In [27]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [10]:

```
df = pd.read_csv('Social_Network_Ads.csv')
```

In [11]:

df

Out[11]:

User ID	Gender	Age	EstimatedSalary	Purchased
15624510	Male	19	19000	0
15810944	Male	35	20000	0
15668575	Female	26	43000	0
15603246	Female	27	57000	0
15804002	Male	19	76000	0
15691863	Female	46	41000	1
15706071	Male	51	23000	1
15654296	Female	50	20000	1
15755018	Male	36	33000	0
15594041	Female	49	36000	1
	15624510 15810944 15668575 15603246 15804002 15691863 15706071 15654296 15755018	15624510 Male 15810944 Male 15668575 Female 15603246 Female 15804002 Male 15691863 Female 15706071 Male 15654296 Female 15755018 Male	15624510 Male 19 15810944 Male 35 15668575 Female 26 15603246 Female 27 15804002 Male 19 15691863 Female 46 15706071 Male 51 15654296 Female 50 15755018 Male 36	15810944 Male 35 20000 15668575 Female 26 43000 15603246 Female 27 57000 15804002 Male 19 76000 15691863 Female 46 41000 15706071 Male 51 23000 15654296 Female 50 20000 15755018 Male 36 33000

400 rows × 5 columns

In [12]:

df.sample(5)

Out[12]:

	User ID	Gender	Age	EstimatedSalary	Purchased
97	15582492	Male	28	123000	1
358	15573926	Male	40	71000	1
35	15713144	Male	35	27000	0
377	15800215	Female	42	53000	0
126	15610801	Male	42	65000	0

In [13]:

```
df=df.iloc[:,2:]
```

In [14]:

df

Out[14]:

	Age	EstimatedSalary	Purchased
0	19	19000	0
1	35	20000	0
2	26	43000	0
3	27	57000	0
4	19	76000	0
395	46	41000	1
396	51	23000	1
397	50	20000	1
398	36	33000	0
399	49	36000	1

400 rows × 3 columns

In [15]:

Out[15]:

((280, 2), (120, 2))

In [16]:

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

# fit the scaler to the train set, it will learn the parameters
scaler.fit(X_train)

# transform train and test sets
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
In [17]:
```

```
scaler.mean_
```

Out[17]:

array([3.78642857e+01, 6.98071429e+04])

In [18]:

```
X_train
```

Out[18]:

	Age	EstimatedSalary
92	26	15000
223	60	102000
234	38	112000
232	40	107000
377	42	53000
323	48	30000
192	29	43000
117	36	52000
47	27	54000
172	26	118000

280 rows × 2 columns

In [19]:

```
X_train_scaled
```

```
Out[19]:
array([[-1.1631724 , -1.5849703 ],
       [ 2.17018137, 0.93098672],
       [\ 0.0133054\ ,\ 1.22017719],
       [ 0.20938504,
                    1.07558195],
       [ 0.40546467, -0.48604654],
       [-0.28081405, -0.31253226],
       [0.99370357, -0.8330751],
       [ 0.99370357, 1.8563962 ],
       [ 0.0133054 , 1.24909623],
       [-0.86905295, 2.26126285],
       [-1.1631724, -1.5849703],
       [ 2.17018137, -0.80415605],
       [-1.35925203, -1.46929411],
       [ 0.40546467, 2.2901819 ],
       [ 0.79762394, 0.75747245],
       [-0.96709276, -0.31253226],
       [ 0.11134522, 0.75747245],
       [-0.96709276. 0.55503912].
```

In [20]:

```
X_train_scaled = pd.DataFrame(X_train_scaled, columns=X_train.columns)
X_test_scaled = pd.DataFrame(X_test_scaled, columns=X_test.columns)
```

In [21]:

np.round(X_train.describe(), 1)

Out[21]:

	Age	EstimatedSalary
count	280.0	280.0
mean	37.9	69807.1
std	10.2	34641.2
min	18.0	15000.0
25%	30.0	43000.0
50%	37.0	70500.0
75%	46.0	88000.0
max	60.0	150000.0

In [22]:

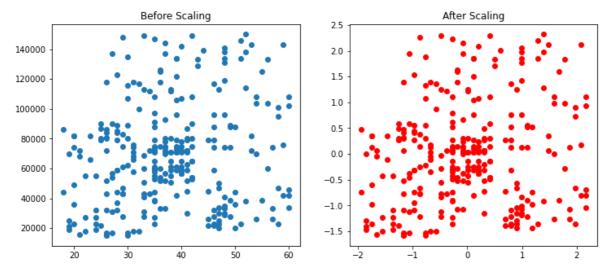
np.round(X_train_scaled.describe(), 1)

Out[22]:

	Age	EstimatedSalary
count	280.0	280.0
mean	0.0	0.0
std	1.0	1.0
min	-1.9	-1.6
25%	-0.8	-0.8
50%	-0.1	0.0
75%	0.8	0.5
max	2.2	2.3

In [23]:

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

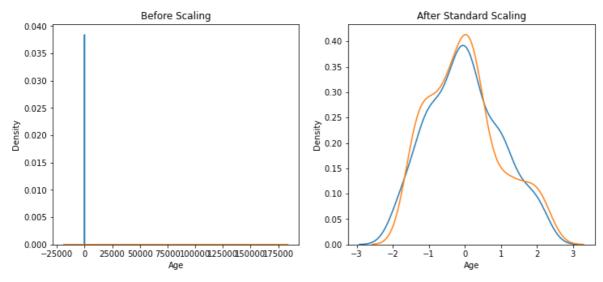


In [24]:

```
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['EstimatedSalary'], ax=ax1)

# after scaling
ax2.set_title('After Standard Scaling')
sns.kdeplot(X_train_scaled['Age'], ax=ax2)
sns.kdeplot(X_train_scaled['EstimatedSalary'], ax=ax2)
plt.show()
```

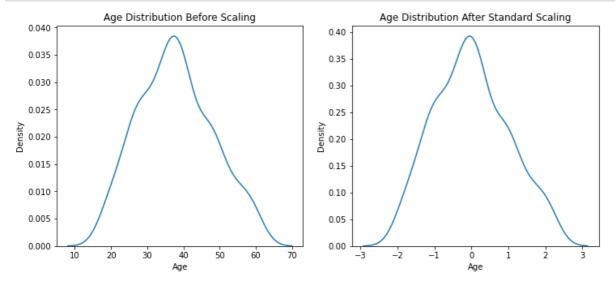


In [25]:

```
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_scaled['Age'], ax=ax2)
plt.show()
```

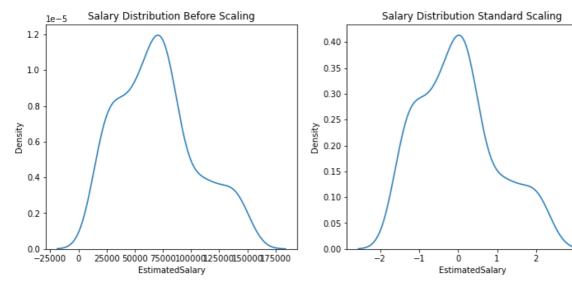


In [26]:

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

# before scaling
ax1.set_title('Salary Distribution Before Scaling')
sns.kdeplot(X_train['EstimatedSalary'], ax=ax1)

# after scaling
ax2.set_title('Salary Distribution Standard Scaling')
sns.kdeplot(X_train_scaled['EstimatedSalary'], ax=ax2)
plt.show()
```



In []: