Feature Scaling to Improve Model accuracy

```
import pandas as pd
```

```
import numpy as np
```

```
import matplotlib.pyplot as plt
```

```
import seaborn as sns
```

Import CSV as Dataframe

```
df=pd.read_csv(r'https://github.com/YBI-Foundation/Dataset/raw/main/Online%20Purchase.csv'
```

Get Information of DataFrame

```
df.head()
```

	Customer_ID	Gender	Age	Salary	Purchased
0	1	Male	35	500	0
1	2	Female	25	300000	1
2	3	Female	100	200000	0
3	15566689	Female	35	57000	0
4	15569641	Female	58	95000	1

```
df.shape
```

```
(403, 5)
```

```
df.columns
```

```
Index(['Customer_ID', 'Gender', 'Age', 'Salary', 'Purchased'], dtype='object')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 403 entries, 0 to 402
Data columns (total 5 columns):
 #   Column       Non-Null Count  Dtype
```

```
 ---  ------       --------------  -----
  0   Customer_ID  403 non-null    int64
  1   Gender       403 non-null    object
  2   Age          403 non-null    int64
  3   Salary       403 non-null    int64
  4   Purchased    403 non-null    int64
 dtypes: int64(4), object(1)
 memory usage: 15.9+ KB
```

```
df.describe()
```

	Customer_ID	Age	Salary	Purchased
count	4.030000e+02	403.000000	403.000000	403.000000
mean	1.557473e+07	37.771712	70465.260546	0.357320
std	1.352373e+06	10.915209	36598.127268	0.479806
min	1.000000e+00	18.000000	500.000000	0.000000
25%	1.562463e+07	29.500000	43000.000000	0.000000
50%	1.569326e+07	37.000000	70000.000000	0.000000
75%	1.575020e+07	46.000000	88000.000000	1.000000
max	1.581524e+07	100.000000	300000.000000	1.000000

We observe that the mean of Age ,Salary are very different due to measurement scale

Get y and X separated

```
y=df['Purchased']
```

```
y.shape
```

```
(403,)
```

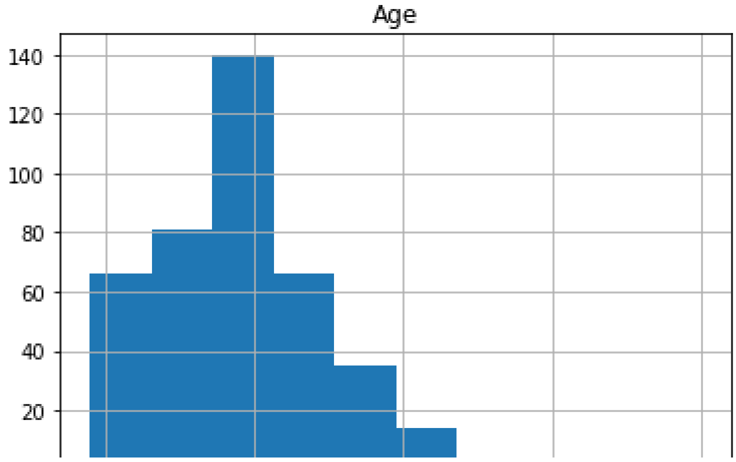
```
X=df[['Age','Salary']]
```

```
X.shape
```

```
(403, 2)
```

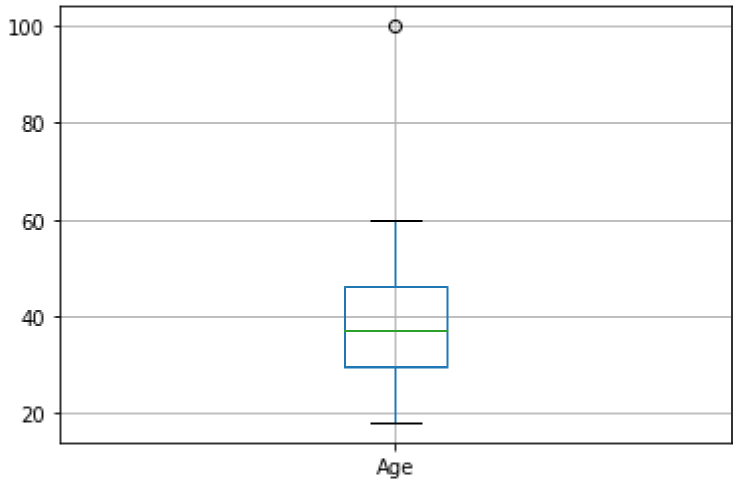
Get Data Visualization

```
df[['Age']].hist();
```



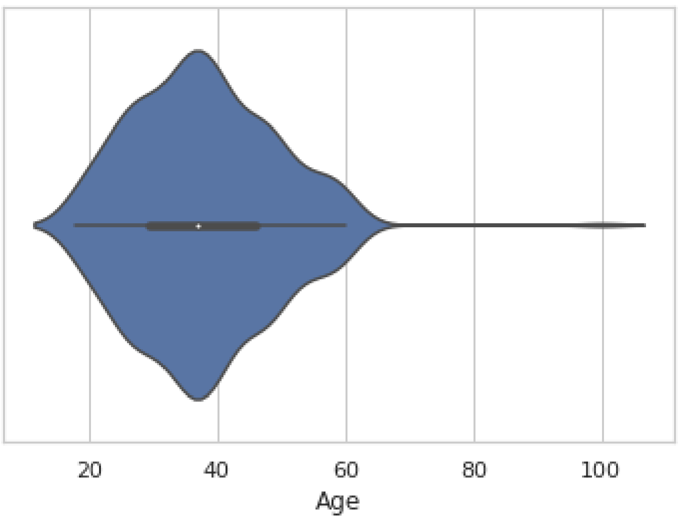

```
df[['Age']].boxplot()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc06590d290>
```



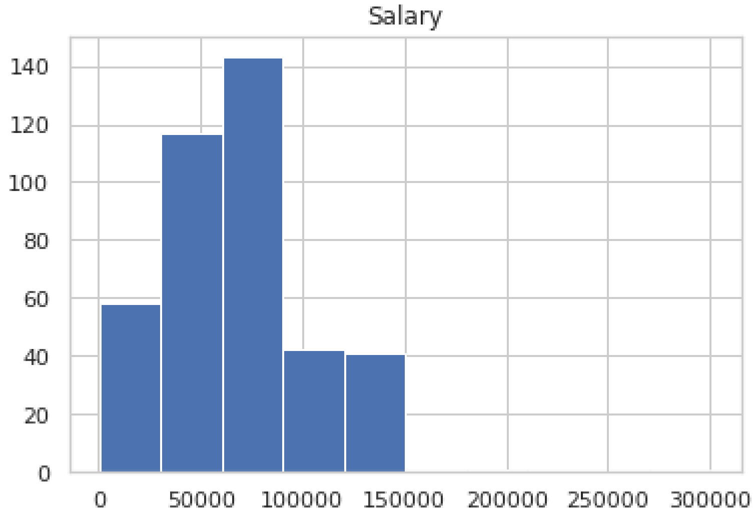

```
sns.set_theme(style="whitegrid")

ax = sns.violinplot(x=df["Age"])
```



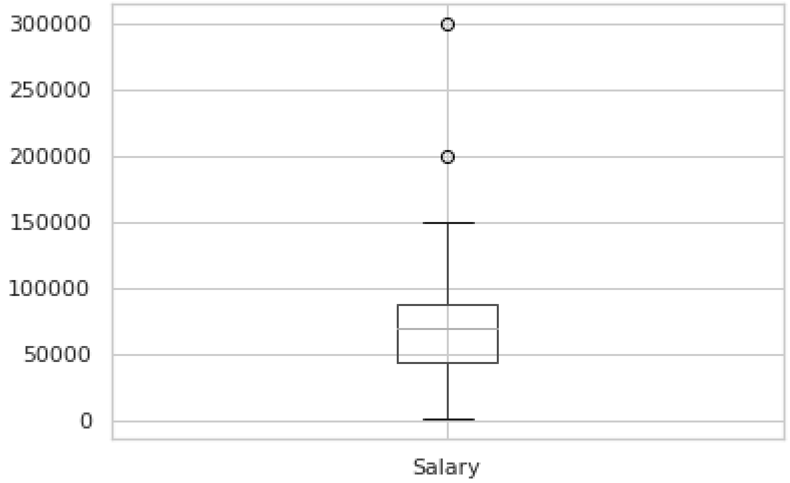
Age has Outlier

```
df[['Salary']].hist();
```




```
df[['Salary']].boxplot()
```

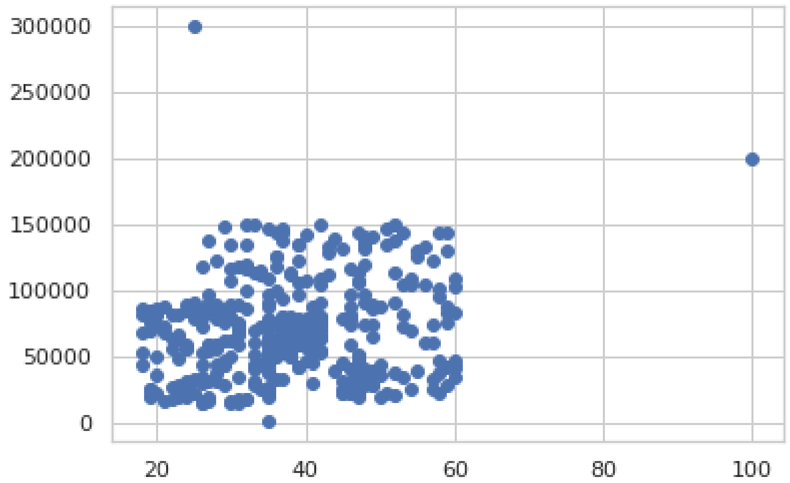
<matplotlib.axes._subplots.AxesSubplot at 0x7fc0657cb550>



Salary has a Outlier

```
plt.scatter(df['Age'],df['Salary'])
```

<matplotlib.collections.PathCollection at 0x7fc062e08410>



Get Train Test Split

```
from sklearn.model_selection import train_test_split
```

```
X_train,X_test,y_train,y_test=train_test_split(X,y, test_size=0.3,stratify=y,random_state=
```

```
X_train.shape,X_test.shape,y_train.shape,y_test.shape
```

```
((282, 2), (121, 2), (282,), (121,))
```

Get Scaling of Features or Attributes or Independent Variable X

```
from sklearn.preprocessing import StandardScaler
```

```
ss=StandardScaler()
```

```
X_train_ss=ss.fit_transform(X_train)
```

```
X_test_ss=ss.fit_transform(X_test)
```

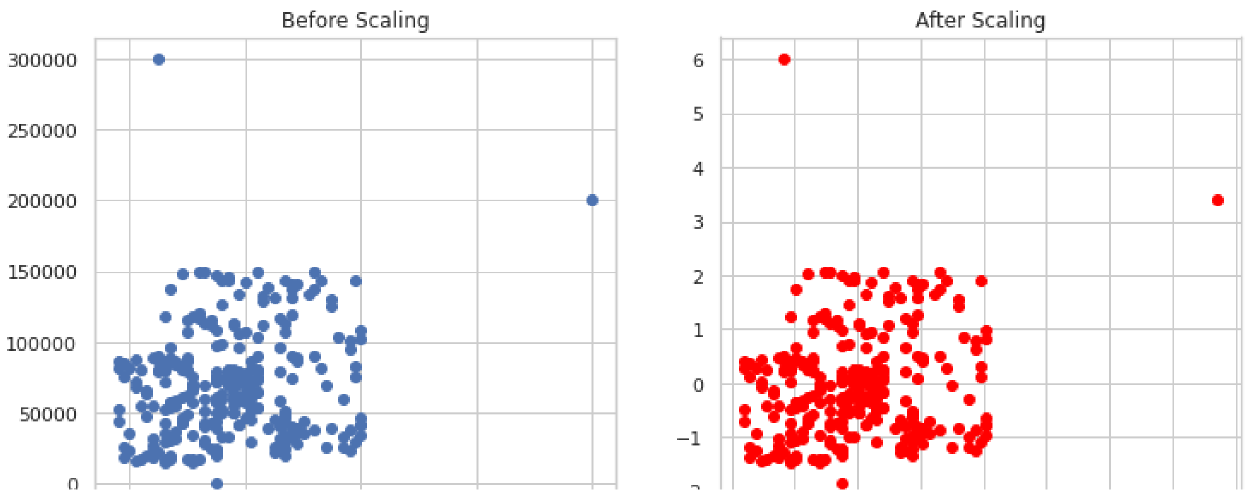
Best is to standardize the train and test samples individually by their own calculated mean and standard deviation .This will help in avoiding any information leakage .

Get Visualization of Impact of Scaling.

```
X_train_ss=pd.DataFrame(X_train_ss, columns=X_train.columns)
X_test_ss=pd.DataFrame(X_test_ss, columns=X_test.columns)
```

Reduced Impact of Outliers

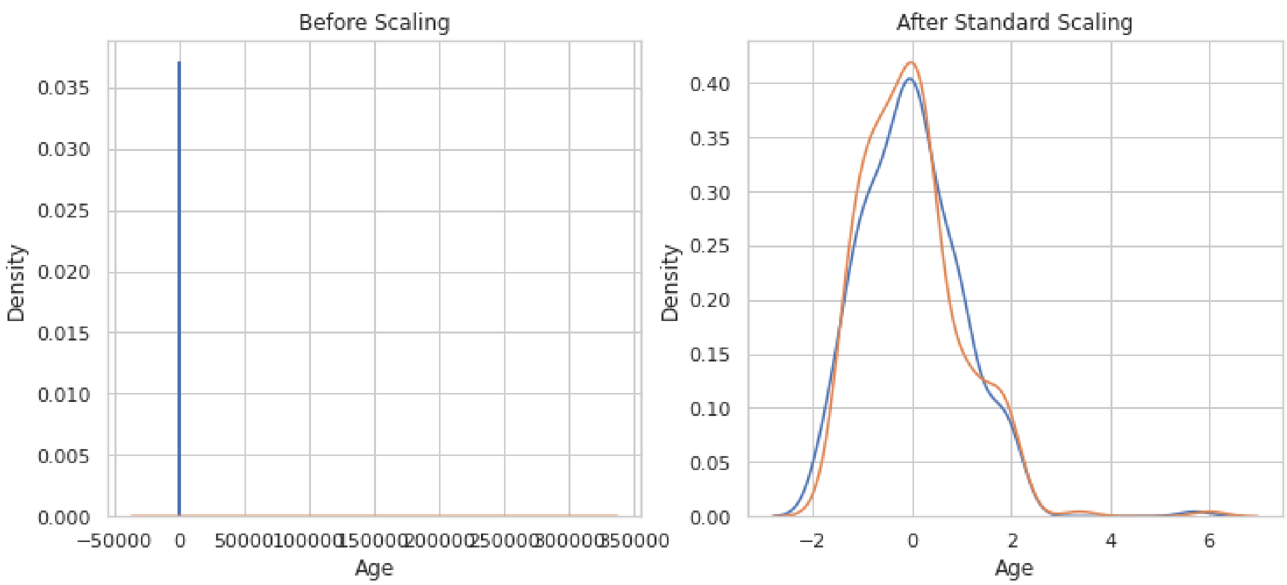
```
fig,(ax1,ax2)=plt.subplots(ncols=2,figsize=(12,5))
ax1.scatter(X_train['Age'],X_train['Salary'])
ax1.set_title('Before Scaling')
ax2.scatter(X_train_ss['Age'],X_train_ss['Salary'],color='red')
ax2.set_title('After Scaling')
plt.show()
```



Uniform Scale and Distribution

KDE(Kernel Density Estimation)

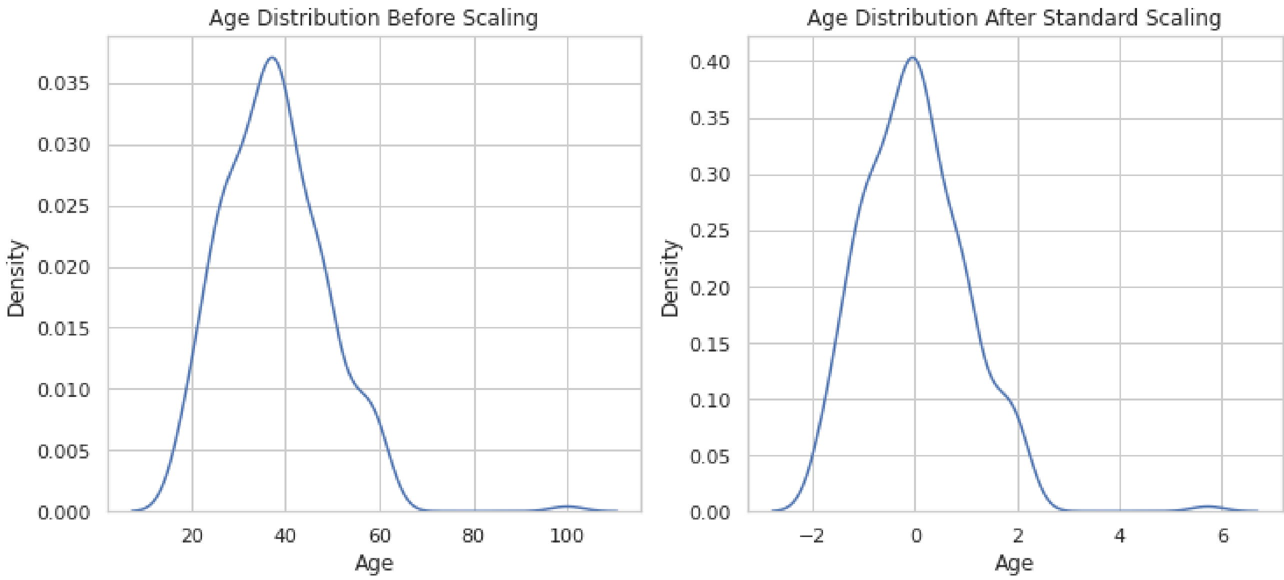
```
fig,(ax1,ax2)=plt.subplots(ncols=2,figsize=(12,5))
#Before scaling
ax1.set_title('Before Scaling')
sns.kdeplot(X_train['Age'],ax=ax1)
sns.kdeplot(X_train['Salary'],ax=ax1)
#After Scaling
ax2.set_title('After Standard Scaling')
sns.kdeplot(X_train_ss['Age'],ax=ax2)
sns.kdeplot(X_train_ss['Salary'],ax=ax2)
plt.show()
```



Compare Distribution Before Scaling and After Sacling

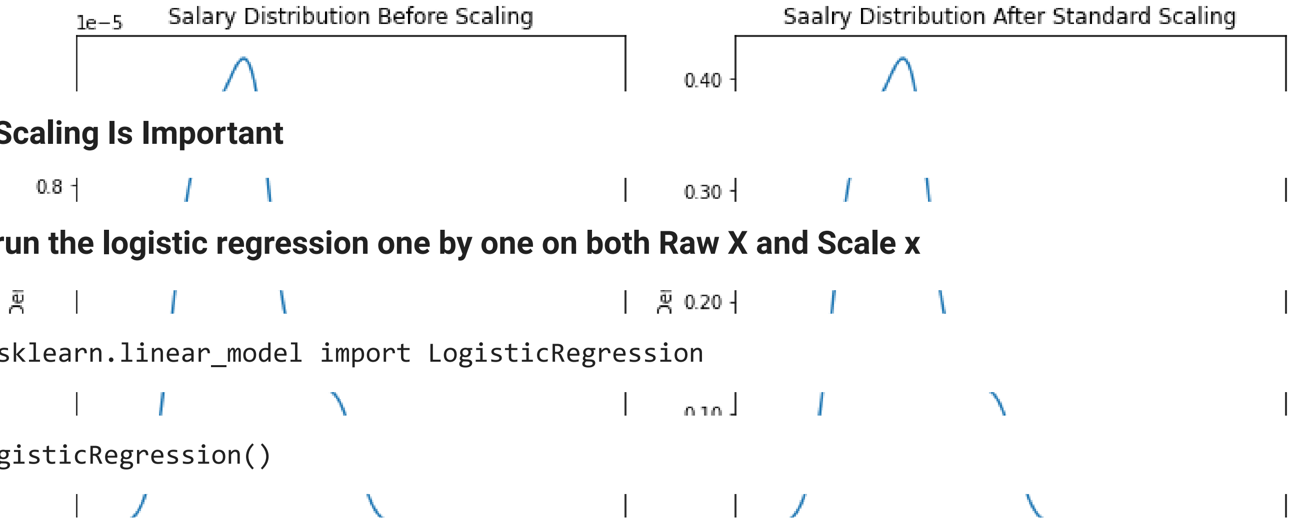
```
fig,(ax1,ax2)=plt.subplots(ncols=2,figsize=(12,5))
#Before scaling
ax1.set_title('Age Distribution Before Scaling')
sns.kdeplot(X_train['Age'],ax=ax1)
#After Scaling
ax2.set_title('Age Distribution After Standard Scaling')
sns.kdeplot(X_train_ss['Age'],ax=ax2)

plt.show()
```




```
fig,(ax1,ax2)=plt.subplots(ncols=2,figsize=(12,5))
#Before scaling
ax1.set_title('Salary Distribution Before Scaling')
sns.kdeplot(X_train['Salary'],ax=ax1)
#After Scaling
ax2.set_title('Saalry Distribution After Standard Scaling')
sns.kdeplot(X_train_ss['Salary'],ax=ax2)

plt.show()
```



Why Scaling Is Important

Lets run the logistic regression one by one on both Raw X and Scale x

```
from sklearn.linear_model import LogisticRegression
```

```
lr=LogisticRegression()
```

```
lr.fit(X_train,y_train)
```

    LogisticRegression()

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

```
from sklearn.metrics import accuracy_score
```

```
accuracy_score(y_test,y_pred)
```

    0.6446280991735537

Accuracy Score with Raw X

```
lr.fit(X_train_ss,y_train)
```

    LogisticRegression()

```
y_pred=lr.predict(X_test_ss)
```

```
accuracy_score(y_test,y_pred)
```

    0.8099173553719008

Accuracy Score with Scaled X

Accuracy of models with Scales Features,attributes,Independent variables or x has significantly improved vis-a-vis Model with Raw X

```
lr.fit(X_train,y_train)
```

    LogisticRegression()

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