Recommender Systems: Collaborative Filtering

In [7]:
```
import pandas as pd
```

In [8]:
```
names = ['userid', 'itemid', 'rating','id','user_id','item_id' ]
df = pd.read_csv('/Users/jyothi/Desktop/Movie/out.csv', sep=',', names=n
ames ,low_memory=False)
df.tail()
```

Out[8]:

	userid	itemid	rating	id	user_id	item_id
500095	2870	3952	4	2870_3952	88	3551
500096	2872	3952	4	2872_3952	90	3551
500097	2882	3952	4	2882_3952	100	3551
500098	3942	3952	2	3942_3952	1157	3551
500099	5359	3952	5	5359_3952	2574	3551

In [3]:
```
df.head()
```

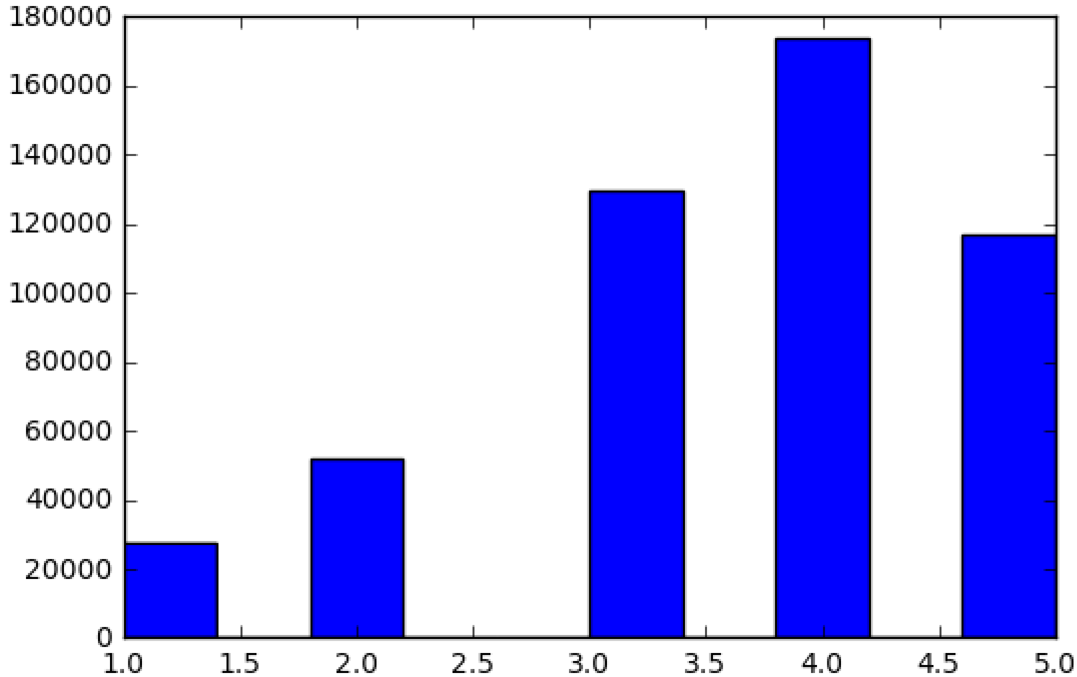
Out[3]:

	userid	itemid	rating	id	user_id	item_id
0	2787	1	5	2787_1	5	1
1	2788	1	5	2788_1	6	1
2	2792	1	3	2792_1	10	1
3	2796	1	3	2796_1	14	1
4	2799	1	5	2799_1	17	1

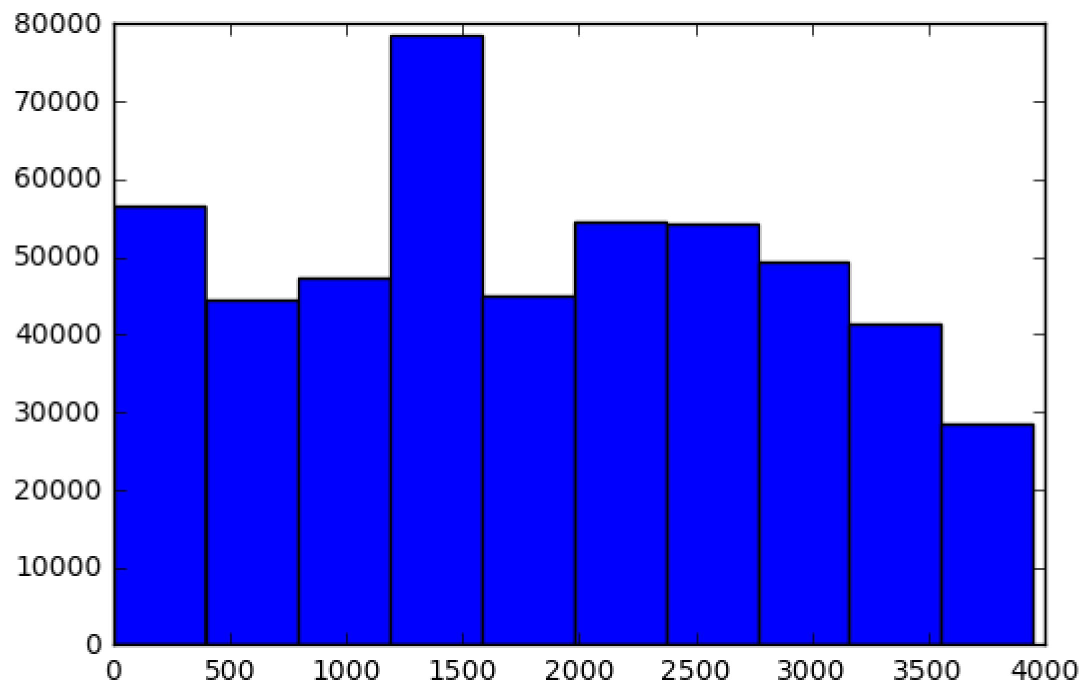
In [4]:
```
import matplotlib.pyplot as plt
```

Histograms -- Ratings, User and Item

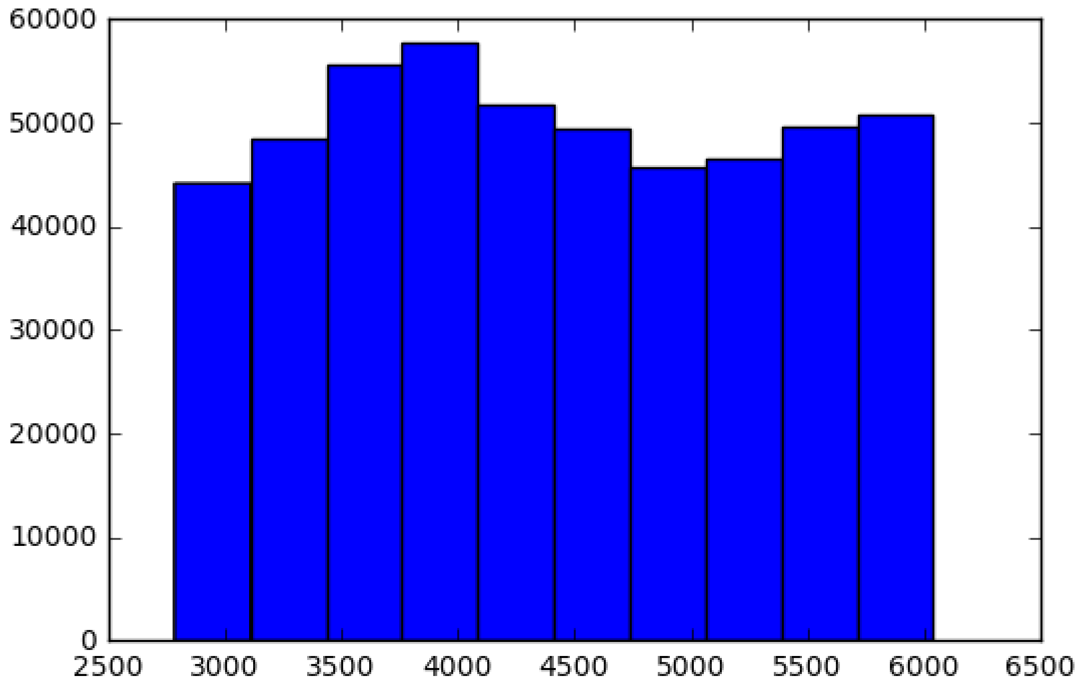
In [5]:
```
plt.hist(df['rating'])
plt.show()
```



In [6]:
```
plt.hist(df['itemid'])
plt.show()
```



In [7]:
```
plt.hist(df['userid'])
plt.show()
```



In [8]:
```
n_users = df.userid.unique().shape[0]
n_users
```

Out[8]: 3255

Creating Matrix

In [9]:
```
df.userid.max()
```

Out[9]: 6040

In [10]:
```
df.itemid.max()
```

Out[10]: 3952

In [11]:
```
n_items = df['itemid'].unique().shape[ 0]
n_items
```

Out[11]: 3551

In [12]:
```
import numpy as np
ratings = np.zeros((df.userid.max(), df.itemid.max()))
for row in df.itertuples():
    ratings[row[5]-1, row[ 6]-1] = row[3]
```

In [21]:
```
ratings.shape
```

Out[21]: (6040, 3952)

Find the Sparsity of Matrix

In [13]:
```
import sklearn
```

In [39]:
```
#ratings = np.zeros((6040, 3952))
```

In [14]:
```
ratings.shape
```

Out[14]:
```
(6040, 3952)
```

In [15]:
```
for row in df.itertuples():
    ratings[row[1]-1, row[2]-1] = row[3]
ratings
```

Out[15]:
```
array([[ 0.,  0.,  0., ...,  0.,  0.,  0.],
       [ 0.,  0.,  0., ...,  0.,  0.,  0.],
       [ 0.,  0.,  3., ...,  0.,  0.,  0.],
       ...,
       [ 0.,  0.,  0., ...,  0.,  0.,  0.],
       [ 0.,  0.,  0., ...,  0.,  0.,  0.],
       [ 3.,  0.,  0., ...,  0.,  0.,  0.]])
```

This means that 4.18% of the user-item ratings have a valu

In [16]:
```
sparsity = float(len(ratings.nonzero()[0]))
sparsity /= (ratings.shape[0] * ratings.shape[1])
sparsity *= 100
print( 'Sparsity: {:4.2f}%'.format(sparsity))
```

```
Sparsity: 4.18%
```

Splitting into Train and test. We will split our data into training and test sets by removing 10 ratings per user from the training set and placing them in the test set.

In [17]:
```
def train_test_split(ratings):
    test = np.zeros(ratings.shape)
    train = ratings.copy()
    for user in range(ratings.shape[0]):
        test_ratings = np.random.choice(ratings[user, :].nonzero()[0],
                                        size=10)
        train[user, test_ratings] = 0.
        test[user, test_ratings] = ratings[user, test_ratings]

    # Test and training are truly disjoint
    assert(np.all((train * test) == 0))
    return train, test
```

In [18]:
```
train, test = train_test_split(ratings)
```

Sparsity of Train and Test

In [19]:
```
sparsity = float(len(train.nonzero()[0]))
sparsity /= (train.shape[0] * train.shape[1])
sparsity *= 100
print( 'Sparsity: {:4.2f}%'.format(sparsity))
```

```
Sparsity: 3.94%
```

In [20]:
```
sparsity = float(len(test.nonzero()[0]))
sparsity /= (test.shape[0] * test.shape[1])
sparsity *= 100
print( 'Sparsity: {:4.2f}%'.format(sparsity))
```

```
Sparsity: 0.24%
```

Find Similarity Matrix

In [21]:
```
def fast_similarity(ratings, kind='user', epsilon=1e-9):
    # epsilon -> small number for handling dived-by-zero errors
    if kind == 'user':
        sim = ratings.dot(ratings.T) + epsilon
    elif kind == 'item':
        sim = ratings.T.dot(ratings) + epsilon
    norms = np.array([np.sqrt(np.diagonal(sim))])
    return (sim / norms / norms.T)
```

In [35]:
```
%timeit fast_similarity(train, kind='user')
```

```
1 loop, best of 3: 4.26 s per loop
```

In [22]:
```
user_similarity = fast_similarity(train, kind='user')
item_similarity = fast_similarity(train, kind='item')
print(item_similarity[:4, :4])
```

```
[[ 1.          0.3866698   0.26892164  0.18719958]
 [ 0.3866698   1.          0.26989166  0.15131605]
 [ 0.26892164  0.26989166  1.          0.22294291]
 [ 0.18719958  0.15131605  0.22294291  1.        ]]
```

In [37]:
```
user_similarity
```

Out[37]:
```
array([[  1.00000000e+00,   3.91522151e-12,   1.91358561e-02, ...,
          3.04897888e-12,   1.44484737e-02,   2.01997061e-02],
       [  3.91522151e-12,   1.00000000e+00,   2.59976270e-12, ...,
          8.28457481e-12,   2.45367930e-12,   1.56816882e-12],
       [  1.91358561e-02,   2.59976270e-12,   1.00000000e+00, ...,
          7.28843505e-02,   3.53778448e-02,   6.32322044e-02],
       ...,
       [  3.04897888e-12,   8.28457481e-12,   7.28843505e-02, ...,
          1.00000000e+00,   1.22291381e-01,   8.18211720e-02],
       [  1.44484737e-02,   2.45367930e-12,   3.53778448e-02, ...,
          1.22291381e-01,   1.00000000e+00,   2.00377167e-01],
       [  2.01997061e-02,   1.56816882e-12,   6.32322044e-02, ...,
          8.18211720e-02,   2.00377167e-01,   1.00000000e+00]])
```

In [38]:
```
item_similarity
```

Out[38]:
```
array([[  1.00000000e+00,   3.81545356e-01,   2.66716365e-01, ...,
          1.67753597e-07,   1.67753597e-07,   4.96668537e-02],
       [  3.81545356e-01,   1.00000000e+00,   2.70862868e-01, ...,
          3.60164561e-07,   3.60164561e-07,   2.43495009e-02],
       [  2.66716365e-01,   2.70862868e-01,   1.00000000e+00, ...,
          5.50148560e-07,   5.50148560e-07,   1.28254044e-12],
       ...,
       [  1.67753597e-07,   3.60164561e-07,   5.50148560e-07, ...,
          1.00000000e+00,   1.00000000e+00,   2.33126202e-06],
       [  1.67753597e-07,   3.60164561e-07,   5.50148560e-07, ...,
          1.00000000e+00,   1.00000000e+00,   2.33126202e-06],
       [  4.96668537e-02,   2.43495009e-02,   1.28254044e-12, ...,
          2.33126202e-06,   2.33126202e-06,   1.00000000e+00]])
```

Predict unknown ratings of each user

In [39]:
```
def predict_fast_simple(ratings, similarity, kind='user'):
    if kind == 'user':
        return similarity.dot(ratings) / np.array([np.abs(similarity).su
m(axis=1)]).T
    elif kind == 'item':
        return ratings.dot(similarity) / np.array([np.abs(similarity).su
m(axis=1)])
```

In [40]:
```
%timeit predict_fast_simple(train, user_similarity, kind='user')
```

```
1 loop, best of 3: 5.34 s per loop
```

In [41]:
```
from sklearn.metrics import mean_squared_error

def get_mse(pred, actual):
    # Ignore nonzero terms.
    pred = pred[actual.nonzero()].flatten()
    actual = actual[actual.nonzero()].flatten()
    return mean_squared_error(pred, actual)
```

Find MSE for User and Item predictions.

In [42]:
```
item_prediction = predict_fast_simple(train, item_similarity, kind='ite
m')
user_prediction = predict_fast_simple(train, user_similarity, kind='use
r')

print ('User-based CF MSE: ' + str(get_mse(user_prediction, test)))
print ('Item-based CF MSE: ' + str(get_mse(item_prediction, test)))
```

```
User-based CF MSE: 10.2596788122
Item-based CF MSE: 12.9836130054
```

Item Based Filtering is less efficient than User based Filtering

In [43]:
```
def predict_topk(ratings, similarity, kind='user', k=40):
    pred = np.zeros(ratings.shape)
    if kind == 'user':
        for i in range(ratings.shape[0]):
            top_k_users = [np.argsort(similarity[:,i])[:-k-1:-1]]
            for j in range(ratings.shape[1]):
                pred[i, j] = similarity[i, :]
[top_k_users].dot(ratings[:, j][top_k_users])
                pred[i, j] /= np.sum(np.abs(similarity[i, :]
[top_k_users]))
    if kind == 'item':
        for j in range(ratings.shape[1]):
            top_k_items = [np.argsort(similarity[:,j])[:-k-1:-1]]
            for i in range(ratings.shape[0]):
                pred[i, j] = similarity[j, :]
[top_k_items].dot(ratings[i, :][top_k_items].T)
                pred[i, j] /= np.sum(np.abs(similarity[j, :]
[top_k_items]))

    return pred
```

Now predict Ratings from top K users ratings. Here we are using Top 40 Users

In [44]:
```
user_pred = predict_topk(train, user_similarity, kind='user', k=40)
print ('Top-k User-based CF MSE: ' + str(get_mse(user_pred, test)))

item_pred = predict_topk(train, item_similarity, kind='item', k=40)
print ('Top-k Item-based CF MSE: ' + str(get_mse(item_pred, test)))
```

```
Top-k User-based CF MSE: 7.38381441793
Top-k Item-based CF MSE: 8.88503342012
```

In [32]:
```
import numpy as np
```

In [33]:
```
np.radians(30)
```

Out[33]: 0.52359877559829882

Now MSE is lesser than previous prection.(Finding rating with total users and Top 40 users)

In [60]:
```
user_pred
```

Out[60]:
```
array([[ 0.29943031,  0.08756301,  0.        , ...,  0.        ,
         0.        ,  0.        ],
       [ 0.22327907,  0.        ,  0.08158382, ...,  0.        ,
         0.        ,  0.        ],
       [ 3.17245671,  0.6988156 ,  1.44712669, ...,  0.        ,
         0.        ,  0.        ],
       ...,
       [ 0.7041948 ,  0.        ,  0.        , ...,  0.        ,
         0.        ,  0.        ],
       [ 2.04696772,  0.47015519,  0.22574728, ...,  0.        ,
         0.        ,  0.        ],
       [ 3.577271  ,  0.69195197,  0.1209941 , ...,  0.        ,
         0.        ,  0.        ]])
```

In [61]:
```
item_pred
```

Out[61]:
```
array([[ 0.42626596,  0.        ,  0.        , ...,  0.        ,
         0.        ,  0.        ],
       [ 0.        ,  0.        ,  0.        , ...,  0.        ,
         0.        ,  0.        ],
       [ 0.18666071,  0.17927339,  1.72634466, ...,  0.        ,
         0.        ,  0.        ],
       ...,
       [ 0.        ,  0.        ,  0.        , ...,  0.        ,
         0.        ,  0.        ],
       [ 0.86905362,  0.30642731,  0.        , ...,  0.        ,
         0.        ,  0.        ],
       [ 2.19570044,  0.18135941,  0.        , ...,  0.        ,
         0.        ,  0.        ]])
```

In [45]:
```
def get_mse(pred, actual):
    pred = pred[actual.nonzero()].flatten()
    actual = actual[actual.nonzero()].flatten()
    return mean_squared_error(pred, actual)
```

Now we try to find best K value

In [46]:
```
user_train_mse =[]
user_test_mse=[]
item_train_mse =[]
item_test_mse=[]
```

In [47]:
```
user_train_mse  += [get_mse(user_pred, train)]
user_test_mse   += [get_mse(user_pred, test)]
```

In [48]:
```
item_train_mse  += [get_mse(item_pred, train)]
item_test_mse   += [get_mse(item_pred, test)]
```

In [49]:
```
user_test_mse
```

Out[49]:
```
[7.3838144179282086]
```

In [50]:
```
user_train_mse
```

Out[50]:
```
[4.3288052799705046]
```

In [51]:
```
item_test_mse
```

Out[51]:
```
[8.8850334201162529]
```

In [52]:
```
item_train_mse
```

Out[52]:
```
[4.6808910485969673]
```

In [62]:
```
user_train_mse =[]
user_test_mse=[]
item_train_mse =[]
item_test_mse=[]
k_array = [5,15, 30, 50]
for k in k_array:
    user_pred = predict_topk(train, user_similarity, kind='user', k=k)
    user_train_mse += [get_mse(user_pred, train)]
    user_test_mse += [get_mse(user_pred, test)]
```

MSE values for k - 5,15, 30 , 50

In [63]:
```
user_train_mse
```

Out[63]:
```
[1.9752069495714824,
 3.4123285396368503,
 4.0859070092084062,
 4.5081987040878877]
```

In [64]:
```
user_test_mse
```

Out[64]:
```
[9.6490481846797032,
 8.0196801829844979,
 7.5215498869530597,
 7.3017715238345833]
```

In [65]:
```
k_array = [5,15, 30, 50]
for k in k_array:
    item_pred = predict_topk(train, item_similarity, kind='item', k=k)

    item_train_mse += [get_mse(item_pred, train)]
    item_test_mse += [get_mse(item_pred, test)]
```

In [66]:
```
item_train_mse
```

Out[66]:
```
[2.0298085644746084, 3.5889731419831725, 4.378313913605365, 4.909723262
7326575]
```

In [67]:
```
item_test_mse
```

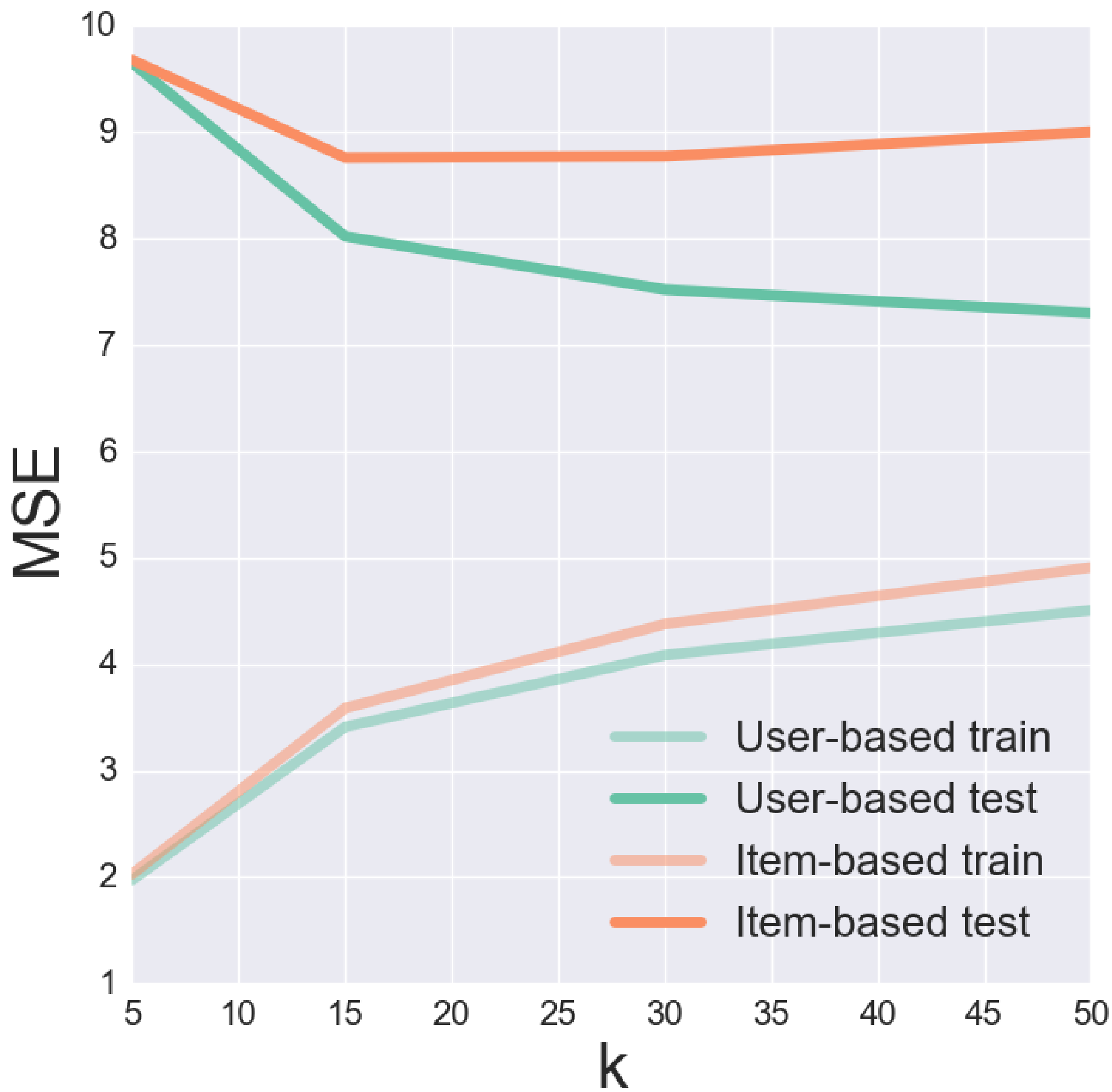
Out[67]:
```
[9.6777407018528674,
 8.7584064718465839,
 8.7724962621564604,
 9.0007304037218816]
```

Plot the values

In [68]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()

pal = sns.color_palette("Set2", 2)

plt.figure(figsize=(8, 8))
plt.plot(k_array, user_train_mse, c=pal[0], label='User-based train', al
pha=0.5, linewidth=5)
plt.plot(k_array, user_test_mse, c=pal[0], label='User-based test', line
width=5)
plt.plot(k_array, item_train_mse, c=pal[1], label='Item-based train', al
pha=0.5, linewidth=5)
plt.plot(k_array, item_test_mse, c=pal[1], label='Item-based test', line
width=5)
plt.legend(loc='best', fontsize=20)
plt.xticks(fontsize=16);
plt.yticks(fontsize=16);
plt.xlabel('k', fontsize=30);
plt.ylabel('MSE', fontsize=30);
```



Looks 15 is the best value to choose

In [5]:
```
def top_k_movies(similarity, mapper, movie_idx, k=6):
    return [mapper[x] for x in np.argsort(similarity[movie_idx,:])[:-k-
1:-1]]
```

In [1]:
```
idx_to_movie = {}
```

In [3]:
```
with open('/Users/jyothi/Desktop/Movie/movie.dat', encoding = "ISO-8859-
1") as f:
    for line in f.readlines():
        info = line.split('::')
        idx_to_movie[int(info[0])-1] = info[1]
```

In [23]:
```
idx = 0
movies = top_k_movies(item_similarity, idx_to_movie, idx)
```

In [24]:
```
movies
```

Out[24]:
```
['Toy Story (1995)',
 'Babe (1995)',
 'Lion King, The (1994)',
 'Mask, The (1994)',
 'Twelve Monkeys (1995)',
 'Clueless (1995)']
```

In [25]:
```
idx = 2
movies = top_k_movies(item_similarity, idx_to_movie, idx)
```

In [26]:
```
movies
```

Out[26]:
```
['Grumpier Old Men (1995)',
 'Ace Ventura: When Nature Calls (1995)',
 'Sabrina (1995)',
 'Road to Wellville, The (1994)',
 'Nine Months (1995)',
 'Grumpy Old Men (1993)']
```

In [27]:
```
idx = 1
movies = top_k_movies(item_similarity, idx_to_movie, idx)
movies
```

Out[27]:
```
['Jumanji (1995)',
 'Mask, The (1994)',
 'Stargate (1994)',
 'Lion King, The (1994)',
 'Holy Smoke (1999)',
 'GoldenEye (1995)']
```

In [31]:
```
idx = 4
movies = top_k_movies(item_similarity, idx_to_movie, idx)
movies
```

Out[31]:
```
['Father of the Bride Part II (1995)',
 'Ace Ventura: When Nature Calls (1995)',
 'Hocus Pocus (1993)',
 'American President, The (1995)',
 'Nine Months (1995)',
 'Liar Liar (1997)']
```

In [ ]:
```

```