In [1]:
```
# Step 0: Import Libraries
import numpy as np
import pandas as pd
import scipy.stats as stats
import matplotlib.pyplot as plt
import sklearn
# Load Data
# Step 1: Data import
from sklearn.datasets import load_boston
boston = load_boston()
bos = pd.DataFrame(boston.data)
```

In [2]:
```
bos.head(5)
```

Out[2]:

	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 [3]:
```
bos.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 13 columns):
0     506 non-null float64
1     506 non-null float64
2     506 non-null float64
3     506 non-null float64
4     506 non-null float64
5     506 non-null float64
6     506 non-null float64
7     506 non-null float64
8     506 non-null float64
9     506 non-null float64
10    506 non-null float64
11    506 non-null float64
12    506 non-null float64
dtypes: float64(13)
memory usage: 51.5 KB
```

In [4]:
```
#The boston variable itself is a dictionary, so we can check for its keys using the snippet
boston.keys()
#Now let’s explore them.
```

Out[4]:
```
dict_keys(['data', 'target', 'feature_names', 'DESCR'])
```

In [5]:
```
boston.feature_names
# These are the columns and needs to be added in the original data
```

Out[5]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

In [6]:
```
bos.columns=boston.feature_names
# Adding columns
```

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

Out[7]:

	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 [8]:
```
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 (http://archive.ics.uci.edu/ml/datasets/Hou
sing)


This dataset was taken from the StatLib library which is maintained at Carnegie Mellon Uni
versity.

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 address reg
ression
problems.

**References**

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and Sour
ces 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, 236-243, University of Massach
usetts, Amherst. Morgan Kaufmann.
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing) (http://archive.ics.u
ci.edu/ml/datasets/Housing))
```

In [9]:
```
boston.target.shape
# So, it turns out that it match the number of rows in the dataset. Let’s add it to the Data
```
Out[9]: (506,)

In [10]:
```
bos['PRICE'] = boston.target
bos.head()
```
Out[10]:

	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

Summary Statistics

Since it’s going to be a very long post if I do all the analysis. So we are just going to the basic. We would like to see the summary statistics of the dataset by running the snippet below.

In [11]:
```
# Step 2: Data Analytics
#bos.describe()
# descriptions
# pd.set_option('precision', 0)
bos.describe()
```
Out[11]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	F
count	506.000000	506.000000	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	68.574901	3.795043	9.549
std	8.596783	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000
75%	3.647423	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000

Split train-test dataset

Unlike titanic dataset, this time we only given a single dataset. No train and test dataset. That’s fine, we can split it by our self.

Basically, before splitting the data to train-test dataset, we would need to split the dataset into two: target value and predictor values. Let’s call the target value Y and predictor values X.

Thus,

Y = Boston Housing Price
X = All other features

In [12]:
```
X = bos.drop('PRICE', axis = 1)
Y = bos['PRICE']
```

In [13]:
```
Y.size
```

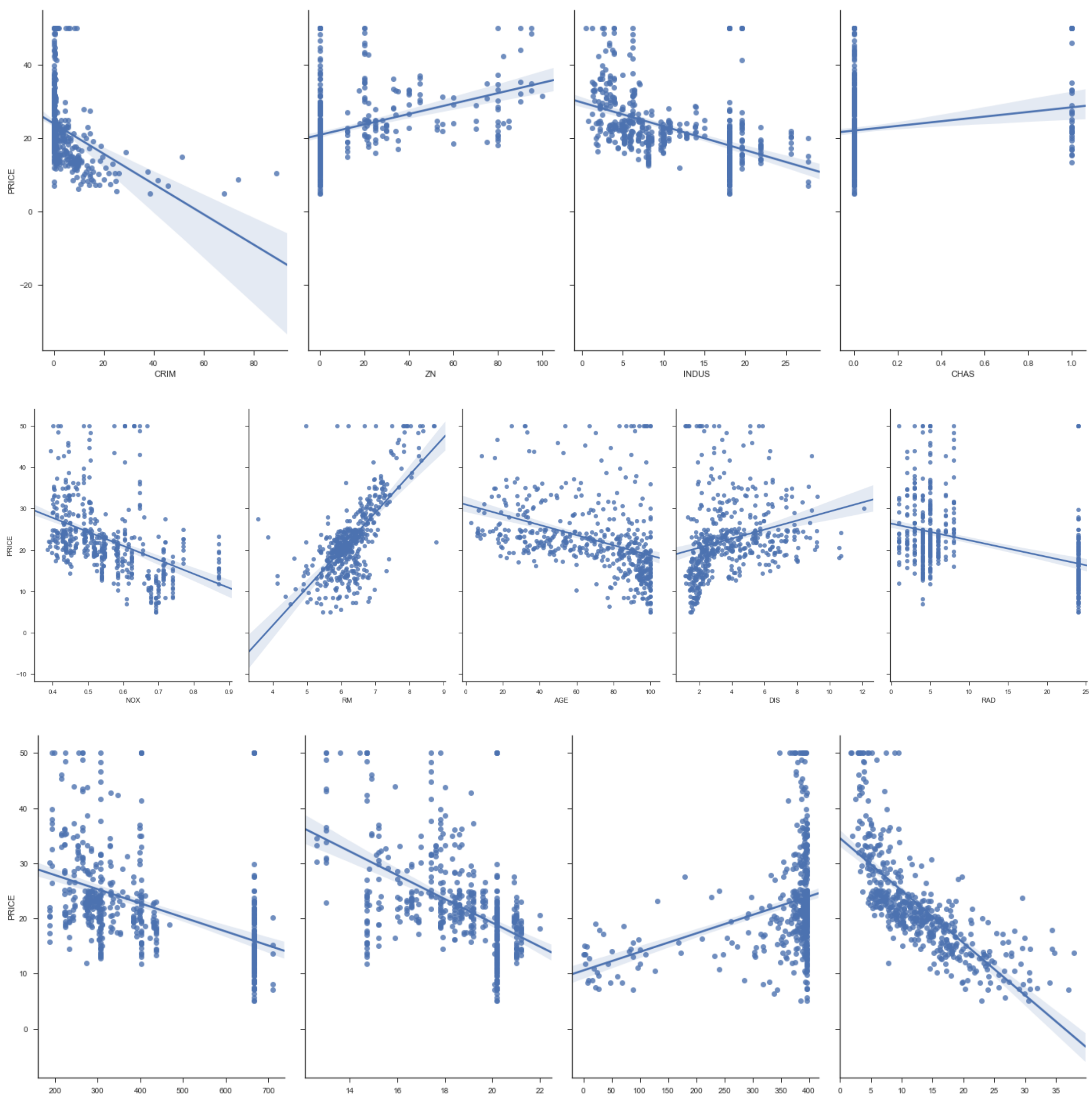
Out[13]:
```
506
```

In [14]:
```
# Step 3: Data Cleaning
bos.isnull().sum()
# There is no null value hence there is no need to do any Data Cleaning to add/delete null v
```

Out[14]:
```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
PRICE      0
dtype: int64
```

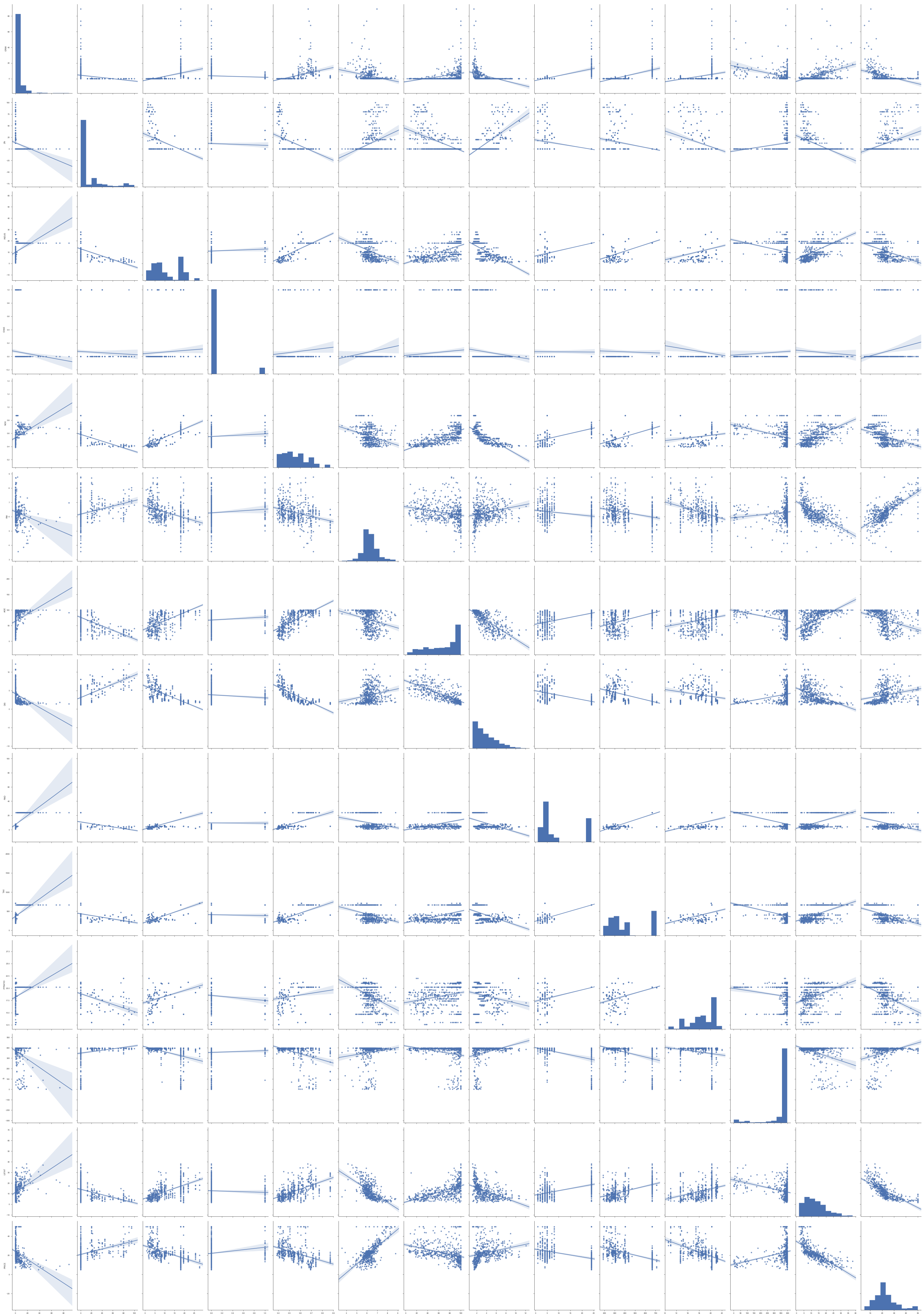
In [15]:
```python
# Step 4: Data Visualization/  Understanding Data (Plot Data)
# Data visualization
from sklearn.linear_model import LinearRegression
#from matplotlib.pyplot import*
#import matplotlib.pyplot as plt
#%matplotlib inline

#plt.scatter(X,Y)
#plt.show()
import seaborn as sns;
sns.set(style="ticks", color_codes=True)
sns.pairplot(bos,  x_vars=['CRIM', 'ZN', 'INDUS', 'CHAS'], y_vars='PRICE', size=7, aspect=0.
sns.pairplot(bos,  x_vars=[ 'NOX', 'RM', 'AGE', 'DIS', 'RAD'], y_vars='PRICE', size=7, aspec
sns.pairplot(bos,  x_vars=['TAX', 'PTRATIO', 'B', 'LSTAT'], y_vars='PRICE', size=7, aspect=0

# In the below diagrams RM and LSAT  has most impact on Price, we may discard other columns.
```

Out[15]: <seaborn.axisgrid.PairGrid at 0x21dac991240>



In [16]:
```
sns.pairplot(bos,size=7, aspect=0.7, kind='reg')
# 'CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD','TAX', 'PTRATIO', 'B', 'LS
```

Out[16]: <seaborn.axisgrid.PairGrid at 0x21dac92cfd0>



In [17]:
```
# correlation
pd.set_option('precision',2)
bos.corr(method='pearson')
```

Out[17]:

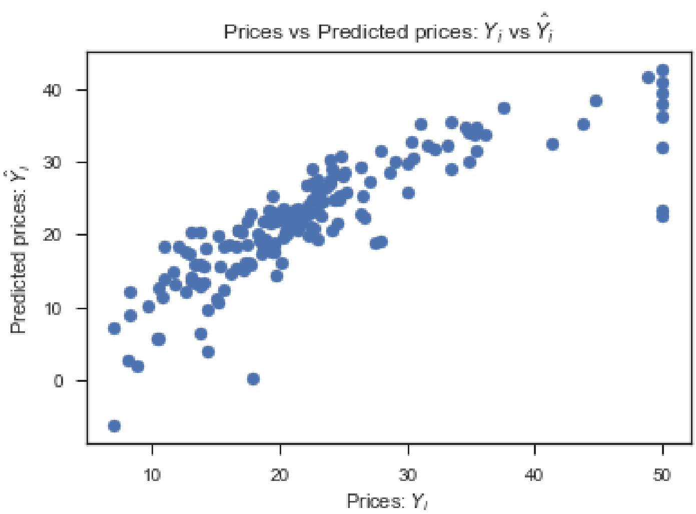
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRI
CRIM	1.00	-0.20	0.40	-5.53e-02	0.42	-0.22	0.35	-0.38	6.22e-01	0.58	0.29	-0.38	0.45	-0
ZN	-0.20	1.00	-0.53	-4.27e-02	-0.52	0.31	-0.57	0.66	-3.12e-01	-0.31	-0.39	0.18	-0.41	0
INDUS	0.40	-0.53	1.00	6.29e-02	0.76	-0.39	0.64	-0.71	5.95e-01	0.72	0.38	-0.36	0.60	-0
CHAS	-0.06	-0.04	0.06	1.00e+00	0.09	0.09	0.09	-0.10	-7.37e-03	-0.04	-0.12	0.05	-0.05	0
NOX	0.42	-0.52	0.76	9.12e-02	1.00	-0.30	0.73	-0.77	6.11e-01	0.67	0.19	-0.38	0.59	-0
RM	-0.22	0.31	-0.39	9.13e-02	-0.30	1.00	-0.24	0.21	-2.10e-01	-0.29	-0.36	0.13	-0.61	0
AGE	0.35	-0.57	0.64	8.65e-02	0.73	-0.24	1.00	-0.75	4.56e-01	0.51	0.26	-0.27	0.60	-0
DIS	-0.38	0.66	-0.71	-9.92e-02	-0.77	0.21	-0.75	1.00	-4.95e-01	-0.53	-0.23	0.29	-0.50	0
RAD	0.62	-0.31	0.60	-7.37e-03	0.61	-0.21	0.46	-0.49	1.00e+00	0.91	0.46	-0.44	0.49	-0
TAX	0.58	-0.31	0.72	-3.56e-02	0.67	-0.29	0.51	-0.53	9.10e-01	1.00	0.46	-0.44	0.54	-0
PTRATIO	0.29	-0.39	0.38	-1.22e-01	0.19	-0.36	0.26	-0.23	4.65e-01	0.46	1.00	-0.18	0.37	-0
B	-0.38	0.18	-0.36	4.88e-02	-0.38	0.13	-0.27	0.29	-4.44e-01	-0.44	-0.18	1.00	-0.37	0
LSTAT	0.45	-0.41	0.60	-5.39e-02	0.59	-0.61	0.60	-0.50	4.89e-01	0.54	0.37	-0.37	1.00	-0
PRICE	-0.39	0.36	-0.48	1.75e-01	-0.43	0.70	-0.38	0.25	-3.82e-01	-0.47	-0.51	0.33	-0.74	1

In [18]:
```
## Step 6: Train_Test_Split
# Now, we can finally split the dataset into train and test with the snippet below.

X_train, X_test, Y_train, Y_test = sklearn.model_selection.train_test_split(X, Y, test_size
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
```

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

In [19]:
```
# Step 7: Train Model
from sklearn.linear_model import LinearRegression

lm = LinearRegression()
lm.fit(X_train, Y_train)

# Step 8: Predict Output
Y_pred = lm.predict(X_test)

# Step 9: Test Model
plt.scatter(Y_test, Y_pred)
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[19]:
```
Text(0.5,1,'Prices vs Predicted prices: $Y_i$ vs $\\hat{Y}_i$')
```



The above Code will fit a model based on X_train and Y_train. Now we already got the linear model, we try to predict it to the X_test and now we got the prediction values which stored into Y_pred. To visualize the differences between actual prices and predicted values we also create a scatter plot.

Ideally, the scatter plot should create a linear line. Since the model does not fit 100%, the scatter plot is not creating a linear line.

Mean Squared Error

To check the level of error of a model, we can Mean Squared Error. It is one of the procedure to measures the average of the squares of error. Basically, it will check the difference between actual value and the predicted value. For the full theory, you can always search it online. To use it, we can use the mean squared error function of scikit-learn by running this snippet of code.

In [20]:
```
# Step 10: Model Evaluation
mse = sklearn.metrics.mean_squared_error(Y_test, Y_pred)
mse
```

Out[20]:
```
28.541367275619
```

Mean Square Error is very high, that means that the model isn’t a really great linear model.

In [21]:
```
# Step 10: Model Evaluation --
# coefficient of determination == R Square
sklearn.metrics.r2_score(Y_test, Y_pred)
```

Out[21]: 0.695538800550634

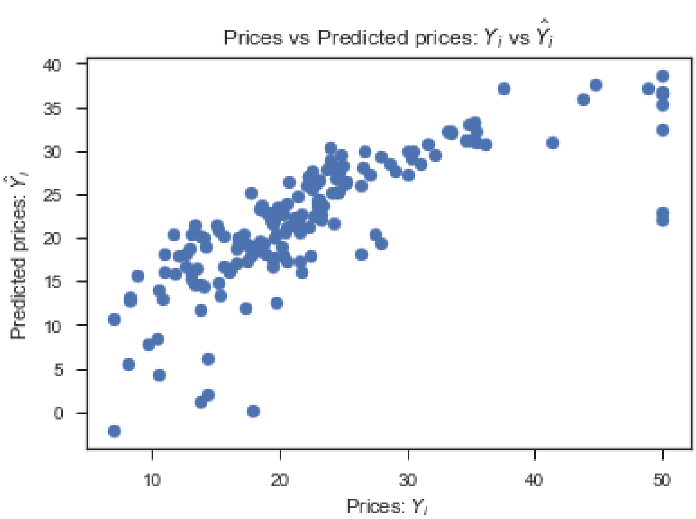
R Square is low i.e. and away from 1, that means that the model isn't a really great linear model.

In [22]:
```
## Step 6: Train_Test_Split
# Now, we can finally split the dataset into train and test with the snippet below.
# Lets take 2 variable in X_Train and Y_Train since it has good co-relationship i.e RM = 0.7
#X[['RM','LSTAT']]
#type(X)

X_train, X_test, Y_train, Y_test = sklearn.model_selection.train_test_split(X[['RM','LSTAT']
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
```

```
(339, 2)
(167, 2)
(339,)
(167,)
```

In [23]:
```
# Step 7: Train Model
from sklearn.linear_model import LinearRegression

lm = LinearRegression()
lm.fit(X_train, Y_train)

# Step 8: Predict Output
Y_pred = lm.predict(X_test)

# Step 9: Test Model
plt.scatter(Y_test, Y_pred)
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[23]: Text(0.5,1,'Prices vs Predicted prices: Y_i vs $\\hat{Y}_i$')



In [24]:
```
# Step 10: Model Evaluation
mse = sklearn.metrics.mean_squared_error(Y_test, Y_pred)
mse
```

Out[24]: 34.719491239643084

In [25]:
```
# Step 10: Model Evaluation --
# coefficient of determination == R Square
sklearn.metrics.r2_score(Y_test, Y_pred)
```

Out[25]: 0.6296344935050335

Even after choosing 2 parameters, it seems this is not best fit for linear regression. This is the conclusion