Module 3 Peer Review

==

Import Libraries

In [1]:
```
import numpy as np
from numpy import count_nonzero, median, mean
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import random
#import squarify


import statsmodels.api as sm
import statsmodels.formula.api as smf
from statsmodels.formula.api import ols
# Import variance_inflation_factor from statsmodels
# from statsmodels.stats.outliers_influence import variance_inflation_factor
# Import Tukey's HSD function
# from statsmodels.stats.multicomp import pairwise_tukeyhsd

import datetime
from datetime import datetime, timedelta, date

# import shap
# import eli5
# from IPython.display import display

#import os
#import zipfile
import scipy
from scipy import stats
from scipy.stats.mstats import normaltest # D'Agostino K^2 Test
from scipy.stats import boxcox
from collections import Counter

import sklearn
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncoder, OneHo

from sklearn.model_selection import KFold, StratifiedKFold, GridSearchCV, Randomize
from sklearn.model_selection import train_test_split, cross_validate

from sklearn.metrics import accuracy_score, auc, classification_report, confusion_m
from sklearn.metrics import precision_score, recall_score, ConfusionMatrixDisplay,
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

from sklearn.feature_selection import f_regression, f_classif, chi2, RFE, RFECV
from sklearn.feature_selection import mutual_info_regression, mutual_info_classif
from sklearn.feature_selection import VarianceThreshold, GenericUnivariateSelect
```

```python
from sklearn.feature_selection import SelectFromModel, SelectKBest, SelectPercentil

from sklearn.linear_model import LogisticRegression, LogisticRegressionCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB, MultinomialNB, BernoulliNB, Categorical

import imblearn

from imblearn.under_sampling import RandomUnderSampler, CondensedNearestNeighbour
from imblearn.under_sampling import EditedNearestNeighbours, TomekLinks
from imblearn.over_sampling import SMOTE
from imblearn.combine import SMOTEENN, SMOTETomek


import feature_engine

from feature_engine.selection import DropConstantFeatures, DropDuplicateFeatures
from feature_engine.selection import DropCorrelatedFeatures, SmartCorrelatedSelecti
from feature_engine.selection import SelectBySingleFeaturePerformance



%matplotlib inline
#sets the default autosave frequency in seconds
%autosave 60
sns.set_style('dark')
sns.set(font_scale=1.2)

plt.rc('axes', titlesize=9)
plt.rc('axes', labelsize=14)
plt.rc('xtick', labelsize=12)
plt.rc('ytick', labelsize=12)

import warnings
warnings.filterwarnings('ignore')

# This module lets us save our models once we fit them.
# import pickle

pd.set_option('display.max_columns',None)
#pd.set_option('display.max_rows', None)
pd.set_option('display.width', 1000)
pd.set_option('display.float_format','{:.2f}'.format)

random.seed(0)
np.random.seed(0)
np.set_printoptions(suppress=True)
```

```
Autosaving every 60 seconds
```

Quick Data Glance

In [2]:
```python
df = pd.read_csv("boston.csv")
```

In [3]:
```python
df.head()
```

Out[3]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat	med
0	0.01	18.00	2.31	0	0.54	6.58	65.20	4.09	1	296	15.30	396.90	4.98	24.0
1	0.03	0.00	7.07	0	0.47	6.42	78.90	4.97	2	242	17.80	396.90	9.14	21.6
2	0.03	0.00	7.07	0	0.47	7.18	61.10	4.97	2	242	17.80	392.83	4.03	34.7
3	0.03	0.00	2.18	0	0.46	7.00	45.80	6.06	3	222	18.70	394.63	2.94	33.4
4	0.07	0.00	2.18	0	0.46	7.15	54.20	6.06	3	222	18.70	396.90	5.33	36.2

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   crim     506 non-null    float64
 1   zn       506 non-null    float64
 2   indus    506 non-null    float64
 3   chas     506 non-null    int64  
 4   nox      506 non-null    float64
 5   rm       506 non-null    float64
 6   age      506 non-null    float64
 7   dis      506 non-null    float64
 8   rad      506 non-null    int64  
 9   tax      506 non-null    int64  
 10  ptratio  506 non-null    float64
 11  black    506 non-null    float64
 12  lstat    506 non-null    float64
 13  medv     506 non-null    float64
dtypes: float64(11), int64(3)
memory usage: 55.5 KB
```

In [5]:
```
df.dtypes.value_counts()
```

Out[5]:
```
float64    11
int64       3
dtype: int64
```

In [6]:
```
# Descriptive Statistical Analysis
df.describe(include="all")
```

Out[6]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptrati
count	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.0
mean	3.61	11.36	11.14	0.07	0.55	6.28	68.57	3.80	9.55	408.24	18.4
std	8.60	23.32	6.86	0.25	0.12	0.70	28.15	2.11	8.71	168.54	2.1
min	0.01	0.00	0.46	0.00	0.39	3.56	2.90	1.13	1.00	187.00	12.6
25%	0.08	0.00	5.19	0.00	0.45	5.89	45.02	2.10	4.00	279.00	17.4
50%	0.26	0.00	9.69	0.00	0.54	6.21	77.50	3.21	5.00	330.00	19.0
75%	3.68	12.50	18.10	0.00	0.62	6.62	94.07	5.19	24.00	666.00	20.2
max	88.98	100.00	27.74	1.00	0.87	8.78	100.00	12.13	24.00	711.00	22.0

In [7]:

```
# Descriptive Statistical Analysis
df.describe(include=["int", "float"])
```

Out[7]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptrati
count	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.0
mean	3.61	11.36	11.14	0.07	0.55	6.28	68.57	3.80	9.55	408.24	18.4
std	8.60	23.32	6.86	0.25	0.12	0.70	28.15	2.11	8.71	168.54	2.1
min	0.01	0.00	0.46	0.00	0.39	3.56	2.90	1.13	1.00	187.00	12.6
25%	0.08	0.00	5.19	0.00	0.45	5.89	45.02	2.10	4.00	279.00	17.4
50%	0.26	0.00	9.69	0.00	0.54	6.21	77.50	3.21	5.00	330.00	19.0
75%	3.68	12.50	18.10	0.00	0.62	6.62	94.07	5.19	24.00	666.00	20.2
max	88.98	100.00	27.74	1.00	0.87	8.78	100.00	12.13	24.00	711.00	22.0

In [8]:

```
df.shape
```

Out[8]:

```
(506, 14)
```

In [9]:

```
df.columns
```

Out[9]:

```
Index(['crim', 'zn', 'indus', 'chas', 'nox', 'rm', 'age', 'dis', 'rad', 'tax', 'pt
ratio', 'black', 'lstat', 'medv'], dtype='object')
```

In [10]:

```
df["chas"] = df["chas"].astype("category")
```

In [11]:

```
df.dtypes.value_counts()
```

Out[11]:

```
float64     11
int64        2
category     1
dtype: int64
```

```
===================================================================
```

Logistic Regression (StatsModel)

In [12]:
```
df.columns
```

Out[12]:
```
Index(['crim', 'zn', 'indus', 'chas', 'nox', 'rm', 'age', 'dis', 'rad', 'tax', 'pt
ratio', 'black', 'lstat', 'medv'], dtype='object')
```

In [13]:
```
df.shape
```

Out[13]:
```
(506, 14)
```

In [14]:
```
X = df[['indus','medv']]
y = df[['chas']]
```

In [15]:
```
X.values, y.values
```

```
Out[15]: (array([[ 2.31, 24.  ],
                [ 7.07, 21.6 ],
                [ 7.07, 34.7 ],
                ...,
                [11.93, 23.9 ],
                [11.93, 22.  ],
                [11.93, 11.9 ]]),
          array([[0],
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        [0]], dtype=int64))
```

In [16]:
```python
X = sm.add_constant(X)
```

In [17]:
```python
logreg1 = sm.Logit(y, X).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.229298
         Iterations 7
```

In [18]:
```python
logreg1.summary()
```

Out[18]:

Logit Regression Results

Dep. Variable:	chas	**No. Observations:**	506
Model:	Logit	**Df Residuals:**	503
Method:	MLE	**Df Model:**	2
Date:	Sun, 09 Jul 2023	**Pseudo R-squ.:**	0.08823
Time:	19:58:08	**Log-Likelihood:**	-116.02
converged:	True	**LL-Null:**	-127.25
Covariance Type:	nonrobust	**LLR p-value:**	1.331e-05

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-5.4786	0.669	-8.184	0.000	-6.791	-4.167
indus	0.0818	0.027	3.039	0.002	0.029	0.135
medv	0.0777	0.016	4.721	0.000	0.045	0.110

In [19]:
```python
logreg_pred1 = logreg1.predict(exog=X)
```

In [20]:
```python
logreg_pred1
```

Out[20]:
```
0      0.03
1      0.04
2      0.10
3      0.06
4      0.08
       ...
501    0.06
502    0.05
503    0.07
504    0.06
505    0.03
Length: 506, dtype: float64
```

Logistic Regression (Scikit Learn)

Logistic Regression model assumptions

- Outcome variable is categorical
- Observations are independent of each other
- No severe multicollinearity among X variables
- No extreme outliers
- Linear relationship between each X variable and the logit of the outcome variable
- Sufficiently large sample size

Let's build our model using **LogisticRegression** from the Scikit-learn package. This function implements logistic regression and can use different numerical optimizers to find parameters, including 'newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga' solvers. You can find extensive information about the pros and cons of these optimizers if you search it in the internet.

The version of Logistic Regression in Scikit-learn, support regularization. Regularization is a technique used to solve the overfitting problem of machine learning models. **C** parameter indicates **inverse of regularization strength** which must be a positive float. Smaller values specify stronger regularization.

Logistic Regression model

In [21]:
```
X = df[['indus','medv']]
y = df[['chas']]
```

In [22]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

In [23]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[23]:
```
((404, 2), (102, 2), (404, 1), (102, 1))
```

In [24]:
```
Counter(y_train), Counter(y_test)
```

Out[24]: (Counter({'chas': 1}), Counter({'chas': 1}))

In [25]:
```
logreg1 = LogisticRegression(max_iter=1000, random_state=0, solver='liblinear')
```

In [26]:
```
logreg1.fit(X_train,y_train)
```

Out[26]: LogisticRegression(max_iter=1000, random_state=0, solver='liblinear')

In [27]:
```
logreg_pred1 = logreg1.predict(X_test)
```

In [28]:
```
logreg_pred1[0:5]
```

Out[28]: array([0, 0, 0, 0, 0], dtype=int64)

In [29]:
```
logreg1.coef_
```

Out[29]: array([[0.01955845, 0.03299472]])

In [30]:
```
logreg1.intercept_
```

Out[30]: array([-3.45893393])

Logistic Model Evaluation

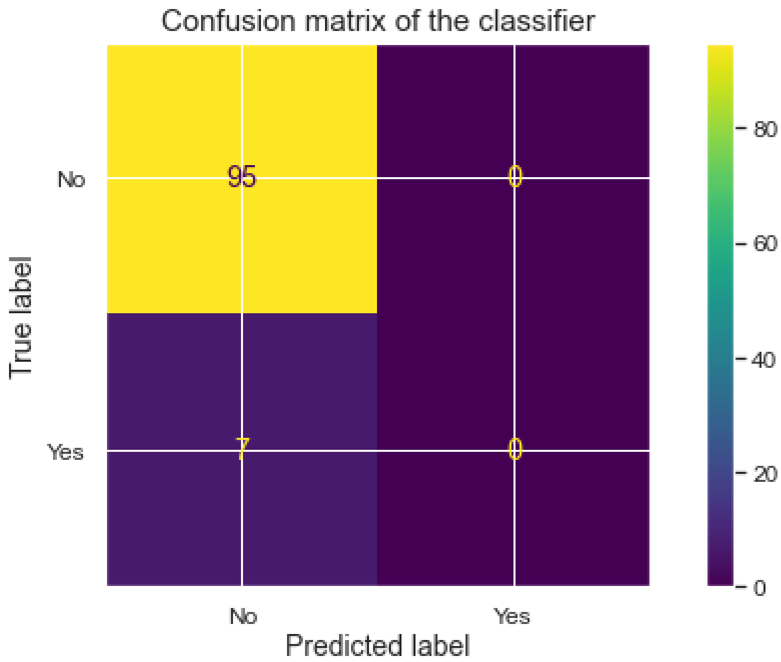
In [31]:
```
print(classification_report(y_test,logreg_pred1))
```

