Seatwork 11.1 Exploratory Data Analysis for Machine Learning

Name: Cuadra, Audrick Zander G.

Section: CPE22S3

Date: April 22, 2024

Instructions:

- Download the datasets here:
- For Linear Regression Analysis: https://archive-beta.ics.uci.edu/dataset/10/automobileLinks to an external site.
- For Logistic Regression Analysis: https://archive-beta.ics.uci.edu/dataset/109/wine
- Perform exploratory data analysis (which must include data pre-processing/wrangling).
- Submit the notebook with the cleaned data and the EDA.

Note:

- Your submission must be PDF file.
- However, submit the link of your python notebook and submit the link in the comments.

Automobile

```
# Install the ucimlrepo package
!pip install ucimlrepo
```

```
Requirement already satisfied: ucimlrepo in /usr/local/lib/python3.10/dist-packages (0.0.6)
```

```
# Import the dataset into your code
from ucimlrepo import fetch_ucirepo

# fetch dataset
automobile = fetch_ucirepo(id=10)

# data (as pandas dataframes)
X = automobile.data.features
y = automobile.data.targets

# metadata
print(automobile.metadata)

# variable information
print(automobile.variables)
```

```
{'uci_id': 10, 'name': 'Automobile', 'repository_url': 'https://archive.ics.uci.edu/dataset/10/automobile', 'data_url': 'https://ar
                 name     role         type demographic  \
0               price  Feature   Continuous        None
1         highway-mpg  Feature   Continuous        None
2            city-mpg  Feature   Continuous        None
3            peak-rpm  Feature   Continuous        None
4          horsepower  Feature   Continuous        None
5   compression-ratio  Feature   Continuous        None
6              stroke  Feature   Continuous        None
7                bore  Feature   Continuous        None
8         fuel-system  Feature  Categorical        None
9         engine-size  Feature   Continuous        None
10   num-of-cylinders  Feature      Integer        None
11        engine-type  Feature  Categorical        None
12        curb-weight  Feature   Continuous        None
13             height  Feature   Continuous        None
14              width  Feature   Continuous        None
15             length  Feature   Continuous        None
16         wheel-base  Feature   Continuous        None
17    engine-location  Feature       Binary        None
18       drive-wheels  Feature  Categorical        None
19         body-style  Feature  Categorical        None
20        num-of-doors  Feature      Integer        None
21         aspiration  Feature       Binary        None
22          fuel-type  Feature       Binary        None
23               make  Feature  Categorical        None
24  normalized-losses  Feature   Continuous        None
25          symboling   Target      Integer        None

                                          description units missing_values
0                         continuous from 5118 to 45400  None            yes
```

1	continuous from 16 to 54	None	no
2	continuous from 13 to 49	None	no
3	continuous from 4150 to 6600	None	yes
4	continuous from 48 to 288	None	yes
5	continuous from 7 to 23	None	no
6	continuous from 2.07 to 4.17	None	yes
7	continuous from 2.54 to 3.94	None	yes
8	1bbl, 2bbl, 4bbl, idi, mfi, mpfi, spdi, spfi	None	no
9	continuous from 61 to 326	None	no
10	eight, five, four, six, three, twelve, two	None	no
11	dohc, dohcv, l, ohc, ohcf, ohcv, rotor	None	no
12	continuous from 1488 to 4066	None	no
13	continuous from 47.8 to 59.8	None	no
14	continuous from 60.3 to 72.3	None	no
15	continuous from 141.1 to 208.1	None	no
16	continuous from 86.6 120.9	None	no
17	front, rear	None	no
18	4wd, fwd, rwd	None	no
19	hardtop, wagon, sedan, hatchback, convertible	None	no
20	four, two	None	yes
21	std, turbo	None	no
22	diesel, gas	None	no
23	alfa-romero, audi, bmw, chevrolet, dodge, hond...	None	no
24	continuous from 65 to 256	None	yes
25	-3, -2, -1, 0, 1, 2, 3	None	no

```
# showing a sample of the 'X' dataframe
X.head()
```

	price	highway-mpg	city-mpg	peak-rpm	horsepower	compression-ratio	stroke	bore	fuel-system	e
0	13495.0	27	21	5000.0	111.0	9.0	2.68	3.47	mpfi	
1	16500.0	27	21	5000.0	111.0	9.0	2.68	3.47	mpfi	
2	16500.0	26	19	5000.0	154.0	9.0	3.47	2.68	mpfi	
3	13950.0	30	24	5500.0	102.0	10.0	3.40	3.19	mpfi	
4	17450.0	22	18	5500.0	115.0	8.0	3.40	3.19	mpfi	

5 rows × 25 columns

```
# showing a sample of the 'y' dataframe
y.head()
```

	symboling
0	3
1	3
2	1
3	2
4	2

Next steps: View recommended plots

```
# importing all the necessary libraries
import pandas as pd
import numpy as np

# concatinating the 'X' and 'y' dataframe
autom_df = pd.concat([X, y], axis=1)
autom_df
```

	price	highway-mpg	city-mpg	peak-rpm	horsepower	compression-ratio	stroke	bore	fuel-system
0	13495.0	27	21	5000.0	111.0	9.0	2.68	3.47	mpfi
1	16500.0	27	21	5000.0	111.0	9.0	2.68	3.47	mpfi
2	16500.0	26	19	5000.0	154.0	9.0	3.47	2.68	mpfi
3	13950.0	30	24	5500.0	102.0	10.0	3.40	3.19	mpfi
4	17450.0	22	18	5500.0	115.0	8.0	3.40	3.19	mpfi
...	...	...	...	...	...	...	...	...	...
200	16845.0	28	23	5400.0	114.0	9.5	3.15	3.78	mpfi
201	19045.0	25	19	5300.0	160.0	8.7	3.15	3.78	mpfi
202	21485.0	23	18	5500.0	134.0	8.8	2.87	3.58	mpfi
203	22470.0	27	26	4800.0	106.0	23.0	3.40	3.01	idi
204	22625.0	25	19	5400.0	114.0	9.5	3.15	3.78	mpfi

205 rows × 26 columns

```
# creating a function that detects and displays the number of duplicates in the dataframe
def countDuplicate(data):
    if data.duplicated().any():
        count = data.duplicated().sum()
        print(count)
    else:
        return "No Duplicates Found!"
```

```
# checking if the concatinated dataframe has any duplicates
countDuplicate(autom_df)
```

```
'No Duplicates Found!'
```

```
# checking the number of nulls in the dataframe
autom_df.isnull().sum()
```

```
price                 4
highway-mpg           0
city-mpg              0
peak-rpm              2
horsepower            2
compression-ratio     0
stroke                4
bore                  4
fuel-system           0
engine-size           0
num-of-cylinders      0
engine-type           0
curb-weight           0
height                0
width                 0
length                0
wheel-base            0
engine-location       0
drive-wheels          0
body-style            0
num-of-doors          2
aspiration            0
fuel-type             0
make                  0
normalized-losses    41
symboling             0
dtype: int64
```

```
autom_df['price'].value_counts()
```

```
price
8921.0     2
18150.0    2
8845.0     2
8495.0     2
7609.0     2
          ..
45400.0    1
```

```
16503.0    1
5389.0     1
6189.0     1
22625.0    1
Name: count, Length: 186, dtype: int64
```

```
autom_df.isnull().sum()
```

```
price                 4
highway-mpg           0
city-mpg              0
peak-rpm              2
horsepower            2
compression-ratio     0
stroke                4
bore                  4
fuel-system           0
engine-size           0
num-of-cylinders      0
engine-type           0
curb-weight           0
height                0
width                 0
length                0
wheel-base            0
engine-location       0
drive-wheels          0
body-style            0
num-of-doors          2
aspiration            0
fuel-type             0
make                  0
normalized-losses    41
symboling             0
dtype: int64
```

```
# using mean to supply each columns that contains a null
autom_df['price'].fillna(autom_df['price'].median(), inplace=True)
```

```
autom_df['peak-rpm'].fillna(autom_df['peak-rpm'].median(), inplace=True)
```

```
autom_df['horsepower'].fillna(autom_df['horsepower'].median(), inplace=True)
```

```
autom_df['stroke'].fillna(autom_df['stroke'].median(), inplace=True)
```

```
autom_df['bore'].fillna(autom_df['bore'].median(), inplace=True)
```

```
autom_df['num-of-doors'].fillna(autom_df['num-of-doors'].median(), inplace=True)
```

```
autom_df['normalized-losses'].fillna(autom_df['normalized-losses'].median(), inplace=True)
```

```
# checking if there are still any nulls in the dataframe
autom_df.isnull().sum()
```

```
price                0
highway-mpg          0
city-mpg             0
peak-rpm             0
horsepower           0
compression-ratio    0
stroke               0
bore                 0
fuel-system          0
engine-size          0
num-of-cylinders     0
engine-type          0
curb-weight          0
height               0
width                0
length               0
wheel-base           0
engine-location      0
drive-wheels         0
body-style           0
num-of-doors         0
aspiration           0
fuel-type            0
make                 0
normalized-losses    0
symboling            0
dtype: int64
```

```
# checking all the categorical values
autom_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   price              205 non-null    float64
 1   highway-mpg        205 non-null    int64
 2   city-mpg           205 non-null    int64
 3   peak-rpm           205 non-null    float64
 4   horsepower         205 non-null    float64
 5   compression-ratio  205 non-null    float64
 6   stroke             205 non-null    float64
 7   bore               205 non-null    float64
 8   fuel-system        205 non-null    object
 9   engine-size        205 non-null    int64
 10  num-of-cylinders   205 non-null    int64
 11  engine-type        205 non-null    object
 12  curb-weight        205 non-null    int64
 13  height             205 non-null    float64
 14  width              205 non-null    float64
 15  length             205 non-null    float64
 16  wheel-base         205 non-null    float64
 17  engine-location    205 non-null    object
 18  drive-wheels       205 non-null    object
 19  body-style         205 non-null    object
 20  num-of-doors       205 non-null    float64
 21  aspiration         205 non-null    object
 22  fuel-type          205 non-null    object
 23  make               205 non-null    object
 24  normalized-losses  205 non-null    float64
 25  symboling          205 non-null    int64
dtypes: float64(12), int64(6), object(8)
memory usage: 41.8+ KB
```

```
# This is to allow the access for the dataframe in which the int conversion hasn't occurred
autom_cat = autom_df.copy()
```

```
# creating a function that converts objects into numerical values
def preprocessing(data, catlist):
    if data[catlist].dtypes == 'object':
        cat_val = data[catlist].unique()
        range_val = range(1, len(cat_val)+1)
        map = dict(zip(cat_val, range_val))
        print(f"{catlist}:", map)
        data[catlist] = data[catlist].map(map)
    return data
for i in autom_df.select_dtypes(include=['object']).columns:
    preprocessing(autom_df, i)
```

```
fuel-system: {'mpfi': 1, '2bbl': 2, 'mfi': 3, '1bbl': 4, 'spfi': 5, '4bbl': 6, 'idi': 7, 'spdi': 8}
engine-type: {'dohc': 1, 'ohcv': 2, 'ohc': 3, 'l': 4, 'rotor': 5, 'ohcf': 6, 'dohcv': 7}
engine-location: {'front': 1, 'rear': 2}
drive-wheels: {'rwd': 1, 'fwd': 2, '4wd': 3}
body-style: {'convertible': 1, 'hatchback': 2, 'sedan': 3, 'wagon': 4, 'hardtop': 5}
aspiration: {'std': 1, 'turbo': 2}
fuel-type: {'gas': 1, 'diesel': 2}
make: {'alfa-romero': 1, 'audi': 2, 'bmw': 3, 'chevrolet': 4, 'dodge': 5, 'honda': 6, 'isuzu': 7, 'jaguar': 8, 'mazda': 9, 'mercede:
```

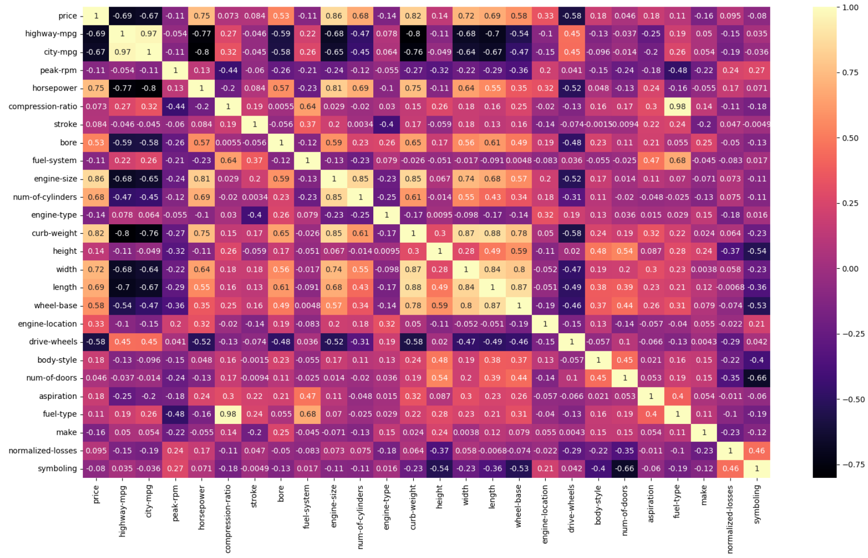
```
# checking the values of the dataframe
autom_df.head()
```

	price	highway-mpg	city-mpg	peak-rpm	horsepower	compression-ratio	stroke	bore	fuel-system
0	13495.0	27	21	5000.0	111.0	9.0	2.68	3.47	1
1	16500.0	27	21	5000.0	111.0	9.0	2.68	3.47	1
2	16500.0	26	19	5000.0	154.0	9.0	3.47	2.68	1
3	13950.0	30	24	5500.0	102.0	10.0	3.40	3.19	1
4	17450.0	22	18	5500.0	115.0	8.0	3.40	3.19	1

5 rows × 26 columns

```
# importing the necessary libraries for plotting
%matplotlib inline
import seaborn as sns
import matplotlib.pyplot as plt

# creating a heatmap to check the correlation of each categories between one another
plt.figure(figsize=(20, 11))
sns.heatmap(autom_df.corr(), annot=True, cmap='magma')
```

```
<Axes: >
```



Linear Regression Model

```
X = autom_df.drop('price', axis=1)
y = autom_df['price']
```

```
print("X",X.shape,"\ny=",y.shape)
```

```
X (205, 25)
y= (205,)
```

Train Test Splitting

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.linear_model import LinearRegression
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=101)
```

```
1 X_train.shape
```

```
(143, 25)
```

```
1 X_test.shape
```

```
(62, 25)
```

```
1 model = LinearRegression()
```

```
1 model.fit(X_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

Model Evaluation

```
1 model.coef_
```

```
array([-1.50604087e+02,  7.37133859e+00,  1.16315603e+00, -2.93324387e+01,
        9.93470741e+02, -5.45481780e+03, -1.06091424e+04, -1.70268232e+02,
        2.05325227e+02, -3.00743877e+03, -5.28868529e+01,  1.41070253e+00,
        2.53044661e+02,  8.90488886e+02,  2.38868227e+01, -8.73652339e+01,
        1.54931808e+04, -2.22018286e+03, -4.10783975e+02,  3.27022203e+02,
        3.14166895e+03, -1.29759009e+04, -1.27546963e+02, -7.53386017e+00,
        3.34227339e+02])
```

```
1 pd.DataFrame(model.coef_, X.columns, columns=['Coedicients'])
```

	Coedicients
highway-mpg	-150.604087
city-mpg	7.371339
peak-rpm	1.163156
horsepower	-29.332439
compression-ratio	993.470741
stroke	-5454.817804
bore	-10609.142408
fuel-system	-170.268232
engine-size	205.325227
num-of-cylinders	-3007.438769
engine-type	-52.886853
curb-weight	1.410703
height	253.044661
width	890.488886
length	23.886823
wheel-base	-87.365234
engine-location	15493.180825
drive-wheels	-2220.182858
body-style	-410.783975
num-of-doors	327.022203
aspiration	3141.668953
fuel-type	-12975.900873
make	-127.546963
normalized-losses	-7.533860
symboling	334.227339

Prediction from our Model

```
y_pred = model.predict(X_test)
```

Regression Evaluation Metrics

```
MAE = metrics.mean_absolute_error(y_test, y_pred)
MSE = metrics.mean_squared_error(y_test, y_pred)
RMSE = np.sqrt(MSE)
```

```
MAE
```

```
2554.5515500553283
```

```
MSE
```

```
14903114.988000777
```

```
RMSE
```

```
3860.4552824765083
```

```
autom_df['price'].mean()
```

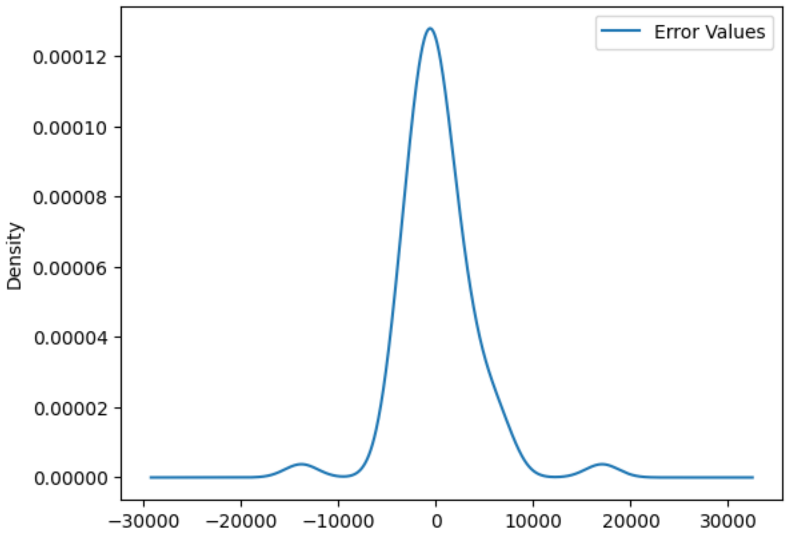
```
13150.307317073171
```

Residual Histogram

```
test_residual = y_test - y_pred
```

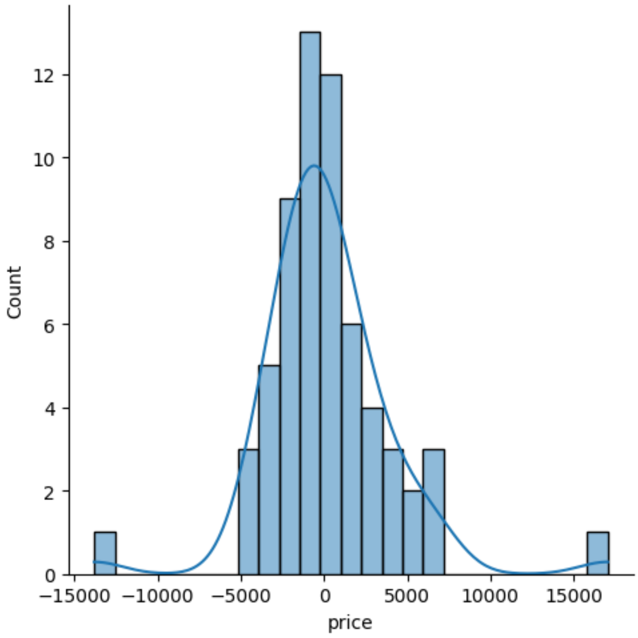
```
pd.DataFrame({'Error Values': (test_residual)}).plot.kde()
```

```
<Axes: ylabel='Density'>
```



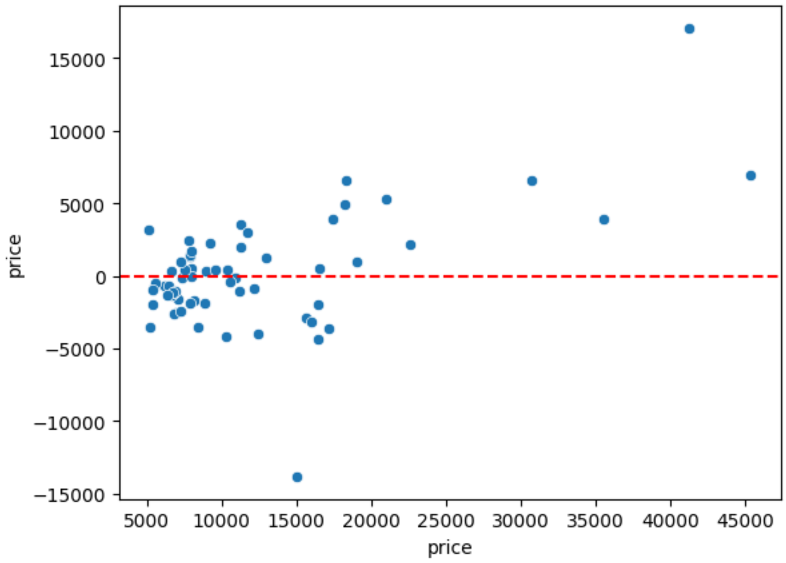

```
sns.displot(test_residual, bins=25, kde=True)
```

```
<seaborn.axisgrid.FacetGrid at 0x78a7dd329240>
```




```
sns.scatterplot(x=y_test, y=test_residual)
plt.axhline(y=0, color='r', ls='--')
```

```
<matplotlib.lines.Line2D at 0x78a7dd352200>
```



Wine

```
# Import the dataset into your code
from ucimlrepo import fetch_ucirepo

# fetch dataset
wine = fetch_ucirepo(id=109)

# data (as pandas dataframes)
X = wine.data.features
y = wine.data.targets

# metadata
print(wine.metadata)

# variable information
print(wine.variables)
```

```
{'uci_id': 109, 'name': 'Wine', 'repository_url': 'https://archive.ics.uci.edu/dataset/109/wine', 'data_url': 'https://archive.ics.
        name     role         type demographic  \
0      class   Target  Categorical        None
1    Alcohol  Feature   Continuous        None
2  Malicacid  Feature   Continuous        None
```

```
3                       Ash  Feature  Continuous        None
4          Alcalinity_of_ash  Feature  Continuous        None
5                  Magnesium  Feature     Integer        None
6              Total_phenols  Feature  Continuous        None
7                 Flavanoids  Feature  Continuous        None
8       Nonflavanoid_phenols  Feature  Continuous        None
9            Proanthocyanins  Feature  Continuous        None
10           Color_intensity  Feature  Continuous        None
11                       Hue  Feature  Continuous        None
12  0D280_0D315_of_diluted_wines  Feature  Continuous        None
13                   Proline  Feature     Integer        None

   description units missing_values
0         None  None             no
1         None  None             no
2         None  None             no
3         None  None             no
4         None  None             no
5         None  None             no
6         None  None             no
7         None  None             no
8         None  None             no
9         None  None             no
10        None  None             no
11        None  None             no
12        None  None             no
13        None  None             no
```

```
1 # displaying the 'X' dataframe
2 X.head()
```

	Alcohol	Malicacid	Ash	Alcalinity_of_ash	Magnesium	Total_phenols	Flavanoids
0	14.23	1.71	2.43	15.6	127	2.80	3.06
1	13.20	1.78	2.14	11.2	100	2.65	2.76
2	13.16	2.36	2.67	18.6	101	2.80	3.24
3	14.37	1.95	2.50	16.8	113	3.85	3.49
4	13.24	2.59	2.87	21.0	118	2.80	2.69

Next steps: View recommended plots

```
1 # displaying the 'y' dataframe
2 y.head()
```

	class
0	1
1	1
2	1
3	1
4	1

Next steps: View recommended plots

```
1 # importing all the necessary libraries
2 import pandas as pd
3 import numpy as np
4
5 # concatenating all the 'X' and 'y' dataframe
6 wine_df = pd.concat([X, y], axis=1)
7 wine_df
```

	Alcohol	Malicacid	Ash	Alcalinity_of_ash	Magnesium	Total_phenols	Flavanoids
0	14.23	1.71	2.43	15.6	127	2.80	3.0
1	13.20	1.78	2.14	11.2	100	2.65	2.7
2	13.16	2.36	2.67	18.6	101	2.80	3.2
3	14.37	1.95	2.50	16.8	113	3.85	3.4
4	13.24	2.59	2.87	21.0	118	2.80	2.6
...	...	...	...	...	...	...	..
173	13.71	5.65	2.45	20.5	95	1.68	0.6
174	13.40	3.91	2.48	23.0	102	1.80	0.7
175	13.27	4.28	2.26	20.0	120	1.59	0.6
176	13.17	2.59	2.37	20.0	120	1.65	0.6
177	14.13	4.10	2.74	24.5	96	2.05	0.7

178 rows × 14 columns

Next steps: View recommended plots

```
# checking if there are any duplicates
countDuplicate(wine_df)
```

```
'No Duplicates Found!'
```

```
# checking there are any nulls in the dataframe
wine_df.isnull().sum()
```

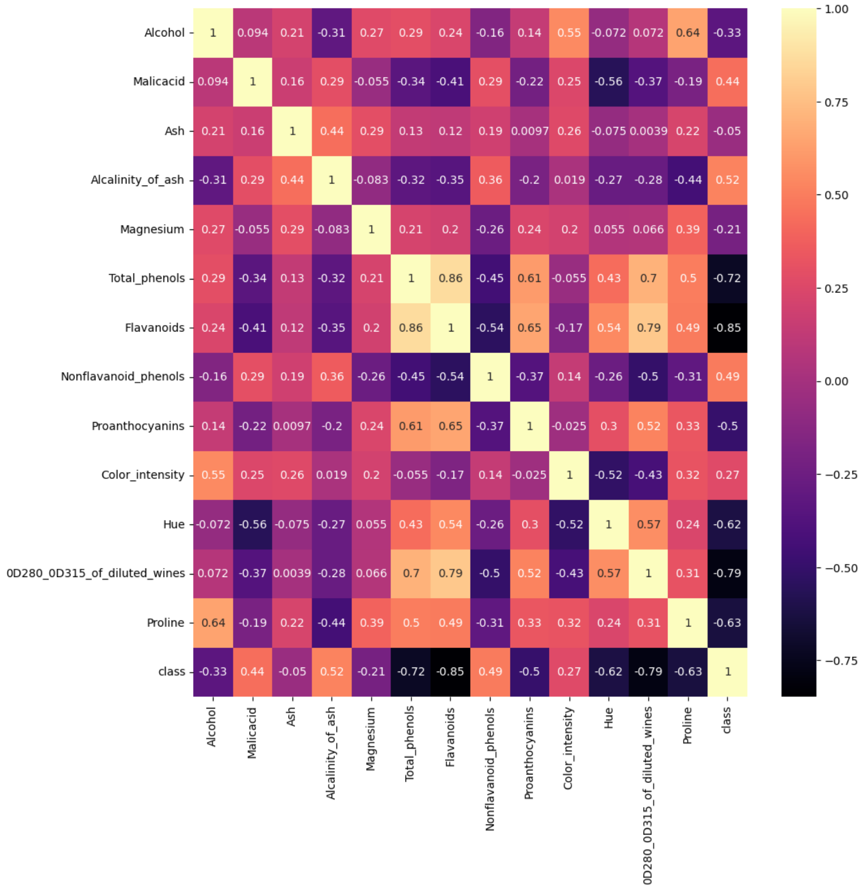
```
Alcohol                         0
Malicacid                       0
Ash                             0
Alcalinity_of_ash               0
Magnesium                       0
Total_phenols                   0
Flavanoids                      0
Nonflavanoid_phenols            0
Proanthocyanins                 0
Color_intensity                 0
Hue                             0
0D280_0D315_of_diluted_wines    0
Proline                         0
class                           0
dtype: int64
```

```
# checking if there are any categorical values in the dataframe
wine_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178 entries, 0 to 177
Data columns (total 14 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   Alcohol                       178 non-null    float64
 1   Malicacid                     178 non-null    float64
 2   Ash                           178 non-null    float64
 3   Alcalinity_of_ash             178 non-null    float64
 4   Magnesium                     178 non-null    int64
 5   Total_phenols                 178 non-null    float64
 6   Flavanoids                    178 non-null    float64
 7   Nonflavanoid_phenols          178 non-null    float64
 8   Proanthocyanins               178 non-null    float64
 9   Color_intensity               178 non-null    float64
 10  Hue                           178 non-null    float64
 11  0D280_0D315_of_diluted_wines  178 non-null    float64
 12  Proline                       178 non-null    int64
 13  class                         178 non-null    int64
dtypes: float64(11), int64(3)
memory usage: 19.6 KB
```

```
plt.figure(figsize=(11,11))
sns.heatmap(wine_df.corr(), annot=True, cmap='magma')
```

```
<Axes: >
```



Logistic Regression

```
# importing libraries
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt # data visualization
import seaborn as sns # statistical data visualization
%matplotlib inline
```

```
import warnings
warnings.filterwarnings('ignore')
```

```
print(round(wine_df.describe()),2)
```

```
       Alcohol  Malicacid    Ash  Alcalinity_of_ash  Magnesium  Total_phenols  \
count    178.0      178.0  178.0              178.0      178.0          178.0
mean      13.0        2.0    2.0               19.0      100.0            2.0
std        1.0        1.0    0.0                3.0       14.0            1.0
```

```
min       11.0       1.0    1.0              11.0      70.0           1.0
25%       12.0       2.0    2.0              17.0      88.0           2.0
50%       13.0       2.0    2.0              20.0      98.0           2.0
75%       14.0       3.0    3.0              22.0     107.0           3.0
max       15.0       6.0    3.0              30.0     162.0           4.0

       Flavanoids  Nonflavanoid_phenols  Proanthocyanins  Color_intensity  \
count       178.0                 178.0            178.0            178.0
mean          2.0                   0.0              2.0              5.0
std           1.0                   0.0              1.0              2.0
min           0.0                   0.0              0.0              1.0
25%           1.0                   0.0              1.0              3.0
50%           2.0                   0.0              2.0              5.0
75%           3.0                   0.0              2.0              6.0
max           5.0                   1.0              4.0             13.0

         Hue  OD280_OD315_of_diluted_wines  Proline  class
count  178.0                         178.0    178.0  178.0
mean     1.0                           3.0    747.0    2.0
std      0.0                           1.0    315.0    1.0
min      0.0                           1.0    278.0    1.0
25%      1.0                           2.0    500.0    1.0
50%      1.0                           3.0    674.0    2.0
75%      1.0                           3.0    985.0    3.0
max      2.0                           4.0   1680.0    3.0   2
```

```
1 wine_df['Alcalinity_of_ash'].min()
```

```
10.6
```

Malicacid:

- Upper bound: 4.5 and Max: 6.0, potential upper bound outlier

Alcalinity_of_ash:

- Upper bound: 29.5 and Max: 30, potential upper bound outlier

Magnesium:

- Upper bound: 135.5 and Max: 162, potential upper bound outlier

Proanthocyanins

- Upper bound: 3.5 and Max: 4, potential upper bound outlier

Color_intensity:

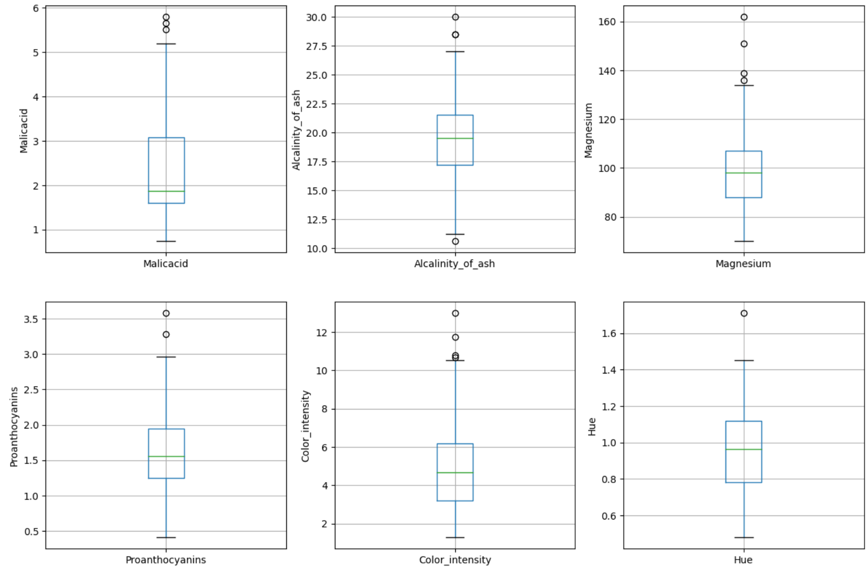
- Upper bound: 10.5 and Max: 13, potential upper bound outlier

Hue:

- Upper bound: 1 and Max: 2, potential upper bound outlier
- Lower bound: 1 and Min: 0, potential lower bound outlier

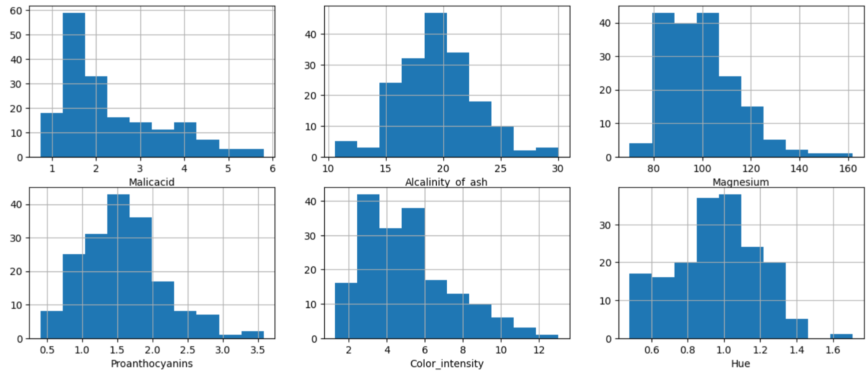
```python
# draw boxplots to visualize the outliers
plt.figure(figsize=(15,10))

plt.subplot(2, 3, 1)
fig = wine_df.boxplot(column='Malicacid')
fig.set_title('')
fig.set_ylabel('Malicacid')

plt.subplot(2, 3, 2)
fig = wine_df.boxplot(column='Alcalinity_of_ash')
fig.set_title('')
fig.set_ylabel('Alcalinity_of_ash')

plt.subplot(2, 3, 3)
fig = wine_df.boxplot(column='Magnesium')
fig.set_title('')
fig.set_ylabel('Magnesium')

plt.subplot(2, 3, 4)
fig = wine_df.boxplot(column='Proanthocyanins')
fig.set_title('')
fig.set_ylabel('Proanthocyanins')

plt.subplot(2, 3, 5)
fig = wine_df.boxplot(column='Color_intensity')
fig.set_title('')
fig.set_ylabel('Color_intensity')

plt.subplot(2, 3, 6)
fig = wine_df.boxplot(column='Hue')
fig.set_title('')
fig.set_ylabel('Hue')
```

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



```
# plot histogram to check distribution
# this is to determine which step would be next
plt.figure(figsize=(15,6))

plt.subplot(2, 3, 1)
fig = wine_df.Malicacid.hist(bins=10)
fig.set_xlabel('Malicacid')
fig.set_ylabel('')

plt.subplot(2, 3, 2)
fig = wine_df.Alcalinity_of_ash.hist(bins=10)
fig.set_xlabel('Alcalinity_of_ash')
fig.set_ylabel('')

plt.subplot(2, 3, 3)
fig = wine_df.Magnesium.hist(bins=10)
fig.set_xlabel('Magnesium')
fig.set_ylabel('')

plt.subplot(2, 3, 4)
fig = wine_df.Proanthocyanins.hist(bins=10)
fig.set_xlabel('Proanthocyanins')
fig.set_ylabel('')

plt.subplot(2, 3, 5)
fig = wine_df.Color_intensity.hist(bins=10)
fig.set_xlabel('Color_intensity')
fig.set_ylabel('')

plt.subplot(2, 3, 6)
fig = wine_df.Hue.hist(bins=10)
fig.set_xlabel('Hue')
fig.set_ylabel('')
```

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




```
# since all 4 are skewed, next step would be interquartile range to find the outliers
IQR = wine_df['Malicacid'].quantile(0.75) - wine_df['Malicacid'].quantile(0.25)
Lower_fence = wine_df['Malicacid'].quantile(0.25) - (IQR * 1.5)
Upper_fence = wine_df['Malicacid'].quantile(0.75) + (IQR * 1.5)
print(f"Malicacid outliers are values < {Lower_fence}  or > {Upper_fence}")
```

```
Malicacid outliers are values < -0.6174999999999997  or > 5.3025
```

```
IQR = wine_df['Alcalinity_of_ash'].quantile(0.75) - wine_df['Alcalinity_of_ash'].quantile(0.25)
Lower_fence = wine_df['Alcalinity_of_ash'].quantile(0.25) - (IQR * 1.5)
Upper_fence = wine_df['Alcalinity_of_ash'].quantile(0.75) + (IQR * 1.5)
print(f"Alcalinity_of_ash outliers are values < {Lower_fence}  or > {Upper_fence}")
```

```
Alcalinity_of_ash outliers are values < 10.749999999999998  or > 27.950000000000003
```

```
IQR = wine_df['Magnesium'].quantile(0.75) - wine_df['Magnesium'].quantile(0.25)
Lower_fence = wine_df['Magnesium'].quantile(0.25) - (IQR * 1.5)
Upper_fence = wine_df['Magnesium'].quantile(0.75) + (IQR * 1.5)
print(f"Magnesium outliers are values < {Lower_fence}  or > {Upper_fence}")
```

```
Magnesium outliers are values < 59.5  or > 135.5
```

```
IQR = wine_df['Proanthocyanins'].quantile(0.75) - wine_df['Proanthocyanins'].quantile(0.25)
Lower_fence = wine_df['Proanthocyanins'].quantile(0.25) - (IQR * 1.5)
Upper_fence = wine_df['Proanthocyanins'].quantile(0.75) + (IQR * 1.5)
print(f"Proanthocyanins outliers are values < {Lower_fence}  or > {Upper_fence}")
```

```
Proanthocyanins outliers are values < 0.20000000000000018  or > 3.0
```

```
IQR = wine_df['Color_intensity'].quantile(0.75) - wine_df['Color_intensity'].quantile(0.25)
Lower_fence = wine_df['Color_intensity'].quantile(0.25) - (IQR * 1.5)
Upper_fence = wine_df['Color_intensity'].quantile(0.75) + (IQR * 1.5)
print(f"Color_intensity outliers are values < {Lower_fence}  or > {Upper_fence}")
```

```
Color_intensity outliers are values < -1.2500000000000009  or > 10.670000000000002
```

```
IQR = wine_df['Hue'].quantile(0.75) - wine_df['Hue'].quantile(0.25)
Lower_fence = wine_df['Hue'].quantile(0.25) - (IQR * 1.5)
Upper_fence = wine_df['Hue'].quantile(0.75) + (IQR * 1.5)
print(f"Hue outliers are values < {Lower_fence}  or > {Upper_fence}")
```

```
Hue outliers are values < 0.2762499999999998  or > 1.6262500000000002
```

```
# Declare feature vector and target variable
X = wine_df.drop(['class'], axis=1)
y = wine_df['class']
```

```
# Split data into seperate training and testing set
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
```

```
# check the shape of X_train and X_test
X_train.shape, X_test.shape
```

```
((142, 13), (36, 13))
```

```
X_train.dtypes
```

```
Alcohol                         float64
Malicacid                       float64
Ash                             float64
Alcalinity_of_ash               float64
Magnesium                         int64
Total_phenols                   float64
Flavanoids                      float64
Nonflavanoid_phenols            float64
Proanthocyanins                 float64
Color_intensity                 float64
Hue                             float64
0D280_0D315_of_diluted_wines    float64
Proline                           int64
dtype: object
```

```
categorical = [i for i in X_train.columns if X_train[i].dtypes=='O']
categorical
```

```
[]
```

Since there are no categorical values in the given dataset we would proceed with checking the nulls

```
X_train.isnull().sum()
```

```
Alcohol                         0
Malicacid                       0
Ash                             0
Alcalinity_of_ash               0
Magnesium                       0
Total_phenols                   0
Flavanoids                      0
Nonflavanoid_phenols            0
Proanthocyanins                 0
Color_intensity                 0
```

```
Hue                             0
OD280_OD315_of_diluted_wines    0
Proline                         0
dtype: int64
```

```
X_test.isnull().any()
```

```
Alcohol                         False
Malicacid                       False
Ash                             False
Alcalinity_of_ash               False
Magnesium                       False
Total_phenols                   False
Flavanoids                      False
Nonflavanoid_phenols            False
Proanthocyanins                 False
Color_intensity                 False
Hue                             False
OD280_OD315_of_diluted_wines    False
Proline                         False
dtype: bool
```

```
def max_value(df3, variable, top):
    return np.where(df3[variable]>top, top, df3[variable])

for df3 in [X_train, X_test]:
    df3['Malicacid'] = max_value(df3, 'Malicacid', 5.30)
    df3['Alcalinity_of_ash'] = max_value(df3, 'Alcalinity_of_ash', 27.95)
    df3['Magnesium'] = max_value(df3, 'Magnesium', 135.5)
    df3['Proanthocyanins'] = max_value(df3, 'Proanthocyanins', 3)
    df3['Color_intensity'] = max_value(df3, 'Color_intensity', 10.67)
    df3['Hue'] = max_value(df3, 'Hue', 1.63)
```

```
X_train['Malicacid'].max(), X_test['Malicacid'].max()
```

```
(5.3, 5.3)
```

```
X_train['Alcalinity_of_ash'].max(), X_test['Alcalinity_of_ash'].max()
```

```
(27.95, 27.95)
```

```
X_train['Magnesium'].max(), X_test['Magnesium'].max()
```

```
(135.5, 132.0)
```

```
X_train['Proanthocyanins'].max(), X_test['Proanthocyanins'].max()
```

```
(3.0, 2.45)
```

```
X_train['Color_intensity'].max(), X_test['Color_intensity'].max()
```

```
(10.67, 10.67)
```

```
X_train['Hue'].max(), X_test['Hue'].max()
```

```
(1.63, 1.38)
```

```
X_train.describe()
```

	Alcohol	Malicacid	Ash	Alcalinity_of_ash	Magnesium	Total_phenols	Flavanoids	Nonflavanoid_phenols	Proanthocya
count	142.000000	142.000000	142.000000	142.000000	142.000000	142.000000	142.000000	142.000000	142.00
mean	12.984859	2.368662	2.366901	19.536620	99.739437	2.258662	1.949155	0.363521	1.60
std	0.807175	1.104345	0.269684	3.392529	13.154391	0.611691	0.975921	0.127709	0.57
min	11.030000	0.740000	1.360000	10.600000	70.000000	1.100000	0.470000	0.130000	0.42
25%	12.347500	1.602500	2.222500	17.250000	89.000000	1.705000	1.037500	0.270000	1.24
50%	13.040000	1.895000	2.360000	19.500000	98.000000	2.210000	2.035000	0.340000	1.55
75%	13.637500	3.222500	2.560000	21.500000	106.750000	2.735000	2.760000	0.450000	1.95
max	14.750000	5.300000	3.220000	27.950000	135.500000	3.880000	3.740000	0.660000	3.00

```
# Feature scaling
X_train.describe()
```

	Alcohol	Malicacid	Ash	Alcalinity_of_ash	Magnesium	Total_phenols	Flavanoids	Nonflavanoid_phenols	Proanthocya
count	142.000000	142.000000	142.000000	142.000000	142.000000	142.000000	142.000000	142.000000	142.00
mean	12.984859	2.368662	2.366901	19.536620	99.739437	2.258662	1.949155	0.363521	1.60
std	0.807175	1.104345	0.269684	3.392529	13.154391	0.611691	0.975921	0.127709	0.57
min	11.030000	0.740000	1.360000	10.600000	70.000000	1.100000	0.470000	0.130000	0.42
25%	12.347500	1.602500	2.222500	17.250000	89.000000	1.705000	1.037500	0.270000	1.24
50%	13.040000	1.895000	2.360000	19.500000	98.000000	2.210000	2.035000	0.340000	1.55
75%	13.637500	3.222500	2.560000	21.500000	106.750000	2.735000	2.760000	0.450000	1.95
max	14.750000	5.300000	3.220000	27.950000	135.500000	3.880000	3.740000	0.660000	3.00

```
cols = X_train.columns
```

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
X_train = pd.DataFrame(X_train, columns=[cols])
```

```
X_test = pd.DataFrame(X_test, columns=[cols])
```

```
X_train.describe()
```

	Alcohol	Malicacid	Ash	Alcalinity_of_ash	Magnesium	Total_phenols	Flavanoids	Nonflavanoid_phenols	Proanthocya
count	142.000000	142.000000	142.000000	142.000000	142.000000	142.000000	142.000000	142.000000	142.00
mean	0.525500	0.357163	0.541345	0.515079	0.454037	0.416785	0.452341	0.440606	0.45
std	0.216983	0.242181	0.144991	0.195535	0.200830	0.220033	0.298447	0.240960	0.22
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
25%	0.354167	0.189145	0.463710	0.383285	0.290076	0.217626	0.173547	0.264151	0.31
50%	0.540323	0.253289	0.537634	0.512968	0.427481	0.399281	0.478593	0.396226	0.43
75%	0.700941	0.544408	0.645161	0.628242	0.561069	0.588129	0.700306	0.603774	0.59
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.00

```
# Model training
# train a logistic regression model on the training set
from sklearn.linear_model import LogisticRegression

# instantiate the model
logreg = LogisticRegression(solver='liblinear', random_state=0)

#fit the model
logreg.fit(X_train, y_train)
```

```
▾ LogisticRegression
LogisticRegression(random_state=0, solver='liblinear')
```

```
# Predicting results
y_pred_test = logreg.predict(X_test)
y_pred_test
```

```
array([1, 3, 2, 1, 2, 2, 1, 3, 2, 2, 3, 3, 1, 2, 3, 2, 1, 1, 3, 1, 2, 1,
       1, 2, 2, 2, 2, 2, 2, 3, 1, 1, 2, 1, 1, 1])
```

```
# predict proba: predicts possibilities for the target variable
logreg.predict_proba(X_test)[:,0]
```

```
array([0.84608661, 0.08048314, 0.33554459, 0.80152316, 0.22039744,
       0.24522358, 0.87468447, 0.03848718, 0.15948773, 0.05898538,
```

```
       0.14507607, 0.0358635 , 0.93262766, 0.47681744, 0.07875799,
       0.12976804, 0.79007758, 0.95638587, 0.08820506, 0.84199176,
       0.47786966, 0.67550962, 0.47265773, 0.23584062, 0.08901126,
       0.15152147, 0.20646317, 0.04988917, 0.07608428, 0.07232845,
       0.83715721, 0.86643051, 0.0791357 , 0.81872064, 0.87889396,
       0.67623076])
```

```
logreg.predict_proba(X_test)[:,1]
```

```
array([0.10773965, 0.04382495, 0.65481533, 0.1525236 , 0.66114073,
       0.74433276, 0.07438344, 0.12116596, 0.78373262, 0.80051396,
       0.1289791 , 0.07885248, 0.03352518, 0.51535383, 0.06169256,
       0.85700534, 0.14896474, 0.01820935, 0.40806803, 0.14198268,
       0.51407897, 0.25405006, 0.43617131, 0.73190936, 0.59297914,
       0.78249892, 0.7421782 , 0.86155799, 0.73512681, 0.0449725 ,
       0.12680024, 0.09818553, 0.64410061, 0.05781283, 0.08848967,
       0.30025453])
```

```
logreg.predict_proba(X_test)[:,2]
```

```
array([0.04617374, 0.87569191, 0.00964009, 0.04595323, 0.11846182,
       0.01044366, 0.05093209, 0.84034686, 0.05677965, 0.14050066,
       0.72594482, 0.88528401, 0.03384715, 0.00782873, 0.85954945,
       0.01322662, 0.06095768, 0.02540478, 0.50372691, 0.01602556,
       0.00805136, 0.07044032, 0.09117095, 0.03225002, 0.31800959,
       0.06597962, 0.05135863, 0.08855284, 0.18878891, 0.88269905,
       0.03604255, 0.03538396, 0.27676368, 0.12346652, 0.03261637,
       0.02351471])
```

```
# Check accuracy score
from sklearn.metrics import accuracy_score

print('Model accuracy score: {0:0.4f}'.format(accuracy_score(y_test, y_pred_test)))
```

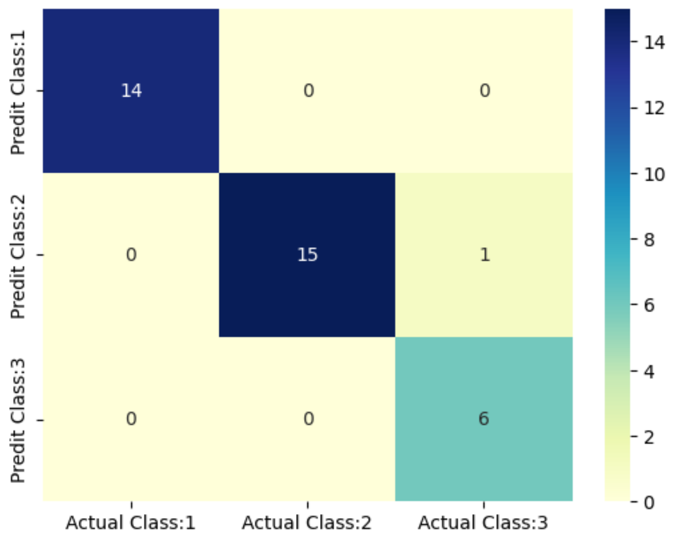
```
Model accuracy score: 0.9722
```

```
# check for overfitting and underfitting
# print the scores on training and test set
train_score = logreg.score(X_train, y_train)
test_score = logreg.score(X_test, y_test)
print(f'Train set score: {train_score}')
print(f'Test set score: {test_score}')
```

```
Train set score: 0.9788732394366197
Test set score: 0.9722222222222222
```

```
# visualize confusion matrix with seaborn heatmap
cm_matrix = pd.DataFrame(data=cm, columns=['Actual Class:1', 'Actual Class:2', 'Actual Class:3'],
                         index=['Predit Class:1', 'Predit Class:2', 'Predit Class:3'])
sns.heatmap(cm_matrix, annot=True, fmt='d', cmap='YlGnBu')
```

```
<Axes: >
```




```
# classification metrices
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred_test))
```

```
              precision    recall  f1-score   support
```

```
           1       1.00      1.00      1.00        14
           2       1.00      0.94      0.97        16
           3       0.86      1.00      0.92         6

    accuracy                           0.97        36
   macro avg       0.95      0.98      0.96        36
weighted avg       0.98      0.97      0.97        36
```

```python
y_pred_prob = logreg.predict_proba(X_test)[0:10]
y_pred_prob
```

```
array([[0.84608661, 0.10773965, 0.04617374],
       [0.08048314, 0.04382495, 0.87569191],
       [0.33554459, 0.65481533, 0.00964009],
       [0.80152316, 0.1525236 , 0.04595323],
       [0.22039744, 0.66114073, 0.11846182],
       [0.24522358, 0.74433276, 0.01044366],
       [0.87468447, 0.07438344, 0.05093209],
       [0.03848718, 0.12116596, 0.84034686],
       [0.15948773, 0.78373262, 0.05677965],
       [0.05898538, 0.80051396, 0.14050066]])
```

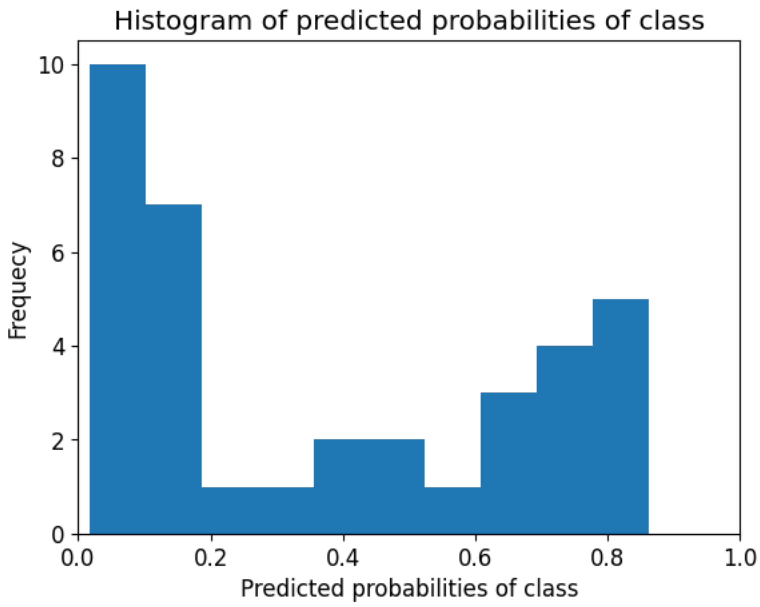
```python
# print the first 10 predicted probabilities
logreg.predict_proba(X_test)[0:10, 1]
```

```
array([0.10773965, 0.04382495, 0.65481533, 0.1525236 , 0.66114073,
       0.74433276, 0.07438344, 0.12116596, 0.78373262, 0.80051396])
```

```python
# store the predicted probabilities
y_pred1 = logreg.predict_proba(X_test)[:,1]
```

```python
# plot histogram of predicted probabilities
# adjust the font size
plt.rcParams['font.size'] = 12

# plot histogram with 10 bins
plt.hist(y_pred1, bins=10)

# set the title of predicted probabilities
plt.title('Histogram of predicted probabilities of class')

# set the x-axis limit
plt.xlim(0,1)

plt.xlabel('Predicted probabilities of class')
plt.ylabel('Frequecy')
```

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




```python
# k-Fold Cross Validation
from sklearn.model_selection import cross_val_score

scores = cross_val_score(logreg, X_train, y_train, cv = 5, scoring='accuracy')
print('Cross-validation scores:{}'.format(scores))
```

```
Cross-validation scores:[0.93103448 0.96551724 0.96428571 1.         0.96428571]
```

```
# compute Average cross-validation score
score_mean = scores.mean()
print(f'Average cross-validation score: {score_mean}')
```

```
Average cross-validation score: 0.9650246305418719
```

```
# Hyperparameter Optimization using GridSearchCV
from sklearn.model_selection import GridSearchCV

parameters = [{'penalty': ['l1', 'l2']},
              {'C':[1, 10, 100, 100]}]

grid_search = GridSearchCV(estimator = logreg,
                           param_grid = parameters,
                           scoring = 'accuracy',
                           cv = 5,
                           verbose=0)

grid_search.fit(X_train, y_train)
```

```
▸ GridSearchCV
▸ estimator: LogisticRegression
▾ LogisticRegression
LogisticRegression(random_state=0, solver='liblinear')
```

```
# examine the best model
# best score achieved during the GridSearchCV
print('GridSearch CV best score : {:.4f}\n\n'.format(grid_search.best_score_))

# print parameters that give the best results
print('Parameters that give the best results :', '\n\n', (grid_search.best_params_))

# print estimator that was chosen by the GridSearch
print('\n\nEstimator that was chosen by the search :', '\n\n', (grid_search.best_estimator_))
```

```
GridSearch CV best score : 0.9650


Parameters that give the best results :

 {'C': 1}


Estimator that was chosen by the search :

 LogisticRegression(C=1, random_state=0, solver='liblinear')
```

```
# calculate Gridsearch CV score on test set
print('Gridsearch CV score on test set: {0:0.4f}'.format(grid_search.score(X_test, y_test)))
```

```
Gridsearch CV score on test set: 0.9722
```

Results and Conclusion

- The logistic regression model accuracy score is 0.9722. Since the value the train sets are above 0.9, we can conclude that the training is accurate on its predictions. Therefore, the model did an excellent work in predicting the class of each columns.