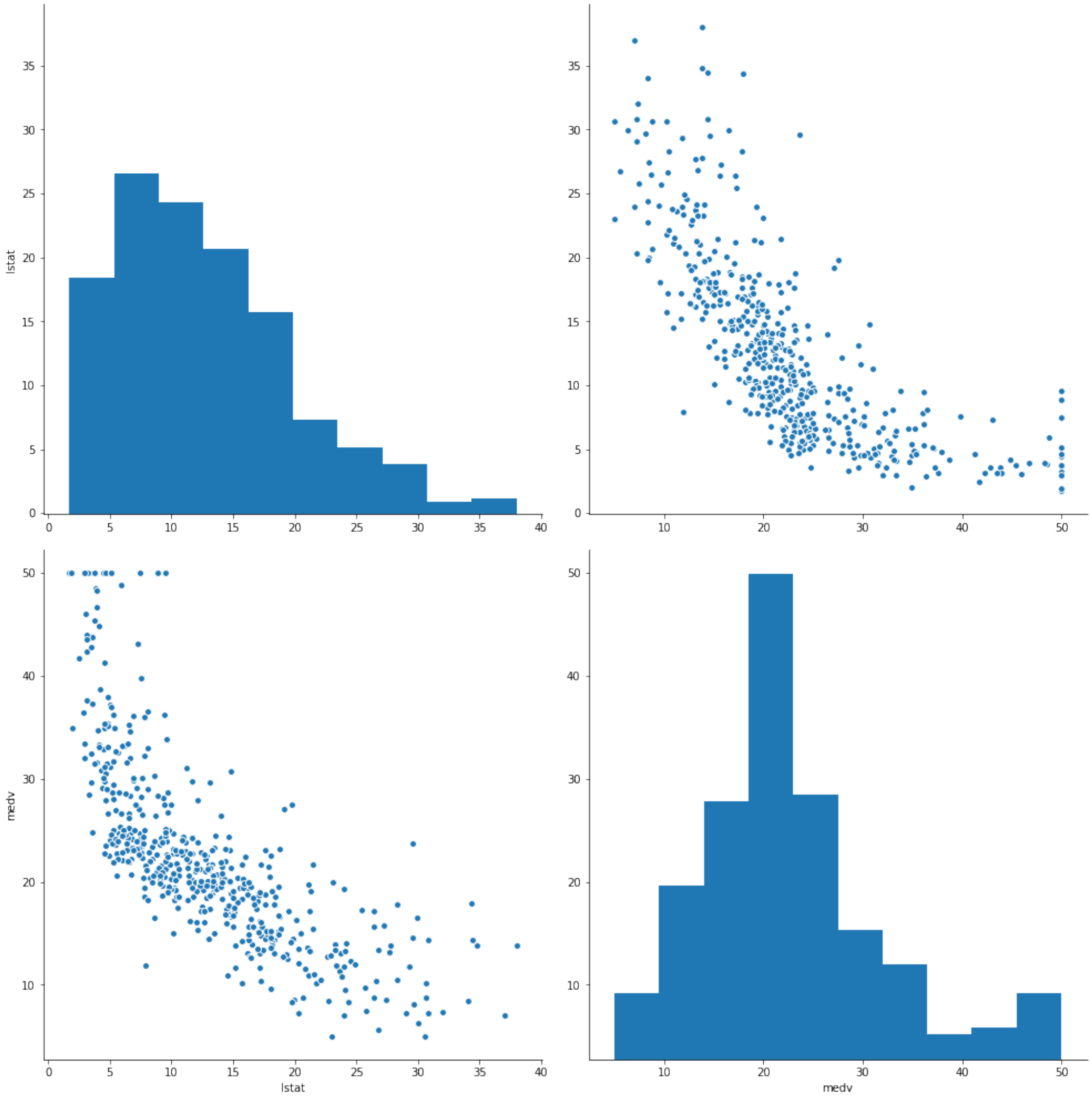
Simple linear regression

March 1, 2018

```
In [53]: # conventional way to import pandas
         import pandas as pd
         # conventional way to import seaborn
         import seaborn as sns
         # conventional way to import numpy
         import numpy as np

         from sklearn import metrics
         import matplotlib.pyplot as plt

         data = pd.read_csv("https://raw.github.com/vincentarelbundock/Rdatasets/master/csv/MAS
```

Viewing the data in seaborn to get a sense of it - MEDV Median value of owner-occupied homes in $1000's - LSTAT lower status of the population

```
In [54]: # visualize the relationship between the features and the response using scatterplots
         #sns.pairplot(data, x_vars='lstat', y_vars='medv', size=7, aspect=0.7, kind='reg')
         sns.pairplot(data[['lstat','medv']],size=7)
         plt.show()
```



Displaying head to see the data

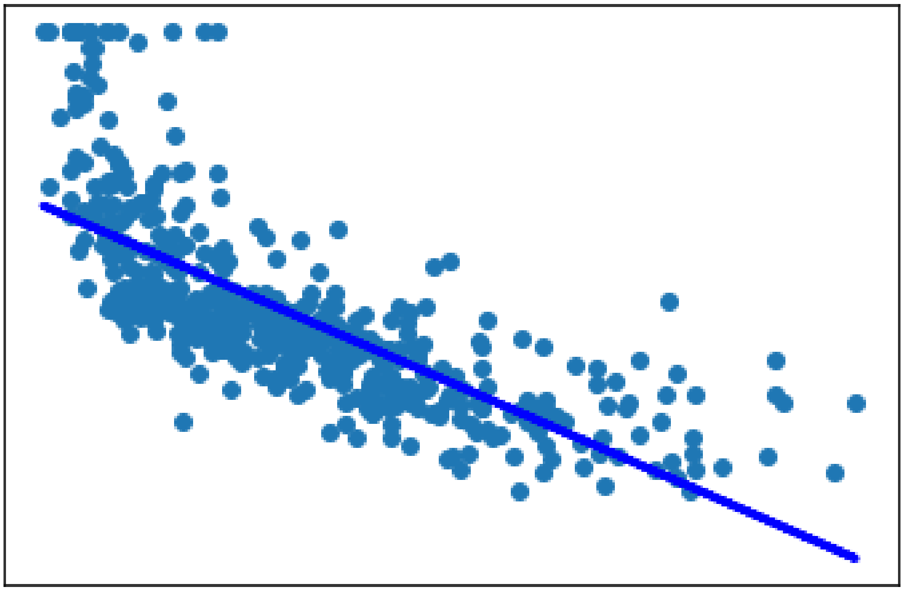
```
In [55]: data.head()

Out[55]:       crim    zn  indus  chas    nox     rm   age     dis  rad  tax  ptratio  \
         1  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296     15.3
         2  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242     17.8
         3  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242     17.8
         4  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222     18.7
         5  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222     18.7

             black  lstat  medv
         1  396.90   4.98  24.0
         2  396.90   9.14  21.6
```

```
3  392.83   4.03  34.7
4  394.63   2.94  33.4
5  396.90   5.33  36.2
```

```
In [56]: # create a Python list of feature names
         feature_cols = ['lstat']

         # use the list to select a subset of the original DataFrame
         X = data[feature_cols].values

         # select a Series from the DataFrame
         y = data['medv'].values

         # import model
         from sklearn.linear_model import LinearRegression

         # instantiate
         linreg = LinearRegression()

         # fit the model to the training data (learn the coefficients)
         linreg.fit(X, y)

         # print the intercept and coefficients
         print('intercept: \n', linreg.intercept_)

         # The coefficients
         print('Coefficients: \n', linreg.coef_)

         # make predictions on the testing set
         y_pred = linreg.predict(X)

         # calculate RMSE using scikit-learn
         np.sqrt(metrics.mean_squared_error(y, y_pred))

         # Explained variance score: 1 is perfect prediction
         print('Variance score: %.2f' % metrics.r2_score(y, y_pred))
```

```
intercept:
 34.5538408794
Coefficients:
 [-0.95004935]
Variance score: 0.54
```

```
In [57]: # Plot outputs
         plt.scatter(X, y)
         plt.plot(X, linreg.predict(X), color='blue', linewidth=3)
         plt.xticks(())
         plt.yticks(())

         plt.show()
```



Display detailed info about the fit. The book also says that the "there is some evidence of non-linearity." So we should reflect that by refing to the R2 score that should be 0.95 to ge a good fit right.

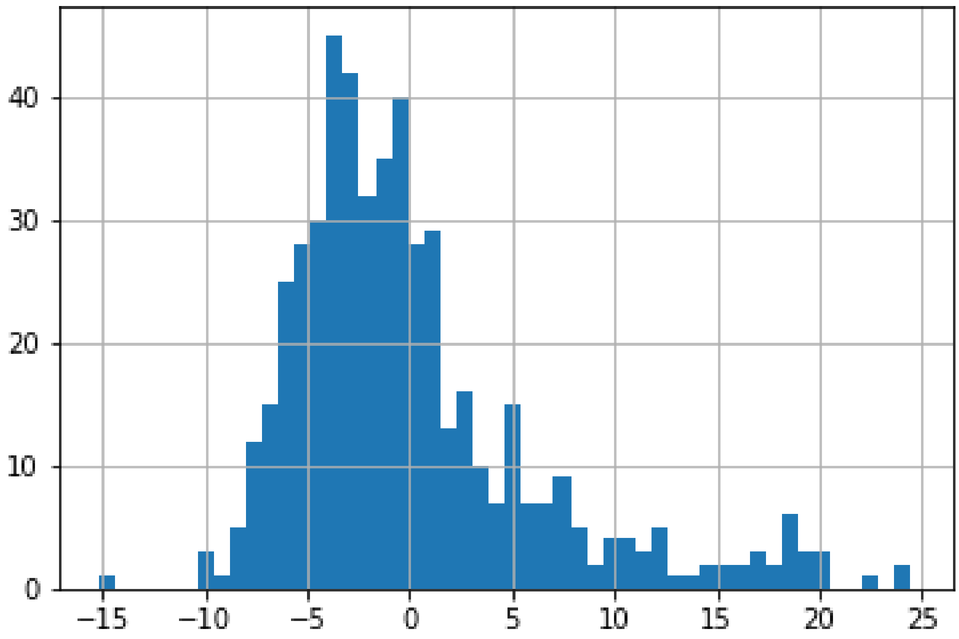
```
In [58]: import statsmodels.api as sm
         from scipy import stats

         X2 = sm.add_constant(X)
         est = sm.OLS(y, X2)
         est2 = est.fit()
         print(est2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.544
Model:                            OLS   Adj. R-squared:                  0.543
Method:                 Least Squares   F-statistic:                     601.6
Date:                Sun, 18 Feb 2018   Prob (F-statistic):           5.08e-88
Time:                        20:06:53   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]
------------------------------------------------------------------------------
const         34.5538      0.563     61.415      0.000      33.448      35.659
x1            -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.
```

The obtained the predictions produced by linear regression. Look at the residuals, the difference between the real target set and the predicted target set:

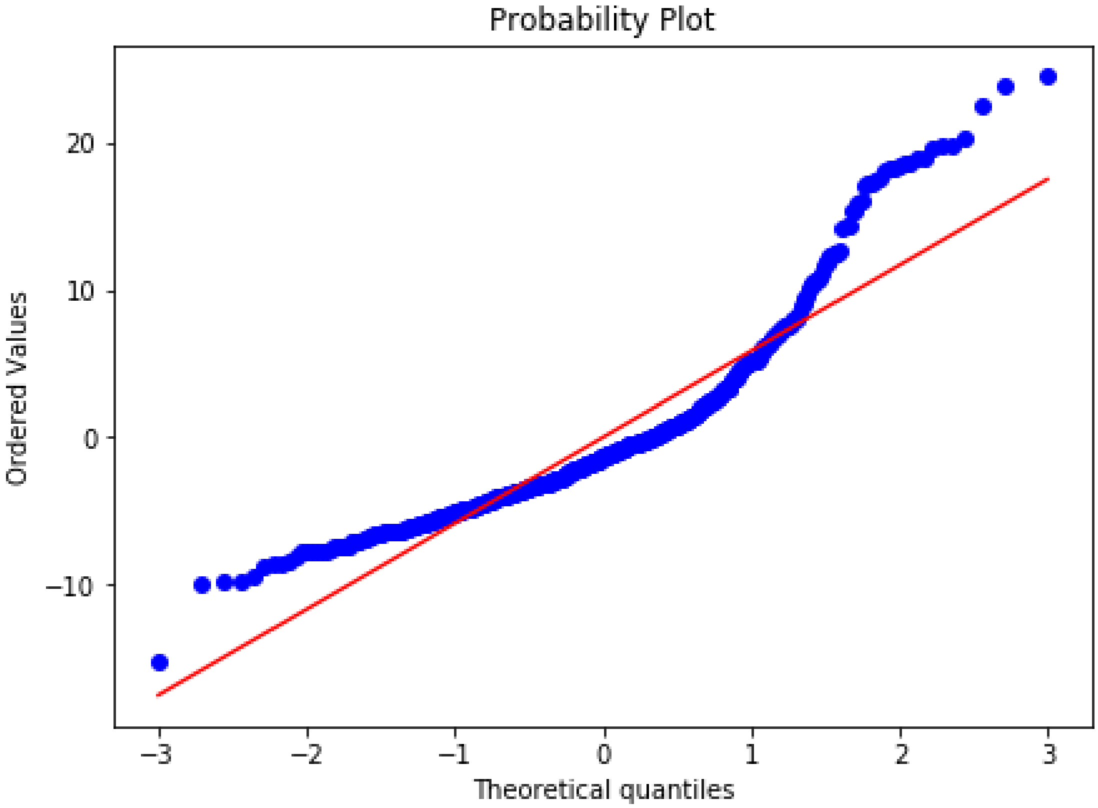
```
In [59]: pd.Series(y - y_pred).hist(bins=50)
         plt.show()
```

