In [2]:
```
import pandas as pd
import numpy as np
import pyspark as ps
from scipy.sparse import csr_matrix
from sklearn.neighbors import NearestNeighbors
```

In [3]:
```
rating_dt = pd.read_csv('../data/ratings.csv')
```

In [4]:
```
#tag_dt = pd.read_csv('tags.csv')
```

In [7]:
```
#movie_dt = pd.read_csv('movies.csv')
```

In [17]:
```
#print(tag_dt.head(5))
print(rating_dt.head(5))
#print(movie_dt.head(5))
```

```
   userId  movieId  rating   timestamp
0       1      307     3.5  1256677221
1       1      481     3.5  1256677456
2       1     1091     1.5  1256677471
3       1     1257     4.5  1256677460
4       1     1449     4.5  1256677264
```

In [3]:
```
rating_dt.shape
```

Out[3]: (27753444, 4)

Sample Data

choose movies that have been rated for over 100 times

In [4]:
```
# filter out movies that has less than 100 rates
movie_rating_count = rating_dt.groupby(['movieId']).size().reset_index(n
ame='Mcount')
movie_poll = movie_rating_count[movie_rating_count.Mcount > 100].movieId
```

In [5]:
```
# sample 1000 items from movie poll
movie_sample = movie_poll.sample(1000, replace=False, random_state=1).va
lues.reshape(-1, 1)

# get rating and users of sampled movies
sample_movie_rating = rating_dt.loc[rating_dt['movieId'].isin(movie_samp
le)]
```

In [6]:
```
# sample 1000 users
user_poll = np.unique(sample_movie_rating['userId'])
np.random.seed(1)
user_test = np.random.choice(user_poll, 1000)
test_user_rating = sample_movie_rating.loc[sample_movie_rating['userId']
.isin(user_test)]
```

KNN Collaborative Filtering

In [8]:
```
# pivot movie, user, rating dataframe into compressed matrix
#
def movie_use_matrix_pivot(df_):
    mu_matrix = df_.pivot(index = 'movieId',
                          columns = 'userId',
                          values = 'rating').fillna(0)
    # compress original matrix
    mu_matrix_cp = csr_matrix(mu_matrix.values)
    return mu_matrix, mu_matrix_cp
```

In [9]:
```
# input: compressed movie-user matrix, distance method, number of neares
t neighbors
# default distance method is adjusted cosine, default neighbor is 5
# output: a pre-trained KNN model
#
def knn_model_fit(mu_matrix_cp, dist_='cosine', n_neighbor_=5):
    # use adjusted cosine distance to find k nearest item
    # default k-neighbor is 5
    knn = NearestNeighbors(metric=dist_, algorithm='brute', n_neighbors=
n_neighbor_, n_jobs=-1)
    knn.fit(mu_matrix_cp)
    return knn
```

In [10]:
```
# input: a pre-trained KNN model (n_neighbor = 5), movie-user matrix, on
e movieid
# output: a list of distance of nearest neighbors, a list of indices of
 nearest neighbors
# to movie-user matrix
#
def single_recommendation(knn_model, mu_matrix, movieid):
    movie_input = mu_matrix.loc[mu_matrix.index == movieid]
    distance, indices = knn_model.kneighbors(movie_input)
    return distance, indices
```

In [13]:
```
# test function
sample_matrix, sample_matrix_cp = movie_use_matrix_pivot(test_user_ratin
g)
sample_matrix_knn = knn_model_fit(sample_matrix_cp, 'cosine', 5)

distance1, indices1 = sample_matrix_knn.kneighbors(sample_matrix.loc[sam
ple_matrix.index == 34])
distance2, indices2 = single_recommendation(sample_matrix_knn, sample_ma
trix, 34)
assert(np.alltrue(indices1 == indices2))
```

In [14]:
```
# input: rating dataset, userid, a rating threshold, movies that are rat
ed below threshold
# will not be counted
# output: a list of high-scored movies that are rated by givern user, a
 list of corresponding ratings
#
def get_rated_movies(data, userid, threshold=2):
    all_rates = data[data['userId'] == userid]
    high_rates = all_rates[all_rates['rating'] >= threshold]['rating'].v
alues
    high_rate_movie = all_rates[all_rates['rating'] >= threshold]['movie
Id'].values
    return high_rate_movie, high_rates
```

In [15]:

```
# input: pre-trained KNN model, movie-user matrix of historical data,
# a list of movies that have been rated by given user, corresponding rat
ings
# output: if number of rated movies < 5, return list of 5 * n recommenda
tion
# if number of rated movies > 5, return list of 20 recommendation base o
n rating itself
# and 5 nearest neighbors
#
def mult_recommendation(knn_model, mu_matrix, ratedmovies, ratings):
    indices_list = []
    distance_list = []
    recommend_list = []

    for count, i in enumerate(ratedmovies):
        distance, indices = single_recommendation(knn_model, mu_matrix,
i)
        indices_list.extend(indices.reshape(-1))
        # adjust distance by rating
        distance_adj = (distance.reshape(-1) / ratings[count]).tolist()
        # find corresponding movieid
        movie_list = mu_matrix.index[indices.reshape(-1)].tolist()
        # delete if same movieid exist in recommendation list
        if movie_list[0] == i:
            movie_list = movie_list[1:]
            distance_adj = distance_adj[1:]

        distance_list.extend(distance_adj)
        recommend_list.extend(movie_list)

    recommend_list = np.array(recommend_list)

    if recommend_list.shape[0] <= 20:
        return recommend_list
    else:
        sorted_recommend = recommend_list[np.array(distance_list).argsor
t()]
        # choose top 20 recommendations
        return sorted_recommend[:20]
```

In [16]:

```
# test function (small dataset)
movies, ratings = get_rated_movies(test_user_rating, 281940, 2)
res = mult_recommendation(sample_matrix_knn, sample_matrix, movies, rati
ngs)
print(movies)
print(res)
print('recommendation list is of length', len(res))
```

```
[  47  301  309  431  509  920  934 1066 1089 1198 1293 1357 1358 1682
 2324 3159 4011 4019 4973 5299 5445 7153]
[4011   47 2542 6874 1198 2542 1222 5445 4011 4973 1387 1500 7153 1089
 5445  515 1527 1387 1089 2302]
recommendation list is of length 20
```

Matrix Factorization Collaborative Filtering

In [8]:
```
from pyspark.ml.evaluation import RegressionEvaluator, BinaryClassificat
ionEvaluator
from pyspark.ml.recommendation import ALS
from pyspark.ml.tuning import TrainValidationSplit, ParamGridBuilder
from pyspark.sql import SparkSession

import seaborn as sns
import matplotlib.pyplot as plt

# initialize spark session
spark = SparkSession.builder.appName('ieor-hw2').getOrCreate()
```

In [9]:
```
# transform pandas df to spark df   --- long run time
test_user_rating_spark = spark.createDataFrame(test_user_rating)
sample_movie_rating_spark = spark.createDataFrame(sample_movie_rating)
```

In [10]:
```
# Create ALS model
als = ALS(
         userCol="userId",
         itemCol="movieId",
         ratingCol="rating",
         nonnegative = True,
         implicitPrefs = False,
         coldStartStrategy="drop"
)
```

Cross Validation Setup

5-fold CV on dataset of 1000 movies and 2.6 million ratings
use RMSE as scoring metric, and search for best 'rank'

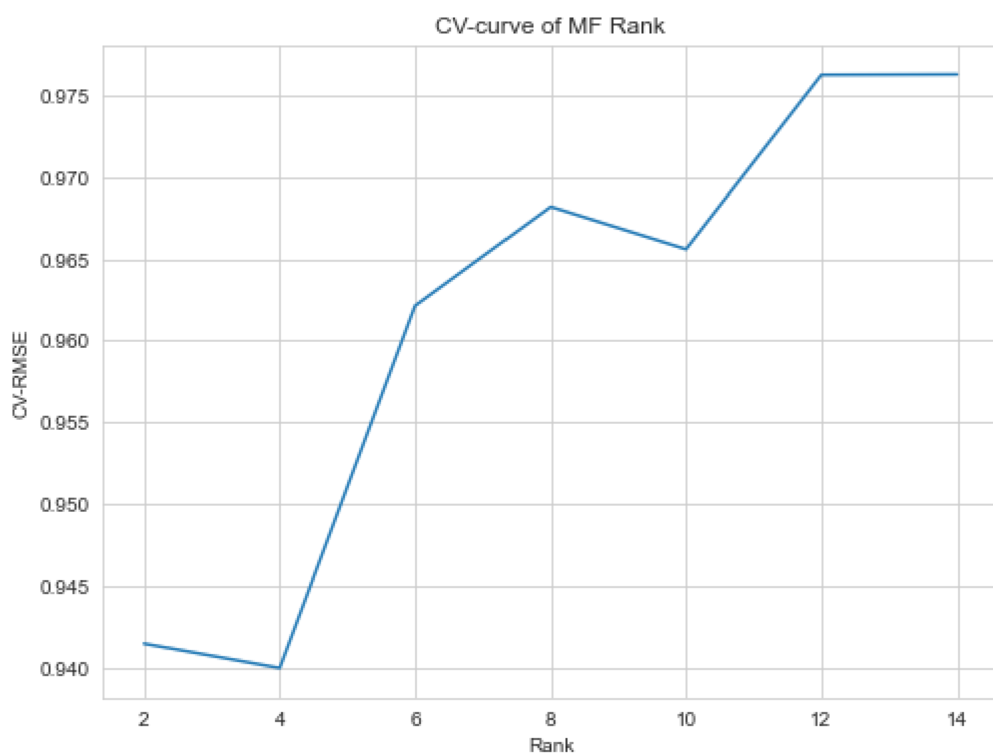
In [12]:
```
# train-test split on large dataset
(train_big,test_big) = sample_movie_rating_spark.randomSplit([0.80, 0.20
], seed=15)
# train-test split on small sample data
(train_small,test_small) = test_user_rating_spark.randomSplit([0.80, 0.2
0], seed=15)
```

In [174]:
```
# setup grid search parameters
# test value of hyperparameter 'rank' from 2, 4, 6, 8, 10, 12, 14
para_grid = ParamGridBuilder() \
                .addGrid(als.rank, range(2, 15, 2))  \
                .build()

# use rmse as scoring metric
evaluator = RegressionEvaluator(metricName='rmse',
                                labelCol='rating',
                                predictionCol='prediction')

# setup validation function
tvs = TrainValidationSplit(estimator = als,
                           estimatorParamMaps = para_grid,
                           evaluator = evaluator,
                           seed=1)
```

In [175]:
```
# fit on big data set   --- long run time
model = tvs.fit(train_big)
```

In [176]:
```
# visualize performance on validation set for each value of rank
ax, fig = plt.subplots(figsize=(8, 6))
sns.set_style("whitegrid")
plt.plot(range(2, 15, 2), model.validationMetrics)
plt.xlabel('Rank')
plt.ylabel('CV-RMSE')
plt.title('CV-curve of MF Rank')
```

Out[176]:
```
Text(0.5, 1.0, 'CV-curve of MF Rank')
```



In [13]:
```
# uncomment to save model for future use
## best.save('als_model')

# uncomment to train from data with best hyperparameters
## als_2 = als.setRank(4)
## best = als_2.fit(train_big)
```

In [308]:
```
# best model has rank 4, iteration 10 (default), regularization paramete
r 0.1 (default)
best = model.bestModel

predictions = best.transform(test_small)
rmse = evaluator.evaluate(predictions)

print("RMSE: " + str(rmse))
print("***BestModel***")
print("  rank: " + str(best.rank))
print("  MaxIter: " + str(best._java_obj.parent().getMaxIter()))
print("  RegParam: " + str(best._java_obj.parent().getRegParam()))
```

```
RMSE: 0.7658987305990971
***BestModel***
  rank: 4
  MaxIter: 10
  RegParam: 0.1
```

MF Model RMSE on Test and Train 100% Dataset

In [71]:
```
test_pred = best.transform(test_big)
test_rmse = evaluator.evaluate(test_pred)
```

In [24]:
```
train_pred = best.transform(train_big)
train_rmse = evaluator.evaluate(train_pred)
```

In [72]:
```
print("Test RMSE: " + str(test_rmse))
print("Train RMSE: " + str(train_rmse))
```

```
Test RMSE: 0.9115554536168751
Train RMSE: 0.7048404634761517
```

Matrix Factorization Recommender Funtion

In [16]:
```
# input: a pre-trained mf model, rating data (spark df), number of recom
mendations for each user
# output: a dict of recommendations sorted descending by predicted ratin
g, key by userid
#
def MF_recommendation(mf_model, data, rec_number=20):
    predictions = mf_model.transform(data)
    user_recommendation = mf_model.recommendForUserSubset(data, rec_numb
er).toPandas()
    rec_dict = {}

    for i in range(0, user_recommendation.shape[0]):
        userid = user_recommendation.iloc[i, 0]
        movieid = [item[0] for item in user_recommendation.iloc[i, 1]]
        rec_dict[userid] = movieid

    return rec_dict
```

In [31]:
```
# test function (sample dataset)
rec = MF_recommendation(best, test_small)
```

In [43]:
```
# iterate through dictionary
# for purpose of display recommendation
from itertools import islice

def take(n, iterable):
    "Return first n items of the iterable as a list"
    return list(islice(iterable, n))
```

In [52]:
```
first_5 = take(5, rec.items())
first_5
for pair in first_5:
    print(f'userId: {pair[0]}')
    print(f'recommend movies: {pair[1]}')
```

```
userId: 231287
recommend movies: [5224, 7153, 4973, 771, 86504, 5772, 800, 72104, 5074
2, 2324, 1357, 515, 171011, 3920, 58425, 1293, 103867, 1295, 1358, 7222
6]
userId: 243392
recommend movies: [171011, 159819, 1198, 167832, 47, 121374, 119153, 48
516, 112556, 147330, 65133, 73681, 55721, 96488, 4011, 6808, 116411, 86
504, 2324, 89492]
userId: 37482
recommend movies: [171011, 159819, 5224, 4973, 86504, 50742, 147330, 58
425, 2324, 1212, 720, 750, 3134, 800, 951, 26903, 177765, 1293, 1284, 7
153]
userId: 115225
recommend movies: [2324, 191351, 93265, 51471, 177765, 167832, 54001, 6
970, 106441, 86504, 170697, 87308, 94503, 134374, 91844, 116855, 10669
6, 89554, 117176, 103867]
userId: 162241
recommend movies: [7153, 171011, 4011, 2542, 91529, 121374, 86504, 47,
106873, 48516, 2324, 1080, 1089, 70286, 3949, 171253, 159819, 4973, 119
153, 1357]
```

Precision, Recall, Coverage Functions

In [53]:
```
# input: rating data (spark df), split point (default 2)
# rating 5, 4, 3 will be considered as positive (as default)
# rating 1, 2 will be considered as negative (as default)
# output: dict of positively rated movie key by user, dict of negative r
ated movie key by user
#
def positive_negative_split(spdf, threshold=2):
    user_rate_df = spdf.toPandas()
    pos_dict = {}
    neg_dict = {}

    for user in np.unique(user_rate_df.userId):
        all_rates = user_rate_df[user_rate_df['userId'] == user]
        positive_rates = all_rates[all_rates['rating'] > threshold]['mov
ieId'].tolist()
        negative_rates = all_rates[all_rates['rating'] <= threshold]['mo
vieId'].tolist()
        pos_dict[user] = positive_rates
        neg_dict[user] = negative_rates

    return pos_dict, neg_dict
```

In [21]:
```
# test function
pos, neg = positive_negative_split(test_big)
```

In [19]:
```
# input: pre-trained MF model, new rating data (spark df), split point
 (default 2)
# predicted rating > 2.5 will be predicted as positive
# predicted rating < 2.5 will be predicted as negative
# output: recall and precision of pre-trained MF model on given data set
#
def precision_recall_cal(mf_model, data, threshold=2):
    pos, neg = positive_negative_split(data, threshold)
    predictions = mf_model.transform(data).toPandas()
    tp = 0
    fp = 0
    p_total = 0

    for user in pos:
        for rated in pos[user]:
            pred = predictions.loc[(predictions.userId == user) & (predi
ctions.movieId == rated),
                                   'prediction'].tolist()
            if pred:
                p_total += 1
                if pred[0] >= threshold + 0.5:
                    tp += 1

    for user in neg:
        for rated in neg[user]:
            pred = predictions.loc[(predictions.userId == user) & (predi
ctions.movieId == rated),
                                   'prediction'].tolist()
            if pred:
                if pred[0] >= threshold + 0.5:
                    fp += 1

    recall = tp / p_total
    precision = tp / (tp + fp)

    return recall, precision
```

In [56]:
```
# test function (sample dataset)
precision_recall_cal(best, test_small, 2)
```

Out[56]: (0.9635523613963038, 0.9310515873015873)

In [58]:
```
#train_recall, train_prec = precision_recall_cal(best, train_big, 2)  --
- long run time
test_recall, test_prec = precision_recall_cal(best, test_big, 2)
```

In [59]:
```
#print(f'Recall on training set: {train_recall}')
#print(f'Precision on training set: {train_prec}')
print(f'Recall on testing set: {test_recall}')
print(f'Precision on testing set: {test_prec}')
```

```
Recall on testing set: 0.9396966422365336
Precision on testing set: 0.9148965505538375
```

In [14]:
```
# calculate number of covered recommendations
def coverage_cal(mf_model, data, rec_number = 20):
    rec_dic = MF_recommendation(mf_model, data, rec_number)
    rec_values = rec_dic.values()
    rec_unique = set()

    for item in rec_values:
        rec_unique.update(item)

    return len(rec_unique)
```

In [20]:
```
# calculate coverage on big data set   --- long run time
train_cover = coverage_cal(best, train_big)
print(f'Recommendation list covered {train_cover}')
```

```
Recommendation list covered 308
```

Model Evaluation on Different Size of Data

In [60]:
```
# random select 25%, 50%, 75% from big dataset
movie_ratings_25 = sample_movie_rating.sample(frac = .25, random_state =
1)
movie_ratings_50 = sample_movie_rating.sample(frac = .50, random_state =
2)
movie_ratings_75 = sample_movie_rating.sample(frac = .75, random_state =
3)
```

In [63]:
```
# convert to spark-df  --- long run time
movie_rating_25_sp = spark.createDataFrame(movie_ratings_25)
movie_rating_50_sp = spark.createDataFrame(movie_ratings_50)
movie_rating_75_sp = spark.createDataFrame(movie_ratings_75)

# train-test split
(train_25,test_25) = movie_rating_25_sp.randomSplit([0.80, 0.20], seed=1
)
(train_50,test_50) = movie_rating_50_sp.randomSplit([0.80, 0.20], seed=1
)
(train_75,test_75) = movie_rating_75_sp.randomSplit([0.80, 0.20], seed=1
)
```

In [66]:
```
als_2 = als.setRank(4)
```

In [65]:
```
# fit mf model on 75% data, rank = 4
model_75 = als_2.fit(train_75)
model_50 = als_2.fit(train_50)
model_25 = als_2.fit(train_25)
```

In [68]:
```
# calculate rmse on both testing and training
pred_75_train = model_75.transform(train_75)
pred_75_test = model_75.transform(test_75)
eva_75_train = evaluator.evaluate(pred_75_train)
eva_75_test = evaluator.evaluate(pred_75_test)

pred_50_train = model_50.transform(train_50)
pred_50_test = model_50.transform(test_50)
eva_50_train = evaluator.evaluate(pred_50_train)
eva_50_test = evaluator.evaluate(pred_50_test)

pred_25_train = model_50.transform(train_25)
pred_25_test = model_50.transform(test_25)
eva_25_train = evaluator.evaluate(pred_25_train)
eva_25_test = evaluator.evaluate(pred_25_test)
```

In [73]:
```
size_rmse_test = [eva_25_test, eva_50_test, eva_75_test, test_rmse]
size_rmse_train = [eva_25_train, eva_50_train, eva_75_train, train_rmse]
```

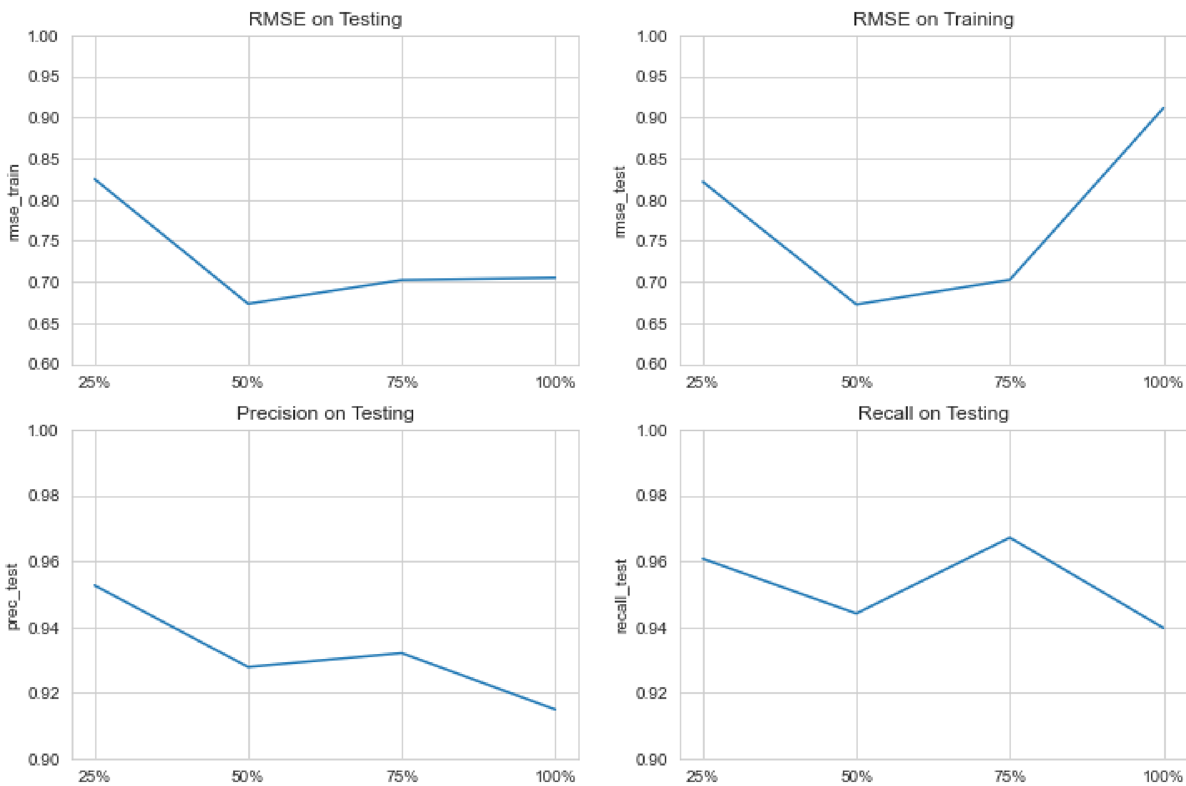
In [75]:
```
# calculate precision and racall on testing  --- long run time
test_25_recall, test_25_prec = precision_recall_cal(model_25, test_25, 2
)
test_50_racall, test_50_prec = precision_recall_cal(model_50, test_25, 2
)
test_75_recall, test_75_prec = precision_recall_cal(model_75, test_75, 2
)
```

In [76]:
```
size_prec_test = [test_25_prec, test_50_prec, test_75_prec, test_prec]
size_recall_test = [test_25_recall, test_50_racall, test_75_recall, test
_recall]
```

In [117]:
```
size_df = pd.DataFrame(size_rmse_test, index=['25%', '50%', '75%', '10
0%'], columns=['rmse_test'])
size_df['rmse_train'] = size_rmse_train
size_df['prec_test'] = size_prec_test
size_df['recall_test'] = size_recall_test
```

In [184]:
```
# visualize model evaluation on different size
fig, axes = plt.subplots(2, 2, figsize=(12, 8))
sns.lineplot(data=size_df.rmse_train, ax=axes[0, 0])
sns.lineplot(data=size_df.rmse_test, ax=axes[0, 1])
sns.lineplot(data=size_df.prec_test, ax=axes[1, 0])
sns.lineplot(data=size_df.recall_test, ax=axes[1, 1])

axes[0, 1].set_ylim([0.6, 1])
axes[0, 0].set_ylim([0.6, 1])
axes[1, 0].set_ylim([0.9, 1])
axes[1, 1].set_ylim([0.9, 1])

axes[0, 0].set_title('RMSE on Testing')
axes[0, 1].set_title('RMSE on Training')
axes[1, 0].set_title('Precision on Testing')
axes[1, 1].set_title('Recall on Testing')
```

Out[184]:
```
Text(0.5, 1.0, 'Recall on Testing')
```



In [ ]: