personalization_knn

November 6, 2019

```
In [0]: import pandas as pd
        import numpy as np
        import random
        import matplotlib.pyplot as plt
        from surprise import Dataset
        from surprise import accuracy
        from surprise import Reader
        from surprise.model_selection import KFold
        from surprise.model_selection import cross_validate
        import time
        import sklearn
        from sklearn.model_selection import train_test_split
        from random import shuffle
        from surprise.prediction_algorithms import NMF
        from surprise.prediction_algorithms import KNNWithMeans
        import seaborn as sns
```

0.0.1 Read train and test datast

```
In [0]: train_ratings = pd.read_csv("train_data.csv")
        test_ratings = pd.read_csv("test_data.csv")
```

```
In [5]: print('train_minimum_rating',min(train_ratings['rating']))
        print('train_maximum_rating',max(train_ratings['rating']))
        print('test_minimum_rating',min(train_ratings['rating']))
        print('test_maximum_rating',max(train_ratings['rating']))
```

```
('train_minimum_rating', 0.5)
('train_maximum_rating', 5.0)
('test_minimum_rating', 0.5)
('test_maximum_rating', 5.0)
```

```
In [0]: reader = Reader(rating_scale=(0.5, 5))
        ratings = Dataset.load_from_df(train_ratings, reader)
```

```
In [0]: raw_ratings = ratings.raw_ratings
        random.seed(42)
        shuffle(raw_ratings)
```

```
In [0]: ratings.raw_ratings = raw_ratings
```

```
In [0]: copy_ratings=ratings
```

0.0.2 define coverage function

```
In [0]: def coverage(threshold1, threshold2,prediction):
            start_time=time.time()
            predictions = pd.DataFrame(prediction)
            pred = predictions.groupby('uid')
            df1= pred.apply(lambda x: x.sort_values(by=["est"],ascending=False))
            df2=df1.reset_index(drop=True)
            df3 = df2.groupby('uid').head(10)

            s1=df3[df3['r_ui'] > threshold1].groupby('uid')['r_ui'].count().reset_index()
            s2 = df3.pivot_table(index=['uid'],aggfunc='size').reset_index()
            s2.columns = ['uid','counts']

            df=pd.merge(s1, s2, on='uid')

            # #number of high true rating(larger than 4) devided by top N predictions
            df['rate']=df['r_ui']/df['counts']

            user_coverage=float(sum(df['rate']> threshold2))/df3['uid'].nunique()

            item=df3.groupby('iid').apply(lambda x: x.sort_values(by=["est"],ascending=False))

            s=item[item['r_ui'] > threshold1].groupby('iid')['r_ui'].count().reset_index()
            ss = item.pivot_table(index=['iid'],aggfunc='size').reset_index()
            ss.columns = ['iid','counts']
            dff=pd.merge(s, ss, on='iid')
            dff['rate']=dff['r_ui']/dff['counts']
            item_coverage=float(sum(dff['rate']> threshold2))/df3['iid'].nunique()

            catalog_coverage = float(df3['iid'].nunique())/predictions['iid'].nunique()
            end_time=time.time()
            duration=end_time-start_time
            return user_coverage, item_coverage, catalog_coverage,duration
```

First we run a 5-fold cv on the train set to see some preliminary results.

```
In [0]: method = KNNWithMeans()
        cross_val = cross_validate(method, ratings, measures=['RMSE', 'MAE'], cv=5, verbose=Tru
```

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

```
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Evaluating RMSE, MAE of algorithm KNNWithMeans on 5 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
MAE (testset)     0.6896  0.6839  0.6860  0.6854  0.6848  0.6859  0.0019
RMSE (testset)    0.8932  0.8853  0.8891  0.8883  0.8863  0.8884  0.0027
Fit time          52.61   55.89   48.68   47.90   43.54   49.72   4.22
Test time         229.95  195.13  206.80  185.43  179.84  199.43  17.80
```

0.0.3 cross-validation on similarity measure

```
In [0]: def try_similarity(options):
            method = KNNWithMeans(sim_option=options)
            cross_val = cross_validate(method, ratings, measures=['RMSE', 'MAE'], return_train_

            train_mae=np.mean(cross_val['train_mae'])
            train_rmse=np.mean(cross_val['train_rmse'])

            val_mae=np.mean(cross_val['test_mae'])
            val_rmse=np.mean(cross_val['test_rmse'])


            return train_rmse,train_mae,val_rmse,val_mae
```

```
In [29]: train_rmse_list2=[]
         train_mae_list2=[]
         val_rmse_list2=[]
         val_mae_list2=[]




         similarity_measure = {
             'cosine': {
                  'name': 'cosine',
                  'user_based': False
                  },
             'pearson_baseline': {
                  'name': 'pearson_baseline',
                  'user_based': False
                  },
             'pearson': {
                  'name': 'pearson',
             'user_based': False
             }
             }

    _min=float('inf')

    for k, v in similarity_measure.items():


        print('similarity measure is', k)


        train_rmse,train_mae,val_rmse,val_mae=try_similarity(v)
        train_rmse_list2.append(train_rmse)
        train_mae_list2.append(train_mae)

        val_rmse_list2.append(val_rmse)
        val_mae_list2.append(val_mae)
        if val_rmse<_min:
            _min=val_rmse
            _similarity_measure=v





    print("similarity  measure that produce the smallest rmse are",_similarity_measure)
```

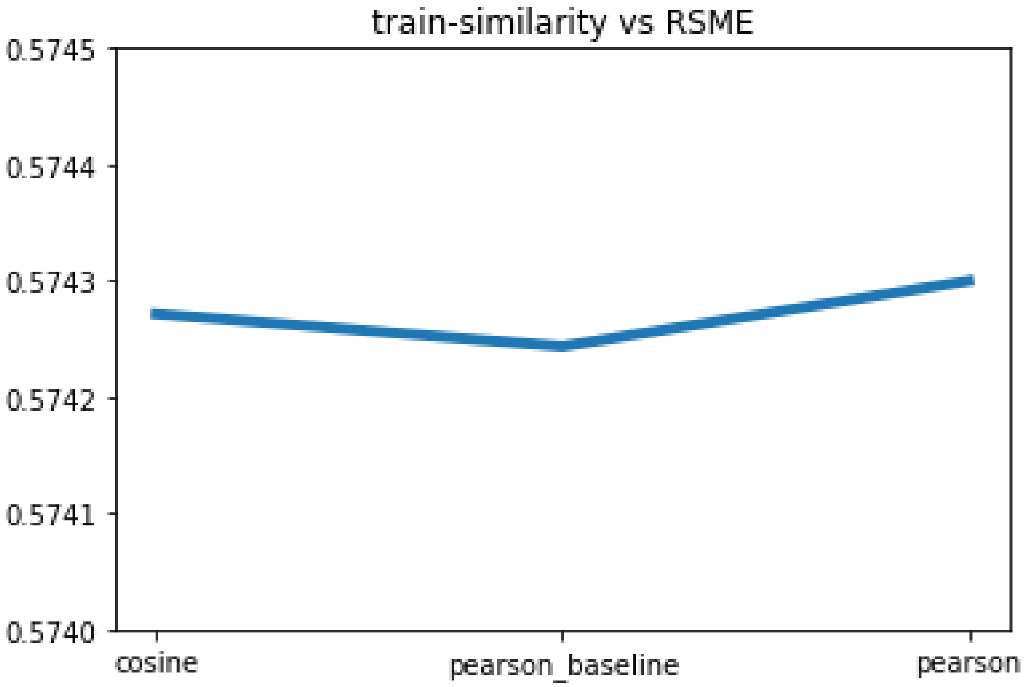
```
('similarity measure is', 'pearson')
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
('similarity measure is', 'pearson_baseline')
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
```

```
Computing the msd similarity matrix...
Done computing similarity matrix.
('similarity measure is', 'cosine')
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
('similarity  measure that produce the smallest rmse are', {'name': 'pearson_baseline', 'user_
```

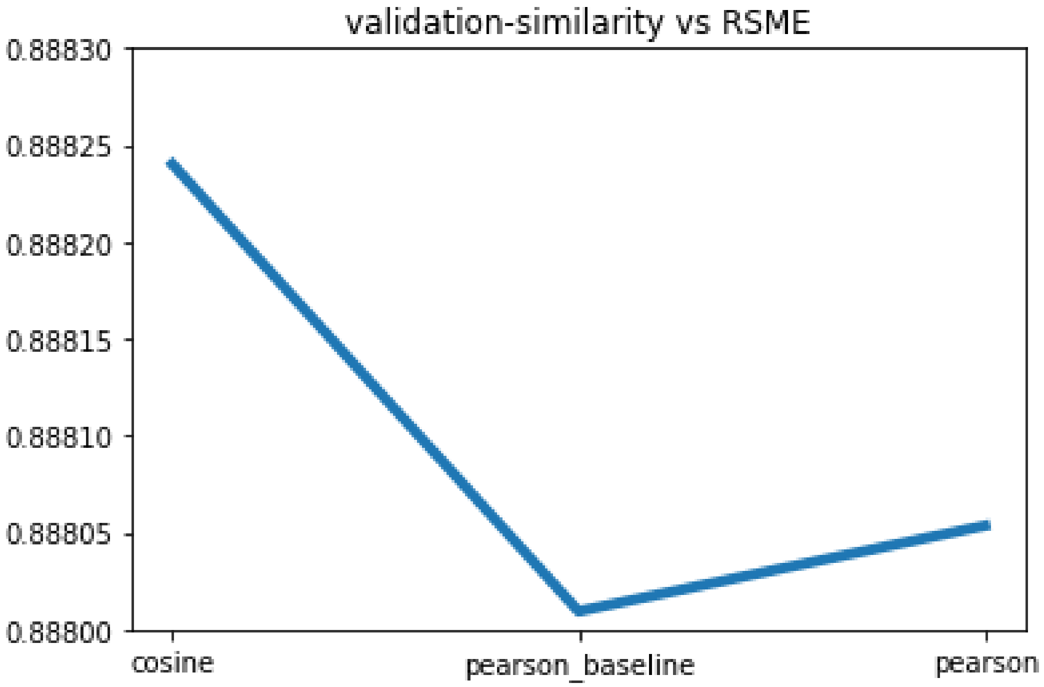
```
In [31]: train_rmse_list2
```

```
Out[31]: [0.5742714680792438, 0.5742435830705317, 0.574299879424325]
```

