In [ ]:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score, silhouette_samples
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.neighbors import KernelDensity
from sklearn.cluster import DBSCAN
from sklearn.svm import OneClassSVM
from sklearn.neighbors import LocalOutlierFactor
```

In [ ]:

```python
trip_advisor = pd.read_csv('tripadvisor_review.csv')
trip_advisor = trip_advisor.drop(['User ID'], axis=1)
trip_advisor_scaled = StandardScaler().fit_transform(trip_advisor)
trip_advisor
```

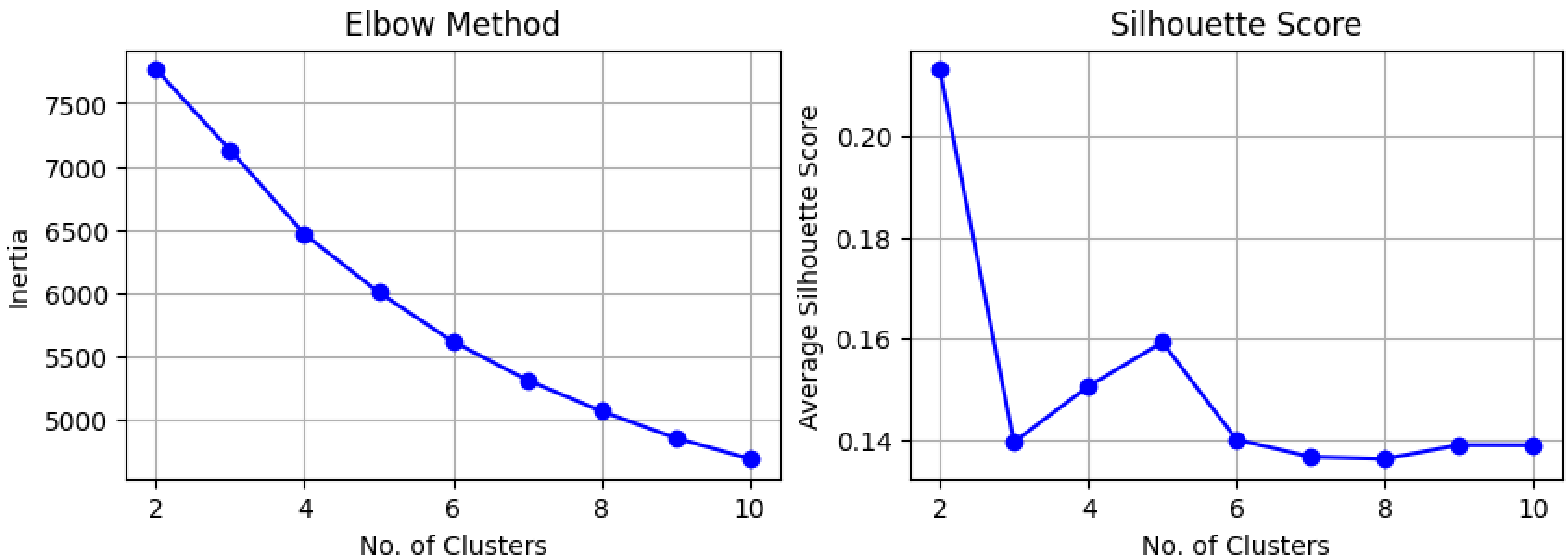
Out[ ]:

	Category 1	Category 2	Category 3	Category 4	Category 5	Category 6	Category 7	Category 8	Category 9	Category 10
0	0.93	1.80	2.29	0.62	0.80	2.42	3.19	2.79	1.82	2.42
1	1.02	2.20	2.66	0.64	1.42	3.18	3.21	2.63	1.86	2.32
2	1.22	0.80	0.54	0.53	0.24	1.54	3.18	2.80	1.31	2.50
3	0.45	1.80	0.29	0.57	0.46	1.52	3.18	2.96	1.57	2.86
4	0.51	1.20	1.18	0.57	1.54	2.02	3.18	2.78	1.18	2.54
...	...	...	...	...	...	...	...	...	...	...
975	0.74	1.12	0.30	0.53	0.88	1.38	3.17	2.78	0.99	3.20
976	1.25	0.92	1.12	0.38	0.78	1.68	3.18	2.79	1.34	2.80
977	0.61	1.32	0.67	0.43	1.30	1.78	3.17	2.81	1.34	3.02
978	0.93	0.20	0.13	0.43	0.30	0.40	3.18	2.98	1.12	2.46
979	0.93	0.56	1.13	0.51	1.34	2.36	3.18	2.87	1.34	2.40

980 rows × 10 columns

Problem 1a

In [ ]:
```
inertia_values = []
silhouette_avgs = []

k_range = range(2, 11)
for k in k_range:
    kmeans = KMeans(n_clusters=k, n_init=10, random_state=42).fit(trip_advisor_scaled)
    cluster_labels = kmeans.labels_
    centroids = kmeans.cluster_centers_
    inertia_values.append(kmeans.inertia_)
    silhouette_avg = silhouette_score(trip_advisor_scaled, cluster_labels)
    silhouette_avgs.append(silhouette_avg)

plt.figure(figsize=(10,3))
plt.subplot(121)
plt.plot(np.arange(2,11),inertia_values,'o-b')
plt.grid()
plt.xlabel('No. of Clusters')
plt.ylabel('Inertia')
plt.title('Elbow Method')
plt.subplot(122)
plt.plot(np.arange(2,11),silhouette_avgs,'o-b')
plt.grid()
plt.xlabel('No. of Clusters')
plt.ylabel('Average Silhouette Score')
plt.title('Silhouette Score')
plt.show()

best_k = k_range[np.argmax(silhouette_avgs)]
best_k, max(silhouette_avgs)
```

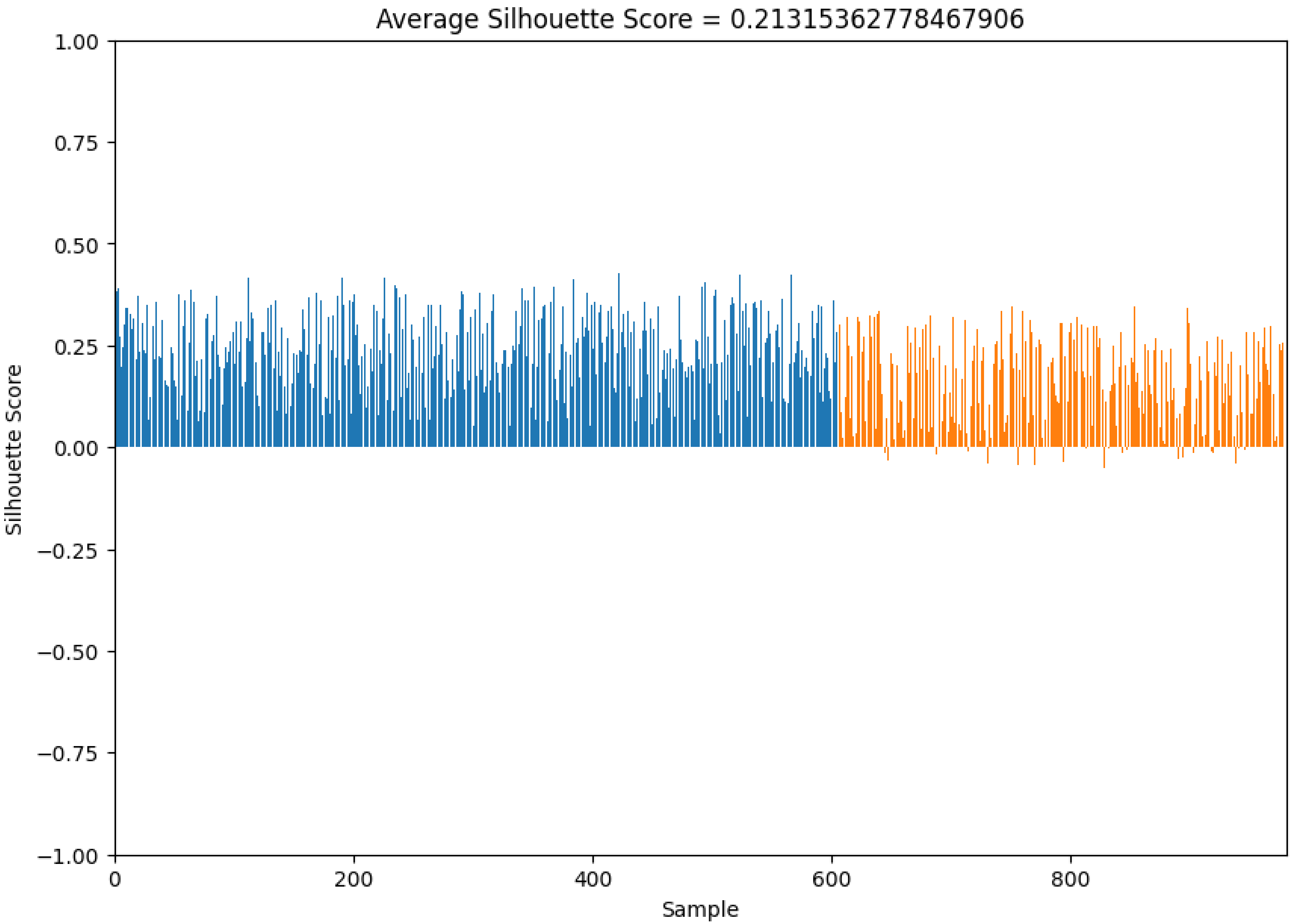


Out[ ]: (2, 0.21315362778467906)

Looking at the Silhouette score, the best K is k=2.

In [ ]:
```
kmeans = KMeans(n_clusters=best_k, n_init=10)
kmeans.fit(trip_advisor_scaled)
cluster_labels = kmeans.labels_
centroids = kmeans.cluster_centers_
inertia = kmeans.inertia_
silhouette_values = silhouette_samples(trip_advisor_scaled, cluster_labels)
silhouette_avg = silhouette_score(trip_advisor_scaled, cluster_labels)

plt.figure(figsize=(10, 7))

sample = 0
for i in range(0, best_k):
    sil = silhouette_values[cluster_labels == i]
    plt.bar(np.arange(sample, sample + sil.size), sil)
    sample += sil.size

plt.xlim([0, len(trip_advisor_scaled)])
plt.ylim([-1, 1])

plt.xlabel('Sample')
plt.ylabel('Silhouette Score')
plt.title(f"Average Silhouette Score = {silhouette_avg}")
```

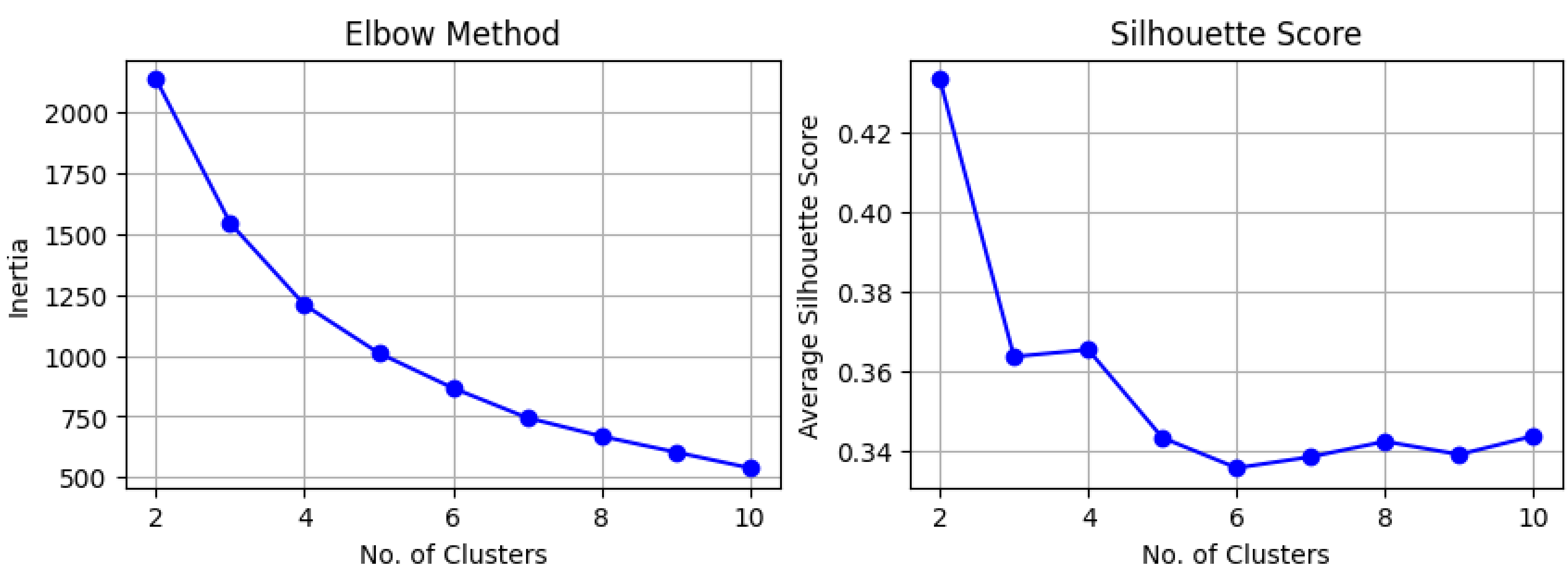
```
plt.show()
```



Problem 1b

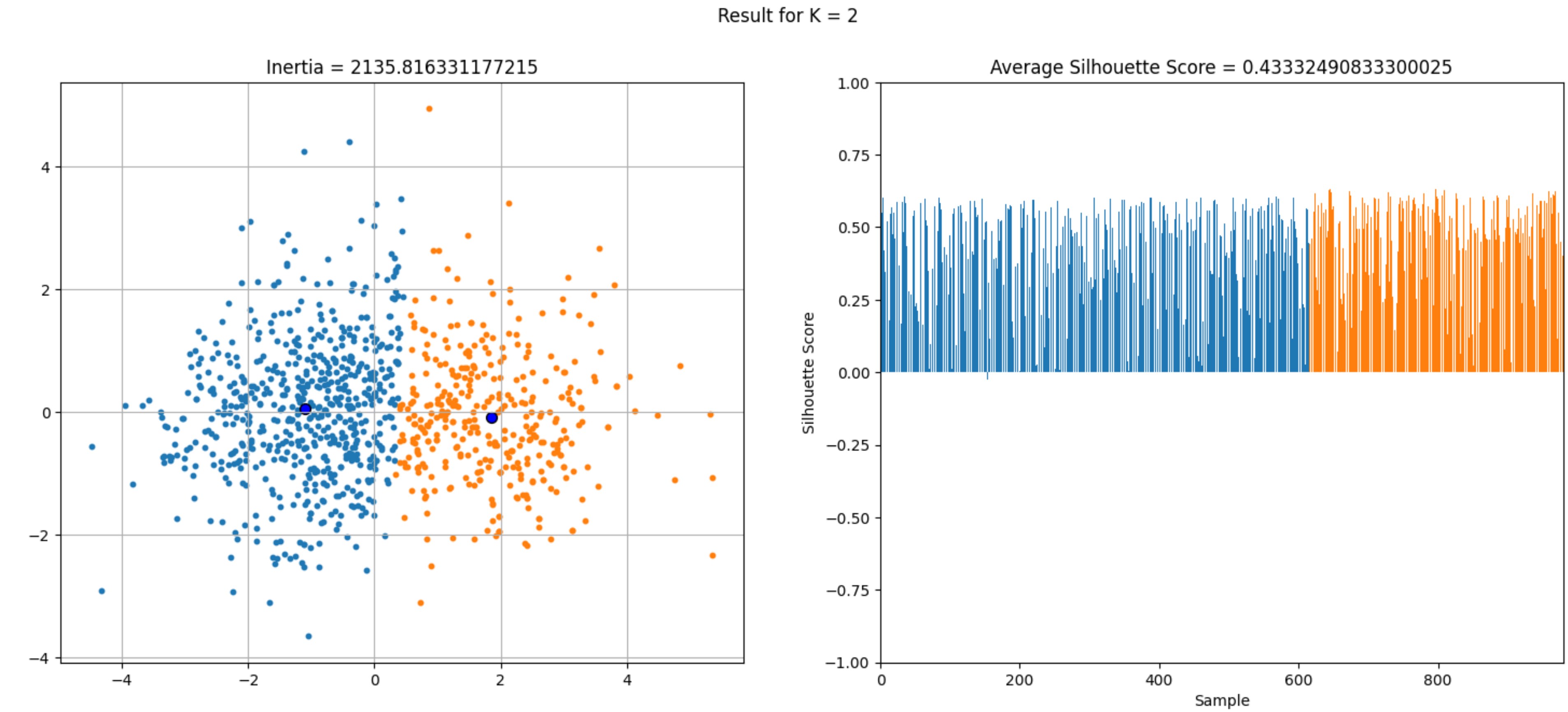
In [ ]:
```
trip_advisor_scaled_pca = PCA(n_components=2).fit_transform(trip_advisor_scaled)

inertia_values = []
```

```python
silhouette_avgs = []

k_range = range(2, 11)
for k in k_range:
    kmeans = KMeans(n_clusters=k, n_init=10, random_state=42).fit(trip_advisor_scaled_pca)
    cluster_labels = kmeans.labels_
    centroids = kmeans.cluster_centers_
    inertia_values.append(kmeans.inertia_)
    silhouette_avg = silhouette_score(trip_advisor_scaled_pca, cluster_labels)
    silhouette_avgs.append(silhouette_avg)

plt.figure(figsize=(10,3))
plt.subplot(121)
plt.plot(np.arange(2,11),inertia_values,'o-b')
plt.grid()
plt.xlabel('No. of Clusters')
plt.ylabel('Inertia')
plt.title('Elbow Method')
plt.subplot(122)
plt.plot(np.arange(2,11),silhouette_avgs,'o-b')
plt.grid()
plt.xlabel('No. of Clusters')
plt.ylabel('Average Silhouette Score')
plt.title('Silhouette Score')
plt.show()

best_k = k_range[np.argmax(silhouette_avgs)]
best_k, max(silhouette_avgs)
```



Out[ ]: (2, 0.43332490833300025)

In [ ]:
```
kmeans = KMeans(n_clusters=best_k, n_init=10)
kmeans.fit(trip_advisor_scaled_pca)
cluster_labels = kmeans.labels_
centroids = kmeans.cluster_centers_
inertia = kmeans.inertia_
silhouette_values = silhouette_samples(trip_advisor_scaled_pca, cluster_labels)
silhouette_avg = silhouette_score(trip_advisor_scaled_pca, cluster_labels)

fig, (ax1, ax2) = plt.subplots(1, 2)
fig.set_size_inches(18, 7)
fig.suptitle(f"Result for K = {best_k}")
for i in range(0,best_k):
    ax1.scatter(trip_advisor_scaled_pca[cluster_labels == i,0], trip_advisor_scaled_pca[cluster_labels == i,1], s=10)
ax1.scatter(centroids[:,0],centroids[:,1], s=50, color='b', edgecolor='k')
ax1.set_title(f"Inertia = {inertia}")
ax1.grid()
sample = 0
for i in range(0,best_k):
    sil = silhouette_values[cluster_labels == i]
    ax2.bar(np.arange(sample,sample + sil.size),sil)
    sample = sample + sil.size
ax2.axis([0, len(trip_advisor_scaled_pca), -1, 1])
ax2.set_xlabel('Sample')
ax2.set_ylabel('Silhouette Score')
ax2.set_title(f"Average Silhouette Score = {silhouette_avg}")
plt.show()
```

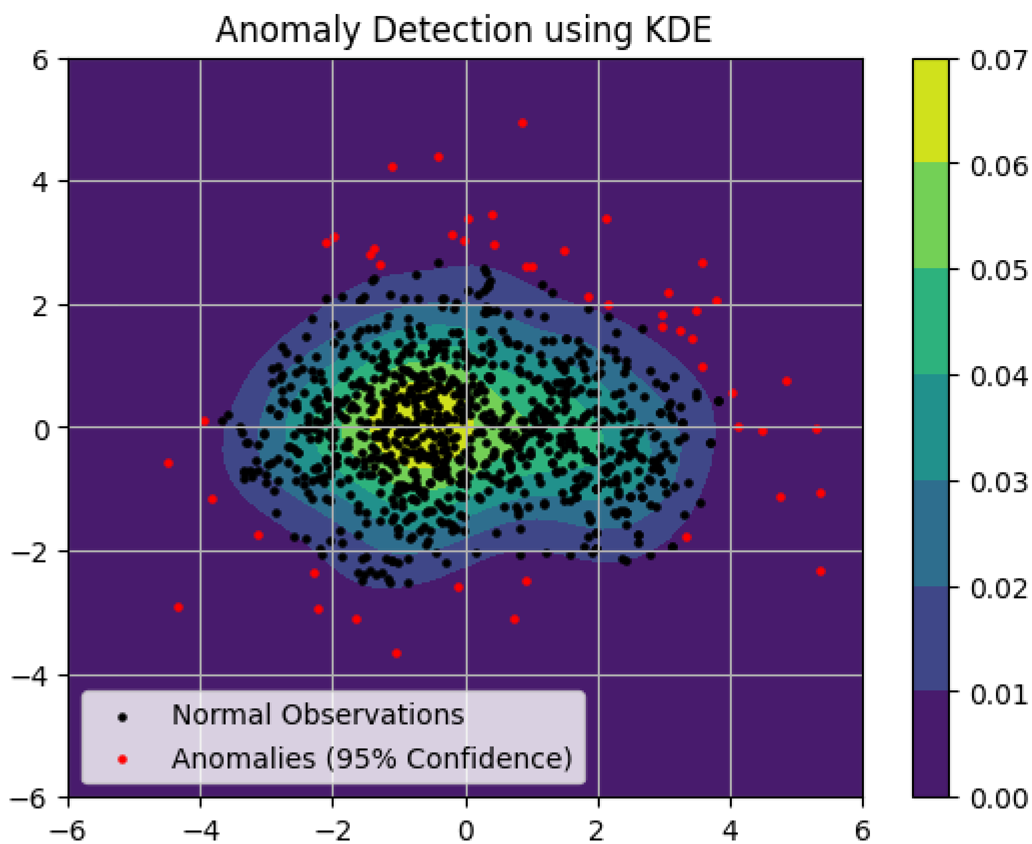


Problem 1c

In [ ]:
```
# Make a meshgrid for plotting surfaces
Xp, Yp = np.meshgrid(np.linspace(-6,6),np.linspace(-6,6))
XY = np.vstack([Xp.ravel(), Yp.ravel()]).T

# Generate the KDE surface as Z
kde = KernelDensity(kernel='gaussian',bandwidth=0.6).fit(trip_advisor_scaled_pca)
Zp = np.exp(kde.score_samples(XY))
Zp = Zp.reshape(Xp.shape)

# Establish a confidence level of 95% (or 5% cutoff)
# for the UCL using the quantile of kde_scores.
scores = kde.score_samples(trip_advisor_scaled_pca)
threshold = np.quantile(scores,0.05)
print(f"Threshold (KDE) = {np.exp(threshold)}")

# Get the anomalous data points
```

```
normals = trip_advisor_scaled_pca[scores > threshold,:]
anomals = trip_advisor_scaled_pca[scores <= threshold,:]

cntr = plt.contourf(Xp, Yp, Zp, cmap='viridis')
plt.scatter(normals[:,0], normals[:,1], s=5, color='k', label='Normal Observations')
plt.scatter(anomals[:,0], anomals[:,1], s=5, color='r', label='Anomalies (95% Confidence)')
plt.title('Anomaly Detection using KDE')
plt.colorbar(cntr)
plt.legend()
plt.grid()
plt.show()
```

```
Threshold (KDE) = 0.007945590602990696
```



Using the K-means clustering and looking at the silhouette score and the elbow method, the optimal number of user groups based on their rating patterns is two.

This means that users can be categorized, albeit broadly, into two clusters with similar rating behaviors.

Anomaly detection using Kernel Density Estimation has shown users with rating patterns that deviate significantly, indicated by the red dots in the scatter plot above.

Problem 2a

In [ ]:
```
waste_df = pd.read_csv('water-treatment.data', header=None, na_values='?')
waste_df
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	...	29	30	31	32	33	34	35	36	37	38
0	D-1/3/90	44101.0	1.50	7.8	NaN	407.0	166.0	66.3	4.5	2110	...	2000.0	NaN	58.8	95.5	NaN	70.0	NaN	79.4	87.3	99.6
1	D-2/3/90	39024.0	3.00	7.7	NaN	443.0	214.0	69.2	6.5	2660	...	2590.0	NaN	60.7	94.8	NaN	80.8	NaN	79.5	92.1	100.0
2	D-4/3/90	32229.0	5.00	7.6	NaN	528.0	186.0	69.9	3.4	1666	...	1888.0	NaN	58.2	95.6	NaN	52.9	NaN	75.8	88.7	98.5
3	D-5/3/90	35023.0	3.50	7.9	205.0	588.0	192.0	65.6	4.5	2430	...	1840.0	33.1	64.2	95.3	87.3	72.3	90.2	82.3	89.6	100.0
4	D-6/3/90	36924.0	1.50	8.0	242.0	496.0	176.0	64.8	4.0	2110	...	2120.0	NaN	62.7	95.6	NaN	71.0	92.1	78.2	87.5	99.5
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
522	D-26/8/91	32723.0	0.16	7.7	93.0	252.0	176.0	56.8	2.3	894	...	942.0	NaN	62.3	93.3	69.8	75.9	79.6	78.6	96.6	99.6
523	D-27/8/91	33535.0	0.32	7.8	192.0	346.0	172.0	68.6	4.0	988	...	950.0	NaN	58.3	97.8	83.0	59.1	91.1	74.6	90.7	100.0
524	D-28/8/91	32922.0	0.30	7.4	139.0	367.0	180.0	64.4	3.0	1060	...	1136.0	NaN	65.0	97.1	76.2	66.4	82.0	77.1	88.9	99.0
525	D-29/8/91	32190.0	0.30	7.3	200.0	545.0	258.0	65.1	4.0	1260	...	1326.0	39.8	65.9	97.1	81.7	70.9	89.5	87.0	89.5	99.8
526	D-30/8/91	30488.0	0.21	7.5	152.0	300.0	132.0	69.7	NaN	1073	...	1224.0	NaN	69.5	NaN	81.7	76.4	NaN	81.7	86.4	NaN

527 rows × 39 columns

In [ ]:
```
waste_df = waste_df.drop(0, axis=1)
waste_df = waste_df.dropna(axis=0)
waste_df
```

Out[ ]:

	1	2	3	4	5	6	7	8	9	10	...	29	30	31	32	33	34	35	36	37	38
3	35023.0	3.50	7.9	205.0	588.0	192.0	65.6	4.5	2430	7.8	...	1840.0	33.1	64.2	95.3	87.3	72.3	90.2	82.3	89.6	100.0
8	29156.0	2.50	7.7	206.0	451.0	194.0	69.1	4.5	1249	7.7	...	1338.0	46.1	43.6	92.5	85.6	58.2	92.2	73.8	90.2	99.4
9	39246.0	2.00	7.8	172.0	506.0	200.0	69.0	5.0	1865	7.8	...	1616.0	21.2	59.7	90.8	88.4	66.1	89.0	69.0	86.5	99.6
10	42393.0	0.70	7.9	189.0	478.0	230.0	67.0	5.5	1410	8.1	...	1575.0	0.6	45.8	92.0	11.6	25.7	19.6	36.0	43.0	36.4
14	40923.0	3.50	7.6	146.0	329.0	188.0	57.4	2.5	1300	7.6	...	1545.0	32.7	33.3	90.0	82.6	61.3	87.0	71.4	78.2	99.2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
516	32363.0	0.10	7.6	159.0	310.0	146.0	68.5	1.6	1096	7.6	...	1083.0	25.2	61.4	91.2	78.6	65.1	86.8	81.0	89.0	99.4
517	31437.0	0.47	7.6	132.0	304.0	148.0	64.9	2.0	939	7.7	...	1012.0	45.6	60.3	94.4	82.5	72.9	89.4	86.2	91.2	99.5
519	28088.0	0.20	7.5	153.0	307.0	124.0	82.3	2.5	1044	7.6	...	1038.0	40.5	54.4	94.0	89.7	75.5	93.5	85.0	90.3	100.0
520	27838.0	0.13	7.6	179.0	265.0	128.0	71.9	1.8	992	7.6	...	1044.0	13.7	45.0	95.0	87.5	71.3	93.9	79.6	89.1	100.0
525	32190.0	0.30	7.3	200.0	545.0	258.0	65.1	4.0	1260	7.4	...	1326.0	39.8	65.9	97.1	81.7	70.9	89.5	87.0	89.5	99.8

380 rows × 38 columns

In [ ]:

```
waste_df_scaled = StandardScaler().fit_transform(waste_df)
waste_df_scaled = pd.DataFrame(waste_df_scaled)
waste_df_scaled
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	...	28	29	
0	-0.343241	0.525785	0.316286	0.250780	1.563544	-0.295154	0.375011	-0.063976	2.446198	-0.228257	...	0.934093	-0.404249	0.40
1	-1.200658	0.095778	-0.530113	0.267095	0.399567	-0.278193	0.651826	-0.063976	-0.558227	-0.675358	...	-0.373975	0.467799	-1.18
2	0.273919	-0.119225	-0.106914	-0.287618	0.866857	-0.227313	0.643917	0.108197	1.008857	-0.228257	...	0.350413	-1.202508	0.06
3	0.733829	-0.678234	0.316286	-0.010261	0.628963	0.027092	0.485737	0.280369	-0.148648	1.113046	...	0.243579	-2.584369	-1.01
4	0.519000	0.525785	-0.953312	-0.711810	-0.636968	-0.329074	-0.273526	-0.752666	-0.428484	-1.122459	...	0.165408	-0.431081	-1.97
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
375	-0.731979	-0.936238	-0.953312	-0.499714	-0.798395	-0.685240	0.604372	-1.062576	-0.947454	-1.122459	...	-1.038431	-0.934186	0.19
376	-0.867307	-0.777136	-0.953312	-0.940221	-0.849372	-0.668280	0.319648	-0.924838	-1.346856	-0.675358	...	-1.223437	0.434259	0.10
377	-1.356738	-0.893238	-1.376511	-0.597604	-0.823884	-0.871804	1.695813	-0.752666	-1.079740	-1.122459	...	-1.155688	0.092148	-0.34
378	-1.393274	-0.923338	-0.953312	-0.173412	-1.180723	-0.837883	0.873278	-0.993707	-1.212026	-1.122459	...	-1.140054	-1.705613	-1.07
379	-0.757262	-0.850237	-2.222910	0.169205	1.198208	0.264536	0.335466	-0.236148	-0.530243	-2.016660	...	-0.405243	0.045191	0.54

380 rows × 38 columns

In [ ]:

```
print(waste_df_scaled.max(axis=0))
```

```
0      3.318797
1      7.233895
2      2.855482
3      4.052195
4      4.562696
5      8.490276
6      1.893538
7     10.782893
8      4.481372
9      2.901450
10     3.332265
11     9.750031
12     2.659568
13    11.442301
14     4.233797
15     2.383433
16     2.752428
17     2.681566
18     6.411890
19     2.627666
20     8.170439
21     5.522953
22     2.476815
23    13.889519
24     6.599546
25     9.546672
26     2.202000
27    17.312502
28     6.432146
29     2.681460
30     2.766907
31     1.050689
32     1.529908
33     2.680527
34     1.372543
35     2.404418
36     1.478899
37     0.207914
dtype: float64
```

In [ ]:

```
dbscan = DBSCAN(eps=5, min_samples=20)
clusters = dbscan.fit_predict(waste_df_scaled)
# clusters = dbscan.fit_predict(waste_df)

outlier_mask = clusters == -1
outliers = waste_df_scaled[outlier_mask]
# outliers = waste_df[outlier_mask]
```

```python
print("Number of Outliers Found:", len(outliers))
print("Outliers:\n", outliers)
```

```
Number of Outliers Found: 70
Outliers:
            0         1         2         3         4         5         6   \
3    0.733829 -0.678234  0.316286 -0.010261  0.628963  0.027092  0.485737
9    0.708108  2.675821 -1.376511 -0.842331 -0.602983  0.111893 -0.463342
17   0.174834 -0.678234  1.585884  0.707602  0.866857 -0.193392  0.462010
42   0.456889  3.320831  1.162684  0.201835  0.611971  0.620702 -0.914155
47   0.299494 -0.549232  0.316286 -0.010261  0.450544  6.590724 -2.796495
..        ...       ...       ...       ...       ...       ...       ...
303 -0.409005 -0.673934 -0.530113 -0.548659 -1.087265 -0.685240  0.817915
324 -0.235534 -0.218127 -0.953312 -1.217578 -0.925838 -0.379955 -0.732248
329 -0.736218  7.233895 -0.953312 -0.173412  0.484528  0.603742 -0.407979
370 -2.900149 -0.742735 -1.376511 -0.646550 -1.979365 -0.464757 -1.871143
374 -1.379390 -0.893238 -0.953312 -0.516029 -0.246143 -0.413876 -0.012530

           7         8         9   ...        28        29        30  \
3    0.280369 -0.148648  1.113046  ...  0.243579 -2.584369 -1.012388
9   -0.305017 -0.970349 -1.569559  ... -0.673631 -0.652447 -0.270441
17   0.693583  0.568751  2.007248  ...  0.003854 -1.698905 -0.030853
42  -0.339452  0.426289  0.665945  ... -0.496443 -1.973936 -0.139054
47   6.650752 -0.637090 -0.228257  ... -0.806523 -0.390833  2.395934
..        ...       ...       ...  ...       ...       ...       ...
303 -0.477190 -0.517523 -0.675358  ... -0.551163 -0.524994 -1.476106
324  6.995097 -0.174088 -0.675358  ... -0.431300 -1.175676 -0.734158
329  0.108197 -0.326726 -1.122459  ... -0.472992  0.776370  0.115990
370 -1.131445 -1.873458 -1.569559  ... -1.963459  1.588045  1.453042
374 -0.408321 -1.067020 -0.675358  ... -1.702888  1.936865  0.602893

           31         32        33         34        35        36         37
3    0.151957 -10.471443 -4.090017 -12.845477 -5.152580 -7.670518 -15.205776
9    0.073318   0.157913 -0.061972  -0.207237  0.372182  0.540919   0.207914
17   0.893411  -1.315178 -0.128630  -1.787017 -0.151089 -3.046442   0.038266
42  -3.117183   0.201239  1.175962  -0.537889  0.712916  0.508007  -0.131381
47   0.949582   0.533406  0.652221   0.068306  0.530380  1.363708   0.207914
..        ...        ...       ...        ...       ...       ...        ...
303 -1.196142  -1.502924  0.661743  -1.603322  0.737254 -3.243912  -3.524332
324  0.455279  -0.506422  0.528427  -1.107345  0.238322 -0.002122   0.159443
329  0.646260  -0.304233 -0.890435  -0.133759 -0.662190  0.376361   0.159443
370 -0.072726  -1.488482 -0.300036   0.582653 -0.138920  0.178892  -0.131381
374  0.679962  -0.362002 -2.556884   0.876565 -0.710866 -1.071748  -0.131381

[70 rows x 38 columns]
```

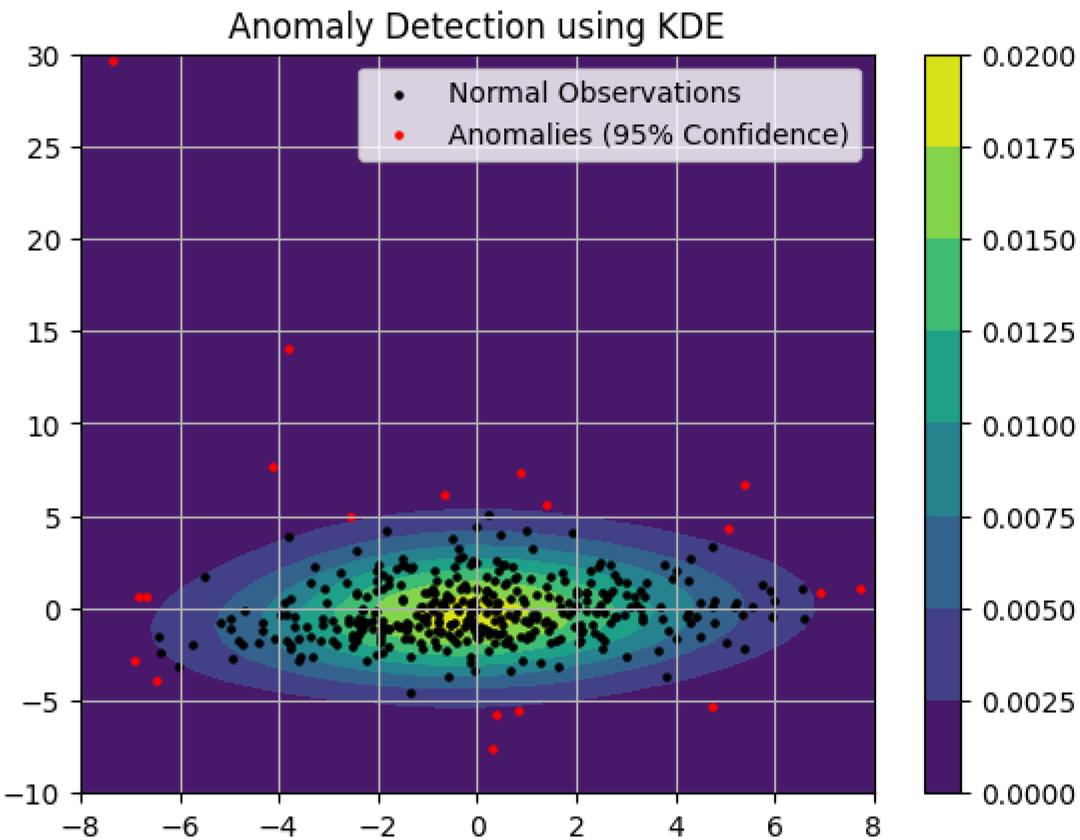
In [ ]:

```python
waste_df_scaled_pca = PCA(n_components=2).fit_transform(waste_df_scaled)
```

In [ ]:

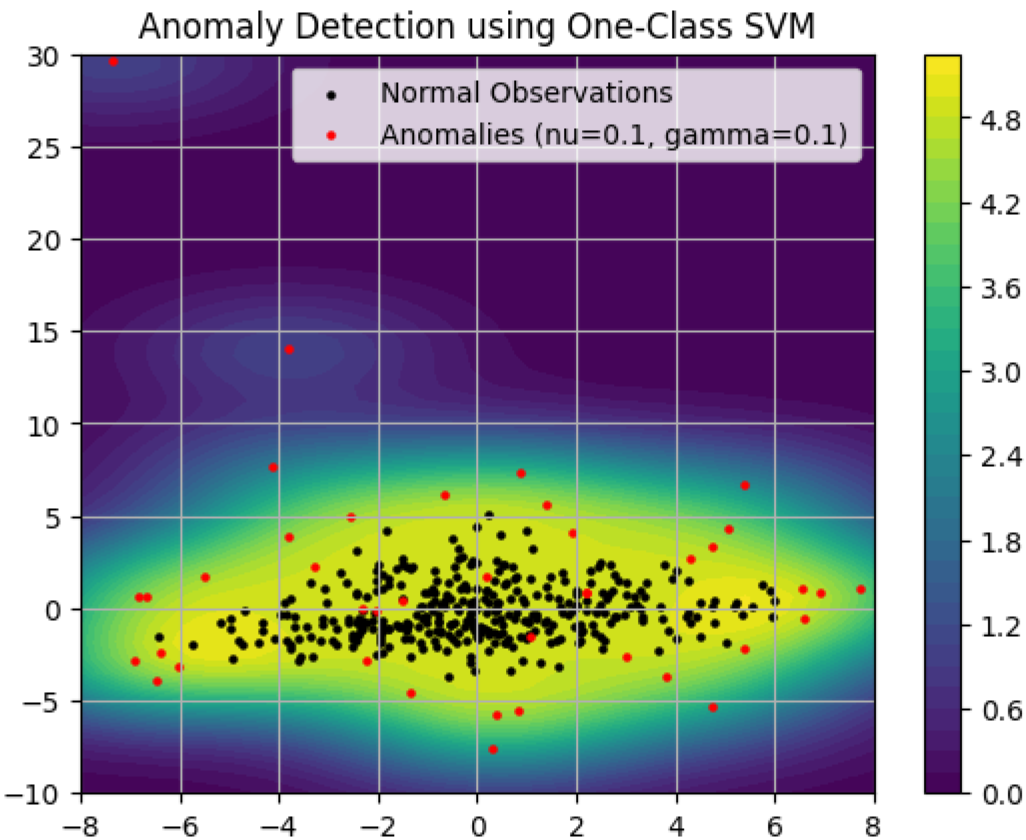
```
# Make a meshgrid for plotting surfaces
Xp, Yp = np.meshgrid(np.linspace(-8,8),np.linspace(-10,30))
XY = np.vstack([Xp.ravel(), Yp.ravel()]).T

# Generate the KDE surface as Z
kde = KernelDensity(kernel='gaussian',bandwidth=2).fit(waste_df_scaled_pca)
Zp = np.exp(kde.score_samples(XY))
Zp = Zp.reshape(Xp.shape)

# Establish a confidence level of 95% (or 5% cutoff)
# for the UCL using the quantile of kde_scores.
scores = kde.score_samples(waste_df_scaled_pca)
threshold = np.quantile(scores,0.05)
print(f"Threshold (KDE) = {np.exp(threshold)}")

# Get the anomalous data points
normals = waste_df_scaled_pca[scores > threshold,:]
anomals = waste_df_scaled_pca[scores <= threshold,:]

cntr = plt.contourf(Xp, Yp, Zp, cmap='viridis')
plt.scatter(normals[:,0], normals[:,1], s=5, color='k', label='Normal Observations')
plt.scatter(anomals[:,0], anomals[:,1], s=5, color='r', label='Anomalies (95% Confidence)')
plt.title('Anomaly Detection using KDE')
plt.colorbar(cntr)
plt.legend()
plt.grid()
plt.show()
```

```
Threshold (KDE) = 0.002268562861665983
```

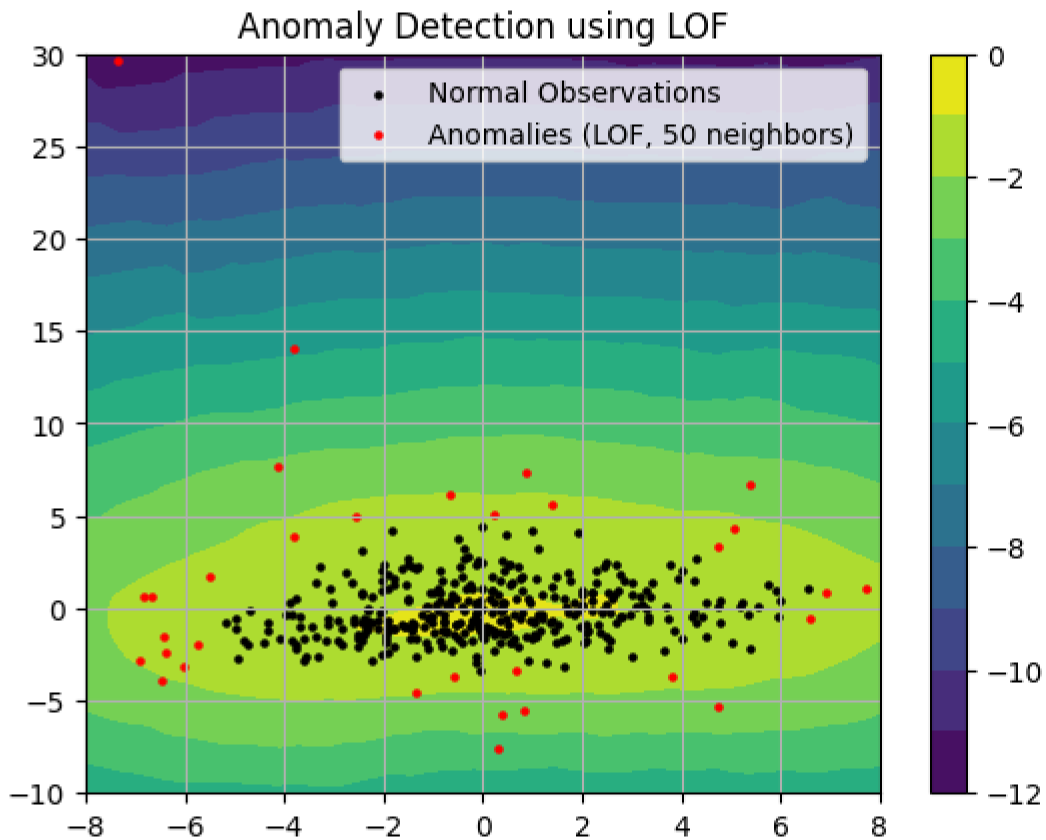


In [ ]:

```
nu = 0.1
gamma = 0.1

ocsvm = OneClassSVM(nu=nu, gamma=gamma).fit(waste_df_scaled_pca)
Zp = ocsvm.score_samples(XY)
Zp = Zp.reshape(Xp.shape)

# Get the anomalous data points
y_pred = ocsvm.predict(waste_df_scaled_pca)
normals = waste_df_scaled_pca[y_pred == 1,:]
anomals = waste_df_scaled_pca[y_pred == -1,:]

cntr = plt.contourf(Xp, Yp, Zp, levels=50, cmap='viridis')
plt.scatter(normals[:,0], normals[:,1], s=5, color='k', label='Normal Observations')
plt.scatter(anomals[:,0], anomals[:,1], s=5, color='r', label=f'Anomalies (nu={nu}, gamma={gamma})')
plt.title('Anomaly Detection using One-Class SVM')
plt.colorbar(cntr)
plt.legend()
plt.grid()
plt.show()
```



In [ ]:
```
n_neighbors = 50

lof = LocalOutlierFactor(n_neighbors=n_neighbors,novelty=True).fit(waste_df_scaled_pca)
Zp = lof.score_samples(XY)
Zp = Zp.reshape(Xp.shape)

# Get the anomalous data points
y_pred = lof.predict(waste_df_scaled_pca)
normals = waste_df_scaled_pca[y_pred == 1,:]
anomals = waste_df_scaled_pca[y_pred == -1,:]

cntr = plt.contourf(Xp, Yp, Zp, levels=10, cmap='viridis')
plt.scatter(normals[:,0], normals[:,1], s=5, color='k', label='Normal Observations')
plt.scatter(anomals[:,0], anomals[:,1], s=5, color='r', label=f'Anomalies (LOF, {n_neighbors} neighbors)')
plt.title('Anomaly Detection using LOF')
plt.colorbar(cntr)
plt.legend()
plt.grid()
plt.show()
```



Comparing the performance of the three methods, it is evident that the parameters play a crucial role in the performance of the anomaly detection method.

Using KDE resulted in the lowest number of anomalies. The One-Class SVM has anomalies within the dataset itself, indicating that the parameters need more tuning. The Local Outlier Factor has also a respectable result visually.

However, again, the performance of each method require careful tuning for them to be effective in this scenario. And each of them can be used provided tuning has been done.

Using a simple DBSCAN, the outlier days are 70. This does not include the days where there are missing values as these days have been dropped in the processing.