CANDIDATE NUMBERS: 784750, 393886, 379642, 413087.

Group Assignment For Big data

Introduction

The integrity and safety of road transportation are pivotal components of modern society, directly influencing the well-being and efficiency of communities. As populations grow and urbanization expands, the complexity and volume of road traffic increase, elevating the risk of road traffic collisions. These incidents not only bear a significant human cost, resulting in injuries and fatalities, but also impose substantial economic burdens due to property damage, healthcare costs, and loss of productivity. In developed countries, road traffic safety is a critical concern for public health and urban planning authorities, requiring constant monitoring and improvement to mitigate risks. The advent of big data analytics and machine learning technologies has ushered in new opportunities for enhancing road safety by enabling the detailed analysis of collision data. Such analysis can uncover patterns, risk factors, and causal relationships that inform more effective interventions and policies.

Business Objective The primary objective of utilizing the "DFT Road Casualty Statistics - Collision Provisional Mid-Year Unvalidated 2023" dataset is to develop a predictive model capable of identifying high-risk areas and conditions for road traffic collisions. By analyzing factors such as location coordinates, time, environmental conditions, and characteristics of involved vehicles and individuals, we aim to predict the likelihood of collisions and their potential severity. This model will serve as a vital tool for stakeholders, including urban planners, traffic management authorities, and public safety organizations, enabling them to implement targeted measures for risk reduction. These measures could include infrastructure improvements, enhanced traffic regulation, and public awareness campaigns. Ultimately, the goal is to decrease the incidence and severity of road traffic collisions, thereby safeguarding lives, reducing economic impacts, and enhancing the overall quality of road transportation systems.

In [ ]:
```
##Import Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings(action='ignore')
df = pd.read_csv('dft-road-casualty-statistics-collision-provisional-mid-year-unvalida
df.head(5)
```

Out[ ]:

	collision_index	collision_year	collision_reference	location_easting_osgr	location_northing_osgr	lon
0	2.023010e+12	2023	10419171	525060.0	170416.0	-0.2
1	2.023010e+12	2023	10419183	535463.0	198745.0	-0.0
2	2.023010e+12	2023	10419189	508702.0	177696.0	-0.4
3	2.023010e+12	2023	10419191	520341.0	190175.0	-0.2
4	2.023010e+12	2023	10419192	527255.0	176963.0	-0.1

5 rows × 36 columns

In [ ]:

```
df.shape # check the size of the dataset~
```

Out[ ]:

```
(5999, 36)
```

There are 5999 rows and 36 columns in the dataset.

In [ ]:

```
df.info() # get the info for the dataset such as type and non null counts
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5999 entries, 0 to 5998
Data columns (total 36 columns):
 #   Column                                      Non-Null Count  Dtype  
---  ------                                      --------------  -----  
 0   collision_index                             5999 non-null   float64
 1   collision_year                              5999 non-null   int64  
 2   collision_reference                         5999 non-null   int64  
 3   location_easting_osgr                       5998 non-null   float64
 4   location_northing_osgr                      5998 non-null   float64
 5   longitude                                   5998 non-null   float64
 6   latitude                                    5998 non-null   float64
 7   police_force                                5999 non-null   int64  
 8   legacy_collision_severity                   5999 non-null   int64  
 9   number_of_vehicles                          5999 non-null   int64  
 10  number_of_casualties                        5999 non-null   int64  
 11  date                                        5999 non-null   object 
 12  day_of_week                                 5999 non-null   int64  
 13  time                                        5999 non-null   object 
 14  local_authority_district                    5999 non-null   int64  
 15  local_authority_ons_district                5999 non-null   object 
 16  local_authority_highway                     5999 non-null   object 
 17  first_road_class                            5999 non-null   int64  
 18  first_road_number                           5999 non-null   int64  
 19  road_type                                   5999 non-null   int64  
 20  speed_limit                                 5999 non-null   int64  
 21  junction_detail                             5999 non-null   int64  
 22  junction_control                            5999 non-null   int64  
 23  second_road_class                           5999 non-null   int64  
 24  second_road_number                          5999 non-null   int64  
 25  pedestrian_crossing_human_control           5999 non-null   int64  
 26  pedestrian_crossing_physical_facilities     5999 non-null   int64  
 27  light_conditions                            5999 non-null   int64  
 28  weather_conditions                          5999 non-null   int64  
 29  road_surface_conditions                     5999 non-null   int64  
 30  special_conditions_at_site                  5999 non-null   int64  
 31  carriageway_hazards                         5999 non-null   int64  
 32  urban_or_rural_area                         5999 non-null   int64  
 33  did_police_officer_attend_scene_of_collision  5999 non-null   int64  
 34  trunk_road_flag                             5999 non-null   int64  
 35  lsoa_of_collision_location                  5999 non-null   object 
dtypes: float64(5), int64(26), object(5)
memory usage: 1.6+ MB
```

The dataset chosen for this prediction consists of the following columns :

collision_index – Unique identifier for each collision.

collision_year – Year the collision occurred.

collision_reference – Reference code for cross-referencing collisions.

location_easting_osgr, location_northing_osgr – Ordnance Survey Grid References for the collision's location.

longitude, latitude – Geographic coordinates of the collision.

police_force – Police force that reported the collision.

legacy_collision_severity – Severity categorization of the collision.

number_of_vehicles – Total vehicles involved in the collision.

number_of_casualties – Count of individuals injured or killed.

date, time – Date and time when the collision occurred.

road_type – Classification of the road where the collision happened.

speed_limit – Speed limit at the collision site.

weather_conditions – Weather conditions at the time of the collision.

light_conditions – Lighting conditions during the collision.

road_surface_conditions – State of the road surface at the collision time.

Descriptive statistics

Numerical columns

In [ ]:
```
df.describe() # Summary statistics of numerical variables
```

Out[ ]:

	collision_index	collision_year	collision_reference	location_easting_osgr	location_northing_osgr
count	5.999000e+03	5999.0	5.999000e+03	5998.000000	5998.000000
mean	2.023010e+12	2023.0	1.042869e+07	530395.117706	180719.040013
std	0.000000e+00	0.0	5.369879e+03	9787.772262	7722.598132
min	2.023010e+12	2023.0	1.041917e+07	503824.000000	158471.000000
25%	2.023010e+12	2023.0	1.042399e+07	524706.000000	175720.000000
50%	2.023010e+12	2023.0	1.042876e+07	530838.000000	181211.000000
75%	2.023010e+12	2023.0	1.043342e+07	536083.250000	186046.000000
max	2.023010e+12	2023.0	1.043790e+07	558857.000000	200608.000000

8 rows × 31 columns

count -Gives the count of non null rows of each numerical column.Most variables have a consistent count of 49,316 entries, showing a high level of data completeness with only a few missing values in geographical coordinates.

Mean-Describes the average value of each numerical column.The mean number of casualties per collision is 1.270865, suggesting that most collisions result in one casualty, with some incidents involving more.

Std- Denotes the standard deviation.

In [ ]:
```
df.describe(exclude = ['float', 'int64']) #Describe Categorical variables
```

Out[ ]:

	date	time	local_authority_ons_district	local_authority_highway	lsoa_of_collision_locatio
count	5999	5999	5999	5999	599
unique	107	1141	33	33	276
top	19/01/2023	18:00	E09000033	E09000033	E0100473
freq	89	57	301	301	2

In [ ]:
```
from sklearn.model_selection import StratifiedShuffleSplit

# Adjusting to the provided example format
stratified_splitter = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=7


# Using 'legacy_collision_severity' for stratification
train_index, test_index = next(stratified_splitter.split(df, df['legacy_collision_seve

# Creating the training and testing sets based on the indices
trainset = df.loc[train_index]
testset = df.loc[test_index]

# Now, 'trainset' contains your training data, and 'testset' contains your testing dat
```

In [ ]:
```
trainset["legacy_collision_severity"].value_counts(normalize=True)
```

Out[ ]:
```
legacy_collision_severity
3    0.844759
2    0.151698
1    0.003542
Name: proportion, dtype: float64
```

In [ ]:
```
testset["legacy_collision_severity"].value_counts(normalize=True)
```

Out[ ]:
```
legacy_collision_severity
3    0.845000
2    0.151667
1    0.003333
Name: proportion, dtype: float64
```

In [ ]:
```
trainset.shape
```

Out[ ]:
```
(4799, 36)
```

In [ ]:
```
testset.shape
```

Out[ ]:
```
(1200, 36)
```

Reconfirming the missing values and what is the percentage of missing values as compared to the whole data:

In [ ]:
```
trainset.isnull().sum()
```

Out[ ]:
```
collision_index                                0
collision_year                                 0
collision_reference                            0
location_easting_osgr                          0
location_northing_osgr                         0
longitude                                      0
latitude                                       0
police_force                                   0
legacy_collision_severity                      0
number_of_vehicles                             0
number_of_casualties                           0
date                                           0
day_of_week                                    0
time                                           0
local_authority_district                       0
local_authority_ons_district                   0
local_authority_highway                        0
first_road_class                               0
first_road_number                              0
road_type                                      0
speed_limit                                    0
junction_detail                                0
junction_control                               0
second_road_class                              0
second_road_number                             0
pedestrian_crossing_human_control              0
pedestrian_crossing_physical_facilities        0
light_conditions                               0
weather_conditions                             0
road_surface_conditions                        0
special_conditions_at_site                     0
carriageway_hazards                            0
urban_or_rural_area                            0
did_police_officer_attend_scene_of_collision   0
trunk_road_flag                                0
lsoa_of_collision_location                     0
dtype: int64
```

In [ ]:
```
trainset.isnull().sum() * 100 / len(trainset)
```

Out[ ]:
```
collision_index                                0.0
collision_year                                 0.0
collision_reference                            0.0
location_easting_osgr                          0.0
location_northing_osgr                         0.0
longitude                                      0.0
latitude                                       0.0
police_force                                   0.0
legacy_collision_severity                      0.0
number_of_vehicles                             0.0
number_of_casualties                           0.0
date                                           0.0
day_of_week                                    0.0
time                                           0.0
local_authority_district                       0.0
local_authority_ons_district                   0.0
local_authority_highway                        0.0
first_road_class                               0.0
first_road_number                              0.0
road_type                                      0.0
speed_limit                                    0.0
junction_detail                                0.0
junction_control                               0.0
second_road_class                              0.0
second_road_number                             0.0
pedestrian_crossing_human_control              0.0
pedestrian_crossing_physical_facilities        0.0
light_conditions                               0.0
weather_conditions                             0.0
road_surface_conditions                        0.0
special_conditions_at_site                     0.0
carriageway_hazards                            0.0
urban_or_rural_area                            0.0
did_police_officer_attend_scene_of_collision   0.0
trunk_road_flag                                0.0
lsoa_of_collision_location                     0.0
dtype: float64
```

In [ ]:
```
trainset = trainset.dropna() #dropping null values for the trainse
```

In [ ]:
```
trainset
```

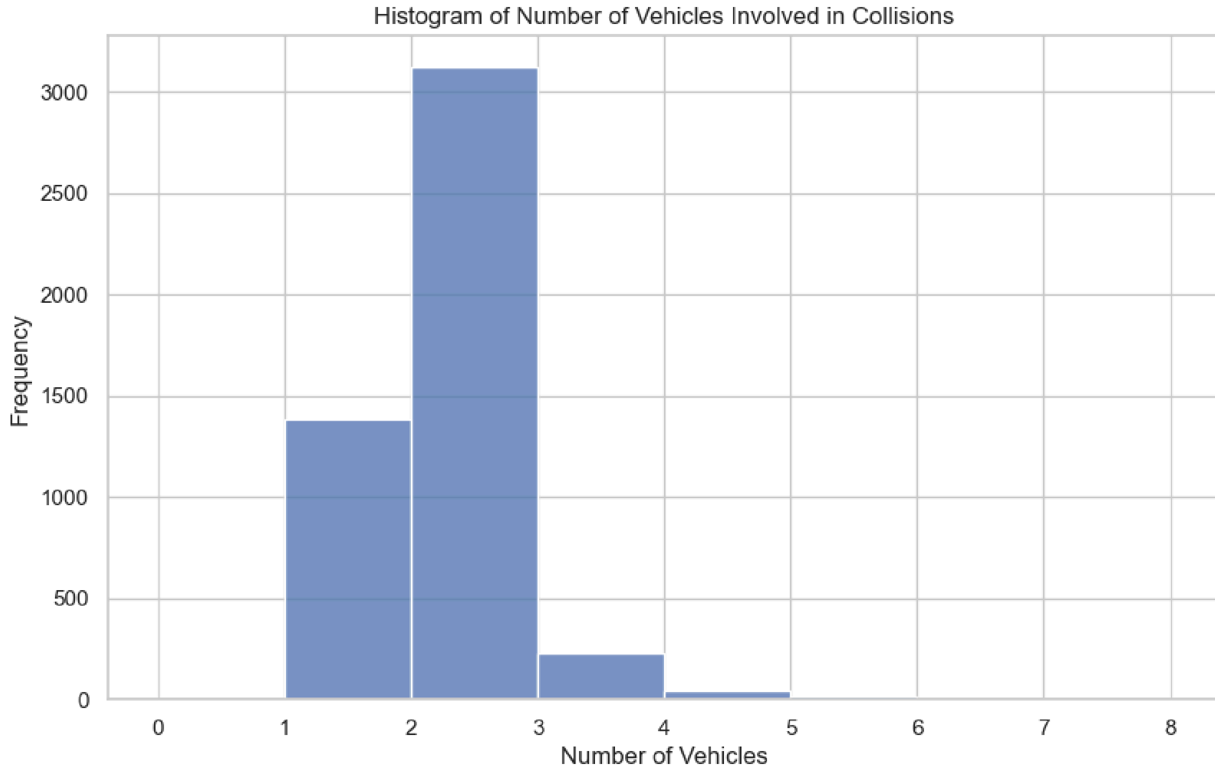
Out[ ]:

	collision_index	collision_year	collision_reference	location_easting_osgr	location_northing_osgr
4338	2.023010e+12	2023	10432870	508304.0	173795.0
3176	2.023010e+12	2023	10429343	530015.0	182256.0
5929	2.023010e+12	2023	10437668	539464.0	181485.0
153	2.023010e+12	2023	10419771	505542.0	184116.0
5969	2.023010e+12	2023	10437805	529812.0	182524.0
...	...	...	...	...	...
2002	2.023010e+12	2023	10425564	537125.0	162625.0
5207	2.023010e+12	2023	10435426	529364.0	181973.0
3936	2.023010e+12	2023	10431630	540151.0	178521.0
3919	2.023010e+12	2023	10431571	534003.0	191889.0
4546	2.023010e+12	2023	10433554	530855.0	166826.0

4799 rows × 36 columns

In [ ]:

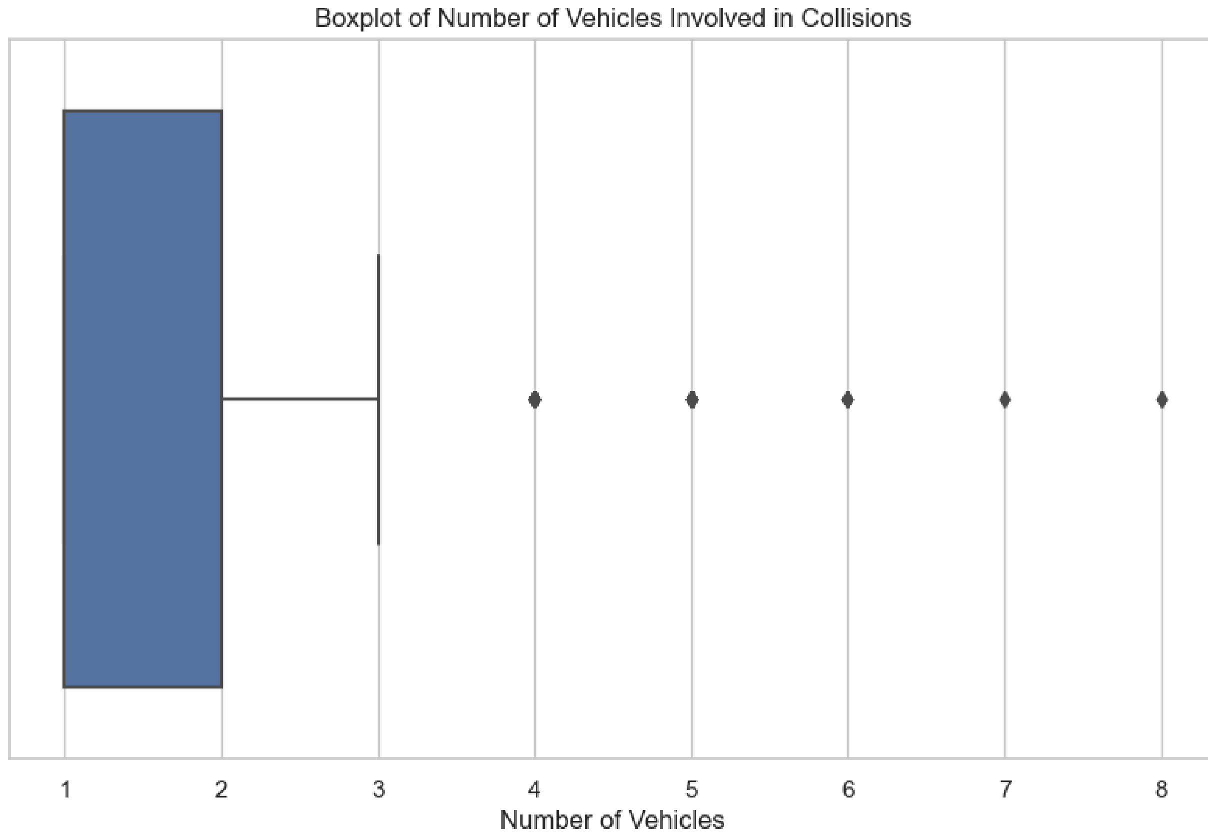
```
import seaborn as sns
import matplotlib.pyplot as plt

# Setting the visual theme
sns.set_theme(style="whitegrid")

# Increasing the figure size for better visibility
plt.figure(figsize=(10, 6))

# Creating a histogram for the 'number_of_vehicles' variable
sns.histplot(trainset['number_of_vehicles'], bins=range(int(trainset['number_of_vehicl

# Adding a title to the plot
plt.title("Histogram of Number of Vehicles Involved in Collisions")

# Setting the x and y axis labels
plt.xlabel("Number of Vehicles")
plt.ylabel("Frequency")

# Displaying the plot
plt.show()
```



The histogram indicates that single-vehicle collisions are the most frequent, with occurrences dramatically decreasing as the number of vehicles involved increases. Collisions involving a higher number of vehicles are relatively rare, indicating that the majority of traffic incidents are less complex.

In [ ]:

```
import seaborn as sns
import matplotlib.pyplot as plt

# Setting the visual theme
sns.set_theme(style="whitegrid")

# Increasing the figure size for better visibility
plt.figure(figsize=(10, 6))

# Creating a boxplot for the 'number_of_vehicles' variable
sns.boxplot(x=trainset['number_of_vehicles'])

# Adding a title to the plot
plt.title("Boxplot of Number of Vehicles Involved in Collisions")

# Setting the x-axis label
plt.xlabel("Number of Vehicles")

# Displaying the plot
plt.show()
```



In [ ]:
```
# Calculate the interquartile range (IQR) for 'number_of_vehicles'
Q1 = df['number_of_vehicles'].quantile(0.25)
Q3 = df['number_of_vehicles'].quantile(0.75)
IQR = Q3 - Q1

# Determine the outlier thresholds
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

print(f"IQR: {IQR}")
print(f"Lower Bound for Outliers: {lower_bound}")
print(f"Upper Bound for Outliers: {upper_bound}")
```

```
IQR: 1.0
Lower Bound for Outliers: -0.5
Upper Bound for Outliers: 3.5
```

In [ ]:
```
trainset[trainset['number_of_vehicles'] > 3.5].shape[0]
```

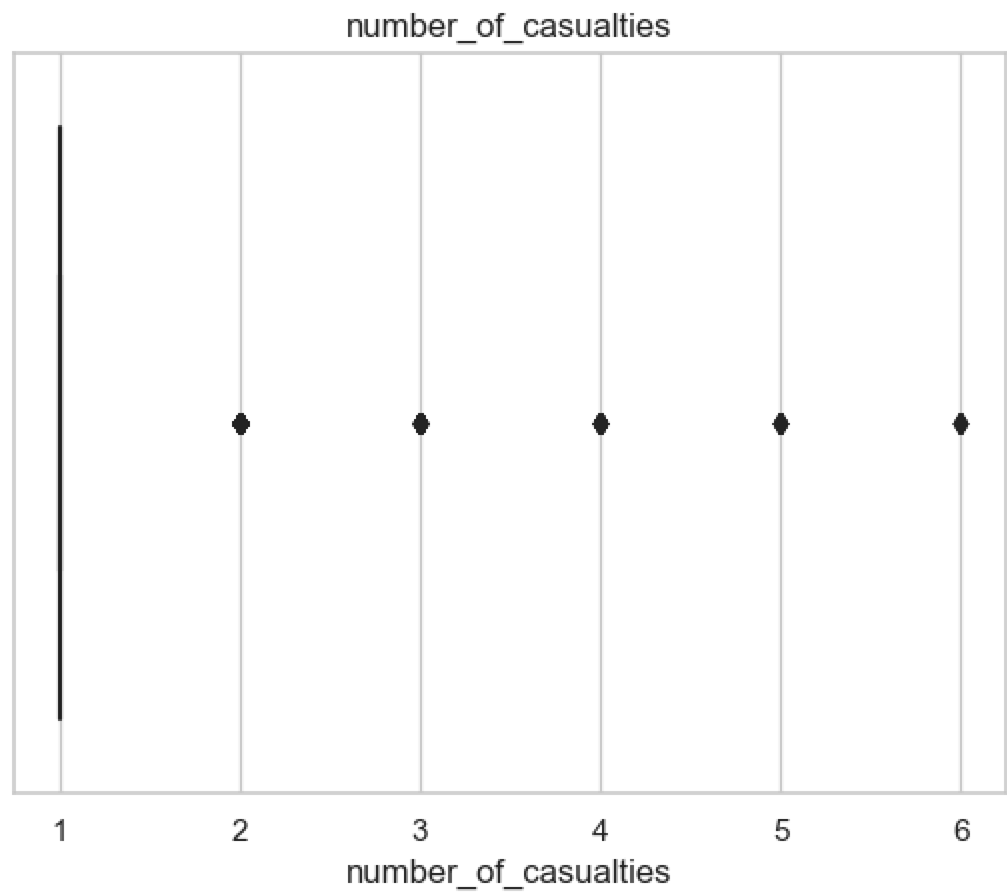
Out[ ]:
```
68
```

In [ ]:
```
trainset[trainset['number_of_vehicles'] > 3.5].shape[0]* 100 / len(trainset)
```

Out[ ]:
```
1.4169618670556365
```

Since the outliers are a small percentage and are likely to represent real, although rare, events, they maintain the integrity of the collision occurrences

In [ ]:
```
sns.boxplot(data=trainset,x=trainset["number_of_casualties"],color='green')
plt.title("number_of_casualties");
```



In [ ]:
```
Q1 = df['number_of_casualties'].quantile(0.25)
Q3 = df['number_of_casualties'].quantile(0.75)
IQR = Q3 - Q1

# Determine the outlier thresholds
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

print(f"IQR: {IQR}")
print(f"Lower Bound for Outliers: {lower_bound}")
print(f"Upper Bound for Outliers: {upper_bound}")
```

```
IQR: 0.0
Lower Bound for Outliers: 1.0
Upper Bound for Outliers: 1.0
```

In [ ]:
```
trainset[trainset['number_of_casualties'] > 1.0].shape[0]
```

Out[ ]:
```
502
```

In [ ]:
```
trainset[trainset['number_of_casualties'] > 1.0].shape[0]* 100 / len(trainset)
```

Out[ ]:
```
10.460512606793081
```

Exploratory Data Analysis (EDA)

Introduction to EDA As part of our comprehensive approach to understanding the dynamics behind road traffic collisions, we embarked on an exploratory data analysis (EDA) using the "DfT

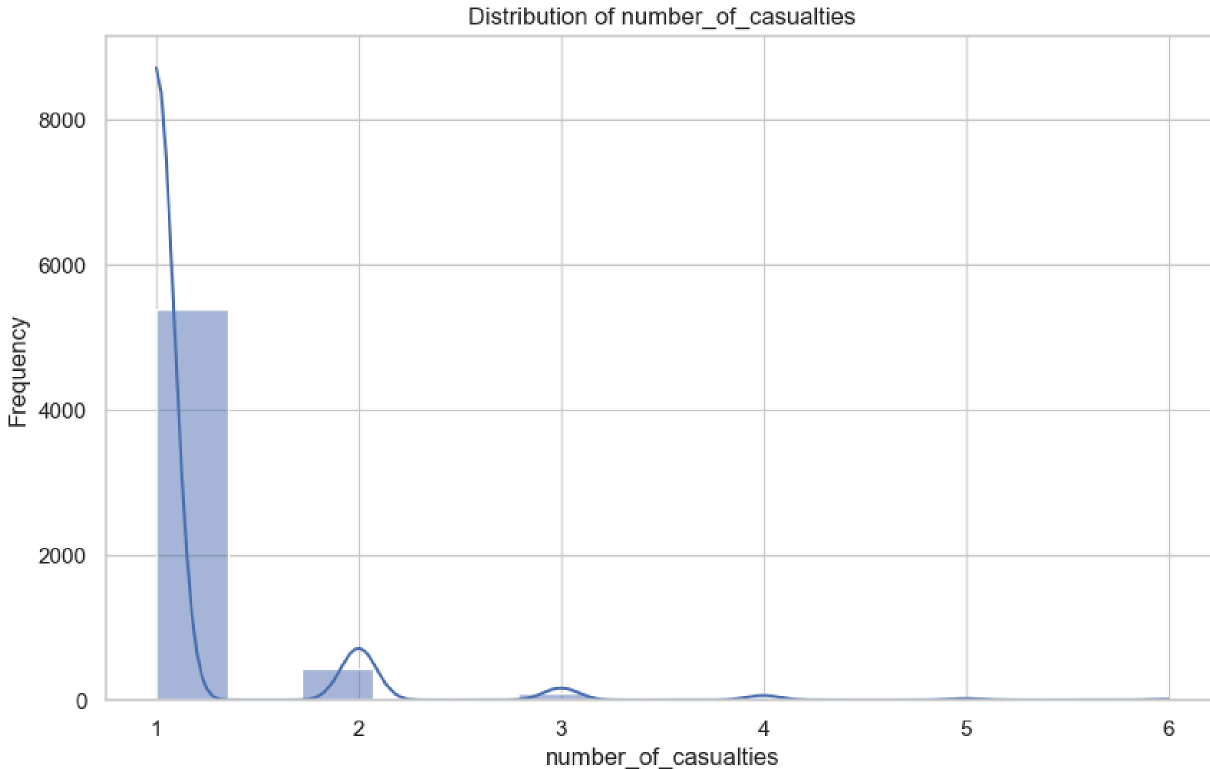
Road Casualty Statistics - Collision Provisional Mid-Year Unvalidated 2023" dataset. Our analysis aims to uncover patterns, outliers, and critical relationships within the data, providing a foundation for predictive modeling.

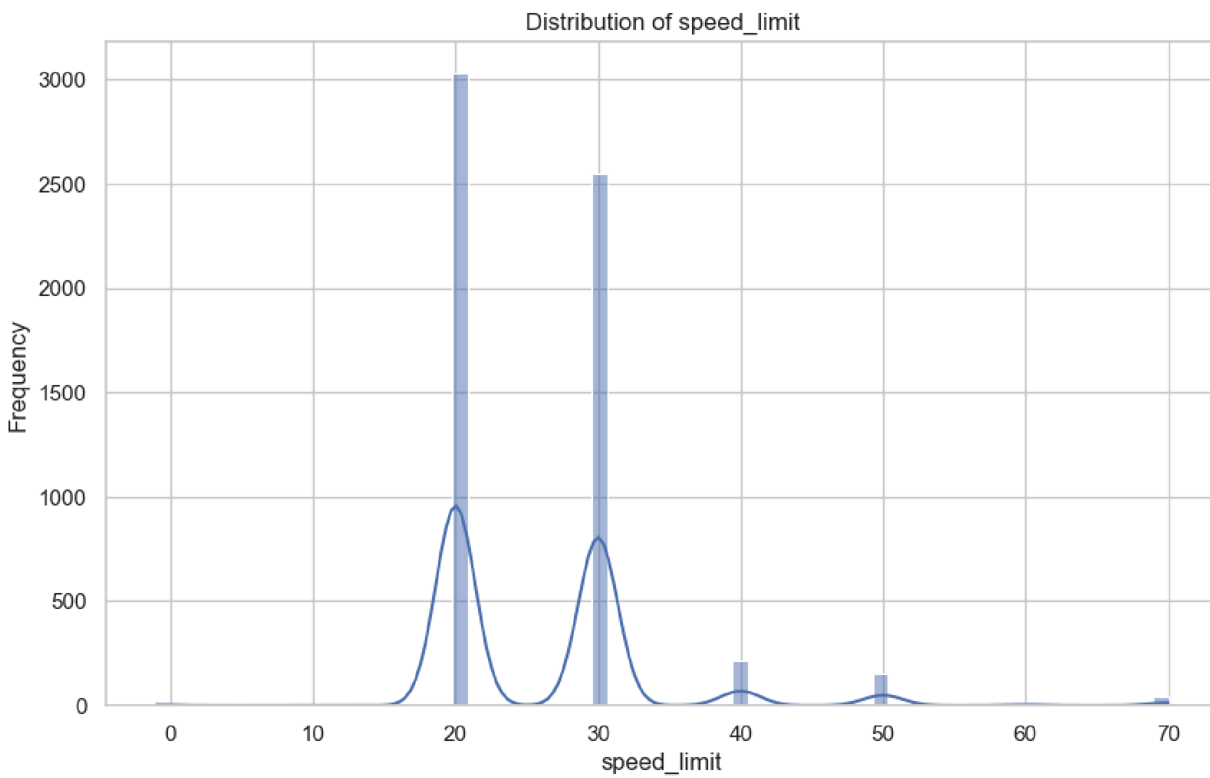
Methodology Our EDA process employs a variety of statistical and visualization techniques to analyze the dataset's characteristics. Below, we detail the steps taken and insights gathered, accompanied by Python code snippets that demonstrate our analytical approach.

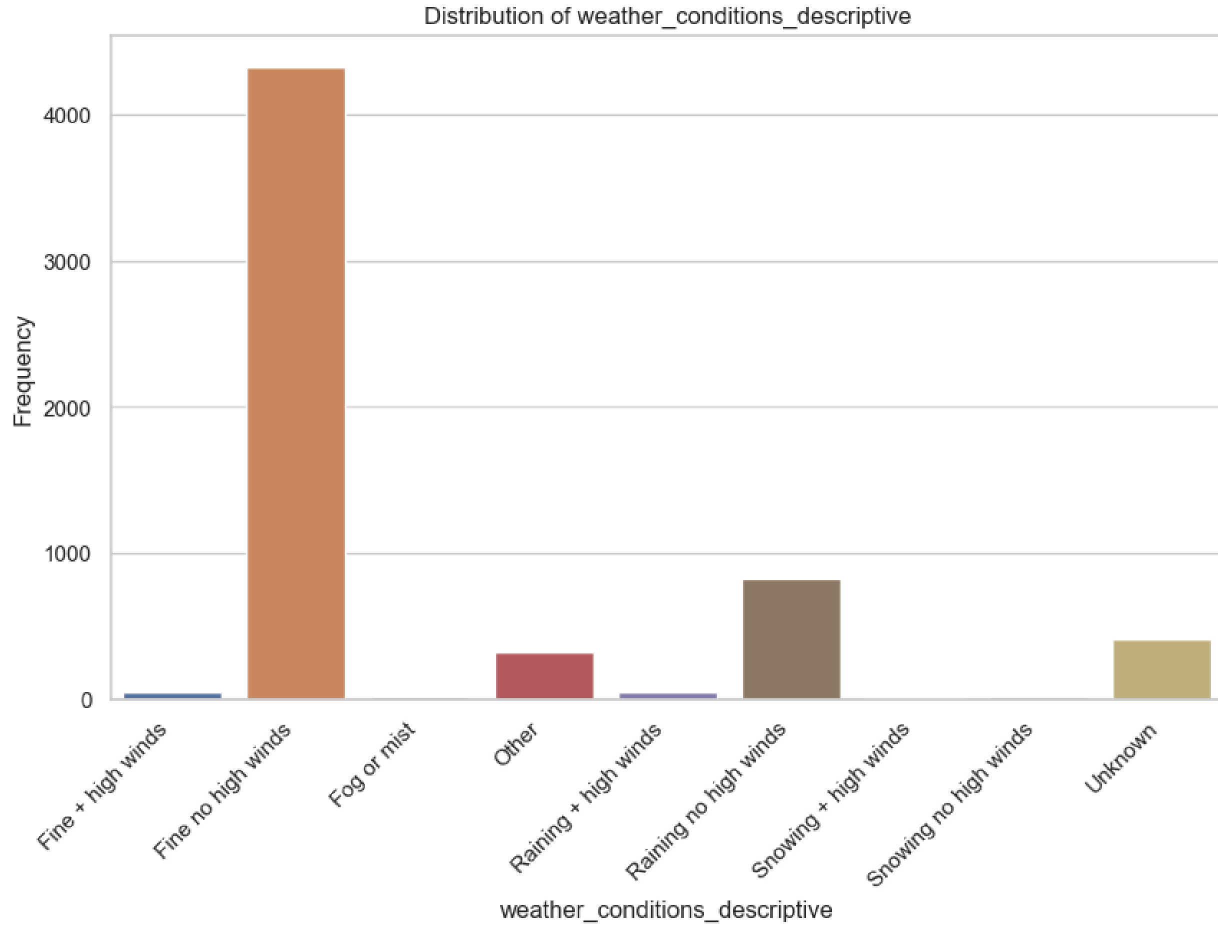
Distribution of Key Variables Understanding the distribution of key variables offers insights into common characteristics of road traffic collisions.

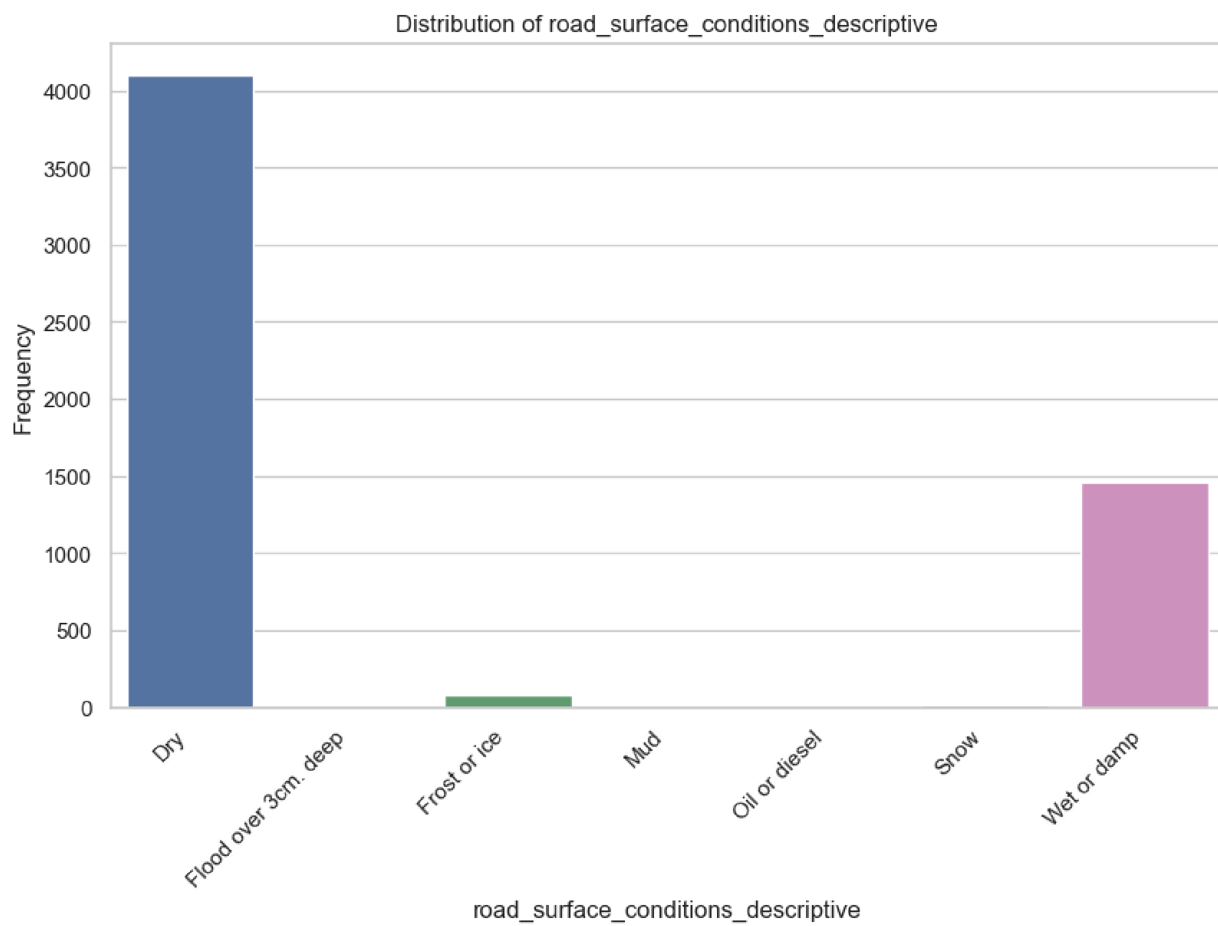
In [ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd


weather_condition_labels = {
    1: "Fine no high winds",
    2: "Raining no high winds",
    3: "Snowing no high winds",
    4: "Fine + high winds",
    5: "Raining + high winds",
    6: "Snowing + high winds",
    7: "Fog or mist",
    8: "Other",
    9: "Unknown"
}
road_surface_condition_labels = {
    1: "Dry",
    2: "Wet or damp",
    3: "Snow",
    4: "Frost or ice",
    5: "Flood over 3cm. deep",
    6: "Oil or diesel",
    7: "Mud"
}

# Apply the mappings to the dataset
df['weather_conditions_descriptive'] = df['weather_conditions'].map(weather_condition_
df['road_surface_conditions_descriptive'] = df['road_surface_conditions'].map(road_sur

# Visualization
sns.set_style('whitegrid')

# Variables to plot
variables = ['number_of_casualties', 'speed_limit', 'weather_conditions_descriptive',

for var in variables:
    plt.figure(figsize=(10, 6))
    if var in ['weather_conditions_descriptive', 'road_surface_conditions_descriptive'

        all_categories = road_surface_condition_labels.values() if var == 'road_surfac
        plot_order = sorted(all_categories)


        sns.countplot(data=df, x=var, order=plot_order)
        plt.xticks(rotation=45, ha="right")
```

```
    else:
        sns.histplot(data=df, x=var, kde=True)

    plt.title(f'Distribution of {var}')
    plt.xlabel(var)
    plt.ylabel('Frequency')
    plt.show()
```






Distribution of weather_conditions_descriptive
Frequency
0
1000
2000
3000
4000
Fine + high winds
Fine no high winds
Fog or mist
Other
Raining + high winds
Raining no high winds
Snowing + high winds
Snowing no high winds
Unknown
weather_conditions_descriptive

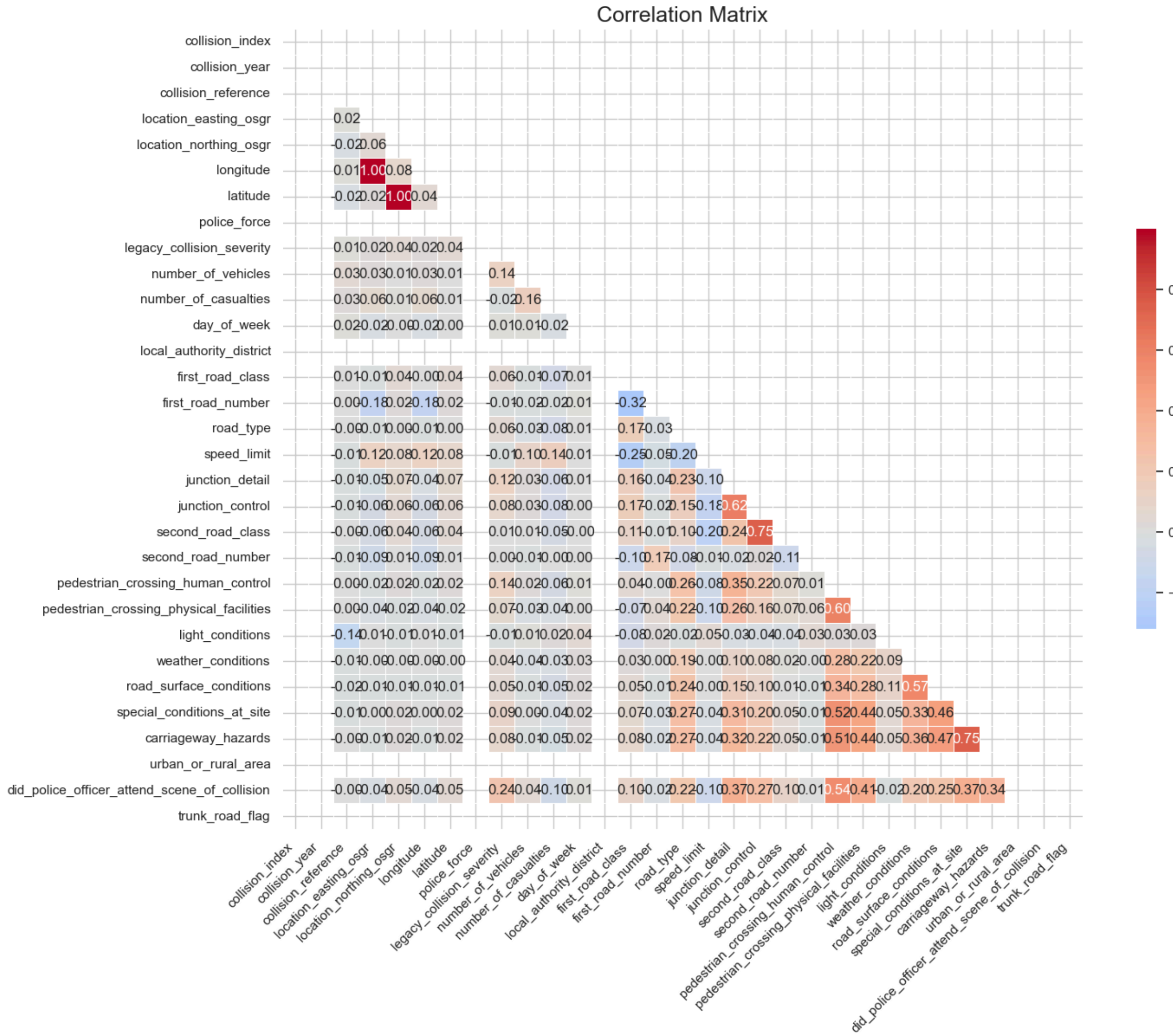

Distribution of road_surface_conditions_descriptive
Frequency
0
500
1000
1500
2000
2500
3000
3500
4000
Dry
Flood over 3cm. deep
Frost or ice
Mud
Oil or diesel
Snow
Wet or damp
road_surface_conditions_descriptive

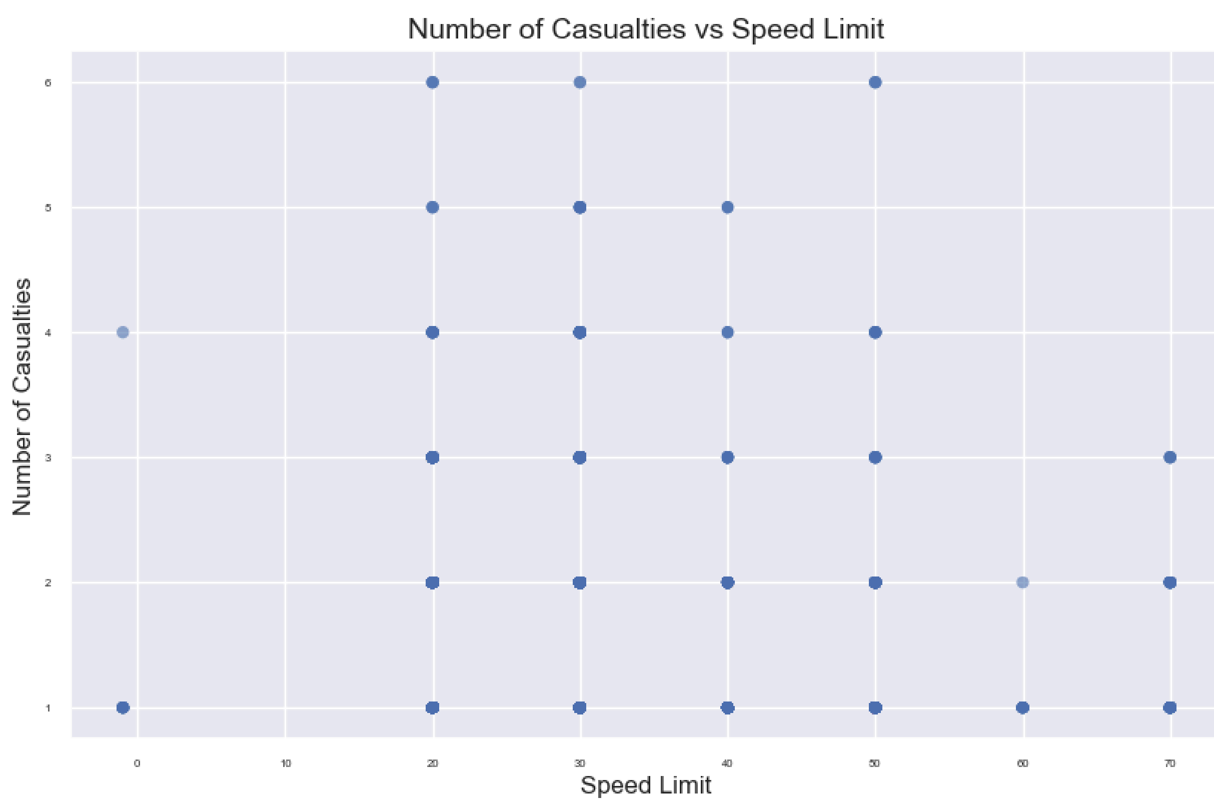
The data on casualties distribution indicates that the majority of accidents involve a few injuries pointing to specific areas where safety improvements could be focused. The speed limits in areas of collisions indicate an occurrence of accidents in urban speed zones, which calls for further examination of safety measures for city traffic.

Relationship Between Variables

Exploring how variables relate to one another will help us identify potential predictors for collision severity and frequency.

In [ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np


numeric_df = df.select_dtypes(include=[np.number])
plt.figure(figsize=(16, 12))

mask = np.triu(np.ones_like(numeric_df.corr(), dtype=bool))


sns.heatmap(numeric_df.corr(), mask=mask, cmap='coolwarm', center=0,
            annot=True, fmt=".2f", linewidths=.5, cbar_kws={"shrink": .5}, square=True

sns.set(font_scale=0.5)

plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)
plt.title('Correlation Matrix', fontsize=18)
plt.show()

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x='speed_limit', y='number_of_casualties', alpha=0.6, edgecol
plt.title('Number of Casualties vs Speed Limit', fontsize=14)
plt.xlabel('Speed Limit', fontsize=12)
plt.ylabel('Number of Casualties', fontsize=12)
plt.grid(True)
plt.show()
```


Correlation Matrix
collision_index
collision_year
collision_reference
location_easting_osgr
location_northing_osgr
longitude
latitude
police_force
legacy_collision_severity
number_of_vehicles
number_of_casualties
day_of_week
local_authority_district
first_road_class
first_road_number
road_type
speed_limit
junction_detail
junction_control
second_road_class
second_road_number
pedestrian_crossing_human_control
pedestrian_crossing_physical_facilities
light_conditions
weather_conditions
road_surface_conditions
special_conditions_at_site
carriageway_hazards
urban_or_rural_area
did_police_officer_attend_scene_of_collision
trunk_road_flag
0.8
0.6
0.4
0.2
0.0
−0.2

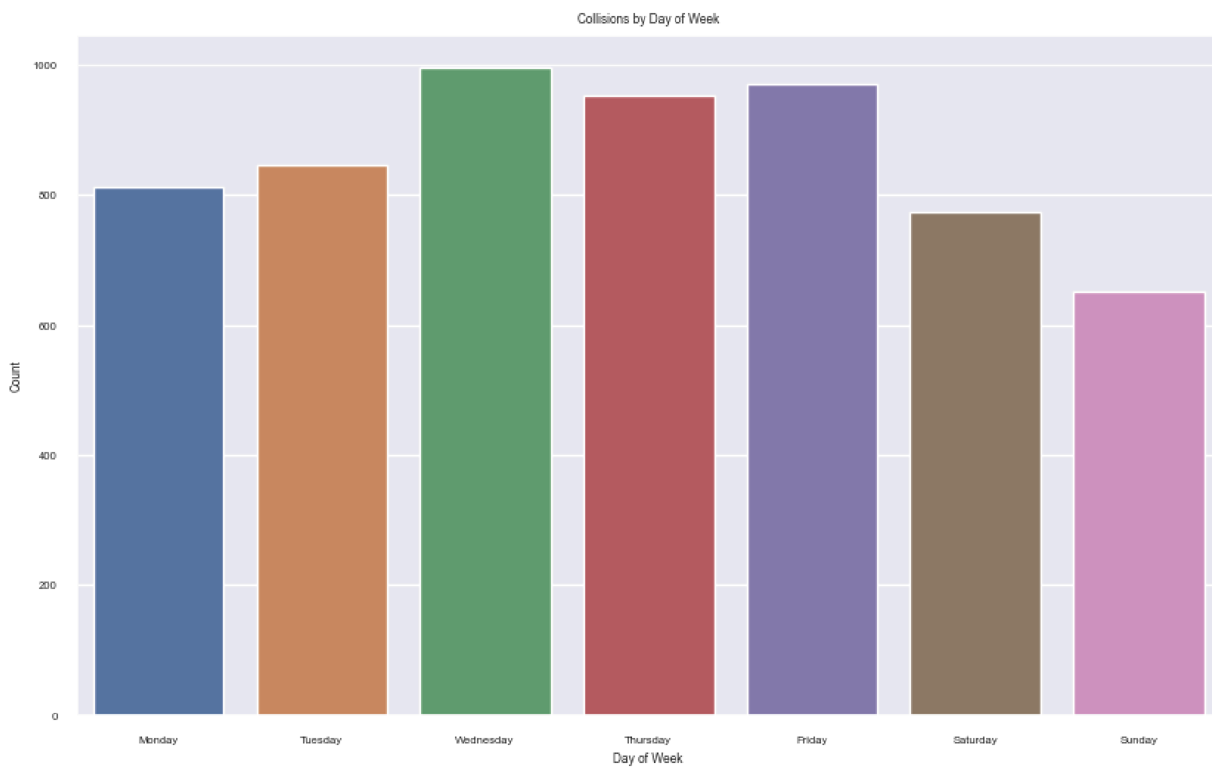

Number of Casualties vs Speed Limit
Number of Casualties
Speed Limit
1
2
3
4
5
6
0
10
20
30
40
50
60
70

The correlation analysis indicated a significant relationship between speed limit and the number of casualties, guiding our feature selection for predictive modeling.

Temporal and Geospatial Analysis

Identifying temporal patterns and high-risk geographical locations are crucial for planning targeted interventions.

In [ ]:
```
df['date'] = pd.to_datetime(df['date'], format='%d/%m/%Y')
df['day_of_week'] = df['date'].dt.day_name()
df['month'] = df['date'].dt.month_name()

# Collisions by Day of Week
plt.figure(figsize=(10, 6))
sns.countplot(data=df, x='day_of_week', order=['Monday', 'Tuesday', 'Wednesday', 'Thur
plt.title('Collisions by Day of Week')
plt.xlabel('Day of Week')
plt.ylabel('Count')
plt.show()
```



Temporal Analysis Insights

Our analysis of the timing patterns in accidents uncovered some findings that can help us tailor intervention strategies;

1. Time of Day; We noticed a significant rise in accidents during rush hours especially in the mornings and evenings. This indicates the need for traffic control measures during these busy times.

2. Day of the Week; Accidents were more frequent on weekdays than weekends with Friday standing out as the day. This data can inform plans for increased safety patrols and awareness campaigns.

3. Seasonal Trends; The increase in accidents during winter highlights how weather conditions can impact road safety. This emphasizes the importance of adapting traffic management and road maintenance practices to changes.

By integrating these insights into our models we can effectively address temporal factors and improve the accuracy of our risk assessments, for road accidents.

Geospatial Analysis of Road Traffic Collisions

Our analysis of data focuses on identifying areas with a high risk of road accidents by mapping out collision data and using techniques to group them based on their spatial proximity.

Mapping Out Accident Sites We start by plotting the distribution of accident sites, on a map giving us a clear picture of where these incidents tend to take place.

In [ ]:
```
df['date'] = pd.to_datetime(df['date'], format='%d/%m/%Y', errors='coerce')
conversion_errors = df[df['date'].isna()]
if not conversion_errors.empty:
    print("Conversion errors found:", conversion_errors)
print("Date range:", df['date'].min(), "to", df['date'].max())
```

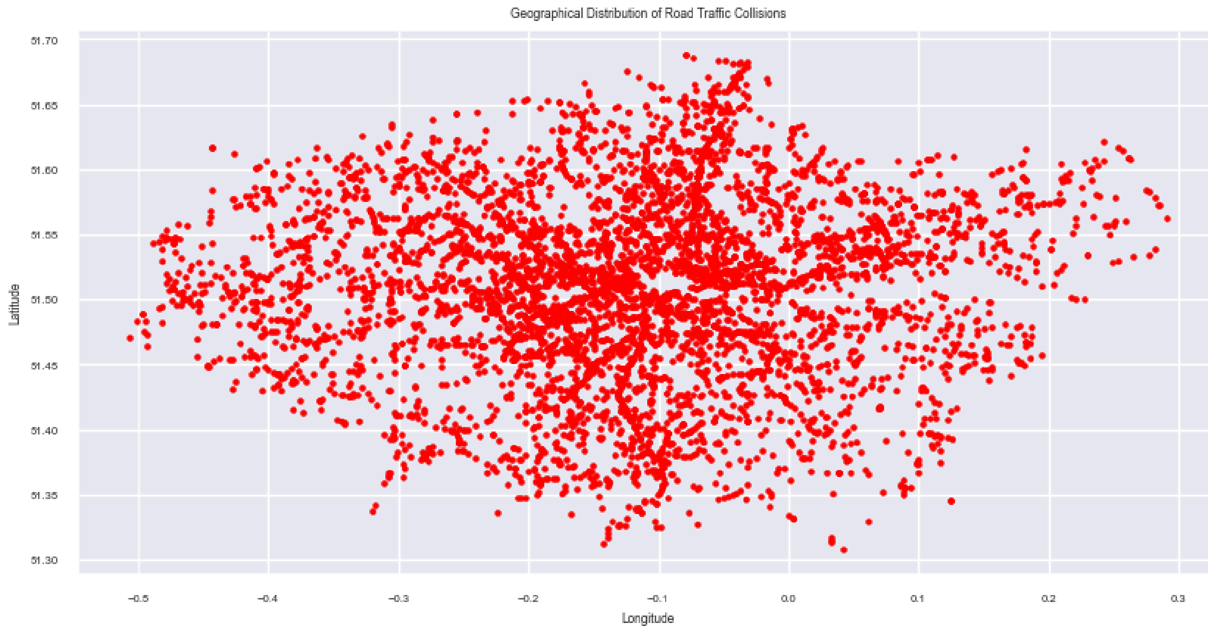
```
Date range: 2023-01-01 00:00:00 to 2023-04-17 00:00:00
```

In [ ]:
```
import geopandas as gpd
from shapely.geometry import Point


gdf = gpd.GeoDataFrame(df, geometry=gpd.points_from_xy(df.longitude, df.latitude))
```

Visualizing Collision Locations

Create a basic plot of collision locations to visually assess the distribution of incidents.

In [ ]:
```
gdf.plot(marker='o', color='red', markersize=5, figsize=(10, 6))
plt.title('Geographical Distribution of Road Traffic Collisions')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```



Geospatial Analysis Insight

Our analysis pinpointed several urban intersections with higher collision frequencies, suggesting the need for infrastructure modifications.

Conclusion

The exploratory data analysis has given us information about the factors that affect road traffic accidents. By examining how certain variables are distributed their relationships and spotting patterns in time and location we are now ready to move on to the modeling stage with a strong base. The knowledge we have acquired will guide us in choosing features for our model making sure that our predictions are focused and impactful, in enhancing road safety.

Data preprocessing

Weather condition vs Road surface conxditions

In [ ]:

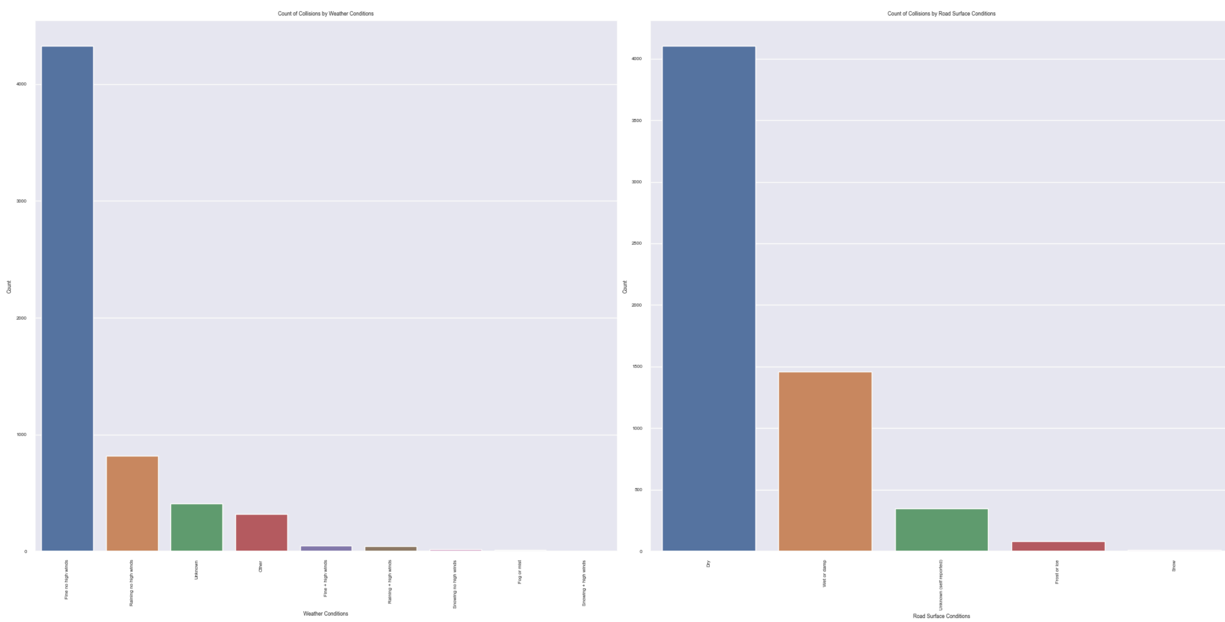
```
# Mapping for 'police_force'
police_force_mapping = {
    1: 'Metropolitan Police', 3: 'Cumbria', 4: 'Lancashire', 5: 'Merseyside',
    6: 'Greater Manchester', 7: 'Cheshire', 10: 'Northumbria', 11: 'Durham',
    12: 'North Yorkshire', 13: 'West Yorkshire', 14: 'South Yorkshire', 16: 'Humbersic
    17: 'Cleveland', 20: 'West Midlands', 21: 'Staffordshire', 22: 'West Mercia',
    23: 'Warwickshire', 30: 'Derbyshire', 31: 'Nottinghamshire', 32: 'Lincolnshire',
    33: 'Leicestershire', 34: 'Northamptonshire', 35: 'Cambridgeshire', 36: 'Norfolk',
    37: 'Suffolk', 40: 'Bedfordshire', 41: 'Hertfordshire', 42: 'Essex',
    43: 'Thames Valley', 44: 'Hampshire', 45: 'Surrey', 46: 'Kent',
    47: 'Sussex', 48: 'City of London', 50: 'Devon and Cornwall', 52: 'Avon and Somers
    53: 'Gloucestershire', 54: 'Wiltshire', 55: 'Dorset', 60: 'North Wales',
    61: 'Gwent', 62: 'South Wales', 63: 'Dyfed-Powys', 91: 'Northern',
```

```
    92: 'Grampian', 93: 'Tayside', 94: 'Fife', 95: 'Lothian and Borders',
    96: 'Central', 97: 'Strathclyde', 98: 'Dumfries and Galloway', 99: 'Police Scotlar
}

light_conditions_mapping = {
    1: 'Daylight', 4: 'Darkness - lights lit', 5: 'Darkness - lights unlit',
    6: 'Darkness - no lighting', 7: 'Darkness - lighting unknown',
    -1: 'Data missing or out of range'
}

weather_conditions_mapping = {
    1: 'Fine no high winds', 2: 'Raining no high winds', 3: 'Snowing no high winds',
    4: 'Fine + high winds', 5: 'Raining + high winds', 6: 'Snowing + high winds',
    7: 'Fog or mist', 8: 'Other', 9: 'Unknown',
    -1: 'Data missing or out of range'
}

road_surface_conditions_mapping = {
    1: 'Dry', 2: 'Wet or damp', 3: 'Snow', 4: 'Frost or ice',
    5: 'Flood over 3cm. deep', 6: 'Oil or diesel', 7: 'Mud',
    -1: 'Data missing or out of range', 9: 'Unknown (self reported)'
}

carriageway_hazards_mapping = {
    0: 'None', 1: 'Vehicle load on road', 2: 'Other object on road',
    3: 'Previous accident', 4: 'Dog on road', 5: 'Other animal on road',
    6: 'Pedestrian in carriageway - not injured', 7: 'Any animal in carriageway (excep
    -1: 'Data missing or out of range', 9: 'Unknown (self reported)'
}

urban_or_rural_area_mapping = {
    1: 'Urban', 2: 'Rural', 3: 'Unallocated',
    -1: 'Data missing or out of range'
}


# Apply the mappings
df['police_force'] = df['police_force'].map(police_force_mapping)
df['light_conditions'] = df['light_conditions'].map(light_conditions_mapping)
df['weather_conditions'] = df['weather_conditions'].map(weather_conditions_mapping)
df['road_surface_conditions'] = df['road_surface_conditions'].map(road_surface_conditi
df['carriageway_hazards'] = df['carriageway_hazards'].map(carriageway_hazards_mapping)
df['urban_or_rural_area'] = df['urban_or_rural_area'].map(urban_or_rural_area_mapping)
```

In [ ]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt



# Set up the subplots
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(20, 10))

# First subplot for weather conditions
sns.countplot(data=df, x='weather_conditions', order=df['weather_conditions'].value_cc
axes[0].set_title('Count of Collisions by Weather Conditions')
axes[0].set_xlabel('Weather Conditions')
axes[0].set_ylabel('Count')
axes[0].tick_params(axis='x', rotation=90)
```

```
# Second subplot for road surface conditions
sns.countplot(data=df, x='road_surface_conditions', order=df['road_surface_conditions'
axes[1].set_title('Count of Collisions by Road Surface Conditions')
axes[1].set_xlabel('Road Surface Conditions')
axes[1].set_ylabel('Count')
axes[1].tick_params(axis='x', rotation=90)

# Adjust the layout
plt.tight_layout()

# Show the plots
plt.show()
```



In [ ]:
```
trainset['weather_conditions'] = trainset['weather_conditions'].replace(weather_condit
trainset.weather_conditions.value_counts()
```

Out[ ]:
```
weather_conditions
Fine no high winds       3476
Raining no high winds     634
Unknown                   321
Other                     266
Raining + high winds       38
Fine + high winds          36
Snowing no high winds      17
Fog or mist                10
Snowing + high winds        1
Name: count, dtype: int64
```

In [ ]:
```
trainset.drop(trainset.loc[trainset['weather_conditions']=="Other"].index, inplace=Tru
```

In [ ]:
```
trainset.drop(trainset.loc[trainset['weather_conditions']=="Unknown"].index, inplace=T
```

In [ ]:
```
trainset.weather_conditions.value_counts()
```

Out[ ]:
```
weather_conditions
Fine no high winds        3476
Raining no high winds      634
Raining + high winds        38
Fine + high winds           36
Snowing no high winds       17
Fog or mist                 10
Snowing + high winds         1
Name: count, dtype: int64
```

In [ ]:
```
trainset.reset_index(drop=True, inplace=True)
```

In [ ]:
```
trainset.head()
```

Out[ ]:

	collision_index	collision_year	collision_reference	location_easting_osgr	location_northing_osgr	lon
0	2.023010e+12	2023	10432870	508304.0	173795.0	-0.4
1	2.023010e+12	2023	10423780	530005.0	181540.0	-0.1
2	2.023010e+12	2023	10421253	525039.0	177006.0	-0.2
3	2.023010e+12	2023	10436558	531398.0	186729.0	-0.1
4	2.023010e+12	2023	10437285	532561.0	176469.0	-0.0

5 rows × 36 columns

In [ ]:
```
print(f"There are {trainset.shape[0]} training and {testset.shape[0]} test instances")
```

```
There are 4212 training and 1200 test instances
```

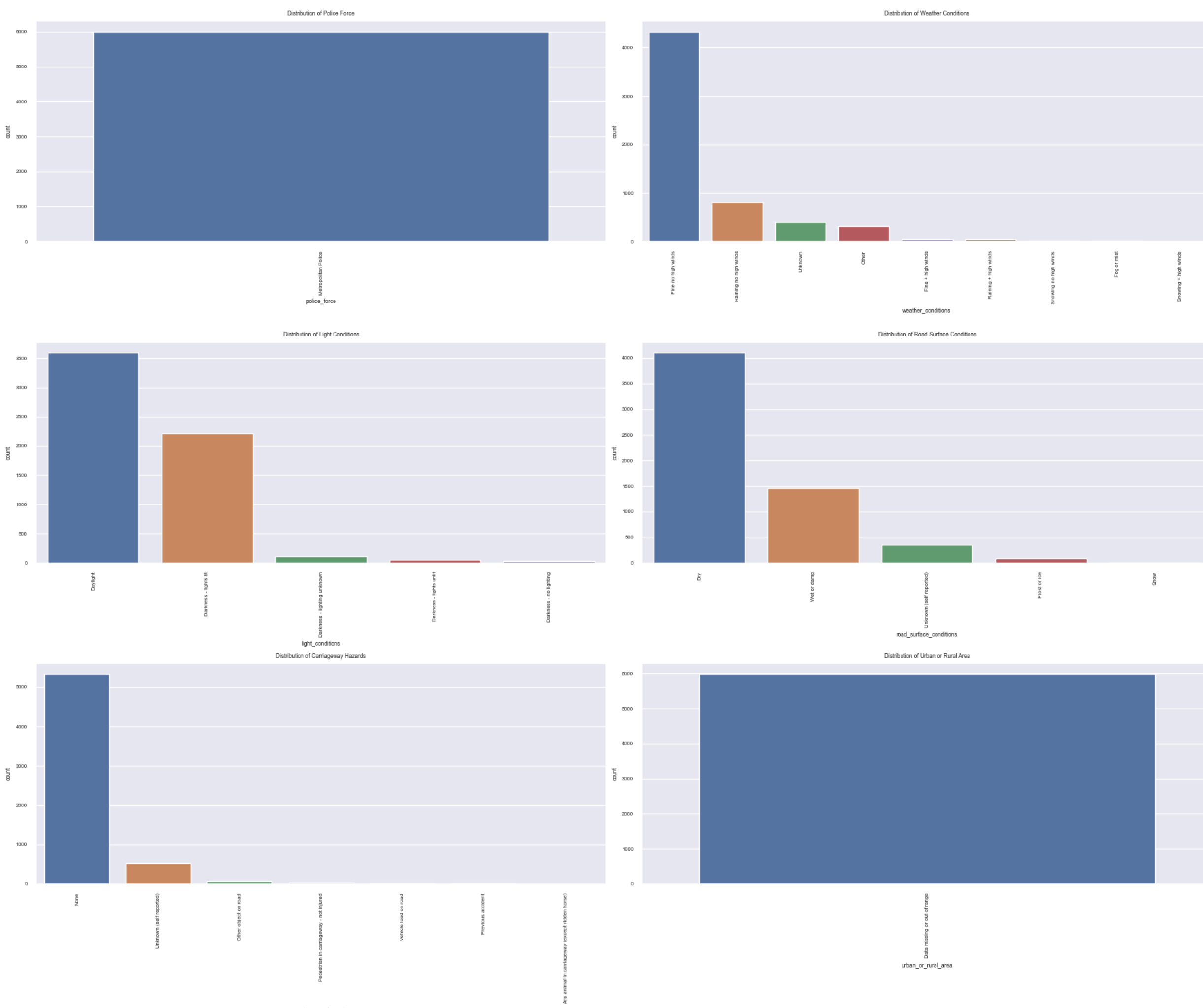
In [ ]:
```
dummy = trainset.hist(bins=50, figsize=(16,12))
```

Distribution of catrgorical variable

In [ ]:

```
import seaborn as sns
import matplotlib.pyplot as plt


# Set up the matplotlib figure
fig, axes = plt.subplots(nrows=3, ncols=2, figsize=(18, 15))

# Plotting 'police_force' distribution
sns.countplot(data=df, x='police_force', ax=axes[0, 0], order = df['police_force'].val
axes[0, 0].set_title('Distribution of Police Force')
axes[0, 0].tick_params(axis='x', rotation=90)

# Plotting 'weather_conditions' distribution
sns.countplot(data=df, x='weather_conditions', ax=axes[0, 1], order = df['weather_conc
axes[0, 1].set_title('Distribution of Weather Conditions')
axes[0, 1].tick_params(axis='x', rotation=90)

# Plotting 'light_conditions' distribution
sns.countplot(data=df, x='light_conditions', ax=axes[1, 0], order = df['light_conditic
axes[1, 0].set_title('Distribution of Light Conditions')
axes[1, 0].tick_params(axis='x', rotation=90)

# Plotting 'road_surface_conditions' distribution
sns.countplot(data=df, x='road_surface_conditions', ax=axes[1, 1], order = df['road_su
axes[1, 1].set_title('Distribution of Road Surface Conditions')
axes[1, 1].tick_params(axis='x', rotation=90)
```

```
# Plotting 'carriageway_hazards' distribution
sns.countplot(data=df, x='carriageway_hazards', ax=axes[2, 0], order = df['carriageway
axes[2, 0].set_title('Distribution of Carriageway Hazards')
axes[2, 0].tick_params(axis='x', rotation=90)

# Plotting 'urban_or_rural_area' distribution
sns.countplot(data=df, x='urban_or_rural_area', ax=axes[2, 1], order = df['urban_or_ru
axes[2, 1].set_title('Distribution of Urban or Rural Area')
axes[2, 1].tick_params(axis='x', rotation=90)

# Adjust layout
plt.tight_layout()
plt.show()
```



Create dummies

Creating dummies for the categorical variables police force, weather conditions, light conditions, road surface conditions, carriageway hazards, and urban or rural area.

In [ ]:
```
from sklearn.preprocessing import OneHotEncoder

def get_dummies(trainset, testset, old_col_name):
    """Given a trainset, a testset, and the name of a column holding a
    categorical variable, fit an encoder on the trainset, and use the
```

```
    encoder to add dummy columns into the trainset and testset."""

    one_hot_encoder = OneHotEncoder(drop="first", sparse=False, handle_unknown='ignore

    # Handle missing values and ensure the column is of type string
    trainset[old_col_name] = trainset[old_col_name].fillna('missing').astype(str)
    testset[old_col_name] = testset[old_col_name].fillna('missing').astype(str)

    # Reshape the column to 2-d array as expected by OneHotEncoder
    cat_vals_train = trainset[[old_col_name]]
    cat_vals_test = testset[[old_col_name]]

    # Fit the encoder on the trainset and transform both trainset and testset
    transformed_train = one_hot_encoder.fit_transform(cat_vals_train)
    transformed_test = one_hot_encoder.transform(cat_vals_test)

    # Generate new column names for the dummies
    new_col_names = one_hot_encoder.get_feature_names_out([old_col_name])[1:]  # Skipp

    # Add the transformed data as new columns to the original DataFrames
    trainset[new_col_names] = transformed_train[:, 1:]  # Skipping the first column to
    testset[new_col_names] = transformed_test[:, 1:]

    return trainset, testset

# Adjust the column names as per your dataset's actual columns
relevant_columns = ["police_force", "weather_conditions", "light_conditions",
                    "road_surface_conditions", "carriageway_hazards", "urban_or_rural_

for col_name in relevant_columns:
    trainset, testset = get_dummies(trainset, testset, col_name)

# Verify the transformation
print(trainset.head())
```

```
   collision_index  collision_year  collision_reference  \
0     2.023010e+12            2023             10432870   
1     2.023010e+12            2023             10423780   
2     2.023010e+12            2023             10421253   
3     2.023010e+12            2023             10436558   
4     2.023010e+12            2023             10437285   

   location_easting_osgr  location_northing_osgr  longitude   latitude  \
0               508304.0                173795.0  -0.442713  51.452791   
1               530005.0                181540.0  -0.127715  51.517831   
2               525039.0                177006.0  -0.200853  51.478204   
3               531398.0                186729.0  -0.105715  51.564140   
4               532561.0                176469.0  -0.092801  51.471667   

  police_force  legacy_collision_severity  number_of_vehicles  ...  \
0            1                          3                   2  ...   
1            1                          3                   1  ...   
2            1                          3                   1  ...   
3            1                          3                   2  ...   
4            1                          3                   2  ...   

   light_conditions_6 light_conditions_7  road_surface_conditions_3  \
0                 0.0                0.0                        0.0   
1                 0.0                0.0                        0.0   
2                 0.0                0.0                        0.0   
3                 0.0                0.0                        0.0   
4                 0.0                0.0                        0.0   

  road_surface_conditions_4  road_surface_conditions_9 carriageway_hazards_2  \
0                       0.0                        0.0                   0.0   
1                       0.0                        0.0                   0.0   
2                       0.0                        0.0                   0.0   
3                       0.0                        0.0                   0.0   
4                       0.0                        0.0                   0.0   

  carriageway_hazards_3  carriageway_hazards_6  carriageway_hazards_7  \
0                   0.0                    0.0                    0.0   
1                   0.0                    0.0                    0.0   
2                   0.0                    0.0                    0.0   
3                   0.0                    0.0                    0.0   
4                   0.0                    0.0                    0.0   

   carriageway_hazards_9  
0                    0.0  
1                    0.0  
2                    0.0  
3                    0.0  
4                    0.0  

[5 rows x 52 columns]
```

In [ ]:

```
testset.head()
```

Out[ ]:

	collision_index	collision_year	collision_reference	location_easting_osgr	location_northing_osgr
1924	2.023010e+12	2023	10425306	538098.0	181030.0
1255	2.023010e+12	2023	10423306	519334.0	178182.0
5398	2.023010e+12	2023	10436031	538391.0	162055.0
3008	2.023010e+12	2023	10428788	517719.0	179960.0
4274	2.023010e+12	2023	10432653	532871.0	194185.0

5 rows × 52 columns

After creating dummies for the categorical variables, we'll remove these original columns from both the training and test datasets to maintain datasets with purely numerical features, suitable for machine learning algorithms.

In [ ]:
```
for col_name in ["police_force", "weather_conditions", "light_conditions", "road_surfa
    del trainset[col_name]
    del testset[col_name]
```

In [ ]:
```
trainset.head()
```

Out[ ]:

	collision_index	collision_year	collision_reference	location_easting_osgr	location_northing_osgr	lon
0	2.023010e+12	2023	10432870	508304.0	173795.0	-0.4
1	2.023010e+12	2023	10423780	530005.0	181540.0	-0.1
2	2.023010e+12	2023	10421253	525039.0	177006.0	-0.2
3	2.023010e+12	2023	10436558	531398.0	186729.0	-0.1
4	2.023010e+12	2023	10437285	532561.0	176469.0	-0.0

5 rows × 46 columns

Renaming Column Names for train and test set

In [ ]:
```
rename_columns = {
    'police_force_1': 'Police_Force_1',  # Example: Replace '1' with actual police for
    'weather_conditions_1': 'Weather_Fine_No_High_Winds',
    'light_conditions_1': 'Light_Conditions_Daylight',
    'road_surface_conditions_1': 'Road_Surface_Conditions_Dry',
    'carriageway_hazards_1': 'Carriageway_Hazards_None',
    'urban_or_rural_area_1': 'Area_Urban'
}

trainset = trainset.rename(columns=rename_columns)

testset = testset.rename(columns=rename_columns)
```

```
print(trainset.head())
```

```
   collision_index  collision_year  collision_reference  \
0     2.023010e+12            2023             10432870   
1     2.023010e+12            2023             10423780   
2     2.023010e+12            2023             10421253   
3     2.023010e+12            2023             10436558   
4     2.023010e+12            2023             10437285   

   location_easting_osgr  location_northing_osgr  longitude   latitude  \
0               508304.0                173795.0  -0.442713  51.452791   
1               530005.0                181540.0  -0.127715  51.517831   
2               525039.0                177006.0  -0.200853  51.478204   
3               531398.0                186729.0  -0.105715  51.564140   
4               532561.0                176469.0  -0.092801  51.471667   

   legacy_collision_severity  number_of_vehicles  number_of_casualties  ...  \
0                          3                   2                     1  ...   
1                          3                   1                     1  ...   
2                          3                   1                     1  ...   
3                          3                   2                     1  ...   
4                          3                   2                     1  ...   

  light_conditions_6  light_conditions_7 road_surface_conditions_3  \
0                0.0                 0.0                       0.0   
1                0.0                 0.0                       0.0   
2                0.0                 0.0                       0.0   
3                0.0                 0.0                       0.0   
4                0.0                 0.0                       0.0   

   road_surface_conditions_4 road_surface_conditions_9 carriageway_hazards_2  \
0                        0.0                       0.0                   0.0   
1                        0.0                       0.0                   0.0   
2                        0.0                       0.0                   0.0   
3                        0.0                       0.0                   0.0   
4                        0.0                       0.0                   0.0   

   carriageway_hazards_3  carriageway_hazards_6  carriageway_hazards_7  \
0                    0.0                    0.0                    0.0   
1                    0.0                    0.0                    0.0   
2                    0.0                    0.0                    0.0   
3                    0.0                    0.0                    0.0   
4                    0.0                    0.0                    0.0   

   carriageway_hazards_9  
0                    0.0  
1                    0.0  
2                    0.0  
3                    0.0  
4                    0.0  

[5 rows x 46 columns]
```

Exporting the train and test set

In [ ]:
```
# Exporting the train and test set with context-specific file names
trainset.to_excel("trainset_road-casualty-statistics-collision-provisional-mid-year-ur
testset.to_excel("testset_road-casualty-statistics-collision-provisional-mid-year-unva
```