Recommendations with IBM - Data Analysis

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Preparations

Import libraries and local scripts along with loading the cleaned data `articles` and `interactions` .

In [1]:
```
!pip install -e ../
```

```
Obtaining file:///C:/Users/netxph/Projects/ibm-recommend
Installing collected packages: ibm-recommend
  Attempting uninstall: ibm-recommend
    Found existing installation: ibm-recommend 0.1.0
    Uninstalling ibm-recommend-0.1.0:
      Successfully uninstalled ibm-recommend-0.1.0
  Running setup.py develop for ibm-recommend
Successfully installed ibm-recommend-0.1.0
```

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import ibm_recommend.project_tests as t

from ibm_recommend.matrix import fit_transform, calculate_accuracy, intersect_data
, plot_accuracy, create_user_item_matrix, get_user_articles

%matplotlib inline
```

In [3]:
```python
articles = pd.read_csv("../data/processed/articles.csv")
articles.article_id = articles.article_id.astype(str)
articles.head()
```

Out[3]:

	article_id	name	description	body
0	0	Detect Malfunctioning IoT Sensors with Streami...	Detect bad readings in real time using Python ...	Skip navigation Sign in SearchLoading...\r\n\r...
1	1	Communicating data science: A guide to present...	See the forest, see the trees. Here lies the c...	No Free Hunch Navigation * kaggle.com\r\n\r\n ...
2	2	This Week in Data Science (April 18, 2017)	Here's this week's news in Data Science and Bi...	☰ * Login\r\n * Sign Up\r\n\r\n * Learning Pat...
3	3	DataLayer Conference: Boost the performance of...	Learn how distributed DBs solve the problem of...	DATALAYER: HIGH THROUGHPUT, LOW LATENCY AT SCA...
4	4	Analyze NY Restaurant data using Spark in DSX	This video demonstrates the power of IBM DataS...	Skip navigation Sign in SearchLoading...\r\n\r...

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1051 entries, 0 to 1050
Data columns (total 4 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   article_id   1051 non-null   object
 1   name         1051 non-null   object
 2   description  1048 non-null   object
 3   body         1037 non-null   object
dtypes: object(4)
memory usage: 33.0+ KB
```

In [5]:
```python
interactions = pd.read_csv("../data/processed/interactions.csv")
interactions.article_id = interactions.article_id.astype(str)
interactions.head()
```

Out[5]:

	user_id	article_id	title	email
0	1	1430	using pixiedust for fast, flexible, and easier...	ef5f11f77ba020cd36e1105a00ab868bbdbf7fe7
1	2	1314	healthcare python streaming application demo	083cbdfa93c8444beaa4c5f5e0f5f9198e4f9e0b
2	3	1429	use deep learning for image classification	b96a4f2e92d8572034b1e9b28f9ac673765cd074
3	4	1338	ml optimization using cognitive assistant	06485706b34a5c9bf2a0ecdac41daf7e7654ceb7
4	5	1276	deploy your python model as a restful api	f01220c46fc92c6e6b161b1849de11faacd7ccb2

In [6]:
```python
interactions.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45993 entries, 0 to 45992
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   user_id     45993 non-null  int64 
 1   article_id  45993 non-null  object
 2   title       45993 non-null  object
 3   email       45976 non-null  object
dtypes: int64(1), object(3)
memory usage: 1.4+ MB
```

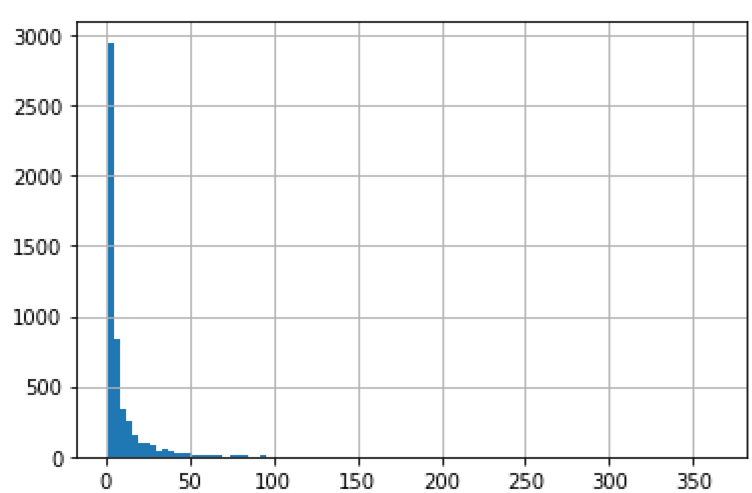
Part I: Exploratory Data Analysis

1. What is the distribution of how many articles a user interacts with in the dataset?

In [7]:
```python
interactions.groupby("email").user_id.count().sort_values(ascending = False)
```

