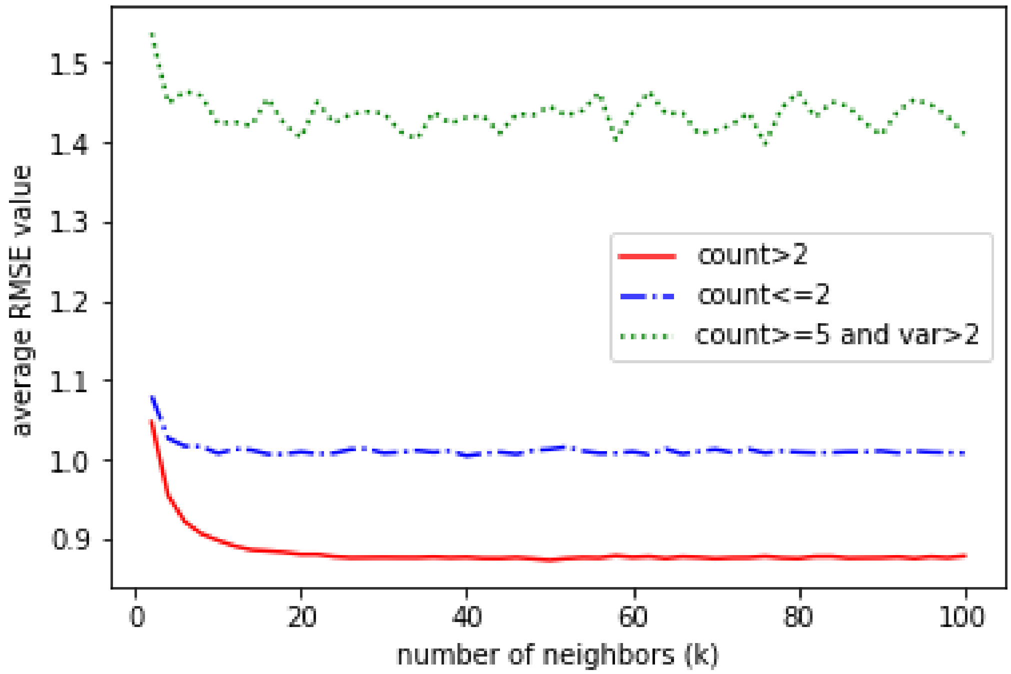
```
            counter += 1
            temp_r.append(r)
            trimmed.append((u, m, r))

        if counter < 5 or np.var(temp_r) < 2:
            for i in range(counter):
                trimmed.pop(-1)

        return trimmed
```

In [54]:
```
kf = KFold(n_splits=10)

# A reader is still needed but only the rating_scale param is requiered.
reader = Reader(rating_scale=(0.5, 5))
data = Dataset.load_from_df(r_data[['userId', 'movieId', 'rating']], reader)

rmse_pop = []
rmse_unpop = []
rmse_highvar = []

if GET_DATA_FROM_FILES and os.path.isfile("./rmse_pop.pkl")\
                    and os.path.isfile("./rmse_unpop.pkl")\
                    and os.path.isfile("./rmse_highvar.pkl"):
    logging.info("Loading rmse_pop, rmse_unpop and rmse_highvar.")
    rmse_pop = pickle.load(open("./rmse_pop.pkl", "rb"))
    rmse_unpop = pickle.load(open("./rmse_unpop.pkl", "rb"))
    rmse_highvar = pickle.load(open("./rmse_highvar.pkl", "rb"))
else:
    for k in k_lst:
        rmse_temp_pop = []
        rmse_temp_unpop = []
        rmse_temp_highvar = []
        algo = surprise.prediction_algorithms.knns.KNNWithMeans(k=k, sim_options=sim_o
        for trainset,testset in kf.split(data):
            algo.fit(trainset)
            predictions_pop = algo.test(trim_popular(testset))
            predictions_unpop = algo.test(trim_unpopular(testset))
            predictions_highvar = algo.test(trim_highvar(testset))
            rmse_temp_pop.append(accuracy.rmse(predictions_pop))
            rmse_temp_unpop.append(accuracy.rmse(predictions_unpop))
            rmse_temp_highvar.append(accuracy.rmse(predictions_highvar))
        rmse_pop.append(np.mean(rmse_temp_pop))
        rmse_unpop.append(np.mean(rmse_temp_unpop))
        rmse_highvar.append(np.mean(rmse_temp_highvar))

    pickle.dump(rmse_pop, open("./rmse_pop.pkl", "wb"))
    pickle.dump(rmse_unpop, open("./rmse_unpop.pkl", "wb"))
```

```
    pickle.dump(rmse_highvar, open("./rmse_highvar.pkl", "wb"))

print(rmse_pop[:5])
```

```
[1.0474940413149139, 0.95481980124888055, 0.92194934099151138, 0.90665093687839526, 0.89817706
```

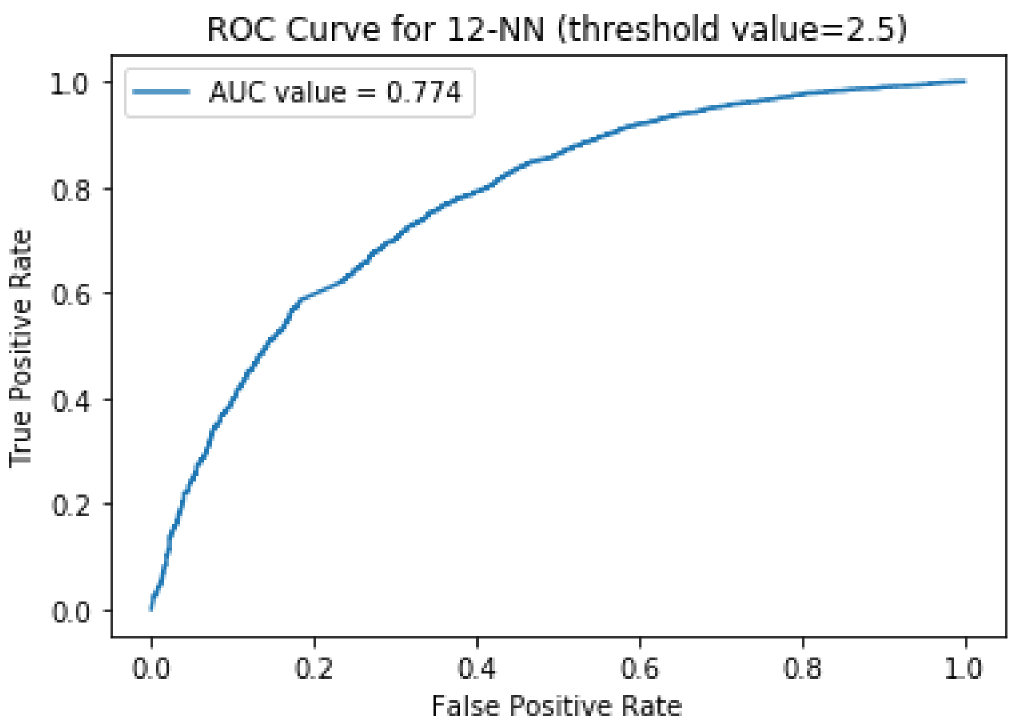
In [55]:
```
l1, = plt.plot(k_lst, rmse_pop, 'r-', label='count>2')
l2, = plt.plot(k_lst, rmse_unpop, 'b-.', label='count<=2')
l3, = plt.plot(k_lst, rmse_highvar, 'g:', label='count>=5 and var>2')
plt.xlabel('number of neighbors (k)')
plt.ylabel('average RMSE value')
plt.legend(handles=[l1, l2, l3])
plt.show()
```

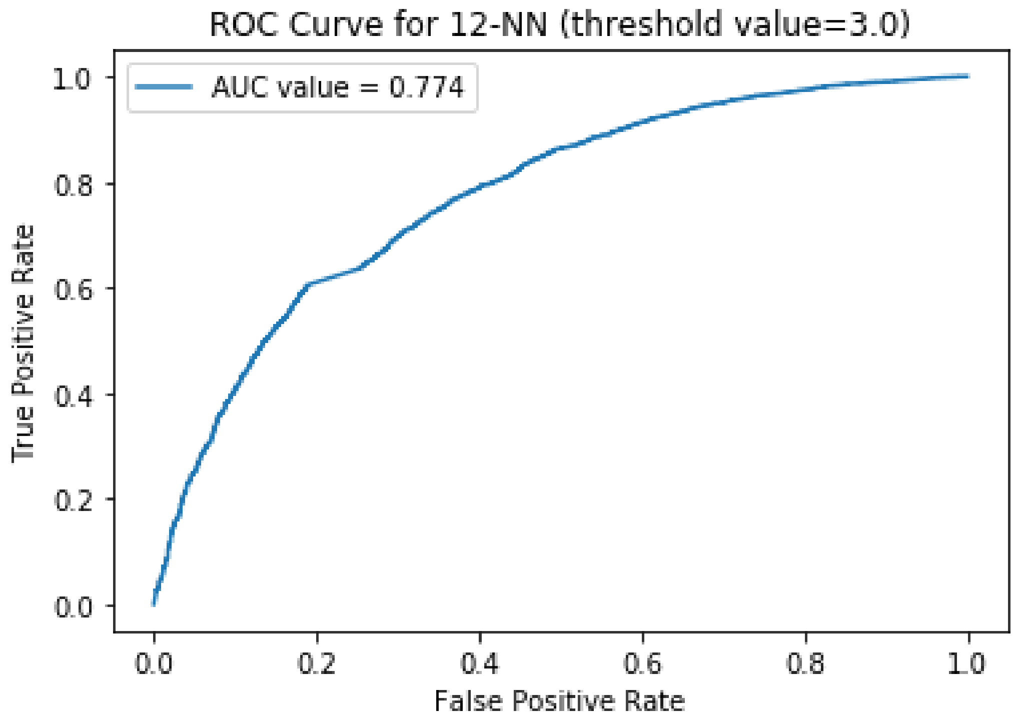


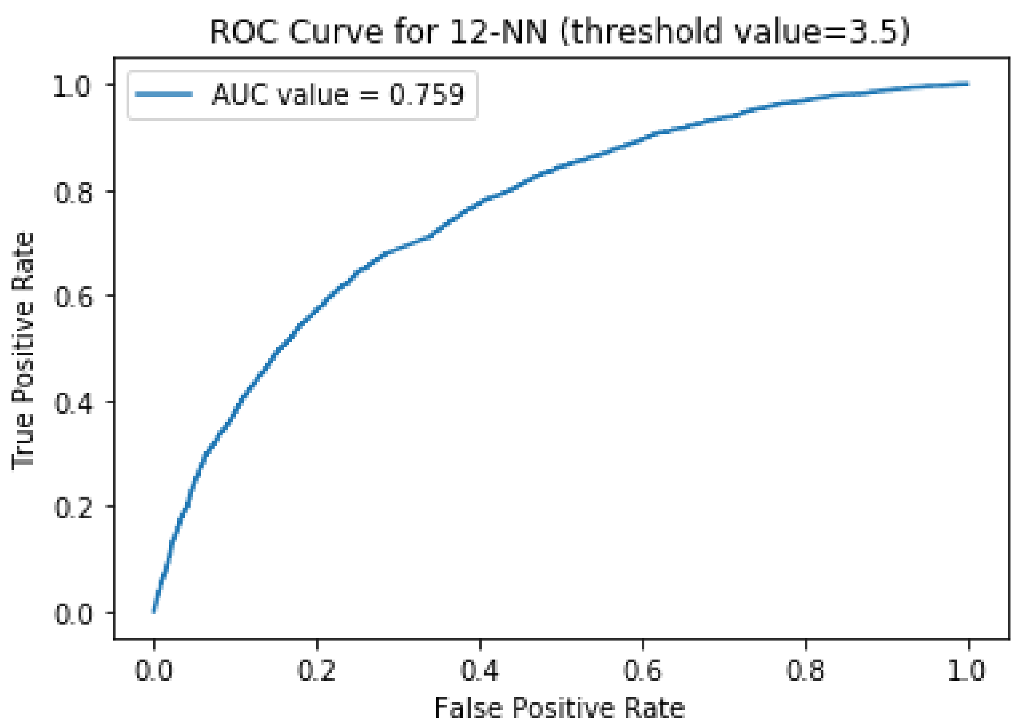
Question 15

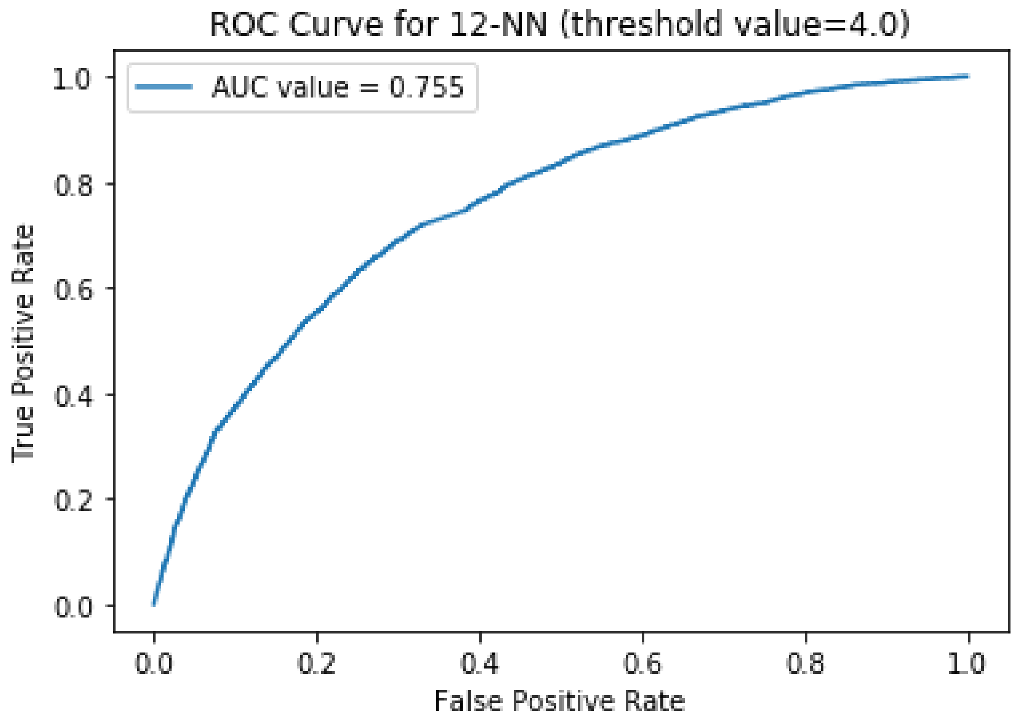
In [56]:
```
from sklearn import metrics
from surprise.model_selection import train_test_split
mink=12
thresholdlist = [2.5, 3, 3.5, 4]

pred = None
if GET_DATA_FROM_FILES and os.path.isfile("./pred_q15.pkl"):
    logging.info("Loading pred_q15.")
```

```
    pred = pickle.load(open("./pred_q15.pkl", "rb"))
else:
    algo = surprise.prediction_algorithms.knns.KNNWithMeans(k=mink, sim_options=sim_o
    trainset, testset = train_test_split(data, test_size=.1)
    algo.fit(trainset)
    pred = algo.test(testset)
    pickle.dump(pred, open("./pred_q15.pkl", "wb"))

for ths in thresholdlist:
    y_true=[]
    y_pred=[]
    for _,_,r_real,r_pred,_ in pred:
        if r_real >= ths:
            y_true.append(1)
        else:
            y_true.append(0)
        y_pred.append(r_pred)
    fpr, tpr, _ = metrics.roc_curve(y_true=y_true, y_score=y_pred, pos_label=1)
    plt.plot(fpr, tpr, label='AUC value = %0.3f' % metrics.roc_auc_score(y_true=y_tru
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve for %d-NN (threshold value=%.1f)' % (mink, ths))
    plt.legend()
    plt.show()
```




ROC Curve for 12-NN (threshold value=3.0)
AUC value = 0.774
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0


ROC Curve for 12-NN (threshold value=3.5)
AUC value = 0.759
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0



Question 16 The optimization problem given by equation 5 can be shown to be convex by calculating the Hessian Matrix. Since the Hessian Matrix is positive semi-definite, the optimization problem is convex.

Equation 5 formulated as a least-squares problem:

$$\min_{V} \left\| W \otimes \left(VU^T - R^T \right) \right\|^2 \tag{1}$$

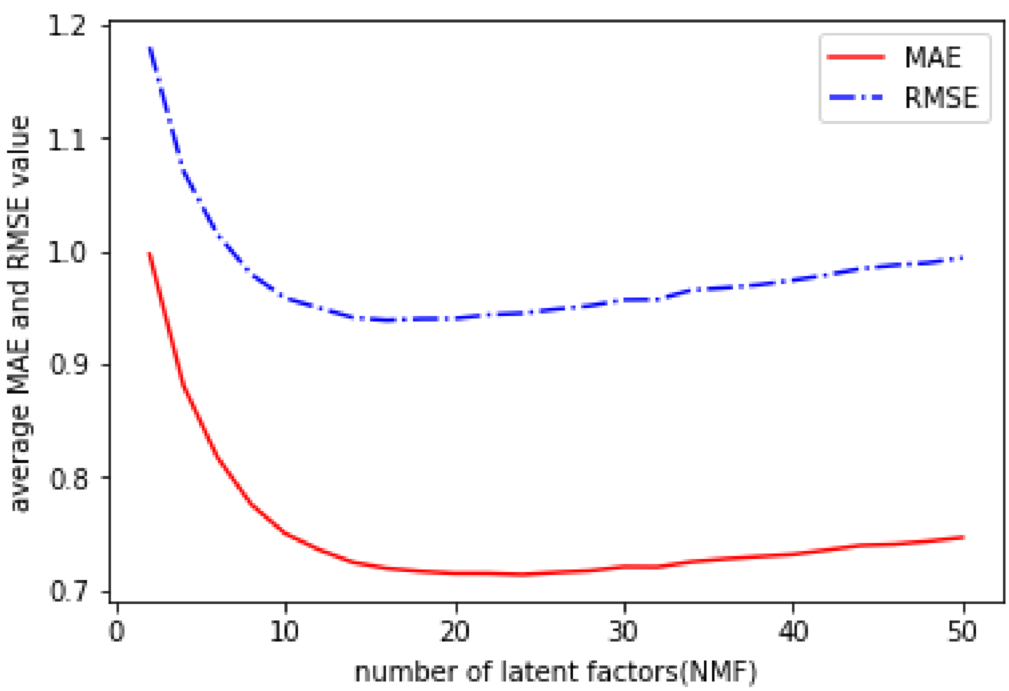
where $\otimes$ is an elementwise filter, U is fixed, and R is the rating matrix

Question 17

```
In [57]: from surprise import NMF
         k_nnmf = range(2,51,2)

         rmse_nnmf=[]
         mae_nnmf=[]

         if GET_DATA_FROM_FILES and os.path.isfile("./rmse_nnmf.pkl")\
                             and os.path.isfile("./mae_nnmf.pkl"):
             logging.info("Loading rmse_nnmf and mae_nnmf.")
             rmse_nnmf = pickle.load(open("./rmse_nnmf.pkl", "rb"))
             mae_nnmf = pickle.load(open("./mae_nnmf.pkl", "rb"))
         else:
```

```
    for k in k_nnmf:
        algo = NMF(n_factors=k)
        result = cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=10)
        rmse_nnmf.append(np.mean(result['test_rmse']))
        mae_nnmf.append(np.mean(result['test_mae']))

    pickle.dump(rmse_nnmf, open("./rmse_nnmf.pkl", "wb"))
    pickle.dump(mae_nnmf, open("./mae_nnmf.pkl", "wb"))
```

```
In [58]: l1, = plt.plot(k_nnmf, mae_nnmf, 'r-', label='MAE')
         l2, = plt.plot(k_nnmf, rmse_nnmf, 'b-.', label='RMSE')
         plt.xlabel('number of latent factors(NMF)')
         plt.ylabel('average MAE and RMSE value')
         plt.legend(handles=[l1, l2])
         plt.show()
```



Question 18

```
In [59]: print('the value of k that gives the minimum average RMSE')
         print(k_nnmf[np.argsort(rmse_nnmf)[0]])
         print('minimum average RMSE:')
         print(np.sort(rmse_nnmf)[0])
```

```
the value of k that gives the minimum average RMSE
16
```

```
minimum average RMSE:
0.93883589244
```

The optimal k value is 16, which is different from the number of movie genre which is 18, but very close.

```
In [60]: print ('the value of k that gives the minimum average MAE :')
         print (k_nnmf[np.argsort(mae_nnmf)[0]])
         print ('minimum average MAE:')
         print (np.sort(mae_nnmf)[0])
```

```
the value of k that gives the minimum average MAE :
24
minimum average MAE:
0.713795966474
```

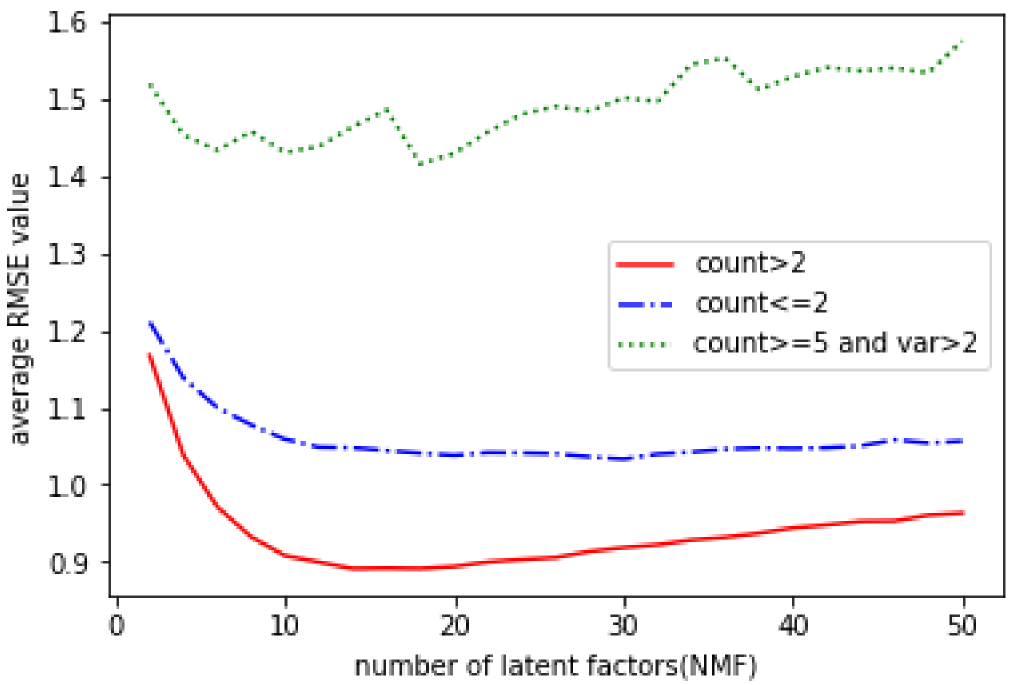
Question 19,20,21

```
In [61]: kf = KFold(n_splits=10)

         rmse_pop_nnmf = []
         rmse_unpop_nnmf = []
         rmse_highvar_nnmf = []

         if GET_DATA_FROM_FILES and os.path.isfile("./rmse_pop_nnmf.pkl")\
                             and os.path.isfile("./rmse_unpop_nnmf.pkl")\
                             and os.path.isfile("./rmse_highvar_nnmf.pkl"):
             logging.info("Loading rmse_pop_nnmf, rmse_unpop_nnmf and rmse_highvar_nnmf.")
             rmse_pop_nnmf = pickle.load(open("./rmse_pop_nnmf.pkl", "rb"))
             rmse_unpop_nnmf = pickle.load(open("./rmse_unpop_nnmf.pkl", "rb"))
             rmse_highvar_nnmf = pickle.load(open("./rmse_highvar_nnmf.pkl", "rb"))
         else:
             for k in k_nnmf:
                 rmse_temp_pop_nnmf = []
                 rmse_temp_unpop_nnmf = []
                 rmse_temp_highvar_nnmf = []
                 algo = NMF(n_factors=k)
                 for trainset,testset in kf.split(data):
                     algo.fit(trainset)
                     predictions_pop_nnmf = algo.test(trim_popular(testset))
                     predictions_unpop_nnmf = algo.test(trim_unpopular(testset))
                     predictions_highvar_nnmf = algo.test(trim_highvar(testset))
                     rmse_temp_pop_nnmf.append(accuracy.rmse(predictions_pop_nnmf))
                     rmse_temp_unpop_nnmf.append(accuracy.rmse(predictions_unpop_nnmf))
                     rmse_temp_highvar_nnmf.append(accuracy.rmse(predictions_highvar_nnmf))
                 rmse_pop_nnmf.append(np.mean(rmse_temp_pop_nnmf))
```

```
            rmse_unpop_nnmf.append(np.mean(rmse_temp_unpop_nnmf))
            rmse_highvar_nnmf.append(np.mean(rmse_temp_highvar_nnmf))

        pickle.dump(rmse_pop_nnmf, open("./rmse_pop_nnmf.pkl", "wb"))
        pickle.dump(rmse_unpop_nnmf, open("./rmse_unpop_nnmf.pkl", "wb"))
        pickle.dump(rmse_highvar_nnmf, open("./rmse_highvar_nnmf.pkl", "wb"))

    print(rmse_pop_nnmf[:5])
```

```
[1.1672330929580468, 1.0380090025238264, 0.97109434424327767, 0.93216450905938031, 0.907867117
```

In [62]:
```
l1, = plt.plot(k_nnmf, rmse_pop_nnmf, 'r-', label='count>2')
l2, = plt.plot(k_nnmf, rmse_unpop_nnmf, 'b-.', label='count<=2')
l3, = plt.plot(k_nnmf, rmse_highvar_nnmf, 'g:', label='count>=5 and var>2')
plt.xlabel('number of latent factors(NMF)')
plt.ylabel('average RMSE value')
plt.legend(handles=[l1, l2, l3])
plt.show()
```



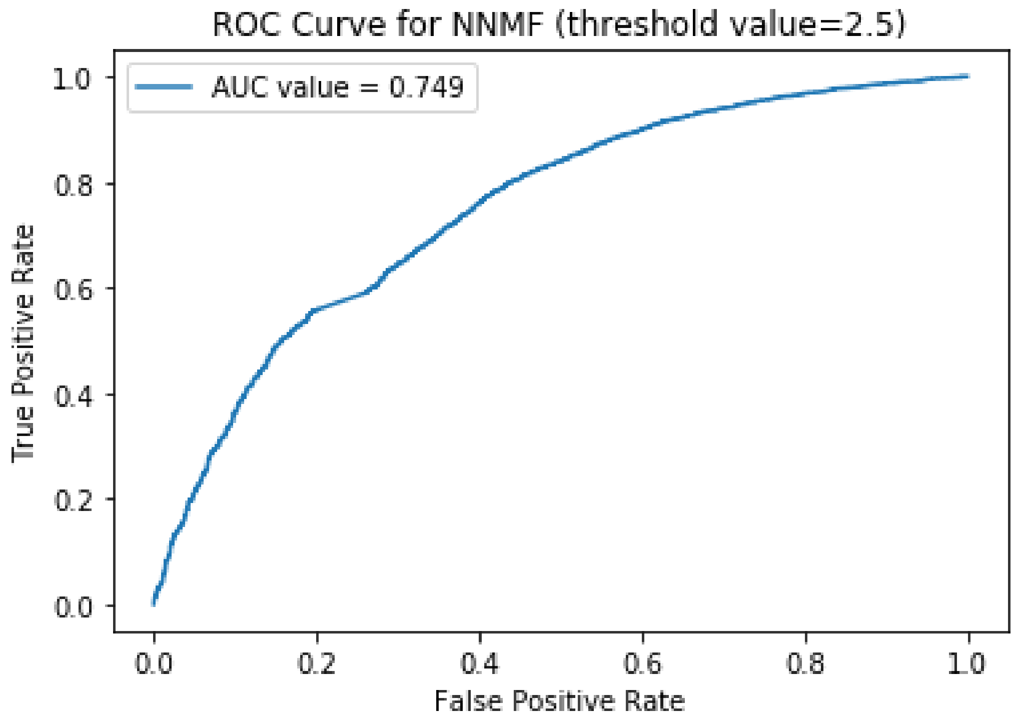
In [63]:
```
i_p = np.argsort(rmse_pop_nnmf)[0]
i_up = np.argsort(rmse_unpop_nnmf)[0]
i_hv = np.argsort(rmse_highvar_nnmf)[0]
print ('k that gives the minimum average RMSE for (popular, unpopular, \
high variance): \n(%d, %d, %d)\n' % (k_nnmf[i_p], k_nnmf[i_up], k_nnmf[i_hv]))
```

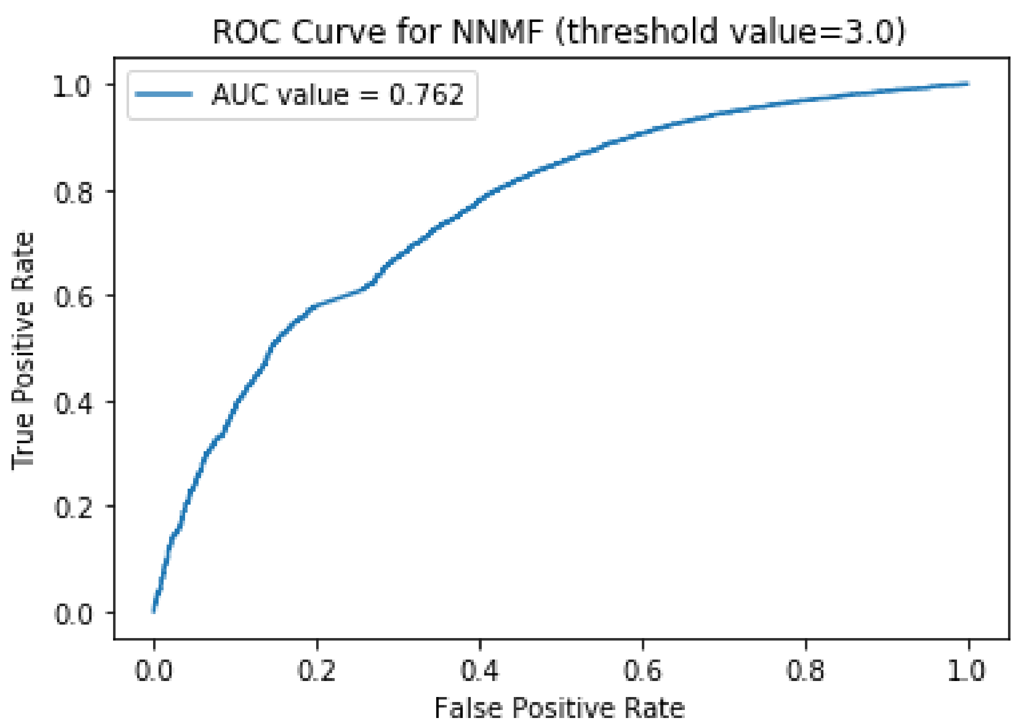
```
        print ('minimum average RMSE for (popular, unpopular, \
        high variance): \n(%.4f, %.4f, %.4f)\n' % (rmse_pop_nnmf[i_p], \
                                                    rmse_unpop_nnmf[i_up], \
                                                     rmse_highvar_nnmf[i_hv]))
```

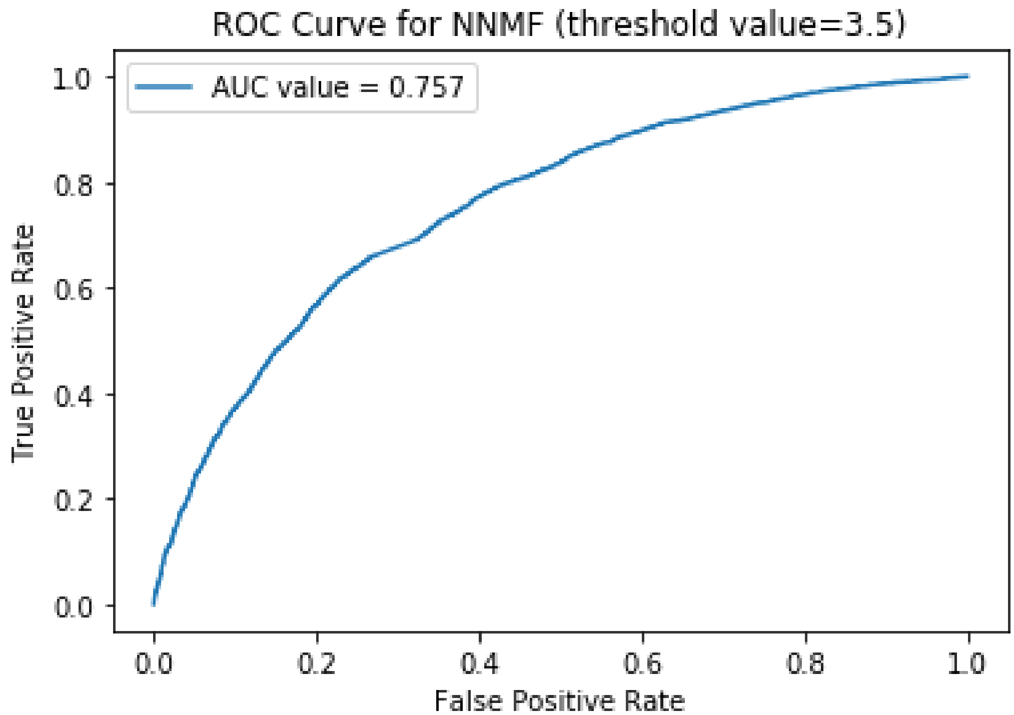
```
k that gives the minimum average RMSE for (popular, unpopular, high variance):
(14, 30, 18)

minimum average RMSE for (popular, unpopular, high variance):
(0.8911, 1.0331, 1.4156)
```

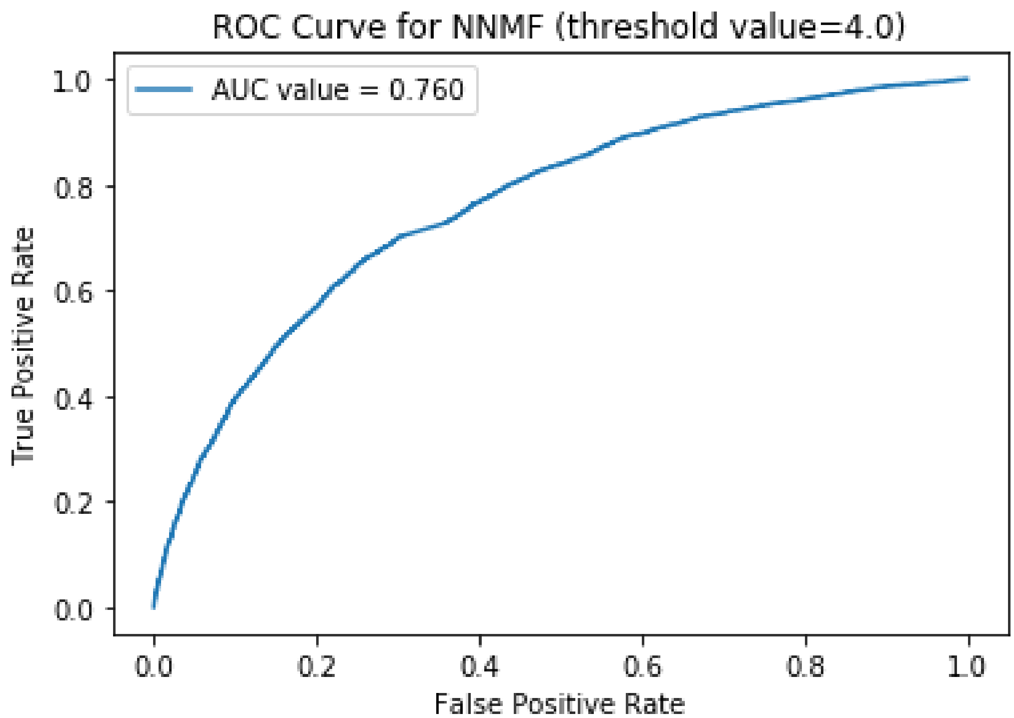
Question 22

```
In [121]: from sklearn import metrics
          from surprise.model_selection import train_test_split
          # use optimal number of latent factors that minimize RMSE
          opt_lfactor_nmf = 16
          thresholdlist = [2.5, 3, 3.5, 4]

          pred = None
          if GET_DATA_FROM_FILES and os.path.isfile("./pred_q22.pkl"):
              logging.info("Loading pred_q22.")
              pred = pickle.load(open("./pred_q22.pkl", "rb"))
          else:
              algo = NMF(n_factors=opt_lfactor_nmf)
              trainset, testset = train_test_split(data, test_size=.1)
              algo.fit(trainset)
              pred = algo.test(testset)
              pickle.dump(pred, open("./pred_q22.pkl", "wb"))

          for ths in thresholdlist:
              y_true=[]
              y_pred=[]
              for _,_,r_real,r_pred,_ in pred:
                  if r_real >= ths:
                      y_true.append(1)
                  else:
                      y_true.append(0)
                  y_pred.append(r_pred)
              fpr, tpr, _ = metrics.roc_curve(y_true=y_true, y_score=y_pred, pos_label=1)
              plt.plot(fpr, tpr, label='AUC value = %0.3f' % metrics.roc_auc_score(y_true=y_tru
              plt.xlabel('False Positive Rate')
              plt.ylabel('True Positive Rate')
              plt.title('ROC Curve for NNMF (threshold value=%.1f)' % ths)
              plt.legend()
              plt.show()
```


ROC Curve for NNMF (threshold value=2.5)
AUC value = 0.749
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0


ROC Curve for NNMF (threshold value=3.0)
AUC value = 0.762
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0


ROC Curve for NNMF (threshold value=3.5)
AUC value = 0.757
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0


ROC Curve for NNMF (threshold value=4.0)
AUC value = 0.760
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0

Question 23

```
In [65]: m_data = pd.read_csv('data/movies.csv', header=0, usecols=[0, 1, 2])
         print(m_data.head())

   movieId                               title  \
0        1                    Toy Story (1995)
1        2                      Jumanji (1995)
2        3             Grumpier Old Men (1995)
3        4            Waiting to Exhale (1995)
4        5  Father of the Bride Part II (1995)

                                        genres
0  Adventure|Animation|Children|Comedy|Fantasy
1                   Adventure|Children|Fantasy
2                               Comedy|Romance
3                         Comedy|Drama|Romance
4                                       Comedy
```

```
In [66]: k_q23=20
         algo = NMF(n_factors=k_q23)
         trainset = data.build_full_trainset()
         algo.fit(trainset)

         for c in range(10):
             col_top10 = np.argsort(-algo.qi[:,c])[:10]
             gcol = [m_data['genres'][i] for i in col_top10]
             print(gcol)
             print('-'*70)
```

```
['Comedy|Drama|Romance', 'Comedy', 'Drama', 'Drama', 'Comedy|Horror', 'Adventure|Animation|Chi
----------------------------------------------------------------------
['Comedy|Romance', 'Animation|Comedy|War', 'Drama', 'Comedy|Drama', 'Drama', 'Drama', 'Adventu
----------------------------------------------------------------------
['Drama|Horror|Thriller', 'Drama|Mystery|Thriller', 'Drama', 'Crime|Drama', 'Adventure|Sci-Fi|T
----------------------------------------------------------------------
['Horror|Sci-Fi|Thriller', 'Sci-Fi|Thriller', 'Mystery|Thriller', 'Drama|Thriller', 'Adventure
----------------------------------------------------------------------
['Crime|Drama', 'Drama', 'Drama', 'Drama', 'Drama|Musical', 'Comedy', 'Action|Adventure|Drama|W
----------------------------------------------------------------------
['Horror|Sci-Fi|Thriller', 'Crime|Drama', 'Comedy|Romance', 'Comedy', 'Comedy|Romance', 'Comedy
----------------------------------------------------------------------
['Crime|Drama|Film-Noir', 'Horror', 'Comedy|Romance', 'Drama|Romance', 'Comedy|Romance', 'Comed
----------------------------------------------------------------------
['Drama', 'Drama|Romance', 'Comedy', 'Comedy', 'Comedy|Drama|Thriller', 'Action|Adventure|Comed
----------------------------------------------------------------------
['Comedy|Musical', 'Comedy|Drama|Thriller', 'Crime|Drama', 'Drama|Thriller', 'Drama|Mystery',
```

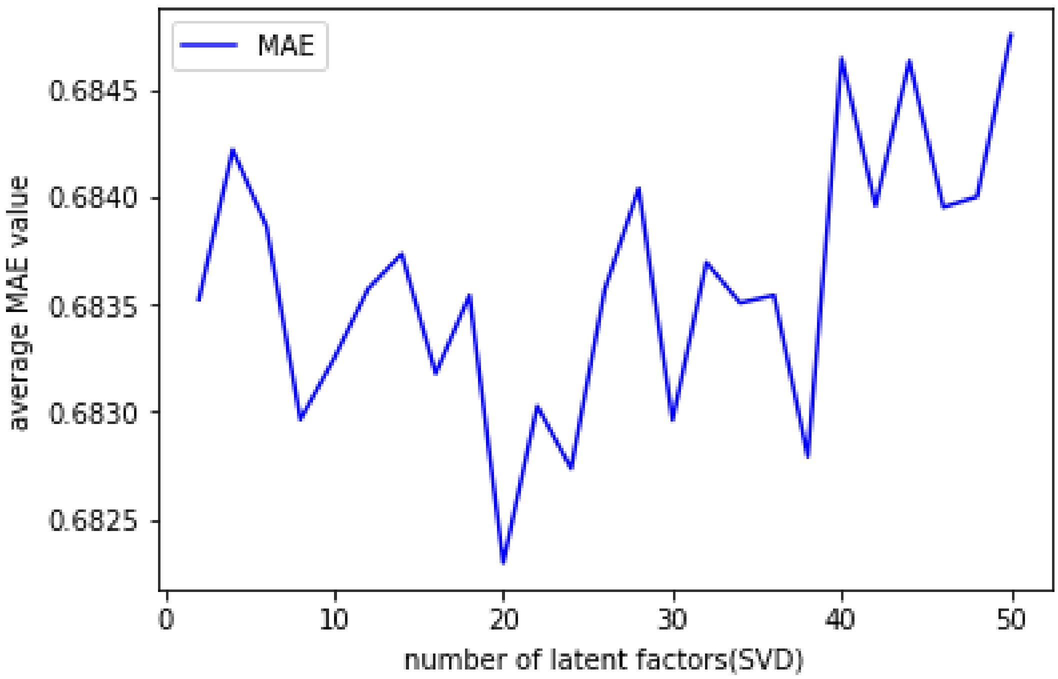
```
--------------------------------------------------------------------
['Crime|Drama', 'Action|Crime|Fantasy|Sci-Fi|Thriller', 'Crime|Drama', 'Crime|Drama', 'Comedy'
--------------------------------------------------------------------
```

Most of the top 10 movies in the first column belong to comedy or drama, and the second column shows the similar pattern but with more romance movies. For the third and fourth column there are some movies belong to the genre of thriller which did not appear in the first two columns. In the fifth column, two action movies were ranked top 10, while only one action movie showed up in top 10 in the fourth column and none of them showed up in the first three columns. There were 4 movies belong to the genre of romance while none of the romance movies showed up in the fifth column. In general, there are some relation between latent factors and movie genre, but not in a salient way. Further analysis on the movies might be needed to confirm the relation.

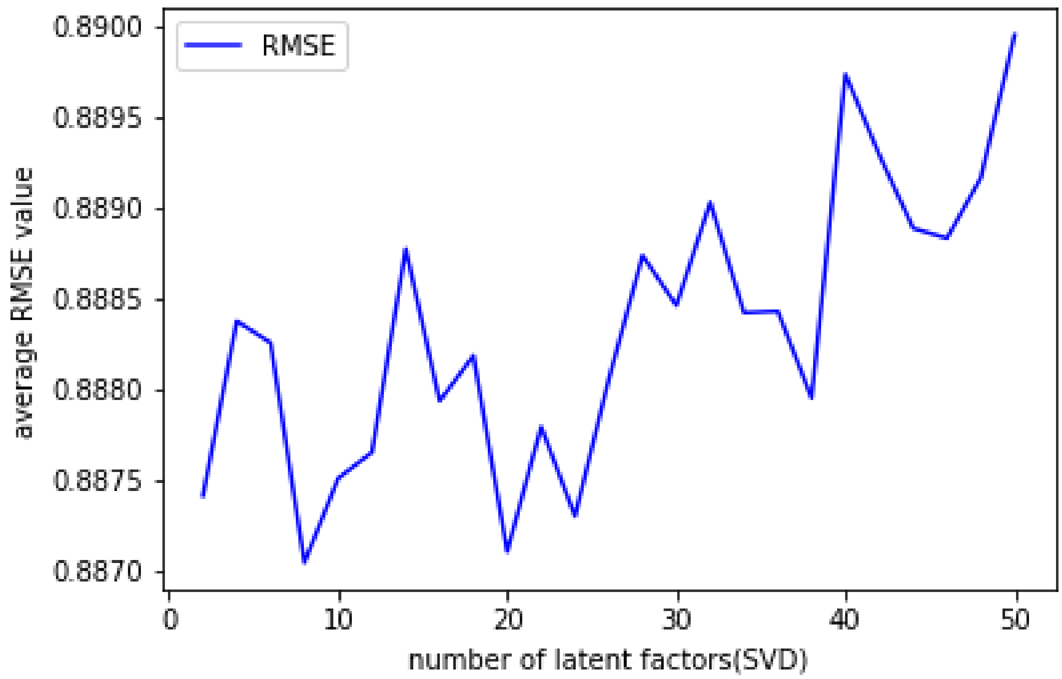
Question 24

```
In [67]: from surprise import SVD
         k_svd = range(2,51,2)

         rmse_svd=[]
         mae_svd=[]

         if GET_DATA_FROM_FILES and os.path.isfile("./rmse_svd.pkl")\
                             and os.path.isfile("./mae_svd.pkl"):
             logging.info("Loading rmse_svd and mae_svd.")
             rmse_svd = pickle.load(open("./rmse_svd.pkl", "rb"))
             mae_svd = pickle.load(open("./mae_svd.pkl", "rb"))
         else:
             for k in k_svd:
                 algo = SVD(n_factors=k, biased=True)
                 result = cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=10)
                 rmse_svd.append(np.mean(result['test_rmse']))
                 mae_svd.append(np.mean(result['test_mae']))

             pickle.dump(rmse_svd, open("./rmse_svd.pkl", "wb"))
             pickle.dump(mae_svd, open("./mae_svd.pkl", "wb"))
```

```
In [68]: l1, = plt.plot(k_svd, mae_svd, 'b-', label='MAE')
         plt.xlabel('number of latent factors(SVD)')
         plt.ylabel('average MAE value')
         plt.legend(handles=[l1])
         plt.show()
```




```
In [69]: l2, = plt.plot(k_svd, rmse_svd, 'b-', label='RMSE')
         plt.xlabel('number of latent factors(SVD)')
         plt.ylabel('average RMSE value')
         plt.legend(handles=[l2])
         plt.show()
```



Question 25

```
In [70]: i = np.argsort(rmse_svd)[0]
         print('the value of k that gives the minimum average RMSE')
         print(k_svd[i])
         print('minimum average RMSE:')
         print(rmse_svd[i])
```

```
the value of k that gives the minimum average RMSE
8
minimum average RMSE:
0.887038486842
```

```
In [71]: i = np.argsort(mae_svd)[0]
         print('the value of k that gives the minimum average MAE')
         print(k_svd[i])
         print('minimum average MAE:')
         print(mae_svd[i])
```

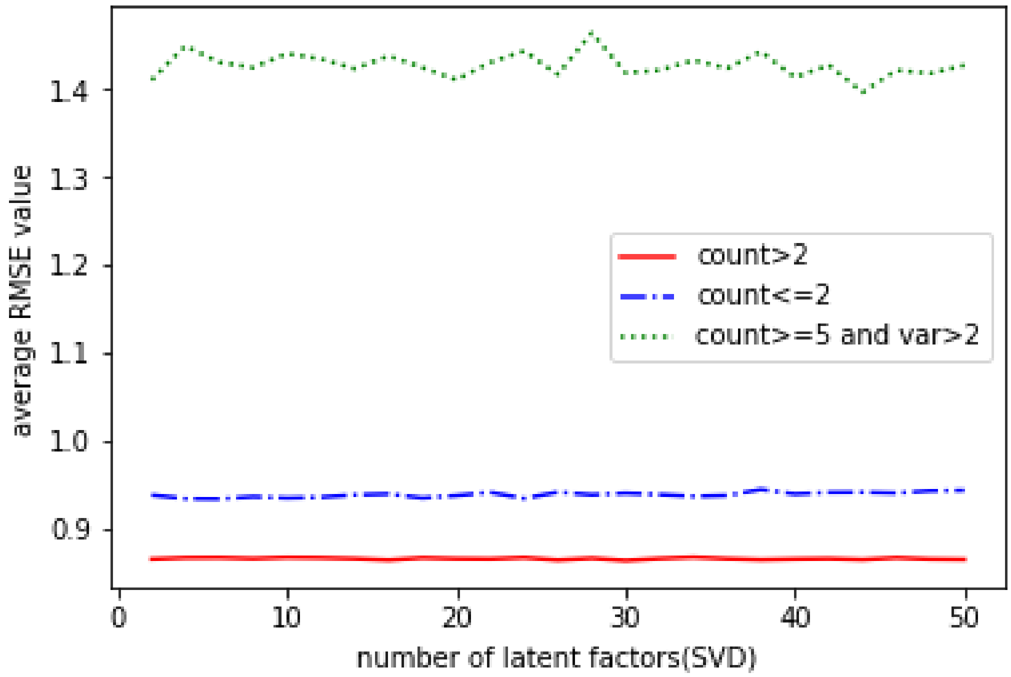
```
the value of k that gives the minimum average MAE
20
minimum average MAE:
0.682298752979
```

Question 26,27,28

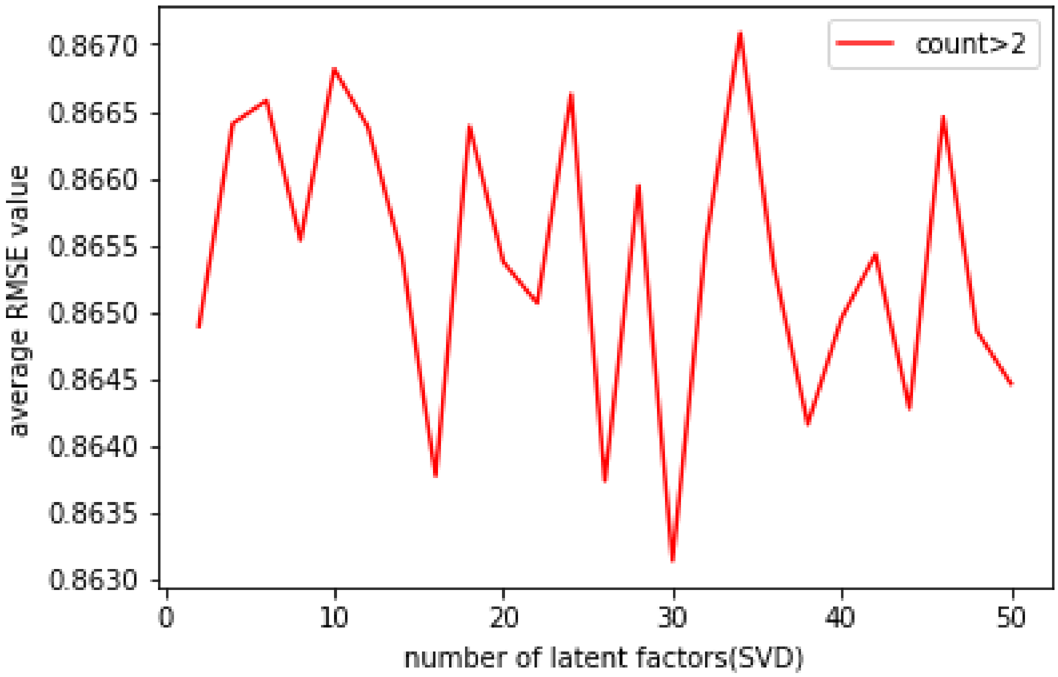
```
In [72]: rmse_pop_svd = []
         rmse_unpop_svd = []
         rmse_highvar_svd = []

         if GET_DATA_FROM_FILES and os.path.isfile("./rmse_pop_svd.pkl")\
                                and os.path.isfile("./rmse_unpop_svd.pkl")\
                                and os.path.isfile("./rmse_highvar_svd.pkl"):
             logging.info("Loading rmse_pop_svd, rmse_unpop_svd and rmse_highvar_svd.")
             rmse_pop_svd = pickle.load(open("./rmse_pop_svd.pkl", "rb"))
             rmse_unpop_svd = pickle.load(open("./rmse_unpop_svd.pkl", "rb"))
             rmse_highvar_svd = pickle.load(open("./rmse_highvar_svd.pkl", "rb"))
         else:
             for k in k_svd:
                 rmse_temp_pop_svd = []
                 rmse_temp_unpop_svd = []
                 rmse_temp_highvar_svd = []
                 algo = SVD(n_factors=k, biased=True)
                 for trainset,testset in kf.split(data):
                     algo.fit(trainset)
                     predictions_pop_svd = algo.test(trim_popular(testset))
                     predictions_unpop_svd = algo.test(trim_unpopular(testset))
                     predictions_highvar_svd = algo.test(trim_highvar(testset))
                     rmse_temp_pop_svd.append(accuracy.rmse(predictions_pop_svd))
                     rmse_temp_unpop_svd.append(accuracy.rmse(predictions_unpop_svd))
                     rmse_temp_highvar_svd.append(accuracy.rmse(predictions_highvar_svd))
                 rmse_pop_svd.append(np.mean(rmse_temp_pop_svd))
                 rmse_unpop_svd.append(np.mean(rmse_temp_unpop_svd))
                 rmse_highvar_svd.append(np.mean(rmse_temp_highvar_svd))

             pickle.dump(rmse_pop_svd, open("./rmse_pop_svd.pkl", "wb"))
             pickle.dump(rmse_unpop_svd, open("./rmse_unpop_svd.pkl", "wb"))
             pickle.dump(rmse_highvar_svd, open("./rmse_highvar_svd.pkl", "wb"))

         print(rmse_pop_svd[:5])
```

```
[0.86489182034745793, 0.86640780476399881, 0.86658046334978012, 0.86553412597164725, 0.8668158
```

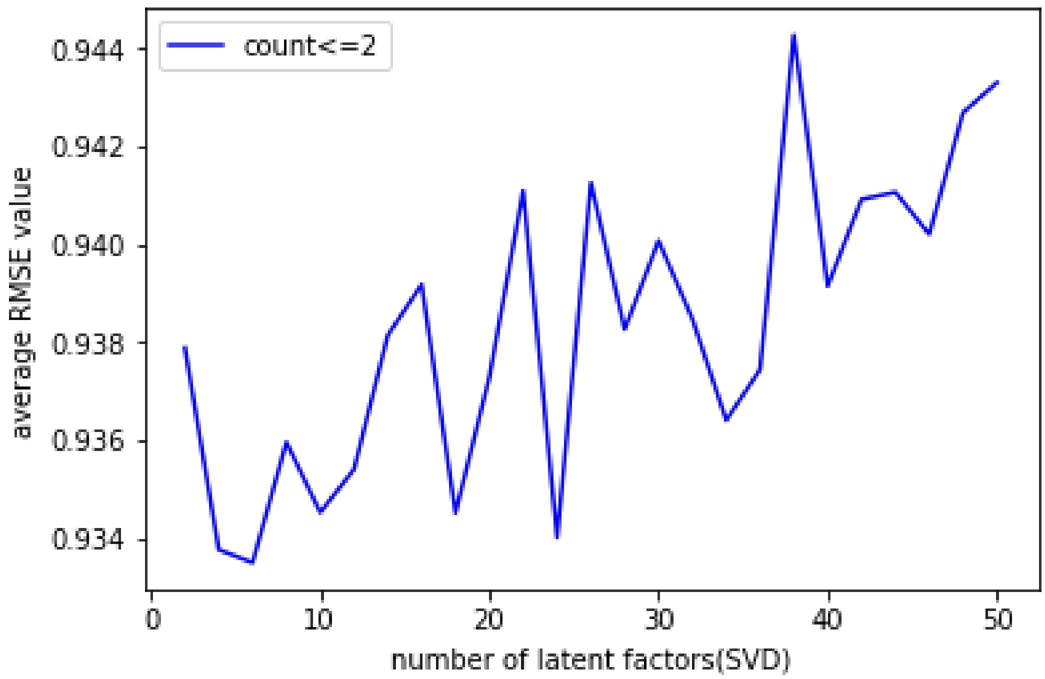
```
In [73]: l1, = plt.plot(k_svd, rmse_pop_svd, 'r-', label='count>2')
         l2, = plt.plot(k_svd, rmse_unpop_svd, 'b-.', label='count<=2')
         l3, = plt.plot(k_svd, rmse_highvar_svd, 'g:', label='count>=5 and var>2')
         plt.xlabel('number of latent factors(SVD)')
         plt.ylabel('average RMSE value')
         plt.legend(handles=[l1, l2, l3])
         plt.show()
```



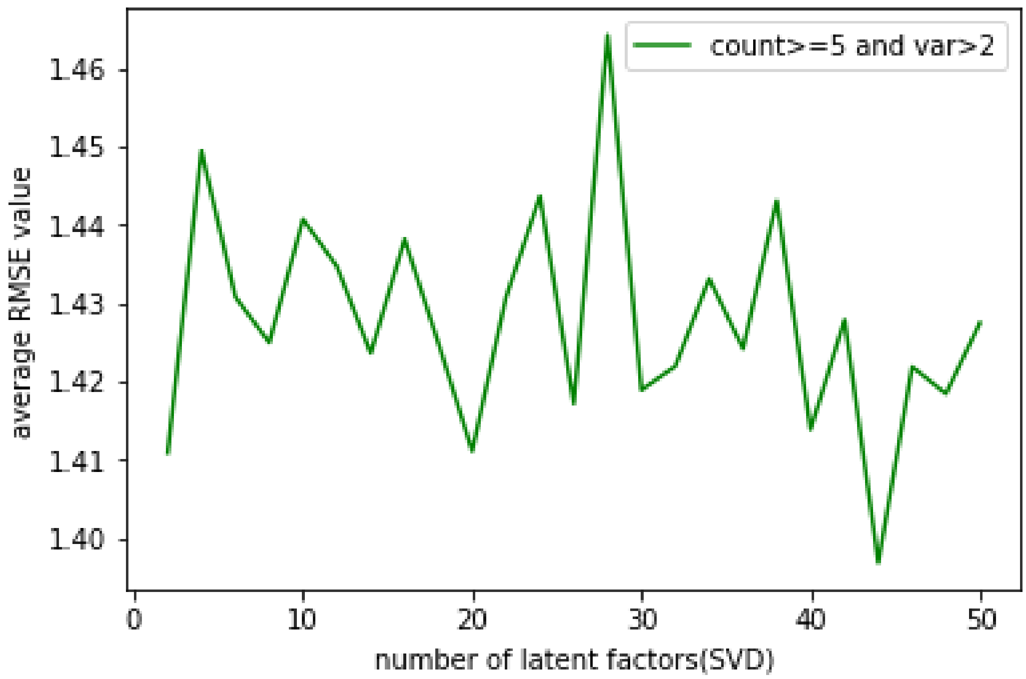
In [74]:
```
l1, = plt.plot(k_svd, rmse_pop_svd, 'r-', label='count>2')
plt.xlabel('number of latent factors(SVD)')
plt.ylabel('average RMSE value')
plt.legend(handles=[l1])
plt.show()
```



In [75]:
```
l2, = plt.plot(k_svd, rmse_unpop_svd, 'b-', label='count<=2')
plt.xlabel('number of latent factors(SVD)')
plt.ylabel('average RMSE value')
plt.legend(handles=[l2])
plt.show()
```



In [76]:
```
l3, = plt.plot(k_svd, rmse_highvar_svd, 'g-', label='count>=5 and var>2')
plt.xlabel('number of latent factors(SVD)')
plt.ylabel('average RMSE value')
plt.legend(handles=[l3])
plt.show()
```



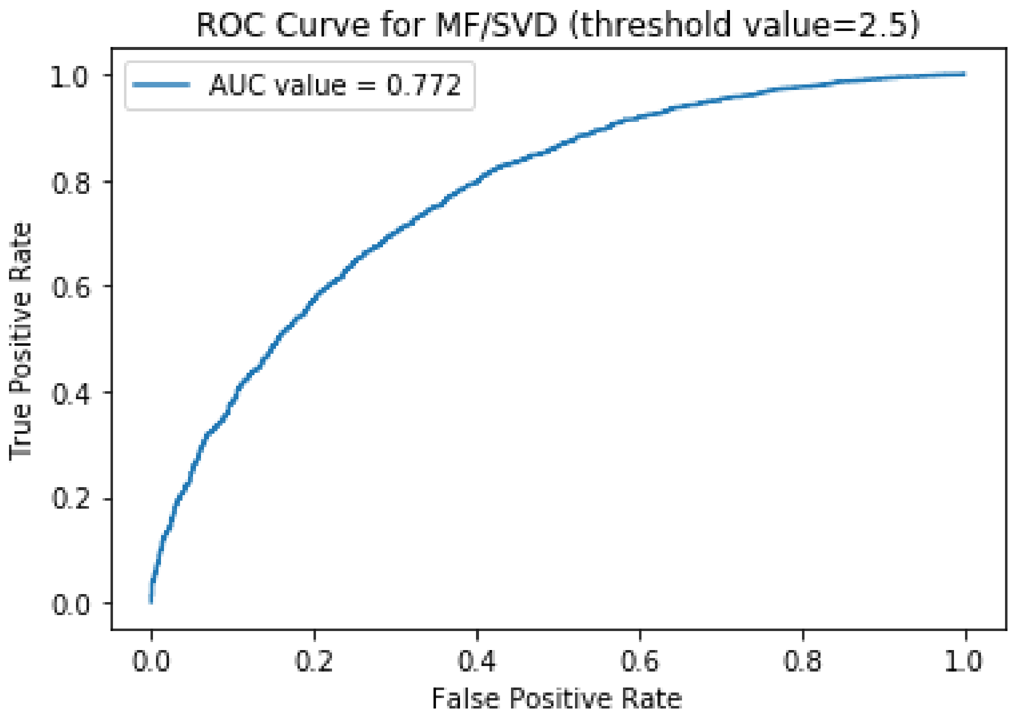

```
In [77]: i_p = np.argsort(rmse_pop_svd)[0]
         i_up = np.argsort(rmse_unpop_svd)[0]
         i_hv = np.argsort(rmse_highvar_svd)[0]
         print ('k that gives the minimum average RMSE for (popular, unpopular, \
         high variance): \n(%d, %d, %d)\n' % (k_svd[i_p], k_svd[i_up], k_svd[i_hv]))

         print ('minimum average RMSE for (popular, unpopular, \
         high variance): \n(%.4f, %.4f, %.4f)\n' % (rmse_pop_svd[i_p], \
                                                    rmse_unpop_svd[i_up], \
                                                     rmse_highvar_svd[i_hv]))
```

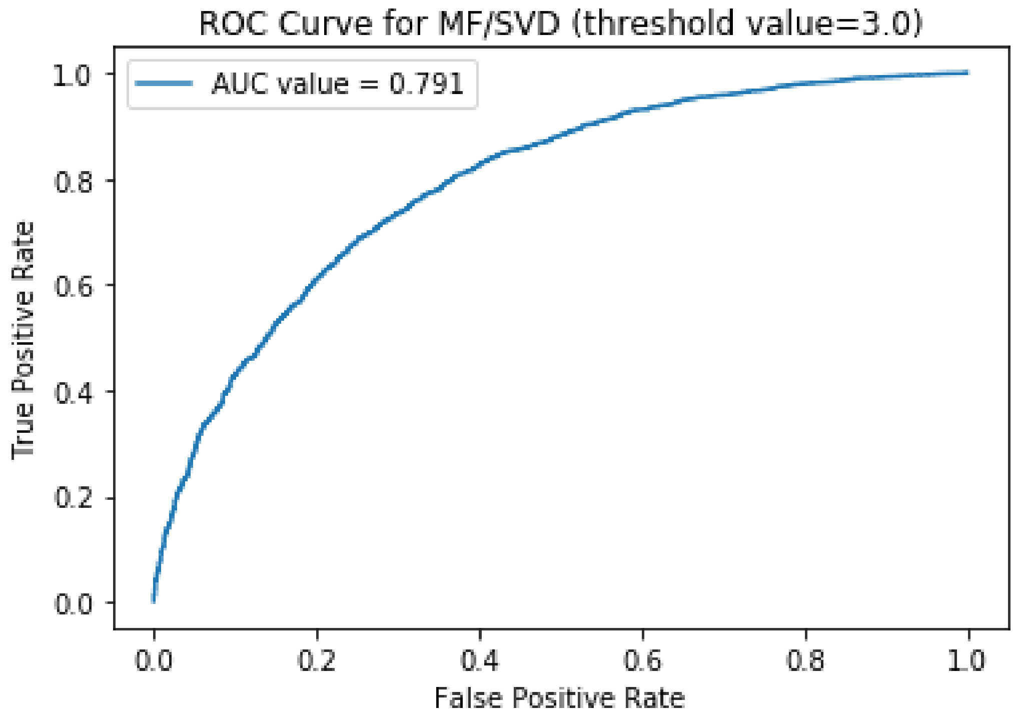
```
k that gives the minimum average RMSE for (popular, unpopular, high variance):
(30, 6, 44)

minimum average RMSE for (popular, unpopular, high variance):
(0.8631, 0.9335, 1.3969)
```

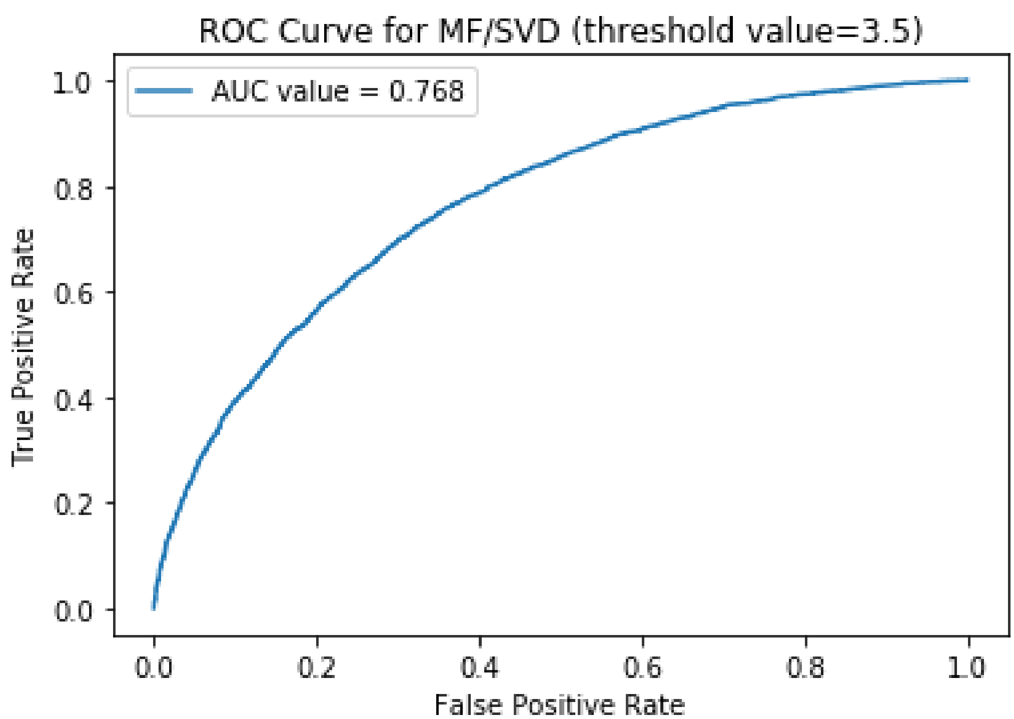
Question 29

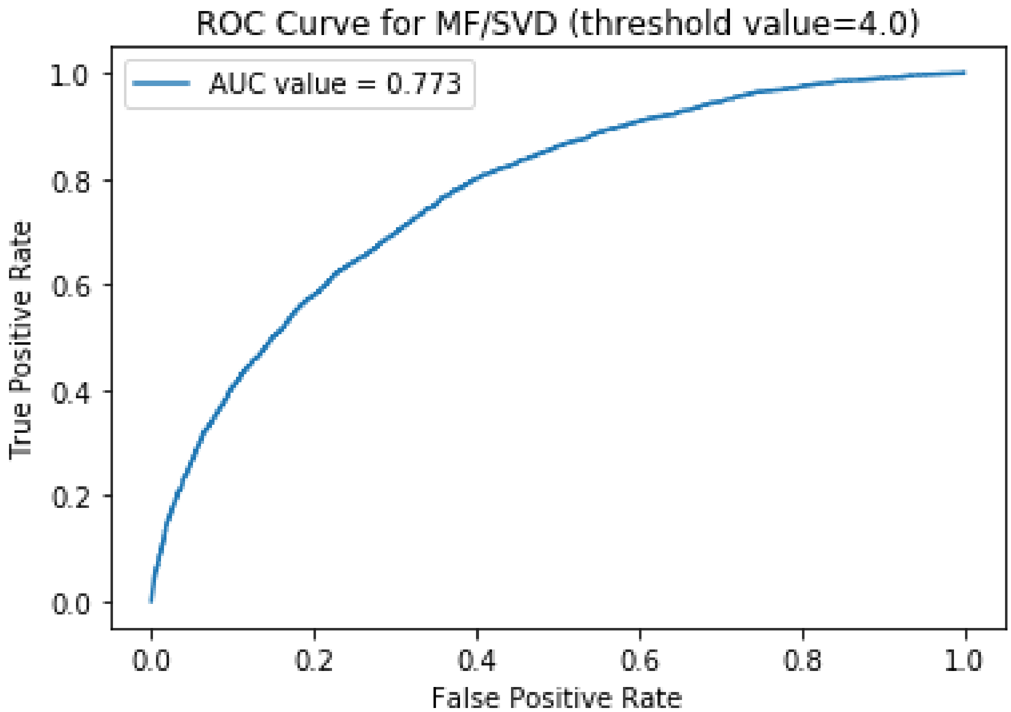
```
In [123]: opt_lfactor_svd = 18

          pred = None
          if GET_DATA_FROM_FILES and os.path.isfile("./pred_q29.pkl"):
```

```
    logging.info("Loading pred_q29.")
    pred = pickle.load(open("./pred_q29.pkl", "rb"))
else:
    algo = SVD(n_factors=opt_lfactor_svd, biased=True)
    trainset, testset = train_test_split(data, test_size=.1)
    algo.fit(trainset)
    pred = algo.test(testset)
    pickle.dump(pred, open("./pred_q29.pkl", "wb"))

for ths in thresholdlist:
    y_true=[]
    y_pred=[]
    for _,_,r_real,r_pred,_ in pred:
        if r_real >= ths:
            y_true.append(1)
        else:
            y_true.append(0)
        y_pred.append(r_pred)
    fpr, tpr, _ = metrics.roc_curve(y_true=y_true, y_score=y_pred, pos_label=1)
    plt.plot(fpr, tpr, label='AUC value = %0.3f' % metrics.roc_auc_score(y_true=y_tru
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve for MF/SVD (threshold value=%.1f)' % ths)
    plt.legend()
    plt.show()
```




ROC Curve for MF/SVD (threshold value=3.0)
AUC value = 0.791
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0


ROC Curve for MF/SVD (threshold value=3.5)
AUC value = 0.768
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0



Question 30

```
In [79]: from surprise import AlgoBase

         class Naive(AlgoBase):

             def __init__(self):

                 # Always call base method before doing anything.
                 AlgoBase.__init__(self)

             def fit(self, trainset):

                 # Here again: call base method before doing anything.
                 AlgoBase.fit(self, trainset)
                 self.udict = dict()

                 try:
                     for uid in self.trainset.all_users():
                         self.udict[uid] = np.mean([r for (_, r) in
                                                    self.trainset.ur[uid]])
```

```
                except StopIteration:
                    pass


            def estimate(self, u, i):
                if u in self.udict:
                    return self.udict[u]
                else:
                    return trainset.global_mean


        algo = Naive()
        algo.fit(trainset)

        result = cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=10, n_jobs=1)
```

```
In [80]: print (np.mean(result['test_rmse']))
         print (np.mean(result['test_mae']))
```

```
0.962137823277
0.749825023377
```

Question 31,32,33

```
In [103]: kf = KFold(n_splits=10)

          rmse_temp_pop_naive = []
          rmse_temp_unpop_naive = []
          rmse_temp_highvar_naive = []
          algo = Naive()
          for trainset,testset in kf.split(data):
              algo.fit(trainset)
              predictions_pop_naive = algo.test(trim_popular(testset))
              predictions_unpop_naive = algo.test(trim_unpopular(testset))
              predictions_highvar_naive = algo.test(trim_highvar(testset))
              rmse_temp_pop_naive.append(accuracy.rmse(predictions_pop_naive, verbose=False))
              rmse_temp_unpop_naive.append(accuracy.rmse(predictions_unpop_naive, verbose=Fals
              rmse_temp_highvar_naive.append(accuracy.rmse(predictions_highvar_naive, verbose=
```

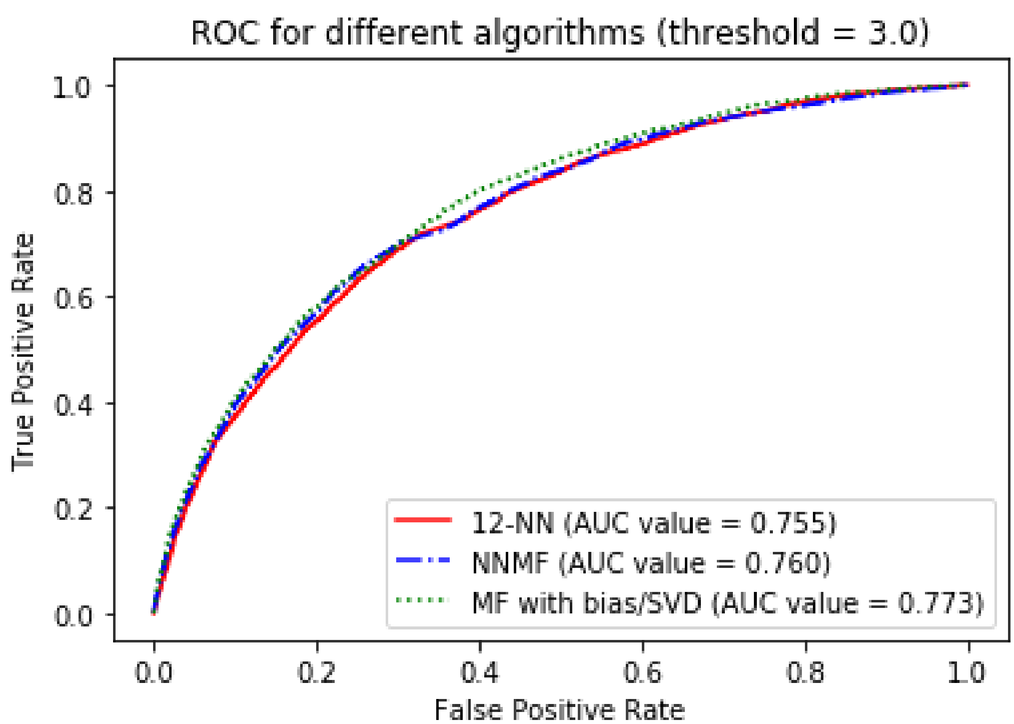
```
In [104]: print('average RMSE for (popular, unpopular, \
          high variance): \n(%.4f, %.4f, %.4f)\n' % (np.mean(rmse_temp_pop_naive), \
                                                     np.mean(rmse_temp_unpop_naive), \
                                                      np.mean(rmse_temp_highvar_naive)))
```

```
average RMSE for (popular, unpopular, high variance):
(0.9483, 0.9944, 1.4508)
```

Question 34

```
In [113]: pred_svd = None
          if GET_DATA_FROM_FILES and os.path.isfile("./pred_q29.pkl"):
              logging.info("Loading pred_q29.")
              pred_svd = pickle.load(open("./pred_q29.pkl", "rb"))
          else:
              algo = SVD(n_factors=opt_lfactor_svd, biased=True)
              trainset, testset = train_test_split(data, test_size=.1)
              algo.fit(trainset)
              pred_svd = algo.test(testset)
              pickle.dump(pred_svd, open("./pred_q29.pkl", "wb"))

          pred_nmf = None
          if GET_DATA_FROM_FILES and os.path.isfile("./pred_q22.pkl"):
              logging.info("Loading pred_q22.")
              pred_nmf = pickle.load(open("./pred_q22.pkl", "rb"))
          else:
              algo = NMF(n_factors=opt_lfactor_nmf)
              trainset, testset = train_test_split(data, test_size=.1)
              algo.fit(trainset)
              pred_nmf = algo.test(testset)
              pickle.dump(pred_nmf, open("./pred_q22.pkl", "wb"))

          pred_knn = None
          if GET_DATA_FROM_FILES and os.path.isfile("./pred_q15.pkl"):
              logging.info("Loading pred_q15.")
              pred_knn = pickle.load(open("./pred_q15.pkl", "rb"))
          else:
              algo = surprise.prediction_algorithms.knns.KNNWithMeans(k=mink, sim_options=sim_
              trainset, testset = train_test_split(data, test_size=.1)
              algo.fit(trainset)
              pred_knn = algo.test(testset)
              pickle.dump(pred_knn, open("./pred_q15.pkl", "wb"))

          thres_q34 = 3.0
          pred_list = [pred_knn, pred_nmf, pred_svd]
          pred_list_name = ['%d-NN' % mink,
                            'NNMF',
                           'MF with bias/SVD']
          pred_line = []
          pred_line_opt = ['r-', 'b-.', 'g:']
          for idx, pred in enumerate(pred_list):
              y_true=[]
              y_pred=[]
              for _,_,r_real,r_pred,_ in pred:
                  if r_real >= ths:
                      y_true.append(1)
```

```
            else:
                y_true.append(0)
            y_pred.append(r_pred)
        fpr, tpr, _ = metrics.roc_curve(y_true=y_true, y_score=y_pred, pos_label=1)
        label = pred_list_name[idx] + ' (AUC value = %0.3f)' % metrics.roc_auc_score(y_t
        l, = plt.plot(fpr, tpr, pred_line_opt[idx], label=label)
        pred_line.append(l)


    plt.legend(handles=pred_line)
    plt.title('ROC for different algorithms (threshold = %.1f)' % thres_q34)
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.show()
```



All three filters (12-NN, NNMF, MF with bias) performed similarly based on the ROC curve. Thus, we can conclude that these three filters are equally good in predicting ratings of movies.

Question 35 Precision in this case measures how many of the recommended movies are liked, while recall measures among all the movies that are liked, how many of them are recommended by the filter.

Question 36

```
In [140]: from collections import defaultdict

          def precision_n_recall(predictions, th=3.0, t=1, verbose=True):

              if not predictions:
                  raise ValueError('Prediction list is empty.')

              user_true_est = defaultdict(list)
              for uid, _, r_ui, est, _ in predictions:
                  user_true_est[uid].append((r_ui, est))

              precision_lst = []
              recall_lst = []
              for uid, true_est in user_true_est.items():
                  true_est.sort(key=lambda x: x[1], reverse=True)
                  recommend_set = true_est[:t]
                  rec = sum((est > th) for (_, est) in recommend_set)
                  like = sum((r_ui > th) for (r_ui, _) in recommend_set)
                  rec_n_like = sum((r_ui > th) and (est > th)\
                                                for (r_ui, est) in recommend_set)
                  if (rec!=0):
                      precision_lst.append(rec_n_like*1.0/rec)
                  if (like!=0):
                      recall_lst.append(rec_n_like*1.0/like)

              precision = np.mean(precision_lst)
              recall = np.mean(recall_lst)
              if verbose:
                  print('Precision: {0:1.3f}'.format(precision))
                  print('Recall: {0:1.3f}'.format(recall))
              return precision, recall

In [145]: t_lst = range(1,26,1)

          knn_precis = defaultdict(list)
          knn_recall = defaultdict(list)
          thres = 3.0

          algo = surprise.prediction_algorithms.knns.KNNWithMeans(k=mink, sim_options=sim_optio

          for trainset,testset in kf.split(data):
              algo.fit(trainset)
              pred = algo.test(testset)
              for t in t_lst:
                  p, r = precision_n_recall(pred, t=t, th = thres, verbose=False)
                  knn_precis[t].append(p)
                  knn_recall[t].append(r)
```

```
ave_precis_knn = [np.mean(ls) for _, ls in knn_precis.items()]
ave_recall_knn = [np.mean(ls) for _, ls in knn_recall.items()]
```

```
Computing the pearson similarity matrix...
Done computing similarity matrix.
Computing the pearson similarity matrix...
Done computing similarity matrix.
Computing the pearson similarity matrix...
Done computing similarity matrix.
Computing the pearson similarity matrix...
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Computing the pearson similarity matrix...
Done computing similarity matrix.
Computing the pearson similarity matrix...
Done computing similarity matrix.
Computing the pearson similarity matrix...
Done computing similarity matrix.
Computing the pearson similarity matrix...
Done computing similarity matrix.
```
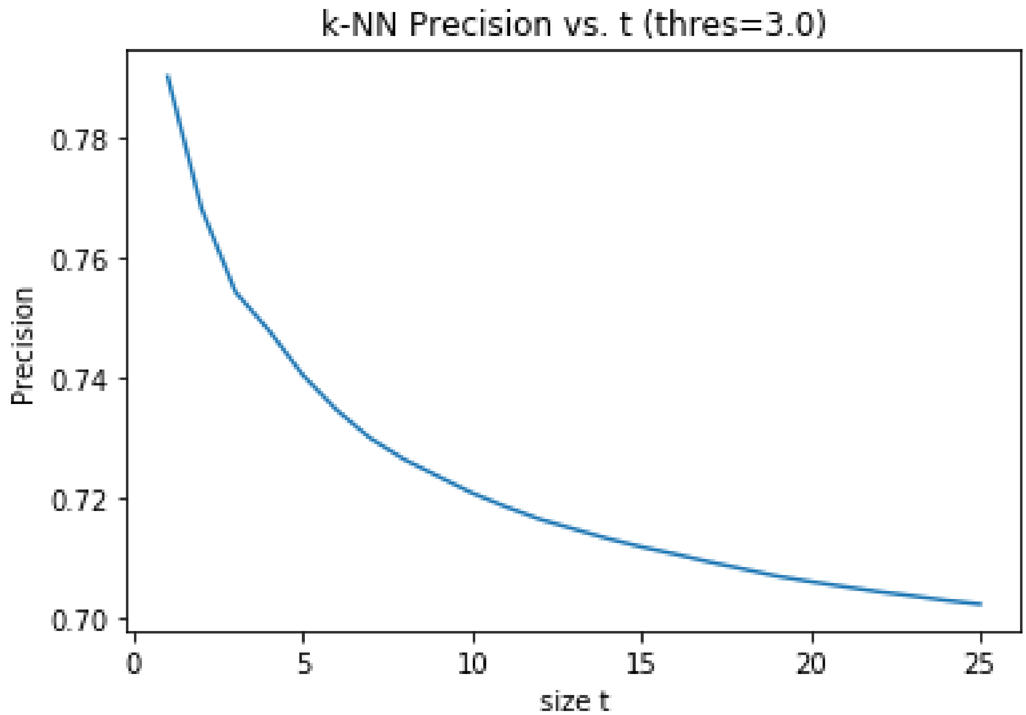
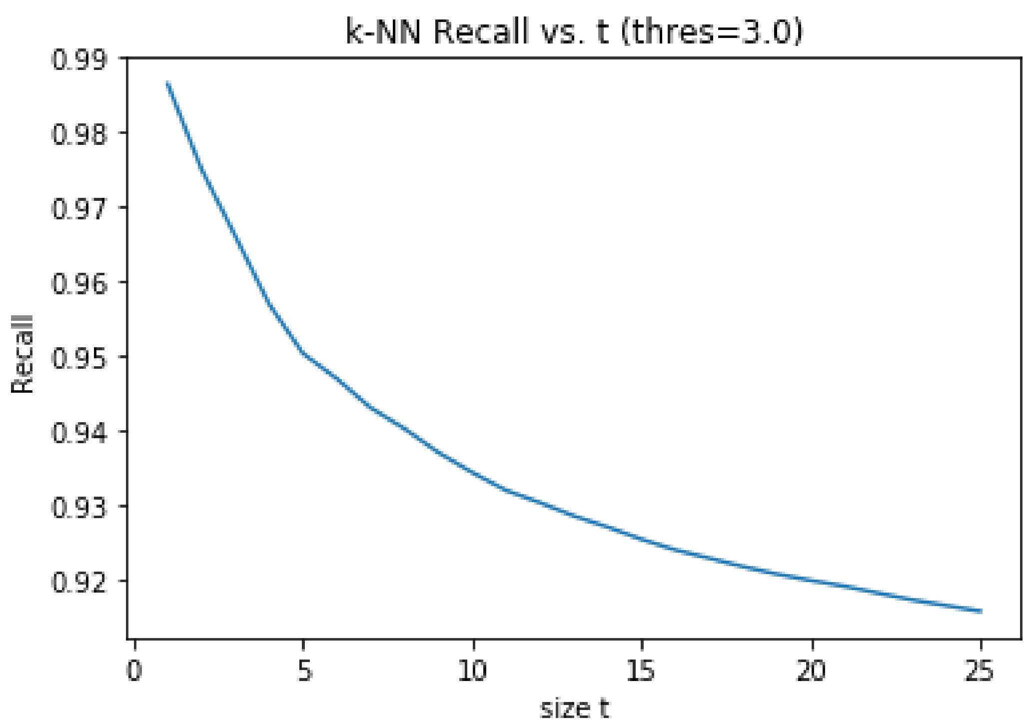
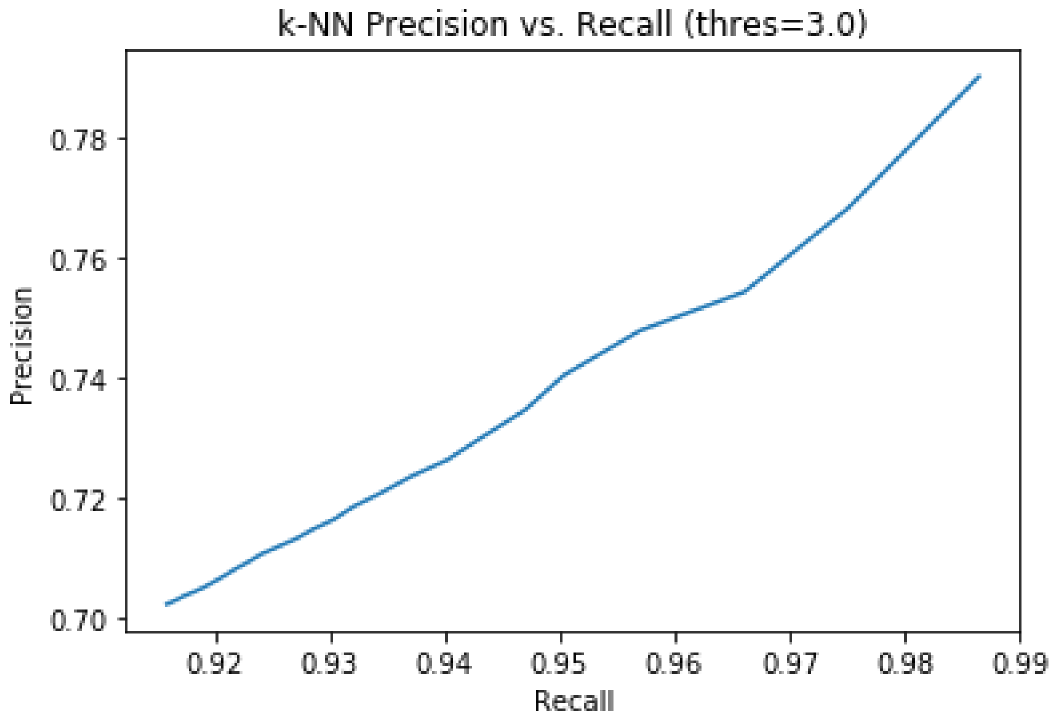

```
In [146]: plt.figure()
          plt.title("k-NN Precision vs. t (thres=%.1f)" % thres)
          plt.ylabel("Precision")
          plt.xlabel("size t")
          plt.plot(t_lst, ave_precis_knn)
          plt.show()

          plt.figure()
          plt.title("k-NN Recall vs. t (thres=%.1f)" % thres)
          plt.ylabel("Recall")
          plt.xlabel("size t")
          plt.plot(t_lst, ave_recall_knn)
          plt.show()

          plt.figure()
          plt.title("k-NN Precision vs. Recall (thres=%.1f)" % thres)
          plt.ylabel("Precision")
          plt.xlabel("Recall")
          plt.plot(ave_recall_knn, ave_precis_knn)
          plt.show()
```


k-NN Precision vs. t (thres=3.0)
Precision
0.78
0.76
0.74
0.72
0.70
0
5
10
15
20
25
size t


k-NN Recall vs. t (thres=3.0)
Recall
0.99
0.98
0.97
0.96
0.95
0.94
0.93
0.92
0
5
10
15
20
25
size t

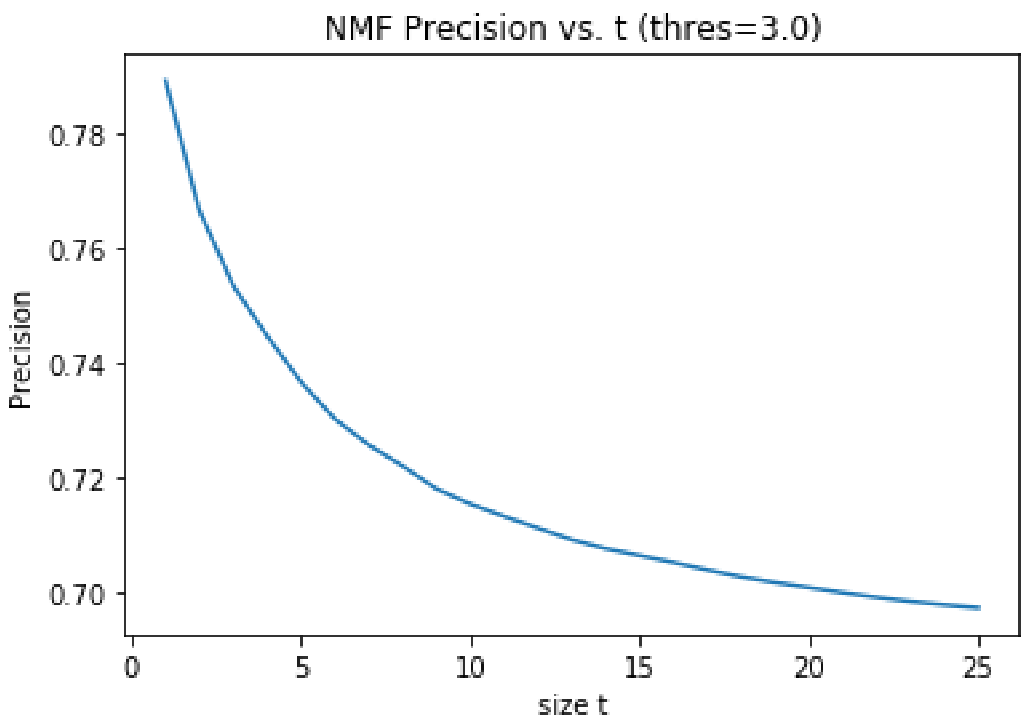


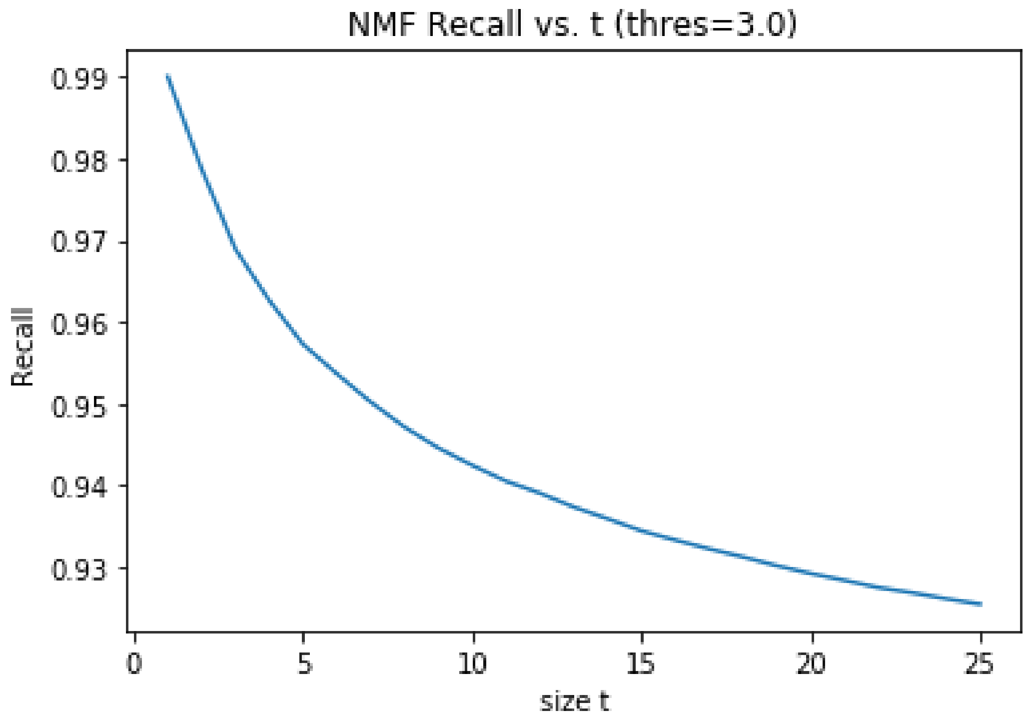
From the graph of precision vs t, it is clear that the precision of k-NN filter decreased when the rank of the movie went lower. From the graph of recall vs t, it is clear that the recall of k-NN filter also decreased when the rank of the movie went lower. From the graph of precision vs recall, we can see that the precision and the recall were positively corelated with each other. In conclusion, the k-NN filter performed better for higher ranked movies.

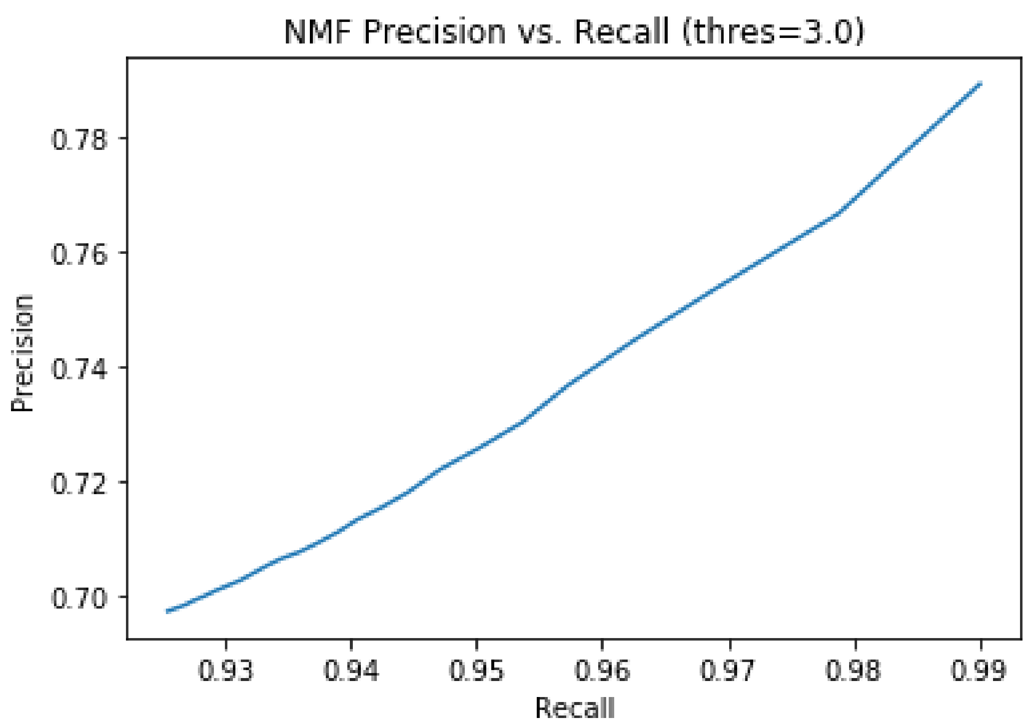
Question 37

```
In [147]: nmf_precis = defaultdict(list)
          nmf_recall = defaultdict(list)
          thres = 3.0

          algo = NMF(n_factors=k_q23)

          for trainset,testset in kf.split(data):
              algo.fit(trainset)
              pred = algo.test(testset)
              for t in t_lst:
                  p, r = precision_n_recall(pred, t=t, th = thres, verbose=False)
                  nmf_precis[t].append(p)
                  nmf_recall[t].append(r)

          ave_precis_nmf = [np.mean(ls) for _, ls in nmf_precis.items()]
          ave_recall_nmf = [np.mean(ls) for _, ls in nmf_recall.items()]
```

In [148]:
```
plt.figure()
plt.title("NMF Precision vs. t (thres=%.1f)" % thres)
plt.ylabel("Precision")
plt.xlabel("size t")
plt.plot(t_lst, ave_precis_nmf)
plt.show()

plt.figure()
plt.title("NMF Recall vs. t (thres=%.1f)" % thres)
plt.ylabel("Recall")
plt.xlabel("size t")
plt.plot(t_lst, ave_recall_nmf)
plt.show()

plt.figure()
plt.title("NMF Precision vs. Recall (thres=%.1f)" % thres)
plt.ylabel("Precision")
plt.xlabel("Recall")
plt.plot(ave_recall_nmf, ave_precis_nmf)
plt.show()
```




NMF Recall vs. t (thres=3.0)
Recall
0.99
0.98
0.97
0.96
0.95
0.94
0.93
0
5
10
15
20
25
size t

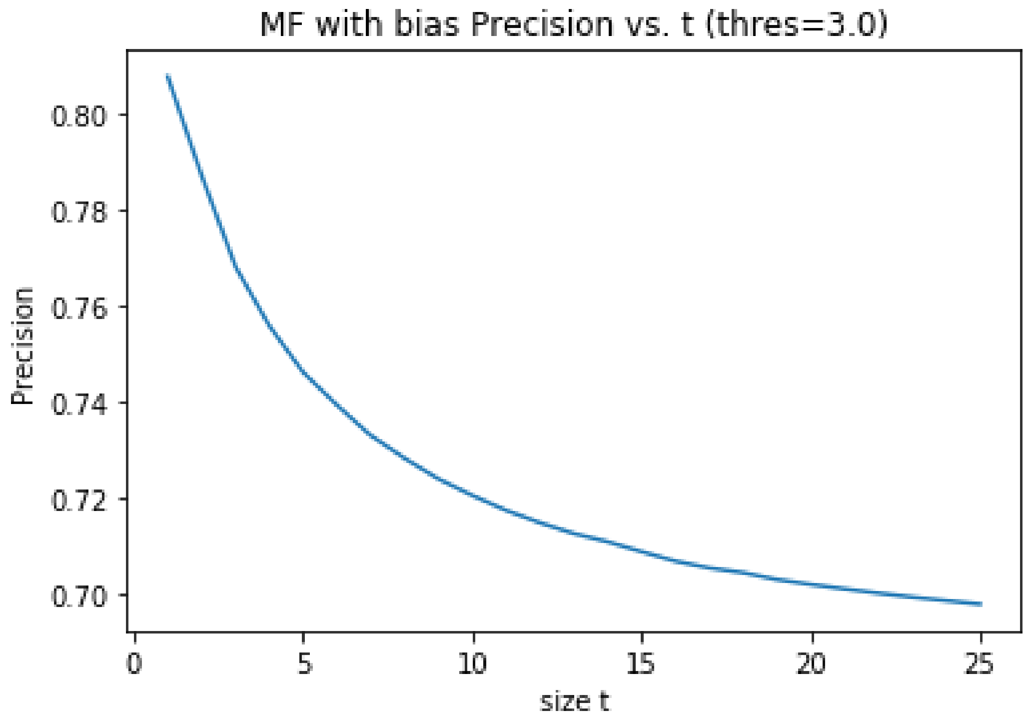

NMF Precision vs. Recall (thres=3.0)
Precision
0.78
0.76
0.74
0.72
0.70
0.93
0.94
0.95
0.96
0.97
0.98
0.99
Recall

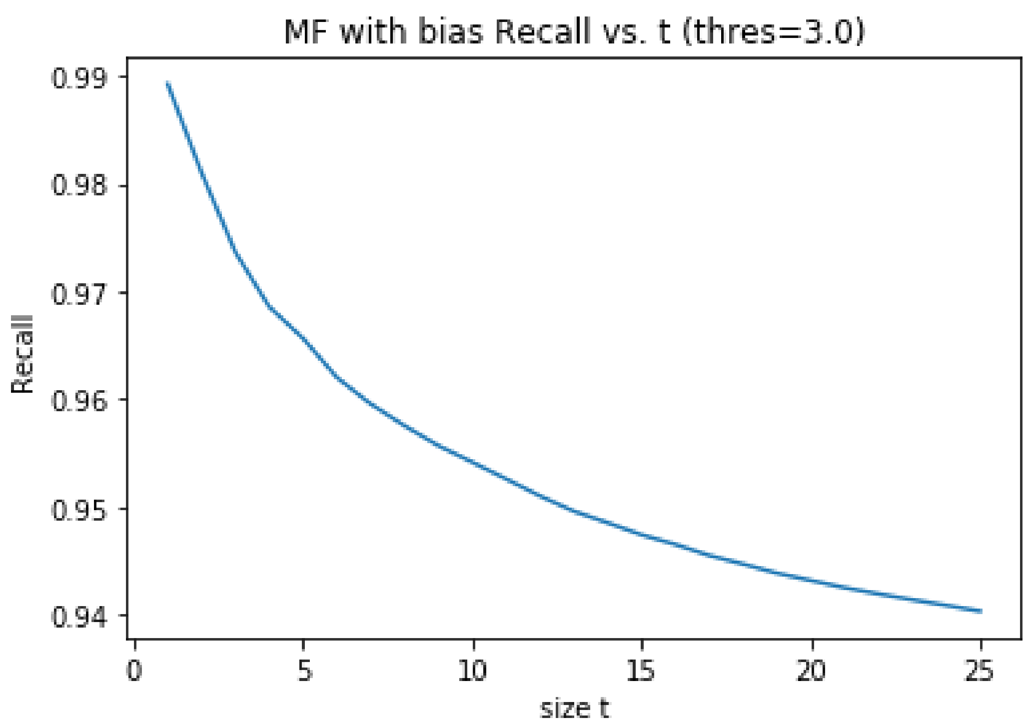
From the graph of precision vs t, it is clear that the precision of NNMF filter decreased when the rank of the movie went lower. From the graph of recall vs t, it is clear that the recall of NNMF filter also decreased when the rank of the movie went lower. From the graph of precision vs recall, we can see that the precision and the recall were positively corelated with each other. In conclusion, the NNMF filter performed better for higher ranked movies.

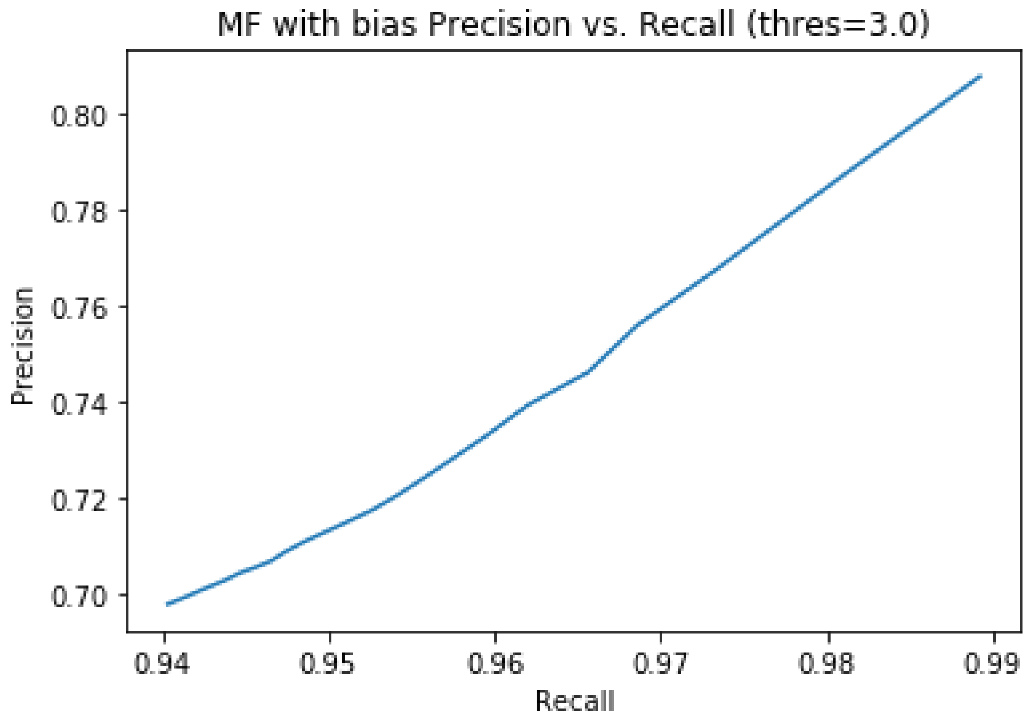
Question 38

In [149]:
```
svd_precis = defaultdict(list)
svd_recall = defaultdict(list)
thres = 3.0

algo = SVD(n_factors=opt_lfactor_svd, biased=True)

for trainset,testset in kf.split(data):
    algo.fit(trainset)
    pred = algo.test(testset)
    for t in t_lst:
        p, r = precision_n_recall(pred, t=t, th = thres, verbose=False)
        svd_precis[t].append(p)
        svd_recall[t].append(r)

ave_precis_svd = [np.mean(ls) for _, ls in svd_precis.items()]
ave_recall_svd = [np.mean(ls) for _, ls in svd_recall.items()]
```

In [150]:
```
plt.figure()
plt.title("MF with bias Precision vs. t (thres=%.1f)" % thres)
plt.ylabel("Precision")
plt.xlabel("size t")
plt.plot(t_lst, ave_precis_svd)
plt.show()

plt.figure()
plt.title("MF with bias Recall vs. t (thres=%.1f)" % thres)
plt.ylabel("Recall")
plt.xlabel("size t")
plt.plot(t_lst, ave_recall_svd)
plt.show()

plt.figure()
plt.title("MF with bias Precision vs. Recall (thres=%.1f)" % thres)
plt.ylabel("Precision")
plt.xlabel("Recall")
plt.plot(ave_recall_svd, ave_precis_svd)
plt.show()
```


MF with bias Precision vs. t (thres=3.0)
Precision
0.80
0.78
0.76
0.74
0.72
0.70
0
5
10
15
20
25
size t

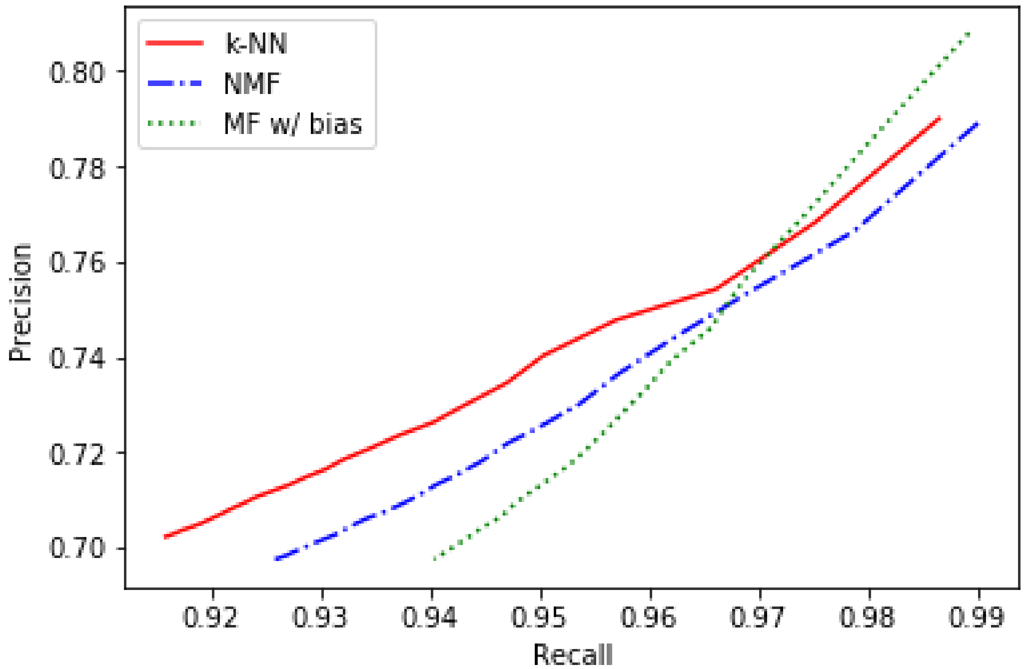

MF with bias Recall vs. t (thres=3.0)
Recall
0.99
0.98
0.97
0.96
0.95
0.94
0
5
10
15
20
25
size t



From the graph of precision vs t, it is clear that the precision of MF filter decreased when the rank of the movie went lower. From the graph of recall vs t, it is clear that the recall of MF filter also decreased when the rank of the movie went lower. From the graph of precision vs recall, we can see that the precision and the recall were positively corelated with each other.

Question 39

```
In [152]: l1, = plt.plot(ave_recall_knn, ave_precis_knn, 'r-', label='k-NN')
          l2, = plt.plot(ave_recall_nmf, ave_precis_nmf, 'b-.', label='NMF')
          l3, = plt.plot(ave_recall_svd, ave_precis_svd, 'g:', label='MF w/ bias')
          plt.xlabel('Recall')
          plt.ylabel('Precision')
          plt.legend(handles=[l1, l2, l3])
          plt.show()
```



All three filters performed similarly well in precision and recall. In general, MF with bias performed better than other two filters in both precision and recall. The precision range of MF filter was 0.70-0.81, and the recall range was 0.94-0.99. k-NN filter and NNMF filter performed approximately the same on precision, while NNMF performed better on recall.