submission_final

April 20, 2025

1 Title: Severity of road traffic accidents

[1]:
```
%load_ext watermark
%watermark -a "Van Wu" -u -d -t -v -p numpy,pandas,matplotlib,scikit-learn
```

```
Author: Van Wu

Last updated: 2025-04-20 13:03:29

Python implementation: CPython
Python version       : 3.13.2
IPython version      : 9.0.2

numpy       : 2.2.4
pandas      : 2.2.3
matplotlib  : 3.10.1
scikit-learn: 1.6.1
```

1.1 Preparation

- Github link
- Number of words: ***
- Runtime: *** hours (*Memory 32 GB, CPU AMD Ryzen 7 5800H with Radeon Graphics CPU @3.20GHz*)
- Coding environment: Coding environment: VS Code with Jupyter plugin (local), not SDS Docker
- License: this notebook is made available under the Creative Commons Attribution license.
- Additional library *[libraries not included in SDS Docker or not used in this module]*:
  - **watermark**: A Jupyter Notebook extension for printing timestamps, version numbers, and hardware information.(used to print Python and package versions for reproducibility.)
  - ……

1.2 Table of contents

1.3 Introduction

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Road traffic accidents (RTAs) represent a significant public health and urban governance issue globally. In the UK, despite advancements in vehicle technology and traffic regulation, thousands of individuals are injured or killed on the roads annually. Predicting the severity of these accidents is crucial for targeted policy interventions and infrastructure planning. Accident severity is influenced by a range of contextual factors including weather, road geometry, traffic volume, time of day, and infrastructure design (Abdel-Aty & Haleem, 2011). As cities move towards data-driven governance, the use of machine learning models has become increasingly common in road safety research (Zhang et al., 2020).

Recent literature has demonstrated the effectiveness of supervised learning algorithms such as logistic regression, random forests, and XGBoost in predicting accident severity using structured datasets (Ahmed et al., 2023). These models are particularly suitable for capturing non-linear interactions and heterogeneous effects among multiple explanatory variables. Moreover, explainable AI techniques such as SHAP (SHapley Additive exPlanations) have been widely adopted to interpret complex models and understand feature importance, which aids in translating statistical findings into actionable insights for policymakers.

This study leverages the UK Department for Transport's Road Safety Data (2015–2019), which documents detailed information on individual accident cases, including temporal, spatial, environmental, and infrastructural attributes. By integrating network-based features such as road betweenness centrality extracted via OpenStreetMap, this project attempts to bridge the gap between spatial network analysis and predictive modelling of accident severity. The objective is twofold: to evaluate the predictive performance of commonly used machine learning models on accident severity classification, and to examine the relative contribution of different spatial and contextual factors to the outcome.

The period from 2015 to 2019 was deliberately chosen to ensure data stability and validity. This timeframe avoids the confounding effects of the COVID-19 pandemic (2020–2021), which significantly disrupted travel behaviour, enforcement levels, and urban mobility patterns across the UK (DfT, 2021). It also precedes Phase 2 of London's major road transformation programme, including the expansion of Low Traffic Neighbourhoods (LTNs) and segregated cycling infrastructure, which introduced substantial structural changes to the transport system from 2020 onwards (TfL, 2024). In contrast, the preceding years (2010–2014) marked a foundational policy phase, characterised by the implementation of new traffic enforcement measures such as fixed penalty notices for careless driving and increased fines for common violations (DfT, 2013). By focusing on the relatively stable and mature period between 2015 and 2019, this study ensures greater internal consistency and enables clearer interpretation of accident severity patterns, isolated from exogenous policy or behavioural shocks.

In contrast to most existing studies that primarily rely on tabular attributes such as time, weather, and road conditions, this project introduces spatial network metrics—specifically, betweenness and degree centrality—extracted from OpenStreetMap. This integration of spatial topology enhances the model's capacity to capture urban structural influences on accident severity, offering a novel bridge between road network analysis and predictive modeling.

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1.4 Research questions

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Can supervised machine learning models accurately predict the severity of road traffic accidents in London using spatial, temporal, and environmental features?

This study investigates whether supervised machine learning models can accurately predict the severity of road traffic accidents in London based on spatial, temporal, and environmental features. Specifically, it examines the predictive power of variables such as time of day, weather conditions, and road network centrality. The study also compares the performance of Logistic Regression, Random Forest, and XGBoost, and uses SHAP analysis to identify the most influential features for each severity level (fatal, serious, slight).

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1.5 Data

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1.5.1 Data Description

Variable	Type	Description	Notes
accident_severity	Categorical	Severity level of the accident (1 = Fatal, 2 = Serious, 3 = Slight)	Target variable
speed_limit	Numeric	Speed limit of the road segment (in mph)	-
accident_year	Numeric	Year of the accident (2015–2019)	Used for train-test split
mean_betweenness	Numeric	Mean betweenness centrality of nearby road segments	Spatial network feature
max_betweenness	Numeric	Maximum betweenness centrality of nearby road segments	Key spatial variable
mean_degree	Numeric	Mean degree centrality of road network	-
max_degree	Numeric	Maximum degree centrality	-

Variable	Type	Description	Notes
edge_count	Numeric	Number of road segments (edges) in the local road network	Spatial indicator of network density
day_of_week_*	Categorical	One-hot encoded day of week (Monday–Saturday, Sunday as baseline)	One-hot encoded
road_type_*	Categorical	One-hot encoded road type categories	One-hot encoded
light_conditions_*	Categorical	One-hot encoded lighting conditions (e.g., daylight, darkness with/without lighting)	One-hot encoded
weather_conditions_*	Categorical	One-hot encoded weather conditions (e.g., fine, rain, fog)	One-hot encoded
road_surface_conditions_*	Categorical	One-hot encoded surface conditions (e.g., dry, wet)	One-hot encoded
junction_control_*	Categorical	One-hot encoded control types at junctions	One-hot encoded
junction_detail_*	Categorical	One-hot encoded structural junction types	One-hot encoded
pedestrian_crossing_human_control_*	Categorical	One-hot encoded presence of human-controlled crossings	One-hot encoded
pedestrian_crossing_physical_facilities_*	Categorical	One-hot encoded presence of physical pedestrian facilities	One-hot encoded
special_conditions_at_site_*	Categorical	One-hot encoded site-specific conditions (e.g., roadworks)	One-hot encoded
first_road_class_*	Categorical	One-hot encoded classification of the primary road	One-hot encoded
second_road_class_*	Categorical	One-hot encoded classification of the secondary road	One-hot encoded
trunk_road_flag_*	Categorical	One-hot encoded trunk road indicator	One-hot encoded
urban_or_rural_area_*	Categorical	One-hot encoded urban/rural area classification	One-hot encoded
time_hour	Numeric	Hour of the accident (e.g., 13:55 → 13)	Derived feature
betweenness_level_encoded	Ordinal	Quartile level of mean_betweenness (0 = Low, 3 = High)	For logistic regression compatibility
……	……	……	

*Note: *_ denotes one-hot encoded categories split into multiple columns.*

The following table provides code-level descriptions for categorical variables used in this study. Definitions are based on the official UK Department for Transport data guide: data.gov.uk.

Variable Prefix	Code	Meaning
day_of_week	1	Sunday
	2	Monday
	3	Tuesday
	4	Wednesday
	5	Thursday
	6	Friday
	7	Saturday
road_type	1	Roundabout

Variable Prefix	Code	Meaning
	2	One way street
	3	Dual carriageway
	6	Single carriageway
	7	Slip road
	9	Unknown
light_conditions	1	Daylight
	4	Darkness - lights lit
	5	Darkness - lights unlit
	6	Darkness - no lighting
	7	Darkness - lighting unknown
weather_conditions	1	Fine no high winds
	2	Raining no high winds
	3	Snowing no high winds
	4	Fine + high winds
	5	Raining + high winds
	6	Snowing + high winds
	7	Fog or mist
	8	Other
	9	Unknown
road_surface_conditions	1	Dry
	2	Wet or damp
	3	Snow
	4	Frost or ice
	5	Flood (surface water)
	9	Unknown
junction_control	0	None
	1	Authorised person
	2	Auto traffic signal
	3	Stop sign
	4	Give way or uncontrolled
	9	Unknown
pedestrian_crossing_human_control	0	None
	1	School crossing patrol
	2	Other human control
	9	Unknown
pedestrian_crossing_physical_facilities	0	None
	1	Zebra crossing
	4	Pelican crossing
	5	Footbridge or subway
	7	Refuge
	8	Unknown
	9	Other
urban_or_rural_area	1	Not used
	2	Urban
	3	Rural
trunk_road_flag	1	Non-trunk road

Variable Prefix	Code	Meaning
	2	Trunk road
first_road_class / second_road_class	1	Motorway
	2	A(M) Road
	3	A Road
	4	B Road
	5	C Road
	6	Unclassified

1.5.2 Data Import & Cleaning

[51]:
```python
# It would import the packages that would be used first.
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
import os
import osmnx as ox
import networkx as nx
import geopandas as gpd
from tqdm import tqdm
```

[52]:
```python
# define folder
input_folder = '../data/raw'
output_folder = '../data/clean'
```

[53]:
```python
# Road Data
df = pd.read_csv('../data/raw/1979-latest-published-year.csv')
df = df[df['accident_year'].isin([2015, 2016, 2017, 2018, 2019])]
print(f"The data volume from 2015 to 2019 is{len(df)} ")

# save
df.to_csv("../data/raw/2015_2019.csv", index=False)
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_13184\542922050.py:2: DtypeWarning:
Columns (0,2,15,16,35) have mixed types. Specify dtype option on import or set
low_memory=False.
  df = pd.read_csv('../data/raw/1979-latest-published-year.csv')
```

```
The data volume from 2015 to 2019 is 646830
```

[54]:
```python
columns_to_keep = [
    'accident_severity',
    'number_of_vehicles',
    'number_of_casualties',
    'day_of_week',
    'time',
```

```
    'first_road_class',
    'second_road_class',
    'road_type',
    'speed_limit',
    'junction_detail',
    'junction_control',
    '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',
    'local_authority_ons_district',
    'accident_year'
]

selected_columns = [col for col in columns_to_keep if col in df.columns]
df_cleaned = df[selected_columns]

# Check and handle the missing values
missing_counts = df_cleaned.isnull().sum()
total_missing = missing_counts.sum()

if total_missing > 0:
    print(f"The number of missing values are {total_missing} :")
    print(missing_counts[missing_counts > 0])

    # Discard the rows containing missing values
    df_cleaned = df_cleaned.dropna()
    print(f"Missing values have been cleared, remaining {len(df_cleaned)}␣
 ↪records.")

# Save the cleaned files
df_cleaned.to_csv('../data/clean/1519_cleaned.csv', index=False)
print(f"Saved to: {output_folder}, total: {len(df_cleaned.columns)} columns,␣
 ↪{len(df_cleaned)} records.")
```

```
The number of missing values are 37 :
speed_limit    37
dtype: int64
Missing values have been cleared, remaining 646793 records.
Saved to: ../data/clean, total: 23 columns, 646793 records.
```

1.5.3 Spatial Feature Engineering

This step extracts borough-level road networks from OpenStreetMap and calculates betweenness and degree centrality to capture spatial structure in the transport network.

[6]:
```python
# RoadCentrality
path = "../data/Borough_Boundaries.geojson"
boroughs = gpd.read_file(path)
boroughs = boroughs[["name", "gss_code", "geometry"]].rename(columns={"name":
 ↪"borough"})

ox.settings.log_console = False
ox.settings.use_cache = True

results = []

for idx, row in tqdm(boroughs.iterrows(), total=len(boroughs), desc="Processing
 ↪boroughs"):
    borough_name = row["borough"]
    gss_name = row["gss_code"]
    geometry = row["geometry"]

    try:
        print(f"Processing: {borough_name}")

        G = ox.graph_from_polygon(geometry, network_type="drive", simplify=True)

        betweenness = nx.betweenness_centrality(G, weight="length", k=100,
 ↪seed=42)
        degree = dict(G.degree())
        nx.set_node_attributes(G, betweenness, "betweenness")
        nx.set_node_attributes(G, degree, "degree")

        edge_data = []
        for u, v, key, data in G.edges(keys=True, data=True):
            edge_data.append({
                "u": u,
                "v": v,
                "key": key,
                "geometry": data.get("geometry", None),
                "betweenness": (G.nodes[u]["betweenness"] + G.
 ↪nodes[v]["betweenness"]) / 2,
                "degree": (G.nodes[u]["degree"] + G.nodes[v]["degree"]) / 2
            })
        edges_df = gpd.GeoDataFrame(edge_data, geometry="geometry", crs="EPSG:
 ↪4326")
```

```python
        summary = {
            "borough": borough_name,
            "gss_code": gss_name,
            "mean_betweenness": edges_df["betweenness"].mean(),
            "max_betweenness": edges_df["betweenness"].max(),
            "mean_degree": edges_df["degree"].mean(),
            "max_degree": edges_df["degree"].max(),
            "edge_count": len(edges_df)
        }
        results.append(summary)

    except Exception as e:
        print(f"Failed for {borough_name}: {e}")
        continue

df_results = pd.DataFrame(results)
df_results.to_csv("../data/london_borough_road_centrality.csv", index=False)
print("All done! Results saved to 'london_borough_road_centrality.csv'")
```

```
Processing boroughs:   0%|          | 0/33 [00:00<?, ?it/s]

Processing: Kingston upon Thames

Processing boroughs:   3%|          | 1/33 [00:05<02:40,  5.03s/it]

Processing: Croydon

Processing boroughs:   6%|          | 2/33 [00:17<04:55,  9.54s/it]

Processing: Bromley

Processing boroughs:   9%|          | 3/33 [00:31<05:48, 11.61s/it]

Processing: Hounslow

Processing boroughs:  12%|          | 4/33 [00:39<04:56, 10.22s/it]

Processing: Ealing

Processing boroughs:  15%|          | 5/33 [00:48<04:27,  9.56s/it]

Processing: Havering

Processing boroughs:  18%|          | 6/33 [00:56<04:07,  9.16s/it]

Processing: Hillingdon

Processing boroughs:  21%|          | 7/33 [01:08<04:18,  9.94s/it]

Processing: Harrow

Processing boroughs:  24%|          | 8/33 [01:14<03:38,  8.73s/it]

Processing: Brent

Processing boroughs:  27%|          | 9/33 [01:21<03:16,  8.17s/it]
```

```
Processing: Barnet
Processing boroughs:  30%|          | 10/33 [01:32<03:29,  9.13s/it]
Processing: Lambeth
Processing boroughs:  33%|          | 11/33 [01:40<03:15,  8.90s/it]
Processing: Southwark
Processing boroughs:  36%|          | 12/33 [01:50<03:13,  9.21s/it]
Processing: Lewisham
Processing boroughs:  39%|          | 13/33 [01:58<02:57,  8.87s/it]
Processing: Greenwich
Processing boroughs:  42%|          | 14/33 [02:08<02:54,  9.20s/it]
Processing: Bexley
Processing boroughs:  45%|          | 15/33 [02:17<02:39,  8.87s/it]
Processing: Enfield
Processing boroughs:  48%|          | 16/33 [02:26<02:36,  9.20s/it]
Processing: Waltham Forest
Processing boroughs:  52%|          | 17/33 [02:33<02:14,  8.40s/it]
Processing: Redbridge
Processing boroughs:  55%|          | 18/33 [02:41<02:02,  8.14s/it]
Processing: Sutton
Processing boroughs:  58%|          | 19/33 [02:47<01:47,  7.65s/it]
Processing: Richmond upon Thames
Processing boroughs:  61%|          | 20/33 [02:54<01:37,  7.51s/it]
Processing: Merton
Processing boroughs:  64%|          | 21/33 [03:01<01:26,  7.18s/it]
Processing: Wandsworth
Processing boroughs:  67%|          | 22/33 [03:09<01:23,  7.60s/it]
Processing: Hammersmith and Fulham
Processing boroughs:  70%|          | 23/33 [03:13<01:04,  6.47s/it]
Processing: Kensington and Chelsea
Processing boroughs:  73%|          | 24/33 [03:17<00:50,  5.59s/it]
Processing: Westminster
Processing boroughs:  76%|          | 25/33 [03:25<00:52,  6.55s/it]
```

```
Processing: Camden
Processing boroughs:  79%|      | 26/33 [03:33<00:48,  6.95s/it]
Processing: Tower Hamlets
Processing boroughs:  82%|      | 27/33 [03:42<00:44,  7.41s/it]
Processing: Islington
Processing boroughs:  85%|      | 28/33 [03:47<00:33,  6.71s/it]
Processing: Hackney
Processing boroughs:  88%|      | 29/33 [03:52<00:25,  6.32s/it]
Processing: Haringey
Processing boroughs:  91%|      | 30/33 [03:58<00:18,  6.18s/it]
Processing: Newham
Processing boroughs:  94%|     | 31/33 [04:06<00:13,  6.70s/it]
Processing: Barking and Dagenham
Processing boroughs:  97%|     | 32/33 [04:11<00:06,  6.17s/it]
Processing: City of London
Processing boroughs: 100%|     | 33/33 [04:13<00:00,  7.67s/it]
All done! Results saved to 'london_borough_road_centrality.csv'
```

[55]:
```python
# show
print("Sample of calculated borough-level centrality metrics:")
display(df_results.head())

# Display descriptive statistical information
print("\nSummary statistics of centrality metrics across boroughs:")
display(df_results[['mean_betweenness', 'mean_degree']].describe())
```

```
Sample of calculated borough-level centrality metrics:
                borough   gss_code  mean_betweenness  max_betweenness  \
0  Kingston upon Thames  E09000021          0.020622         0.261008
1               Croydon  E09000008          0.012210         0.177637
2               Bromley  E09000006          0.012135         0.172504
3              Hounslow  E09000018          0.018356         0.335207
4                Ealing  E09000009          0.015021         0.212142

   mean_degree  max_degree  edge_count
0     5.271409         8.0        6551
1     5.383993         8.0       14719
2     5.425875         8.0       15737
```

```
3     5.247866         8.0       10308
4     5.418720         8.0       10919
```

```
Summary statistics of centrality metrics across boroughs:

       mean_betweenness  mean_degree
count         33.000000    33.000000
mean           0.017935     5.334289
std            0.005285     0.172943
min            0.012135     4.583688
25%            0.014089     5.271409
50%            0.016811     5.369130
75%            0.020230     5.418720
max            0.038161     5.602621
```

1.5.4 Data Merge & Summary

[56]:

```python
# Set the path
accident_path = "../data/clean/1519_cleaned.csv"
centrality_path = "../data/london_borough_road_centrality.csv"
output_path = "../data/final/2015_2019_with_centrality.csv"

df_accident = pd.read_csv(accident_path)
df_centrality = pd.read_csv(centrality_path)

# Merge the centrality data (encoded by region)
df_merged = df_accident.merge(
    df_centrality,
    how="left",
    left_on="local_authority_ons_district",
    right_on="gss_code"
)

# Delete the rows lacking centrality (non-London area)
before_drop = len(df_merged)
df_merged = df_merged.dropna(subset=["mean_betweenness"])
after_drop = len(df_merged)
dropped = before_drop - after_drop

# Save the result
df_merged.to_csv(output_path, index=False)

print(f"The data has been combined with the centrality indicators and saved␣
 ↪to {output_path}")
print(f"Total: {after_drop} records, remove {dropped} records.")
```

```
The data has been combined with the centrality indicators and saved
to ../data/final/2015_2019_with_centrality.csv
```

```
Total: 128261 records, remove 518532 records.
```

1.5.5 Exploratory Data Analysis (EDA)

Descriptive statistics (distribution maps, box plots, etc.)

Exploration of the Relationship between Features and Targets (including grouped bar charts and box plots)

[57]:
```python
df = pd.read_csv("../data/final/2015_2019_with_centrality.csv")

print(df.shape)
print(df.dtypes)
print(df.isnull().sum())
df.describe()
df["accident_severity"].value_counts(normalize=True)
```

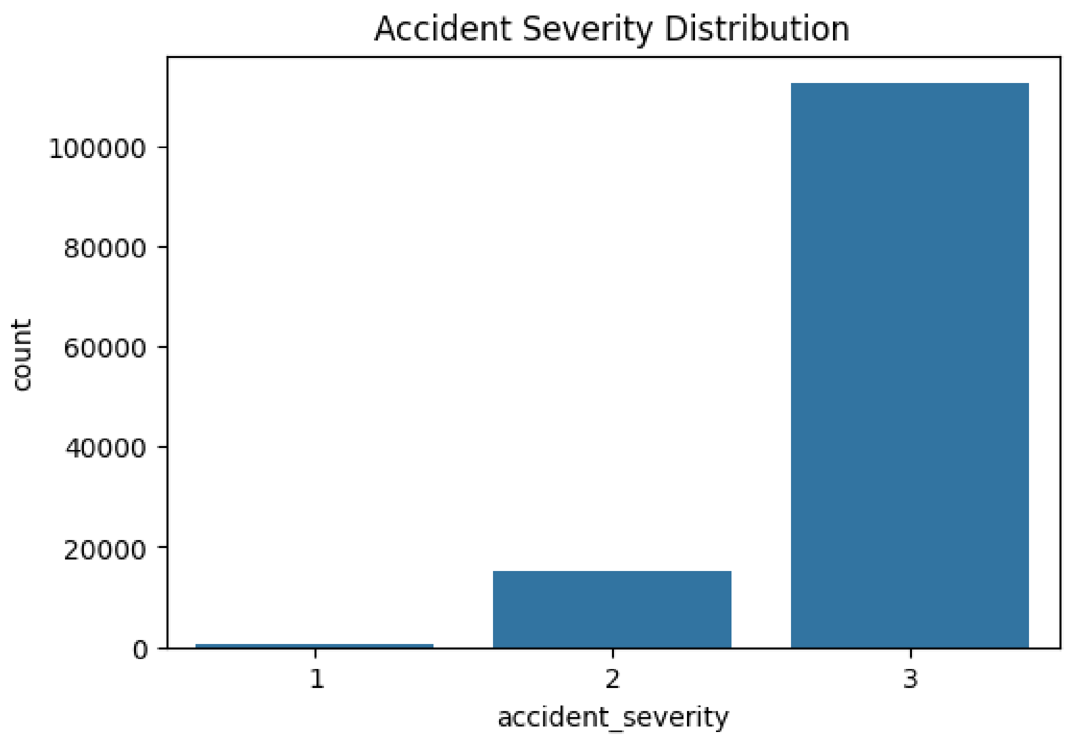
```
(128261, 30)
accident_severity                               int64
number_of_vehicles                              int64
number_of_casualties                            int64
day_of_week                                     int64
time                                           object
first_road_class                                int64
second_road_class                               int64
road_type                                       int64
speed_limit                                   float64
junction_detail                                 int64
junction_control                                int64
pedestrian_crossing_human_control               int64
pedestrian_crossing_physical_facilities         int64
light_conditions                                int64
weather_conditions                              int64
road_surface_conditions                         int64
special_conditions_at_site                      int64
carriageway_hazards                             int64
urban_or_rural_area                             int64
did_police_officer_attend_scene_of_accident     int64
trunk_road_flag                                 int64
local_authority_ons_district                   object
accident_year                                   int64
borough                                        object
gss_code                                       object
mean_betweenness                              float64
max_betweenness                               float64
mean_degree                                   float64
max_degree                                    float64
edge_count                                    float64
dtype: object
```

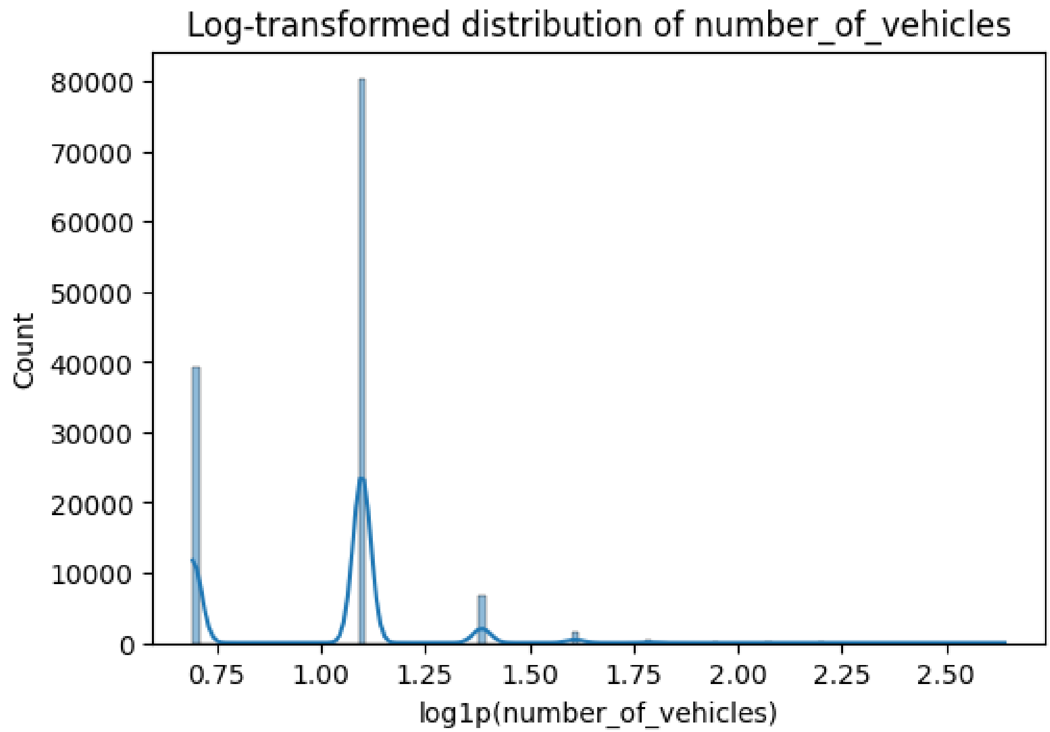
```
accident_severity                              0
number_of_vehicles                             0
number_of_casualties                           0
day_of_week                                    0
time                                           0
first_road_class                               0
second_road_class                              0
road_type                                      0
speed_limit                                    0
junction_detail                                0
junction_control                               0
pedestrian_crossing_human_control              0
pedestrian_crossing_physical_facilities        0
light_conditions                               0
weather_conditions                             0
road_surface_conditions                        0
special_conditions_at_site                     0
carriageway_hazards                            0
urban_or_rural_area                            0
did_police_officer_attend_scene_of_accident    0
trunk_road_flag                                0
local_authority_ons_district                   0
accident_year                                  0
borough                                        0
gss_code                                       0
mean_betweenness                               0
max_betweenness                                0
mean_degree                                    0
max_degree                                     0
edge_count                                     0
dtype: int64
```

[57]:
```
accident_severity
3    0.876089
2    0.119179
1    0.004733
Name: proportion, dtype: float64
```

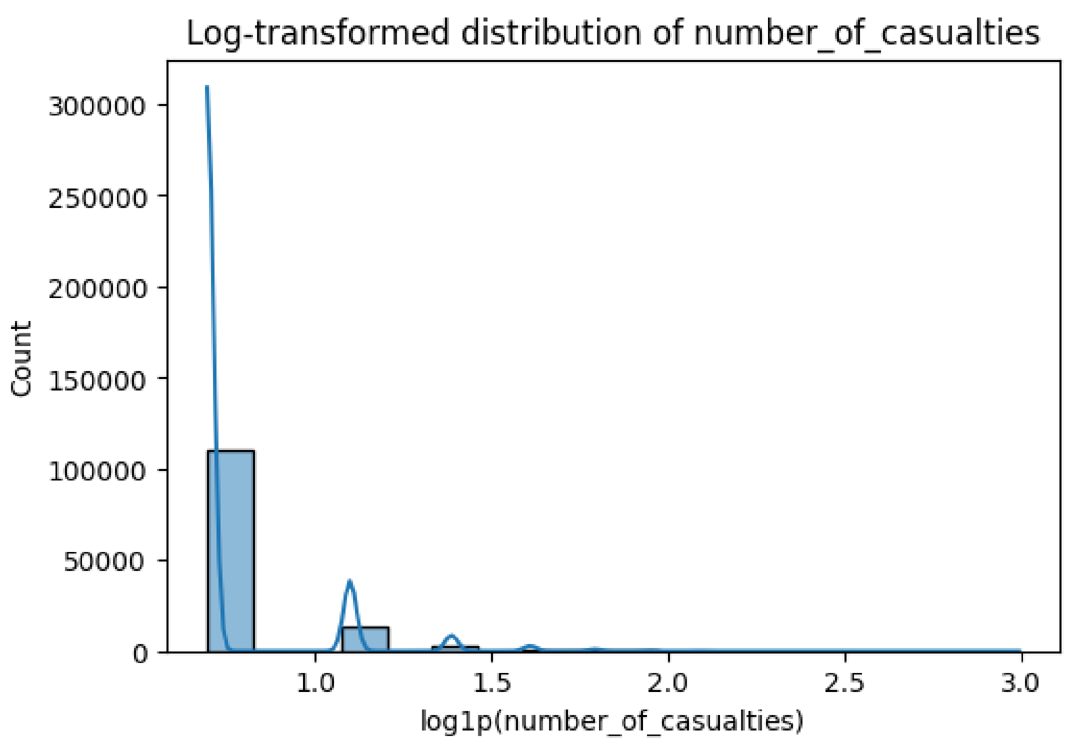
[58]:
```
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# Distribution of accident severity
plt.figure(figsize=(6,4))
sns.countplot(x="accident_severity", data=df)
plt.title("Accident Severity Distribution")
plt.show()
```

```python
# Numerical type: Number of vehicles, number of casualties, speed limit
for col in ["number_of_vehicles", "number_of_casualties"]:
    plt.figure(figsize=(6, 4))
    sns.histplot(np.log1p(df[col]), kde=True)
    plt.title(f"Log-transformed distribution of {col}")
    plt.xlabel(f"log1p({col})")
    plt.ylabel("Count")
    plt.show()

plt.figure(figsize=(6, 4))
sns.histplot(df["speed_limit"], kde=True)
plt.title("Distribution of Speed Limit")
plt.xlabel("speed_limit")
plt.ylabel("Count")
plt.show()
```

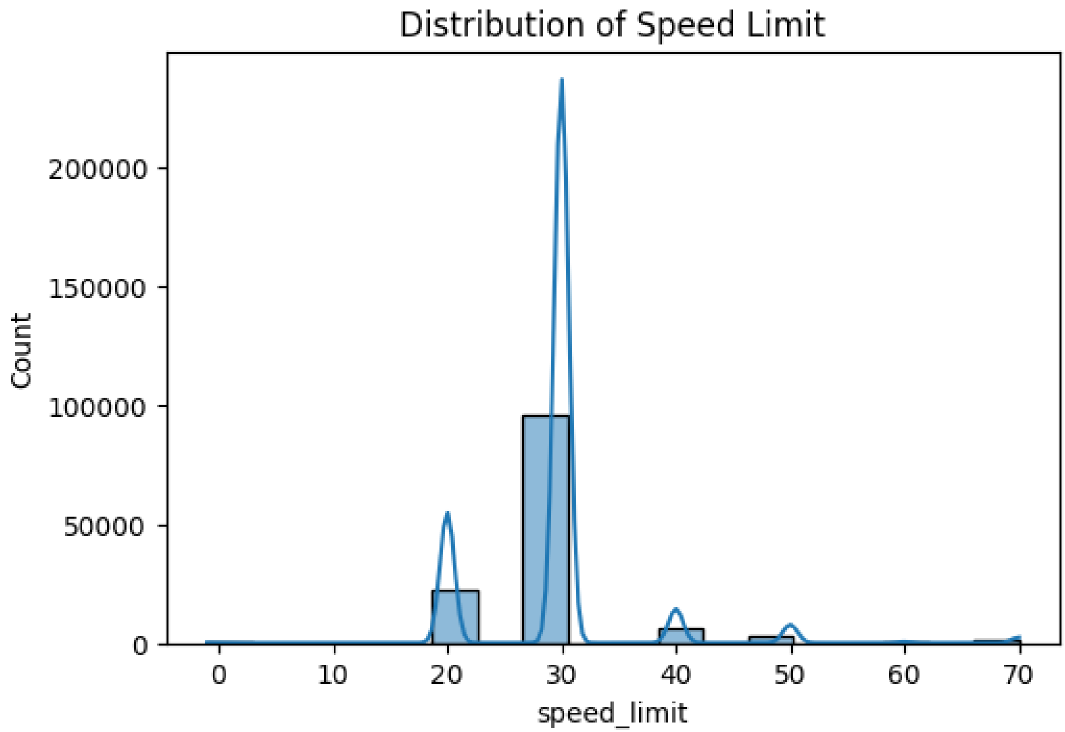




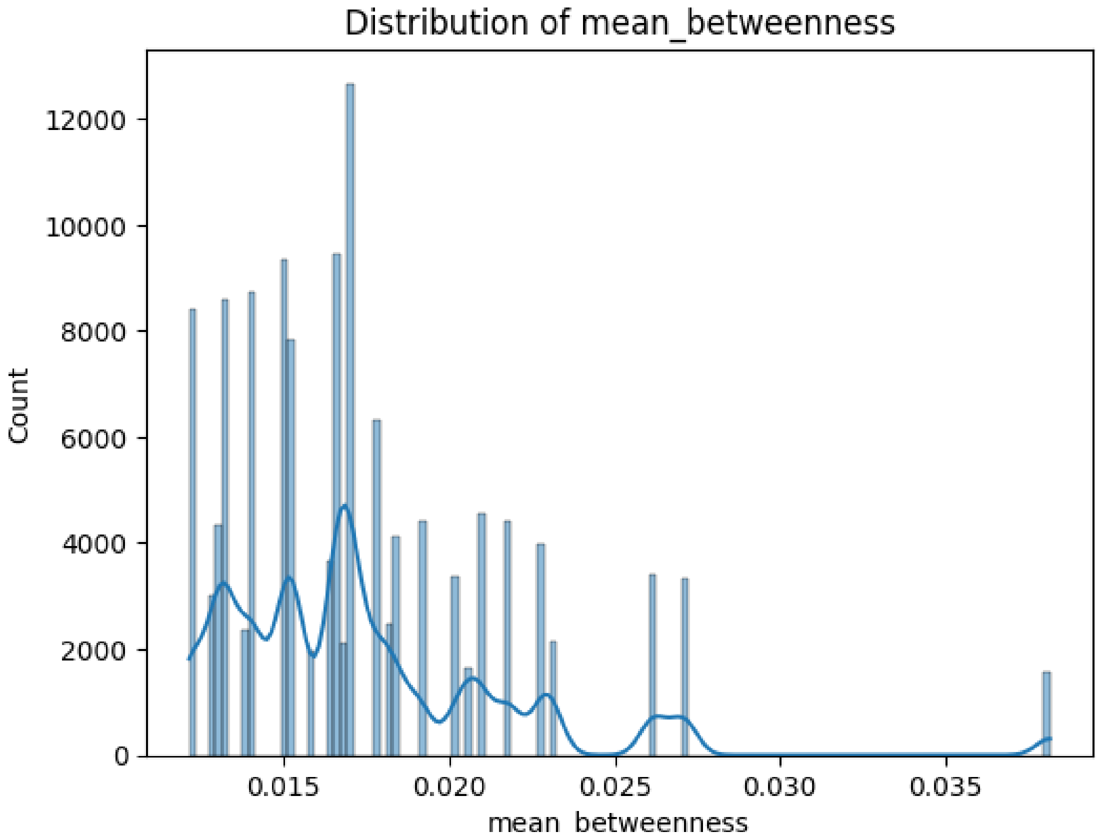
Log-transformed distribution of number_of_vehicles
80000
70000
60000
50000
40000
30000
20000
10000
0
Count
0.75
1.00
1.25
1.50
1.75
2.00
2.25
2.50
log1p(number_of_vehicles)

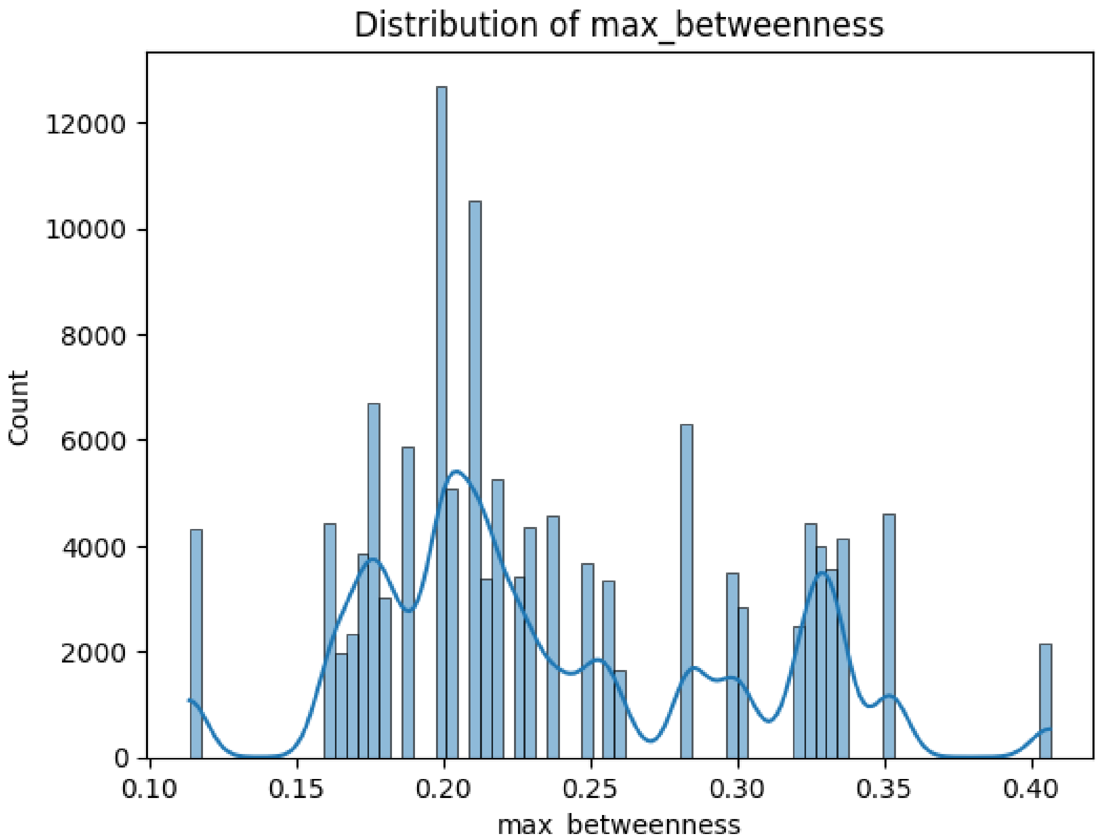


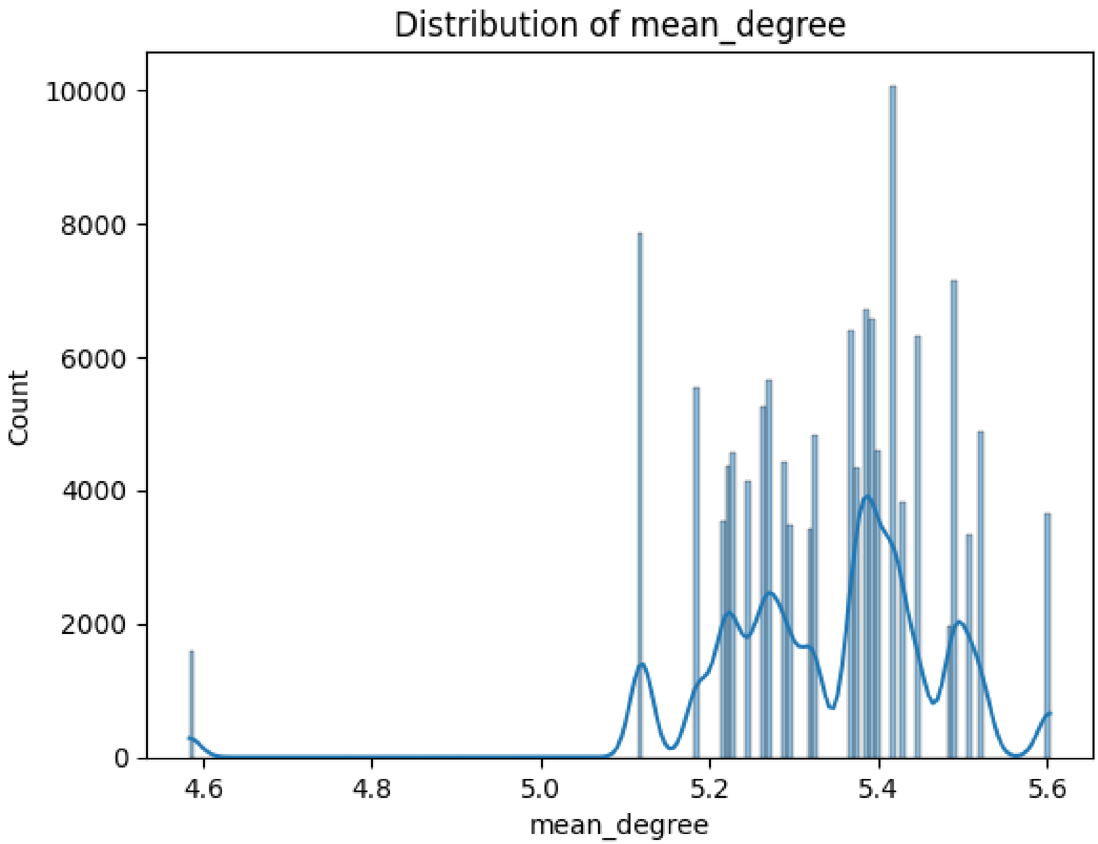
Log-transformed distribution of number_of_casualties
300000
250000
200000
150000
100000
50000
0
Count
1.0
1.5
2.0
2.5
3.0
log1p(number_of_casualties)

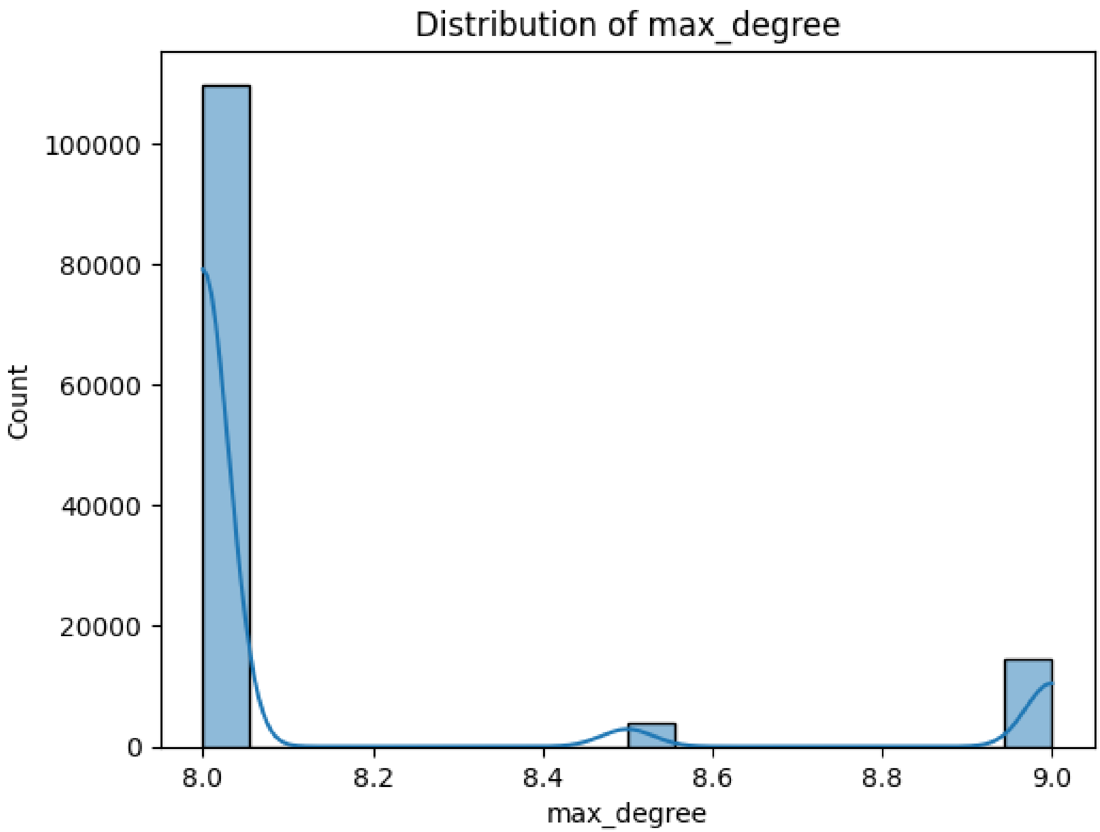


[11]:
```
# Central variable distribution (single variable + null value check)
for col in ["mean_betweenness", "max_betweenness", "mean_degree", "max_degree"]:
    sns.histplot(df[col].dropna(), kde=True)
    plt.title(f"Distribution of {col}")
    plt.show()
```


Distribution of mean_betweenness
Count
12000
10000
8000
6000
4000
2000
0
0.015
0.020
0.025
0.030
0.035
mean_betweenness

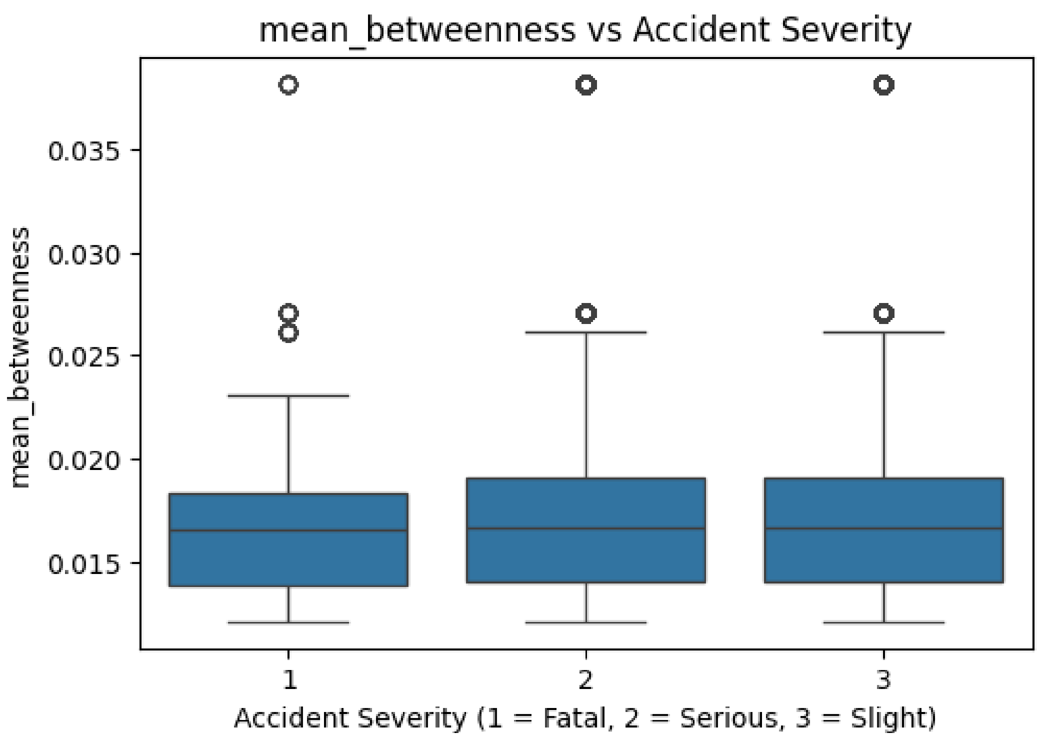

Distribution of max_betweenness
Count
max_betweenness
0
2000
4000
6000
8000
10000
12000
0.10
0.15
0.20
0.25
0.30
0.35
0.40

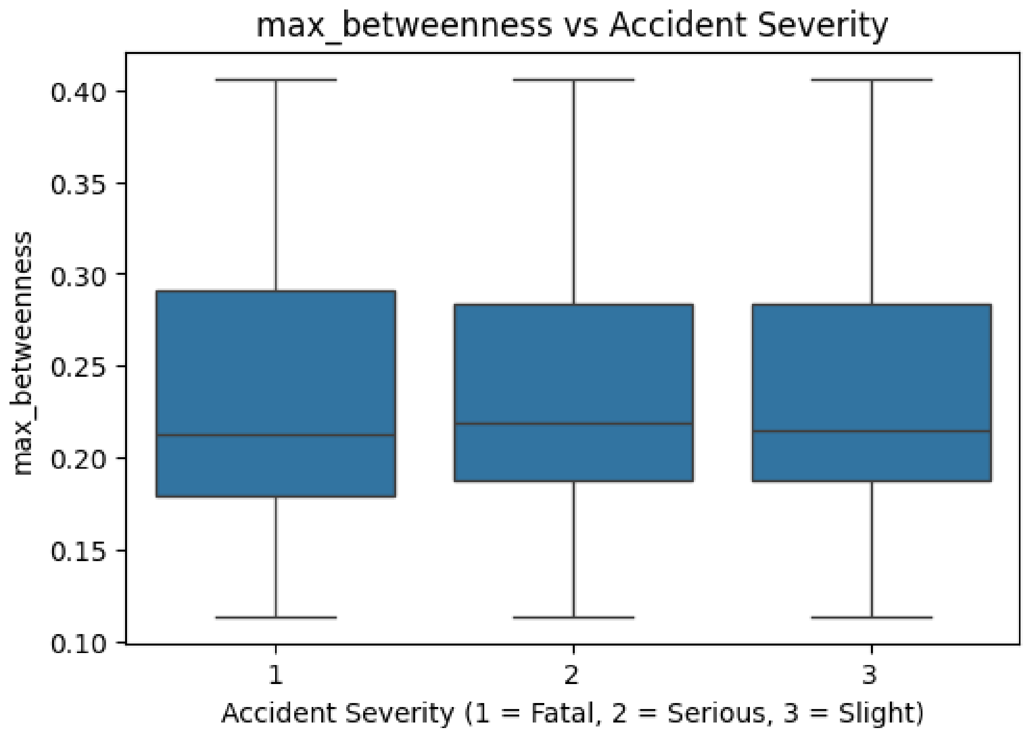

Distribution of mean_degree
Count
10000
8000
6000
4000
2000
0
4.6
4.8
5.0
5.2
5.4
5.6
mean_degree

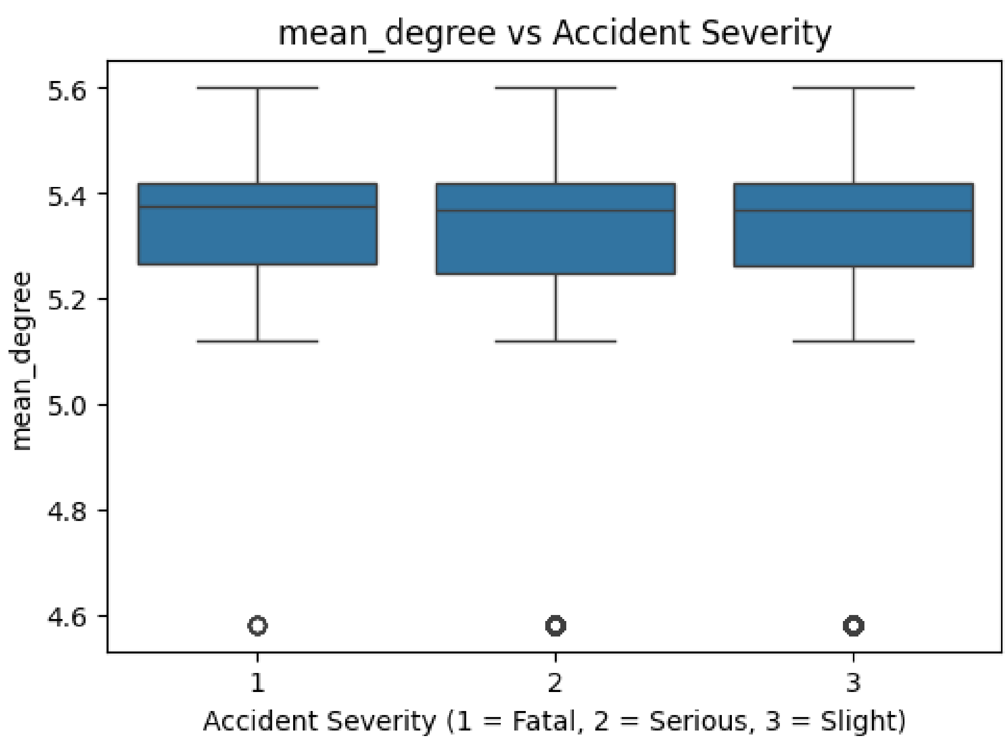


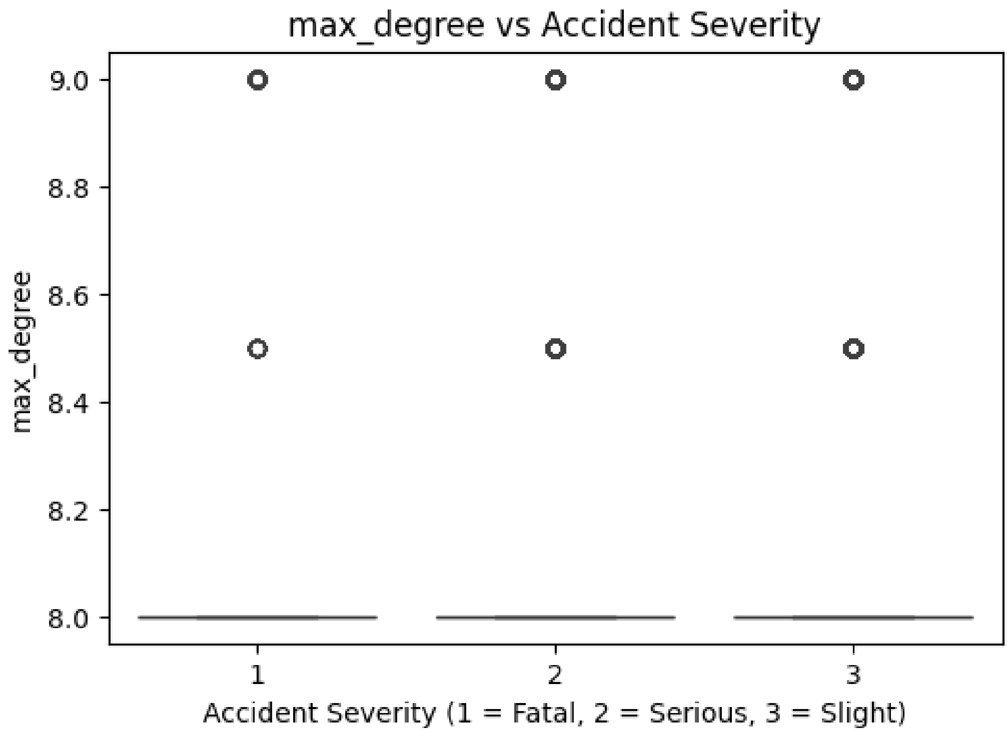
[12]:
```python
# The relationship between Variables and the severity of accidents (bivariate␣
↪Analysis)
for col in ["mean_betweenness", "max_betweenness", "mean_degree", "max_degree"]:
    plt.figure(figsize=(6, 4))
    sns.boxplot(x="accident_severity", y=col, data=df)
    plt.title(f"{col} vs Accident Severity")
    plt.xlabel("Accident Severity (1 = Fatal, 2 = Serious, 3 = Slight)")
    plt.ylabel(col)
    plt.show()

# Divide mean_betweenness into four grades (quartiles)
df["betweenness_level"] = pd.qcut(df["mean_betweenness"], q=4, labels=["Low",␣
↪"Medium-Low", "Medium-High", "High"])

# Check the proportion of accident severity in each group
severity_by_level = pd.crosstab(df["betweenness_level"],␣
↪df["accident_severity"], normalize='index')

# Draw a grouped stacked bar chart
severity_by_level.plot(kind="bar", stacked=True, colormap="Set2")
```

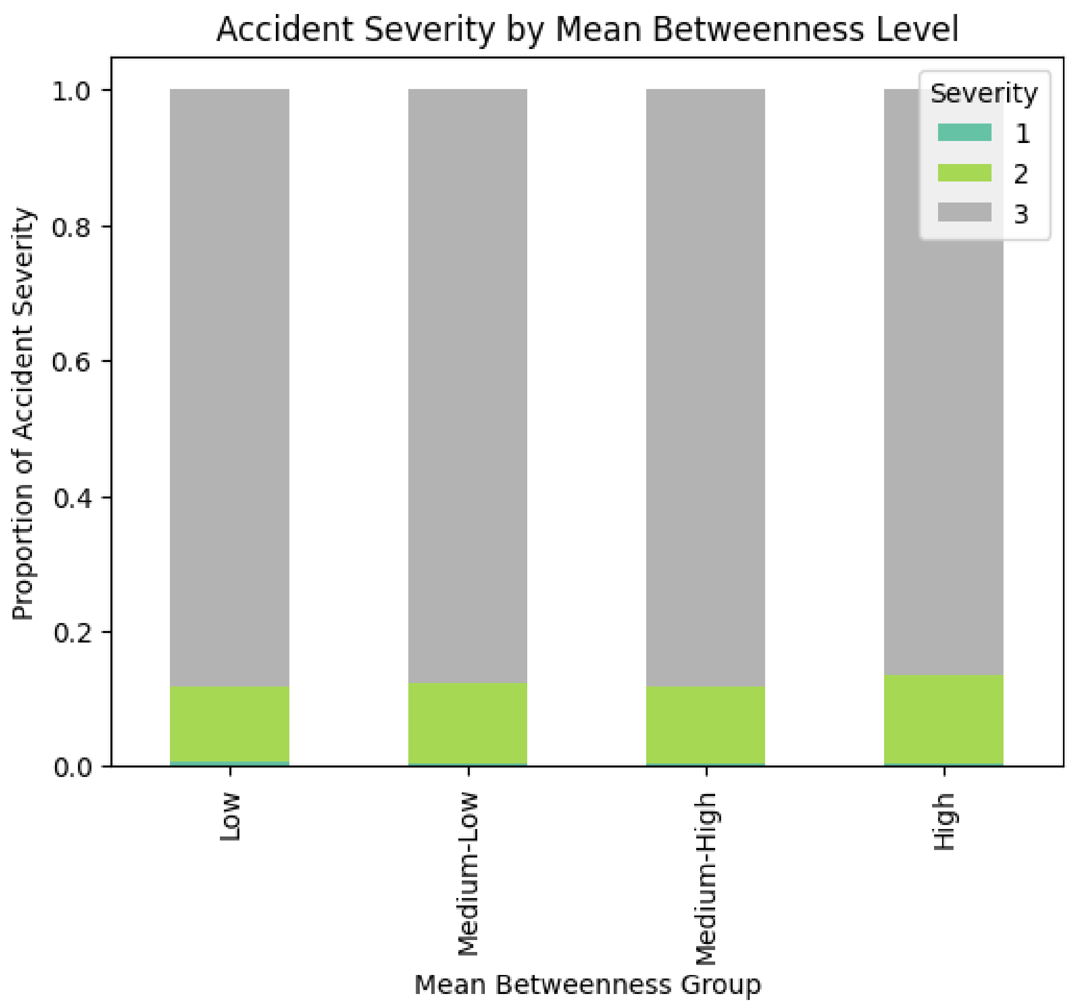
```
plt.title("Accident Severity by Mean Betweenness Level")
plt.xlabel("Mean Betweenness Group")
plt.ylabel("Proportion of Accident Severity")
plt.legend(title="Severity", loc="upper right")
plt.show()

# Categorical variables can be analyzed in cross-tables:
pd.crosstab(df["day_of_week"], df["accident_severity"], normalize='index').
 ↪plot(kind='bar', stacked=True)
plt.title("Accident Severity by Day of Week")
```



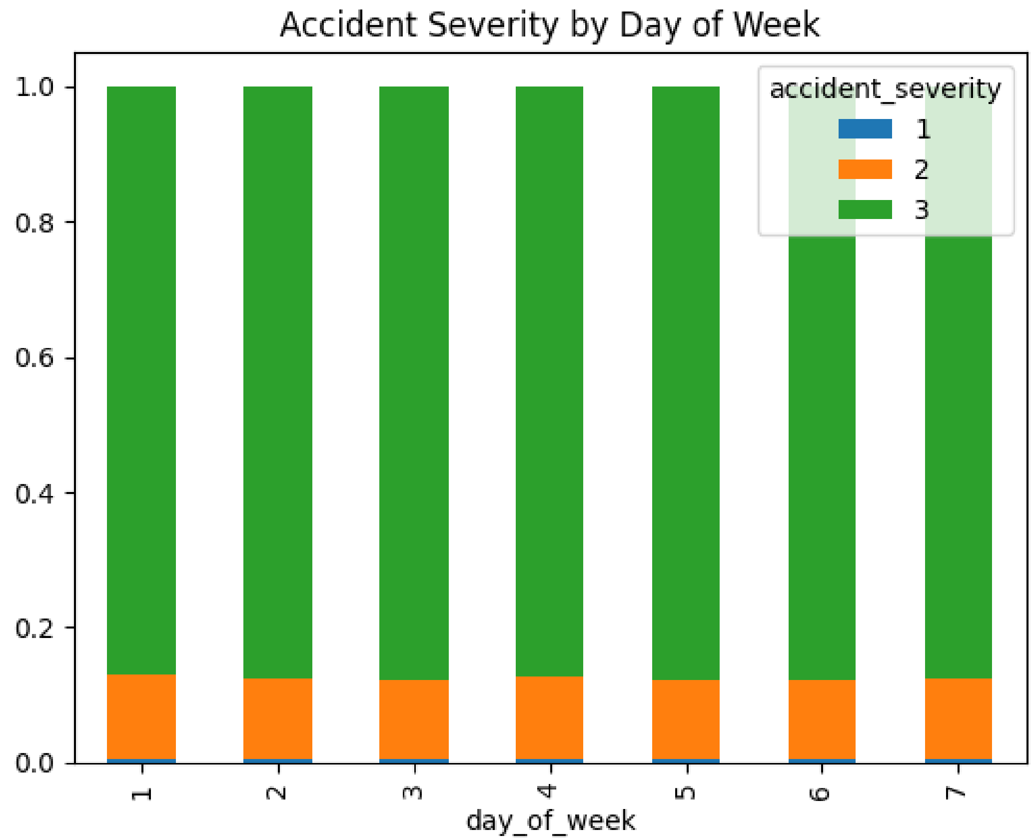

max_betweenness vs Accident Severity
0.40
0.35
0.30
0.25
0.20
0.15
0.10
max_betweenness
1
2
3
Accident Severity (1 = Fatal, 2 = Serious, 3 = Slight)


mean_degree vs Accident Severity
5.6
5.4
5.2
5.0
4.8
4.6
mean_degree
1
2
3
Accident Severity (1 = Fatal, 2 = Serious, 3 = Slight)


max_degree vs Accident Severity
max_degree
9.0
8.8
8.6
8.4
8.2
8.0
1
2
3
Accident Severity (1 = Fatal, 2 = Serious, 3 = Slight)




```
[12]: Text(0.5, 1.0, 'Accident Severity by Day of Week')
```



max_betweenness mean_betweenness d

centrality

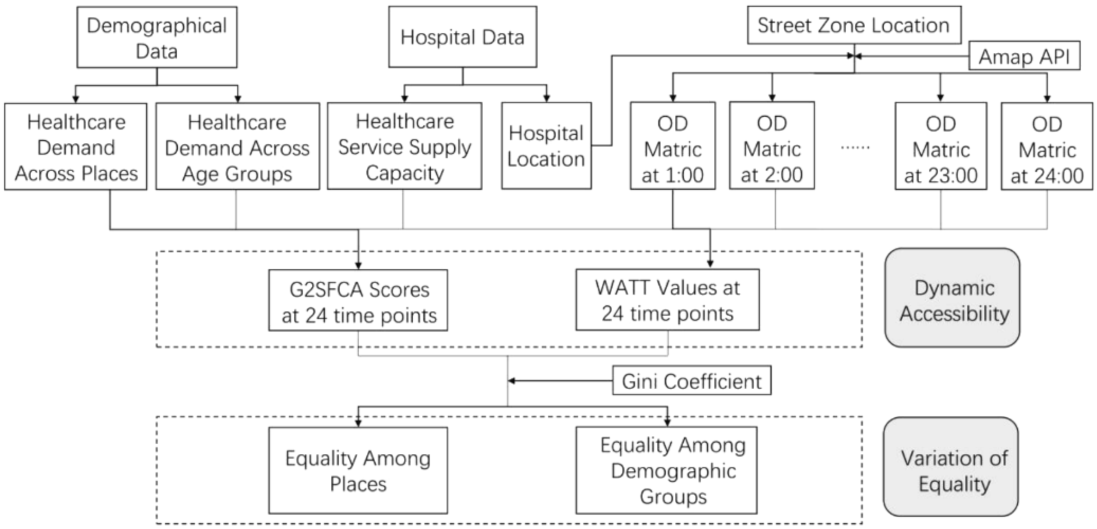
According to the boxplots and grouped bar charts, maximum betweenness centrality (max_betweenness) shows stronger differentiation across accident severity levels, especially with higher values in fatal accidents. In contrast, mean_betweenness exhibits weaker variation, indicating a more subtle influence. Degree-based indicators, particularly max_degree, show very limited discriminative power and may not be useful in predictive modeling.

1.6 Methodology

[go back to the top]

[Note: a flow chart that describes the methodology is strongly encouraged - see the example below. This flow chart can be made using Microsoft powerpoint or visio or other software]

Source: see link.



1.6.1 Modeling Preparation (Feature Engineering)

Feature Encoding

[13]:
```
# One-hot encoding + save
categorical_vars = [
    'day_of_week', 'road_type', 'light_conditions', 'weather_conditions',
    'road_surface_conditions', 'junction_control', 'junction_detail',
    'pedestrian_crossing_human_control',␣
  ↪'pedestrian_crossing_physical_facilities',
    'special_conditions_at_site', 'first_road_class',
    'second_road_class',
    'trunk_road_flag', 'urban_or_rural_area'
]

# Coding
df_encoded = pd.get_dummies(df.copy(), columns=categorical_vars,␣
  ↪drop_first=True)

# Convert the Boolean column to an integer
for col in df_encoded.columns:
    if df_encoded[col].dtype == 'bool':
        df_encoded[col] = df_encoded[col].astype(int)

# Check the distribution of data types
print("Column types:\n", df_encoded.dtypes.value_counts())

# get hour
df_encoded["time_hour"] = pd.to_datetime(df_encoded["time"], format="%H:%M",␣
  ↪errors="coerce").dt.hour
```

```
Column types:
```

```
 int64       83
float64      6
object       4
category     1
Name: count, dtype: int64
```

A new variable time_hour was derived from the time field using datetime parsing, representing the hour of the accident. Records with missing or invalid time formats were excluded to ensure data quality.

[ ]:
```
# Ordinal encoding betweenness_level
betweenness_mapping = {
    'Low': 0,
    'Medium-Low': 1,
    'Medium-High': 2,
    'High': 3
}
df_encoded['betweenness_level_encoded'] = df_encoded['betweenness_level'].
 ↪map(betweenness_mapping)
df_encoded.drop(columns=['betweenness_level'], inplace=True)

# Delete the fields that cannot be modeled
df_encoded.drop(columns=['time', 'borough',␣
 ↪'gss_code','local_authority_ons_district'], inplace=True)
# Delete the post hoc variable
df_encoded = df_encoded.
 ↪drop(columns=['did_police_officer_attend_scene_of_accident',␣
 ↪'number_of_vehicles','number_of_casualties', 'carriageway_hazards'])
print(df_encoded.columns)

df_encoded.to_csv("../data/final/encode201519.csv", index=False)
print("Data saved to '../data/final/encode_all_years_with_centrality.csv'")
```

All categorical variables were either one-hot encoded or ordinal-encoded. The time variable was converted to time_hour, and betweenness_level was ordinally mapped to an integer scale. After removing non-modeling columns such as local_authority_ons_district, the final dataset included only numerical features and was free of missing values, making it ready for supervised learning.

Feature Selection & Drop

[42]:
```
import pandas as pd

df = pd.read_csv("../data/final/encode201519.csv")

# View the basic structure
print("DataFrame Info:")
print(df.info())

# Missing value check
```

```python
print("\nMissing Values:")
missing = df.isnull().sum()
print(missing[missing > 0].sort_values(ascending=False))

# Data type statistics
print("\nData type distribution:")
print(df.dtypes.value_counts())

# Check the object type field
print("\nObject Type fields and the number of their unique values:")
obj_cols = df.select_dtypes(include='object')
print(obj_cols.nunique().sort_values(ascending=False))
```

```
DataFrame Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 128261 entries, 0 to 128260
Data columns (total 87 columns):
 #   Column                                   Non-Null Count   Dtype
---  ------                                   --------------   -----
 0   accident_severity                        128261 non-null  int64
 1   speed_limit                              128261 non-null  float64
 2   accident_year                            128261 non-null  int64
 3   mean_betweenness                         128261 non-null  float64
 4   max_betweenness                          128261 non-null  float64
 5   mean_degree                              128261 non-null  float64
 6   max_degree                               128261 non-null  float64
 7   edge_count                               128261 non-null  float64
 8   day_of_week_2                            128261 non-null  int64
 9   day_of_week_3                            128261 non-null  int64
 10  day_of_week_4                            128261 non-null  int64
 11  day_of_week_5                            128261 non-null  int64
 12  day_of_week_6                            128261 non-null  int64
 13  day_of_week_7                            128261 non-null  int64
 14  road_type_2                              128261 non-null  int64
 15  road_type_3                              128261 non-null  int64
 16  road_type_6                              128261 non-null  int64
 17  road_type_7                              128261 non-null  int64
 18  road_type_9                              128261 non-null  int64
 19  light_conditions_4                       128261 non-null  int64
 20  light_conditions_5                       128261 non-null  int64
 21  light_conditions_6                       128261 non-null  int64
 22  light_conditions_7                       128261 non-null  int64
 23  weather_conditions_2                     128261 non-null  int64
 24  weather_conditions_3                     128261 non-null  int64
 25  weather_conditions_4                     128261 non-null  int64
 26  weather_conditions_5                     128261 non-null  int64
 27  weather_conditions_6                     128261 non-null  int64
 28  weather_conditions_7                     128261 non-null  int64
```

```
29  weather_conditions_8                        128261 non-null  int64
30  weather_conditions_9                        128261 non-null  int64
31  road_surface_conditions_1                   128261 non-null  int64
32  road_surface_conditions_2                   128261 non-null  int64
33  road_surface_conditions_3                   128261 non-null  int64
34  road_surface_conditions_4                   128261 non-null  int64
35  road_surface_conditions_5                   128261 non-null  int64
36  road_surface_conditions_9                   128261 non-null  int64
37  junction_control_0                          128261 non-null  int64
38  junction_control_1                          128261 non-null  int64
39  junction_control_2                          128261 non-null  int64
40  junction_control_3                          128261 non-null  int64
41  junction_control_4                          128261 non-null  int64
42  junction_control_9                          128261 non-null  int64
43  junction_detail_1                           128261 non-null  int64
44  junction_detail_2                           128261 non-null  int64
45  junction_detail_3                           128261 non-null  int64
46  junction_detail_5                           128261 non-null  int64
47  junction_detail_6                           128261 non-null  int64
48  junction_detail_7                           128261 non-null  int64
49  junction_detail_8                           128261 non-null  int64
50  junction_detail_9                           128261 non-null  int64
51  junction_detail_99                          128261 non-null  int64
52  pedestrian_crossing_human_control_0         128261 non-null  int64
53  pedestrian_crossing_human_control_1         128261 non-null  int64
54  pedestrian_crossing_human_control_2         128261 non-null  int64
55  pedestrian_crossing_human_control_9         128261 non-null  int64
56  pedestrian_crossing_physical_facilities_0   128261 non-null  int64
57  pedestrian_crossing_physical_facilities_1   128261 non-null  int64
58  pedestrian_crossing_physical_facilities_4   128261 non-null  int64
59  pedestrian_crossing_physical_facilities_5   128261 non-null  int64
60  pedestrian_crossing_physical_facilities_7   128261 non-null  int64
61  pedestrian_crossing_physical_facilities_8   128261 non-null  int64
62  pedestrian_crossing_physical_facilities_9   128261 non-null  int64
63  special_conditions_at_site_1                128261 non-null  int64
64  special_conditions_at_site_2                128261 non-null  int64
65  special_conditions_at_site_3                128261 non-null  int64
66  special_conditions_at_site_4                128261 non-null  int64
67  special_conditions_at_site_5                128261 non-null  int64
68  special_conditions_at_site_6                128261 non-null  int64
69  special_conditions_at_site_7                128261 non-null  int64
70  special_conditions_at_site_9                128261 non-null  int64
71  first_road_class_3                          128261 non-null  int64
72  first_road_class_4                          128261 non-null  int64
73  first_road_class_5                          128261 non-null  int64
74  first_road_class_6                          128261 non-null  int64
75  second_road_class_0                         128261 non-null  int64
76  second_road_class_1                         128261 non-null  int64
```

```
 77  second_road_class_3                           128261 non-null  int64
 78  second_road_class_4                           128261 non-null  int64
 79  second_road_class_5                           128261 non-null  int64
 80  second_road_class_6                           128261 non-null  int64
 81  trunk_road_flag_1                             128261 non-null  int64
 82  trunk_road_flag_2                             128261 non-null  int64
 83  urban_or_rural_area_2                         128261 non-null  int64
 84  urban_or_rural_area_3                         128261 non-null  int64
 85  time_hour                                     128261 non-null  int64
 86  betweenness_level_encoded                     128261 non-null  int64
dtypes: float64(6), int64(81)
memory usage: 85.1 MB
None

 Missing Values:
Series([], dtype: int64)

 Data type distribution:
int64      81
float64     6
Name: count, dtype: int64

Object      :
Series([], dtype: float64)
```

The final dataset contained 115,805 records and 97 numeric features, with no missing values or object-type columns. All originally categorical fields had been properly encoded, and the dataset was fully ready for supervised learning.

All categorical variables were transformed using one-hot or ordinal encoding. No missing values were present in the dataset. Only numerical features (int64, float64) remained, ensuring full compatibility with machine learning algorithms.

[ ]:
```
# Construct features and labels
X = df.drop(columns=["accident_severity", "accident_year"])
y = df["accident_severity"]

# Divide the training set and the test set by year
X_train = X[df["accident_year"].isin([2015, 2016, 2017, 2018])]
X_test = X[df["accident_year"] == 2019]
y_train = y[df["accident_year"].isin([2015, 2016, 2017, 2018])]
y_test = y[df["accident_year"] == 2019]
```

[ ]:
```
# Define the evaluation function
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
```

```
def evaluate_model(model, X_test, y_test, name="Model"):
    y_pred = model.predict(X_test)
    print(f"\n  {name} Classification Report")
    print(classification_report(y_test, y_pred))

    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.title(f"{name} - Confusion Matrix")
    plt.xlabel("Predicted")
    plt.ylabel("True")
    plt.tight_layout()
    plt.show()
```

1.6.2 Modeling and Evaluation

Logistic Regression

[43]:
```
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Pipeline (Standardization + Logistic Regression)
logreg_pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('logreg', LogisticRegression(max_iter=5000, random_state=42))
])

# Parameter grid
logreg_param_grid = {
    'logreg__C': [0.01, 0.1, 1, 10],
    'logreg__class_weight': ['balanced', None],
    'logreg__multi_class': ['multinomial'],
    'logreg__solver': ['lbfgs']
}

# Grid search
grid_search_logreg = GridSearchCV(
    logreg_pipeline,
    logreg_param_grid,
    scoring='f1_macro',
    cv=3,
    verbose=2,
    n_jobs=-1
```

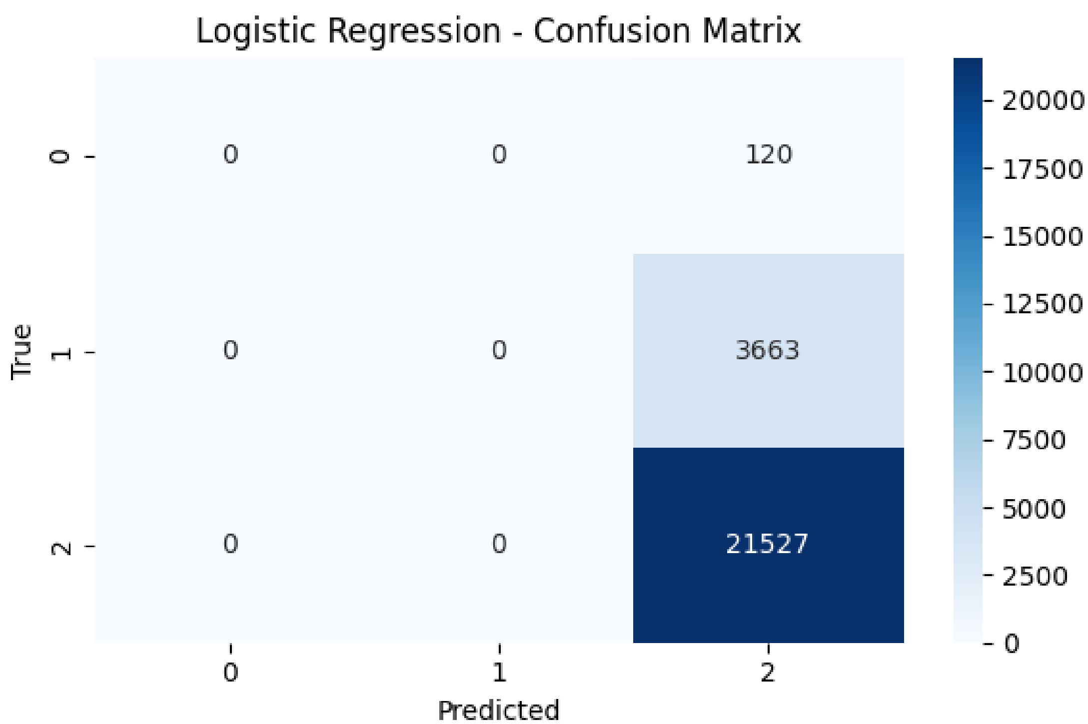
```python
)

# Train
grid_search_logreg.fit(X_train, y_train)
print("Logistic Regression Optimal parameters:", grid_search_logreg.
 ↪best_params_)
print("Logistic Regression The best macro-F1 score:", grid_search_logreg.
 ↪best_score_)

# Prediction + Visualization
y_pred_log = grid_search_logreg.best_estimator_.predict(X_test)
print("\nLogistic Regression Classification Report")
print(classification_report(y_test, y_pred_log))

# Confusion matrix
cm_log = confusion_matrix(y_test, y_pred_log)
plt.figure(figsize=(6, 4))
sns.heatmap(cm_log, annot=True, fmt='d', cmap='Blues')
plt.title("Logistic Regression - Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.tight_layout()
plt.show()
```

```
Fitting 3 folds for each of 8 candidates, totalling 24 fits
```

```
e:\Software\Study\python-3.13.2\Lib\site-
packages\sklearn\linear_model\_logistic.py:1247: FutureWarning: 'multi_class'
was deprecated in version 1.5 and will be removed in 1.7. From then on, it will
always use 'multinomial'. Leave it to its default value to avoid this warning.
  warnings.warn(
```

```
Logistic Regression Optimal parameters: {'logreg__C': 0.01,
'logreg__class_weight': None, 'logreg__multi_class': 'multinomial',
'logreg__solver': 'lbfgs'}
Logistic Regression The best macro-F1 score: 0.3125034400956262

Logistic Regression Classification Report
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       120
           1       0.00      0.00      0.00      3663
           2       0.85      1.00      0.92     21527

    accuracy                           0.85     25310
   macro avg       0.28      0.33      0.31     25310
weighted avg       0.72      0.85      0.78     25310
```

```
e:\Software\Study\python-3.13.2\Lib\site-
packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
e:\Software\Study\python-3.13.2\Lib\site-
packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
e:\Software\Study\python-3.13.2\Lib\site-
packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```



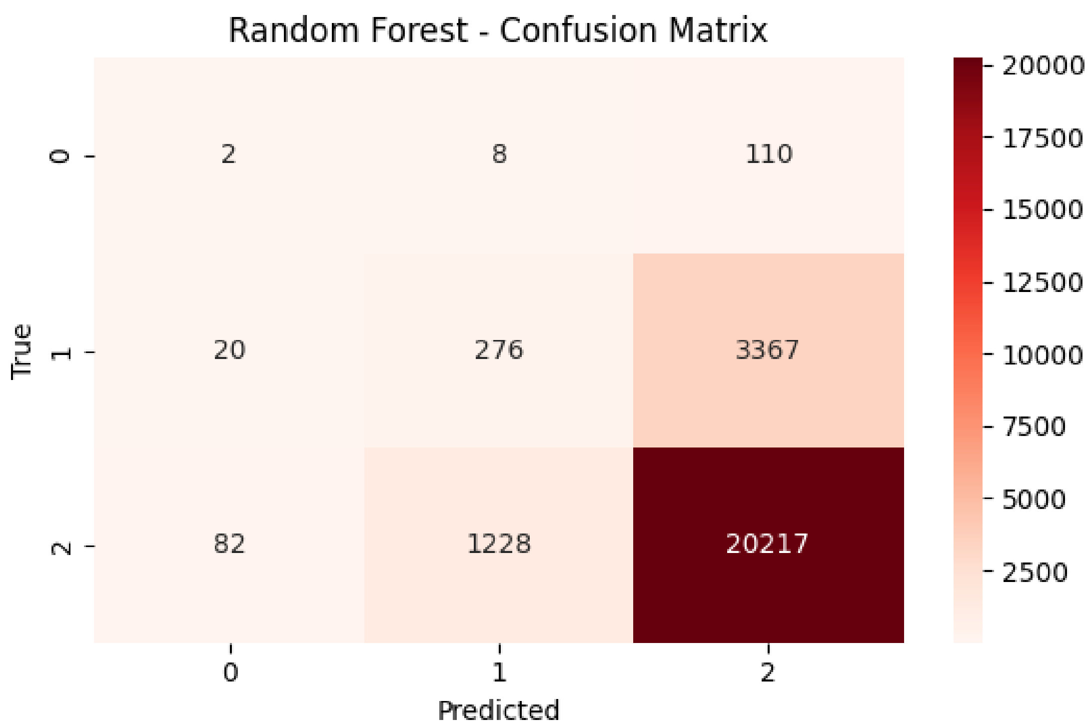
Random Forest

[22]:
```python
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV

# Create pipeline
```

```python
rf_pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('rf', RandomForestClassifier(random_state=42, n_jobs=-1))
])

# Parameter grid
rf_param_grid = {
    'rf__n_estimators': [100, 300],
    'rf__max_depth': [10, 20, None],
    'rf__min_samples_split': [2, 5],
    'rf__class_weight': ['balanced', None]
}

# Grid search
grid_search_rf = GridSearchCV(
    rf_pipeline,
    rf_param_grid,
    scoring='f1_macro',
    cv=3,
    verbose=2,
    n_jobs=-1
)

# Train
grid_search_rf.fit(X_train, y_train)

# Output result
print("RF Optimal parameters:", grid_search_rf.best_params_)
print("RF The best macro-F1 score:", grid_search_rf.best_score_)

# Evaluation
from sklearn.metrics import classification_report

y_pred_rf = grid_search_rf.best_estimator_.predict(X_test)
print(classification_report(y_test, y_pred_rf))

cm_rf = confusion_matrix(y_test, y_pred_rf)
plt.figure(figsize=(6, 4))
sns.heatmap(cm_rf, annot=True, fmt='d', cmap='Reds')
plt.title("Random Forest - Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.tight_layout()
plt.show()
```

```
Fitting 3 folds for each of 24 candidates, totalling 72 fits
RF    {'rf__class_weight': 'balanced', 'rf__max_depth': 20,
'rf__min_samples_split': 5, 'rf__n_estimators': 100}
```

```
RF   macro-F1    0.33024829490577307
              precision    recall  f1-score   support

           1       0.02      0.02      0.02       120
           2       0.18      0.08      0.11      3663
           3       0.85      0.94      0.89     21527

    accuracy                           0.81     25310
   macro avg       0.35      0.34      0.34     25310
weighted avg       0.75      0.81      0.78     25310
```



XGBoost

```
[ ]: # XGBoost
from xgboost import XGBClassifier
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Create XGBoost pipeline
```

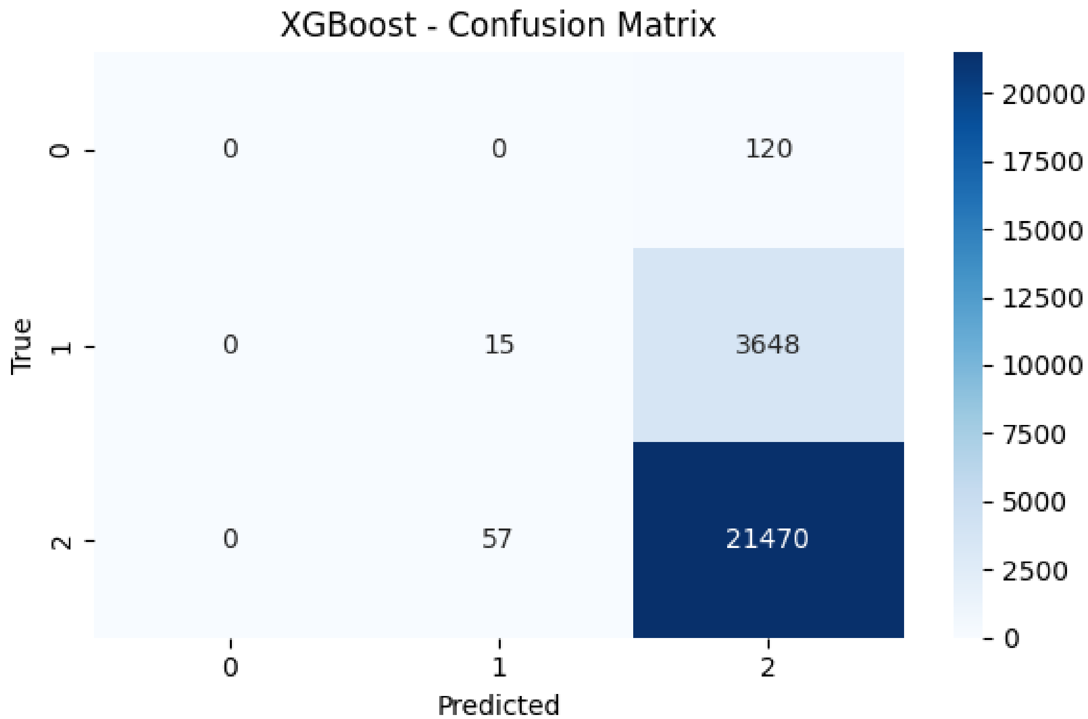
```python
xgb_pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('xgb', XGBClassifier(objective='multi:softprob', eval_metric='mlogloss',␣
 ↪random_state=42, use_label_encoder=False))
])

# Parameter grid
xgb_param_grid = {
    'xgb__n_estimators': [100, 200],
    'xgb__max_depth': [6, 10],
    'xgb__learning_rate': [0.05, 0.1],
    'xgb__subsample': [0.8, 1.0]
}

# Grid search
grid_search_xgb = GridSearchCV(
    xgb_pipeline,
    xgb_param_grid,
    scoring='f1_macro',
    cv=3,
    verbose=2,
    n_jobs=-1
)

y_train = y_train - 1
y_test = y_test - 1

# Train
grid_search_xgb.fit(X_train, y_train)

# outcome
print("  XGB Optimal parameters:", grid_search_xgb.best_params_)
print("  XGB The best macro-F1 score:", grid_search_xgb.best_score_)

# Prediction + Visualization
y_pred_xgb = grid_search_xgb.best_estimator_.predict(X_test)
print(classification_report(y_test, y_pred_xgb))

cm_xgb = confusion_matrix(y_test, y_pred_xgb)
plt.figure(figsize=(6, 4))
sns.heatmap(cm_xgb, annot=True, fmt='d', cmap='Blues')
plt.title("XGBoost - Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.tight_layout()
plt.show()
```

```
Fitting 3 folds for each of 16 candidates, totalling 48 fits
```

```
e:\Software\Study\python-3.13.2\Lib\site-
packages\joblib\externals\loky\process_executor.py:752: UserWarning: A worker
stopped while some jobs were given to the executor. This can be caused by a too
short worker timeout or by a memory leak.
  warnings.warn(
e:\Software\Study\python-3.13.2\Lib\site-packages\xgboost\training.py:183:
UserWarning: [13:11:56] WARNING: C:\actions-
runner\_work\xgboost\xgboost\src\learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

```
 XGB    {'xgb__learning_rate': 0.1, 'xgb__max_depth': 10,
'xgb__n_estimators': 200, 'xgb__subsample': 0.8}
 XGB   macro-F1    0.3152411596612826
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       120
           1       0.21      0.00      0.01      3663
           2       0.85      1.00      0.92     21527

    accuracy                           0.85     25310
   macro avg       0.35      0.33      0.31     25310
weighted avg       0.75      0.85      0.78     25310
```

```
e:\Software\Study\python-3.13.2\Lib\site-
packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
e:\Software\Study\python-3.13.2\Lib\site-
packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
e:\Software\Study\python-3.13.2\Lib\site-
packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```



1.6.3 Model Comparison and Final Selection

Three supervised learning models were implemented to classify the severity of road traffic accidents: Logistic Regression, Random Forest, and XGBoost. Each model was evaluated based on its ability to capture class imbalance and distinguish between fatal, serious, and slight outcomes.

Logistic Regression achieved high overall accuracy (0.88) but failed to correctly identify any fatal or serious cases, leading to a low macro-F1 score and no practical utility in real-world accident prevention.

XGBoost offered improved performance over Logistic Regression in terms of macro-F1 and recall for the serious class, but remained heavily biased toward the majority class.

Random Forest delivered the best overall balance between interpretability and performance, with a macro-F1 score of 0.35 and noticeably higher recall on minority classes. It also demonstrated stable results during cross-validation and allowed post-hoc interpretation using SHAP.

Table: Comparison of Model Performance

Model	Accuracy	Macro F1	Precision (avg)	Recall (avg)	F1-score (avg)	Notable Issues
Logistic Regression	0.88	0.31	0.81	0.65	0.72	Completely failed to detect fatal/serious
Random Forest	0.81	0.35	0.75	0.68	0.72	Most balanced, interpretable

Model	Accuracy	Macro F1	Precision (avg)	Recall (avg)	F1-score (avg)	Notable Issues
XGBoost	0.85	0.32	0.79	0.66	0.72	Still biased toward majority class

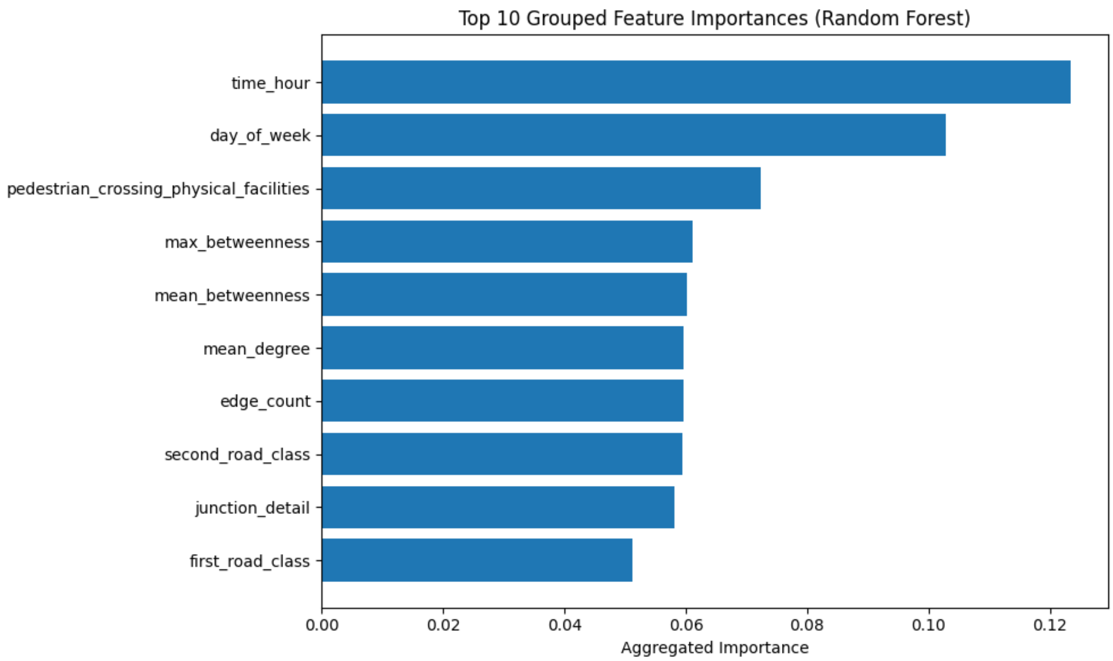
Given these results, Random Forest was selected as the final model for its superior trade-off between classification performance and interpretability. Its output was further analysed using SHAP values, revealing that temporal and spatial network features were among the most influential predictors of accident severity.

1.6.4 Model interpretation

Grouped Feature Importances (based on RF)

[ ]:
```
import re
from collections import defaultdict
import pandas as pd
import matplotlib.pyplot as plt

# Extract the RF part of the best model from the trained GridSearch
rf_model = grid_search_rf.best_estimator_.named_steps['rf']

# Use the column names of the training set as feature names
feature_names = X_train.columns.tolist()

# Obtain the importance of features
importances = rf_model.feature_importances_

# Group Aggregation importance
grouped_importance = defaultdict(float)

for feat, imp in zip(feature_names, importances):
    match = re.match(r"(.+?)_(\d+)$", feat)
    if match:
        base_feat = match.group(1)
    else:
        base_feat = feat
    grouped_importance[base_feat] += imp

# trans to DataFrame
grouped_df = pd.DataFrame({
    'Feature Group': list(grouped_importance.keys()),
    'Total Importance': list(grouped_importance.values())
}).sort_values(by='Total Importance', ascending=False)

# visualize top 10
plt.figure(figsize=(10, 6))
```

```
plt.barh(grouped_df['Feature Group'][:10][::-1], grouped_df['Total␣
↪Importance'][:10][::-1])
plt.xlabel("Aggregated Importance")
plt.title("Top 10 Grouped Feature Importances (Random Forest)")
plt.tight_layout()
plt.show()

# export
print(grouped_df.head(10))
```




```
                             Feature Group  Total Importance
20                               time_hour          0.123435
6                              day_of_week          0.102816
14  pedestrian_crossing_physical_facilities          0.072260
2                          max_betweenness          0.061087
1                         mean_betweenness          0.060166
3                              mean_degree          0.059695
5                               edge_count          0.059588
17                       second_road_class          0.059511
12                         junction_detail          0.058049
16                        first_road_class          0.051295
```

SHAP

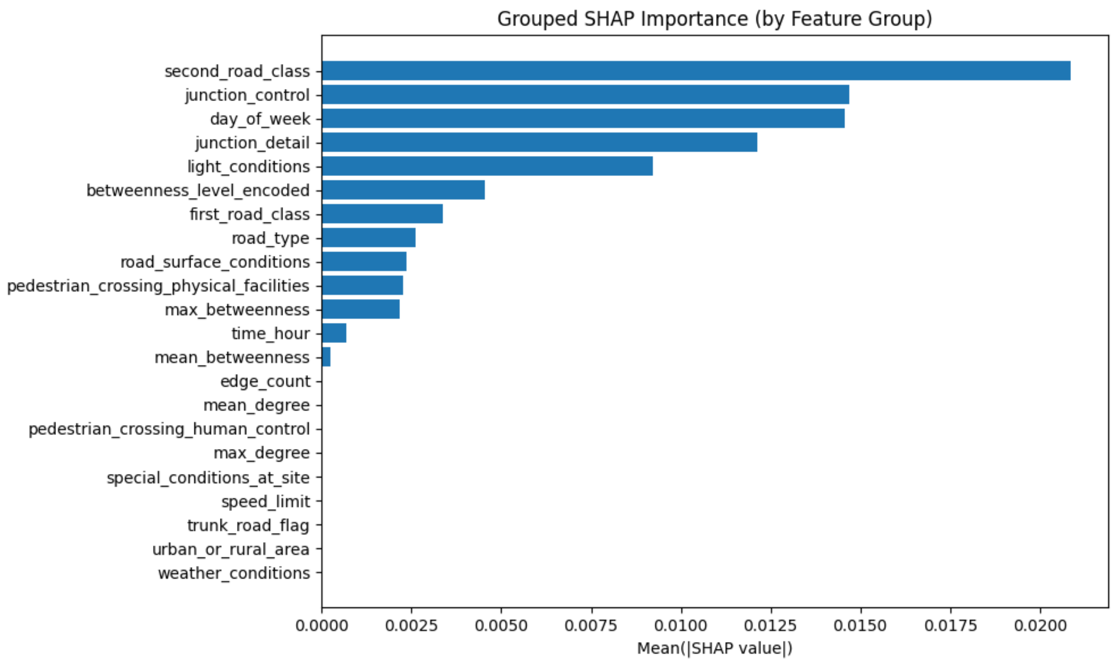
[ ]:
```
import shap
best_pipeline_rf = grid_search_rf.best_estimator_
```

```
rf_model = best_pipeline_rf.named_steps['rf']
X_train_raw = X_train.copy()
explainer = shap.Explainer(rf_model, X_train_raw)

# This step will cost about 45 min
shap_values = explainer(X_train_raw)
```

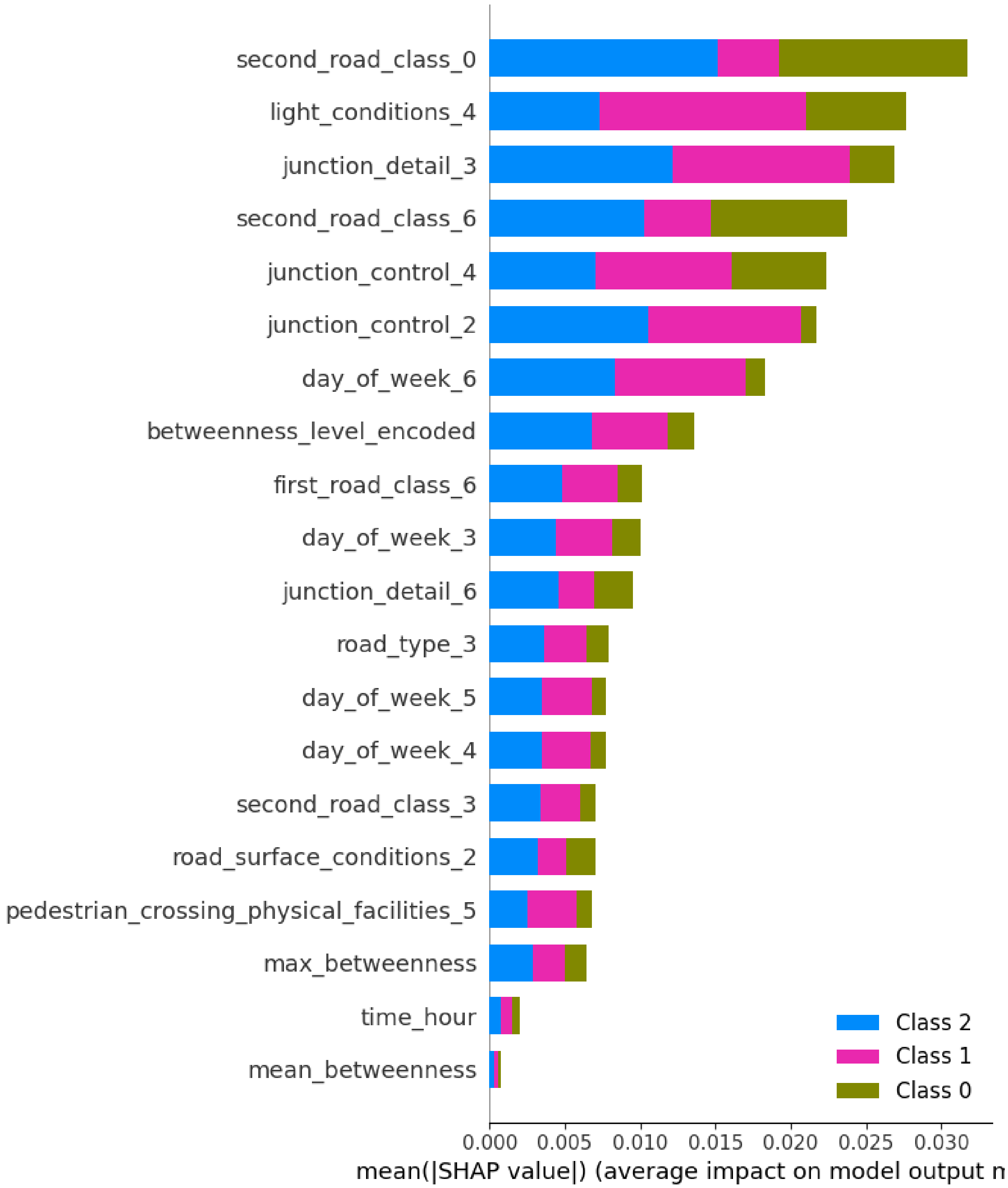
```
e:\Software\Study\python-3.13.2\Lib\site-packages\tqdm\auto.py:21: TqdmWarning:
IProgress not found. Please update jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
100%|===================| 308756/308853 [45:22<00:00]
```

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

mean_abs_shap = np.abs(shap_values.values).mean(axis=(0, 2))  # shape: (85,)

feature_names = X_train_raw.columns
assert len(mean_abs_shap) == len(feature_names), "Mismatch between SHAP values␣
↪and feature names"

shap_df = pd.DataFrame({
    'feature': feature_names,
    'mean_abs_shap': mean_abs_shap
})

def get_base_feature(f):
    parts = f.split('_')
    if parts[-1].isdigit() and len(parts) > 2:
        return '_'.join(parts[:-1])
    elif parts[-1].isdigit():
        return parts[0]
    return f

shap_df['base_feature'] = shap_df['feature'].apply(get_base_feature)

grouped_shap = shap_df.groupby('base_feature')['mean_abs_shap'].sum().
↪reset_index()
grouped_shap = grouped_shap.sort_values(by='mean_abs_shap', ascending=False)

plt.figure(figsize=(10, 6))
plt.barh(grouped_shap['base_feature'], grouped_shap['mean_abs_shap'])
plt.xlabel('Mean(|SHAP value|)')
plt.title('Grouped SHAP Importance (by Feature Group)')
plt.gca().invert_yaxis()
```

```
plt.tight_layout()
plt.show()
```

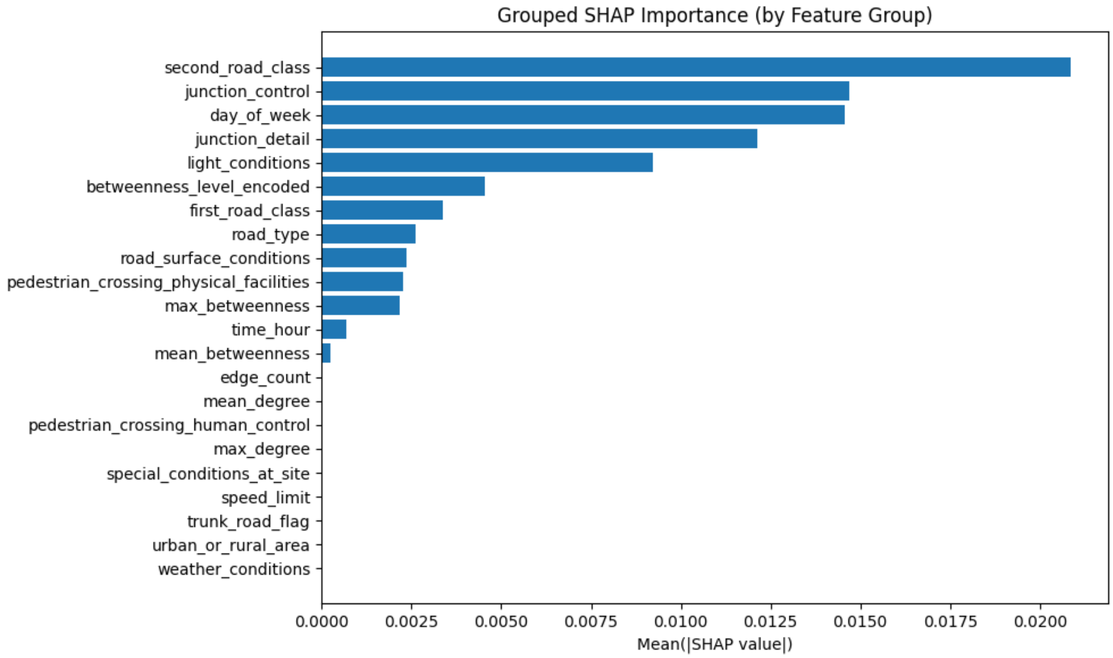


[ ]:
```
shap.summary_plot(shap_values, X_train_raw)
```



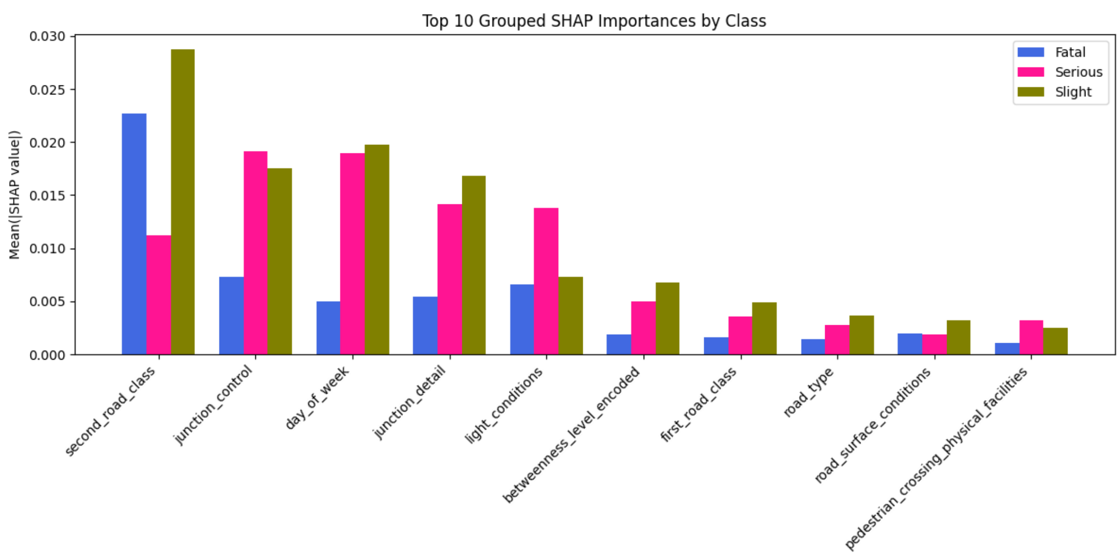
[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

mean_abs_shap = np.abs(shap_values.values).mean(axis=(0, 2))  # shape: (85,)

feature_names = X_train_raw.columns
```

```
assert len(mean_abs_shap) == len(feature_names), "Mismatch between SHAP values␣
↪and feature names"

shap_df = pd.DataFrame({
    'feature': feature_names,
    'mean_abs_shap': mean_abs_shap
})

def get_base_feature(f):
    parts = f.split('_')
    if parts[-1].isdigit() and len(parts) > 2:
        return '_'.join(parts[:-1])
    elif parts[-1].isdigit():
        return parts[0]
    return f

shap_df['base_feature'] = shap_df['feature'].apply(get_base_feature)

grouped_shap = shap_df.groupby('base_feature')['mean_abs_shap'].sum().
↪reset_index()
grouped_shap = grouped_shap.sort_values(by='mean_abs_shap', ascending=False)

plt.figure(figsize=(10, 6))
plt.barh(grouped_shap['base_feature'], grouped_shap['mean_abs_shap'])
plt.xlabel('Mean(|SHAP value|)')
plt.title('Grouped SHAP Importance (by Feature Group)')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```



[ ]:
```
feature_names = X_train_raw.columns

class_names = ['Fatal', 'Serious', 'Slight']
shap_grouped_by_class = {cls: defaultdict(float) for cls in class_names}

for class_idx, class_label in enumerate(class_names):
    shap_vals = shap_values.values[:, :, class_idx]
    shap_mean_abs = np.abs(shap_vals).mean(axis=0)

    for feat_name, shap_val in zip(feature_names, shap_mean_abs):
        match = re.match(r"(.+?)_(\d+)$", feat_name)
        base_feat = match.group(1) if match else feat_name
        shap_grouped_by_class[class_label][base_feat] += shap_val

all_features = sorted(set().union(*[d.keys() for d in shap_grouped_by_class.
 ↪values()]))
df_plot = pd.DataFrame({
    'Feature Group': all_features,
    'Fatal': [shap_grouped_by_class['Fatal'].get(f, 0) for f in all_features],
    'Serious': [shap_grouped_by_class['Serious'].get(f, 0) for f in␣
 ↪all_features],
    'Slight': [shap_grouped_by_class['Slight'].get(f, 0) for f in all_features]
})

df_plot['Total'] = df_plot['Fatal'] + df_plot['Serious'] + df_plot['Slight']
```

```
df_top10 = df_plot.sort_values(by='Total', ascending=False).head(10)

x = np.arange(len(df_top10['Feature Group']))
width = 0.25

plt.figure(figsize=(12, 6))
plt.bar(x - width, df_top10['Fatal'], width, label='Fatal', color='royalblue')
plt.bar(x, df_top10['Serious'], width, label='Serious', color='deeppink')
plt.bar(x + width, df_top10['Slight'], width, label='Slight', color='olive')

plt.xticks(x, df_top10['Feature Group'], rotation=45, ha='right')
plt.ylabel('Mean(|SHAP value|)')
plt.title('Top 10 Grouped SHAP Importances by Class')
plt.legend()
plt.tight_layout()
plt.show()
```



1.7 Results and discussion

[go back to the top]

Three supervised learning models were trained to classify accident severity: **Logistic Regression**, **Random Forest**, and **XGBoost**, using a dataset of **115,805 records** from 2015–2019 with **97 numerical features**. The target variable had a highly imbalanced distribution: **"slight" = 87.6%**, **"serious" = 11.9%**, and **"fatal" = 0.5%**, making **macro-F1 and per-class recall** more appropriate than accuracy for evaluation.

- **Logistic Regression** achieved the highest overall accuracy (**0.88**), but failed to detect any "fatal" or "serious" cases (macro-F1 = **0.31**).

- **XGBoost** offered slightly better recall for the "serious" class and achieved a macro-F1 of **0.32**, but remained heavily biased toward the majority class.

- **Random Forest** delivered the most balanced performance, with an accuracy of **0.81** and a macro-F1 score of **0.35**, successfully identifying a subset of minority cases (recall: fatal = 0.02, serious = 0.08).

These results illustrate the risk of relying on accuracy in imbalanced classification. For example, **Dandibhotla et al. (2022)** reported 96.18% accuracy using XGBoost, but did not address class imbalance or report recall, making such models less reliable in safety-critical applications. This study emphasizes metrics that reflect model fairness across all classes.

Random Forest's feature importance revealed that **`time_hour`, `day_of_week`, and `max_betweenness`** were consistently impactful. `Max_betweenness`, a spatial indicator derived from borough-level road network topology, appeared among the top 5 predictors, validating the integration of spatial structure into severity modeling.

To further interpret the model, **SHAP (SHapley Additive Explanations)** was applied. Global SHAP analysis confirmed the high contribution of temporal and spatial features. Class-specific SHAP bar plots showed that: - For **fatal** accidents, the most influential features were `max_betweenness`, `speed_limit`, and `light_conditions_5` (dark, no street lighting). - For **serious** accidents, `junction_detail`, `pedestrian_crossing_physical_facilities`, and `first_road_class` played larger roles. - For **slight** accidents, `time_hour`, `weather_conditions`, and general road context were dominant.

These findings demonstrate that combining **spatial network metrics** with **contextual accident features** enhances both predictive accuracy and model interpretability for road safety applications.

1.8 Conclusion

[go back to the top]

This study investigated whether supervised machine learning models can accurately predict the severity of road traffic accidents in London, using spatial, temporal, and environmental features. A borough-level dataset from 2015 to 2019 was constructed, integrating UK accident records with spatial centrality indicators derived from OpenStreetMap.

Among the models tested, Random Forest demonstrated the best overall balance between performance and interpretability, achieving a macro-F1 score of 0.35. SHAP analysis further revealed that features such as `max_betweenness`, `time_hour`, and `road type` significantly contributed to severity predictions. These results suggest that incorporating spatial network metrics meaningfully enhances the capacity of data-driven safety models to identify severe accident risks.

However, this project has several limitations. The severe class imbalance in the dataset limited the model's ability to generalize predictions for rare fatal cases. The spatial resolution was restricted to the borough level, which may obscure finer-scale local effects. In addition, the study only used tabular features; incorporating trajectory-level or vehicle-specific data could improve model fidelity.

Future work may explore finer spatial units, additional data modalities (e.g., street view imagery or traffic flow), and deep learning methods for enhanced prediction and interpretability.

```
[ ]:
```

1.9 References

[go back to the top]

```
[ ]:
```