In [1]:
```
import warnings
warnings.filterwarnings('ignore')
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
housing = pd.DataFrame(pd.read_csv("Housing.csv"))
housing.head()
```

Out[2]:

| | price | area | bedrooms | bathrooms | stories | mainroad | guestroom | basement | hotwaterhea |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 13300000 | 7420 | 4 | 2 | 3 | yes | no | no | |
| **1** | 12250000 | 8960 | 4 | 4 | 4 | yes | no | no | |
| **2** | 12250000 | 9960 | 3 | 2 | 2 | yes | no | yes | |
| **3** | 12215000 | 7500 | 4 | 2 | 2 | yes | no | yes | |
| **4** | 11410000 | 7420 | 4 | 1 | 2 | yes | yes | yes | |

## Data Inspection

In [3]:
```
housing.shape
```

Out[3]: (545, 13)

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 545 entries, 0 to 544
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   price             545 non-null    int64 
 1   area              545 non-null    int64 
 2   bedrooms          545 non-null    int64 
 3   bathrooms         545 non-null    int64 
 4   stories           545 non-null    int64 
 5   mainroad          545 non-null    object
 6   guestroom         545 non-null    object
 7   basement          545 non-null    object
 8   hotwaterheating   545 non-null    object
 9   airconditioning   545 non-null    object
 10  parking           545 non-null    int64 
 11  prefarea          545 non-null    object
 12  furnishingstatus  545 non-null    object
dtypes: int64(6), object(7)
memory usage: 55.5+ KB
```

In [6]:
```
housing.describe()
```

Out[6]:

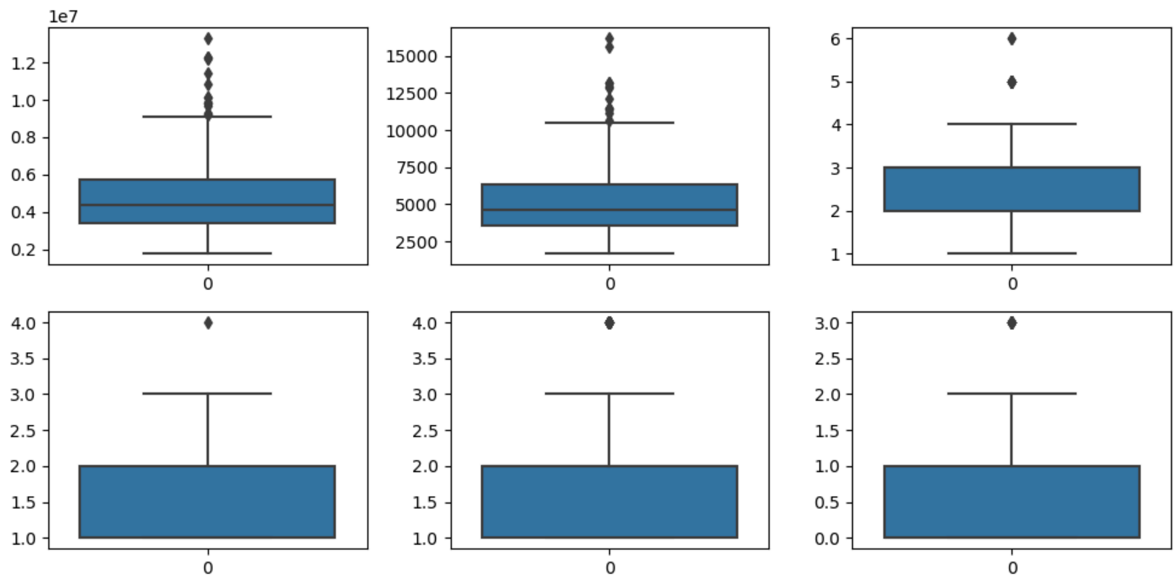
| | price | area | bedrooms | bathrooms | stories | parking |
|---|---|---|---|---|---|---|
| **count** | 5.450000e+02 | 545.000000 | 545.000000 | 545.000000 | 545.000000 | 545.000000 |
| **mean** | 4.766729e+06 | 5150.541284 | 2.965138 | 1.286239 | 1.805505 | 0.693578 |
| **std** | 1.870440e+06 | 2170.141023 | 0.738064 | 0.502470 | 0.867492 | 0.861586 |
| **min** | 1.750000e+06 | 1650.000000 | 1.000000 | 1.000000 | 1.000000 | 0.000000 |
| **25%** | 3.430000e+06 | 3600.000000 | 2.000000 | 1.000000 | 1.000000 | 0.000000 |
| **50%** | 4.340000e+06 | 4600.000000 | 3.000000 | 1.000000 | 2.000000 | 0.000000 |
| **75%** | 5.740000e+06 | 6360.000000 | 3.000000 | 2.000000 | 2.000000 | 1.000000 |
| **max** | 1.330000e+07 | 16200.000000 | 6.000000 | 4.000000 | 4.000000 | 3.000000 |

## Data Cleaning

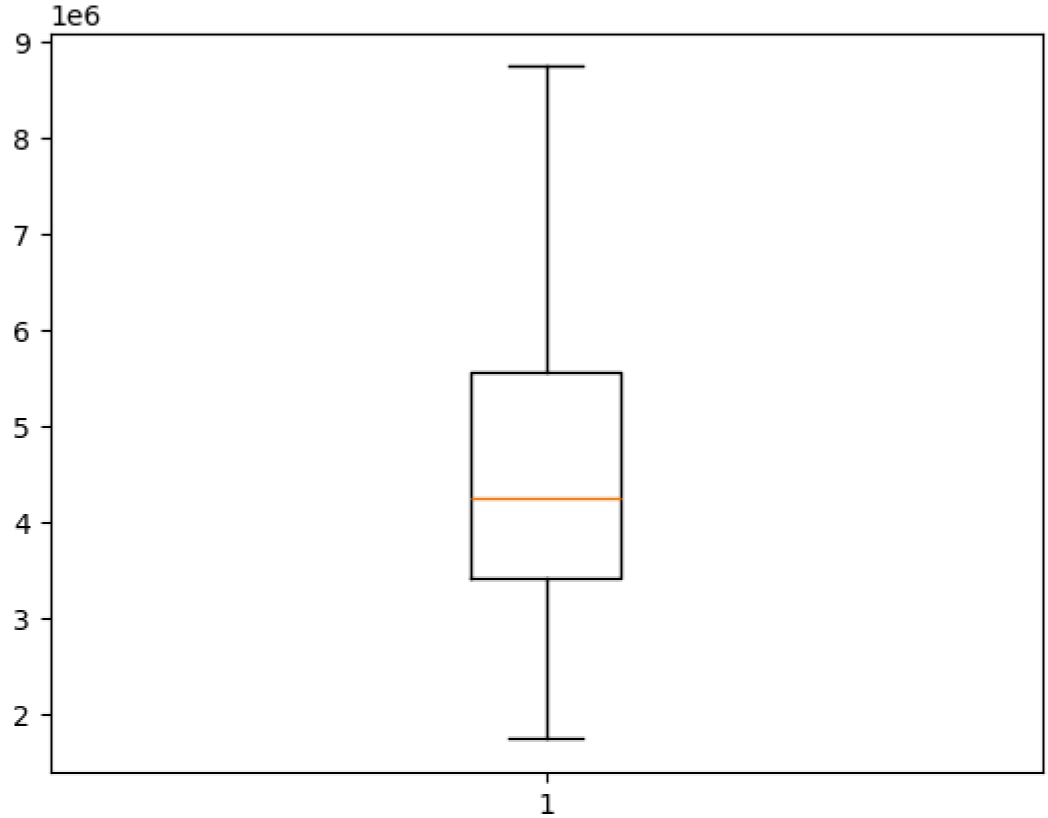
In [8]:
```
# Checking Null values
housing.isnull().sum()*100/housing.shape[0]
```

Out[8]:
```
price               0.0
area                0.0
bedrooms            0.0
bathrooms           0.0
stories             0.0
mainroad            0.0
guestroom           0.0
basement            0.0
hotwaterheating     0.0
airconditioning     0.0
parking             0.0
prefarea            0.0
furnishingstatus    0.0
dtype: float64
```

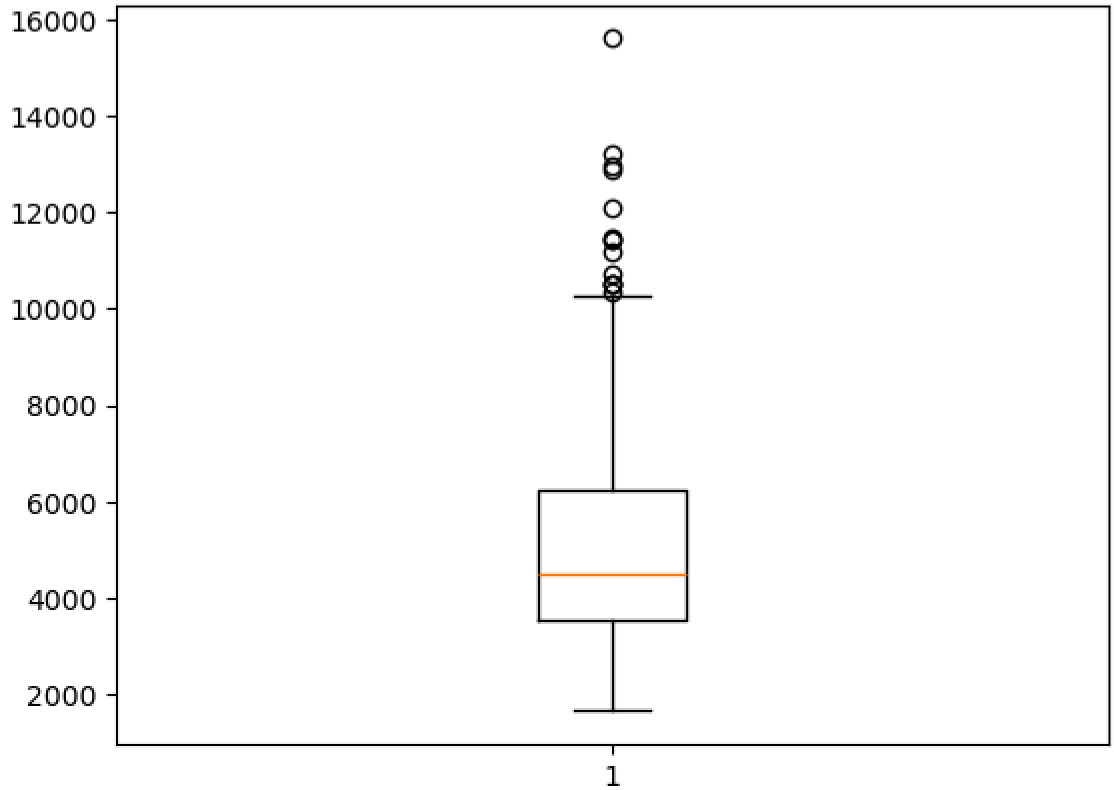
In [10]:
```
# Outlier Analysis
fig, axs = plt.subplots(2,3, figsize = (10,5))
plt1 = sns.boxplot(housing['price'], ax = axs[0,0])
plt2 = sns.boxplot(housing['area'], ax = axs[0,1])
plt3 = sns.boxplot(housing['bedrooms'], ax = axs[0,2])
plt1 = sns.boxplot(housing['bathrooms'], ax = axs[1,0])
plt2 = sns.boxplot(housing['stories'], ax = axs[1,1])
plt3 = sns.boxplot(housing['parking'], ax = axs[1,2])

plt.tight_layout()
```



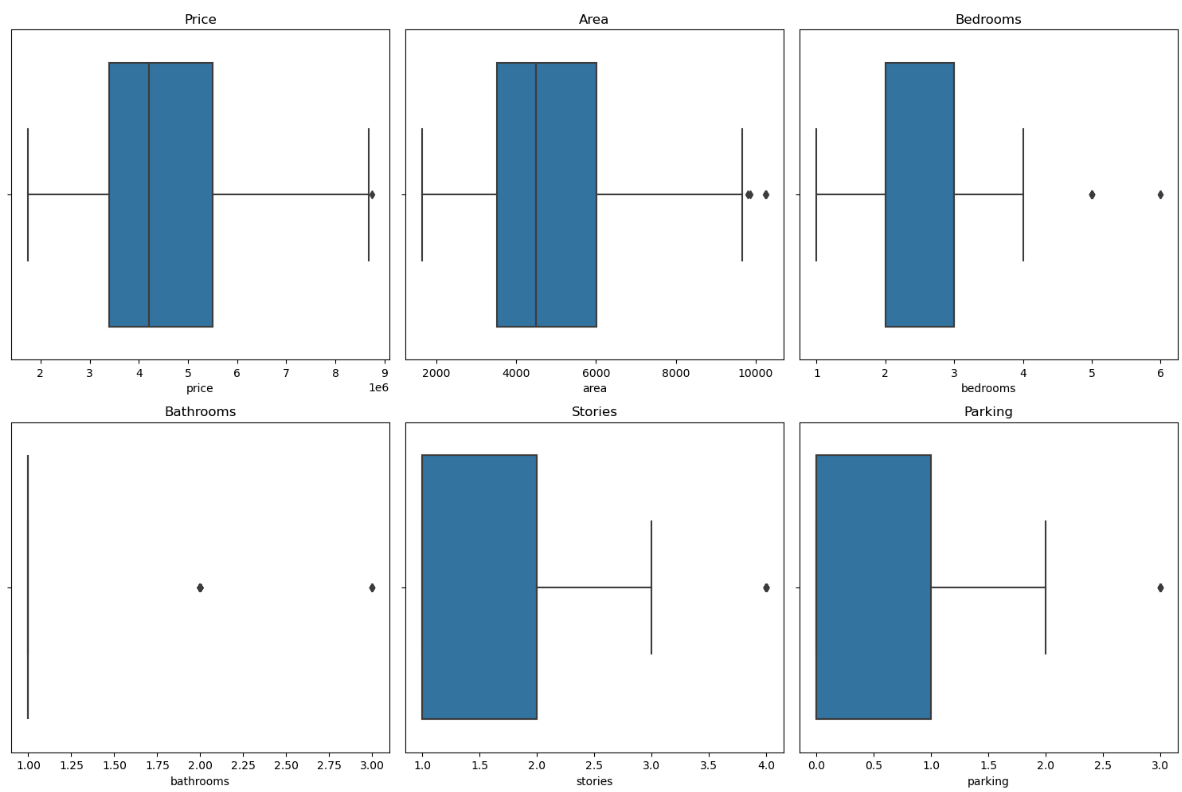
In [20]:
```
# outlier treatment for price
plt.boxplot(housing.price)
Q1 = housing.price.quantile(0.25)
Q3 = housing.price.quantile(0.75)
IQR = Q3 - Q1
housing = housing[(housing.price >= Q1 - 1.5*IQR) & (housing.price <= Q3 + 1.5
```



In [21]:
```
# outlier treatment for area
plt.boxplot(housing.area)
Q1 = housing.area.quantile(0.25)
Q3 = housing.area.quantile(0.75)
IQR = Q3 - Q1
housing = housing[(housing.area >= Q1 - 1.5*IQR) & (housing.area <= Q3 + 1.5*I
```



In [23]:
```
fig, axs = plt.subplots(2, 3, figsize=(15, 10))

# Boxplots
sns.boxplot(x=housing['price'], ax=axs[0, 0])
sns.boxplot(x=housing['area'], ax=axs[0, 1])
sns.boxplot(x=housing['bedrooms'], ax=axs[0, 2])
sns.boxplot(x=housing['bathrooms'], ax=axs[1, 0])
sns.boxplot(x=housing['stories'], ax=axs[1, 1])
sns.boxplot(x=housing['parking'], ax=axs[1, 2])


axs[0, 0].set_title('Price')
axs[0, 1].set_title('Area')
axs[0, 2].set_title('Bedrooms')
axs[1, 0].set_title('Bathrooms')
axs[1, 1].set_title('Stories')
axs[1, 2].set_title('Parking')

# Adjust layout
plt.tight_layout()
```

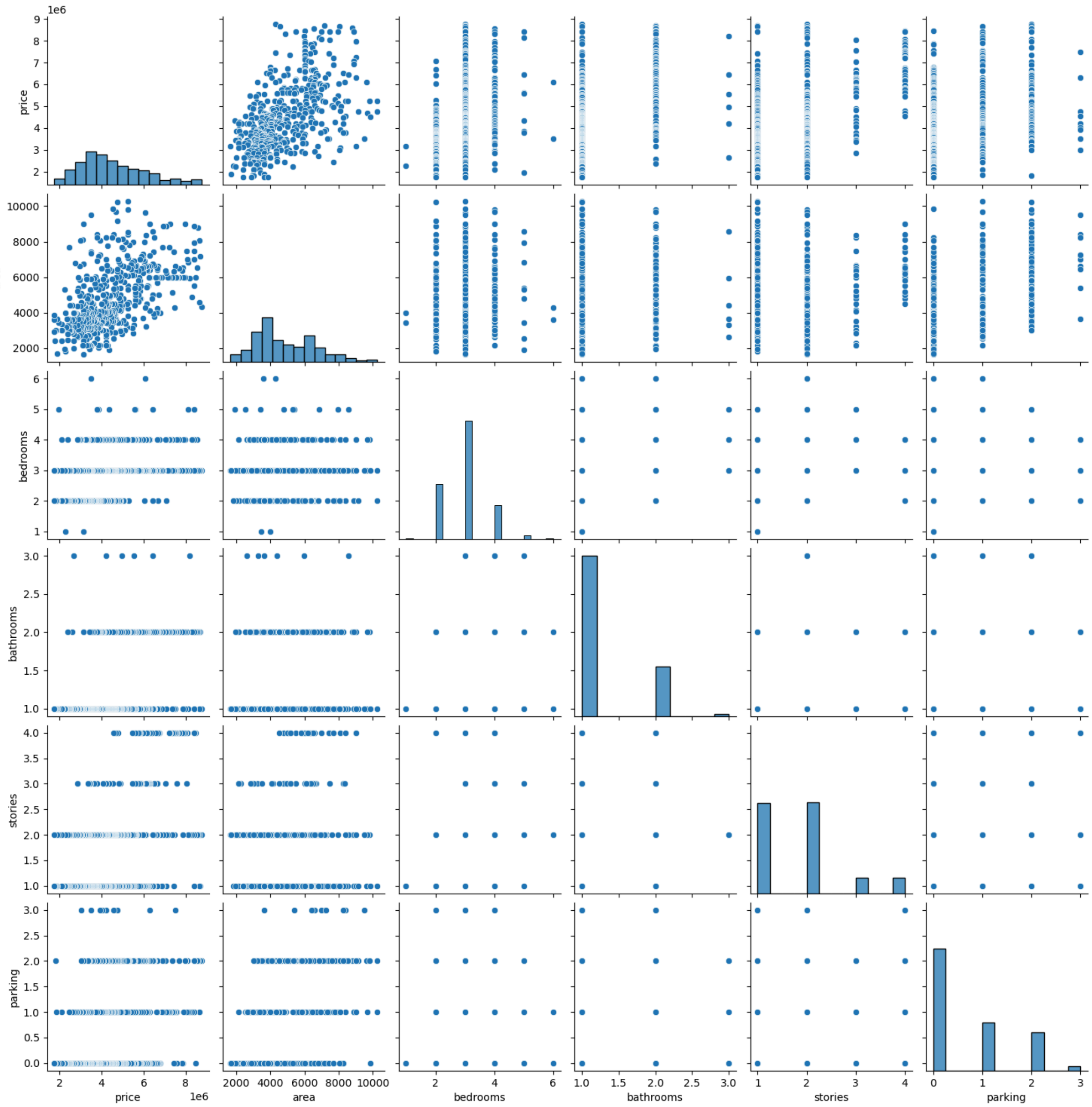



## Exploratory Data Analytics

Let's now spend some time doing what is arguably the most important step - understanding the data.

If there is some obvious multicollinearity going on, this is the first place to catch it Here's where you'll also identify if some predictors directly have a strong association with the outcome variable Visualising Numeric Variables Let's make a pairplot of all the numeric variables

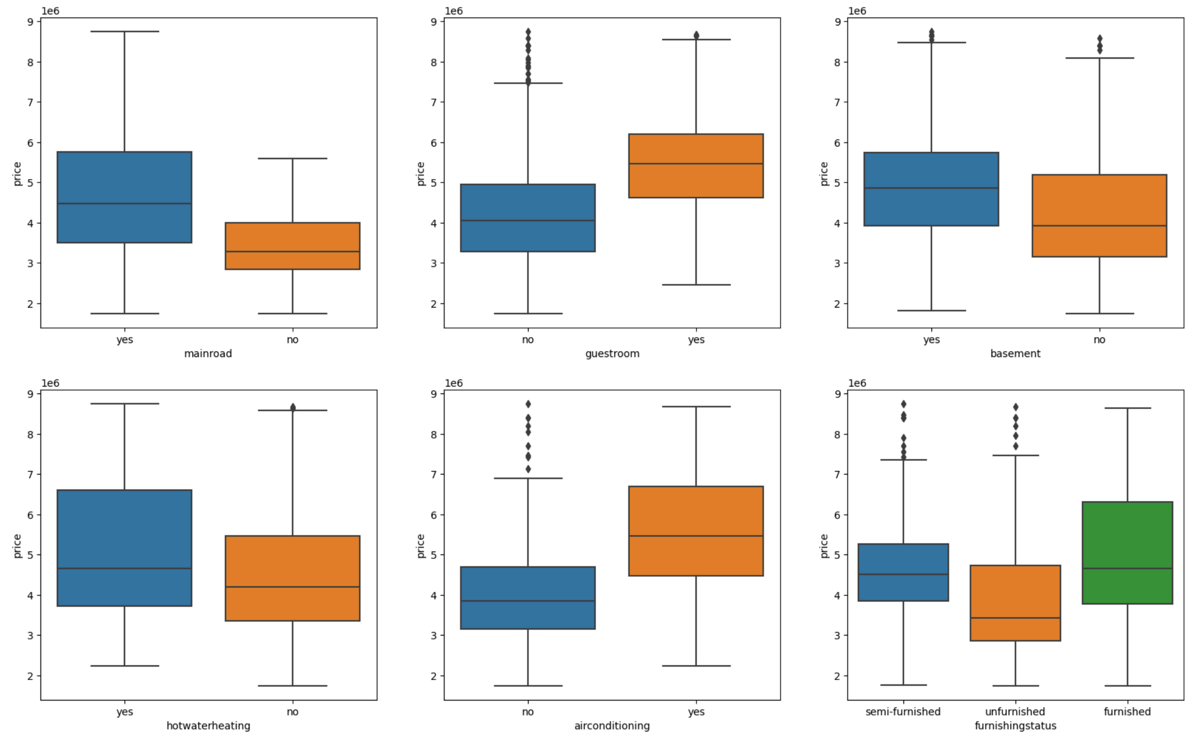
In [24]:
```
sns.pairplot(housing)
plt.show()
```




## Visualising Categorical Variables¶

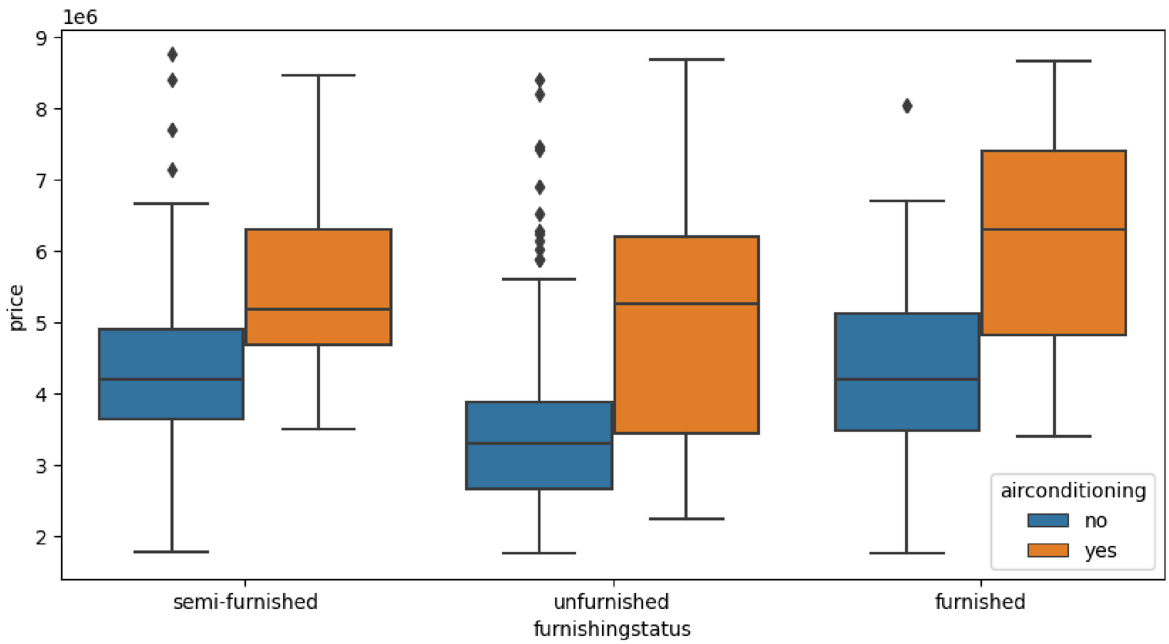
As you might have noticed, there are a few categorical variables as well. Let's make a boxplot for some of these variables.

In [27]:
```
plt.figure(figsize=(20, 12))
plt.subplot(2,3,1)
sns.boxplot(x = 'mainroad', y = 'price', data = housing)
plt.subplot(2,3,2)
sns.boxplot(x = 'guestroom', y = 'price', data = housing)
plt.subplot(2,3,3)
sns.boxplot(x = 'basement', y = 'price', data = housing)
plt.subplot(2,3,4)
sns.boxplot(x = 'hotwaterheating', y = 'price', data = housing)
plt.subplot(2,3,5)
sns.boxplot(x = 'airconditioning', y = 'price', data = housing)
plt.subplot(2,3,6)
sns.boxplot(x = 'furnishingstatus', y = 'price', data = housing)
plt.show()
```




***We can also visualise some of these categorical features parallely by using the hue argument. Below is the plot for furnishingstatus with airconditioning as the hue.***

In [32]:
```
plt.figure(figsize = (10, 5))
sns.boxplot(x = 'furnishingstatus', y = 'price', hue = 'airconditioning', data
plt.show()
```




## Data Preparation

**You can see that your dataset has many columns with values as 'Yes' or 'No'.**

But in order to fit a regression line, we would need numerical values and not string. Hence, we need to convert them to 1s and 0s, where 1 is a 'Yes' and 0 is a 'No'.

In [33]:
```
 #List of variables to map

varlist =  ['mainroad', 'guestroom', 'basement', 'hotwaterheating', 'aircondit

# Defining the map function
def binary_map(x):
    return x.map({'yes': 1, "no": 0})

# Applying the function to the housing list
housing[varlist] = housing[varlist].apply(binary_map)
```

In [34]:
```
# Check the housing dataframe now

housing.head()
```

Out[34]:

| | price | area | bedrooms | bathrooms | stories | mainroad | guestroom | basement | hotwaterhea |
|---|---|---|---|---|---|---|---|---|---|
| **20** | 8750000 | 4320 | 3 | 1 | 2 | 1 | 0 | 1 | |
| **21** | 8680000 | 7155 | 3 | 2 | 1 | 1 | 1 | 1 | |
| **22** | 8645000 | 8050 | 3 | 1 | 1 | 1 | 1 | 1 | |
| **23** | 8645000 | 4560 | 3 | 2 | 2 | 1 | 1 | 1 | |
| **24** | 8575000 | 8800 | 3 | 2 | 2 | 1 | 0 | 0 | |

## Dummy Variables

The variable furnishingstatus has three levels. We need to convert these levels into integer as well.

For this, we will use something called dummy variables.

In [35]:
```
# Get the dummy variables for the feature 'furnishingstatus' and store it in a
status = pd.get_dummies(housing['furnishingstatus'])
```

In [37]:
```
# Check what the dataset 'status' looks like
status.head()
```

Out[37]:

| | furnished | semi-furnished | unfurnished |
|---|---|---|---|
| **20** | False | True | False |
| **21** | False | False | True |
| **22** | True | False | False |
| **23** | True | False | False |
| **24** | True | False | False |

#### Now, you don't need three columns. You can drop the furnished column, as the type of furnishing can be identified with just the last two columns where —

00 will correspond to furnished 01 will correspond to unfurnished 10 will correspond to semi-furnished

In [41]:
```
#dropping the first column from status df using 'drop_first= True'
status = pd.get_dummies(housing['furnishingstatus'], drop_first = True)
```

In [42]:
```
#Adding results to original housing df
housing = pd.concat([housing, status], axis = 1)
```

In [43]:
```
housing.head()
```

Out[43]:

| | price | area | bedrooms | bathrooms | stories | mainroad | guestroom | basement | hotwaterhea |
|---|---|---|---|---|---|---|---|---|---|
| 20 | 8750000 | 4320 | 3 | 1 | 2 | 1 | 0 | 1 | |
| 21 | 8680000 | 7155 | 3 | 2 | 1 | 1 | 1 | 1 | |
| 22 | 8645000 | 8050 | 3 | 1 | 1 | 1 | 1 | 1 | |
| 23 | 8645000 | 4560 | 3 | 2 | 2 | 1 | 1 | 1 | |
| 24 | 8575000 | 8800 | 3 | 2 | 2 | 1 | 0 | 0 | |

In [44]:
```
# Drop 'furnishingstatus' as dummies is already created

housing.drop(['furnishingstatus'], axis = 1, inplace = True)
```

In [45]:
```
housing.head()
```

Out[45]:

| | price | area | bedrooms | bathrooms | stories | mainroad | guestroom | basement | hotwaterhea |
|---|---|---|---|---|---|---|---|---|---|
| 20 | 8750000 | 4320 | 3 | 1 | 2 | 1 | 0 | 1 | |
| 21 | 8680000 | 7155 | 3 | 2 | 1 | 1 | 1 | 1 | |
| 22 | 8645000 | 8050 | 3 | 1 | 1 | 1 | 1 | 1 | |
| 23 | 8645000 | 4560 | 3 | 2 | 2 | 1 | 1 | 1 | |
| 24 | 8575000 | 8800 | 3 | 2 | 2 | 1 | 0 | 0 | |

### Splitting the Data into Training and Testing Sets

In [49]:
```
from sklearn.model_selection import train_test_split

# We specify this so that the train and test data set always have the same row
np.random.seed(0)
df_train, df_test = train_test_split(housing, train_size = 0.7, test_size = 0.
```

### Rescaling the Features¶

As you saw in the demonstration for Simple Linear Regression, scaling doesn't impact your model. Here we can see that except for area, all the columns have small integer values. So it is extremely important to rescale the variables so that they have a comparable scale. If we don't have comparable scales, then some of the coefficients as obtained by fitting the regression model might be very large or very small as compared to the other coefficients. This might become very annoying at the time of model evaluation. So it is advised to use standardization or normalization so that the units of the coefficients obtained are all on the same scale. As you know, there are two common ways of rescaling:

Min-Max scaling Standardisation (mean-0, sigma-1) This time, we will use MinMax scaling

In [50]:
```
from sklearn.preprocessing import MinMaxScaler
```

In [52]:
```
scaler = MinMaxScaler()
```

In [55]:
```
# Applying scaler() to all the columns except 'yes-no' and 'dummy' variables
num_vars = ['area', 'bedrooms', 'bathrooms', 'stories', 'parking','price']
df_train[num_vars] = scaler.fit_transform(df_train[num_vars])
```

In [56]:
```
df_train.head()
```

Out[56]:

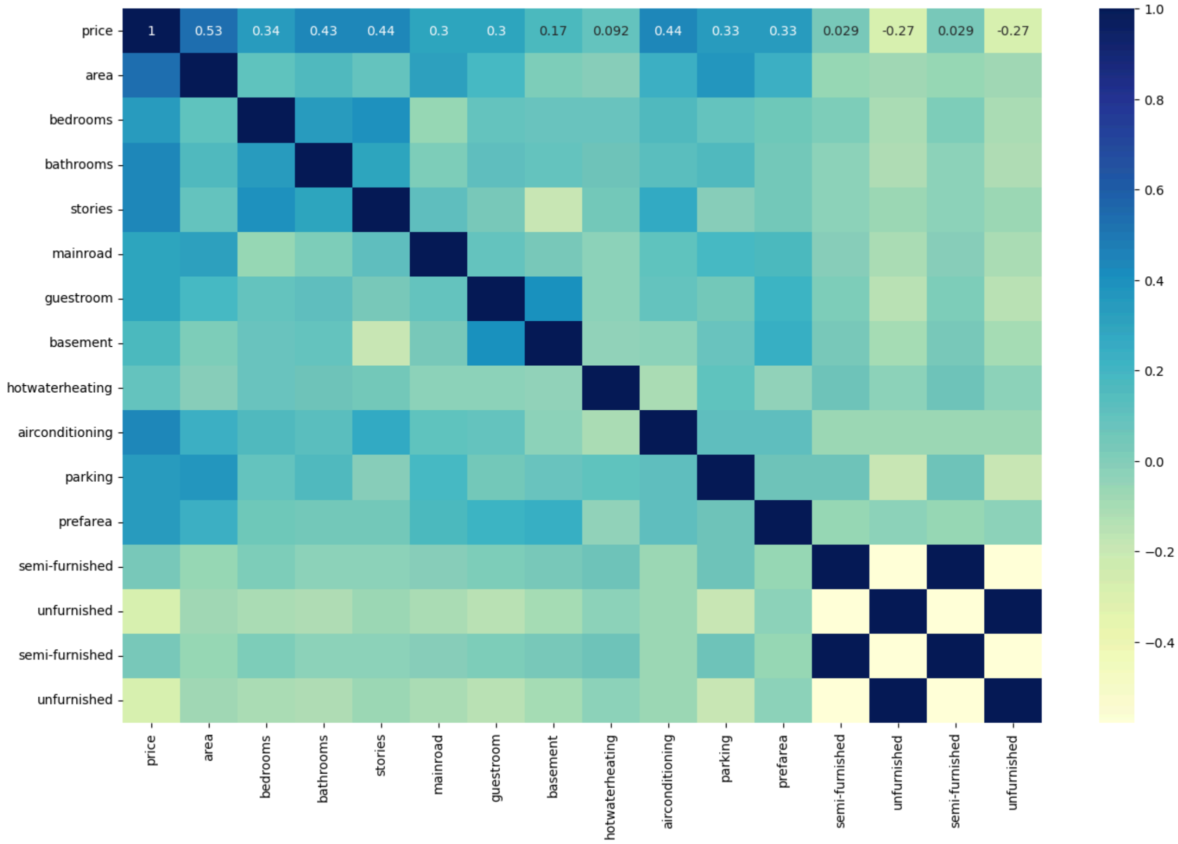
| | price | area | bedrooms | bathrooms | stories | mainroad | guestroom | basement | hotwate |
|---|---|---|---|---|---|---|---|---|---|
| **100** | 0.640 | 0.576251 | 0.25 | 0.5 | 0.000000 | 1 | 0 | 1 | |
| **487** | 0.160 | 0.436554 | 0.50 | 0.0 | 0.333333 | 1 | 0 | 0 | |
| **248** | 0.399 | 0.285215 | 0.00 | 0.5 | 0.000000 | 1 | 1 | 1 | |
| **109** | 0.620 | 0.577998 | 0.50 | 0.5 | 0.333333 | 1 | 1 | 0 | |
| **499** | 0.130 | 0.230501 | 0.25 | 1.0 | 0.333333 | 0 | 1 | 0 | |

In [58]:
```
df_train.describe()
```

Out[58]:

| | price | area | bedrooms | bathrooms | stories | mainroad | guestroom | ba |
|---|---|---|---|---|---|---|---|---|
| **count** | 357.000000 | 357.000000 | 357.000000 | 357.000000 | 357.000000 | 357.000000 | 357.000000 | 357 |
| **mean** | 0.391666 | 0.374467 | 0.238095 | 0.127451 | 0.265173 | 0.851541 | 0.182073 | 0 |
| **std** | 0.216398 | 0.200460 | 0.186533 | 0.233747 | 0.287088 | 0.356054 | 0.386446 | 0 |
| **min** | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0 |
| **25%** | 0.230000 | 0.227008 | 0.000000 | 0.000000 | 0.000000 | 1.000000 | 0.000000 | 0 |
| **50%** | 0.350000 | 0.331781 | 0.250000 | 0.000000 | 0.333333 | 1.000000 | 0.000000 | 0 |
| **75%** | 0.530000 | 0.506403 | 0.250000 | 0.000000 | 0.333333 | 1.000000 | 0.000000 | 1 |
| **max** | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 1 |

In [60]:
```
#checking the highly correlated variables

plt.figure(figsize = (16, 10))
sns.heatmap(df_train.corr(), annot = True, cmap="YlGnBu")
plt.show()
```




#### Dividing into X and Y sets for the model building

In [61]:
```
y_train = df_train.pop('price')
X_train = df_train
```

#### Model Building

This time, we will be using the LinearRegression function from SciKit Learn for its compatibility with RFE (which is a utility from sklearn)

In [62]:
```
#Recursive feature elimination
```

In [63]:
```
# Importing RFE and LinearRegression
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
```

In [ ]:

In [66]:
```
lm = LinearRegression()
lm.fit(X_train, y_train)

# Run RFE with the number of features to select equal to 6
rfe = RFE(estimator=lm, n_features_to_select=6)
rfe = rfe.fit(X_train, y_train)

# Get the support and ranking of features
support = rfe.support_
ranking = rfe.ranking_

print("Selected Features: ", support)
print("Feature Ranking: ", ranking)
```

```
Selected Features:  [ True False  True  True False False False  True  True Fa
lse  True False
 False False False]
Feature Ranking:  [ 1  5  1  1  6  3  7  1  1  2  1 10  4  9  8]
```

In [68]:
```
list(zip(X_train.columns,rfe.support_,rfe.ranking_))
```

Out[68]:
```
[('area', True, 1),
 ('bedrooms', False, 5),
 ('bathrooms', True, 1),
 ('stories', True, 1),
 ('mainroad', False, 6),
 ('guestroom', False, 3),
 ('basement', False, 7),
 ('hotwaterheating', True, 1),
 ('airconditioning', True, 1),
 ('parking', False, 2),
 ('prefarea', True, 1),
 ('semi-furnished', False, 10),
 ('unfurnished', False, 4),
 ('semi-furnished', False, 9),
 ('unfurnished', False, 8)]
```

In [71]:
```
col = X_train.columns[rfe.support_]
col
```

Out[71]:
```
Index(['area', 'bathrooms', 'stories', 'hotwaterheating', 'airconditioning',
       'prefarea'],
      dtype='object')
```

In [73]:
```
X_train.columns[~rfe.support_]
```

Out[73]:
```
Index(['bedrooms', 'mainroad', 'guestroom', 'basement', 'parking',
       'semi-furnished', 'unfurnished', 'semi-furnished', 'unfurnished'],
      dtype='object')
```

### Building model using statsmodel, for the detailed statistics

In [75]:
```
# Creating X_test dataframe with RFE selected variables
X_train_rfe = X_train[col]
```

In [76]:
```
# Adding a constant variable
import statsmodels.api as sm
X_train_rfe = sm.add_constant(X_train_rfe)
```

In [77]:
```
lm = sm.OLS(y_train,X_train_rfe).fit()   # Running the linear model
```

In [78]:
```
# summary of our linear model
print(lm.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:                  price   R-squared:                       0.59
6
Model:                            OLS   Adj. R-squared:                  0.58
9
Method:                 Least Squares   F-statistic:                     85.9
1
Date:                Sun, 19 May 2024   Prob (F-statistic):           8.72e-6
6
Time:                        15:19:39   Log-Likelihood:                 201.9
8
No. Observations:                 357   AIC:                            -390.
0
Df Residuals:                     350   BIC:                            -362.
8
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
======
                      coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
------
const               0.1024      0.017      6.167      0.000       0.070
0.135
area                0.3919      0.039     10.059      0.000       0.315
0.469
bathrooms           0.2301      0.033      6.899      0.000       0.165
0.296
stories             0.1902      0.028      6.861      0.000       0.136
0.245
hotwaterheating     0.1100      0.037      2.968      0.003       0.037
0.183
airconditioning     0.1153      0.017      6.809      0.000       0.082
0.149
prefarea            0.1045      0.019      5.567      0.000       0.068
0.141
==============================================================================
=
Omnibus:                       20.973   Durbin-Watson:                   1.97
2
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               29.36
6
Skew:                           0.449   Prob(JB):                     4.20e-0
7
Kurtosis:                       4.081   Cond. No.                         6.8
1
==============================================================================
=

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

In [80]:
```
# Calculate the VIFs for the model
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [84]:
```
vif = pd.DataFrame()
X = X_train_rfe
vif['Features'] = X.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[84]:

| | Features | VIF |
|---|---|---|
| 0 | const | 5.11 |
| 3 | stories | 1.17 |
| 5 | airconditioning | 1.15 |
| 1 | area | 1.13 |
| 2 | bathrooms | 1.12 |
| 6 | prefarea | 1.06 |
| 4 | hotwaterheating | 1.02 |

### Residual Analysis of the train data

So, now to check if the error terms are also normally distributed (which is infact, one of the major assumptions of linear regression), let us plot the histogram of the error terms and see what it looks like.

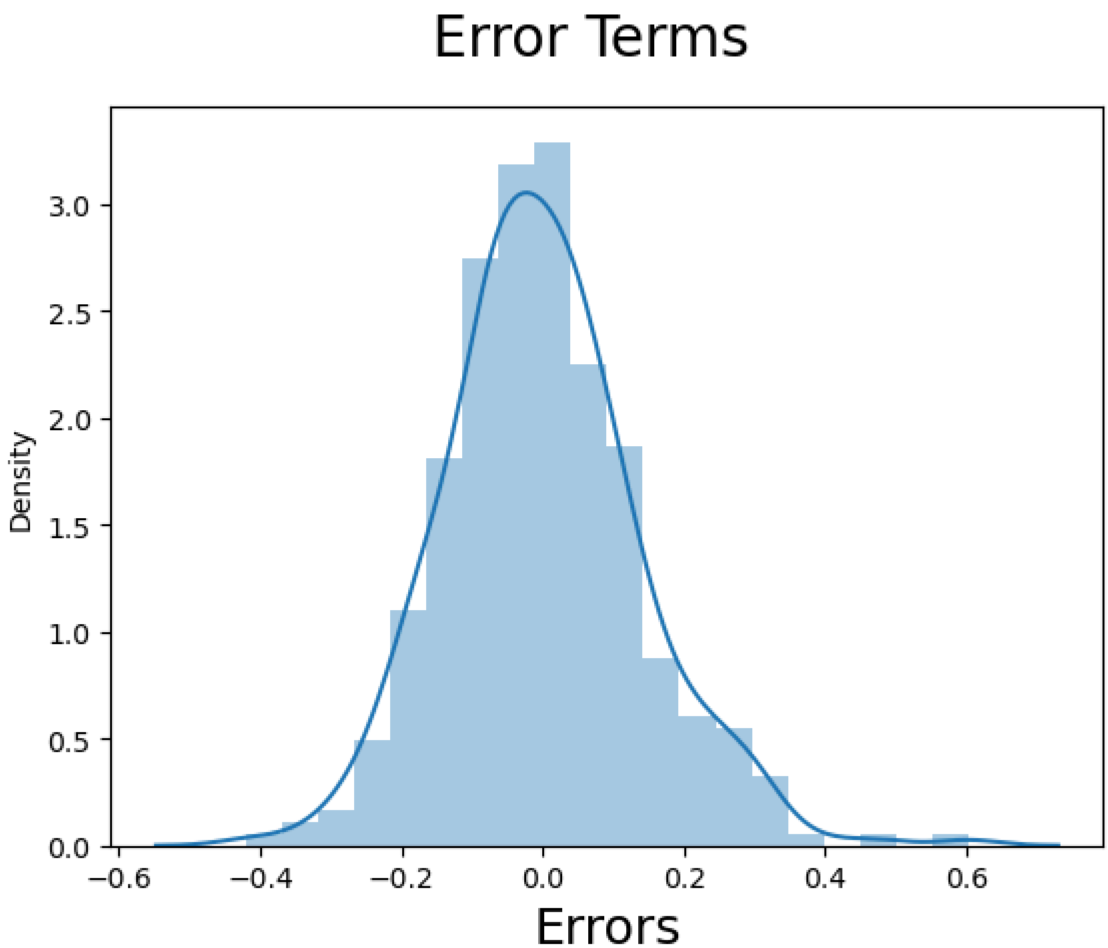
In [85]:
```
y_train_price = lm.predict(X_train_rfe)
```

In [86]:
```
res = (y_train_price - y_train)
```

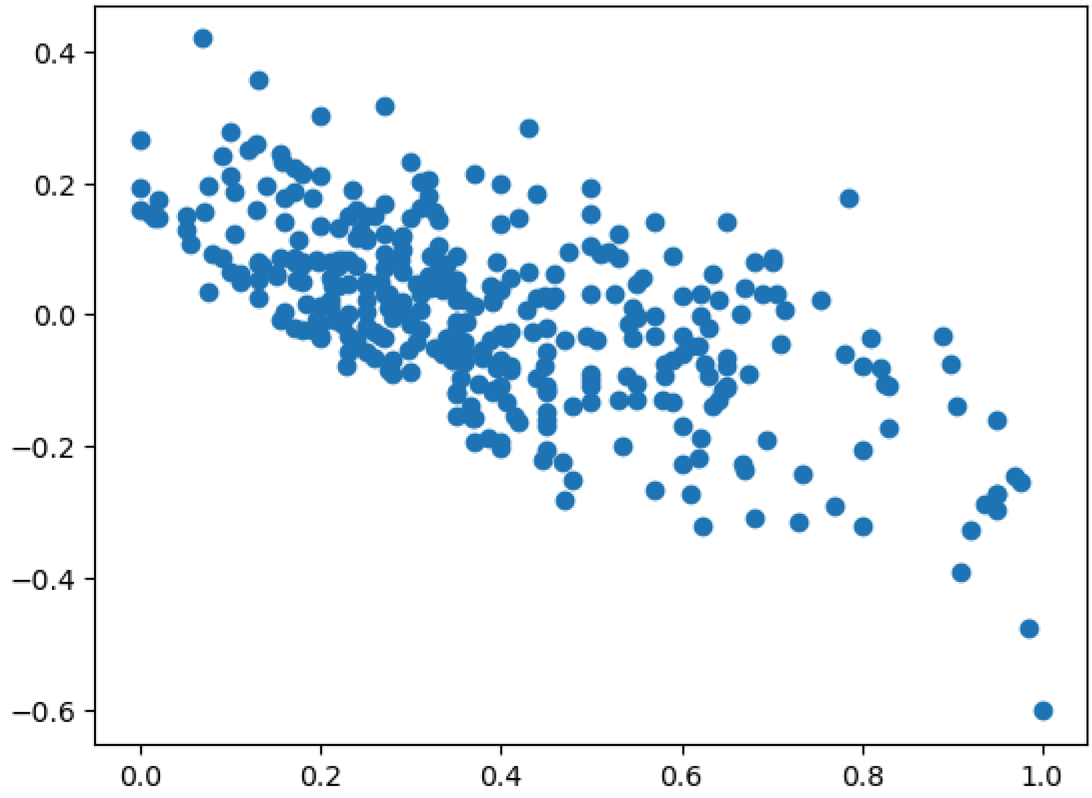
In [87]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [89]:
```
# Plotting the histogram of the error terms
fig = plt.figure()
sns.distplot((y_train - y_train_price), bins = 20)
fig.suptitle('Error Terms', fontsize = 20)                  # Plot heading
plt.xlabel('Errors', fontsize = 18)                         # X-label
```

Out[89]:
```
Text(0.5, 0, 'Errors')
```



In [90]:
```
plt.scatter(y_train,res)
plt.show()
```




## Model Evaluation

Applying the scaling on the test sets

In [91]:
```
num_vars = ['area','stories', 'bathrooms', 'airconditioning', 'prefarea','park
```

In [92]:
```
df_test[num_vars] = scaler.fit_transform(df_test[num_vars])
```

#### Dividing into X_test and y_test

In [93]:
```
y_test = df_test.pop('price')
X_test = df_test
```

In [94]:
```
# Adding constant variable
X_test = sm.add_constant(X_test)
```

In [95]:
```
#Checking the predictions of model
```

In [100]:
```
# Creating X_test_new dataframe by dropping variables from X_test
X_test_rfe = X_test[X_train_rfe.columns]
```

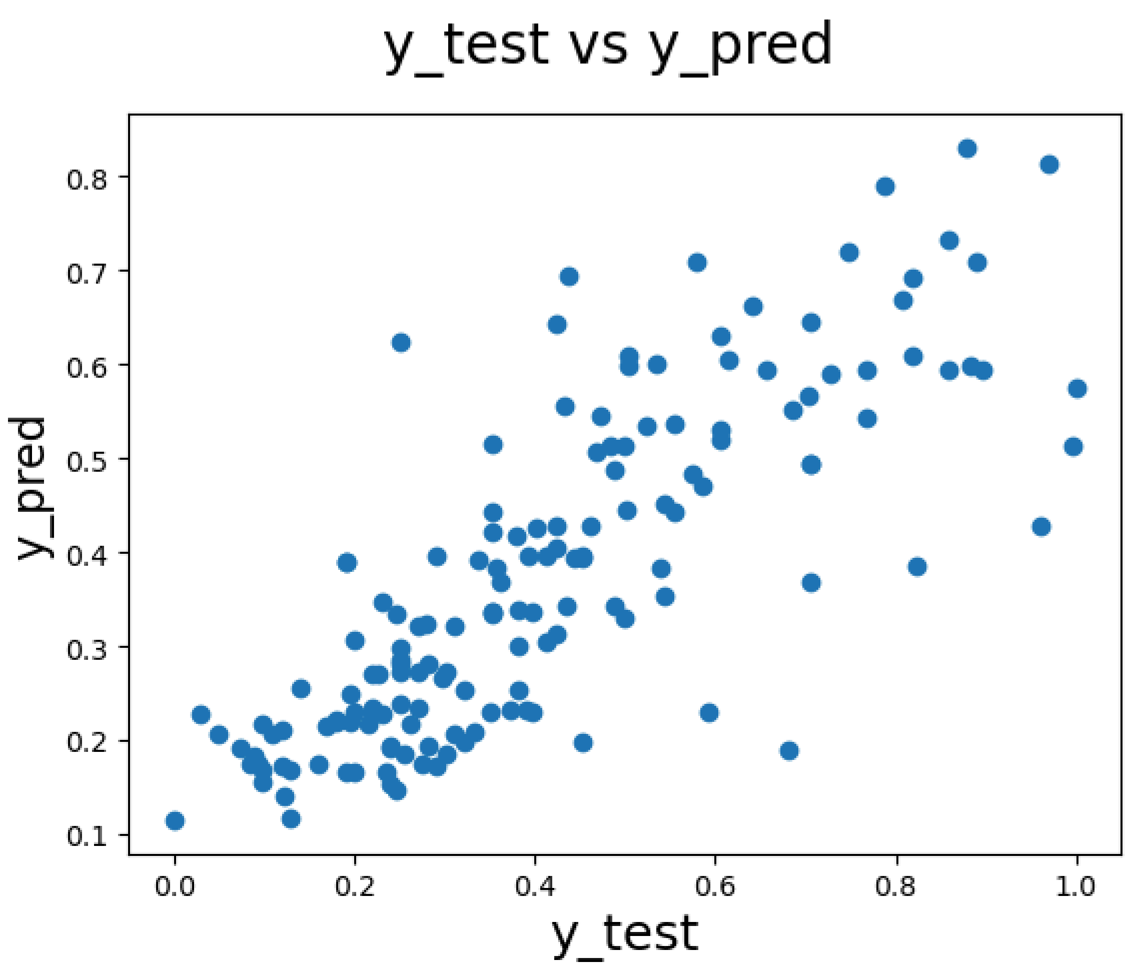
In [102]:
```
# Making predictions
y_pred = lm.predict(X_test_rfe)
```

In [106]:
```
from sklearn.metrics import r2_score
r2_score(y_test, y_pred)
```

Out[106]: 0.6114550544117663

In [107]:
```
# Plotting y_test and y_pred
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[107]: Text(0, 0.5, 'y_pred')



### We can see that the equation of our best fitted line is:

$price = 0.35 \times area + 0.20 \times bathrooms + 0.19 \times stories + 0.10 \times airconditioning + 0.10 \times parking + 0.11 \times prefar$

In [ ]: