Project Description:

General Instruction

- There will be two datasets for this project—one for classification models and the second for regression models.
- Read data into Jupyter notebook use pandas to import data into a data frame.
- Your submission should be commented on appropriately. Use the markdown cells in the iPython notebook to prepare your final report.
- Fifty percent of the grade is based on your Python code submission. The other 50 percent of your grade is based on the evaluation score of the prediction.
- The exam should be syntax error-free. Run your code before the final submission.

Required Tasks

- Explore each data set using different descriptive and plotting methods.
- Explore each dataset, check for missing data and apply proper data imputation methods.
- Apply the same preprocessing techniques on the classification_test and regression_test. Note that these two datasets don't have target columns.
- Scale each dataset. Explain your choice of data scaling method.
- Apply clustering methods discussed in class to study the structure of each dataset. Discuss how the outcome of clustering will help you better understand the structure of data. Provide result interpretation for each clustering model.
- Regression dataset: Apply all the regression models you have learned in this class. Discuss the results and outcomes. Models with hyperparameters explain how you find the best value of the hyperparameters.
- Find the best regression model among the list of models trained on the regression_train dataset. Use this model to predict the target values of the regression_test.
- Classification dataset: Apply all the classification models you have learned in this course. Discuss the results and outcomes. Discuss the choice of evaluation method and how it helps you find the best values of the model hyperparameters.
- Find the best classification model among the list of models trained on the classification_train dataset. Use this model to predict the target values of the classification_test.

Devliverable

Submit ONLY the iPython notebook or the .py file of your work. Use the following frame for your submission. Please don't remove the headers in the following structure.

Make sure to list the name and student id of all the group members in your iPython notebook file.

Rubric

Descriptio	Fair	Good	excelent
Preprocessing	Demonstrate limited understanding of preprocessing steps	Demonstrate a moderate ability to find a way to apply the preprocessing step to prepare the dataset for Machine learning models	Demonstrate the ability to choose the appropriate preprocessing model to prepare the dataset
learning model	Demonstrate limited understanding of methods used to train learning models	Demonstrate the ability to understand techniques used to train learning models with some effectiveness. This includes optimization algorithms, initialization, regularization, and hyperparameter search methods	Demonstrate ability to understand and apply various algorithms as well as initialization, regularization, and hyperparameter search methods
Final prediction	Demonstrate limited understanding of strategies to structure and end to end machine learning project	Demonstrate ability to understand classic ML strategies such as error analysis, data split, data collection and evaluation metric selection with some effectiveness	Demonstrates ability to structure the project and apply methods such as error analysis, data split, data collection, design a labeling process and select proper evaluation metrics to improve performance.

INTRODUCTION

We group of 5 members worked together in this project.

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In this project, data sets for classification and regression are provided. We explored the datasets and performed data transformations as per the requirement. To understand the structure of data, we performed different clustering methods by scaling the data. Different classification and regression algorithms are applied to develop a model. Best model is applied for test data to predict target values.

Importing libraries used for both classification and regression

In [1]:

```
#Import modules

#preprocessing
import numpy as np
import pandas as pd

import warnings
#In some executions, we can get warnings which we can ignore them by using
warnings.filterwarnings("ignore")

#Visualization
import matplotlib.pyplot as plt
import seaborn as sns

#encoding
from sklearn.preprocessing import LabelEncoder

#scaling
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler

#Clustering
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.cluster import KMeans

#Metrics
from sklearn.metrics import silhouette_score
from mlxtend.plotting import plot_decision_regions

#Regression
import scipy.stats as st
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_er
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

#decisiontree
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import DecisionTreeRegressor, plot_tree

#evaluation
from sklearn.metrics import confusion_matrix
from sklearn.metrics import recall_score, precision_score, f1_score
from sklearn.metrics import classification_report, precision_recall_curve
from sklearn.metrics import accuracy_score, recall_score, f1_score
```

Data Preprocessing

Loading the dataset "Regression"

In [2]:
```
# Load the dataset
#Train dataset
df = pd.read_csv("train_regression.csv")

#Test dataset
df_test = pd.read_csv("test_regression.csv")
```

Shape of the dataset

In [3]:
```
# number rows * columns
print("Train dataset shape : ", df.shape)
print("Test dataset shape : ", df_test.shape)
```

```
Train dataset shape :  (6570, 13)
Test dataset shape :  (2190, 12)
```

Replacing the binomial columns to Numeric data

In [4]:
```
# Get the unique value counts in functioning day column
df['Functioning Day'].value_counts()
```

Out[4]:
```
Yes    6180
No      194
Name: Functioning Day, dtype: int64
```

In [1]:
```
# replace the more rows with 1 and less rows with 0
df['Functioning Day'].replace({'Yes':1,'No':0},inplace = True)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call la
st)
Input In [1], in <module>
      1 # replace the more rows with 1 and less rows with 0
----> 2 df['Functioning Day'].replace({'Yes':1,'No':0},inplace = True)

NameError: name 'df' is not defined
```

In [6]:
```
# Get the unique value counts in holiday column
df['Holiday'].value_counts()
```

Out[6]:
```
No Holiday    6082
Holiday        321
Name: Holiday, dtype: int64
```

In [7]:
```
# replace the more rows with 1 and less rows with 0
df['Holiday'].replace({'No Holiday':1,'Holiday':0},inplace = True)
```

Test Data : data transformation

In [8]:
```
## Get the unique value counts in functioning day column
df_test['Functioning Day'].value_counts()
```

Out[8]:
```
Yes    2027
No       87
Name: Functioning Day, dtype: int64
```

In [9]:
```
# replace the more rows with 1 and less rows with 0
df_test['Functioning Day'].replace({'Yes':1,'No':0},inplace = True)
```

In [10]:
```
# Get the unique value counts in holiday column
df_test['Holiday'].value_counts()
```

Out[10]:
```
No Holiday    2025
Holiday         98
Name: Holiday, dtype: int64
```

In [11]:
```
# replace the more rows with 1 and less rows with 0
df_test['Holiday'].replace({'No Holiday':1,'Holiday':0},inplace = True)
```

Train Data: Applying one-hot vector to column seasons for nominal data transformation

In [12]:
```
# getting valuecounts
df['Seasons'].value_counts()
```

Out[12]:
```
Spring    1604
Summer    1593
Autumn    1588
Winter    1576
Name: Seasons, dtype: int64
```

In [13]:

```
# Creating one-hot vector
df_Seasons = pd.get_dummies(df['Seasons'])
df_Seasons
```

Out[13]:

	Autumn	Spring	Summer	Winter
0	1	0	0	0
1	0	1	0	0
2	0	0	0	1
3	0	1	0	0
4	1	0	0	0
...	...	...	...	...
6565	0	0	1	0
6566	1	0	0	0
6567	0	0	1	0
6568	0	1	0	0
6569	0	1	0	0

6570 rows × 4 columns

In [14]:

```
# Adding columns to the actual dataset, dervied using one-hot vector
df[df_Seasons.columns] = df_Seasons

#Drop the Seasons column with nominal data
df.drop('Seasons',axis = 1 , inplace = True)
```

In [15]:

```
# To view the sample data after one hot vector transformation
df.head()
```

Out[15]:

	Hour	Temperature(C)	Humidity(%)	Wind speed (m/s)	Visibility (10m)	Dew point temperature(C)	Solar Radiation (MJ/m2)	Rainfall(
0	23.0	3.8	83.0	1.1	390.0	1.1	0.00	
1	14.0	24.0	47.0	2.3	520.0	11.9	2.87	
2	19.0	-7.1	33.0	2.0	1887.0	-20.6	0.00	
3	12.0	12.3	97.0	0.8	238.0	11.8	0.14	
4	4.0	3.6	70.0	0.8	1934.0	-1.3	0.00	

Test Data : nominal columns to numeric column conversion (One - hot vector) in for seasons

In [16]:

```
print("Seasons columns distinct value counts:\n",df_test['Seasons'].value_
df_test_Seasons = pd.get_dummies(df_test['Seasons'])
print(df_test_Seasons)

# Adding columns to the actual dataset, dervied using one-hot vector
df_test[df_test_Seasons.columns] = df_test_Seasons

#Drop the Seasons column with nominal data
df_test.drop('Seasons',axis = 1 , inplace = True)

# To view the sample data after one hot vector transformation
print(df_test.head())
```

```
Seasons columns distinct value counts:
 Summer    556
Spring    536
Autumn    524
Winter    514
Name: Seasons, dtype: int64
      Autumn  Spring  Summer  Winter
0          0       1       0       0
1          1       0       0       0
2          0       0       0       1
3          0       0       0       1
4          0       0       1       0
...      ...     ...     ...     ...
2185       0       0       0       1
2186       0       0       1       0
2187       0       0       1       0
2188       1       0       0       0
2189       0       0       1       0

[2190 rows x 4 columns]
   Hour  Temperature(C)  Humidity(%)  Wind speed (m/s)  Visibility (10m)
\
0   3.0            10.7         73.0               1.3            2000.0
1   2.0            21.7         78.0               1.0            2000.0
2  17.0             3.6         65.0               NaN            1061.0
3  22.0            -9.7         51.0               2.8            2000.0
4  15.0            33.6         58.0               3.6            1448.0

   Dew point temperature(C)  Solar Radiation (MJ/m2)  Rainfall(mm)  \
0                       6.0                     0.00           0.0
1                      17.6                     0.00           0.0
2                      -2.3                     0.03           NaN
3                       NaN                     0.00           NaN
4                      24.1                     1.98           0.0

   Snowfall (cm)  Holiday  Functioning Day  Autumn  Spring  Summer  Wint
er
0            0.0      1.0              1.0       0       1       0
0
1            0.0      1.0              1.0       1       0       0
0
2            0.4      1.0              1.0       0       0       0
1
3            0.0      1.0              1.0       0       0       0
1
4            0.0      1.0              1.0       0       0       1
0
```

Descriptive methods

In [17]:

```
#Using Describe method we can find the descriptive statistics of the datas
#Later using this descriptive method the null values can be handled

print("Train data: \n",df.describe())
print("*****************************************************************
print("Test data: \n",df_test.describe())
```

```
Train data:
              Hour  Temperature(C)  Humidity(%)  Wind speed (m/s)  \
count  6393.000000     6361.000000  6360.000000       6377.000000
mean     11.490537       12.808175    58.034277          1.724886
std       6.909840       12.002438    20.347046          1.039019
min       0.000000      -17.500000     0.000000          0.000000
25%       6.000000        3.200000    42.000000          0.900000
50%      12.000000       13.600000    57.000000          1.500000
75%      17.000000       22.600000    74.000000          2.300000
max      23.000000       39.300000    98.000000          7.400000

       Visibility (10m)  Dew point temperature(C)  Solar Radiation (MJ/m
2)  \
count        6380.00000               6373.000000               6369.0000
00
mean         1440.36395                  3.894131                  0.5726
02
std           607.84974                 13.080417                  0.8740
21
min            33.00000                -30.600000                  0.0000
00
25%           950.75000                 -5.000000                  0.0000
00
50%          1705.00000                  4.900000                  0.0100
00
75%          2000.00000                 14.600000                  0.9400
00
max          2000.00000                 26.800000                  3.5200
00

       Rainfall(mm)  Snowfall (cm)      Holiday  Functioning Day  \
count   6359.000000    6380.000000  6403.000000      6374.000000
mean       0.145668       0.073809     0.949867         0.969564
std        1.161931       0.415938     0.218236         0.171798
min        0.000000       0.000000     0.000000         0.000000
25%        0.000000       0.000000     1.000000         1.000000
50%        0.000000       0.000000     1.000000         1.000000
75%        0.000000       0.000000     1.000000         1.000000
max       35.000000       8.800000     1.000000         1.000000

       Rented Bike Count       Autumn       Spring       Summer       Wi
nter
count        6570.000000  6570.000000  6570.000000  6570.000000  6570.00
0000
mean          707.845814     0.241705     0.244140     0.242466     0.23
9878
std           644.683576     0.428149     0.429609     0.428607     0.42
7041
min             0.000000     0.000000     0.000000     0.000000     0.00
0000
25%           195.000000     0.000000     0.000000     0.000000     0.00
0000
50%           509.000000     0.000000     0.000000     0.000000     0.00
0000
75%          1065.750000     0.000000     0.000000     0.000000     0.00
0000
max          3556.000000     1.000000     1.000000     1.000000     1.00
```

```
0000
**********************************************************************
*****
Test data:
              Hour  Temperature(C)  Humidity(%)  Wind speed (m/s)  \
count  2129.000000     2129.000000  2123.000000       2099.000000   
mean     11.569751       13.207985    58.873293          1.732778   
std       6.957372       11.811618    20.392484          1.030194   
min       0.000000      -17.800000     0.000000          0.000000   
25%       5.000000        4.200000    43.000000          1.000000   
50%      12.000000       14.500000    58.000000          1.500000   
75%      18.000000       22.600000    75.000000          2.300000   
max      23.000000       39.400000    98.000000          6.900000   

       Visibility (10m)  Dew point temperature(C)  Solar Radiation (MJ/m
2)  \
count       2109.000000               2128.000000               2134.0000
00   
mean        1434.098625                  4.473966                  0.5551
27   
std          607.015359                 12.988355                  0.8523
63   
min           27.000000                -28.700000                  0.0000
00   
25%          911.000000                 -3.900000                  0.0000
00   
50%         1693.000000                  5.500000                  0.0050
00   
75%         2000.000000                 15.225000                  0.9000
00   
max         2000.000000                 27.200000                  3.4400
00   

       Rainfall(mm)  Snowfall (cm)      Holiday  Functioning Day       A
utumn  \
count   2114.000000    2146.000000  2123.000000      2114.000000  2190.0
00000   
mean       0.157616       0.074651     0.953839         0.958846     0.2
39269   
std        1.038602       0.443897     0.209883         0.198694     0.4
26735   
min        0.000000       0.000000     0.000000         0.000000     0.0
00000   
25%        0.000000       0.000000     1.000000         1.000000     0.0
00000   
50%        0.000000       0.000000     1.000000         1.000000     0.0
00000   
75%        0.000000       0.000000     1.000000         1.000000     0.0
00000   
max       18.500000       7.100000     1.000000         1.000000     1.0
00000   

            Spring       Summer       Winter  
count  2190.000000  2190.000000  2190.000000  
mean      0.244749     0.253881     0.234703  
std       0.430036     0.435330     0.423910  
min       0.000000     0.000000     0.000000  
```

25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000
75%	0.000000	1.000000	0.000000
max	1.000000	1.000000	1.000000

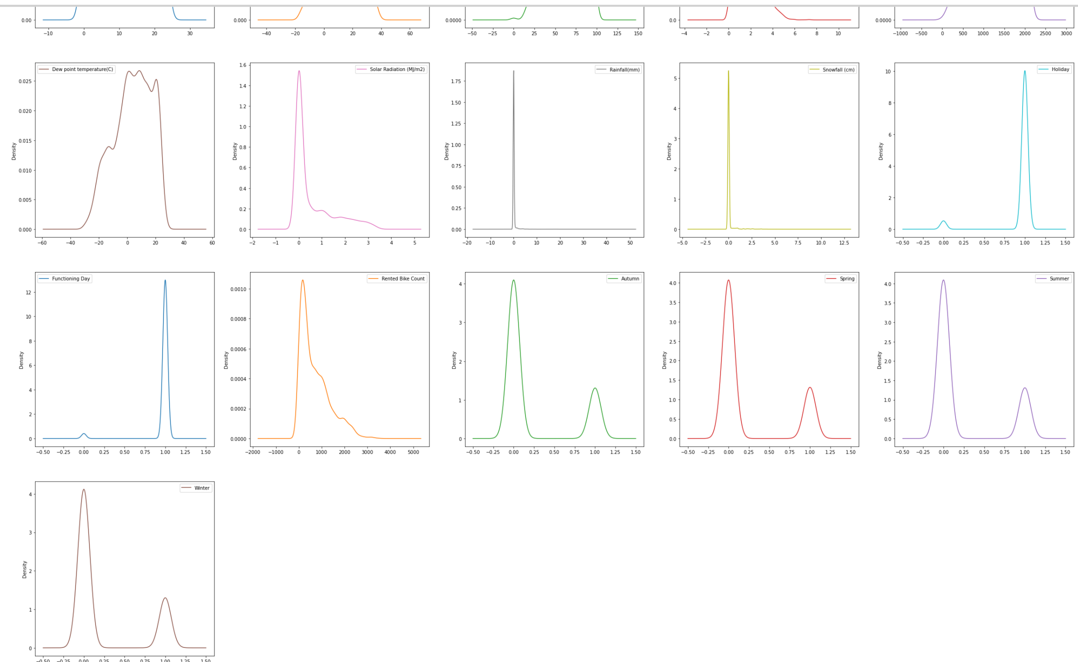
Visualization for data preprocessing step

1) Density Plots

2) Hist Plots

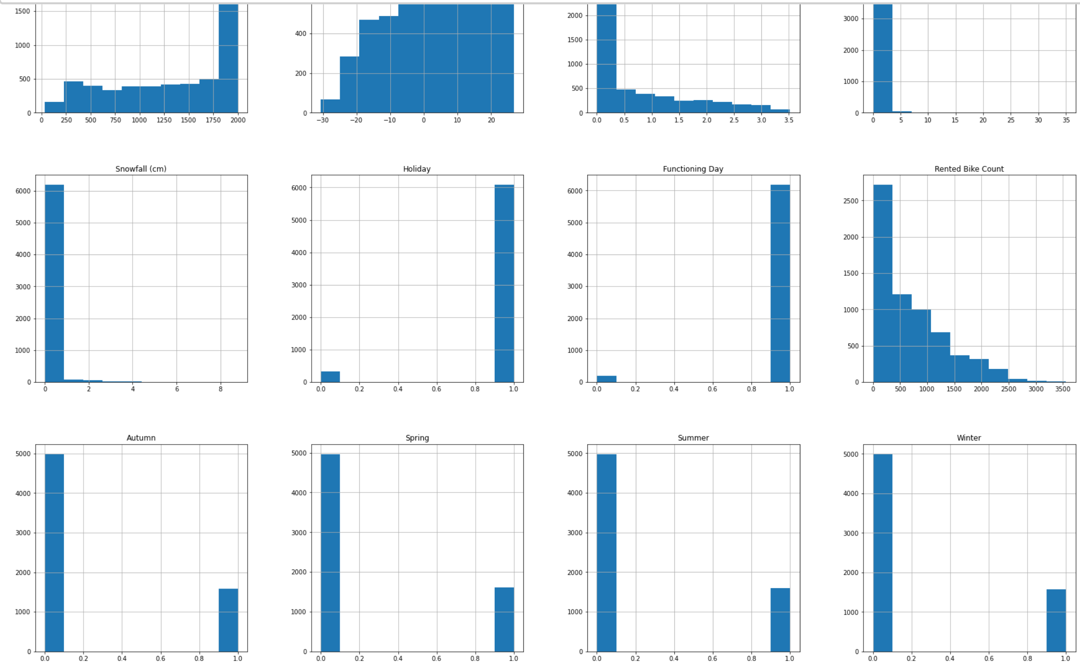
Train Data: Using density plots to assesses the distribution of data in the column

In [18]:
```
df.plot(kind = 'kde' , subplots = True , layout=(5,5), sharex=False, share
```



In [19]:

```python
histPlot = df.hist(figsize=(30,30))
```



In [20]:

```python
# To check the number of null values in each column

df.isna().sum()
```

Out[20]:

```
Hour                         177
Temperature(C)               209
Humidity(%)                  210
Wind speed (m/s)             193
Visibility (10m)             190
Dew point temperature(C)     197
Solar Radiation (MJ/m2)      201
Rainfall(mm)                 211
Snowfall (cm)                190
Holiday                      167
Functioning Day              196
Rented Bike Count              0
Autumn                         0
Spring                         0
Summer                         0
Winter                         0
dtype: int64
```

In [21]:

```python
# Replace with mean

df['Hour'].fillna(df['Hour'].mean(),inplace = True)
df['Temperature(C)'].fillna(df['Temperature(C)'].mean(),inplace = True)
df['Dew point temperature(C)'].fillna(df['Dew point temperature(C)'].mean(
```

In [22]:

```
# Replace with median
df['Humidity(%)'].fillna(df['Humidity(%)'].median(),inplace = True)
df['Wind speed (m/s)'].fillna(df['Wind speed (m/s)'].median(),inplace = Tr
df['Visibility (10m)'].fillna(df['Visibility (10m)'].median(),inplace = Tr
df['Solar Radiation (MJ/m2)'].fillna(df['Solar Radiation (MJ/m2)'].median(
df['Rainfall(mm)'].fillna(df['Rainfall(mm)'].median(),inplace = True)
df['Snowfall (cm)'].fillna(df['Snowfall (cm)'].median(),inplace = True)
df['Holiday'].fillna(df['Holiday'].median(),inplace = True)
df['Functioning Day'].fillna(df['Functioning Day'].median(),inplace = True
```

In [23]:

```
#After filling the missing values
df.isna().sum()
```

Out[23]:

```
Hour                       0
Temperature(C)             0
Humidity(%)                0
Wind speed (m/s)           0
Visibility (10m)           0
Dew point temperature(C)   0
Solar Radiation (MJ/m2)    0
Rainfall(mm)               0
Snowfall (cm)              0
Holiday                    0
Functioning Day            0
Rented Bike Count          0
Autumn                     0
Spring                     0
Summer                     0
Winter                     0
dtype: int64
```

KDE Plots analysis and usage of mean or media to fill missing values

Columns replaced by mean

Hour - it looks almost like normal distribution mean is 11 from there the data is spread in equal quadrants. Temperature - it looks almost like normal distribution mean is 12 from there the data is spread in equal quadrants. Dew point temperature(C) - it looks almost like normal distribution mean is 3 from there the data is spread in equal quadrants.

columns replaced by median

Humidity(%) - mean is 73 we need to use the median as the data is skewed

Wind speed (m/s) - mean = ~1 we need to use median as the data is skewed

Visibility (10m) - mean = 1440 we need to use the media as the data is skewed

Solar Radiation (MJ/m2) - mean = 0.5 we need to use mediana s the data is skewed

Rainfall(mm) - mean = 0.14 we need to use media as the data is skewed

Snowfall (cm) - mean = 0.07 we need to use median as the data is skewed

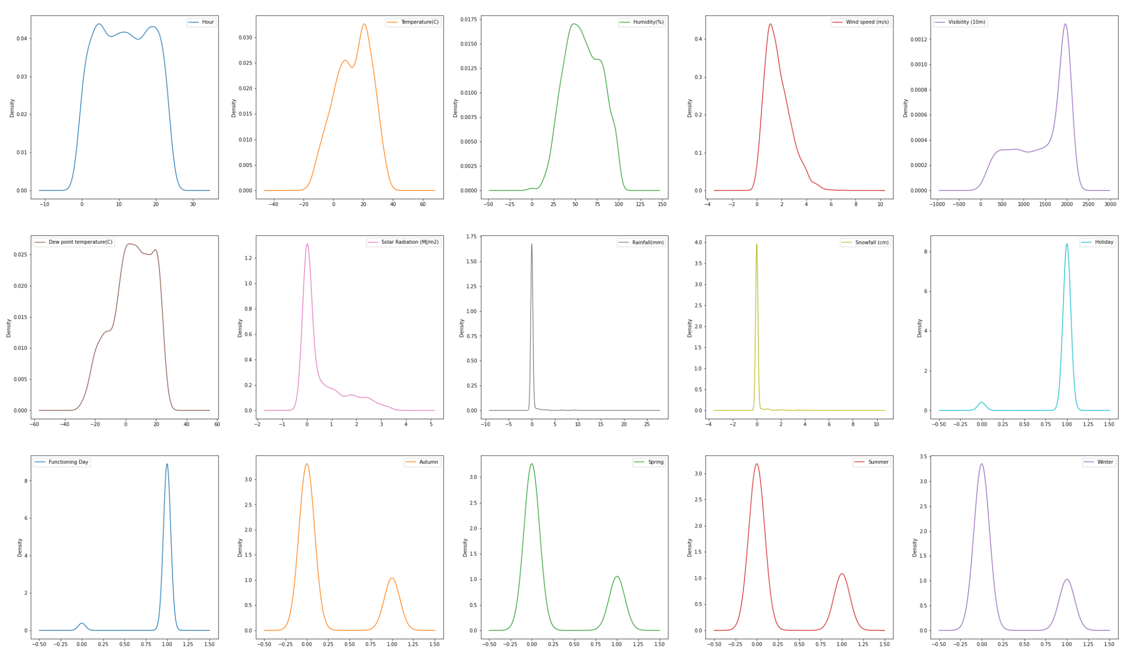
Holiday - mean = 0.9 we have to use median as the data is skewed

Functioning Day - mean = 0.9 we have to use the median as the data is skewed

Test Data : Using density plots to assesses the distribution of data in the column

In [24]:
```
df_test.plot(kind = 'kde' , subplots = True , layout=(5,5), sharex=False,
```

Out[24]:
```
array([[<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>],
       [<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>],
       [<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>],
       [<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>],
       [<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>]], dtype=object)
```



In [25]:
```
# To check the number of null values in each column

df_test.isna().sum()
```

Out[25]:
```
Hour                          61
Temperature(C)                61
Humidity(%)                   67
Wind speed (m/s)              91
Visibility (10m)              81
Dew point temperature(C)      62
Solar Radiation (MJ/m2)       56
Rainfall(mm)                  76
Snowfall (cm)                 44
Holiday                       67
Functioning Day               76
Autumn                         0
Spring                         0
Summer                         0
Winter                         0
dtype: int64
```

In [26]:
```
# Replace with mean

df_test['Hour'].fillna(df['Hour'].mean(),inplace = True)
df_test['Temperature(C)'].fillna(df['Temperature(C)'].mean(),inplace = Tru
df_test['Dew point temperature(C)'].fillna(df['Dew point temperature(C)'].
```

In [27]:
```
# Replace with median
df_test['Humidity(%)'].fillna(df['Humidity(%)'].median(),inplace = True)
df_test['Wind speed (m/s)'].fillna(df['Wind speed (m/s)'].median(),inplace
df_test['Visibility (10m)'].fillna(df['Visibility (10m)'].median(),inplace
df_test['Solar Radiation (MJ/m2)'].fillna(df['Solar Radiation (MJ/m2)'].me
df_test['Rainfall(mm)'].fillna(df['Rainfall(mm)'].median(),inplace = True)
df_test['Snowfall (cm)'].fillna(df['Snowfall (cm)'].median(),inplace = Tru
df_test['Holiday'].fillna(df['Holiday'].median(),inplace = True)
df_test['Functioning Day'].fillna(df['Functioning Day'].median(),inplace =
```

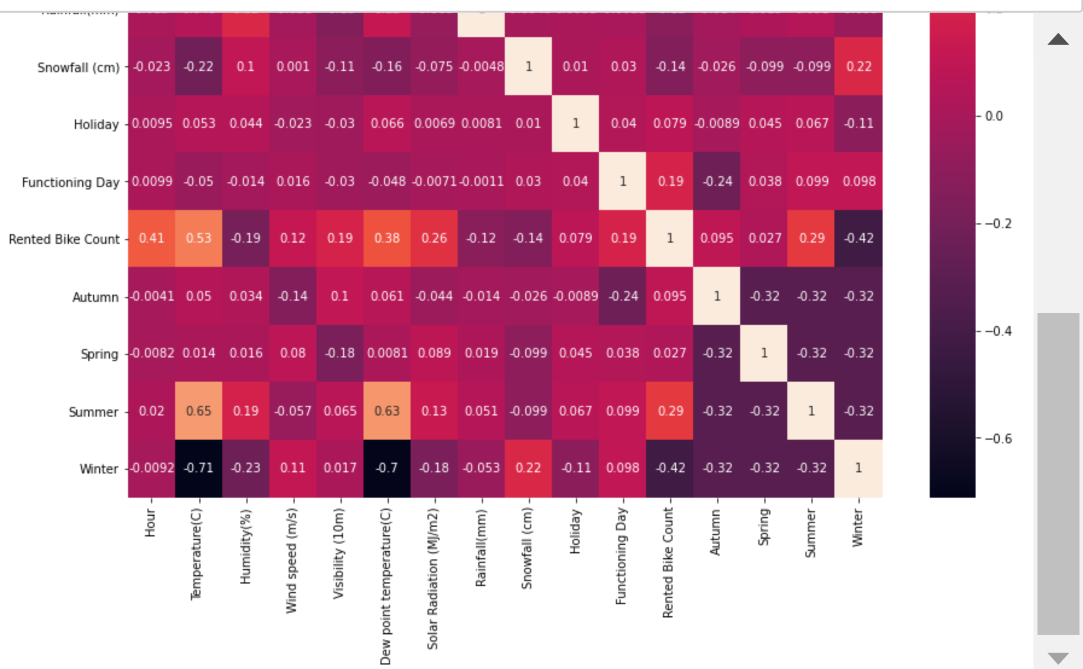
In [28]:
```python
#After filling the missing values
df_test.isna().sum()
```

Out[28]:
```
Hour                         0
Temperature(C)               0
Humidity(%)                  0
Wind speed (m/s)             0
Visibility (10m)             0
Dew point temperature(C)     0
Solar Radiation (MJ/m2)      0
Rainfall(mm)                 0
Snowfall (cm)                0
Holiday                      0
Functioning Day              0
Autumn                       0
Spring                       0
Summer                       0
Winter                       0
dtype: int64
```

Using Correlation Matrix to check the relation between different columns

Target column - 'Rented Bike Count'

In [29]:
```python
plt.figure(figsize=(14,14))
correlation=df.corr()
sns.heatmap(correlation,annot=True)
```



Feature and Target datasets

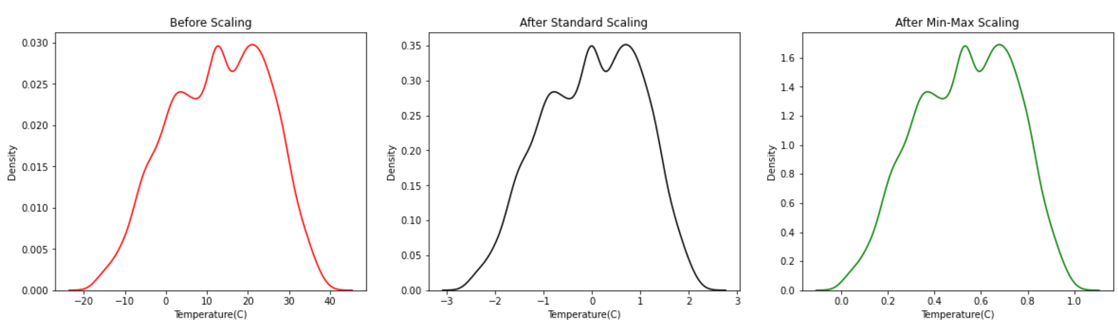
In [30]:
```
X = df.drop('Rented Bike Count', axis = 1)

y = df['Rented Bike Count']
```

Scaling Techniques Used

1) MinMax Scaling

2) Standard Scaling

In [31]:
```
#Applying Min-Max scaler
scaler = MinMaxScaler()
minmax_df = scaler.fit_transform(X)
minmax_df = pd.DataFrame(minmax_df, columns =X.columns)

#Applying StandardScaler
scaler = StandardScaler()
standard_df = scaler.fit_transform(X)
standard_df = pd.DataFrame(standard_df, columns = X.columns)


fig, (ax1, ax2, ax3) = plt.subplots(ncols = 3, figsize =(20, 5))
ax1.set_title('Before Scaling')
sns.kdeplot(X['Temperature(C)'], ax = ax1,color ='r')

ax2.set_title('After Standard Scaling')
sns.kdeplot(standard_df['Temperature(C)'], ax = ax2, color ='black')

ax3.set_title('After Min-Max Scaling')
sns.kdeplot(minmax_df['Temperature(C)'], ax = ax3, color ='g')
plt.show()
```



Looking at the above graphs plots drawn on top of scaled data , we have choosed - "Min-Max Scaling"

Below are the reasons

With standard scaling the values turned to be very minute or very large for the given data which in turn creates a problem while clustering so we have choosen the min-max scaling technique

Using Standard scaler with distance thresold 20 the number of clusters formed are 15 and there grouping has fatalities the silhoutee is also very less. But with min-max scaling the number of best clusters turned to be 4 and data is also grouped equally.

[1624 1693 1617 1636]

Silhoutte score for cluster 4 and test data is 0.4820674488558203 for Min-Max Scaling

Test Data: Applying Scaling for test data features with chosen MIN-MAX Scaling technique

In [32]:
```
#Scaling for test dataset
minmax_dft = scaler.fit_transform(df_test)
minmax_dft = pd.DataFrame(minmax_dft, columns = df_test.columns)
```

Clustering - Unsupervised Learning

Agglomerative Clustering

In [33]:
```
#decleration
model = AgglomerativeClustering(distance_threshold = 20, n_clusters = None
                                linkage = 'ward')

# Train the model
model = model.fit(minmax_df)
model.n_clusters_
```

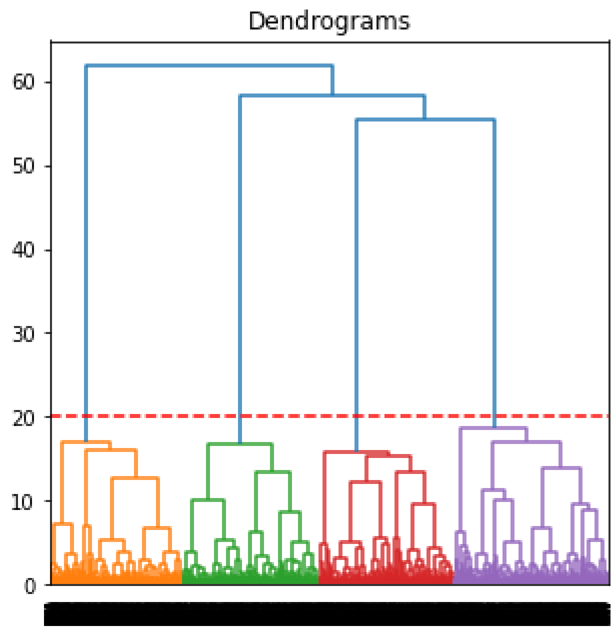
Out[33]: 4

In [34]:
```
#using the above number of clusters
cluster = AgglomerativeClustering(n_clusters=4, affinity='euclidean', link
cluster.fit_predict(minmax_df)
```

Out[34]: array([3, 0, 1, ..., 2, 0, 0])

In [35]:

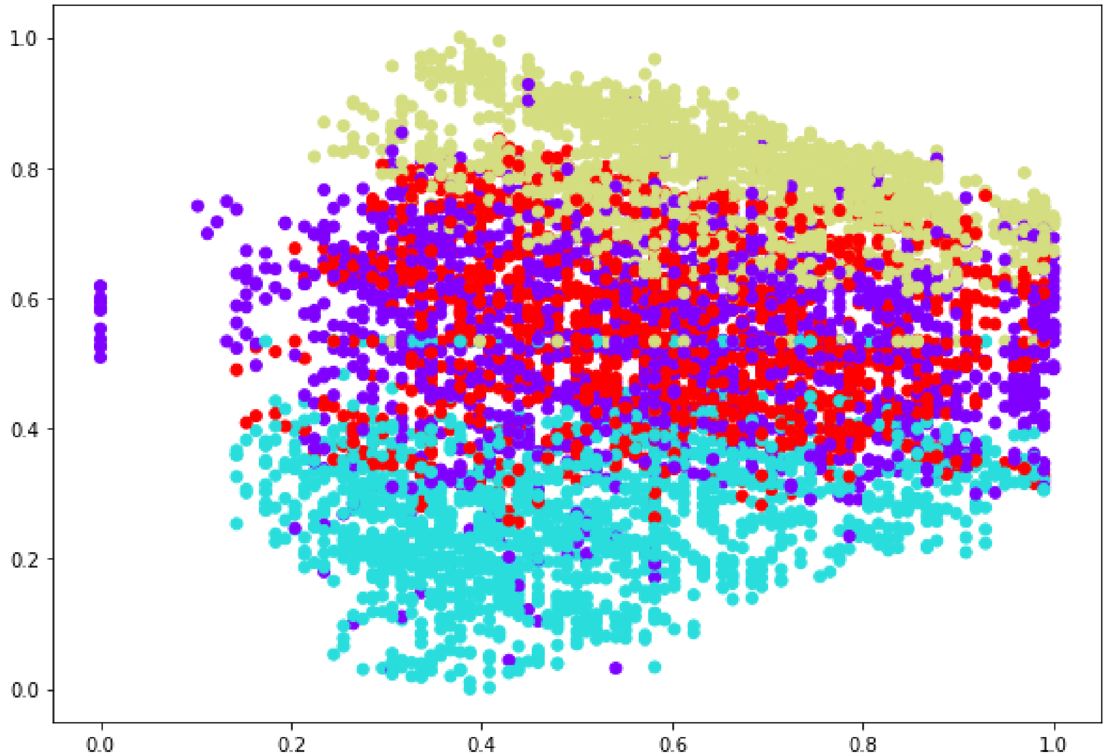
```
#It is taking approx 3 mins to execute this cell

plt.subplots(figsize = (5,5))
plt.title("Dendrograms")
dendrogram(linkage(minmax_df, method = 'ward'))
plt.axhline(y = 20, c = 'r', linestyle = '--')

plt.show()
```



From the above dendogram, we can summarize that there are 4 clusters as per agglomerative clustering. This number is optimal number for choosing clusters. These clusters are united finally by one cluster as it is bottom up approach. Red line at 20 cuts the clusters, at which number of clusters is taken.

In [36]:
```
#visualize the clustering data on 2 columns
plt.figure(figsize=(10, 7))
plt.scatter(minmax_df['Humidity(%)'], minmax_df['Temperature(C)'], c=clust
```

Out[36]: `<matplotlib.collections.PathCollection at 0x7fa391245820>`



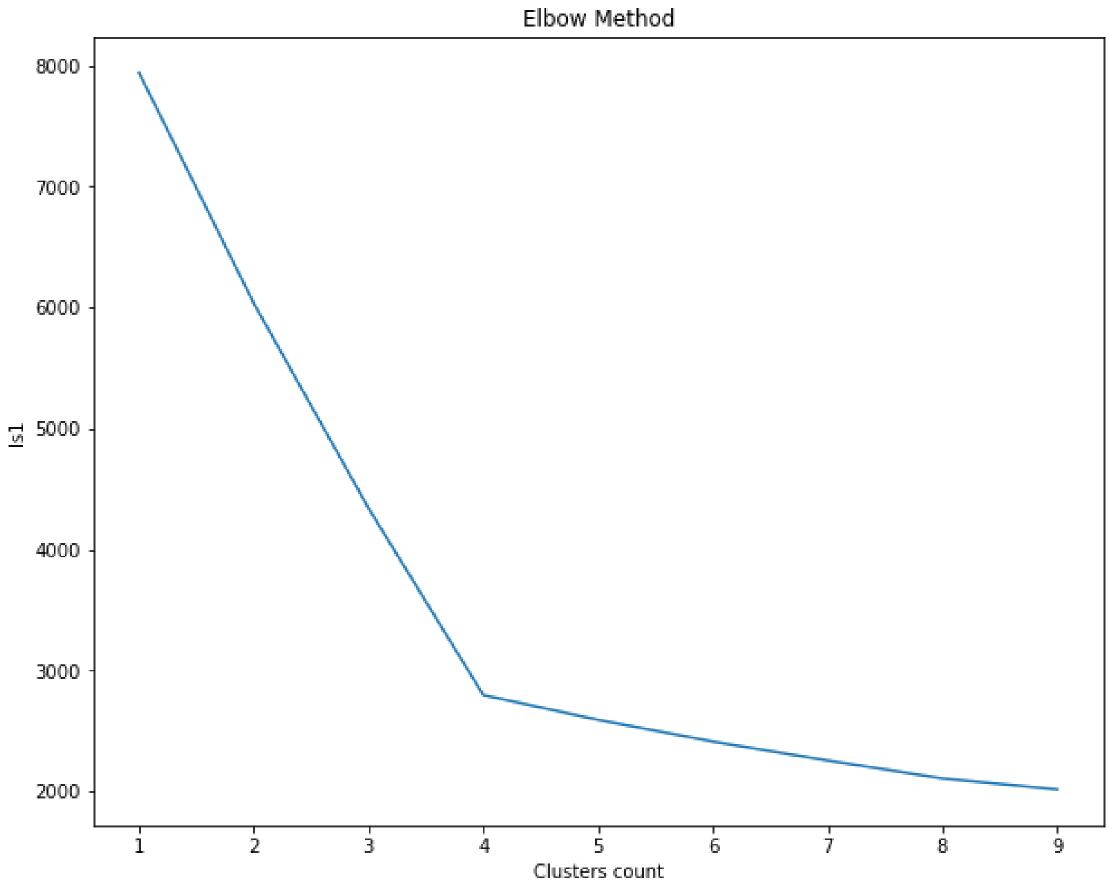
These 4 colours indicate 4 different clusters.

Kmeans Clustering

Using "Elbow Method" , inertia attribute to record the cluster wellness for K-Means

In [37]:

```
ls1=[]

#Loop to view the performace for 1 to 9 clusters
for i in range(1,10):
    #Initialize
    kmeans = KMeans(n_clusters = i,init ='k-means++', random_state =0)
    #Compute k-means clustering.
    kmeans.fit(minmax_df)
    ls1.append(kmeans.inertia_)
plt.figure(figsize=(10, 8))
plt.plot(range(1,10), ls1)
plt.title('Elbow Method')
plt.xlabel('Clusters count')
plt.ylabel('ls1')
plt.show()
```



In [38]:

```
for i in range(2,10):
    Kmean_cluster = KMeans(n_clusters = i , random_state = 0)

    Kmean_cluster.fit(minmax_df)

    Kmean_label = Kmean_cluster.labels_

    Kmean_count = np.bincount(Kmean_label)
    print(Kmean_count)
    print(f'Silhoutte score for cluster {i} and test data is ' +
          str(silhouette_score(minmax_df, Kmean_cluster.labels_)))
```

```
[1577 4993]
Silhoutte score for cluster 2 and test data is 0.27344861826306355
[1593 1577 3400]
Silhoutte score for cluster 3 and test data is 0.37083657901900924
[1624 1690 1619 1637]
Silhoutte score for cluster 4 and test data is 0.4820913627038414
[1606 1602 1591 1033  738]
Silhoutte score for cluster 5 and test data is 0.41763246433442675
[1126 1599 1018 1608  489  730]
Silhoutte score for cluster 6 and test data is 0.3707960004232965
[ 969 1133 1594  988  716  682  488]
Silhoutte score for cluster 7 and test data is 0.31225702922965276
[ 693 1149 1430  931  725  511  165  966]
Silhoutte score for cluster 8 and test data is 0.3031447380521718
[ 483  957  427  877 1111  620  713  652  730]
Silhoutte score for cluster 9 and test data is 0.2592412140425004
```

In [39]:

```
kmeans = KMeans(n_clusters = 4,init ='k-means++', random_state =0)
kmeans.fit(minmax_df)
kmeans.transform(minmax_df)
```

Out[39]:

```
array([[1.64644737, 1.57613821, 0.86096217, 1.68911968],
       [1.76971845, 0.77964172, 1.67364961, 1.62186141],
       [0.47526902, 1.59333451, 1.59621544, 1.7428177 ],
       ...,
       [1.716658  , 1.55096288, 1.62155629, 0.74964382],
       [1.53166664, 0.64552348, 1.51486669, 1.57991581],
       [1.66706656, 0.75442042, 1.65691197, 1.6829452 ]])
```

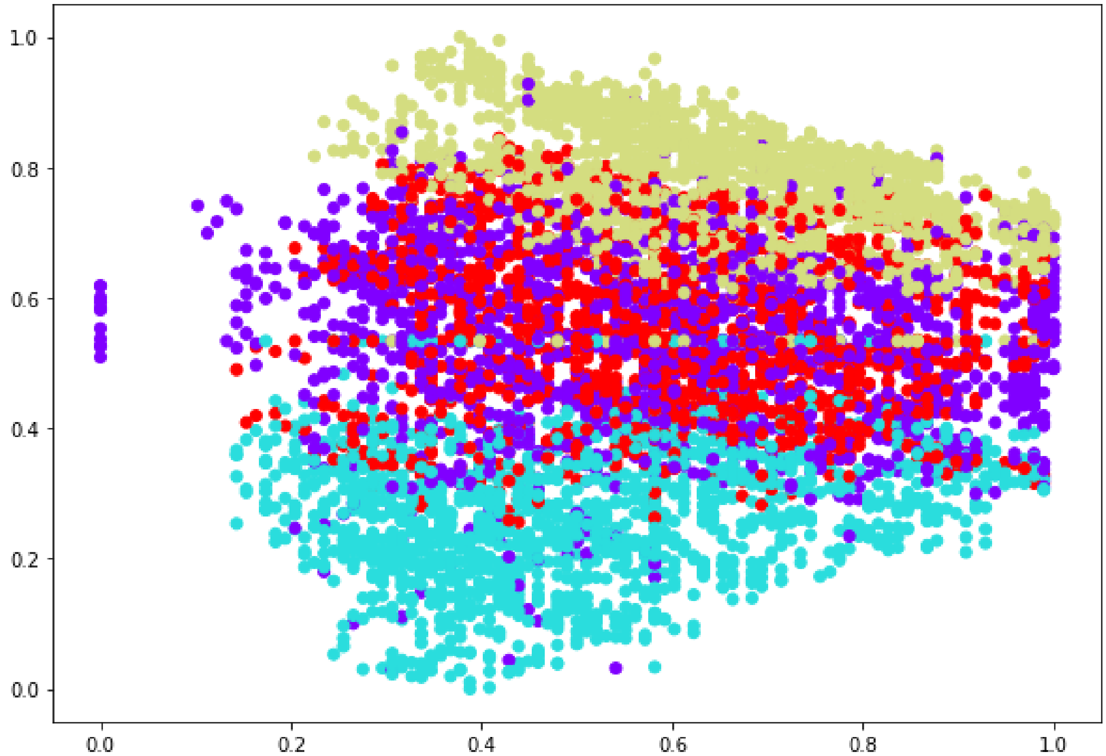
In [40]:

```
#SSE is defined as the sum of the squared distance between centroid and ec
print ('final value of the sum of squared errors is: {:.4f}'.format(kmeans
```

```
final value of the sum of squared errors is: 2794.9303
```

In [41]:
```
#visualize the clustering data on 2 columns
plt.figure(figsize=(10, 7))
plt.scatter(minmax_df['Humidity(%)'], minmax_df['Temperature(C)'], c=clust
```

Out[41]: <matplotlib.collections.PathCollection at 0x7fa3711d9b50>



In [42]:

```
#Cluster values

Kmeans=KMeans(n_clusters=4)
cols=['Hour','Temperature(C)','Humidity(%)','Wind speed (m/s)','Visibility
      'Dew point temperature(C)','Solar Radiation (MJ/m2)','Rainfall(mm)',
      'Holiday','Functioning Day','Autumn','Spring','Summer','Winter']
Kmeans.fit(minmax_df[cols])
centers=Kmeans.cluster_centers_
centersDf = pd.DataFrame(centers, columns=cols )
print ("centers values are:")
print(centersDf)
```

```
centers values are:
       Hour  Temperature(C)  Humidity(%)  Wind speed (m/s)  Visibility
(10m)  \
0  0.496930        0.552936     0.602158          0.200317          0.77
8510
1  0.495453        0.538145     0.601452          0.251231          0.61
0634
2  0.510885        0.771659     0.658675          0.218491          0.75
6439
3  0.495158        0.269940     0.504370          0.258844          0.73
3430

   Dew point temperature(C)  Solar Radiation (MJ/m2)  Rainfall(mm)  \
0                  0.625097                 0.138748      0.003076
1                  0.605689                 0.194702      0.005232
2                  0.850919                 0.216467      0.006849
3                  0.320230                 0.080288      0.000927

   Snowfall (cm)   Holiday  Functioning Day        Autumn        Spring
\
0   5.764563e-03  0.946602         0.899879  9.635922e-01  2.775558e-17
1   1.844968e-04  0.968731         0.982562  2.775558e-17  9.645219e-01
2   8.673617e-18  0.977356         1.000000  8.326673e-17  5.551115e-17
3   2.689510e-02  0.911385         1.000000  2.775558e-17  0.000000e+00

         Summer        Winter
0 -8.604228e-16  2.220446e-16
1 -8.604228e-16  1.942890e-16
2  9.749082e-01  2.220446e-16
3 -8.604228e-16  9.698462e-01
```

In [43]:
```
kmeans.cluster_centers_
```

Out[43]:
```
array([[ 4.95329454e-01,  2.69855128e-01,  5.04153262e-01,
         2.58695580e-01,  7.33906251e-01,  3.20269619e-01,
         8.04638519e-02,  9.27163969e-04,  2.67297358e-02,
         9.11330049e-01,  1.00000000e+00,  5.55111512e-17,
         0.00000000e+00, -8.04911693e-16,  9.70443350e-01],
       [ 4.96116677e-01,  5.38043080e-01,  5.99945659e-01,
         2.52286902e-01,  6.13586605e-01,  6.04982536e-01,
         1.95720145e-01,  5.14792899e-03,  3.56374395e-04,
         9.68639053e-01,  9.81656805e-01,  2.77555756e-17,
         9.49112426e-01, -8.60422844e-16,  2.22044605e-16],
       [ 4.95585867e-01,  5.53016087e-01,  6.03994655e-01,
         1.98545983e-01,  7.76890340e-01,  6.25800083e-01,
         1.36930414e-01,  3.13068031e-03,  5.86781964e-03,
         9.46263125e-01,  8.99320568e-01,  9.80852378e-01,
         0.00000000e+00, -8.32667268e-16,  1.11022302e-16],
       [ 5.11356752e-01,  7.71439292e-01,  6.58478052e-01,
         2.18461589e-01,  7.57302765e-01,  8.50633600e-01,
         2.15938593e-01,  6.83654769e-03,  6.93889390e-18,
         9.77397679e-01,  1.00000000e+00,  2.77555756e-17,
        -2.77555756e-17,  9.73121564e-01,  1.66533454e-16]])
```

In [44]:
```
kmeans.labels_
```

Out[44]:
```
array([2, 1, 0, ..., 3, 1, 1], dtype=int32)
```

From the above output its clear that Data is clustered into 4 groups

In [45]:
```
# view the data after scaling
minmax_df.head()
```

Out[45]:

	Hour	Temperature(C)	Humidity(%)	Wind speed (m/s)	Visibility (10m)	Dew point temperature(C)	Solar Radiation (MJ/m2)	R
0	1.000000	0.375000	0.846939	0.148649	0.181495	0.552265	0.000000	
1	0.608696	0.730634	0.479592	0.310811	0.247585	0.740418	0.815341	
2	0.826087	0.183099	0.336735	0.270270	0.942552	0.174216	0.000000	
3	0.521739	0.524648	0.989796	0.108108	0.104220	0.738676	0.039773	
4	0.173913	0.371479	0.714286	0.108108	0.966446	0.510453	0.000000	

Regression Model Training and Evaluation

Regression - Statistical Approach

In [46]:
```
# choosing the feature set
X = minmax_df
```

In [47]:
```
# add a constant column to take care of the intercept
X = sm.add_constant(X)

# build the model Ordinary least squares method
model = sm.OLS(y,X).fit()
```

In [48]:
```
model.summary()
```

Functioning Day	921.2618	33.230	27.724	0.000	856.121	986.403
Autumn	131.1279	32.648	4.016	0.000	67.127	195.129
Spring	15.2594	32.524	0.469	0.639	-48.498	79.017
Summer	-7.6878	35.071	-0.219	0.826	-76.439	61.063
Winter	-223.0439	35.259	-6.326	0.000	-292.163	-153.925

Omnibus:	983.037	**Durbin-Watson:**	1.969
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1872.662
Skew:	0.938	**Prob(JB):**	0.00
Kurtosis:	4.823	**Cond. No.**	70.5

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly

Observation :

From the above summary we can see the p value is greater for 0.05 significance level which means that they dont have any reason to reject the null-hypotesis.

So, the columns that are having p>0.05 are dropped and model is using fit method without these columns as below.

In [49]:
```
#Dropping columns with p>0.05
X_mod = X.drop(['Spring', 'Summer', 'Snowfall (cm)'], axis = 1)
X_mod = sm.add_constant(X_mod)
#Ordinary least squares method
model = sm.OLS(y,X_mod).fit()
model.summary()
```

Out[49]:

OLS Regression Results

Dep. Variable:	Rented Bike Count	**R-squared:**	0.533
Model:	OLS	**Adj. R-squared:**	0.532
Method:	Least Squares	**F-statistic:**	624.3
Date:	Sun, 24 Apr 2022	**Prob (F-statistic):**	0.00
Time:	15:25:40	**Log-Likelihood:**	-49319.
No. Observations:	6570	**AIC:**	9.866e+04
Df Residuals:	6557	**BIC:**	9.875e+04
Df Model:	12		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-896.5693	61.297	-14.627	0.000	-1016.732	-776.407
Hour	649.4515	19.899	32.637	0.000	610.443	688.460
Temperature(C)	947.1070	94.191	10.055	0.000	762.461	1131.753
Humidity(%)	-915.5885	56.860	-16.102	0.000	-1027.053	-804.124
Wind speed (m/s)	125.3283	44.445	2.820	0.005	38.201	212.456
Visibility (10m)	55.2916	22.001	2.513	0.012	12.162	98.421
Dew point temperature(C)	518.0812	96.881	5.348	0.000	328.164	707.999
Solar Radiation (MJ/m2)	-199.8453	29.378	-6.803	0.000	-257.435	-142.255
Rainfall(mm)	-1993.6978	171.435	-11.629	0.000	-2329.766	-1657.630
Holiday	114.8807	25.461	4.512	0.000	64.968	164.793
Functioning Day	919.6958	33.124	27.765	0.000	854.762	984.629
Autumn	125.8573	14.514	8.671	0.000	97.405	154.309
Winter	-235.1295	20.460	-11.492	0.000	-275.238	-195.021

Omnibus:	979.539	**Durbin-Watson:**	1.968
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1858.123
Skew:	0.936	**Prob(JB):**	0.00
Kurtosis:	4.811	**Cond. No.**	69.5

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Simple Linear Regression

For the simple linear regression we are considering only the column ' Temperature' has high correlation with the target column compared to anyother column Correlation coefficient = 0.54

In [50]:
```
# selecting the temperature column as feature for prediction
x = minmax_df['Temperature(C)']
```

In [51]:
```
#Intializing
model = st.linregress(x,y)
model
```

Out[51]:
```
LinregressResult(slope=1656.2725591269673, intercept=-175.9323241392378
3, rvalue=0.5341770903950772, pvalue=0.0, stderr=32.34283944064384)
```

In [52]:
```
#solving linear regresssion equation with slope and intercept
y_predict = model.slope * x + model.intercept

#Calculating the regression error ϵ
epsilon = y - y_predict
```

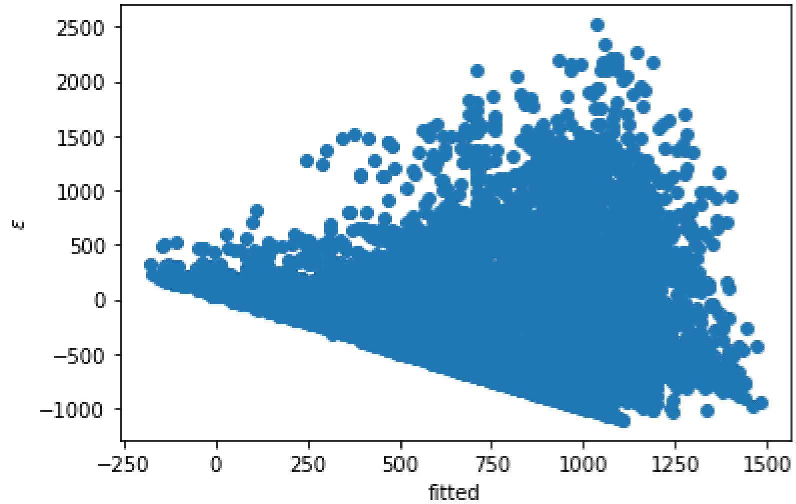
Checking simple linear regression assumptions has a mean of zero has constant variance is normal

In [53]:
```
# has a mean of zero
epsilon.mean()
```

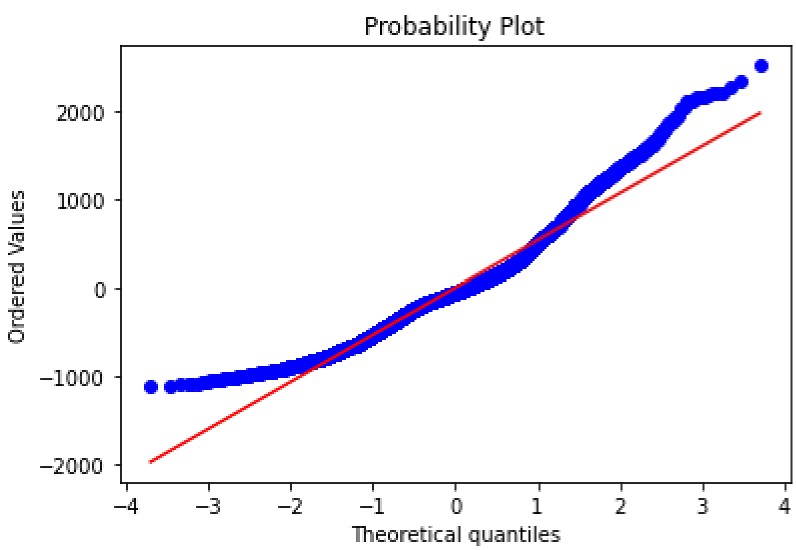
Out[53]:
```
8.427015216198936e-14
```

In [54]:
```
# has constant variance

%matplotlib inline
plt.scatter(y_predict, epsilon)
plt.xlabel('fitted')
plt.ylabel('$\epsilon$')
```

Out[54]:
```
Text(0, 0.5, '$\\epsilon$')
```



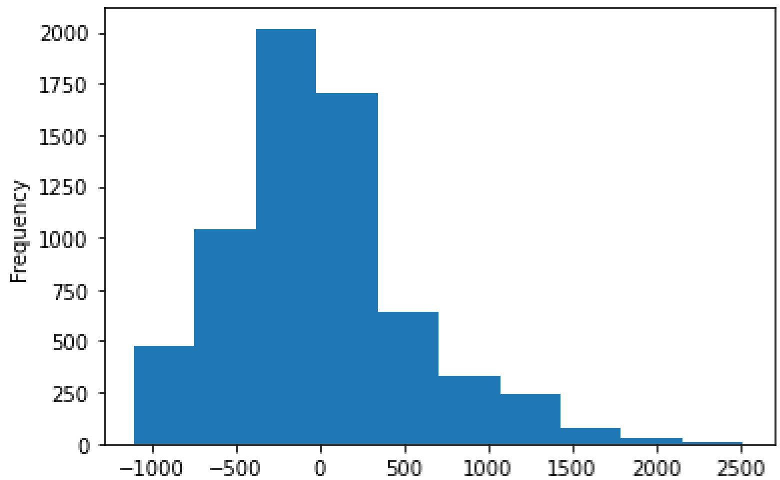
In [55]:
```
# is normal
%matplotlib inline
st.probplot(epsilon, dist = 'norm', plot = plt)
plt.show()
```



Here the plotted points seems to have a non linear pattern

In [56]:
```
%matplotlib inline
epsilon.plot(kind = 'hist', bins = 10)
```

Out[56]: <AxesSubplot:ylabel='Frequency'>



Try the following transformations:

ln(y)

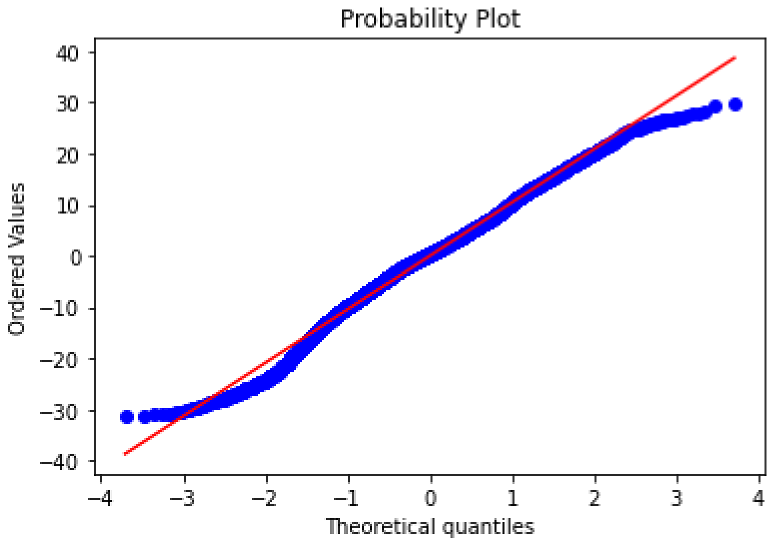
1/y

sqrt(y)

2^y

In [57]:
```
# Transforming y as y^1/2
y_modified = np.sqrt(y)
model = st.linregress(x,y_modified)

ym_predict = model.slope * x + model.intercept
#Calculating the regression error ϵ
epsilon = y_modified - ym_predict
```

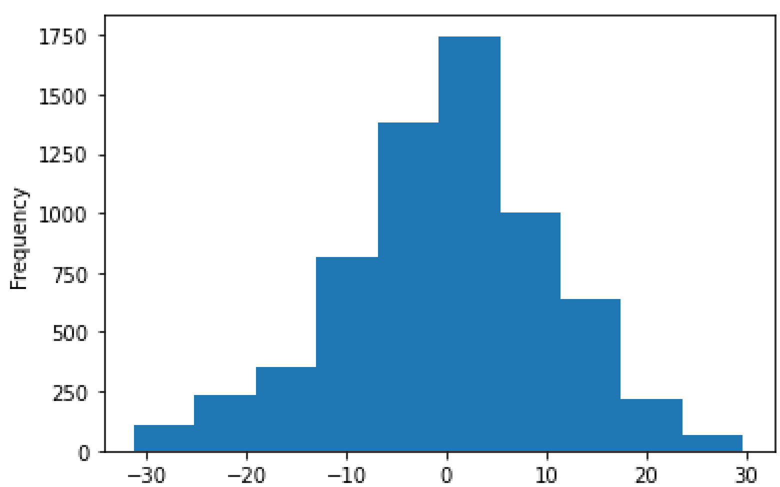
In [58]:
```
# is normal
%matplotlib inline
st.probplot(epsilon, dist = 'norm', plot = plt)
plt.show()
```



plotted points lie reasonably close to the diagonal line on the plot then conclude that the "normality" assumption holds on y_modified

In [59]:
```
%matplotlib inline
epsilon.plot(kind = 'hist', bins = 10)
```

Out[59]: <AxesSubplot:ylabel='Frequency'>

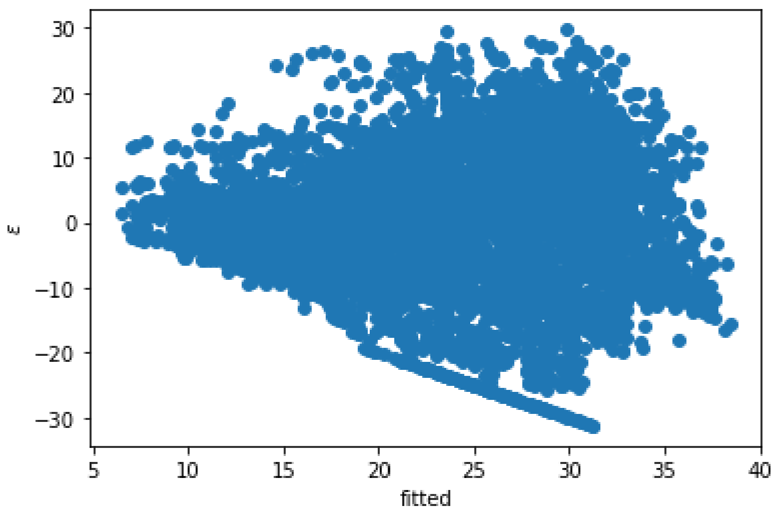


In [60]:
```
epsilon.mean()
```

Out[60]: 3.6884414007759845e-15

In [61]:
```
# has constant variance

%matplotlib inline
plt.scatter(ym_predict, epsilon)
plt.xlabel('fitted')
plt.ylabel('$\epsilon$')
```

Out[61]:
```
Text(0, 0.5, '$\\epsilon$')
```



Correlation

In [62]:
```
np.corrcoef(x, y_modified)
```

Out[62]:
```
array([[1.        , 0.53602101],
       [0.53602101, 1.        ]])
```

t - test for the population correlation coefficient

The output of st.pearson r are the correlation coefficient and the two-tailed p-value obtained.

In [63]:
```
val = st.pearsonr(x, y_modified)
```

In [64]:
```
print('Correlation coefficient: ', val[0])
print('p-value (two-tailed): %.5f'%val[1])
```

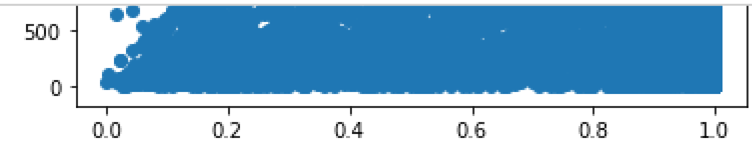
```
Correlation coefficient:  0.536021009568777
p-value (two-tailed): 0.00000
```

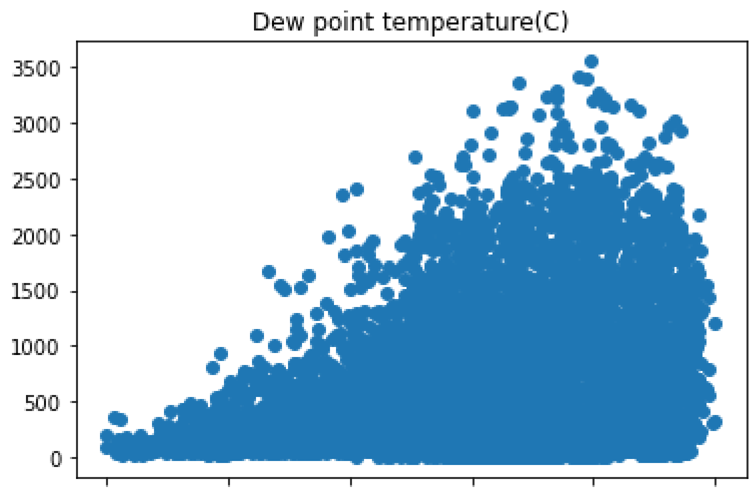
Since the p - value is less than the significance level α =0.05 sufficinet evidence exists that a positive linear relationship exists between x and y_modified.

Multiple Regression

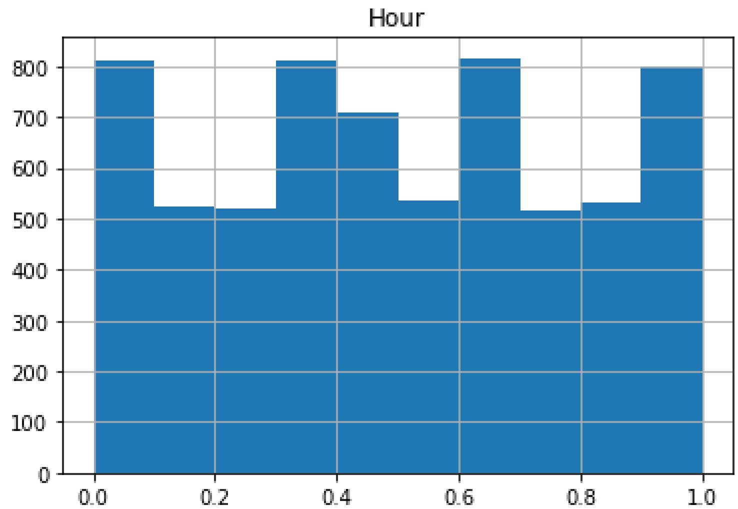
In [65]:
```
# choosing the feature set
X = minmax_df.drop(['Spring', 'Summer', 'Snowfall (cm)'], axis = 1)
```

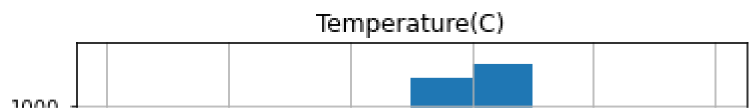
In [66]:
```
#Scatter plots for all feature columns

%matplotlib inline

for col in X.columns:
    plt.scatter(X[col], y)
    plt.title(col)
    plt.show()
```





In [67]:
```
%matplotlib inline
# Histograms for all feature columns
for col in X.columns:
    hist = X[col].hist(bins = 10)
    plt.title(col)
    plt.show()
```





In [68]:

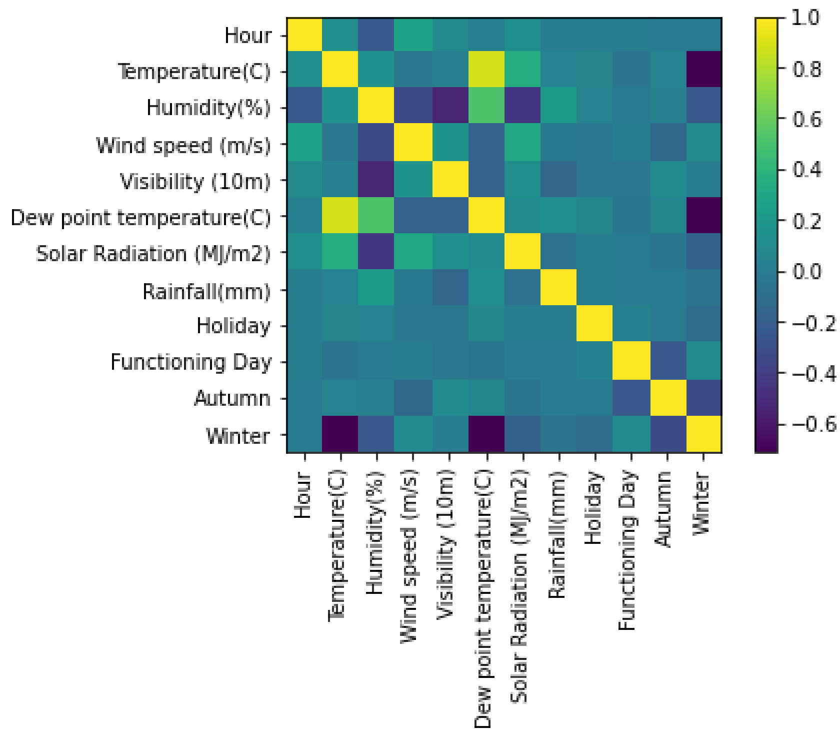
```
#Pearson product-moment correlation coefficients.
np.corrcoef(X.T)
```

Out[68]:

```
array([[ 1.        ,  0.13484548, -0.22759732,  0.27611962,  0.09296656,
         0.01991854,  0.14265979,  0.01508463,  0.00947895,  0.00992338,
        -0.00411265, -0.00915392],
       [ 0.13484548,  1.        ,  0.15504209, -0.03300283,  0.03294344,
         0.88685319,  0.35057207,  0.04756486,  0.05285473, -0.04976006,
         0.05044068, -0.71155101],
       [-0.22759732,  0.15504209,  1.        , -0.33366848, -0.5300461 ,
         0.51932343, -0.43423169,  0.22054833,  0.0440666 , -0.01400295,
         0.03418909, -0.23226014],
       [ 0.27611962, -0.03300283, -0.33366848,  1.        ,  0.17550684,
        -0.17051289,  0.31410882, -0.02092862, -0.02304582,  0.01584164,
        -0.13697707,  0.10700788],
       [ 0.09296656,  0.03294344, -0.5300461 ,  0.17550684,  1.        ,
        -0.17098815,  0.13897234, -0.1462326 , -0.03034325, -0.03013896,
         0.1000562 ,  0.01710534],
       [ 0.01991854,  0.88685319,  0.51932343, -0.17051289, -0.17098815,
         1.        ,  0.10247867,  0.11954436,  0.06627413, -0.04805509,
         0.06106048, -0.69929434],
       [ 0.14265979,  0.35057207, -0.43423169,  0.31410882,  0.13897234,
         0.10247867,  1.        , -0.06805702,  0.00694719, -0.00705505,
        -0.04402995, -0.17865902],
       [ 0.01508463,  0.04756486,  0.22054833, -0.02092862, -0.1462326 ,
         0.11954436, -0.06805702,  1.        ,  0.00812551, -0.00106015,
        -0.01445689, -0.05296894],
       [ 0.00947895,  0.05285473,  0.0440666 , -0.02304582, -0.03034325,
         0.06627413,  0.00694719,  0.00812551,  1.        ,  0.03971332,
        -0.00892691, -0.10582274],
       [ 0.00992338, -0.04976006, -0.01400295,  0.01584164, -0.03013896,
        -0.04805509, -0.00705505, -0.00106015,  0.03971332,  1.        ,
        -0.23545332,  0.09798973],
       [-0.00411265,  0.05044068,  0.03418909, -0.13697707,  0.1000562 ,
         0.06106048, -0.04402995, -0.01445689, -0.00892691, -0.23545332,
         1.        , -0.31715914],
       [-0.00915392, -0.71155101, -0.23226014,  0.10700788,  0.01710534,
        -0.69929434, -0.17865902, -0.05296894, -0.10582274,  0.09798973,
        -0.31715914,  1.        ]])
```

In [69]:

```
%matplotlib inline

plt.imshow(np.corrcoef(X.T))
plt.xticks(np.arange(12), X.columns, rotation = 90)
plt.yticks(np.arange(12), X.columns)
plt.colorbar()
plt.show()
```



Regression - Machine learning approach

Multivariate - 2

Model trainining with 70% as train data and 30% as test data.

In [70]:

```
#Using train_test_split to split the data
X_train, X_valid, y_train, y_valid = train_test_split(X,y, test_size = 0.3

#Scaling the splitted data
scaler = MinMaxScaler()

#Fit the data
scaler.fit(X_train)

#Transform the data

#Train data
X_train_scaled = scaler.transform(X_train)
#Test data
X_valid_scaled = scaler.transform(X_valid)

#Applying linear regression for tain data
lreg = LinearRegression()
lreg.fit(X_train_scaled, y_train)

#Calculate the scores for the train and test data
print('train r2-score: ', lreg.score(X_train_scaled, y_train))
print('validation r2-score: ', lreg.score(X_valid_scaled, y_valid))
```

```
train r2-score:  0.5411449121467613
validation r2-score:  0.5134431436761961
```

Model trainining with 80% as train data and 20% as test data.

In [71]:

```
#Using train_test_split to split the data
X_train, X_valid, y_train, y_valid = train_test_split(X,y, test_size = 0.2

#Scaling the splitted data
scaler = MinMaxScaler()

#Fit the data
scaler.fit(X_train)

#Transform the data

#Train data
X_train_scaled = scaler.transform(X_train)
#Test data
X_valid_scaled = scaler.transform(X_valid)

#Applying linear regression for tain data
lreg = LinearRegression()
lreg.fit(X_train_scaled, y_train)

#Calculate the scores for the train and test data
print('train r2-score: ', lreg.score(X_train_scaled, y_train))
print('validation r2-score: ', lreg.score(X_valid_scaled, y_valid))
```

```
train r2-score:  0.5374113286330617
validation r2-score:  0.516156183957653
```

Model trainining with 90% as train data and 10% as test data.

In [72]:

```
#Using train_test_split to split the data
X_train, X_valid, y_train, y_valid = train_test_split(X,y, test_size = 0.:

#Scaling the splitted data
scaler = MinMaxScaler()

#Fit the data
scaler.fit(X_train)

#Transform the data

#Train data
X_train_scaled = scaler.transform(X_train)
#Test data
X_valid_scaled = scaler.transform(X_valid)

#Applying linear regression for tain data
lreg = LinearRegression()
lreg.fit(X_train_scaled, y_train)
print(lreg.intercept_)
print(lreg.coef_)

#Calculate the scores for the train and test data
print('train r2-score: ', lreg.score(X_train_scaled, y_train))
print('validation r2-score: ', lreg.score(X_valid_scaled, y_valid))
```

```
-909.6433917211231
[  648.31735662  1003.57420299  -912.11001627   128.52135817
    53.58650211   485.57546056  -206.57808174 -1963.23330722
   120.5057467    915.80956603   123.89129649  -231.53745252]
train r2-score:  0.5343015187669671
validation r2-score:  0.522966372124259
```

Linear Regression metrics

In [73]:

```

ypred = lreg.predict(X_valid_scaled)
mse = mean_squared_error(y_valid,ypred)
#Metrics
print("Mean Square Error: " , mse)
print("Root Mean Square Error: ", mse**(1/2.0))
print('Mean Absolute Error is:', mean_absolute_error(y_valid,ypred))
```

```
Mean Square Error:  198319.3916422973
Root Mean Square Error:  445.33065428094807
Mean Absolute Error is: 332.4748076001624
```

simple linear regression

In [74]:

```
# Simple linear regression test-train split
x = minmax_df['Temperature(C)']
y = df["Rented Bike Count"]

#splitting data into training and testing data
trainDataX,testDataX, trainDataY, testDataY = train_test_split(x,y, test_s
```

In [75]:

```
from sklearn.linear_model import LinearRegression
# Re-shape the data
XTrain= trainDataX.values.reshape(-1, 1)
YTrain= trainDataY.values.reshape(-1, 1)
XTest= testDataX.values.reshape(-1, 1)
YTest= testDataY.values.reshape(-1, 1)
trainDataX.shape, trainDataY.shape
```

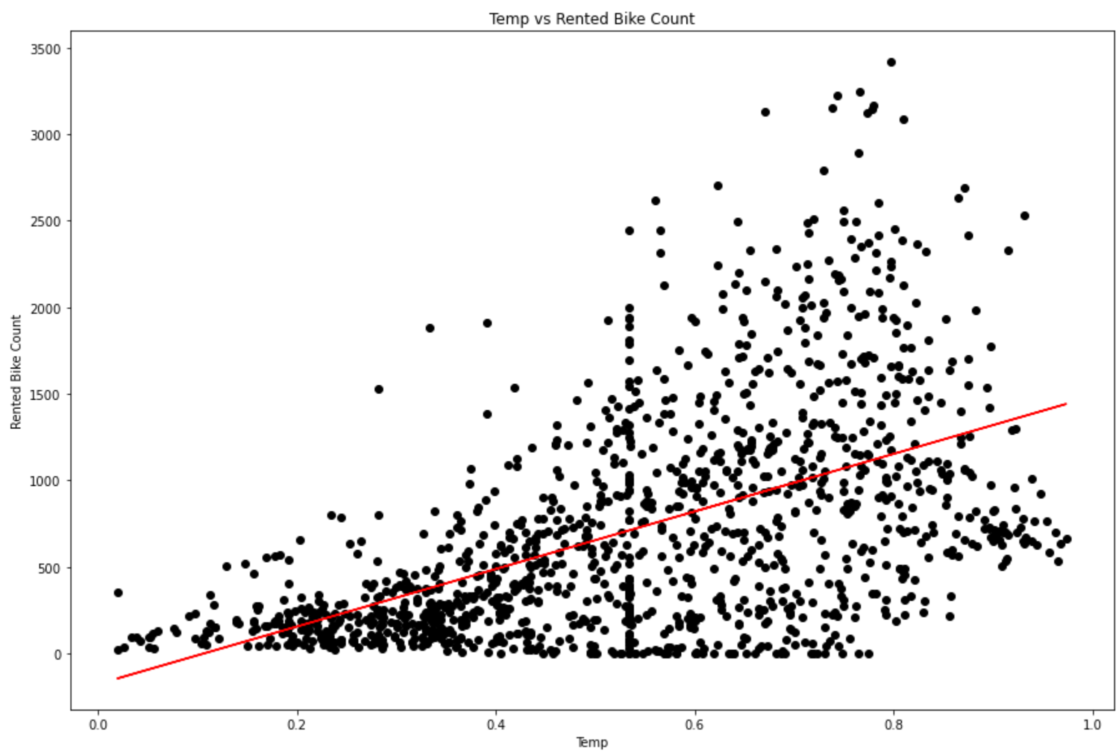
Out[75]: ((5256,), (5256,))

In [76]:

```
# Linear regression model fitting

regre = LinearRegression()
regre.fit(XTrain, YTrain)
print(regre.intercept_)
print(regre.coef_)

#to make predictions on test data
Yprediction = regre.predict(XTest)
```

```
[-178.25020162]
[[1662.08102873]]
```

In [77]:
```
#Visualise the testdata and predicted data
import matplotlib.pyplot as plt
from PIL.Image import core as _imaging
%matplotlib inline
#to draw scatterplot
fig, ax = plt.subplots(figsize=(15,10))
plt.scatter(testDataX, testDataY,color='black')
plt.plot(testDataX, Yprediction, color = 'red')
plt.title("Temp vs Rented Bike Count")
plt.xlabel("Temp")
plt.ylabel("Rented Bike Count")
plt.show()
plt.close()
```



In [78]:
```
from sklearn import metrics
print('Mean Absolute Error is:', metrics.mean_absolute_error(YTest, Ypredi
print('Mean Squared Error is:', metrics.mean_squared_error(YTest, Ypredict
print('Root Mean Squared Error is:', np.sqrt(metrics.mean_squared_error(YT
print('r2_score :', r2_score(YTest, Yprediction))
```

```
Mean Absolute Error is: 413.5176825718873
Mean Squared Error is: 307018.8702813908
Root Mean Squared Error is: 554.0928354358958
r2_score : 0.2813215709521881
```

Multivariate - 1

In [79]:

```
from sklearn.preprocessing import normalize

v1 = minmax_df[['Temperature(C)','Hour','Dew point temperature(C)']]

#diving into train and test data
trainVar1,testVar1,trainVar2,testVar2 = train_test_split(v1,y, train_size=
#normalizing raw data and finding intercept and slope
regressor = LinearRegression().fit(normalize(trainVar1), trainVar2)
print(regressor.intercept_)
print(regressor.coef_)
#making predictions using test data
Ypredict = regressor.predict(normalize(testVar1))
print('Mean Absolute Error is:', metrics.mean_absolute_error(testVar2, Ypr
print('Mean Squared Error is:', metrics.mean_squared_error(testVar2, Ypred
print('Root Mean Squared Error is:', np.sqrt(metrics.mean_squared_error(te
print('r2_score :', r2_score(testVar2, Ypredict))
```

```
-2957.68199454129
[3854.49204007 2180.91602147  891.22512659]
Mean Absolute Error is: 436.33653640889287
Mean Squared Error is: 326828.5221652952
Root Mean Squared Error is: 571.6891831802445
r2_score : 0.2349505792184876
```

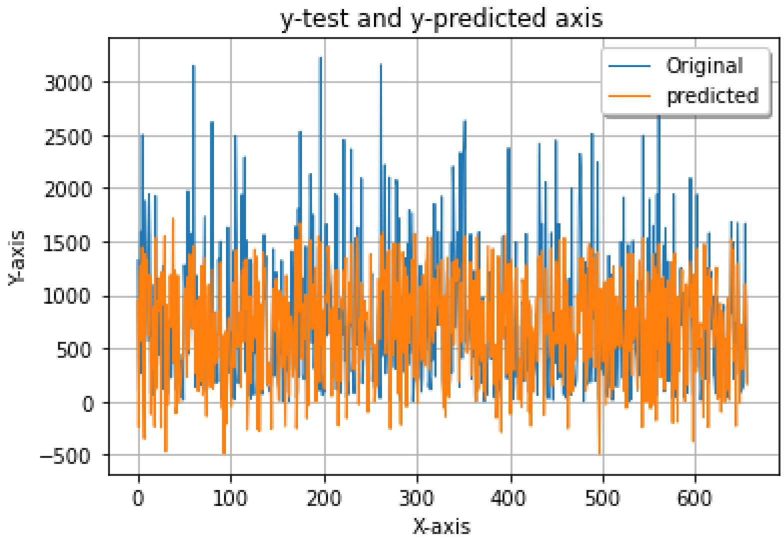
SGD Regressor

In [80]:

```
from sklearn.linear_model import SGDRegressor

sgd = SGDRegressor(random_state = 0, max_iter = 100000, learning_rate = 'c
sgd.fit(X_train_scaled, y_train)

ypred = sgd.predict(X_valid_scaled)

mse = mean_squared_error(y_valid,ypred)

#Metrics
print("Mean Square Error: " , mse)
print("Root Mean Square Error: ", mse**(1/2.0))
print('Mean Absolute Error is:', mean_absolute_error(y_valid,ypred))
print('train r2-score: ', sgd.score(X_train_scaled, y_train))
print('validation r2-score: ', sgd.score(X_valid_scaled, y_valid))
```

```
Mean Square Error:  200890.8662516909
Root Mean Square Error:  448.20850756282044
Mean Absolute Error is: 333.627292439148
train r2-score:  0.5293175216503467
validation r2-score:  0.5167809968477861
```

In [81]:
```
x_ax = range(len(y_valid))
plt.plot(x_ax, y_valid, linewidth = 1, label = "Original")
plt.plot(x_ax, ypred, linewidth = 1.1, label = "predicted")
plt.title("y-test and y-predicted axis")
plt.xlabel('X-axis')
plt.ylabel('Y-axis')
plt.legend(loc = 'best', fancybox = True, shadow = True)
plt.grid(True)
plt.show()
```

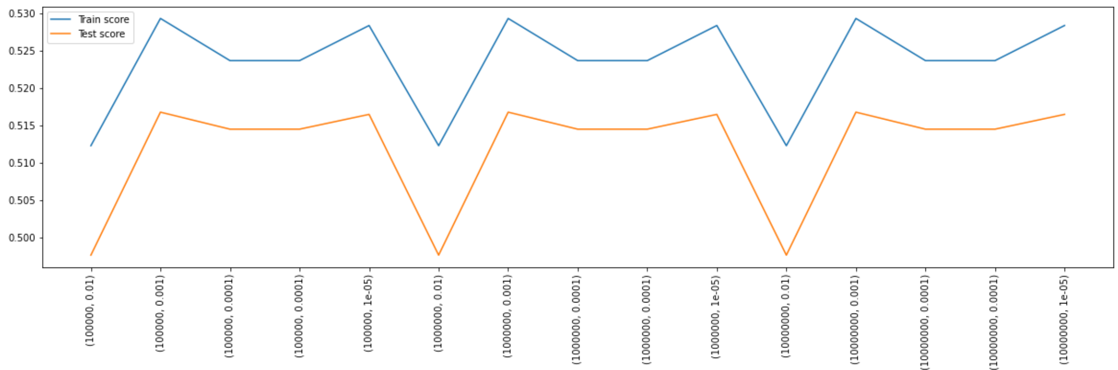


In [82]:
```
sgd.n_iter_
```

Out[82]: 56

In [83]:
```
train_score = []
validation_score = []
index = []

for max_iter in [100000, 1000000, 10000000]:
    for eta0 in [0.01, 0.001, 0.0001, 0.0001, 0.00001]:
        sgd = SGDRegressor(random_state = 0, max_iter = max_iter, learning
        sgd.fit(X_train_scaled, y_train)
        train_score.append(sgd.score(X_train_scaled, y_train))
        validation_score.append(sgd.score(X_valid_scaled, y_valid))
        index.append((max_iter, eta0))
```

In [84]:
```
%matplotlib inline
# To view the test and train scores
plt.subplots(figsize = (20,5))
plt.plot(range(len(index)),  train_score, label = 'Train score')
plt.plot(range(len(index)), validation_score, label = 'Test score')
plt.xticks(range(len(index)), index, rotation = 90)
plt.legend()
plt.show()
```

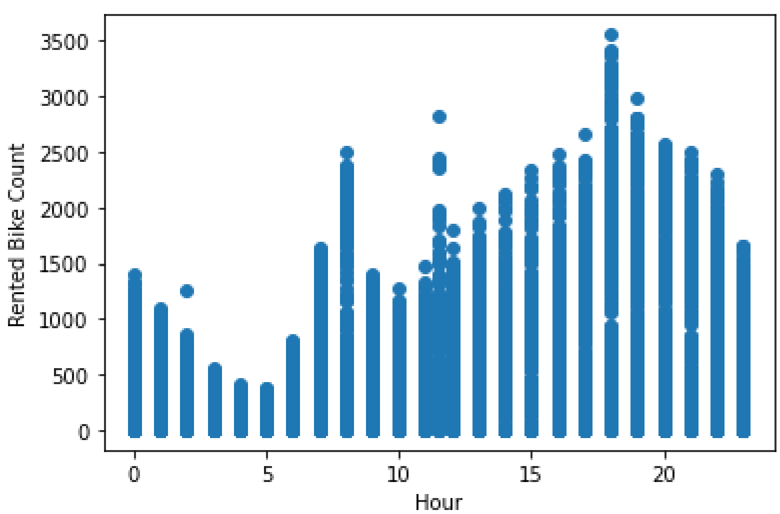


Irrespective of the training rate the test and train scores. So there is no reasons to use the sgd regressor to predict the values.

In [85]:
```
X_tree = df.drop('Rented Bike Count', axis = 1)

y_tree = df['Rented Bike Count']
```

In [86]:
```
%matplotlib inline
plt.scatter(df['Hour'], df['Rented Bike Count'])
plt.xlabel('Hour')
plt.ylabel('Rented Bike Count')
```

Out[86]:
```
Text(0, 0.5, 'Rented Bike Count')
```

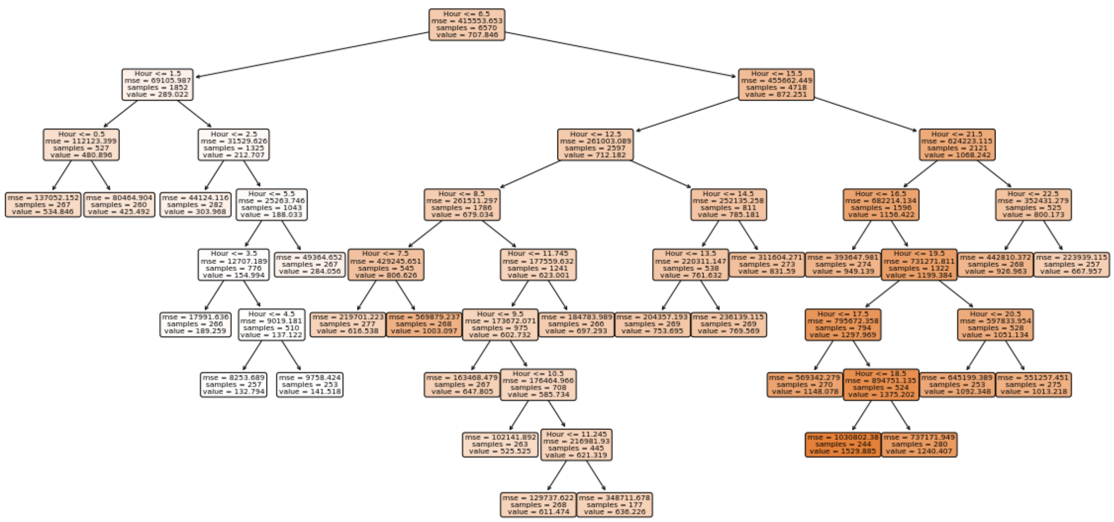


Decision Tree Regressor

In [87]:
```
dt = DecisionTreeRegressor(random_state = 0)
dt.fit(df['Hour'].values.reshape(-1,1), df['Rented Bike Count'].values)
```

Out[87]: DecisionTreeRegressor(random_state=0)

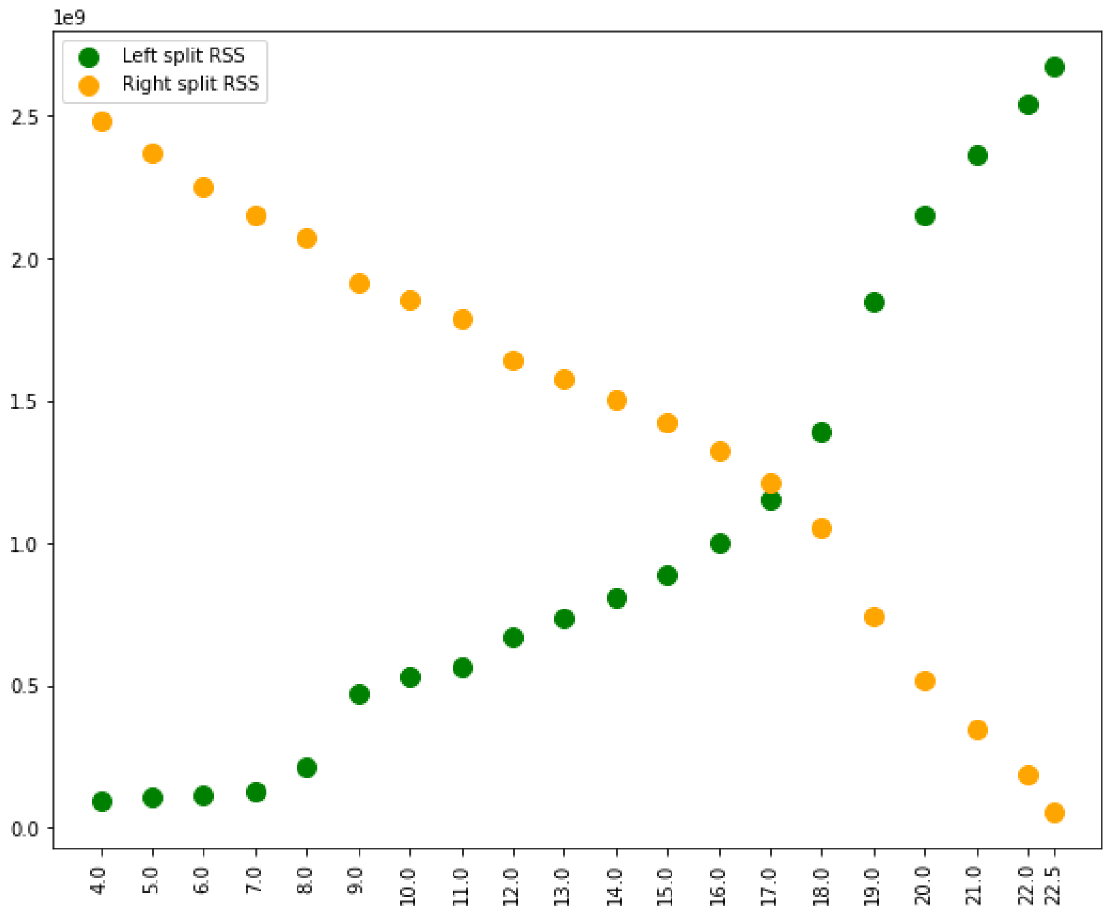
In [88]:
```
plt.subplots(figsize = (20,10))
plot_tree(dt,
               feature_names=['Hour'],
               filled=True,
               rounded = True)
plt.show()
```



In [89]:
```
vals = [4.0,5,6.0,7.0,8.0,9.0,10.0,11.0,12.0,13.0,14.0,15.0,16.0,17.0,18.
```

In [90]:
```
rss1 = []
rss2 = []
for val in vals:
    mean = df[df['Hour'] < val]['Rented Bike Count'].mean()
    rss = ((df[df['Hour'] < val]['Rented Bike Count'] - mean)** 2).sum()
    rss1.append(rss)
    mean = df[df['Hour'] >= val]['Rented Bike Count'].mean()
    rss = ((df[df['Hour'] >= val]['Rented Bike Count'] - mean)** 2).sum()
    rss2.append(rss)
```

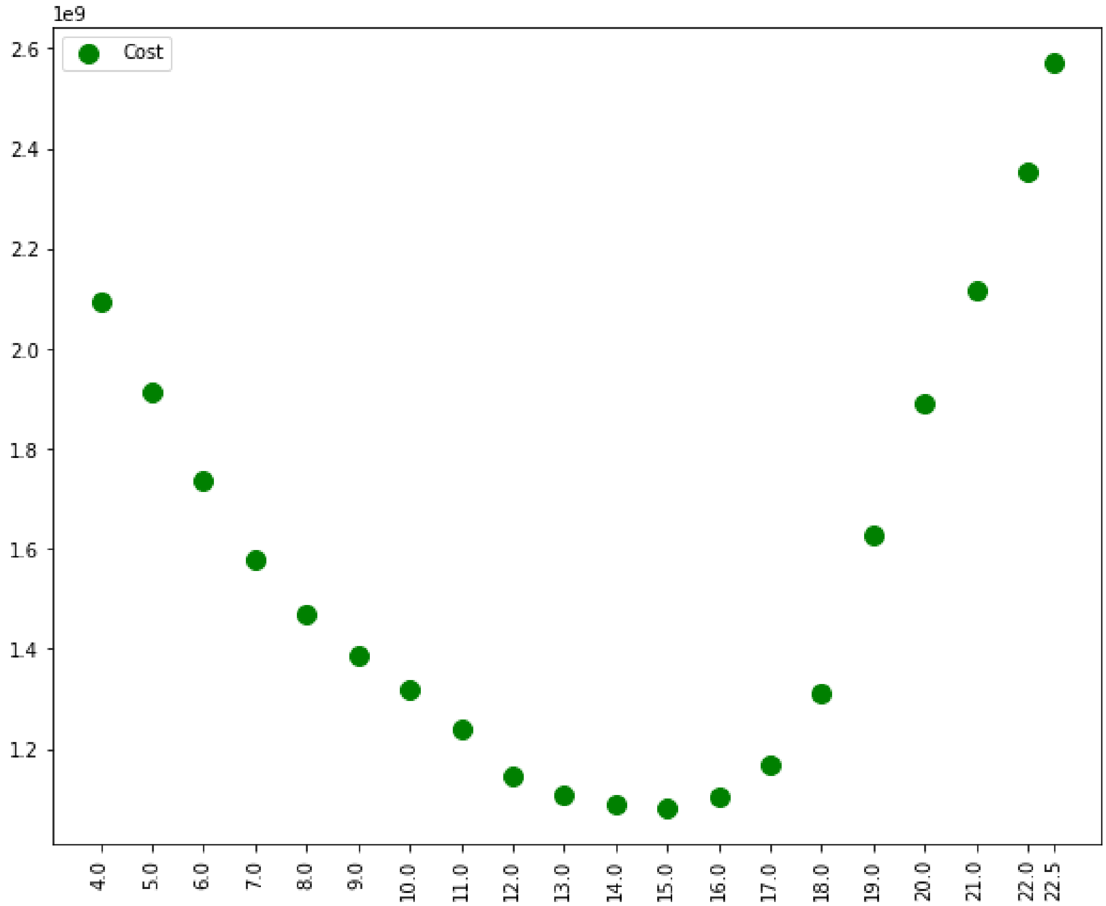
In [91]:
```
#It is taking approx 1 mins to execute this cell

%matplotlib inline

plt.subplots(figsize = (10, 8))
plt.scatter(vals, rss1, label = 'Left split RSS', s= 100, c = 'g')
plt.scatter(vals, rss2, label = 'Right split RSS', s = 100, c = 'orange')
plt.legend()
plt.xticks(vals, rotation = 90)
plt.show()
```



In [92]:
```
rss1 = np.array(rss1)
rss2 = np.array(rss2)

cost = []
index = 0
for val in vals:
    left = df[df['Hour'] < val].shape[0]/df.shape[0]
    right = df[df['Hour'] >= val].shape[0]/df.shape[0]
    cost.append(left*rss1[index] + right*rss2[index])
    index += 1
```

In [93]:

```
#It is taking approx 1 mins to execute this cell

%matplotlib inline

plt.subplots(figsize = (10, 8))
plt.scatter(vals, cost, label = 'Cost', s= 100, c = 'g')
plt.legend()
plt.xticks(vals, rotation = 90)
plt.show()
```



In [94]:

```
from sklearn.tree import DecisionTreeRegressor,plot_tree

X_train_orig, X_test_orig, y_train, y_test = train_test_split(X_tree, y_tr

scaler = StandardScaler()
scaler.fit(X_train_orig)
X_train = scaler.transform(X_train_orig)
X_test = scaler.transform(X_test_orig)
```

In [95]:

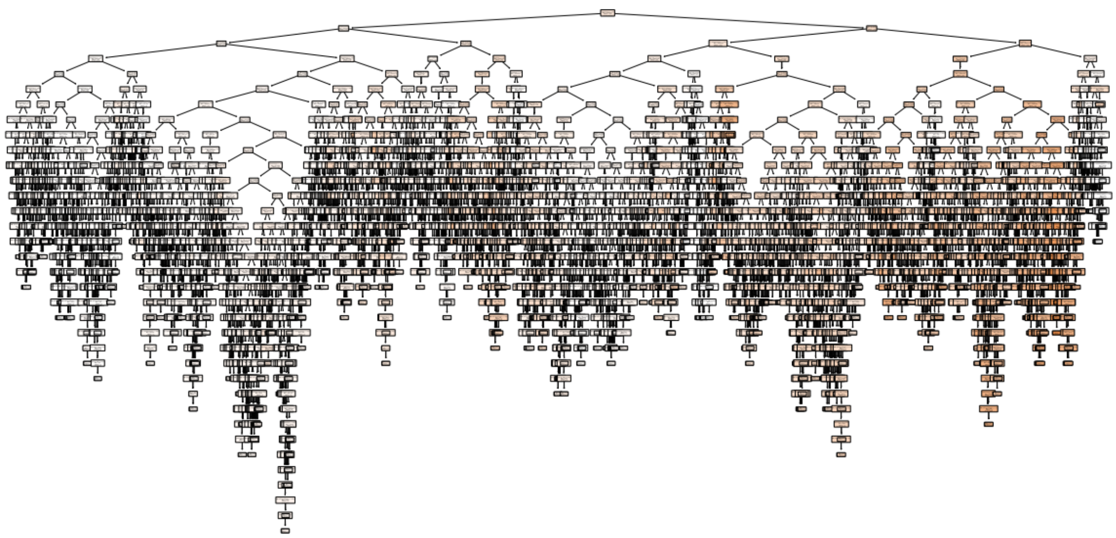
```
dtreg = DecisionTreeRegressor(random_state= 0)
dtreg.fit(X_train, y_train)
```

Out[95]: DecisionTreeRegressor(random_state=0)

In [96]:
```
print('Train r2-score:', dtreg.score(X_train, y_train))
print('Test r2-score:', dtreg.score(X_test, y_test))
```

```
Train r2-score: 1.0
Test r2-score: 0.7077368890801894
```

In [97]:
```
#It is taking approx 2 mins to execute this cell

plt.subplots(figsize = (20, 10))
plot_tree(dtreg,
               feature_names=X_train_orig.columns,

               filled=True,
               rounded = True)
plt.show()
```

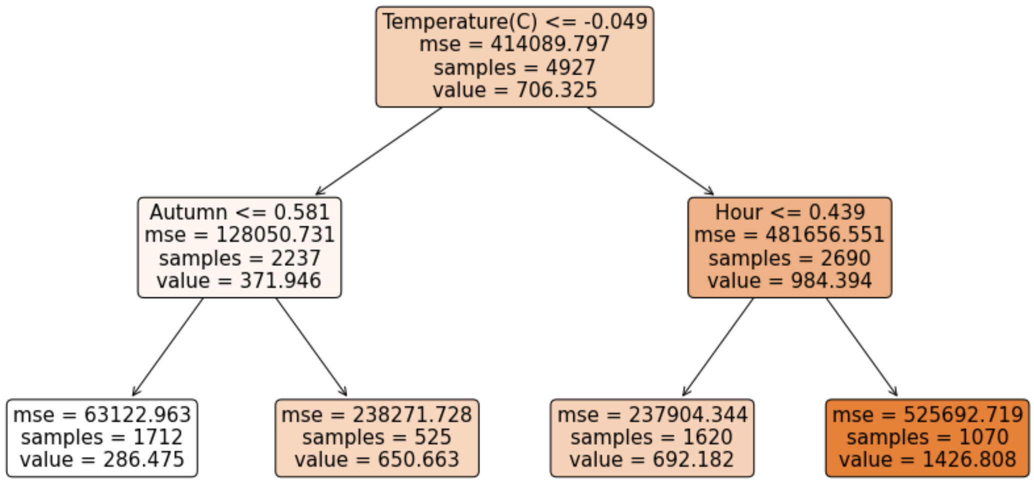


Early stopping: max_depth = 2

In [98]:
```
dtreg = DecisionTreeRegressor(random_state= 0, max_depth = 2)
dtreg.fit(X_train, y_train)
```

Out[98]:
```
DecisionTreeRegressor(max_depth=2, random_state=0)
```

In [99]:
```
plt.subplots(figsize = (15, 8))
plot_tree(dtreg,
               feature_names=X_train_orig.columns,
               filled=True,
               rounded = True)
plt.show()
```



In [100]:
```
X_tree.shape
```

Out[100]:
```
(6570, 15)
```

In [101]:
```
new_observation = pd.DataFrame(X_test, columns= X_tree.columns).iloc[0]
dtreg.predict([new_observation])
```

Out[101]:
```
array([692.18209877])
```

Regression Model Prediction

In [102]:
```
#Test data set choosed with mimmax scaler after removing the multicolinear

Xt = minmax_dft.drop(['Spring', 'Summer', 'Snowfall (cm)'],axis = 1)

# 3- Predict and evaluate
y_pred = lreg.predict(X) #Using the model trained the muliple columns with
yt_pred = lreg.predict(Xt)# Prediction for the test data

#Prediction score
print('score:', lreg.score(X,y))
```

```
score: 0.5331853477283591
```

Error Evaluation

In [103]:
```
# mean_squared_error(actual, predicted)
np.sqrt(mean_squared_error(y, y_pred))
```

Out[103]: 440.43902439513005

In [104]:
```
mean_squared_error(y, y_pred)
```

Out[104]: 193986.53421013395

In [105]:
```
# mean_absolute_error(actual, predicted)
mean_absolute_error(y, y_pred)
```

Out[105]: 329.1109147838864

In [106]:
```
#r2_score(actual, predicted)
r2_score(y, y_pred)
```

Out[106]: 0.5331853477283591

Summary :

Model Evaluation and Model Prediction :

Statistical Approach : Using Ordinary Least Squares method ,

--> Used all the feature columns in the OLS method which has resulting adjusted r value - 0.531 --> Upon Looking at the model summary few columns has multi-collinearity .So,dropped these columns. To Avoid overfitting.

Columns Dropped: -->'Spring', 'Summer', 'Snowfall (cm)'

-->After dropping the above 3 columns OLS is performed again and found the adjusted r-value as 0.532.

Feature Selection : Used the columns that has p < 0.05 significance level

The features used to train and test and predict are as below

• Hour • Temperature(C) • Humidity(%) • Wind speed (m/s) • Visibility (10m) • Dew point temperature(C) • Solar Radiation (MJ/m2) • Rainfall(mm) • Holiday • Functioning Day • Autumn • Winter

Machine learning Approach : LInear Regressor Used to predict the test data target column.

Below is the reasons specifie to choose the linear regressor upon SGD regressor.

Using the above list of columns model is trained with [70,30],[80,20] and [90,10].

Model trained with 90% of train data has better validation score compared to others.

Linear Regression : Has a better test and train validation scores on the scaled data.

Methods used :

Simple linear regression - Temperature as the feature column Multiple linear regression - using the columns with high correlation 'Temperature(C)','Hour','Dew point temperature(C)'.

SGD Regressor : Has a similar results slightly less than the linear regression with different learning rates [0.01, 0.001, 0.0001, 0.0001, 0.00001] as observed above with graph. There is no better performance .

This method has sighly higher metrics compared to linear regression.

Decision Regressor : Using this model the test and train scores are 1.0 and 0.70 respectively . As the train and test scores has wide difference the model is underfitting . So, this is not choosen

So,we have used the Linear regression from the sklearn package to predict the values of the test dataset with the prediction score ~0.53 for both validation and training set.

Used the metrics package to define the MSE,MAE,R2-scores. Those scores for this model are comparetively low from the other models

```
Simple Linear Regression    Mulivariate -1    Multivariate -2     SGD
Regressor    OLS Method
```

RMSE 554.09 571.68 440.4 457.08 NA MSE 307018.87 326828.52 193961.32 208929.21 NA MAE 413.51 436.33 329.04 336.62 NA R2-score 0.28 0.23 0.53 0.53 0.52!

From the above table Multivate - 2 has better Metrics thatn all other .

So,we have choosed the Multivariate - 2 with the columns listed above to predict the Target column in the test dataset.

Classification

Data preparation

In [107]:
```
#File gets uploaded and can be seen in the form of dataframe with index st

#train dataset
clasDf_train = pd.read_csv("train_classification.csv")

#test dataset
clasDf_test = pd.read_csv("test_classification.csv")
```

In [108]:
```
#To get only top 5 rows of the dataframe, we need to use head().
clasDf_train.head()
```

Out[108]:

	Age	Sex	ALB	ALP	ALT	AST	BIL	CHE	CHOL	CREA	GGT	PROT	Category
0	39	f	46.4	59.2	14.1	18.9	4.5	7.90	4.55	61.0	14.5	77.3	0=Blood Donor
1	37	m	46.1	44.3	42.7	26.5	6.4	10.86	5.05	74.0	22.2	73.1	0=Blood Donor
2	32	m	50.9	65.5	23.2	21.2	6.9	8.69	4.10	83.0	13.7	71.3	0=Blood Donor
3	46	f	36.7	62.3	10.8	17.4	3.7	6.17	4.07	67.0	15.1	69.0	0=Blood Donor
4	56	m	23.0	105.6	5.1	123.0	43.0	1.80	2.40	62.7	35.9	62.8	3=Cirrhosis

In [109]:
```
clasDf_test.head()
#It is observed that, train and test data has same feature set but target
```

Out[109]:

	Age	Sex	ALB	ALP	ALT	AST	BIL	CHE	CHOL	CREA	GGT	PROT
0	36	m	47.8	89.0	48.5	38.4	8.6	8.26	5.62	96.0	21.9	76.2
1	56	f	45.1	79.1	39.0	30.5	5.2	6.47	5.10	64.0	145.3	66.7
2	51	m	45.9	66.7	31.8	28.1	9.0	10.08	5.61	85.0	36.2	73.0
3	55	m	44.7	71.6	22.9	22.1	5.5	6.82	4.61	105.0	59.2	72.7
4	45	m	43.2	68.2	27.8	42.3	6.6	10.93	6.61	105.0	27.2	74.5

VISUALIZATIONS TO UNDERSTAND DATA FROM DATASET BEFORE DATA TRANSFORMATION

Shape of the dataset

In [110]:

```
#shape is used to know the number of rows and columns present in the datas
print("Train dataset shape : ", clasDf_train.shape)
print("Test dataset shape : ", clasDf_test.shape)
```

```
Train dataset shape :  (553, 13)
Test dataset shape :  (62, 12)
```

Describe function

In [111]:

```
#To know the descriptive statistics of the dataframe, describe is used.
clasDf_train.describe()

#From this statictics, we can see the mean, standard deviation, minimum va
#By using this, we can get overview of the structure of data.
```

Out[111]:

	Age	ALB	ALP	ALT	AST	BIL	CHE
count	553.000000	552.000000	536.000000	552.000000	553.000000	553.000000	553.000000
mean	47.459313	41.641123	67.962127	28.574457	34.576492	11.314828	8.170253
std	10.202420	5.843118	26.643695	25.308527	30.292877	18.839697	2.196384
min	19.000000	14.900000	11.300000	0.900000	10.600000	1.800000	1.420000
25%	39.000000	38.875000	52.275000	16.475000	21.700000	5.400000	6.940000
50%	47.000000	42.000000	65.550000	23.000000	26.200000	7.300000	8.180000
75%	55.000000	45.225000	80.125000	33.200000	33.000000	11.500000	9.570000
max	77.000000	82.200000	416.600000	325.300000	319.800000	254.000000	16.410000

In [112]:
```
#descriptive statistics for test dataset
clasDf_train.describe()
```

Out[112]:

	Age	ALB	ALP	ALT	AST	BIL	CHE
count	553.000000	552.000000	536.000000	552.000000	553.000000	553.000000	553.000000
mean	47.459313	41.641123	67.962127	28.574457	34.576492	11.314828	8.170253
std	10.202420	5.843118	26.643695	25.308527	30.292877	18.839697	2.196384
min	19.000000	14.900000	11.300000	0.900000	10.600000	1.800000	1.420000
25%	39.000000	38.875000	52.275000	16.475000	21.700000	5.400000	6.940000
50%	47.000000	42.000000	65.550000	23.000000	26.200000	7.300000	8.180000
75%	55.000000	45.225000	80.125000	33.200000	33.000000	11.500000	9.570000
max	77.000000	82.200000	416.600000	325.300000	319.800000	254.000000	16.410000

Seaborn is one of the python data visualization library based on matplotlib. Seaborn helps to understand data with the help of charts and graphs. In our project, we have used seaborn to analyze the data of attribute "Sex" which gives the count of male and female present in the given dataset.

Data visualization for train dataset and test dataset

1.Count plot

```
    Count plot is used to retrive count of values present in that par
ticular column
```

2.Hist plot

```
    To understand the underlying frequency distribution, hist plot is
drawn
```

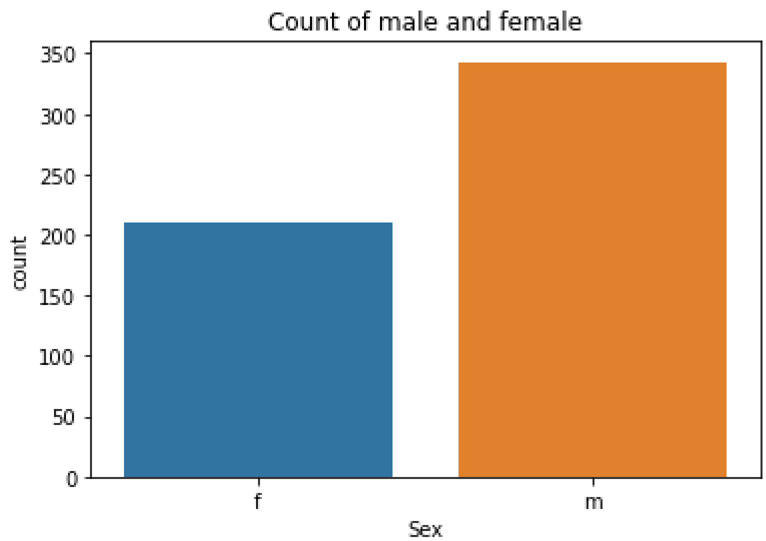
3.Heat Map

```
    To determine correlation between columns present in the dataset
```

Train dataset visualizations

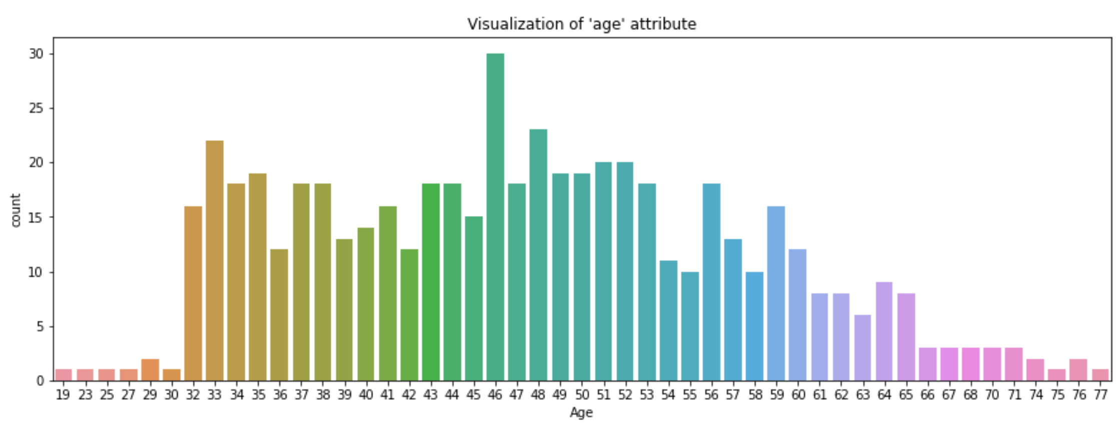
In [113]:
```
sns.countplot(x="Sex",data=clasDf_train)
plt.title("Count of male and female")

#This visualization concludes that count of male is more than female
#Similaily we can find the statistics of more attributes using this librar
```

Out[113]: Text(0.5, 1.0, 'Count of male and female')

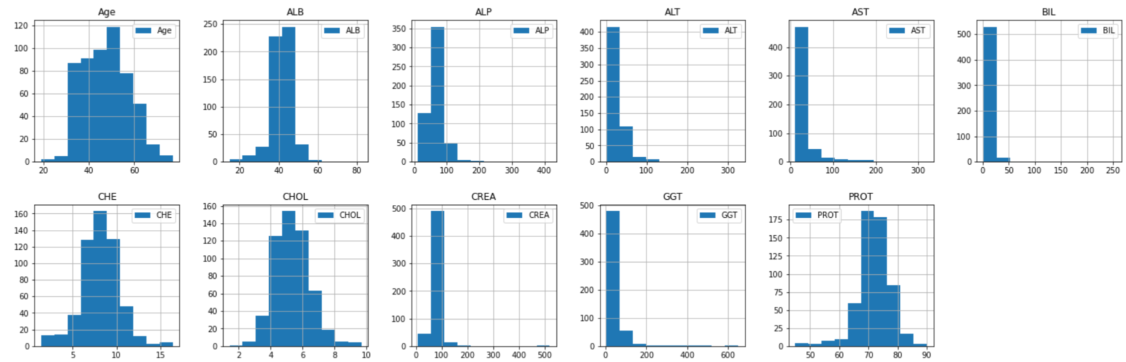


In [114]:
```
#Here, we are analyzing the column 'age' with the help of visualizations u

plt.figure(figsize =(15,5))
sns.countplot(x="Age",data=clasDf_train)
plt.title("Visualization of 'age' attribute")

#This visualization shows us that persons with age 46 are more in number.
```

Out[114]: Text(0.5, 1.0, "Visualization of 'age' attribute")

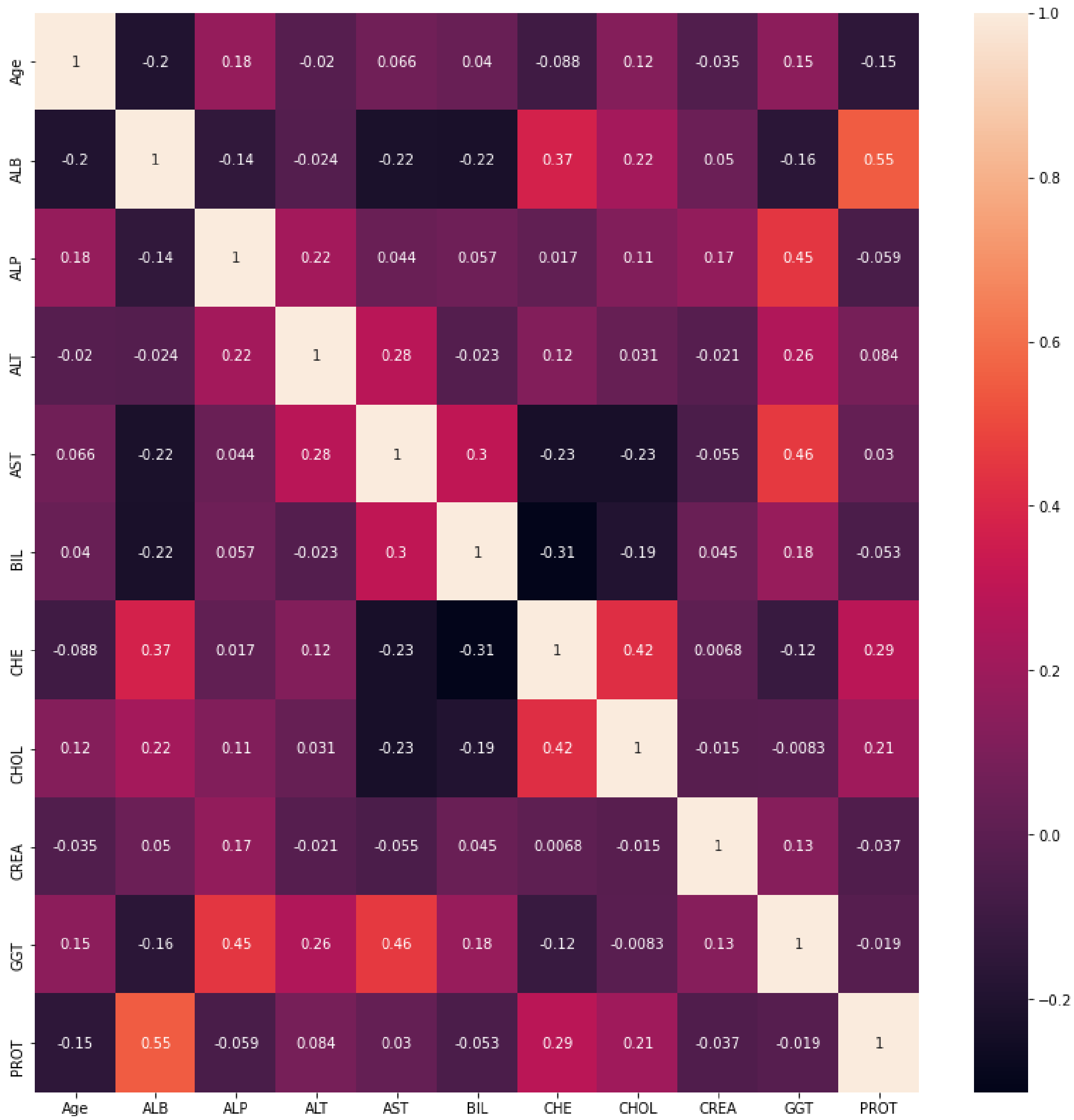


In [115]:
```python
histPlot = clasDf_train.hist(figsize=(25,25),layout=(6,6),legend = True)
```



In [116]:
```python
plt.figure(figsize=(14,14))
correlation=clasDf_train.corr()
sns.heatmap(correlation,annot=True)
```

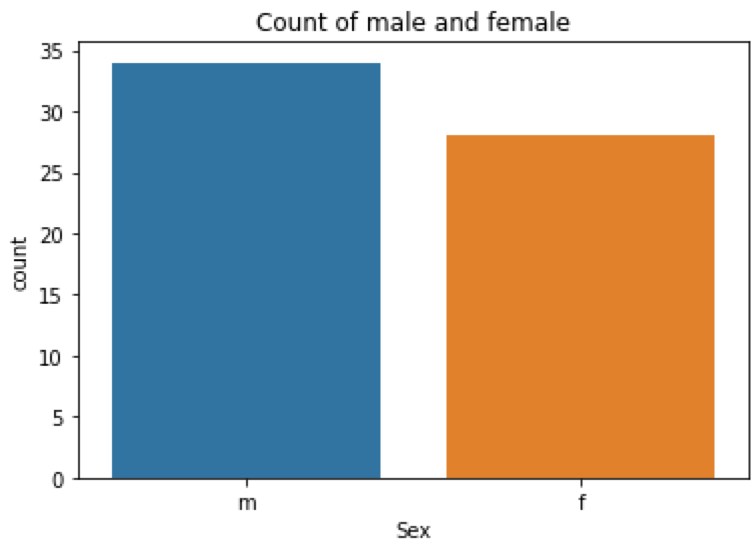
Out[116]: <AxesSubplot:>



Test dataset visualizations

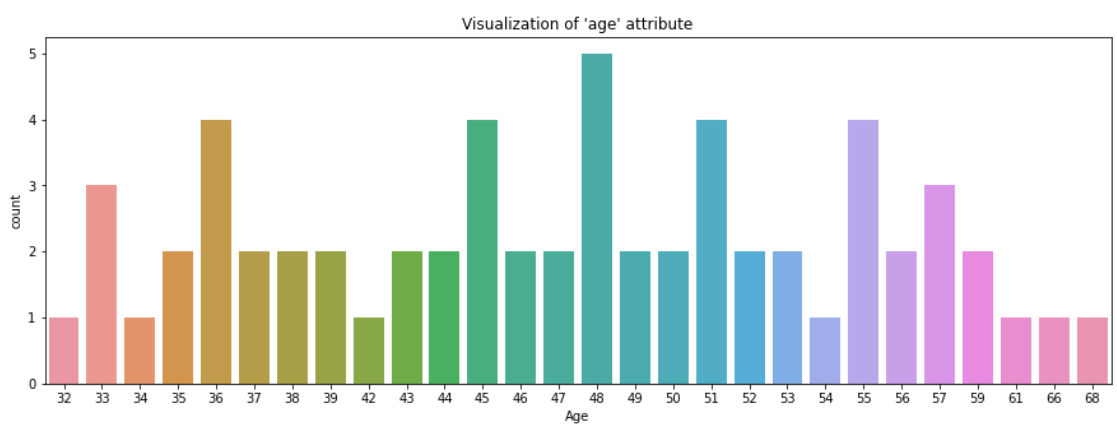
In [117]:
```
sns.countplot(x="Sex",data=clasDf_test)
plt.title("Count of male and female")

#We can observe that count of male is more than female from the visualizat
```

Out[117]: Text(0.5, 1.0, 'Count of male and female')



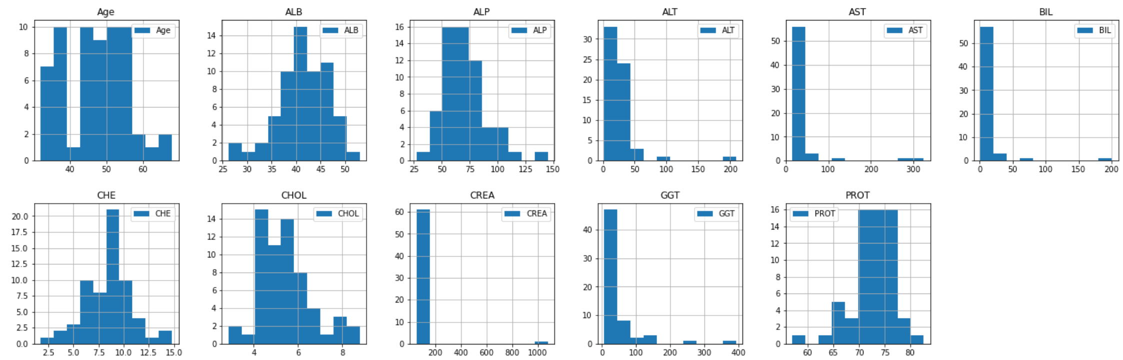
In [118]:
```
plt.figure(figsize =(15,5))
sns.countplot(x="Age",data=clasDf_test)
plt.title("Visualization of 'age' attribute")


#This visualization shows us that persons with age 48 are more in number.
```

Out[118]: Text(0.5, 1.0, "Visualization of 'age' attribute")



In [119]:

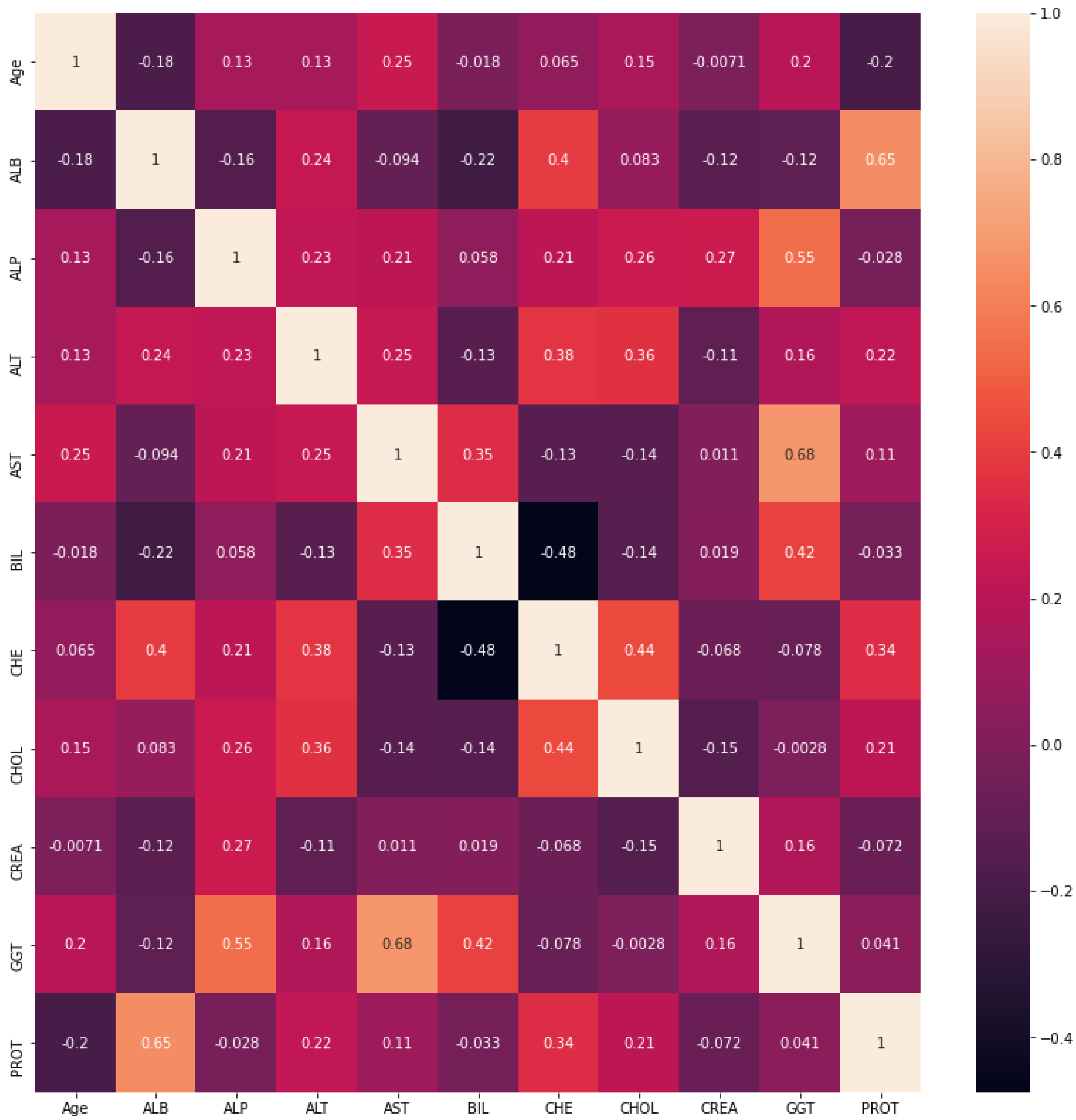
```
histPlot = clasDf_test.hist(figsize=(25,25),layout=(6,6),legend = True)
```



In [120]:

```
plt.figure(figsize=(14,14))
correlation=clasDf_test.corr()
sns.heatmap(correlation,annot=True)
```

Out[120]: <AxesSubplot:>



DATA TRANSFORMATION

```
Data which is not numerical need to be transformed to numerical for p
erforming classification.
```

Replacing the binomial columns to Numeric data in train dataset

In [121]:
```
print("Before data transformation, value counts of column 'Sex'")
clasDf_train['Sex'].value_counts()
```

```
Before data transformation, value counts of column 'Sex'
```

Out[121]:
```
m    343
f    210
Name: Sex, dtype: int64
```

In [122]:
```
# replace the more rows with 1 and less rows with 0
clasDf_train['Sex'].replace({'m':1,'f':0},inplace = True)
```

In [123]:
```
print("Before data transformation, value counts of column 'Sex'")
clasDf_train['Sex'].value_counts()
```

```
Before data transformation, value counts of column 'Sex'
```

Out[123]:
```
1    343
0    210
Name: Sex, dtype: int64
```

Applying label encoding for target column to transform it into numerical values

In [124]:
```
print("Before data transformation, value counts of column 'Category'")
clasDf_train['Category'].value_counts()
```

```
Before data transformation, value counts of column 'Category'
```

Out[124]:
```
0=Blood Donor             478
3=Cirrhosis                26
1=Hepatitis                22
2=Fibrosis                 21
0s=suspect Blood Donor      6
Name: Category, dtype: int64
```

In [125]:

```
#label encoder is used to transform nominal data into numberical.
#Here, Category column is target column, so we cannot perform one hot vect
#This may be tough for us during model development. So we perform label en

labelencoder = LabelEncoder()
clasDf_train['Category']= labelencoder.fit_transform(clasDf_train['Categor
print("After data transformation, value counts of column 'Category'")
clasDf_train['Category'].value_counts()
```

```
After data transformation, value counts of column 'Category'
```

Out[125]:

```
0    478
4     26
2     22
3     21
1      6
Name: Category, dtype: int64
```

In [126]:

```
#Now all the columns in the train dataset are numberical.
clasDf_train.head()
```

Out[126]:

	Age	Sex	ALB	ALP	ALT	AST	BIL	CHE	CHOL	CREA	GGT	PROT	Category
0	39	0	46.4	59.2	14.1	18.9	4.5	7.90	4.55	61.0	14.5	77.3	0
1	37	1	46.1	44.3	42.7	26.5	6.4	10.86	5.05	74.0	22.2	73.1	0
2	32	1	50.9	65.5	23.2	21.2	6.9	8.69	4.10	83.0	13.7	71.3	0
3	46	0	36.7	62.3	10.8	17.4	3.7	6.17	4.07	67.0	15.1	69.0	0
4	56	1	23.0	105.6	5.1	123.0	43.0	1.80	2.40	62.7	35.9	62.8	4

Data transformation for test data

In [127]:

```
print("Before data transformation, value counts of column 'Sex'")
clasDf_test['Sex'].value_counts()
```

```
Before data transformation, value counts of column 'Sex'
```

Out[127]:

```
m    34
f    28
Name: Sex, dtype: int64
```

In [128]:

```
# replace the more rows with 1 and less rows with 0
clasDf_test['Sex'].replace({'m':1,'f':0},inplace = True)
```

In [129]:
```
print("Before data transformation, value counts of column 'Sex'")
clasDf_test['Sex'].value_counts()
```

```
Before data transformation, value counts of column 'Sex'
```

Out[129]:
```
1    34
0    28
Name: Sex, dtype: int64
```

In [130]:
```
#Now all the columns in the test dataset are numberical.
clasDf_test.head()
```

Out[130]:

	Age	Sex	ALB	ALP	ALT	AST	BIL	CHE	CHOL	CREA	GGT	PROT
0	36	1	47.8	89.0	48.5	38.4	8.6	8.26	5.62	96.0	21.9	76.2
1	56	0	45.1	79.1	39.0	30.5	5.2	6.47	5.10	64.0	145.3	66.7
2	51	1	45.9	66.7	31.8	28.1	9.0	10.08	5.61	85.0	36.2	73.0
3	55	1	44.7	71.6	22.9	22.1	5.5	6.82	4.61	105.0	59.2	72.7
4	45	1	43.2	68.2	27.8	42.3	6.6	10.93	6.61	105.0	27.2	74.5

Missing Values

In [131]:
```
#After transforming all the data into numberical, we need to check missing
#and need to replace them.
clasDf_train.isna().sum()

#From this, we can see that, there are missing values in 5 columns in trai
```

Out[131]:
```
Age          0
Sex          0
ALB          1
ALP         17
ALT          1
AST          0
BIL          0
CHE          0
CHOL         9
CREA         0
GGT          0
PROT         1
Category     0
dtype: int64
```

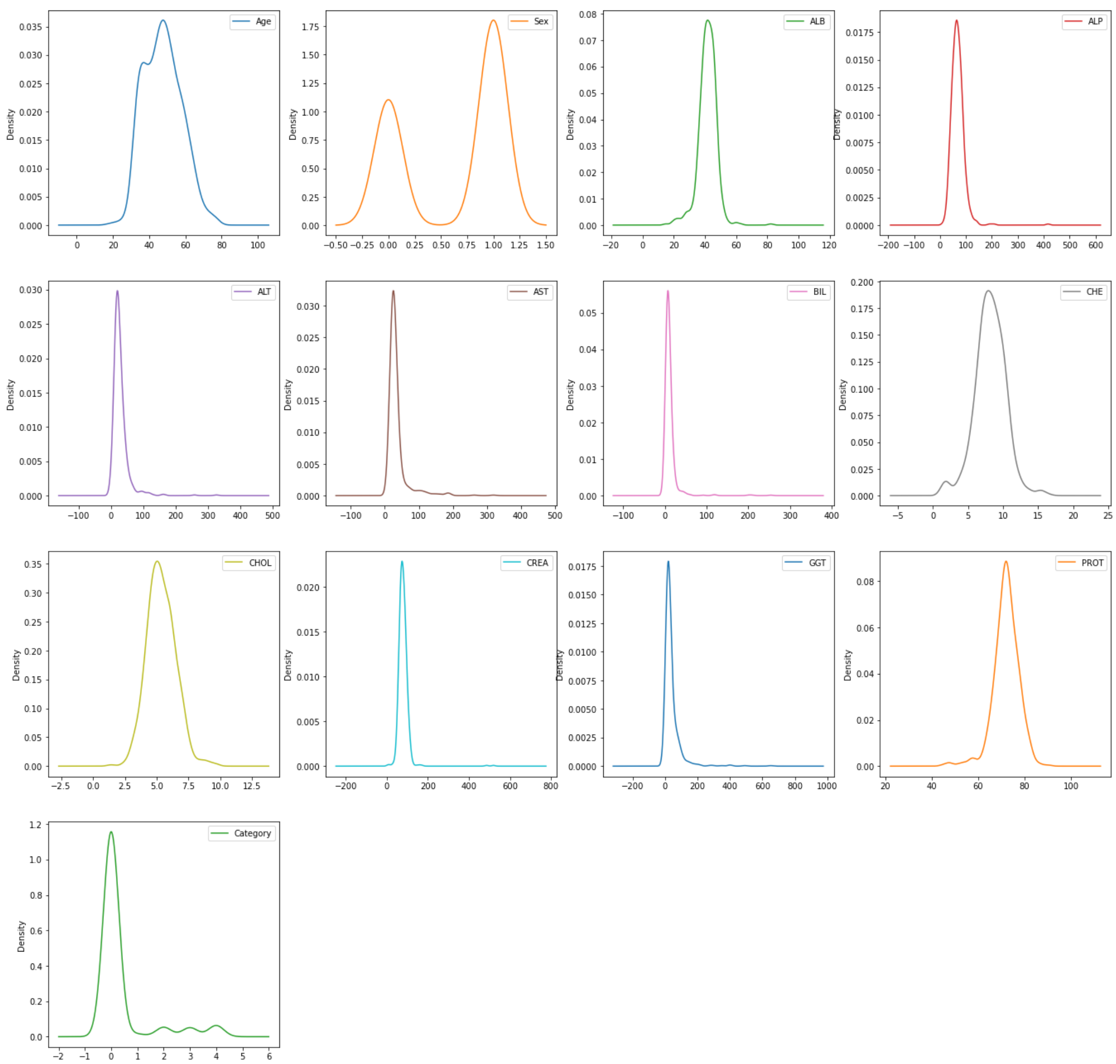
KDE Plots analysis and usage of mean or media to fill missing values

In [132]:

```
clasDf_train.plot(kind = 'kde' , subplots = True , layout=(4,4),
                  sharex=False, sharey=False, figsize=(23,23))
```

Out[132]:

```
array([[<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>],
       [<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>],
       [<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>],
       [<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Densit
y'>]],
      dtype=object)
```



From KDE plots, it is observed that for columns 'ALB','ALP','ALT','PROT', data is skewed. so we are replacing null values with its median. For column 'CHOL', there is no skewness, so null values are replaced with mean.

In [133]:
```
#Here, based on skewness, we are filling missing values using fillna()
clasDf_train['ALB'].fillna(clasDf_train['ALB'].median(),inplace = True)
clasDf_train['ALP'].fillna(clasDf_train['ALP'].median(),inplace = True)
clasDf_train['ALT'].fillna(clasDf_train['ALT'].median(),inplace = True)
clasDf_train['CHOL'].fillna(clasDf_train['CHOL'].mean(),inplace = True)
clasDf_train['PROT'].fillna(clasDf_train['PROT'].median(),inplace = True)
```

In [134]:
```
#crosschecking missing values in dataframe after replacing them.
clasDf_train.isna().sum()
```

Out[134]:
```
Age         0
Sex         0
ALB         0
ALP         0
ALT         0
AST         0
BIL         0
CHE         0
CHOL        0
CREA        0
GGT         0
PROT        0
Category    0
dtype: int64
```

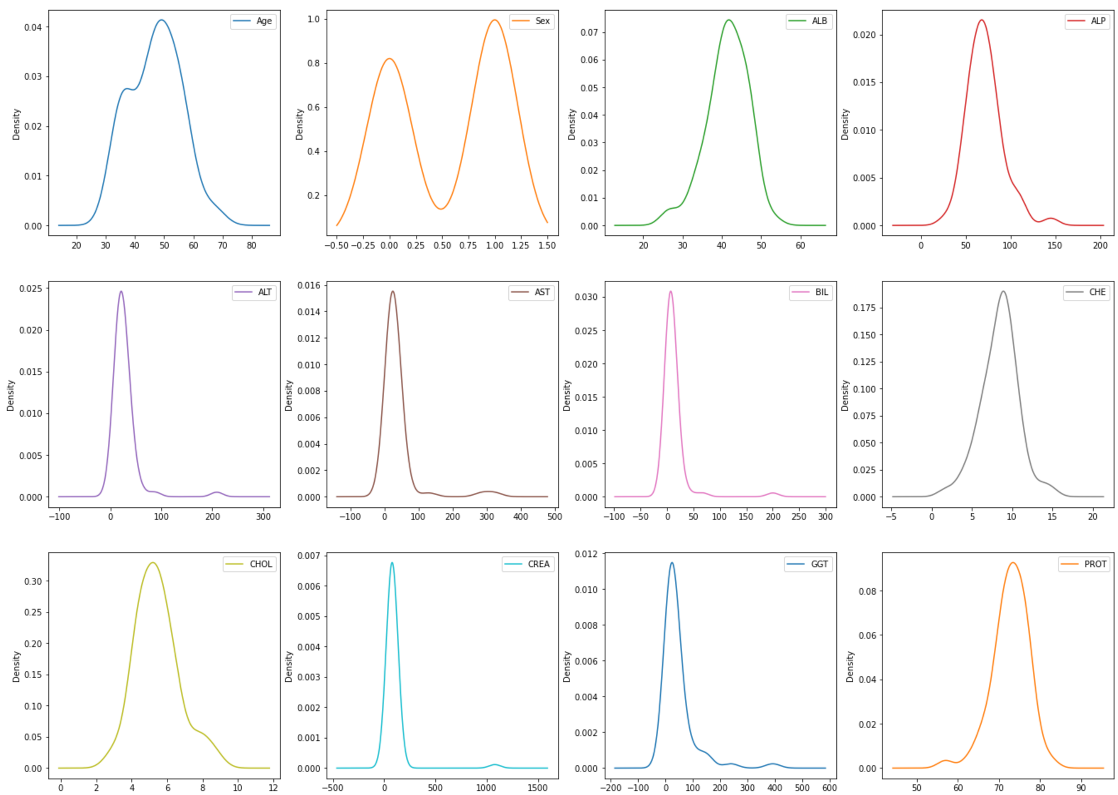
Test Data : Using density plots to assesses the distribution of data in the column

In [135]:
```
#After transforming all the data into numberical, we need to check missing
#and need to replace them.
clasDf_test.isna().sum()

#From this, we can observe that there are missing values in 2 columns.
```

Out[135]:
```
Age     0
Sex     0
ALB     0
ALP     1
ALT     0
AST     0
BIL     0
CHE     0
CHOL    1
CREA    0
GGT     0
PROT    0
dtype: int64
```

In [136]:
```python
clasDf_test.plot(kind = 'kde' , subplots = True , layout=(4,4),
                 sharex=False, sharey=False, figsize=(23,23))
```

Out[136]:
```
array([[<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>],
       [<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>],
       [<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>],
       [<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
        <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Densit
y'>]],
      dtype=object)
```



In [137]:
```python
#Here, based on skewness, we are filling missing values using fillna()

clasDf_test['ALP'].fillna(clasDf_test['ALP'].median(),inplace = True)
clasDf_test['CHOL'].fillna(clasDf_test['CHOL'].mean(),inplace = True)
```

In [138]:
```
clasDf_test.isna().sum()
```

Out[138]:
```
Age     0
Sex     0
ALB     0
ALP     0
ALT     0
AST     0
BIL     0
CHE     0
CHOL    0
CREA    0
GGT     0
PROT    0
dtype: int64
```

Feature and Target datasets

Target column is "Category"

In [139]:
```
clasDf_feature = clasDf_train[clasDf_train.columns[:-1]]
clasDf_target = clasDf_train['Category']
```

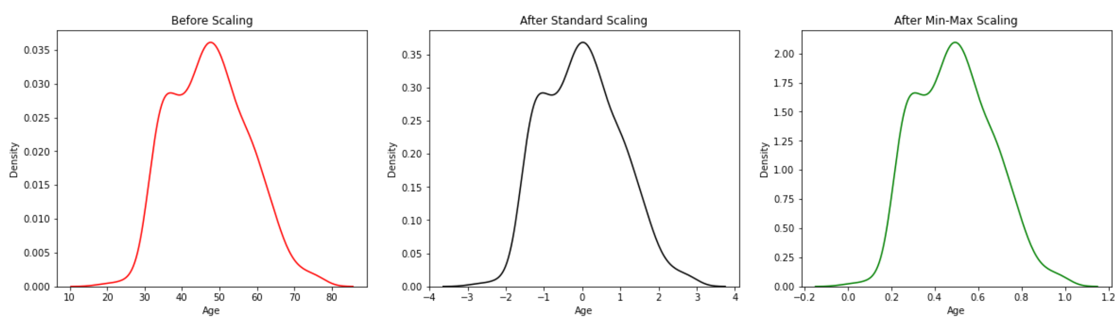
Scaling Techniques Used

1) MinMax Scaling

2) Standard Scaling

In [140]:

```
#Applying standard scaling method
scaler = preprocessing.StandardScaler()
clasDfTrain_standScal = scaler.fit_transform(clasDf_feature)
clasDfTrain_standScal = pd.DataFrame(clasDfTrain_standScal, columns =clasD

#Applying minmax scalar method
scaler_minMax = preprocessing.MinMaxScaler()
clasDfTrain_mmScal = scaler_minMax.fit_transform(clasDf_feature)
clasDfTrain_mmScal = pd.DataFrame(clasDfTrain_mmScal, columns =clasDf_feat

fig, (ax1, ax2, ax3) = plt.subplots(ncols = 3, figsize =(20, 5))

#plotting density graph of column 'age' before scaling
ax1.set_title('Before Scaling')
sns.kdeplot(clasDf_feature['Age'], ax = ax1,color ='r')

#plotting density graph of column 'age' after standard scaling
ax2.set_title('After Standard Scaling')
sns.kdeplot(clasDfTrain_standScal['Age'], ax = ax2, color ='black')

#plotting density graph of column 'age' after minmax scaling
ax3.set_title('After Min-Max Scaling')
sns.kdeplot(clasDfTrain_mmScal['Age'], ax = ax3, color ='g')
plt.show()
```



Looking at the above graphs plots drawn on top of scaled data , we have choosed - "Min-Max Scaling"

Below are the reasons

With standard scaling the values turned to be very minute or very large for the given data which in turn creates a problem while clustering. So, we have choosen the min-max scaling technique

In [141]:
```
# view the train data after scaling
clasDfTrain_mmScal.head()
```

Out[141]:

	Age	Sex	ALB	ALP	ALT	AST	BIL	CHE	CHOL	
0	0.344828	0.0	0.468053	0.118184	0.040691	0.026843	0.010706	0.432288	0.378641	0.
1	0.310345	1.0	0.463596	0.081421	0.128853	0.051423	0.018239	0.629753	0.439320	0.
2	0.224138	1.0	0.534918	0.133728	0.068742	0.034282	0.020222	0.484990	0.324029	0.
3	0.465517	0.0	0.323923	0.125833	0.030518	0.021992	0.007534	0.316878	0.320388	0.
4	0.637931	1.0	0.120357	0.232667	0.012947	0.363519	0.163362	0.025350	0.117718	0.

Scaling test dataset using minmax scaler

In [142]:
```
#Scaling for test dataset
clasDfTest_mmScal = scaler.fit_transform(clasDf_test)
clasDfTest_mmScal = pd.DataFrame(clasDfTest_mmScal, columns = clasDf_test.
```

In [143]:
```
# view the data after scaling
clasDfTest_mmScal.head()
```

Out[143]:

	Age	Sex	ALB	ALP	ALT	AST	BIL	CHE	
0	-1.270491	0.907485	1.226938	0.921340	0.788168	0.033712	-0.136051	-0.075641	0.
1	1.049699	-1.101946	0.706569	0.412231	0.434144	-0.119177	-0.267187	-0.863127	-0.
2	0.469651	0.907485	0.860752	-0.225441	0.165832	-0.165624	-0.120623	0.725044	0.
3	0.933689	0.907485	0.629478	0.026542	-0.165832	-0.281742	-0.255616	-0.709149	-0.
4	-0.226406	0.907485	0.340384	-0.148304	0.016770	0.109188	-0.213190	1.098990	0.

Clustering

1. Agglomerative clustering
2. K means Clustering

Agglomerative clustering

It is an unsupervised machine learning hierarchical clustering algorithm. It seperates the data into clusters in bottom up approach. Based on dendogram, we can analyze the clusters.

In [144]:
```
agModel = AgglomerativeClustering(distance_threshold = 15, n_clusters = No

# Train the model
agModel = agModel.fit(clasDfTrain_mmScal)
agModel.n_clusters_
```

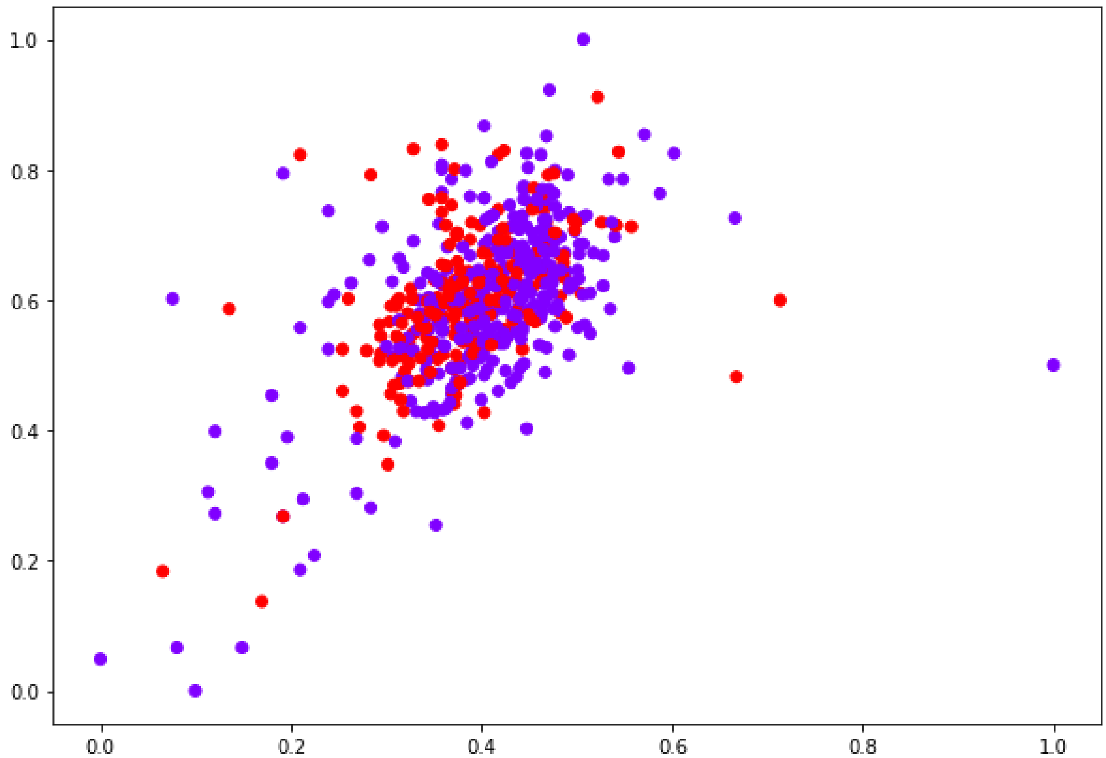
Out[144]:
```
2
```

In [145]:
```
#We can see the values of 0s and 1s in the output since we got 2 clusters.
#0 represents the points that belong to the first cluster and 1 represents

agCluster = AgglomerativeClustering(n_clusters=2, affinity='euclidean', li
agCluster.fit_predict(clasDfTrain_mmScal)
```

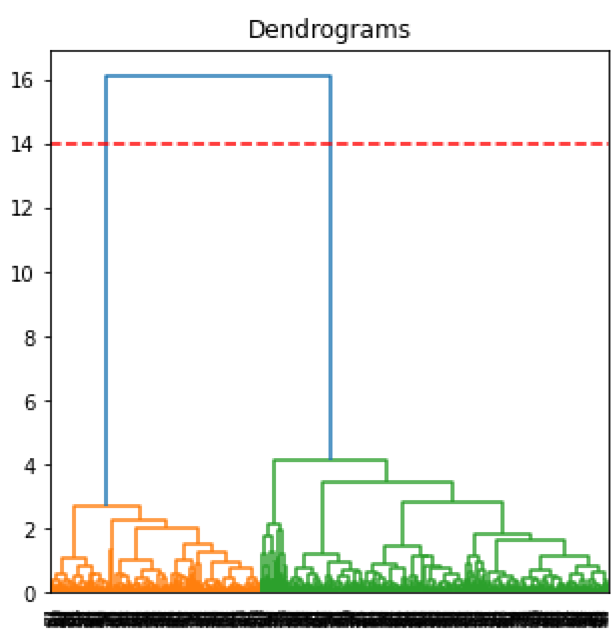
Out[145]:
```
array([1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0,
       1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1,
       1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0,
       0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0,
       0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1,
       1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1,
       1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1,
       0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1,
       0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1,
       1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1,
       1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1,
       1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0,
       1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1,
       0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0,
       0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0,
       0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1,
       1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0,
       1, 0, 0])
```

In [146]:
```
plt.figure(figsize=(10, 7))
plt.scatter(clasDfTrain_mmScal['ALB'], clasDfTrain_mmScal['PROT'], c=agClu
```

Out[146]: <matplotlib.collections.PathCollection at 0x7fa39182ab20>



In [147]:
```
plt.subplots(figsize = (5,5))
plt.title("Dendrograms")
dendrogram(linkage(clasDfTrain_mmScal, method = 'ward'))
plt.axhline(y = 14, c = 'r', linestyle = '--')

plt.show()
```



By seeing the above dendogram, we can summerize that, most of the data is clustered into green colured cluster and rest with orange coloured cluster. Red line at number 14 is y line, which cuts the dendogram and results in number of clusters. Blue line combines that two clusters into one as it is bottom up approach.

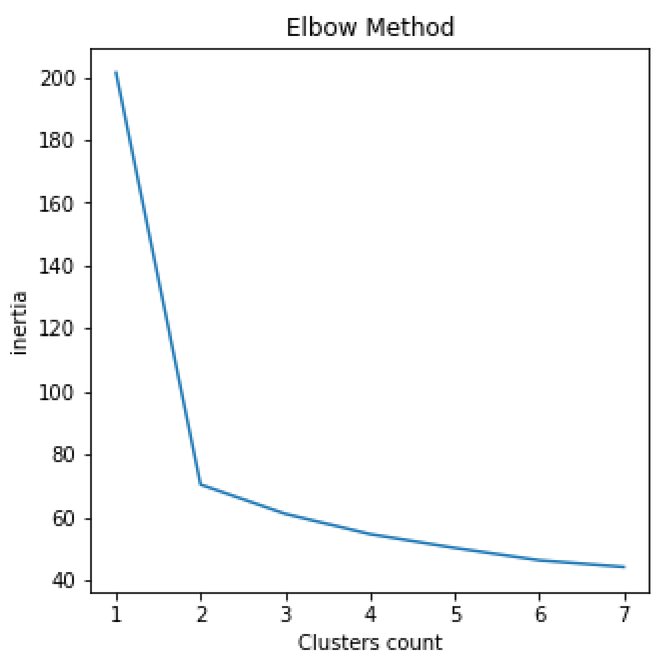
K means clustering

```
K means is an unsupervised algorithm which divides the data into k nu
mber of clusters. This K value can be determined by using Elbow metho
d.
```

Elbow method

In [148]:

```
#implementing elbow method
inertia=[]
from sklearn.cluster import KMeans
for i in range(1,8):
    kmeans = KMeans(n_clusters = i,init ='k-means++', random_state =0)
    kmeans.fit(clasDfTrain_mmScal)
    inertia.append(kmeans.inertia_)
plt.figure(figsize=(5,5))
plt.plot(range(1,8), inertia)
plt.title('Elbow Method')
plt.xlabel('Clusters count')
plt.ylabel('inertia')
plt.show()
```



By using this Elbow graph, we can determine the value of K. i.e; optimal value of K. Here, from above figure, we can see that graph is distorting at value 2. Which clearly says that value of K is 2.

Silhouette score

```
We can also predict the optimal value of K by using Silhouette score.
The more the score, the best the cluster value.
```

In [149]:

```
for i in range(2,8):
    Kmean_cluster = KMeans(n_clusters = i , random_state = 0)

    Kmean_cluster.fit(clasDfTrain_mmScal)

    Kmean_label = Kmean_cluster.labels_

    Kmean_count = np.bincount(Kmean_label)
    print(Kmean_count)
    print(f'Silhoutte score for cluster {i} and test data is ' +
          str(silhouette_score(clasDfTrain_mmScal, Kmean_cluster.labels_))
```

```
[210 343]
Silhoutte score for cluster 2 and test data is 0.5976122524066481
[226 210 117]
Silhoutte score for cluster 3 and test data is 0.38512532393513005
[170 210  26 147]
Silhoutte score for cluster 4 and test data is 0.3664357919664037
[170 114  26 147  96]
Silhoutte score for cluster 5 and test data is 0.21421145511661685
[111 114  24 106  96 102]
Silhoutte score for cluster 6 and test data is 0.20242201005694657
[106  71  23 102 112  38 101]
Silhoutte score for cluster 7 and test data is 0.19939855655467512
```

By analyzing the score of clusters from 2 to 8, we can conclude that the value of K is 2.

In [150]:

```
ckmeans = KMeans(n_clusters = 2,init ='k-means++', random_state =0)
ckmeans.fit(clasDfTrain_mmScal)
ckmeans.transform(clasDfTrain_mmScal)
```

Out[150]:

```
array([[0.24512303, 1.02970636],
       [1.04652999, 0.26516364],
       [1.06271974, 0.33876916],
       ...,
       [0.24568382, 1.04129543],
       [1.00849811, 0.11739699],
       [1.27400237, 0.7753272 ]])
```

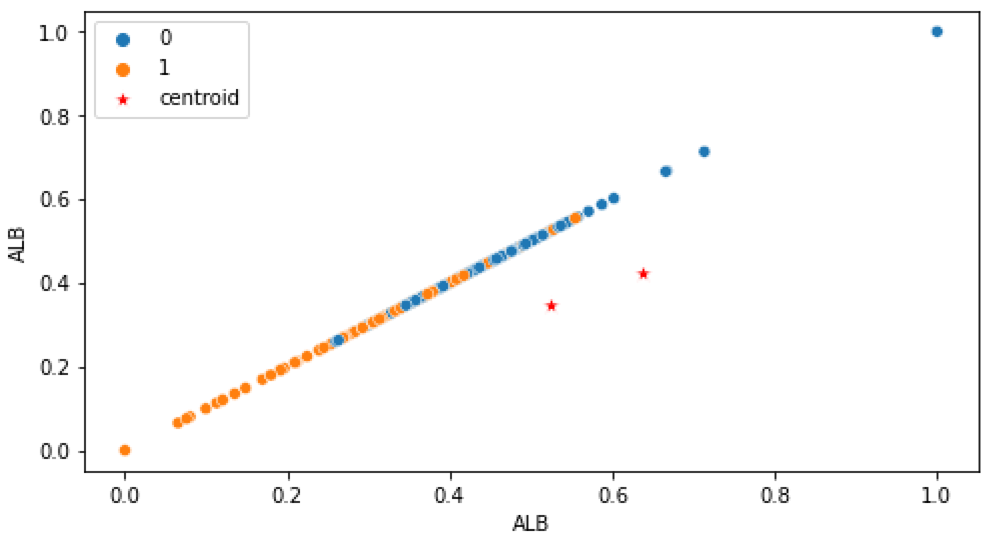
In [151]:
```
#SSE is defined as the sum of the squared distance between centroid and ec
print ('final value of the sum of squared errors is: {:.4f}'.format(ckmear
```

```
final value of the sum of squared errors is: 70.3710
```

In [152]:
```
Kmeans=KMeans(n_clusters=2)
col=["ALB","ALP","ALT","AST","BIL","CHE","CHOL","CREA","GGT","PROT"]
Kmeans.fit(clasDfTrain_mmScal[col])
new_value = Kmeans.predict(clasDfTrain_mmScal[col])
centers=Kmeans.cluster_centers_
centersDf = pd.DataFrame(centers, columns=col )
print ("centers values are:")
print(centersDf)
clasDfTrain_mmScal["new_cluster"]=new_value
```

```
centers values are:
        ALB       ALP       ALT       AST       BIL       CHE      CHOL  \
0  0.422748  0.141669  0.090956  0.067752  0.028619  0.518208  0.525969
1  0.344725  0.135374  0.073513  0.097833  0.056602  0.309632  0.375648

       CREA       GGT      PROT
0  0.141019  0.047261  0.637850
1  0.139344  0.065744  0.524459
```

In [153]:
```
fig, ax = plt.subplots(10,1,figsize=(8,50))
for x,y in enumerate(col):
    sns.scatterplot('ALB',y,hue="new_cluster",data = clasDfTrain_mmScal,ax
    sns.scatterplot('PROT', y,color='red',s =90, marker="*",data=centersDf
                    label = 'centroid', ax=ax[x])
```



From the above visualizations, we can get cluster analysis of each columns in respect to other columns and their centroids are marked. (Centroids are represented in red

colour)

In [154]:
```
#Cluster centers are
ckmeans.cluster_centers_
```

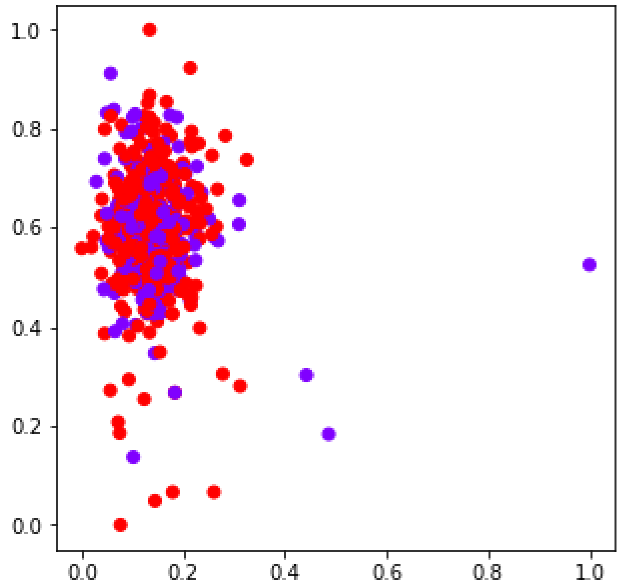
Out[154]:
```
array([[ 4.98193760e-01, -1.11022302e-15,  3.84193023e-01,
         1.41909579e-01,  7.08516822e-02,  5.85412431e-02,
         2.35772818e-02,  4.21007656e-01,  4.83705995e-01,
         1.23778772e-01,  3.93475955e-02,  5.97576907e-01],
       [ 4.86076204e-01,  1.00000000e+00,  4.05408098e-01,
         1.38218172e-01,  9.41113983e-02,  8.91777520e-02,
         4.63905966e-02,  4.68261640e-01,  4.72958627e-01,
         1.50695201e-01,  6.18054152e-02,  6.03001883e-01]])
```

In [155]:
```
#Labels of clusters
ckmeans.labels_
```

Out[155]:
```
array([0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1,
       0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0,
       0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1,
       1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1,
       1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 0,
       0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0,
       0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0,
       1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
       1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0,
       0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1,
       1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0,
       0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0,
       0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1,
       0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0,
       1, 1, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1,
       1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1,
       1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0,
       0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0,
       1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1,
       1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1,
       0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1,
       1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1,
       0, 1, 1], dtype=int32)
```

In [156]:
```
#visualize the clustering data on 2 columns
plt.figure(figsize=(5, 5))
plt.scatter(clasDfTrain_mmScal['ALP'], clasDfTrain_mmScal['PROT'], c=ckmea
```

Out[156]: <matplotlib.collections.PathCollection at 0x7fa3804a5e50>



In [157]:
```
clasDfTrain_mmScal.drop('new_cluster',axis = 1 , inplace = True)
```

Classification model training

```
Logistic Regression
Multinomial Logistic Regression
Decision Trees
```

Logistic Regression

Model trainining with 70% as train data and 30% as test data.

In [158]:
```
#taking feature set as all columns in the dataset expect target column
X = clasDf_train[clasDf_train.columns[:-1]]

#considering target column as y
y = clasDf_train[clasDf_train.columns[-1]]
```

In [159]:
```
X_train70, X_test30, y_train70, y_test30 = train_test_split(X, y, random_s
#scaling the splitted data using minmax scaler
scaler = MinMaxScaler()
X_train70 = scaler.fit_transform(X_train70)
X_test30 = scaler.transform(X_test30)
```

In [160]:
```
#developing logistic regression model
lr = LogisticRegression(random_state= 0)
lr.fit(X_train70, y_train70)
```

Out[160]:
```
LogisticRegression(random_state=0)
```

In [161]:
```
#model score of train and test data
print('train score:', lr.score(X_train70, y_train70))
print('test score:', lr.score(X_test30, y_test30))

#By analyzing the score, we can say that the model is well worked with bot
#which means, it is not overfitted.
```

```
train score: 0.9043927648578811
test score: 0.8734939759036144
```

Model trainining with 75% as train data and 25% as test data.

In [162]:
```
X_train75, X_test25, y_train75, y_test25 = train_test_split(X, y, random_s

scaler = MinMaxScaler()
X_train75 = scaler.fit_transform(X_train75)
X_test25 = scaler.transform(X_test25)
```

In [163]:
```
lre = LogisticRegression(random_state= 0)
lre.fit(X_train75, y_train75)
```

Out[163]:
```
LogisticRegression(random_state=0)
```

In [164]:
```
print('train score:', lre.score(X_train75, y_train75))
print('test score:', lre.score(X_test25, y_test25))
```

```
train score: 0.9009661835748792
test score: 0.8776978417266187
```

Model trainining with 80% as train data and 20% as test data.

In [165]:
```
X_train80, X_test20, y_train80, y_test20 = train_test_split(X, y, random_s

scaler = MinMaxScaler()
X_train80 = scaler.fit_transform(X_train80)
X_test20 = scaler.transform(X_test20)
print(X_train80.shape,X_test20.shape, y_train80.shape, y_test20.shape)
```

```
(442, 12) (111, 12) (442,) (111,)
```

In [166]:
```
lreg = LogisticRegression(random_state= 0)
lreg.fit(X_train80, y_train80)
```

Out[166]:
```
LogisticRegression(random_state=0)
```

In [167]:
```
print('train score:', lreg.score(X_train80, y_train80))
print('test score:', lreg.score(X_test20, y_test20))
```

```
train score: 0.9027149321266968
test score: 0.8918918918918919
```

Model developed with 70-30 ration of train and test data has higher score with train data when compared to other models. But test score is better with 80-20 ratio model, for which train score is also 90%. So, for further analysis, we are considering model with 80-20 ration of train and test data.

In [168]:
```
#predicting y using test data
ypredTest = lreg.predict(X_test20)
ypredTest
```

Out[168]:
```
array([0, 0, 4, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 4, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 4, 0, 0, 0, 0, 0, 0,
       0])
```

In [169]:
```
# predicting y using train data
ypredTrain = lreg.predict(X_train80)
ypredTrain
```

Out[169]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 4, 0, 3, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 4, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 4, 0, 0, 0, 0, 4, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       2, 0, 0, 0, 0, 0, 0, 4, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 4, 0, 0, 0, 4, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 4, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 4, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 4, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 4, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 4, 0, 0,
       0, 4, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0])
```

In [170]:
```
pp = lreg.predict_proba(X_train80)[:,1]
```

In [171]:
```
#model score for trained test and untrained test data
lreg.score(X_test20, y_test20)
```

Out[171]:
```
0.8918918918918919
```

In [172]:
```
lreg.predict_proba(X_test20)
```

Out[172]:
```
array([[9.21406858e-01, 5.86095311e-03, 3.52856088e-02, 2.43681182e-0
2,
        1.30784615e-02],
       [9.18347355e-01, 3.15741130e-03, 3.22283261e-02, 2.97603382e-0
2,
        1.65065698e-02],
       [1.40210921e-01, 3.65945816e-02, 1.03983176e-01, 1.92550670e-0
1,
        5.26660652e-01],
       [8.43261287e-01, 1.11575810e-02, 6.19505537e-02, 4.11723885e-0
2,
        4.24581900e-02],
       [8.96955518e-01, 4.98732377e-03, 3.10533274e-02, 3.39639529e-0
2,
        3.30398780e-02],
       [8.99822399e-01, 8.66572367e-03, 4.08970014e-02, 2.41221733e-0
2,
        2.64927025e-02],
       [9.21329000e-01, 3.64993931e-03, 4.58270681e-02, 2.04206378e-0
```

In [173]:
```
lreg.predict_proba(X_test20)[:,1]
```

Out[173]:
```
array([0.00586095, 0.00315741, 0.03659458, 0.01115758, 0.00498732,
       0.00866572, 0.00364994, 0.00824896, 0.00624561, 0.00978884,
       0.006446  , 0.00156998, 0.00667669, 0.0140494 , 0.01453812,
       0.00162136, 0.04300923, 0.00319879, 0.00461298, 0.00498506,
       0.00810245, 0.00195763, 0.00284015, 0.00812162, 0.00307152,
       0.01153607, 0.00559035, 0.0090099 , 0.02152508, 0.04046862,
       0.00291248, 0.00986079, 0.01599487, 0.00741239, 0.00174432,
       0.00674528, 0.00155981, 0.00489524, 0.00773563, 0.00257558,
       0.00453844, 0.0033366 , 0.01402264, 0.00613527, 0.00746432,
       0.03851888, 0.00656298, 0.02004241, 0.00844238, 0.00577798,
       0.00262434, 0.00808271, 0.00690415, 0.01690344, 0.01505976,
       0.00990077, 0.03002733, 0.00473063, 0.00230118, 0.00829411,
       0.00483446, 0.00596605, 0.00175574, 0.07678573, 0.00258748,
       0.01266188, 0.01368873, 0.00597185, 0.0103398 , 0.00314939,
       0.00472986, 0.00695773, 0.00297525, 0.00481166, 0.00560854,
       0.00403098, 0.00170885, 0.00164989, 0.01075422, 0.00660817,
       0.00504104, 0.00873124, 0.01000552, 0.00581841, 0.0016503 ,
       0.00213993, 0.01295163, 0.00424977, 0.01884391, 0.00612902,
       0.00206352, 0.00066679, 0.00432375, 0.0025962 , 0.00302285,
       0.00834597, 0.0099319 , 0.00238696, 0.00565714, 0.0068884 ,
       0.00282794, 0.01085399, 0.00145636, 0.04252821, 0.0036761 ,
       0.00376393, 0.00649663, 0.00369974, 0.00451597, 0.00848459,
       0.01219087])
```

Changing the threshold

In [174]:
```
y_test_predict = np.where(lreg.predict_proba(X_test20)[:,1]> 0.4, 1, 0)
y_test_predict
```

Out[174]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0])
```

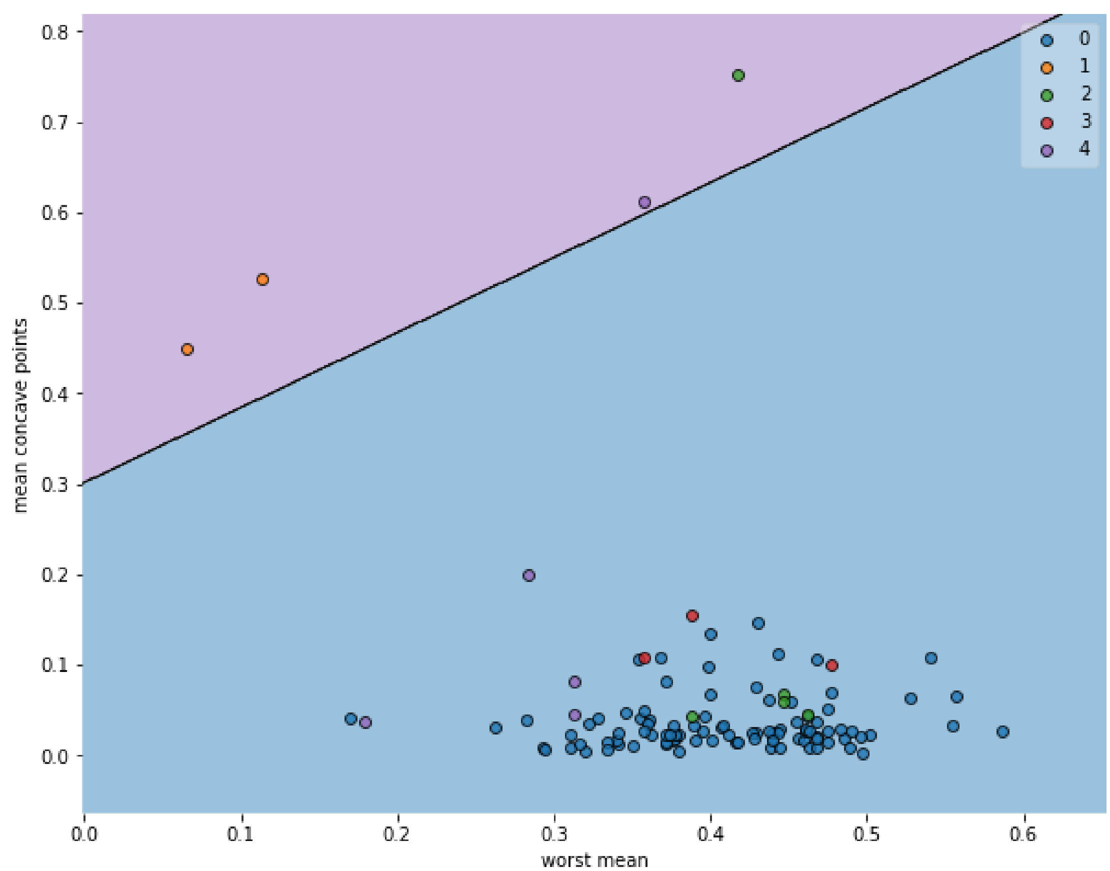
In [175]:
```
y_test_predict = np.where(lreg.predict_proba(X_test20)[:,1]> 0.6, 1, 0)
y_test_predict
```

Out[175]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0])
```

Plotting

In [176]:
```
X_train80_2 = X_train80[:,[2, 10]]
X_test20_2 = X_test20[:,[2, 10]]
```

In [177]:
```
plt.subplots(figsize = (10,8))
lreg = LogisticRegression(random_state = 0)
lreg.fit(X_train80_2, y_train80)

plot_decision_regions(X = X_test20_2 , y = y_test20.to_numpy(),
                      clf = lreg, markers = 'o',
                      zoom_factor = 15)
plt.xlabel('worst mean')
plt.ylabel('mean concave points')
plt.show()
```

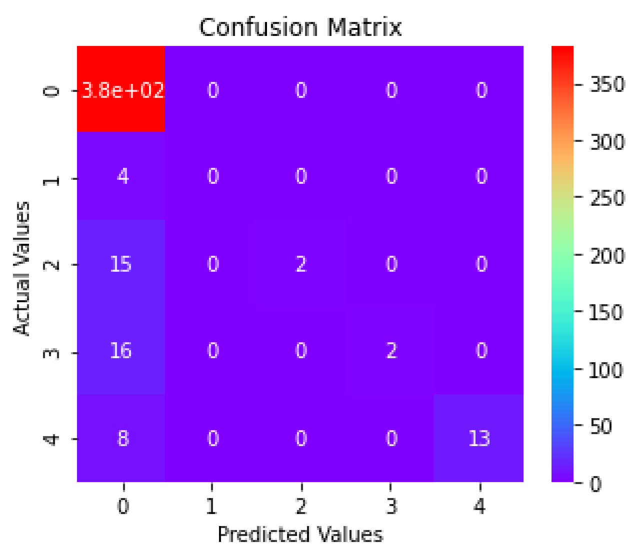


Model evaluation

In [178]:
```
print('Train confusion matrix: ')
cmTrain = confusion_matrix(y_train80,ypredTrain)
print(cmTrain)
print('Test confusion matrix: ')
cmTest = confusion_matrix(y_test20,ypredTest)
print(cmTest)
```

```
Train confusion matrix:
[[382   0   0   0   0]
 [  4   0   0   0   0]
 [ 15   0   2   0   0]
 [ 16   0   0   2   0]
 [  8   0   0   0  13]]
Test confusion matrix:
[[96  0  0  0  0]
 [ 1  0  0  1  0]
 [ 5  0  0  0  0]
 [ 3  0  0  0  0]
 [ 2  0  0  0  3]]
```

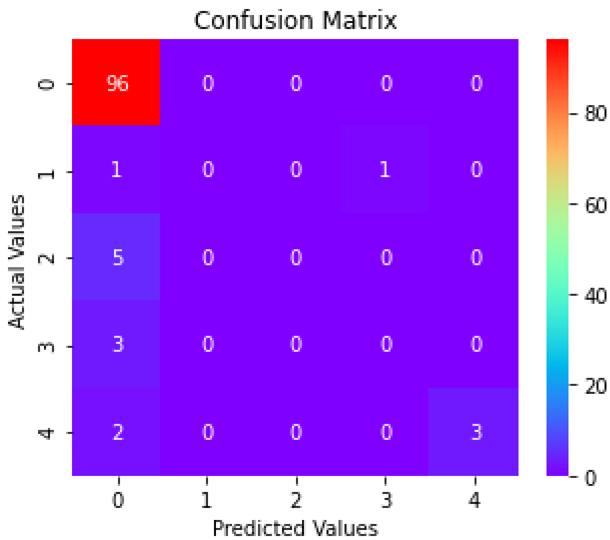
In [179]:
```
#Confusion matrix plot for trained data
plt.figure(figsize=(5,4))
sns.heatmap(cmTrain, annot=True,cmap = 'rainbow')
plt.title('Confusion Matrix')
plt.ylabel('Actual Values')
plt.xlabel('Predicted Values')
plt.show()
```



Confusion matrix contains actual and prediicted values of the target column. It shows True positive, True negative, False positive, false negative values in the form of matrix. By using this matrix, we can calculate precision, recall and f1 score manually.

In [180]:

```
#Confusion matrix plot for test data
plt.figure(figsize=(5,4))
sns.heatmap(cmTest, annot=True,cmap = 'rainbow')
plt.title('Confusion Matrix')
plt.ylabel('Actual Values')
plt.xlabel('Predicted Values')
plt.show()
```



In [181]:

```
#classification report for train
print(classification_report(y_train80, ypredTrain))
```

```
              precision    recall  f1-score   support

           0       0.90      1.00      0.95       382
           1       0.00      0.00      0.00         4
           2       1.00      0.12      0.21        17
           3       1.00      0.11      0.20        18
           4       1.00      0.62      0.76        21

    accuracy                           0.90       442
   macro avg       0.78      0.37      0.42       442
weighted avg       0.90      0.90      0.87       442
```

Classification report for train data and test data consists of precision , recall, f1-score and support values for target column. It also contains accuracy, macro average and weighted average.

In [182]:
```
#classification report for test
print(classification_report(y_test20, ypredTest))
```

```
              precision    recall  f1-score   support

           0       0.90      1.00      0.95        96
           1       0.00      0.00      0.00         2
           2       0.00      0.00      0.00         5
           3       0.00      0.00      0.00         3
           4       1.00      0.60      0.75         5

    accuracy                           0.89       111
   macro avg       0.38      0.32      0.34       111
weighted avg       0.82      0.89      0.85       111
```

In [183]:
```
clasDf_train.head()
```

Out[183]:

	Age	Sex	ALB	ALP	ALT	AST	BIL	CHE	CHOL	CREA	GGT	PROT	Category
0	39	0	46.4	59.2	14.1	18.9	4.5	7.90	4.55	61.0	14.5	77.3	0
1	37	1	46.1	44.3	42.7	26.5	6.4	10.86	5.05	74.0	22.2	73.1	0
2	32	1	50.9	65.5	23.2	21.2	6.9	8.69	4.10	83.0	13.7	71.3	0
3	46	0	36.7	62.3	10.8	17.4	3.7	6.17	4.07	67.0	15.1	69.0	0
4	56	1	23.0	105.6	5.1	123.0	43.0	1.80	2.40	62.7	35.9	62.8	4

Multinomial Logistic Regression

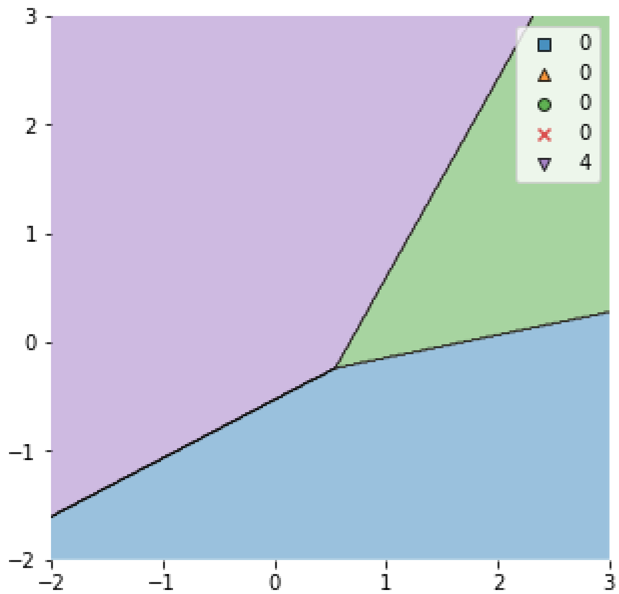
In [184]:
```
#Here, multinomial logistic regression model is developed.
#I am considering top 4 columns with high correlation values as feature se

multiX = clasDf_train[['ALB','AST','GGT','PROT']]
multiY = clasDf_train[clasDf_train.columns[-1]]
```

In [185]:
```
#we are not mentioning ratio of split here. Model by default does that in
X_trainMulti, X_testMulti, y_trainMulti, y_testMulti = train_test_split(mu

#scaling data before applying regression.
scaler = MinMaxScaler()
X_trainMulti = scaler.fit_transform(X_trainMulti)
X_testMulti = scaler.transform(X_testMulti)

#here, multi class indicates that we are passing multinomial features.
multilreg = LogisticRegression(multi_class="multinomial",random_state = 0)
multilreg.fit(X_trainMulti, y_trainMulti)
```

Out[185]:
```
LogisticRegression(multi_class='multinomial', random_state=0)
```

In [186]:
```
from mlxtend.plotting import plot_decision_regions
fig, ax = plt.subplots(figsize = (5,5))
value=1.5
width=0.75
plot_decision_regions(X_trainMulti, y_trainMulti.to_numpy(), clf = multilr
                      zoom_factor = 0.5, filler_feature_values={2: value, 
                  filler_feature_ranges={2: width, 3: width},legend =2, ax

handles, labels = ax.get_legend_handles_labels()
ax.legend(handles, multiY)
```

Out[186]: <matplotlib.legend.Legend at 0x7fa38100c6a0>

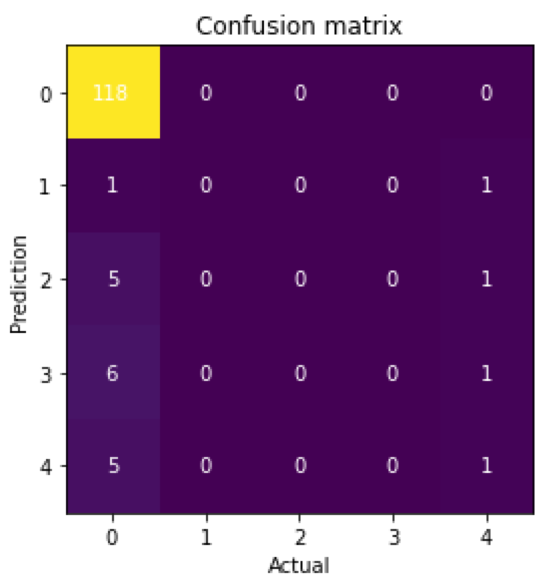


Multinomial logistic regression evaluation

In [187]:
```
#predicting Y values using test data.
multiYPred = multilreg.predict(X_testMulti)

#calculating model accuracy score using y prediction and test data.
print("Accuracy is : {:.3f}".format(accuracy_score(y_testMulti, multiYPred

#we have got model accuracy as 85%, which can be considered as so far bett

#building confusion matrix for getting true and false positive and negativ
#which is used to calculate precision, recall and f1 score.
print("Confusion matrix:\n{}".format(confusion_matrix(y_testMulti, multiYP
```

```
Accuracy is : 0.856
Confusion matrix:
[[118   0   0   0   0]
 [  1   0   0   0   1]
 [  5   0   0   0   1]
 [  6   0   0   0   1]
 [  5   0   0   0   1]]
```

In [188]:
```
%matplotlib inline
confusion = confusion_matrix(y_testMulti, multiYPred)

fig, ax = plt.subplots()
plt.imshow(confusion)
plt.title("Confusion matrix")

ax.set_xticks(np.arange(len(confusion)))
ax.set_yticks(np.arange(len(confusion[0])))

# Loop over data dimensions and create text annotations.
for i in range(len(confusion)):
    for j in range(len(confusion[0])):
        text = ax.text(j, i, confusion[i, j],
                       ha="center", va="center", color="w")
fig.tight_layout()
plt.xlabel('Actual')
plt.ylabel('Prediction')
plt.show()
```



In [189]:
```
#to evaluate system performances using data, we calculate macro and micro
print('Macro precision: ', precision_score(y_testMulti, multiYPred, averag
print('Micro precision: ', precision_score(y_testMulti, multiYPred, averag
print('Macro recall: ', recall_score(y_testMulti, multiYPred, average= 'ma
print('Micro recall: ', precision_score(y_testMulti, multiYPred, average=
print('Macro f1-score: ', f1_score(y_testMulti, multiYPred, average= 'macr
print('Micro f1-score: ', f1_score(y_testMulti, multiYPred, average= 'micr
```

```
Macro precision:  0.22481481481481486
Micro precision:  0.8561151079136691
Macro recall:  0.23333333333333334
Micro recall:  0.8561151079136691
Macro f1-score:  0.22656126482213437
Micro f1-score:  0.8561151079136691
```

Decision Trees

Decision Trees are supervised machine learning algorithms that can be used for both classification and regression.
Here, I am using decision tree classifier for classification. Tree is build by using nodes and leaves.

In [190]:
```
#feature and training set
dx =clasDf_train[clasDf_train.columns[:-1]] #taking all the columns except
dy = clasDf_train[clasDf_train.columns[-1]]
```

In [191]:
```
#we are not mentioning ratio of split here. Model by default does that in
X_trainD, X_testD, y_trainD, y_testD = train_test_split(dx, dy, random_sta
```

In [192]:
```
#scaling the data using standard scaler for developing model.
scaler = StandardScaler()
scaler.fit(X_trainD)
X_trainD = scaler.transform(X_trainD)
X_testD = scaler.transform(X_testD)
```

In [193]:
```
# instantiating and training the model
dt = DecisionTreeClassifier(random_state = 0)
dt.fit(X_trainD, y_trainD)
```

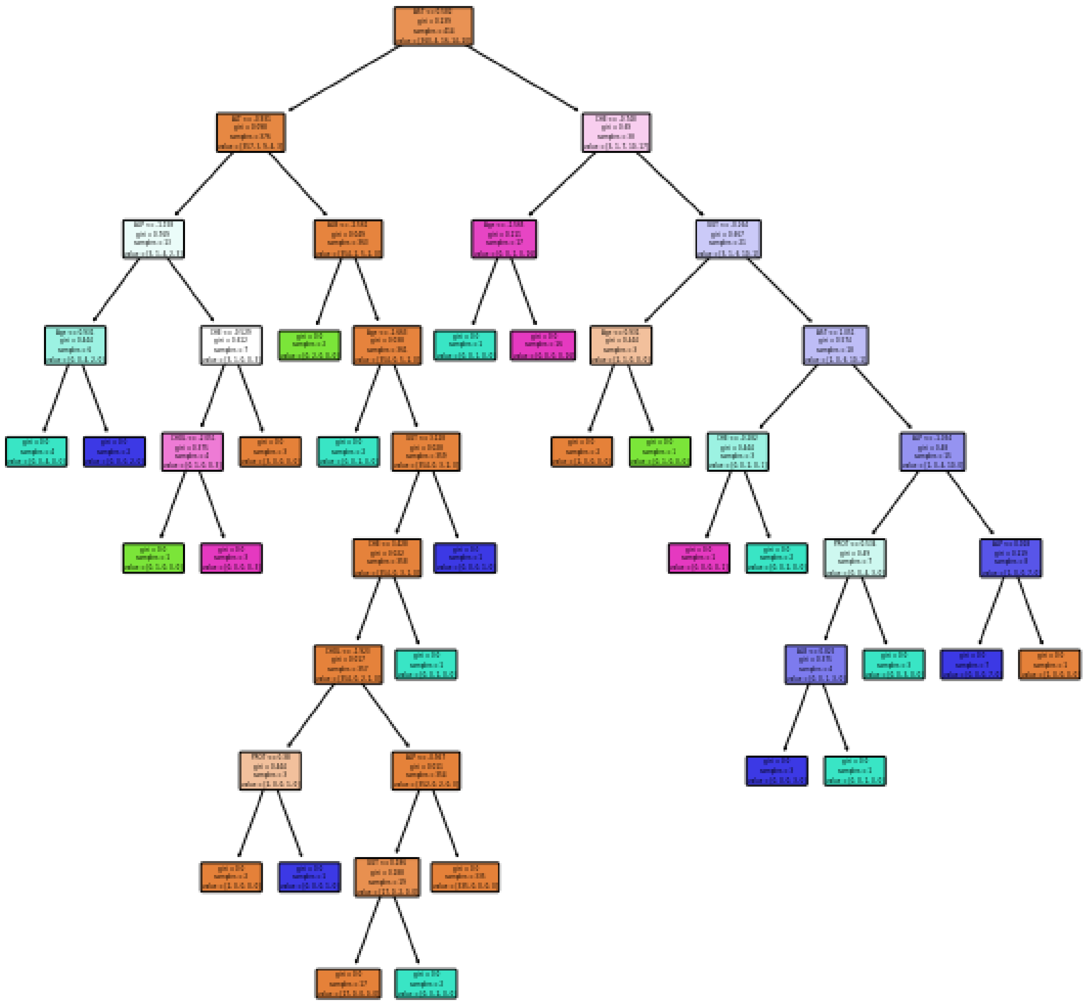
Out[193]:
```
DecisionTreeClassifier(random_state=0)
```

In [194]:
```
#deriving acuracy of the model using train data and test data seperately

print("Accuracy on training set: {:.3f}".format(dt.score(X_trainD, y_trair
print("Accuracy on test set: {:.3f}".format(dt.score(X_testD, y_testD)))



#To be surprised, our model is giving 100% accuracy with trained data and
```

```
Accuracy on training set: 1.000
Accuracy on test set: 0.906
```

Plotting Decision Tree

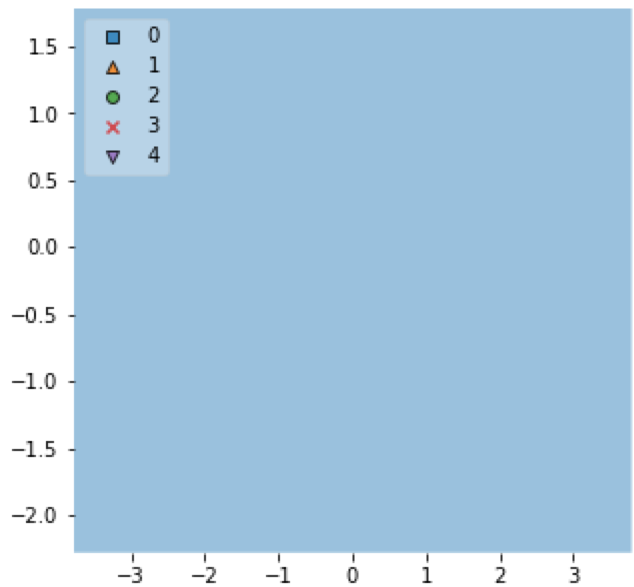
In [195]:
```
from sklearn import tree

plt.subplots(figsize = (10,10))
tree.plot_tree(dt,
               feature_names=dx.columns,
               filled=True,
               rounded = True)
plt.show()
```



Plotting Decision Boundary

In [196]:
```
from mlxtend.plotting import plot_decision_regions
value=1.5
width=0.75
plt.subplots(figsize = (5,5))
plot_decision_regions(X = X_trainD,
                      y = y_trainD.values,
                      clf = dt,
                      filler_feature_values={2: value, 3:value, 4:value, 5
                                             7:value, 8:value, 9:
                  filler_feature_ranges={2: width, 3: width,4: width,5: wi
                                         9: width,10: width,11: width},lege
```

Out[196]: <AxesSubplot:>



Early Stopping: `max_depth`

    Max_depth = 3
    Max_depth = 2

max_depth = 3

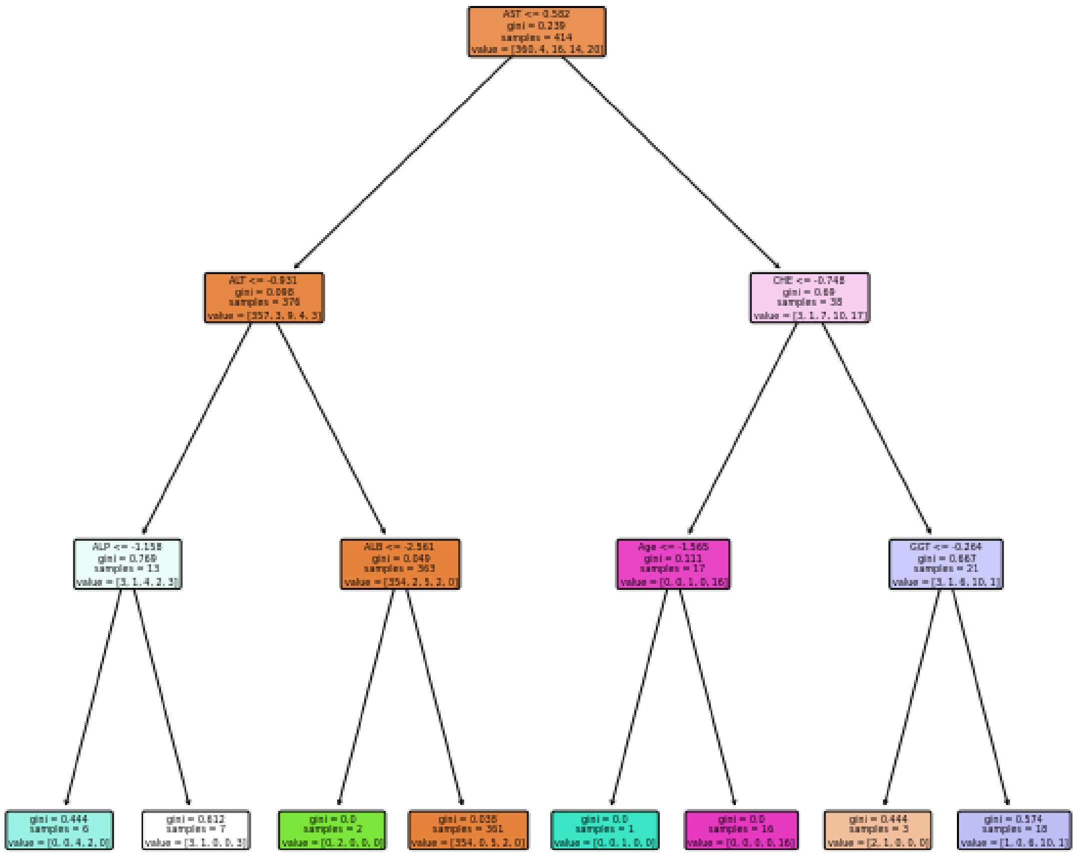
In [197]:
```
dt = DecisionTreeClassifier(random_state = 0, max_depth = 3)
dt.fit(X_trainD, y_trainD)
```

Out[197]: DecisionTreeClassifier(max_depth=3, random_state=0)

In [198]:
```
print("Accuracy on training set: {:.3f}".format(dt.score(X_trainD, y_trair
print("Accuracy on test set: {:.3f}".format(dt.score(X_testD, y_testD)))
```

```
Accuracy on training set: 0.947
Accuracy on test set: 0.899
```

In [199]:
```
plt.subplots(figsize = (10,10))
tree.plot_tree(dt,
               feature_names=dx.columns,
               filled=True,
               rounded = True)
plt.show()
```



max_depth = 2

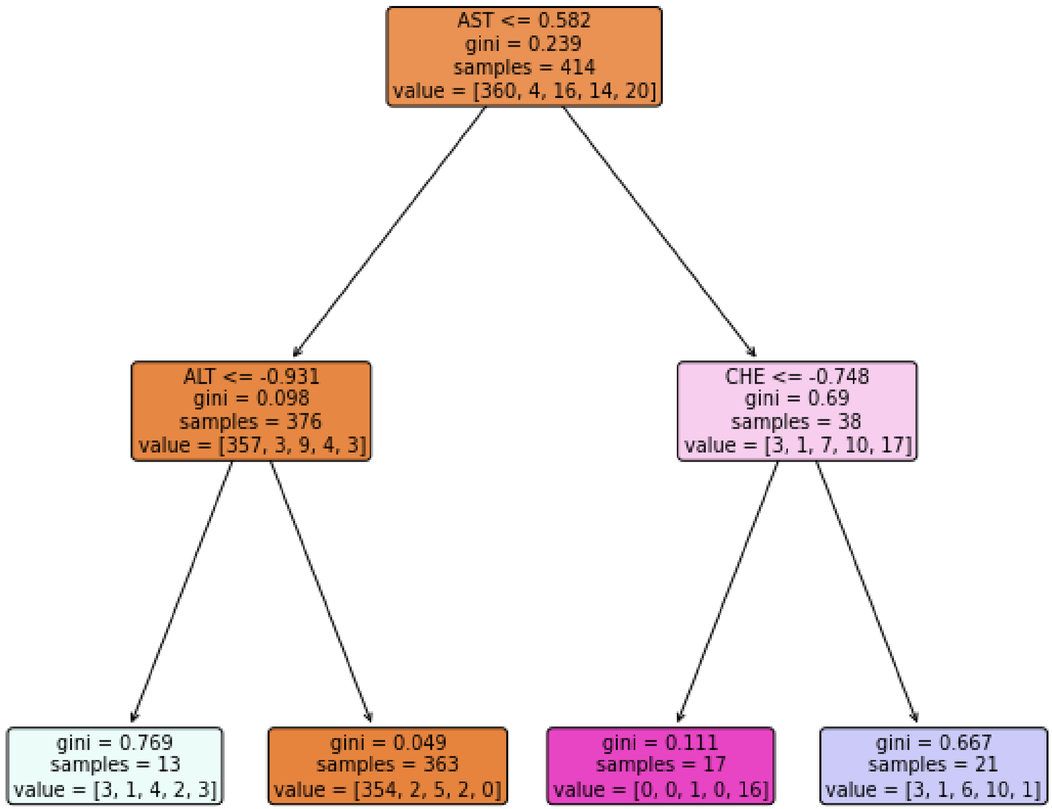
In [200]:
```
dt = DecisionTreeClassifier(random_state = 0, max_depth = 2)
dt.fit(X_trainD, y_trainD)
```

Out[200]:
```
DecisionTreeClassifier(max_depth=2, random_state=0)
```

In [201]:
```
print("Accuracy on training set: {:.3f}".format(dt.score(X_trainD, y_trair
print("Accuracy on test set: {:.3f}".format(dt.score(X_testD, y_testD)))
```

```
Accuracy on training set: 0.928
Accuracy on test set: 0.871
```

In [202]:
```
plt.subplots(figsize = (10,10))
tree.plot_tree(dt,
               feature_names=dx.columns,
               filled=True,
               rounded = True)
plt.show()
```



By comparing both the models with max depth as 2 and 3, we got more accuracy for maxdepth 3 with 94% on training data and 89.9% on test data

Without implementing the concept of maxdepth, we are getting more accuracy for decision tree classifier.

By this, we can say that early stopping with max depth constraint may decrease the accuracy of the model.

Early Stopping: `min_samples_split`

In [203]:

```
#Implementing decision tree classifier model with min samples split concep
#here we considered the samples values as 28

#This means, here 28 samples are needed for splitting the internal node.

dt = DecisionTreeClassifier(random_state = 0, min_samples_split= 28)
dt.fit(X_trainD, y_trainD)
```

Out[203]:

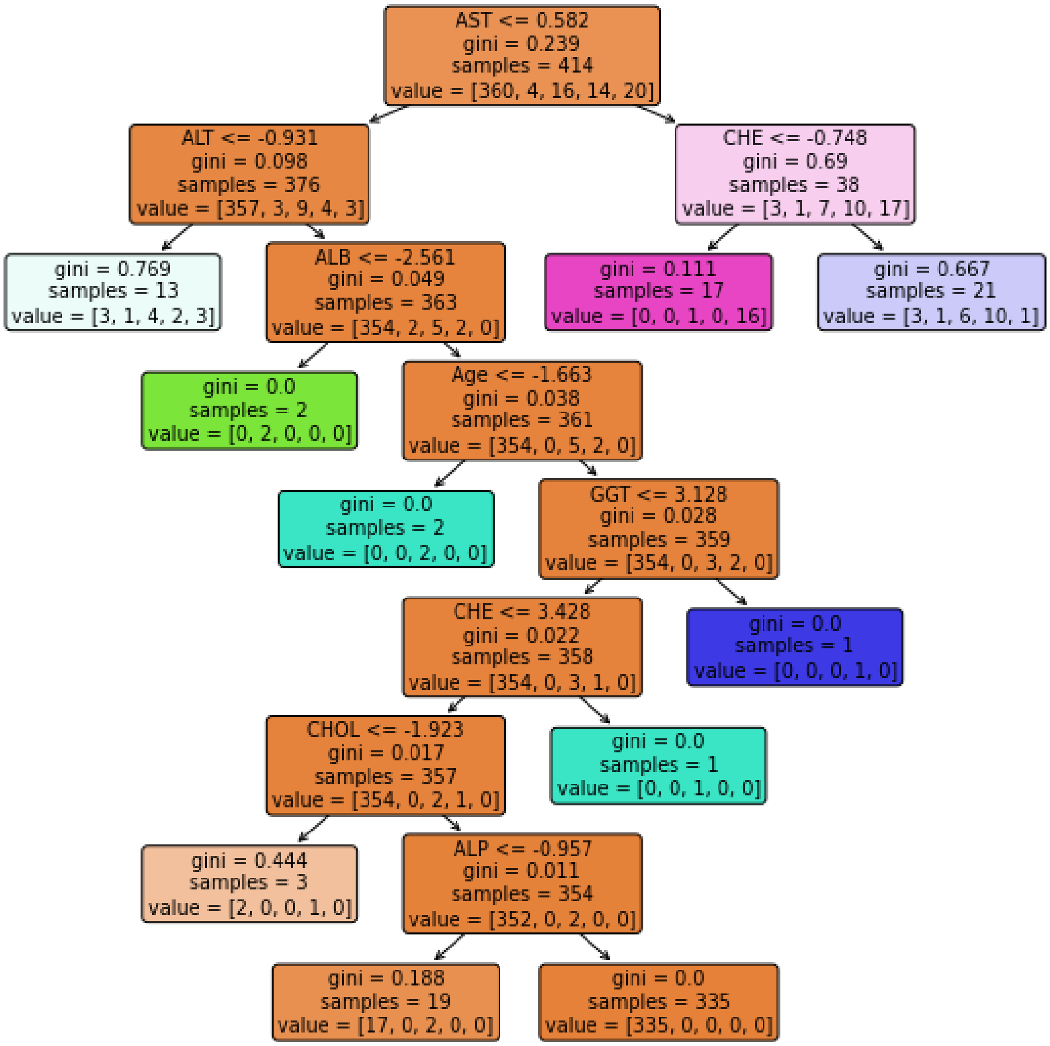
```
DecisionTreeClassifier(min_samples_split=28, random_state=0)
```

In [204]:

```
print("Accuracy on training set: {:.3f}".format(dt.score(X_trainD, y_trair
print("Accuracy on test set: {:.3f}".format(dt.score(X_testD, y_testD)))
```

```
Accuracy on training set: 0.942
Accuracy on test set: 0.885
```

In [205]:
```
plt.subplots(figsize = (10,10))
tree.plot_tree(dt,
               feature_names=dx.columns,
               filled=True,
               rounded = True)
plt.show()
```



Early Stopping: `min_impurity_decrease`

In [206]:
```
dt = DecisionTreeClassifier(random_state = 0, min_impurity_decrease= 0.01)
dt.fit(X_trainD, y_trainD)
```

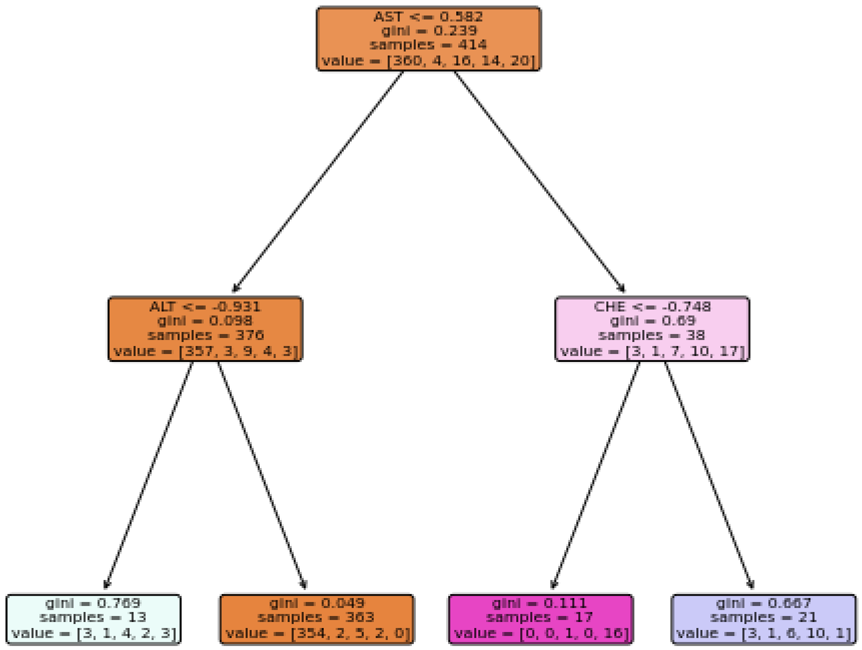
Out[206]:
```
DecisionTreeClassifier(min_impurity_decrease=0.01, random_state=0)
```

In [207]:
```
print("Accuracy on training set: {:.3f}".format(dt.score(X_trainD, y_trair
print("Accuracy on test set: {:.3f}".format(dt.score(X_testD, y_testD)))
```

```
Accuracy on training set: 0.928
Accuracy on test set: 0.871
```

In [208]:

```
plt.subplots(figsize = (8,8))
tree.plot_tree(dt,
               feature_names=dx.columns,
               filled=True,
               rounded = True)
plt.show()
```



Analyzing best model

The accuracy of the logistic regression model is 'train score: 0.9027149321266968 test score: 0.8918918918918919'

The accuracy of the decision tree model is 'Accuracy on training set: 1.000 Accuracy on test set: 0.906'

Based on accuracy of the model, we are considering decision model as the best model and proceeding with this for test data prediction.

Classification Prediction

In [209]:

```
#predicting target values using decision tree model for test classificatio
dt.predict(clasDfTest_mmScal)
```

Out[209]:

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