## Traffic Crashes in Chicago

Urban traffic accidents pose significant challenges, leading to considerable human suffering and economic losses. In Chicago, the annual toll includes numerous traffic collisions that result in injuries, fatalities, and substantial property damage. Identifying the factors that lead to these incidents and forecasting their severity are crucial steps for city planners and public safety officials aiming to enhance road safety. This initiative utilizes the City of Chicago's Traffic Crashes dataset to develop predictive models that pinpoint high-risk situations and offer actionable insights.

## Project Overview

This initiative seeks to examine Chicago's traffic accident data to forecast the leading contributory causes of these incidents. By employing machine learning algorithms, the project aims to pinpoint critical factors that lead to accidents, thereby guiding policy decisions to enhance traffic safety and mitigate future collisions. The dataset encompasses various attributes related to accidents, including weather conditions, lighting, and roadway surface states. The primary focus is on the 'Primary Contributory Cause,' approached as a multi-class classification challenge.

## Business Understanding

Traffic accidents represent a critical public safety concern. Identifying the factors that lead to these incidents enables city planners, traffic engineers, and policymakers to implement more effective safety measures. This project aims to develop a model that accurately predicts the primary contributory causes of accidents, providing actionable insights to reduce their frequency and severity.

## Data Understanding

he dataset for this project is sourced from the City of Chicago's Traffic Crashes database, which provides comprehensive details for each incident, including:

- Crash Date: Specifies the exact date and time when the crash occurred.
- Traffic Control Device: Identifies the type of traffic control mechanism in place at the location of the crash.
- Weather Conditions: Describes the atmospheric conditions present at the time of the accident.
- Roadway Surface Conditions: Indicates the state of the road surface during the crash.
- Lighting Conditions: Details the level of illumination at the crash scene.

## Data Preparation

## Importing Libraries

```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pickle, sklearn
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, roc_curve, roc_auc_score
from numbers import Number
```

## Reading and accessing the data

```
df = pd.read_csv("Traffic_Crashes.csv")
print(df.head())
```

```
print(df.info())
print(df.describe())
```

```
 42  CRASH_HOUR                     12228 non-null  float64
 43  CRASH_DAY_OF_WEEK              12228 non-null  float64
 44  CRASH_MONTH                    12228 non-null  float64
 45  LATITUDE                       7319 non-null   float64
 46  LONGITUDE                      7319 non-null   float64
 47  LOCATION                       7319 non-null   object
dtypes: float64(17), object(31)
memory usage: 4.5+ MB
None
       POSTED_SPEED_LIMIT     LANE_CNT      STREET_NO  BEAT_OF_OCCURRENCE  \
count        12228.000000  2792.000000   12228.000000        12226.000000
mean            27.786310     2.827006    3421.278950         1257.807623
std              7.873938     3.327865    5162.221619          673.510866
min              0.000000     0.000000       0.000000          111.000000
25%             25.000000     2.000000     524.000000          711.000000
50%             30.000000     2.000000    2600.000000         1431.000000
75%             30.000000     4.000000    5549.750000         1654.000000
max             65.000000    99.000000  451100.000000         6100.000000

          NUM_UNITS  INJURIES_TOTAL  INJURIES_FATAL  INJURIES_INCAPACITATING  \
count  12228.000000    12202.000000    12202.000000             12202.000000
mean       2.009814        0.186855        0.001147                 0.019669
std        0.452795        0.571570        0.033855                 0.165770
min        1.000000        0.000000        0.000000                 0.000000
25%        2.000000        0.000000        0.000000                 0.000000
50%        2.000000        0.000000        0.000000                 0.000000
75%        2.000000        0.000000        0.000000                 0.000000
max       12.000000       15.000000        1.000000                 5.000000

       INJURIES_NON_INCAPACITATING  INJURIES_REPORTED_NOT_EVIDENT  \
count                 12202.000000                   12202.000000
mean                      0.105311                       0.060728
std                       0.422473                       0.319567
min                       0.000000                       0.000000
25%                       0.000000                       0.000000
50%                       0.000000                       0.000000
75%                       0.000000                       0.000000
max                       6.000000                      10.000000

       INJURIES_NO_INDICATION  INJURIES_UNKNOWN    CRASH_HOUR  \
count            12202.000000           12202.0  12228.000000
mean                 2.003196               0.0     13.099280
std                  1.130632               0.0      5.588017
min                  0.000000               0.0      0.000000
25%                  1.000000               0.0      9.000000
50%                  2.000000               0.0     14.000000
75%                  2.000000               0.0     17.000000
max                 27.000000               0.0     23.000000

       CRASH_DAY_OF_WEEK   CRASH_MONTH     LATITUDE    LONGITUDE
count       12228.000000  12228.000000  7319.000000  7319.000000
mean            4.056919      6.644913    41.629907   -87.201947
std             1.975403      3.383338     3.087444     6.465016
min             1.000000      1.000000     0.000000   -87.933994
25%             2.000000      4.000000    41.781627   -87.722542
50%             4.000000      7.000000    41.878390   -87.678604
75%             6.000000      9.000000    41.924490   -87.634584
max             7.000000     12.000000    42.019410     0.000000
```

```
df.columns
```

```
Index(['CRASH_RECORD_ID', 'CRASH_DATE_EST_I', 'CRASH_DATE',
       'POSTED_SPEED_LIMIT', 'TRAFFIC_CONTROL_DEVICE', 'DEVICE_CONDITION',
       'WEATHER_CONDITION', 'LIGHTING_CONDITION', 'FIRST_CRASH_TYPE',
       'TRAFFICWAY_TYPE', 'LANE_CNT', 'ALIGNMENT', 'ROADWAY_SURFACE_COND',
       'ROAD_DEFECT', 'REPORT_TYPE', 'CRASH_TYPE', 'INTERSECTION_RELATED_I',
       'NOT_RIGHT_OF_WAY_I', 'HIT_AND_RUN_I', 'DAMAGE', 'DATE_POLICE_NOTIFIED',
       'PRIM_CONTRIBUTORY_CAUSE', 'SEC_CONTRIBUTORY_CAUSE', 'STREET_NO',
       'STREET_DIRECTION', 'STREET_NAME', 'BEAT_OF_OCCURRENCE',
       'PHOTOS_TAKEN_I', 'STATEMENTS_TAKEN_I', 'DOORING_I', 'WORK_ZONE_I',
       'WORK_ZONE_TYPE', 'WORKERS_PRESENT_I', 'NUM_UNITS',
       'MOST_SEVERE_INJURY', 'INJURIES_TOTAL', 'INJURIES_FATAL',
       'INJURIES_INCAPACITATING', 'INJURIES_NON_INCAPACITATING',
       'INJURIES_REPORTED_NOT_EVIDENT', 'INJURIES_NO_INDICATION',
       'INJURIES_UNKNOWN', 'CRASH_HOUR', 'CRASH_DAY_OF_WEEK', 'CRASH_MONTH',
       'LATITUDE', 'LONGITUDE', 'LOCATION'],
      dtype='object')
```

## Check for any Missing values

```
missing_values = df.isnull().sum()
print(missing_values[missing_values > 0])
```

```
CRASH_DATE_EST_I                13291
LANE_CNT                        11394
REPORT_TYPE                       342
INTERSECTION_RELATED_I          11313
NOT_RIGHT_OF_WAY_I              13657
HIT_AND_RUN_I                   10489
PRIM_CONTRIBUTORY_CAUSE             1
SEC_CONTRIBUTORY_CAUSE              1
STREET_NO                           1
STREET_DIRECTION                    4
STREET_NAME                         2
BEAT_OF_OCCURRENCE                  3
PHOTOS_TAKEN_I                  14120
STATEMENTS_TAKEN_I              13957
DOORING_I                       14259
WORK_ZONE_I                     14201
WORK_ZONE_TYPE                  14214
WORKERS_PRESENT_I               14260
NUM_UNITS                           1
MOST_SEVERE_INJURY                 31
INJURIES_TOTAL                     31
INJURIES_FATAL                     31
INJURIES_INCAPACITATING            31
INJURIES_NON_INCAPACITATING        31
INJURIES_REPORTED_NOT_EVIDENT      31
INJURIES_NO_INDICATION             31
INJURIES_UNKNOWN                   31
CRASH_HOUR                          1
CRASH_DAY_OF_WEEK                   1
CRASH_MONTH                         1
LATITUDE                         5913
LONGITUDE                        5913
LOCATION                         5913
dtype: int64
```

## Check for Duplicte values

```
duplicate_rows = df[df.duplicated()]
print(duplicate_rows)
```

```
Empty DataFrame
Columns: [CRASH_RECORD_ID, CRASH_DATE_EST_I, CRASH_DATE, POSTED_SPEED_LIMIT, TRAFFIC_CONTROL_DEVICE, DEVICE_CONDITION, W
Index: []

[0 rows x 48 columns]
```

## Dealing with missing values

```
df['WEATHER_CONDITION'].fillna(df['WEATHER_CONDITION'].mode()[0], inplace=True)
df['LIGHTING_CONDITION'].fillna(df['LIGHTING_CONDITION'].mode()[0], inplace=True)
df['ROADWAY_SURFACE_COND'].fillna(df['ROADWAY_SURFACE_COND'].mode()[0], inplace=True)
df['TRAFFIC_CONTROL_DEVICE'].fillna(df['TRAFFIC_CONTROL_DEVICE'].mode()[0], inplace=True)
df['DEVICE_CONDITION'].fillna(df['DEVICE_CONDITION'].mode()[0], inplace=True)
df['DEVICE_CONDITION'].fillna(df['DEVICE_CONDITION'].mode()[0], inplace=True)
df['INTERSECTION_RELATED_I'].fillna(df['INTERSECTION_RELATED_I'].mode()[0], inplace=True)
df['NOT_RIGHT_OF_WAY_I'].fillna(df['NOT_RIGHT_OF_WAY_I'].mode()[0], inplace=True)
df['MOST_SEVERE_INJURY'].fillna(df['MOST_SEVERE_INJURY'].mode()[0], inplace=True)
df.drop(['PHOTOS_TAKEN_I', 'STATEMENTS_TAKEN_I', 'DOORING_I', 'WORK_ZONE_I',
         'WORK_ZONE_TYPE', 'WORKERS_PRESENT_I', 'STREET_NO', 'STREET_DIRECTION',
         'STREET_NAME', 'BEAT_OF_OCCURRENCE','CRASH_DATE_EST_I'], axis=1, inplace=True)
df['HIT_AND_RUN_I'].fillna(df['HIT_AND_RUN_I'].mode()[0], inplace=True)
df['LANE_CNT'].fillna(df['LANE_CNT'].median(), inplace=True)
df['LATITUDE'].fillna(df['LATITUDE'].median(), inplace=True)
df['LONGITUDE'].fillna(df['LONGITUDE'].median(), inplace=True)
injury_columns = [
    'INJURIES_TOTAL', 'INJURIES_FATAL', 'INJURIES_INCAPACITATING',
    'INJURIES_NON_INCAPACITATING', 'INJURIES_REPORTED_NOT_EVIDENT',
    'INJURIES_NO_INDICATION', 'INJURIES_UNKNOWN'
]
df[injury_columns] = df[injury_columns].fillna(0)
df['LOCATION'].fillna(method='ffill', inplace=True)
df['REPORT_TYPE'].fillna(df['REPORT_TYPE'].mode()[0], inplace=True)
df['LOCATION'].fillna(method='bfill', inplace=True)
```

```
<ipython-input-8-f502b43b8812>:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[c


  df['WEATHER_CONDITION'].fillna(df['WEATHER_CONDITION'].mode()[0], inplace=True)
```

```
<ipython-input-8-f502b43b8812>:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[c


  df['LIGHTING_CONDITION'].fillna(df['LIGHTING_CONDITION'].mode()[0], inplace=True)
<ipython-input-8-f502b43b8812>:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[c


  df['ROADWAY_SURFACE_COND'].fillna(df['ROADWAY_SURFACE_COND'].mode()[0], inplace=True)
<ipython-input-8-f502b43b8812>:4: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[c


  df['TRAFFIC_CONTROL_DEVICE'].fillna(df['TRAFFIC_CONTROL_DEVICE'].mode()[0], inplace=True)
<ipython-input-8-f502b43b8812>:5: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[c


  df['DEVICE_CONDITION'].fillna(df['DEVICE_CONDITION'].mode()[0], inplace=True)
<ipython-input-8-f502b43b8812>:6: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[c


  df['DEVICE_CONDITION'].fillna(df['DEVICE_CONDITION'].mode()[0], inplace=True)
<ipython-input-8-f502b43b8812>:7: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[c


  df['INTERSECTION_RELATED_I'].fillna(df['INTERSECTION_RELATED_I'].mode()[0], inplace=True)
<ipython-input-8-f502b43b8812>:8: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[c


  df['NOT_RIGHT_OF_WAY_I'].fillna(df['NOT_RIGHT_OF_WAY_I'].mode()[0], inplace=True)
<ipython-input-8-f502b43b8812>:9: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we
```

```
missing_values = df.isnull().sum()
print(missing_values[missing_values > 0])
```

```
PRIM_CONTRIBUTORY_CAUSE    1
SEC_CONTRIBUTORY_CAUSE     1
NUM_UNITS                  1
CRASH_HOUR                 1
CRASH_DAY_OF_WEEK          1
CRASH_MONTH                1
dtype: int64
```

## Feature Engineering

The dataset has pre-engineered features, such as CRASH_HOUR and CRASH_MONTH. To identify the top 10 features most relevant to our target variable, we will empdeployloy a machine learning model.

In the following cell, we will implement a Logistic Regression model with preprocessing pipelines to efficiently handle our large dataset. This approach will also prepare both categorical and numerical features for modeling.

```
df_sampled = df.sample(frac=0.01, random_state=42)

X = df_sampled.drop('PRIM_CONTRIBUTORY_CAUSE', axis=1)
y = df_sampled['PRIM_CONTRIBUTORY_CAUSE']


categorical_cols = X.select_dtypes(include=['object']).columns
numerical_cols = X.select_dtypes(exclude=['object']).columns


preprocessor = ColumnTransformer(
```

```
    transformers=[
        ('num', SimpleImputer(strategy='median'), numerical_cols),
        ('cat', Pipeline(steps=[
            ('imputer', SimpleImputer(strategy='most_frequent')),
            ('onehot', OneHotEncoder(handle_unknown='ignore'))
        ]), categorical_cols)
    ])


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


X_train = preprocessor.fit_transform(X_train)
X_test = preprocessor.transform(X_test)

model = LogisticRegression(max_iter=100, random_state=42, n_jobs=-1)
model.fit(X_train, y_train)
```

```
▾ LogisticRegression
LogisticRegression(n_jobs=-1, random_state=42)
```

## Next we xtract coefficients by creating features then analyze the importance of each feature.

Feature Name Construction The code reconstructs feature names after preprocessing, including those generated through one-hot encoding for categorical variables.

Model Coefficients It retrieves the coefficients from the trained Logistic Regression model to analyze the contribution of each feature to the predictions.

Feature Importance By sorting the coefficients based on their absolute values, the code highlights the most influential features in the model, offering insights into the key factors driving the target variable.

```
feature_names = []

for col in numerical_cols:
    feature_names.append(col)

for col in categorical_cols:
    categories = preprocessor.named_transformers_['cat']['onehot'].categories_[categorical_cols.get_loc(col)]
    feature_names.extend([f"{col}_{category}" for category in categories])

coefficients = model.coef_[0]

importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Coefficient': coefficients
})

importance_df['Abs_Coefficient'] = np.abs(importance_df['Coefficient'])
importance_df = importance_df.sort_values(by='Abs_Coefficient', ascending=False)

print(importance_df.head(20))
```

```
                                            Feature  Coefficient  \
256                     DEVICE_CONDITION_NO CONTROLS    -0.318587
250             TRAFFIC_CONTROL_DEVICE_NO CONTROLS    -0.312541
452  LOCATION_POINT (-87.585945066953 41.744151639042)     0.300816
11                                CRASH_DAY_OF_WEEK    -0.294536
272                         FIRST_CRASH_TYPE_ANGLE     0.285345
8                           INJURIES_NO_INDICATION     0.254969
283                       FIRST_CRASH_TYPE_TURNING     0.249495
15                                  CRASH_HOUR_sin     0.237472
319                             DAMAGE_OVER $1,500     0.215492
20                                 CRASH_MONTH_cos     0.212613
12                                     CRASH_MONTH    -0.211625
318                           DAMAGE_$501 - $1,500    -0.194453
282         FIRST_CRASH_TYPE_SIDESWIPE SAME DIRECTION    -0.193910
10                                      CRASH_HOUR     0.186789
423       DATE_POLICE_NOTIFIED_12/09/2022 03:00:00 PM     0.182103
238               CRASH_DATE_12/09/2022 09:30:00 AM     0.182103
55   CRASH_RECORD_ID_44828fc89be461507825bad5770b14...     0.182103
19                                 CRASH_MONTH_sin     0.180517
253           TRAFFIC_CONTROL_DEVICE_TRAFFIC SIGNAL     0.173753
278                       FIRST_CRASH_TYPE_REAR END    -0.169107

     Abs_Coefficient
256         0.318587
250         0.312541
```

```
452          0.300816
11           0.294536
272          0.285345
8            0.254969
283          0.249495
15           0.237472
319          0.215492
20           0.212613
12           0.211625
318          0.194453
282          0.193910
10           0.186789
423          0.182103
238          0.182103
55           0.182103
19           0.180517
253          0.173753
278          0.169107
```

Let's convert time-related features into a format that effectively represents their cyclic nature, which can enhance both the performance and interpretability of our machine learning models.

```
df['CRASH_HOUR_sin'] = np.sin(2 * np.pi * df['CRASH_HOUR'] / 24)
df['CRASH_HOUR_cos'] = np.cos(2 * np.pi * df['CRASH_HOUR'] / 24)

df['CRASH_DAY_OF_WEEK_sin'] = np.sin(2 * np.pi * df['CRASH_DAY_OF_WEEK'] / 7)
df['CRASH_DAY_OF_WEEK_cos'] = np.cos(2 * np.pi * df['CRASH_DAY_OF_WEEK'] / 7)

df['CRASH_MONTH_sin'] = np.sin(2 * np.pi * df['CRASH_MONTH'] / 12)
df['CRASH_MONTH_cos'] = np.cos(2 * np.pi * df['CRASH_MONTH'] / 12)
```

## Enhancing Model Predictive Power

Additional engineered features can be integrated into the raw dataset to improve the model's ability to predict the primary contributory causes of traffic accidents by incorporating crucial contextual information.

Features such as

### Weekend:

Traffic patterns during weekends often differ significantly from weekdays, influencing both the likelihood and types of crashes. Including a feature that identifies whether a crash occurred on a weekend allows the model to better distinguish between these patterns.

### Speed Weather Interaction:

The impact of speed limits on crashes can vary depending on weather conditions. For instance, high speed limits are particularly risky in adverse weather. This interaction feature enables the model to capture the relationship between speed and weather, improving predictive accuracy.

```
df['Speed_Weather_Interaction'] = df['POSTED_SPEED_LIMIT'] * df['WEATHER_CONDITION'].factorize()[0]
df['Is_Weekend'] = df['CRASH_DAY_OF_WEEK'].apply(lambda x: 1 if x in [6, 7] else 0)
```

Let's analyze the frequency of causes to assess how closely each feature correlates with the target variable.

```
cause_counts = df['PRIM_CONTRIBUTORY_CAUSE'].value_counts()
print(cause_counts)
```

```
PRIM_CONTRIBUTORY_CAUSE
UNABLE TO DETERMINE                                                               5252
FAILING TO YIELD RIGHT-OF-WAY                                                     1689
FOLLOWING TOO CLOSELY                                                             1442
NOT APPLICABLE                                                                     763
IMPROPER OVERTAKING/PASSING                                                        744
IMPROPER LANE USAGE                                                                638
IMPROPER BACKING                                                                   586
DRIVING SKILLS/KNOWLEDGE/EXPERIENCE                                                538
FAILING TO REDUCE SPEED TO AVOID CRASH                                             526
IMPROPER TURNING/NO SIGNAL                                                         483
DISREGARDING TRAFFIC SIGNALS                                                       274
WEATHER                                                                            242
OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRESSIVE MANNER   176
DISREGARDING STOP SIGN                                                             110
EQUIPMENT - VEHICLE CONDITION                                                       99
VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)                                97
DISTRACTION - FROM INSIDE VEHICLE                                                   88
PHYSICAL CONDITION OF DRIVER                                                        75
DRIVING ON WRONG SIDE/WRONG WAY                                                     75
```

```
UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)              69
DISTRACTION - FROM OUTSIDE VEHICLE                                              59
ROAD ENGINEERING/SURFACE/MARKING DEFECTS                                        38
EXCEEDING AUTHORIZED SPEED LIMIT                                                33
EXCEEDING SAFE SPEED FOR CONDITIONS                                             33
ROAD CONSTRUCTION/MAINTENANCE                                                   31
DISREGARDING OTHER TRAFFIC SIGNS                                                23
EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST                               22
DISREGARDING ROAD MARKINGS                                                      21
CELL PHONE USE OTHER THAN TEXTING                                               12
TURNING RIGHT ON RED                                                            12
HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)                                 12
ANIMAL                                                                           7
DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER, ETC.)      6
DISREGARDING YIELD SIGN                                                          4
TEXTING                                                                          4
BICYCLE ADVANCING LEGALLY ON RED LIGHT                                           4
RELATED TO BUS STOP                                                              3
OBSTRUCTED CROSSWALKS                                                            2
PASSING STOPPED SCHOOL BUS                                                       1
Name: count, dtype: int64
```

## Binning Rare Causes:

This process reduces the number of categories the model needs to differentiate, particularly for categories with very few samples, helping to prevent overfitting.

```
threshold = 0.01 * len(df)
rare_causes = cause_counts[cause_counts < threshold].index
df['PRIM_CONTRIBUTORY_CAUSE_BINNED'] = df['PRIM_CONTRIBUTORY_CAUSE'].replace(rare_causes, 'Other')
```

## Filtering to Top N Causes:

Focuses on the most frequent causes, which are likely to have the greatest impact on your analysis.

```
top_n_causes = df['PRIM_CONTRIBUTORY_CAUSE_BINNED'].value_counts().head(10).index
df = df[df['PRIM_CONTRIBUTORY_CAUSE_BINNED'].isin(top_n_causes)]
```

## Mode-Based Feature:

Introduces a contextual feature to help the model capture the relationship between weather conditions and speed limits.

```
df['Weather_Condition_Mode'] = df.groupby('POSTED_SPEED_LIMIT')['WEATHER_CONDITION'].transform(lambda x: x.mode()[0])
```

Drop columns we don't need

```
df.drop(['CRASH_HOUR', 'CRASH_DAY_OF_WEEK', 'CRASH_MONTH', 'POSTED_SPEED_LIMIT'], axis=1, inplace=True)
y = df['PRIM_CONTRIBUTORY_CAUSE_BINNED']
```

Since we have already defined our X and y, we need to redefine them to ensure the target variable aligns with the newly created features.

```
X = df.drop(['PRIM_CONTRIBUTORY_CAUSE', 'PRIM_CONTRIBUTORY_CAUSE_BINNED'], axis=1)
y = df['PRIM_CONTRIBUTORY_CAUSE_BINNED']
```

## EDA Analysis

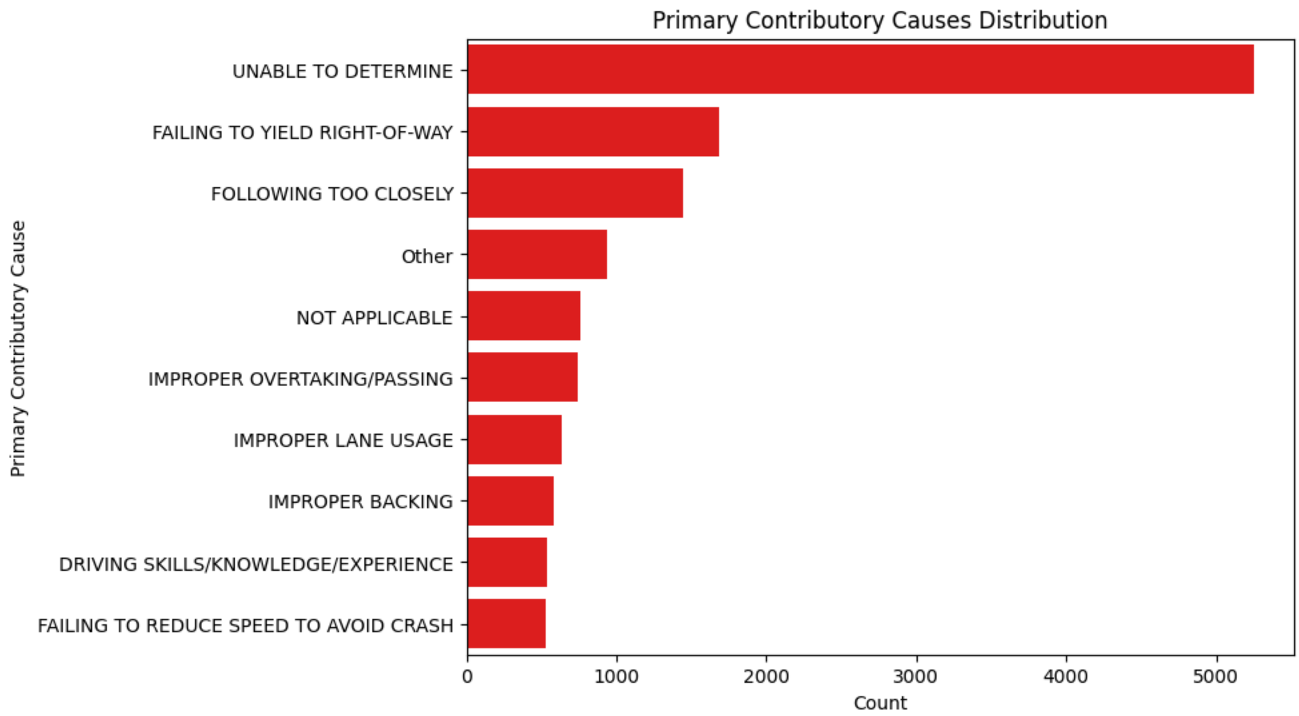
The three analysis below were deplyoyed in this instance

## Univariate Analysis:

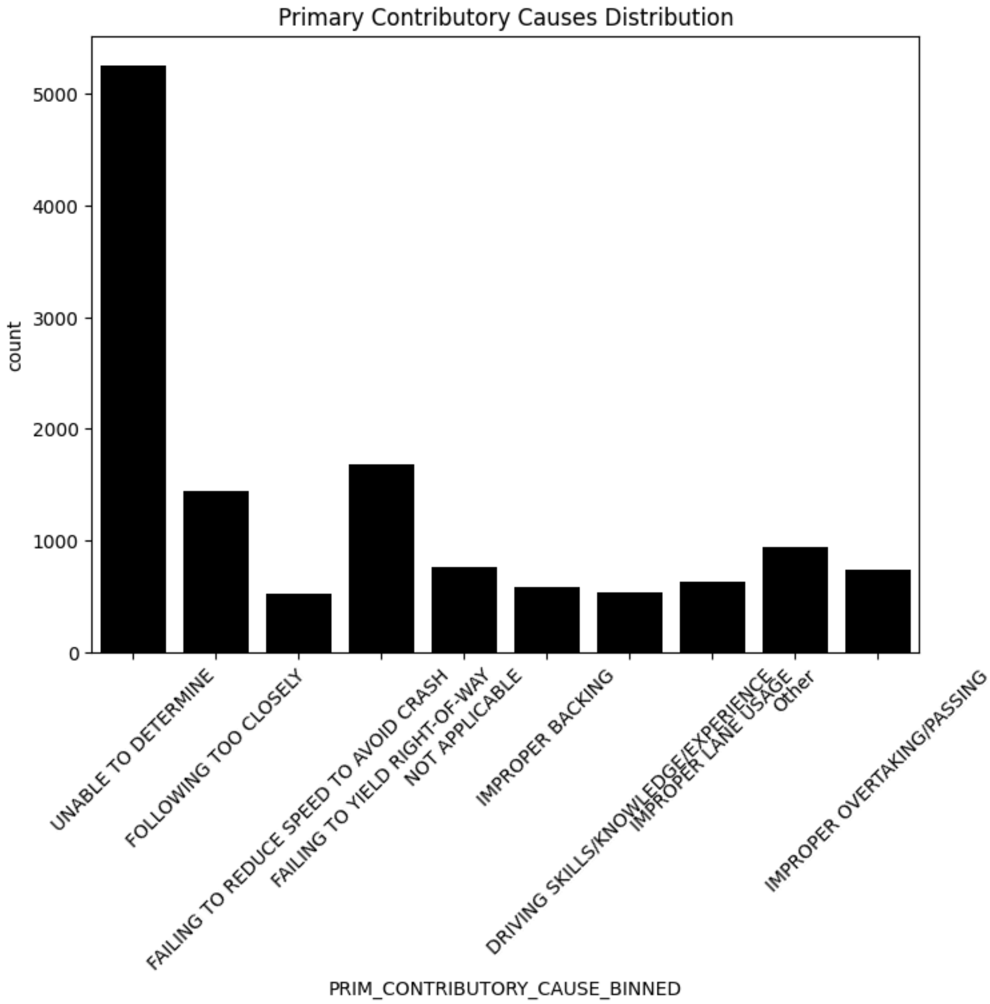
Histograms and box plots were utilized to analyze the distribution of numerical features and explore their association with the target variable.

```
plt.figure(figsize=(8, 6))
sns.countplot(
    y='PRIM_CONTRIBUTORY_CAUSE_BINNED',
    data=df,
    order=df['PRIM_CONTRIBUTORY_CAUSE_BINNED'].value_counts().index,
```

```
    color='red'
)
plt.title('Primary Contributory Causes Distribution')
plt.xlabel('Count')
plt.ylabel('Primary Contributory Cause')
plt.show()
```



