Exploring the DBSCAN algorithm

Density-Based Spatial Clustering of Applications with Noise(DBSCAN) is an unsupervised machine learning model, which is robust to noise in the data.

Theoretical Understanding

- **Assumption**:Clusters are regions of high density, separated by regions of low density.

Features

- number of clusters need not be mentioned beforehand.
- 2 parameters:
  - *epsilon*: Radius of circle created around each data point to check density. (Calculated from K-distance graph)
  - *minPoints*: min number of points to be present in the above circle, inorder to label that point as a **core point**. (This should be *atleast 1 greater than the number of dimensions*, Generally it is twice the dimensions.)
- Scans through the entire dataset only once.
- Distance is usually calculated with Euclidean distance.

Terms

- *Core point*: A point that has atleast *minPoints* number of elements in the circle of radius *epsilon* around it.
- *Border Point*: if the number of elements is les than *minPoints*, then it is border point.
- *Noise* : If no other point within *epsilon* radius, it is noise.

Reachability and Connectivity

- Reachability - if a data point can be accessed from another data point directly or indirectly
  - Directly Density-Reachable: A point X is directly density-reachable from point Y w.r.t *epsilon*,*minPoints* if,
    - X is in the circle with radius *epsilon* where Y is the core point. This is the same concept as an *open ball* in Real Analysis.
  - Density-Reachable : A point X is density-reachable from point Y w.r.t *epsilon*, *minPoints* if there is a chain of points p1, p2, p3, ..., pn and p1=X and pn=Y such that pi+1 is directly density-reachable from pi.
- Connectivity - whether two data points belong to the same cluster or not.
  - Density-Connected: A point X is density-connected from point Y if both of them lie in the same circle with radius *epsilon* , and a core point Z.

About the dataset

The dataset contains data about customers at a mall.

In [ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [ ]:
```
X=pd.read_csv("Mall_Customers.csv")
X.head()
```

Out[ ]:

	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

In [ ]:
```
X.drop(columns=["CustomerID"],inplace=True) #customer ID is not important
```

In [ ]:
```
X.columns
```

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

In [ ]:
```
X.describe(include="all")  #initial descriptive statistics
```

Out[ ]:

	Gender	Age	Annual Income (k$)	Spending Score (1-100)
count	200	200.000000	200.000000	200.000000
unique	2	NaN	NaN	NaN
top	Female	NaN	NaN	NaN
freq	112	NaN	NaN	NaN
mean	NaN	38.850000	60.560000	50.200000
std	NaN	13.969007	26.264721	25.823522
min	NaN	18.000000	15.000000	1.000000
25%	NaN	28.750000	41.500000	34.750000
50%	NaN	36.000000	61.500000	50.000000
75%	NaN	49.000000	78.000000	73.000000
max	NaN	70.000000	137.000000	99.000000

The dataset is slightly unbalanced in terms of Gender.

In [ ]:
```
X.isna().sum() #check for null values
```

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

No null values

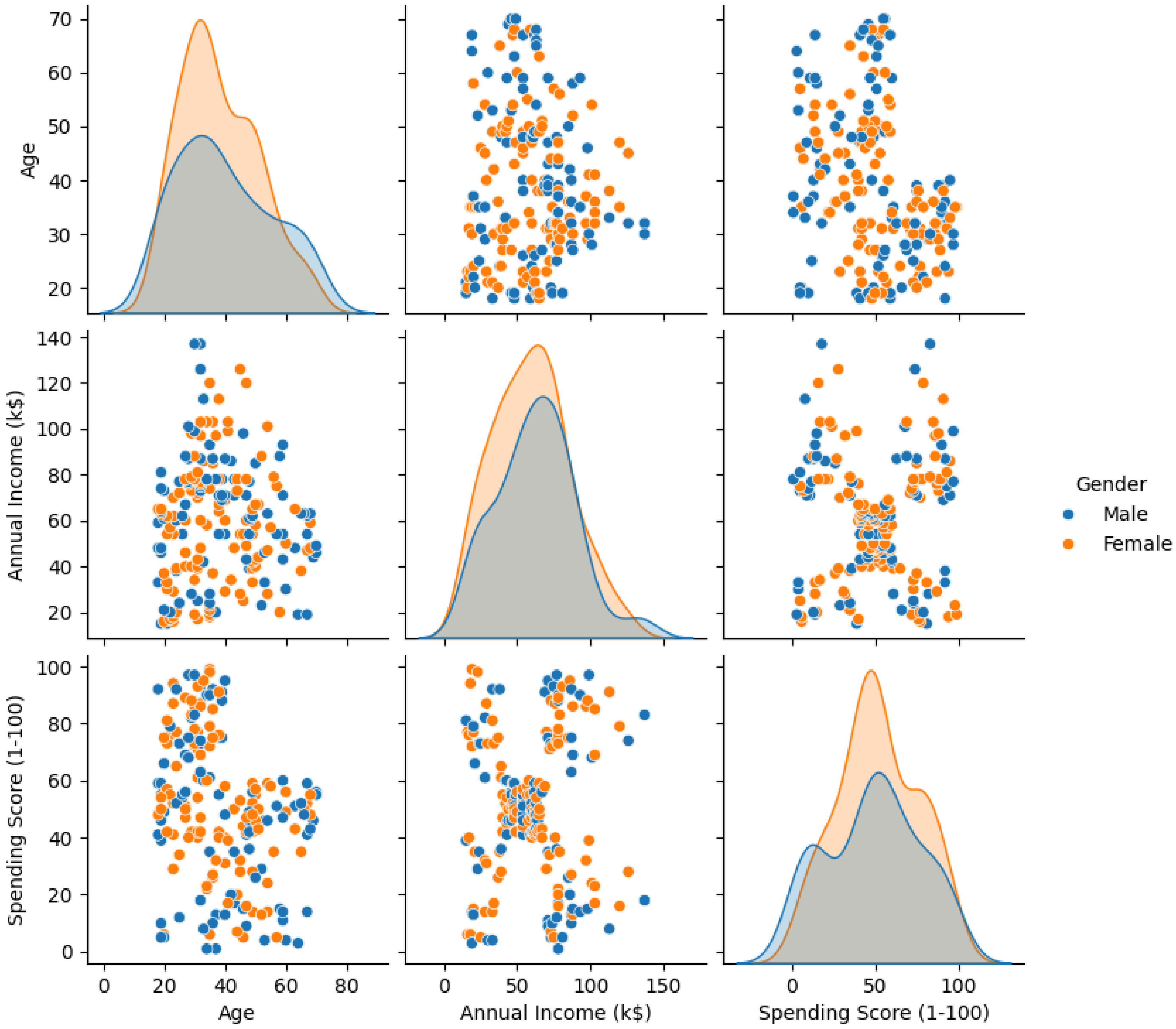
Basic EDA

In [ ]:
```
X_corr=X.drop(columns=["Gender"])
sns.heatmap(X_corr.corr(),annot=True) #correlation
```

Out[ ]: <Axes: >

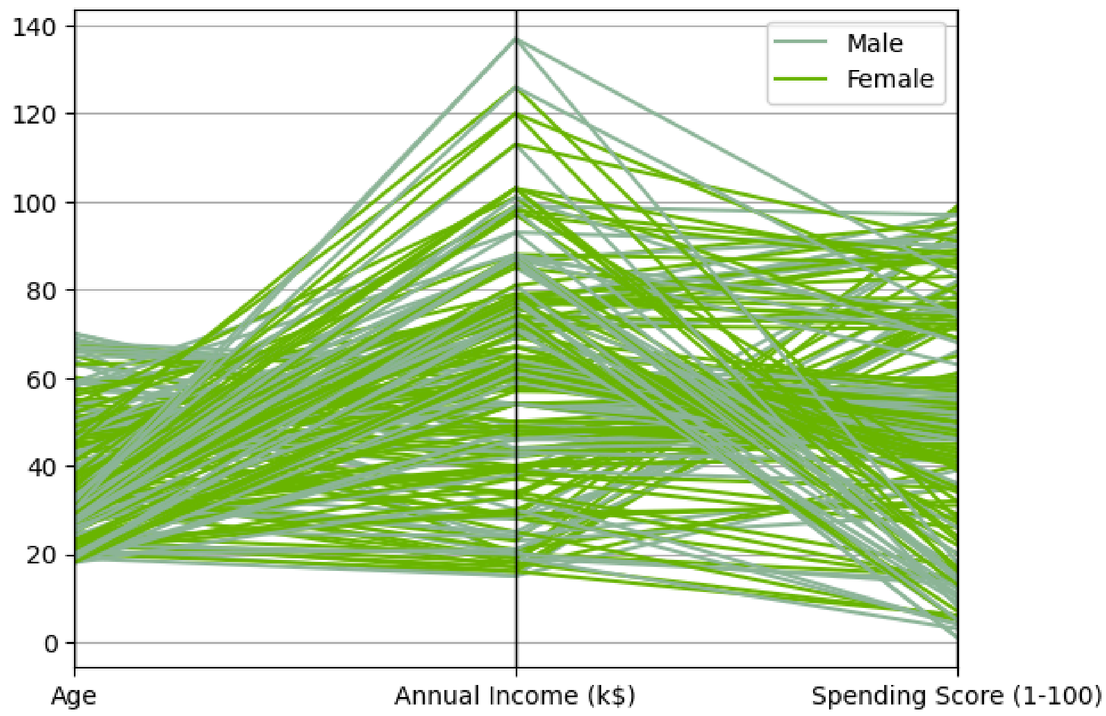
In [ ]:
```
sns.pairplot(X,hue="Gender",diag_kind="kde") #bivariate analysis
```

Out[ ]: <seaborn.axisgrid.PairGrid at 0x2294b24de50>



In [ ]:
```
pd.plotting.parallel_coordinates(X, class_column="Gender")
```

Out[ ]: <Axes: >



In [ ]:
```
import plotly.express as px

fig = px.parallel_coordinates(X, color="Spending Score (1-100)",
                              color_continuous_scale=px.colors.diverging.delta_r,
                              color_continuous_midpoint=2,width=600,height=400,labels={'Gender':'Gender','Age':'Age', 'Annual Income (k$)':'Annual Income' , 'S
fig.show()
```

Data Preprocessing

In [ ]:
```
from sklearn.cluster import DBSCAN
from sklearn import metrics
from sklearn.preprocessing import MinMaxScaler
```

In [ ]:
```
X["Gender"].replace("Male",1,inplace=True)
X["Gender"].replace("Female",2,inplace=True)
X.head()
```

Out[ ]:

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

In [ ]:
```
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
trf1 = ColumnTransformer([
    ('col_gender',OneHotEncoder(sparse_output=False,handle_unknown='ignore'),[0])
],remainder='passthrough')
x_trans=trf1.fit_transform(X)
x_trans=pd.DataFrame(x_trans,columns=['Male','Female', 'Age', 'Annual Income', 'Spending Score'])
x_trans.head()
```

Out[ ]:

	Male	Female	Age	Annual Income	Spending Score
0	1.0	0.0	19.0	15.0	39.0
1	1.0	0.0	21.0	15.0	81.0
2	0.0	1.0	20.0	16.0	6.0
3	0.0	1.0	23.0	16.0	77.0
4	0.0	1.0	31.0	17.0	40.0

In [ ]:
```
trf2=MinMaxScaler()
x_trans[['Age', 'Annual Income', 'Spending Score']]=trf2.fit_transform(x_trans[['Age', 'Annual Income', 'Spending Score']])
```

In [ ]:
```
x_trans.head()
```

Out[ ]:

	Male	Female	Age	Annual Income	Spending Score
0	1.0	0.0	0.019231	0.000000	0.387755
1	1.0	0.0	0.057692	0.000000	0.816327
2	0.0	1.0	0.038462	0.008197	0.051020
3	0.0	1.0	0.096154	0.008197	0.775510
4	0.0	1.0	0.250000	0.016393	0.397959

DBSCAN

Many trials of DBSCAN was done, and in some cases, like when eps=3, all points were clustered into one group. this is normal, becuase all features were scaled betweeen 0 to 1, and so definitely, all points will be within 1 unit distance of each other.

GridSearchCV for DBSCAN was not working because Silhouette Coefficient could not be passed into it as an evaluation metrics. So I made one that suited my needs.

Many resources have mentioned that Euclidean distance becomes less acurate with increase in dimensionality. On the other hand, among the other distance metrics, Mahalanobis and Manhattan distances were frequently claimed to be good for high dimensional data. A comparison of these metrics is also done.

In [ ]:
```
x_trans.head()
```

Out[ ]:

	Male	Female	Age	Annual Income	Spending Score
0	1.0	0.0	0.019231	0.000000	0.387755
1	1.0	0.0	0.057692	0.000000	0.816327
2	0.0	1.0	0.038462	0.008197	0.051020
3	0.0	1.0	0.096154	0.008197	0.775510
4	0.0	1.0	0.250000	0.016393	0.397959

eps=0.1,0.2 with euclidean distance

In [ ]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.cluster import DBSCAN
import numpy as np


clustering = DBSCAN()
parameters={'eps':[0.1,0.2],"min_samples":[7,8,9,10,11,12,13,14,15,16,17,18,19,20]}
for eps in parameters["eps"]:
    for samples in parameters["min_samples"]:

        clustering = DBSCAN(eps=eps, min_samples=samples).fit(x_trans)
        x_trans.insert(0, 'cluster',clustering.labels_)
        components = clustering.components_
        labels =clustering.labels_
        x_trans['cluster'].astype(str)

        unique=x_trans['cluster'].value_counts()
        if len(unique)>1:  #checking for more than one cluster
            sc = metrics.silhouette_score(x_trans.iloc[:,1:], labels)
            if sc>0.5: #checking for silhouete score more than 0.5
                print("eps:",eps,"samples:",samples)
                print("Silhouette Coefficient:%0.2f" % sc)
                print(unique)
        x_trans.drop(columns=["cluster"],inplace=True)
```

eps=0.3,0.4 with euclidean distance

In [ ]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.cluster import DBSCAN
import numpy as np



clustering = DBSCAN()
parameters={'eps':[0.3,0.4],"min_samples":[7,8,9,10,11,12,13,14,15,16,17,18,19,20]}

for eps in parameters["eps"]:
```

```
    for samples in parameters["min_samples"]:
        clustering = DBSCAN(eps=eps, min_samples=samples).fit(x_trans)
        x_trans.insert(0, 'cluster',clustering.labels_)
        components = clustering.components_
        labels =clustering.labels_
        x_trans['cluster'].astype(str)

        unique=x_trans['cluster'].value_counts()
        if len(unique)>1:
            sc = metrics.silhouette_score(x_trans.iloc[:,1:], labels)
            if sc>0.5:
                print("eps:",eps,"samples:",samples)
                print("Silhouette Coefficient:%0.2f" % sc)
                print(unique)
        x_trans.drop(columns=["cluster"],inplace=True)
```

```
eps: 0.4 samples: 7
Silhouette Coefficient:0.63
cluster
1    112
0     88
Name: count, dtype: int64
eps: 0.4 samples: 8
Silhouette Coefficient:0.63
cluster
1    112
0     88
Name: count, dtype: int64
eps: 0.4 samples: 9
Silhouette Coefficient:0.63
cluster
1    112
0     88
Name: count, dtype: int64
eps: 0.4 samples: 10
Silhouette Coefficient:0.63
cluster
1    112
0     88
Name: count, dtype: int64
eps: 0.4 samples: 11
Silhouette Coefficient:0.63
cluster
1    112
0     88
Name: count, dtype: int64
eps: 0.4 samples: 13
Silhouette Coefficient:0.53
cluster
 1    111
 0     87
-1      2
Name: count, dtype: int64
eps: 0.4 samples: 14
Silhouette Coefficient:0.53
cluster
 0    111
 1     87
-1      2
Name: count, dtype: int64
eps: 0.4 samples: 15
Silhouette Coefficient:0.53
cluster
 0    111
 1     87
-1      2
Name: count, dtype: int64
eps: 0.4 samples: 16
Silhouette Coefficient:0.53
cluster
 0    111
 1     87
-1      2
Name: count, dtype: int64
eps: 0.4 samples: 17
Silhouette Coefficient:0.50
cluster
 0    111
 1     85
-1      4
Name: count, dtype: int64
eps: 0.4 samples: 18
Silhouette Coefficient:0.50
cluster
 0    111
 1     85
-1      4
Name: count, dtype: int64
```

configs that gave score>0.5 are: |eps|min_sample|silhouette_score| ----|-------|----| |0.4|7|0.63| |0.4|8|0.63| |0.4|9|0.63| |0.4|10|0.63| |0.4|11|0.63| |0.4|13|0.53| |0.4|14|0.53| |0.4|15|0.53| |0.4|16|0.53|

However in all the cases were silhouette score was 0.63, it just clustered on the basis on gender.

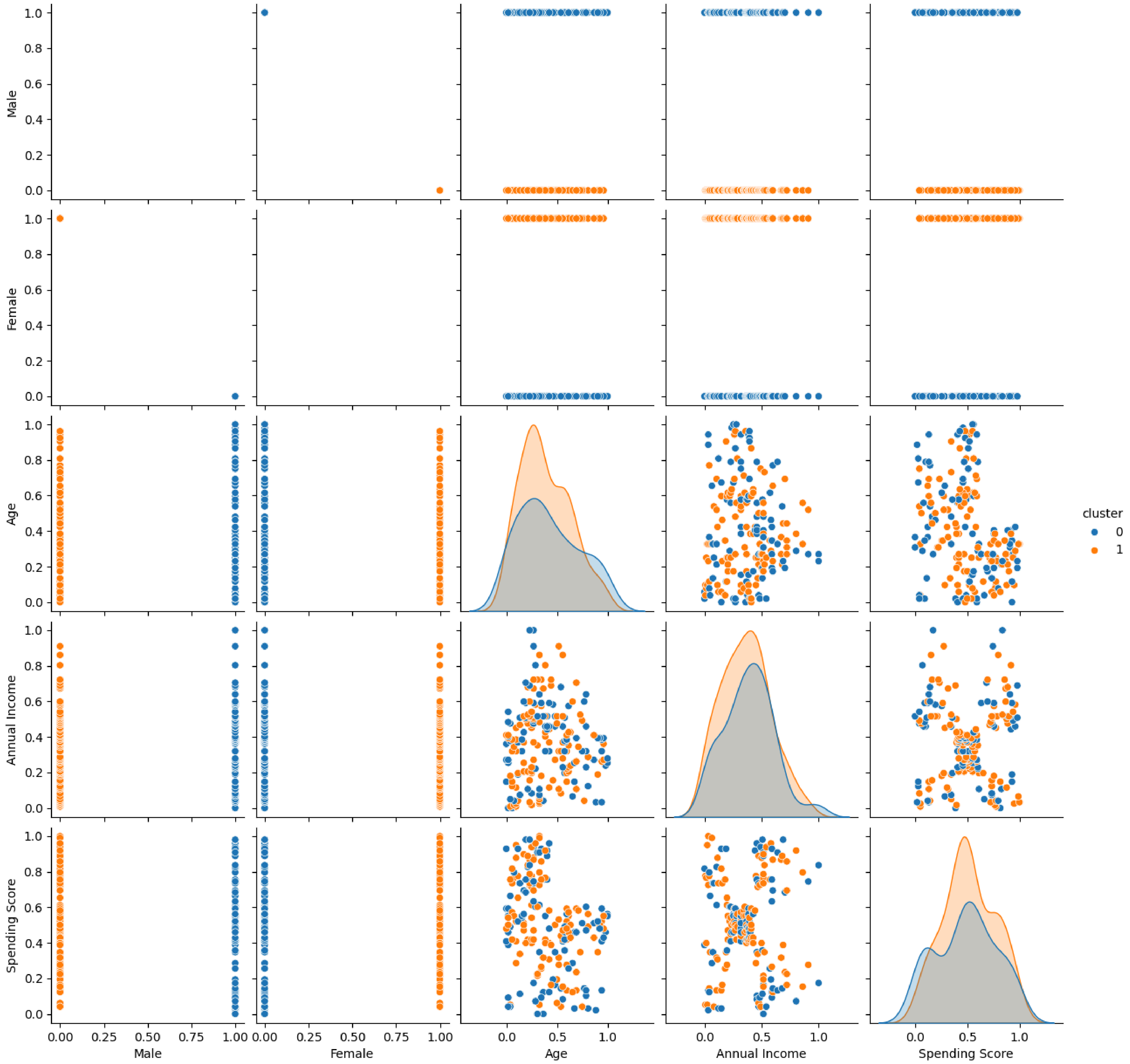
In [ ]:
```
from sklearn.cluster import DBSCAN
import numpy as np


clustering = DBSCAN(eps=0.4, min_samples=7).fit(x_trans)
components = clustering.components_
labels =clustering.labels_
core_sample_indices = clustering.core_sample_indices_
```

```
x_trans.insert(0, 'cluster',clustering.labels_)

x_trans.head(10)
x_trans['cluster'].astype(str)
print(x_trans['cluster'].value_counts())
from sklearn import metrics
sc = metrics.silhouette_score(x_trans.iloc[:,1:], labels)
print("Silhouette Coefficient:%0.2f" % sc)
sns.pairplot(x_trans,hue="cluster")
x_trans.drop(columns=["cluster"],inplace=True)
```

```
cluster
1    112
0     88
Name: count, dtype: int64
Silhouette Coefficient:0.63
```



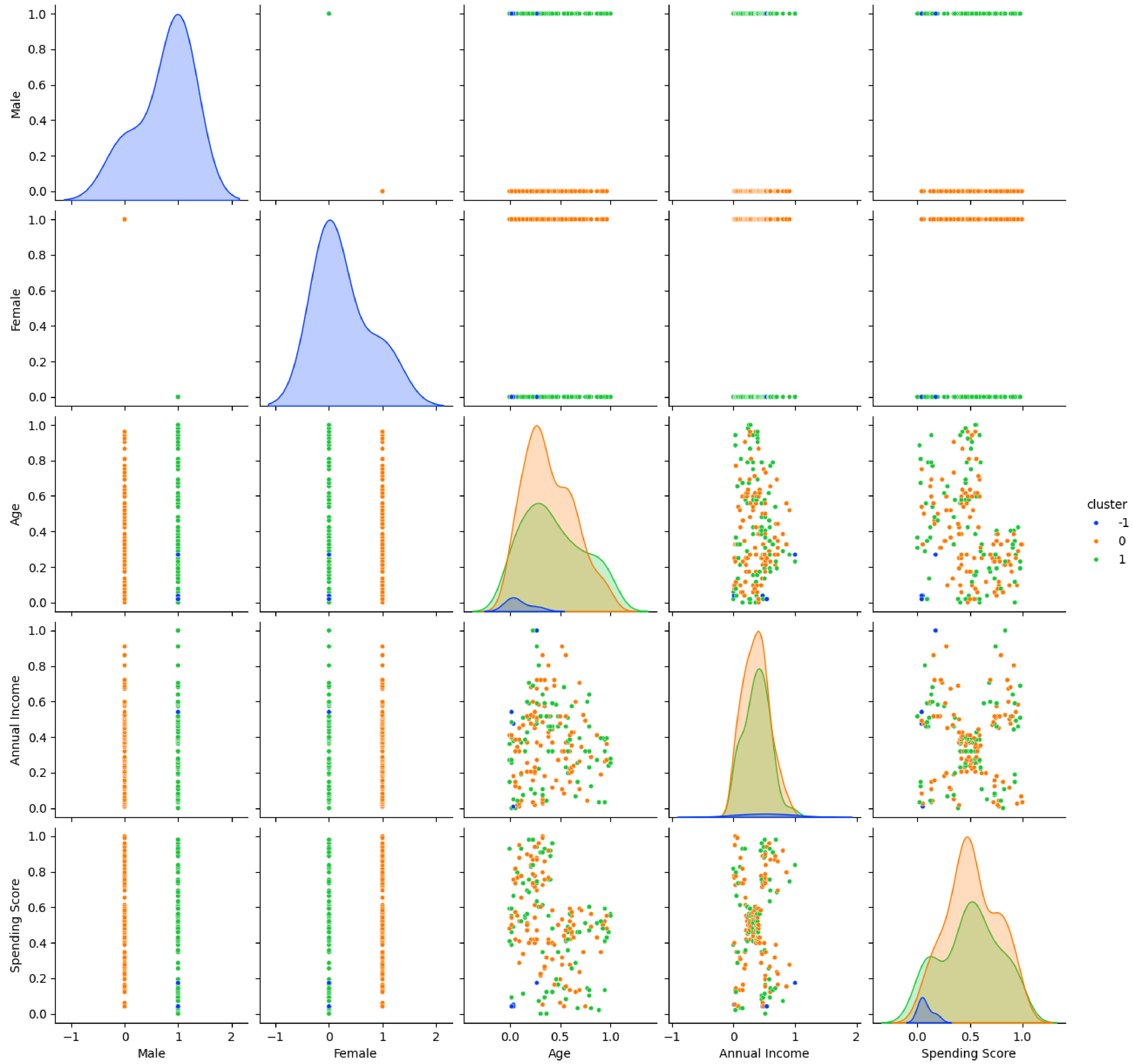
Let's see what the clusters with 0.53 score looked like.

In [ ]:
```
clustering = DBSCAN(eps=0.4, min_samples=18).fit(x_trans)
components = clustering.components_
labels =clustering.labels_


x_trans.insert(0, 'cluster',clustering.labels_)

x_trans.head(10)
x_trans['cluster'].astype(str)
print(x_trans['cluster'].value_counts())
from sklearn import metrics
sc = metrics.silhouette_score(x_trans.iloc[:,1:], labels)
print("Silhouette Coefficient:%0.2f" % sc)
sns.pairplot(x_trans,hue="cluster",diag_kind='kde',palette="bright",plot_kws={"s":15})
x_trans.drop(columns=["cluster"],inplace=True)
```

```
cluster
 0    111
 1     85
-1      4
Name: count, dtype: int64
Silhouette Coefficient:0.50
```



This has also more or less clustered in terms of gender, but this time, we have a cluster with label-1 which stands for outliers. In the pairplot, they are blue in color. It should be noted that the position of a point is an effect of each of the dimensions and a pairplot is a limited representation of this because it shows the position due to 2 variables at a time.

Dropping Gender column to see how DBSCAN clusters.

In [ ]:
```
x_without_gender=x_trans.drop(columns=["Male","Female"])
```

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



plt.close()
clustering = DBSCAN()
parameters={'eps':[0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9],"min_samples":[4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20]}
for eps in parameters["eps"]:
    for samples in parameters["min_samples"]:
        clustering = DBSCAN(eps=eps, min_samples=samples).fit(x_without_gender)
        x_without_gender.insert(0, 'cluster',clustering.labels_)
        components = clustering.components_
        labels =clustering.labels_
        x_without_gender['cluster'].astype(str)
        unique=x_without_gender['cluster'].value_counts()

        if len(unique)>1:
            sc = metrics.silhouette_score(x_without_gender.iloc[:,1:], labels)
            print(sc)
            if sc>0:
                print("eps:",eps,"samples:",samples)
                print("Silhouette Coefficient:%0.2f" % sc)
                print(unique)

        x_without_gender.drop(columns=["cluster"],inplace=True)
```

```
0.15059761879205907
eps: 0.1 samples: 4
Silhouette Coefficient:0.15
cluster
-1    77
 4    32
 2    28
 1    27
 3    20
 0    10
 5     6
Name: count, dtype: int64
0.04535562391226983
eps: 0.1 samples: 5
Silhouette Coefficient:0.05
cluster
-1    98
 6    28
 2    23
 5    19
 3    14
 0     7
 4     6
 1     5
Name: count, dtype: int64
0.02301072386472666
eps: 0.1 samples: 6
Silhouette Coefficient:0.02
cluster
-1    109
 6     25
 1     20
 4     20
 0      7
 2      7
 5      7
 3      5
Name: count, dtype: int64
-0.08026244931739537
-0.13127707066520627
-0.17514655666399914
-0.204847170762306
-0.11986625186929058
-0.15788574833086322
0.2218840942532772
eps: 0.2 samples: 4
Silhouette Coefficient:0.22
cluster
 0    195
-1      5
Name: count, dtype: int64
0.22294991661772784
eps: 0.2 samples: 5
Silhouette Coefficient:0.22
cluster
 0    194
-1      6
Name: count, dtype: int64
0.2179342786052629
eps: 0.2 samples: 6
Silhouette Coefficient:0.22
cluster
 0    190
-1     10
Name: count, dtype: int64
0.22721677633431117
eps: 0.2 samples: 7
Silhouette Coefficient:0.23
cluster
 0    189
-1     11
Name: count, dtype: int64
0.242615572137511
eps: 0.2 samples: 8
Silhouette Coefficient:0.24
cluster
 0    187
-1     13
Name: count, dtype: int64
0.23328503932966277
eps: 0.2 samples: 9
Silhouette Coefficient:0.23
cluster
 0    181
-1     19
Name: count, dtype: int64
0.23328503932966277
eps: 0.2 samples: 10
Silhouette Coefficient:0.23
cluster
 0    181
-1     19
Name: count, dtype: int64
0.23185333973886407
eps: 0.2 samples: 11
Silhouette Coefficient:0.23
cluster
 0    179
-1     21
Name: count, dtype: int64
0.22224366862621103
eps: 0.2 samples: 12
Silhouette Coefficient:0.22
cluster
```

```
 0    177
-1     23
Name: count, dtype: int64
0.2152960648765477
eps: 0.2 samples: 13
Silhouette Coefficient:0.22
cluster
 0    167
-1     33
Name: count, dtype: int64
0.2152960648765477
eps: 0.2 samples: 14
Silhouette Coefficient:0.22
cluster
 0    167
-1     33
Name: count, dtype: int64
0.21779876590185382
eps: 0.2 samples: 15
Silhouette Coefficient:0.22
cluster
 0    166
-1     34
Name: count, dtype: int64
0.22594181562210625
eps: 0.2 samples: 16
Silhouette Coefficient:0.23
cluster
 0    150
-1     50
Name: count, dtype: int64
0.23772493363439623
eps: 0.2 samples: 17
Silhouette Coefficient:0.24
cluster
 0    146
-1     54
Name: count, dtype: int64
0.18647181950901598
eps: 0.2 samples: 18
Silhouette Coefficient:0.19
cluster
 0    136
-1     64
Name: count, dtype: int64
0.18012775746255932
eps: 0.2 samples: 19
Silhouette Coefficient:0.18
cluster
 0    133
-1     67
Name: count, dtype: int64
0.1594890588180914
eps: 0.2 samples: 20
Silhouette Coefficient:0.16
cluster
 0    98
-1    68
 1    34
Name: count, dtype: int64
0.2475994366499519
eps: 0.3 samples: 10
Silhouette Coefficient:0.25
cluster
 0    199
-1      1
Name: count, dtype: int64
0.2475994366499519
eps: 0.3 samples: 11
Silhouette Coefficient:0.25
cluster
 0    199
-1      1
Name: count, dtype: int64
0.2475994366499519
eps: 0.3 samples: 12
Silhouette Coefficient:0.25
cluster
 0    199
-1      1
Name: count, dtype: int64
0.2475994366499519
eps: 0.3 samples: 13
Silhouette Coefficient:0.25
cluster
 0    199
-1      1
Name: count, dtype: int64
0.27862118452439905
eps: 0.3 samples: 14
Silhouette Coefficient:0.28
cluster
 0    198
-1      2
Name: count, dtype: int64
0.27862118452439905
eps: 0.3 samples: 15
Silhouette Coefficient:0.28
cluster
 0    198
-1      2
Name: count, dtype: int64
0.2627176465809177
eps: 0.3 samples: 16
```

```
Silhouette Coefficient:0.26
cluster
 0    197
-1      3
Name: count, dtype: int64
0.2627176465809177
eps: 0.3 samples: 17
Silhouette Coefficient:0.26
cluster
 0    197
-1      3
Name: count, dtype: int64
0.29007392552072675
eps: 0.3 samples: 18
Silhouette Coefficient:0.29
cluster
 0    195
-1      5
Name: count, dtype: int64
0.29007392552072675
eps: 0.3 samples: 19
Silhouette Coefficient:0.29
cluster
 0    195
-1      5
Name: count, dtype: int64
0.29007392552072675
eps: 0.3 samples: 20
Silhouette Coefficient:0.29
cluster
 0    195
-1      5
Name: count, dtype: int64
```

Only one cluster is formed in most cases, clusters labelled -1 are outliers. This shows how DBSCAN can be used for outlier detection. We plot 3D plots of all cases where we get silhouette score highest.

In [ ]:
```
%matplotlib notebook
```

In [ ]:
```
eps=0.3
min_sample=20
clustering = DBSCAN(eps=0.3, min_samples=20).fit(x_without_gender)
x_without_gender.insert(0, 'cluster',clustering.labels_)
components = clustering.components_
labels =clustering.labels_
x_without_gender['cluster'].astype(str)
unique=x_without_gender['cluster'].value_counts()

if len(unique)>1:
    sc = metrics.silhouette_score(x_without_gender.iloc[:,1:], labels)
    print(sc)
    if sc>0:
        print("eps:",eps,"samples:",samples)
        print("Silhouette Coefficient:%0.2f" % sc)
        print(unique)
        fig = px.scatter_3d(x_without_gender, x='Age', y='Annual Income', z='Spending Score', color='cluster',
                      title='3D Scatter Plot ')

        # Update layout to adjust plot size
        fig.update_layout(
            width=800,  # Width of the plot
            height=600  # Height of the plot
        )

        # Show the plot
        fig.show()
x_without_gender.drop(columns=["cluster"],inplace=True)
```

```
0.29007392552072675
eps: 0.3 samples: 20
Silhouette Coefficient:0.29
cluster
 0    195
-1      5
Name: count, dtype: int64
```

This plot clearly shows us the outliers.

Note: Plotly plots in my system have some kind of bug, they don't convert to HTML. A video which contains the interaction with the plot has been uploaded

In [ ]:
```
eps=0.1
min_sample=4
clustering = DBSCAN(eps=eps, min_samples=min_sample).fit(x_without_gender)
x_without_gender.insert(0, 'cluster',clustering.labels_)
components = clustering.components_
labels =clustering.labels_
x_without_gender['cluster'].astype(str)
unique=x_without_gender['cluster'].value_counts()

if len(unique)>1:
    sc = metrics.silhouette_score(x_without_gender.iloc[:,1:], labels)
    print(sc)
    if sc>0:
        print("eps:",eps,"samples:",samples)
        print("Silhouette Coefficient:%0.2f" % sc)
        print(unique)
        fig = px.scatter_3d(x_without_gender, x='Age', y='Annual Income', z='Spending Score', color='cluster',
                      title='3D Scatter Plot ')

        # Update layout to adjust plot size
        fig.update_layout(
            width=800,  # Width of the plot
            height=600  # Height of the plot
```

```
        )

        # Show the plot
        fig.show()
x_without_gender.drop(columns=["cluster"],inplace=True)
```

```
0.15059761879205907
eps: 0.1 samples: 20
Silhouette Coefficient:0.15
cluster
-1    77
 4    32
 2    28
 1    27
 3    20
 0    10
 5     6
Name: count, dtype: int64
```

Note: Plotly plots in my system have some kind of bug, they don't convert to HTML. A video which contains the interaction with the plot has been uploaded

In this configuration of DBSCAN we get some dense clusters, the non-dense regions are marked as outliers. These were the observable features:

- Cluster 0: Low annual Income , Young, High Spending Scores
- Cluster 1: Low Annual Income, Young, Average Spending Score
- Cluster 2: Average Annual Income, Middle Aged, Median Spending Score
- Cluster 3: Aged, Median Income, Median Spending Score
- Cluster 4: Young, High Annual Income, High Spending Score
- Cluster 5: Middle Age, Median Annual Income, Low Spending Score

Conclusion

DBSCAN is useful in detecting outliers and for identifying dense group of datapoints.

References

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