PART II: Machine Learning: Supervised - Linear Regression

In [1]:
```
#Import Python Libraries (NumPy and Pandas)
import pandas as pd
import numpy as np
```

In [2]:
```
#Import modules and libraries for data visualization
from pandas.plotting import scatter_matrix
from matplotlib import pyplot
```

In [3]:
```
#Import scikit-learn module for the algorithm/model (linear regression)
from sklearn.linear_model import LinearRegression
```

In [4]:
```
#Import scikit-learn module to split the dataset in to train it and test subdatasets
from sklearn.model_selection import train_test_split
```

In [5]:
```
#Import scikit-learn module for K-fold cross-validation (algorithm/model evaluation and validation)
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
```

In [6]:
```
#Import scikit-learn module classification report to use for information about how the system try to classify
from sklearn.metrics import classification_report
```

Step 1: Load the data

In [ ]:
```

```

In [7]:
```
filename = "/Users/miriamgarcia/Downloads/housing_boston_w_hdrs.csv"
df=pd.read_csv(filename)
print(df)
```

```
        CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD  TAX  \
0    0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296
1    0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242
2    0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242
3    0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222
4    0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222
..       ...   ...    ...   ...    ...    ...   ...     ...  ...  ...
447  0.06263   0.0  11.93     0  0.573  6.593  69.1  2.4786    1  273
448  0.04527   0.0  11.93     0  0.573  6.120  76.7  2.2875    1  273
449  0.06076   0.0  11.93     0  0.573  6.976  91.0  2.1675    1  273
450  0.10959   0.0  11.93     0  0.573  6.794  89.3  2.3889    1  273
451  0.04741   0.0  11.93     0  0.573  6.030  80.8  2.5050    1  273

     PTRATIO       B  LSTAT  MEDV
0       15.3  396.90   4.98  24.0
1       17.8  396.90   9.14  21.6
2       17.8  392.83   4.03  34.7
3       18.7  394.63   2.94  33.4
4       18.7  396.90   5.33  36.2
..       ...     ...    ...   ...
447     21.0  391.99   9.67  22.4
448     21.0  396.90   9.08  20.6
449     21.0  396.90   5.64  23.9
450     21.0  393.45   6.48  22.0
451     21.0  396.90   7.88  11.9

[452 rows x 14 columns]
```

Step 2: Preprocess the dataset

In [8]:
```
#Clean data and find any missing values
#From looking at the data above we knew that ZN and CHAS had zeros.
#Since most are missing values, it is best to drop them entirely.
df = df.drop("ZN",1)
df = df.drop("CHAS",1)
```

In [9]:
```
#Count the number of NaN values in each
print(df.isnull().sum())
```

```
CRIM       0
INDUS      0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
MEDV       0
dtype: int64
```

In [10]:
```
#Now there is no invalid zero value in any column of the original data.
```

Step 3: Perform the Exploratory Data Analysis (EDA)

In [11]:
```
#Get the dimensions/shape of the dataset
# which will give us the number of records/rows x number of variables/columns
print(df.shape)
```

```
(452, 12)
```

In [12]:
```
# Now find the data types of all variables/attributes of the data set
print(df.dtypes)
```

```
CRIM       float64
INDUS      float64
NOX        float64
RM         float64
AGE        float64
DIS        float64
RAD          int64
TAX          int64
PTRATIO    float64
B          float64
LSTAT      float64
MEDV       float64
dtype: object
```

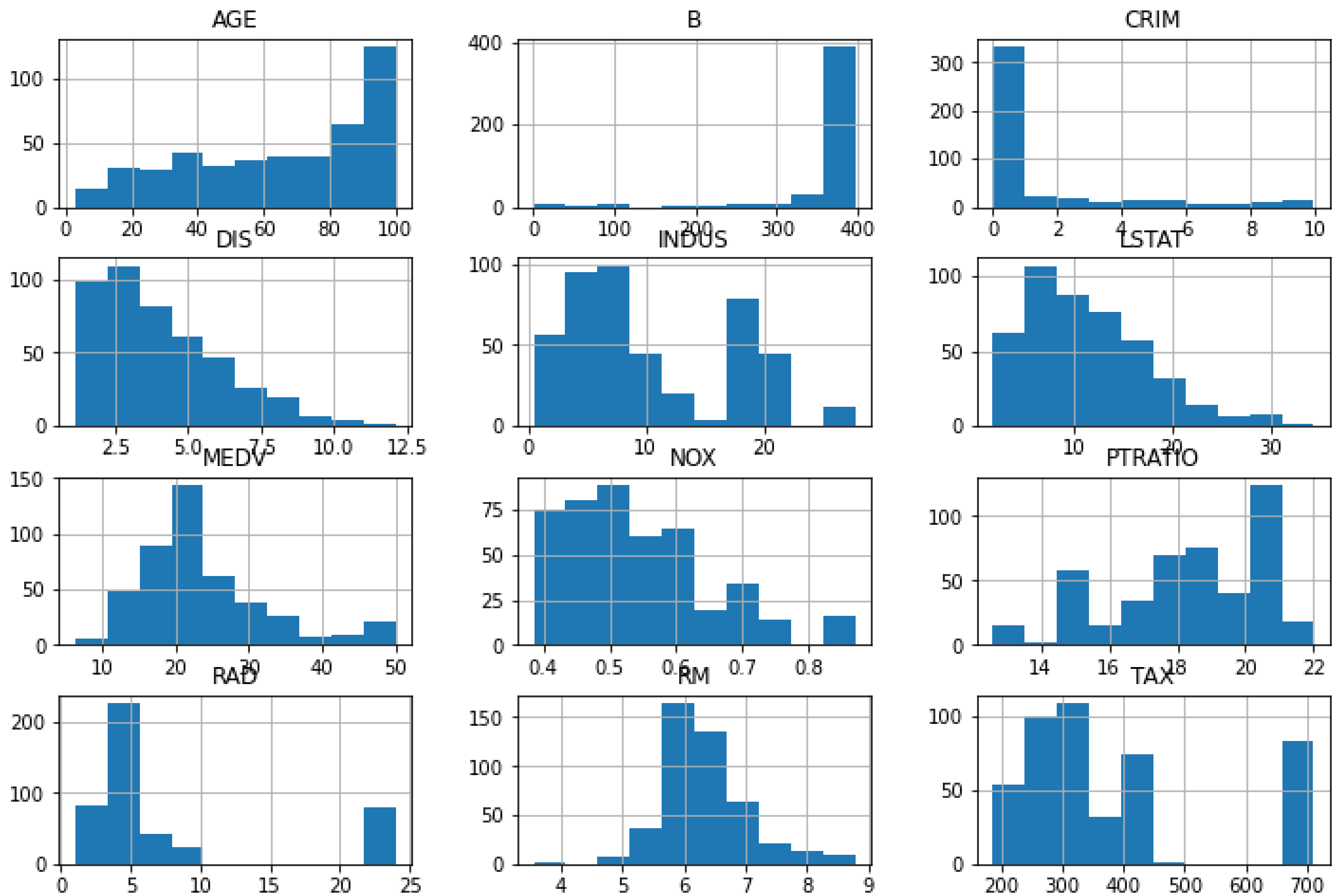
In [13]:
```
#Get several records/rows at the top of the dataset, we get 5 to get a feel of the data.
print(df.head(5))
```

```
      CRIM  INDUS    NOX     RM   AGE     DIS  RAD  TAX  PTRATIO       B  \
0  0.00632   2.31  0.538  6.575  65.2  4.0900    1  296     15.3  396.90
1  0.02731   7.07  0.469  6.421  78.9  4.9671    2  242     17.8  396.90
2  0.02729   7.07  0.469  7.185  61.1  4.9671    2  242     17.8  392.83
3  0.03237   2.18  0.458  6.998  45.8  6.0622    3  222     18.7  394.63
4  0.06905   2.18  0.458  7.147  54.2  6.0622    3  222     18.7  396.90

   LSTAT  MEDV
0   4.98  24.0
1   9.14  21.6
2   4.03  34.7
3   2.94  33.4
4   5.33  36.2
```

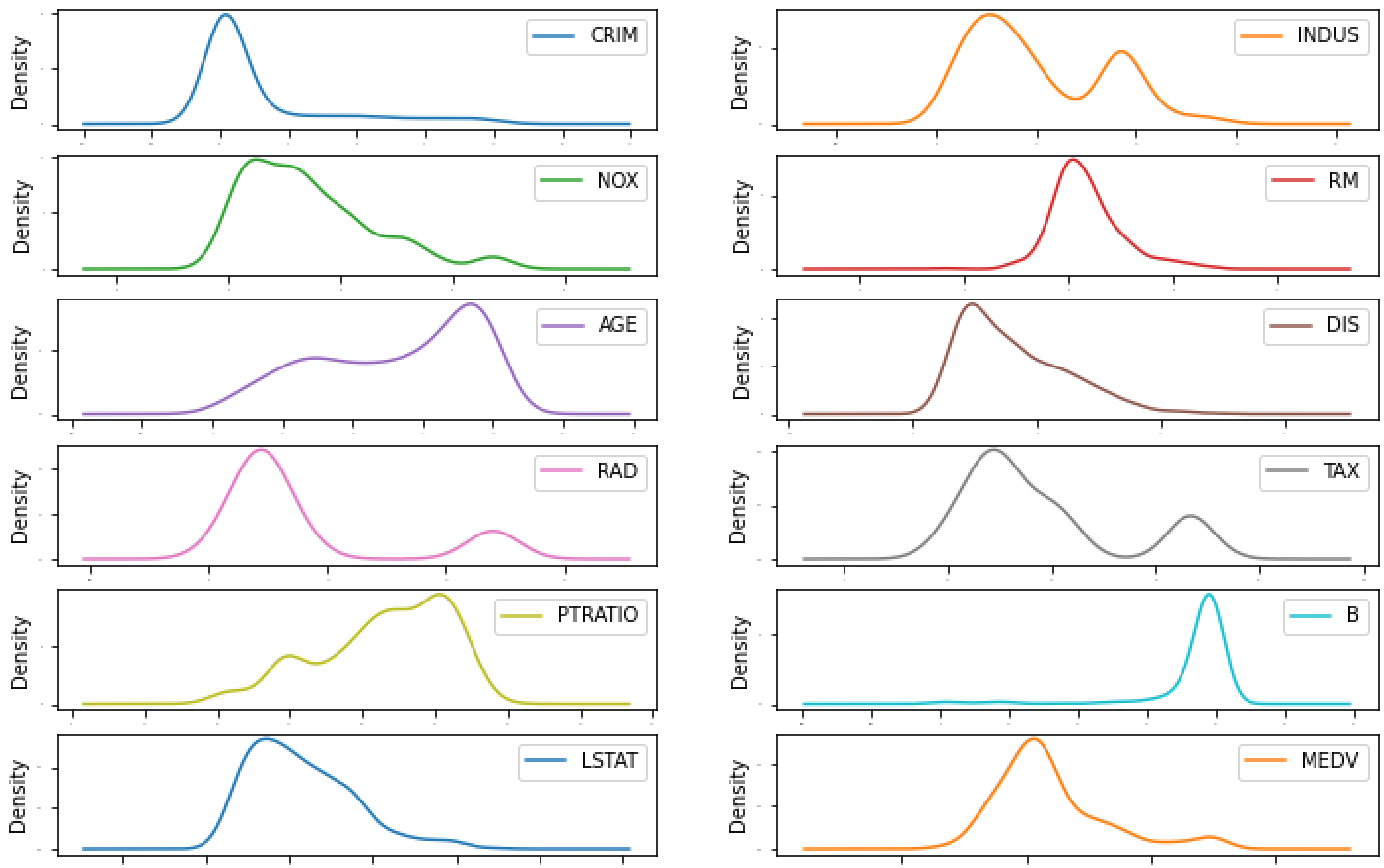
In [14]:
```
#We can get the summary statistics of the numeric variables/attributes of the dataset.
print(df.describe())
```

```
             CRIM       INDUS         NOX          RM         AGE         DIS  \
count  452.000000  452.000000  452.000000  452.000000  452.000000  452.000000   
mean     1.420825   10.304889    0.540816    6.343538   65.557965    4.043570   
std      2.495894    6.797103    0.113816    0.666808   28.127025    2.090492   
min      0.006320    0.460000    0.385000    3.561000    2.900000    1.129600   
25%      0.069875    4.930000    0.447000    5.926750   40.950000    2.354750   
50%      0.191030    8.140000    0.519000    6.229000   71.800000    3.550400   
75%      1.211460   18.100000    0.605000    6.635000   91.625000    5.401100   
max      9.966540   27.740000    0.871000    8.780000  100.000000   12.126500   

              RAD         TAX     PTRATIO           B       LSTAT        MEDV  
count  452.000000  452.000000  452.000000  452.000000  452.000000  452.000000  
mean     7.823009  377.442478   18.247124  369.826504   11.441881   23.750442  
std      7.543494  151.327573    2.200064   68.554439    6.156437    8.808602  
min      1.000000  187.000000   12.600000    0.320000    1.730000    6.300000  
25%      4.000000  276.750000   16.800000  377.717500    6.587500   18.500000  
50%      5.000000  307.000000   18.600000  392.080000   10.250000   21.950000  
75%      7.000000  411.000000   20.200000  396.157500   15.105000   26.600000  
max     24.000000  711.000000   22.000000  396.900000   34.410000   50.000000  
```

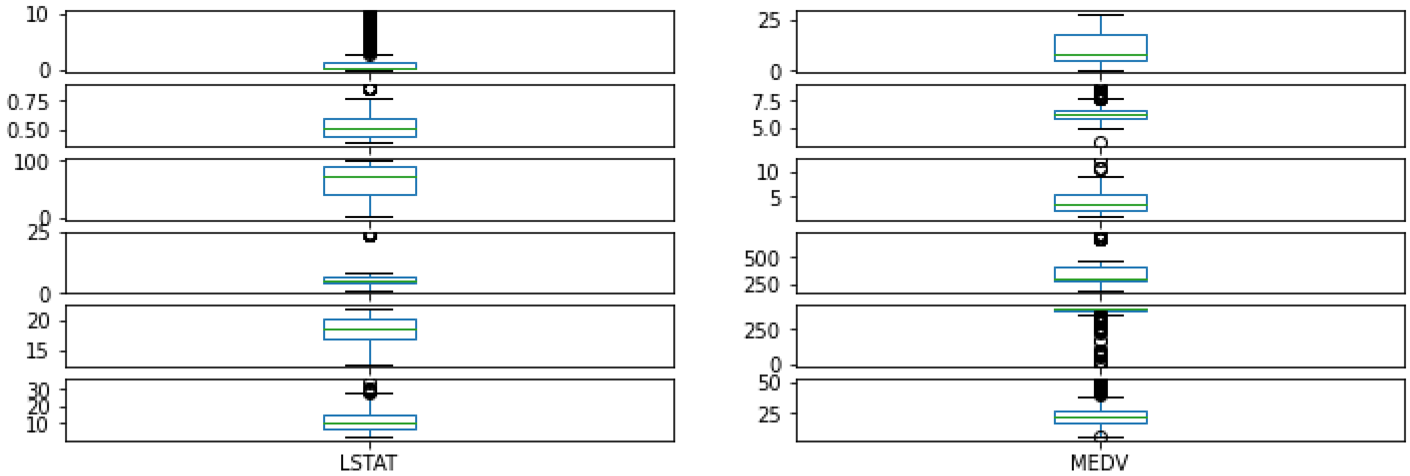
In [15]:
```
#Plot histrogram for each numeric
df.hist(figsize=(12, 8))
pyplot.show()
```



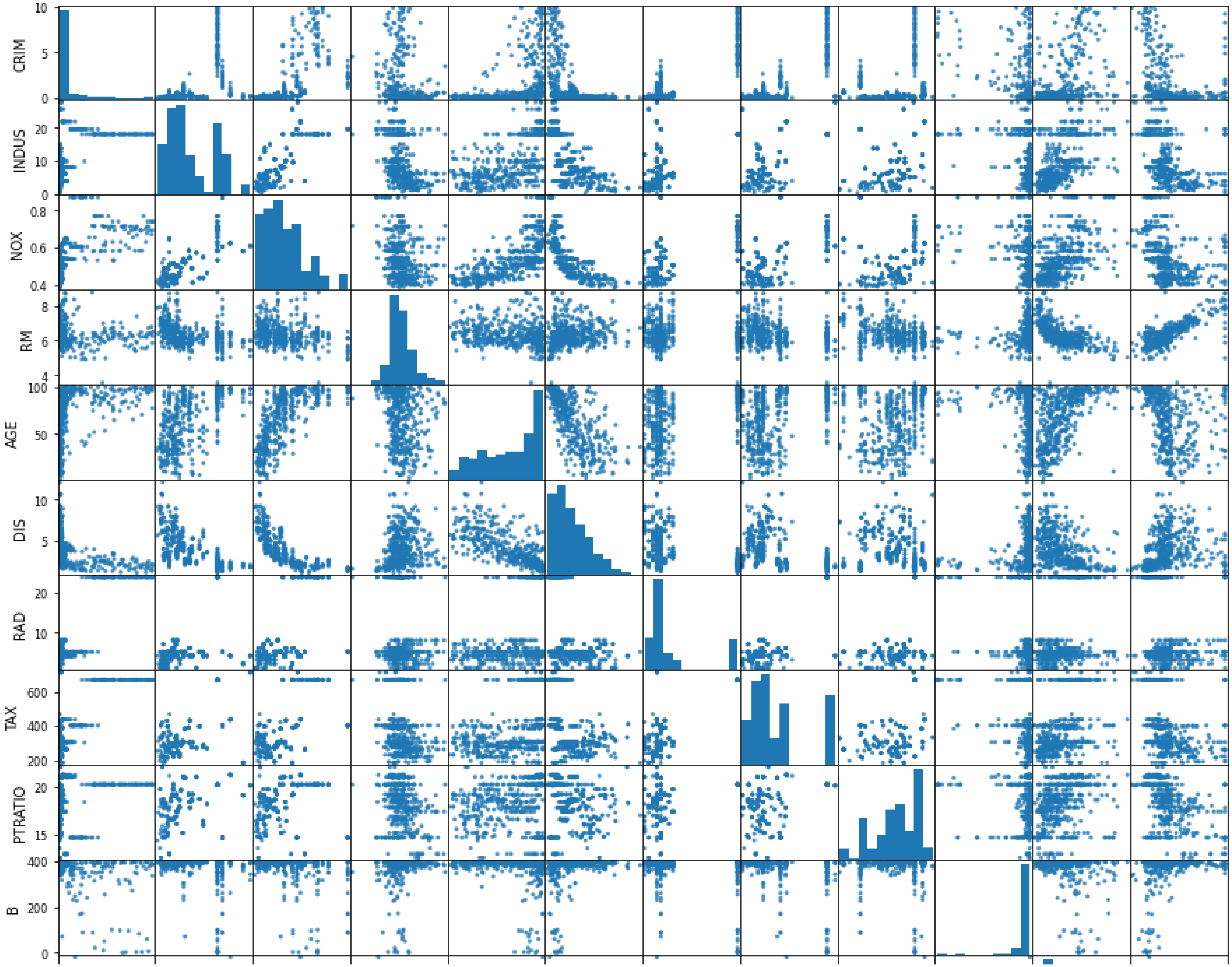
In [16]:
```
#Calculate density plots
# 5 numeric variables -> at Least 5 plots -> Layout (2, 3): 2 rows, each row with 3 plots
df.plot(kind='density', subplots=True, layout=(12, 2), sharex=False, legend=True, fontsize=1,
figsize=(12, 16))
pyplot.show()
```

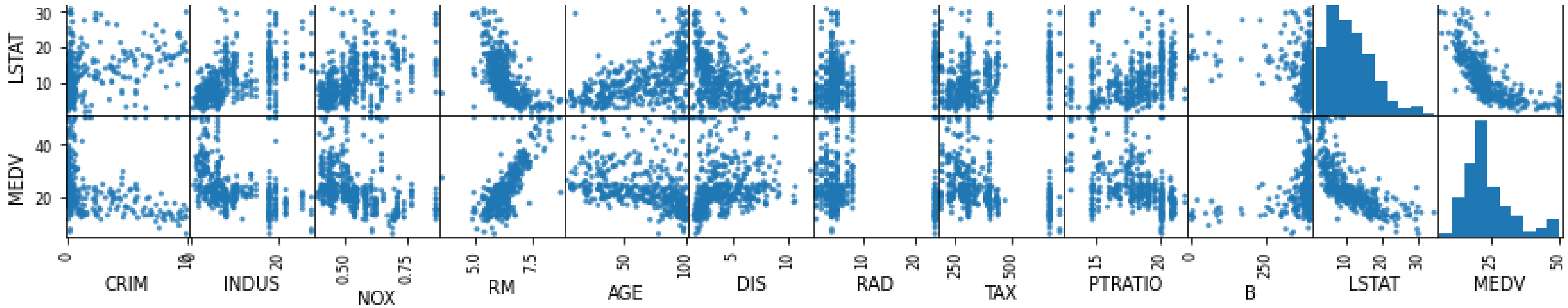


In [17]:
```
#Calculate box plots
df.plot(kind='box', subplots=True, layout=(12,2), sharex=False, figsize=(12,8))
pyplot.show()
```



In [18]:
```
#Calculate scatter plot matrices
scatter_matrix(df, alpha=0.8, figsize=(15, 15))
pyplot.show()
```





Step 4: Separate the dataset into the input and output NumPy arrays

In [19]:
```
#Then we separate the dataset into input and output NumPy arrays
#We want to store the dataframe values into a NumPy array
array = df.values
#Then we want to separate the array into input and output components by slicing it
#For X (input)[:, 5] --> all the rows, columns from 0 - 4 (5 - 1)
X = array[:,0:11]
#And for Y (output)[:, 5] --> all the rows, column index 5 (Last column)
Y = array[:,1]
```

In [20]:
```
print(X)
```

```
[[6.3200e-03 2.3100e+00 5.3800e-01 ... 1.5300e+01 3.9690e+02 4.9800e+00]
 [2.7310e-02 7.0700e+00 4.6900e-01 ... 1.7800e+01 3.9690e+02 9.1400e+00]
 [2.7290e-02 7.0700e+00 4.6900e-01 ... 1.7800e+01 3.9283e+02 4.0300e+00]
 ...
 [6.0760e-02 1.1930e+01 5.7300e-01 ... 2.1000e+01 3.9690e+02 5.6400e+00]
 [1.0959e-01 1.1930e+01 5.7300e-01 ... 2.1000e+01 3.9345e+02 6.4800e+00]
 [4.7410e-02 1.1930e+01 5.7300e-01 ... 2.1000e+01 3.9690e+02 7.8800e+00]]
```

In [21]:
```
print(Y)
```

```
[ 2.31  7.07  7.07  2.18  2.18  2.18  7.87  7.87  7.87  7.87  7.87  7.87
  7.87  8.14  8.14  8.14  8.14  8.14  8.14  8.14  8.14  8.14  8.14  8.14
  8.14  8.14  8.14  8.14  8.14  8.14  8.14  8.14  8.14  8.14  8.14  5.96
  5.96  5.96  5.96  2.95  2.95  6.91  6.91  6.91  6.91  6.91  6.91  6.91
  6.91  6.91  5.64  5.64  5.64  5.64  4.    1.22  0.74  1.32  5.13  5.13
  5.13  5.13  5.13  5.13  1.38  3.37  3.37  6.07  6.07  6.07 10.81 10.81
 10.81 10.81 12.83 12.83 12.83 12.83 12.83 12.83  4.86  4.86  4.86  4.86
  4.49  4.49  4.49  4.49  3.41  3.41  3.41  3.41 15.04 15.04 15.04  2.89
  2.89  2.89  2.89  2.89  8.56  8.56  8.56  8.56  8.56  8.56  8.56  8.56
  8.56  8.56  8.56 10.01 10.01 10.01 10.01 10.01 10.01 10.01 10.01 10.01
 25.65 25.65 25.65 25.65 25.65 25.65 25.65 21.89 21.89 21.89 21.89 21.89
 21.89 21.89 21.89 21.89 21.89 21.89 21.89 21.89 21.89 21.89 19.58 19.58
 19.58 19.58 19.58 19.58 19.58 19.58 19.58 19.58 19.58 19.58 19.58 19.58
 19.58 19.58 19.58 19.58 19.58 19.58 19.58 19.58 19.58 19.58 19.58 19.58
 19.58 19.58 19.58 19.58  4.05  4.05  4.05  4.05  4.05  4.05  4.05  2.46
  2.46  2.46  2.46  2.46  2.46  2.46  2.46  3.44  3.44  3.44  3.44  3.44
  3.44  2.93  2.93  0.46  1.52  1.52  1.52  1.47  1.47  2.03  2.03  2.68
  2.68 10.59 10.59 10.59 10.59 10.59 10.59 10.59 10.59 10.59 10.59 10.59
 13.89 13.89 13.89 13.89  6.2   6.2   6.2   6.2   6.2   6.2   6.2   6.2
  6.2   6.2   6.2   6.2   6.2   6.2   6.2   6.2   6.2   6.2   4.93  4.93
  4.93  4.93  4.93  4.93  5.86  5.86  5.86  5.86  5.86  5.86  5.86  5.86
  5.86  5.86  3.64  3.64  3.75  3.97  3.97  3.97  3.97  3.97  3.97  3.97
  3.97  3.97  3.97  3.97  3.97  6.96  6.96  6.96  6.96  6.96  6.41  6.41
  6.41  6.41  6.41  3.33  3.33  3.33  3.33  1.21  2.97  2.25  1.76  5.32
  5.32  5.32  4.95  4.95  4.95 13.92 13.92 13.92 13.92 13.92  2.24  2.24
  2.24  6.09  6.09  6.09  2.18  2.18  2.18  2.18  9.9   9.9   9.9   9.9
  9.9   9.9   9.9   9.9   9.9   9.9   9.9   9.9   7.38  7.38  7.38  7.38
  7.38  7.38  7.38  7.38  3.24  3.24  3.24  6.06  6.06  5.19  5.19  5.19
  5.19  5.19  5.19  5.19  5.19  1.52  1.89  3.78  3.78  4.39  4.39  4.15
  2.01  1.25  1.25  1.69  1.69  2.02  1.91  1.91 18.1  18.1  18.1  18.1
 18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1
 18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1
 18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1
 18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1
 18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1
 18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1  18.1
 18.1  18.1  27.74 27.74 27.74 27.74 27.74  9.69  9.69  9.69  9.69  9.69
  9.69  9.69  9.69 11.93 11.93 11.93 11.93 11.93]
```

In [22]:
```
#Now we want to split the dataset --> training sub-dataset: 67%; and test sub-dataset:
test_size = 0.33
# Selection of records to include in which sub-dataset must be done randomly
#and use this seed for randomization
seed = 10
# Split the dataset (both input & outout) into training/testing datasets
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=test_size,
random_state=seed)
```

Step 5: Split the input/output arrays into the training/testing datasets

In [23]:
```
print(X_train)
```

```
[[7.15100e-02 4.49000e+00 4.49000e-01 ... 1.85000e+01 3.95150e+02
  8.44000e+00]
 [8.79212e+00 1.81000e+01 5.84000e-01 ... 2.02000e+01 3.65000e+00
  1.71600e+01]
 [3.51140e-01 7.38000e+00 4.93000e-01 ... 1.96000e+01 3.96900e+02
  7.70000e+00]
 ...
 [6.27390e-01 8.14000e+00 5.38000e-01 ... 2.10000e+01 3.95620e+02
  8.47000e+00]
 [1.69020e-01 2.56500e+01 5.81000e-01 ... 1.91000e+01 3.85020e+02
  1.48100e+01]
 [7.61620e-01 3.97000e+00 6.47000e-01 ... 1.30000e+01 3.92400e+02
  1.04500e+01]]
```

In [24]:
```
print(Y_train)
```

```
[ 4.49 18.1   7.38  3.44 15.04  7.38  8.14  3.97  1.25  8.14 13.92  7.07
  5.13  5.13  8.14  9.9   2.46 13.89 18.1   4.05  8.14  9.69  3.97 19.58
 18.1  10.59 25.65 18.1  18.1   3.33  0.46  9.9   6.41  5.86  5.96 21.89
 18.1   6.41 18.1   3.24 18.1   4.93  2.93 25.65  5.96 18.1   8.14  3.33
  5.19  6.2   3.44  1.52  8.56  2.18  6.06  5.19  5.19  6.2  19.58 18.1
  2.68 18.1   9.69  8.56  6.96  5.86  5.13  4.05  1.52  8.14  5.19  8.56
  4.95 21.89 21.89  6.91 18.1   7.38  5.13 19.58 12.83  7.38 27.74  3.24
 19.58  5.96 13.89  6.2   5.19 18.1  11.93  1.91  5.86 21.89 10.01  9.9
  1.52  6.07  5.86  2.31  5.64  6.41  3.97 18.1   1.22 18.1  18.1   4.15
  4.86  3.97 10.59 18.1  18.1   2.46  4.49  6.91  2.24 19.58  9.69 18.1
 18.1   2.18  3.97 21.89 18.1   1.52  2.46  7.87  3.97  8.14 18.1   3.97
 11.93  8.56  2.95  8.14 10.59 18.1  19.58 18.1  13.92 10.59 19.58  9.69
  8.14  3.64 10.59 21.89 18.1   1.69 19.58  9.69  6.2   6.2  19.58  9.9
  3.97 10.01  2.02  6.91 18.1  18.1  18.1   4.86  2.89  6.07  2.89  8.14
  3.64  5.86 18.1  19.58  4.39 19.58 10.59 18.1  27.74  3.41  6.91  6.2
  5.19 18.1   5.64  4.05  6.96 18.1  18.1   5.64  8.14 18.1   5.19  5.19
  6.96  2.25  2.18  8.14 21.89 19.58  2.03  6.91 18.1   6.2  18.1   6.2
  6.91  6.2  12.83  2.46 18.1   6.2   3.97 10.01  7.87 19.58  6.2   4.49
  5.86 21.89 19.58 18.1   6.96 18.1   4.95  2.46 18.1   2.18 18.1  18.1
 18.1   2.18 21.89  6.91  1.69  5.86  5.32  2.97  2.68 21.89 19.58 18.1
 10.81 10.01 18.1  11.93 18.1  13.89 12.83  9.69 18.1   5.86 15.04 27.74
 15.04  8.14  1.21  4.95  9.9   8.14  7.38 21.89  3.41 19.58  1.76  1.89
  2.01 21.89 18.1  18.1   4.93  8.14 12.83 18.1   2.46  4.05 27.74  1.47
  8.14  5.13 25.65 18.1   3.78  4.   18.1   4.93 18.1   8.14 18.1  18.1
  2.95  3.75 10.81  7.87 11.93 18.1   6.2  19.58 25.65 18.1   7.38  8.14
 25.65  3.97]
```

Step 6: Build and train the model

In [25]:
```
#Now we can build the model
model = LinearRegression()
#Then train the model using the training sub-dataset
model.fit(X_train, Y_train)
#Print out the coefficients and the intercept
#Print intercept and coefficients
print (model.intercept_)
print (model.coef_)
```

```
-1.1546319456101628e-13
[1.28737288e-14 1.00000000e+00 2.36396189e-14 3.44288400e-15
 1.52655666e-16 3.42087469e-15 5.27355937e-16 1.11022302e-16
 1.37910516e-16 2.77555756e-17 2.22044605e-16]
```

In [26]:
```
#We can pair the feature names with the coefficients
#and print out the list with their correspondent variable name
names_2 = ['CRIM','INDUS','NOX','RM','AGE','DIS','RAD','TAX','PTRATIO','B','LSTAT','MEDV']
```

In [27]:
```
coeffs_zip = zip(names_2, model.coef_)
```

In [28]:
```
#Convert iterator into set
coeffs = set(coeffs_zip)
```

In [29]:
```
#Print (coeffs)
for coef in coeffs:
    print (coef)
```

```
('CRIM', 1.287372880437735e-14)
('NOX', 2.3639618908222193e-14)
('DIS', 3.4208746946262636e-15)
('INDUS', 0.9999999999999994)
('B', 2.7755575615628914e-17)
('TAX', 1.1102230246251565e-16)
('PTRATIO', 1.3791051634015616e-16)
('AGE', 1.5265566588595902e-16)
('RM', 3.4428839987277193e-15)
('RAD', 5.273559366969494e-16)
('LSTAT', 2.220446049250313e-16)
```

In [30]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

Out[30]:
```
LinearRegression(n_jobs=1)
```

Step 7: Calculate the R2 value

In [31]:
```
R_squared = model.score(X_test, Y_test)
print(R_squared)
```

```
1.0
```

In [32]:
```
#Here we get a perfect R-Squared score of 1. A higher R-Squared
#indicates a higher correlatio between the independent variables and the dependent variables.
```

Step 8: Predict the "Median value of owner-occupied homes in 1000 dollars"

Scenario 1: It is assumed that two new suburbs/towns/developments have been established in the Boston area. The agency has collected the housing data of these two new suburbs/towns/developments.

In [33]:
```
#We will use the mean values of the described statistics for the first "made up housing records"
#The suburb area has the following predictors:
#CRIM:1.42
#INDUS:10.30
#NOX:0.54
#RM: 6.34
#AGE:65.56 (proportion of owner-occupied units built prior to 1940)
#DIS: 4.04 (weighted distances to five Boston employment centers)
#RAD: 7.82 (index of accessibility to radial highways)
#TAX: 377.44
#PTRATIO: 18.25 (pupil-teacher ratio by town)
#B:369.83
#LSTAT:23.75
```

In [34]:
```
model.predict([[1.42, 10.30, 0.54, 6.34, 65.56,4.04,7.82,377.44,18.25,369.83,23.75]])
```

Out[34]:
```
array([10.3])
```

In [35]:
```
#The model predicts that the median value of owner-occupied homes
#in 1000 dollars in the above suburb should be around 10,300 under this scenario
```

In [36]:
```
#We will now have a "made up housing record" in order to retrain our model.
#The suburb area has the following predictors:
#CRIM:2.8
#INDUS:11.30
#NOX:0.55
#RM: 6.39
#AGE:45.56 (proportion of owner-occupied units built prior to 1940)
#DIS: 8.04 (weighted distances to five Boston employment centers)
#RAD: 4.82 (index of accessibility to radial highways)
#TAX: 277.44
#PTRATIO: 13.25 (pupil-teacher ratio by town)
#B:269.83
#LSTAT:21.75
```

In [37]:
```
model.predict([[2.8, 11.30, 0.55, 6.39, 45.56,8.04,4.82,277.44,13.25,269.83,21.75]])
```

Out[37]:
```
array([11.3])
```

In [38]:
```
#With this second scenario, the model predicts that the median value of owner-occupied homes
#in 1000 dollars in the above suburb should be around 11,300
```

Step 9: Evaluate the model using the 10-fold cross-validation

In [39]:
```
# Evaluate the algorithm
# Specify the K-size in this case 10-fold
num_folds = 10
#We must use the same seed value so that the same subsets can be obtained
# for each time the process is repeated
seed = 10
# Split the whole data set into folds
kfold = KFold(n_splits=num_folds, random_state=seed)
# For Linear regression, we can use MSE (mean squared error) value
# to evaluate the model/algorithm
scoring = 'neg_mean_squared_error'
# Train the model and run K-foLd cross-validation to validate/evaluate the model
results = cross_val_score(model, X, Y, cv=kfold, scoring=scoring)
# Print out the evaluation results
# Result: the average of all the results obtained from the k-foLd cross-validation
print(results.mean())
```

```
-1.1773044465875376e-26

/Users/miriamgarcia/opt/anaconda3/lib/python3.8/site-packages/sklearn/model_selection/_split.py:293: FutureWar
ning: Setting a random_state has no effect since shuffle is False. This will raise an error in 0.24. You shoul
d leave random_state to its default (None), or set shuffle=True.
  warnings.warn(
```

In [41]:
```
#After we train we evaluate Use K-Fold to determine if the model is acceptable
#We pass the whole set because the system will divide for us -1.177 average
#of all errors (mean of square errors)
```

In [42]:
```
#
```

In [ ]:
```
```