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main

100-days-of-machine-learning / day24-standardization / day24.ipynb

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1 contributor

1318 lines (1318 sloc) 221 KB

In [42]:
```
import numpy as np # linear algebra
import pandas as pd # data processing
import matplotlib.pyplot as plt
import seaborn as sns
```

In [43]:
```
df = pd.read_csv('Social_Network_Ads.csv')
```

In [44]:
```
df=df.iloc[:,2:]
```

In [45]:
```
df.sample(5)
```

Out[45]:

| | Age | EstimatedSalary | Purchased |
|---|---|---|---|
| **137** | 30 | 107000 | 1 |
| **251** | 37 | 52000 | 0 |
| **262** | 55 | 125000 | 1 |
| **144** | 34 | 25000 | 0 |
| **292** | 55 | 39000 | 1 |

# Train test split

In [46]:
```
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
```

Out[46]:
```
((280, 2), (120, 2))
```

# StandardScaler

In [47]:
```
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 [48]:
```
scaler.mean_
```

Out[48]: array([3.78642857e+01, 6.98071429e+04])

In [49]:
```
X_train
```

Out[49]:

| | 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 [52]:
```
X_train_scaled
```

Out[52]:

| | Age | EstimatedSalary |
|---|---|---|
| **0** | -1.163172 | -1.584970 |
| **1** | 2.170181 | 0.930987 |
| **2** | 0.013305 | 1.220177 |
| **3** | 0.209385 | 1.075582 |
| **4** | 0.405465 | -0.486047 |
| **...** | ... | ... |
| **275** | 0.993704 | -1.151185 |
| **276** | -0.869053 | -0.775237 |
| **277** | -0.182774 | -0.514966 |
| **278** | -1.065133 | -0.457127 |
| **279** | -1.163172 | 1.393691 |

280 rows × 2 columns

In [51]:

```
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 [9]:

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

Out[9]:

| | 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 [10]:

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

Out[10]:

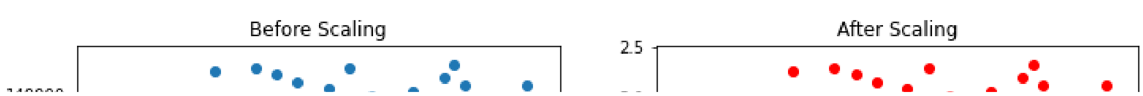
| | Age | EstimatedSalary |
|---|---|---|
| **count** | 280.0 | 280.0 |
| **mean** | 0.0 | 0.0 |
| **std** | 1.0 | 1.0 |
| **min** | -1.9 | -1.6 |
| **25%** | -0.8 | -0.8 |
| **50%** | -0.1 | 0.0 |
| **75%** | 0.8 | 0.5 |
| **max** | 2.2 | 2.3 |

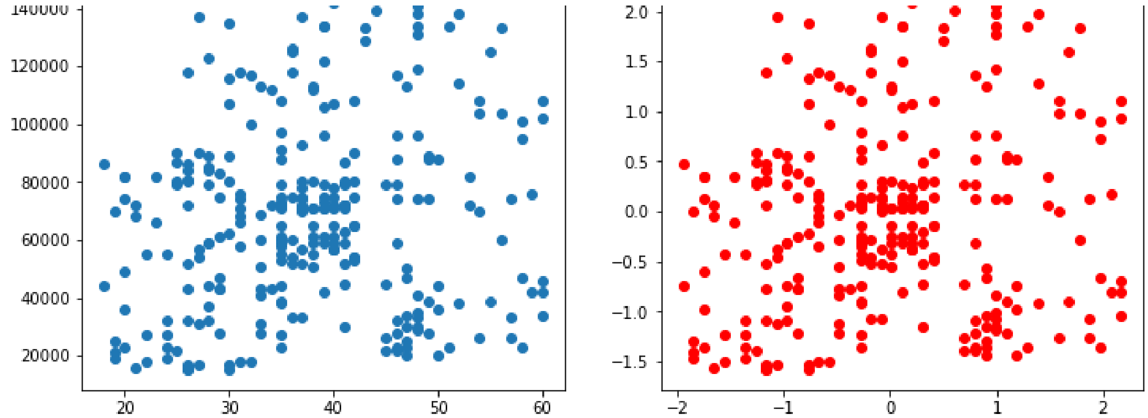
# Effect of Scaling

In [11]:

```
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()
```



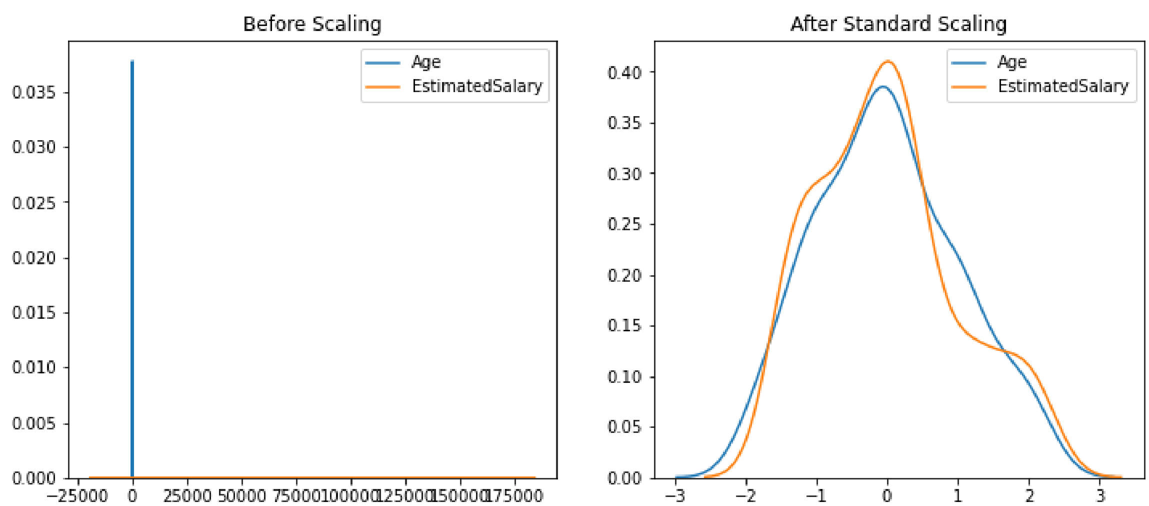


In [12]:

```
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()
```



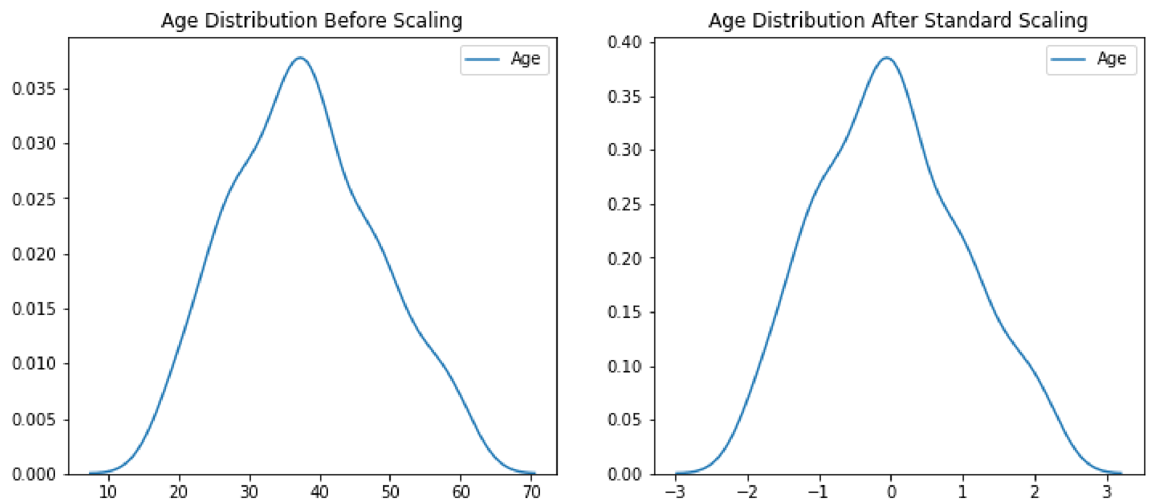

# Comparison of Distributions

In [13]:

```
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()
```

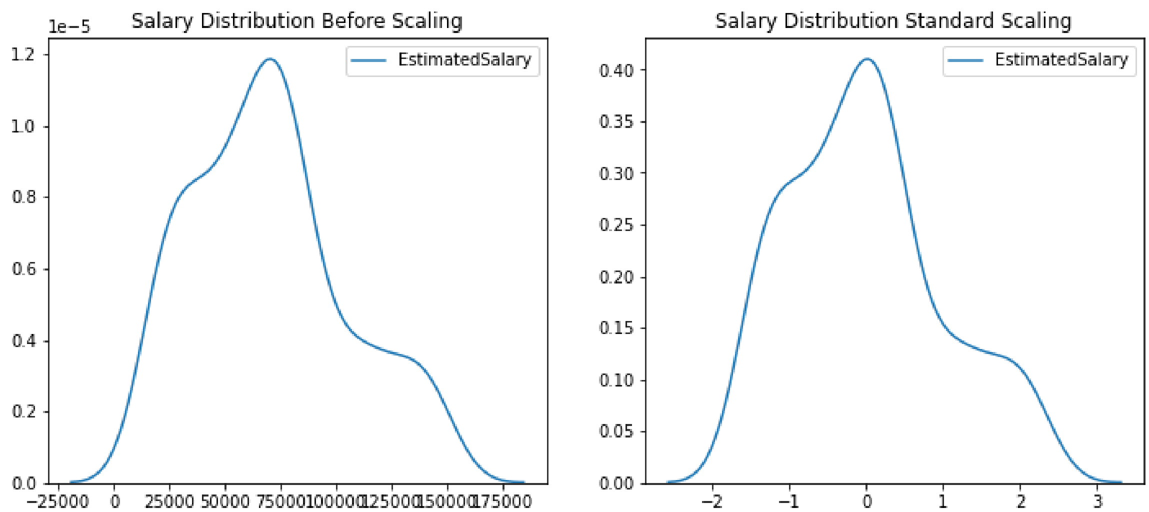



In [14]:

```
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?

In [15]:

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

In [17]:

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

In [18]:

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

```
lr_scaled.fit(X_train_scaled,y_train)
```

Out[18]: LogisticRegression()

In [20]:
```
y_pred = lr.predict(X_test)
y_pred_scaled = lr_scaled.predict(X_test_scaled)
```

In [21]:
```
from sklearn.metrics import accuracy_score
```

In [22]:
```
print("Actual",accuracy_score(y_test,y_pred))
print("Scaled",accuracy_score(y_test,y_pred_scaled))
```

```
Actual 0.6583333333333333
Scaled 0.8666666666666667
```

In [23]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [24]:
```
dt = DecisionTreeClassifier()
dt_scaled = DecisionTreeClassifier()
```

In [25]:
```
dt.fit(X_train,y_train)
dt_scaled.fit(X_train_scaled,y_train)
```

Out[25]: DecisionTreeClassifier()

In [26]:
```
y_pred = dt.predict(X_test)
y_pred_scaled = dt_scaled.predict(X_test_scaled)
```

In [27]:
```
print("Actual",accuracy_score(y_test,y_pred))
print("Scaled",accuracy_score(y_test,y_pred_scaled))
```

```
Actual 0.875
Scaled 0.875
```

In [29]:
```
df.describe()
```

Out[29]:

| | 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

In [34]:
```
df = df.append(pd.DataFrame({'Age':[5,90,95],'EstimatedSalary':[1000,250000,350
```

In [32]:
```
df
```

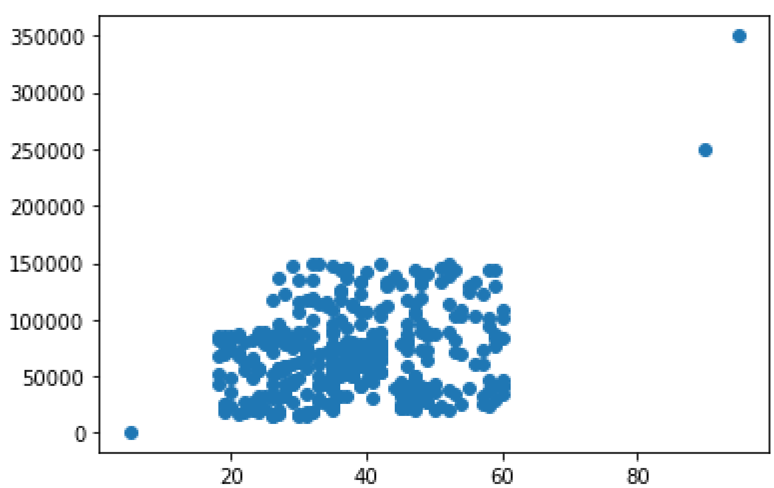
Out[32]:

| | 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 [36]:
```
plt.scatter(df['Age'], df['EstimatedSalary'])
```

Out[36]:




In [37]:
```
from sklearn.model_selection import train_test_split
```

```
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
```

Out[37]: ((282, 2), (121, 2))

In [38]:

```
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)
```

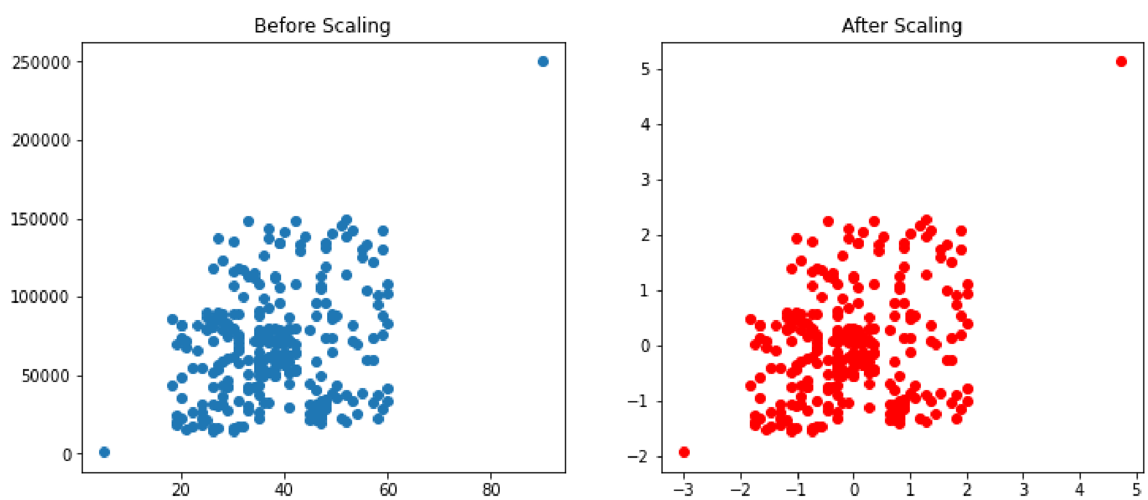
In [40]:

```
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 [41]:

```
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 [ ]: