```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from google.colab import drive
```

```
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
df = pd.read_csv('/content/drive/MyDrive/python-Saylani/Social_Network_Ads.csv')
```

```
df.head()
```

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0

```
df=df.iloc[:,2:]
df.head()
```

	Age	EstimatedSalary	Purchased
0	19	19000	0
1	35	20000	0
2	26	43000	0
3	27	57000	0
4	19	76000	0

```
df.sample(5)
```

	Age	EstimatedSalary	Purchased
140	19	85000	0
153	36	50000	0
259	45	131000	1
92	26	15000	0
244	41	72000	0

```
df.shape
```

```
(400, 3)
```

```
x=df.drop('Purchased',axis=1)
y=df['Purchased']
```

```
x
```

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

400 rows × 2 columns

```
y
```

	Purchased
0	0
1	0
2	0
3	0
4	0
...	...
395	1
396	1
397	1
398	0
399	1

400 rows × 1 columns

dtype: int64

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)

x_train.shape, x_test.shape
```

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

StandardScaler

```
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)
```

```
scaler.mean_
```

```
array([3.73964286e+01, 6.91321429e+04])
```

```
x_train
```

	Age	EstimatedSalary
360	43	129000
57	28	79000
119	41	59000
293	37	77000
41	33	51000
...	...	...
71	24	27000
184	33	60000
270	43	133000
20	45	22000
117	36	52000

280 rows × 2 columns

```
x_train_scaled
```

```
array([[ 0.53144872,  1.75536638],
       [-0.89116736,  0.2893323 ],
       [ 0.34176658, -0.29708134],
       [-0.03759771,  0.23069093],
       [-0.416962  , -0.53164679],
       [ 0.05724336,  1.28623547],
       [-0.98600843, -0.32640202],
       [ 1.57470052, -1.26466383],
       [ 2.14374695, -0.79553292],
       [-0.70148522, -0.59028815],
       [-0.416962  , -0.82485361],
       [-0.79632629, -0.76621224],
       [ 1.19533623,  0.55321843],
       [ 0.24692551, -0.3557227 ],
       [-0.89116736,  0.52389775],
       [-1.27053165, -1.35262588],
       [-0.22727986, -0.73689156],
       [-0.70148522,  0.31865298],
       [ 0.24692551,  1.11031138],
       [-0.51180307,  1.4035182 ],
       [ 0.81597194, -0.29708134],
       [ 0.24692551, -0.64892952],
       [ 0.43660765, -0.44368474],
       [-0.22727986,  1.13963207],
       [-1.4602138 , -0.17979861],
       [ 1.19533623, -0.73689156],
       [-1.74473701, -1.29398451],
       [-1.27053165,  0.43593571],
       [-1.27053165, -0.41436406],
       [ 1.00565409,  0.6118598 ],
       [-1.08084951,  0.08408753],
       [-0.70148522, -0.20911929],
       [-0.79632629, -0.64892952],
       [ 1.2901773 ,  1.90196979],
       [-0.98600843, -0.44368474],
       [-1.83957809, -0.50232611],
       [-1.64989594, -0.59028815],
       [-0.22727986, -0.64892952],
       [-0.13243878,  1.66740434],
       [-1.74473701,  0.02544616],
       [-0.416962  , -1.11806042],
       [ 0.24692551, -0.12115725],
       [-0.98600843, -1.11806042],
       [-1.64989594,  0.14272889],
       [-1.17569058,  0.31865298],
       [ 0.34176658,  0.52389775],
       [ 2.04890588,  0.20137025],
       [-0.13243878,  1.63808365],
       [-0.79632629,  0.40661502],
       [-1.08084951, -1.1473811 ],
```

```
       [-0.70148522,  0.52389775],
       [-0.03759771, -0.20911929],
       [ 1.00565409, -1.0007777 ],
       [-1.17569058,  0.52389775],
       [ 1.76438266,  1.87264911],
       [ 0.15208443,  0.23069093],
       [ 0.43660765,  0.31865298],
       [-0.03759771,  0.31865298],
```

```
x_train_scaled = pd.DataFrame(x_train_scaled, columns=x_train.columns)
x_test_scaled = pd.DataFrame(x_test_scaled, columns=x_test.columns)
```

```
x_train.describe()
```

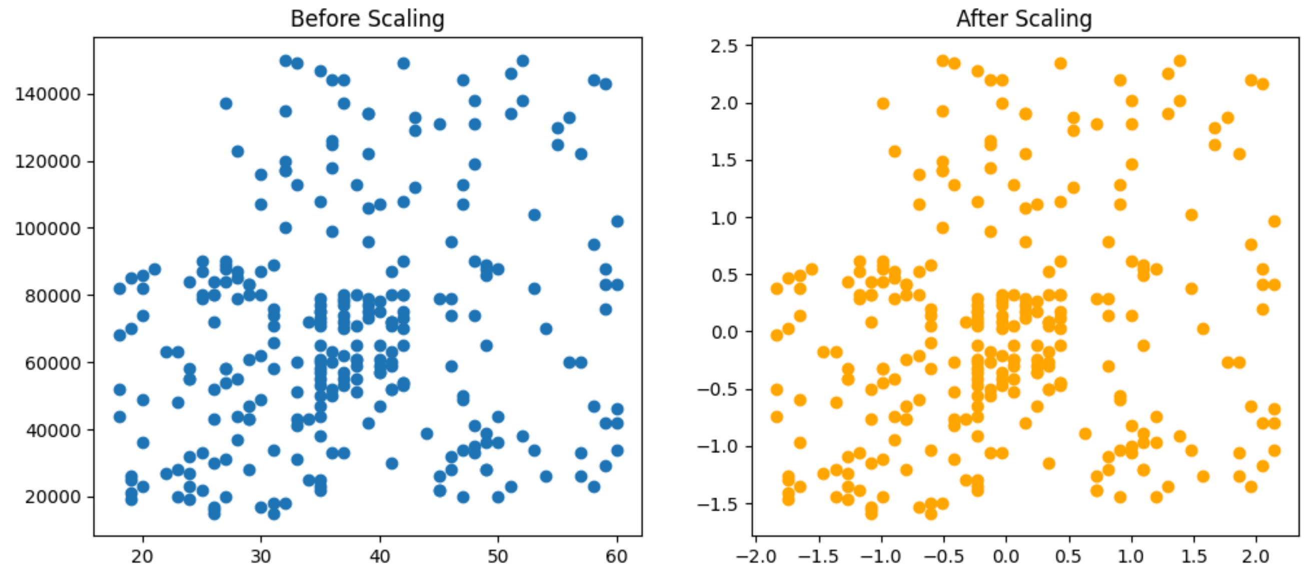
	Age	EstimatedSalary
count	280.000000	280.000000
mean	37.396429	69132.142857
std	10.562834	34166.685587
min	18.000000	15000.000000
25%	29.000000	43000.000000
50%	37.000000	65000.000000
75%	45.000000	86250.000000
max	60.000000	150000.000000

```
x_train_scaled.describe()
```

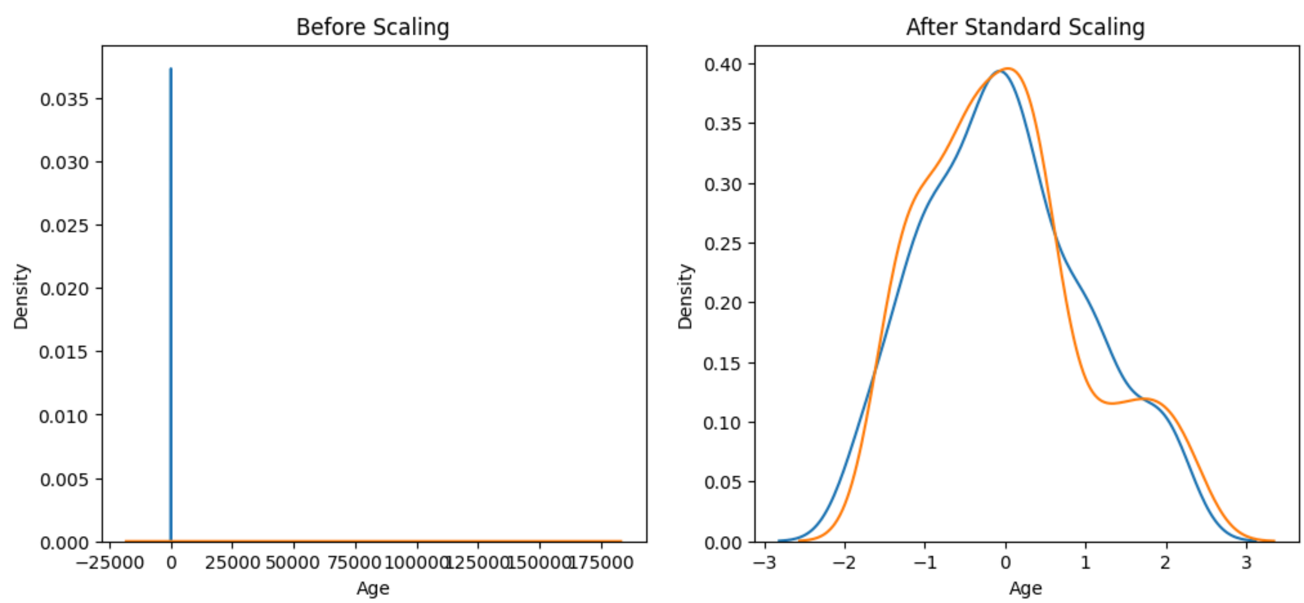
	Age	EstimatedSalary
count	2.800000e+02	2.800000e+02
mean	-9.516197e-17	6.661338e-17
std	1.001791e+00	1.001791e+00
min	-1.839578e+00	-1.587191e+00
25%	-7.963263e-01	-7.662122e-01
50%	-3.759771e-02	-1.211572e-01
75%	7.211309e-01	5.019072e-01
max	2.143747e+00	2.371101e+00

Effect of Scaling

```
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='orange')
ax2.set_title("After Scaling")
plt.show()
```



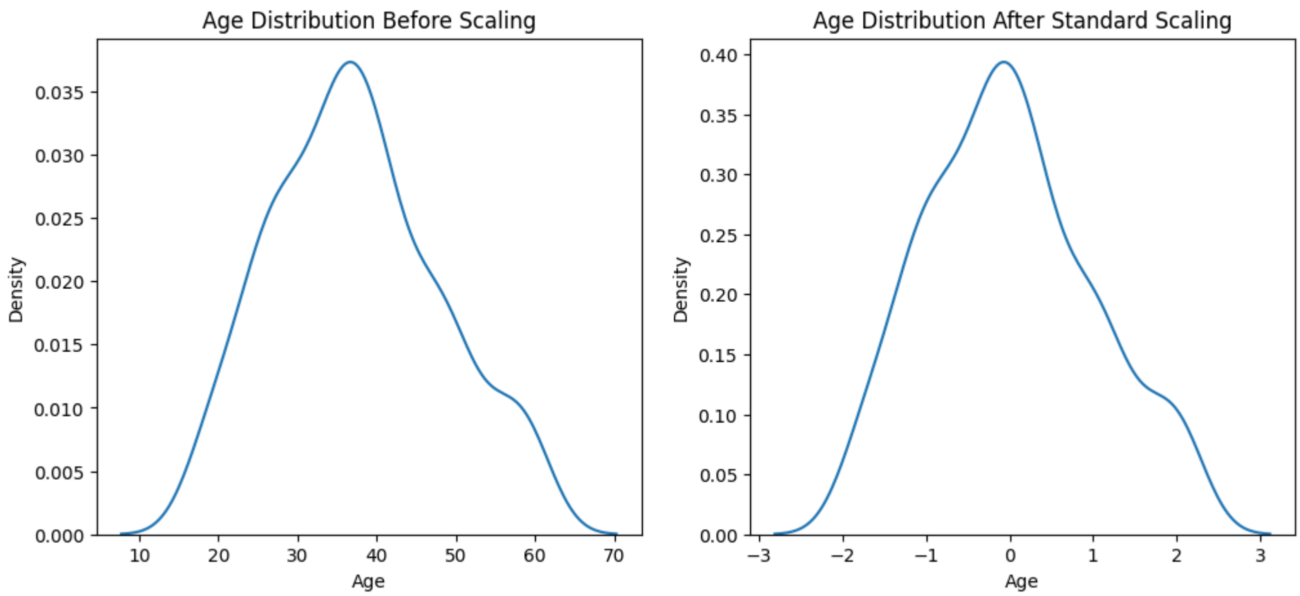

```
fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(12, 5))

# 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()
```



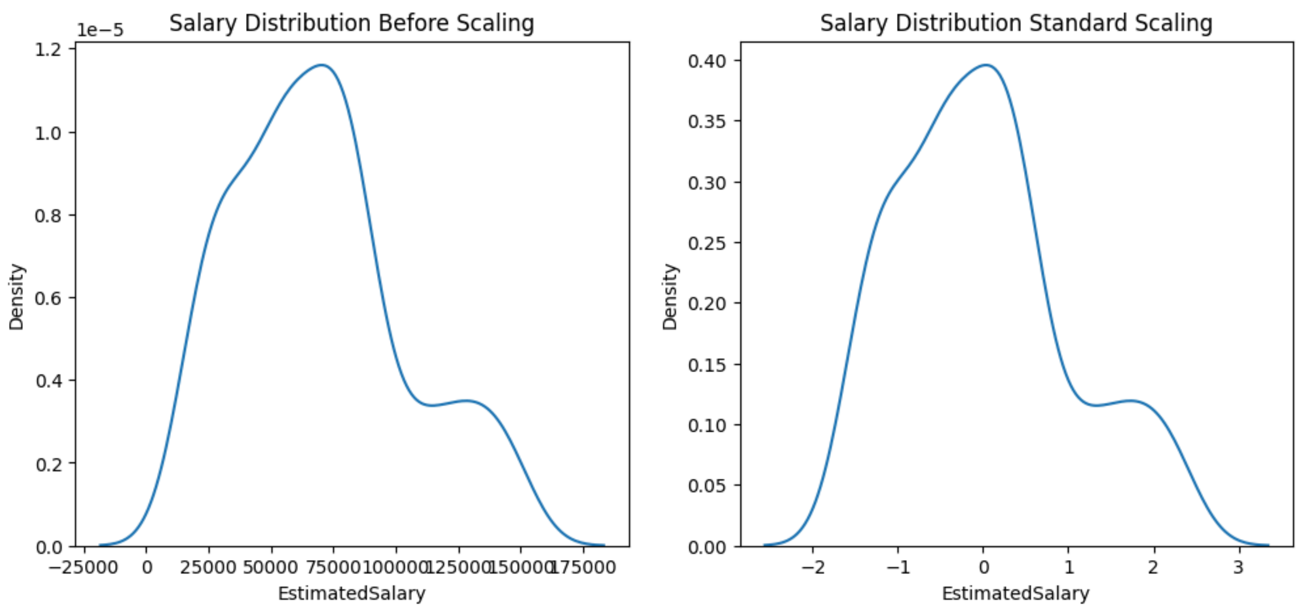
Comparison of Distributions

```
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()
```




```
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()
```



Why scaling is important?

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

```
lr = LogisticRegression()
lr_scaled = LogisticRegression()
```

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

```
▾ LogisticRegression
LogisticRegression()
```

```
y_pred = lr.predict(x_test)
y_pred_scaled = lr_scaled.predict(x_test_scaled)
```

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

```
print("Actual",accuracy_score(y_test,y_pred))
print("Scaled",accuracy_score(y_test,y_pred_scaled))
```

```
Actual 0.7666666666666667
Scaled 0.7833333333333333
```

```
from sklearn.tree import DecisionTreeClassifier
```

```
dt = DecisionTreeClassifier()
dt_scaled = DecisionTreeClassifier()
```

```
dt.fit(x_train,y_train)
dt_scaled.fit(x_train_scaled,y_train)
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

```
y_pred = dt.predict(x_test)
y_pred_scaled = dt_scaled.predict(x_test_scaled)
```

```
print("Actual",accuracy_score(y_test,y_pred))
print("Scaled",accuracy_score(y_test,y_pred_scaled))
```

```
Actual 0.8833333333333333
Scaled 0.8833333333333333
```

```
df.describe()
```

	Age	EstimatedSalary	Purchased
count	400.000000	400.000000	400.000000
mean	37.655000	69742.500000	0.357500
std	10.482877	34096.960282	0.479864
min	18.000000	15000.000000	0.000000
25%	29.750000	43000.000000	0.000000
50%	37.000000	70000.000000	0.000000
75%	46.000000	88000.000000	1.000000
max	60.000000	150000.000000	1.000000

Effect of Outlier

```
df = df.append(pd.DataFrame({'Age':[5,90,95],'EstimatedSalary':[1000,250000,350000],'Purchased':[0,1,1]}),ignore_index=True)
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
/tmp/ipython-input-2365817244.py in <cell line: 0>()
----> 1 df = df.append(pd.DataFrame({'Age':[5,90,95],'EstimatedSalary':[1000,250000,350000],'Purchased':
[0,1,1]}),ignore_index=True)

/usr/local/lib/python3.12/dist-packages/pandas/core/generic.py in __getattr__(self, name)
   6297         ):
   6298             return self[name]
-> 6299         return object.__getattribute__(self, name)
   6300
   6301     @final

AttributeError: 'DataFrame' object has no attribute 'append'
```

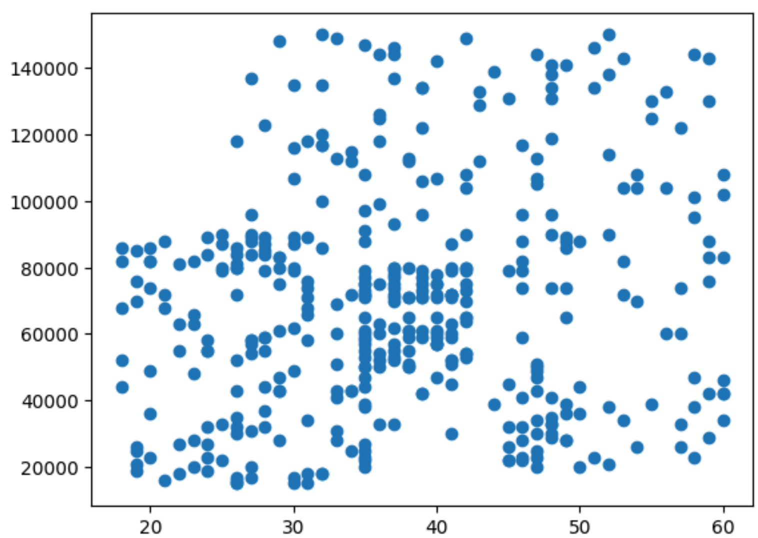
```
df
```

	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

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

```
<matplotlib.collections.PathCollection at 0x7fc69994f5f0>
```




```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df.drop('Purchased', axis=1),
                                                    df['Purchased'],
                                                    test_size=0.3,
                                                    random_state=0)

X_train.shape, X_test.shape
```

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

```
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)
```

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

```
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()
```