Out[7]:
```
email
2b6c0f514c2f2b04ad3c4583407dccd0810469ee    364
77959baaa9895a7e2bdc9297f8b27c1b6f2cb52a    363
2f5c7feae533ce046f2cb16fb3a29fe00528ed66    170
a37adec71b667b297ed2440a9ff7dad427c7ac85    169
8510a5010a5d4c89f5b07baac6de80cd12cfaf93    160
                                           ...
1b520f0f65c0aee52d4235f92fb2de58fa966635      1
7a67e4a2902a20062e1f2a6835b6e099b34b4f6c      1
c4b7e639e91b1d18e5b9c000f0ad3354888fcdde      1
7a7fb282789944665ffc1cddee5ddbdbd7ca9f64      1
9655144418d25a0e074616840447e6e5dbef0069      1
Name: user_id, Length: 5148, dtype: int64
```

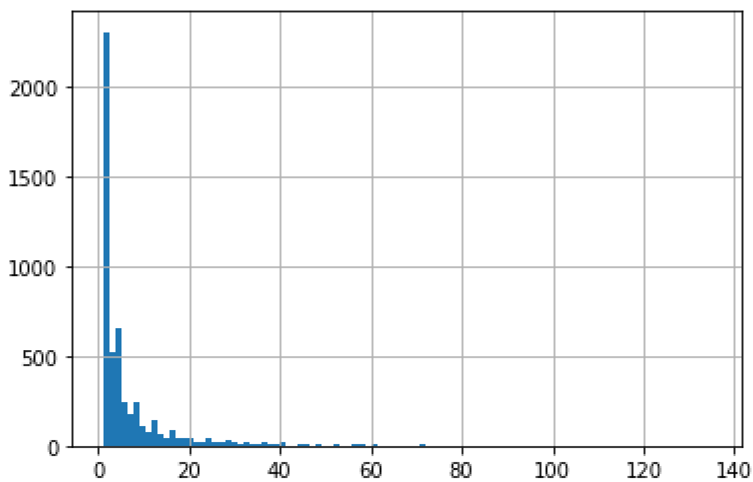
In [8]:
```python
# non-unique interactions

interactions.groupby("email").user_id.count().hist(bins=100);
```



In [9]:
```
interactions[["email", "article_id"]].drop_duplicates().groupby("email").article_i
d.count().sort_values(ascending = False)
```

Out[9]:
```
email
2b6c0f514c2f2b04ad3c4583407dccd0810469ee    135
77959baaa9895a7e2bdc9297f8b27c1b6f2cb52a    135
d9032ff68d0fd45dfd18c0c5f7324619bb55362c    101
c60bb0a50c324dad0bffd8809d121246baef372b    100
a37adec71b667b297ed2440a9ff7dad427c7ac85     97
                                           ...
1ab433bafebd7f8b6322c05def9b41e0f029ea83      1
8283f83275dbd8cc8a2dd4d35a25f4a86310afbd      1
c1ad3e68598e288e5df72275ba03444ee218aab8      1
1ab7c183ceb155cab3b9dcc92f36039b025cd86e      1
262b5095f21d3addbff0ab212a968a467cc7592b      1
Name: article_id, Length: 5148, dtype: int64
```

In [10]:
```
# unique interactions

interactions[["email", "article_id"]].drop_duplicates().groupby("email").article_i
d.count().hist(bins=100);
```



In [11]:
```
median_val = interactions.groupby("email").count().median().values[0]
print(f"50% of individuals interact with {median_val} number of articles or fewe
r.")

max_views_by_user = interactions.groupby("email").count().max().values[0]
print(f"The maximum number of user-article interactions by any 1 user is {max_view
s_by_user}.")
```

```
50% of individuals interact with 3.0 number of articles or fewer.
The maximum number of user-article interactions by any 1 user is 364.
```

2. Find out the following

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 [12]:
```
unique_articles = interactions.article_id.nunique()
print(f"The number of unique articles that have at least one interaction: {unique_articles}")

total_articles = len(articles)
print(f"The number of unique articles on the IBM platform: {total_articles}")

unique_users = interactions.email.nunique()
print(f"The number of unique users: {unique_users}")

user_article_interactions = len(interactions)
print(f"The number of user-article interactions: {user_article_interactions}")
```

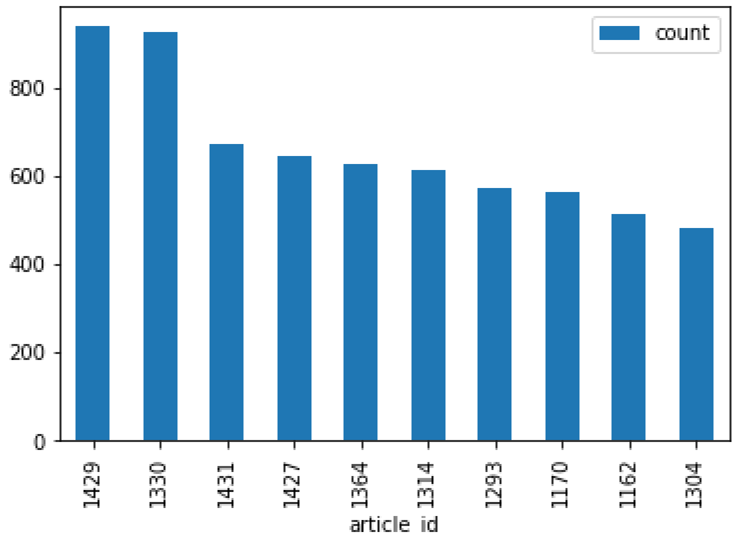
```
The number of unique articles that have at least one interaction: 714
The number of unique articles on the IBM platform: 1051
The number of unique users: 5148
The number of user-article interactions: 45993
```

`3.` 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 [13]:
```
most_viewed_article_id = str(interactions.groupby("article_id").count().email.sort_values(ascending = False).index[0])
print(f"The most viewed article in the dataset as a string with one value following the decimal: {most_viewed_article_id}")

max_views = interactions.groupby("article_id").count().email.sort_values(ascending = False).values[0]
print(f"The most viewed article in the dataset was viewed how many times? {max_views}")
```

```
The most viewed article in the dataset as a string with one value following the
decimal: 1429
The most viewed article in the dataset was viewed how many times? 937
```

In [14]:
```python
interactions[["article_id", "user_id"]] \
    .groupby("article_id") \
    .count() \
    .reset_index() \
    .rename(columns={"user_id": "count"}) \
    .set_index("article_id") \
    .sort_values("count", ascending=False) \
    .head(10) \
    .plot(kind="bar");
```



In [15]:
```python
sol_1_dict = {
    '`50% of individuals have _____ or fewer interactions.`': median_val,
    '`The total number of user-article interactions in the dataset is ______.`': u
ser_article_interactions,
    '`The maximum number of user-article interactions by any 1 user is ______.`':
max_views_by_user,
    '`The most viewed article in the dataset was viewed _____ times.`': max_views,
    '`The article_id of the most viewed article is ______.`': most_viewed_article_
id,
    '`The number of unique articles that have at least 1 rating ______.`': unique_
articles,
    '`The number of unique users in the dataset is ______`': unique_users,
    '`The number of unique articles on the IBM platform`': total_articles
}

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

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

Part II: Rank-Based Recommendations

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

1. Return the n top articles ordered with most interactions as the top.

In [16]:
```
def get_top_articles(data, n):
    '''
    INPUT:
    n - (int) the number of top articles to return
    data - (pandas dataframe) df as defined at the top of the notebook

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

    '''

    article_interacts = data \
        .groupby(by=["article_id", "title"]) \
        .agg(interacts = ("title", "count")) \
        .reset_index() \
        .sort_values(by="interacts", ascending = False)

    top_articles = article_interacts.title.head(n).tolist()

    return top_articles

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

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

    '''

    article_interacts = data \
        .groupby(by=["article_id", "title"]) \
        .agg(interacts = ("title", "count")) \
        .reset_index() \
        .sort_values(by="interacts", ascending = False)

    top_articles = article_interacts.article_id.head(n).tolist()

    return top_articles
```

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

```
['use deep learning for image classification', 'insights from new york car accid
ent reports', 'visualize car data with brunel', 'use xgboost, scikit-learn & ibm
watson machine learning apis', 'predicting churn with the spss random tree algor
ithm', 'healthcare python streaming application demo', 'finding optimal location
s of new store using decision optimization', 'apache spark lab, part 1: basic co
ncepts', 'analyze energy consumption in buildings', 'gosales transactions for lo
gistic regression model']
['1429', '1330', '1431', '1427', '1364', '1314', '1293', '1170', '1162', '1304']
```

In [18]:
```
# Test your function by returning the top 5, 10, and 20 articles
top_5 = get_top_articles(interactions, 5)
top_10 = get_top_articles(interactions, 10)
top_20 = get_top_articles(interactions, 20)

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

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

Part III: User-User Based Collaborative Filtering

`1.` 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**.

In [19]:
```
# create the user-article matrix with 1's and 0's

user_item = create_user_item_matrix(interactions)
```

In [20]:
```
## Tests: You should just need to run this cell.  Don't change the code.
assert user_item.shape[0] == 5149, "Oops!  The number of users in the user-article matrix doesn't look right."
assert user_item.shape[1] == 714, "Oops!  The number of articles in the user-article matrix doesn't look right."
assert user_item.sum(axis=1)[1] == 36, "Oops!  The number of articles seen by user 1 doesn't look right."
print("You have passed our quick tests!  Please proceed!")
```

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

`2.` 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 [21]:
```
def compute_similarities(data, user1, user2):
    '''
    INPUT:
    user1 - (int) user id
    user2 - (int) user id
    data - (pandas dataframe) df as defined at the top of the notebook

    OUTPUT:
    similarity - (float) similarity score between user1 and user2

    Description:
    Compute the cosine similarity between two users based on the user-item matrix
    '''
    user1_articles = data.loc[user1][data.loc[user1] == 1].index.values
    user2_articles = data.loc[user2][data.loc[user2] == 1].index.values

    common_articles = np.intersect1d(user1_articles, user2_articles, assume_unique
=True)

    # since it's just zeros and ones, we can just sum the common articles

    return len(common_articles)
```

In [22]:
```
def find_similar_users(data, user_id, rec_num = 5):
    '''
    INPUT:
    data - (pandas dataframe) matrix of users by articles:
    user_id - (int) a user_id
                1's when a user has interacted with an article, 0 otherwise
    rec_num - (int) the number of recommendations you would like for the user

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

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

    '''

    similar_users = pd.DataFrame(
        [[i, compute_similarities(data, user_id, i)] for i in data.index.values if
 i != user_id],
        columns=["user_id", "similarity"]
    ) \
    .sort_values(by="similarity", ascending=False) \
    .head(rec_num) \
    .user_id.tolist()

    return 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(user_item, 1, rec_num=10)))
print("The 5 most similar users to user 3933 are: {}".format(find_similar_users(user_item, 3933)))
print("The 3 most similar users to user 46 are: {}".format(find_similar_users(user_item, 46, rec_num=3)))
```

```
The 10 most similar users to user 1 are: [3933, 23, 3782, 203, 4459, 3870, 131, 46, 4201, 395]
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.

```
In [24]: def get_article_names(data, article_ids):
    '''
    INPUT:
    data - (pandas dataframe) df as defined at the top of the notebook
    article_ids - (list) a list of article ids

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

    return data[data.article_id.isin(article_ids)].title.unique().tolist()

def user_user_recs(data, user_id, rec_num=10):
    '''
    INPUT:
    data - (pandas dataframe) matrix of users by articles:
                1's when a user has interacted with an article, 0 otherwise
    user_id - (int) a user id
    rec_num - (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 a
s recs
    Does this until m recommendations are found

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

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

    '''

    recs = []
    matrix = create_user_item_matrix(data)
    user_articles = get_user_articles(data, user_id)[0]
    similar_users = find_similar_users(matrix, user_id)

    for user in similar_users:
        articles = get_user_articles(data, user)[0]
        for article in articles:
            if article not in user_articles and article not in recs:
                recs.append(article)
                if len(recs) == rec_num:
                    return recs

    return recs # return even if rec_num is not met
```

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

Out[25]:
```
['healthcare python streaming application demo',
 'ml optimization using cognitive assistant',
 'the nurse assignment problem',
 'predicting churn with the spss random tree algorithm',
 'analyze energy consumption in buildings',
 'gosales transactions for logistic regression model',
 'insights from new york car accident reports',
 'model bike sharing data with spss',
 'analyze accident reports on amazon emr spark',
 'movie recommender system with spark machine learning']
```

In [26]:
```
# Test your functions here - No need to change this code - just run this cell
assert set(get_article_names(interactions, ['1024', '1176', '1305', '1314', '1422'
, '1427'])) == set(['using deep learning to reconstruct high-resolution audio', 'b
uild a python app on the streaming analytics service', 'gosales transactions for n
aive bayes model', 'healthcare python streaming application demo', 'use r datafram
es & ibm watson natural language understanding', 'use xgboost, scikit-learn & ibm
 watson machine learning apis']), "Oops! Your the get_article_names function does
n't work quite how we expect."
assert set(get_article_names(interactions, ['1320', '232', '844'])) == set(['housi
ng (2015): united states demographic measures','self-service data preparation with
 ibm data refinery','use the cloudant-spark connector in python notebook']), "Oop
s! Your the get_article_names function doesn't work quite how we expect."
assert set(get_user_articles(interactions, 20)[0]) == set(['1320', '232', '844'])
assert set(get_user_articles(interactions, 20)[1]) == set(['housing (2015): united
 states demographic measures', 'self-service data preparation with ibm data refine
ry','use the cloudant-spark connector in python notebook'])
assert set(get_user_articles(interactions, 2)[0]) == set(['1024', '1176', '1305',
'1314', '1422', '1427'])
assert set(get_user_articles(interactions, 2)[1]) == set(['using deep learning to
 reconstruct high-resolution audio', 'build a python app on the streaming analytic
s service', 'gosales transactions for naive bayes model', 'healthcare python strea
ming application demo', 'use r dataframes & ibm watson natural language understand
ing', 'use xgboost, scikit-learn & ibm watson machine learning apis'])
print("If this is all you see, you passed all of our tests!  Nice job!")
```

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

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

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

In [27]:

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


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

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

    '''
    matrix = create_user_item_matrix(data)

    neighbors_df = pd.DataFrame(
        [[i, compute_similarities(matrix, user_id, i)] for i in matrix.index.value
s if i != user_id],
        columns=["neighbor_id", "similarity"]
    ) \
    .sort_values(by="similarity", ascending=False)


    neighbors_df["num_interactions"]  = neighbors_df.neighbor_id.apply(lambda x: l
en(data[data.user_id == x]))
    neighbors_df = neighbors_df.sort_values(by=["similarity", "num_interactions"],
 ascending=False)

    return neighbors_df # Return the dataframe specified in the doc_string


def user_user_recs_part2(data, user_id, rec_num=10):
    '''
    INPUT:
    data - (pandas dataframe) matrix of users by articles:
            1's when a user has interacted with an article, 0 otherwise
    user_id - (int) a user id
    rec_num - (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 a
s recs
    Does this until m recommendations are found

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

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

    '''

    recs = []
    user_articles = get_user_articles(data, user_id)[0]
    similar_users = get_top_sorted_users(data, user_id)

    for user in similar_users.neighbor_id:
        articles = get_user_articles(data, user)[0]

        for article in articles:
            if article not in user_articles and article not in recs:
                recs.append(article)
                if len(recs) == rec_num:
                    break

        if len(recs) == rec_num:
            break

    rec_names = get_article_names(data, recs)

    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(interactions, 20, 10)
print("The top 10 recommendations for user 20 are the following article ids:")
print(rec_ids)
print()
print("The top 10 recommendations for user 20 are the following article names:")
print(rec_names)
```

```
The top 10 recommendations for user 20 are the following article ids:
['1330', '1427', '1364', '1170', '1162', '1304', '1351', '1160', '1354', '1368']

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

5. Test the created function

In [29]:

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

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

In [30]:
```
## 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?

Cold Start Problem

The above recommendation is no use when dealing with new users. The only way we can provide recommendations is by providing rank-based recommendations. If the user profile is also available, we can perhaps try to look for users that has profile similarities and retrieve the articles interacted.

Rank-based recommendations can be improved to include novelty, serendipity and diversity.

`7.` Provide the top 10 recommended articles you would provide for the a new user below.

In [31]:
```
new_user = '0.0'

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

In [32]:
```
assert set(new_user_recs) == set(['1314','1429','1293','1427','1162','1364','1304'
,'1170','1431','1330']), "Oops!  It makes sense that in this case we would want to
 recommend the most popular articles, because we don't know anything about these u
sers."

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

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

Part IV: Matrix Factorization

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

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

In [33]:
```
# Load the matrix here
user_item_matrix = pd.read_pickle('../models/user_item_matrix.p')
```

In [34]:
```
# quick look at the matrix
user_item_matrix.head()
```

Out[34]:

article_id user_id	0.0	100.0	1000.0	1004.0	1006.0	1008.0	101.0	1014.0	1015.0	1016.0	...	977.0	98.0	981.0	9
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	1.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	1.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	

5 rows × 714 columns

2. In this situation, you can use Singular Value Decomposition from [numpy (https://docs.scipy.org/doc/numpy-1.14.0/reference/generated/numpy.linalg.svd.html)](https://docs.scipy.org/doc/numpy-1.14.0/reference/generated/numpy.linalg.svd.html) on the user-item matrix. Perform SVD, and explain why this is different than in the lesson.

In [35]:
```
# Perform SVD on the User-Item Matrix Here

u, s, vt = np.linalg.svd(user_item_matrix)
u.shape, s.shape, vt.shape
```

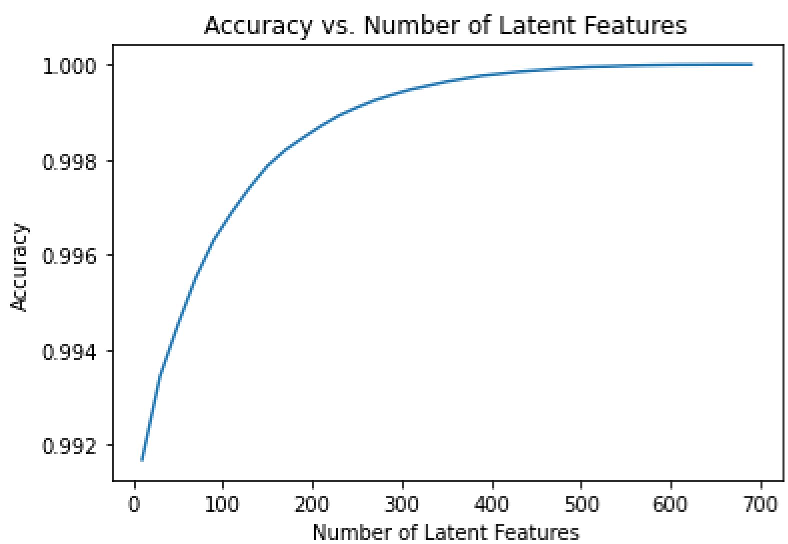
Out[35]:
```
((5149, 5149), (714,), (714, 714))
```

The Case of Interactions

As rating is not provided in the data, we can only rely on interactions. Interactions data has only 2 definite data, `1 - interacted` and `0 - not interacted`. Since the table has no nulls, SVD can work as recommender in this type of table.

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 [36]:
```
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)/(user_item_matrix.shape[0]*user_
item_matrix.shape[1]));
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.

- 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 [37]:
```
interactions_train = interactions.head(40000)
interactions_test = interactions.tail(5993)

interactions_train.shape, interactions_test.shape
```

Out[37]: ((40000, 4), (5993, 4))

In [38]:
```
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 colu
mn)
    user_item_test - a user-item matrix of the testing dataframe
                    (unique users for each row and unique articles for each colum
n)
    test_idx - all of the test user ids
    test_arts - all of the test article ids

    '''

    user_item_train = create_user_item_matrix(df_train)
    user_item_test = create_user_item_matrix(df_test)

    test_idx = user_item_test.index.tolist()
    test_arts = user_item_test.columns.tolist()


    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(interactions_train, interactions_test)
```

In [39]:
```
_test_users_in_train = len(np.intersect1d(user_item_train.index, user_item_test.in
dex))
_test_users_in_train
```

Out[39]: 20

In [40]:
```
_test_users_not_in_train = len(test_idx) - _test_users_in_train
_test_users_not_in_train
```

Out[40]: 662

In [41]:
```
_test_art_in_train = len(np.intersect1d(user_item_train.columns, user_item_test.co
lumns))
_test_art_in_train
```

Out[41]: 574

In [42]:
```
_test_art_not_in_train = len(user_item_test.columns) - _test_art_in_train
_test_art_not_in_train
```

Out[42]: 0

In [43]:
```
# 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, # letter her
e,
    'How many users in the test set are we not able to make predictions for becaus
e of the cold start problem?': a, # letter here,
    'How many articles can we make predictions for in the test set?': b, # letter
 here,
    'How many articles in the test set are we not able to make predictions for bec
ause of the cold start problem?': d# letter here
}

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

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

In [44]:
```
# Uncomment this if use the randomized data instead

# from sklearn.model_selection import train_test_split

# interactions_train, interactions_test = train_test_split(interactions, test_size
=0.2, random_state=42)

# user_item_train, user_item_test, test_idx, test_arts = create_test_and_train_use
r_item(interactions_train, interactions_test)
```

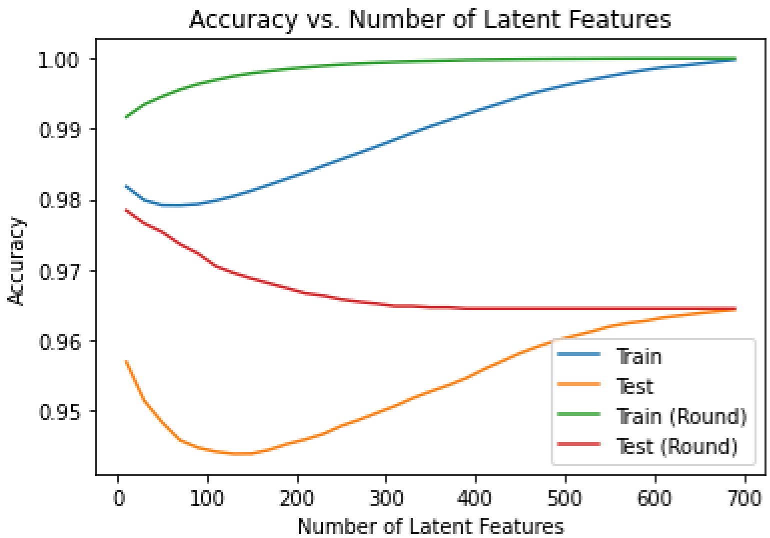
In [45]:
```
_, user_item_test_sub = intersect_data(user_item_train, user_item_test)

# fit SVD on the user_item_train matrix
u, s, vt = np.linalg.svd(user_item_train)

s.shape, u.shape, vt.shape
```

Out[45]:
```
((714,), (4487, 4487), (714, 714))
```

In [46]:

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

num_latent_feats = np.arange(10,700,20)
train_accuracy = []
test_accuracy = []
train_accuracy_round = []
test_accuracy_round = []

for k in num_latent_feats:
    s_k, u_train, vt_train = np.diag(s[:k]), u[:, :k], vt[:k, :]

    u_test = u_train[user_item_train.index.isin(user_item_test.index), :]
    vt_test = vt_train[:, user_item_train.columns.isin(user_item_test.columns)]


    user_item_train_preds = fit_transform(s_k, u_train, vt_train, use_round=False)
    user_item_test_preds = fit_transform(s_k, u_test, vt_test, use_round=False)
    user_item_train_round_preds = fit_transform(s_k, u_train, vt_train)
    user_item_test_round_preds = fit_transform(s_k, u_test, vt_test)

    train_accuracy.append(calculate_accuracy(user_item_train, user_item_train_pred
s))
    test_accuracy.append(calculate_accuracy(user_item_test_sub, user_item_test_pre
ds))
    train_accuracy_round.append(calculate_accuracy(user_item_train, user_item_trai
n_round_preds))
    test_accuracy_round.append(calculate_accuracy(user_item_test_sub, user_item_te
st_round_preds))

print(np.mean(train_accuracy))
plot_accuracy(num_latent_feats, train_accuracy, "Train")

print(np.mean(test_accuracy))
plot_accuracy(num_latent_feats, test_accuracy, "Test")

print(np.mean(train_accuracy))
plot_accuracy(num_latent_feats, train_accuracy_round, "Train (Round)")

print(np.mean(test_accuracy))
plot_accuracy(num_latent_feats, test_accuracy_round, "Test (Round)")
```

```
0.9897606936976432
0.9539354177080506
0.9897606936976432
0.9539354177080506
```



`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?

The Number of Latent Features

With the interactions at 40000 training and 5993 for the test, only 20 users, 574 articles are able to be predicted. As plotted, with train dataset, we can see that accuracy improves as we increase the latent features, however, with test dataset, we can see that accuracy is getting worse as we increase the latent features. This maybe due to overfitting.

By the nature of the dataset itself, most users has interacted with 3 articles among the total of 1051. This means that the accuracy of this model even if it's high, it won't mean much, because even models with all zeroes, will still get high accuracy.

One interesting data we observed is that, by not using `around` we can see a different trend in the relationship of accuracy and latent features. The test result is getting better once pass around 150 latent features. With this interesting finding, instead of rounding off to nearest 1s and 0s, we can use the non-rounded form so we can sort and recommend articles to users.

With the different recommendations techniques above, we can definitely create a good recommendation system that can cover 1) existing users with article interactions with either nearest neighbor and matrix factorization 2) new users with rank based recommendations 3) additional recommendations by finding related articles to ones interacted.

Extras

Below is the recommendation library created.

In [47]:
```
from ibm_recommend.recommendations import Recommender, CollaborativeRecommender, R
ankBasedRecommender, SVDRecommender
import joblib

recommender = Recommender([
    SVDRecommender(),
    CollaborativeRecommender(),
    RankBasedRecommender()
])

recommender.fit(interactions)
joblib.dump(recommender, "../models/recommender.pkl")
```

Out[47]:
```
['../models/recommender.pkl']
```

In [48]:
```
def print_rec(data, user_id, rec):
    print(f"Recommendations [{user_id}]")
    print()
    for key in rec:
        print(key)
        for name in get_article_names(data, rec[key]):
            print(f"* {name}")

        print()
```

In [49]:
```
model = joblib.load("../models/recommender.pkl")

rec = model.recommend(4484)
print_rec(interactions, 4484, rec)
```

In [ ]:
```
rec_new_user = model.recommend(0)
print_rec(interactions, 0, rec_new_user)
```

Conclusion

Most users interacted with 3 articles out of 1051. This goes to say that there might be no visibility for the user about the other articles, or have no time to investigate the articles one by one and find what interests them. An experiment with a recommendation system is a good idea on providing users more relevant information available to them on their dashboard. A few things we'd like to improve in this experiments are:

- Increasing the number of interactions per user

We are going to perform A/B testing where in half of the users will have no recommendations on their home page, while the other half will have recommendations. Before else, we are going to establish our invariant metric and ensure that the there is no significant difference in both populations (alternative hypothesis). Assignment will be done through randomization.

- H0: There is a significant difference between the two populations
- H1: There is no significant difference between the two populations

As for our evaluation metric, we are going to measure the increase of interactions per user (alternative hypothesis).

- H0: The number of interactions is the same or better for those who don't have recommendations
- H1: The number of interactions has increased for those who have recommendations

Along with these goals, we should expand as well the metrics we are gathering, to improve future experiments as well:

- Time spent on an article
- Number of interactions with the recommended articles
- A ranking on articles
- User profile
- Categorizing articles

The recommendation system we are going to build is the combination of these strategies:

1. When user has interacted with an article, we'll make use of matrix factorization or nearest neighbor to recommend articles to the user. We'll run this separately to determine which one is better, and perhaps run also another test that combines them both.
2. For new users, we are going to make use of Rank-Based recommendations

In [ ]:

```
from subprocess import call
call(['python', '-m', 'nbconvert', '02 - Data and Recommendation Analysis.ipynb',
'--to', 'webpdf', '--allow-chromium-download', '--template', 'classic'])
```