In [2]:
```
#Name:Pawar ved balasaheb(T512037)
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [4]:
```
df = pd.read_csv("Mall_Customers.csv")
```

In [6]:
```
df.head()
```

Out[6]:

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

In [8]:
```
df.tail()
```

Out[8]:

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

In [10]:
```
df.shape
```

Out[10]:
```
(200, 5)
```

In [12]:
```
df.columns
```

Out[12]:
```
Index(['CustomerID', 'Genre', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

In [14]:
```
df.drop("CustomerID",axis=1,inplace=True)
```

In [16]:
```
df
```

Out[16]:

	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	Male	19	15	39
1	Male	21	15	81
2	Female	20	16	6
3	Female	23	16	77
4	Female	31	17	40
...	...	...	...	...
195	Female	35	120	79
196	Female	45	126	28
197	Male	32	126	74
198	Male	32	137	18
199	Male	30	137	83

200 rows × 4 columns

In [18]:
```
print("Missing values:")
df.isnull().sum()
```

```
Missing values:
```

Out[18]:
```
Genre                     0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

In [20]:
```
df.describe()
```

Out[20]:

	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000
mean	38.850000	60.560000	50.200000
std	13.969007	26.264721	25.823522
min	18.000000	15.000000	1.000000
25%	28.750000	41.500000	34.750000
50%	36.000000	61.500000	50.000000
75%	49.000000	78.000000	73.000000
max	70.000000	137.000000	99.000000

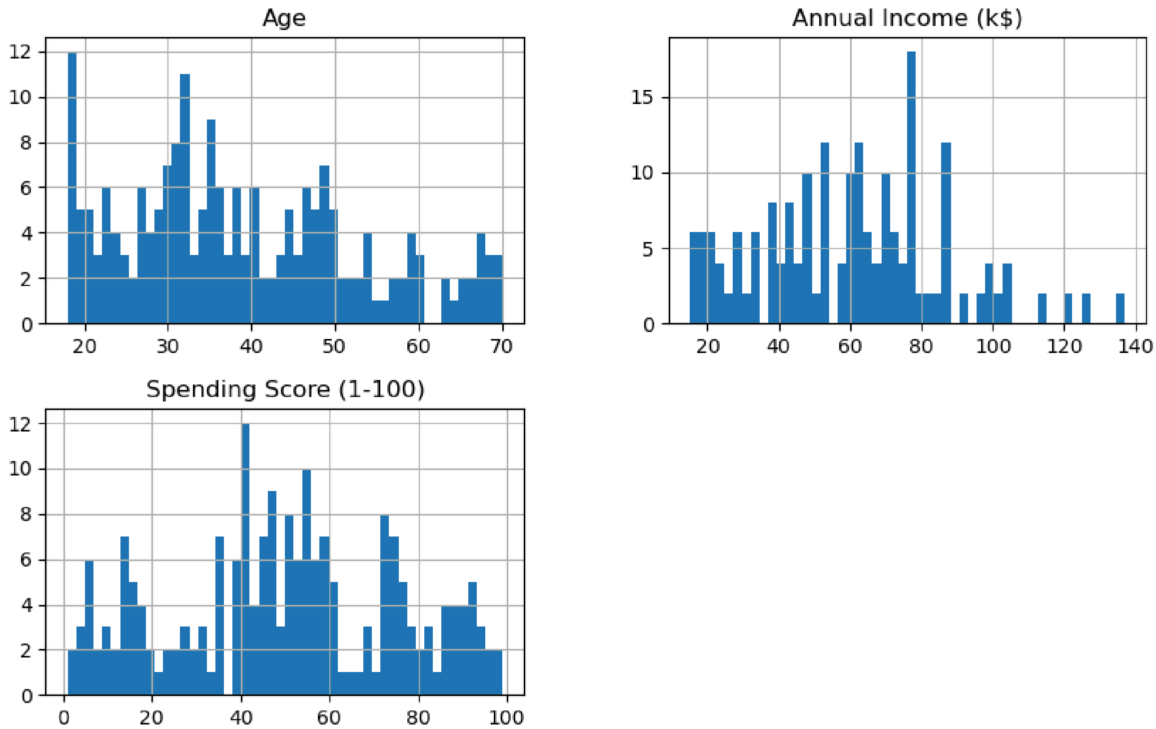
In [22]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Genre                   200 non-null    object
 1   Age                     200 non-null    int64
 2   Annual Income (k$)      200 non-null    int64
 3   Spending Score (1-100)  200 non-null    int64
dtypes: int64(3), object(1)
memory usage: 6.4+ KB
```

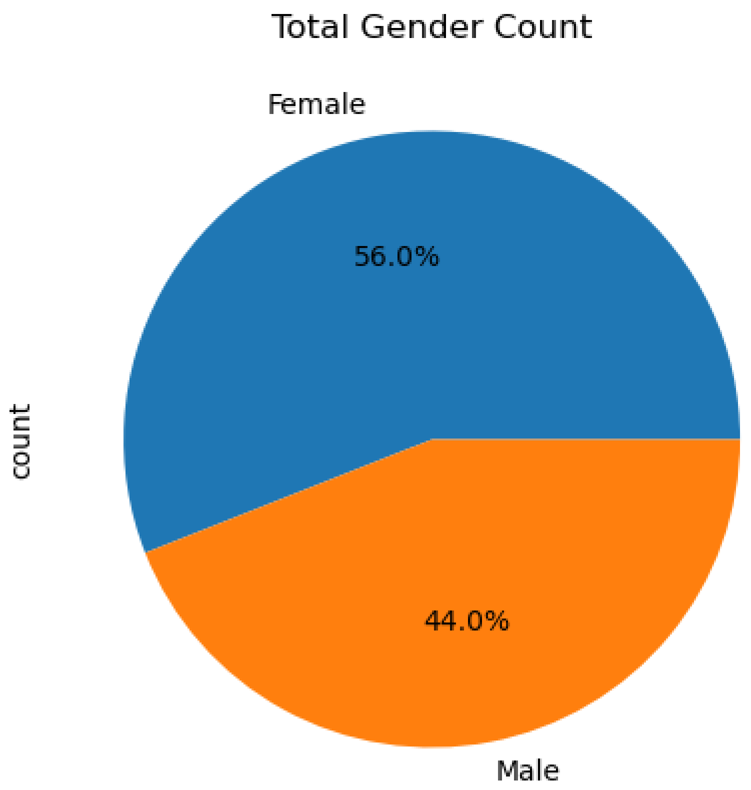
In [24]:
```python
df.nunique()
```

Out[24]:
```
Genre                      2
Age                       51
Annual Income (k$)        64
Spending Score (1-100)    84
dtype: int64
```

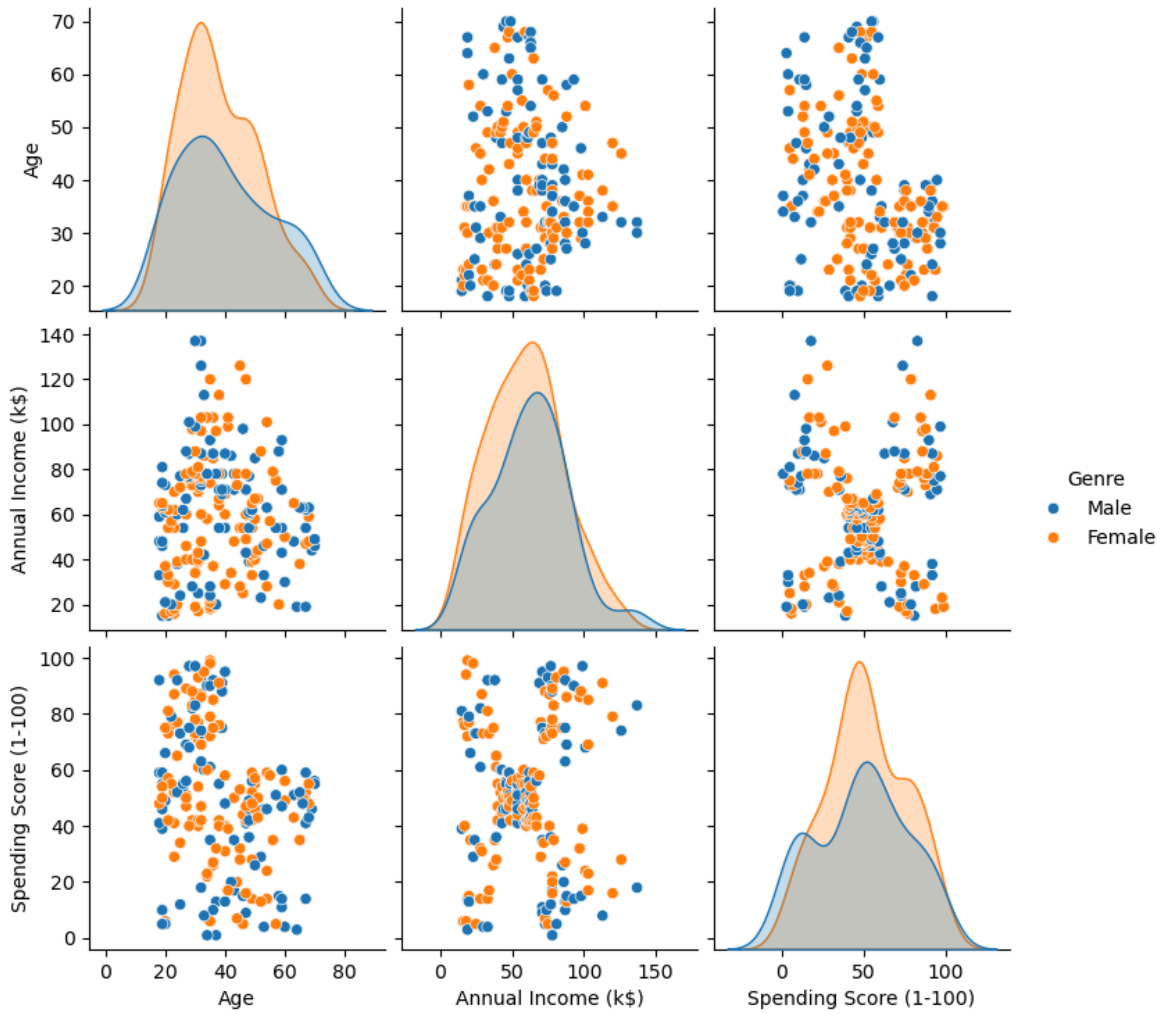
In [34]:
```python
df.hist(bins = 50,figsize = (10,6));
```



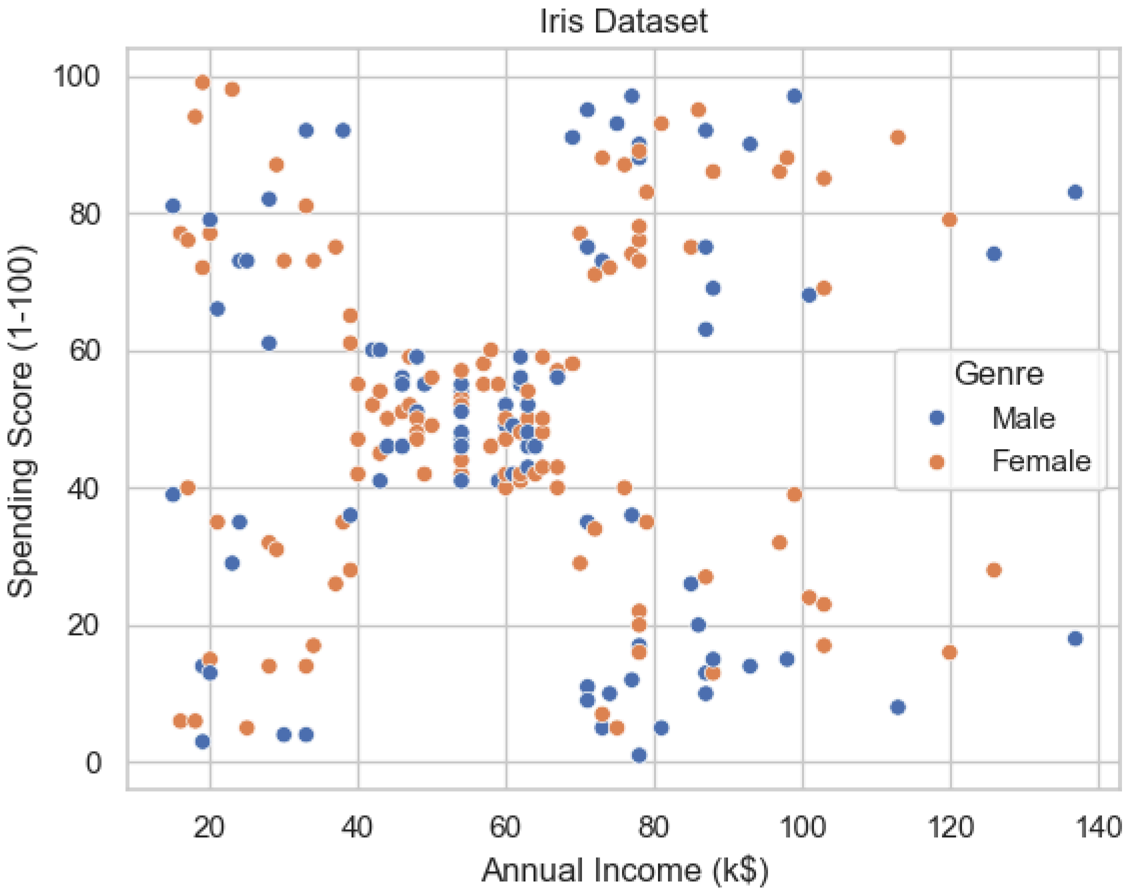
In [36]:
```python
df['Genre'].value_counts().plot(kind='pie',figsize=(5,5),autopct='%1.1f%%')
plt.title("Total Gender Count")
plt.show()
```



In [38]:
```
sns.pairplot(df,hue="Genre");
```



In [40]:
```
sns.set(style = 'whitegrid')
sns.scatterplot(y = 'Spending Score (1-100)',x ='Annual Income (k$)',data = df,h
plt.title('Iris Dataset')
plt.show()
```



In [42]:
```
# LabelEncoder for encoding binary categories in a column
from sklearn.preprocessing import LabelEncoder
from sklearn import metrics
le = LabelEncoder()
# One single vector so it is ovbious what we want to encode
df["Genre"] = le.fit_transform(df["Genre"])
```

In [44]:
```
df
```

Out[44]:

	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1	19	15	39
1	1	21	15	81
2	0	20	16	6
3	0	23	16	77
4	0	31	17	40
...	...	...	...	...
195	0	35	120	79
196	0	45	126	28
197	1	32	126	74
198	1	32	137	18
199	1	30	137	83

200 rows × 4 columns

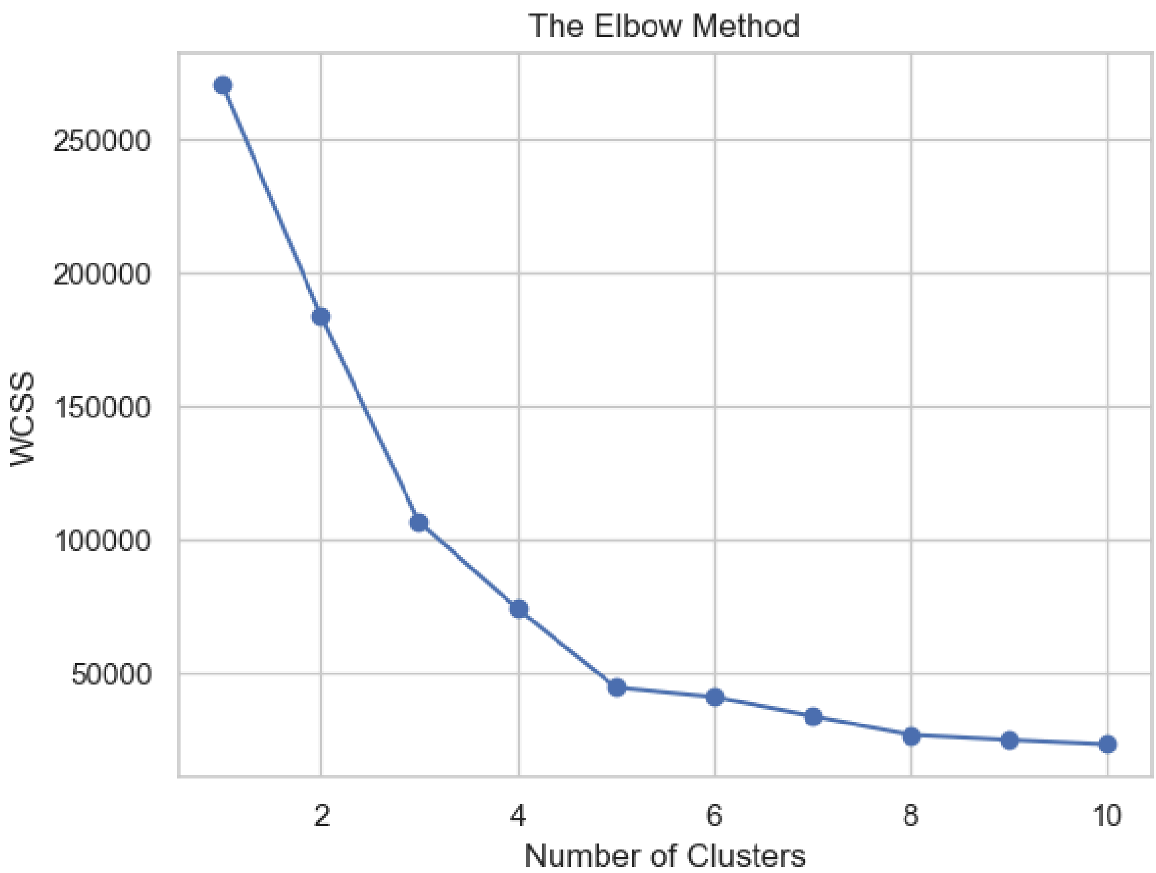
In [46]:

```
# Finding the optimum number of clusters using k-means
data = df.copy()
x = data.iloc[:,[2,3]]

#importing Kmean model
from sklearn.cluster import KMeans
wcss = []
for i in range(1,11):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(x)
    # appending the WCSS to the list
    #(kmeans.inertia_ returns the WCSS value for an initialized cluster)
    wcss.append(kmeans.inertia_)
    print('k:',i ,"-> wcss:",kmeans.inertia_)
```

```
k: 1 -> wcss: 269981.28
k: 2 -> wcss: 183653.32894736837
k: 3 -> wcss: 106348.37306211118
k: 4 -> wcss: 73880.64496247197
k: 5 -> wcss: 44448.45544793371
k: 6 -> wcss: 40825.16946386946
k: 7 -> wcss: 33642.579220779226
k: 8 -> wcss: 26686.83778518779
k: 9 -> wcss: 24766.47160979344
k: 10 -> wcss: 23103.122085983916
```

In [48]:

```
# Plotting the results onto a line graph, allowing us to observe 'The elbow'

plt.plot(range(1,11),wcss,marker='o')
plt.title('The Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()
```

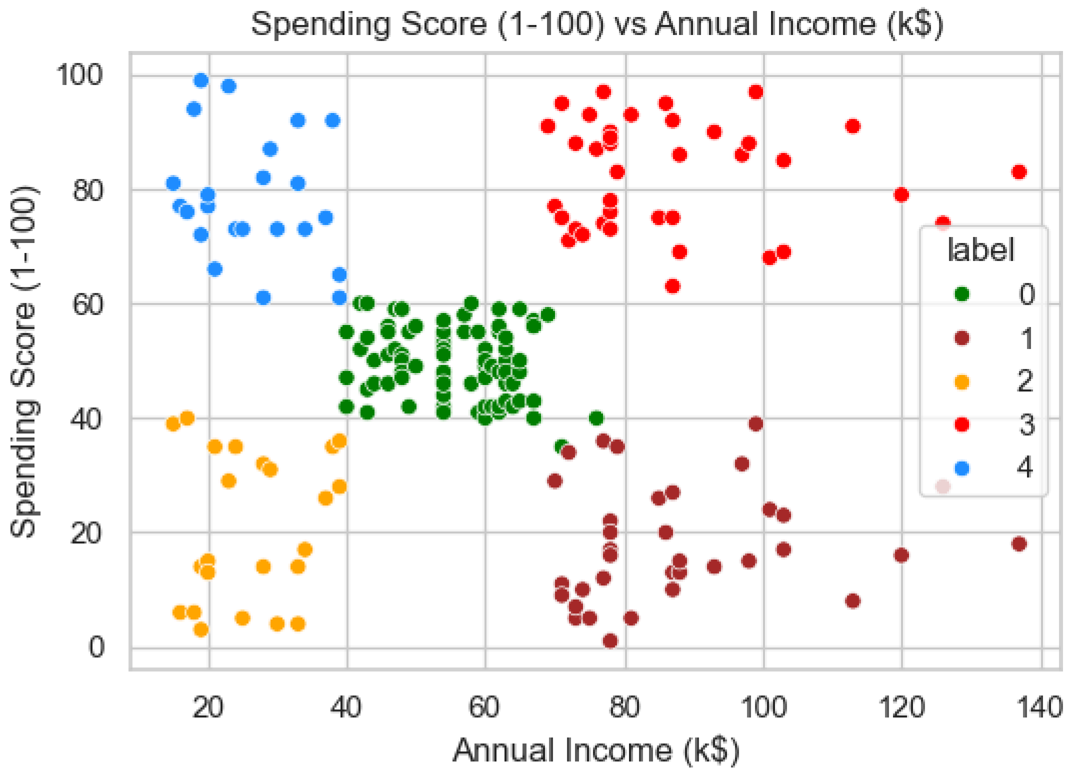


In [50]:
```
#Taking 5 clusters
km1=KMeans(n_clusters=5)
#Fitting the input data
km1.fit(data)
#predicting the labels of the input data
y=km1.predict(data)
#adding the labels to a column named label
data["label"] = y
#The new dataframe with the clustering done
data.head()
```

Out[50]:

	Genre	Age	Annual Income (k$)	Spending Score (1-100)	label
0	1	19	15	39	2
1	1	21	15	81	4
2	0	20	16	6	2
3	0	23	16	77	4
4	0	31	17	40	2

In [52]:
```
#Scatterplot of the clusters
plt.figure(figsize=(6,4))
sns.scatterplot(x = 'Annual Income (k$)',y = 'Spending Score (1-100)',hue="label
                 palette=['green','brown','orange','red','dodgerblue'],data = da
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.title('Spending Score (1-100) vs Annual Income (k$)')
plt.show()
```



In [54]:
```
X=data.iloc[:,:4]
y=data.iloc[:,-1]
```

In [56]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Shape of train Test Split
print(X_train.shape,y_train.shape)
print(X_test.shape,y_test.shape)
```

```
(160, 4) (160,)
(40, 4) (40,)
```

In [58]:
```
from sklearn.cluster import KMeans
km=KMeans(n_clusters=5)
km.fit(X_train)

#predicting the target value from the model for the samples
y_train_km = km.predict(X_train)
y_test_km = km.predict(X_test)
```

In [60]:
```
from sklearn.metrics.cluster import adjusted_rand_score

acc_train_gmm = adjusted_rand_score(y_train,y_train_km)
acc_test_gmm = adjusted_rand_score(y_test,y_test_km)

print("K mean : Accuracy on training Data: {:.3f}".format(acc_train_gmm))
print("K mean : Accuracy on test Data: {:.3f}".format(acc_test_gmm))
```

```
K mean : Accuracy on training Data: 0.965
K mean : Accuracy on test Data: 0.912
```

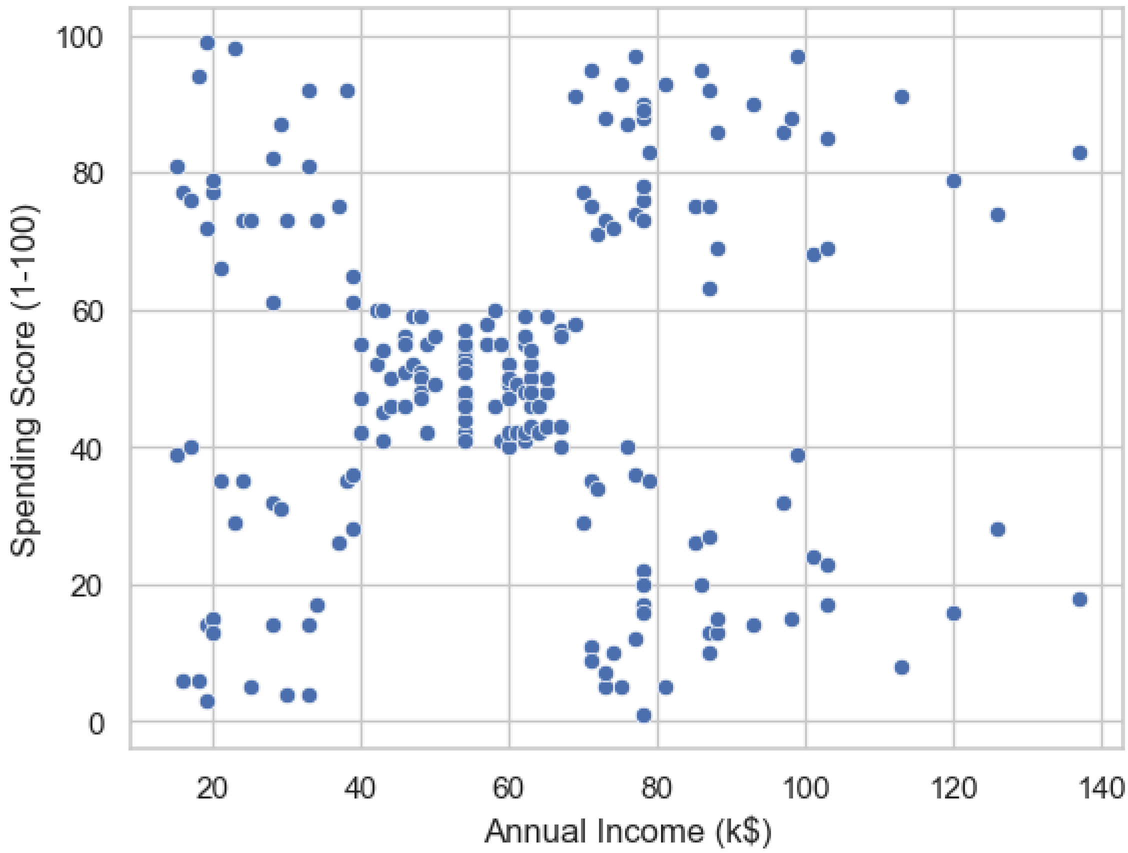
In [62]:
```
data = df.copy()
data = data.iloc[:,[2,3]]
data
```

Out[62]:

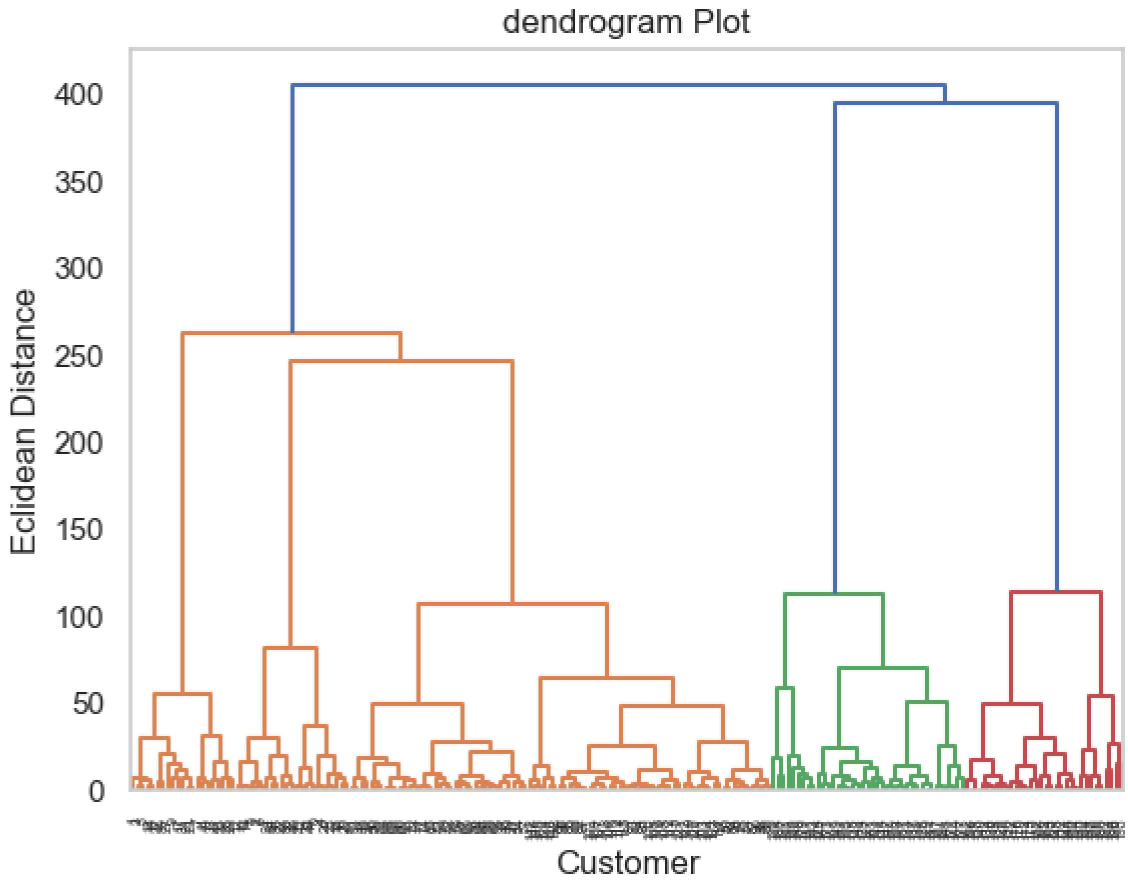
	Annual Income (k$)	Spending Score (1-100)
0	15	39
1	15	81
2	16	6
3	16	77
4	17	40
...	...	...
195	120	79
196	126	28
197	126	74
198	137	18
199	137	83

200 rows × 2 columns

In [64]:
```
sns.scatterplot(x="Annual Income (k$)",y="Spending Score (1-100)",data = data );
```



In [66]:
```
import scipy.cluster.hierarchy as shc
dendrogram = shc.dendrogram(shc.linkage(data,method="ward"))
plt.title("dendrogram Plot")
plt.xlabel("Customer")
plt.ylabel("Eclidean Distance")
plt.grid(False)
```



In [68]:
```
from sklearn.cluster import AgglomerativeClustering
agc = AgglomerativeClustering(n_clusters=5)
data["label"] = agc.fit_predict(data)
data
```

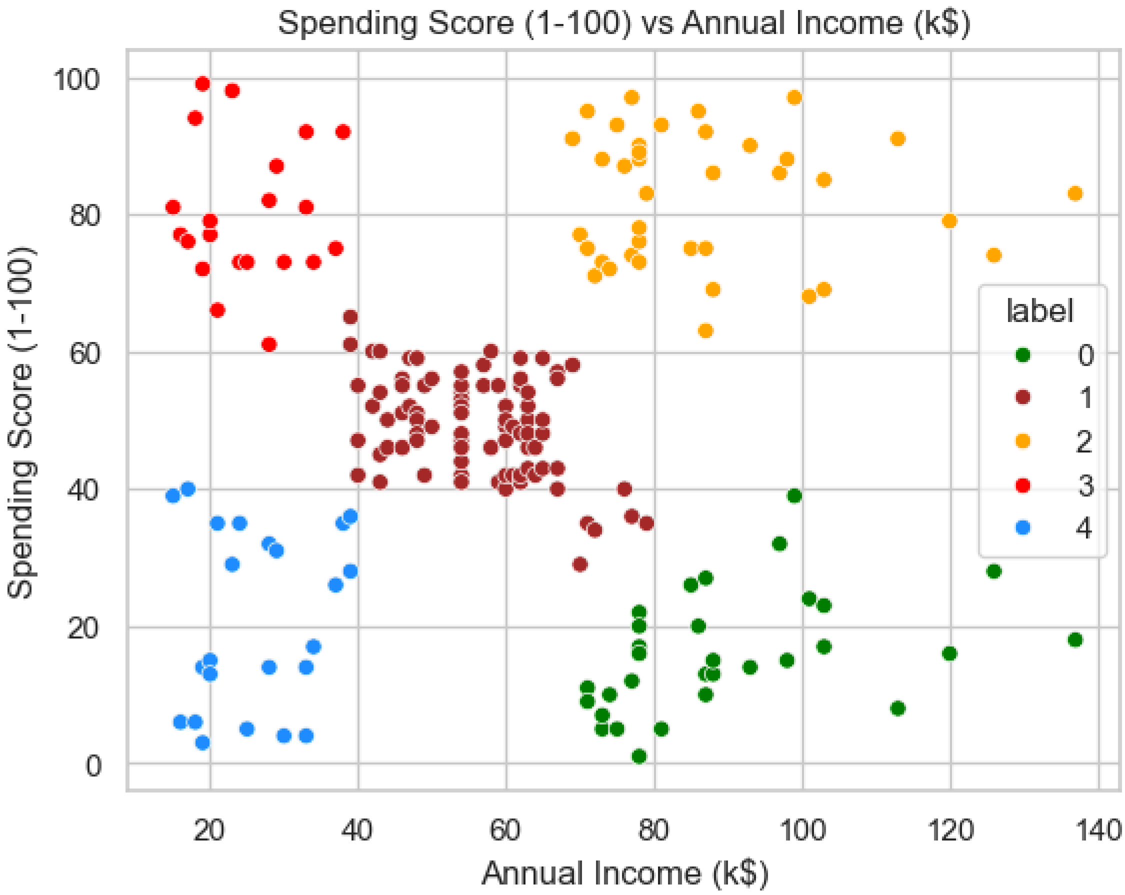
Out[68]:

	Annual Income (k$)	Spending Score (1-100)	label
0	15	39	4
1	15	81	3
2	16	6	4
3	16	77	3
4	17	40	4
...	...	...	...
195	120	79	2
196	126	28	0
197	126	74	2
198	137	18	0
199	137	83	2

200 rows × 3 columns

In [70]:
```
#Scatterplot of the clusters
sns.scatterplot(x = 'Annual Income (k$)',y = 'Spending Score (1-100)',hue="label
```

```
                 palette=['green','brown','orange','red','dodgerblue'],data = da
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.title('Spending Score (1-100) vs Annual Income (k$)')
plt.show()
```




```
In [ ]:
```