In [1]:

```
import pandas as pd
```

In [2]:

```
import numpy as np
```

In [3]:

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

In [4]:

```
import seaborn as sns
```

In [5]:

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

In [6]:

```
df.head()
```

Out[6]:

	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

In [7]:

```
df.shape
```

Out[7]:

```
(403, 5)
```

In [8]:

```
df.columns
```

Out[8]:

```
Index(['Customer_ID', 'Gender', 'Age', 'Salary', 'Purchased'], dtype='objec
t')
```

In [9]:

```
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
```

In [10]:

```
df.describe()
```

Out[10]:

	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

In [11]:

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

In [12]:

```
y.shape
```

Out[12]:

```
(403,)
```

In [13]:

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

In [14]:

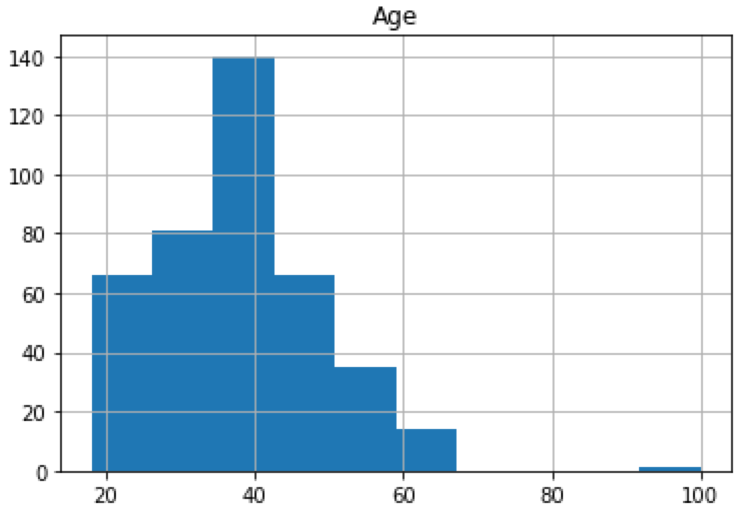
```
x.shape
```

Out[14]:

```
(403, 2)
```

In [15]:

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

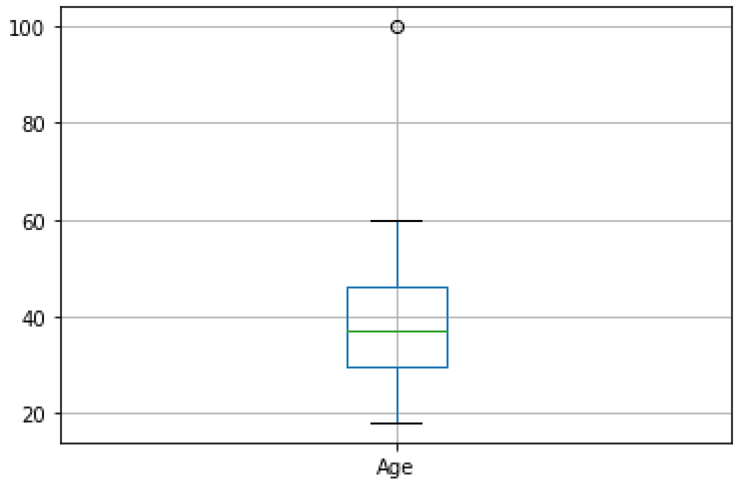


In [16]:

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

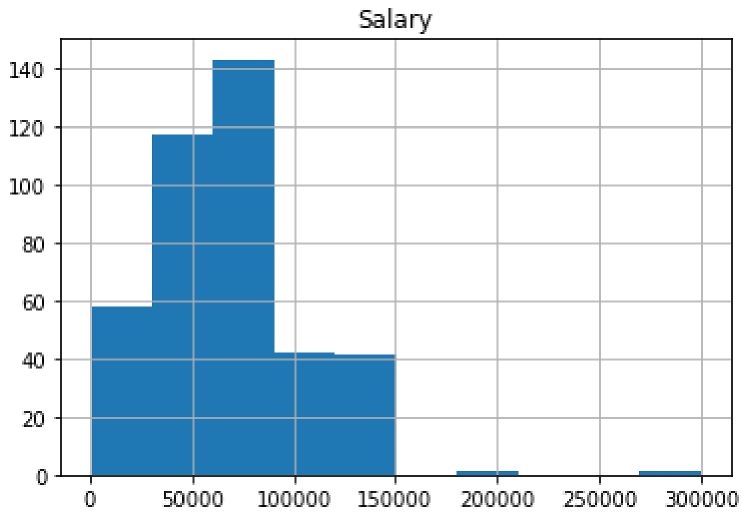
Out[16]:

```
<AxesSubplot:>
```



In [17]:

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

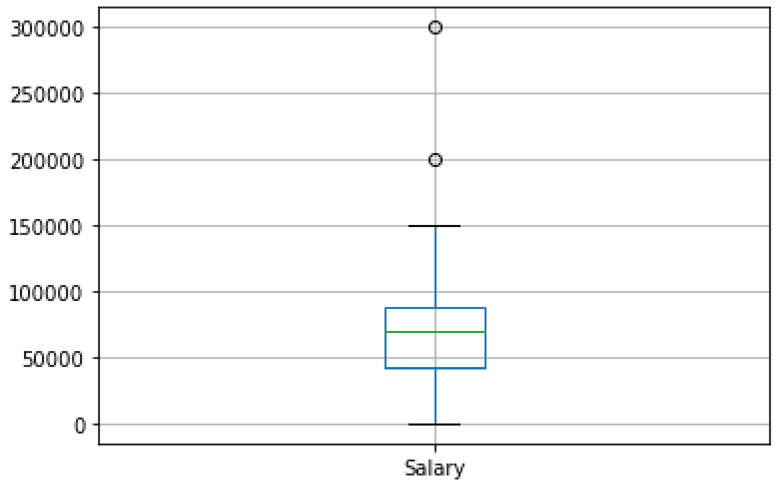


In [18]:

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

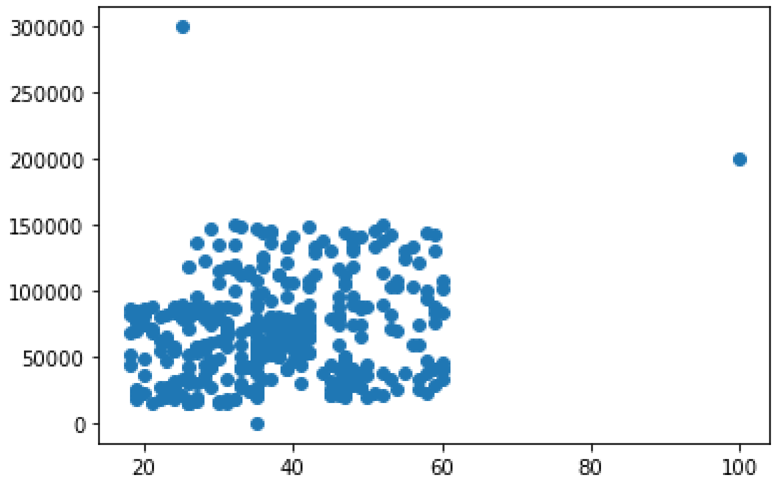
Out[18]:

```
<AxesSubplot:>
```



In [19]:

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



In [20]:

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

In [21]:

```
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size = 0.3, stratify=y, rando
```

In [22]:

```
x_train.shape, x_test.shape, y_train.shape,y_test.shape
```

Out[22]:

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

In [23]:

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

In [24]:

```
ss = StandardScaler()
```

In [25]:

```
x_train_ss = ss.fit_transform(x_train)
```

In [26]:

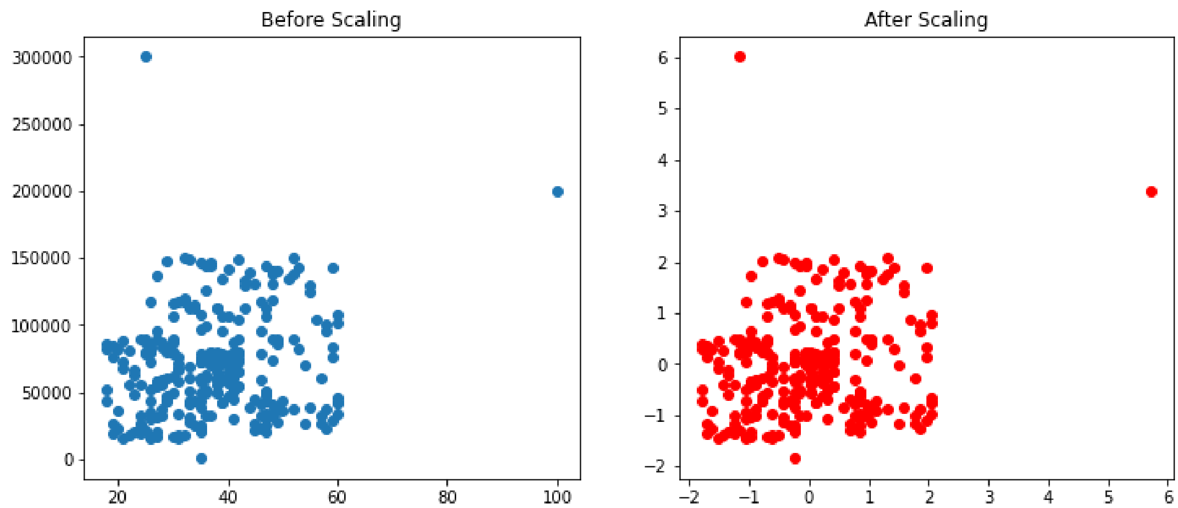
```
x_test_ss = ss.fit_transform(x_test)
```

In [27]:

```
x_train_ss=pd.DataFrame(x_train_ss, columns=x_train.columns)
x_test_ss=pd.DataFrame(x_test_ss, columns=x_test.columns)
```

In [28]:

```
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()
```

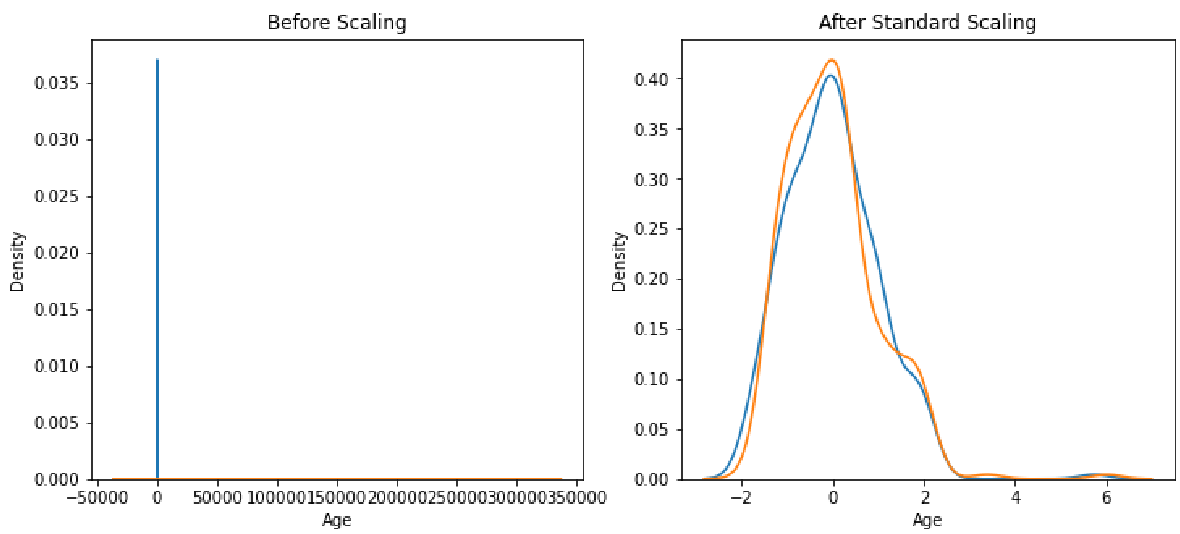


In [29]:

```
fig, (ax1, ax2)= plt.subplots(ncols=2, figsize=(12, 5))

ax1.set_title("Before Scaling")
sns.kdeplot(x_train['Age'], ax=ax1)
sns.kdeplot(x_train['Salary'], ax=ax1)

ax2.set_title("After Standard Scaling")
sns.kdeplot(x_train_ss['Age'], ax=ax2)
sns.kdeplot(x_train_ss['Salary'], ax=ax2)
plt.show()
```

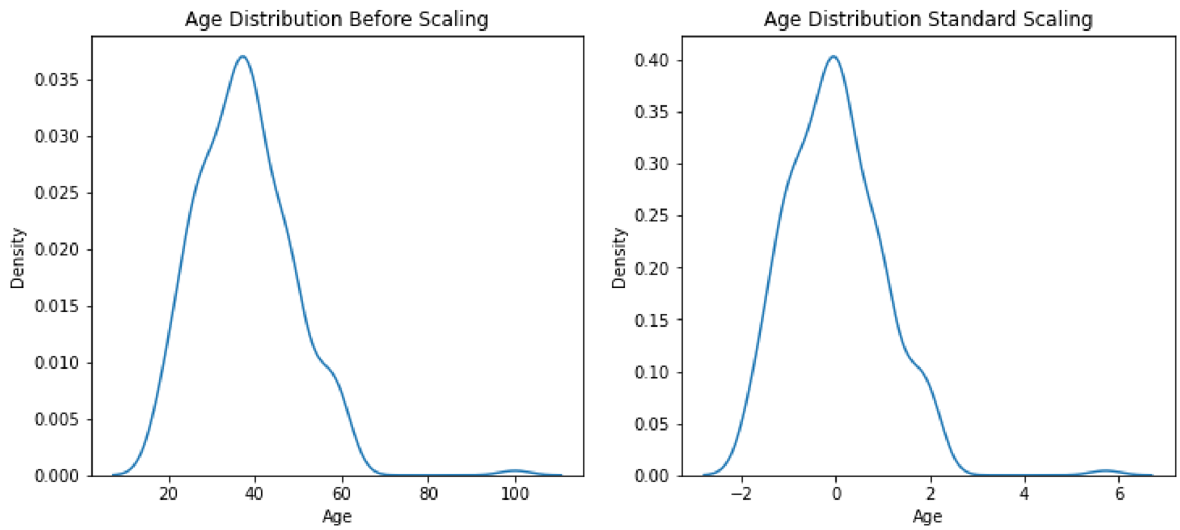


In [30]:

```
fig, (ax1, ax2)= plt.subplots(ncols=2, figsize=(12, 5))

ax1.set_title("Age Distribution Before Scaling")
sns.kdeplot(x_train['Age'], ax=ax1)


ax2.set_title("Age Distribution Standard Scaling")
sns.kdeplot(x_train_ss['Age'], ax=ax2)
plt.show()
```

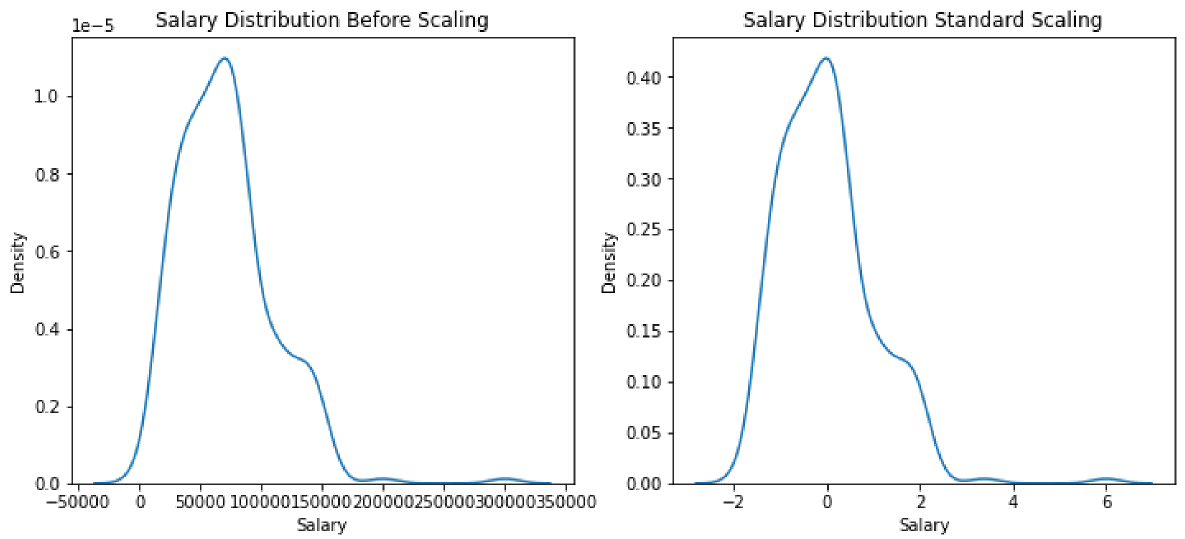


In [32]:

```
fig, (ax1, ax2)= plt.subplots(ncols=2, figsize=(12, 5))

ax1.set_title("Salary Distribution Before Scaling")
sns.kdeplot(x_train['Salary'], ax=ax1)


ax2.set_title("Salary Distribution Standard Scaling")
sns.kdeplot(x_train_ss['Salary'], ax=ax2)
plt.show()
```



In [33]:

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

In [34]:

```
lr = LogisticRegression()
```

In [35]:

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

Out[35]:

```
LogisticRegression()
```

In [36]:

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

In [37]:

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

In [38]:

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

Out[38]:

```
0.6446280991735537
```

In [39]:

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

Out[39]:

```
LogisticRegression()
```

In [40]:

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

In [41]:

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

Out[41]:

```
0.8099173553719008
```

In [ ]:

```

```