REGRESSION

SINGLE LINEAR, MULTIPLE LINEAR and POLYNOMIAL REGRESSION

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
data = pd.read_csv('Housing.csv')
```

In [3]:
```
data.head()
```

Out[3]:

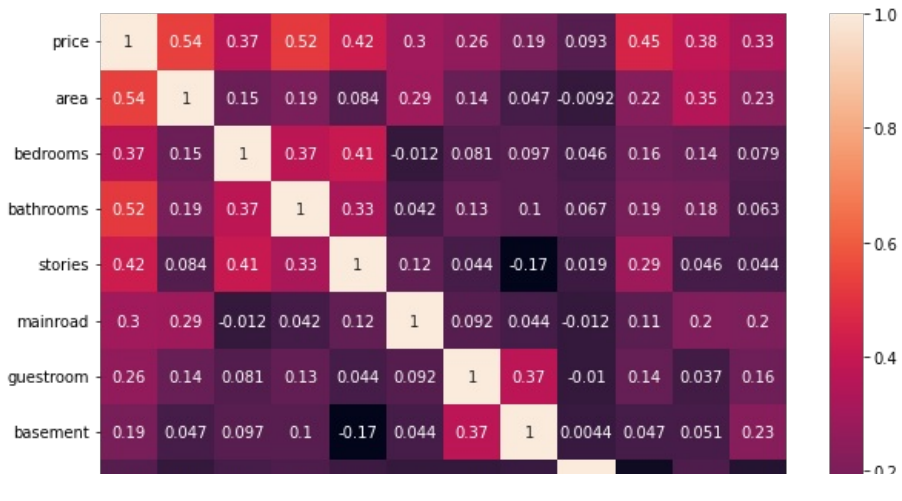
	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating	airconditioning	parking	prefarea	furnishi
0	13300000	7420	4	2	3	yes	no	no	no	yes	2	yes	
1	12250000	8960	4	4	4	yes	no	no	no	yes	3	no	
2	12250000	9960	3	2	2	yes	no	yes	no	no	2	yes	semi
3	12215000	7500	4	2	2	yes	no	yes	no	yes	3	yes	
4	11410000	7420	4	1	2	yes	yes	yes	no	yes	2	no	

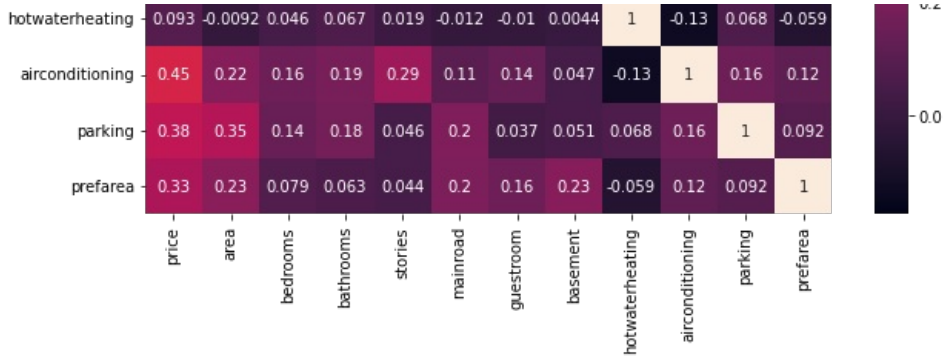
In [4]:
```
data.count()
```

Out[4]:
```
price              545
area               545
bedrooms           545
bathrooms          545
stories            545
mainroad           545
guestroom          545
basement           545
hotwaterheating    545
airconditioning    545
parking            545
prefarea           545
furnishingstatus   545
dtype: int64
```

In [5]:
```
# mainroad, guestroom, basement, hotwaterheating, airconditioning, prefarea and basement are binary values.Conver
data['mainroad'] = data['mainroad'].replace({'no': 0, 'yes': 1})
data['guestroom'] = data['guestroom'].replace({'no': 0, 'yes': 1})
data['hotwaterheating']  = data['hotwaterheating'].replace({'no': 0, 'yes': 1})
data['airconditioning'] = data['airconditioning'].replace({'no': 0, 'yes': 1})
data['prefarea'] = data['prefarea'].replace({'no': 0, 'yes': 1})
data['basement'] = data['basement'].replace({'no': 0, 'yes' : 1})
```

In [6]:
```
# Correlation Heatmap
plt.figure(figsize=[10,8])
ax = sns.heatmap(data.corr(), annot = True)
```





In [7]:
```
# From the correlation heatmap we can see that hotwaterheating is not much useful for price prediction. We can dr
data = data.drop(['hotwaterheating'],axis = 1)
data.head()
```

Out[7]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	airconditioning	parking	prefarea	furnishingstatus
0	13300000	7420	4	2	3	1	0	0	1	2	1	furnished
1	12250000	8960	4	4	4	1	0	0	1	3	0	furnished
2	12250000	9960	3	2	2	1	0	1	0	2	1	semi-furnished
3	12215000	7500	4	2	2	1	0	1	1	3	1	furnished
4	11410000	7420	4	1	2	1	1	1	1	2	0	furnished

SIMPLE LINEAR REGRESSION

In the correlation heatmap above we can see that price is higly correlated with the area of the house. Lets build a SIMPLE LINEAR REGRESSION MODEL considering area and price of the house.

In [8]:
```
SLR = data[['area','price']]
```

In [9]:
```
msk = np.random.rand(len(SLR)) < 0.75
train = SLR[msk]
test = SLR[~msk]
```

In [10]:
```
train_x = np.asanyarray(train[['area']])
train_y = np.asanyarray(train[['price']])
```

In [11]:
```
# With Library - Sklearn
from sklearn import linear_model
SLregr = linear_model.LinearRegression()
SLregr.fit(train_x, train_y)

# The coefficients

m = SLregr.coef_
c = SLregr.intercept_

y = m * train_x + c

print ('Coefficients: ', m,'\nIntercept: ',c)
```

```
Coefficients:  [[445.04188678]]
Intercept:  [2456587.91517204]
```

In [12]:
```
#Without Library - Step by step
train_x_avg = np.average(train_x)
train_y_avg = np.average(train_y)

# m = slope : c = y_intercept : y = mx + c
m_1 = np.sum((train_x - train_x_avg) * (train_y - train_y_avg)) / np.sum((train_x - train_x_avg)**2)
c_1 = train_y_avg - m * train_x_avg

y_1 = m_1 * train_x + c_1
```

```
print('Coefficients :',m_1,'\nIntercept :',c_1)
```

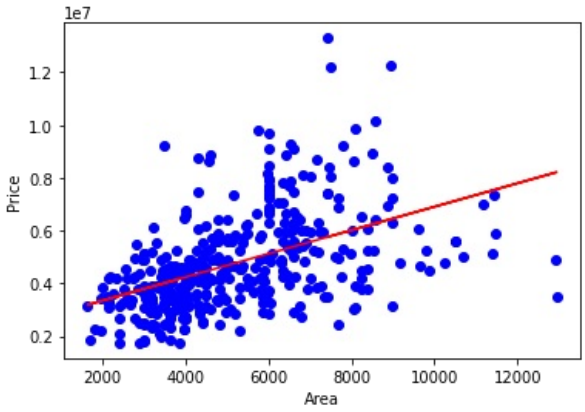
```
Coefficients : 445.0418867796629
Intercept : [[2456587.91517204]]
```

In [13]:

```
# With Library - Scatter plot with regression line built with using inbuilt library sklearn
plt.scatter(train.area, train.price,  color='blue')
plt.plot(train_x,y, '-r')
plt.xlabel("Area")
plt.ylabel("Price")
```

Out[13]:

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

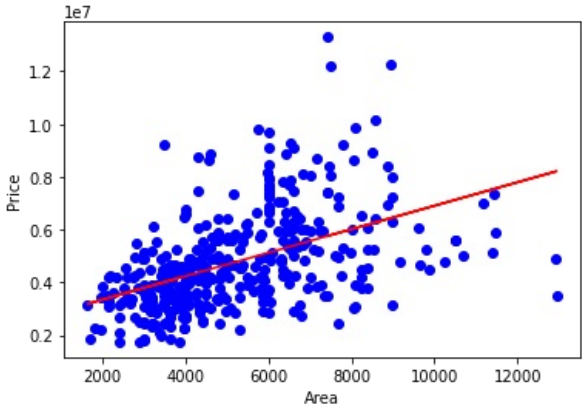


In [14]:

```
#Without Library - Scatter plot with regression line built without using inbuilt library sklearn
plt.scatter(train.area, train.price,  color='blue')
plt.plot(train_x,y_1, '-r')
plt.xlabel("Area")
plt.ylabel("Price")
```

Out[14]:

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



In [15]:

```
#Calculated the accuracy of the model, where the model is built with the use of sklearn
from sklearn.metrics import r2_score
from sklearn.metrics import mean_absolute_error as MAE
from sklearn.metrics import mean_squared_error as MSE

test_x = np.asanyarray(test[['area']])
test_y = np.asanyarray(test[['price']])
test_y_ = SLregr.predict(test_x)

print('Mean absolute error (MAE) :',MAE(test_y_,test_y))
print('Residual sum of squares (MSE) :',MSE(test_y_,test_y))
print('R2-score:',r2_score(test_y , test_y_) )
```

```
Mean absolute error (MAE) : 1117049.0273439265
Residual sum of squares (MSE) : 2266862754908.8833
R2-score: 0.41160885431463656
```

In [16]:

```
#Calculated the accuracy of the model, where the model is built without any libraries
```

```
#calculated the accuracy of the model, where the model is built without any libraries
y_t = m_1 * test_x + c_1
print("Mean absolute error: %.2f" % np.mean(np.absolute(test_y - y_t)))
print("Residual sum of squares (MSE): %.2f" % np.mean((test_y - y_t) ** 2))
print("R2-score: %.2f" % (1 - np.sum((test_y - y_t)**2) / np.sum((test_y - train_y_avg)**2)))
```

```
Mean absolute error: 1117049.03
Residual sum of squares (MSE): 2266862754908.88
R2-score: 0.41
```

In [18]:

```
# Output of Model built with Library
x_in = int(input('Enter the area :'))
y_out = m* x_in + c
y_out = int(np.round(y_out))
print(y_out, 'is the estimated price of the house considering the area.')
```

```
Enter the area :5000
4681797 is the estimated price of the house considering the area.
```

In [19]:

```
# Output of model built without Library
x_in = int(input('Enter the area :'))
y_1 = m_1 * x_in + c_1
y_out = int(np.round(y_1))
print(y_out, 'is the estimated price of the house considering the area.')
```

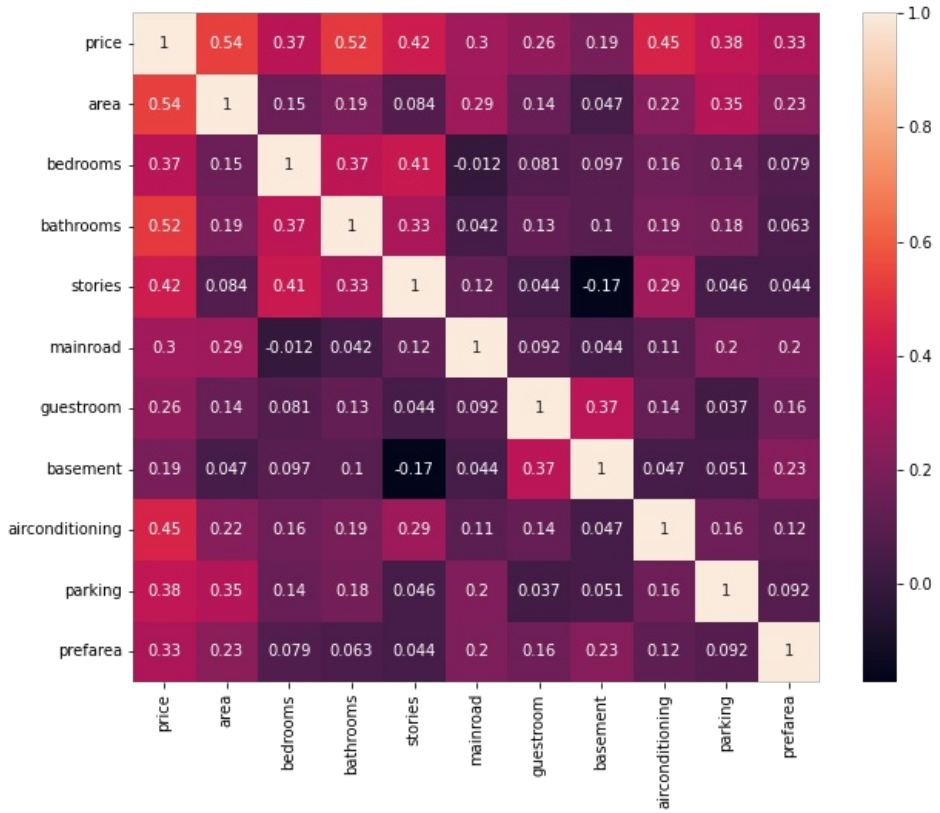
```
Enter the area :5000
4681797 is the estimated price of the house considering the area.
```

MULTIPLE LINEAR REGRESSION

Let us consider multiple independent variables and build a REGRESSION MODEL

In [20]:

```
plt.figure(figsize=[10,8])
ax = sns.heatmap(data.corr(), annot = True)
```



Let us consider parking,airconditioning, stories, bathrooms, bedrooms and area as Independent variables as the correlation values of these variables are greater than 0.35 with respect to price - Dependent Variable

In [21]:
```
MLR = data[['parking','airconditioning','stories','bathrooms','bedrooms','area','price']]
MLR.head()
```

Out[21]:

	parking	airconditioning	stories	bathrooms	bedrooms	area	price
0	2	1	3	2	4	7420	13300000
1	3	1	4	4	4	8960	12250000
2	2	0	2	2	3	9960	12250000
3	3	1	2	2	4	7500	12215000
4	2	1	2	1	4	7420	11410000

In [22]:
```
msk = np.random.rand(len(SLR)) < 0.75
train = MLR[msk]
test = MLR[~msk]

train_x = np.asanyarray(train[['area','parking','airconditioning','stories','bathrooms','bedrooms']])
train_y = np.asanyarray(train[['price']])

test_x = np.asanyarray(test[['area','parking','airconditioning','stories','bathrooms','bedrooms']])
test_y = np.asanyarray(test[['price']])
```

In [23]:
```
print(train_x.shape)
print(train_y.shape)
print(test_x.shape)
print(test_y.shape)
```

```
(399, 6)
(399, 1)
(146, 6)
(146, 1)
```

In [24]:
```
MLregr = linear_model.LinearRegression()
x = np.asanyarray(train_x)
y = np.asanyarray(train_y)
MLregr.fit (x, y)

# The coefficients
m = MLregr.coef_
c = MLregr.intercept_

y = m * train_x + c

print ('Coefficients: ', m,'\nIntercept: ',c)
```

```
Coefficients:  [[3.00569353e+02 3.36500296e+05 9.41034476e+05 4.57267268e+05
  1.03304052e+06 1.66652032e+05]]
Intercept:  [22408.84592338]
```

In [25]:
```
y_t = MLregr.predict(test_x)
```

In [26]:
```
print('Mean absolute error (MAE) :',MAE(test_y,y_t))
print('Residual sum of squares (MSE) :',MSE(test_y,y_t))
print('R2-score:',r2_score(test_y , y_t) )
```

```
Mean absolute error (MAE) : 786517.3471069139
Residual sum of squares (MSE) : 1147483820529.4138
R2-score: 0.6504469296449442
```

In [27]:
```
x_in = []
a = ['area','parking','airconditioning','stories','bathrooms','bedrooms']
for i in a:
    b = int(input(i+' : '))
    x_in.append(b)
print('')
x_in = np.asanyarray(x_in)
x_in = x_in.reshape(1,x_in.shape[0])

y_out = MLregr.predict(x_in)
```

```
y_out = int(np.round(y_out))
print(y_out,' is the estimated price of the house considering the attributes : Area, Parking, Airconditioning, St
```

```
area : 5000
parking : 2
airconditioning : 2
stories : 2
bathrooms : 3
bedrooms : 4

8760589  is the estimated price of the house considering the attributes : Area, Parking, Airconditioning, Stories
, Bathrooms and Bedrooms.
```

We are getting a better result when we consider multiple attributes for training the regression model.

POLYNOMIAL REGRESSION

In [28]:
```
from sklearn.preprocessing import PolynomialFeatures

PNR = data[['area','price']]

msk = np.random.rand(len(PNR)) < 0.75
train = PNR[msk]
test = PNR[~msk]

train_x_polys = np.asanyarray(train[['area']])
train_y_poly = np.asanyarray(train[['price']])

test_x_polys = np.asanyarray(test[['area']])
test_y_poly = np.asanyarray(test[['price']])


poly = PolynomialFeatures(degree=2)
train_x_poly = poly.fit_transform(train_x_polys)
test_x_poly = poly.fit_transform(test_x_polys)
```

In [29]:
```
PNRegr = linear_model.LinearRegression()
PNRegr.fit(train_x_poly, train_y_poly)

# The coefficients
print ('Coefficients: ', PNRegr.coef_)
print ('Intercept: ',PNRegr.intercept_)


y_t = PNRegr.predict(test_x_poly)
```

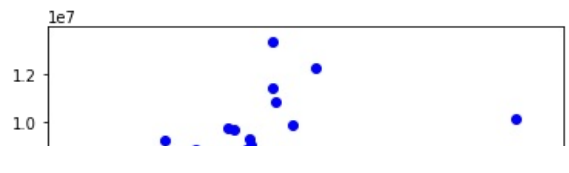
```
Coefficients:  [[ 0.00000000e+00  1.08157346e+03 -4.86703221e-02]]
Intercept:  [675267.22908704]
```

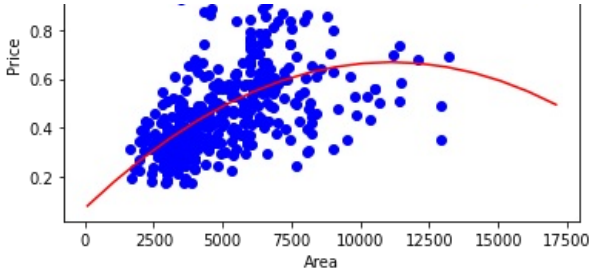
In [30]:
```
print('Mean absolute error (MAE) :',MAE(test_y_poly,y_t))
print('Residual sum of squares (MSE) :',MSE(test_y_poly,y_t))
print('R2-score:',r2_score(test_y_poly , y_t) )
```

```
Mean absolute error (MAE) : 1178922.9034995774
Residual sum of squares (MSE) : 2479858866549.3594
R2-score: 0.33219993346328003
```

In [31]:
```
plt.scatter(train.area, train.price,  color='blue')
XX = np.arange(100, 17500, 1000)
yy = PNRegr.intercept_[0]+ PNRegr.coef_[0][1]*XX + PNRegr.coef_[0][2]*np.power(XX, 2) #+ clf3.coef_[0][3]*np.powe
plt.plot(XX, yy, '-r' )
plt.xlabel("Area")
plt.ylabel("Price")
```

Out[31]:
```
Text(0, 0.5, 'Price')
```





In [32]:

```
x_in = int(input('Enter the area :'))
x_in = np.array(x_in)
x_in = x_in.reshape(1,1)
y = PNRegr.predict(poly.fit_transform(x_in))
y_out = int(np.round(y))
print(y_out, 'is the estimated price of the house considering the area.')
```

```
Enter the area :5000
4866376 is the estimated price of the house considering the area.
```

Considering the accuracies of SIMPLE, MULTIPLE AND POLYNOMIAL Regression :

Simple Linear Regression :

Mean absolute error (MAE) : 1117049.0273439265
Residual sum of squares (MSE) : 2266862754908.8833
R2-score: 0.41160885431463656

Multiple Linear Regression :

Mean absolute error (MAE) : 786517.3471069139
Residual sum of squares (MSE) : 1147483820529.4138
R2-score: 0.6504469296449442

Polyomial Regression :

Mean absolute error (MAE) : 1178922.9034995774
Residual sum of squares (MSE) : 2479858866549.3594
R2-score: 0.33219993346328003

We can see that MLTIPLE LINEAR REGRESSION provides better accuracy !!!