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.

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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.

```
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.sort_values(by="article_id").head(5)
```

```
       article_id
title  \
1935          0.0  detect malfunctioning iot sensors with streami...

40755         0.0  detect malfunctioning iot sensors with streami...
```

```
42948         0.0  detect malfunctioning iot sensors with streami...

2328          0.0  detect malfunctioning iot sensors with streami...

19242         0.0  detect malfunctioning iot sensors with streami...


                                          email
1935   384255292a8223e84f05ca1e1deaa450c993e148
40755  8bd0afc488016810c287ac4ec844895d570b0af4
42948  451a9a4a4cb1cc4e5f38d04e8859cc3fb275cc66
2328   ca7d48adf2c7394ed5a8776de959fa8047e43d4b
19242  a60b7e945a8f2114d5dfbdd53182ad1d526534e2
```

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

```
                                            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  Here’s this week’s 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
```

Part I : Exploratory Data Analysis

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

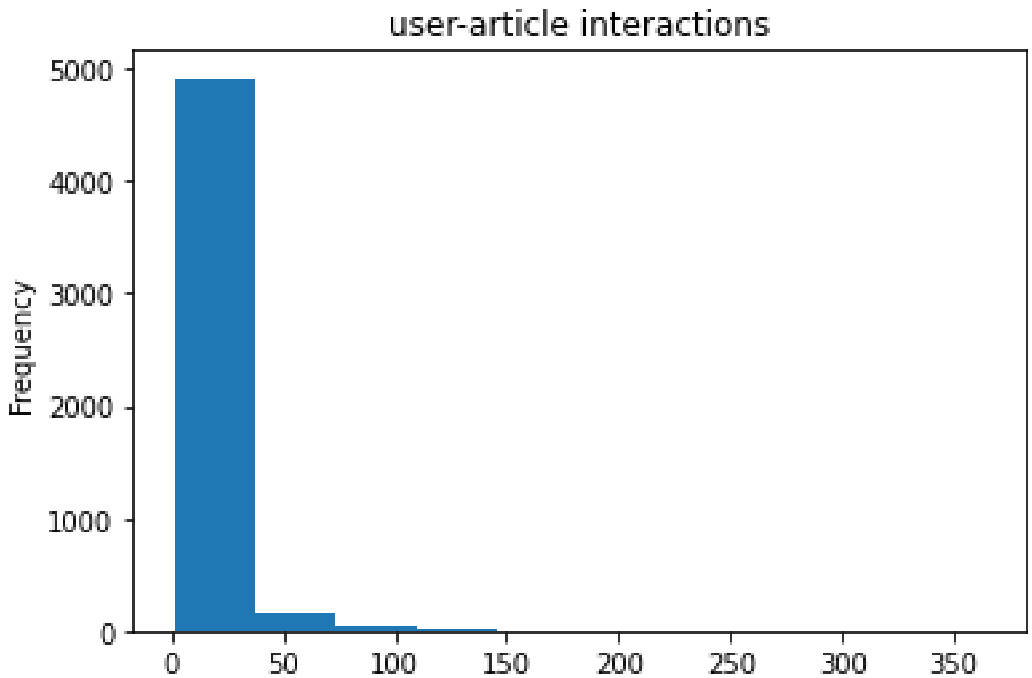
1. What is the distribution of how many articles a user interacts with in the dataset? Provide a visual and descriptive statistics to assist with giving a look at the number of times each user interacts with an article.

```
# To find the number of articles an user has interacted with, lets
first group the  "user-item-interactions" dataset by the "email"
column
groupby_email = df.groupby(by="email")

# check to see if groupby_email DataframeGroupBy object is
instantiated
groupby_email

<pandas.core.groupby.generic.DataFrameGroupBy object at
0x000002C048DF7640>

# Lets now see the number of articles each user has interacted with
user_interaction_counts=groupby_email["article_id"].count()
user_interaction_counts

email
0000b6387a0366322d7fbfc6434af145adf7fed1    13
001055fc0bb67f71e8fa17002342b256a30254cd     4
00148e4911c7e04eeff8def7bbbdaf1c59c2c621     3
001a852ecbd6cc12ab77a785efa137b2646505fe     6
001fc95b90da5c3cb12c501d201a915e4f093290     2
                                            ..
ffc6cfa435937ca0df967b44e9178439d04e3537     2
ffc96f8fbb35aac4cb0029332b0fc78e7766bb5d     4
ffe3d0543c9046d35c2ee3724ea9d774dff98a32    32
fff9fc3ec67bd18ed57a34ed1e67410942c4cd81    10
fffb93a166547448a0ff0232558118d59395fecd    13
Name: article_id, Length: 5148, dtype: int64

# Fill in the median and maximum number of user_article interactions
below

median_val = user_interaction_counts.median() #50% of individuals
interact with 3 number of articles or fewer.
max_views_by_user = user_interaction_counts.max() # The maximum number
of user-article interactions by any 1 user is 364.
median_val,max_views_by_user

(3.0, 364)

# lets now look at some stats around the counts of articles
interaction by the users using the describe() method
user_interaction_counts.describe()

count    5148.000000
mean        8.930847
std        16.802267
```

```
min         1.000000
25%         1.000000
50%         3.000000
75%         9.000000
max       364.000000
Name: article_id, dtype: float64
```

looks like the the max number of articles any 1 user has interacted with is 364 and the median is 3, and on average an user has interacted with around 9 articles

```python
# lets create a function to plot a simple visual that shows the
frequency distribution of user interactions  with the articles

from matplotlib.pyplot import title


def plot_user_interactions_counts(df,plot_type):
    """
    A function to plot a visual around the user interaction counts
with the articles

    Paramters
    df: name of the df that is grouped by email and has counts of
articles per email
    plot_type: kind of chart in a string format

    Returns
    Plot with frequency of user interaction  with the articles
    """

    return df.plot(kind=plot_type, title="user-article interactions")

# Calling the plot_user_interactions_counts function to plot the user
interaction counts using a histogram
plot_user_interactions_counts(user_interaction_counts,"hist");
```



the above histogram shows the distribution of interactions

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

```
# Find and explore duplicate articles
# lets first look at a sample of the dataframe
df_content.sample(5)

                                               doc_body  \
805  CONNECTING TO COMPOSE FOR MYSQL\r\nShare on Tw...
49   Compose The Compose logo Articles Sign in Free...
502  G. Adam Cox Blocked Unblock Follow Following J...
3    DATALAYER: HIGH THROUGHPUT, LOW LATENCY AT SCA...
386  Skip to main content IBM developerWorks / Deve...

                                        doc_description  \
805  Here, we'll take you from provisioning your ow...
49   We'll also look at using PostGIS to filter our...
502  The SETI@IBMCloud project and the SETI Institu...
3    Learn how distributed DBs solve the problem of...
386  See how to load new geospatial data into your ...

                                          doc_full_name doc_status
article_id
805                        Connecting to Compose for MySQL       Live
802
49   GeoFile: Using OpenStreetMap Data in Compose P...       Live
49
502  Defensive IBM Object Storage Containers – IBM ...       Live
```

```
501
3    DataLayer Conference: Boost the performance of...       Live
3
386  Load geospatial data into dashDB to analyze in...       Live
385
```

```
# lets first check for any duplicte rows as whole
df_content.duplicated().sum()
```

```
0
```

there are no duplicate rows as a whole (repeated rows)

```
# lets check for duplicate article ids
df_content[df_content.duplicated(subset=["article_id"])]
```

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

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

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

```
# Lets take an article Id from the above results and have a look at
the duplicate rows with that article Id
df_content[df_content.loc[:,"article_id"]==221]
```

```
                                              doc_body  \
221  * United States\r\n\r\nIBM® * Site map\r\n\r\n...
692  Homepage Follow Sign in / Sign up Homepage * H...

                                       doc_description  \
```

```
221  When used to make sense of huge amounts of con...
692  One of the earliest documented catalogs was co...

                                          doc_full_name doc_status
article_id
221  How smart catalogs can turn the big data flood...       Live
221
692  How smart catalogs can turn the big data flood...       Live
221
```

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

```
# Test if the drop duplicate method worked by pulling an article id
from one of the previous results (pre-drop)
df_content[df_content.loc[:,"article_id"]==221]
```

```
                                               doc_body  \
221  * United States\r\n\r\nIBM® * Site map\r\n\r\n...

                                        doc_description  \
221  When used to make sense of huge amounts of con...

                                          doc_full_name doc_status
article_id
221  How smart catalogs can turn the big data flood...       Live
221
```

Looks like the drop_duplicate method worked fine

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.

```
# to look at the number of unique articles that have an interaction
with a user , lets first look at articles in the df
df["article_id"]
```

```
0        1430.0
1        1314.0
2        1429.0
3        1338.0
4        1276.0
          ...
45988    1324.0
45989     142.0
45990     233.0
```

```
45991    1160.0
45992      16.0
Name: article_id, Length: 45993, dtype: float64
```

```
# lets do a unique value count using the nunique() method on the above
series to find out the number of unique articles that have an
interaction with a user
df["article_id"].nunique()
```

```
714
```

```
# to find the number of unique articles in the dataset (whether they
have any interactions or not). Lets look at the articles in df_content
and use the nunique() method
df_content["article_id"].nunique()
```

```
1051
```

```
# to find number of unique users in the dataset. (excluding null
values), lets just call the nunique() method on the email column of
the df dataframe
df["email"].nunique()
```

```
5148
```

```
# to find the number of user-article interactions in the dataset, lets
just call the shape attribute on the df dataframe and use slice
notation to find the number of rows
df.shape[0]
```

```
45993
```

```
unique_articles = df["article_id"].nunique() # The number of unique
articles that have at least one interaction
total_articles = df_content["article_id"].nunique() # The number of
unique articles on the IBM platform
unique_users = df["email"].nunique() # The number of unique users
user_article_interactions = df.shape[0] # The number of user-article
interactions
```

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

```
# to find the most viewed article_id, as well as how often it was
viewed.
# lets call the value_counts() method on the article_id column of the
df dataframe
# and also use the head(1) method to display the top most article_id
df["article_id"].value_counts(ascending=False).head(1)
```

```
1429.0    937
Name: article_id, dtype: int64

most_viewed_article_id = '1429.0'  # The most viewed article in the
dataset as a string with one value following the decimal
max_views = 937 # The most viewed article in the dataset was viewed
how many times?

## 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()

   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

## 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_article_interactions,
    '`The maximum number of user-article interactions by any 1 user is
______.`': max_views_by_user,
    '`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_articles,
    '`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!
```

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.

```
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
    top_articles=list(df.title.value_counts().head(n).index) #
value_counts() method to create series of counts of titles and head()
function to retrieve the top n records
    return top_articles # Return the top article titles from df (not
df_content)

def get_top_article_ids(n, df=df):
    '''
```

```
    INPUT:
    n - (int) the number of top articles to return
    df - (pandas dataframe) df as defined at the top of the notebook

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

    '''
    # Your code here
    top_articles=list(df.article_id.value_counts().head(n).index) #
value_counts() method to create series of counts of ids and head()
function to retrieve the top n records
    top_articles = [str(x) for x in top_articles]
    return top_articles # Return the top article ids

print(get_top_articles(10))
print(get_top_article_ids(10))
```

```
['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', 'healthcare python streaming
application demo', 'finding optimal locations of new store using
decision optimization', 'apache spark lab, part 1: basic concepts',
'analyze energy consumption in buildings', 'gosales transactions for
logistic regression model']
['1429.0', '1330.0', '1431.0', '1427.0', '1364.0', '1314.0', '1293.0',
'1170.0', '1162.0', '1304.0']
```

```
# 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.
```

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.

```
# 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 where a user interacted with
    an article and a 0 otherwise
    '''

    unstacked=df.groupby(['user_id',
'article_id']).count().unstack().fillna(0) # group by user id and
article ids and perfrom count agg and unstack rows to columns while
filling nulls with 0s
    unstacked.columns= unstacked.columns.droplevel() # drop the extra
column level (level not needed for our matrix)
    user_item=unstacked.applymap(lambda x: 1 if x > 1 else x ) #
making sure all the values inside the matrix is either 0 or 1

    return user_item # return the user_item matrix

user_item = create_user_item_matrix(df)

## 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 doesn't look right."
assert user_item.shape[1] == 714, "Oops!  The number of articles in
the user-article matrix doesn't look right."
assert user_item.sum(axis=1)[1] == 36, "Oops!  The number of articles
seen by user 1 doesn't look right."
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.

```python
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 users)
                    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_series = user_item.dot(user_item.T)[user_id]
    # sort by similarity
    most_similar_users=similarity_series.sort_values(ascending =
False)
    # create list of just the ids
    most_similar_users=list(most_similar_users.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 similar


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

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

```
df.head()
```

```
   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
```

```
user_item.head()
```

```
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]
```

```
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)
    '''
    # create a list of article names identified by the the title
column associated with the list of article ids
    article_names = [df[df["article_id"] == float(x)]["title"].max()
for x in article_ids]

    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 ids
                    (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
    '''
    # pull all the article ids for the user which donot zeros for
their values in the user_item df
    article_ids = user_item.loc[user_id][user_item.loc[user_id] !=
0].index.astype(str)
    # pass the article_ids to the get_article_names function to get
the article names for those ids
    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

    '''
    # Ids of articles seen by user (we don't want to recommend these)
    user_seen = get_user_articles(user_id)[0]
    # Similar users to the current user
    similar_users = find_similar_users(user_id)

    # Keep the recommended articles here
    recs = []

    # Go through the similar users and identify articles they like the
user hasn't seen
    for similar_user in similar_users:
```

```
        similar_user_seen = get_user_articles(similar_user)[0]
        # Obtain recommendations from similar user without the
articles seen by the user
        new_recs = np.setdiff1d(similar_user_seen, user_seen,
assume_unique=True)
        # Update recs with new recs; concat rec and new_rec arrays and
return only unique values
        recs = np.unique(np.concatenate([new_recs, recs], axis = 0))

        # If we have enough recommendations exit the loop
        if len(recs) > m-1:
            break



    return recs[:m] # return your recommendations for this user_id

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

```
['recommender systems: approaches & algorithms',
 '1448    i ranked every intro to data science course on...\nName:
title, dtype: object',
 'data tidying in data science experience',
 'a tensorflow regression model to predict house values',
 '520    using notebooks with pixiedust for fast, flexi...\nName:
title, dtype: object',
 'airbnb data for analytics: mallorca reviews',
 'airbnb data for analytics: vancouver listings',
 'analyze facebook data using ibm watson and watson studio',
 'analyze accident reports on amazon emr spark',
 'analyze energy consumption in buildings']
```

```
# 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'])) == set(['using deep learning to reconstruct
high-resolution audio', 'build a python app on the streaming analytics
service', 'gosales transactions for naive bayes model', 'healthcare
python streaming application demo', 'use r dataframes & ibm watson
natural language understanding', 'use xgboost, scikit-learn & ibm
watson machine learning apis']), "Oops! Your the get_article_names
function doesn't work quite how we expect."
assert set(get_article_names(['1320.0', '232.0', '844.0'])) ==
set(['housing (2015): united states demographic measures','self-
service data preparation with ibm data refinery','use the cloudant-
spark connector in python notebook']), "Oops! Your the
get_article_names function doesn't work quite how we expect."
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 measures', 'self-service data preparation with ibm
data refinery','use the cloudant-spark connector in python notebook'])
assert set(get_user_articles(2)[0]) == set(['1024.0', '1176.0',
'1305.0', '1314.0', '1422.0', '1427.0'])
assert set(get_user_articles(2)[1]) == set(['using deep learning to
reconstruct high-resolution audio', 'build a python app on the
streaming analytics service', 'gosales transactions for naive bayes
model', 'healthcare python streaming application demo', 'use r
dataframes & ibm watson natural language understanding', 'use xgboost,
scikit-learn & ibm watson machine learning apis'])
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.

```
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 user_id
                    num_interactions - the number of articles viewed
by the user - if a u

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

```
    '''
    # create an empty dataframe with "neighbor_id",
"similarity","num_interactions" columns
    neighbors_df=pd.DataFrame(columns=["neighbor_id",
"similarity","num_interactions"])

    # set the "neighbor_id" column and remove the own user_id of the
user
    neighbors_df["neighbor_id"]=[id for id in
range(1,user_item.shape[0]) if id != user_id]

    # set the "similarity" column to most similar using dot product
    neighbors_df["similarity"] =
neighbors_df["neighbor_id"].apply(lambda x:
np.dot(user_item.loc[user_id], user_item.loc[x]))


    # set the "num_interactions" column to user_interactions_counts
series
    # create a series of user_interactions_counts created using
grouping of "user_id"
    user_interactions_counts = df.groupby(["user_id"])
["article_id"].count()

neighbors_df["num_interactions"]=neighbors_df["neighbor_id"].apply(lam
bda x: user_interactions_counts.loc[x].sum())

    # sort dataframe ascending by "similarity","num_interactions" and
reset index to start from 0

neighbors_df=neighbors_df.sort_values(by=["similarity","num_interactio
ns"],ascending=False).reset_index(drop=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 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 4
    before choosing those with fewer total interactions.

    '''



    # article ids,names read by our user ; don't want to recommend
these
    user_articles_ids_read, user_articles_names_read =
get_user_articles(user_id, user_item)

    # top similar user ids closest to our user
    similar_users = get_top_sorted_users(user_id, df, user_item)
["neighbor_id"]

    # keep the recommended articles here
    recs = []

    for similar_user in similar_users:
        # articles read by similar user
        sim_articles_ids_read, sim_articles_names_read =
get_user_articles(similar_user, user_item)
        # obtain recommendations from similar user without the
articles read by our user
        new_recs = np.setdiff1d(sim_articles_ids_read,
user_articles_ids_read, assume_unique=True)
        # Update recs with new recs; concat rec and new_rec arrays and
return only unique values
        recs = np.unique(np.concatenate([new_recs, recs], axis = 0))
        # break the loop once the number of recs have been reached
        if len(recs) > m-1:
            break


    recs = recs[:m]
    #recs = recs.tolist() # convert to a list
```

```
    rec_names = get_article_names(recs)


    return recs, rec_names
```

```
# 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:
['using deep learning to reconstruct high-resolution audio', 'airbnb
data for analytics: chicago listings', 'tensorflow quick tips',
'airbnb data for analytics: venice calendar', 'airbnb data for
analytics: venice listings', 'airbnb data for analytics: venice
reviews', 'airbnb data for analytics: vienna calendar', 'airbnb data
for analytics: vienna listings', 'airbnb data for analytics:
washington d.c. listings', 'analyze accident reports on amazon emr
spark']
```

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.

```
get_top_sorted_users(1)
```

	neighbor_id	similarity	num_interactions
0	3933	35.0	45
1	23	17.0	364
2	3782	17.0	363
3	203	15.0	160
4	4459	15.0	158
...	...	...	...
5142	5131	0.0	1
5143	5141	0.0	1
5144	5144	0.0	1
5145	5147	0.0	1
5146	5148	0.0	1

```
[5147 rows x 3 columns]
```

```python
get_top_sorted_users(1).iloc[0]
```

```
neighbor_id         3933.0
similarity            35.0
num_interactions      45.0
Name: 0, dtype: float64
```

```python
get_top_sorted_users(131).iloc[9]
```

```
neighbor_id         242.0
similarity           25.0
num_interactions    148.0
Name: 9, dtype: float64
```

```python
### Tests with a dictionary of results

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

## 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.

If we were given a new user, I would use the get_top_articles() function and provide the user with the rank based recommendations (suggest the top ranked articles) and that is because we do not have any user-article interaction information about the user. We cannot find similar users (neighbours) if we do not have that information. The other methods individually (content, collabrative, knowledge) may not be as useful in such a situation.

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.

```python
new_user = '0.0'

# What would your recommendations be for this new user '0.0'?  As a
new user, they have no observed articles.
# Provide a list of the top 10 article ids you would give to
new_user_recs = get_top_article_ids(10)# Your recommendations here
```

```python
new_user_recs
```

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

```python
assert set(new_user_recs) ==
set(['1314.0','1429.0','1293.0','1427.0','1162.0','1364.0','1304.0','1
170.0','1431.0','1330.0']), "Oops!  It makes sense that in this case
we would want to recommend the most popular articles, because we don't
know anything about these users."

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

```
That's right!  Nice job!
```

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.

```python
# Load the matrix here
user_item_matrix = pd.read_pickle('user_item_matrix.p')
```

```python
# a quick look at the matrix
user_item_matrix.head()
```

```
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.

```
# 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

# checking to see if any rows in the user_item_matrix has an NaNs
user_item_matrix.isna().sum().sort_values(ascending=False)
```

```
article_id
0.0       0
485.0     0
443.0     0
444.0     0
446.0     0
```

```
         ..
1338.0    0
134.0     0
1340.0    0
1343.0    0
997.0     0
Length: 714, dtype: int64
```

there are no rows in the matrix that has null values

```python
# checking to see if any rows in the user_item_matrix have values
other than 0 and 1
(~user_item_matrix.isin([0,1])).sum().sort_values(ascending=False)
```

```
article_id
0.0       0
485.0     0
443.0     0
444.0     0
446.0     0
         ..
1338.0    0
134.0     0
1340.0    0
1343.0    0
997.0     0
Length: 714, dtype: int64
```

fortunately there are no rows in the matrix that have values other than 0's and 1's

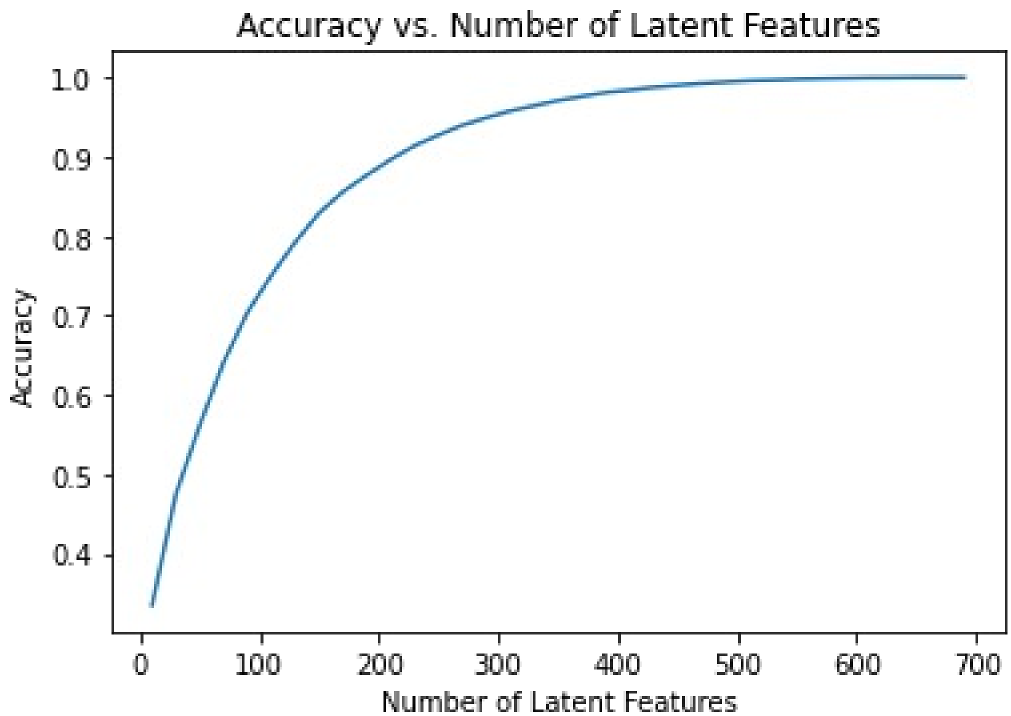
Provide your response here.

As there are no null values in the user_item_matrix , SVD is a very good candidate. Also the matrix has only 1's and 0's (interactions vs no interactions). As far as the lesson is concerned the matrix had lot of null values and FunkSVD was opted. But in our scenario SVD should work just fine.

`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.

```python
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?

```
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

    '''

    user_item_train = create_user_item_matrix(df_train) # Returns a
train matrix with user ids as rows and article ids on the columns
    user_item_test = create_user_item_matrix(df_test) # Returns a test
matrix with user ids as rows and article ids on the columns

    test_idx = user_item_test.index # all of the test user ids
    test_arts = user_item_test.columns # all of the test article ids

    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(df_train, df_test)

# How many users can we make predictions for in the test set?
test_set_users = len(test_idx)
print("No of users in test set: ",test_set_users) # no. of users in
test set
train_idx = user_item_train.index # users in training set
print("No of users in train set: ",len(train_idx))
train_test_user_intersect = len((test_idx).intersection(train_idx)) #
Return the number of users exist in both test and train
print("No of users we can make predictions for in  train set:
",train_test_user_intersect)
```

```
# How many users in the test set are we not able to make predictions
for because of the cold start problem?
print("No of users in the test set are we not able to make predictions
for because of the cold start problem: ",
np.abs((train_test_user_intersect)-len(test_idx)))

# How many movies can we make predictions for in the test set?
print("No of articles can we make predictions for in the test set:
",len(test_arts))

# How many articles are we not able to make predictions for because of
the cold start problem?
print("No of articles in the test set: ",len(test_arts))
train_arts=user_item_train.columns
print("No of articles in the train set: ",len(train_arts))

train_test_articles_diff = len((test_arts).difference(train_arts)) #
Return the number of articles exist in test but not train
print("Movies in the test set we're not able to make predictions for
because of the cold start problem: ",train_test_articles_diff)
```

```
No of users in test set:  682
No of users in train set:  4487
No of users we can make predictions for in  train set:  20
No of users in the test set are we not able to make predictions for
because of the cold start problem:  662
No of articles can we make predictions for in the test set:  574
No of articles in the test set:  574
No of articles in the train set:  714
Movies in the test set we're not able to make predictions for because
of the cold start problem:  0
```

```
# Replace the values in the dictionary below
a = 662
b = 574
c = 20
d = 0



sol_4_dict = {
    'How many users can we make predictions for in the test set?': c,
    'How many users in the test set are we not able to make
predictions for because of the cold start problem?': a,
    'How many movies can we make predictions for in the test set?': b,
# replacing "articles" with "movies" to match code in project_tests.py
https://knowledge.udacity.com/questions/770708
    'How many movies in the test set are we not able to make
predictions for because of the cold start problem?': d # replacing
"articles" with "movies" to match code in project_tests.py
https://knowledge.udacity.com/questions/770708
```

```
}

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 20 test users that were also in the
training set.  All of the other users that are in the test set we have
no data on.  Therefore, we cannot make predictions for these users
using SVD.
```

`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.

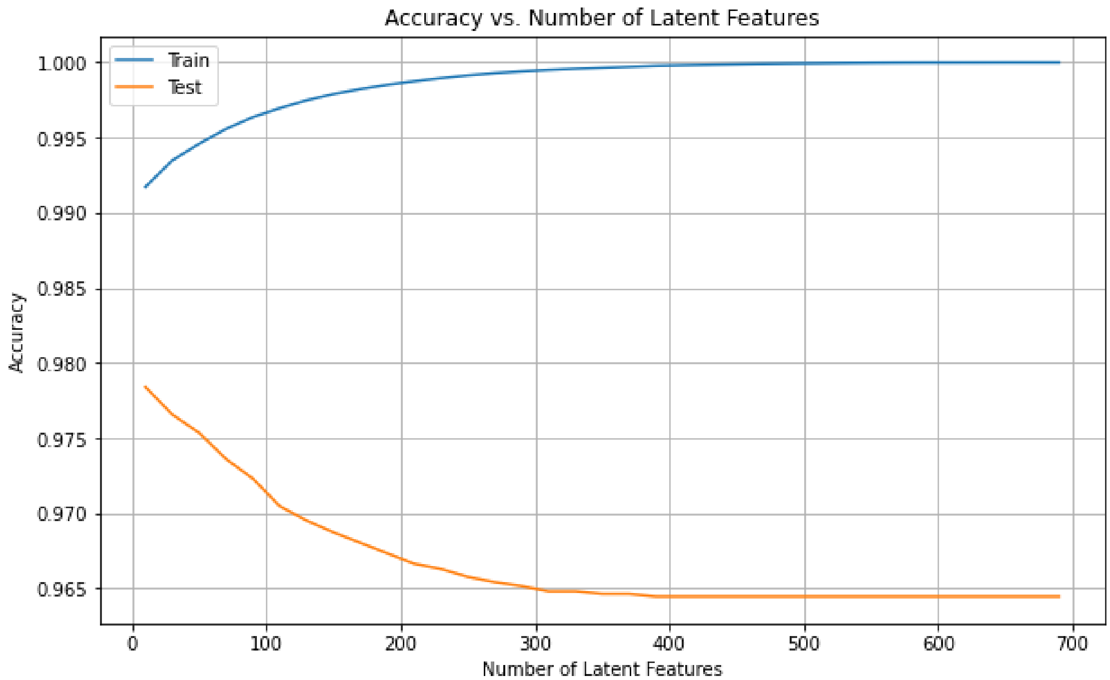
Use the cells below to explore how well SVD works towards making predictions for recommendations on the test data.

```
# lets look at a sample of 3 records from user_item_train
user_item_train.sample(3)
```

```
article_id  0.0     2.0     4.0     8.0     9.0     12.0    14.0
15.0    \
user_id

590           0.0     0.0     0.0     0.0     0.0     0.0     0.0
0.0
2756          0.0     0.0     0.0     0.0     0.0     0.0     0.0
0.0
3219          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                     ...

590           0.0     0.0   ...     0.0     0.0     0.0     0.0
0.0
2756          0.0     0.0   ...     0.0     1.0     0.0     0.0
0.0
3219          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
590           0.0     0.0     0.0     0.0     0.0
2756          0.0     0.0     0.0     0.0     0.0
3219          0.0     0.0     0.0     0.0     0.0
```

```
[3 rows x 714 columns]

# 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 then use the cells below

# print the shapes of u,s,vt_train
print(f"u_train_shape: {u_train.shape}, s_train_shape:
{s_train.shape}, vt_train_shape: {vt_train.shape} ")

u_train_shape: (4487, 4487), s_train_shape: (714,), vt_train_shape:
(714, 714)

# Use these cells to see how well you can use the training
# decomposition to predict on test data

# latent features
num_latent_feats = np.arange(10,700+10,20)
# keep sum of errors in train here
sum_errors_train = []
# keep sum of errors in test here
sum_errors_test = []

# common users
row_index = user_item_train.index.isin(test_idx)
# common articles
col_index = user_item_train.columns.isin(test_arts)

u_test = u_train[row_index, :]
vt_test = vt_train[:, col_index]

# users we can predict for in test
test_users_predict =
np.intersect1d(user_item_train.index.tolist(),user_item_test.index.to_
list())
# test matrix with the users from above
user_intersect_train_test = user_item_test.loc[test_users_predict]

for k in num_latent_feats:
    # restructure with k latent features
    s_train_new, u_train_new, vt_train_new = np.diag(s_train[:k]),
u_train[:, :k], vt_train[:k, :]
    u_test_new, vt_test_new = u_test[:, :k], vt_test[:k, :]

    # take dot product
    user_item_train_pred = np.around(np.dot(np.dot(u_train_new,
s_train_new), vt_train_new))
    user_item_test_pred = 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_train_pred)
    diffs_test = np.subtract(user_intersect_train_test,
user_item_test_pred)

    # calculate total errors
    train_errors = np.sum(np.sum(np.abs(diffs_train)))
    test_errors = np.sum(np.sum(np.abs(diffs_test)))

    # keep track of total errors
    sum_errors_train.append(train_errors)
    sum_errors_test.append(test_errors)

# plot the train and test accuracy vs. the number of latent features
fig, ax = plt.subplots(figsize = (10, 6))

plt.plot(num_latent_feats,
        1 -
(np.array(sum_errors_train)/(user_item_train.shape[0]*user_item_train.
shape[1])),
        label="Train");

plt.plot(num_latent_feats,
         1 -
(np.array(sum_errors_test)/(user_intersect_train_test.shape[0]*user_in
tersect_train_test.shape[1])),
         label="Test");

ax.grid("on")
plt.legend();
plt.xlabel("Number of Latent Features");
plt.ylabel("Accuracy");
plt.title("Accuracy vs. Number of Latent Features");
```



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.

As we can see from the visualization the accuracy of the training set increases as the number of latent features increases, but sadly that's the not the case with our test test. For the test data with increase of latent features the the accuracy only tends to decrease.One plausible cause is overfitting meaning the model pefroms very well on the training data but does not generalize well on test and inference data (https://stackoverflow.com/questions/37776333/why-too-many-features-cause-over-fitting). To avoid this scenario we may need to lower the number of latent features.

Also we have noticed that the matrix used is loaded with sparse features which might also be causing the model not to perform well on the training data (https://www.kdnuggets.com/2021/01/sparse-features-machine-learning-models.html#:~:text=Model%20algorithms%20and%20diagnostic%20measures,This%20is%20called%20overfitting)

We know that we can only make predictions for 20 users in the training data as there is only a small overlap of users between these splits. Maybe an improved accuracy can be observed with the an increase in the overlap of users and not just 20 users or we can use a rank based recoomendation system for the rest of users that we can cannot make recommendations for. Also another method to consider would be to create an A/B test or something similar to it to measure how we can use our new recoomendation system to a section of users and rank based recommendation system to the other group and measure the click rate and time spent on the recommended articles and determine if our new recommendation system is working. When we look at training data accuracy in the visual above there is a steep drop after 50 features and continues to drop till it plateaued out at 400 features from where it remained flat. So around 50 latent features would be an optimal number of latent features in this case.

References

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