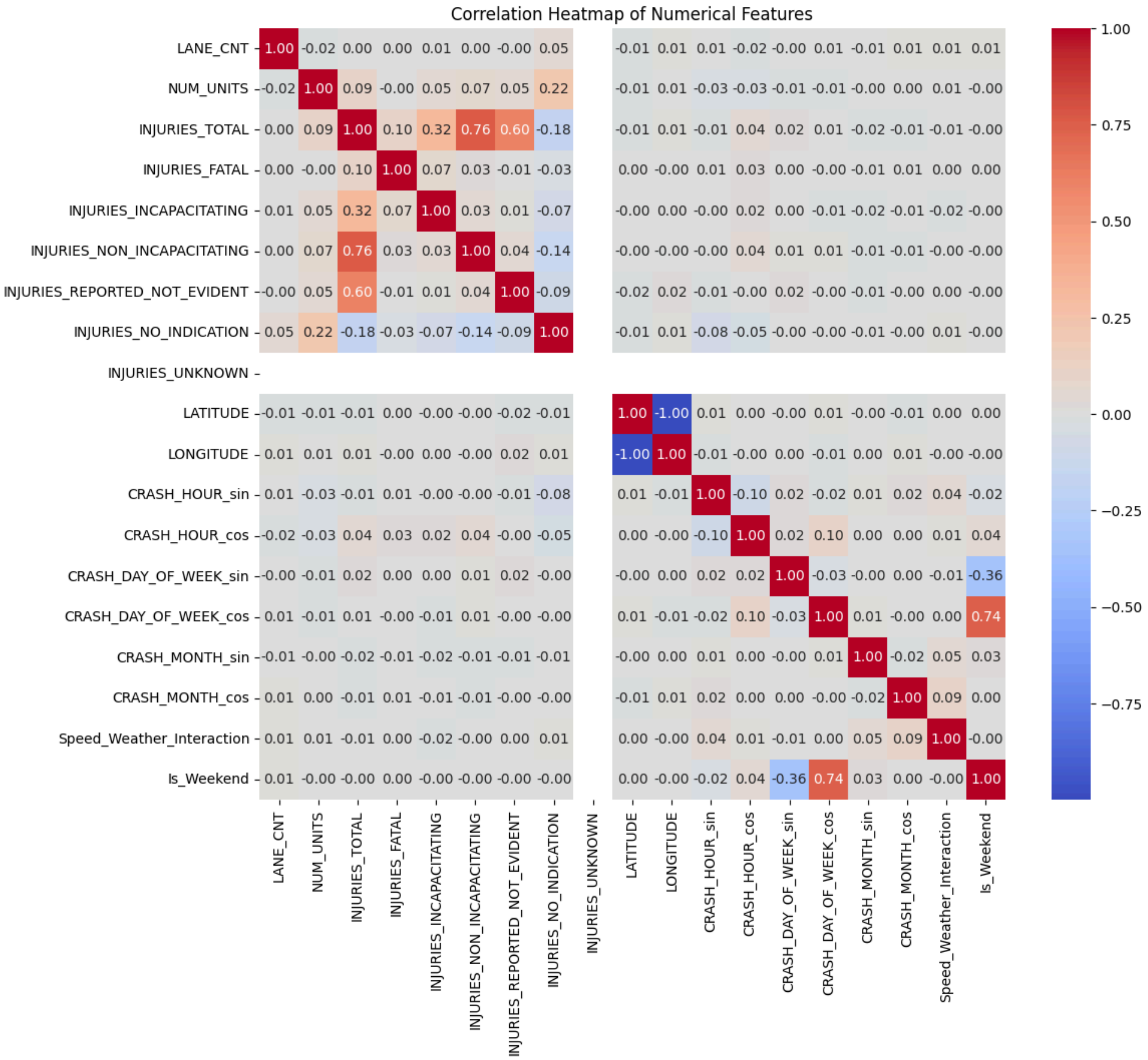

```
plt.figure(figsize=(8, 6))
sns.countplot(data=df, x='PRIM_CONTRIBUTORY_CAUSE_BINNED', color='black')  # Set the bar color to black
plt.title('Primary Contributory Causes Distribution')
plt.xticks(rotation=45)
plt.show()
```




## Bivariate Analysis:

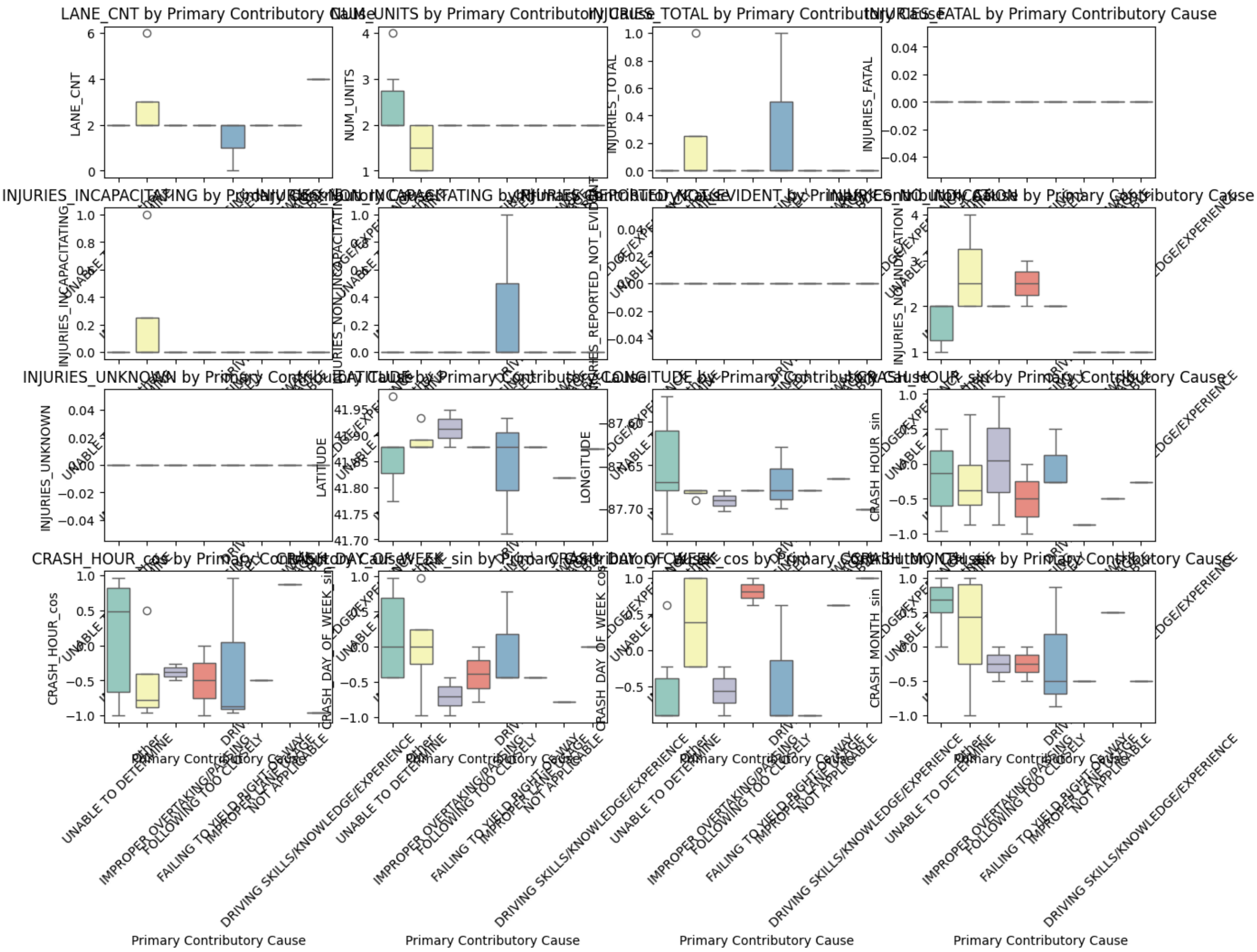
Pair plots and heatmaps below are used to examine the relationships between features and their association with the Primary Contributory Cause.

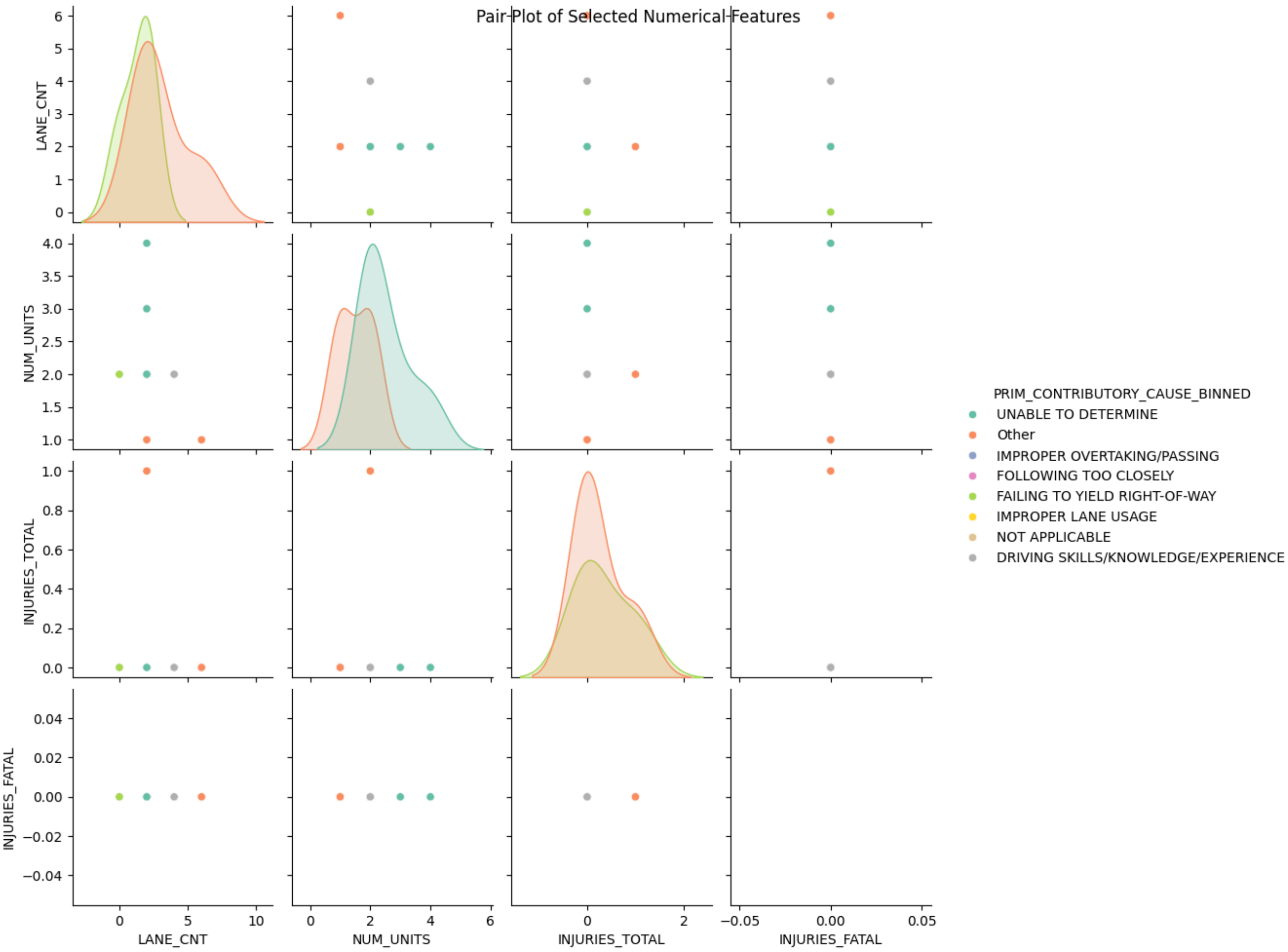
```
# Redefine numerical_cols to include only existing columns
numerical_cols = df.select_dtypes(exclude=['object']).columns

# Now calculate the correlation matrix
plt.figure(figsize=(12, 10))
correlation_matrix = df[numerical_cols].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```




```
import warnings # Import the warnings module

warnings.filterwarnings("ignore", category=FutureWarning)
warnings.filterwarnings("ignore", category=UserWarning)
limited_samples = 20
df_sampled = df.sample(n=limited_samples, random_state=42)

# ... (rest of your code)

plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_cols[:16]):
    plt.subplot(4, 4, i + 1)
    sns.boxplot(x='PRIM_CONTRIBUTORY_CAUSE_BINNED', y=col, data=df_sampled, palette="Set3")
    plt.title(f'{col} by Primary Contributory Cause')
    plt.xlabel('Primary Contributory Cause')
    plt.ylabel(col)
    plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

selected_numerical_cols = numerical_cols[:4]
sns.pairplot(df_sampled[selected_numerical_cols.tolist() + ['PRIM_CONTRIBUTORY_CAUSE_BINNED']],
             hue='PRIM_CONTRIBUTORY_CAUSE_BINNED',
             diag_kind='kde',
```

```
                palette="Set2")
plt.suptitle('Pair Plot of Selected Numerical Features')
plt.show()
```

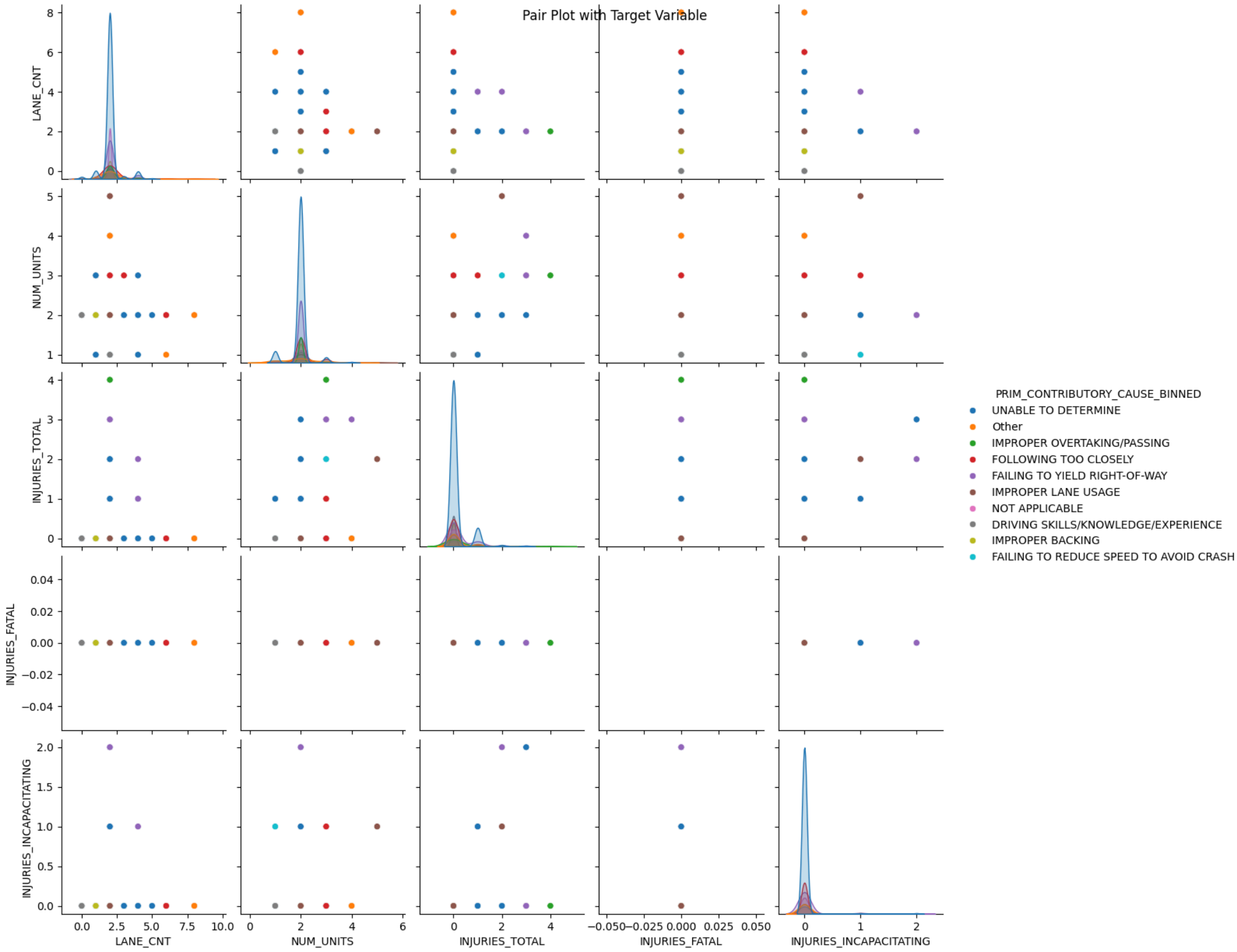

LANE_CNT by Primary Contributory Cause
INJURIES_FATAL by Primary Contributory Cause
Primary Contributory Cause
Primary Contributory Cause
Primary Contributory Cause
Primary Contributory Cause


Pair Plot of Selected Numerical Features
LANE_CNT
NUM_UNITS
INJURIES_TOTAL
INJURIES_FATAL
PRIM_CONTRIBUTORY_CAUSE_BINNED
UNABLE TO DETERMINE
Other
IMPROPER OVERTAKING/PASSING
FOLLOWING TOO CLOSELY
FAILING TO YIELD RIGHT-OF-WAY
IMPROPER LANE USAGE
NOT APPLICABLE
DRIVING SKILLS/KNOWLEDGE/EXPERIENCE

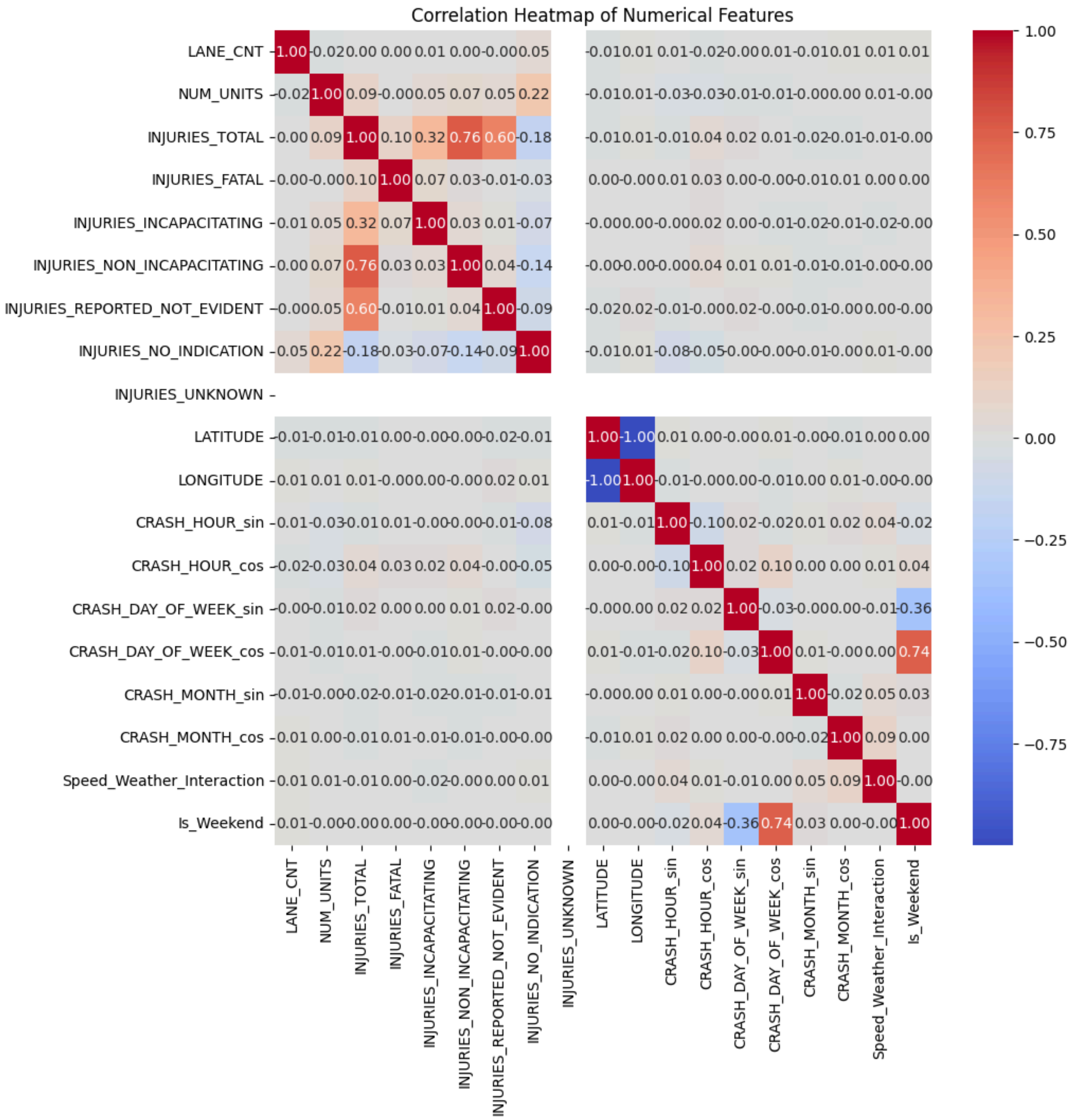
## Multivariate Analysis:

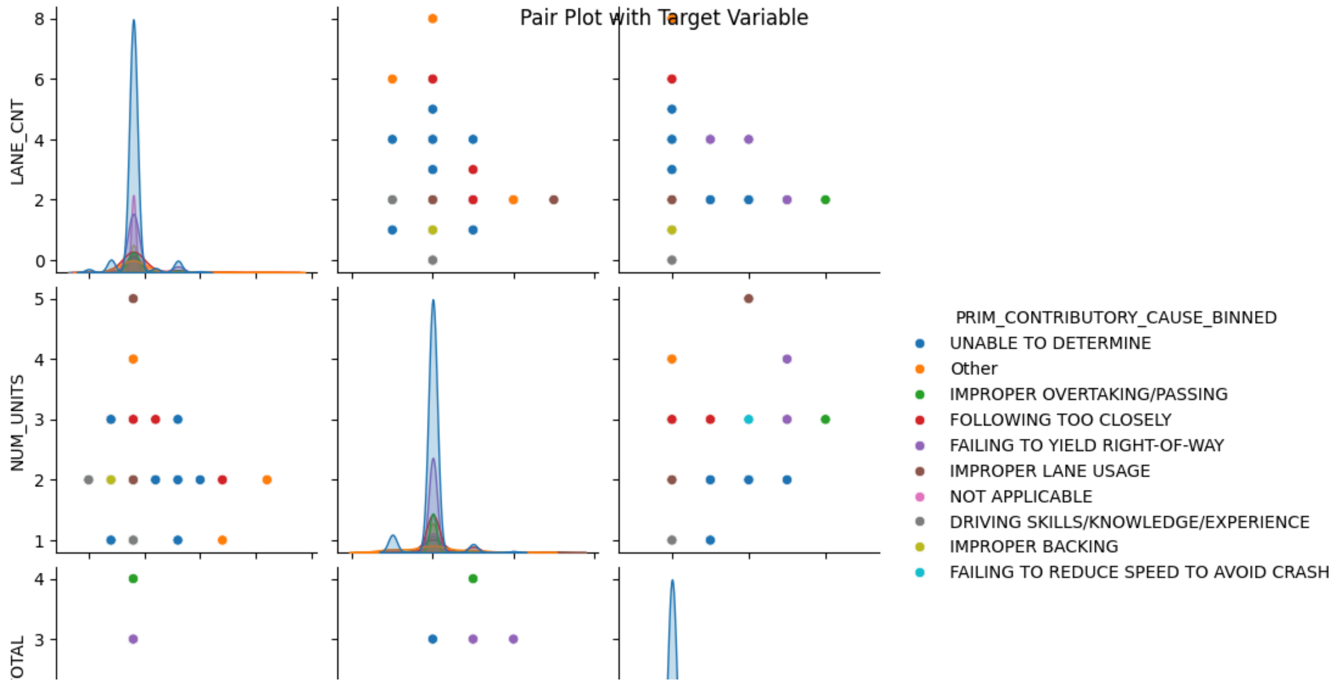
To analyze how combinations of features influence accident outcomes we use interaction plots

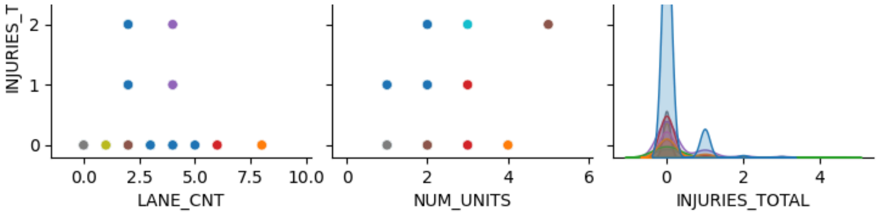
```
df_sampled = df.sample(frac=0.05, random_state=42)
sns.pairplot(df_sampled, hue='PRIM_CONTRIBUTORY_CAUSE_BINNED', vars=numerical_cols[:5])
plt.suptitle('Pair Plot with Target Variable')
plt.show()
```




```
plt.figure(figsize=(10, 10))
correlation_matrix = df[numerical_cols].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap of Numerical Features')
plt.show()

df_sampled = df.sample(frac=0.05, random_state=42)
sns.pairplot(df_sampled, hue='PRIM_CONTRIBUTORY_CAUSE_BINNED', vars=numerical_cols[:3])
plt.suptitle('Pair Plot with Target Variable')
plt.show()
```


Correlation Heatmap of Numerical Features
LANE_CNT
NUM_UNITS
INJURIES_TOTAL
INJURIES_FATAL
INJURIES_INCAPACITATING
INJURIES_NON_INCAPACITATING
INJURIES_REPORTED_NOT_EVIDENT
INJURIES_NO_INDICATION
INJURIES_UNKNOWN
LATITUDE
LONGITUDE
CRASH_HOUR_sin
CRASH_HOUR_cos
CRASH_DAY_OF_WEEK_sin
CRASH_DAY_OF_WEEK_cos
CRASH_MONTH_sin
CRASH_MONTH_cos
Speed_Weather_Interaction
Is_Weekend
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75


Pair Plot with Target Variable
LANE_CNT
NUM_UNITS
OTAL
PRIM_CONTRIBUTORY_CAUSE_BINNED
UNABLE TO DETERMINE
Other
IMPROPER OVERTAKING/PASSING
FOLLOWING TOO CLOSELY
FAILING TO YIELD RIGHT-OF-WAY
IMPROPER LANE USAGE
NOT APPLICABLE
DRIVING SKILLS/KNOWLEDGE/EXPERIENCE
IMPROPER BACKING
FAILING TO REDUCE SPEED TO AVOID CRASH




## Data Modeling

Several machine learning models will be trained and evaluated, including:

1. Logistic Regression
2. Regularized Logistic Regression
3. Decision Trees
4. Random Forest
5. Gradient Boosting

## Define the Baseline model

In this project we will use Logistic Regression as our Baseline model. We will use pipeline preprocessor, by defining then split, train and evaluate the model.

```
from sklearn.metrics import accuracy_score, classification_report
df_sampled = df.sample(frac=0.01, random_state=42)

X = df_sampled.drop('PRIM_CONTRIBUTORY_CAUSE', axis=1)
y = df_sampled['PRIM_CONTRIBUTORY_CAUSE']

categorical_cols = X.select_dtypes(include=['object']).columns
numerical_cols = X.select_dtypes(exclude=['object']).columns

preprocessor = ColumnTransformer(
    transformers=[
        ('num', SimpleImputer(strategy='median'), numerical_cols),
        ('cat', Pipeline(steps=[
            ('imputer', SimpleImputer(strategy='most_frequent')),
            ('onehot', OneHotEncoder(handle_unknown='ignore'))
        ]), categorical_cols)
    ])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

baseline_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', LogisticRegression(max_iter=100, random_state=42))
])

baseline_model.fit(X_train, y_train)

y_pred = baseline_model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"Baseline Model Accuracy: {accuracy:.4f}")
print("Classification Report:")
print(report)
```

```
Baseline Model Accuracy: 0.7037
Classification Report:
                                          precision    recall  f1-score   support

         DRIVING ON WRONG SIDE/WRONG WAY       0.00      0.00      0.00         1
      DRIVING SKILLS/KNOWLEDGE/EXPERIENCE       0.00      0.00      0.00         1
            EQUIPMENT - VEHICLE CONDITION       0.00      0.00      0.00         0
   FAILING TO REDUCE SPEED TO AVOID CRASH       0.00      0.00      0.00         1
            FAILING TO YIELD RIGHT-OF-WAY       1.00      1.00      1.00         3
                     FOLLOWING TOO CLOSELY       0.75      1.00      0.86         3
```

```
        HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)       0.00      0.00      0.00         1
                                       IMPROPER BACKING       0.00      0.00      0.00         1
                                    IMPROPER LANE USAGE       0.00      0.00      0.00         1
                             IMPROPER OVERTAKING/PASSING      0.00      0.00      0.00         1
                                    UNABLE TO DETERMINE       0.80      1.00      0.89        12
UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)    0.00      0.00      0.00         1
      VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)       1.00      1.00      1.00         1

                                               accuracy                           0.70        27
                                              macro avg       0.27      0.31      0.29        27
                                           weighted avg       0.59      0.70      0.64        27
```

The above output gives us the precision, F1-score and accuracy of our baseline model.

Building models for model selection

```
!pip install scikit-learn
# Import necessary libraries
from sklearn.linear_model import RidgeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.preprocessing import OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
import pandas as pd
df_sampled = df.sample(frac=0.01, random_state=42)
models = {
    'Logistic Regression': LogisticRegression(max_iter=100, random_state=42),
    'Ridge Classifier': RidgeClassifier(),
    'Lasso Logistic Regression': LogisticRegression(penalty='l1', solver='saga', max_iter=100, random_state=42),
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'Random Forest': RandomForestClassifier(n_estimators=100, random_state=42, n_jobs=-1),
    'Gradient Boosting': GradientBoostingClassifier(random_state=42)
}


for name, model in models.items():
# Create a pipeline with the preprocessor and the model
    pipeline = Pipeline(steps=[('preprocessor', preprocessor), ('model', model)])

    cv_scores = cross_val_score(pipeline, X_train, y_train, cv=3, scoring='accuracy')


    pipeline.fit(X_train, y_train)


    y_pred = pipeline.predict(X_test)
    # Evaluate the model
    print(f'Test Set Accuracy: {accuracy_score(y_test, y_pred):.4f}')
    print(classification_report(y_test, y_pred))
    print(confusion_matrix(y_test, y_pred))
    print('\n')
```

```
                       DRIVING ON WRONG SIDE/WRONG WAY       0.00      0.00      0.00         1
                     DRIVING SKILLS/KNOWLEDGE/EXPERIENCE       1.00      1.00      1.00         1
                         EQUIPMENT - VEHICLE CONDITION       0.00      0.00      0.00         0
                  FAILING TO REDUCE SPEED TO AVOID CRASH       1.00      1.00      1.00         1
                         FAILING TO YIELD RIGHT-OF-WAY       1.00      1.00      1.00         3
                                 FOLLOWING TOO CLOSELY       1.00      1.00      1.00         3
         HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)       0.00      0.00      0.00         1
                                      IMPROPER BACKING       1.00      1.00      1.00         1
                                   IMPROPER LANE USAGE       1.00      1.00      1.00         1
                           IMPROPER OVERTAKING/PASSING       1.00      1.00      1.00         1
                                   UNABLE TO DETERMINE       0.86      1.00      0.92        12
UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)       0.00      0.00      0.00         1
           VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)       1.00      1.00      1.00         1

                                              accuracy                           0.89        27
                                             macro avg       0.68      0.69      0.69        27
                                          weighted avg       0.83      0.89      0.85        27

[[ 0  0  0  0  0  0  0  0  0  0  1  0  0]
 [ 0  1  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  1  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  3  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  3  0  0  0  0  0  0  0]
 [ 0  0  1  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  1  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  1  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  1  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0 12  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  1  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  1]]
```

The above are the classification metrics of our models before Tuning

## Model Tuning

Hyperparameter tuning is conducted to optimize each model:

```python
from sklearn.model_selection import RandomizedSearchCV
from sklearn.pipeline import Pipeline
import numpy as np

param_grids = {
    'Logistic Regression': {
        'model__C': [0.01, 0.1, 1],
        'model__solver': ['lbfgs', 'liblinear']
    },
    'Ridge Classifier': {
        'model__alpha': [0.1, 1, 10]
    },
    'Lasso Logistic Regression': {
        'model__C': [0.1, 1, 10]
    },
    'Decision Tree': {
        'model__max_depth': [10, 20],
        'model__min_samples_split': [2, 5]
    },
    'Random Forest': {
        'model__n_estimators': [100, 200],
        'model__max_depth': [10, 20],
        'model__min_samples_split': [2, 5]
    },
    'Gradient Boosting': {
        'model__learning_rate': [0.01, 0.1],
        'model__n_estimators': [100, 200],
        'model__max_depth': [3, 5]
    }
}

best_models = {}
for name, model in models.items():
    pipeline = Pipeline(steps=[('preprocessor', preprocessor), ('model', model)])

    random_search = RandomizedSearchCV(pipeline, param_distributions=param_grids[name],
                                       n_iter=5, cv=3, scoring='accuracy', n_jobs=-1,
                                       random_state=42)

    random_search.fit(X_train, y_train)

    best_models[name] = random_search.best_estimator_
```

```
for name, model in best_models.items():
    print(f"Best parameters for {name}: {model.get_params()['model']}")
```

```
Best parameters for Logistic Regression: LogisticRegression(C=1, random_state=42, solver='liblinear')
Best parameters for Ridge Classifier: RidgeClassifier(alpha=0.1)
Best parameters for Lasso Logistic Regression: LogisticRegression(C=0.1, penalty='l1', random_state=42, solver='saga')
Best parameters for Decision Tree: DecisionTreeClassifier(max_depth=10, random_state=42)
Best parameters for Random Forest: RandomForestClassifier(max_depth=20, min_samples_split=5, n_estimators=200,
                       n_jobs=-1, random_state=42)
Best parameters for Gradient Boosting: GradientBoostingClassifier(n_estimators=200, random_state=42)
```

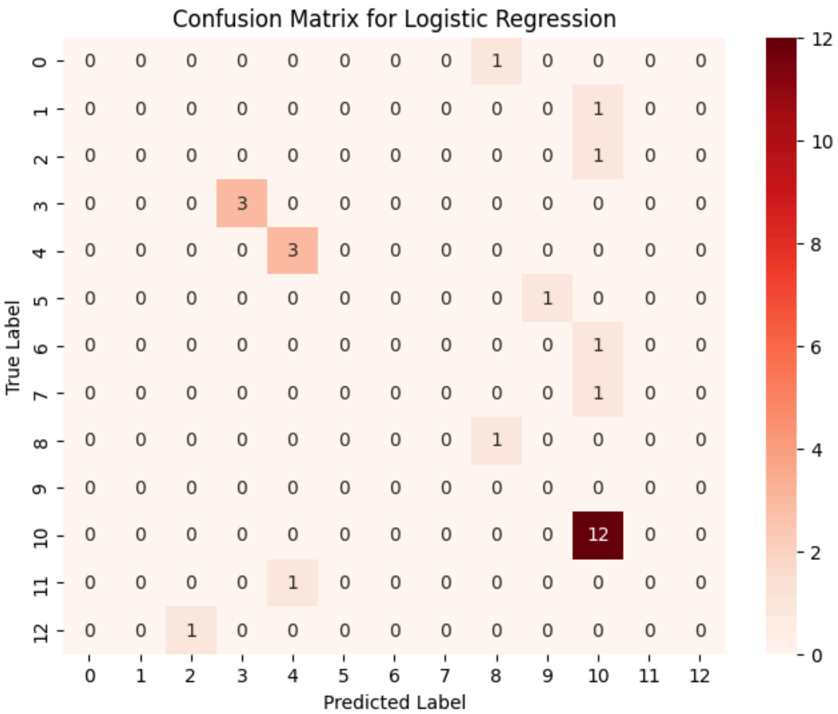
```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.pipeline import Pipeline
import numpy as np


param_grids = {
    'Logistic Regression': {
        'model__C': [0.01, 0.1, 1, 10],
        'model__solver': ['lbfgs', 'liblinear']
    },
    'Ridge Classifier': {
        'model__alpha': [0.01, 0.1, 1, 10]
    },
    'Lasso Logistic Regression': {
        'model__C': [0.01, 0.1, 1, 10]
    },
    'Decision Tree': {
        'model__max_depth': [None, 10, 20],
        'model__min_samples_split': [2, 5, 10]
    },
    'Random Forest': {
        'model__n_estimators': [100, 200],
        'model__max_depth': [None, 10],
        'model__min_samples_split': [2, 5]
    },
    'Gradient Boosting': {
        'model__learning_rate': [0.01, 0.1],
        'model__n_estimators': [100, 200],
        'model__max_depth': [3, 5]
    }
}

best_models = {}
for name, model in models.items():
    pipeline = Pipeline(steps=[('preprocessor', preprocessor), ('model', model)])

    random_search = RandomizedSearchCV(pipeline, param_distributions=param_grids[name],
                                       n_iter=10, cv=3, scoring='accuracy', n_jobs=-1,
                                       random_state=42)

    random_search.fit(X_train, y_train)

    best_models[name] = random_search.best_estimator_

for name, model in best_models.items():
    print(f"Best parameters for {name}: {model.get_params()['model']}")
```

```
Best parameters for Logistic Regression: LogisticRegression(C=10, random_state=42, solver='liblinear')
Best parameters for Ridge Classifier: RidgeClassifier(alpha=0.01)
Best parameters for Lasso Logistic Regression: LogisticRegression(C=0.01, penalty='l1', random_state=42, solver='saga')
Best parameters for Decision Tree: DecisionTreeClassifier(random_state=42)
Best parameters for Random Forest: RandomForestClassifier(n_estimators=200, n_jobs=-1, random_state=42)
Best parameters for Gradient Boosting: GradientBoostingClassifier(random_state=42)
```

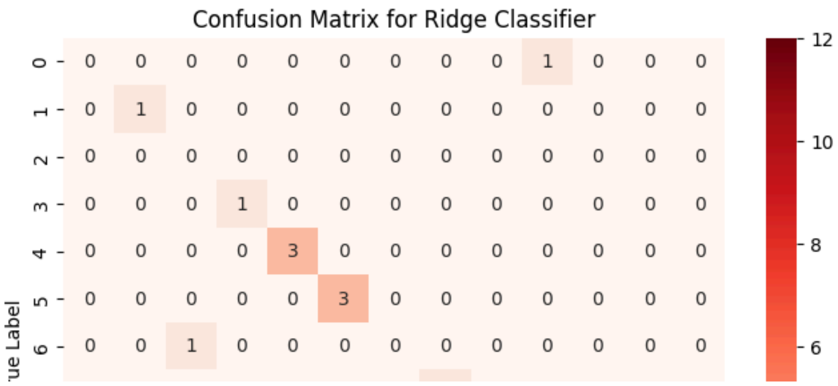
```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

final_results = {}

for name, model in best_models.items():

    y_pred = model.predict(X_test)

    accuracy = accuracy_score(y_test, y_pred)

    final_results[name] = accuracy

    print(f"Model: {name}")
    print(classification_report(y_test, y_pred))
```

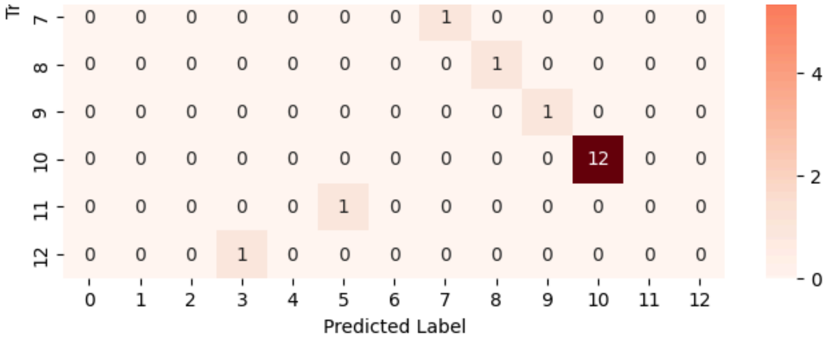
```
    plt.figure(figsize=(8, 6))
    cm = confusion_matrix(y_test, y_pred)
    sns.heatmap(cm, annot=True, fmt='d', cmap='Reds')
    plt.title(f'Confusion Matrix for {name}')
    plt.xlabel('Predicted Label')
    plt.ylabel('True Label')
    plt.show()

# Create a dataframe for final results
final_results_df = pd.DataFrame(list(final_results.items()), columns=['Model', 'Test Accuracy'])

# Sort results
final_results_df = final_results_df.sort_values(by='Test Accuracy', ascending=False)


plt.figure(figsize=(10, 6))
sns.barplot(x='Test Accuracy', y='Model', data=final_results_df, palette='Reds')
plt.title('Final Model Performance Comparison on Test Set')
plt.xlabel('Test Accuracy')
plt.ylabel('Model')
plt.xlim(0, 1)
plt.show()
```

```
Model: Logistic Regression
                                                                     precision    recall  f1-score   support

                               DRIVING ON WRONG SIDE/WRONG WAY          0.00      0.00      0.00         1
                            DRIVING SKILLS/KNOWLEDGE/EXPERIENCE         0.00      0.00      0.00         1
                          FAILING TO REDUCE SPEED TO AVOID CRASH        0.00      0.00      0.00         1
                                 FAILING TO YIELD RIGHT-OF-WAY          1.00      1.00      1.00         3
                                       FOLLOWING TOO CLOSELY            0.75      1.00      0.86         3
                   HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)      0.00      0.00      0.00         1
                                            IMPROPER BACKING            0.00      0.00      0.00         1
                                         IMPROPER LANE USAGE            0.00      0.00      0.00         1
                                  IMPROPER OVERTAKING/PASSING           0.50      1.00      0.67         1
                                 PHYSICAL CONDITION OF DRIVER           0.00      0.00      0.00         0
                                          UNABLE TO DETERMINE           0.75      1.00      0.86        12
  UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)    0.00      0.00      0.00         1
                        VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)  0.00      0.00      0.00         1

                                                    accuracy                          0.70        27
                                                   macro avg        0.23      0.31      0.26        27
                                                weighted avg        0.55      0.70      0.61        27
```




```
Model: Ridge Classifier
                                                                     precision    recall  f1-score   support

                               DRIVING ON WRONG SIDE/WRONG WAY          0.00      0.00      0.00         1
                            DRIVING SKILLS/KNOWLEDGE/EXPERIENCE         1.00      1.00      1.00         1
                                  EQUIPMENT - VEHICLE CONDITION         0.00      0.00      0.00         0
                          FAILING TO REDUCE SPEED TO AVOID CRASH        0.50      1.00      0.67         1
                                 FAILING TO YIELD RIGHT-OF-WAY          1.00      1.00      1.00         3
                                       FOLLOWING TOO CLOSELY            0.75      1.00      0.86         3
                   HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)      0.00      0.00      0.00         1
                                            IMPROPER BACKING            1.00      1.00      1.00         1
                                         IMPROPER LANE USAGE            1.00      1.00      1.00         1
                                  IMPROPER OVERTAKING/PASSING           0.50      1.00      0.67         1
                                          UNABLE TO DETERMINE           1.00      1.00      1.00        12
  UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)    0.00      0.00      0.00         1
                        VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)  0.00      0.00      0.00         1

                                                    accuracy                          0.85        27
                                                   macro avg        0.52      0.62      0.55        27
                                                weighted avg        0.79      0.85      0.81        27
```

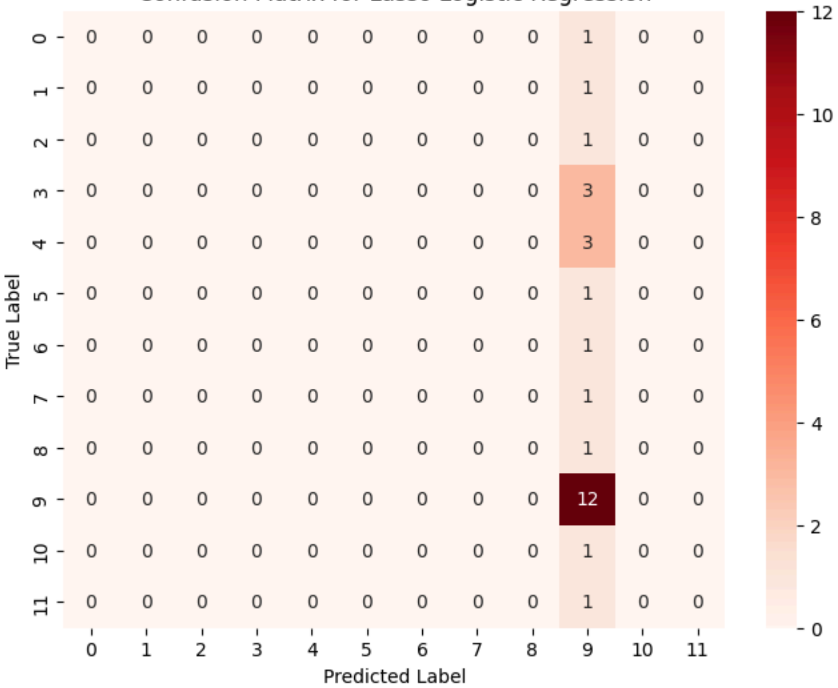





Model: Lasso Logistic Regression

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| DRIVING ON WRONG SIDE/WRONG WAY | 0.00 | 0.00 | 0.00 | 1 |
| DRIVING SKILLS/KNOWLEDGE/EXPERIENCE | 0.00 | 0.00 | 0.00 | 1 |
| FAILING TO REDUCE SPEED TO AVOID CRASH | 0.00 | 0.00 | 0.00 | 1 |
| FAILING TO YIELD RIGHT-OF-WAY | 0.00 | 0.00 | 0.00 | 3 |
| FOLLOWING TOO CLOSELY | 0.00 | 0.00 | 0.00 | 3 |
| HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE) | 0.00 | 0.00 | 0.00 | 1 |
| IMPROPER BACKING | 0.00 | 0.00 | 0.00 | 1 |
| IMPROPER LANE USAGE | 0.00 | 0.00 | 0.00 | 1 |
| IMPROPER OVERTAKING/PASSING | 0.00 | 0.00 | 0.00 | 1 |
| UNABLE TO DETERMINE | 0.44 | 1.00 | 0.62 | 12 |
| UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED) | 0.00 | 0.00 | 0.00 | 1 |
| VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.) | 0.00 | 0.00 | 0.00 | 1 |
| accuracy | | | 0.44 | 27 |
| macro avg | 0.04 | 0.08 | 0.05 | 27 |
| weighted avg | 0.20 | 0.44 | 0.27 | 27 |

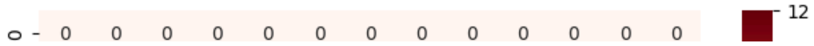
Confusion Matrix for Lasso Logistic Regression

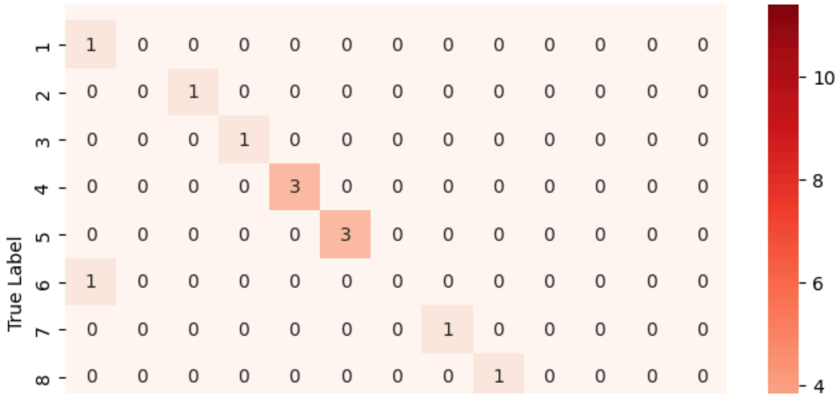



Model: Decision Tree

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| DISTRACTION - FROM INSIDE VEHICLE | 0.00 | 0.00 | 0.00 | 0 |
| DRIVING ON WRONG SIDE/WRONG WAY | 0.00 | 0.00 | 0.00 | 1 |
| DRIVING SKILLS/KNOWLEDGE/EXPERIENCE | 1.00 | 1.00 | 1.00 | 1 |
| FAILING TO REDUCE SPEED TO AVOID CRASH | 1.00 | 1.00 | 1.00 | 1 |
| FAILING TO YIELD RIGHT-OF-WAY | 1.00 | 1.00 | 1.00 | 3 |
| FOLLOWING TOO CLOSELY | 1.00 | 1.00 | 1.00 | 3 |
| HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE) | 0.00 | 0.00 | 0.00 | 1 |
| IMPROPER BACKING | 1.00 | 1.00 | 1.00 | 1 |
| IMPROPER LANE USAGE | 1.00 | 1.00 | 1.00 | 1 |
| IMPROPER OVERTAKING/PASSING | 1.00 | 1.00 | 1.00 | 1 |
| UNABLE TO DETERMINE | 1.00 | 1.00 | 1.00 | 12 |
| UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED) | 0.00 | 0.00 | 0.00 | 1 |
| VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.) | 0.00 | 0.00 | 0.00 | 1 |
| accuracy | | | 0.85 | 27 |
| macro avg | 0.62 | 0.62 | 0.62 | 27 |
| weighted avg | 0.85 | 0.85 | 0.85 | 27 |

Confusion Matrix for Decision Tree




True Label
1
2
3
4
5
6
7
8
10
8
6
4