In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
```

In [3]:
```
data = pd.read_csv("student_scores.csv")
```

In [4]:
```
data.shape
```

Out[4]:
```
(25, 2)
```

In [5]:
```
data.head()
```

Out[5]:

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

In [6]:
```
data.describe()
```

Out[6]:

	Hours	Scores
count	25.000000	25.000000
mean	5.012000	51.480000
std	2.525094	25.286887
min	1.100000	17.000000
25%	2.700000	30.000000
50%	4.800000	47.000000
75%	7.400000	75.000000
max	9.200000	95.000000

In [7]:
```
data.Hours.quantile(0.25)
```

Out[7]: 2.7

In [8]:
```
data.Hours.quantile(0.75)
```

Out[8]: 7.4

Outliers handling

In [9]:
```
iqr = data.Hours.quantile(0.75) - data.Hours.quantile(0.25) # q3 - q1
iqr
```

Out[9]: 4.7

values greater than q3 + 1.5iqr -> outliers, values lesser than q3 - 1.5iqr -> outliers

In [10]:
```
upper_threshold = data.Hours.quantile(0.75) + (1.5 * iqr) # q3 + 1.5iqr
lower_threshold = data.Hours.quantile(0.25) - (1.5 * iqr) # q1 - 1.5iqr
upper_threshold, lower_threshold
```

Out[10]:
```
(14.450000000000001, -4.3500000000000005)
```

In [11]:
```
data.isnull().sum()
# check for null values
```

Out[11]:
```
Hours     0
Scores    0
dtype: int64
```

In [12]:
```
data = data.drop_duplicates()
# delete duplicates
data.shape
```

Out[12]:
```
(25, 2)
```

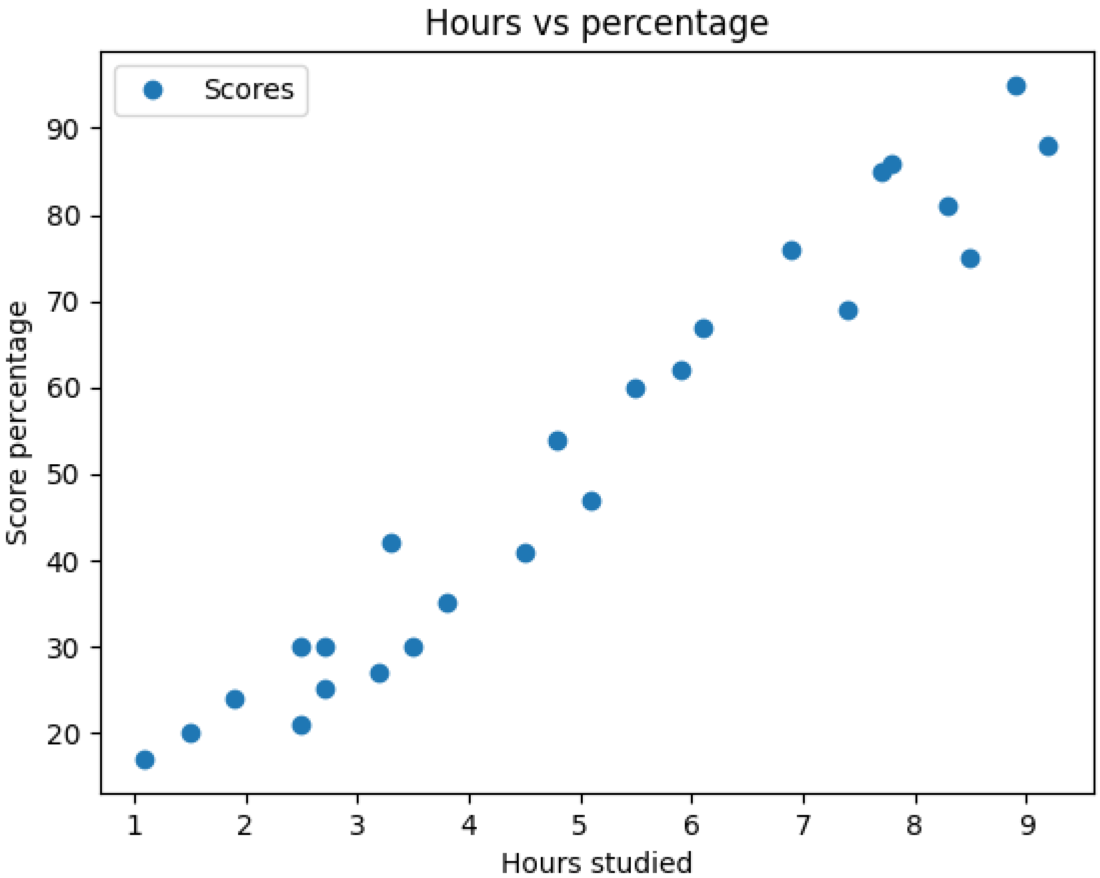
In [13]:
```
data.dtypes
# check datatypes for each feature
```

Out[13]:
```
Hours     float64
Scores      int64
dtype: object
```

EDA

Plot between feature and the target variable

In [14]:
```
data.plot(x='Hours', y='Scores', style='o')
plt.title('Hours vs percentage')
plt.xlabel('Hours studied')
plt.ylabel('Score percentage')
plt.show()
```



There is relationship between feature and target and there is linear relaionship between the feature and the target. So, no transformation is required

In [15]:
```
data.corr()
# compute the correlation between the features and target
```

Out[15]:

	Hours	Scores
Hours	1.000000	0.976191
Scores	0.976191	1.000000

There is a linear relationship between feature(Hours) and target(Scores) - We can go ahead and develop a linear regression model. No transformation required

Encoding is not required because there is no catagorical data in the dataset

Split

Now have to split the data

In [16]:
```
x = data.loc[:, ['Hours']].values
# select all rows and column except the last column, which is the feature
y = data.loc[:, 'Scores'].values # target
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, random_state=45)
```

In [17]:
```
y_test
```

Out[17]:
```
array([30, 30, 42, 85, 24, 86, 35], dtype=int64)
```

In [18]:
```
x_test
```

Out[18]:
```
array([[2.5],
       [2.7],
       [3.3],
       [7.7],
       [1.9],
       [7.8],
       [3.8]])
```

In [19]:
```
x,y
```

Out[19]:
```
(array([[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]]),
 array([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], dtype=int64))
```

Model

Model for alogrithm: score = (m * hours) + c

In [20]:
```
regressor = LinearRegression()
regressor.fit(x_train, y_train)
```

Out[20]:
```
▾ LinearRegression
LinearRegression()
```

In [21]:
```
regressor.intercept_ # c
```

Out[21]:
```
1.431512900311212
```

In [22]:
```
regressor.coef_ # m
```

Out[22]:
```
array([9.72000803])
```

So, predicted score = 9.72 * hours + 1.43 -> Can do this calculation by below line of code

In [23]:
```
regressor.predict([[8]])
# Can predict the score, 8 -> hours
```

Out[23]:
```
array([79.19157715])
```

In [24]:
```
regressor.predict([[13]])
# perils of extrapolations -> Out of range in the dataset. So, no guarantee that ML algorithm will work
```

Out[24]:
```
array([127.79161731])
```

In [25]:
```python
y_pred = regressor.predict(x_test)
# applied feature of the x_test, it'll give final prediction
```

In [26]:
```python
y_pred
```

Out[26]:
```
array([25.73153298, 27.67553458, 33.5075394 , 76.27557474, 19.89952816,
       77.24757554, 38.36754342])
```

In [27]:
```python
compare = pd.DataFrame({'Actual Score': y_test, 'Predicted Score': y_pred})
compare
```

Out[27]:

	Actual Score	Predicted Score
0	30	25.731533
1	30	27.675535
2	42	33.507539
3	85	76.275575
4	24	19.899528
5	86	77.247576
6	35	38.367543

Evaluation metrics

In [28]:
```python
print(f'R2 Score: {metrics.r2_score(y_test, y_pred)}')
# To find best prediction
print(regressor.score(x_test, y_test))
# Another way to find R2 score
```

```
R2 Score: 0.9347551352640703
0.9347551352640703
```