

Traffic Collision Analysis of Accident 'Black Spots' in London

through Spatial Clustering & Supervised Learning

London Road Safety Dataset: [London Collisions 2022](#)

London Spatial Dataset: [London Boundaries](#)

1 Introduction

Black spots are areas on the public road network where the number of accidents is significantly higher than expected (Karamanlis, I. et al., 2023). Globally, road safety issues are becoming increasingly severe. According to the "Global Status Report on Road Safety 2018" released by the World Health Organization, approximately 1.35 million people die each year due to road traffic accidents, making it the leading cause of death for individuals aged 5 to 29. These figures not only highlight the severity of the issue but also remind us of the urgent need to take measures to improve road safety. Indeed, the United Nations Environment Programme (UNEP, 2003) also indicates that the socio-economic costs of road traffic accidents are among the most significant of all human activities. Therefore, identifying and improving black spots is an essential strategy for enhancing road safety and reducing accident occurrence.

2 Literature Review

Research on traffic accident black spots has been enriched by a range of influential studies, each employing distinct methodologies. Karamanlis et al. (2023) emphasize the critical role of black spot analysis in enhancing road safety. Additionally, Anderson (2005) explores the spatial variations in road collisions in London, attributing these to factors such as engineering flaws and personal mobility.

Furthermore, Szénási and Csiba (2014) investigate the application of DBSCAN clustering analysis for pinpointing black spots, showcasing how this method effectively aggregates locations prone to frequent accidents. Siamidoudaran and Iscioglu (2019) demonstrate the application of supervised learning in predicting the severity of injuries from accidents, thereby improving the accuracy of risk assessments in road safety.

Together, these studies highlight the importance of scientific approaches in the identification and management of traffic accident black spots, contributing significantly to the advancement of road safety.

3 Research Question

This report aims to address the following research questions: "Is it possible to categorize or describe the characteristics of severe traffic collision areas, known as 'Black Spots', in London for

the year 2022?" and "Can lessons be learned from these clustering patterns to optimize urban traffic planning?"

```
In [1]: import warnings  
warnings.filterwarnings("ignore")
```

```
In [2]: # First, Load all the packages...  
import pysal as ps  
import numpy as np  
import pandas as pd  
import seaborn as sns  
import geopandas as gpd  
import matplotlib.pyplot as plt  
import plotly.express as px  
  
from math import ceil  
  
from sklearn.neighbors import NearestNeighbors  
from sklearn.model_selection import train_test_split  
from sklearn.cluster import KMeans, DBSCAN, OPTICS, AgglomerativeClustering  
from sklearn.preprocessing import RobustScaler, MinMaxScaler, StandardScaler  
from sklearn.ensemble import RandomForestClassifier  
from sklearn.metrics import classification_report, accuracy_score  
from sklearn.multiclass import OneVsRestClassifier  
fromesda.adbscan import ADBSCAN  
  
from scipy.cluster.hierarchy import dendrogram  
from shapely.geometry import Point  
  
import spopt  
from spopt.region import MaxPHeuristic as MaxP  
import matplotlib.pyplot as plt  
  
import libpysal
```

4 Presentation of Data

London Road Safety Dataset ([London Collisions 2022](#)) encapsulates traffic collisions occurring throughout London in 2022, provided by official road safety data from the UK government. Additionally, it comprises detailed records of individual traffic incidents as reported to local authorities. Each entry includes specifics of where and when collisions occurred, the type of location, involved vehicles, severity of injuries, and more details.

4.1 Data Input

In this section, we load and process the 2022 London Road Safety data along with London's spatial boundary data, merging them to analyze accidents within specific geographic areas (MSOA) of the city.

```
In [3]: # read the road safety data  
accidents = pd.read_csv(  
    "https://data.dft.gov.uk/road-accidents-safety-data/dft-road-casualty-statistics-collision"  
    low_memory=False,  
)  
accidents.head()
```

Out[3]:

	accident_index	accident_year	accident_reference	location_easting_osgr	location_northing_osgr
0	2022010352073	2022	010352073	525199.0	177928
1	2022010352573	2022	010352573	546214.0	179866
2	2022010352575	2022	010352575	551119.0	174789
3	2022010352578	2022	010352578	528889.0	192230
4	2022010352580	2022	010352580	539773.0	190404

5 rows × 36 columns



In [4]:

```
url = 'https://data.london.gov.uk/download/statistical-gis-boundary-files-london/9ba8c833-6370-4b11-abdc-314aa020d5e0/statistical-gis-boundaries-london.zip'
! wget $url
```

-- 2024-04-20 03:51:23 -- https://data.london.gov.uk/download/statistical-gis-boundary-files-london/9ba8c833-6370-4b11-abdc-314aa020d5e0/statistical-gis-boundaries-london.zip
Resolving data.london.gov.uk (data.london.gov.uk)... 104.26.7.203, 172.67.72.228, 104.26.6.203, ...
Connecting to data.london.gov.uk (data.london.gov.uk)|104.26.7.203|:443... connected.
HTTP request sent, awaiting response... 302 Found
Location: https://airdrive-secure.s3-eu-west-1.amazonaws.com/london/dataset/statistical-gis-boundary-files-london/2016-10-03T13%3A52%3A28/statistical-gis-boundaries-london.zip?X-Amz-Algorithm=AWS4-HMAC-SHA256&X-Amz-Credential=AKIAJJDIMAVZJDICKHA%2F20240420%2Feu-west-1%2Fs3%2Faws4_request&X-Amz-Date=20240420T035128Z&X-Amz-Expires=300&X-Amz-Signature=9899c3b096c62637901b081f05953d658922856d8b4b2e3445a296409c77f34e&X-Amz-SignedHeaders=host [following]
--2024-04-20 03:51:28-- https://airdrive-secure.s3-eu-west-1.amazonaws.com/london/dataset/statistical-gis-boundary-files-london/2016-10-03T13%3A52%3A28/statistical-gis-boundaries-london.zip?X-Amz-Algorithm=AWS4-HMAC-SHA256&X-Amz-Credential=AKIAJJDIMAVZJDICKHA%2F20240420%2Feu-west-1%2Fs3%2Faws4_request&X-Amz-Date=20240420T035128Z&X-Amz-Expires=300&X-Amz-Signature=9899c3b096c62637901b081f05953d658922856d8b4b2e3445a296409c77f34e&X-Amz-SignedHeaders=host
Resolving airdrive-secure.s3-eu-west-1.amazonaws.com (airdrive-secure.s3-eu-west-1.amazonaws.com)... 3.5.64.192, 3.5.72.138, 3.5.71.167, ...
Connecting to airdrive-secure.s3-eu-west-1.amazonaws.com (airdrive-secure.s3-eu-west-1.amazonaws.com)|3.5.64.192|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 28666674 (27M) [application/zip]
Saving to: 'statistical-gis-boundaries-london.zip'

statistical-gis-bou 100%[=====] 27.34M 1.00MB/s in 2m 0s

2024-04-20 03:53:31 (232 KB/s) - 'statistical-gis-boundaries-london.zip' saved [28666674/2866674]

In [5]:

```
# read the London's spatial boundary data (MSOA)
gdf_london_msoa = gpd.read_file(f"zip://statistical-gis-boundaries-london.zip!statistical-gis-boundaries-london.shp")
gdf_london_msoa.head()
```

		MSOA11CD	MSOA11NM	LAD11CD	LAD11NM	RGN11CD	RGN11NM	USUALRES	HHOLDI
0	E02000001	City of London 001	E09000001	City of London	E12000007	London	7375	7	
1	E02000002	Barking and Dagenham 001	E09000002	Barking and Dagenham	E12000007	London	6775	6	
2	E02000003	Barking and Dagenham 002	E09000002	Barking and Dagenham	E12000007	London	10045	10	
3	E02000004	Barking and Dagenham 003	E09000002	Barking and Dagenham	E12000007	London	6182	5	
4	E02000005	Barking and Dagenham 004	E09000002	Barking and Dagenham	E12000007	London	8562	8	



```
In [6]: accidents_gdf = gpd.GeoDataFrame(
    accidents,
    geometry=gpd.points_from_xy(accidents.longitude, accidents.latitude)
)

# Set the coordinate reference system (CRS) to WGS84.
accidents_gdf.crs = {"init": "epsg:4326"}
gdf_london_msoa = gdf_london_msoa.to_crs("EPSG:4326")

# Spatially connect 'accidents_gdf' to 'gdf_London_msoa'
joined = gpd.sjoin(accidents_gdf, gdf_london_msoa, how="left", op='within')

# Copy MSOA code to new column 'msoa_of_accident_Location'
accidents['msoa_of_accident_location'] = joined['MSOA11CD']

accidents.head()
```

	accident_index	accident_year	accident_reference	location_easting_osgr	location_northing_osgr
0	2022010352073	2022	010352073	525199.0	177928
1	2022010352573	2022	010352573	546214.0	179866
2	2022010352575	2022	010352575	551119.0	174789
3	2022010352578	2022	010352578	528889.0	192230
4	2022010352580	2022	010352580	539773.0	190404

5 rows × 37 columns



4.2 Data Pre-processing

```
In [7]: # Pick the orriented varribles before exploration data analysis
accidents = accidents[['accident_index', 'accident_severity', 'number_of_vehicles', 'number_o:
    'road_type', 'speed_limit', 'second_road_class', 'pedestrian_crossing_physical_facil:
    'urban_or_rural_area', 'longitude', 'latitude']]

# Pick out the 'London' rows
gss_codes = gdf_london_msoa['MSOA11CD'].unique()
accidents = accidents[accidents['msoa_of_accident_location'].isin(gss_codes)]

# Drop the rows which have null value
accidents = accidents.dropna()
```

To analyze the numeric attributes of the road safety dataset, descriptive statistics have been computed as detailed in the provided code above. Key observations from this analysis include:

- The cleaned dataset comprises 23,443 records.
- The average number of vehicles involved in collisions (1.82) suggests that most accidents involve more than one vehicle.
- The mean accident severity rating is 2.83, indicating that most reported accidents are of moderate severity.
- The average number of casualties per accident is relatively low at 1.16, reflecting that most accidents result in fewer injuries.

```
In [8]: # Check the numeric columns and descriptive statistics
print(accidents.describe(include = [np.number]))
```

```

accident_severity  number_of_vehicles  number_of_casualties \
count            23469.00000          23469.00000          23469.00000
mean             2.833056           1.820188           1.159956
std              0.384300           0.623840           0.543314
min              1.000000           1.000000           1.000000
25%              3.000000           1.000000           1.000000
50%              3.000000           2.000000           1.000000
75%              3.000000           2.000000           1.000000
max              3.000000           13.000000          16.000000

day_of_week      first_road_class   road_type        speed_limit \
count            23469.00000          23469.00000          23469.00000
mean             4.165154           3.911372           5.241084           26.342409
std              1.939557           1.248446           2.041853           7.603702
min              1.000000           1.000000           1.000000           20.000000
25%              3.000000           3.000000           3.000000           20.000000
50%              4.000000           3.000000           6.000000           30.000000
75%              6.000000           5.000000           6.000000           30.000000
max              7.000000           6.000000           9.000000           70.000000

second_road_class  pedestrian_crossing_physical_facilities \
count            23469.00000                      23469.00000
mean             4.043632                        2.732669
std              2.377180                        3.285093
min              0.000000                        0.000000
25%              3.000000                        0.000000
50%              5.000000                        1.000000
75%              6.000000                        5.000000
max              6.000000                        9.000000

light_conditions  weather_conditions   road_surface_conditions \
count            23469.00000          23469.00000          23469.00000
mean             2.022626           1.986450           1.55013
std              1.546107           2.379119           1.66809
min              1.000000           1.000000           1.00000
25%              1.000000           1.000000           1.00000
50%              1.000000           1.000000           1.00000
75%              4.000000           1.000000           1.00000
max              7.000000           9.000000           9.00000

urban_or_rural_area  longitude       latitude
count            23469.00000          23469.00000          23469.00000
mean             1.028889          -0.121903          51.509996
std              0.167499           0.142148           0.068528
min              1.000000          -0.508592          51.294892
25%              1.000000          -0.204350          51.465912
50%              1.000000          -0.115516          51.514507
75%              1.000000          -0.037785          51.556095
max              2.000000           0.301856           51.691585

```

4.3 Data Preparation

For clustering and spatial analysis, it is essential to select the necessary data for merging by neighborhoods. The spatial clustering analysis will concentrate on the four numerical variables detailed in the table below.

Variables	Definition
Severity of Accidents	The average severity of accidents within a specific neighborhood.
Frequency of Collision Accidents	Frequency of Collision Accidents happening in a specific neighbourhood.

Variables

Definition

Average Number of Vehicles

The average number of vehicles involved per traffic accident in a specific neighborhood.

Average Number of Casualties

The average number of casualties per traffic accident in a specific neighborhood.

In [9]: *# Group by MSOA_ID and return the mean/count in the group.*

```
a = pd.DataFrame(accidents.groupby('msoa_of_accident_location')['accident_severity'].mean())
b = pd.DataFrame(accidents.groupby('msoa_of_accident_location')['accident_index'].count())
c = pd.DataFrame(accidents.groupby('msoa_of_accident_location')['number_of_vehicles'].mean())
d = pd.DataFrame(accidents.groupby('msoa_of_accident_location')['number_of_casualties'].mean()

# change the columns' name
b.rename(columns={'accident_index':'Freq'},inplace=True)
c.rename(columns={'number_of_vehicles':'average_number_of_vehicles'},inplace=True)
d.rename(columns={'number_of_casualties':'average_number_of_casualties'},inplace=True)

# Then we should merge these four attributes' values
temp_1 = a.join(b)
temp_2 = temp_1.join(c)
temp_3 = temp_2.join(d)
dfm = temp_3.copy()
dfm.head()
```

Out[9]:

	accident_severity	Freq	average_number_of_vehicles	average_number_
--	-------------------	------	----------------------------	-----------------

msoa_of_accident_location

E02000001	2.659091	176	1.693182
E02000002	2.888889	18	2.277778
E02000003	2.884615	52	1.673077
E02000004	2.750000	4	2.000000
E02000005	2.700000	10	1.900000

The following descriptive statistics will help us understand how to scale these four values. For instance, the average number of accidents per neighborhood is approximately 23.85, with a substantial variability indicated by a standard deviation of 17.59. This suggests that while some neighborhoods might experience few accidents, others could have significantly more, with the maximum reaching 224 accidents.

In [10]: `dfm.describe()`

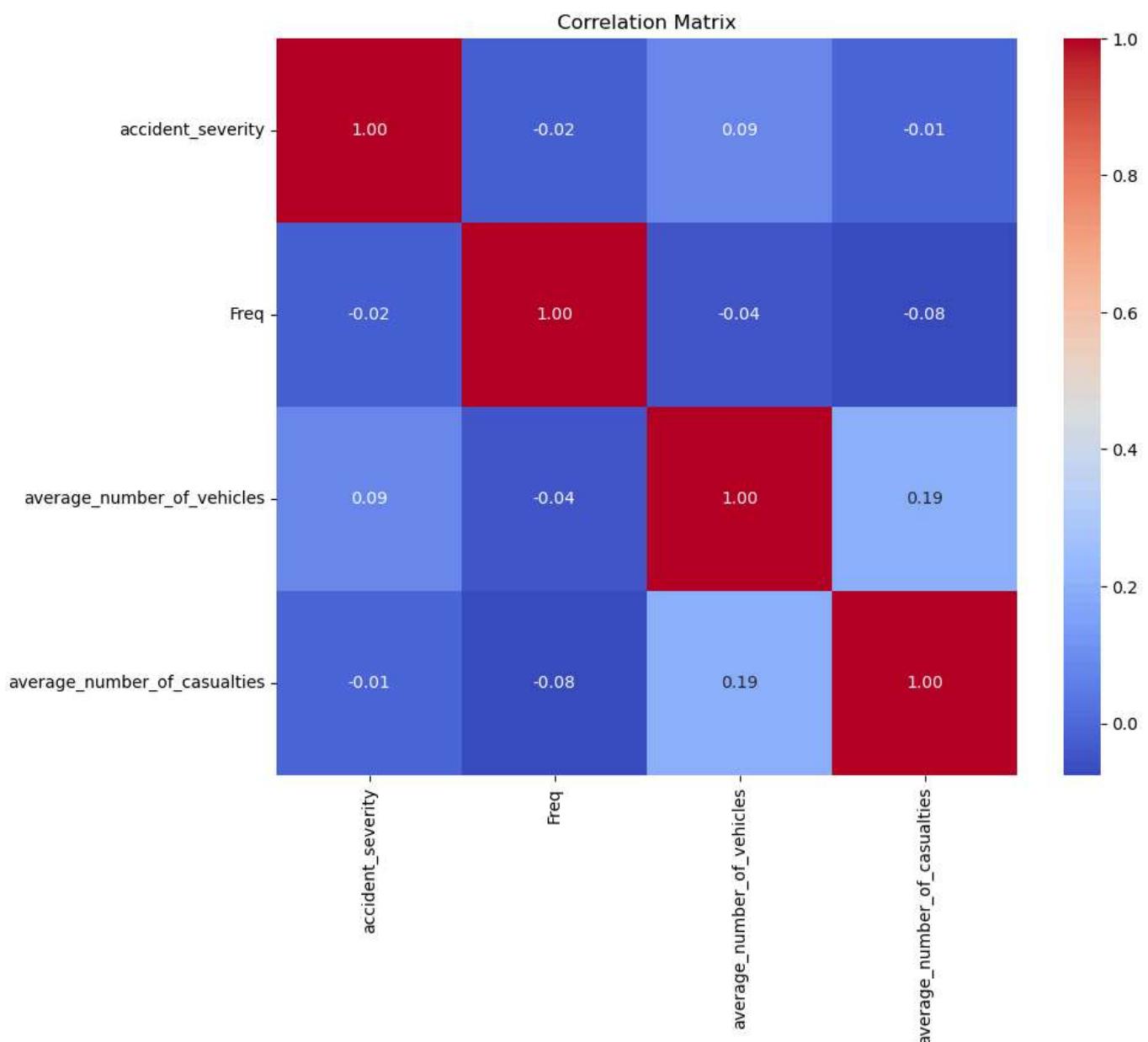
Out[10]:

	accident_severity	Freq	average_number_of_vehicles	average_number_of_casualties
count	983.000000	983.000000	983.000000	983.000000
mean	2.834708	23.874873	1.826043	1.168800
std	0.102265	17.663799	0.182672	0.158103
min	2.250000	1.000000	1.000000	1.000000
25%	2.777778	13.000000	1.724747	1.060606
50%	2.842105	20.000000	1.814815	1.142857
75%	2.904762	30.000000	1.923077	1.235294
max	3.000000	224.000000	3.000000	2.461538

In [11]:

```
# Calculate the correlation matrix
corr = dfm.corr()

# Heat mapping with Seaborn
plt.figure(figsize=(10,8))
sns.heatmap(corr, annot=True, fmt=".2f", cmap="coolwarm", cbar=True)
plt.title("Correlation Matrix")
plt.show()
```

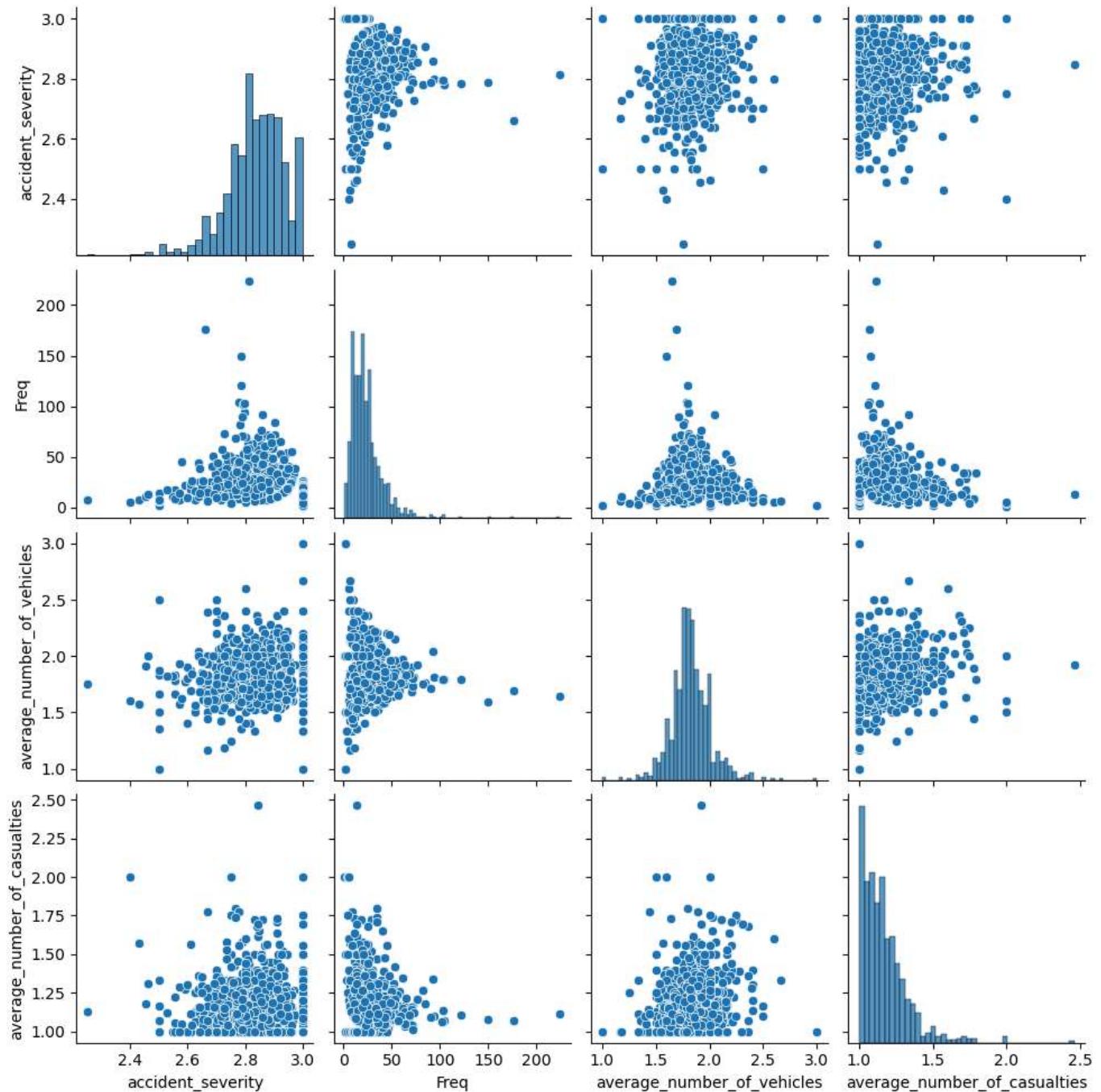


After examining the merged DataFrame containing the four variables, we find that the likelihood of significant relationships between these attributes is relatively low based on the correlation matrix. Additionally, by employing exploratory data analysis methods, we can clearly observe the distribution patterns within the merged DataFrame.

4.4 Descriptive Statistics

```
In [12]: sns.pairplot(dfm)
```

```
Out[12]: <seaborn.axisgrid.PairGrid at 0x7efc2ecf4c50>
```



The map below illustrates the distribution of traffic accidents across London's Middle Super Output Areas (MSOAs), with accidents highlighted in red. Key observations from this map include:

- Concentration of Accidents: A significant cluster of accidents is evident in central London, correlating with the region's high traffic density and increased accident rates.

- Accidents on Major Roads: Accidents are particularly concentrated on A-roads, which are known to handle heavier traffic and, consequently, experience higher accident rates.
- Consistency with Literature: Supporting findings by Balawi & Goktug Tenekeci (2024), about 60% of traffic accidents in London happen on A-roads, consistent with the patterns shown on the map.

```
In [13]: # Creating a GeoDataFrame of the accidents location
accidents_gdf = gpd.GeoDataFrame(
    accidents,
    geometry=gpd.points_from_xy(accidents.longitude, accidents.latitude),
    crs="EPSG:4326"
)

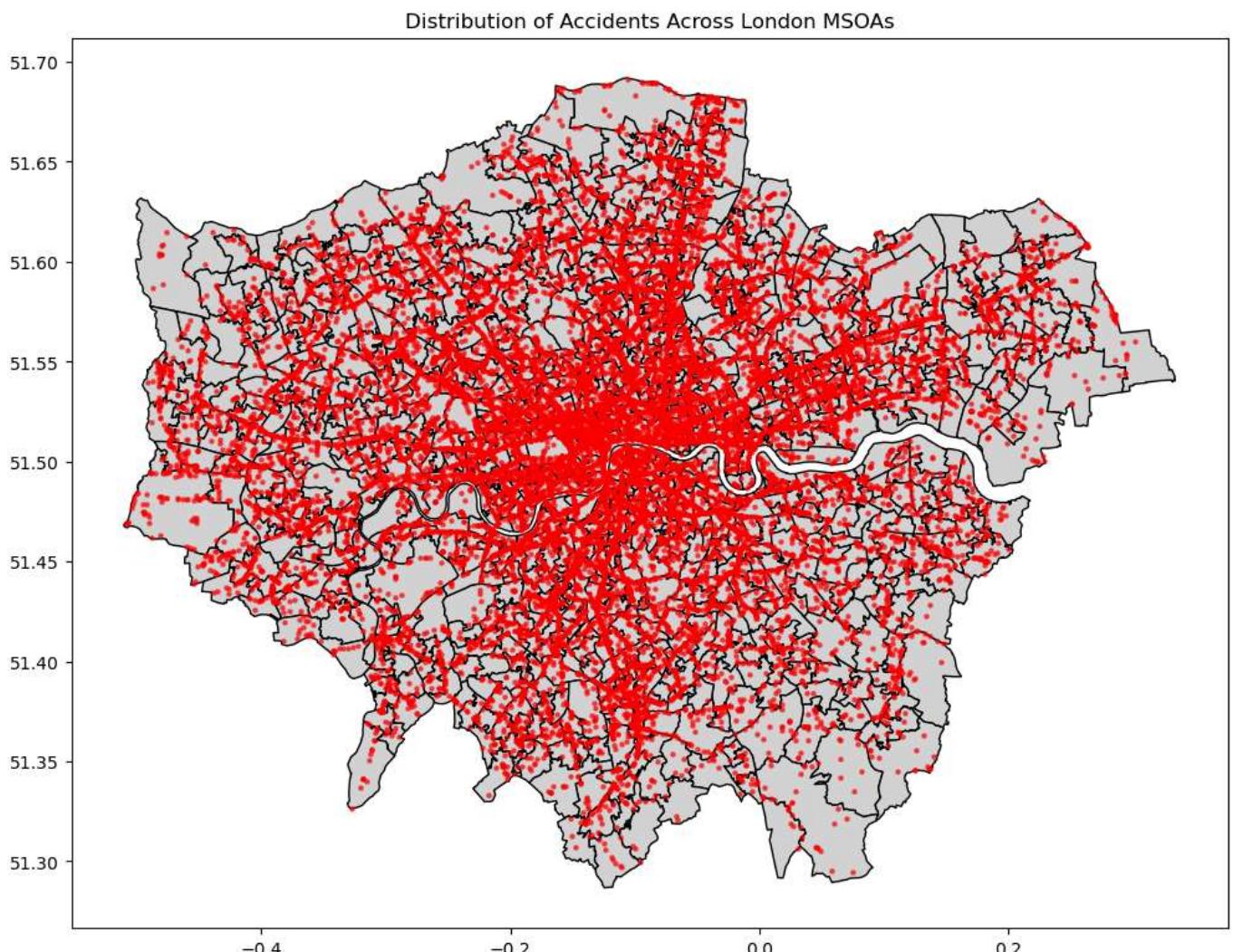
# Ensure that the CRS of the GeoDataFrame for the London region is consistent with the accident locations
gdf_london_msoa = gdf_london_msoa.to_crs("EPSG:4326") # 将CRS转换为WGS 84

fig, ax = plt.subplots(1, 1, figsize=(12, 12))

# Mapping the London boroughs
gdf_london_msoa.plot(ax=ax, color='lightgrey', edgecolor='black')

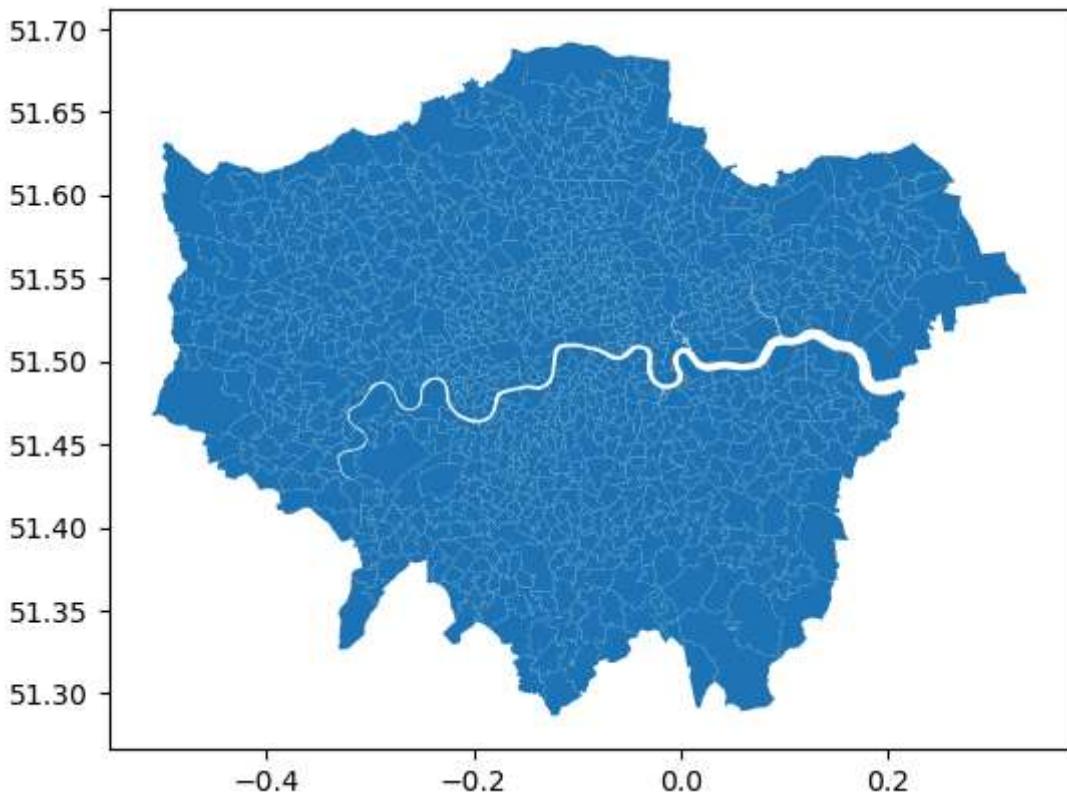
# Plotting accident points on the base map
accidents_gdf.plot(ax=ax, markersize=5, color='red', alpha=0.6)

# Add legend and title
ax.set_title('Distribution of Accidents Across London MSOAs')
plt.show()
```



```
In [14]: # merge with original case
# dfmg = dfm with geo info
dfmg = pd.merge(gdf_london_msoa, dfm, left_on='MSOA11CD', right_on='msoa_of_accident_location')
dfmg.plot()
```

```
Out[14]: <Axes: >
```



The map presented above is the result of successfully merging two DataFrames, with the completeness of the map suggesting that the merge was executed without any data loss.

```
In [15]: # We can inspect the min and max in these three value in London
print('Frequency of Collision Accidents')
print(dfmg[dfmg.Freq.isin([dfmg.Freq.max(), dfmg.Freq.min()])][['Freq']])
```

```
Frequency of Collision Accidents
   Freq
419      1
944    224
```

The key findings from this merged spatial and numeric dataset:

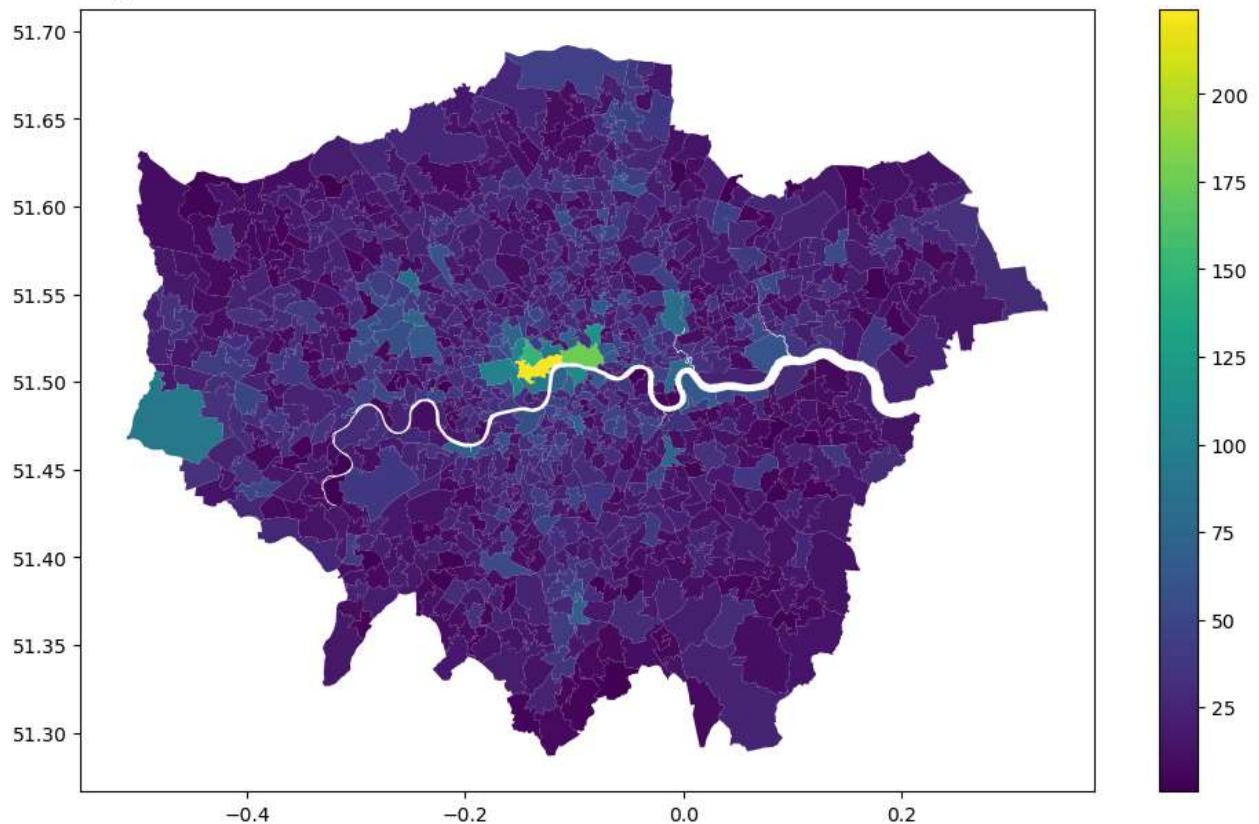
- The highest frequency of collision accidents is found in Westminster 018, with 224 incidents, located in the city center of London.
- The lowest frequency of collision accidents occurs in Harrow 003, with only one recorded incident, situated on the northwestern edge of London.

```
In [16]: tfont = {'fontname':'DejaVu Sans', 'horizontalalignment':'left'}
f = plt.figure()
f.set_size_inches(12,7)

ax1 = f.add_subplot()
dfmg.plot(column='Freq', legend=True, cmap='viridis', figsize=(12,6), ax=ax1)

f.subplots_adjust(top=0.92)
f.suptitle("Frequency of Collision Accidents in London (Raw)", x=0.025, size=24, **tfont);
plt.show()
```

Frequency of Collision Accidents in London (Raw)



The above frequency distribution shows that the closer you are to the city centre, the more frequent the accident "black spots" are, but there are some exceptions.

5 Methodology

This study focuses on identifying 'black spots' through spatial clustering and supervised learning techniques. It involves data normalization, the use of clustering algorithms such as DBSCAN and K-means, and the application of RF for advanced data classification.

5.1 Standardisation

This study concentrates on four variables detailed in the table below. The range of `accident_severity` is from 2.25 to 3.00; `average_number_of_vehicles` varies from 1 to 3; `average_number_of_casualties` spans from 1.00 to 2.46; and `Freq` extends from 1 to 224. All numerical data will undergo rescaling to fit within a (-1,1) range, a process known as standardization.

Variables	Definition	Value Scale
Severity of Accident	The average severity of accidents within a specific neighborhood.	(2.25, 3.00)
Average Number of Vehicles	The average number of vehicles involved per traffic accident in a specific neighborhood.	(1, 3)
Average Number of Casualties	The average number of casualties per traffic accident in a specific neighborhood.	(1.00, 2.46)
Frequency of Collision Accidents	Frequency of Collision Accidents happening in a specific neighbourhood.	(1, 224)

In [17]: `rs = RobustScaler(quantile_range=(10.0, 90.0))`

```
to_cluster = dfmg[['MSOA11CD', 'accident_severity', 'Freq', 'average_number_of_vehicles', 'average_number_of_casualties']]
to_cluster.head()

# normalise the value
normed = to_cluster.copy()
for c in to_cluster.columns.values:
    normed[c] = rs.fit_transform(to_cluster[c].values.reshape(-1,1))
normed.head()
```

Out[17]:

	accident_severity	Freq	average_number_of_vehicles	average_number_of_casualties
MSOA11CD				
E02000001	-0.772428	4.457143		-0.324355
E02000002	0.197454	-0.057143		1.234568
E02000003	0.179418	0.914286		-0.377968
E02000004	-0.388738	-0.457143		0.493827
E02000005	-0.599768	-0.285714		0.227160

MSOA11CD	accident_severity	Freq	average_number_of_vehicles	average_number_of_casualties
E02000001	-0.772428	4.457143		-0.324355
E02000002	0.197454	-0.057143		1.234568
E02000003	0.179418	0.914286		-0.377968
E02000004	-0.388738	-0.457143		0.493827
E02000005	-0.599768	-0.285714		0.227160

5.2 DBSCAN Clustering Analysis

After normalizing the four variables, DBSCAN clustering analysis can be performed to fit them. The parameters set for this DBSCAN cluster are as follows:

Epsilon (eps) is the maximum distance between two samples for one to be considered within the neighborhood of the other. The correct selection of DBSCAN parameters is crucial and depends on the dataset and the distance function used. Epsilon is set at 0.5, and the minimum number of points required in a neighborhood for a point to be considered a core point (minPts) is set at 3. Finally, the silhouette score method will be applied to evaluate the quality of the clustering results.

In [18]: `minPts = 3
epsilon = 0.5
dbsc = DBSCAN(eps=epsilon, min_samples=minPts)
dbsc.fit(normed)`

`clusters = dbsc.labels_`

```

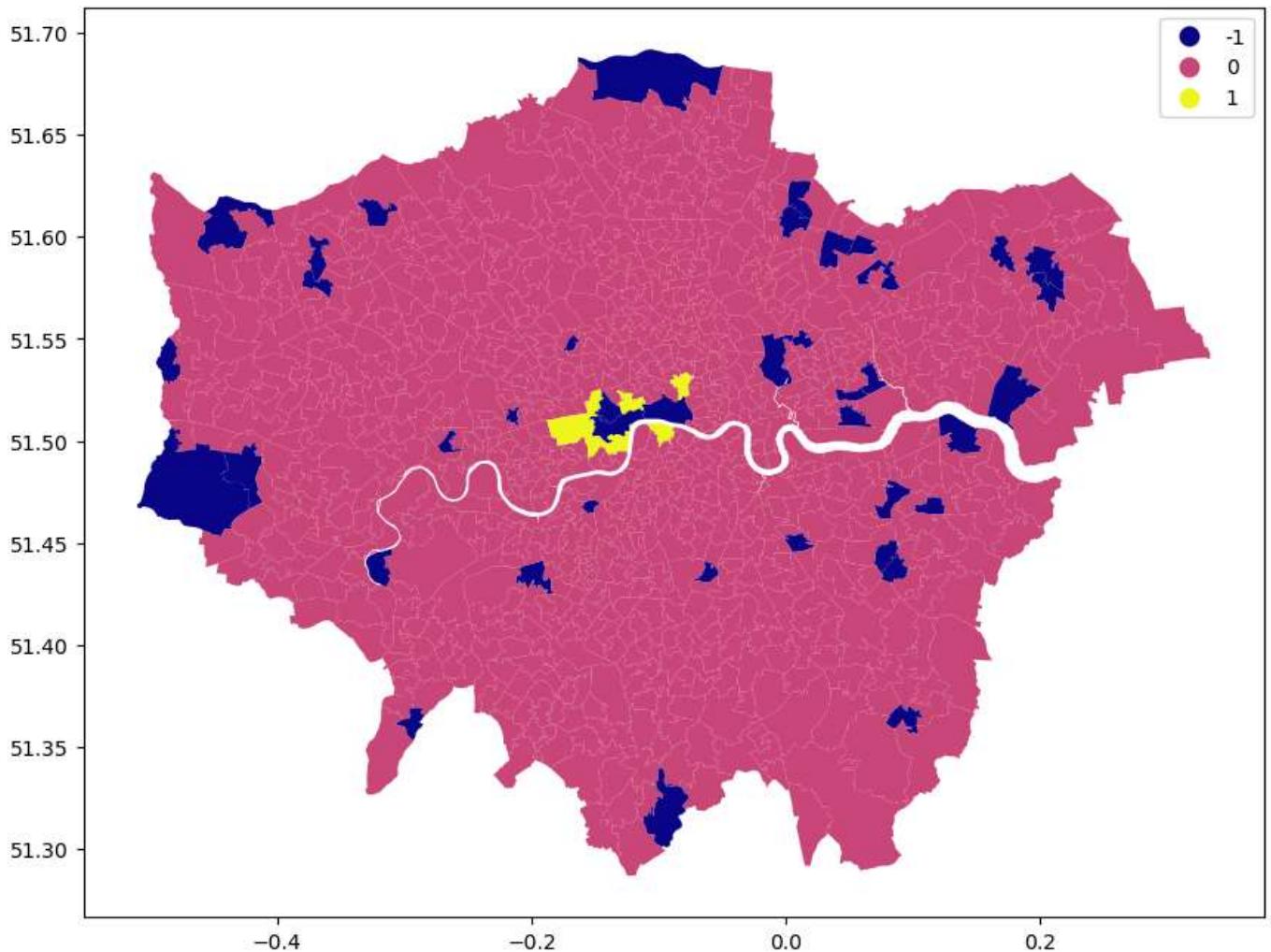
dfmg['DBSCAN_Cluster'] = clusters
dfmg.plot(column='DBSCAN_Cluster', categorical=True, legend=True, figsize=(12,8), cmap = 'plasma')

from sklearn import metrics
print("Silhouette Score is :")
print(metrics.silhouette_score(normed, clusters))

```

Silhouette Score is :

0.481413555180166



The silhouette score indicates that the DBSCAN clustering provides a reasonable structure. According to the tutorial, it is important to note that the areas marked in blue on the map represent noise samples for the DBSCAN method. Next, we will visualize the cluster centroids using a radar plot.

```

In [19]: def radar_plot_cluster_centroids1(df_cluster_centroid):
    # parameters
    # df_cluster_centroid: a dataframe with rows representing a cluster centroid and columns
    # representing different categories

    # add an additional element to both categories and restaurants that's identical to the first
    # manually 'close' the line
    categories = df_cluster_centroid.columns.values.tolist()[1:]
    categories += [categories[0]]

    label_loc = np.linspace(start=0, stop=2 * np.pi, num=len(categories))

    plt.figure(figsize=(12, 8))
    ax = plt.subplot(polar=True)
    for index, row in df_cluster_centroid.iterrows():
        centroid = row.tolist()[1:]
        centroid += [centroid[0]]
        label = "Cluster {}".format(row['cluster'])

```

```

        ax.plot(label_loc, centroid, label=label)
    plt.title('Cluster centroid comparison', size=20, y=1.05)
    lines, labels = plt.thetagrids(np.degrees(label_loc), labels=categories)
    plt.legend()
    plt.show()

```

In [20]:

```

df_dbscan = normed.copy()
df_dbscan['cluster'] = dbsc.labels_

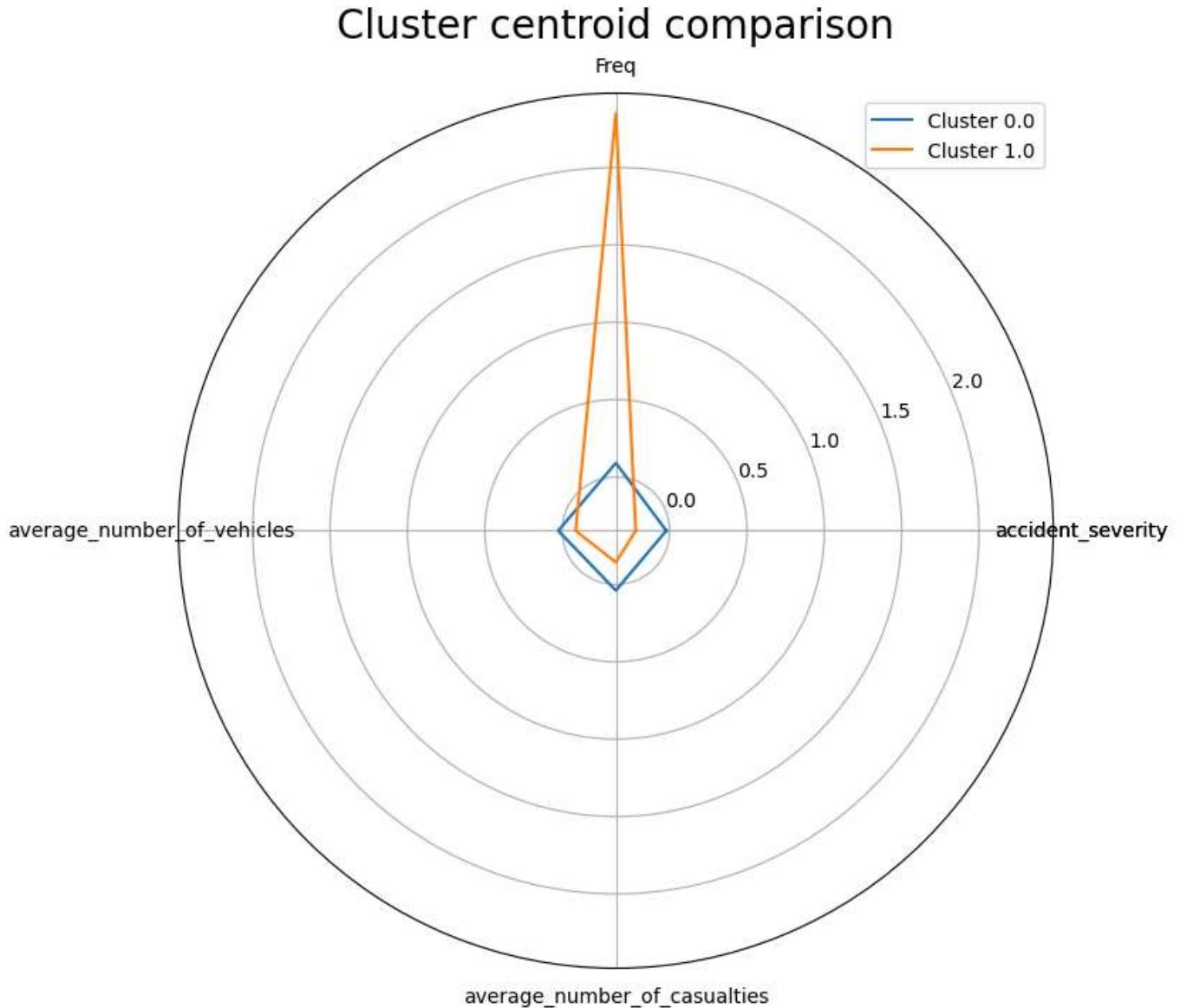
```

```

# Calculate cluster centres and remove noisy points
df_dbscan_centroid1 = df_dbscan.groupby('cluster').mean()
df_dbscan_centroid1.drop(-1, inplace=True)
df_dbscan_centroid1.reset_index(inplace=True)

radar_plot_cluster_centroids1(df_dbscan_centroid1)

```



However, it is essential to append the new labels from the DBSCAN analysis to the original dataset, as all real data has been rescaled in the normalization process.

In [21]:

```

summary_df_dbscan = \
    dfmg[['accident_severity', 'Freq', 'average_number_of_vehicles', 'average_number_of_casua'] \
        .mean() \
        .round(2)

summary_df_dbscan

```

Out[21]:

accident_severity Freq average_number_of_vehicles average_number_of_casua

DBSCAN_Cluster

DBSCAN_Cluster	accident_severity	Freq	average_number_of_vehicles	average_number_of_casua
-1	2.79	28.86		1.87
0	2.84	23.15		1.82
1	2.79	102.33		1.78



5.3 K-means Clustering Analysis

Simultaneously, the K-means clustering analysis is applied to the London Road Safety Dataset to explore its latent features. K-means clustering involves forming clusters and determining the number of centroids, as illustrated below. Similar to the aforementioned DBSCAN analysis, it is advisable to append the K-means clustering labels to the London Road Safety Dataset.

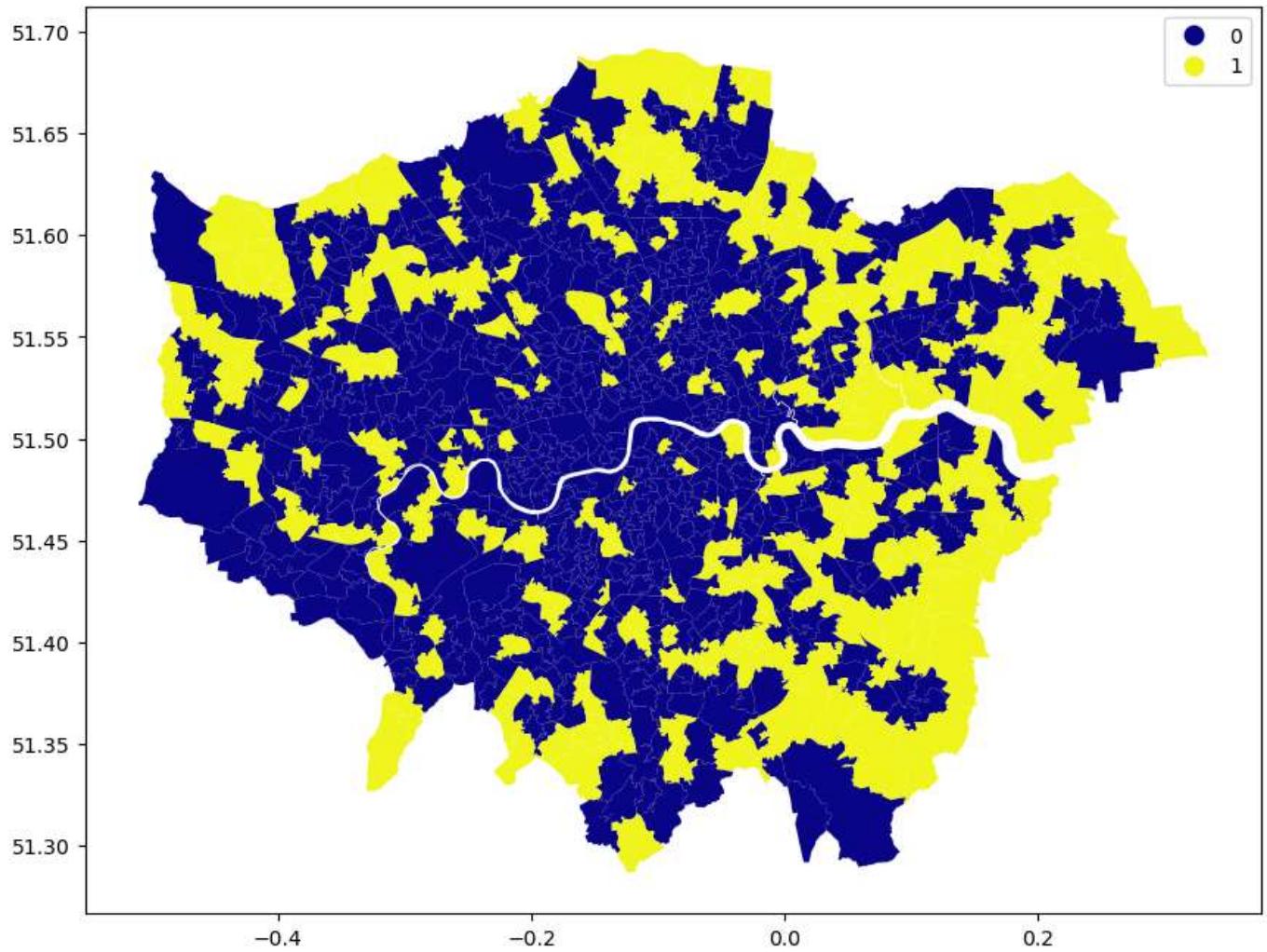
In [22]:

```
from sklearn.cluster import KMeans
k_cluster = 2
random_seed = 1
kmeans_method = KMeans(n_clusters=k_cluster, random_state=random_seed)
kmeans_method.fit(normed)

dfmg['Kmeans_Cluster'] = kmeans_method.labels_
dfmg.plot(column='Kmeans_Cluster', categorical=True, legend=True, figsize=(12,8), cmap = 'plasma')
from sklearn import metrics
print("Silhouette Score is :")
print(metrics.silhouette_score(normed, dfmg['Kmeans_Cluster']))
```

Silhouette Score is :

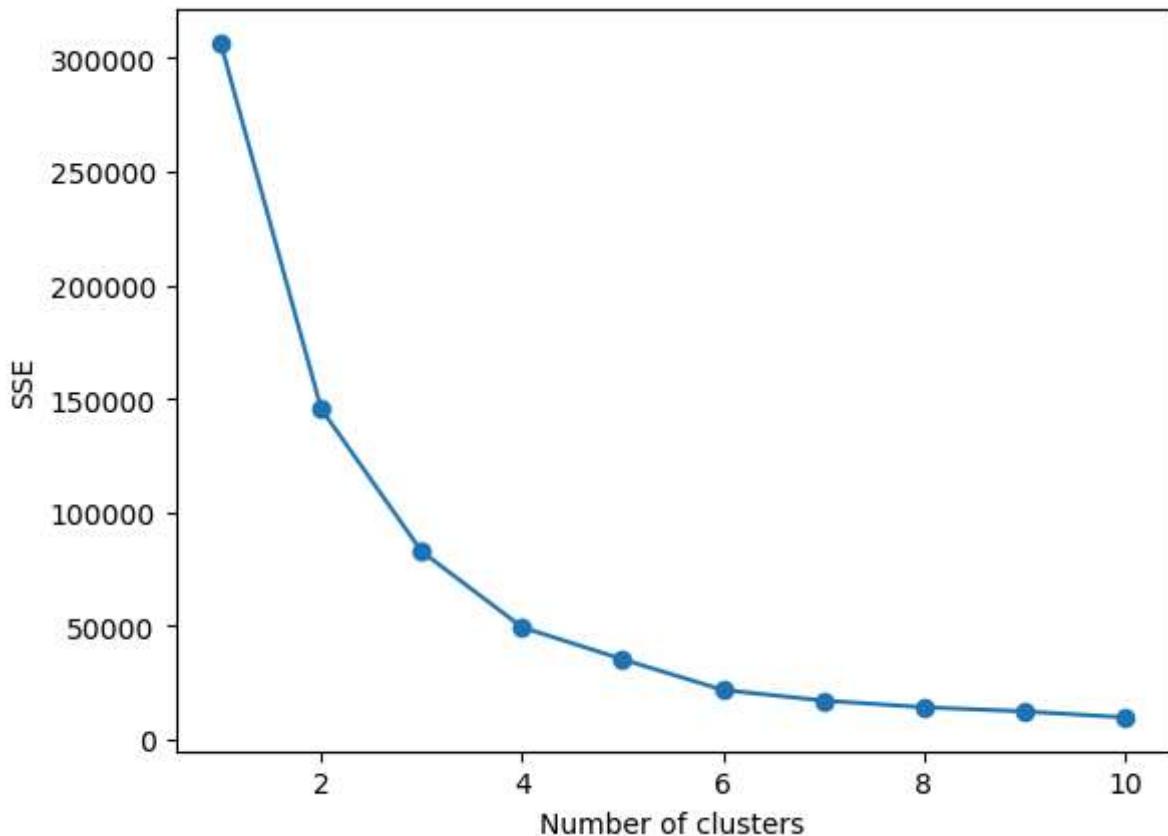
0.21749564861115095



The optimization solution involves using the SSE (Sum of Squared Errors) plot to determine the optimal number of clusters. The SSE plot below identifies the best k value for clustering. Subsequently, this study will re-run the K-Means function with k set to 3.

```
In [23]: # calculate SSE for a range of number of cluster
list_SSE = []
min_k = 1
max_k = 10
range_k = range(min_k, max_k+1)
for i in range_k:
    km = KMeans(
        n_clusters=i, init='random',
        n_init=10, max_iter=300,
        tol=1e-04, random_state=0
    )
    km.fit(to_cluster)
    # inertia is a concept in physics. Roughly it means SSE of clustering.
    list_SSE.append(km.inertia_)

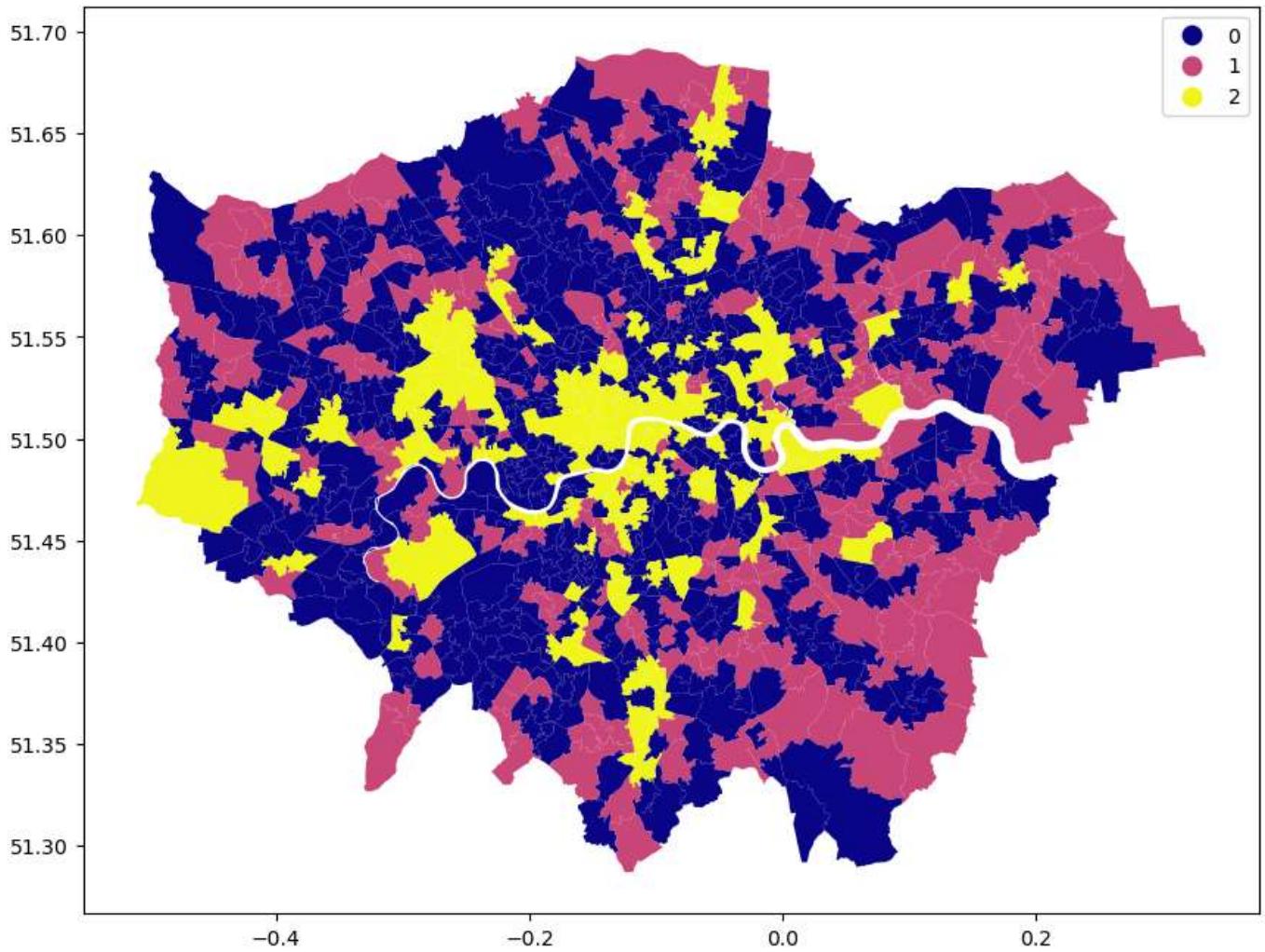
# plot
plt.plot(range_k, list_SSE, marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('SSE')
plt.show()
```



```
In [24]: from sklearn.cluster import KMeans
k_cluster = 3
random_seed = 1
kmeans_method = KMeans(n_clusters=k_cluster, random_state=random_seed)
kmeans_method.fit(normed)

dfmg['Kmeans_Cluster'] = kmeans_method.labels_
dfmg.plot(column='Kmeans_Cluster', categorical=True, legend=True, figsize=(12,8), cmap = 'plasma')
from sklearn import metrics
print("Silhouette Score is :")
print(metrics.silhouette_score(normed, dfmg['Kmeans_Cluster']))
```

Silhouette Score is :
0.22306314322316226



```
In [25]: # adapted from this tutorial: https://towardsdatascience.com/how-to-make-stunning-radar-charts
def radar_plot_cluster_centroids2(df_cluster_centroid):
    # parameters
    # df_cluster_centroid: a dataframe with rows representing a cluster centroid and columns i

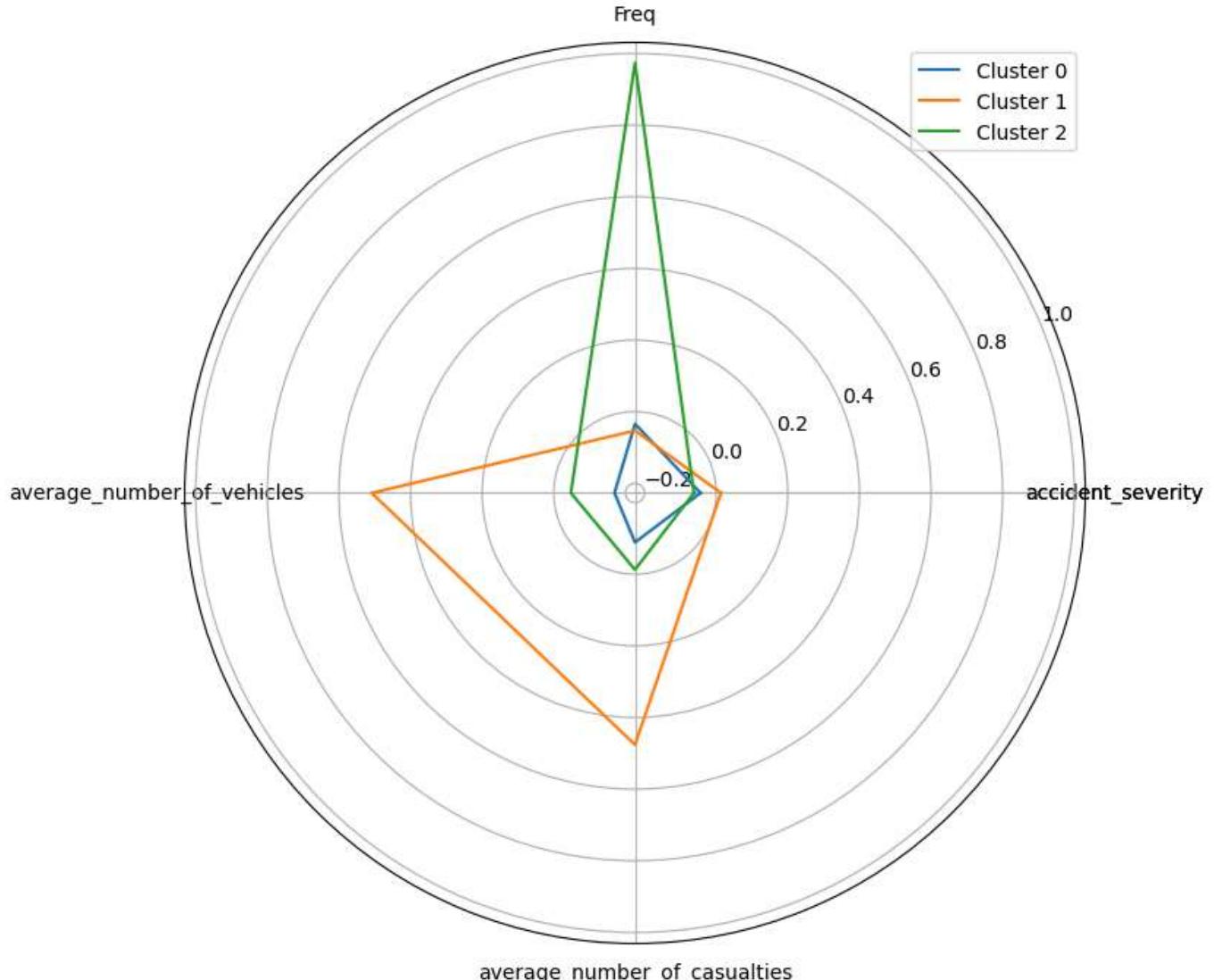
    # add an additional element to both categories and restaurants that's identical to the first
    # manually 'close' the line
    categories = df_cluster_centroid.columns.values.tolist()
    categories = [*categories, categories[0]]

    label_loc = np.linspace(start=0, stop=2 * np.pi, num=len(categories))

    plt.figure(figsize=(12, 8))
    plt.subplot(polar=True)
    for index, row in df_cluster_centroid.iterrows():
        centroid = row.tolist()
        centroid = [*centroid, centroid[0]]
        label = "Cluster {}".format(index)
        plt.plot(label_loc, centroid, label=label)
    plt.title('Cluster centroid comparison', size=20, y=1.05)
    lines, labels = plt.thetagrids(np.degrees(label_loc), labels=categories)
    plt.legend()
    plt.show()
```

```
In [26]: df_cluster_centroid2 = pd.DataFrame(kmeans_method.cluster_centers_, columns=normed.columns)
radar_plot_cluster_centroids2(df_cluster_centroid2)
```

Cluster centroid comparison



```
In [27]: summary_df_Kmeans = \
    dfmg[['accident_severity', 'Freq', 'average_number_of_vehicles', 'average_number_of_casualties']] \
    .mean() \
    .round(2)

summary_df_Kmeans
```

```
Out[27]:
```

Kmeans_Cluster	accident_severity	Freq	average_number_of_vehicles	average_number_of_casualties
0	2.83	18.81	1.75	1
1	2.85	18.16	2.01	1
2	2.83	54.08	1.80	1

5.4 RF Classification Analysis

The Random Forest (RF) model is crucial for classifying traffic accidents using characteristics identified during the initial clustering phase. It employs labels derived from K-means clustering as target categories, effectively categorizing accidents within predetermined clusters. Key attributes such as day of the week, road type, and speed limit are standardized and leveraged to train the RF model, which then predicts the severity or type of accidents. The model's accuracy is

evaluated using performance metrics to ensure precise and reliable classification within the established clusters.

```
In [28]: accidents= pd.merge(accidents, dfmg[['MSOA11CD', 'Kmeans_Cluster']],
                         left_on='msoa_of_accident_location',
                         right_on='MSOA11CD', how='left')

accidents.rename(columns={'Kmeans_Cluster': 'cluster_label'}, inplace=True)

accidents.drop(columns=['MSOA11CD'], inplace=True)

accidents.head()
```

```
Out[28]:   accident_index  accident_severity  number_of_vehicles  number_of_casualties  day_of_week  ms
0  2022010352073                3                  2                  1                  4
1  2022010352573                3                  2                  1                  7
2  2022010352575                3                  2                  1                  7
3  2022010352578                3                  2                  2                  7
4  2022010352580                3                  4                  3                  7
```



```
In [29]: # Selection of features and Labels
features = accidents[['day_of_week', 'first_road_class', 'road_type', 'speed_limit', 'second_
                     'pedestrian_crossing_physical_facilities', 'light_conditions', 'weather_
                     'road_surface_conditions', 'urban_or_rural_area']]
labels = accidents['cluster_label']

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(features, labels, test_size=0.2, random_s_

# Creating a Random Forest Classifier Example
random_forest = RandomForestClassifier(n_estimators=100, random_state=42)

# Training Models
random_forest.fit(X_train, y_train)

# Prediction using test sets
y_pred = random_forest.predict(X_test)

# Output classification reports and accuracy
print(classification_report(y_test, y_pred))
print(f"Accuracy: {accuracy_score(y_test, y_pred):.2f}")
```

	precision	recall	f1-score	support
0	0.48	0.60	0.54	2141
1	0.32	0.20	0.25	963
2	0.44	0.39	0.41	1590
accuracy			0.45	4694
macro avg	0.41	0.40	0.40	4694
weighted avg	0.43	0.45	0.44	4694

Accuracy: 0.45

The Random Forest model exhibits moderate overall performance with an accuracy of 45%. It predicts Class 0 most effectively, evidenced by reasonable precision and recall. Class 2 displays

moderate predictive accuracy with balanced metrics. However, Class 1 demonstrates poor predictive capabilities.

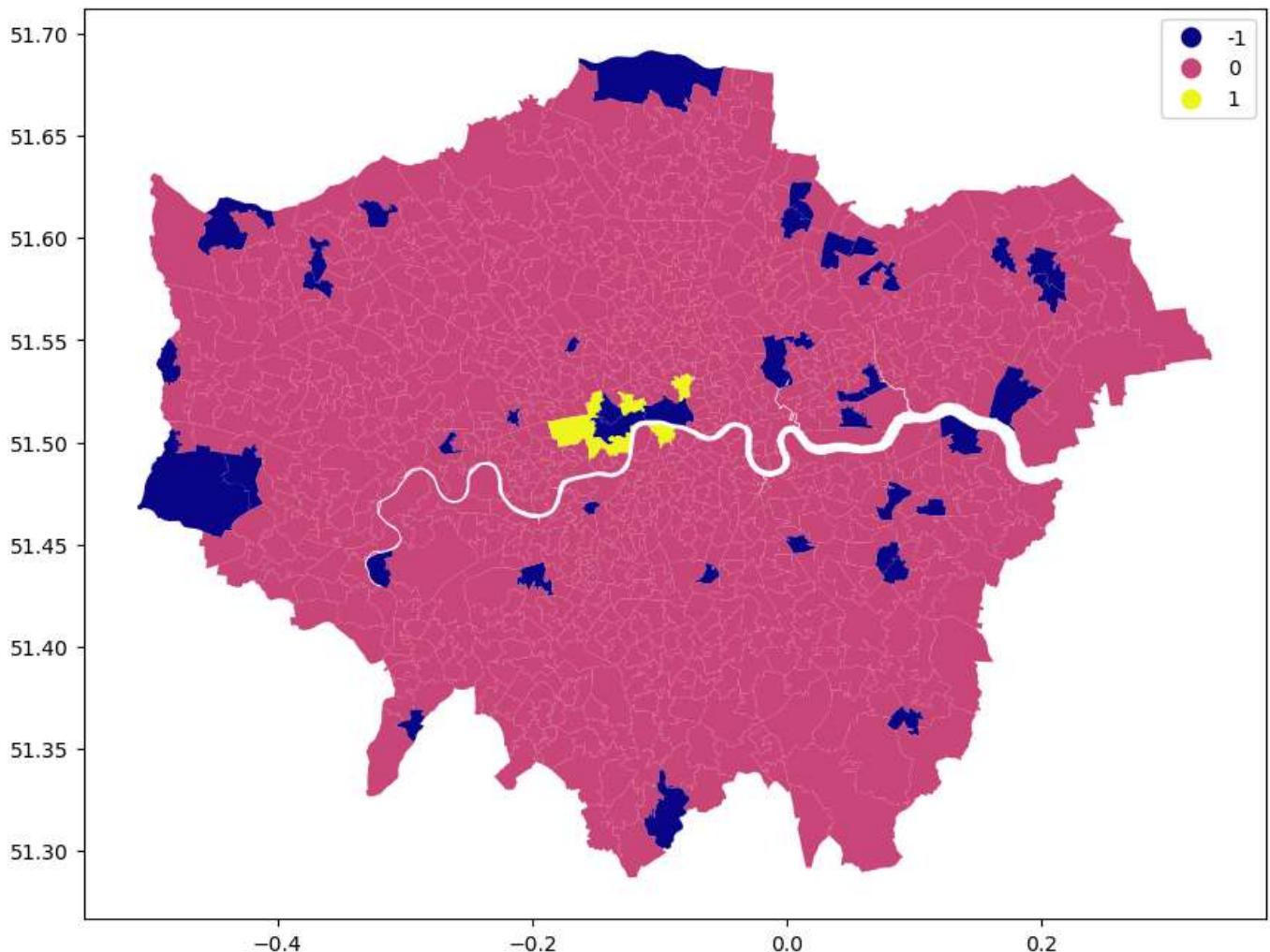
6 Results and Discussion

6.1 DBSCAN

The DBSCAN clustering results, as depicted on the geographic distribution map, show cluster '0' extensively throughout London, indicating a ubiquitous occurrence of traffic accidents across various districts. In stark contrast, the sparse instances of cluster '1' deviate significantly from the urban norm, potentially pointing to areas with unique traffic dynamics or a higher propensity for severe incidents. Noise points, labeled as '-1', represent outliers that diverge from common accident patterns, calling for individualized analysis to understand their unique contexts.

```
In [30]: dfmg.plot(column='DBSCAN_Cluster', categorical=True, legend=True, figsize=(12,8), cmap = 'plasma')
```

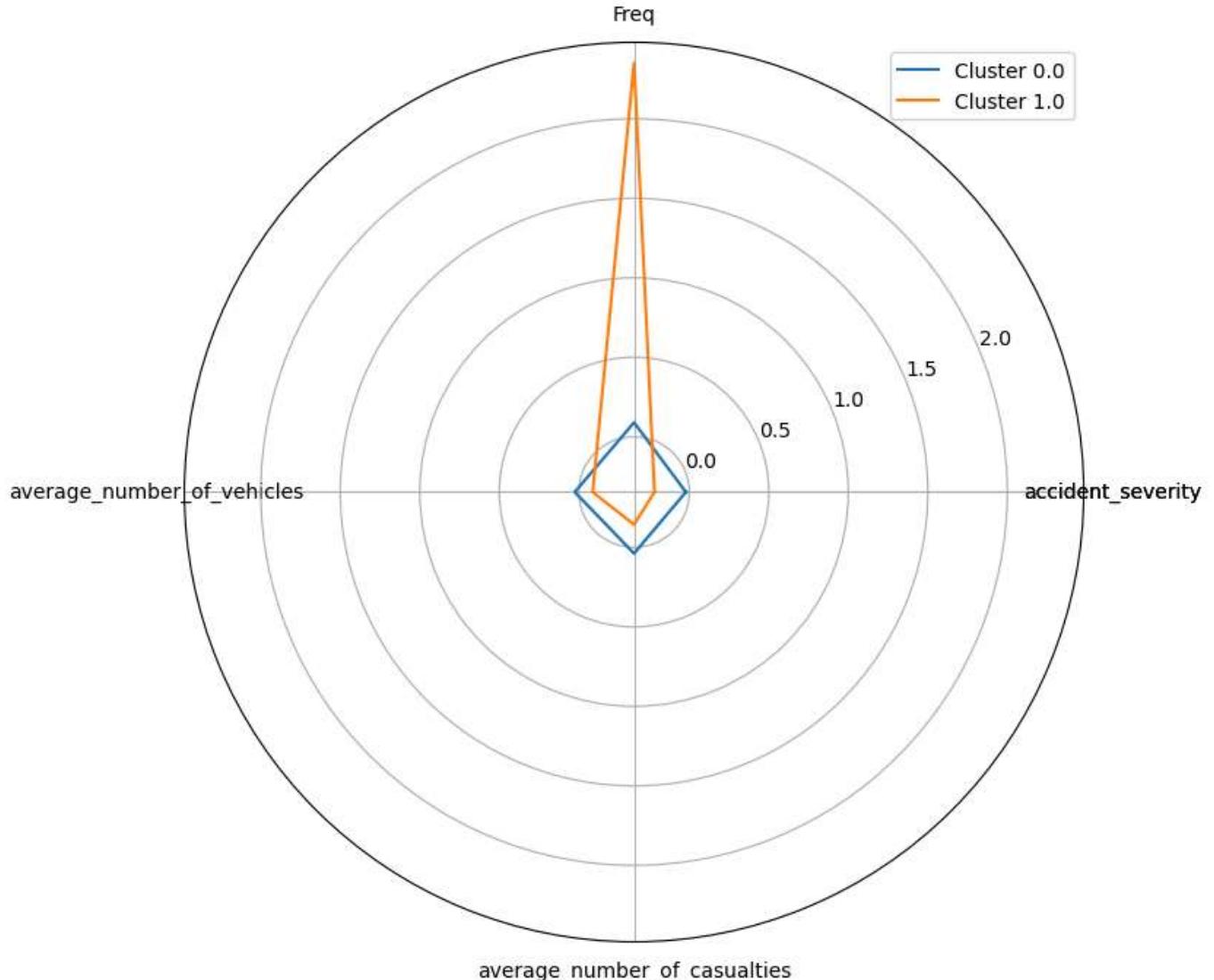
```
Out[30]: <Axes: >
```



The radar chart offers a comparative visualization of the centroids for clusters '0' and '1', accentuating the pronounced profile of cluster '1' with its exceptionally high frequency of occurrences—essentially, the aforementioned 'black spots' that markedly exceed the usual incident rate of cluster '0'. These areas emerge as pivotal targets for the enhancement of traffic safety measures and infrastructural planning.

```
In [31]: radar_plot_cluster_centroids1(df_dbSCAN_centroid1)
```

Cluster centroid comparison



Upon meticulous scrutiny of the cluster table, the noise cluster '-1' is discerned to comprise accidents with escalated severity, an increased number of involved vehicles, and higher casualties. This anomaly could signify scenarios of augmented hazard, albeit less frequent yet bearing substantial risk and impact, which mandates the formulation of specific remedial measures.

In [32]: `summary_df_dbSCAN`

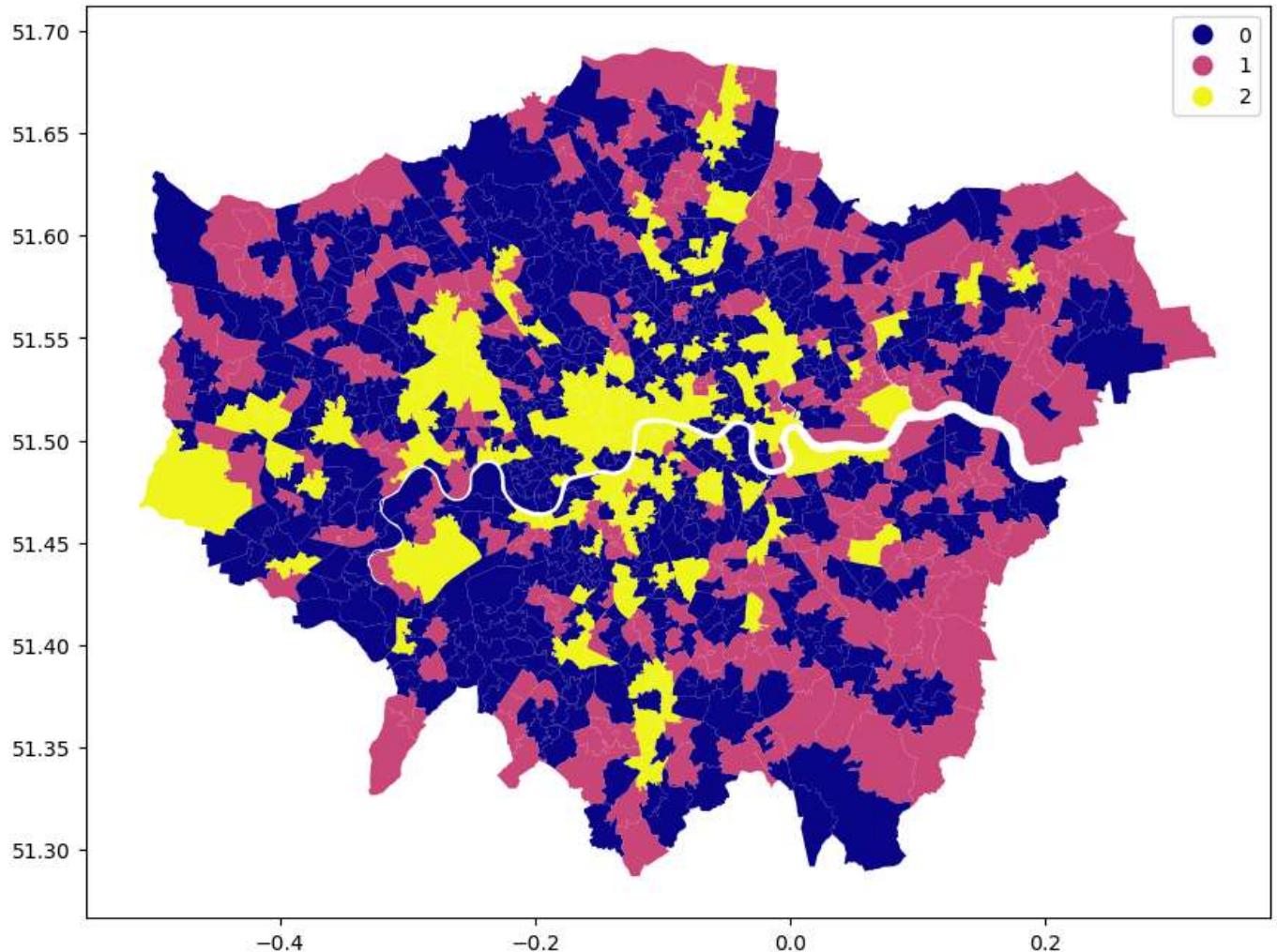
DBSCAN_Cluster	accident_severity	Freq	average_number_of_vehicles	average_number_of_casualties
-1	2.79	28.86		1.87
0	2.84	23.15		1.82
1	2.79	102.33		1.78

6.2 Kmeans

The K-means clustering map offers an intricate portrayal of traffic accidents across London, dividing them into three principal clusters. Cluster '0', pervasive across the metropolis, signifies a consistent pattern of urban traffic incidents. Alternatively, the infrequent yet pronounced Cluster

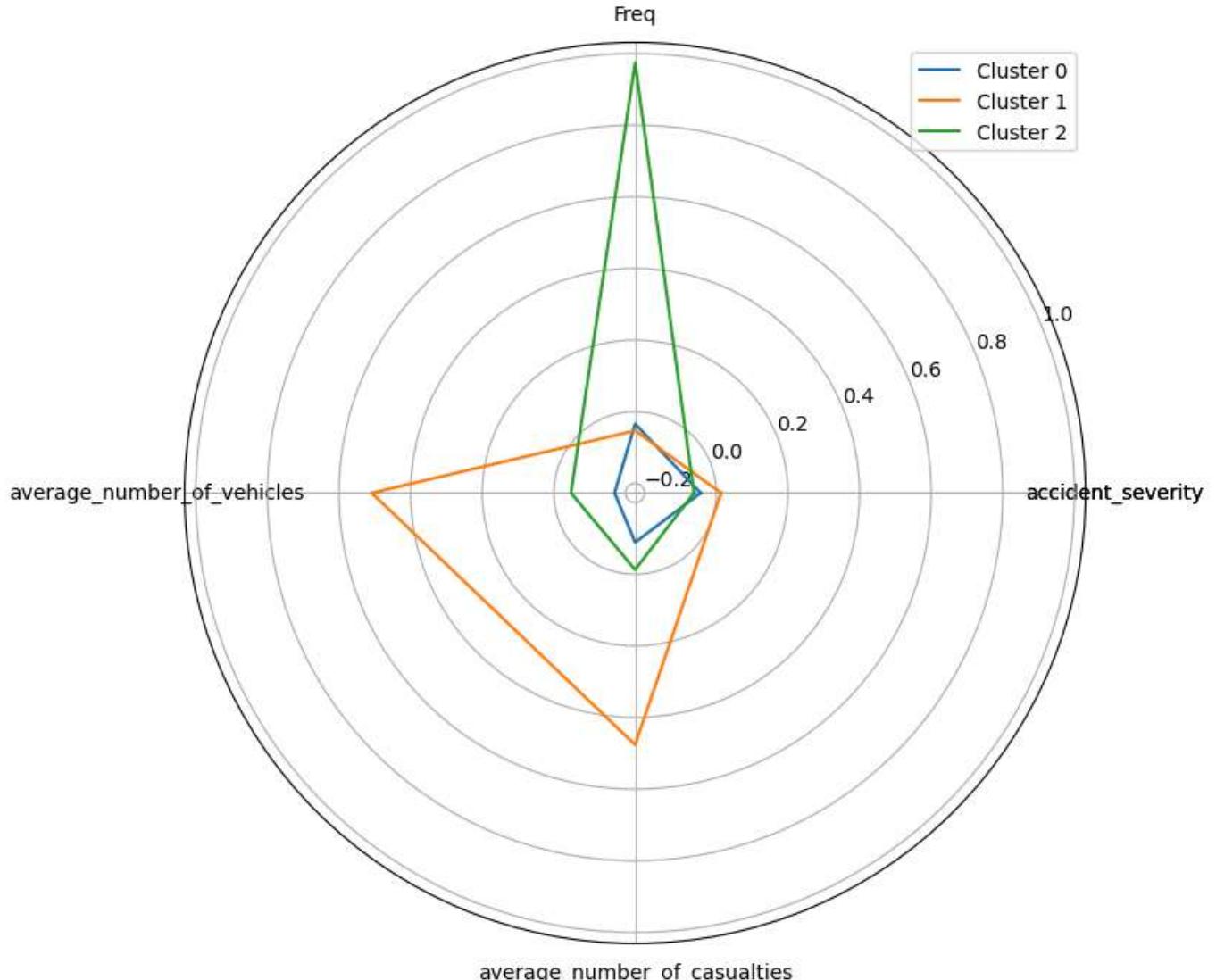
'1' may reflect specific anomalous conditions, with its increased vehicle and casualty averages pointing to more grave incidents. Cluster '2' stands out with its heightened accident rate, signaling areas in dire need of targeted safety measures.

```
In [33]: fig_kmeans_4 = dfmg.plot(column='Kmeans_Cluster', categorical=True, legend=True, figsize=(12,8))
```



```
In [34]: radar_plot_cluster_centroids2(df_cluster_centroid2)
```

Cluster centroid comparison



Both the radar chart and the tabular data enhance our understanding by quantifying each cluster's characteristics. They suggest that Cluster '0', despite its lower frequency of accidents, does not necessarily correlate with lower severity or fewer casualties. This observation contradicts common perceptions about the frequency and impact of accidents. Cluster '1', with its heightened vehicle and casualty rates, suggests a propensity for more severe accidents, necessitating tailored traffic management strategies. Cluster '2', with its acute frequency of incidents, highlights "black spots" that urgently require road safety advancements and infrastructural changes to avert future incidents.

In [35]: `summary_df_Kmeans`

Kmeans_Cluster	accident_severity	Freq	average_number_of_vehicles	average_number_of_casualt	
0	2.83	18.81		1.75	1
1	2.85	18.16		2.01	1
2	2.83	54.08		1.80	1

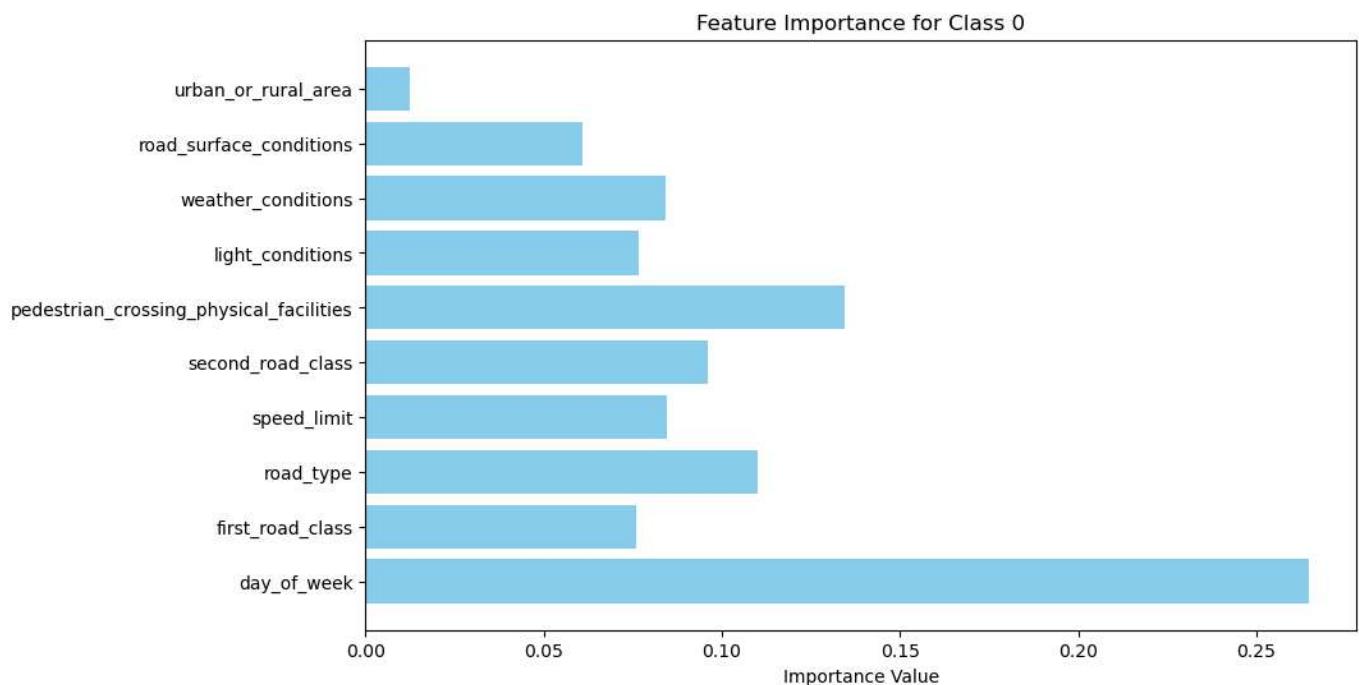
The feature importance charts for a Random Forest model reveal key factors influencing the classification of traffic accidents into Kmeans clusters:

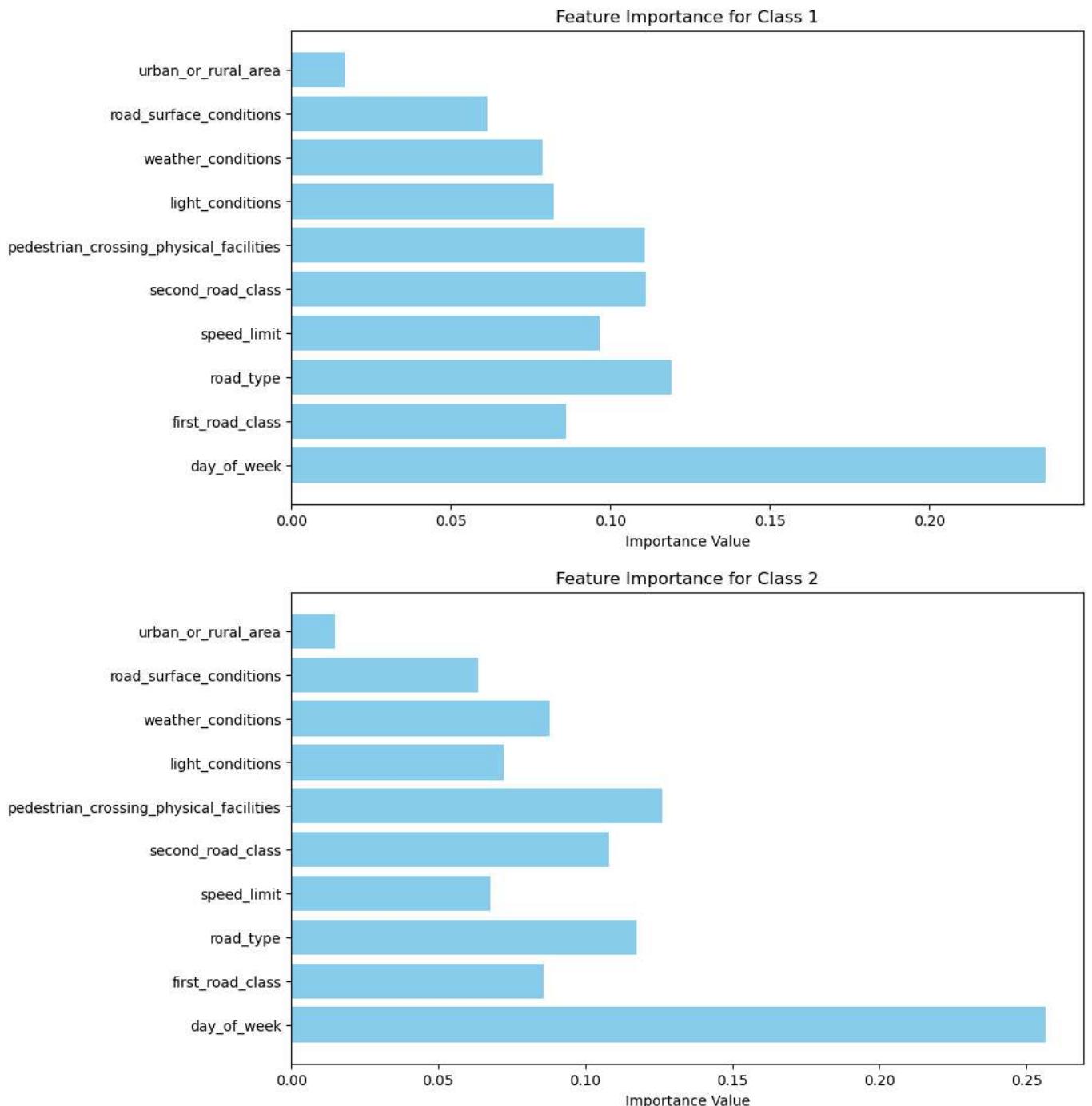
- For Class 0, the timing of accidents ('day of the week') is paramount, while the type of road plays a secondary role. The setting ('urban or rural area') seems negligible, suggesting a uniform risk across environments.
- Class 1 is dominated by the type of road and the speed limit, hinting that structural road features and traffic regulation significantly affect accident classification.
- In Class 2, visibility ('light conditions') is the most critical factor, with environmental conditions ('weather' and 'road surface') also being influential.

```
In [36]: # Further analysis of which features are most critical to the prediction of cluster labels

# Initialize OVR classifier using Random Forest
ovr_classifier = OneVsRestClassifier(random_forest)
ovr_classifier.fit(X_train, y_train)

# Plot feature importances for each class
for i, estimator in enumerate(ovr_classifier.estimators_):
    plt.figure(figsize=(10, 6))
    plt.barh(features.columns, estimator.feature_importances_, color='skyblue')
    plt.xlabel('Importance Value')
    plt.title(f'Feature Importance for Class {ovr_classifier.classes_[i]}')
    plt.show()
```





The feature importance from the Random Forest model highlights the primacy of temporal and environmental conditions over geographical settings in predicting traffic accident clusters. 'Day of the week' and 'light conditions' emerge as critical indicators, overshadowing 'urban or rural' distinctions. This suggests that policy interventions may benefit from focusing on when and under what conditions accidents occur, rather than solely on where they take place. The data advocates for targeted safety measures at times and in conditions most conducive to accidents, potentially offering a more nuanced approach to traffic safety strategies.

7 Conclusion

In conclusion, this study's comprehensive analysis has identified and characterized traffic collision 'black spots' in London. Through the integration of spatial clustering and supervised learning methods, we have discerned the influence of temporal, environmental, and infrastructural factors on accident occurrences. The research underscores the complexity of urban traffic accidents and reinforces the critical need for targeted safety interventions, transcending traditional urban-rural distinctions. This study contributes to the overarching goal

of enhancing road safety and mitigating the socio-economic impacts of traffic-related injuries and fatalities.

References

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