BenPrescott_Assignment1_MSDS422WI

January 22, 2021

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Date: 1/22/2021

Assignment: Assignment 1

1 Load Libraries & Define Functions

[1]:
```
#Loading required libraries

%matplotlib inline

import numpy as np
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
import seaborn as sns
import os
import pickle
from pandas_profiling import ProfileReport
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet,␣
↪LogisticRegression, RidgeClassifier
from sklearn.model_selection import StratifiedKFold      #
from sklearn.metrics import accuracy_score, roc_auc_score, f1_score,␣
↪precision_score, recall_score, mean_squared_error, mean_absolute_error,␣
↪max_error, confusion_matrix
from sklearn.base import clone
from sklearn.metrics import r2_score
from sklearn.model_selection import cross_validate
from sklearn.metrics import SCORERS
from sklearn import preprocessing
from sklearn.model_selection import GridSearchCV
from scipy import stats #SciPy package to assist in using zscore to separate␣
↪extreme outliers.
import scikitplot as skplt
```

[141]:
```
# Function to clean and normalize a dataframe. Will be used later. Performs the␣
↪following functions:
## Drops duplicates, remove rows with NaN values (small number)
## Changes Code column to object type (string)
## Removes outliers within zscore of 3
## Normalizes data
## Creates new dataframe with cleaned and scaled values

def clean_and_normalize(df):
    df.drop_duplicates(inplace=True)
    df.dropna(axis=0,how='any',inplace=True)
    df['Code'] = df['Code'].astype('str',copy=True)
    df = df[(np.abs(stats.zscore(df.iloc[:,3:])) < 3).all(axis=1)]
    df.reset_index(inplace=True, drop=True)
    # Commenting out the section for normalizing the data unless needed
    dfvals = df.iloc[:,3:].values
    scaler = preprocessing.MinMaxScaler()
    scaled = scaler.fit_transform(dfvals)
    scdf = pd.DataFrame(scaled)
    df2 = pd.concat([df,scdf],axis=1)
    df2.drop(df2.columns[3:12],axis=1,inplace=True)
    df2.columns = df.columns
    return df2
```

2 Import & Read Data

[131]:
```
#Read pickle file and view first 5 rows
radonDF=pd.read_pickle(r'assign-1-radon-data.pickle')
radonDF.head()
```

[131]:

	Code	State	County	Lung Cancer Mortality	Radon	Obesity	Age Over 65	Currently Smoke	Ever Smoke	Median HH Income	Mort Rank	Radon Rank
0	1001	AL	Autauga_County	97.0293	1.5	31.3	10.2	26.4	48.60	56.58	2523	1113.5
1	13103	GA	Effingham_County	94.4043	0.5	31.1	8.0	26.6	49.65	63.26	2409	
2	13217	GA	Newton_County	91.8648	1.3	32.1	9.9	27.4	49.95	51.18	2281	
3	13225	GA	Peach_County	93.6161	1.6	30.1	9.8	27.5	47.55	41.73	2366	
4	21077	KY	Gallatin_County	141.4099	0.6	30.9	10.3	27.9	54.60	47.68	2878	

```
1       270.5
2       974.5
3      1184.0
4       364.5
```

[132]:
```
#View dataframe information and each column's summary stats
print(radonDF.info())
radonDF.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2881 entries, 0 to 2880
Data columns (total 12 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Code                   2881 non-null   int64
 1   State                  2881 non-null   object
 2   County                 2881 non-null   object
 3   Lung Cancer Mortality  2881 non-null   float64
 4   Radon                  2881 non-null   float64
 5   Obesity                2881 non-null   float64
 6   Age Over 65            2881 non-null   float64
 7   Currently Smoke        2881 non-null   float64
 8   Ever Smoke             2881 non-null   float64
 9   Median HH Income       2880 non-null   float64
 10  Mort Rank              2881 non-null   int64
 11  Radon Rank             2881 non-null   float64
dtypes: float64(8), int64(2), object(2)
memory usage: 270.2+ KB
None
```

[132]:

	Code	Lung Cancer Mortality	Radon	Obesity	\
count	2881.000000	2881.000000	2881.000000	2881.000000	
mean	29879.143006	78.126974	3.082013	29.042798	
std	14774.495273	17.650253	3.640046	3.727609	
min	1001.000000	6.761900	0.000000	11.500000	
25%	18171.000000	67.312800	1.000000	27.300000	
50%	29061.000000	79.159500	2.100000	29.200000	
75%	42051.000000	89.711200	4.000000	31.100000	
max	56043.000000	205.746400	99.700000	43.900000	

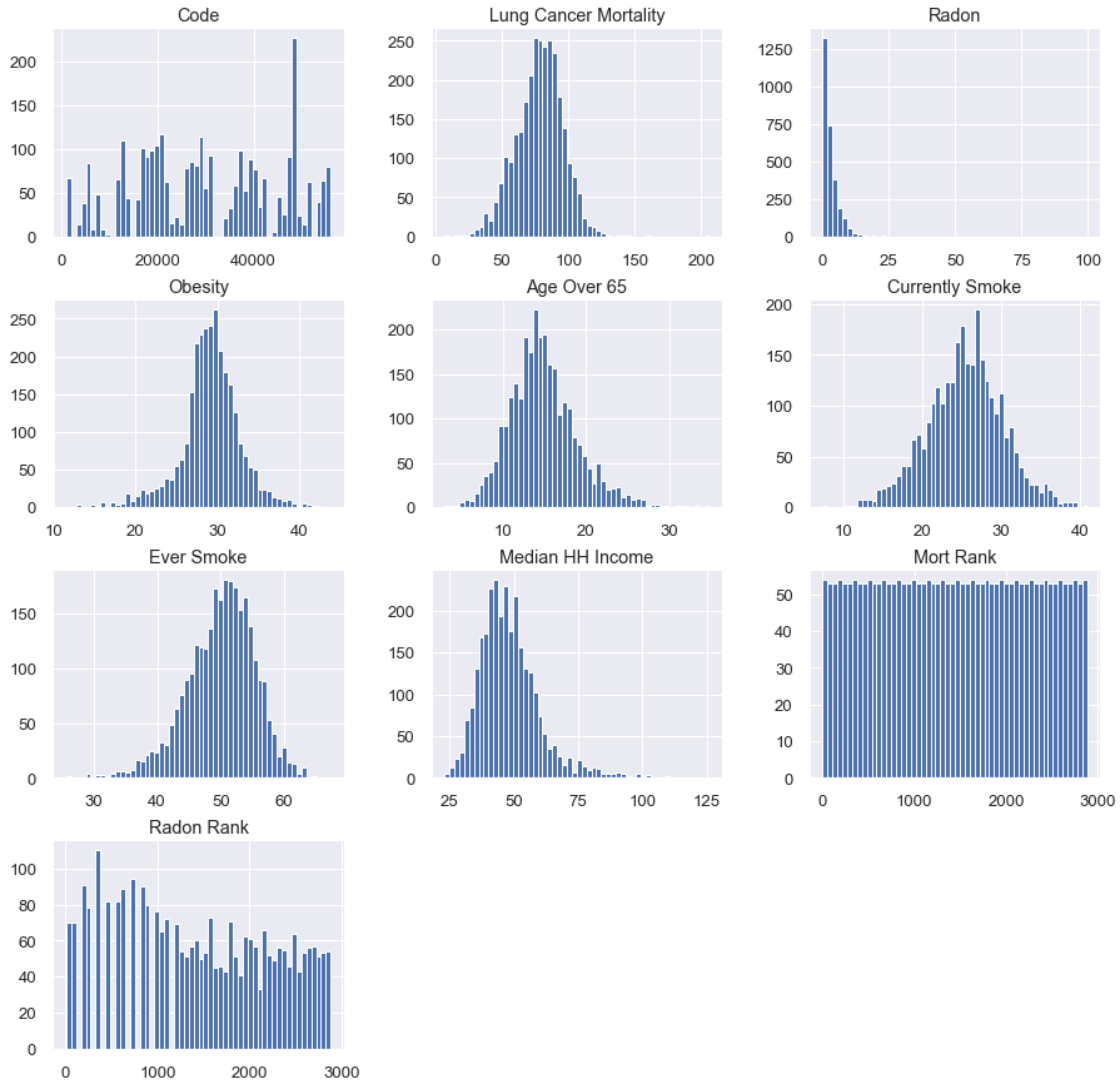
	Age Over 65	Currently Smoke	Ever Smoke	Median HH Income	\
count	2881.000000	2881.000000	2881.000000	2880.000000	
mean	14.814821	25.355745	49.932090	48.149885	
std	4.031764	4.809338	5.462211	11.929568	
min	3.000000	7.300000	25.650000	22.890000	
25%	12.200000	22.200000	46.600000	40.267500	
50%	14.400000	25.500000	50.450000	46.485000	

```
75%      17.100000        28.400000    53.650000         53.730000
max      34.700000        40.900000    67.300000        125.900000

         Mort Rank   Radon Rank
count  2881.000000  2881.000000
mean   1441.000000  1441.000000
std     831.817388   831.639368
min       1.000000     5.500000
25%     721.000000   719.500000
50%    1441.000000  1465.500000
75%    2161.000000  2161.500000
max    2881.000000  2881.000000
```

3 Initial Visualization & Review

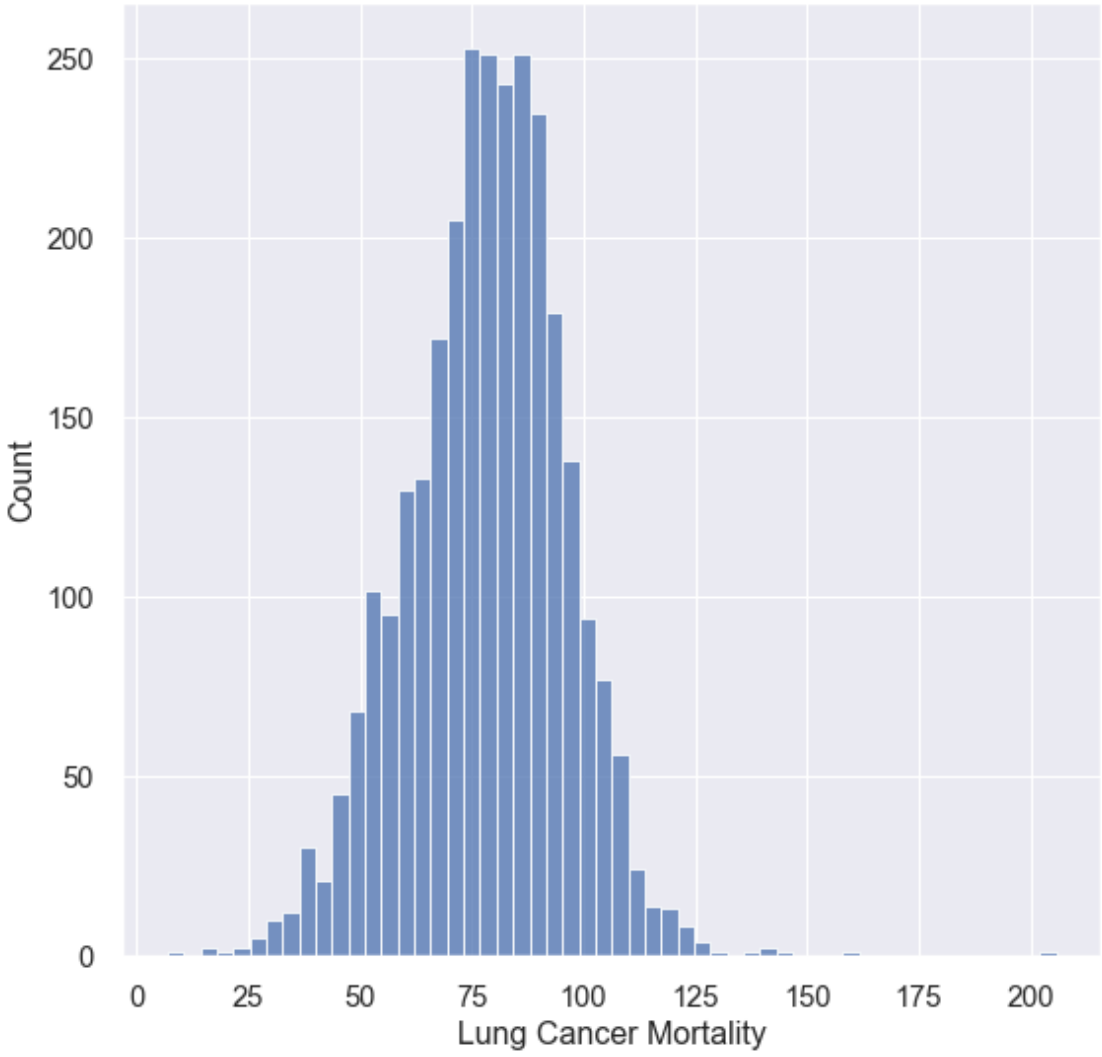
[133]:
```
#Viewing histogram for each column
figure(num=None, dpi=80, facecolor='w', edgecolor='k')
bincount = int(round(np.sqrt(radonDF['Lung Cancer Mortality'].count())))
radonDF.hist(bins = bincount,figsize=(15,15))
plt.show()
```

```
<Figure size 480x320 with 0 Axes>
```



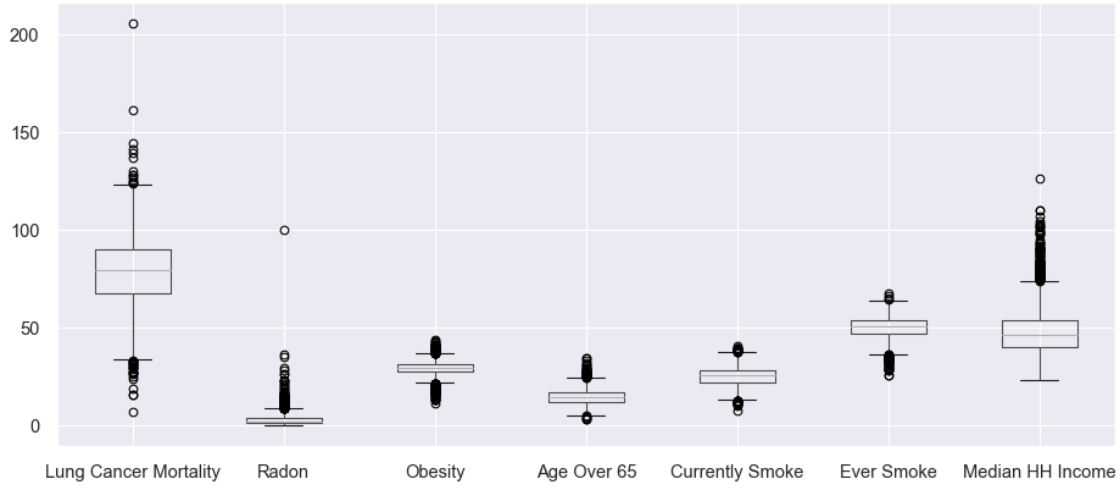
[134]:
```
#Some potential outliers can be seen when increasing the size of the plot

figure(num=None, figsize=(8,8), dpi=80, facecolor='w', edgecolor='k')
bincount = int(round(np.sqrt(radonDF['Lung Cancer Mortality'].count())))
sns.histplot(radonDF['Lung Cancer Mortality'], bins = bincount)
```

[134]: <matplotlib.axes._subplots.AxesSubplot at 0x273a6e61e08>



[142]:
```
#Boxplot to view original dataframe outliers.
#Some that look like extreme outliers can be seen.
figure(num=None, figsize=(14,6), dpi=80, facecolor='w', edgecolor='k')
radonDF.iloc[:, 3:10].boxplot()
```

[142]: <matplotlib.axes._subplots.AxesSubplot at 0x273a25e9948>



[136]:
```
#Reviewing skew to determine if any values are heavily skewed. Radon is the␣
 ↪worst.
#Also reviewing initial correlation matrix, sorted by lung cancer mortality.
print(radonDF.skew())
corr = radonDF.corr()
corr = corr.sort_values(by=['Lung Cancer Mortality'],ascending=False)
corr
```

```
Code                    -0.008340
Lung Cancer Mortality   -0.048973
Radon                    8.485467
Obesity                 -0.431950
Age Over 65              0.644795
Currently Smoke         -0.067711
Ever Smoke              -0.556990
Median HH Income         1.339536
Mort Rank                0.000000
Radon Rank               0.000991
dtype: float64
```

[136]:

	Code	Lung Cancer Mortality	Radon	Obesity	\
Lung Cancer Mortality	-0.078423	1.000000	-0.306642	0.401948	
Mort Rank	-0.076938	0.964567	-0.325306	0.402830	
Currently Smoke	-0.046306	0.561653	-0.125965	0.466656	
Obesity	0.002392	0.401948	-0.185046	1.000000	
Ever Smoke	0.001627	0.344672	0.065564	0.146270	
Code	1.000000	-0.078423	0.006749	0.002392	
Age Over 65	0.032407	-0.191148	0.098597	-0.004855	
Median HH Income	0.081627	-0.289640	0.192119	-0.506193	
Radon	0.006749	-0.306642	1.000000	-0.185046	

```
Radon Rank             0.037284              -0.425764  0.717992 -0.275533

                      Age Over 65  Currently Smoke  Ever Smoke  \
Lung Cancer Mortality   -0.191148         0.561653    0.344672
Mort Rank               -0.203919         0.552162    0.319670
Currently Smoke         -0.077268         1.000000    0.722805
Obesity                 -0.004855         0.466656    0.146270
Ever Smoke               0.279120         0.722805    1.000000
Code                     0.032407        -0.046306    0.001627
Age Over 65              1.000000        -0.077268    0.279120
Median HH Income        -0.259605        -0.519155   -0.230779
Radon                    0.098597        -0.125965    0.065564
Radon Rank               0.127271        -0.163439    0.115783

                      Median HH Income  Mort Rank  Radon Rank
Lung Cancer Mortality         -0.289640   0.964567   -0.425764
Mort Rank                     -0.301378   1.000000   -0.448300
Currently Smoke               -0.519155   0.552162   -0.163439
Obesity                       -0.506193   0.402830   -0.275533
Ever Smoke                    -0.230779   0.319670    0.115783
Code                           0.081627  -0.076938    0.037284
Age Over 65                   -0.259605  -0.203919    0.127271
Median HH Income               1.000000  -0.301378    0.270648
Radon                          0.192119  -0.325306    0.717992
Radon Rank                     0.270648  -0.448300    1.000000
```

4 Data Cleaning

[144]:
```
#Creating a copy of the original dataframe.
radonDF_clean = radonDF.copy()
radonDF_clean.head()
```

[144]:
```
    Code State            County  Lung Cancer Mortality  Radon  Obesity  \
0   1001    AL    Autauga_County                97.0293    1.5     31.3
1  13103    GA  Effingham_County                94.4043    0.5     31.1
2  13217    GA     Newton_County                91.8648    1.3     32.1
3  13225    GA      Peach_County                93.6161    1.6     30.1
4  21077    KY   Gallatin_County               141.4099    0.6     30.9

   Age Over 65  Currently Smoke  Ever Smoke  Median HH Income  Mort Rank  \
0         10.2             26.4       48.60             56.58       2523
1          8.0             26.6       49.65             63.26       2409
2          9.9             27.4       49.95             51.18       2281
3          9.8             27.5       47.55             41.73       2366
4         10.3             27.9       54.60             47.68       2878
```

```
   Radon Rank
0      1113.5
1       270.5
2       974.5
3      1184.0
4       364.5
```

[145]:
```
#Sending copy of dataframe thruogh clean and normalize function.
#Reviewing cleaned dataframe's skew values and information.
radonDF_clean = clean_and_normalize(radonDF_clean)
print(radonDF_clean.skew(),'\n')
radonDF_clean.info()
```

```
Code                     0.002904
Lung Cancer Mortality   -0.195949
Radon                    1.552110
Obesity                 -0.192575
Age Over 65              0.476199
Currently Smoke          0.031820
Ever Smoke              -0.319852
Median HH Income         0.776699
Mort Rank               -0.037090
Radon Rank               0.004537
dtype: float64

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2707 entries, 0 to 2706
Data columns (total 12 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Code                   2707 non-null   object
 1   State                  2707 non-null   object
 2   County                 2707 non-null   object
 3   Lung Cancer Mortality  2707 non-null   float64
 4   Radon                  2707 non-null   float64
 5   Obesity                2707 non-null   float64
 6   Age Over 65            2707 non-null   float64
 7   Currently Smoke        2707 non-null   float64
 8   Ever Smoke             2707 non-null   float64
 9   Median HH Income       2707 non-null   float64
 10  Mort Rank              2707 non-null   float64
 11  Radon Rank             2707 non-null   float64
dtypes: float64(9), object(3)
memory usage: 253.9+ KB
```

[150]:
```
#Creating a new column with values for each unique state.
#Might be used later to assist in prediction. TBD
```

```
radonDF_clean["StateEncod"] = radonDF_clean["State"].astype('category')
radonDF_clean["StateEncod"] = radonDF_clean["StateEncod"].cat.codes
radonDF_clean
```

[150]:

	Code	State	County	Lung Cancer Mortality	Radon	\
0	1001	AL	Autauga_County	0.681874	0.107143	
1	13103	GA	Effingham_County	0.656289	0.035714	
2	13217	GA	Newton_County	0.631537	0.092857	
3	13225	GA	Peach_County	0.648607	0.114286	
4	21151	KY	Madison_County	0.634524	0.150000	
…	…	…	…	…	…	
2702	8109	CO	Saguache_County	0.212827	0.100000	
2703	25007	MA	Dukes_County	0.465591	0.328571	
2704	37135	NC	Orange_County	0.495032	0.142857	
2705	49027	UT	Millard_County	0.000863	0.050000	
2706	49051	UT	Wasatch_County	0.036400	0.257143	

	Obesity	Age Over 65	Currently Smoke	Ever Smoke	Median HH Income	\
0	0.599099	0.271930	0.520000	0.475120	0.544044	
1	0.590090	0.175439	0.527273	0.508828	0.655489	
2	0.635135	0.258772	0.556364	0.518459	0.453954	
3	0.545045	0.254386	0.560000	0.441413	0.296296	
4	0.554054	0.254386	0.563636	0.486356	0.373207	
…	…	…	…	…	…	
2702	0.103604	0.298246	0.225455	0.032103	0.170838	
2703	0.004505	0.456140	0.054545	0.430177	0.675509	
2704	0.189189	0.192982	0.120000	0.256822	0.627294	
2705	0.130631	0.368421	0.192727	0.208668	0.471138	
2706	0.202703	0.192982	0.127273	0.149278	0.853187	

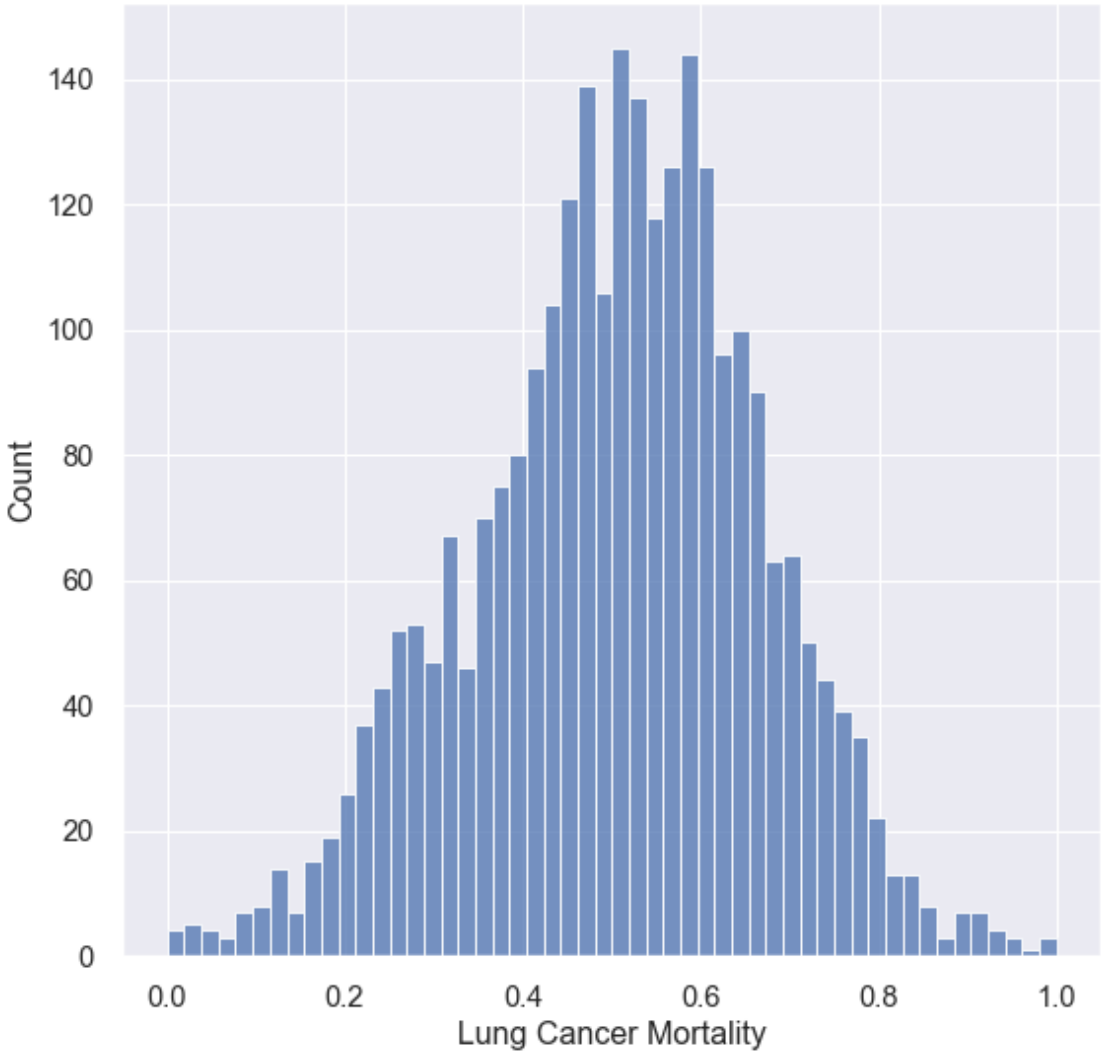
	Mort Rank	Radon Rank	StateEncod
0	0.877224	0.389592	0
1	0.837461	0.093179	8
2	0.792815	0.340717	8
3	0.822463	0.414381	8
4	0.796303	0.513361	14
…	…	…	…
2702	0.050576	0.365506	4
2703	0.401116	0.799754	16
2704	0.466690	0.494023	24
2705	0.000349	0.159986	39
2706	0.002790	0.719233	39

[2707 rows x 13 columns]

[151]:
```
#Reviewing cleaned dataframe's lung cancer mortality histogram.
#Skew, potential outliers and kurtosis is smaller.
```

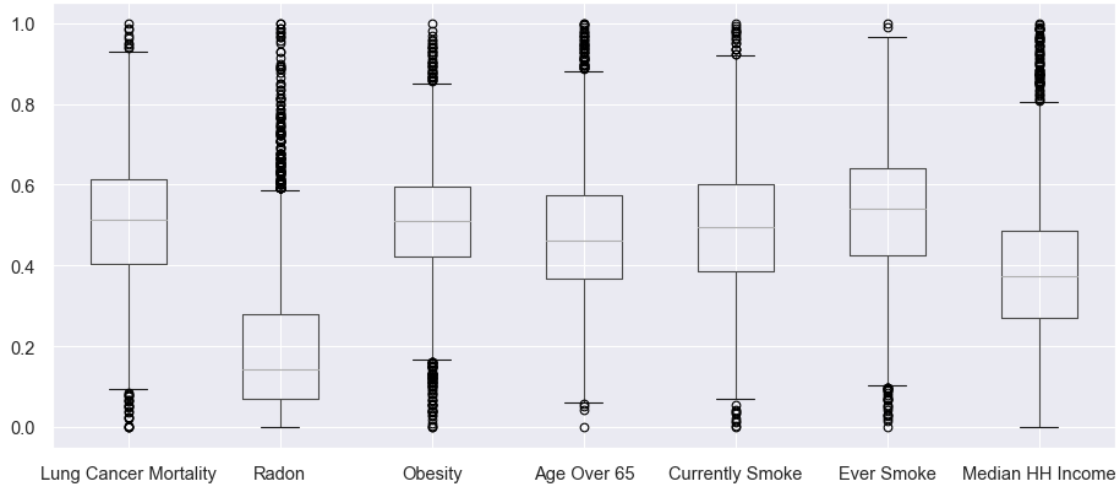
```
figure(num=None, figsize=(8,8), dpi=80, facecolor='w', edgecolor='k')
bincount = int(round(np.sqrt(radonDF_clean['Lung Cancer Mortality'].count())))
sns.histplot(radonDF_clean['Lung Cancer Mortality'], bins = bincount)
```

[151]: <matplotlib.axes._subplots.AxesSubplot at 0x273a158d188>



[152]:
```
#Reviewing that outliers are not as extreme as before.
#This is likely a poor representation due to features being scaled.
figure(num=None, figsize=(14,6), dpi=80, facecolor='w', edgecolor='k')
radonDF_clean.iloc[:, 3:10].boxplot()
```

[152]: <matplotlib.axes._subplots.AxesSubplot at 0x273a8216e88>



4.1 Reviewing Cleaned Data

[153]:
```
#Reviewing cleaned data's correlation matrix.
#Initial review shows Mort Rank and Currently Smoke are the two with strongest␣
↪correlations.
#Assumption is Mort Rank might cause overfitting.
corr = radonDF_clean.corr()
corr = corr.sort_values(by=['Lung Cancer Mortality'],ascending=False)
corr
```

[153]:

	Lung Cancer Mortality	Radon	Obesity	Age Over 65	\
Lung Cancer Mortality	1.000000	-0.395864	0.379899	-0.253557	
Mort Rank	0.977171	-0.407824	0.384446	-0.258810	
Currently Smoke	0.551418	-0.160566	0.434593	-0.118439	
Obesity	0.379899	-0.222083	1.000000	-0.063005	
Ever Smoke	0.301454	0.098806	0.106770	0.255906	
StateEncod	-0.091399	-0.020646	-0.028694	0.026484	
Age Over 65	-0.253557	0.192320	-0.063005	1.000000	
Median HH Income	-0.299266	0.245112	-0.457184	-0.228212	
Radon	-0.395864	1.000000	-0.222083	0.192320	
Radon Rank	-0.438097	0.892053	-0.277016	0.167317	

	Currently Smoke	Ever Smoke	Median HH Income	\
Lung Cancer Mortality	0.551418	0.301454	-0.299266	
Mort Rank	0.541294	0.282906	-0.307208	
Currently Smoke	1.000000	0.709910	-0.493878	
Obesity	0.434593	0.106770	-0.457184	
Ever Smoke	0.709910	1.000000	-0.192479	
StateEncod	-0.054079	0.004306	0.091697	
Age Over 65	-0.118439	0.255906	-0.228212	

```
Median HH Income             -0.493878   -0.192479          1.000000
Radon                        -0.160566    0.098806          0.245112
Radon Rank                   -0.158503    0.133384          0.273377

                        Mort Rank  Radon Rank  StateEncod
Lung Cancer Mortality    0.977171   -0.438097   -0.091399
Mort Rank                1.000000   -0.452299   -0.089318
Currently Smoke          0.541294   -0.158503   -0.054079
Obesity                  0.384446   -0.277016   -0.028694
Ever Smoke               0.282906    0.133384    0.004306
StateEncod              -0.089318    0.017819    1.000000
Age Over 65             -0.258810    0.167317    0.026484
Median HH Income        -0.307208    0.273377    0.091697
Radon                   -0.407824    0.892053   -0.020646
Radon Rank              -0.452299    1.000000    0.017819
```

[155]:
```
radonDF_clean.iloc[:,[4,5,6,7,8,11,12]]
```

[155]:
```
          Radon   Obesity  Age Over 65  Currently Smoke  Ever Smoke  \
0     0.107143  0.599099     0.271930         0.520000    0.475120
1     0.035714  0.590090     0.175439         0.527273    0.508828
2     0.092857  0.635135     0.258772         0.556364    0.518459
3     0.114286  0.545045     0.254386         0.560000    0.441413
4     0.150000  0.554054     0.254386         0.563636    0.486356
…          …         …            …                …           …
2702  0.100000  0.103604     0.298246         0.225455    0.032103
2703  0.328571  0.004505     0.456140         0.054545    0.430177
2704  0.142857  0.189189     0.192982         0.120000    0.256822
2705  0.050000  0.130631     0.368421         0.192727    0.208668
2706  0.257143  0.202703     0.192982         0.127273    0.149278

      Radon Rank  StateEncod
0       0.389592           0
1       0.093179           8
2       0.340717           8
3       0.414381           8
4       0.513361          14
…          …          …
2702    0.365506           4
2703    0.799754          16
2704    0.494023          24
2705    0.159986          39
2706    0.719233          39

[2707 rows x 7 columns]
```

5 Model Training

5.1 Linear Regression, Ridge Regression, Lasso Regression & Elastic Net

[202]:
```
#Creating X and y variables for train/test split.
#Leveraging 7 features to aid in predicting, including encoded states.
y = radonDF_clean['Lung Cancer Mortality'].to_numpy(copy=True)
X = radonDF_clean.iloc[:,[4,5,6,7,8,11,12]].to_numpy(copy=True)

print(y.shape)
print(X.shape)
```

```
(2707,)
(2707, 7)
```

[203]:
```
#Train/Test split. Using split of 70/30.

np.random.seed(66) #Setting random seed for reproducibility
Xtrain, Xtest, ytrain, ytest = train_test_split(X, y, test_size=0.30,␣
 ↪random_state=50) #Train/Test split with 30% Test
```

[160]:
```
#Loading and training Linear Regression model.
regMod = LinearRegression()
regMod.fit(Xtrain,ytrain)
print(f'Linear intercept estimate: {regMod.intercept_:5.3f}')
print(f'Linear estimated coefficients: {regMod.coef_[0]:5.3f}')

#Loading and training Ridge Regression model.
ridgeMod = Ridge(alpha=1, solver="cholesky")
ridgeMod.fit(X,y)
print(f'Ridge intercept estimate: {ridgeMod.intercept_:5.3f}')
print(f'Ridge estimated coefficients: {ridgeMod.coef_[0]:5.3f}')

#Loading and training Lasso Regression model.
lassoMod = Lasso(alpha=.001)
lassoMod.fit(X,y)
print(f'Lasso intercept estimate: {regMod.intercept_:5.3f}')
print(f'Lasso estimated coefficients: {regMod.coef_[0]:5.3f}')

#Loading and training Elastic Net model.
elasticMod = ElasticNet(alpha=0.001, l1_ratio=0.5)
elasticMod.fit(X,y)
print(f'ElasticNet intercept estimate: {regMod.intercept_:5.3f}')
print(f'ElasticNet estimated coefficients: {regMod.coef_[0]:5.3f}')
```

```
Linear intercept estimate: 0.385
Linear estimated coefficients: 0.014
Ridge intercept estimate: 0.411
```

```
Ridge estimated coefficients: 0.024
Lasso intercept estimate: 0.385
Lasso estimated coefficients: 0.014
ElasticNet intercept estimate: 0.385
ElasticNet estimated coefficients: 0.014
```

[161]:
```
#Using Cross Validation to review linear regression generalization estimates.

linRegCV=cross_validate(clone(regMod),X, y, cv=10, return_train_score=True,
                        scoring=('r2','neg_mean_squared_error'))

print(f'Summary Across Folds')
pd.DataFrame(linRegCV).iloc[:,2:].describe()
```

```
Summary Across Folds
```

[161]:

	test_r2	train_r2	test_neg_mean_squared_error	\
count	10.000000	10.000000	10.000000	
mean	0.252796	0.467833	-0.014491	
std	0.136057	0.014776	0.002182	
min	-0.082017	0.439396	-0.018542	
25%	0.218783	0.462687	-0.016047	
50%	0.274794	0.469855	-0.014272	
75%	0.332163	0.479597	-0.012464	
max	0.390483	0.483560	-0.011978	

	train_neg_mean_squared_error
count	10.000000
mean	-0.014022
std	0.000228
min	-0.014283
25%	-0.014239
50%	-0.014030
75%	-0.013852
max	-0.013615

5.2 Regression Prediction & Performance

[162]:
```
#Using each model to predict y values from Xtest.

ytestPred = regMod.predict(Xtest) #Linear Regression Prediction
ytestPredRidge = ridgeMod.predict(Xtest) #Ridge Regression Prediction
ytestPredLasso = lassoMod.predict(Xtest) #Lasso Regression Prediction
ytestPredElastic = elasticMod.predict(Xtest) #Elastic Net Prediction
```

[163]:
```
#Linear Regression Evaluation
trainR2 = regMod.score(Xtrain,ytrain) #Training data R2 value
```

```
testR2 = r2_score(ytest,ytestPred) #Test data R2 value
testMSE = mean_squared_error(ytest, ytestPred, squared=False) #Root Mean␣
↪Squared Error value
testMAX = max_error(ytest,ytestPred) #Maximum prediction error

#Ridge Regression Evaluation
trainR2Ridge = ridgeMod.score(Xtrain,ytrain) #Training data R2 value
testR2Ridge = r2_score(ytest,ytestPredRidge) #Test data R2 value
testMSERidge = mean_squared_error(ytest, ytestPredRidge, squared=True) #Root␣
↪Mean Squared Error value
testMAXRidge = max_error(ytest,ytestPredRidge) #Maximum prediction error

#Lasso Regression Evaluation
trainR2Lasso = lassoMod.score(Xtrain,ytrain) #Training data R2 value
testR2Lasso = r2_score(ytest,ytestPredLasso) #Test data R2 value
testMSELasso = mean_squared_error(ytest, ytestPredLasso, squared=True) #Root␣
↪Mean Squared Error value
testMAXLasso = max_error(ytest,ytestPredLasso) #Maximum prediction error

#Elastic Net Evaluation
trainR2Elastic = elasticMod.score(Xtrain,ytrain) #Training data R2 value
testR2Elastic = r2_score(ytest,ytestPredElastic) #Test data R2 value
testMSEElastic = mean_squared_error(ytest, ytestPredElastic, squared=True)␣
↪#Root Mean Squared Error value
testMAXElastic = max_error(ytest,ytestPredElastic) #Maximum prediction error
```

[164]:
```
#Reviewing different model's metrics.

print(f'Linear Regression Metrics -- Training R\u00b2 = {trainR2:0.2f}, Test␣
↪R\u00b2 = {testR2:0.2f}, MSE = {testMSE:0.2f}, Test Max Error = {testMAX:0.
↪2f}')
print(f'Ridge Regression Metrics -- Training R\u00b2 = {trainR2Ridge:0.2f},␣
↪Test R\u00b2 = {testR2Ridge:0.2f}, MSE = {testMSERidge:0.2f}, Test Max Error␣
↪= {testMAXRidge:0.2f}')
print(f'Lasso Regression Metrics -- Training R\u00b2 = {trainR2Lasso:0.2f},␣
↪Test R\u00b2 = {testR2Lasso:0.2f}, MSE = {testMSELasso:0.2f}, Test Max Error␣
↪= {testMAXLasso:0.2f}')
print(f'Elastic Net Metrics -- Training R\u00b2 = {trainR2Elastic:0.2f}, Test␣
↪R\u00b2 = {testR2Elastic:0.2f}, MSE = {testMSEElastic:0.2f}, Test Max Error␣
↪= {testMAXElastic:0.2f}')
```

```
Linear Regression Metrics -- Training R² = 0.47, Test R² = 0.47, MSE = 0.12,
Test Max Error = 0.55
Ridge Regression Metrics -- Training R² = 0.46, Test R² = 0.48, MSE = 0.01, Test
Max Error = 0.53
Lasso Regression Metrics -- Training R² = 0.46, Test R² = 0.47, MSE = 0.01, Test
Max Error = 0.53
```

```
Elastic Net Metrics -- Training R² = 0.46, Test R² = 0.47, MSE = 0.01, Test Max
Error = 0.53
```

[165]:
```
#Creating subplots of each regression model for visualization.
#All models seem to perform similarly, with a small benefit in Ridge Regression.
sns.set(font_scale=1.2)
fig, ax = plt.subplots(2, 2, figsize=(18,12))
fig.suptitle('Regression Model Evaluation Plots')
ax[0,0].set_title(f'Linear Regression: Test R2 = {testR2:0.2f}, MSE = {testMSE:
↪0.2f}')
ax[0,1].set_title(f'Ridge Regression: Test R2 = {testR2Ridge:0.2f}, MSE =␣
↪{testMSERidge:0.2f}')
ax[1,0].set_title(f'Lasso Regression: Test R2 = {testR2Lasso:0.2f}, MSE =␣
↪{testMSELasso:0.2f}')
ax[1,1].set_title(f'Elastic Net: Test R2 = {testR2Elastic:0.2f}, MSE =␣
↪{testMSEElastic:0.2f}')
sns.regplot(ax = ax[0,0], x=ytest, y=ytestPred, color="teal")
sns.regplot(ax = ax[0,1], x=ytest, y=ytestPredRidge, color="sandybrown")
sns.regplot(ax = ax[1,0], x=ytest, y=ytestPredLasso, color="plum")
sns.regplot(ax = ax[1,1], x=ytest, y=ytestPredElastic, color="lightseagreen")
```

[165]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x273a89e1448>
```

5.3 Basic Logistic Regression

[191]:
```
#Creating a copy of the dataframe to use since we'll be adding a new column.
#Creating column HiRisk for classifying mortality 1 if over .64 (arbitrary␣
 ↪number) and 0 if under.
radonDF2_clean = radonDF_clean.copy()
radonDF2_clean['HiRisk'] = np.where(radonDF2_clean['Lung Cancer Mortality']>.
 ↪64,1,0)
```

[192]:
```
#Assigning the new HiRisk category to y.
#Assigning features for prediction to X.
y = radonDF2_clean['HiRisk'].to_numpy(copy=True)
X = radonDF2_clean[['Radon','Obesity','Currently Smoke']].to_numpy(copy=True)
print(y.shape,X.shape)
```

```
(2707,) (2707, 3)
```

[193]:
```
#Train/Test split. Using 80/20 split.
np.random.seed(67) #creating random seed for reproducibility
Xtrain, Xtest, ytrain, ytest = train_test_split(X, y, test_size=0.20,␣
 ↪random_state=50)
```

[194]:
```
#Loading Logistic Regression with L2 penalty and .0001 for regularization.
logReg = LogisticRegression(penalty="l2",n_jobs=-1,verbose=0, random_state=50,␣
 ↪C=0.0001)

#Training the logistic regression model and predicting y values from Xtest.
logReg.fit(Xtrain,ytrain)
ypred = logReg.predict(Xtest)

#Reviewing score.
score = logReg.score(Xtest,ytest)
score
```

[194]:
```
0.8007380073800738
```

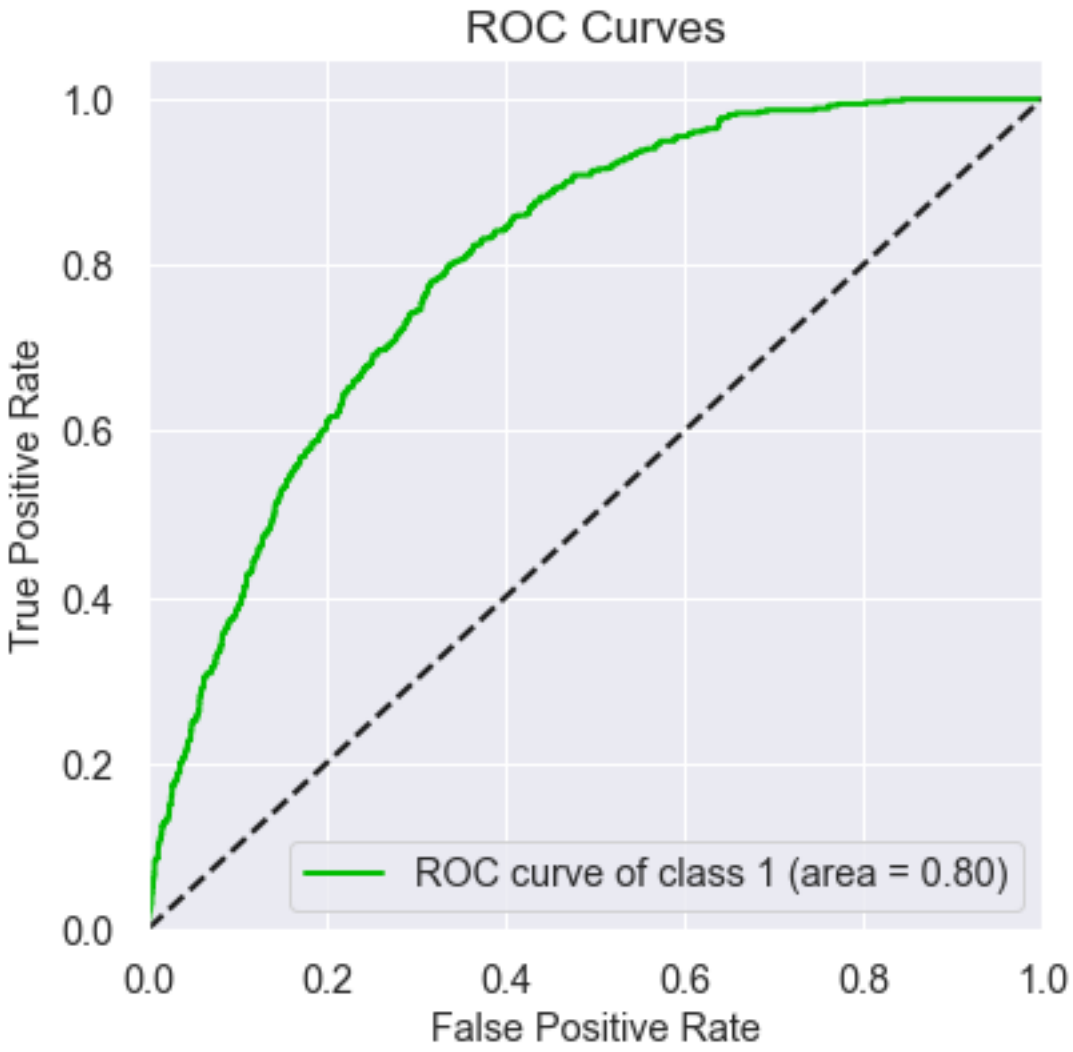
[195]:
```
# Using Kfold Cross Validation to determine how well the model may generalize.␣
 ↪Scores all seem pretty consistent.

logRegCV=cross_validate(clone(logReg),X, y, cv=10, return_train_score=True,
                        scoring=('accuracy','roc_auc'))

print('Fold summary stats:')
pd.DataFrame(logRegCV).iloc[:,2:].describe()
```

```
Fold summary stats:
```

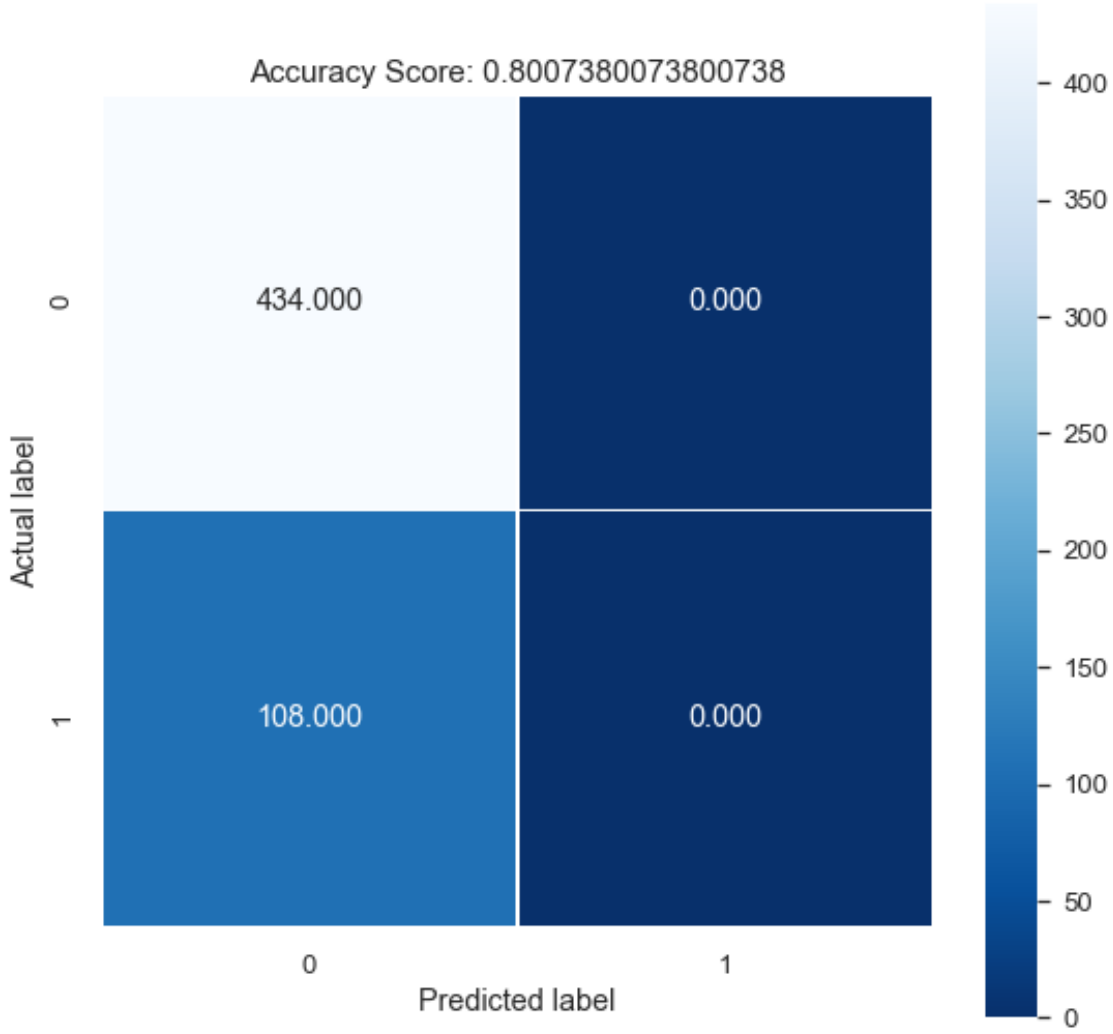
[195]:

	test_accuracy	train_accuracy	test_roc_auc	train_roc_auc
count	10.000000	10.000000	10.000000	10.000000
mean	0.801997	0.801995	0.798223	0.802195
std	0.001638	0.000182	0.171967	0.020587
min	0.800738	0.801724	0.515020	0.766078
25%	0.800738	0.801805	0.670998	0.796701
50%	0.800738	0.802135	0.829835	0.803963
75%	0.803704	0.802135	0.934879	0.817985
max	0.804428	0.802135	0.996957	0.829860

[196]:
```
#Reviewing ROC curve and AUC
yp = logReg.predict_proba(X)
skplt.metrics.plot_roc(y, yp,
                       classes_to_plot=1,
                      plot_micro=False,
                      plot_macro=False,
                      figsize=(6,6)
                      )
plt.show();
```



[197]:
```
#Generating confusion matrix to determine number of predictions made correctly.
#434 were predicted correctly, 108 incorrectly.
cm = confusion_matrix(ytest, ypred)
plt.figure(figsize=(9,9))
sns.heatmap(cm, annot=True, fmt=".3f", linewidths=.5, square = True, cmap =␣
↪'Blues_r');
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title = 'Accuracy Score: {0}'.format(score)
plt.title(all_sample_title, size = 15);
```



5.4 Ridge Classifier

[198]:
```
#Ridge classifier likely not much different than logistic regression, due to␣
 ↪data being scaled during pre-processing.

#Using Grid Search CV to assist in finding best parameters
parms = {'alpha': [0.0001, 0.001, 0.01, 0.1, 1.0],'normalize':[True,False],
         'solver':['auto','svd','cholesky','lsqr','sparse_cg','sag','saga']}
ridReg=RidgeClassifier()
ridParmCV = GridSearchCV(ridReg,n_jobs=-1,verbose=0,
                    refit=True,
                    cv = 10,
                    scoring="accuracy",
                    return_train_score=True,
```

```
                    param_grid=parms
                     )
ridParmCV
ridParmFit = ridParmCV.fit(X,y)
ridParmFit.best_params_
```

[198]:
```
{'alpha': 1.0, 'normalize': True, 'solver': 'auto'}
```

[199]:
```
#Using best parameters from grid search output
logRegRidge = RidgeClassifier(alpha=1,normalize=True, solver='auto').fit(X, y)

#Training ridge classifier & predicting values
logRegRidge.fit(Xtrain,ytrain)
pred = logRegRidge.predict(Xtest)

#Reviewing score
score = logRegRidge.score(Xtest,ytest)
score
```

[199]:
```
0.8007380073800738
```

[200]:
```
# Using cross validation to help estimate how the model will generalize

ridRegCV=cross_validate(clone(logRegRidge),X, y, cv=10, return_train_score=True,
                        scoring=('accuracy','roc_auc'))

print(f'Fold summary stats:')
pd.DataFrame(ridRegCV).iloc[:,2:].describe()
```

```
Fold summary stats:
```

[200]:

	test_accuracy	train_accuracy	test_roc_auc	train_roc_auc
count	10.000000	10.000000	10.000000	10.000000
mean	0.801997	0.802241	0.796147	0.801530
std	0.001638	0.000524	0.177342	0.020602
min	0.800738	0.801724	0.503072	0.764998
25%	0.800738	0.801888	0.670016	0.795964
50%	0.800738	0.802135	0.827657	0.803843
75%	0.803704	0.802196	0.940134	0.817406
max	0.804428	0.803366	0.999391	0.828504

[201]:
```
cm = confusion_matrix(ytest, pred)
plt.figure(figsize=(9,9))
sns.heatmap(cm, annot=True, fmt=".3f", linewidths=.5, square = True, cmap =␣
↪'Blues_r');
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
```

```
all_sample_title = 'Accuracy Score: {0}'.format(score)
plt.title(all_sample_title, size = 15);
```