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 [148]:
```
# Packages setup
import pandas as pd
import numpy as np
from sklearn.cluster import DBSCAN
from sklearn import metrics
from sklearn.preprocessing import StandardScaler
from sklearn import preprocessing
%matplotlib notebook
import matplotlib.pyplot as plt
import seaborn
from mpl_toolkits.mplot3d import Axes3D
plt.rcParams['font.size']=14
```

In [24]:
```
# Samples and Epsilon setup

min_samples = np.arange(1,11)
epsilon = np.arange(0.05, 0.51,0.01)
```

In [26]:
```
# Data setup

X = pd.read_csv('../data/3D_spatial_network.txt.gz', header=None, name
X = X.drop(['osm'], axis=1).sample(10000)
X.head()
```

Out[26]:

	lat	lon	alt
406390	8.693072	57.086466	41.912668
111956	9.709177	57.366395	5.359875
246198	8.178176	56.661887	1.687816
36703	10.063686	57.035660	1.601037
420155	10.421709	57.585527	2.184374

In [33]:
```
# Data scaling

X_scaled = X.copy()
X_scaled['alt'] = (X.alt - X.alt.mean())/X.alt.std()
X_scaled['lat'] = (X.lat - X.lat.mean())/X.lat.std()
X_scaled['lon'] = (X.lon - X.lon.mean())/X.lon.std()
X_scaled.head()
```

Out[33]:

	lat	lon	alt
406390	-1.655123	0.005717	1.087067
111956	-0.032622	0.968760	-0.898902
246198	-2.477300	-1.454973	-1.098411
36703	0.533452	-0.169073	-1.103125
420155	1.105137	1.722644	-1.071432

In [36]:
```
# DBSCAN test setup

dbscan = DBSCAN(eps=.05,min_samples=1)
X_scaled.cluster = dbscan.fit_predict(X_scaled[['lat','lon', 'alt']])
metrics.silhouette_score(X_scaled[['lon', 'lat', 'alt']], X_scaled.clu
```

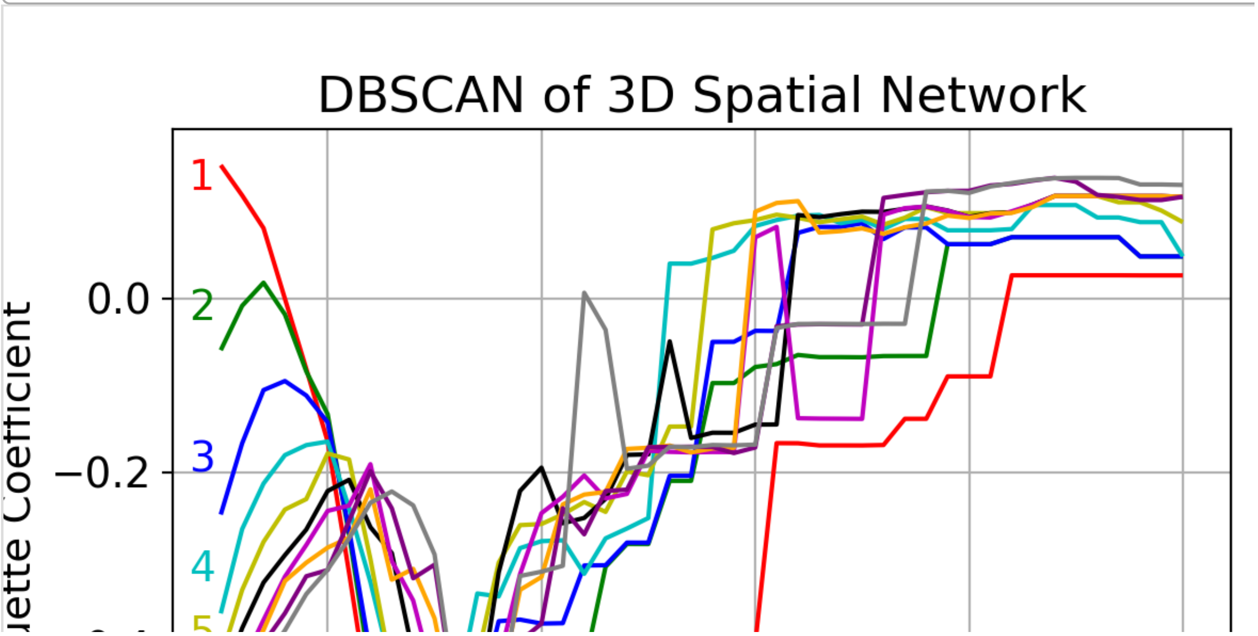
Out[36]: 0.1531248445430671

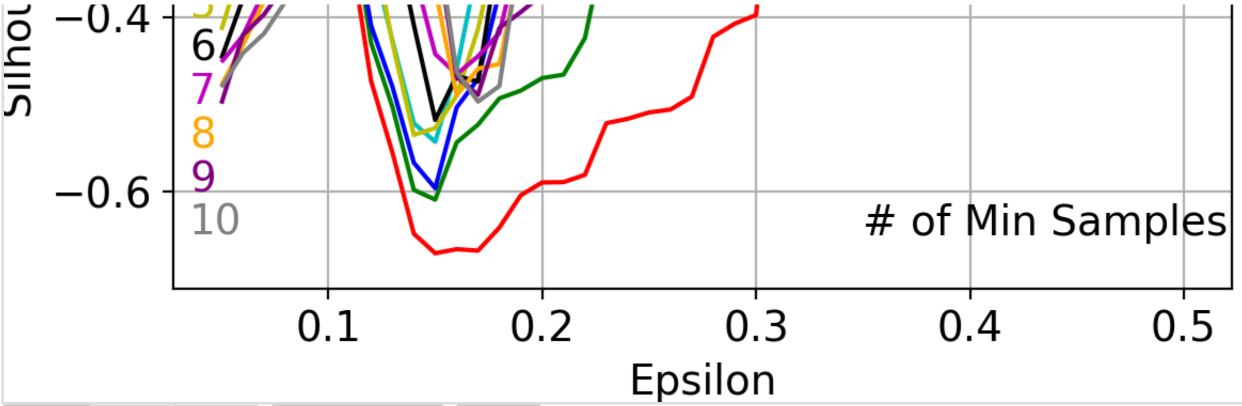
In [38]:
```
# For loop
sil_scores = []
for m in min_samples:
    scores = []
    for eps in epsilon:

        dbscan = DBSCAN(eps=eps,min_samples=m)

        X_scaled.cluster = dbscan.fit_predict(X_scaled[['lat','lon', '

        # calculate silouette score here
        score = metrics.silhouette_score(X_scaled[['lon', 'lat', 'alt'

        scores.append(score)

    sil_scores.append(scores)
```

In [112]:

```
# Plotting the Results

from matplotlib.collections import LineCollection

sil_scores_array = np.asarray(sil_scores)
colors = ['r', 'g', 'b', 'c', 'y', 'k', 'm', 'orange', 'purple', 'grey

plt_eps = np.tile(epsilon, sil_scores_array.shape[0]).reshape(*sil_scc
v = np.stack((plt_eps, sil_scores), axis = -1)
c = LineCollection(v, colors=colors)

fig, ax = plt.subplots()
ax.add_collection(c)
ax.autoscale()
ax.set_title('DBSCAN of 3D Spatial Network')
ax.annotate('1', xy=(0.04, 0.125), xytext=(0.035, 0.125), color = 'r')
ax.annotate('2', xy=(0.04, -0.025), xytext=(0.035, -0.025), color = 'g
ax.annotate('3', xy=(0.04, -0.2), xytext=(0.035, -0.2), color = 'b')
ax.annotate('4', xy=(0.04, -0.325), xytext=(0.035, -0.325), color = 'c
ax.annotate('5', xy=(0.04, -0.4), xytext=(0.035, -0.4), color = 'y')
ax.annotate('6', xy=(0.04, -0.45), xytext=(0.035, -0.45), color = 'k')
ax.annotate('7', xy=(0.04, -0.5), xytext=(0.035, -0.5), color = 'm')
ax.annotate('8', xy=(0.04, -0.55), xytext=(0.035, -0.55), color = 'ora
ax.annotate('9', xy=(0.04, -0.6), xytext=(0.035, -0.6), color = 'purpl
ax.annotate('10', xy=(0.04, -0.65), xytext=(0.035, -0.65), color = 'gr
ax.annotate('# of Min Samples', xy=(0.4, -0.65), xytext=(0.35, -0.65))
plt.xlabel('Epsilon')
plt.ylabel('Silhouette Coefficient')
plt.grid(True)
plt.show()
```

Figure 2





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)](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 [190]:
```
# Data setup

crime = pd.read_csv('/Users/obelisk/Downloads/Crime.csv', index_col=0,
crime = crime.drop(['Offence Code', 'CR Number', 'Dispatch Date / Time
                    'NIBRS Code', 'Victims', 'Crime Name2', 'Crime Nam
                    'Police District Name', 'Block Address', 'State',
                    'Sector', 'Beat', 'PRA', 'Address Number', 'Street
                    'Street Name','Street Suffix', 'Street Type', 'Enc
                    'Police District Number','Location'], axis=1).samp
crime.head()
```

Out[190]:

Incident ID	Crime Name1	City	Place	Start_Date_Time	Latitude	Longitude
201227438	Crime Against Property	POOLESVILLE	Other/Unknown	02/15/2019 05:00:00 PM	39.139240	-77.397869
201091764	Crime Against Society	SILVER SPRING	Street - In vehicle	08/02/2016 01:30:00 AM	39.092304	-76.984018
201222638	Crime Against Property	GAITHERSBURG	Street - Commercial	01/10/2019 07:00:00 PM	39.130334	-77.175987
201313197	Other	DERWOOD	Government Building	12/17/2020 09:32:00 AM	39.107938	-77.148079
201198665	Crime Against Property	GAITHERSBURG	Street - Commercial	07/23/2018 11:00:00 PM	39.115515	-77.245928

In [191]:
```
# Data cleaning

crime.City = crime.City.replace('MT AIRY', 'MOUNT AIRY', regex = True)

crime = crime.dropna()

crime = crime[(crime[['Longitude']] != 0).all(axis=1)]

crime['DateTime'] = pd.to_datetime(crime['Start_Date_Time'])

crime['Hour_of_Day'] = crime.DateTime.dt.hour

crime = crime.drop(columns = ['Start_Date_Time','DateTime'])

crime.head()
```

Out[191]:

	Crime Name1	City	Place	Latitude	Longitude	Hour_of_Day
Incident ID						
201227438	Crime Against Property	POOLESVILLE	Other/Unknown	39.139240	-77.397869	17
201091764	Crime Against Society	SILVER SPRING	Street - In vehicle	39.092304	-76.984018	1
201222638	Crime Against Property	GAITHERSBURG	Street - Commercial	39.130334	-77.175987	19
201313197	Other	DERWOOD	Government Building	39.107938	-77.148079	9
201198665	Crime Against Property	GAITHERSBURG	Street - Commercial	39.115515	-77.245928	23

In [193]:
```
# Converting to numeric

enc = preprocessing.OrdinalEncoder()

enc.fit(crime[['Crime Name1']])
crime['Crime_Cat'] = enc.transform(crime[['Crime Name1']])
crime.head()
```

Out[193]:

	Crime Name1	City	Place	Latitude	Longitude	Hour_of_Day	Crin
Incident ID							
201227438	Crime Against Property	POOLESVILLE	Other/Unknown	39.139240	-77.397869	17	
201091764	Crime Against Society	SILVER SPRING	Street - In vehicle	39.092304	-76.984018	1	
201222638	Crime Against Property	GAITHERSBURG	Street - Commercial	39.130334	-77.175987	19	
201313197	Other	DERWOOD	Government Building	39.107938	-77.148079	9	
201198665	Crime Against Property	GAITHERSBURG	Street - Commercial	39.115515	-77.245928	23	

In [194]:
```
# Data scaling

crime_scaled = crime.copy()

crime_scaled['Latitude'] = (crime.Latitude - crime.Latitude.mean())/cr
crime_scaled['Longitude'] = (crime.Longitude - crime.Longitude.mean())
crime_scaled['Hour_of_Day'] = (crime.Hour_of_Day - crime.Hour_of_Day.m
crime_scaled['Crime_Cat'] = (crime.Crime_Cat - crime.Crime_Cat.mean())

crime_scaled.head()
```

Out[194]:

Incident ID	Crime Name1	City	Place	Latitude	Longitude	Hour_of_Day	Crime
201227438	Crime Against Property	POOLESVILLE	Other/Unknown	0.796172	-2.943855	0.556458	-0.60
201091764	Crime Against Society	SILVER SPRING	Street - In vehicle	0.132083	1.392993	-1.769114	0.17
201222638	Crime Against Property	GAITHERSBURG	Street - Commercial	0.670153	-0.618699	0.847154	-0.60
201313197	Other	DERWOOD	Government Building	0.353284	-0.326246	-0.606328	1.74
201198665	Crime Against Property	GAITHERSBURG	Street - Commercial	0.460492	-1.351632	1.428547	-0.60

In [222]:
```
# DBSCAN test setup

dbscan = DBSCAN(eps=0.075,min_samples=1)
crime_scaled.cluster = dbscan.fit_predict(crime_scaled[['Crime_Cat','L
metrics.silhouette_score(crime_scaled[['Crime_Cat','Latitude','Longitu
```

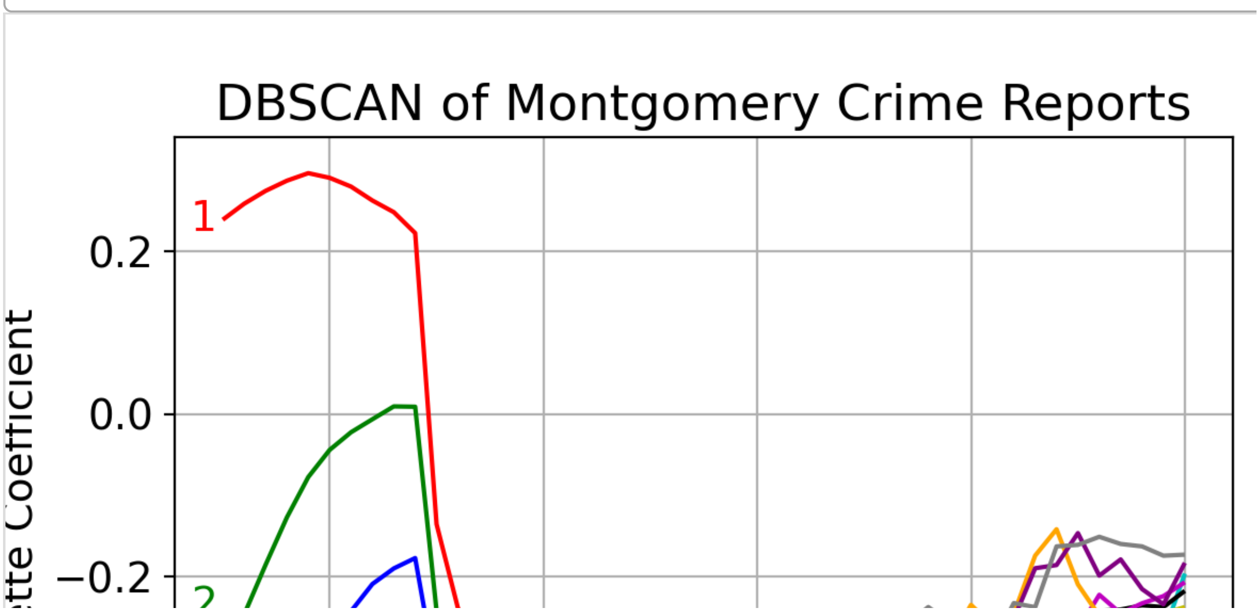
Out[222]: 0.2815168503464045

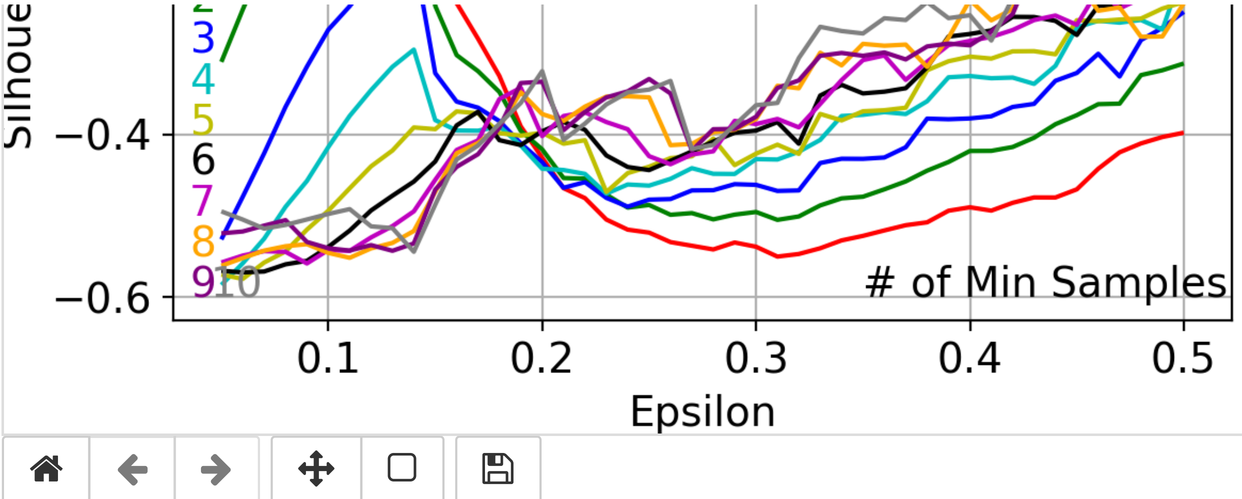
In [197]:
```
# Have for loop will cluster

crime_sil_scores = []
for m in min_samples:
    crime_scores = []
    for eps in epsilon:

        dbscan = DBSCAN(eps=eps,min_samples=m)

        crime_scaled.cluster = dbscan.fit_predict(crime_scaled[['Crime

        # calculate silouette score here
        crime_score = metrics.silhouette_score(crime_scaled[['Crime_Ca

        crime_scores.append(crime_score)

    crime_sil_scores.append(crime_scores)
```

In [208]:

```
# Plotting the Results

from matplotlib.collections import LineCollection

crime_sil_scores_array = np.asarray(crime_sil_scores)
crime_colors = ['r', 'g', 'b', 'c', 'y', 'k', 'm', 'orange', 'purple',

crime_plt_eps = np.tile(epsilon, crime_sil_scores_array.shape[0]).resh
crime_v = np.stack((crime_plt_eps, crime_sil_scores), axis = -1)
crime_c = LineCollection(crime_v, colors=crime_colors)

fig, ax = plt.subplots()
ax.add_collection(crime_c)
ax.autoscale()
ax.set_title('DBSCAN of Montgomery Crime Reports')
ax.annotate('1', xy=(0.04, 0.225), xytext=(0.035, 0.225), color = 'r')
ax.annotate('2', xy=(0.04, -0.25), xytext=(0.035, -0.25), color = 'g')
ax.annotate('3', xy=(0.04, -0.3), xytext=(0.035, -0.3), color = 'b')
ax.annotate('4', xy=(0.04, -0.35), xytext=(0.035, -0.35), color = 'c')
ax.annotate('5', xy=(0.04, -0.4), xytext=(0.035, -0.4), color = 'y')
ax.annotate('6', xy=(0.04, -0.45), xytext=(0.035, -0.45), color = 'k')
ax.annotate('7', xy=(0.04, -0.5), xytext=(0.035, -0.5), color = 'm')
ax.annotate('8', xy=(0.04, -0.55), xytext=(0.035, -0.55), color = 'ora
ax.annotate('9', xy=(0.04, -0.6), xytext=(0.035, -0.6), color = 'purpl
ax.annotate('10', xy=(0.05, -0.6), xytext=(0.045, -0.6), color = 'grey
ax.annotate('# of Min Samples', xy=(0.4, -0.6), xytext=(0.35, -0.6))
plt.xlabel('Epsilon')
plt.ylabel('Silhouette Coefficient')
plt.grid(True)
plt.show()
```

Figure 8

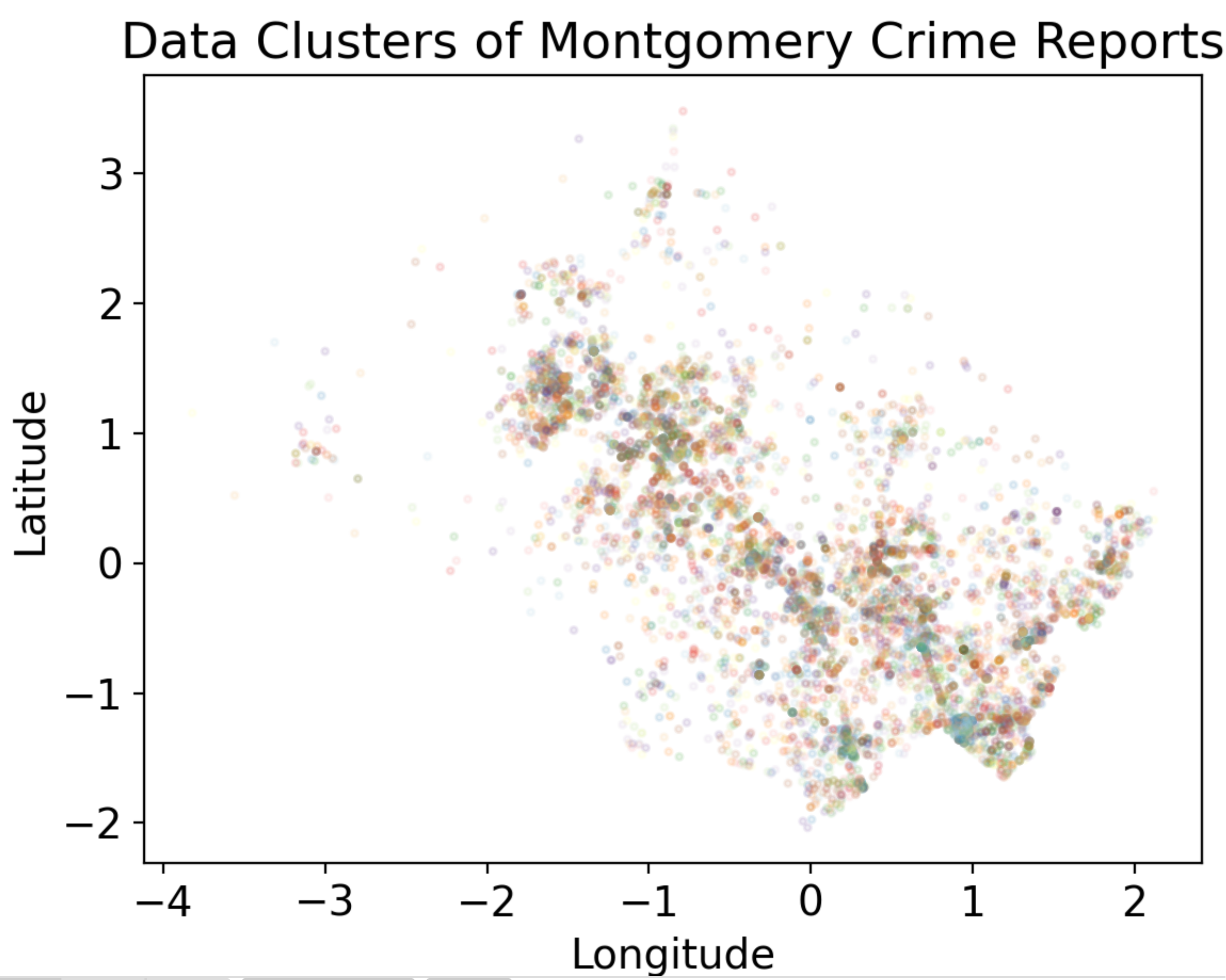




Silhoue
−0.4
−0.6
2
3
4
5
6
7
8
9
10
# of Min Samples
0.1
0.2
0.3
0.4
0.5
Epsilon

In [223]:
```
# Cluster plotting 1

fig = plt.figure()
plt.scatter(crime_scaled.Longitude, crime_scaled.Latitude,
            alpha=.1, s=5, c=crime_scaled.cluster, cmap='Paired')
plt.title('Data Clusters of Montgomery Crime Reports')
plt.ylabel('Latitude')
plt.xlabel('Longitude')
```

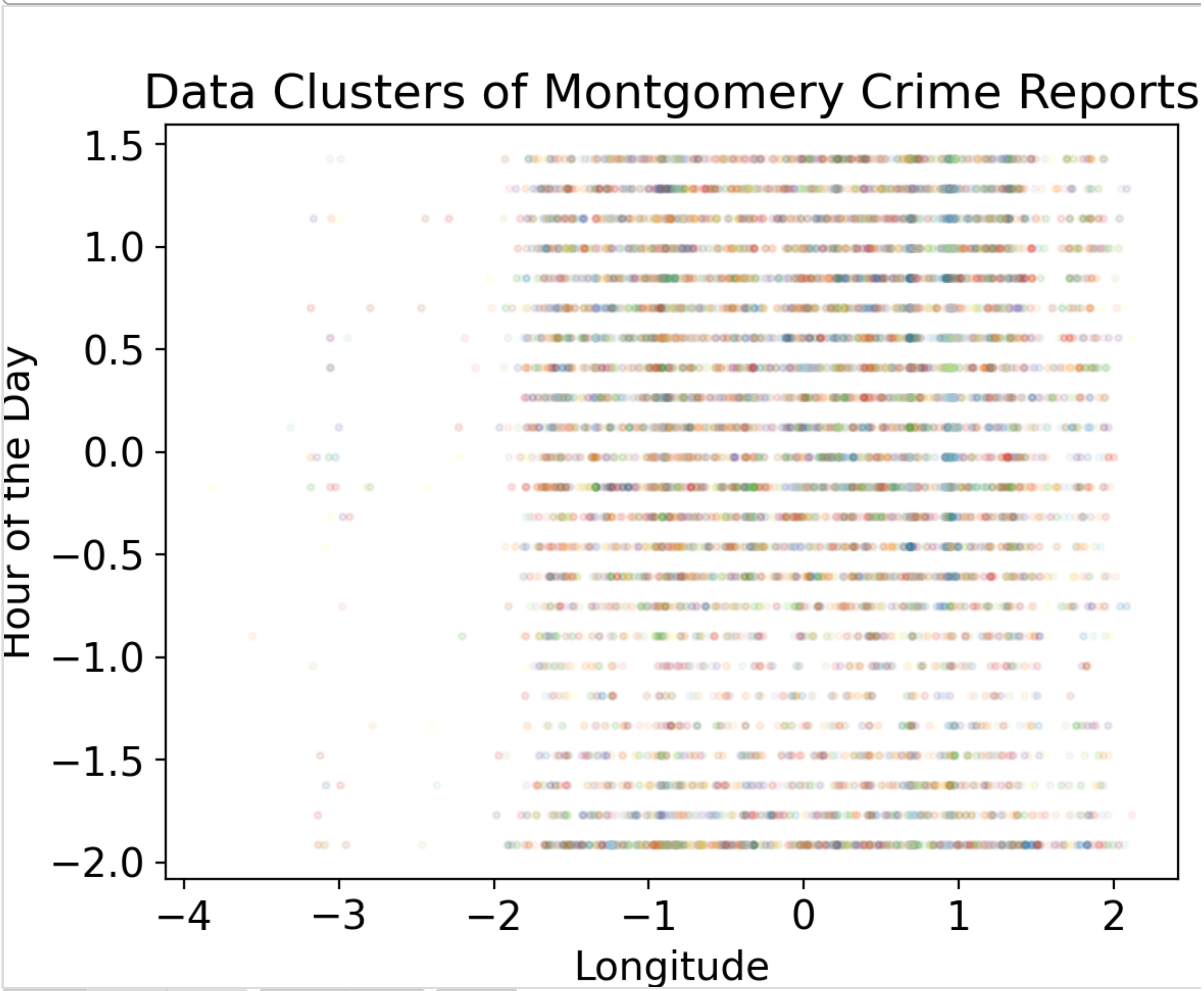
Figure 12



Out[223]: `Text(0.5, 0, 'Longitude')`

In [224]:
```
# Cluster plotting 2

fig = plt.figure()
plt.scatter(crime_scaled.Longitude, crime_scaled.Hour_of_Day,
            alpha=.1, s=5, c=crime_scaled.cluster, cmap='Paired')
plt.title('Data Clusters of Montgomery Crime Reports')
plt.ylabel('Hour of the Day')
plt.xlabel('Longitude')
```

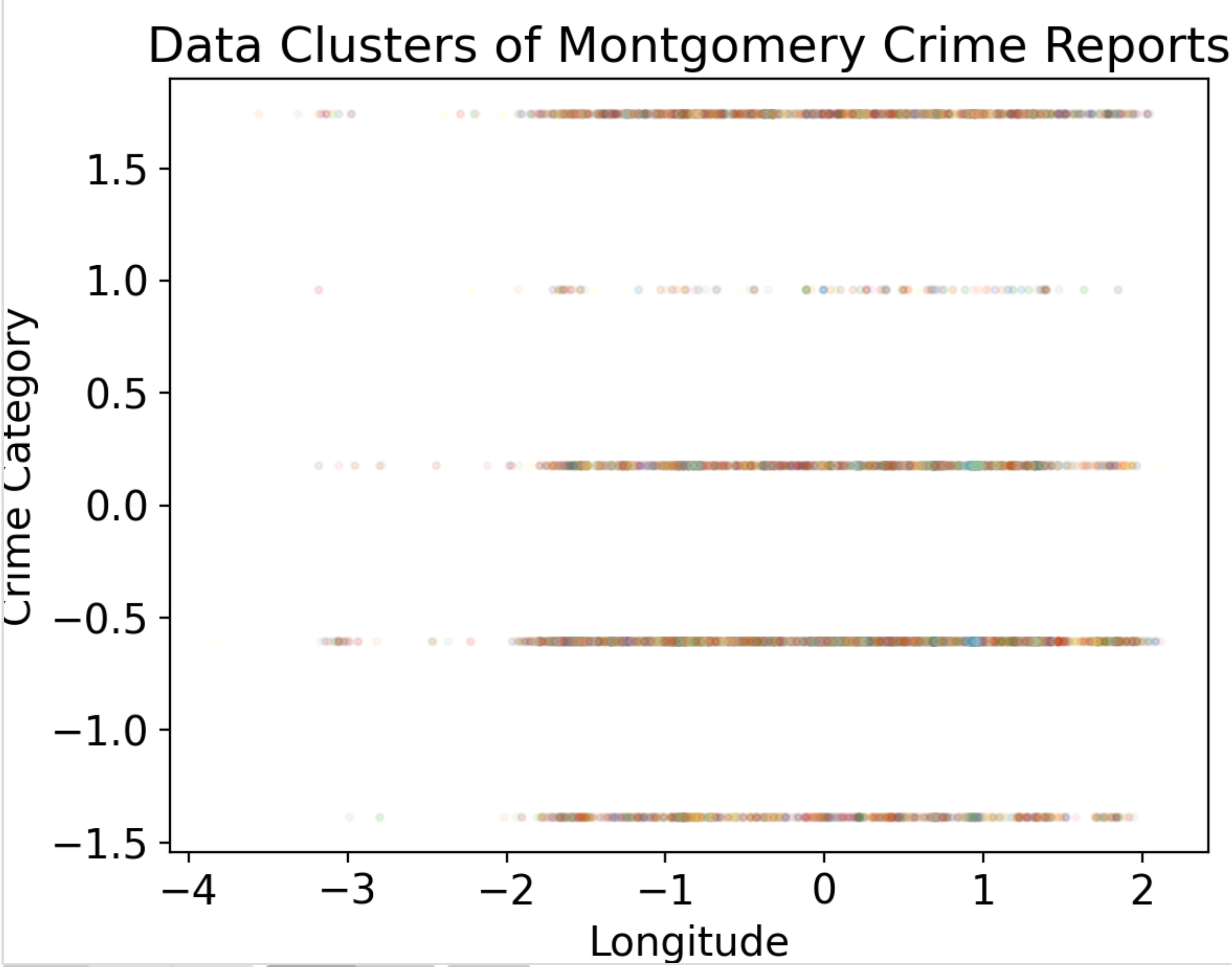
Figure 13



Out[224]: Text(0.5, 0, 'Longitude')

In [225]:
```
# Cluster plotting 3

fig = plt.figure()
plt.scatter(crime_scaled.Longitude, crime_scaled.Crime_Cat,
            alpha=.1, s=5, c=crime_scaled.cluster, cmap='Paired')
plt.title('Data Clusters of Montgomery Crime Reports')
plt.ylabel('Crime Category')
plt.xlabel('Longitude')
```

Figure 14



Out[225]:
```
Text(0.5, 0, 'Longitude')
```

In [215]:
```
# PCA Setup

from mpl_toolkits.mplot3d import Axes3D


from sklearn import decomposition
from sklearn import datasets
```

In [217]:
```
# Dataset Prep

crime_pca = crime_scaled.copy()

crime_pca = crime_pca.drop(columns = ['Crime Name1','City', 'Place'])

crime_pca.head()
```

Out[217]:

	Latitude	Longitude	Hour_of_Day	Crime_Cat
Incident ID				
201227438	0.796172	-2.943855	0.556458	-0.605847
201091764	0.132083	1.392993	-1.769114	0.176574
201222638	0.670153	-0.618699	0.847154	-0.605847
201313197	0.353284	-0.326246	-0.606328	1.741417
201198665	0.460492	-1.351632	1.428547	-0.605847

In [218]:
```
# PCA Process

pca = decomposition.PCA(n_components=3)
pca.fit_transform
pca.fit(crime_pca)
crime_trans = pca.transform(crime_pca)
crime_trans
```

Out[218]:
```
array([[ 2.58211125, -1.00776809, -0.0427214 ],
       [-0.76631343,  1.42090494,  1.16547732],
       [ 0.83442251, -1.08392966, -0.20915608],
       ...,
       [-1.59340151, -0.51354379,  0.27385849],
       [-0.73502934, -0.77287471,  0.04096059],
       [-1.59686051, -0.51349789,  0.27405024]])
```