LAB MST

October 29, 2020

1 LAB MST

1.1 Karan Trehan

1.1.1 18BCS6033

1.1.2 18AITAIML1 - Group B

[1]:
```
# Supress Warnings
import warnings
warnings.filterwarnings('ignore')
```

1.2 Importing the Required Libraries

[2]:
```
#For Data Handling
import numpy as np
import pandas as pd

#For Data Visualization/Exploratory Analysis
from matplotlib import pyplot as plt
import seaborn as sns

#For Statistical Calculations
import scipy.stats as st

#For Regression
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor

sns.set_palette('bright')
sns.set(color_codes=True)
%matplotlib inline
```

1.3 Reading and Understanding the Data

Let's start with the following steps:

1. Importing data using the pandas library
2. Understanding the structure of the data

[3]:
```
#Reading the Dataset
df = pd.read_csv("B1.csv")
```

[4]:
```
#Checking the first 10 rows
df.head(10)
```

[4]:
```
   number of claims  \
0               108
1                19
2                13
3               124
4                40
5                57
6                23
7                14
8                45
9                10

   total payment for all the claims in thousands of Swedish Kronor
0                                              392.5
1                                               46.2
2                                               15.7
3                                              422.2
4                                              119.4
5                                              170.9
6                                               56.9
7                                               77.5
8                                              214.0
9                                               65.3
```

[5]:
```
#Checking information about the Dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 63 entries, 0 to 62
Data columns (total 2 columns):
 number of claims                                                   63 non-null
int64
total payment for all the claims in thousands of Swedish Kronor    63 non-null
float64
dtypes: float64(1), int64(1)
memory usage: 1.1 KB
```

[6]:
```
#Renaming the Columns
new_columns = ['noOfClaims' , 'totalPayment']
df.columns = new_columns
```

Since there are two columns and both have 63 non-null values, Hence there are no, missing values.

[7]:
```
#Viewing the Statistical Measures/Details of the Dataset
df.describe()
```

[7]:
```
       noOfClaims  totalPayment
count   63.000000     63.000000
mean    22.904762     98.187302
std     23.351946     87.327553
min      0.000000      0.000000
25%      7.500000     38.850000
50%     14.000000     73.400000
75%     29.000000    140.000000
max    124.000000    422.200000
```

After a Soft Analysis, we can see that `noOfClaims` and `totalPayment` have outliers which need to be treated

1.4 Checking for Missing and Duplicated Values

[8]:
```
#Checking for duplicacy in the DataFrame using '.duplicated()' method and then␣
↪checking the number of rows using
# '.shape[0]'
print("Number of Duplicate Rows in the DataFrame:" , df[df.duplicated()].
↪shape[0])
```

```
Number of Duplicate Rows in the DataFrame: 0
```

[9]:
```
#Checking the Percentage of Columns having Missing Values in both the DataFrames
print('-+-'*10)
print(round(df.isnull().sum()/len(df)*100,2))
print('-+-'*10)
```

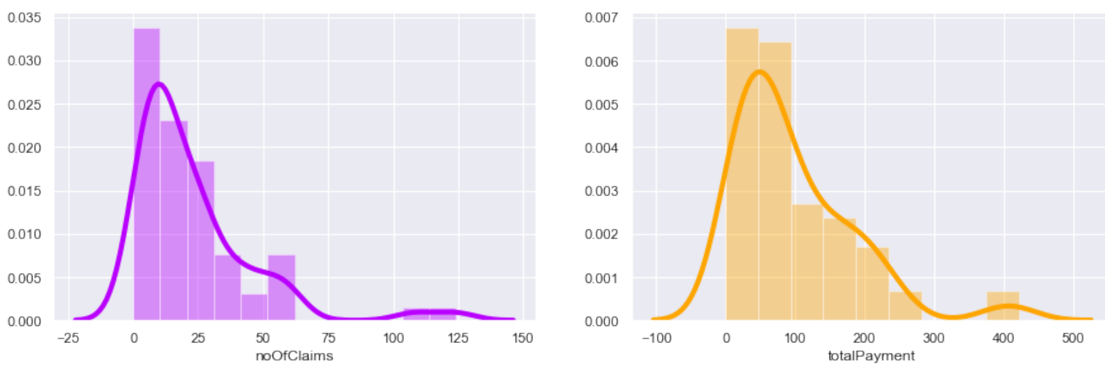
```
-+--+--+--+--+--+--+--+--+--+-
noOfClaims      0.0
totalPayment    0.0
dtype: float64
-+--+--+--+--+--+--+--+--+--+-
```

- Explicitly checking the Missing Value Count.
- Inferring again that there are no Missing Values

2 Data Visualization

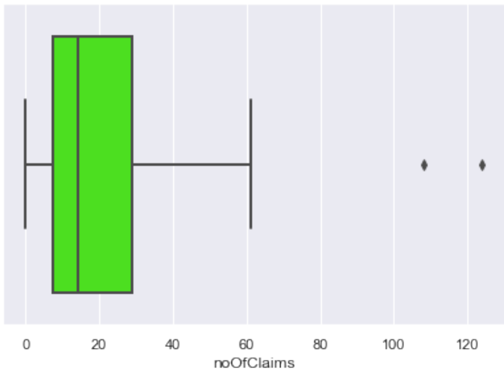
2.1 Univariate Analysis

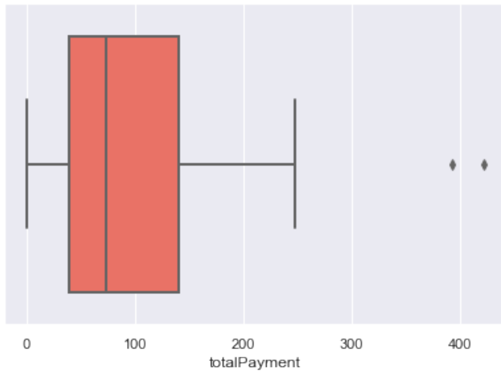
[10]:
```
#Peforming the Univariate Analysis - Distribution Plot
fig, axs = plt.subplots(1,2, figsize = (15, 5))
fig.subplots_adjust(top=0.8)

sns.
 ↪distplot(df['noOfClaims'],ax=axs[0],color='#BA00FF',kde_kws=dict(linewidth=4),hist=True)
axs[0].set_xlabel('noOfClaims', fontsize = 'large')

sns.
 ↪distplot(df['totalPayment'],ax=axs[1],color='orange',kde_kws=dict(linewidth=4),hist=True)
axs[1].set_xlabel('totalPayment', fontsize = 'large')

plt.show()
```



Both the Columns are skewed

[11]:
```
#Peforming the Univariate Analysis - BoxPlot
fig, axs = plt.subplots(1,2, figsize = (15, 5))
fig.subplots_adjust(top=0.8)

sns.boxplot(df['noOfClaims'] , ax = axs[0], color= '#3BFF00',linewidth=2)
axs[0].set_xlabel('noOfClaims', fontsize = 'large')

sns.boxplot(df['totalPayment'] , ax=axs[1], color='#FF6050', linewidth=2)
axs[1].set_xlabel('totalPayment', fontsize = 'large')

plt.show()
```

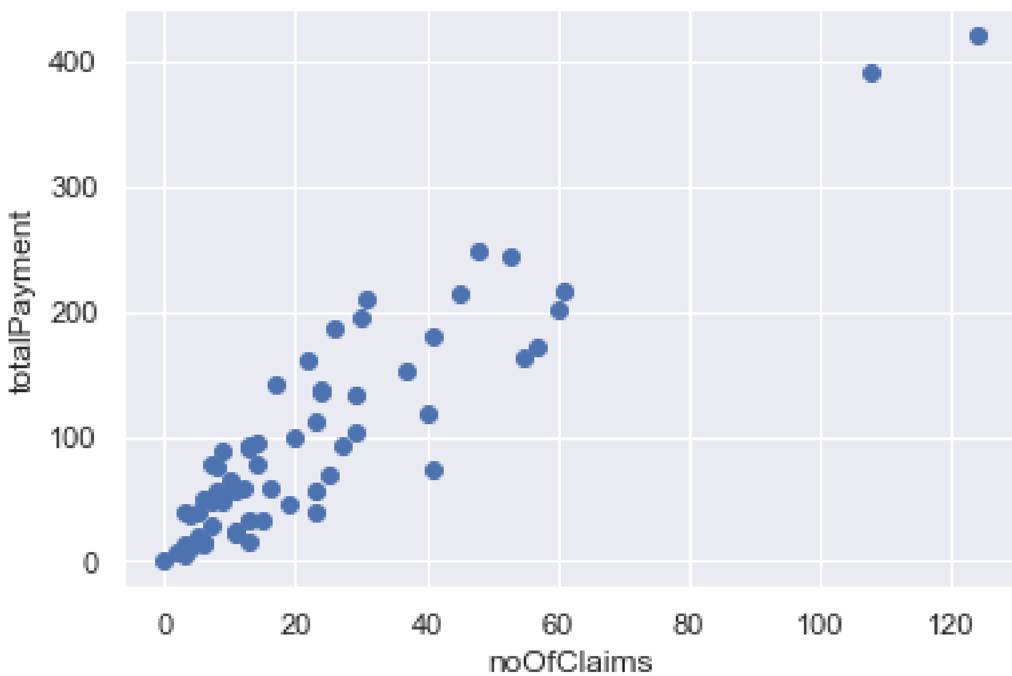




- We can infer that both the columns consist of Outliers that need to be treated.
- Presence of Skewness

2.2 Bi-Variate Analysis

[12]:
```
#Peforming the Bivariate Analysis - ScatterPlot

plt.scatter(df['noOfClaims'], df['totalPayment'], color = 'b')
plt.xlabel('noOfClaims', fontsize = 'large')
plt.ylabel('totalPayment', fontsize = 'large')

plt.show()
```



- Presence of Outliers can be seen.
- Data is following a linear relationship

2.3 Performing Outlier Analysis and Removal

[13]:
```
#Calculating Inter Quartile Range, we can infer the presence of outliers␣
↪statistically
q1 = df.quantile(0.25)
q3 = df.quantile(0.75)
IQR = q3 - q1
print(IQR)
```

```
noOfClaims       21.50
totalPayment    101.15
dtype: float64
```

[14]:
```
#Dropping the Outliers
print(df.shape)
df = df[~((df < (q1 - 1.5 * IQR)) |(df > (q3 + 1.5 * IQR))).any(axis=1)]
print(df.shape)
```

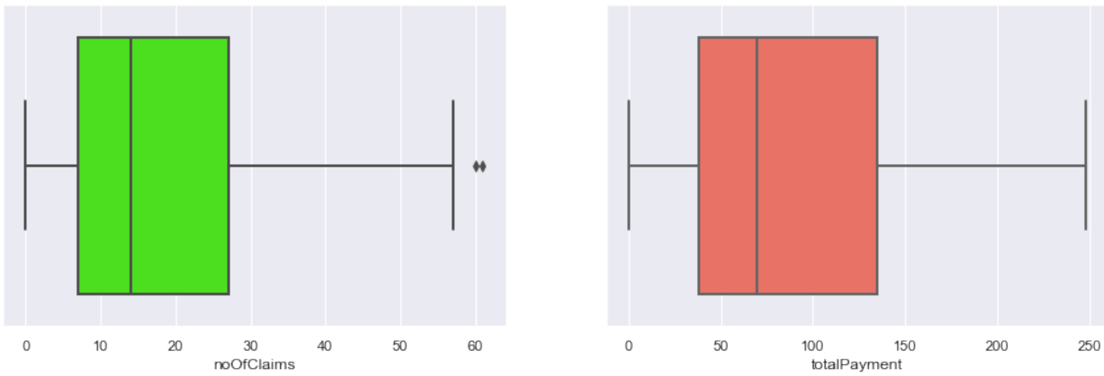
```
(63, 2)
(61, 2)
```

[15]:
```
df['noOfClaims']
```

[15]:
```
1     19
2     13
4     40
5     57
6     23
      ..
58     9
59    31
60    14
61    53
62    26
Name: noOfClaims, Length: 61, dtype: int64
```

[16]:
```
#Peforming the Univariate Analysis - BoxPlot
fig, axs = plt.subplots(1,2, figsize = (15, 5))
fig.subplots_adjust(top=0.8)

sns.boxplot(df['noOfClaims'] , ax = axs[0], color= '#3BFF00',linewidth=2)
axs[0].set_xlabel('noOfClaims', fontsize = 'large')
```

```
sns.boxplot(df['totalPayment'] , ax=axs[1], color='#FF6050', linewidth=2)
axs[1].set_xlabel('totalPayment', fontsize = 'large')

plt.show()
```



2.4 Performing Transformation of Variables to remove Skewness

[17]:
```
df.skew()
```

[17]:
```
noOfClaims      1.080648
totalPayment    0.775697
dtype: float64
```

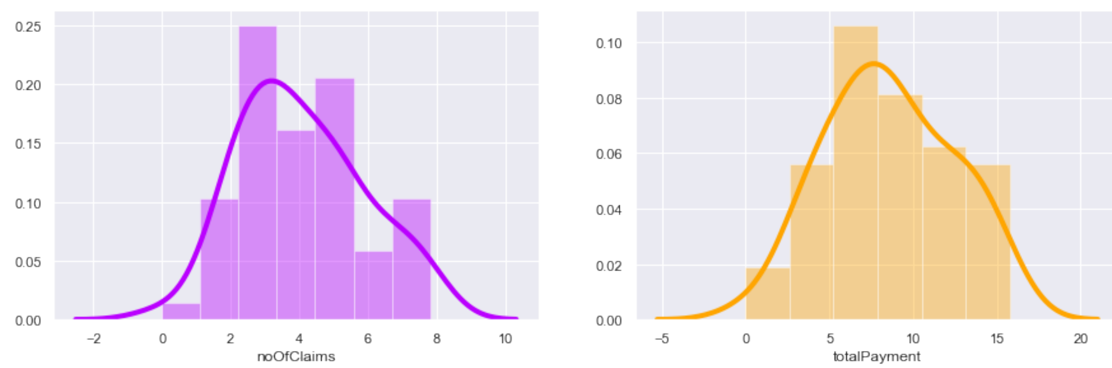
[18]:
```
#Creating two lists for columns which are Right Skewednand Left Skewed
right_skewed=[]
left_skewed=[]

#Column Names of Columns having Skewness greater than 0.5 are placed in the␣
 ↪right_skewed list and vice versa for left_skewed
for i in df.columns:
    if st.skew(df[i])>0.5:
        right_skewed.append(i)
    elif st.skew(df[i])<-0.5:
        left_skewed.append(i)

#Printing the Lists
print('Right Skewed :\n ', right_skewed,'\n\nLeft  Skewed :\n ',left_skewed)
```

```
Right Skewed :
  ['noOfClaims', 'totalPayment']

Left  Skewed :
  []
```

- Both the columns are skewed towards the right

[19]:
```python
#If the columns in the right_skewed list have minimum value 0, then they undergo Square-Root Transformation
#Else the columns undergo Logarithmic Transformation
for i in right_skewed:
    if (min(df[i]) == 0):
        df[i]= np.sqrt((df[i]))
    else:
        df[i]= np.log((df[i]))
```

[20]:
```python
#Peforming the Univariate Analysis - Distribution Plot
fig, axs = plt.subplots(1,2, figsize = (15, 5))
fig.subplots_adjust(top=0.8)

sns.distplot(df['noOfClaims'],ax=axs[0],color='#BA00FF',kde_kws=dict(linewidth=4),hist=True)
axs[0].set_xlabel('noOfClaims', fontsize = 'large')

sns.distplot(df['totalPayment'],ax=axs[1],color='orange',kde_kws=dict(linewidth=4),hist=True)
axs[1].set_xlabel('totalPayment', fontsize = 'large')

plt.show()
```



- We can see that the skewness has been rectified.
- Both the plots are normally distributed

[21]:
```python
#Checking the stats to observe any change
df.describe()
```

[21]:

	noOfClaims	totalPayment
count	61.000000	61.000000
mean	4.081519	8.603733

```
std       1.801912     3.776291
min       0.000000     0.000000
25%       2.645751     6.172520
50%       3.741657     8.318654
75%       5.196152    11.614646
max       7.810250    15.751190
```

Now the Statistics Look Normal.

2.5 Splitting the Dataset into Train and Test Datasets

[22]:
```
# y = df.pop('totalPayment')
# X = df
df_train, df_test = train_test_split(df, train_size = 0.7, test_size = 0.3,␣
↪random_state = 100)
```

2.6 Scaling the Features

[23]:
```
#Scaling the Features between 0 - 1, for easier and efficient performance by the␣
↪Model
scaler = MinMaxScaler()
num_vars = df.columns
df_train[num_vars] = scaler.fit_transform(df_train[num_vars])
df_test[num_vars] = scaler.fit_transform(df_test[num_vars])
```

[24]:
```
y_train = df_train.pop('totalPayment')
X_train = df_train
y_test = df_test.pop('totalPayment')
X_test = df_test
```

[25]:
```
X_train.head()
```

[25]:
```
    noOfClaims
40    0.342609
44    0.938391
28    0.192547
56    0.635239
49    0.049693
```

[26]:
```
y_train.head()
```

[26]:
```
40    0.540807
44    0.780872
28    0.233230
56    0.867810
49    0.309005
```

```
Name: totalPayment, dtype: float64
```

2.7 Model-1 Using Ordinary Least Square Linear Model

[27]:
```
# Adding a constant manually because OLS otherwise fits the line through the␣
 ↪origin
X_train_lm = sm.add_constant(X_train[list(X_train.columns)])

# Create a first fitted model
lr = sm.OLS(y_train, X_train_lm).fit()

#Viewing Summary
print(lr.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           totalPayment   R-squared:                       0.746
Model:                            OLS   Adj. R-squared:                  0.740
Method:                 Least Squares   F-statistic:                     117.8
Date:                Thu, 29 Oct 2020   Prob (F-statistic):           1.73e-13
Time:                        12:37:40   Log-Likelihood:                 23.882
No. Observations:                  42   AIC:                            -43.76
Df Residuals:                      40   BIC:                            -40.29
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.1190      0.039      3.045      0.004       0.040       0.198
noOfClaims     0.8116      0.075     10.852      0.000       0.660       0.963
==============================================================================
Omnibus:                        4.161   Durbin-Watson:                   1.752
Prob(Omnibus):                  0.125   Jarque-Bera (JB):                1.762
Skew:                          -0.002   Prob(JB):                        0.414
Kurtosis:                       1.997   Cond. No.                         4.15
==============================================================================

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

[28]:
```
#Creating a function for Error Terms Distribution Plot
def errorTermsPlot(y,y_hat,color,typ,xlabel):
    # Plot the histogram of the error terms
    fig = plt.figure()
    sns.distplot(((y) - y_hat), bins = 20,color=color,kde_kws=dict(linewidth=4))
```

```
    fig.suptitle('Error Terms for ' + typ + ' Data' , fontsize = 15)
↪      # Plot heading
    plt.xlabel(xlabel, fontsize = 12)
```

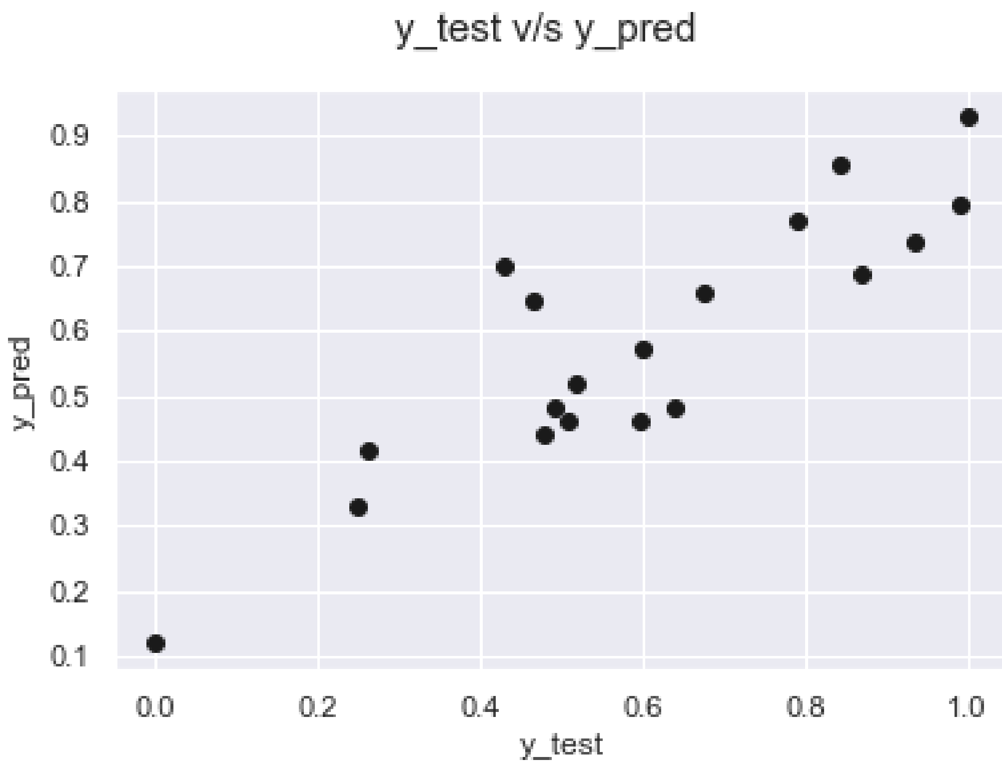
[29]:
```
#Predicting y_train based on X_train_lm
y_train_pred = lr.predict(X_train_lm)

#Plotting the Graph
errorTermsPlot(y_train,y_train_pred,'r','Training','Errors')
```

[30]:
```
# Creating X_test_new dataframe by dropping variables from X_test
X_test_new = X_test[X_train.columns.values]

# Adding a constant variable
X_test_new = sm.add_constant(X_test_new)

# Making predictions
y_pred = lr.predict(X_test_new)
```

[31]:
```
#Creating a function for y_test vs y_pred Plot
def yTest_vs_yPredPlot(y,y_hat,color):
    # Plotting y_test and y_pred to understand the spread.
```

```
    fig = plt.figure()
    plt.scatter(y,y_hat,color=color)
    fig.suptitle('y_test v/s y_pred', fontsize=15)              # Plot heading
    plt.xlabel('y_test', fontsize=12)                            # X-label
    plt.ylabel('y_pred', fontsize=12)
```

[32]:
```
#Plotting y_test vs y_pred for Model 1
yTest_vs_yPredPlot(y_test,y_pred,'k')
```



[33]:
```
#Plotting the Graph for Test Errors
errorTermsPlot(y_pred,y_test,'#EFBE01','Testing','y_pred-y_test')
```

2.8 Model-2 Using Linear Regression Model from scikit-learn

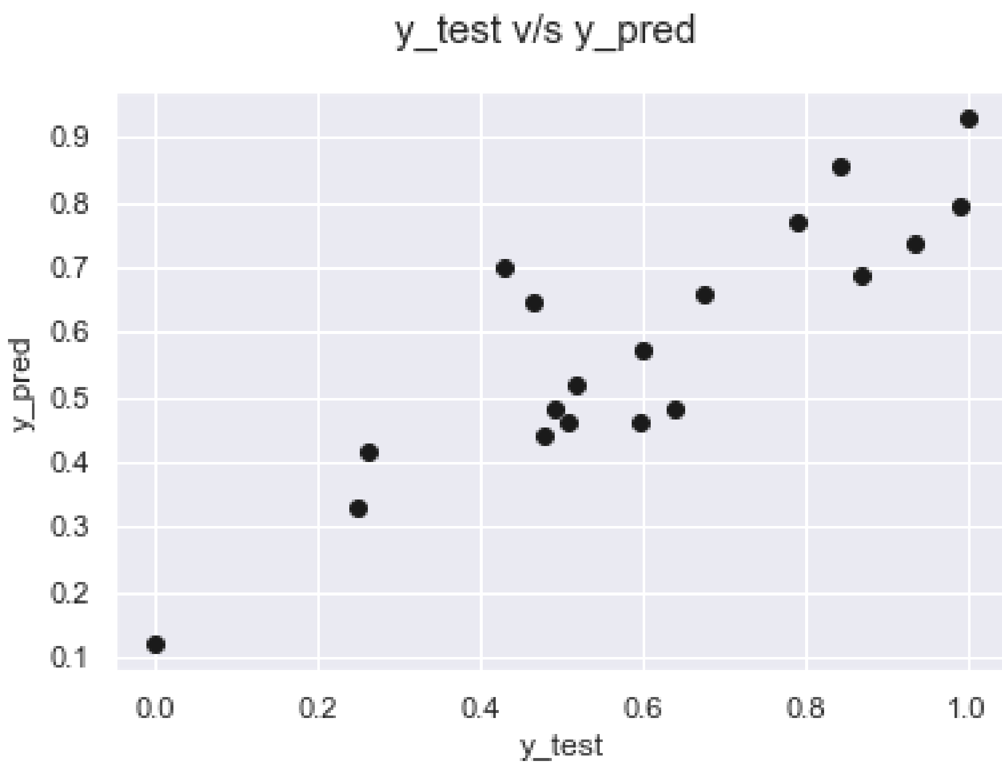
[34]:
```
# initialize the linear regression model
lModel = LinearRegression()

# fitting the model on X_train and y_train
lModel.fit(X_train,y_train)
```

[34]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

[35]:
```
#Predicting y_train based on X_train_lm
y_train_pred2 = lModel.predict(X_train)

#Plotting the Graph
errorTermsPlot(y_train,y_train_pred2,'r','Training','Errors')
```

[36]:
```
# Making predictions
y_pred2 = lModel.predict(X_test)
```

[37]:
```
#Plotting y_test vs y_pred for Model 1
yTest_vs_yPredPlot(y_test,y_pred2,'k')
```



[38]:
```
#Plotting the Graph for Test Errors
errorTermsPlot(y_pred2,y_test,'#EFBE01','Testing','y_pred-y_test')
```

2.9 Model-3 Using Decision Tree Regressor Model from scikit-learn

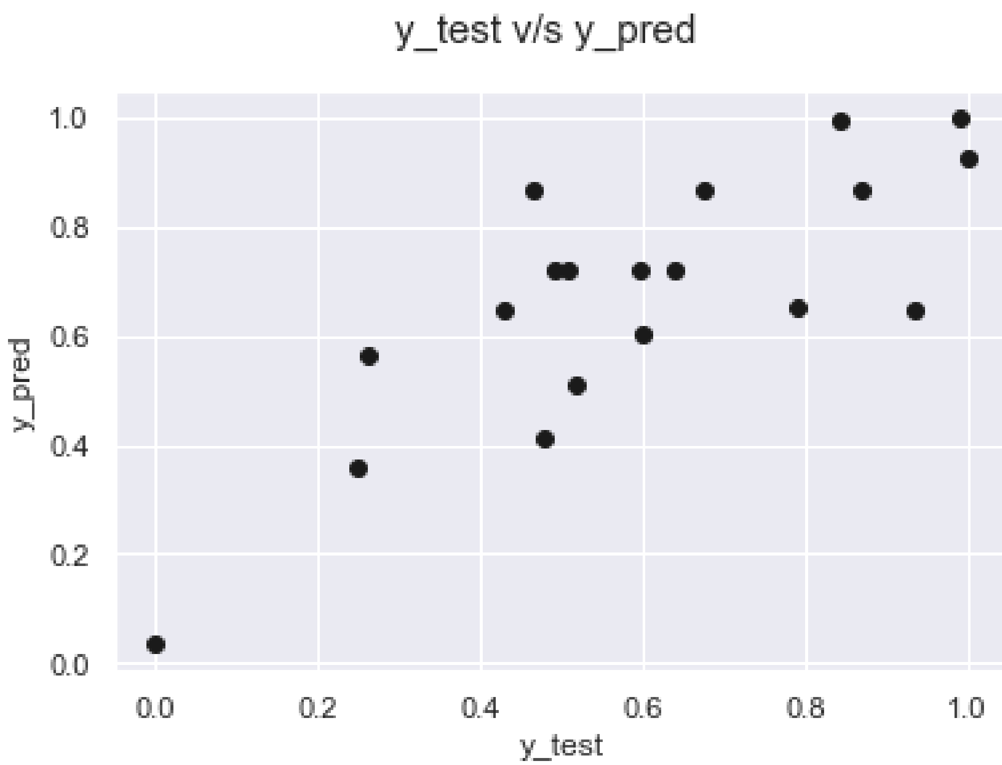
[39]:
```
# defining a decision tree model with a depth of 5. You can further tune the␣
↪hyperparameters to improve the score
dt_reg = DecisionTreeRegressor(max_depth=5)

dt_reg.fit(X_train, y_train)
```

[39]:
```
DecisionTreeRegressor(criterion='mse', max_depth=5, max_features=None,
                      max_leaf_nodes=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      presort=False, random_state=None, splitter='best')
```

[40]:
```
#Predicting y_train based on X_train_lm
y_train_pred3 = dt_reg.predict(X_train)

#Plotting the Graph
errorTermsPlot(y_train,y_train_pred3,'r','Training','Errors')
```

[41]:
```
# Making predictions
y_pred3 = dt_reg.predict(X_test)
```

[42]:
```
#Plotting y_test vs y_pred for Model 1
yTest_vs_yPredPlot(y_test,y_pred3,'k')
```



[43]:
```
#Plotting the Graph for Test Errors
errorTermsPlot(y_pred3,y_test,'#EFBE01','Testing','y_pred-y_test')
```

2.10 Selecting the Best Model by checking Error Metrics of all the Data Models

[44]:
```
#Defining the Funtion 'errorMetrics' which will Calculate various␣
↪parameters(Squared error, Mean Squared error,
#Root Mean Squared error and R-Squared Value)
def errorMetrics(y_pred,y):
    error = y_pred - y

    SE = np.square(error) # squared errors
    MSE = np.mean(SE) # mean squared errors
    RMSE = np.sqrt(MSE) # Root Mean Squared Error, RMSE
    Rsquared = 1.0 - (np.var(error) / np.var(y))
    print('Squared Error',round(sum(SE),3) ,
          '\nMean Squared Error' , round(MSE,3),
          '\nRoot Mean Squared Error' , round(RMSE,3),
          '\nR Squared' , round(Rsquared,3),'\n\n')
    return Rsquared
```

[45]:
```
#Passing the pred_variables to the function
pred_variables=[[y_train_pred,y_train],
                [y_pred,y_test],
                [y_train_pred2,y_train],
```

```python
                 [y_pred2,y_test],
                 [y_train_pred3,y_train],
                 [y_pred3,y_test]]

#Creating a Dictionary from which we will create a Dataframe later on
d = {'Train R2':[],'Test R2':[]}
j=1

for i in pred_variables:
    print('*'*40)
    if(j%2==0):
        print('---------Test Error of Model',int(j/2),'---------')
    else:
        print('---------Train Error of Model',int(j-(j/2)+1),'--------')

    #Calculating R2 value and appending them to Test R2 and Train R2 respectively
    r = errorMetrics(i[0],i[1])
    if(j%2==0):
        d['Test R2'].append(r)
    else:
        d['Train R2'].append(r)
    j+=1
print('*'*40)

#Creating a DataFrame from the above dictionary
models = pd.DataFrame(d,index=['OLS Model','Linear Regression Model' , 'Decision␣
 ↪Tree Regressor Model' ])
models
```

```
****************************************
---------Train Error of Model 1 --------
Squared Error 0.789
Mean Squared Error 0.019
Root Mean Squared Error 0.137
R Squared 0.746


****************************************
---------Test Error of Model 1 ---------
Squared Error 0.315
Mean Squared Error 0.017
Root Mean Squared Error 0.129
R Squared 0.759


****************************************
---------Train Error of Model 2 --------
```

```
Squared Error 0.789
Mean Squared Error 0.019
Root Mean Squared Error 0.137
R Squared 0.746


****************************************
---------Test Error of Model 2 ---------
Squared Error 0.315
Mean Squared Error 0.017
Root Mean Squared Error 0.129
R Squared 0.759


****************************************
---------Train Error of Model 3 --------
Squared Error 0.409
Mean Squared Error 0.01
Root Mean Squared Error 0.099
R Squared 0.869


****************************************
---------Test Error of Model 3 ---------
Squared Error 0.599
Mean Squared Error 0.032
Root Mean Squared Error 0.178
R Squared 0.624


****************************************
```

[45]:

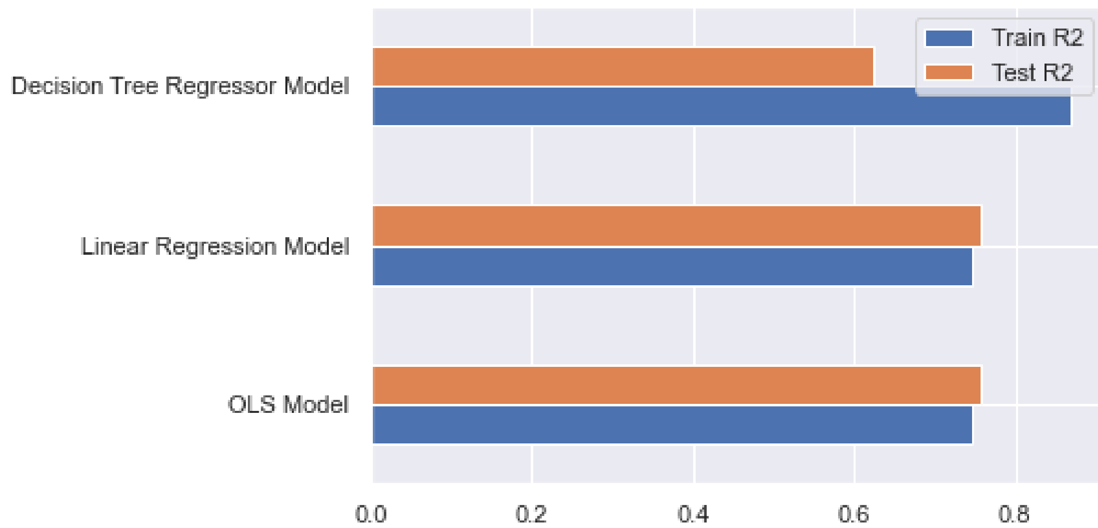
	Train R2	Test R2
OLS Model	0.746459	0.758646
Linear Regression Model	0.746459	0.758646
Decision Tree Regressor Model	0.868630	0.623743

[46]:

```python
#Plotting the Bar Graph for all the Variables in the DataFrame 'models'
models.plot(kind='barh')
```

[46]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f6ea6ec0c8>
```



We can finally observe that:

1. Decision Tree Regressor Model performs highly on Training Dataset but very poorly on testing Dataset

2. Linear Regression Model performs fairly.

3. OLS Model performs best on both the datasets.

So I will choose OLS Model

[47]:
```
#Creating Equation for OLS Model
l = np.around(np.array(lr.params.values),3)
s=''
for i in zip(lr.params.index,l):
    s += str(i[0]) + '    *      ' + str(i[1]) + '    +    '
print(s)
```

```
const    *      0.119    +    noOfClaims    *      0.812    +
```

2.10.1 Final Equation

`total payment` = `const` * 0.119 + `noOfClaims` * 0.812

Thank You!

[ ]:
```
```