```python
# Alexis Blackwell
# Ice 3
# importing libraries
import pandas as pd
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
```

(Tutorial) Binarizing data

Following is a sample of binarizing listen counts in Million Song Dataset

The Echo Nest Taste Profile Subset

http://labrosa.ee.columbia.edu/millionsong/sites/default/files/challenge/train_triplets.txt.zip

```python
listen_count = pd.read_csv('train_triplets.txt.zip', header=None,
delimiter='\t') # read in csv file
listen_count.head()  # user - song - count
```

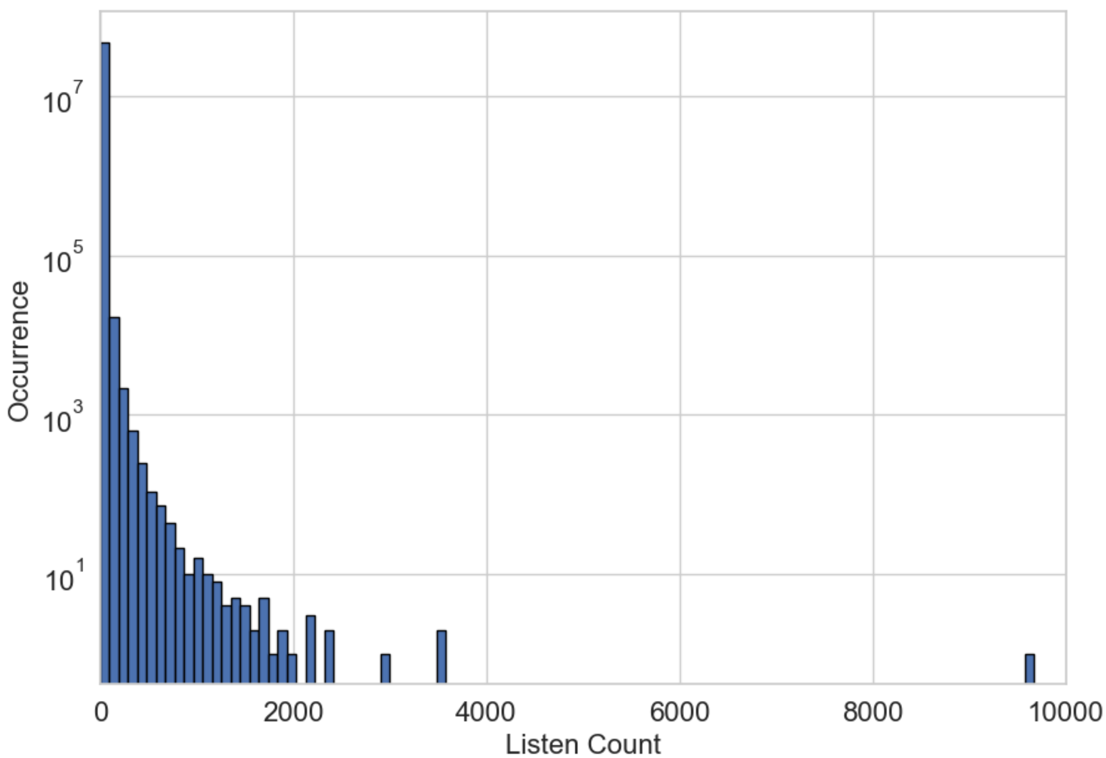
```
                                          0                   1  2
0  b80344d063b5ccb3212f76538f3d9e43d87dca9e  SOAKIMP12A8C130995  1
1  b80344d063b5ccb3212f76538f3d9e43d87dca9e  SOAPDEY12A81C210A9  1
2  b80344d063b5ccb3212f76538f3d9e43d87dca9e  SOBBMDR12A8C13253B  2
3  b80344d063b5ccb3212f76538f3d9e43d87dca9e  SOBFNSP12AF72A0E22  1
4  b80344d063b5ccb3212f76538f3d9e43d87dca9e  SOBFOVM12A58A7D494  1
```

```python
np.max(listen_count[2])
```

```
9667
```

Binarizing and visualizing listen counts

```python
sns.set_style('whitegrid')
plt.figure(figsize=(10, 7))
plt.hist(listen_count[2], bins = 100, edgecolor='black')
plt.yscale('log', nonpositive='clip')
plt.tick_params(axis='both', which='major', labelsize=16)
plt.xlim([0,10000])
_ = plt.xlabel('Listen Count', fontsize=16)
_ = plt.ylabel('Occurrence', fontsize=16)
```



Task 1.1 Read data from Athletes.xlsx file and keep it in a proper type for the following operations

The athletes information of 2021 Olympics in Tokyo

https://www.kaggle.com/arjunprasadsarkhel/2021-olympics-in-tokyo/download

```
# write your code here
athlete_csv = pd.read_csv(r'C:\Users\black\
CSCE5222_Feature_Engineering\Feature_Engineering_ICE_3\archive\
Athletes.csv',
                          encoding="latin-1") # open csv file
athlete_csv.head() # check
```

```
                Name     NOC           Discipline
0    AALERUD Katrine  Norway         Cycling Road
1         ABAD Nestor   Spain  Artistic Gymnastics
2   ABAGNALE Giovanni   Italy               Rowing
3      ABALDE Alberto   Spain           Basketball
4       ABALDE Tamara   Spain           Basketball
```

This first step is just to read in the data from the CSV file and make sure to read that data into a Dataframe. This will be useful for later steps which involve plotting this data and performing data manipulation.

Task 1.2 Extracting the data in column 'NOC' and encoding them, then binarizing and visualizing them (number of athletes on x-axis, number of countries on y-axis)

```
print(athlete_csv.NOC.unique().tolist()) # converts unique values to a list
countries = athlete_csv.NOC.unique().tolist() # converts those unique countries to a list
size_countries = len(countries) # get number of countries
print(size_countries) # check
np.max(athlete_csv['NOC']) # see max country
```

```
['Norway', 'Spain', 'Italy', 'France', 'Chile', 'Sudan', 'Islamic
Republic of Iran', 'Azerbaijan', 'Netherlands', 'Australia', 'United
States of America', 'Qatar', 'Egypt', 'Belgium', 'Malaysia',
'Singapore', 'Maldives', 'Saudi Arabia', 'Germany', 'Uzbekistan',
'Indonesia', 'Kazakhstan', 'Bahrain', 'Japan', 'Ethiopia', 'Canada',
'Malta', 'Sri Lanka', 'Morocco', 'Austria', 'Mauritania', 'ROC',
'Libya', 'Nauru', 'Switzerland', 'South Africa', 'Guyana', 'Georgia',
'Portugal', 'Jordan', 'Palestine', 'India', 'Cyprus', 'Nigeria',
'Tunisia', 'Mexico', 'Colombia', 'El Salvador', 'Romania', 'Poland',
'Federated States of Micronesia', 'Brazil', 'Turkey', 'Sweden', 'Great
Britain', 'Hungary', 'Lithuania', 'Puerto Rico', 'Angola', 'Congo',
'Monaco', 'Rwanda', 'Kenya', 'Armenia', 'Samoa', 'Brunei Darussalam',
'Bangladesh', 'Benin', "Côte d'Ivoire", 'Trinidad and Tobago',
"People's Republic of China", 'Senegal', 'Algeria', 'Tajikistan',
'Pakistan', 'Kyrgyzstan', 'Latvia', 'Oman', 'Kuwait', 'Iraq', 'Refugee
Olympic Team', 'Yemen', 'Cuba', 'Argentina', 'Serbia', 'Ukraine',
'Niger', 'Djibouti', 'Somalia', 'Bulgaria', 'Bermuda', 'Ireland',
'Jamaica', 'Estonia', 'United Arab Emirates', 'Israel', 'Paraguay',
'Costa Rica', 'Dominican Republic', 'Honduras', 'Cape Verde',
'Greece', 'Venezuela', 'Uganda', 'Peru', 'Belarus', 'San Marino',
'Ghana', 'Ecuador', 'Botswana', 'Republic of Korea', 'New Zealand',
'Bahamas', 'Denmark', 'Philippines', 'Guam', 'Madagascar', 'Haiti',
'Czech Republic', 'Montenegro', 'Afghanistan', 'Uruguay', 'Panama',
'Finland', 'Cameroon', 'Syrian Arab Republic', 'Turkmenistan', 'Hong
Kong, China', 'Togo', 'Seychelles', 'Mongolia', 'Slovenia', 'Guinea',
'Slovakia', 'Fiji', 'Zambia', 'Nicaragua', 'Sierra Leone',
'Guatemala', 'Papua New Guinea', 'Gambia', 'Lebanon', 'Cook Islands',
'Barbados', 'Luxembourg', 'Republic of Moldova', 'Nepal', 'Croatia',
'Kiribati', 'North Macedonia', 'Malawi', 'Democratic Republic of the
Congo', "Lao People's Democratic Republic", 'Thailand', 'St Vincent
and the Grenadines', 'Albania', 'Guinea-Bissau', 'Bolivia', 'Bosnia
and Herzegovina', 'Chinese Taipei', 'Saint Lucia', 'Palau',
'Mauritius', 'Saint Kitts and Nevis', 'Cayman Islands', 'American
Samoa', 'Belize', 'Vanuatu', 'Virgin Islands, US', 'Sao Tome and
Principe', 'Democratic Republic of Timor-Leste', 'Eritrea', 'Mali',
'Burkina Faso', 'Tonga', 'Namibia', 'Vietnam', 'Eswatini', 'Andorra',
'Aruba', 'Comoros', 'Equatorial Guinea', 'Liberia', 'Grenada',
'Solomon Islands', 'Marshall Islands', 'Burundi', 'United Republic of
```

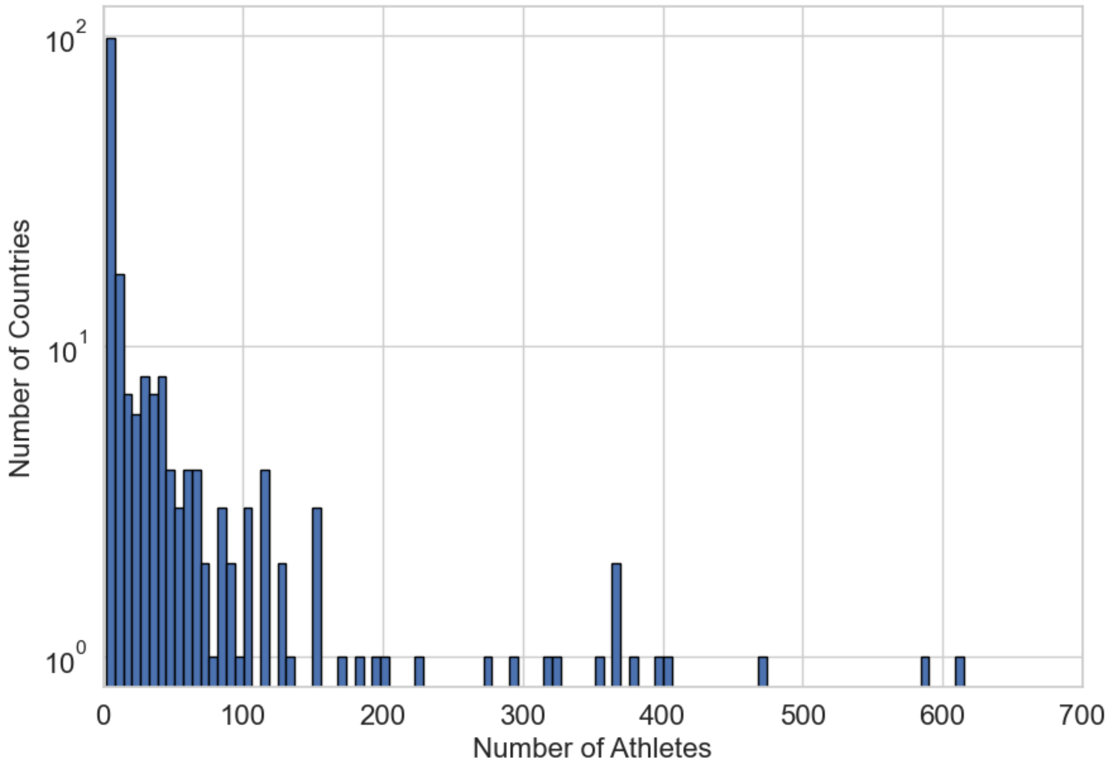
```
Tanzania', 'Gabon', 'Kosovo', 'Antigua and Barbuda', 'Mozambique',
'Iceland', 'South Sudan', 'Liechtenstein', 'Cambodia', 'Chad',
'Bhutan', 'Zimbabwe', 'Lesotho', 'Dominica', 'Tuvalu', 'Virgin
Islands, British', 'Central African Republic', 'Myanmar', 'Suriname']
206
```

```
'Zimbabwe'
```

```
# write you code here
# Binarize the data
a_c = athlete_csv['NOC'].value_counts() # count each athelete for each
country
print(a_c) # display results
```

```
United States of America       615
Japan                          586
Australia                      470
People's Republic of China     401
Germany                        400
                              ...
United Republic of Tanzania      2
Saint Kitts and Nevis            2
Marshall Islands                 2
Vanuatu                          2
South Sudan                      2
Name: NOC, Length: 206, dtype: int64
```

```
# Plot the Graph
sns.set_style('whitegrid')
plt.figure(figsize=(10, 7))
plt.hist(a_c, bins = 100, edgecolor='black')
plt.yscale(value='log')#nonpositive='clip')
plt.tick_params(axis='both', which='major', labelsize=16)
plt.xlim([0,700])
_ = plt.xlabel('Number of Athletes', fontsize=16)
_ = plt.ylabel('Number of Countries', fontsize=16)
```



After plotting the graph of number of Athletes vs the Number of Countries, it can be seen that the data is tail-heavy. This means that the majority of the data is at the smaller numbers with a few larger numbers spread towards the end of the graph. Overall, this shows a skew in the data.

(Tutorial) Quantizing data

```
# create 20 random numbers in the range (0,100)
small_counts = np.random.randint(0, 100, 20)
small_counts
```

```
array([13,  1, 92, 55, 92, 30, 58, 57, 68, 16, 57, 43, 51,  7, 21, 78,
51,
        3, 30, 14])
```

```
# divided by 10 to project digits into the range (0,10)
np.floor_divide(small_counts, 10)
```

```
array([1, 0, 9, 5, 9, 3, 5, 5, 6, 1, 5, 4, 5, 0, 2, 7, 5, 0, 3, 1],
      dtype=int32)
```

```
large_counts = [296, 8286, 64011, 80, 3, 725, 867, 2215, 7689, 11495,
91897, 44, 28, 7971, 926, 122, 22222]
np.floor(np.log10(large_counts))
```

```
array([2., 3., 4., 1., 0., 2., 2., 3., 3., 4., 4., 1., 1., 3., 2., 2.,
4.])
```

Example: computing deciles of Yelp business review counts

Yelp_academic_dataset_business
https://github.com/melqkiades/yelp/blob/master/notebooks/yelp_academic_dataset_business.json

```
import json

def load_json_df(filename, num_bytes = -1):
    '''Load the first `num_bytes` of the filename as a json blob,
convert each line into a row in a Pandas data frame.'''
    fs = open(filename, encoding='utf-8')
    df = pd.DataFrame([json.loads(x) for x in
fs.readlines(num_bytes)])
    fs.close()
    return df

biz_df = load_json_df(r'C:\Users\black\CSCE5222_Feature_Engineering\
Feature_Engineering_ICE_3\yelp_academic_dataset_business.json')
biz_df.shape
```

```
(15585, 15)
```

```
biz_df.head()
```

```
              business_id
full_address  \
0  O_X3PGhk3Y5JWVi866qlJg                  1501 W Bell Rd\nPhoenix, AZ
85023
1  QbrM7wqtmoNncqjc6GtFaQ            18501 N 83rd Avenue\nGlendale, AZ
85308
2  7lbvsGKzhjuX3oJtaXJvOg  5000 S Arizona Mills Cir\nSte 590\nTempe,
AZ 8...
3  gjxoKVsRJwEoa8zd9XxlAw               912 W Sycamore Pl\nChandler, AZ
85225
4  V28yjMqyZnbCtabroJN_aA             1745 W Glendale Ave\nPhoenix, AZ
85021

                                               hours  open  \
0  {'Monday': {'close': '18:00', 'open': '11:00'}...  True
1                                                 {}  True
2  {'Monday': {'close': '21:00', 'open': '10:00'}...  True
3  {'Monday': {'close': '19:00', 'open': '06:00'}...  True
4                                                 {}  True

                                          categories      city
review_count  \
0  [Active Life, Arts & Entertainment, Stadiums &...   Phoenix
29
1  [Tires, Automotive, Fashion, Shopping, Departm...  Glendale
3
```

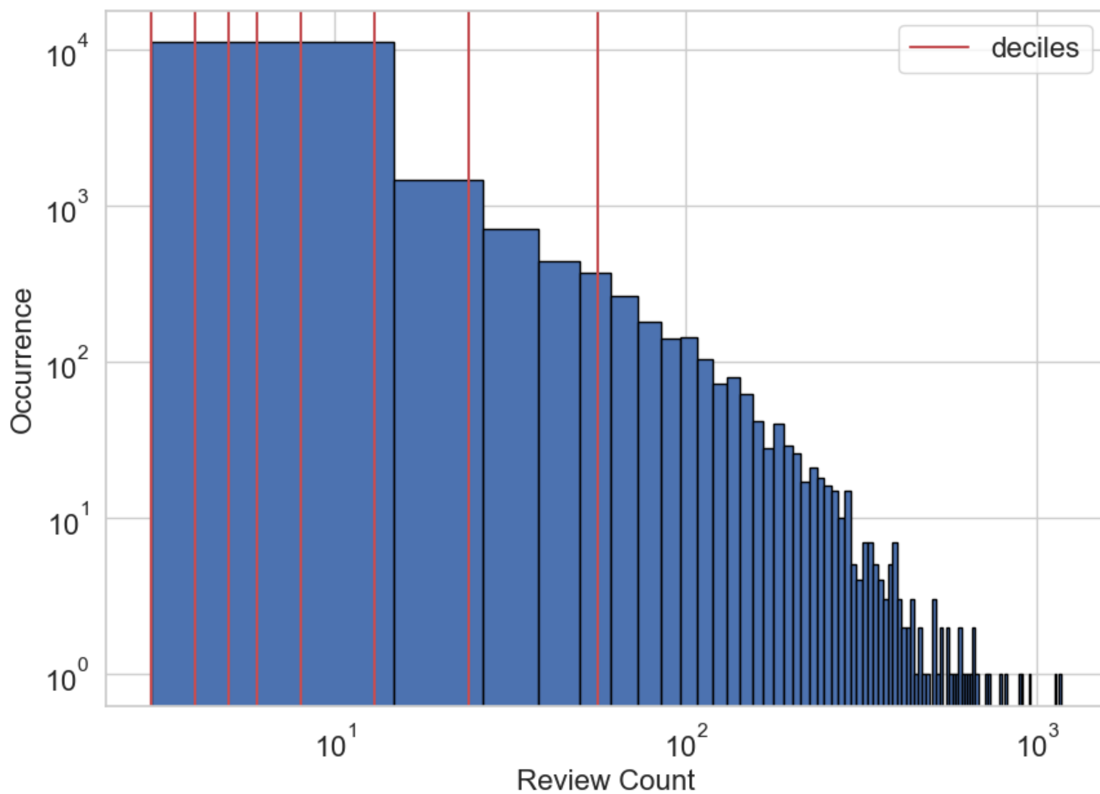
```
2  [Women's Clothing, Men's Clothing, Fashion, Sh...     Tempe
7
3     [Pet Services, Pet Boarding/Pet Sitting, Pets]  Chandler
4
4                               [Veterinarians, Pets]   Phoenix
3

                            name neighborhoods   longitude state
stars  \
0      Turf Paradise Race Course            [] -112.092329    AZ
4.0
1        Sam's Club Members Only            [] -112.234755    AZ
3.5
2                     Forever 21            [] -111.964485    AZ
3.5
3          Loving Hands Pet Care            [] -111.857818    AZ
5.0
4  Amec Mid-City Animal Hospital            [] -112.097232    AZ
5.0

    latitude                                         attributes
type
0  33.638573  {'Take-out': False, 'Wi-Fi': 'free', 'Good For...
business
1  33.648545  {'Parking': {'garage': False, 'street': False,...
business
2  33.383123  {'Parking': {'garage': False, 'street': False,...
business
3  33.356472                                                 {}
business
4  33.538493                                                 {}
business
```

```
deciles = biz_df['review_count'].quantile([.1, .2, .3, .4, .5, .6, .7,
.8, .9])
deciles
```

```
0.1     3.0
0.2     3.0
0.3     4.0
0.4     5.0
0.5     6.0
0.6     8.0
0.7    13.0
0.8    24.0
0.9    56.0
Name: review_count, dtype: float64
```

```
sns.set_style('whitegrid')
fig, ax = plt.subplots(figsize=(10, 7))
biz_df['review_count'].hist(ax=ax, bins=100, edgecolor='black')
```

```
for pos in deciles:
    handle = plt.axvline(pos, color='r')
ax.legend([handle], ['deciles'], fontsize=16)
ax.set_xscale('log', nonpositive='clip')
ax.set_yscale('log', nonpositive='clip')
ax.tick_params(labelsize=16)
_ = ax.set_xlabel('Review Count', fontsize=16)
_ = ax.set_ylabel('Occurrence', fontsize=16)
```



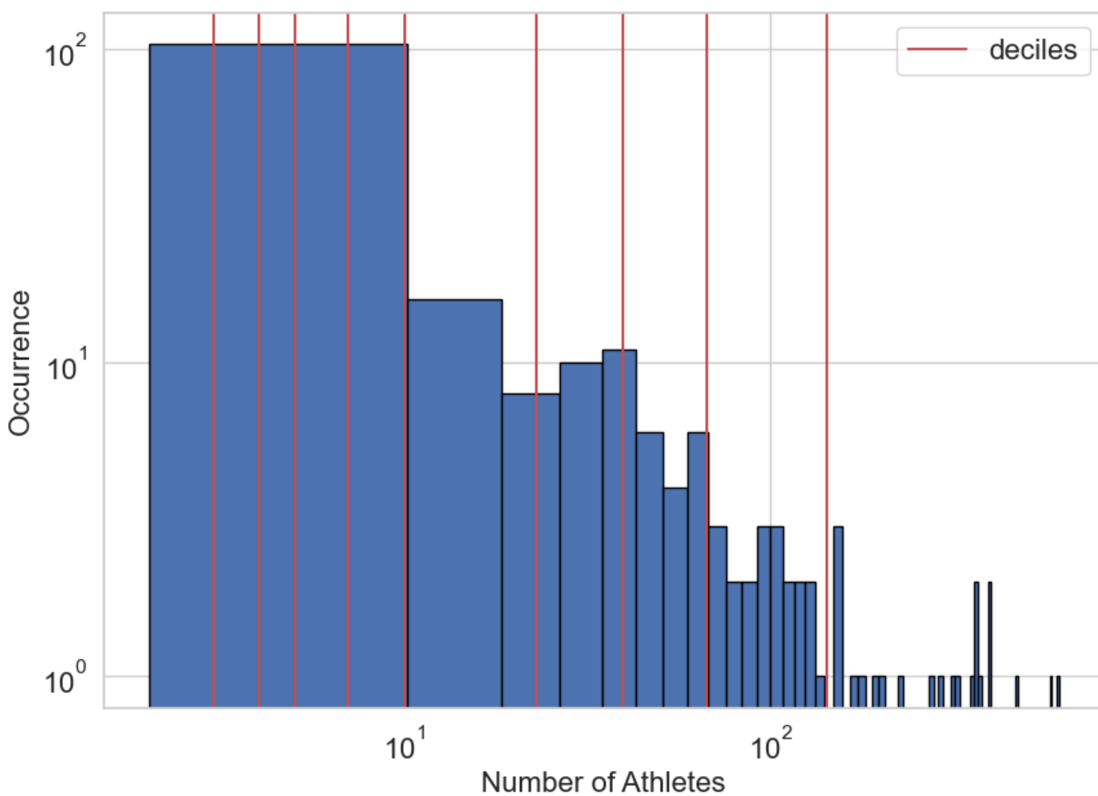
Task 2. Computing the quantiles of the number of athletes from each country and visualizing the histogram (data was used in task 1). Applying log transform on the number of athletes and visualizing the histogram again.

```
# write the code here
deciles = a_c.quantile([.1, .2, .3, .4, .5, .6, .7, .8, .9]) # compute
the quantile of athletes
deciles # check values
log = np.log2(a_c)
log_values = pd.DataFrame(data=log)

log_values.head()
```

```
                                  NOC
United States of America     9.264443
Japan                        9.194757
Australia                    8.876517
```

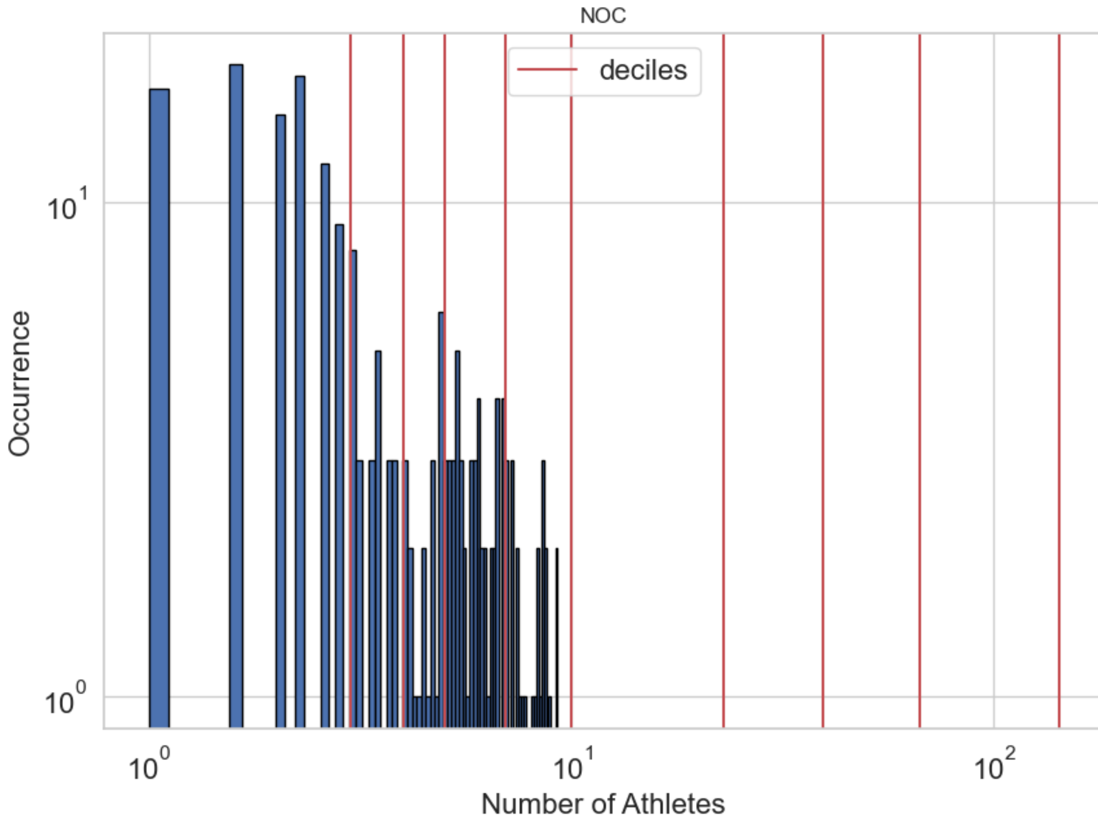
```
People's Republic of China  8.647458
Germany                     8.643856
```

```
sns.set_style('whitegrid')
fig, ax = plt.subplots(figsize=(10, 7))
a_c.hist(ax=ax, bins=75, edgecolor='black') # plot the histogram using the original data
for pos in deciles:
    handle = plt.axvline(pos, color='r')
ax.legend([handle], ['deciles'], fontsize=16) # use the deciles in the legend
ax.set_xscale('log', nonpositive='clip')
ax.set_yscale('log', nonpositive='clip')
ax.tick_params(labelsize=16)
_ = ax.set_xlabel('Number of Athletes', fontsize=16)
_ = ax.set_ylabel('Occurrence', fontsize=16)
```




```
sns.set_style('whitegrid')
fig, ax = plt.subplots(figsize=(10, 7))
log_values.hist(ax=ax, bins=75, edgecolor='black')
for pos in deciles:
    handle = plt.axvline(pos, color='r')
ax.legend([handle], ['deciles'], fontsize=16)
ax.set_xscale('log')
ax.set_yscale('log')
ax.tick_params(labelsize=16)
```

```
_ = ax.set_xlabel('Number of Athletes', fontsize=16)
_ = ax.set_ylabel('Occurrence', fontsize=16)
```



After plotting this graph, it can be seen that the data is slightly more spread out after converting the data from the base values to the log values. More of the data is found towards the larger numbers with less data being found in the beginning of the graph. Based on the graphs generated it seems as though the data is more spread out.

Question 1. Comparing the histograms before and after applying log transform and answer the question: why do we need to apply log transform on some data?

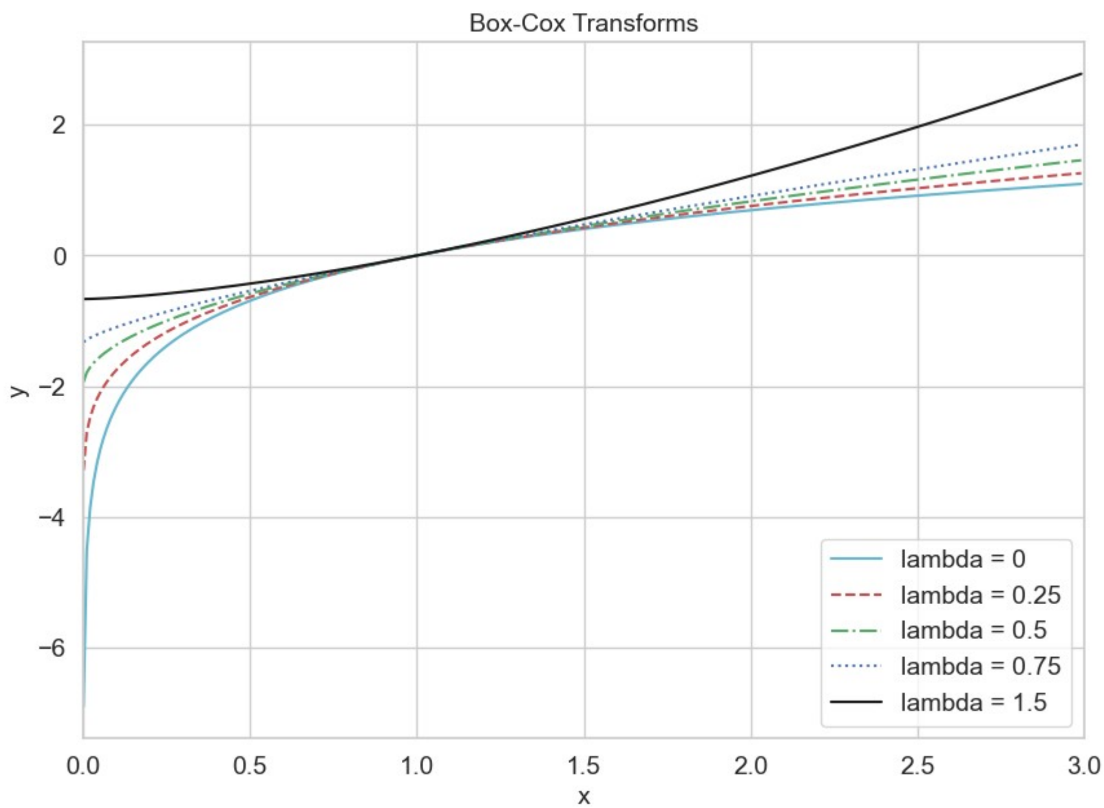
We need the log transform in order to accurately

(Tutorial) Box-Cox transform

```
x = np.arange(0.001, 3, 0.01)
lambda0 = np.log(x)
one_quarter = (x**0.25 - 1)/0.25
square_root = (x**0.5 - 1)/0.5
three_quarters = (x**0.75 - 1)/0.75
one_point_five = (x**1.5 - 1)/1.5
```

```
fig, ax = plt.subplots(figsize=(10, 7))
plt.plot(x, lambda0, 'c',
         x, one_quarter, 'r--',
         x, square_root, 'g-.',
         x, three_quarters, 'b:',
         x, one_point_five, 'k')
plt.legend(['lambda = 0', 'lambda = 0.25', 'lambda = 0.5', 'lambda = 
0.75', 'lambda = 1.5'],
           loc='lower right',
           prop={'size': 14})
ax.tick_params(labelsize=14)
ax.set_xlim([0.0,3.0])
ax.set_xlabel('x', fontsize=14)
ax.set_ylabel('y', fontsize=14)
ax.set_title('Box-Cox Transforms', fontsize=14)
```

```
Text(0.5, 1.0, 'Box-Cox Transforms')
```



Example: Visualizing the histograms of original, log transformed, and Box-Cox transformed review counts

```
from scipy import stats

rc_log = stats.boxcox(biz_df['review_count'], lmbda=0)
rc_bc, bc_params = stats.boxcox(biz_df['review_count'])
```

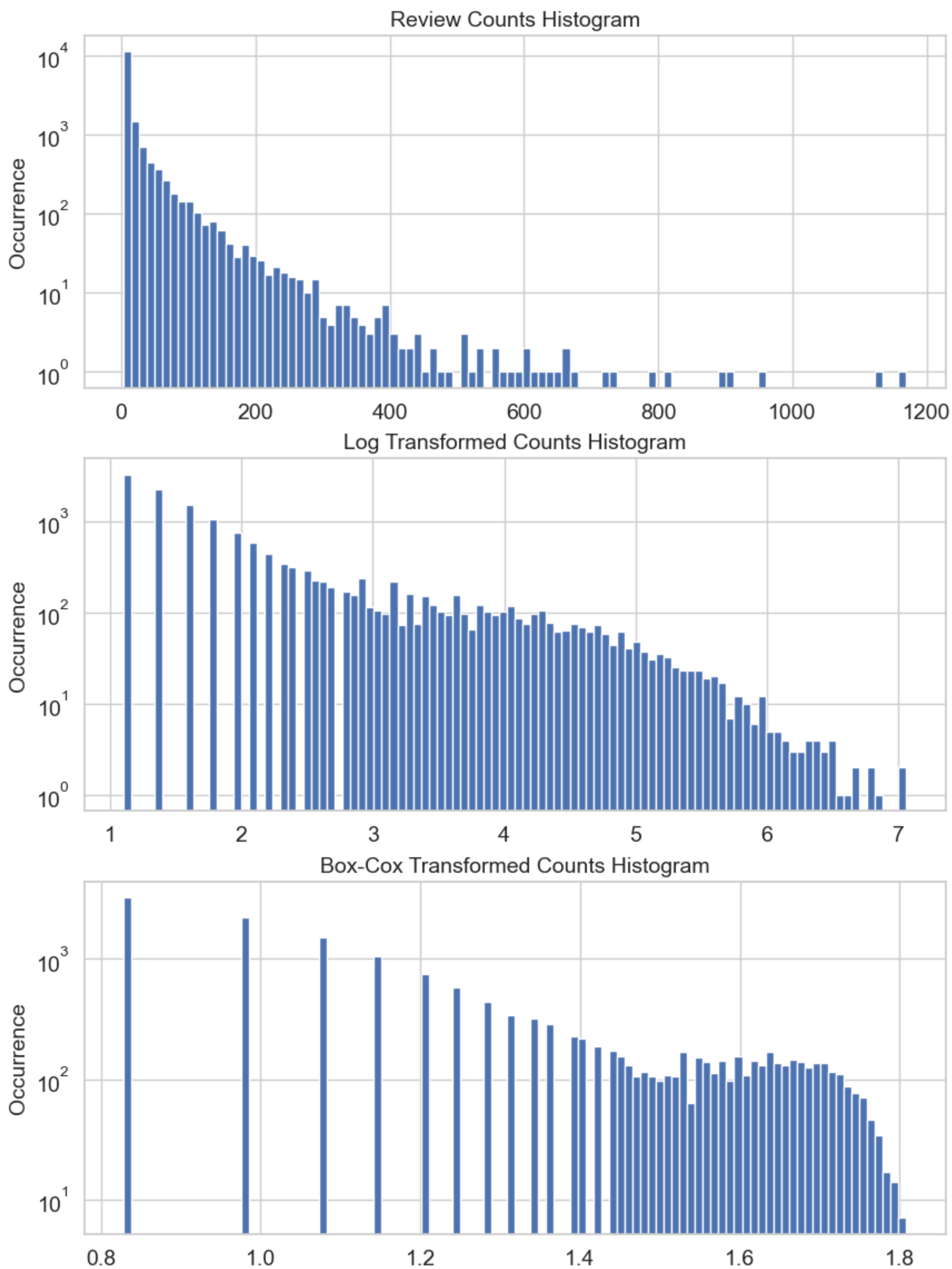
```
biz_df['rc_bc'] = rc_bc
biz_df['rc_log'] = rc_log

biz_df.head()
```

```
              business_id
full_address  \
0  O_X3PGhk3Y5JWVi866qlJg                  1501 W Bell Rd\nPhoenix, AZ
85023
1  QbrM7wqtmoNncqjc6GtFaQ            18501 N 83rd Avenue\nGlendale, AZ
85308
2  7lbvsGKzhjuX3oJtaXJvOg  5000 S Arizona Mills Cir\nSte 590\nTempe,
AZ 8...
3  gjxoKVsRJwEoa8zd9XxlAw              912 W Sycamore Pl\nChandler, AZ
85225
4  V28yjMqyZnbCtabroJN_aA             1745 W Glendale Ave\nPhoenix, AZ
85021

                                               hours  open  \
0  {'Monday': {'close': '18:00', 'open': '11:00'}...  True
1                                                 {}  True
2  {'Monday': {'close': '21:00', 'open': '10:00'}...  True
3  {'Monday': {'close': '19:00', 'open': '06:00'}...  True
4                                                 {}  True

                                          categories      city
review_count  \
0  [Active Life, Arts & Entertainment, Stadiums &...   Phoenix
29
1  [Tires, Automotive, Fashion, Shopping, Departm...  Glendale
3
2  [Women's Clothing, Men's Clothing, Fashion, Sh...     Tempe
7
3     [Pet Services, Pet Boarding/Pet Sitting, Pets]  Chandler
4
4                              [Veterinarians, Pets]   Phoenix
3

                            name neighborhoods   longitude state
stars  \
0      Turf Paradise Race Course            [] -112.092329    AZ
4.0
1        Sam's Club Members Only            [] -112.234755    AZ
3.5
2                     Forever 21            [] -111.964485    AZ
3.5
3          Loving Hands Pet Care            [] -111.857818    AZ
5.0
4  Amec Mid-City Animal Hospital            [] -112.097232    AZ
5.0
```

```
    latitude                                         attributes
type  \
0  33.638573  {'Take-out': False, 'Wi-Fi': 'free', 'Good For...
business
1  33.648545  {'Parking': {'garage': False, 'street': False,...
business
2  33.383123  {'Parking': {'garage': False, 'street': False,...
business
3  33.356472                                                 {}
business
4  33.538493                                                 {}
business

      rc_bc    rc_log
0  1.549713  3.367296
1  0.828300  1.098612
2  1.203501  1.945910
3  0.975365  1.386294
4  0.828300  1.098612
```

```
fig, (ax1, ax2, ax3) = plt.subplots(3,1, figsize=(10, 14))

#
biz_df['review_count'].hist(ax=ax1, bins=100)
ax1.set_yscale('log', nonpositive='clip')
ax1.tick_params(labelsize=14)
ax1.set_title('Review Counts Histogram', fontsize=14)
ax1.set_xlabel('')
ax1.set_ylabel('Occurrence', fontsize=14)

#
biz_df['rc_log'].hist(ax=ax2, bins=100)
ax2.set_yscale('log', nonpositive='clip')
ax2.tick_params(labelsize=14)
ax2.set_title('Log Transformed Counts Histogram', fontsize=14)
ax2.set_xlabel('')
ax2.set_ylabel('Occurrence', fontsize=14)

# Box-Cox
biz_df['rc_bc'].hist(ax=ax3, bins=100)
ax3.set_yscale('log', nonpositive='clip')
ax3.tick_params(labelsize=14)
ax3.set_title('Box-Cox Transformed Counts Histogram', fontsize=14)
ax3.set_xlabel('')
ax3.set_ylabel('Occurrence', fontsize=14)
```

```
Text(0, 0.5, 'Occurrence')
```



Task 3. Visualizing the histograms of original, log transformed, and Box-Cox transformed athletes numbers (data used in task 1 and task 2)

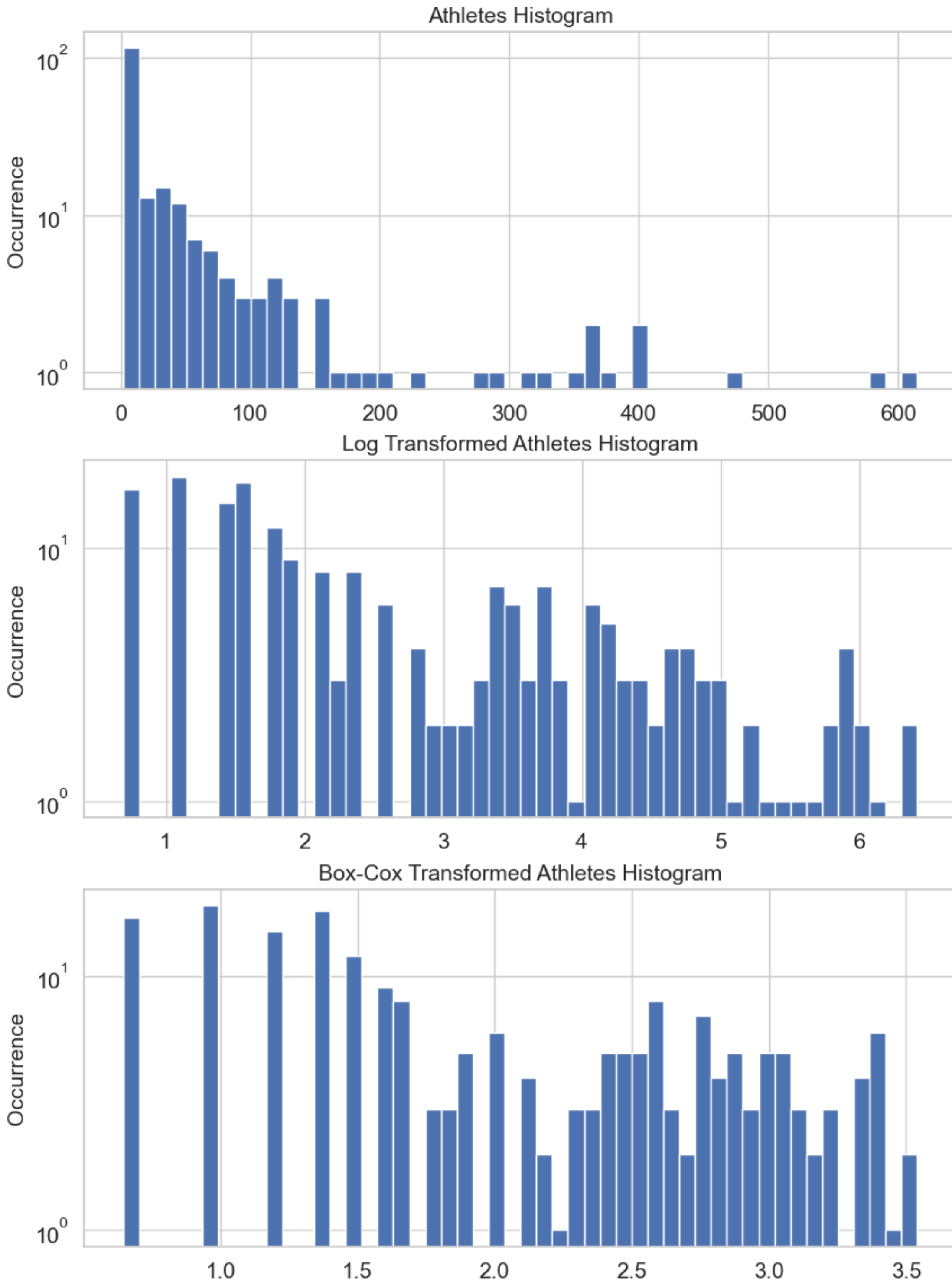
```
# write your code here
# data conversion
ac_log = stats.boxcox(a_c, lmbda=0)
```

```python
ac_bc, bc_params = stats.boxcox(a_c)
plot_data = pd.DataFrame()
plot_data['Countries'] = countries
plot_data['Log'] = ac_log
plot_data['Box-Cox'] = ac_bc

plot_data.head()
```

```
  Countries       Log   Box-Cox
0    Norway  6.421622  3.541425
1     Spain  6.373320  3.528677
2     Italy  6.152733  3.468800
3    France  5.993961  3.423968
4     Chile  5.991465  3.423251
```

```python
# plot figures
fig, (ax1, ax2, ax3) = plt.subplots(3,1, figsize=(10, 14))
bin_s = 50 # smaller than 100 due to less data
# Original
a_c.hist(ax=ax1, bins=bin_s)
ax1.set_yscale('log', nonpositive='clip')
ax1.tick_params(labelsize=14)
ax1.set_title('Athletes Histogram', fontsize=14)
ax1.set_xlabel('')
ax1.set_ylabel('Occurrence', fontsize=14)

# Log Transform
plot_data['Log'].hist(ax=ax2, bins=bin_s)
ax2.set_yscale('log', nonpositive='clip')
ax2.tick_params(labelsize=14)
ax2.set_title('Log Transformed Athletes Histogram', fontsize=14)
ax2.set_xlabel('')
ax2.set_ylabel('Occurrence', fontsize=14)

# Box-Cox
plot_data['Box-Cox'].hist(ax=ax3, bins=bin_s)
ax3.set_yscale('log', nonpositive='clip')
ax3.tick_params(labelsize=14)
ax3.set_title('Box-Cox Transformed Athletes Histogram', fontsize=14)
ax3.set_xlabel('')
ax3.set_ylabel('Occurrence', fontsize=14)
```

```
Text(0, 0.5, 'Occurrence')
```



Based on the graphs generated above, it would seem as though both the log transform and the Box-Cox transfrom do spread the data out to generate a more equal dataset. The original data is tail-heavy and that data present at the beginning of the graph would bias any model that uses the untransformed data. Both the log transform and the Box-Cox transform reduce the amount of skew that is present in the data as show by the graphs. The

Box-Cox seems based on visuals, to have the most even distribution of data though the Log transform is also fairly equalized.

Question 2. Listing another transform method other than log and box-cox transform. Explain when to use them.

Answer to Q2: write your answer here

Feature scaling example

Online News Popularity Dataset: https://archive.ics.uci.edu/ml/machine-learning-databases/00332/OnlineNewsPopularity.zip

```
import sklearn.preprocessing as preproc
```

```
news_df = pd.read_csv(r'C:\Users\black\CSCE5222_Feature_Engineering\
Feature_Engineering_ICE_3\OnlineNewsPopularity\OnlineNewsPopularity\
OnlineNewsPopularity.csv', delimiter=', ',engine = 'python')
news_df.head()
```

```
                                                 url  timedelta  \
0  http://mashable.com/2013/01/07/amazon-instant-...      731.0
1  http://mashable.com/2013/01/07/ap-samsung-spon...      731.0
2  http://mashable.com/2013/01/07/apple-40-billio...      731.0
3  http://mashable.com/2013/01/07/astronaut-notre...      731.0
4   http://mashable.com/2013/01/07/att-u-verse-apps/      731.0

   n_tokens_title  n_tokens_content  n_unique_tokens  n_non_stop_words
\
0            12.0             219.0         0.663594               1.0

1             9.0             255.0         0.604743               1.0

2             9.0             211.0         0.575130               1.0

3             9.0             531.0         0.503788               1.0

4            13.0            1072.0         0.415646               1.0


   n_non_stop_unique_tokens  num_hrefs  num_self_hrefs  num_imgs  ...
\
0                  0.815385        4.0             2.0       1.0  ...

1                  0.791946        3.0             1.0       1.0  ...

2                  0.663866        3.0             1.0       1.0  ...
```

```
3                  0.665635        9.0             0.0       1.0  ...

4                  0.540890       19.0            19.0      20.0  ...


   min_positive_polarity  max_positive_polarity  avg_negative_polarity
\
0               0.100000                    0.7              -0.350000

1               0.033333                    0.7              -0.118750

2               0.100000                    1.0              -0.466667

3               0.136364                    0.8              -0.369697

4               0.033333                    1.0              -0.220192


   min_negative_polarity  max_negative_polarity  title_subjectivity  \
0                 -0.600              -0.200000            0.500000
1                 -0.125              -0.100000            0.000000
2                 -0.800              -0.133333            0.000000
3                 -0.600              -0.166667            0.000000
4                 -0.500              -0.050000            0.454545

   title_sentiment_polarity  abs_title_subjectivity  \
0                 -0.187500                0.000000
1                  0.000000                0.500000
2                  0.000000                0.500000
3                  0.000000                0.500000
4                  0.136364                0.045455

   abs_title_sentiment_polarity  shares
0                      0.187500     593
1                      0.000000     711
2                      0.000000    1500
3                      0.000000    1200
4                      0.136364     505

[5 rows x 61 columns]
```

```
# Min-max scaling
news_df['minmax'] =
preproc.minmax_scale(news_df[['n_tokens_content']])
news_df['minmax'].values
```

```
array([0.02584376, 0.03009205, 0.02489969, ..., 0.05215955,
0.08048147,
       0.01852726])
```

```python
# Standardization
news_df['standardized'] =
preproc.StandardScaler().fit_transform(news_df[['n_tokens_content']])
news_df['standardized'].values
```

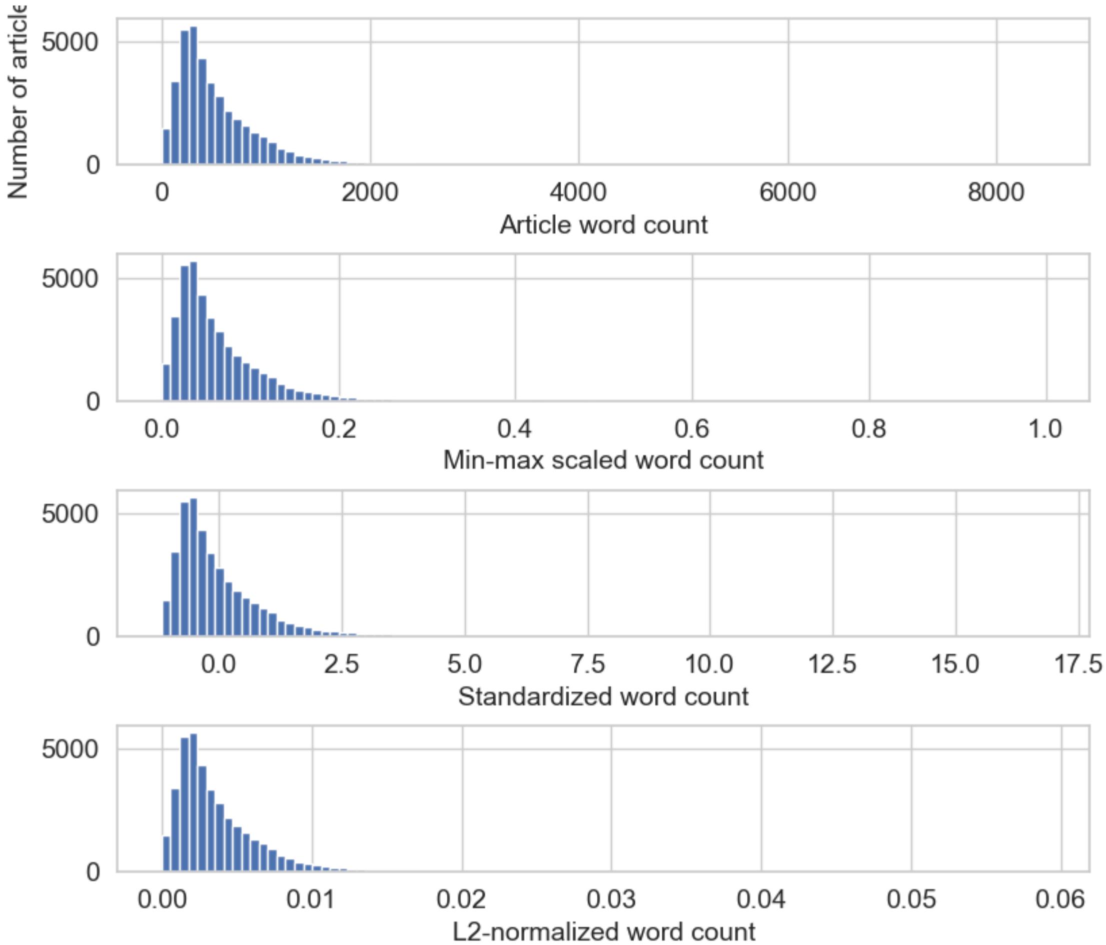
```
array([-0.69521045, -0.61879381, -0.71219192, ..., -0.2218518 ,
        0.28759248, -0.82681689])
```

```python
# L2-normalization
news_df['l2_normalized'] =
preproc.normalize(news_df[['n_tokens_content']], axis=0)
news_df['l2_normalized'].values
```

```
array([0.00152439, 0.00177498, 0.00146871, ..., 0.00307663,
0.0047472 ,
       0.00109283])
```

```python
fig, (ax1, ax2, ax3, ax4) = plt.subplots(4,1, figsize=(8, 7))
fig.tight_layout(h_pad=2.0)

news_df['n_tokens_content'].hist(ax=ax1, bins=100)
ax1.tick_params(labelsize=14)
ax1.set_xlabel('Article word count', fontsize=14)
ax1.set_ylabel('Number of articles', fontsize=14)

news_df['minmax'].hist(ax=ax2, bins=100)
ax2.tick_params(labelsize=14)
ax2.set_xlabel('Min-max scaled word count', fontsize=14)
# ax2.set_ylabel('Number of articles', fontsize=14)

news_df['standardized'].hist(ax=ax3, bins=100)
ax3.tick_params(labelsize=14)
ax3.set_xlabel('Standardized word count', fontsize=14)
# ax3.set_ylabel('Number of articles', fontsize=14)

news_df['l2_normalized'].hist(ax=ax4, bins=100)
ax4.tick_params(labelsize=14)
ax4.set_xlabel('L2-normalized word count', fontsize=14)
# ax4.set_ylabel('Number of articles', fontsize=14)
```

```
Text(0.5, 44.249999999999986, 'L2-normalized word count')
```



Task 4. Visualizing the histograms of original and scaled data (the data used in the previous tasks)

```
# write your code here
# Min-max scaling
dataset = pd.DataFrame()
dataset['Original'] = a_c
dataset['Minmax'] = preproc.minmax_scale(a_c) #use minmax scale
display(dataset)
```

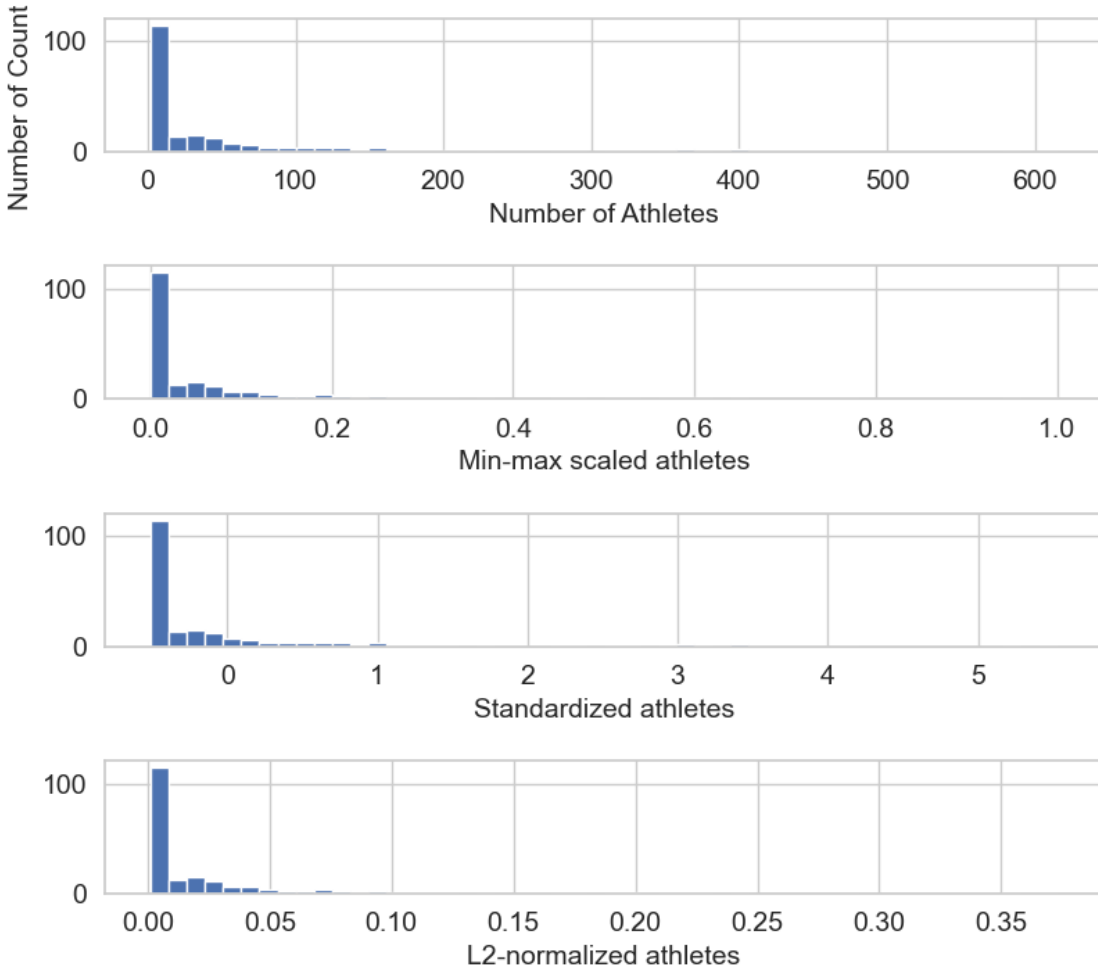
	Original	Minmax
United States of America	615	1.000000
Japan	586	0.952692
Australia	470	0.763458
People's Republic of China	401	0.650897
Germany	400	0.649266
...	...	...
United Republic of Tanzania	2	0.000000
Saint Kitts and Nevis	2	0.000000
Marshall Islands	2	0.000000
Vanuatu	2	0.000000
South Sudan	2	0.000000

```
[206 rows x 2 columns]

# Standardization
dataset['Standardized'] =
preproc.StandardScaler().fit_transform(dataset[['Original']]) # use
the Standard Scaler
display(dataset)

                             Original    Minmax  Standardized
United States of America          615  1.000000      5.526837
Japan                             586  0.952692      5.241232
Australia                         470  0.763458      4.098814
People's Republic of China        401  0.650897      3.419272
Germany                           400  0.649266      3.409423
...                               ...       ...           ...
United Republic of Tanzania         2  0.000000     -0.510254
Saint Kitts and Nevis               2  0.000000     -0.510254
Marshall Islands                    2  0.000000     -0.510254
Vanuatu                             2  0.000000     -0.510254
South Sudan                         2  0.000000     -0.510254

[206 rows x 3 columns]

# L2-normalization
dataset['L2_normalized'] = preproc.normalize(dataset[['Original']],
axis=0) # normalize the original values
display(dataset)

                             Original    Minmax  Standardized
L2_normalized
United States of America          615  1.000000      5.526837
0.372872
Japan                             586  0.952692      5.241232
0.355290
Australia                         470  0.763458      4.098814
0.284959
People's Republic of China        401  0.650897      3.419272
0.243125
Germany                           400  0.649266      3.409423
0.242518
...                               ...       ...           ...
...
United Republic of Tanzania         2  0.000000     -0.510254
0.001213
Saint Kitts and Nevis               2  0.000000     -0.510254
0.001213
Marshall Islands                    2  0.000000     -0.510254
0.001213
Vanuatu                             2  0.000000     -0.510254
0.001213
```

```
South Sudan                             2  0.000000     -0.510254
0.001213

[206 rows x 4 columns]
```

```python
# plot the feature scaling
fig, (ax1, ax2, ax3, ax4) = plt.subplots(4,1, figsize=(8, 7))
fig.tight_layout(h_pad=3.0)

num_bins = 50
dataset['Original'].hist(ax=ax1, bins=num_bins)
ax1.tick_params(labelsize=14)
ax1.set_xlabel('Number of Athletes', fontsize=14)
ax1.set_ylabel('Number of Countries', fontsize=14)

dataset['Minmax'].hist(ax=ax2, bins=num_bins)
ax2.tick_params(labelsize=14)
ax2.set_xlabel('Min-max scaled athletes', fontsize=14)
# ax2.set_ylabel('Number of articles', fontsize=14)

dataset['Standardized'].hist(ax=ax3, bins=num_bins)
ax3.tick_params(labelsize=14)
ax3.set_xlabel('Standardized athletes', fontsize=14)
# ax3.set_ylabel('Number of articles', fontsize=14)

dataset['L2_normalized'].hist(ax=ax4, bins=num_bins)
ax4.tick_params(labelsize=14)
ax4.set_xlabel('L2-normalized athletes', fontsize=14)
# ax4.set_ylabel('Number of articles', fontsize=14)
```

```
Text(0.5, 44.249999999999986, 'L2-normalized athletes')
```



Overall, the idea behind feature scaling is to reduce the bias that large data values have on a model. Datasets that have a skew of a large amount of data around a single value can cause issues in the model. Min-max aims to scale the feature by assigning values between a minimum and a maximum range. Standardization works by centering the data around 0 and then incorporating a standard deviation of 1. Lastly L2 normalized word count works by calculating the sum of squares for each row in the dataset. This sum of squares value is then used to normalize the data by aiming to force the sum of squares values to be equal to 1. From the graphs plotted above, this can be seen as the x values in the min-max scaled graph range from 0 to about .2. The standardized athletes graph has a range of about -1 to 1, and the L2-normalized athlete graph has a scale of approximately 0 to .7.

Question 3. Comparing the four histograms, listing the similarities and differences between them.

Answer to Q3: type your answer here

Question 4. Comparing the histograms of feature scaling and the histograms of transforms, listing the main difference between them.

Answer to Q4: type your answer here

Example of interaction features in prediction

```
from sklearn import linear_model
from sklearn.model_selection import train_test_split
import sklearn.preprocessing as preproc

news_df.columns

Index(['url', 'timedelta', 'n_tokens_title', 'n_tokens_content',
       'n_unique_tokens', 'n_non_stop_words',
'n_non_stop_unique_tokens',
       'num_hrefs', 'num_self_hrefs', 'num_imgs', 'num_videos',
       'average_token_length', 'num_keywords',
'data_channel_is_lifestyle',
       'data_channel_is_entertainment', 'data_channel_is_bus',
       'data_channel_is_socmed', 'data_channel_is_tech',
       'data_channel_is_world', 'kw_min_min', 'kw_max_min',
'kw_avg_min',
       'kw_min_max', 'kw_max_max', 'kw_avg_max', 'kw_min_avg',
'kw_max_avg',
       'kw_avg_avg', 'self_reference_min_shares',
'self_reference_max_shares',
       'self_reference_avg_sharess', 'weekday_is_monday',
'weekday_is_tuesday',
       'weekday_is_wednesday', 'weekday_is_thursday',
'weekday_is_friday',
       'weekday_is_saturday', 'weekday_is_sunday', 'is_weekend',
'LDA_00',
       'LDA_01', 'LDA_02', 'LDA_03', 'LDA_04', 'global_subjectivity',
       'global_sentiment_polarity', 'global_rate_positive_words',
       'global_rate_negative_words', 'rate_positive_words',
       'rate_negative_words', 'avg_positive_polarity',
'min_positive_polarity',
       'max_positive_polarity', 'avg_negative_polarity',
       'min_negative_polarity', 'max_negative_polarity',
'title_subjectivity',
       'title_sentiment_polarity', 'abs_title_subjectivity',
       'abs_title_sentiment_polarity', 'shares', 'minmax',
'standardized',
       'l2_normalized'],
      dtype='object')

features = ['n_tokens_title', 'n_tokens_content', 'n_unique_tokens',
'n_non_stop_words', 'n_non_stop_unique_tokens',
```

```
            'num_hrefs', 'num_self_hrefs', 'num_imgs', 'num_videos',
'average_token_length', 'num_keywords',
            'data_channel_is_lifestyle',
'data_channel_is_entertainment', 'data_channel_is_bus',
            'data_channel_is_socmed', 'data_channel_is_tech',
'data_channel_is_world']

X = news_df[features]
y = news_df[['shares']]
```

```
X.shape
```

```
(39644, 17)
```

```
display(X)
display(y)
```

```
       n_tokens_title  n_tokens_content  n_unique_tokens
n_non_stop_words  \
0                12.0             219.0         0.663594
1.0
1                 9.0             255.0         0.604743
1.0
2                 9.0             211.0         0.575130
1.0
3                 9.0             531.0         0.503788
1.0
4                13.0            1072.0         0.415646
1.0
...               ...               ...              ...
...
39639            11.0             346.0         0.529052
1.0
39640            12.0             328.0         0.696296
1.0
39641            10.0             442.0         0.516355
1.0
39642             6.0             682.0         0.539493
1.0
39643            10.0             157.0         0.701987
1.0

       n_non_stop_unique_tokens  num_hrefs  num_self_hrefs
num_imgs  \
0                      0.815385        4.0             2.0       1.0

1                      0.791946        3.0             1.0       1.0

2                      0.663866        3.0             1.0       1.0

3                      0.665635        9.0             0.0       1.0
```

```
4                      0.540890       19.0             19.0      20.0

...                         ...        ...              ...       ...

39639                  0.684783        9.0              7.0       1.0

39640                  0.885057        9.0              7.0       3.0

39641                  0.644128       24.0              1.0      12.0

39642                  0.692661       10.0              1.0       1.0

39643                  0.846154        1.0              1.0       0.0


       num_videos  average_token_length  num_keywords  \
0             0.0              4.680365           5.0
1             0.0              4.913725           4.0
2             0.0              4.393365           6.0
3             0.0              4.404896           7.0
4             0.0              4.682836           7.0
...           ...                   ...           ...
39639         1.0              4.523121           8.0
39640        48.0              4.405488           7.0
39641         1.0              5.076923           8.0
39642         0.0              4.975073           5.0
39643         2.0              4.471338           4.0

       data_channel_is_lifestyle  data_channel_is_entertainment  \
0                            0.0                            1.0
1                            0.0                            0.0
2                            0.0                            0.0
3                            0.0                            1.0
4                            0.0                            0.0
...                          ...                            ...
39639                        0.0                            0.0
39640                        0.0                            0.0
39641                        0.0                            0.0
39642                        0.0                            0.0
39643                        0.0                            1.0

       data_channel_is_bus  data_channel_is_socmed
data_channel_is_tech  \
0                      0.0                     0.0
0.0
1                      1.0                     0.0
0.0
2                      1.0                     0.0
```

```
0.0
3                      0.0                        0.0
0.0
4                      0.0                        0.0
1.0
...                    ...                        ...                      .
..
39639                  0.0                        0.0
1.0
39640                  0.0                        1.0
0.0
39641                  0.0                        0.0
0.0
39642                  0.0                        0.0
0.0
39643                  0.0                        0.0
0.0

       data_channel_is_world
0                        0.0
1                        0.0
2                        0.0
3                        0.0
4                        0.0
...                      ...
39639                    0.0
39640                    0.0
39641                    0.0
39642                    1.0
39643                    0.0

[39644 rows x 17 columns]

       shares
0         593
1         711
2        1500
3        1200
4         505
...       ...
39639    1800
39640    1900
39641    1900
39642    1100
39643    1300

[39644 rows x 1 columns]
```

```
X2 = preproc.PolynomialFeatures(include_bias=False).fit_transform(X)
X1_train, X1_test, X2_train, X2_test, y_train, y_test =
train_test_split(X, X2, y, test_size=0.3, random_state=123)

def evaluate_feature(X_train, X_test, y_train, y_test):
    """Fit a linear regression model on the training set and score on
the test set"""
    model = linear_model.LinearRegression().fit(X_train, y_train)
    r_score = model.score(X_test, y_test)
    return (model, r_score)

(m1, r1) = evaluate_feature(X1_train, X1_test, y_train, y_test)
print("R-squared score with singleton features: %0.5f" % r1)

(m2, r2) = evaluate_feature(X2_train, X2_test, y_train, y_test)
print("R-squared score with pairwise features: %0.10f" % r2)

R-squared score with singleton features: 0.00924
R-squared score with pairwise features: 0.0113228095
```

Task 5. Interaction features in prediction with dry bean dataset

Dry bean dataset:
https://archive.ics.uci.edu/ml/machine-learning-databases/00602/DryBeanDataset.zip

note: Try to encode categorical data into numeric data (the last column 'class') first. Then apply the interation features and compare the r-squared scores of the singleton features and the interaction features

```
# write your code here
# load data
bean_df = pd.read_csv(r'C:\Users\black\CSCE5222_Feature_Engineering\
Feature_Engineering_ICE_3\DryBeanDataset\DryBeanDataset\
Dry_Bean_Dataset.csv',engine = 'python')
bean_df.columns

Index(['Area', 'Perimeter', 'MajorAxisLength', 'MinorAxisLength',
       'AspectRation', 'Eccentricity', 'ConvexArea', 'EquivDiameter',
'Extent',
       'Solidity', 'roundness', 'Compactness', 'ShapeFactor1',
'ShapeFactor2',
       'ShapeFactor3', 'ShapeFactor4', 'Class'],
      dtype='object')

class_values = bean_df.Class.unique().tolist()
print(class_values)
bean_features = [ # store the features

'Area','Perimeter','MajorAxisLength','MinorAxisLength','AspectRation',
'Eccentricity','ConvexArea','EquivDiameter',
```

```
'Extent','Solidity','roundness','Compactness','ShapeFactor1','ShapeFac
tor2','ShapeFactor3','ShapeFactor4']
```

```
['SEKER', 'BARBUNYA', 'BOMBAY', 'CALI', 'HOROZ', 'SIRA', 'DERMASON']
```

```
X_b = bean_df[bean_features]

# bin the data based on the class
df_beanclass = pd.DataFrame(columns=['Class'])
for i in range(0,13611):
    if bean_df.iloc[i]['Class'] == 'SEKER':
        df_beanclass.loc[i,'Class'] = 1
    elif bean_df.iloc[i]['Class'] == 'BARBUNYA':
        df_beanclass.loc[i,'Class'] = 2
    elif bean_df.iloc[i]['Class'] == 'BOMBAY':
        df_beanclass.loc[i,'Class'] = 3
    elif bean_df.iloc[i]['Class'] == 'CALI':
        df_beanclass.loc[i,'Class'] = 4
    elif bean_df.iloc[i]['Class'] == 'HOROZ':
        df_beanclass.loc[i,'Class'] = 5
    elif bean_df.iloc[i]['Class'] == 'SIRA':
        df_beanclass.loc[i,'Class'] = 6
    elif bean_df.iloc[i]['Class'] == 'DERMASON':
        df_beanclass.loc[i,'Class'] = 7

display(df_beanclass)
y_b = df_beanclass[['Class']]

X_b.shape
```

```
      Class
0         1
1         1
2         1
3         1
4         1
...     ...
13606     7
13607     7
13608     7
13609     7
13610     7

[13611 rows x 1 columns]
```

```
(13611, 16)
```

```
display(X_b) # check
display(y_b) # check
```

```
        Area  Perimeter  MajorAxisLength  MinorAxisLength  
AspectRation  \
0      28395    610.291       208.178117       173.888747      
1.197191   
1      28734    638.018       200.524796       182.734419      
1.097356   
2      29380    624.110       212.826130       175.931143      
1.209713   
3      30008    645.884       210.557999       182.516516      
1.153638   
4      30140    620.134       201.847882       190.279279      
1.060798   
...      ...        ...              ...              ...           ..
.   
13606  42097    759.696       288.721612       185.944705      
1.552728   
13607  42101    757.499       281.576392       190.713136      
1.476439   
13608  42139    759.321       281.539928       191.187979      
1.472582   
13609  42147    763.779       283.382636       190.275731      
1.489326   
13610  42159    772.237       295.142741       182.204716      
1.619841   

       Eccentricity  ConvexArea  EquivDiameter    Extent  Solidity  
roundness  \
0          0.549812       28715     190.141097  0.763923  0.988856   
0.958027   
1          0.411785       29172     191.272751  0.783968  0.984986   
0.887034   
2          0.562727       29690     193.410904  0.778113  0.989559   
0.947849   
3          0.498616       30724     195.467062  0.782681  0.976696   
0.903936   
4          0.333680       30417     195.896503  0.773098  0.990893   
0.984877   
...             ...         ...            ...       ...       ...        
...   
13606      0.765002       42508     231.515799  0.714574  0.990331   
0.916603   
13607      0.735702       42494     231.526798  0.799943  0.990752   
0.922015   
13608      0.734065       42569     231.631261  0.729932  0.989899   
0.918424   
13609      0.741055       42667     231.653247  0.705389  0.987813   
0.907906   
13610      0.786693       42600     231.686223  0.788962  0.989648   
0.888380   
```

```
       Compactness  ShapeFactor1  ShapeFactor2  ShapeFactor3
ShapeFactor4
0         0.913358      0.007332      0.003147      0.834222
0.998724
1         0.953861      0.006979      0.003564      0.909851
0.998430
2         0.908774      0.007244      0.003048      0.825871
0.999066
3         0.928329      0.007017      0.003215      0.861794
0.994199
4         0.970516      0.006697      0.003665      0.941900
0.999166
...            ...           ...           ...           ...
...
13606     0.801865      0.006858      0.001749      0.642988
0.998385
13607     0.822252      0.006688      0.001886      0.676099
0.998219
13608     0.822730      0.006681      0.001888      0.676884
0.996767
13609     0.817457      0.006724      0.001852      0.668237
0.995222
13610     0.784997      0.007001      0.001640      0.616221
0.998180

[13611 rows x 16 columns]

      Class
0         1
1         1
2         1
3         1
4         1
...     ...
13606     7
13607     7
13608     7
13609     7
13610     7

[13611 rows x 1 columns]
```

```
X2_b =
preproc.PolynomialFeatures(include_bias=False).fit_transform(X_b) #
this step generates polynomial and interaction features
# split the data into training and testing datasets
X1_b_train, X1_b_test, X2_b_train, X2_b_test, y_b_train, y_b_test =
train_test_split(X_b, X2_b, y_b, test_size=0.3,random_state=123)

(mb1, rb1) = evaluate_feature(X1_b_train, X1_b_test, y_b_train,
y_b_test) # run evaluation
```

```
print("R-squared score with singleton features: %0.5f" % rb1) # print results

(mb2, rb2) = evaluate_feature(X2_b_train, X2_b_test, y_b_train, y_b_test) # run evaluation
print("R-squared score with pairwise features: %0.10f" % rb2) # print results
```

```
R-squared score with singleton features: 0.78178
R-squared score with pairwise features: 0.8493158410
```

From the R-squared score, it can be seen that the the pairwise features has the higher R-squared score with .849. The singleton feature still has a good R-squared score of .781 which shows that the singleton features would work well in this model as R-squared scores range from 0 to 1. However, since the R-squared score is higher for the pairwise features, this could indicate that pairwise features work best in this model.