Recommendations_with_IBM

January 12, 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

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

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

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

%matplotlib inline

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

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

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

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

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

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

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

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

1.1.1 Part I : Exploratory Data Analysis

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

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

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

Out[3]: (45993, 3)

In [4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45993 entries, 0 to 45992
Data columns (total 3 columns):
```

```
article_id    45993 non-null float64
title         45993 non-null object
email         45976 non-null object
dtypes: float64(1), object(2)
memory usage: 1.1+ MB
```

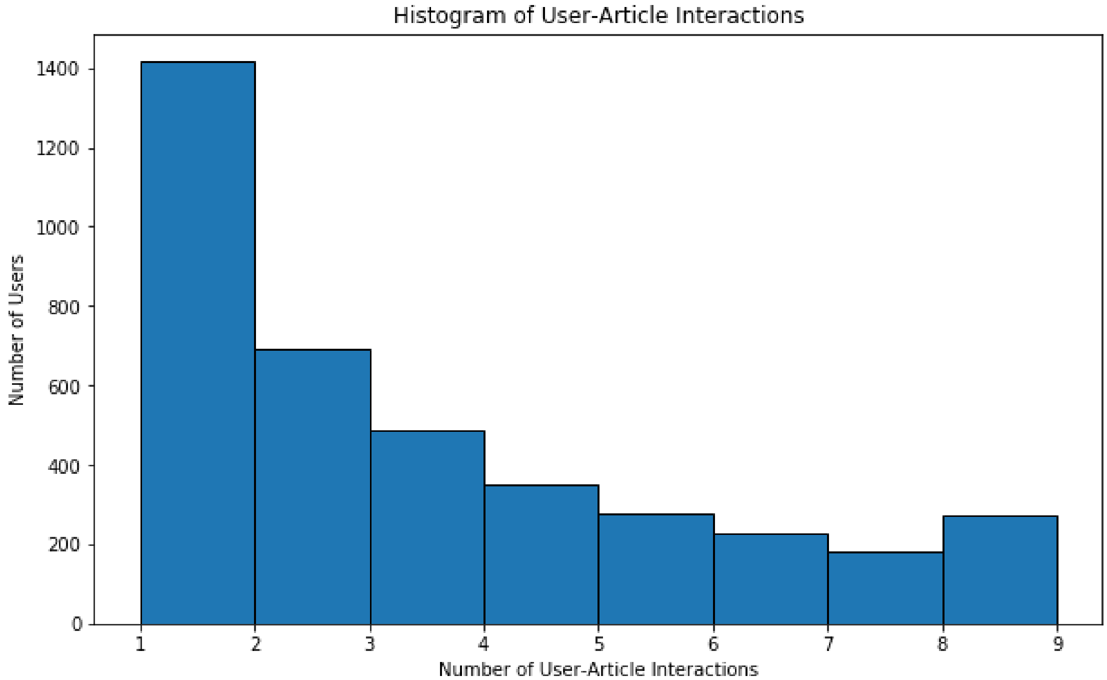
In [5]: `df.groupby('email').agg('count').iloc[:,0].sort_values(ascending=False)`

Out[5]:
```
email
2b6c0f514c2f2b04ad3c4583407dccd0810469ee    364
77959baaa9895a7e2bdc9297f8b27c1b6f2cb52a    363
2f5c7feae533ce046f2cb16fb3a29fe00528ed66    170
a37adec71b667b297ed2440a9ff7dad427c7ac85    169
8510a5010a5d4c89f5b07baac6de80cd12cfaf93    160
f8c978bcf2ae2fb8885814a9b85ffef2f54c3c76    158
284d0c17905de71e209b376e3309c0b08134f7e2    148
d9032ff68d0fd45dfd18c0c5f7324619bb55362c    147
18e7255ee311d4bd78f5993a9f09538e459e3fcc    147
c60bb0a50c324dad0bffd8809d121246baef372b    145
276d9d8ca0bf52c780b5a3fc554fa69e74f934a3    145
56832a697cb6dbce14700fca18cffcced367057f    144
b2d2c70ed5de62cf8a1d4ded7dd141cfbbdd0388    142
ceef2a24a2a82031246814b73e029edba51e8ea9    140
8dc8d7ec2356b1b106eb3d723f3c234e03ab3f1e    137
e38f123afecb40272ba4c47cb25c96a9533006fa    136
53db7ac77dbb80d6f5c32ed5d19c1a8720078814    132
6c14453c049b1ef4737b08d56c480419794f91c2    131
fd824fc62b4753107e3db7704cd9e8a4a1c961f1    116
c45f9495a76bf95d2633444817f1be8205ad542d    114
12bb8a9740400ced27ae5a7d4c990ac3b7e3c77d    104
3427a5a4065625363e28ac8e85a57a9436010e9c    103
497935037e41a94d2ae02488d098c7abda9a30bc    102
0d644205ecefdef33e3346bb3551f5e68dc57c58    102
e90de4b883d9de64a47774ad7ad49ca6fd69d4fe    101
015aaf617598e413a35d6d2249e26b7f3c40adb7    101
db1c400ffb74f14390deba2140bd31d2e1dc5c4e     98
7dc02db8b76fffbdfe29542da672d4d5fd5ed4ae     97
2e205a44014ca7bdbf07fc32f3c9d17699671d03     96
4070b8d82484ed99cdb9bbc2ebf4e9aca06fd934     95
                                            ...
42d4a9f766f2770e88a566cb65438a9b92446e6a      1
99a8fdeab6072b892f3477f2d91628df09cce12b      1
998ca3bffaaeb42f77cac8daf5f632a0c00b1c30      1
40002a2b20cee2d68bb9489ebd403ef9993100c2      1
9bbcd23976d1f9857fbb5e11291d37a2a2768341      1
9beb8742d40fb0619598cc3ae384165bca8d0794      1
efebe789cddce15baf08adab2c3da793896eb3cb      1
```

```
3e15c6b4972e54052ef3084190bdf1167b5db1a8     1
9db953fb65f5d57d8b8d82a0d04471dd5b7bac7b     1
9d3363969ba2a7f1d012d5c55af76652fc6ddc36     1
9d0375f208a9f91db408b5cf8da78e976fed3a55     1
9cfcf871ffb197ba5ad6bc6408ab5dc66d5b796d     1
9cfa28d68d71ba3fb1bf4745319be2258b87eb92     1
9ce6218339bd9186a3d0fe7da3494bc5af43dcba     1
9ce1e204a22ba4cd4a0a53da42238ae830b5879d     1
9cdb6449c080df01e366ce9c66f07a549be838d9     1
9cc6d232298678b4e24cf97ca0c74675fc2f132e     1
efe31a945040de5c0b5857b0072dc9254e96b37d     1
9c2394077e008013b92ec391eaf908d5ef3dd611     1
dc323e9b8ca2a9bf6397e43063fc093ae90788ea     1
9cb9845ca344b23b49ad94f4fddbcf95fedc0617     1
9cadbc14289d0db3937f00f4f2aab8d49b49680a     1
3f7be78857cda042074028beed41d088e5dd6a99     1
efded4d12cb4d1f53515e503d4ad3c4ca850a4da     1
3faaf951e4fa83cd67032688320d03d832ae708c     1
efdb4c363358224cd99d45053e2dbddf659e25ce     1
3fac88958dc7903b380743597f44a79cf76ea128     1
9c4b5dda1282c94128a7dc778951a313cce8055b     1
3fbe4978a20ee5ddc07648f2762b808ea18cedd1     1
6755c5d49a97e785583f65a92f72bc09459905a9     1
Name: article_id, Length: 5148, dtype: int64
```

In [6]:
```python
# Fill in the median and maximum number of user_article interactios below

median_val = df.groupby('email').agg('count').iloc[:,0].median()# 50% of individuals int
max_views_by_user =df.groupby('email').agg('count').max()[0] # The maximum number of use
```

In [7]:
```python
# Group by 'email' and count the number of interactions
user_interactions = df.groupby('email').agg('count')

# Increase the plot size
plt.figure(figsize=(10, 6))

# Create a histogram
plt.hist(user_interactions['article_id'], bins=range(1, int(user_interactions['article_i

# Set labels and title
plt.xlabel('Number of User-Article Interactions')
plt.ylabel('Number of Users')
plt.title('Histogram of User-Article Interactions')

# Show the plot
plt.show()
```



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

In [8]:
```
# Find and explore duplicate articles
```

In [9]:
```
# 1. Explore Duplicate Articles
duplicate_articles = df_content[df_content.duplicated(subset='article_id', keep=False)]
duplicate_articles.shape
```

Out[9]: (10, 5)

In [10]:
```
# Remove any rows that have the same article_id - only keep the first
# 2. Remove Duplicate Articles
df_content = df_content.drop_duplicates(subset='article_id', keep='first')
```

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

In [11]:
```
unique_articles =df['article_id'].nunique()# The number of unique articles that have at
total_articles = df_content['article_id'].nunique()# The number of unique articles on t
unique_users = df['email'].nunique()# The number of unique users
user_article_interactions = df.shape[0]# The number of user-article interactions
```

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

In [12]:
```
most_viewed_article_id = str(df.article_id.value_counts().index[0])# The most viewed ar
max_views = df.article_id.value_counts().head(1).values[0]# The most viewed article in
```

In [13]:
```
## No need to change the code here - this will be helpful for later parts of the notebo
# Run this cell to map the user email to a user_id column and remove the email column

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

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

        email_encoded.append(coded_dict[val])
    return email_encoded

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

# show header
df.head()
```

Out[13]:

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

In [14]:
```
## If you stored all your results in the variable names above,
## you shouldn't need to change anything in this cell

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

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

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

1.1.2 Part II: Rank-Based Recommendations

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

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

```
In [15]: df[df['article_id'].isin(df['article_id'].value_counts().head(10).index)]
```

Out[15]:

	article_id	title	user_id
1	1314.0	healthcare python streaming application demo	2
2	1429.0	use deep learning for image classification	3
6	1429.0	use deep learning for image classification	7
8	1314.0	healthcare python streaming application demo	9
13	1314.0	healthcare python streaming application demo	4
14	1170.0	apache spark lab, part 1: basic concepts	10
20	1314.0	healthcare python streaming application demo	18
29	1364.0	predicting churn with the spss random tree alg...	24
31	1162.0	analyze energy consumption in buildings	25
37	1431.0	visualize car data with brunel	28
41	1429.0	use deep learning for image classification	3
42	1427.0	use xgboost, scikit-learn & ibm watson machine...	31
45	1431.0	visualize car data with brunel	33
50	1162.0	analyze energy consumption in buildings	36
53	1427.0	use xgboost, scikit-learn & ibm watson machine...	38
55	1162.0	analyze energy consumption in buildings	40
56	1304.0	gosales transactions for logistic regression m...	41
60	1427.0	use xgboost, scikit-learn & ibm watson machine...	6
61	1427.0	use xgboost, scikit-learn & ibm watson machine...	43
66	1330.0	insights from new york car accident reports	32
68	1427.0	use xgboost, scikit-learn & ibm watson machine...	46
75	1429.0	use deep learning for image classification	7
78	1314.0	healthcare python streaming application demo	51
79	1162.0	analyze energy consumption in buildings	52
80	1429.0	use deep learning for image classification	40
81	1162.0	analyze energy consumption in buildings	53
87	1330.0	insights from new york car accident reports	10
90	1427.0	use xgboost, scikit-learn & ibm watson machine...	51
92	1364.0	predicting churn with the spss random tree alg...	6
93	1314.0	healthcare python streaming application demo	60
...	...	...	...
45741	1429.0	use deep learning for image classification	5138
45742	1162.0	analyze energy consumption in buildings	5138
45768	1330.0	insights from new york car accident reports	5138

```
45779      1293.0  finding optimal locations of new store using d...     5138
45782      1314.0       healthcare python streaming application demo     5138
45786      1330.0         insights from new york car accident reports     5138
45792      1431.0                      visualize car data with brunel     4293
45798      1364.0  predicting churn with the spss random tree alg...     4293
45800      1364.0  predicting churn with the spss random tree alg...     4293
45802      1330.0         insights from new york car accident reports     4293
45803      1330.0         insights from new york car accident reports     4293
45805      1364.0  predicting churn with the spss random tree alg...     4293
45814      1170.0            apache spark lab, part 1: basic concepts     4293
45815      1431.0                      visualize car data with brunel     4293
45816      1364.0  predicting churn with the spss random tree alg...     4293
45817      1431.0                      visualize car data with brunel     4293
45820      1431.0                      visualize car data with brunel     4293
45826      1364.0  predicting churn with the spss random tree alg...     4293
45827      1364.0  predicting churn with the spss random tree alg...     4293
45829      1364.0  predicting churn with the spss random tree alg...     4293
45835      1330.0         insights from new york car accident reports     5139
45873      1314.0       healthcare python streaming application demo     5140
45903      1330.0         insights from new york car accident reports     5140
45913      1364.0  predicting churn with the spss random tree alg...     5140
45924      1330.0         insights from new york car accident reports     5140
45942      1427.0  use xgboost, scikit-learn & ibm watson machine...     5140
45943      1330.0         insights from new york car accident reports     5140
45957      1330.0         insights from new york car accident reports     5143
45958      1431.0                      visualize car data with brunel     5143
45960      1330.0         insights from new york car accident reports     5143

[6551 rows x 3 columns]
```

In [16]:
```
df['article_id'].value_counts().head(10)
```

Out[16]:
```
1429.0    937
1330.0    927
1431.0    671
1427.0    643
1364.0    627
1314.0    614
1293.0    572
1170.0    565
1162.0    512
1304.0    483
Name: article_id, dtype: int64
```

In [17]:
```
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

        '''
        # Count the occurrences of each article_id
        article_counts = df['article_id'].value_counts()

        # Get the top n article_ids
        top_article_ids = article_counts.head(n).index

        # Get the corresponding article titles
        top_articles = df[df['article_id'].isin(top_article_ids)]['title'].unique().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

        '''
        # Count the occurrences of each article_id
        article_counts = df['article_id'].value_counts()

        # Get the top n article_ids
        top_article_ids = article_counts.head(n).index

        return top_article_ids.astype(str).tolist()
```

In [18]:
```
print(get_top_articles(10))
print(get_top_article_ids(10))
```

```
['healthcare python streaming application demo', 'use deep learning for image classification', '
['1429.0', '1330.0', '1431.0', '1427.0', '1364.0', '1314.0', '1293.0', '1170.0', '1162.0', '1304
```

In [19]:
```
# 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 [20]:
```
# 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
    '''
    # Create a binary matrix where interactions are represented by 1 and missing values
    user_item = df.pivot_table(index='user_id', columns='article_id', aggfunc=lambda x:

    return user_item # return the user_item matrix

user_item = create_user_item_matrix(df)
```

In [21]:
```
## 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 [22]: 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 a list of users ordered by similarity

             '''
             # Compute similarity of each user to the provided user
             similarity = user_item.loc[user_id].dot(user_item.T)

             # Sort by similarity in descending order
             similarity = similarity.sort_values(ascending=False)

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

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

             return most_similar_users
```

```
In [23]: # 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 [24]: 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)
             '''
             # Filter the DataFrame to get rows with the specified article_ids
             articles = df[df['article_id'].isin(article_ids)]

             # Get the unique article names
             article_names = articles['title'].unique().tolist()

             return article_names


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

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

             Description:
             Provides a list of the article_ids and article titles that have been seen by a user
             '''
             # Your code here
             # Get the row corresponding to the user_id
             user_row = user_item.loc[user_id]

             # Extract the article_ids where the user has interacted (value is 1)
             article_ids = user_row[user_row == 1].index.get_level_values(1).astype(str).tolist(
             article_names = df[df['article_id'].isin(article_ids)]['title'].tolist()

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

```python
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
    user_item - (pandas dataframe) matrix of users by articles:
                1's when a user has interacted with an article, 0 otherwise

    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

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

    # Initialize the recommendations list
    recs = []

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

    # Loop through similar users and recommend articles the user hasn't seen
    for user in similar_users:
        # Get the articles seen by the similar user
        sim_user_articles, _ = get_user_articles(user, user_item)

        # Filter out articles the given user has already seen
        new_recs = np.setdiff1d(sim_user_articles, seen_article_ids, assume_unique=True

        # Add new recommendations to the list
        recs.extend(new_recs)

        # Check if we have enough recommendations
        if len(recs) >= m:
            break
```

```
        # Trim the list to the desired number of recommendations
        recs = recs[:m]

        return recs
```

In [25]:
```
# Check Results
get_article_names(user_user_recs(1, 10)) # Return 10 recommendations for user 1
```

Out[25]:
```
['got zip code data? prep it for analytics.  ibm watson data lab  medium',
 'timeseries data analysis of iot events by using jupyter notebook',
 'graph-based machine learning',
 'using brunel in ipython/jupyter notebooks',
 'experience iot with coursera',
 'the 3 kinds of context: machine learning and the art of the frame',
 'deep forest: towards an alternative to deep neural networks',
 'this week in data science (april 18, 2017)',
 'higher-order logistic regression for large datasets',
 'using machine learning to predict parking difficulty']
```

In [26]:
```
# 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 [27]:
```
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 the number of i
                    highest of each is higher in the dataframe

    '''
    # Ensure the index of user_item is of integer type
    user_item.index = user_item.index.astype(int)

    # Create a DataFrame with neighbor_id, similarity, and num_interactions columns
    neighbors_df = pd.DataFrame({
        'neighbor_id': user_item.index,  # set neighbor_id column equal to user_item in
        'similarity': user_item.loc[user_id].dot(user_item.T),  # calculate similarity
        'num_interactions': df.groupby('user_id').count()['article_id']
    })

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

    # Reset the index
    neighbors_df = neighbors_df.reset_index(drop=True)

    # Drop the row with the user_id as itself will be most similar
    neighbors_df = neighbors_df[neighbors_df.neighbor_id != user_id]

    return neighbors_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 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.

        '''
        recs = set()  # recommendations to be made (using set for constant-time membership

        user_articles_ids_seen, _ = get_user_articles(user_id, user_item)  # article ids se
        closest_neighs = get_top_sorted_users(user_id, df, user_item).neighbor_id.tolist()

        for neigh_id in closest_neighs:
            neigh_articles_ids_seen, _ = get_user_articles(neigh_id, user_item)  # articles
            new_recs = set(neigh_articles_ids_seen) - set(user_articles_ids_seen)  # find t
            recs.update(new_recs)  # update the set of recommendations

            if len(recs) >= m:
                break

        recs = list(recs)[:m]  # convert to a list and limit to m recommendations
        rec_names = get_article_names(recs, df=df)

        return recs, rec_names
```

In [28]:
```
# 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:
['730.0', '1356.0', '1329.0', '1426.0', '1324.0', '1163.0', '302.0', '205.0', '1153.0', '1085.0'

The top 10 recommendations for user 20 are the following article names:
['ibm watson facebook posts for 2015', 'analyze open data sets with spark & pixiedust', 'develop
```

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 [29]:
```
### Tests with a dictionary of results
```

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

```
In [30]: user1_most_sim
```

```
Out[30]: 3933
```

```
In [31]: user131_10th_sim
```

```
Out[31]: 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.

When dealing with a new user without any prior interactions, a practical approach is to rely on Rank-Based Recommendations using the `get_top_articles` function. This involves recommending the most popular articles since we lack information about the user's preferences or interactions with other users. As we gather more data about the user, we can gradually transition to a more nuanced recommendation strategy, incorporating a blend of Rank-Based, Content-Based, and Collaborative Filtering techniques to provide more personalized and relevant suggestions. This evolution allows for a more comprehensive and tailored recommendation system as we learn more about the user's preferences and behaviors over time.

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)# Your recommendations here
```

```
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!
```

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

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

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

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

```
In [ ]: def make_content_recs():
            '''
            INPUT:

            OUTPUT:

            '''
```

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

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

Write an explanation of your content based recommendation system here.

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

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

```
In [ ]: # make recommendations for a brand new user


        # make a recommendations for a user who only has interacted with article id '1427.0'
```

1.1.8 Part V: Matrix Factorization

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

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

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

In [36]: # quick look at the matrix
         user_item_matrix.head()

Out[36]: 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]

In [37]: user_item_matrix.isnull().sum().sum()

Out[37]: 0
```

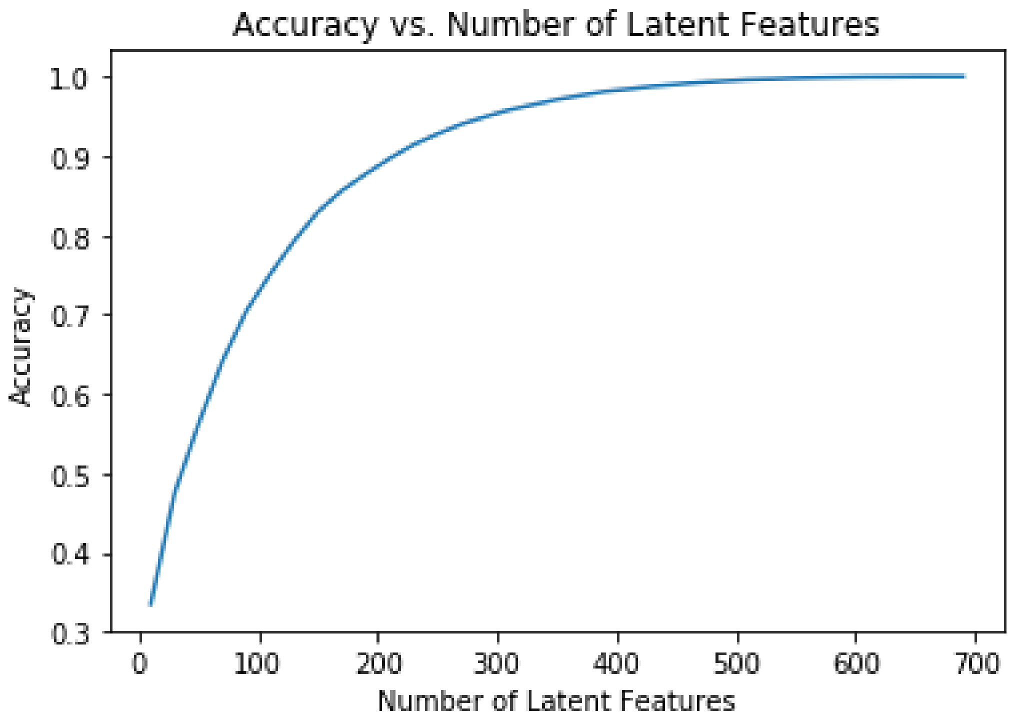
2. In this situation, you can use Singular Value Decomposition from numpy on the user-item matrix. Use the cell to perform SVD, and explain why this is different than in the lesson.

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

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

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

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

there are no missing values, thats why we can use SVD instead of FunkSVD

3. Now for the tricky part, how do we choose the number of latent features to use? Running the below cell, you can see that as the number of latent features increases, we obtain a lower error rate on making predictions for the 1 and 0 values in the user-item matrix. Run the cell below to get an idea of how the accuracy improves as we increase the number of latent features.

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

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

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

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

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


plt.plot(num_latent_feats, 1 - np.array(sum_errs)/df.shape[0]);
plt.xlabel('Number of Latent Features');
plt.ylabel('Accuracy');
plt.title('Accuracy vs. Number of Latent Features');
```



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

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

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

In [41]:
```
df_train = df.head(40000)
df_test = df.tail(5993)

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

    OUTPUT:
    user_item_train - a user-item matrix of the training dataframe
```

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

    '''
    # Your code here
    user_item_train = create_user_item_matrix(df_train)
    user_item_test = create_user_item_matrix(df_test)
    test_idx = user_item_test.index
    test_arts = user_item_test.columns
    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 [51]: len(user_item_train)

Out[51]: 4487

In [53]: len(user_item_test)

Out[53]: 682

In [49]: train_idx = user_item_train.index
         train_idx

Out[49]: Int64Index([   1,    2,    3,    4,    5,    6,    7,    8,    9,   10,
                     ...
                     4478, 4479, 4480, 4481, 4482, 4483, 4484, 4485, 4486, 4487],
                    dtype='int64', name='user_id', length=4487)

In [60]: train_arts = user_item_train.columns #714 movies in train set
         train_arts

Out[60]: MultiIndex(levels=[['title'], [0.0, 2.0, 4.0, 8.0, 9.0, 12.0, 14.0, 15.0, 16.0, 18.0, 2
                    labels=[[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
                    names=[None, 'article_id'])

In [54]: test_idx

Out[54]: Int64Index([2917, 3024, 3093, 3193, 3527, 3532, 3684, 3740, 3777, 3801,
                     ...
                     5140, 5141, 5142, 5143, 5144, 5145, 5146, 5147, 5148, 5149],
                    dtype='int64', name='user_id', length=682)

In [56]: len(test_arts)

Out[56]: 574
```

```
In [58]: len(test_idx.difference(train_idx))

Out[58]: 662

In [61]: len(test_arts.difference(train_arts))

Out[61]: 0

In [63]: # 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.

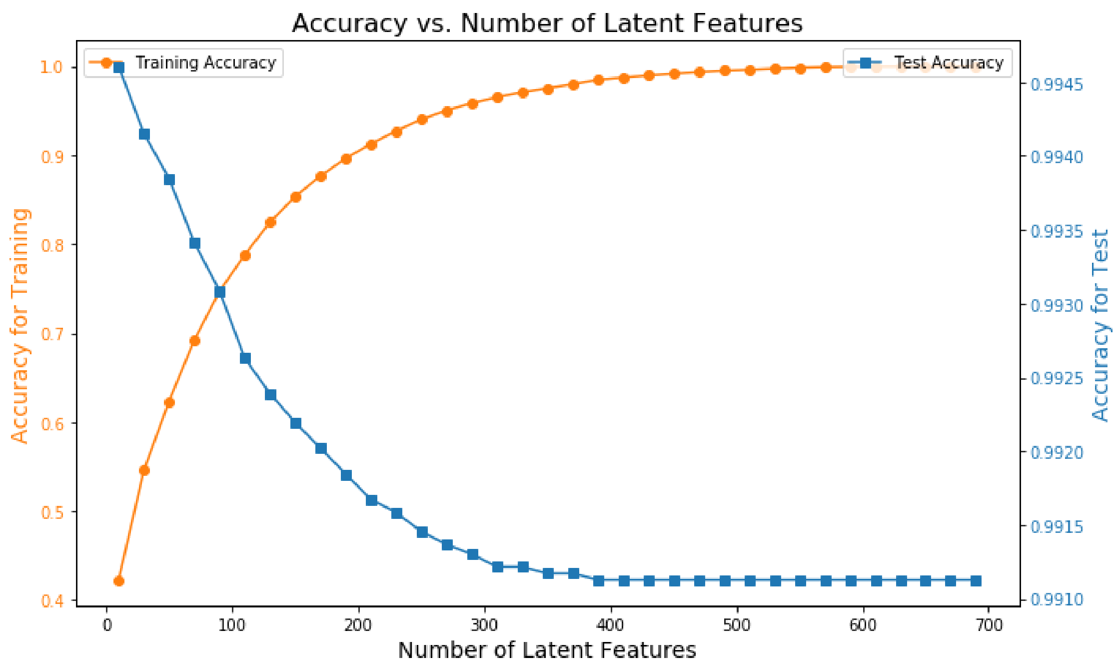
Use the cells below to explore how well SVD works towards making predictions for recommendations on the test data.

```
In [64]: # fit SVD on the user_item_train matrix
         u_train, s_train, vt_train = np.linalg.svd(user_item_train) # fit svd similar to above

In [65]: # Use these cells to see how well you can use the training
         # decomposition to predict on test data
         s_train.shape, u_train.shape, vt_train.shape

Out[65]: ((714,), (4487, 4487), (714, 714))

In [69]: num_latent_feats = np.arange(10, 700 + 10, 20)
         sum_errs_train = []
         sum_errs_test = []

         # Find rows that are present both in training and test set (= users we can make predict
```

```python
user_ids_can_predict = np.intersect1d(user_item_train.index, user_item_test.index)

# Find the indices of these users in user_item_train and derive u_test by reducing u_tr
row_idxs = user_item_train.index.isin(user_ids_can_predict)
u_test = u_train[row_idxs, :]

# Also reduce user_item_test to those indices
user_item_test_subset = user_item_test.loc[user_ids_can_predict]

# Find the columns present both in training and test set
col_idxs = user_item_train.columns.isin(user_item_test.columns)
vt_test = vt_train[:, col_idxs]

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

    # Take dot product
    user_item_train_pred = np.around(np.dot(np.dot(u_train_new, s_train_new), vt_train_
    user_item_test_pred = np.around(np.dot(np.dot(u_test_new, s_train_new), vt_test_new

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

    # Total errors and keep track of them
    err_train = np.sum(np.sum(np.abs(diffs_train)))
    err_test = np.sum(np.sum(np.abs(diffs_test)))

    sum_errs_train.append(err_train)
    sum_errs_test.append(err_test)
```

In [70]:
```python
# Plotting the training and test accuracies
fig, ax1 = plt.subplots(figsize=(10, 6))

color = 'tab:orange'
ax1.set_xlabel('Number of Latent Features', fontsize=14)
ax1.set_ylabel('Accuracy for Training', color=color, fontsize=14)
ax1.plot(num_latent_feats, 1 - np.array(sum_errs_train) / df.shape[0], color=color, mar
ax1.tick_params(axis='y', labelcolor=color)
ax1.set_title('Accuracy vs. Number of Latent Features', fontsize=16)
ax1.legend(loc='upper left')

ax2 = ax1.twinx()  # instantiate a second axes that shares the same x-axis

color = 'tab:blue'
ax2.set_ylabel('Accuracy for Test', color=color, fontsize=14)  # we already handled the
```

```
ax2.plot(num_latent_feats, 1 - np.array(sum_errs_test) / df.shape[0], color=color, mark
ax2.tick_params(axis='y', labelcolor=color)
ax2.legend(loc='upper right')

fig.tight_layout()  # otherwise, the right y-label is slightly clipped
plt.show()
```



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?

From the analysis above, it is evident that the training data's accuracy improves as the number of latent features increases. However, a contrasting trend is observed in the accuracy of the test data, indicating a potential issue with overfitting as latent features increase. Hence, it is advisable to maintain a relatively low number of latent features to mitigate this effect.

Moreover, increasing the latent featres decrease the accuracy of the test dataset but not for the training set. Its worth to note that this dataset is for 20 users hence the high accuracy for the test

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

1.2 Conclusion

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

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

1.3 Directions to Submit

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

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

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

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