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.

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.

Table of Contents

In [ ]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import project_tests as t
from scipy.stats import iqr

import seaborn as sns


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']

# Adjusting the article id to be string instead of float
df.article_id = df.article_id.astype(str)

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

Out[ ]:

	article_id	title	email
0	1430.0	using pixiedust for fast, flexible, and easier...	ef5f11f77ba020cd36e1105a00ab868bbdbf7fe7
1	1314.0	healthcare python streaming application demo	083cbdfa93c8444beaa4c5f5e0f5f9198e4f9e0b
2	1429.0	use deep learning for image classification	b96a4f2e92d8572034b1e9b28f9ac673765cd074
3	1338.0	ml optimization using cognitive assistant	06485706b34a5c9bf2a0ecdac41daf7e7654ceb7
4	1276.0	deploy your python model as a restful api	f01220c46fc92c6e6b161b1849de11faacd7ccb2

In [ ]:

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

Out[ ]:

	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

	doc_body	doc_description	doc_full_name	doc_status	article_id
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...	Here's this week's 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

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 visual and descriptive statistics to assist with giving a look at the number of times each user interacts with an article.

In [ ]:

```
# Resume dataset with number of articles by user
df_count_articles = df[['article_id', 'email']].groupby('email').agg(n_article=('article_id', '

df_count_articles
```

Out[ ]:

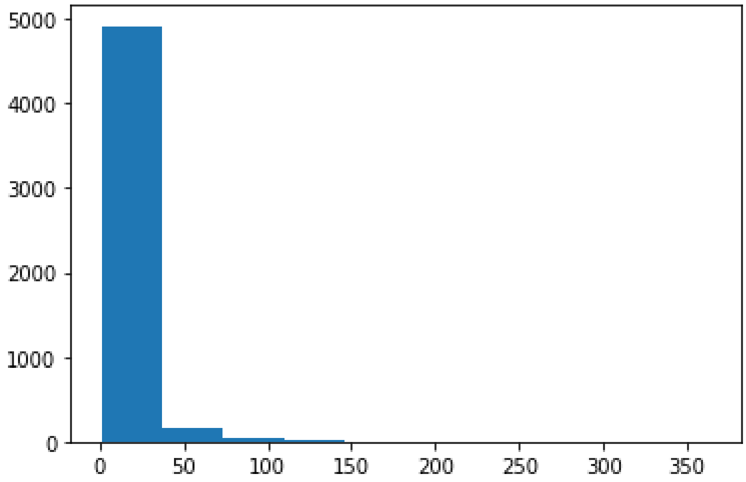
email	n_article
6755c5d49a97e785583f65a92f72bc09459905a9	1
3fbe4978a20ee5ddc07648f2762b808ea18cedd1	1
9c4b5dda1282c94128a7dc778951a313cce8055b	1
3fac88958dc7903b380743597f44a79cf76ea128	1
efdb4c363358224cd99d45053e2dbddf659e25ce	1
...	...
8510a5010a5d4c89f5b07baac6de80cd12cfaf93	160
a37adec71b667b297ed2440a9ff7dad427c7ac85	169
2f5c7feae533ce046f2cb16fb3a29fe00528ed66	170
77959baaa9895a7e2bdc9297f8b27c1b6f2cb52a	363
2b6c0f514c2f2b04ad3c4583407dccd0810469ee	364

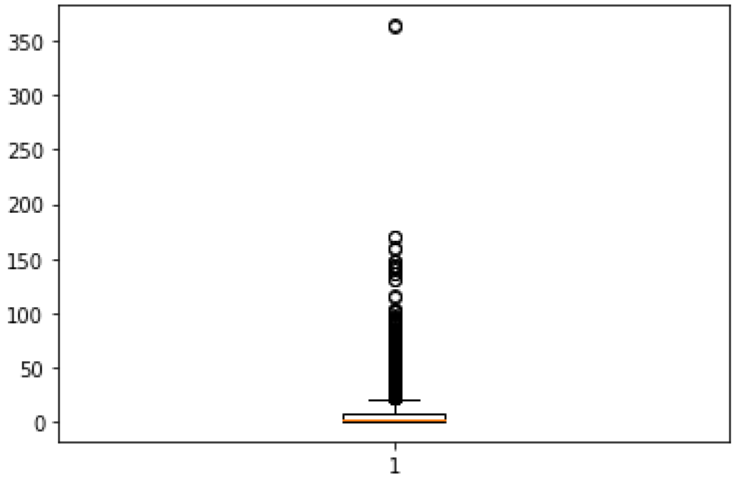
5148 rows × 1 columns

To see better the distribuition of interactions

In [ ]:

```
plt.hist(df_count_articles)
plt.show()

plt.boxplot(df_count_articles)
plt.show()

df_count_articles.describe().T
```





Out[ ]:

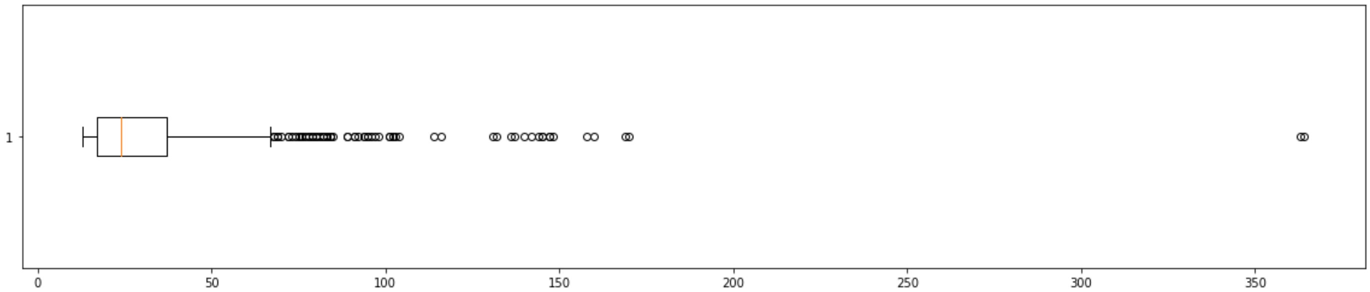
	count	mean	std	min	25%	50%	75%	max
n_article	5148.0	8.930847	16.802267	1.0	1.0	3.0	9.0	364.0

By statistics, it is seen that majority of users interacts with at least 3 articles (median).

Some user are outliers in the dataset, with more than normal.

In [ ]:

```
# Interquartile range
iqr_value = iqr(df_count_articles)



# Filtering the dataset and see the boxplot
plt.figure(figsize=(20,4))
plt.boxplot(df_count_articles[df_count_articles.n_article > 1.5*iqr_value], vert=False )
plt.show()

# Describe it
df_count_articles[df_count_articles.n_article > 1.5*iqr_value].describe().T
```



Out[ ]:

	count	mean	std	min	25%	50%	75%	max
n_article	934.0	32.801927	28.624493	13.0	17.0	24.0	37.0	364.0

Outliers begins in 10 articles and goes until 364, with two users in the region of values

Observing these users closely:

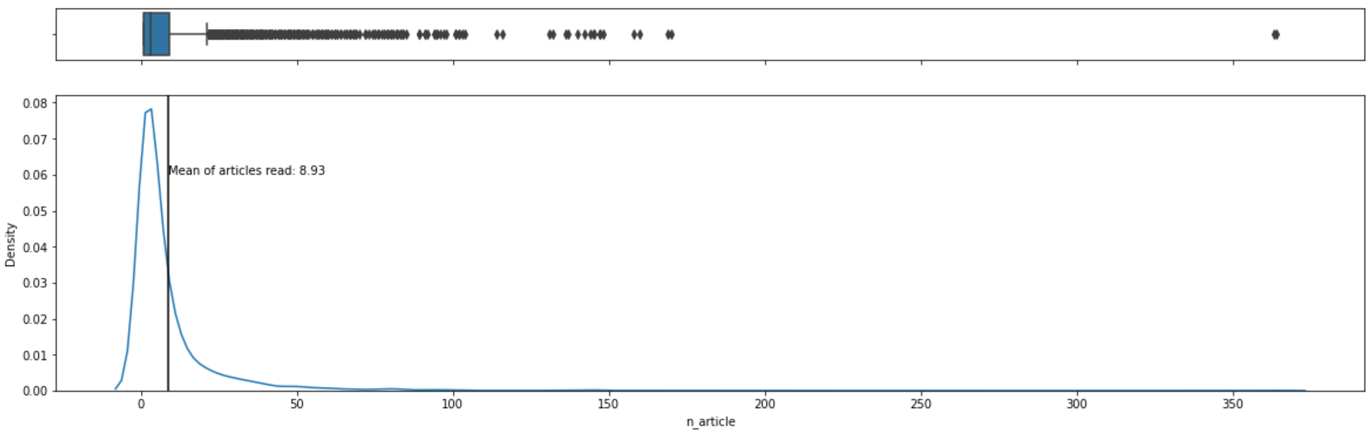
In [ ]:
```
# Get the index of two users with bigger number of articles
inds = df_count_articles.index[-2:]

df_2 = df.loc[df.email.isin(inds)]

# Number of unique articles
unique_articles = df.article_id.nunique()
# Number of articles that two users seen toghter
unique_articles_2 = df_2.article_id.nunique()
# Porportion
print(f'Together, the two users saw {(unique_articles_2/unique_articles)*100:.2f}% of total art
```

```
Together, the two users saw 19.05% of total articles
```

Only two users saw almost 20% of articles in dataset.
Maybe the both will show a great simmilarity.

Summarize the statics of interactions

In [ ]:
```
df_count_articles

f, (ax_box, ax_hist) = plt.subplots(2, figsize=(20,6), sharex=True, gridspec_kw={"height_ratios

# assigning a graph to each ax
sns.boxplot(data=df_count_articles, x='n_article', ax=ax_box)
sns.kdeplot(data=df_count_articles, x='n_article', ax=ax_hist)

mean_ = df_count_articles.n_article.mean()
ax_hist.axvline(mean_, color='black')
ax_hist.annotate(f'Mean of articles read: {mean_:.2f}', (mean_, 0.06) )

# Remove x axis name for the boxplot
ax_box.set(xlabel='')
plt.show()
```



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

median_val = df_count_articles.n_article.median()
max_views_by_user = df_count_articles.n_article.max()

print(f"50% of individuals interact with {median_val:.0f} number of articles or fewer.")
print(f'The maximum number of user-article interactions by any 1 user is {max_views_by_user}.')
```

```
50% of individuals interact with 3 number of articles or fewer.
The maximum number of user-article interactions by any 1 user is 364.
```

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

In [ ]:
```
# Find and explore duplicate articles
df_content.article_id.duplicated().sum()
```

Out[ ]: 5

In [ ]:
```
df_content.loc[df_content.article_id.duplicated(keep=False)]
```

Out[ ]:

	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...	Today's 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 *...	Today's 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

There is 5 articles duplicated in the dataset

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

3. Use the cells below to find:

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

In [ ]:
```
unique_articles = df.article_id.nunique() # The number of unique articles that have at least or
total_articles = df_content_new.article_id.nunique() # The number of unique articles on the IBM
unique_users = df.email.nunique(dropna=True) # The number of unique users
user_article_interactions = df[['article_id', 'email']].shape[0] # The number of user-article i

print(f'a: {unique_articles} unique articles that have at least one interaction' )
print(f'b: {total_articles} unique articles on the IBM platform')
```

```
print(f'c: {unique_users} unique users')
print(f'd: {user_article_interactions} user-article interactions')
```

```
a: 714 unique articles that have at least one interaction
b: 1051 unique articles on the IBM platform
c: 5148 unique users
d: 45993 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 find using other information that all of these null values likely belonged to a single user.

In [ ]:

```
most_viewed_article_id = df.article_id.value_counts().keys()[0] # The most viewed article in th
max_views = df.article_id.value_counts().values[0] # The most viewed article in the dataset was
most_viewed_article_title = df.loc[df.article_id == most_viewed_article_id].title.unique()[0]

print(f'The most viewed article was with id {most_viewed_article_id} and title \"{most_viewed_a
```

```
The most viewed article was with id 1429.0 and title "use deep learning for image classificatio
n".
It was viewed 937 times
```

In [ ]:

```
## 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.loc[:, '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 = df.assign(user_id=email_encoded)

# show header
df.head()
```

Out[ ]:

	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 [ ]:

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

most_viewed_article_id = str(most_viewed_article_id)

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_i
    '`The maximum number of user-article interactions by any 1 user is ______.`': max_views_by_
    '`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.

In [ ]:

```python
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

    '''
    # Dataset with number of interactions
    df_interaction = df.groupby(['article_id', 'title'], as_index=False). \
        agg(count=('article_id', 'count')). \
        sort_values('count', ascending=False)

    top_articles = list(df_interaction.iloc[:n]['title'])

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

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

    OUTPUT:
    top_articles - (list) A list of the top 'n' article ids
    '''
    # Dataset with number of interactions
    df_interaction = df.groupby(['article_id', 'title'], as_index=False). \
        agg(count=('article_id', 'count')). \
        sort_values('count', ascending=False)

    top_articles = list(df_interaction.iloc[:n]['article_id'])

    return top_articles # Return the top article ids
```

In [ ]:

```python
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 api
s', 'predicting churn with the spss random tree algorithm', 'healthcare python streaming applic
ation demo', 'finding optimal locations of new store using decision optimization', 'apache spar
k lab, part 1: basic concepts', 'analyze energy consumption in buildings', 'gosales transaction
s for logistic regression model']
['1429.0', '1330.0', '1431.0', '1427.0', '1364.0', '1314.0', '1293.0', '1170.0', '1162.0', '130
4.0']
```

In [ ]:

```
# 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.

In [ ]:

```
# 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
    an article and a 0 otherwise
    '''

    # First, create a new column with 1's
    user_item = df[['user_id', 'article_id']].assign(interact=int(1))
    # Then, pivot the table, using max aggregation
    user_item = user_item.pivot_table(index='user_id', columns='article_id',
        values='interact', aggfunc='max')
    # Finally, fill empty values with 0
    user_item = user_item.fillna(0)
```

```
    return user_item

user_item = create_user_item_matrix(df)
```

In [ ]:

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

```
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

    '''
    # User matrix for user_id input
    user_mat = user_item.loc[user_id]

    sim_arr = []
    # Iterate for each user in dataframe
    for user, user_row in user_item.iterrows():
        sim_dict = {}
        # Calculate similarity
        sim = np.dot(user_mat, user_row)
        # Create a dict to hold the result
        sim_dict['user'] = user
        sim_dict['sim'] = sim
        # Creat a list of dicts
        sim_arr.append(sim_dict)

    # Create a dataframe to manipulate
    sim_df = pd.DataFrame(sim_arr)

    # sort by similarity
    sim_df = sim_df.sort_values('sim', ascending=False)

    # create list of just the ids
    most_similar_users = sim_df.user.to_numpy()

    # remove the own user's id
    most_similar_users = np.delete(most_similar_users,
        np.where(most_similar_users == user_id))
```

```
    return most_similar_users
```

In [ ]:

```
# 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.

In [ ]:

```
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)
    '''

    # Resume dataset
    df_articles = df[['article_id', 'title']].drop_duplicates()
    # Location the article
    article_names = []
    for id in article_ids:
        title_ = df_articles.loc[df_articles.article_id == id].title.iloc[0]
        article_names.append(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 ids

    Description:
    Provides a list of the article_ids and article titles that have been seen by a user
    '''
    # The matrix of selected user
    user_mat = user_item.loc[user_id]
    article_ids = list(user_mat.loc[user_mat != 0].index.to_numpy())

    # Get the name of articles
    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

    '''
    # Get the similar users
    sim_users = find_similar_users(user_id)
    # Get the already seen article by user
    articles_user = get_user_articles(user_id)[0]

    recs = np.zeros(0) # initiate recs array
    for user in sim_users:
        # Get the articles from similar user
        sim_user_articles = get_user_articles(user)[0]
        # Subtracting the already seen articles by user
        rec_articles = np.setdiff1d(sim_user_articles, articles_user)

        # Summing on rec array
        recs = np.append(recs, rec_articles)
        # Dropping duplicates articles
        recs = np.unique(recs)

        # Testing for size
        num = recs.size
        if num >= m:
            recs = recs[:m]
            break

    recs = list(recs)

    return recs
```

In [ ]:

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

Out[ ]:

```
['recommender systems: approaches & algorithms',
 '1448    i ranked every intro to data science course on...\r\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...\r\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']
```

In [ ]:

```
# Test your functions here - No need to change this code - just run this cell
assert set(get_article_names(['1024.0', '1176.0', '1305.0', '1314.0', '1422.0', '1427.0'])) ==
assert set(get_article_names(['1320.0', '232.0', '844.0'])) == set(['housing (2015): united sta
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 measure
```

```
assert set(get_user_articles(2)[0]) == set(['1024.0', '1176.0', '1305.0', '1314.0', '1422.0', '
assert set(get_user_articles(2)[1]) == set(['using deep learning to reconstruct high-resolution
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 [ ]:

```
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
                    highest of each is higher in the dataframe

    '''
    # The matrix of selected user
    user_mat = user_item.loc[user_id]

    sim_arr = []
    # Iterate for each user in dataframe
    for user, user_row in user_item.iterrows():
        if user != user_id:
            sim_dict = {} # initiate a dict

            # Calculate the similarity
            sim = np.dot(user_mat, user_row)
            # Calculate the interaction of user
            inter = df.loc[df.user_id == user].shape[0]

            # Create a dict to hold the result
            sim_dict['neighbor_id'] = user
            sim_dict['similarity'] = sim
            sim_dict['num_interactions'] = inter
            # Creat a list of dicts
            sim_arr.append(sim_dict)

    # Create a dataframe to manipulate
    neighbors_df = pd.DataFrame(sim_arr)

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

```
    return neighbors_df

def get_top_sorted_articles(user_id, user_item=user_item, df=df):
    '''
    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_df - (dataframe) a dataframe with artcile ids sorted para interactions


    Description:
    Provides a dataframe of articles id that have been seen by a user
    sorted by article total interactions.
    '''

    # The matrix of selected user
    user_mat = user_item.loc[user_id]
    # Get the article seen by user
    article_ids = list(user_mat.loc[user_mat != 0].index.to_numpy())

    # Create the dataframe with total interactions
    article_df = df.groupby('article_id', as_index=False). \
        agg(inter=('article_id', 'count')). \
        sort_values('inter', ascending=False)

    article_df = article_df.loc[article_df.article_id.isin(article_ids)]

    return article_df


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.

    '''

    # Get the similar users
    sim_users = get_top_sorted_users(user_id)
    # Get the already seen article by user
    articles_user = get_user_articles(user_id)[0]

    # Initiate a empty dataframe with same columns of article_df
    recs = pd.DataFrame(columns=['article_id', 'inter'])
```

```python
    for user in sim_users.neighbor_id:
        # Get the articles dataframe from similar user, sorted by iteractions
        sim_user_articles = get_top_sorted_articles(user)
        # Filtering the dataframe without already seen articles
        condition = ~(sim_user_articles.article_id.isin(articles_user))
        sim_user_articles = sim_user_articles.loc[condition]

        # After filter, it would not have new articles, so, skip
        if sim_user_articles.size == 0:
            pass

        # Concat with recs dataframe
        recs = pd.concat([recs,sim_user_articles])
        # Drop duplicates and sort again by iteractions
        recs = recs.drop_duplicates(subset=['article_id']). \
            sort_values('inter', ascending=False)

        # Check for recommedation number
        if recs.article_id.size >= m:
            recs = recs.article_id.iloc[:m].to_numpy()
            break

    # Transfrom it in a list
    recs = list(recs)
    rec_names = get_article_names(recs)

    return recs, rec_names
```

In [ ]:

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

# Comparing with previous user-user function
rec_ids = user_user_recs(20, 10)
print("\nThe top 10 recommendations for user 20 were the following article ids:")
print(rec_ids)
print()
print("The top 10 recommendations for user 20 were the following article names:")
print(get_article_names(rec_ids))
```

```
The top 10 recommendations for user 20 are the following article ids:
['1330.0', '1427.0', '1364.0', '1170.0', '1162.0', '1304.0', '1351.0', '1160.0', '1354.0', '136
8.0']

The top 10 recommendations for user 20 are the following article names:
['insights from new york car accident reports', 'use xgboost, scikit-learn & ibm watson machine
learning apis', 'predicting churn with the spss random tree algorithm', 'apache spark lab, part
1: basic concepts', 'analyze energy consumption in buildings', 'gosales transactions for logist
ic regression model', 'model bike sharing data with spss', 'analyze accident reports on amazon
emr spark', 'movie recommender system with spark machine learning', 'putting a human face on ma
chine learning']

The top 10 recommendations for user 20 were the following article ids:
['1052.0', '1059.0', '1161.0', '1162.0', '1163.0', '1164.0', '1169.0', '1172.0', '1173.0', '117
5.0']

The top 10 recommendations for user 20 were the following article names:
['access db2 warehouse on cloud and db2 with python', 'airbnb data for analytics: amsterdam cal
endar', 'analyze data, build a dashboard with spark and pixiedust', 'analyze energy consumption
in buildings', 'analyze open data sets with spark & pixiedust', 'analyze open data sets with pa
ndas dataframes', 'annual precipitation by country 1990-2009', 'apache spark lab, part 3: machi
ne learning', 'births attended by skilled health staff (% of total) by country', 'breast cancer
detection with xgboost, wml and scikit']
```

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

user1_most_sim = find_similar_users(1)[0] # Find the user that is most similar to user 1
user131_10th_sim = find_similar_users(131)[10] # Find the 10th most similar user to user 131
```

In [ ]:
```
## 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.

The best function to recommend to a new user is **get_top_articles**, which recommends based on the articles with the most interactions overall.

This is because the operating principle of the other functions of written recommendations is the **crossing of users and the previous interaction with the articles**.
For new users, **who do not have interactions recorded**, the functions would return errors and it is not possible to use this method to recommend.

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 [ ]:
```
new_user = '0.0'

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

In [ ]:
```
assert set(new_user_recs) == set(['1314.0','1429.0','1293.0','1427.0','1162.0','1364.0','1304.(

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

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

Part IV: 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 [ ]:
```
# Load the matrix here
```

```python
# Using the previous matrix
user_item_matrix = user_item # pd.read_pickle('user_item_matrix.p')
```

In [ ]:

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

Out[ ]:

article_id	0.0	100.0	1000.0	1004.0	1006.0	1008.0	101.0	1014.0	1015.0	1016.0	...	977.0	98.0	981.0	9
user_id															
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	1.0	
2	0.0	0.0	0.0	0.0	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	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	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	0.0	...	0.0	0.0	0.0	

5 rows × 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 [ ]:

```python
# Perform SVD on the User-Item Matrix Here

# Singular value decomposition on user_item_matrices
# Full matrices is set to false
u, s, vt = np.linalg.svd(user_item_matrix, full_matrices=False)

print(f'''The SVD genarates
    U matriz with {u.shape[0]} x {u.shape[1]}
    Sigma matriz with {s.shape[0]} and
    V transpose with {vt.shape[0]} x {vt.shape[1]}''')
```

```
The SVD genarates
    U matriz with 5149 x 714
    Sigma matriz with 714 and
    V transpose with 714 x 714
```

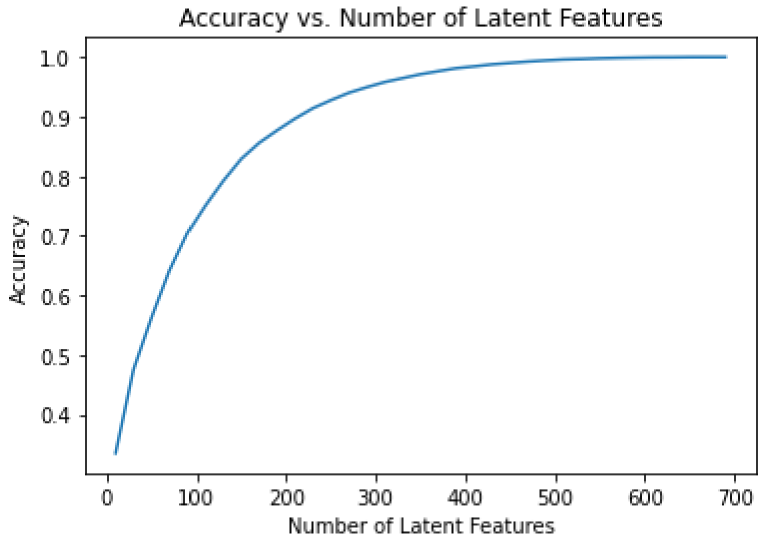
SVD is possible in this case as there are no missing values.

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 [ ]:

```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?

In [ ]:

```
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

    '''
    # Create the matrix
    user_item_train = create_user_item_matrix(df_train)
    user_item_test = create_user_item_matrix(df_test)

    # For test
    test_idx = df_test.user_id.unique()
```

```
    test_arts = df_test.article_id.unique()

    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_trair
```

In [ ]:

```
# Get the number of ids in train df
train_idx = user_item_train.index
train_arts = user_item_train.columns

# User that we can make predictions
users_ok = np.intersect1d(test_idx,train_idx).size
# User that is not present in the train
users_nok = np.setdiff1d(test_idx, train_idx).size

# Articles in the test and train df
arts_ok = np.intersect1d(test_arts,train_arts).size
# Articles that is not present in the train
arts_nok = np.setdiff1d(test_arts, train_arts).size

print(f'{users_ok} users possible to make predictions')
print(f'{users_nok} users are not possible to make predictions')
print(f'{arts_ok} articles possible to make predictions')
print(f'{arts_nok} articles are not possible to make predictions')
```

```
20 users possible to make predictions
662 users are not possible to make predictions
574 articles possible to make predictions
0 articles are not possible to make predictions
```

In [ ]:

```
# 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 colc
    'How many articles can we make predictions for in the test set?': b,
    'How many articles in the test set are we not able to make predictions for because of the c
}

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 o
nly 20 test users that were also in the training set.  All of the other users that are in the t
est 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.

In [ ]:

```
# Fit SVD on the user_item_train matrix
u_train, s_train, vt_train = np.linalg.svd(user_item_train.to_numpy(), full_matrices=False) # j
```

In [ ]:

```
# Find the user and articles there is in the train df
```

```python
# It is only possible to predict for these users
users_in_train = np.intersect1d(test_idx, user_item_train.index)
articles_in_train = np.intersect1d(test_arts, user_item_train.columns)

# Filtring the test df
user_item_test_ok = user_item_test.loc[users_in_train, articles_in_train]
```

In [ ]:

```python
# Functions to assist

def predict_iter(user_id, article_id,
    user_item_train=user_item_train, u_train=u_train, s_train = s_train,
    vt_train=vt_train, latent_factors=714):
    '''
    Function to get the predicted value from train matrix
    Input
        user_id - (int) user id to make prediction
        article_id - (int) article id to make prediction
        user_item_train - (array) the user_item train matrix
        u_train - (array) U matrix from SVD on train
        s_train - (array) S matrix from SVD on train
        vt_train - (array) VT matrix from SVD on train
        latent_factors - (int) number of latent factors to use
    Output
        pred - (float) the predict value for the user and article ids

    Description
        First, find the relative position of user id and article id
        in the train matrix. With theses cordinate, make the dot
        product of U, S and VT matrix reduced to that positions.
    '''
    # Relative position of user id and artcile id in train
    users_train = user_item_train.index
    article_train = user_item_train.columns
    user_pos = np.where(users_train == user_id)[0][0]
    article_pos = np.where(article_train == article_id)[0][0]

    # Reduce the U, S and VT matrix considering the positons and
    # latent factors
    s_train_ = np.diag(s_train[:latent_factors]) # make it diagonal
    u_train_ = u_train[user_pos,:latent_factors]
    vt_train_ = vt_train[:latent_factors,article_pos]

    # Dot product return the predict value
    pred = np.dot(np.dot(u_train_, s_train_), vt_train_)

    return pred

def calculate_acc_train(latent_factors=714):
    '''
    Funtion to retunr the RMSE for prediction using SVD on training set
    Input
        latent_factors - (int) number of latent_factors to use
    Output
        acc_train - (float) the accuracy for train with latent_factors
    '''
    # Slicing the matrices
    s_train_ = np.diag(s_train[:latent_factors])
    u_train_ = u_train[:,:latent_factors]
    vt_train_ = vt_train[:latent_factors,:]
    # Predictions
    pred_matrix_train = np.dot(np.dot(u_train_, s_train_), vt_train_)
    # Diffrences
    diffs = np.subtract(user_item_train, pred_matrix_train)
    # Error calculattion
```

```python
    sum_errs_train = np.sum(np.sum(np.abs(diffs)))
    n = user_item_train.size
    # Calculate the accuracy
    acc_train = 1 - (sum_errs_train/n)

    return acc_train
```

In [ ]:

```python
# First, last see the errors using all latent factors

sum_errs = 0
n_total = user_item_test_ok.size

# Iterate over user and article in the test matrix (only possible one)
for user in user_item_test_ok.index:
    for article in user_item_test_ok.columns:
        # Get the real value
        real = user_item_test_ok.loc[user,article]
        # Using predict function
        pred = predict_iter(user, article)
        # Get the error of prediction
        error = real - pred
        # Acumulate the error
        sum_errs += abs(error)

# Calculate the RMSE
# rmse = np.sqrt(sse/n_total).round(2)

print(f'Using all latent factors we have:')
print(f'Sum of Erros: {sum_errs.round(2)}')
print(f'The overal accuracy: {(1 - (sum_errs/n_total)).round(2)}')
```

```
Using all latent factors we have:
Sum of Erros: 408.0
The overal accuracy: 0.96
```

Theses are the values using all latent factors.

That means it is using the all information inside the training set to make predictions.

But it is important to obsever the graphic behavoir of this metric.

In [ ]:

```python
# Testing different numbers of latent factors

# Range to iterate 10 to 710
latent_factors_list = np.arange(10,714,20)

# Initiate empty dict to alocate results
acc_test_list = []
acc_train_list = []
n_test = user_item_test_ok.size

print('Number of Latent Factors | Accuracy test | Accuracy train')
for n_latent_factor in latent_factors_list:
    cnt = 0
    sum_errs_test = 0
    for user in user_item_test_ok.index:
        for article in user_item_test_ok.columns:
            real = user_item_test_ok.loc[user,article]
            pred = predict_iter(user, article, latent_factors=n_latent_factor)
            cnt += 1
            error = real - pred
            sum_errs_test += abs(error)
```

```
    # Accuracy for test
    acc_test = 1 - (sum_errs_test/n_test)
    acc_test_list.append(acc_test)
    # Accuracy for training
    acc_train = calculate_acc_train(n_latent_factor)
    acc_train_list.append(acc_train)

    # Printing the iterations
    print(f'\t\t\t{n_latent_factor} \t\t  |    {acc_test:.4f}     | \t  {acc_train:.4f}')
```

```
Number of Latent Factors | Accuracy test | Accuracy train
                        10          |   0.9569     |        0.9818
                        30          |   0.9514     |        0.9799
                        50          |   0.9483     |        0.9792
                        70          |   0.9457     |        0.9791
                        90          |   0.9447     |        0.9793
                        110         |   0.9441     |        0.9798
                        130         |   0.9438     |        0.9805
                        150         |   0.9438     |        0.9812
                        170         |   0.9444     |        0.9821
                        190         |   0.9452     |        0.9829
                        210         |   0.9459     |        0.9838
                        230         |   0.9466     |        0.9847
                        250         |   0.9478     |        0.9857
                        270         |   0.9486     |        0.9866
                        290         |   0.9496     |        0.9875
                        310         |   0.9506     |        0.9885
                        330         |   0.9517     |        0.9894
                        350         |   0.9527     |        0.9904
                        370         |   0.9536     |        0.9912
                        390         |   0.9546     |        0.9921
                        410         |   0.9559     |        0.9929
                        430         |   0.9570     |        0.9937
                        450         |   0.9581     |        0.9945
                        470         |   0.9591     |        0.9953
                        490         |   0.9599     |        0.9959
                        510         |   0.9606     |        0.9965
                        530         |   0.9612     |        0.9970
                        550         |   0.9619     |        0.9975
                        570         |   0.9624     |        0.9980
                        590         |   0.9627     |        0.9984
                        610         |   0.9632     |        0.9987
                        630         |   0.9635     |        0.9990
                        650         |   0.9638     |        0.9993
                        670         |   0.9641     |        0.9996
                        690         |   0.9643     |        0.9998
                        710         |   0.9645     |        1.0000
```

The graph is ploted bellow

In [ ]:

```
# Ploting results

plt.figure(figsize=(10,6))
plt.plot(latent_factors_list, acc_test_list, label='Test' )
plt.plot(latent_factors_list, acc_train_list, label='Train')
plt.xlabel('Number of Latent Features')
plt.ylabel('Root mean square error')
plt.title('Accuracy for training and testing data vs number of latent factors')
plt.legend()
plt.show()
```

The curves above show that with little latent factors, close to 10, it is already possible to achieve black of 95% accuracy in the test data. This can be explained by the SVD theory, since the first factors calculated by the technique have most of the explained variability of the data, being more effective in predicting the original value.

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 the machine learning training/testing method, it was possible to observe the performance of the recommendation engine offline and thus get an idea of how the recommendations made would fit into a possible application in real life.

Thanks to this, it was observed that it was not necessary to use all the latent factors of the SVD to make a prediction. As few factors explain most of the variance, with some of them an accuracy of 95% was already achieved.
However, in reality, it is necessary to think about the purpose of the recommendation engine. It necessarily needs interaction with real users to make sense. Therefore, measurements such as accuracy for SVD can be somewhat fanciful, since the prediction was made based on static training data.

Another point to note is the amount in the test base used to evaluate the model. As calculated, from the dataset with 5993 lines, containing 682 unique users, it was only possible to evaluate the model with 20 of them, the rest being considered new users, for whom the created model cannot make predictions. As a result, we have little mass of data to really ensure that the model is ready to be used.

To really prove the efficiency of the recommendation engine, the ideal would be to apply an A/B test in the real environment.

As the platform requires registration to be used, two groups could be randomly separated based on the userID. The first group would continue without the created recommendation engine and the second group would receive recommendations from the developed algorithm.

The metric of interest could be iteration rate per user. The higher this rate, it means that users are reading more the articles, which may be influenced by the recommendation engine. Another metric that could be seen is the reading time of each article. For articles that are more interesting, the user spends more time on the screen.

For the test time it is necessary to know more about the interaction environment. Depending on the number of interactions per day, this time may vary.

For example, imagining 500 interactions a day. The average interaction rate per user is 8.9 with a standard deviation of 16. If we want to prove that the algorithm has increased this rate to 9.9, we would need 8038 rows of data with a test power of 80% and a 5% significance level. This mass of data would be collected in 16 days and the per-user interaction metric could be tracked until the end of the experiment, only then can the real gain and impact of the algorithm be measured.