Model Selection using RFE(HOUSING CASE STUDY)

Importing and Understanding Data

In [1]:
```
import pandas as pd
import numpy as np
```

In [2]:
```
# Importing Housing.csv
housing = pd.read_csv('Housing.csv')
```

In [3]:
```
# Looking at the first five rows
housing.head()
```

Out[3]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hot\
0	13300000	7420	4	2	3	yes	no	no	no
1	12250000	8960	4	4	4	yes	no	no	no
2	12250000	9960	3	2	2	yes	no	yes	no
3	12215000	7500	4	2	2	yes	no	yes	no
4	11410000	7420	4	1	2	yes	yes	yes	no

Data Preparation

In [4]:
```
# Converting Yes to 1 and No to 0
housing['mainroad'] = housing['mainroad'].map({'yes': 1, 'no': 0})
housing['guestroom'] = housing['guestroom'].map({'yes': 1, 'no': 0})
housing['basement'] = housing['basement'].map({'yes': 1, 'no': 0})
housing['hotwaterheating'] = housing['hotwaterheating'].map({'yes': 1, 'no': 0
})
housing['airconditioning'] = housing['airconditioning'].map({'yes': 1, 'no': 0
})
housing['prefarea'] = housing['prefarea'].map({'yes': 1, 'no': 0})
```

In [5]:
```
# Creating dummy variable for variable furnishingstatus and dropping the first
one
status = pd.get_dummies(housing['furnishingstatus'],drop_first=True)
```

In [6]:
```
#Adding the results to the master dataframe
housing = pd.concat([housing,status],axis=1)
```

In [7]:
```
# Dropping the variable 'furnishingstatus'
housing.drop(['furnishingstatus'],axis=1,inplace=True)
```

Creating a new variable

In [8]:
```
# Let us create the new metric and assign it to "areaperbedroom"
housing['areaperbedroom'] = housing['area']/housing['bedrooms']
```

In [9]:
```
# Metric: bathrooms per bedroom
housing['bbratio'] = housing['bathrooms']/housing['bedrooms']
```

Rescaling the Features

It is extremely important to rescale the variables so that they have a comparable scale. There are twocoon ways of rescaling

1. Normalisation (min-max scaling) and
2. standardisation (mean-o, sigma-1) Let's try normalisation

In [10]:
```
#defining a normalisation function
def normalize (x):
    return ( (x-np.mean(x))/ (max(x) - min(x)))


# applying normalize ( ) to all columns
housing = housing.apply(normalize)
```

Splitting data into training and testing sets

In [11]:
```
# Putting feature variable to X
X = housing[['area', 'bedrooms', 'bathrooms', 'stories', 'mainroad',
       'guestroom', 'basement', 'hotwaterheating', 'airconditioning',
       'parking', 'prefarea', 'semi-furnished', 'unfurnished',
       'areaperbedroom', 'bbratio']]

# Putting response variable to y
y = housing['price']
```

In [12]:
```
#random_state is the seed used by the random number generator, it can be any i
nteger.
from sklearn.cross_validation import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7 ,test
_size = 0.3, random_state=100)
```

```
C:\Users\Sumit\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: De
precationWarning: This module was deprecated in version 0.18 in favor of the
model_selection module into which all the refactored classes and functions ar
e moved. Also note that the interface of the new CV iterators are different f
rom that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [13]:
```
# UDF for calculating vif value
def vif_cal(input_data, dependent_col):
    vif_df = pd.DataFrame( columns = ['Var', 'Vif'])
    x_vars=input_data.drop([dependent_col], axis=1)
    xvar_names=x_vars.columns
    for i in range(0,xvar_names.shape[0]):
        y=x_vars[xvar_names[i]]
        x=x_vars[xvar_names.drop(xvar_names[i])]
        rsq=sm.OLS(y,x).fit().rsquared
        vif=round(1/(1-rsq),2)
        vif_df.loc[i] = [xvar_names[i], vif]
    return vif_df.sort_values(by = 'Vif', axis=0, ascending=False, inplace=Fal
se)
```

RFE

In [15]:
```
# Importing RFE and LinearRegression
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
```

In [16]:
```
# Running RFE with the output number of the variable equal to 9
lm = LinearRegression()
rfe = RFE(lm, 9)             # running RFE
rfe = rfe.fit(X_train, y_train)
print(rfe.support_)           # Printing the boolean results
print(rfe.ranking_)
```

```
[ True False  True  True  True False False  True  True False  True False
 False  True  True]
[1 3 1 1 1 4 6 1 1 2 1 7 5 1 1]
```

In [17]:
```
col = X_train.columns[rfe.support_]
```

Building model using sklearn

In [18]:
```
# Creating X_test dataframe with RFE selected variables
X_train_rfe = X_train[col]
```

In [20]:
```
# Adding a constant variable
import statsmodels.api as sm
X_train_rfe = sm.add_constant(X_train_rfe)
```

```
C:\Users\Sumit\Anaconda3\lib\site-packages\statsmodels\compat\pandas.py:56: F
utureWarning: The pandas.core.datetools module is deprecated and will be remo
ved in a future version. Please use the pandas.tseries module instead.
  from pandas.core import datetools
```

In [21]:
```
lm = sm.OLS(y_train,X_train_rfe).fit()   # Running the linear model
```

In [22]:
```
#Let's see the summary of our linear model
print(lm.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:                  price   R-squared:                       0.66
0
Model:                            OLS   Adj. R-squared:                  0.65
2
Method:                 Least Squares   F-statistic:                     80.1
4
Date:                Tue, 13 Mar 2018   Prob (F-statistic):           1.88e-8
1
Time:                        15:56:09   Log-Likelihood:                 369.5
4
No. Observations:                 381   AIC:                            -719.
1
Df Residuals:                     371   BIC:                            -679.
7
Df Model:                           9
Covariance Type:            nonrobust
==============================================================================
======
                      coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
------
const               0.0034      0.005      0.704      0.482      -0.006
0.013
area                0.7022      0.130      5.421      0.000       0.447
0.957
bathrooms           0.1718      0.098      1.759      0.079      -0.020
0.364
stories             0.0814      0.019      4.321      0.000       0.044
0.118
mainroad            0.0647      0.014      4.470      0.000       0.036
0.093
hotwaterheating     0.1002      0.022      4.523      0.000       0.057
0.144
airconditioning     0.0776      0.011      6.806      0.000       0.055
0.100
prefarea            0.0631      0.012      5.286      0.000       0.040
0.087
areaperbedroom     -0.4095      0.143     -2.868      0.004      -0.690
-0.129
bbratio             0.1156      0.080      1.450      0.148      -0.041
0.272
==============================================================================
=
Omnibus:                       85.512   Durbin-Watson:                   2.10
8
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              273.42
9
Skew:                           0.998   Prob(JB):                     4.22e-6
0
Kurtosis:                       6.638   Cond. No.                         46.
6
==============================================================================
=
```

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

In [23]:
```
# Calculating Vif value
vif_cal(input_data=housing.drop(['area','bedrooms','stories','basement','semi-
furnished','areaperbedroom'], axis=1), dependent_col="price")
```

Out[23]:

	Var	Vif
0	bathrooms	2.35
8	bbratio	2.19
5	parking	1.12
4	airconditioning	1.11
1	mainroad	1.10
6	prefarea	1.09
7	unfurnished	1.07
2	guestroom	1.06
3	hotwaterheating	1.04

Making Predictions

In [24]:
```
# Now let's use our model to make predictions.

# Creating X_test_6 dataframe by dropping variables from X_test
X_test_rfe = X_test[col]

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

# Making predictions
y_pred = lm.predict(X_test_rfe)
```

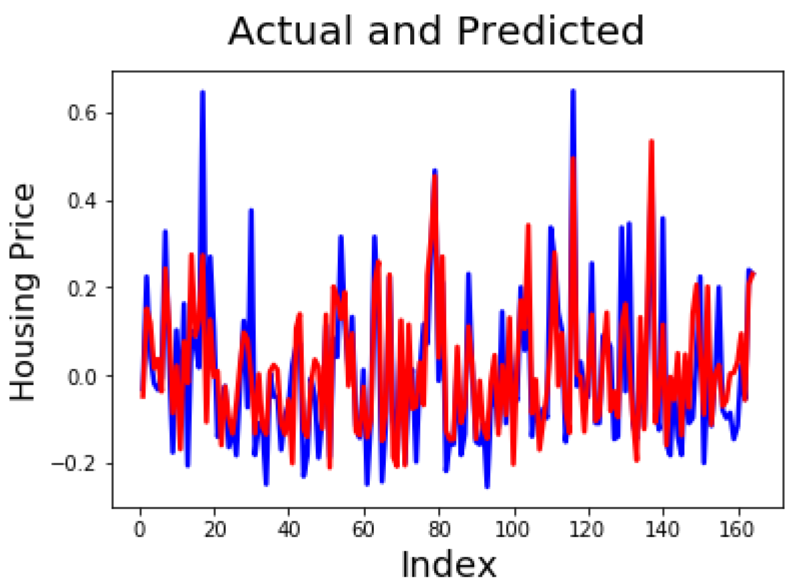
Model Evaluation

In [25]:
```
# Now let's check how well our model is able to make predictions.

# Importing the required libraries for plots.
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

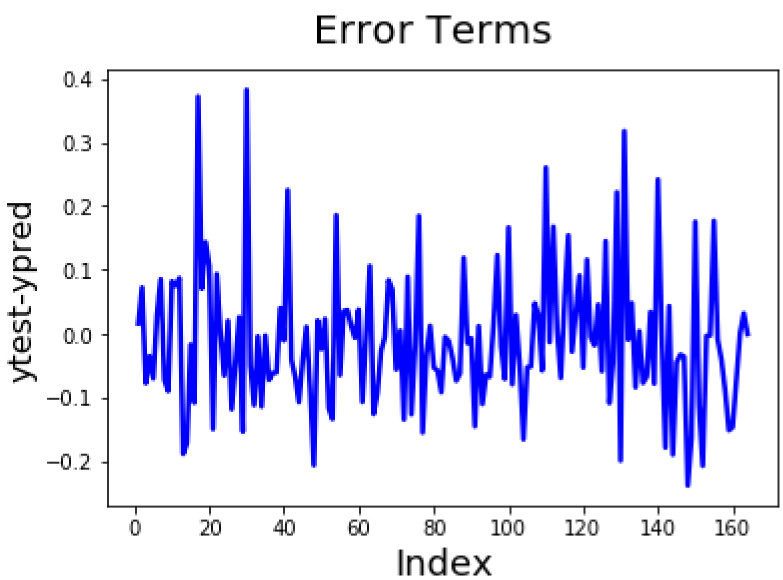
In [26]:
```
# Actual and Predicted
import matplotlib.pyplot as plt
c = [i for i in range(1,165,1)] # generating index
fig = plt.figure()
plt.plot(c,y_test, color="blue", linewidth=2.5, linestyle="-") #Plotting Actua
l
plt.plot(c,y_pred, color="red",  linewidth=2.5, linestyle="-") #Plotting predi
cted
fig.suptitle('Actual and Predicted', fontsize=20)              # Plot heading
plt.xlabel('Index', fontsize=18)                               # X-label
plt.ylabel('Housing Price', fontsize=16)                       # Y-label
```

Out[26]: Text(0,0.5,'Housing Price')



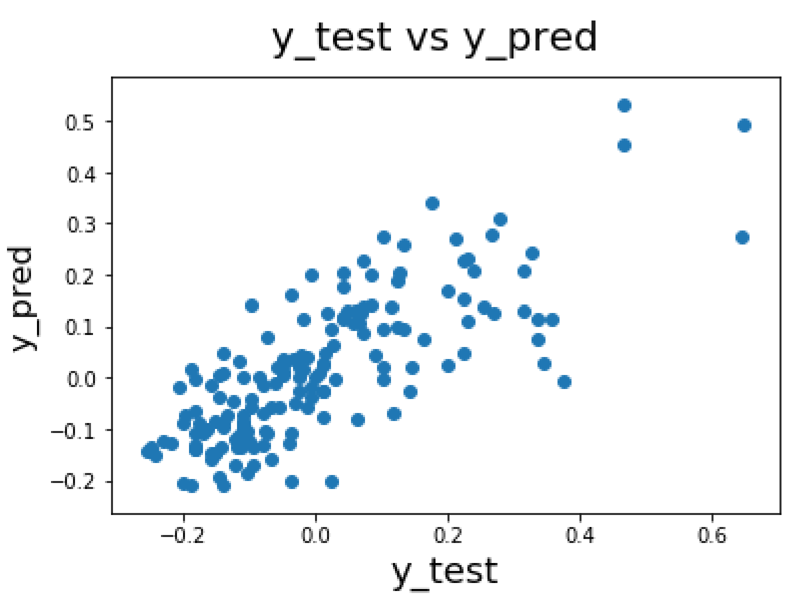
In [27]:
```
# Error terms
c = [i for i in range(1,165,1)]
fig = plt.figure()
plt.plot(c,y_test-y_pred, color="blue", linewidth=2.5, linestyle="-")
fig.suptitle('Error Terms', fontsize=20)              # Plot heading
plt.xlabel('Index', fontsize=18)                      # X-label
plt.ylabel('ytest-ypred', fontsize=16)                # Y-label
```

Out[27]: Text(0,0.5,'ytest-ypred')



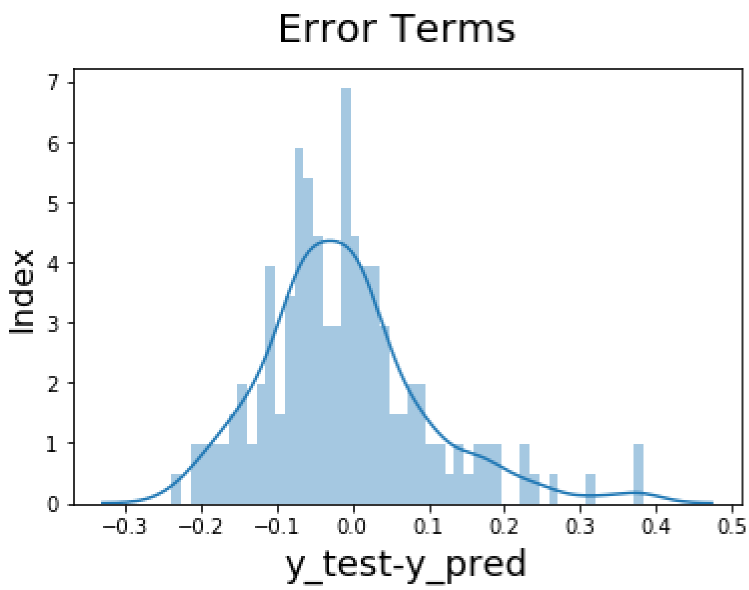
In [28]:
```
# Plotting y_test and y_pred to understand the spread.
fig = plt.figure()
plt.scatter(y_test,y_pred)
fig.suptitle('y_test vs y_pred', fontsize=20)              # Plot heading
plt.xlabel('y_test', fontsize=18)                          # X-label
plt.ylabel('y_pred', fontsize=16)                          # Y-label
```

Out[28]: Text(0,0.5,'y_pred')



In [29]:
```
# Plotting the error terms to understand the distribution.
fig = plt.figure()
sns.distplot((y_test-y_pred),bins=50)
fig.suptitle('Error Terms', fontsize=20)                  # Plot heading
plt.xlabel('y_test-y_pred', fontsize=18)                  # X-label
plt.ylabel('Index', fontsize=16)                          # Y-label
```

Out[29]: Text(0,0.5,'Index')



In [30]:
```
# Now let's check the Root Mean Square Error of our model.
import numpy as np
from sklearn import metrics
print('RMSE :', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
RMSE : 0.108203525381
```