Recommendations_with_IBM

March 30, 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 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]: # Show df_content to get an idea of the data
        df_content.head()
```

```
Out[2]:                                             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.

```
In [3]: df[['email','article_id']].groupby(['email']).count().describe()
```

```
Out[3]:         article_id
        count  5148.000000
        mean      8.930847
        std      16.802267
        min       1.000000
        25%       1.000000
        50%       3.000000
```

```
75%        9.000000
max      364.000000
```

In [4]:

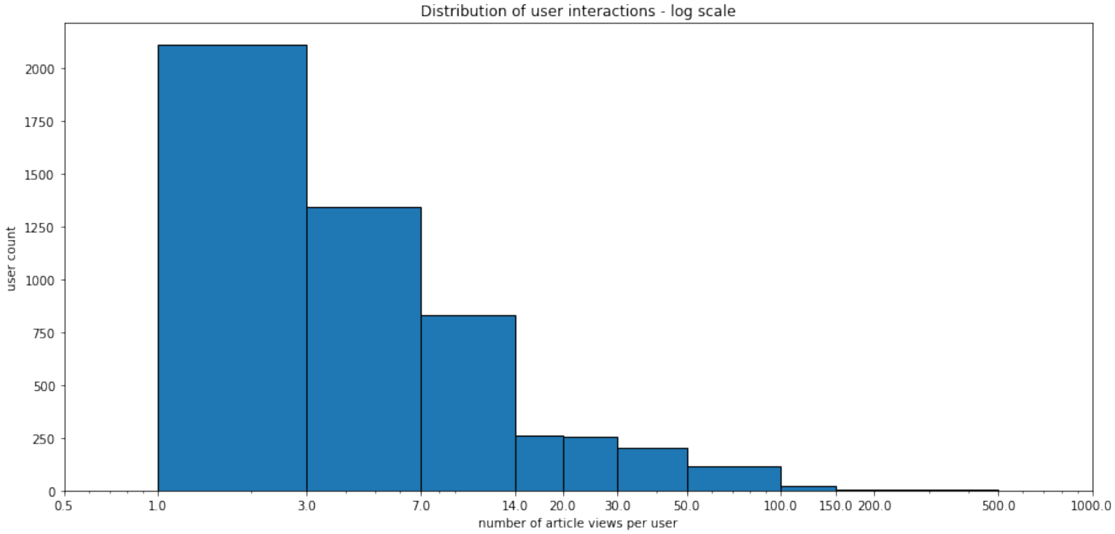
```
df[['email','article_id']].groupby(['email']).count()['article_id'].head(5)
```

Out[4]:

```
email
0000b6387a0366322d7fbfc6434af145adf7fed1    13
001055fc0bb67f71e8fa17002342b256a30254cd     4
00148e4911c7e04eeff8def7bbbdaf1c59c2c621     3
001a852ecbd6cc12ab77a785efa137b2646505fe     6
001fc95b90da5c3cb12c501d201a915e4f093290     2
Name: article_id, dtype: int64
```

In [5]:

```
hist_bins = [0,1,3,7,14,20,30,50,100,150,200,500]
hist_ticks = np.array([0.5, 1,3,7,14,20,30,50,100,150,200,500,1000])
plt.figure(figsize=(15,7))
plt.hist(df[['email','article_id']].groupby(['email']).count()['article_id'],bins=hist_b
plt.yscale('linear')
plt.xscale('log')
plt.xticks(hist_ticks,hist_ticks.astype(str))
plt.title('Distribution of user interactions - log scale')
plt.xlabel('number of article views per user')
plt.ylabel('user count')
plt.show()
```



In [6]:

```
# Fill in the median and maximum number of user_article interactios below
most_articles = df.article_id.value_counts(dropna=False)
user_interaction = df.email.value_counts(dropna=False)

median_val = len(np.cumsum(most_articles.values)[np.cumsum(most_articles.values) <= len(
max_views_by_user = user_interaction.iloc[0] # The maximum number of user-article intera
```

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

```
In [7]: # Find and explore duplicate articles
        is_duplicate = df_content.duplicated(subset=['article_id'])
        duplicated_articles_id = df_content['article_id'][is_duplicate]
        duplicated_articles_name = df_content['doc_full_name'][is_duplicate]
        print('Duplicated IDs of articles: {}'.format(duplicated_articles_id.values))
        print('Duplicated names of articles: {}'.format(duplicated_articles_name.values))
```

```
Duplicated IDs of articles: [ 50 221 398 577 232]
Duplicated names of articles: ['Graph-based machine learning'
 'How smart catalogs can turn the big data flood into an ocean of opportunity'
 'Using Apache Spark as a parallel processing framework for accessing REST based data services'
 'Use the Primary Index'
 'Self-service data preparation with IBM Data Refinery']
```

```
In [8]: # Remove any rows that have the same article_id - only keep the first
        df_content = df_content.drop_duplicates(subset=['article_id'],keep='first')
```

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 [9]: print('number of unique articles that have one interaction with a user: {}'.format(len(d
        print('number of unique articles that they have any interactions or not: {}'.format(len(
        print('number of unique users (excluding null values): {}'.format(len(df['email'].unique
        print('number of user-article interactions: {}'.format(df.shape[0]))
```

```
number of unique articles that have one interaction with a user: 714
number of unique articles that they have any interactions or not: 1051
number of unique users (excluding null values): 5149
number of user-article interactions: 45993
```

```
In [10]: unique_articles = len(most_articles) # The number of unique articles that have at least
         total_articles = df_content.shape[0] # The number of unique articles on the IBM platfor
         unique_users = len(user_interaction)-1 # The number of unique users
         user_article_interactions = len(df) # 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 [11]: df.groupby(['article_id']).count().sort_values(['title'],ascending=False).head(10)
```

Out[11]:

```
            title  email
article_id
1429.0        937    937
1330.0        927    927
1431.0        671    671
1427.0        643    643
1364.0        627    627
1314.0        614    614
1293.0        572    572
1170.0        565    565
1162.0        512    512
1304.0        483    483
```

In [12]:

```
most_viewed_article_id = str(most_articles.index[0]) # The most viewed article in the d
max_views = most_articles.iloc[0] # The most viewed article in the dataset was viewed h
```

In [13]:

```
## 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[13]:

```
   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 [14]:

```
## 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.

```
In [15]: 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
             df_top_n = df.groupby(['article_id']).count().sort_values(['title'],ascending=False
             top_articles_idx = df_top_n.index

             top_articles = list(df.loc[df['article_id'].isin(top_articles_idx),:]['title'].uniq

             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
    df_top_n = df.groupby(['article_id']).count().sort_values(['title'],ascending=False
    top_articles = list(df_top_n.index)

    return top_articles # Return the top article ids
```

```
In [16]: print(get_top_articles(10))
         print(get_top_article_ids(10))
```

```
['healthcare python streaming application demo', 'use deep learning for image classification', '
[1429.0, 1330.0, 1431.0, 1427.0, 1364.0, 1314.0, 1293.0, 1170.0, 1162.0, 1304.0]
```

```
In [17]: # 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.

```
In [18]: # 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
             user_item = df.groupby(['user_id', 'article_id'])['article_id'].count().unstack()
             user_item = user_item.fillna(0)
             for col in user_item.columns.values:
                 user_item[col] = user_item[col].apply(lambda x: x if x == 0 else 1)

             return user_item # return the user_item matrix

         user_item = create_user_item_matrix(df)

In [19]: # user_item top 5 dataset
         user_item.head()
```

```
Out[19]: 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 [20]: ## 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.

```
In [21]: 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
             similarity = user_item.dot(np.transpose(user_item.iloc[user_id-1,:]))
             # sort by similarity
             similarity = similarity.sort_values(ascending=False)
             # create list of just the ids
             most_similar_users = list(similarity.index.values)
             # remove the own user's id
             most_similar_users.remove(user_id)

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

```
In [22]: # 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, 131, 3870, 46, 4201, 5041]
The 5 most similar users to user 3933 are: [1, 23, 3782, 4459, 203]
The 3 most similar users to user 46 are: [4201, 23, 3782]
```

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.

```
In [23]: 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_names = list(set(list(df[df['article_id'].isin(article_ids)]['title'])))

             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
             article_ids = [str(aid) for aid in list(user_item.iloc[user_id-1].sort_values(ascen
    article_names = get_article_names(article_ids)

    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
    close_users = find_similar_users(user_id)
    userArticles_seen = set(get_user_articles(user_id)[0])

    recs = []

    for uid in close_users:
        articles_seen = set(get_user_articles(uid)[0])
        for aid in articles_seen.difference(userArticles_seen):
            if len(recs) > m:
                break
            recs.append(aid)

    return recs # return your recommendations for this user_id
```

In [24]:
```
# Check Results
get_article_names(user_user_recs(1, 10)) # Return 10 recommendations for user 1
```

Out[24]:
```
['perform sentiment analysis with lstms, using tensorflow',
 'the nurse assignment problem',
 'web picks (week of 4 september 2017)',
 'improving real-time object detection with yolo',
 'model bike sharing data with spss',
 'get started with streams designer by following this roadmap',
 'automating web analytics through python',
 'this week in data science (april 18, 2017)',
 'build a python app on the streaming analytics service',
 'discover hidden facebook usage insights',
 'airbnb data for analytics: mallorca reviews']
```

```
In [25]: # 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.

```
In [26]: 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 provided
                             num_interactions - the number of articles viewed by the user - if a

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

```
    '''
    # Your code here
    similarity = user_item.dot(np.transpose(user_item.iloc[user_id-1,:])).sort_values(a
    sim_df = similarity.to_frame('similarity').reset_index()
    numOf_interactions = df['user_id'].value_counts().to_frame('num_of_interactions')

    neighbors_df = pd.merge(sim_df, numOf_interactions, left_on='user_id', right_index=
    neighbors_df.rename(columns={'user_id':'neighbor_id'}, inplace=True)
    neighbors_df = neighbors_df.sort_values(by=['similarity', 'num_of_interactions'], a
    neighbors_df.drop(axis=0, index=0, inplace=True)
    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 rec
    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
    neighbors_df = get_top_sorted_users(user_id)

    recs = []
    userArticles_seen = set(get_user_articles(user_id)[0])

    for neighbor in neighbors_df['neighbor_id'].values:
        neighborArticles_seen = set(get_user_articles(neighbor)[0])
        for aid in neighborArticles_seen.difference(userArticles_seen):
            if len(recs) > m:
                break
            recs.append(aid)
            rec_names = get_article_names(recs)

            return recs, rec_names
```

```
In [27]: # 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:
['1338.0', '1409.0', '880.0', '205.0', '1424.0', '1278.0', '164.0', '1176.0', '1426.0', '911.0',

The top 10 recommendations for user 20 are the following article names:
['ml optimization using cognitive assistant', 'uci: red wine quality', 'use spark for python to
```

```
In [28]: get_top_sorted_users(1).head()
```

```
Out[28]:    neighbor_id  similarity  num_of_interactions
         1         3933        35.0                   45
         2           23        17.0                  364
         3         3782        17.0                  363
         4          203        15.0                  160
         5         4459        15.0                  158
```

```
In [29]: get_top_sorted_users(131).head()
```

```
Out[29]:    neighbor_id  similarity  num_of_interactions
         1         3870        74.0                  144
         2         3782        39.0                  363
         3           23        38.0                  364
         5          203        33.0                  160
         4         4459        33.0                  158
```

```
In [30]: ### Tests with a dictionary of results

         # Find the user that is most similar to user 1
         user1_most_sim = get_top_sorted_users(1)['neighbor_id'].iloc[0]
         # Find the 10th most similar user to user 131
         user131_10th_sim = get_top_sorted_users(131)['neighbor_id'].iloc[9]
```

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 [31]: ## 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.

Provide your response here.

We should use the function get_top_article_ids to make recommendations becuase new user have no interactions and so we won't find them user-item and new user receive the top 10 of the most interacted articles among the whole user base. The recommended top articles ordered with most interactions as the top by other users.

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 [32]: new_user = '0.0'

         # What would your recommendations be for this new user '0.0'?  As a new user, they have
         # Provide a list of the top 10 article ids you would give to
         new_user_recs =  [str(aid) for aid in get_top_article_ids(10)] # Your recommendations h

In [33]: 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 [34]: 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 [35]: # 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 [36]: # Load the matrix here
         user_item_matrix = pd.read_pickle('user_item_matrix.p')
```

```
In [37]: # quick look at the matrix
         user_item_matrix.head()
```

```
Out[37]: 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 [38]: # Perform SVD on the User-Item Matrix Here

         u, s, vt = np.linalg.svd(user_item_matrix) # use the built in to get the three matrices
```

```
In [39]: s.shape, u.shape, vt.shape
```

```
Out[39]: ((714,), (5149, 5149), (714, 714))
```

Provide your response here.

Singular Value Decomposition from numpy works when there are no null values. As in the lesson, the matrix was full of null values so numpy SVD dosen't work. In this case, our matrix has only 2 values, i.e. 1 if user made interaction and 0 when an interaction was not made. Hence, there are no null values, and hence we can perform numpy's SVD.

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

         for k in num_latent_feats:
             # restructure with k latent features
```

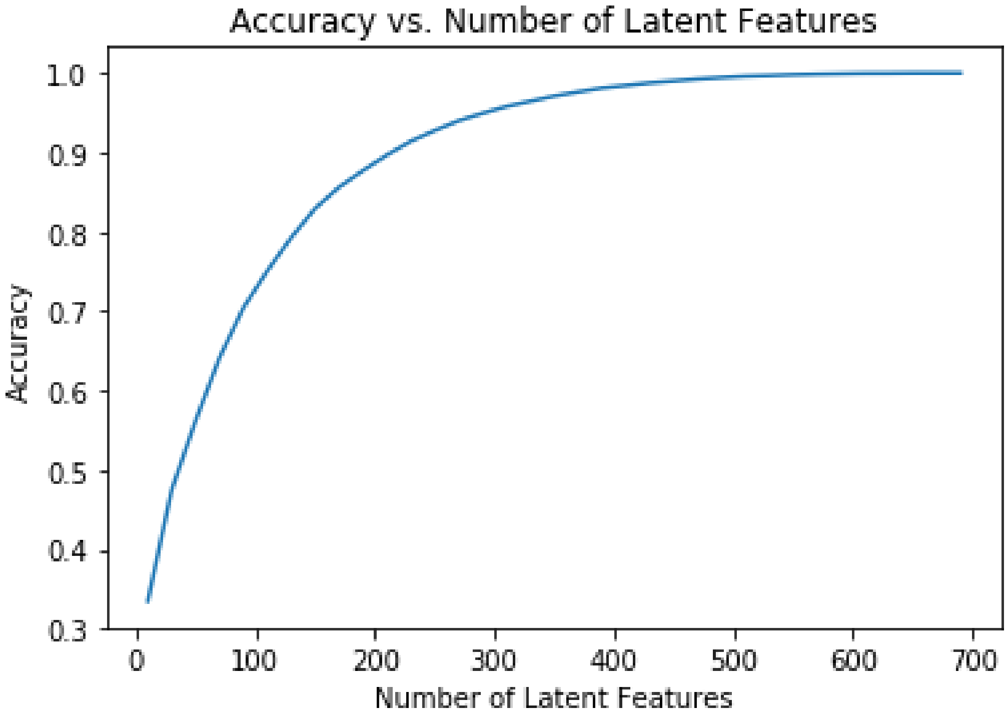
```
    s_new, u_new, vt_new = np.diag(s[:k]), u[:, :k], vt[:k, :]

    # 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');
```



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 [41]: 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 = create_user_item_matrix(df_test)
             test_idx = list(user_item_test.index.values)
             test_arts = user_item_test.columns.values

             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 [42]: user_item_train.shape, user_item_test.shape
```

```
Out[42]: ((4487, 714), (682, 574))
```

```
In [43]: # 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, # letter here,
             '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, # letter here,
        'How many movies in the test set are we not able to make predictions for because of
    }

    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.

```
In [44]: # fit SVD on the user_item_train matrix
         u_train, s_train, vt_train = np.linalg.svd(user_item_train)
```

```
In [45]: u_train.shape, s_train.shape, vt_train.shape
         # fit svd similar to above then use the cells below
```

```
Out[45]: ((4487, 4487), (714,), (714, 714))
```

```
In [46]: # Use these cells to see how well you can use the training
         # decomposition to predict on test data

         num_latent_feats = np.arange(10,700+10,20)
         sum_errs_train = []
         sum_errs_test = []



         # Decomposition
         row_index = user_item_train.index.isin(test_idx)     # Getting index of common users in
         col_index = user_item_train.columns.isin(test_arts) # Getting columns ('article_id') of

         # Creating u_test and vt_test using the above
         u_test = u_train[row_index,:]
         vt_test = vt_train[:,col_index]

         # subsetting common users from user_item_train
         common_users = np.intersect1d(list(user_item_train.index),list(user_item_test.index))

         for k in num_latent_feats:

             # restructure with k latent features for training and test set #
             s_train_new, u_train_new, vt_train_new = np.diag(s_train[:k]), u_train[:, :k], vt_t
             u_test_new, vt_test_new = u_test[:, :k], vt_test[:k, :]
```

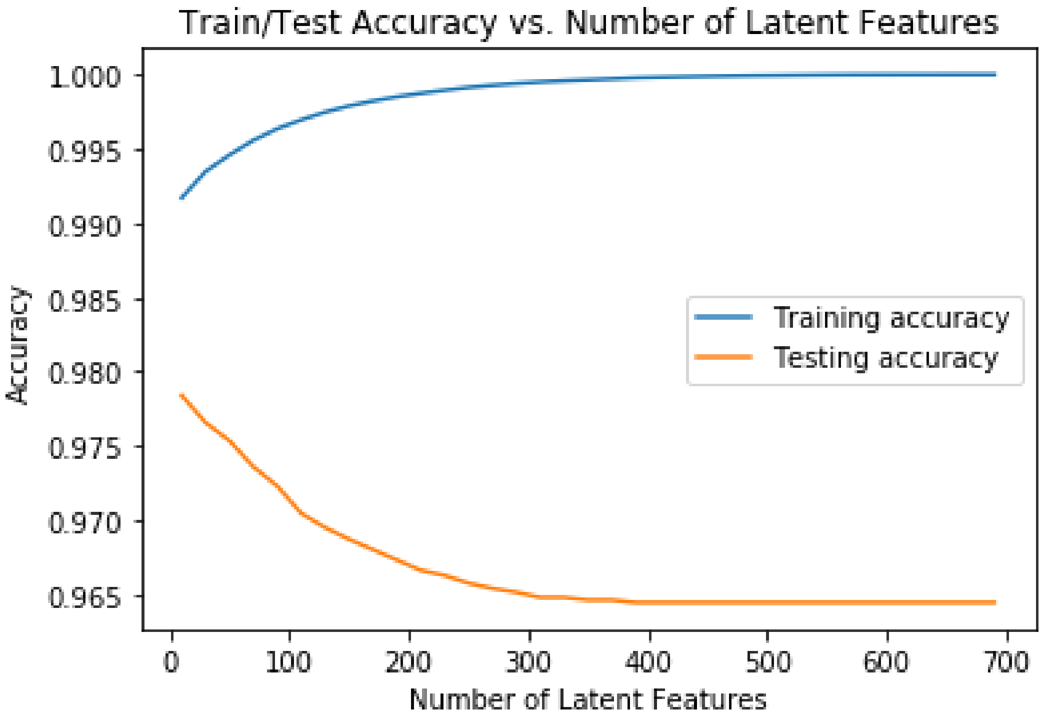
```
    # take dot product
    user_item_est_train = np.around(np.dot(np.dot(u_train_new, s_train_new), vt_train_n
    user_item_est_test = np.around(np.dot(np.dot(u_test_new, s_train_new), vt_test_new)

    # compute error for each prediction to actual value
    diffs_train = np.subtract(user_item_train, user_item_est_train)
    diffs_test = np.subtract(user_item_test.loc[common_users,:], user_item_est_test)


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

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


plt.plot(num_latent_feats, 1 - np.array(sum_errs_train)/(user_item_train.shape[0]*user_
plt.plot(num_latent_feats, 1 - np.array(sum_errs_test)/(user_item_test.loc[common_users
         , label = 'Testing accuracy');
plt.xlabel('Number of Latent Features');
plt.ylabel('Accuracy');
plt.title('Train/Test Accuracy vs. Number of Latent Features');
plt.legend(loc='best');
```



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?

Your response here.

The training accuracy rises as the number of latent features increases. This might be due to overfitting and also indicates that over-fitting occurs with higher latent features.

We can only predict for 20 users. Therefore cold-start problem exists and the current model in not robust.

Accuracy is not a good metric as the training and testing sets are highly imbalanced. F-beta score or F-score with higher emphasis on precision might be a better metric in this case.

We might use different methods of recommendations, combine them and then do our recommendations. To improve recommendations and solve cold-start problem, rank based recommendations and content based recommendations could be used. In order to determine if there is an improvement in recommendations.

I would like to prefer to conduct A/B test forming a control and experiment group, decide an appropriate metric such as article view rate, determine the experiment sizing, measure the metrics and perform simulation based hypothesis tests and draw conclusion if the recommendation system improves on how users currently find articles.

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!