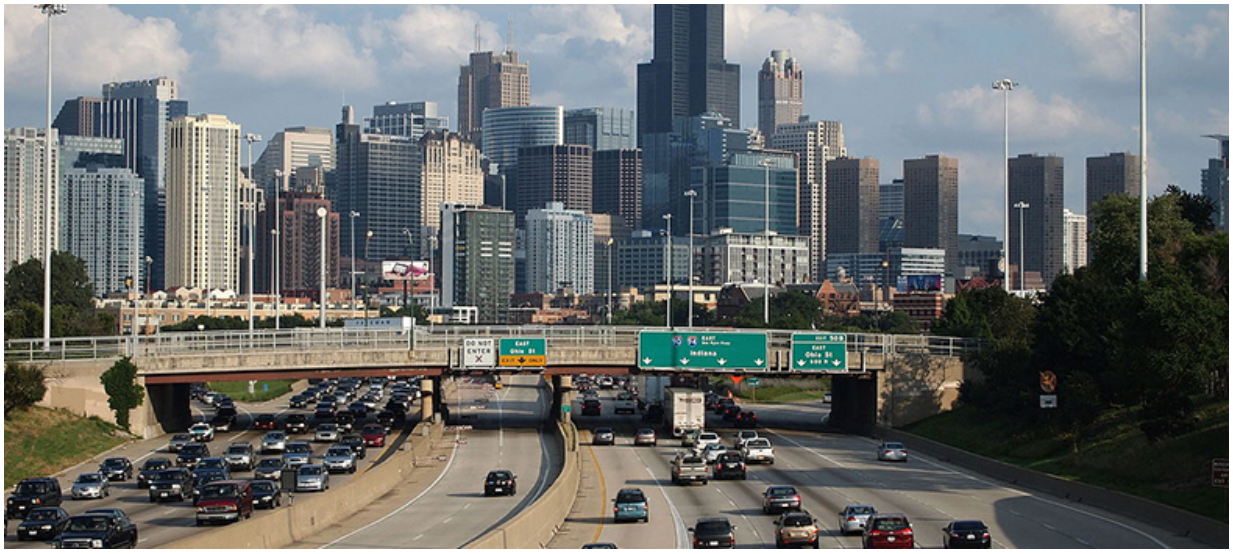


Chicago Car Crashes: Analyzing the Causes of The City's Traffic Accidents

By Sameeha Ramadhan

The goal of this analysis is to examine and determine the main causes of car accidents in Chicago that result in injuries. The data used are the Chicago Car Crash datasets and is processed and filtered to reflect crashes that occured in 2021 alone.

In this project, I will be using the data from the city of Chicago to build a classification model that can help predict why car accidents occur, as well as identify a number of trends from the incidents. Doing so will aid in allowing the city to take the correct measures to help prevent accidents and their resulting injuries from occurring.

I will be using the **OSEMin/OSEMN** process in this project.

Obtain

Importing the Packages

In [ ]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, BaggingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, r2_score, recall_score, precision
from sklearn.metrics import classification_report, confusion_matrix, plot_con
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder, RobustScaler

from sklearn.tree import DecisionTreeClassifier
from sklearn import tree

from sklearn.compose import ColumnTransformer

from sklearn.metrics import f1_score
from sklearn.metrics import make_scorer
f1_scorer = make_scorer(f1_score, pos_label="1")

#!pip install shap
import shap
shap.initjs()

#!pip install dataframe_image
import dataframe_image as dfi

import folium

import warnings
warnings.filterwarnings('ignore')
```

Loading the Data

In [2]:

