Recommendations_with_IBM

February 21, 2024

1 Recommendations with IBM

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

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

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

1.1 Table of Contents

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

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

        %matplotlib inline

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

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

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

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

In [2]:
```
# Show df_content to get an idea of the data
df_content.head()
```

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

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

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

In [3]:
```
df.shape
```

Out[3]:
```
(45993, 3)
```

In [4]:
```
df_content.shape
```

Out[4]:
```
(1056, 5)
```

1.1.1 Part I : Exploratory Data Analysis

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

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

In [5]:
```
df.isna().sum()
```

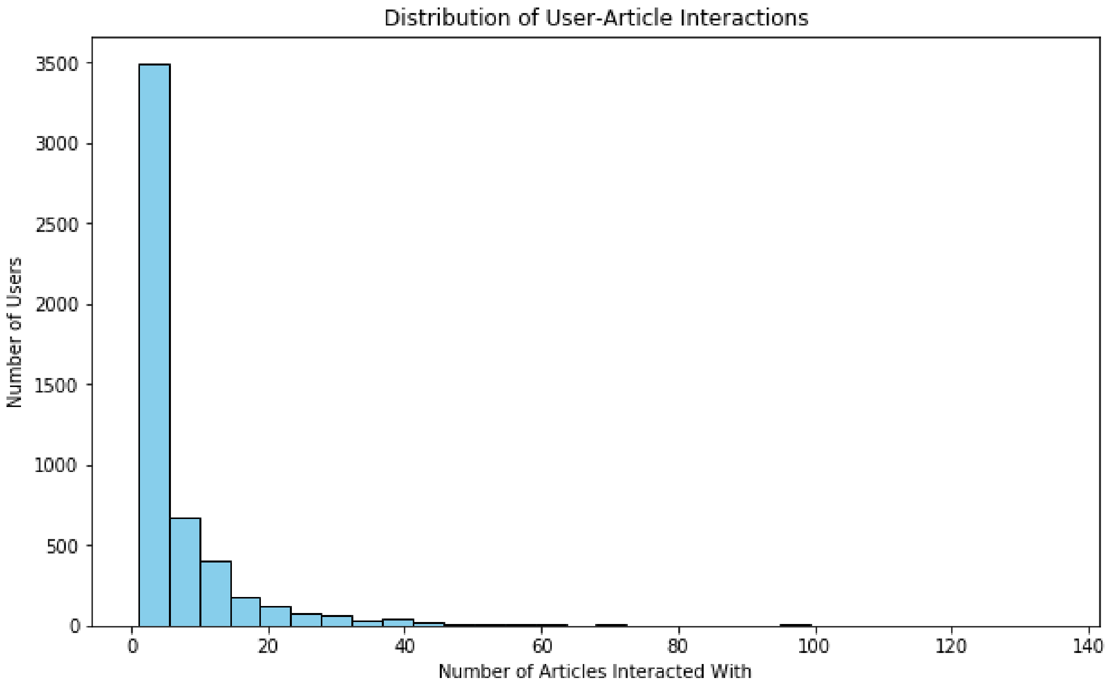
Out[5]:
```
article_id     0
title          0
email         17
dtype: int64
```

In [6]:
```
# Including repeated interactions with the same articles and not removing NaN rows in co
df[['email','article_id']].groupby(['email']).count().describe()
```

Out[6]:

	article_id
count	5148.000000
mean	8.930847
std	16.802267
min	1.000000
25%	1.000000
50%	3.000000
75%	9.000000
max	364.000000

In [7]:
```
# Exclude rows with NaN values in the 'email' column before analysis
df_cleaned = df.dropna(subset=['email'])

# Analysis: Counting the number of articles each user interacts with
user_article_counts = df_cleaned.groupby('email')['article_id'].nunique()

# Generating descriptive statistics
descriptive_stats = user_article_counts.describe()

# Visualizing the distribution of user-article interactions
plt.figure(figsize=(10, 6))
user_article_counts.hist(bins=30, color='skyblue', edgecolor='black')
plt.title('Distribution of User-Article Interactions')
plt.xlabel('Number of Articles Interacted With')
plt.ylabel('Number of Users')
plt.grid(False)  # Cleaner look without gridlines
plt.show()

# Display descriptive statistics
print("Descriptive Statistics for User-Article Interactions:")
print(descriptive_stats)
```




```
Descriptive Statistics for User-Article Interactions:
count    5148.000000
mean        6.540210
std         9.990676
min         1.000000
25%         1.000000
50%         3.000000
75%         7.000000
max       135.000000
Name: article_id, dtype: float64
```

In [8]:
```
median = user_article_counts.median()
median
```

Out[8]: 3.0

In [9]:
```
# Count the number of interactions per user and find the maximum
max_interactions_by_user = df['email'].value_counts().max()
max_interactions_by_user
```

Out[9]: 364

In [10]:
```
# Fill in the median and maximum number of user_article interactios below

median_val = median # 50% of individuals interact with ____ number of articles or fewer
max_views_by_user = max_interactions_by_user# The maximum number of user-article intera
```

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

In [11]:
```
# Find and explore duplicate articles


# Explore duplicates in 'article_id'
duplicate_articles = df_content[df_content.duplicated(subset='article_id', keep=False)]

# Display duplicate 'article_id' entries
print("Duplicate 'article_id' Rows in 'df_content':")
print(duplicate_articles)
```

```
Duplicate 'article_id' Rows in 'df_content':
                                               doc_body  \
50   Follow Sign in / Sign up Home About Insight Da...
221  * United States\r\n\r\nIBMő * Site map\r\n\r\n...
232  Homepage Follow Sign in Get started Homepage *...
365  Follow Sign in / Sign up Home About Insight Da...
399  Homepage Follow Sign in Get started * Home\r\n...
578  This video shows you how to construct queries ...
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  \
50                         Community Detection at Scale
221  When used to make sense of huge amounts of con...
232  If you are like most data scientists, you are ...
365  During the seven-week Insight Data Engineering...
399  Todays world of data science leverages data f...
578  This video shows you how to construct queries ...
692  One of the earliest documented catalogs was co...
761  Todays world of data science leverages data f...
970  This video shows you how to construct queries ...
971  If you are like most data scientists, you are ...

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

In [12]:
```python
# Remove any rows that have the same article_id - only keep the first

# Remove duplicate 'article_id' entries, keeping the first occurrence
df_content_cleaned = df_content.drop_duplicates(subset='article_id', keep='first')

# Display the cleaned DataFrame to confirm duplicates are removed
print("\nCleaned 'df_content' DataFrame without Duplicates:")
print(df_content_cleaned)
```

```
Cleaned 'df_content' DataFrame without Duplicates:
                                               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...
5     Compose is all about immediacy. You want a new...
6     UPGRADING YOUR POSTGRESQL TO 9.5Share on Twitt...
7     Follow Sign in / Sign up 135 8 * Share\r\n * 1...
8     * Host\r\n * Competitions\r\n * Datasets\r\n *...
9     THE GRADIENT FLOW\r\nDATA / TECHNOLOGY / CULTU...
10    OFFLINE-FIRST IOS APPS WITH SWIFT & PART 1: TH...
11    Warehousing data from Cloudant to dashDB great...
12    Skip to main content IBM developerWorks / Deve...
13    Maureen McElaney Blocked Unblock Follow Follow...
14    Raj Singh Blocked Unblock Follow Following Dev...
15    * Home\r\n * Community\r\n * Projects\r\n * Bl...
16    * Home\r\n * Research\r\n * Partnerships and C...
17    Enterprise Pricing Articles Sign in Free 30-Da...
18    Homepage Follow Sign in / Sign up * Home\r\n *...
19    METRICS MAVEN: MODE D'EMPLOI - FINDING THE MOD...
20    Homepage Follow Sign in / Sign up Homepage * H...
21    Raj Singh Blocked Unblock Follow Following Dev...
22    IMPORTING JSON DOCUMENTS WITH NOSQLIMPORT\r\nG...
23    This video shows you how to build and query a ...
24    THE CONVERSATIONAL INTERFACE IS THE NEW PARADI...
25    Skip navigation Upload Sign in SearchLoading...
26    GOOGLE RESEARCH BLOG The latest news from Rese...
27    Skip navigation Upload Sign in SearchLoading...
28    ACCESS DENIED\r\nSadly, your client does not s...
29    Homepage Follow Sign in / Sign up Homepage * H...
...                                                 ...
1026  Enterprise Pricing Articles Sign in Free 30-Da...
1027  Skip navigation Sign in SearchLoading...\r\n\r...
1028  Compose The Compose logo Articles Sign in Free...
1029  Follow Sign in / Sign up * Home\r\n * About In...
1030  Homepage Follow Sign in / Sign up Homepage * H...
```

```
1031  Develop in the cloud at the click of a button!...
1032  BLAZINGLY FAST GEOSPATIAL QUERIES WITH REDIS\r...
1033  Blog Home Dataquest.io Learn Data Science in Y...
1034  DATALAYER: MANAGING (OR NOT) THE DATA IN IMMUT...
1035  Skip to contentWin-Vector Blog\r\n\r\nThe Win-...
1036  This work is licensed under a Creative Commons...
1037                                                NaN
1038  The relational database has been the dominant ...
1039  Skip to main content IBM developerWorks / Deve...
1040  Skip to contentDinesh Nirmal's Blog\r\n\r\nA b...
1041  Compose The Compose logo Articles Sign in Free...
1042  Glynn Bird Blocked Unblock Follow Following De...
1043  MENU\r\nClose\r\nSubscribe SubscribeREDUCING O...
1044  Homepage IBM Watson Data Lab Follow Sign in / ...
1045  Although it is built around a JavaScript engin...
1046  Margriet Groenendijk Blocked Unblock Follow Fo...
1047  Homepage Follow Sign in / Sign up Homepage * H...
1048  Homepage Follow Sign in Get started * Home\r\n...
1049  * \r\n * \r\n * \r\n * \r\n * \r\n * \r\n * \r...
1050  1A SPEED GUIDE TO REDIS LUA SCRIPTING\r\nShare...
1051  PouchDB-find is a new API and syntax that allo...
1052  We compare discriminative and generative learn...
1053  Essays about data, building products and boots...
1054                                                NaN
1055  Homepage Follow Sign in / Sign up Homepage * H...

                                        doc_description  \
0     Detect bad readings in real time using Python ...
1     See the forest, see the trees. Here lies the c...
2     Heres this weeks news in Data Science and Bi...
3     Learn how distributed DBs solve the problem of...
4     This video demonstrates the power of IBM DataS...
5              Using Compose's PostgreSQL data browser.
6     Upgrading your PostgreSQL deployment to versio...
7     For a company like Slack that strives to be as...
8     Kaggle is your home for data science. Learn ne...
9     [A version of this post appears on the OReill...
10    Apple's sample app, Food Tracker, taught you i...
11    Replicating data to a relational dashDB databa...
12    This recipe showcases how one can analyze the ...
13    Theres a reason youve been hearing a lot abo...
14    Who are those people lurking behind the statis...
15    Early methods to integrate machine learning us...
16    The performance of supervised predictive model...
17    We've always considered MySQL as a potential C...
18    It has never been easier to build AI or machin...
19    In our Metrics Maven series, Compose's data sc...
20    It is often useful to use RStudio for one piec...
```

```
21    Youre doing your data a disservice if you don...
22    Introducing nosqlimport, an npm module to help...
23    This video shows you how to build and query a ...
24    Botkit provides a simple framework to handle t...
25    Want to learn more about how we created the Da...
26    Much of driving is spent either stuck in traff...
27    This talk assumes you have a basic understandi...
28    In this paper, we propose gcForest, a decision...
29    Im very happy and proud to announce that IBM ...
...                                                ...
1026  Varun Singh, a software engineer at IBM's Wats...
1027  This video shows you how to create and adminis...
1028  With the latest 0.2.1 version of Transporter, ...
1029  Audio super-resolution aims to reconstruct a h...
1030  Since then, this metric has been ubiquitously ...
1031  Build a word game app and see how to manage an...
1032  Use Redis and and Python scripts to speed your...
1033  In this post, youll learn to query, update, a...
1034  Adron Hall of Thrashing Code and Home Depot, t...
1035  Describes the use of Laplace noise in machine ...
1036  A full guide to Elasticsearch, the real-time d...
1037  See how quick and easy it is to set up a dashD...
1038  The relational database has been the dominant ...
1039  Building your first data warehouse doesnt hav...
1040  In my last blog Business differentiation thro...
1041  MongoDB's aggregation pipeline makes finding d...
1042  Which write API endpoint is the right write ca...
1043        Nothing spoils a plot like (too much) data.
1044  Getting started with custom visualizations, si...
1045  Although it is built around a JavaScript engin...
1046  Last week I attended the GeoPython conference ...
1047  In this post, we will go through how to read a...
1048  As more devices become internet enabled, harne...
1049  Continuing my previous work on exploring Arlin...
1050  Lua is a compact language which can be embedde...
1051  PouchDB uses MapReduce as its default search m...
1052  We compare discriminative and generative learn...
1053  In order to demystify some of the magic behind...
1054  Learn how to use IBM dashDB as data store for ...
1055  Once you get used to developing in a Notebook ...

                                          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
5                Browsing PostgreSQL Data with Compose       Live           5
```

6	Upgrading your PostgreSQL to 9.5	Live	6
7	Data Wrangling at Slack	Live	7
8	Data Science Bowl 2017	Live	8
9	Using Apache Spark to predict attack vectors a...	Live	9
10	Offline-First iOS Apps with Swift & Cloudant S...	Live	10
11	Warehousing GeoJSON documents	Live	11
12	Timeseries Data Analysis of IoT events by usin...	Live	12
13	Bridging the Gap Between Python and Scala Jupy...	Live	13
14	Got zip code data? Prep it for analytics. IB...	Live	14
15	Apache Spark 2.0: Extend Structured Streaming...	Live	15
16	Higher-order Logistic Regression for Large Dat...	Live	16
17	Compose for MySQL now for you	Live	17
18	The Greatest Public Datasets for AI Startup ...	Live	18
19	Finding the Mode in PostgreSQL	Live	19
20	Working interactively with RStudio and noteboo...	Live	20
21	Mapping for Data Science with PixieDust and Ma...	Live	21
22	Move CSVs into different JSON doc stores	Live	22
23	Tutorial: How to build and query a Cloudant ge...	Live	23
24	The Conversational Interface is the New Paradigm	Live	24
25	Creating the Data Science Experience	Live	25
26	Using Machine Learning to predict parking diff...	Live	26
27	Getting The Best Performance With PySpark	Live	27
28	Deep Forest: Towards An Alternative to Deep Ne...	Live	28
29	Experience IoT with Coursera	Live	29
...	...	...	...
1026	Redis and MongoDB in the biomedical domain	Live	1021
1027	Create and administer a data catalog using IBM...	Live	1022
1028	How to move data with Compose Transporter - Fr...	Live	1023
1029	Using Deep Learning to Reconstruct High-Resolu...	Live	1024
1030	Data tidying in Data Science Experience	Live	1025
1031	Build a simple word game app using Cloudant on...	Live	1026
1032	Blazingly Fast Geospatial Queries with Redis	Live	1027
1033	Working with SQLite Databases using Python and...	Live	1028
1034	DataLayer Conference: Managing (or not) the Da...	Live	1029
1035	Laplace noising versus simulated out of sample...	Live	1030
1036	The Definitive Guide	Live	1031
1037	Get started with dashDB on Bluemix	Live	1032
1038	The Many Flavors of NoSQL at That Conference	Live	1033
1039	Your First Data Warehouse Is Easy. Meet the ODS.	Live	1034
1040	Machine Learning for the Enterprise.	Live	1035
1041	Finding Duplicate Documents in MongoDB	Live	1036
1042	Piecemeal, Bulk, or Batch? IBM Watson Data L...	Live	1037
1043	Reducing overplotting in scatterplots	Live	1038
1044	You Too Can Make Magic (in Jupyter Notebooks w...	Live	1039
1045	How I Stopped Worrying & Learned to Love the M...	Live	1040
1046	Mapping All the Things with Python IBM Watso...	Live	1041
1047	Use IBM Data Science Experience to Read and Wr...	Live	1042
1048	Use IoT data in Streams Designer for billing a...	Live	1043

```
1049                          Mapping Points with Folium       Live        1044
1050                A Speed Guide To Redis Lua Scripting       Live        1045
1051             A look under the covers of PouchDB-find       Live        1046
1052  A comparison of logistic regression and naive ...       Live        1047
1053  What I Learned Implementing a Classifier from ...       Live        1048
1054                                Use dashDB with Spark       Live        1049
1055  Jupyter Notebooks with Scala, Python, or R Ker...       Live        1050

[1051 rows x 5 columns]
```

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

In [13]:
```python
##a. The number of unique articles that have an interaction with a user.

# Calculate the number of unique articles that have at least one interaction with a use
# after filtering out rows with NaN in 'email'
unique_articles_interacted = df_cleaned['article_id'].nunique()
print(f"The number of unique articles that have an interaction with a user: {unique_art

##b. The number of unique articles in the dataset (whether they have any interactions o

# Calculate the number of unique articles in the dataset
unique_articles_total = df_content['article_id'].nunique()
print(f"The total number of unique articles in the dataset: {unique_articles_total}")

##c. The number of unique users in the dataset. (excluding null values)

# Calculating for unique users
unique_users = df['email'].nunique()

print(f"The number of unique users: {unique_users}")

#d. The number of user-article interactions in the dataset.

# Total interations with all NaN emails, more than 1 article interactions
user_article_interactions = df.shape[0]
print(f"The number of user-article interactions: {user_article_interactions}")
```

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

```
In [14]: unique_articles = 714 # The number of unique articles that have at least one interactio
         total_articles = 1051 # The number of unique articles on the IBM platform
         unique_users = 5148 # The number of unique users
         user_article_interactions = 45993# The number of user-article interactions
```

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

```
In [15]: # Count the number of views each article received
         article_views = df['article_id'].value_counts()

         # Identify the most viewed article_id and its number of views
         most_viewed_article_id = article_views.idxmax()
         max_views = article_views.max()

         print(f"The most viewed article_id: {most_viewed_article_id}")
         print(f"How often it was viewed: {max_views}")
```

```
The most viewed article_id: 1429.0
How often it was viewed: 937
```

```
In [16]: most_viewed_article_id = '1429.0' # The most viewed article in the dataset as a string
         max_views = 937 # The most viewed article in the dataset was viewed how many times?
```

```
In [17]: ## No need to change the code here - this will be helpful for later parts of the notebo
         # Run this cell to map the user email to a user_id column and remove the email column

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

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

                 email_encoded.append(coded_dict[val])
             return email_encoded

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

         # show header
         df.head()
```

Out[17]:

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

In [18]:

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

sol_1_dict = {
    '`50% of individuals have _____ or fewer interactions.`': median_val,
    '`The total number of user-article interactions in the dataset is ______.`': user_a
    '`The maximum number of user-article interactions by any 1 user is ______.`': max_v
    '`The most viewed article in the dataset was viewed _____ times.`': max_views,
    '`The article_id of the most viewed article is ______.`': most_viewed_article_id,
    '`The number of unique articles that have at least 1 rating ______.`': unique_artic
    '`The number of unique users in the dataset is ______`': unique_users,
    '`The number of unique articles on the IBM platform`': total_articles
}

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

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

1.1.2 Part II: Rank-Based Recommendations

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

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

In [19]:

```
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

    '''
    # Identify the top 'n' article_ids based on interaction count, maintaining order
    top_articles_idx = df['article_id'].value_counts().head(n).index

    # Filter the original df to only include rows with the top 'n' article_ids
```

```
        # and then drop duplicates to avoid repeating titles.
        df_filtered = df[df['article_id'].astype(str).isin(top_articles_idx.astype(str))].d

        # Ensure the titles are ordered according to the interaction count by reindexing
        df_filtered = df_filtered.set_index('article_id').reindex(top_articles_idx)

        # Extract the titles
        top_articles = df_filtered['title'].tolist()

        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

        '''
        # Identify the top 'n' article_ids based on interaction count
        top_article_ids = df['article_id'].value_counts().head(n).index

        # Convert article_ids to strings to match the requirement
        top_article_ids = top_article_ids.astype(str).tolist()

        return top_article_ids # Return the top article ids
```

In [20]:
```
print(get_top_articles(10))
print(get_top_article_ids(10))
```

```
['use deep learning for image classification', 'insights from new york car accident reports', 'v
['1429.0', '1330.0', '1431.0', '1427.0', '1364.0', '1314.0', '1293.0', '1170.0', '1162.0', '1304
```

In [21]:
```
# Test your function by returning the top 5, 10, and 20 articles
top_5 = get_top_articles(5)
top_10 = get_top_articles(10)
top_20 = get_top_articles(20)

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

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

1.1.3 Part III: User-User Based Collaborative Filtering

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

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

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

```
In [22]: # create the user-article matrix with 1's and 0's

         def create_user_item_matrix(df):
             '''
             INPUT:
             df - pandas dataframe with article_id, title, user_id columns

             OUTPUT:
             user_item - user item matrix

             Description:
             Return a matrix with user ids as rows and article ids on the columns with 1 values
             an article and a 0 otherwise
             '''
             # Ensure article_id is in the correct format
             df['article_id'] = df['article_id'].astype(str)

             # Creating the user-article matrix with 1's and 0's
             user_item = df.groupby(['user_id', 'article_id']).size().unstack(fill_value=0)

             # Convert the interaction counts (>0) to 1
             user_item = (user_item > 0).astype(int)

             return user_item # return the user_item matrix

         user_item = create_user_item_matrix(df)
```

```
In [23]: ## Tests: You should just need to run this cell.  Don't change the code.
         assert user_item.shape[0] == 5149, "Oops!  The number of users in the user-article matr
         assert user_item.shape[1] == 714, "Oops!  The number of articles in the user-article ma
         assert user_item.sum(axis=1)[1] == 36, "Oops!  The number of articles seen by user 1 do
         print("You have passed our quick tests!  Please proceed!")
```

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

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

Use the tests to test your function.

```
In [24]: def find_similar_users(user_id, user_item=user_item):
             '''
             INPUT:
             user_id - (int) a user_id
             user_item - (pandas dataframe) matrix of users by articles:
                         1's when a user has interacted with an article, 0 otherwise

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

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

             '''

             # Compute similarity of each user to the provided user
             similarity = user_item.dot(user_item.loc[user_id])

             # Sort by similarity
             similarity = similarity.sort_values(ascending=False)

             # Create list of just the ids
             most_similar_users = similarity.index.tolist()

             # Remove the own user's id
             most_similar_users.remove(user_id)

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

```
In [25]: # Do a spot check of your function
         print("The 10 most similar users to user 1 are: {}".format(find_similar_users(1)[:10]))
         print("The 5 most similar users to user 3933 are: {}".format(find_similar_users(3933)[:
         print("The 3 most similar users to user 46 are: {}".format(find_similar_users(46)[:3]))
```

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

```
The 3 most similar users to user 46 are: [4201, 23, 3782]
```

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

```
In [26]: def get_article_names(article_ids, df=df):
             '''
             INPUT:
             article_ids - (list) a list of article ids
             df - (pandas dataframe) df as defined at the top of the notebook

             OUTPUT:
             article_names - (list) a list of article names associated with the list of article
                             (this is identified by the title column)
             '''

             # Convert article_ids to string format to match df['article_id'] type
             article_ids = [str(article_id) for article_id in article_ids]

             # Get the article names for the given article_ids
             article_names = df[df['article_id'].isin(article_ids)]['title'].drop_duplicates().t

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


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

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

             Description:
             Provides a list of the article_ids and article titles that have been seen by a user
             '''

             # Find all articles that a user has interacted with
             article_ids = user_item.loc[user_id, user_item.loc[user_id] == 1].index.tolist()

             # Retrieve article names using the get_article_names function
             article_names = get_article_names(article_ids, df)
```

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


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

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

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

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

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

    '''

    # Find similar users
    similar_users = find_similar_users(user_id, user_item)

    # Get articles seen by the user
    user_articles, _ = get_user_articles(user_id, user_item)

    # Initialize a set for recommendations to ensure unique entries
    recs = set()

    # Loop through similar users to get recommendations
    for similar_user in similar_users:
        if len(recs) >= m:
            break
        similar_user_articles, _ = get_user_articles(similar_user, user_item)

        # Add articles not already seen by user to recommendations
        recs.update(set(similar_user_articles) - set(user_articles))

    # Ensure the number of recommendations does not exceed m
    recs = list(recs)[:m]

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

```
In [27]: # Check Results
         get_article_names(user_user_recs(1, 10)) # Return 10 recommendations for user 1

Out[27]: ['the unit commitment problem',
          'graph-based machine learning',
          'analyze accident reports on amazon emr spark',
          'using brunel in ipython/jupyter notebooks',
          'data visualization playbook: telling the data story',
          'deep learning with data science experience',
          'declarative machine learning',
          'deep forest: towards an alternative to deep neural networks',
          'get social with your notebooks in dsx',
          'using bigdl in dsx for deep learning on spark']
```

```
In [28]: # Test your functions here - No need to change this code - just run this cell
         assert set(get_article_names(['1024.0', '1176.0', '1305.0', '1314.0', '1422.0', '1427.0
         assert set(get_article_names(['1320.0', '232.0', '844.0'])) == set(['housing (2015): un
         assert set(get_user_articles(20)[0]) == set(['1320.0', '232.0', '844.0'])
         assert set(get_user_articles(20)[1]) == set(['housing (2015): united states demographic
         assert set(get_user_articles(2)[0]) == set(['1024.0', '1176.0', '1305.0', '1314.0', '14
         assert set(get_user_articles(2)[1]) == set(['using deep learning to reconstruct high-re
         print("If this is all you see, you passed all of our tests!  Nice job!")

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

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

- Instead of arbitrarily choosing when we obtain users who are all the same closeness to a given user - choose the users that have the most total article interactions before choosing those with fewer article interactions.
- Instead of arbitrarily choosing articles from the user where the number of recommended articles starts below m and ends exceeding m, choose articles with the articles with the most total interactions before choosing those with fewer total interactions. This ranking should be what would be obtained from the **top_articles** function you wrote earlier.

```
In [29]: def get_top_sorted_users(user_id, df=df, user_item=user_item):
             '''
             INPUT:
             user_id - (int)
             df - (pandas dataframe) df as defined at the top of the notebook
             user_item - (pandas dataframe) matrix of users by articles:
                     1's when a user has interacted with an article, 0 otherwise


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

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

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

    '''

    # Compute similarity
    user_similarity = user_item.dot(user_item.loc[user_id])
    user_similarity = user_similarity.drop(user_id).reset_index()
    user_similarity.columns = ['neighbor_id', 'similarity']

    # Compute number of interactions
    num_interactions = df.groupby(['user_id'])['article_id'].count().reset_index()
    num_interactions.columns = ['neighbor_id', 'num_interactions']

    # Merge the two dataframes
    neighbors_df = pd.merge(user_similarity, num_interactions, on='neighbor_id')

    # Sort by similarity, then by number of interactions
    neighbors_df = neighbors_df.sort_values(by=['similarity', 'num_interactions'], asce

    return neighbors_df # Return the dataframe specified in the doc_string


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

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

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

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

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

```
    '''

    # Get sorted users based on similarity and number of interactions
    top_users = get_top_sorted_users(user_id)

    # Get articles seen by the user
    user_articles, _ = get_user_articles(user_id, user_item)

    # Group articles by interaction count
    article_interactions = df.groupby('article_id').count()['user_id'].sort_values(asce

    recs = []
    for neighbor_id in top_users['neighbor_id']:
        if len(recs) >= m:
            break
        neighbor_articles, _ = get_user_articles(neighbor_id, user_item)

        # Filter articles the user hasn't seen
        new_recs = np.setdiff1d(neighbor_articles, user_articles, assume_unique=True)

        # Sort new recommendations based on article popularity/interaction count
        sorted_new_recs = article_interactions.loc[new_recs].sort_values(ascending=Fals

        # Extend the recommendation list with sorted articles, avoiding duplicates
        for article_id in sorted_new_recs:
            if article_id not in recs:
                recs.append(article_id)
            if len(recs) >= m:
                break

    # Ensure only the top m recommendations are returned if exceeding the limit
    recs = recs[:m]

    # Fetch article names
    rec_names = get_article_names(recs, df)

    return recs, rec_names
```

In [30]:
```
# Quick spot check - don't change this code - just use it to test your functions
rec_ids, rec_names = user_user_recs_part2(20, 10)
print("The top 10 recommendations for user 20 are the following article ids:")
print(rec_ids)
print()
print("The top 10 recommendations for user 20 are the following article names:")
print(rec_names)
```

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

```
The top 10 recommendations for user 20 are the following article names:
['apache spark lab, part 1: basic concepts', 'predicting churn with the spss random tree algorit
```

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

```
In [31]: ### Tests with a dictionary of results

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

         print(f"The user that is most similar to user 1 is user {user1_most_sim}.")
         print(f"The 10th most similar user to user 131 is user {user131_10th_sim}.")
```

```
The user that is most similar to user 1 is user 3933.
The 10th most similar user to user 131 is user 242.
```

```
In [32]: ## 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.

For a new user, often referred to as the "Cold Start" problem, user-based collaborative filtering methods (like those implemented in find_similar_users, get_user_articles, and user_user_recs_part2) would not be effective. This is because these methods rely on the user's past interactions to find similar users or items, and a new user would have no such history.

2 Better Methods for New Users:

1. Rank-Based Recommendations:

Use the get_top_article_ids or get_top_articles functions to recommend the most popular articles across all users. This approach doesn't require user-specific interaction data and is suitable for new users. This method assumes that what is popular among all users might also be of interest to the new user.

2. Content-Based Filtering:

Develop a model that uses article content (like article text or tags) to recommend articles similar to those that a user has read. For new users, you could ask them to select a few topics of interest at signup and use those preferences to seed their recommendations. For a brand new user without any interactions, recommendations could be based on featured or trending content within their expressed topics of interest.

Provide your response here.

`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 [33]: new_user = '0.0'

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

         # Ensure the article IDs are in string format as specified
         new_user_recs = [str(article_id) for article_id in new_user_recs]

         print("Top 10 recommended article IDs for a new user:", new_user_recs)
```

```
Top 10 recommended article IDs for a new user: ['1429.0', '1330.0', '1431.0', '1427.0', '1364.0'
```

```
In [34]: assert set(new_user_recs) == set(['1314.0','1429.0','1293.0','1427.0','1162.0','1364.0'

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

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

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

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

`1.` Use the function body below to create a content based recommender. Since there isn't one right answer for this recommendation tactic, no test functions are provided. Feel free to change the function inputs if you decide you want to try a method that requires more input values. The input values are currently set with one idea in mind that you may use to make content based recommendations. One additional idea is that you might want to choose the most popular recommendations that meet your 'content criteria', but again, there is a lot of flexibility in how you might make these recommendations.

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

In [35]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import linear_kernel

def make_content_recs(article_id, df_content=df_content, top_n=10):
    """
    INPUT:
    article_id - (str) a article_id from df_content
    df_content - (pandas dataframe) dataframe as defined at the top of the notebook con
    top_n - (int) the number of recommendations to return

    OUTPUT:
    recommendations - (list) a list of article_ids that are recommended based on conten

    Description:
    This function computes the TF-IDF vectorization of article content and uses cosine
    to find the most similar articles to the provided article_id.
    """

    # Fill any missing values
    df_content_filled = df_content.fillna("")

    # Combine doc_body, doc_description, and doc_full_name to form a combined content c
    df_content_filled['combined_content'] = df_content_filled['doc_body'] + " " + \
                                            df_content_filled['doc_description'] + " "
                                            df_content_filled['doc_full_name']

    # Additional checks for article_id existence
    if article_id not in df_content_filled['article_id'].values:
        print(f"Article ID {article_id} not found in the content.")
        return []

    # Initialize a TfidfVectorizer
    tfidf = TfidfVectorizer(stop_words='english')

    # Fit and transform the combined content to form TF-IDF matrix
    tfidf_matrix = tfidf.fit_transform(df_content_filled['combined_content'])

    # Compute the cosine similarity matrix
    cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)

    # Get the index of the article that matches the article_id
    idx = df_content_filled.index[df_content_filled['article_id'] == article_id].tolist

    # Get the pairwsie similarity scores of all articles with that article
    sim_scores = list(enumerate(cosine_sim[idx]))
```

```
        # Sort the articles based on the similarity scores
        sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)

        # Get the scores of the top_n most similar articles
        sim_scores = sim_scores[1:top_n+1]  # exclude the first one since it's the article

        # Get the article indices
        article_indices = [i[0] for i in sim_scores]

        # Return the top_n most similar article IDs
        recommendations = df_content_filled.iloc[article_indices]['article_id'].tolist()

        return recommendations
```

```
In [36]: # Define the article_id from which we want to find similar articles
         article_id_to_test = 1024

         # Test the function to get top 2 similar articles
         recommendations = make_content_recs(article_id_to_test, df_content, top_n=2)

         # Print the recommended article IDs
         print("Recommended article IDs for article {}: {}".format(article_id_to_test, recommend
```

```
Recommended article IDs for article 1024: [919, 656]
```

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

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

Write an explanation of your content based recommendation system here.

3 Possible Improvements:

3.1 Text Preprocessing:

Before vectorization, preprocessing the text data could improve the quality of recommendations. This could include steps like lowercasing, removing punctuation, lemmatization, and removing stop words to reduce noise.

```
In [37]: '''
         # Example preprocessing step
         from sklearn.feature_extraction.text import TfidfVectorizer
         from nltk.corpus import stopwords
```

```
import re
from nltk.stem import WordNetLemmatizer
import nltk
nltk.download(['stopwords','wordnet'])

lemmatizer = WordNetLemmatizer()
stop_words = stopwords.words('english')

def preprocess_text(text):
    # Lowercase
    text = text.lower()
    # Remove non-alphabetic characters
    text = re.sub(r'[^a-zA-Z\s]', '', text)
    # Lemmatize and remove stop words
    text = ' '.join([lemmatizer.lemmatize(word) for word in text.split() if word not in
    return text

# Assuming df_content is available and preprocess_text is defined
df_content['combined_content'] = df_content.apply(lambda x: preprocess_text(x['doc_body

# Continue with TF-IDF vectorization
tfidf = TfidfVectorizer(stop_words='english')
tfidf_matrix = tfidf.fit_transform(df_content['combined_content'])


# Followed by similarity calculation and recommendation generation as before
'''
```

```
Out[37]: "\n# Example preprocessing step\nfrom sklearn.feature_extraction.text import TfidfVecto
```

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

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

```
In [38]: '''
         # make recommendations for a brand new user
         def recommend_for_new_user(top_n=5, df_content=df_content):
             """
             Recommends articles for a new user based on content popularity or diversity.
             """
             # Assuming get_top_article_ids was implemented to fetch popular articles
             # Here we simulate fetching articles based on diversity or recency
             diverse_articles = df_content.sample(n=top_n)['article_id'].tolist()
             recommendations = get_article_names(diverse_articles, df_content)
```

```
    return recommendations
recommended_article_ids = recommend_for_new_user()
print("Content-based recommendations of articles for new user: ",recommended_article_id

# make a recommendations for a user who only has interacted with article id '1427.0'
recommended_article_ids = make_content_recs(1427.0, df_content, top_n=10)

print(f"Content-based recommendations for article {1427.0}: {recommended_article_ids}")
'''
```

```
Out[38]: '\n# make recommendations for a brand new user\ndef recommend_for_new_user(top_n=5, df_
```

3.1.2 Part V: Matrix Factorization

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

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

```
In [39]: # Load the matrix here
         user_item_matrix = pd.read_pickle('user_item_matrix.p')
```

```
In [40]: # quick look at the matrix
         user_item_matrix.head()
```

```
Out[40]: article_id  0.0  100.0  1000.0  1004.0  1006.0  1008.0  101.0  1014.0  1015.0  \
         user_id
         1           0.0    0.0     0.0     0.0     0.0     0.0    0.0     0.0     0.0
         2           0.0    0.0     0.0     0.0     0.0     0.0    0.0     0.0     0.0
         3           0.0    0.0     0.0     0.0     0.0     0.0    0.0     0.0     0.0
         4           0.0    0.0     0.0     0.0     0.0     0.0    0.0     0.0     0.0
         5           0.0    0.0     0.0     0.0     0.0     0.0    0.0     0.0     0.0

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

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

```
[5 rows x 714 columns]
```

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

```
In [41]: # Perform SVD on the User-Item Matrix Here

         u, s, vt = np.linalg.svd(user_item, full_matrices=False)# use the built in to get the t
```

Provide your response here.

3.2 Absence of NaNs:

If the User-Item matrix in your context does not contain NaN values, because the user-item interactions are modeled simply as 0 (no interaction) or 1 (interaction occurred); then every entry in the matrix is known. This fully observed matrix negates the need for FunkSVD, which is specifically designed to handle missing data.

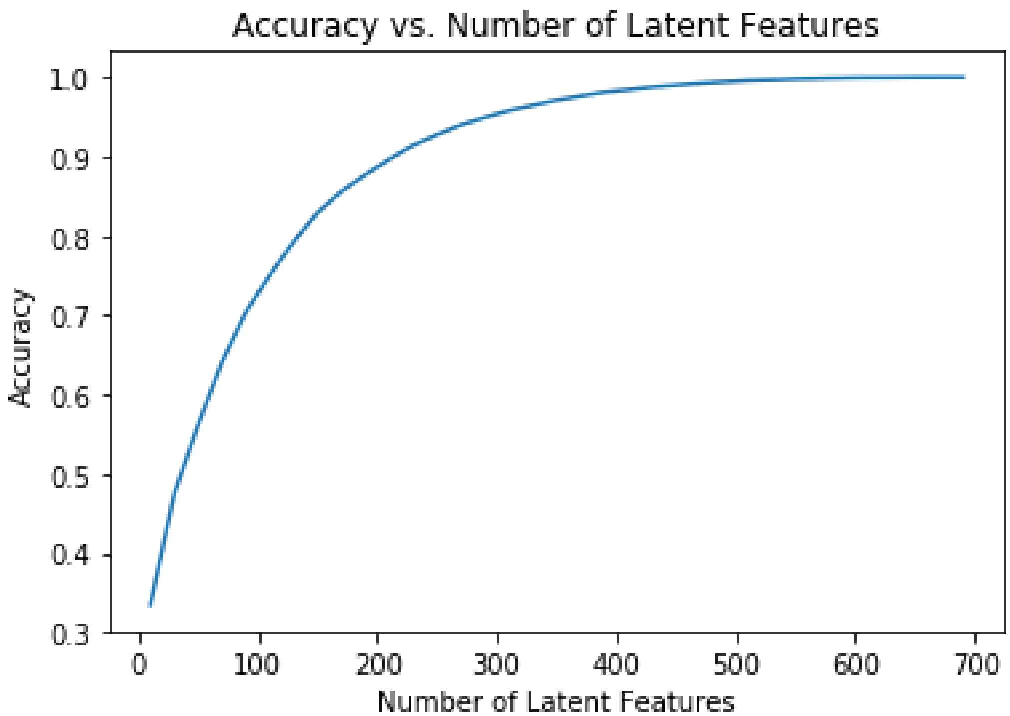
3.3 Simplicity of the Model:

By using a binary representation (0-1) for user-item interactions, the matrix avoids the complications that arise with sparse, real-valued matrices (e.g., ratings). This simplification makes traditional SVD suitable because it can leverage the complete dataset without needing to account for or impute 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 [42]: num_latent_feats = np.arange(10,700+10,20)
         sum_errs = []

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

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

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

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


         plt.plot(num_latent_feats, 1 - np.array(sum_errs)/df.shape[0]);
```

```python
plt.xlabel('Number of Latent Features');
plt.ylabel('Accuracy');
plt.title('Accuracy vs. Number of Latent Features');
```



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

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

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

In [43]:
```python
df_train = df.head(40000)
df_test = df.tail(5993)

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

```
        df_test - test dataframe

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

        '''

        # Create user-item matrix for the training data
        user_item_train = df_train.groupby(['user_id', 'article_id']).size().unstack(fill_v
        user_item_train = user_item_train.applymap(lambda x: 1 if x > 0 else 0)

        # Create user-item matrix for the testing data
        user_item_test = df_test.groupby(['user_id', 'article_id']).size().unstack(fill_val
        user_item_test = user_item_test.applymap(lambda x: 1 if x > 0 else 0)

        # Extract all user ids from the test set
        test_idx = list(df_test['user_id'].unique())

        # Extract all article ids from the test set
        test_arts = list(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(
```

In [44]:
```
# How many users can we make predictions for in the test set?
users_in_both_sets = user_item_train.index.isin(test_idx)
users_can_predict = sum(users_in_both_sets)
print("How many users can we make predictions for in the test set?: ", users_can_predic

# How many users are we not able to make predictions for because of the cold start prob
users_cannot_predict = len(test_idx) - users_can_predict
print("How many users are we not able to make predictions for because of the cold start

# How many articles can we make predictions for in the test set?
articles_in_both_sets = user_item_train.columns.isin(test_arts)
articles_can_predict = sum(articles_in_both_sets)
print("How many articles can we make predictions for in the test set?: ", articles_can_

# How many articles are we not able to make predictions for because of the cold start p
articles_cannot_predict = len(test_arts) - articles_can_predict
print("How many articles are we not able to make predictions for because of the cold st
```

```
How many users can we make predictions for in the test set?:  20
```

```
How many users are we not able to make predictions for because of the cold start problem?:  662
How many articles can we make predictions for in the test set?:  574
How many articles are we not able to make predictions for because of the cold start problem?:  0
```

```
In [45]: # Replace the values in the dictionary below
         a = 662
         b = 574
         c = 20
         d = 0



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

         t.sol_4_test(sol_4_dict)
```

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

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

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

```
In [46]: # fit SVD on the user_item_train matrix
         u_train, s_train, vt_train =np.linalg.svd(user_item_train, full_matrices=False) # fit s
```

```
In [47]: # Use these cells to see how well you can use the training
         # decomposition to predict on test data
```

```
In [48]: # Find test users and articles that are also in the training set
         test_users_subset = np.intersect1d(user_item_test.index, user_item_train.index)
         test_articles_subset = np.intersect1d(user_item_test.columns, user_item_train.columns)

         # Create the test user-item matrix for users and articles that also exist in the traini
         user_item_test_subset = user_item_test.loc[test_users_subset, test_articles_subset]
```

```
In [49]: from sklearn.metrics import accuracy_score

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

```python
for k in num_latent_feats:
    # restructure with k latent features
    s_train_k, u_train_k, vt_train_k = np.diag(s_train[:k]), u_train[:, :k], vt_train[:

    # take dot product
    user_item_est = np.dot(np.dot(u_train_k, s_train_k), vt_train_k)

    # Get the subset of rows from the estimated matrix that matches the test set subset
    user_row_idxs = user_item_train.index.isin(test_users_subset)
    article_col_idxs = user_item_train.columns.isin(test_articles_subset)
    user_item_est_subset = user_item_est[user_row_idxs, :][:, article_col_idxs]

    # Calculate the error for each prediction to actual value
    diffs = np.subtract(user_item_test_subset.values, user_item_est_subset)

    # Calculate the overall error
    err = np.sum(np.sum(np.abs(diffs)))
    sum_errs.append(err)

    # Calculate accuracy
    preds_binary = user_item_est_subset.round()
    accuracy = accuracy_score(user_item_test_subset.values.flatten(), preds_binary.flat
    print(f"Latent Features: {k}, Accuracy: {accuracy:.4f}")
```

```
Latent Features: 10, Accuracy: 0.9784
Latent Features: 30, Accuracy: 0.9766
Latent Features: 50, Accuracy: 0.9753
Latent Features: 70, Accuracy: 0.9736
Latent Features: 90, Accuracy: 0.9723
Latent Features: 110, Accuracy: 0.9705
Latent Features: 130, Accuracy: 0.9695
Latent Features: 150, Accuracy: 0.9687
Latent Features: 170, Accuracy: 0.9680
Latent Features: 190, Accuracy: 0.9673
Latent Features: 210, Accuracy: 0.9666
Latent Features: 230, Accuracy: 0.9663
Latent Features: 250, Accuracy: 0.9658
Latent Features: 270, Accuracy: 0.9654
Latent Features: 290, Accuracy: 0.9652
Latent Features: 310, Accuracy: 0.9648
Latent Features: 330, Accuracy: 0.9648
Latent Features: 350, Accuracy: 0.9646
Latent Features: 370, Accuracy: 0.9646
Latent Features: 390, Accuracy: 0.9645
Latent Features: 410, Accuracy: 0.9645
Latent Features: 430, Accuracy: 0.9645
Latent Features: 450, Accuracy: 0.9645
```

```
Latent Features: 470, Accuracy: 0.9645
Latent Features: 490, Accuracy: 0.9645
Latent Features: 510, Accuracy: 0.9645
Latent Features: 530, Accuracy: 0.9645
Latent Features: 550, Accuracy: 0.9645
Latent Features: 570, Accuracy: 0.9645
Latent Features: 590, Accuracy: 0.9645
Latent Features: 610, Accuracy: 0.9645
Latent Features: 630, Accuracy: 0.9645
Latent Features: 650, Accuracy: 0.9645
Latent Features: 670, Accuracy: 0.9645
Latent Features: 690, Accuracy: 0.9645
```

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

Your response here.

The results from the previous question show an interesting trend, as the number of latent features increases, the accuracy of predictions on the test data slightly decreases. This might seem counterintuitive initially, but it can be explained by the concept of overfitting. When the model uses more latent features, it becomes more tailored to the training data (hence possibly achieving higher accuracy there), but it may not generalize well to unseen data, leading to a decrease in test accuracy.

4 Observations:

4.1 High Baseline Accuracy:

The accuracy starts very high (at 0.9784 for 10 latent features) and only slightly decreases as the number of latent features increases. This high baseline could be due to the sparsity of the user-item matrix where the majority of entries are zeros, meaning that predicting a non-interaction is often correct.

4.2 Diminishing Returns on Adding Features:

The incremental decrease in accuracy suggests diminishing returns on adding more latent features beyond a certain point. It indicates that a relatively small number of latent features are sufficient to capture the majority of the useful variance in the data.

5 Recommendations for Evaluation:

Given these observations, determining the effectiveness of the recommendation systems (SVD-based or others) in improving user engagement with articles requires a more holistic evaluation approach beyond accuracy:

5.1 A/B Testing:

Implement A/B testing by exposing one group of users to recommendations generated by the SVD model and another group to a control version (e.g., random recommendations or no recommendations). Metrics such as click-through rates, time spent on recommended articles, or number of articles read could provide direct evidence of the system's effectiveness.

5.2 Diversity and Novelty:

Evaluate the diversity and novelty of the recommendations. A system that suggests a wide range of topics or uncovers less obvious articles might enhance user engagement by providing a more enriching experience.

5.3 User Satisfaction Surveys:

Collect user feedback on the relevance and usefulness of recommendations through surveys. User perceptions can offer valuable insights that raw performance metrics might not capture.

5.4 Usage Metrics:

Monitor changes in overall platform engagement metrics, such as daily active users or session length, after the introduction of the recommendation system. Improvements in these metrics could indicate a positive impact on user experience.

6 Conclusion:

While the SVD-based recommendation system demonstrates high accuracy, optimizing the number of latent features is crucial to balance model complexity and generalizability. However, assessing the system's real-world effectiveness requires a broader set of evaluation strategies, including A/B testing and user feedback, to ensure that the recommendations meaningfully enhance the user experience. The aim is not just to make accurate predictions but to drive more meaningful interactions on the platform.

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

6.1 Conclusion

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

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

6.2 Directions to Submit

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

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

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

```
In [50]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Recommendations_with_IBM.ipynb'])
```

```
Out[50]: 0
```