Machine Learning Group Assignment

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E-Portfolio on the UK Road Safety Dataset: Group Assignment

Candidate Numbers: 141715, 835522, 750476, 788719

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1 Importing Libraries and Preparing Environment

[2]:
```
#Base Libraries
import numpy as np
import pandas as pd
import warnings
```

```python
from scipy import stats
from timeit import default_timer as timer
from datetime import timedelta

#Library for Plotting
import seaborn as sns
import matplotlib.pyplot as plt

#Library for Data Preprocessing and Cleaning
from sklearn.exceptions import ConvergenceWarning
from sklearn.model_selection import train_test_split, StratifiedShuffleSplit
from sklearn.base import TransformerMixin, BaseEstimator
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer, SimpleImputer
from sklearn.preprocessing import OneHotEncoder
from sklearn.ensemble import IsolationForest

#Prevent warnings of the code from showing
warnings.filterwarnings(action = 'ignore')
```

2 Context and Project Objective

In 2023, approximately 23,000 road collisions occurred across London boroughs; while most caused only minor injuries, around 3,500 involved burns or fractures, and 101 resulted in at least one fatality (Trust For London, 2025). Four datasets from the Department for Transport were merged, cleaned, and split into training and testing sets. Irrelevant variables were removed, and the data underwent imputation, log transformation, and outlier detection.

This project aims to build a machine learning model to predict the severity of traffic accidents using variables related to driver behavior, vehicle type, and environmental conditions. The model will support Lambeth, Wandsworth, Croydon, Westminster & Southwark boroughs to enhance road safety through targeted interventions and awareness campaigns.

3 Data Preparation

3.1 Loading Data

[7]:
```python
#Load in the datasets
vehicle_data = pd.read_csv('dft-road-casualty-statistics-vehicle-2023.csv')
casualty_data = pd.read_csv('dft-road-casualty-statistics-casualty-2023.csv')
collision_data = pd.read_csv('dft-road-casualty-statistics-collision-2023.csv')
guide_data = pd.
 ↪read_excel('dft-road-casualty-statistics-road-safety-open-dataset-data-guide-2024.
 ↪xlsx')
```

[8]:
```python
#Verify the data is loaded in correctly
vehicle_data.head()
```

[8]:

```
   accident_index  accident_year accident_reference  vehicle_reference  \
0  2023010419171           2023           10419171                  1
1  2023010419183           2023           10419183                  1
2  2023010419183           2023           10419183                  2
3  2023010419183           2023           10419183                  3
4  2023010419189           2023           10419189                  1

   vehicle_type  towing_and_articulation  vehicle_manoeuvre  \
0            11                        0                  4
1            11                        0                 18
2             9                        0                  9
3             9                        0                  8
4             9                        0                 18

   vehicle_direction_from  vehicle_direction_to  \
0                       1                     5
1                       5                     1
2                       1                     6
3                       7                     1
4                       7                     3

   vehicle_location_restricted_lane  …             generic_make_model  \
0                                 0  …  ALEXANDER DENNIS MODEL MISSING
1                                 0  …                WRIGHTBUS GEMINI
2                                 0  …                    TOYOTA YARIS
3                                 0  …                    BMW 2 SERIES
4                                 0  …                    LEXUS RX 400

   driver_imd_decile  driver_home_area_type  lsoa_of_driver  escooter_flag  \
0                  3                      1       E01001177              0
1                  6                      1       E01001419              0
2                  3                      1       E01001546              0
3                  4                      1       E01001686              0
4                  5                      1       E01002443              0

   dir_from_e  dir_from_n  dir_to_e  dir_to_n  driver_distance_banding
0         NaN         NaN       NaN       NaN                        2
1         NaN         NaN       NaN       NaN                        2
2         NaN         NaN       NaN       NaN                        1
3         NaN         NaN       NaN       NaN                        4
4         NaN         NaN       NaN       NaN                        1

[5 rows x 34 columns]
```

[9]:

```
#Verify the total number of samples and features of the data
vehicle_data.shape
```

[9]: (189815, 34)

[10]:
```
#Check the information of the dataset
vehicle_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 189815 entries, 0 to 189814
Data columns (total 34 columns):
 #   Column                            Non-Null Count   Dtype
---  ------                            --------------   -----
 0   accident_index                    189815 non-null  object
 1   accident_year                     189815 non-null  int64
 2   accident_reference                189815 non-null  object
 3   vehicle_reference                 189815 non-null  int64
 4   vehicle_type                      189815 non-null  int64
 5   towing_and_articulation           189815 non-null  int64
 6   vehicle_manoeuvre                 189815 non-null  int64
 7   vehicle_direction_from            189815 non-null  int64
 8   vehicle_direction_to              189815 non-null  int64
 9   vehicle_location_restricted_lane  189815 non-null  int64
 10  junction_location                 189815 non-null  int64
 11  skidding_and_overturning          189815 non-null  int64
 12  hit_object_in_carriageway         189815 non-null  int64
 13  vehicle_leaving_carriageway       189815 non-null  int64
 14  hit_object_off_carriageway        189815 non-null  int64
 15  first_point_of_impact             189815 non-null  int64
 16  vehicle_left_hand_drive           189815 non-null  int64
 17  journey_purpose_of_driver         189815 non-null  int64
 18  sex_of_driver                     189815 non-null  int64
 19  age_of_driver                     189815 non-null  int64
 20  age_band_of_driver                189815 non-null  int64
 21  engine_capacity_cc                189815 non-null  int64
 22  propulsion_code                   189815 non-null  int64
 23  age_of_vehicle                    189815 non-null  int64
 24  generic_make_model                189815 non-null  object
 25  driver_imd_decile                 189815 non-null  int64
 26  driver_home_area_type             189815 non-null  int64
 27  lsoa_of_driver                    189815 non-null  object
 28  escooter_flag                     189815 non-null  int64
 29  dir_from_e                        19527 non-null   float64
 30  dir_from_n                        19527 non-null   float64
 31  dir_to_e                          19363 non-null   float64
 32  dir_to_n                          19363 non-null   float64
 33  driver_distance_banding           189815 non-null  int64
dtypes: float64(4), int64(26), object(4)
memory usage: 49.2+ MB
```

[11]:
```
#Verify the data is loaded in correctly
casualty_data.head()
```

[11]:
```
   accident_index  accident_year accident_reference  vehicle_reference  \
0  2023010419171           2023           10419171                  1
1  2023010419183           2023           10419183                  2
2  2023010419183           2023           10419183                  3
3  2023010419189           2023           10419189                  1
4  2023010419191           2023           10419191                  2

   casualty_reference  casualty_class  sex_of_casualty  age_of_casualty  \
0                   1               3                2               20
1                   1               1                1               25
2                   2               2                2               38
3                   1               1                1               50
4                   1               1                1               34

   age_band_of_casualty  casualty_severity  …  pedestrian_movement  \
0                     4                  3  …                    1
1                     5                  3  …                    0
2                     7                  3  …                    0
3                     8                  3  …                    0
4                     6                  3  …                    0

   car_passenger  bus_or_coach_passenger  pedestrian_road_maintenance_worker  \
0              0                       0                                   0
1              0                       0                                   0
2              2                       0                                   0
3              0                       0                                   0
4              0                       0                                   0

   casualty_type  casualty_home_area_type  casualty_imd_decile  \
0              0                        1                   10
1              9                        1                    3
2              9                       -1                   -1
3              9                        1                    5
4              1                        1                    2

   lsoa_of_casualty enhanced_casualty_severity  casualty_distance_banding
0         E01030370                         -1                          3
1         E01001546                         -1                          1
2                -1                         -1                         -1
3         E01002443                         -1                          1
4         E01004679                         -1                          2

[5 rows x 21 columns]
```

[12]:
```python
#Verify the total number of samples and features of the data
casualty_data.shape
```

[12]: (132977, 21)

[13]:
```python
#Check the information of the dataset
casualty_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 132977 entries, 0 to 132976
Data columns (total 21 columns):
 #   Column                            Non-Null Count   Dtype
---  ------                            --------------   -----
 0   accident_index                    132977 non-null  object
 1   accident_year                     132977 non-null  int64
 2   accident_reference                132977 non-null  object
 3   vehicle_reference                 132977 non-null  int64
 4   casualty_reference                132977 non-null  int64
 5   casualty_class                    132977 non-null  int64
 6   sex_of_casualty                   132977 non-null  int64
 7   age_of_casualty                   132977 non-null  int64
 8   age_band_of_casualty              132977 non-null  int64
 9   casualty_severity                 132977 non-null  int64
 10  pedestrian_location               132977 non-null  int64
 11  pedestrian_movement               132977 non-null  int64
 12  car_passenger                     132977 non-null  int64
 13  bus_or_coach_passenger            132977 non-null  int64
 14  pedestrian_road_maintenance_worker 132977 non-null  int64
 15  casualty_type                     132977 non-null  int64
 16  casualty_home_area_type           132977 non-null  int64
 17  casualty_imd_decile               132977 non-null  int64
 18  lsoa_of_casualty                  132977 non-null  object
 19  enhanced_casualty_severity        132977 non-null  int64
 20  casualty_distance_banding         132977 non-null  int64
dtypes: int64(18), object(3)
memory usage: 21.3+ MB
```

[14]:
```python
#Verify the data is loaded in correctly
collision_data.head()
```

[14]:
```
  accident_index  accident_year accident_reference  location_easting_osgr  \
0  2023010419171           2023           10419171               525060.0
1  2023010419183           2023           10419183               535463.0
2  2023010419189           2023           10419189               508702.0
3  2023010419191           2023           10419191               520341.0
4  2023010419192           2023           10419192               527255.0

   location_northing_osgr  longitude   latitude  police_force  \
```

```
0              170416.0  -0.202878  51.418974             1
1              198745.0  -0.042464  51.671155             1
2              177696.0  -0.435789  51.487777             1
3              190175.0  -0.263972  51.597575             1
4              176963.0  -0.168976  51.477324             1

   accident_severity  number_of_vehicles  …  light_conditions  \
0                  3                   1  …                 4
1                  3                   3  …                 4
2                  3                   2  …                 4
3                  3                   2  …                 4
4                  3                   2  …                 4

  weather_conditions  road_surface_conditions special_conditions_at_site  \
0                  8                        2                          0
1                  1                        1                          0
2                  1                        1                          0
3                  9                        1                          0
4                  1                        1                          0

   carriageway_hazards urban_or_rural_area  \
0                    0                   1
1                    0                   1
2                    0                   1
3                    0                   1
4                    0                   1

  did_police_officer_attend_scene_of_accident  trunk_road_flag  \
0                                           1                2
1                                           1                2
2                                           1                2
3                                           1                2
4                                           1                2

   lsoa_of_accident_location  enhanced_severity_collision
0                  E01003383                           -1
1                  E01001547                           -1
2                  E01002448                           -1
3                  E01000129                           -1
4                  E01004583                           -1

[5 rows x 37 columns]
```

[15]:
```
#Verify the total number of samples and features of the data
collision_data.shape
```

[15]:
```
(104258, 37)
```

[16]:
```
#Check the information of the dataset
collision_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 104258 entries, 0 to 104257
Data columns (total 37 columns):
 #   Column                                       Non-Null Count   Dtype
---  ------                                       --------------   -----
 0   accident_index                               104258 non-null  object
 1   accident_year                                104258 non-null  int64
 2   accident_reference                           104258 non-null  object
 3   location_easting_osgr                        104246 non-null  float64
 4   location_northing_osgr                       104246 non-null  float64
 5   longitude                                    104246 non-null  float64
 6   latitude                                     104246 non-null  float64
 7   police_force                                 104258 non-null  int64
 8   accident_severity                            104258 non-null  int64
 9   number_of_vehicles                           104258 non-null  int64
 10  number_of_casualties                         104258 non-null  int64
 11  date                                         104258 non-null  object
 12  day_of_week                                  104258 non-null  int64
 13  time                                         104258 non-null  object
 14  local_authority_district                     104258 non-null  int64
 15  local_authority_ons_district                 104258 non-null  object
 16  local_authority_highway                      104258 non-null  object
 17  first_road_class                             104258 non-null  int64
 18  first_road_number                            104258 non-null  int64
 19  road_type                                    104258 non-null  int64
 20  speed_limit                                  104258 non-null  int64
 21  junction_detail                              104258 non-null  int64
 22  junction_control                             104258 non-null  int64
 23  second_road_class                            104258 non-null  int64
 24  second_road_number                           104258 non-null  int64
 25  pedestrian_crossing_human_control            104258 non-null  int64
 26  pedestrian_crossing_physical_facilities      104258 non-null  int64
 27  light_conditions                             104258 non-null  int64
 28  weather_conditions                           104258 non-null  int64
 29  road_surface_conditions                      104258 non-null  int64
 30  special_conditions_at_site                   104258 non-null  int64
 31  carriageway_hazards                          104258 non-null  int64
 32  urban_or_rural_area                          104258 non-null  int64
 33  did_police_officer_attend_scene_of_accident  104258 non-null  int64
 34  trunk_road_flag                              104258 non-null  int64
 35  lsoa_of_accident_location                    104258 non-null  object
 36  enhanced_severity_collision                  104258 non-null  int64
dtypes: float64(4), int64(26), object(7)
memory usage: 29.4+ MB
```

3.2 Merging the Three Datasets

[18]:
```
#The three datasets were merged using accident_index, with the unique value for␣
↪each accident acting as the key.
#Merge the Casualty and the Vehicle dataset first
accident_1 = pd.merge(casualty_data, vehicle_data, on = 'accident_index',␣
↪how='inner')

#Merge the result with the Collision dataset:
accident = pd.merge(accident_1, collision_data, on = 'accident_index',␣
↪how='inner')
accident.head()
```

[18]:
```
   accident_index  accident_year_x accident_reference_x  vehicle_reference_x  \
0  2023010419171             2023             10419171                    1
1  2023010419183             2023             10419183                    2
2  2023010419183             2023             10419183                    2
3  2023010419183             2023             10419183                    2
4  2023010419183             2023             10419183                    3

   casualty_reference  casualty_class  sex_of_casualty  age_of_casualty  \
0                   1               3                2               20
1                   1               1                1               25
2                   1               1                1               25
3                   1               1                1               25
4                   2               2                2               38

   age_band_of_casualty  casualty_severity  …  light_conditions  \
0                     4                  3  …                 4
1                     5                  3  …                 4
2                     5                  3  …                 4
3                     5                  3  …                 4
4                     7                  3  …                 4

   weather_conditions  road_surface_conditions  special_conditions_at_site  \
0                   8                        2                           0
1                   1                        1                           0
2                   1                        1                           0
3                   1                        1                           0
4                   1                        1                           0

   carriageway_hazards  urban_or_rural_area  \
0                    0                    1
1                    0                    1
2                    0                    1
3                    0                    1
4                    0                    1
```

```
   did_police_officer_attend_scene_of_accident  trunk_road_flag  \
0                                            1                2
1                                            1                2
2                                            1                2
3                                            1                2
4                                            1                2

  lsoa_of_accident_location  enhanced_severity_collision
0                 E01003383                           -1
1                 E01001547                           -1
2                 E01001547                           -1
3                 E01001547                           -1
4                 E01001547                           -1

[5 rows x 90 columns]
```

[19]:

```
#Check the information of the new merged dataset
accident.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 161607 entries, 0 to 161606
Data columns (total 90 columns):
 #   Column                                      Non-Null Count   Dtype
---  ------                                      --------------   -----
 0   accident_index                              161607 non-null  object
 1   accident_year_x                             161607 non-null  int64
 2   accident_reference_x                        161607 non-null  object
 3   vehicle_reference_x                         161607 non-null  int64
 4   casualty_reference                          161607 non-null  int64
 5   casualty_class                              161607 non-null  int64
 6   sex_of_casualty                             161607 non-null  int64
 7   age_of_casualty                             161607 non-null  int64
 8   age_band_of_casualty                        161607 non-null  int64
 9   casualty_severity                           161607 non-null  int64
 10  pedestrian_location                         161607 non-null  int64
 11  pedestrian_movement                         161607 non-null  int64
 12  car_passenger                               161607 non-null  int64
 13  bus_or_coach_passenger                      161607 non-null  int64
 14  pedestrian_road_maintenance_worker          161607 non-null  int64
 15  casualty_type                               161607 non-null  int64
 16  casualty_home_area_type                     161607 non-null  int64
 17  casualty_imd_decile                         161607 non-null  int64
 18  lsoa_of_casualty                            161607 non-null  object
 19  enhanced_casualty_severity                  161607 non-null  int64
 20  casualty_distance_banding                   161607 non-null  int64
 21  accident_year_y                             161607 non-null  int64
 22  accident_reference_y                        161607 non-null  object
```

```
23  vehicle_reference_y                   161607 non-null  int64
24  vehicle_type                          161607 non-null  int64
25  towing_and_articulation               161607 non-null  int64
26  vehicle_manoeuvre                     161607 non-null  int64
27  vehicle_direction_from                161607 non-null  int64
28  vehicle_direction_to                  161607 non-null  int64
29  vehicle_location_restricted_lane      161607 non-null  int64
30  junction_location                     161607 non-null  int64
31  skidding_and_overturning              161607 non-null  int64
32  hit_object_in_carriageway             161607 non-null  int64
33  vehicle_leaving_carriageway           161607 non-null  int64
34  hit_object_off_carriageway            161607 non-null  int64
35  first_point_of_impact                 161607 non-null  int64
36  vehicle_left_hand_drive               161607 non-null  int64
37  journey_purpose_of_driver             161607 non-null  int64
38  sex_of_driver                         161607 non-null  int64
39  age_of_driver                         161607 non-null  int64
40  age_band_of_driver                    161607 non-null  int64
41  engine_capacity_cc                    161607 non-null  int64
42  propulsion_code                       161607 non-null  int64
43  age_of_vehicle                        161607 non-null  int64
44  generic_make_model                    161607 non-null  object
45  driver_imd_decile                     161607 non-null  int64
46  driver_home_area_type                 161607 non-null  int64
47  lsoa_of_driver                        161607 non-null  object
48  escooter_flag                         161607 non-null  int64
49  dir_from_e                            12355 non-null   float64
50  dir_from_n                            12355 non-null   float64
51  dir_to_e                              12236 non-null   float64
52  dir_to_n                              12236 non-null   float64
53  driver_distance_banding               161607 non-null  int64
54  accident_year                         161607 non-null  int64
55  accident_reference                    161607 non-null  object
56  location_easting_osgr                 161591 non-null  float64
57  location_northing_osgr                161591 non-null  float64
58  longitude                             161591 non-null  float64
59  latitude                              161591 non-null  float64
60  police_force                          161607 non-null  int64
61  accident_severity                     161607 non-null  int64
62  number_of_vehicles                    161607 non-null  int64
63  number_of_casualties                  161607 non-null  int64
64  date                                  161607 non-null  object
65  day_of_week                           161607 non-null  int64
66  time                                  161607 non-null  object
67  local_authority_district              161607 non-null  int64
68  local_authority_ons_district          161607 non-null  object
69  local_authority_highway               161607 non-null  object
70  first_road_class                      161607 non-null  int64
```

```
 71  first_road_number                           161607 non-null  int64
 72  road_type                                   161607 non-null  int64
 73  speed_limit                                 161607 non-null  int64
 74  junction_detail                             161607 non-null  int64
 75  junction_control                            161607 non-null  int64
 76  second_road_class                           161607 non-null  int64
 77  second_road_number                          161607 non-null  int64
 78  pedestrian_crossing_human_control           161607 non-null  int64
 79  pedestrian_crossing_physical_facilities     161607 non-null  int64
 80  light_conditions                            161607 non-null  int64
 81  weather_conditions                          161607 non-null  int64
 82  road_surface_conditions                     161607 non-null  int64
 83  special_conditions_at_site                  161607 non-null  int64
 84  carriageway_hazards                         161607 non-null  int64
 85  urban_or_rural_area                         161607 non-null  int64
 86  did_police_officer_attend_scene_of_accident 161607 non-null  int64
 87  trunk_road_flag                             161607 non-null  int64
 88  lsoa_of_accident_location                   161607 non-null  object
 89  enhanced_severity_collision                 161607 non-null  int64
dtypes: float64(8), int64(70), object(12)
memory usage: 111.0+ MB
```

3.3 Dropping Columns

[21]:
```
#Examine the available columns that can be dropped
accident.columns
```

[21]:
```
Index(['accident_index', 'accident_year_x', 'accident_reference_x',
       'vehicle_reference_x', 'casualty_reference', 'casualty_class',
       'sex_of_casualty', 'age_of_casualty', 'age_band_of_casualty',
       'casualty_severity', 'pedestrian_location', 'pedestrian_movement',
       'car_passenger', 'bus_or_coach_passenger',
       'pedestrian_road_maintenance_worker', 'casualty_type',
       'casualty_home_area_type', 'casualty_imd_decile', 'lsoa_of_casualty',
       'enhanced_casualty_severity', 'casualty_distance_banding',
       'accident_year_y', 'accident_reference_y', 'vehicle_reference_y',
       'vehicle_type', 'towing_and_articulation', 'vehicle_manoeuvre',
       'vehicle_direction_from', 'vehicle_direction_to',
       'vehicle_location_restricted_lane', 'junction_location',
       'skidding_and_overturning', 'hit_object_in_carriageway',
       'vehicle_leaving_carriageway', 'hit_object_off_carriageway',
       'first_point_of_impact', 'vehicle_left_hand_drive',
       'journey_purpose_of_driver', 'sex_of_driver', 'age_of_driver',
       'age_band_of_driver', 'engine_capacity_cc', 'propulsion_code',
       'age_of_vehicle', 'generic_make_model', 'driver_imd_decile',
       'driver_home_area_type', 'lsoa_of_driver', 'escooter_flag',
       'dir_from_e', 'dir_from_n', 'dir_to_e', 'dir_to_n',
```

```
       'driver_distance_banding', 'accident_year', 'accident_reference',
       'location_easting_osgr', 'location_northing_osgr', 'longitude',
       'latitude', 'police_force', 'accident_severity', 'number_of_vehicles',
       'number_of_casualties', 'date', 'day_of_week', 'time',
       'local_authority_district', 'local_authority_ons_district',
       'local_authority_highway', '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_accident',
       'trunk_road_flag', 'lsoa_of_accident_location',
       'enhanced_severity_collision'],
      dtype='object')
```

[22]:
```
#Columns were dropped based on whether the target variable accident severity␣
↪were influenced by them or not.
#The columns below were the ones that were picked.
main_accident = accident.loc[:, ['accident_index', 'time', 'number_of_vehicles',
                                  'number_of_casualties', 'date',␣
↪'local_authority_ons_district',
                                  'road_type', 'speed_limit', 'junction_detail',␣
↪'junction_control',
                                  'light_conditions','weather_conditions',␣
↪'road_surface_conditions',
                                 ␣
↪'urban_or_rural_area','vehicle_location_restricted_lane',␣
↪'junction_location',
                                  'skidding_and_overturning',␣
↪'hit_object_in_carriageway',
                                  'vehicle_leaving_carriageway',␣
↪'hit_object_off_carriageway', 'first_point_of_impact',
                                  'journey_purpose_of_driver',␣
↪'sex_of_driver','age_of_driver',
                                  'vehicle_type', 'vehicle_manoeuvre',␣
↪'casualty_type',
                                  'accident_severity']]
```

[23]:
```
#Verify that the columns were kept
main_accident.columns
```

[23]:
```
Index(['accident_index', 'time', 'number_of_vehicles', 'number_of_casualties',
       'date', 'local_authority_ons_district', 'road_type', 'speed_limit',
       'junction_detail', 'junction_control', 'light_conditions',
```

```
 'weather_conditions', 'road_surface_conditions', 'urban_or_rural_area',
 'vehicle_location_restricted_lane', 'junction_location',
 'skidding_and_overturning', 'hit_object_in_carriageway',
 'vehicle_leaving_carriageway', 'hit_object_off_carriageway',
 'first_point_of_impact', 'journey_purpose_of_driver', 'sex_of_driver',
 'age_of_driver', 'vehicle_type', 'vehicle_manoeuvre', 'casualty_type',
 'accident_severity'],
dtype='object')
```

3.4 Variable Description

Variables are categorised into 3 main types:

- **Numeric**: Variables containing numeric values.
- **Categorical**: Variables containing text data / each unique value indicates a category.
- **Date/Time**: Variables containing date or time values, like accident date or timestamp.

No.	Input data	Definition	Category
1	accident_index	Unique reference for the accident	Categorical
2	number_of_vehicles	Number of vehicles involved in the accident	Numeric
3	number_of_casualties	Number of casualties in the accident	Numeric
4	date	Date of the accident (in Date/Time format)	Date/Time
5	local_authority_ons_district	Local authority districts where the accident occurred using codes from Office for National Statistics (ONS)	Categorical
6	road_type	Type of road where the accident occurred	Categorical
7	speed_limit	Speed limit on the road at the accident location	Numeric
8	junction_detail	Details about the junction at the accident location	Categorical
9	junction_control	Type of control at the junction	Categorical
10	light_conditions	Light conditions at the time of the accident	Categorical
11	weather_conditions	Weather conditions during the accident	Categorical
12	road_surface_conditions	Road surface conditions at the accident location	Categorical
13	urban_or_rural_area	Whether the accident occurred in an urban or rural area	Categorical
14	vehicle_location_restricted_lane	Whether the vehicle was in a restricted lane at the time of the accident	Categorical
15	junction_location	Location of the junction where the accident occurred	Categorical
16	skidding_and_overturning	Whether the vehicle skidded or overturned during the accident	Categorical
17	hit_object_in_carriageway	Whether the vehicle hit an object in the carriageway	Categorical

No.	Input data	Definition	Category
18	vehicle_leaving_carriageway	Whether the vehicle left the carriageway during the accident	Categorical
19	hit_object_off_carriageway	Whether the vehicle hit an object off the carriageway	Categorical
20	first_point_of_impact	First point of impact in the accident	Categorical
21	journey_purpose_of_driver	Purpose of the driver's journey at the time of the accident	Categorical
22	sex_of_driver	Gender of the driver involved in the accident	Categorical
23	age_of_driver	Age of the driver at the time of the accident	Numeric
24	vehicle_type	Type of vehicle involved in the accident	Categorical
25	vehicle_manoeuvre	Manoeuvre the vehicle was performing at the time of the accident	Categorical
26	casualty_type	Type of casualty	Categorical
27	accident_severity	Severity of the casualty	Categorical

[25]:
```
#Filter the main_accident dataset to only include accidents occurred in London

#These are rows that the local_authority_ons_district column starts with the␣
↪prefix 'E09'
main_accident_filtered =␣
↪main_accident[main_accident['local_authority_ons_district'].str.
↪startswith('E09', na=False)]
```

[26]:
```
#Verify the samples and features of the dataset after the filtering
main_accident_filtered.shape
```

[26]:
```
(48149, 28)
```

[27]:
```
#Drop duplicates
main_accident_filtered.drop_duplicates(keep = 'first', inplace = True)
```

[28]:
```
#Verify the samples and features of the dataset after dropping duplicates
main_accident_filtered.shape
```

[28]:
```
(42129, 28)
```

[29]:
```
#Check example samples
main_accident_filtered.head()
```

[29]:
```
   accident_index   time  number_of_vehicles  number_of_casualties        date  \
0  2023010419171  01:24                   1                     1  01/01/2023
1  2023010419183  02:25                   3                     2  01/01/2023
2  2023010419183  02:25                   3                     2  01/01/2023
3  2023010419183  02:25                   3                     2  01/01/2023
7  2023010419189  03:50                   2                     1  01/01/2023
```

```
  local_authority_ons_district  road_type  speed_limit  junction_detail  \
0                    E09000024          2           20                9
1                    E09000010          6           30                3
2                    E09000010          6           30                3
3                    E09000010          6           30                3
7                    E09000017          1           30                1

   junction_control  …  vehicle_leaving_carriageway  \
0                 4  …                            0
1                 4  …                            0
2                 4  …                            0
3                 4  …                            0
7                 4  …                            0

   hit_object_off_carriageway  first_point_of_impact  \
0                           0                      1
1                           0                      1
2                           0                      4
3                           0                      1
7                           0                      4

   journey_purpose_of_driver  sex_of_driver  age_of_driver  vehicle_type  \
0                          1              1             61            11
1                          1              1             54            11
2                          6              1             25             9
3                          6              1             42             9
7                          6              1             50             9

   vehicle_manoeuvre  casualty_type  accident_severity
0                  4              0                  3
1                 18              9                  3
2                  9              9                  3
3                  8              9                  3
7                 18              9                  3

[5 rows x 28 columns]
```

[30]:
```
#Count the number of accidents in each London district
main_accident_filtered['local_authority_ons_district'].value_counts()
```

[30]:
```
local_authority_ons_district
E09000033    2223
E09000008    2080
E09000032    1963
E09000022    1908
E09000028    1889
```

```
E09000010    1881
E09000030    1868
E09000014    1797
E09000005    1663
E09000009    1579
E09000003    1565
E09000025    1475
E09000023    1464
E09000012    1397
E09000007    1290
E09000018    1251
E09000017    1189
E09000020    1178
E09000026    1164
E09000011    1132
E09000006    1131
E09000013    1115
E09000019    1065
E09000031     941
E09000016     936
E09000002     837
E09000024     823
E09000004     743
E09000015     723
E09000029     683
E09000027     668
E09000021     508
Name: count, dtype: int64
```

[31]:

```
#Top 5 boroughs with the highest number of accidents are:
boroughs = ['E09000033', 'E09000008', 'E09000032', 'E09000022', 'E09000028']

#Filter the 'main_accident_filtered' dataframe to include only rows for these␣
 ↪top 5 boroughs
top_5_boroughs = main_accident_filtered.
 ↪loc[main_accident_filtered['local_authority_ons_district'].isin(boroughs)]

#Display the summary information about the filtered dataframe
top_5_boroughs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 10063 entries, 11 to 48187
Data columns (total 28 columns):
 #   Column                             Non-Null Count  Dtype
---  ------                             --------------  -----
 0   accident_index                     10063 non-null  object
 1   time                               10063 non-null  object
 2   number_of_vehicles                 10063 non-null  int64
```

```
 3   number_of_casualties             10063 non-null  int64
 4   date                             10063 non-null  object
 5   local_authority_ons_district     10063 non-null  object
 6   road_type                        10063 non-null  int64
 7   speed_limit                      10063 non-null  int64
 8   junction_detail                  10063 non-null  int64
 9   junction_control                 10063 non-null  int64
 10  light_conditions                 10063 non-null  int64
 11  weather_conditions               10063 non-null  int64
 12  road_surface_conditions          10063 non-null  int64
 13  urban_or_rural_area              10063 non-null  int64
 14  vehicle_location_restricted_lane 10063 non-null  int64
 15  junction_location                10063 non-null  int64
 16  skidding_and_overturning         10063 non-null  int64
 17  hit_object_in_carriageway        10063 non-null  int64
 18  vehicle_leaving_carriageway      10063 non-null  int64
 19  hit_object_off_carriageway       10063 non-null  int64
 20  first_point_of_impact            10063 non-null  int64
 21  journey_purpose_of_driver        10063 non-null  int64
 22  sex_of_driver                    10063 non-null  int64
 23  age_of_driver                    10063 non-null  int64
 24  vehicle_type                     10063 non-null  int64
 25  vehicle_manoeuvre                10063 non-null  int64
 26  casualty_type                    10063 non-null  int64
 27  accident_severity                10063 non-null  int64
dtypes: int64(24), object(4)
memory usage: 2.2+ MB
```

[32]:
```
#Convert the object type of the date and time columns into a datetime type.
top_5_boroughs["date"] = pd.to_datetime(top_5_boroughs["date"], format="%d/%m/
 ↪%Y")
top_5_boroughs["time"] = pd.to_datetime(top_5_boroughs["time"], format="%H:%M")

#Check to see if the changes were made
print(top_5_boroughs.dtypes)
```

```
accident_index                          object
time                            datetime64[ns]
number_of_vehicles                       int64
number_of_casualties                     int64
date                            datetime64[ns]
local_authority_ons_district            object
road_type                                int64
speed_limit                              int64
junction_detail                          int64
junction_control                         int64
light_conditions                         int64
weather_conditions                       int64
```

```
road_surface_conditions                      int64
urban_or_rural_area                          int64
vehicle_location_restricted_lane             int64
junction_location                            int64
skidding_and_overturning                     int64
hit_object_in_carriageway                    int64
vehicle_leaving_carriageway                  int64
hit_object_off_carriageway                   int64
first_point_of_impact                        int64
journey_purpose_of_driver                    int64
sex_of_driver                                int64
age_of_driver                                int64
vehicle_type                                 int64
vehicle_manoeuvre                            int64
casualty_type                                int64
accident_severity                            int64
dtype: object
```

[33]:
```
#Split the original dataframe into two different dataframes
#The X dataframe has all the variables except the target variable
X = top_5_boroughs.loc[:,[col for col in top_5_boroughs.columns if col !=␣
↪'accident_severity']]

#The y dataframe contains the target variable
y = top_5_boroughs.loc[:,'accident_severity']
```

[34]:
```
#Check the shape of the two dataframes
print(X.shape)
print(y.shape)
```

```
(10063, 27)
(10063,)
```

[35]:
```
#Check for any missing values in both the X and y dataframes. -1 is a stand-in␣
↪value to represent missing values.

search_value = -1

#Search for any -1 value
X_columns_with_value = X.columns[(X == search_value).any(axis=0)]
has_negative_one = (y == -1).any().any()

#Print the values
print(f"The following columns in the X dataframe have -1 values:␣
↪\n{X_columns_with_value}\n")
print(f"There are -1 values in the y dataframe: {has_negative_one}")
```

```
The following columns in the X dataframe have -1 values:
```

```
Index(['junction_control', 'age_of_driver'], dtype='object')

There are -1 values in the y dataframe: False
```

[36]:
```
#Change all the -1 values into nan values to show that they represent missing␣
↪values
X = X.replace(-1, np.nan)

#Check if the changes were implemented
X.isnull().sum()
```

[36]:
```
accident_index                        0
time                                  0
number_of_vehicles                    0
number_of_casualties                  0
date                                  0
local_authority_ons_district          0
road_type                             0
speed_limit                           0
junction_detail                       0
junction_control                   1718
light_conditions                      0
weather_conditions                    0
road_surface_conditions               0
urban_or_rural_area                   0
vehicle_location_restricted_lane      0
junction_location                     0
skidding_and_overturning              0
hit_object_in_carriageway             0
vehicle_leaving_carriageway           0
hit_object_off_carriageway            0
first_point_of_impact                 0
journey_purpose_of_driver             0
sex_of_driver                         0
age_of_driver                      2492
vehicle_type                          0
vehicle_manoeuvre                     0
casualty_type                         0
dtype: int64
```

4 Data Splitting

4.1 Class Distribution of Target Variable

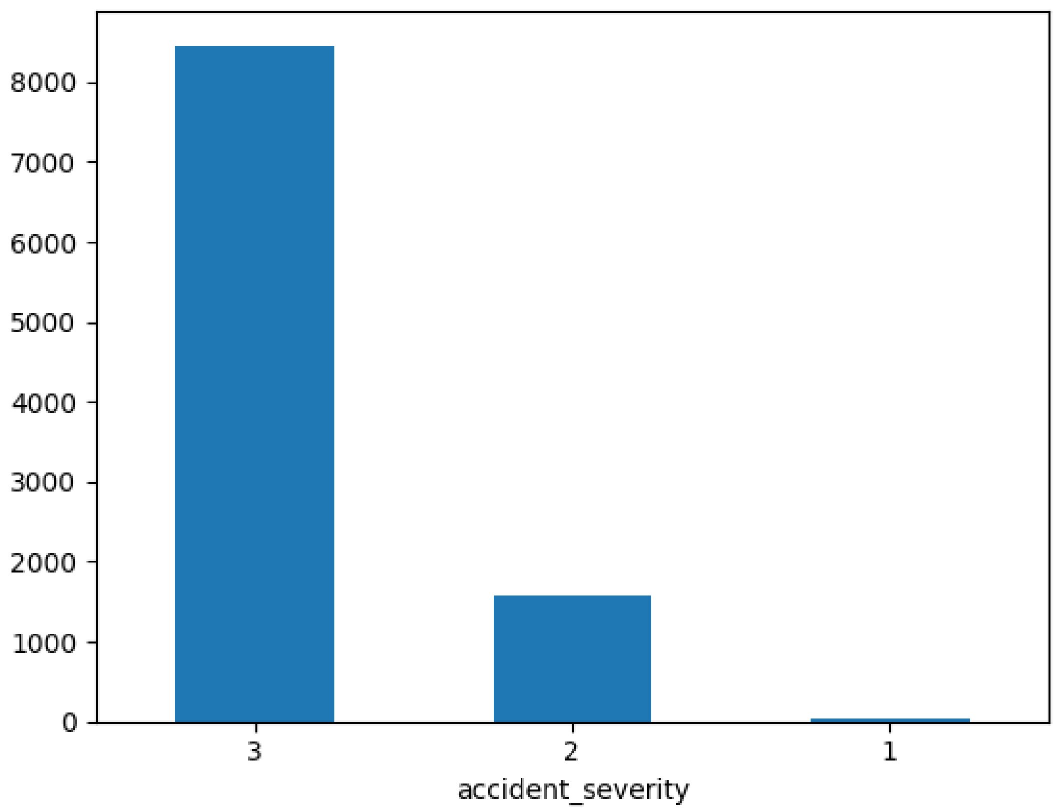
Split the X and Y datasets into training and test sets. The y_train and y_test sets only have the target variable.

[39]:
```
#Calculate percentage proportions
percentage_proportions = top_5_boroughs['accident_severity'].
    ↪value_counts(normalize=True) * 100
#Format each value in the Series using lamda
formatted_percentages = percentage_proportions.apply(lambda x: f'{x:.2f}%')
print(formatted_percentages)
```

```
accident_severity
3    84.11%
2    15.62%
1     0.27%
Name: proportion, dtype: object
```

[40]:
```
#Highlight the number of counts for each level of severity in the target␣
    ↪variable
top_5_boroughs["accident_severity"].value_counts().plot(kind="bar", rot=0)
```

[40]: `<Axes: xlabel='accident_severity'>`



As a result of the uneven distribution of the classes within the target variable using stratifiedshufflesplit, this is because using random sampling may introduce a bias into the proportion.

[42]:
```
#Split the data from the two dataframes into smaller subsets; there should be a␣
↪training set and a testing set for each of the two dataframes.
#Reset indices in case the two dataframes are not aligned.
X = X.reset_index(drop=True)
y = y.reset_index(drop=True)

#The test set should be 20% of the total dataset while the training set should␣
↪be 80%.
stratified_splitter = StratifiedShuffleSplit(n_splits=1, test_size=0.2,␣
↪random_state=7)
train_index, test_index = next(stratified_splitter.split(X, y))

#Apply indices to both X and y
X_train, X_test = X.iloc[train_index], X.iloc[test_index]
y_train, y_test = y.iloc[train_index], y.iloc[test_index]


#Show the shape of the four dataframes
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(8050, 27)
(2013, 27)
(8050,)
(2013,)
```

[43]:
```
#Create a function that measures the proportions of an accident's severity
def accident_severity_proportions(data):
    target = data["accident_severity"] if isinstance(data, pd.DataFrame) else␣
↪data
    return target.value_counts() / len(data)

#Create a random split
rand_train_set, rand_test_set = train_test_split(top_5_boroughs, test_size=0.2,␣
↪random_state=7)

#Create a temporary dataframe for easy visualization
df_tmp = pd.DataFrame({
    "Overall": accident_severity_proportions(top_5_boroughs),
    "Random test set": accident_severity_proportions(rand_test_set),
    "Stratified test set": accident_severity_proportions(y_test),
}).sort_index()

#Add two columns for the percent of the difference to the overall proportion
```

```
df_tmp["Rand. %error"] = 100 * df_tmp["Random test set"] / df_tmp["Overall"] -␣
↪100
df_tmp["Strat. %error"] = 100 * df_tmp["Stratified test set"] /␣
↪df_tmp["Overall"] - 100

#Visualize table
df_tmp
```

[43]:

```
                    Overall  Random test set  Stratified test set  \
accident_severity
1                  0.002683         0.001987             0.002484
2                  0.156216         0.156483             0.156483
3                  0.841101         0.841530             0.841033

                   Rand. %error  Strat. %error
accident_severity
1                    -25.940645      -7.425806
2                      0.170931       0.170931
3                      0.051004      -0.008058
```

5 Exploratory Data Analysis

Exploratory data analysis on the training set includes descriptive statistics and visualisations for numerical and categorical predictors to identify distributions, outliers, and value counts.

5.1 Univariate Analysis

5.1.1 Target Variable

[48]:

```
#Check the target variables training dataset
y_train.head()
```

[48]:

```
2142    3
1930    3
8757    3
9327    3
7125    2
Name: accident_severity, dtype: int64
```

[49]:

```
#Descriptive Statistics of the Target Variable

#Frequency counts
frequency_counts = pd.DataFrame(y_train.value_counts().sort_index())

#Mode
mode_value = y_train.mode()[0]
```

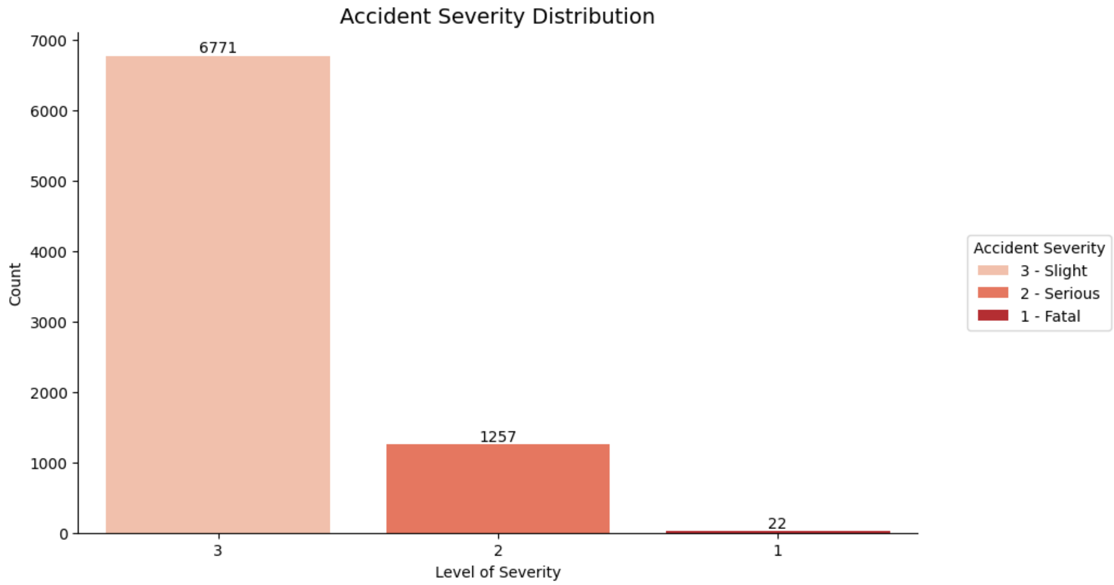
```
#Median
median_value = y_train.median()

#Percentiles (25th, 50th, 75th)
percentiles = pd.DataFrame(y_train.quantile([0.25, 0.5, 0.75]))

#Summary
print("Frequency Counts:\n", frequency_counts)
print("\nMode:", mode_value)
print("Median:", median_value)
print("\nPercentiles (25th, 50th, 75th):\n", percentiles)
```

```
Frequency Counts:
                    count
accident_severity
1                      22
2                    1257
3                    6771

Mode: 3
Median: 3.0

Percentiles (25th, 50th, 75th):
       accident_severity
0.25                3.0
0.50                3.0
0.75                3.0
```

The mode of the accident severity is 3, which means that most of the accidents had a slight severity, backed up by the frequencies of the accident severity and the percentile table indicates that 75% of the accidents have a severity rating of slight.

[51]:
```
#Set the size of the figure
plt.figure(figsize=(10, 6))

#Visualise the distribution of the target variables
ax = sns.countplot(x=y_train, order=y.value_counts().index, palette='Reds')

#Add counts on bars
for container in ax.containers:
    ax.bar_label(container, fontsize=10)

#Label the plot and create a legend
plt.title('Accident Severity Distribution', fontsize=14)
plt.legend(title='Accident Severity', labels=['3 - Slight', '2 - Serious', '1 -␣
↪Fatal'], bbox_to_anchor=(1.05, 0.5), loc='center left')
plt.xlabel('Level of Severity')
plt.ylabel('Count')
```

```
plt.xticks(ha='center')

#Cleaner borders
sns.despine()

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



The data suggests that while fatal accidents are the least frequent, there is a significant number of slight accidents, indicating a need for targeted safety interventions to reduce overall accident rates.

5.1.2 Predictor Variables

Numerical Variables

[55]:
```
#There are four numerical predictor variables: Number of vehicles, number of
 ↪casualties, the speed limit, and the age of the drivers.
#Descriptive statistics
def q1(x):
    return x.quantile(0.25)

def q3(x):
    return x.quantile(0.75)

def iqr(x):
    return q3(x) - q1(x)

def get_mode(x):
    return x.mode().iloc[0]
```

```
#Calculate statistics with proper naming
stats = X_train[['number_of_vehicles', 'number_of_casualties', 'speed_limit',␣
↪'age_of_driver']].agg([
    'min',
    'max',
    q1,
    'median',
    q3,
    iqr,
    get_mode
]).rename(index={
    'q1': '25%',
    'median': '50%',
    'q3': '75%',
    'iqr': 'IQR',
    'get_mode': 'mode'
})

#Format and transpose results
stats_df = stats.transpose().reset_index().rename(columns={'index': 'variable'})
stats_df = stats_df[['variable', 'min', '25%', '50%', '75%', 'max', 'IQR',␣
↪'mode']]
stats_df = stats_df.set_index('variable')

print("Descriptive Statistics:")
display(stats_df)
```

```
Descriptive Statistics:

                       min   25%   50%   75%   max   IQR  mode
variable
number_of_vehicles     1.0   2.0   2.0   2.0  17.0   0.0   2.0
number_of_casualties   1.0   1.0   1.0   1.0   7.0   0.0   1.0
speed_limit           20.0  20.0  20.0  30.0  60.0  10.0  20.0
age_of_driver          8.0  28.0  36.0  48.0  93.0  20.0  33.0
```

number_of_vehicles

- As indicated in the table above and the plot below the highest number of vehicles involved in a single accident was 17.
- 75% of accidents consisted of 2 or less vehicles.

number_of_casualties

- The highest number of casualties in an accident was 7, however this is an outlier because the majority of accidents only had 1 casualty.
- The percentile ranges for casualties are 1, suggesting that most accidents involved only one individual facing harm.

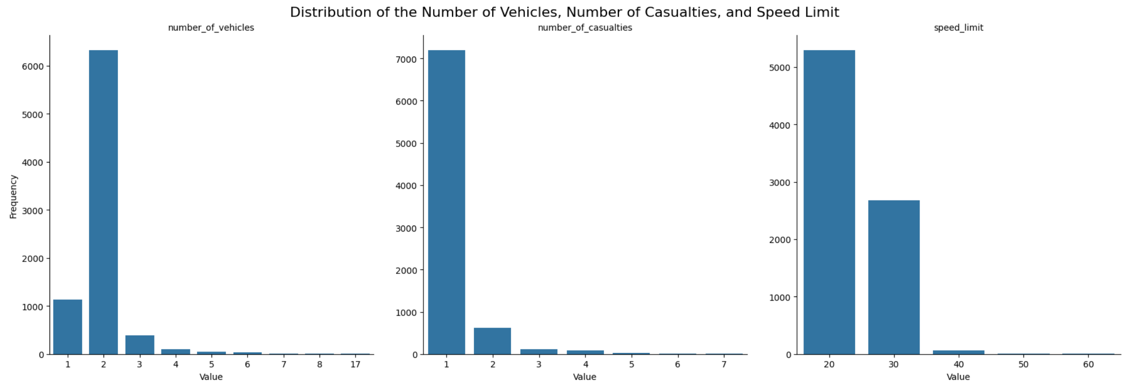
speed_limit

- For the speed limit, the 25th and 50th percentiles are 20, while the 75th percentile is 30, suggesting that 75% of the speed limits are 30 or below.

age_of_driver

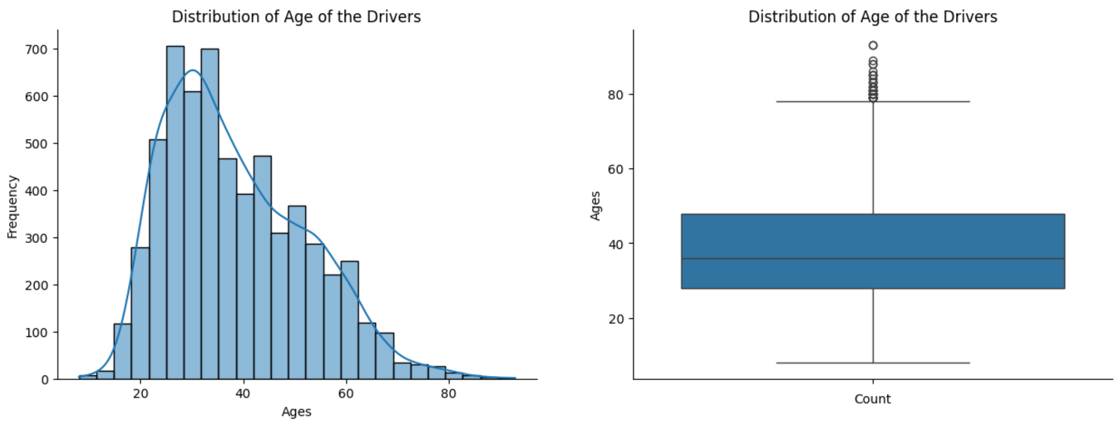
- Most drivers involved in the accidents were around 30.
- The maximum age of a driver in an accident was 93, while the minimum age was 5.

[60]:
```
#Prepare and reshape the data into 3 columns using FacetGrid with the melt␣
↪function
facet_data =␣
↪X_train[['number_of_vehicles','number_of_casualties','speed_limit']].melt()

#Create the FacetGrid which plots facets by their 'variable' column
g = sns.FacetGrid(facet_data, col="variable", col_wrap=3, height=6,␣
↪sharex=False, sharey=False)

#Map the appropriate plot to each facet based on the variable type
def plot_facet(variable, **kwargs):
    data = kwargs.pop('data')
    sns.countplot(x=data['value'], **kwargs)

g.map_dataframe(plot_facet, 'value')

#Remove gridlines from all plots using a for loop
for ax in g.axes.flat:
    ax.grid(False)

#Set the title for each facet dynamically to the column name
g.set_titles("{col_name}")

#Set labels for the x and y axes
g.set_axis_labels("Value", "Frequency")

#Main title for the entire plot and adjust its position
g.fig.suptitle("Distribution of the Number of Vehicles, Number of Casualties,␣
↪and Speed Limit", fontsize=16, y=1.02)

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



Most accidents involved two vehicles, at least one casualty, and occurred on 20 mph roads.

[62]:
```
#Set the figure size
fig = plt.figure(figsize=(15, 5))

#Histogram
plt.subplot(1, 2, 1)

#Define plot object using histplot
hist = sns.histplot(X_train.loc[:, 'age_of_driver'], bins=25, kde=True)

#Setting graph title and labels
hist.set_title('Distribution of Age of the Drivers')
hist.set(xlabel='Ages', ylabel='Frequency')

#Boxplot
plt.subplot(1,2,2)

#Define plot object
box = sns.boxplot(X_train.loc[:,'age_of_driver'])

#Setting graph title
box.set_title( 'Distribution of Age of the Drivers')
box.set(xlabel = 'Count', ylabel = 'Ages')

#Remove borders (spines)
sns.despine(fig=fig, right=True, top=True)

plt.show()
```



Most drivers were aged 25–35, with few outliers over 80.

Categorical Variables

[65]:
```
#There are 20 categorical predictor variables.
#Converting all the numerical values into their actual values in the dataset
for column in X_train.columns:
    if column in guide_data['field name'].values:
        #Creating a dictionary to map code/format to label for each field_name
        mapping_dict = guide_data[guide_data['field name'] == column].
 ↪set_index('code/format')['label'].to_dict()
        #Replacing the values in top_5_boroughs based on the mapping dictionary
        if mapping_dict:
            X_train[column] = X_train[column].map(mapping_dict).
 ↪fillna(X_train[column])

for column in X_test.columns:
    if column in guide_data['field name'].values:
        #Creating a dictionary to map code/format to label for each field_name
        mapping_dict = guide_data[guide_data['field name'] == column].
 ↪set_index('code/format')['label'].to_dict()
        #Replacing the values in top_5_boroughs based on the mapping dictionary
        if mapping_dict:
            X_test[column] = X_test[column].map(mapping_dict).
 ↪fillna(X_test[column])

#Examine the newly converted data
X_train.head()
```

[65]:
```
      accident_index                time  number_of_vehicles  \
2142   2023010435768 1900-01-01 19:35:00                 2.0
1930   2023010434377 1900-01-01 15:09:00                 1.0
8757   2023010477755 1900-01-01 17:00:00                 2.0
```

```
9327   2023010481441 1900-01-01 17:15:00                2.0
7125   2023010467051 1900-01-01 18:40:00                2.0

      number_of_casualties       date local_authority_ons_district  \
2142                   1.0 2023-02-27                      Lambeth
1930                   1.0 2023-03-24                      Lambeth
8757                   1.0 2023-11-10                      Lambeth
9327                   1.0 2023-12-01                      Lambeth
7125                   1.0 2023-09-19                   Wandsworth

               road_type  speed_limit                   junction_detail  \
2142             Unknown           30  Not at junction or within 20 metres
1930             Unknown           20  Not at junction or within 20 metres
8757  Single carriageway           30             T or staggered junction
9327             Unknown           20             unknown (self reported)
7125  Single carriageway           20  Not at junction or within 20 metres

             junction_control  … hit_object_in_carriageway  \
2142                      NaN  …   unknown (self reported)
1930                      NaN  …   unknown (self reported)
8757  Give way or uncontrolled  …   unknown (self reported)
9327   unknown (self reported)  …   unknown (self reported)
7125                      NaN  …                         0

     vehicle_leaving_carriageway hit_object_off_carriageway  \
2142     unknown (self reported)    unknown (self reported)
1930     unknown (self reported)    unknown (self reported)
8757     unknown (self reported)    unknown (self reported)
9327     unknown (self reported)    unknown (self reported)
7125   Did not leave carriageway                          0

       first_point_of_impact journey_purpose_of_driver sex_of_driver  \
2142                   Front                 Not known          Male
1930  unknown (self reported)                 Not known     Not known
8757  unknown (self reported)   Journey as part of work          Male
9327  unknown (self reported)                 Not known        Female
7125           Did not impact   Journey as part of work          Male

     age_of_driver                         vehicle_type  \
2142          26.0           Motorcycle 125cc and under
1930           NaN                                  Car
8757          25.0           Motorcycle 125cc and under
9327          64.0                                  Car
7125          60.0  Bus or coach (17 or more pass seats)

            vehicle_manoeuvre                                 casualty_type
2142  unknown (self reported)  Motorcycle 125cc and under rider or passenger
```

```
1930   unknown (self reported)                                    Car occupant
8757   unknown (self reported)  Motorcycle 125cc and under rider or passenger
9327   unknown (self reported)                                      Pedestrian
7125   Waiting to go - held up  Bus or coach occupant (17 or more pass seats)

[5 rows x 27 columns]
```

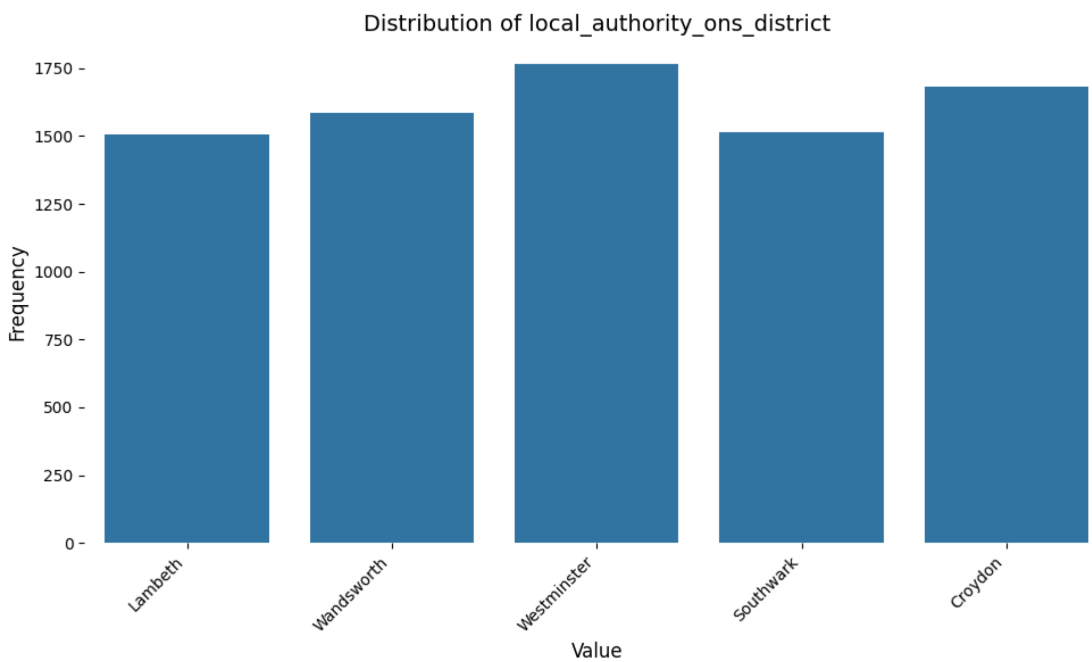
[66]:

```
#Create functions used for analyzing descriptive statistics and plot the␣
 ↪categorical variable

#Function to describe the variable
def describe_column(data, column):
    # Get value counts and mode
    value_counts_result = data[column].value_counts().reset_index()
    value_counts_result.columns = ['Category', 'Frequency']
    mode_value = data[column].mode().iloc[0]  # Get the first mode

    # Display the result
    print(f"Descriptive Statistics for {column}:")
    print(f"Mode: {mode_value}")
    display(value_counts_result)
    print("\n" + "-"*80)  # Separator for readability

#Function to plot the variable
def plot_countplot(data, column):

    #Create figure
    plt.figure(figsize=(10, 6))

    #Create countplot
    ax = sns.countplot(data=data, x=column)

    #Apply customizations
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')
    ax.grid(False)
    ax.set_title(f'Distribution of {column}', fontsize=14)
    ax.set_xlabel('Value', fontsize=12)
    ax.set_ylabel('Frequency', fontsize=12)

    #Remove plot borders
    for spine in ax.spines.values():
        spine.set_visible(False)

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

local_authority_ons_district

[68]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'local_authority_ons_district')
plot_countplot(X_train, 'local_authority_ons_district')
```

```
Descriptive Statistics for local_authority_ons_district:
Mode: Westminster

      Category  Frequency
0  Westminster       1764
1      Croydon       1681
2   Wandsworth       1587
3    Southwark       1513
4      Lambeth       1505

--------------------------------------------------------------------------------
```

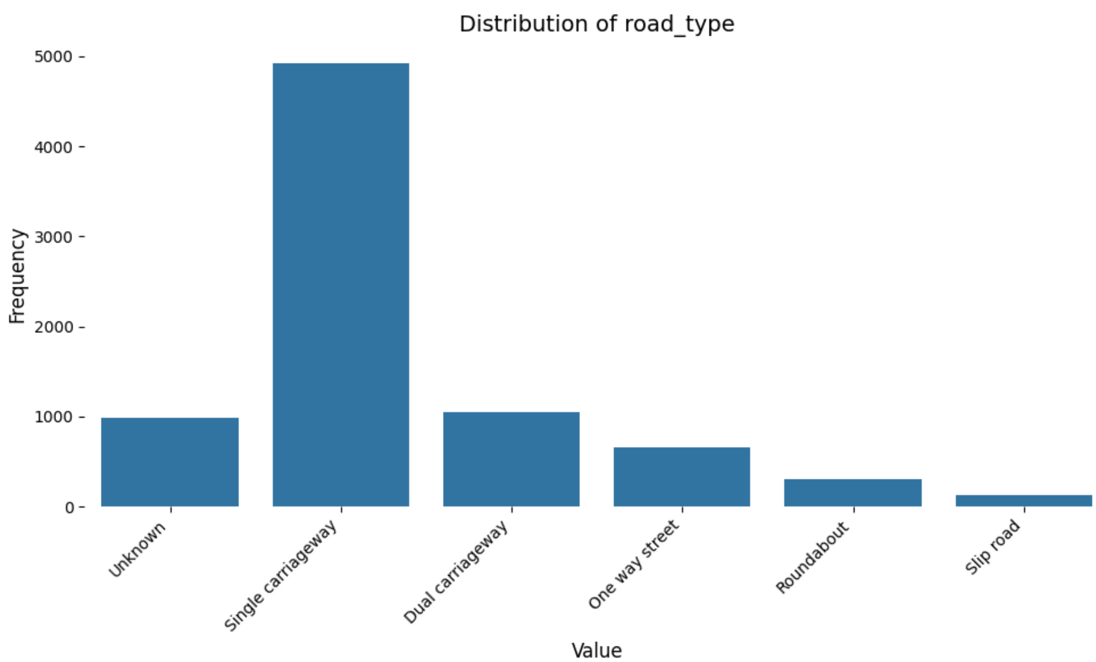


Accidents were most frequent in Westminster (1,764), with most boroughs reporting 1,505–1,764 incidents.

road_type

[71]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'road_type')
plot_countplot(X_train, 'road_type')
```

```
Descriptive Statistics for road_type:
Mode: Single carriageway

             Category  Frequency
0  Single carriageway       4923
1    Dual carriageway       1053
2             Unknown        984
3      One way street        657
4          Roundabout        303
5           Slip road        130

--------------------------------------------------------------------------------
```



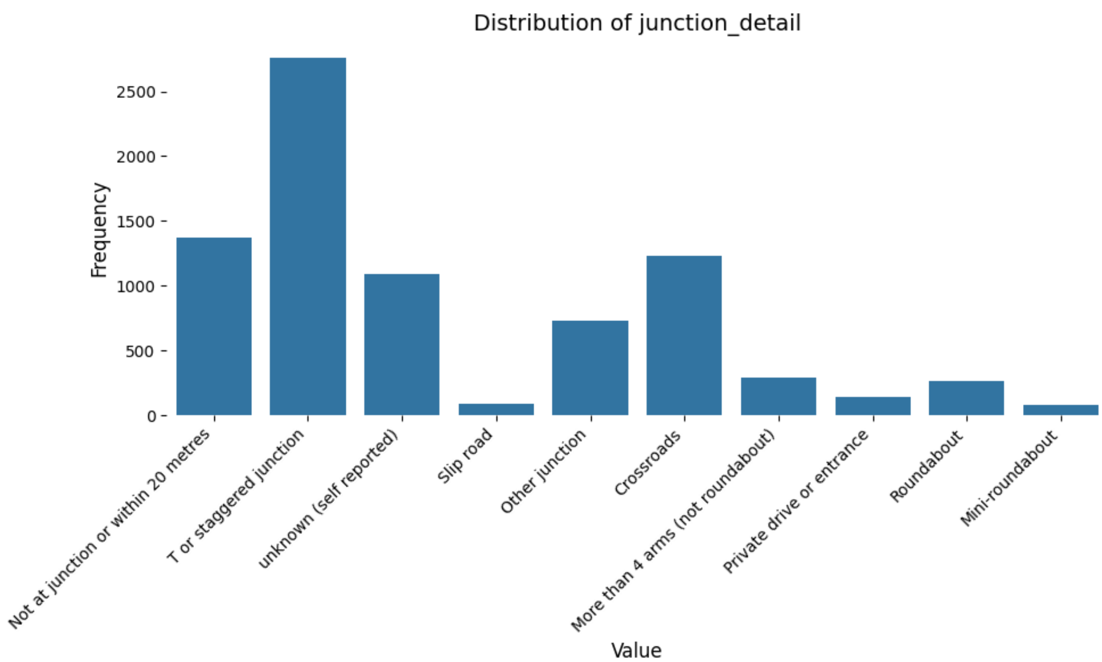
Single carriageways had the most accidents (4,923), suggesting higher risk due to traffic volume.

junction_detail

[74]:
```
#Use the previously created functions to describe and plot the categorical
variable
describe_column(X_train, 'junction_detail')
plot_countplot(X_train, 'junction_detail')
```

```
Descriptive Statistics for junction_detail:
Mode: T or staggered junction

                               Category  Frequency
0               T or staggered junction       2759
1  Not at junction or within 20 metres       1371
```

```
2                      Crossroads       1234
3           unknown (self reported)     1087
4                  Other junction        733
5  More than 4 arms (not roundabout)     292
6                      Roundabout        268
7         Private drive or entrance      139
8                       Slip road         84
9                  Mini-roundabout        83

--------------------------------------------------------------------------------
```



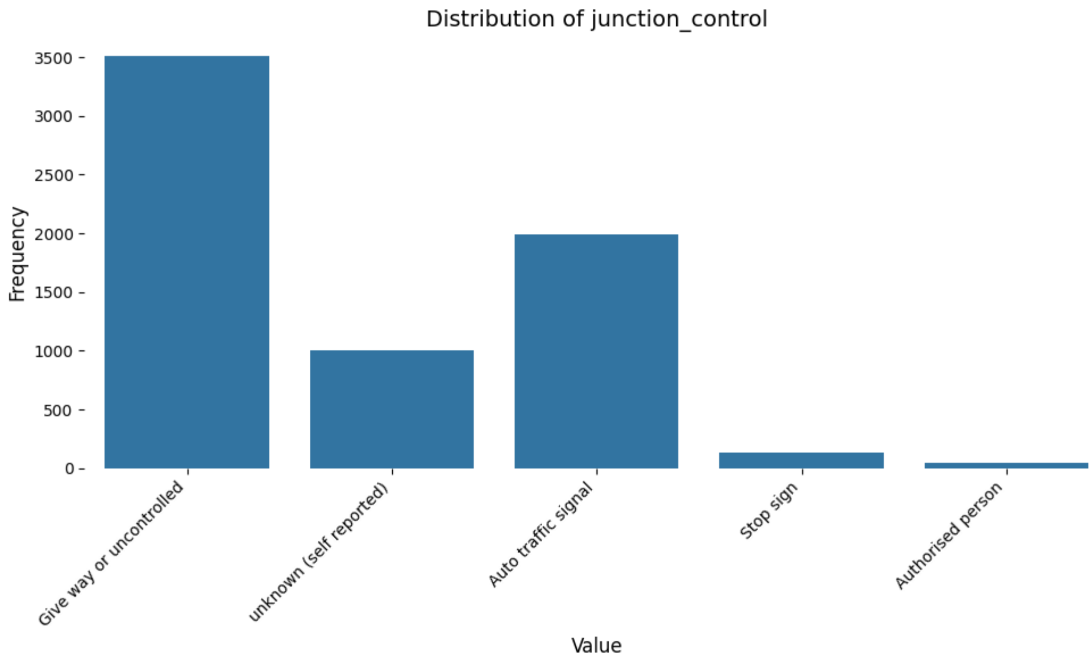
Accidents were rarer at slip roads and mini-roundabouts (<100), with higher rates at busy junctions like T-junctions and crossroads.

junction_control

[77]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'junction_control')
plot_countplot(X_train, 'junction_control')
```

```
Descriptive Statistics for junction_control:
Mode: Give way or uncontrolled

                  Category  Frequency
0  Give way or uncontrolled       3506
1        Auto traffic signal      1991
```

```
2   unknown (self reported)       1004
3                 Stop sign        136
4          Authorised person        42

--------------------------------------------------------------------------------
```

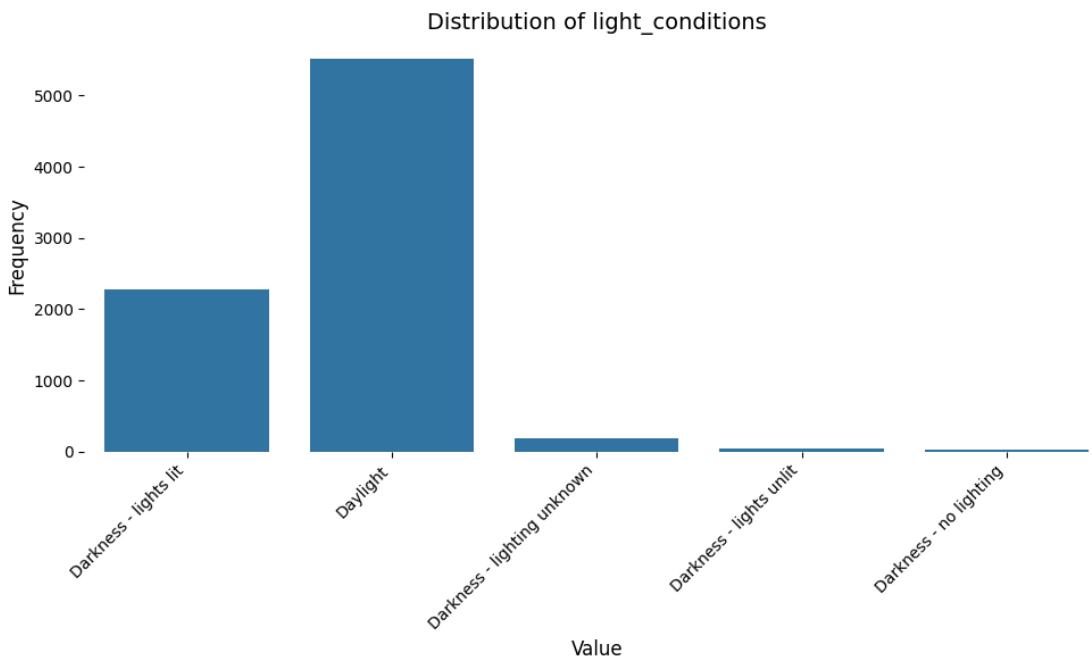


Junction controls such as "Stop sign" and "Authorised person" had the lowest number of accidents, while give-way signs saw the highest accident rates.

light_conditions

[80]:
```python
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'light_conditions')
plot_countplot(X_train, 'light_conditions')
```

```
Descriptive Statistics for light_conditions:
Mode: Daylight

                      Category  Frequency
0                     Daylight       5523
1          Darkness - lights lit       2273
2   Darkness - lighting unknown        180
3        Darkness - lights unlit         40
4         Darkness - no lighting         34

--------------------------------------------------------------------------------
```

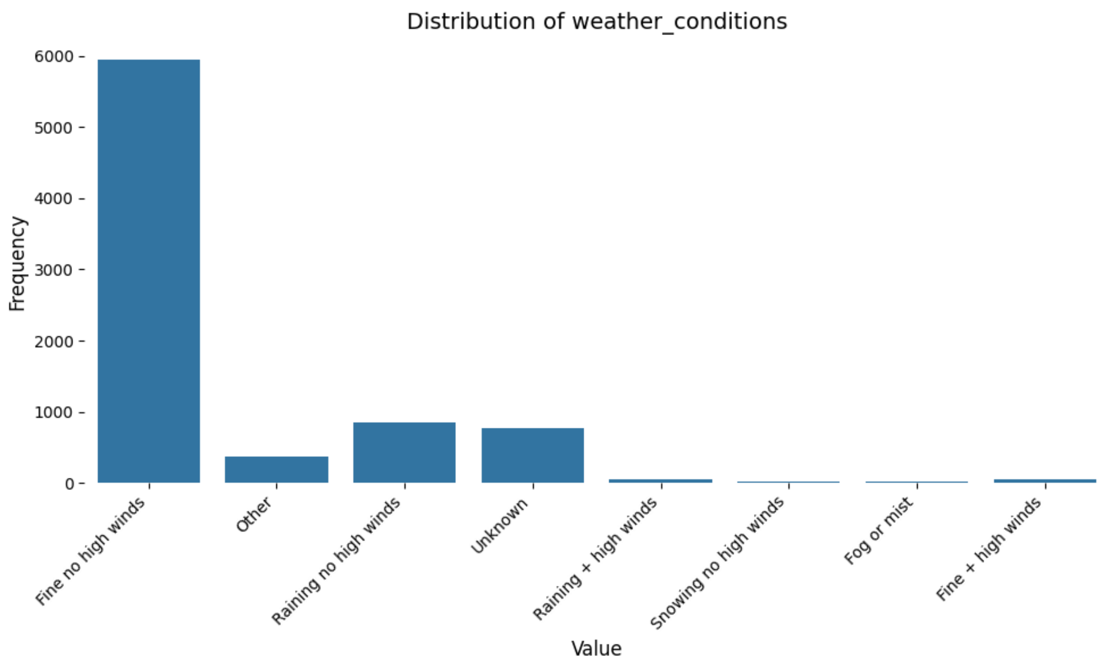


Accidents were the most common in daylight conditions (5523), while poorly lit or unlit conditions saw far fewer, highlighting the importance of visibility.

weather_conditions

[83]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'weather_conditions')
plot_countplot(X_train, 'weather_conditions')
```

```
Descriptive Statistics for weather_conditions:
Mode: Fine no high winds

                 Category  Frequency
0      Fine no high winds       5952
1   Raining no high winds        854
2                 Unknown        766
3                   Other        364
4    Raining + high winds         48
5       Fine + high winds         41
6             Fog or mist         13
7   Snowing no high winds         12


--------------------------------------------------------------------------------
```

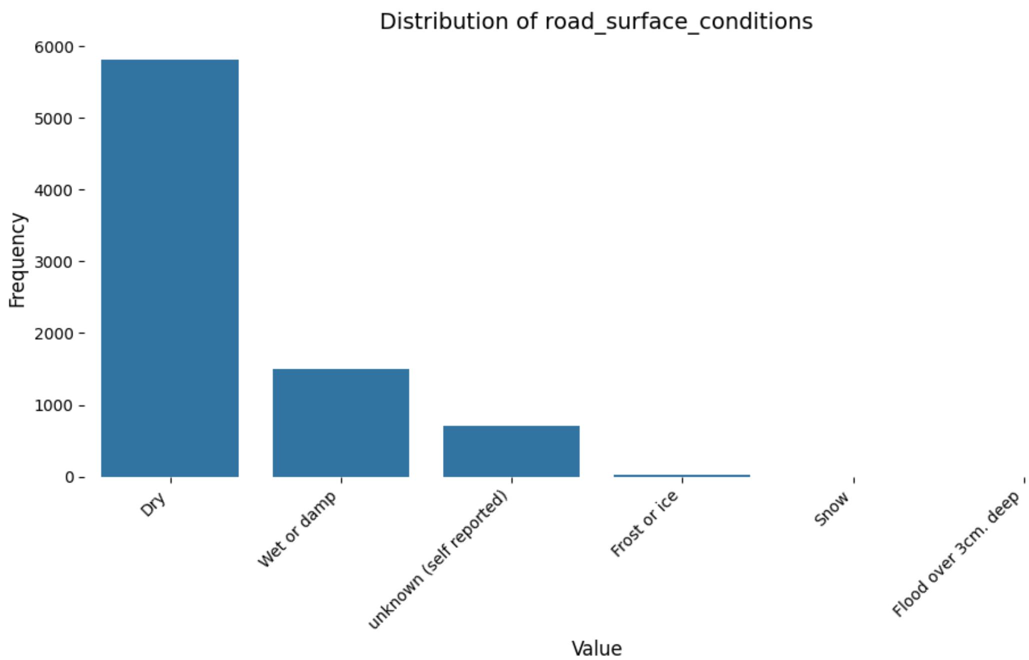


Most accidents occured in Fine conditions with no high winds (5952), while the four weather conditions starting from right saw <50 each.

road_surface_conditions

[86]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'road_surface_conditions')
plot_countplot(X_train, 'road_surface_conditions')
```

```
Descriptive Statistics for road_surface_conditions:
Mode: Dry

                  Category  Frequency
0                      Dry       5817
1               Wet or damp      1503
2  unknown (self reported)        705
3             Frost or ice         22
4        Flood over 3cm. deep          2
5                     Snow          1


--------------------------------------------------------------------------------
```



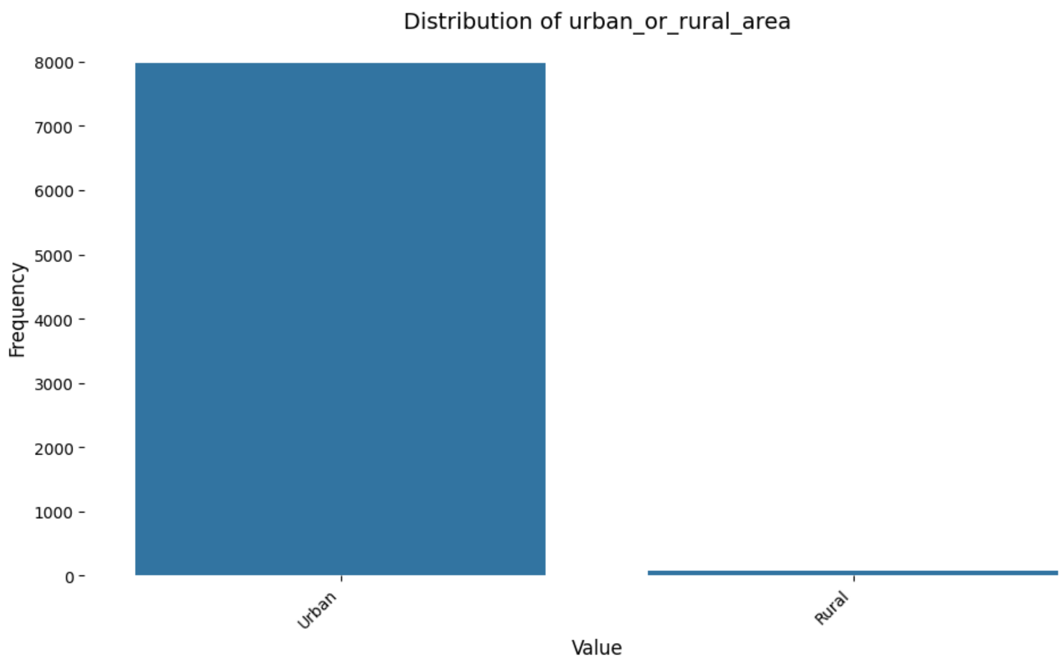
Most accidents occurred on dry roads (5,817), followed by wet conditions (1,503), with frost, ice, and flooding incidents being rare (<22).

urban_or_rural_area

[89]:

```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'urban_or_rural_area')
plot_countplot(X_train, 'urban_or_rural_area')
```

```
Descriptive Statistics for urban_or_rural_area:
Mode: Urban

  Category  Frequency
0    Urban       7984
1    Rural         66

--------------------------------------------------------------------------------
```

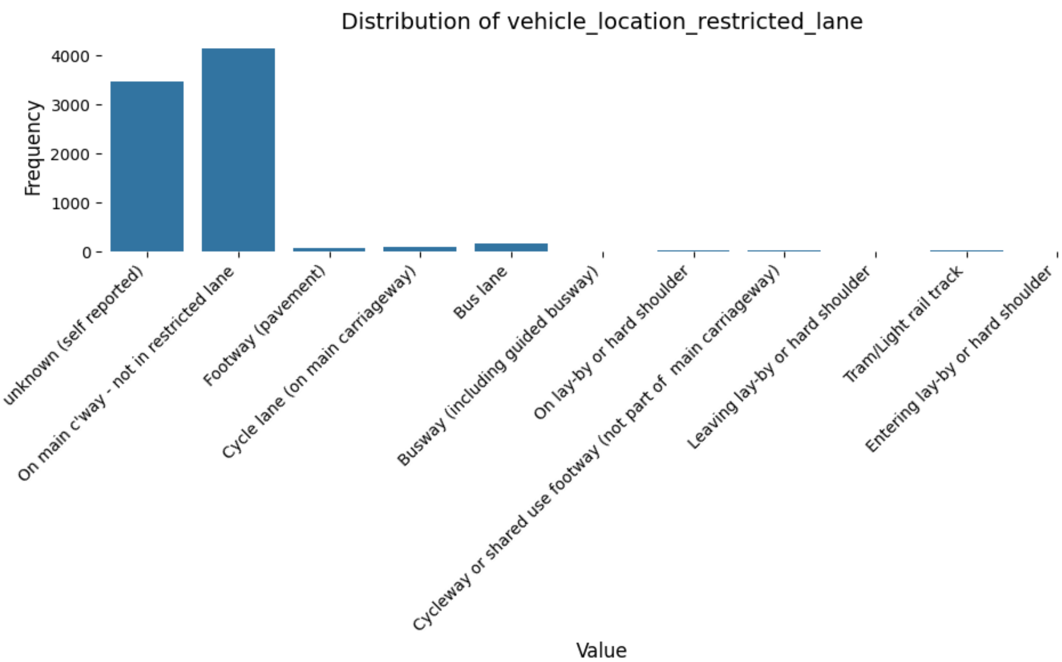


Urban areas saw 7,984 accidents vs. 66 in rural areas, highlighting higher risk in densely populated areas.

vehicle_location_restricted_lane

[92]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'vehicle_location_restricted_lane')
plot_countplot(X_train, 'vehicle_location_restricted_lane')
```

```
Descriptive Statistics for vehicle_location_restricted_lane:
Mode: On main c'way - not in restricted lane

                                            Category  Frequency
0             On main c'way - not in restricted lane       4140
1                              unknown (self reported)       3479
2                                             Bus lane        172
3                      Cycle lane (on main carriageway)         97
4                                   Footway (pavement)         80
5   Cycleway or shared use footway (not part of  m…        29
6                          On lay-by or hard shoulder         23
7                               Tram/Light rail track         13
8                      Leaving lay-by or hard shoulder          7
9                      Busway (including guided busway)          5
10                     Entering lay-by or hard shoulder          5

--------------------------------------------------------------------------------
```



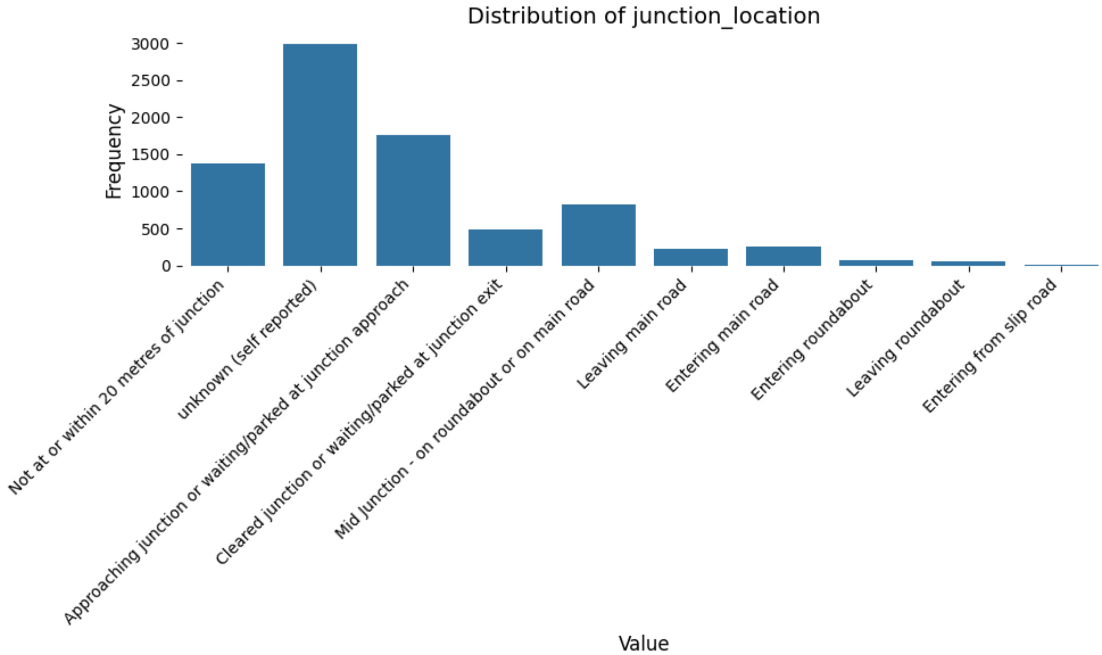
Most accidents occurred on main carriageways (4,140) and unknown locations (3,479), while restricted lanes saw far fewer incidents.

junction_location

[95]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'junction_location')
plot_countplot(X_train, 'junction_location')
```

```
Descriptive Statistics for junction_location:
Mode: unknown (self reported)
```

	Category	Frequency
0	unknown (self reported)	2984
1	Approaching junction or waiting/parked at junc…	1764
2	Not at or within 20 metres of junction	1371
3	Mid Junction - on roundabout or on main road	827
4	Cleared junction or waiting/parked at junction…	493
5	Entering main road	249
6	Leaving main road	221
7	Entering roundabout	73
8	Leaving roundabout	50
9	Entering from slip road	18

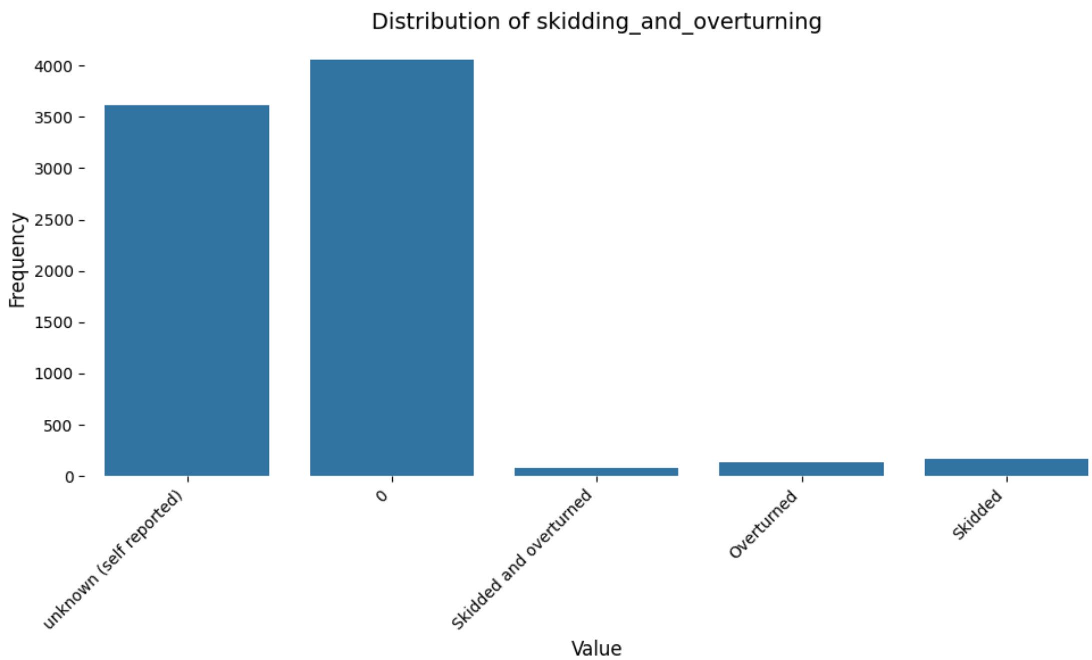


Out of all the reported known junction locations approaching junction or waiting/parked at junction apporach was the highest (1764) followed by not at or within 20 metres of junction (1371)

skidding_and_overturning

[98]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'skidding_and_overturning')
plot_countplot(X_train, 'skidding_and_overturning')
```

```
Descriptive Statistics for skidding_and_overturning:
Mode: 0

                   Category  Frequency
0                         0       4060
1   unknown (self reported)       3613
2                   Skidded        166
3                Overturned        132
4    Skidded and overturned         79


--------------------------------------------------------------------------------
```

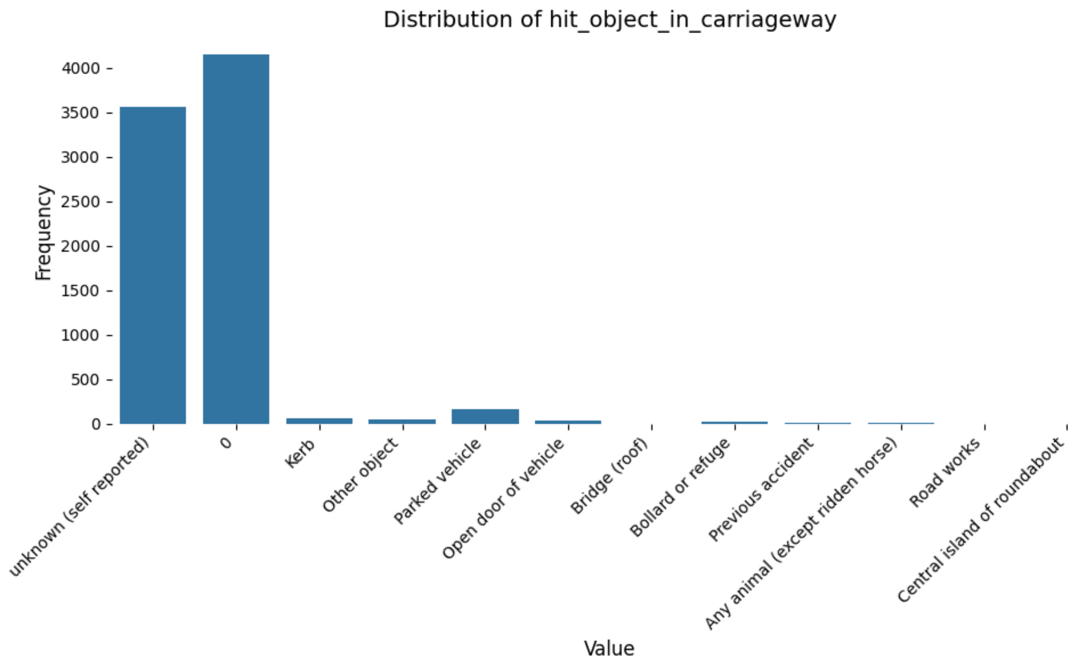


Most incidents didn't involve any skidding or overturning (4,060), but while such events were rare to happen, they were still relevant for safety improvements.

hit_object_in_carriageway

[101]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'hit_object_in_carriageway')
plot_countplot(X_train, 'hit_object_in_carriageway')
```

```
Descriptive Statistics for hit_object_in_carriageway:
Mode: 0

                              Category  Frequency
0                                    0       4143
1              unknown (self reported)       3559
2                       Parked vehicle        159
3                                 Kerb         62
4                         Other object         50
5                 Open door of vehicle         36
6                    Bollard or refuge         28
7                    Previous accident          6
8    Any animal (except ridden horse)           4
9                        Bridge (roof)          1
10                          Road works          1
11        Central island of roundabout          1
```

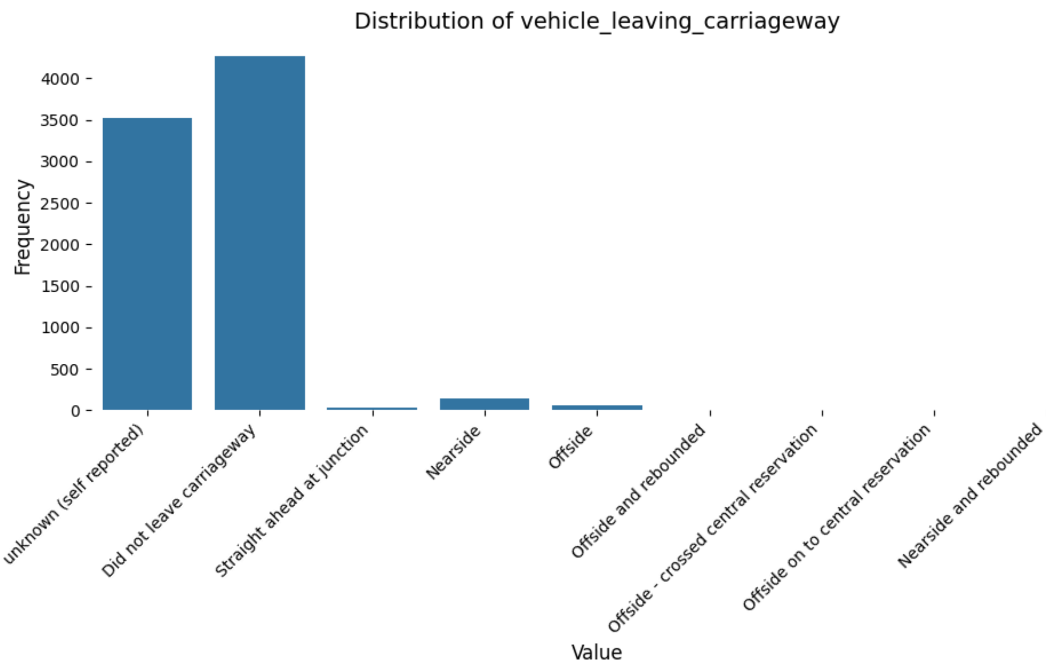


Most incidents didn't involve hitting objects in carriageway (4,143), with parked vehicles being the most common among the few object-related cases.

vehicle_leaving_carriageway

[104]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'vehicle_leaving_carriageway')
plot_countplot(X_train, 'vehicle_leaving_carriageway')
```

```
Descriptive Statistics for vehicle_leaving_carriageway:
Mode: Did not leave carriageway

                                Category  Frequency
0              Did not leave carriageway       4271
1                unknown (self reported)       3529
2                               Nearside        147
3                                Offside         56
4             Straight ahead at junction         28
5                    Offside and rebounded          8
6                   Nearside and rebounded          6
7       Offside on to central reservation          3
8   Offside - crossed central reservation          2
```

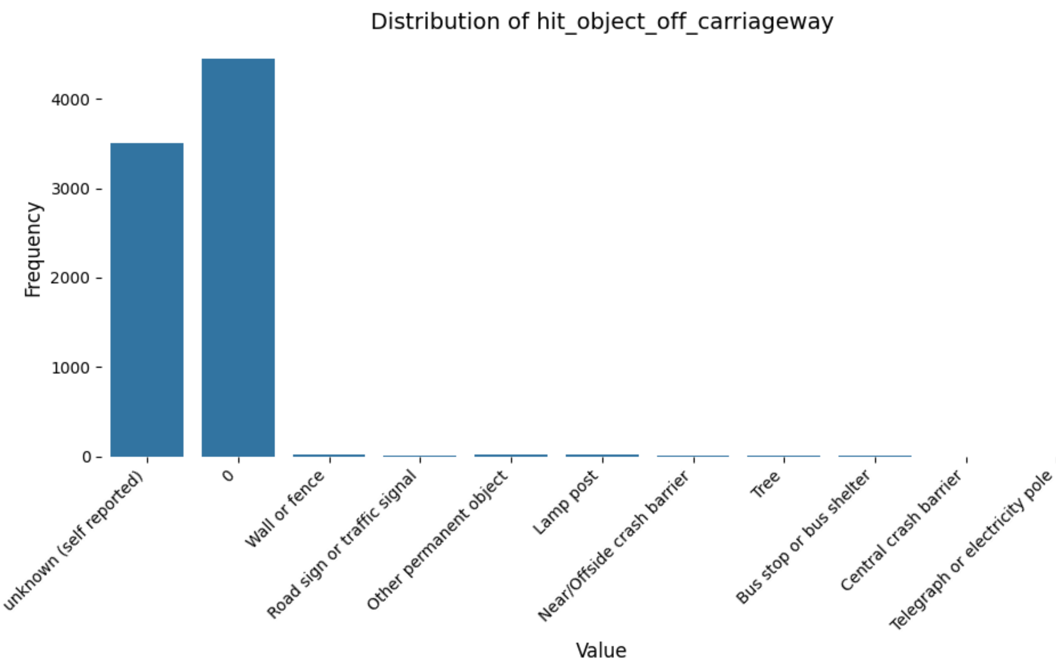


Most incidents didn't involve vehicles leaving the carriageway (4,271), but when they did, nearside departures (147) were most common followed by offside (56).

hit_object_off_carriageway

[107]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'hit_object_off_carriageway')
plot_countplot(X_train, 'hit_object_off_carriageway')
```

```
Descriptive Statistics for hit_object_off_carriageway:
Mode: 0

                          Category  Frequency
0                                0       4452
1          unknown (self reported)       3502
2                    Wall or fence         27
3                        Lamp post         19
4           Other permanent object         18
5     Road sign or traffic signal          13
6                             Tree          6
7             Bus stop or bus shelter         6
8        Near/Offside crash barrier          4
9    Telegraph or electricity pole          2
10            Central crash barrier          1


--------------------------------------------------------------------------------
```

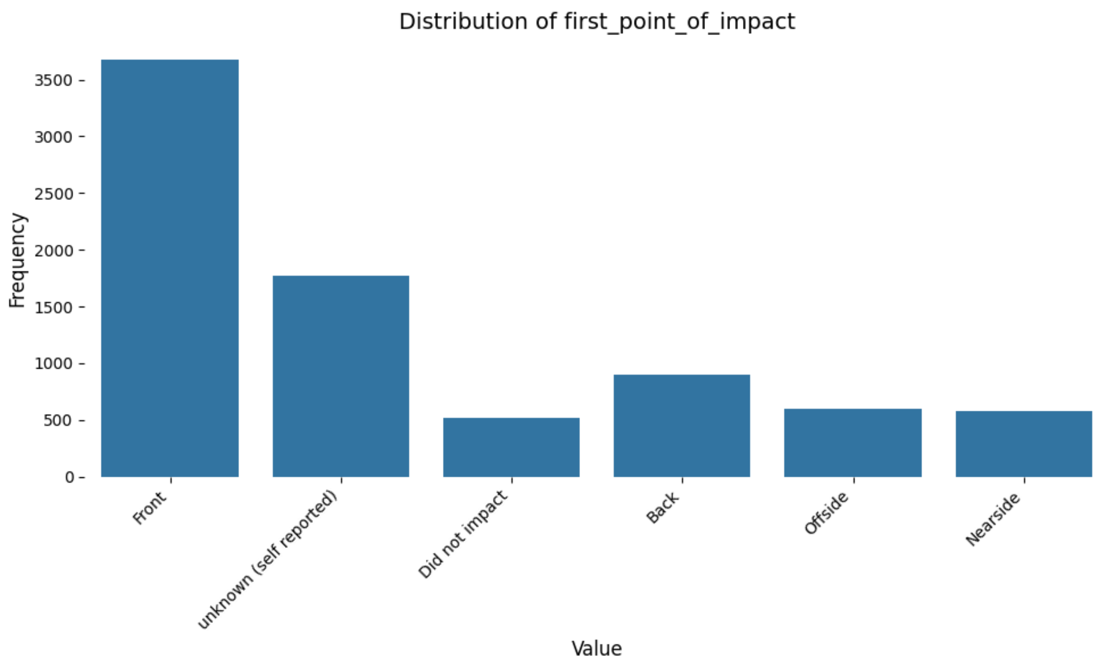


Most incidents didn't involve hitting objects off the carriageway, but walls or fences (27), and lamp posts (19) were the most commonly struck when they did.

first_point_of_impact

[110]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'first_point_of_impact')
plot_countplot(X_train, 'first_point_of_impact')
```

```
Descriptive Statistics for first_point_of_impact:
Mode: Front

                  Category  Frequency
0                    Front       3680
1  unknown (self reported)       1769
2                     Back        904
3                  Offside        600
4                Nearside        579
5            Did not impact       518


--------------------------------------------------------------------------------
```

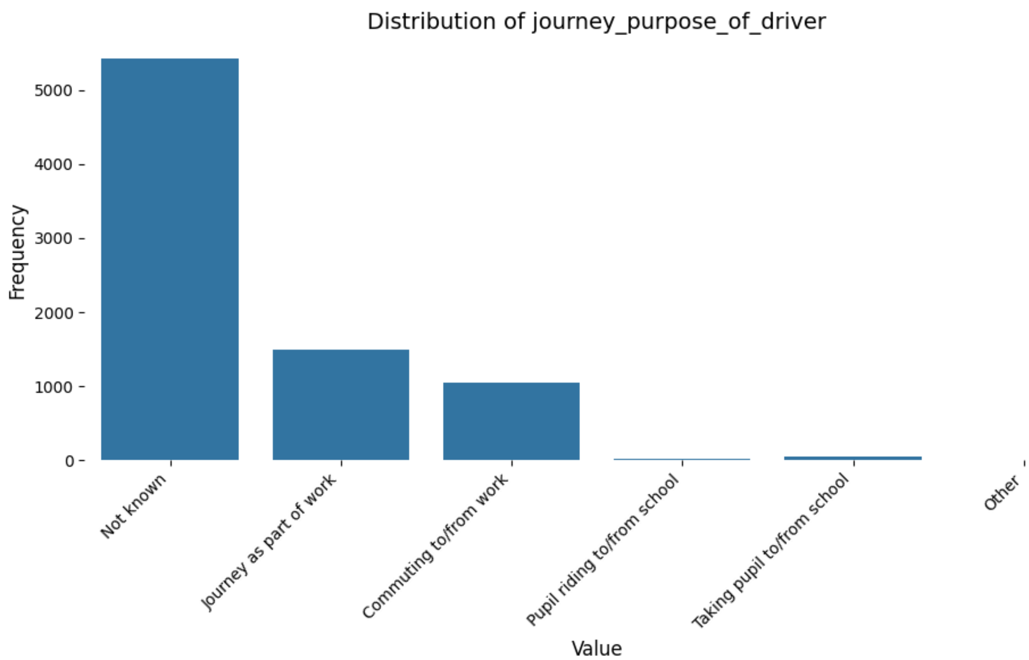


Frontal impacts were the most common (3,680), followed by rear impacts (904) amongst the reported areas of impact, highlighting the prevalence of head-on or rear-end collisions.

journey_purpose_of_driver

[113]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'journey_purpose_of_driver')
plot_countplot(X_train, 'journey_purpose_of_driver')
```

```
Descriptive Statistics for journey_purpose_of_driver:
Mode: Not known

                      Category  Frequency
0                    Not known       5423
1         Journey as part of work       1501
2          Commuting to/from work       1052
3   Taking pupil to/from school         57
4    Pupil riding to/from school         16
5                        Other          1


--------------------------------------------------------------------------------
```

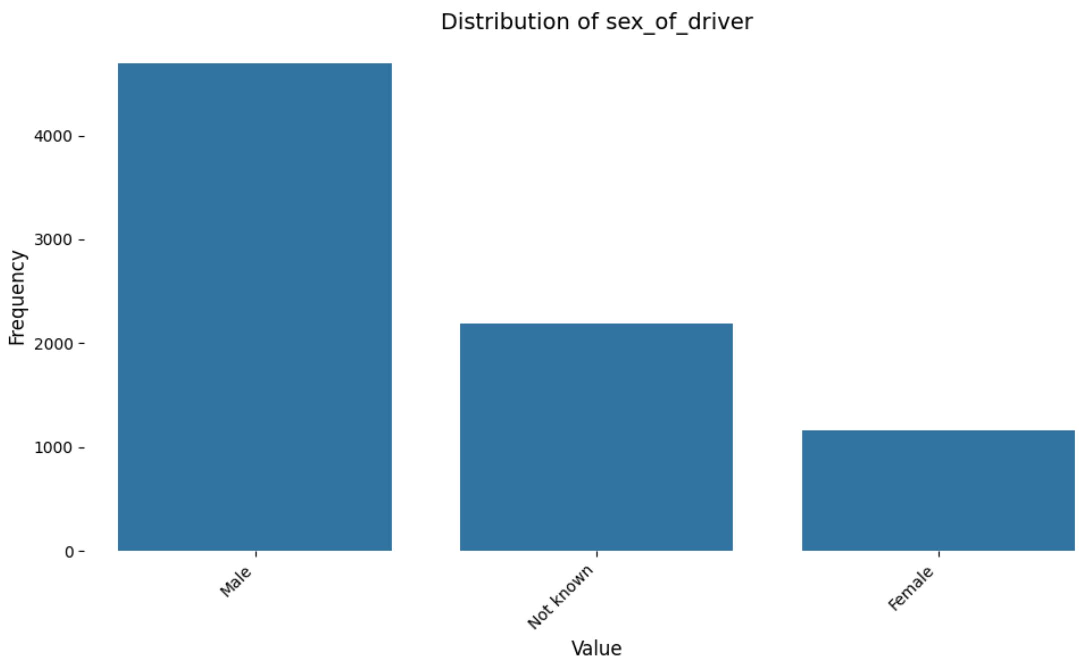


Out of the known journey purpose of the driver journey as part of work involved the highest number of accidents (1501), followed by work-related travel (1,052) and commuting (1,052), with school related journeys being rare.

sex_of_driver

[116]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'sex_of_driver')
plot_countplot(X_train, 'sex_of_driver')
```

```
Descriptive Statistics for sex_of_driver:
Mode: Male

    Category  Frequency
0       Male       4697
1  Not known       2186
2     Female       1167

--------------------------------------------------------------------------------
```



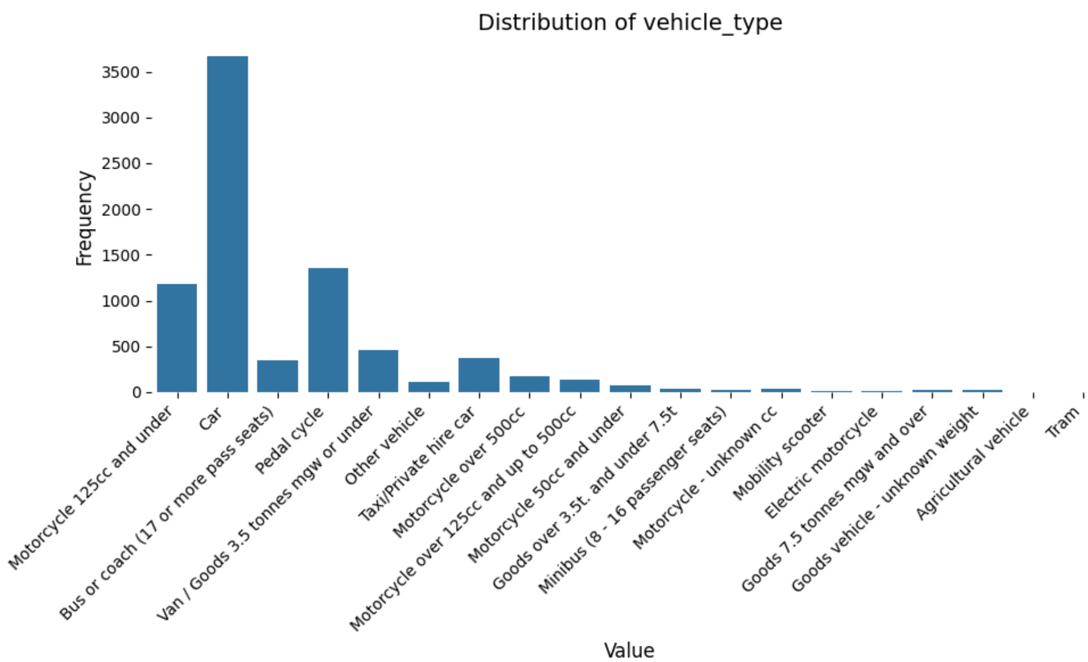
Male drivers were involved in most incidents (4,697), but many cases (2,186) lacked gender data, highlighting gaps in demographic reporting.

vehicle_type

[119]:
```
#Use the previously created functions to describe and plot the categorical
variable
describe_column(X_train, 'vehicle_type')
plot_countplot(X_train, 'vehicle_type')
```

```
Descriptive Statistics for vehicle_type:
Mode: Car

                                Category  Frequency
0                                    Car       3667
1                            Pedal cycle       1361
2               Motorcycle 125cc and under       1180
3      Van / Goods 3.5 tonnes mgw or under        454
4                     Taxi/Private hire car        369
5     Bus or coach (17 or more pass seats)        352
6                     Motorcycle over 500cc        180
7    Motorcycle over 125cc and up to 500cc        139
8                            Other vehicle        109
9                 Motorcycle 50cc and under         79
10                 Motorcycle - unknown cc         35
11           Goods over 3.5t. and under 7.5t        32
12             Goods 7.5 tonnes mgw and over        25
```

```
13         Goods vehicle - unknown weight         19
14       Minibus (8 - 16 passenger seats)         19
15                    Electric motorcycle         17
16                       Mobility scooter         10
17                    Agricultural vehicle         2
18                                   Tram          1

--------------------------------------------------------------------------------
```



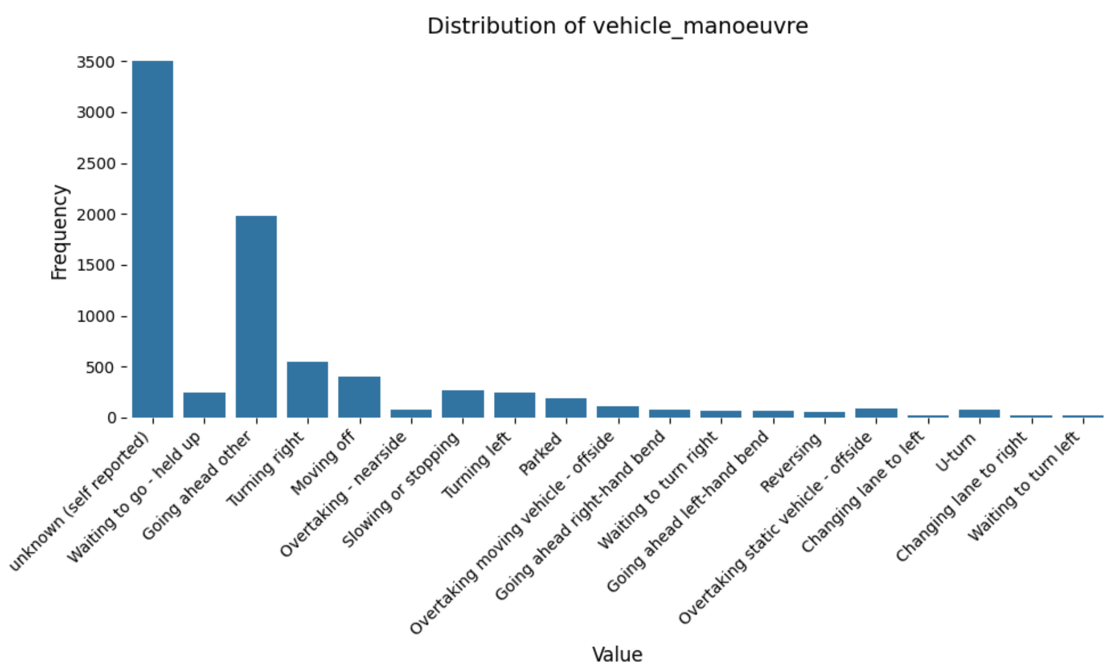
Cars were most involved in incidents (3,667), followed by pedal cycles (1,361) and small motorcycles (1,180), highlighting the dominance of personal vehicles in accidents.

vehicle_manoeuvre

[122]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'vehicle_manoeuvre')
plot_countplot(X_train, 'vehicle_manoeuvre')
```

```
Descriptive Statistics for vehicle_manoeuvre:
Mode: unknown (self reported)

                          Category  Frequency
0            unknown (self reported)       3503
1                  Going ahead other       1985
2                      Turning right        541
3                         Moving off        398
```

```
4                   Slowing or stopping       270
5                          Turning left       248
6                Waiting to go - held up      240
7                                Parked       186
8    Overtaking moving vehicle - offside      113
9    Overtaking static vehicle - offside       83
10                               U-turn        81
11          Going ahead right-hand bend        79
12                Overtaking - nearside        77
13           Going ahead left-hand bend        69
14                Waiting to turn right        68
15                            Reversing        49
16               Changing lane to left         24
17              Changing lane to right         19
18                 Waiting to turn left        17

--------------------------------------------------------------------------------
```



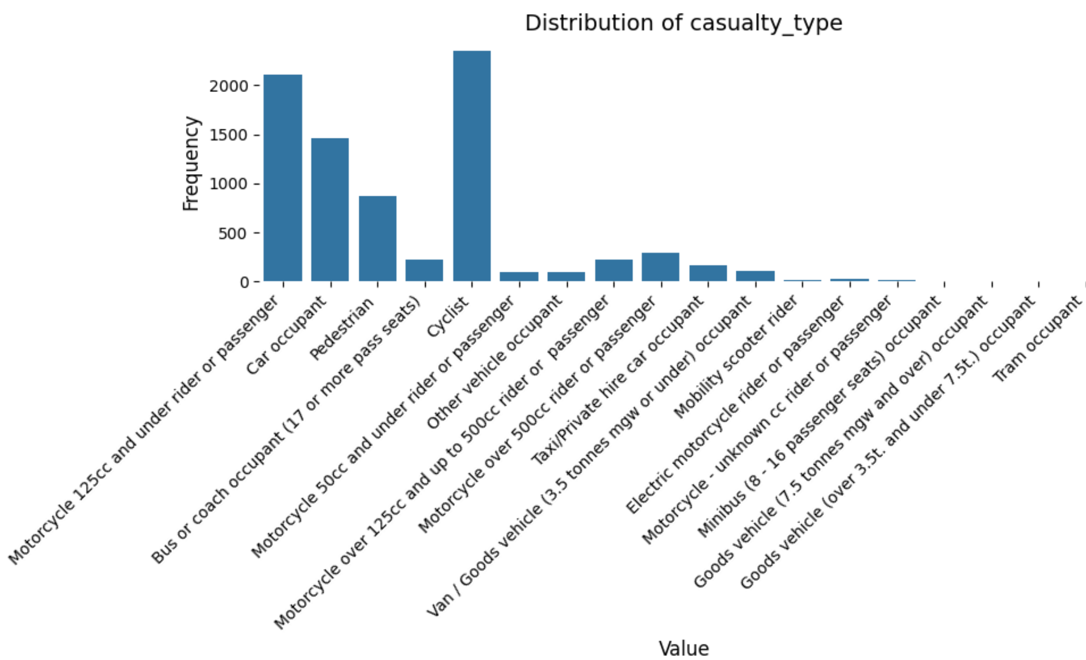
Most manoeuvres were marked as "unknown" (3,503), with "Going ahead other" (1,985) being the most common known action, while complex moves like lane changes were rare.

casualty_type

[125]:
```
#Use the previously created functions to describe and plot the categorical␣
↪variable
describe_column(X_train, 'casualty_type')
```

```
plot_countplot(X_train, 'casualty_type')
```

```
Descriptive Statistics for casualty_type:
Mode: Cyclist

                                              Category  Frequency
0                                              Cyclist       2344
1       Motorcycle 125cc and under rider or passenger       2104
2                                         Car occupant       1455
3                                           Pedestrian        871
4            Motorcycle over 500cc rider or passenger        290
5   Motorcycle over 125cc and up to 500cc rider or…       227
6       Bus or coach occupant (17 or more pass seats)        224
7                         Taxi/Private hire car occupant        169
8   Van / Goods vehicle (3.5 tonnes mgw or under) …       108
9                               Other vehicle occupant         93
10       Motorcycle 50cc and under rider or passenger         92
11             Electric motorcycle rider or passenger         28
12          Motorcycle - unknown cc rider or passenger         17
13                              Mobility scooter rider         15
14           Minibus (8 - 16 passenger seats) occupant          6
15  Goods vehicle (over 3.5t. and under 7.5t.) occ…         3
16   Goods vehicle (7.5 tonnes mgw and over) occupant          2
17                                       Tram occupant          2

--------------------------------------------------------------------------------
```



Cyclists and small motorcycle riders were involved in the most accidents, highlighting higher risks for vulnerable two-wheel road users.

5.2 Bivariate Analysis

Relationships between the target and independent variables were explored using visualizations to assess their potential impact.

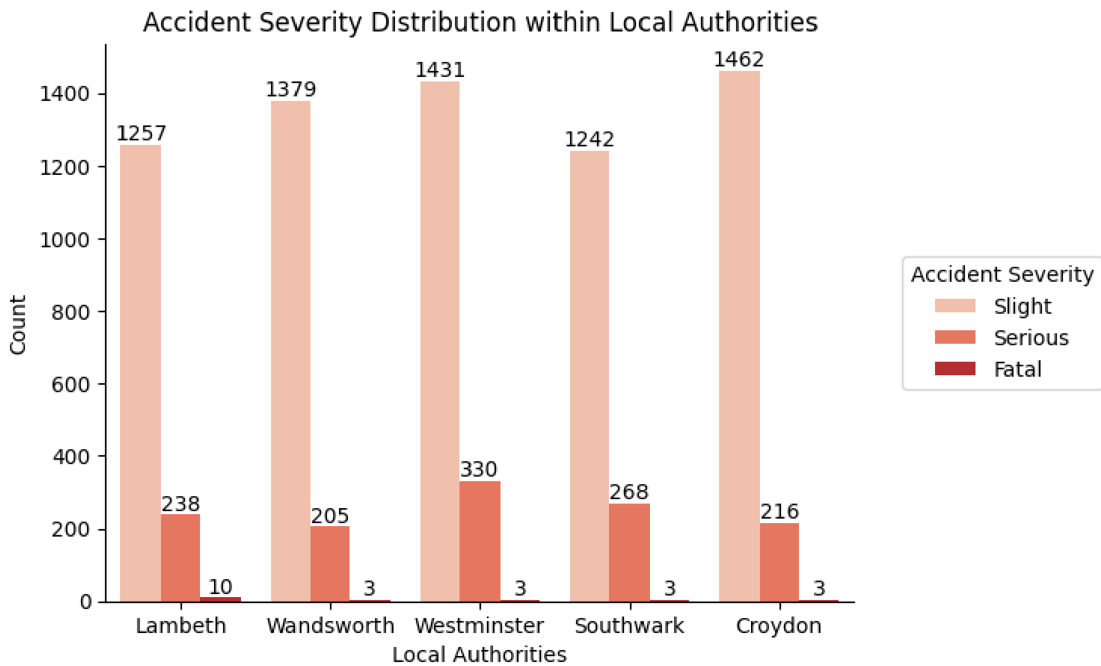
[129]:
```
#Create a copy y_train dataset that has all its numerical codes converted into␣
↪their actual categorical labels:
y_train_with_labels = pd.DataFrame(y_train).copy()

for column in y_train_with_labels.columns:
    if column in guide_data['field name'].values:
        # Creating a dictionary to map code/format to label for each field_name
        mapping_dict = guide_data[guide_data['field name'] == column].
↪set_index('code/format')['label'].to_dict()
        # Replacing the values in top_5_boroughs based on the mapping dictionary
        if mapping_dict:
            y_train_with_labels[column] = y_train_with_labels[column].
↪map(mapping_dict).fillna(y_train_with_labels[column])

y_train_with_labels.head()
```

[129]:

	accident_severity
2142	Slight
1930	Slight
8757	Slight
9327	Slight
7125	Serious

[130]:
```
#Merge the datasets
merged_data = pd.merge(X_train, y_train_with_labels, left_index=True,␣
↪right_index=True)

#Plot accident_severity and location_authority_ons_district on a horizontal bar␣
↪chart
ax = sns.countplot(data=merged_data, x='local_authority_ons_district',␣
↪hue='accident_severity', palette='Reds')

#Plot the counts of the bars
for container in ax.containers:
    ax.bar_label(container, fontsize=10)

#Move the legend to the right of the plot and center the plot
plt.title('Accident Severity Distribution within Local Authorities')
```

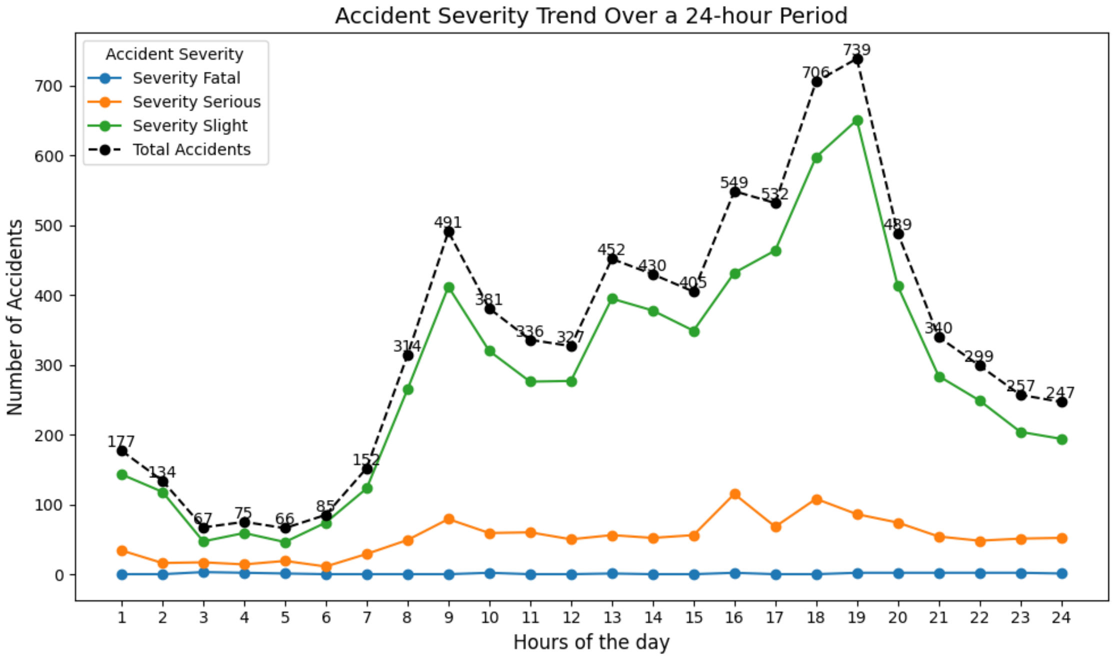
```
plt.legend(title='Accident Severity', bbox_to_anchor=(1.05, 0.5), loc='center␣
↪left')
plt.xlabel('Local Authorities')
plt.ylabel('Count')

#Cleaner borders
sns.despine()
plt.show()
```



Across five London boroughs, slight accidents dominate, with serious cases less common and fatal ones rare.

[132]:
```
#Line graph for the trend of severity on accidents in a 24 hour period
#Extract the hour from 'time'
merged_data['hour_only'] = merged_data['time'].dt.hour

#Grouping by 'hour_only' and 'accident_severity' to get counts
severity_counts = merged_data.groupby(['hour_only', 'accident_severity']).
↪size().unstack(fill_value=0)

#Adding a total column for the total number of accidents in each hour
severity_counts['Total'] = severity_counts.sum(axis=1)

#Plotting the trend for each accident severity level and total accidents
plt.figure(figsize=(10, 6))
```

```python
#Loop through each unique accident severity level and plot it
for severity in severity_counts.columns[:-1]:  #Exclude 'Total' column from␣
 ↪this loop
    plt.plot(severity_counts.index, severity_counts[severity], marker='o',␣
 ↪label=f"Severity {severity}")

#Plotting the total number of accidents line
plt.plot(severity_counts.index, severity_counts['Total'], marker='o',␣
 ↪label="Total Accidents", linestyle='--', color='black')

#Adding labels for each point on the total line
for x, y in zip(severity_counts.index, severity_counts['Total']):
    plt.text(x, y, str(int(y)), color='black', ha='center', va='bottom')

#Adding labels and title
plt.title("Accident Severity Trend Over a 24-hour Period", fontsize=14)
plt.xlabel("Hours of the day", fontsize=12)
plt.ylabel("Number of Accidents", fontsize=12)

#Adding a legend
plt.legend(title="Accident Severity", loc="upper left")

#Show the plot
plt.tight_layout()
plt.xticks(severity_counts.index, severity_counts.index + 1)  #Label x-axis␣
 ↪from 1 to 24
plt.show()
```



Accidents peak between 18:00–22:00, mostly slight in severity, with fatal and serious cases remaining low; overall trends form a U-shape, likely tied to rush hour traffic.

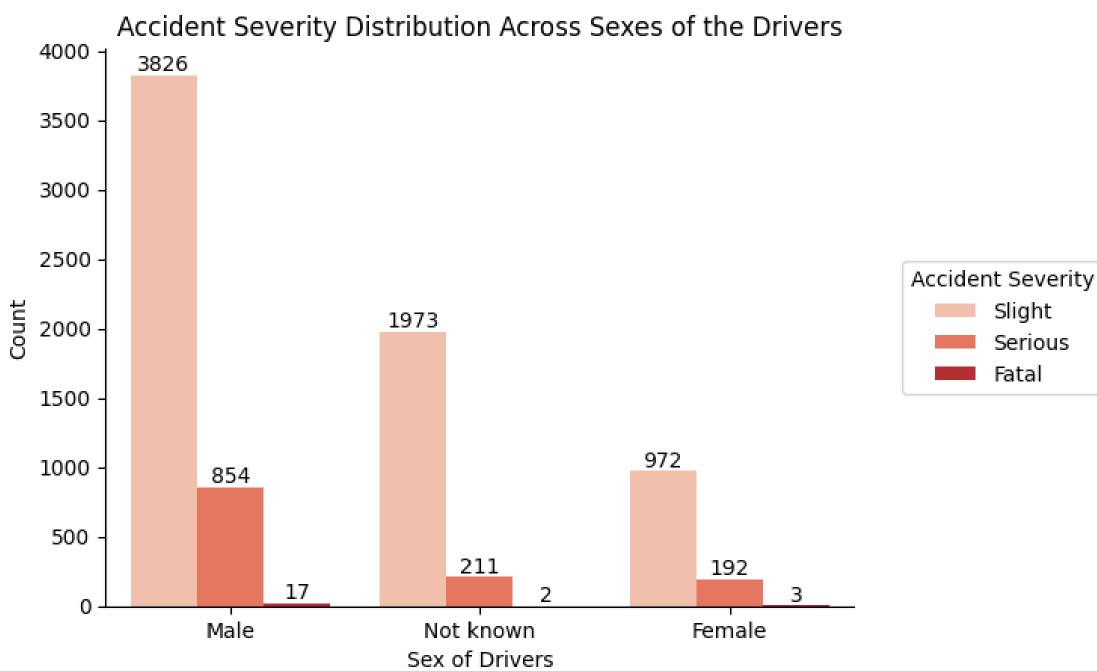
[134]:
```
#Bar graph of accident severity by time of day
#Function below classifies periods in a day based on the hour
def categorize_time(time):
    #Extract hour from the timestamp
    hour = time.hour
    if  0 <= hour < 6:
        return "Night"
    elif 6 <= hour < 12:
        return "Morning"
    elif 12 <= hour < 18:
        return "Afternoon"
    elif 18 <= hour < 21:
        return "Evening"
    else:
        return "Night"


#Apply categorization to 'time' column
merged_data['Time of Day'] = merged_data['time'].apply(categorize_time)

#Group by 'Time of Day' and 'Accident Severity' to get counts
severity_counts = merged_data.groupby(['Time of Day', 'accident_severity']).
 ↪size().unstack(fill_value=0)
```

```
# Plotting the bar graph
ax= severity_counts.plot(kind='bar', figsize=(10, 6))
ax.set_xticklabels(ax.get_xticklabels(), rotation=0, ha='center')

#Adding labels
for line in ax.lines:
    for x, y in zip(line.get_xdata(), line.get_ydata()):
        ax.text(x, y, str(int(y)), color='black', ha='center', va='bottom')

#Adding labels and title
plt.title("Accident Severity by Time of Day", fontsize=14)
plt.xlabel("Time of Day", fontsize=12)
plt.ylabel("Number of Accidents", fontsize=12)
plt.legend(title='Accident Severity', loc="upper left")

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

Most accidents occur in the afternoon (12–18h), with slight accidents dominating; mornings see slightly more incidents than evenings.

[136]:
```
#Plot accident_severity and sex_of_driver on a horizontal bar chart
```

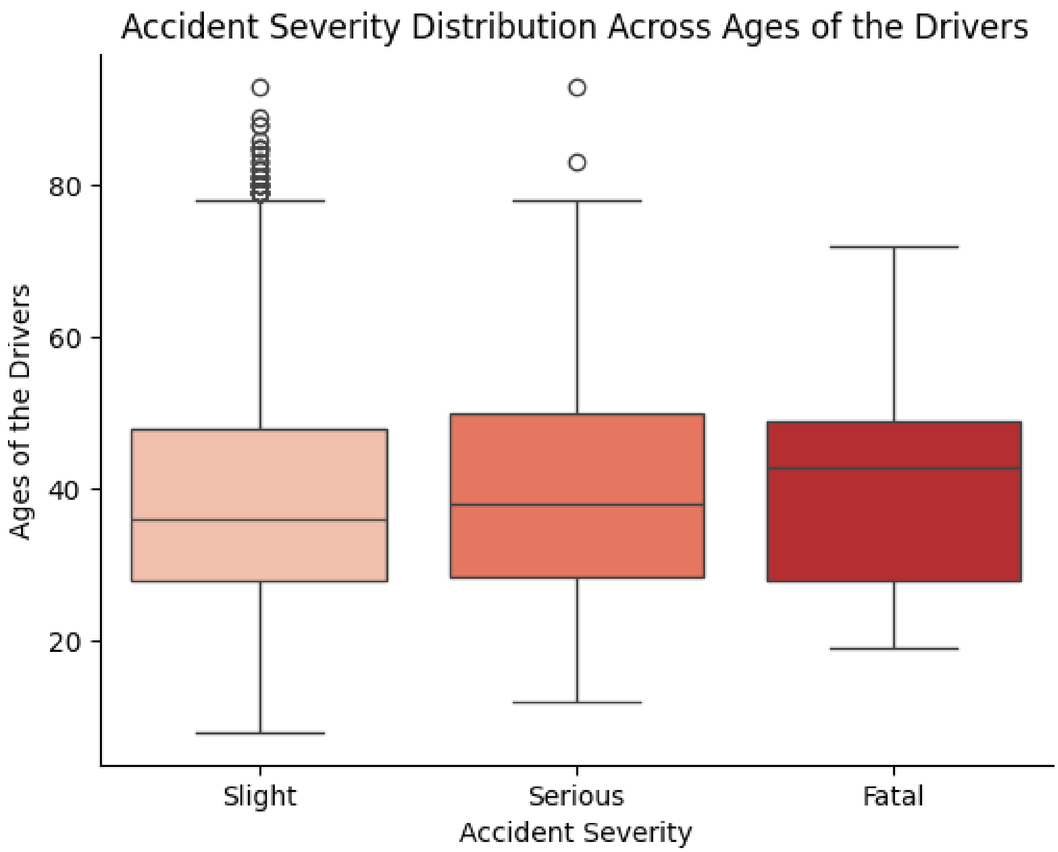
```
ax = sns.countplot(data=merged_data, x='sex_of_driver',␣
↪hue='accident_severity', palette='Reds')

#Plot the counts of the bars
for container in ax.containers:
    ax.bar_label(container, fontsize=10)

#Move the legend to the right of the plot and center the plot
#Label the axes
plt.title('Accident Severity Distribution Across Sexes of the Drivers')
plt.legend(title='Accident Severity', bbox_to_anchor=(1.05, 0.5), loc='center␣
↪left')
plt.xlabel('Sex of Drivers')
plt.ylabel('Count')

#Cleaner borders
sns.despine()
plt.show()
```



Males are involved in more accidents across all severities, with 1,973 slight, 854 serious, and 17 fatal cases, while females show lower figures.

[138]:
```
#Box plot of the accident severity and ages of the drivers
sns.boxplot(data=merged_data, x='accident_severity', y='age_of_driver',␣
↪palette='Reds')
```

```python
#Move the legend to the right of the plot and center the plot
plt.title('Accident Severity Distribution Across Ages of the Drivers')
plt.xlabel('Accident Severity')
plt.ylabel('Ages of the Drivers')

#Cleaner borders
sns.despine()
plt.show()
```



The boxplot shows that fatal accidents are more common among older drivers, while slight accidents compared with serious and fatal involve a younger age range.

6 Data Preprocessing

6.1 Handling Missing Values

[142]:
```
#Any missing values in both the training and testing datasets will be imputed␣
 ↪using Iterative Imputer.
#To do that, dummy variables will be created from the categorical variables.

#Create dummy variables from the categorical variables, which are listed below
cat_cols = ['local_authority_ons_district','road_type','junction_detail',
            'junction_control','light_conditions','weather_conditions',
            'road_surface_conditions','urban_or_rural_area',
            'vehicle_location_restricted_lane','junction_location',
            'skidding_and_overturning',
            'hit_object_in_carriageway','vehicle_leaving_carriageway',
            'hit_object_off_carriageway','first_point_of_impact',
            'journey_purpose_of_driver','sex_of_driver','vehicle_type',
            'vehicle_manoeuvre','casualty_type']

#Fit an encoder and transform the **trainset**
cat_vals = X_train[cat_cols]
cat_vals = X_test[cat_cols]

#Replace 0 with 'No' in the specified categorical columns
X_train[cat_cols] = X_train[cat_cols].replace(0, 'No')
X_test[cat_cols] = X_test[cat_cols].replace(0, 'No')

one_hot_encoder = OneHotEncoder(drop="first", sparse_output=False)
```

[143]:
```
#Fit and transform the training data
transformed = one_hot_encoder.fit_transform(X_train[cat_cols])

#Get the new column names after one-hot encoding
new_col_names = one_hot_encoder.get_feature_names_out(cat_cols)

#Add the transformed columns to X_train
for i, new_col_name in enumerate(new_col_names):
    X_train[new_col_name] = transformed[:, i]

#Check the updated X_train
X_train.head()
```

[143]:
```
      accident_index                time  number_of_vehicles  \
2142    2023010435768 1900-01-01 19:35:00                 2.0
1930    2023010434377 1900-01-01 15:09:00                 1.0
8757    2023010477755 1900-01-01 17:00:00                 2.0
9327    2023010481441 1900-01-01 17:15:00                 2.0
7125    2023010467051 1900-01-01 18:40:00                 2.0
```

```
     number_of_casualties       date local_authority_ons_district  \
2142                  1.0 2023-02-27                      Lambeth   
1930                  1.0 2023-03-24                      Lambeth   
8757                  1.0 2023-11-10                      Lambeth   
9327                  1.0 2023-12-01                      Lambeth   
7125                  1.0 2023-09-19                   Wandsworth   

              road_type  speed_limit                      junction_detail  \
2142            Unknown           30  Not at junction or within 20 metres   
1930            Unknown           20  Not at junction or within 20 metres   
8757  Single carriageway          30             T or staggered junction   
9327            Unknown           20             unknown (self reported)   
7125  Single carriageway          20  Not at junction or within 20 metres   

             junction_control  …  \
2142                      NaN  …   
1930                      NaN  …   
8757  Give way or uncontrolled  …   
9327   unknown (self reported)  …   
7125                      NaN  …   

     casualty_type_Motorcycle - unknown cc rider or passenger  \
2142                                                0.0         
1930                                                0.0         
8757                                                0.0         
9327                                                0.0         
7125                                                0.0         

     casualty_type_Motorcycle 125cc and under rider or passenger  \
2142                                                1.0            
1930                                                0.0            
8757                                                1.0            
9327                                                0.0            
7125                                                0.0            

     casualty_type_Motorcycle 50cc and under rider or passenger  \
2142                                                0.0           
1930                                                0.0           
8757                                                0.0           
9327                                                0.0           
7125                                                0.0           

     casualty_type_Motorcycle over 125cc and up to 500cc rider or  passenger  \
2142                                                0.0                         
1930                                                0.0                         
8757                                                0.0                         
```

```
9327                                              0.0
7125                                              0.0

     casualty_type_Motorcycle over 500cc rider or passenger  \
2142                                              0.0
1930                                              0.0
8757                                              0.0
9327                                              0.0
7125                                              0.0

     casualty_type_Other vehicle occupant casualty_type_Pedestrian  \
2142                                  0.0                       0.0
1930                                  0.0                       0.0
8757                                  0.0                       0.0
9327                                  0.0                       1.0
7125                                  0.0                       0.0

     casualty_type_Taxi/Private hire car occupant casualty_type_Tram occupant  \
2142                                          0.0                          0.0
1930                                          0.0                          0.0
8757                                          0.0                          0.0
9327                                          0.0                          0.0
7125                                          0.0                          0.0

     casualty_type_Van / Goods vehicle (3.5 tonnes mgw or under) occupant
2142                                              0.0
1930                                              0.0
8757                                              0.0
9327                                              0.0
7125                                              0.0

[5 rows x 184 columns]
```

[144]:
```
#Do the same for the test data
#Transform the testing data
transformed = one_hot_encoder.transform(X_test[cat_cols])

#Get the new column names after one-hot encoding
new_col_names = one_hot_encoder.get_feature_names_out(cat_cols)

#Add the transformed columns to X_test
for i, new_col_name in enumerate(new_col_names):
    X_test[new_col_name] = transformed[:, i]

#Check the updated X_train
X_test.head()
```

[144]:

```
      accident_index                time  number_of_vehicles  \
8631   2023010476974 1900-01-01 08:10:00                 2.0
9500   2023010482861 1900-01-01 17:45:00                 2.0
1958   2023010434525 1900-01-01 18:00:00                 3.0
4498   2023010450998 1900-01-01 17:55:00                 2.0
7743   2023010471555 1900-01-01 11:58:00                 2.0

      number_of_casualties       date local_authority_ons_district  \
8631                   2.0 2023-11-08                      Croydon
9500                   1.0 2023-12-06                      Croydon
1958                   1.0 2023-03-27                    Southwark
4498                   1.0 2023-06-23                      Lambeth
7743                   1.0 2023-10-12                      Lambeth

               road_type  speed_limit                     junction_detail  \
8631  Single carriageway           30  Not at junction or within 20 metres
9500             Unknown           30              unknown (self reported)
1958  Single carriageway           30              T or staggered junction
4498  Single carriageway           20              T or staggered junction
7743  Single carriageway           20    More than 4 arms (not roundabout)

              junction_control  …  \
8631                       NaN  …
9500   unknown (self reported)  …
1958  Give way or uncontrolled  …
4498  Give way or uncontrolled  …
7743        Auto traffic signal  …

     casualty_type_Motorcycle - unknown cc rider or passenger  \
8631                                                0.0
9500                                                0.0
1958                                                0.0
4498                                                0.0
7743                                                0.0

     casualty_type_Motorcycle 125cc and under rider or passenger  \
8631                                                0.0
9500                                                1.0
1958                                                1.0
4498                                                0.0
7743                                                0.0

     casualty_type_Motorcycle 50cc and under rider or passenger  \
8631                                                0.0
9500                                                0.0
1958                                                0.0
4498                                                0.0
```

```
7743                                                 0.0

     casualty_type_Motorcycle over 125cc and up to 500cc rider or  passenger  \
8631                                                 0.0
9500                                                 0.0
1958                                                 0.0
4498                                                 0.0
7743                                                 0.0

     casualty_type_Motorcycle over 500cc rider or passenger  \
8631                                                 0.0
9500                                                 0.0
1958                                                 0.0
4498                                                 0.0
7743                                                 0.0

     casualty_type_Other vehicle occupant casualty_type_Pedestrian  \
8631                                  0.0                      0.0
9500                                  0.0                      0.0
1958                                  0.0                      0.0
4498                                  0.0                      0.0
7743                                  0.0                      0.0

     casualty_type_Taxi/Private hire car occupant casualty_type_Tram occupant  \
8631                                          0.0                         0.0
9500                                          0.0                         0.0
1958                                          0.0                         0.0
4498                                          0.0                         0.0
7743                                          0.0                         0.0

     casualty_type_Van / Goods vehicle (3.5 tonnes mgw or under) occupant
8631                                                 0.0
9500                                                 0.0
1958                                                 0.0
4498                                                 0.0
7743                                                 0.0

[5 rows x 184 columns]
```

[145]:
```
#With the dummy variables created, drop the categorical variables that were␣
↪used to create them
#List of columns to delete
columns_to_delete =␣
↪['local_authority_ons_district','road_type','junction_detail',
                     'junction_control','light_conditions','weather_conditions',
                    'road_surface_conditions','urban_or_rural_area',
                     'vehicle_location_restricted_lane','junction_location',
```

```
                        'skidding_and_overturning','hit_object_in_carriageway',
                        'vehicle_leaving_carriageway','hit_object_off_carriageway',
                        'first_point_of_impact','journey_purpose_of_driver',
                        'sex_of_driver','vehicle_type','vehicle_manoeuvre',
                        'casualty_type']

#Drop the columns from the DataFrame
X_train = X_train.drop(columns=columns_to_delete)
```

[146]:
```
#Check if the columns are dropped
X_train.head()
```

[146]:
```
      accident_index                time  number_of_vehicles  \
2142   2023010435768 1900-01-01 19:35:00                 2.0
1930   2023010434377 1900-01-01 15:09:00                 1.0
8757   2023010477755 1900-01-01 17:00:00                 2.0
9327   2023010481441 1900-01-01 17:15:00                 2.0
7125   2023010467051 1900-01-01 18:40:00                 2.0

      number_of_casualties       date  speed_limit  age_of_driver  \
2142                   1.0 2023-02-27           30           26.0
1930                   1.0 2023-03-24           20            NaN
8757                   1.0 2023-11-10           30           25.0
9327                   1.0 2023-12-01           20           64.0
7125                   1.0 2023-09-19           20           60.0

      local_authority_ons_district_Lambeth  \
2142                                   1.0
1930                                   1.0
8757                                   1.0
9327                                   1.0
7125                                   0.0

      local_authority_ons_district_Southwark  \
2142                                     0.0
1930                                     0.0
8757                                     0.0
9327                                     0.0
7125                                     0.0

      local_authority_ons_district_Wandsworth  …  \
2142                                      0.0  …
1930                                      0.0  …
8757                                      0.0  …
9327                                      0.0  …
7125                                      1.0  …
```

```
      casualty_type_Motorcycle - unknown cc rider or passenger  \
2142                                              0.0
1930                                              0.0
8757                                              0.0
9327                                              0.0
7125                                              0.0

      casualty_type_Motorcycle 125cc and under rider or passenger  \
2142                                              1.0
1930                                              0.0
8757                                              1.0
9327                                              0.0
7125                                              0.0

      casualty_type_Motorcycle 50cc and under rider or passenger  \
2142                                              0.0
1930                                              0.0
8757                                              0.0
9327                                              0.0
7125                                              0.0

      casualty_type_Motorcycle over 125cc and up to 500cc rider or  passenger  \
2142                                              0.0
1930                                              0.0
8757                                              0.0
9327                                              0.0
7125                                              0.0

      casualty_type_Motorcycle over 500cc rider or passenger  \
2142                                              0.0
1930                                              0.0
8757                                              0.0
9327                                              0.0
7125                                              0.0

      casualty_type_Other vehicle occupant  casualty_type_Pedestrian  \
2142                                   0.0                       0.0
1930                                   0.0                       0.0
8757                                   0.0                       0.0
9327                                   0.0                       1.0
7125                                   0.0                       0.0

      casualty_type_Taxi/Private hire car occupant  \
2142                                          0.0
1930                                          0.0
8757                                          0.0
9327                                          0.0
```

```
7125                                           0.0

      casualty_type_Tram occupant  \
2142                          0.0
1930                          0.0
8757                          0.0
9327                          0.0
7125                          0.0

      casualty_type_Van / Goods vehicle (3.5 tonnes mgw or under) occupant
2142                                                0.0
1930                                                0.0
8757                                                0.0
9327                                                0.0
7125                                                0.0

[5 rows x 164 columns]
```

[147]:
```python
#List of columns to delete
columns_to_delete =␣
↪['local_authority_ons_district','road_type','junction_detail',
                     'junction_control','light_conditions','weather_conditions',
                    'road_surface_conditions','urban_or_rural_area',
                     'vehicle_location_restricted_lane','junction_location',
                     'skidding_and_overturning','hit_object_in_carriageway',
                     'vehicle_leaving_carriageway','hit_object_off_carriageway',
                     'first_point_of_impact','journey_purpose_of_driver',
                     'sex_of_driver','vehicle_type','vehicle_manoeuvre',
                     'casualty_type']

#Drop the columns from the DataFrame
X_test = X_test.drop(columns=columns_to_delete)
```

[148]:
```python
#Check how many NaN values there are in the X_train dataset
X_train.isnull().values.sum()
```

[148]:
```
np.int64(2009)
```

[149]:
```python
#Check how many NaN values there are in the y_train dataset
y_train.isnull().sum()
```

[149]:
```
np.int64(0)
```

[150]:
```python
#Check how many NaN values there are in the X_test dataset
X_test.isnull().values.sum()
```

[150]:
```
np.int64(483)
```

[151]:
```
#Check how many NaN values there are in the y_test dataset
y_test.isnull().sum()
```

[151]: np.int64(0)

[152]:
```
#Create copies of the training and testing datasets for X that only have the␣
↪date and time columns
#Will prevent errors from cropping up when the imputer is ran
X_train_dropped_columns = X_train[['date','time']]
X_test_dropped_columns = X_test[['date','time']]
```

[153]:
```
#Date and time columns are dropped from the two X datasets
X_train = X_train.drop(columns=['date','time']).copy()
X_test = X_test.drop(columns=['date','time']).copy()
```

[154]:
```
start = timer()
#The imputer is ran on the X_train dataset
imputer = IterativeImputer(max_iter = 30)
X_train = pd.DataFrame(imputer.fit_transform(X_train),
                            columns = X_train.columns,
                            index = X_train.index)

#Check to see if any NaN values are still remaining
X_train.isnull().sum().sum()

#Print the execution time
print("Execution time HH:MM:SS:", timedelta(seconds=timer() - start))
```

```
Execution time HH:MM:SS: 0:00:34.129053
```

[155]:
```
#Run the imputer on the X_test dataset as well
X_test = pd.DataFrame(imputer.transform(X_test),
                            columns = X_test.columns,
                            index = X_test.index)

#Check to see if there any NaN values remaining
X_test.isnull().sum().sum()
```

[155]: np.int64(0)

[156]:
```
#Add the dropped date and time columns back into the train and test datasets␣
↪for X
X_train = pd.concat([X_train, X_train_dropped_columns], axis=1)
X_test = pd.concat([X_test, X_test_dropped_columns], axis=1)
```

[157]:
```
#Check if the changes have taken place using a visualization
pd.options.display.float_format = '{:.0f}'.format
```

```
X_train.head()
```

[157]:

```
         accident_index  number_of_vehicles  number_of_casualties  speed_limit  \
2142      2023010435768                   2                     1           30
1930      2023010434377                   1                     1           20
8757      2023010477755                   2                     1           30
9327      2023010481441                   2                     1           20
7125      2023010467051                   2                     1           20

      age_of_driver  local_authority_ons_district_Lambeth  \
2142             26                                     1
1930             40                                     1
8757             25                                     1
9327             64                                     1
7125             60                                     0

      local_authority_ons_district_Southwark  \
2142                                       0
1930                                       0
8757                                       0
9327                                       0
7125                                       0

      local_authority_ons_district_Wandsworth  \
2142                                        0
1930                                        0
8757                                        0
9327                                        0
7125                                        1

      local_authority_ons_district_Westminster  road_type_One way street  …  \
2142                                         0                         0  …
1930                                         0                         0  …
8757                                         0                         0  …
9327                                         0                         0  …
7125                                         0                         0  …

      casualty_type_Motorcycle 50cc and under rider or passenger  \
2142                                                  0
1930                                                  0
8757                                                  0
9327                                                  0
7125                                                  0

      casualty_type_Motorcycle over 125cc and up to 500cc rider or  passenger  \
2142                                                  0
1930                                                  0
```

```
8757                                                    0
9327                                                    0
7125                                                    0

      casualty_type_Motorcycle over 500cc rider or passenger  \
2142                                                    0
1930                                                    0
8757                                                    0
9327                                                    0
7125                                                    0

      casualty_type_Other vehicle occupant  casualty_type_Pedestrian  \
2142                                     0                         0
1930                                     0                         0
8757                                     0                         0
9327                                     0                         1
7125                                     0                         0

      casualty_type_Taxi/Private hire car occupant  \
2142                                             0
1930                                             0
8757                                             0
9327                                             0
7125                                             0

      casualty_type_Tram occupant  \
2142                            0
1930                            0
8757                            0
9327                            0
7125                            0

      casualty_type_Van / Goods vehicle (3.5 tonnes mgw or under) occupant  \
2142                                                    0
1930                                                    0
8757                                                    0
9327                                                    0
7125                                                    0

           date                time
2142 2023-02-27 1900-01-01 19:35:00
1930 2023-03-24 1900-01-01 15:09:00
8757 2023-11-10 1900-01-01 17:00:00
9327 2023-12-01 1900-01-01 17:15:00
7125 2023-09-19 1900-01-01 18:40:00

[5 rows x 164 columns]
```

[158]:
```
#Do the same for the X_test dataset as well
X_test.head()
```

[158]:
```
       accident_index  number_of_vehicles  number_of_casualties  speed_limit  \
8631    2023010476974                   2                     2           30
9500    2023010482861                   2                     1           30
1958    2023010434525                   3                     1           30
4498    2023010450998                   2                     1           20
7743    2023010471555                   2                     1           20

      age_of_driver  local_authority_ons_district_Lambeth  \
8631             47                                     0
9500             40                                     0
1958             25                                     0
4498             26                                     1
7743             23                                     1

      local_authority_ons_district_Southwark  \
8631                                       0
9500                                       0
1958                                       1
4498                                       0
7743                                       0

      local_authority_ons_district_Wandsworth  \
8631                                        0
9500                                        0
1958                                        0
4498                                        0
7743                                        0

      local_authority_ons_district_Westminster  road_type_One way street  …  \
8631                                         0                         0  …
9500                                         0                         0  …
1958                                         0                         0  …
4498                                         0                         0  …
7743                                         0                         0  …

      casualty_type_Motorcycle 50cc and under rider or passenger  \
8631                                                  0
9500                                                  0
1958                                                  0
4498                                                  0
7743                                                  0

      casualty_type_Motorcycle over 125cc and up to 500cc rider or  passenger  \
8631                                                  0
```

```
9500                                                0
1958                                                0
4498                                                0
7743                                                0

      casualty_type_Motorcycle over 500cc rider or passenger  \
8631                                                0
9500                                                0
1958                                                0
4498                                                0
7743                                                0

      casualty_type_Other vehicle occupant  casualty_type_Pedestrian  \
8631                                     0                         0
9500                                     0                         0
1958                                     0                         0
4498                                     0                         0
7743                                     0                         0

      casualty_type_Taxi/Private hire car occupant  \
8631                                             0
9500                                             0
1958                                             0
4498                                             0
7743                                             0

      casualty_type_Tram occupant  \
8631                            0
9500                            0
1958                            0
4498                            0
7743                            0

      casualty_type_Van / Goods vehicle (3.5 tonnes mgw or under) occupant  \
8631                                                0
9500                                                0
1958                                                0
4498                                                0
7743                                                0

           date                time
8631 2023-11-08 1900-01-01 08:10:00
9500 2023-12-06 1900-01-01 17:45:00
1958 2023-03-27 1900-01-01 18:00:00
4498 2023-06-23 1900-01-01 17:55:00
7743 2023-10-12 1900-01-01 11:58:00
```

```
[5 rows x 164 columns]
```

6.2 Outlier Detection

To avoid bias in modeling, outliers identified during EDA will be removed using Isolation Forest.

[161]:
```python
#Check the size of the X_train and X_test datasets
X_train.shape, X_test.shape
```

[161]:
```
((8050, 164), (2013, 164))
```

[162]:
```python
#Check to see if the first few rows contain any outliers
X_train.head()
```

[162]:
```
        accident_index  number_of_vehicles  number_of_casualties  speed_limit  \
2142   2023010435768                   2                     1           30
1930   2023010434377                   1                     1           20
8757   2023010477755                   2                     1           30
9327   2023010481441                   2                     1           20
7125   2023010467051                   2                     1           20

      age_of_driver  local_authority_ons_district_Lambeth  \
2142             26                                     1
1930             40                                     1
8757             25                                     1
9327             64                                     1
7125             60                                     0

      local_authority_ons_district_Southwark  \
2142                                       0
1930                                       0
8757                                       0
9327                                       0
7125                                       0

      local_authority_ons_district_Wandsworth  \
2142                                        0
1930                                        0
8757                                        0
9327                                        0
7125                                        1

      local_authority_ons_district_Westminster  road_type_One way street  …  \
2142                                         0                         0  …
1930                                         0                         0  …
8757                                         0                         0  …
9327                                         0                         0  …
7125                                         0                         0  …
```

```
      casualty_type_Motorcycle 50cc and under rider or passenger  \
2142                                                 0
1930                                                 0
8757                                                 0
9327                                                 0
7125                                                 0

      casualty_type_Motorcycle over 125cc and up to 500cc rider or  passenger  \
2142                                                 0
1930                                                 0
8757                                                 0
9327                                                 0
7125                                                 0

      casualty_type_Motorcycle over 500cc rider or passenger  \
2142                                                 0
1930                                                 0
8757                                                 0
9327                                                 0
7125                                                 0

      casualty_type_Other vehicle occupant  casualty_type_Pedestrian  \
2142                                     0                         0
1930                                     0                         0
8757                                     0                         0
9327                                     0                         1
7125                                     0                         0

      casualty_type_Taxi/Private hire car occupant  \
2142                                             0
1930                                             0
8757                                             0
9327                                             0
7125                                             0

      casualty_type_Tram occupant  \
2142                            0
1930                            0
8757                            0
9327                            0
7125                            0

      casualty_type_Van / Goods vehicle (3.5 tonnes mgw or under) occupant  \
2142                                                 0
1930                                                 0
8757                                                 0
```

```
9327                                               0
7125                                               0

           date                 time
2142 2023-02-27 1900-01-01 19:35:00
1930 2023-03-24 1900-01-01 15:09:00
8757 2023-11-10 1900-01-01 17:00:00
9327 2023-12-01 1900-01-01 17:15:00
7125 2023-09-19 1900-01-01 18:40:00

[5 rows x 164 columns]
```

[163]:
```
#For the Isolation Forest to work, the date and time columns must be split into␣
 ↪year, month, day, hour, and minute.
#Split the date and time columns in the X_train dataset into year, month, day,␣
 ↪hour, and minute columns
X_train['year'] = X_train['date'].dt.year
X_train['month'] = X_train['date'].dt.month
X_train['day'] = X_train['date'].dt.day
X_train['hour'] = X_train['time'].dt.hour
X_train['minute'] = X_train['time'].dt.minute

#Drop the time and date columns as they are no longer necesssary
X_train = X_train.drop(columns=['time','date'])
```

[164]:
```
#The Isolation Forest is trained on the X_train dataset
clf = IsolationForest(n_estimators=100, random_state=7, contamination=0.03).
 ↪fit(X_train)
yhat = clf.predict(X_train)
yhat
```

[164]:
```
array([1, 1, 1, …, 1, 1, 1])
```

[165]:
```
start = timer()

#Run the Isolation Forest on the X_train
X_train = X_train[yhat != -1]
y_train = y_train[yhat != -1]
X_train.shape

#Print the execution time
print("Execution time HH:MM:SS:", timedelta(seconds=timer() - start))
```

```
Execution time HH:MM:SS: 0:00:00.004325
```

[166]:
```
start = timer()

#Do the same for the X_test
```

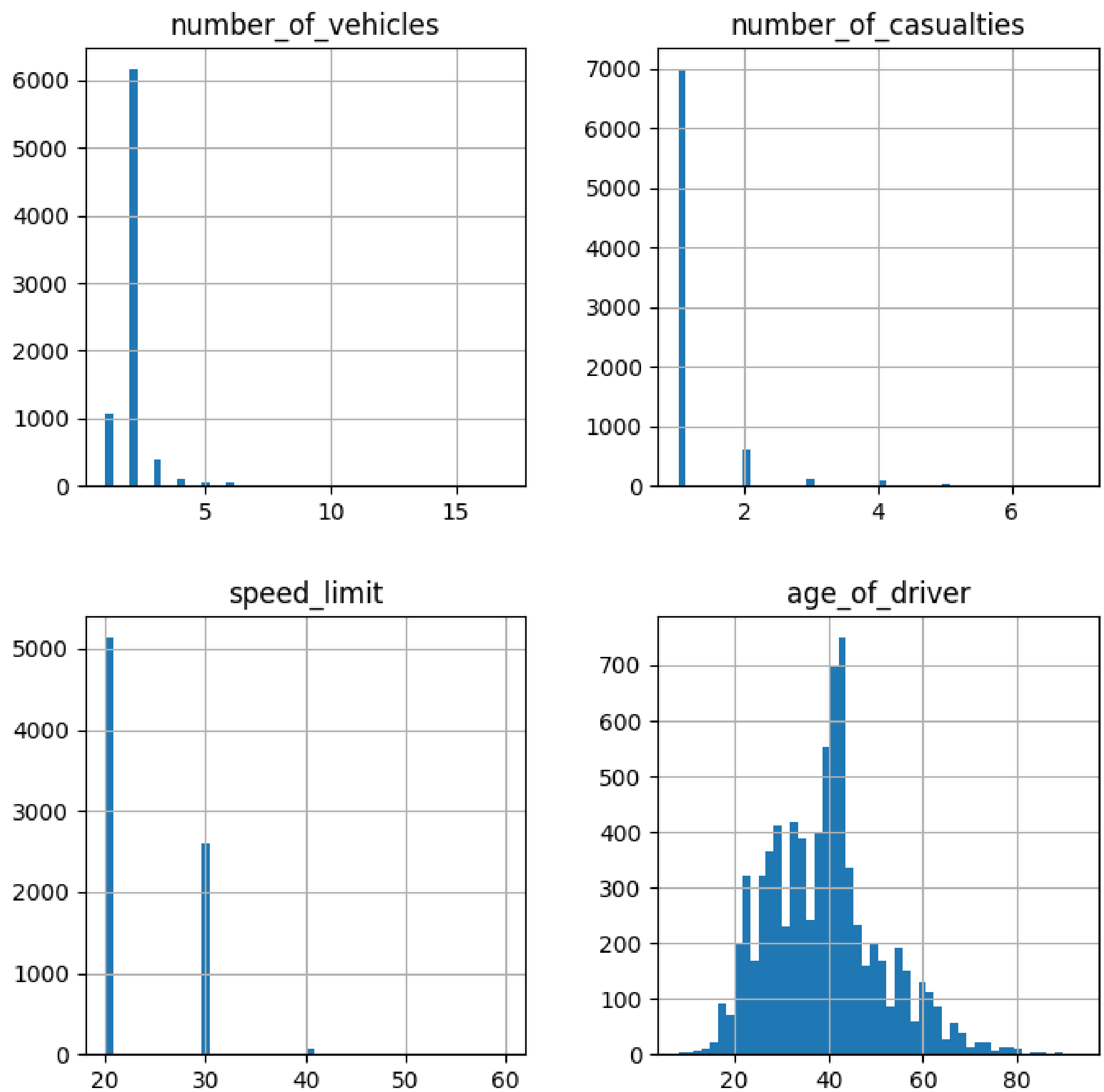
```
X_test['year'] = X_test['date'].dt.year
X_test['month'] = X_test['date'].dt.month
X_test['day'] = X_test['date'].dt.day
X_test['hour'] = X_test['time'].dt.hour
X_test['minute'] = X_test['time'].dt.minute
X_test = X_test.drop(columns=['date','time'])

hat = clf.predict(X_test)
X_test = X_test[hat == 1]
y_test = y_test[hat != -1]
X_test.shape

#Print the execution time
print("Execution time HH:MM:SS:", timedelta(seconds=timer() - start))
```

```
Execution time HH:MM:SS: 0:00:00.031387
```

6.3 Log Transformation

[168]:
```
#Apply log transformation on the numerical variables so that they are in log␣
↪form and scaled to one another
#Create histograms for the variables that log transformation will be conducted␣
↪on
X_train[['number_of_vehicles', 'number_of_casualties', 'speed_limit',␣
↪'age_of_driver']].hist(bins=50, figsize=(8,8))
```

[168]:
```
array([[<Axes: title={'center': 'number_of_vehicles'}>,
        <Axes: title={'center': 'number_of_casualties'}>],
       [<Axes: title={'center': 'speed_limit'}>,
        <Axes: title={'center': 'age_of_driver'}>]], dtype=object)
```

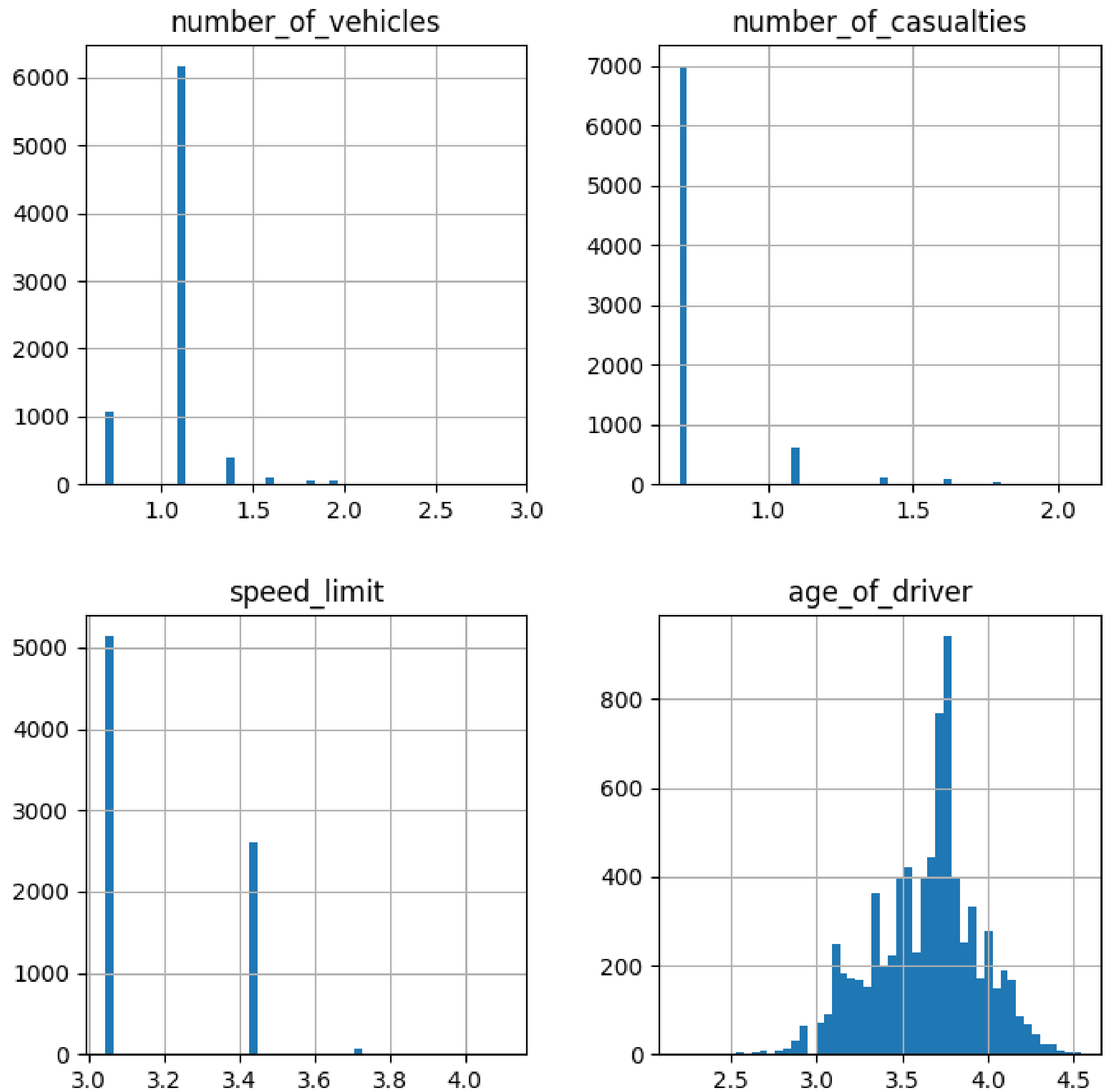


[169]:
```
#Apply log transformation on the variables
for col in ['number_of_vehicles', 'number_of_casualties', 'speed_limit',␣
↪'age_of_driver']:
    X_train.loc[:, col] = np.log(X_train.loc[:, col] + 1)
    X_test.loc[:, col] = np.log(X_test.loc[:, col] + 1)
```

[170]:
```
#Create histograms again for the newly transformed variables
X_train[['number_of_vehicles', 'number_of_casualties', 'speed_limit',␣
↪'age_of_driver']].hist(bins=50, figsize=(8,8))
```

[170]:
```
array([[<Axes: title={'center': 'number_of_vehicles'}>,
        <Axes: title={'center': 'number_of_casualties'}>],
       [<Axes: title={'center': 'speed_limit'}>,
```

<Axes: title={'center': 'age_of_driver'}>]], dtype=object)



After log transformation, the distributions of skewed variables like number of vehicles, casualties, speed limit, and driver age appear more normalized and less concentrated at lower values.

6.4 Feature Engineering

A new feature was created using year, month, and day. The new feature, day of week, will be used in the individual assignment to highlight on what day in a week an accident occurred.

[174]:
```
#Create a new feature using the year, month, and day columns
X_train['date_combined'] = pd.to_datetime(X_train[['year', 'month', 'day']])

#Extract the day of the week as a number (1=Monday, 2=Tuesday, etc.)
```

```
X_train['day_of_week'] = X_train['date_combined'].dt.weekday + 1  # +1 to make␣
↪Monday = 1, Sunday = 7

#Drop the intermediate 'date_combined' column
X_train = X_train.drop(columns=['date_combined','year','day','minute'])

X_train.head()
```

[174]:

```
       accident_index  number_of_vehicles  number_of_casualties  speed_limit  \
2142    2023010435768                   1                     1            3
1930    2023010434377                   1                     1            3
8757    2023010477755                   1                     1            3
9327    2023010481441                   1                     1            3
7125    2023010467051                   1                     1            3

      age_of_driver  local_authority_ons_district_Lambeth  \
2142              3                                     1
1930              4                                     1
8757              3                                     1
9327              4                                     1
7125              4                                     0

      local_authority_ons_district_Southwark  \
2142                                       0
1930                                       0
8757                                       0
9327                                       0
7125                                       0

      local_authority_ons_district_Wandsworth  \
2142                                        0
1930                                        0
8757                                        0
9327                                        0
7125                                        1

      local_authority_ons_district_Westminster  road_type_One way street  …  \
2142                                         0                          0  …
1930                                         0                          0  …
8757                                         0                          0  …
9327                                         0                          0  …
7125                                         0                          0  …

      casualty_type_Motorcycle over 125cc and up to 500cc rider or  passenger  \
2142                                                  0
1930                                                  0
8757                                                  0
```

```
9327                                                   0
7125                                                   0

      casualty_type_Motorcycle over 500cc rider or passenger  \
2142                                                   0
1930                                                   0
8757                                                   0
9327                                                   0
7125                                                   0

      casualty_type_Other vehicle occupant  casualty_type_Pedestrian  \
2142                                     0                         0
1930                                     0                         0
8757                                     0                         0
9327                                     0                         1
7125                                     0                         0

      casualty_type_Taxi/Private hire car occupant  \
2142                                             0
1930                                             0
8757                                             0
9327                                             0
7125                                             0

      casualty_type_Tram occupant  \
2142                            0
1930                            0
8757                            0
9327                            0
7125                            0

      casualty_type_Van / Goods vehicle (3.5 tonnes mgw or under) occupant  \
2142                                                   0
1930                                                   0
8757                                                   0
9327                                                   0
7125                                                   0

      month  hour  day_of_week
2142      2    19            1
1930      3    15            5
8757     11    17            5
9327     12    17            5
7125      9    18            2

[5 rows x 165 columns]
```

[175]:
```python
#Do the same for X_test
X_test['date_combined'] = pd.to_datetime(X_test[['year', 'month', 'day']])

#Extract the day of the week as a number (1=Monday, 2=Tuesday, etc.)
X_test['day_of_week'] = X_test['date_combined'].dt.weekday + 1  # +1 to make␣
↪Monday = 1, Sunday = 7

#Drop the intermediate 'date_combined' column
X_test = X_test.drop(columns=['date_combined','year','day','minute'])

X_test.head()
```

[175]:
```
      accident_index  number_of_vehicles  number_of_casualties  speed_limit  \
9500   2023010482861                   1                     1            3
1958   2023010434525                   1                     1            3
4498   2023010450998                   1                     1            3
7743   2023010471555                   1                     1            3
7059   2023010466701                   1                     1            3

      age_of_driver  local_authority_ons_district_Lambeth  \
9500              4                                     0
1958              3                                     0
4498              3                                     1
7743              3                                     1
7059              3                                     0

      local_authority_ons_district_Southwark  \
9500                                       0
1958                                       1
4498                                       0
7743                                       0
7059                                       0

      local_authority_ons_district_Wandsworth  \
9500                                        0
1958                                        0
4498                                        0
7743                                        0
7059                                        0

      local_authority_ons_district_Westminster  road_type_One way street  …  \
9500                                         0                         0  …
1958                                         0                         0  …
4498                                         0                         0  …
7743                                         0                         0  …
7059                                         0                         0  …
```

```
     casualty_type_Motorcycle over 125cc and up to 500cc rider or  passenger  \
9500                                                  0
1958                                                  0
4498                                                  0
7743                                                  0
7059                                                  0

     casualty_type_Motorcycle over 500cc rider or passenger  \
9500                                                  0
1958                                                  0
4498                                                  0
7743                                                  0
7059                                                  0

     casualty_type_Other vehicle occupant  casualty_type_Pedestrian  \
9500                                    0                         0
1958                                    0                         0
4498                                    0                         0
7743                                    0                         0
7059                                    0                         0

     casualty_type_Taxi/Private hire car occupant  \
9500                                            0
1958                                            0
4498                                            0
7743                                            0
7059                                            0

     casualty_type_Tram occupant  \
9500                           0
1958                           0
4498                           0
7743                           0
7059                           0

     casualty_type_Van / Goods vehicle (3.5 tonnes mgw or under) occupant  \
9500                                                  0
1958                                                  0
4498                                                  0
7743                                                  0
7059                                                  0

     month  hour  day_of_week
9500    12    17            3
1958     3    18            1
4498     6    17            5
7743    10    11            4
```

```
7059      9     8             1

[5 rows x 165 columns]
```

The fatal class and the serious class in the target variable were combined, because there were too little counts for both of the classes, as shown previously in the bar plot in the exploratory data analysis.

[177]:
```
#For both of the datasets that contained the target variable, the fatal class␣
↪and the serious class were combined
y_train = y_train.replace(1, 2)
y_test = y_test.replace(1, 2)
```

[178]:
```
#Descriptive Statistics of the Target Variable

#Frequency counts
frequency_counts = pd.DataFrame(y_train.value_counts().sort_index())

#Mode
mode_value = y_train.mode()[0]

#Median
median_value = y_train.median()

#Summary
print("Frequency Counts:\n", frequency_counts)
print("\nMode:", mode_value)
print("Median:", median_value)
```

```
Frequency Counts:
                    count
accident_severity
2                   1232
3                   6576

Mode: 3
Median: 3.0
```

7 Conclusion

In the assignment, a new dataset was generated by picking out variables that the target variable was most related to. The acutal predictive model will be created in the individual assignment; it will the predict the severity of a car collision accident occurring in the London boroughs based on the independent variables. Knowing what elements influence an accident to be more severe will enable the London councils to better focus on more important areas.

8 Data Exporting

The code below exports the transformed and split datasets in this notebook to CSV files so that they can be used for the individual assignment.

[183]:
```
X_train.to_csv("X_train.csv")
y_train.to_csv("y_train.csv")
X_test.to_csv("X_test.csv")
y_test.to_csv("y_test.csv")
```