In [94]:

```
# Importing the libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import make_blobs
from sklearn.cluster import KMeans
from sklearn.datasets import make_classification
from sklearn.metrics import accuracy_score, confusion_matrix,classification_report,log_lo
ss
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import CountVectorizer
```

In [95]:

```
# #import dataset
# Use the absolute path to the CSV file
file_path = '/Users/saheedadeitan/Downloads/BusyQA_bootcamp//segmentation data.csv'
# Read the CSV file into a DataFrame
df = pd.read_csv(file_path)
# Display the first few rows of the DataFrame to verify the import
df.describe()
```

Out[95]:

	ID	Sex	Marital status	Age	Education	Income	Occupation	Settlement size
count	2.000000e+03	2000.000000	2000.000000	2000.000000	2000.00000	2000.000000	2000.000000	2000.000000
mean	1.000010e+08	0.457000	0.496500	35.909000	1.03800	120954.419000	0.810500	0.739000
std	5.774946e+02	0.498272	0.500113	11.719402	0.59978	38108.824679	0.638587	0.812533
min	1.000000e+08	0.000000	0.000000	18.000000	0.00000	35832.000000	0.000000	0.000000
25%	1.000005e+08	0.000000	0.000000	27.000000	1.00000	97663.250000	0.000000	0.000000
50%	1.000010e+08	0.000000	0.000000	33.000000	1.00000	115548.500000	1.000000	1.000000
75%	1.000015e+08	1.000000	1.000000	42.000000	1.00000	138072.250000	1.000000	1.000000
max	1.000020e+08	1.000000	1.000000	76.000000	3.00000	309364.000000	2.000000	2.000000

In [97]:

```
df.head()
```

Out[97]:

	ID	Sex	Marital status	Age	Education	Income	Occupation	Settlement size
0	100000001	0	0	67	2	124670	1	2
1	100000002	1	1	22	1	150773	1	2
2	100000003	0	0	49	1	89210	0	0
3	100000004	0	0	45	1	171565	1	1
4	100000005	0	0	53	1	149031	1	1

In [98]:

```
# no of rows
print('Number of rows: ' + str(df.shape[0]))
```

```
Number of rows: 2000
```

In [99]:

```python
print('Number of columns: ' + str(len(df.columns)))
print('Columns in df: ' + str(df.columns))
```

```
Number of columns: 8
Columns in df: Index(['ID', 'Sex', 'Marital status', 'Age', 'Education', 'Income',
       'Occupation', 'Settlement size'],
      dtype='object')
```

In [100]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   ID               2000 non-null   int64
 1   Sex              2000 non-null   int64
 2   Marital status   2000 non-null   int64
 3   Age              2000 non-null   int64
 4   Education        2000 non-null   int64
 5   Income           2000 non-null   int64
 6   Occupation       2000 non-null   int64
 7   Settlement size  2000 non-null   int64
dtypes: int64(8)
memory usage: 125.1 KB
```

In [101]:

```python
#Getting the data types of the dataset
df.dtypes
```

Out[101]:

```
ID                 int64
Sex                int64
Marital status     int64
Age                int64
Education          int64
Income             int64
Occupation         int64
Settlement size    int64
dtype: object
```

In [102]:

```python
#Finding out if there are Null values
null_counts = df.isna().sum()
null_counts
```

Out[102]:

```
ID                 0
Sex                0
Marital status     0
Age                0
Education          0
Income             0
Occupation         0
Settlement size    0
dtype: int64
```

In [103]:

```python
df.shape
```

Out[103]:

```
(2000, 8)
```

In [104]:

```
df['Settlement size'].unique()
```

Out[104]:

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

In [105]:

```
df['Age'].unique()
```

Out[105]:

```
array([67, 22, 49, 45, 53, 35, 61, 28, 25, 24, 60, 32, 44, 31, 48, 26, 36,
       39, 42, 34, 63, 27, 30, 57, 33, 37, 58, 23, 29, 52, 50, 46, 51, 41,
       40, 66, 47, 56, 54, 20, 21, 38, 70, 65, 74, 68, 43, 55, 64, 75, 19,
       62, 59, 73, 72, 76, 71, 18])
```

In [106]:

```
df['Income'].unique()
```

Out[106]:

```
array([124670, 150773,  89210, ...,  86400,  97968,  68416])
```

In [107]:

```
df['Marital status'].unique()
```

Out[107]:

```
array([0, 1])
```

In [108]:

```
# check for deuplicates
df.duplicated()
```

Out[108]:

```
0       False
1       False
2       False
3       False
4       False
        ...
1995    False
1996    False
1997    False
1998    False
1999    False
Length: 2000, dtype: bool
```

In [109]:

```
df['ID'].unique()
```

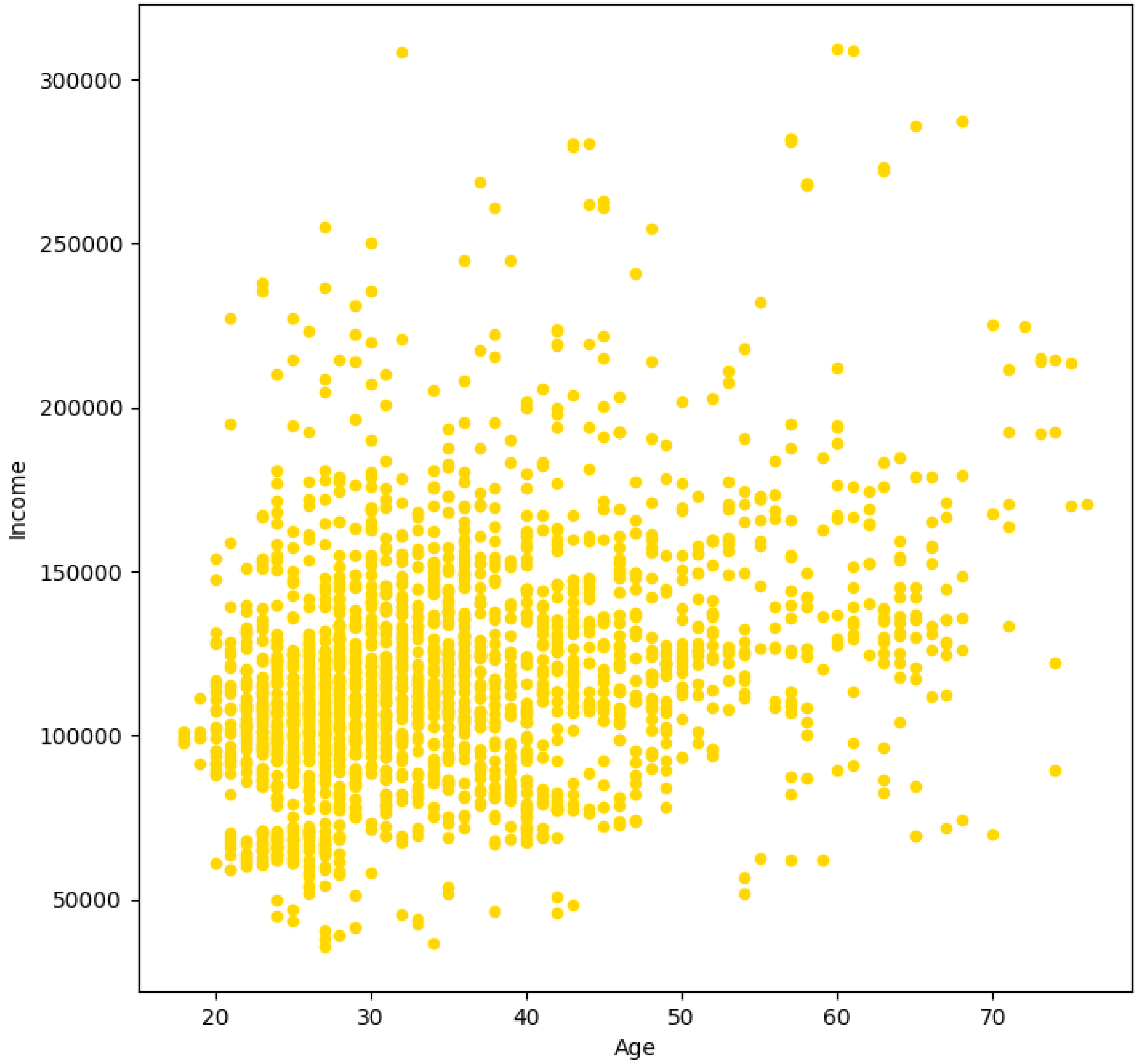
Out[109]:

```
array([100000001, 100000002, 100000003, ..., 100001998, 100001999,
       100002000])
```

In [110]:

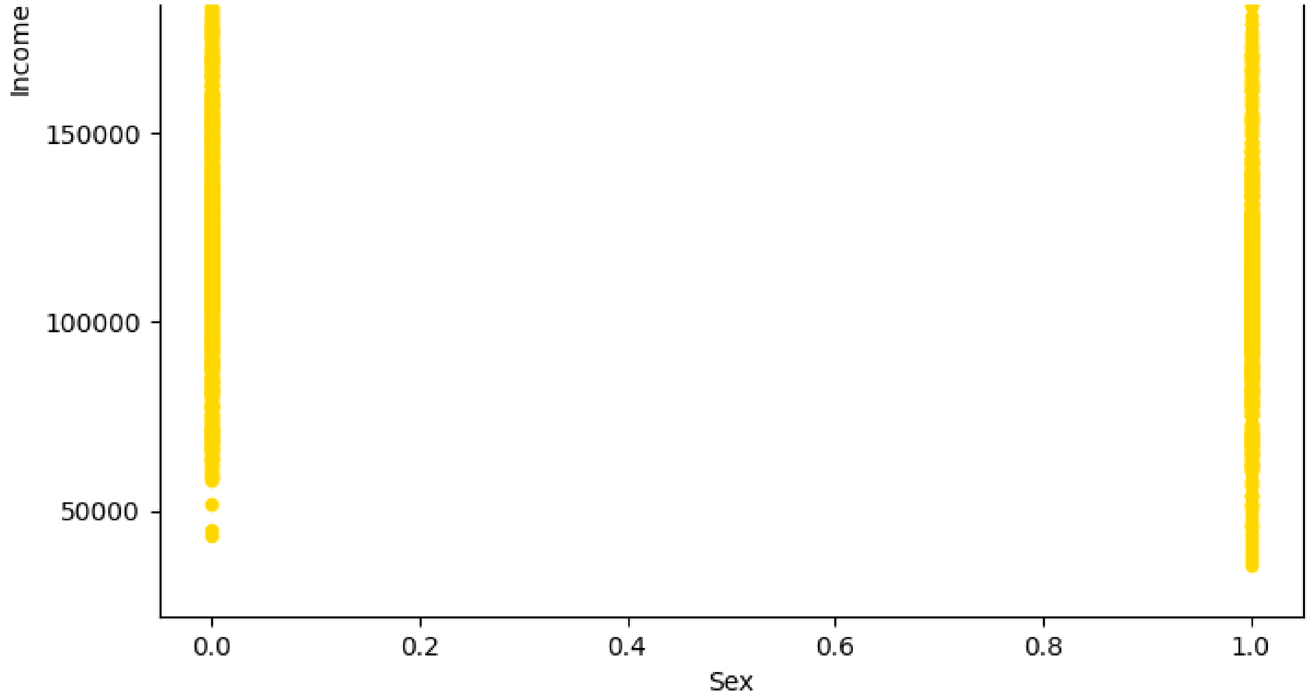
```
# to detect outlier, we use scatter plot
#  i am looking for any data points that seem out of place or unusual compared to the res
t of the data
#  as they may indicate errors, anomalies, or interesting phenomena within the dataset.
# Scatter plot using pandas
ax1 = df.plot.scatter(x='Age',
                      y='Income',
                      c='gold', figsize = (8,8))
plt.xlabel('Age')
```

```
plt.ylabel('Income')
plt.show()
```



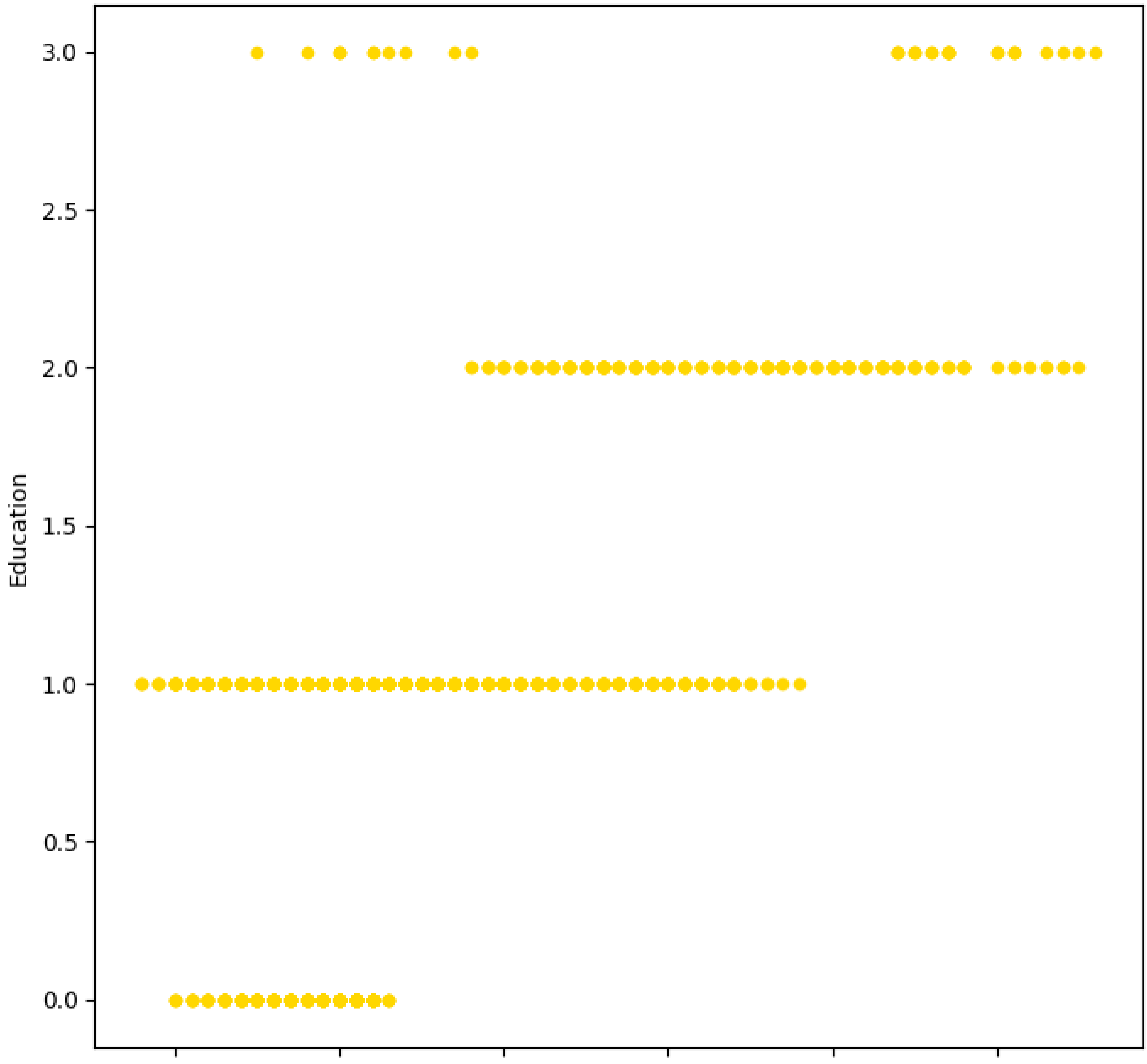
In [111]:

```
# sex vs income
ax1 = df.plot.scatter(x='Sex',
                      y='Income',
                      c='gold', figsize = (8,8))
plt.xlabel('Sex')
plt.ylabel('Income')
plt.show()
```



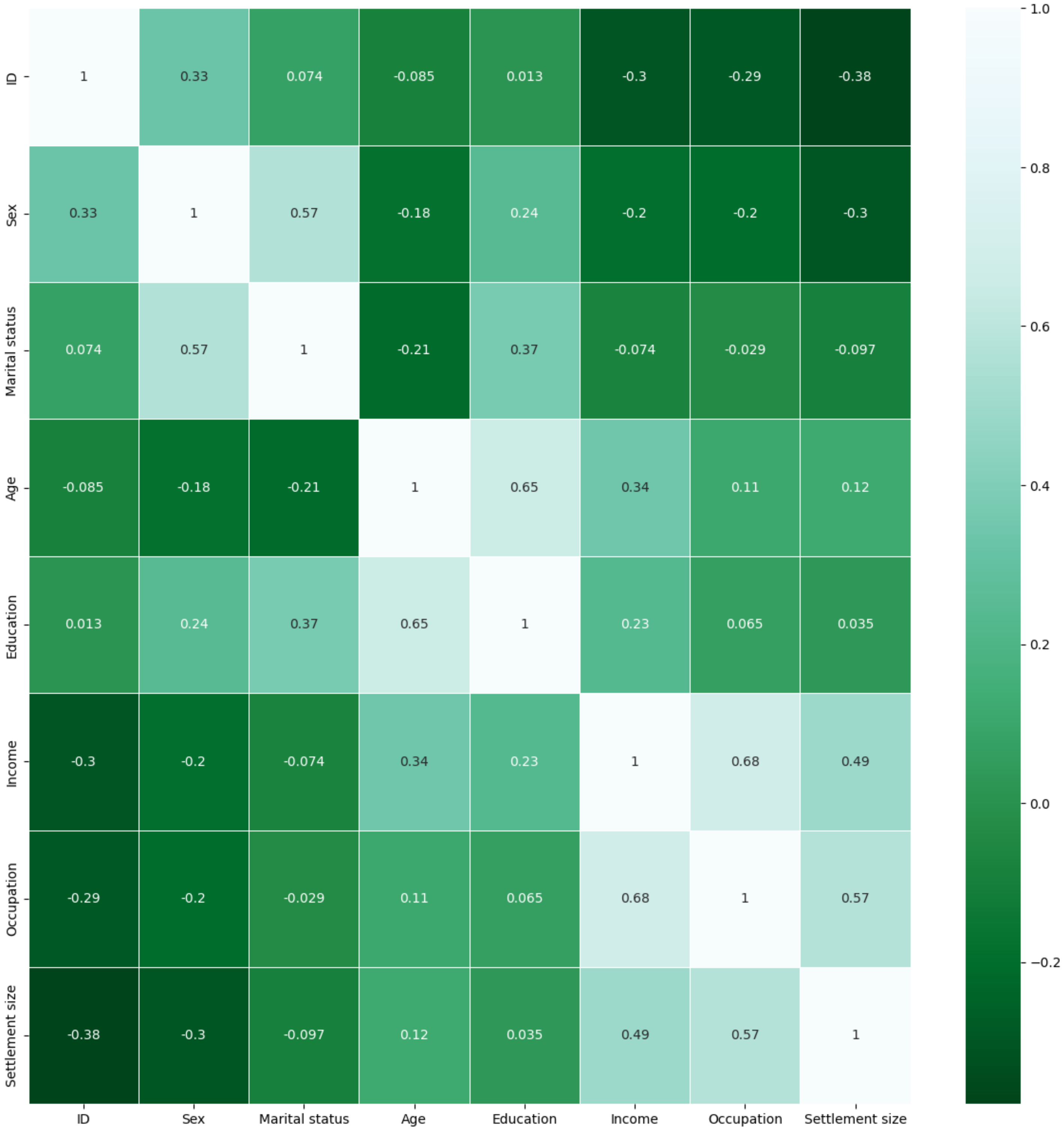
In [112]:

```
# Age vs income
ax1 = df.plot.scatter(x='Age',
                      y='Education',
                      c='gold', figsize = (8,8))
plt.xlabel('Age')
plt.ylabel('Education')
plt.show()
```



In [113]:

```python
# EDA - Multivariant analysis to understand the data
# it shows the statistical relationship between all the variables
a = df.corr()
plt.rcParams['figure.figsize']=(15,15)
ax = sns.heatmap(a, linewidth=0.5, cmap= 'BuGn_r', annot = True)
plt.show()
```



In [114]:

```python
# scaling data

from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
data_scaled = scaler.fit_transform(df)
```

```
# statistics of scaled data
pd.DataFrame(data_scaled).describe()
```

Out[114]:

	0	1	2	3	4	5	6	7
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	0.500000	0.457000	0.496500	0.308776	0.346000	0.311197	0.405250	0.369500
std	0.288892	0.498272	0.500113	0.202059	0.199927	0.139321	0.319294	0.406266
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.250000	0.000000	0.000000	0.155172	0.333333	0.226048	0.000000	0.000000
50%	0.500000	0.000000	0.000000	0.258621	0.333333	0.291434	0.500000	0.500000
75%	0.750000	1.000000	1.000000	0.413793	0.333333	0.373778	0.500000	0.500000
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

In [115]:

```
data_scaled[0]
```

Out[115]:

```
array([0.        , 0.        , 0.        , 0.84482759, 0.66666667,
       0.32478101, 0.5       , 1.        ])
```

In [116]:

```
from sklearn.cluster import KMeans
# K-Means Clustering
# defining the kmeans function with initialization as k-means++
kmeans = KMeans(n_clusters=2, init='k-means++')

# fitting the k means algorithm on scaled data
kmeans.fit(data_scaled)
```

Out[116]:

```
▾ KMeans  i ?

KMeans(n_clusters=2)
```

In [118]:

```
# after scaling, the inertia is 1218.6
kmeans.inertia_
```

Out[118]:

```
1218.602967369794
```

In [ ]:

```

```

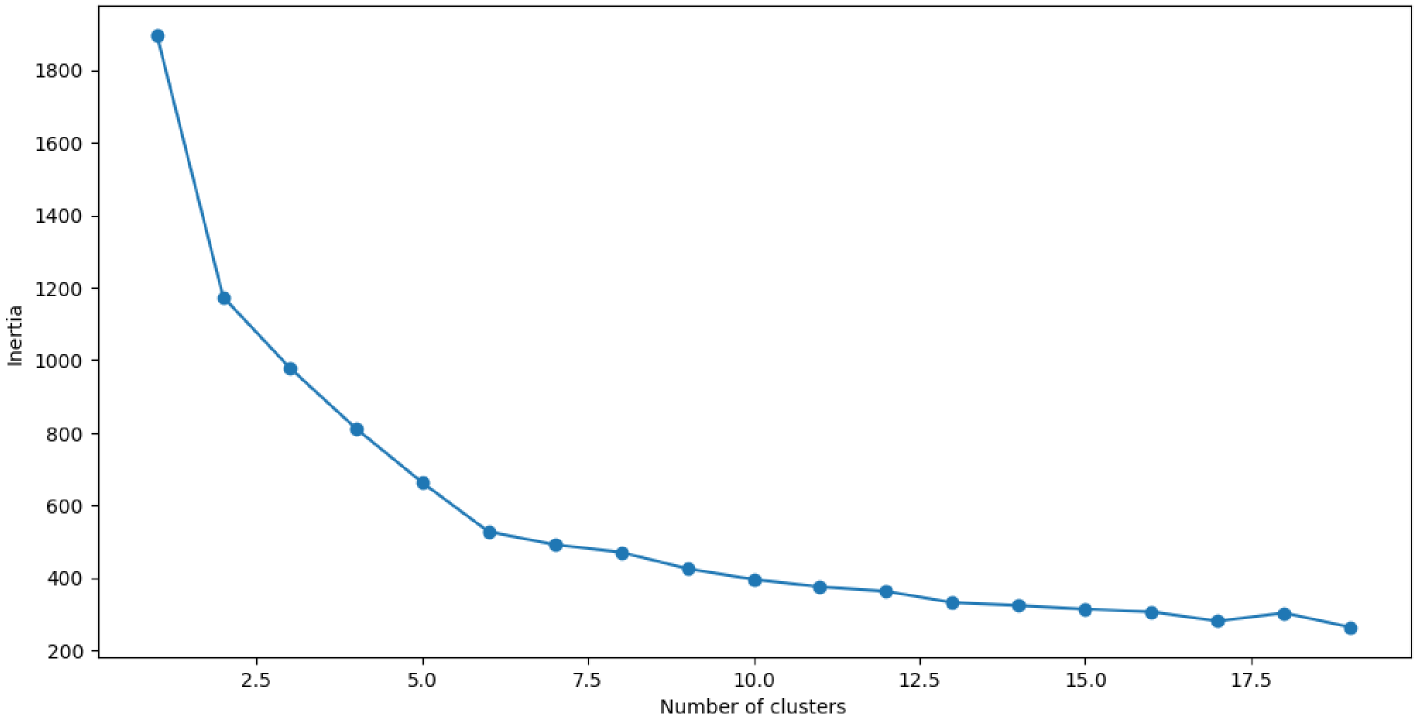
In [126]:

```
# Using elbow
import warnings
warnings.filterwarnings("ignore")
# fitting multiple k-means algorithms and storing the values in an empty list
SSE = []
for cluster in range(1,20):
    # kmeans = KMeans(n_jobs = -1, n_clusters = cluster, init='k-means++')
    kmeans = KMeans(n_clusters = cluster, init='k-means++')
    kmeans.fit(data_scaled)
    SSE.append(kmeans.inertia_)
```

```
# converting the results into a dataframe and plotting them
# Here on the loop shown below, i notice that the elboe happens around 5 and 6 clusters.
i will use silhouette scores to have a better insight on number of clusters to use
frame = pd.DataFrame({'Cluster':range(1,20), 'SSE':SSE})
plt.figure(figsize=(12,6))
plt.plot(frame['Cluster'], frame['SSE'], marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
```

Out[126]:

```
Text(0, 0.5, 'Inertia')
```



In [120]:

```
# Silhouette method to assess the quality
from sklearn.metrics import silhouette_score

sil = []
kmax = 10

# dissimilarity would not be defined for a single cluster, thus, minimum number of cluste
rs should be 2
for k in range(2, kmax+1):
  kmeans = KMeans(n_clusters = k).fit(data_scaled)
  labels = kmeans.labels_
  sil.append(silhouette_score(data_scaled, labels, metric = 'euclidean'))


sil
```

Out[120]:

```
[0.3607728451743172,
 0.3146895289713897,
 0.31829570162980597,
 0.341864960458405l,
 0.282577929658467 4,
 0.3592024511576246,
 0.31636302886053835,
 0.30643972688090254,
 0.328012981286968]
```

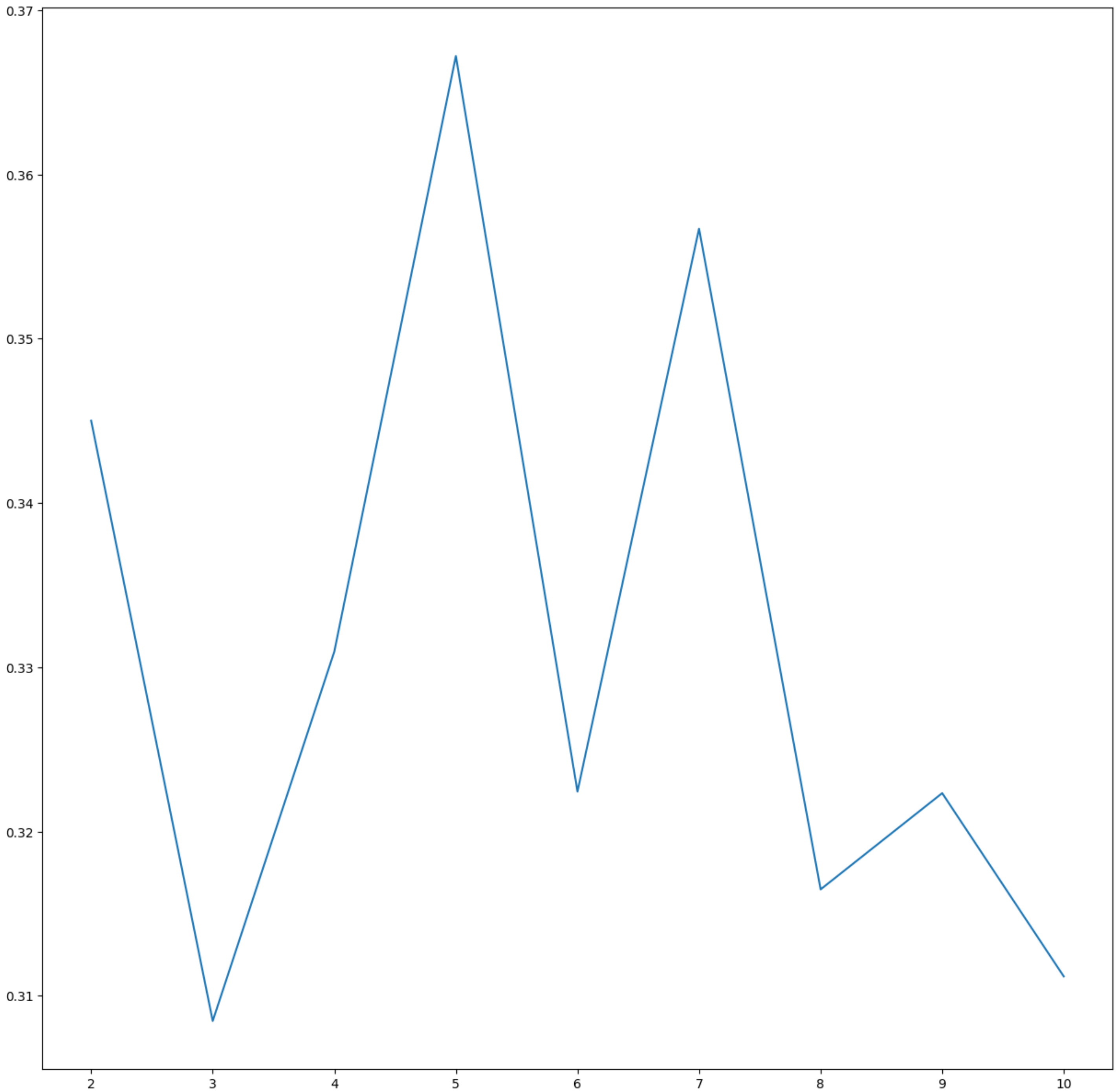
In [90]:

```
# from below, we see a clusters in 3, 6, 8 and 10 on x axis
y1 = np.linspace(2, 10, 9)
```

```
plt.plot(y1, sil)
```

Out[90]:

```
[<matplotlib.lines.Line2D at 0x132106bd0>]
```



In [91]:

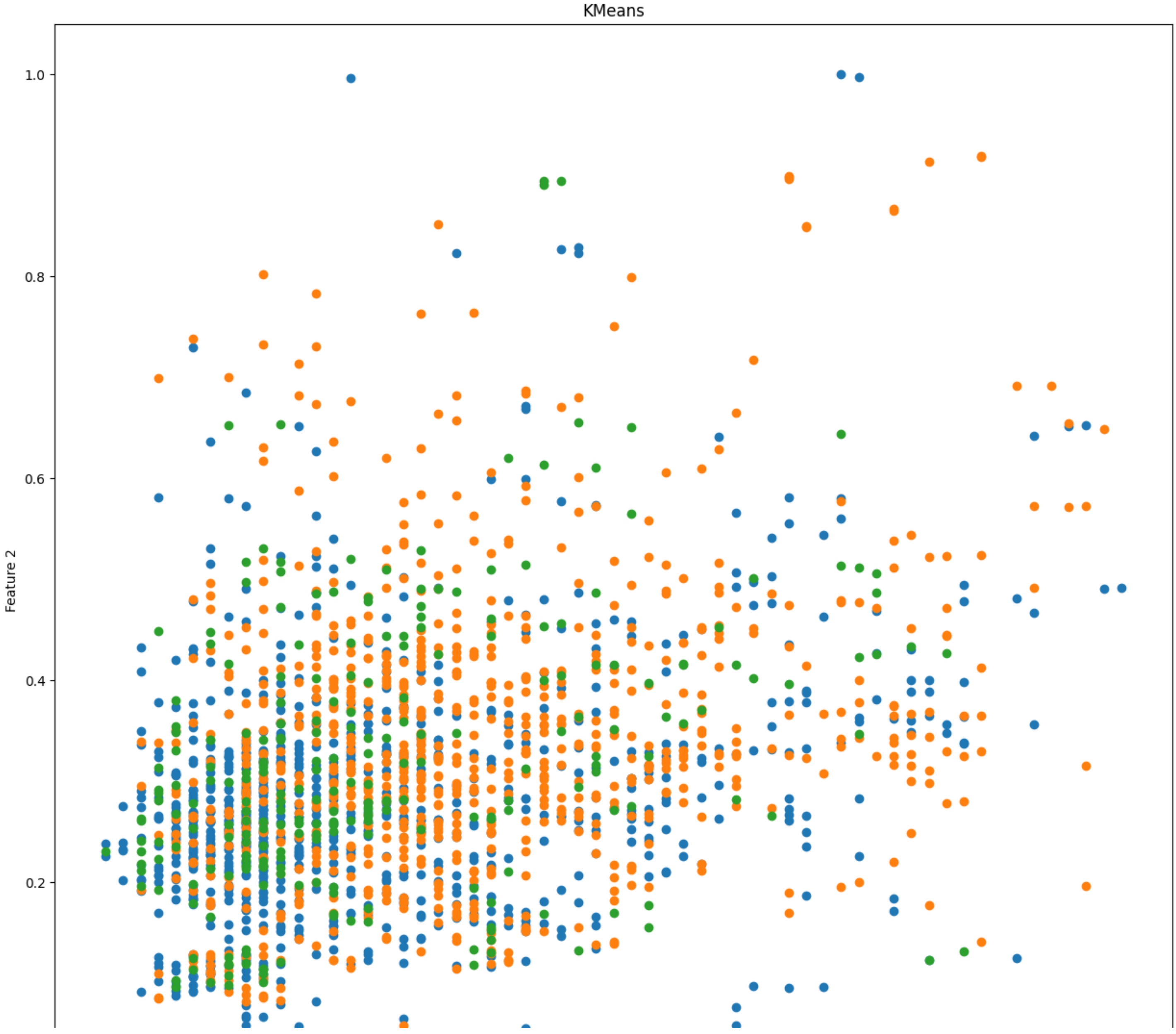
```
# k means using 3 clusters and k-means++ initialization
kmeans = KMeans(n_clusters = 3, init='k-means++')
kmeans.fit(data_scaled)
pred = kmeans.predict(data_scaled)

frame = pd.DataFrame(data_scaled)
frame['cluster'] = pred
frame['cluster'].value_counts()
```

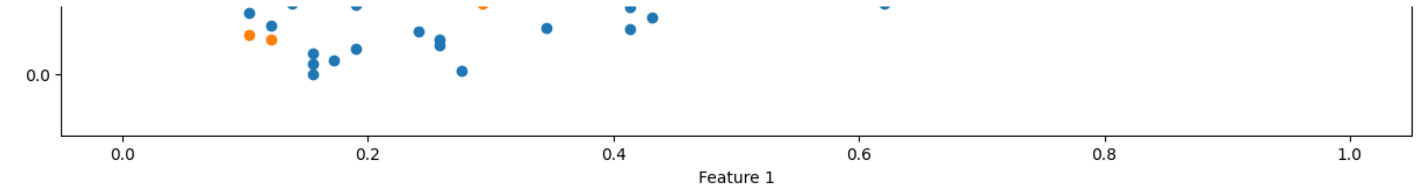
Out[91]:

```
cluster
2    1007
1     736
0     257
Name: count, dtype: int64
```

In [128]:

```python
# Visualisation of clusters(K means)
from numpy import unique
from numpy import where
from sklearn.datasets import make_classification
from sklearn.cluster import KMeans
from matplotlib import pyplot


# define dataset
X = data_scaled
# define the model
model = KMeans(n_clusters=3)  #i use clusters as 3 instead of 2
# fit the model
model.fit(X)
# assign a cluster to each example
yhat = model.predict(X)
# retrieve unique clusters
clusters = unique(yhat)

# create scatter plot for samples from each cluster
for cluster in clusters:
    # get row indexes for samples with this cluster
    row_ix = where(yhat == cluster)
    # create scatter of these samples
    pyplot.scatter(X[row_ix, 3], X[row_ix, 5])
# show the plot
plt.xlabel("Feature 1")
plt.ylabel("Feature 2")
plt.title("KMeans")
pyplot.show()
```

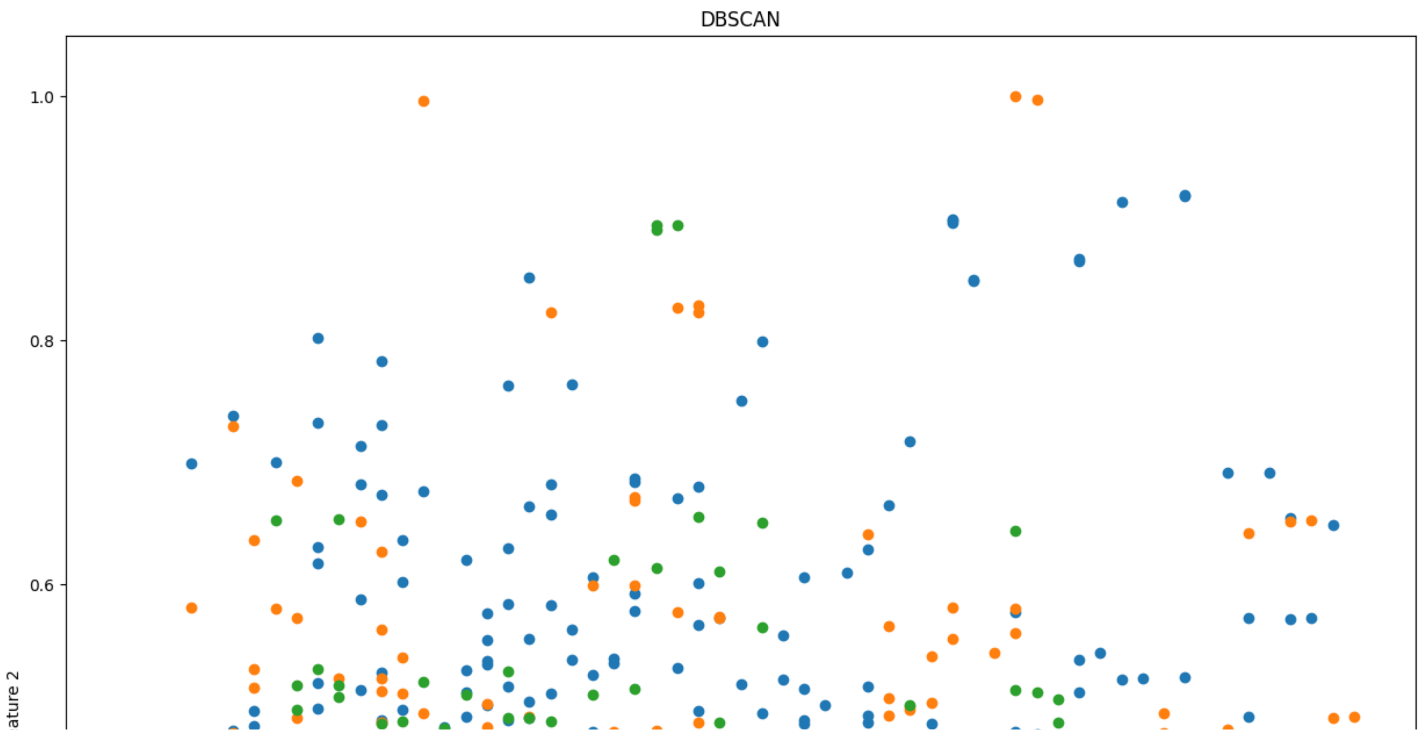


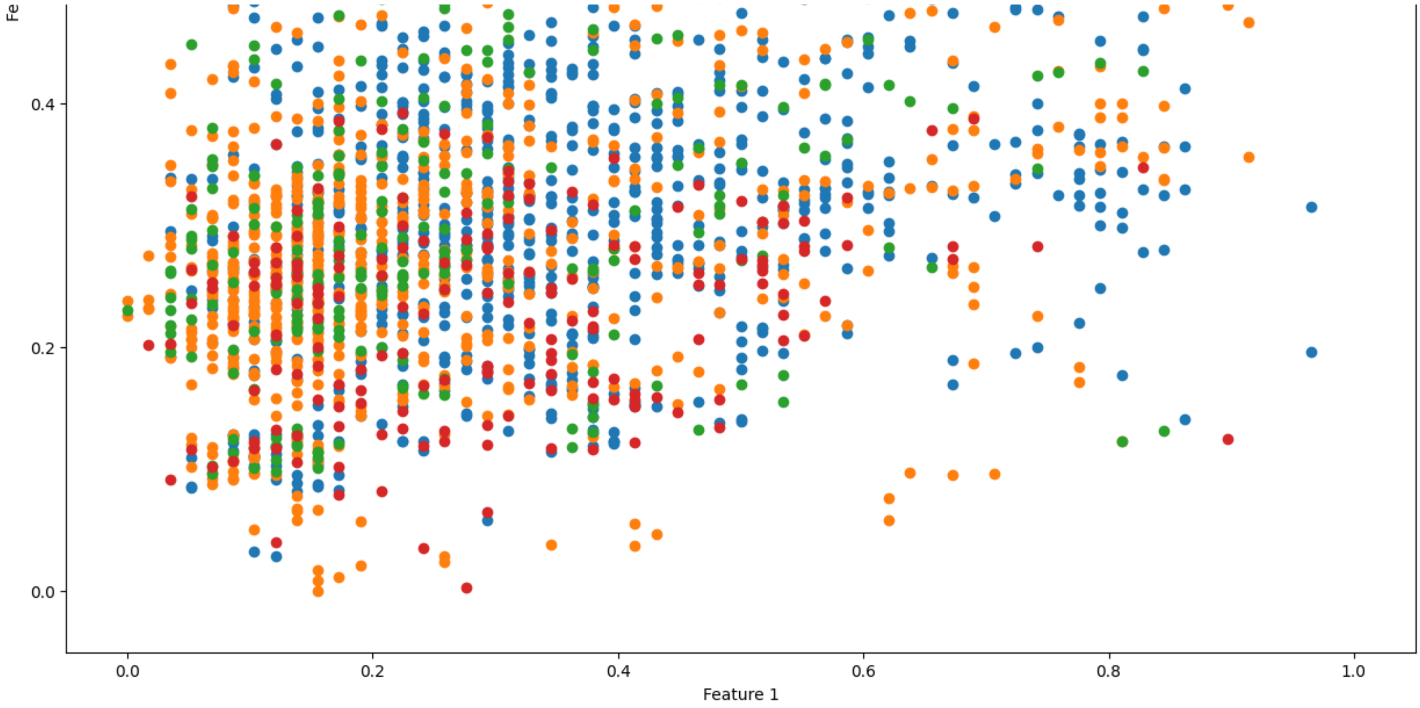


In [ ]:

In [122]:

```
# DBSCAN clustering
from sklearn.cluster import DBSCAN
import matplotlib.gridspec as gridspec
import matplotlib.pyplot as plt
import numpy as np
from numpy import unique
from numpy import where
from sklearn.datasets import make_classification
from sklearn.cluster import OPTICS,cluster_optics_dbscan
from matplotlib import pyplot

# define dataset

X = data_scaled
# define the model

model = DBSCAN(eps=0.8, min_samples=10, metric='euclidean')

# fit model and predict clusters
yhat = model.fit_predict(X)

# retrieve unique clusters
clusters = unique(yhat)
# create scatter plot for samples from each cluster
for cluster in clusters:
    # get row indexes for samples with this cluster
    row_ix = where(yhat == cluster)
    # create scatter of these samples
    pyplot.scatter(X[row_ix, 3], X[row_ix, 5])
# show the plot
plt.xlabel("Feature 1")
plt.ylabel("Feature 2")
plt.title("DBSCAN")
pyplot.show()
```

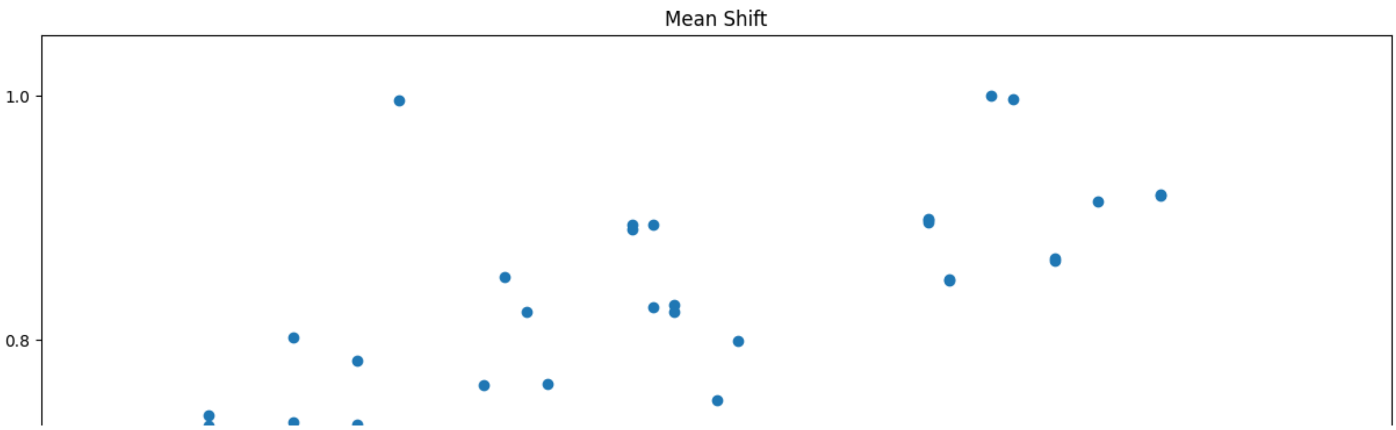


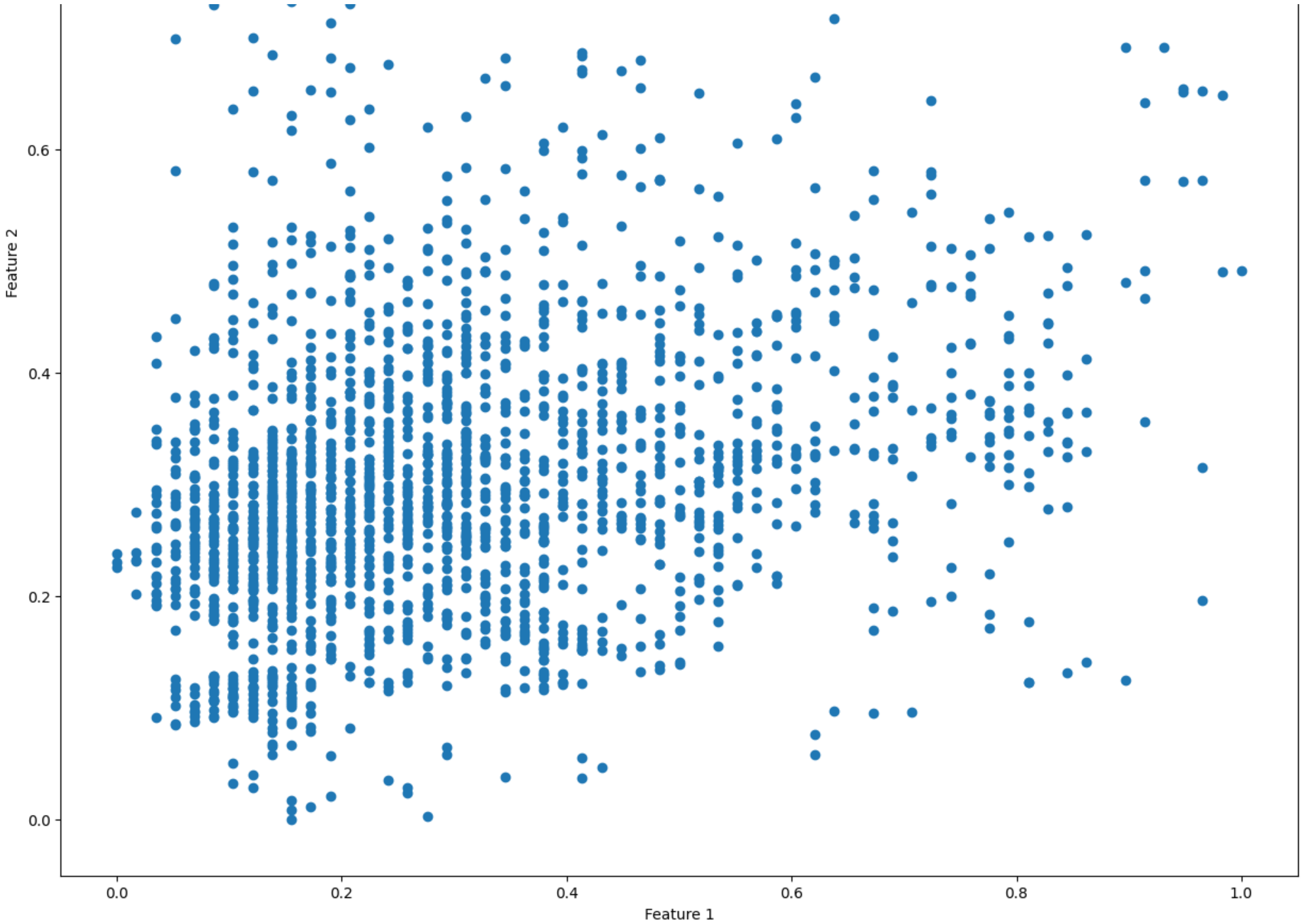


In [ ]:

In [123]:

```
# # Mean Shift Clustering

from numpy import unique
from numpy import where
from sklearn.datasets import make_classification
from sklearn.cluster import MeanShift
from matplotlib import pyplot

# define dataset
X = data_scaled
# define the model
model = MeanShift()
# fit model and predict clusters
yhat = model.fit_predict(X)
# retrieve unique clusters
clusters = unique(yhat)
# create scatter plot for samples from each cluster
for cluster in clusters:
    # get row indexes for samples with this cluster
    row_ix = where(yhat == cluster)
    # create scatter of these samples
    pyplot.scatter(X[row_ix, 3], X[row_ix, 5])
# show the plot
plt.xlabel("Feature 1")
plt.ylabel("Feature 2")
plt.title("Mean Shift")
pyplot.show()
```





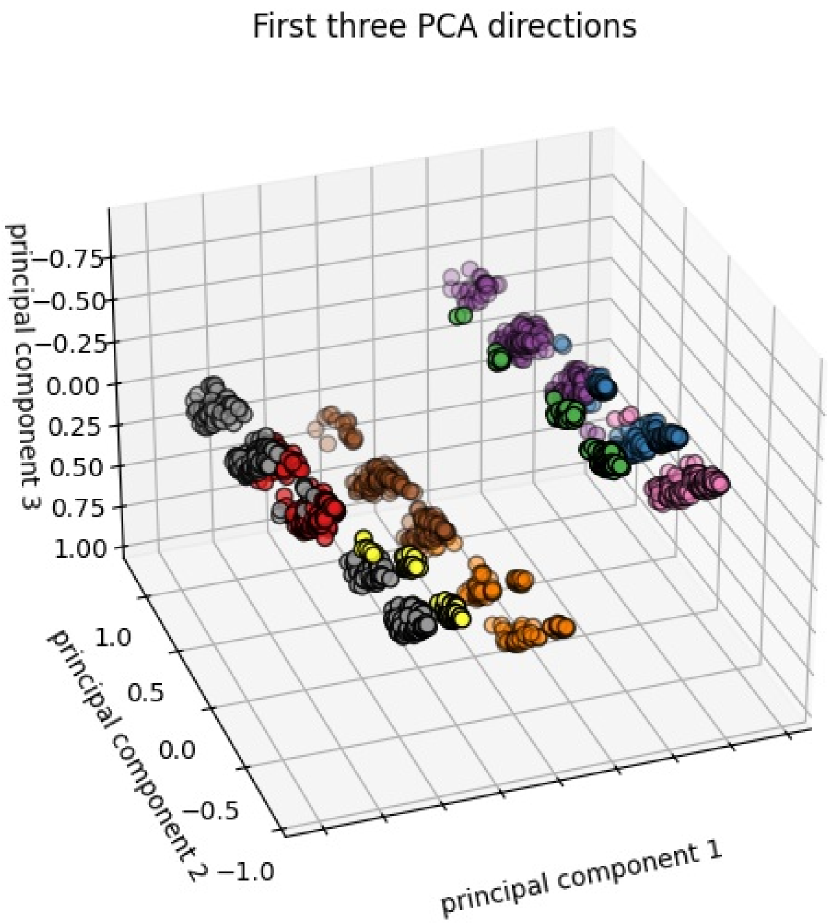
In [183]:

```
# Dimensional Reduction
# PCA
from mpl_toolkits.mplot3d import Axes3D
from sklearn.decomposition import PCA
from sklearn import datasets


# Initialize PCA with number of components
pca = PCA(n_components=3)

# Fit_transform PCA model to data
principalComponents = pca.fit_transform(data)

PCAdf = pd.DataFrame(data = principalComponents , columns = ['principal component 1', 'p
rincipal component 2','principal component 3'])

datapoints = PCAdf.values
X_reduced = datapoints
m, f = datapoints.shape
k = 3

# Print explained variance ratio
print("Explained variance ratio:", pca.explained_variance_ratio_)

# Print the first few rows of transformed data
print("First few rows of transformed data:")
print(X_reduced[:5])
```

```
Explained variance ratio: [0.45077153 0.23900528 0.10531903]
First few rows of transformed data:
[[ 0.90821547  0.40459117 -0.09888653]
 [-0.41103093  0.85657503 -0.14745133]
 [ 0.53934522 -0.56603118  0.34352406]
 [ 0.77870261  0.04799076  0.05297678]
 [ 0.78336366  0.03825262  0.05080702]]
```

In [191]:

```
#Visualization

# Importing necessary libraries
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

# Creating 3D plot
fig = plt.figure(1, figsize=(8, 6))
ax = fig.add_subplot(azim=110, elev=-150, projection='3d')

# Plotting data

ax.scatter(X_reduced[:, 0], X_reduced[:, 1], X_reduced[:, 2], c=labels,
           cmap=plt.cm.Set1, edgecolor='k', s=40)
# Setting titles and labels
ax.set_title("First three PCA directions")
ax.set_xlabel("principal component 1")
ax.set_ylabel("principal component 2")
ax.set_zlabel("principal component 3")

# Setting tick labels for x-axis
ax.set_xticklabels([])

# Show plot
plt.show()
```



In [174]:

```
from sklearn.cluster import KMeans
# K-Means Clustering
# defining the kmeans function with initialization as k-means++
kmeans = KMeans(n_clusters=2, init='k-means++')

# fitting the k means algorithm on PCA data
kmeans.fit(data)
```

Out[174]:

▾ KMeans i ?

```
KMeans(n_clusters=2)
```

In [175]:

```
# after PCA, kmeans.inertia is 1174.29 unlike before when it wasn't under PCA, it was 121
8.6
kmeans.inertia_
```

Out[175]:

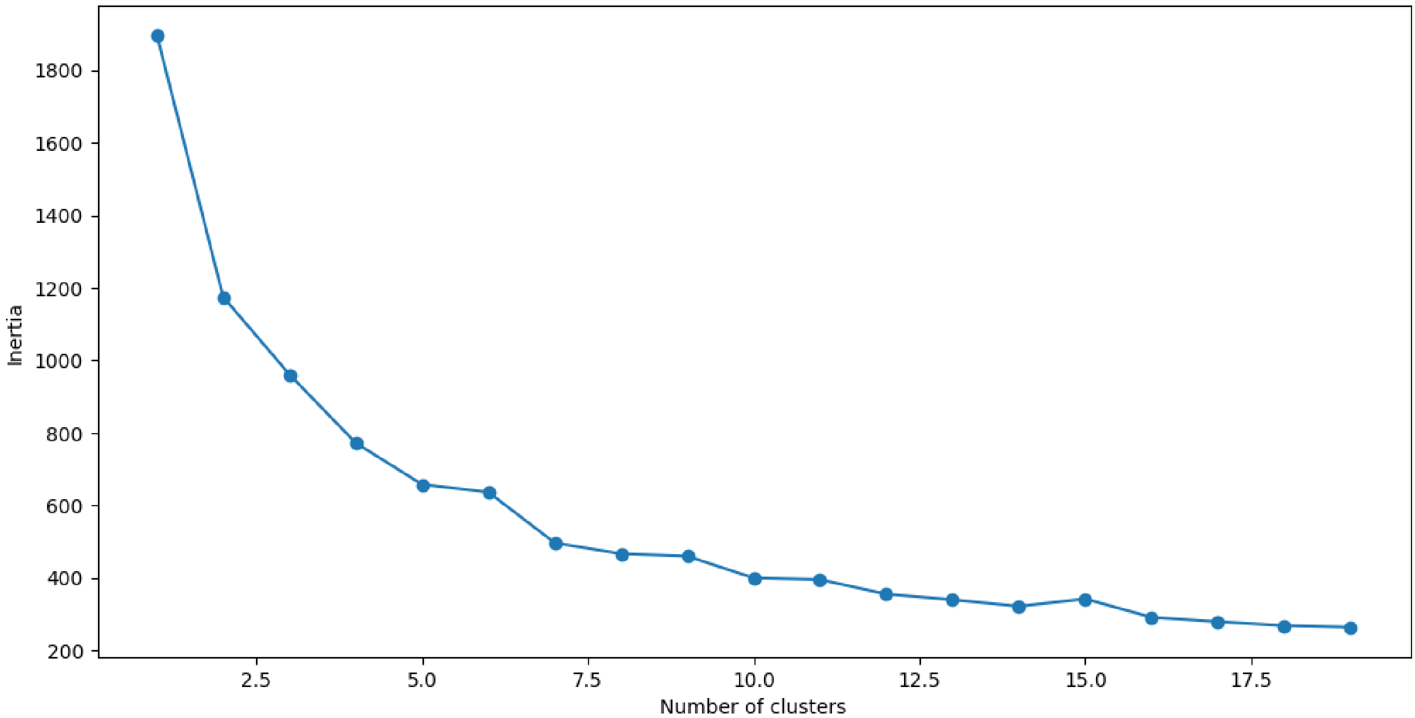
```
1174.2949105420175
```

In [176]:

```
# Using elbow
import warnings
warnings.filterwarnings("ignore")
# fitting multiple k-means algorithms and storing the values in an empty list
SSE = []
for cluster in range(1,20):
    # kmeans = KMeans(n_jobs = -1, n_clusters = cluster, init='k-means++')
    kmeans = KMeans(n_clusters = cluster, init='k-means++')
    kmeans.fit(data)
    SSE.append(kmeans.inertia_)

# converting the results into a dataframe and plotting them
# Here on the loop shown below, i notice that the elboe happens around 2.5 and 6 clusters
. i will use silhouette scores to have a better insight on number of clusters to use
frame = pd.DataFrame({'Cluster':range(1,20), 'SSE':SSE})
plt.figure(figsize=(12,6))
plt.plot(frame['Cluster'], frame['SSE'], marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
```

Out[176]:

```
Text(0, 0.5, 'Inertia')
```



In [177]:

```
# K-Means Clustering on reduced dimensional data
# Silhouette method
from sklearn.metrics import silhouette_score

sil = []
kmax = 10
```

```
# dissimilarity would not be defined for a single cluster, thus, minimum number of cluste
rs should be 2
for k in range(2, kmax+1):
  kmeans = KMeans(n_clusters = k).fit(data)
  labels = kmeans.labels_
  sil.append(silhouette_score(data, labels, metric = 'euclidean'))

sil
```

Out[177]:

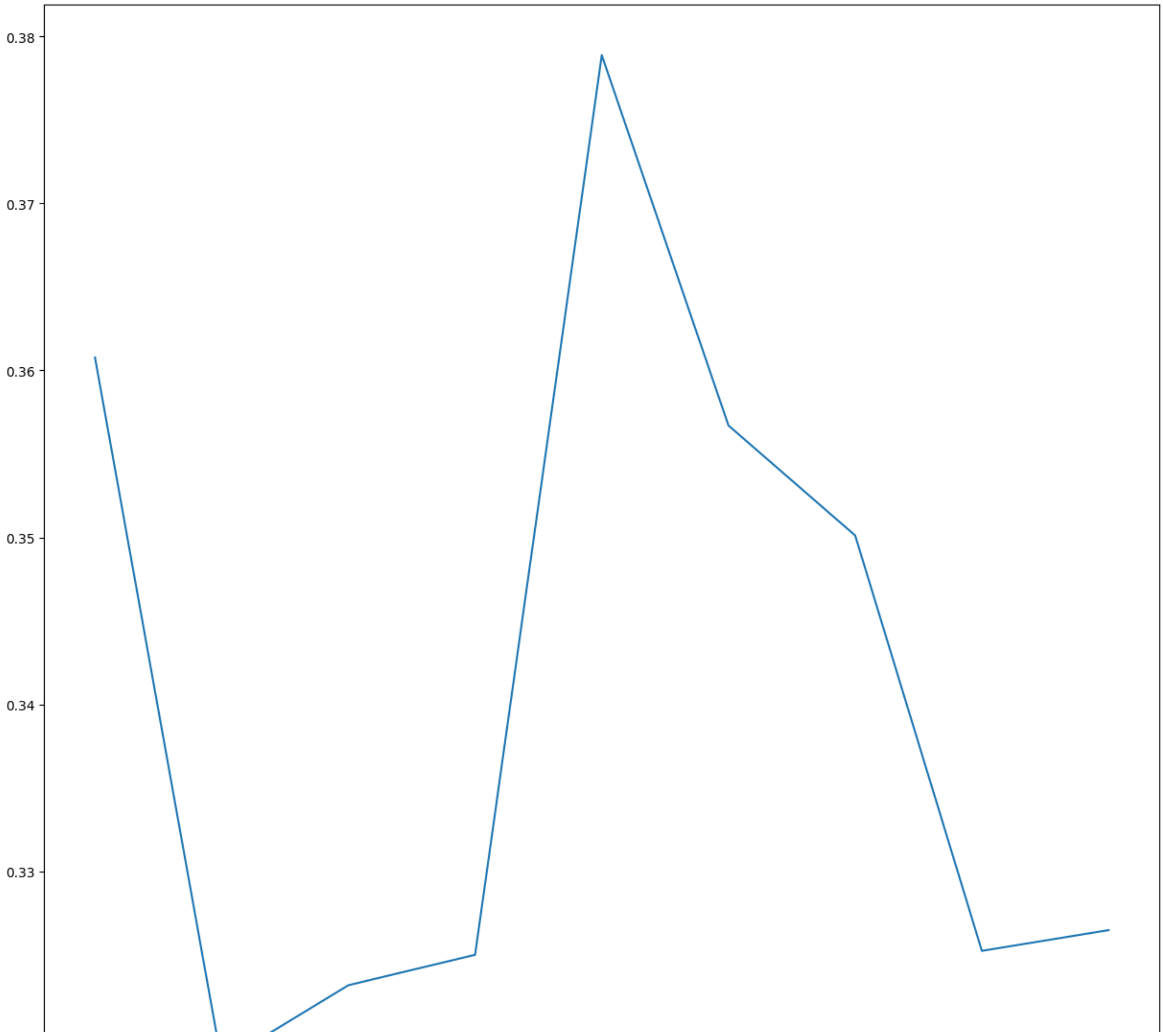
```
[0.3607728451743172,
 0.31856617961357186,
 0.3231783019401877,
 0.3249989763297604,
 0.3788809928229282,
 0.3567013118877957,
 0.35011423045800627,
 0.3252355966324679,
 0.3264778703986175]
```

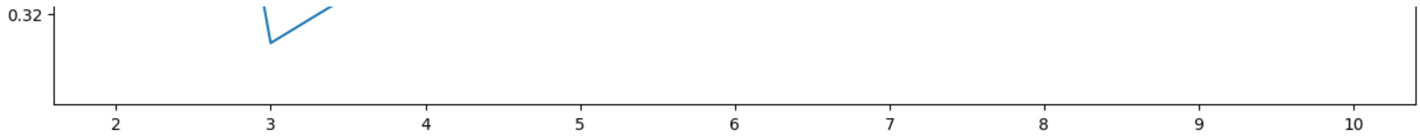
In [179]:

```
# after PCA, we can see clusters in 3, 5, 7 and 9 on x axis
y1 = np.linspace(2, 10, 9)
plt.plot(y1, sil)
```

Out[179]:

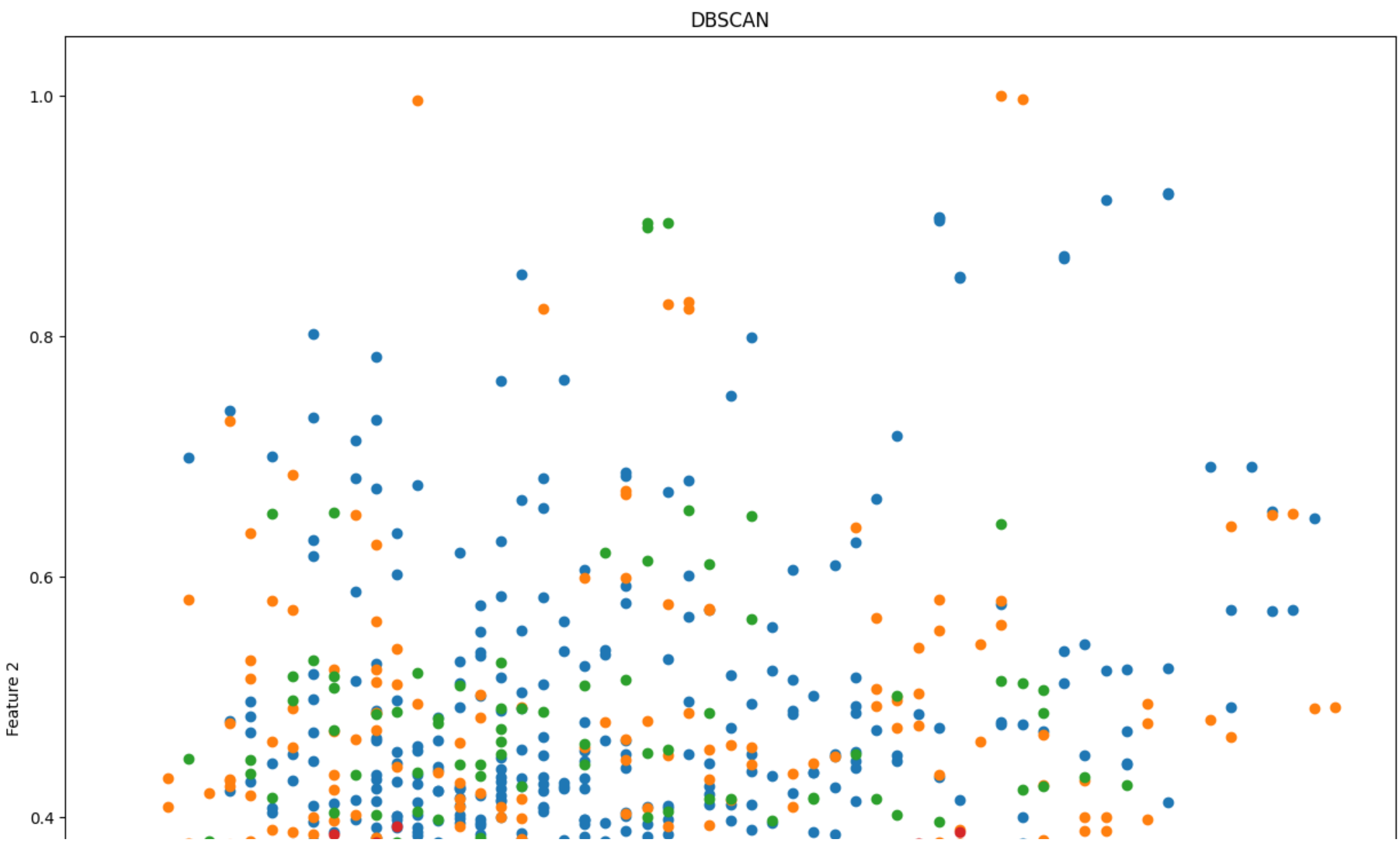
```
[<matplotlib.lines.Line2D at 0x131f48110>]
```

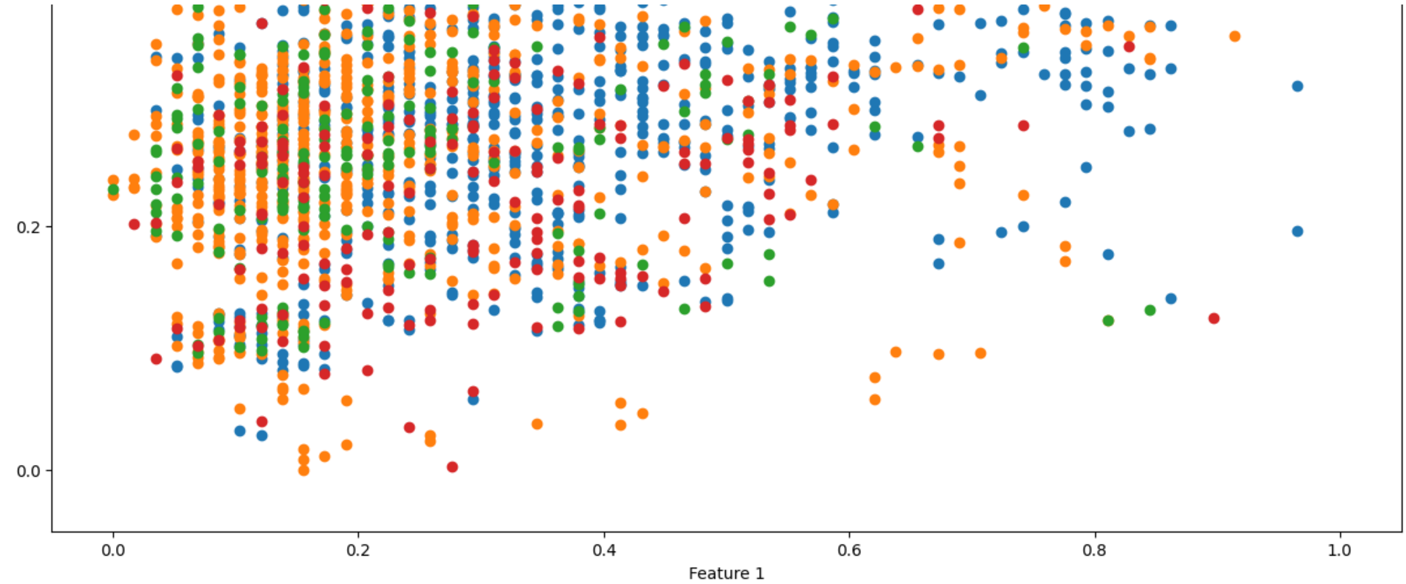




In [180]:

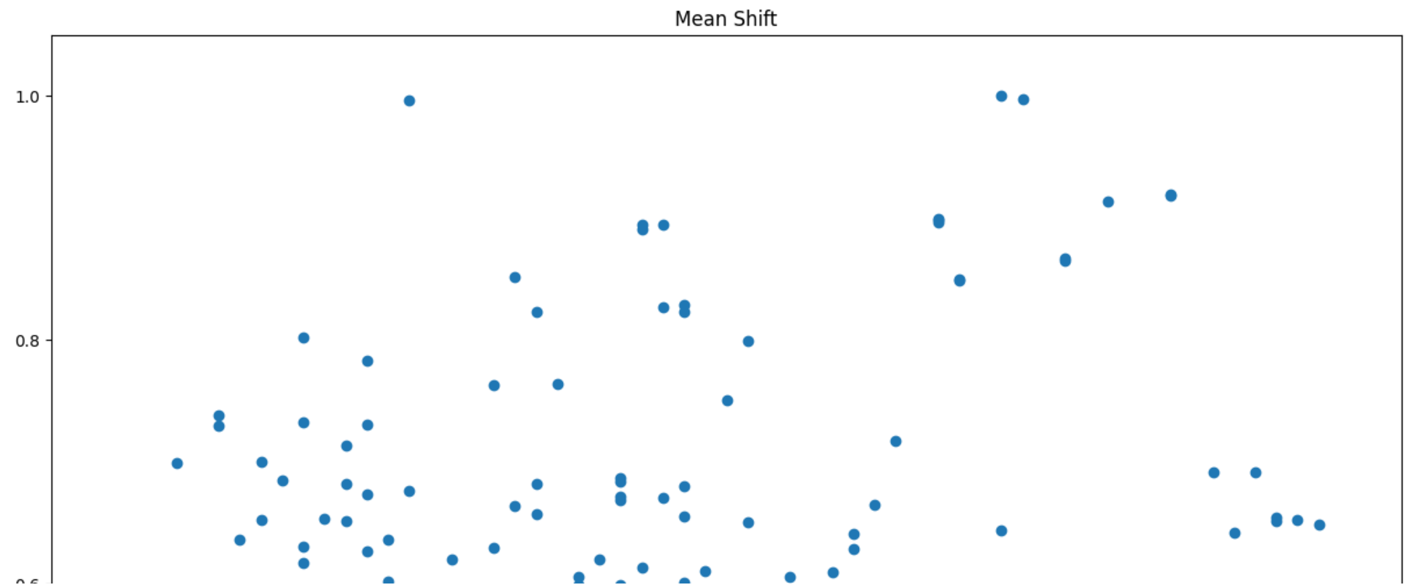
```
# DBSCAN on reduced dimensional data
# it is poerful and faster than mean shift, it shows different colors of the clusters com
pared to the rest.
# DBSCAN clustering
from sklearn.cluster import DBSCAN
import matplotlib.gridspec as gridspec
import matplotlib.pyplot as plt
import numpy as np
from numpy import unique
from numpy import where
from sklearn.datasets import make_classification
from sklearn.cluster import OPTICS,cluster_optics_dbscan
from matplotlib import pyplot

# define dataset
X = data
# define the model

model = DBSCAN(eps=0.8, min_samples=10, metric='euclidean')

# fit model and predict clusters
yhat = model.fit_predict(X)

# retrieve unique clusters
clusters = unique(yhat)
# create scatter plot for samples from each cluster
for cluster in clusters:
    # get row indexes for samples with this cluster
    row_ix = where(yhat == cluster)
    # create scatter of these samples
    pyplot.scatter(X[row_ix, 3], X[row_ix, 5])
# show the plot
plt.xlabel("Feature 1")
plt.ylabel("Feature 2")
plt.title("DBSCAN")
pyplot.show()
```

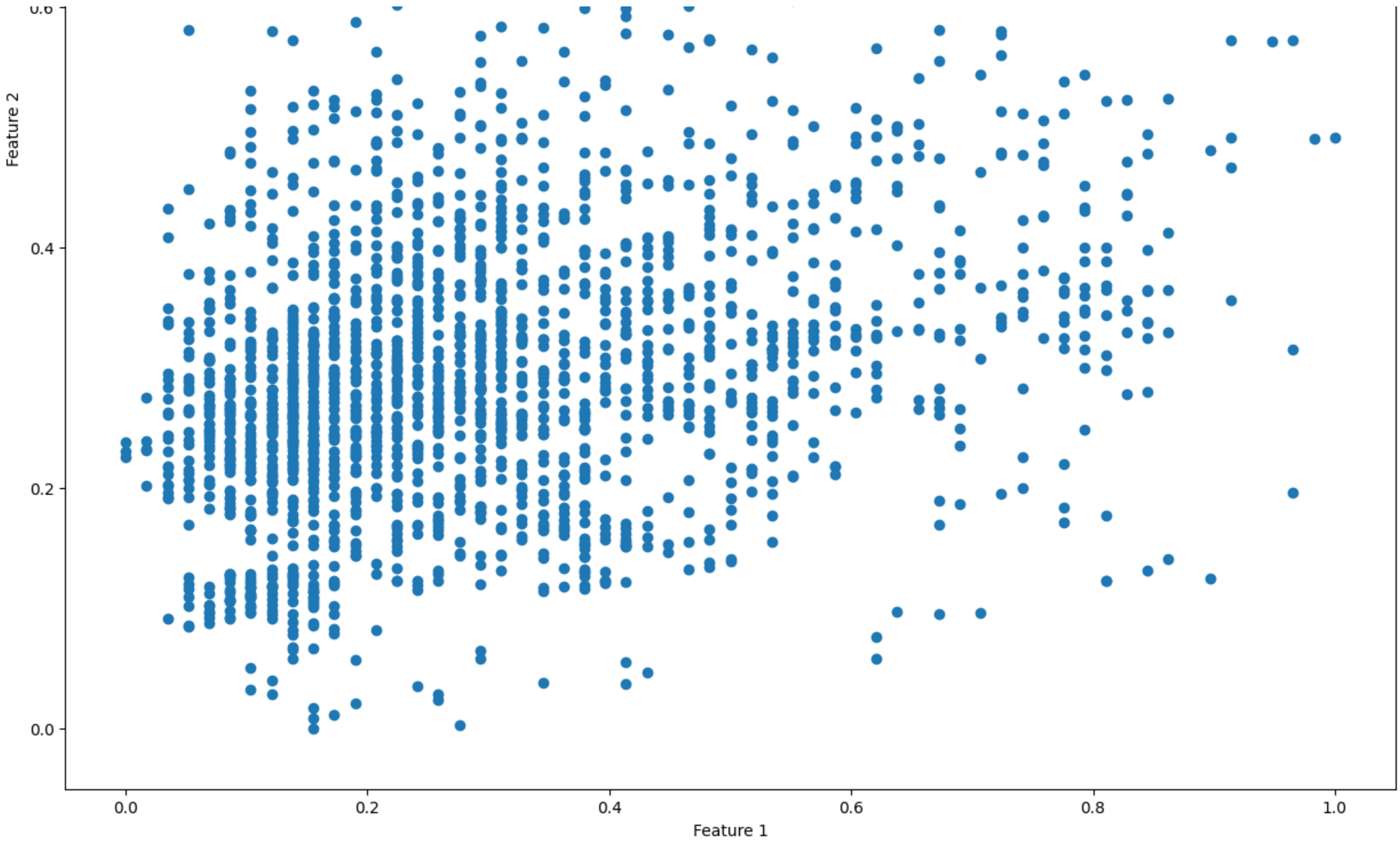




In [181]:

```
# Mean Shift Clustering on reduced dimensional data
# i noticed it takes time to run the code and it shows all clusters in one color
# # Mean Shift Clustering

from numpy import unique
from numpy import where
from sklearn.datasets import make_classification
from sklearn.cluster import MeanShift
from matplotlib import pyplot

# define dataset

X = data
# define the model
model = MeanShift()
# fit model and predict clusters
yhat = model.fit_predict(X)
# retrieve unique clusters
clusters = unique(yhat)
# create scatter plot for samples from each cluster
for cluster in clusters:
    # get row indexes for samples with this cluster
    row_ix = where(yhat == cluster)
    # create scatter of these samples
    pyplot.scatter(X[row_ix, 3], X[row_ix, 5])
# show the plot
plt.xlabel("Feature 1")
plt.ylabel("Feature 2")
plt.title("Mean Shift")
pyplot.show()
```





0.6
0.4
0.2
0.0
Feature 2
0.0
0.2
0.4
0.6
0.8
1.0
Feature 1