Final Project Submission

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Problem Overview

Each year more than 42,000 people are needlessly killed on American streets and thousands more are injured. We call this suffering traffic “accidents” — but, in reality, we have the power to prevent traffic collisions. To counter these fatalities and injuries, the Department of Transportations (DOTs) across the US are working towards a new vision for safety called "Vision Zero".

Vision Zero recognizes that people will sometimes make mistakes, so the road system and related policies should be designed to ensure those inevitable mistakes do not result in severe injuries or fatalities. This means that system designers and policymakers are expected to improve the roadway environment, policies (such as speed management), and other related systems to lessen the severity of crashes by working with stakeholders ranging from auto manufacturers to policy makers.

Similarly, the Chicago DOT wants to conduct a study to improve theiir methodolodies of determining crash causes. There are usually a lot of crashes that result in causes never being identified and also serveral car crashes can form an underlying pattern. Chicago DOT waants to understand what multitude of factors can play some of the biggest roles in causing these crashes.

That is why this notebook is going to explore developing a model for predicting primmary contributary causes to car crashes and identifyng the top 10 factors that we find the biggest roles in these causes. We will use the data available to predict the primary contributory cause of a car accident, given information about the car, the people in the car, the road conditions etc.

Data Sources

The data being used is from the Chicago Polic Department (CPD) and is provided oninee by the City of Chicago. The data is from 2015 to the present day. It is updated daily but the data being used as a part of this project is recent until 3rd February 2023.

There are 3 datasets being used for analysis:

1. Traffic crashes data summary: https://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3ifhttps://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3ifv (https://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3ifhttps://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3ifv)

2. Vehicles information involved in a crash: https://data.cityofchicago.org/Transportation/Traffic-Crashes-Vehicles/68nd-jvt3 (https://data.cityofchicago.org/Transportation/Traffic-Crashes-Vehicles/68nd-jvt3)

3. People information involved in a crash: [https://data.cityofchicago.org/Transportation/Traffic-Crashes-People/u6pd-qa9d (https://data.cityofchicago.org/Transportation/Traffic-Crashes-People/u6pd-qa9d)](https://data.cityofchicago.org/Transportation/Traffic-Crashes-People/u6pd-qa9d)

Considering that this is the official dataset of the City of Chicago regarding traffic crashes, it can be easily concluded that it would be the most reliable dataset available. Using this dataset will also increase the confidence of the client on the results and recommendations of this project.

Data Understanding

This section will be exploratory to understand the different features of the data. All three datasets will be explored separately. Using the source documentation, data and the features will be interpreted and determinations will be made about which features are relevant to identifying the causes of car crashes. Towards the end of exploring the data, avenues of analysis that can be used will also become clearer. As data is explored, any anomalies or issues require further cleaning/processing will be identified and handled in the `Data Preparation` section.

To start things off, lets import all the libraries and functions that will be used in this notebook.

```python
import pandas as pd #imports the pandas library as pd to work on databases
import sqlite3 as sql # imports the sqlite3 library to leverage sql with pandas
from datetime import datetime # for datetime manipulation
import matplotlib.pyplot as plt # importing matplotlib for visualizations

%matplotlib inline
import numpy as np # imports the numpy library
import datetime as dt #import datetime module
import seaborn as sns #import seaborn
from collections import Counter #import Counter
import statsmodels.api as sm #import stats models
from statsmodels.stats.outliers_influence import variance_inflation_factor

#import scikit library functions
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.datasets import make_regression
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split, cross_validate, ShuffleSplit
from sklearn.feature_selection import RFECV


#import scipy libraries
from scipy import stats as stats

#import plotly
import plotly.express as px
import plotly.graph_objects as go

#import libraries to deal with unbaalanced dataset
from imblearn.over_sampling import SMOTE
from imblearn.over_sampling import SMOTENC
from sklearn.compose import ColumnTransformer
from imblearn.over_sampling import SMOTENC

#import metrics
from sklearn import metrics
import itertools
# from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
```

Traffic Crashes - Crashes

This is the summary data for all the crashes. Thee dataset was downloaded and stores in the `data` folder as `Traffic_Crashes-Crashes` . The overview of the contents of this data is aavailable below and at [https://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3if (https://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3if)](https://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3if).

Crash data shows information about each traffic crash on city streets within the City of Chicago limits and under the jurisdiction of Chicago Police Department (CPD). Data are shown as is from the electronic crash reporting system (E-Crash) at CPD, excluding any personally identifiable information. Records are added to the data portal when a crash report is finalized or when amendments are made to an existing report in E-Crash. Data from E-Crash are available for some police districts in 2015, but citywide data are not available until September 2017. About half of all crash reports, mostly minor crashes, are self-reported at the police district by the driver(s) involved and the other half are recorded at the scene by the police officer responding to the crash. Many of the crash parameters, including street condition data, weather condition, and posted speed limits, are recorded by the reporting officer based on best available information at the time, but many of these may disagree with posted information or other assessments on road conditions. If any new or updated information on a crash is received, the reporting officer may amend the crash report at a later time. A traffic crash within the city limits for which CPD is not the responding police agency, typically crashes on interstate highways, freeway ramps, and on local roads along the City boundary, are excluded from this dataset.

As per Illinois statute, only crashes with a property damage value of $1,500 or more or involving bodily injury to any person(s) and that happen on a public roadway and that involve at least one moving vehicle, except bike dooring, are considered reportable crashes. However, CPD records every reported traffic crash event, regardless of the statute of limitations, and hence any formal Chicago crash dataset released by Illinois Department of Transportation may not include all the crashes listed here.

In [ ]:

```
#import the dataset using the API endpoint
crashes_df = pd.read_csv('data/Traffic_Crashes-Crashes.csv')

#preview thee first 5 rows
crashes_df.head()
```

Out[302]:

	CRASH_RECORD_ID	RD_NO	CRASH_DATE_EST_I	CRASH_DATE	POSTED_SPEED_LIMIT	TRAFFIC_CONTROL_DEVICE	DEVICE_C
0	79c7a2ce89f446262efd86df3d72d18b04ba487024b7c4...	JC199149	NaN	03/25/2019 02:43:00 PM	30	TRAFFIC SIGNAL	FUN F
1	792b539deaaad65ee5b4a9691d927a34d298eb33d42af0...	JB422857	NaN	09/05/2018 08:40:00 AM	30	NO CONTROLS	NO C
2	0115ade9a755e835255508463f7e9c4a9a0b47e9304238...	JF318029	NaN	07/15/2022 12:45:00 AM	30	UNKNOWN	U
3	05b1982cdba5d8a00e7e76ad1ecdab0e598429f78481d2...	JF378711	NaN	08/29/2022 11:30:00 AM	30	TRAFFIC SIGNAL	FUN F
4	017040c61958d2fa977c956b2bd2d6759ef7754496dc96...	JF324552	NaN	07/15/2022 06:50:00 PM	30	TRAFFIC SIGNAL	FUN F

5 rows × 49 columns

In [ ]:

```
#Explore the info for all the features
crashes_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 692784 entries, 0 to 692783
Data columns (total 49 columns):
 #   Column                         Non-Null Count   Dtype  
---  ------                         --------------   -----  
 0   CRASH_RECORD_ID                692784 non-null  object 
 1   RD_NO                          688672 non-null  object 
 2   CRASH_DATE_EST_I               52531 non-null   object 
 3   CRASH_DATE                     692784 non-null  object 
 4   POSTED_SPEED_LIMIT             692784 non-null  int64  
 5   TRAFFIC_CONTROL_DEVICE         692784 non-null  object 
 6   DEVICE_CONDITION               692784 non-null  object 
 7   WEATHER_CONDITION              692784 non-null  object 
 8   LIGHTING_CONDITION             692784 non-null  object 
 9   FIRST_CRASH_TYPE               692784 non-null  object 
 10  TRAFFICWAY_TYPE                692784 non-null  object 
 11  LANE_CNT                       198997 non-null  float64
 12  ALIGNMENT                      692784 non-null  object 
 13  ROADWAY_SURFACE_COND           692784 non-null  object 
 14  ROAD_DEFECT                    692784 non-null  object 
 15  REPORT_TYPE                    673774 non-null  object 
 16  CRASH_TYPE                     692784 non-null  object 
 17  INTERSECTION_RELATED_I         158797 non-null  object 
 18  NOT_RIGHT_OF_WAY_I             32485 non-null   object 
 19  HIT_AND_RUN_I                  214969 non-null  object 
 20  DAMAGE                         692784 non-null  object 
 21  DATE_POLICE_NOTIFIED           692784 non-null  object 
 22  PRIM_CONTRIBUTORY_CAUSE        692784 non-null  object 
 23  SEC_CONTRIBUTORY_CAUSE         692784 non-null  object 
 24  STREET_NO                      692784 non-null  int64  
 25  STREET_DIRECTION               692780 non-null  object 
 26  STREET_NAME                    692783 non-null  object 
 27  BEAT_OF_OCCURRENCE             692779 non-null  float64
 28  PHOTOS_TAKEN_I                 8586 non-null    object 
 29  STATEMENTS_TAKEN_I             14493 non-null   object 
 30  DOORING_I                      2128 non-null    object 
 31  WORK_ZONE_I                    4046 non-null    object 
 32  WORK_ZONE_TYPE                 3170 non-null    object 
 33  WORKERS_PRESENT_I              1048 non-null    object 
 34  NUM_UNITS                      692784 non-null  int64  
 35  MOST_SEVERE_INJURY             691281 non-null  object 
 36  INJURIES_TOTAL                 691292 non-null  float64
 37  INJURIES_FATAL                 691292 non-null  float64
 38  INJURIES_INCAPACITATING        691292 non-null  float64
 39  INJURIES_NON_INCAPACITATING    691292 non-null  float64
 40  INJURIES_REPORTED_NOT_EVIDENT  691292 non-null  float64
 41  INJURIES_NO_INDICATION         691292 non-null  float64
 42  INJURIES_UNKNOWN               691292 non-null  float64
 43  CRASH_HOUR                     692784 non-null  int64  
 44  CRASH_DAY_OF_WEEK              692784 non-null  int64  
 45  CRASH_MONTH                    692784 non-null  int64  
```

```
 46  LATITUDE                        688378 non-null  float64
 47  LONGITUDE                       688378 non-null  float64
 48  LOCATION                        688378 non-null  object
dtypes: float64(11), int64(6), object(32)
memory usage: 259.0+ MB
```

There are a number of columns with missing values but they can also simply be categorical columns that don't apply to all records. The documentation on the columns available on [https://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3if (https://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3if)](https://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3if) can be used to explore the columns separately. The descriptions have also been listed below.

1. `CRASH_RECORD_ID` : This number can be used to link to the same crash in the Vehicles and People datasets. This number also serves as a unique ID in this dataset. This will be important for joining the databases.

2. `RD_NO` : Chicago Police Department report number. For privacy reasons, this column is blank for recent crashes. This column can be ignored since this does not give us any insight into the causes of crashes. **DROP COLUMN**

3. `CRASH_DATE_EST_I` : Crash date estimated by desk officer or reporting party (only used in cases where crash is reported at police station days after the crash). This column can be ignored since there are missing values here. There is another column for Crash Dates but has no missing values. **DROP COLUMN**

4. `CRASH_DATE` : Date and time of crash as entered by the reporting officer. This gives us insight into if there are periods where there are more crashes than others. If there is a discernable pattern, appropriate preventative measures can be taken. The time and date will have to be separated out for individual analysis. Also the initial description of thee dataset mentions that 2018 onwards citywide E-craash daat aiss available. Therefore, the data will be filtered out accordingly. Also, the daata has to be changed to datetime versions for proper use.

5. `POSTED_SPEED_LIMIT` : Posted speed limit, as determined by reporting officer. This is the speed limit for the area where the crash happened. This coupled with the speed that the car was travelling at can help inform if the crash was at high speeds. Consequently, this can be a critical contirbutor in determining the cause of the crash.

6. `TRAFFIC_CONTROL_DEVICE` : Traffic control device present at crash location, as determined by reporting officer. It would be important to understand the contents of this column before making a decision on its use.

In [ ]:

```
# checking null values
crashes_df.isna().sum()
```

Out[304]:
```
CRASH_RECORD_ID                       0
RD_NO                              4112
CRASH_DATE_EST_I                 640253
CRASH_DATE                            0
POSTED_SPEED_LIMIT                    0
TRAFFIC_CONTROL_DEVICE                0
DEVICE_CONDITION                      0
WEATHER_CONDITION                     0
LIGHTING_CONDITION                    0
FIRST_CRASH_TYPE                      0
TRAFFICWAY_TYPE                       0
LANE_CNT                         493787
ALIGNMENT                             0
ROADWAY_SURFACE_COND                  0
ROAD_DEFECT                           0
REPORT_TYPE                       19010
CRASH_TYPE                            0
INTERSECTION_RELATED_I           533987
NOT_RIGHT_OF_WAY_I               660299
HIT_AND_RUN_I                    477815
DAMAGE                                0
DATE_POLICE_NOTIFIED                  0
PRIM_CONTRIBUTORY_CAUSE               0
SEC_CONTRIBUTORY_CAUSE                0
STREET_NO                             0
STREET_DIRECTION                      4
STREET_NAME                           1
BEAT_OF_OCCURRENCE                    5
PHOTOS_TAKEN_I                   684198
STATEMENTS_TAKEN_I               678291
DOORING_I                        690656
WORK_ZONE_I                      688738
WORK_ZONE_TYPE                   689614
WORKERS_PRESENT_I                691736
NUM_UNITS                             0
MOST_SEVERE_INJURY                 1503
INJURIES_TOTAL                     1492
INJURIES_FATAL                     1492
INJURIES_INCAPACITATING            1492
INJURIES_NON_INCAPACITATING        1492
INJURIES_REPORTED_NOT_EVIDENT      1492
INJURIES_NO_INDICATION             1492
INJURIES_UNKNOWN                   1492
CRASH_HOUR                            0
CRASH_DAY_OF_WEEK                     0
CRASH_MONTH                           0
LATITUDE                           4406
LONGITUDE                          4406
LOCATION                           4406
dtype: int64
```

In [ ]:

```
#check unique values
crashes_df['TRAFFIC_CONTROL_DEVICE'].value_counts()
```

Out[305]:

```
NO CONTROLS                 397249
TRAFFIC SIGNAL              192000
STOP SIGN/FLASHER            68792
UNKNOWN                      24545
OTHER                         4515
LANE USE MARKING              1226
YIELD                          977
OTHER REG. SIGN                721
OTHER WARNING SIGN             591
RAILROAD CROSSING GATE         448
PEDESTRIAN CROSSING SIGN       384
DELINEATORS                    271
SCHOOL ZONE                    263
FLASHING CONTROL SIGNAL        248
POLICE/FLAGMAN                 243
OTHER RAILROAD CROSSING        159
RR CROSSING SIGN                93
NO PASSING                      40
BICYCLE CROSSING SIGN           19
Name: TRAFFIC_CONTROL_DEVICE, dtype: int64
```

There are multiple categories but the `NO CONTROLS` category stands out with almost 50% share in the data for this column. The other categorieswould be location dependent signage. This data can be used to determine whether `NO CCONTROLS` plays a significantlt higher part in certain types of crashes. The data in this column can be grouped together to only two categories, `NO CONTROLS` and `CONTROLS` .

7. `DEVICE_CONDITION` : Condition of traffic control device, as determined by reporting officer. This would be an important aspect to consider. Lets explore the contents of this column.

In [ ]:

```
#check unique values
crashes_df['DEVICE_CONDITION'].value_counts()
```

Out[306]:

```
NO CONTROLS                 401903
FUNCTIONING PROPERLY        238515
UNKNOWN                      41164
OTHER                         5347
FUNCTIONING IMPROPERLY        3373
NOT FUNCTIONING               2143
WORN REFLECTIVE MATERIAL       258
MISSING                         81
Name: DEVICE_CONDITION, dtype: int64
```

Considering that this column also has a demarcated category of `NO CONTROLS` with categories highlighting whther there were any issues with the traffic control devices present, it would be more useful to use this column rather than using the `TRAFFIC_CONTROL_DEVICE` column. It is also clear that having no controls is the biggest contributor to traffic crashes but what kind of impact they have is something that has to be explored.

Therefore, **DROP `TRAFFIC_CONTROL_DEVICE` COLUMN**

`WEATHER_CONDITION` : Weather condition at time of crash, as determined by reporting officer. This will definitely be a big factor in predicting the cause of crashes as well since the weather can play a big part in traffic accidents. Lets take a look at the contents of the column.

In [ ]:

```
#check unique values
crashes_df['WEATHER_CONDITION'].value_counts()
```

Out[307]:

```
CLEAR                       546474
RAIN                         59674
UNKNOWN                      34543
SNOW                         25734
CLOUDY/OVERCAST              20505
OTHER                         2204
FREEZING RAIN/DRIZZLE         1229
FOG/SMOKE/HAZE                1031
SLEET/HAIL                     881
BLOWING SNOW                   367
SEVERE CROSS WIND GATE         138
BLOWING SAND, SOIL, DIRT         4
Name: WEATHER_CONDITION, dtype: int64
```

The unkown data has to be dealt with in the **Data Preparation** section but all other data will be valuable to carry forward. It seems like the most car crashes take place in the clear weather while the worse the weather is the fewer car crashes there are. This might be becausee people naturally are more carefull during bad weather. Nonetheless this has to be inveestigated more to see whether inclement weather accidents are more serious or impact specific types of vehicles. It can also be that there are less vehicles on the road during inclement weather therefore while the numbers might be low, the ratio of cars on the road and number of accidents might be high.

`LIGHTING_CONDITION` : Light condition at time of crash, as determined by reporting office. This is also another big factor. Theoretically, bad lighting conditions can play a big part in car crashes. This column can prove to be critial. Lets invvestigate it to understand the contents.

In [ ]:

```
#check unique values
crashes_df['LIGHTING_CONDITION'].value_counts()
```

Out[308]:

```
DAYLIGHT                  445517
DARKNESS, LIGHTED ROAD    153269
DARKNESS                   33364
UNKNOWN                    28678
DUSK                       20317
DAWN                       11639
Name: LIGHTING_CONDITION, dtype: int64
```

In [ ]:
```
crashes_df['LIGHTING_CONDITION'].value_counts(normalize=True)
```

Out[309]:
```
DAYLIGHT                   0.643082
DARKNESS, LIGHTED ROAD     0.221236
DARKNESS                   0.048159
UNKNOWN                    0.041395
DUSK                       0.029327
DAWN                       0.016800
Name: LIGHTING_CONDITION, dtype: float64
```

Similar to the weather conditions data, it looks like the best lighting condition has the most accidents. This can be either be because peoplee are generally more careful when there's less light or that there are fewer cars on the road therefore fewer accidents. Nonetheless, lighting is an important factor when it comes to visibility. It would be beneficial to keeep this data and let thee model decide whether it provides useful information or not.

`ROAD_DEFECT` : Road defects, as determined by reporting officer. This might be important. Lets take a look at the data first.

In [ ]:
```
#check unique values
crashes_df['ROAD_DEFECT'].value_counts()
```

Out[310]:
```
NO DEFECTS            565943
UNKNOWN               112665
RUT, HOLES              5561
OTHER                   3858
WORN SURFACE            2859
SHOULDER DEFECT         1350
DEBRIS ON ROADWAY        548
Name: ROAD_DEFECT, dtype: int64
```

In [ ]:
```
#check the ratios
crashes_df['ROAD_DEFECT'].value_counts(normalize=True)
```

Out[311]:
```
NO DEFECTS            0.816911
UNKNOWN               0.162626
RUT, HOLES            0.008027
OTHER                 0.005569
WORN SURFACE          0.004127
SHOULDER DEFECT       0.001949
DEBRIS ON ROADWAY     0.000791
Name: ROAD_DEFECT, dtype: float64
```

It is important to note that No defects has thee largest number of crashes. This might be a sign that smooth and good quality roads lead people to be less careful of the road conditions. Although the data is skewed, it might be helpful to see how big of a part it plays in the crashes from a higher level.

`REPORT_TYPE` : Administrative report type (at scene, at desk, amended). This column can be ignored for the purposes of this analysis.

DROP REPORT_TYPE COLUMN

CRASH_TYPE : A general severity classification for the crash. Can be either Injury and/or Tow Due to Crash or No Injury / Drive Away. This data will be used to filter on crashes that had injuries or fatalities. While the eventual goal is to have no crashes, the goal of this analysis is to support work towards Vision Zero which focuses on fatalities and injuries. Lets investigate the contents if this column before movving on.

In [ ]:
```
#check unique values
crashes_df['CRASH_TYPE'].value_counts()
```

Out[312]:
```
NO INJURY / DRIVE AWAY                 510406
INJURY AND / OR TOW DUE TO CRASH       182378
Name: CRASH_TYPE, dtype: int64
```

With only 180,000 records, out data size will be significantly reduced but helps us focus on the main problem.

INTERSECTION_RELATED_I : A field observation by the police officer whether an intersection played a role in the crash. Does not represent whether or not the crash occurred within the intersection. Lets investigate the contents of this column.

In [ ]:
```
#check unique values
crashes_df['INTERSECTION_RELATED_I'].value_counts()
```

Out[313]:
```
Y    151396
N      7401
Name: INTERSECTION_RELATED_I, dtype: int64
```

Usually at intersections, there is a large amount of non-straight traffic movements, cars slowing down, pedestrain movement and generally a heightened probability of crashes. This is one of the reeasons that DOT creates signalized intersectinos. This would be important to carry forwaard to understand whether this general understanding of intersections plays a big part in crashes or not. If it does, DOT could be able to hone in on intersection types that play a significant role and develop traffic engineering plans accordingly.

NOT_RIGHT_OF_WAY_I : Whether the crash begun or first contact was made outside of the public right-of-way. This column also has almost 50% of its values missing. Also, this gives us insight into the circumstances around a crash but not significant insight into the cause of a crash.

DROP NOT_RIGHT_OF_WAY_I COLUMN

HIT_AND_RUN_I : Crash did/did not involve a driver who caused the crash and fled the scene without exchanging information and/or rendering aid. This gives us inight into the aftermaths of the crash but no significant insight into the cause of it.

DROP HIT_AND_RUN_I COLUMN

DAMAGE : A field observation of estimated damage. Similar to the previous two, this doesn't provide insight into the causes of the crash.

DROP DAMAGE COLUMN

DATE_POLICE_NOTIFIED : Calendar date on which police were notified of the crash. Similarly, this doesn't provide any insight into the causes of the crash.

DROP DATE_POLICE_NOTIFIED COLUMN

`PRIM_CONTRIBUTORY_CAUSE` : The factor which was most significant in causing the crash, as determined by officer judgment. This will be the target column that will be used. Lets investigate the contents of this column.

In [ ]:
```
#check unique values
crashes_df['PRIM_CONTRIBUTORY_CAUSE'].value_counts()
```

Out[314]:
```
UNABLE TO DETERMINE                                                                 266260
FAILING TO YIELD RIGHT-OF-WAY                                                        75716
FOLLOWING TOO CLOSELY                                                                69035
NOT APPLICABLE                                                                       36421
IMPROPER OVERTAKING/PASSING                                                          33504
FAILING TO REDUCE SPEED TO AVOID CRASH                                               29613
IMPROPER BACKING                                                                     28228
IMPROPER LANE USAGE                                                                  25526
IMPROPER TURNING/NO SIGNAL                                                           22879
DRIVING SKILLS/KNOWLEDGE/EXPERIENCE                                                  22419
DISREGARDING TRAFFIC SIGNALS                                                         13383
WEATHER                                                                              11029
OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRESSIVE MANNER      8804
DISREGARDING STOP SIGN                                                                7705
DISTRACTION - FROM INSIDE VEHICLE                                                     4829
EQUIPMENT - VEHICLE CONDITION                                                         4415
PHYSICAL CONDITION OF DRIVER                                                          4221
VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)                                  3977
DRIVING ON WRONG SIDE/WRONG WAY                                                       3580
UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)                    3418
DISTRACTION - FROM OUTSIDE VEHICLE                                                    2959
EXCEEDING AUTHORIZED SPEED LIMIT                                                      1982
ROAD ENGINEERING/SURFACE/MARKING DEFECTS                                              1795
EXCEEDING SAFE SPEED FOR CONDITIONS                                                   1684
ROAD CONSTRUCTION/MAINTENANCE                                                         1548
DISREGARDING OTHER TRAFFIC SIGNS                                                      1509
EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST                                     1305
CELL PHONE USE OTHER THAN TEXTING                                                      944
DISREGARDING ROAD MARKINGS                                                             891
HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)                                        748
ANIMAL                                                                                 577
TURNING RIGHT ON RED                                                                   485
DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER, ETC.)            327
RELATED TO BUS STOP                                                                    291
TEXTING                                                                                282
DISREGARDING YIELD SIGN                                                                247
PASSING STOPPED SCHOOL BUS                                                              87
BICYCLE ADVANCING LEGALLY ON RED LIGHT                                                  76
OBSTRUCTED CROSSWALKS                                                                   65
MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT                                               20
Name: PRIM_CONTRIBUTORY_CAUSE, dtype: int64
```

While there are a lot of categories, there seem to be several overlapping ones which we can group later on during the Data Preparation phase.

`SEC_CONTRIBUTORY_CAUSE` : The factor which was second most significant in causing the crash, as determined by officer judgment. Similar to the previous one, this will be an important column in analysis.

In [ ]:

```
#check unique values
crashes_df['SEC_CONTRIBUTORY_CAUSE'].value_counts()
```

Out[315]:

```
NOT APPLICABLE                                                                   282372
UNABLE TO DETERMINE                                                              251338
FAILING TO REDUCE SPEED TO AVOID CRASH                                            26909
DRIVING SKILLS/KNOWLEDGE/EXPERIENCE                                               21221
FAILING TO YIELD RIGHT-OF-WAY                                                     21098
FOLLOWING TOO CLOSELY                                                             18283
IMPROPER OVERTAKING/PASSING                                                       10318
IMPROPER LANE USAGE                                                                9863
WEATHER                                                                            8260
IMPROPER TURNING/NO SIGNAL                                                         6921
IMPROPER BACKING                                                                   5666
OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRESSIVE MANNER    4457
DISREGARDING TRAFFIC SIGNALS                                                       2749
VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)                               2245
PHYSICAL CONDITION OF DRIVER                                                       2178
DISTRACTION - FROM INSIDE VEHICLE                                                  2135
DISREGARDING STOP SIGN                                                             2061
EXCEEDING AUTHORIZED SPEED LIMIT                                                   1473
EXCEEDING SAFE SPEED FOR CONDITIONS                                                1438
EQUIPMENT - VEHICLE CONDITION                                                      1405
DRIVING ON WRONG SIDE/WRONG WAY                                                    1369
DISTRACTION - FROM OUTSIDE VEHICLE                                                 1190
UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)                 1165
HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)                                     895
ROAD CONSTRUCTION/MAINTENANCE                                                       837
DISREGARDING ROAD MARKINGS                                                          729
DISREGARDING OTHER TRAFFIC SIGNS                                                    724
ROAD ENGINEERING/SURFACE/MARKING DEFECTS                                            717
CELL PHONE USE OTHER THAN TEXTING                                                   530
EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST                                   384
ANIMAL                                                                              331
RELATED TO BUS STOP                                                                 307
TURNING RIGHT ON RED                                                                254
BICYCLE ADVANCING LEGALLY ON RED LIGHT                                              224
DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER, ETC.)         214
DISREGARDING YIELD SIGN                                                             183
TEXTING                                                                             129
PASSING STOPPED SCHOOL BUS                                                           86
OBSTRUCTED CROSSWALKS                                                                71
MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT                                            55
Name: SEC_CONTRIBUTORY_CAUSE, dtype: int64
```

While there are a lot of categories, there seem to be several overlapping ones which we can group later on during the Data Preparation phase.

`STREET_NO` : Street address number of crash location, as determined by reporting officer. While this is a valuable data point, there are latitude and longtitude data points which can proove to be more useful.

DROP STREET_NO COLUMN

Similarly, `STREET_DIRECTION` , `STREET_NAME` , and `BEAT_OF_OCCURRENCE` can be **DROPPED**.

Also `PHOTOS_TAKEN_I` and `STATEMENTS_TAKEN_I` are relevant to the police investigation records but not for the purposes of this notebook's analysis. Therefore they can be **DROPPED**

`WORK_ZONE_I` , `WORK_ZONE_TYPE` , and `WORKERS_PRESENT_I` are important columns to caarry forward. Usually these aree critical areas where speed limits are significantly reduced and there is a lot of worker traffic during shift hours. These can be very sensitive areas that can be significant towards attaining Vision Zero therefore it will be interesting to see their contribution towards crashes.

Nonetheless we can drop the `WORK_ZONE_TYPE` column since the granularity of the analysis isn't specifically based on work zone type crashes. If aa significant correlation is found, then this area can be further investigated in future analysis.

`NUM_UNITS` will be an important data point since it gives information on the number of units involved in the crash.

Similarly, aligning with the Vision Zero goal, `INJURIES_TOTAL` and `INJURIES_FATAL` would be valuable columns to use in analysis.

The other Injuries columns can be **DROPPED**.

`CRASH_HOUR` , `CRASH_DAY_OF_WEEK` , and `CRASH_MONTH` can be used instead of the timesatamp in column `CRASH_DATE` since these are broken down values. Nonetheless, what would be valuable from the timestamp column is the year of the crash. It might be possible that the year can play a big part in recognizing patterns of the accidents.

`LATITUDE` and `LONGITUDE` will be used for location data for crashes. This will helo determine if there are specific areas that more volatile to crashes as compared to others.

SUMMARY

The following columns will be carried forward:

1. CRASH_RECORD_ID
2. CRASH_DATE
3. POSTED_SPEED_LIMIT
4. DEVICE_CONDITION
5. WEATHER_CONDITION
6. CRASH_TYPE

7. PRIM_CONTRIBUTORY_CAUSE
8. SEC_CONTRIBUTORY_CAUSE
9. WORK_ZONE_I
10. WORKERS_PRESENT_I
11. INJURIES_TOTAL
12. INJURIES_FATAL
13. CRASH_HOUR
14. CRASH_DAY_OF_WEEK
15. CRASH_MONTH
16. LATITUDE
17. LONGITUDE
18. LIGHTING_CONDITION
19. NUM_UNITS

Traffic Crashes - Vechiles

This is the summary data for all the crashes. Thee dataset was downloaded and stores in the `data` folder as `Traffic_Crashes-Vehicles` . The overview of the contents of this data is aavailable below and at [https://data.cityofchicago.org/Transportation/Traffic-Crashes-Vehicles/68nd-jvt3 (https://data.cityofchicago.org/Transportation/Traffic-Crashes-Vehicles/68nd-jvt3)](https://data.cityofchicago.org/Transportation/Traffic-Crashes-Vehicles/68nd-jvt3).

This dataset contains information about vehicles (or units as they are identified in crash reports) involved in a traffic crash. This dataset should be used in conjunction with the traffic Crash and People dataset available in the portal. “Vehicle” information includes motor vehicle and non-motor vehicle modes of transportation, such as bicycles and pedestrians. Each mode of transportation involved in a crash is a “unit” and get one entry here. Each vehicle, each pedestrian, each motorcyclist, and each bicyclist is considered an independent unit that can have a trajectory separate from the other units. However, people inside a vehicle including the driver do not have a trajectory separate from the vehicle in which they are travelling and hence only the vehicle they are travelling in get any entry here. This type of identification of “units” is needed to determine how each movement affected the crash. Data for occupants who do not make up an independent unit, typically drivers and passengers, are available in the People table. Many of the fields are coded to denote the type and location of damage on the vehicle. Vehicle information can be linked back to Crash data using the “CRASH_RECORD_ID” field. Since this dataset is a combination of vehicles, pedestrians, and pedal cyclists not all columns are applicable to each record.

In [ ]:

```
#import the dataset using the API endpoint
vehicles_df = pd.read_csv('data/Traffic_Crashes-Vehicles.csv')

#preview thee first 5 rows
vehicles_df.head()
```

```
<ipython-input-316-e77540458d9f>:2: DtypeWarning: Columns (19,21,40,41,42,44,48,49,50,53,55,58,59,61,71) have mixed type
s. Specify dtype option on import or set low_memory=False.
  vehicles_df = pd.read_csv('data/Traffic_Crashes-Vehicles.csv')
```

Out[316]:

	CRASH_UNIT_ID	CRASH_RECORD_ID	RD_NO	CRASH_DATE	UNIT_NO	UNIT_TYPE	NUM_PASSENGERS	VEHICLE_ID	CMRC_VEH
0	829999	24ddf9fd8542199d832e1c223cc474e5601b356f1d77a6...	JD124535	01/22/2020 06:25:00 AM	1	DRIVER	NaN	796949.0	Na
1	749947	81dc0de2ed92aa62baccab641fa377be7feb1cc47e6554...	JC451435	09/28/2019 03:30:00 AM	1	DRIVER	NaN	834816.0	Na
2	749949	81dc0de2ed92aa62baccab641fa377be7feb1cc47e6554...	JC451435	09/28/2019 03:30:00 AM	2	PARKED	NaN	834819.0	Na
3	749950	81dc0de2ed92aa62baccab641fa377be7feb1cc47e6554...	JC451435	09/28/2019 03:30:00 AM	3	PARKED	NaN	834817.0	Na
4	871921	af84fb5c8d996fcd3aefd36593c3a02e6e7509eeb27568...	JD208731	04/13/2020 10:50:00 PM	2	DRIVER	NaN	827212.0	Na

In [ ]:

```
#Explore the info for all the features
vehicles_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1416095 entries, 0 to 1416094
Data columns (total 72 columns):
 #   Column                  Non-Null Count    Dtype
---  ------                  --------------    -----
 0   CRASH_UNIT_ID           1416095 non-null  int64
 1   CRASH_RECORD_ID         1416095 non-null  object
 2   RD_NO                   1408273 non-null  object
 3   CRASH_DATE              1416095 non-null  object
 4   UNIT_NO                 1416095 non-null  int64
 5   UNIT_TYPE               1414134 non-null  object
 6   NUM_PASSENGERS          209579 non-null   float64
 7   VEHICLE_ID              1384025 non-null  float64
 8   CMRC_VEH_I              26451 non-null    object
 9   MAKE                    1384020 non-null  object
 10  MODEL                   1383876 non-null  object
 11  LIC_PLATE_STATE         1258222 non-null  object
 12  VEHICLE_YEAR            1159243 non-null  float64
 13  VEHICLE_DEFECT          1384025 non-null  object
 14  VEHICLE_TYPE            1384025 non-null  object
 15  VEHICLE_USE             1384025 non-null  object
 16  TRAVEL_DIRECTION        1384025 non-null  object
 17  MANEUVER                1384025 non-null  object
 18  TOWED_I                 173461 non-null   object
 19  FIRE_I                  1132 non-null     object
 20  OCCUPANT_CNT            1384025 non-null  float64
 21  EXCEED_SPEED_LIMIT_I    2397 non-null     object
 22  TOWED_BY                129266 non-null   object
 23  TOWED_TO                79553 non-null    object
 24  AREA_00_I               50097 non-null    object
 25  AREA_01_I               374799 non-null   object
 26  AREA_02_I               227990 non-null   object
 27  AREA_03_I               134586 non-null   object
 28  AREA_04_I               135984 non-null   object
 29  AREA_05_I               210775 non-null   object
 30  AREA_06_I               219467 non-null   object
 31  AREA_07_I               198788 non-null   object
 32  AREA_08_I               210912 non-null   object
 33  AREA_09_I               85333 non-null    object
 34  AREA_10_I               123385 non-null   object
 35  AREA_11_I               241587 non-null   object
 36  AREA_12_I               237530 non-null   object
 37  AREA_99_I               156879 non-null   object
 38  FIRST_CONTACT_POINT     1371395 non-null  object
 39  CMV_ID                  14819 non-null    float64
 40  USDOT_NO                8455 non-null     object
 41  CCMC_NO                 1842 non-null     object
 42  ILCC_NO                 1284 non-null     object
 43  COMMERCIAL_SRC          10012 non-null    object
 44  GVWR                    8380 non-null     object
 45  CARRIER_NAME            14182 non-null    object
```

```
 46  CARRIER_STATE             13322 non-null    object
 47  CARRIER_CITY              13087 non-null    object
 48  HAZMAT_PLACARDS_I         290 non-null      object
 49  HAZMAT_NAME               54 non-null       object
 50  UN_NO                     508 non-null      object
 51  HAZMAT_PRESENT_I          10846 non-null    object
 52  HAZMAT_REPORT_I           10529 non-null    object
 53  HAZMAT_REPORT_NO          1 non-null        object
 54  MCS_REPORT_I              10584 non-null    object
 55  MCS_REPORT_NO             7 non-null        object
 56  HAZMAT_VIO_CAUSE_CRASH_I  10689 non-null    object
 57  MCS_VIO_CAUSE_CRASH_I     10489 non-null    object
 58  IDOT_PERMIT_NO            824 non-null      object
 59  WIDE_LOAD_I               125 non-null      object
 60  TRAILER1_WIDTH            2674 non-null     object
 61  TRAILER2_WIDTH            320 non-null      object
 62  TRAILER1_LENGTH           2180 non-null     float64
 63  TRAILER2_LENGTH           65 non-null       float64
 64  TOTAL_VEHICLE_LENGTH      2644 non-null     float64
 65  AXLE_CNT                  3912 non-null     float64
 66  VEHICLE_CONFIG            12287 non-null    object
 67  CARGO_BODY_TYPE           11753 non-null    object
 68  LOAD_TYPE                 11241 non-null    object
 69  HAZMAT_OUT_OF_SERVICE_I   10214 non-null    object
 70  MCS_OUT_OF_SERVICE_I      10458 non-null    object
 71  HAZMAT_CLASS              983 non-null      object
dtypes: float64(9), int64(2), object(61)
memory usage: 777.9+ MB
```

`CRASH_UNIT_ID` , `RD_NO` , `UNIT_NO` , `VEHICLE_ID` , and `CMRC_VEH_I` , are unique IDs for crash reports which can be ignored for the purposes of the analysis. These columns will be **DROPPED**

`MAKE` , `MODEL` , `LIC_PLATE_STATE` , `VEHICLE_YEAR` , and `TRAVEL_DIRECTION` are speciific informations relevant to the vehicle. These are valuable information to keep track but these don;t provide valuable insights into causes for crashes. While the argument can be made that the make or vehicle year of a car can showcase which brands of cars and which years are involved in the most crashes, these singular data points can inform biased policies. For instance, older cars are usually owned by people who can't afford the expensive new models. Moreover, the more important aspect to know would be what kind of safety features did these cars have to understand how helpful ccertain safety features have but that data is not availabl. Therefore, these columns will be **DROPPED**.

`VEHICLE_DEFECT` : This column might contain some intersting data. Lets investigate the contents of this column.

In [ ]:
```
#check unique values
vehicles_df['VEHICLE_DEFECT'].value_counts()
```

Out[318]:
```
NONE                  768370
UNKNOWN               601707
OTHER                   6782
BRAKES                  4566
TIRES                    700
STEERING                 650
WHEELS                   365
SUSPENSION               241
ENGINE/MOTOR             183
FUEL SYSTEM              150
LIGHTS                    86
WINDOWS                   82
CARGO                     47
SIGNALS                   38
RESTRAINT SYSTEM          21
TRAILER COUPLING          19
EXHAUST                   18
Name: VEHICLE_DEFECT, dtype: int64
```

while thiss information is useful, 98% of the data is skewed towards None, Unkown or Other values that don't provide us any valuable insights. We can use oversampling methodlogies to help balance out the data to provide valuable insights.

`VEHICLE_TYPE` : The type of vehicle, if relevant. Lets investigate the contents of this column.

In [ ]:
```
#check unique values
vehicles_df['VEHICLE_TYPE'].value_counts()
```

Out[319]:
```
PASSENGER                                   870964
SPORT UTILITY VEHICLE (SUV)                 186498
UNKNOWN/NA                                  131562
VAN/MINI-VAN                                 67371
PICKUP                                       43239
TRUCK - SINGLE UNIT                          26270
OTHER                                        16301
BUS OVER 15 PASS.                            14529
TRACTOR W/ SEMI-TRAILER                      13251
BUS UP TO 15 PASS.                            3487
MOTORCYCLE (OVER 150CC)                       3217
SINGLE UNIT TRUCK WITH TRAILER                2131
OTHER VEHICLE WITH TRAILER                    1774
TRACTOR W/O SEMI-TRAILER                      1766
AUTOCYCLE                                      648
MOPED OR MOTORIZED BICYCLE                     382
MOTOR DRIVEN CYCLE                             326
ALL-TERRAIN VEHICLE (ATV)                      160
FARM EQUIPMENT                                  72
3-WHEELED MOTORCYCLE (2 REAR WHEELS)            49
RECREATIONAL OFF-HIGHWAY VEHICLE (ROV)          20
SNOWMOBILE                                       8
Name: VEHICLE_TYPE, dtype: int64
```

This data will be very valuable to discern how different types of vehicles get into accidents and understand the trends in causes. The imbalance in the data has to be aaddresssed later in th eDaata Preparations Section.

`VEHICLE_USE` : The normal use of the vehicle, if relevant. In conjunction with previous column, this column can be used to createe grouped categories of vehicles such as Personal, Rideshare, etc. We can also see that there are more unknown records in this collumn than the previous one. We can use the previous column to reduce the number of unkowns n our data.

In [ ]:

```
#check unique values
vehicles_df['VEHICLE_USE'].value_counts()
```

Out[320]:

```
PERSONAL                         894350
UNKNOWN/NA                       279642
NOT IN USE                        71810
OTHER                             43301
TAXI/FOR HIRE                     18505
COMMERCIAL - SINGLE UNIT          17164
RIDESHARE SERVICE                 11623
CTA                                9315
POLICE                             9055
CONSTRUCTION/MAINTENANCE           6300
COMMERCIAL - MULTI-UNIT            5689
OTHER TRANSIT                      3964
SCHOOL BUS                         3724
TOW TRUCK                          2657
AMBULANCE                          1638
FIRE                               1357
STATE OWNED                        1162
DRIVER EDUCATION                   1107
MASS TRANSIT                        832
LAWN CARE/LANDSCAPING               526
AGRICULTURE                         143
CAMPER/RV - SINGLE UNIT              68
MILITARY                             55
HOUSE TRAILER                        22
CAMPER/RV - TOWED/MULTI-UNIT         16
Name: VEHICLE_USE, dtype: int64
```

`MANEUVER` : The action the unit was taking prior to the crash, as determined by the reporting officer. This will be important too understand what kind of maneuvers can cause the most crashes. These will also go hand in hand with location data to understand if certain areas have accidents occuring at specific manevers. Lets investigate this column to understand the values in it.

In [ ]:
```
#check unique values
vehicles_df['MANEUVER'].value_counts()
```

Out[321]:
```
STRAIGHT AHEAD                        630603
PARKED                                190912
UNKNOWN/NA                            108064
SLOW/STOP IN TRAFFIC                  105648
TURNING LEFT                           81375
BACKING                                57054
TURNING RIGHT                          45377
PASSING/OVERTAKING                     33216
CHANGING LANES                         26814
OTHER                                  23226
ENTERING TRAFFIC LANE FROM PARKING     16299
MERGING                                 9569
STARTING IN TRAFFIC                     8157
U-TURN                                  7783
LEAVING TRAFFIC LANE TO PARK            6719
AVOIDING VEHICLES/OBJECTS               6021
SKIDDING/CONTROL LOSS                   5624
ENTER FROM DRIVE/ALLEY                  5414
PARKED IN TRAFFIC LANE                  4193
SLOW/STOP - LEFT TURN                   3042
DRIVING WRONG WAY                       2001
SLOW/STOP - RIGHT TURN                  1929
NEGOTIATING A CURVE                     1860
SLOW/STOP - LOAD/UNLOAD                 1663
TURNING ON RED                           538
DRIVERLESS                               530
DIVERGING                                216
DISABLED                                 178
Name: MANEUVER, dtype: int64
```

Some of these categories can be grouped together to make claassificatin analysis less granular. This will be done in the Data Preparation section.

`TOWED_I`, `FIRE_I`, `TOWED_BY`, and `TOWED_TO` are relevant details for keeping record of a crash but these columns won't be useful data to understand the causes and trends of crashes. These columns will be **DROPPED**.

`OCCUPANT_CNT` which is the number of people in the unit will be very valuable records to use in our analysis. This can show whether an increased number of occupants in vehicles is correlated to certain types of traffic crashes.

`AREA_00_I` to `AREA_99_I` are encoded columns but do not have any details on what information do they represent. Lets investigate the contents of these columns to see if there is more insight.

In [ ]:
```
#check unique values
print(vehicles_df['AREA_00_I'].value_counts().to_string())
```

```
Y    43954
N     6143
```

In [ ]:
```
#check unique values
vehicles_df['AREA_02_I'].value_counts()
```

Out[323]:
```
Y    217069
N     10921
Name: AREA_02_I, dtype: int64
```

In [ ]:
```
#check unique values
vehicles_df['AREA_03_I'].value_counts()
```

Out[324]:
```
Y    128418
N      6168
Name: AREA_03_I, dtype: int64
```

In [ ]:
```
#check unique values
vehicles_df['AREA_04_I'].value_counts()
```

Out[325]:
```
Y    129920
N      6064
Name: AREA_04_I, dtype: int64
```

In [ ]:
```
#check unique values
vehicles_df['AREA_99_I'].value_counts()
```

Out[326]:
```
Y    151041
N      5838
Name: AREA_99_I, dtype: int64
```

Most of these are just indicators but there's no information on what do these indicators represent. With no extra information on what areas these columns represent, these columns will bee **DROPPED**. Moreover, we the latitude and longitude to help us understand the location.

`FIRST_CONTACT_POINT` : This column does not have a description. LLets investigate the column values to understand more.

In [ ]:
```
#check unique values
vehicles_df['FIRST_CONTACT_POINT'].value_counts()
```

Out[327]:
```
FRONT                   207316
OTHER                   168617
REAR-LEFT               156455
UNKNOWN                 131938
REAR                    117386
FRONT-LEFT              100587
TOTAL (ALL AREAS)        95027
SIDE-RIGHT               89210
FRONT-RIGHT              87356
SIDE-LEFT                81838
ROOF                     56741
REAR-RIGHT               50777
UNDER CARRIAGE           16646
NONE                     11501
Name: FIRST_CONTACT_POINT, dtype: int64
```

This column represents the first point of contact of an accident. This information can provide us insight into how vehiicles/people are getting into crashes. If its front/rear/sideways, etc. This will be valuable information t ocarry forward.

`CMV_ID`, `USDOT_NO`, `CCMC_NO`, `ILCC_NO`, and `COMMERCIAL_SRC` are specific information for record keeping of the crash reports. These do not provide any insights into the causes of accidents. They will be **DROPPED**.

The following are the columns specific to Comemrcial Trailer/Tractor crashes. These will be **DROPPED**

`GVWR` : Gross Vehicle Weight Rating (GVWR)

`CARRIER_NAME` : This is the name of the company that owns the tractor/trailer

`CARRIER_STATE` : This is the state where the carrier is registered

`CARRIER_CITY` : This is the city where the carrier is located

`HAZMAT_PLACARDS_I` : This is the hazmat warning on the tractor/trailer regarding the contents. When carrying certain types of content, carriers are mandated to have hazmat signs displayed.

`HAZMAT_NAME` : This is the name of what kind of hazmat was being carried

`UN_NO` : This is the 4 digit number thata identifies hazardouss equipment

The following information will be **DROPPED** because it is relevant to the hazmat reports involved in a traffic accident.

`HAZMAT_PRESENT_I`, `HAZMAT_REPORT_I`, `HAZMAT_REPORT_NO`, `MCS_REPORT_I`, `MCS_REPORT_NO`, `HAZMAT_VIO_CAUSE_CRASH_I`, `MCS_VIO_CAUSE_CRASH_I`, `WIDE_LOAD_I`, and `IDOT_PERMIT_NO`

While the following colummns have interesting information to analyse about trailer lengths, it would be more useful to just use the `TOTAL_VEHICLE_LENGTH` column. Also, we can the `TRAILER2_LENGTH` column can be used to idenitfy whether there were more than one trailers or not.

Therefore, `TRAILER1_WIDTH` , `TRAILER2_WIDTH` , and `TRAILER1_LENGTH` will be **Dropped**.

`AXLE_CNT` : This will provide indication of what kind of a vehicle it is. There has to be some cleaning done on this dataset depending on the contents of this column. Lets invetigate this column.

In [ ]:
```
#check unique values
vehicles_df['AXLE_CNT'].value_counts()
```

Out[328]:
```
2.0        1238
5.0        1222
3.0         875
6.0         250
4.0         197
1.0          57
8.0          25
7.0          14
18.0         10
9.0           7
16.0          4
10.0          4
12.0          2
20.0          1
53.0          1
52.0          1
77.0          1
55.0          1
99.0          1
26009.0       1
Name: AXLE_CNT, dtype: int64
```

It is clear that there are a few typos here. Also, not all records have values for axlle count which will be dealt with later. Nonetheless, the `VEHICLE_CONFIG` column can provide more valuable information with regaaards to vehicl type for tractor/trailers therefore this column will be **DROPPED**

`VEHICLE_CONFIG` : This has data on the type of tractor/trailer which will be useful to understand the pattern of vehicle configurations and crashes. Lets take a quick look at the data.

In [ ]:

```
#check unique values
vehicles_df['VEHICLE_CONFIG'].value_counts()
```

Out[329]:

```
TRACTOR/SEMI-TRAILER                  4841
SINGLE UNIT TRUCK, 2 AXLES, 6 TIRES   2450
BUS                                   1910
TRUCK/TRACTOR                          985
TRUCK/TRAILER                          819
UNKNOWN HEAVY TRUCK                    712
SINGLE UNIT TRUCK, 3 OR MORE AXLES     538
TRACTOR/DOUBLES                         32
Name: VEHICLE_CONFIG, dtype: int64
```

`CARGO_BODY_TYPE` : This is anothere type of vehicle description that would you useful iin understanding what kind of vocational vehicles are involved in crashes. Lets snvestigate the contents of this column.

In [ ]:

```
#check unique values
vehicles_df['CARGO_BODY_TYPE'].value_counts()
```

Out[330]:

```
VAN/ENCLOSED BOX    5173
OTHER               2643
BUS                 1836
FLATBED              907
DUMP                 412
GARBAGE/REFUSE       336
TANK                 234
CONCRETE MIXER       109
AUTO TRANSPORTER     103
Name: CARGO_BODY_TYPE, dtype: int64
```

`LOAD_TYE` : If cargo body type column is used, using Loaad Type will increase the level of graanularity. f our model isn't performing good enough, we can reconsider using more granular data. **DROP LOAD_TYPE COLUMN**

In [ ]:

```
#check unique values
vehicles_df['LOAD_TYPE'].value_counts()
```

Out[331]:

```
OTHER                     6119
UNKNOWN                   4453
CONSTRUCTION EQUIPMENT     389
BUILDING MATERIALS         213
STEEL COILS                 47
FARM EQUIPMENT              20
Name: LOAD_TYPE, dtype: int64
```

The following columns are more relevaant to Hazmats.

`HAZMAT_OUT_OF_SERVICE_I` , `MCS_OUT_OF_SERVICE_I` , `HAZMAT_CLASS` **DROP**

SUMMARY

The following columns will be carried forward:

1. `CRASH_RECORD_ID`
2. `VEHICLE_DEFECT`
3. `VEHICLE_TYPE`
4. `VEHICLE_USE`
5. `MANEUVER`
6. `OCCUPANT_CNT`
7. `FIRST_CONTACT_POINT`
8. `VEHICLE_CONFIG`

Traffic Crashes - People

This data contains information about people involved in a crash and if any injuries were sustained. This dataset should be used in combination with the traffic Crash and Vehicle dataset. Each record corresponds to an occupant in a vehicle listed in the Crash dataset. Some people involved in a crash may not have been an occupant in a motor vehicle, but may have been a pedestrian, bicyclist, or using another non-motor vehicle mode of transportation. Injuries reported are reported by the responding police officer. Fatalities that occur after the initial reports are typically updated in these records up to 30 days after the date of the crash. Person data can be linked with the Crash and Vehicle dataset using the “CRASH_RECORD_ID” field. A vehicle can have multiple occupants and hence have a one to many relationship between Vehicle and Person dataset. However, a pedestrian is a “unit” by itself and have a one to one relationship between the Vehicle and Person table.

In [ ]:

```
#import the dataset using the API endpoint
people_df = pd.read_csv('data/Traffic_Crashes-People.csv')

#preview thee first 5 rows
people_df.head()
```

```
<ipython-input-332-904a295451e4>:2: DtypeWarning: Columns (20,24,25,26,29) have mixed types. Specify dtype option on impo
rt or set low_memory=False.
  people_df = pd.read_csv('data/Traffic_Crashes-People.csv')
```

Out[332]:

	PERSON_ID	PERSON_TYPE	CRASH_RECORD_ID	RD_NO	VEHICLE_ID	CRASH_DATE	SEAT_NO	CITY	STATE	ZIPCODE	...
0	O749947	DRIVER	81dc0de2ed92aa62baccab641fa377be7feb1cc47e6554...	JC451435	834816.0	09/28/2019 03:30:00 AM	NaN	CHICAGO	IL	60651	...
1	O871921	DRIVER	af84fb5c8d996fcd3aefd36593c3a02e6e7509eeb27568...	JD208731	827212.0	04/13/2020 10:50:00 PM	NaN	CHICAGO	IL	60620	...
2	O10018	DRIVER	71162af7bf22799b776547132ebf134b5b438dcf3dac6b...	HY484534	9579.0	11/01/2015 05:00:00 AM	NaN	NaN	NaN	NaN	...
3	O10038	DRIVER	c21c476e2ccc41af550b5d858d22aaac4ffc88745a1700...	HY484750	9598.0	11/01/2015 08:00:00 AM	NaN	NaN	NaN	NaN	...
4	O10039	DRIVER	eb390a4c8e114c69488f5fb8a097fe629f5a92fd528cf4...	HY484778	9600.0	11/01/2015 10:15:00 AM	NaN	NaN	NaN	NaN	...

5 rows × 30 columns

In [ ]:
```
people_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1530385 entries, 0 to 1530384
Data columns (total 30 columns):
 #   Column                 Non-Null Count    Dtype  
---  ------                 --------------    -----  
 0   PERSON_ID              1530385 non-null  object 
 1   PERSON_TYPE            1530385 non-null  object 
 2   CRASH_RECORD_ID        1530385 non-null  object 
 3   RD_NO                  1521511 non-null  object 
 4   VEHICLE_ID             1500311 non-null  float64
 5   CRASH_DATE             1530385 non-null  object 
 6   SEAT_NO                309565 non-null   float64
 7   CITY                   1117449 non-null  object 
 8   STATE                  1132411 non-null  object 
 9   ZIPCODE                1021601 non-null  object 
 10  SEX                    1506380 non-null  object 
 11  AGE                    1085359 non-null  float64
 12  DRIVERS_LICENSE_STATE  899668 non-null   object 
 13  DRIVERS_LICENSE_CLASS  760585 non-null   object 
 14  SAFETY_EQUIPMENT       1526028 non-null  object 
 15  AIRBAG_DEPLOYED        1501485 non-null  object 
 16  EJECTION               1511675 non-null  object 
 17  INJURY_CLASSIFICATION  1529714 non-null  object 
 18  HOSPITAL               263368 non-null   object 
 19  EMS_AGENCY             163631 non-null   object 
 20  EMS_RUN_NO             26932 non-null    object 
 21  DRIVER_ACTION          1218047 non-null  object 
 22  DRIVER_VISION          1217601 non-null  object 
 23  PHYSICAL_CONDITION     1218903 non-null  object 
 24  PEDPEDAL_ACTION        28502 non-null    object 
 25  PEDPEDAL_VISIBILITY    28446 non-null    object 
 26  PEDPEDAL_LOCATION      28499 non-null    object 
 27  BAC_RESULT             1219061 non-null  object 
 28  BAC_RESULT VALUE       1824 non-null     float64
 29  CELL_PHONE_USE         1158 non-null     object 
dtypes: float64(4), object(26)
memory usage: 350.3+ MB
```

`PERSON_ID` : A unique identifier for each person record. IDs starting with P indicate passengers. IDs starting with O indicate a person who was not a passenger in the vehicle (e.g., driver, pedestrian, cyclist, etc.). Considering that the Person Type column gives us more detailed information, there won't be a need to keep this column.**DROP**

`PERSON_TYPE` : Type of roadway user involved in crash

In [ ]:
```
#check unique values
people_df['PERSON_TYPE'].value_counts()
```

Out[334]:
```
DRIVER                 1191234
PASSENGER               309565
PEDESTRIAN               17588
BICYCLE                  10478
NON-MOTOR VEHICLE         1253
NON-CONTACT VEHICLE        267
Name: PERSON_TYPE, dtype: int64
```

`CRASH_RECORD_ID` : This number can be used to link to the same crash in the Crashes and Vehicles datasets. This number also serves as a unique ID in the Crashes dataset. Hence, this will be important to keep for joining and comparing the datasets.

`RD_NO` : Chicago Police Department report number. For privacy reasons, this column is blank for recent crashes. This is a column for record-keeping purposed. **DROP**

`VEHICLE_ID` : The corresponding CRASH_UNIT_ID from the Vehicles dataset. We will keep this incase we need t ogroup or reference any datsets.

`CRASH_DATE` : Date and time of crash as entered by the reporting officer. **DROP**

`SEAT_NO` : Code for seating position of motor vehicle occupant: 1= driver, 2= center front, 3 = front passenger, 4 = second row left, 5 = second row center, 6 = second row right, 7 = enclosed passengers, 8 = exposed passengers, 9= unknown position, 10 = third row left, 11 = third row center, 12 = third row right.

In [ ]:
```
#check unique values
people_df['SEAT_NO'].value_counts()
```

Out[335]:
```
3.0     150042
6.0      52277
4.0      41331
5.0      14578
1.0      13563
2.0      12780
12.0      7996
7.0       7163
10.0      6805
11.0      2678
8.0        352
Name: SEAT_NO, dtype: int64
```

There are missing values in thi column which can be subsituted with code *9* which is for the unkown position.

The values also have to be converted to categories for data analysis later. Nonetheless, this doesn't help us identify the cause of thee crash in any way. It can be insightful for further granular operations to understand why certain people were injured or harmed more than others. It will **DROPPED**

`CITY`, `STATE`, `ZIPCODE`, `DRIVERS_LICENSE_STATE`, `DRIVERS_LICENSE_CLASS` are people specific information to aaa vehicle that won't help out **DROPPED**

`AGE` can be an imprtant factor to look at and might be linked to the cause of crashes. It can provide insights into if certain age groups are more involved in crashes. If this feature does turn out to be one of the top 10 features, then it can provide the DOT on how to focus it's training or awareness campaigns to fight Vision Zero program.

`SAFETY_EQUIPMENT`: Safety equipment used by vehicle occupant in crash, if any. Very important information that can have a high correlation to injuries or faatalities.

In [ ]:

```
#check unique values
people_df['SAFETY_EQUIPMENT'].value_counts()
```

Out[336]:

```
SAFETY BELT USED                                741510
USAGE UNKNOWN                                   699868
NONE PRESENT                                     47896
SAFETY BELT NOT USED                              8625
CHILD RESTRAINT USED                              7821
HELMET NOT USED                                   6525
CHILD RESTRAINT - FORWARD FACING                  3409
BICYCLE HELMET (PEDACYCLIST INVOLVED ONLY)        2457
CHILD RESTRAINT - TYPE UNKNOWN                    1718
CHILD RESTRAINT - REAR FACING                     1610
HELMET USED                                       1358
DOT COMPLIANT MOTORCYCLE HELMET                    974
BOOSTER SEAT                                       913
CHILD RESTRAINT NOT USED                           668
SHOULD/LAP BELT USED IMPROPERLY                    190
NOT DOT COMPLIANT MOTORCYCLE HELMET                186
WHEELCHAIR                                         163
CHILD RESTRAINT USED IMPROPERLY                    107
STRETCHER                                           30
Name: SAFETY_EQUIPMENT, dtype: int64
```

`AIRBAG_DEPLOYED`: Whether vehicle occupant airbag deployed as result of crash. This doesn't play a paart in causing the crash **DROP**

`EJECTION`: Whether vehicle occupant was ejected or extricated from the vehicle as a result of crash **DROP**

`INJURY_CLASSIFICATION`: Severity of injury person sustained in the crash. This information can be used to understand which columns to keep since Vision Zero focuses on reducing injuries and fatalities.

In [ ]:
```
#check unique values
people_df['INJURY_CLASSIFICATION'].value_counts()
```

Out[337]:
```
NO INDICATION OF INJURY     1399940
NONINCAPACITATING INJURY      73185
REPORTED, NOT EVIDENT         41738
INCAPACITATING INJURY         14003
FATAL                           848
Name: INJURY_CLASSIFICATION, dtype: int64
```

`HOSPITAL` , `EMS_AGENCY` , `EMS_RUN_NO` are specific recrd keeping columns that won't be useful**DROP**

`DRIVER_ACTION` : Driver action that contributed to the crash, as determined by reporting officer. This will be important in identifying the cause of the crashes.

In [ ]:
```
#check unique values
people_df['DRIVER_ACTION'].value_counts()
```

Out[338]:
```
NONE                                    438974
UNKNOWN                                 301595
FAILED TO YIELD                         110980
OTHER                                   107701
FOLLOWED TOO CLOSELY                     74349
IMPROPER BACKING                         37076
IMPROPER TURN                            31917
IMPROPER LANE CHANGE                     31451
IMPROPER PASSING                         27025
DISREGARDED CONTROL DEVICES              21109
TOO FAST FOR CONDITIONS                  18947
WRONG WAY/SIDE                            4794
IMPROPER PARKING                          4556
OVERCORRECTED                             1955
EVADING POLICE VEHICLE                    1940
CELL PHONE USE OTHER THAN TEXTING         1867
EMERGENCY VEHICLE ON CALL                 1110
TEXTING                                    504
STOPPED SCHOOL BUS                         145
LICENSE RESTRICTIONS                        52
Name: DRIVER_ACTION, dtype: int64
```

`DRIVER_VISION` : What, if any, objects obscured the driver’s vision at time of crash. This will be another importnt piece of information in identifying car crashes.

In [ ]:
```
#check unique values
people_df['DRIVER_VISION'].value_counts()
```

Out[339]:
```
NOT OBSCURED              632631
UNKNOWN                   554663
OTHER                      12394
MOVING VEHICLES             7183
PARKED VEHICLES             4415
WINDSHIELD (WATER/ICE)      3476
BLINDED - SUNLIGHT          1451
TREES, PLANTS                535
BUILDINGS                    442
BLINDED - HEADLIGHTS         120
HILLCREST                     93
BLOWING MATERIALS             88
EMBANKMENT                    77
SIGNBOARD                     33
Name: DRIVER_VISION, dtype: int64
```

`PHYSICAL_CONDITION` : Driver's apparent physical condition at time of crash, as observed by the reporting officer

In [ ]:
```
#check unique values
people_df['PHYSICAL_CONDITION'].value_counts()
```

Out[340]:
```
NORMAL                           801930
UNKNOWN                          394225
IMPAIRED - ALCOHOL                 5489
REMOVED BY EMS                     4515
OTHER                              3579
FATIGUED/ASLEEP                    3260
EMOTIONAL                          2710
ILLNESS/FAINTED                    1138
HAD BEEN DRINKING                   929
IMPAIRED - DRUGS                    644
IMPAIRED - ALCOHOL AND DRUGS        331
MEDICATED                           153
Name: PHYSICAL_CONDITION, dtype: int64
```

This column provides valuable information on whether the driver was in a state to drive or not. Add missing values to unknown categories. Bin different categories together.

`PEDPEDAL_ACTION` : Action of pedestrian or cyclist at the time of crash

In [ ]:
```
#check unique values
people_df['PEDPEDAL_ACTION'].value_counts()
```

Out[341]:
```
CROSSING - WITH SIGNAL                                     5861
WITH TRAFFIC                                               4420
UNKNOWN/NA                                                 3698
OTHER ACTION                                               3456
CROSSING - NO CONTROLS (NOT AT INTERSECTION)               1682
NO ACTION                                                  1508
CROSSING - NO CONTROLS (AT INTERSECTION)                   1422
CROSSING - AGAINST SIGNAL                                  1361
NOT AT INTERSECTION                                        1005
AGAINST TRAFFIC                                             874
CROSSING - CONTROLS PRESENT (NOT AT INTERSECTION)           826
STANDING IN ROADWAY                                         674
TURNING LEFT                                                390
PARKED VEHICLE                                              326
ENTER FROM DRIVE/ALLEY                                      275
WORKING IN ROADWAY                                          196
TURNING RIGHT                                               177
INTOXICATED PED/PEDAL                                       176
PLAYING IN ROADWAY                                          109
PLAYING/WORKING ON VEHICLE                                   21
TO/FROM DISABLED VEHICLE                                     20
SCHOOL BUS (WITHIN 50 FT.)                                   15
WAITING FOR SCHOOL BUS                                       10
Name: PEDPEDAL_ACTION, dtype: int64
```

Group together multiple categories

`PEDPEDAL_VISIBILITY` : Visibility of pedestrian of cyclist safety equipment in use at time of crash

In [ ]:
```
#check unique values
people_df['PEDPEDAL_VISIBILITY'].value_counts()
```

Out[342]:
```
NO CONTRASTING CLOTHING    22345
CONTRASTING CLOTHING        3753
OTHER LIGHT SOURCE USED     1635
REFLECTIVE MATERIAL          713
Name: PEDPEDAL_VISIBILITY, dtype: int64
```

`PEDPEDAL_LOCATION` : Location of pedestrian or cyclist at the time of crash

In [ ]:
```
#check unique values
people_df['PEDPEDAL_LOCATION'].value_counts()
```

Out[343]:
```
IN ROADWAY          12781
IN CROSSWALK         9487
UNKNOWN/NA           2375
NOT IN ROADWAY       1273
BIKEWAY              1227
BIKE LANE             794
DRIVEWAY ACCESS       416
SHOULDER              146
Name: PEDPEDAL_LOCATION, dtype: int64
```

`BAC_RESULT` : Status of blood alcohol concentration testing for driver or other person involved in crash

In [ ]:
```
#check unique values
people_df['BAC_RESULT'].value_counts()
```

Out[344]:
```
TEST NOT OFFERED                       1200818
TEST REFUSED                             12968
TEST PERFORMED, RESULTS UNKNOWN           3007
TEST TAKEN                                2268
Name: BAC_RESULT, dtype: int64
```

Since this column seems more like record-keeping whereas the results value if more vallluble. **DROP**

`BAC_RESULT VALUE` : Driver’s blood alcohol concentration test result (fatal crashes may include pedestrian or cyclist results)

In [ ]:

```
#check unique values
people_df['BAC_RESULT VALUE'].value_counts()
```

```
Out[345]: 0.00    176
          0.17    127
          0.18    126
          0.21    110
          0.14    102
          0.20     95
          0.16     90
          0.19     87
          0.15     80
          0.22     76
          0.23     73
          0.12     68
          0.13     68
          0.11     64
          0.24     59
          0.25     41
          0.26     40
          0.27     34
          0.10     34
          0.09     32
          0.28     28
          0.08     19
          0.29     18
          0.03     17
          0.07     17
          0.30     16
          0.33     15
          0.04     15
          0.05     11
          0.32      9
          0.35      9
          0.02      8
          0.31      8
          0.06      8
          0.38      6
          0.36      4
          0.34      4
          0.39      3
          0.44      3
          0.01      3
          1.00      2
          0.79      2
          0.88      2
          0.45      2
          0.60      2
          0.95      1
          0.40      1
          0.47      1
          0.99      1
          0.41      1
          0.80      1
```

```
0.58      1
0.37      1
0.85      1
0.67      1
0.98      1
Name: BAC_RESULT VALUE, dtype: int64
```

`CELL_PHONE_USE` : Whether person was/was not using cellphone at the time of the crash, as determined by the reporting officer

In [ ]:

```
#check unique values
people_df['CELL_PHONE_USE'].value_counts()
```

Out[346]:

```
Y    752
N    406
Name: CELL_PHONE_USE, dtype: int64
```

SUMMARY

Columns to keep:

1. `PERSON_TYPE`
2. `CRASH_RECORD_ID`
3. `VEHICLE_ID`
4. `AGE`
5. `SAFETY_EQUIPMENT`
6. `INJURY_CLASSIFICATION`
7. `DRIVER_ACTION`
8. `DRIVER_VISION`
9. `PHYSICAL_CONDITION`
10. `PEDPEDAL_ACTION`
11. `BAC_RESULT VALUE`

Data Limitations

There are several Data limitations that we have to keep in mind with regards to these dataset.

```
1. Only using CPD data, there might be data missing that is not reported to the CPD
2. Interstate highways, freeway ramps, and on local roads along the City boundary, are excluded from this dataset
3. Around half of the data is self reported and may have bias in them, missing or incorrect information
4. There's no data on the traffic volume, congestion level, or the speed the vehiclees were moving at
5. There are large imbalancces in the dataset and some columns have a lot of missing values. Later on during cleani
ng and processing, there has to be an assumption that the report created was accurate and there were no glaring det
ailss overlooked like Intersections, Work Zones, etc.
6. The data has to be binned together to reduce the granularity of the dataset which can impact the data
7. The large imbalances would require either getting rid of a large number of records or creating a lot of ssynthet
ic data for oversampling
8. A lot of the primary and ssecondary causes are overlapping information. There is no set standard that clearly bi
ifurcates the different categories of car crashes which can cause the precision of results to go down.
```

Data Preparation

Crashes-Crashes

First filter out the column that will be proceeded with.

In [ ]:

```
#Select the columns that need to be kept
cln_crashes = crashes_df[['CRASH_RECORD_ID',
'CRASH_DATE',
'POSTED_SPEED_LIMIT',
'DEVICE_CONDITION',
'WEATHER_CONDITION',
'LIGHTING_CONDITION',
'CRASH_TYPE',
'INTERSECTION_RELATED_I',
'ROAD_DEFECT',
'PRIM_CONTRIBUTORY_CAUSE',
'SEC_CONTRIBUTORY_CAUSE',
'NUM_UNITS',
'WORK_ZONE_I',
'WORKERS_PRESENT_I',
'INJURIES_TOTAL',
'INJURIES_FATAL',
'CRASH_HOUR',
'CRASH_DAY_OF_WEEK',
'CRASH_MONTH',
'LATITUDE',
'LONGITUDE']]
```

Lets takae a look at the summary of the daataframe to understand null vlues and other characteristics

In [ ]:
```
cln_crashes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 692784 entries, 0 to 692783
Data columns (total 21 columns):
 #   Column                   Non-Null Count   Dtype  
---  ------                   --------------   -----  
 0   CRASH_RECORD_ID          692784 non-null  object 
 1   CRASH_DATE               692784 non-null  object 
 2   POSTED_SPEED_LIMIT       692784 non-null  int64  
 3   DEVICE_CONDITION         692784 non-null  object 
 4   WEATHER_CONDITION        692784 non-null  object 
 5   LIGHTING_CONDITION       692784 non-null  object 
 6   CRASH_TYPE               692784 non-null  object 
 7   INTERSECTION_RELATED_I   158797 non-null  object 
 8   ROAD_DEFECT              692784 non-null  object 
 9   PRIM_CONTRIBUTORY_CAUSE  692784 non-null  object 
 10  SEC_CONTRIBUTORY_CAUSE   692784 non-null  object 
 11  NUM_UNITS                692784 non-null  int64  
 12  WORK_ZONE_I              4046 non-null    object 
 13  WORKERS_PRESENT_I        1048 non-null    object 
 14  INJURIES_TOTAL           691292 non-null  float64
 15  INJURIES_FATAL           691292 non-null  float64
 16  CRASH_HOUR               692784 non-null  int64  
 17  CRASH_DAY_OF_WEEK        692784 non-null  int64  
 18  CRASH_MONTH              692784 non-null  int64  
 19  LATITUDE                 688378 non-null  float64
 20  LONGITUDE                688378 non-null  float64
dtypes: float64(4), int64(5), object(12)
memory usage: 111.0+ MB
```

There are 7 columns with missing values with 3 columns having a significantly high number than the rest. Lets go through one by one and fix these.

In [ ]:
```
#Indentify the value counts
cln_crashes['WORK_ZONE_I'].value_counts()
```

Out[349]:
```
Y    3170
N     876
Name: WORK_ZONE_I, dtype: int64
```

In [ ]:
```
cln_crashes['WORKERS_PRESENT_I'].value_counts()
```

Out[350]:
```
Y    932
N    116
Name: WORKERS_PRESENT_I, dtype: int64
```

Both of these columns arae indicators in the form of Yes or No. We are going to assume that if a crash happens in a work zone with workers present, it would be aa significant thing to note. Relying on the thoroughness of the responding officer, we will replace the missing values with No. This is an assumption that a responding officer will easilly notice aa work site and note it down considering that work sites are significantly big landmarks.

In [ ]:
```
#replace thee Null values with N to indicate No
cln_crashes['WORK_ZONE_I'].fillna('N',inplace=True)
cln_crashes['WORKERS_PRESENT_I'].fillna('N',inplace=True)
```

```
<ipython-input-351-cb695187d75f>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  cln_crashes['WORK_ZONE_I'].fillna('N',inplace=True)
<ipython-input-351-cb695187d75f>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  cln_crashes['WORKERS_PRESENT_I'].fillna('N',inplace=True)
```

Lets check the value counts after replacing the missing values

In [ ]:
```
cln_crashes['WORK_ZONE_I'].value_counts()
```

Out[352]:
```
N    689614
Y      3170
Name: WORK_ZONE_I, dtype: int64
```

In [ ]:
```
cln_crashes['WORKERS_PRESENT_I'].value_counts()
```

Out[353]:
```
N    691852
Y       932
Name: WORKERS_PRESENT_I, dtype: int64
```

Similarly, for intersection related events, the assumption is going to be that it is a significant thing to miss. Intersections are very clear landmarks which are difficult to miss. The missing values will be replaced by No

In [ ]:
```
#replace Null values with N
cln_crashes['INTERSECTION_RELATED_I'].fillna('N',inplace=True)
```

```
<ipython-input-354-d6473f561668>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  cln_crashes['INTERSECTION_RELATED_I'].fillna('N',inplace=True)
```

In [ ]:

```
cln_crashes['INTERSECTION_RELATED_I'].value_counts()
```

Out[355]:

```
N    541388
Y    151396
Name: INTERSECTION_RELATED_I, dtype: int64
```

Before dealing with the other 4 columns that have a small percentage of records with missing values, lets filter out the crash type to see if we automatically drop the missing records.

Since the goal is to recognise car crash causes that can help with Vision Zero, we will only use the crashes where there was an injury or fatality.

Therefore the next step will be to filter out the crashes according to crash types.

In [ ]:

```
#investigate the different values in crash type
cln_crashes['CRASH_TYPE'].value_counts()
```

Out[356]:

```
NO INJURY / DRIVE AWAY              510406
INJURY AND / OR TOW DUE TO CRASH    182378
Name: CRASH_TYPE, dtype: int64
```

In [ ]:

```
#filter out records for injury related events
cln_crashes = cln_crashes[cln_crashes['CRASH_TYPE'] == 'INJURY AND / OR TOW DUE TO CRASH']

#look at the new summaary for the dataframe
cln_crashes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 182378 entries, 0 to 692777
Data columns (total 21 columns):
 #   Column                   Non-Null Count   Dtype  
---  ------                   --------------   -----  
 0   CRASH_RECORD_ID          182378 non-null  object 
 1   CRASH_DATE               182378 non-null  object 
 2   POSTED_SPEED_LIMIT       182378 non-null  int64  
 3   DEVICE_CONDITION         182378 non-null  object 
 4   WEATHER_CONDITION        182378 non-null  object 
 5   LIGHTING_CONDITION       182378 non-null  object 
 6   CRASH_TYPE               182378 non-null  object 
 7   INTERSECTION_RELATED_I   182378 non-null  object 
 8   ROAD_DEFECT              182378 non-null  object 
 9   PRIM_CONTRIBUTORY_CAUSE  182378 non-null  object 
 10  SEC_CONTRIBUTORY_CAUSE   182378 non-null  object 
 11  NUM_UNITS                182378 non-null  int64  
 12  WORK_ZONE_I              182378 non-null  object 
 13  WORKERS_PRESENT_I        182378 non-null  object 
 14  INJURIES_TOTAL           181739 non-null  float64
 15  INJURIES_FATAL           181739 non-null  float64
 16  CRASH_HOUR               182378 non-null  int64  
 17  CRASH_DAY_OF_WEEK        182378 non-null  int64  
 18  CRASH_MONTH              182378 non-null  int64  
 19  LATITUDE                 181319 non-null  float64
 20  LONGITUDE                181319 non-null  float64
dtypes: float64(4), int64(5), object(12)
memory usage: 30.6+ MB
```

Looks like there are still columns with missing values. Compared to the total number of records, the number of records that these columns aree missing is significantly very small. With that consdieration, it would be better to drop tee records with missing values.

In [ ]:

```
#drop records with missing values
cln_crashes.dropna(inplace=True)
```

In [ ]:
```
#investigate the summarry
cln_crashes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 180681 entries, 0 to 692777
Data columns (total 21 columns):
 #   Column                   Non-Null Count   Dtype  
---  ------                   --------------   -----  
 0   CRASH_RECORD_ID          180681 non-null  object 
 1   CRASH_DATE               180681 non-null  object 
 2   POSTED_SPEED_LIMIT       180681 non-null  int64  
 3   DEVICE_CONDITION         180681 non-null  object 
 4   WEATHER_CONDITION        180681 non-null  object 
 5   LIGHTING_CONDITION       180681 non-null  object 
 6   CRASH_TYPE               180681 non-null  object 
 7   INTERSECTION_RELATED_I   180681 non-null  object 
 8   ROAD_DEFECT              180681 non-null  object 
 9   PRIM_CONTRIBUTORY_CAUSE  180681 non-null  object 
 10  SEC_CONTRIBUTORY_CAUSE   180681 non-null  object 
 11  NUM_UNITS                180681 non-null  int64  
 12  WORK_ZONE_I              180681 non-null  object 
 13  WORKERS_PRESENT_I        180681 non-null  object 
 14  INJURIES_TOTAL           180681 non-null  float64
 15  INJURIES_FATAL           180681 non-null  float64
 16  CRASH_HOUR               180681 non-null  int64  
 17  CRASH_DAY_OF_WEEK        180681 non-null  int64  
 18  CRASH_MONTH              180681 non-null  int64  
 19  LATITUDE                 180681 non-null  float64
 20  LONGITUDE                180681 non-null  float64
dtypes: float64(4), int64(5), object(12)
memory usage: 30.3+ MB
```

Next, lets break up the Crash Date column to extract the year since we already have the hour, month, and daay of the week in separate columns.

In [ ]:
```
#investigate the current values
cln_crashes['CRASH_DATE']
```

Out[360]:
```
0         03/25/2019 02:43:00 PM
11        07/15/2020 11:45:00 AM
14        07/15/2022 04:10:00 PM
18        07/15/2022 09:00:00 PM
21        06/21/2019 02:37:00 PM
                   ...          
692765    11/23/2022 05:58:00 PM
692767    11/24/2022 05:27:00 AM
692771    11/22/2022 08:00:00 PM
692776    11/24/2022 01:10:00 AM
692777    11/22/2022 04:30:00 PM
Name: CRASH_DATE, Length: 180681, dtype: object
```

Looks like these are strings. They have to be converted to datetime for extraction

In [ ]:
```
#convert the data type to Datetime
cln_crashes['CRASH_DATE'] = cln_crashes['CRASH_DATE'].map(
                            lambda x: dt.datetime.strptime(x, '%m/%d/%Y %H:%M:%S %p'))
```

In [ ]:
```
#investigate the new values
cln_crashes['CRASH_DATE']
```

Out[362]:
```
0        2019-03-25 02:43:00
11       2020-07-15 11:45:00
14       2022-07-15 04:10:00
18       2022-07-15 09:00:00
21       2019-06-21 02:37:00
                ...
692765   2022-11-23 05:58:00
692767   2022-11-24 05:27:00
692771   2022-11-22 08:00:00
692776   2022-11-24 01:10:00
692777   2022-11-22 04:30:00
Name: CRASH_DATE, Length: 180681, dtype: datetime64[ns]
```

In [ ]:
```
#keep only the year
cln_crashes['CRASH_DATE'] = cln_crashes['CRASH_DATE'].dt.year
```

In [ ]:
```
#rename column to year
cln_crashes.rename(columns={'CRASH_DATE': 'CRASH_YEAR'},inplace = True)
```

In [ ]:
```
#investigate summary after change
cln_crashes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 180681 entries, 0 to 692777
Data columns (total 21 columns):
 #   Column                   Non-Null Count   Dtype  
---  ------                   --------------   -----  
 0   CRASH_RECORD_ID          180681 non-null  object 
 1   CRASH_YEAR               180681 non-null  int64  
 2   POSTED_SPEED_LIMIT       180681 non-null  int64  
 3   DEVICE_CONDITION         180681 non-null  object 
 4   WEATHER_CONDITION        180681 non-null  object 
 5   LIGHTING_CONDITION       180681 non-null  object 
 6   CRASH_TYPE               180681 non-null  object 
 7   INTERSECTION_RELATED_I   180681 non-null  object 
 8   ROAD_DEFECT              180681 non-null  object 
 9   PRIM_CONTRIBUTORY_CAUSE  180681 non-null  object 
 10  SEC_CONTRIBUTORY_CAUSE   180681 non-null  object 
 11  NUM_UNITS                180681 non-null  int64  
 12  WORK_ZONE_I              180681 non-null  object 
 13  WORKERS_PRESENT_I        180681 non-null  object 
 14  INJURIES_TOTAL           180681 non-null  float64
 15  INJURIES_FATAL           180681 non-null  float64
 16  CRASH_HOUR               180681 non-null  int64  
 17  CRASH_DAY_OF_WEEK        180681 non-null  int64  
 18  CRASH_MONTH              180681 non-null  int64  
 19  LATITUDE                 180681 non-null  float64
 20  LONGITUDE                180681 non-null  float64
dtypes: float64(4), int64(6), object(11)
memory usage: 30.3+ MB
```

Since the datasource mentions that citywide data isn't availale until September 2017, we will be conservative and give a couplee of months for the new system to be incorporated properly and use records from 2018 onwards.

In [ ]:
```
#filter records to keep 2018 onwards
cln_crashes = cln_crashes[cln_crashes['CRASH_YEAR'] >= 2018]
```

In [ ]:

```
#investigate the summary after filtering
cln_crashes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 158209 entries, 0 to 692777
Data columns (total 21 columns):
 #   Column                   Non-Null Count   Dtype  
---  ------                   --------------   -----  
 0   CRASH_RECORD_ID          158209 non-null  object 
 1   CRASH_YEAR               158209 non-null  int64  
 2   POSTED_SPEED_LIMIT       158209 non-null  int64  
 3   DEVICE_CONDITION         158209 non-null  object 
 4   WEATHER_CONDITION        158209 non-null  object 
 5   LIGHTING_CONDITION       158209 non-null  object 
 6   CRASH_TYPE               158209 non-null  object 
 7   INTERSECTION_RELATED_I   158209 non-null  object 
 8   ROAD_DEFECT              158209 non-null  object 
 9   PRIM_CONTRIBUTORY_CAUSE  158209 non-null  object 
 10  SEC_CONTRIBUTORY_CAUSE   158209 non-null  object 
 11  NUM_UNITS                158209 non-null  int64  
 12  WORK_ZONE_I              158209 non-null  object 
 13  WORKERS_PRESENT_I        158209 non-null  object 
 14  INJURIES_TOTAL           158209 non-null  float64
 15  INJURIES_FATAL           158209 non-null  float64
 16  CRASH_HOUR               158209 non-null  int64  
 17  CRASH_DAY_OF_WEEK        158209 non-null  int64  
 18  CRASH_MONTH              158209 non-null  int64  
 19  LATITUDE                 158209 non-null  float64
 20  LONGITUDE                158209 non-null  float64
dtypes: float64(4), int64(6), object(11)
memory usage: 26.6+ MB
```

The number of records have reduced but a significant chunk is still there. Lets proceed further with cleaning the other columns

The next one is device condition

In [ ]:

```
#look at the value counts of the different categories
cln_crashes['DEVICE_CONDITION'].value_counts()
```

Out[368]:

```
NO CONTROLS                 79463
FUNCTIONING PROPERLY        67803
UNKNOWN                      7842
OTHER                        1443
FUNCTIONING IMPROPERLY        971
NOT FUNCTIONING               588
WORN REFLECTIVE MATERIAL       67
MISSING                        32
Name: DEVICE_CONDITION, dtype: int64
```

This column contains multiple categories that can be grouped together. To reduce the amount of granularity of the data, 3 main categories can be focused on.

1. No controls: shows that there were no controls in that area
2. Functioning properly: shows that there were controls and were working properly
3. Not Functioning properly: shows that there were controls but weren't working properly

In [ ]:
```
#replace values with the binned category
cln_crashes['DEVICE_CONDITION'].replace(['UNKNOWN',
                                          'OTHER',
                                          'FUNCTIONING IMPROPERLY',
                                          'NOT FUNCTIONING',
                                          'WORN REFLECTIVE MATERIAL',
                                          'MISSING'], 'NOT FUNCTIONING PROPERLY', inplace=True)
```

In [ ]:
```
#look at the new value counts
cln_crashes['DEVICE_CONDITION'].value_counts()
```

Out[370]:
```
NO CONTROLS                 79463
FUNCTIONING PROPERLY        67803
NOT FUNCTIONING PROPERLY    10943
Name: DEVICE_CONDITION, dtype: int64
```

Next, lets investigate the Weather Condition column

In [ ]:
```
#look at the value counts
cln_crashes['WEATHER_CONDITION'].value_counts()
```

Out[371]:
```
CLEAR                      124418
RAIN                        16925
SNOW                         6227
CLOUDY/OVERCAST              5346
UNKNOWN                      3242
OTHER                         742
FREEZING RAIN/DRIZZLE         512
FOG/SMOKE/HAZE                328
SLEET/HAIL                    298
BLOWING SNOW                  138
SEVERE CROSS WIND GATE         33
Name: WEATHER_CONDITION, dtype: int64
```

Similarly, to reduce teh granularity of the dataset, multiple categories in this dataset can be binned together to represent 2 main categories:

1. Clear: shows clear weather
2. Not Clear: shows that the weather wasn't clear and could have been a cause of obstruction

In [ ]:
```
#replace values with the binned category
cln_crashes['WEATHER_CONDITION'].replace(['RAIN',
                                          'SNOW',
                                          'CLOUDY/OVERCAST',
                                          'UNKNOWN',
                                          'OTHER',
                                          'FREEZING RAIN/DRIZZLE',
                                          'FOG/SMOKE/HAZE',
                                          'SLEET/HAIL',
                                          'BLOWING SNOW',
                                          'SEVERE CROSS WIND GATE'], 'NOT CLEAR', inplace=True)
```

In [ ]:
```
#look at the new value counts
cln_crashes['WEATHER_CONDITION'].value_counts()
```

Out[373]:
```
CLEAR        124418
NOT CLEAR     33791
Name: WEATHER_CONDITION, dtype: int64
```

Lets investigate the Lighting Condition next.

In [ ]:
```
#look at the value counts
cln_crashes['LIGHTING_CONDITION'].value_counts()
```

Out[374]:
```
DAYLIGHT                   89319
DARKNESS, LIGHTED ROAD     50881
DARKNESS                    7480
DUSK                        4661
DAWN                        3232
UNKNOWN                     2636
Name: LIGHTING_CONDITION, dtype: int64
```

Lighting conditions is a lot more granular whereas we can work with a slighly less granular approach. Day Time and Night Time would be sufficient categories to indicate what time of dat the crash ocurred. If Lighting Conditions are a significant cause, these can be explored further.

For the unknown category, we can take a look at the crash hour and assign the correct bin aaccordingly.

In [ ]:
```
#bin categories for Night time
cln_crashes['LIGHTING_CONDITION'].replace(['DARKNESS, LIGHTED ROAD',
                                           'DARKNESS, LIGHTED ROAD',
                                           'DARKNESS',
                                           'DAWN',
                                           'OTHER',
                                           ], 'NIGHT TIME', inplace=True)


#bin categories for daytime
cln_crashes['LIGHTING_CONDITION'].replace(['DAYLIGHT',
                                           'DUSK',
                                           ], 'DAY TIME', inplace=True)
```

In [ ]:
```
#check new value counts
cln_crashes['LIGHTING_CONDITION'].value_counts()
```

Out[376]:
```
DAY TIME      93980
NIGHT TIME    61593
UNKNOWN        2636
Name: LIGHTING_CONDITION, dtype: int64
```

In [ ]:
```
#check unkown category crash hour
cln_crashes[cln_crashes['LIGHTING_CONDITION'] == 'UNKNOWN']['CRASH_HOUR'].value_counts()
```

Out[377]:
```
0     175
18    161
17    159
16    143
19    141
20    126
22    122
21    121
6     119
15    118
7     116
23    106
5     104
14    104
8     100
2      95
1      93
9      86
4      85
12     83
10     77
3      74
11     71
13     57
Name: CRASH_HOUR, dtype: int64
```

In [ ]:
```
#assign day time according to general guidelines
cln_crashes.loc[(cln_crashes['LIGHTING_CONDITION'] == 'UNKNOWN') &
            ((cln_crashes['CRASH_HOUR']>=6) | (cln_crashes['CRASH_HOUR']<=19)),
               'LIGHTING_CONDITION'] = 'DAY TIME'
```

In [ ]:
```
#assign night time according to general guidelines
cln_crashes.loc[(cln_crashes['LIGHTING_CONDITION'] == 'UNKNOWN') &
            ((cln_crashes['CRASH_HOUR']<=5) | (cln_crashes['CRASH_HOUR']>=18)),
               'LIGHTING_CONDITION'] = 'NIGHT TIME'
```

In [ ]:
```
#check new value counts
cln_crashes['LIGHTING_CONDITION'].value_counts()
```

Out[380]:
```
DAY TIME      96616
NIGHT TIME    61593
Name: LIGHTING_CONDITION, dtype: int64
```

In [ ]:
```
#check dataframe summary after changes
cln_crashes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 158209 entries, 0 to 692777
Data columns (total 21 columns):
 #   Column                   Non-Null Count   Dtype  
---  ------                   --------------   -----  
 0   CRASH_RECORD_ID          158209 non-null  object 
 1   CRASH_YEAR               158209 non-null  int64  
 2   POSTED_SPEED_LIMIT       158209 non-null  int64  
 3   DEVICE_CONDITION         158209 non-null  object 
 4   WEATHER_CONDITION        158209 non-null  object 
 5   LIGHTING_CONDITION       158209 non-null  object 
 6   CRASH_TYPE               158209 non-null  object 
 7   INTERSECTION_RELATED_I   158209 non-null  object 
 8   ROAD_DEFECT              158209 non-null  object 
 9   PRIM_CONTRIBUTORY_CAUSE  158209 non-null  object 
 10  SEC_CONTRIBUTORY_CAUSE   158209 non-null  object 
 11  NUM_UNITS                158209 non-null  int64  
 12  WORK_ZONE_I              158209 non-null  object 
 13  WORKERS_PRESENT_I        158209 non-null  object 
 14  INJURIES_TOTAL           158209 non-null  float64
 15  INJURIES_FATAL           158209 non-null  float64
 16  CRASH_HOUR               158209 non-null  int64  
 17  CRASH_DAY_OF_WEEK        158209 non-null  int64  
 18  CRASH_MONTH              158209 non-null  int64  
 19  LATITUDE                 158209 non-null  float64
 20  LONGITUDE                158209 non-null  float64
dtypes: float64(4), int64(6), object(11)
memory usage: 26.6+ MB
```

Lets investigate the road defect column.

In [ ]:
```
#check value counts
cln_crashes['ROAD_DEFECT'].value_counts()
```

Out[382]:
```
NO DEFECTS           134050
UNKNOWN               20600
RUT, HOLES             1147
OTHER                  1014
WORN SURFACE            924
SHOULDER DEFECT         326
DEBRIS ON ROADWAY       148
Name: ROAD_DEFECT, dtype: int64
```

2 binned categories will be sufficient to use.

1. No Defects: shows that there were no defects at the crash location
2. Defects: shows that there were defects at the crash location

In [ ]:
```
#bin categories
cln_crashes['ROAD_DEFECT'].replace(['UNKNOWN','RUT, HOLES',
                                         'OTHER',
                                         'WORN SURFACE',
                                         'SHOULDER DEFECT',
                                         'DEBRIS ON ROADWAY',
                                         ], 'DEFECTS', inplace=True)
```

In [ ]:
```
#check new value counts
cln_crashes['ROAD_DEFECT'].value_counts()
```

Out[384]:
```
NO DEFECTS    134050
DEFECTS        24159
Name: ROAD_DEFECT, dtype: int64
```

The next column to be investigated will be Number of Units. This column contains information on how many units weeree involved in the crash.

In [ ]:
```
#check the value counts
cln_crashes['NUM_UNITS'].value_counts()
```

Out[385]:
```
2     116347
3      18777
1      16256
4       4848
5       1324
6        409
7        140
8         56
9         26
10        11
11         5
12         4
18         3
14         1
15         1
16         1
Name: NUM_UNITS, dtype: int64
```

There are a few definite anomalies. It is very rare to see 5 or more units involved in a crash. That would mean that either there was a big pile up of vehicles because of a rare type of crash.

In [ ]:
```
#check the value counts percentages
cln_crashes['NUM_UNITS'].value_counts(normalize=True).mul(100).round(4).astype(str) + '%'
```

Out[386]:
```
2     73.5401%
3     11.8685%
1      10.275%
4      3.0643%
5      0.8369%
6      0.2585%
7      0.0885%
8      0.0354%
9      0.0164%
10      0.007%
11     0.0032%
12     0.0025%
18     0.0019%
14     0.0006%
15     0.0006%
16     0.0006%
Name: NUM_UNITS, dtype: object
```

Crashes with 5 or more units involved is extremely rare and totals to slightly more than 1%. Considering how rare these occurances are, it would be useful to ignore them and focus on the bigger pieces of the pie.

In [ ]:
```python
#filter records for 5 or more
cln_crashes = cln_crashes[cln_crashes['NUM_UNITS']<5]
```

In [ ]:
```python
# cln_crashes.loc[cln_crashes['NUM_UNITS']>=6, 'NUM_UNITS'] = 6
```

In [ ]:
```python
#check new vlaue counts
cln_crashes['NUM_UNITS'].value_counts()
```

Out[389]:
```
2    116347
3     18777
1     16256
4      4848
Name: NUM_UNITS, dtype: int64
```

Next is the Primary Contributary Cause. This will be the target variable later on. Letss investigate thiss columnn.

In [ ]:
```python
#check valaue counts
cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].value_counts()
```

Out[390]:
```
UNABLE TO DETERMINE                                                                 47841
FAILING TO YIELD RIGHT-OF-WAY                                                       25493
FAILING TO REDUCE SPEED TO AVOID CRASH                                              11184
FOLLOWING TOO CLOSELY                                                               10207
DISREGARDING TRAFFIC SIGNALS                                                         7968
NOT APPLICABLE                                                                       6268
IMPROPER TURNING/NO SIGNAL                                                           5575
DRIVING SKILLS/KNOWLEDGE/EXPERIENCE                                                  4456
IMPROPER OVERTAKING/PASSING                                                          4052
IMPROPER LANE USAGE                                                                  3913
DISREGARDING STOP SIGN                                                               3691
WEATHER                                                                              3256
OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRESSIVE MANNER     3199
PHYSICAL CONDITION OF DRIVER                                                         2435
EQUIPMENT - VEHICLE CONDITION                                                        2302
UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)                   2245
DISTRACTION - FROM INSIDE VEHICLE                                                    1732
DRIVING ON WRONG SIDE/WRONG WAY                                                      1650
VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)                                 1488
```

In [ ]:
```python
#check total number of uniique categories
len(cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].unique())
```

Out[391]:
```
40
```

40 categories are a lot of categories to deal with. It would be very tedious for the model and proessing capability.

Thereе is clear overlap between multiple categoriesss in this column. These can be binned together to 2 major categories to make this dataset more manageable.

1. Traffic Rules Violated: shows that there were traffic violations to be the primary cause of the crash
2. Reckless/Improper Driving: shows that the drivver was not being safe with their driving

In [ ]:

```
#bin categories

#traffic ruless violated
cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].replace(['DISREGARDING TRAFFIC SIGNALS',
                                                 'DISREGARDING STOP SIGN',
                                                 'PASSING STOPPED SCHOOL BUS',
                                                 'RELATED TO BUS STOP',
                                                 'DISREGARDING YIELD SIGN',
                                                 'TURNING RIGHT ON RED',
                                                 'TURNING RIGHT ON RED',
                                                 'DISREGARDING OTHER TRAFFIC SIGNS',
                                                 'DRIVING ON WRONG SIDE/WRONG WAY',
                                                 'DISREGARDING ROAD MARKINGS',
                                                 'FAILING TO YIELD RIGHT-OF-WAY',
                                          ], 'TRAFFIC RULES VIOLATED', inplace=True)

#Reckless/Improper Driving
cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].replace(['IMPROPER TURNING/NO SIGNAL',
                                                 'DRIVING SKILLS/KNOWLEDGE/EXPERIENCE',
                                                 'IMPROPER OVERTAKING/PASSING',
                                                 'IMPROPER LANE USAGE',
                                                 'OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRESS
                                                 'DRIVING ON WRONG SIDE/WRONG WAY',
                                                 'IMPROPER BACKING',
                                                 'EXCEEDING AUTHORIZED SPEED LIMIT',
                                                 'EXCEEDING SAFE SPEED FOR CONDITIONS',
                                                 'FAILING TO REDUCE SPEED TO AVOID CRASH',
                                                 'FOLLOWING TOO CLOSELY',
                                                 'PHYSICAL CONDITION OF DRIVER',
                                                 'UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)',
                                                 'DISTRACTION - FROM INSIDE VEHICLE',
                                                 'CELL PHONE USE OTHER THAN TEXTING',
                                                 'HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)',
                                                 'DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER,

                                                 'EQUIPMENT - VEHICLE CONDITION',
                                                 'TEXTING',
                                                 'MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT',
                                                 'BICYCLE ADVANCING LEGALLY ON RED LIGHT',
                                                 'OBSTRUCTED CROSSWALKS',
                                                 'ANIMAL',
                                                 'ROAD CONSTRUCTION/MAINTENANCE',
                                                 'ROAD ENGINEERING/SURFACE/MARKING DEFECTS',
                                                 'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST',
                                                 'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
                                                 'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
                                                 'DISTRACTION - FROM OUTSIDE VEHICLE',
                                                 'WEATHER''MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT',
                                                 'BICYCLE ADVANCING LEGALLY ON RED LIGHT',
                                                 'OBSTRUCTED CROSSWALKS',
                                                 'ANIMAL',
```

```
                                                    'ROAD CONSTRUCTION/MAINTENANCE',
                                                    'ROAD ENGINEERING/SURFACE/MARKING DEFECTS',
                                                    'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST',
                                                    'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
                                                    'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
                                                    'DISTRACTION - FROM OUTSIDE VEHICLE',
                                                    'WEATHER'
                                                ], 'RECKLESS/IMPROPER DRIVING', inplace=True)
```

In [ ]:

```
# #bin categories

# #traffic ruless violated
# cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].replace(['DISREGARDING TRAFFIC SIGNALS',
#                                                 'DISREGARDING STOP SIGN',
#                                                 'PASSING STOPPED SCHOOL BUS',
#                                                 'RELATED TO BUS STOP',
#                                                 'DISREGARDING YIELD SIGN',
#                                                 'TURNING RIGHT ON RED',
#                                                 'TURNING RIGHT ON RED',
#                                                 'DISREGARDING OTHER TRAFFIC SIGNS',
#                                                 'DRIVING ON WRONG SIDE/WRONG WAY',
#                                                 'DISREGARDING ROAD MARKINGS',
#                                                 'FAILING TO YIELD RIGHT-OF-WAY'
#                                         ], 'TRAFFIC RULES VIOLATED', inplace=True)

# #Reckless/Improper Driving
# cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].replace(['IMPROPER TURNING/NO SIGNAL',
#                                                 'DRIVING SKILLS/KNOWLEDGE/EXPERIENCE',
#                                                 'IMPROPER OVERTAKING/PASSING',
#                                                 'IMPROPER LANE USAGE',
#                                                 'OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRE
#                                                 'DRIVING ON WRONG SIDE/WRONG WAY',
#                                                 'IMPROPER BACKING',
#                                                 'EXCEEDING AUTHORIZED SPEED LIMIT',
#                                                 'EXCEEDING SAFE SPEED FOR CONDITIONS',
#                                                 'FAILING TO REDUCE SPEED TO AVOID CRASH',
#                                                 'FOLLOWING TOO CLOSELY'
#                                         ], 'RECKLESS/IMPROPER DRIVING', inplace=True)

# # #Overspeeding
# # cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].replace(['EXCEEDING AUTHORIZED SPEED LIMIT',
# #                                                 'EXCEEDING SAFE SPEED FOR CONDITIONS'
# #                                         ], 'OVERSPEEDING', inplace=True)

# # #Overspeeding
# # cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].replace(['WEATHER'
# #                                         ], "NATURE'S IMPACT", inplace=True)

# #Obstructions
# cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].replace(['MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT',
#                                                 'BICYCLE ADVANCING LEGALLY ON RED LIGHT',
#                                                 'OBSTRUCTED CROSSWALKS',
#                                                 'ANIMAL',
#                                                 'ROAD CONSTRUCTION/MAINTENANCE',
#                                                 'ROAD ENGINEERING/SURFACE/MARKING DEFECTS',
#                                                 'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST',
#                                                 'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
#                                                 'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
#                                                 'DISTRACTION - FROM OUTSIDE VEHICLE',
#                                                 'WEATHER'
```

```
#                                          ], 'OBSTRUCTIONS', inplace=True)

# #Compromised Driving
# cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].replace(['PHYSICAL CONDITION OF DRIVER',
#                                                 'UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)',
#                                                 'DISTRACTION - FROM INSIDE VEHICLE',
#                                                 'CELL PHONE USE OTHER THAN TEXTING',
#                                                 'HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)',
#                                                 'DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER

#                                                 'EQUIPMENT - VEHICLE CONDITION',
#                                                 'TEXTING'
#                                          ], 'COMPROMISED DRIVING', inplace=True)
```

In [ ]:

```
#check new vaalue counts
cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].value_counts()
```

Out[394]:

```
RECKLESS/IMPROPER DRIVING    61900
UNABLE TO DETERMINE          47841
TRAFFIC RULES VIOLATED       40219
NOT APPLICABLE                6268
Name: PRIM_CONTRIBUTORY_CAUSE, dtype: int64
```

In [ ]:

```
#check new vaalue counts percentages
cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].value_counts(normalize=True).mul(100).round(4).astype(str) + '%'
```

Out[395]:

```
RECKLESS/IMPROPER DRIVING    39.6216%
UNABLE TO DETERMINE          30.6226%
TRAFFIC RULES VIOLATED       25.7438%
NOT APPLICABLE                4.0121%
Name: PRIM_CONTRIBUTORY_CAUSE, dtype: object
```

Next is the second contributory cause. We can use the same binn categories as we did for the primary one but before we do that, we are going to see if there is a ssecondary contributory cause listed for records that were unable to determine or not applicable. The goal is to only have a singular cause column. Primaary cause will take precedence but where we don't have enough information, we can use the secondary one to fill the gaps.

In [ ]:
```
#check value counts
cln_crashes['SEC_CONTRIBUTORY_CAUSE'].value_counts()
```

Out[396]:
```
NOT APPLICABLE                                                            61028
UNABLE TO DETERMINE                                                       50601
FAILING TO REDUCE SPEED TO AVOID CRASH                                     8974
FAILING TO YIELD RIGHT-OF-WAY                                              6721
DRIVING SKILLS/KNOWLEDGE/EXPERIENCE                                        5338
FOLLOWING TOO CLOSELY                                                      2960
WEATHER                                                                    2708
IMPROPER TURNING/NO SIGNAL                                                 1984
IMPROPER LANE USAGE                                                        1939
OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRESSIVE MANNER     1665
IMPROPER OVERTAKING/PASSING                                                1542
DISREGARDING TRAFFIC SIGNALS                                               1459
PHYSICAL CONDITION OF DRIVER                                               1061
VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)                        938
DISREGARDING STOP SIGN                                                      877
DISTRACTION - FROM INSIDE VEHICLE                                           733
UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)          716
EQUIPMENT - VEHICLE CONDITION                                               691
DRIVING ON WRONG SIDE/WRONG WAY                                             609
EXCEEDING AUTHORIZED SPEED LIMIT                                            490
DISTRACTION - FROM OUTSIDE VEHICLE                                          440
EXCEEDING SAFE SPEED FOR CONDITIONS                                         403
DISREGARDING OTHER TRAFFIC SIGNS                                            326
IMPROPER BACKING                                                            320
HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)                             247
DISREGARDING ROAD MARKINGS                                                  234
ROAD CONSTRUCTION/MAINTENANCE                                               193
CELL PHONE USE OTHER THAN TEXTING                                           185
ROAD ENGINEERING/SURFACE/MARKING DEFECTS                                    173
EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST                           137
DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER, ETC.)  87
TURNING RIGHT ON RED                                                         84
DISREGARDING YIELD SIGN                                                      78
RELATED TO BUS STOP                                                          76
ANIMAL                                                                       71
BICYCLE ADVANCING LEGALLY ON RED LIGHT                                       44
TEXTING                                                                      36
OBSTRUCTED CROSSWALKS                                                        30
PASSING STOPPED SCHOOL BUS                                                   18
MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT                                    12
Name: SEC_CONTRIBUTORY_CAUSE, dtype: int64
```

In [ ]:

```
#bin categories

#traffic ruless violated
cln_crashes['SEC_CONTRIBUTORY_CAUSE'].replace(['DISREGARDING TRAFFIC SIGNALS',
                                               'DISREGARDING STOP SIGN',
                                               'PASSING STOPPED SCHOOL BUS',
                                               'RELATED TO BUS STOP',
                                               'DISREGARDING YIELD SIGN',
                                               'TURNING RIGHT ON RED',
                                               'TURNING RIGHT ON RED',
                                               'DISREGARDING OTHER TRAFFIC SIGNS',
                                               'DRIVING ON WRONG SIDE/WRONG WAY',
                                               'DISREGARDING ROAD MARKINGS',
                                               'FAILING TO YIELD RIGHT-OF-WAY',
                                        ], 'TRAFFIC RULES VIOLATED', inplace=True)

#Reckless/Improper Driving
cln_crashes['SEC_CONTRIBUTORY_CAUSE'].replace(['IMPROPER TURNING/NO SIGNAL',
                                               'DRIVING SKILLS/KNOWLEDGE/EXPERIENCE',
                                               'IMPROPER OVERTAKING/PASSING',
                                               'IMPROPER LANE USAGE',
                                               'OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRES
                                               'DRIVING ON WRONG SIDE/WRONG WAY',
                                               'IMPROPER BACKING',
                                               'EXCEEDING AUTHORIZED SPEED LIMIT',
                                               'EXCEEDING SAFE SPEED FOR CONDITIONS',
                                               'FAILING TO REDUCE SPEED TO AVOID CRASH',
                                               'FOLLOWING TOO CLOSELY',
                                               'PHYSICAL CONDITION OF DRIVER',
                                               'UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)',
                                               'DISTRACTION - FROM INSIDE VEHICLE',
                                               'CELL PHONE USE OTHER THAN TEXTING',
                                               'HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)',
                                               'DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER,

                                               'EQUIPMENT - VEHICLE CONDITION',
                                               'TEXTING',
                                               'MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT',
                                               'BICYCLE ADVANCING LEGALLY ON RED LIGHT',
                                               'OBSTRUCTED CROSSWALKS',
                                               'ANIMAL',
                                               'ROAD CONSTRUCTION/MAINTENANCE',
                                               'ROAD ENGINEERING/SURFACE/MARKING DEFECTS',
                                               'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST',
                                               'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
                                               'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
                                               'DISTRACTION - FROM OUTSIDE VEHICLE',
                                               'WEATHER''MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT',
                                               'BICYCLE ADVANCING LEGALLY ON RED LIGHT',
                                               'OBSTRUCTED CROSSWALKS',
                                               'ANIMAL',
```

```
                                            'ROAD CONSTRUCTION/MAINTENANCE',
                                            'ROAD ENGINEERING/SURFACE/MARKING DEFECTS',
                                            'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST',
                                            'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
                                            'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
                                            'DISTRACTION - FROM OUTSIDE VEHICLE',
                                            'WEATHER'
                                       ], 'RECKLESS/IMPROPER DRIVING', inplace=True)

# #traffic ruless violated
# cln_crashes['SEC_CONTRIBUTORY_CAUSE'].replace(['DISREGARDING TRAFFIC SIGNALS',
#                                                'DISREGARDING STOP SIGN',
#                                                'PASSING STOPPED SCHOOL BUS',
#                                                'RELATED TO BUS STOP',
#                                                'DISREGARDING YIELD SIGN',
#                                                'TURNING RIGHT ON RED',
#                                                'TURNING RIGHT ON RED',
#                                                'DISREGARDING OTHER TRAFFIC SIGNS',
#                                                'DRIVING ON WRONG SIDE/WRONG WAY',
#                                                'DISREGARDING ROAD MARKINGS',
#                                                'FAILING TO YIELD RIGHT-OF-WAY'
#                                         ], 'TRAFFIC RULES VIOLATED', inplace=True)

# #Reckless/Improper Driving
# cln_crashes['SEC_CONTRIBUTORY_CAUSE'].replace(['IMPROPER TURNING/NO SIGNAL',
#                                                'DRIVING SKILLS/KNOWLEDGE/EXPERIENCE',
#                                                'IMPROPER OVERTAKING/PASSING',
#                                                'IMPROPER LANE USAGE',
#                                                'OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGR
#                                                'DRIVING ON WRONG SIDE/WRONG WAY',
#                                                'IMPROPER BACKING',
#                                                'EXCEEDING AUTHORIZED SPEED LIMIT',
#                                                'EXCEEDING SAFE SPEED FOR CONDITIONS',
#                                                'FAILING TO REDUCE SPEED TO AVOID CRASH',
#                                                'FOLLOWING TOO CLOSELY'
#                                         ], 'RECKLESS/IMPROPER DRIVING', inplace=True)


# #Obstructions
# cln_crashes['SEC_CONTRIBUTORY_CAUSE'].replace(['MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT',
#                                                'BICYCLE ADVANCING LEGALLY ON RED LIGHT',
#                                                'OBSTRUCTED CROSSWALKS',
#                                                'ANIMAL',
#                                                'ROAD CONSTRUCTION/MAINTENANCE',
#                                                'ROAD ENGINEERING/SURFACE/MARKING DEFECTS',
#                                                'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST',
#                                                'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
#                                                'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
#                                                'DISTRACTION - FROM OUTSIDE VEHICLE',
#                                                'WEATHER'
#                                         ], 'OBSTRUCTIONS', inplace=True)
```

```
# #Compromised Driving
# cln_crashes['SEC_CONTRIBUTORY_CAUSE'].replace(['PHYSICAL CONDITION OF DRIVER',
#                                                'UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)'
#                                                'DISTRACTION - FROM INSIDE VEHICLE',
#                                                'CELL PHONE USE OTHER THAN TEXTING',
#                                                'HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)',
#                                                'DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYE

#                                                'EQUIPMENT - VEHICLE CONDITION',
#                                                'TEXTING'
#                                         ], 'COMPROMISED DRIVING', inplace=True)
```

In [ ]:

```
#check new vaalue counts
cln_crashes['SEC_CONTRIBUTORY_CAUSE'].value_counts()
```

Out[398]:

```
NOT APPLICABLE              61028
UNABLE TO DETERMINE         50601
RECKLESS/IMPROPER DRIVING   34117
TRAFFIC RULES VIOLATED      10482
Name: SEC_CONTRIBUTORY_CAUSE, dtype: int64
```

In [ ]:

```
#bin categories

#traffic ruless violated
cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].replace(['DISREGARDING TRAFFIC SIGNALS',
                                                'DISREGARDING STOP SIGN',
                                                'PASSING STOPPED SCHOOL BUS',
                                                'RELATED TO BUS STOP',
                                                'DISREGARDING YIELD SIGN',
                                                'TURNING RIGHT ON RED',
                                                'TURNING RIGHT ON RED',
                                                'DISREGARDING OTHER TRAFFIC SIGNS',
                                                'DRIVING ON WRONG SIDE/WRONG WAY',
                                                'DISREGARDING ROAD MARKINGS',
                                                'FAILING TO YIELD RIGHT-OF-WAY',
                                        ], 'TRAFFIC RULES VIOLATED', inplace=True)

#Reckless/Improper Driving
cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].replace(['IMPROPER TURNING/NO SIGNAL',
                                                'DRIVING SKILLS/KNOWLEDGE/EXPERIENCE',
                                                'IMPROPER OVERTAKING/PASSING',
                                                'IMPROPER LANE USAGE',
                                                'OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRESS
                                                'DRIVING ON WRONG SIDE/WRONG WAY',
                                                'IMPROPER BACKING',
                                                'EXCEEDING AUTHORIZED SPEED LIMIT',
                                                'EXCEEDING SAFE SPEED FOR CONDITIONS',
                                                'FAILING TO REDUCE SPEED TO AVOID CRASH',
                                                'FOLLOWING TOO CLOSELY',
                                                'PHYSICAL CONDITION OF DRIVER',
                                                'UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)',
                                                'DISTRACTION - FROM INSIDE VEHICLE',
                                                'CELL PHONE USE OTHER THAN TEXTING',
                                                'HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)',
                                                'DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER,

                                                'EQUIPMENT - VEHICLE CONDITION',
                                                'TEXTING',
                                                'MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT',
                                                'BICYCLE ADVANCING LEGALLY ON RED LIGHT',
                                                'OBSTRUCTED CROSSWALKS',
                                                'ANIMAL',
                                                'ROAD CONSTRUCTION/MAINTENANCE',
                                                'ROAD ENGINEERING/SURFACE/MARKING DEFECTS',
                                                'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST',
                                                'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
                                                'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
                                                'DISTRACTION - FROM OUTSIDE VEHICLE',
                                                'WEATHER''MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT',
                                                'BICYCLE ADVANCING LEGALLY ON RED LIGHT',
                                                'OBSTRUCTED CROSSWALKS',
                                                'ANIMAL',
```

```
                                                       'ROAD CONSTRUCTION/MAINTENANCE',
                                                       'ROAD ENGINEERING/SURFACE/MARKING DEFECTS',
                                                       'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST',
                                                       'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
                                                       'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
                                                       'DISTRACTION - FROM OUTSIDE VEHICLE',
                                                       'WEATHER'
                                                ], 'RECKLESS/IMPROPER DRIVING', inplace=True)

# #Overspeeding
# cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].replace(['EXCEEDING AUTHORIZED SPEED LIMIT',
#                                                  'EXCEEDING SAFE SPEED FOR CONDITIONS'
#                                           ], 'OVERSPEEDING', inplace=True)

# #Overspeeding
# cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].replace(['WEATHER'
#                                           ], "NATURE'S IMPACT", inplace=True)

#Obstructions
# cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].replace(['MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT',
#                                                  'BICYCLE ADVANCING LEGALLY ON RED LIGHT',
#                                                  'OBSTRUCTED CROSSWALKS',
#                                                  'ANIMAL',
#                                                  'ROAD CONSTRUCTION/MAINTENANCE',
#                                                  'ROAD ENGINEERING/SURFACE/MARKING DEFECTS',
#                                                  'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST',
#                                                  'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
#                                                  'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
#                                                  'DISTRACTION - FROM OUTSIDE VEHICLE',
#                                                  'WEATHER'
#                                           ], 'OBSTRUCTIONS', inplace=True)

#Compromised Driving
# cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].replace(['PHYSICAL CONDITION OF DRIVER',
#                                                  'UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)',
#                                                  'DISTRACTION - FROM INSIDE VEHICLE',
#                                                  'CELL PHONE USE OTHER THAN TEXTING',
#                                                  'HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)',
#                                                  'DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER

#                                                  'EQUIPMENT - VEHICLE CONDITION',
#                                                  'TEXTING'
#                                           ], 'COMPROMISED DRIVING', inplace=True)
```

In [ ]:
```
#check new vaalue counts
cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].value_counts()
```

Out[400]:
```
RECKLESS/IMPROPER DRIVING    61900
UNABLE TO DETERMINE          47841
TRAFFIC RULES VIOLATED       40219
NOT APPLICABLE                6268
Name: PRIM_CONTRIBUTORY_CAUSE, dtype: int64
```

Now we will check whether there are any records that have 'unable to determine' listed the in primary column but have a cause listed in the secondary column.

In [ ]:
```
#check value counts for primary unable to determine cause
cln_crashes[cln_crashes['PRIM_CONTRIBUTORY_CAUSE'] == 'UNABLE TO DETERMINE']['SEC_CONTRIBUTORY_CAUSE'].value_counts()
```

Out[401]:
```
UNABLE TO DETERMINE          27467
NOT APPLICABLE               18248
RECKLESS/IMPROPER DRIVING     1751
TRAFFIC RULES VIOLATED         375
Name: SEC_CONTRIBUTORY_CAUSE, dtype: int64
```

The majority of the records are also either 'Unable to Determine' or 'Not Applicable' but there are some records where we can leverage this data to fill up gaps in the primary column.

In [ ]:
```
#check value counts for primary not applicable cause
cln_crashes[cln_crashes['PRIM_CONTRIBUTORY_CAUSE'] == 'NOT APPLICABLE']['SEC_CONTRIBUTORY_CAUSE'].value_counts()
```

Out[402]:
```
NOT APPLICABLE               5753
UNABLE TO DETERMINE           314
RECKLESS/IMPROPER DRIVING     156
TRAFFIC RULES VIOLATED         45
Name: SEC_CONTRIBUTORY_CAUSE, dtype: int64
```

Similarly, the majority of the records are also either 'Unable to Determine' or 'Not Applicable' but there are some records where we can leverage this data to fill up gaps in the primary column.

Now, lets fill in the gaps for primary causes

In [ ]:

```
#identify the records from thee primary column and replace with secondary information
for ind, row in cln_crashes[['PRIM_CONTRIBUTORY_CAUSE', 'SEC_CONTRIBUTORY_CAUSE']].iterrows():
    if (row['PRIM_CONTRIBUTORY_CAUSE'] != row['SEC_CONTRIBUTORY_CAUSE']) & (
        (row['PRIM_CONTRIBUTORY_CAUSE'] == 'UNABLE TO DETERMINE') |
         (row['PRIM_CONTRIBUTORY_CAUSE'] == 'NOT APPLICABLE')):
            cln_crashes['PRIM_CONTRIBUTORY_CAUSE'][ind] = row['SEC_CONTRIBUTORY_CAUSE']
```

```
<ipython-input-403-a1cd0603bb70>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  cln_crashes['PRIM_CONTRIBUTORY_CAUSE'][ind] = row['SEC_CONTRIBUTORY_CAUSE']
```

In [ ]:

```
cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].value_counts()
```

Out[404]:

```
RECKLESS/IMPROPER DRIVING    63807
TRAFFIC RULES VIOLATED       40639
UNABLE TO DETERMINE          27781
NOT APPLICABLE               24001
Name: PRIM_CONTRIBUTORY_CAUSE, dtype: int64
```

We can set aside the Unable to determine category and predict it with our final model to get an understanding of what it could have been.

For the Not Applicable Category, there is no explanation as to what this means. Rather than using data that we don't understand, it would be better to drop it.

In [ ]:

```
#filter out not applicaable category
cln_crashes = cln_crashes[cln_crashes['PRIM_CONTRIBUTORY_CAUSE'] != 'NOT APPLICABLE']
```

In [ ]:

```
#check new vaalue counts
cln_crashes['PRIM_CONTRIBUTORY_CAUSE'].value_counts()
```

Out[406]:

```
RECKLESS/IMPROPER DRIVING    63807
TRAFFIC RULES VIOLATED       40639
UNABLE TO DETERMINE          27781
Name: PRIM_CONTRIBUTORY_CAUSE, dtype: int64
```

With only unable to determine left, the secondary column can be dropped

In [ ]:
```
#drop column
cln_crashes.drop(columns=['SEC_CONTRIBUTORY_CAUSE'],axis=1, inplace=True)
```

```
&lt;ipython-input-407-797889bb1b8c&gt;:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  cln_crashes.drop(columns=['SEC_CONTRIBUTORY_CAUSE'],axis=1, inplace=True)
```

In [ ]:
```
#check dataframe summaary after all changes
cln_crashes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 132227 entries, 0 to 692777
Data columns (total 20 columns):
 #   Column                   Non-Null Count   Dtype  
---  ------                   --------------   -----  
 0   CRASH_RECORD_ID          132227 non-null  object 
 1   CRASH_YEAR               132227 non-null  int64  
 2   POSTED_SPEED_LIMIT       132227 non-null  int64  
 3   DEVICE_CONDITION         132227 non-null  object 
 4   WEATHER_CONDITION        132227 non-null  object 
 5   LIGHTING_CONDITION       132227 non-null  object 
 6   CRASH_TYPE               132227 non-null  object 
 7   INTERSECTION_RELATED_I   132227 non-null  object 
 8   ROAD_DEFECT              132227 non-null  object 
 9   PRIM_CONTRIBUTORY_CAUSE  132227 non-null  object 
 10  NUM_UNITS                132227 non-null  int64  
 11  WORK_ZONE_I              132227 non-null  object 
 12  WORKERS_PRESENT_I        132227 non-null  object 
 13  INJURIES_TOTAL           132227 non-null  float64
 14  INJURIES_FATAL           132227 non-null  float64
 15  CRASH_HOUR               132227 non-null  int64  
 16  CRASH_DAY_OF_WEEK        132227 non-null  int64  
 17  CRASH_MONTH              132227 non-null  int64  
 18  LATITUDE                 132227 non-null  float64
 19  LONGITUDE                132227 non-null  float64
dtypes: float64(4), int64(6), object(10)
memory usage: 21.2+ MB
```

That sums up the cleaning for this dataset. Lets taake a look at the next one.

Crashes-Vehicle

We will start by extracting the columns identified in the Data Understanding portion and then addressing the data.

In [ ]:

```
#extract columns
cln_veh = vehicles_df[['CRASH_RECORD_ID',
                        'VEHICLE_DEFECT',
                        'VEHICLE_TYPE',
                        'VEHICLE_USE',
                        'MANEUVER',
                        'OCCUPANT_CNT',
                        'FIRST_CONTACT_POINT',
                        'VEHICLE_CONFIG']].copy()
```

In [ ]:

```
#check summary
cln_veh.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1416095 entries, 0 to 1416094
Data columns (total 8 columns):
 #   Column               Non-Null Count    Dtype
---  ------               --------------    -----
 0   CRASH_RECORD_ID      1416095 non-null  object
 1   VEHICLE_DEFECT       1384025 non-null  object
 2   VEHICLE_TYPE         1384025 non-null  object
 3   VEHICLE_USE          1384025 non-null  object
 4   MANEUVER             1384025 non-null  object
 5   OCCUPANT_CNT         1384025 non-null  float64
 6   FIRST_CONTACT_POINT  1371395 non-null  object
 7   VEHICLE_CONFIG       12287 non-null    object
dtypes: float64(1), object(7)
memory usage: 86.4+ MB
```

There are alot of columns with missing values. Interestingly, there are certain records that have craash record IDs but don't have information for any other columns. Lets see how many these are.

In [ ]:

```
cln_veh[cln_veh['VEHICLE_TYPE'].isnull()]#check vehicle type records wiith null values
```

Out[411]:

	CRASH_RECORD_ID	VEHICLE_DEFECT	VEHICLE_TYPE	VEHICLE_USE	MANEUVER	OCCUPANT_CNT	FIRST_CONTACT_POI
11	55a20437d79a3176ac805c65b13940186970246ab14ce5...	NaN	NaN	NaN	NaN	NaN	Na
26	af61b8eabb1b375bd1f6ff97f6ecce3e0f3592d4930381...	NaN	NaN	NaN	NaN	NaN	Na
40	034f42deaec11021e28cda25717373e36351025652ccf1...	NaN	NaN	NaN	NaN	NaN	Na
62	f84c48d4194761d1bb3808061f35ebf796508fb209deb5...	NaN	NaN	NaN	NaN	NaN	Na
89	7218ea2ed9cf304383636ee5194c83019beb6a7a1ec311...	NaN	NaN	NaN	NaN	NaN	Na
...	...	...	...	...	...	...	
1415712	fe8e3bf92de539ddffb7f696dac444289517b3a1a2c1a6...	NaN	NaN	NaN	NaN	NaN	Na
1415723	7924f00c55a8ac8a56064c60cd1b9a0ff63a2c27c4bc16...	NaN	NaN	NaN	NaN	NaN	Na
1415750	d082175fc7fb3397a3fbb2469355ed527ed9ade4d5f2af...	NaN	NaN	NaN	NaN	NaN	Na
1415921	3bcc07fc108ea9b0d417243d6be6818b2d319dba8b5bd9...	NaN	NaN	NaN	NaN	NaN	Na
1416020	3793de677675a7e9ac41b0a3b85396417d00f9637ae08a...	NaN	NaN	NaN	NaN	NaN	Na

32070 rows × 8 columns

These are ~2% of the records. We can drop these off knowing that they don;t have any valuable information and won't impact our analysis.

In [ ]:

```
#drop null records using subset Vehicle type
cln_veh = cln_veh.dropna(subset=['VEHICLE_TYPE'])
```

In [ ]:

```
#check summary
cln_veh.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1384025 entries, 0 to 1416094
Data columns (total 8 columns):
 #   Column              Non-Null Count    Dtype  
---  ------              --------------    -----  
 0   CRASH_RECORD_ID     1384025 non-null  object 
 1   VEHICLE_DEFECT      1384025 non-null  object 
 2   VEHICLE_TYPE        1384025 non-null  object 
 3   VEHICLE_USE         1384025 non-null  object 
 4   MANEUVER            1384025 non-null  object 
 5   OCCUPANT_CNT        1384025 non-null  float64
 6   FIRST_CONTACT_POINT 1371395 non-null  object 
 7   VEHICLE_CONFIG      12287 non-null    object 
dtypes: float64(1), object(7)
memory usage: 95.0+ MB
```

Lets bin the Vehicle Defect Column categories into less granular detail. We are interested in understanding whether a vehicle defect can play a part in crashes or not. Accordingly, If it later on shows to lay a significant part, insights can be generated as to how can the number of vehile defects be reduced.

In [ ]:
```
#check vlaue counts
cln_veh['VEHICLE_DEFECT'].value_counts()
```

Out[414]:
```
NONE                 768370
UNKNOWN              601707
OTHER                  6782
BRAKES                 4566
TIRES                   700
STEERING                650
WHEELS                  365
SUSPENSION              241
ENGINE/MOTOR            183
FUEL SYSTEM             150
LIGHTS                   86
WINDOWS                  82
CARGO                    47
SIGNALS                  38
RESTRAINT SYSTEM         21
TRAILER COUPLING         19
EXHAUST                  18
Name: VEHICLE_DEFECT, dtype: int64
```

We can leave the unkown category as is for now and then later on deduce how mnay we have left after joining the datasets. If there are still many, we can tackle it aaccordingly.

We will create aa new column identifying whether there is a defect or not. The Unknown categories will show up with a 'U'

In [ ]:
```
#create the lambda function
z = lambda x: 'U' if (x == 'UNKNOWN') else 'Y' if (x != 'NONE') else 'N'
```

In [ ]:
```
#map the lambda function to creaate the new column
cln_veh['VEHICLE_DEFECT_I'] = cln_veh['VEHICLE_DEFECT'].map(z)
```

In [ ]:
```
#check vlaue counts
cln_veh['VEHICLE_DEFECT_I'].value_counts()
```

Out[417]:
```
N    768370
U    601707
Y     13948
Name: VEHICLE_DEFECT_I, dtype: int64
```

In [ ]:
```
#drop Vehicle defect column
cln_veh = cln_veh.drop(['VEHICLE_DEFECT'],axis=1)
```

In [ ]:
```
#check summary
cln_veh.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1384025 entries, 0 to 1416094
Data columns (total 8 columns):
 #   Column               Non-Null Count    Dtype  
---  ------               --------------    -----  
 0   CRASH_RECORD_ID      1384025 non-null  object 
 1   VEHICLE_TYPE         1384025 non-null  object 
 2   VEHICLE_USE          1384025 non-null  object 
 3   MANEUVER             1384025 non-null  object 
 4   OCCUPANT_CNT         1384025 non-null  float64
 5   FIRST_CONTACT_POINT  1371395 non-null  object 
 6   VEHICLE_CONFIG       12287 non-null    object 
 7   VEHICLE_DEFECT_I     1384025 non-null  object 
dtypes: float64(1), object(7)
memory usage: 95.0+ MB
```

Lets peform binning on the Vehicle Type column also to make the data more manageable.

```
In [ ]: #check value counts
        cln_veh['VEHICLE_TYPE'].value_counts()
```

```
Out[420]: PASSENGER                                  870964
          SPORT UTILITY VEHICLE (SUV)                186498
          UNKNOWN/NA                                 131562
          VAN/MINI-VAN                                67371
          PICKUP                                      43239
          TRUCK - SINGLE UNIT                         26270
          OTHER                                       16301
          BUS OVER 15 PASS.                           14529
          TRACTOR W/ SEMI-TRAILER                     13251
          BUS UP TO 15 PASS.                           3487
          MOTORCYCLE (OVER 150CC)                      3217
          SINGLE UNIT TRUCK WITH TRAILER               2131
          OTHER VEHICLE WITH TRAILER                   1774
          TRACTOR W/O SEMI-TRAILER                     1766
          AUTOCYCLE                                     648
          MOPED OR MOTORIZED BICYCLE                    382
          MOTOR DRIVEN CYCLE                            326
          ALL-TERRAIN VEHICLE (ATV)                     160
          FARM EQUIPMENT                                 72
          3-WHEELED MOTORCYCLE (2 REAR WHEELS)           49
          RECREATIONAL OFF-HIGHWAY VEHICLE (ROV)         20
          SNOWMOBILE                                      8
          Name: VEHICLE_TYPE, dtype: int64
```

Through domain knowledge we can bin these categories together in the following manner:

1. Regulaar Personal Use: These are vehicles that usually have everyday passengers using them for commutin or traveling like Passenger vehicles, SUVs, Pick-up, Van/Mini-Van
2. Public Transit: These arae vehicles that are be a part of mass transit systems such as Buses
3. Commercial: These are trator/trailers
4. Motorcycles/cycle: These are self-explanotory
5. Vocational/Recreational: Such as Faarm Equipment, snowmobile, etc

In [ ]:

```
#bin categories

#Regular Personal
cln_veh['VEHICLE_TYPE'].replace(['PASSENGER',
                                'SPORT UTILITY VEHICLE (SUV)',
                                'VAN/MINI-VAN',
                                'PICKUP'
                                ], 'REGULAR PERSONAL', inplace=True)

#Public Transit
cln_veh['VEHICLE_TYPE'].replace(['BUS OVER 15 PASS.',
                                'BUS UP TO 15 PASS.'
                                ], 'PUBLIC', inplace=True)

#Commercial
cln_veh['VEHICLE_TYPE'].replace(['TRUCK - SINGLE UNIT',
                                'SPORT UTILITY VEHICLE (SUV)',
                                'TRACTOR W/ SEMI-TRAILER',
                                'OTHER VEHICLE WITH TRAILER',
                                'TRACTOR W/O SEMI-TRAILER',
                                'SINGLE UNIT TRUCK WITH TRAILER'
                                ], 'COMMERCIAL', inplace=True)

#Motorcycle / cycle
cln_veh['VEHICLE_TYPE'].replace(['MOTORCYCLE (OVER 150CC)',
                                'AUTOCYCLE',
                                'MOPED OR MOTORIZED BICYCLE',
                                '3-WHEELED MOTORCYCLE (2 REAR WHEELS)',
                                 'MOTOR DRIVEN CYCLE'
                                ], 'MOTORCYCLE/CYCLE', inplace=True)

#Vocational/Recreational
cln_veh['VEHICLE_TYPE'].replace(['ALL-TERRAIN VEHICLE (ATV)',
                                'FARM EQUIPMENT',
                                'MOPED OR MOTORIZED BICYCLE',
                                'RECREATIONAL OFF-HIGHWAY VEHICLE (ROV)',
                                'SNOWMOBILE'
                                ], 'RECREATIONAL/VOCATIONAL', inplace=True)
```

In [ ]:

```
#check value counts
cln_veh['VEHICLE_TYPE'].value_counts(normalize=True)
```

Out[422]:

```
REGULAR PERSONAL           0.843967
UNKNOWN/NA                 0.095058
COMMERCIAL                 0.032653
PUBLIC                     0.013017
OTHER                      0.011778
MOTORCYCLE/CYCLE           0.003340
RECREATIONAL/VOCATIONAL    0.000188
Name: VEHICLE_TYPE, dtype: float64
```

With no information for the other section, it will be beneficial to drop those records.

The unknown ones can be kept and dealt with aafter merging the different datasets.

We can also see that the Recreational and motorcycle records total out to be even less than 1% of the total records. These will be extremely difficult to balance out alongside skewing our modeling to anomalies. Therefore, these records will be dropped.

In [ ]:
```
#filter out the records with 'other' vehicle types
cln_veh = cln_veh[(cln_veh['VEHICLE_TYPE'] != 'OTHER') &
                  (cln_veh['VEHICLE_TYPE'] != 'RECREATIONAL/VOCATIONAL')&
                  (cln_veh['VEHICLE_TYPE'] != 'MOTORCYCLE/CYCLE')
                 ]
```

In [ ]:
```
#check new value counts
cln_veh['VEHICLE_TYPE'].value_counts()
```

Out[424]:
```
REGULAR PERSONAL    1168072
UNKNOWN/NA           131562
COMMERCIAL            45192
PUBLIC                18016
Name: VEHICLE_TYPE, dtype: int64
```

In [ ]:
```
#check summary
cln_veh.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1362842 entries, 0 to 1416094
Data columns (total 8 columns):
 #   Column              Non-Null Count    Dtype
---  ------              --------------    -----
 0   CRASH_RECORD_ID     1362842 non-null  object
 1   VEHICLE_TYPE        1362842 non-null  object
 2   VEHICLE_USE         1362842 non-null  object
 3   MANEUVER            1362842 non-null  object
 4   OCCUPANT_CNT        1362842 non-null  float64
 5   FIRST_CONTACT_POINT 1350828 non-null  object
 6   VEHICLE_CONFIG      11730 non-null    object
 7   VEHICLE_DEFECT_I    1362842 non-null  object
dtypes: float64(1), object(7)
memory usage: 93.6+ MB
```

Considering that vevhicles types were binned according to usage, the Vehicle Use column would be a deeper dive column that can be explored if more granular details aree required.

In [ ]:
```
#drop vehicle use column
cln_veh = cln_veh.drop(['VEHICLE_USE'],axis=1)
```

Lets explore the Maeuver column. We know from previous exploration that this column also contains multiple categories that can bee grouped together. Lets take a look at the values and forulate the binning strategy.

In [ ]:
```
#check value counts
cln_veh['MANEUVER'].value_counts()
```

Out[427]:
```
STRAIGHT AHEAD                        621064
PARKED                                188320
UNKNOWN/NA                            106882
SLOW/STOP IN TRAFFIC                  104646
TURNING LEFT                           80286
BACKING                                55472
TURNING RIGHT                          44296
PASSING/OVERTAKING                     32542
CHANGING LANES                         26559
OTHER                                  22353
ENTERING TRAFFIC LANE FROM PARKING     16146
MERGING                                 9439
STARTING IN TRAFFIC                     8050
U-TURN                                  7682
LEAVING TRAFFIC LANE TO PARK            6624
AVOIDING VEHICLES/OBJECTS               5889
SKIDDING/CONTROL LOSS                   5495
ENTER FROM DRIVE/ALLEY                  5354
PARKED IN TRAFFIC LANE                  4015
SLOW/STOP - LEFT TURN                   3004
DRIVING WRONG WAY                       1967
SLOW/STOP - RIGHT TURN                  1896
NEGOTIATING A CURVE                     1807
SLOW/STOP - LOAD/UNLOAD                 1633
TURNING ON RED                           532
DRIVERLESS                               506
DIVERGING                                208
DISABLED                                 175
Name: MANEUVER, dtype: int64
```

The overlapping categories can be binned in the direction they were moving to make the modeling easier. If more details are required, data can bee subsequently maade more granular.

1. STRAIGHT: STRAIGHT AHEAD, NEGOTIATING A CURVE
2. TURNING: TURNING LEFT, TURNING RIGHT, U-TURN, SLOW/STOP - LEFT TURN, SLOW/STOP - RIGHT TURN, TURNING ON RED
3. ENTERING/EXITING TRAFFIC: PARKED, LEAVING TRAFFIC LANE TO PARK, ENTERING TRAFFIC LANE FROM PARKING, MERGING, LEAVING TRAFFIC LANE TO PARK, ENTER FROM DRIVE/ALLEY, PARKED IN TRAFFIC L ANE, DIVERGING
4. START/STOP: SLOW/STOP IN TRAFFIC, STARTING IN TRAFFIC, SLOW/STOP - LOAD/UNLOAD
5. Lane Change: CHANGING LANES, PASSING/OVERTAKING
6. Respone to External Obstructions: AVOIDING VEHICLES/OBJECTS, SKIDDING/CONTROL LOSS

In [ ]:

```
#bin categories

#Straight
cln_veh['MANEUVER'].replace(['STRAIGHT AHEAD',
                            'NEGOTIATING A CURVE'
                            ], 'STRAIGHT', inplace=True)

#Turning
cln_veh['MANEUVER'].replace(['TURNING LEFT',
                            'TURNING RIGHT',
                             'U-TURN', 'SLOW/STOP - LEFT TURN', 'SLOW/STOP - RIGHT TURN',
                             'TURNING ON RED'
                            ], 'TURNING', inplace=True)

#ENTERING/EXITING TRAFFIC
cln_veh['MANEUVER'].replace(['PARKED', 'LEAVING TRAFFIC LANE TO PARK', 'ENTERING TRAFFIC LANE FROM PARKING',
                            'MERGING', 'LEAVING TRAFFIC LANE TO PARK', 'ENTER FROM DRIVE/ALLEY',
                             'PARKED IN TRAFFIC LANE',
                             'DIVERGING'
                            ], 'ENTERING/EXITING TRAFFIC', inplace=True)

#START/STOP
cln_veh['MANEUVER'].replace(['SLOW/STOP IN TRAFFIC', 'STARTING IN TRAFFIC', 'SLOW/STOP - LOAD/UNLOAD'
                            ], 'START/STOP', inplace=True)

#Lane Change
cln_veh['MANEUVER'].replace(['CHANGING LANES', 'PASSING/OVERTAKING'
                            ], 'LANE CHANGE', inplace=True)

#External Obstructions
cln_veh['MANEUVER'].replace(['AVOIDING VEHICLES/OBJECTS', 'SKIDDING/CONTROL LOSS'
                            ], 'EXTERNAL OBSTRUCTIONS', inplace=True)
```

In [ ]:
```
#check new value counts
cln_veh['MANEUVER'].value_counts(normalize=True)
```

Out[429]:
```
STRAIGHT                    0.457038
ENTERING/EXITING TRAFFIC    0.168843
TURNING                     0.101036
START/STOP                  0.083890
UNKNOWN/NA                  0.078426
LANE CHANGE                 0.043366
BACKING                     0.040703
OTHER                       0.016402
EXTERNAL OBSTRUCTIONS       0.008353
DRIVING WRONG WAY           0.001443
DRIVERLESS                  0.000371
DISABLED                    0.000128
Name: MANEUVER, dtype: float64
```

The unkown category will be handled after merging it with the other datasets.

The Other category doesn;t have any clear information so it can be harmful noisse in the dataset therefore these records will be dropped.

Driverless and Disabled are extreme anomalies that total out to be less than 1% therefore they will be dropped aswell.

In [ ]:
```
#drop other category and anomalies
cln_veh = cln_veh[(cln_veh['MANEUVER'] != 'OTHER') &
                  (cln_veh['MANEUVER'] != 'DRIVERLESS') &
                  (cln_veh['MANEUVER'] != 'DISABLED')]
```

In [ ]:
```
#check new value counts
cln_veh['MANEUVER'].value_counts(normalize=True)
```

Out[431]:
```
STRAIGHT                    0.464896
ENTERING/EXITING TRAFFIC    0.171746
TURNING                     0.102773
START/STOP                  0.085332
UNKNOWN/NA                  0.079774
LANE CHANGE                 0.044112
BACKING                     0.041403
EXTERNAL OBSTRUCTIONS       0.008497
DRIVING WRONG WAY           0.001468
Name: MANEUVER, dtype: float64
```

In [ ]:

```
#check summary
cln_veh.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1339808 entries, 0 to 1416094
Data columns (total 7 columns):
 #   Column               Non-Null Count    Dtype  
---  ------               --------------    -----  
 0   CRASH_RECORD_ID      1339808 non-null  object 
 1   VEHICLE_TYPE         1339808 non-null  object 
 2   MANEUVER             1339808 non-null  object 
 3   OCCUPANT_CNT         1339808 non-null  float64
 4   FIRST_CONTACT_POINT  1328112 non-null  object 
 5   VEHICLE_CONFIG       11457 non-null    object 
 6   VEHICLE_DEFECT_I     1339808 non-null  object 
dtypes: float64(1), object(6)
memory usage: 81.8+ MB
```

In [ ]:

```
#check value counts
cln_veh['VEHICLE_CONFIG'].value_counts()
```

Out[433]:

```
TRACTOR/SEMI-TRAILER                    4665
SINGLE UNIT TRUCK, 2 AXLES, 6 TIRES     2231
BUS                                     1827
TRUCK/TRACTOR                            918
TRUCK/TRAILER                            759
UNKNOWN HEAVY TRUCK                      535
SINGLE UNIT TRUCK, 3 OR MORE AXLES       493
TRACTOR/DOUBLES                           29
Name: VEHICLE_CONFIG, dtype: int64
```

This is the level of detail that can be explored as further insights analysis. The Vehicle Type feature already covers whether the vehicle involved in the crash is a commercial vehicle or not.

In [ ]:

```
#drop vehicle config
cln_veh = cln_veh.drop(['VEHICLE_CONFIG'],axis=1)
```

The only one left is Occupant Count. This column has information on how many individuals there were in a vehicle involved in the crash. Lets explore this column further to understand how to processs it.

In [ ]:
```
#check value counts
cln_veh['OCCUPANT_CNT'].value_counts()
```

Out[435]:
```
1.0     967827
0.0     180457
2.0     134861
3.0      35752
4.0      14027
5.0       4599
6.0       1244
7.0        459
8.0        186
9.0         90
11.0        56
10.0        52
12.0        36
13.0        31
15.0        18
14.0        13
16.0        12
20.0        10
18.0        10
19.0         9
36.0         5
28.0         5
26.0         5
21.0         4
17.0         4
22.0         3
30.0         3
29.0         3
27.0         3
25.0         3
33.0         3
41.0         2
39.0         2
99.0         2
35.0         2
44.0         1
24.0         1
43.0         1
60.0         1
34.0         1
37.0         1
23.0         1
31.0         1
47.0         1
38.0         1
Name: OCCUPANT_CNT, dtype: int64
```

There are several different number of paassenger bins. These can be grouped grouped together to represent certain common instancess.

0: No passenger present

1-2: This is very common having either only the driver or a adriver with a passenger

3-5: 5 is the max a normaal car can hold

6-9: These number of passengers is usually an indication of Mini-Vans or Vans

10+: This is usually a larger van or a Bus which means that these amount of passengers would represent a public/mass transit vehicle.

In [ ]:
```
#create lambda function for binning
b = lambda x:'10+' if x>=10 else '6-9' if x>=6 else '3-5' if x>=3 else '1-2' if x>=1 else '0'
```

In [ ]:
```
#bin the counts
cln_veh['OCCUPANT_CAT'] = cln_veh['OCCUPANT_CNT'].map(b)
```

In [ ]:
```
#check value counts
cln_veh['OCCUPANT_CAT'].value_counts()
```

Out[438]:
```
1-2    1102688
0       180457
3-5      54378
6-9       1979
10+        306
Name: OCCUPANT_CAT, dtype: int64
```

In [ ]:
```
#drop occupant count column
cln_veh = cln_veh.drop(['OCCUPANT_CNT'],axis=1)
```

In [ ]:
```
cln_veh.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1339808 entries, 0 to 1416094
Data columns (total 6 columns):
 #   Column              Non-Null Count    Dtype 
---  ------              --------------    ----- 
 0   CRASH_RECORD_ID     1339808 non-null  object
 1   VEHICLE_TYPE        1339808 non-null  object
 2   MANEUVER            1339808 non-null  object
 3   FIRST_CONTACT_POINT 1328112 non-null  object
 4   VEHICLE_DEFECT_I    1339808 non-null  object
 5   OCCUPANT_CAT        1339808 non-null  object
dtypes: object(6)
memory usage: 71.6+ MB
```

Next, lets take a look at First Contact Point.

In [ ]:
```
#check value counts
cln_veh['FIRST_CONTACT_POINT'].value_counts()
```

Out[441]:
```
FRONT                    201383
OTHER                    163550
REAR-LEFT                152128
UNKNOWN                  128086
REAR                     114191
FRONT-LEFT                97447
TOTAL (ALL AREAS)         92103
SIDE-RIGHT                86002
FRONT-RIGHT               84497
SIDE-LEFT                 78829
ROOF                      54337
REAR-RIGHT                48892
UNDER CARRIAGE            16044
NONE                      10623
Name: FIRST_CONTACT_POINT, dtype: int64
```

The other category for this column is a big chunk of the dataset. Nonetheless, modeling it with other data might show a clear relationship between certain type of accidents and the other category. Consdiering that it is a large chunk of the dataset, we will leave it in place. If our modeling results end up being unsatisfactory, these kind of records would be the first ones we would want to remove.

We will leave the unkown category as is and circle back to it after alll datasets have been joined. It is possible that in the process of joining, these records get dropped automatically.

Also, there is a higher granularity of data where as it can be grouped into simple subsections of a vehicle.

1. None
2. Front
3. Rear
4. Side
5. Top/Bottom
6. Total

In [ ]:
```
#bin categories

#Front
cln_veh['FIRST_CONTACT_POINT'].replace([
                                        'FRONT', 'FRONT-LEFT', 'FRONT-RIGHT'
                                        ],'FRONT', inplace=True)

#Rear
cln_veh['FIRST_CONTACT_POINT'].replace([
                                        'REAR','REAR-LEFT', 'REAR-RIGHT'
                                        ],'REAR', inplace=True)

#SIDE
cln_veh['FIRST_CONTACT_POINT'].replace([
                                        'SIDE-RIGHT', 'SIDE-LEFT'
                                        ],'SIDE', inplace=True)

#TOP/BOTTOM
cln_veh['FIRST_CONTACT_POINT'].replace([
                                        'ROOF', 'UNDER CARRIAGE'
                                        ],'TOP/BOTTOM', inplace=True)
```

In [ ]:
```
#check new value counts
cln_veh['FIRST_CONTACT_POINT'].value_counts()
```

Out[443]:
```
FRONT                 383327
REAR                  315211
SIDE                  164831
OTHER                 163550
UNKNOWN               128086
TOTAL (ALL AREAS)      92103
TOP/BOTTOM             70381
NONE                   10623
Name: FIRST_CONTACT_POINT, dtype: int64
```

In [ ]:
```
#drop missing values
cln_veh = cln_veh.dropna()
```

In [ ]:

```
#final dataframe check
cln_veh.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1328112 entries, 0 to 1416094
Data columns (total 6 columns):
 #   Column               Non-Null Count    Dtype 
---  ------               --------------    ----- 
 0   CRASH_RECORD_ID      1328112 non-null  object
 1   VEHICLE_TYPE         1328112 non-null  object
 2   MANEUVER             1328112 non-null  object
 3   FIRST_CONTACT_POINT  1328112 non-null  object
 4   VEHICLE_DEFECT_I     1328112 non-null  object
 5   OCCUPANT_CAT         1328112 non-null  object
dtypes: object(6)
memory usage: 70.9+ MB
```

No we can move on and merge this dataset with the crashes dataset.

In [ ]:

```
#merge using crash record ID
veh_crsh = pd.merge(cln_crashes, cln_veh, how='inner', on='CRASH_RECORD_ID' )
```

In [ ]:
```
#check new dataframe's info
veh_crsh.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 250241 entries, 0 to 250240
Data columns (total 25 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   CRASH_RECORD_ID          250241 non-null  object
 1   CRASH_YEAR               250241 non-null  int64
 2   POSTED_SPEED_LIMIT       250241 non-null  int64
 3   DEVICE_CONDITION         250241 non-null  object
 4   WEATHER_CONDITION        250241 non-null  object
 5   LIGHTING_CONDITION       250241 non-null  object
 6   CRASH_TYPE               250241 non-null  object
 7   INTERSECTION_RELATED_I   250241 non-null  object
 8   ROAD_DEFECT              250241 non-null  object
 9   PRIM_CONTRIBUTORY_CAUSE  250241 non-null  object
 10  NUM_UNITS                250241 non-null  int64
 11  WORK_ZONE_I              250241 non-null  object
 12  WORKERS_PRESENT_I        250241 non-null  object
 13  INJURIES_TOTAL           250241 non-null  float64
 14  INJURIES_FATAL           250241 non-null  float64
 15  CRASH_HOUR               250241 non-null  int64
 16  CRASH_DAY_OF_WEEK        250241 non-null  int64
 17  CRASH_MONTH              250241 non-null  int64
 18  LATITUDE                 250241 non-null  float64
 19  LONGITUDE                250241 non-null  float64
 20  VEHICLE_TYPE             250241 non-null  object
 21  MANEUVER                 250241 non-null  object
 22  FIRST_CONTACT_POINT      250241 non-null  object
 23  VEHICLE_DEFECT_I         250241 non-null  object
 24  OCCUPANT_CAT             250241 non-null  object
dtypes: float64(4), int64(6), object(15)
memory usage: 49.6+ MB
```

In [ ]:
```
#check dataset
veh_crsh.head()
```

Out[448]:

	CRASH_RECORD_ID	CRASH_YEAR	POSTED_SPEED_LIMIT	DEVICE_CONDITION	WEATHER_CONDITION	LIGHTING_CONDITION	CR
0	79c7a2ce89f446262efd86df3d72d18b04ba487024b7c4...	2019	30	FUNCTIONING PROPERLY	CLEAR	DAY TIME	IN, OI
1	79c7a2ce89f446262efd86df3d72d18b04ba487024b7c4...	2019	30	FUNCTIONING PROPERLY	CLEAR	DAY TIME	IN, OI
2	7b3545fb91352d7fc46ba142d9044a5508671db4d01d02...	2020	25	FUNCTIONING PROPERLY	CLEAR	DAY TIME	IN, OI
3	03d3679ef44bb8aa0f2060cb0376f3eeb1d9dbb2197322...	2022	30	FUNCTIONING PROPERLY	NOT CLEAR	DAY TIME	IN, OI
4	79704e1b747fbf5f740f1255785934dfe659ff910d4782...	2019	30	FUNCTIONING PROPERLY	CLEAR	DAY TIME	IN, OI

5 rows × 25 columns

In [ ]:
```
#check unique records fr crash reecord ID
len(veh_crsh['CRASH_RECORD_ID'].unique())
```

Out[449]: 129487

In [ ]:
```
#check difference of unique reecords and total records
diff = (len(veh_crsh) - len(veh_crsh['CRASH_RECORD_ID'].unique()))
print(diff)

#check the ratio to understand the ratio
print('The ratio of number of crashes to total number of records: ', len(veh_crsh)/diff)
```

```
120754
The ratio of number of crashes to total number of records:  2.072320585653477
```

We can see that there are approximately on average 2 vehicles per crash. There are for sure severaal records where crashes took place between a vehicle and a pedestrian or cyclist. The multiple records for the same craash ID represent that there was more than one vehicle involved in a crash.

Next we'll clen up the people database and merge it with this one. Then we will deal with the unkown values that we have carried forward from this dataset.

People

First, lets extract the columns to keep.

In [ ]:

```
#extract columns
cln_people = people_df[
    ['PERSON_TYPE',
    'CRASH_RECORD_ID',
    'VEHICLE_ID',
    'AGE',
    'SAFETY_EQUIPMENT',
    'INJURY_CLASSIFICATION',
    'DRIVER_ACTION',
    'DRIVER_VISION',
    'PHYSICAL_CONDITION',
    'PEDPEDAL_ACTION',
    'BAC_RESULT VALUE']
]
```

In [ ]:

```
#check dataframe info
cln_people.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1530385 entries, 0 to 1530384
Data columns (total 11 columns):
 #   Column                 Non-Null Count    Dtype
---  ------                 --------------    -----
 0   PERSON_TYPE            1530385 non-null  object
 1   CRASH_RECORD_ID        1530385 non-null  object
 2   VEHICLE_ID             1500311 non-null  float64
 3   AGE                    1085359 non-null  float64
 4   SAFETY_EQUIPMENT       1526028 non-null  object
 5   INJURY_CLASSIFICATION  1529714 non-null  object
 6   DRIVER_ACTION          1218047 non-null  object
 7   DRIVER_VISION          1217601 non-null  object
 8   PHYSICAL_CONDITION     1218903 non-null  object
 9   PEDPEDAL_ACTION        28502 non-null    object
 10  BAC_RESULT VALUE       1824 non-null     float64
dtypes: float64(3), object(8)
memory usage: 128.4+ MB
```

There are a few missing records in Vehicle ID but since we are joining on Crash REcord ID, we can ignore these missing records and drop the Vehicle ID column eventually.

Lets evaluate the specific Person Type column and correlare whether the data is clean from a perspective of every relevant category

In [ ]:
```
cln_people['PERSON_TYPE'].value_counts()
```

Out[453]:
```
DRIVER                  1191234
PASSENGER                309565
PEDESTRIAN                17588
BICYCLE                   10478
NON-MOTOR VEHICLE          1253
NON-CONTACT VEHICLE         267
Name: PERSON_TYPE, dtype: int64
```

Lets look at the Passenger category. We want to make sure that there is no values in the Driver Action and Driver Visibility columns.

In [ ]:
```
#check info for Passenger person type
cln_people[cln_people['PERSON_TYPE'] == 'PASSENGER'].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 309565 entries, 54 to 1530384
Data columns (total 11 columns):
 #   Column                 Non-Null Count   Dtype  
---  ------                 --------------   -----  
 0   PERSON_TYPE            309565 non-null  object 
 1   CRASH_RECORD_ID        309565 non-null  object 
 2   VEHICLE_ID             309565 non-null  float64
 3   AGE                    188759 non-null  float64
 4   SAFETY_EQUIPMENT       309302 non-null  object 
 5   INJURY_CLASSIFICATION  309241 non-null  object 
 6   DRIVER_ACTION          0 non-null       object 
 7   DRIVER_VISION          0 non-null       object 
 8   PHYSICAL_CONDITION     0 non-null       object 
 9   PEDPEDAL_ACTION        0 non-null       object 
 10  BAC_RESULT VALUE       0 non-null       float64
dtypes: float64(3), object(8)
memory usage: 28.3+ MB
```

The data is as was anticipated with no mistakes in the Driver Action and Driver Visbility feature. NExt lets ecplore the Age colum. It has a some missing values which we will have to deal with.

In [ ]:

```
#check value counts
cln_people['AGE'].value_counts()
```

Out[455]:

```
 25.0     30759
 27.0     30617
 26.0     30613
 28.0     29972
 24.0     29722
          ...  
-40.0         1
-47.0         1
-49.0         1
-177.0        1
 106.0        1
Name: AGE, Length: 116, dtype: int64
```

Looks like there are several negative values as well. These caan be typos and we can use the absolute Mathematics operation t convert them back into positive integers.

In [ ]:

```
#convert negative values to positive
cln_people['AGE'] = cln_people['AGE'].abs()
```

```
<ipython-input-456-cbaf058256f5>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-v
iew-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  cln_people['AGE'] = cln_people['AGE'].abs()
```

In [ ]:

```
#check new value counts
cln_people['AGE'].value_counts()
```

Out[457]:

```
25.0     30759
27.0     30617
26.0     30613
28.0     29972
24.0     29722
         ...  
110.0        5
108.0        5
105.0        3
177.0        1
106.0        1
Name: AGE, Length: 112, dtype: int64
```

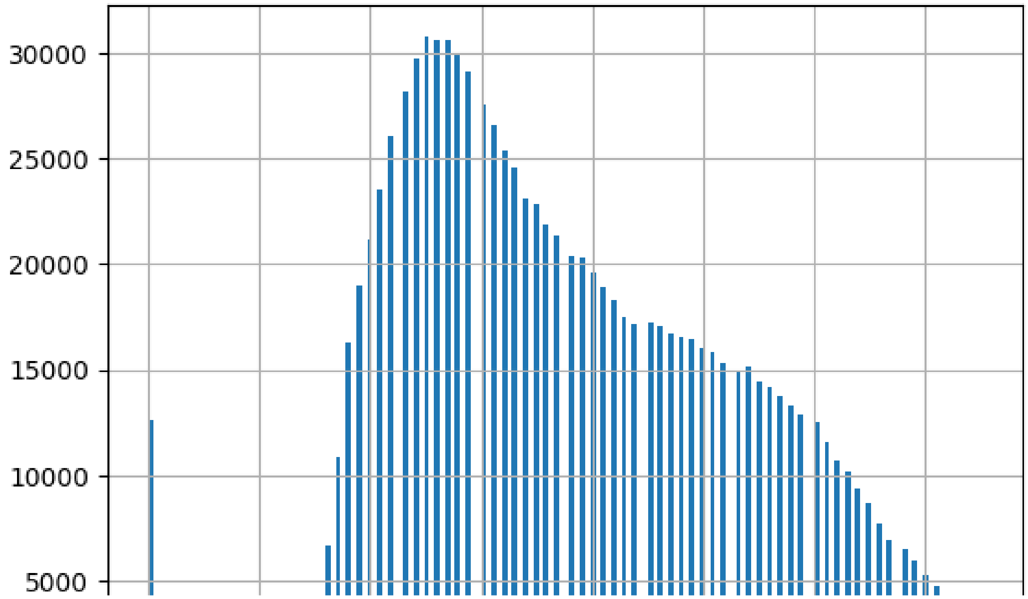
The longest a person haas lived in the US is 119 years therefore there are a few age values that don;t seem realistic. As of 2021, the official numbers for the percentage of US population older than 75 was ~6.7%

Based on this fact, to increase the confidence in the dataset and remove any possible erros in entering ages, it would be important to limit the ages that we model for. It would be safe to drop records with 75+ ages and still cater to the majority of the population.

In [ ]:
```
#select records with ages less than or equal to 75
cln_people = cln_people[cln_people['AGE'] <= 75]
```

Lets take a look at the filtered out data's disstribution. Ideally, we would see a smaller amount people under the age of 18 because they are mostly passengers or with adults. Vice versa, we should see a hiigher number of people involved in crashes older than 18 years.

In [ ]:
```
#plot a histogram
cln_people['AGE'].hist(bins='auto');
```



Now we haave to deal with the missing values for the Age column. There are almost 500k records missing age values. This is a very large number so we can't drop these. We can impute values using the person type column. For drivers, we will use the median age from the records of that specific category.

In [ ]:
```
#impute the values of age for the driver person type
cln_people[cln_people['PERSON_TYPE'] == 'DRIVER']['AGE'].fillna(
                                            cln_people[cln_people['PERSON_TYPE'] == 'DRIVER']['AGE'].median(),
                                            inplace= True)
```

```
<ipython-input-460-5cefa873a844>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-v
iew-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  cln_people[cln_people['PERSON_TYPE'] == 'DRIVER']['AGE'].fillna(
```

In [ ]:
```
    #impute the values of age for the passenger person type
    cln_people[cln_people['PERSON_TYPE'] == 'PASSENGER']['AGE'].fillna(
                                            cln_people[cln_people['PERSON_TYPE'] == 'PASSENGER']['AGE'].median(),
                                            inplace= True)
```

```
<ipython-input-461-9fef07efa0a4>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-v
iew-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  cln_people[cln_people['PERSON_TYPE'] == 'PASSENGER']['AGE'].fillna(
```

In [ ]:
```
    #impute the values of age for the pedestrian person type
    cln_people[cln_people['PERSON_TYPE'] == 'PEDESTRIAN']['AGE'].fillna(
                                            cln_people[cln_people['PERSON_TYPE'] == 'PEDESTRIAN']['AGE'].median(),
                                            inplace= True)
```

```
<ipython-input-462-cc840edc0814>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-v
iew-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  cln_people[cln_people['PERSON_TYPE'] == 'PEDESTRIAN']['AGE'].fillna(
```

In [ ]:
```
    #impute the values of age for the biycle person type
    cln_people[cln_people['PERSON_TYPE'] == 'BICYCLE']['AGE'].fillna(
                                                cln_people[cln_people['PERSON_TYPE'] == 'BICYCLE']['AGE'].median(),
                                                inplace= True)
```

```
<ipython-input-463-4c6cad64944a>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-v
iew-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  cln_people[cln_people['PERSON_TYPE'] == 'BICYCLE']['AGE'].fillna(
```

In [ ]:
```
    #impute the values of age for the NON-MOTOR VEHICLE person type
    cln_people[cln_people['PERSON_TYPE'] == 'NON-MOTOR VEHICLE']['AGE'].fillna(
                                    cln_people[cln_people['PERSON_TYPE'] == 'NON-MOTOR VEHICLE']['AGE'].median(),
                                    inplace= True)
```

```
<ipython-input-464-a94c76633dbd>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-v
iew-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  cln_people[cln_people['PERSON_TYPE'] == 'NON-MOTOR VEHICLE']['AGE'].fillna(
```

In [ ]:

```
#impute the values of age for the NON-CONTACT VEHICLE person type
cln_people[cln_people['PERSON_TYPE'] == 'NON-CONTACT VEHICLE']['AGE'].fillna(
                                    cln_people[cln_people['PERSON_TYPE'] == 'NON-CONTACT VEHICLE']['AGE'].median(),
                                    inplace= True)
```

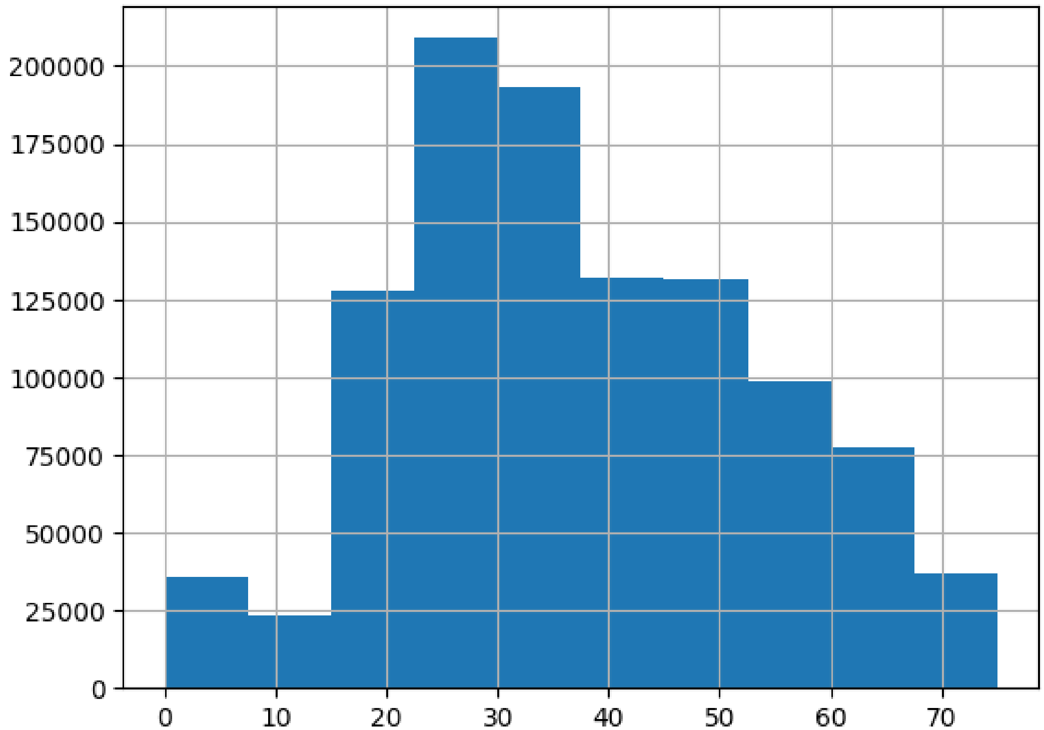
```
<ipython-input-465-1eb64ab57a96>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-v
iew-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  cln_people[cln_people['PERSON_TYPE'] == 'NON-CONTACT VEHICLE']['AGE'].fillna(
```

Lets take a look at the distribution again

In [ ]:

```
#plot the histogram
cln_people['AGE'].hist();
```



In [ ]:
```
#check dataframe info
cln_people.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1065747 entries, 0 to 1530383
Data columns (total 11 columns):
 #   Column                 Non-Null Count    Dtype  
---  ------                 --------------    -----  
 0   PERSON_TYPE            1065747 non-null  object 
 1   CRASH_RECORD_ID        1065747 non-null  object 
 2   VEHICLE_ID             1040480 non-null  float64
 3   AGE                    1065747 non-null  float64
 4   SAFETY_EQUIPMENT       1062718 non-null  object 
 5   INJURY_CLASSIFICATION  1065722 non-null  object 
 6   DRIVER_ACTION          877978 non-null   object 
 7   DRIVER_VISION          877639 non-null   object 
 8   PHYSICAL_CONDITION     878764 non-null   object 
 9   PEDPEDAL_ACTION        24714 non-null    object 
 10  BAC_RESULT VALUE       1793 non-null     float64
dtypes: float64(3), object(8)
memory usage: 97.6+ MB
```

Next we will tackle the Safety Equipment column. There are a few missing values which we will explore how to tackle. There are also a lot of categoricaal values in this column. The informaation that we are trying to extract from this column is whether safety equipment was used or not. There are also some unkown values that we have to tackle.

We can drop the records with missing values because they are a small perentage of the total and then group the remaining categories. First, lets take a look at the categories in this column.

In [ ]:
```
#drop missing values
cln_people = cln_people.dropna(subset=['SAFETY_EQUIPMENT'])
```

In [ ]:
```
#check info
cln_people.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1062718 entries, 0 to 1530383
Data columns (total 11 columns):
 #   Column                 Non-Null Count    Dtype
---  ------                 --------------    -----
 0   PERSON_TYPE            1062718 non-null  object
 1   CRASH_RECORD_ID        1062718 non-null  object
 2   VEHICLE_ID             1040473 non-null  float64
 3   AGE                    1062718 non-null  float64
 4   SAFETY_EQUIPMENT       1062718 non-null  object
 5   INJURY_CLASSIFICATION  1062707 non-null  object
 6   DRIVER_ACTION          876229 non-null   object
 7   DRIVER_VISION          876088 non-null   object
 8   PHYSICAL_CONDITION     876429 non-null   object
 9   PEDPEDAL_ACTION        21735 non-null    object
 10  BAC_RESULT VALUE       1792 non-null     float64
dtypes: float64(3), object(8)
memory usage: 97.3+ MB
```

In [ ]:
```
#check value counts
cln_people['SAFETY_EQUIPMENT'].value_counts()
```

Out[470]:
```
SAFETY BELT USED                              641119
USAGE UNKNOWN                                 354429
NONE PRESENT                                   38030
SAFETY BELT NOT USED                            6816
CHILD RESTRAINT USED                            5894
HELMET NOT USED                                 5534
CHILD RESTRAINT - FORWARD FACING                2490
BICYCLE HELMET (PEDACYCLIST INVOLVED ONLY)      2129
CHILD RESTRAINT - REAR FACING                   1278
CHILD RESTRAINT - TYPE UNKNOWN                  1273
HELMET USED                                     1267
DOT COMPLIANT MOTORCYCLE HELMET                  857
BOOSTER SEAT                                     730
CHILD RESTRAINT NOT USED                         395
NOT DOT COMPLIANT MOTORCYCLE HELMET              133
SHOULD/LAP BELT USED IMPROPERLY                  129
WHEELCHAIR                                       109
CHILD RESTRAINT USED IMPROPERLY                   89
STRETCHER                                         17
Name: SAFETY_EQUIPMENT, dtype: int64
```

In [ ]:
```
#create a lists of categories for Indication thta Safety equipment was used
sf_equip = ['SAFETY BELT USED', 'CHILD RESTRAINT USED', 'CHILD RESTRAINT - FORWARD FACING',
            'BICYCLE HELMET (PEDACYCLIST INVOLVED ONLY)', 'CHILD RESTRAINT - TYPE UNKNOWN',
           'CHILD RESTRAINT - REAR FACING', 'HELMET USED', 'DOT COMPLIANT MOTORCYCLE HELMET',
           'BOOSTER SEAT', 'WHEELCHAIR', 'STRETCHER']

#set up a lambda functin for grouping categories into 2 bins:
#Equipment Used and Not Used/Misused
f1 = (lambda x: 'SAFETY EQUIPMENT USED' if x in sf_equip
      else ('USAGE UNKNOWN' if x =='USAGE UNKNOWN' else 'SAFETY EQUIPMENT MISSING/MISUSED'))
```

In [ ]:
```
#bin ccategories
cln_people['SAFETY_EQUIPMENT'] = cln_people['SAFETY_EQUIPMENT'].map(f1)
```

In [ ]:
```
cln_people['SAFETY_EQUIPMENT'].value_counts()
```

Out[473]:
```
SAFETY EQUIPMENT USED               657163
USAGE UNKNOWN                       354429
SAFETY EQUIPMENT MISSING/MISUSED     51126
Name: SAFETY_EQUIPMENT, dtype: int64
```

We will keep the Usage Unkown category for now since it is a large chunk of the dataset and reevaluate after merging to see how to deal with it.

Neext is Injury Classifiation which also has a come missing values. The purpose of this column is to understand whether there was any injury/fatality or not. Therefore we will grooup categories accordingly. First, Lets check the value contents and go from there.

In [ ]:
```
#checkk value counts
cln_people['INJURY_CLASSIFICATION'].value_counts()
```

Out[474]:
```
NO INDICATION OF INJURY     947526
NONINCAPACITATING INJURY     64936
REPORTED, NOT EVIDENT        37511
INCAPACITATING INJURY        12085
FATAL                          649
Name: INJURY_CLASSIFICATION, dtype: int64
```

We can group together the multiple categories into 2 categories of Injury and No Injury.

Also, we can assume that an injury is something that is very evident and involves emeergency responsee in crashes. For missing values, we can impute the values with No Indication of Injury.

In [ ]:
```
#impute missing values
cln_people['INJURY_CLASSIFICATION'].fillna('NO INDICATION OF INJURY',inplace=True)
```

In [ ]:
```
#bin categories

#INJURY
cln_people['INJURY_CLASSIFICATION'].replace(['NONINCAPACITATING INJURY', 'REPORTED, NOT EVIDENT',
                                             'INCAPACITATING INJURY', 'FATAL'
                                            ], 'INJUIRY', inplace=True)
```

In [ ]:
```
#check new value counts
cln_people['INJURY_CLASSIFICATION'].value_counts()
```

Out[477]:
```
NO INDICATION OF INJURY    947537
INJUIRY                    115181
Name: INJURY_CLASSIFICATION, dtype: int64
```

In [ ]:
```
#check info
cln_people.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1062718 entries, 0 to 1530383
Data columns (total 11 columns):
 #   Column                 Non-Null Count    Dtype
---  ------                 --------------    -----
 0   PERSON_TYPE            1062718 non-null  object
 1   CRASH_RECORD_ID        1062718 non-null  object
 2   VEHICLE_ID             1040473 non-null  float64
 3   AGE                    1062718 non-null  float64
 4   SAFETY_EQUIPMENT       1062718 non-null  object
 5   INJURY_CLASSIFICATION  1062718 non-null  object
 6   DRIVER_ACTION          876229 non-null   object
 7   DRIVER_VISION          876088 non-null   object
 8   PHYSICAL_CONDITION     876429 non-null   object
 9   PEDPEDAL_ACTION        21735 non-null    object
 10  BAC_RESULT VALUE       1792 non-null     float64
dtypes: float64(3), object(8)
memory usage: 97.3+ MB
```

Lets check the Driver Action Column next. We saw earlier that the Pedestrian Person Type didn't have any values for this column. Lets explore whhat the division of person types is for the missing values in the Driver Action column.

In [ ]:
```
#check person type vaalue counts
cln_people.PERSON_TYPE.value_counts()
```

Out[479]:
```
DRIVER                  854811
PASSENGER               185993
PEDESTRIAN               12764
BICYCLE                   8792
NON-MOTOR VEHICLE          277
NON-CONTACT VEHICLE         81
Name: PERSON_TYPE, dtype: int64
```

In [ ]:
```
#check person type split for driver aactino null values
cln_people[cln_people['DRIVER_ACTION'].isnull()].PERSON_TYPE.value_counts()
```

Out[480]:
```
PASSENGER            185993
PEDESTRIAN              400
BICYCLE                  89
NON-MOTOR VEHICLE         7
Name: PERSON_TYPE, dtype: int64
```

All the Passenger person type records can be populated with 'Not a Driver' category and the rest can be dropped.

In [ ]:
```
#replace the passenger person type null values in driver aaction column with PASSENGER
cln_people.loc[cln_people.PERSON_TYPE == 'PASSENGER', 'DRIVER_ACTION'] = cln_people.DRIVER_ACTION.fillna(
                                                                                  'PASSENGER')
```

In [ ]:
```
#check person type split for driver aactino null values
cln_people[cln_people['DRIVER_ACTION'].isnull()].PERSON_TYPE.value_counts()
```

Out[482]:
```
PEDESTRIAN           400
BICYCLE               89
NON-MOTOR VEHICLE      7
Name: PERSON_TYPE, dtype: int64
```

In [ ]:
```
#drop records with null values in the Driver Action column
cln_people.dropna(subset=['DRIVER_ACTION'],inplace=True)
```

In [ ]:

```
#check new value counts
cln_people['DRIVER_ACTION'].value_counts()
```

Out[484]:

```
NONE                                  395225
PASSENGER                             185993
UNKNOWN                               152429
OTHER                                  84170
FAILED TO YIELD                        78998
FOLLOWED TOO CLOSELY                   50961
IMPROPER TURN                          22215
IMPROPER BACKING                       22027
IMPROPER LANE CHANGE                   19951
IMPROPER PASSING                       13647
DISREGARDED CONTROL DEVICES            13157
TOO FAST FOR CONDITIONS                12684
WRONG WAY/SIDE                          2716
IMPROPER PARKING                        2603
OVERCORRECTED                           1513
CELL PHONE USE OTHER THAN TEXTING       1343
EVADING POLICE VEHICLE                  1148
EMERGENCY VEHICLE ON CALL                926
TEXTING                                  351
```

In [ ]:

```
cln_people.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1062222 entries, 0 to 1530383
Data columns (total 11 columns):
 #   Column                 Non-Null Count    Dtype  
---  ------                 --------------    -----  
 0   PERSON_TYPE            1062222 non-null  object 
 1   CRASH_RECORD_ID        1062222 non-null  object 
 2   VEHICLE_ID             1040473 non-null  float64
 3   AGE                    1062222 non-null  float64
 4   SAFETY_EQUIPMENT       1062222 non-null  object 
 5   INJURY_CLASSIFICATION  1062222 non-null  object 
 6   DRIVER_ACTION          1062222 non-null  object 
 7   DRIVER_VISION          875919 non-null   object 
 8   PHYSICAL_CONDITION     876134 non-null   object 
 9   PEDPEDAL_ACTION        21243 non-null    object 
 10  BAC_RESULT VALUE       1792 non-null     float64
dtypes: float64(3), object(8)
memory usage: 97.2+ MB
```

Next we haave to clean the Driver Vision column. This column also has several missing values which we ssaw earlier can mostly be Passenger person type which can be replaced with the Passenger category. Therefre lets first take a look at the missing values for this column.

In [ ]:
```
#check person type split for driver aactino null values
cln_people[cln_people['DRIVER_VISION'].isnull()].PERSON_TYPE.value_counts()
```

Out[486]:
```
PASSENGER            185993
PEDESTRIAN              247
BICYCLE                  59
NON-MOTOR VEHICLE         4
Name: PERSON_TYPE, dtype: int64
```

In [ ]:
```
#replace the passenger person type null values in driver vision column with PASSENGER
cln_people.loc[cln_people.PERSON_TYPE == 'PASSENGER', 'DRIVER_VISION'] = cln_people.DRIVER_VISION.fillna(
                                                                        'PASSENGER')
```

In [ ]:
```
#check person type split for driver vision null values
cln_people[cln_people['DRIVER_VISION'].isnull()].PERSON_TYPE.value_counts()
```

Out[488]:
```
PEDESTRIAN           247
BICYCLE               59
NON-MOTOR VEHICLE      4
Name: PERSON_TYPE, dtype: int64
```

In [ ]:
```
#drop the other records with the missing values becaue they are a very small percentage of the total dataset
#drop records with null values in the Driver Vision column
cln_people.dropna(subset=['DRIVER_VISION'],inplace=True)
```

In [ ]:
```
#check total number of remaining null values in driver vision column
#should be zero
cln_people['DRIVER_VISION'].isnull().sum()
```

Out[490]:
```
0
```

The purpose of this column is to understand whether obstructed driver vision played a part in the crash or not. We can Group the different categories into two main bins; 1. Obscured, 2. Not Obscured

In [ ]:
```
#check value counts
cln_people['DRIVER_VISION'].value_counts()
```

Out[491]:
```
NOT OBSCURED              580090
UNKNOWN                   268389
PASSENGER                 185993
OTHER                      10936
MOVING VEHICLES             6659
PARKED VEHICLES             4106
WINDSHIELD (WATER/ICE)      3144
BLINDED - SUNLIGHT          1330
TREES, PLANTS                497
BUILDINGS                    401
BLINDED - HEADLIGHTS         105
HILLCREST                     89
BLOWING MATERIALS             75
EMBANKMENT                    68
SIGNBOARD                     30
Name: DRIVER_VISION, dtype: int64
```

In [ ]:
```
#bin category
cln_people['DRIVER_VISION'].replace(['MOVING VEHICLES',
                                     'PARKED VEHICLES',
                                     'WINDSHIELD (WATER/ICE)',
                                     'BLINDED - SUNLIGHT',
                                     'TREES, PLANTS',
                                     'BUILDINGS',
                                     'BLINDED - HEADLIGHTS',
                                     'HILLCREST',
                                     'BLOWING MATERIALS',
                                     'EMBANKMENT',
                                     'SIGNBOARD', 'OTHER'], 'OBSCURED', inplace=True)
```

In [ ]:
```
#check new value counts
cln_people['DRIVER_VISION'].value_counts()
```

Out[493]:
```
NOT OBSCURED    580090
UNKNOWN         268389
PASSENGER       185993
OBSCURED         27440
Name: DRIVER_VISION, dtype: int64
```

In [ ]:
```
#check info
cln_people.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1061912 entries, 0 to 1530383
Data columns (total 11 columns):
 #   Column                 Non-Null Count    Dtype  
---  ------                 --------------    -----  
 0   PERSON_TYPE            1061912 non-null  object 
 1   CRASH_RECORD_ID        1061912 non-null  object 
 2   VEHICLE_ID             1040473 non-null  float64
 3   AGE                    1061912 non-null  float64
 4   SAFETY_EQUIPMENT       1061912 non-null  object 
 5   INJURY_CLASSIFICATION  1061912 non-null  object 
 6   DRIVER_ACTION          1061912 non-null  object 
 7   DRIVER_VISION          1061912 non-null  object 
 8   PHYSICAL_CONDITION     875872 non-null   object 
 9   PEDPEDAL_ACTION        20936 non-null    object 
 10  BAC_RESULT VALUE       1792 non-null     float64
dtypes: float64(3), object(8)
memory usage: 97.2+ MB
```

Next is the Physial Condition Column. We know from previous exploration that Passengers will be the biggest contributors to the missing data in this column because this feature concerns the driver's physical condition at the time of crash. Therefore we will perform similar imputation as in the previous cases.

The primary focus of using this column is to understand whether the driver's condition was impaired or not. Thoose will be the 2 categories that the available categories will be binned as.

Also there are multiple catgories in this column, as explored earlier. A big chunk of the data is Unknown. Considering that if the driver's condition would have been explicitlly normal, it would have been obvious, the unknown and other category can be categorized as Impaired.

In [ ]:
```
#check person type split for physical condition null values
cln_people[cln_people['PHYSICAL_CONDITION'].isnull()].PERSON_TYPE.value_counts()
```

Out[495]:
```
PASSENGER             185993
PEDESTRIAN                27
BICYCLE                   17
NON-MOTOR VEHICLE          2
NON-CONTACT VEHICLE        1
Name: PERSON_TYPE, dtype: int64
```

In [ ]:
```
#replace the passenger person type null values in physical condition column with PASSENGER
cln_people.loc[cln_people.PERSON_TYPE == 'PASSENGER', 'PHYSICAL_CONDITION'] = cln_people.PHYSICAL_CONDITION.fillna(
                                                                                    'PASSENGER')
```

In [ ]:
```
#drop the other records with the missing values becaue they are a very small percentage of the total dataset
#drop records with null values in the Physical Condition column
cln_people.dropna(subset=['PHYSICAL_CONDITION'],inplace=True)
```

In [ ]:
```
#check total number of remaining null values
#should be zero
cln_people['PHYSICAL_CONDITION'].isnull().sum()
```

Out[498]:
```
0
```

In [ ]:
```
#check value counts
cln_people['PHYSICAL_CONDITION'].value_counts()
```

Out[499]:
```
NORMAL                              735810
PASSENGER                           185993
UNKNOWN                             119897
IMPAIRED - ALCOHOL                    5054
REMOVED BY EMS                        4016
FATIGUED/ASLEEP                       3025
OTHER                                 2754
EMOTIONAL                             2489
ILLNESS/FAINTED                       1047
HAD BEEN DRINKING                      764
IMPAIRED - DRUGS                       585
IMPAIRED - ALCOHOL AND DRUGS           291
MEDICATED                              140
Name: PHYSICAL_CONDITION, dtype: int64
```

In [ ]:
```
#bin caategories
cln_people['PHYSICAL_CONDITION'].replace(['IMPAIRED - ALCOHOL',
                                         'REMOVED BY EMS',
                                         'FATIGUED/ASLEEP',
                                         'EMOTIONAL',
                                         'ILLNESS/FAINTED',
                                         'HAD BEEN DRINKING',
                                         'IMPAIRED - DRUGS',
                                         'IMPAIRED - ALCOHOL AND DRUGS',
                                         'MEDICATED', 'UNKNOWN', 'OTHER'], 'IMPAIRED', inplace=True)
```

In [ ]:
```
#check new value counts
cln_people['PHYSICAL_CONDITION'].value_counts()
```

Out[501]:
```
NORMAL       735810
PASSENGER    185993
IMPAIRED     140062
Name: PHYSICAL_CONDITION, dtype: int64
```

In [ ]:
```
#check info
cln_people.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1061865 entries, 0 to 1530383
Data columns (total 11 columns):
 #   Column                 Non-Null Count    Dtype  
---  ------                 --------------    -----  
 0   PERSON_TYPE            1061865 non-null  object 
 1   CRASH_RECORD_ID        1061865 non-null  object 
 2   VEHICLE_ID             1040472 non-null  float64
 3   AGE                    1061865 non-null  float64
 4   SAFETY_EQUIPMENT       1061865 non-null  object 
 5   INJURY_CLASSIFICATION  1061865 non-null  object 
 6   DRIVER_ACTION          1061865 non-null  object 
 7   DRIVER_VISION          1061865 non-null  object 
 8   PHYSICAL_CONDITION     1061865 non-null  object 
 9   PEDPEDAL_ACTION        20891 non-null    object 
 10  BAC_RESULT VALUE       1792 non-null     float64
dtypes: float64(3), object(8)
memory usage: 97.2+ MB
```

Next we look at the PedPEdal Action Column which focuses on the aaction of the pedestriaan or cyclist at the time of crash. There are a lot of missisng but considering that the values in this column are focusing only on Pedestraiaan and bicyclist, it might be posssible that the missing value are drivers and passsengerss.

We will evaluate the person type for the null values in this column and then investigate the non null values.

In [ ]:
```
#check value counts for person type
cln_people['PERSON_TYPE'].value_counts()
```

Out[503]:
```
DRIVER                 854811
PASSENGER              185993
PEDESTRIAN              12090
BICYCLE                  8627
NON-MOTOR VEHICLE         264
NON-CONTACT VEHICLE        80
Name: PERSON_TYPE, dtype: int64
```

In [ ]:
```
#check person type split for physical condition null values
cln_people[cln_people['PEDPEDAL_ACTION'].isnull()].PERSON_TYPE.value_counts()
```

Out[504]:
```
DRIVER                 854811
PASSENGER              185993
NON-MOTOR VEHICLE         101
NON-CONTACT VEHICLE        68
PEDESTRIAN                  1
Name: PERSON_TYPE, dtype: int64
```

Looks like most of the non null values are either drivers or passengers which is what was expected. We can replace Drivers and Passengers with their categories explicitly.

In [ ]:
```
#replace the passenger person type null values in pedpedal actin column with PASSENGER
cln_people.loc[cln_people.PERSON_TYPE == 'PASSENGER', 'PEDPEDAL_ACTION'] = cln_people.PEDPEDAL_ACTION.fillna(
                                                                                    'PASSENGER')

#replace the driver person type null values in pedpedal actin column with DRIVER
cln_people.loc[cln_people.PERSON_TYPE == 'DRIVER', 'PEDPEDAL_ACTION'] = cln_people.PEDPEDAL_ACTION.fillna(
                                                                                    'DRIVER')
```

In [ ]:
```
#check the new person type split for physical condition null values
cln_people[cln_people['PEDPEDAL_ACTION'].isnull()].PERSON_TYPE.value_counts()
```

Out[506]:
```
NON-MOTOR VEHICLE      101
NON-CONTACT VEHICLE     68
PEDESTRIAN               1
Name: PERSON_TYPE, dtype: int64
```

In [ ]:
```
#drop the remaining missing values
cln_people.dropna(subset=['PEDPEDAL_ACTION'],inplace=True)
```

In [ ]:
```
#check the new person type split for physical condition non null values
cln_people[cln_people['PEDPEDAL_ACTION'].notnull()].PERSON_TYPE.value_counts()
```

Out[508]:
```
DRIVER                 854811
PASSENGER              185993
PEDESTRIAN              12089
BICYCLE                  8627
NON-MOTOR VEHICLE         163
NON-CONTACT VEHICLE        12
Name: PERSON_TYPE, dtype: int64
```

In [ ]:

```
cln_people['PEDPEDAL_ACTION'].value_counts()
```

Out[509]:

```
DRIVER                                              854811
PASSENGER                                           185993
CROSSING - WITH SIGNAL                                4346
WITH TRAFFIC                                          3682
OTHER ACTION                                          2493
UNKNOWN/NA                                            2382
NO ACTION                                             1190
CROSSING - NO CONTROLS (NOT AT INTERSECTION)          1155
CROSSING - NO CONTROLS (AT INTERSECTION)              1009
CROSSING - AGAINST SIGNAL                              933
NOT AT INTERSECTION                                    724
AGAINST TRAFFIC                                        637
CROSSING - CONTROLS PRESENT (NOT AT INTERSECTION)      585
STANDING IN ROADWAY                                    454
TURNING LEFT                                           323
PARKED VEHICLE                                         245
ENTER FROM DRIVE/ALLEY                                 202
TURNING RIGHT                                          153
WORKING IN ROADWAY                                     134
```

In [ ]:

```
cln_people.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1061695 entries, 0 to 1530383
Data columns (total 11 columns):
 #   Column                 Non-Null Count    Dtype  
---  ------                 --------------    -----  
 0   PERSON_TYPE            1061695 non-null  object 
 1   CRASH_RECORD_ID        1061695 non-null  object 
 2   VEHICLE_ID             1040420 non-null  float64
 3   AGE                    1061695 non-null  float64
 4   SAFETY_EQUIPMENT       1061695 non-null  object 
 5   INJURY_CLASSIFICATION  1061695 non-null  object 
 6   DRIVER_ACTION          1061695 non-null  object 
 7   DRIVER_VISION          1061695 non-null  object 
 8   PHYSICAL_CONDITION     1061695 non-null  object 
 9   PEDPEDAL_ACTION        1061695 non-null  object 
 10  BAC_RESULT VALUE       1792 non-null     float64
dtypes: float64(3), object(8)
memory usage: 97.2+ MB
```

NExt, we will look at the BAC result value column. This column has a lot of missing values. The main information that we want to extract from this column is identifying whether the driver was intoxicated or not.

We will first check the person type splits for the null values in this column and explore further from there.

In [ ]:
```
#check value counts for person type
cln_people['PERSON_TYPE'].value_counts()
```

Out[511]:
```
DRIVER                  854811
PASSENGER               185993
PEDESTRIAN               12089
BICYCLE                   8627
NON-MOTOR VEHICLE          163
NON-CONTACT VEHICLE         12
Name: PERSON_TYPE, dtype: int64
```

In [ ]:
```
#check the new person type splits
cln_people[cln_people['BAC_RESULT VALUE'].isnull()].PERSON_TYPE.value_counts()
```

Out[512]:
```
DRIVER                  853023
PASSENGER               185993
PEDESTRIAN               12087
BICYCLE                   8625
NON-MOTOR VEHICLE          163
NON-CONTACT VEHICLE         12
Name: PERSON_TYPE, dtype: int64
```

In [ ]:
```
#check the new person type splits for non null values
cln_people[cln_people['BAC_RESULT VALUE'].notnull()].PERSON_TYPE.value_counts()
```

Out[513]:
```
DRIVER        1788
BICYCLE          2
PEDESTRIAN       2
Name: PERSON_TYPE, dtype: int64
```

Looks like the values in this column are for only drivers, biycle and Pedestrians. We will use the values from this column and the general standard to populate aa neew column indicating if the person was intxicated or not.

In [ ]:
```
#chek value counts
cln_people['BAC_RESULT VALUE'].value_counts()
```

Out[514]:
```
0.00    172
0.17    127
0.18    126
0.21    110
0.14    102
0.20     94
0.16     89
0.19     83
0.15     76
0.22     75
0.23     69
0.12     66
0.13     66
0.11     64
0.24     59
0.26     40
0.25     39
0.10     33
0.27     33
```

Legally people are not allowed to drive with a BAC greater than 0.8. We will ussee that as our baaseline for categorizing whether a person waas intoxicated or not.

We also have some very high values for BAC which do not make sensee considering BAC 0.30% to 0.40%: In this percentage range, you'll likely have alcohol poisoning, a potentially life-threatening condition, and experience loss of consciousness. BAC Over 0.40%: This is a potentially fatal blood alcohol level.

Therefore we will drop records with BAC greater than 0.40 beccause it would be nearly impossible for people with that high of a BAC to be on the streets.

In [ ]:
```
#drop records
cln_people.drop((cln_people[cln_people['BAC_RESULT VALUE']>0.40].index),inplace=True)
```

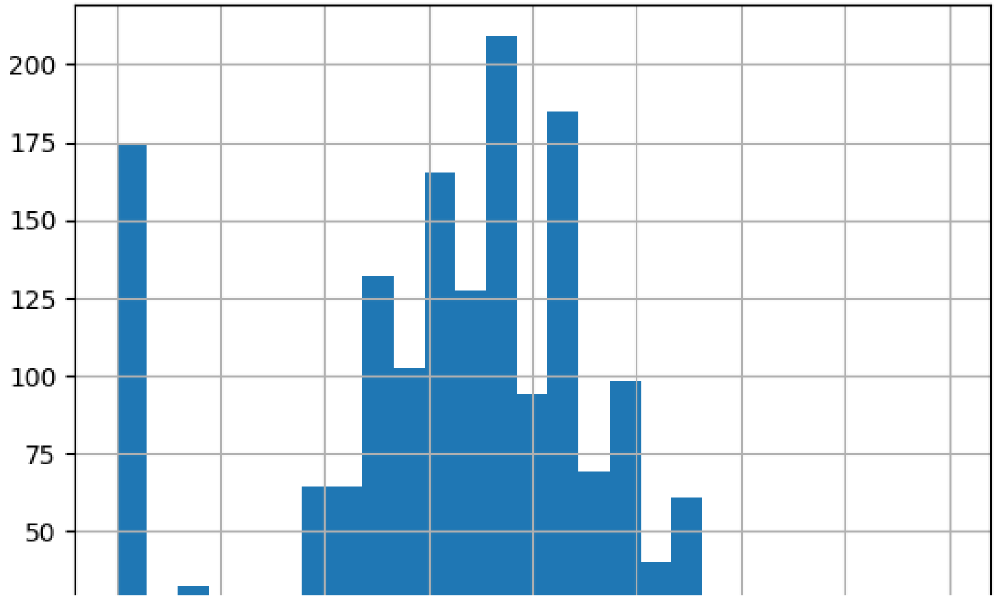
In [ ]:

```
#check new value counts
cln_people['BAC_RESULT VALUE'].value_counts()
```

Out[516]:

```
0.00    172
0.17    127
0.18    126
0.21    110
0.14    102
0.20     94
0.16     89
0.19     83
0.15     76
0.22     75
0.23     69
0.12     66
0.13     66
0.11     64
0.24     59
0.26     40
0.25     39
0.10     33
0.27     33
0.09     31
0.28     28
0.08     18
0.29     18
0.03     17
0.30     16
0.07     16
0.33     15
0.04     15
0.05     10
0.35      9
0.32      9
0.02      8
0.06      8
0.31      7
0.38      6
0.36      4
0.34      4
0.39      3
0.01      3
0.37      1
0.40      1
Name: BAC_RESULT VALUE, dtype: int64
```

In [ ]:
```
cln_people['BAC_RESULT VALUE'].hist(bins='auto');
```



In [ ]:
```
#create new column for intoxication indication using BAC results value

#create a lambda function for maapping purposes
e = lambda x: 'Y' if x > 0.08 else 'N'

#map the funtion and create the new column
cln_people.INTOXICATED_I = cln_people['BAC_RESULT VALUE'].map(e)
```

```
<ipython-input-518-f04e5ed22f42>:7: UserWarning: Pandas doesn't allow columns to be created via a new attribute name - se
e https://pandas.pydata.org/pandas-docs/stable/indexing.html#attribute-access (https://pandas.pydata.org/pandas-docs/stab
le/indexing.html#attribute-access)
  cln_people.INTOXICATED_I = cln_people['BAC_RESULT VALUE'].map(e)
```

In [ ]:
```
#check value counts
cln_people.INTOXICATED_I.value_counts()
```

Out[519]:
```
N    1060170
Y       1503
Name: BAC_RESULT VALUE, dtype: int64
```

In [ ]:
```
#drop BAC result value column
cln_people = cln_people.drop(['BAC_RESULT VALUE'], axis=1)
```

In [ ]:
```
cln_people.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1061673 entries, 0 to 1530383
Data columns (total 10 columns):
 #   Column                 Non-Null Count    Dtype  
---  ------                 --------------    -----  
 0   PERSON_TYPE            1061673 non-null  object 
 1   CRASH_RECORD_ID        1061673 non-null  object 
 2   VEHICLE_ID             1040398 non-null  float64
 3   AGE                    1061673 non-null  float64
 4   SAFETY_EQUIPMENT       1061673 non-null  object 
 5   INJURY_CLASSIFICATION  1061673 non-null  object 
 6   DRIVER_ACTION          1061673 non-null  object 
 7   DRIVER_VISION          1061673 non-null  object 
 8   PHYSICAL_CONDITION     1061673 non-null  object 
 9   PEDPEDAL_ACTION        1061673 non-null  object 
dtypes: float64(2), object(8)
memory usage: 89.1+ MB
```

In [ ]:
```
#drop vehicle ID column
cln_people = cln_people.drop(['VEHICLE_ID'], axis=1)
```

Now we can move onto merging the all the daatasets together.

In [ ]:
```
# merge veh_crsh with peoples cleaned dataset on crash record id
veh_crsh_ppl = pd.merge(veh_crsh, cln_people, how='inner', on='CRASH_RECORD_ID' )
```

In [ ]:

```python
#preview the first 5 rows
veh_crsh_ppl.head()
```

Out[524]:

	CRASH_RECORD_ID	CRASH_YEAR	POSTED_SPEED_LIMIT	DEVICE_CONDITION	WEATHER_CONDITION	LIGHTING_CONDITION	CRA
0	79c7a2ce89f446262efd86df3d72d18b04ba487024b7c4...	2019	30	FUNCTIONING PROPERLY	CLEAR	DAY TIME	INJ OR .
1	79c7a2ce89f446262efd86df3d72d18b04ba487024b7c4...	2019	30	FUNCTIONING PROPERLY	CLEAR	DAY TIME	INJ OR .
2	79c7a2ce89f446262efd86df3d72d18b04ba487024b7c4...	2019	30	FUNCTIONING PROPERLY	CLEAR	DAY TIME	INJ OR .
3	79c7a2ce89f446262efd86df3d72d18b04ba487024b7c4...	2019	30	FUNCTIONING PROPERLY	CLEAR	DAY TIME	INJ OR .
4	79c7a2ce89f446262efd86df3d72d18b04ba487024b7c4...	2019	30	FUNCTIONING PROPERLY	CLEAR	DAY TIME	INJ OR .

5 rows × 33 columns

In [ ]:

```python
veh_crsh_ppl.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 534692 entries, 0 to 534691
Data columns (total 33 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   CRASH_RECORD_ID         534692 non-null  object
 1   CRASH_YEAR              534692 non-null  int64
 2   POSTED_SPEED_LIMIT      534692 non-null  int64
 3   DEVICE_CONDITION        534692 non-null  object
 4   WEATHER_CONDITION       534692 non-null  object
 5   LIGHTING_CONDITION      534692 non-null  object
 6   CRASH_TYPE              534692 non-null  object
 7   INTERSECTION_RELATED_I  534692 non-null  object
 8   ROAD_DEFECT             534692 non-null  object
 9   PRIM_CONTRIBUTORY_CAUSE 534692 non-null  object
 10  NUM_UNITS               534692 non-null  int64
 11  WORK_ZONE_I             534692 non-null  object
 12  WORKERS_PRESENT_I       534692 non-null  object
 13  INJURIES_TOTAL          534692 non-null  float64
 14  INJURIES_FATAL          534692 non-null  float64
```

Lets take a look at the unkown categories we left behind in the vehicles database. If the number of records with unkown values has gone down, we will drop the unknown values. In the scenario where they haven't, we will have to deal with them accordingly.

In [ ]:
```
#check value counts of vehicle type
veh_crsh_ppl.VEHICLE_TYPE.value_counts()
```

Out[526]:
```
REGULAR PERSONAL    500908
UNKNOWN/NA           15787
COMMERCIAL           11948
PUBLIC                6049
Name: VEHICLE_TYPE, dtype: int64
```

In [ ]:
```
#drop records with unknown values in the vehicle type column
veh_crsh_ppl = veh_crsh_ppl[veh_crsh_ppl.VEHICLE_TYPE != 'UNKNOWN/NA']
```

In [ ]:
```
#check value counts of MANEUVER
veh_crsh_ppl.MANEUVER.value_counts()
```

Out[528]:
```
STRAIGHT                    317756
TURNING                      77729
START/STOP                   47605
ENTERING/EXITING TRAFFIC     40080
LANE CHANGE                  14331
UNKNOWN/NA                    9393
EXTERNAL OBSTRUCTIONS         7064
BACKING                       3415
DRIVING WRONG WAY             1532
Name: MANEUVER, dtype: int64
```

In [ ]:
```
#drop records with unknown values in the MANEUVER column
veh_crsh_ppl = veh_crsh_ppl[veh_crsh_ppl.MANEUVER != 'UNKNOWN/NA']
```

In [ ]:
```
#check new value counts of MANEUVER
veh_crsh_ppl.MANEUVER.value_counts()
```

Out[530]:
```
STRAIGHT                    317756
TURNING                      77729
START/STOP                   47605
ENTERING/EXITING TRAFFIC     40080
LANE CHANGE                  14331
EXTERNAL OBSTRUCTIONS         7064
BACKING                       3415
DRIVING WRONG WAY             1532
Name: MANEUVER, dtype: int64
```

In [ ]:
```
#check value counts of FIRST_CONTACT_POINT
veh_crsh_ppl.FIRST_CONTACT_POINT.value_counts()
```

Out[531]:
```
FRONT                 148418
OTHER                 113946
REAR                  101427
TOTAL (ALL AREAS)      54697
SIDE                   50269
TOP/BOTTOM             29538
UNKNOWN                 9370
NONE                    1847
Name: FIRST_CONTACT_POINT, dtype: int64
```

In [ ]:
```
#drop records with unknown values in the FIRST_CONTACT_POINT column
veh_crsh_ppl = veh_crsh_ppl[veh_crsh_ppl.FIRST_CONTACT_POINT != 'UNKNOWN']
```

In [ ]:
```
#check new value counts of FIRST_CONTACT_POINT
veh_crsh_ppl.FIRST_CONTACT_POINT.value_counts()
```

Out[533]:
```
FRONT                 148418
OTHER                 113946
REAR                  101427
TOTAL (ALL AREAS)      54697
SIDE                   50269
TOP/BOTTOM             29538
NONE                    1847
Name: FIRST_CONTACT_POINT, dtype: int64
```

In [ ]:
```
#check value counts of VEHICLE_DEFECT_I
veh_crsh_ppl.VEHICLE_DEFECT_I.value_counts()
```

Out[534]:
```
N    297389
U    195608
Y      7145
Name: VEHICLE_DEFECT_I, dtype: int64
```

The number of unkowns in this column are still very high. Unfortunately, there is not enough information to impute these values. We will carry them forward into our modeling because there might be other variabless that link with it to form a trend of the causes of traffic accidents.

In [ ]:
```
veh_crsh_ppl.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 500142 entries, 0 to 534691
Data columns (total 33 columns):
 #   Column                    Non-Null Count   Dtype  
---  ------                    --------------   -----  
 0   CRASH_RECORD_ID           500142 non-null  object 
 1   CRASH_YEAR                500142 non-null  int64  
 2   POSTED_SPEED_LIMIT        500142 non-null  int64  
 3   DEVICE_CONDITION          500142 non-null  object 
 4   WEATHER_CONDITION         500142 non-null  object 
 5   LIGHTING_CONDITION        500142 non-null  object 
 6   CRASH_TYPE                500142 non-null  object 
 7   INTERSECTION_RELATED_I    500142 non-null  object 
 8   ROAD_DEFECT               500142 non-null  object 
 9   PRIM_CONTRIBUTORY_CAUSE   500142 non-null  object 
 10  NUM_UNITS                 500142 non-null  int64  
 11  WORK_ZONE_I               500142 non-null  object 
 12  WORKERS_PRESENT_I         500142 non-null  object 
 13  INJURIES_TOTAL            500142 non-null  float64
 14  INJURIES_FATAL            500142 non-null  float64
 15  CRASH_HOUR                500142 non-null  int64  
 16  CRASH_DAY_OF_WEEK         500142 non-null  int64  
 17  CRASH_MONTH               500142 non-null  int64  
 18  LATITUDE                  500142 non-null  float64
 19  LONGITUDE                 500142 non-null  float64
 20  VEHICLE_TYPE              500142 non-null  object 
 21  MANEUVER                  500142 non-null  object 
 22  FIRST_CONTACT_POINT       500142 non-null  object 
 23  VEHICLE_DEFECT_I          500142 non-null  object 
 24  OCCUPANT_CAT              500142 non-null  object 
 25  PERSON_TYPE               500142 non-null  object 
 26  AGE                       500142 non-null  float64
 27  SAFETY_EQUIPMENT          500142 non-null  object 
 28  INJURY_CLASSIFICATION     500142 non-null  object 
 29  DRIVER_ACTION             500142 non-null  object 
 30  DRIVER_VISION             500142 non-null  object 
 31  PHYSICAL_CONDITION        500142 non-null  object 
 32  PEDPEDAL_ACTION           500142 non-null  object 
dtypes: float64(5), int64(6), object(22)
memory usage: 129.7+ MB
```

Next, lets look at processing this merged dataset to prepare it for modelling but first, lets separate out the unable to determine categories from the Primary Contributary Cause column to check later whether our model can provide some insights into what coud have been the causes for it.

In [ ]:
```
veh_crsh_ppl.PRIM_CONTRIBUTORY_CAUSE.value_counts()
```

Out[536]:
```
RECKLESS/IMPROPER DRIVING    250998
TRAFFIC RULES VIOLATED       178527
UNABLE TO DETERMINE           70617
Name: PRIM_CONTRIBUTORY_CAUSE, dtype: int64
```

In [ ]:
```
#separate out unable to determine categories
u_veh_crsh_ppl = veh_crsh_ppl[veh_crsh_ppl.PRIM_CONTRIBUTORY_CAUSE == 'UNABLE TO DETERMINE']

#separate out the rest
veh_crsh_ppl = veh_crsh_ppl[veh_crsh_ppl.PRIM_CONTRIBUTORY_CAUSE != 'UNABLE TO DETERMINE']
```

Lets take a look at how the dataset looks after filtering out the Unable to Determine causes.

In [ ]:
```
#unable to determine cause dataset
u_veh_crsh_ppl.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 70617 entries, 35 to 534691
Data columns (total 33 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   CRASH_RECORD_ID          70617 non-null  object 
 1   CRASH_YEAR               70617 non-null  int64  
 2   POSTED_SPEED_LIMIT       70617 non-null  int64  
 3   DEVICE_CONDITION         70617 non-null  object 
 4   WEATHER_CONDITION        70617 non-null  object 
 5   LIGHTING_CONDITION       70617 non-null  object 
 6   CRASH_TYPE               70617 non-null  object 
 7   INTERSECTION_RELATED_I   70617 non-null  object 
 8   ROAD_DEFECT              70617 non-null  object 
 9   PRIM_CONTRIBUTORY_CAUSE  70617 non-null  object 
 10  NUM_UNITS                70617 non-null  int64  
 11  WORK_ZONE_I              70617 non-null  object 
 12  WORKERS_PRESENT_I        70617 non-null  object 
 13  INJURIES_TOTAL           70617 non-null  float64
 14  INJURIES_FATAL           70617 non-null  float64
 15  CRASH_HOUR               70617 non-null  int64  
 16  CRASH_DAY_OF_WEEK        70617 non-null  int64  
 17  CRASH_MONTH              70617 non-null  int64  
 18  LATITUDE                 70617 non-null  float64
 19  LONGITUDE                70617 non-null  float64
 20  VEHICLE_TYPE             70617 non-null  object 
 21  MANEUVER                 70617 non-null  object 
 22  FIRST_CONTACT_POINT      70617 non-null  object 
 23  VEHICLE_DEFECT_I         70617 non-null  object 
 24  OCCUPANT_CAT             70617 non-null  object 
 25  PERSON_TYPE              70617 non-null  object 
 26  AGE                      70617 non-null  float64
 27  SAFETY_EQUIPMENT         70617 non-null  object 
 28  INJURY_CLASSIFICATION    70617 non-null  object 
 29  DRIVER_ACTION            70617 non-null  object 
 30  DRIVER_VISION            70617 non-null  object 
 31  PHYSICAL_CONDITION       70617 non-null  object 
 32  PEDPEDAL_ACTION          70617 non-null  object 
dtypes: float64(5), int64(6), object(22)
memory usage: 18.3+ MB
```

In [ ]:
```
#dataset with the causes
veh_crsh_ppl.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 429525 entries, 0 to 534689
Data columns (total 33 columns):
 #   Column                   Non-Null Count   Dtype  
---  ------                   --------------   -----  
 0   CRASH_RECORD_ID          429525 non-null  object 
 1   CRASH_YEAR               429525 non-null  int64  
 2   POSTED_SPEED_LIMIT       429525 non-null  int64  
 3   DEVICE_CONDITION         429525 non-null  object 
 4   WEATHER_CONDITION        429525 non-null  object 
 5   LIGHTING_CONDITION       429525 non-null  object 
 6   CRASH_TYPE               429525 non-null  object 
 7   INTERSECTION_RELATED_I   429525 non-null  object 
 8   ROAD_DEFECT              429525 non-null  object 
 9   PRIM_CONTRIBUTORY_CAUSE  429525 non-null  object 
 10  NUM_UNITS                429525 non-null  int64  
 11  WORK_ZONE_I              429525 non-null  object 
 12  WORKERS_PRESENT_I        429525 non-null  object 
 13  INJURIES_TOTAL           429525 non-null  float64
 14  INJURIES_FATAL           429525 non-null  float64
 15  CRASH_HOUR               429525 non-null  int64  
 16  CRASH_DAY_OF_WEEK        429525 non-null  int64  
 17  CRASH_MONTH              429525 non-null  int64  
 18  LATITUDE                 429525 non-null  float64
 19  LONGITUDE                429525 non-null  float64
 20  VEHICLE_TYPE             429525 non-null  object 
 21  MANEUVER                 429525 non-null  object 
 22  FIRST_CONTACT_POINT      429525 non-null  object 
 23  VEHICLE_DEFECT_I         429525 non-null  object 
 24  OCCUPANT_CAT             429525 non-null  object 
 25  PERSON_TYPE              429525 non-null  object 
 26  AGE                      429525 non-null  float64
 27  SAFETY_EQUIPMENT         429525 non-null  object 
 28  INJURY_CLASSIFICATION    429525 non-null  object 
 29  DRIVER_ACTION            429525 non-null  object 
 30  DRIVER_VISION            429525 non-null  object 
 31  PHYSICAL_CONDITION       429525 non-null  object 
 32  PEDPEDAL_ACTION          429525 non-null  object 
dtypes: float64(5), int64(6), object(22)
memory usage: 111.4+ MB
```

We don't have any missing values and the unable to determine is a largely significant dataset with almost 70,000 records.

Now we need to encode the categorical columns because ML models are better adept at handling numerical data as compared to categorical data.

In [ ]:

```
# Finding Category Columns
cat_columns = veh_crsh_ppl.dtypes[veh_crsh_ppl.dtypes == 'object'].index

# Finding unique counts for categorical columns
cat_unique = veh_crsh_ppl[cat_columns].nunique()

#separate the list of the categorical columns
cat = veh_crsh_ppl[cat_columns].columns

cat
```

Out[540]:

```
Index(['CRASH_RECORD_ID', 'DEVICE_CONDITION', 'WEATHER_CONDITION',
       'LIGHTING_CONDITION', 'CRASH_TYPE', 'INTERSECTION_RELATED_I',
       'ROAD_DEFECT', 'PRIM_CONTRIBUTORY_CAUSE', 'WORK_ZONE_I',
       'WORKERS_PRESENT_I', 'VEHICLE_TYPE', 'MANEUVER', 'FIRST_CONTACT_POINT',
       'VEHICLE_DEFECT_I', 'OCCUPANT_CAT', 'PERSON_TYPE', 'SAFETY_EQUIPMENT',
       'INJURY_CLASSIFICATION', 'DRIVER_ACTION', 'DRIVER_VISION',
       'PHYSICAL_CONDITION', 'PEDPEDAL_ACTION'],
      dtype='object')
```

In [ ]:

```
# Finding Category Columns for the unable to determine dataset
cat_columns_u = u_veh_crsh_ppl.dtypes[u_veh_crsh_ppl.dtypes == 'object'].index

# Finding unique counts for categorical columns
cat_unique_u = u_veh_crsh_ppl[cat_columns_u].nunique()

#separate the list of the categorical columns
cat_u = u_veh_crsh_ppl[cat_columns_u].columns

cat_u
```

Out[541]:

```
Index(['CRASH_RECORD_ID', 'DEVICE_CONDITION', 'WEATHER_CONDITION',
       'LIGHTING_CONDITION', 'CRASH_TYPE', 'INTERSECTION_RELATED_I',
       'ROAD_DEFECT', 'PRIM_CONTRIBUTORY_CAUSE', 'WORK_ZONE_I',
       'WORKERS_PRESENT_I', 'VEHICLE_TYPE', 'MANEUVER', 'FIRST_CONTACT_POINT',
       'VEHICLE_DEFECT_I', 'OCCUPANT_CAT', 'PERSON_TYPE', 'SAFETY_EQUIPMENT',
       'INJURY_CLASSIFICATION', 'DRIVER_ACTION', 'DRIVER_VISION',
       'PHYSICAL_CONDITION', 'PEDPEDAL_ACTION'],
      dtype='object')
```

We will use the caategoricaal columns names to loop through it one by one and label encode the categories in the column using integers from zero onwards

In [ ]:

```
label_list=[]
label_list_u=[]
for j in cat[1:]: #loop through the categorical variables
    label_encoding = veh_crsh_ppl[j].unique() #separate the unique variables in the specific column
    label_encoding = { label_encoding[i] : i for i in range(len(label_encoding))} #label encode
    label_list.append([j,label_encoding])


    #do the same thing for the unable to determine dataset
    label_encoding_u = u_veh_crsh_ppl[j].unique()
    label_encoding_u = { label_encoding_u[i] : i for i in range(len(label_encoding_u))}
    label_list_u.append([j,label_encoding])

    #encode both datasets
    veh_crsh_ppl[j] = veh_crsh_ppl[j].apply(lambda x : label_encoding[x])
#     print(j, veh_crsh_ppl[j].unique())

    u_veh_crsh_ppl[j] = u_veh_crsh_ppl[j].apply(lambda x : label_encoding_u[x])
#     print(j, u_veh_crsh_ppl[j].unique())

print(label_list)
print(label_list_u)
```

[['DEVICE_CONDITION', {'FUNCTIONING PROPERLY': 0, 'NOT FUNCTIONING PROPERLY': 1, 'NO CONTROLS': 2}], ['WEATHER_CONDITIO
N', {'CLEAR': 0, 'NOT CLEAR': 1}], ['LIGHTING_CONDITION', {'DAY TIME': 0, 'NIGHT TIME': 1}], ['CRASH_TYPE', {'INJURY AND
/ OR TOW DUE TO CRASH': 0}], ['INTERSECTION_RELATED_I', {'Y': 0, 'N': 1}], ['ROAD_DEFECT', {'NO DEFECTS': 0, 'DEFECTS':
1}], ['PRIM_CONTRIBUTORY_CAUSE', {'RECKLESS/IMPROPER DRIVING': 0, 'TRAFFIC RULES VIOLATED': 1}], ['WORK_ZONE_I', {'N': 0,
'Y': 1}], ['WORKERS_PRESENT_I', {'N': 0, 'Y': 1}], ['VEHICLE_TYPE', {'REGULAR PERSONAL': 0, 'COMMERCIAL': 1, 'PUBLIC':
2}], ['MANEUVER', {'TURNING': 0, 'STRAIGHT': 1, 'START/STOP': 2, 'EXTERNAL OBSTRUCTIONS': 3, 'DRIVING WRONG WAY': 4, 'LAN
E CHANGE': 5, 'ENTERING/EXITING TRAFFIC': 6, 'BACKING': 7}], ['FIRST_CONTACT_POINT', {'FRONT': 0, 'NONE': 1, 'REAR': 2,
'OTHER': 3, 'SIDE': 4, 'TOTAL (ALL AREAS)': 5, 'TOP/BOTTOM': 6}], ['VEHICLE_DEFECT_I', {'N': 0, 'U': 1, 'Y': 2}], ['OCCUP
ANT_CAT', {'1-2': 0, '3-5': 1, '0': 2, '6-9': 3, '10+': 4}], ['PERSON_TYPE', {'PASSENGER': 0, 'DRIVER': 1, 'BICYCLE': 2,
'PEDESTRIAN': 3, 'NON-MOTOR VEHICLE': 4, 'NON-CONTACT VEHICLE': 5}], ['SAFETY_EQUIPMENT', {'SAFETY EQUIPMENT USED': 0, 'S
AFETY EQUIPMENT MISSING/MISUSED': 1, 'USAGE UNKNOWN': 2}], ['INJURY_CLASSIFICATION', {'NO INDICATION OF INJURY': 0, 'INJU
IRY': 1}], ['DRIVER_ACTION', {'PASSENGER': 0, 'IMPROPER TURN': 1, 'NONE': 2, 'OTHER': 3, 'WRONG WAY/SIDE': 4, 'FAILED TO
YIELD': 5, 'CELL PHONE USE OTHER THAN TEXTING': 6, 'UNKNOWN': 7, 'IMPROPER LANE CHANGE': 8, 'IMPROPER BACKING': 9, 'FOLLO
WED TOO CLOSELY': 10, 'TOO FAST FOR CONDITIONS': 11, 'DISREGARDED CONTROL DEVICES': 12, 'IMPROPER PASSING': 13, 'EVADING
POLICE VEHICLE': 14, 'OVERCORRECTED': 15, 'TEXTING': 16, 'IMPROPER PARKING': 17, 'EMERGENCY VEHICLE ON CALL': 18, 'STOPPE
D SCHOOL BUS': 19, 'LICENSE RESTRICTIONS': 20}], ['DRIVER_VISION', {'PASSENGER': 0, 'UNKNOWN': 1, 'NOT OBSCURED': 2, 'OBS
CURED': 3}], ['PHYSICAL_CONDITION', {'PASSENGER': 0, 'NORMAL': 1, 'IMPAIRED': 2}], ['PEDPEDAL_ACTION', {'PASSENGER': 0,
'DRIVER': 1, 'AGAINST TRAFFIC': 2, 'CROSSING - CONTROLS PRESENT (NOT AT INTERSECTION)': 3, 'CROSSING - WITH SIGNAL': 4,
'OTHER ACTION': 5, 'CROSSING - NO CONTROLS (NOT AT INTERSECTION)': 6, 'WITH TRAFFIC': 7, 'NO ACTION': 8, 'PLAYING IN ROAD
WAY': 9, 'INTOXICATED PED/PEDAL': 10, 'ENTER FROM DRIVE/ALLEY': 11, 'CROSSING - NO CONTROLS (AT INTERSECTION)': 12, 'CROS
SING - AGAINST SIGNAL': 13, 'UNKNOWN/NA': 14, 'NOT AT INTERSECTION': 15, 'STANDING IN ROADWAY': 16, 'TURNING LEFT': 17,
'WORKING IN ROADWAY': 18, 'TURNING RIGHT': 19, 'PARKED VEHICLE': 20, 'WAITING FOR SCHOOL BUS': 21, 'TO/FROM DISABLED VEHI
CLE': 22, 'PLAYING/WORKING ON VEHICLE': 23, 'SCHOOL BUS (WITHIN 50 FT.)': 24}]]
[['DEVICE_CONDITION', {'FUNCTIONING PROPERLY': 0, 'NOT FUNCTIONING PROPERLY': 1, 'NO CONTROLS': 2}], ['WEATHER_CONDITIO
N', {'CLEAR': 0, 'NOT CLEAR': 1}], ['LIGHTING_CONDITION', {'DAY TIME': 0, 'NIGHT TIME': 1}], ['CRASH_TYPE', {'INJURY AND
/ OR TOW DUE TO CRASH': 0}], ['INTERSECTION_RELATED_I', {'Y': 0, 'N': 1}], ['ROAD_DEFECT', {'NO DEFECTS': 0, 'DEFECTS':
1}], ['PRIM_CONTRIBUTORY_CAUSE', {'RECKLESS/IMPROPER DRIVING': 0, 'TRAFFIC RULES VIOLATED': 1}], ['WORK_ZONE_I', {'N': 0,
'Y': 1}], ['WORKERS_PRESENT_I', {'N': 0, 'Y': 1}], ['VEHICLE_TYPE', {'REGULAR PERSONAL': 0, 'COMMERCIAL': 1, 'PUBLIC':
2}], ['MANEUVER', {'TURNING': 0, 'STRAIGHT': 1, 'START/STOP': 2, 'EXTERNAL OBSTRUCTIONS': 3, 'DRIVING WRONG WAY': 4, 'LAN
E CHANGE': 5, 'ENTERING/EXITING TRAFFIC': 6, 'BACKING': 7}], ['FIRST_CONTACT_POINT', {'FRONT': 0, 'NONE': 1, 'REAR': 2,
'OTHER': 3, 'SIDE': 4, 'TOTAL (ALL AREAS)': 5, 'TOP/BOTTOM': 6}], ['VEHICLE_DEFECT_I', {'N': 0, 'U': 1, 'Y': 2}], ['OCCUP
ANT_CAT', {'1-2': 0, '3-5': 1, '0': 2, '6-9': 3, '10+': 4}], ['PERSON_TYPE', {'PASSENGER': 0, 'DRIVER': 1, 'BICYCLE': 2,
'PEDESTRIAN': 3, 'NON-MOTOR VEHICLE': 4, 'NON-CONTACT VEHICLE': 5}], ['SAFETY_EQUIPMENT', {'SAFETY EQUIPMENT USED': 0, 'S
AFETY EQUIPMENT MISSING/MISUSED': 1, 'USAGE UNKNOWN': 2}], ['INJURY_CLASSIFICATION', {'NO INDICATION OF INJURY': 0, 'INJU
IRY': 1}], ['DRIVER_ACTION', {'PASSENGER': 0, 'IMPROPER TURN': 1, 'NONE': 2, 'OTHER': 3, 'WRONG WAY/SIDE': 4, 'FAILED TO
YIELD': 5, 'CELL PHONE USE OTHER THAN TEXTING': 6, 'UNKNOWN': 7, 'IMPROPER LANE CHANGE': 8, 'IMPROPER BACKING': 9, 'FOLLO
WED TOO CLOSELY': 10, 'TOO FAST FOR CONDITIONS': 11, 'DISREGARDED CONTROL DEVICES': 12, 'IMPROPER PASSING': 13, 'EVADING
POLICE VEHICLE': 14, 'OVERCORRECTED': 15, 'TEXTING': 16, 'IMPROPER PARKING': 17, 'EMERGENCY VEHICLE ON CALL': 18, 'STOPPE
D SCHOOL BUS': 19, 'LICENSE RESTRICTIONS': 20}], ['DRIVER_VISION', {'PASSENGER': 0, 'UNKNOWN': 1, 'NOT OBSCURED': 2, 'OBS
CURED': 3}], ['PHYSICAL_CONDITION', {'PASSENGER': 0, 'NORMAL': 1, 'IMPAIRED': 2}], ['PEDPEDAL_ACTION', {'PASSENGER': 0,
'DRIVER': 1, 'AGAINST TRAFFIC': 2, 'CROSSING - CONTROLS PRESENT (NOT AT INTERSECTION)': 3, 'CROSSING - WITH SIGNAL': 4,
'OTHER ACTION': 5, 'CROSSING - NO CONTROLS (NOT AT INTERSECTION)': 6, 'WITH TRAFFIC': 7, 'NO ACTION': 8, 'PLAYING IN ROAD
WAY': 9, 'INTOXICATED PED/PEDAL': 10, 'ENTER FROM DRIVE/ALLEY': 11, 'CROSSING - NO CONTROLS (AT INTERSECTION)': 12, 'CROS
SING - AGAINST SIGNAL': 13, 'UNKNOWN/NA': 14, 'NOT AT INTERSECTION': 15, 'STANDING IN ROADWAY': 16, 'TURNING LEFT': 17,
'WORKING IN ROADWAY': 18, 'TURNING RIGHT': 19, 'PARKED VEHICLE': 20, 'WAITING FOR SCHOOL BUS': 21, 'TO/FROM DISABLED VEHI
CLE': 22, 'PLAYING/WORKING ON VEHICLE': 23, 'SCHOOL BUS (WITHIN 50 FT.)': 24}]]

We filtered out the types of crashes to only keep the ones that had inlved injuries. Considering that crash type has been filtered to only the injuries or fatalities, we can drop this columnm.

In [ ]:
```
veh_crsh_ppl.drop('CRASH_TYPE', axis= 1, inplace= True)
u_veh_crsh_ppl.drop('CRASH_TYPE', axis= 1, inplace= True)
```

The Craash Record IDs are more of a primary key for this dataset therefore we will set this aas the index so as not to interfere with our mdelling but still have it available if we need it. After setting the index, we will extract the unique indices so as to keep records relating to the same crash in the same train/test dataset.

In [ ]:
```
veh_crsh_ppl
```

Out[544]:

	CRASH_RECORD_ID	CRASH_YEAR	POSTED_SPEED_LIMIT	DEVICE_CONDITION	WEATHER_CONDITION	LIGHTING_CONDITIOI
0	79c7a2ce89f446262efd86df3d72d18b04ba487024b7c4...	2019	30	0	0	
1	79c7a2ce89f446262efd86df3d72d18b04ba487024b7c4...	2019	30	0	0	
2	79c7a2ce89f446262efd86df3d72d18b04ba487024b7c4...	2019	30	0	0	
3	79c7a2ce89f446262efd86df3d72d18b04ba487024b7c4...	2019	30	0	0	
4	79c7a2ce89f446262efd86df3d72d18b04ba487024b7c4...	2019	30	0	0	
...	...	...	...	...	...	.
534685	2aab54e2b2e6559f3cfe240f84690dd78a991a5e818ca9...	2022	30	0	0	
534686	2aab54e2b2e6559f3cfe240f84690dd78a991a5e818ca9...	2022	30	0	0	
534687	2aab54e2b2e6559f3cfe240f84690dd78a991a5e818ca9...	2022	30	0	0	
534688	22a4d7218110c786c6e8394f9843d1185ed50677358144...	2022	45	1	0	
534689	22a4d7218110c786c6e8394f9843d1185ed50677358144...	2022	45	1	0	

429525 rows × 32 columns

In [ ]:
```
veh_crsh_ppl.set_index('CRASH_RECORD_ID',inplace=True)

u_veh_crsh_ppl.set_index('CRASH_RECORD_ID',inplace=True)
```

In [ ]:
```
# u_veh_crsh_ppl.set_index('CRASH_RECORD_ID',inplace=True)
```

In [ ]:
```
veh_crsh_ppl.PRIM_CONTRIBUTORY_CAUSE.value_counts()
```

Out[547]:
```
0    250998
1    178527
Name: PRIM_CONTRIBUTORY_CAUSE, dtype: int64
```

In [ ]:

```
# Get the unique indices
groups = veh_crsh_ppl.index.unique()
groups
```

Out[548]:

```
Index(['79c7a2ce89f446262efd86df3d72d18b04ba487024b7c42d58be7bc0ee3b2779be1916679231382b4a4bfe14200bd305d9c6feb7cd70839f8
63dd944b040212d',
       '7b3545fb91352d7fc46ba142d9044a5508671db4d01d0226f0a56f7774954d7d98030e5c47efb4aec51122cc57d15a820e826eb99e4559eba
e383c5715f637e6',
       '79704e1b747fbf5f740f1255785934dfe659ff910d4782b606f87f714d6a7292cbced2d9f08e091569f06bdd38051ba0bb15ccb125e1f32f1
6ed5620e05ba305',
       '7b3850c200a1f73cc7c800e48ece28907dc6599da0d905a94b842b362ca7163041da962602dbc4bb6560dd9fe15395b42d971b1dacf6894ff
2fff3d8bc59f7f5',
       '0be13986626ce381917a49f7811f38d79ea151cef6b2322903bd4bb7550913142d9e6d41f9026b377d136d94aa589147e79f5116887430079
820b042be1c05d3',
       '798cc771c20c11dcc335369c87eb8458964dd30b94bd00498f0b30ccb8d4f78f9bfa9aaad56ed7629ae75c6cf10451b31582783285f24e17b
d9aef61805c9907',
       '02b2ca12c9b8702eb0a31619ff12860901a5e02bf584d17292bedbc09feda9261bde4a747d70f59750aa388b3a974d1dcf76770e204961655
e623442e7ee013b',
       '0ee9250ed16a30706717ad05779ac5aecc304d84bfd6762fe5f22879ce8dda7db54974485e4f3daccc2824f834c40be7321a1ac6ff363a430
c047e87537731ad',
       '79a9c11b06e5d529811576e6d109e250056fb31724b246104f72a89e2ca3f62a90f51fa0635b771fbf174e5e20380ecc8bebf5b6e9276799f
913fdcbd2623bb4',
       '7b1b05ed5eb0a764604b983288ffe852e202253d4cb25431957b5859f81e8938c15aee47c10f7510ea52036328b31a54d206dba24fb211d30
17fc6cda08579c1',
       ...
       '1779a3107d1807ac3e6dc25f9f6d6cb1417783b3a35e905f1ac50e153f9e16dfb8efca0cf223ed0cca59f37a0eeed740cdff53a17301e255f
712acf564826aa1',
       '09687987b252aa9985177b33c90639b717eafff7e3017a8e1278eb903b4f343759450b17330709bba980ffa2f25931bbe3a67b967db82fa05
9b89ddf2b0cbd78',
       '2235099fa618f474922621f156ea0a822983689f916d32d983ae4ea6d05a5c8100e01bd41ad32ed790c1113574e572a4f6e38df94cde78368
4169b692bcb3b1f',
       'b8e91c563747739f4a5cf5015e7cf80505366a7efec96f88daa0b47de505d75f646ea98b8b4f71ca7c25f1f6e9e2f2a2e73617eae621f8b59
c98b9eb416f2297',
       '18dfa728f98d658e38429d68fb8b53577e479a4c16fef488f452585a02ba18812aee10dbdf47f988c136b973ed0a5c2f002445b0fb40946ee
51a90849b75eedf',
       '2e8bde95e08865115cfea29811c9847e85da0ece6fd3544e7c27dad6183a62419018a3fabedbe1886ce6c6329d15869c7c9ecb981fd7a5b36
97fead1df772671',
       'b04bf37d9186ab3d9dc0a84722fc25bc5855055aac952b3312c03fea57b9e8226a8165d889cec4b0e1e89543feb7c4c8366b5bb57a85a36f3
ada4842532f63aa',
       'bba25d76519c479b96c5cdf11437ade0e3608c6cc7f88714cd92d8ccd5810a3b9534f6b37ec797cafb4be10cbcb06565c954fd3a69ce98277
39d76bca3db9b59',
       '2aab54e2b2e6559f3cfe240f84690dd78a991a5e818ca907234636fbe2b1e1ce89d5aaa15a61976ab1ea8e6935de88ac2771bd9acae6101a3
9c1f186a40ec9a4',
       '22a4d7218110c786c6e8394f9843d1185ed506773581445e1a8261e83bbd1de51e60fd43a0637d7d1c2bdad80f40acf6530dd11490e1b1479
8f6ae83a6354f2b'],
      dtype='object', name='CRASH_RECORD_ID', length=94308)
```

In [ ]:
```
# checking the shape and final result
print(veh_crsh_ppl.shape)
veh_crsh_ppl.head()
```

(429525, 31)

Out[549]:

	CRASH_YEAR	POSTED_S
CRASH_RECORD_ID		
79c7a2ce89f446262efd86df3d72d18b04ba487024b7c42d58be7bc0ee3b2779be1916679231382b4a4bfe14200bd305d9c6feb7cd70839f863dd944b040212d	2019	
79c7a2ce89f446262efd86df3d72d18b04ba487024b7c42d58be7bc0ee3b2779be1916679231382b4a4bfe14200bd305d9c6feb7cd70839f863dd944b040212d	2019	
79c7a2ce89f446262efd86df3d72d18b04ba487024b7c42d58be7bc0ee3b2779be1916679231382b4a4bfe14200bd305d9c6feb7cd70839f863dd944b040212d	2019	
79c7a2ce89f446262efd86df3d72d18b04ba487024b7c42d58be7bc0ee3b2779be1916679231382b4a4bfe14200bd305d9c6feb7cd70839f863dd944b040212d	2019	
79c7a2ce89f446262efd86df3d72d18b04ba487024b7c42d58be7bc0ee3b2779be1916679231382b4a4bfe14200bd305d9c6feb7cd70839f863dd944b040212d	2019	

5 rows × 31 columns

Modeling and Evaluation

Now we will split our datasets into X and y sets to use for modeling. Before we can start modeling, we still need to deal with the imbalance of the datsets which we will do after splitting int train and test sets to avoid data leakage.

In [ ]:
```
#split into X and y
X = veh_crsh_ppl.drop('PRIM_CONTRIBUTORY_CAUSE',axis=1)
y = veh_crsh_ppl['PRIM_CONTRIBUTORY_CAUSE']

Xu = u_veh_crsh_ppl.drop('PRIM_CONTRIBUTORY_CAUSE',axis=1)
```

In [ ]:
```
from sklearn.model_selection import GroupShuffleSplit
```

Since we want to keep the records associated with the same crash together, we will use the Group Shuffle Split method to keep these together.

We will purposefully keep the test size to 0.1 becaause we will be undersampling the dataset for training the model. We waant to make ssure that we can capture an appropriate amount of data for proper training. Also, to keep a heaalthy ratio of train and test ssize. Considering that it is not an unsupervissed learning model, having a much larger amount of test data as compared to the model's training data can cause the model's scoress to be severly worse.

We will resample our trsining data to be 200,000 or less records which will briing the aamount of test data to 20% of the training data.

In [ ]:

```
# Split the indices into train and test sets
group_splitter = GroupShuffleSplit(n_splits=1, test_size=0.1, random_state=42)
train_idx, test_idx = next(group_splitter.split(X=X, groups=X.index))

# Get the data for the train and test sets
X_train = X.loc[X.index.isin(X.index[train_idx])]
y_train = y.loc[y.index.isin(X.index[train_idx])]

X_test = X.loc[X.index.isin(X.index[test_idx])]
y_test = y.loc[y.index.isin(X.index[test_idx])]
```

In [ ]:
```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 386915 entries, 79c7a2ce89f446262efd86df3d72d18b04ba487024b7c42d58be7bc0ee3b2779be1916679231382b4a4bfe14200bd305d9
c6feb7cd70839f863dd944b040212d to 22a4d7218110c786c6e8394f9843d1185ed506773581445e1a8261e83bbd1de51e60fd43a0637d7d1c2bdad
80f40acf6530dd11490e1b14798f6ae83a6354f2b
Data columns (total 30 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   CRASH_YEAR               386915 non-null  int64
 1   POSTED_SPEED_LIMIT       386915 non-null  int64
 2   DEVICE_CONDITION         386915 non-null  int64
 3   WEATHER_CONDITION        386915 non-null  int64
 4   LIGHTING_CONDITION       386915 non-null  int64
 5   INTERSECTION_RELATED_I   386915 non-null  int64
 6   ROAD_DEFECT              386915 non-null  int64
 7   NUM_UNITS                386915 non-null  int64
 8   WORK_ZONE_I              386915 non-null  int64
 9   WORKERS_PRESENT_I        386915 non-null  int64
 10  INJURIES_TOTAL           386915 non-null  float64
 11  INJURIES_FATAL           386915 non-null  float64
 12  CRASH_HOUR               386915 non-null  int64
 13  CRASH_DAY_OF_WEEK        386915 non-null  int64
 14  CRASH_MONTH              386915 non-null  int64
 15  LATITUDE                 386915 non-null  float64
 16  LONGITUDE                386915 non-null  float64
 17  VEHICLE_TYPE             386915 non-null  int64
 18  MANEUVER                 386915 non-null  int64
 19  FIRST_CONTACT_POINT      386915 non-null  int64
 20  VEHICLE_DEFECT_I         386915 non-null  int64
 21  OCCUPANT_CAT             386915 non-null  int64
 22  PERSON_TYPE              386915 non-null  int64
 23  AGE                      386915 non-null  float64
 24  SAFETY_EQUIPMENT         386915 non-null  int64
 25  INJURY_CLASSIFICATION    386915 non-null  int64
 26  DRIVER_ACTION            386915 non-null  int64
 27  DRIVER_VISION            386915 non-null  int64
 28  PHYSICAL_CONDITION       386915 non-null  int64
 29  PEDPEDAL_ACTION          386915 non-null  int64
dtypes: float64(5), int64(25)
memory usage: 91.5+ MB
```

Since we have converted all of our data to numerical formaat, it wuld be helpful to scale the dataset so thaat all of it is on the saame scale and normalized. This way no single column with a lot of categories or columns that have higgh integer value data would bias the model into a poor performance.

We will use standard scaler because it will normalize our dataset, take care of outliers and be helpful to any gradient descent algorithms we waant to use.

In [ ]:
```
# Scale the data to ensure that all features have the same range of values
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

scaler_u = StandardScaler()
Xu_scaled = scaler_u.fit_transform(Xu)
```

In [ ]:
```
# Convert X_train_scaled back to a DataFrame
X_train_scaled_df = pd.DataFrame(X_train_scaled, columns=X_train.columns, index=X_train.index)

# Convert X_test_scaled back to a DataFrame
X_test_scaled_df = pd.DataFrame(X_test_scaled, columns=X_test.columns, index=X_test.index)


Xu_train_scaled_df = pd.DataFrame(Xu_scaled, columns=Xu.columns)
```

Random under Sampling

Now, we want to undersample the data to deal with the imabalnce in our dataset. Undersampling is a technique used to address the issue of imbalanced datasets. When the classes in a dataset are imbalanced, the model trained on this dataset may be biased towards the majority class and may have poor performance on the minority class. By undersampling, we reduce the number of instances of the majority class so that the number of instances in the majority class is more balanced with the number of instances in the minority class. This helps to reduce the bias towards the majority class and can lead to improved model performance on the minority class.

Using a smaller dataset can also be computationally better from an efficiency and cost standpoint.

In [ ]:
```
from imblearn.under_sampling import RandomUnderSampler
from collections import Counter
from imblearn.under_sampling import ClusterCentroids
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
```

In [ ]:
```
# undersample = RandomUnderSampler(sampling_strategy='majority')
# oversample = SMOTE(sampling_strategy='auto', k_neighbors=5)

# # Undersample the majority class
# X_under, y_under = undersample.fit_resample(X_train_scaled_df, y_train)

# # Oversample the minority classes
# X3_resampled, y3_resampled = oversample.fit_resample(X_under, y_under)
```

In [ ]:
```
# rus = RandomUnderSampler(sampling_strategy='not minority',random_state=42)
# X1_train_scaled_resampled, y1_train_resampled = rus.fit_resample(X_train_scaled_df, y_train)
```

In [ ]:
```
# rus = RandomUnderSampler(sampling_strategy='majority',random_state=42)
# X2_train_scaled_resampled, y2_train_resampled = rus.fit_resample(X_train_scaled_df, y_train)
```

In [ ]:
```
#check original traaining target variable distribution
y_train.value_counts()
```

Out[560]:
```
0    226042
1    160873
Name: PRIM_CONTRIBUTORY_CAUSE, dtype: int64
```

In [ ]:
```
#check ratios of values to the highest value to understand the gaps
y = max(y_train.value_counts())
for x in y_train.value_counts():
    print(x, y, x/y)
```

```
226042 226042 1.0
160873 226042 0.7116951716937561
```

In [ ]:
```
#chck test target variable value counts
y_test.value_counts()
```

Out[562]:
```
0    24956
1    17654
Name: PRIM_CONTRIBUTORY_CAUSE, dtype: int64
```

In [ ]:
```
# # Define the ratios for each class
# class_ratios = {0: 174130, 1: 160873, 2: 50000, 3: 50000}

# # Create the SMOTE object with the specified ratios
# oversample = SMOTE(sampling_strategy=class_ratios, k_neighbors=5)

# # Oversample the minority classes
# X1_train_scaled_resampled, y1_train_resampled = oversample.fit_resample(X_train_scaled_df, y_train)
```

In [ ]:
```
# define the undersampling ratio
desired_samples = {0: 100000, 1: 100000}#, 2: 50000, 3: 50000}

# instantiate the RandomUnderSampler
under_sampler = RandomUnderSampler(sampling_strategy=desired_samples)

# perform undersampling on the training data
X_train_scaled_resampled, y_train_resampled = under_sampler.fit_resample(X_train_scaled_df, y_train)
```

In [ ]:
```
#check totaal nummber of records in undersampled set
len(X_train_scaled_resampled)
```

Out[565]:
```
200000
```

In [ ]:
```
#check totaal nummber of records in undersampled set
y_train_resampled.value_counts()
```

Out[566]:
```
0    100000
1    100000
Name: PRIM_CONTRIBUTORY_CAUSE, dtype: int64
```

In [ ]:
```
# y1_train_resampled.value_counts()
```

In [ ]:
```
# y2_train_resampled.value_counts()
```

In [ ]:
```
# y3_resampled.value_counts()
```

In [ ]:

```
#check records in the test dataset
X_test_scaled_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 42610 entries, 3b6433e9b96e2ba2d3008cd0dc7c9d2eae4478f2562b8853d7530d21624140eba89f5b54aa2c0f6369f937331d26d7df6d0
18f6a24198f40a338c86772b9c212 to 8e9df537ef66f506c3c279ed198592d0b1ba55b4c0d9d99d42f9100701a598c48ff24d95e98d0505127bc8fc
87b48418ffa5c6eb18ff6283ebe5346f77d9c7e8
Data columns (total 30 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   CRASH_YEAR              42610 non-null  float64
 1   POSTED_SPEED_LIMIT      42610 non-null  float64
 2   DEVICE_CONDITION        42610 non-null  float64
 3   WEATHER_CONDITION       42610 non-null  float64
 4   LIGHTING_CONDITION      42610 non-null  float64
 5   INTERSECTION_RELATED_I  42610 non-null  float64
 6   ROAD_DEFECT             42610 non-null  float64
 7   NUM_UNITS               42610 non-null  float64
 8   WORK_ZONE_I             42610 non-null  float64
 9   WORKERS_PRESENT_I       42610 non-null  float64
 10  INJURIES_TOTAL          42610 non-null  float64
 11  INJURIES_FATAL          42610 non-null  float64
 12  CRASH_HOUR              42610 non-null  float64
 13  CRASH_DAY_OF_WEEK       42610 non-null  float64
 14  CRASH_MONTH             42610 non-null  float64
 15  LATITUDE                42610 non-null  float64
 16  LONGITUDE               42610 non-null  float64
 17  VEHICLE_TYPE            42610 non-null  float64
 18  MANEUVER                42610 non-null  float64
 19  FIRST_CONTACT_POINT     42610 non-null  float64
 20  VEHICLE_DEFECT_I        42610 non-null  float64
 21  OCCUPANT_CAT            42610 non-null  float64
 22  PERSON_TYPE             42610 non-null  float64
 23  AGE                     42610 non-null  float64
 24  SAFETY_EQUIPMENT        42610 non-null  float64
 25  INJURY_CLASSIFICATION   42610 non-null  float64
 26  DRIVER_ACTION           42610 non-null  float64
 27  DRIVER_VISION           42610 non-null  float64
 28  PHYSICAL_CONDITION      42610 non-null  float64
 29  PEDPEDAL_ACTION         42610 non-null  float64
dtypes: float64(30)
memory usage: 10.1+ MB
```

After Undersampling, the test data is almost 21% of the training data that will be used for modelling. This is a good ratio to have confidence that the results won't be skewed because of a large test set.

Feature Selection

With 30 different features, it will be computationally extremely expensive to model 200,000 records over 30 features. We will use feature selection thrugh the SelectKBest model using the Mutual information method. Mutual information measures the dependence between variables, and can be used to identify which variables have the most information about the target variable. It is a non-parametric method that does not assume a particular functional form of the relationship between the variables therefore we don't have to worry if the relationship between the target and the predictors is linear or not.

Also this will help us identify the features provided us the most information about thee cause. This is one of the things thta Chicago DOT was trying to understand. Based on these features, the DOT can conduct further eexploratory analysis to understand where to make improvements. Therefore we will also save these feaatures for use further.

In [ ]:
```
import pandas as pd
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.feature_selection import mutual_info_classif
```

In [ ]:
```
# Apply SelectKBest class to extract top 10 best features
k=10
kbest = SelectKBest(score_func=mutual_info_classif, k=k)
fit = kbest.fit(X_train_scaled_resampled, y_train_resampled)

# Create a new dataframe with only the selected features
selected_features_indices = kbest.get_support(indices=True)
selected_features = pd.DataFrame({'Feature': X_train.columns, 'Score': fit.scores_})
selected_features.sort_values('Score', ascending=False).head(k)
```

Out[572]:

	Feature	Score
15	LATITUDE	0.322234
16	LONGITUDE	0.321154
26	DRIVER_ACTION	0.107081
5	INTERSECTION_RELATED_I	0.087196
19	FIRST_CONTACT_POINT	0.048737
2	DEVICE_CONDITION	0.044018
18	MANEUVER	0.041911
7	NUM_UNITS	0.033197
21	OCCUPANT_CAT	0.014254
3	WEATHER_CONDITION	0.013157

For mutual_info_classif, a higher score indicates a stronger mutual information between the target variable and the features, which means the feature is more relevant for prediction. We now have the factors that are impacting the cause of the crash the most. These can prvide valuable insights to DOT about how to reduce certain types of crashes.

Therefore we will extract the top 10 features and create new datasets that we will model on.

In [ ]:
```
#use the indices to select the relevant features from the trainiing data
X_train_fselect = X_train_scaled_resampled.iloc[:, selected_features_indices]

features_used = X_train_fselect.columns

#use the indices to select the relevant features from the test data
X_test_fselect = X_test_scaled_df.iloc[:, selected_features_indices]

#use the indices to select the relevant features from the unable to determine data
Xu_fselect = Xu_train_scaled_df.iloc[:, selected_features_indices]

#since random forest is well adept at handling imabalnced dataset, we will use the original
#dataset without resampling
X_train_scaled_fselect = X_train_scaled_df.iloc[:, selected_features_indices]
X_test_scaled_fselect = X_test_scaled_df.iloc[:, selected_features_indices]
```

In [ ]:
```
# Creating data structure  of model and evaluation accuracy to record all models results for comparison

models ={
    'Model Name':[],
    'Accuracy':[],
    'CV Score':[],
    'Precision':[],
    'Recall':[],
}
```

Now we will move on to the modelling side. Although, we will look at multiple scores to understand the performance of the model, we will focus on the accuracy score and the recall score since we want to be able to predict the causes of car crashes as aaccurately as possible since that will drive further insights for the DOT staff to take further action.

Baseline Model

We will start with a Baseline model of a Decision Tree Classifier. Decision tree classifiers are good for multi-categorical data modeling because they can handle both categorical and continuous features, and are able to handle interactions and non-linear relationships between features.

In [ ]:
```
# from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
```

In [ ]:
```
#initialize the classifier
DT = DecisionTreeClassifier()
```

In [ ]:
```
#fit the model
DT.fit(X_train_fselect,y_train_resampled)
```

Out[577]:
```
DecisionTreeClassifier()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Lets take a look at the cross-validation score to get aan early glimpse of how the model is performing.

In [579]:
```
# Evaluate the model with cross-validation
cv_scores = cross_val_score(DT, X_train_fselect, y_train_resampled, cv=3)
print("Cross-validation scores:", cv_scores)
print("Mean CV score:", np.mean(cv_scores))
```

```
Cross-validation scores: [0.7805511  0.7796511  0.78218282]
Mean CV score: 0.7807950069390746
```

The mean CV scre is very high fo r a baseline model. This either shows that our baseline model id performing extremely well or it is overfitting on the training data. The only way to figure this out is to predict values using the test features and compare the scores With the model trained, we will go ahead and predict using the test features.

In [ ]:
```
#predict
y_pred = DT.predict(X_test_fselect)
```

In [580]:
```
#calcualte the accuraacy score
accuracy = accuracy_score(y_test, y_pred)

accuracy
```

Out[580]:
```
0.6994836892748181
```

Lets also take a look at a few other scoring methods to holistically understand the performaance of the model.

In [583]:
```
from sklearn.metrics import precision_score, recall_score, classification_report
```

In [584]:
```
precision = precision_score(y_test, y_pred,average='weighted')
recall = recall_score(y_test, y_pred,average='weighted')

print("Precision:", precision)
print("Recall:", recall)
```

```
Precision: 0.7042995037922452
Recall: 0.6994836892748181
```

In [585]:
```
#print the classification report
report = classification_report(y_test, y_pred)
print(report)
```

```
              precision    recall  f1-score   support

           0       0.76      0.71      0.74     24956
           1       0.63      0.68      0.65     17654

    accuracy                           0.70     42610
   macro avg       0.69      0.70      0.69     42610
weighted avg       0.70      0.70      0.70     42610
```

The precision aand accuracy of the model are very similar with both ~70%. Interestingly, the precision for category 0 (Reckless/Improper Driving) is significantly hiigher than category 1 (Traffic Rules Violated). If we continue to see the same trend, this would mean that while binning the data, we lost certain valuable information that would provide more consistent discernable information to our model. Similarly it would also help with accuracy is more discernable information or more information about certaain underlying patterns is fed with more granularity to the model. This is something that can be explored as a part of further improvements to make the dataset more granular and explore the level of granularity through the MLE method to understand what level of granularity provides the most value for the computing efforts required for training the model.

With an accuracy of almost 70% while the CV wasa ~78%, it is clear that the model has slightly overfitted to the training data. Nonetheless, a baseline performmance of 70% without any hyperparameter tuning looks reasonably good. Considering that we got a good result for the baseline, we will start of analyzing the other models through hyperparameter tuning so that we are confident that we are finding the most optimized results.

Nonetheless, we should explore the confusion matrix to understand the performance of the mmodel further

In [581]:
```
#import confusiion matrix
from sklearn.metrics import confusion_matrix
```

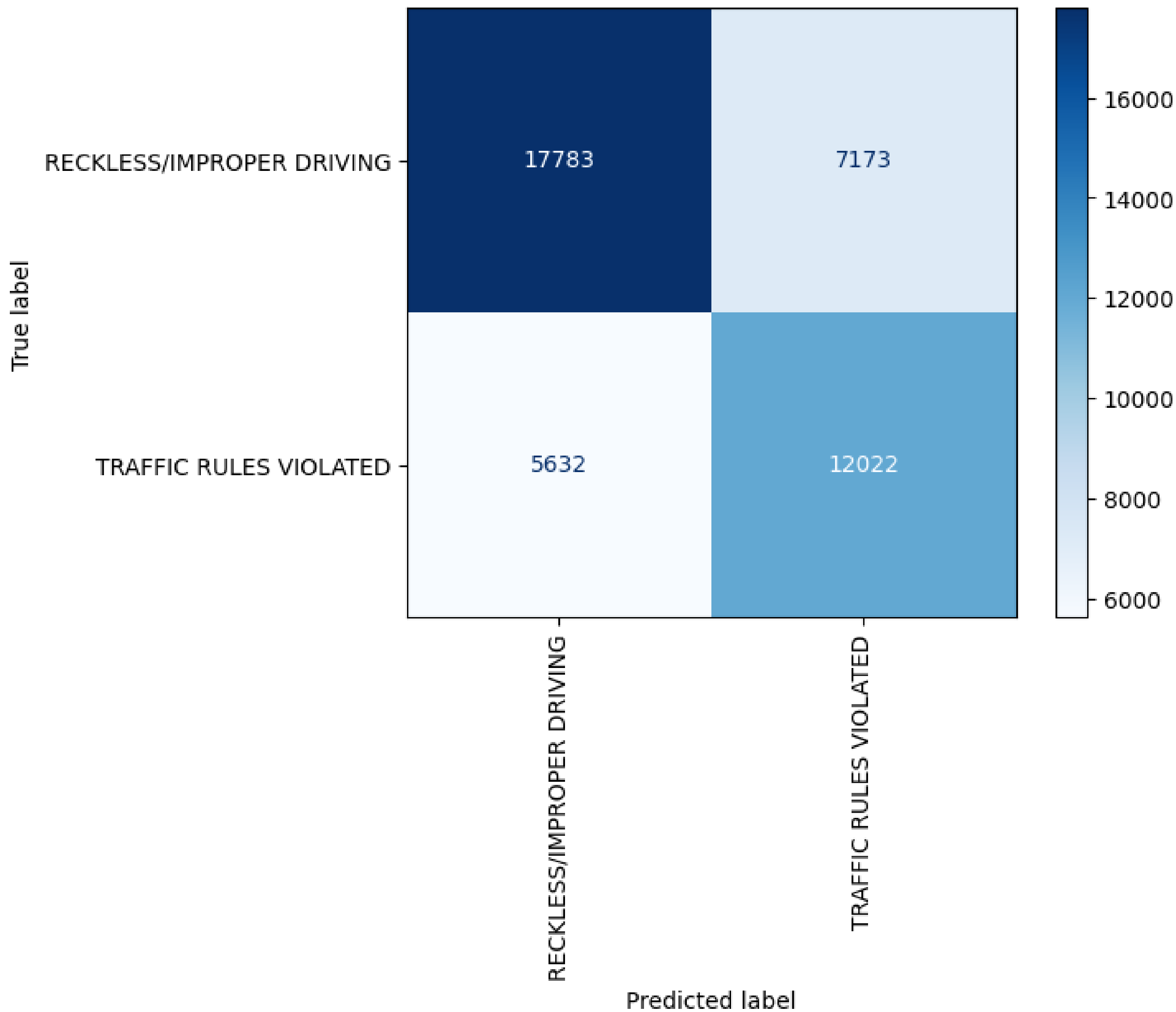
We can take a look at a confusion maatrix to understand how is our model performing.

In [582]:

```
cm = confusion_matrix(y_test, y_pred)
# {'RECKLESS/IMPROPER DRIVING': 0, 'TRAFFIC RULES VIOLATED': 1, 'COMPROMISED DRIVING': 2, 'OBSTRUCTIONS': 3}
# define the label names
label_names = ['RECKLESS/IMPROPER DRIVING',
          'TRAFFIC RULES VIOLATED']
          # 'COMPROMISED DRIVING',
          # 'OBSTRUCTIONS']

# define the axis labels
x_labels = label_names
y_labels = label_names

#plot confusion matrix
# ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names, cmap=plt.cm.Blues)
disp_dt = ConfusionMatrixDisplay.from_predictions(y_test,
                                                  y_pred,
                                                  display_labels=label_names,
                                                  cmap=plt.cm.Blues,
                                                  xticks_rotation='vertical')
```



The test set had more records on Records on Reckless/Improper driving as compared to the Traaffic Rules Violated category but the accuraacy and recall scores are similar. This shows that the model isn't biased towards a asingular category which can improve our confidence in the results. Nonetheless, training and testing with the complete dataset can provide more confidence i nthe vaalidity of these results.

We will store the scores of this model for compaarison with other models.

In [586]:
```
# result in model data structure

models['Model Name'].append('Decision Tree Classifier')
models['Accuracy'].append(accuracy)
models['CV Score'].append(np.mean(cv_scores))
models['Precision'].append(precision)
models['Recall'].append(recall)
```

KNN Model

While Decision Trees can be a powerful and flexible algorithm for classification tasks, they can suffer from overfitting and can be sensitive to the choice of hyperparameters. K-Nearest Neighbors (KNN), on the other hand, is a non-parametric algorithm that makes no assumptions about the underlying distribution of the data and can be less prone to overfitting.

KNN can also be more effective than Decision Trees for datasets with well-separated clusters like ours, as it relies on the distance between data points to make predictions rather than fitting a model to the data. By exploring KNN as an alternative to Decision Trees, we may be able to find a more robust and accurate model for our specific dataset.

We can use hyperparameter tuning to optimize the performance.

We will optimize for 4 parameters:

```
1. n_neighbours: This is the number of neighbours the model uses to make the prediction. BEcause of the large set o
f out data, it would be helpful to start with a range that can cover small and large number of neighbours. Therefor
e we caan use 5, 10, 25, 50, 100, 1000].

2. weights: We will investigate the uniform and distance metrics.

3. metric: We will use Euclidean, Manhattan and Minkowski distance as parameters

4. algorithm: We will set this to auto and let knn choose the best algorithm to use according to the dataset.  This
will also help us computationally.
```

In [587]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
```

In [588]:
```
# Define the KNN classifier and the parameter grid for grid search
knn = KNeighborsClassifier()

# Define parameter grid distribution
param_grid = {'n_neighbors': [7,9,11],
              'weights': ['uniform','distance'],'metric': ['manhattan'],
              'algorithm': ['auto', 'ball_tree']}

# Perform grid search with cross-validation to find the best hyperparameters
grid_search = GridSearchCV(knn, param_grid=param_grid, cv=3, scoring='accuracy')

#grid_search.fit(X_train_knn_dr, y_train_resampled2)
grid_search.fit(X_train_fselect, y_train_resampled)

# Print best parameters and best score
print("Best parameters: ", grid_search.best_params_)
print("Best score: ", grid_search.best_score_)
```

```
Best parameters:  {'algorithm': 'auto', 'metric': 'manhattan', 'n_neighbors': 11, 'weights': 'distance'}
Best score:  0.7877949918143488
```

In [589]:
```
# Select the model with the most optimized parameters
best_knn = grid_search.best_estimator_
```

In [590]:
```
# Evaluate the model with cross-validation

cv_scores = cross_val_score(best_knn, X_train_fselect, y_train_resampled, cv=3, scoring='accuracy')
print("Cross-validation scores:", cv_scores)
print("Mean CV score:", np.mean(cv_scores))
```

```
Cross-validation scores: [0.78922105 0.78800606 0.78615786]
Mean CV score: 0.7877949918143488
```

79% mean CV score is similar to the Decision Tree classifier which we used as the baseline without any parameter optimization. The actual performance of the model can only be judged by the predictions that are made based on the test features. Lets predict the vavlues and analyze the performance of the model through the scores and the classification report.

In [ ]:
```
#predict the values
y_pred = best_knn.predict(X_test_fselect)
```

In [591]:
```
# # Make predictions on test set with best parameters
# best_knn = grid_search.best_estimator_
# y_pred = best_knn.predict(X_test_fselect)
```

In [594]:

```
# Calculate the accuracy score
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

precision = precision_score(y_test, y_pred,average='weighted')
recall = recall_score(y_test, y_pred,average='weighted')

print("Precision:", precision)
print("Recall:", recall)
```

```
Accuracy: 0.7344989439098804
Precision: 0.7437342525091911
Recall: 0.7344989439098804
```

In [592]:

```
# Calculate the confusion matrix and classification report
cm = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)
# print("Confusion matrix:\n", conf_mat)
print("Classification report:\n", class_report)
```

```
Classification report:
               precision    recall  f1-score   support

           0       0.81      0.72      0.76     24956
           1       0.66      0.75      0.70     17654

    accuracy                           0.73     42610
   macro avg       0.73      0.74      0.73     42610
weighted avg       0.74      0.73      0.74     42610
```

Althoug hthe mean CV scres were similiar to the baseline model, the improved accuracy score by almost 3.5% shows that the tuning the hyperparameters and optimizing improved the performace. Something to keep in mind though is that the KNN model with the parameter optimization took almost 10x the time it took the Decision Tree model. The increased computing resources invested into this model resulted in 3.5% higher accuracy.

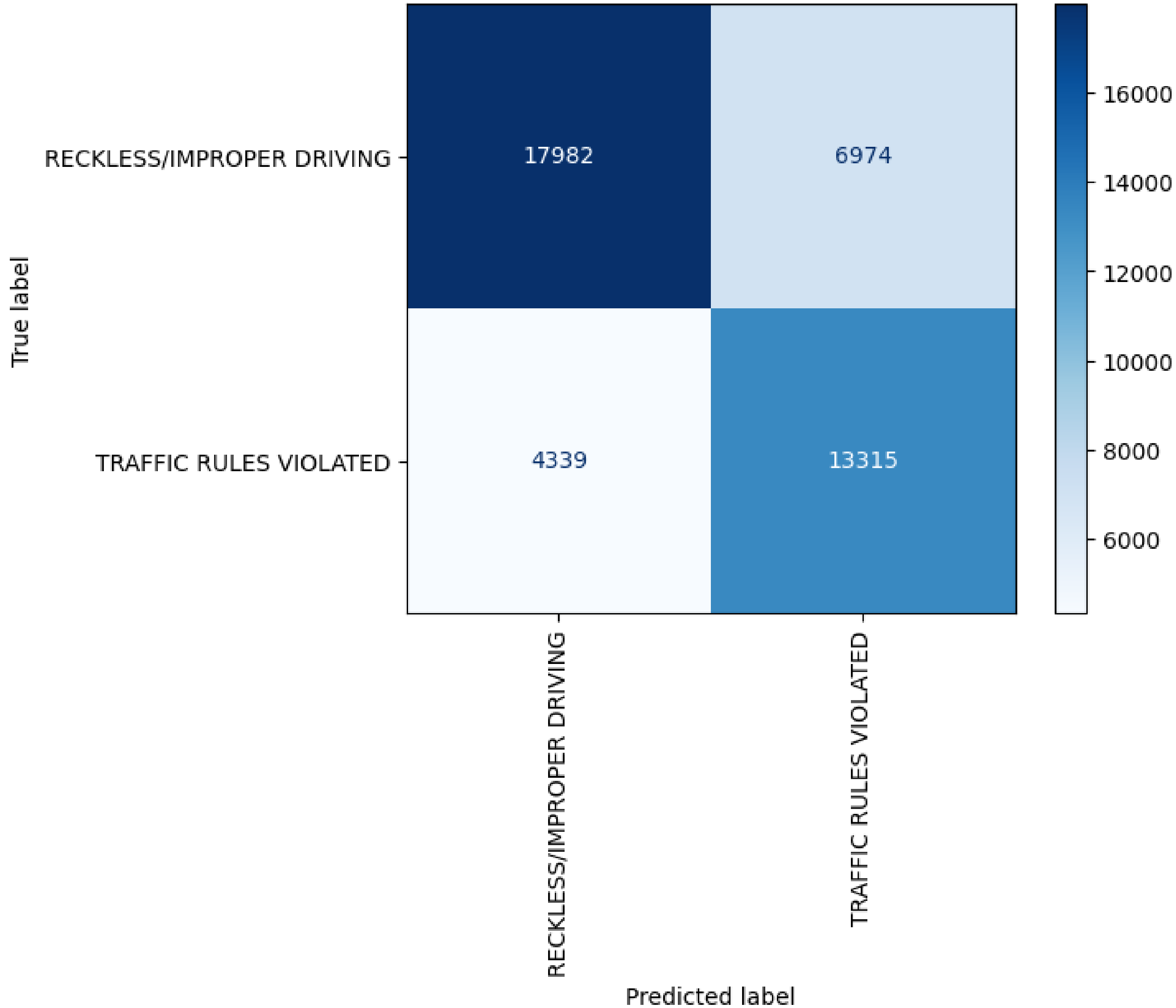
Nonetheless, we can see almost 5% improvement on the precision of Category 0 (Reckless/Improper Driving). This is an indication that there was an underlying discernable information that this model was able to identify better than the baseline model but this only translated to 1% improvement in the recall score for Reckless/Improper Driving.

Similarly, KNN is performing significantly better for Category 1 (Traffic Rules Violated). The precision and accuracy have both improved by 3% and 7% respectively. The biggest gain has been for Categry 1 considering there is a 7% improvement in accurately predicting Car Crashes caused by Traffic Rules Violation

In [593]:
```
# {'RECKLESS/IMPROPER DRIVING': 0, 'TRAFFIC RULES VIOLATED': 1, 'COMPROMISED DRIVING': 2, 'OBSTRUCTIONS': 3}
# define the label names
label_names = ['RECKLESS/IMPROPER DRIVING',
          'TRAFFIC RULES VIOLATED']
          # 'COMPROMISED DRIVING',
          # 'OBSTRUCTIONS']

# define the axis labels
x_labels = label_names
y_labels = label_names

#plot confusion matrix
# ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names, cmap=plt.cm.Blues)
disp_knn = ConfusionMatrixDisplay.from_predictions(y_test,
                                                  y_pred,
                                                  display_labels=label_names,
                                                  cmap=plt.cm.Blues,
                                                  xticks_rotation='vertical')
```



We can see vvissually thrugh the confusion matrix that there have been improvements.

In [595]:
```
# result in model data structure

models['Model Name'].append('KNN MODEL')
models['Accuracy'].append(accuracy)
models['CV Score'].append(np.mean(cv_scores))
models['Precision'].append(precision)
models['Recall'].append(recall)
```

Random Forests Model

We are going to try a Random Forest Modele now t osee if we cana get better results. Random forests aare generally better equipped to handle imbalanced datasets wiithout the need to undersample or creaate synthetic datapoints. Random forests model are also better ata handling larger datasets which can help with the amount of data that we have.

We can set te class_weight parameter to balanced for the random forest to deal with the imabalanced dataset withouot loosing any original data to random sampling.

We can also tune several different hyperparameters and use randomized search to see which ones would be the best to use.

```
1. n_estimators: Since we have such a large dataset, we will teest between 100-2000 to see what would be our optimi
zied option

2. max_depth: We will test out different options to see how many branches the trees should make

3. min_samples_split: We will check what is the minimum amount of splits that thee model needs to perform

4. min_samples leaf: Whta is the minimum number of leafs that it needs to create for optimized performance
```

In [596]:

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
```

In [598]:

```
# Define Random Forest classifier with random state
RFC = RandomForestClassifier(class_weight="balanced", random_state=54)

# Define parameter distribution
param_dist = {'n_estimators': [50,100, 200],
#               'max_samples_split': [2, 5, 10], 'max_samples_leaf': [1, 2, 4],
              # 'max_depth': [None, 10, 20, 40],
              'max_features': ['sqrt', 'log2'],
              'min_samples_split': [1, 2, 5],
              'min_samples_leaf': [1, 2, 4]}

# Perform random search with cross validation
random_search = RandomizedSearchCV(RFC, param_distributions=param_dist, cv=3, n_iter=50, random_state=42)
random_search.fit(X_train_fselect, y_train_resampled)

# Print best parameters and best score
print("Best parameters: ", random_search.best_params_)
print("Best score: ", random_search.best_score_)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py:378: FitFailedWarning:
48 fits failed out of a total of 150.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
48 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py", line 686, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_forest.py", line 340, in fit
    self._validate_params()
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 600, in _validate_params
    validate_parameter_constraints(
  File "/usr/local/lib/python3.10/dist-packages/sklearn/utils/_param_validation.py", line 97, in validate_parameter_const
raints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'min_samples_split' parameter of RandomForestClassifier must b
e an int in the range [2, inf) or a float in the range (0.0, 1.0]. Got 1 instead.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_search.py:952: UserWarning: One or more of the test scor
es are non-finite: [       nan 0.802925   0.80156499 0.81022    0.81218    0.81461
 0.81218    0.802925   0.811735   0.81461    0.8119     0.81567
 0.80331    0.8124     0.81451    0.81377           nan 0.80156499
        nan 0.8124     0.80331    0.809525          nan 0.81154
 0.811735          nan 0.802925          nan        nan        nan
        nan 0.81377    0.8119            nan        nan        nan
 0.80156499        nan 0.81286    0.81022    0.81567    0.80331
 0.81154           nan 0.802925          nan 0.80331           nan
 0.81451    0.809525  ]
  warnings.warn(

Best parameters:  {'n_estimators': 200, 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_features': 'sqrt'}
Best score:  0.8156700008657878
```

In [599]:

```python
#choosee the best model using the optimized parameters
best_rf = random_search.best_estimator_
```

In [600]:

```python
# Evaluate the model with cross-validation
cv_scores = cross_val_score(best_rf, X_train_fselect, y_train_resampled, cv=5)
print("Cross-validation scores:", cv_scores)
print("Mean CV score:", np.mean(cv_scores))
```

```
Cross-validation scores: [0.822825 0.8235   0.8209   0.824125 0.82425 ]
Mean CV score: 0.82312
```

The mean CV score jumped significantly for this model as compared to KNN. KNN had a CV of 79% while the Random Forests mdel has a CV of 82%. This is a good and a bad sign. This showcases that either the model will perform significantly bettwe than Decisioon Trees or it has overfitted significantly more to the training data. Significantly higher over-fitting without better performance is a sign that we need to improve random sampling of our dataset and increase granularity. Nonetheless, we will have to see how well our model performs in pediting the values.

In [ ]:

```
#predict values
y_pred = best_rf.predict(X_test_fselect)
```

In [603]:

```
# Calculate the accuracy score
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

precision = precision_score(y_test, y_pred,average='weighted')
recall = recall_score(y_test, y_pred,average='weighted')

print("Precision:", precision)
print("Recall:", recall)
```

```
Accuracy: 0.7563013377141516
Precision: 0.7639453164083382
Recall: 0.7563013377141516
```

In [601]:

```
# Calculate the confusion matrix and classification report
cm = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)
# print("Confusion matrix:\n", conf_mat)
print("Classification report:\n", class_report)
```

```
Classification report:
               precision    recall  f1-score   support

           0       0.82      0.75      0.78     24956
           1       0.68      0.77      0.72     17654

    accuracy                           0.76     42610
   macro avg       0.75      0.76      0.75     42610
weighted avg       0.76      0.76      0.76     42610
```

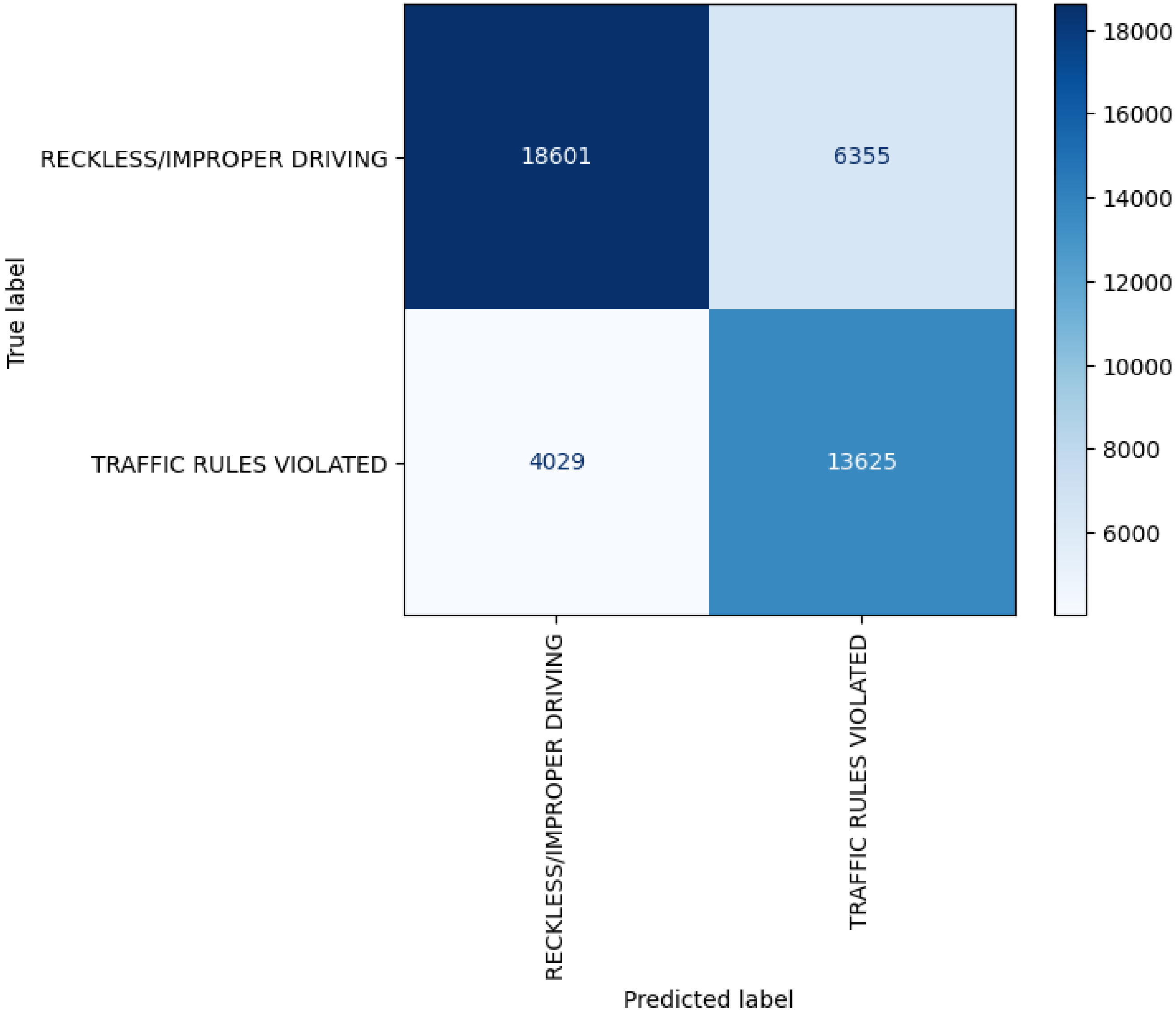
As the CV score increased by 3%, the accuracy of the model alsso increased by 3%. Which is a good sign that the model is not overfitting and impacting the results significantly more than the KNN model. Precision and recall went up for Category 0 (Recklesss/Improper Driving) by 1% and 3%. The precision and accuracy of Category 1 (Traffic Rules Violated) also increased 2% each. Nonetheless, we can ssee that the model has been sslightly underperforming for Category 1 as compared to Category 0. Lets take a moment to visualize thesse results and try out the XG boost model before comparing all of our models together to select the final model.

In [602]:

```
# {'RECKLESS/IMPROPER DRIVING': 0, 'TRAFFIC RULES VIOLATED': 1, 'COMPROMISED DRIVING': 2, 'OBSTRUCTIONS': 3}
# define the label names
label_names = ['RECKLESS/IMPROPER DRIVING',
          'TRAFFIC RULES VIOLATED']
          # 'COMPROMISED DRIVING',
          # 'OBSTRUCTIONS']

# define the axis labels
x_labels = label_names
y_labels = label_names

#plot confusion matrix
# ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names, cmap=plt.cm.Blues)
disp_rf = ConfusionMatrixDisplay.from_predictions(y_test,
                                                  y_pred,
                                                  display_labels=label_names,
                                                  cmap=plt.cm.Blues,
                                                  xticks_rotation='vertical')
```



Talk about model performance

In [604]:

```
# result in model data structure

models['Model Name'].append('Random Forest Classifier')
models['Accuracy'].append(accuracy)
models['CV Score'].append(np.mean(cv_scores))
models['Precision'].append(precision)
models['Recall'].append(recall)
```

XG Boost Model

We would want to try another model to see if we can improve performance. We will try XGBoost nex which is one of the most popular ensemble method. XGBoost (Extreme Gradient Boosting) and Random Forest are both ensemble learning algorithms used in machine learning for classification and regression tasks. There are a few pros of using XGBoost as compared to Random Forests.

```
1. Handling of non-linear data: XGBoost can handle non-linear relationships between the features and the target var
iable better than Random Forest. This is because XGBoost uses a gradient boosting approach that builds a sequence o
f weak models to improve the overall prediction accuracy. Each model tries to capture the remaining error of the pr
evious models, allowing the model to learn complex non-linear patterns in the data.

2. Regularization: XGBoost uses regularization techniques such as L1, L2 regularization and dropout to prevent over
fitting and improve the model's generalization ability. Random Forest, on the other hand, relies on bootstrapping a
nd feature bagging to reduce overfitting.

3. Speed: XGBoost is often faster than Random Forest due to its implementation using parallel processing techniques
and the use of efficient data structures such as Compressed Sparse Column (CSC) matrix.

4. Handling missing values: XGBoost can handle missing values in the data, whereas Random Forest cannot. XGBoost ca
n learn how to use information from other variables to fill in missing data points, which can help improve the mode
l's accuracy.
```

We will also use gridsearch for hyperparameter tuning for 3 parameters.

```
1.n_estimators: Since oour dataset is significantly larger, we will use three different iterations, 500,1000,2500.

2. learning rate: The learning rate, also known as the step size, controls the magnitude of the updates made to the
model parameters at each step during the training process. The learning rate determines the extent to which the alg
orithm should rely on new information compared to the previous information while updating the model parameters.

3. max_depth: We will try out 6, 9 and 11
```

In [605]:
```
from xgboost import XGBClassifier

# Defing XG Boosting Classifier along with random state
XG = XGBClassifier(random_state=54 , reg_alpha=0.1)

# Define parameter grid
param_grid = {'n_estimators': [50,100,500],
              'learning_rate': [0.3, 0.5, 1],
              'max_depth': [3, 9, 11]}

# Perform grid search
grid_search = GridSearchCV(XG, param_grid, cv=3, scoring='accuracy')
grid_search.fit(X_train_fselect, y_train_resampled)

# Print best parameters and best score
print("Best parameters: ", grid_search.best_params_)
print("Best score: ", grid_search.best_score_)
```

```
Best parameters:  {'learning_rate': 0.5, 'max_depth': 11, 'n_estimators': 500}
Best score:  0.87819500406893
```

In [606]:
```
# Set up the model with the optimized parameters
best_xgb = grid_search.best_estimator_
```

In [607]:
```
# Evaluate the model with cross-validation
cv_scores = cross_val_score(best_xgb, X_train_fselect, y_train_resampled, cv=3)
print("Cross-validation scores:", cv_scores)
print("Mean CV score:", np.mean(cv_scores))
```

```
Cross-validation scores: [0.87770561 0.87787061 0.87900879]
Mean CV score: 0.87819500406893
```

Continuing with the trend of higher CV scores, the XGBoost model also has increased the CV by almost 5% which is aa significant jump from Random Forests. Whether this is a result of over-fitting or model improvement is sommething we have to fiigure out through scoring on test data predictions.

In [ ]:
```
# Make predictions on test set with best parameters
y_pred = best_xgb.predict(X_test_fselect)
```

In [610]:
```
# Calculate the accuracy score
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

precision = precision_score(y_test, y_pred,average='weighted')
recall = recall_score(y_test, y_pred,average='weighted')

print("Precision:", precision)
print("Recall:", recall)
```

```
Accuracy: 0.7355080966909177
Precision: 0.7384996074522764
Recall: 0.7355080966909177
```

In [608]:
```
# Calculate the confusion matrix and classification report
cm = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)
# print("Confusion matrix:\n", conf_mat)
print("Classification report:\n", class_report)
```

```
Classification report:
               precision    recall  f1-score   support

           0       0.79      0.75      0.77     24956
           1       0.67      0.71      0.69     17654

    accuracy                           0.74     42610
   macro avg       0.73      0.73      0.73     42610
weighted avg       0.74      0.74      0.74     42610
```

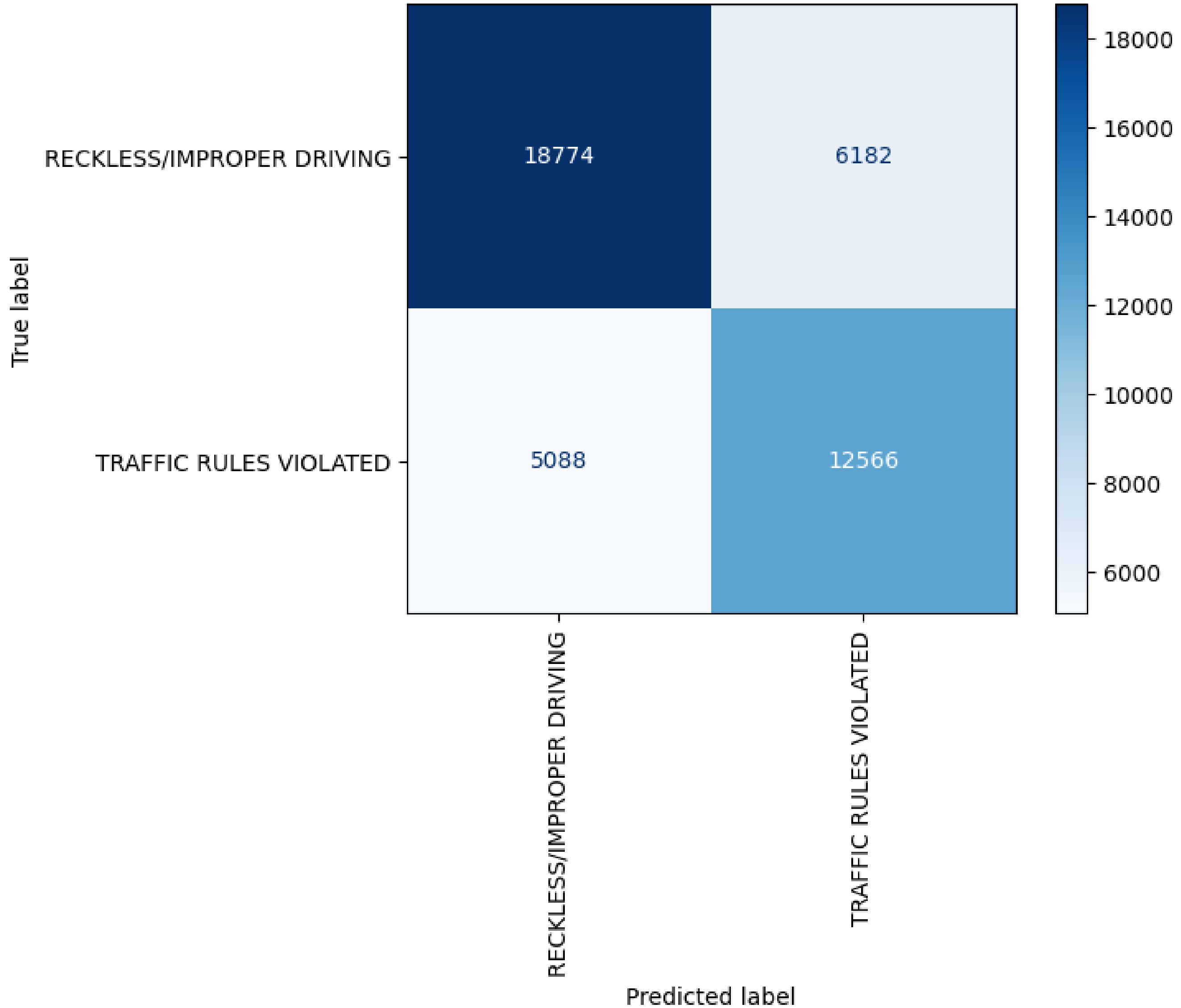
We can see that the model has started to overfit on the training data. Although the CV score was signifcantly higher, the performance on the test scores is worse. Overall, the accuracy has decreased by 2% which has mainly been because of reduced performance for Category 1 (Traffc rules violated). The precision for both categories has also reduced by 3% and 1% respectively.

In [609]:

```
# {'RECKLESS/IMPROPER DRIVING': 0, 'TRAFFIC RULES VIOLATED': 1, 'COMPROMISED DRIVING': 2, 'OBSTRUCTIONS': 3}
# define the label names
label_names = ['RECKLESS/IMPROPER DRIVING',
          'TRAFFIC RULES VIOLATED']
          # 'COMPROMISED DRIVING',
          # 'OBSTRUCTIONS']

# define the axis labels
x_labels = label_names
y_labels = label_names

#plot confusion matrix
# ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names, cmap=plt.cm.Blues)
disp_xg = ConfusionMatrixDisplay.from_predictions(y_test,
                                                  y_pred,
                                                  display_labels=label_names,
                                                  cmap=plt.cm.Blues,
                                                  xticks_rotation='vertical')
```



In [611]:

```
# result in model data structure

models['Model Name'].append('XG Booster Classifier')
models['Accuracy'].append(accuracy)
models['CV Score'].append(np.mean(cv_scores))
models['Precision'].append(precision)
models['Recall'].append(recall)
```

Models Comparison

Lets move onto comparing all of our 4 classifiers. We will sstart by comparing them based on out main KPI, the accuracy of the model.

In [612]:
```
# Creating Dataframe of Model Evaluation
models = pd.DataFrame(models)

# top model based on Accurary
models.sort_values(by='Accuracy', ascending= False)
```

Out[612]:

	Model Name	Accuracy	CV Score	Precision	Recall
2	Random Forest Classifier	0.756301	0.823120	0.763945	0.756301
3	XG Booster Classifier	0.735508	0.878195	0.738500	0.735508
1	KNN MODEL	0.734499	0.787795	0.743734	0.734499
0	Decision Tree Classifier	0.699484	0.780795	0.704300	0.699484

Random Forests is the clear winner for accuracy have very similar scores for accuracy which showcases that cconsidering the lower computing redources required for the KNN model, it is more economical to use KNN rather than XGBoost. Decision Tree, the baseline model, had the worst accuracy performance which was expected because no hyper paaraameter tuning wasn't used to optimize the baseline model.

In [613]:
```
# top model based on CV Score
models.sort_values(by='CV Score', ascending= False)
```

Out[613]:

	Model Name	Accuracy	CV Score	Precision	Recall
3	XG Booster Classifier	0.735508	0.878195	0.738500	0.735508
2	Random Forest Classifier	0.756301	0.823120	0.763945	0.756301
1	KNN MODEL	0.734499	0.787795	0.743734	0.734499
0	Decision Tree Classifier	0.699484	0.780795	0.704300	0.699484

Based on the CV score, we can see that the XGBoost Classifier has the highesst CVV score with the 2nd highest accuracy score. It shows that while the other 3 models might be over-fitting to the training data, XGboost over-fitted enough to impact it's performance significantly as compared to Random Forests which saw an increase in overfiting and an increase in performance on test data, unlike XGBoost.

In [614]:
```
# top model based on Recall Score
models.sort_values(by='Recall', ascending= False)
```

Out[614]:

	Model Name	Accuracy	CV Score	Precision	Recall
2	Random Forest Classifier	0.756301	0.823120	0.763945	0.756301
3	XG Booster Classifier	0.735508	0.878195	0.738500	0.735508
1	KNN MODEL	0.734499	0.787795	0.743734	0.734499
0	Decision Tree Classifier	0.699484	0.780795	0.704300	0.699484

Final Model Evlauation

We have looked at a few different performance metric but as wee talked about earalier, our main focus will be accuracy so that we know how confident can DOT be in the predictions of the model to use in analysis for traffic engineering improvements.

In [615]:
```
models.sort_values(by='Accuracy', ascending= False).head(1)
```

Out[615]:

	Model Name	Accuracy	CV Score	Precision	Recall
2	Random Forest Classifier	0.756301	0.82312	0.763945	0.756301

The obvious choice based on Accuray is the Random Forest classifier. Accuracy and Precission follow closely together to each other and accuracy is the highest amongst all other models.

There is definitely room for further improvement with a few more hyparameters being tuned and revisiting some of the ones that have been optimized. For instance the maximum range provided to the n_estimators for hyperparameter tuning was 200 which was selected as the value for the best parameter. Perhaps, with a higher range, the model might pick a value greater than 200 and reduce overfitting, consequently improving the model performance. Similarly, minimum samples split had the maximum range capped at 5 and the model chose the maximum value as the best value for the parameter. Similar tweaking could be made to investigate improving model performance using this parameter.

Similar iterations could be applied to the other models to invvestigate how their performances will increase. There were multiple iteraations applied which can be seen in the notebook iterataions folder. For the purposes of this notebook, time constraints and computational ressources, the parameter grid selected was chosen to be used for modelling.

We will use the Random Forest Model to predict the dataset where the car crashes cause was Unable to Determine. This will showcase the application of this model.

In [616]:
```
unable_to_determine_preds = best_rf.predict(Xu_fselect)
```

In [618]:

```
# use the unique() function to find the unique values and their counts
unique_values, counts = np.unique(unable_to_determine_preds, return_counts=True)

# print the unique values and their counts
for value, count in zip(unique_values, counts):
    print(value, ":", count)
```

```
0 : 32458
1 : 38159
```

The highest number of records for primary contributaaaary cause was Unable to Determine with almost 260,000 records out of a totaal of 690,000 which is a ~38% of the records. Being able to predict the causes of these crashes with 76% will be able to help the CDOT to significantly improve work towards Vision Zero and reduce the uncertainty in one of their singular biggest car crash cause.

Also, looking at the features that showcased to play the largest imapct were the ones listed below. CDOT understands that their are always multiple factorss at play fora cause and it iss difficult to boil down and identify a singular cause. While there might be a singular cause that is very apparent, there can be certain trens, underlying patterns or other causes that can help the stakeholders derive insights into how to tackle certain causes of crashes and mitigate injuries/fatalities. This will grealy help CDOt mode further in its goal towards Vision Zero

In [619]:

```
features_used
```

Out[619]:

```
Index(['DEVICE_CONDITION', 'WEATHER_CONDITION', 'INTERSECTION_RELATED_I',
       'NUM_UNITS', 'LATITUDE', 'LONGITUDE', 'MANEUVER', 'FIRST_CONTACT_POINT',
       'OCCUPANT_CAT', 'DRIVER_ACTION'],
      dtype='object')
```

These features show that thesse areas would be valuable for the DOT to explore further towards their goal of Vision Zero. These features have provided the most information on the taarget variables indicating that they are significant factors to evaluate for strategic conversatiions.

Recommendations

Talk about whether the model is performing well or not

Improvements

```
1. The model can be improved with higher granular datasets but will require higher computng resources. This will al
low the models to haave better predictions aand provide more detailed insights.
```

2. Random Sampling can be performed using centroidal methods. This will allow for a more uniform of distribution. Currently, the RAndom Sampling methods don't taake into account that there are multiple records for the same crash ID. Using Centroidal methods will allow for improved accuracy with sampling so that all records for the same crash have representation in the training sets.

3. Use pipelines for faster performance. This will bring down the computng speeds because a lot of similar processes can be performed a the same time.

4. A few parameter searches reached maximum, try it more iterations with higher values. We saw that some of the grid searched we did outputted the best parameters as the maximum value of the range of that paaraameter fed into the search. It would be beneficial to do several more multiple iterations to improve the overall parameter grid.

5. Reduce the amount of bins used. Keep binning to the target variable only. This will allow for the predictor variables to be more discernable. This can allow the model to improve predictions when higher granular data is used for the Target Variable

6. Use all the features rather than using only the op 10 features. This might help improve accuracy by providing more information for the models to disern the categories.

7. Use all the records rather than undersampling to provide more information for the models.

8. Train with more data for the Taaraget Variable categories that had low number of records in the original Chicago DOT dataset

9. Rather than dropping features in the Data Understanding section, use all features to determine which ones provide the most information and then select the top 10 features. It is possible that there aare highly informational columns that were dropped.

Next Steps

It would be helpful to further refine the models to increase the accuracy to be greater thaan 90% to create a model that has a very high level of confidence.

Alongside, CDOT can start investigating the top 10 factors based on their scoring from the feature selection section.

Revisiting the results from the feature selection scores for the Top 10 factors:

1. Latitude: 0.32
2. Longitude: 0.32
3. Driver Action: 0.11
4. Intersection Related Indicator: 0.09
5. First Contact Point: 0.05
6. Device Condition: 0.04
7. Maneuver: 0.04
8. Number of Units: 0.03
9. Occupant Category: 0.01
10. Weather Condition: 0.01

With Latitude and Longitude being the biggest contributors, it is clear that there is a trend in certain locations of the type of aciidents taking place. This can be explored to identify if there aare certain areas that have deisgns or mobility patternss that make it more prone to accidents/crashes and appropriate measures can be taken to mitigate these.

The next is driver action which can showcase if there are certain certain drivver actions are causing an increase of crashes. This is one of the columns where the original granularity of the dataset was maintained. This shows that higher graanularity can be useful for the models. Alongside this, Driver Actions can be analyzed based on correlation with the Causes to understand what kind of actions are causing higher amount of crashes and appropriate measures can be taken to inform drivers about the dangers of certain actions or use traffic engineering principles to make it difficult to take certain actions.

Intersection related is interesting because Intersections have one of the most diverse mobility traffic with mutiple movements taking place at the same time. This feature can be explored further to understand which crashes are highly correlated with the presence of intersections and take appropriatae steps to mitigaate those risks.

Similarly, the remaining factors can be explored to further analyze the kind of correlations that these feature have to causes and create policy and mitigation measures to move CDOT closer to Vision Zero.