Build the linear regression model using scikit learn in boston data to predict 'Price' based on other dependent variable. Here is the code to load the data import numpy as np import pandas as pd import scipy.stats as stats import matplotlib.pyplot as plt import sklearn from sklearn.datasets import load_boston boston = load_boston() bos = pd.DataFrame(boston.data)

Import dataset

In [26]:
```
%matplotlib inline

import numpy as np
import pandas as pd
import scipy.stats as stats
import matplotlib.pyplot as plt
import sklearn
```

In [27]:
```
from sklearn.datasets import load_boston
boston = load_boston()
```

In [28]:
```
bos = pd.DataFrame(boston.data)
bos.head()
```

Out[28]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

In [29]:
```
bos.columns = boston.feature_names
bos.head()
```

Out[29]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

In [30]:
```
bos['PRICE'] = boston.target
```

In [31]:
```
bos.head()
```

Out[31]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

Import linear regression from sci-kit learn module.

In [32]:
```
from sklearn.linear_model import LinearRegression

X = bos.drop('PRICE', axis = 1 )
X.head()
```

Out[32]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

In [33]:
```
lm = LinearRegression()
lm
```

Out[33]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

In [34]:
```
lm.fit(X, bos.PRICE)
```

Out[34]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

In [35]:
```
print("Estimated intercept co-efficient :", lm.intercept_)
```

```
Estimated intercept co-efficient : 36.491103280363404
```

In [36]:
```
 print("No of Co-efficients :", len(lm.coef_))
```

```
No of Co-efficients : 13
```

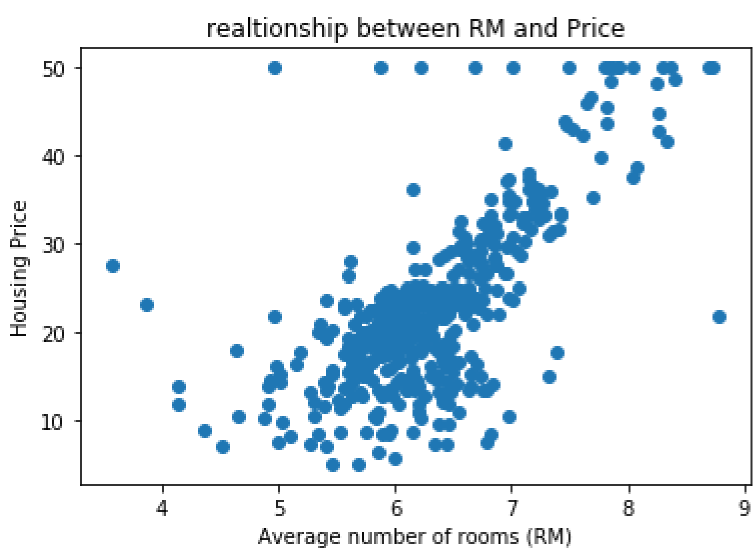
In [37]:
```
pd.DataFrame(list(zip(X.columns, lm.coef_)),)
```

Out[37]:

	0	1
0	CRIM	-0.107171
1	ZN	0.046395
2	INDUS	0.020860
3	CHAS	2.688561
4	NOX	-17.795759
5	RM	3.804752
6	AGE	0.000751
7	DIS	-1.475759
8	RAD	0.305655
9	TAX	-0.012329
10	PTRATIO	-0.953464
11	B	0.009393
12	LSTAT	-0.525467

RM and prices has high correlation. scatter plot between prices and RM.

In [38]:
```
plt.scatter(bos.RM, bos.PRICE)
plt.xlabel("Average number of rooms (RM)")
plt.ylabel("Housing Price")
plt.title("realtionship between RM and Price")
plt.show()
```

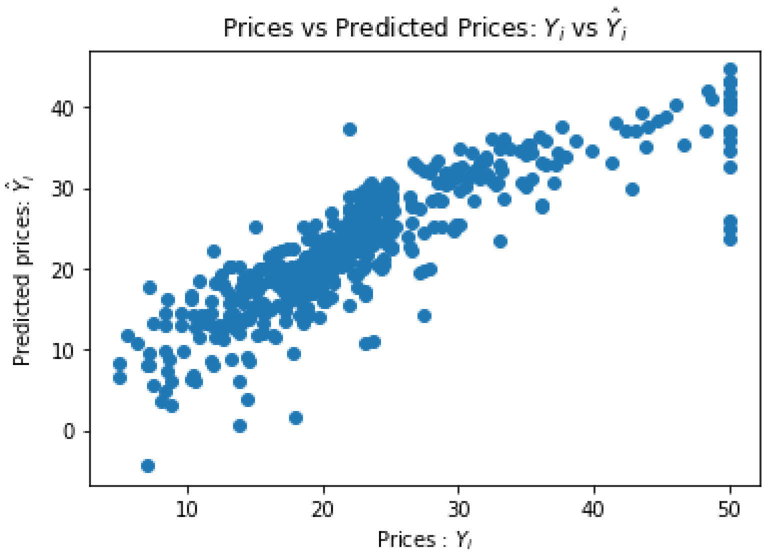


In [39]:
```
lm.predict(X)[0:5]
```

Out[39]: array([30.00821269, 25.0298606 , 30.5702317 , 28.60814055, 27.94288232])

In [40]:
```
plt.scatter(bos.PRICE, lm.predict(X))
plt.xlabel("Prices : $Y_i$")
plt.ylabel("Predicted prices: $\hat{Y}_i$")
plt.title("Prices vs Predicted Prices: $Y_i$ vs $\hat{Y}_i$")
```

Out[40]:
```
Text(0.5,1,'Prices vs Predicted Prices: $Y_i$ vs $\\hat{Y}_i$')
```



there is some error in the prediction as the housing prices increase.

In [41]:
```
mseFull = np.mean((bos.PRICE - lm.predict(X)) ** 2)
print(mseFull)
```

```
21.897779217687486
```

mean squared error calculation

In [42]:
```
lm = LinearRegression()
lm.fit(X[['PTRATIO']] , bos.PRICE)
```

Out[42]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

In [43]:
```
msePTRATIO = np.mean((bos.PRICE - lm.predict(X[['PTRATIO']])) ** 2)
print(msePTRATIO)
```

```
62.65220001376927
```

The mean squared error has increased. So this shows that a single feature is not a good predictor of housing prices.

Spliting the dataset to train-test

In [44]:
```
X_train = X[:50]
X_test  = X[-50:]

y_train = bos.PRICE[:50]
y_test  = bos.PRICE[-50:]

print(X_train.shape)
print(y_train.shape)

print(X_test.shape)
print(y_test.shape)
```

```
(50, 13)
(50,)
(50, 13)
(50,)
```

In [45]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, bos.PRICE, test_size=.33,
```

In [46]:
```
print(X_train.shape)
print(y_train.shape)

print(X_test.shape)
print(y_test.shape)
```

```
(339, 13)
(339,)
(167, 13)
(167,)
```

In [47]:
```
lm = LinearRegression()
lm.fit(X_train, y_train)
```

Out[47]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

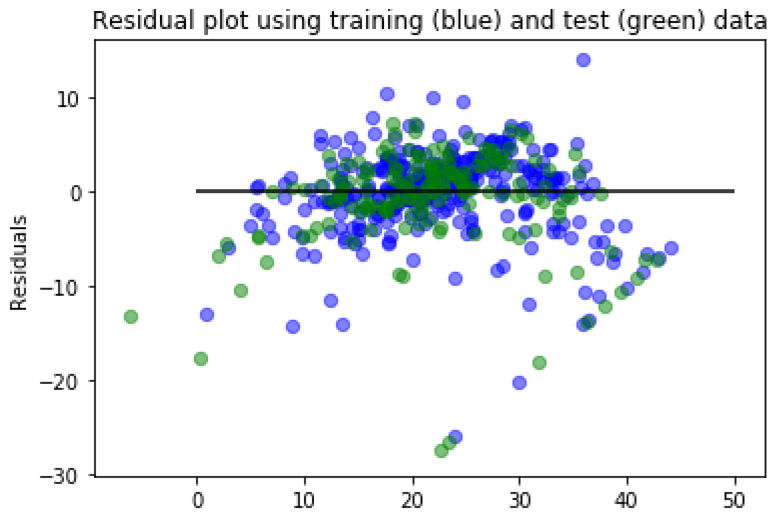
In [48]:
```
pred_train = lm.predict(X_train)
pred_test = lm.predict(X_test)
```

In [49]:
```
print("Fit a model X_train, and calculate MSE with Y_train:", np.mean((y_train  -
print("Fit a model X_train, and calculate MSE with X_test, Y_test:", np.mean((y_t
```

```
Fit a model X_train, and calculate MSE with Y_train: 19.54675847353466
Fit a model X_train, and calculate MSE with X_test, Y_test: 28.541367275619013
```

In [50]:
```
plt.scatter(lm.predict(X_train), lm.predict(X_train) - y_train, c='b', s=40, alph
plt.scatter(lm.predict(X_test), lm.predict(X_test) - y_test, c='g', s=40, alpha=0
plt.hlines(y=0, xmin=0, xmax =50)
plt.title('Residual plot using training (blue) and test (green) data')
plt.ylabel('Residuals')
```

Out[50]: Text(0,0.5,'Residuals')



In [ ]: