Amazon_Product_Recommendation

November 15, 2020

0.1 Amazon Product Recommendation

Online E-commerce websites like Amazon, Filpkart uses different recommendation models to provide different suggestions to different users. Amazon currently uses item-to-item collaborative filtering, which scales to massive data sets and produces high-quality recommendations in real time. This type of filtering matches each of the user's purchased and rated items to similar items, then combines those similar items into a recommendation list for the user. In this project we are going to build recommendation model for the electronics products of Amazon.

Attribute Information: overall: Rating of the corresponding product by the corresponding user

verified: Every user is either reviewed or not

reviewTime: Time when review is provide

reviewerID: Every user identified with a unique id

asin: Every product identified with a unique id(Second Column)

reviewerName: Name of the user

timestamp: Time of the rating (Fourth Column)

Problem Statement: Our objective is to build a recommendation system to recommend products to customers based on the their previous ratings for other products. For this purpose, first we will perform exploratory data analysis and then implement recommendation algorithms including Popularity-Based, Collaborative filtering.

Both these recommendation systems can be defined as below:

Popularity based systems: It works by recommeding items viewed and purchased by most people and are rated high.It is not a personalized recommendation and is mostly useful for the test case of recommending products to new customers.

Collaborative Filtering: It is based on assumption that people like things similar to other things they like, and things that are liked by other people with similar taste. There are two ways of doing this. One is user based and second is item based collaborative filtering.

0.1.1 Reading the data

[86]:

```python
# Importing libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import TruncatedSVD
from sklearn.model_selection import train_test_split
```

[3]:

```python
# Loading the product data into data frames

allbeauty_df = pd.read_json("C:\Data\All_Beauty.json", lines = True)
fashion_df = pd.read_json("C:\Data\AMAZON_FASHION.json", lines = True)
appliances_df = pd.read_json("C:\Data\Appliances.json", lines = True)
```

[11]:

```python
# Checking the shape of the data

print(allbeauty_df.shape, fashion_df.shape, appliances_df.shape)
```

```
(371345, 12) (883636, 12) (602777, 12)
```

[12]:

```python
# Checking the allbeauty data

allbeauty_df.head()
```

[12]:

```
   overall  verified   reviewTime      reviewerID        asin  \
0        1      True  02 19, 2015  A1V6B6TNIC10QE  0143026860
1        4      True  12 18, 2014  A2F5GHSXFQ0W6J  0143026860
2        4      True  08 10, 2014  A1572GUYS7DGSR  0143026860
3        5      True  03 11, 2013   A1PSGLFK1NSVO  0143026860
4        5      True  12 25, 2011   A6IKXKZMTKGSC  0143026860

        reviewerName                                          reviewText  \
0  theodore j bigham                                               great
1       Mary K. Byke  My  husband wanted to reading about the Negro ...
2            David G  This book was very informative, covering all a...
3               TamB  I am already a baseball fan and knew a bit abo...
4         shoecanary  This was a good story of the Black leagues. I ...

                                             summary  unixReviewTime vote  \
0                                           One Star      1424304000  NaN
1      … to reading about the Negro Baseball and th…      1418860800  NaN
2                                     Worth the Read      1407628800  NaN
3                                          Good Read      1362960000  NaN
4                More than facts, a good story read!      1324771200    5
```

```
  style image
0   NaN   NaN
1   NaN   NaN
2   NaN   NaN
3   NaN   NaN
4   NaN   NaN
```

[13]:

```python
# Checking the fashion data

fashion_df.head()
```

[13]:

```
   overall  verified   reviewTime      reviewerID        asin  reviewerName  \
0        5      True  10 20, 2014  A1D4G1SNUZWQOT  7106116521         Tracy
1        2      True  09 28, 2014  A3DDWDH9PX2YX2  7106116521     Sonja Lau
2        4     False  08 25, 2014  A2MWC41EW7XL15  7106116521      Kathleen
3        2      True  08 24, 2014  A2UH2QQ275NV45  7106116521   Jodi Stoner
4        3     False  07 27, 2014   A89F3LQADZBS5  7106116521  Alexander D.

                                          reviewText  \
0                             Exactly what I needed.
1  I agree with the other review, the opening is …
2  Love these… I am going to order another pack…
3                                too tiny an opening
4                                               Okay

                                             summary  unixReviewTime  vote  \
0                             perfect replacements!!      1413763200   NaN
1  I agree with the other review, the opening is …      1411862400   3.0
2                                My New 'Friends' !!      1408924800   NaN
3                                          Two Stars      1408838400   NaN
4                                        Three Stars      1406419200   NaN

  style image
0   NaN   NaN
1   NaN   NaN
2   NaN   NaN
3   NaN   NaN
4   NaN   NaN
```

[14]:

```python
# Checking the appliances data

appliances_df.head()
```

[14]:

```
   overall  vote verified   reviewTime      reviewerID        asin  \
0        5     2     False  11 27, 2013  A3NHUQ33CFH3VM  1118461304
1        5  NaN     False   11 1, 2013  A3SK6VNBQDNBJE  1118461304
2        5  NaN     False  10 10, 2013  A3SOFHUR27FO3K  1118461304
```

```
3        5  NaN     False   10 9, 2013  A1HOG1PYCAE157  1118461304
4        5   10     False   09 7, 2013  A26JGAM6GZMM4V  1118461304

                             style              reviewerName  \
0      {'Format:': ' Hardcover'}                    Greeny
1  {'Format:': ' Kindle Edition'}           Leif C. Ulstrup
2      {'Format:': ' Hardcover'}  Harry Gilbert Miller III
3      {'Format:': ' Hardcover'}           Rebecca Ripley
4      {'Format:': ' Hardcover'}            Robert Morris

                                          reviewText  \
0  Not one thing in this book seemed an obvious o…
1  I have enjoyed Dr. Alan Gregerman's weekly blo…
2  Alan Gregerman believes that innovation comes …
3  Alan Gregerman is a smart, funny, entertaining…
4  As I began to read this book, I was again remi…

                                             summary  unixReviewTime image
0                Clear on what leads to innovation      1385510400   NaN
1  Becoming more innovative by opening yourself t…      1383264000   NaN
2            The World from Different Perspectives      1381363200   NaN
3              Strangers are Your New Best Friends      1381276800   NaN
4  How and why it is imperative to engage, learn …      1378512000   NaN
```

0.1.2 Data Preprocessing

[15]:

```
# Retrieving the columns neccessary for the analysis

allbeauty_df2 =␣
 ↪allbeauty_df[['overall','verified','reviewerID','reviewTime','asin']]
fashion_df2 =␣
 ↪fashion_df[['overall','verified','reviewerID','reviewTime','asin']]
appliances_df2 =␣
 ↪appliances_df[['overall','verified','reviewerID','reviewTime','asin']]
```

[16]:

```
# Combining all the dataframes into a single dataframe

df = allbeauty_df2.append(fashion_df2).append(appliances_df2)
```

[17]:

```
# Checking the shape of the final dataframe

df.shape
```

[17]:

```
(1857758, 5)
```

[18]:
```
# Checking the data in final dataframe

df.head()
```

[18]:
```
   overall  verified      reviewerID   reviewTime        asin
0        1      True  A1V6B6TNIC10QE  02 19, 2015  0143026860
1        4      True  A2F5GHSXFQ0W6J  12 18, 2014  0143026860
2        4      True  A1572GUYS7DGSR  08 10, 2014  0143026860
3        5      True   A1PSGLFK1NSVO  03 11, 2013  0143026860
4        5      True   A6IKXKZMTKGSC  12 25, 2011  0143026860
```

[19]:
```
# Renaming the dataframe columns as required

df = df.rename(columns={'overall':'rating','asin':'itemID'})
```

[21]:
```
# Checking the dataframe

df.head()
```

[21]:
```
   rating  verified      reviewerID   reviewTime      itemID
0       1      True  A1V6B6TNIC10QE  02 19, 2015  0143026860
1       4      True  A2F5GHSXFQ0W6J  12 18, 2014  0143026860
2       4      True  A1572GUYS7DGSR  08 10, 2014  0143026860
3       5      True   A1PSGLFK1NSVO  03 11, 2013  0143026860
4       5      True   A6IKXKZMTKGSC  12 25, 2011  0143026860
```

[24]:
```
# Checking the info of the dataframe

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1857758 entries, 0 to 602776
Data columns (total 5 columns):
rating        int64
verified      bool
reviewerID    object
reviewTime    object
itemID        object
dtypes: bool(1), int64(1), object(3)
memory usage: 72.6+ MB
```

[27]:
```
# Checking max and min values of ratings

print(df.rating.max(),df.rating.min())
```

```
5 1
```

[57]:
```
# Checking if rating has any invalid entries

df.rating.unique()
```

[57]:
```
array([5, 4, 2, 3, 1], dtype=int64)
```

[30]:
```
# Converting boolean data of verified column to integer data of 0 and 1

df['verified'] = df['verified'].astype(int)
```

[31]:
```
# Validing the column change

df.head()
```

[31]:
```
   rating  verified     reviewerID  reviewTime      itemID
0       1         1  A1V6B6TNIC10QE  02 19, 2015  0143026860
1       4         1  A2F5GHSXFQ0W6J  12 18, 2014  0143026860
2       4         1  A1572GUYS7DGSR  08 10, 2014  0143026860
3       5         1   A1PSGLFK1NSVO  03 11, 2013  0143026860
4       5         1   A6IKXKZMTKGSC  12 25, 2011  0143026860
```

[56]:
```
# Checking for NaN values in the dataframe

df.isnull().sum()
```

[56]:
```
rating        0
verified      0
reviewerID    0
reviewTime    0
itemID        0
dtype: int64
```

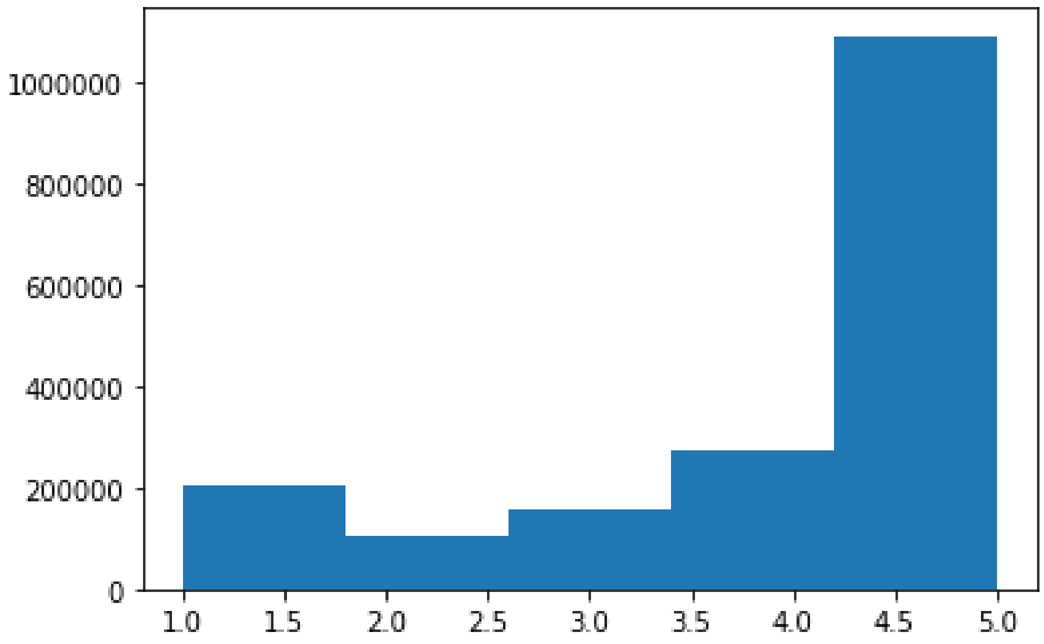
[60]:
```
# Checking for invalid entried in verfied column

df.verified.value_counts()
```

[60]:
```
1    1689696
0     139547
Name: verified, dtype: int64
```

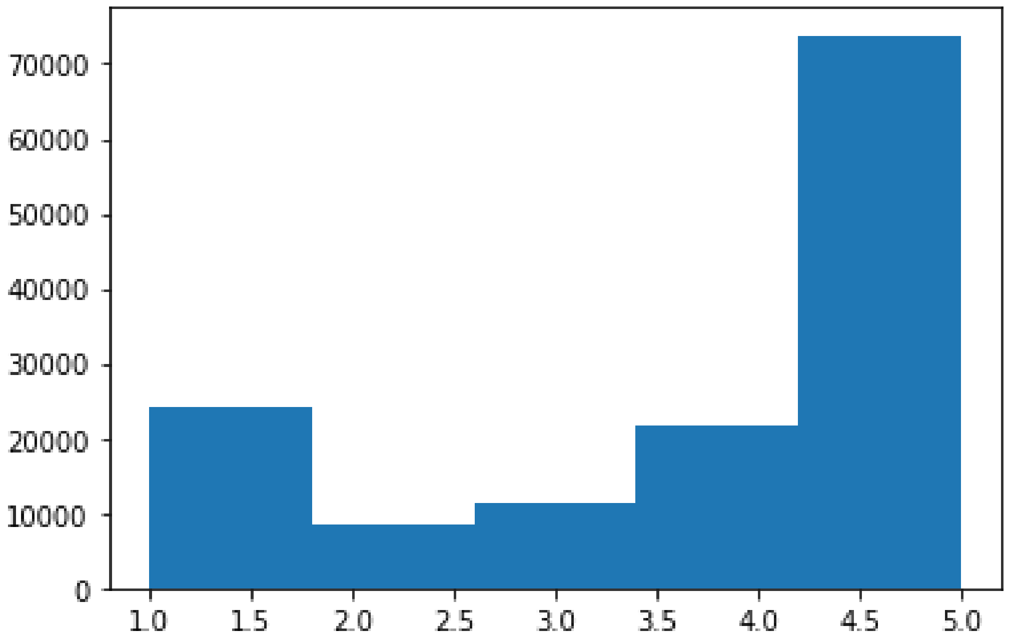
[61]:
```
# Visualizing ratings

plt.hist(df.rating, 5, alpha=1);
```



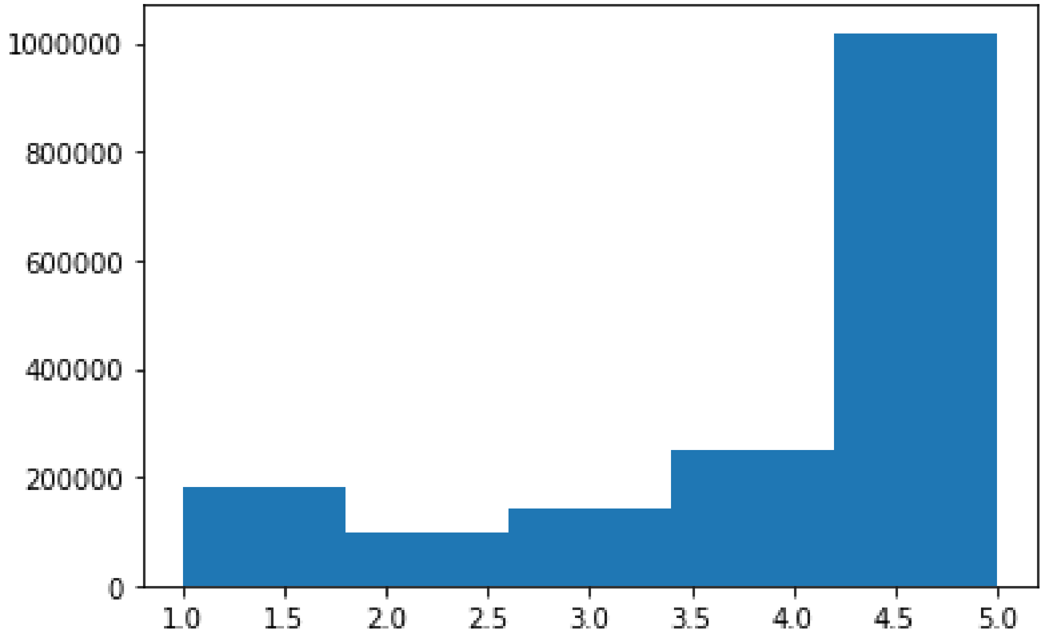
[62]:
```
# Visualizing ratings

plt.hist(df[df.verified==0].rating, 5, alpha=1);
```



[63]:
```
# Visualizing ratings

plt.hist(df[df.verified==1].rating, 5, alpha=1);
```



Looking at the histogram we can see that non verified users show a bigger 1 rating which could be impacting the overall low ratings for the products. This is a business call to handle this data to be removed or kept.

[38]:
```
# Checking for duplicate values

df[df.duplicated(subset=['rating','reviewerID','reviewTime','itemID'],␣
 ↪keep='first')].head()
```

[38]:
```
       rating  verified      reviewerID   reviewTime      itemID
6905        4         1   ACTVXNBEPLW2S  01 25, 2015  B000052YAN
7166        5         1  A3AMP8ZS2WQ94N  11 19, 2014  B0000530HU
9557        5         0  A1CJPRUT6GHTGO  01 30, 2007  B000067E30
11543       2         0   A6HO1UBMBOZTY  09 13, 2006  B00009RB0Z
12224       3         1  A2LHFW4Q0UWIFA  10 26, 2016  B00011QUDE
```

[41]:
```
# Validating duplicate results

df[df.reviewerID=='ACTVXNBEPLW2S']
```

[41]:
```
      rating  verified     reviewerID   reviewTime      itemID
6904       4         1  ACTVXNBEPLW2S  01 25, 2015  B000052YAN
```

```
6905        4         1  ACTVXNBEPLW2S  01 25, 2015  B000052YAN
32550       5         1  ACTVXNBEPLW2S   05 9, 2014  B000GGFZLC
```

There are several duplicate recording in the dataframe. These duplicate records will be removed, however while doing so we make sure that one entry is retained and all other duplicates will be removed.

[43]:

```
# Sorting the values based on reviewTime

df.sort_values("reviewTime", ascending= [0], inplace=True)
```

[45]:

```
# Validating the sort

df.head()
```

[45]:

```
        rating  verified    reviewerID  reviewTime      itemID
492858       5         1  A2NU79MV53K6QC  12 9, 2017  B003DA62R0
155958       5         1  A3GEVGOC9H36LL  12 9, 2017  B00HNK96UK
410390       5         1   A2GMFY423DP50  12 9, 2017  B00319B2K4
366153       4         1  A3993649BUWPHY  12 9, 2017  B00UIZLE48
350051       5         1   AYDQ9IJCYCQAG  12 9, 2017  B000P8991Y
```

[47]:

```
# Checking the length of dataframe before removing duplicates

len(df)
```

[47]:

```
1857758
```

[48]:

```
# Removing the duplicates while keeping the first value of the duplicates

df.drop_duplicates(keep='first',inplace=True)
```

[49]:

```
# Checking the length of dataframe after removing duplicates

len(df)
```

[49]:

```
1829243
```

[52]:

```
# Validating to see if duplicates are removed

df[df.reviewerID=='ACTVXNBEPLW2S']
```

[52]:

```
       rating  verified    reviewerID   reviewTime      itemID
32550       5         1  ACTVXNBEPLW2S   05 9, 2014  B000GGFZLC
6904        4         1  ACTVXNBEPLW2S  01 25, 2015  B000052YAN
```

0.1.3 For New Customers

Popularity based model Since a new customer will not have any historical data the right approach to recommend the products is by making use of the popularity based model. This model will have all the items which got the highest rating and at the top.

[64]:
```
# Creating a new dataframe and creating the count per item and mean rating per␣
 ↪item

df2 = pd.DataFrame({'count':df.groupby('itemID')['rating'].count(),'ratingMean':
 ↪df.groupby('itemID')['rating'].mean()}).reset_index()
```

[65]:
```
# Printing the maximum count and minimum count values

print(df2['count'].max(), df2['count'].min())
```

```
8668 1
```

[66]:
```
# Printing the record count and the items who got less than 500 ratings

print(len(df2), len(df2[df2['count']<500]))
```

```
249027 248717
```

[68]:
```
# Getting the items which has ratings greater than 500 and mean rating greater␣
 ↪than 4. Again this could be a business call

df2 = df2[(df2['count']>500) & (df2['ratingMean']>=4.0)]
```

[69]:
```
# Printing the maximum and minimum ratigs count

print(df2['count'].max(), df2['count'].min())
```

```
8668 505
```

[71]:
```
# Sorting dataframe by rating mean in descending order

df2 = pd.DataFrame(df2.sort_values(by = ['ratingMean'], ascending= False))
```

[72]:
```
# Printing the top 15 records of the popular products

df2.head(15)
```

[72]:
```
           itemID  count  ratingMean
1906   B0009RF9DW    772    4.933938
2913   B000FI4S1E    773    4.931436
46577  B00DM8J11Q   1416    4.868644
7478   B0012Y0ZG2   1101    4.852861
```

```
26947   B006H7HB7K   526   4.851711
200880  B01B5BWTNS   528   4.844697
21677   B0053F80JA  1366   4.838946
6230    B000URXP6E  1003   4.838485
111843  B00RLSCLJM  3529   4.826296
243     B00006L9LC   712   4.814607
64878   B00I0W0AI8   541   4.813309
22925   B005AR75A6   538   4.812268
57466   B00G8Q7JZ4   629   4.802862
62      1620213982  4792   4.798414
14730   B002Z3N1HE  1189   4.793103
```

0.1.4 Collaborative Filtering

Collaborative filtering is a technique that can filter out items that a user might like on the basis of reactions by similar users.

It works by searching a large group of people and finding a smaller set of users with tastes similar to a particular user. It looks at the items they like and combines them to create a ranked list of suggestions. Here we use the SVD approach to provide product recommendations based on item.

SVD - Singular Value Decomposition One of the popular algorithms to factorize a matrix is the singular value decomposition(SVD) algorithm. First I build a user-item matrix. Then we decompose this matrix using SVD to extract constituent arrays of feature vectors and correlation out of it.

[74]:

```
# Filtering out the values with user ratings which are less than 50

df3 = df.groupby('itemID').filter(lambda x:x['rating'].count()>50)
```

[78]:

```
# Getting a subset of the data

df4 = df3.head(10000)
```

[79]:

```
# Checking the record counts

print(len(df3), len(df4))
```

```
941800 10000
```

[80]:

```
# Creating the utility matrix with reviewerID and itemID

utility_matrix =df4.pivot_table(values='rating', index='reviewerID',␣
↪columns='itemID', fill_value=0)
```

[82]:

```
# Checking the utility matrix

utility_matrix.head()
```

[82]:
```
itemID                1620213982  B00004YWK2  B000050B6H  B000050FDY  \
reviewerID
A0090831Q386KET36YQW           0           0           0           0
A0122375SQ8Z42DUL03J           0           0           0           0
A0207585A6YBSJJPD5FS           0           0           0           0
A0634459IUT5LVFM9YZZ           0           0           0           0
A1000I7I07B7OI                 0           0           0           0

itemID                B000052YAN  B0000530HU  B00005JS5C  B00005OU6T  \
reviewerID
A0090831Q386KET36YQW           0           0           0           0
A0122375SQ8Z42DUL03J           0           0           0           0
A0207585A6YBSJJPD5FS           0           0           0           0
A0634459IUT5LVFM9YZZ           0           0           0           0
A1000I7I07B7OI                 0           0           0           0

itemID                B000068PBJ  B00006IV17  …  B01H8A05N6  B01HBLM8EQ  \
reviewerID                                    …
A0090831Q386KET36YQW           0           0  …           0           0
A0122375SQ8Z42DUL03J           0           0  …           0           0
A0207585A6YBSJJPD5FS           0           0  …           0           0
A0634459IUT5LVFM9YZZ           0           0  …           0           0
A1000I7I07B7OI                 0           0  …           0           0

itemID                B01HBPGP28  B01HBSH2EK  B01HC6G4D6  B01HC7ZP1M  \
reviewerID
A0090831Q386KET36YQW           0           0           0           0
A0122375SQ8Z42DUL03J           0           0           0           0
A0207585A6YBSJJPD5FS           0           0           0           0
A0634459IUT5LVFM9YZZ           0           0           0           0
A1000I7I07B7OI                 0           0           0           0

itemID                B01HC9ONI6  B01HDZ4OOM  B01HEISONU  B01HI7K476
reviewerID
A0090831Q386KET36YQW           0           0           0           0
A0122375SQ8Z42DUL03J           0           0           0           0
A0207585A6YBSJJPD5FS           0           0           0           0
A0634459IUT5LVFM9YZZ           0           0           0           0
A1000I7I07B7OI                 0           0           0           0

[5 rows x 3332 columns]
```

[83]:
```
# Checking the shape of the utility matrix

utility_matrix.shape
```

[83]:
```
(9343, 3332)
```

[84]:

```
# Creating the transpose of the matrix

utility_matrix = utility_matrix.T
utility_matrix.head()
```

[84]:

```
reviewerID  A0090831Q386KET36YQW  A0122375SQ8Z42DUL03J  A0207585A6YBSJJPD5FS  \
itemID
1620213982                   0.0                   0.0                   0.0
B00004YWK2                   0.0                   0.0                   0.0
B000050B6H                   0.0                   0.0                   0.0
B000050FDY                   0.0                   0.0                   0.0
B000052YAN                   0.0                   0.0                   0.0

reviewerID  A0634459IUT5LVFM9YZZ  A1000I7I07B7OI  A1003HDK1GHMSP  \
itemID
1620213982                   0.0             0.0             0.0
B00004YWK2                   0.0             0.0             0.0
B000050B6H                   0.0             0.0             0.0
B000050FDY                   0.0             0.0             0.0
B000052YAN                   0.0             0.0             0.0

reviewerID  A101GQRGM79ZAX  A101LWC4TVG0VT  A101NXBK4DJ454  A102G6SC7VE2HS  \
itemID
1620213982             0.0             0.0             0.0             0.0
B00004YWK2             0.0             0.0             0.0             0.0
B000050B6H             0.0             0.0             0.0             0.0
B000050FDY             0.0             0.0             0.0             0.0
B000052YAN             0.0             0.0             0.0             0.0

reviewerID  …  AZW33SSW09BZ6  AZW7OWXHAHGKT  AZX1PZRBP1FJD  AZX3R9XUGMQWD  \
itemID      …
1620213982  …            0.0            0.0            0.0            0.0
B00004YWK2  …            0.0            0.0            0.0            0.0
B000050B6H  …            0.0            0.0            0.0            0.0
B000050FDY  …            0.0            0.0            0.0            0.0
B000052YAN  …            0.0            0.0            0.0            0.0

reviewerID  AZXFF73ZZM0FV  AZYA6NBTF2843  AZYEIBAO4SWEO  AZYNASCEZ6FXX  \
itemID
1620213982            0.0            0.0            0.0            0.0
B00004YWK2            0.0            0.0            0.0            0.0
B000050B6H            0.0            0.0            0.0            0.0
B000050FDY            0.0            0.0            0.0            0.0
B000052YAN            0.0            0.0            0.0            0.0

reviewerID  AZYQE4YLJCLBI  AZZSKNX254F5D
itemID
```

```
1620213982           0.0            0.0
B00004YWK2           0.0            0.0
B000050B6H           0.0            0.0
B000050FDY           0.0            0.0
B000052YAN           0.0            0.0

[5 rows x 9343 columns]
```

[85]:

```
# Checking the shape of the transposed matrix

utility_matrix.shape
```

[85]:

```
(3332, 9343)
```

[87]:

```
# Creating the SVD model and fiting the utility matrix

SVD = TruncatedSVD(n_components=10)
decomposed_utility = SVD.fit_transform(utility_matrix)
decomposed_utility.shape
```

[87]:

```
(3332, 10)
```

[90]:

```
# Creating the correlation matrix using the decomposed utility matrix

correlation_matrix = np.corrcoef(decomposed_utility)
correlation_matrix.shape
```

[90]:

```
(3332, 3332)
```

[119]:

```
# Creating a method for recommendation system

def recommendation_system(i):
    item_names = list(utility_matrix.index)
    item_ID = item_names.index(i)
    result = list(utility_matrix.index[correlation_matrix[item_ID] > 0.70])
    result.remove(i)
    return result[0:15]
```

[120]:

```
# Recommending the top 15 correlated items based on the item search

recommendation_system('B00005JS5C')
```

[120]:

```
['B0000530HU',
 'B00006IV17',
 'B000146LKS',
 'B00020UR4C',
 'B00021KD2C',
 'B0002GTTOU',
 'B0002JOZNM',
 'B0002PU864',
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