In [3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [10]:
```
from sklearn import datasets
boston = datasets.load_boston()
```

In [11]:
```
boston.data.shape
```

Out[11]:
```
(506, 13)
```

In [12]:
```
boston.feature_names
```

Out[12]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

In [13]:
```
data = pd.DataFrame(boston.data)
data.columns = boston.feature_names
```

In [14]:
```
data
```

Out[14]:

| | CRIM | ZN | INDUS | CHAS | NOX | RM | AGE | DIS | RAD | TAX | PTRATIO | B | LST |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **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 |
| **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 |
| **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 |
| **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 |
| **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 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **501** | 0.06263 | 0.0 | 11.93 | 0.0 | 0.573 | 6.593 | 69.1 | 2.4786 | 1.0 | 273.0 | 21.0 | 391.99 | 9 |
| **502** | 0.04527 | 0.0 | 11.93 | 0.0 | 0.573 | 6.120 | 76.7 | 2.2875 | 1.0 | 273.0 | 21.0 | 396.90 | 9 |
| **503** | 0.06076 | 0.0 | 11.93 | 0.0 | 0.573 | 6.976 | 91.0 | 2.1675 | 1.0 | 273.0 | 21.0 | 396.90 | 5 |
| **504** | 0.10959 | 0.0 | 11.93 | 0.0 | 0.573 | 6.794 | 89.3 | 2.3889 | 1.0 | 273.0 | 21.0 | 393.45 | 6 |
| **505** | 0.04741 | 0.0 | 11.93 | 0.0 | 0.573 | 6.030 | 80.8 | 2.5050 | 1.0 | 273.0 | 21.0 | 396.90 | 7 |

506 rows × 13 columns

In [15]:
```
boston.target.shape
```

Out[15]:
```
(506,)
```

In [16]:
```
data['Price'] = boston.target
```

In [17]:
```
data.head
```

Out[17]:
```
<bound method NDFrame.head of         CRIM    ZN  INDUS  CHAS    NOX     RM
AGE     DIS  RAD    TAX  \
0    0.00632  18.0   2.31   0.0  0.538  6.575  65.2  4.0900  1.0  296.0
1    0.02731   0.0   7.07   0.0  0.469  6.421  78.9  4.9671  2.0  242.0
2    0.02729   0.0   7.07   0.0  0.469  7.185  61.1  4.9671  2.0  242.0
3    0.03237   0.0   2.18   0.0  0.458  6.998  45.8  6.0622  3.0  222.0
4    0.06905   0.0   2.18   0.0  0.458  7.147  54.2  6.0622  3.0  222.0
..       ...   ...    ...   ...    ...    ...   ...     ...  ...    ...
501  0.06263   0.0  11.93   0.0  0.573  6.593  69.1  2.4786  1.0  273.0
502  0.04527   0.0  11.93   0.0  0.573  6.120  76.7  2.2875  1.0  273.0
503  0.06076   0.0  11.93   0.0  0.573  6.976  91.0  2.1675  1.0  273.0
504  0.10959   0.0  11.93   0.0  0.573  6.794  89.3  2.3889  1.0  273.0
505  0.04741   0.0  11.93   0.0  0.573  6.030  80.8  2.5050  1.0  273.0

     PTRATIO       B  LSTAT  Price
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
..       ...     ...    ...    ...
501     21.0  391.99   9.67   22.4
502     21.0  396.90   9.08   20.6
503     21.0  396.90   5.64   23.9
504     21.0  393.45   6.48   22.0
505     21.0  396.90   7.88   11.9

[506 rows x 14 columns]>
```

In [18]:
```
data.describe()
```

Out[18]:

| | CRIM | ZN | INDUS | CHAS | NOX | RM | AGE | |
|---|---|---|---|---|---|---|---|---|
| **count** | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.0 |
| **mean** | 3.613524 | 11.363636 | 11.136779 | 0.069170 | 0.554695 | 6.284634 | 68.574901 | 3.7 |
| **std** | 8.601545 | 23.322453 | 6.860353 | 0.253994 | 0.115878 | 0.702617 | 28.148861 | 2.1 |
| **min** | 0.006320 | 0.000000 | 0.460000 | 0.000000 | 0.385000 | 3.561000 | 2.900000 | 1.1 |
| **25%** | 0.082045 | 0.000000 | 5.190000 | 0.000000 | 0.449000 | 5.885500 | 45.025000 | 2.1 |
| **50%** | 0.256510 | 0.000000 | 9.690000 | 0.000000 | 0.538000 | 6.208500 | 77.500000 | 3.2 |
| **75%** | 3.677083 | 12.500000 | 18.100000 | 0.000000 | 0.624000 | 6.623500 | 94.075000 | 5.1 |
| **max** | 88.976200 | 100.000000 | 27.740000 | 1.000000 | 0.871000 | 8.780000 | 100.000000 | 12.1 |

In [19]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   CRIM     506 non-null    float64
 1   ZN       506 non-null    float64
 2   INDUS    506 non-null    float64
 3   CHAS     506 non-null    float64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      506 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    float64
 9   TAX      506 non-null    float64
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    506 non-null    float64
 13  Price    506 non-null    float64
dtypes: float64(14)
memory usage: 55.5 KB
```

In [20]:
```
# Input Data
x = boston.data

# Output Data
y = boston.target
```

In [21]:
```
# splitting data to training and testing dataset.

from sklearn.model_selection import train_test_split

xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size =0.2, random_st

print("xtrain shape : ", xtrain.shape)
print("xtest shape : ", xtest.shape)
print("ytrain shape : ", ytrain.shape)
print("ytest shape : ", ytest.shape)
```

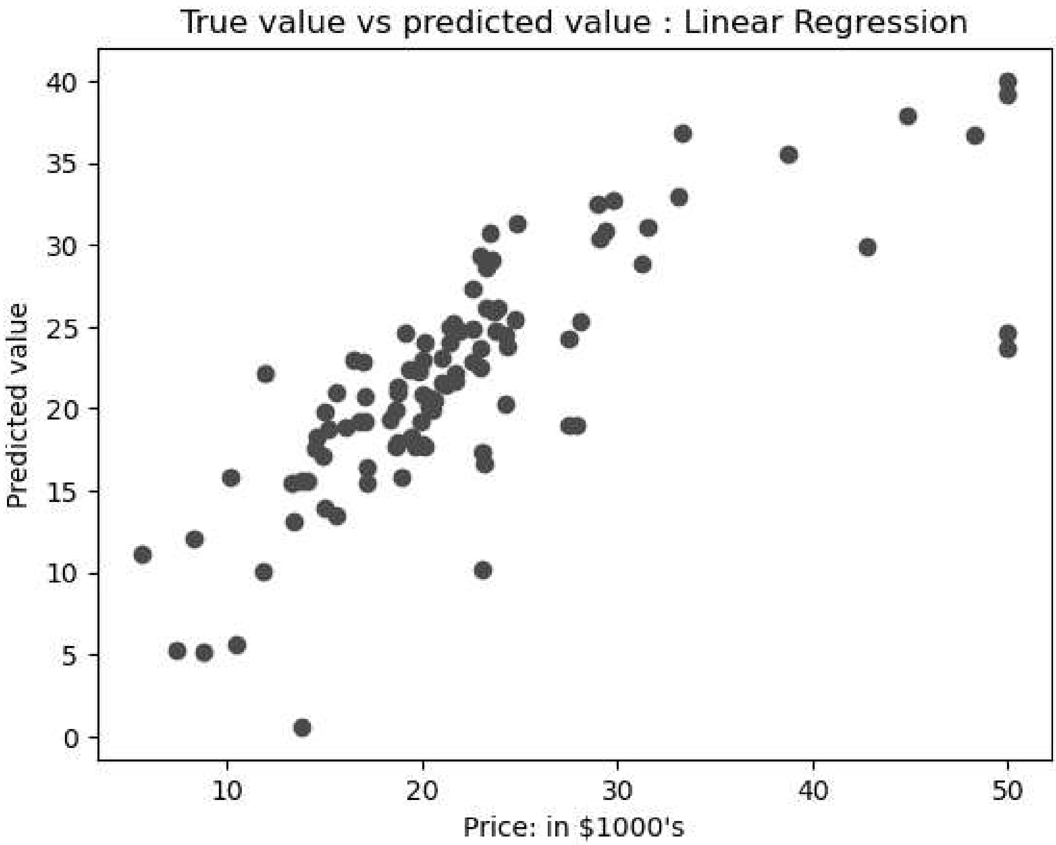
```
xtrain shape :  (404, 13)
xtest shape :  (102, 13)
ytrain shape :  (404,)
ytest shape :  (102,)
```

In [22]:
```
# Fitting Multi Linear regression model to training model
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()

regressor.fit(xtrain, ytrain)

# predicting the test set results
y_pred = regressor.predict(xtest)
```

In [23]:
```
# Plotting Scatter graph to show the prediction
# results - &#39;ytrue&#39; value vs &#39;y_pred&#39; value
plt.scatter(ytest, y_pred, c = 'green')
plt.xlabel("Price: in $1000's")
plt.ylabel("Predicted value")
plt.title("True value vs predicted value : Linear Regression")
plt.show()
```




In [24]:
```
from sklearn.metrics import mean_squared_error, mean_absolute_error
mse = mean_squared_error(ytest, y_pred)
mae = mean_absolute_error(ytest,y_pred)
print("Mean Squared Error : ", mse)
print("Mean Absolute Error : ", mae)
```

```
Mean Squared Error :  33.44897999767653
Mean Absolute Error :  3.842909220444498
```