Recommendations_with_IBM

December 31, 2021

1 Recommendations with IBM

In this notebook, you will be putting your recommendation skills to use on real data from the IBM Watson Studio platform.

You may either submit your notebook through the workspace here, or you may work from your local machine and submit through the next page. Either way assure that your code passes the project RUBRIC. **Please save regularly.**

By following the table of contents, you will build out a number of different methods for making recommendations that can be used for different situations.

1.1 Table of Contents

At the end of the notebook, you will find directions for how to submit your work. Let's get started by importing the necessary libraries and reading in the data.

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        import project_tests as t
        import pickle

        %matplotlib inline

        df = pd.read_csv('data/user-item-interactions.csv')
        df_content = pd.read_csv('data/articles_community.csv')
        del df['Unnamed: 0']
        del df_content['Unnamed: 0']

        # Show df to get an idea of the data
        df.head()
```

```
Out[1]:    article_id                                              title  \
        0      1430.0  using pixiedust for fast, flexible, and easier...
        1      1314.0       healthcare python streaming application demo
        2      1429.0         use deep learning for image classification
        3      1338.0          ml optimization using cognitive assistant
```

```
4      1276.0          deploy your python model as a restful api

                                      email
0  ef5f11f77ba020cd36e1105a00ab868bbdbf7fe7
1  083cbdfa93c8444beaa4c5f5e0f5f9198e4f9e0b
2  b96a4f2e92d8572034b1e9b28f9ac673765cd074
3  06485706b34a5c9bf2a0ecdac41daf7e7654ceb7
4  f01220c46fc92c6e6b161b1849de11faacd7ccb2
```

In [2]:
```python
df.shape[0]
```

Out[2]:
```
45993
```

In [3]:
```python
df_content.shape[0]
```

Out[3]:
```
1056
```

In [4]:
```python
# Show df_content to get an idea of the data
df_content.head()
```

Out[4]:
```
                                            doc_body  \
0  Skip navigation Sign in SearchLoading...\r\n\r...
1  No Free Hunch Navigation * kaggle.com\r\n\r\n ...
2   * Login\r\n * Sign Up\r\n\r\n * Learning Pat...
3  DATALAYER: HIGH THROUGHPUT, LOW LATENCY AT SCA...
4  Skip navigation Sign in SearchLoading...\r\n\r...

                                     doc_description  \
0  Detect bad readings in real time using Python ...
1  See the forest, see the trees. Here lies the c...
2  Heres this weeks news in Data Science and Bi...
3  Learn how distributed DBs solve the problem of...
4  This video demonstrates the power of IBM DataS...

                                       doc_full_name doc_status  article_id
0  Detect Malfunctioning IoT Sensors with Streami...       Live           0
1  Communicating data science: A guide to present...       Live           1
2         This Week in Data Science (April 18, 2017)       Live           2
3  DataLayer Conference: Boost the performance of...       Live           3
4      Analyze NY Restaurant data using Spark in DSX       Live           4
```

1.1.1 Part I : Exploratory Data Analysis

Use the dictionary and cells below to provide some insight into the descriptive statistics of the data.

`1.` What is the distribution of how many articles a user interacts with in the dataset? Provide a visual and descriptive statistics to assist with giving a look at the number of times each user interacts with an article.

a. Exploratory analysis about "number of users interact with an article"

- Number of times each user interacts with an article

In [5]:
```
df.groupby(['article_id','email']).size()
```

Out[5]:
```
article_id  email
0.0         2841916b462a2b89d36f4f95ca2d1f42559a5788    1
            384255292a8223e84f05ca1e1deaa450c993e148    3
            451a9a4a4cb1cc4e5f38d04e8859cc3fb275cc66    1
            74ca1ae8b034f7fad73a54d55fb1f58747f00493    1
            8bd0afc488016810c287ac4ec844895d570b0af4    1
            a60b7e945a8f2114d5dfbdd53182ad1d526534e2    1
            ad06c765d31179e56f309438367ecb30e1059620    1
            ca7d48adf2c7394ed5a8776de959fa8047e43d4b    1
            db8ac9b2f552db35750239ada8bfcb59b3ae48c0    1
            df722d3aac72766b93d4a65d8b4ac084a968d684    1
            e667c9a1cd56368dfa2f4b974ab2d848585552d7    1
            e6ed9e15addba353fe3c1f36d865a63fa254b9cc    1
2.0         0246d11c827f90850ce7062e9554c9d5eeb30027    1
            0286bfe26356436658cf4b29b232f0700f0bb9ce    2
            12815feeacc6f27dff5b3441a54418d2d51001ef    1
            12bb8a9740400ced27ae5a7d4c990ac3b7e3c77d    1
            15a1660b6450e064200f1272d9b3d049cf8cf5f1    1
            1d74fc07ef225ff993b9f80dfba85a6bd2bd55b8    1
            249d60fc4edda28cd8fd76f549ecc43259e07038    1
            26b8f921fac7a4d81f2749d64c10020491281545    1
            2b6c0f514c2f2b04ad3c4583407dccd0810469ee    3
            2f5c7feae533ce046f2cb16fb3a29fe00528ed66    1
            3427a5a4065625363e28ac8e85a57a9436010e9c    3
            387f29d1e6f4360fa1a2c9607edfa184520bd716    1
            3e9be703aad3a99412af09cdefcdf28fe5ff2a32    1
            40222b846f3cef9a645dfb34fc15f7c1c244e393    1
            40a942b88fbc6b891eb335e12fbc589870098153    1
            449235d86e9d80f808112130da55d08bfb41703d    1
            4594c0796c9f32915d3f5c05c2cc5378ffcd40b4    1
            497935037e41a94d2ae02488d098c7abda9a30bc    1
                                                       ..
1440.0      a4ce0a47da79499778f8cf4c94fd5cd0fde39002    1
            aaaf1a153d6b2f025b275c68324b6dd6d15f22ff    2
            e685741240520687a02b033e21938ddf3acdab7f    2
1441.0      3c3b60c3fb094373d6aa9420b2f8c08cd6a23354    1
            3cdbb321cad01f39848fcde8288109a73ee7febb    2
            436337957e43e0b1db33a58e87971319214d03a9    2
            6cce7568da5452718e1a3702edffac34a8da74ec    1
            8c37a3959fb30f349adff02cc545907dafd41b2a    1
            d5843ed71361c87b364f578f20a48101289d60f9    1
1442.0      0bd8ddb0c5cec4623a6bb663592747ad55477680    1
            21026417853cd181c161ae20651318978bf177b0    1
            5ad53e0336bcd4aef788745048a451f9c383bf81    1
```

```
                66fd330648798030d5fe39b4ea5b8f61e618eb6e     1
1443.0          32c368e390424c9326f736d32725e1e167abcbe4     2
                3d840ffab77365a1b2e5ccd464bd439a347d6105     1
                4ac1eb6a4d2dfbd4e18042c0908de9d3dd7c39b0     2
                4accff186b3c4fb061b11ad6ae1920556bd68382     2
                6cce7568da5452718e1a3702edffac34a8da74ec     1
                8a7982ea3a9d4fe4fd7389e0a94a539ccc81a7bc     1
                9676b33c28cfc8f8dea534ebfd26ec140f8e442f     5
                c20e17b171ff2a34b4d684b4fe3af3be7e0700f3     2
                d53071c9f495307a7a2b9d3619f7ec6e8721e1b7     1
                d5843ed71361c87b364f578f20a48101289d60f9     1
                ecee962fad63a7828319b3aa0a6557f94fc5691e     1
                fa19d1470e496ac4a7bd0eeb07d17b2b3a2f9e30     3
1444.0          6cce7568da5452718e1a3702edffac34a8da74ec     1
                c45f9495a76bf95d2633444817f1be8205ad542d     1
                d313c83ab3ed388ba16042a6cd33fce57d6a9e9a     1
                d5843ed71361c87b364f578f20a48101289d60f9     1
                fd824fc62b4753107e3db7704cd9e8a4a1c961f1     1
Length: 33669, dtype: int64
```

- Number of users interact with an article

In [6]:
```
article_interact_unique = df.groupby(['article_id'])['email'].nunique()
article_interact_unique
```

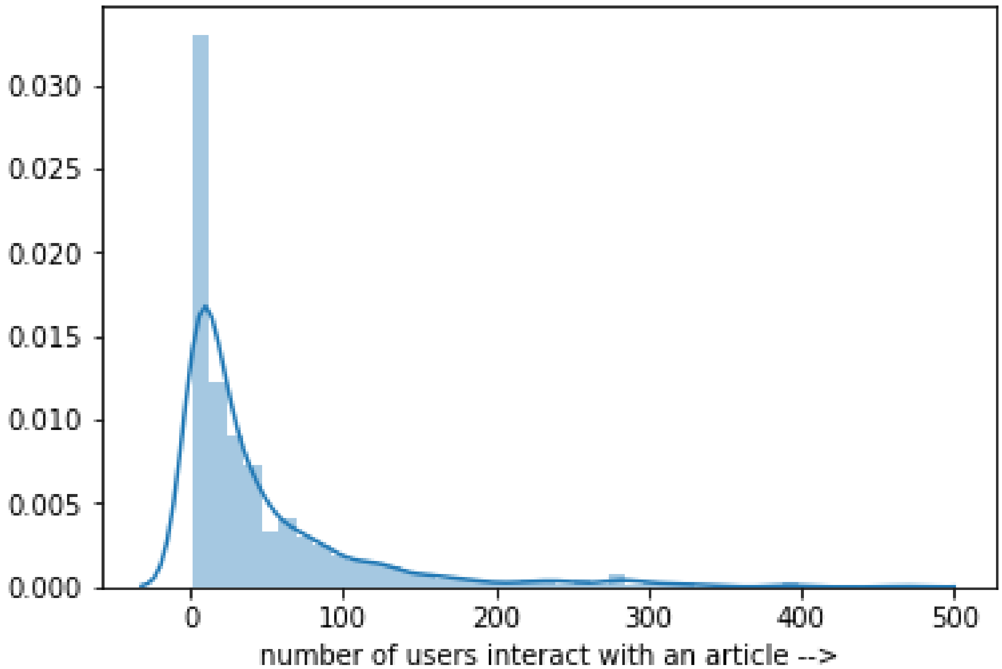
Out[6]:
```
article_id
0.0        12
2.0        44
4.0        13
8.0        82
9.0        10
12.0       99
14.0       89
15.0       26
16.0       56
18.0       68
20.0      186
25.0       15
26.0       80
28.0       39
29.0       41
30.0       17
32.0       60
33.0      109
34.0       86
36.0       18
39.0       59
40.0       64
```

```
43.0      299
48.0       11
50.0       69
51.0      107
53.0       93
54.0       20
57.0      128
58.0       11
          ...
1412.0     19
1414.0      4
1415.0     10
1416.0     73
1418.0     41
1419.0      6
1420.0     94
1421.0      3
1422.0    105
1423.0    102
1424.0    115
1425.0     57
1426.0     96
1427.0    308
1428.0     91
1429.0    397
1430.0    237
1431.0    320
1432.0    232
1433.0     86
1434.0     36
1435.0     75
1436.0    282
1437.0    127
1439.0     43
1440.0      8
1441.0      6
1442.0      4
1443.0     12
1444.0      5
Name: email, Length: 714, dtype: int64
```

- The distribution of "how many user interact with an article"

In [7]:
```
x2 = pd.Series(article_interact_unique, name="number of users interact with an article -
sns.distplot(x2)
```

Out[7]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff08d3c6e10>
```



b. Exploratory analysis about "number of articles a user interacts with"

- Number of times a user interacts with articles

In [8]:
```
df.groupby(['email','article_id']).size()
```

Out[8]:
```
email                                     article_id
0000b6387a0366322d7fbfc6434af145adf7fed1  43.0          2
                                          124.0         1
                                          173.0         1
                                          288.0         1
                                          349.0         1
                                          618.0         1
                                          732.0         1
                                          1162.0        1
                                          1232.0        1
                                          1314.0        1
                                          1337.0        1
                                          1354.0        1
001055fc0bb67f71e8fa17002342b256a30254cd  124.0         1
                                          254.0         1
                                          390.0         1
                                          1386.0        1
00148e4911c7e04eeff8def7bbbdaf1c59c2c621  258.0         1
                                          932.0         1
                                          1386.0        1
```

```
001a852ecbd6cc12ab77a785efa137b2646505fe  232.0          1
                                          349.0          1
                                          593.0          1
                                          957.0          1
                                          1364.0         2
001fc95b90da5c3cb12c501d201a915e4f093290  379.0          1
                                          1364.0         1
0042719415c4fca7d30bd2d4e9d17c5fc570de13  20.0           1
                                          1060.0         1
00772abe2d0b269b2336fc27f0f4d7cb1d2b65d7  732.0          1
                                          1427.0         2
                                                        ..
ffe3d0543c9046d35c2ee3724ea9d774dff98a32  617.0          1
                                          701.0          1
                                          727.0          1
                                          782.0          1
                                          784.0          1
                                          878.0          1
                                          943.0          1
                                          986.0          1
                                          1047.0         1
                                          1162.0         1
                                          1165.0         1
                                          1314.0         2
                                          1360.0         2
                                          1386.0         1
                                          1422.0         3
                                          1425.0         1
                                          1427.0         1
fff9fc3ec67bd18ed57a34ed1e67410942c4cd81  116.0          1
                                          232.0          1
                                          268.0          2
                                          525.0          1
                                          684.0          3
                                          962.0          1
                                          1431.0         1
fffb93a166547448a0ff0232558118d59395fecd  329.0          1
                                          981.0          1
                                          1304.0         1
                                          1305.0         8
                                          1430.0         1
                                          1437.0         1
Length: 33669, dtype: int64
```

- Number of articles a user interacts with.

In [9]:
```
user_interact_unique = df.groupby(['email'])['article_id'].nunique()
user_interact_unique
```

```
Out[9]: email
0000b6387a0366322d7fbfc6434af145adf7fed1    12
001055fc0bb67f71e8fa17002342b256a30254cd     4
00148e4911c7e04eeff8def7bbbdaf1c59c2c621     3
001a852ecbd6cc12ab77a785efa137b2646505fe     5
001fc95b90da5c3cb12c501d201a915e4f093290     2
0042719415c4fca7d30bd2d4e9d17c5fc570de13     2
00772abe2d0b269b2336fc27f0f4d7cb1d2b65d7     2
008ba1d5b4ebf54babf516a2d5aa43e184865da5    10
008ca24b82c41d513b3799d09ae276d37f92ce72     1
008dfc7a327b5186244caec48e0ab61610a0c660    10
009af4e0537378bf8e8caf0ad0e2994f954d822e     1
00bda305223d05f6df5d77de41abd2a0c7d895fe     4
00c2d5190e8c6b821b0e3848bf56f6e47e428994     3
00ced21f957bbcee5edf7b107b2bd05628b04774     4
00d9337ecd5f70fba1c4c7a78e21b3532e0112c4     1
00e524e4f13137a6fac54f9c71d7769c6507ecde     8
00f8341cbecd6af00ba8c78b3bb6ec49adf83248     2
00f946b14100f0605fa25089437ee9486378872c     1
01041260c97ab9221d923b0a2c525437f148d589     2
0108ce3220657a9a89a85bdec959b0f2976dd51c     3
011455e91a24c1fb815a4deac6b6eaf5ad16819e     9
01198c58d684d79c9026abe355cfb532cb524dc5     1
011ae4de07ffb332b0f51c155a35c23c80294962    29
011fcfb582be9534e9a275336f7e7c3717100381     4
0129dfcdb701b6e1d309934be6393004c6683a2d    12
01327bbc4fd7bfe8ad62e599453d2876b928e725     3
01455f0ab0a5a22a93d94ad35f6e78431aa90625     6
014dedab269f1453c647598c92a3fa37b39eed97     2
014e4fe6e6c5eb3fe5ca0b16c16fb4599df6375c     1
01560f88312a91894d254e6406c25df19f0ad5e8     9
                                            ..
fe5396e3762c36767c9c915f7ed1731691d7e4b4     1
fe5480ff15f0ac51eeb2314a192351f168d7aad7     1
fe56a49b62752708ed2f6e30677c57881f7b78d1    10
fe5885b80e91be887510a0b6dd04e011178d6364     3
fe5f9d7528518e00b0a73c7a3994afc335496961     3
fe66aa534c7824eca663b84b99a437a98a9b026e     2
fe69c72c964a8346dbc7763309c4e07d818d360f     2
fe88d1f683f308b32fb3d7554f007cc55cc48df5     1
fe8c1cb974e39d8ea8c005044e927b3f0de8acd0     2
fe90d98b0287090fe8e653bafba6ed3eff19331e     1
fe9327be39fd457df70e83d3fc8cba9b8b3f95b1     1
feaea388105a4ccc48795b191bbf0c26a23b1356     4
fef0c6be3a2ed226e1fb8a811b0ee68a389f6f3c    11
fef28e45f7217026b2684d1783a2e18b061bdffb     3
fef3bc88def1aa787c99957ded7d5b2c0edc040e     3
ff27ffd93e21154b8a9cf2722f2cc0f75dc39eff     1
```

```
ff288722b76eba5209cdbf9158c6dfbf229b9129     1
ff452614b91f4c9bd965150b1a82e7bf18f59334     2
ff4d3e1c359cfbb73bcae07fa1eb62c45da2b161     3
ff55d0c0b2a4f56aae87c2a21afb7070ab34383d     1
ff6e82c763fe2443643e48a03e239eb635f406dc    13
ff7a0f59ba022102ad22981141a7182c4d8273c3     5
ff833869969184d86f870f98405e7988eccc2309     9
ff979e07f9d906a32ba35a9b75fd9585f6306dbc    15
ffaefa3a1bc2d074d9a14c9924d4e67a46c35410     1
ffc6cfa435937ca0df967b44e9178439d04e3537     1
ffc96f8fbb35aac4cb0029332b0fc78e7766bb5d     2
ffe3d0543c9046d35c2ee3724ea9d774dff98a32    27
fff9fc3ec67bd18ed57a34ed1e67410942c4cd81     7
fffb93a166547448a0ff0232558118d59395fecd     6
Name: article_id, Length: 5148, dtype: int64
```

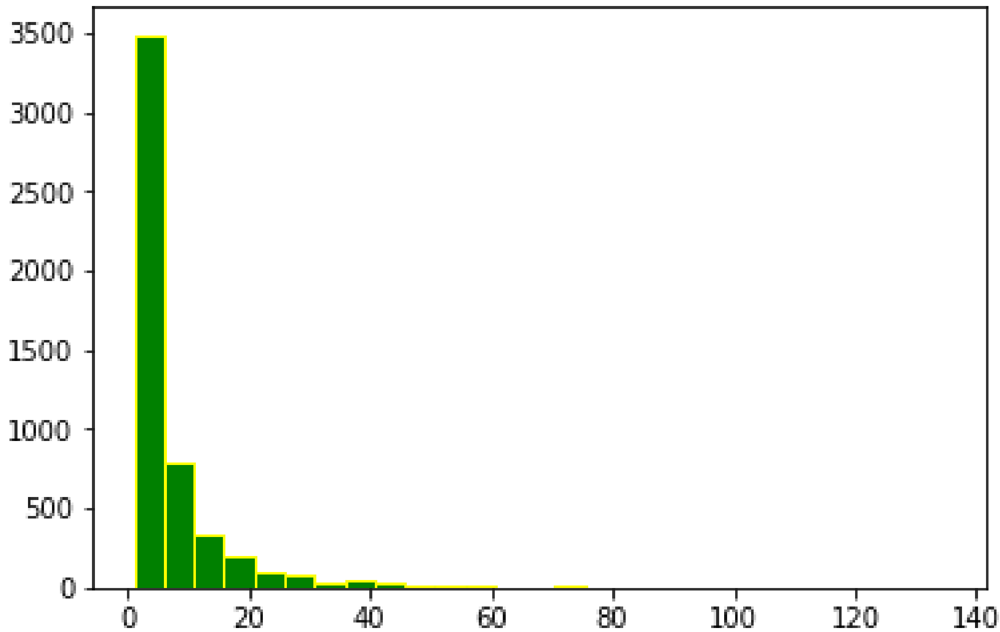
- Visualize the distribution of how many articles a user interacts with

In [10]:
```
user_interact_unique.max()
```

Out[10]:
```
135
```

In [11]:
```
# data visualization
plt.hist(user_interact_unique, bins = 27, ec="yellow", fc="green") #bins =27 for bin_si
```

Out[11]:
```
(array([  3.48900000e+03,   7.84000000e+02,   3.38000000e+02,
          1.92000000e+02,   1.02000000e+02,   8.10000000e+01,
          3.30000000e+01,   4.00000000e+01,   2.30000000e+01,
          1.20000000e+01,   1.30000000e+01,   1.50000000e+01,
          4.00000000e+00,   4.00000000e+00,   1.00000000e+01,
          0.00000000e+00,   0.00000000e+00,   0.00000000e+00,
          0.00000000e+00,   5.00000000e+00,   1.00000000e+00,
          0.00000000e+00,   0.00000000e+00,   0.00000000e+00,
          0.00000000e+00,   0.00000000e+00,   2.00000000e+00]),
 array([   1.        ,    5.96296296,   10.92592593,   15.88888889,
          20.85185185,   25.81481481,   30.77777778,   35.74074074,
          40.7037037 ,   45.66666667,   50.62962963,   55.59259259,
          60.55555556,   65.51851852,   70.48148148,   75.44444444,
          80.40740741,   85.37037037,   90.33333333,   95.2962963 ,
         100.25925926,  105.22222222,  110.18518519,  115.14814815,
         120.11111111,  125.07407407,  130.03703704,  135.        ]),
 <a list of 27 Patch objects>)
```



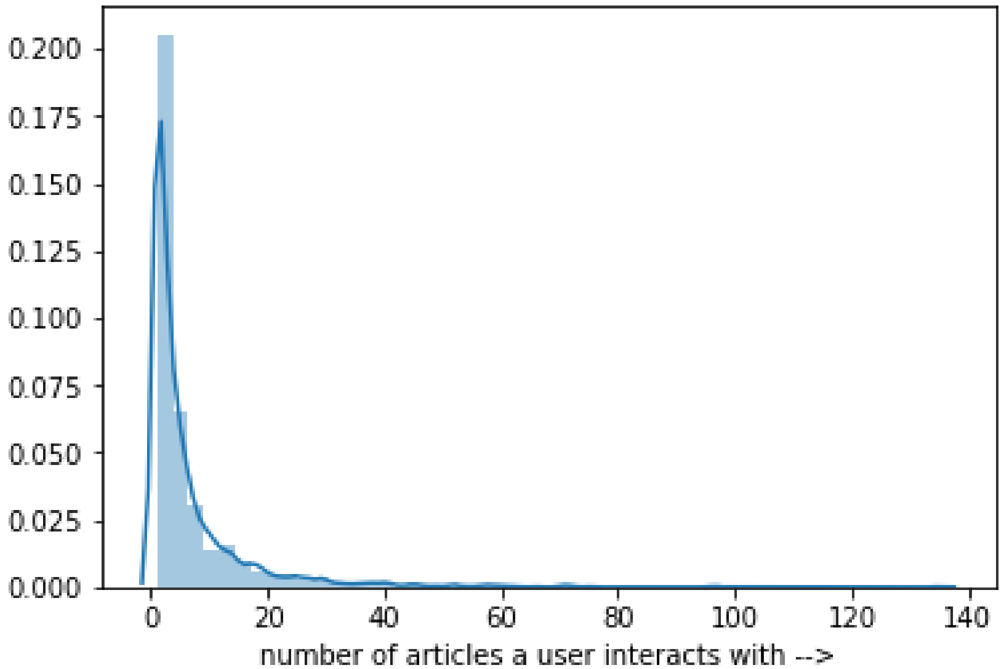
using Seaborn for seeing better distribution

```
In [12]: sns.__version__ # don't support histplot, only can support distplot
```

```
Out[12]: '0.8.1'
```

```
In [13]: x1 = pd.Series(user_interact_unique, name="number of articles a user interacts with -->
         sns.distplot(x1)
```

```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff08b1f3550>
```



- Cumulative distribution statistics of "how many articles a user interacts with" (use Mathplotlib because seaborn ver 0.8.1 doesnot support histplot)

```
In [14]: plt.hist(user_interact_unique, bins = 100, ec="yellow", fc="green", cumulative = True)
```

```
Out[14]: (array([ 2309.,  2833.,  3489.,  3735.,  3912.,  4159.,  4273.,  4353.,
                  4495.,  4564.,  4611.,  4693.,  4738.,  4776.,  4822.,  4844.,
                  4861.,  4905.,  4920.,  4940.,  4971.,  4986.,  4993.,  5008.,
                  5013.,  5019.,  5034.,  5043.,  5049.,  5067.,  5069.,  5071.,
                  5082.,  5087.,  5088.,  5093.,  5094.,  5096.,  5104.,  5106.,
                  5107.,  5112.,  5118.,  5120.,  5124.,  5125.,  5126.,  5126.,
                  5128.,  5128.,  5128.,  5130.,  5138.,  5138.,  5138.,  5140.,
                  5140.,  5140.,  5140.,  5140.,  5140.,  5140.,  5140.,  5140.,
                  5140.,  5140.,  5140.,  5140.,  5140.,  5140.,  5142.,  5144.,
                  5144.,  5145.,  5146.,  5146.,  5146.,  5146.,  5146.,  5146.,
                  5146.,  5146.,  5146.,  5146.,  5146.,  5146.,  5146.,  5146.,
                  5146.,  5146.,  5146.,  5146.,  5146.,  5146.,  5146.,  5146.,
                  5146.,  5146.,  5146.,  5148.]),
          array([   1.  ,    2.34,    3.68,    5.02,    6.36,    7.7 ,    9.04,
                   10.38,   11.72,   13.06,   14.4 ,   15.74,   17.08,   18.42,
                   19.76,   21.1 ,   22.44,   23.78,   25.12,   26.46,   27.8 ,
                   29.14,   30.48,   31.82,   33.16,   34.5 ,   35.84,   37.18,
                   38.52,   39.86,   41.2 ,   42.54,   43.88,   45.22,   46.56,
                   47.9 ,   49.24,   50.58,   51.92,   53.26,   54.6 ,   55.94,
                   57.28,   58.62,   59.96,   61.3 ,   62.64,   63.98,   65.32,
```

```
         66.66,    68.  ,    69.34,    70.68,    72.02,    73.36,    74.7 ,
         76.04,    77.38,    78.72,    80.06,    81.4 ,    82.74,    84.08,
         85.42,    86.76,    88.1 ,    89.44,    90.78,    92.12,    93.46,
         94.8 ,    96.14,    97.48,    98.82,   100.16,   101.5 ,   102.84,
        104.18,   105.52,   106.86,   108.2 ,   109.54,   110.88,   112.22,
        113.56,   114.9 ,   116.24,   117.58,   118.92,   120.26,   121.6 ,
        122.94,   124.28,   125.62,   126.96,   128.3 ,   129.64,   130.98,
        132.32,   133.66,   135.  ]),
 <a list of 100 Patch objects>)
```

- Calculate the descriptive parameters: the median value of "how many articles a user interacts with" distribution

```
In [15]: median_val = np.median(user_interact_unique)
         median_val
```

```
Out[15]: 3.0
```

- Calculate the descriptive parameters: the max value of "how many articles a user interacts with"

```
In [16]: df.groupby(['email']).size().max()
```

```
Out[16]: 364
```

- Fill in the descriptive parameters

```
In [17]: # Fill in the median and maximum number of user_article interactios below

         median_val = 3.0 # 50% of individuals interact with 3.0 number of articles or fewer.
         max_views_by_user = 364 # The maximum number of user-article interactions by any 1 user
```

2. Explore and remove duplicate articles from the **df_content** dataframe.

```
In [18]: # Check the number of items in df_content (articles)
         df_content.shape[0]

Out[18]: 1056

In [19]: # Find and explore duplicate articles
         df_content[df_content.duplicated(subset=['article_id'], keep='first') == True]

Out[19]:                                               doc_body  \
         365  Follow Sign in / Sign up Home About Insight Da...
         692  Homepage Follow Sign in / Sign up Homepage * H...
         761  Homepage Follow Sign in Get started Homepage *...
         970  This video shows you how to construct queries ...
         971  Homepage Follow Sign in Get started * Home\r\n...

                                               doc_description  \
         365  During the seven-week Insight Data Engineering...
         692  One of the earliest documented catalogs was co...
         761  Todays world of data science leverages data f...
         970  This video shows you how to construct queries ...
         971  If you are like most data scientists, you are ...

                                                 doc_full_name doc_status  article_id
         365                        Graph-based machine learning       Live          50
         692  How smart catalogs can turn the big data flood...       Live         221
         761  Using Apache Spark as a parallel processing fr...       Live         398
         970                             Use the Primary Index       Live         577
         971  Self-service data preparation with IBM Data Re...       Live         232

In [20]: # Remove any rows that have the same article_id - only keep the first
         df_content_drop = df_content.drop_duplicates(subset=['article_id'], keep='first') #drop

In [21]: df_content_drop.shape[0] #check the number of articles after drop the duplicated rows

Out[21]: 1051
```

3. Use the cells below to find:
a. The number of unique articles that have an interaction with a user.
b. The number of unique articles in the dataset (whether they have any interactions or not). **c.** The number of unique users in the dataset. (excluding null values) **d.** The number of user-article interactions in the dataset.

```
In [22]: # The number of unique articles that have at least one interaction
         article_interact_unique.shape[0]
```

```
Out[22]: 714
```

```
In [23]: # The number of unique articles on the IBM platform
         df_content_drop.shape[0]
```

```
Out[23]: 1051
```

```
In [24]: # The number of unique users
         user_interact_unique.shape[0]
```

```
Out[24]: 5148
```

```
In [25]: # The number of user-article interactions
         df.shape[0]
```

```
Out[25]: 45993
```

```
In [26]: unique_articles = article_interact_unique.shape[0] # The number of unique articles that
         total_articles = df_content_drop.shape[0] # The number of unique articles on the IBM pl
         unique_users = user_interact_unique.shape[0] # The number of unique users
         user_article_interactions = df.shape[0] # The number of user-article interactions
```

4. Use the cells below to find the most viewed **article_id**, as well as how often it was viewed. After talking to the company leaders, the `email_mapper` function was deemed a reasonable way to map users to ids. There were a small number of null values, and it was found that all of these null values likely belonged to a single user (which is how they are stored using the function below).

```
In [27]: # The most viewed article in the dataset was viewed how many times?
         df.groupby(['article_id']).size().max()
```

```
Out[27]: 937
```

```
In [28]: article_interactions = df.groupby(['article_id']).size()
         article_interactions
```

```
Out[28]: article_id
         0.0        14
         2.0        58
         4.0        13
         8.0        85
         9.0        10
         12.0      157
         14.0       89
         15.0       26
         16.0       61
         18.0       78
         20.0      249
```

```
25.0       15
26.0       89
28.0       42
29.0       75
30.0       17
32.0       64
33.0      141
34.0       93
36.0       18
39.0       68
40.0       70
43.0      460
48.0       11
50.0       89
51.0      124
53.0      115
54.0       20
57.0      140
58.0       11
         ...
1412.0     25
1414.0      4
1415.0     11
1416.0    102
1418.0     43
1419.0      6
1420.0    113
1421.0      3
1422.0    163
1423.0    155
1424.0    131
1425.0     71
1426.0    138
1427.0    643
1428.0    120
1429.0    937
1430.0    336
1431.0    671
1432.0    340
1433.0    108
1434.0     42
1435.0    120
1436.0    481
1437.0    218
1439.0     59
1440.0     10
1441.0      8
1442.0      4
```

```
1443.0     22
1444.0      5
Length: 714, dtype: int64
```

In [29]:
```
article_interactions[article_interactions == article_interactions.max()]
```

Out[29]:
```
article_id
1429.0    937
dtype: int64
```

In [30]:
```
most_viewed_article_id = '1429.0' # The most viewed article in the dataset as a string
max_views = 937 # The most viewed article in the dataset was viewed how many times?
```

In [31]:
```
## No need to change the code here - this will be helpful for later parts of the notebo
# Run this cell to map the user email to a user_id column and remove the email column

def email_mapper():
    coded_dict = dict()
    cter = 1
    email_encoded = []

    for val in df['email']:
        if val not in coded_dict:
            coded_dict[val] = cter
            cter+=1

        email_encoded.append(coded_dict[val])
    return email_encoded

email_encoded = email_mapper()
del df['email']
df['user_id'] = email_encoded

# show header
df.head()
```

Out[31]:

	article_id	title	user_id
0	1430.0	using pixiedust for fast, flexible, and easier...	1
1	1314.0	healthcare python streaming application demo	2
2	1429.0	use deep learning for image classification	3
3	1338.0	ml optimization using cognitive assistant	4
4	1276.0	deploy your python model as a restful api	5

In [32]:
```
## If you stored all your results in the variable names above,
## you shouldn't need to change anything in this cell

sol_1_dict = {
    '`50% of individuals have _____ or fewer interactions.`': median_val,
    '`The total number of user-article interactions in the dataset is ______.`': user_a
```

```
        '`The maximum number of user-article interactions by any 1 user is ______.`': max_v
        '`The most viewed article in the dataset was viewed _____ times.`': max_views,
        '`The article_id of the most viewed article is ______.`': most_viewed_article_id,
        '`The number of unique articles that have at least 1 rating ______.`': unique_artic
        '`The number of unique users in the dataset is ______`': unique_users,
        '`The number of unique articles on the IBM platform`': total_articles
    }

    # Test your dictionary against the solution
    t.sol_1_test(sol_1_dict)
```

```
It looks like you have everything right here! Nice job!
```

1.1.2 Part II: Rank-Based Recommendations

Unlike in the earlier lessons, we don't actually have ratings for whether a user liked an article or not. We only know that a user has interacted with an article. In these cases, the popularity of an article can really only be based on how often an article was interacted with.

1. Fill in the function below to return the **n** top articles ordered with most interactions as the top. Test your function using the tests below.

- Draft the functions with n = 10

In [33]:
```
df.groupby(['article_id']).size()
```

Out[33]:
```
article_id
0.0        14
2.0        58
4.0        13
8.0        85
9.0        10
12.0      157
14.0       89
15.0       26
16.0       61
18.0       78
20.0      249
25.0       15
26.0       89
28.0       42
29.0       75
30.0       17
32.0       64
33.0      141
34.0       93
36.0       18
39.0       68
40.0       70
```

```
43.0      460
48.0       11
50.0       89
51.0      124
53.0      115
54.0       20
57.0      140
58.0       11
          ...
1412.0     25
1414.0      4
1415.0     11
1416.0    102
1418.0     43
1419.0      6
1420.0    113
1421.0      3
1422.0    163
1423.0    155
1424.0    131
1425.0     71
1426.0    138
1427.0    643
1428.0    120
1429.0    937
1430.0    336
1431.0    671
1432.0    340
1433.0    108
1434.0     42
1435.0    120
1436.0    481
1437.0    218
1439.0     59
1440.0     10
1441.0      8
1442.0      4
1443.0     22
1444.0      5
Length: 714, dtype: int64
```

In [34]:
```
article_interactions_nlargest = df.groupby(['article_id']).size().nlargest(10)
article_interactions_nlargest
```

Out[34]:
```
article_id
1429.0    937
1330.0    927
1431.0    671
```

```
1427.0    643
1364.0    627
1314.0    614
1293.0    572
1170.0    565
1162.0    512
1304.0    483
dtype: int64
```

In [35]:
```
article_interactions_nlargest.index
```

Out[35]:
```
Float64Index([1429.0, 1330.0, 1431.0, 1427.0, 1364.0, 1314.0, 1293.0, 1170.0,
              1162.0, 1304.0],
             dtype='float64', name='article_id')
```

In [36]:
```
article_interactions_nlargest.index.map(str)
```

Out[36]:
```
Index(['1429.0', '1330.0', '1431.0', '1427.0', '1364.0', '1314.0', '1293.0',
       '1170.0', '1162.0', '1304.0'],
      dtype='object', name='article_id')
```

In [37]:
```
article_interactions_nlargest.index.map(str).tolist()
```

Out[37]:
```
['1429.0',
 '1330.0',
 '1431.0',
 '1427.0',
 '1364.0',
 '1314.0',
 '1293.0',
 '1170.0',
 '1162.0',
 '1304.0']
```

In [38]:
```
top_articles_index = article_interactions_nlargest.index.tolist()
top_articles_index
```

Out[38]:
```
[1429.0,
 1330.0,
 1431.0,
 1427.0,
 1364.0,
 1314.0,
 1293.0,
 1170.0,
 1162.0,
 1304.0]
```

In [39]:
```
df.head()
```

```
Out[39]:    article_id                                              title  user_id
         0      1430.0  using pixiedust for fast, flexible, and easier...        1
         1      1314.0       healthcare python streaming application demo        2
         2      1429.0         use deep learning for image classification        3
         3      1338.0          ml optimization using cognitive assistant        4
         4      1276.0          deploy your python model as a restful api        5
```

```
In [40]: df_drop = df[['article_id','title']]
         df_drop.head()
```

```
Out[40]:    article_id                                              title
         0      1430.0  using pixiedust for fast, flexible, and easier...
         1      1314.0       healthcare python streaming application demo
         2      1429.0         use deep learning for image classification
         3      1338.0          ml optimization using cognitive assistant
         4      1276.0          deploy your python model as a restful api
```

```
In [41]: df_drop = df_drop.drop_duplicates(subset=['article_id'], keep='first')
         df_drop.head()
```

```
Out[41]:    article_id                                              title
         0      1430.0  using pixiedust for fast, flexible, and easier...
         1      1314.0       healthcare python streaming application demo
         2      1429.0         use deep learning for image classification
         3      1338.0          ml optimization using cognitive assistant
         4      1276.0          deploy your python model as a restful api
```

```
In [42]: df_drop.shape[0]
```

```
Out[42]: 714
```

```
In [43]: df_drop[df_drop['article_id'].isin(top_articles_index)]
```

```
Out[43]:      article_id                                              title
         1        1314.0       healthcare python streaming application demo
         2        1429.0         use deep learning for image classification
         14       1170.0             apache spark lab, part 1: basic concepts
         29       1364.0  predicting churn with the spss random tree alg...
         31       1162.0              analyze energy consumption in buildings
         37       1431.0                       visualize car data with brunel
         42       1427.0  use xgboost, scikit-learn & ibm watson machine...
         56       1304.0  gosales transactions for logistic regression m...
         66       1330.0          insights from new york car accident reports
         154      1293.0  finding optimal locations of new store using d...
```

```
In [44]: top_articles_id = df.groupby(['article_id']).size().nlargest(10).index.map(str).tolist(
         top_articles_id
```

```
Out[44]: ['1429.0',
          '1330.0',
          '1431.0',
          '1427.0',
          '1364.0',
          '1314.0',
          '1293.0',
          '1170.0',
          '1162.0',
          '1304.0']
```

- Fill in the functions

```
In [45]: def get_top_articles(n, df=df):
             '''
             INPUT:
             n - (int) the number of top articles to return
             df - (pandas dataframe) df as defined at the top of the notebook

             OUTPUT:
             top_articles - (list) A list of the top 'n' article titles

             '''
             # Your code here
             article_interactions_nlargest = df.groupby(['article_id']).size().nlargest(n)
             top_articles_index = article_interactions_nlargest.index.tolist()
             df_drop = df[['article_id','title']]
             df_drop = df_drop.drop_duplicates(subset=['article_id'], keep='first')
             top_articles = df_drop[df_drop['article_id'].isin(top_articles_index)]['title']

             return top_articles # Return the top article titles from df (not df_content)

         def get_top_article_ids(n, df=df):
             '''
             INPUT:
             n - (int) the number of top articles to return
             df - (pandas dataframe) df as defined at the top of the notebook

             OUTPUT:
             top_articles - (list) A list of the top 'n' article titles

             '''
             # Your code here
             top_articles = df.groupby(['article_id']).size().nlargest(n).index.map(str).tolist(

             return top_articles # Return the top article ids
```

```
In [46]: print(get_top_articles(10))
         print(get_top_article_ids(10))
```

```
1           healthcare python streaming application demo
2             use deep learning for image classification
14              apache spark lab, part 1: basic concepts
29     predicting churn with the spss random tree alg...
31               analyze energy consumption in buildings
37                        visualize car data with brunel
42     use xgboost, scikit-learn & ibm watson machine...
56     gosales transactions for logistic regression m...
66            insights from new york car accident reports
154    finding optimal locations of new store using d...
Name: title, dtype: object
['1429.0', '1330.0', '1431.0', '1427.0', '1364.0', '1314.0', '1293.0', '1170.0', '1162.0', '1304
```

```
In [47]: # Test your function by returning the top 5, 10, and 20 articles
         top_5 = get_top_articles(5)
         top_10 = get_top_articles(10)
         top_20 = get_top_articles(20)

         # Test each of your three lists from above
         t.sol_2_test(get_top_articles)
```

```
Your top_5 looks like the solution list! Nice job.
Your top_10 looks like the solution list! Nice job.
Your top_20 looks like the solution list! Nice job.
```

1.1.3 Part III: User-User Based Collaborative Filtering

1. Use the function below to reformat the **df** dataframe to be shaped with users as the rows and articles as the columns.

- Each **user** should only appear in each **row** once.
- Each **article** should only show up in one **column**.
- **If a user has interacted with an article, then place a 1 where the user-row meets for that article-column**. It does not matter how many times a user has interacted with the article, all entries where a user has interacted with an article should be a 1.
- **If a user has not interacted with an item, then place a zero where the user-row meets for that article-column**.

Use the tests to make sure the basic structure of your matrix matches what is expected by the solution.

a. Draft the function

```
In [48]: df.head()
```

Out[48]:
```
   article_id                                              title  user_id
0      1430.0  using pixiedust for fast, flexible, and easier...        1
1      1314.0       healthcare python streaming application demo        2
2      1429.0         use deep learning for image classification        3
3      1338.0          ml optimization using cognitive assistant        4
4      1276.0          deploy your python model as a restful api        5
```

In [49]:
```
df['article_id'].shape[0]
```

Out[49]:
```
45993
```

In [50]:
```
df_article_col = df.drop_duplicates(subset=['article_id'], keep='first')['article_id']
df_article_col.head()
```

Out[50]:
```
0    1430.0
1    1314.0
2    1429.0
3    1338.0
4    1276.0
Name: article_id, dtype: float64
```

In [51]:
```
df_article_col.shape[0]
```

Out[51]:
```
714
```

In [52]:
```
df_user_row = df.drop_duplicates(subset=['user_id'], keep='first')['user_id']
df_user_row.head()
```

Out[52]:
```
0    1
1    2
2    3
3    4
4    5
Name: user_id, dtype: int64
```

In [53]:
```
df_user_row.shape[0]
```

Out[53]:
```
5149
```

In [54]:
```
interactions = df.groupby(['user_id','article_id']).size()
interactions.head()
```

Out[54]:
```
user_id  article_id
1        43.0          1
         109.0         1
         151.0         1
         268.0         1
         310.0         2
dtype: int64
```

```
In [55]: df_interactions = df.groupby(['user_id','article_id']).size().index.to_frame()
         df_interactions.head()
```

```
Out[55]:                     user_id  article_id
         user_id article_id
         1       43.0              1        43.0
                 109.0             1       109.0
                 151.0             1       151.0
                 268.0             1       268.0
                 310.0             1       310.0
```

```
In [56]: df_interactions['interaction'] = interactions
         df_interactions
```

```
Out[56]:                     user_id  article_id  interaction
         user_id article_id
         1       43.0              1        43.0            1
                 109.0             1       109.0            1
                 151.0             1       151.0            1
                 268.0             1       268.0            1
                 310.0             1       310.0            2
                 329.0             1       329.0            1
                 346.0             1       346.0            1
                 390.0             1       390.0            1
                 494.0             1       494.0            1
                 525.0             1       525.0            1
                 585.0             1       585.0            2
                 626.0             1       626.0            1
                 668.0             1       668.0            2
                 732.0             1       732.0            1
                 768.0             1       768.0            1
                 910.0             1       910.0            1
                 968.0             1       968.0            1
                 981.0             1       981.0            1
                 1052.0            1      1052.0            2
                 1170.0            1      1170.0            2
                 1183.0            1      1183.0            2
                 1185.0            1      1185.0            2
                 1232.0            1      1232.0            1
                 1293.0            1      1293.0            1
                 1305.0            1      1305.0            1
                 1363.0            1      1363.0            2
                 1368.0            1      1368.0            1
                 1391.0            1      1391.0            1
                 1400.0            1      1400.0            1
                 1406.0            1      1406.0            2
         ...                     ...         ...          ...
         5143    485.0          5143       485.0            1
```

```
            495.0       5143        495.0           1
            588.0       5143        588.0           2
            1324.0      5143       1324.0           1
            1330.0      5143       1330.0           2
            1343.0      5143       1343.0           1
            1354.0      5143       1354.0           1
            1360.0      5143       1360.0           1
            1398.0      5143       1398.0           3
            1400.0      5143       1400.0           3
            1409.0      5143       1409.0           1
            1430.0      5143       1430.0           2
            1431.0      5143       1431.0           1
            1436.0      5143       1436.0           1
5144        270.0       5144        270.0           1
5145        20.0        5145         20.0           1
            138.0       5145        138.0           1
            962.0       5145        962.0           2
            1165.0      5145       1165.0           1
            1305.0      5145       1305.0           1
5146        142.0       5146        142.0           1
            1125.0      5146       1125.0           1
            1157.0      5146       1157.0           1
            1282.0      5146       1282.0           1
            1324.0      5146       1324.0           3
            1394.0      5146       1394.0           1
            1416.0      5146       1416.0           1
5147        233.0       5147        233.0           1
5148        1160.0      5148       1160.0           1
5149        16.0        5149         16.0           1

[33682 rows x 3 columns]
```

In [57]:
```python
user_article_matrix = df_interactions.pivot(*df_interactions.columns).fillna(0)
user_article_matrix
```

Out[57]:
```
article_id  0.0     2.0     4.0     8.0     9.0     12.0    14.0    15.0    \
user_id
1              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
2              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3              0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0
4              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
5              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
6              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
7              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
8              0.0     0.0     0.0     0.0     0.0     0.0     1.0     0.0
9              0.0     0.0     0.0     0.0     0.0     0.0     1.0     0.0
10             0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
11             0.0     0.0     0.0     0.0     0.0     2.0     0.0     0.0
```

12	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
13	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
14	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
15	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
16	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
18	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
19	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
20	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
21	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
22	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
23	0.0	3.0	0.0	0.0	0.0	7.0	1.0	0.0
24	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
25	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
26	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
27	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
28	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
29	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...
5120	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5121	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5122	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
5123	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5124	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5125	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5126	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5127	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5128	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5129	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5130	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5131	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5132	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5133	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5134	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5135	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5136	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5137	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5138	0.0	0.0	0.0	0.0	0.0	2.0	1.0	0.0
5139	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
5140	0.0	3.0	0.0	0.0	0.0	1.0	0.0	0.0
5141	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5142	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
5143	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5144	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5145	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5146	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5147	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

```
5148          0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
5149          0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0

article_id  16.0   18.0     ...   1434.0  1435.0  1436.0  1437.0  1439.0  \
user_id                     ...
1             0.0    0.0    ...      0.0     0.0     1.0     0.0     1.0
2             0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
3             0.0    0.0    ...      0.0     0.0     1.0     0.0     0.0
4             0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
5             0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
6             0.0    0.0    ...      0.0     0.0     1.0     0.0     0.0
7             0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
8             0.0    0.0    ...      0.0     0.0     4.0     0.0     0.0
9             1.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
10            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
11            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
12            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
13            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
14            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
15            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
16            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
17            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
18            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
19            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
20            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
21            0.0    0.0    ...      0.0     0.0     2.0     3.0     0.0
22            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
23            1.0    0.0    ...      0.0     0.0     6.0     0.0     1.0
24            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
25            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
26            0.0    0.0    ...      0.0     0.0     4.0     0.0     0.0
27            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
28            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
29            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
30            0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
...           ...    ...    ...      ...     ...     ...     ...     ...
5120          0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
5121          0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
5122          0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
5123          0.0    0.0    ...      0.0     0.0     1.0     1.0     0.0
5124          0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
5125          0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
5126          0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
5127          0.0    0.0    ...      1.0     0.0     0.0     0.0     0.0
5128          0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
5129          0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
5130          0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
5131          0.0    0.0    ...      0.0     0.0     0.0     0.0     0.0
```

```
5132          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5133          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5134          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5135          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5136          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5137          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5138          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5139          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5140          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5141          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5142          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5143          0.0     0.0   ...     0.0     0.0     1.0     0.0     0.0
5144          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5145          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5146          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5147          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5148          0.0     0.0   ...     0.0     0.0     0.0     0.0     0.0
5149          1.0     0.0   ...     0.0     0.0     0.0     0.0     0.0

article_id  1440.0  1441.0  1442.0  1443.0  1444.0
user_id
1              0.0     0.0     0.0     0.0     0.0
2              0.0     0.0     0.0     0.0     0.0
3              0.0     0.0     0.0     0.0     0.0
4              0.0     0.0     0.0     0.0     0.0
5              0.0     0.0     0.0     0.0     0.0
6              0.0     0.0     0.0     0.0     0.0
7              0.0     0.0     0.0     0.0     0.0
8              0.0     0.0     0.0     0.0     0.0
9              0.0     0.0     0.0     0.0     0.0
10             0.0     0.0     0.0     0.0     0.0
11             0.0     0.0     0.0     0.0     0.0
12             0.0     0.0     0.0     0.0     0.0
13             0.0     0.0     0.0     0.0     0.0
14             0.0     0.0     0.0     0.0     0.0
15             0.0     0.0     0.0     0.0     0.0
16             0.0     0.0     0.0     0.0     0.0
17             0.0     0.0     0.0     0.0     0.0
18             0.0     0.0     0.0     0.0     0.0
19             0.0     0.0     0.0     0.0     0.0
20             0.0     0.0     0.0     0.0     0.0
21             0.0     0.0     0.0     0.0     0.0
22             0.0     0.0     0.0     0.0     0.0
23             0.0     0.0     0.0     0.0     0.0
24             1.0     0.0     0.0     0.0     0.0
25             0.0     0.0     0.0     0.0     0.0
26             0.0     0.0     0.0     0.0     0.0
27             0.0     0.0     0.0     0.0     0.0
```

```
28            0.0    0.0    0.0    0.0    0.0
29            0.0    0.0    0.0    0.0    0.0
30            0.0    0.0    0.0    0.0    0.0
...           ...    ...    ...    ...    ...
5120          0.0    0.0    0.0    0.0    0.0
5121          0.0    0.0    0.0    0.0    0.0
5122          0.0    0.0    0.0    0.0    0.0
5123          0.0    0.0    0.0    0.0    0.0
5124          0.0    0.0    0.0    0.0    0.0
5125          0.0    0.0    0.0    0.0    0.0
5126          0.0    0.0    0.0    0.0    0.0
5127          0.0    0.0    0.0    0.0    0.0
5128          0.0    0.0    0.0    0.0    0.0
5129          0.0    0.0    0.0    0.0    0.0
5130          0.0    0.0    0.0    0.0    0.0
5131          0.0    0.0    0.0    0.0    0.0
5132          0.0    0.0    0.0    0.0    0.0
5133          0.0    0.0    0.0    0.0    0.0
5134          0.0    0.0    0.0    0.0    0.0
5135          0.0    0.0    0.0    0.0    0.0
5136          0.0    0.0    0.0    0.0    0.0
5137          0.0    0.0    0.0    0.0    0.0
5138          0.0    0.0    0.0    0.0    0.0
5139          0.0    0.0    0.0    0.0    0.0
5140          0.0    0.0    0.0    0.0    0.0
5141          0.0    0.0    0.0    0.0    0.0
5142          0.0    0.0    0.0    0.0    0.0
5143          0.0    0.0    0.0    0.0    0.0
5144          0.0    0.0    0.0    0.0    0.0
5145          0.0    0.0    0.0    0.0    0.0
5146          0.0    0.0    0.0    0.0    0.0
5147          0.0    0.0    0.0    0.0    0.0
5148          0.0    0.0    0.0    0.0    0.0
5149          0.0    0.0    0.0    0.0    0.0

[5149 rows x 714 columns]
```

In [58]:
```
user_article_matrix [user_article_matrix > 1] = 1
user_article_matrix
```

Out[58]:
```
article_id  0.0    2.0    4.0    8.0    9.0    12.0   14.0   15.0   \
user_id
1             0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
2             0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
3             0.0    0.0    0.0    0.0    0.0    1.0    0.0    0.0
4             0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
5             0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
6             0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
```

7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
9	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
12	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
13	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
14	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
15	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
16	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
18	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
19	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
20	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
21	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
22	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
23	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0
24	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
25	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
26	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
27	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
28	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
29	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...
5120	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5121	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5122	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
5123	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5124	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5125	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5126	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5127	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5128	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5129	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5130	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5131	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5132	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5133	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5134	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5135	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5136	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5137	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5138	0.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0
5139	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
5140	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0
5141	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5142	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0

```
5143          0.0    0.0     0.0    0.0    0.0    0.0    0.0    0.0
5144          0.0    0.0     0.0    0.0    0.0    0.0    0.0    0.0
5145          0.0    0.0     0.0    0.0    0.0    0.0    0.0    0.0
5146          0.0    0.0     0.0    0.0    0.0    0.0    0.0    0.0
5147          0.0    0.0     0.0    0.0    0.0    0.0    0.0    0.0
5148          0.0    0.0     0.0    0.0    0.0    0.0    0.0    0.0
5149          0.0    0.0     0.0    0.0    0.0    0.0    0.0    0.0

article_id  16.0    18.0     ...   1434.0  1435.0  1436.0  1437.0  1439.0  \
user_id                      ...
1             0.0    0.0     ...      0.0     0.0     1.0     0.0     1.0
2             0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
3             0.0    0.0     ...      0.0     0.0     1.0     0.0     0.0
4             0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
5             0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
6             0.0    0.0     ...      0.0     0.0     1.0     0.0     0.0
7             0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
8             0.0    0.0     ...      0.0     0.0     1.0     0.0     0.0
9             1.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
10            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
11            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
12            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
13            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
14            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
15            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
16            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
17            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
18            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
19            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
20            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
21            0.0    0.0     ...      0.0     0.0     1.0     1.0     0.0
22            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
23            1.0    0.0     ...      0.0     0.0     1.0     0.0     1.0
24            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
25            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
26            0.0    0.0     ...      0.0     0.0     1.0     0.0     0.0
27            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
28            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
29            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
30            0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
...           ...    ...     ...      ...     ...     ...     ...     ...
5120          0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
5121          0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
5122          0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
5123          0.0    0.0     ...      0.0     0.0     1.0     1.0     0.0
5124          0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
5125          0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
5126          0.0    0.0     ...      0.0     0.0     0.0     0.0     0.0
```

```
5127          0.0     0.0    ...      1.0     0.0     0.0     0.0     0.0
5128          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5129          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5130          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5131          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5132          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5133          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5134          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5135          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5136          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5137          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5138          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5139          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5140          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5141          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5142          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5143          0.0     0.0    ...      0.0     0.0     1.0     0.0     0.0
5144          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5145          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5146          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5147          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5148          0.0     0.0    ...      0.0     0.0     0.0     0.0     0.0
5149          1.0     0.0    ...      0.0     0.0     0.0     0.0     0.0

article_id  1440.0  1441.0  1442.0  1443.0  1444.0
user_id
1             0.0     0.0     0.0     0.0     0.0
2             0.0     0.0     0.0     0.0     0.0
3             0.0     0.0     0.0     0.0     0.0
4             0.0     0.0     0.0     0.0     0.0
5             0.0     0.0     0.0     0.0     0.0
6             0.0     0.0     0.0     0.0     0.0
7             0.0     0.0     0.0     0.0     0.0
8             0.0     0.0     0.0     0.0     0.0
9             0.0     0.0     0.0     0.0     0.0
10            0.0     0.0     0.0     0.0     0.0
11            0.0     0.0     0.0     0.0     0.0
12            0.0     0.0     0.0     0.0     0.0
13            0.0     0.0     0.0     0.0     0.0
14            0.0     0.0     0.0     0.0     0.0
15            0.0     0.0     0.0     0.0     0.0
16            0.0     0.0     0.0     0.0     0.0
17            0.0     0.0     0.0     0.0     0.0
18            0.0     0.0     0.0     0.0     0.0
19            0.0     0.0     0.0     0.0     0.0
20            0.0     0.0     0.0     0.0     0.0
21            0.0     0.0     0.0     0.0     0.0
22            0.0     0.0     0.0     0.0     0.0
```

```
23          0.0   0.0   0.0   0.0   0.0
24          1.0   0.0   0.0   0.0   0.0
25          0.0   0.0   0.0   0.0   0.0
26          0.0   0.0   0.0   0.0   0.0
27          0.0   0.0   0.0   0.0   0.0
28          0.0   0.0   0.0   0.0   0.0
29          0.0   0.0   0.0   0.0   0.0
30          0.0   0.0   0.0   0.0   0.0
...         ...   ...   ...   ...   ...
5120        0.0   0.0   0.0   0.0   0.0
5121        0.0   0.0   0.0   0.0   0.0
5122        0.0   0.0   0.0   0.0   0.0
5123        0.0   0.0   0.0   0.0   0.0
5124        0.0   0.0   0.0   0.0   0.0
5125        0.0   0.0   0.0   0.0   0.0
5126        0.0   0.0   0.0   0.0   0.0
5127        0.0   0.0   0.0   0.0   0.0
5128        0.0   0.0   0.0   0.0   0.0
5129        0.0   0.0   0.0   0.0   0.0
5130        0.0   0.0   0.0   0.0   0.0
5131        0.0   0.0   0.0   0.0   0.0
5132        0.0   0.0   0.0   0.0   0.0
5133        0.0   0.0   0.0   0.0   0.0
5134        0.0   0.0   0.0   0.0   0.0
5135        0.0   0.0   0.0   0.0   0.0
5136        0.0   0.0   0.0   0.0   0.0
5137        0.0   0.0   0.0   0.0   0.0
5138        0.0   0.0   0.0   0.0   0.0
5139        0.0   0.0   0.0   0.0   0.0
5140        0.0   0.0   0.0   0.0   0.0
5141        0.0   0.0   0.0   0.0   0.0
5142        0.0   0.0   0.0   0.0   0.0
5143        0.0   0.0   0.0   0.0   0.0
5144        0.0   0.0   0.0   0.0   0.0
5145        0.0   0.0   0.0   0.0   0.0
5146        0.0   0.0   0.0   0.0   0.0
5147        0.0   0.0   0.0   0.0   0.0
5148        0.0   0.0   0.0   0.0   0.0
5149        0.0   0.0   0.0   0.0   0.0

[5149 rows x 714 columns]
```

b. Fill in the function

In [59]:
```python
# create the user-article matrix with 1's and 0's

def create_user_item_matrix(df):
    '''
```

```
        INPUT:
        df - pandas dataframe with article_id, title, user_id columns

        OUTPUT:
        user_item - user item matrix

        Description:
        Return a matrix with user ids as rows and article ids on the columns with 1 values
        an article and a 0 otherwise
        '''
        # Fill in the function here
        interactions = df.groupby(['user_id','article_id']).size()
        df_interactions = df.groupby(['user_id','article_id']).size().index.to_frame()
        df_interactions['interaction'] = interactions
        user_item = df_interactions.pivot(*df_interactions.columns).fillna(0)
        user_item [user_item > 1] = 1

        return user_item # return the user_item matrix

    user_item = create_user_item_matrix(df)
```

c. Test the function

```
In [60]: ## Tests: You should just need to run this cell.  Don't change the code.
         assert user_item.shape[0] == 5149, "Oops!  The number of users in the user-article matr
         assert user_item.shape[1] == 714, "Oops!  The number of articles in the user-article ma
         assert user_item.sum(axis=1)[1] == 36, "Oops!  The number of articles seen by user 1 do
         print("You have passed our quick tests!  Please proceed!")

You have passed our quick tests!  Please proceed!
```

2. Complete the function below which should take a user_id and provide an ordered list of the most similar users to that user (from most similar to least similar). The returned result should not contain the provided user_id, as we know that each user is similar to him/herself. Because the results for each user here are binary, it (perhaps) makes sense to compute similarity as the dot product of two users.

Use the tests to test your function.

a. Draft the function

Computes the similarity of every pair of users based on the dot product

```
In [61]: # check the user_item matrix and its dimensions
         user_item

Out[61]: article_id  0.0     2.0     4.0     8.0     9.0     12.0    14.0    15.0    \
         user_id
         1              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
         2              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
         3              0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0
```

4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
9	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
12	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
13	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
14	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
15	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
16	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
18	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
19	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
20	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
21	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
22	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
23	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0
24	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
25	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
26	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
27	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
28	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
29	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...
5120	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5121	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5122	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
5123	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5124	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5125	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5126	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5127	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5128	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5129	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5130	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5131	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5132	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5133	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5134	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5135	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5136	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5137	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5138	0.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0
5139	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

```
5140           0.0     1.0     0.0     0.0     0.0     1.0     0.0     0.0
5141           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
5142           0.0     0.0     0.0     0.0     0.0     0.0     1.0     0.0
5143           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
5144           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
5145           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
5146           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
5147           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
5148           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
5149           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0

article_id  16.0    18.0    ...    1434.0  1435.0  1436.0  1437.0  1439.0  \
user_id                     ...
1              0.0     0.0  ...       0.0     0.0     1.0     0.0     1.0
2              0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
3              0.0     0.0  ...       0.0     0.0     1.0     0.0     0.0
4              0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
5              0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
6              0.0     0.0  ...       0.0     0.0     1.0     0.0     0.0
7              0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
8              0.0     0.0  ...       0.0     0.0     1.0     0.0     0.0
9              1.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
10             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
11             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
12             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
13             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
14             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
15             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
16             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
17             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
18             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
19             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
20             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
21             0.0     0.0  ...       0.0     0.0     1.0     1.0     0.0
22             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
23             1.0     0.0  ...       0.0     0.0     1.0     0.0     1.0
24             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
25             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
26             0.0     0.0  ...       0.0     0.0     1.0     0.0     0.0
27             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
28             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
29             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
30             0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
...            ...     ...  ...       ...     ...     ...     ...     ...
5120           0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
5121           0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
5122           0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
5123           0.0     0.0  ...       0.0     0.0     1.0     1.0     0.0
```

```
5124          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5125          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5126          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5127          0.0    0.0   ...    1.0    0.0    0.0    0.0    0.0
5128          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5129          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5130          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5131          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5132          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5133          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5134          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5135          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5136          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5137          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5138          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5139          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5140          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5141          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5142          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5143          0.0    0.0   ...    0.0    0.0    1.0    0.0    0.0
5144          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5145          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5146          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5147          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5148          0.0    0.0   ...    0.0    0.0    0.0    0.0    0.0
5149          1.0    0.0   ...    0.0    0.0    0.0    0.0    0.0

article_id  1440.0  1441.0  1442.0  1443.0  1444.0
user_id
1              0.0     0.0     0.0     0.0     0.0
2              0.0     0.0     0.0     0.0     0.0
3              0.0     0.0     0.0     0.0     0.0
4              0.0     0.0     0.0     0.0     0.0
5              0.0     0.0     0.0     0.0     0.0
6              0.0     0.0     0.0     0.0     0.0
7              0.0     0.0     0.0     0.0     0.0
8              0.0     0.0     0.0     0.0     0.0
9              0.0     0.0     0.0     0.0     0.0
10             0.0     0.0     0.0     0.0     0.0
11             0.0     0.0     0.0     0.0     0.0
12             0.0     0.0     0.0     0.0     0.0
13             0.0     0.0     0.0     0.0     0.0
14             0.0     0.0     0.0     0.0     0.0
15             0.0     0.0     0.0     0.0     0.0
16             0.0     0.0     0.0     0.0     0.0
17             0.0     0.0     0.0     0.0     0.0
18             0.0     0.0     0.0     0.0     0.0
19             0.0     0.0     0.0     0.0     0.0
```

```
20              0.0     0.0     0.0     0.0     0.0
21              0.0     0.0     0.0     0.0     0.0
22              0.0     0.0     0.0     0.0     0.0
23              0.0     0.0     0.0     0.0     0.0
24              1.0     0.0     0.0     0.0     0.0
25              0.0     0.0     0.0     0.0     0.0
26              0.0     0.0     0.0     0.0     0.0
27              0.0     0.0     0.0     0.0     0.0
28              0.0     0.0     0.0     0.0     0.0
29              0.0     0.0     0.0     0.0     0.0
30              0.0     0.0     0.0     0.0     0.0
...             ...     ...     ...     ...     ...
5120            0.0     0.0     0.0     0.0     0.0
5121            0.0     0.0     0.0     0.0     0.0
5122            0.0     0.0     0.0     0.0     0.0
5123            0.0     0.0     0.0     0.0     0.0
5124            0.0     0.0     0.0     0.0     0.0
5125            0.0     0.0     0.0     0.0     0.0
5126            0.0     0.0     0.0     0.0     0.0
5127            0.0     0.0     0.0     0.0     0.0
5128            0.0     0.0     0.0     0.0     0.0
5129            0.0     0.0     0.0     0.0     0.0
5130            0.0     0.0     0.0     0.0     0.0
5131            0.0     0.0     0.0     0.0     0.0
5132            0.0     0.0     0.0     0.0     0.0
5133            0.0     0.0     0.0     0.0     0.0
5134            0.0     0.0     0.0     0.0     0.0
5135            0.0     0.0     0.0     0.0     0.0
5136            0.0     0.0     0.0     0.0     0.0
5137            0.0     0.0     0.0     0.0     0.0
5138            0.0     0.0     0.0     0.0     0.0
5139            0.0     0.0     0.0     0.0     0.0
5140            0.0     0.0     0.0     0.0     0.0
5141            0.0     0.0     0.0     0.0     0.0
5142            0.0     0.0     0.0     0.0     0.0
5143            0.0     0.0     0.0     0.0     0.0
5144            0.0     0.0     0.0     0.0     0.0
5145            0.0     0.0     0.0     0.0     0.0
5146            0.0     0.0     0.0     0.0     0.0
5147            0.0     0.0     0.0     0.0     0.0
5148            0.0     0.0     0.0     0.0     0.0
5149            0.0     0.0     0.0     0.0     0.0

[5149 rows x 714 columns]
```

In [62]:
```python
# need to transpose to match the matrix dimension when calculate the dot product
user_item.transpose()
```

Out[62]:
```
user_id     1     2     3     4     5     6     7     8     9     10    ...   \
```

article_id											...
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
8.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
9.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
12.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
14.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	...
15.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
16.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	...
18.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
20.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...
25.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
26.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
28.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	...
29.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
30.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
32.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	...
33.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
34.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	...
36.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
39.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
40.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	...
43.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
48.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
50.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
51.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
53.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
54.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
57.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	...
58.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
...	...	...	...	...	...	...	...	...	...	...	...
1412.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1414.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1415.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1416.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1418.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1419.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1420.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1421.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1422.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	...
1423.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1424.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1425.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1426.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1427.0	1.0	1.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	...
1428.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	...
1429.0	1.0	0.0	1.0	0.0	0.0	1.0	1.0	0.0	0.0	1.0	...

1430.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	...
1431.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	...
1432.0	0.0	0.0	1.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	...
1433.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1434.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1435.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1436.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	...
1437.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1439.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1440.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1441.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1442.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1443.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1444.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...

user_id	5140	5141	5142	5143	5144	5145	5146	5147	5148	5149
article_id										
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
12.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
15.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
16.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
18.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
20.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
25.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
26.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
28.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
29.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
32.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
33.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
34.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
36.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
39.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
40.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
43.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
48.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
50.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
51.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
53.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
54.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
57.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
58.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...

```
1412.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1414.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1415.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1416.0        0.0   0.0   0.0   0.0   0.0   0.0   1.0   0.0   0.0   0.0
1418.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1419.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1420.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1421.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1422.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1423.0        1.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1424.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1425.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1426.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1427.0        1.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1428.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1429.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1430.0        1.0   0.0   0.0   1.0   0.0   0.0   0.0   0.0   0.0   0.0
1431.0        0.0   0.0   0.0   1.0   0.0   0.0   0.0   0.0   0.0   0.0
1432.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1433.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1434.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1435.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1436.0        0.0   0.0   0.0   1.0   0.0   0.0   0.0   0.0   0.0   0.0
1437.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1439.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1440.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1441.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1442.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1443.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1444.0        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0

[714 rows x 5149 columns]
```

In [63]:
```python
# set the owner's id and get the interaction data of this user
selected_user_id = 3
useri = user_item[user_item.index == selected_user_id]
useri
```

Out[63]:
```
article_id  0.0     2.0     4.0     8.0     9.0     12.0    14.0    15.0    \
user_id
3              0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0

article_id  16.0    18.0     ...    1434.0  1435.0  1436.0  1437.0  1439.0  \
user_id                      ...
3              0.0     0.0   ...       0.0     0.0     1.0     0.0     0.0

article_id  1440.0  1441.0  1442.0  1443.0  1444.0
user_id
```

```
3               0.0     0.0     0.0     0.0     0.0

[1 rows x 714 columns]
```

```
In [64]: # use the dot product to calculate the similarity of other users to the owner
         useri.dot(user_item.transpose())
```

```
Out[64]: user_id  1     2     3     4     5     6     7     8     9     10    ...   \
         user_id                                                          ...
         3         6.0   1.0  40.0   5.0   1.0   7.0   1.0   5.0   2.0   5.0 ...

         user_id  5140  5141  5142  5143  5144  5145  5146  5147  5148  5149
         user_id
         3         7.0   0.0   0.0   5.0   0.0   2.0   0.0   0.0   0.0   0.0

         [1 rows x 5149 columns]
```

Find the way to sort by similarity

```
In [65]: # cannot sort the pivot matrix directly
         useri.dot(user_item.transpose()).sort_values(by = "user_id", axis = 1, ascending = True
```

```
Out[65]: user_id  1     2     3     4     5     6     7     8     9     10    ...   \
         user_id                                                          ...
         3         6.0   1.0  40.0   5.0   1.0   7.0   1.0   5.0   2.0   5.0 ...

         user_id  5140  5141  5142  5143  5144  5145  5146  5147  5148  5149
         user_id
         3         7.0   0.0   0.0   5.0   0.0   2.0   0.0   0.0   0.0   0.0

         [1 rows x 5149 columns]
```

```
In [66]: # test to use stack, cannot use because of duplicated 'user_id'
         useri.dot(user_item.transpose()).stack()
```

```
Out[66]: user_id  user_id
         3        1           6.0
                  2           1.0
                  3          40.0
                  4           5.0
                  5           1.0
                  6           7.0
                  7           1.0
                  8           5.0
                  9           2.0
                  10          5.0
                  11         13.0
                  12          0.0
                  13          2.0
```

14	1.0
15	1.0
16	1.0
17	3.0
18	2.0
19	0.0
20	0.0
21	12.0
22	4.0
23	23.0
24	3.0
25	0.0
26	4.0
27	4.0
28	10.0
29	0.0
30	0.0
	...
5120	0.0
5121	0.0
5122	0.0
5123	4.0
5124	3.0
5125	0.0
5126	0.0
5127	3.0
5128	0.0
5129	1.0
5130	1.0
5131	0.0
5132	0.0
5133	1.0
5134	3.0
5135	0.0
5136	0.0
5137	0.0
5138	13.0
5139	2.0
5140	7.0
5141	0.0
5142	0.0
5143	5.0
5144	0.0
5145	2.0
5146	0.0
5147	0.0
5148	0.0
5149	0.0

```
Length: 5149, dtype: float64
```

In [67]:
```python
# need to to melt the pivot matrix to sort the similarity
similarity = useri.dot(user_item.transpose()).melt().sort_values(by = 'value', ascendin
similarity.head()
```

Out[67]:
```
      user_id  value
3352     3353   40.0
2           3   40.0
22         23   23.0
3781     3782   23.0
3763     3764   17.0
```

Create list of just the user ids

In [68]:
```python
# get the user_id
most_similar_users = similarity['user_id']
most_similar_users.head()
```

Out[68]:
```
3352    3353
2          3
22        23
3781    3782
3763    3764
Name: user_id, dtype: int64
```

Remove the own user's id

In [69]:
```python
# the owner's id
selected_user_id
```

Out[69]:
```
3
```

In [70]:
```python
# remove the owner's id
most_similar_users = most_similar_users[most_similar_users!= selected_user_id]
most_similar_users
```

Out[70]:
```
3352    3353
22        23
3781    3782
3763    3764
97        98
4458    4459
202      203
48        49
3696    3697
3595    3596
51        52
911      912
```

3539	3540
203	204
39	40
4931	4932
241	242
5137	5138
3869	3870
3909	3910
3965	3966
2925	2926
130	131
10	11
3577	3578
4773	4774
764	765
124	125
213	214
4784	4785
	...
2484	2485
2485	2486
2454	2455
2453	2454
2447	2448
2442	2443
2405	2406
2407	2408
2408	2409
2410	2411
2411	2412
2412	2413
2418	2419
2419	2420
2420	2421
2423	2424
2425	2426
2426	2427
2427	2428
2428	2429
2431	2432
2432	2433
2433	2434
2435	2436
2436	2437
2437	2438
2438	2439
2440	2441
2441	2442

```
5148    5149
Name: user_id, Length: 5148, dtype: int64
```

In [71]:
```python
# test the top similar users
most_similar_users.reset_index(drop=True, inplace=True)
most_similar_users[:10]
```

Out[71]:
```
0    3353
1      23
2    3782
3    3764
4      98
5    4459
6     203
7      49
8    3697
9    3596
Name: user_id, dtype: int64
```

In [72]:
```python
print(type(most_similar_users))
```

```
<class 'pandas.core.series.Series'>
```

In [73]:
```python
most_similar_users.tolist()
```

Out[73]:
```
[3353,
 23,
 3782,
 3764,
 98,
 4459,
 203,
 49,
 3697,
 3596,
 52,
 912,
 3540,
 204,
 40,
 4932,
 242,
 5138,
 3870,
 3910,
 3966,
 2926,
 131,
```

```
11,
3578,
4774,
765,
125,
214,
4785,
21,
619,
195,
3024,
754,
4755,
3141,
656,
4642,
290,
371,
28,
3784,
2161,
4201,
2982,
135,
334,
3485,
273,
186,
134,
4038,
288,
696,
4471,
4706,
3794,
4824,
211,
807,
46,
3801,
383,
3621,
3057,
4392,
58,
3172,
4293,
126,
```

```
113,
4883,
4892,
111,
184,
3740,
4161,
295,
72,
395,
3006,
67,
322,
4134,
5041,
3532,
3622,
1058,
3264,
755,
3483,
791,
223,
3169,
215,
3695,
750,
209,
199,
197,
187,
4209,
471,
4277,
170,
4449,
479,
1059,
4595,
3136,
3775,
60,
741,
3938,
5140,
3358,
648,
3058,
```

```
3967,
621,
4618,
3877,
591,
3856,
4934,
3079,
6,
64,
56,
722,
689,
538,
1068,
4904,
2989,
249,
1062,
90,
469,
4623,
4788,
5059,
3072,
4323,
4308,
235,
3589,
3636,
5057,
1355,
244,
3486,
1897,
2908,
5079,
280,
420,
261,
4272,
4484,
4543,
193,
4778,
4404,
4792,
3061,
```

```
196,
268,
1,
4660,
3783,
492,
693,
129,
3684,
3968,
688,
761,
3960,
38,
669,
651,
3933,
55,
3208,
4137,
665,
3878,
745,
726,
712,
488,
536,
4206,
4900,
3651,
3417,
4231,
860,
418,
3007,
1105,
256,
4491,
65,
69,
5080,
4494,
670,
4526,
409,
3147,
697,
4511,
```

```
262,
668,
347,
5078,
3238,
4,
3520,
3310,
8,
3829,
1384,
10,
330,
3100,
362,
3439,
3879,
1262,
1163,
640,
5143,
313,
312,
582,
375,
646,
3918,
1240,
3118,
647,
2981,
88,
85,
173,
3674,
4225,
3197,
4802,
790,
511,
220,
3474,
794,
2913,
4241,
4167,
3614,
4876,
```

```
456,
2903,
3611,
4145,
4142,
227,
145,
521,
169,
438,
545,
733,
542,
2975,
2290,
3163,
3741,
4842,
464,
4680,
1261,
1310,
500,
3414,
4872,
352,
4667,
3237,
3466,
1265,
3108,
900,
842,
1272,
3245,
4696,
1302,
896,
854,
644,
3441,
3240,
907,
3198,
715,
1251,
379,
770,
```

```
3291,
1139,
1040,
411,
753,
751,
535,
560,
1063,
700,
886,
723,
706,
1076,
512,
1026,
3495,
5023,
4720,
3420,
1215,
714,
649,
3296,
1198,
510,
3421,
970,
3176,
3500,
658,
1162,
3402,
600,
87,
4515,
4453,
4021,
239,
2974,
251,
3329,
4497,
2718,
2994,
3354,
294,
1588,
```

```
3765,
76,
1567,
2423,
5077,
287,
66,
3957,
2953,
2288,
225,
3336,
4200,
152,
3378,
3693,
5118,
4268,
3637,
3633,
5105,
5123,
3710,
4088,
4086,
3724,
114,
4378,
110,
4386,
3732,
3553,
155,
3812,
45,
1426,
3818,
3802,
3884,
1476,
3898,
319,
3535,
1353,
3082,
296,
22,
1386,
```

```
310,
3835,
48,
321,
26,
3943,
601,
3949,
1401,
3043,
27,
3831,
3864,
2202,
786,
4085,
4082,
3212,
3213,
4099,
4098,
785,
666,
4107,
4933,
833,
3206,
809,
808,
4148,
3442,
3691,
3824,
2144,
2636,
4877,
2790,
609,
3211,
797,
2186,
2194,
4119,
736,
4071,
3235,
3225,
707,
```

```
3919,
3986,
703,
3757,
699,
2487,
698,
3763,
3969,
660,
661,
683,
673,
3768,
3956,
4186,
713,
3754,
4039,
2270,
2284,
3888,
641,
2304,
4044,
2308,
3807,
2377,
2312,
4915,
4015,
4010,
721,
719,
3749,
3518,
895,
847,
3042,
4557,
1213,
1208,
4725,
1548,
1197,
3124,
3017,
1172,
```

```
1156,
3561,
1577,
3005,
4527,
4517,
1137,
3570,
3488,
4768,
1612,
1114,
2993,
1110,
4560,
3117,
2983,
1225,
1331,
4668,
1322,
1350,
1317,
3514,
1354,
1359,
1301,
1291,
4636,
1281,
1395,
4697,
1408,
1266,
4620,
1264,
3063,
1443,
1250,
1478,
3506,
1635,
1094,
3669,
932,
925,
4336,
3616,
```

```
923,
4834,
3618,
4319,
3632,
3634,
4285,
1345,
894,
4843,
4274,
3464,
866,
862,
2007,
858,
4204,
856,
3667,
851,
926,
938,
1084,
943,
1082,
1668,
1671,
4472,
3366,
3581,
1061,
2955,
2948,
1048,
3477,
4427,
1038,
4393,
1801,
1014,
1003,
992,
987,
980,
2919,
2907,
2901,
4577,
```

```
3833,
266,
35,
490,
32,
285,
271,
3325,
3326,
5086,
253,
252,
248,
508,
509,
208,
121,
3338,
4970,
181,
176,
5111,
3430,
168,
558,
5115,
3346,
4958,
3376,
304,
5070,
4992,
323,
3408,
5012,
424,
413,
410,
406,
17,
404,
3292,
3301,
5001,
5034,
3305,
3412,
365,
```

```
354,
5046,
24,
346,
3313,
5052,
5053,
5055,
4995,
324,
122,
445,
584,
107,
100,
5127,
598,
5124,
82,
86,
4943,
94,
575,
4949,
74,
5134,
63,
83,
5058,
335,
1375,
1394,
1385,
1389,
4648,
3523,
4632,
4026,
326,
1405,
3081,
1360,
3083,
4025,
1311,
3094,
2728,
3093,
```

```
351,
3092,
1325,
1329,
5048,
1337,
1338,
2731,
1340,
344,
4658,
4019,
2342,
4022,
4652,
1406,
120,
3069,
2328,
308,
5145,
4591,
3885,
3046,
4588,
305,
4041,
1487,
3809,
3538,
1499,
1500,
3808,
3542,
1509,
75,
102,
4571,
4599,
1455,
1452,
1420,
4626,
1303,
3067,
1413,
2319,
2316,
```

```
3065,
1418,
4619,
3056,
3527,
5066,
1427,
315,
1433,
3320,
1437,
1439,
92,
4685,
18,
359,
1095,
2416,
1112,
1115,
1118,
414,
2415,
1128,
1129,
2579,
1132,
1134,
1135,
3972,
4759,
1142,
1145,
3492,
3975,
1091,
1089,
5013,
4791,
4801,
4800,
442,
4795,
440,
4794,
1051,
2586,
1056,
```

```
3970,
1057,
4790,
3406,
434,
1067,
1070,
1071,
5011,
1150,
403,
5018,
2376,
3998,
370,
5039,
4700,
1270,
1271,
3396,
3107,
4001,
4707,
363,
1283,
1284,
2564,
3102,
3034,
360,
1300,
3400,
1245,
1169,
3876,
1170,
3499,
1183,
1187,
2653,
1191,
3404,
1202,
3505,
1243,
1218,
1219,
3300,
```

```
1223,
4716,
381,
1238,
1239,
2541,
299,
4564,
4248,
5106,
2488,
2440,
4291,
177,
4073,
4275,
5110,
4269,
171,
3641,
4266,
1984,
115,
1988,
5139,
4255,
4252,
4250,
3627,
4311,
2255,
2899,
4367,
4364,
4363,
4356,
4068,
1850,
4352,
3727,
2898,
1915,
3917,
200,
1882,
198,
3341,
188,
```

3625,
1914,
4076,
166,
4373,
2842,
5117,
140,
4087,
59,
4130,
2164,
4127,
3703,
2447,
3951,
132,
3705,
3715,
4110,
4108,
4097,
2205,
2209,
3713,
144,
4144,
4149,
160,
4234,
4230,
164,
3658,
51,
4215,
163,
2235,
3344,
57,
4194,
3671,
153,
54,
2097,
4170,
2116,
149,
2917,

2921,
3360,
2980,
3564,
1595,
4522,
4045,
1608,
4049,
3243,
4510,
1027,
4502,
1633,
1636,
2992,
4498,
4495,
2988,
1655,
4487,
2279,
4529,
1582,
284,
3554,
3889,
3714,
4553,
1541,
297,
292,
1549,
1550,
3803,
1574,
3556,
103,
5075,
1561,
3015,
2303,
1569,
1572,
4482,
4061,
213,
2978,

```
2945,
 4420,
 4417,
 1762,
 1766,
 2941,
 2940,
 3595,
 4409,
 2935,
 1787,
 2932,
 2931,
 4390,
 4389,
 1807,
 4385,
 ...]
```

```
In [74]: def find_similar_users(user_id, user_item=user_item):
             '''
             INPUT:
             user_id - (int) a user_id
             user_item - (pandas dataframe) matrix of users by articles:
                         1's when a user has interacted with an article, 0 otherwise

             OUTPUT:
             similar_users - (list) an ordered list where the closest users (largest dot product
                             are listed first

             Description:
             Computes the similarity of every pair of users based on the dot product
             Returns an ordered

             '''
             # compute similarity of each user to the provided user
             useri = user_item[user_item.index == user_id]
             useri.dot(user_item.transpose())

             # sort by similarity
             similarity = useri.dot(user_item.transpose()).melt().sort_values(by = 'value', asce

             # create list of just the ids
             most_similar_users = similarity['user_id']

             # remove the own user's id
             most_similar_users = most_similar_users[most_similar_users!= user_id]
             most_similar_users.reset_index(drop=True, inplace=True)
```

```
        most_similar_users = most_similar_users.tolist()

        return most_similar_users # return a list of the users in order from most to least
```

In [75]:
```
# Do a spot check of your function
print("The 10 most similar users to user 1 are: {}".format(find_similar_users(1)[:10]))
print("The 5 most similar users to user 3933 are: {}".format(find_similar_users(3933)[:
print("The 3 most similar users to user 46 are: {}".format(find_similar_users(46)[:3]))
```

```
The 10 most similar users to user 1 are: [3933, 23, 3782, 203, 4459, 3870, 131, 4201, 46, 5041]
The 5 most similar users to user 3933 are: [1, 23, 3782, 203, 4459]
The 3 most similar users to user 46 are: [4201, 3782, 23]
```

3. Now that you have a function that provides the most similar users to each user, you will want to use these users to find articles you can recommend. Complete the functions below to return the articles you would recommend to each user.

a. Draft the functions

Get article names from article ids

In [76]:
```
df.head()
```

Out[76]:

	article_id	title	user_id
0	1430.0	using pixiedust for fast, flexible, and easier...	1
1	1314.0	healthcare python streaming application demo	2
2	1429.0	use deep learning for image classification	3
3	1338.0	ml optimization using cognitive assistant	4
4	1276.0	deploy your python model as a restful api	5

In [77]:
```
article_ids_list = ['1430.0', '1276.0', '1429.0']
article_ids_list = np.array(article_ids_list, dtype=np.float64)
article_ids_list
```

Out[77]:
```
array([ 1430.,  1276.,  1429.])
```

In [78]:
```
df_article_drop=df.drop_duplicates(subset=['article_id'], keep='first')[['article_id','
df_article_drop.head()
```

Out[78]:

	article_id	title
0	1430.0	using pixiedust for fast, flexible, and easier...
1	1314.0	healthcare python streaming application demo
2	1429.0	use deep learning for image classification
3	1338.0	ml optimization using cognitive assistant
4	1276.0	deploy your python model as a restful api

In [79]:
```
# isin doesn't keep the order of article_ids -> cannot use
article_names = df_article_drop[df_article_drop['article_id'].isin(article_ids_list)==T
article_names
```

```
Out[79]: 0    using pixiedust for fast, flexible, and easier...
         2           use deep learning for image classification
         4            deploy your python model as a restful api
         Name: title, dtype: object
```

```
In [80]: article_names = df_article_drop.set_index('article_id').loc[article_ids_list].reset_ind
         article_names
```

```
Out[80]: 0    using pixiedust for fast, flexible, and easier...
         1            deploy your python model as a restful api
         2           use deep learning for image classification
         Name: title, dtype: object
```

Get the articles seen by a user

```
In [81]: selected_user_id = 20
         user_article = user_item[user_item.index == selected_user_id]
         user_article
```

```
Out[81]: article_id  0.0     2.0     4.0     8.0     9.0     12.0    14.0    15.0    \
         user_id
         20             0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0

         article_id  16.0    18.0     ...    1434.0  1435.0  1436.0  1437.0  1439.0  \
         user_id                      ...
         20             0.0     0.0   ...       0.0     0.0     0.0     0.0     0.0

         article_id  1440.0  1441.0  1442.0  1443.0  1444.0
         user_id
         20             0.0     0.0     0.0     0.0     0.0

         [1 rows x 714 columns]
```

```
In [82]: user_article=user_article.melt()
         user_article.head()
```

```
Out[82]:    article_id  value
         0         0.0    0.0
         1         2.0    0.0
         2         4.0    0.0
         3         8.0    0.0
         4         9.0    0.0
```

```
In [83]: article_ids_list = user_article[user_article['value'] == 1.0]['article_id']
         #article_ids_list.reset_index(drop=True, inplace=True)
         article_ids_list.head()
```

```
Out[83]: 104     232.0
         347     844.0
         619    1320.0
         Name: article_id, dtype: float64
```

Recommend the articles the user hasn't seen before from the articles of close users

In [84]:
```
#find the list of close users
user_id = 1
closeness_loop = find_similar_users(user_id, user_item)
closeness_loop
```

Out[84]:
```
[3933,
 23,
 3782,
 203,
 4459,
 3870,
 131,
 4201,
 46,
 5041,
 395,
 3697,
 49,
 322,
 242,
 3622,
 3910,
 98,
 754,
 2982,
 290,
 3540,
 4642,
 3764,
 912,
 268,
 40,
 3775,
 4932,
 4134,
 52,
 621,
 5138,
 1355,
 4785,
 3651,
 3637,
 256,
 273,
 371,
 204,
```

```
3784,
3621,
3596,
21,
135,
4038,
3532,
64,
186,
184,
3483,
214,
2926,
696,
249,
3141,
765,
619,
4755,
4778,
4892,
3136,
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334,
4293,
1897,
4934,
125,
4484,
445,
4206,
4774,
3684,
5013,
60,
38,
656,
2790,
187,
10,
4209,
665,
3856,
3632,
288,
5140,
4706,
5079,
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54,
72,
67,
3740,
58,
3024,
2430,
409,
733,
4883,
3354,
3408,
193,
4277,
4225,
3485,
195,
3949,
3358,
4543,
379,
170,
211,
3693,
807,
223,
591,
3794,
3353,
235,
90,
3818,
3197,
4404,
295,
261,
263,
3006,
4471,
3572,
3879,
362,
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69,
3578,
2981,
324,
689,
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2975,
87,
1040,
8,
3,
113,
3169,
111,
4595,
244,
330,
1059,
4824,
511,
2161,
4933,
1353,
319,
1330,
4082,
4088,
304,
312,
659,
3589,
598,
750,
280,
4037,
4167,
365,
3067,
3329,
1271,
639,
3118,
640,
4021,
251,
1244,
647,
215,
4130,
3264,
4901,
3057,
383,
3741,
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3100,
3710,
641,
155,
4697,
3005,
4788,
456,
82,
557,
558,
88,
4495,
3172,
1567,
3898,
2908,
4502,
1062,
2903,
3801,
114,
4510,
4792,
4802,
3523,
3305,
926,
3636,
3829,
11,
510,
907,
22,
24,
26,
4453,
890,
45,
535,
471,
3500,
63,
65,
3376,
670,
829,
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168,
4231,
4248,
5023,
4526,
1163,
1162,
3943,
4725,
3441,
3535,
418,
3237,
126,
4515,
4517,
373,
438,
1633,
3732,
4449,
3474,
521,
490,
492,
321,
2897,
512,
4241,
4323,
1705,
4282,
5034,
4620,
2144,
607,
668,
4588,
1426,
669,
3633,
1386,
3336,
536,
538,
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1446,
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4268,
3611,
343,
4356,
4272,
1401,
3061,
3058,
4255,
4254,
4274,
4511,
3292,
3654,
4522,
3430,
542,
649,
4497,
253,
5057,
745,
3960,
181,
3421,
3970,
3971,
763,
197,
3783,
213,
2305,
995,
5077,
3877,
57,
56,
3425,
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4843,
4002,
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860,
3417,
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3802,
1068,
843,
122,
828,
824,
5124,
845,
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4732,
145,
4882,
794,
3518,
85,
164,
5078,
4904,
4668,
688,
707,
4648,
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698,
277,
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697,
3812,
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4071,
1301,
927,
9,
6,
681,

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296,
3208,
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4623,
305,
5059,
5070,
700,
4768,
41,
722,
1272,
1281,
37,
726,
2579,
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1671,
532,
4861,
987,
3196,
938,
4842,
4504,
885,
842,
4450,
2993,
565,
1566,
4969,
889,
1668,
1014,
866,
1018,
4795,
3007,
4855,
518,
3618,
555,
4491,
871,
895,
3191,
4496,
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998,
970,
4786,
977,
4837,
854,
1038,
2989,
1574,
1058,
1513,
3610,
712,
4943,
4586,
1262,
1264,
3069,
631,
3072,
727,
1413,
1405,
4909,
721,
4663,
3108,
3564,
1437,
4647,
648,
650,
651,
3079,
4921,
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3093,
662,
687,
1343,
4618,
4619,
1354,
1261,
741,
4506,
785,
833,
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4876,
798,
791,
790,
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4711,
3031,
674,
1499,
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4707,
1198,
1213,
596,
3042,
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4554,
761,
760,
757,
4685,
1240,
1247,
4947,
1673,
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260,
92,
354,
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4142,
2447,
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4137,
346,
335,
4110,
332,
2128,
132,
326,
4100,
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95,
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3378,
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3327,
375,
2845,
3720,
2029,
4173,
3434,
120,
5053,
3335,
3917,
4015,
2336,
2248,
2251,
4020,
245,
2335,
241,
3972,
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2324,
2320,
2312,
205,
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310,
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3749,
2410,
3338,
294,
3414,
2174,
2176,
3757,
3763,
2197,
2199,
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3363,
163,
169,
4047,
4045,
3695,
4161,
209,
4336,
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3884,
74,
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4311,
2510,
3310,
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86,
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4,
4390,
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89,
1227,
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2661,
3951,
975,
2637,
2370,
2377,
3195,
2,
2667,
2376,
4717,
1229,
3790,
1230,
1165,
2374,
925,
974,
2646,
2621,
2725,
3543,
1214,
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3833,
1219,
931,
939,
2728,
950,
4695,
953,
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1208,
930,
3198,
3147,
1200,
1199,
955,
1223,
2342,
4700,
2350,
1225,
2355,
1194,
957,
3947,
2488,
1154,
2465,
3159,
3163,
4800,
2507,
1003,
3912,
3883,
3885,
2450,
2451,
2682,
3888,
2458,
1025,
1026,
2384,
3889,
1065,
3520,
1063,
3890,
1061,
1031,
2475,
4783,
2479,
2482,
2484,
2485,

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3878,
996,
1098,
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2387,
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2561,
2406,
3872,
1139,
2487,
4809,
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2552,
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1129,
1127,
2516,
988,
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1234,
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4275,
1543,
1879,
2901,
4296,
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4300,
4302,
4503,
3674,
4307,
2912,
4316,
1523,
1512,
4321,
3600,
1449,
2007,
3711,
3052,
3051,
4559,
4557,
1476,
4199,
4553,
1994,
3046,
4545,
1988,
4230,
1498,
4233,
4319,
2919,
2850,
1752,
4456,
2992,
4378,
4379,
4444,
1655,
3629,
4384,
1661,
4386,
4437,
1665,
4392,
4401,
4414,
1685,

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4494,
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4329,
2924,
3664,
919,
1588,
4485,
2932,
3009,
1595,
1780,
4363,
4364,
2941,
1766,
1620,
1627,
1764,
3713,
4577,
3986,
1284,
4658,
4034,
4652,
4039,
1302,
3565,
4049,
3566,
1313,
2768,
2208,
2205,
1320,
2202,
4057,
1329,
2180,
4660,
3559,
1340,
3765,
2304,
```

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3991,
3554,
2742,
2288,
4674,
4673,
2284,
4004,
4016,
1265,
2258,
4667,
2257,
1274,
4025,
3768,
4068,
4073,
3065,
3745,
4608,
4107,
2800,
3737,
4127,
4128,
2813,
2815,
3733,
3581,
1409,
1411,
2819,
2826,
2830,
1427,
4170,
1389,
3746,
4076,
1384,
1347,
2164,
1350,
3088,
2163,
1352,
2788,
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4624,
4086,
1359,
1361,
3087,
4091,
4096,
1370,
3082,
3081,
1807,
4638,
3824,
233,
706,
709,
4915,
711,
4914,
227,
714,
226,
3482,
4910,
220,
219,
723,
5083,
730,
4907,
734,
3255,
239,
636,
246,
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3428,
276,
661,
272,
271,
666,
667,
673,
266,
264,
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262,
3426,
254,
248,
736,
189,
751,
3420,
149,
3413,
146,
3238,
5108,
3368,
3488,
3235,
809,
810,
4877,
3373,
4872,
112,
110,
822,
104,
150,
780,
151,
159,
752,
753,
755,
176,
759,
173,
166,
770,
152,
156,
153,
771,
773,
4891,
778,
3240,
638,
635,
...]
```

b. Fill in the functions

```
In [85]: def get_article_names(article_ids, df=df):
             '''
             INPUT:
             article_ids - (list) a list of article ids
             df - (pandas dataframe) df as defined at the top of the notebook

             OUTPUT:
             article_names - (list) a list of article names associated with the list of article
                             (this is identified by the title column)
             '''
             # Your code here
             article_ids = np.array(article_ids, dtype=np.float64)
             df_article_drop=df.drop_duplicates(subset=['article_id'], keep='first')[['article_i
             #article_names = df_article_drop[df_article_drop['article_id'].isin(article_ids)==T
             article_names = df_article_drop.set_index('article_id').loc[article_ids].reset_inde
             #article_names.reset_index(drop=True, inplace=True)
             article_names = article_names.tolist()

             return article_names # Return the article names associated with list of article ids


         def get_user_articles(user_id, user_item=user_item):
             '''
             INPUT:
             user_id - (int) a user id
             user_item - (pandas dataframe) matrix of users by articles:
                         1's when a user has interacted with an article, 0 otherwise

             OUTPUT:
             article_ids - (list) a list of the article ids seen by the user
             article_names - (list) a list of article names associated with the list of article
                             (this is identified by the doc_full_name column in df_content)

             Description:
             Provides a list of the article_ids and article titles that have been seen by a user
             '''
             # Your code here
             user_article_list = user_item[user_item.index == user_id]
             user_article_list = user_article_list.melt()
             article_ids = user_article_list[user_article_list['value'] == 1.0]['article_id']
             #article_ids.reset_index(drop=True, inplace=True)
             article_ids = article_ids.tolist()

             article_ids = [str(x) for x in article_ids]

             article_names = get_article_names(article_ids, df=df)
```

```
    return article_ids, article_names # return the ids and names


def user_user_recs(user_id, m=10):
    '''
    INPUT:
    user_id - (int) a user id
    m - (int) the number of recommendations you want for the user

    OUTPUT:
    recs - (list) a list of recommendations for the user

    Description:
    Loops through the users based on closeness to the input user_id
    For each user - finds articles the user hasn't seen before and provides them as rec
    Does this until m recommendations are found

    Notes:
    Users who are the same closeness are chosen arbitrarily as the 'next' user

    For the user where the number of recommended articles starts below m
    and ends exceeding m, the last items are chosen arbitrarily

    '''
    # Your code here
    closeness_loop = find_similar_users(user_id, user_item)
    r = 0
    recs = []
    #read_article_ids, read_article_names = get_user_articles(user_id, user_item)
    read_article_ids, read_article_names = get_user_articles(user_id)
    for i in closeness_loop:
        #rec_article_ids , rec_article_names = get_user_articles(i, user_item)
        rec_article_ids , rec_article_names = get_user_articles(i)
        for j in rec_article_ids:
            if (j not in read_article_ids):
                r = r + 1
                recs.append(j)
                if r == m:
                    break
        if r == m:
            break
    return recs # return your recommendations for this user_id
```

In [86]:
```
# Check Results
article_ids = [1430.0, 1429.0, 1276.0]
#get_article_names(article_ids, df)
get_article_names(article_ids)
```

Out[86]: ['using pixiedust for fast, flexible, and easier data analysis and experimentation',
 'use deep learning for image classification',
 'deploy your python model as a restful api']

In [87]:
```python
# Check Results
#get_user_articles(1, user_item)
get_user_articles(1)
```

Out[87]:
```
(['43.0',
  '109.0',
  '151.0',
  '268.0',
  '310.0',
  '329.0',
  '346.0',
  '390.0',
  '494.0',
  '525.0',
  '585.0',
  '626.0',
  '668.0',
  '732.0',
  '768.0',
  '910.0',
  '968.0',
  '981.0',
  '1052.0',
  '1170.0',
  '1183.0',
  '1185.0',
  '1232.0',
  '1293.0',
  '1305.0',
  '1363.0',
  '1368.0',
  '1391.0',
  '1400.0',
  '1406.0',
  '1427.0',
  '1429.0',
  '1430.0',
  '1431.0',
  '1436.0',
  '1439.0'],
 ['deep learning with tensorflow course by big data university',
  'tensorflow quick tips',
  'jupyter notebook tutorial',
  'sector correlations shiny app',
```

```
 'time series prediction using recurrent neural networks (lstms)',
 'introduction to market basket analysis in\xa0python',
 'fighting gerrymandering: using data science to draw fairer congressional districts',
 'introducing ibm watson studio ',
 'python for loops explained (python for data science basics #5)',
 'new shiny cheat sheet and video tutorial',
 'tidyverse practice: mapping large european cities',
 'analyze db2 warehouse on cloud data in rstudio in dsx',
 'shiny: a data scientists best friend',
 'rapidly build machine learning flows with dsx',
 'python if statements explained (python for data science basics #4)',
 'working with ibm cloud object storage in python',
 'shiny 0.13.0',
 'super fast string matching in python',
 'access db2 warehouse on cloud and db2 with python',
 'apache spark lab, part 1: basic concepts',
 'categorize urban density',
 'classify tumors with machine learning',
 'country statistics: life expectancy at birth',
 'finding optimal locations of new store using decision optimization',
 'gosales transactions for naive bayes model',
 'predict loan applicant behavior with tensorflow neural networking',
 'putting a human face on machine learning',
 'sudoku',
 'uci ml repository: chronic kidney disease data set',
 'uci: iris',
 'use xgboost, scikit-learn & ibm watson machine learning apis',
 'use deep learning for image classification',
 'using pixiedust for fast, flexible, and easier data analysis and experimentation',
 'visualize car data with brunel',
 'welcome to pixiedust',
 'working with ibm cloud object storage in r'])
```

In [88]:
```
# Check Results
get_article_names(user_user_recs(1, 10)) # Return 10 recommendations for user 1
```

Out[88]:
```
['this week in data science (april 18, 2017)',
 'timeseries data analysis of iot events by using jupyter notebook',
 'got zip code data? prep it for analytics.  ibm watson data lab  medium',
 'higher-order logistic regression for large datasets',
 'using machine learning to predict parking difficulty',
 'deep forest: towards an alternative to deep neural networks',
 'experience iot with coursera',
 'using brunel in ipython/jupyter notebooks',
 'graph-based machine learning',
 'the 3 kinds of context: machine learning and the art of the frame']
```

In [89]:
```
get_article_names(['1024.0','1176.0', '1305.0', '1314.0', '1422.0', '1427.0'])
```

```
Out[89]: ['using deep learning to reconstruct high-resolution audio',
          'build a python app on the streaming analytics service',
          'gosales transactions for naive bayes model',
          'healthcare python streaming application demo',
          'use r dataframes & ibm watson natural language understanding',
          'use xgboost, scikit-learn & ibm watson machine learning apis']
```

```
In [90]: get_article_names(['1314.0'])
```

```
Out[90]: ['healthcare python streaming application demo']
```

```
In [91]: get_article_names(['1320.0', '232.0', '844.0'])
```

```
Out[91]: ['housing (2015): united states demographic measures',
          'self-service data preparation with ibm data refinery',
          'use the cloudant-spark connector in python notebook']
```

```
In [92]: get_user_articles(2)[0]
```

```
Out[92]: ['1024.0', '1176.0', '1305.0', '1314.0', '1422.0', '1427.0']
```

```
In [93]: get_user_articles(20)[0]
```

```
Out[93]: ['232.0', '844.0', '1320.0']
```

```
In [94]: # Test your functions here - No need to change this code - just run this cell
         assert set(get_article_names(['1024.0', '1176.0', '1305.0', '1314.0', '1422.0', '1427.0
         assert set(get_article_names(['1320.0', '232.0', '844.0'])) == set(['housing (2015): un
         assert set(get_user_articles(20)[0]) == set(['1320.0', '232.0', '844.0'])
         assert set(get_user_articles(20)[1]) == set(['housing (2015): united states demographic
         assert set(get_user_articles(2)[0]) == set(['1024.0', '1176.0', '1305.0', '1314.0', '14
         assert set(get_user_articles(2)[1]) == set(['using deep learning to reconstruct high-re
         print("If this is all you see, you passed all of our tests!  Nice job!")
```

```
If this is all you see, you passed all of our tests!  Nice job!
```

4. Now we are going to improve the consistency of the **user_user_recs** function from above.

- Instead of arbitrarily choosing when we obtain users who are all the same closeness to a given user - choose the users that have the most total article interactions before choosing those with fewer article interactions.

- Instead of arbitrarily choosing articles from the user where the number of recommended articles starts below m and ends exceeding m, choose articles with the articles with the most total interactions before choosing those with fewer total interactions. This ranking should be what would be obtained from the **top_articles** function you wrote earlier.

a. Draft the functions

- The neighbor data frame including the neighbor's similarity and the number of articles viewed by the neighbor

Calculate the neighbor's similarity

```
In [95]: selected_user_id = 3
         useri = user_item[user_item.index == selected_user_id]
         useri
```

```
Out[95]: article_id  0.0     2.0     4.0     8.0     9.0     12.0    14.0    15.0    \
         user_id
         3              0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0

         article_id  16.0    18.0     ...    1434.0  1435.0  1436.0  1437.0  1439.0  \
         user_id                      ...
         3              0.0     0.0   ...       0.0     0.0     1.0     0.0     0.0

         article_id  1440.0  1441.0  1442.0  1443.0  1444.0
         user_id
         3              0.0     0.0     0.0     0.0     0.0

         [1 rows x 714 columns]
```

```
In [96]: neighbors = useri.dot(user_item.transpose()).melt().sort_values(by = 'user_id', ascendi
         neighbors.columns = ['user_id', 'similarity']
         neighbors.head()
```

```
Out[96]:    user_id  similarity
         0        1         6.0
         1        2         1.0
         2        3        40.0
         3        4         5.0
         4        5         1.0
```

Calculate the number of articles viewed by the neighbor

```
In [97]: df.groupby(['user_id']).size()
```

```
Out[97]: user_id
         1         47
         2          6
         3         82
         4         45
         5          5
         6         19
         7          4
         8         82
         9         32
         10        22
```

11	35
12	13
13	21
14	28
15	17
16	3
17	35
18	3
19	8
20	3
21	137
22	37
23	364
24	30
25	10
26	27
27	34
28	42
29	1
30	5
	...
5120	1
5121	1
5122	1
5123	13
5124	22
5125	1
5126	2
5127	29
5128	4
5129	29
5130	1
5131	1
5132	2
5133	3
5134	9
5135	3
5136	2
5137	2
5138	95
5139	13
5140	101
5141	1
5142	2
5143	25
5144	1
5145	6
5146	9

```
5147      1
5148      1
5149      1
Length: 5149, dtype: int64
```

In [98]:
```
df.groupby(['user_id']).size().tolist()
```

Out[98]:
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[47,
 6,
 82,
 45,
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 82,
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...]
```

```
In [99]: neighbors['num_interactions'] = df.groupby(['user_id']).size().tolist()
         neighbors.head()
```

```
Out[99]:    user_id  similarity  num_interactions
         0        1         6.0                47
         1        2         1.0                 6
         2        3        40.0                82
         3        4         5.0                45
         4        5         1.0                 5
```

```
In [100]: neighbors = neighbors.sort_values(by = ['similarity','num_interactions'], ascending =
          neighbors.head()
```

```
Out[100]:       user_id  similarity  num_interactions
          2           3        40.0                82
          3352     3353        40.0                80
          22         23        23.0               364
          3781     3782        23.0               363
          97         98        17.0               170
```

- Recommendations for the user

```
In [101]: rec_article_ids_test = ['1430.0','1429.0']
          rec_article_ids_test
```

```
Out[101]: ['1430.0', '1429.0']
```

```
In [102]: df.head()
```

```
Out[102]:    article_id                                              title  user_id
          0      1430.0  using pixiedust for fast, flexible, and easier...        1
          1      1314.0       healthcare python streaming application demo        2
          2      1429.0         use deep learning for image classification        3
          3      1338.0          ml optimization using cognitive assistant        4
          4      1276.0          deploy your python model as a restful api        5
```

```
In [103]: rec_article_ids_test = np.array(rec_article_ids_test, dtype=np.float64)
          count_interactions = df.set_index('article_id').loc[rec_article_ids_test].reset_index(
          count_interactions.head()
```

```
Out[103]:    article_id                                              title  user_id
          0      1430.0  using pixiedust for fast, flexible, and easier...        1
          1      1430.0  using pixiedust for fast, flexible, and easier...       15
          2      1430.0  using pixiedust for fast, flexible, and easier...       33
          3      1430.0  using pixiedust for fast, flexible, and easier...       41
          4      1430.0  using pixiedust for fast, flexible, and easier...       21
```

```
In [104]: count_interactions = count_interactions.groupby('article_id').size().sort_values(ascen
          count_interactions
```

Out[104]: article_id
```
1429.0    937
1430.0    336
dtype: int64
```

In [105]:
```
list_articles_sorted = count_interactions.index
list_articles_sorted = [str(x) for x in list_articles_sorted]
list_articles_sorted
```

Out[105]: ['1429.0', '1430.0']

In [106]:
```
# The function to sort the articles descending by the number of interactions
def get_sorted_articles(article_ids, df=df):
    '''
    INPUT:
    article_ids - list of articles
    df - (pandas dataframe) df as defined at the top of the notebook

    OUTPUT:
    articles_sorted - list of articles that are sorted from the most interactions to t

    '''
    article_ids = np.array(article_ids, dtype=np.float64)
    count_interactions = df.set_index('article_id').loc[article_ids].reset_index(inpla
    count_interactions = count_interactions.groupby('article_id').size().sort_values(a
    articles_sorted = count_interactions.index
    articles_sorted = [str(x) for x in articles_sorted]

    return articles_sorted
```

In [107]:
```
# Test
get_sorted_articles(rec_article_ids_test, df)
```

Out[107]: ['1429.0', '1430.0']

b. Fill in the functions

In [108]:
```
def get_top_sorted_users(user_id, df=df, user_item=user_item):
    '''
    INPUT:
    user_id - (int)
    df - (pandas dataframe) df as defined at the top of the notebook
    user_item - (pandas dataframe) matrix of users by articles:
            1's when a user has interacted with an article, 0 otherwise


    OUTPUT:
    neighbors_df - (pandas dataframe) a dataframe with:
                    neighbor_id - is a neighbor user_id
```

```
                    similarity - measure of the similarity of each user to the provide
                    num_interactions - the number of articles viewed by the user - if

    Other Details - sort the neighbors_df by the similarity and then by number of inte
                    highest of each is higher in the dataframe

    '''
    # Your code here
    user_article_i = user_item[user_item.index == user_id]
    neighbors_df = user_article_i.dot(user_item.transpose()).melt().sort_values(by = '
    neighbors_df.columns = ['user_id', 'similarity']
    neighbors_df['num_interactions'] = df.groupby(['user_id']).size().tolist()
    neighbors_df = neighbors_df[neighbors_df['user_id'] != user_id]
    neighbors_df = neighbors_df.sort_values(by = ['similarity','num_interactions'], as

    return neighbors_df # Return the dataframe specified in the doc_string


def user_user_recs_part2(user_id, m=10):
    '''
    INPUT:
    user_id - (int) a user id
    m - (int) the number of recommendations you want for the user

    OUTPUT:
    recs - (list) a list of recommendations for the user by article id
    rec_names - (list) a list of recommendations for the user by article title

    Description:
    Loops through the users based on closeness to the input user_id
    For each user - finds articles the user hasn't seen before and provides them as re
    Does this until m recommendations are found

    Notes:
    * Choose the users that have the most total article interactions
    before choosing those with fewer article interactions.

    * Choose articles with the articles with the most total interactions
    before choosing those with fewer total interactions.

    '''
    # Your code here
    closeness_list = get_top_sorted_users(user_id, df, user_item)['user_id'].tolist()
    r = 0
    recs = []
    read_article_ids, read_article_names = get_user_articles(user_id)

    for i in closeness_list:
```

```
            if i == user_id:
                continue
            rec_article_ids , rec_article_names = get_user_articles(i)
            rec_article_ids = get_sorted_articles(rec_article_ids, df)
            for j in rec_article_ids:
                if (j not in read_article_ids):
                    r = r + 1
                    recs.append(j)
                    if r == m:
                        break
            if r == m:
                break

        rec_names = get_article_names(recs, df=df)
        return recs, rec_names
```

In [109]:
```
# Test
get_top_sorted_users(3, df, user_item)
```

Out[109]:

	user_id	similarity	num_interactions
3352	3353	40.0	80
22	23	23.0	364
3781	3782	23.0	363
97	98	17.0	170
3763	3764	17.0	169
202	203	16.0	160
4458	4459	16.0	158
48	49	16.0	147
3696	3697	16.0	145
51	52	15.0	132
3595	3596	15.0	131
911	912	14.0	102
3539	3540	14.0	101
241	242	13.0	148
3909	3910	13.0	147
130	131	13.0	145
3869	3870	13.0	144
203	204	13.0	97
5137	5138	13.0	95
2925	2926	13.0	83
39	40	13.0	78
4931	4932	13.0	76
10	11	13.0	35
3965	3966	13.0	33
20	21	12.0	137
4784	4785	12.0	136
618	619	12.0	84
194	195	12.0	72

```
3577     3578        12.0              70
764       765        12.0              68
...       ...         ...             ...
5055     5056         0.0               1
5059     5060         0.0               1
5064     5065         0.0               1
5067     5068         0.0               1
5070     5071         0.0               1
5072     5073         0.0               1
5075     5076         0.0               1
5083     5084         0.0               1
5084     5085         0.0               1
5086     5087         0.0               1
5090     5091         0.0               1
5091     5092         0.0               1
5097     5098         0.0               1
5099     5100         0.0               1
5100     5101         0.0               1
5103     5104         0.0               1
5106     5107         0.0               1
5112     5113         0.0               1
5115     5116         0.0               1
5118     5119         0.0               1
5119     5120         0.0               1
5120     5121         0.0               1
5121     5122         0.0               1
5124     5125         0.0               1
5130     5131         0.0               1
5140     5141         0.0               1
5143     5144         0.0               1
5146     5147         0.0               1
5147     5148         0.0               1
5148     5149         0.0               1

[5148 rows x 3 columns]
```

In [110]:
```python
# Quick spot check - don't change this code - just use it to test your functions
rec_ids, rec_names = user_user_recs_part2(20, 10)
print("The top 10 recommendations for user 20 are the following article ids:")
print(rec_ids)
print()
print("The top 10 recommendations for user 20 are the following article names:")
print(rec_names)
```

```
The top 10 recommendations for user 20 are the following article ids:
['1330.0', '1427.0', '1364.0', '1170.0', '1162.0', '1304.0', '1351.0', '1160.0', '1354.0', '1368

The top 10 recommendations for user 20 are the following article names:
```

```
['insights from new york car accident reports', 'use xgboost, scikit-learn & ibm watson machine
```

5. Use your functions from above to correctly fill in the solutions to the dictionary below. Then test your dictionary against the solution. Provide the code you need to answer each following the comments below.

```
In [111]: get_top_sorted_users(1, df, user_item).head(1)
```

```
Out[111]:       user_id  similarity  num_interactions
          3932     3933        35.0                45
```

```
In [112]: get_top_sorted_users(131, df, user_item).head(10)
```

```
Out[112]:       user_id  similarity  num_interactions
          3869     3870        74.0               144
          3781     3782        39.0               363
          22         23        38.0               364
          202       203        33.0               160
          4458     4459        33.0               158
          97         98        29.0               170
          3763     3764        29.0               169
          48         49        29.0               147
          3696     3697        29.0               145
          241       242        25.0               148
```

```
In [113]: ### Tests with a dictionary of results

          user1_most_sim = get_top_sorted_users(1, df, user_item)['user_id'].tolist()[0] # Find
          user131_10th_sim = get_top_sorted_users(131, df, user_item)['user_id'].tolist()[9] # F
```

```
In [114]: ## Dictionary Test Here
          sol_5_dict = {
              'The user that is most similar to user 1.': user1_most_sim,
              'The user that is the 10th most similar to user 131': user131_10th_sim
          }

          t.sol_5_test(sol_5_dict)
```

```
This all looks good!  Nice job!
```

6. If we were given a new user, which of the above functions would you be able to use to make recommendations? Explain. Can you think of a better way we might make recommendations? Use the cell below to explain a better method for new users.

If we were given a new user, we cannot use user_user_recs_part2(new_user, m) because with a new user we cannot calculate the similarity of existing users to the new user. We should recommend the new user just the articles with the highest interactions and the function get_top_article_ids(m, df) can be used

7. Using your existing functions, provide the top 10 recommended articles you would provide for the a new user below. You can test your function against our thoughts to make sure we are all on the same page with how we might make a recommendation.

```
In [115]: new_user = 0
          user_user_recs_part2(new_user, 10)

Out[115]: ([], [])
```

The above result is ok because with a new user we cannot calculate the similarity of existing users to the new user.

```
In [116]: get_top_sorted_users(new_user, df, user_item).head()

Out[116]:       user_id  similarity  num_interactions
          22        NaN         NaN               364
          3781      NaN         NaN               363
          97        NaN         NaN               170
          3763      NaN         NaN               169
          202       NaN         NaN               160
```

Thus we should recommend the new user just the articles with the highest interactions.

```
In [117]: articles_new_user = df.groupby('article_id').size().sort_values(ascending = False).hea
          articles_new_user

Out[117]: article_id
          1429.0    937
          1330.0    927
          1431.0    671
          1427.0    643
          1364.0    627
          1314.0    614
          1293.0    572
          1170.0    565
          1162.0    512
          1304.0    483
          dtype: int64

In [118]: articles_new_user = articles_new_user.index
          articles_new_user = [str(x) for x in articles_new_user]
          articles_new_user

Out[118]: ['1429.0',
           '1330.0',
           '1431.0',
           '1427.0',
           '1364.0',
           '1314.0',
           '1293.0',
           '1170.0',
           '1162.0',
           '1304.0']
```

Or an existing function in Part II can be used to get this article ids list

```
In [119]: get_top_article_ids(10, df)

Out[119]: ['1429.0',
           '1330.0',
           '1431.0',
           '1427.0',
           '1364.0',
           '1314.0',
           '1293.0',
           '1170.0',
           '1162.0',
           '1304.0']
```

Fill in the result

```
In [120]: new_user = '0.0'

          # What would your recommendations be for this new user '0.0'?  As a new user, they hav
          # Provide a list of the top 10 article ids you would give to
          new_user_recs = ['1429.0',
           '1330.0',
           '1431.0',
           '1427.0',
           '1364.0',
           '1314.0',
           '1293.0',
           '1170.0',
           '1162.0',
           '1304.0'] # Copy from above or we can put get_top_article_ids(10, df) here

In [121]: assert set(new_user_recs) == set(['1314.0','1429.0','1293.0','1427.0','1162.0','1364.0

          print("That's right!  Nice job!")

That's right!  Nice job!
```

1.1.4 Part IV: Content Based Recommendations (EXTRA - NOT REQUIRED)

Another method we might use to make recommendations is to perform a ranking of the highest ranked articles associated with some term. You might consider content to be the **doc_body**, **doc_description**, or **doc_full_name**. There isn't one way to create a content based recommendation, especially considering that each of these columns hold content related information.

1. Use the function body below to create a content based recommender. Since there isn't one right answer for this recommendation tactic, no test functions are provided. Feel free to change the function inputs if you decide you want to try a method that requires more input values. The input values are currently set with one idea in mind that you may use to make content based

recommendations. One additional idea is that you might want to choose the most popular recommendations that meet your 'content criteria', but again, there is a lot of flexibility in how you might make these recommendations.

1.1.5 This part is NOT REQUIRED to pass this project. However, you may choose to take this on as an extra way to show off your skills.

```
In [ ]: def make_content_recs():
            '''
            INPUT:

            OUTPUT:

            '''
```

2. Now that you have put together your content-based recommendation system, use the cell below to write a summary explaining how your content based recommender works. Do you see any possible improvements that could be made to your function? Is there anything novel about your content based recommender?

1.1.6 This part is NOT REQUIRED to pass this project. However, you may choose to take this on as an extra way to show off your skills.

Write an explanation of your content based recommendation system here.

3. Use your content-recommendation system to make recommendations for the below scenarios based on the comments. Again no tests are provided here, because there isn't one right answer that could be used to find these content based recommendations.

1.1.7 This part is NOT REQUIRED to pass this project. However, you may choose to take this on as an extra way to show off your skills.

```
In [ ]: # make recommendations for a brand new user


        # make a recommendations for a user who only has interacted with article id '1427.0'
```

1.1.8 Part V: Matrix Factorization

In this part of the notebook, you will build use matrix factorization to make article recommendations to the users on the IBM Watson Studio platform.

1. You should have already created a **user_item** matrix above in **question 1** of **Part III** above. This first question here will just require that you run the cells to get things set up for the rest of **Part V** of the notebook.

```
In [122]: # Load the matrix here
          user_item_matrix = pd.read_pickle('user_item_matrix.p')
```

```
In [123]: # quick look at the matrix
          user_item_matrix.head()
```

```
Out[123]: article_id  0.0  100.0  1000.0  1004.0  1006.0  1008.0  101.0  1014.0  1015.0  \
          user_id
          1           0.0    0.0     0.0     0.0     0.0     0.0    0.0     0.0     0.0
          2           0.0    0.0     0.0     0.0     0.0     0.0    0.0     0.0     0.0
          3           0.0    0.0     0.0     0.0     0.0     0.0    0.0     0.0     0.0
          4           0.0    0.0     0.0     0.0     0.0     0.0    0.0     0.0     0.0
          5           0.0    0.0     0.0     0.0     0.0     0.0    0.0     0.0     0.0

          article_id  1016.0  ...   977.0  98.0  981.0  984.0  985.0  986.0  990.0  \
          user_id             ...
          1              0.0  ...     0.0   0.0    1.0    0.0    0.0    0.0    0.0
          2              0.0  ...     0.0   0.0    0.0    0.0    0.0    0.0    0.0
          3              0.0  ...     1.0   0.0    0.0    0.0    0.0    0.0    0.0
          4              0.0  ...     0.0   0.0    0.0    0.0    0.0    0.0    0.0
          5              0.0  ...     0.0   0.0    0.0    0.0    0.0    0.0    0.0

          article_id  993.0  996.0  997.0
          user_id
          1             0.0    0.0    0.0
          2             0.0    0.0    0.0
          3             0.0    0.0    0.0
          4             0.0    0.0    0.0
          5             0.0    0.0    0.0

          [5 rows x 714 columns]
```

2. In this situation, you can use Singular Value Decomposition from numpy on the user-item matrix. Use the cell to perform SVD, and explain why this is different than in the lesson.

```
In [124]: # Perform SVD on the User-Item Matrix Here

          u, s, vt = np.linalg.svd(user_item_matrix, full_matrices=True, compute_uv=True) # use

          u.shape, vt.shape, s.shape
```

```
Out[124]: ((5149, 5149), (714, 714), (714,))
```

So we can use SVD to do decomposition for the user_item_matrix.

In this result: - the u matrix is a square matrix with the number of rows and columns equaling the number of users, - the v transpose matrix is also a square matrix with the number of rows and columns equaling the number of articles (items), - and the sigma matrix is about the latent features.

In the lesson there existed just 4 latent features but here there exist a much bigger number of latent features but the SVD can help to do the singular value decomposition, then to compute the prediction and evaluate the accuracy of the prediction as in the next section (section 3).

3. Now for the tricky part, how do we choose the number of latent features to use? Running the below cell, you can see that as the number of latent features increases, we obtain a lower error rate on making predictions for the 1 and 0 values in the user-item matrix. Run the cell below to get an idea of how the accuracy improves as we increase the number of latent features.

```
In [125]: num_latent_feats = np.arange(10,700+10,20)
          sum_errs = []

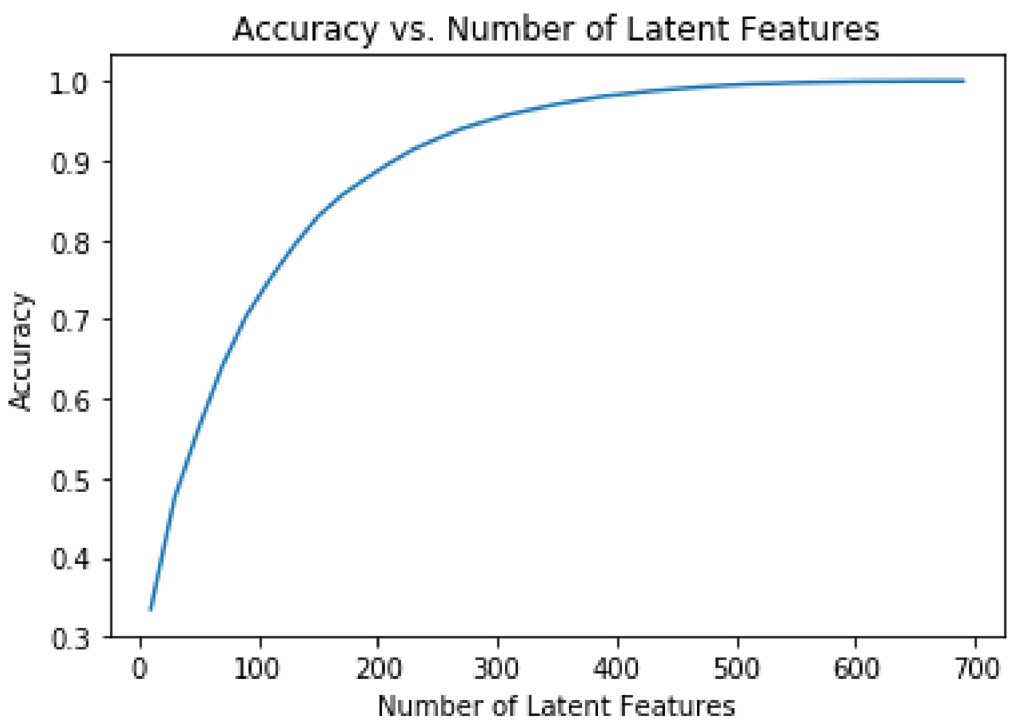
          for k in num_latent_feats:
              # restructure with k latent features
              s_new, u_new, vt_new = np.diag(s[:k]), u[:, :k], vt[:k, :]

              # take dot product
              user_item_est = np.around(np.dot(np.dot(u_new, s_new), vt_new))

              # compute error for each prediction to actual value
              diffs = np.subtract(user_item_matrix, user_item_est)

              # total errors and keep track of them
              err = np.sum(np.sum(np.abs(diffs)))
              sum_errs.append(err)


          plt.plot(num_latent_feats, 1 - np.array(sum_errs)/df.shape[0]);
          plt.xlabel('Number of Latent Features');
          plt.ylabel('Accuracy');
          plt.title('Accuracy vs. Number of Latent Features');
```




```
In [126]: user_item_est.shape[0]
```

Out[126]: 5149

```
In [127]: user_item_matrix.shape[0]
```

Out[127]: 5149

```
In [128]: user_item_est.shape[1]
```

Out[128]: 714

```
In [129]: user_item_matrix.shape[1]
```

Out[129]: 714

4. From the above, we can't really be sure how many features to use, because simply having a better way to predict the 1's and 0's of the matrix doesn't exactly give us an indication of if we are able to make good recommendations. Instead, we might split our dataset into a training and test set of data, as shown in the cell below.

Use the code from question 3 to understand the impact on accuracy of the training and test sets of data with different numbers of latent features. Using the split below:

- How many users can we make predictions for in the test set?
- How many users are we not able to make predictions for because of the cold start problem?
- How many articles can we make predictions for in the test set?
- How many articles are we not able to make predictions for because of the cold start problem?

```
In [130]: df_train = df.head(40000)
          df_test = df.tail(5993)
```

```
In [131]: df_train.head()
```

```
Out[131]:    article_id                                              title  user_id
          0      1430.0  using pixiedust for fast, flexible, and easier...        1
          1      1314.0       healthcare python streaming application demo        2
          2      1429.0         use deep learning for image classification        3
          3      1338.0          ml optimization using cognitive assistant        4
          4      1276.0          deploy your python model as a restful api        5
```

```
In [132]: user_item_train = create_user_item_matrix(df_train)
          user_item_train.head()
```

```
Out[132]: article_id  0.0     2.0     4.0     8.0     9.0     12.0    14.0    15.0    \
          user_id
          1              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
          2              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
          3              0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0
          4              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
          5              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
```

```
article_id  16.0    18.0     ...    1434.0  1435.0  1436.0  1437.0  1439.0  \
user_id                      ...
1             0.0     0.0    ...       0.0     0.0     1.0     0.0     1.0
2             0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
3             0.0     0.0    ...       0.0     0.0     1.0     0.0     0.0
4             0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
5             0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0

article_id  1440.0  1441.0  1442.0  1443.0  1444.0
user_id
1             0.0     0.0     0.0     0.0     0.0
2             0.0     0.0     0.0     0.0     0.0
3             0.0     0.0     0.0     0.0     0.0
4             0.0     0.0     0.0     0.0     0.0
5             0.0     0.0     0.0     0.0     0.0

[5 rows x 714 columns]
```

In [133]:
```
user_item_test_all = create_user_item_matrix(df_test)
user_item_test_all.head()
```

Out[133]:
```
article_id  0.0     2.0     4.0     8.0     9.0     12.0    14.0    15.0    \
user_id
2917          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3024          0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0
3093          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3193          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3527          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0

article_id  16.0    18.0     ...    1432.0  1433.0  1434.0  1435.0  1436.0  \
user_id                      ...
2917          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
3024          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
3093          0.0     0.0    ...       0.0     0.0     0.0     0.0     1.0
3193          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
3527          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0

article_id  1437.0  1439.0  1440.0  1441.0  1443.0
user_id
2917          0.0     0.0     0.0     0.0     0.0
3024          0.0     0.0     0.0     0.0     0.0
3093          0.0     0.0     0.0     0.0     0.0
3193          0.0     0.0     0.0     0.0     0.0
3527          0.0     0.0     0.0     0.0     0.0

[5 rows x 574 columns]
```

In [134]:
```
user_item_train.shape
```

Out[134]: (4487, 714)

In [135]:
```
user_item_test_all.shape
```

Out[135]: (682, 574)

In [136]:
```
test_article_ids_all = user_item_test_all.columns.tolist()
test_article_ids_all = [str(x) for x in test_article_ids_all]
test_article_ids_all
```

Out[136]:
```
['0.0',
 '2.0',
 '4.0',
 '8.0',
 '9.0',
 '12.0',
 '14.0',
 '15.0',
 '16.0',
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'1157.0',
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'1274.0',
'1276.0',
'1277.0',
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'1279.0',
'1280.0',
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'1354.0',
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'1358.0',
'1359.0',
'1360.0',
'1361.0',
'1362.0',
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'1430.0',
'1431.0',
'1432.0',
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'1434.0',
```

```
 '1435.0',
 '1436.0',
 '1437.0',
 '1439.0',
 '1440.0',
 '1441.0',
 '1443.0']
```

In [137]:
```
test_user_ids_all = user_item_test_all.index.tolist()
test_user_ids_all[:5]
```

Out[137]:
```
[2917, 3024, 3093, 3193, 3527]
```

In [138]:
```
train_user_ids = user_item_train.index.tolist()
len(train_user_ids)
```

Out[138]:
```
4487
```

In [139]:
```
len(test_user_ids_all)
```

Out[139]:
```
682
```

In [140]:
```
list(set(test_user_ids_all) & set(train_user_ids))
```

Out[140]:
```
[3968,
 3777,
 4002,
 3684,
 4293,
 2917,
 4487,
 4231,
 3527,
 4204,
 3532,
 3024,
 4274,
 3801,
 3093,
 3989,
 3990,
 3193,
 3740,
 3998]
```

In [141]:
```
test_user_ids_intersection = list(set(test_user_ids_all) & set(train_user_ids))
len(test_user_ids_intersection)
```

Out[141]:
```
20
```

```
In [142]: user_item_test_all.index

Out[142]: Int64Index([2917, 3024, 3093, 3193, 3527, 3532, 3684, 3740, 3777, 3801,
                      ...
                      5140, 5141, 5142, 5143, 5144, 5145, 5146, 5147, 5148, 5149],
                     dtype='int64', name='user_id', length=682)
```

```
In [143]: user_item_test_all.index.isin(test_user_ids_intersection)

Out[143]: array([ True,  True,  True,  True,  True,  True,  True,  True,  True,
                 True,  True,  True,  True,  True,  True,  True,  True,  True,
                 True,  True, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False, False,
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                False, False, False, False, False, False, False, False, False,
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                False, False, False, False, False, False, False, False, False,
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                False, False, False, False, False, False, False, False, False,
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                False, False, False, False, False, False, False, False, False,
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                False, False, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False, False,
```

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       False, False, False, False, False, False, False, False, False,
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       False, False, False, False, False, False, False, False, False,
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       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False], dtype=bool)
```

In [144]:
```
user_item_test_intersection = user_item_test_all[user_item_test_all.index.isin(test_us
user_item_test_intersection
```

Out[144]:
```
article_id  0.0     2.0     4.0     8.0     9.0     12.0    14.0    15.0    \
user_id
2917           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3024           0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0
3093           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3193           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3527           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
```

```
3532          0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0
3684          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3740          0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0
3777          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3801          0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0
3968          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3989          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3990          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3998          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
4002          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
4204          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
4231          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
4274          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
4293          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
4487          0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0

article_id  16.0    18.0     ...    1432.0  1433.0  1434.0  1435.0  1436.0  \
user_id                      ...
2917          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
3024          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
3093          0.0     0.0    ...       0.0     0.0     0.0     0.0     1.0
3193          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
3527          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
3532          0.0     0.0    ...       0.0     0.0     0.0     0.0     1.0
3684          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
3740          0.0     0.0    ...       0.0     0.0     0.0     0.0     1.0
3777          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
3801          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
3968          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
3989          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
3990          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
3998          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
4002          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
4204          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
4231          0.0     0.0    ...       0.0     0.0     0.0     0.0     1.0
4274          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0
4293          0.0     0.0    ...       0.0     0.0     0.0     0.0     1.0
4487          0.0     0.0    ...       0.0     0.0     0.0     0.0     0.0

article_id  1437.0  1439.0  1440.0  1441.0  1443.0
user_id
2917          0.0     0.0     0.0     0.0     0.0
3024          0.0     0.0     0.0     0.0     0.0
3093          0.0     0.0     0.0     0.0     0.0
3193          0.0     0.0     0.0     0.0     0.0
3527          0.0     0.0     0.0     0.0     0.0
3532          0.0     0.0     0.0     0.0     0.0
3684          0.0     0.0     0.0     0.0     0.0
```

```
3740           0.0     0.0     0.0     0.0     0.0
3777           0.0     0.0     0.0     0.0     0.0
3801           0.0     0.0     0.0     0.0     0.0
3968           0.0     0.0     0.0     0.0     0.0
3989           0.0     0.0     0.0     0.0     0.0
3990           0.0     0.0     0.0     0.0     0.0
3998           0.0     0.0     0.0     0.0     0.0
4002           0.0     0.0     0.0     0.0     0.0
4204           0.0     0.0     0.0     0.0     0.0
4231           0.0     0.0     0.0     0.0     0.0
4274           0.0     0.0     0.0     0.0     0.0
4293           0.0     0.0     0.0     0.0     0.0
4487           0.0     0.0     0.0     0.0     0.0

[20 rows x 574 columns]
```

In [145]:
```python
df_train = df.head(40000)
df_test = df.tail(5993)

def create_test_and_train_user_item(df_train, df_test):
    '''
    INPUT:
    df_train - training dataframe
    df_test - test dataframe

    OUTPUT:
    user_item_train - a user-item matrix of the training dataframe
                      (unique users for each row and unique articles for each column)
    user_item_test - a user-item matrix of the testing dataframe
                    (unique users for each row and unique articles for each column)
    test_idx - all of the test user ids
    test_arts - all of the test article ids

    '''
    # Your code here
    user_item_train = create_user_item_matrix(df_train)
    user_item_test_all = create_user_item_matrix(df_test)
    test_idx_all = user_item_test_all.index.tolist()
    train_idx = user_item_train.index.tolist()

    test_idx = list(set(test_idx_all) & set(train_idx))
    user_item_test = user_item_test_all[user_item_test_all.index.isin(test_idx)]

    test_arts = user_item_test.columns.tolist()
    test_arts = [str(x) for x in test_arts]

    return user_item_train, user_item_test, test_idx, test_arts
```

```
user_item_train, user_item_test, test_idx, test_arts = create_test_and_train_user_item
```

```
In [146]: user_item_train.shape[0]
```

```
Out[146]: 4487
```

```
In [147]: user_item_train.shape[1]
```

```
Out[147]: 714
```

```
In [148]: user_item_test.head()
```

```
Out[148]: article_id  0.0     2.0     4.0     8.0     9.0     12.0    14.0    15.0    \
          user_id
          2917           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
          3024           0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0
          3093           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
          3193           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
          3527           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0

          article_id  16.0    18.0     ...    1432.0  1433.0  1434.0  1435.0  1436.0  \
          user_id                      ...
          2917           0.0     0.0   ...       0.0     0.0     0.0     0.0     0.0
          3024           0.0     0.0   ...       0.0     0.0     0.0     0.0     0.0
          3093           0.0     0.0   ...       0.0     0.0     0.0     0.0     1.0
          3193           0.0     0.0   ...       0.0     0.0     0.0     0.0     0.0
          3527           0.0     0.0   ...       0.0     0.0     0.0     0.0     0.0

          article_id  1437.0  1439.0  1440.0  1441.0  1443.0
          user_id
          2917           0.0     0.0     0.0     0.0     0.0
          3024           0.0     0.0     0.0     0.0     0.0
          3093           0.0     0.0     0.0     0.0     0.0
          3193           0.0     0.0     0.0     0.0     0.0
          3527           0.0     0.0     0.0     0.0     0.0

          [5 rows x 574 columns]
```

```
In [149]: len(test_idx)
```

```
Out[149]: 20
```

```
In [150]: user_item_test.shape[0]
```

```
Out[150]: 20
```

```
In [151]: user_item_test
```

```
Out[151]: article_id  0.0     2.0     4.0     8.0     9.0     12.0    14.0    15.0    \
user_id
2917            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3024            0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0
3093            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3193            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3527            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3532            0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0
3684            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3740            0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0
3777            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3801            0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0
3968            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3989            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3990            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3998            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
4002            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
4204            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
4231            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
4274            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
4293            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
4487            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0

article_id  16.0    18.0     ...    1432.0  1433.0  1434.0  1435.0  1436.0  \
user_id                      ...
2917            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
3024            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
3093            0.0     0.0  ...       0.0     0.0     0.0     0.0     1.0
3193            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
3527            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
3532            0.0     0.0  ...       0.0     0.0     0.0     0.0     1.0
3684            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
3740            0.0     0.0  ...       0.0     0.0     0.0     0.0     1.0
3777            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
3801            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
3968            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
3989            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
3990            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
3998            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
4002            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
4204            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
4231            0.0     0.0  ...       0.0     0.0     0.0     0.0     1.0
4274            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
4293            0.0     0.0  ...       0.0     0.0     0.0     0.0     1.0
4487            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0

article_id  1437.0  1439.0  1440.0  1441.0  1443.0
user_id
```

```
2917          0.0     0.0     0.0     0.0     0.0
3024          0.0     0.0     0.0     0.0     0.0
3093          0.0     0.0     0.0     0.0     0.0
3193          0.0     0.0     0.0     0.0     0.0
3527          0.0     0.0     0.0     0.0     0.0
3532          0.0     0.0     0.0     0.0     0.0
3684          0.0     0.0     0.0     0.0     0.0
3740          0.0     0.0     0.0     0.0     0.0
3777          0.0     0.0     0.0     0.0     0.0
3801          0.0     0.0     0.0     0.0     0.0
3968          0.0     0.0     0.0     0.0     0.0
3989          0.0     0.0     0.0     0.0     0.0
3990          0.0     0.0     0.0     0.0     0.0
3998          0.0     0.0     0.0     0.0     0.0
4002          0.0     0.0     0.0     0.0     0.0
4204          0.0     0.0     0.0     0.0     0.0
4231          0.0     0.0     0.0     0.0     0.0
4274          0.0     0.0     0.0     0.0     0.0
4293          0.0     0.0     0.0     0.0     0.0
4487          0.0     0.0     0.0     0.0     0.0

[20 rows x 574 columns]
```

In [152]:
```
user_item_test_all.shape[0]
```

Out[152]: 682

In [153]:
```
user_item_test_all.shape[0] - len(test_idx)
```

Out[153]: 662

In [154]:
```
len(test_arts)
```

Out[154]: 574

In [155]:
```
user_item_test_all.shape[1]
```

Out[155]: 574

In [156]:
```
user_item_test_all.shape[1] - len(test_arts)
```

Out[156]: 0

In [157]:
```
# Replace the values in the dictionary below
a = 662
b = 574
c = 20
d = 0
```

```
sol_4_dict = {
    'How many users can we make predictions for in the test set?': c,
    'How many users in the test set are we not able to make predictions for because of
    'How many movies can we make predictions for in the test set?': b,
    'How many movies in the test set are we not able to make predictions for because o
}

t.sol_4_test(sol_4_dict)
```

```
Awesome job!  That's right!  All of the test movies are in the training data, but there are only
```

5. Now use the **user_item_train** dataset from above to find U, S, and V transpose using SVD. Then find the subset of rows in the **user_item_test** dataset that you can predict using this matrix decomposition with different numbers of latent features to see how many features makes sense to keep based on the accuracy on the test data. This will require combining what was done in questions 2 - 4.

Use the cells below to explore how well SVD works towards making predictions for recommendations on the test data.

- **Decompose the training set user-item matrix**

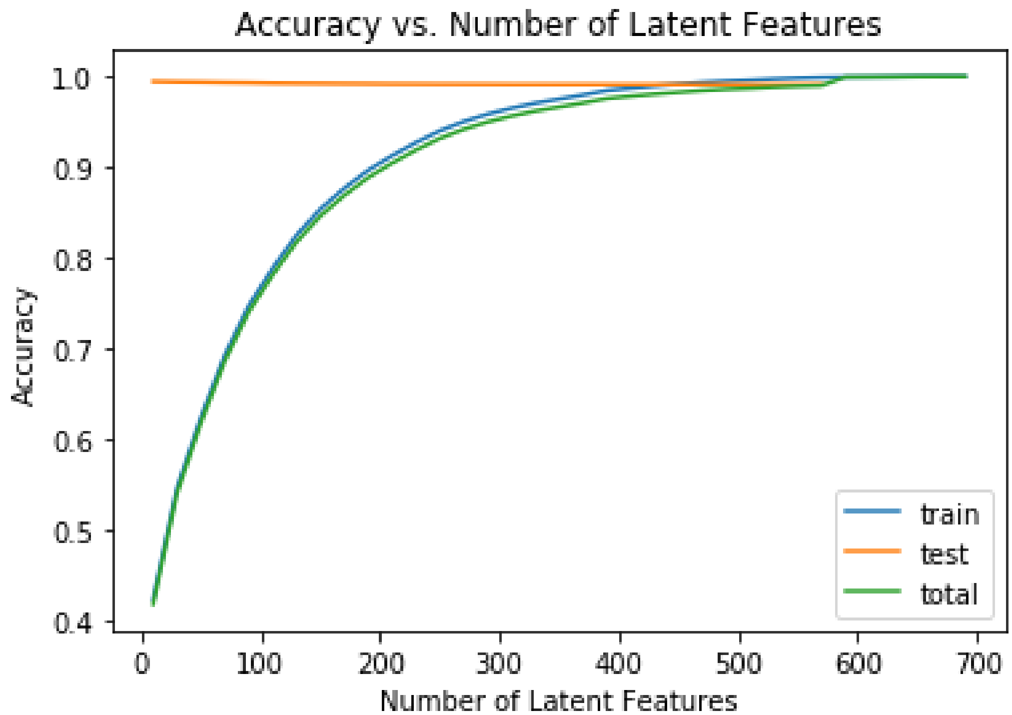
```
In [158]: # fit SVD on the user_item_train matrix
          u_train, s_train, vt_train = np.linalg.svd(user_item_train, full_matrices=True, comput

          s_train.shape, u_train.shape, vt_train.shape
```

```
Out[158]: ((714,), (4487, 4487), (714, 714))
```

- **Use this decomposition to predict values for the user-item test dataset and check the accuracy of the predictions from the train set and compared with the test set**

```
In [173]: # Use these cells to see how well you can use the training decomposition to predict on
          num_latent_feats_train = np.arange(10,700+10,20)
          sum_errs_train = []

          for k_train in num_latent_feats_train:
              # restructure with k latent features
              s_new_train, u_new_train, vt_new_train = np.diag(s_train[:k_train]), u_train[:, :k

              # take dot product
              user_item_est_train = np.around(np.dot(np.dot(u_new_train, s_new_train), vt_new_tr

              # compute error for each prediction to actual value
              diffs_train = np.subtract(user_item_train, user_item_est_train)

              # total errors and keep track of them
              err_train = np.sum(np.sum(np.abs(diffs_train)))
              sum_errs_train.append(err_train)
```

```
# Create the decomposed the u, s , vt matrices from the test set
row_idx = user_item_train.index.isin(test_idx)
col_idx = user_item_train.columns.isin(test_arts)
u_test = u_train[row_idx, :]
vt_test = vt_train[:, col_idx]
s_test = s_train[col_idx]

num_latent_feats_test = np.arange(10,580+10,20)
sum_errs_test = []

for k_test in num_latent_feats_test:
    # restructure with k latent features
    s_new_test, u_new_test, vt_new_test = np.diag(s_test[:k_test]), u_test[:, :k_test]

    # take dot product
    user_item_est_test = np.around(np.dot(np.dot(u_new_test, s_new_test), vt_new_test)

    # compute error for each prediction to actual value
    diffs_test = np.subtract(user_item_test, user_item_est_test)

    # total errors and keep track of them
    err_test = np.sum(np.sum(np.abs(diffs_test)))
    sum_errs_test.append(err_test)

sum_errs_total = np.append(np.array(sum_errs_test), [0.0, 0.0, 0.0, 0.0, 0.0, 0.0]) +
#sum_errs_total = np.array(sum_errs_test) + np.array(sum_errs_train)

plt.plot(num_latent_feats_train, 1 - np.array(sum_errs_train)/df.shape[0], label = 'tr
plt.plot(num_latent_feats_test, 1 - np.array(sum_errs_test)/df.shape[0], label = 'test
plt.plot(num_latent_feats_train, 1 - np.array(sum_errs_total)/df.shape[0], label = 'to
plt.legend();
plt.xlabel('Number of Latent Features');
plt.ylabel('Accuracy');
plt.title('Accuracy vs. Number of Latent Features');
```



In [188]: user_item_est.shape[0]

Out[188]: 4487

In [189]: user_item_test.shape[0]

Out[189]: 682

In [190]: user_item_est.shape[1]

Out[190]: 714

In [191]: user_item_test.shape[1]

Out[191]: 574

6. Use the cell below to comment on the results you found in the previous question. Given the circumstances of your results, discuss what you might do to determine if the recommendations you make with any of the above recommendation systems are an improvement to how users currently find articles?

The accuracy is a good metric to use here in this case. It can provide us with a fair assessment of the model's performance when we can evaluate . But the current assessment framework is not robust enough to make conclusive results about the model as comparing the accuracy in section 3. and 5. And consider about the number of train and test users, we cannot make predictions for all users in the test set, it's not sufficient. It's understandable as we see the

similarity we base on is very simple, the users are considered similar to each other just by only 1 metric that's the history of article the users interacted with.

I see we can use an online evaluation technique like A/B testing here to improve. I will separate the user groups base on device types, cookies, IP addresses... that show up more information such as location, OS, device, time... And the experiment should be run for the time base at least a month, then more metrics of user similarity will be tracked during this experiment such as location, timing behavior... Those new metrics will help to improve the prediction results more conclusive.

Extras Using your workbook, you could now save your recommendations for each user, develop a class to make new predictions and update your results, and make a flask app to deploy your results. These tasks are beyond what is required for this project. However, from what you learned in the lessons, you certainly capable of taking these tasks on to improve upon your work here!

1.2 Conclusion

Congratulations! You have reached the end of the Recommendations with IBM project!

Tip: Once you are satisfied with your work here, check over your report to make sure that it is satisfies all the areas of the rubric. You should also probably remove all of the "Tips" like this one so that the presentation is as polished as possible.

1.3 Directions to Submit

Before you submit your project, you need to create a .html or .pdf version of this notebook in the workspace here. To do that, run the code cell below. If it worked correctly, you should get a return code of 0, and you should see the generated .html file in the workspace directory (click on the orange Jupyter icon in the upper left).

Alternatively, you can download this report as .html via the **File** > **Download as** submenu, and then manually upload it into the workspace directory by clicking on the orange Jupyter icon in the upper left, then using the Upload button.

Once you've done this, you can submit your project by clicking on the "Submit Project" button in the lower right here. This will create and submit a zip file with this .ipynb doc and the .html or .pdf version you created. Congratulations!

```
In [ ]: from subprocess import call
        call(['python', '-m', 'nbconvert', 'Recommendations_with_IBM.ipynb'])
```