Problem: Crime investigation

Dataset and Notebook For completing this notebook, you will be using dataset available at: https://data.police.uk/data/ (https://data.police.uk/data/). To get the dataset, perform: Provide Date at top (March 2021 to March 2022). In Forces, tick West Midland Police and click generate file. Then press download to download the data. Create a folder 'crime' in the same folder where this notebook is placed. Extract the zip file to this folder.

In [2]:

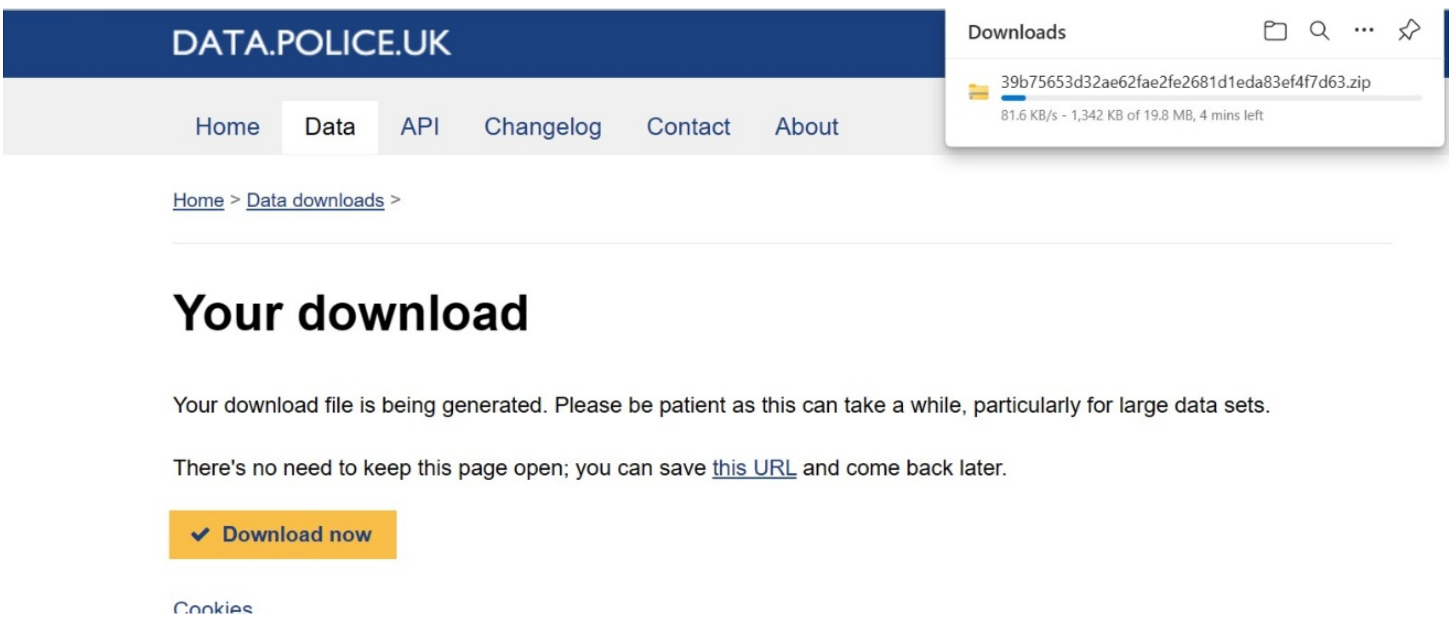
```
import pandas as pd
import matplotlib.pyplot as plt
import folium
import os, re
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import normalize
from IPython.display import IFrame
from sklearn.cluster import AgglomerativeClustering
import scipy.cluster.hierarchy as shc
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

Note

we generate Data file from March-21 to March-22

In [66]:

```
path_to_data = './crime'
cd = os.path.dirname(os.path.abspath(path_to_data))
i = 0
columns = range(1,100)
dfList = []
for root, dirs, files in os.walk(cd):
    for fname in files:
        if re.match("^.*.csv$", fname):
            frame = pd.read_csv(os.path.join(root, fname))
            frame['key'] = "file{}".format(i)
            dfList.append(frame)
            i += 1
dataset = pd.concat(dfList)
```



In [67]:

```
dataset.head()
```

Out[67]:

	Crime ID	Month	Reported by	Falls within	Longitude	Latitude	Location	LS co
0	5414100b888e6913bd56d115d5b5aeeda5279b57d3836a...	2021-03	West Midlands Police	West Midlands Police	-1.851038	52.593177	On or near Longdon Drive	E010094
1	NaN	2021-03	West Midlands Police	West Midlands Police	-1.841944	52.597265	On or near Chelsea Drive	E010094
2	NaN	2021-03	West Midlands Police	West Midlands Police	-1.845780	52.593827	On or near Hook Drive	E010094
3	NaN	2021-03	West Midlands Police	West Midlands Police	-1.845780	52.593827	On or near Hook Drive	E010094
4	628c0858167cb41ee69f05e5163d1e88e8c145f3c2dae1...	2021-03	West Midlands Police	West Midlands Police	-1.841944	52.597265	On or near Chelsea Drive	E010094

In [68]:

```
name_number = 'chay.csv'
dataset.to_csv(name_number, index=False)
```

In [69]:

```
data = pd.read_csv(name_number)
```

In [70]:

```
data.head(10)
```

Out[70]:

	Crime ID	Month	Reported by	Falls within	Longitude	Latitude	Location	LS co
0	5414100b888e6913bd56d115d5b5aeeda5279b57d3836a...	2021-03	West Midlands Police	West Midlands Police	-1.851038	52.593177	On or near Longdon Drive	E010094
1	NaN	2021-03	West Midlands Police	West Midlands Police	-1.841944	52.597265	On or near Chelsea Drive	E010094
2	NaN	2021-03	West Midlands Police	West Midlands Police	-1.845780	52.593827	On or near Hook Drive	E010094
3	NaN	2021-03	West Midlands	West Midlands	-1.845780	52.593827	On or near Hook	E010094

	Crime ID	Month	Reported by	Falls within	Longitude	Latitude	Location	LS co
4	628c0858167cb41ee69f05e5163d1e88e8c145f3c2dae1...	2021-03	West Midlands Police	West Midlands Police	-1.841944	52.597265	On or near Chelsea Drive	E010094
5	ba081a0e0b22453830efcc3f59aa570fe3e0622ea15c61...	2021-03	West Midlands Police	West Midlands Police	-1.839063	52.597809	On or near Byron Court	E010094
6	5563fb7229d0f786f202f080a1ecb983b8241cc94922a9...	2021-03	West Midlands Police	West Midlands Police	-1.839063	52.597809	On or near Byron Court	E010094
7	3cb1ca2e256368032fc59c84da11def497c7295965a551...	2021-03	West Midlands Police	West Midlands Police	-1.841944	52.597265	On or near Chelsea Drive	E010094
8	cca91d618a2f45b08a3fc4177bbdd1ae8457a3d6711d6e...	2021-03	West Midlands Police	West Midlands Police	-1.841944	52.597265	On or near Chelsea Drive	E010094
9	7f943d0084634e67996914cbbdd312aa55a1a1432437ed...	2021-03	West Midlands Police	West Midlands Police	-1.840641	52.598270	On or near Badgers Bank Road	E010094

In [71]:

```
data['Crime type']
```

Out[71]:

```
0                         Vehicle crime
1                  Anti-social behaviour
2                  Anti-social behaviour
3                  Anti-social behaviour
4              Criminal damage and arson
                       ...
419476    Violence and sexual offences
419477    Violence and sexual offences
419478    Violence and sexual offences
419479    Violence and sexual offences
419480                     Other crime
Name: Crime type, Length: 419481, dtype: object
```

In [72]:

```
data['Crime type'].value_counts()
```

Out[72]:

```
Crime type
Violence and sexual offences    183970
Public order                     38447
Vehicle crime                    34790
Anti-social behaviour            33045
Criminal damage and arson        31729
Other theft                      23793
Burglary                         21397
Shoplifting                      15396
Robbery                           8352
Drugs                             8186
Other crime                       7217
Possession of weapons             6495
Theft from the person             3968
Bicycle theft                     2696
Name: count, dtype: int64
```

Question 1:Using a similar approach display the number of crimes in each month. You can use the "Month" column to do that.

In [93]:

```
data['Month'].value_counts()
```

Out[93]:

```
Month
2021-07    34608
2021-11    33771
2021-06    33535
2021-10    32990
2022-03    32597
2021-09    32594
2021-12    32204
2021-03    32115
2021-08    32095
2021-05    31923
2022-01    31283
2021-04    29969
2022-02    29797
Name: count, dtype: int64
```

In [73]:

```
data['town'] = data['LSOA name'].str.split(' ').str[0]
data['town']
```

Out[73]:

```
0            Birmingham
1            Birmingham
2            Birmingham
3            Birmingham
4            Birmingham
                ...
419476    Wolverhampton
419477    Wolverhampton
419478    Wolverhampton
419479    Wolverhampton
419480    Wolverhampton
Name: town, Length: 419481, dtype: object
```

In [74]:

```
data.head()
```

Out[74]:

	Crime ID	Month	Reported by	Falls within	Longitude	Latitude	Location	LS co
0	5414100b888e6913bd56d115d5b5aeeda5279b57d3836a...	2021-03	West Midlands Police	West Midlands Police	-1.851038	52.593177	On or near Longdon Drive	E010094
1	NaN	2021-03	West Midlands Police	West Midlands Police	-1.841944	52.597265	On or near Chelsea Drive	E010094
2	NaN	2021-03	West Midlands Police	West Midlands Police	-1.845780	52.593827	On or near Hook Drive	E010094
3	NaN	2021-03	West Midlands	West Midlands	-1.845780	52.593827	On or near Hook	E010094

	Crime ID	Month	Reported by	Falls within	Longitude	Latitude	Location	LS co
4	628c0858167cb41ee69f05e5163d1e88e8c145f3c2dae1...	2021-03	West Midlands Police	West Midlands Police	-1.841944	52.597265	On or near Chelsea Drive	E010094

In [75]:

```
towns = ['Wolverhampton']
filtered_data = data[data.town.str.contains('|'.join(towns), na=False)]
filtered_data.head()
```

Out[75]:

	Crime ID	Month	Reported by	Falls within	Longitude	Latitude	Location
29062	cb3409a57a028062ccdcac0ec50d250d4e20f13015da09...	2021-03	West Midlands Police	West Midlands Police	-2.129703	52.619162	On or near Supermarket
29063	b012aec75fee67d5026d520721de342ba4668c791418df...	2021-03	West Midlands Police	West Midlands Police	-2.129317	52.618605	On or near Barrington Close
29064	204b5d3a5b711719ede93b28276100a51481c62734507f...	2021-03	West Midlands Police	West Midlands Police	-2.119967	52.618462	On or near Elston Hall Lane
29065	3761912046d212f4887fec64caf6b6cf896700f77e6f89...	2021-03	West Midlands Police	West Midlands Police	-2.120391	52.616843	On or near Ringwood Road
29066	97d9e6665dcf000c107f7ad32661a883855381d6e83ae0...	2021-03	West Midlands Police	West Midlands Police	-2.129427	52.620663	On or near Three Tuns Parade

Question 2: Display crime types in Wolverhampton.

In [97]:

```
Wolverhampton_town = data[data['town'] == 'Wolverhampton']

crime_wolverhampton = Wolverhampton_town['Crime type'].unique()

print(crime_wolverhampton)
```

```
['Bicycle theft' 'Burglary' 'Criminal damage and arson' 'Drugs'
 'Public order' 'Vehicle crime' 'Violence and sexual offences'
 'Anti-social behaviour' 'Other crime' 'Other theft' 'Shoplifting'
 'Possession of weapons' 'Robbery' 'Theft from the person']
```

In [76]:

```
filtered_data['LSOA code'].value_counts().nlargest(10)
```

Out[76]:

```
LSOA code
E01010521    3394
E01010564    1351
E01010414     990
E01010410     737
E01010450     691
E01010453     540
E01010473     537
E01010464     537
```

```
E01010530     534
E01010463     518
Name: count, dtype: int64
```

Question 3:Provide a prime landmark of alteast 2 LSOA code. If there is no recognisable prime landmark, provide name(s) of the nearby streets/roads sorrounding that area.

Land Mark of LOAS Code: E01010450

Postcode ▲ Latitude Longitude Easting Northing

WV14 0BP 52.56531 -2.079704 394694 296390

WV14 0BT 52.565402 -2.079621 394700 296400

Land Mark of LOAS Code:E01010564

Postcode Latitude Longitude Easting Northing

WV10 0TH 52.594598 -2.096267 393576 299649

WV10 0TJ 52.595227 -2.096387 393568 299719

In [77]:

```
filtered_important_data = filtered_data[['LSOA code','Crime type']]
filtered_important_data.head()
```

Out[77]:

	LSOA code	Crime type
29062	E01010434	Bicycle theft
29063	E01010434	Burglary
29064	E01010434	Burglary
29065	E01010434	Criminal damage and arson
29066	E01010434	Drugs

In [78]:

```
filtered_important_data = filtered_data[['LSOA code','Crime type']]
filtered_important_data = pd.get_dummies(filtered_important_data, columns=['Crime type'])
clustering_data = filtered_important_data.groupby(['LSOA code']).agg({'Crime type_Anti-soc
ial behaviour':'sum',
'Crime type_Bicycle theft':'sum',
'Crime type_Burglary':'sum',
'Crime type_Criminal damage and arson':'sum',
'Crime type_Drugs':'sum',
'Crime type_Other crime':'sum',
'Crime type_Other theft':'sum',
'Crime type_Possession of weapons':'sum',
'Crime type_Public order':'sum',
'Crime type_Robbery':'sum',
'Crime type_Shoplifting':'sum',
'Crime type_Theft from the person':'sum',
'Crime type_Vehicle crime':'sum',
'Crime type_Violence and sexual offences':'sum'}).reset_index()
```

In [79]:

```
clustering_data[:5]
```

Out[79]:

	LSOA code	Crime type_Anti-social behaviour	Crime type_Bicycle theft	Crime type_Burglary	Crime type_Criminal damage and arson	Crime type_Drugs	Crime type_Other crime	Crime type_Other theft	Crime type_Possession of weapons	typ
0	E01010410	80	4	37	48	1	9	137	7	
1	E01010411	6	0	6	19	2	7	5	1	
2	E01010412	26	0	14	41	1	9	10	6	
3	E01010413	19	1	14	21	2	7	9	4	
4	E01010414	80	11	84	105	8	20	36	11	

In [80]:

```
clustering_data_original=clustering_data.copy()
clustering_data_original.head()
```

Out[80]:

	LSOA code	Crime type_Anti-social behaviour	Crime type_Bicycle theft	Crime type_Burglary	Crime type_Criminal damage and arson	Crime type_Drugs	Crime type_Other crime	Crime type_Other theft	Crime type_Possession of weapons	typ
0	E01010410	80	4	37	48	1	9	137	7	
1	E01010411	6	0	6	19	2	7	5	1	
2	E01010412	26	0	14	41	1	9	10	6	
3	E01010413	19	1	14	21	2	7	9	4	
4	E01010414	80	11	84	105	8	20	36	11	

In [81]:

```
clustering_data.drop(['LSOA code'], axis= 1,inplace = True, errors = 'ignore')
clustering_data.head()
```

Out[81]:

	Crime type_Anti-social behaviour	Crime type_Bicycle theft	Crime type_Burglary	Crime type_Criminal damage and arson	Crime type_Drugs	Crime type_Other crime	Crime type_Other theft	Crime type_Possession of weapons	Crime type_Public order	typ
0	80	4	37	48	1	9	137	7	67	
1	6	0	6	19	2	7	5	1	12	
2	26	0	14	41	1	9	10	6	32	
3	19	1	14	21	2	7	9	4	16	
4	80	11	84	105	8	20	36	11	101	

In [82]:

```
data_scaled = normalize(clustering_data)
data_scaled = pd.DataFrame(data_scaled, columns=clustering_data.columns)
data_scaled.head()
```

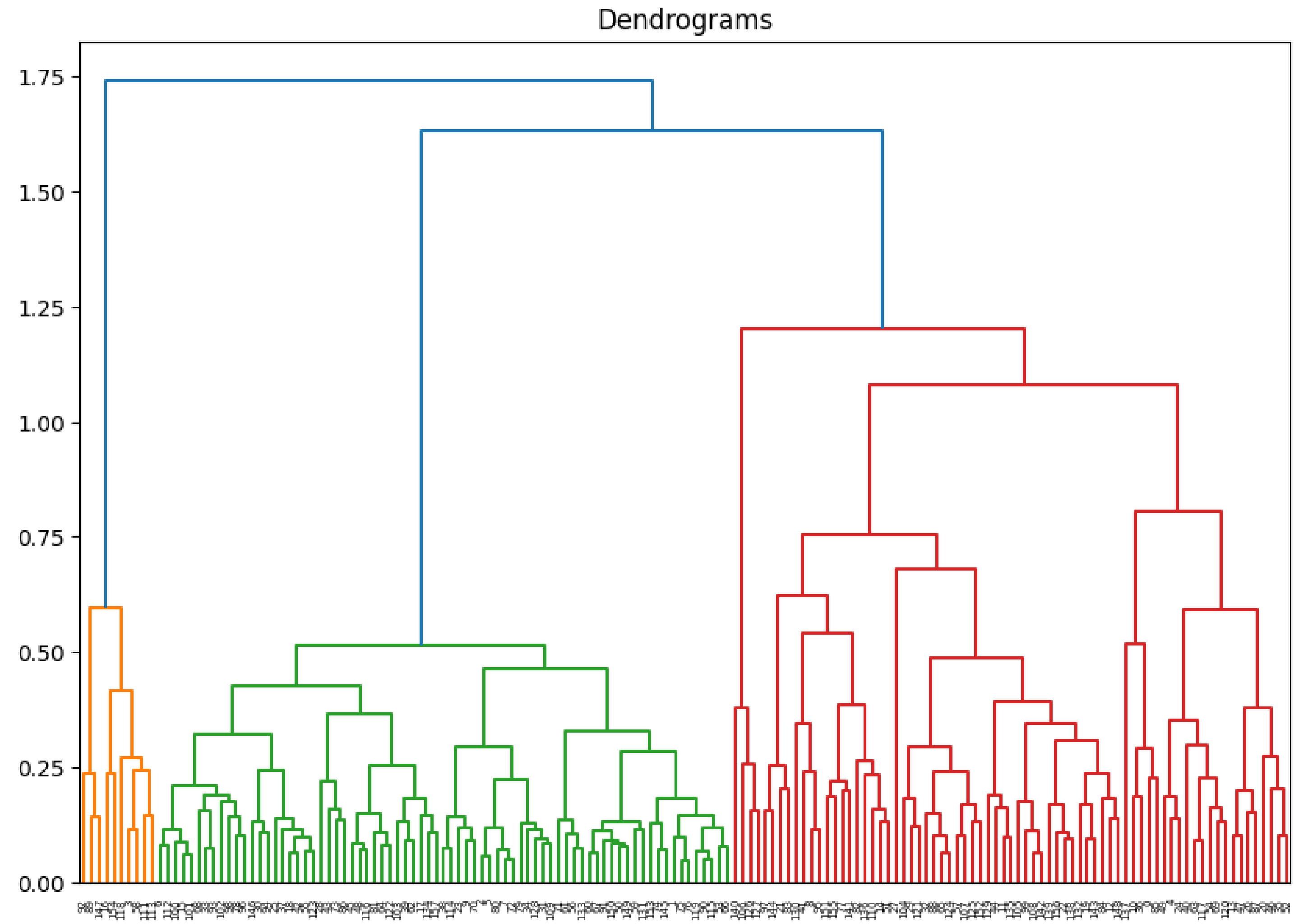
Out[82]:

Crime type_Anti-social	Crime type_Bicycle	Crime type_Burglary	Crime type_Criminal damage and	Crime type_Drugs	Crime type_Other	Crime type_Other	Crime type_Possession	Crime type_Public	typ

	type_Anti-social behaviour Crime	type_Bicycle theft Crime	type_Burglary Crime	type_Criminal damage and arson Crime	type_Drugs Crime	type_Other crime Crime	type_Other theft Crime	type_Possession of weapons Crime	type_Public order Crime	typ
0	0.267750	0.013688	0.123835	0.160650	0.003347	0.030122	0.458522	0.023428	0.224241	
1	0.045799	0.000000	0.045799	0.145030	0.015266	0.053432	0.038166	0.007633	0.091598	
2	0.120507	0.000000	0.064889	0.190031	0.004635	0.041714	0.046349	0.027809	0.148317	
3	0.128168	0.006746	0.094440	0.141659	0.013491	0.047220	0.060711	0.026983	0.107931	
4	0.196675	0.027043	0.206509	0.258136	0.019667	0.049169	0.088504	0.027043	0.248302	

In [83]:

```
plt.figure(figsize=(10, 7))
plt.title("Dendrograms")
dend=shc.dendrogram(shc.linkage(data_scaled, method='ward'))
```

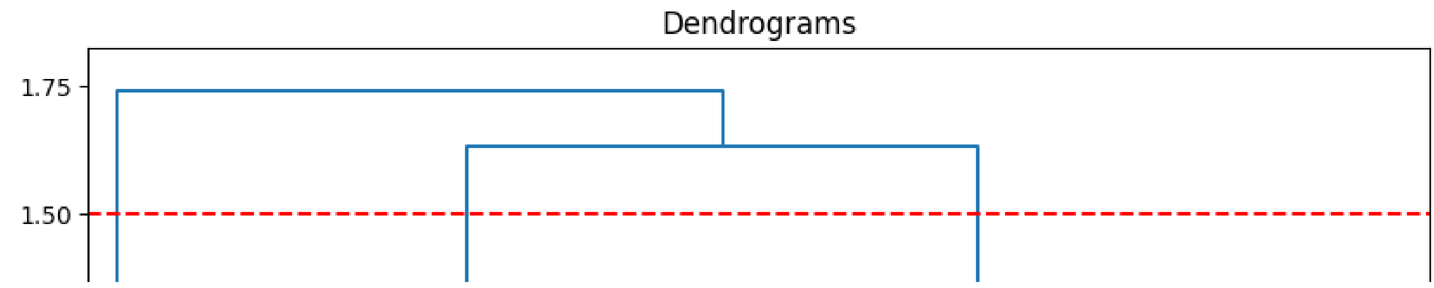


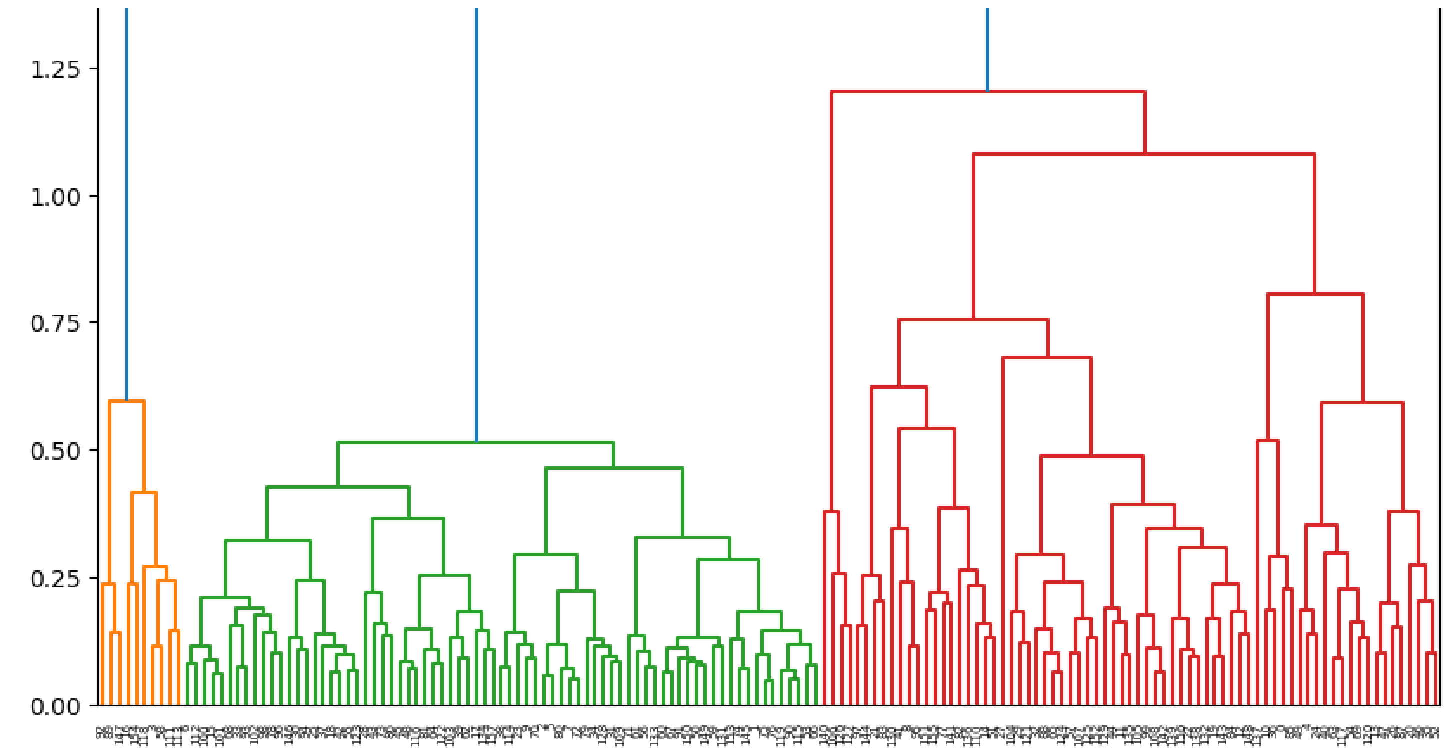
In [84]:

```
plt.figure(figsize=(10, 7))
plt.title("Dendrograms")
dend = shc.dendrogram(shc.linkage(data_scaled, method='ward'))
plt.axhline(y=1.5, color='r', linestyle='--')
```

Out[84]:

<matplotlib.lines.Line2D at 0x1885f0ae5c0>





Question 4:Discuss what happens when you decide to cut the dendogram in different level.

When you decide to cut the dendrogram at different levels, it affects the number of clusters you identify in the dataset. The dendrogram is a visual representation of the hierarchical clustering process, where each point on the vertical axis represents a cluster and the horizontal axis represents the distance between clusters. Cutting the dendrogram at a certain height means deciding the number of clusters you want to form.

Let's explore what happens when you cut the dendrogram at different levels:

Cutting at a high distance: If you cut the dendrogram at a high distance (e.g., higher than the threshold of 1.5 in your example), you will get a small number of large clusters. The clusters will be more generalized and might not capture the finer patterns in the data.

Cutting at a moderate distance: Cutting the dendrogram at a moderate distance will result in a moderate number of clusters. This might provide a balance between capturing meaningful patterns and avoiding over-segmentation.

Cutting at a low distance: Cutting the dendrogram at a low distance (e.g., lower than the threshold of 1.5) will lead to a large number of small clusters. The clusters will be more specific and might capture noise or irrelevant patterns in the data.

Choosing the appropriate level to cut the dendrogram is subjective and domain-specific. It depends on the nature of the data, the problem you are trying to solve, and your knowledge of the domain. Different levels of cutting might reveal different insights from the data. In practice, you can experiment with different thresholds and evaluate the clustering results to find the one that best aligns with your objectives.

It's worth noting that hierarchical clustering is just one of the clustering techniques, and depending on the dataset and the problem, other clustering algorithms like k-means, DBSCAN, etc., might be more suitable. Each method has its own strengths and weaknesses, and the choice of clustering algorithm should be based on the characteristics of the data and the specific problem at hand.

In [85]:

```
cluster = AgglomerativeClustering(n_clusters=3, affinity='euclidean', linkage='ward')
cluster_ids = cluster.fit_predict(data_scaled)
```

```
c:\Users\Tajummal\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\cluste
r\_agglomerative.py:983: FutureWarning: Attribute `affinity` was deprecated in version 1.2
and will be removed in 1.4. Use `metric` instead
  warnings.warn(
```

In [86]:

In [86]:

```
clustering_data['cluster'] = cluster_ids
clustering_data.head()
```

Out[86]:

	Crime type_Anti-social behaviour	Crime type_Bicycle theft	Crime type_Burglary	Crime type_Criminal damage and arson	Crime type_Drugs	Crime type_Other crime	Crime type_Other theft	Crime type_Possession of weapons	Crime type_Public order	typ
0	80	4	37	48	1	9	137	7	67	
1	6	0	6	19	2	7	5	1	12	
2	26	0	14	41	1	9	10	6	32	
3	19	1	14	21	2	7	9	4	16	
4	80	11	84	105	8	20	36	11	101	

In [87]:

```
hiarchical_cluster = pd.DataFrame(round(clustering_data.groupby('cluster').mean(),1))
hiarchical_cluster
```

Out[87]:

cluster	Crime type_Anti-social behaviour	Crime type_Bicycle theft	Crime type_Burglary	Crime type_Criminal damage and arson	Crime type_Drugs	Crime type_Other crime	Crime type_Other theft	Crime type_Possession of weapons	Crim type_Publi orde
0	15.8	1.3	11.3	16.3	2.6	3.4	11.4	2.2	17.
1	49.2	11.7	31.0	42.6	13.5	8.6	42.6	12.1	71.
2	17.3	1.5	11.9	20.7	4.1	5.3	11.4	4.2	21.

Question 5. Discuss the cluster results based on your dataset.

Based on the dataset and clustering results, we have three clusters with the following characteristics:

Cluster ID 1 (High-risk areas):

This cluster includes LSOA codes with the highest number of crimes across all crime types. It has significantly higher values for almost all crime types, indicating that these areas are at a higher risk in terms of crime. Cluster ID 0 (Lower/mild-risk areas):

This cluster includes LSOA codes with the lowest number of crimes across all crime types. It has lower values for all crime types compared to the other clusters, suggesting that these areas are relatively safer with fewer reported crimes. Cluster ID 2 (Moderate-risk areas):

This cluster includes the rest of the LSOA codes that fall between the high-risk and low-risk areas. It has moderate values for crime types, indicating that these areas have a moderate number of reported crimes. These cluster results can provide valuable insights for understanding the distribution of crime across different areas. Cluster ID 1 represents high-risk areas that may require additional attention and resources for crime prevention and law enforcement. Cluster ID 0 identifies areas with lower crime rates, which could be considered safer and potentially suitable for residential or commercial development.

The clustering results can assist in identifying patterns and spatial distribution of crime across different areas, which can help law enforcement agencies, policymakers, and local communities in making informed decisions related to crime prevention strategies, resource allocation, and urban planning.

It's important to note that the effectiveness and interpretation of the clustering results depend on the quality and representativeness of the dataset used for clustering. Additionally, the choice of distance metric, linkage method,

and the number of clusters (k) can also influence the clustering outcomes. As such, it's always recommended to validate and evaluate the clustering results through domain knowledge and further analysis to ensure they align with the specific context and problem at hand

In [88]:

```
clustering_data_original['cluster'] = cluster_ids
clusters = clustering_data_original[['LSOA code', 'cluster']]
```

In [89]:

```
clusters.head()
```

Out[89]:

	LSOA code	cluster
0	E01010410	0
1	E01010411	2
2	E01010412	2
3	E01010413	1
4	E01010414	0

In [90]:

```
clustered_full = pd.merge(filtered_data, clusters, on='LSOA code')
clustered_full.head()
```

Out[90]:

	Crime ID	Month	Reported by	Falls within	Longitude	Latitude	Location	
0	cb3409a57a028062ccdcac0ec50d250d4e20f13015da09...	2021-03	West Midlands Police	West Midlands Police	-2.129703	52.619162	On or near Supermarket	E01(
1	b012aec75fee67d5026d520721de342ba4668c791418df...	2021-03	West Midlands Police	West Midlands Police	-2.129317	52.618605	On or near Barrington Close	E01(
2	204b5d3a5b711719ede93b28276100a51481c62734507f...	2021-03	West Midlands Police	West Midlands Police	-2.119967	52.618462	On or near Elston Hall Lane	E01(
3	3761912046d212f4887fec64caf6b6cf896700f77e6f89...	2021-03	West Midlands Police	West Midlands Police	-2.120391	52.616843	On or near Ringwood Road	E01(
4	97d9e6665dcf000c107f7ad32661a883855381d6e83ae0...	2021-03	West Midlands Police	West Midlands Police	-2.129427	52.620663	On or near Three Tuns Parade	E01(

In [91]:

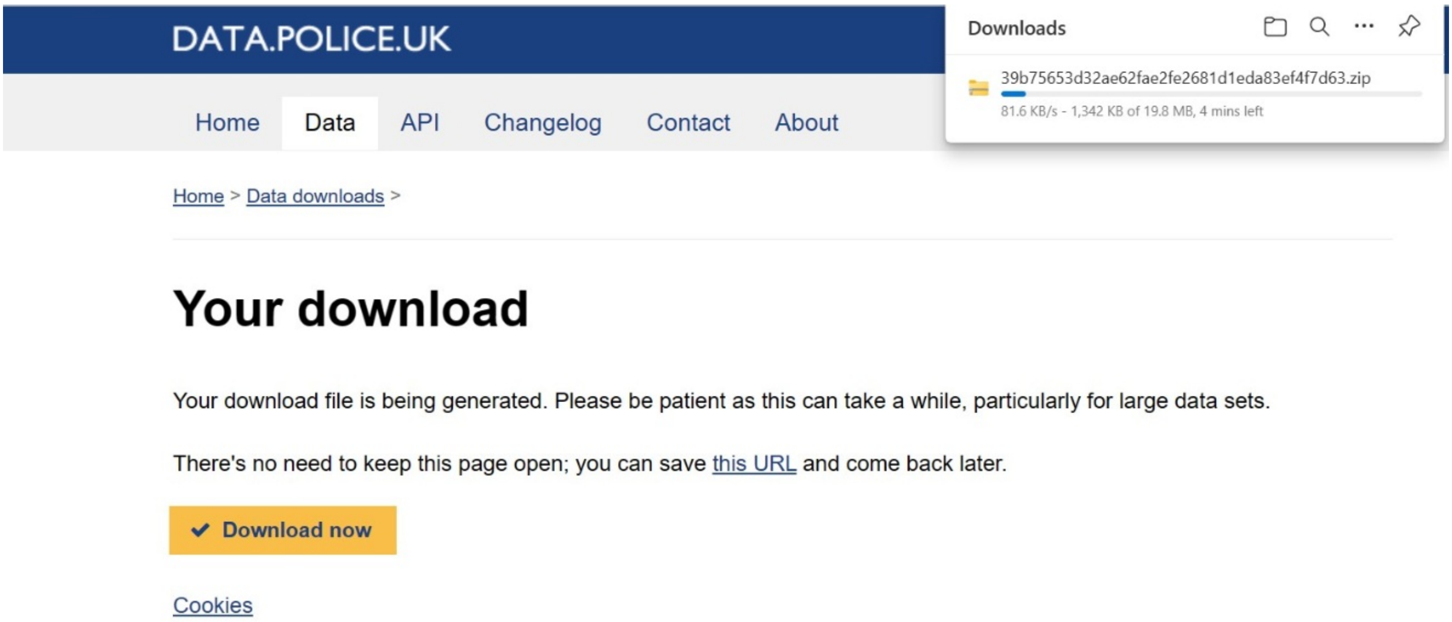
```
def get_color(cluster_id):
    if cluster_id == 1:
        return 'darkred'
    if cluster_id == 0:
        return 'green'
    if cluster_id == 2:
        return 'yellow'
```

In [92]:

```
#create a map
```

```
this_map = folium.Map(location =[clustered_full["Latitude"].mean(), clustered_full["Longit
ude"].mean()],zoom_start=5)
def plot_dot(point):
    '''input: series that contains a numeric named latitude and a numeric named longitude
    this function creates a CircleMarker and adds it to your this_map'''
    folium.CircleMarker(location=[point.Latitude, point.Longitude],
                        radius=2,
                        color=point.color,
                        weight=1).add_to(this_map)


clustered_full["color"] = clustered_full["cluster"].apply(lambda x: get_color(x))
#use df.apply(,axis=1) to iterate through every row in your dataframe
clustered_full.apply(plot_dot, axis = 1)
#Set the zoom to the maximum possible
this_map.fit_bounds(this_map.get_bounds())
#Save the map to an HTML file
this_map.save(os.path.join('Crime_map.html'))
```



Question :Change the number of clusters to a different value and perform the clustering algorithm and draw the graph again. Discuss your results briefly.

In [102]:

```
cluster = AgglomerativeClustering(n_clusters=5, affinity='euclidean', linkage='ward')
cluster_ids = cluster.fit_predict(data_scaled)
clustering_data['cluster'] = cluster_ids
clustering_data.head()
hiarchical_cluster = pd.DataFrame(round(clustering_data.groupby('cluster').mean(),1))
hiarchical_cluster
```

```
c:\Users\Tajummal\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\cluste
r\_agglomerative.py:983: FutureWarning: Attribute `affinity` was deprecated in version 1.2
and will be removed in 1.4. Use `metric` instead
  warnings.warn(
```

Out[102]:

	Crime type_Anti-social behaviour	Crime type_Bicycle theft	Crime type_Burglary	Crime type_Criminal damage and arson	Crime type_Drugs	Crime type_Other crime	Crime type_Other theft	Crime type_Possession of weapons	Crim type_Publi orde
cluster									
0	33.6	3.2	16.4	30.6	5.2	5.5	24.9	4.0	32.

cluster	Crime type_Anti-social behaviour	Crime type_Bicycle theft	Crime type_Burglary	Crime type_Criminal damage and arson	Crime type_Drugs	Crime type_Other crime	Crime type_Other theft	Crime type_Possession of weapons	Crime type_Publi orde
1	8.3	0.6	9.5	10.6	1.4	2.6	5.8	1.5	11
2	17.3	1.5	11.9	20.7	4.4	5.3	11.4	4.2	21
3	7.0	0.2	5.2	4.0	1.2	1.8	3.2	0.8	5.
4	49.2	11.7	31.0	42.6	13.5	8.6	42.6	12.1	71

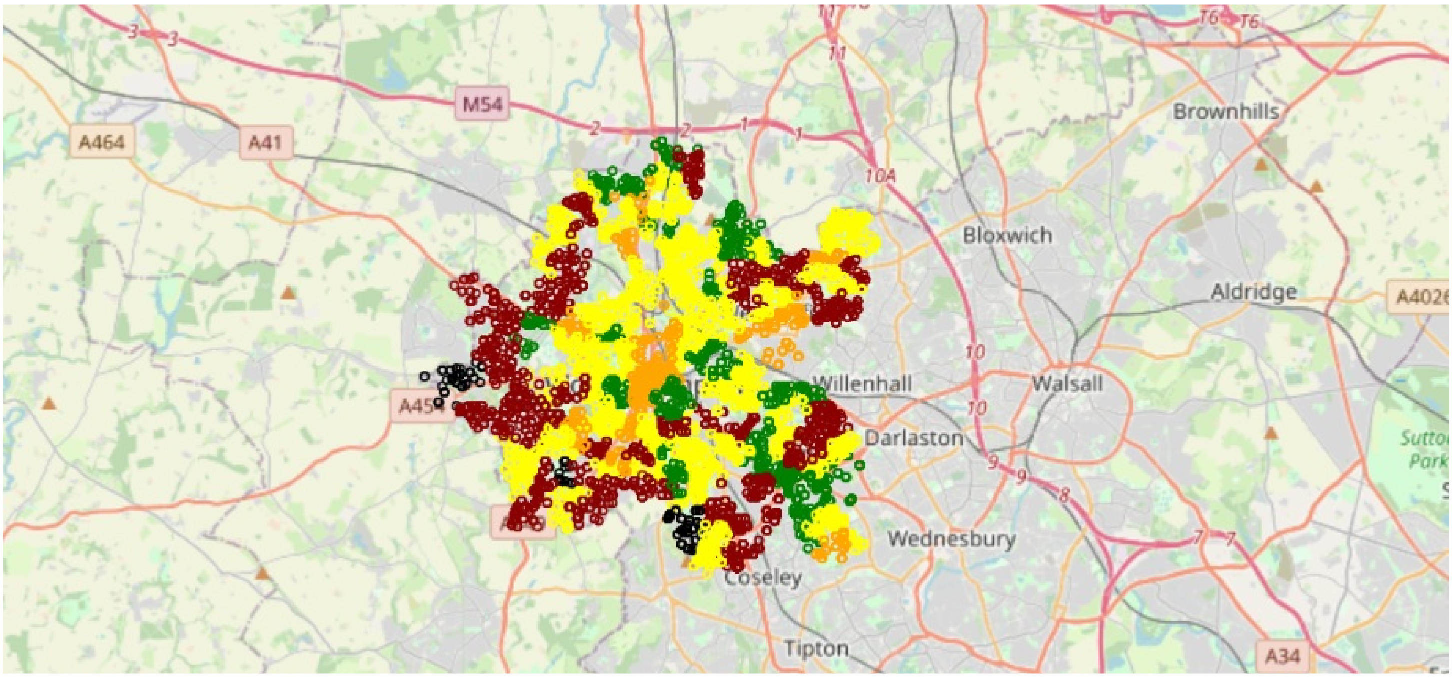
In [103]:

```
clustering_data_original['cluster'] = cluster_ids
clusters = clustering_data_original[['LSOA code', 'cluster']]
clusters.head()
clustered_full = pd.merge(filtered_data, clusters, on='LSOA code')
clustered_full.head()
def get_color(cluster_id):
    if cluster_id == 1:
        return 'darkred'
    if cluster_id == 0:
        return 'green'
    if cluster_id == 2:
        return 'yellow'
    if cluster_id == 3:
        return 'black'
    if cluster_id == 4:
        return 'orange'
```

In [104]:

```
#create a map
this_map = folium.Map(location =[clustered_full["Latitude"].mean(), clustered_full["Longit
ude"].mean()],zoom_start=5)
def plot_dot(point):
    '''input: series that contains a numeric named latitude and a numeric named longitude
    this function creates a CircleMarker and adds it to your this_map'''
    folium.CircleMarker(location=[point.Latitude, point.Longitude],
                        radius=2,
                        color=point.color,
                        weight=1).add_to(this_map)


clustered_full["color"] = clustered_full["cluster"].apply(lambda x: get_color(x))
#use df.apply(,axis=1) to iterate through every row in your dataframe
clustered_full.apply(plot_dot, axis = 1)
#Set the zoom to the maximum possible
this_map.fit_bounds(this_map.get_bounds())
#Save the map to an HTML file
this_map.save(os.path.join('new_Crime_5_clusters_map.html'))
```



Question :Consider a different towns (example : dudley) and perform the clustering again. You should choose the number of clusters from the dendrogramaccordingly. Discuss your results briefly

we have selected Town=Birmingham

In [106]:

```
towns = ['Birmingham']
filtered_data = data[data.town.str.contains('|'.join(towns), na=False)]
filtered_data.head()
```

Out[106]:

	Crime ID	Month	Reported by	Falls within	Longitude	Latitude	Location	LS co
0	5414100b888e6913bd56d115d5b5aeeda5279b57d3836a...	2021-03	West Midlands Police	West Midlands Police	-1.851038	52.593177	On or near Longdon Drive	E010094
1	NaN	2021-03	West Midlands Police	West Midlands Police	-1.841944	52.597265	On or near Chelsea Drive	E010094
2	NaN	2021-03	West Midlands Police	West Midlands Police	-1.845780	52.593827	On or near Hook Drive	E010094
3	NaN	2021-03	West Midlands Police	West Midlands Police	-1.845780	52.593827	On or near Hook Drive	E010094
4	628c0858167cb41ee69f05e5163d1e88e8c145f3c2dae1...	2021-03	West Midlands Police	West Midlands Police	-1.841944	52.597265	On or near Chelsea Drive	E010094

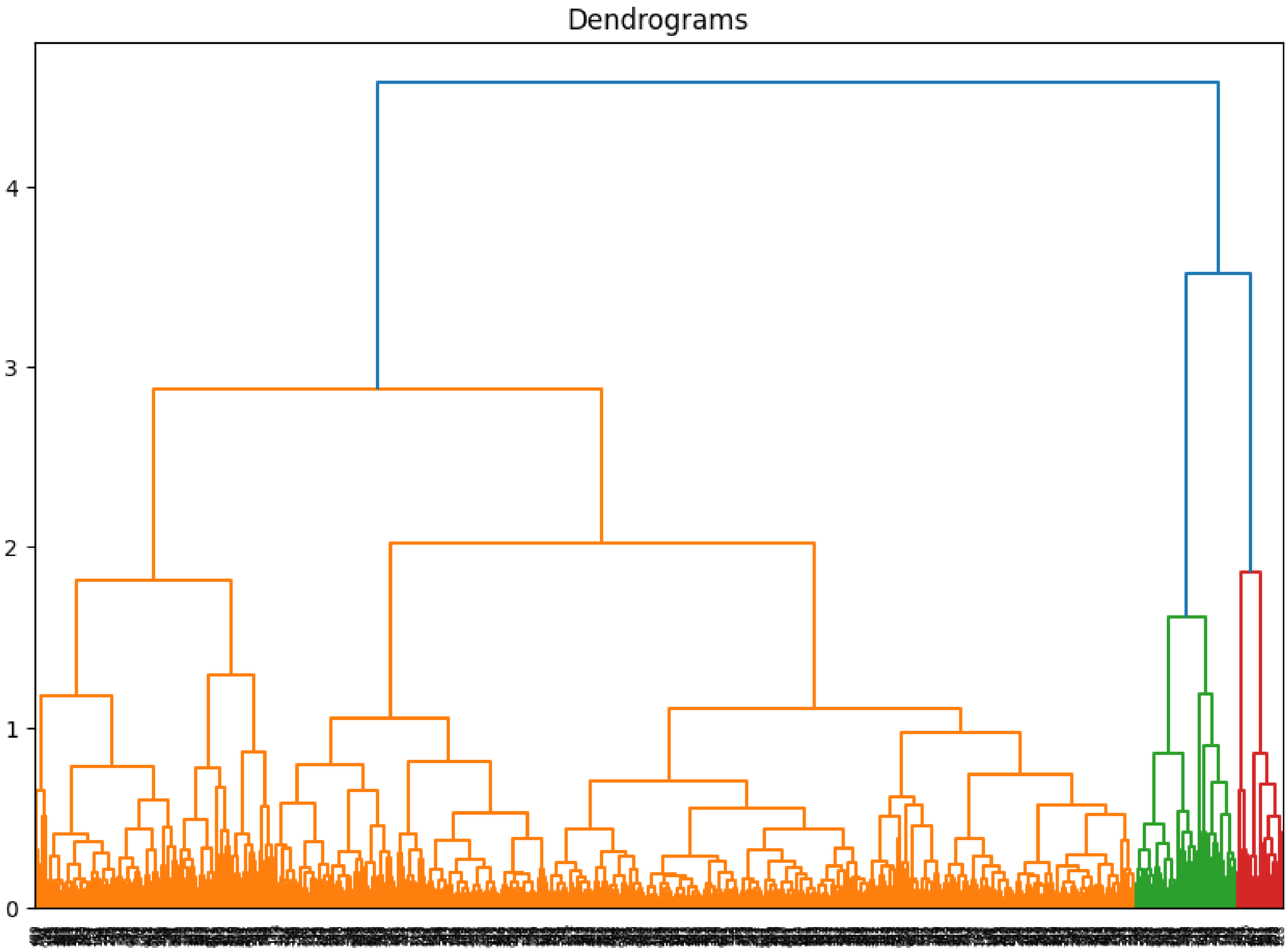
In [107]:

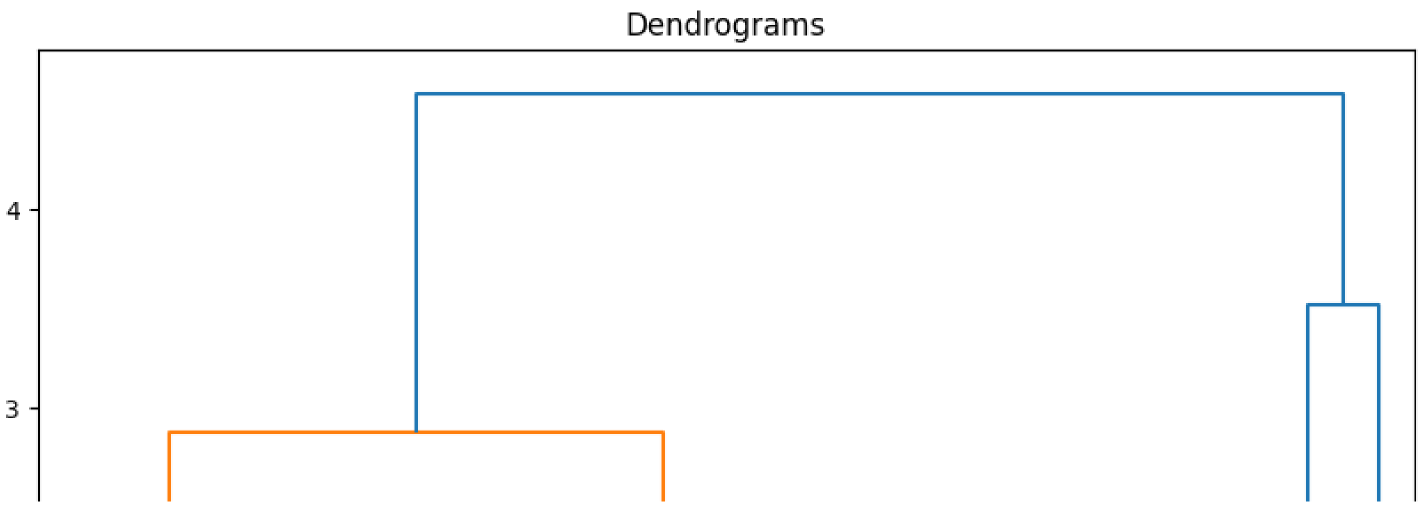
```
filtered_data['LSOA code'].value_counts().nlargest(10)
filtered_important_data = filtered_data[['LSOA code','Crime type']]
filtered_important_data.head()
filtered_important_data = filtered_data[['LSOA code','Crime type']]
filtered_important_data = pd.get_dummies(filtered_important_data, columns=['Crime type'])
clustering_data = filtered_important_data.groupby(['LSOA code']).agg({'Crime type_Anti-soc
ial behaviour':'sum',
'Crime type_Bicycle theft':'sum',
'Crime type_Burglary':'sum',
'Crime type_Criminal damage and arson':'sum',
'Crime type_Drugs':'sum',
'Crime type_Other crime':'sum',
'Crime type_Other theft':'sum',
'Crime type_Possession of weapons':'sum',
'Crime type_Public order':'sum',
'Crime type_Robbery':'sum',
'Crime type_Shoplifting':'sum',
'Crime type_Theft from the person':'sum',
'Crime type_Vehicle crime':'sum',
```

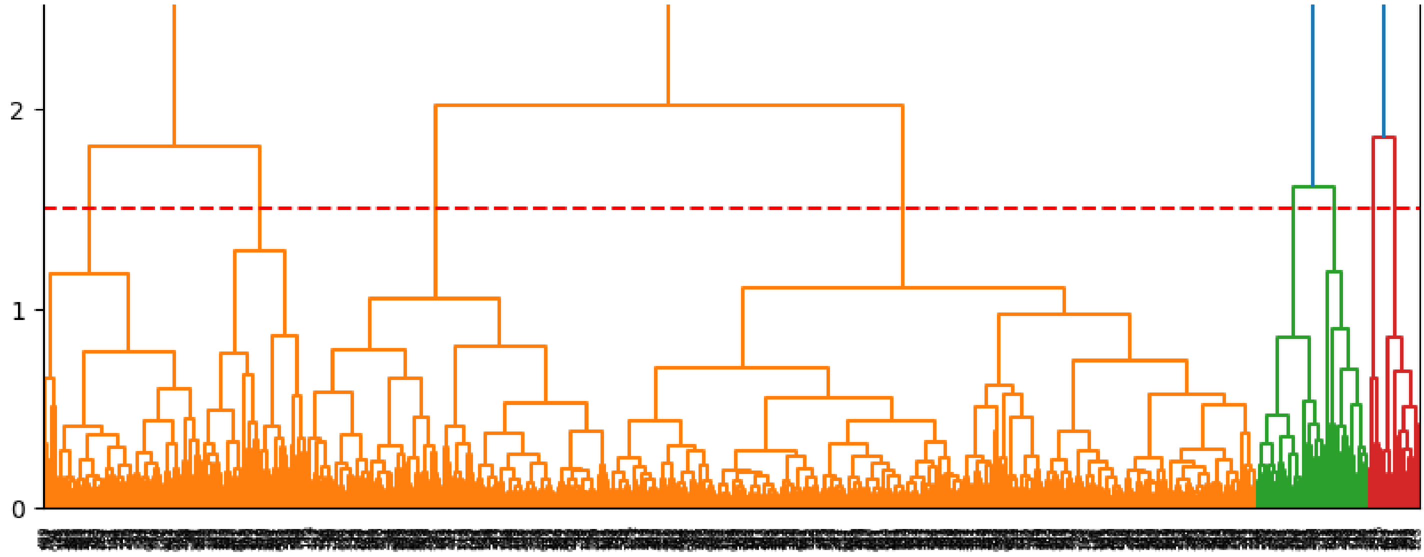
```
'Crime type_Violence and sexual offences':'sum'}).reset_index()
clustering_data[:5]
clustering_data_original=clustering_data.copy()
clustering_data_original.head()
clustering_data.drop(['LSOA code'], axis= 1,inplace = True, errors = 'ignore')
clustering_data.head()
data_scaled = normalize(clustering_data)
data_scaled = pd.DataFrame(data_scaled, columns=clustering_data.columns)
data_scaled.head()
plt.figure(figsize=(10, 7))
plt.title("Dendrograms")
dend=shc.dendrogram(shc.linkage(data_scaled, method='ward'))
plt.figure(figsize=(10, 7))
plt.title("Dendrograms")
dend = shc.dendrogram(shc.linkage(data_scaled, method='ward'))
plt.axhline(y=1.5, color='r', linestyle='--')
```

Out[107]:

```
<matplotlib.lines.Line2D at 0x18845323940>
```







In [ ]: