In [1]:
```python
from sklearn.datasets import load_boston
import pandas as pd

import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns


import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```python
boston = load_boston()
```

In [3]:
```python
type(boston)
```

Out[3]:
```
sklearn.utils.Bunch
```

In [4]:
```python
boston.keys()
```

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

In [5]:
```python
boston.feature_names
```

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

In [6]:
```python
boston.data[0:2]
```

Out[6]:
```
array([[6.3200e-03, 1.8000e+01, 2.3100e+00, 0.0000e+00, 5.3800e-01,
        6.5750e+00, 6.5200e+01, 4.0900e+00, 1.0000e+00, 2.9600e+02,
        1.5300e+01, 3.9690e+02, 4.9800e+00],
       [2.7310e-02, 0.0000e+00, 7.0700e+00, 0.0000e+00, 4.6900e-01,
        6.4210e+00, 7.8900e+01, 4.9671e+00, 2.0000e+00, 2.4200e+02,
        1.7800e+01, 3.9690e+02, 9.1400e+00]])
```

In [7]:
```
df = pd.DataFrame(boston.data)
df.head()
```

Out[7]:

	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 [8]:
```
boston.feature_names
```

Out[8]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

In [9]:
```
df.columns = boston.feature_names
df.head()
```

Out[9]:

	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 [10]:
```
df['PRICE'] = boston.target
df.head()
```

Out[10]:

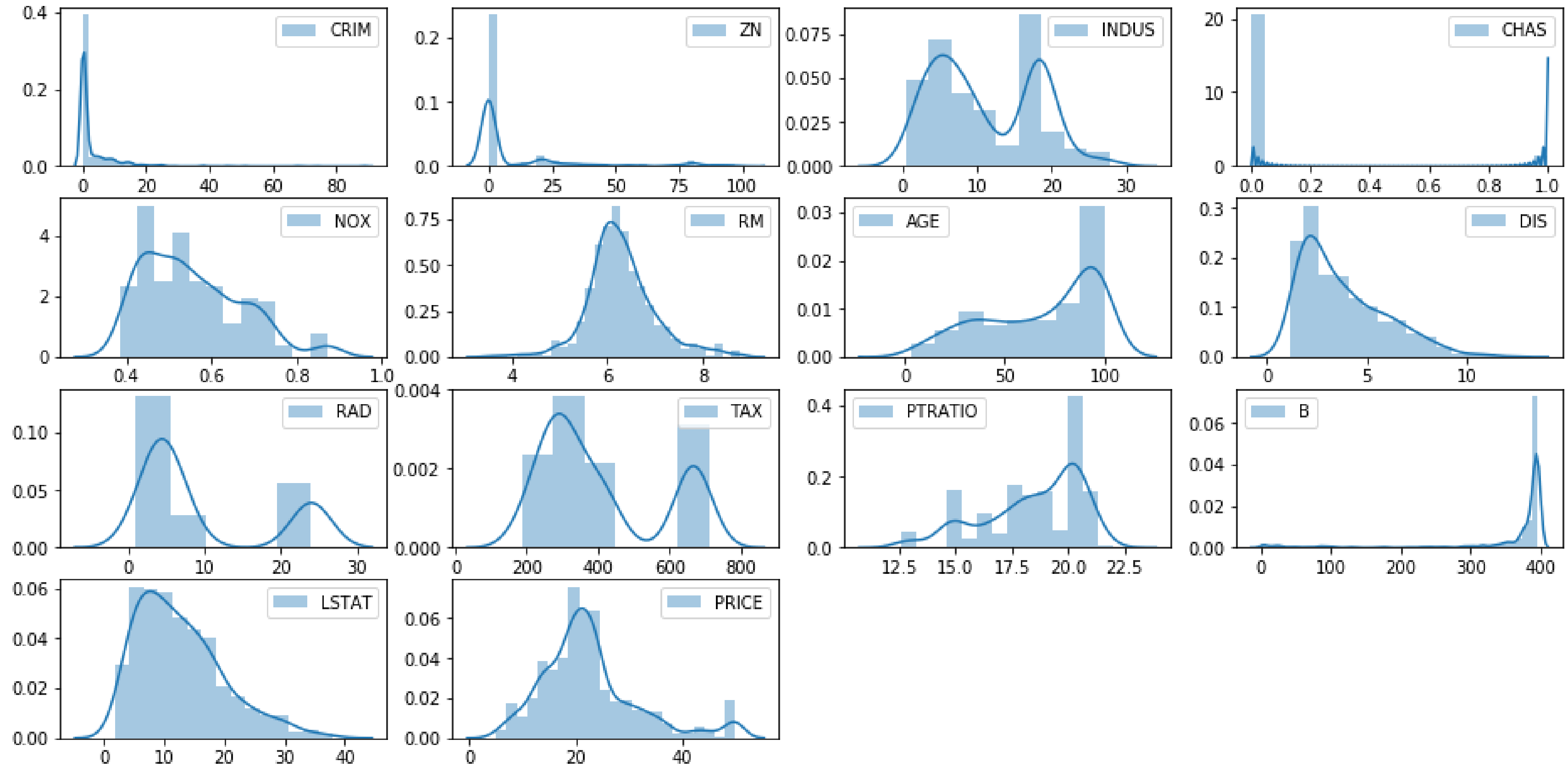
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03	34.7
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

In [11]:
```
df.columns[0]
```

Out[11]:
```
'CRIM'
```

Visualization

In [12]:
```
fig = plt.figure(figsize=(16,8))
for col in range(14):
    fig.add_subplot(4,4,col+1)
    sns.distplot(df.iloc[:,col], label=str(df.columns[col]))
    plt.xlabel(' ')
    plt.legend()
```



In [ ]:

```

```

In [13]:

```
corr_ = df.corr(method='pearson')
```

In [14]:

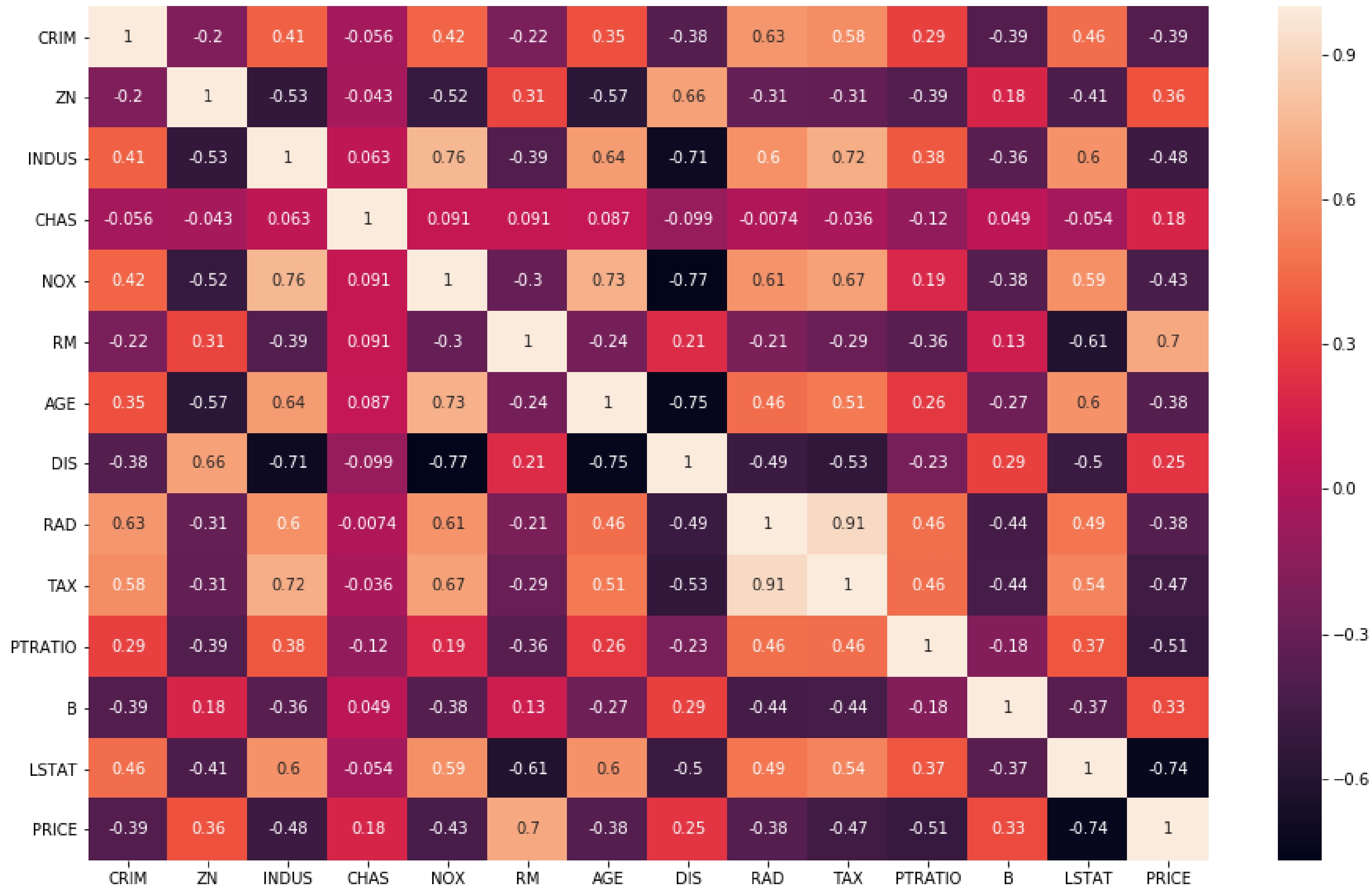
```
np.shape(corr_)
```

Out[14]:

```
(14, 14)
```

In [15]:
```python
plt.figure(figsize=(16,10))
sns.heatmap(corr_, annot=True)
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe9756cd710>



In [16]:
```
corr_['PRICE']
```

Out[16]:
```
CRIM      -0.388305
ZN         0.360445
INDUS     -0.483725
CHAS       0.175260
NOX       -0.427321
RM         0.695360
AGE       -0.376955
DIS        0.249929
RAD       -0.381626
TAX       -0.468536
PTRATIO   -0.507787
B          0.333461
LSTAT     -0.737663
PRICE      1.000000
Name: PRICE, dtype: float64
```

In [17]:
```
l1 = corr_['PRICE'].values.tolist()
l1.remove(l1[-1])
l1[0:3]
```

Out[17]:
```
[-0.3883046085868114, 0.3604453424505447, -0.483725160028373]
```

In [18]:
```
l = l1
ls = np.sort(l).tolist()
ls1 = ls[-1::-1]
ls1[0:3]
```

Out[18]:
```
[0.6953599470715389, 0.3604453424505447, 0.33346081965706653]
```

In [19]:
```
idx = np.argsort(l).tolist()
idx
```

Out[19]:
```
[12, 10, 2, 9, 4, 0, 8, 6, 3, 7, 11, 1, 5]
```

In [20]:
```
label = corr_['PRICE'].index.tolist()
label[0:2]
```

Out[20]:
```
['CRIM', 'ZN']
```

In [21]:
```
type(label)
```

Out[21]:
```
list
```

In [22]:
```
label1 = []
```

In [23]:
```
for itm in idx:
    label1.append(label[itm])
```

In [24]:
```python
label1[-1::-1]
```

Out[24]:
```
['RM',
 'ZN',
 'B',
 'DIS',
 'CHAS',
 'AGE',
 'RAD',
 'CRIM',
 'NOX',
 'TAX',
 'INDUS',
 'PTRATIO',
 'LSTAT']
```

In [25]:
```python
label1s = label1[-1::-1]
label1s[0:2]
```

Out[25]:
```
['RM', 'ZN']
```

In [26]:
```
df_corr = pd.DataFrame({'itm':labells, 'corr':ls1})
df_corr
```

Out[26]:

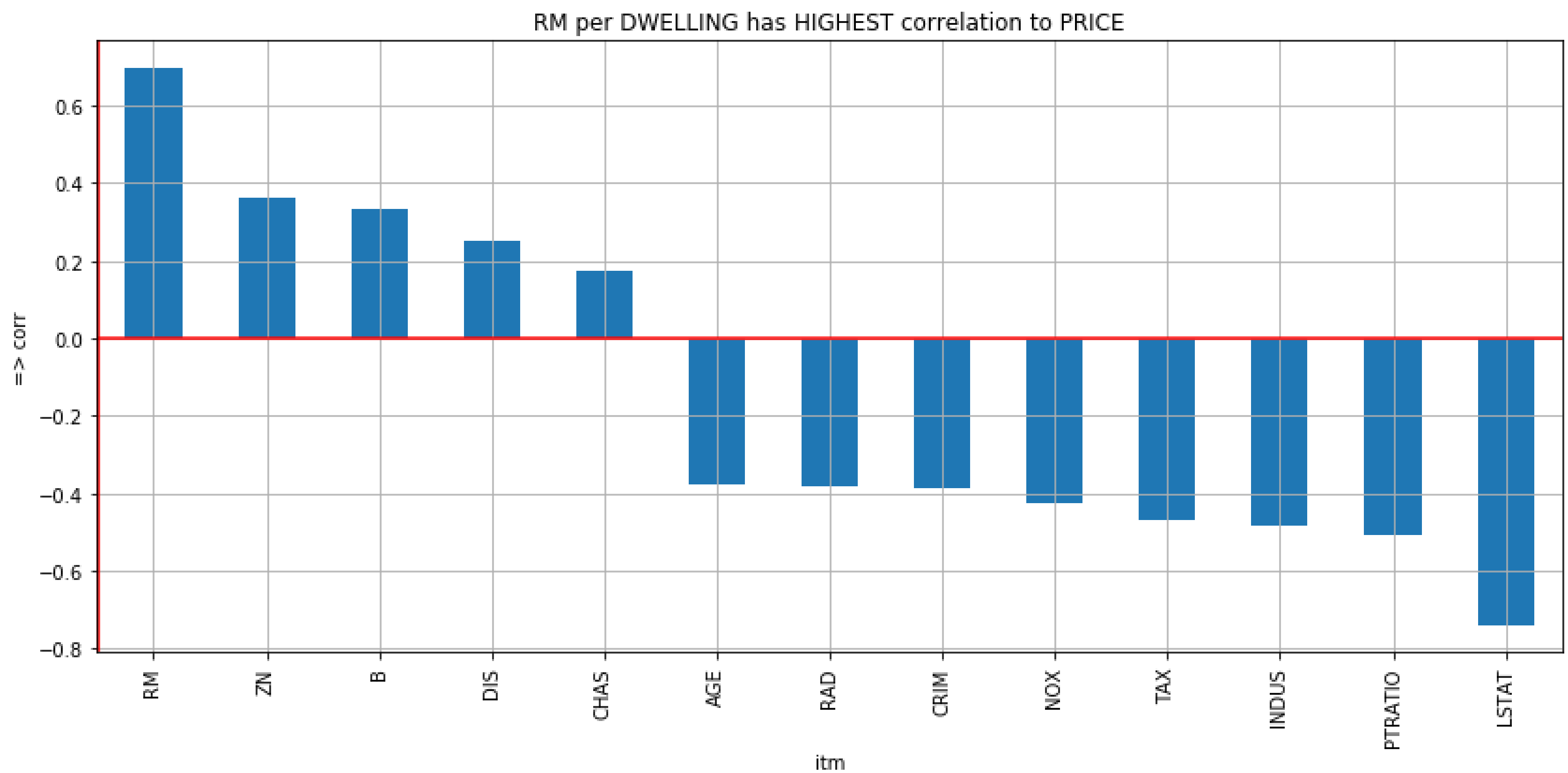
	itm	corr
0	RM	0.695360
1	ZN	0.360445
2	B	0.333461
3	DIS	0.249929
4	CHAS	0.175260
5	AGE	-0.376955
6	RAD	-0.381626
7	CRIM	-0.388305
8	NOX	-0.427321
9	TAX	-0.468536
10	INDUS	-0.483725
11	PTRATIO	-0.507787
12	LSTAT	-0.737663

In [27]:
```
df_corr_1 = df_corr.set_index(df_corr['itm'])
df_corr_1.head()
```

Out[27]:

	itm	corr
itm		
RM	RM	0.695360
ZN	ZN	0.360445
B	B	0.333461
DIS	DIS	0.249929
CHAS	CHAS	0.175260

In [28]:
```
df_corr_1['corr'].plot(kind='bar', figsize=(14,6))
plt.axvline(-0.49, color='red', linestyle='-')
plt.axhline(0, color='red', linestyle='-')
plt.title('RM per DWELLING has HIGHEST correlation to PRICE')
plt.ylabel('=> corr')
plt.grid()
plt.show()
```



In [29]:
```python
print(boston.DESCR)
```

```
.. _boston_dataset:

Boston house prices dataset
---------------------------

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Value (attribute 14) is usually t
he 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.
https://archive.ics.uci.edu/ml/machine-learning-databases/housing/ (https://archive.ics.uci.edu/ml/mac
hine-learning-databases/housing/)


This dataset was taken from the StatLib library which is maintained at Carnegie 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,
```

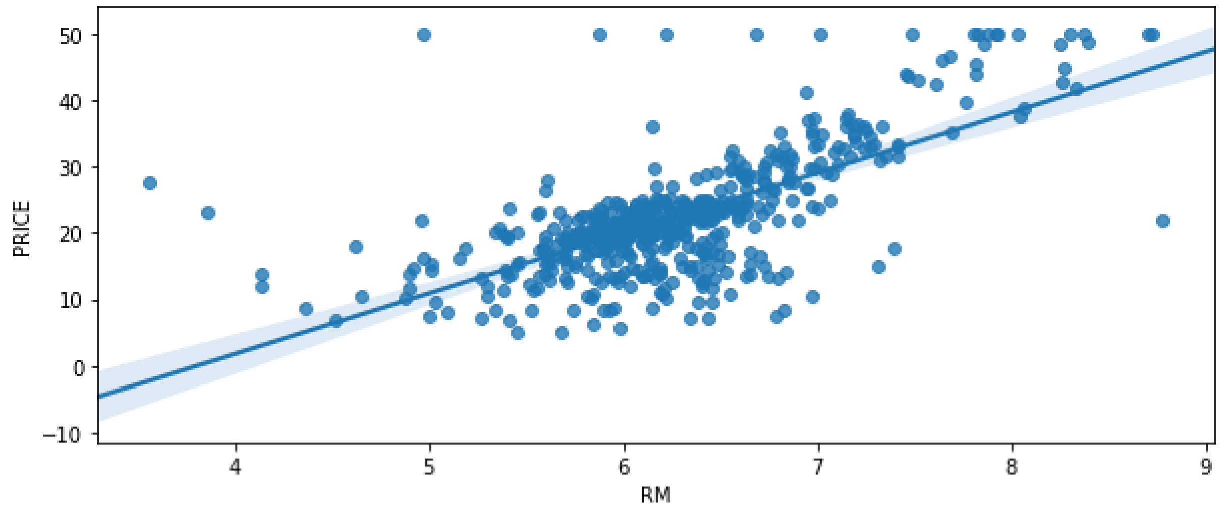
```
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics
...', Wiley, 1980.   N.B. Various transformations are used in the table on
pages 244-261 of the latter.

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

.. topic:: References

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and Sources of Colli
nearity', 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 Massachusetts, Amherst. Morgan Ka
ufmann.
```

Regression

RM vs PRICE

In [30]:
```
plt.figure(figsize=(10,4))
sns.regplot(x="RM", y="PRICE", data=df)
```

Out[30]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe97575f898>
```



In [31]:
```
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

In [32]:
```
ols_pr_rm = ols('PRICE ~ RM', df).fit()
ols_pr_rm.summary()
```

Out[32]:

OLS Regression Results

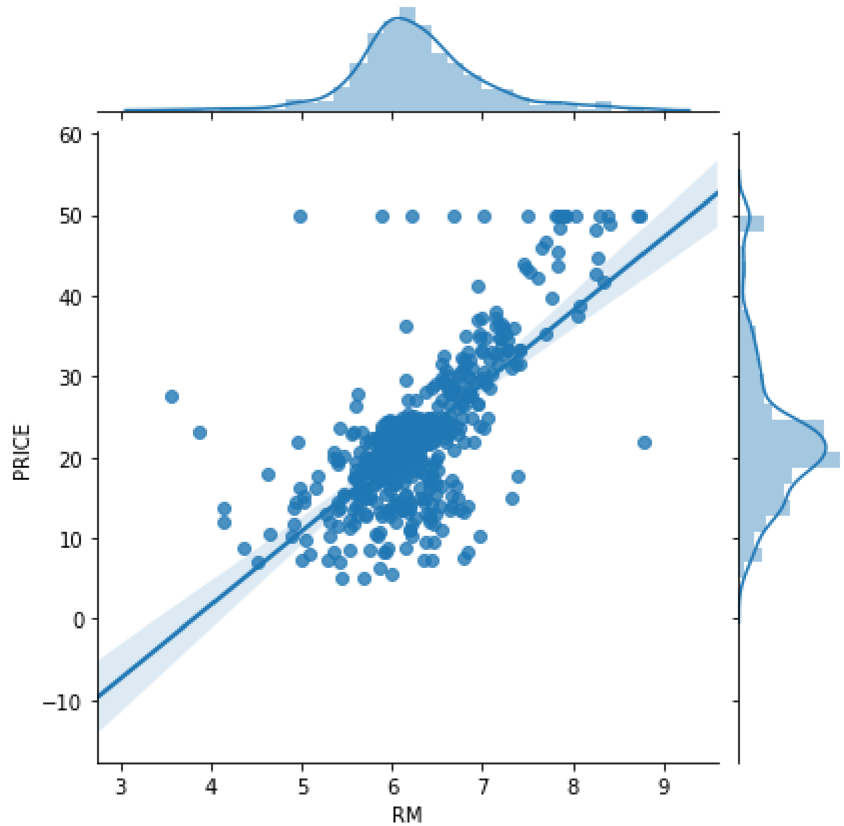
Dep. Variable:	PRICE	**R-squared:**	0.484
Model:	OLS	**Adj. R-squared:**	0.483
Method:	Least Squares	**F-statistic:**	471.8
Date:	Mon, 16 Nov 2020	**Prob (F-statistic):**	2.49e-74
Time:	00:42:17	**Log-Likelihood:**	-1673.1
No. Observations:	506	**AIC:**	3350.
Df Residuals:	504	**BIC:**	3359.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-34.6706	2.650	-13.084	0.000	-39.877	-29.465
RM	9.1021	0.419	21.722	0.000	8.279	9.925

Omnibus:	102.585	**Durbin-Watson:**	0.684
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	612.449
Skew:	0.726	**Prob(JB):**	1.02e-133
Kurtosis:	8.190	**Cond. No.**	58.4

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [33]:
```
sns.jointplot(x="RM", y="PRICE", data=df, kind="reg")
```
Out[33]: <seaborn.axisgrid.JointGrid at 0x7fe976ba8550>

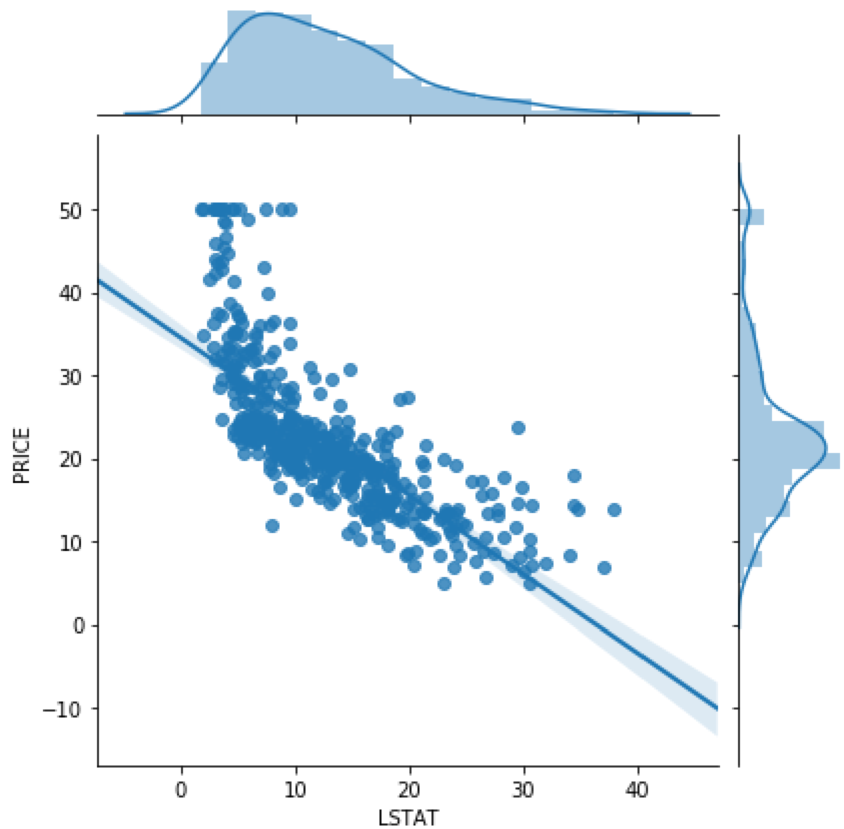


In [34]:
```
66.6/7.3
```
Out[34]: 9.123287671232877

LSTAT vs PRICE

In [35]:
```
sns.jointplot(x='LSTAT', y='PRICE', data=df, kind='reg')
```

Out[35]: <seaborn.axisgrid.JointGrid at 0x7fe976d68be0>



In [36]:
```
ols_pr_lstat = ols("PRICE ~ LSTAT", data=df).fit()  # ols -> ordinary least square
ols_pr_lstat.summary()
```

Out[36]:

OLS Regression Results

Dep. Variable:	PRICE	**R-squared:**	0.544
Model:	OLS	**Adj. R-squared:**	0.543
Method:	Least Squares	**F-statistic:**	601.6
Date:	Mon, 16 Nov 2020	**Prob (F-statistic):**	5.08e-88
Time:	00:42:21	**Log-Likelihood:**	-1641.5
No. Observations:	506	**AIC:**	3287.
Df Residuals:	504	**BIC:**	3295.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	34.5538	0.563	61.415	0.000	33.448	35.659
LSTAT	-0.9500	0.039	-24.528	0.000	-1.026	-0.874

Omnibus:	137.043	**Durbin-Watson:**	0.892
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	291.373
Skew:	1.453	**Prob(JB):**	5.36e-64
Kurtosis:	5.319	**Cond. No.**	29.7

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [37]:
```
ols_pr_rm.params[1]
```

Out[37]: 9.102108981180306

In [38]:
```
g = df_corr_1.index.tolist()
g
```

Out[38]:
```
['RM',
 'ZN',
 'B',
 'DIS',
 'CHAS',
 'AGE',
 'RAD',
 'CRIM',
 'NOX',
 'TAX',
 'INDUS',
 'PTRATIO',
 'LSTAT']
```

In [49]:
```
for itm in g:
    str1 = str(" PRICE ~ ") + str(itm)
    str2 = str(str1)
    ols_fit = ols(str2, data=df).fit()
    print(ols_fit.params[1])
```

```
9.102108981180306
0.14213999415535545
0.03359306011501362
1.0916130158411057
6.346157112526515
-0.12316272123567987
-0.40309539555252993
-0.41519027791509056
-33.9160550086611
-0.025568099481987235
-0.6484900536157133
-2.157175296060963
-0.9500493537579908
```

In [ ]:
```

```

In [50]:
```
df.columns
```
Out[50]:
```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT', 'PRICE'],
      dtype='object')
```
In [51]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.metrics import classification_report, accuracy_score
```
In [52]:
```
x_tr, x_t, y_tr, y_t = train_test_split(df[["RM"]].values, df[["PRICE"]].values, test_size=0.15, random_
np.shape(x_tr), np.shape(y_tr), np.shape(x_t), np.shape(y_t)
```
Out[52]:
```
((430, 1), (430, 1), (76, 1), (76, 1))
```
In [53]:
```
lr = LinearRegression()
lr.fit(x_tr, y_tr)
y_p = lr.predict(x_t)
```
In [54]:
```
y_p[0:5].tolist(), y_t[0:5].tolist()
```
Out[54]:
```
([[31.48770152144715],
  [25.052497893143745],
  [21.202071345460823],
  [20.774246173496053],
  [17.50316621284876]],
 [[34.6], [31.5], [20.6], [14.5], [16.2]])
```
In [55]:
```
r2_score(y_t, y_p), mean_squared_error(y_t, y_p)
```
Out[55]:
```
(0.6254819615240168, 26.940868860063624)
```
In [ ]:
```

```

In [56]:
```
X=df[ ['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT'] ].values
np.shape(X)
```

Out[56]:
```
(506, 13)
```

In [57]:
```
y = df[['PRICE']].values
np.shape(y)
```

Out[57]:
```
(506, 1)
```

In [58]:
```
x_tr, x_t, y_tr, y_t = train_test_split(X, y, test_size=0.15, random_state=100)
lr.fit(x_tr, y_tr)
y_p = lr.predict(x_t)
r2_score(y_t, y_p), mean_squared_error(y_t, y_p)
```

Out[58]:
```
(0.8273125828534873, 12.422229588884392)
```

In [ ]:

In [ ]:

In [ ]:

In [ ]: