movie_recom_ALS_manxilu

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```
In [1]: import findspark
        findspark.init()
        import math
        import numpy as np
        import pandas as pd
        import seaborn as sns
        import matplotlib.pyplot as plt
        import math
        %matplotlib inline
```

```
In [2]: from pyspark.sql import SparkSession, Column, Row, functions as F
```

```
In [3]: spark = (SparkSession.builder\
                .master("local[*]")\
                .appName("spark movie recommender")\
                .getOrCreate())
        sc = spark.sparkContext
```

0.1 Data ETL and Exploration

```
In [4]: movies = spark.read.load("../movie_recommender/movies.csv", format='csv', header = Tru
        ratings = spark.read.load("../movie_recommender/ratings.csv", format='csv', header = T
        links = spark.read.load("../movie_recommender/links.csv",format='csv', header = True)
        tags = spark.read.load("../movie_recommender/tags.csv",format='csv', header = True)
```

```
In [5]: movies.show(1)
        ratings.show(1)
        links.show(1)
        tags.show(1)
```

```
+-------+----------------+--------------------+
|movieId|           title|              genres|
+-------+----------------+--------------------+
|      1|Toy Story (1995)|Adventure|Animati...|
+-------+----------------+--------------------+
only showing top 1 row

+------+-------+------+---------+
```

```
|userId|movieId|rating| timestamp|
+------+-------+------+----------+
|     1|     31|   2.5|1260759144|
+------+-------+------+----------+
only showing top 1 row

+-------+------+------+
|movieId| imdbId|tmdbId|
+-------+------+------+
|      1|0114709|   862|
+-------+------+------+
only showing top 1 row

+------+-------+--------------------+----------+
|userId|movieId|                 tag| timestamp|
+------+-------+--------------------+----------+
|    15|    339|sandra 'boring' b...|1138537770|
+------+-------+--------------------+----------+
only showing top 1 row
```

```
In [6]: # sparsity
        num_users=ratings.select('userId').distinct().count()
        num_movies=ratings.select('movieId').distinct().count()
        num_ratings = ratings.count()
        sparsity=1-(num_ratings*1.0)/(num_users*num_movies)
        print("The sparsity is ", sparsity)
```

```
('The sparsity is ', 0.9835608583913366)
```

```
In [7]: # List movies not rated before
        print("The following movieId are not rated")
        all_movies = ratings.select('movieId').union(tags.select('movieId'))
        rated = ratings.select('movieId')
        not_rated = all_movies.subtract(rated)
        not_rated.distinct().show()
```

```
The following movieId are not rated
+-------+
|movieId|
+-------+
| 144172|
|  94969|
| 132547|
|   7335|
| 110871|
|   5984|
```

```
| 131796|
| 132800|
| 128235|
|  39421|
|  82313|
| 111251|
|  42217|
| 132549|
|   8767|
| 161582|
| 155064|
| 111249|
|  48711|
| 132458|
+-------+
only showing top 20 rows
```

```
In [8]: #Number of movies for each gene category
        movies.select('genres').distinct().show()
        gene_set = set()
        for row in movies.collect():
            gene = row["genres"]
            gene_set.update(gene.split("|"))
        gene_set = list(gene_set)
        gene=[str(i) for i in gene_set]

        gene_count=dict((i, movies.filter(movies["genres"].contains(i)).count()) for i in gene
        print("The number of movies for each category is ",gene_count)
```

```
+--------------------+
|              genres|
+--------------------+
|Comedy|Horror|Thr...|
|Adventure|Sci-Fi|...|
|Action|Adventure|...|
| Action|Drama|Horror|
|Comedy|Drama|Horr...|
|Action|Animation|...|
|Animation|Childre...|
|Action|Adventure|...|
| Adventure|Animation|
|    Adventure|Sci-Fi|
|Documentary|Music...|
|Adventure|Childre...|
|  Documentary|Sci-Fi|
| Musical|Romance|War|
```

```
|Action|Adventure|...|
|Adventure|Childre...|
|Crime|Drama|Fanta...|
|Comedy|Mystery|Th...|
|   Adventure|Fantasy|
|Action|Animation|...|
+--------------------+
only showing top 20 rows

('The number of movies for each category is ', {'Mystery': 543, 'Romance': 1545, 'IMAX': 153,
```

```
In [9]: #Rating distribution
        print("The rating distribution")
        rd=ratings.select('rating').groupBy('rating').count().orderBy("rating").show()
```

```
The rating distribution
+------+-----+
|rating|count|
+------+-----+
|   0.5| 1101|
|   1.0| 3326|
|   1.5| 1687|
|   2.0| 7271|
|   2.5| 4449|
|   3.0|20064|
|   3.5|10538|
|   4.0|28750|
|   4.5| 7723|
|   5.0|15095|
+------+-----+
```

0.2 Collaborative Filtering

0.2.1 With ALS algorithm, we can use gird search to tune the hyperparameters

```
In [10]: def grid_ALS(train_data, validation_data, num_iters, reg_param, ranks):
             min_error = float('inf')
             best_rank = -1
             best_regularization = 0
             best_model = None
             for rank in ranks:
                 for reg in reg_param:
                     model = ALS.train(train_data, rank, iterations = num_iters, lambda_ = reg
                     predictions = model.predictAll(validation_data.map(lambda x: (x[0], x[1])
                     rate_and_preds = validation_data.map(lambda x: ((int(x[0]), int(x[1])), fl
                     error = math.sqrt(rate_and_preds.map(lambda r: (r[1][0] - r[1][1])**2).mea
```

```
                print ('{} latent factors and regularization = {}: validation RMSE is {}'
                if error < min_error:
                    min_error = error
                    best_rank = rank
                    best_regularization = reg
                    best_model = model
        print ('\nThe best model has {} latent factors and regularization = {}'.format(bes
        return best_model
```

In [11]:
```
# Prep: RDD based API
# reload "ratings.csv" using sc.textFile and then convert it to the form of (user, it
from pyspark.mllib.recommendation import ALS,MatrixFactorizationModel, Rating
movie_rating = sc.textFile("../movie_recommender/ratings.csv")
header = movie_rating.take(1)[0]
rating_data = movie_rating.filter(lambda line: line!=header).map(lambda line: line.spl

train, validation, test = rating_data.randomSplit([6,2,2],seed = 7856)
test_RDD = test.map(lambda x: (x[0], x[1]))

# With the ALS model, we can use a grid search to find the optimal hyperparameters.
num_iterations = 10
ranks = [8, 10, 12]
reg_params = [0.05, 0.1, 0.2]

import time
start_time = time.time()

final_model = grid_ALS(train, validation, num_iterations, reg_params, ranks)

print ('Total Runtime: {:.2f} seconds'.format(time.time() - start_time))
```

```
8 latent factors and regularization = 0.05: validation RMSE is 1.04127692828
8 latent factors and regularization = 0.1: validation RMSE is 0.959453703021
8 latent factors and regularization = 0.2: validation RMSE is 0.937054258064
10 latent factors and regularization = 0.05: validation RMSE is 1.05954349932
10 latent factors and regularization = 0.1: validation RMSE is 0.965392217993
10 latent factors and regularization = 0.2: validation RMSE is 0.936760044029
12 latent factors and regularization = 0.05: validation RMSE is 1.04863309899
12 latent factors and regularization = 0.1: validation RMSE is 0.960966780654
12 latent factors and regularization = 0.2: validation RMSE is 0.934213475984

The best model has 12 latent factors and regularization = 0.2
Total Runtime: 89.42 seconds
```

In [12]:
```
def plot_learning_curve(iter_setting, train_data, validation_data, reg, rank):
    train_rmse = []
    valid_rmse = []
```

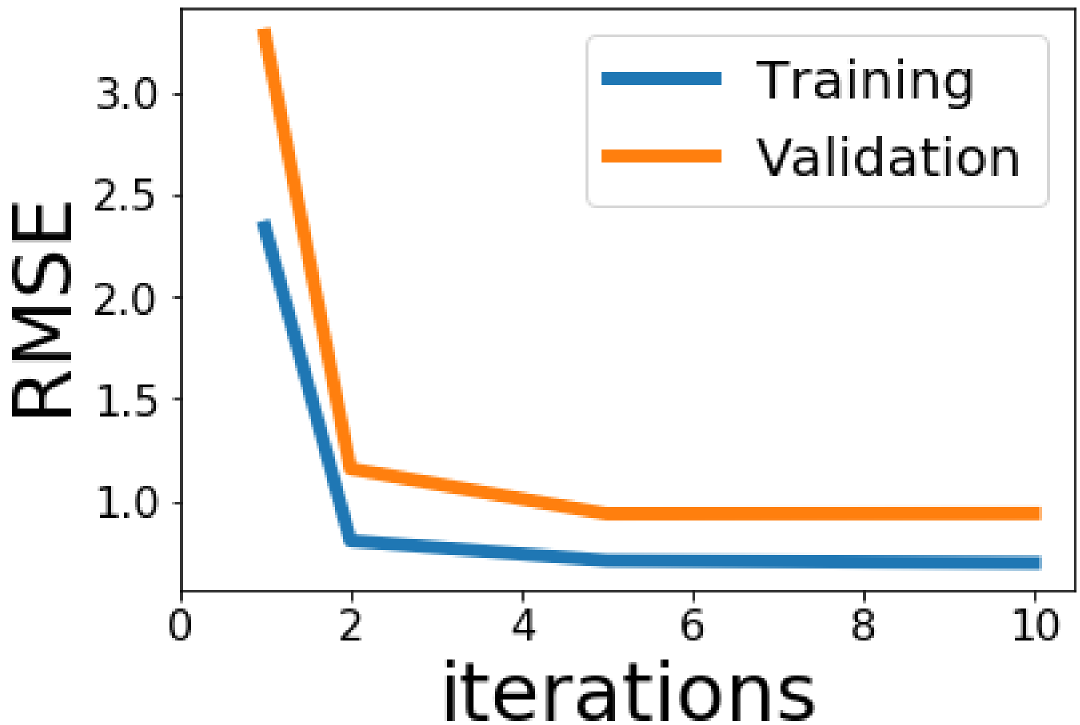
```
        for iteration in iter_setting:

            model = ALS.train(train_data, rank, iterations = iteration, lambda_ = reg)

            # Training RMSE
            predictions = model.predictAll(train_data.map(lambda x: (x[0], x[1])))\
                          .map(lambda x: ((x[0], x[1]), x[2]))
            rate_and_preds = train_data.map(lambda x: ((int(x[0]), int(x[1])), float(x[2]
                             .join(predictions)
            error = math.sqrt(rate_and_preds.map(lambda r: (r[1][0] - r[1][1])**2).mean()
            train_rmse.append(error)
            # Validation RMSE
            predictions = model.predictAll(validation_data.map(lambda x: (x[0], x[1])))\
                          .map(lambda x: ((x[0], x[1]), x[2]))
            rate_and_preds = validation_data.map(lambda x: ((int(x[0]), int(x[1])), float
                             .join(predictions)
            error = math.sqrt(rate_and_preds.map(lambda r: (r[1][0] - r[1][1])**2).mean()
            valid_rmse.append(error)

        plt.plot(iter_setting, train_rmse, label='Training', linewidth=5)
        plt.plot(iter_setting, valid_rmse, label='Validation', linewidth=5)
        plt.xticks(range(0, max(iter_setting) + 1, 2), fontsize=16)
        plt.yticks(fontsize=16)
        plt.xlabel('iterations', fontsize=30)
        plt.ylabel('RMSE', fontsize=30)
        plt.legend(loc='best', fontsize=20)
        plt.show()
```

```
In [13]: iter_array = [1, 2, 5, 10]
         plot_learning_curve(iter_array, train, validation, 0.2, 8)
```




```
In [14]: # check testing error
         predictions = final_model.predictAll(test.map(lambda x: (x[0], x[1]))).map(lambda x:
         rates_and_preds = test.map(lambda r: ((int(r[0]), int(r[1])), float(r[2]))).join(pred
         error = math.sqrt(rates_and_preds.map(lambda r: (r[1][0] - r[1][1])**2).mean())
         print ('For testing data the RMSE is %s' % (error))
```

```
For testing data the RMSE is 0.908986799055
```

The error is slightly better than validation RMSE.

0.3 Top 20 Recommendation for New User with more than 50 ratings by others

```
In [15]: new_user_ID = 0
         new_user_RDD = sc.parallelize([
              (0,260,4), # Star Wars (1977)
              (0,1,3), # Toy Story (1995)
              (0,16,3), # Casino (1995)
              (0,25,4), # Leaving Las Vegas (1995)
              (0,32,4), # Twelve Monkeys (a.k.a. 12 Monkeys) (1995)
              (0,335,1), # Flintstones, The (1994)
              (0,379,1), # Timecop (1994)
              (0,296,3), # Pulp Fiction (1994)
```

```
            (0,858,5) , # Godfather, The (1972)
            (0,50,4) # Usual Suspects, The (1995)
        ])
        # convert rated list for new user
        new_user_rated=new_user_RDD.map(lambda x: x[1]).collect()
        # all users id
        all_movies_id= movies.select("movieId").distinct().rdd.flatMap(lambda x: x).collect()
        all_movies_id= [int(x) for x in all_movies_id]
        # unrated for new user 0
        unrated=[(0,x) for x in all_movies_id if x not in new_user_rated]
        unrated_RDD=sc.parallelize(unrated)
```

```
In [16]: # all movies titles tuple and all ratings counts tuple
        all_movies_titles = movies.select("movieId","title")\
                            .rdd.map(lambda x: (int(x[0]),x[1])).collect()
        all_rating_counts = ratings.select('movieId').groupBy('movieId').count()\
                            .orderBy("count",ascending=False)\
                            .rdd.map(lambda x: (int(x[0]),x[1])).collect()
        t=sc.parallelize(all_movies_titles)
        c=sc.parallelize(all_rating_counts)

        # train new model with new total data
        added_total_rating=rating_data.union(new_user_RDD)
        # predict unrated movie for new user
        new_model=ALS.train(added_total_rating,8,10,0.2)
        # convert to (movieId, rating) for unrated movies
        new_recommend=new_model.predictAll(unrated_RDD).map(lambda x: (x[1], x[2]))
```

```
In [17]: recommendation=t.join(c).join(new_recommend)\
                        .map(lambda x: (x[0],x[1][0][0],x[1][1],x[1][0][1]))
        top20=recommendation.filter(lambda x: x[3]>=50).takeOrdered(20, key=lambda x: -x[2])
        print ('TOP recommended movies (with more than 20 reviews):\n%s' %
                '\n'.join(map(str, top20)))
```

```
TOP recommended movies (with more than 20 reviews):
(1252, u'Chinatown (1974)', 3.8223591375164623, 76)
(913, u'Maltese Falcon, The (1941)', 3.7880575533141325, 62)
(2019, u'Seven Samurai (Shichinin no samurai) (1954)', 3.7808703305903824, 54)
(1230, u'Annie Hall (1977)', 3.764281499805653, 80)
(750, u'Dr. Strangelove or: How I Learned to Stop Worrying and Love the Bomb (1964)', 3.755419
(903, u'Vertigo (1958)', 3.7503751676418213, 69)
(1228, u'Raging Bull (1980)', 3.7407110800815877, 50)
(111, u'Taxi Driver (1976)', 3.7279950545952225, 118)
(923, u'Citizen Kane (1941)', 3.7229807753573865, 85)
(904, u'Rear Window (1954)', 3.7075527567766224, 92)
(1221, u'Godfather: Part II, The (1974)', 3.702161064537438, 135)
(1219, u'Psycho (1960)', 3.7015143816116423, 77)
(908, u'North by Northwest (1959)', 3.6941362621849367, 87)
```

```
(745, u'Wallace & Gromit: A Close Shave (1995)', 3.6854539360723284, 62)
(608, u'Fargo (1996)', 3.6733066535645382, 224)
(912, u'Casablanca (1942)', 3.667215283529995, 117)
(246, u'Hoop Dreams (1994)', 3.662437651120716, 61)
(969, u'African Queen, The (1951)', 3.6551592913369024, 50)
(1247, u'Graduate, The (1967)', 3.645794185075827, 89)
(4226, u'Memento (2000)', 3.644527143462763, 132)
```