Shuxi_EDA_1112

May 10, 2025

[13]:
```
import os

path = "/Users/chenshuxi/Documents/MMA/MMA fall/INSY662_Elizabeth/Final Project/
↪traffic collision"
os.chdir(path)
```

[14]:
```
import pandas as pd
import numpy as np

# Display all columns in the console
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
```

[15]:
```
df = pd.read_excel("Init Filtered Colmns_Montreal.xlsx")
df.head()
```

[15]:
```
              Seq_Num    Acc_Date             Street    Near_To  Acc_Type  \
0      SPVM _ 2012 _ 1  2012/02/01         ST CHARLES       STAT      31.0
1     SPVM _ 2012 _ 10  2012/01/03  TERR VILLE DE MTL        NaN      31.0
2    SPVM _ 2012 _ 100  2012/02/24     JACQUES BIZARD   CHERRIER      31.0
3   SPVM _ 2012 _ 1000  2012/10/11       BD SALABERRY        NaN      31.0
4  SPVM _ 2012 _ 10000  2012/04/22     PL DU COMMERCE        NaN      31.0

   Surface_Cond  Light_Cond  Environ_Type  Road_Cat  Road_Aspect  Loc_Code  \
0          16.0         1.0           1.0      21.0         11.0      33.0
1          11.0         NaN           NaN       NaN          NaN       NaN
2          11.0         3.0           3.0      13.0         21.0      32.0
3          11.0         1.0           3.0      21.0         11.0      40.0
4          12.0         1.0           3.0      21.0         11.0      40.0

   Pos_Code  Road_Config  Work_Zone  Weather_Cond  Num_Veh_Invld  Num_Death  \
0       NaN          4.0        NaN          11.0              2          0
1       NaN          NaN        NaN          11.0              2          0
2       NaN          1.0        NaN          11.0              2          0
3       NaN          2.0        NaN          11.0              2          0
4       NaN          NaN        NaN          12.0              2          0

   Num_Serious_Inj  Num_Minor_Inj          Acc_Time  Total_Victims  \
```

```
0                 0               0       Non précisé              0
1                 0               0       Non précisé              0
2                 0               0  02:00:00-02:59:00             0
3                 0               0  15:00:00-15:59:00             0
4                 0               0  15:00:00-15:59:00             0

                                     Severity  Num_Light_Veh  Num_Heavy_Truck  \
0  Property damage below reporting threshold              1                0
1                       Property damage only              1                0
2  Property damage below reporting threshold              2                0
3                       Property damage only              2                0
4  Property damage below reporting threshold              1                0

   Num_Equip  Num_Bus  Num_Bike  Num_Moped  Num_Moto  Num_Taxi  Num_Emerg  \
0          0        0         0          0         0         0          0
1          0        0         0          0         0         0          0
2          0        0         0          0         0         0          0
3          0        0         0          0         0         0          0
4          0        0         0          0         0         0          0

   Num_Snowmobile  Num_OffRoad  Num_Other_Veh  Num_Unspec_Veh  Num_Ped_Death  \
0               0            0              0               1              0
1               0            0              0               1              0
2               0            0              0               0              0
3               0            0              0               0              0
4               0            0              0               1              0

   Num_Ped_Inj  Num_Ped_Vic  Num_Moto_Death  Num_Moto_Inj  Num_Moto_Vic  \
0            0            0               0             0             0
1            0            0               0             0             0
2            0            0               0             0             0
3            0            0               0             0             0
4            0            0               0             0             0

   Num_Bike_Death  Num_Bike_Inj  Num_Bike_Vic  Speed_Limit Loc_Quality  \
0               0             0             0          NaN           A
1               0             0             0          NaN           B
2               0             0             0         50.0           A
3               0             0             0          NaN           A
4               0             0             0          NaN           A

   Loc_Accuracy Loc_Imprecise  Lontitude   Latitude
0             3             N -73.861616  45.455505
1             4             N -73.878549  45.486871
2             1             O -73.871542  45.490564
3             1             N -73.804841  45.484648
4             1             N -73.543590  45.467136
```

Check duplicate

[16]:
```
print(df.shape)
# Check for duplicated rows
duplicates = df[df.duplicated()]
print(len(duplicates) > 0)
```

```
(218128, 50)
False
```

Missing values

[17]:
```
mis_col_dict = []
for col in df.columns:
    if df[col].isnull().any():
        mis_col_dict.append({
            "feature" : col,
            "NA_count": df[col].isnull().sum(),
            "missing %": np.round((df[col].isnull().sum()*100) / len(df), 2)
        })

missing_df = pd.DataFrame(mis_col_dict)
missing_df
```

[17]:

	feature	NA_count	missing %
0	Street	12264	5.62
1	Near_To	71031	32.56
2	Acc_Type	10054	4.61
3	Surface_Cond	12746	5.84
4	Light_Cond	12909	5.92
5	Environ_Type	7044	3.23
6	Road_Cat	6344	2.91
7	Road_Aspect	9903	4.54
8	Loc_Code	17743	8.13
9	Pos_Code	168943	77.45
10	Road_Config	21947	10.06
11	Work_Zone	213230	97.75
12	Weather_Cond	13589	6.23
13	Speed_Limit	80812	37.05
14	Lontitude	7	0.00
15	Latitude	7	0.00

Drop features with >50% missing values: Part_Sit, Road_Cond, Pos_Code, Work_Zone

[18]:
```
dropped_cols = missing_df.loc[missing_df["missing %"] > 50, "feature"].tolist()
df.drop(dropped_cols, axis = 1, inplace = True)
```

Variables need impution

[19]:
```
imp_cols = missing_df.loc[missing_df["missing %"] < 50, "feature"].tolist()
imp_cols
```

[19]:
```
['Street',
 'Near_To',
 'Acc_Type',
 'Surface_Cond',
 'Light_Cond',
 'Environ_Type',
 'Road_Cat',
 'Road_Aspect',
 'Loc_Code',
 'Road_Config',
 'Weather_Cond',
 'Speed_Limit',
 'Lontitude',
 'Latitude']
```

Understand the distribution and characteristics of the variables

[20]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 218128 entries, 0 to 218127
Data columns (total 48 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   Seq_Num          218128 non-null  object
 1   Acc_Date         218128 non-null  object
 2   Street           205864 non-null  object
 3   Near_To          147097 non-null  object
 4   Acc_Type         208074 non-null  float64
 5   Surface_Cond     205382 non-null  float64
 6   Light_Cond       205219 non-null  float64
 7   Environ_Type     211084 non-null  float64
 8   Road_Cat         211784 non-null  float64
 9   Road_Aspect      208225 non-null  float64
 10  Loc_Code         200385 non-null  float64
 11  Road_Config      196181 non-null  float64
 12  Weather_Cond     204539 non-null  float64
 13  Num_Veh_Invld    218128 non-null  int64
 14  Num_Death        218128 non-null  int64
 15  Num_Serious_Inj  218128 non-null  int64
 16  Num_Minor_Inj    218128 non-null  int64
 17  Acc_Time         218128 non-null  object
 18  Total_Victims    218128 non-null  int64
 19  Severity         218128 non-null  object
 20  Num_Light_Veh    218128 non-null  int64
 21  Num_Heavy_Truck  218128 non-null  int64
 22  Num_Equip        218128 non-null  int64
 23  Num_Bus          218128 non-null  int64
 24  Num_Bike         218128 non-null  int64
```

```
 25  Num_Moped        218128 non-null  int64
 26  Num_Moto         218128 non-null  int64
 27  Num_Taxi         218128 non-null  int64
 28  Num_Emerg        218128 non-null  int64
 29  Num_Snowmobile   218128 non-null  int64
 30  Num_OffRoad      218128 non-null  int64
 31  Num_Other_Veh    218128 non-null  int64
 32  Num_Unspec_Veh   218128 non-null  int64
 33  Num_Ped_Death    218128 non-null  int64
 34  Num_Ped_Inj      218128 non-null  int64
 35  Num_Ped_Vic      218128 non-null  int64
 36  Num_Moto_Death   218128 non-null  int64
 37  Num_Moto_Inj     218128 non-null  int64
 38  Num_Moto_Vic     218128 non-null  int64
 39  Num_Bike_Death   218128 non-null  int64
 40  Num_Bike_Inj     218128 non-null  int64
 41  Num_Bike_Vic     218128 non-null  int64
 42  Speed_Limit      137316 non-null  float64
 43  Loc_Quality      218128 non-null  object
 44  Loc_Accuracy     218128 non-null  int64
 45  Loc_Imprecise    218128 non-null  object
 46  Lontitude        218121 non-null  float64
 47  Latitude         218121 non-null  float64
dtypes: float64(12), int64(28), object(8)
memory usage: 79.9+ MB
```

Distribution and characteristics of the variables

[21]:
```
df.describe()
```

[21]:
```
            Acc_Type   Surface_Cond     Light_Cond   Environ_Type  \
count  208074.000000  205382.000000  205219.000000  211084.000000
mean       33.668450      12.346598       1.607522       2.657601
std         9.398566       5.484986       0.900421       0.936559
min        31.000000      11.000000       1.000000       1.000000
25%        31.000000      11.000000       1.000000       2.000000
50%        31.000000      11.000000       1.000000       3.000000
75%        31.000000      12.000000       3.000000       3.000000
max        99.000000      99.000000       4.000000       9.000000

            Road_Cat    Road_Aspect       Loc_Code    Road_Config  \
count  211784.000000  208225.000000  200385.000000  196181.000000
mean       14.484173      11.396072      38.815775       2.676156
std         2.927533       1.734314      18.408337       1.955614
min        11.000000      11.000000       0.000000       1.000000
25%        13.000000      11.000000      32.000000       1.000000
50%        13.000000      11.000000      33.000000       2.000000
75%        14.000000      11.000000      34.000000       3.000000
```

```
max        29.000000      24.000000      99.000000       9.000000

        Weather_Cond  Num_Veh_Invld      Num_Death  Num_Serious_Inj  \
count  204539.000000  218128.000000  218128.000000    218128.000000
mean       12.321063       1.950057       0.001233         0.008926
std         6.800747       0.584206       0.035871         0.102454
min        11.000000       1.000000       0.000000         0.000000
25%        11.000000       2.000000       0.000000         0.000000
50%        11.000000       2.000000       0.000000         0.000000
75%        12.000000       2.000000       0.000000         0.000000
max        99.000000      31.000000       2.000000         6.000000

       Num_Minor_Inj  Total_Victims  Num_Light_Veh  Num_Heavy_Truck  \
count  218128.000000  218128.000000  218128.000000    218128.000000
mean        0.260035       0.270195       1.486013         0.103297
std         0.570941       0.582353       0.783895         0.316357
min         0.000000       0.000000       0.000000         0.000000
25%         0.000000       0.000000       1.000000         0.000000
50%         0.000000       0.000000       1.000000         0.000000
75%         0.000000       0.000000       2.000000         0.000000
max        24.000000      27.000000      30.000000         3.000000

           Num_Equip        Num_Bus       Num_Bike      Num_Moped  \
count  218128.000000  218128.000000  218128.000000  218128.000000
mean        0.014464       0.025866       0.040022       0.006134
std         0.119854       0.160886       0.197527       0.079013
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000       0.000000
75%         0.000000       0.000000       0.000000       0.000000
max         2.000000       3.000000       7.000000       2.000000

            Num_Moto       Num_Taxi      Num_Emerg  Num_Snowmobile  \
count  218128.000000  218128.000000  218128.000000   218128.000000
mean        0.013717       0.032999       0.033421        0.000028
std         0.118189       0.184393       0.190024        0.005245
min         0.000000       0.000000       0.000000        0.000000
25%         0.000000       0.000000       0.000000        0.000000
50%         0.000000       0.000000       0.000000        0.000000
75%         0.000000       0.000000       0.000000        0.000000
max         3.000000       7.000000       4.000000        1.000000

         Num_OffRoad  Num_Other_Veh  Num_Unspec_Veh  Num_Ped_Death  \
count  218128.000000  218128.000000   218128.000000  218128.000000
mean        0.000087       0.005501        0.188509       0.000720
std         0.009333       0.074400        0.393864       0.026989
min         0.000000       0.000000        0.000000       0.000000
```

```
25%         0.000000       0.000000        0.000000       0.000000
50%         0.000000       0.000000        0.000000       0.000000
75%         0.000000       0.000000        0.000000       0.000000
max         1.000000       3.000000        5.000000       2.000000

         Num_Ped_Inj    Num_Ped_Vic  Num_Moto_Death   Num_Moto_Inj  \
count  218128.000000  218128.000000   218128.000000  218128.000000
mean        0.050324       0.051043        0.000078       0.007949
std         0.228718       0.230306        0.008828       0.093090
min         0.000000       0.000000        0.000000       0.000000
25%         0.000000       0.000000        0.000000       0.000000
50%         0.000000       0.000000        0.000000       0.000000
75%         0.000000       0.000000        0.000000       0.000000
max         8.000000       8.000000        1.000000       3.000000

        Num_Moto_Vic  Num_Bike_Death   Num_Bike_Inj   Num_Bike_Vic  \
count  218128.000000   218128.000000  218128.000000  218128.000000
mean        0.008027        0.000142       0.030037       0.030180
std         0.093501        0.011921       0.171655       0.172043
min         0.000000        0.000000       0.000000       0.000000
25%         0.000000        0.000000       0.000000       0.000000
50%         0.000000        0.000000       0.000000       0.000000
75%         0.000000        0.000000       0.000000       0.000000
max         3.000000        1.000000       2.000000       2.000000

         Speed_Limit   Loc_Accuracy      Lontitude       Latitude
count  137316.000000  218128.000000  218121.000000  218121.000000
mean       45.459961       1.207342     -73.622575      45.526686
std         8.713415       0.586687       0.077750       0.053785
min         0.000000       1.000000     -73.970506      45.402674
25%        40.000000       1.000000     -73.646169      45.489343
50%        50.000000       1.000000     -73.607135      45.524395
75%        50.000000       1.000000     -73.571695      45.562558
max       100.000000       4.000000     -73.479864      45.702491
```

- Acc_Date should be converted to datetime

[22]:
```
df["Acc_Date"] = pd.to_datetime(df["Acc_Date"], format='%Y/%m/%d')

df['Weekday'] = df['Acc_Date'].dt.day_name()
df['Month'] = df['Acc_Date'].dt.month_name()
df['Year'] = df['Acc_Date'].dt.year

print(df[["Acc_Date", "Weekday", "Month", "Year"]].dtypes)
```

```
Acc_Date    datetime64[ns]
Weekday             object
Month               object
```

```
Year                 int32
dtype: object
```

- Acc_Time should be converted from interval to numbers (0 ~ 23)

[23]:
```python
time_dict = {f"{str(hour).zfill(2)}:00:00-{str(hour).zfill(2)}:59:00": hour for␣
↪hour in range(24)}
time_dict["Non précisé", ] = np.nan

df["Acc_Time"] = df["Acc_Time"].map(time_dict)
df["Acc_Time"].head()
```

[23]:
```
0     NaN
1     NaN
2     2.0
3    15.0
4    15.0
Name: Acc_Time, dtype: float64
```

NA imupation

Acc_Time is part of a time series or sequence, I impute missing values based on previous, using a rolling window imputation.

For columns of a numeric type that represent categorical variables, I replace missing values with the value from the previous row.

Why?

Because this dataset seems like a time series or ordered datasets, it has a sequential pattern, so I assume that adjacent rows are likely to have similar or identical categorizations, whic.

[24]:
```python
print("# of Not specified time: ", len(df[df["Acc_Time"] == ""]))
print("-----------------------")
print(df["Acc_Time"].value_counts())
print("-----------------------")

# impute NA with mode
df["Acc_Time"].replace("", np.nan, inplace=True) # replace empty strings with␣
↪NaN
df["Acc_Time"].fillna(method='ffill', inplace=True)

# backward fill to handle NaN values for first two rows
df["Acc_Time"].fillna(method='bfill', inplace=True)
df["Acc_Time"] = df["Acc_Time"].astype('Int64')

# Check the value counts
print(df["Acc_Time"].value_counts().head())
```

```
# of Not specified time:  0
-----------------------
```

```
Acc_Time
16.0    15594
15.0    15157
17.0    14648
14.0    13243
13.0    12231
12.0    12108
8.0     11607
18.0    11017
11.0    10870
10.0    10383
9.0     10215
19.0     8402
7.0      8245
20.0     7281
21.0     6805
22.0     5854
23.0     5191
0.0      4238
6.0      4125
3.0      3572
1.0      2932
2.0      2685
4.0      2251
5.0      2246
Name: count, dtype: int64
-----------------------
Acc_Time
16    16823
15    16337
17    15829
14    14428
13    13318
Name: count, dtype: Int64
```

```
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/3256454990.py:7
: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df["Acc_Time"].replace("", np.nan, inplace=True) # replace empty strings with
```

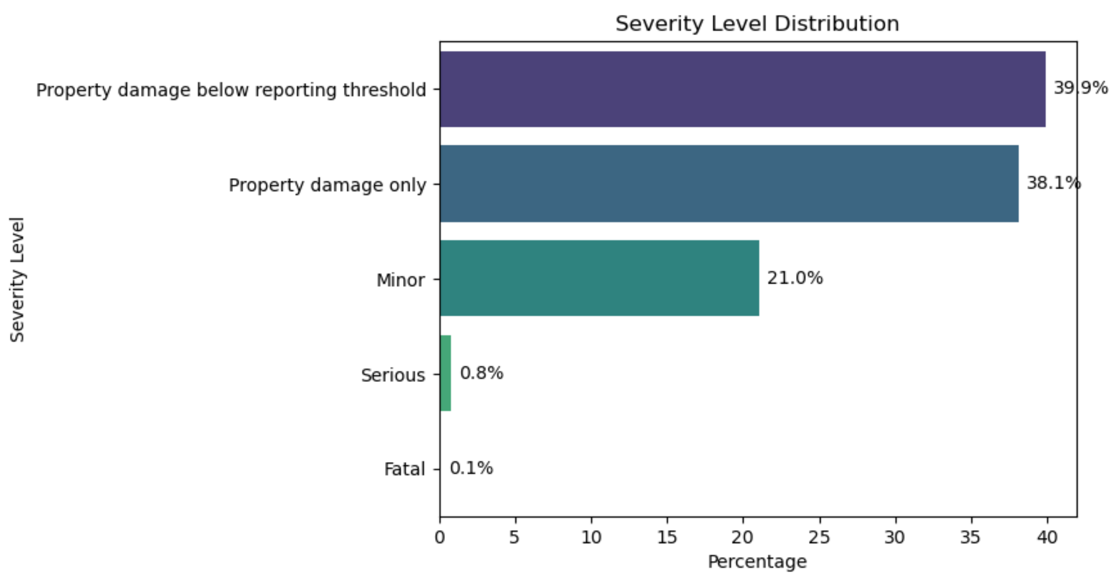
```
NaN
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/3256454990.py:8
: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df["Acc_Time"].fillna(method='ffill', inplace=True)
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/3256454990.py:8
: FutureWarning: Series.fillna with 'method' is deprecated and will raise in a
future version. Use obj.ffill() or obj.bfill() instead.
  df["Acc_Time"].fillna(method='ffill', inplace=True)
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/3256454990.py:1
1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df["Acc_Time"].fillna(method='bfill', inplace=True)
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/3256454990.py:1
1: FutureWarning: Series.fillna with 'method' is deprecated and will raise in a
future version. Use obj.ffill() or obj.bfill() instead.
  df["Acc_Time"].fillna(method='bfill', inplace=True)
```

One by one variable distribution and fixing Target variable: Severity

[25]:
```
import seaborn as sns
import matplotlib.pyplot as plt

severity_counts = df['Severity'].value_counts()
percentages = (severity_counts / severity_counts.sum()) * 100

sns.barplot(x=percentages, y=severity_counts.index, palette="viridis")

for i, percentage in enumerate(percentages):
```

```
    plt.text(x=percentage + 0.5, y=i, s=f'{percentage:.1f}%', va='center')

plt.xlabel('Percentage')
plt.ylabel('Severity Level')
plt.title('Severity Level Distribution')

plt.show()
```

```
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/429158471.py:7:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=percentages, y=severity_counts.index, palette="viridis")
```



Data imbalance issues related to the Severity attribute.

even if certain severity levels are rare, they carry the most important info for understanding the risk factors associated with them. collapsing rare levels into one group can be a useful technique for improving model performance in many cases, but in the context of a collision dataset where severity levels such as “serious” or “fatal” are crucial to understanding the data and the overall analysis, they are critical for predictive modeling, safety assessments, and decision-making, it may not be the best approach.

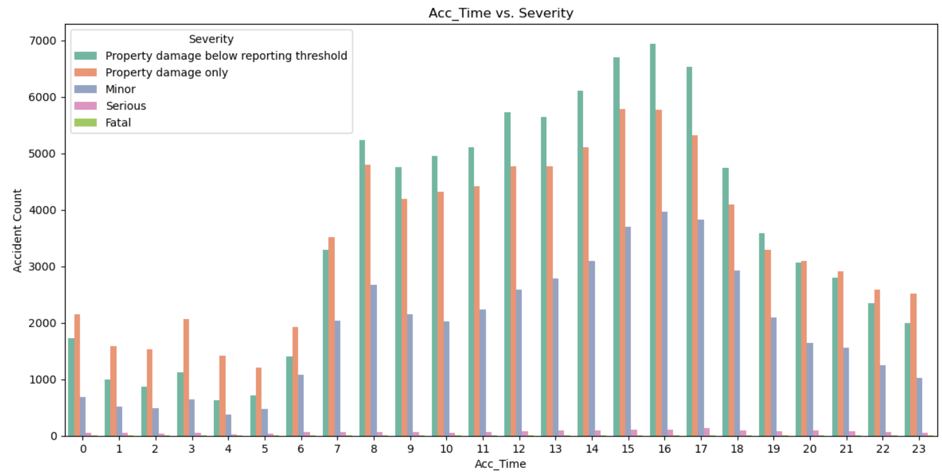
But the rarity in the data set risks the model seeing it as an outlier, which in turn biases predictions towards more common categories.

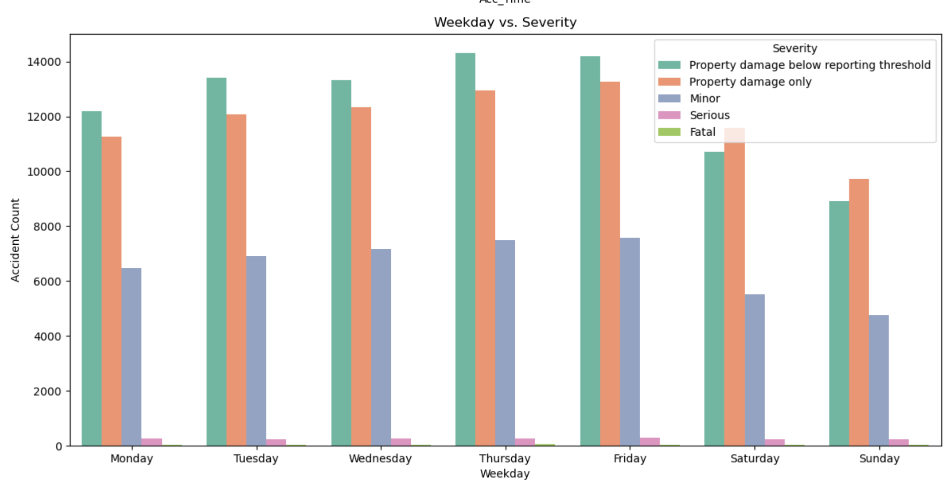
To address this imbalance, there’re two ways:

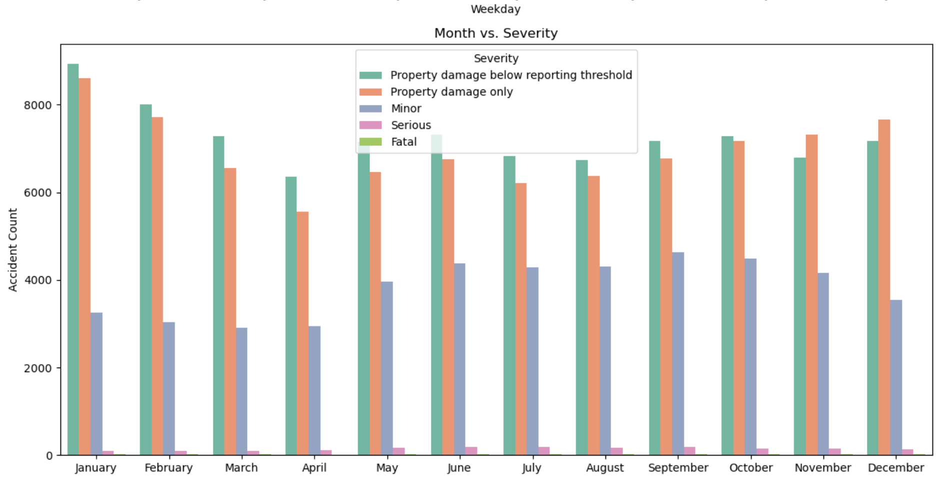
1. we can use balancing technique SMOTE to fix it.
2. we can try classification models that are specifically designed to handle imbalanced data(decision trees, RF, XGBoost…). These models can focus on learning the minority class better without needing to collapse it.

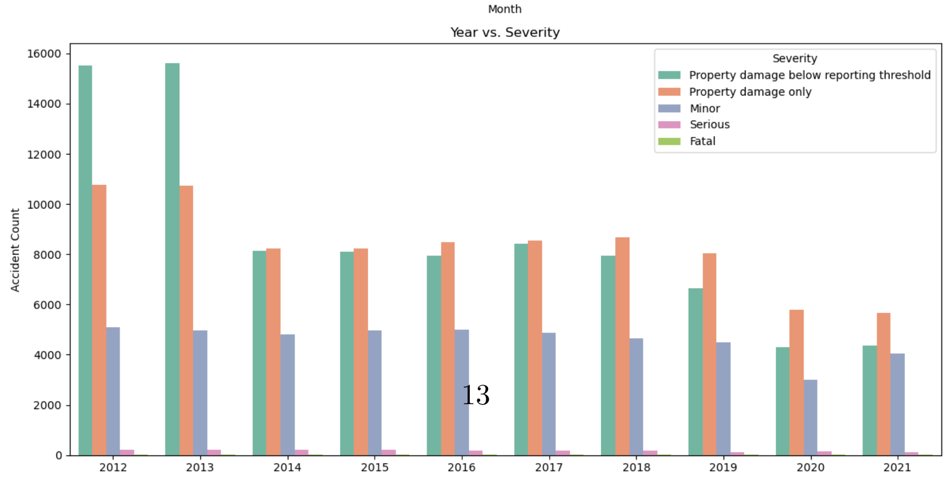
Time-related variables 1. Hourly Distribution 2. Weekly Distribution 3. Monthly Distribution 4. Yearly Distribution

[26]:
```
hour_order = list(range(24))
weekday_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',␣
 ↪'Saturday', 'Sunday']
month_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July',␣
 ↪'August', 'September', 'October', 'November', 'December']
time_cols = ["Acc_Time", "Weekday", "Month", "Year"]

fig, axes = plt.subplots(nrows=len(time_cols), ncols=1, figsize=(12, 6 *␣
 ↪len(time_cols)))

for i, col in enumerate(time_cols):
    if col == 'Acc_Time':
        sns.countplot(x=col, hue='Severity', data=df, palette='Set2',␣
 ↪ax=axes[i], order=hour_order)
    elif col == 'Weekday':
        sns.countplot(x=col, hue='Severity', data=df, palette='Set2',␣
 ↪ax=axes[i], order=weekday_order)
    elif col == 'Month':
        sns.countplot(x=col, hue='Severity', data=df, palette='Set2',␣
 ↪ax=axes[i], order=month_order)
    else:
        sns.countplot(x=col, hue='Severity', data=df, palette='Set2',␣
 ↪ax=axes[i])

    axes[i].set_title(f'{col} vs. Severity')
    axes[i].set_xlabel(col)
    axes[i].set_ylabel('Accident Count')
    axes[i].tick_params(axis='x')

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


Acc_Time vs. Severity
Severity
Property damage below reporting threshold
Property damage only
Minor
Serious
Fatal
Accident Count
0
1000
2000
3000
4000
5000
6000
7000
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
Acc_Time


Weekday vs. Severity
Severity
Property damage below reporting threshold
Property damage only
Minor
Serious
Fatal
Accident Count
0
2000
4000
6000
8000
10000
12000
14000
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Weekday


Month vs. Severity
Severity
Property damage below reporting threshold
Property damage only
Minor
Serious
Fatal
Accident Count
0
2000
4000
6000
8000
January
February
March
April
May
June
July
August
September
October
November
December
Month


Year vs. Severity
Severity
Property damage below reporting threshold
Property damage only
Minor
Serious
Fatal
Accident Count
0
2000
4000
6000
8000
10000
12000
14000
16000
2012 2013 2014 2015 2016 2017 2018 2019 2020 2021
Year

- A clear peak between 3:00 p.m. and 5:00 p.m.

  This increase mostly happens in categories like property damage below reporting threshold, property damage only, and minor accidents—probably due to the evening rush hour when traffic is heaviest. Serious accidents show a similar rise during this time, but fatal accidents don't really follow a clear pattern throughout the day. This could mean that fatal accidents are more influenced by factors other than just traffic volume, like impaired driving.

- Accidents occur most frequently during the week and peak on Friday.

  Fridays tend to see a bump as people head home from work and start their weekend plans, likely affecting traffic flow and driving habits.

- A seasonal pattern during a year.

