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Dataset: (http://bit.ly/w-data)

TASK -1 Prediction using Supervised ML

Hey everyone! This is a Simple Linear Regression project in which i have to predict the percentage of marks that a student is expected to score based upon the number of hours they studied. This is a simple linear regression task as it involves just two variables.

This video will guide you through the process of retrieving answers to all these questions.

Let us get started!

Importing libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

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

Importing Dataset

In [2]:
```
# Now reading the data from the link provided
link = "http://bit.ly/w-data"
data = pd.read_csv(link)
data.head(8)
```

Out[2]:

	Hours	Scores
0	2.5	21
1	5.1	47
2	3.2	27
3	8.5	75
4	3.5	30
5	1.5	20
6	9.2	88
7	5.5	60

Data Preprocessing

In [3]:
```
# Before doing any task on the data our first aim to understand the data.
data.dtypes
```

Out[3]:
```
Hours     float64
Scores      int64
dtype: object
```

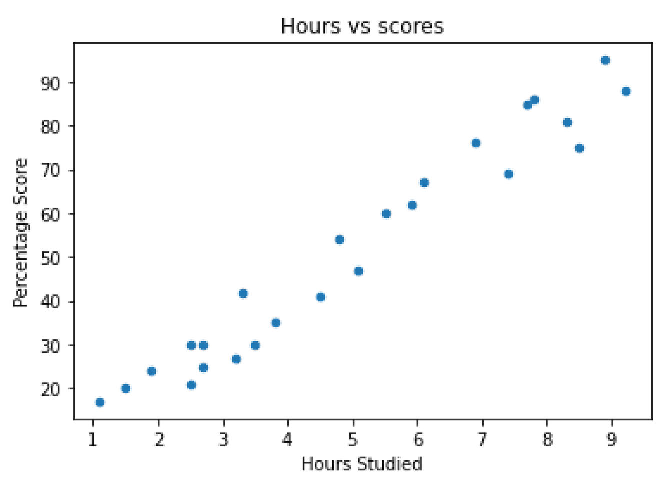
In [4]:
```
# Finding any missing value in the data
print(data.isna().sum())
print("\nSince the sum of all the cells of Hours and Scores is zero so we can say that we don't have any misssing value in our dataset.")
```

```
Hours     0
Scores    0
dtype: int64

Since the sum of all the cells of Hours and Scores is zero so we can say that we don't have any misssing value in our dataset.
```

Now we plot our data points on graph to see if we can find any relationship between the data.

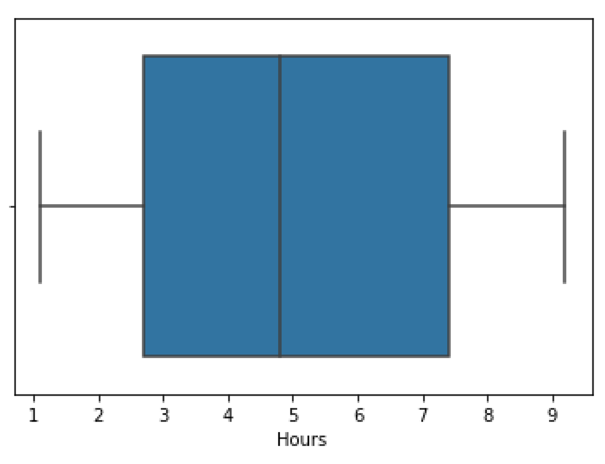
In [5]:
```
data.plot(kind='scatter',x='Hours',y='Scores')
plt.title('Hours vs scores')
plt.xlabel('Hours Studied')
plt.ylabel('Percentage Score')
plt.show()
```



From the above graph, we can clearly see that there is a positive linear relation between the number of hours studied and percentage of score.

In [6]:
```
# Outlier detection
sns.boxplot(data['Hours'])
```

Out[6]: <AxesSubplot:xlabel='Hours'>



Here we can see we don't have any outliers to remove so we proceed to our next steps.

In [7]:
```
x = data.iloc[:, :-1].values
y = data.iloc[:, 1].values
```

In [8]:
```
from sklearn.model_selection import train_test_split
```

In [9]:
```
X_train, X_test, y_train, y_test = train_test_split(x,y,random_state=6,train_size=.80)
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(20, 1)
(5, 1)
(20,)
(5,)
```

Training the data

In [10]:
```
from sklearn.linear_model import LinearRegression
my_model=LinearRegression()
my_model.fit(X_train,y_train)
```

Out[10]: LinearRegression()

In [11]:
```
print(my_model.coef_)
print(my_model.intercept_)
```

```
[10.05312869]
1.3923258559622198
```

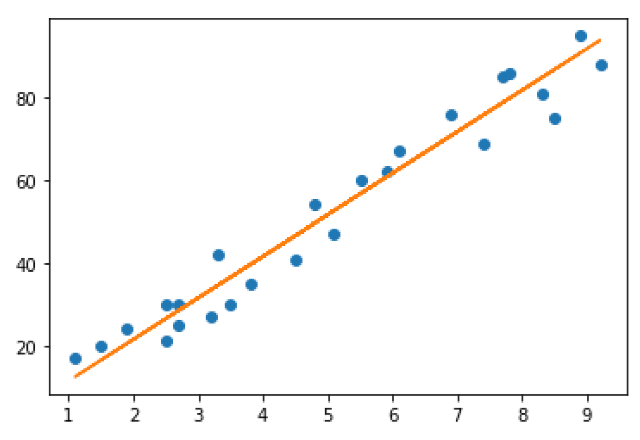
In [12]:
```
y_pred=my_model.predict(X_test)
y_pred
```

Out[12]: array([39.59421488, 56.68453365, 16.47201889, 93.8811098 , 84.83329398])

Plotting the regression line

In [13]:
```
plt.plot(x, y, 'o')
plt.plot(x, my_model.coef_*x + my_model.intercept_)
```

Out[13]: [<matplotlib.lines.Line2D at 0x2a54b607550>]



In [14]:
```
# Comparing Actual vs Predicted scores
df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
df
```

Out[14]:

	Actual	Predicted
0	35	39.594215
1	60	56.684534
2	20	16.472019
3	88	93.881110
4	81	84.833294

In [15]:
```
# What will be predicted score if a student studies for 9.25 hrs/ day?
hours = 9.25
pred = my_model.predict([[hours]])
print("No of Hours = {}".format(hours))
print("Predicted Score = {}".format(pred[0]))
```

```
No of Hours = 9.25
Predicted Score = 94.38376623376621
```

Evaluating coefficient's statistical significance

In [16]:
```
import statsmodels.formula.api as smf

my_stat_model = smf.ols(formula='Scores ~ Hours', data=data).fit()
#confidence interval
my_stat_model.conf_int()
```

Out[16]:

	0	1
Intercept	-2.753470	7.720817
Hours	8.838823	10.712784

In [17]:
```
# Now we have the coefficient then now find the p_value of the coefficient
print(my_stat_model.pvalues)
print()
# how to check that
print(my_stat_model.pvalues.loc['Hours'] < .05)
```

```
Intercept    3.367785e-01
Hours        9.132624e-17
dtype: float64

True
```

In [18]:
```
my_stat_model.rsquared
```

Out[18]: 0.9529481969048356

Since our rsquared value is close to 1 we can say that our model is predicting well on the test data.

In [19]:
```
my_stat_model.summary()
```

Out[19]:

OLS Regression Results

Dep. Variable:	Scores	**R-squared:**	0.953
Model:	OLS	**Adj. R-squared:**	0.951
Method:	Least Squares	**F-statistic:**	465.8
Date:	Fri, 02 Jul 2021	**Prob (F-statistic):**	9.13e-17
Time:	10:38:16	**Log-Likelihood:**	-77.514
No. Observations:	25	**AIC:**	159.0
Df Residuals:	23	**BIC:**	161.5
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.4837	2.532	0.981	0.337	-2.753	7.721
Hours	9.7758	0.453	21.583	0.000	8.839	10.713

Omnibus:	7.616	**Durbin-Watson:**	1.460
Prob(Omnibus):	0.022	**Jarque-Bera (JB):**	2.137
Skew:	-0.216	**Prob(JB):**	0.343
Kurtosis:	1.634	**Cond. No.**	13.0

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

Evaluating the model

This step is important to compare how well our algorithm performing on a particular dataset. Here, I'm using MAE, MSE and RMSE. There are many such metrics.

In [20]:
```
from sklearn.metrics import mean_absolute_error,mean_squared_error
print('Mean Absolute Error:', mean_absolute_error(y_test, y_pred))
print('Mean squared Error:', mean_squared_error(y_test, y_pred))
print('Root mean squared Error:', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
Mean Absolute Error: 4.230413223140487
Mean squared Error: 18.7654746734428
Root mean squared Error: 4.331913511768534
```