

Recommendations_with_IBM

November 4, 2022

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

I. Section ?? II. Section ?? III. Section ?? IV. Section ?? V. Section ?? VI. Section ??

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]: df.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45993 entries, 0 to 45992
Data columns (total 3 columns):
article_id    45993 non-null float64
title         45993 non-null object
email         45976 non-null object
dtypes: float64(1), object(2)
memory usage: 1.1+ MB

```

```
In [3]: # Show df_content to get an idea of the data
df_content.head()
```

```

Out[3]:
                                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

```

```
In [4]: df_content.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1056 entries, 0 to 1055
Data columns (total 5 columns):

```

```

doc_body          1042 non-null object
doc_description    1053 non-null object
doc_full_name      1056 non-null object
doc_status         1056 non-null object
article_id         1056 non-null int64
dtypes: int64(1), object(4)
memory usage: 41.3+ KB

```

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 [5]: # number of articles
print("The number of articles is {}".format(df.shape[0]))

# number of contents
print("The number of contents is {}".format(df_content.shape[0]))

# unique articles in data base
print("The number of unique articles in data base is {}".format(df.article_id.nunique()))

# missing articles
for i in list(df.columns):
    print("The number of missing", i, "is {}".format(int(df[i].isnull().mean()*df.shape[0])))

# missing articles content
for i in list(df_content.columns):
    print("The number of missing", i, "in contents is {}".format(int(df_content[i].isnull().mean()*df_content.shape[0])))

```

```

The number of articles is 45993.
The number of contents is 1056.
The number of unique articles in data base is 714.
The number of missing article_id is 0.
The number of missing title is 0.
The number of missing email is 17.
The number of missing doc_body in contents is 14.
The number of missing doc_description in contents is 3.
The number of missing doc_full_name in contents is 0.
The number of missing doc_status in contents is 0.
The number of missing article_id in contents is 0.

```

```

In [6]: # create data for iteration of the users and acticles
article_iteration = pd.DataFrame(df.groupby('email')['article_id'].count().reset_index())

```

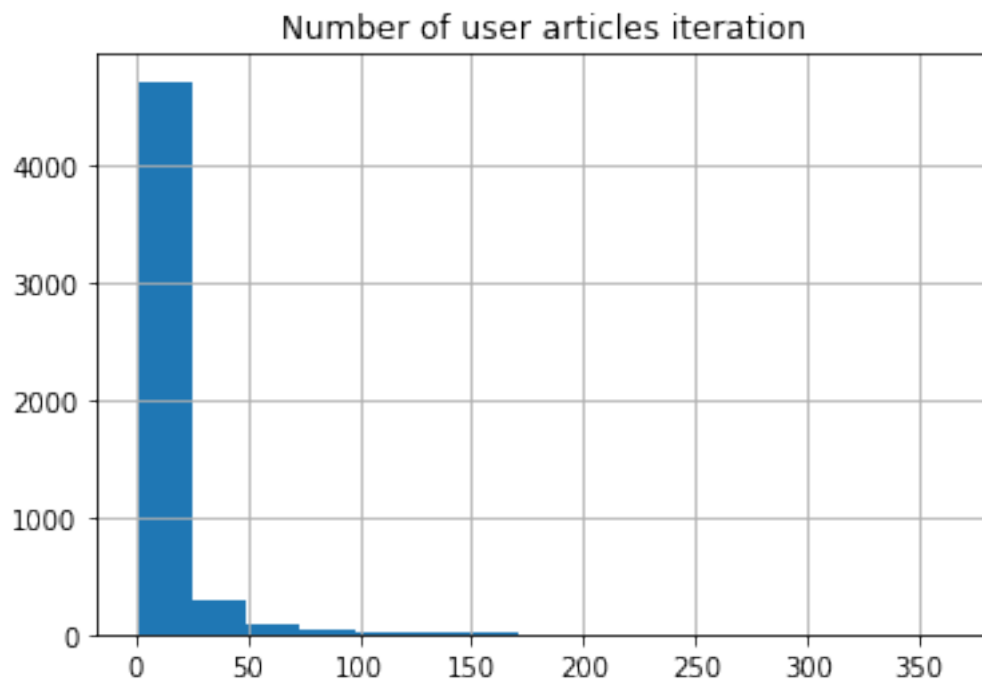
```
article_iteration = article_iteration.sort_values(by=['article_id'],ascending=False)
article_iteration.head()
```

```
Out[6]:
```

	email	article_id
910	2b6c0f514c2f2b04ad3c4583407dccd0810469ee	364
2426	77959baaa9895a7e2bdc9297f8b27c1b6f2cb52a	363
985	2f5c7feae533ce046f2cb16fb3a29fe00528ed66	170
3312	a37adec71b667b297ed2440a9ff7dad427c7ac85	169
2680	8510a5010a5d4c89f5b07baac6de80cd12cfaf93	160

```
In [7]: # Distribution plot by user iteration
article_iteration.hist(bins=15);
plt.title('Number of user articles iteration')
```

```
Out[7]: Text(0.5,1,'Number of user articles iteration')
```



```
In [8]: # print the information
print("50% of individuals interact with {} number of articles or fewer.".format(article_
print("The maximum number of user-article interactions by any 1 user is {}".format(arti
```

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

```
In [9]: # Fill in the median and maximum number of user_article interactios below
```

```
median_val = 3 # 50% of individuals interact with ____ 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 [10]: # Find and explore duplicate articles
print("The number of duplicates in article_id is {}".format(int(df_content.article_id.
duplicated_user=list(df_content['article_id'][df_content.duplicated('article_id')])
print("The articles duplicated are {}".format(duplicated_user))
```

The number of duplicates in article_id is 5.
The articles duplicated are [50, 221, 398, 577, 232]

```
In [11]: df_content[df_content['article_id'].isin(duplicated_user)]
```

```
Out[11]:
```

	doc_body \	doc_description \	doc_full_name	doc_status	article_id
50	Follow Sign in / Sign up Home About Insight Da...	Community Detection at Scale	Graph-based machine learning	Live	50
221	* United States\r\n\r\nIBM® * Site map\r\n\r\n...	When used to make sense of huge amounts of con...	How smart catalogs can turn the big data flood...	Live	221
232	Homepage Follow Sign in Get started Homepage *...	If you are like most data scientists, you are ...	Self-service data preparation with IBM Data Re...	Live	232
365	Follow Sign in / Sign up Home About Insight Da...	During the seven-week Insight Data Engineering...	Graph-based machine learning	Live	50
399	Homepage Follow Sign in Get started * Home\r\n...	Todays world of data science leverages data f...	Using Apache Spark as a parallel processing fr...	Live	398
578	This video shows you how to construct queries ...	This video shows you how to construct queries ...	Use the Primary Index	Live	577
692	Homepage Follow Sign in / Sign up Homepage * H...	One of the earliest documented catalogs was co...	How smart catalogs can turn the big data flood...	Live	221
761	Homepage Follow Sign in Get started Homepage *...	Todays world of data science leverages data f...	Using Apache Spark as a parallel processing fr...	Live	398
970	This video shows you how to construct queries ...	This video shows you how to construct queries ...	Use the Primary Index	Live	577
971	Homepage Follow Sign in Get started * Home\r\n...	If you are like most data scientists, you are ...	Self-service data preparation with IBM Data Re...	Live	232

```
In [12]: # Remove any rows that have the same article_id - only keep the first
df_content = df_content.drop_duplicates('article_id',keep='first')
# check the process
print("The number the duplicated is {}".format(df_content.duplicated().sum()))
print(df_content.shape)
df_content.head()
```

The number the duplicated is 0
(1051, 5)

```
Out[12]:
```

	doc_body \	doc_description \	doc_full_name	doc_status	article_id
0	Skip navigation Sign in SearchLoading...\r\n\r...	Detect bad readings in real time using Python ...	Detect Malfunctioning IoT Sensors with Streami...	Live	0
1	No Free Hunch Navigation * kaggle.com\r\n\r\n ...	See the forest, see the trees. Here lies the c...	Communicating data science: A guide to present...	Live	1
2	* Login\r\n * Sign Up\r\n\r\n * Learning Pat...	Heres this weeks news in Data Science and Bi...	This Week in Data Science (April 18, 2017)	Live	2
3	DATALAYER: HIGH THROUGHPUT, LOW LATENCY AT SCA...	Learn how distributed DBs solve the problem of...	DataLayer Conference: Boost the performance of...	Live	3
4	Skip navigation Sign in SearchLoading...\r\n\r...	This video demonstrates the power of IBM DataS...	Analyze NY Restaurant data using Spark in DSX	Live	4

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 [13]: # unique articles with users in data contents
print("The number of unique articles that have an interaction with a user is {}".format(

#unique articles in the dataset
print("The number of unique articles in the dataset {}".format(df_content.shape[0]))

# unique users names in data base
print("The number of unique users is {}".format(df.email.nunique()))

# unique number of user-article
print("The number of user-article interactions in the dataset is {}".format(df.shape[0])
```

The number of unique articles that have an interaction with a user is 714.
The number of unique articles in the dataset 1051.
The number of unique users is 5148.
The number of user-article interactions in the dataset is 45993.

```
In [14]: unique_articles = 714 # The number of unique articles that have at least one interaction
total_articles = 1051 # The number of unique articles on the IBM platform
unique_users = 5148 # The number of unique users
user_article_interactions = 45993 # 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 [15]: df.groupby('article_id')['email'].count().sort_values(ascending=False).reset_index().head(5)
```

```
Out[15]:
```

	article_id	email
0	1429.0	937
1	1330.0	927
2	1431.0	671
3	1427.0	643
4	1364.0	627

```
In [16]: 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 [17]: ## No need to change the code here - this will be helpful for later parts of the notebook
# 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[17]:
```

	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 [18]: ## 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 [19]: list(df.groupby('title')['user_id'].count().sort_values(ascending=False).head(5).index)
```

```
Out[19]: ['use deep learning for image classification',
          'insights from new york car accident reports',
          'visualize car data with brunel',
          'use xgboost, scikit-learn & ibm watson machine learning apis',
          'predicting churn with the spss random tree algorithm']
```

```
In [20]: list(df.groupby('article_id')['title'].count().sort_values(ascending=False).head(5).index)
```

```
Out[20]: [1429.0, 1330.0, 1431.0, 1427.0, 1364.0]
```

```
In [21]: 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
    #create a list of the top 5 titles
    top_articles = list(df.groupby('title')['user_id'].count().sort_values(ascending=False).head(n))

    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
    # create a list of the top article id

    top_articles = list(df.groupby('article_id')['title'].count().sort_values(ascending=False).head(n))

    return top_articles # Return the top article ids

In [22]: print(get_top_articles(10))
         print(get_top_article_ids(10))

['use deep learning for image classification', 'insights from new york car accident reports', 'v
[1429.0, 1330.0, 1431.0, 1427.0, 1364.0, 1314.0, 1293.0, 1170.0, 1162.0, 1304.0]

In [23]: # 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 [24]: df.groupby(['user_id', 'article_id'])['title'].count().unstack().head()
```

```
Out[24]: article_id  0.0      2.0      4.0      8.0      9.0      12.0      14.0      15.0  \
user_id
1           NaN      NaN      NaN      NaN      NaN      NaN      NaN      NaN
2           NaN      NaN      NaN      NaN      NaN      NaN      NaN      NaN
3           NaN      NaN      NaN      NaN      NaN      1.0      NaN      NaN
4           NaN      NaN      NaN      NaN      NaN      NaN      NaN      NaN
5           NaN      NaN      NaN      NaN      NaN      NaN      NaN      NaN

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

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

[5 rows x 714 columns]
```

```
In [25]: # 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
# create matrix
user_item = df.groupby(['user_id', 'article_id'])['title'].count().unstack()
# fill nan with 0
user_item = user_item.fillna(0)
# change type
user_item = user_item.astype('int')
# put all iteration with 1

user_item[user_item > 1] = 1

return user_item # return the user_item matrix

user_item = create_user_item_matrix(df)

```

In [26]: *## 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 matrix is not 5149"
assert user_item.shape[1] == 714, "Oops! The number of articles in the user-article matrix is not 714"
assert user_item.sum(axis=1)[1] == 36, "Oops! The number of articles seen by user 1 does not equal 36"
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 [27]: `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(user_item.loc[user_id])
```

```
# sort by similarity
```

```
similarity_sort = similarity.sort_values(ascending=False)
```

```
# create list of just the ids
```

```
most_similar_users = list(similarity_sort.index)
```

```
# 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 [28]: # 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)[:5]))
```

```
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 [29]: 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 ids (this is identified by the title column)

```
'''
```

```
# Your code here
```

```
# create a list of article names
```

```
article_names = list(np.unique(df[df.article_id.astype('str').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
    # create a list of article id
    article_ids = user_item.loc[user_id]
    article_ids = [str(name_id) for name_id in article_ids[article_ids==1].index]
    # create a list of article names
    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 recs
    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
# use the function a get the article id
user_articles = pd.Series(get_user_articles(user_id)[0])
# use the fuctiona a get the users id
similar_user = find_similar_users(user_id)

#iterate for recommendation for users
recs_total = list(df[df['user_id'].isin(similar_user)]['article_id'].astype('str'))
recs = pd.Series([x for x in recs_total if x not in user_articles])
recs = list(set(recs))[:m]
return recs # return your recommendations for this user_id

```

In [30]: # Check Results

```

get_article_names(user_user_recs(1, 10)) # Return 10 recommendations for user 1

```

Out[30]: ['airbnb data for analytics: paris calendar',
'analyze precipitation data',
'announcing dsx environments in beta!',
'building custom machine learning algorithms with apache systemml',
'finding optimal locations of new store using decision optimization',
'how can data scientists collaborate to build better business',
'migrating to python 3 with pleasure',
'this week in data science (april 4, 2017)',
'this week in data science (august 02, 2016)',
'working interactively with rstudio and notebooks in dsx']

In [31]: # 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', '1431.0', '1439.0', '1442.0', '1443.0', '1444.0', '1445.0', '1446.0', '1447.0', '1448.0', '1449.0', '1450.0', '1451.0', '1452.0', '1453.0', '1454.0', '1455.0', '1456.0', '1457.0', '1458.0', '1459.0', '1460.0', '1461.0', '1462.0', '1463.0', '1464.0', '1465.0', '1466.0', '1467.0', '1468.0', '1469.0', '1470.0', '1471.0', '1472.0', '1473.0', '1474.0', '1475.0', '1476.0', '1477.0', '1478.0', '1479.0', '1480.0', '1481.0', '1482.0', '1483.0', '1484.0', '1485.0', '1486.0', '1487.0', '1488.0', '1489.0', '1490.0', '1491.0', '1492.0', '1493.0', '1494.0', '1495.0', '1496.0', '1497.0', '1498.0', '1499.0'])) == set(['housing (2015): united states demographic trends', 'the rise of the sharing economy', 'the future of work', 'the future of education', 'the future of healthcare', 'the future of transportation', 'the future of energy', 'the future of finance', 'the future of technology', 'the future of the environment', 'the future of the city', 'the future of the workplace', 'the future of the classroom', 'the future of the hospital', 'the future of the factory', 'the future of the office', 'the future of the home', 'the future of the car', 'the future of the plane', 'the future of the ship', 'the future of the train', 'the future of the bus', 'the future of the truck', 'the future of the boat', 'the future of the carpool', 'the future of the train', 'the future of the bus', 'the future of the truck', 'the future of the boat', 'the future of the carpool'])
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 trends', 'the rise of the sharing economy', 'the future of work', 'the future of education', 'the future of healthcare', 'the future of transportation', 'the future of energy', 'the future of finance', 'the future of technology', 'the future of the environment', 'the future of the city', 'the future of the workplace', 'the future of the classroom', 'the future of the hospital', 'the future of the factory', 'the future of the office', 'the future of the home', 'the future of the car', 'the future of the plane', 'the future of the ship', 'the future of the train', 'the future of the bus', 'the future of the truck', 'the future of the boat', 'the future of the carpool', 'the future of the train', 'the future of the bus', 'the future of the truck', 'the future of the boat', 'the future of the carpool'])
assert set(get_user_articles(2)[0]) == set(['1024.0', '1176.0', '1305.0', '1314.0', '1422.0', '1427.0', '1431.0', '1439.0', '1442.0', '1443.0', '1444.0', '1445.0', '1446.0', '1447.0', '1448.0', '1449.0', '1450.0', '1451.0', '1452.0', '1453.0', '1454.0', '1455.0', '1456.0', '1457.0', '1458.0', '1459.0', '1460.0', '1461.0', '1462.0', '1463.0', '1464.0', '1465.0', '1466.0', '1467.0', '1468.0', '1469.0', '1470.0', '1471.0', '1472.0', '1473.0', '1474.0', '1475.0', '1476.0', '1477.0', '1478.0', '1479.0', '1480.0', '1481.0', '1482.0', '1483.0', '1484.0', '1485.0', '1486.0', '1487.0', '1488.0', '1489.0', '1490.0', '1491.0', '1492.0', '1493.0', '1494.0', '1495.0', '1496.0', '1497.0', '1498.0', '1499.0'])
assert set(get_user_articles(2)[1]) == set(['using deep learning to reconstruct high-resolution face images', 'the rise of the sharing economy', 'the future of work', 'the future of education', 'the future of healthcare', 'the future of transportation', 'the future of energy', 'the future of finance', 'the future of technology', 'the future of the environment', 'the future of the city', 'the future of the workplace', 'the future of the classroom', 'the future of the hospital', 'the future of the factory', 'the future of the office', 'the future of the home', 'the future of the car', 'the future of the plane', 'the future of the ship', 'the future of the train', 'the future of the bus', 'the future of the truck', 'the future of the boat', 'the future of the carpool', 'the future of the train', 'the future of the bus', 'the future of the truck', 'the future of the boat', 'the future of the carpool'])
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 [78]: 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
        #create the dataframe
        neighbors_df = pd.DataFrame(columns=['neighbor_id', 'similarity', 'num_interactions'])
        #define user
        neighbors_df['neighbor_id'] = user_item.index
        #define most iterations
        neighbors_df['similarity'] = user_item.dot(user_item.loc[user_id]).values
        #the number of acticles viewed
        interactions = df.groupby('user_id')['article_id'].count()
        neighbors_df['num_interactions'] = neighbors_df.neighbor_id.apply(lambda x: interactions[x])
        neighbors_df = neighbors_df[neighbors_df.neighbor_id != user_id]

        neighbors_df.sort_values(by=['similarity', 'num_interactions'], ascending=[False, False])

        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 recs
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
# get user actiles
user_articles = get_user_articles(user_id)[0]

top_neighbors = list(get_top_sorted_users(user_id)['neighbor_id'].values)

recs = np.array([])
for user in top_neighbors:
    other_user_articles = get_user_articles(user, user_item)[0]

    new_recs = np.setdiff1d(other_user_articles, user_articles, assume_unique=True)

    recs = np.unique(np.concatenate([new_recs, recs], axis=0))

    if len(recs) >= m:
        break

recs = list(recs[:m])
rec_names = get_article_names(recs)

return recs, rec_names
```

```
In [79]: # 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:

['1024.0', '1085.0', '109.0', '1150.0', '1151.0', '1152.0', '1153.0', '1154.0', '1157.0', '1160.0']

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

['airbnb data for analytics: chicago listings', 'airbnb data for analytics: venice calendar', 'a

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 [80]: print(get_top_sorted_users(1).head(1))
         print(get_top_sorted_users(131).head(10))
```

	neighbor_id	similarity	num_interactions
3932	3933	35	45
	neighbor_id	similarity	num_interactions
3869	3870	74	144
3781	3782	39	363
22	23	38	364
202	203	33	160
4458	4459	33	158
97	98	29	170
3763	3764	29	169
48	49	29	147
3696	3697	29	145
241	242	25	148

```
In [35]: ### Tests with a dictionary of results
```

```
user1_most_sim = 3933 # Find the user that is most similar to user 1
user131_10th_sim = 242 # Find the 10th most similar user to user 131
```

```
In [36]: ## 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.

This project considered two types of recommendations systems, for the case that we need to do a recommendation for new users, the best approach is using rank-based, because it is a new user does not have iterations with the data base. For that we have to use a ranked-Based recommendation system

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 [37]: 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(id_user) for id_user in get_top_article_ids(10)] # Your recommenda

In [38]: 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 [39]: # Load the matrix here
```

```
user_item_matrix = pd.read_pickle('user_item_matrix.p')
```

```
In [40]: # quick look at the matrix
```

```
user_item_matrix.head()
```

```
Out[40]: 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 [41]: # 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
```

We can use SVD because we do not have NaN values and this project we do not have any rankings in the information we have the possibility of articles, if the article has more than one iteration we considered that just have 1 and all the NaN values take a 0.

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

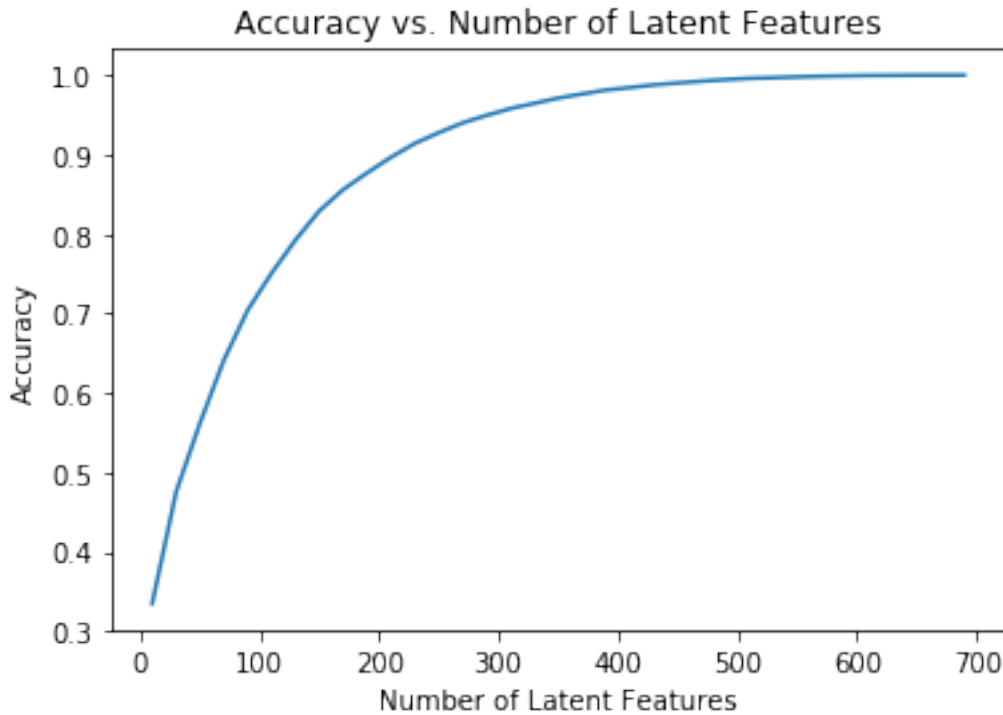
```
for k in num_latent_feats:
    # restructure with k latent features
    s_new, u_new, vt_new = np.diag(s[:k]), u[:, :k], vt[:k, :]

    # 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 [43]: 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 = 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 [44]: #print train shape
print("The train matrix is {}".format(user_item_train.shape))
#print test shape
print("The test matrix is {}".format(user_item_test.shape))
# print prediction
print("The number of predictions {}".format(len(pd.Series(x for x in user_item_train.i

The train matrix is (4487, 714).
The test matrix is (682, 574).
The number of predictions 20.

In [45]: # 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 articles can we make predictions for in the test set?': b, # letter here,
    'How many articles in the test set are we not able to make predictions for because
}

t.sol_4_test(sol_4_dict)

```

Awesome job! That's right! All of the test articles are in the training data, but there are on

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 [46]: # fit SVD on the user_item_train matrix
         u_train, s_train, vt_train = np.linalg.svd(user_item_train) # fit svd similar to above

In [47]: # Use these cells to see how well you can use the training
         # decomposition to predict on test data
         decom_idx_train = user_item_train.index.isin(test_idx)
         decom_cols_train = user_item_train.columns.isin(test_arts)

In [48]: #define U test
         u_test = u_train[decom_idx_train,:]
         #Define VT test
         vt_test = vt_train[:,decom_cols_train]

In [49]: train_idx = user_item_train.index
         decom_idx = list(set(train_idx)&set(test_idx))
         decom_cols = user_item_train.columns.intersection(test_arts)
         user_item_test = user_item_test.loc[decom_idx]

In [50]: num_latent_feats = np.arange(10,700+10,20)
         sum_train_errs = []
         sum_test_errs = []

         for k in num_latent_feats:
             # restructure with k latent features
             s_new_train, u_new_train, vt_new_train = np.diag(s_train[:k]), u_train[:, :k], vt_train[:, :k]
             u_new_test, vt_new_test = u_test[:, :k], vt_test[:, :k]

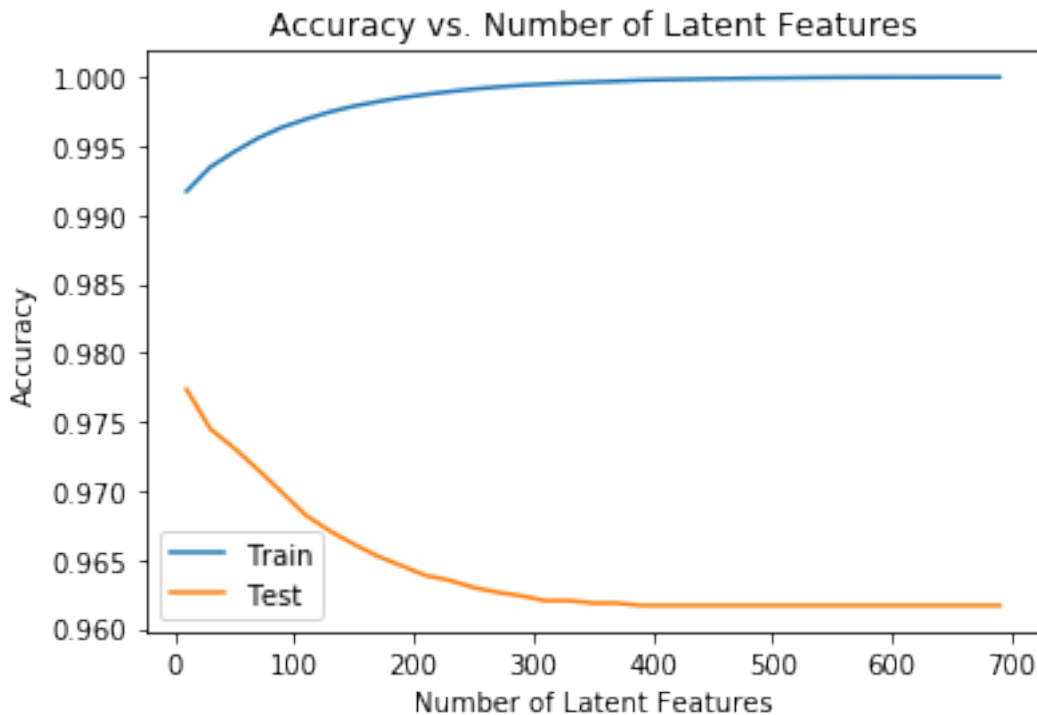
             # take dot product
             user_item_train_pred = np.around(np.dot(np.dot(u_new_train, s_new_train), vt_new_train))
             user_item_test_pred = np.around(np.dot(np.dot(u_new_test, s_new_train), vt_new_test))

             # compute error for each prediction to actual value
             diffs_train = np.subtract(user_item_train, user_item_train_pred)
             diffs_test = np.subtract(user_item_test, user_item_test_pred)

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

             err_test = np.sum(np.sum(np.abs(diffs_test)))
             sum_test_errs.append(err_test)
```

```
plt.plot(num_latent_feats, 1 - np.array(sum_train_errs)/(user_item_train.shape[0]*user_item_train.shape[1]));
plt.plot(num_latent_feats, 1 - np.array(sum_test_errs)/(user_item_test.shape[0]*user_item_test.shape[1]));
plt.xlabel('Number of Latent Features');
plt.ylabel('Accuracy');
plt.title('Accuracy vs. Number of Latent Features');
plt.legend();
```



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?

Using ranked base we make recommendation system has good fitting and good accuracy over the number the latent features be in near to 1 we can see that in the blue line for train. Otherwise the test does not have the same behavior because over new features loss accuracy and create a gap between train in test that happens because we have a small database and just with implement a SVD right away that wil produce a incredible model and performance from in it. This means that we need a combination of ranked base system and a colaborative filter recommendation for give a good performance model for new users and also for right now users this make that have a well recommendation.

If we implement a A/B test as we did in the software example in the lessons. That will give new features also create new feactures base en scale of ranking(1-5) base on the usefull of the article. Also cookies can help base in the click that a users do and the time spend in each article. This could increase the accuracy that it is a good metric for this kind of exercises

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 are 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 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** sub-menu, 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 [51]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Recommendations_with_IBM.ipynb'])
```

```
Out[51]: 0
```

```
In [ ]:
```