```
# Importing libraries

import numpy as np
import pandas as pd
import datetime
import missingno

from sklearn.preprocessing import StandardScaler, OneHotEncoder

from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer

from sklearn.cluster import DBSCAN
from sklearn.neighbors import NearestNeighbors
from sklearn.metrics import silhouette_samples, silhouette_score


import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import plotly.express as px
import plotly.graph_objects as go
from ipywidgets import widgets


import warnings
warnings.filterwarnings('ignore')
```

```
from google.colab import output
output.enable_custom_widget_manager()
```

```
pip install -U kaleido
```

```
Collecting kaleido
  Downloading kaleido-0.2.1-py2.py3-none-manylinux1_x86_64.whl (79.9 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 79.9/79.9 MB 9.2 MB/s eta 0:00:00
Installing collected packages: kaleido
ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This behaviour is the sou
lida 0.0.10 requires fastapi, which is not installed.
lida 0.0.10 requires python-multipart, which is not installed.
lida 0.0.10 requires uvicorn, which is not installed.
Successfully installed kaleido-0.2.1
```

Load the data

```
# Import the dataset into a DataFrame

customer_df = pd.read_csv('Lab3_data_mod2.csv')
customer_df.head()
```

	CustomerID	Gender	Age	Income	Spending Score
0	1	Male	19.0	15000.0	39
1	2	Male	21.0	15000.0	81
2	3	Female	20.0	16000.0	6
3	4	Female	23.0	16000.0	77
4	5	Female	31.0	17000.0	40

```
customer_df.shape
```

```
(200, 5)
```

```
columns = customer_df.columns.values
columns
```

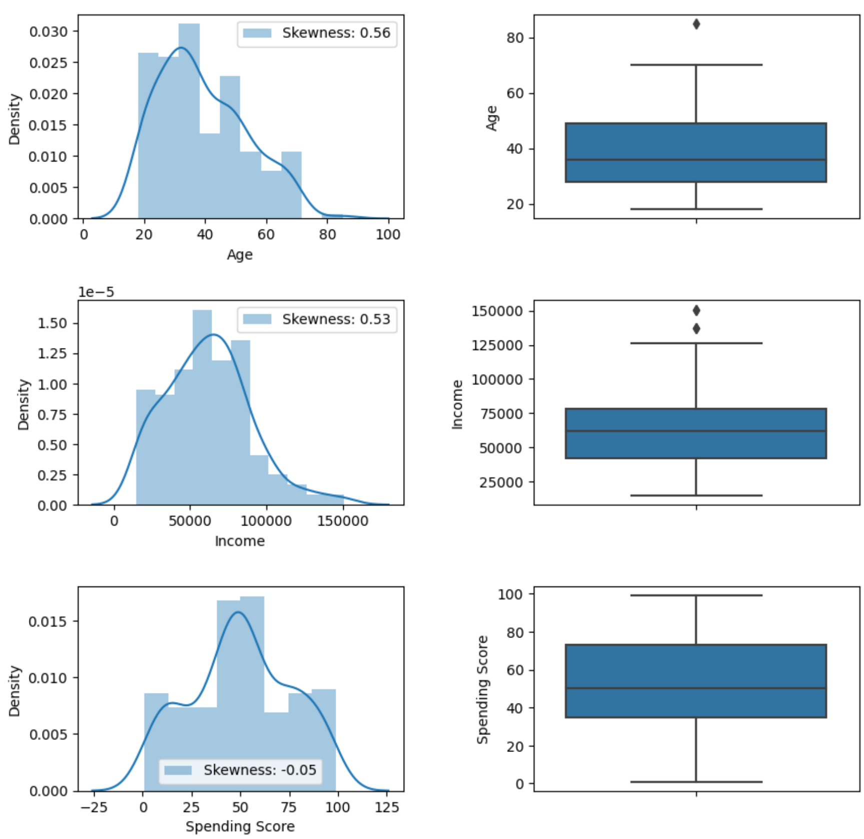
```
array(['CustomerID', 'Gender', 'Age', 'Income', 'Spending Score'],
      dtype=object)
```

Data Exploration and Visualisation

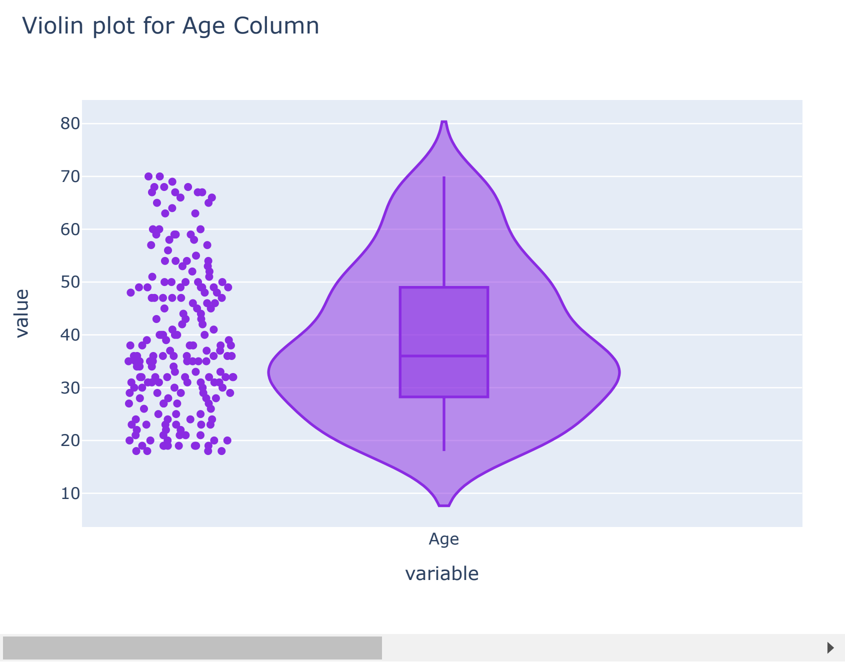
Create plots to understand the distribution of the each feature in the data

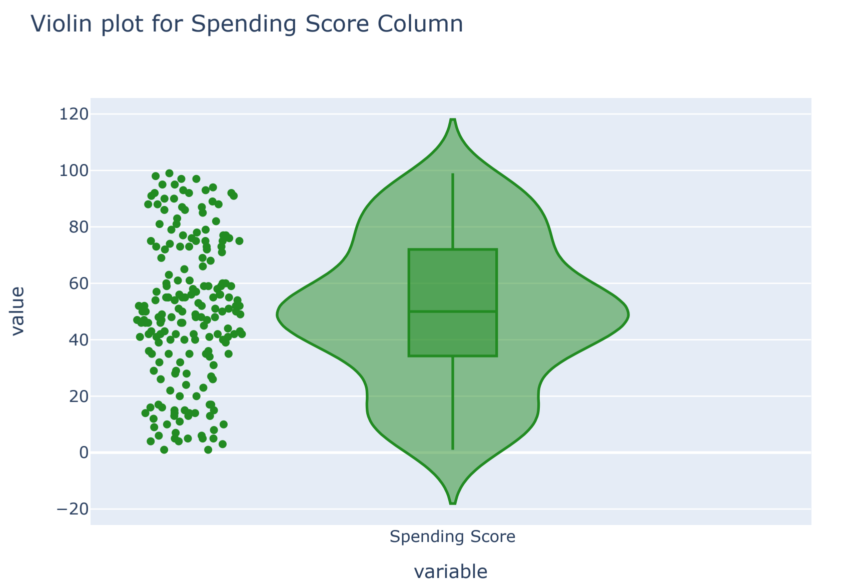
```
fig, axes = plt.subplots(3, 2, figsize=(10, 10))

sns.distplot(customer_df['Age'], label = 'Skewness: %.2f'%(customer_df['Age'].skew()), ax=axes[0,0])
axes[0,0].legend(loc = 'best')
sns.boxplot(y = customer_df['Age'], ax=axes[0,1])

sns.distplot(customer_df['Income'], label = 'Skewness: %.2f'%(customer_df['Income'].skew()), ax=axes[1,0])
axes[1,0].legend(loc = 'best')
sns.boxplot(y = customer_df['Income'], ax=axes[1,1])

sns.distplot(customer_df['Spending Score'], label = 'Skewness: %.2f'%(customer_df['Spending Score'].skew()), ax=axes[2,0])
axes[2,0].legend(loc = 'best')
sns.boxplot(y = customer_df['Spending Score'], ax=axes[2,1])

plt.subplots_adjust(wspace=0.4,
                    hspace=0.4)
fig.suptitle('Distplot and Boxplot of Numerical columns')
plt.show()

# Observation - Skewed Distributions
```

Distplot and Boxplot of Numerical columns

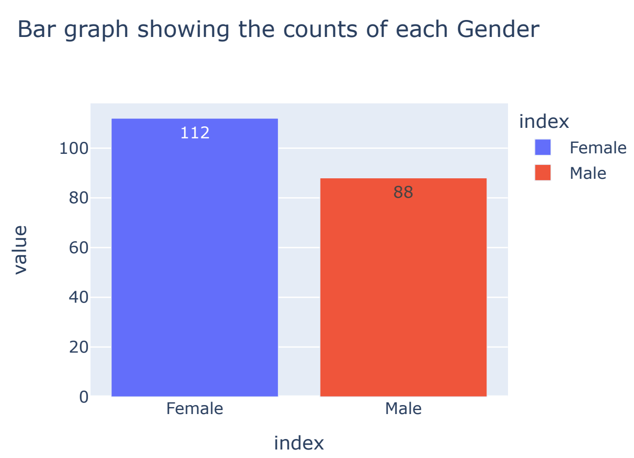



```
fw1 = go.FigureWidget(px.violin(customer_df['Age'], box=True, height = 500, points='all', title = 'Violin plot for Age Column', color_d:
fw2 = go.FigureWidget(px.violin(customer_df['Income'], box=True, points='all', title = 'Violin plot for Income Column', color_discrete_s
fw3 = go.FigureWidget(px.violin(customer_df['Spending Score'], box=True, height = 500, points='all', title = 'Violin plot for Spending S

dashboard1=widgets.VBox([widgets.HBox([fw1, fw2]), widgets.HBox([fw3])])
dashboard1
```



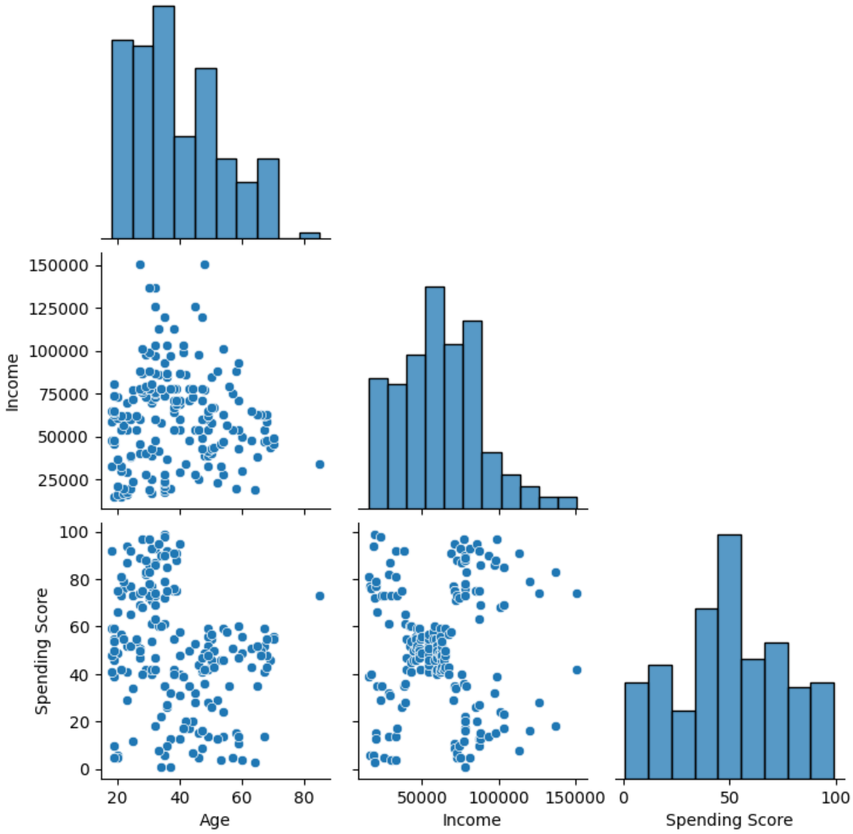



```
gender_vals = customer_df['Gender'].value_counts()
px.bar(gender_vals, title = 'Bar graph showing the counts of each Gender', text = gender_vals, color = gender_vals.index, height = 400,
```

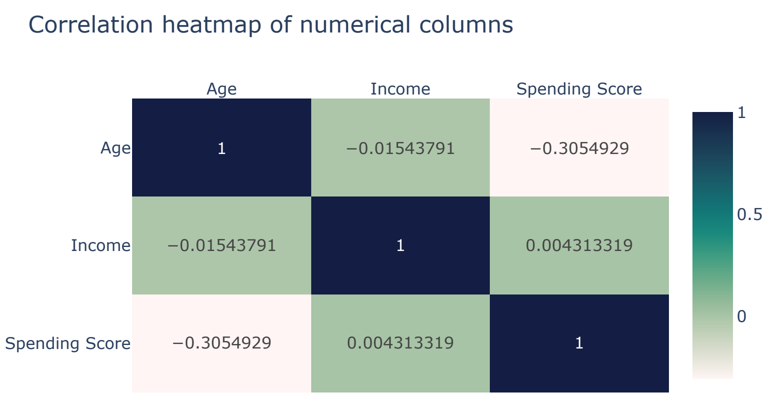


Create plots to understand the distribution of data with respect to the other features

```
# Correlation using pairplot

#customer_df_num = customer_df.select_dtypes(include = ['float64', 'int64']).drop('CustomerID')
customer_df_num = customer_df[['Age', 'Income', 'Spending Score']]

for i in range(0, len(customer_df_num.columns),5):
    sns.pairplot(customer_df_num, x_vars = customer_df_num.columns[i:i+3], corner = True)
```




```
cols = customer_df_num.columns
correlation_matrix = customer_df_num[cols].corr()

fig = px.imshow(correlation_matrix, text_auto=True, aspect="auto", color_continuous_scale = 'tempo', width=600, height=400,
                title = 'Correlation heatmap of numerical columns')
fig.update_xaxes(side="top")

fig.show()
```



Feature Preprocessing

```
customer_df.duplicated().sum()

# Observation - Since the number returned is zero, it implies that every row in our dataset is unique.
```

```
0
```

```
customer_df.info()

# Observation - From the "Non-Null Count" it can be seen that there are some missing vaues in the given data.
```

```
<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             197 non-null    float64
 3   Income          197 non-null    float64
 4   Spending Score  200 non-null    int64  
dtypes: float64(2), int64(2), object(1)
memory usage: 7.9+ KB
```

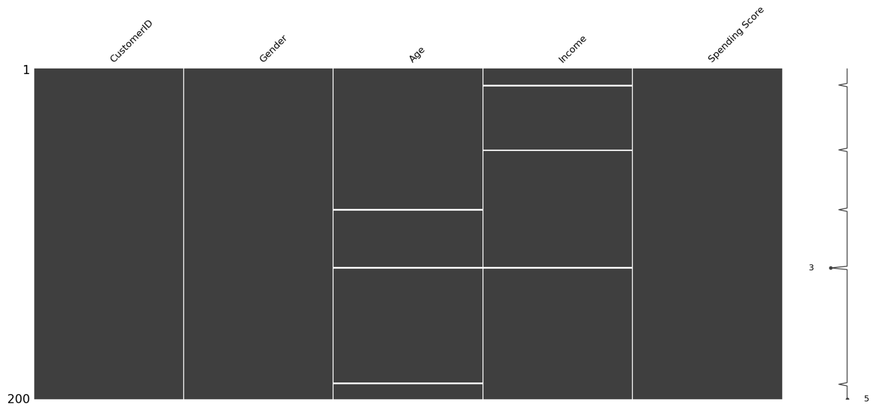
Checking for missing values and fill them

```
customer_df.isna().sum()

# Observation - There are 3 NaN values in the columns 'Age'and 'Income'.
```

```
CustomerID        0
Gender            0
Age               3
Income            3
Spending Score    0
dtype: int64
```

```
# Visual representation of the missing data in the dataset

missingno.matrix(customer_df)
```

```
<Axes: >
```



```
''' To find the median of the values of the said column for a particular group '''

def find_median(col):
  median_value = customer_df[col].median()
  return median_value
```

```
median_values = {}
```

```
median_age = find_median('Age')
median_values['Age'] = median_age
median_age
```

```
36.0
```

```
median_income = find_median('Income')
median_values['Income'] = median_income
median_income
```

```
62000.0
```

```
customer_df.fillna(value = median_values, inplace = True)

customer_df.isna().sum()

# Observation - There are no more NaN values remaining in the columns 'Age'and 'Income'.
```

```
CustomerID        0
Gender            0
Age               0
Income            0
Spending Score    0
dtype: int64
```

Identify any outliers and remove them

Since the distribution of the numerical columns are skewed, outliers are detected using Inter-Quartile Range (IQR) proximity rule

```
def find_upper_outliers(col, upper_limit):
  outliers = customer_df[customer_df[col] > upper_limit]
  num_outliers = len(outliers)
  print(f'Number of upper outliers = {num_outliers}')
  return outliers
```

```
def find_lower_outliers(col, lower_limit):
  outliers = customer_df[customer_df[col] < lower_limit]
  num_outliers = len(outliers)
  print(f'Number of lower outliers = {num_outliers}')
  return outliers
```

```
def find_ouliers(col):
  # Finding lower quartile
  Q1 = customer_df[col].quantile(0.25)
  print('Lower quartile = ', Q1)

  # Finding upper quartile
  Q3 = customer_df[col].quantile(0.75)
  print('Upper quartile = ', Q3)

  # Finding IQR value
  IQR = Q3 - Q1
  print('IQR = ', IQR)

  # Finding upper limit for outlier detection
  upper_limit = Q3 + 1.5 * IQR
  print('\nUpper limit = ', upper_limit)

  # Finding lower limit for outlier detection
  lower_limit = Q1 - 1.5 * IQR
  print(f'Lower limit = {lower_limit}\n')

  # Finding upper outliers
  outliers_upper = find_upper_outliers(col, upper_limit)
  indices = list(outliers_upper.index)

  # Finding lower outliers
  outliers_lower = find_lower_outliers(col, lower_limit)
  indices.extend(outliers_lower.index)

  outliers = outliers_upper.append(outliers_lower)
  return outliers, indices
```

```
# Finding outliers for Age column

outliers_age, indices_age = find_ouliers('Age')
```

```
Lower quartile =  28.75
Upper quartile =  49.0
IQR =  20.25

Upper limit =  79.375
Lower limit = -1.625

Number of upper outliers = 1
Number of lower outliers = 0
```

```
indices_age
```

```
[37]
```

```
outliers_age
```

	CustomerID	Gender	Age	Income	Spending Score
37	38	Female	85.0	34000.0	73

```
# Finding outliers for Income column

outliers_income, indices_income = find_ouliers('Income')
```

```
Lower quartile =  42750.0
Upper quartile =  78000.0
IQR =  35250.0

Upper limit =  130875.0
Lower limit = -10125.0

Number of upper outliers = 4
Number of lower outliers = 0
```

```
indices_income
```

```
[98, 147, 198, 199]
```

```
outliers_income
```

	CustomerID	Gender	Age	Income	Spending Score
98	99	Male	48.0	150250.0	42
147	148	Female	27.0	150753.0	74
198	199	Male	32.0	137000.0	18

```
# Finding outliers for Spending Score column

outliers_spend, indices_spend = find_ouliers('Spending Score')
```

```
Lower quartile =  34.75
Upper quartile =  73.0
IQR =  38.25

Upper limit =  130.375
Lower limit = -22.625

Number of upper outliers = 0
Number of lower outliers = 0
```

```
indices_age.extend(indices_income)
indices_age.extend(indices_spend)
indices = indices_age
indices
```

```
[37, 98, 147, 198, 199]
```

```
# Remove the outliers

customer_df = customer_df.drop(index = indices)
customer_df.shape

# Observation - 5 Outlier rows have been removed
```

```
(195, 5)
```

1. Perform feature scaling

2. Encode categorical features into numerical data

```
numeric_features = ['Age', 'Income', 'Spending Score']
numeric_transformer = Pipeline(steps=[('scaler', StandardScaler())])
```

```
categorical_features = ['Gender']
categorical_transformer = Pipeline(steps=[('onehot', OneHotEncoder(handle_unknown='ignore'))])
```

```
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)],
    verbose_feature_names_out = True)
```

```
customer_df.drop('CustomerID', axis = 1, inplace = True)
customer_df.columns.values
```

```
array(['Gender', 'Age', 'Income', 'Spending Score'], dtype=object)
```

```
transformed_data = preprocessor.fit_transform(customer_df)
```

```
preprocessor.feature_names_in_
```

```
array(['Gender', 'Age', 'Income', 'Spending Score'], dtype=object)
```

```
col_names = list(map(lambda x: x.split('__')[1], preprocessor.get_feature_names_out()))
col_names
```

```
['Age', 'Income', 'Spending Score', 'Gender_Female', 'Gender_Male']
```

```
transformed_df = pd.DataFrame(transformed_data, columns = col_names)
transformed_df.head()
```

	Age	Income	Spending Score	Gender_Female	Gender_Male
0	-1.424678	-1.801498	-0.426965	0.0	1.0
1	-1.281918	-1.801498	1.203266	0.0	1.0

Perform clustering using DBSCAN

```
transformed_df.drop('Gender_Female', axis = 1, inplace =True)
transformed_df.drop('Gender_Male', axis = 1, inplace =True)
```

```
transformed_df.columns
```

```
Index(['Age', 'Income', 'Spending Score'], dtype='object')
```

```
epsilon_range = list(np.arange(0.3, 1.1, 0.1))
n_samp_range = range(3, 6 + 1)
```

```
sil_df = pd.DataFrame(columns = list(n_samp_range), index = epsilon_range)
sil_df
```

	3	4	5	6
0.3	NaN	NaN	NaN	NaN
0.4	NaN	NaN	NaN	NaN
0.5	NaN	NaN	NaN	NaN
0.6	NaN	NaN	NaN	NaN
0.7	NaN	NaN	NaN	NaN
0.8	NaN	NaN	NaN	NaN
0.9	NaN	NaN	NaN	NaN
1.0	NaN	NaN	NaN	NaN

```
for ep in epsilon_range:
  for min_p in n_samp_range:
    #clt = Pipeline(steps=[('preprocessor', preprocessor),
                    #  ('clusterer', DBSCAN(eps = ep, min_samples = min_p))])

    #pipe_fit = clt.fit_transform(customer_df)
    #clustering = pipe_fit[-1].labels_
    clustering = DBSCAN(eps = ep, min_samples = min_p).fit(transformed_df)
    n_clusters = len(set(clustering.labels_))

    silhouette_avg = silhouette_score(transformed_df, clustering.labels_)
    print(f'The average silhouette_score for epison = {ep} and minPoints = {min_p} is : {silhouette_avg}\t n_clusters = {n_clusters}')

    sil_df.loc[ep, min_p] = silhouette_avg
  print()
```

```
The average silhouette_score for epison = 0.3 and minPoints = 3 is : -0.09091047997505972        n_clusters = 13
The average silhouette_score for epison = 0.3 and minPoints = 4 is : -0.10532282165281859        n_clusters = 9
The average silhouette_score for epison = 0.3 and minPoints = 5 is : -0.19914827198051324        n_clusters = 11
The average silhouette_score for epison = 0.3 and minPoints = 6 is : -0.21709088175675248        n_clusters = 4

The average silhouette_score for epison = 0.4 and minPoints = 3 is : 0.06040437906532299         n_clusters = 10
The average silhouette_score for epison = 0.4 and minPoints = 4 is : 0.027062311089518083        n_clusters = 7
The average silhouette_score for epison = 0.4 and minPoints = 5 is : 0.00025489891414393035      n_clusters = 9
The average silhouette_score for epison = 0.4 and minPoints = 6 is : -0.008616371048534906       n_clusters = 9

The average silhouette_score for epison = 0.5 and minPoints = 3 is : 0.10824010478498591         n_clusters = 11
The average silhouette_score for epison = 0.5 and minPoints = 4 is : 0.1260695624870645  n_clusters = 9
The average silhouette_score for epison = 0.5 and minPoints = 5 is : 0.11513138838865707         n_clusters = 5
The average silhouette_score for epison = 0.5 and minPoints = 6 is : 0.10730157673933524         n_clusters = 5

The average silhouette_score for epison = 0.6000000000000001 and minPoints = 3 is : 0.17322768624656723  n_clusters = 4
The average silhouette_score for epison = 0.6000000000000001 and minPoints = 4 is : 0.15541735712240784  n_clusters = 4
The average silhouette_score for epison = 0.6000000000000001 and minPoints = 5 is : 0.19032474396746915  n_clusters = 3
The average silhouette_score for epison = 0.6000000000000001 and minPoints = 6 is : 0.07455743397031321  n_clusters = 6

The average silhouette_score for epison = 0.7000000000000002 and minPoints = 3 is : 0.13751738797719865  n_clusters = 3
The average silhouette_score for epison = 0.7000000000000002 and minPoints = 4 is : 0.1390360687251488   n_clusters = 3
The average silhouette_score for epison = 0.7000000000000002 and minPoints = 5 is : 0.22941044684809828  n_clusters = 2
The average silhouette_score for epison = 0.7000000000000002 and minPoints = 6 is : 0.21699684207298936  n_clusters = 2

The average silhouette_score for epison = 0.8000000000000003 and minPoints = 3 is : 0.2582723237061966   n_clusters = 2
```

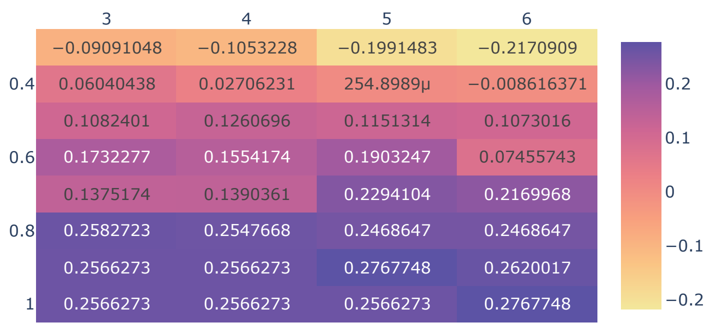
```
The average silhouette_score for epison = 0.8000000000000003 and minPoints = 4 is : 0.2547668349054036   n_clusters = 2
The average silhouette_score for epison = 0.8000000000000003 and minPoints = 5 is : 0.24686472960865125  n_clusters = 2
The average silhouette_score for epison = 0.8000000000000003 and minPoints = 6 is : 0.24686472960865125  n_clusters = 2

The average silhouette_score for epison = 0.9000000000000001 and minPoints = 3 is : 0.2566273479086497   n_clusters = 2
The average silhouette_score for epison = 0.9000000000000001 and minPoints = 4 is : 0.2566273479086497   n_clusters = 2
The average silhouette_score for epison = 0.9000000000000001 and minPoints = 5 is : 0.27677481802627363  n_clusters = 2
The average silhouette_score for epison = 0.9000000000000001 and minPoints = 6 is : 0.2620017200036174   n_clusters = 2

The average silhouette_score for epison = 1.0000000000000002 and minPoints = 3 is : 0.2566273479086497   n_clusters = 2
The average silhouette_score for epison = 1.0000000000000002 and minPoints = 4 is : 0.2566273479086497   n_clusters = 2
The average silhouette_score for epison = 1.0000000000000002 and minPoints = 5 is : 0.2566273479086497   n_clusters = 2
The average silhouette_score for epison = 1.0000000000000002 and minPoints = 6 is : 0.27677481802627363  n_clusters = 2
```

```
sil_df
```

	3	4	5	6
0.3	-0.09091	-0.105323	-0.199148	-0.217091
0.4	0.060404	0.027062	0.000255	-0.008616
0.5	0.10824	0.12607	0.115131	0.107302
0.6	0.173228	0.155417	0.190325	0.074557
0.7	0.137517	0.139036	0.22941	0.216997
0.8	0.258272	0.254767	0.246865	0.246865
0.9	0.256627	0.256627	0.276775	0.262002
1.0	0.256627	0.256627	0.256627	0.276775

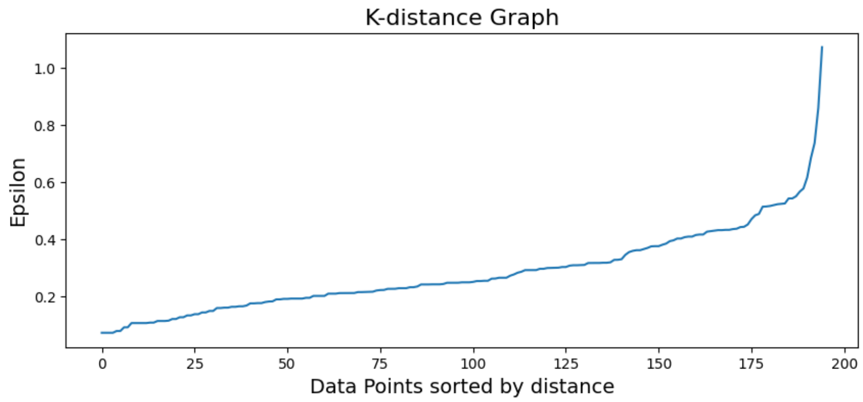
```
fig = px.imshow(sil_df, text_auto = True, aspect = 'auto', color_continuous_scale = 'sunset', width = 600, height = 400, title = 'Heatma
fig.update_xaxes(side = 'top')

fig.show()
```

Heatmap of Epsilon, minPoints and Silhouette scores




```
neigh = NearestNeighbors(n_neighbors = 2)
nbrs = neigh.fit(transformed_df)
distances, indices = nbrs.kneighbors(transformed_df)
```

```
# Plotting K-distance Graph
distances = np.sort(distances, axis=0)
distances = distances[:,1]
plt.figure(figsize=(10, 4))
plt.plot(distances)
plt.title('K-distance Graph',fontsize=16)
plt.xlabel('Data Points sorted by distance',fontsize=14)
plt.ylabel('Epsilon',fontsize=14)
plt.show()

# Observation = Epilon value is approximately 0.5
```



Therefore, optimal epison = 0.5 and minPoints = 5

Using the optimal hyperparameters, fit a DBSCAN model on your data

```
clustering = DBSCAN(eps = 0.5, min_samples = 5).fit(transformed_df)
predicted_labels = clustering.labels_
predicted_labels
```

```
array([-1,  0, -1,  0, -1,  0, -1, -1, -1,  0, -1, -1, -1,  0, -1,  0, -1,
        0, -1, -1, -1,  0, -1,  0, -1,  0, -1, -1, -1,  0, -1,  0, -1,  0,
       -1,  0, -1, -1,  0, -1,  0,  1,  1,  1, -1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1, -1,  2, -1,  2, -1,  2, -1,  2,  3,  2, -1,  2, -1,  2,  3,  2,
       -1,  2, -1,  2, -1,  2, -1,  2, -1, -1,  2,  3,  2,  3,  2,  3,  2,
       -1,  2, -1,  2, -1,  2, -1,  2, -1,  2,  3,  2, -1, -1,  3,  2, -1,
        2, -1,  2, -1,  2, -1,  2, -1,  2, -1,  2, -1,  2, -1, -1, -1,  2,
       -1, -1, -1, -1, -1, -1, -1, -1])
```

```
cluster_ids = set(predicted_labels)
cluster_ids
```

```
{-1, 0, 1, 2, 3}
```

```
n_clusters = len(cluster_ids)
n_clusters

# Observation - The number of clusters formed by DBSCAN for epislon = 0.5 and minPoints = 5 is 5.
```

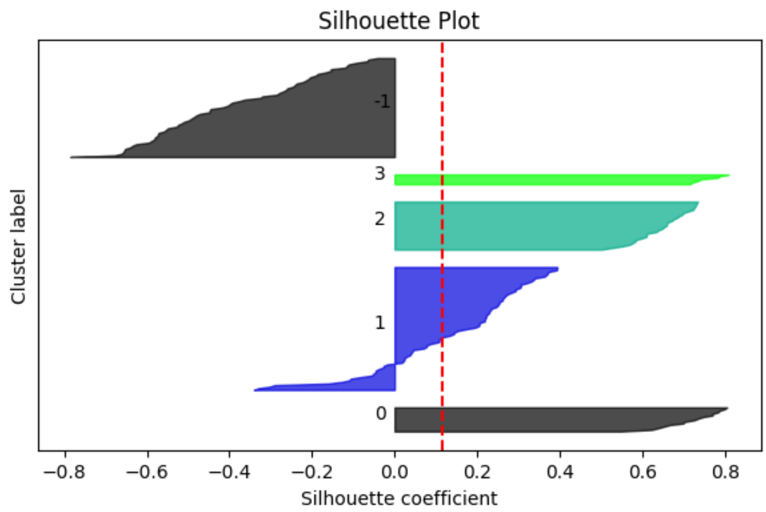
```
5
```

```
num_noise = np.count_nonzero(predicted_labels == -1)
num_noise
```

```
63
```

```
fig, (ax1) = plt.subplots(1, 1)
fig.set_size_inches(7, 4)

sample_silhouette_values = silhouette_samples(transformed_df, predicted_labels)
silhouette_avg = silhouette_score(transformed_df, predicted_labels)

y_lower = 10

for i in cluster_ids:
    # Aggregate the silhouette scores for samples belonging to
    # cluster i, and sort them
    ith_cluster_silhouette_values = sample_silhouette_values[predicted_labels == i]

    ith_cluster_silhouette_values.sort()

    size_cluster_i = ith_cluster_silhouette_values.shape[0]
    y_upper = y_lower + size_cluster_i

    color = cm.nipy_spectral(float(i) / n_clusters)
    ax1.fill_betweenx(
        np.arange(y_lower, y_upper),
        0,
        ith_cluster_silhouette_values,
        facecolor = color,
        edgecolor = color,
        alpha = 0.7,
    )

    # Label the silhouette plots with their cluster numbers at the middle
    ax1.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))

    # Compute the new y_lower for next plot
    y_lower = y_upper + 10  # 10 for the 0 samples

ax1.set_title('Silhouette Plot')
ax1.set_xlabel('Silhouette coefficient')
ax1.set_ylabel('Cluster label')

# The vertical line for average silhouette score of all the values
ax1.axvline(x = silhouette_avg, color='red', linestyle='--')

ax1.set_yticks([])  # Clear the yaxis labels / ticks
```

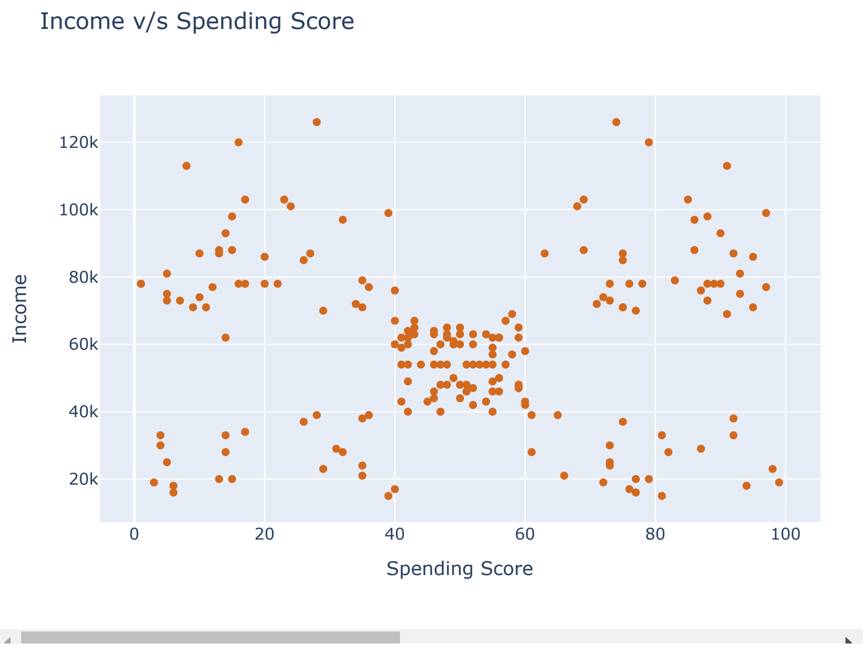
```
[]
```



Visualize clusters

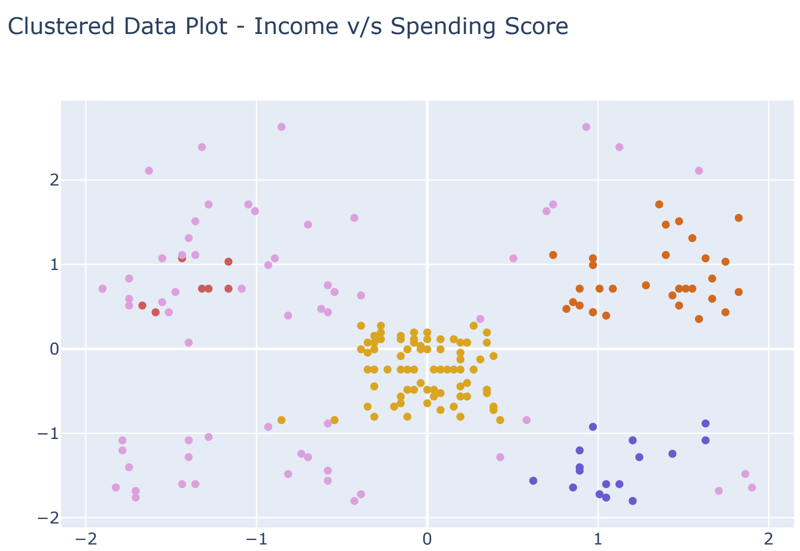
Visualize the clusters formed by plotting points in 2D for 'spending score' and 'annual income'

```
fw1 = go.FigureWidget(px.scatter(customer_df, x = 'Spending Score', y = 'Income', width = 700, height = 500, color_discrete_sequence = ['
                                 title = 'Income v/s Spending Score'))
fw2 = go.FigureWidget(px.scatter(transformed_df, x = 'Spending Score', y = 'Income', width = 700, height = 500, color_discrete_sequence =
                                 title = 'Standardized Income v/s Spending Score'))

dashboard2 = widgets.VBox([widgets.HBox([fw1, fw2])])
dashboard2
```



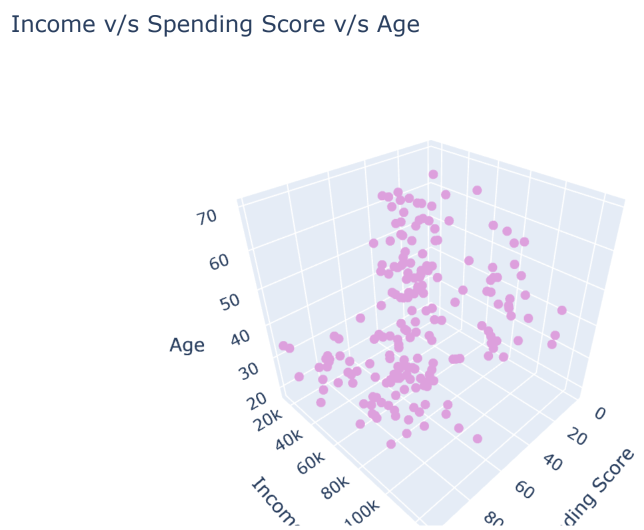

```
fig = go.Figure()


trace_1 = go.Scatter(x = transformed_df.loc[predicted_labels == 0, 'Spending Score'],
                     y = transformed_df.loc[predicted_labels == 0, 'Income'],
                     name = 'Cluster 1',
                     mode = 'markers',
                     marker=go.Marker(color = 'slateblue'),
                     showlegend=True
)

trace_2 = go.Scatter(x = transformed_df.loc[predicted_labels == 1, 'Spending Score'],
                     y = transformed_df.loc[predicted_labels == 1, 'Income'],
                     name = 'Cluster 2',
                     mode = 'markers',
                     marker = go.Marker(color = 'goldenrod'),
                     showlegend = True
)

trace_3 = go.Scatter(x = transformed_df.loc[predicted_labels == 2, 'Spending Score'],
                     y = transformed_df.loc[predicted_labels == 2, 'Income'],
                     name = 'Cluster 3',
                     mode = 'markers',
                     marker = go.Marker(color = 'chocolate'),
                     showlegend = True
)

trace_4 = go.Scatter(x = transformed_df.loc[predicted_labels == 3, 'Spending Score'],
                     y = transformed_df.loc[predicted_labels == 3, 'Income'],
                     name = 'Cluster 4',
                     mode = 'markers',
                     marker = go.Marker(color = 'indianred'),
                     showlegend = True
)

trace_5 = go.Scatter(x = transformed_df.loc[predicted_labels == -1, 'Spending Score'],
                     y = transformed_df.loc[predicted_labels == -1, 'Income'],
                     name = '(5) Noise Cluster',
                     mode = 'markers',
                     marker = go.Marker(color = 'plum'),
                     showlegend = True
)


fig.add_trace(trace_1)
fig.add_trace(trace_2)
fig.add_trace(trace_3)
fig.add_trace(trace_4)
fig.add_trace(trace_5)
fig.update_layout(width = 800, height=500)
fig.update_layout({'title': {'text': 'Clustered Data Plot - Income v/s Spending Score'}})

fig.show()
fig.write_image('Clustered Data Plot - Income vs Spending Score.png')
```

```
/usr/local/lib/python3.10/dist-packages/plotly/graph_objs/_deprecations.py:434: Depre

plotly.graph_objs.Marker is deprecated.
Please replace it with one of the following more specific types
  - plotly.graph_objs.scatter.Marker
  - plotly.graph_objs.histogram.selected.Marker
  - etc.
```



Visualize clusters formed by plotting points in 3D for 'spending score' and 'annual income' and 'age'

```
fig1 = px.scatter_3d(customer_df, x = 'Spending Score', y = 'Income', z = 'Age', width = 700, height = 500, color_discrete_sequence = [
                                 title = 'Income v/s Spending Score v/s Age')
fig1.update_traces(marker_size = 4)

fig2 = px.scatter_3d(transformed_df, x = 'Spending Score', y = 'Income', z = 'Age', width = 700, height = 500, color_discrete_sequence =
                                 title = 'Standardized Income v/s Spending Score v/s Age')
fig2.update_traces(marker_size = 4)

fw1 = go.FigureWidget(fig1)
fw2 = go.FigureWidget(fig2)


dashboard3 = widgets.VBox([widgets.HBox([fw1, fw2])])
dashboard3
```



```
fig = go.Figure()


trace_1 = go.Scatter3d(x = transformed_df.loc[predicted_labels == 0, 'Spending Score'],
                       y = transformed_df.loc[predicted_labels == 0, 'Income'],
                       z = transformed_df.loc[predicted_labels == 0, 'Age'],
                       name = 'Cluster 1',
                       mode = 'markers',
                       marker=go.Marker(color = 'slateblue'),
                       showlegend=True
)

trace_2 = go.Scatter3d(x = transformed_df.loc[predicted_labels == 1, 'Spending Score'],
                       y = transformed_df.loc[predicted_labels == 1, 'Income'],
                       z = transformed_df.loc[predicted_labels == 1, 'Age'],
                       name = 'Cluster 2',
                       mode = 'markers',
                       marker = go.Marker(color = 'goldenrod'),
                       showlegend = True
)

trace_3 = go.Scatter3d(x = transformed_df.loc[predicted_labels == 2, 'Spending Score'],
                       y = transformed_df.loc[predicted_labels == 2, 'Income'],
                       z = transformed_df.loc[predicted_labels == 2, 'Age'],
                       name = 'Cluster 3',
                       mode = 'markers',
                       marker = go.Marker(color = 'chocolate'),
                       showlegend = True
)

trace_4 = go.Scatter3d(x = transformed_df.loc[predicted_labels == 3, 'Spending Score'],
                       y = transformed_df.loc[predicted_labels == 3, 'Income'],
                       z = transformed_df.loc[predicted_labels == 3, 'Age'],
                       name = 'Cluster 4',
                       mode = 'markers',
                       marker = go.Marker(color = 'indianred'),
                       showlegend = True
)

trace_5 = go.Scatter3d(x = transformed_df.loc[predicted_labels == -1, 'Spending Score'],
                       y = transformed_df.loc[predicted_labels == -1, 'Income'],
                       z = transformed_df.loc[predicted_labels == -1, 'Age'],
                       name = '(5) Noise Cluster',
                       mode = 'markers',
                       marker = go.Marker(color = 'plum'),
                       showlegend = True
)


fig.add_trace(trace_1)
fig.add_trace(trace_2)
fig.add_trace(trace_3)
fig.add_trace(trace_4)
fig.add_trace(trace_5)
fig.update_traces(marker_size = 4)

fig.update_layout(width = 800, height=500)
```