Introduction to DBSCAN

Let's briefly explore visually the differences between DBSCAN and other clustering techniques, such as K-Means Clustering.

DBSCAN and Clustering Examples

In [2]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:

```
blobs = pd.read_csv("D:\\Study\\Programming\\python\\Python course from udemy\\Udemy - 2
022 Python for Machine Learning & Data Science Masterclass\\24 - DBSCAN - Density-based s
patial clustering of applications with noise\\33643080-cluster-blobs.csv")
```

In [4]:

```
blobs.head()
```

Out[4]:

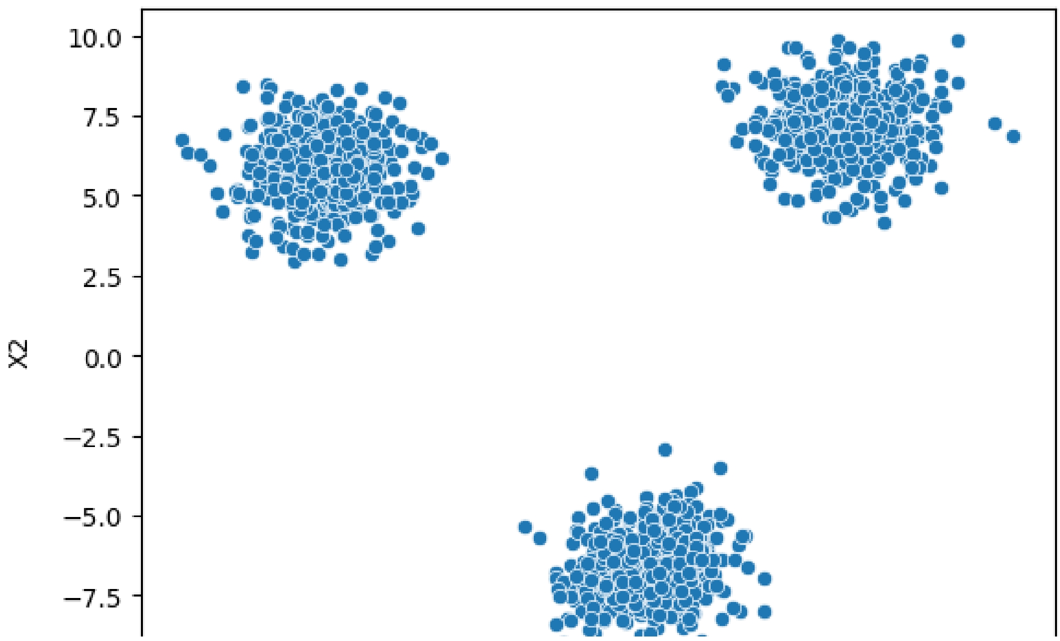
	X1	X2
0	4.645333	6.822294
1	4.784032	6.422883
2	-5.851786	5.774331
3	-7.459592	6.456415
4	4.918911	6.961479

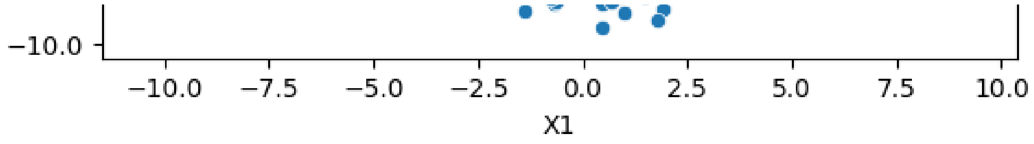
In [6]:

```
sns.scatterplot(data=blobs,x='X1',y='X2')
```

Out[6]:

```
<AxesSubplot: xlabel='X1', ylabel='X2'>
```





In [7]:

```
moons = pd.read_csv("D:\\Study\\Programming\\python\Python course from udemy\\Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\24 - DBSCAN - Density-based spatial clustering of applications with noise\\33643082-cluster-moons.csv")
```

In [8]:

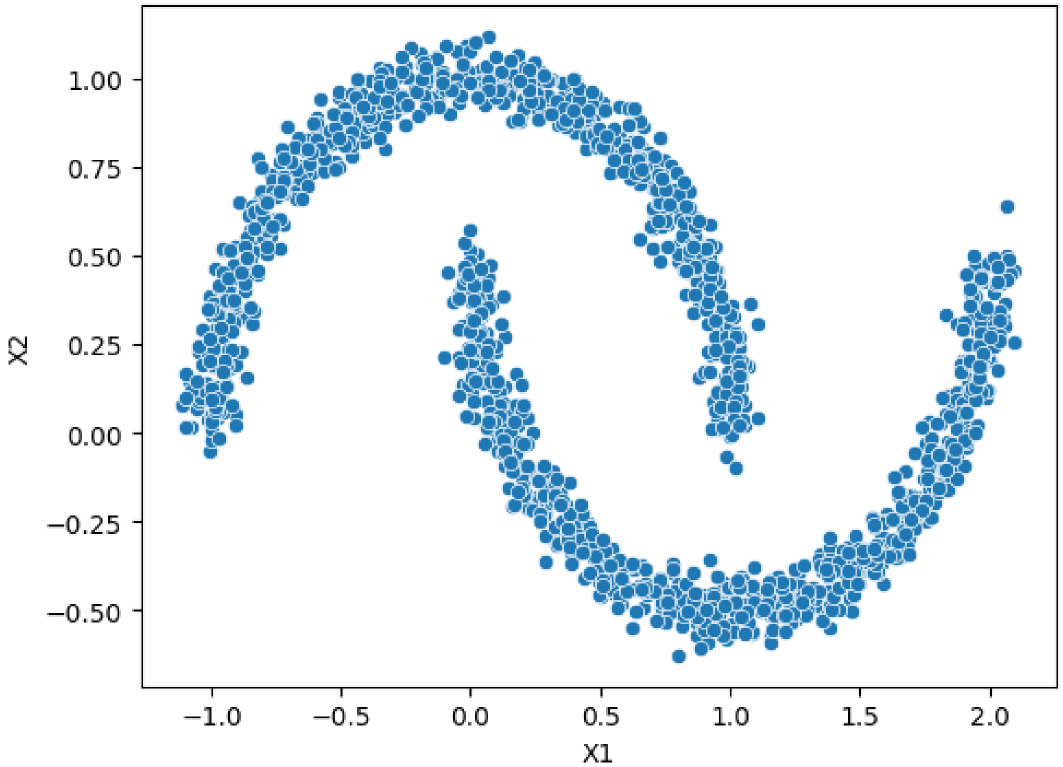
```
moons.head()
```

Out[8]:

	X1	X2
0	0.674362	-0.444625
1	1.547129	-0.239796
2	1.601930	-0.230792
3	0.014563	0.449752
4	1.503476	-0.389164

In [10]:

```
sns.scatterplot(data=moons,x='X1',y='X2');
```



In [11]:

```
circles =pd.read_csv("D:\\Study\\Programming\\python\\Python course from udemy\\Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\24 - DBSCAN - Density-based spatial clustering of applications with noise\\33643060-cluster-circles.csv")
```

In [12]:

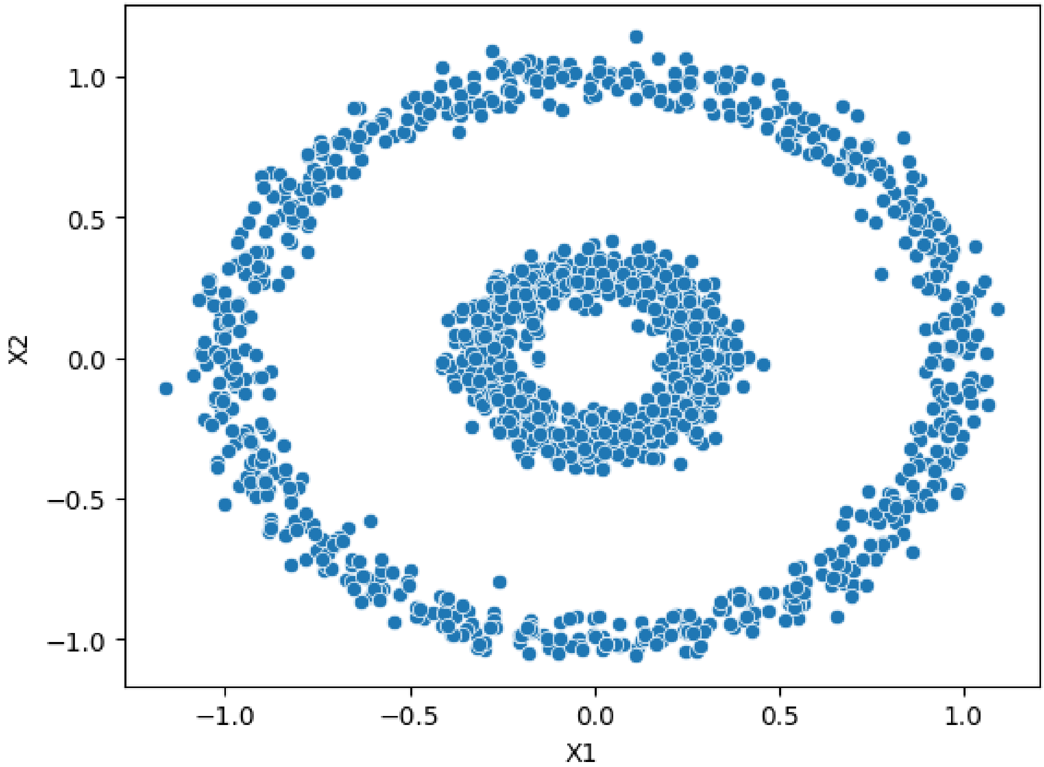
```
circles.head()
```

Out[12]:

	X1	X2
0	-0.348677	0.010157
1	-0.176587	-0.954283
2	0.301703	-0.113045
3	-0.782889	-0.719468
4	-0.733280	-0.757354

In [15]:

```
sns.scatterplot(data=circles,x='X1',y='X2');
```



Label Discovery

In [21]:

```
def display_categories(model,data):
    labels = model.fit_predict(data)
    sns.scatterplot(data=data, x='X1',y='X2',hue=labels,palette='Set1')
```

Kmeans Results

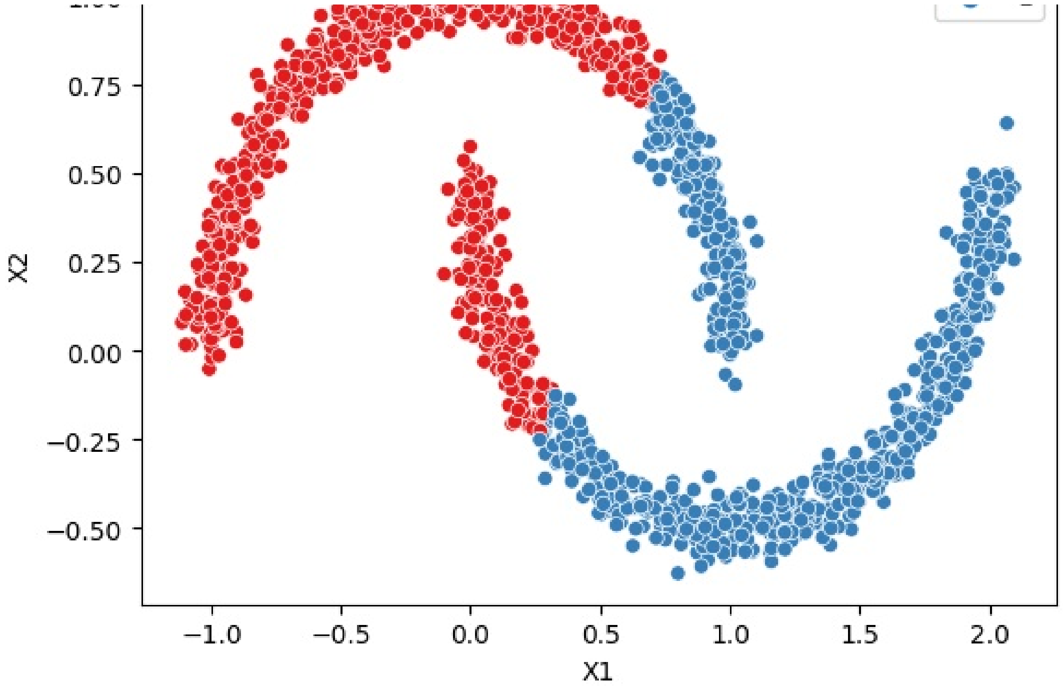
In [19]:

```
from sklearn.cluster import KMeans
model = KMeans(n_clusters=2)
```

In [22]:

```
display_categories(model,moons)
```

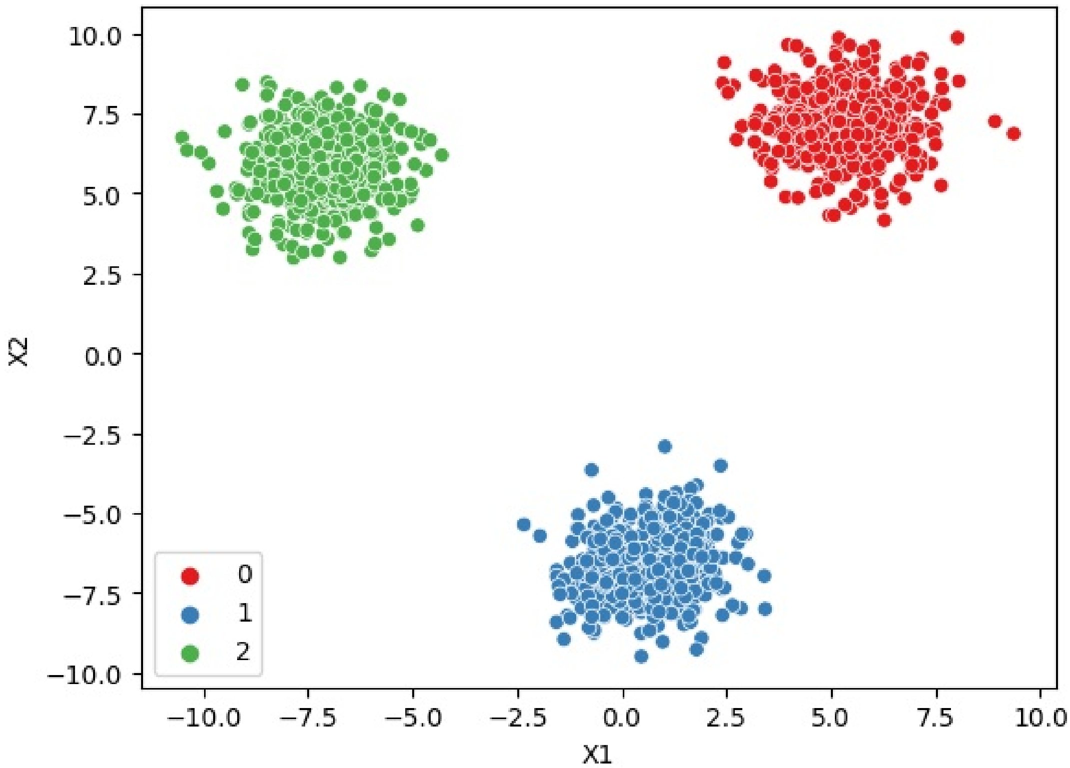
```
C:\Users\Chromsy\AppData\Roaming\Python\Python39\site-packages\sklearn\cluster\_kmeans.py
:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4.
Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```



In [23]:

```
model = KMeans(n_clusters=3)
display_categories(model,blobs)
```

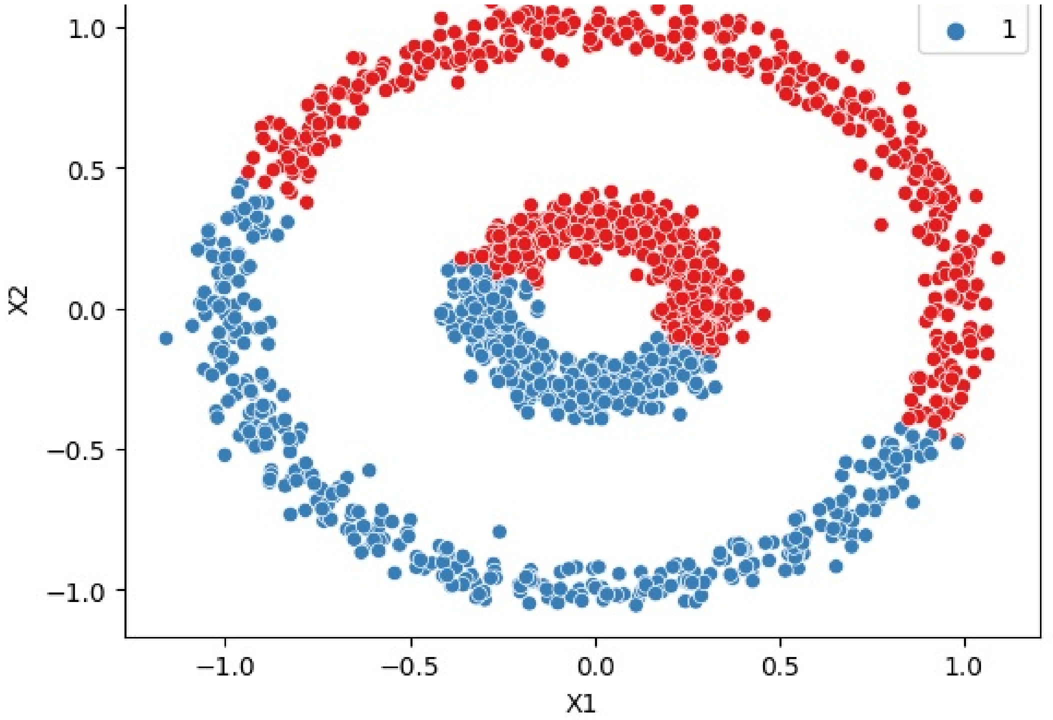
```
C:\Users\Chromsy\AppData\Roaming\Python\Python39\site-packages\sklearn\cluster\_kmeans.py
:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4.
Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```



In [24]:

```
model = KMeans(n_clusters=2)
display_categories(model,circles)
```

```
C:\Users\Chromsy\AppData\Roaming\Python\Python39\site-packages\sklearn\cluster\_kmeans.py
:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4.
Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```



DBSCAN Results

In [25]:

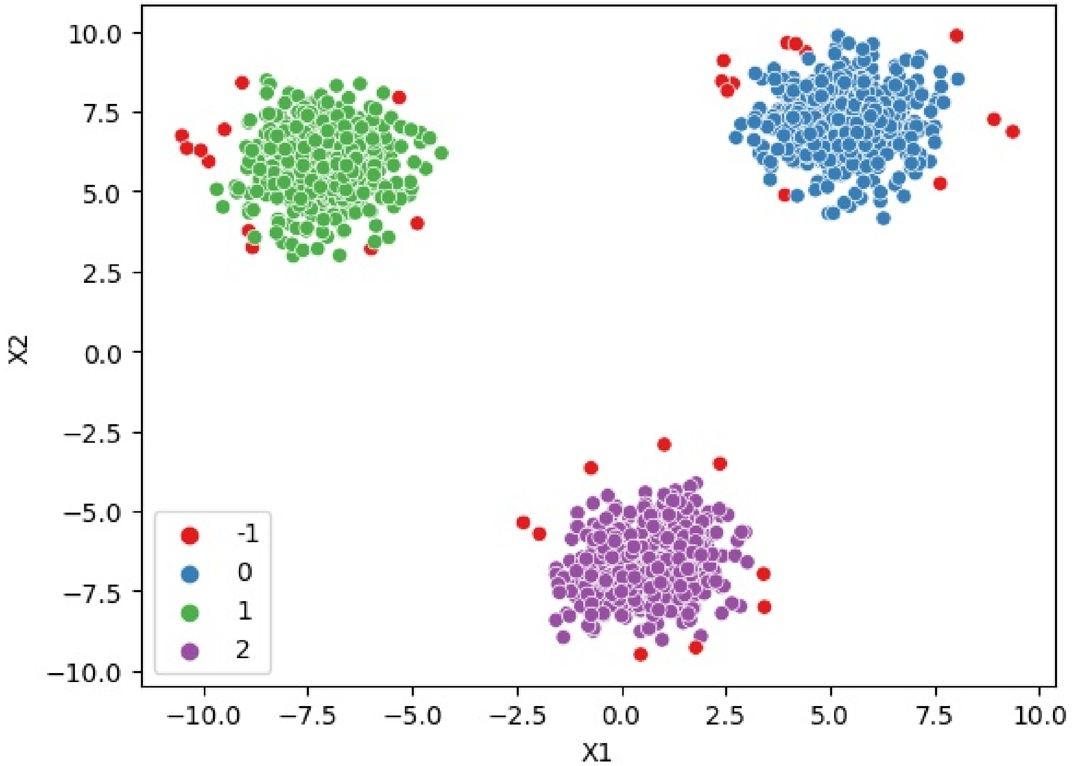
```
from sklearn.cluster import DBSCAN
```

In [26]:

```
model = DBSCAN(eps=0.6)
```

In [27]:

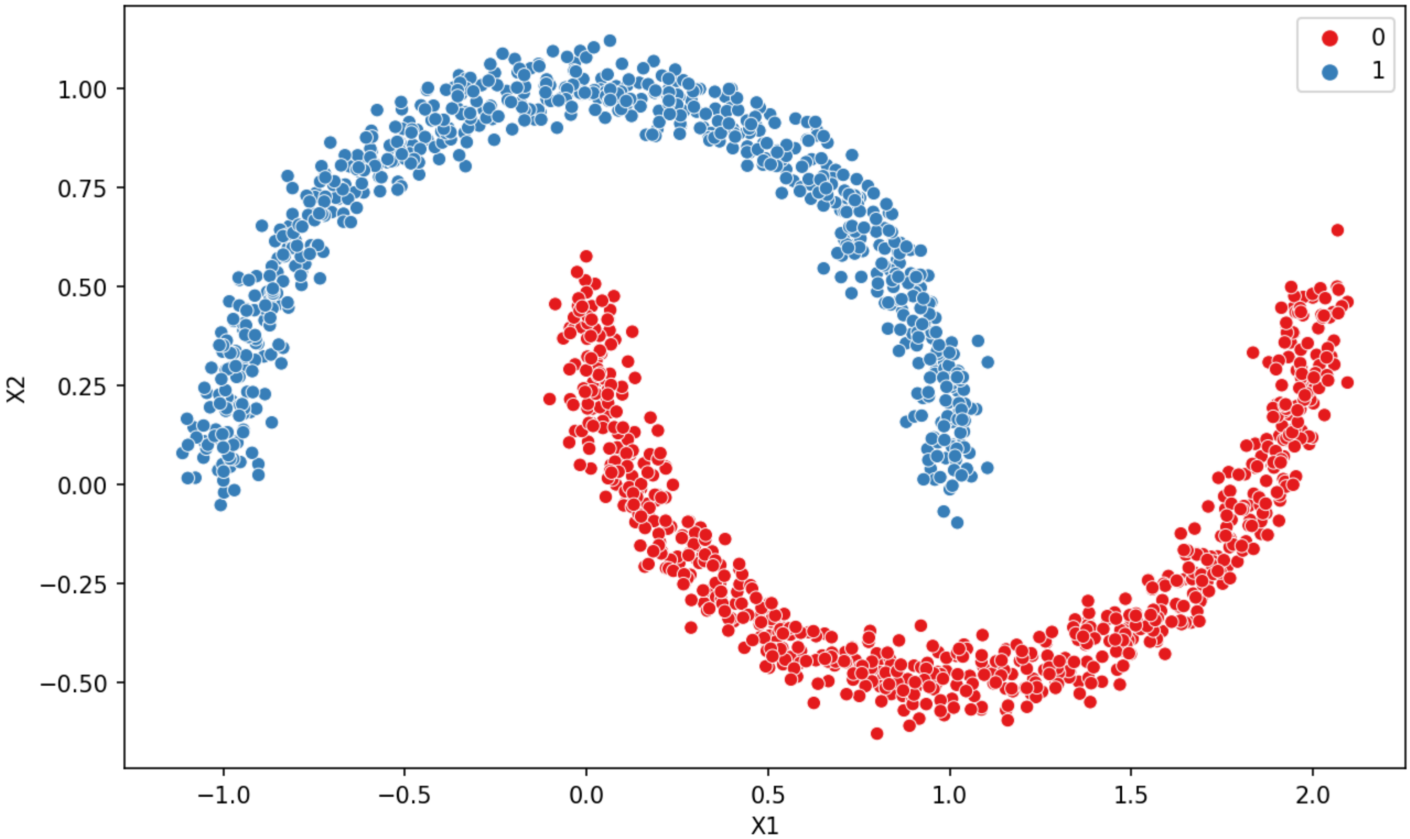
```
display_categories(model,blobs)
```



In [28]:

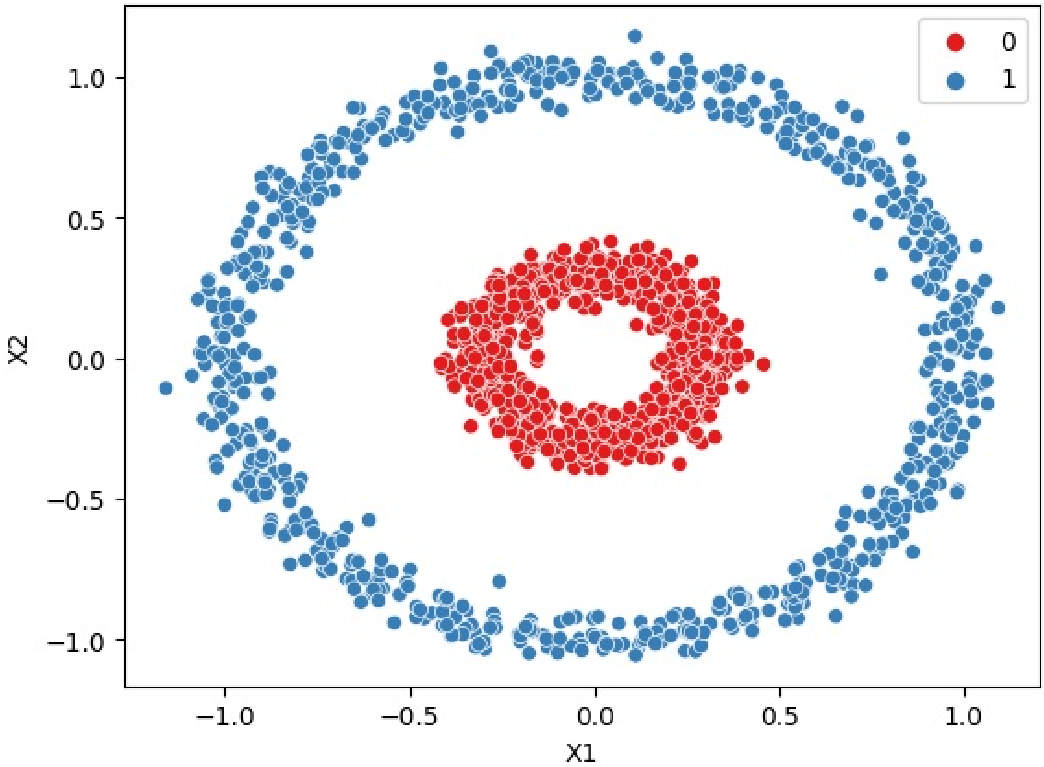
```
model = DBSCAN(eps=0.15)
plt.figure(figsize=(10,6),dpi=150)
```

```
display_categories(model,moons)
```



In [29]:

```
display_categories(model,circles)
```



Let's further explore DBSCAN Hyperparameters!

DBSCAN Hyperparameters

Let's explore the hyperparameters for DBSCAN and how they can change results!

DBSCAN and Clustering Examples

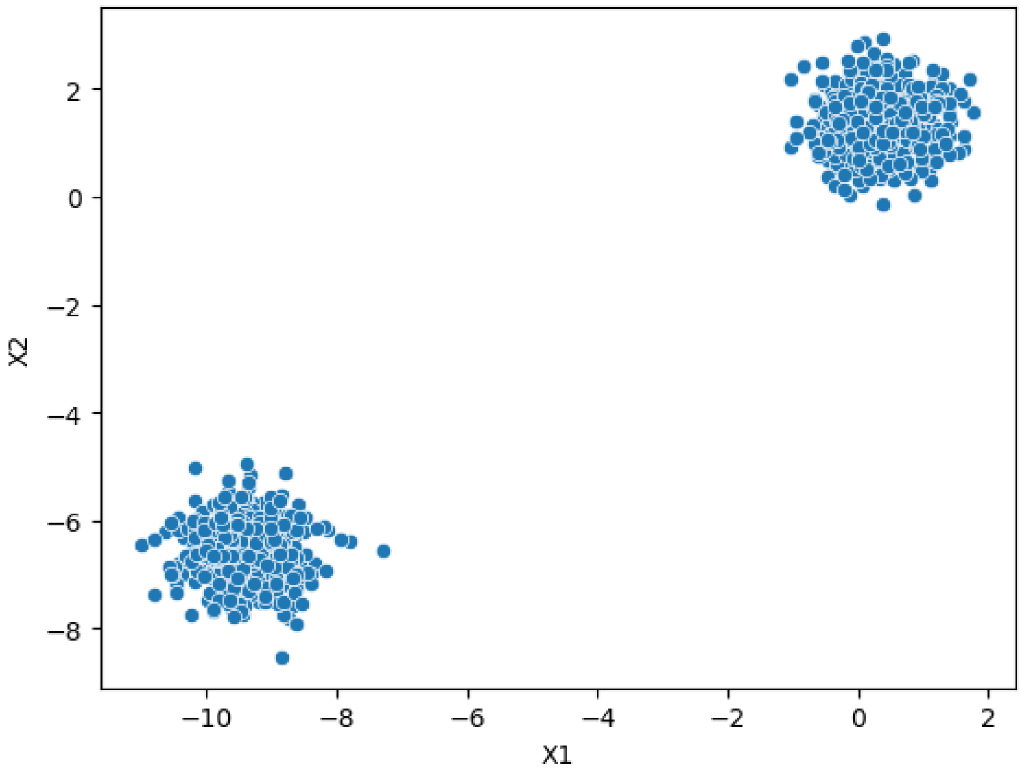
DBSCAN and Clustering Examples

In [38]:

```
two_blobs = pd.read_csv("D:\\Study\\Programming\\python\\Python course from udemy\\Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\24 - DBSCAN - Density-based spatial clustering of applications with noise\\33643072-cluster-two-blobs.csv")
two_blobs_outliers = pd.read_csv("D:\\Study\\Programming\\python\\Python course from udemy\\Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\24 - DBSCAN - Density-based spatial clustering of applications with noise\\33643070-cluster-two-blobs-outliers.csv")
```

In [39]:

```
sns.scatterplot(data=two_blobs,x='X1',y='X2');
```

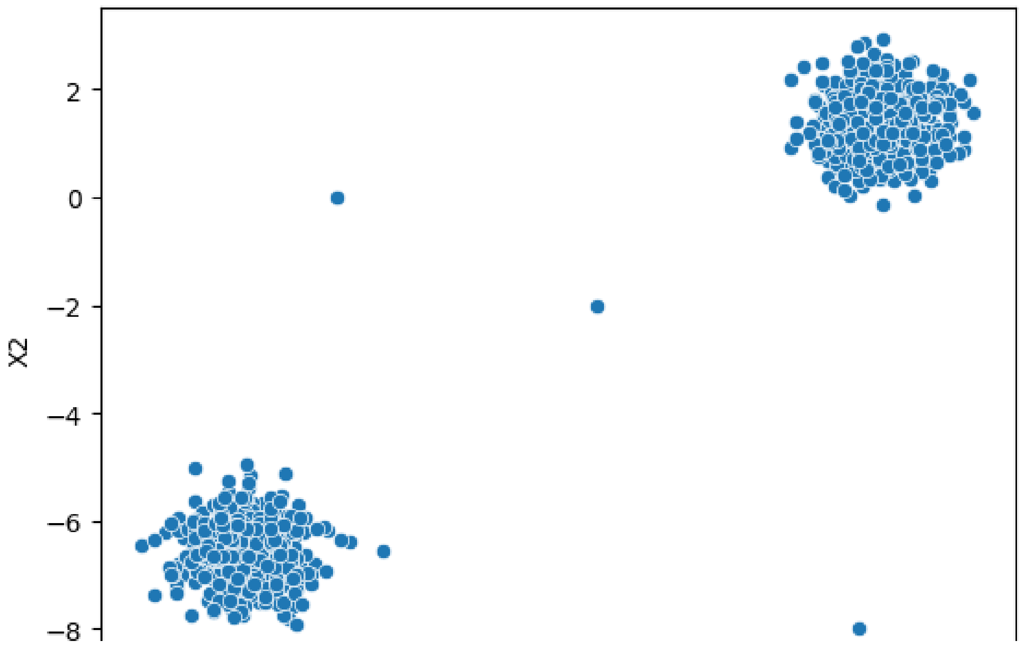


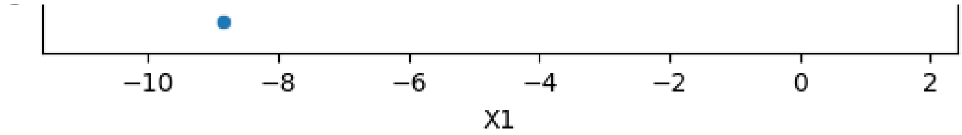
In [40]:

```
# plt.figure(figsize=(10,6),dpi=200)
sns.scatterplot(data=two_blobs_outliers,x='X1',y='X2')
```

Out[40]:

```
<AxesSubplot: xlabel='X1', ylabel='X2'>
```





Label Discovery

In [41]:

```
def display_categories(model,data):
    labels = model.fit_predict(data)
    sns.scatterplot(data=data,x='X1',y='X2',hue=labels,palette='Set1')
```

DBSCAN

In [43]:

```
from sklearn.cluster import DBSCAN
```

In [44]:

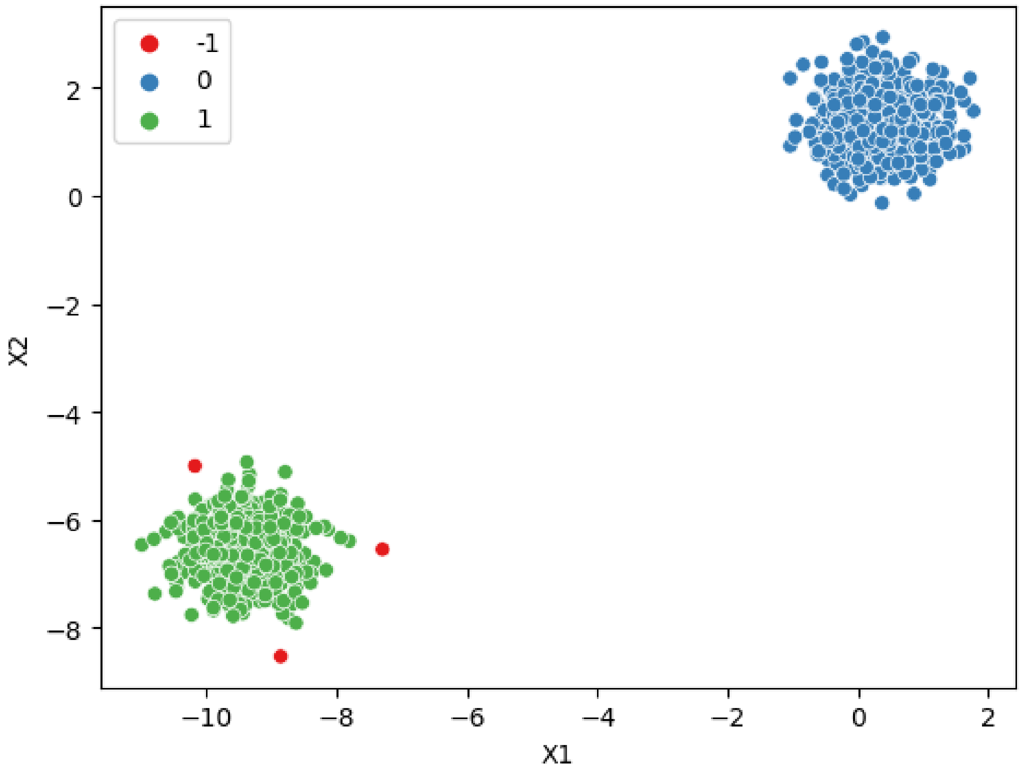
```
#help(DBSCAN)
```

In [45]:

```
dbscan = DBSCAN()
```

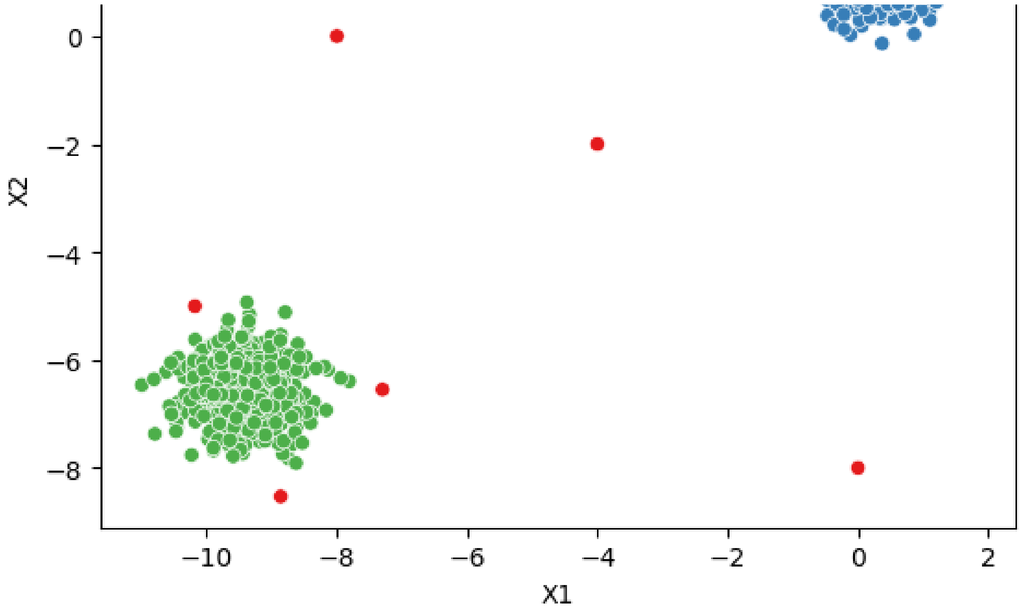
In [46]:

```
display_categories(dbscan,two_blobs)
```



In [47]:

```
display_categories(dbscan,two_blobs_outliers)
```

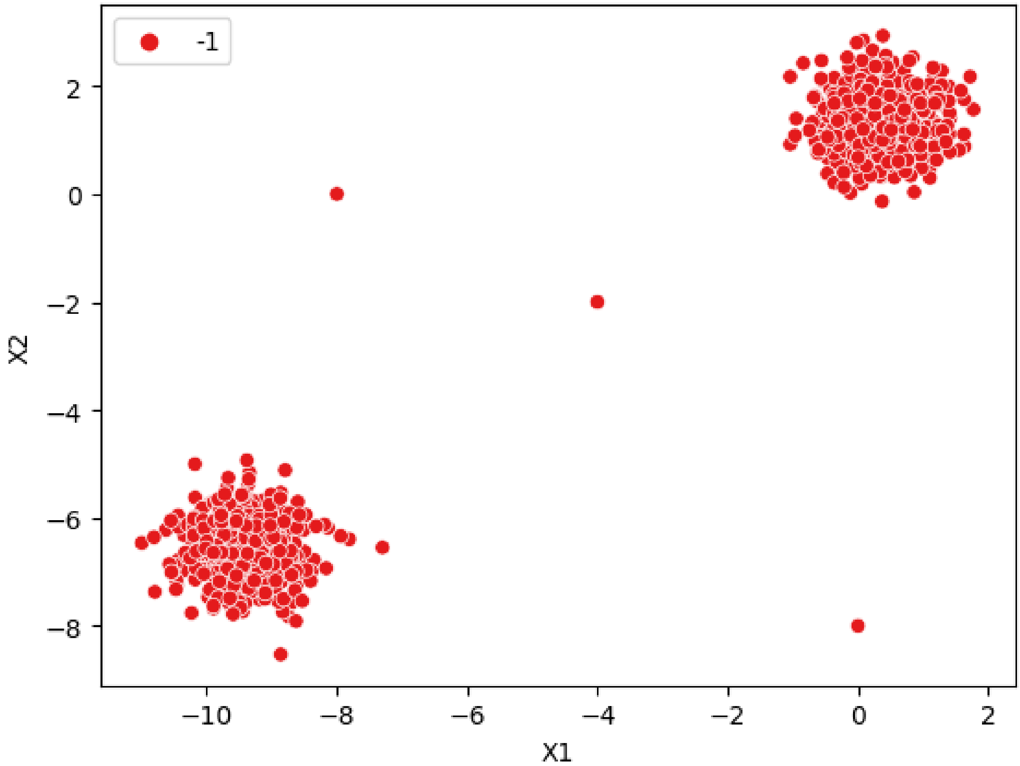


Epsilon

```
eps : float, default=0.5
 |      The maximum distance between two samples for one to be considered
 |      as in the neighborhood of the other. This is not a maximum bound
 |      on the distances of points within a cluster. This is the most
 |      important DBSCAN parameter to choose appropriately for your data set
 |      and distance function.
```

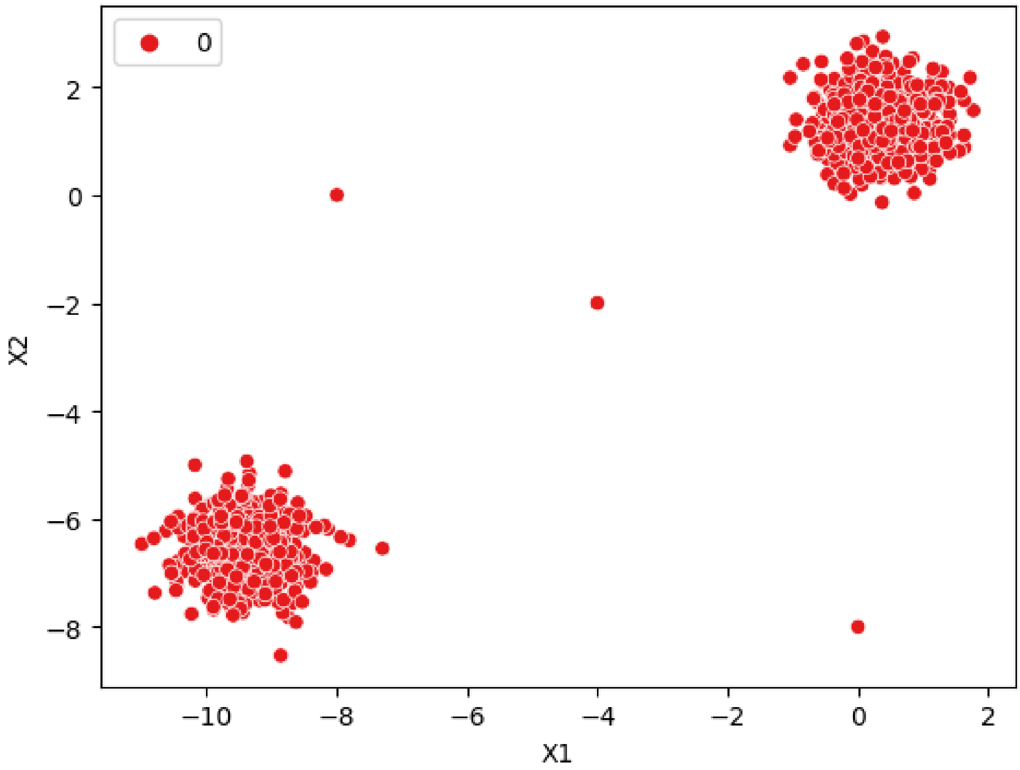
In [48]:

```
# Tiny Epsilon --> Tiny Max Distance --> Everything is an outlier (class=-1)
dbscan = DBSCAN(eps = 0.001)
display_categories(dbscan,two_blobs_outliers)
```



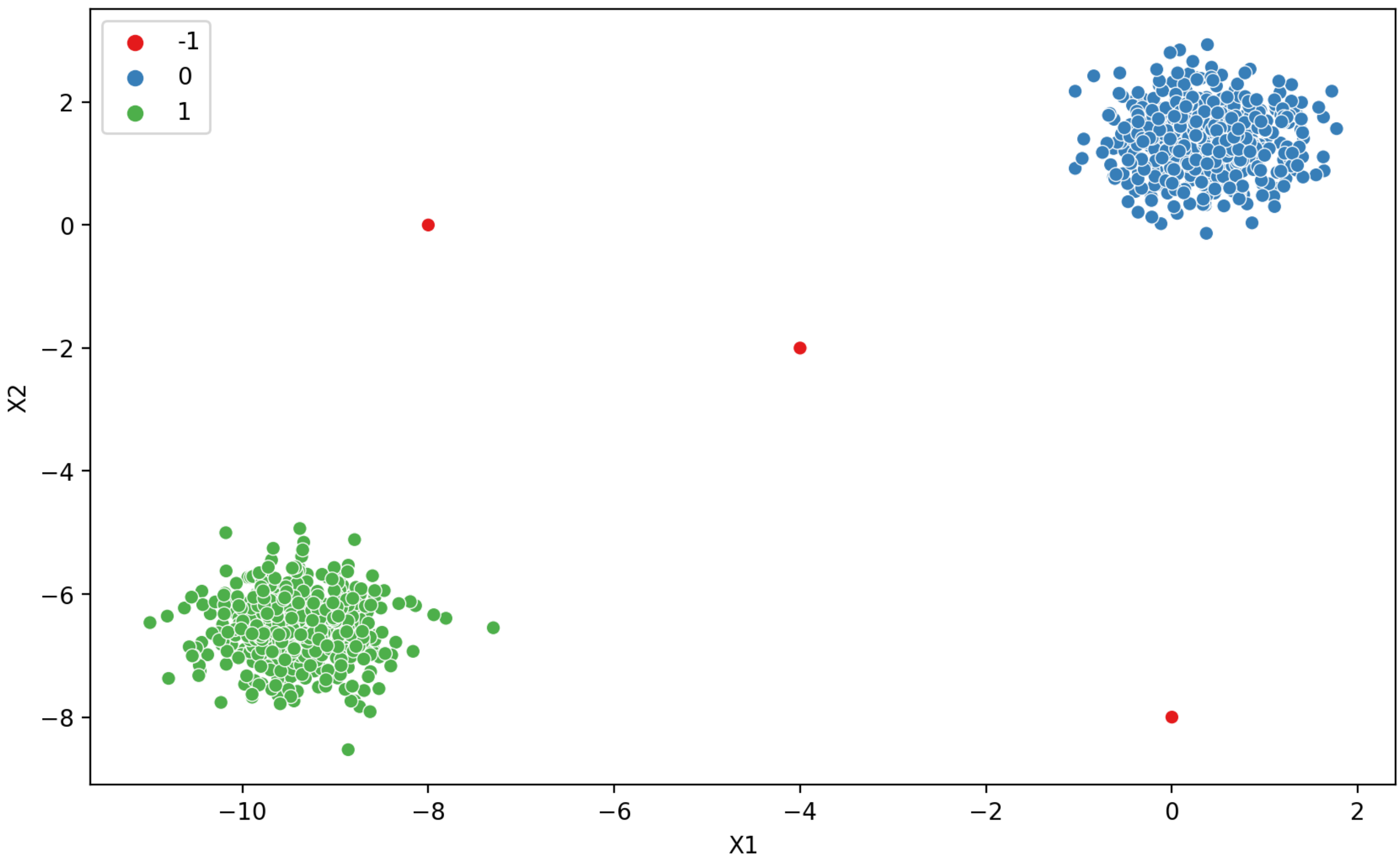
In [49]:

```
# Huge Epsilon --> Huge Max Distance --> Everything is in the same cluster (class=0)
dbscan = DBSCAN(eps=10)
display_categories(dbscan,two_blobs_outliers)
```



In [51]:

```
# How to find a good epsilon?
plt.figure(figsize=(10,6),dpi=200)
dbscan = DBSCAN(eps=1)
display_categories(dbscan,two_blobs_outliers)
```



In [52]:

```
dbscan.labels_
```

Out[52]:

```
array([ 0,  1,  0, ..., -1, -1, -1], dtype=int64)
```

In [53]:

```
dbscan.labels_ == -1
```

Out[53]:

```
array([False, False, False, ...,  True,  True,  True])
```

In [54]:

```
np.sum(dbscan.labels_ == -1)
```

Out[54]:

```
3
```

In [55]:

```
100 * np.sum(dbscan.labels_ == -1)/ len(dbscan.labels_)
```

Out[55]:

```
0.29910269192422734
```

Charting reasonable Epsilon values

In [59]:

```
# bend the knee! https://raghavan.usc.edu/papers/kneedle-simplex11.pdf
```

In [60]:

```
# np.arnage(start=0.01,stop=10,step=0.01)
```

In [63]:

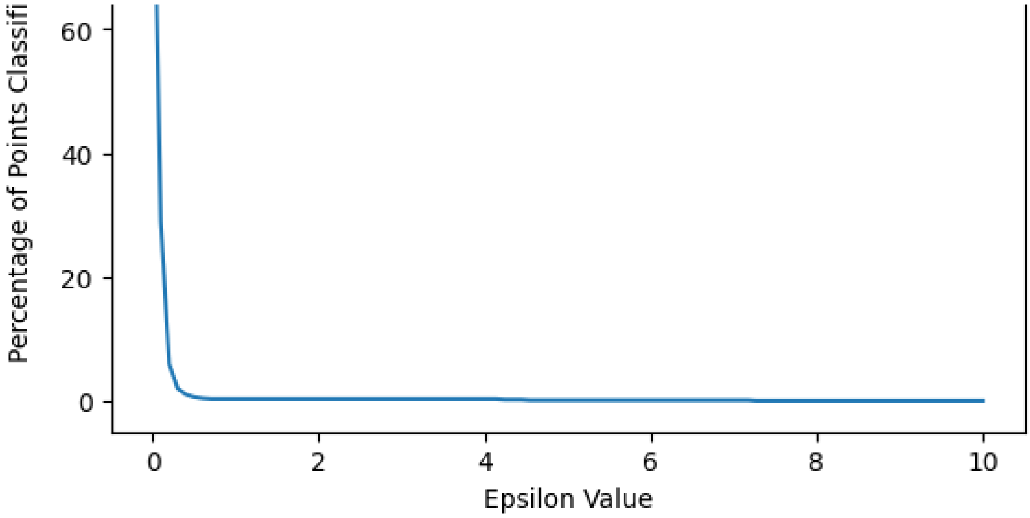
```
outlier_percent = []
number_of_outlier = []

for eps in np.linspace(0.001,10,100):

    # Create Model
    dbscan = DBSCAN(eps=eps)
    dbscan.fit(two_blobs_outliers)

    # Log Number of Outliers
    number_of_outlier.append(np.sum(dbscan.labels_ == -1))

    # Log percentage of points that are outliers
    perc_outliers = 100 * np.sum(dbscan.labels_ == -1)/ len(dbscan.labels_)

    outlier_percent.append(perc_outliers)
```

In [64]:

```
sns.lineplot(x=np.linspace(0.001,10,100),y=outlier_percent)
plt.ylabel("Percentage of Points Classified as Outliers")
plt.xlabel("Epsilon Value")
```

Out[64]:

```
Text(0.5, 0, 'Epsilon Value')
```

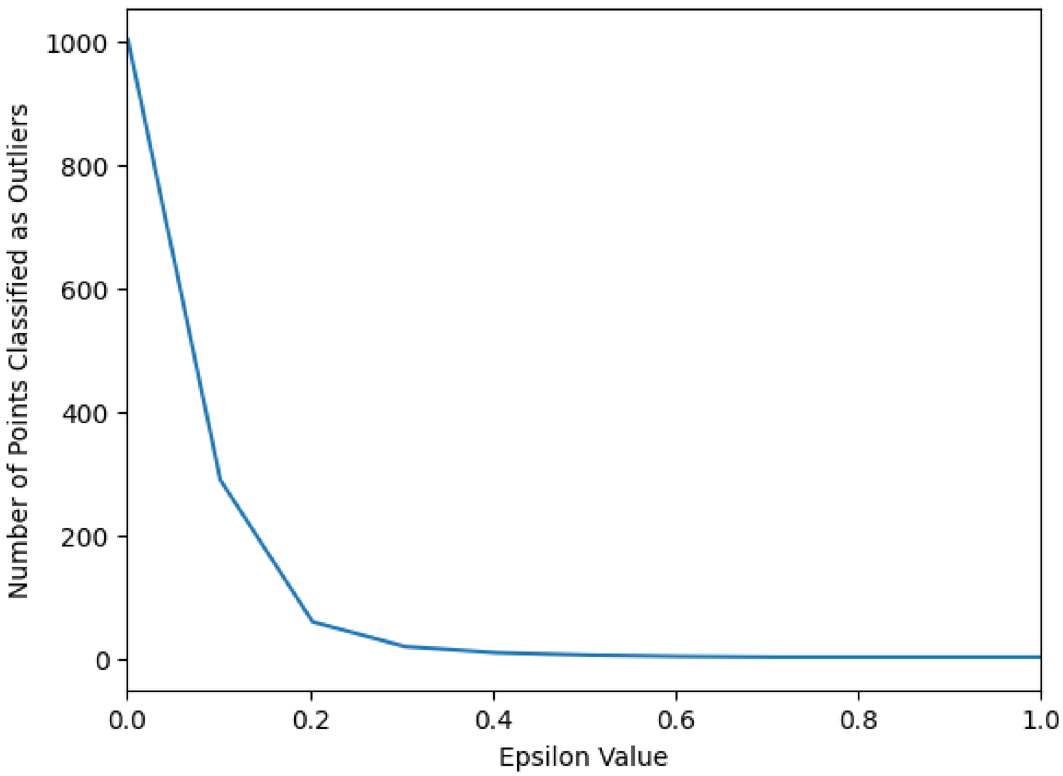


In [66]:

```
sns.lineplot(x=np.linspace(0.001,10,100),y=number_of_outlier)
plt.ylabel("Number of Points Classified as Outliers")
plt.xlabel("Epsilon Value")
plt.xlim(0,1)
```

Out[66]:

```
(0.0, 1.0)
```



Do we want to think in terms of percentage targeting instead?

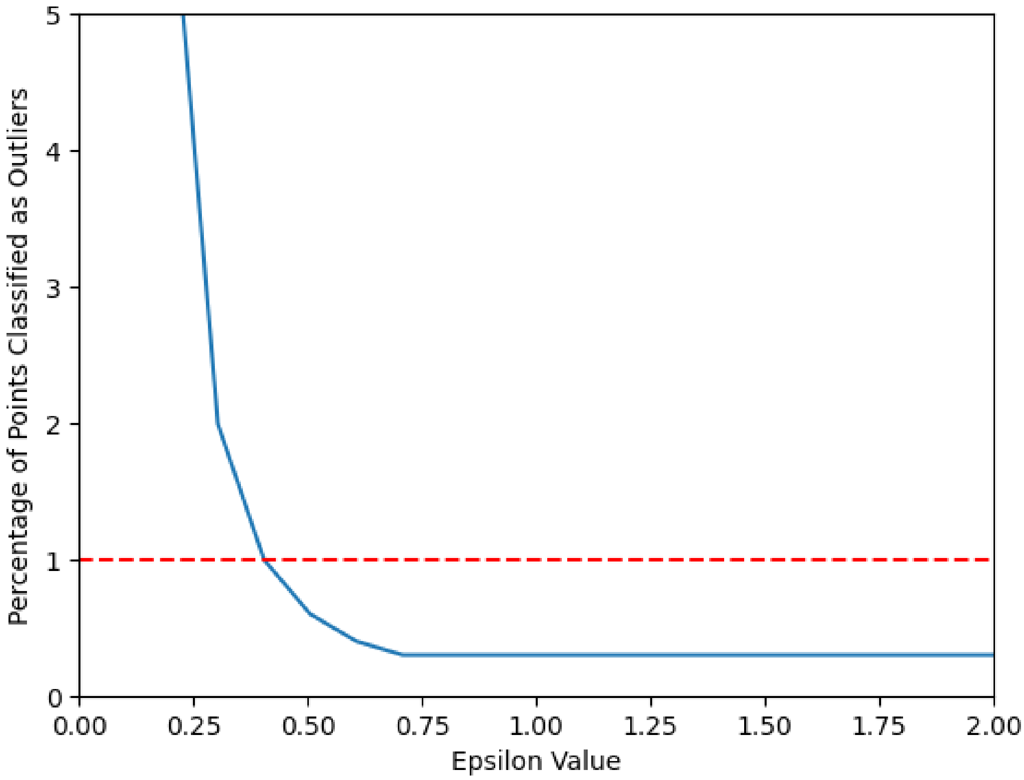
If so, you could "target" a percentage, like choose a range producing 1%-5% as outliers.

In [67]:

```
sns.lineplot(x=np.linspace(0.001,10,100),y=outlier_percent)
plt.ylabel("Percentage of Points Classified as Outliers")
plt.xlabel("Epsilon Value")
plt.ylim(0,5)
plt.xlim(0,2)
plt.hlines(y=1,xmin=0,xmax=2,colors='red',ls='--')
```

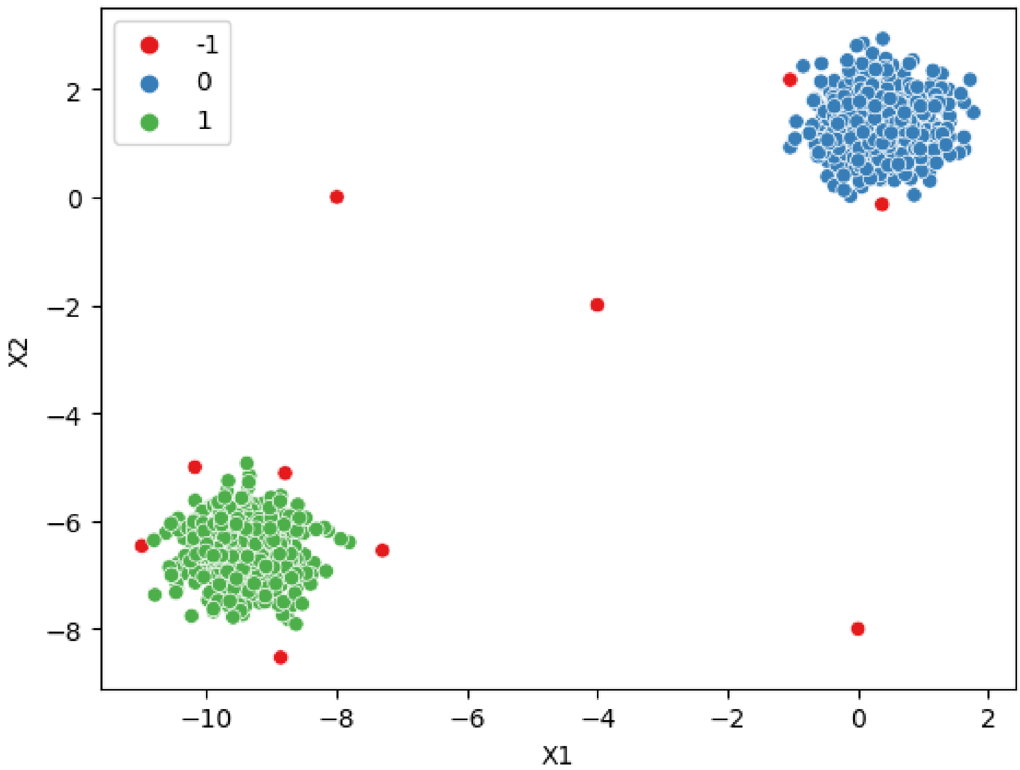
Out[67]:

```
<matplotlib.collections.LineCollection at 0x1bfb0155940>
```



In [68]:

```
# How to find a good epsilon?
dbscan = DBSCAN(eps=0.4)
display_categories(dbscan,two_blobs_outliers)
```



Do we want to think in terms of number of outliers targeting instead?

If so, you could "target" a number of outliers, such as 3 points as outliers.

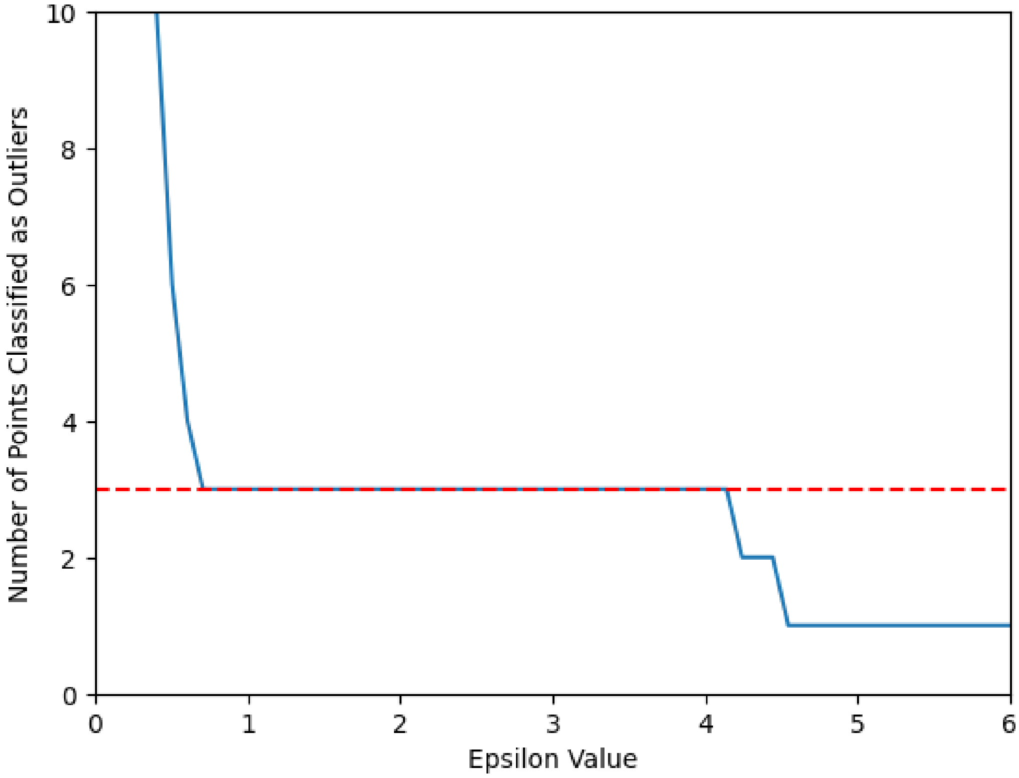
In [70]:

```
sns.lineplot(x=np.linspace(0.001,10,100),y=number_of_outlier)
plt.ylabel("Number of Points Classified as Outliers")
plt.xlabel("Epsilon Value")
```

```
plt.ylim(0,10)
plt.xlim(0,6)
plt.hlines(y=3,xmin=0,xmax=10,colors='red',ls='--')
```

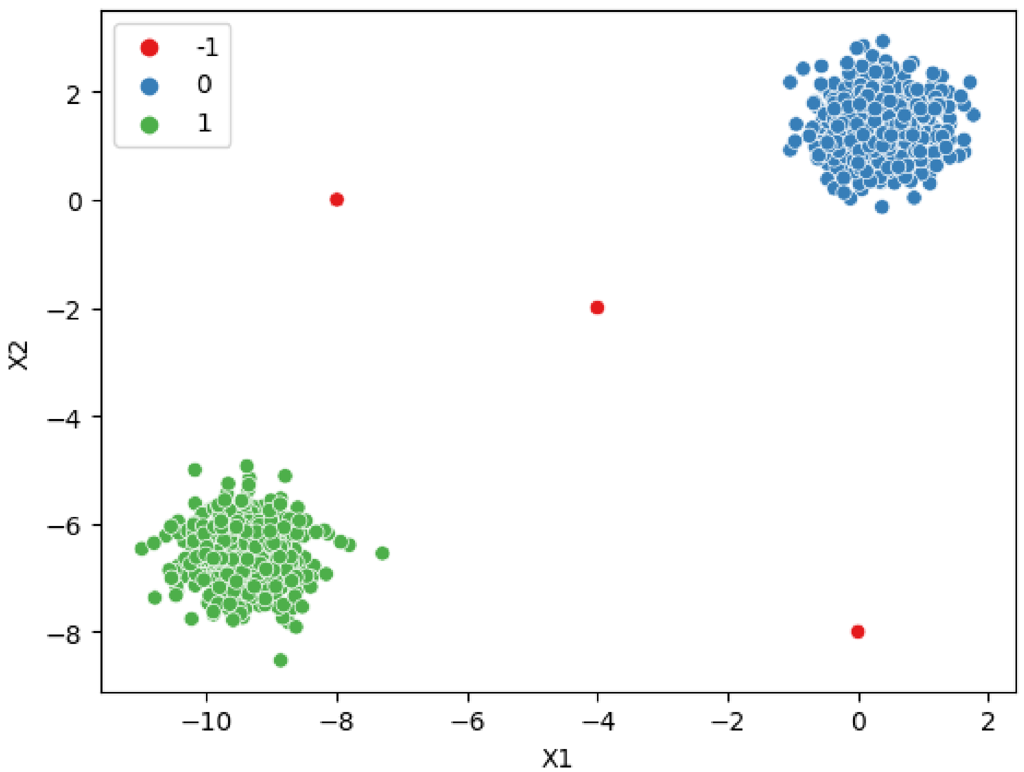
Out[70]:

```
<matplotlib.collections.LineCollection at 0x1bfb010e190>
```



In [71]:

```
# How to find a good epsilon?
dbscan = DBSCAN(eps=0.75)
display_categories(dbscan,two_blobs_outliers)
```



Minimum Samples

```
|  min_samples : int, default=5
```

```
    |      The number of samples (or total weight) in a neighborhood for a point
    |      to be considered as a core point. This includes the point itself.
```

How to choose minimum number of points?

https://stats.stackexchange.com/questions/88872/a-routine-to-choose-eps-and-minpts-for-dbscan

In [72]:

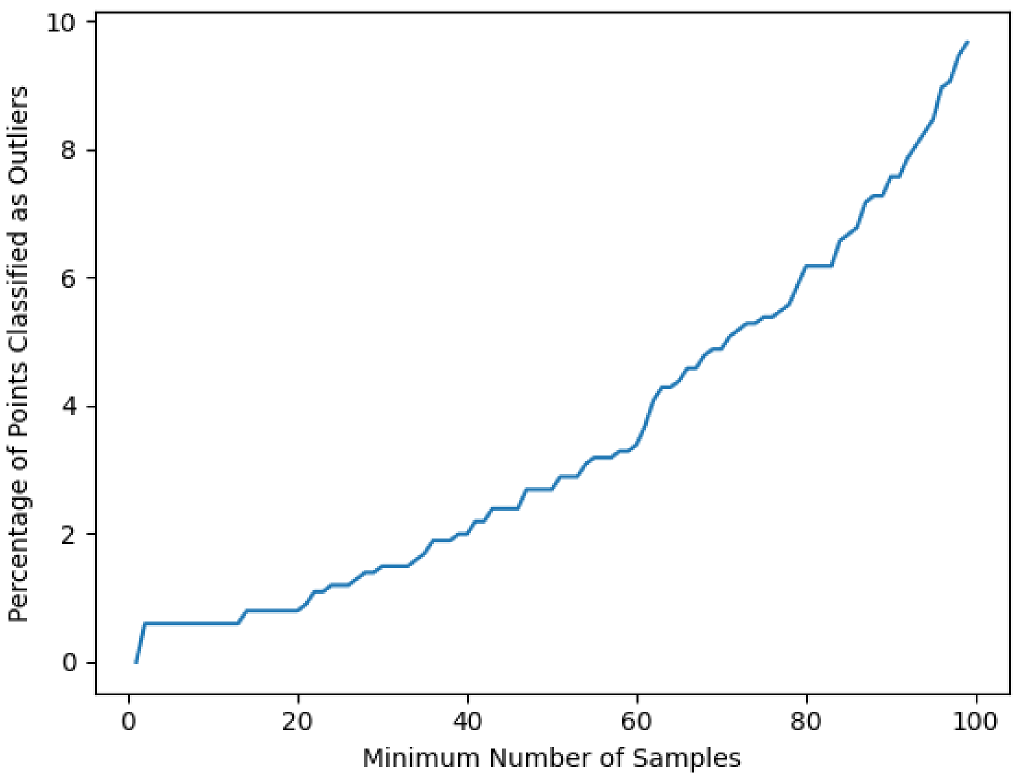
```
outlier_percent = []

for n in np.arange(1,100):

    # Create Model
    dbscan = DBSCAN(min_samples=n)
    dbscan.fit(two_blobs_outliers)

    # Log percentage of points that are outliers
    perc_outliers = 100 * np.sum(dbscan.labels_ == -1) / len(dbscan.labels_)

    outlier_percent.append(perc_outliers)
```

In [73]:

```
sns.lineplot(x=np.arange(1,100),y=outlier_percent)
plt.ylabel("Percentage of Points Classified as Outliers")
plt.xlabel("Minimum Number of Samples")
```

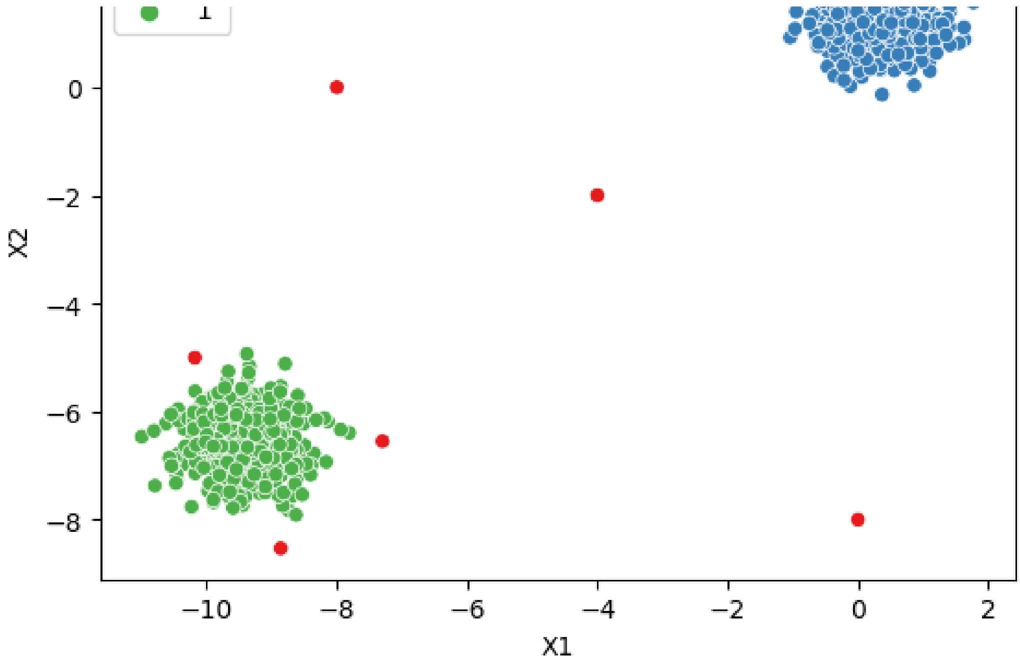
Out[73]:

```
Text(0.5, 0, 'Minimum Number of Samples')
```



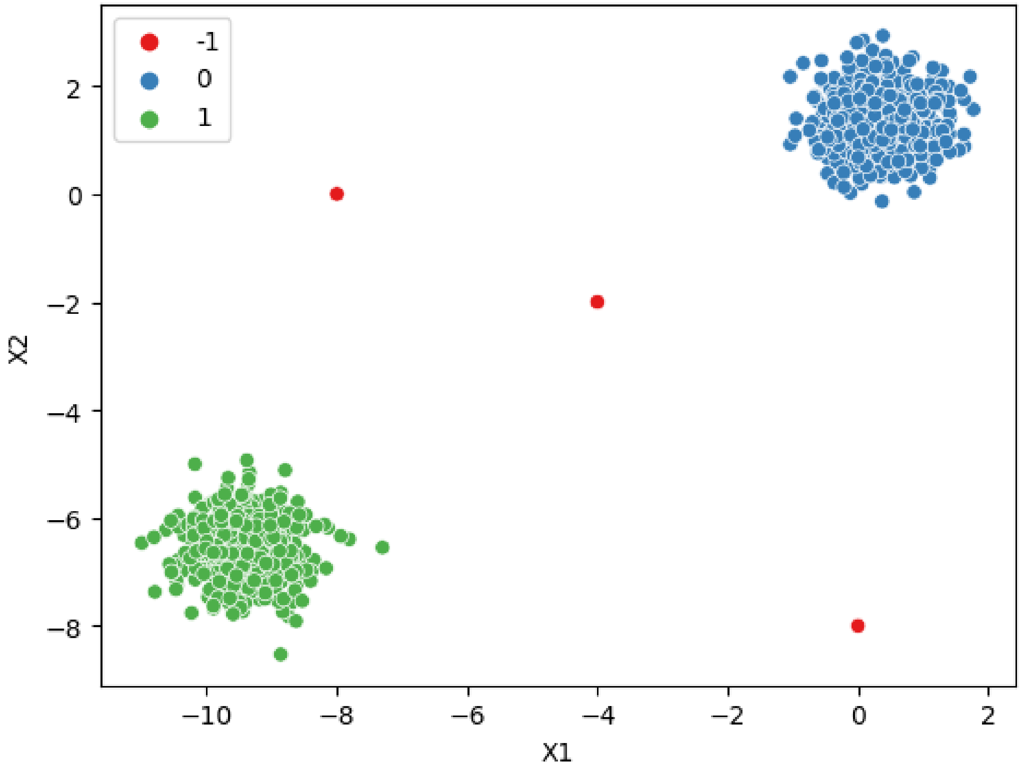
In [74]:

```
num_dim = two_blobs_outliers.shape[1]

dbscan = DBSCAN(min_samples=2*num_dim)
display_categories(dbscan,two_blobs_outliers)
```



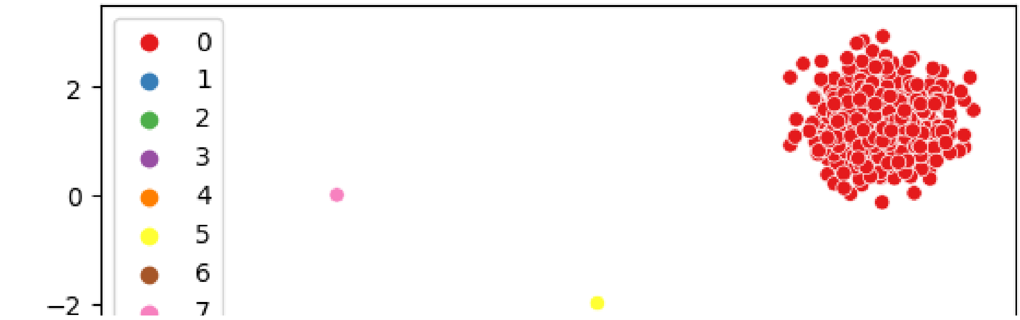
In [75]:

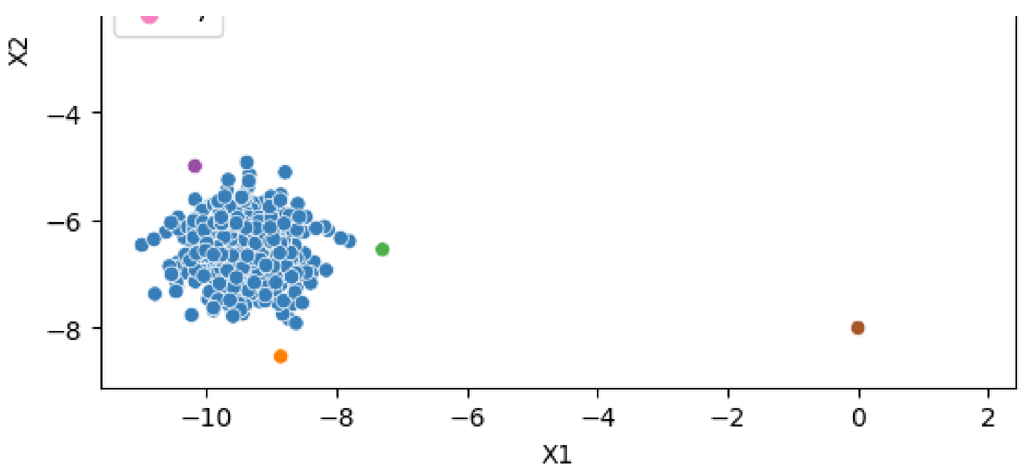
```
num_dim = two_blobs_outliers.shape[1]

dbscan = DBSCAN(eps=0.75,min_samples=2*num_dim)
display_categories(dbscan,two_blobs_outliers)
```



In [76]:

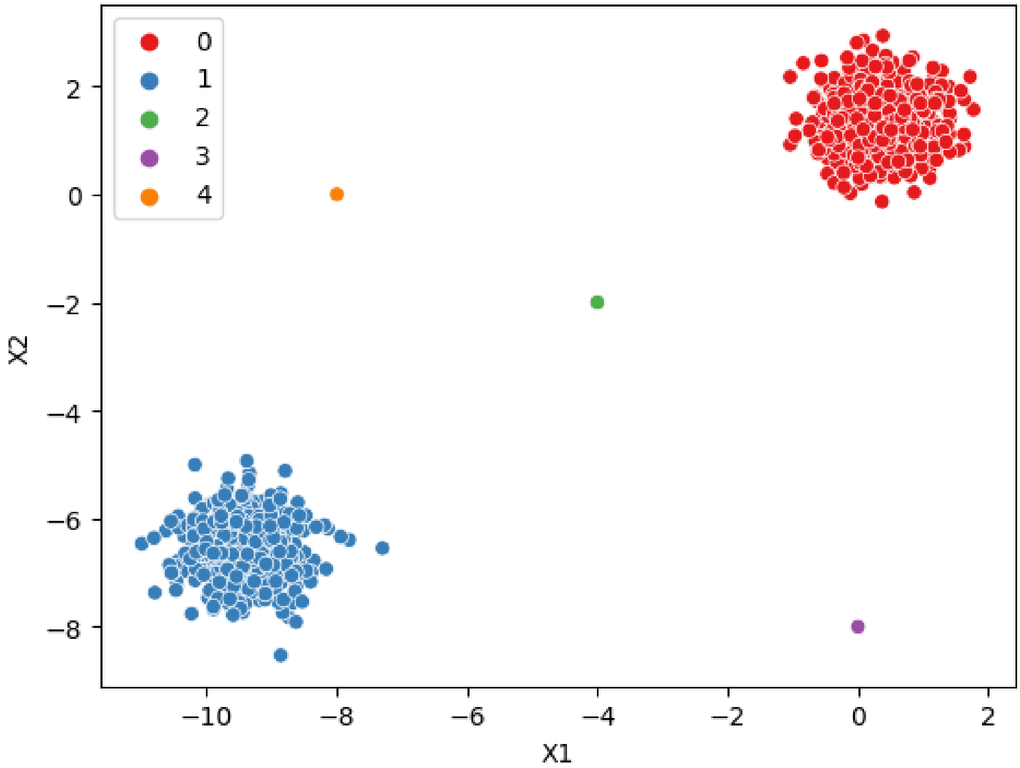
```
dbscan = DBSCAN(min_samples=1)
display_categories(dbscan,two_blobs_outliers)
```





In [77]:

```
dbscan = DBSCAN(eps=0.75,min_samples=1)
display_categories(dbscan,two_blobs_outliers)
```



DBSCAN Project

The Data

Source: https://archive.ics.uci.edu/ml/datasets/Wholesale+customers

Margarida G. M. S. Cardoso, margarida.cardoso '@' iscte.pt, ISCTE-IUL, Lisbon, Portugal

Data Set Information:

Provide all relevant information about your data set.

Attribute Information:

```
1) FRESH: annual spending (m.u.) on fresh products (Continuous);
2) MILK: annual spending (m.u.) on milk products (Continuous);
3) GROCERY: annual spending (m.u.)on grocery products (Continuous);
4) FROZEN: annual spending (m.u.)on frozen products (Continuous)
5) DETERGENTS_PAPER: annual spending (m.u.) on detergents and paper products (Cont
inuous)
```

```
6) DELICATESSEN: annual spending (m.u.)on and delicatessen products (Continuous);
7) CHANNEL: customers  Channel - Horeca (Hotel/Restaurant/CafÃ©) or Retail channel
(Nominal)
8) REGION: customers  Region Lisnon, Oporto or Other (Nominal)
```

Relevant Papers:

Cardoso, Margarida G.M.S. (2013). Logical discriminant models â€“ Chapter 8 in Quantitative Modeling in Marketing and Management Edited by Luiz Moutinho and Kun-Huang Huarng. World Scientific. p. 223-253. ISBN 978-9814407717

Jean-Patrick Baudry, Margarida Cardoso, Gilles Celeux, Maria JosÃ© Amorim, Ana Sousa Ferreira (2012). Enhancing the selection of a model-based clustering with external qualitative variables. RESEARCH REPORT NÂ° 8124, October 2012, Project-Team SELECT. INRIA Saclay - ÃŽle-de-France, Projet select, UniversitÃ© Paris-Sud 11

DBSCAN and Clustering Examples

COMPLETE THE TASKS IN BOLD BELOW:

TASK: Run the following cells to import the data and view the DataFrame.

In [30]:

```
df = pd.read_csv("D:\\Study\\Programming\\python\\Python course from udemy\\Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\24 - DBSCAN - Density-based spatial clustering of applications with noise\\33643066-wholesome-customers-data.csv")
```

In [31]:

```
df.head()
```

Out[31]:

	Channel	Region	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
0	2	3	12669	9656	7561	214	2674	1338
1	2	3	7057	9810	9568	1762	3293	1776
2	2	3	6353	8808	7684	2405	3516	7844
3	1	3	13265	1196	4221	6404	507	1788
4	2	3	22615	5410	7198	3915	1777	5185

In [32]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 440 entries, 0 to 439
Data columns (total 8 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Channel           440 non-null    int64
 1   Region            440 non-null    int64
 2   Fresh             440 non-null    int64
 3   Milk              440 non-null    int64
 4   Grocery           440 non-null    int64
 5   Frozen            440 non-null    int64
 6   Detergents_Paper  440 non-null    int64
 7   Delicassen        440 non-null    int64
dtypes: int64(8)
memory usage: 27.6 KB
```

In [ ]:

```

```