  We see a peak in accidents in the winter months of January and February, and again in summer during June and July. The winter peak is likely due to challenging weather conditions, while the summer increase could be tied to higher travel rates. December also stands out with more accidents, probably because of the holiday travel rush around Christmas and New Year.

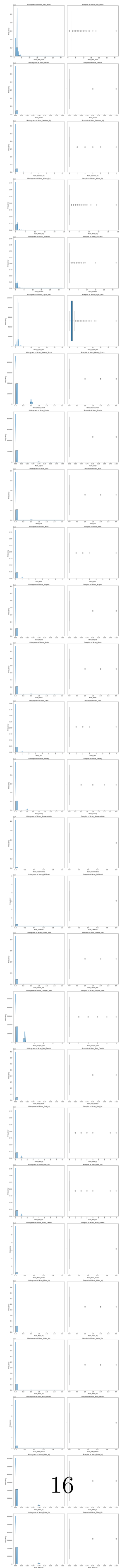
- Historical trends

  Back in 2013, the accident rate was unusually high across all categories, especially for property damage incidents. Since 2014, tho, the number of accidents has generally been declining with a few small fluctuations. There was a slight uptick in 2018 and 2019, but numbers fell sharply in 2020. Overall, Montreal's seeing a positive trend in reduced accidents, which might reflect better road safety measures. The big drop in 2020 may also have been influenced by external factors, like policy changes, advances in vehicle safety, or even the reduced traffic from the COVID-19 pandemic.

Frequency data (Discrete numerical variables)

[27]:
```python
num_columns = [col for col in df.columns if col.startswith('Num') or col.
 ↪startswith('Total')]

fig, axes = plt.subplots(nrows=len(num_columns), ncols=2, figsize=(12, 6 *␣
 ↪len(num_columns)))

for i, col in enumerate(num_columns):
    # histogram
    sns.histplot(df[col], ax=axes[i, 0], kde=True)
    axes[i, 0].set_title(f'Histogram of {col}')
    axes[i, 0].set_xlabel(col)
    axes[i, 0].set_ylabel('Frequency')

    # box plot
    sns.boxplot(x=df[col], ax=axes[i, 1])
    axes[i, 1].set_title(f'Boxplot of {col}')
    axes[i, 1].set_xlabel(col)
```

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



[28]:

```python
zero_percentage = {}
for col in num_columns:
    zero_count = (df[col] == 0).sum()
    total_count = df[col].shape[0]
    zero_percentage[col] = (zero_count / total_count) * 100

zero_percentage_df = pd.DataFrame(list(zero_percentage.items()),␣
 ↪columns=['Column', 'Zero_Percentage'])
zero_percentage_df
```

[28]:

	Column	Zero_Percentage
0	Num_Veh_Invld	0.000000
1	Num_Death	99.879429
2	Num_Serious_Inj	99.172504
3	Num_Minor_Inj	78.815191
4	Total_Victims	78.020245
5	Num_Light_Veh	7.038986
6	Num_Heavy_Truck	90.037501
7	Num_Equip	98.559103
8	Num_Bus	97.447370
9	Num_Bike	96.020227
10	Num_Moped	99.393934
11	Num_Moto	98.648958
12	Num_Taxi	96.796376
13	Num_Emerg	96.845889
14	Num_Snowmobile	99.997249
15	Num_OffRoad	99.991290
16	Num_Other_Veh	99.452615
17	Num_Unspec_Veh	81.250458
18	Num_Ped_Death	99.928482
19	Num_Ped_Inj	95.154221
20	Num_Ped_Vic	95.086371
21	Num_Moto_Death	99.992206
22	Num_Moto_Inj	99.243563
23	Num_Moto_Vic	99.235770
24	Num_Bike_Death	99.985788
25	Num_Bike_Inj	97.012763
26	Num_Bike_Vic	96.998551

Given that nearly all of these discrete numerical predictors represent count data with a significant number of zeros, where each zero carries meaningful information, we converted them into binary variables. This transformation indicates whether the associated item (e.g., number of vehicles, bikes, etc.) was involved in the collision, rather than treating the original counts as numerical values.

(Note: Using transformations like log or inverse would hinder interpretability, which is crucial for us, as our primary goal is to identify the most critical combination of factors influencing collision severity for government use. Maintaining interpretability allows us to provide clearer insights for policy and decision-making.)

This method is straightforward and interpretable, especially for highly zero-inflated count predictors. By indicating the presence or absence of a count, we simplify the information for the classifier and allow it to capture meaningful distinctions without overcomplicating the model. (Often used in classification tasks with sparse data, where zero counts are common e.g., in healthcare, fraud detection)

Use Count Models to create new features:

- Hurdle Models or Zero-Inflated Models: These can be used to pre-process the count predictors by capturing the zero-inflation and non-zero distributions separately. We can create two new features:
- A binary feature indicating whether the value is zero or non-zero.
- A transformed count for the non-zero values (using Poisson distribution or Negative Binomial distribution, check whether the mean and variance are equal.)
  - zero-inflated model: differentiates the zeros into two groups is that excessive zeros are often due to the existence of a subpopulation of subjects who are not at risk for certain outcomes during the study period.
  - hurdle model: assumes all zero data are from one "structural" source with one part of the model being a binary model for modeling whether the response variable is zero or positive, and another part using a truncated model, such as a truncated Poisson or a truncated NB distribution for the positive data.

  (Notes:

  - structural zeros (excessive zeros): subjects always produce zero counts
  - sampling zeros: subjects who are exposed to the outcome but did not or did not report the experience of the outcome during the study period)

[29]:
```
# exclude Num_Veh_Invld and Total_Victims are important variables, the remaning␣
↪variables need to be converted into binary
# Num_Death, Num_Serious_Inj, Num_Minor_Inj should also be removed since they␣
↪will become "binary severity"
# all Num variables associated with viehcle injuries / death become redundant␣
↪since Vehicle counts binary has covered them
excluded_cols = ["Num_Veh_Invld", "Total_Victims", "Num_Death",␣
↪"Num_Serious_Inj", "Num_Minor_Inj", "Num_Death", "Num_Serious_Inj",␣
↪"Num_Minor_Inj", "Total_Victims",
                 "Num_Ped_Death", "Num_Ped_Inj", "Num_Ped_Vic",␣
↪"Num_Moto_Death", "Num_Moto_Inj", "Num_Moto_Vic", "Num_Bike_Death",␣
↪"Num_Bike_Inj", "Num_Bike_Vic"]
zero_cols = zero_percentage_df.loc[~zero_percentage_df["Column"].
↪isin(excluded_cols), "Column"].tolist()
```

```python
binary_df = df[df.columns.difference(excluded_cols)].copy()

for col in zero_cols:
    binary_df[col] = (df[col] > 0).astype(int)

binary_df["Num_Veh_Invld"] = df["Num_Veh_Invld"]
binary_df["Total_Victims"] = df["Total_Victims"]

binary_df.head()
```

[29]:

```
     Acc_Date  Acc_Time  Acc_Type  Environ_Type   Latitude  Light_Cond  \
0  2012-02-01         2      31.0           1.0  45.455505         1.0
1  2012-01-03         2      31.0           NaN  45.486871         NaN
2  2012-02-24         2      31.0           3.0  45.490564         3.0
3  2012-10-11        15      31.0           3.0  45.484648         1.0
4  2012-04-22        15      31.0           3.0  45.467136         1.0

   Loc_Accuracy  Loc_Code Loc_Imprecise Loc_Quality  Lontitude     Month  \
0             3      33.0             N           A -73.861616  February
1             4       NaN             N           B -73.878549   January
2             1      32.0             O           A -73.871542  February
3             1      40.0             N           A -73.804841   October
4             1      40.0             N           A -73.543590     April

     Near_To  Num_Bike  Num_Bus  Num_Emerg  Num_Equip  Num_Heavy_Truck  \
0       STAT         0        0          0          0                0
1        NaN         0        0          0          0                0
2   CHERRIER         0        0          0          0                0
3        NaN         0        0          0          0                0
4        NaN         0        0          0          0                0

   Num_Light_Veh  Num_Moped  Num_Moto  Num_OffRoad  Num_Other_Veh  \
0              1          0         0            0              0
1              1          0         0            0              0
2              1          0         0            0              0
3              1          0         0            0              0
4              1          0         0            0              0

   Num_Snowmobile  Num_Taxi  Num_Unspec_Veh  Road_Aspect  Road_Cat  \
0               0         0               1         11.0      21.0
1               0         0               1          NaN       NaN
2               0         0               0         21.0      13.0
3               0         0               0         11.0      21.0
4               0         0               1         11.0      21.0

   Road_Config            Seq_Num  \
0          4.0      SPVM _ 2012 _ 1
```

```
1          NaN     SPVM _ 2012 _ 10
2          1.0    SPVM _ 2012 _ 100
3          2.0   SPVM _ 2012 _ 1000
4          NaN  SPVM _ 2012 _ 10000

                                 Severity  Speed_Limit             Street  \
0  Property damage below reporting threshold          NaN        ST CHARLES
1                      Property damage only          NaN  TERR VILLE DE MTL
2  Property damage below reporting threshold         50.0     JACQUES BIZARD
3                      Property damage only          NaN      BD SALABERRY
4  Property damage below reporting threshold          NaN    PL DU COMMERCE

   Surface_Cond  Weather_Cond    Weekday  Year  Num_Veh_Invld  Total_Victims
0          16.0          11.0  Wednesday  2012              2              0
1          11.0          11.0    Tuesday  2012              2              0
2          11.0          11.0     Friday  2012              2              0
3          11.0          11.0   Thursday  2012              2              0
4          12.0          12.0     Sunday  2012              2              0
```

[30]:
```
new_num_columns = [col for col in binary_df.columns if col.startswith('Num') or␣
 ↪col.startswith('Total')]
severity_counts = binary_df[new_num_columns + ["Severity"]].groupby("Severity").
 ↪sum()
severity_counts
```

[30]:
```
                                           Num_Bike  Num_Bus  Num_Emerg  \
Severity
Fatal                                            31       16          3
Minor                                          6285     1857        500
Property damage below reporting threshold      1829     1888       4753
Property damage only                            257     1725       1605
Serious                                         279       82         19

                                           Num_Equip  Num_Heavy_Truck  \
Severity
Fatal                                              5               56
Minor                                            266             2169
Property damage below reporting threshold       1415             8182
Property damage only                            1441            11194
Serious                                           16              130

                                           Num_Light_Veh  Num_Moped  Num_Moto  \
Severity
Fatal                                                187          1        17
Minor                                              41966        696      1573
Property damage below reporting threshold          80170        493       770
Property damage only                               78931        100       456
```

```
Serious                                            1520         32       131

                                           Num_OffRoad  Num_Other_Veh  \
Severity
Fatal                                                0              1
Minor                                                5             63
Property damage below reporting threshold            7            661
Property damage only                                 6            467
Serious                                              1              2

                                           Num_Snowmobile  Num_Taxi  \
Severity
Fatal                                                   0        10
Minor                                                   1      2166
Property damage below reporting threshold               3      2076
Property damage only                                    2      2651
Serious                                                 0        85

                                           Num_Unspec_Veh  Num_Veh_Invld  \
Severity
Fatal                                                   4            383
Minor                                                 709          84938
Property damage below reporting threshold           26239         166422
Property damage only                                13914         170718
Serious                                                32           2901

                                           Total_Victims
Severity
Fatal                                                340
Minor                                              56205
Property damage below reporting threshold              0
Property damage only                                   0
Serious                                             2392
```

[31]:

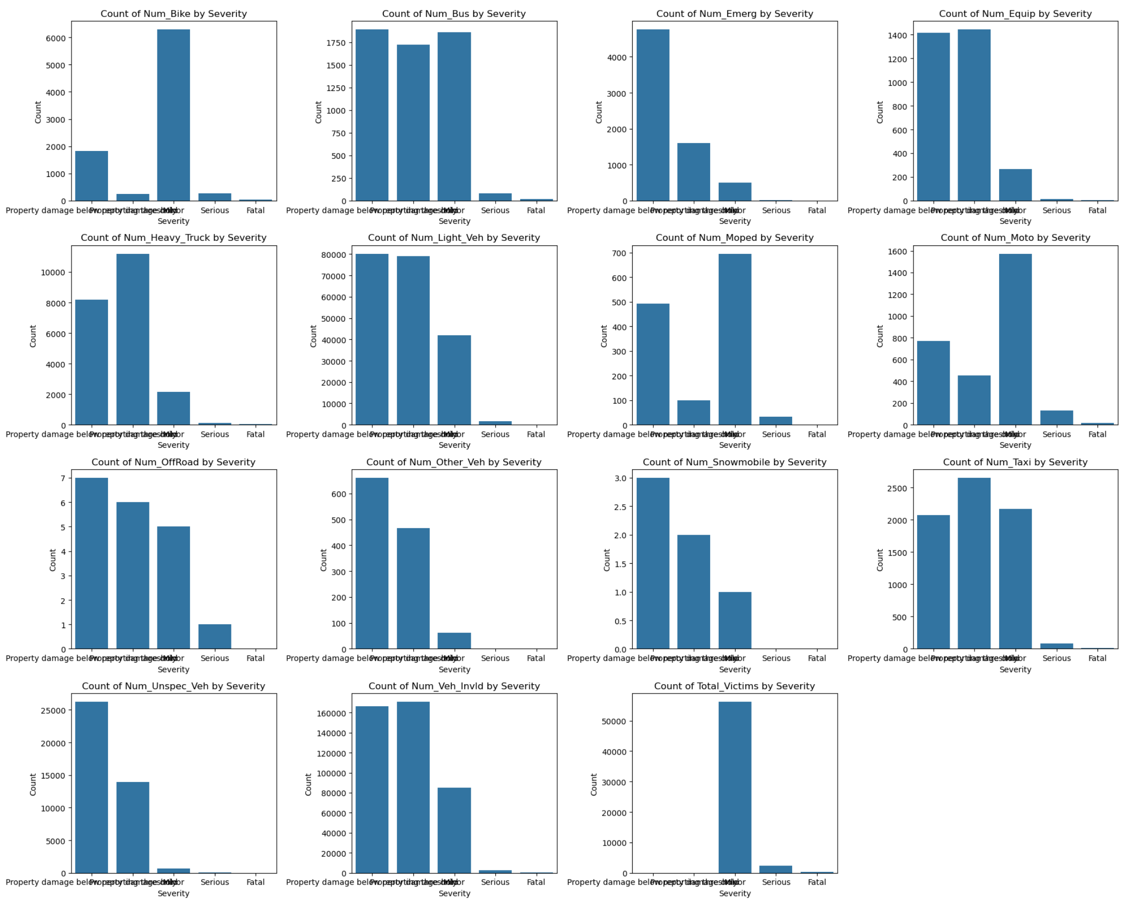
```python
import math

cols = 4
rows = math.ceil(len(new_num_columns) / cols)

fig, axes = plt.subplots(rows, cols, figsize=(20, rows * 4))
axes = axes.flatten()

for i, col in enumerate(new_num_columns):
    sns.barplot(
        data=binary_df,
        x="Severity",
        y=col,
```

```
        estimator=sum,
        ci=None,

        ax=axes[i]
    )

    axes[i].set_title(f'Count of {col} by Severity')
    axes[i].set_xlabel('Severity')
    axes[i].set_ylabel('Count')

for i in range(len(new_num_columns), len(axes)):
    fig.delaxes(axes[i])

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

```
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:
```

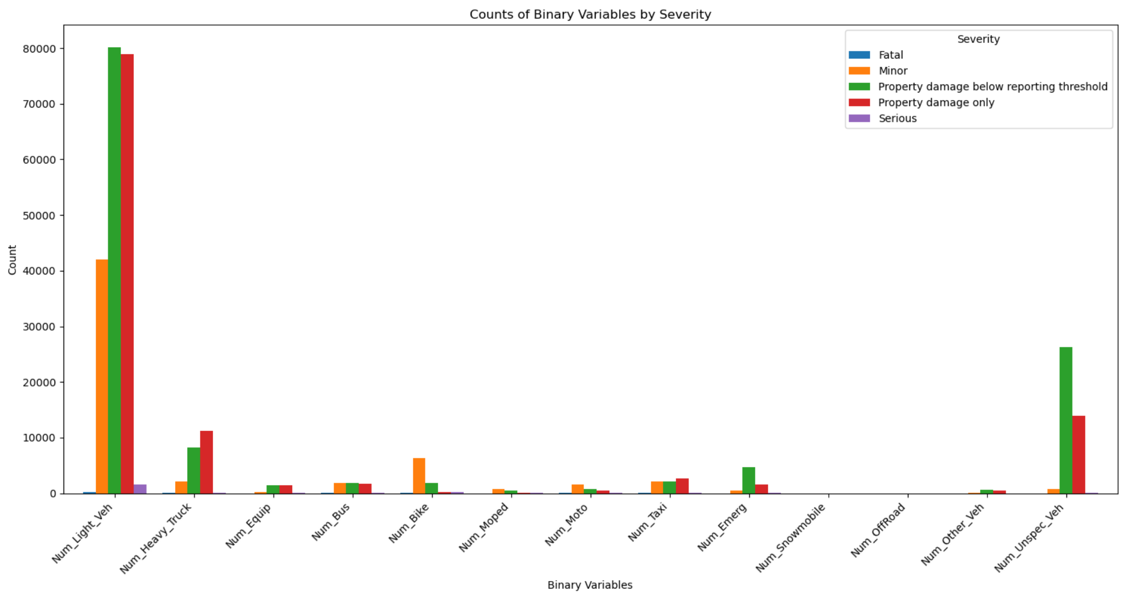
```
The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:
```

```
The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1932807899.py:1
0: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
```



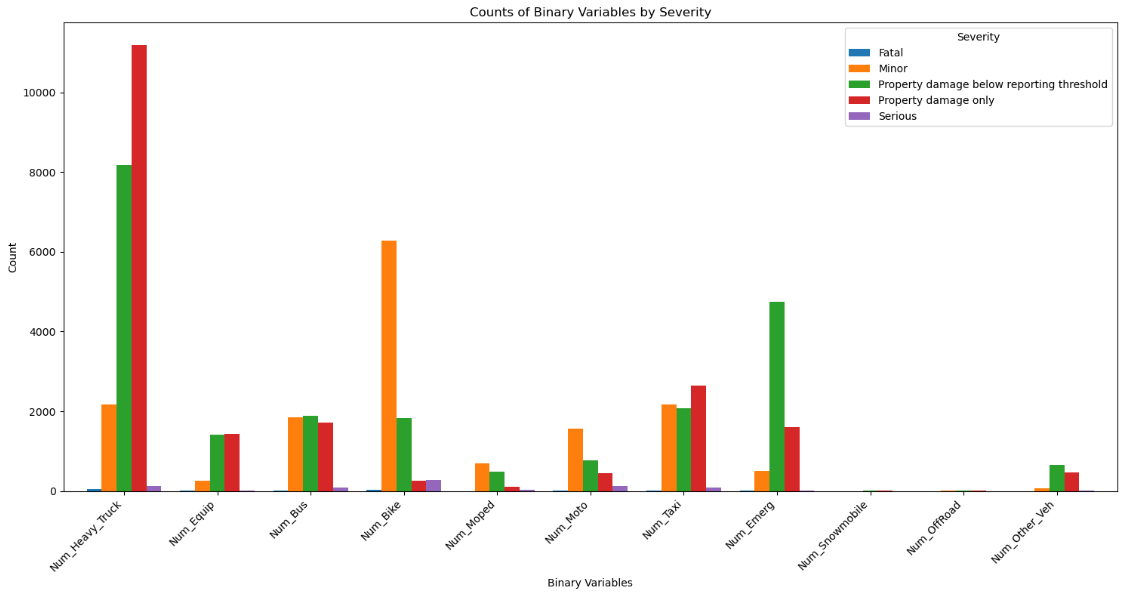
[32]:
```
severity_counts = binary_df.groupby("Severity")[zero_cols].sum().T
severity_counts.plot(kind="bar", figsize=(15, 8), width=0.8)

plt.title("Counts of Binary Variables by Severity")
plt.xlabel("Binary Variables")
plt.ylabel("Count")
plt.xticks(rotation=45, ha="right")
plt.legend(title="Severity", loc="upper right")
```

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



Exclude Num_Light_Veh, Num_Unspec_Veh for better a view at other binaries

[33]:
```
zero_cols_excld = [col for col in zero_cols if col != 'Num_Light_Veh' and col !
↪= 'Num_Unspec_Veh']

severity_counts = binary_df.groupby("Severity")[zero_cols_excld].sum().T

severity_counts.plot(kind="bar", figsize=(15, 8), width=0.8)

plt.title("Counts of Binary Variables by Severity")
plt.xlabel("Binary Variables")
plt.ylabel("Count")
plt.xticks(rotation=45, ha="right")
plt.legend(title="Severity", loc="upper right")

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



- Light Vehicles: Most common vehicle type, be the strongest predictor for serious/fatal outcomes
- Heavy Trucks: The second key predictor for serious/fatal outcomes despite lower absolute numbers, showing the highest proportion of severe accidents - relative to total incidents.
- Motorcycles: Similar to Heavy Trucks, showing a high proportion of serious/fatal accidents relative to total counts, despite having fewer overall incidents than many other vehicle types.
- Bicycles: Follow motocycles, demonstrating significant serious/fatal incidents relative to their total count.
- Taxi: Shows a moderate number of total incidents, with a small but notable proportion of serious/fatal outcomes.
- Bus: Has a balanced distribution across different severity levels, and shows lower proportions of fatal accidents.
- Emergency Vehicles: Despite operating in high-stress situations and high speeds, they show relatively low fatal/serious accident rates (likely due to specialized driver training and other vehicles yielding right of way).
- Equipment, Off-road vehicles, Other vehicles: Shows relatively low incident numbers overall with primarily property damage outcomes, making them less significant predictors of serious/fatal accidents.

Missing values handling Initially, I tried KNN for imputing missing values in the Street variable, because it's categorical, and KNN can work well with categorical data, especially if the dataset has other relevant features (like proximity to other locations or features that might influence the street of the accident). These features correlate with the street location. so I thought KNN can be a very robust candidate in predicting missing street values.

But!!! it's way too computationally intensive, such that 40 mins later (after brushing my teeeth and taking a bath), it's still running and showed no sign to stop.

I'm done.

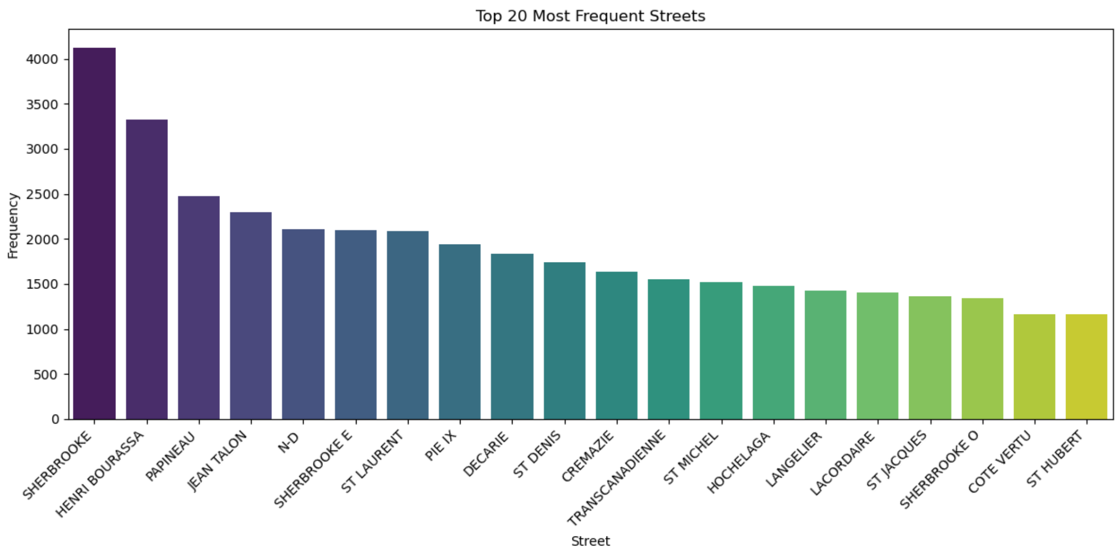
[34]:
```
for col in imp_cols:
    binary_df[col] = binary_df[col].ffill().bfill()

for col in imp_cols:
    print(f"Number of missing values in {col} after imputation:",␣
 ↪binary_df[col].isna().sum())
```

```
Number of missing values in Street after imputation: 0
Number of missing values in Near_To after imputation: 0
Number of missing values in Acc_Type after imputation: 0
Number of missing values in Surface_Cond after imputation: 0
Number of missing values in Light_Cond after imputation: 0
Number of missing values in Environ_Type after imputation: 0
Number of missing values in Road_Cat after imputation: 0
Number of missing values in Road_Aspect after imputation: 0
Number of missing values in Loc_Code after imputation: 0
Number of missing values in Road_Config after imputation: 0
Number of missing values in Weather_Cond after imputation: 0
Number of missing values in Speed_Limit after imputation: 0
Number of missing values in Lontitude after imputation: 0
Number of missing values in Latitude after imputation: 0
```

Categorical Data Top 20 street

[35]:
```
top_20_streets = binary_df['Street'].value_counts().head(20)

plt.figure(figsize=(12, 6))
sns.barplot(x=top_20_streets.index, y=top_20_streets.values, palette="viridis")

plt.title('Top 20 Most Frequent Streets')
plt.xlabel('Street')
plt.ylabel('Frequency')
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for better␣
 ↪readability

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

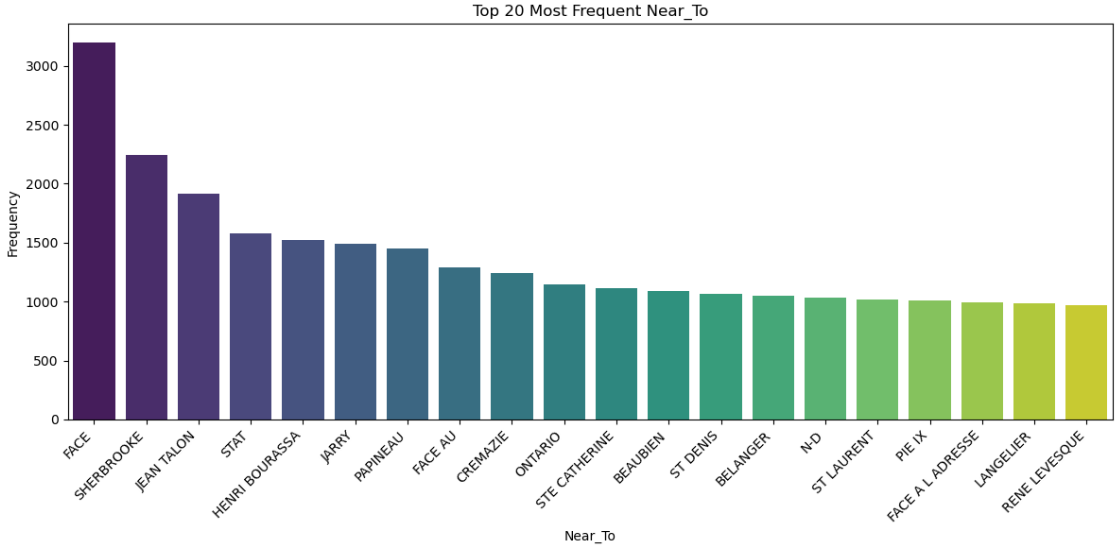
```
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/1863338866.py:4
: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=top_20_streets.index, y=top_20_streets.values,
palette="viridis")
```



Top 20 Near_To

[36]:
```
top_20_streets = binary_df['Near_To'].value_counts().head(20)

plt.figure(figsize=(12, 6))
sns.barplot(x=top_20_streets.index, y=top_20_streets.values, palette="viridis")

plt.title('Top 20 Most Frequent Near_To')
plt.xlabel('Near_To')
plt.ylabel('Frequency')
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for better␣
 ↪readability

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

```
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_81339/122408310.py:4:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=top_20_streets.index, y=top_20_streets.values,
palette="viridis")
```



[37]:
```python
Cat_lst =␣
↪['Acc_Type','Surface_Cond','Light_Cond','Environ_Type','Road_Cat','Road_Aspect','Loc_Code',
↪'Weather_Cond','Speed_Limit']

rows = len(Cat_lst)
cols = 2

plt.figure(figsize=(25, 5 * rows))

for idx, col in enumerate(Cat_lst):
    plt.subplot(rows, cols, 2*idx + 1)
    value_counts = binary_df[col].value_counts(normalize=True) * 100
    value_counts.plot(kind='bar', color='skyblue')

    plt.title(f'Percentage Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Percentage (%)')
    plt.xticks(rotation=45)

    for i, v in enumerate(value_counts):
        plt.text(i, v + 1, f'{v:.2f}%', ha='center', va='bottom', fontsize=10)

    plt.subplot(rows, cols, 2*idx + 2)
    sns.countplot(x=col, hue='Severity', data=binary_df, palette='Set2')
    plt.title(f'Distribution of {col} by Severity')
    plt.xticks(rotation=45)
    plt.xlabel(col)
    plt.ylabel('Count')
```

```
plt.subplots_adjust(hspace=0.5, wspace=0.3)

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


Percentage Distribution of Acc_Type
Distribution of Acc_Type by Severity
Percentage Distribution of Surface_Cond
Distribution of Surface_Cond by Severity
Percentage Distribution of Light_Cond
Distribution of Light_Cond by Severity
Percentage Distribution of Environ_Type
Distribution of Environ_Type by Severity
Percentage Distribution of Road_Cat
Distribution of Road_Cat by Severity
Percentage Distribution of Road_Aspect
Distribution of Road_Aspect by Severity
Percentage Distribution of Loc_Code
Distribution of Loc_Code by Severity
Percentage Distribution of Road_Config
Distribution of Road_Config by Severity
Percentage Distribution of Weather_Cond
Distribution of Weather_Cond by Severity
Percentage Distribution of Speed_Limit
Distribution of Speed_Limit by Severity
Percentage (%)
Count
Severity
Property damage below reporting threshold
Property damage only
Minor
Serious
Fatal

Here we face another problem regarding the severity. certain rare categories within the categorical variables (e.g., Road_Aspect, Surface_Cond, Weather_Cond, etc.) are strongly associated with severe or fatal accidents, so collapsing them into an "other" group will risk losing important information.

Instead, we have to retain those rarer categories while still ensuring that they do not overwhelm the model.

binary encoding for categorical variables will create too many columns, definitely not a wise choise.

So I'm thinking two approaches

1. Using models such as Random Forests, which can handle categorical variables with many levels better than traditional models (e.g., logistic regression). They don't require dummy variables but can process categorical variables directly by learning how different levels of the categories interact with the target variable.

2. Target Encoding Instead of one-hot encoding, we could replace each category with the mean of the target variable (Severity in our case).

   What do I mean by target encoding?

   In target encoding, replace each category in a categorical variable with the mean of the target variable for that category.

   1. assign weights to 5 severity levels (1 ~ 5)
   2. grouby those categories, and calculate the average Severity score for each levels in that categorical variable.
   3. Each level in that categorical variable will be replaced by the re-classified level based on 5 quantile mean Severity score for that category.

We can thus capture the relationship between categorical variable and Severity.

Target Encoding

[26]:
```
severity_mapping = {
    'Property damage below reporting threshold': 1,
    'Property damage only': 2,
    'Minor': 3,
    'Serious': 4,
    'Fatal': 5
}

binary_df['Severity_weighted'] = binary_df['Severity'].map(severity_mapping)

category_mean_severity_dfs = {}

for col in Cat_lst:
    category_mean_severity = binary_df.groupby(col)['Severity_weighted'].mean().
  ↪reset_index()
```

```
    category_mean_severity.columns = [col, 'Severity_Score']
    category_mean_severity = category_mean_severity.
 ↪sort_values(by='Severity_Score', ascending=False)

    category_mean_severity['Severity_Group'] = pd.qcut(
        category_mean_severity['Severity_Score'],
        q=5,
        labels=[
            f'{col}_Severity_level1', # Severity_Score is the lowest
            f'{col}_Severity_level2',
            f'{col}_Severity_level3',
            f'{col}_Severity_level4',
            f'{col}_Severity_level5' # Severity_Score is the highest
        ]
    )

    category_mean_severity_dfs[col] = category_mean_severity
    severity_group_mapping = dict(zip(category_mean_severity[col],␣
 ↪category_mean_severity['Severity_Group']))
    binary_df[col] = binary_df[col].map(severity_group_mapping)


binary_df.drop(columns=["Severity_weighted"], inplace=True)
print(binary_df.head())
```

```
    Acc_Date  Acc_Time                  Acc_Type  \
0 2012-02-01         2  Acc_Type_Severity_level2
1 2012-01-03         2  Acc_Type_Severity_level2
2 2012-02-24         2  Acc_Type_Severity_level2
3 2012-10-11        15  Acc_Type_Severity_level2
4 2012-04-22        15  Acc_Type_Severity_level2

                 Environ_Type   Latitude                Light_Cond  \
0  Environ_Type_Severity_level3  45.455505  Light_Cond_Severity_level4
1  Environ_Type_Severity_level3  45.486871  Light_Cond_Severity_level4
2  Environ_Type_Severity_level1  45.490564  Light_Cond_Severity_level5
3  Environ_Type_Severity_level1  45.484648  Light_Cond_Severity_level4
4  Environ_Type_Severity_level1  45.467136  Light_Cond_Severity_level4

   Loc_Accuracy                  Loc_Code Loc_Imprecise Loc_Quality  \
0             3  Loc_Code_Severity_level2             N           A
1             4  Loc_Code_Severity_level2             N           B
2             1  Loc_Code_Severity_level5             O           A
3             1  Loc_Code_Severity_level1             N           A
4             1  Loc_Code_Severity_level1             N           A
```

```
   Lontitude     Month   Near_To  Num_Bike  Num_Bus  Num_Emerg  Num_Equip  \
0 -73.861616  February      STAT         0        0          0          0
1 -73.878549   January      STAT         0        0          0          0
2 -73.871542  February  CHERRIER         0        0          0          0
3 -73.804841   October  CHERRIER         0        0          0          0
4 -73.543590     April  CHERRIER         0        0          0          0

   Num_Heavy_Truck  Num_Light_Veh  Num_Moped  Num_Moto  Num_OffRoad  \
0                0              1          0         0            0
1                0              1          0         0            0
2                0              1          0         0            0
3                0              1          0         0            0
4                0              1          0         0            0

   Num_Other_Veh  Num_Snowmobile  Num_Taxi  Num_Unspec_Veh  \
0              0               0         0               1
1              0               0         0               1
2              0               0         0               0
3              0               0         0               0
4              0               0         0               1

                 Road_Aspect                  Road_Cat  \
0  Road_Aspect_Severity_level1  Road_Cat_Severity_level1
1  Road_Aspect_Severity_level1  Road_Cat_Severity_level1
2  Road_Aspect_Severity_level2  Road_Cat_Severity_level5
3  Road_Aspect_Severity_level1  Road_Cat_Severity_level1
4  Road_Aspect_Severity_level1  Road_Cat_Severity_level1

                 Road_Config              Seq_Num  \
0  Road_Config_Severity_level5      SPVM _ 2012 _ 1
1  Road_Config_Severity_level5     SPVM _ 2012 _ 10
2  Road_Config_Severity_level1    SPVM _ 2012 _ 100
3  Road_Config_Severity_level2   SPVM _ 2012 _ 1000
4  Road_Config_Severity_level2  SPVM _ 2012 _ 10000

                                  Severity                 Speed_Limit  \
0  Property damage below reporting threshold  Speed_Limit_Severity_level4
1                       Property damage only  Speed_Limit_Severity_level4
2  Property damage below reporting threshold  Speed_Limit_Severity_level4
3                       Property damage only  Speed_Limit_Severity_level4
4  Property damage below reporting threshold  Speed_Limit_Severity_level4

              Street                  Surface_Cond  \
0         ST CHARLES  Surface_Cond_Severity_level1
1  TERR VILLE DE MTL  Surface_Cond_Severity_level3
2     JACQUES BIZARD  Surface_Cond_Severity_level3
3       BD SALABERRY  Surface_Cond_Severity_level3
4     PL DU COMMERCE  Surface_Cond_Severity_level4
```

```
                Weather_Cond    Weekday  Year  Num_Veh_Invld  Total_Victims
0  Weather_Cond_Severity_level4  Wednesday  2012              2              0
1  Weather_Cond_Severity_level4    Tuesday  2012              2              0
2  Weather_Cond_Severity_level4     Friday  2012              2              0
3  Weather_Cond_Severity_level4   Thursday  2012              2              0
4  Weather_Cond_Severity_level3     Sunday  2012              2              0
```

Here are the 5 quantile classification for each categorical variable (***Export them to excel)

[27]:
```
category_mean_severity_dfs
```

[27]:
```
{'Acc_Type':     Acc_Type  Severity_Score            Severity_Group
 1       32.0        2.739193  Acc_Type_Severity_level5
 27      72.0        2.641791  Acc_Type_Severity_level5
 2       33.0        2.546854  Acc_Type_Severity_level5
 26      71.0        2.462810  Acc_Type_Severity_level5
 31      99.0        2.240868  Acc_Type_Severity_level5
 28      73.0        2.161290  Acc_Type_Severity_level5
 13      44.0        2.154412  Acc_Type_Severity_level5
 30      75.0        2.115819  Acc_Type_Severity_level4
 14      45.0        2.101449  Acc_Type_Severity_level4
 9       40.0        2.077288  Acc_Type_Severity_level4
 15      46.0        2.064935  Acc_Type_Severity_level4
 12      43.0        2.043404  Acc_Type_Severity_level4
 16      47.0        2.038217  Acc_Type_Severity_level4
 3       34.0        2.030303  Acc_Type_Severity_level3
 5       36.0        2.000000  Acc_Type_Severity_level3
 29      74.0        1.969697  Acc_Type_Severity_level3
 10      41.0        1.871104  Acc_Type_Severity_level3
 18      49.0        1.850514  Acc_Type_Severity_level3
 19      50.0        1.823419  Acc_Type_Severity_level3
 11      42.0        1.806617  Acc_Type_Severity_level2
 23      54.0        1.772727  Acc_Type_Severity_level2
 22      53.0        1.771186  Acc_Type_Severity_level2
 20      51.0        1.736264  Acc_Type_Severity_level2
 0       31.0        1.725587  Acc_Type_Severity_level2
 21      52.0        1.725490  Acc_Type_Severity_level2
 4       35.0        1.721154  Acc_Type_Severity_level1
 24      55.0        1.677419  Acc_Type_Severity_level1
 25      59.0        1.642959  Acc_Type_Severity_level1
 7       38.0        1.525210  Acc_Type_Severity_level1
 8       39.0        1.508227  Acc_Type_Severity_level1
 17      48.0        1.503030  Acc_Type_Severity_level1
 6       37.0        1.397351  Acc_Type_Severity_level1,
 'Surface_Cond':     Surface_Cond  Severity_Score                Severity_Group
 9           20.0        2.472222  Surface_Cond_Severity_level5
 2           13.0        1.989933  Surface_Cond_Severity_level5
```

```
3           14.0        1.920690  Surface_Cond_Severity_level4
1           12.0        1.905889  Surface_Cond_Severity_level4
0           11.0        1.843799  Surface_Cond_Severity_level3
7           18.0        1.840281  Surface_Cond_Severity_level3
4           15.0        1.834775  Surface_Cond_Severity_level2
8           19.0        1.684932  Surface_Cond_Severity_level2
6           17.0        1.670228  Surface_Cond_Severity_level1
5           16.0        1.653157  Surface_Cond_Severity_level1
10          99.0        1.496134  Surface_Cond_Severity_level1,
'Light_Cond':    Light_Cond  Severity_Score             Severity_Group
2         3.0        1.876115  Light_Cond_Severity_level5
0         1.0        1.816334  Light_Cond_Severity_level4
1         2.0        1.808461  Light_Cond_Severity_level2
3         4.0        1.735686  Light_Cond_Severity_level1,
'Environ_Type':    Environ_Type  Severity_Score               Severity_Group
5           6.0        2.069444  Environ_Type_Severity_level5
4           5.0        1.998473  Environ_Type_Severity_level5
3           4.0        1.963267  Environ_Type_Severity_level4
6           7.0        1.916392  Environ_Type_Severity_level3
0           1.0        1.839724  Environ_Type_Severity_level3
1           2.0        1.828747  Environ_Type_Severity_level2
2           3.0        1.820845  Environ_Type_Severity_level1
7           9.0        1.665035  Environ_Type_Severity_level1,
'Road_Cat':     Road_Cat  Severity_Score            Severity_Group
2       13.0        2.006421  Road_Cat_Severity_level5
1       12.0        1.960662  Road_Cat_Severity_level5
0       11.0        1.910992  Road_Cat_Severity_level5
9       23.0        1.905512  Road_Cat_Severity_level4
4       15.0        1.904675  Road_Cat_Severity_level4
6       19.0        1.800940  Road_Cat_Severity_level3
3       14.0        1.743489  Road_Cat_Severity_level3
8       22.0        1.585790  Road_Cat_Severity_level3
12      29.0        1.576108  Road_Cat_Severity_level2
11      25.0        1.562500  Road_Cat_Severity_level2
5       16.0        1.482346  Road_Cat_Severity_level1
7       21.0        1.413874  Road_Cat_Severity_level1
10      24.0        1.289474  Road_Cat_Severity_level1,
'Road_Aspect':    Road_Aspect  Severity_Score              Severity_Group
5         22.0        2.064877  Road_Aspect_Severity_level5
7         24.0        2.064815  Road_Aspect_Severity_level5
3         14.0        2.027413  Road_Aspect_Severity_level4
6         23.0        1.992849  Road_Aspect_Severity_level3
1         12.0        1.957976  Road_Aspect_Severity_level3
4         21.0        1.928374  Road_Aspect_Severity_level2
2         13.0        1.885874  Road_Aspect_Severity_level1
0         11.0        1.821088  Road_Aspect_Severity_level1,
'Loc_Code':     Loc_Code  Severity_Score            Severity_Group
```

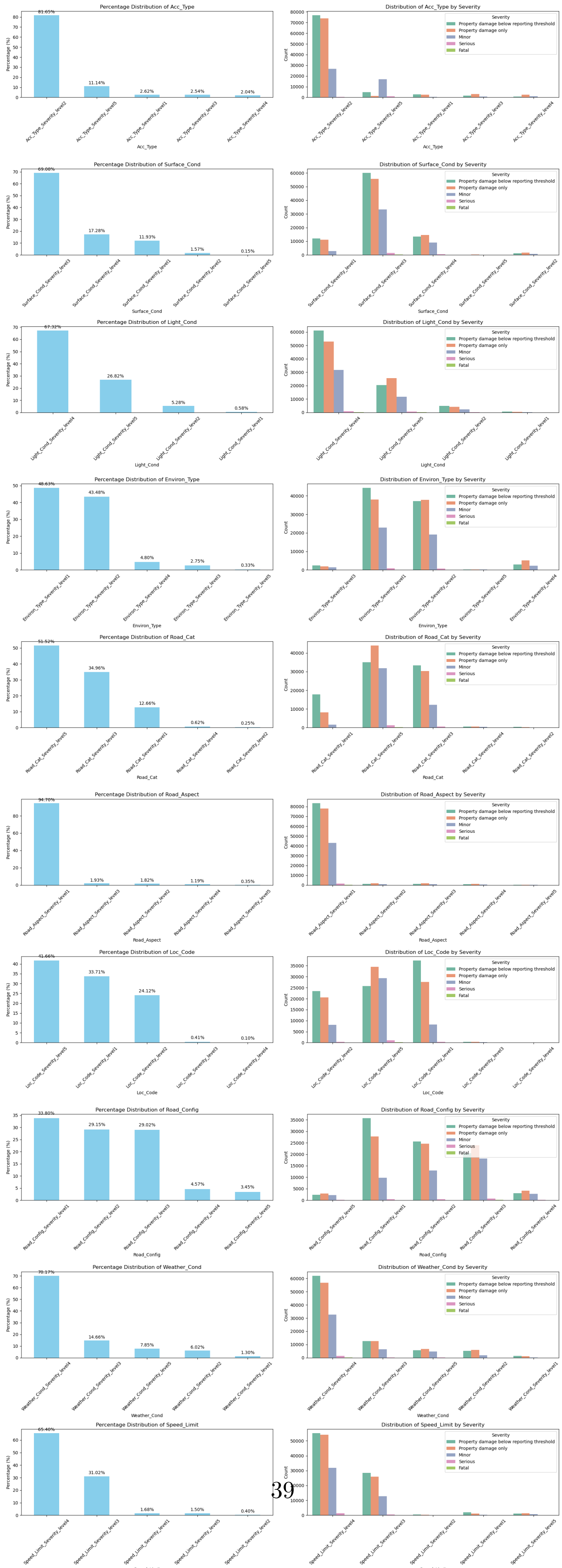
```
2       32.0        2.067996  Loc_Code_Severity_level5
0        0.0        2.000000  Loc_Code_Severity_level5
7       37.0        1.998861  Loc_Code_Severity_level5
6       36.0        1.978102  Loc_Code_Severity_level4
8       38.0        1.945652  Loc_Code_Severity_level4
9       39.0        1.889408  Loc_Code_Severity_level3
5       35.0        1.815574  Loc_Code_Severity_level3
1       31.0        1.766497  Loc_Code_Severity_level2
3       33.0        1.721683  Loc_Code_Severity_level2
4       34.0        1.707890  Loc_Code_Severity_level1
11      99.0        1.539499  Loc_Code_Severity_level1
10      40.0        1.441352  Loc_Code_Severity_level1,
'Road_Config':    Road_Config  Severity_Score               Severity_Group
3          4.0        2.025491  Road_Config_Severity_level5
4          5.0        2.007317  Road_Config_Severity_level4
2          3.0        1.991707  Road_Config_Severity_level3
1          2.0        1.818822  Road_Config_Severity_level2
0          1.0        1.703022  Road_Config_Severity_level1
5          9.0        1.488413  Road_Config_Severity_level1,
'Weather_Cond':    Weather_Cond  Severity_Score                Severity_Group
4          15.0        2.078061  Weather_Cond_Severity_level5
3          14.0        1.957197  Weather_Cond_Severity_level5
5          16.0        1.840517  Weather_Cond_Severity_level4
0          11.0        1.827586  Weather_Cond_Severity_level4
1          12.0        1.826797  Weather_Cond_Severity_level3
2          13.0        1.817629  Weather_Cond_Severity_level3
8          19.0        1.816143  Weather_Cond_Severity_level2
6          17.0        1.758682  Weather_Cond_Severity_level2
7          18.0        1.757225  Weather_Cond_Severity_level1
9          99.0        1.420846  Weather_Cond_Severity_level1,
'Speed_Limit':     Speed_Limit  Severity_Score               Severity_Group
6          60.0        1.953795  Speed_Limit_Severity_level5
7          70.0        1.908558  Speed_Limit_Severity_level5
5          50.0        1.859091  Speed_Limit_Severity_level4
9          90.0        1.838983  Speed_Limit_Severity_level4
3          30.0        1.809649  Speed_Limit_Severity_level3
4          40.0        1.777470  Speed_Limit_Severity_level3
8          80.0        1.736264  Speed_Limit_Severity_level2
2          20.0        1.673548  Speed_Limit_Severity_level2
10        100.0        1.666667  Speed_Limit_Severity_level1
0           0.0        1.570766  Speed_Limit_Severity_level1
1          10.0        1.546949  Speed_Limit_Severity_level1}
```

Key findings: (after looking into the code's meaning)

- For Surface Conditions, oily and water accumulation conditions are most severe
- In Lighting Conditions, illuminated night paths show highest severity
- Rural and forestry environments show highest severity scores

- Main arteries and numbered roads have higher severity levels
- Curved roads, especially at slope transitions, are most dangerous
- Intersections and bridges show higher severity scores
- Roads with crossable fittings show highest severity in configuration
- Heavy rain and shower conditions are most severe
- Moderate speed limits (60-70 km/h) show higher severity than very high speeds
- Pedestrian and cyclist collisions show the highest severity scores

[28]:
```
rows = len(Cat_lst)
cols = 2

plt.figure(figsize=(18, 5 * rows))

for idx, col in enumerate(Cat_lst):
    plt.subplot(rows, cols, 2*idx + 1)
    value_counts = binary_df[col].value_counts(normalize=True) * 100
    value_counts.plot(kind='bar', color='skyblue')

    plt.title(f'Percentage Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Percentage (%)')
    plt.xticks(rotation=45)

    for i, v in enumerate(value_counts):
        plt.text(i, v + 1, f'{v:.2f}%', ha='center', va='bottom', fontsize=10)

    plt.subplot(rows, cols, 2*idx + 2)
    sns.countplot(x=col, hue='Severity', data=binary_df, palette='Set2')
    plt.title(f'Distribution of {col} by Severity')
    plt.xticks(rotation=45)
    plt.xlabel(col)
    plt.ylabel('Count')

plt.subplots_adjust(hspace=0.5, wspace=0.3)

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


Percentage Distribution of Acc_Type
81.65%
11.14%
2.62%
2.54%
2.04%
Distribution of Acc_Type by Severity
Severity
Property damage below reporting threshold
Property damage only
Minor
Serious
Fatal
Percentage Distribution of Surface_Cond
69.08%
17.28%
11.93%
1.57%
0.15%
Distribution of Surface_Cond by Severity
Percentage Distribution of Light_Cond
67.32%
26.82%
5.28%
0.58%
Distribution of Light_Cond by Severity
Percentage Distribution of Environ_Type
48.63%
43.48%
4.80%
2.75%
0.33%
Distribution of Environ_Type by Severity
Percentage Distribution of Road_Cat
51.52%
34.96%
12.66%
0.62%
0.25%
Distribution of Road_Cat by Severity
Percentage Distribution of Road_Aspect
94.70%
1.93%
1.82%
1.19%
0.35%
Distribution of Road_Aspect by Severity
Percentage Distribution of Loc_Code
41.66%
33.71%
24.12%
0.41%
0.10%
Distribution of Loc_Code by Severity
Percentage Distribution of Road_Config
33.80%
29.15%
29.02%
4.57%
3.45%
Distribution of Road_Config by Severity
Percentage Distribution of Weather_Cond
70.17%
14.66%
7.85%
6.02%
1.30%
Distribution of Weather_Cond by Severity
Percentage Distribution of Speed_Limit
65.40%
31.02%
1.68%
1.50%
0.40%
Distribution of Speed_Limit by Severity

(The insight below is from the re-classified levels' meaning. Refer to Appendix table 1)

Critical Road conditions & Infrastructure asscociated with serious/fatal accidences

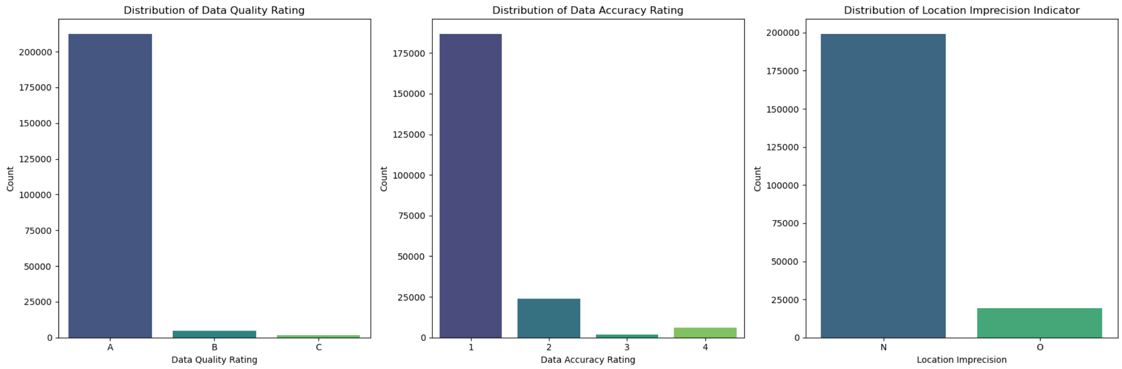
- Acc_Type (Level 5)
  - Pedestrian collision (32), No collision: rollover (72), Cyclist collision (33), Without collision: rollover (71), Other (99), Without collision: submersion (73), Fixed object: guardrail section (44) –> Pedestrian collisions and cyclist collisions show the highest severity scores. Rollover incidents (both with and without prior collision.) Collisions with fixed objects like guardrails and impact attenuators
- Surface_Cond (Level 3, 4)
  - Dried (11), Icy (18)
  - Wet (12), Sand/gravel on road (14)
- Light_Cond (Level 1, 2)
  - Night and illuminated path (3)
  - Day and light (1)
- Environ_Type (Level 3)
  - Business/commercial (3), Other (9), Residential (2)
- Road_Cat (Level 5, 3)
  - Public road: main artery (13), numbered road (12), highway ramp (11)
  - Public road: other (19), residential street (14), Off public roads: private land (22)
- Road_Aspect (Level 1)
  - Straight down slope (13), Straight flat (11)
- Loc_Code (Level 1, 2, 5)
  - Between intersections (34), Other (99), Shopping center (40)
  - Traffic circle (31), Near intersection (33)
  - Intersection (32), Not specified (0), Other bridge/viaduct (37)
- Road_Config (Level 1, 2, 3)
  - One way (1), Other (9)
  - Two directions, one lane per direction (2)
  - Two directions, multiple lanes per direction (3)
- Weather_Cond (Level 4)
  - Strong wind (16), Clear (11)
- Speed_Limit (Level 3, 4)
  - 30 km/h, 40 km/h
  - 50 km/h, 90 km/h

Geolocation Quality

[29]:
```python
fig, axes = plt.subplots(1, 3, figsize=(18, 6))

# Data Quality Rating
sns.countplot(data=binary_df, x='Loc_Quality', ax=axes[0], palette='viridis')
axes[0].set_title('Distribution of Data Quality Rating')
axes[0].set_xlabel('Data Quality Rating')
axes[0].set_ylabel('Count')
```

```
# Data Accuracy Rating
sns.countplot(data=binary_df, x='Loc_Accuracy', ax=axes[1], palette='viridis')
axes[1].set_title('Distribution of Data Accuracy Rating')
axes[1].set_xlabel('Data Accuracy Rating')
axes[1].set_ylabel('Count')

# Location Imprecision Indicator
sns.countplot(data=binary_df, x='Loc_Imprecise', ax=axes[2], palette='viridis')
axes[2].set_title('Distribution of Location Imprecision Indicator')
axes[2].set_xlabel('Location Imprecision')
axes[2].set_ylabel('Count')

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

```
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_31500/3176920429.py:4
: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(data=binary_df, x='Loc_Quality', ax=axes[0], palette='viridis')
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_31500/3176920429.py:1
0: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(data=binary_df, x='Loc_Accuracy', ax=axes[1], palette='viridis')
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_31500/3176920429.py:1
6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(data=binary_df, x='Loc_Imprecise', ax=axes[2],
palette='viridis')
```



Good news is that most data are reliable combination(A, 1, N).

But there's still some problematic data, and in order to capture those imperfection while also reducing the complexity of model, I converted them into weighted scores to dimentionality purpose. This approach allows us to condense multiple related features into a single, simplify the model without the lost of the underlying information.

[30]:
```
binary_df['Loc_Quality'] = binary_df['Loc_Quality'].map({'A': 3/3, 'B': 2/3, 'C': 1/3})
binary_df['Loc_Accuracy'] = binary_df['Loc_Accuracy'].map({1: 4/4, 2: 3/4, 3: 2/4, 4: 1/4})
binary_df['Loc_Imprecise'] = binary_df['Loc_Imprecise'].map({'O': 1/2, 'N': 1/1})
binary_df["Credibility_Score"] = binary_df['Loc_Quality'] * binary_df['Loc_Accuracy'] * binary_df["Loc_Imprecise"]

binary_df["Credibility_Score"].head()
```

[30]:
```
0    0.500000
1    0.166667
2    0.500000
3    1.000000
4    1.000000
Name: Credibility_Score, dtype: float64
```

[31]:
```
binary_df.drop(columns=["Loc_Quality", "Loc_Accuracy", "Loc_Imprecise"], inplace=True)
binary_df["Credibility_Score"].value_counts()
```

[31]:
```
Credibility_Score
1.000000    171325
0.750000     20152
0.500000     16684
0.166667      4509
```

```
0.375000      3803
0.083333      1477
0.250000       178
Name: count, dtype: int64
```

Credibility_Score to be left-skewed. But this distribution aligns with the real-world meaning of our data, then it's okay to keep it as is.

Tree-based models (e.g., Decision Trees, RF, XGBoost…) handle skewed data quite well. These models are not affected by skewness since they split data based on conditions and don't rely on assumptions of normality.

We can still use Llinear models, but they are sensitive to skewed data. If we consider using a linear model, we should consider applying transformations (log transformation, Box-Cox, inverse X) to reduce skewness.

Numerical data Lontitude, Latitude, Credibility_Score, Total_Victims, Num_Veh_Invld

[32]:
```
num_cols = ['Lontitude', 'Latitude', 'Credibility_Score', 'Total_Victims',␣
 ↪'Num_Veh_Invld']

n_cols = 2
n_rows = math.ceil(len(num_cols) / n_cols)

fig, axes = plt.subplots(n_rows, n_cols, figsize=(14, n_rows * 6))
axes = axes.flatten()

for i, col in enumerate(num_cols):
    sns.boxplot(x='Severity', y=col, data=binary_df, palette="Set3", ax=axes[i])
    axes[i].set_title(f'Box Plot of {col} by Severity Levels')
    axes[i].set_xlabel('Severity')
    axes[i].set_ylabel(col)
    axes[i].tick_params(axis='x', rotation=45)

for j in range(i + 1, n_rows * n_cols):
    fig.delaxes(axes[j])

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

```
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_31500/2449319953.py:1
0: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(x='Severity', y=col, data=binary_df, palette="Set3", ax=axes[i])
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_31500/2449319953.py:1
```

```
0: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(x='Severity', y=col, data=binary_df, palette="Set3", ax=axes[i])
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_31500/2449319953.py:1
0: FutureWarning:

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effect.

  sns.boxplot(x='Severity', y=col, data=binary_df, palette="Set3", ax=axes[i])
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_31500/2449319953.py:1
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effect.

  sns.boxplot(x='Severity', y=col, data=binary_df, palette="Set3", ax=axes[i])
/var/folders/zk/tdbf0qq57717wv6g_psgrjk40000gn/T/ipykernel_31500/2449319953.py:1
0: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(x='Severity', y=col, data=binary_df, palette="Set3", ax=axes[i])
```
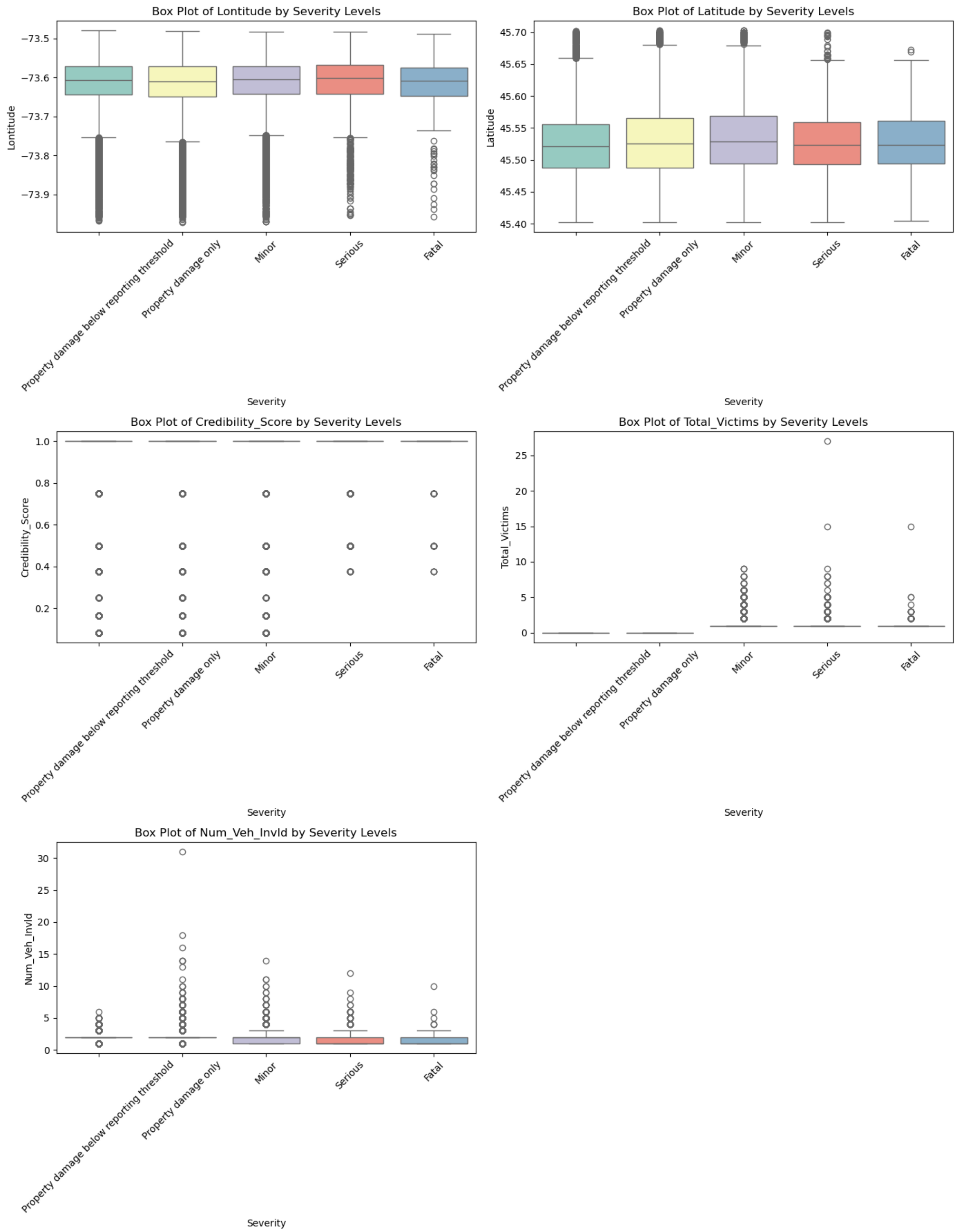



- Latitude and Longtitude: It's reasonable there's minimal variation across severity levels, because we only focus on Montreal.
- Credibility_Score: The distribution is quite similar across all severity levels, since most of the data quality is good.

- Total_Victims: Minor, Serious, Fatal tend to have cases with more victims. Strong positive relationship with severity, more victims generally indicates higher severity. Likely a good predictor.
- Num_Veh_Invld: Though most accidents across all categories involve 1-5 vehicles, higher severity levels tend to have more cases with multiple vehicles involved. Likely a good predictor.

Summary of the relationship between target and each predictors Longitude and Latitude: - Minimal variation in severity across Montreal's focused location. - Potential for increased predictive value if transformed into location-based categories (e.g., intersections or high-risk zones) when combined with road features.

Credibility_Score: - No clear relationship with accident severity. - May serve better as a data quality indicator or weighting factor in analysis to account for data accuracy.

Total_Victims and Num_Veh_Invld: - Strongest predictors of accident severity. - Higher counts correlate with increased severity, indicating a direct relationship between the number of victims/vehicles and accident impact.

Critical Road Conditions and Infrastructure: - Accident Types: Pedestrian and cyclist collisions, rollovers, and collisions with fixed objects (e.g., guardrails) are linked to higher severity. - Surface Conditions: Icy or gravel-covered roads are associated with severe outcomes, as well as nighttime or illuminated conditions in business/commercial areas. - Road Categories: Main arteries, numbered roads, and highway ramps show higher severity, likely due to increased speeds and traffic volumes. - Road Configuration: One-way streets and two-lane, two-directional roads are notably associated with higher severity scores.

Vehicle Types: - Light vehicles are most commonly involved in accidents and strongly predict serious outcomes. - Heavy trucks and motorcycles have the highest proportions of severe accidents relative to their counts, indicating elevated risks. - Bicycles and taxis also show significant serious and fatal outcomes relative to total incidents.

Time-Related Variables: - Hourly Pattern: Clear peak between 3:00 p.m. and 5:00 p.m., with minor and property damage incidents often occurring during rush hour; serious accidents follow a similar pattern, though fatal accidents lack a consistent daily pattern (suggesting factors like impaired driving). - Weekly and Monthly Trends: Fridays see increased accidents, likely due to end-of-week traffic flow changes. - Weekly and Monthly Trends: Peaks in January, February, June, and July due to winter weather and summer travel rates, with a December spike tied to holiday travel. - Historical Trends: Overall downward trend in accidents since 2013, with a notable drop in 2020 (likely due to pandemic-related factors and improved road safety). Minor fluctuations with slight increases in 2018 and 2019 within the broader trend of reduced accidents.

Potential Kkey predictors from EDA:

Acc_Type, Surface_Cond, Light_Cond, Road_Cat, Road_Config, Num_Heavy_Truck, Num_Moto, Num_Bike, Num_Taxi, Num_Veh_Invld, Total_Victims, Speed_Limit, Weather_Cond

[ ]:
```
# binary_df.to_excel("processed_df.xlsx")
```

0.0.1 Feature selection

1. Separate method by numerical and categorical predictors
   - Numerical predictors - ANOVA
   - Categorical predictors - Chi-Square test
   - Pearson Correlation MAtrix
2. Combine results using a RF model (feature importance)

Correlation between variables Numerical predictors

Check their relationships with the target variable by using ANOVA F-test.

[34]:
```
from scipy.stats import f_oneway

Num_time_cols = ['Year', 'Acc_Time']

New_num_cols = Num_time_cols + num_cols

for col in Num_time_cols:
    binary_df[col] = binary_df[col].astype('int')

binary_df['Severity'] = binary_df['Severity'].astype('category')

for col in New_num_cols:
    groups = [binary_df[binary_df['Severity'] == level][col] for level in␣
 ↪binary_df['Severity'].cat.categories]
    f_stat, p_val = f_oneway(*groups)
    print(f"ANOVA for {col}: F-statistic = {f_stat}, p-value = {p_val}")
```

```
ANOVA for Year: F-statistic = 772.8234779178508, p-value = 0.0
ANOVA for Acc_Time: F-statistic = 154.02596130943869, p-value =
7.800963306823726e-132
ANOVA for Lontitude: F-statistic = 35.90670884973424, p-value =
4.830834107306805e-30
ANOVA for Latitude: F-statistic = 147.1267964732364, p-value =
7.053481267002212e-126
ANOVA for Credibility_Score: F-statistic = 23.28632794264611, p-value =
2.852632394247448e-19
ANOVA for Total_Victims: F-statistic = 176980.22107702174, p-value = 0.0
ANOVA for Num_Veh_Invld: F-statistic = 1275.8127938373611, p-value = 0.0
```

Categorical Variables

Chi-Square Test: For each categorical predictor, calculate the Chi-square statistic between the feature and the target variable. Use this because our target is categorical, we need this for testing associations between varibales.

[35]:
```
from scipy.stats import chi2_contingency

Cat_time_cols = ['Month', 'Weekday']
```

```python
binary_cols = [col for col in binary_df.columns if col.startswith('Num')]
New_cat_cols = Cat_lst + Cat_time_cols + binary_cols

for col in New_cat_cols:
    binary_df[col] = binary_df[col].astype('category')

for col in New_cat_cols:
    contingency_table = pd.crosstab(binary_df[col], binary_df['Severity'])

    chi2_stat, p_val, dof, expected = chi2_contingency(contingency_table)

    print(f"Chi-Square test for {col} and {'Severity'}:")
    print(f"Chi2-statistic = {chi2_stat}, p-value = {p_val}, Degrees of Freedom␣
 ↪= {dof}")
    print("\n")
```

```
Chi-Square test for Acc_Type and Severity:
Chi2-statistic = 47584.117099284485, p-value = 0.0, Degrees of Freedom = 16


Chi-Square test for Surface_Cond and Severity:
Chi2-statistic = 2405.5493745537433, p-value = 0.0, Degrees of Freedom = 16


Chi-Square test for Light_Cond and Severity:
Chi2-statistic = 1375.11175425184, p-value = 3.227011049865598e-287, Degrees of
Freedom = 12


Chi-Square test for Environ_Type and Severity:
Chi2-statistic = 1165.3293917722751, p-value = 4.099002092017347e-238, Degrees
of Freedom = 16


Chi-Square test for Road_Cat and Severity:
Chi2-statistic = 14495.644282556343, p-value = 0.0, Degrees of Freedom = 16


Chi-Square test for Road_Aspect and Severity:
Chi2-statistic = 692.0520429535441, p-value = 6.353140973000376e-137, Degrees of
Freedom = 16


Chi-Square test for Loc_Code and Severity:
Chi2-statistic = 15492.099356113144, p-value = 0.0, Degrees of Freedom = 16


Chi-Square test for Road_Config and Severity:
```

```
Chi2-statistic = 7321.496098485598, p-value = 0.0, Degrees of Freedom = 16


Chi-Square test for Weather_Cond and Severity:
Chi2-statistic = 1339.1066946895896, p-value = 1.9920447934087697e-275, Degrees
of Freedom = 16


Chi-Square test for Speed_Limit and Severity:
Chi2-statistic = 1035.7764398380903, p-value = 2.4385074113956054e-210, Degrees
of Freedom = 16


Chi-Square test for Month and Severity:
Chi2-statistic = 1754.6916058537324, p-value = 0.0, Degrees of Freedom = 44


Chi-Square test for Weekday and Severity:
Chi2-statistic = 303.0758805918229, p-value = 4.0269645292489855e-50, Degrees of
Freedom = 24


Chi-Square test for Num_Bike and Severity:
Chi2-statistic = 15745.368902662745, p-value = 0.0, Degrees of Freedom = 4


Chi-Square test for Num_Bus and Severity:
Chi2-statistic = 582.4947496055082, p-value = 9.519691464649478e-125, Degrees of
Freedom = 4


Chi-Square test for Num_Emerg and Severity:
Chi2-statistic = 2595.449420502048, p-value = 0.0, Degrees of Freedom = 4


Chi-Square test for Num_Equip and Severity:
Chi2-statistic = 314.7470496019942, p-value = 7.132292800327274e-67, Degrees of
Freedom = 4


Chi-Square test for Num_Heavy_Truck and Severity:
Chi2-statistic = 2618.963840916215, p-value = 0.0, Degrees of Freedom = 4


Chi-Square test for Num_Light_Veh and Severity:
Chi2-statistic = 1088.9555520594417, p-value = 1.8753546623314753e-234, Degrees
of Freedom = 4
```

```
Chi-Square test for Num_Moped and Severity:
Chi2-statistic = 1001.5882405148636, p-value = 1.615855685928151e-215, Degrees
of Freedom = 4


Chi-Square test for Num_Moto and Severity:
Chi2-statistic = 2560.6132849055516, p-value = 0.0, Degrees of Freedom = 4


Chi-Square test for Num_OffRoad and Severity:
Chi2-statistic = 5.123261387644691, p-value = 0.27488232175975896, Degrees of
Freedom = 4


Chi-Square test for Num_Other_Veh and Severity:
Chi2-statistic = 220.4765861109244, p-value = 1.480375699849575e-46, Degrees of
Freedom = 4


Chi-Square test for Num_Snowmobile and Severity:
Chi2-statistic = 0.3007963617567132, p-value = 0.9897627072898548, Degrees of
Freedom = 4


Chi-Square test for Num_Taxi and Severity:
Chi2-statistic = 542.0395426571621, p-value = 5.397706877637681e-116, Degrees of
Freedom = 4


Chi-Square test for Num_Unspec_Veh and Severity:
Chi2-statistic = 16959.115251503412, p-value = 0.0, Degrees of Freedom = 4


Chi-Square test for Num_Veh_Invld and Severity:
Chi2-statistic = 20727.11665168865, p-value = 0.0, Degrees of Freedom = 64
```

Except for Num_OffRoad, Num_Snowmobile, all numerical and categorical variables show significant relationships with the target. Should drop them!!

Feature selection model Excluding Seq_Num, Street, Near_To:

- Since Seq_Num is simply an identifier with no predictive value, it's best excluded.
- Both Street and Near_To may contain too many unique levels, which can result in sparse data and may not generalize well in a model. Also, these location-based columns are redundant if Latitude and Longitude variables are already in the dataset.

And Num_OffRoad, Num_Snowmobile

[38]:
```
binary_df.drop(columns=["Seq_Num", "Street", "Near_To", "Num_OffRoad",␣
↪"Num_Snowmobile"], inplace=True)
binary_df.columns
```

[38]:
```
Index(['Acc_Date', 'Acc_Time', 'Acc_Type', 'Environ_Type', 'Latitude',
       'Light_Cond', 'Loc_Code', 'Lontitude', 'Month', 'Num_Bike', 'Num_Bus',
       'Num_Emerg', 'Num_Equip', 'Num_Heavy_Truck', 'Num_Light_Veh',
       'Num_Moped', 'Num_Moto', 'Num_Other_Veh', 'Num_Taxi', 'Num_Unspec_Veh',
       'Road_Aspect', 'Road_Cat', 'Road_Config', 'Severity', 'Speed_Limit',
       'Surface_Cond', 'Weather_Cond', 'Weekday', 'Year', 'Num_Veh_Invld',
       'Total_Victims', 'Credibility_Score'],
      dtype='object')
```

Encode categorical variables

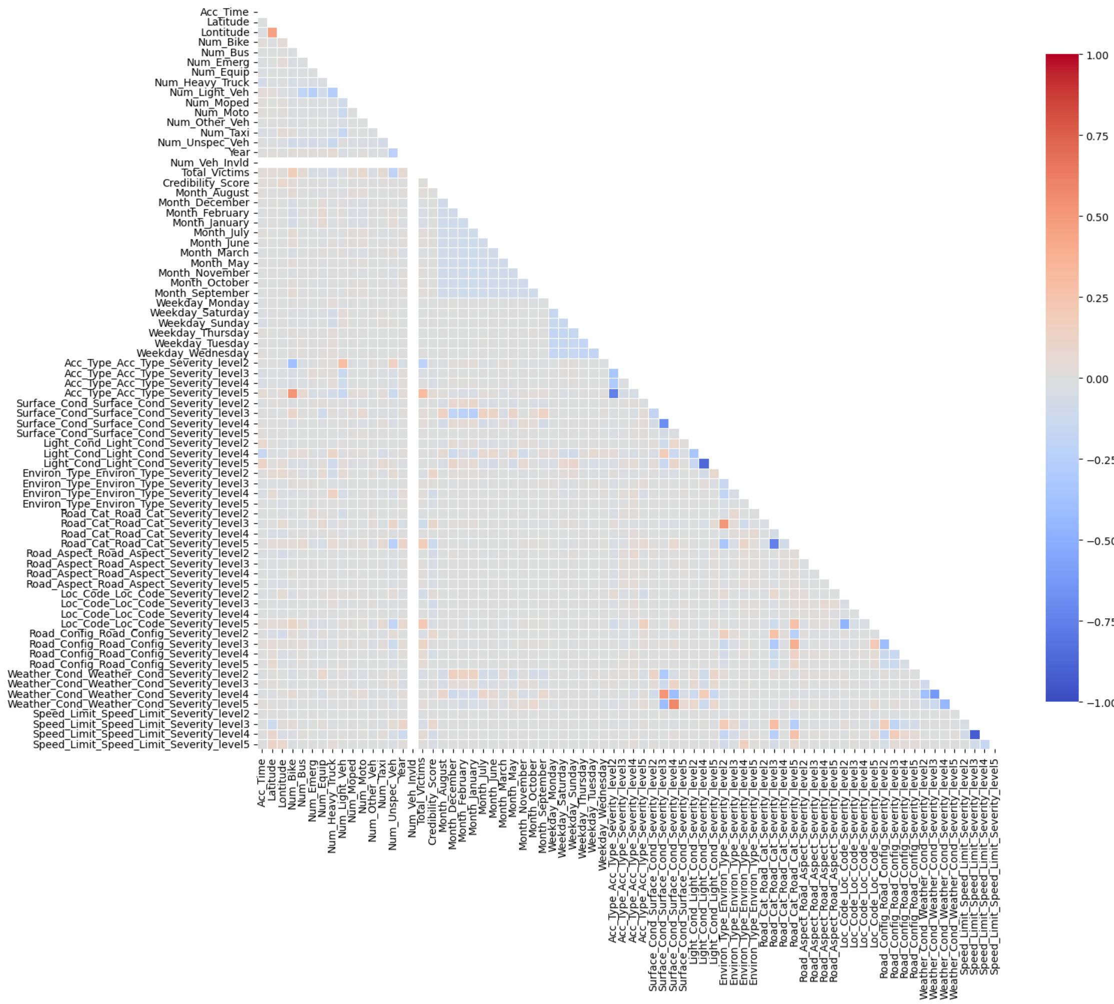
[265]:
```
binary_cols = [col for col in binary_df.columns if col.startswith('Num')]
for col in binary_cols:
    binary_df[col] = binary_df[col].astype('bool')

dummy_cols = Cat_time_cols + Cat_lst
binary_df_encoded = pd.get_dummies(binary_df, columns=dummy_cols,␣
↪drop_first=True)
binary_df_encoded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 218128 entries, 0 to 218127
Data columns (total 76 columns):
 #   Column                                   Non-Null Count   Dtype
---  ------                                   --------------   -----
 0   Acc_Date                                 218128 non-null  datetime64[ns]
 1   Acc_Time                                 218128 non-null  int64
 2   Latitude                                 218128 non-null  float64
 3   Lontitude                                218128 non-null  float64
 4   Num_Bike                                 218128 non-null  bool
 5   Num_Bus                                  218128 non-null  bool
 6   Num_Emerg                                218128 non-null  bool
 7   Num_Equip                                218128 non-null  bool
 8   Num_Heavy_Truck                          218128 non-null  bool
 9   Num_Light_Veh                            218128 non-null  bool
 10  Num_Moped                                218128 non-null  bool
 11  Num_Moto                                 218128 non-null  bool
 12  Num_Other_Veh                            218128 non-null  bool
 13  Num_Taxi                                 218128 non-null  bool
 14  Num_Unspec_Veh                           218128 non-null  bool
 15  Severity                                 218128 non-null  category
 16  Year                                     218128 non-null  int64
 17  Num_Veh_Invld                            218128 non-null  bool
```

```
18  Total_Victims                               218128 non-null  int64
19  Credibility_Score                           218128 non-null  float64
20  Month_August                                218128 non-null  bool
21  Month_December                              218128 non-null  bool
22  Month_February                              218128 non-null  bool
23  Month_January                               218128 non-null  bool
24  Month_July                                  218128 non-null  bool
25  Month_June                                  218128 non-null  bool
26  Month_March                                 218128 non-null  bool
27  Month_May                                   218128 non-null  bool
28  Month_November                              218128 non-null  bool
29  Month_October                               218128 non-null  bool
30  Month_September                             218128 non-null  bool
31  Weekday_Monday                              218128 non-null  bool
32  Weekday_Saturday                            218128 non-null  bool
33  Weekday_Sunday                              218128 non-null  bool
34  Weekday_Thursday                            218128 non-null  bool
35  Weekday_Tuesday                             218128 non-null  bool
36  Weekday_Wednesday                           218128 non-null  bool
37  Acc_Type_Acc_Type_Severity_level2           218128 non-null  bool
38  Acc_Type_Acc_Type_Severity_level3           218128 non-null  bool
39  Acc_Type_Acc_Type_Severity_level4           218128 non-null  bool
40  Acc_Type_Acc_Type_Severity_level5           218128 non-null  bool
41  Surface_Cond_Surface_Cond_Severity_level2   218128 non-null  bool
42  Surface_Cond_Surface_Cond_Severity_level3   218128 non-null  bool
43  Surface_Cond_Surface_Cond_Severity_level4   218128 non-null  bool
44  Surface_Cond_Surface_Cond_Severity_level5   218128 non-null  bool
45  Light_Cond_Light_Cond_Severity_level2       218128 non-null  bool
46  Light_Cond_Light_Cond_Severity_level4       218128 non-null  bool
47  Light_Cond_Light_Cond_Severity_level5       218128 non-null  bool
48  Environ_Type_Environ_Type_Severity_level2   218128 non-null  bool
49  Environ_Type_Environ_Type_Severity_level3   218128 non-null  bool
50  Environ_Type_Environ_Type_Severity_level4   218128 non-null  bool
51  Environ_Type_Environ_Type_Severity_level5   218128 non-null  bool
52  Road_Cat_Road_Cat_Severity_level2           218128 non-null  bool
53  Road_Cat_Road_Cat_Severity_level3           218128 non-null  bool
54  Road_Cat_Road_Cat_Severity_level4           218128 non-null  bool
55  Road_Cat_Road_Cat_Severity_level5           218128 non-null  bool
56  Road_Aspect_Road_Aspect_Severity_level2     218128 non-null  bool
57  Road_Aspect_Road_Aspect_Severity_level3     218128 non-null  bool
58  Road_Aspect_Road_Aspect_Severity_level4     218128 non-null  bool
59  Road_Aspect_Road_Aspect_Severity_level5     218128 non-null  bool
60  Loc_Code_Loc_Code_Severity_level2           218128 non-null  bool
61  Loc_Code_Loc_Code_Severity_level3           218128 non-null  bool
62  Loc_Code_Loc_Code_Severity_level4           218128 non-null  bool
63  Loc_Code_Loc_Code_Severity_level5           218128 non-null  bool
64  Road_Config_Road_Config_Severity_level2     218128 non-null  bool
65  Road_Config_Road_Config_Severity_level3     218128 non-null  bool
```

```
 66  Road_Config_Road_Config_Severity_level4    218128 non-null  bool
 67  Road_Config_Road_Config_Severity_level5    218128 non-null  bool
 68  Weather_Cond_Weather_Cond_Severity_level2  218128 non-null  bool
 69  Weather_Cond_Weather_Cond_Severity_level3  218128 non-null  bool
 70  Weather_Cond_Weather_Cond_Severity_level4  218128 non-null  bool
 71  Weather_Cond_Weather_Cond_Severity_level5  218128 non-null  bool
 72  Speed_Limit_Speed_Limit_Severity_level2    218128 non-null  bool
 73  Speed_Limit_Speed_Limit_Severity_level3    218128 non-null  bool
 74  Speed_Limit_Speed_Limit_Severity_level4    218128 non-null  bool
 75  Speed_Limit_Speed_Limit_Severity_level5    218128 non-null  bool
dtypes: bool(68), category(1), datetime64[ns](1), float64(3), int64(3)
memory usage: 26.0 MB
```

[266]:
```python
binary_df_encoded_numeric = binary_df_encoded.drop(["Severity", "Acc_Date"],␣
 ↪axis=1)
corr_matrix = binary_df_encoded_numeric.corr(method='pearson')

plt.figure(figsize=(16, 14))
mask = np.triu(np.ones_like(corr_matrix, dtype=bool))

sns.heatmap(corr_matrix,
            mask=mask,
            cmap='coolwarm',
            annot=False,
            linewidths=0.5,
            cbar_kws={'shrink': 0.8},
            square=True,
            xticklabels=corr_matrix.columns,
            yticklabels=corr_matrix.columns,
            vmin=-1, vmax=1,
            center=0)

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

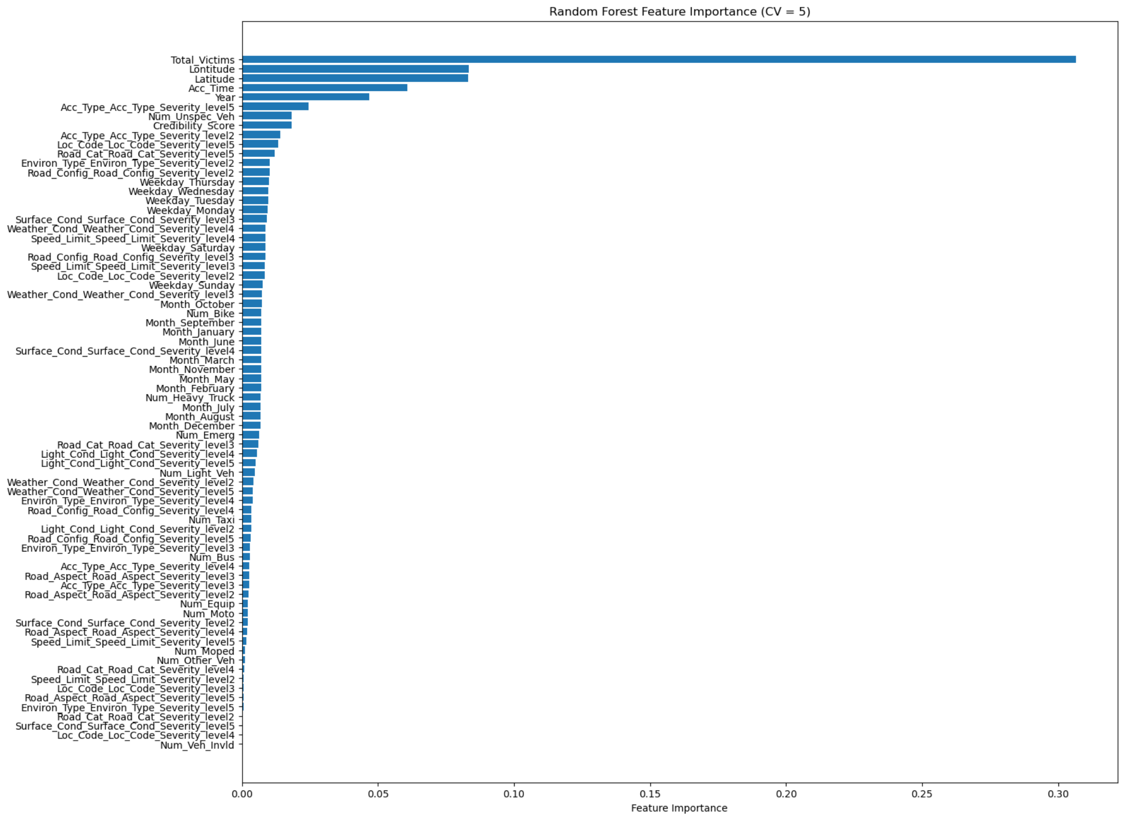


Overall, our varibales are uncorrelated.

[ ]:
```
# binary_df_encoded.to_excel("dummified&processed_df.xlsx")
```

[271]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score, StratifiedKFold
from sklearn.preprocessing import LabelEncoder

binary_df_encoded_fs = binary_df_encoded.drop(["Acc_Date"], axis=1)

X = binary_df_encoded_fs.drop(columns=['Severity'])
y = binary_df_encoded_fs['Severity']

label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)
```

```python
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
rf = RandomForestClassifier(n_estimators=100, random_state=42)

importances = np.zeros(X.shape[1])

for train_index, test_index in cv.split(X, y):
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    y_train, y_test = y[train_index], y[test_index]

    rf.fit(X_train, y_train)
    importances += rf.feature_importances_

# normalization
importances /= cv.get_n_splits()


# visualization
feature_importances_df = pd.DataFrame({
    'feature': X.columns,
    'importance': importances
})

feature_importances_df = feature_importances_df.sort_values(by='importance',␣
 ↪ascending=False)
plt.figure(figsize=(16, 14))
plt.barh(feature_importances_df['feature'],␣
 ↪feature_importances_df['importance'])
plt.xlabel('Feature Importance')
plt.title('Random Forest Feature Importance (CV = 5)')
plt.gca().invert_yaxis()
plt.show()

top_n = 30
selected_features = feature_importances_df.head(top_n)['feature'].tolist()
X_selected = X[selected_features]
```



From the Random Forest (RF) analysis, we've identified another set of important variables that significantly influence the target outcome:

Total_Victims, Longitude, Latitude, Year, Acc_Time, Acc_Type, Num_Unspec_Veh, Credibility_Score……

(ReCall from EDA, we've found some important varibales: Acc_Type, Surface_Cond, Light_Cond, Road_Cat, Road_Config, Num_Heavy_Truck, Num_Moto, Num_Bike, Num_Taxi, Num_Veh_Invld, Total_Victims, Speed_Limit, Weather_Cond)

These variables appear in two waves of importance (RF feature selection + EDA findings) strongly suggests their critical role in influencing the outcome, which means it's recommended to including these variables in modeling part.

0.0.2 Modelling

Some ideas of interaction terms that could be considered in building models:

- Between different vehicle types
- Between vehicle counts and geographic features