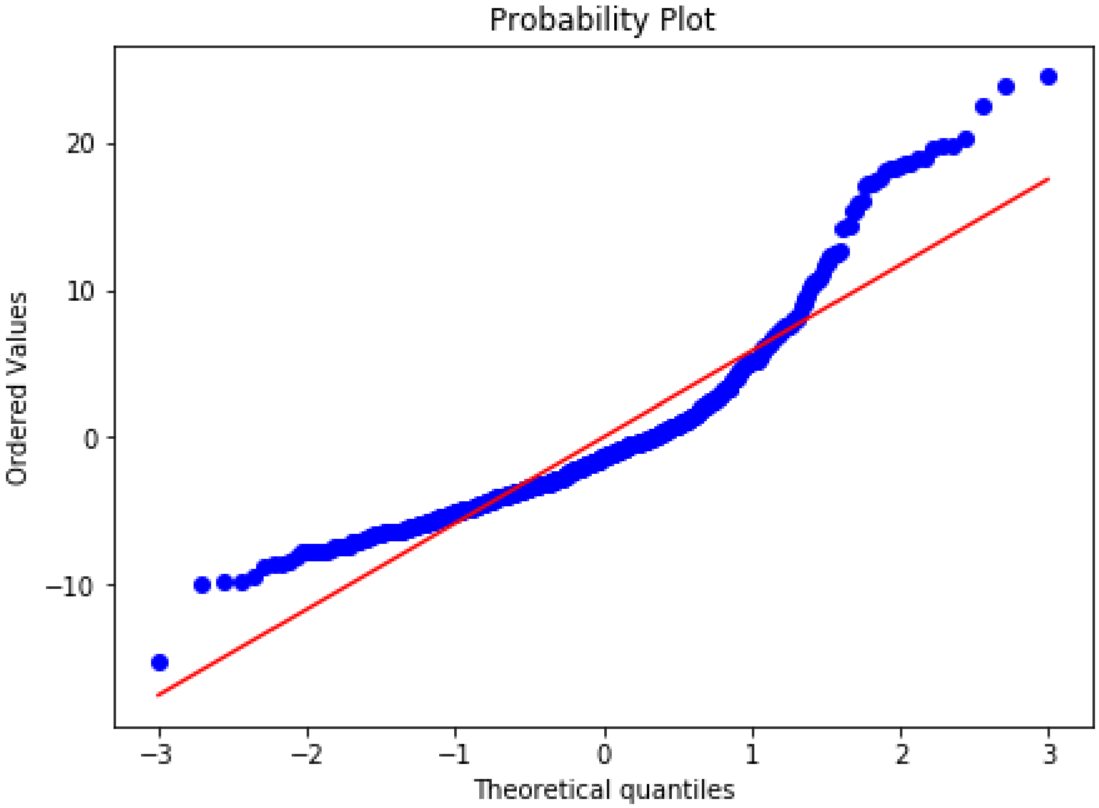


Q-Q plot. As it shows in the plot the data is not normal distrubuted.

```
In [61]: from scipy.stats import probplot
         f = plt.figure(figsize=(7, 5))
         ax = f.add_subplot(111)
```

```
tuple_out = probplot(y - y_pred, plot=ax)
plt.show()
```




Probability Plot
Ordered Values
20
10
0
−10
Theoretical quantiles
−3
−2
−1
0
1
2
3