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Data Science Techniques

Linear Regression using Scikit-Learn



- ► In this tutorial, we study the most fundamental machine learning algorithms i.e., linear regression using Scikit-learn machine learning library.
- ► We discuss the Python implementation of both simple linear regression and multiple linear regression.

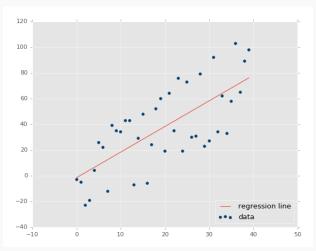
Linear Regression Theory - Review



- ► Linear regression performs the task to predict a dependent variable value (y) based on a given independent variable (x) using a linear relationship between x and y.
- ▶ If we plot the independent variable (x) on the x—axis and dependent variable (y) on the y—axis, linear regression gives us a straight line that best fits the data points, as shown in the figure below.

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The equation of the above line is:

$$y = mx + b$$

- ► Here, b is the intercept and m is the slope of the line.
- ► Basically, the linear regression algorithm gives us the most optimal value for the intercept and the slope (in two dimensions).
- ► The y and x variables remain the same, since they are the data features and cannot be changed.
- ► The values that we can control are the intercept(b) and slope(m).
- ► There can be multiple straight lines depending upon the values of intercept and slope.
- Basically what the linear regression algorithm does is it fits multiple lines on the data points and returns the line that results in the least error.

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Linear Regression Theory - Review



- This same concept can be extended to cases where there are more than two variables and is called multiple linear regression.
 - ► For instance, consider a scenario where you have to predict the price of the house based upon its area, number of bedrooms, the average income of the people in the area, the age of the house, and so on.
- ► In this case, the dependent variable (target variable) is dependent upon several independent variables. A regression model involving multiple variables can be represented as:

$$y = b_0 + m_1b_1 + m_2b_2 + m_3b_3 + \ldots + m_nb_n$$

Linear Regression Theory - Review



- ► The above equation is called **hyperplane**.
- ► Linear regression in two dimensions is a straight line; in three dimensions it is a plane; and in more than three dimensions, a hyperplane.

For discussing the simple linear regression using Scikit-learn, we use the dataset on weather reports from the period of World war II to compare with missions in the bombing operations dataset. This is a publicly available dataset and can be downloaded from here

The dataset contains information on weather conditions recorded on each day at various weather stations around the world. Information includes precipitation, snowfall, temperatures, wind speed and whether the day included thunderstorms or other poor weather conditions.

Our task is to predict the maximum temperature taking input feature as the minimum temperature.

Import the required packages

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as seabornInstance
from sklearn.model_selection import
    train_test_split
from sklearn.linear_model import
    LinearRegression
from sklearn import metrics
```

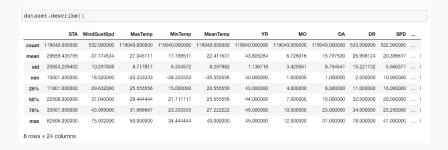
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We now import the CSV dataset into a DataFrame using pandas:

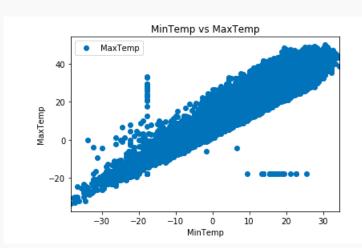
```
dataset = pd.read_csv('Weather.csv')
```

We now explore the dataset attributes and statistical description

```
print('Dataset size is: ',dataset.shape)
print(dataset.describe())
```

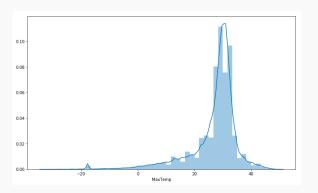


Before proceeding to linear regression, first let's plot our data points related to MinTemp and MaxTemp on a 2-D graph to view our dataset and see if we can manually find any relationship between the data:



We now plot Average Maximum Temperature along with univariate distribution of observations. For this we will use seaborn.distplot()

```
plt.figure(figsize=(15,10))
plt.tight_layout()
seabornInstance.distplot(dataset['MaxTemp'])
```



Observe that Average Maximum temperature which is in between 25 and 35.

- Our next step is to divide the data into "attributes" and "labels".
- ► Attributes are the independent variables while labels are dependent variables whose values are to be predicted.
- ► In our dataset, we only have two columns.
- We want to predict the MaxTemp depending upon the MinTemp recorded.
- ► Therefore our attribute set will consist of the "MinTemp" column which is stored in the X variable, and the label will be the "MaxTemp" column which is stored in y variable.

- Next, we split 80% of the data to the training set while 20% of the data to test set using tranin_test_split() function of sklearn.model_selection.
- ► The test_size variable is where we actually specify the proportion of the test set.

```
1 X_train, X_test, y_train, y_test =
    train_test_split(X, y, test_size=0.2,
    random_state=0)
2
print('Training Attributes size is: ',
   X_train.shape)
print('Testing Attributes size is: ',
   X_{test.shape}
print('Training Labels size is: ',y_train.
    shape)
print('Testing Lables size is: ' ,y_test.
   shape)
```

- ► After splitting the data into training and testing sets, finally, the time is to train our algorithm.
- ► For that, we need to import LinearRegression class, instantiate it, and call the fit() method along with our training data.

```
regressor = LinearRegression()
regressor.fit(X_train, y_train) #training
the algorithm
```

- ► The linear regression model basically finds the best value for the intercept and slope, which results in a line that best fits the data.
- ► To see the value of the intercept and slope calculated by the linear regression algorithm for our dataset, execute the following code.

```
print('Intercept is: ',regressor.intercept_) #To
    retrieve the intercept:
print('Coefficient is: ',regressor.coef_) #For
    retrieving the slope:
```

Result is:

```
1 10.66185201
2 0.92033997
```

This means that for every one unit of change in Min temperature, the change in the Max temperature is about 0.92%.

- Now that we have trained our algorithm, it's time to make some predictions.
- ► To do so, we will use our test data and see how accurately our algorithm predicts the percentage score.
- ➤ To make predictions on the test data, execute the following code.

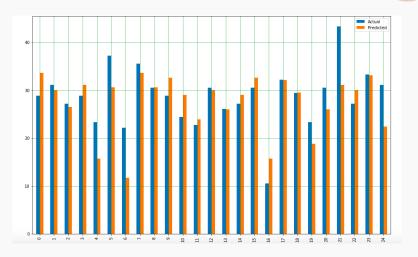
```
y_pred = regressor.predict(X_test)
```

► Now compare the actual output values for 'X_test' with the predicted values.

```
df = pd.DataFrame({'Actual': y_test.flatten
      (), 'Predicted': y_pred.flatten()})
df
```

	Actual	Predicted
0	28.888889	33.670351
1	31.111111	30.091251
2	27.222222	26.512151
3	28.888889	31.113851
4	23.333333	15.774852
5	37.222222	30.602551
6	22.22222	11.684452
7	35.555556	33.670351
8	30.555556	30.602551
9	28.888889	32.647751
10	24.44444	29.068651
11	22.777778	23.955652
12	30.555556	30.091251
13	26.111111	26.000851
14	27.222222	29.068651
15	30.555556	32.647751

We can also visualize comparison result as a bar graph. Note: As the number of records is huge, for representation purpose we will consider the first 25 records only.



▶ We now plot the straight line with the test data.

The straight line above shows that our algorithm is working correctly.

- ► The final step in our modelling approach is to evaluate the performance of our algorithm.
- ► This is very important step to compare how well different algorithms perform on a particular dataset.

- ► For regession algorithms, three evaluation metrics are commonly used:
 - Mean Absolute Error (MAE) is the mean of the absolute of the errors. It is calculated as:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |Y_i - y_i|$$

2. Mean Squared Error (MSE) is the mean of the squared errors. It is calculated as:

MSE =
$$\frac{1}{n} \sum_{i=1}^{n} (Y_i - y_i)^2$$

Root Mean Squared Error (RMSE) is the square root of the mean of the squared errors. It is calculated as:

RMSE =
$$\sqrt{\frac{1}{n} \sum_{i=1}^{n} (Y_i - y_i)^2}$$

► The above tree metrics can be computed using the pre-built functions in sklearn.metrics library.

```
print('Mean Absolute Error:', metrics.
    mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.
    mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(
    metrics.mean_squared_error(y_test,
    y_pred)))
```

Output:

- ➤ Observe that the RMS error is 4.19, which is more than 10% of the mean value of the percentages of all the temperature i.e, 22.41.
- ► This means that our algorithm was not very accurate but can still make reasonably good predictions.