In [4]:
```
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)
bos.head(5)
```

Out[4]:

	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 [5]:
```
boston.keys()
```

Out[5]: dict_keys(['data', 'target', 'feature_names', 'DESCR'])

In [6]:
```
boston.data.shape
```

Out[6]: (506, 13)

In [7]:
```
bos.describe()
```

Out[7]:

	0	1	2	3	4	5	
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000(
mean	3.593761	11.363636	11.136779	0.069170	0.554695	6.284634	68.5749(
std	8.596783	23.322453	6.860353	0.253994	0.115878	0.702617	28.1488(
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.90000(
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.0250(
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.5000(
75%	3.647423	12.500000	18.100000	0.000000	0.624000	6.623500	94.0750(
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000(

In [8]:
```
boston.keys()
```

Out[8]: dict_keys(['data', 'target', 'feature_names', 'DESCR'])

In [9]:
```
display(boston.feature_names)
```

```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

In [10]:
```
display(boston.target)
```

```
array([24. , 21.6, 34.7, 33.4, 36.2, 28.7, 22.9, 27.1, 16.5, 18.9, 15. ,
       18.9, 21.7, 20.4, 18.2, 19.9, 23.1, 17.5, 20.2, 18.2, 13.6, 19.6,
       15.2, 14.5, 15.6, 13.9, 16.6, 14.8, 18.4, 21. , 12.7, 14.5, 13.2,
       13.1, 13.5, 18.9, 20. , 21. , 24.7, 30.8, 34.9, 26.6, 25.3, 24.7,
       21.2, 19.3, 20. , 16.6, 14.4, 19.4, 19.7, 20.5, 25. , 23.4, 18.9,
       35.4, 24.7, 31.6, 23.3, 19.6, 18.7, 16. , 22.2, 25. , 33. , 23.5,
       19.4, 22. , 17.4, 20.9, 24.2, 21.7, 22.8, 23.4, 24.1, 21.4, 20. ,
       20.8, 21.2, 20.3, 28. , 23.9, 24.8, 22.9, 23.9, 26.6, 22.5, 22.2,
       23.6, 28.7, 22.6, 22. , 22.9, 25. , 20.6, 28.4, 21.4, 38.7, 43.8,
       33.2, 27.5, 26.5, 18.6, 19.3, 20.1, 19.5, 19.5, 20.4, 19.8, 19.4,
       21.7, 22.8, 18.8, 18.7, 18.5, 18.3, 21.2, 19.2, 20.4, 19.3, 22. ,
       20.3, 20.5, 17.3, 18.8, 21.4, 15.7, 16.2, 18. , 14.3, 19.2, 19.6,
       23. , 18.4, 15.6, 18.1, 17.4, 17.1, 13.3, 17.8, 14. , 14.4, 13.4,
       15.6, 11.8, 13.8, 15.6, 14.6, 17.8, 15.4, 21.5, 19.6, 15.3, 19.4,
       17. , 15.6, 13.1, 41.3, 24.3, 23.3, 27. , 50. , 50. , 50. , 22.7,
       25. , 50. , 23.8, 23.8, 22.3, 17.4, 19.1, 23.1, 23.6, 22.6, 29.4,
       23.2, 24.6, 29.9, 37.2, 39.8, 36.2, 37.9, 32.5, 26.4, 29.6, 50. ,
       32. , 29.8, 34.9, 37. , 30.5, 36.4, 31.1, 29.1, 50. , 33.3, 30.3,
       34.6, 34.9, 32.9, 24.1, 42.3, 48.5, 50. , 22.6, 24.4, 22.5, 24.4,
       20. , 21.7, 19.3, 22.4, 28.1, 23.7, 25. , 23.3, 28.7, 21.5, 23. ,
       26.7, 21.7, 27.5, 30.1, 44.8, 50. , 37.6, 31.6, 46.7, 31.5, 24.3,
       31.7, 41.7, 48.3, 29. , 24. , 25.1, 31.5, 23.7, 23.3, 22. , 20.1,
       22.2, 23.7, 17.6, 18.5, 24.3, 20.5, 24.5, 26.2, 24.4, 24.8, 29.6,
       42.8, 21.9, 20.9, 44. , 50. , 36. , 30.1, 33.8, 43.1, 48.8, 31. ,
       36.5, 22.8, 30.7, 50. , 43.5, 20.7, 21.1, 25.2, 24.4, 35.2, 32.4,
       32. , 33.2, 33.1, 29.1, 35.1, 45.4, 35.4, 46. , 50. , 32.2, 22. ,
       20.1, 23.2, 22.3, 24.8, 28.5, 37.3, 27.9, 23.9, 21.7, 28.6, 27.1,
       20.3, 22.5, 29. , 24.8, 22. , 26.4, 33.1, 36.1, 28.4, 33.4, 28.2,
       22.8, 20.3, 16.1, 22.1, 19.4, 21.6, 23.8, 16.2, 17.8, 19.8, 23.1,
       21. , 23.8, 23.1, 20.4, 18.5, 25. , 24.6, 23. , 22.2, 19.3, 22.6,
       19.8, 17.1, 19.4, 22.2, 20.7, 21.1, 19.5, 18.5, 20.6, 19. , 18.7,
       32.7, 16.5, 23.9, 31.2, 17.5, 17.2, 23.1, 24.5, 26.6, 22.9, 24.1,
       18.6, 30.1, 18.2, 20.6, 17.8, 21.7, 22.7, 22.6, 25. , 19.9, 20.8,
       16.8, 21.9, 27.5, 21.9, 23.1, 50. , 50. , 50. , 50. , 50. , 13.8,
       13.8, 15. , 13.9, 13.3, 13.1, 10.2, 10.4, 10.9, 11.3, 12.3,  8.8,
        7.2, 10.5,  7.4, 10.2, 11.5, 15.1, 23.2,  9.7, 13.8, 12.7, 13.1,
       12.5,  8.5,  5. ,  6.3,  5.6,  7.2, 12.1,  8.3,  8.5,  5. , 11.9,
       27.9, 17.2, 27.5, 15. , 17.2, 17.9, 16.3,  7. ,  7.2,  7.5, 10.4,
        8.8,  8.4, 16.7, 14.2, 20.8, 13.4, 11.7,  8.3, 10.2, 10.9, 11. ,
        9.5, 14.5, 14.1, 16.1, 14.3, 11.7, 13.4,  9.6,  8.7,  8.4, 12.8,
       10.5, 17.1, 18.4, 15.4, 10.8, 11.8, 14.9, 12.6, 14.1, 13. , 13.4,
       15.2, 16.1, 17.8, 14.9, 14.1, 12.7, 13.5, 14.9, 20. , 16.4, 17.7,
       19.5, 20.2, 21.4, 19.9, 19. , 19.1, 19.1, 20.1, 19.9, 19.6, 23.2,
       29.8, 13.8, 13.3, 16.7, 12. , 14.6, 21.4, 23. , 23.7, 25. , 21.8,
       20.6, 21.2, 19.1, 20.6, 15.2,  7. ,  8.1, 13.6, 20.1, 21.8, 24.5,
       23.1, 19.7, 18.3, 21.2, 17.5, 16.8, 22.4, 20.6, 23.9, 22. , 11.9])
```

In [11]:
```
print(boston.DESCR)
```

```
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
otherwise)
        - 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


This dataset was taken from the StatLib library which is maintained at Carneg
ie Mellon 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 tha
t address 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
Proceedings on the Tenth International Conference of Machine Learning, 236-24
3, University of Massachusetts, Amherst. Morgan Kaufmann.
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing)
```

In [12]:
```
bos = pd.DataFrame(boston.data)
bos.head()
```

Out[12]:

	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 [13]:
```
bos.columns = boston.feature_names
bos.head()
```

Out[13]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B
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
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
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
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
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

In [14]:
```
bos['Price'] = boston.target
bos.head()
```

Out[14]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B
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
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
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
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
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

In [15]:
```
from sklearn.linear_model import LinearRegression
X = bos.drop('Price',axis=1)
Y = bos['Price']
lm = LinearRegression() #initialize the model
lm
```

Out[15]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

In [16]:
```
lm.fit(X,Y)
```

Out[16]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

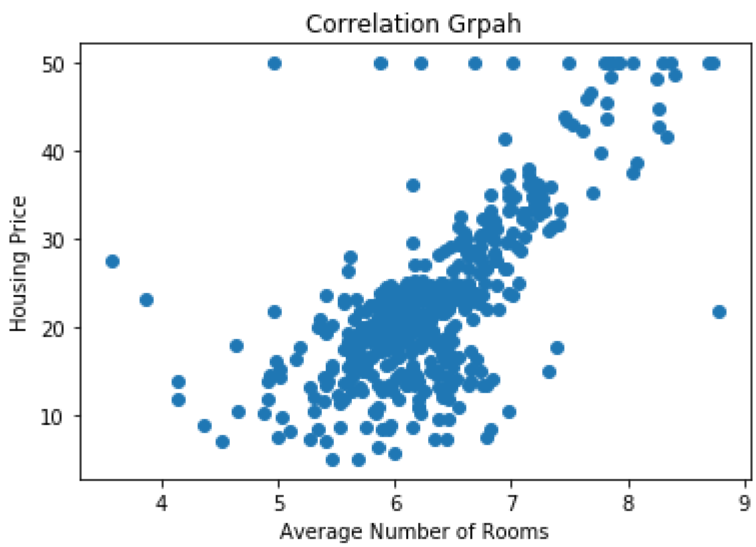
In [17]:
```
print ('Estimated Beta Coefficient:',lm.coef_)
```

```
Estimated Beta Coefficient: [-1.07170557e-01  4.63952195e-02  2.08602395e-02
2.68856140e+00
 -1.77957587e+01  3.80475246e+00  7.51061703e-04 -1.47575880e+00
  3.05655038e-01 -1.23293463e-02 -9.53463555e-01  9.39251272e-03
 -5.25466633e-01]
```

In [18]:
```
print ('Number of Coefficients:', len(lm.coef_))
```

```
Number of Coefficients: 13
```

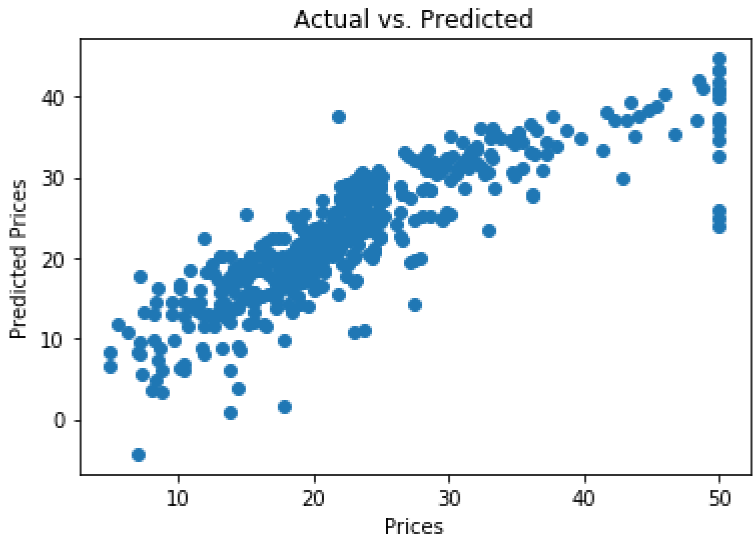
In [19]:
```
plt.scatter(bos.RM,bos.Price)
plt.xlabel('Average Number of Rooms')
plt.ylabel('Housing Price')
plt.title('Correlation Grpah')
plt.show()
```



In [20]:
```
lm.predict(X)[0:5]
```

Out[20]:
```
array([30.00821269, 25.0298606 , 30.5702317 , 28.60814055, 27.94288232])
```

In [21]:
```
plt.scatter(bos.Price,lm.predict(X))
plt.xlabel('Prices')
plt.ylabel('Predicted Prices')
plt.title('Actual vs. Predicted')
plt.show()
```



In [22]:
```
#error calculation
np.mean((bos.Price-lm.predict(X))**2)
```

Out[22]: 21.897779217687486

In [33]:
```
import statsmodels.formula.api as smf


lm = smf.ols(formula='Price ~ CRIM + ZN + INDUS + CHAS + NOX + RM + AGE + DIS
 + RAD + TAX + PTRATIO + B + LSTAT', data=bos).fit()
lm.conf_int()
lm.summary()
```

Out[33]:

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.741
Model:	OLS	**Adj. R-squared:**	0.734
Method:	Least Squares	**F-statistic:**	108.1
Date:	Tue, 24 Jul 2018	**Prob (F-statistic):**	6.95e-135
Time:	22:10:37	**Log-Likelihood:**	-1498.8
No. Observations:	506	**AIC:**	3026.
Df Residuals:	492	**BIC:**	3085.
Df Model:	13		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	36.4911	5.104	7.149	0.000	26.462	46.520
CRIM	-0.1072	0.033	-3.276	0.001	-0.171	-0.043
ZN	0.0464	0.014	3.380	0.001	0.019	0.073
INDUS	0.0209	0.061	0.339	0.735	-0.100	0.142
CHAS	2.6886	0.862	3.120	0.002	0.996	4.381
NOX	-17.7958	3.821	-4.658	0.000	-25.302	-10.289
RM	3.8048	0.418	9.102	0.000	2.983	4.626
AGE	0.0008	0.013	0.057	0.955	-0.025	0.027
DIS	-1.4758	0.199	-7.398	0.000	-1.868	-1.084
RAD	0.3057	0.066	4.608	0.000	0.175	0.436
TAX	-0.0123	0.004	-3.278	0.001	-0.020	-0.005
PTRATIO	-0.9535	0.131	-7.287	0.000	-1.211	-0.696
B	0.0094	0.003	3.500	0.001	0.004	0.015
LSTAT	-0.5255	0.051	-10.366	0.000	-0.625	-0.426

Omnibus:	178.029	**Durbin-Watson:**	1.078
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	782.015
Skew:	1.521	**Prob(JB):**	1.54e-170
Kurtosis:	8.276	**Cond. No.**	1.51e+04