

**A Project Report
on
ARTIST RECOMMENDATION SYSTEM USING
COLLABORATIVE FILTERING**

**submitted in partial fulfillment of the requirements for the award of the degree
of
BACHELOR OF TECHNOLOGY
in
COMPUTER SCIENCE AND ENGINEERING**

by

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(NBA Accredited – EEE, ECE, CSE and IT)
(Approved by AICTE, New Delhi and Affiliated to JNTUH, Hyderabad)
Bachupally, Hyderabad – 500090**

May, 2021

DECLARATION

We hereby declare that the work presented in this project entitled “**ARTIST RECOMMENDATION SYSTEM USING COLLABORATIVE FILTERING**” submitted towards completion of Project Work in IV year of B.Tech., CSE at ‘BVRIT HYDERABAD College of Engineering for Women’, Hyderabad is an authentic record of our original work carried out under the guidance of Ms. A.Kranthi, Assistant Professor, Department of CSE.

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Certificate

This is to certify that the Project Work report on “**ARTIST RECOMMENDATION SYSTEM USING COLLABORATIVE FILTERING**” is a bona fide work carried out by Ms. N.HARSHINI (17WH1A05A9) ; Ms. MNS.YAMINI (17WH1A05A7) ; Ms. M.AKSHITHA (17WH1A0568) in the partial fulfillment for the award of B.Tech. degree in **Computer Science and Engineering, BVRIT HYDERABAD College of Engineering for Women, Bachupally, Hyderabad**, affiliated to Jawaharlal Nehru Technological University Hyderabad, Hyderabad under my guidance and supervision.

The results embodied in the project work have not been submitted to any other University or Institute for the award of any degree or diploma.

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ABSTRACT

With commercial music streaming service which can be accessed from mobile devices, the availability of digital music currently is abundant compared to previous era. Sorting out all this digital music is a very time-consuming and causes information fatigue. Therefore, it is very useful to develop a music recommender system that can search in the music libraries automatically and suggest suitable songs to users. By using music recommender system, the music provider can predict and then offer the appropriate songs to their users based on the characteristics of the music that has been heard previously. The project develops a music recommender system that can give recommendations based on similarity of features on audio listened by the user. This study uses matrix factorization and collaborative filtering to look similarity between features. The results of this study indicate that users prefer recommendations that consider music genres compared to recommendations based solely on similarity.

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1. INTRODUCTION

With commercial music streaming service which can be accessed from mobile devices, the availability of digital music currently is abundant compared to previous era. Sorting out all this digital music is a very time-consuming and causes information fatigue. Therefore, it is very useful to develop a music recommender system that can search in the music libraries automatically and suggest suitable songs to users. By using music recommender system, the music provider can predict and then offer the appropriate songs to their users based on the characteristics of the music that has been heard previously.

1.1 Objectives

The project develops a music recommender system that can give recommendations based on similarity of features on audio listened by the user. This study uses matrix factorization and collaborative filtering to look similarity between features. The results of this study indicate that users prefer recommendations that consider music genres compared to recommendations based solely on similarity.

1.2 Methodology

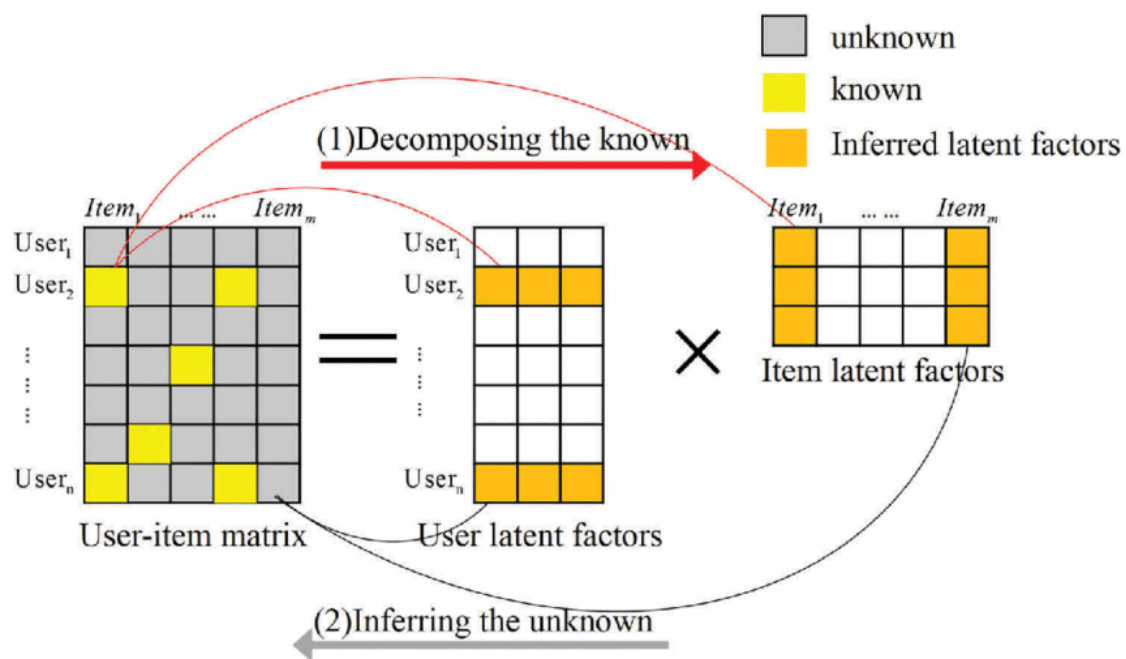
To provide artist recommendations to the users, large amount of song data is required. The songs are downloaded from the user_artist_data database. In this section the methodology followed is discussed in detail.

1.2.1 Dataset

The original data file user_artist_data.txt contained about 141,000 unique users, and 1.6 million unique artists. About 24.2 million users' plays of artists are recorded, along with their count. Note that when plays are scribbled, the client application submits the name of the artist being played. This name could be misspelled or nonstandard, and this may only be detected later. For example, "The Smiths", "Smiths, The", and "the smiths" may appear as distinct artist IDs in the data set, even though they clearly refer to the same artist. So, the data set includes artist_alias.txt, which maps artist IDs that are known misspellings or variants to the canonical ID of that artist. The artist_data.txt file then provides a map from the canonical artist ID to the name of the artist.

1.2.2 Matrix Factorization

Matrix factorization is a common and effective way to implement a recommendation system. Matrix factorization attempts to learn ways to quantitatively characterize both users and items in a lower-dimensional space (as opposed to looking at every item the user has ever rated), such that these characterizations can be used to predict user behavior and preferences for a known set of possible items. In recent years, matrix factorization has become increasingly popular due to its accuracy and scalability.



1.2.3 Collaborative Filtering

Collaborative Filtering is one of the most widely used and successful technologies in recommendation systems. Collaborative filtering-based recommendation techniques have achieved great success, and have a wide range of application prospects in many fields such as e-commerce and social networks. However, as big data arise, the Collaborative Filtering-based approach often suffers from several shortcomings, such as data sparsity, cold start, and scalability issues, which seriously affect the recommended quality of recommendation systems. To tackle the aforementioned problems, many data mining and machine learning techniques such as clustering, singular value decomposition (SVD), probability matrix factorization (PMF), and non-negative matrix factorization (NMF) are proposed to improve the performance of recommendation systems.

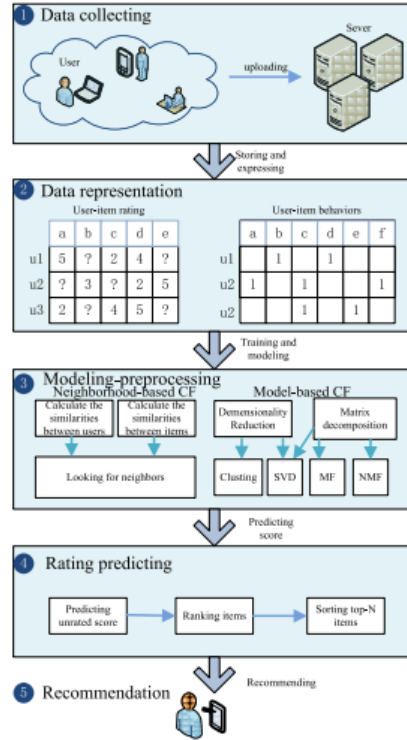


Fig 1.2.3.1 Framework of Collaborative Filtering based recommendation system

1.2.4 Alternating Least Squares (ALS) Algorithm

The alternating least squares (ALS) algorithm factorizes a given matrix R into two factors U and V such that $R \approx UTV$. The unknown row dimension is given as a parameter to the algorithm and is called latent factors. Since matrix factorization can be used in the context of recommendation, the matrices U and V can be called user and item matrix, respectively. The i th column of the user matrix is denoted by u_i and the i th column of the item matrix is v_i . The matrix R can be called the ratings matrix with $(R)_{i,j} = r_{i,j}$.

$$\operatorname{argmin}_{U,V} \sum_{i,j | r_{i,j} \neq 0} (r_{i,j} - u_i^T v_j)^2 + \lambda (\sum_i \|u_i\|^2 + \sum_j \|v_j\|^2) \quad \text{with } \lambda$$
 being the regularization factor, n_{ui} being the number of items the user i has rated and n_{vj} being the number of times the item j has been rated. This regularization scheme to avoid overfitting is called weighted- λ -regularization.

By fixing one of the matrices U or V , we obtain a quadratic form which can be solved directly. The solution of the modified problem is guaranteed to monotonically decrease the overall cost function. By applying this step

alternately to the matrices U and V, we can iteratively improve the matrix factorization.

The matrix R is given in its sparse representation as a tuple of (i,j,r) where i denotes the row index, j the column index and r is the matrix value at position (i,j).

		Item			
		W	X	Y	Z
User	A		4.5	2.0	
	B	4.0		3.5	
	C		5.0		2.0
	D		3.5	4.0	1.0

Rating Matrix

$$=$$

A	1.2	0.8
B	1.4	0.9
C	1.5	1.0
D	1.2	0.8

User Matrix

$$\times$$

		W	X	Y	Z
		1.5	1.2	1.0	0.8
1.7	0.6	1.1	0.4		

Item Matrix

1.2.5 What is PySpark ?

PySpark is a tool created by Apache Spark Community for using Python with Spark. It allows working with RDD (Resilient Distributed Dataset) in Python. It also offers PySpark Shell to link Python APIs with Spark core to initiate Spark Context. Spark is the name engine to realize cluster computing, while PySpark is Python's library to use Spark.

Spark is based on a computational engine, meaning it takes care of the scheduling, distributing and monitoring application. Each task is done across various worker machines called computing clusters. A computing cluster refers to the division of tasks. One machine performs one task, while the others contribute to the final output through a different task. In the end, all the tasks are aggregated to produce an output.

Spark is designed to work with

- Python
- Java
- Scala
- SQL

A significant feature of Spark is the vast amount of built-in libraries, including MLlib for machine learning. Spark is also designed to work with Hadoop clusters and can read a broad type of files, including Hive data, CSV, JSON, Casandra data among others.

1.2.6 PySpark - MLlib

Apache Spark offers a Machine Learning API called MLlib. PySpark has this machine learning API in Python as well. It supports different kinds of algorithms. Collaborative Filtering is commonly used for recommender systems. These techniques aim to fill in the missing entries of a user-item association matrix. MLlib supports model-based collaborative filtering meaning it would give-out the model instead of directly generating the recommendations.

PySpark MLlib is a machine-learning library. It is a wrapper over PySpark Core to do data analysis using machine-learning algorithms. It works on distributed systems and is scalable. We can find implementations of classification, clustering, linear regression, and other machine-learning algorithms in PySpark MLlib.

In MLlib, Users and products are described by a small set of latent factors that can be used to predict missing entries. MLlib uses the alternating least squares (ALS) algorithm to learn these latent factors.

- `mllib.recommendation` – Collaborative filtering is commonly used for recommender systems. These techniques aim to fill in the missing entries of a user item association matrix.

1.3 Organization of Project

The technique which is developed is taking input as a user data and train the uploaded data from the dataset using convolutional recurrent neural network and collaborative filtering. Based on user's maximum play count, then recommends artists as a result.

We have three modules in our project.

- Model Evaluation
- Model Construction
- Trying Some Artist Recommendations

Necessary Package Imports

```
In [ ] : from pyspark.mllib.recommendation
import * import random from operator import *
```

Loading data

Load the three datasets into RDDs and name them `artistData`, `artistAlias`, and `userArtistData`. View the README, or the files themselves, to see how this data is formatted. Some of the files have tab delimiters while some have space delimiters. Make sure that `userArtistDataRDD` contains only the canonical artist IDs.

Data Exploration

Finding the three users with the highest number of total play counts (sum of all counters) and printing the user ID, the total play count, and the mean play count (average number of times a user played an artist).

The output should look as follows:

User 1059637 has a total play count of 674412 and a mean play count of 1878.

User 2064012 has a total play count of 548427 and a mean play count of 9455.

User 2069337 has a total play count of 393515 and a mean play count of 1519

Splitting Data for Testing

Using the `randomSplit` function to divide the data (`userArtistData`) into: A training set, `trainData`, that will be used to train the model. This set constitutes 40% of the data. A validation set, `validationData`, used to perform parameter tuning. This set constitutes 40% of the data. A test set, `testData`, is used for a final evaluation of the model. This

set constitutes 20% of the data. Using a random seed value of 13. Since these datasets will be repeatedly used this will probably be needed to persist them in memory using the cache function.

In addition, print out the first 3 elements of each set as well as their sizes; if you created these sets correctly, your output should look as follows:

```
[(1059637, 1000049, 1), (1059637, 1000056, 1), (1059637, 1000113, 5)] [(1059637, 1000010, 238), (1059637, 1000062, 11), (1059637, 1000112, 4 23)] [(1059637, 1000094, 1), (1059637, 1000130, 19129), (1059637, 1000139, 4)] 19817 19633 10031
```

2. THEORETICAL ANALYSIS OF THE PROPOSED PROJECT

2.1 Requirements Gathering

2.1.1 Software Requirements

Programming Language : Python 3.6

Dataset : user_artist_data.txt, artist_alias.txt, artist_data.txt Datasets

Packages : pyspark

Tool : Google Colaboratory

2.1.2 Hardware Requirements

Operating System: Windows 10

Processor : Intel Core i5-8265U

CPU Speed : 1.80 GHz

Memory : 4 GB (RAM)

2.2 Technologies Description

Python

Python is an interpreted high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991, Python has a design philosophy that emphasizes code readability, notably using significant whitespace.

Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library.

- Python is Interpreted – Python is processed at runtime by the interpreter. You do not need to compile your program before executing it. This is similar to PERL and PHP.
- Python is Interactive – you can actually sit at a Python prompt and interact with the interpreter directly to write your programs.

Python also acknowledges that speed of development is important. Readable and terse code is part of this, and so is access to powerful constructs that avoid tedious repetition of code. Maintainability also ties into this may be an all but useless metric, but it does say something about how much code you have to scan, read and/or

understand to troubleshoot problems or tweak behaviors. This speed of development, the ease with which a programmer of other languages can pick up basic Python skills and the huge standard library is key to another area where Python excels. All its tools have been quick to implement, saved a lot of time, and several of them have later been patched and updated by people with no Python background - without breaking.

Datasets

The original data file `user_artist_data.txt` contained about 141,000 unique users, and 1.6 million unique artists. About 24.2 million users' plays of artists are recorded, along with their count. Note that when plays are scribbled, the client application submits the name of the artist being played. This name could be misspelled or nonstandard, and this may only be detected later. For example, "The Smiths", "Smiths, The", and "the smiths" may appear as distinct artist IDs in the data set, even though they clearly refer to the same artist. So, the data set includes `artist_alias.txt`, which maps artist IDs that are known misspellings or variants to the canonical ID of that artist. The `artist_data.txt` file then provides a map from the canonical artist ID to the name of the artist.

user_artist_data_small - Notepad

```
File Edit Format View Help
1059637 1000010 238
1059637 1000049 1
1059637 1000056 1
1059637 1000062 11
1059637 1000094 1
1059637 1000112 423
1059637 1000113 5
1059637 1000114 2
1059637 1000123 2
1059637 1000130 19129
1059637 1000139 4
1059637 1000241 188
1059637 1000263 180
1059637 1000289 2
1059637 1000305 1
1059637 1000320 21
1059637 1000340 1
1059637 1000427 20
1059637 1000428 12
1059637 1000433 10
1059637 1000445 88
1059637 1000527 1
1059637 1000617 4
1059637 1000632 250
1059637 1000676 3
1059637 1000790 18
1059637 1000877 1
1059637 1000890 1
```

Fig 2.2.1: user_artist_data_small dataset

artist_data_small - Notepad

File Edit Format View Help

```

1240105 André Visior
1240113 riow arai
1240132 Outkast & Rage Against the Machine
6776115 小松正夫
1030848 Raver's Nature
6671601 Erguner, Kudsi
1106617 Bloque
1240185 Lexy & K. Paul
6671631 Rev. W.M. Mosley
6671632 Labelle, Patti
1240238 the Chinese Stars
1240262 The Gufs
6718605 Bali Music
6828988 Southern Conference Featuring Dr. Ace
1240415 Paul & Paula
1009439 Cinnamon
1018275 School Of Fish
6671680 Armstrong, Louis & His Hot Five
1240508 The Ozark Mountain Daredevils
1240510 The Mercury Program
1240516 Del Close & John Brent
1002584 Nena
6990766 Phil Hendrie - 11/06/98
1240554 Ami Yoshida
1124756 utabi
10023740 Red & Blue feat. Cathy Dennis
1240589 Sebastian Bach & Friends
1240603 The Wake

```

Fig 2.2.2: artist_data_small dataset

artist_alias_small - Notepad

File Edit Format View Help

```

1027859 1252408
1017615 668
6745885 1268522
1018110 1018110
1014609 1014609
6713071 2976
1014175 1014175
1008798 1008798
1013851 1013851
6696814 1030672
1036747 1239516
1278781 1021980
2035175 1007565
1327067 1308328
2006482 1140837
1314530 1237371
1160800 1345290
1255401 1055061
1307351 1055061
1234249 1005225
6622310 1094137
1261919 6977528
2103190 1002909
9929875 1009048
2118737 1011363
9929864 1000699
6666813 1305683
1172822 1127113

```

Fig 2.2.3: artist_alias_small dataset

PySpark

PySpark is the Python API written in python to support Apache Spark. ... Apache Spark is written in Scala and can be integrated with Python, Scala, Java, R, SQL languages. Spark is basically a computational engine, that works with huge sets of data by processing them in parallel and batch systems.

Google Colab

Colab is a free Jupyter notebook environment that runs entirely in the cloud. Most importantly, it does not require a setup and the notebooks that you create can be simultaneously edited by team members - just the way you edit documents in Google Docs. Colab supports many popular machine learning libraries which can be easily loaded into notebook.

Google Colab offers:

- Write and execute code in Python
- Document your code that supports mathematical equations
- Create/Upload/Share notebooks
- Import/Save notebooks from/to Google Drive
- Import/Publish notebooks from GitHub
- Import external datasets from Kaggle
- Integrate PyTorch, TensorFlow, Keras, OpenCV
- Free Cloud service with free GPU

3. DESIGN

3.1 Data Flow Diagram

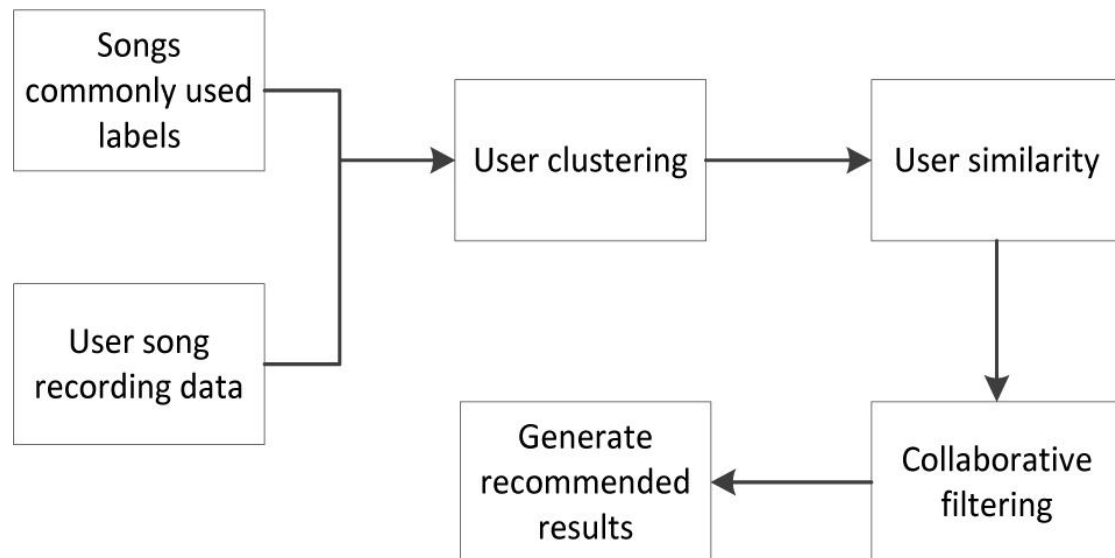


Fig 3.1.1: Data Flow Diagram

The above image is the data flow of artist recommendation system using collaborative filtering. From the database user_artist_data.txt artist labels and user mean play count is considered, then user clustering is performed, and on considering user similarity in artist labels, collaborative filtering is done where top artists are recommended based on the play history of the user.

4. IMPLEMENTATION

4.1 Coding

```

!pip install pyspark
from pyspark.mllib.recommendation import *
import random
import pandas as pd
from operator import *
from pyspark import SparkContext
sc = SparkContext.getOrCreate()
artistData = sc.textFile("/content/sample_data/artist_data_small.txt").map(lambda l:
l.split("\t")).map(lambda l: (int(l[0]), l[1]))
artistAlias = sc.textFile("/content/sample_data/artist_alias_small.txt").map(lambda l:
l.split("\t")).map(lambda l: (int(l[0]), int(l[1])))
artistAliasDict = artistAlias.collectAsMap()
def canonical(ele):
    if ele in artistAliasDict:
        return artistAliasDict.get(ele)
    return int(ele)
userArtistData =
sc.textFile("/content/sample_data/user_artist_data_small.txt").map(lambda line:
line.split(" ")).map(lambda e: (int(e[0]), canonical(e[1]), int(e[2])))
import array
from collections import namedtuple
from pyspark import SparkContext, since
from pyspark.rdd import RDD
from pyspark.mllib.common import JavaModelWrapper, callMLlibFunc, inherit_doc
from pyspark.mllib.util import JavaLoader, JavaSaveable
from pyspark.sql import DataFrame
__all__ = ['MatrixFactorizationModel', 'ALS', 'Rating']
class Rating(namedtuple("Rating", ["user", "product", "rating"])):
    @since("0.9.0")
    def predict(self, user, product):
        """ Predicts rating for the given user and product. """

```

```

        return self._java_model.predict(int(user), int(product))

@since("0.9.0")
def predictAll(self, user_product):
    """ Returns a list of predicted ratings for input user and product pairs. """
    assert isinstance(user_product, RDD), "user_product should be RDD of (user,
product)"
    first = user_product.first()
    assert len(first) == 2, "user_product should be RDD of (user, product)"
    user_product = user_product.map(lambda u_p: (int(u_p[0]), int(u_p[1])))
    return self.call("predict", user_product)

@since("1.2.0")
def userFeatures(self):
    """ Returns a paired RDD, where the first element is the user and the second is an
array of features corresponding to that user. """
    return self.call("getUserFeatures").mapValues(lambda v: array.array('d', v))

@since("1.2.0")
def productFeatures(self):
    """ Returns a paired RDD, where the first element is the product and the second is an
array of features corresponding to that product. """
    return self.call("getProductFeatures").mapValues(lambda v: array.array('d', v))

@since("1.4.0")
def recommendUsers(self, product, num):
    """ Recommends the top "num" number of users for a given product and returns a list
of Rating objects sorted by the predicted rating in descending order. """
    return list(self.call("recommendUsers", product, num))

@since("1.4.0")
def recommendProducts(self, user, num):

```

"""Recommends the top "num" number of products for a given user and returns a list of Rating objects sorted by the predicted rating in descending order."""

```
return list(self.call("recommendProducts", user, num))
```

```
def recommendProductsForUsers(self, num):
```

""" Recommends the top "num" number of products for all users. The number of recommendations returned per user may be less than "num". """

```
return self.call("wrappedRecommendProductsForUsers", num)
```

```
temp1 = pd.read_csv("/content/sample_data/artist_alias_small.csv")
```

```
temp1.head()
```

```
temp1.describe()
```

```
temp2= pd.read_csv("/content/sample_data/artist_data_small.csv")
```

```
temp2.head()
```

```
temp2.describe()
```

```
temp3 = pd.read_csv("/content/sample_data/user_artist_data_small.csv")
```

```
temp3.head()
```

```
temp3.describe()
```

```
userPlayList = userArtistData.map(lambda x: (x[0], (x[1],
```

```
x[2]))).aggregateByKey((0,0),\
```

```
(lambda x,y: (x[0] + 1, x[1] + y[1])),\
```

```
(lambda rdd1, rdd2: (rdd1[0]+rdd2[0], rdd1[1]+rdd2[1]))).map(lambda t:
(t[0], t[1][1], t[1][1]/t[1][0]))
```

```
top3Users = userPlayList.sortBy(ascending=False, keyfunc=(lambda x: x[1])).take(3)
```

```
for t in top3Users:
```

```
    print("User " + str(t[0]) + " has a total play count of " + str(t[1]) + " and a mean play
count of " + str(t[2]) + ".")
```

```
trainData, validationData, testData = userArtistData.randomSplit([0.4,0.4,0.2], 13)
```

```

print(trainData.take(3))
print(validationData.take(3))
print(testData.take(3))
print(trainData.count())
print(validationData.count())
print(testData.count())
trainData.cache()
validationData.cache()
testData.cache()

def modelEval(model, dataset):

    #get all users and artists
    allUser = set(userArtistData.map(lambda x: (x[0])).collect())
    allArtist = set(userArtistData.map(lambda x: (x[1])).collect())

    #get dictionary of user and their artists for traindata and validation data
    trainUserArtist = trainData.map(lambda x: (x[0], {x[1]})).reduceByKey(lambda
x,y: x.union(y)).collectAsMap()
    datasetUserArtist = validationData.map(lambda x: (x[0],
{x[1]})).reduceByKey(lambda x,y: x.union(y)).collectAsMap()

    overAllScore = 0
    for user in allUser:
        # all actual user preferred artists
        actualUserArtist = datasetUserArtist[user]
        # all artist except that from traindata
        nonTrainDataArtist = allArtist - trainUserArtist[user]
        # prepare the test data consisting of tuples (user, product) => (user, artist)
        test = map(lambda x: (user, x), nonTrainDataArtist)
        # convert the set into rdd as rdd is required by predictAll method
        testRDD = sc.parallelize(test)
        # predict the ratings

```

```

predictedUserArtist = model.predictAll(testRDD)
# sort the ratings in descending order of ratings
sortedPrediction = predictedUserArtist.sortBy(ascending=False,
keyfunc=lambda x: x.rating)
# get number of top artists equal to number of actual artist for the user
c = len(actualUserArtist)
predictedSet = set(sortedPrediction.map(lambda x: x.product).take(c))
# take the intersection of actual artist and predicted artist for a user and calculate
the score
correctPrediction = predictedSet.intersection(actualUserArtist)
overAllScore += float(len(correctPrediction)) / c

return "The model score for rank "+str(model.rank)+" is
"+str(overAllScore/len(allUser))

model = ALS.trainImplicit(trainData, rank=2, seed=345)
print(modelEval(model, validationData))
model = ALS.trainImplicit(trainData, rank=10, seed=345)
print(modelEval(model, validationData))
model = ALS.trainImplicit(trainData, rank=20, seed=345)
print(modelEval(model, validationData))

bestModel = ALS.trainImplicit(trainData, rank=10, seed=345)
modelEval(bestModel, testData)
artistDict = artistData.collectAsMap()
userid=2010008
ratings = bestModel.recommendProducts(userid, 5)
ratingsArtists = map(lambda r : r.product, ratings)
i=1
print("Artist recommendations for user with ",userid," are:")
for artist in ratingsArtists:
    print("Artist "+ str(i)+ ":",artistDict[artist])
    i+=1

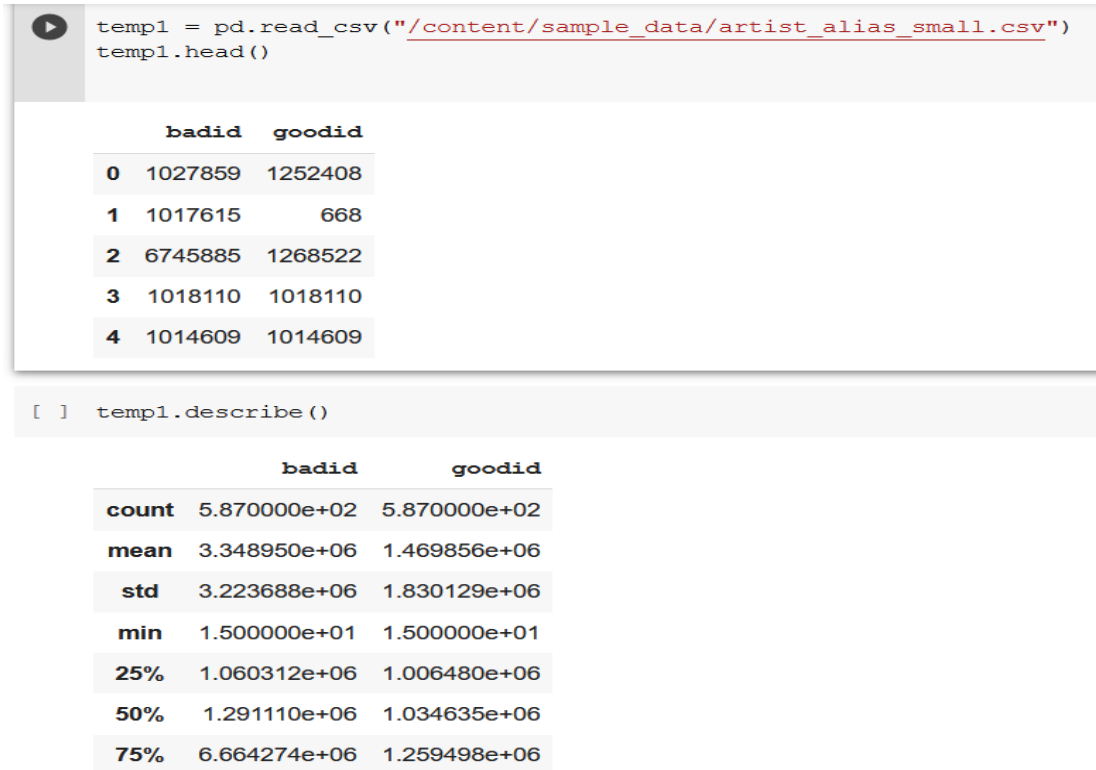
```


4.2 TEST CASES

Test Case Id	Test Scenario	Expected Result	Actual Result	Pass/Fail
TC01	Check whether packages are imported	Should import without errors	As Expected	Pass
TC02	Check whether datasets are defined and described	Show datasets	As Expected	Pass
TC03	Check whether model evaluation is working	Creation of model	As Expected	Pass
TC04	Check training, testing and validation of datasets	Divide the data for training, testing and validation	As Expected	Pass
TC05	Check artist recommendations	Show top artists for a user	As Expected	Pass

Fig 4.2.1: Test Cases

4.3 DATASET TRAINING SCREENSHOTS



The screenshot displays a Jupyter Notebook interface. The first code cell contains the following Python code:

```
temp1 = pd.read_csv("/content/sample_data/artist_alias_small.csv")
temp1.head()
```

The output of this code is a DataFrame with 5 rows and 2 columns, 'badid' and 'goodid'.

	badid	goodid
0	1027859	1252408
1	1017615	668
2	6745885	1268522
3	1018110	1018110
4	1014609	1014609

The second code cell contains the following Python code:

```
[ ] temp1.describe()
```

The output of this code is a summary statistics DataFrame for the 'badid' and 'goodid' columns.

	badid	goodid
count	5.870000e+02	5.870000e+02
mean	3.348950e+06	1.469856e+06
std	3.223688e+06	1.830129e+06
min	1.500000e+01	1.500000e+01
25%	1.060312e+06	1.006480e+06
50%	1.291110e+06	1.034635e+06
75%	6.664274e+06	1.259498e+06

Fig 4.3.1: Running artist_alias_small.csv dataset

```
[ ] temp2= pd.read_csv("/content/sample_data/artist_data_small.csv")
temp2.head()
```

	artistid	artist_name
0	1240113	riow arai
1	1240132	Outkast & Rage Against the Machine
2	6776115	小松正夫
3	1030848	Raver's Nature
4	6671601	Erguner, Kudsi

```
[ ] temp2.describe()
```

	artistid
count	3.053700e+04
mean	2.723610e+06
std	2.875962e+06
min	1.000000e+00
25%	1.033180e+06
50%	1.238800e+06
75%	2.164639e+06

Fig 4.3.2: Running artist_data_small.csv

```
[ ] temp3 = pd.read_csv("/content/sample_data/user_artist_data_small.csv")
temp3.head()
```

	userid	artistid	playcount
0	1059637	1000010	238
1	1059637	1000049	1
2	1059637	1000056	1
3	1059637	1000062	11
4	1059637	1000094	1

```
[ ] temp3.describe()
```

	userid
count	4.948100e+04
mean	1.328420e+06
std	4.529913e+05
min	1.000647e+06
25%	1.024631e+06
50%	1.059245e+06
75%	2.010008e+06
max	2.288164e+06

Fig 4.3.3: Running user_artist_data_small dataset

```
[ ] trainData, validationData, testData = userArtistData.randomSplit([0.4,0.4,0.2], 13)
print(trainData.take(3))
print(validationData.take(3))
print(testData.take(3))
print(trainData.count())
print(validationData.count())
print(testData.count())
trainData.cache()
validationData.cache()
testData.cache()

[(1059637, 1000049, 1), (1059637, 1000056, 1), (1059637, 1000114, 2)]
[(1059637, 1000010, 238), (1059637, 1000062, 11), (1059637, 1000123, 2)]
[(1059637, 1000094, 1), (1059637, 1000112, 423), (1059637, 1000113, 5)]
19769
19690
10022
PythonRDD[26] at RDD at PythonRDD.scala:53
```

Fig 4.3.4: Command to train the dataset

```
[ ] model = ALS.trainImplicit(trainData, rank=2, seed=345)
print(modelEval(model, validationData))
model = ALS.trainImplicit(trainData, rank=10, seed=345)
print(modelEval(model, validationData))
model = ALS.trainImplicit(trainData, rank=20, seed=345)
print(modelEval(model, validationData))
```

```
The model score for rank 2 is 0.08616827592156559
The model score for rank 10 is 0.09441971719854263
The model score for rank 20 is 0.08408995233356337
```

```
[ ] bestModel = ALS.trainImplicit(trainData, rank=10, seed=345)
modelEval(bestModel, testData)
```

```
'The model score for rank 10 is 0.09441971719854263'
```

Fig 4.3.5: Model Evaluation

4.4 OUTPUT SCREENSHOTS

```
▶ artistDict = artistData.collectAsMap()
  userid=2069337
  ratings = bestModel.recommendProducts(userid, 5)
  ratingsArtists = map(lambda r : r.product, ratings)
  i=1
  print("Artist recommendations for user with ",userid," are:")
  for artist in ratingsArtists:
    print("Artist "+ str(i)+ ":",artistDict[artist])
    i+=1
```

☞ Artist recommendations for user with 2069337 are:
Artist 1: Bright Eyes
Artist 2: Franz Ferdinand
Artist 3: Green Day
Artist 4: Rage Against the Machine
Artist 5: Interpol

Fig 4.4.1: Output showing artist recommendations

```
▶ artistDict = artistData.collectAsMap()
  userid=1070932
  ratings = bestModel.recommendProducts(userid, 5)
  ratingsArtists = map(lambda r : r.product, ratings)
  i=1
  print("Artist recommendations for user with ",userid," are:")
  for artist in ratingsArtists:
    print("Artist "+ str(i)+ ":",artistDict[artist])
    i+=1
```

☞ Artist recommendations for user with 1070932 are:
Artist 1: Iron & Wine
Artist 2: Death Cab for Cutie
Artist 3: Dredg
Artist 4: The Used
Artist 5: Bad Religion

Fig 4.4.2: Output showing artist recommendations

```
▶ artistDict = artistData.collectAsMap()
  userid=1059637
  ratings = bestModel.recommendProducts(userid, 5)
  ratingsArtists = map(lambda r : r.product, ratings)
  i=1
  print("Artist recommendations for user with ",userid," are:")
  for artist in ratingsArtists:
    print("Artist "+ str(i)+ ":",artistDict[artist])
    i+=1
```

Artist recommendations for user with 1059637 are:
Artist 1: Something Corporate
Artist 2: My Chemical Romance
Artist 3: Further Seems Forever
Artist 4: Taking Back Sunday
Artist 5: Brand New

Fig 4.4.3: Output showing artist recommendations

5. CONCLUSION AND FUTURE SCOPE

The application helps users to get artist recommendations from their playing history using collaborative filtering. With commercial music streaming service which can be accessed from mobile devices, the availability of digital music currently is abundant compared to previous era. Sorting out all this digital music is a very time-consuming and causes information fatigue. Therefore, it is very useful to develop a music recommender system that can search in the music libraries automatically and suggest suitable songs to users. By using music recommender system, the music provider can predict and then offer the appropriate songs to their users based on the characteristics of the music that has been heard previously.

The future enhancement of this application is

- To increase the accuracy.
- To display recommendations dynamically.

6. REFERENCES

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