Recommendations_with_IBM

March 9, 2022

1 Recommendations with IBM

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

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

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

1.1 Table of Contents

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

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

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

        %matplotlib inline

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

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

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

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

In [2]:
```
# 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.

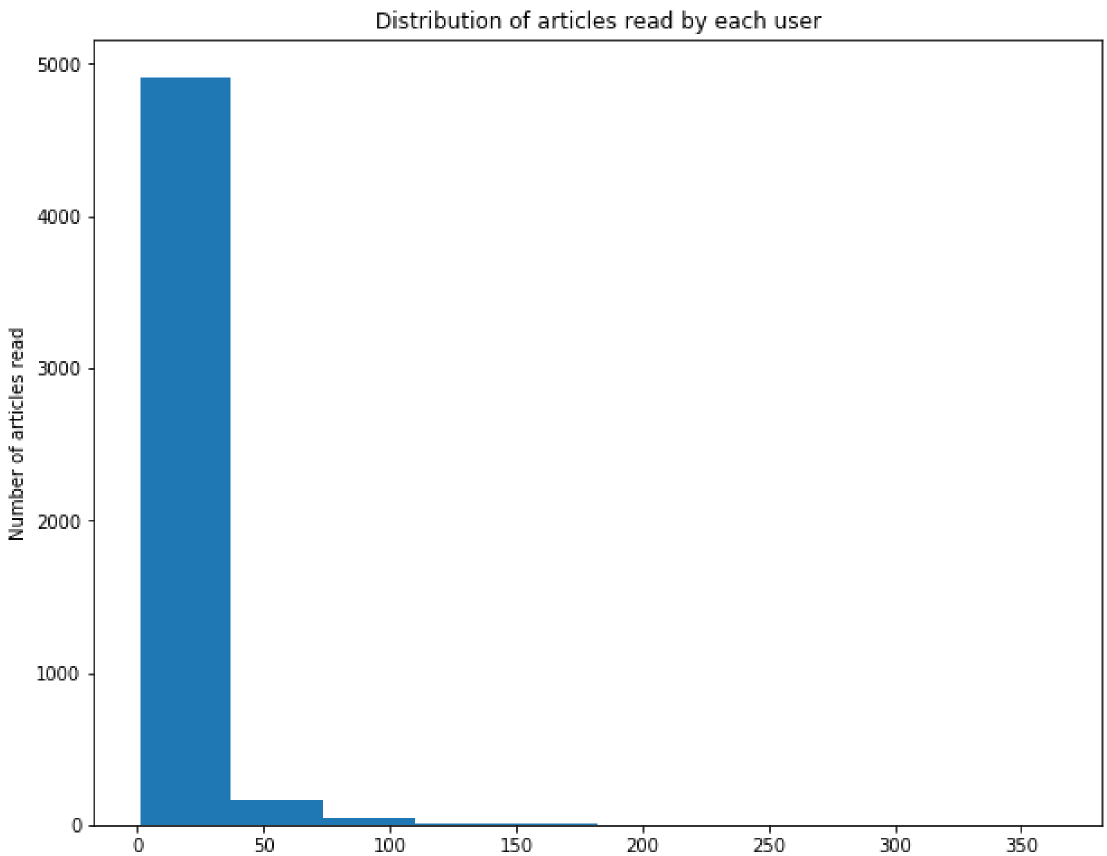
1. What is the distribution of how many articles a user interacts with in the dataset? Provide a visual and descriptive statistics to assist with giving a look at the number of times each user interacts with an article.

In [3]:
```
#Describe the number of times each user interacts with an article using the describe fun
user_article=df['email'].value_counts()
user_article.describe()
```

Out[3]:
```
count    5148.000000
mean        8.930847
std        16.802267
min         1.000000
25%         1.000000
```

```
50%         3.000000
75%         9.000000
max       364.000000
Name: email, dtype: float64
```

In [4]:
```
plt.figure(figsize=(10,8))
plt.hist(user_article) #normed=True, alpha=.5, label='actual');
plt.ylabel('Number of articles read');
plt.title('Distribution of articles read by each user');
```



In [5]:
```
# Fill in the median and maximum number of user_article interactios below
#The values were estimated from the descriptive analysis above
median_val = 3.0 # 50% of individuals interact with ____ number of articles or fewer.
max_views_by_user = 364 # The maximum number of user-article interactions by any 1 user
```

In [6]:
```
# Find and explore duplicate articles
df_content[df_content[['article_id']].duplicated() == True]
```

Out[6]:
```
                                              doc_body  \
365  Follow Sign in / Sign up Home About Insight Da...
692  Homepage Follow Sign in / Sign up Homepage * H...
```

```
761  Homepage Follow Sign in Get started Homepage *...
970  This video shows you how to construct queries ...
971  Homepage Follow Sign in Get started * Home\r\n...

                                       doc_description  \
365  During the seven-week Insight Data Engineering...
692  One of the earliest documented catalogs was co...
761  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
365                          Graph-based machine learning       Live          50
692  How smart catalogs can turn the big data flood...       Live         221
761  Using Apache Spark as a parallel processing fr...       Live         398
970                                 Use the Primary Index       Live         577
971  Self-service data preparation with IBM Data Re...       Live         232
```

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

In [7]:
```
# Remove any rows that have the same article_id - only keep the first
df_content.drop_duplicates(subset='article_id', inplace=True)
df_content.shape
```

Out[7]: (1051, 5)

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 [8]:
```
#Retreive the values from the affected dataframes
a = df['article_id'].nunique()
b = df_content['article_id'].nunique()
c = df['email'].nunique()
d = df.shape[0]

a, b, c, d
```

Out[8]: (714, 1051, 5148, 45993)

In [9]:
```
unique_articles = 714 # The number of unique articles that have at least one interaction
total_articles = 1051 # The number of unique articles on the IBM platform
unique_users = 5148 # The number of unique users
user_article_interactions = 45993 # The number of user-article interactions
```

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

In [10]:
```
#The most viewed article by email
most_viewed_article = df.groupby(['article_id']).count()['email'].sort_values(ascending

most_viewed_article.head()
```

Out[10]:
```
article_id
1429.0    937
1330.0    927
1431.0    671
1427.0    643
1364.0    627
Name: email, dtype: int64
```

In [11]:
```
most_viewed_article_id = '1429.0'     # The most viewed article in the dataset as a stri
max_views = 937 # The most viewed article in the dataset was viewed how many times?
```

In [12]:
```
## 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[12]:

	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 [13]:
```
## 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 [14]: n=5
         df['title'].value_counts().sort_values(ascending=False)[:n].index.tolist()
```

```
Out[14]: ['use deep learning for image classification',
          'insights from new york car accident reports',
          'visualize car data with brunel',
          'use xgboost, scikit-learn & ibm watson machine learning apis',
          'predicting churn with the spss random tree algorithm']
```

```
In [15]: df['article_id'].value_counts().sort_values(ascending=False)[:n,].index.tolist()
```

```
Out[15]: [1429.0, 1330.0, 1431.0, 1427.0, 1364.0]
```

```
In [16]: 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

             '''
             # Get the count of titles and sort the values in descending order
```

```
    #Filter the n number of items from the sorted dataframe
    top_articles = df['title'].value_counts().sort_values(ascending=False)[:n].index.to

    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 article id and sort in descending order
    #top_id = df['article_id'].value_counts().sort_values(ascending=False)

    #get top list of n number of ids
    top_articles = df['article_id'].value_counts().sort_values(ascending=False)[:n,].in

    return top_articles # Return the top article ids
```

In [17]:
```
print(get_top_articles(10))
print(get_top_article_ids(10))
```

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

In [18]:
```
# 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 [19]:
```
func = lambda x: x.max() #x.sum()

new_df = df[['user_id', 'article_id']]
new_df['interaction'] = 1
user_item = new_df.groupby(['user_id', 'article_id'])['interaction'].apply(func).unstac
user_item.iloc[user_item.isnull()] = 0
```

In [20]:
```
user_item.head()
```

Out[20]:
```
article_id  0.0     2.0     4.0     8.0     9.0     12.0    14.0    15.0    \
user_id
1              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
2              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3              0.0     0.0     0.0     0.0     0.0     1.0     0.0     0.0
4              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
5              0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0

article_id  16.0    18.0     ...    1434.0  1435.0  1436.0  1437.0  1439.0  \
user_id                      ...
1              0.0     0.0   ...       0.0     0.0     1.0     0.0     1.0
2              0.0     0.0   ...       0.0     0.0     0.0     0.0     0.0
3              0.0     0.0   ...       0.0     0.0     1.0     0.0     0.0
4              0.0     0.0   ...       0.0     0.0     0.0     0.0     0.0
5              0.0     0.0   ...       0.0     0.0     0.0     0.0     0.0

article_id  1440.0  1441.0  1442.0  1443.0  1444.0
user_id
1              0.0     0.0     0.0     0.0     0.0
2              0.0     0.0     0.0     0.0     0.0
3              0.0     0.0     0.0     0.0     0.0
4              0.0     0.0     0.0     0.0     0.0
5              0.0     0.0     0.0     0.0     0.0

[5 rows x 714 columns]
```

In [21]:
```
# 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
    '''
    # Remove duplicate and use pivot to reshape the dataframe
    new_df = df.drop_duplicates()

    #create a pivot table to reshape to a matrix form
    try:
        #user_item = new_df.pivot(index='user_id', columns='article_id', values='title'
        new_df = df[['user_id', 'article_id']]
        #create a column with 1 value where an interaction exist in the new dataframe
        new_df['interaction'] = 1
        user_item = new_df.groupby(['user_id', 'article_id'])['interaction'].apply(lamb

        #fill all NaN with 0
        user_item.iloc[user_item.isnull()] = 0
    except:
        user_item = new_df.pivot(index='user_id', columns='article_id')


    return user_item # return the user_item matrix

user_item = create_user_item_matrix(df)
```

In [22]:
```
list(df.columns)
```

Out[22]:
```
['article_id', 'title', 'user_id']
```

In [23]:
```
user_item.shape, user_item.sum(axis=1)[1]
```

Out[23]:
```
((5149, 714), 36.0)
```

In [24]:
```
## Tests: Youuser_item.sum(axis=1)[1] should just need to run this cell.  Don't change
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 [25]:
```
#user_idx = np.where(user_item['user_id'] == 1)[0][0]
user_content_matrix = user_item.dot(np.transpose(user_item))
current_user_content = user_content_matrix.loc[1, :]
```

In [26]:
```
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
    #using the example in the class lesson - movie_content.dot(np.transpose(movie_conte
    #since the similarity is based on the dot product, calculate the dot product first
    user_content_matrix = user_item.dot(np.transpose(user_item))

    #select from the row of the current user to the last row and the all columns
    current_user_content = user_content_matrix.loc[user_id, :]

    # sort by similarity
    similar_user_content = current_user_content.sort_values(ascending=False)

    # create list of just the ids
    similar_users = list(similar_user_content[similar_user_content.values > 0].index)

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

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

In [27]:
```
# 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 [28]:
```
article_ids=['1024.0', '1176.0', '1305.0', '1314.0', '1422.0', '1427.0']
list(set(df.query('article_id in @article_ids')['title']))
```

Out[28]:
```
['use xgboost, scikit-learn & ibm watson machine learning apis',
 'gosales transactions for naive bayes model',
 'use r dataframes & ibm watson natural language understanding',
 'using deep learning to reconstruct high-resolution audio',
 'healthcare python streaming application demo',
 'build a python app on the streaming analytics service']
```

In [29]:
```
def get_article_names(article_ids, df=df):
    '''
    INPUT:
    article_ids - (list) a list of article ids
    df - (pandas dataframe) df as defined at the top of the notebook

    OUTPUT:
    article_names - (list) a list of article names associated with the list of article
                    (this is identified by the title column)
    '''
    # Create a list of article titles based on article_ids
    '''article_names = []
    for id in article_ids:
        title = df[df['article_id']]==id]['title'][0]
        article_names.append(title)'''
    #Change the article_id field to string irrespective of the data type
    df['article_id'] = df['article_id'].astype(str)
    article_names = list(set(df.query('article_id in @article_ids')['title']))

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


def get_user_articles(user_id, user_item=user_item):
    '''
    INPUT:
    user_id - (int) a user id
    user_item - (pandas dataframe) matrix of users by articles:
```

```python
                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
    '''
    # Create a list of article ids and article names from the user position and all col
    user_data = user_item.loc[user_id, :]
    article_ids = list(set(user_data[user_data.values==1].index))
    article_ids = [str(id) for id in article_ids]
    article_names = get_article_names(article_ids)

    return article_ids, article_names # return the ids and names


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

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

    Description:
    Loops through the users based on closeness to the input user_id
    For each user - finds articles the user hasn't seen before and provides them as 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

    '''

    #retreive users similar to the current user id using the function find_similar_user
    similar_users = find_similar_users(user_id)

    #get the article_ids seen by this user
    user_article_ids , _ = get_user_articles(user_id)

    #define an empty array
```

```
        recs = []
        #Loops through the users based on closeness to the input user_id
        for similar_user_id in similar_users:
            #For each user - finds article_ids the user hasn't seen before and provides the
            article_ids, _ = get_user_articles(similar_user_id)
            #https://numpy.org/doc/stable/reference/generated/numpy.setdiff1d.html
            #not_seen_articles = list(set(article_names).difference(user_article_names))
            #using the above set function, 1D array of values in user_article_ids that are
            not_seen_article_ids = np.setdiff1d(user_article_ids, article_ids) #list(set(us

            if len(not_seen_article_ids) > 0:
                recs.extend(not_seen_article_ids)
                #remove duplicates
                recs = list(dict.fromkeys(recs))

            #Check if we have the required recommendations
            if len(recs) >= m:
                break

        #return only m number of recommendation
        return recs[:m] # return your recommendations for this user_id
```

In [30]:
```
# Check Results
#user_user_recs(1, 10)
get_article_names(user_user_recs(1, 10)) # Return 10 recommendations for user 1
```

Out[30]:
```
['predict loan applicant behavior with tensorflow neural networking',
 'time series prediction using recurrent neural networks (lstms)',
 'uci: iris',
 'country statistics: life expectancy at birth',
 'sector correlations shiny app',
 'categorize urban density',
 'introduction to market basket analysis in\xa0python',
 'uci ml repository: chronic kidney disease data set',
 'fighting gerrymandering: using data science to draw fairer congressional districts',
 'jupyter notebook tutorial']
```

In [31]:
```
# Test your functions here - No need to change this code - just run this cell
assert set(get_article_names(['1024.0', '1176.0', '1305.0', '1314.0', '1422.0', '1427.0
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 [32]:
```
user_content_matrix = user_item.dot(np.transpose(user_item))
current_user_content = user_content_matrix.loc[1, :]
```

In [29]:
```
similarity_df = pd.DataFrame(current_user_content[current_user_content.values>0])
similarity_df.reset_index(level=0, inplace=True)
similarity_df.rename(columns={"user_id": "neighbor_id", 1: "similarity"}, inplace=True)
similarity_df.head()
```

Out[29]:

	neighbor_id	similarity
0	1	36.0
1	2	2.0
2	3	6.0
3	4	3.0
4	6	4.0

In [51]:
```
interaction_df = pd.DataFrame(df.groupby(by='user_id').count()['article_id'])
interaction_df.reset_index(level=0, inplace=True)
interaction_df.rename(columns = {'article_id': 'num_interactions'}, inplace=True)
interaction_df.head()
```

Out[51]:

	user_id	num_interactions
0	1	47
1	2	6
2	3	82
3	4	45
4	5	5

In [53]:
```
neighbors_df = pd.concat([similarity_df, interaction_df], axis=1, join="inner")
del neighbors_df['user_id']
neighbors_df = neighbors_df[neighbors_df['neighbor_id'] != 1].sort_values(['num_interac

list(neighbors_df['neighbor_id'])

neighbors_df.head()
#len(close_user_ids)
```

Out[53]:

	neighbor_id	similarity	num_interactions
22	31	1	364

```
97            134            4               170
202           287            1               160
241           340            1               148
48             61            2               147
```

```
In [33]: 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

             '''
             #Create a similarity dataframe
             #To create the neighbour_df, i decided to create two separate dataframes inheriting
             user_content_matrix = user_item.dot(np.transpose(user_item))
             current_user_content = user_content_matrix.loc[user_id, :]

             # Create a similarity dataframe based on current_user_content
             similarity_df = pd.DataFrame(current_user_content[current_user_content.values > 0])
             similarity_df.reset_index(level=0, inplace=True)
             similarity_df.rename(columns={"user_id": "neighbor_id", user_id: "similarity"}, inp

             #create user article interactions
             interaction_df = pd.DataFrame(df.groupby(by='user_id').count()['article_id'])
             interaction_df.reset_index(level=0, inplace=True)
             interaction_df.rename(columns = {'article_id': 'num_interactions'}, inplace=True)

             #Create the neighbour_df by concatenating the two datasets
             neighbors_df = pd.concat([similarity_df, interaction_df], axis=1, join="inner")
             #delete the user_id field
             del neighbors_df['user_id']

             #get for all neighbors
             neighbors_df = neighbors_df[neighbors_df['neighbor_id'] != user_id]
```

```
    #sort the new dataframe by similarity and then by number of interactions
    neighbors_df = neighbors_df.sort_values(['similarity', 'num_interactions'], ascendi

    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.

    '''
    #
    #retreive users close to the current user id using the function get_top_sorted_user
    neighbors_df = get_top_sorted_users(user_id)
    neighbor_ids = list(neighbors_df.sort_values(['num_interactions','similarity'], asc
    #get the article_ids seen by this user
    user_article_ids , _ = get_user_articles(user_id)

    #define an empty array
    recs = []
    #Loops through the users based on closeness to the input user_id
    for neighbor_id in neighbor_ids:
        #For each user - finds article_ids the user hasn't seen before and provides the
        article_ids, _ = get_user_articles(neighbor_id)
        #https://numpy.org/doc/stable/reference/generated/numpy.setdiff1d.html
        not_seen_article_ids = np.setdiff1d(article_ids, user_article_ids)

        if len(not_seen_article_ids) > 0:
            recs.extend(not_seen_article_ids)
            #remove duplicates
```

```
                recs = list(dict.fromkeys(recs))

            #Check if we have the required recommendations
            if len(recs) >= m:
                break

        #get the rec_names using the function get_article_names
        rec_names = get_article_names(recs)

        return recs[:m], rec_names[:m]
```

In [34]:
```
# Quick spot check - don't change this code - just use it to test your functions
rec_ids, rec_names = user_user_recs_part2(20, 10)
print("The top 10 recommendations for user 20 are the following article ids:")
print(rec_ids)
print()
print("The top 10 recommendations for user 20 are the following article names:")
print(rec_names)
```

```
The top 10 recommendations for user 20 are the following article ids:
['1024.0', '1085.0', '109.0', '1150.0', '1151.0', '1152.0', '1153.0', '1154.0', '1157.0', '1160.

The top 10 recommendations for user 20 are the following article names:
['uci: red wine quality', 'ml optimization using cognitive assistant', "a beginner's guide to va
```

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 [35]:
```
get_top_sorted_users(1).iloc[0], get_top_sorted_users(131).iloc[9]
```

Out[35]:
```
(neighbor_id         3933.0
 similarity            35.0
 num_interactions       1.0
 Name: 1883, dtype: float64, neighbor_id         242.0
 similarity           25.0
 num_interactions      8.0
 Name: 211, dtype: float64)
```

In [36]:
```
### Tests with a dictionary of results
user1_most_sim = list(get_top_sorted_users(1)['neighbor_id'])[0] # find_similar_users(1
user131_10th_sim = list(get_top_sorted_users(131)['neighbor_id'])[9] #find_similar_user
```

In [37]:
```
user1_most_sim, user131_10th_sim
```

Out[37]:
```
(3933, 242)
```

```
In [38]: ## Dictionary Test Here
         sol_5_dict = {
             'The user that is most similar to user 1.': user1_most_sim,
             'The user that is the 10th most similar to user 131': user131_10th_sim,
         }

         t.sol_5_test(sol_5_dict)
```

```
This all looks good!  Nice job!
```

6. If we were given a new user, which of the above functions would you be able to use to make recommendations? Explain. Can you think of a better way we might make recommendations? Use the cell below to explain a better method for new users.

Provide your response here. #### A new user in this case does not have any observed scores, hence the get_top_article_ids function can be used to make recommendations, which could be a temporarity solution to cater for this recommendation. Kindly note that user_user_recs_part2 requires an existing user data, hence it is not recommended for this use case.

A better ways to make these recommendations where new users are involved would be to combine Knowledge or rank based and Content based recommendations with FunkSVD. 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 [39]: 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
         #list_of_ids = get_top_article_ids(10)
         #list_of_ids
         new_user_recs = get_top_article_ids(10)
```

```
In [40]: 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 [41]: # Load the matrix here
         user_item_matrix = pd.read_pickle('user_item_matrix.p')
```

```
In [42]: # quick look at the matrix
         user_item_matrix.head()
```

```
Out[42]: 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 [43]: # 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
```

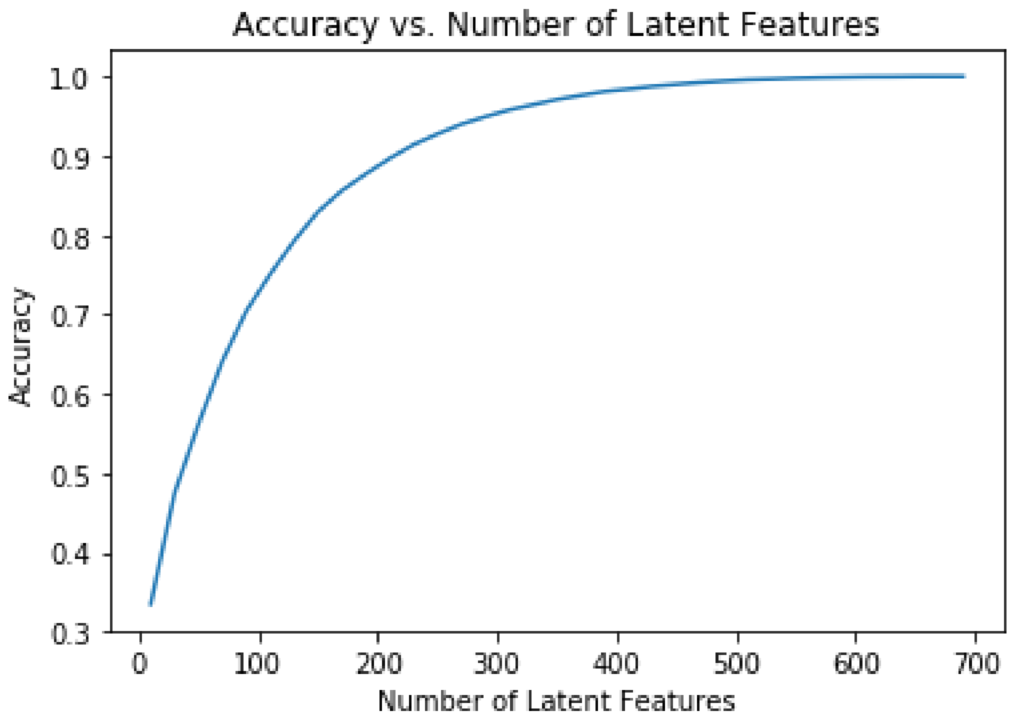
```
In [52]: vt
```

```
Out[52]: array([[ -2.21822365e-03,  -1.13697491e-03,  -8.25820256e-03, ...,
                  -7.89214713e-03,  -2.78398235e-02,  -3.49679488e-04],
                [  2.07736845e-03,   3.86642452e-04,   1.51981454e-03, ...,
                  -1.56120895e-02,   9.70825293e-04,  -4.30034249e-04],
                [ -4.32111291e-04,   2.46676561e-03,   4.28288891e-03, ...,
                   1.20613591e-02,   1.21832171e-02,   1.08416259e-03],
                ...,
                [  0.00000000e+00,   3.15631941e-16,   1.84475856e-16, ...,
                   5.48706963e-17,   9.44710455e-17,   1.23662293e-16],
                [  0.00000000e+00,  -2.38531913e-16,   2.65894675e-18, ...,
                   1.71338757e-16,   7.09063975e-17,  -1.89755859e-16],
                [  0.00000000e+00,   2.26402240e-17,   3.39637767e-16, ...,
                  -7.85447059e-17,  -6.56620070e-17,  -9.63564231e-17]])
```

MY RESPONSE: #### FunkSVD is an improvement of the standard SVD because it carters for Null or non exsiting values (NaN). The difference between the data used in our lesson and that used in this exercise is that the lesson data comprised of user rating data and where rating did not exist, NaN values substituted for them. In this case the user_item_matrix is composed of ones and zeros and NaN values are absent from it. That was why SVD is prefarred for use

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 [44]:
```
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 [77]:
```
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 a user item matrix using the previous function create_user_item_matrix
        #a user-item matrix of the training dataframe
        user_item_train = create_user_item_matrix(df_train)
        #a user-item matrix of the testing dataframe
        user_item_test = create_user_item_matrix(df_test)

        train_idx = user_item_train.index.values
        train_arts = user_item_train.columns.values

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

        common_idx = [s for s in train_idx if s in test_idx]
        common_arts = [s for s in train_arts if s in test_arts]

        user_item_test = user_item_test.loc[common_idx, common_arts]

        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 [78]:
```
user_item_train.shape, user_item_test.shape, len(test_idx), len(test_arts)
```

Out[78]: ((4487, 714), (20, 574), 682, 574)

In [79]:
```
# find the common users in both test and train dataset
print(user_item_train.index.isin(test_idx).sum())
# total number of user in test set
print(len(test_idx))
print(len(test_idx) - user_item_train.index.isin(test_idx).sum())
# find the common articles in both test and train set
print(user_item_train.columns.isin(test_arts).sum())
# How many articles in the test set are we not able to make predictions for because of
print(len(test_arts) - len([s for x in list(set(user_item_train.columns.values)) if x i
```

```
20
682
662
574
```

```
0
```

```
In [80]: # 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 movies can we make predictions for in the test set?': b,
             'How many movies in the test set are we not able to make predictions for because of
         }

         t.sol_4_test(sol_4_dict)
```

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

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 [81]: # fit SVD on the user_item_train matrix
         #using https://docs.scipy.org/doc/numpy-1.14.0/reference/generated/numpy.linalg.svd.htm
         u_train, s_train, vt_train = np.linalg.svd(user_item_train)# fit svd similar to above t
```

```
In [82]: u_train.shape, s_train.shape, vt_train.shape
```

```
Out[82]: ((4487, 4487), (714,), (714, 714))
```

```
In [83]: user_item_train.head()
```

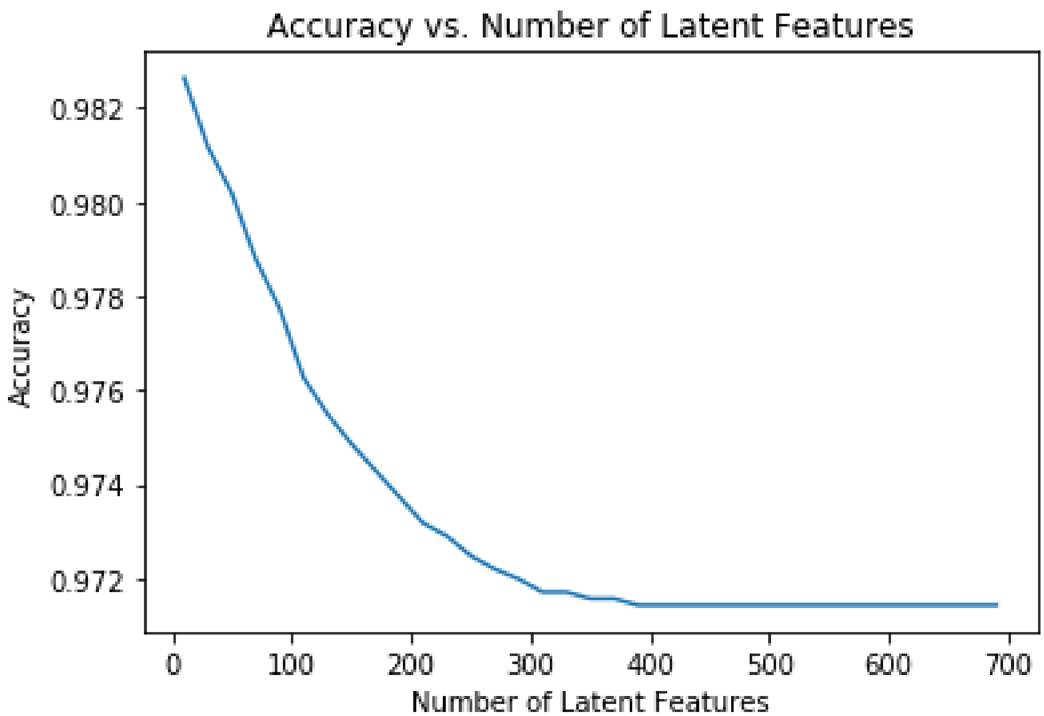
```
Out[83]: article_id  0.0  100.0  1000.0  1004.0  1006.0  1008.0  101.0  1014.0  1015.0  \
         user_id
         1           0.0    0.0     0.0     0.0     0.0     0.0    0.0     0.0     0.0
         2           0.0    0.0     0.0     0.0     0.0     0.0    0.0     0.0     0.0
         3           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 [87]:
```
#Now use the user_item_train dataset from above to find U, S, and V transpose using SVD

#  get users in train set available in the test set
user_idx = user_item_train.index.isin(test_idx)

#get the articles in train set available in test set
arts_idx = user_item_train.columns.isin(test_arts)

#use the common data (idx and articles to get the matrix for the test set)
u_test = u_train[user_idx, :]
vt_test = vt_train[:, arts_idx]
```

In [88]:
```
latent_feats = np.arange(10, 700+10, 20)

sum_errs = []


for k in 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_test_predicted = np.around(np.dot(np.dot(u_test_new, s_train_new), vt_tes

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

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

```
In [90]: no_of_interactions = user_item_test.shape[0] * user_item_train.shape[1]
         plt.plot(num_latent_feats, 1 - np.array(sum_errs)/no_of_interactions);
         plt.xlabel('Number of Latent Features');
         plt.ylabel('Accuracy');
         plt.title('Accuracy vs. Number of Latent Features');
         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?

My Response. #### In the first graph, you would notice that as the latent features increased, there was a corresponding increase in the accurracy of the result but in the graph above, the reverse is the case. The currect graph shows a drastic decrease in the accuracy as the latent features increases. You can also attribute this reduction to the size of data in the test set which may not be a sufficient sample size that could be used to draw conclusions and make accurate recommendations.

Hence due to the above, it would be proper to employ A/B Testing in order to use data from a randomize experiment from two or more sources and measure the maximum impact, drive business metrics and reduce guesswork. Because this experiment was based on a single source of data taken from different points (top and button), hence the test set was probably guessed which A/B Testing would have eliminated. ### 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 [262]:
```
from subprocess import call
call(['python', '-m', 'nbconvert', 'Recommendations_with_IBM.ipynb'])
```

Out[262]: 0

In [ ]: