

9.1. Data Science – Machine Learning – Linear Regression Example

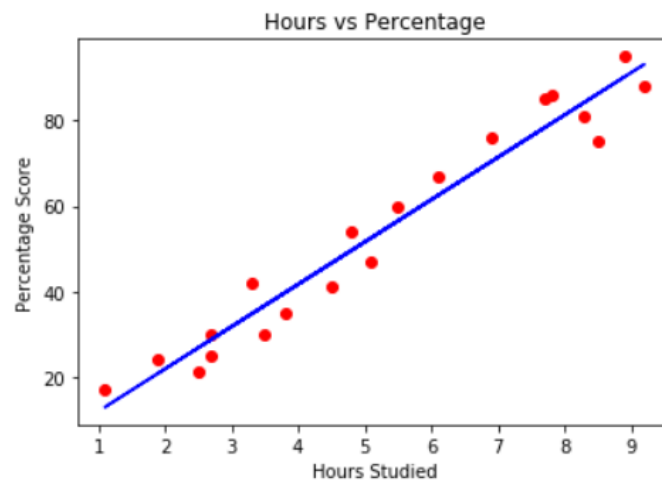
Contents

1. Scenario	2
2. Maths behind	3
3. Loading dataset	4
4. Plotting the data	5
5. Intercept & coefficient	10
6. Important info	12
7. Making Predictions.....	12
8. Evaluating the Algorithm	15
9. Evaluation metrics.....	15

9.1. Data Science – Machine Learning – Linear Regression Example

1. Scenario

- ✓ Let's find the relationship in between **marks** and **number of study hours**
- ✓ We want to find out the **marks** for given **number of study hours** to a student
- ✓ If we plot the independent variable (hours) on the x-axis and dependent variable (percentage) on the y-axis then linear regression gives us a straight line that best fits the data points.



2. Maths behind

- ✓ We know that the equation of a straight line is basically
 - $y = mx + b$
- ✓ Where **b** is the **intercept** and **m** is the **slope** of the line.
- ✓ So basically, the linear regression algorithm gives us the most optimal value for the **intercept** and the **slope**.
- ✓ The y and x variables remain the same
- ✓ 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.

3. Loading dataset

- ✓ Once we have dataset then we need to load by using pandas
- ✓ If we load dataset then it returns the DataFrame

Program Name Loading student_scores dataset
demo1.py

```
import pandas as pd

df = pd.read_csv('student_scores.csv')

print(df.head())
```

Output

	Hours	Scores
0	2.5	21
1	5.1	47
2	3.2	27
3	8.5	75
4	3.5	30

4. Plotting the data

- ✓ Let's plot our data points to see the relationship between the data.

Program Name Plotting the dataset
demo2.py

```
import pandas as pd
import matplotlib.pyplot as plt

df = pd.read_csv('student_scores.csv')

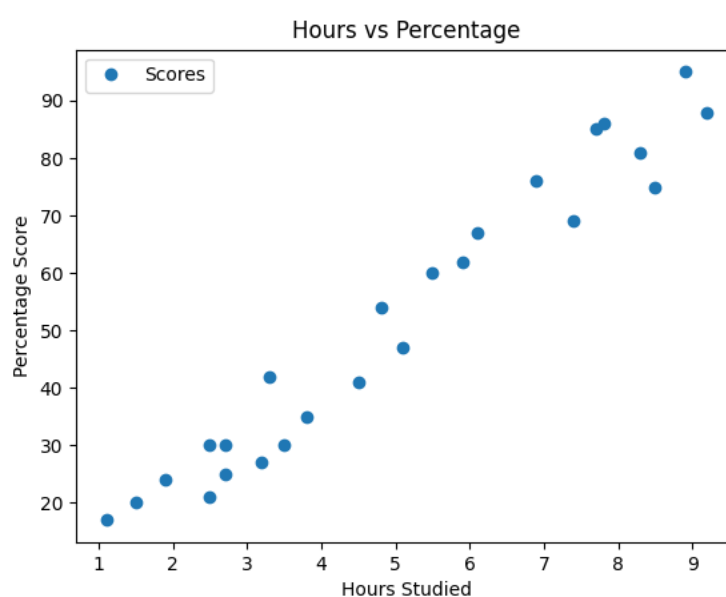
df.plot(x='Hours', y='Scores', style='o')

plt.title('Hours vs Percentage')

plt.xlabel('Hours Studied')
plt.ylabel('Percentage Score')

plt.show()
```

Output



Program Name Preparing the data
demo3.py

```
import pandas as pd

df = pd.read_csv('student_scores.csv')

X = df.iloc[:, :-1].values
y = df.iloc[:, 1].values

print(X)
print(y)
```

Output

```
[[2.5]
 [5.1]
 [3.2]
 [8.5]
 [3.5]
 [1.5]
 [9.2]
 [5.5]
 [8.3]
 [2.7]
 [7.7]
 [5.9]
 [4.5]
 [3.3]
 [1.1]
 [8.9]
 [2.5]
 [1.9]
 [6.1]
 [7.4]
 [2.7]
 [4.8]
 [3.8]
 [6.9]
 [7.8]]
[21 47 27 75 30 20 88 60 81 25 85 62 41 42 17 95 30 24 67 69 30 54 35 76
 86]
```

Program Splitting the data
Name demo4.py

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

df = pd.read_csv('student_scores.csv')

X = df.iloc[:, :-1].values
y = df.iloc[:, 1].values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 0)

print("X_train")
print(X_train)

print()
print("X_test")
print(X_test)

print()
print("Y_train")
print(y_train)

print()
print("y_test")
print(y_test)
```

Output

```
X_train
[[3.8]
 [1.9]
 [7.8]
 [6.9]
 [1.1]
 [5.1]
 [7.7]
 [3.3]
 [8.3]
 [9.2]
 [6.1]
 [3.5]
 [2.7]
 [5.5]
 [2.7]
 [8.5]
 [2.5]
 [4.8]
 [8.9]
 [4.5]]

X_test
[[1.5]
 [3.2]
 [7.4]
 [2.5]
 [5.9]]

Y_train
[35 24 86 76 17 47 85 42 81 88 67 30 25 60 30 75 21 54 95 41]

y_test
[20 27 69 30 62]
```


Program Name Training the model
demo5.py

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

df = pd.read_csv('student_scores.csv')

X = df.iloc[:, :-1].values
y = df.iloc[:, 1].values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state=0)

regressor = LinearRegression()
regressor.fit(X_train, y_train)

print("Model got trained with data")
```

Output

Model got trained with data

5. Intercept & coefficient

- ✓ In the theory section we said that linear regression model basically finds the best value for the intercept and slope, which results in a line that best fits the data.
- ✓ We can get the values of the intercept and slop from linear regression

Program Name Getting intercept from created model
demo6.py

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

df = pd.read_csv('student_scores.csv')

X = df.iloc[:, :-1].values
y = df.iloc[:, 1].values

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=0)

regressor = LinearRegression()
regressor.fit(X_train, y_train)

print(regressor.intercept_)
```

Output

2.018160041434669

Program Name Getting coefficient from created model
demo7.py

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

df = pd.read_csv('student_scores.csv')

X = df.iloc[:, :-1].values
y = df.iloc[:, 1].values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 0)

regressor = LinearRegression()
regressor.fit(X_train, y_train)

print(regressor.coef_)
```

Output

```
[9.91065648]
```

6. Important info

- ✓ This means that for every one unit of change in hours studied, the change in the score is about 9.91%.
- ✓ In simpler words, if a student studies **one hour more** than they previously studied for an exam, they can expect to achieve an increase of **9.91%** in the **score** achieved by the student previously.

7. Making Predictions

- ✓ Now successfully we have trained our algorithm.
- ✓ So, it's time to make some predictions.
- ✓ We need to use our test data and see how accurately our algorithm predicts the percentage score.

Program Name Making predictions
demo8.py

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

df = pd.read_csv('student_scores.csv')

X = df.iloc[:, :-1].values
y = df.iloc[:, 1].values

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=0)

regressor = LinearRegression()
regressor.fit(X_train, y_train)

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

Output

```
[16.88414476 33.73226078 75.357018 26.79480124
60.49103328]
```

Great

- ✓ The `y_pred` is a numpy array that contains all the predicted values for the input values in the `X_test` series.

Comparison

- ✓ To compare the actual output values for `X_test` with the predicted values.

Program Name Comparing the predicted result
demo9.py

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

df = pd.read_csv('student_scores.csv')

X = df.iloc[:, :-1].values
y = df.iloc[:, 1].values

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=0)

regressor = LinearRegression()
regressor.fit(X_train, y_train)

y_pred = regressor.predict(X_test)

d = {'Actual': y_test, 'Predicted': y_pred}

compare_df = pd.DataFrame(d)
print(compare_df)
```

Output

	Actual	Predicted
0	20	16.884145
1	27	33.732261
2	69	75.357018
3	30	26.794801
4	62	60.491033

- ✓ Though our model is not very precise, the predicted percentages are close to the actual ones.

8. Evaluating the Algorithm

- ✓ We need to evaluate the performance of algorithm.
- ✓ This step is particularly important to compare how well different algorithms perform on a particular dataset.
- ✓ For regression algorithms there are three evaluation metrics are commonly used

9. Evaluation metrics

- ✓ Mean Absolute Error (**MAE**)
- ✓ Mean Squared Error (**MSE**)
- ✓ Root Mean Squared Error (**RMSE**)

Mean Absolute Error (MAE)

- ✓ Mean Absolute Error (**MAE**) is the mean of the absolute value of the errors.

Mean Squared Error (MSE)

- ✓ Mean Squared Error (**MSE**) is the mean of the squared errors.

Root Mean Squared Error (RMSE)

- ✓ Root Mean Squared Error (**RMSE**) is the square root of the mean of the squared errors

The diagram shows the formula for Mean Absolute Error (MAE) with several annotations:

- A blue box around $\frac{1}{n}$ is labeled "Divide by the total number of data points".
- A green box around y is labeled "Actual output value".
- An orange box around \hat{y} is labeled "Predicted output value".
- A bracket under the difference $y - \hat{y}$ is labeled "The absolute value of the residual".
- The summation symbol Σ is labeled "Sum of".

$$MAE = \frac{1}{n} \sum |y - \hat{y}|$$

The diagram shows the formula for Mean Squared Error (MSE) with one annotation:

- A bracket under the difference $y - \hat{y}$ is labeled "The square of the difference between actual and predicted".

$$MSE = \frac{1}{n} \sum (y - \hat{y})^2$$

We no need to calculate manually

- ✓ We don't have to perform these calculations manually.
- ✓ The scikit-Learn library comes with pre-built functions that can be used to find out these values for us.

Program Name Loading student_scores dataset
demo10.py

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics

df = pd.read_csv('student_scores.csv')

X = df.iloc[:, :-1].values
y = df.iloc[:, 1].values

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=0)

regressor = LinearRegression()
regressor.fit(X_train, y_train)

y_pred = regressor.predict(X_test)

mae = metrics.mean_absolute_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
rmse = np.sqrt(metrics.mean_squared_error(y_test, y_pred))

print('Mean Absolute Error:', mae)
print('Mean Squared Error:', mse)
print('Root Mean Squared Error:', rmse)
```

Output

Mean Absolute Error: 4.18385989900298

Mean Squared Error: 21.598769307217413

Root Mean Squared Error: 4.647447612100368