Boston Housing Data Analysis

In [50]:

```
# import relevant libraries

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


# OPTIONAL:
# import pearson correlation library
from scipy.stats import pearsonr

# to show grid lines in plots
sns.set_style('whitegrid')

# to make all plots well positioned in the notebook
%matplotlib inline
```

In [51]:

```
# Import the Boston DataSet

from sklearn.datasets import load_boston
```

In [52]:

```
# store the dataset

boston = load_boston()
```

In [53]:

```
# check the different keys

boston.keys()
```

Out[53]:

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

In [54]:

```
# You can choose to print each of these keys to see their content

# kindly delete the '#' and run the code to see


## for data
# print(boston['data'])

## for target or predictors
# print(boston['target'])

## for feature_names OR predictor/column names
# print(boston['feature_names'])

## for DESCR: description of each feature/predictor
print(boston['DESCR'])

## for filename
# (not relevant)
```

.. _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 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.
https://archive.ics.uci.edu/ml/machine-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 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 Massachusetts, Amherst. Morgan Kaufmann.

Exploratory Data Analysis

Let's explore the data a little !

First, let us put the data in a Dataframe

In [55]:

```
# chect the current data type

type(boston['data'])
```

Out[55]:

```
numpy.ndarray
```

In [56]:

```
# Convert the numpy array " boston['data'] " into a dataframe

bostonData_array = boston['data']

#boston_df = pd.DataFrame(bostonData_array, columns = ['CRIM','ZN','INDUS','CHAS', 'NO
X', 'RM',
 #                                                    'AGE', 'DIS', 'RAD', 'TAX', ' PT
RATIO', 'B', 'LSTAT'])

boston_df = pd.DataFrame(bostonData_array, columns = boston['feature_names'])

# add the RESPONSE Variable
boston_df['Med. Worth of Home'] = boston['target']

boston_df.head()
```

Out[56]:

	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

(1) Compare

the 'Average number of rooms per dwelling [RM]' (predictor) with the 'Median value of owner-occupied homes in $1000's [boston['target']] (the response vairable).

Does the correlation make sense?

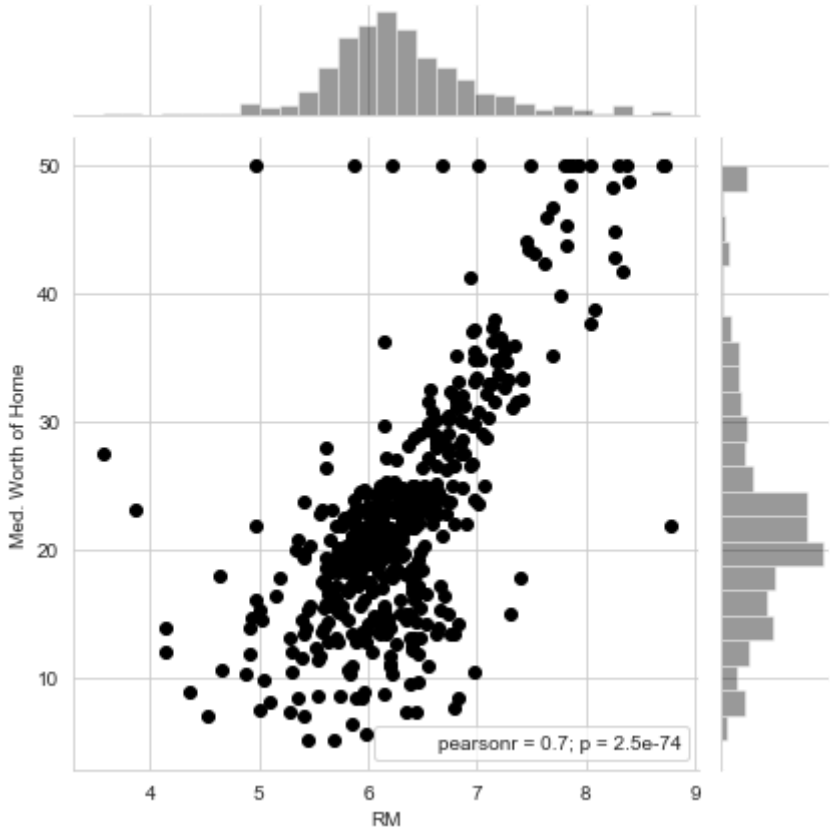
In [57]:

```
sns.jointplot(x = 'RM',
              y = 'Med. Worth of Home',
              data = boston_df ,
              color = 'k',
              stat_func = pearsonr)   # optional for the correlation value and p-value
```

```
C:\Newfolder\lib\site-packages\seaborn\axisgrid.py:1840: UserWarning: Join
tGrid annotation is deprecated and will be removed in a future release.
  warnings.warn(UserWarning(msg))
```

Out[57]:

```
<seaborn.axisgrid.JointGrid at 0x1a8ccf7f790>
```



YES, correlation makes sense.

There exist is a positive correlation/relationship between RM (Average number of rooms per dwelling) and boston['target'] (Median value of owner-occupied homes in $1000's). This could possibly infer that, higher average number of rooms per dwelling would result to a higher median value of the homes.

In [ ]:

```
```

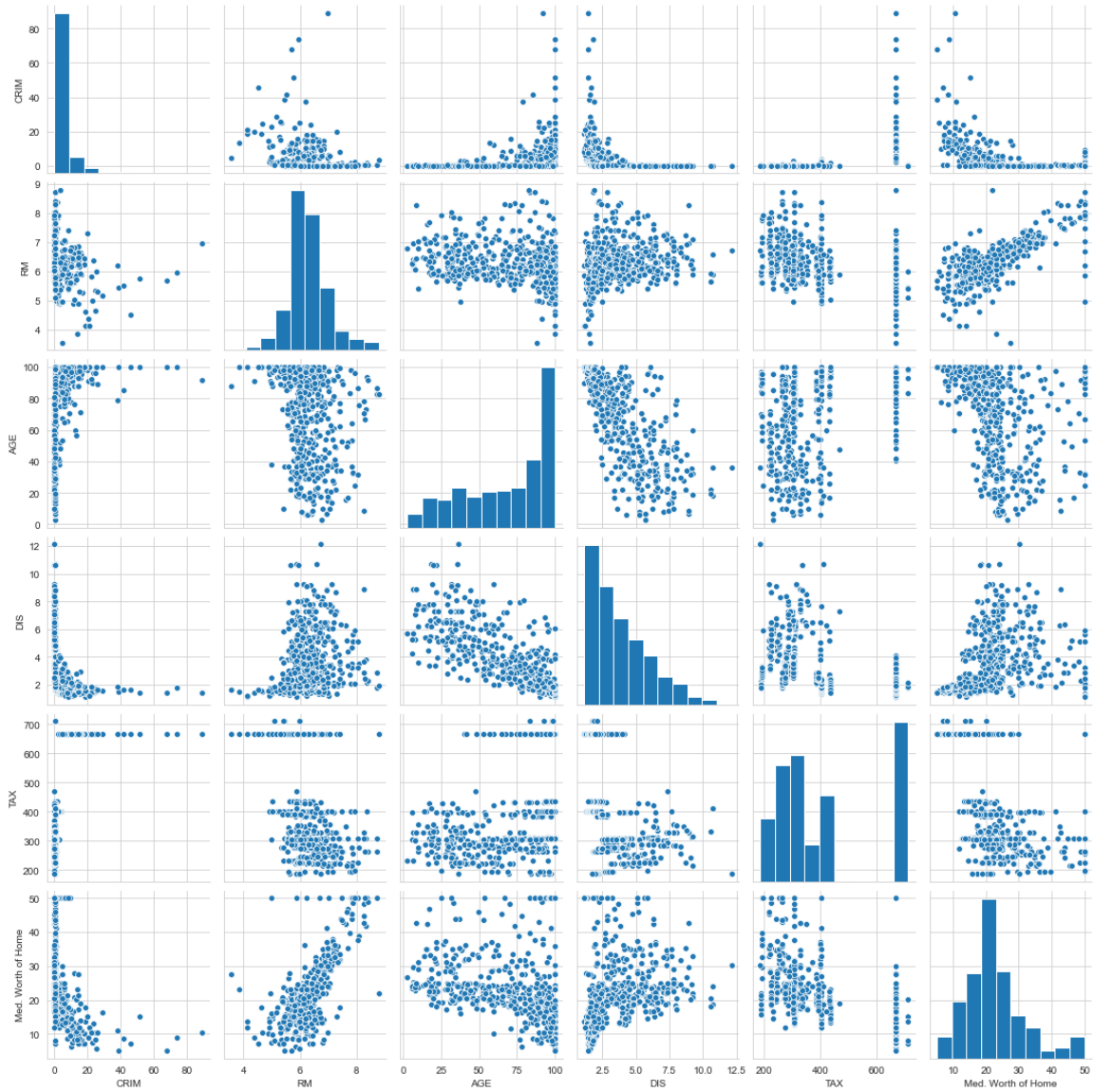
(2) Let us do a pair plot to see the relationship between "selected" predictors/columns and their correlation

In [58]:

```
sns.pairplot(data = boston_df[
                                ['CRIM', 'RM', 'AGE', 'DIS', 'TAX', 'Med. Worth of Hom
e']
                              ]
             )
```

Out[58]:

```
<seaborn.axisgrid.PairGrid at 0x1a8cca066d0>
```



In [ ]:

```
```

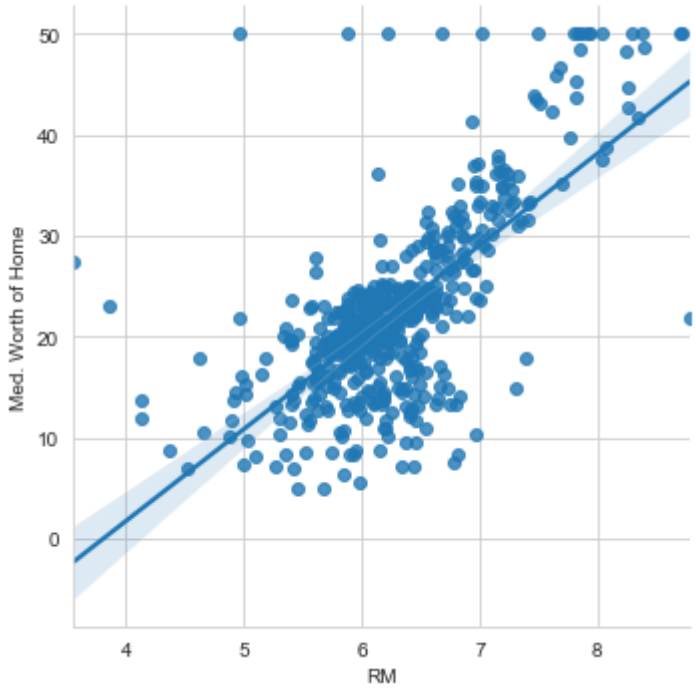
We can as well create a linear model plot

In [59]:

```
sns.lmplot(x = 'RM', y = 'Med. Worth of Home', data = boston_df)
```

Out[59]:

```
<seaborn.axisgrid.FacetGrid at 0x1a8ce0d49a0>
```



In [60]:

```
## It will be nice to represent this 'RM' and 'Med. Worth of Home' with a hex plot
```

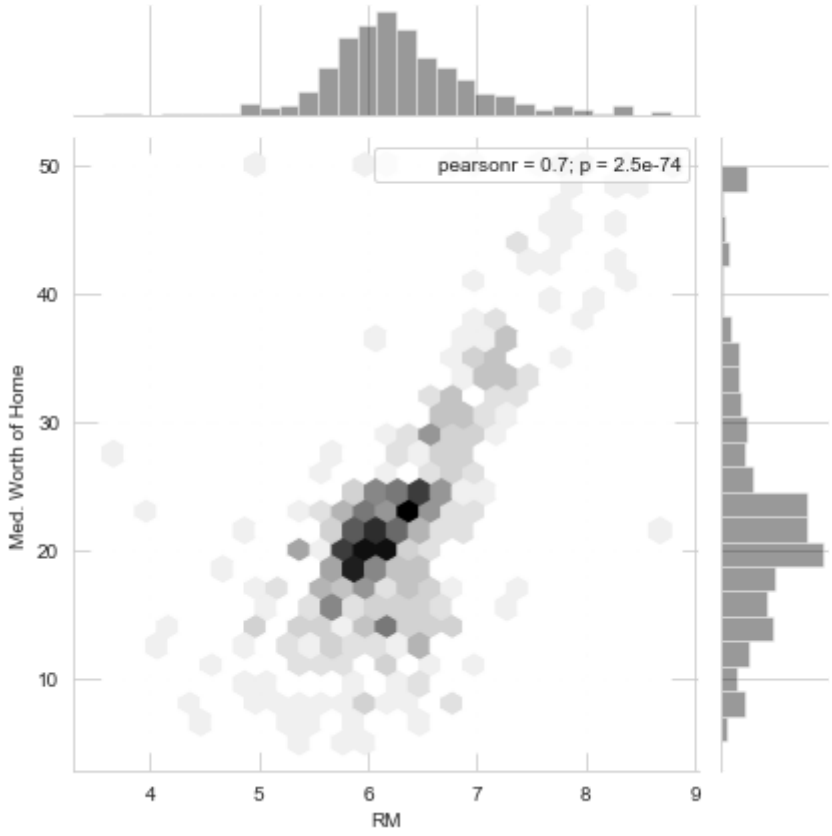
In [61]:

```
sns.jointplot(x = 'RM',
              y = 'Med. Worth of Home',
              data = boston_df ,
              kind = 'hex',          # also try 'scatter', 'reg', 'resid', 'kde' *it is
optional
              color = 'k',
              stat_func = pearsonr)
```

```
C:\Newfolder\lib\site-packages\seaborn\axisgrid.py:1840: UserWarning: Join
tGrid annotation is deprecated and will be removed in a future release.
  warnings.warn(UserWarning(msg))
```

Out[61]:

```
<seaborn.axisgrid.JointGrid at 0x1a8ce590a00>
```



Interpretation:

```
** There is a dense between 5.5 to 7.0 in 'RM' which corresponds to between 15.0
to 25.0 in the Median Worth of Home,
** This implies that most owner-occupied homes in Boston have an average of 6 ro
oms per dwelling and the median worth of these homes is around between 150,000 t
o 250,000
** We see that there is a strong correlation between the average number of rooms
per dwelling and the Median Value or Worth of the Homes. Correlation is strong b
eing 0.7.
```

In [ ]:

```
```

Training and Testing Data

Now that we've explored the data a bit, let's go ahead and split the data into training and testing sets.

Our variable X will equal the numerical features/columns which is boston['data']

Our variable y will equal the response variable which is boston['target'], i.e. Median value of owner-occupied homes in $1000's

In [62]:

```
# predictors

X = boston['data']
```

In [63]:

```
# response (predicands)

y = boston['target']
```

In [64]:

```
# Split data into training and testing set

from sklearn.model_selection import train_test_split
```

In [65]:

```
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size = 0.3, # 30% of data shou
ld be used to test so # 70% to train
                                                    random_state = 101)
```

Train the Model with train-data

In [66]:

```
# import LinearRegression

from sklearn.linear_model import LinearRegression
```

In [67]:

```
# create an object for the linear regression

lm = LinearRegression()
```

In [68]:

```
# train and fit 'lm' on the training data

lm.fit(X = X_train,
       y = y_train)
```

Out[68]:

```
LinearRegression()
```

In [69]:

```
# Get the coefficients of the predictors

lm.coef_

print('Coefficients: ', lm.coef_)
```

```
Coefficients:  [-8.85049752e-02  5.02928536e-02  2.03483110e-02  3.7542705
4e+00
 -1.77483714e+01  3.24776492e+00  1.20008182e-02 -1.40916141e+00
  2.63880691e-01 -1.03440009e-02 -9.51780874e-01  6.11600491e-03
 -5.97133217e-01]
```

In [70]:

```
# Get the intercept of the predictors


lm.intercept_

# print('Intercept = %0.3f' % lm.intercept_)   # to 3 decimal place
```

Out[70]:

```
40.218929012550646
```

In [ ]:

```
```

In [71]:

```
## The model is thus given by:


print("Our linear model is: "
      " 'Medain Value of Home (Y)' = {:.4} + {:.4}*CRIM + {:.4}*ZN + {:.4}*INDUS + {:.
4}*CHAS + {:.4}*NOX + {:.4}*RM + "
                                     " {:.4}*AGE + {:.4}*DIS + {:.4}*RAD + {:.4}*
TAX + {:.4}*PTRATIO + {:.4}*B + "
                                     " {:.4}*LSTAT ".format(
                                lm.intercept_,
                               lm.coef_[0], lm.coef_[1], lm.coef_[2], lm.coef_[3], lm.
coef_[4], lm.coef_[5],
                           lm.coef_[6], lm.coef_[7], lm.coef_[8], lm.coef_[9], lm.coef_
[10], lm.coef_[11], lm.coef_[12]))
```

```
Our linear model is:  'Medain Value of Home (Y)' = 40.22 + -0.0885*CRIM +
0.05029*ZN + 0.02035*INDUS + 3.754*CHAS + -17.75*NOX + 3.248*RM +  0.012*A
GE + -1.409*DIS + 0.2639*RAD + -0.01034*TAX + -0.9518*PTRATIO + 0.006116*B
+  -0.5971*LSTAT
```

In [ ]:

```
```

Prediction of Model

We evaluate its performance of our model by predicting the test values!

In [72]:

```
predictions = lm.predict(X = X_test)
```

In [73]:

```
predictions
```

Out[73]:

```
array([40.11113508, 27.38971873, 16.64700435, 16.98475572, 31.12920137,
       32.17489772, 38.5534506 ,  8.16734819, 33.48547457,  7.21877263,
       30.45404514, 13.44085219, 16.25354375, 17.34359227, 25.1543491 ,
       20.44171457,  7.30340549, 33.13892161, 28.41293108, 24.58522513,
       12.44673568, 20.25489284, 22.48601345, 24.42119495, 33.92740928,
       18.63104614, 32.32820984, 18.67352155, 27.36115374, 34.46174375,
       19.84089751, 18.40373436, 37.15821555, 44.94610923, 30.27513579,
       22.00760066, 16.0127978 , 18.16328402,  4.33298095, 30.93867591,
       24.15262229, 17.17277775, 34.10334259, 13.89433899, 17.46893797,
       25.30893285, 30.35309561, 16.10339452, 26.91513852, 22.98227547,
       32.14815603, 37.34454946, 22.90074019, 17.56894548, 30.18430234,
        0.10360753, 20.22573888, 16.82248142, 23.15487984, 21.16760077,
       30.5734497 ,  3.15502223, 15.92340596, 20.06361892, 10.43608925,
       24.28745773, 24.00445196, 19.86245393, 17.63614975, 19.44871423,
       23.81075322, 21.16261396, 23.47439589, 19.98453898, 27.05134381,
       21.84066905, 36.80150664,  8.16676015, 28.70036278, 17.12188494,
       15.50979745, 19.294246  , 30.15336215, 17.37264235, 10.73425764,
       21.52916918, 21.69200241, 33.12540671, 22.30189309, 21.94929448,
       12.85610293, 11.57605846, 22.66292798, 33.65426492,  6.08353957,
       34.76875886,  7.95929671, 31.90690271,  8.7752099 , 20.72989525,
       32.72047022, 21.34319049, 27.16332024, 24.1623896 , 22.68986244,
       25.17800744, 24.52779596, 30.66139018, 37.3362994 , 33.2147882 ,
       23.21825086, 36.13381973, 23.89682341, 22.07728572, 30.06489707,
       27.24105283, 29.31188864, 31.45057926, 26.74107102, 29.58735987,
       16.90021886, 20.60029568, 21.96586941, 36.77042006, 25.24859328,
       23.08568697, 15.32758657,  5.918702  , 14.80932341, 23.67342037,
       26.74592331, 34.09978093, 23.93815977, 19.9868425 , 24.73687974,
       26.10434151, 30.71721237, 26.62262586, 34.1263333 , 22.67915823,
       13.13096496, 36.60828941, 32.25783559, 15.89281425, 24.785974  ,
       19.32107821, 19.5968184 , 24.52106619, 26.34621695, 29.83423805,
       16.69898193, 16.61243821])
```

Compare:

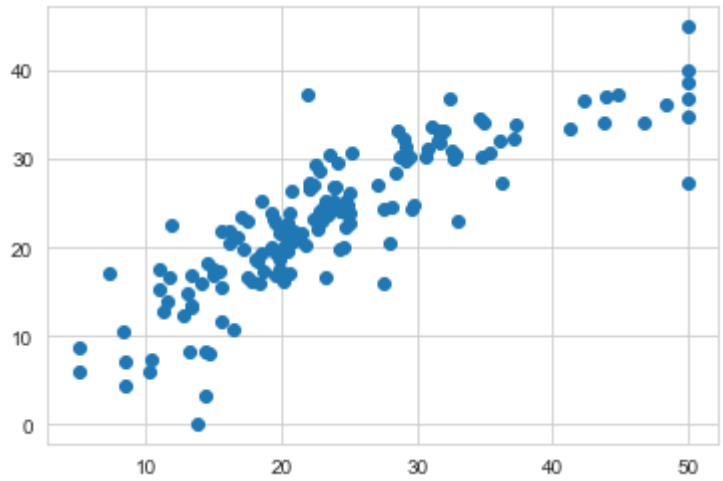
Now let's see how strong the relationship is, between our predictions and the real (original y-values)

In [74]:

```
# Using a scatter plot to check for correlation



# Using matplotlib

plt.scatter(x = y_test,
            y = predictions)
```

Out[74]:

```
<matplotlib.collections.PathCollection at 0x1a8ce71acd0>
```



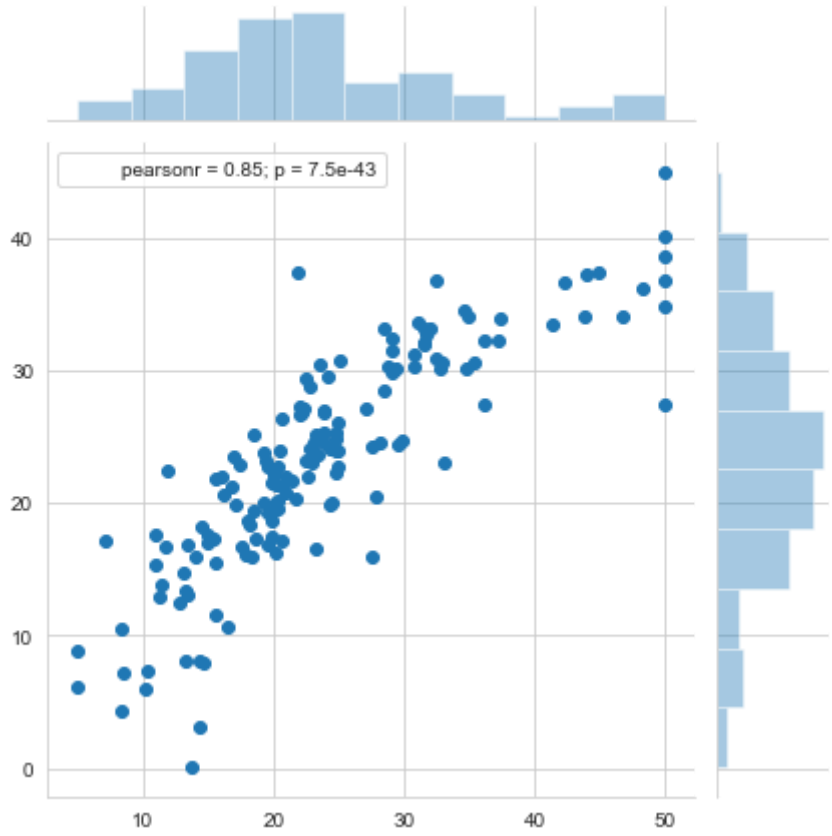
In [75]:

```
# Using seaborn scatterplot

#sns.scatterplot(x = y_test,        # original or real values from data
#                y = predictions)   # predicted values



# Using Seaborn Jointplot (so we can call the correlation value)

sns.jointplot(x = y_test,
              y = predictions,
              kind = 'scatter',
              stat_func = pearsonr)
```

```
C:\Newfolder\lib\site-packages\seaborn\axisgrid.py:1840: UserWarning: Join
tGrid annotation is deprecated and will be removed in a future release.
  warnings.warn(UserWarning(msg))
```

Out[75]:

```
<seaborn.axisgrid.JointGrid at 0x1a8ce730c40>
```



Interpreation:

```
** There is obviously a strong correlation between our prediction and the origin
al values. Correlation value is 0.85,   hence our model is good enough to be use
d for predictions in real life.
```

In [ ]:

```
```

Evaluating the Model

Let's evaluate our model performance by calculating the residual sum of squares and the variance score (R^2)

In [76]:

```
# import the library

from sklearn import metrics
```

Quick important note:

The RMSE is the square root of the variance of the residuals. It indicates the absolute fit of the model to the data–how close the observed data points are to the model's predicted values. Whereas R-squared is a relative measure of fit, RMSE is an absolute measure of fit. As the square root of a variance, RMSE can be interpreted as the standard deviation of the unexplained variance, and has the useful property of being in the same units as the response variable. Lower values of RMSE indicate better fit**. RMSE is a good measure of how accurately the model predicts the response, and it is the most important criterion for fit if the main purpose of the model is prediction. (Source: https://www.theanalysisfactor.com/assessing-the-fit-of-regression-models/ (https://www.theanalysisfactor.com/assessing-the-fit-of-regression-models/)**

In [77]:

```
# for MAE:

mae = metrics.mean_absolute_error(y_true = y_test,
                                  y_pred = predictions)


# for MSE:

mse = metrics.mean_squared_error(y_true = y_test,
                                 y_pred = predictions)


# for RMSE

rmse = np.sqrt( metrics.mean_squared_error(y_true = y_test,
                                           y_pred = predictions)
               )

print("MAE: ", mae )
print("MSE: ", mse )
print("RMSE:", rmse)
```

```
MAE:  3.8356963614189143
MSE:  28.547585271468098
RMSE: 5.342994036256085
```

In [78]:

```
# Since the RMSE is low, we can say that our model accurately predicts the reponse.
```

In [ ]:

```

```

Residuals:

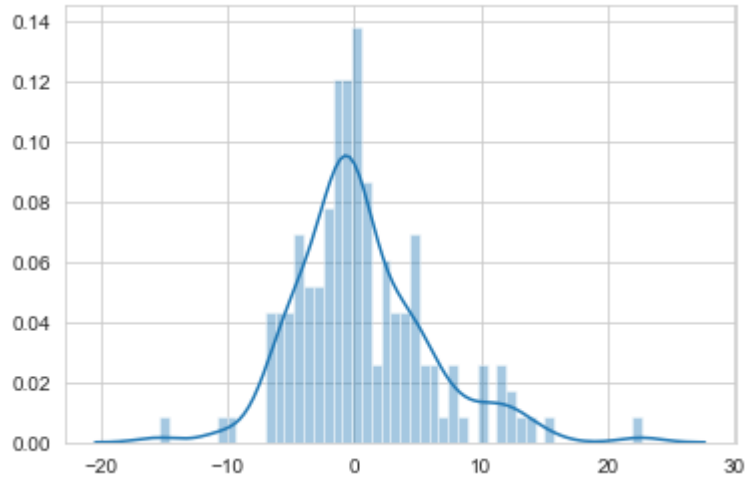
** Let's quickly explore the residuals to make sure everything was okay with our data. We do this by ploting the histogram of the residuals to ensure it is normmally distributed **

In [79]:

```
# Using Seaborn

sns.distplot(a = (y_test - predictions),   # this is how residual is calculated
             bins = 50)
```

Out[79]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a8ce6c59a0>
```



In [80]:

```
# YES: there is a good level of normality in our residuals. Hence, we finally accepts t
he model
```

In [ ]:

```

```

Further Thoughts:

** We can tell how powerful each predictor/variable is in the model, usign the c
oeeficients of the predictors.
** We can tell the significance of each predictor/variable in predicting the res
ponse variable, using their p-values

Effect of predictors on model

In [81]:

```
# Create a dataframe that will take the coefficeint and also the column names




# recall the column names
boston_df.columns
```

Out[81]:

```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'T
AX',
       'PTRATIO', 'B', 'LSTAT', 'Med. Worth of Home'],
      dtype='object')
```

In [82]:

```
# remove the last column (i.e. the predictor)

boston_df.drop(labels = 'Med. Worth of Home',   # name of the column to drop
               axis = 1,      # means column, axis = 0 means row
               inplace = True)    # make the drop permanent

# now check the columns again
boston_df.columns
```

Out[82]:

```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'T
AX',
       'PTRATIO', 'B', 'LSTAT'],
      dtype='object')
```

In [83]:

```
# DataFrame

cdf = pd.DataFrame(data = lm.coef_,
                   index = boston_df.columns,
                   columns = ['Coefficient'])

cdf
```

Out[83]:

	Coefficient
CRIM	-0.088505
ZN	0.050293
INDUS	0.020348
CHAS	3.754271
NOX	-17.748371
RM	3.247765
AGE	0.012001
DIS	-1.409161
RAD	0.263881
TAX	-0.010344
PTRATIO	-0.951781
B	0.006116
LSTAT	-0.597133

In [84]:

```
# Let's sort the values of by the Coefficient column


cdf.sort_values(by = ['Coefficient'],
                ascending = False)
```

Out[84]:

	Coefficient
CHAS	3.754271
RM	3.247765
RAD	0.263881
ZN	0.050293
INDUS	0.020348
AGE	0.012001
B	0.006116
TAX	-0.010344
CRIM	-0.088505
LSTAT	-0.597133
PTRATIO	-0.951781
DIS	-1.409161
NOX	-17.748371

Interpretation:

** We see the effect of each predictor (based on their coefficients) in the abov
e table in descendeing order
** Clearly, 'CHAS'':Charles River dummy variable (= 1 if tract bounds river; 0 o
therwise)' and 'RM: ''average number of rooms per dwelling', happens to give the
most positive (increasing) effect on the model
** And 'NOX: '' nitric oxides concentration (parts per 10 million)' gives the mo
st negative (decreasing) effect on the model.

In [ ]:

```

```