In [43]:
```
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)
```

In [44]:

Out[44]:
```
dict_keys(['data', 'target', 'feature_names', 'DESCR'])
```

In [45]:

Out[45]:
```
(506, 13)
```

In [46]:

```
['CRIM' 'ZN' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD' 'TAX' 'PTRATIO'
 'B' 'LSTAT']
```

In [47]:

```
Boston House Prices dataset
===========================

Notes
------
Data Set Characteristics:

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive

    :Median Value (attribute 14) is usually the target

    :Attribute Information (in order):
        - CRIM     per capita crime rate by town
        - ZN       proportion of residential land zoned for lots over 25,000 sq.ft
.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds river; 0 othe
rwise)
        - NOX      nitric oxides concentration (parts per 10 million)
        - RM       average number of rooms per dwelling
        - AGE      proportion of owner-occupied units built prior to 1940
        - DIS      weighted distances to five Boston employment centres
        - RAD      index of accessibility to radial highways
        - TAX      full-value property-tax rate per $10,000
        - PTRATIO  pupil-teacher ratio by town
        - B        1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's

    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.

This is a copy of UCI ML housing dataset.
http://archive.ics.uci.edu/ml/datasets/Housing (http://archive.ics.uci.edu/ml/data
sets/Housing)


This dataset was taken from the StatLib library which is maintained at Carnegie Me
llon University.

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic
prices and the demand for clean air', J. Environ. Economics & Management,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics
...', Wiley, 1980.   N.B. Various transformations are used in the table on
pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning papers that add
ress regression
problems.

**References**

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data
and Sources of Collinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In Proc
eedings on the Tenth International Conference of Machine Learning, 236-243, Univer
sity of Massachusetts, Amherst. Morgan Kaufmann.
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing) (http://archi
ve.ics.uci.edu/ml/datasets/Housing))
```

In [48]:

Out[48]:

	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 [49]:

```
bos.columns = boston.feature_names
```

Out[49]:

	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 [50]:

Out[50]:

```
array([24. , 21.6, 34.7, 33.4, 36.2])
```

In [51]:

In [52]:

Out[52]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE
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	24.0
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	21.6
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	34.7
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	33.4
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	36.2

In [53]:

```
#Skikit learning
from sklearn.linear_model import LinearRegression
X = bos.drop('PRICE', axis = 1)
#linear object
lm = LinearRegression()
```

Out[53]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

In [54]:

```
#Intercept and coefficients
```

```
Estimated intercept coefficient: 36.49110328036171
```

In [55]:

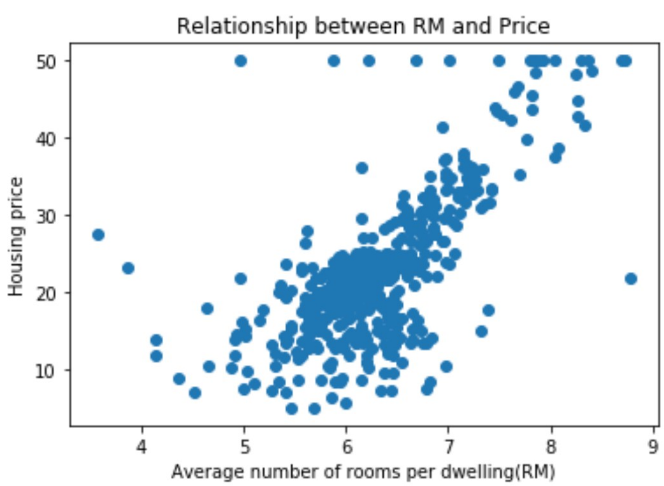
```
number of coefficients: 13
```

In [56]:
```
#column 0 is 'features' and 1 is 'estimated coefficients'
```

Out[56]:

	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

In [57]:
```
#plot between true housing prices and true RM
plt.scatter(bos.RM, bos.PRICE)
plt.xlabel("Average number of rooms per dwelling(RM)")
plt.ylabel("Housing price")
plt.title("Relationship between RM and Price")
```



In [58]:
```
#predicting prices for first 25 houses
```

Out[58]:
```
array([30.00821269, 25.0298606 , 30.5702317 , 28.60814055, 27.94288232,
       25.25940048, 23.00433994, 19.5347558 , 11.51696539, 18.91981483,
       18.9958266 , 21.58970854, 20.90534851, 19.55535931, 19.2837957 ,
       19.30000174, 20.52889993, 16.9096749 , 16.17067411, 18.40781636,
       12.52040454, 17.67104565, 15.82934891, 13.80368317, 15.67708138])
```

In [65]:
```
#plot between true prices and predicted prices
plt.scatter(bos.PRICE, lm.predict(X))
plt.xlabel("True Prices: $Y_i$")
plt.ylabel("Predicted prices: $\hat{Y}_i$")
```

Out[65]:
```
Text(0.5,1,'True prices vs Predicted prices:')
```

In [60]:
```
#Mean Squared Error
mseFull = np.mean((bos.PRICE - lm.predict(X))**2)
```

```
21.897779217687496
```

In [61]:
```
#Train-test split
from sklearn.cross_validation import cross_val_score
X_train, X_test, Y_train, Y_test = sklearn.cross_validation.train_test_split(X, bos.PR


print("Fit a model X_train, and calculate MSE with Y_train:", np.mean((Y_train-lm.pred
print("Fit a model X_train, and calculate MSE with X_test, Y_test:",np.mean(Y_test - l
```

```
Fit a model X_train, and calculate MSE with Y_train: 20.08073988170908
Fit a model X_train, and calculate MSE with X_test, Y_test: 0.13807544449442505
```

In [62]:
```
#Residuals vs Residual plot (blue) Training and (green) tezt data
plt.scatter(lm.predict(X_train),lm.predict(X_train) - Y_train,c='b',s=40,alpha=0.5)
plt.scatter(lm.predict(X_test),lm.predict(X_test) - Y_test,c='g',s=40)
plt.hlines(y = 0, xmin = 0, xmax = 50)
plt.title("Residual plot using training(blue) and test(green) data")
plt.ylabel("Residuals")
```

Out[62]:
```
Text(0,0.5,'Residuals')
```