Clustering

1. DBSCAN

Using DBSCAN iterate (for-loop) through different values of `min_samples` (1 to 10) and `epsilon` (.05 to .5, in steps of .01) to find clusters in the road-data used in the Lesson and calculate the Silohouette Coeff for `min_samples` and `epsilon`. Plot ***one*** line plot with the multiple lines generated from the min_samples and epsilon values. Use a 2D array to store the SilCoeff values, one dimension represents `min_samples`, the other represents epsilon.

Expecting a plot of `epsilon vs sil_score`.

In [1]:
```
import pandas as pd
import numpy as np
%matplotlib notebook
import matplotlib.pyplot as plt
import seaborn
from mpl_toolkits.mplot3d import Axes3D
plt.rcParams['font.size'] = 14
from sklearn.cluster import KMeans
%matplotlib inline
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
from sklearn.cluster import DBSCAN
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_score
```

In [2]:
```
= pd.read_csv('~/Desktop/3D_spatial_network.txt.gz', header=None, names=[
= X.drop(['osm'], axis=1).sample(10000)
head()
```

Out[2]:

	lat	lon	alt
377677	10.575942	57.731303	2.784482
272474	9.638730	57.301489	4.471924
341553	8.923912	57.038541	3.829726
82770	8.839187	56.779897	21.547875
74902	9.544737	56.980292	20.400420

In [3]:
```
min_samples = np.arange(1,11,1)
epsilons = np.arange(0.05, 0.51, 0.01)
```

In [4]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_scaled
```

Out[4]:
```
array([[ 1.37278213,  2.25134786, -1.05101111],
       [-0.12822529,  0.76460049, -0.96005257],
       [-1.27305513, -0.14495103, -0.99466909],
       ...,
       [-1.76349576, -0.09839319,  0.51740483],
       [ 0.50187902,  0.88696212,  0.34185741],
       [ 0.3801444 , -1.06830141,  0.33453349]])
```

In [5]:
```
N = 7
XX = X.copy()
km = KMeans(n_clusters=N, random_state=1)
X['cluster'] = km.fit_predict(X[['lon', 'lat', 'alt']])
```

In [6]:
```
dbscan = DBSCAN(eps=.12)
XX.cluster = dbscan.fit_predict(XX[['lat','lon', 'alt']])
```

```
/var/folders/7h/csh63nwx4m92q80m3txjgngr0000gn/T/ipykernel_6522/1990501
922.py:2: UserWarning: Pandas doesn't allow columns to be created via a
new attribute name - see https://pandas.pydata.org/pandas-docs/stable/i
ndexing.html#attribute-access (https://pandas.pydata.org/pandas-docs/st
able/indexing.html#attribute-access)
  XX.cluster = dbscan.fit_predict(XX[['lat','lon', 'alt']])
```

In [7]:
```
#Silhouette Coefficients
all_scores = np.zeros((len(min_samples), len(epsilons)))
```

In [8]:
```
for i, min_samples in enumerate(min_samples):
    for j, eps in enumerate(epsilons):
        dbscan = DBSCAN(eps=eps, min_samples=min_samples)
        clusters = dbscan.fit_predict(XX[['lat', 'lon', 'alt']])
        if len(np.unique(clusters)) > 1:
           silhouette_avg = silhouette_score(XX[['lat', 'lon', 'alt']],
           all_scores[i, j] = silhouette_avg
        else:
            all_scores[i, j] = np.nan

#Plot
plt.figure(figsize=(10, 6))
for i, min_samples in enumerate(min_samples):
    plt.plot(epsilons, all_scores[i, :], label=f'min_samples = {min_samp

plt.title('Road DBSCAN')
plt.xlabel('Epsilon')
plt.ylabel('Silhouette Coefficient')
plt.grid(True)
plt.show()
```

```
---------------------------------------------------------------------------
----
TypeError                                 Traceback (most recent call l
ast)
/var/folders/7h/csh63nwx4m92q80m3txjgngr0000gn/T/ipykernel_6522/7900195
96.py in <module>
     11 #Plot
     12 plt.figure(figsize=(10, 6))
---> 13 for i, min_samples in enumerate(min_samples):
     14     plt.plot(epsilons, all_scores[i, :], label=f'min_samples =
{min_samples}')
     15

TypeError: 'numpy.int64' object is not iterable


<Figure size 1000x600 with 0 Axes>
```

In [ ]:
```
# plot the results
plt.figure()
for i, min_sample in enumerate(min_samples):
    plt.plot(epsilons, all_scores[i, :], label=f'{min_sample}')

plt.xlabel('Epsilon')
plt.ylabel('Silhouette Coefficient')
plt.grid(True)
plt.legend(title = 'Min Samples', fontsize = 'x-small')
plt.title('Epsilon vs. Silhouette Coefficient for Multiple Min Sample Va
plt.show()
```

2. Clustering your own data

Using your own data, find relevant clusters/groups within your data (repeat the above). If your data is labeled with a class that you are attempting to predict, be sure to not use it in training and clustering.

You may use the labels to compare with predictions to show how well the clustering performed using one of the clustering metrics (http://scikit-learn.org/stable/modules/clustering.html#clustering-performance-evaluation (http://scikit-learn.org/stable/modules/clustering.html#clustering-performance-evaluation)).

If you don't have labels, use the silhouette coefficient to show performance. Find the optimal fit for your data but you don't need to be as exhaustive as above.

Additionally, show the clusters in 2D or 3D plots.

As a bonus, try using PCA first to condense your data from N columns to less than N.

Two items are expected:

- Metric Evaluation Plot (like in 1.)
- Plots of the clustered data

In [9]:
```
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn import decomposition
from sklearn import metrics

tornado = pd.read_csv('~/Desktop/us_tornado.csv')
tornado.head
```

Out[9]:
```
<bound method NDFrame.head of           yr  mo  dy        date  st  mag
inj  fat     slat     slon     elat  \
0      1950   1   3  1950-01-03  IL    3    3    0  39.1000 -89.3000  3
9.1200
1      1950   1   3  1950-01-03  MO    3    3    0  38.7700 -90.2200  3
8.8300
2      1950   1   3  1950-01-03  OH    1    1    0  40.8800 -84.5800
0.0000
3      1950   1  13  1950-01-13  AR    3    1    1  34.4000 -94.3700
0.0000
4      1950   1  25  1950-01-25  IL    2    0    0  41.1700 -87.3300
0.0000
...     ...  ..  ..         ...  ..  ...  ...  ...      ...      ...
...
67553  2021  12  30  2021-12-30  GA    1    0    0  31.1703 -83.3804  3
1.1805
67554  2021  12  30  2021-12-30  GA    1    0    0  31.6900 -82.7300  3
1.7439
67555  2021  12  31  2021-12-31  AL    1    0    0  34.2875 -85.7878  3
4.2998
67556  2021  12  31  2021-12-31  GA    1    0    0  33.7372 -84.9998  3
3.7625
67557  2021  12  31  2021-12-31  GA    1    6    0  33.5676 -83.9877  3
3.5842

          elon    len  wid
0     -89.2300   3.60  130
1     -90.0300   9.50  150
2       0.0000   0.10   10
3       0.0000   0.60   17
4       0.0000   0.10  100
...        ...    ...  ...
67553 -83.3453   2.19  150
67554 -82.5412  11.71  300
67555 -85.7805   0.95   50
67556 -84.9633   2.75  150
67557 -83.9498   2.50   75

[67558 rows x 14 columns]>
```

In [ ]:
```
tornado = tornado.drop(['Country'], axis=1)
tornado = tornado.drop(tornado.index[0])
tornado.head()
```

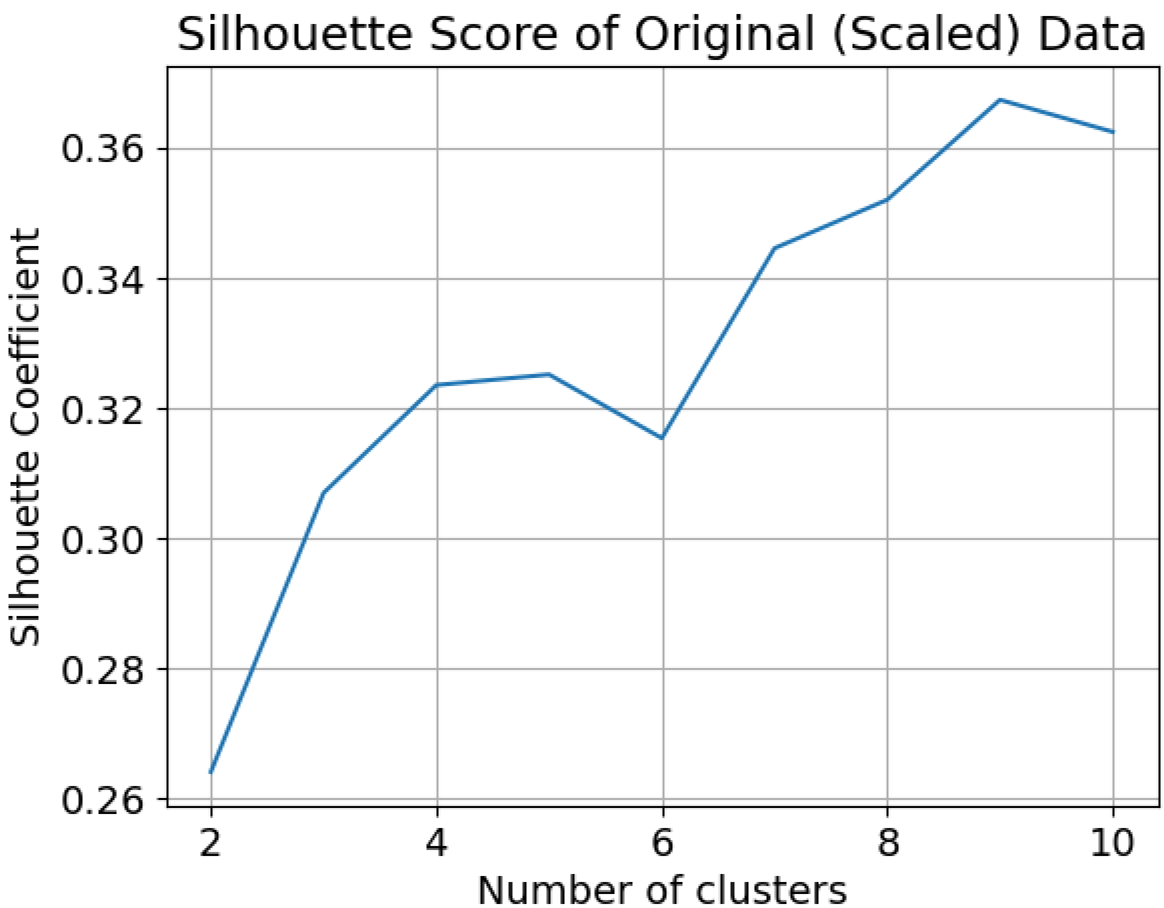
In [11]:
```
tornado.dropna(inplace=True)
```

In [12]:
```
centers = [[1, 1], [-1, -1], [1, -1]]
```

In [13]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [14]:
```
k_range = range(2, 11)
scores = []
for k in k_range:
    km = KMeans(n_clusters=k, random_state=1)
    labels = km.fit_predict(X_scaled)
    scores.append(metrics.silhouette_score(X_scaled, labels))
```

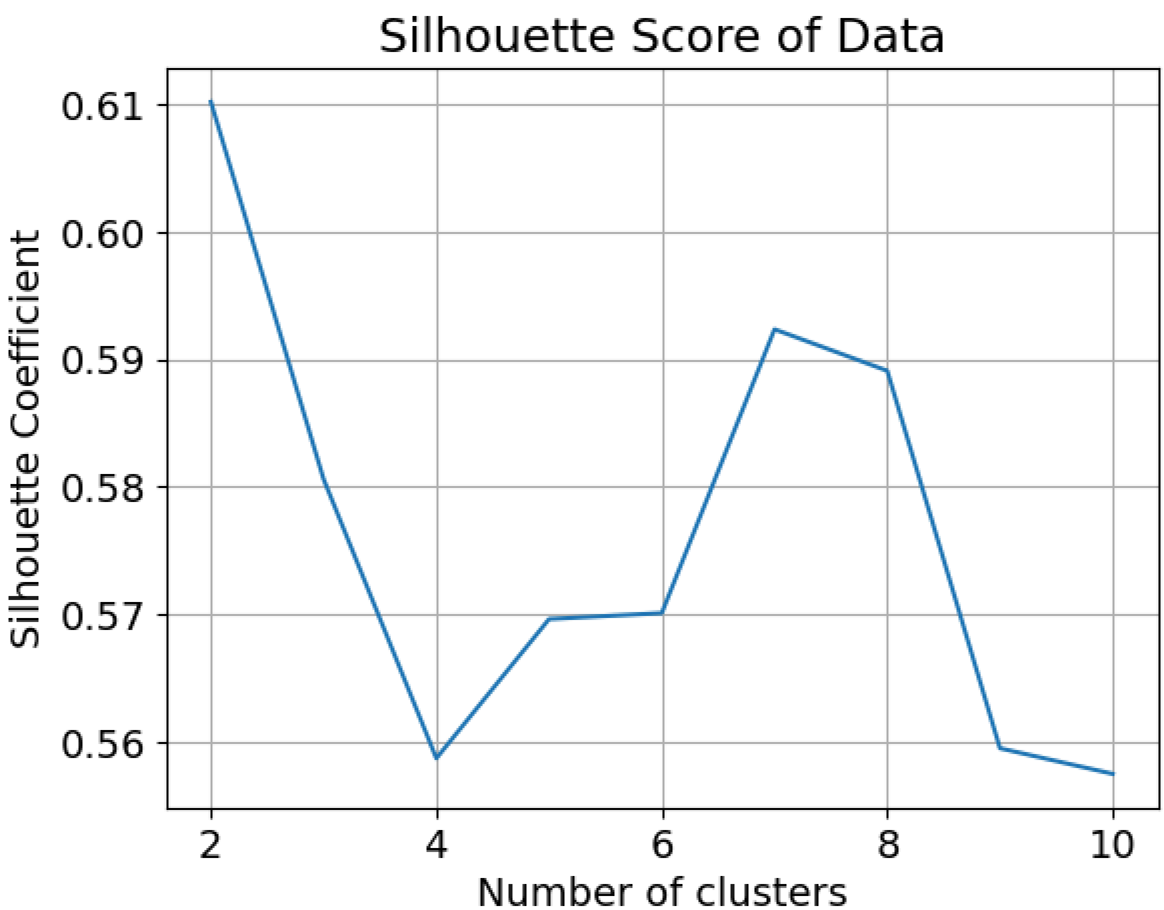
In [15]:
```
plt.figure()
plt.plot(k_range, scores)
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Coefficient')
plt.title('Silhouette Score of Original (Scaled) Data')
plt.grid(True)
plt.show()
```



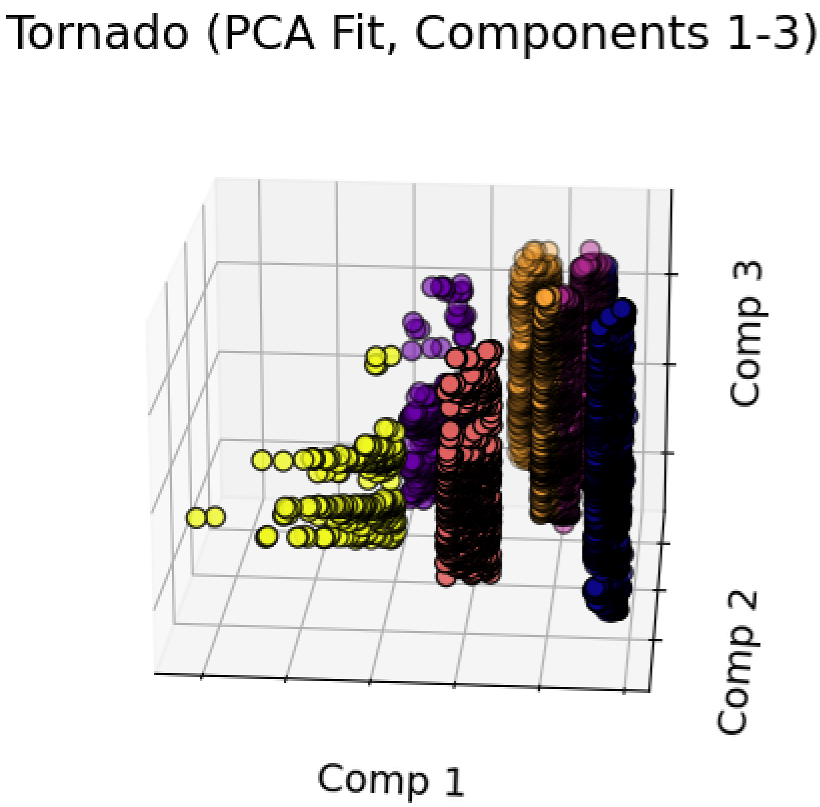
In [19]:
```
pca = decomposition.PCA(n_components=4)
pca.fit(X)
X = pca.transform(X)
```

In [20]:
```
scores2 = []
for k in k_range:
    km2 = KMeans(n_clusters=k, random_state=1)
    labels2 = km2.fit_predict(X)
    scores2.append(metrics.silhouette_score(X, labels2))
```

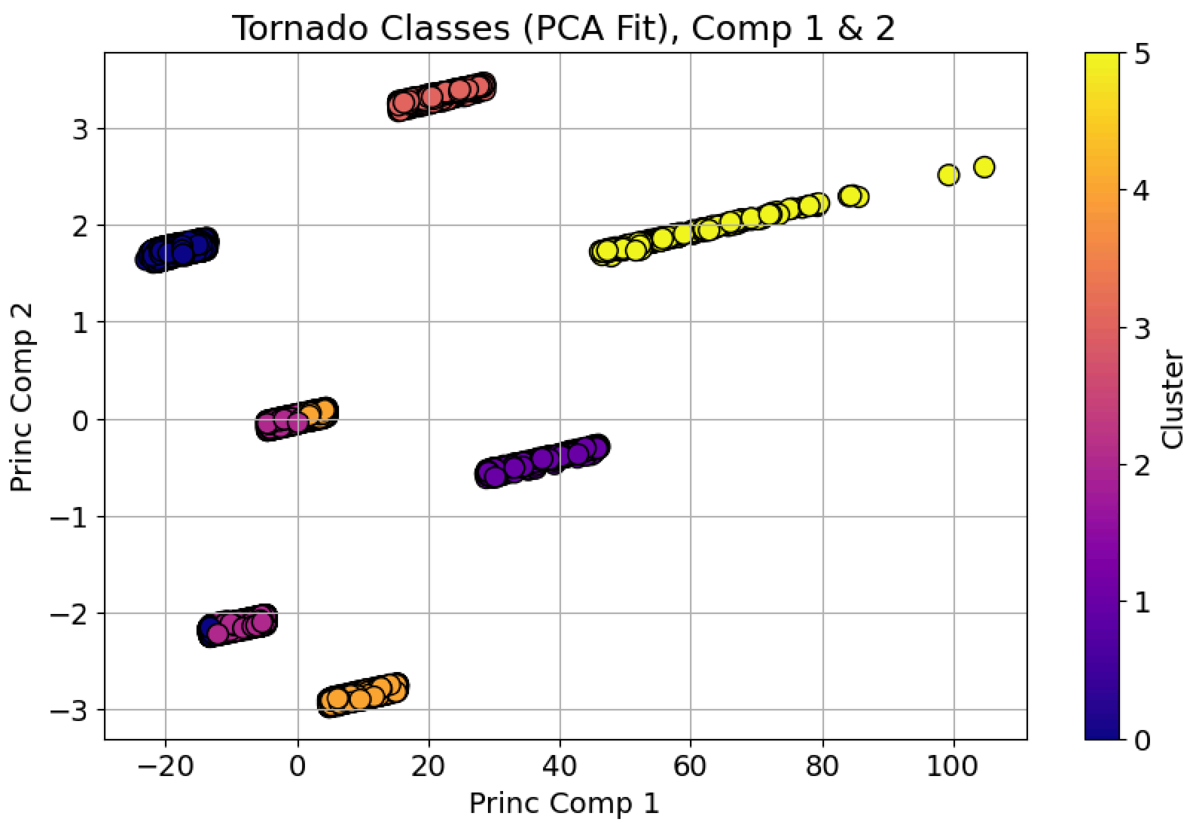
In [23]:
```
plt.figure()
plt.plot(k_range, scores2)
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Coefficient')
plt.title('Silhouette Score of Data')
plt.grid(True)
plt.show()
```



In [24]:
```
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d', elev=20, azim=95)

kmeans = KMeans(n_clusters=6, n_init=10, random_state=1)
cluster_labels = kmeans.fit_predict(X)

ax.scatter(X[:, 0], X[:, 1], X[:, 2], c=cluster_labels, cmap='plasma', e
ax.set_title(f'Tornado (PCA Fit, Components 1-3)')
ax.set_xlabel('Comp 1')
ax.set_ylabel('Comp 2')
ax.set_zlabel('Comp 3')

ax.set_xticklabels([])
ax.set_yticklabels([])
ax.set_zticklabels([])

plt.show()
```



In [28]:
```
plt.figure(figsize=(10, 6))
plt.scatter(X[:, 0], X[:, 1], c=cluster_labels, cmap='plasma', edgecolor
plt.title(f'Tornado Classes (PCA Fit), Comp 1 & 2')
plt.xlabel('Princ Comp 1')
plt.ylabel('Princ Comp 2')
plt.colorbar(label='Cluster')
plt.grid(True)
plt.show()
```



In [ ]: