ADNAN MENDERES UNIVERSITY CSE424 BIG DATA ANALYSIS

Term Project

Recommendation System with Spark

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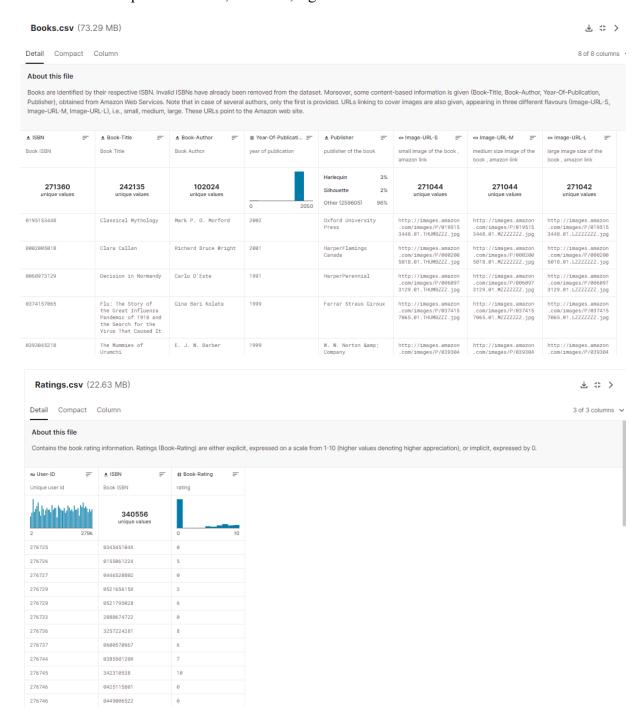
Dataset Information

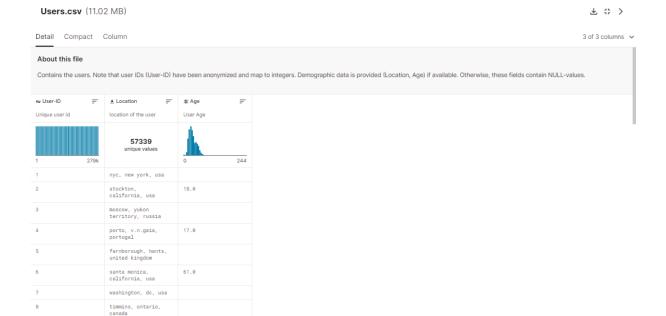
This dataset is large enough to build good recommendation model and you may face memory issue while training a model using that dataset. Dataset includes books, users and book ratings files.

Books File Description: ISBN, Book-Title, Book-Author, Year-Of-Publication, Publisher, Image-URL-S, Image-URL-M, Image-URL-L.

Book Ratings File Description: User-ID, ISBN, Book-Rating.

Users File Description: User-ID, Location, Age.





Reads files from specified path using textFile with 'sc' method. Returns an RDD where each item represents a row in the file.

```
In [3]: dfUser = sc.textFile("C:/Users/USER/Desktop/dataset/Users.csv")
    dfBooks = sc.textFile("C:/Users/USER/Desktop/dataset/Books.csv")
    dfRatings = sc.textFile("C:/Users/USER/Desktop/dataset/Book-Ratings.csv")
```

Split DF's for each fields

```
In [4]: users_fields = dfUser.map(lambda lines: lines.replace('"','').split(";"))
books_fields = dfBooks.map(lambda lines: lines.replace('"','').split(";"))
rating_fields = dfRatings.map(lambda lines: lines.replace('"','').split(";"))
```

This code creates a new RDD, clearing and transforming the values for further analysis.

```
In [5]: def handle_isbn(lst2):
    lst = lst2.collect()
    arr=[]
    arr2=[]
    for i in lst:
        arr.append(re.sub("[^0-9]",'1',i))
    for i in arr:
        if len(i)>=9:
            arr2.append(int(i[len(i)-9:]))
    return sc.parallelize(arr2)

def handle_isbn_str(line):
    line1 = re.sub("[^0-9]",'1',line)
    if len(line1)>=9:
        line2 = int(line1[len(line1)-9:])
        return int(line2)
    else:
        return int(line1)
```

USERS Fields & BOOKS Fields & BOOK Rating Fields

```
In [7]: users_id = users_fields.map(lambda field: field[0])
    users_location = users_fields.map(lambda field: field[1])
    users_age = users_fields.map(lambda field: field[2])

    books_isbn = handle_isbn(books_fields.map(lambda field: field[1])
    books_name = books_fields.map(lambda field: field[1])
    books_writer = books_fields.map(lambda field: field[2])
    books_press = books_fields.map(lambda field: field[3])

rating_users_id = rating_fields.map(lambda field: float(field[0]))
    rating_books_isbn = handle_isbn(rating_fields.map(lambda field: field[1]))
    rating_books_rating = rating_fields.map(lambda field: float(field[2]))
```

Calculate baseline statistics for filtered age values.

```
In [8]: age_list = users_age.map(lambda item: handle_age(item))
    age_list_filtered = age_list.filter(lambda item: item <= 90 and item >=0 )
    age_counts = collections.OrderedDict(sorted(age_list_filtered.countByValue().items()))
    age_list_filtered.stats()

Out[8]: (count: 167666, mean: 34.54562045972393, stdev: 13.769988967606224, max: 90.0, min: 0.0)
```

USERS' Countries Location & TOP 10 Countries That The Most Users Data Collected

Calculates basic statistics for books ratings.

```
In [12]: rating_books_rating.stats()
Out[12]: (count: 397245, mean: 7.601852760890583, stdev: 1.8412729800421157, max: 10.0, min: 1.0)
```

Computer Information

```
In [2]: import socket
import platform
hostname = socket.gethostname()
ip = socket.gethostbyname(hostname)
uname = platform.uname()
print(f"Nostname: {Nostname}")
print(f"Ip address: {ip}")
print(f"System: {uname.system}")
print(f"Release: {uname.release}")
print(f"Version: {uname.version}")
print(f"Machine: {uname.wersion}")
print(f"Machine: {uname.machine}")
print(f"Processor: {uname.processor}")

Hostname: LAPTOP-UEQCSDT9
Ip address: 192.168.0.20
System: Windows
Release: 10
Version: 10.0.22621
Machine: AMD64
Processor: Intel64 Family 6 Model 142 Stepping 12, GenuineIntel
```

MSE (Mean Squared Error)

```
In [93]: print("Mean Squared Error Scores For Each Model:", )
            for i in modelsArray:
                 print(f'Model {arr[c]} = {i[-2]}')
            Mean Squared Error Scores For Each Model:
            Model 10_10_01 = 53.31545601995979
Model 10_50_01 = 18.02675073795958
            Model 10_200_01 = 21.837385101121505
            Model 10_10_1 = 10.94068188592083
            Model 10_50_1 = 13.861513642908823
             Model 10_200_1 = 10.534852160638245
            Model 50 10 01 = 36.69128644997727
            Model 50_50_01 = 16.16370876131336
            Model 50_200_01 = 10.18378878151358

Model 50_10_1 = 10.267777032909267

Model 50_50_1 = 11.94532434385151

Model 50_200_1 = 9.970174517018798
            Model 200_10_01 = 32.01450161397515
            Model 200_10_1 = 14.741212207519643
Model 200_50_01 = 16.57593515367748
            Model 200_50_1 = 10.222840141615677
            Model 200_200_01 = 11.863358392374645
Model 200_200_1 = 9.980126049794423
```

To determine the best model for the dataset based on the Mean Squared Error (MSE) scores provided, we need to identify the model with the lowest MSE score. A lower MSE indicates better accuracy and closer predictions to the actual values.

From the given scores, the model with the lowest MSE is "Model 200_200_1" with an MSE of 9.980126049794423. This model has the smallest error, indicating it provides the closest predictions to the actual values in the dataset. Therefore, based on the provided MSE scores, "Model 200_200_1" is considered the best model for the dataset. It achieves the lowest MSE, indicating better accuracy in predicting the target variable compared to other models.

Root Mean Squared Error

```
In [94]: print("Root Mean Squared Error Scores For Each Model:", )
          for i in modelsArrav:
              print(f'Model \{arr[c]\} = \{i[-1]\}')
          Root Mean Squared Error Scores For Each Model:
          Model 10_10_01 = 7.301743354840664
          Model 10_50_01 = 4.245792121378481
          Model 10_200_01 = 4.673048801491539
          Model 10_10_1 = 3.3076701597832923
Model 10_50_1 = 3.723105376283194
          Model 10_200_1 = 3.2457436991602164
          Model 50_10_01 = 6.057333278760321
          Model 50_50_01 = 4.020411516413881
          Model 50 200 01 = 4,184724899605621
          Model 50_10_1 = 3.2043372220958997
          Model 50_50_1 = 3.4562008540956515
          Model 50 200 1 = 3.1575583156956575
          Model 200_10_01 = 5.658135878005684
          Model 200_10_1 = 3.8394286303458802
          Model 200_50_01 = 4.0713554442811155
Model 200_50_1 = 3.197317647906707
          Model 200_200_01 = 3.444322631864594
          Model 200_200_1 = 3.1591337499058856
```

To determine the best model for the dataset based on the Root Mean Squared Error (RMSE) scores provided, we need to identify the model with the lowest RMSE score. A lower RMSE indicates better accuracy and closer predictions to the actual values.

From the given scores, the model with the lowest RMSE is "Model 200_200_1" with an RMSE of 3.1591337499058856. This model has the smallest error, indicating it provides the closest predictions to the actual values in the dataset. Therefore, based on the provided RMSE scores, "Model 200_200_1" is considered the best model for the dataset. It achieves the lowest RMSE, indicating better accuracy in predicting the target variable compared to other models.

Work Sharing Policy

Nagihan does the initial research of the project and finds some sample code and different datasets and is responsible for ALS learning and merging the dataset, removing punctuation, removing blank and repetitive items. (Extracted and filtered RDDs.)

Elize created a histogram for the average age, printed the location of the users' countries and the top 10 countries with the most user data collected by code.

Emin was responsible for the cosine similarity function and built the model using the ALS train dataset.

Melih was helpful in researching and writing all the codes in general.