- Dataset can be found at [Swedish Insurance (https://www.math.muni.cz/~kolacek/docs/frvs/M7222/data/AutoInsurSweden.txt)](https://www.math.muni.cz/~kolacek/docs/frvs/M7222/data/AutoInsurSweden.txt)
- More about K-Means clustering at [Linear Regression with Linear Algebra (https://machinelearningmastery.com/implement-simple-linear-regression-scratch-python)](https://machinelearningmastery.com/implement-simple-linear-regression-scratch-python)

In [1]:

```
import pandas as pd
import numpy as np

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

In [2]:

```
df = pd.read_csv("swedish_insurance.csv")
df.head()
```

Out[2]:

	X	Y
0	108	392.5
1	19	46.2
2	13	15.7
3	124	422.2
4	40	119.4

What does the dataset contain ?

age: age of primary beneficiary

sex: insurance contractor gender, female, male

bmi: Body mass index, providing an understanding of body, weights that are relatively high or low relative to height, objective index of body weight (kg / m ^ 2) using the ratio of height to weight, ideally 18.5 to 24.9

children: Number of children covered by health insurance / Number of dependents

smoker: Smoking

region: the beneficiary's residential area in the US, northeast, southeast, southwest, northwest.

charges: Individual medical costs billed by health insurance

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 63 entries, 0 to 62
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   X       63 non-null     int64  
 1   Y       63 non-null     float64
dtypes: float64(1), int64(1)
memory usage: 1.1 KB
```

What is the algorithm

```
Linear regression is a supervised regression algorithm.
Linear regression is a linear approach to modelling the relationship between a scalar response and one or more
explanatory variables (also known as dependent and independent variables)
```

How does the algorithm work

```
1. Calculate Mean and Variance
2. Calculate Covariance
3. Estimate Coefficients (Slope and intercept)
4. Make Predictions
5. Predict Insurance
```

Advantages and Disadvantges of the algorithm

```
Advantages:
* Linear regression performs exceptionally well for linearly separable data
* Easier to implement, interpret and efficient to train
```

```
* It handles overfitting pretty well using dimensionally reduction techniques, regularization, and cross-validation
* One more advantage is the extrapolation beyond a specific data set

Disadvantages:
* The assumption of linearity between dependent and independent variables
* It is often quite prone to noise and overfitting
* Linear regression is quite sensitive to outliers
* It is prone to multicollinearity
```

How is it performed on the dataset

In [4]:

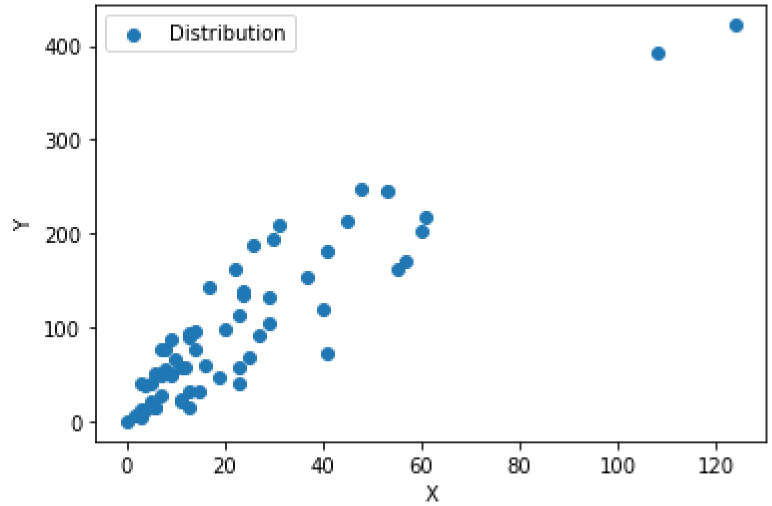
```python
df.head()
```

Out[4]:

	X	Y
0	108	392.5
1	19	46.2
2	13	15.7
3	124	422.2
4	40	119.4

In [5]:

```
plt.scatter(df['X'], df['Y'], label='Distribution')
plt.xlabel('X')
plt.ylabel("Y")
plt.legend()
plt.show();
```



In [6]:

```
X = df.values
```

In [7]:

```
train, test = train_test_split(X, random_state=42, test_size=0.3)
```

In [8]:

```
# Calculate root mean squared error
def rmse_metric(actual, predicted):
    sum_error = 0.0
    for i in range(len(actual)):
        prediction_error = predicted[i] - actual[i]
        sum_error += (prediction_error ** 2)
    mean_error = sum_error / float(len(actual))
    return np.sqrt(mean_error)
```

In [9]:

```python
# Calculate the mean value of a list of numbers
def mean(values):
    return np.sum(values) / float(len(values))

# Calculate covariance between x and y
def covariance(x, mean_x, y, mean_y):
    covar = 0.0
    for i in range(len(x)):
        covar += (x[i] - mean_x) * (y[i] - mean_y)
    return covar

# Calculate the variance of a list of numbers
def variance(values, mean):
    return np.sum([(x-mean)**2 for x in values])
```

In [10]:

```python
# Calculate coefficients
def coefficients(dataset):
    x = [row[0] for row in dataset]
    y = [row[1] for row in dataset]
    x_mean, y_mean = mean(x), mean(y)
    b1 = covariance(x, x_mean, y, y_mean) / variance(x, x_mean)
    b0 = y_mean - b1 * x_mean
    return [b0, b1]

# Simple linear regression algorithm
def simple_linear_regression(train, test):
    train_preds = []
    test_preds = []
    b0, b1 = coefficients(train)
    for row in train:
        yhat = b0 + b1 * row[0]
        train_preds.append(yhat)
    for row in test:
        yhat = b0 + b1 * row[0]
        test_preds.append(yhat)
    return train_preds, test_preds
```

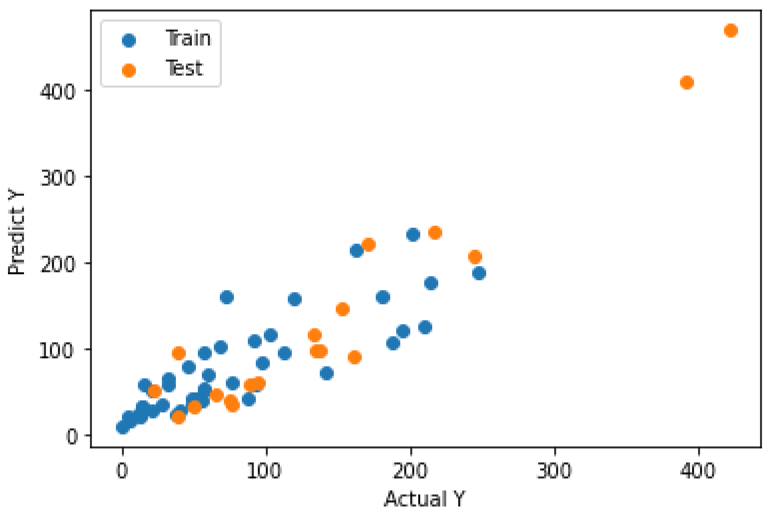
In [11]:

```python
train_preds, test_preds = simple_linear_regression(train, test)
train_y = [row[-1] for row in train]
test_y = [row[-1] for row in test]
train_rmse = rmse_metric(train_y, train_preds)
test_rmse = rmse_metric(test_y, test_preds)
print("RMSE on train: {}".format(train_rmse))
print("RMSE on test: {}".format(test_rmse))
```

```
RMSE on train: 36.123674251566065
RMSE on test: 36.121762633585256
```

In [12]:

```python
plt.scatter(train_y, train_preds, label="Train")
plt.scatter(test_y, test_preds, label="Test")
plt.xlabel("Actual Y")
plt.ylabel("Predict Y")
plt.legend()
plt.show();
```



Summary

- The model fits for both training and testing dataset
- Although the data seems linearly dependent, the variance in the data is resulting in the higher RMSE

- Feature Engineering might help reduce the RMSE

```
In [ ]:
```