DIC_Project_Phase_2_prob1_50608504

November 5, 2024

1 Phase 1

1.1 1: Problem Statement

1.1.1 1.1.1 Problem Statement

This project's goal is to make a detailed analysis on why road accidents are occurring a lot and in what trend, will be helpful in improving road safety measures & make the policy options which can reduce the number of accidents. This research would help to know the impacts of accident severity on the driver attributes, vehicle conditions, surface conditions and environmental conditions.

1.1.2 1.1.2 Potential Contribution & Importance

Road accidents pose a threat to health globally by resulting in significant fatalities and injuries of individuals worldwide. This evaluation plays a role in finding factors that play a vital role in accident prevention. The evidence of this review may support the implementation of measures of safety, improvement of driver education programs, and modification of road systems that can reduce accidents and save lives.

Piyush Gulhane:

Question 1: What is the Impact of area, type of road cross-section, type of roads and road alignment on different types of Accidents

- This analysis will help us identify accident prone areas, common mistakes in road infrastructure, alignment and help us identify potential dark spots. It will help in future planning for Roads construction to avoid such road engineering mistakes like installing traffic signals, gradient of road, signboards, etc.
- Many a times slope of road, busy cross sections and other factors has influence on the accident, to identify and rectify these factors help in reduction of accidents.

Question 2: What is the impact of Environmental factors, Light(visibility) impact, Road surface, time of the day, etc. * This analysis will help us understand conditions/situations which forced human error, Most of time unavailability of light, less visibility, heavy rain can increase probability of accident. Appropriate changes in vehicle engineering and roads can help reduce casualties. * It is significant to identify conditions which affect driving experience.

1.2 3: Data Retrieval

The dataset has been taken from KAGGLE. For this task, we have uploaded a copy of the dataset to a github repository and downloading the data from the github repository directly to the dataframe

[143]:
```python
import pandas as pd
import warnings
import matplotlib.pyplot as plt
import seaborn as sns

warnings.filterwarnings('ignore')
dataset = pd.read_csv('/content/RTA Dataset.csv')
#dataset = pd.read_csv('https://raw.githubusercontent.com/hmalpani/RTA-Dataset/
↪main/RTA_Dataset.csv')
```

[144]:
```python
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12316 entries, 0 to 12315
Data columns (total 32 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   Time                         12316 non-null  object
 1   Day_of_week                  12316 non-null  object
 2   Age_band_of_driver           12316 non-null  object
 3   Sex_of_driver                12316 non-null  object
 4   Educational_level            11575 non-null  object
 5   Vehicle_driver_relation      11737 non-null  object
 6   Driving_experience           11487 non-null  object
 7   Type_of_vehicle              11366 non-null  object
 8   Owner_of_vehicle             11834 non-null  object
 9   Service_year_of_vehicle      8388 non-null   object
 10  Defect_of_vehicle            7889 non-null   object
 11  Area_accident_occured        12077 non-null  object
 12  Lanes_or_Medians             11931 non-null  object
 13  Road_allignment              12174 non-null  object
 14  Types_of_Junction            11429 non-null  object
 15  Road_surface_type            12144 non-null  object
 16  Road_surface_conditions      12316 non-null  object
 17  Light_conditions             12316 non-null  object
 18  Weather_conditions           12316 non-null  object
 19  Type_of_collision            12161 non-null  object
 20  Number_of_vehicles_involved  12316 non-null  int64
 21  Number_of_casualties         12316 non-null  int64
 22  Vehicle_movement             12008 non-null  object
 23  Casualty_class               12316 non-null  object
 24  Sex_of_casualty              12316 non-null  object
 25  Age_band_of_casualty         12316 non-null  object
 26  Casualty_severity            12316 non-null  object
```

```
 27  Work_of_casuality          9118 non-null   object
 28  Fitness_of_casuality       9681 non-null   object
 29  Pedestrian_movement        12316 non-null  object
 30  Cause_of_accident          12316 non-null  object
 31  Accident_severity          12316 non-null  object
dtypes: int64(2), object(30)
memory usage: 3.0+ MB
```

[145]:
```python
dataset.head()
```

[145]:
```
       Time Day_of_week Age_band_of_driver Sex_of_driver   Educational_level  \
0  17:02:00      Monday              18-30          Male   Above high school
1  17:02:00      Monday              31-50          Male  Junior high school
2  17:02:00      Monday              18-30          Male  Junior high school
3   1:06:00      Sunday              18-30          Male  Junior high school
4   1:06:00      Sunday              18-30          Male  Junior high school

  Vehicle_driver_relation Driving_experience      Type_of_vehicle  \
0                Employee              1-2yr           Automobile
1                Employee         Above 10yr  Public (> 45 seats)
2                Employee              1-2yr      Lorry (41?100Q)
3                Employee             5-10yr  Public (> 45 seats)
4                Employee              2-5yr                  NaN

  Owner_of_vehicle Service_year_of_vehicle  … Vehicle_movement  \
0            Owner              Above 10yr  …   Going straight
1            Owner                 5-10yrs  …   Going straight
2            Owner                     NaN  …   Going straight
3     Governmental                     NaN  …   Going straight
4            Owner                 5-10yrs  …   Going straight

    Casualty_class Sex_of_casualty Age_band_of_casualty Casualty_severity  \
0               na              na                   na                na
1               na              na                   na                na
2  Driver or rider            Male                31-50                 3
3       Pedestrian          Female                18-30                 3
4               na              na                   na                na

  Work_of_casuality Fitness_of_casuality Pedestrian_movement  \
0               NaN                  NaN    Not a Pedestrian
1               NaN                  NaN    Not a Pedestrian
2            Driver                  NaN    Not a Pedestrian
3            Driver               Normal    Not a Pedestrian
4               NaN                  NaN    Not a Pedestrian

            Cause_of_accident Accident_severity
0              Moving Backward     Slight Injury
```

```
1                   Overtaking     Slight Injury
2   Changing lane to the left    Serious Injury
3  Changing lane to the right     Slight Injury
4                   Overtaking     Slight Injury

[5 rows x 32 columns]
```

1.3 4: Data Cleaning

1.3.1 1) Remove Duplicate Values:

Removing duplicate values is an essential step of data cleaning for any data science project. It helps in reducing the bias where certain data points are represented multiple times. If the duplicate values are not removed, it can skew the results and therefore lead to incorrect conclusions

[146]:
```python
# Remove duplicates
cleaned_dataset = dataset.drop_duplicates()
```

1.3.2 2) Validation

[147]:
```python
# Remove entries with 'Number_of_vehicles_involved' = 0
cleaned_dataset = cleaned_dataset[cleaned_dataset['Number_of_vehicles_involved'] != 0]
```

1.3.3 3) Detection and Removal of Outliers

[148]:
```python
# code for outliers handling

numerical_columns = ['Number_of_vehicles_involved', 'Number_of_casualties']
for column in numerical_columns:
    if not pd.api.types.is_numeric_dtype(cleaned_dataset[column]):
        print(f"Column '{column}' should be numeric but contains non-numeric data.")

def detect_outliers(column):
    Q1 = cleaned_dataset[column].quantile(0.05)
    Q3 = cleaned_dataset[column].quantile(0.95)
    IQR = Q3 - Q1
    outliers = cleaned_dataset[(cleaned_dataset[column] < (Q1 - 1.5 * IQR)) | (cleaned_dataset[column] > (Q3 + 1.5 * IQR))]
    return outliers

for column in numerical_columns:
    outliers = detect_outliers(column)
    if not outliers.empty:
        print(f"Outliers detected in column '{column}':\n", outliers.shape)

def remove_outliers(df, column):
```

```
    Q1 = cleaned_dataset[column].quantile(0.05)
    Q3 = cleaned_dataset[column].quantile(0.95)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return cleaned_dataset[(cleaned_dataset[column] >= lower_bound) &␣
 ↪(cleaned_dataset[column] <= upper_bound)]

print("Shape before removing outliers:", cleaned_dataset.shape)
# Remove outliers from both columns
cleaned_dataset = remove_outliers(cleaned_dataset,␣
 ↪'Number_of_vehicles_involved')
cleaned_dataset = remove_outliers(cleaned_dataset, 'Number_of_casualties')

# Check the shape of the DataFrame after removal
print("Shape after removing outliers:", cleaned_dataset.shape)
```

```
Outliers detected in column 'Number_of_vehicles_involved':
 (7, 32)
Shape before removing outliers: (12316, 32)
Shape after removing outliers: (12309, 32)
```

1.3.4 4) Handling Missing Values:

In this step of Data Cleaning, we either remove or impute the missing values in the dataset

[149]:
```
# Find the number of missing values
missing_value_count = cleaned_dataset.isnull().sum()
missing_value_count
```

[149]:
```
Time                          0
Day_of_week                   0
Age_band_of_driver            0
Sex_of_driver                 0
Educational_level           741
Vehicle_driver_relation     579
Driving_experience          829
Type_of_vehicle             950
Owner_of_vehicle            482
Service_year_of_vehicle    3923
Defect_of_vehicle          4427
Area_accident_occured       239
Lanes_or_Medians            385
Road_allignment             142
Types_of_Junction           887
Road_surface_type           172
Road_surface_conditions       0
Light_conditions              0
```

```
Weather_conditions               0
Type_of_collision              155
Number_of_vehicles_involved      0
Number_of_casualties             0
Vehicle_movement               306
Casualty_class                   0
Sex_of_casualty                  0
Age_band_of_casualty             0
Casualty_severity                0
Work_of_casuality             3197
Fitness_of_casuality          2634
Pedestrian_movement              0
Cause_of_accident                0
Accident_severity                0
dtype: int64
```

[150]:

```
dataset_columns = cleaned_dataset.columns.tolist()
missing_values_columns = missing_value_count[missing_value_count > 0].index.
 ↪tolist()
print(missing_values_columns)
```

```
['Educational_level', 'Vehicle_driver_relation', 'Driving_experience',
'Type_of_vehicle', 'Owner_of_vehicle', 'Service_year_of_vehicle',
'Defect_of_vehicle', 'Area_accident_occured', 'Lanes_or_Medians',
'Road_allignment', 'Types_of_Junction', 'Road_surface_type',
'Type_of_collision', 'Vehicle_movement', 'Work_of_casuality',
'Fitness_of_casuality']
```

[151]:

```
# Replace missing values
cleaned_dataset['Educational_level'].
 ↪fillna(cleaned_dataset['Educational_level'].mode()[0], inplace=True)
cleaned_dataset['Vehicle_driver_relation'].fillna('Unknown', inplace=True)
cleaned_dataset['Driving_experience'].
 ↪fillna(cleaned_dataset['Driving_experience'].mode()[0], inplace=True)
cleaned_dataset['Type_of_vehicle'].fillna('Unknown', inplace=True)
cleaned_dataset['Owner_of_vehicle'].fillna('Unknown', inplace=True)
cleaned_dataset['Service_year_of_vehicle'].fillna('Unknown', inplace=True)
cleaned_dataset['Defect_of_vehicle'].fillna('No defect', inplace=True)
cleaned_dataset['Area_accident_occured'].fillna('Unknown', inplace=True)
cleaned_dataset['Lanes_or_Medians'].fillna('Unknown', inplace=True)
cleaned_dataset['Road_allignment'].fillna('Unknown', inplace=True)
cleaned_dataset['Types_of_Junction'].fillna('Unknown', inplace=True)
cleaned_dataset['Road_surface_type'].fillna('Unknown', inplace=True)
cleaned_dataset['Type_of_collision'].fillna('Unknown', inplace=True)
cleaned_dataset['Vehicle_movement'].fillna('Unknown', inplace=True)
cleaned_dataset['Work_of_casuality'].fillna('Unknown', inplace=True)
cleaned_dataset['Fitness_of_casuality'].fillna('Unknown', inplace=True)
```

1.3.5 5) Correcting Errors:

In this data cleaning, we identify and fix the errors or incosistencies present in the data

[152]:
```
cleaned_dataset['Type_of_vehicle'] = cleaned_dataset['Type_of_vehicle'].
 ↪replace('Lorry (41?100Q)', 'Lorry (41 - 100 Q)')
cleaned_dataset['Type_of_vehicle'] = cleaned_dataset['Type_of_vehicle'].
 ↪replace('Lorry (11?40Q)', 'Lorry (11 - 40 Q)')
cleaned_dataset['Type_of_vehicle'] = cleaned_dataset['Type_of_vehicle'].
 ↪replace('Public (13?45 seats)', 'Public (13 - 45 seats)')
cleaned_dataset['Area_accident_occured'] =␣
 ↪cleaned_dataset['Area_accident_occured'].replace('  Recreational areas',␣
 ↪'Recreational areas')
cleaned_dataset['Area_accident_occured'] =␣
 ↪cleaned_dataset['Area_accident_occured'].replace('  Market areas', 'Market␣
 ↪areas')
cleaned_dataset['Area_accident_occured'] =␣
 ↪cleaned_dataset['Area_accident_occured'].replace(' Church areas', 'Church␣
 ↪areas')
cleaned_dataset['Area_accident_occured'] =␣
 ↪cleaned_dataset['Area_accident_occured'].replace(' Hospital areas',␣
 ↪'Hospital areas')
cleaned_dataset['Area_accident_occured'] =␣
 ↪cleaned_dataset['Area_accident_occured'].replace(' Industrial areas',␣
 ↪'Industrial areas')
cleaned_dataset['Area_accident_occured'] =␣
 ↪cleaned_dataset['Area_accident_occured'].replace(' Outside rural areas',␣
 ↪'Outside rural areas')
cleaned_dataset['Area_accident_occured'] =␣
 ↪cleaned_dataset['Area_accident_occured'].replace('Rural village areasOffice␣
 ↪areas', 'Rural Office areas')
cleaned_dataset['Road_allignment'] = cleaned_dataset['Road_allignment'].
 ↪replace('Tangent road with mountainous terrain and', 'Tangent road with␣
 ↪mountainous terrain')
cleaned_dataset['Fitness_of_casuality'] =␣
 ↪cleaned_dataset['Fitness_of_casuality'].replace('NormalNormal', 'Normal')
cleaned_dataset['Casualty_severity'] = cleaned_dataset['Casualty_severity'].
 ↪replace('na', 'Unknown')
```

1.3.6 6) Standardize the Data

a) Convert all the entries in `Time` column to a consistent format.
b) Convert `Over 51` to `51 and Over` in the `Age_band_of_driver` column

[153]:
```
# Standardize the 'Time' column
cleaned_dataset['Time'] = pd.to_datetime(cleaned_dataset['Time'], format='%H:%M:
 ↪%S').dt.time
```

```
# Make 'Over 51' to '51 and Over' for Driver Age band
cleaned_dataset['Age_band_of_driver'] = cleaned_dataset['Age_band_of_driver'].
 ↪replace('Over 51', '51 and Over')
```

1.3.7 7) Parsing the data

Convert all the text in the dataset to lowercase to ensure consistency. This helps in avoiding the situations where same words with different cases are considered different

[154]:
```
# Make all the characters to lowercase
cleaned_dataset = cleaned_dataset.map(lambda x: x.lower() if isinstance(x, str)␣
 ↪else x)
```

1.3.8 8) Feature Engineering

[155]:
```
print(cleaned_dataset['Time'].head())
cleaned_dataset['Hour'] = pd.to_datetime(cleaned_dataset['Time'], format='%H:%M:
 ↪%S').dt.hour
Time_of_dat = ['Night', 'Morning', 'Noon', 'Evening']

def categorize_time_of_day(hour):
    if 5 <= hour < 12:
        return 2
    elif 12 <= hour < 17:
        return 3
    elif 17 <= hour < 21:
        return 4
    else:
        return 1


cleaned_dataset['Time_of_day'] = cleaned_dataset['Hour'].
 ↪apply(categorize_time_of_day)

print("Data head after categorizing and encoding Time_of_day:\n")
cleaned_dataset[['Time', 'Hour', 'Time_of_day']].head()
```

```
0    17:02:00
1    17:02:00
2    17:02:00
3    01:06:00
4    01:06:00
Name: Time, dtype: object
Data head after categorizing and encoding Time_of_day:
```

[155]:

	Time	Hour	Time_of_day
0	17:02:00	17	4

```
1  17:02:00    17            4
2  17:02:00    17            4
3  01:06:00     1            1
4  01:06:00     1            1
```

9) Ordinal & One Hot Encoding

[156]:
```python
from sklearn.preprocessing import OneHotEncoder

encoding_dict = {
    'Day_of_week': 'ordinal',
    'Age_band_of_driver': 'ordinal',
    'Sex_of_driver': 'one_hot',
    'Educational_level': 'ordinal',
    'Vehicle_driver_relation': 'one_hot',
    'Driving_experience': 'ordinal',
    'Type_of_vehicle': 'one_hot',
    'Owner_of_vehicle': 'one_hot',
    'Service_year_of_vehicle': 'ordinal',
    'Defect_of_vehicle': 'one_hot',
    'Area_accident_occured': 'one_hot',
    'Lanes_or_Medians': 'one_hot',
    'Road_allignment': 'one_hot',
    'Types_of_Junction': 'one_hot',
    'Road_surface_type': 'one_hot',
    'Road_surface_conditions': 'ordinal',
    'Light_conditions': 'one_hot',
    'Weather_conditions': 'one_hot',
    'Type_of_collision': 'one_hot',
    'Vehicle_movement': 'one_hot',
    'Casualty_class': 'one_hot',
    'Sex_of_casualty': 'one_hot',
    'Age_band_of_casualty': 'ordinal',
    'Casualty_severity': 'ordinal',
    'Work_of_casuality': 'one_hot',
    'Fitness_of_casuality': 'one_hot',
    'Pedestrian_movement': 'one_hot',
    'Cause_of_accident': 'one_hot',
    'Accident_severity': 'ordinal'
}

ordinal_mappings = {
    'Day_of_week': {
        'Monday': 0, 'Tuesday': 1, 'Wednesday': 2, 'Thursday': 3,
        'Friday': 4, 'Saturday': 5, 'Sunday': 6, 'Unknown': -1
    },
    'Age_band_of_driver': {
        'Under 18': 0, '18-30': 1, '31-50': 2, 'Over 51': 3, 'Unknown': -1
```

```
    },
    'Educational_level': {
        'Illiterate': 0, 'Writing & reading': 1, 'Elementary school': 2,
        'Junior high school': 3, 'High school': 4, 'Above high school': 5,
        'Unknown': -1
    },
    'Driving_experience': {
        'No Licence': 0, 'Below 1yr': 1, '1-2yr': 2, '2-5yr': 3, '5-10yr': 4,
        'Above 10yr': 5, 'unknown': -1
    },
    'Service_year_of_vehicle': {
        'Below 1yr': 0, '1-2yr': 1, '2-5yrs': 2, '5-10yrs': 3,
        'Above 10yr': 4, 'Unknown': -1
    },
    'Road_surface_conditions': {
        'Dry': 0, 'Wet or damp': 1, 'Snow': 2, 'Flood over 3cm. deep': 3,␣
↪'Unknown': -1
    },
    'Age_band_of_casualty': {
        'Under 18': 0, '18-30': 1, '31-50': 2, 'Over 51': 3, '5': 4, 'na': -1,␣
↪'Unknown': -1
    },
    'Casualty_severity': {
        '3': 0, '2': 1, '1': 2, 'na': -1, 'Unknown': -1
    },
    'Accident_severity': {
        'Slight Injury': 0, 'Serious Injury': 1, 'Fatal injury': 2, 'Unknown':␣
↪-1
    }
}

def apply_encoding(df, encoding_dict, ordinal_mappings):
    one_hot_encoder = OneHotEncoder(sparse_output=False, drop='first')

    for column, encoding_type in encoding_dict.items():
        if encoding_type == 'ordinal':
            # Apply ordinal encoding using a mapping dictionary
            if column in ordinal_mappings:
                df[f"{column}_ordinal"] = df[column].
↪map(ordinal_mappings[column])
            else:
                print(f"No ordinal mapping provided for column: {column}")

        elif encoding_type == 'one_hot':
            one_hot_encoded_df = pd.get_dummies(df[column], prefix=column,␣
↪drop_first=True)
            df = pd.concat([df, one_hot_encoded_df], axis=1)
```

```
        else:
            print(f"Unknown encoding type: {encoding_type} for column:␣
↪{column}")

    return df

cleaned_dataset = apply_encoding(cleaned_dataset, encoding_dict,␣
↪ordinal_mappings)

cleaned_dataset.head()
```

```
[156]:       Time Day_of_week Age_band_of_driver Sex_of_driver   Educational_level  \
0  17:02:00      monday              18-30          male   above high school
1  17:02:00      monday              31-50          male  junior high school
2  17:02:00      monday              18-30          male  junior high school
3  01:06:00      sunday              18-30          male  junior high school
4  01:06:00      sunday              18-30          male  junior high school

  Vehicle_driver_relation Driving_experience      Type_of_vehicle  \
0                employee              1-2yr           automobile
1                employee        above 10yr  public (> 45 seats)
2                employee              1-2yr   lorry (41 - 100 q)
3                employee             5-10yr  public (> 45 seats)
4                employee              2-5yr              unknown

  Owner_of_vehicle Service_year_of_vehicle  …  \
0            owner             above 10yr  …
1            owner                5-10yrs  …
2            owner                unknown  …
3     governmental                unknown  …
4            owner                5-10yrs  …

  Cause_of_accident_no priority to pedestrian  \
0                                       False
1                                       False
2                                       False
3                                       False
4                                       False

  Cause_of_accident_no priority to vehicle Cause_of_accident_other  \
0                                    False                   False
1                                    False                   False
2                                    False                   False
3                                    False                   False
4                                    False                   False
```

```
  Cause_of_accident_overloading Cause_of_accident_overspeed  \
0                         False                       False
1                         False                       False
2                         False                       False
3                         False                       False
4                         False                       False

  Cause_of_accident_overtaking Cause_of_accident_overturning  \
0                        False                         False
1                         True                         False
2                        False                         False
3                        False                         False
4                         True                         False

  Cause_of_accident_turnover Cause_of_accident_unknown  \
0                      False                     False
1                      False                     False
2                      False                     False
3                      False                     False
4                      False                     False

  Accident_severity_ordinal
0                       NaN
1                       NaN
2                       NaN
3                       NaN
4                       NaN

[5 rows x 184 columns]
```

[157]:

```
def categorize_time_of_dayby3(hour):
    if 3<= hour < 6:
        return 'Early Morning'
    elif 6 <= hour < 9:
        return 'Morning'
    elif 9 <= hour < 12:
        return 'Pre-Noon'
    elif 12 <= hour < 15:
        return 'Post-Noon'
    elif 15 <= hour < 18:
        return 'Evening'
    elif 18 <= hour < 21:
        return 'Night'
    elif 21 <= hour < 24:
        return 'Late-Night'
    else:
        return 'Midnight'
```

```
df_new=cleaned_dataset
df_new['Time_of_day_3hr'] = df_new['Hour'].apply(categorize_time_of_dayby3)
```

Question 1:

Analysis of impact of Roads,type of Road cross-section, type of Roads and Road alignment on different types of Accidents

Algorithm 1 : K-Nearest Neighbors(KNN)

- KNN is a Supervised learning Algorithm that makes classification based on the k nearest neighbours of the given data point.
- Class is assigned to data point based on the majority of the nearest points.
- K is determined by trial and error. Select the value that gives best accuracy and performance

Why KNN?

KNN is simple , easy to train and is effective for dataset with medium size,

It is a lazy learning alogrithm where predictions are made at runtime.

Less number of parameters to consider while training.

[158]:
```
cleaned_df = pd.DataFrame(df_new)
dfknn=␣
↪cleaned_df[['Time_of_day_3hr','Area_accident_occured','Lanes_or_Medians','Road_allignment',
dfknn.head(10)
```

[158]:
```
  Time_of_day_3hr Area_accident_occured   Lanes_or_Medians  \
0         Evening     residential areas            unknown
1         Evening          office areas  undivided two way
2         Evening    recreational areas              other
3        Midnight          office areas              other
4        Midnight      industrial areas              other
5       Post-Noon               unknown            unknown
6         Evening     residential areas  undivided two way
7         Evening     residential areas              other
8         Evening      industrial areas              other
9         Evening     residential areas  undivided two way

                              Road_allignment Types_of_Junction  \
0                tangent road with flat terrain       no junction
1                tangent road with flat terrain       no junction
2                                       unknown       no junction
3  tangent road with mild grade and flat terrain           y shape
4                tangent road with flat terrain           y shape
5                                       unknown           y shape
6                tangent road with flat terrain          crossing
7                tangent road with flat terrain           y shape
```

```
8                 tangent road with flat terrain           y shape
9                 tangent road with flat terrain           y shape

                        Type_of_collision Vehicle_movement  \
0  collision with roadside-parked vehicles   going straight
1           vehicle with vehicle collision   going straight
2          collision with roadside objects   going straight
3           vehicle with vehicle collision   going straight
4           vehicle with vehicle collision   going straight
5           vehicle with vehicle collision           u-turn
6           vehicle with vehicle collision  moving backward
7           vehicle with vehicle collision           u-turn
8  collision with roadside-parked vehicles   going straight
9  collision with roadside-parked vehicles           u-turn

            Cause_of_accident Accident_severity
0             moving backward     slight injury
1                  overtaking     slight injury
2   changing lane to the left    serious injury
3  changing lane to the right     slight injury
4                  overtaking     slight injury
5                 overloading     slight injury
6                       other     slight injury
7      no priority to vehicle     slight injury
8  changing lane to the right     slight injury
9             moving backward    serious injury
```

[159]:

```
from sklearn.preprocessing import LabelEncoder
LE = LabelEncoder()
dfknn=dfknn.apply(LE.fit_transform)
```

KNN model that fits to given training data and calculates the performance based on testing data.

It checks the performance for k ranging from 2 to 10, allowing us to select the best value of k

[160]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler

def knn_model(x,y):
  X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.20,␣
↪random_state=42)
  bestaccuracy=0
  corresponding_k=0

  for i in range(2,10):
```

```
    k = i
    knn = KNeighborsClassifier(n_neighbors=k)

    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)

    accuracy = accuracy_score(y_test, y_pred)
    if accuracy>bestaccuracy:
      bestaccuracy = accuracy
      corresponding_k=i
    print(f"Accuracy for k :{i}=>", accuracy)
  return corresponding_k,bestaccuracy
```

Predicting Accident Severity based on data

The analysis helps us understand injury that are caused due to accidents. analysing the Type of collision, reasons behind it and other factors help to take steps to improve facilities, infrastructure the help to reduce the fatal injury.

The data learned from this dataset can be used to identify and rectify features in different location where similar factors are seen.

[161]:
```
dfc= cleaned_df.groupby('Accident_severity').size()
dfc.head(10)
```

[161]:
```
Accident_severity
fatal injury        158
serious injury     1743
slight injury     10408
dtype: int64
```

[162]:
```
from sklearn.model_selection import train_test_split
from sklearn.utils import resample

majority_class = dfknn[dfknn.Accident_severity == 2]
minority_class = dfknn[dfknn.Accident_severity == 0]
minority_class1 = dfknn[dfknn.Accident_severity == 1]

minority_upsampled = resample(minority_class,␣
 ↪replace=True,n_samples=len(majority_class),random_state=42)

minority_upsampled1 = resample(minority_class1, replace=True,␣
 ↪n_samples=len(majority_class),  random_state=42)

upsampled_data = pd.concat([majority_class, minority_upsampled,␣
 ↪minority_upsampled1])

x = upsampled_data.drop('Accident_severity', axis=1)
```

```
y = upsampled_data['Accident_severity']

k,accuracy= knn_model(x,y)
print(f"Best Accuracy for k :{k} with accuracy=>", accuracy)
```

```
Accuracy for k :2=> 0.8499599679743794
Accuracy for k :3=> 0.8526821457165733
Accuracy for k :4=> 0.82257806244996
Accuracy for k :5=> 0.8214571657325861
Accuracy for k :6=> 0.7972778222578062
Accuracy for k :7=> 0.7942353883106485
Accuracy for k :8=> 0.7743795036028823
Accuracy for k :9=> 0.7694155324259407
Best Accuracy for k :3 with accuracy=> 0.8526821457165733
```

Using KNN algorithm to predict accident severity based on area,type of crossing, vechile movement etc gives **accuracy of about 85% for k = 3**

Predicting Type of Junction based on data

It assists in avoiding the design of junctions in areas, locations, etc which result in more accidents

We can train the model to get most appropiate section of road that should be present based on such data analysis and selecting one which has lowest impact on accident count along with other variables.

From graphs we see the distribution of different vehicle movement aat cross section. Suggesting measures to allow restrict particular direction movement of vehicle, like u-tuen can be restricted or one -way traffic etc.

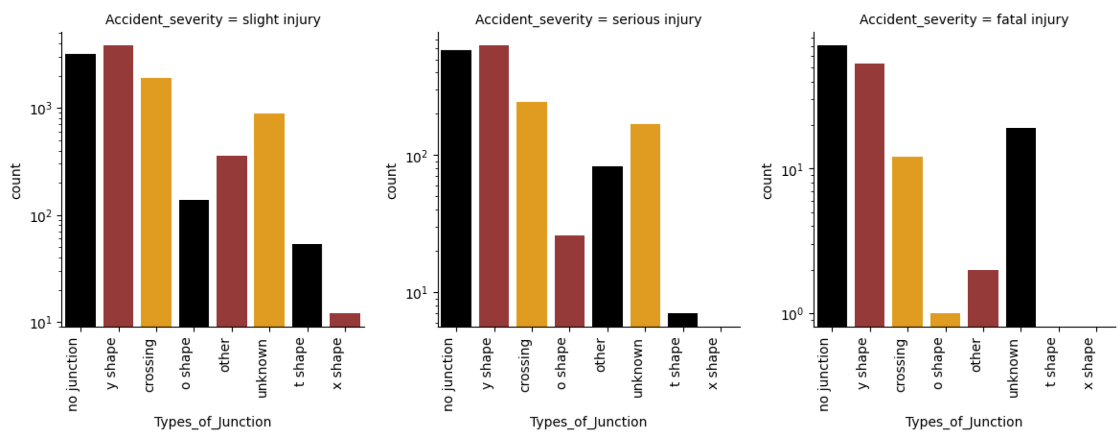
[163]:
```
dfc= cleaned_df.groupby('Types_of_Junction').size()
dfc.head(10)
```

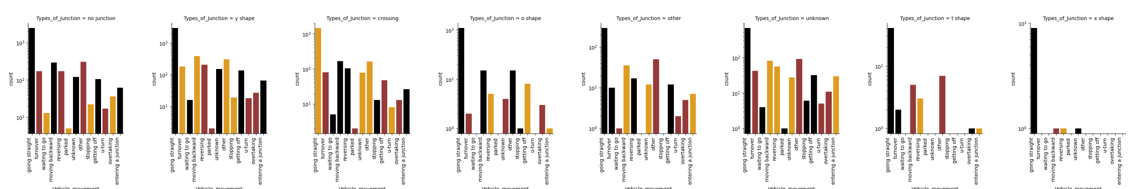
[163]:
```
Types_of_Junction
crossing       2177
no junction    3830
o shape         164
other           445
t shape          60
unknown        1078
x shape          12
y shape        4543
dtype: int64
```

[164]:
```
grid = sns.FacetGrid(data=df_new, col='Accident_severity', height=4, aspect=1,␣
↪sharey=False)
grid.map(sns.countplot, 'Types_of_Junction', palette=['black', 'brown',␣
↪'orange'])
for x in grid.axes.flat:
    x.set_yscale('log')
```

```
    for label in x.get_xticklabels():
        label.set_rotation(90)
        label.set_ha('right')
plt.show()

grid = sns.FacetGrid(data=df_new, col='Types_of_Junction', height=4, aspect=1, sharey=False)
# mapping bar plot and the data on to the grid
grid.map(sns.countplot, 'Vehicle_movement', palette=['black', 'brown', 'orange'])
for ax in grid.axes.flat:
    ax.set_yscale('log')
    for label in ax.get_xticklabels():
        label.set_rotation(90)
        label.set_ha('right')
plt.show()
```





Graph shows the vehicle movements at cross sections which led to accidents.

[165]:
```
from sklearn.model_selection import train_test_split
from sklearn.utils import resample

majority_class = dfknn[dfknn.Types_of_Junction == 1]
minority_class = dfknn[dfknn.Types_of_Junction == 0]
```

```
minority_upsampled = resample(minority_class,replace=True,␣
 ↪n_samples=len(majority_class), random_state=42)

minority_class1 = dfknn[dfknn.Types_of_Junction == 2]
minority_upsampled1 = resample(minority_class1,replace=True,␣
 ↪n_samples=len(majority_class), random_state=42)
minority_class2 = dfknn[dfknn.Types_of_Junction == 4]
minority_upsampled2 = resample(minority_class2,replace=True, ␣
 ↪n_samples=len(majority_class), random_state=42)
minority_class3 = dfknn[dfknn.Types_of_Junction == 5]
minority_upsampled3 = resample(minority_class3,replace=True,  ␣
 ↪n_samples=len(majority_class),random_state=42)
minority_class4 = dfknn[dfknn.Types_of_Junction == 6]
minority_upsampled4 = resample(minority_class4,replace=True,␣
 ↪n_samples=len(majority_class),  random_state=42)
minority_class5 = dfknn[dfknn.Types_of_Junction == 3]
minority_upsampled5 = resample(minority_class5,replace=True,  ␣
 ↪n_samples=len(majority_class), random_state=42)
minority_class6 = dfknn[dfknn.Types_of_Junction == 7]
minority_upsampled6 = resample(minority_class6,replace=True,␣
 ↪n_samples=len(majority_class),random_state=42)

upsampled_data = pd.concat([majority_class, minority_upsampled,␣
 ↪minority_upsampled1,minority_upsampled2,minority_upsampled3,minority_upsampled4,minority_up

x = upsampled_data.drop('Types_of_Junction',axis=1)
y=  upsampled_data['Types_of_Junction']
k,accuracy= knn_model(x,y)
print(f"Best Accuracy for k :{k} with accuracy=>", accuracy)
```

```
Accuracy for k :2=> 0.7315600522193212
Accuracy for k :3=> 0.7242167101827677
Accuracy for k :4=> 0.7018603133159269
Accuracy for k :5=> 0.6940274151436031
Accuracy for k :6=> 0.6817885117493473
Accuracy for k :7=> 0.6656331592689295
Accuracy for k :8=> 0.6568211488250653
Accuracy for k :9=> 0.6460509138381201
Best Accuracy for k :2 with accuracy=> 0.7315600522193212
```

Using KNN algorithm to predict Juction Type based on area,accident severity, vechile movement etc gives **accuracy of about 73% for k = 2**

Predicting Movement of vehicle involved in accident based on data

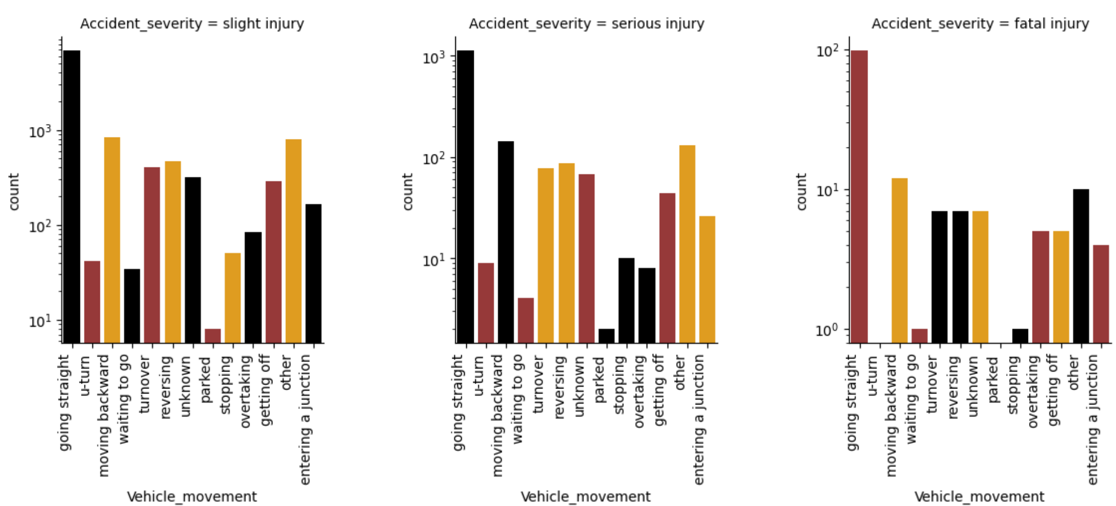
This helps to get the vehicle movement which led to accident. Helping to generate awareness and warnings to drive safely, avoid overtaking etc.

If some roads are designed, then to avoid accidents using already known factors measures can be taken to restrict accident prone vehicle movement.

[166]:
```
dfc= cleaned_df.groupby('Vehicle_movement').size()
dfc.head(10)
```

[166]:
```
Vehicle_movement
entering a junction     193
getting off             339
going straight         8154
moving backward         984
other                   937
overtaking               96
parked                   10
reversing               563
stopping                 61
turnover                489
dtype: int64
```

[167]:
```
grid = sns.FacetGrid(data=df_new, col='Accident_severity', height=4, aspect=1,␣
 ↪sharey=False)
grid.map(sns.countplot, 'Vehicle_movement', palette=['black', 'brown',␣
 ↪'orange'])
for x in grid.axes.flat:
    x.set_yscale('log')
    for label in x.get_xticklabels():
        label.set_rotation(90)
        label.set_ha('right')
plt.show()
```



[168]:

```
from sklearn.model_selection import train_test_split
from sklearn.utils import resample

majority_class = dfknn[dfknn.Vehicle_movement == 2]
minority_class = dfknn[dfknn.Vehicle_movement == 0]
minority_upsampled = resample(minority_class,replace=True,␣
 ↪n_samples=len(majority_class), random_state=42)

minority_class1 = dfknn[dfknn.Vehicle_movement == 1]
minority_upsampled1 = resample(minority_class1,replace=True,␣
 ↪n_samples=len(majority_class), random_state=42)
minority_class2 = dfknn[dfknn.Vehicle_movement == 4]
minority_upsampled2 = resample(minority_class2,replace=True, ␣
 ↪n_samples=len(majority_class), random_state=42)
minority_class3 = dfknn[dfknn.Vehicle_movement == 5]
minority_upsampled3 = resample(minority_class3,replace=True,  ␣
 ↪n_samples=len(majority_class),random_state=42)
minority_class4 = dfknn[dfknn.Vehicle_movement == 6]
minority_upsampled4 = resample(minority_class4,replace=True,␣
 ↪n_samples=len(majority_class),  random_state=42)
minority_class5 = dfknn[dfknn.Vehicle_movement == 3]
minority_upsampled5 = resample(minority_class5,replace=True,  ␣
 ↪n_samples=len(majority_class), random_state=42)
minority_class6 = dfknn[dfknn.Vehicle_movement == 7]
minority_upsampled6 = resample(minority_class6,replace=True,␣
 ↪n_samples=len(majority_class),random_state=42)
minority_class7 = dfknn[dfknn.Vehicle_movement == 8]
minority_upsampled7 = resample(minority_class7,replace=True,␣
 ↪n_samples=len(majority_class),random_state=42)
minority_class8 = dfknn[dfknn.Vehicle_movement == 9]
minority_upsampled8 = resample(minority_class8,replace=True,␣
 ↪n_samples=len(majority_class),random_state=42)
minority_class9 = dfknn[dfknn.Vehicle_movement == 10]
minority_upsampled9 = resample(minority_class9,replace=True,␣
 ↪n_samples=len(majority_class),random_state=42)
minority_class10 = dfknn[dfknn.Vehicle_movement == 11]
minority_upsampled10 = resample(minority_class10,replace=True,␣
 ↪n_samples=len(majority_class),random_state=42)
minority_class11 = dfknn[dfknn.Vehicle_movement == 12]
minority_upsampled11 = resample(minority_class11,replace=True,␣
 ↪n_samples=len(majority_class),random_state=42)

upsampled_data = pd.concat([majority_class, minority_upsampled,␣
 ↪minority_upsampled1,minority_upsampled2,minority_upsampled3,minority_upsampled4,minority_up

x = upsampled_data.drop('Vehicle_movement',axis=1)
```

```
y=  upsampled_data['Vehicle_movement']
k,accuracy= knn_model(x,y)
```

```
Accuracy for k :2=> 0.8794868166595915
Accuracy for k :3=> 0.8880241498042545
Accuracy for k :4=> 0.8850997594453092
Accuracy for k :5=> 0.8789208056223763
Accuracy for k :6=> 0.8790151407952455
Accuracy for k :7=> 0.8742512145653507
Accuracy for k :8=> 0.8713268242064054
Accuracy for k :9=> 0.8642516862412151
```

Using KNN algorithm to predict Vehicle movement at time of acccident based on area,type of crossing, lanes, time of day etc gives **accuracy of about 88% for k = 5**

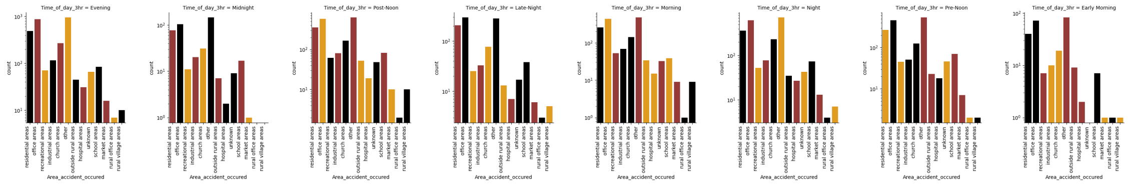
Predicting Area of Accident based on data

Graph shows the day-phase wise accidents in particular area,

[169]:
```
dfc= cleaned_df.groupby('Area_accident_occured').size()
dfc.head(15)
```

[169]:
```
Area_accident_occured
church areas            1059
hospital areas           121
industrial areas         456
market areas              63
office areas            3451
other                   3816
outside rural areas      218
recreational areas       327
residential areas       2059
rural office areas        20
rural village areas       44
school areas             414
unknown                  261
dtype: int64
```

[170]:
```
grid = sns.FacetGrid(data=df_new, col='Time_of_day_3hr', height=4, aspect=1,␣
 ↪sharey=False)
# mapping bar plot and the data on to the grid
grid.map(sns.countplot, 'Area_accident_occured', palette=['black', 'brown',␣
 ↪'orange'])
for ax in grid.axes.flat:
    ax.set_yscale('log')
    for label in ax.get_xticklabels():
        label.set_rotation(90)
        label.set_ha('right')
plt.show()
```



[171]:
```
from sklearn.model_selection import train_test_split
from sklearn.utils import resample

majority_class = dfknn[dfknn.Area_accident_occured == 5]
minority_class = dfknn[dfknn.Area_accident_occured == 0]
minority_upsampled = resample(minority_class,replace=True,␣
 ↪n_samples=len(majority_class), random_state=42)
minority_class1 = dfknn[dfknn.Area_accident_occured == 1]
minority_upsampled1 = resample(minority_class1,replace=True,␣
 ↪n_samples=len(majority_class), random_state=42)
minority_class2 = dfknn[dfknn.Area_accident_occured == 4]
minority_upsampled2 = resample(minority_class2,replace=True, ␣
 ↪n_samples=len(majority_class), random_state=42)
minority_class3 = dfknn[dfknn.Area_accident_occured == 2]
minority_upsampled3 = resample(minority_class3,replace=True,  ␣
 ↪n_samples=len(majority_class),random_state=42)
minority_class4 = dfknn[dfknn.Area_accident_occured == 6]
minority_upsampled4 = resample(minority_class4,replace=True,␣
 ↪n_samples=len(majority_class),  random_state=42)
minority_class5 = dfknn[dfknn.Area_accident_occured == 3]
minority_upsampled5 = resample(minority_class5,replace=True,  ␣
 ↪n_samples=len(majority_class), random_state=42)
minority_class6 = dfknn[dfknn.Area_accident_occured == 7]
minority_upsampled6 = resample(minority_class6,replace=True,␣
 ↪n_samples=len(majority_class),random_state=42)
minority_class7 = dfknn[dfknn.Area_accident_occured == 8]
minority_upsampled7 = resample(minority_class7,replace=True,␣
 ↪n_samples=len(majority_class),random_state=42)
minority_class8 = dfknn[dfknn.Area_accident_occured == 9]
minority_upsampled8 = resample(minority_class8,replace=True,␣
 ↪n_samples=len(majority_class),random_state=42)
minority_class9 = dfknn[dfknn.Area_accident_occured == 10]
minority_upsampled9 = resample(minority_class9,replace=True,␣
 ↪n_samples=len(majority_class),random_state=42)
minority_class10 = dfknn[dfknn.Area_accident_occured == 11]
minority_upsampled10 = resample(minority_class10,replace=True,␣
 ↪n_samples=len(majority_class),random_state=42)
minority_class11 = dfknn[dfknn.Area_accident_occured == 12]
```

```
minority_upsampled11 = resample(minority_class11,replace=True,␣
 ↪n_samples=len(majority_class),random_state=42)

upsampled_data = pd.concat([majority_class, minority_upsampled,␣
 ↪minority_upsampled1,minority_upsampled2,minority_upsampled3,minority_upsampled4,minority_up

x = upsampled_data.drop('Area_accident_occured',axis=1)
y =  upsampled_data['Area_accident_occured']
k,accuracy= knn_model(x,y)
```

```
Accuracy for k :2=> 0.7674863938722032
Accuracy for k :3=> 0.7691997581132836
Accuracy for k :4=> 0.7613384398306793
Accuracy for k :5=> 0.7481354565611772
Accuracy for k :6=> 0.7413827857286838
Accuracy for k :7=> 0.7320096754686555
Accuracy for k :8=> 0.7212255593630317
Accuracy for k :9=> 0.7137673856077403
```

Using KNN algorithm to predict Area of Accident severity based on type of crossing, vechile movement,time of day etc gives **accuracy of about 77% for k = 3**

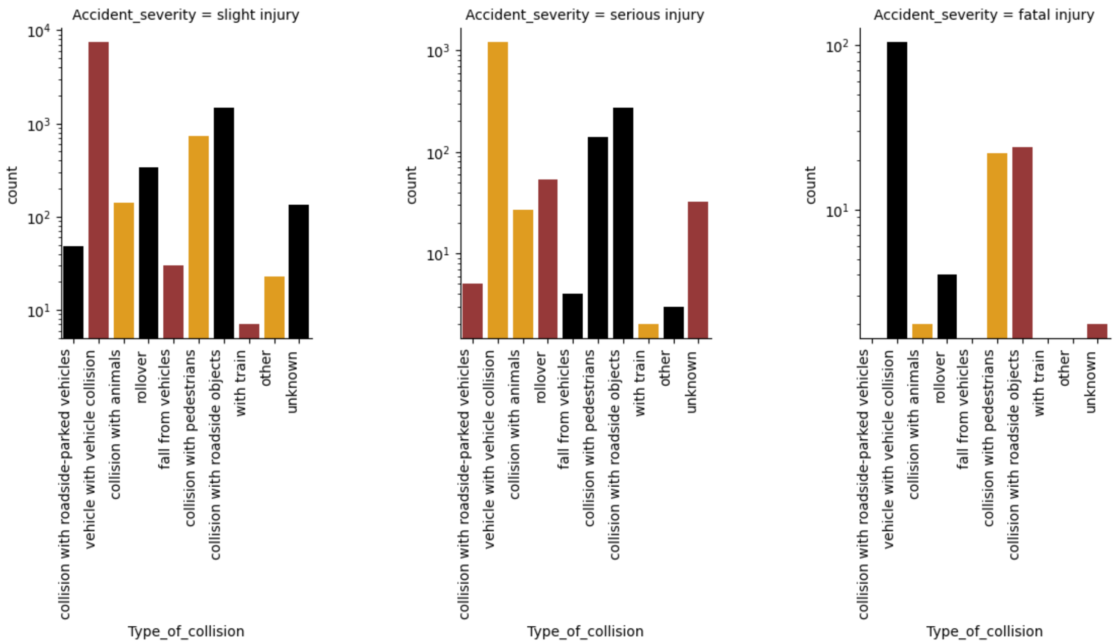
Predicting Collision type based on data

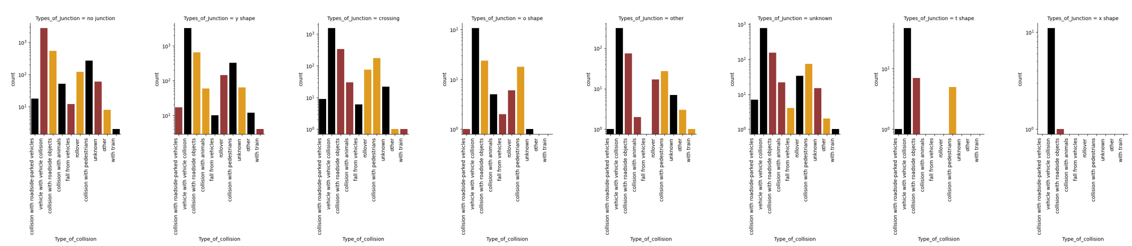
[172]:
```
dfc= cleaned_df.groupby('Type_of_collision').size()
dfc.head(10)
```

[172]:
```
Type_of_collision
collision with animals                        171
collision with pedestrians                    896
collision with roadside objects              1785
collision with roadside-parked vehicles        54
fall from vehicles                             34
other                                          26
rollover                                      396
unknown                                       169
vehicle with vehicle collision               8769
with train                                      9
dtype: int64
```

[173]:
```
grid = sns.FacetGrid(data=df_new, col='Accident_severity', height=4, aspect=1,␣
 ↪sharey=False)
grid.map(sns.countplot, 'Type_of_collision', palette=['black', 'brown',␣
 ↪'orange'])
for x in grid.axes.flat:
    x.set_yscale('log')
    for label in x.get_xticklabels():
        label.set_rotation(90)
```

```
        label.set_ha('right')
plt.show()
grid = sns.FacetGrid(data=df_new, col='Types_of_Junction', height=4, aspect=1,␣
 ↪sharey=False)
grid.map(sns.countplot, 'Type_of_collision', palette=['black', 'brown',␣
 ↪'orange'])
for x in grid.axes.flat:
    x.set_yscale('log')
    for label in x.get_xticklabels():
        label.set_rotation(90)
        label.set_ha('right')
plt.show()
```





```
[174]: from sklearn.model_selection import train_test_split
       from sklearn.utils import resample
```

```
majority_class = dfknn[dfknn.Type_of_collision == 8]
minority_class = dfknn[dfknn.Type_of_collision == 0]
minority_upsampled = resample(minority_class,replace=True,␣
↪n_samples=len(majority_class), random_state=42)

minority_class1 = dfknn[dfknn.Type_of_collision == 3]
minority_upsampled1 = resample(minority_class1,replace=True,␣
↪n_samples=len(majority_class), random_state=42)
minority_class2 = dfknn[dfknn.Type_of_collision == 4]
minority_upsampled2 = resample(minority_class2,replace=True, ␣
↪n_samples=len(majority_class), random_state=42)
minority_class3 = dfknn[dfknn.Type_of_collision == 5]
minority_upsampled3 = resample(minority_class3,replace=True,  ␣
↪n_samples=len(majority_class),random_state=42)
minority_class4 = dfknn[dfknn.Type_of_collision == 6]
minority_upsampled4 = resample(minority_class4,replace=True,␣
↪n_samples=len(majority_class),  random_state=42)
minority_class5 = dfknn[dfknn.Type_of_collision == 1]
minority_upsampled5 = resample(minority_class5,replace=True,  ␣
↪n_samples=len(majority_class), random_state=42)
minority_class6 = dfknn[dfknn.Type_of_collision == 7]
minority_upsampled6 = resample(minority_class6,replace=True,␣
↪n_samples=len(majority_class),random_state=42)
minority_class7 = dfknn[dfknn.Type_of_collision == 2]
minority_upsampled7 = resample(minority_class7,replace=True,␣
↪n_samples=len(majority_class), random_state=42)
minority_class8 = dfknn[dfknn.Type_of_collision == 9]
minority_upsampled8 = resample(minority_class8,replace=True,␣
↪n_samples=len(majority_class), random_state=42)

upsampled_data = pd.concat([majority_class, minority_upsampled,␣
↪minority_upsampled1,minority_upsampled2,minority_upsampled3,minority_upsampled4,minority_up
x = upsampled_data.drop('Type_of_collision', axis=1)
y = upsampled_data['Type_of_collision']
k,accuracy= knn_model(x,y)
print(f"Best Accuracy for k :{k} with accuracy=>", accuracy)
```

```
Accuracy for k :2=> 0.903352719808416
Accuracy for k :3=> 0.9052913673166838
Accuracy for k :4=> 0.8957121678640666
Accuracy for k :5=> 0.8941726536663246
Accuracy for k :6=> 0.886589120766336
Accuracy for k :7=> 0.8798608735317596
Accuracy for k :8=> 0.8730756072528224
Accuracy for k :9=> 0.8667464933287718
Best Accuracy for k :3 with accuracy=> 0.9052913673166838
```

Using KNN algorithm to predict Area of Accident severity based on type of crossing, vechile movement,time of day etc gives **accuracy of about 90.5% for k = 3**

Key Takeaway

- From the KNN model implementation, we are able to predict the issues that can rise during design and construction phase taking into consideration the area of road(how traffic flow is) , time of day(Peak traffic flows, will road has capacity to handle traffic), decision of Junction based on the obseres vehicle moment, type of collision etc.
- It helps authorities to design better roads keeping into consideration all the factors.
- Where there are limitations, proper measures can be taken to avoid accidents and injury caused due to it.
- According to many study's, road engineering contributes significant share for reasons behind road accident.
- Such models with help of data and technology will helps to reduce such incidents in future.