Project Description

What is Customer Segmentation?

-> Customer segmentation is the process of identifying different groups of customers based on the category they belong such as demographics or behaviors so that the sales/marketing team can reach out to those specific customers effectively.

-> When you perform customer segmentation, you find similar characteristics in each customer's behaviour and needs. Then, those are generalized into

groups to satisfy demands with various strategies. Moreover, those strategies can be an input of the:

i) Focused marketing efforts on particular demographics

ii) Iintroduction of features in line with user deman

iii) Creation of the product roadmapap

We are going perform segmentation by using the following algorithms

i) K-means

iii) DBSCAN (Density Based Spatial Clustering of Applications with Noise)

Primary goal to help data supermarket increase their business by getting more memberships.

for this we will try and explore different clustering techniques and perform a customer segmentation. That is nothing but identifying and making groups based on some

similar characteristics of customer preferences and purchasing history and allow companies to market to each gorup more efficiently.

We shall further develop some clustering models to gain better understandidng of the type of the customer.

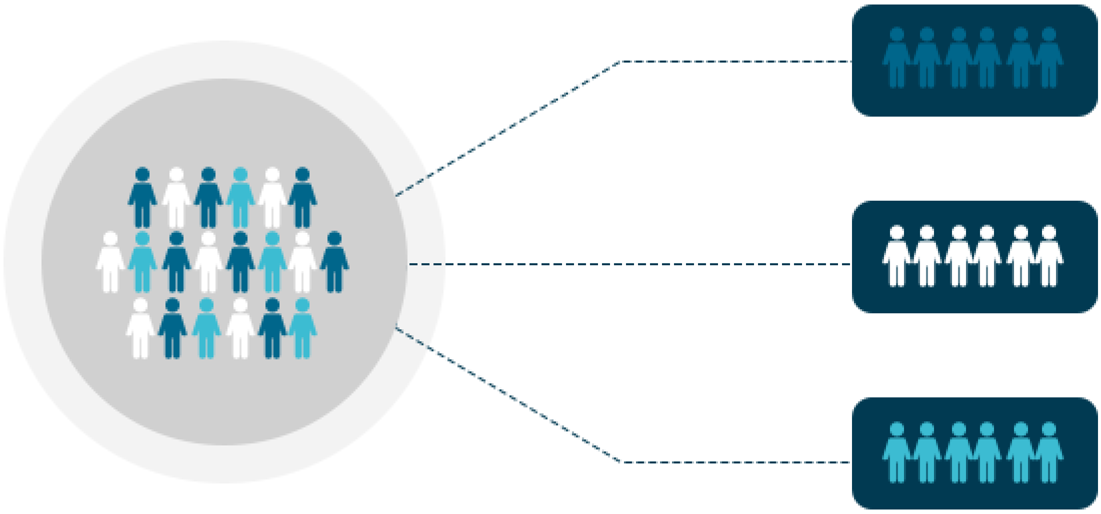
This includes clustering algorithms such as K-means and DBSCAN.

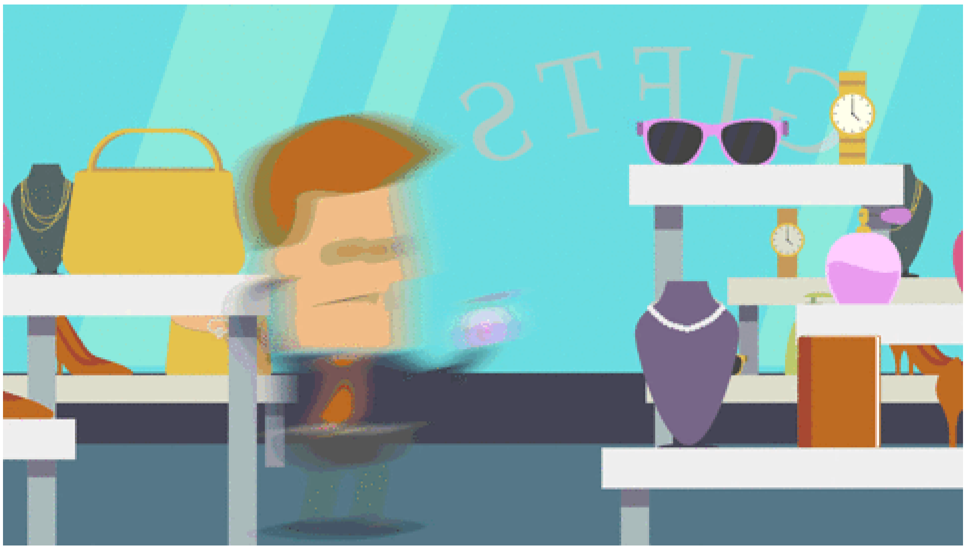
Data Overview

The data consists of 200 customers with information related to their age, gender, annual income, and spending score.

The spending score is a numeric variable ranging from 1 to 100 and was assigned to customers based on behavior parameters and purchasing data.

The data set also contains the customer's ID. which will be dropped before beginning





Let us now import some python libraries that required to perform further analysis

In [1]:
```
import os, warnings
warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
import plotly.figure_factory as ff
from plotly.subplots import make_subplots
from plotly.offline import plot, iplot, init_notebook_mode
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN
```

In [2]:
```
cust_data = pd.read_csv('/Users/aumkarringe/Documents/Data Clustering/
cust_data.head(20)
```

Out[2]:

	CustomerID	Gender	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
5	6	Female	22	17	76
6	7	Female	35	18	6
7	8	Female	23	18	94
8	9	Male	64	19	3
9	10	Female	30	19	72
10	11	Male	67	19	14
11	12	Female	35	19	99
12	13	Female	58	20	15
13	14	Female	24	20	77
14	15	Male	37	20	13
15	16	Male	22	20	79
16	17	Female	35	21	35
17	18	Male	20	21	66
18	19	Male	52	23	29
19	20	Female	35	23	98

Data Summary

In [3]:
```
#.shpae function returns the dimensions for the given dataset i.e. num
# In following case we have 200 rows and 5 columns
cust_data.shape
```

Out[3]: (200, 5)

In [4]:
```
# this method is used to get a statistical overview of the dataset it
cust_data.describe()
```

Out[4]:

	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000	200.000000
mean	100.500000	38.850000	60.560000	50.200000
std	57.879185	13.969007	26.264721	25.823522
min	1.000000	18.000000	15.000000	1.000000
25%	50.750000	28.750000	41.500000	34.750000
50%	100.500000	36.000000	61.500000	50.000000
75%	150.250000	49.000000	78.000000	73.000000
max	200.000000	70.000000	137.000000	99.000000

In [5]:
```
cust_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   CustomerID              200 non-null    int64 
 1   Gender                  200 non-null    object
 2   Age                     200 non-null    int64 
 3   Annual Income (k$)      200 non-null    int64 
 4   Spending Score (1-100)  200 non-null    int64 
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

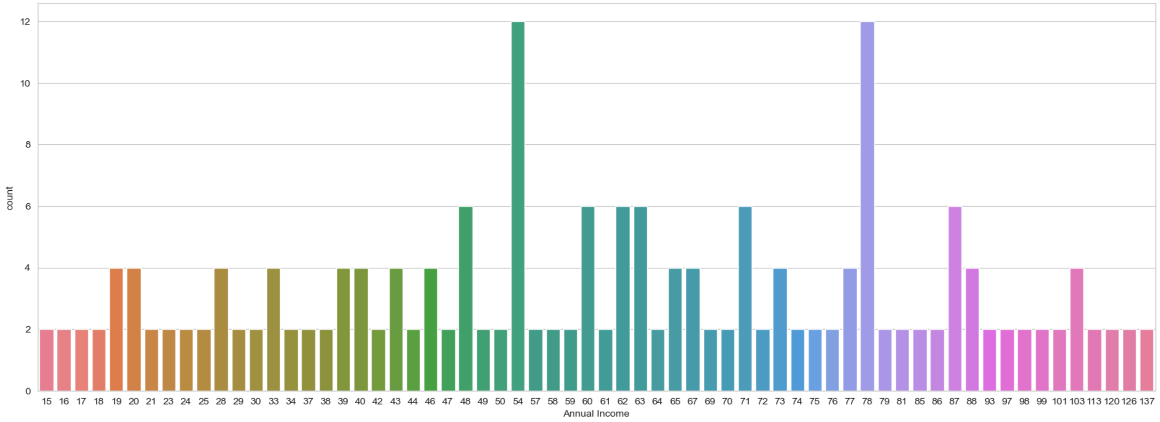
In [6]:
```
#Here we are checking if there are any null values in the dataset.
cust_data.isnull().values.any()
```

Out[6]:
```
False
```

In [7]:
```
cust_data.rename(columns={"Annual Income (k$)": "Annual Income", "Sper
```

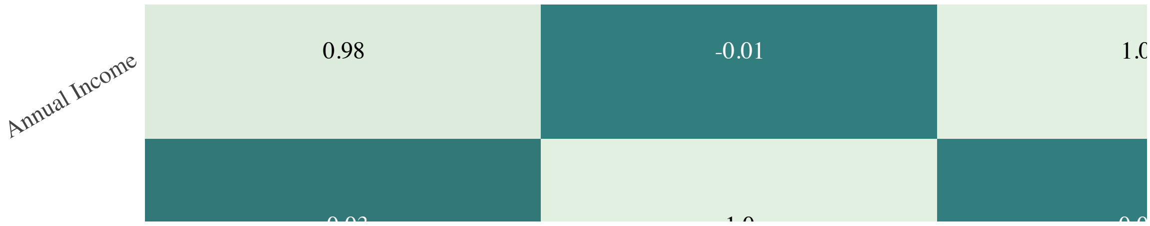
EDA (Exploratory Data Analysis)

In [8]:
```
# Here we are counting the number of customers based on their annual i

sns.set_style('whitegrid')
plt.figure(figsize=(20, 7))
sns.countplot(x="Annual Income", data=cust_data, palette='husl');
```



In [9]:
```
import pandas as pd
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import plotly.figure_factory as ff

# Assuming cust_data is your DataFrame containing customer data

# Modify cust_data to convert 'Annual Income' to dollars
cust_data['Annual Income'] = cust_data['Annual Income'].mul(1000)

# Grouping data for plots
p1 = cust_data.groupby('Gender')['Age'].mean().round(0).astype(int).re
p2 = cust_data.groupby('Gender')['Annual Income'].mean().reset_index()
p3 = cust_data.groupby('Gender')['Spending Score'].mean().round(0).ast

# Creating a layout template
temp = dict(layout=go.Layout(font=dict(family="Franklin Gothic", size=

# Creating subplots
fig = make_subplots(rows=3, cols=2,
                    subplot_titles=("Distribution of Age by Gender",
                                    "Customers Average Age",
                                    "Distribution of Income by Gender"
                                    "Customers Average Income",
                                    "Distribution of Spending by Gende
                                    "Customers Average Spending")
                   )

# Adding histograms for age distribution by gender
fig.add_trace(go.Histogram(x=cust_data[cust_data.Gender == 'Male']['Ag
                           marker=dict(color='#508B8D', opacity=0.7, l
                           nbinsx=20, name="Men"),
              row=1, col=1)
fig.add_trace(go.Histogram(x=cust_data[cust_data.Gender == 'Female']['
                           marker=dict(color='#F3D6CB', opacity=0.7, l
                           nbinsx=20, name="Women"),
              row=1, col=1)

# Adding bar chart for average age by gender
fig.add_trace(go.Bar(x=p1['Gender'], y=p1['Age'], text=p1['Age'], text
                     marker=dict(color=['#508B8D', '#F0CABD'], opacity
                     hovertemplate='Average Age Among %{x} = %{y} year
              row=1, col=2)

# Adding histograms for income distribution by gender
fig.add_trace(go.Histogram(x=cust_data[cust_data.Gender == 'Male']['Ar
                           marker=dict(color='#508B8D', line=dict(widt
                           opacity=0.7, name="Men", nbinsx=20, showleg
              row=2, col=1)
fig.add_trace(go.Histogram(x=cust_data[cust_data.Gender == 'Female']['
                           marker=dict(color='#F3D6CB', line=dict(widt
                           opacity=0.7, name="Women", nbinsx=20, showl
              row=2, col=1)

# Adding bar chart for average income by gender
fig.add_trace(go.Bar(x=p2['Gender'], y=p2['Annual Income'], text=p2['A
                     texttemplate='$%{text:,.0f}', textposition='outsi
                     marker=dict(color=['#508B8D', '#F0CABD'], opacity
                     hovertemplate='Average Income Among %{x} = $%{y}<
              row=2, col=2)
```

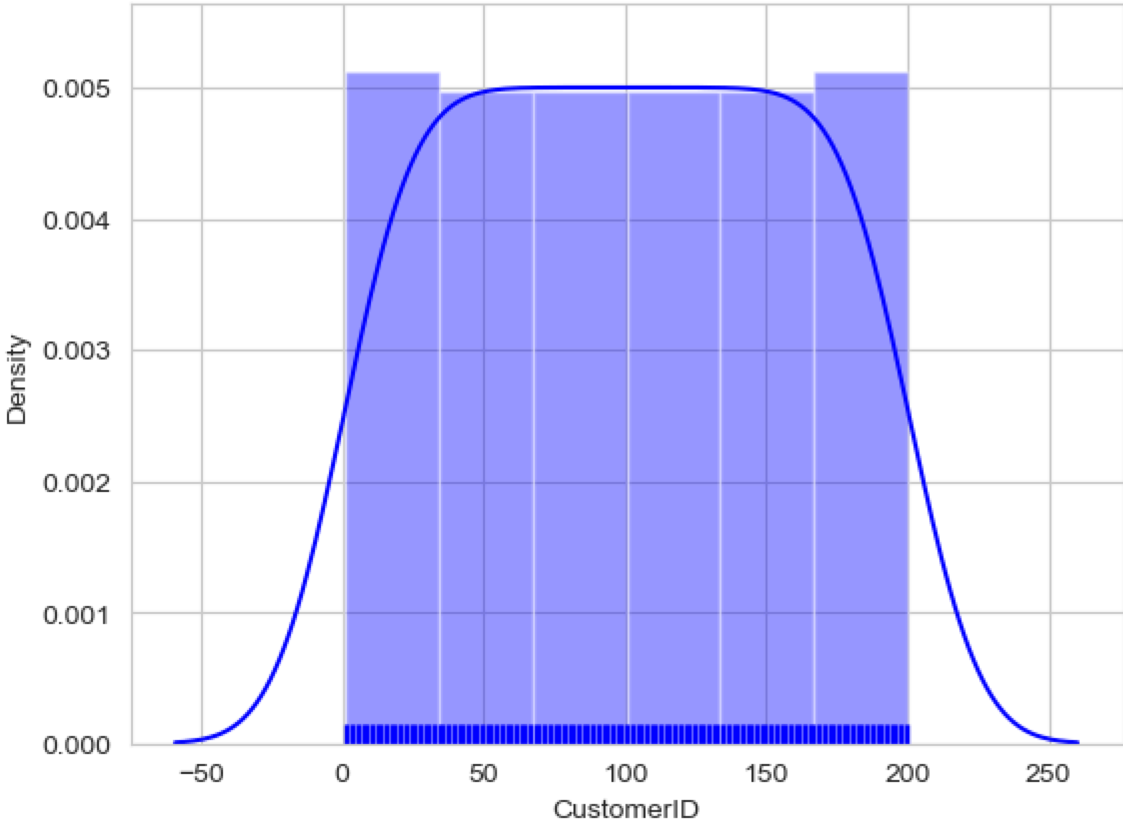
```
# Adding histograms for spending score distribution by gender
fig.add_trace(go.Histogram(x=cust_data[cust_data.Gender == 'Male']['Sp
                           marker=dict(color='#508B8D', line=dict(widt
                           opacity=0.7, name="Men", nbinsx=20, showleg
              row=3, col=1)
fig.add_trace(go.Histogram(x=cust_data[cust_data.Gender == 'Female']['
                           marker=dict(color='#F3D6CB', line=dict(widt
                           opacity=0.7, name="Women", nbinsx=20, showl
              row=3, col=1)

# Adding bar chart for average spending score by gender
fig.add_trace(go.Bar(x=p3['Gender'], y=p3['Spending Score'], text=p3['
                     texttemplate='%{text}', textposition='outside',
                     marker=dict(color=['#508B8D', '#F0CABD'], opacity
                     hovertemplate='Average Spending Score Among %{x}
              row=3, col=2)

# Updating traces and layout
fig.update_traces(marker=dict(line=dict(width=1, color='#000000')))
fig.update_layout(template=temp, barmode='overlay', height=1500, width
                  legend=dict(orientation="h", yanchor="bottom", xanch
                  xaxis1_title="Age", yaxis1_title='Probability Densit
                  xaxis2_title="Gender", yaxis2_title="Age", yaxis2_ra
                  xaxis3_title="Annual Income, $", yaxis3_title='Proba
                  xaxis4_title="Gender", yaxis4_title="Annual Income,
                  xaxis5_title="Spending Score", yaxis5_title='Probabi
                  xaxis6_title="Gender", yaxis6_title="Spending Score"
                  )
fig.show()

# Pairplots
fig = ff.create_scatterplotmatrix(cust_data, diag='box', index='Gender
fig.update_traces(marker=dict(size=9, opacity=0.85, line=dict(width=1,
fig.update_layout(title="Mall Customer Pair Plots", template=temp,
                  legend=dict(orientation="h", yanchor="bottom", y=1.0
                  height=900, width=700)
fig.show()

# Excluding non-numeric columns before calculating correlations
numeric_data = cust_data.select_dtypes(include=['number'])
corr = numeric_data.corr()

# Plotting correlation heatmap
x = corr.columns.tolist()
y = corr.index.tolist()
z = corr.values
text = corr.values.round(2)

fig = ff.create_annotated_heatmap(z=z, x=x, y=y, annotation_text=text,
                                  reversescale=True, showscale=True,
                                  hovertemplate="Correlation of %{x} a
fig.update_layout(template=temp, title="Mall Customer Correlations", y
fig.show()
```

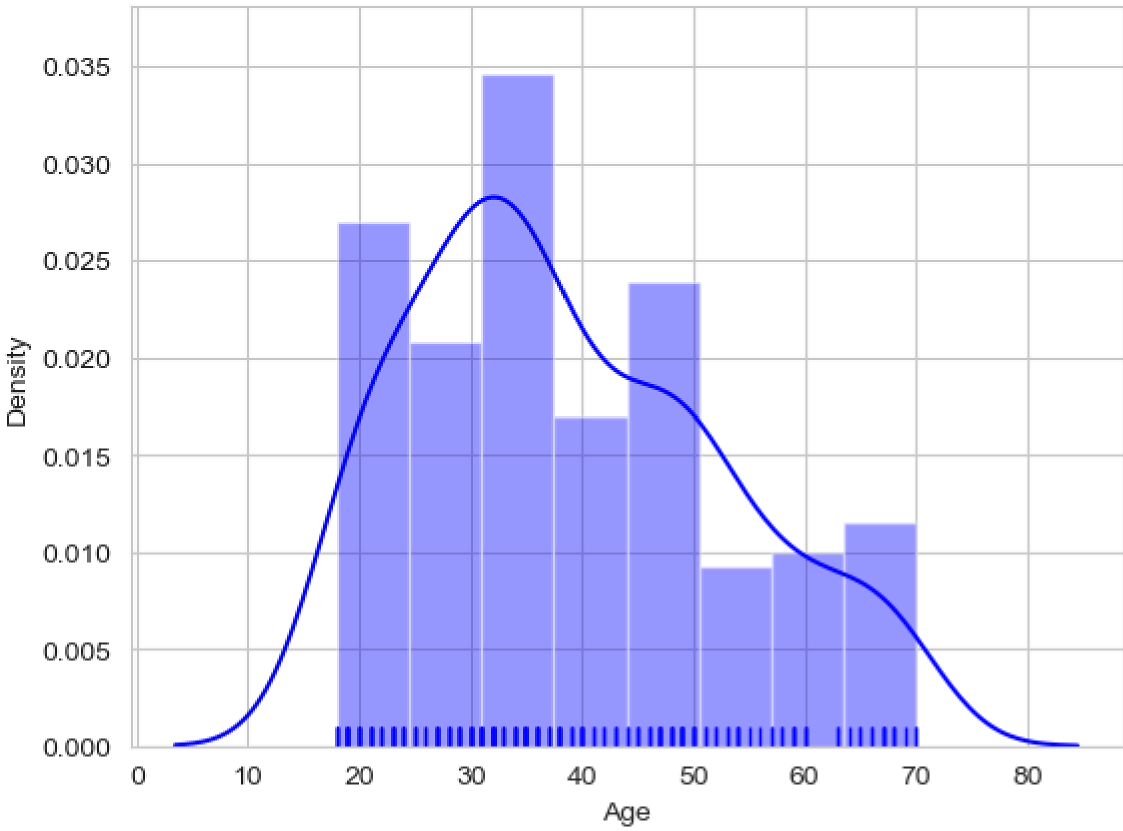


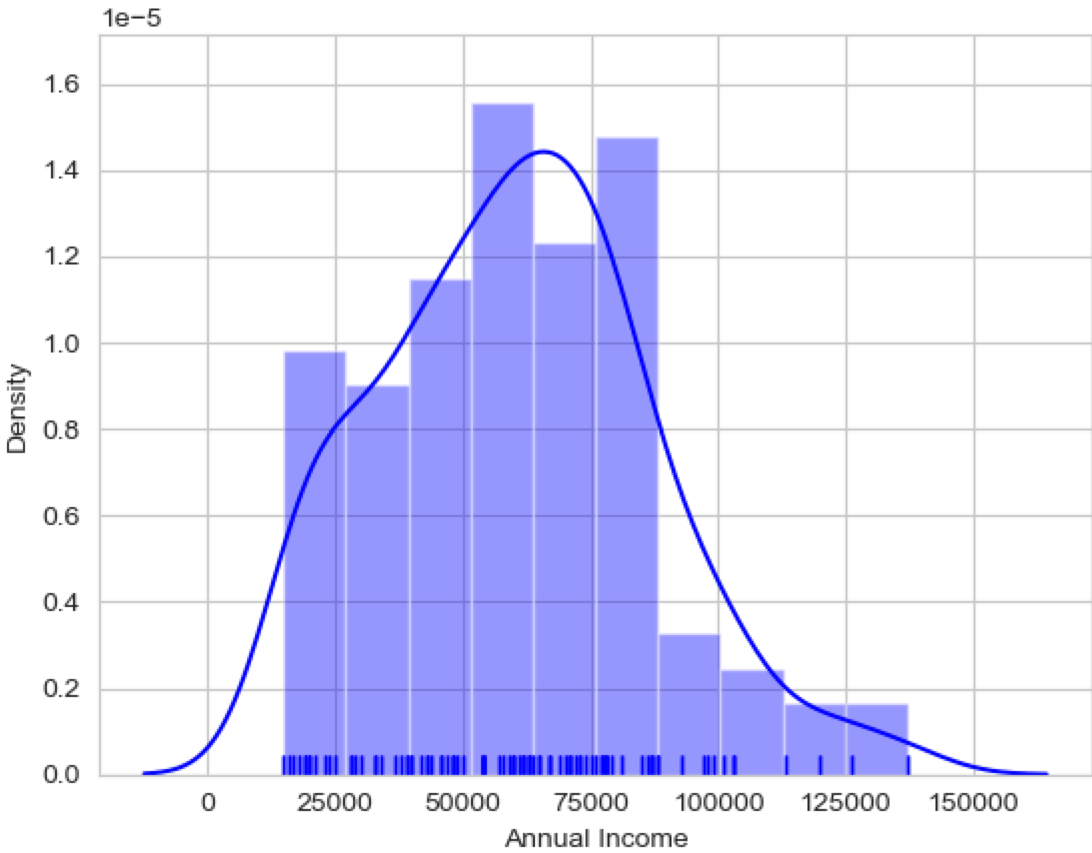
Plotting Distribution for each Column in dataset

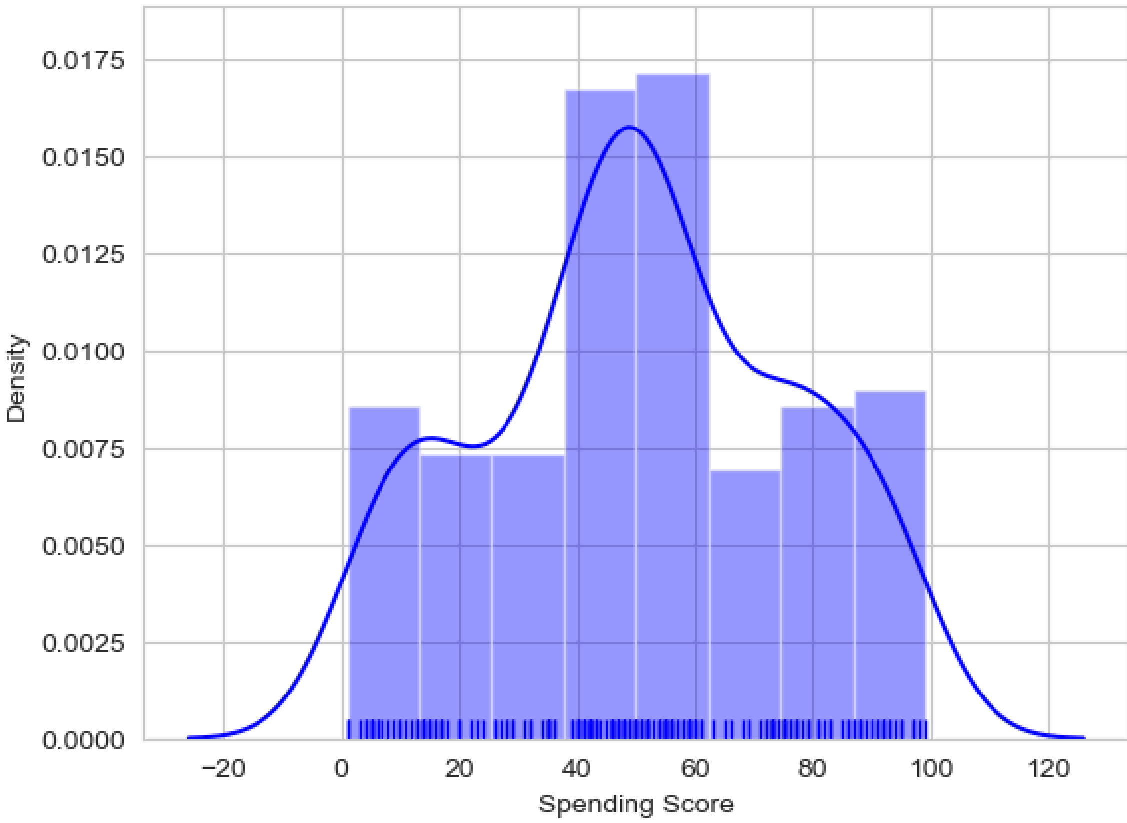
In [10]:
```
def distributionPlot(columnName):
    if not columnName == 'Gender':
        plt.figure()
        sns.distplot(cust_data[columnName], color="blue", rug=True);
```

In [11]:
```
for column in cust_data.columns:
    distributionPlot(column)
```

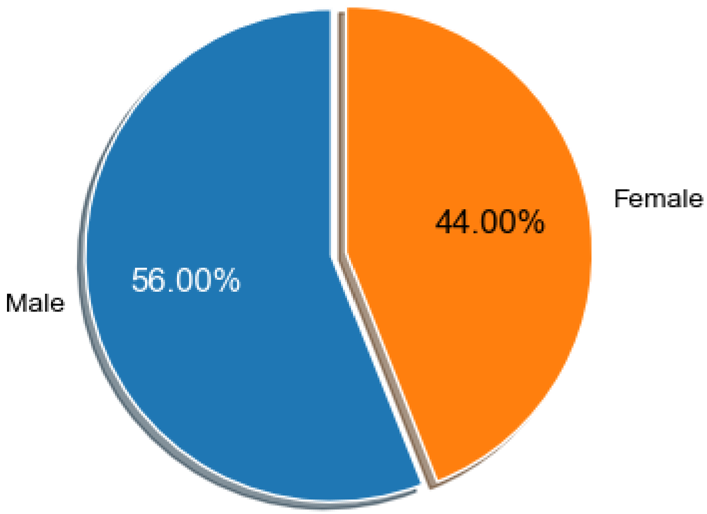




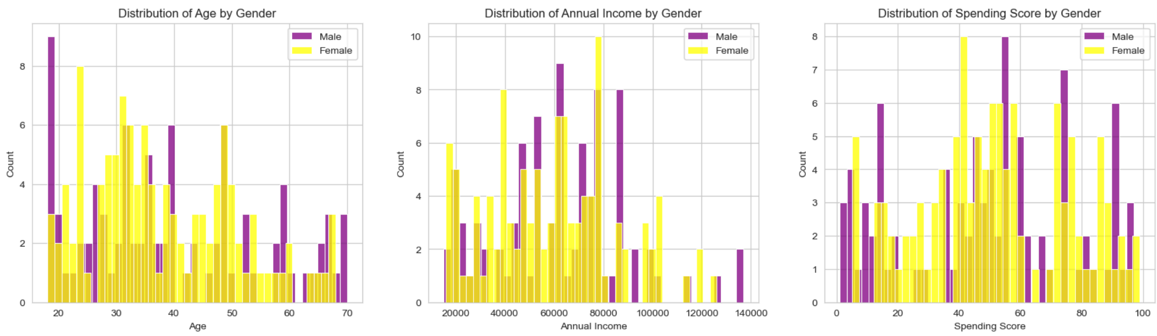

1e−5
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Density
0
25000
50000
75000
100000
125000
150000
Annual Income


0.0175
0.0150
0.0125
0.0100
0.0075
0.0050
0.0025
0.0000
Density
−20
0
20
40
60
80
100
120
Spending Score

In [12]:
```
values = cust_data['Gender'].value_counts()
labels = ['Male', 'Female']

fig, ax = plt.subplots(figsize=(4, 4), dpi=100)
explode = (0, 0.06)

patches, texts, autotexts = ax.pie(values, labels=labels, autopct='%1.
                                   startangle=90, explode=explode)

plt.setp(texts, color='black')
plt.setp(autotexts, size=12, color='white')
autotexts[1].set_color('black')
plt.show()
```



In [13]:
```
fig, ax = plt.subplots(1, 3, figsize=(20, 5))

# Plotting histograms for Age
sns.histplot(cust_data[cust_data['Gender'] == 'Male']['Age'], bins=40,
sns.histplot(cust_data[cust_data['Gender'] == 'Female']['Age'], bins=4
ax[0].set_title('Distribution of Age by Gender')
ax[0].legend()

# Plotting histograms for Annual Income
sns.histplot(cust_data[cust_data['Gender'] == 'Male']['Annual Income']
sns.histplot(cust_data[cust_data['Gender'] == 'Female']['Annual Income
ax[1].set_title('Distribution of Annual Income by Gender')
ax[1].legend()

# Plotting histograms for Spending Score
sns.histplot(cust_data[cust_data['Gender'] == 'Male']['Spending Score'
sns.histplot(cust_data[cust_data['Gender'] == 'Female']['Spending Scor
ax[2].set_title('Distribution of Spending Score by Gender')
ax[2].legend()

plt.show()
```



Summary of EDA (Exploratory Data Analysis)

Overall, the distributions are fairly proportional between men and women. On average, men are slightly older than women and tend to have higher

incomes, while women tend to spend more than men. Based on the correlations and scatterplots, the variables in the data set do not have very

strong relationships with each other. There is a weak negative association between Age and Spending Score of -0.33 and in the scatterplot above,

we see that as customers get older, they tend to spend less than younger customers.

Let's move onto creating model

We will now use elbow method to get the number ideal clusters

A fundamental step for any unsupervised algorithm is to determine the optimal number of clusters into which the data may be clustered. Since we do

not have any predefined number of clusters in unsupervised learning. We tend to use some method that can help us decide the best number of clusters.

In the case of K-Means clustering, we use Elbow Method for defining the best number of clustering.

A fundamental step for any unsupervised algorithm is to determine the optimal number of clusters into which the data may be clustered. Since we do

not have any predefined number of clusters in unsupervised learning. We tend to use some method that can help us decide the best number of

clusters. In the case of K-Means clustering, we use Elbow Method for defining the best number of clustering

For determining K(numbers of clusters) we use Elbow method. Elbow Method is a technique that we use to determine the number of centroids(k) to

use in a k-means clustering algorithm. In this method to determine the k-value we continuously iterate for k=1 to k=n (Here n is the

hyperparameter that we choose as per our requirement). For every value of k, we calculate the within-cluster sum of squares (WCSS) value.

WCSS - It is defined as the sum of square distances between the centroids and each points..

Now For determining the best number of clusters(k) we plot a graph of k versus their WCSS value.

ref - [https://www.geeksforgeeks.org/elbow-method-for-optimal-value-of-k-in-kmeans/e (https://www.geeksforgeeks.org/elbow-method-for-optimal-value-of-k-in-kmeans/e)](https://www.geeksforgeeks.org/elbow-method-for-optimal-value-of-k-in-kmeans/e).

The first clustering technique we will explore is K-Means Clustering. K-Means Clustering is a simple yet powerful clustering method that creates k

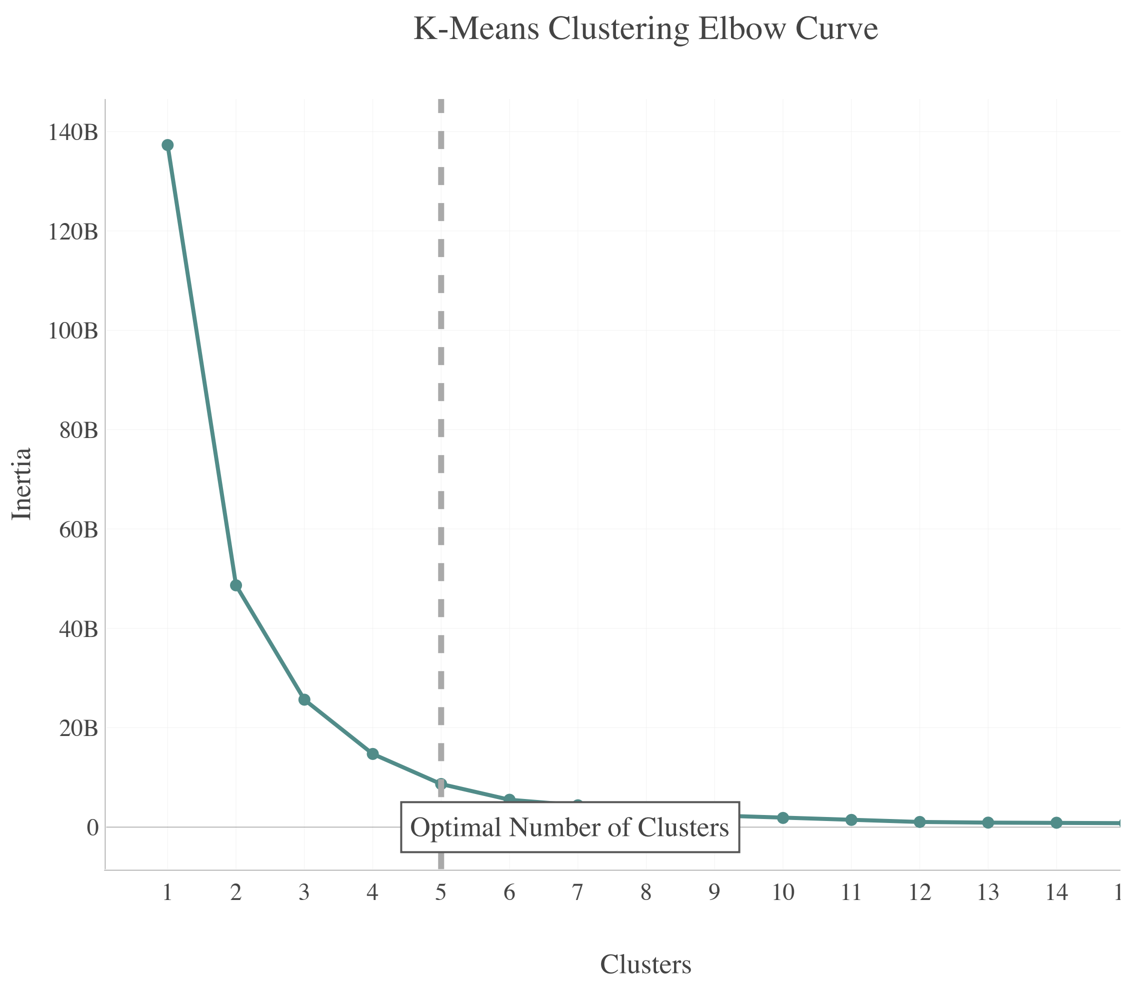
distinct segments of the data where the variation within the clusters is as small as possible. To find the optimal number of clusters, I will try

different values of k

and calculate the inertia, or distortion score, for each model. Inertia measures the cluster similarity by computing the total distance between the

data points and their closest cluster center. Clusters with similar observations tend to have smaller distances between them and a lower distortion score overall.

In [14]:
```
# K-Means Clustering
clust_df = cust_data.copy()
clust_df['Gender'] = [1 if i == "Women" else 0 for i in clust_df.Gende

k_means = list()
for clust in range(1,16):
    km = KMeans(n_clusters=clust, init='k-means++', random_state=21).f
    k_means.append(pd.Series({'Clusters': clust,
                              'Inertia': km.inertia_,
                              'model': km}))

# Plot results
plot_km = (pd.concat(k_means, axis=1).T
           [['Clusters','Inertia']]
           .set_index('Clusters'))

fig = px.line(plot_km, x=plot_km.index, y='Inertia', markers=True)
fig.add_vline(x=5, line_width=3, line_dash="dash", line_color="darkgre
fig.add_annotation(
    xref="x domain",
    yref="y",
    x=.31,
    y=75e3,
    text="Optimal Number of Clusters",
    axref="x domain",
    ayref="y",
    ax=.43,
    ay=12e4,
    arrowhead=2,
    bordercolor="#585858",
    borderpad=4,
    bgcolor='white',
    font=dict(size=14)
)
fig.update_traces(line_color='#518C89')
fig.update_layout(template=temp, title="K-Means Clustering Elbow Curve
                  xaxis=dict(tickmode = 'linear', showline=True), yaxi
fig.show()
```



The graph above shows the inertia values for each K-Means model with clusters between 1 and 15. The inflection point in the graph occurs at about

5 clusters, where the inertia begins to plateau. This indicates that the optimal number of clusters, k is equal to 5. Below is a plot of the clusters

based on their spending score and income.

In [16]:
```
# K-Means with 5 clusters
km = KMeans(n_clusters=5, random_state=21)
km_pred = km.fit_predict(clust_df)
plot_km=clust_df.copy()
plot_km['K-Means Cluster'] = km_pred
plot_km=plot_km.sort_values(by='K-Means Cluster')
plot_km['K-Means Cluster'] = plot_km['K-Means Cluster'].astype(str)

# Plot of clusters
fig = px.scatter(plot_km, x="Spending Score", y="Annual Income", color
                 color_discrete_sequence=px.colors.qualitative.Prism)
fig.update_traces(marker=dict(size=11, opacity=0.75, line=dict(width=1
fig.update_layout(template=temp, title="K-Means Cluster Profiles,<br>C
                  width=700, legend_title='Cluster',
                  xaxis=dict(title='Spending Score', showline=True, ze
                  yaxis=dict(title='Income, $', ticksuffix='k', showli
fig.show()
```

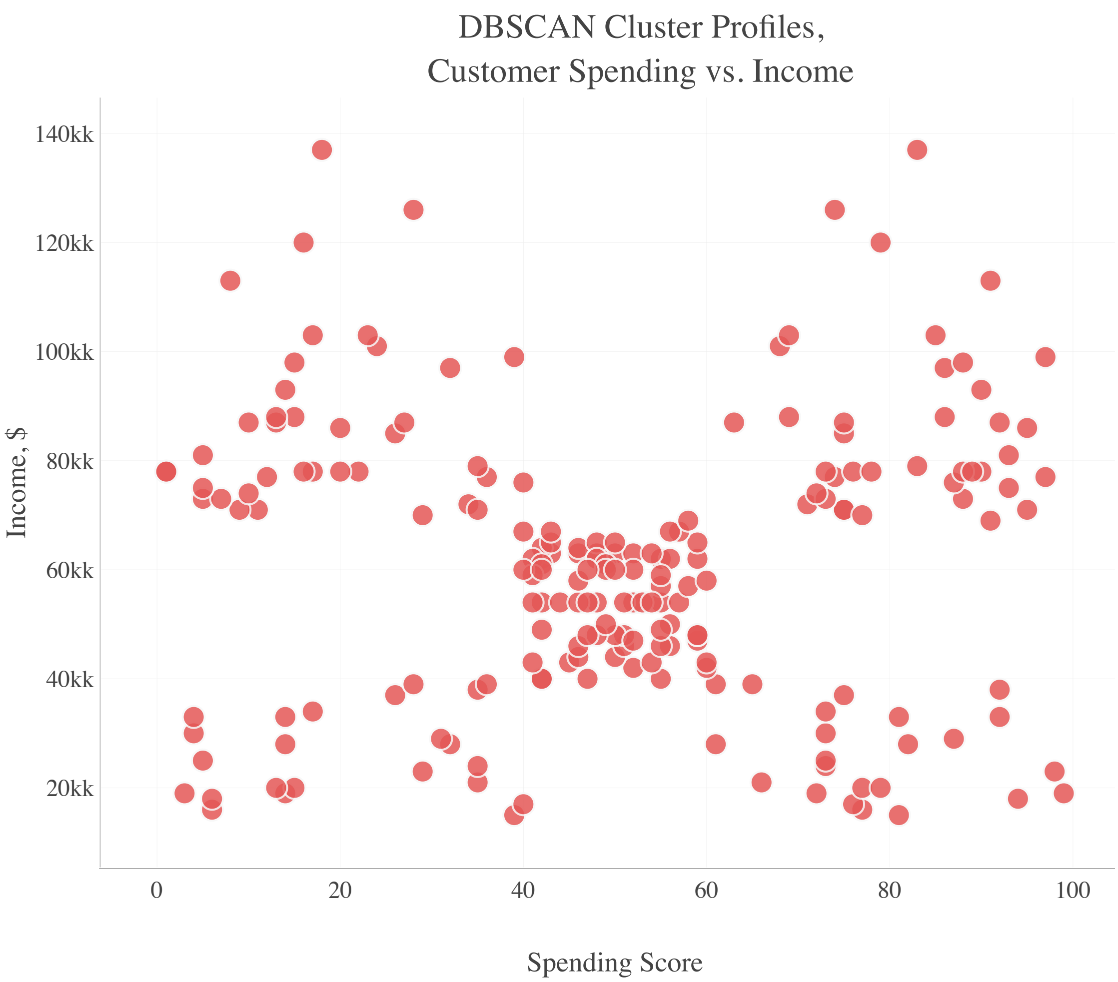
The K-Means model segments the data into distinct clusters based on customer's spending and income. Cluster 0 in the center of the graph consists of customers with average spending scores, between 35-61, and incomes between $40, 000and$71,000. The two clusters on the left, Clusters 1 and 3, both identify customers with lower spending scores that are below 40 and subdivides the groups

DBSCAN

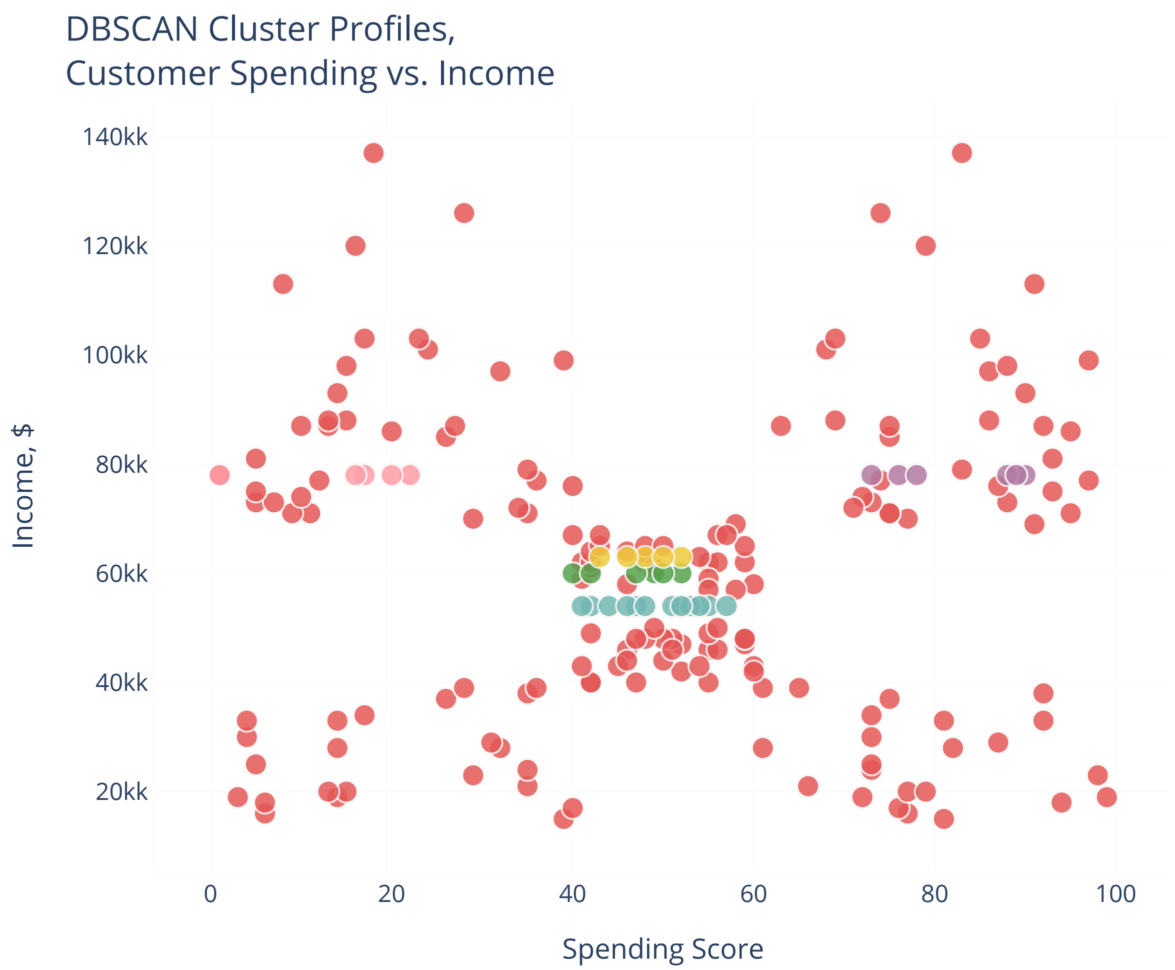
Let us know apply DBSCAN Algorithm

In [17]:

```
db=DBSCAN(eps=15, min_samples=11, metric='euclidean')  #17,15 14,7 12
db_preds=db.fit_predict(clust_df)
plot_db=clust_df.copy()
plot_db['DB Cluster'] = db_preds
plot_db=plot_db.sort_values(by='DB Cluster')
plot_db['DB Cluster'] = plot_db['DB Cluster'].astype(str).apply(lambda


# Plot of clusters
fig = px.scatter(plot_db, x="Spending Score", y="Annual Income", color
                 color_discrete_sequence=px.colors.qualitative.T10[2:]
fig.update_traces(marker=dict(size=11, opacity=0.85, line=dict(width=1
fig.update_layout(template=temp, title="DBSCAN Cluster Profiles,<br>Cu
                  width=700, legend_title = 'Cluster',
                  xaxis=dict(title='Spending Score',showline=True, zer
                  yaxis=dict(title='Income, $',ticksuffix='k',showline
fig.show()
```



In [18]:
```
from sklearn.cluster import DBSCAN
import plotly.express as px

# Adjusted DBSCAN parameters
db = DBSCAN(eps=20, min_samples=5)
db_preds = db.fit_predict(clust_df)
plot_db = clust_df.copy()
plot_db['DB Cluster'] = db_preds
plot_db = plot_db.sort_values(by='DB Cluster')
plot_db['DB Cluster'] = plot_db['DB Cluster'].astype(str).apply(lambda

# Plot clusters
fig = px.scatter(plot_db, x="Spending Score", y="Annual Income", color
                 color_discrete_sequence=px.colors.qualitative.T10[2:]
fig.update_traces(marker=dict(size=11, opacity=0.85, line=dict(width=1
fig.update_layout(template='plotly_white', title="DBSCAN Cluster Profi
                  width=700, legend_title='Cluster',
                  xaxis=dict(title='Spending Score', showline=True, ze
                  yaxis=dict(title='Income, $', ticksuffix='k', showli
fig.show()
```



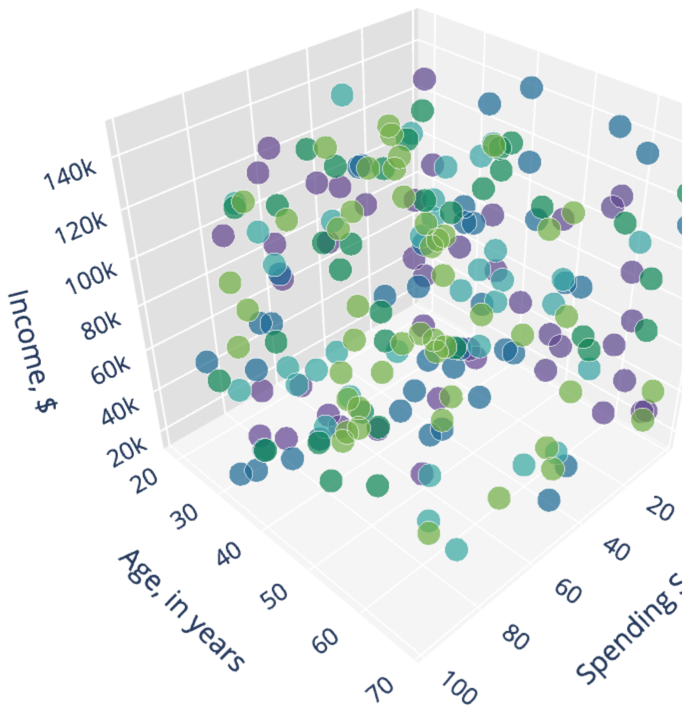
In [19]:
```
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import plotly.express as px

# Sample data creation (replace with actual data)
import pandas as pd
import numpy as np

# Example data (Replace with your actual data)
np.random.seed(42)
n_samples = 200
data = {
    'Spending Score': np.random.randint(1, 100, n_samples),
    'Age': np.random.randint(18, 70, n_samples),
    'Annual Income': np.random.randint(15, 150, n_samples)
}
plot_km = pd.DataFrame(data)
plot_km['K-Means Cluster'] = np.random.randint(0, 5, n_samples)
plot_db = pd.DataFrame(data)
plot_db['DB Cluster'] = np.random.randint(0, 4, n_samples)

# Create the subplots
fig = make_subplots(
    rows=2, cols=1,
    vertical_spacing=0.1,
    specs=[[{'type': 'scatter3d'}], [{'type': 'scatter3d'}]],
    subplot_titles=(
        "K-Means Clustering with 5 clusters",
        "DBSCAN with 4 clusters"
    )
)

# Add K-Means clusters to the first subplot
for i in range(5):
    fig.add_trace(
        go.Scatter3d(
            x=plot_km[plot_km['K-Means Cluster'] == i]['Spending Score
            y=plot_km[plot_km['K-Means Cluster'] == i]['Age'],
            z=plot_km[plot_km['K-Means Cluster'] == i]['Annual Income'
            mode='markers',
            marker=dict(
                size=7,
                color=px.colors.qualitative.Prism[i],
                line=dict(width=1, color='#F7F7F7'),
                opacity=0.7
            ),
            name=f'Cluster {i}',
            legendgroup='KMeans'
        ),
        row=1, col=1
    )

# Add DBSCAN clusters to the second subplot
for i, cluster in enumerate(plot_db['DB Cluster'].unique()):
    fig.add_trace(
        go.Scatter3d(
            x=plot_db[plot_db['DB Cluster'] == cluster]['Spending Scor
            y=plot_db[plot_db['DB Cluster'] == cluster]['Age'],
            z=plot_db[plot_db['DB Cluster'] == cluster]['Annual Income
            mode='markers',
            marker=dict(
```

```
                size=7,
                color=px.colors.qualitative.T10[i],
                line=dict(width=1, color='#F7F7F7'),
                opacity=0.8
            ),
            name=f'DB Cluster {cluster}',
            legendgroup='DBSCAN'
        ),
        row=2, col=1
    )

# Update layout for all subplots
fig.update_traces(
    hovertemplate='Customer Spending Score: %{x}<br>Income: $%{z}<br>A
)
fig.update_layout(
    title="Customer Segments based on Income, Spending, and Age",
    template='plotly_white',
    height=1200,
    legend_tracegroupgap=500,
    scene=dict(
        aspectmode='cube',
        xaxis=dict(
            title='Spending Score',
            backgroundcolor="#F3F3F3",
            gridcolor="white",
            showbackground=True,
            zerolinecolor="white"
        ),
        yaxis=dict(
            title='Age, in years',
            backgroundcolor="#E4E4E4",
            gridcolor="white",
            showbackground=True,
            zerolinecolor="white"
        ),
        zaxis=dict(
            title='Income, $',
            ticksuffix='k',
            backgroundcolor="#F6F6F6",
            gridcolor="white",
            showbackground=True,
            zerolinecolor="white"
        )
    ),
    scene2=dict(
        aspectmode='cube',
        xaxis=dict(
            title='Spending Score',
            backgroundcolor="#F3F3F3",
            gridcolor="white",
            showbackground=True,
            zerolinecolor="white"
        ),
        yaxis=dict(
            title='Age, in years',
            backgroundcolor="#E4E4E4",
            gridcolor="white",
            showbackground=True,
            zerolinecolor="white"
        ),
```

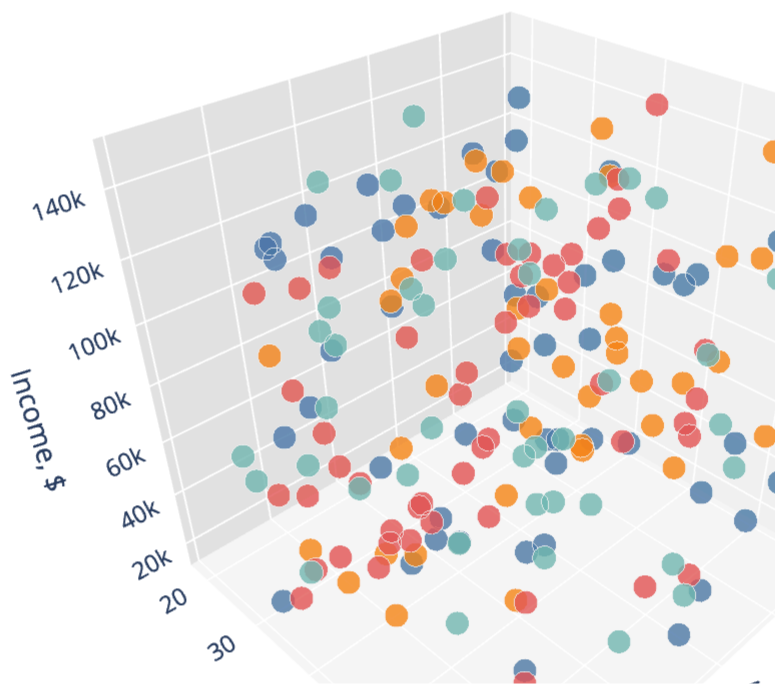
```
        zaxis=dict(
            title='Income, $',
            ticksuffix='k',
            backgroundcolor="#F6F6F6",
            gridcolor="white",
            showbackground=True,
            zerolinecolor="white"
        )
    )
)

fig.show()
```

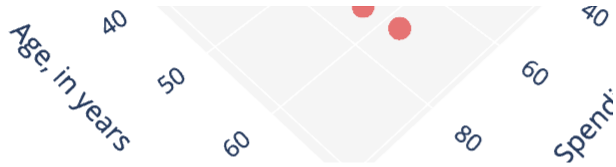
Customer Segments based on Income, Spending, and Age

K-Means Clustering with 5 clusters



DBSCAN with 4 clusters




40
50
60
Age, in years
40
60
80
Spend