```
              precision    recall  f1-score   support

           0       0.93      1.00      0.96        95
           1       0.00      0.00      0.00         7

    accuracy                           0.93       102
   macro avg       0.47      0.50      0.48       102
weighted avg       0.87      0.93      0.90       102
```

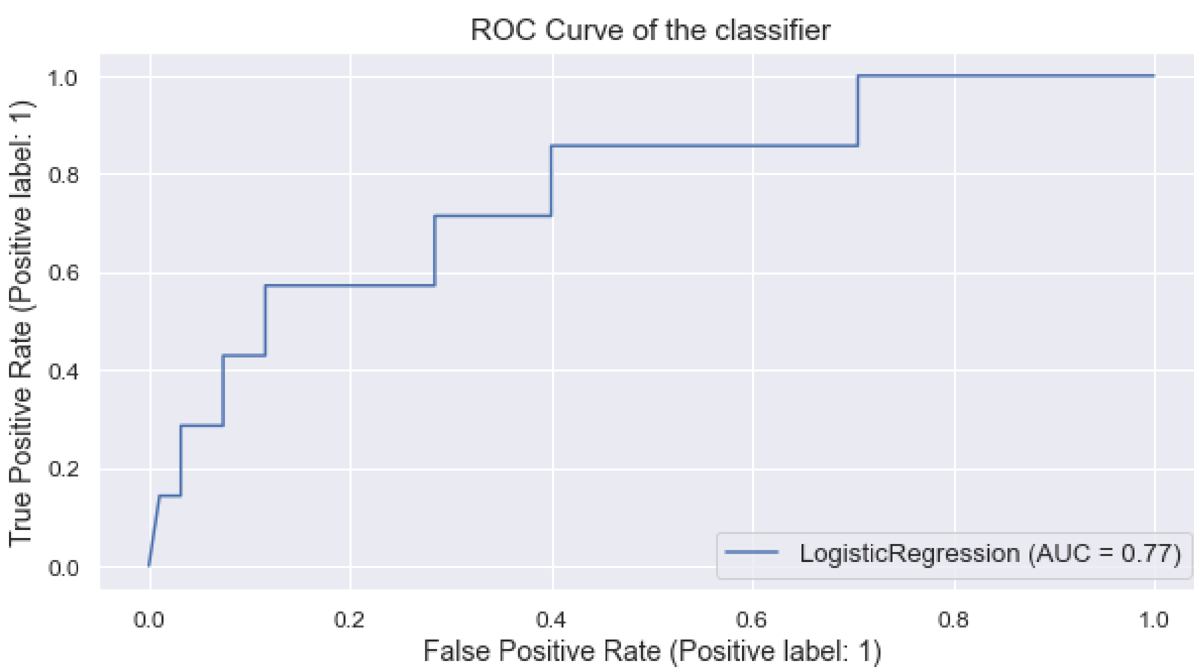
In [32]:
```
cm = confusion_matrix(y_test,logreg_pred1)
cm
```

Out[32]:
```
array([[95,  0],
       [ 7,  0]], dtype=int64)
```

In [33]:
```
fig, ax = plt.subplots(figsize=(10,5))

ConfusionMatrixDisplay.from_estimator(estimator=logreg1, X=X_test, y=y_test, ax=ax,
ax.set_title('Confusion matrix of the classifier', size=15)
plt.show()
```



In [34]:
```
fig, ax = plt.subplots(figsize=(10,5))

RocCurveDisplay.from_estimator(estimator=logreg1, X=X_test, y=y_test, ax=ax)
ax.set_title('ROC Curve of the classifier', size=15)

plt.show()
```



In [35]:
```
lrtable = pd.DataFrame()
lrtable = lrtable.append({'Model': "Logistic Regression",
                          'F1':  f1_score(y_test, logreg_pred1),
                          'Recall': recall_score(y_test, logreg_pred1),
                          'Precision': precision_score(y_test, logreg_pred1),
                          'Accuracy': accuracy_score(y_test, logreg_pred1),
                          'ROC-AUC': roc_auc_score(y_test, logreg_pred1)
```

```
                         },
                           ignore_index=True)

lrtable
```

Out[35]:

	Model	F1	Recall	Precision	Accuracy	ROC-AUC
0	Logistic Regression	0.00	0.00	0.00	0.93	0.50

Deliverable 2

We have fitted a model to predict a response variable with two classes (Yes/ No).

Interpretation - Regression Model -Both the predictor variables "INDUS" and "MEDV" predict higher probability that the tract will bound Charles river.

Error Matrix - The error rate is around 7%. However, the error rate across two classes is quite different. For positive class, the prediction error is close to 94%, while for the negative class it is merely 0.5 %

Deliverable 3

In [ ]:

```

```

In [ ]:

```

```

==