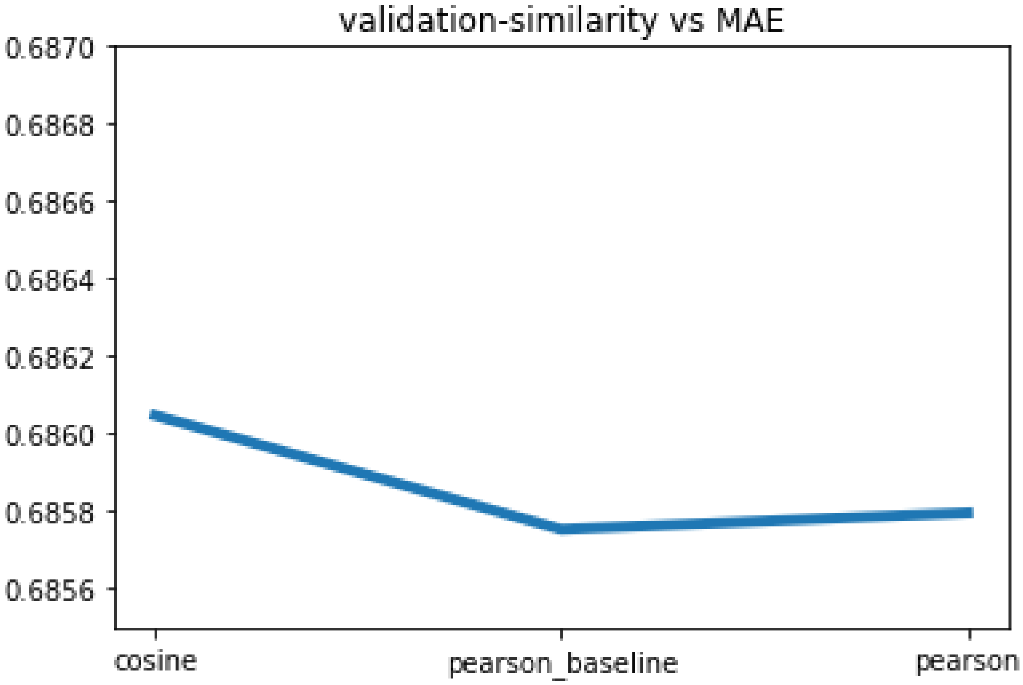
```
In [61]: measure_list=['cosine', 'pearson_baseline', 'pearson']
         lines = plt.plot(measure_list,train_rmse_list2)
         plt.setp(lines[0], linewidth=4)
         #plt.setp(lines[1], linewidth=2)
         #plt.setp(lines[2], markersize=10)
         plt.ylim(0.574, 0.5745)
         # plt.legend(('train_mae', 'test_mae'),
         #             loc='upper right')
         plt.title('train-similarity vs RSME')
         plt.savefig('train-similarity vs RSME.jpg')
         plt.show()
```



```
In [59]: val_rmse_list2

Out[59]: [0.8882402636248046, 0.8880093120223037, 0.8880535904651804]

In [62]: measure_list=['cosine', 'pearson_baseline', 'pearson']
         lines = plt.plot(measure_list,val_rmse_list2)
         plt.setp(lines[0], linewidth=4)
         #plt.setp(lines[1], linewidth=2)
         #plt.setp(lines[2], markersize=10)
         plt.ylim(0.888, 0.8883)
         # plt.legend(('train_mae', 'test_mae'),
         #            loc='upper right')
         plt.title('validation-similarity vs RSME')
         plt.savefig('validation-similarity vs RSME.jpg')
         plt.show()
```



```
In [63]: val_mae_list2

Out[63]: [0.6860475819568472, 0.6857530678860657, 0.6857958678485091]

In [65]: measure_list=['cosine', 'pearson_baseline', 'pearson']
         lines = plt.plot(measure_list,val_mae_list2)
         plt.setp(lines[0], linewidth=4)
         #plt.setp(lines[1], linewidth=2)
         #plt.setp(lines[2], markersize=10)
         plt.ylim(0.6855, 0.687)
         # plt.legend(('train_mae', 'test_mae'),
         #            loc='upper right')
         plt.title('validation-similarity vs MAE')
         plt.savefig('validation-similarity vs MAE.jpg')
         plt.show()
```



0.0.4 cross-validation on neighborhood size

```
In [0]: def try_neighbor(kNeighbor,_similarity_measure):
            method = KNNWithMeans(min_k=kNeighbor,sim_option=_similarity_measure)
            cross_val = cross_validate(method, ratings, measures=['RMSE', 'MAE'], return_train_

            train_mae=np.mean(cross_val['train_mae'])
            train_rmse=np.mean(cross_val['train_rmse'])

            val_mae=np.mean(cross_val['test_mae'])
            val_rmse=np.mean(cross_val['test_rmse'])


            return train_rmse,train_mae,val_rmse,val_mae
```

```
In [27]: train_rmse_list=[]
         train_mae_list=[]
         val_rmse_list=[]
         val_mae_list=[]


         neighbor_num = np.arange(5, 70 , 10)

         _min=float('inf')
         for num in neighbor_num:
```

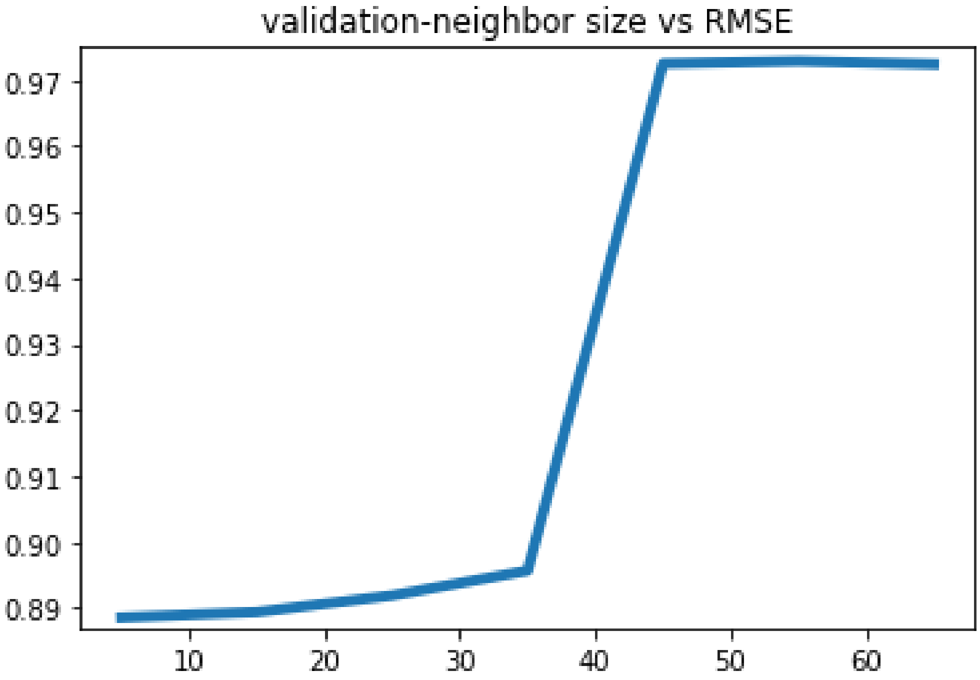
```
    print('number of neighbor', num)



    train_rmse,train_mae,val_rmse,val_mae=try_neighbor(num,{'name': 'pearson_baseline
    train_rmse_list.append(train_rmse)
    train_mae_list.append(train_mae)

    val_rmse_list.append(val_rmse)
    val_mae_list.append(val_mae)
    if val_rmse<_min:
        _min=val_rmse
        _num=num





print("number of neighbor that produce the smallest rmse are", _num)
```

```
('number of neighbor', 5)
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
('number of neighbor', 15)
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
('number of neighbor', 25)
Computing the msd similarity matrix...
```

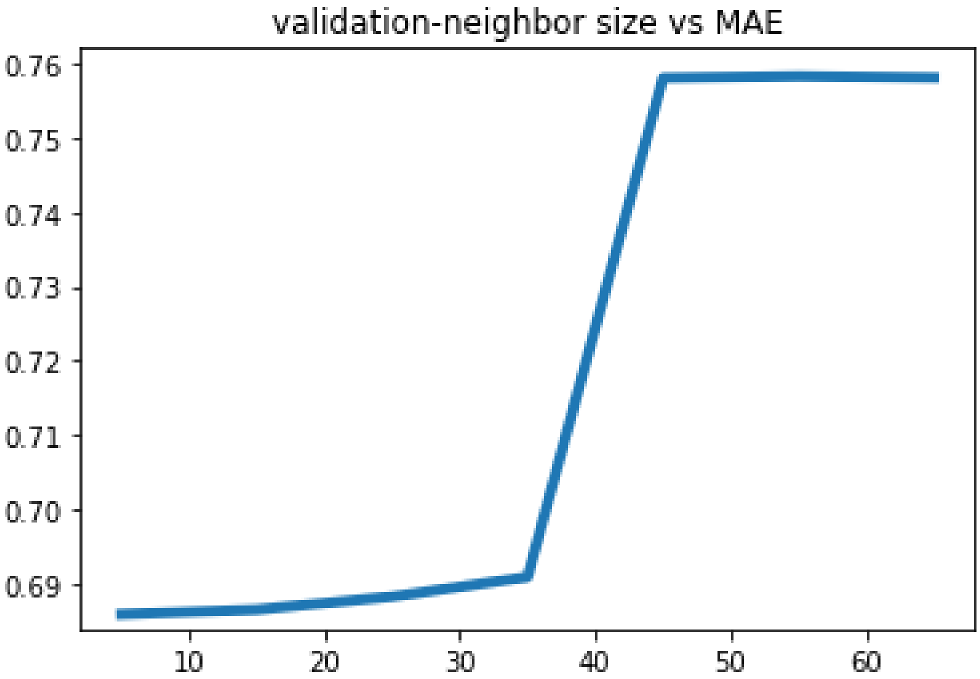
```
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
('number of neighbor', 35)
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
('number of neighbor', 45)
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
('number of neighbor', 55)
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
('number of neighbor', 65)
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
```

```
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
('number of neighbor that produce the smallest rmse are', 5)
```

```
In [33]: lines = plt.plot(neighbor_num,val_rmse_list)
         plt.setp(lines[0], linewidth=4)

         plt.ylim(0.887, 0.975)

         plt.title('validation-neighbor size vs RMSE')
         plt.savefig('validation-neighborsize_vs_RMSE.jpg')
         plt.show()
```



```
In [36]: lines = plt.plot(neighbor_num,val_mae_list)
         plt.setp(lines[0], linewidth=4)

         plt.ylim(0.684, 0.762)

         plt.title('validation-neighbor size vs MAE')
         plt.savefig('validation-neighborsize_vs_MAE.jpg')
         plt.show()
```



0.0.5 evaluate on test set with the parameters we searched

```
In [37]: train_ratings = pd.read_csv("train_data.csv")
         test_ratings = pd.read_csv("test_data.csv")
         reader = Reader(rating_scale=(0.5, 5))
         ratings = Dataset.load_from_df(train_ratings, reader)
         raw_ratings = ratings.raw_ratings
         random.seed(42)
         shuffle(raw_ratings)
         ratings.raw_ratings = raw_ratings

         train_set = ratings.build_full_trainset()
         reader = Reader(rating_scale=(0.5, 5))
         test_rates = Dataset.load_from_df(test_ratings, reader)
         test=test_rates.raw_ratings
         test_set = ratings.construct_testset(test)
```

```
In [38]: method = KNNWithMeans(min_k=5,sim_option={
                  'name': 'pearson_baseline',
                  'user_based': False
                  })
         method.fit(train_set)
         test_result = method.test(test_set)
         test_rmse = accuracy.rmse(test_result)
         test_mae = accuracy.mae(test_result)
         r_user_coverage,r_item_coverage,r_catelog_coverage,_=coverage(4.0, 0.5,test_result)
```

```
Computing the msd similarity matrix...
Done computing similarity matrix.
RMSE: 0.8868
MAE:  0.6843
```

```
In [39]: print(r_user_coverage,r_item_coverage,r_catelog_coverage)
```

```
(0.17297840281265695, 0.090234375, 0.8539026017344896)
```

0.0.6 Evaluate the relationship between running time and scale of dataset

```
In [0]: train_ratings = pd.read_csv("train_data.csv")
        test_ratings = pd.read_csv("test_data.csv")
```

```
In [0]: reader = Reader(rating_scale=(0.5, 5))
        ratings = Dataset.load_from_df(train_ratings, reader)
        raw_ratings = ratings.raw_ratings
        random.seed(42)
        shuffle(raw_ratings)
        ratings.raw_ratings = raw_ratings
        copy_ratings=ratings
```

```
In [0]: def default_knn(train_set,test_set):
            start_time = time.time()
            method = KNNWithMeans()
            method.fit(train_set)

            print('evaluate on train set')
            train_result = method.test(train_set.build_testset())
            train_rmse = accuracy.rmse(train_result)
            train_mae = accuracy.mae(train_result)
            r_user_coverage,r_item_coverage,r_catelog_coverage,_=coverage(4.0, 0.5,train_resul

            print('evaluate on test set')
            test_result = method.test(test_set)
            #print(len(test_result))
            test_rmse = accuracy.rmse(test_result)
            test_mae = accuracy.mae(test_result)

            e_user_coverage,e_item_coverage,e_catelog_coverage,_=coverage(4.0, 0.5,test_result)
            return train_rmse,test_rmse,train_mae,test_mae,\
        r_user_coverage,r_item_coverage,r_catelog_coverage,\
        e_user_coverage,e_item_coverage,e_catelog_coverage
```

```
In [0]: def change_size(size,copy_ratings):
            use_rating=copy_ratings

            use_raw_ratings = use_rating.raw_ratings
        #    print(len(use_raw_ratings))
        #     random.seed(42)
        #     shuffle(use_raw_ratings)

            use_part, holdout_group= train_test_split(use_raw_ratings, test_size=size, random_
            train, test= train_test_split(use_part, test_size=0.2, random_state=50)
            #train, test= train_test_split(use_part, test_size=0.15, random_state=42)
            #print(train)
            use_rating.raw_ratings = train
            train_set = use_rating.build_full_trainset()
            test_set = use_rating.construct_testset(test)

            start_time = time.time()
            print('use'+" "+str(round((1-size)*100,2))+"% of data")
            train_rmse,test_rmse,train_mae,test_mae,\
            r_user_coverage,r_item_coverage,r_catelog_coverage,\
            e_user_coverage,e_item_coverage,e_catelog_coverage =default_knn(train_set,test_set

            end_time = time.time()

            duration=end_time-start_time
            return train_rmse,test_rmse,train_mae,test_mae,duration,\
        r_user_coverage,r_item_coverage,r_catelog_coverage,\
        e_user_coverage,e_item_coverage,e_catelog_coverage
```

```
In [15]: size_train_rmse_list=[]
         size_train_mae_list=[]
         size_test_rmse_list=[]
         size_test_mae_list=[]
         size_e_u_cov=[]
         size_e_i_cov=[]
         size_e_c_cov=[]
         size_r_u_cov=[]
         size_r_i_cov=[]
         size_r_c_cov=[]
         size_list = np.arange(0.1, 1.0, 0.1)
         duration_list=[]
         for size in size_list:
             reader = Reader(rating_scale=(0.5, 5))
             ratings = Dataset.load_from_df(train_ratings, reader)
             raw_ratings = ratings.raw_ratings
             random.seed(42)
             shuffle(raw_ratings)
             ratings.raw_ratings = raw_ratings
```

```
        copy_ratings=ratings
        train_rmse,train_mae,test_rmse,test_mae,duration,\
        r_user_coverage,r_item_coverage,r_catelog_coverage,\
        e_user_coverage,e_item_coverage,e_catelog_coverage=change_size(size,copy_ratings)
        size_train_rmse_list.append(train_rmse)
        size_train_mae_list.append(train_mae)

        size_test_rmse_list.append(test_rmse)
        size_test_mae_list.append(test_mae)

        size_e_u_cov.append(e_user_coverage)
        size_e_i_cov.append(e_item_coverage)
        size_e_c_cov.append(e_catelog_coverage)

        size_r_u_cov.append(r_user_coverage)
        size_r_i_cov.append(r_item_coverage)
        size_r_c_cov.append(r_catelog_coverage)

        duration_list.append(duration)
        print('duration is',duration)
```

```
use 90.0% of data
Computing the msd similarity matrix...
Done computing similarity matrix.
evaluate on train set
RMSE: 0.5677
MAE:  0.4209
evaluate on test set
RMSE: 0.8889
MAE:  0.6855
('duration is', 442.4302878379822)
use 80.0% of data
Computing the msd similarity matrix...
Done computing similarity matrix.
evaluate on train set
RMSE: 0.5607
MAE:  0.4156
evaluate on test set
RMSE: 0.8910
MAE:  0.6875
('duration is', 376.3689777851105)
use 70.0% of data
Computing the msd similarity matrix...
Done computing similarity matrix.
evaluate on train set
RMSE: 0.5543
MAE:  0.4108
evaluate on test set
```

```
RMSE: 0.8943
MAE:  0.6888
('duration is', 300.5175588130951)
use 60.0% of data
Computing the msd similarity matrix...
Done computing similarity matrix.
evaluate on train set
RMSE: 0.5486
MAE:  0.4065
evaluate on test set
RMSE: 0.9002
MAE:  0.6926
('duration is', 225.91154599189758)
use 50.0% of data
Computing the msd similarity matrix...
Done computing similarity matrix.
evaluate on train set
RMSE: 0.5435
MAE:  0.4033
evaluate on test set
RMSE: 0.9056
MAE:  0.6966
('duration is', 163.902508020401)
use 40.0% of data
Computing the msd similarity matrix...
Done computing similarity matrix.
evaluate on train set
RMSE: 0.5409
MAE:  0.4030
evaluate on test set
RMSE: 0.9122
MAE:  0.7006
('duration is', 110.61429595947266)
use 30.0% of data
Computing the msd similarity matrix...
Done computing similarity matrix.
evaluate on train set
RMSE: 0.5374
MAE:  0.4026
evaluate on test set
RMSE: 0.9322
MAE:  0.7135
('duration is', 73.14063787460327)
use 20.0% of data
Computing the msd similarity matrix...
Done computing similarity matrix.
evaluate on train set
RMSE: 0.5361
```

```
MAE:  0.4051
evaluate on test set
RMSE: 0.9677
MAE:  0.7372
('duration is', 43.750141859054565)
use 10.0% of data
Computing the msd similarity matrix...
Done computing similarity matrix.
evaluate on train set
RMSE: 0.5347
MAE:  0.4054
evaluate on test set
RMSE: 1.0760
MAE:  0.8234
('duration is', 23.693558931350708)
```

```
In [0]: sample_size_list=[1-i for i in size_list]
        model_size = pd.DataFrame()
        model_size['Sample_size']=sample_size_list
        model_size['Running_time']=duration_list
        model_size['RMSE_test']=size_test_rmse_list
        model_size['MAE_test']=size_test_mae_list
        model_size['Catalog_Coverage_test']=size_e_c_cov
        model_size['User_Coverage_test']=size_e_u_cov
        model_size['Item_Coverage_test']=size_e_i_cov
        # model_size = pd.DataFrame(
        #     {'Sample_size': sample_size_list,
        #      'Running_time': duration_list,
        #      #'RMSE_train': size_train_rmse_list,
        #      'RMSE_test': size_test_rmse_list,
        #      #'MAE_train': size_train_mae_list,
        #      'MAE_test': size_test_mae_list,
        #      #'Catalog_Coverage_train': r_catelog_coverage,
        #      'Catalog_Coverage_test': e_catelog_coverage,
        #      #'User_Coverage_train': r_user_coverage,
        #      'User_Coverage_test': e_user_coverage,
        #      #'Item_Coverage_train': r_item_coverage,
        #      'Item_Coverage_test': e_item_coverage
        #     })
        # print(model_size)
```

Show all results in a table

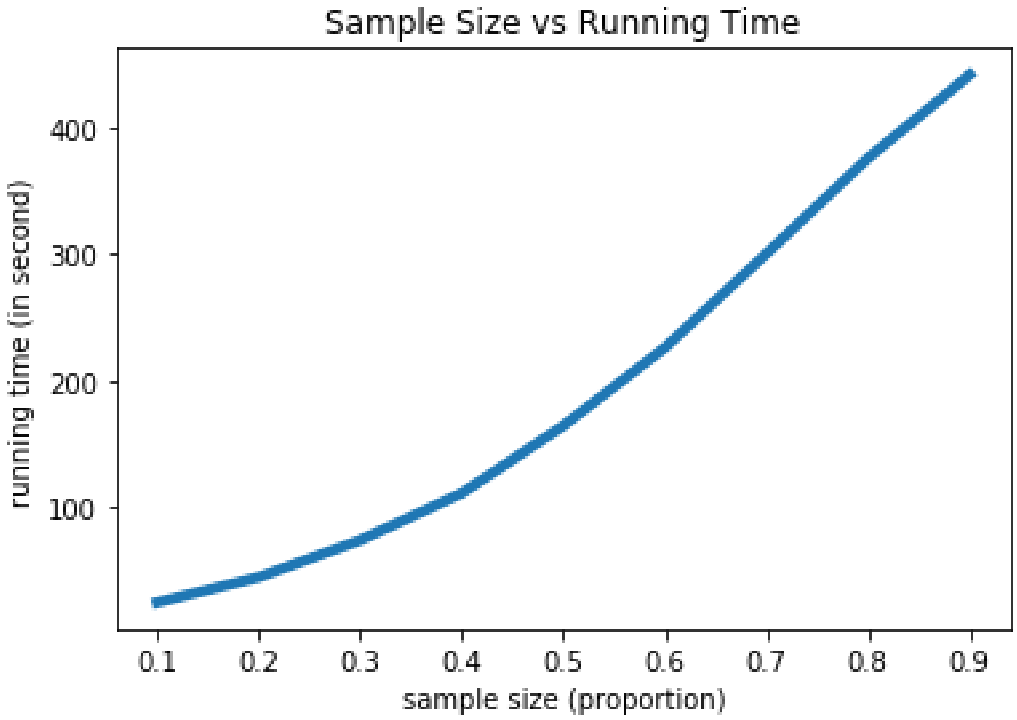
```
In [17]: model_size
```

```
Out[17]:    Sample_size  Running_time  ...  User_Coverage_test  Item_Coverage_test
         0          0.9    442.430288  ...            0.170248            0.088053
```

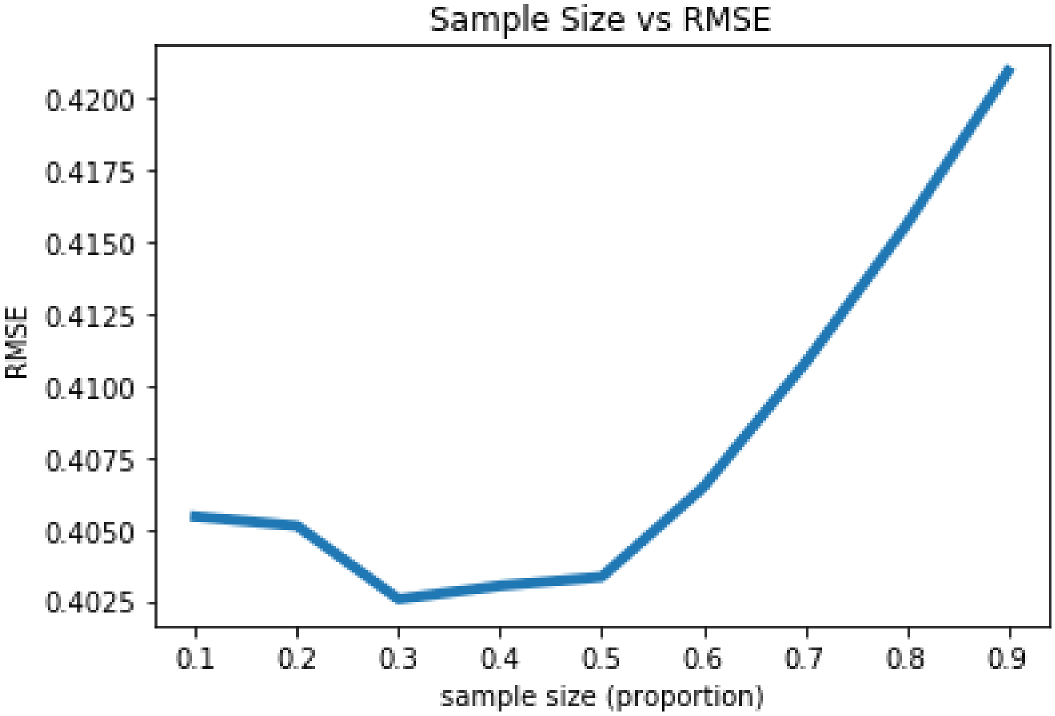
```
1          0.8    376.368978  ...          0.164899          0.090135
2          0.7    300.517559  ...          0.163310          0.084356
3          0.6    225.911546  ...          0.162923          0.088475
4          0.5    163.902508  ...          0.168214          0.087274
5          0.4    110.614296  ...          0.170131          0.080032
6          0.3     73.140638  ...          0.180743          0.096568
7          0.2     43.750142  ...          0.183816          0.096406
8          0.1     23.693559  ...          0.191933          0.091353

[9 rows x 7 columns]
```

0.0.7 Plot graph

```
In [42]: lines = plt.plot(sample_size_list,duration_list)
         plt.setp(lines[0], linewidth=4)
         #plt.setp(lines[1], linewidth=2)
         #plt.setp(lines[2], markersize=10)


         plt.xlabel('sample size (proportion)')
         plt.ylabel('running time (in second)')
         plt.title('Sample Size vs Running Time')
         plt.savefig('S vs time')
         plt.show()
```



```
In [45]: lines = plt.plot(sample_size_list,size_test_rmse_list)
         plt.setp(lines[0], linewidth=4)
         #plt.setp(lines[1], linewidth=2)
         #plt.setp(lines[2], markersize=10)


         plt.xlabel('sample size (proportion)')
         plt.ylabel('RMSE')
         plt.title('Sample Size vs RMSE')
         plt.savefig('S vs RMSE')
         plt.show()
```



```
In [0]: model_size.to_csv('model_size.csv',index=False)
```