```
#Loading the data
pd.set_option('display.max_columns', None)
crashes = pd.read_csv('data/Traffic_Crashes_-_Crashes.csv')
vehicles = pd.read_csv('data/Traffic_Crashes_-_Vehicles.csv')
passengers = pd.read_csv('data/Traffic_Crashes_-_People.csv')
```

Crashes

In [3]:
```
crashes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 498336 entries, 0 to 498335
Data columns (total 49 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   CRASH_RECORD_ID                 498336 non-null  object
 1   RD_NO                           494403 non-null  object
 2   CRASH_DATE_EST_I                37501 non-null   object
 3   CRASH_DATE                      498336 non-null  object
 4   POSTED_SPEED_LIMIT              498336 non-null  int64
 5   TRAFFIC_CONTROL_DEVICE          498336 non-null  object
 6   DEVICE_CONDITION                498336 non-null  object
 7   WEATHER_CONDITION               498336 non-null  object
 8   LIGHTING_CONDITION              498336 non-null  object
 9   FIRST_CRASH_TYPE                498336 non-null  object
 10  TRAFFICWAY_TYPE                 498336 non-null  object
 11  LANE_CNT                        198966 non-null  float64
 12  ALIGNMENT                       498336 non-null  object
 13  ROADWAY_SURFACE_COND            498336 non-null  object
 14  ROAD_DEFECT                     498336 non-null  object
 15  REPORT_TYPE                     486124 non-null  object
 16  CRASH_TYPE                      498336 non-null  object
 17  INTERSECTION_RELATED_I          112512 non-null  object
 18  NOT_RIGHT_OF_WAY_I              23523 non-null   object
 19  HIT_AND_RUN_I                   147648 non-null  object
 20  DAMAGE                          498336 non-null  object
 21  DATE_POLICE_NOTIFIED            498336 non-null  object
 22  PRIM_CONTRIBUTORY_CAUSE         498336 non-null  object
 23  SEC_CONTRIBUTORY_CAUSE          498336 non-null  object
 24  STREET_NO                       498336 non-null  int64
 25  STREET_DIRECTION                498333 non-null  object
 26  STREET_NAME                     498335 non-null  object
 27  BEAT_OF_OCCURRENCE              498331 non-null  float64
 28  PHOTOS_TAKEN_I                  6247 non-null    object
 29  STATEMENTS_TAKEN_I              10083 non-null   object
 30  DOORING_I                       1580 non-null    object
 31  WORK_ZONE_I                     3189 non-null    object
 32  WORK_ZONE_TYPE                  2516 non-null    object
 33  WORKERS_PRESENT_I               771 non-null     object
 34  NUM_UNITS                       498336 non-null  int64
 35  MOST_SEVERE_INJURY              497314 non-null  object
 36  INJURIES_TOTAL                  497325 non-null  float64
 37  INJURIES_FATAL                  497325 non-null  float64
 38  INJURIES_INCAPACITATING         497325 non-null  float64
 39  INJURIES_NON_INCAPACITATING     497325 non-null  float64
 40  INJURIES_REPORTED_NOT_EVIDENT   497325 non-null  float64
 41  INJURIES_NO_INDICATION          497325 non-null  float64
 42  INJURIES_UNKNOWN                497325 non-null  float64
 43  CRASH_HOUR                      498336 non-null  int64
 44  CRASH_DAY_OF_WEEK               498336 non-null  int64
 45  CRASH_MONTH                     498336 non-null  int64
 46  LATITUDE                        495550 non-null  float64
 47  LONGITUDE                       495550 non-null  float64
 48  LOCATION                        495550 non-null  object
```

```
dtypes: float64(11), int64(6), object(32)
memory usage: 186.3+ MB
```

In [4]:
```
len(crashes)
```

Out[4]:
```
498336
```

In [5]:
```
#Filtering for the current year of 2021
crashes['CRASH_DATE'] = crashes['CRASH_DATE'].astype(str)

crashes = crashes[crashes['CRASH_DATE'].str.contains("2021")]

len(crashes)
```

Out[5]:
```
31625
```

Vehicles

In [6]:
```
vehicles.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1017922 entries, 0 to 1017921
Data columns (total 72 columns):
 #   Column                    Non-Null Count    Dtype  
---  ------                    --------------    -----  
 0   CRASH_UNIT_ID             1017922 non-null  int64  
 1   CRASH_RECORD_ID           1017922 non-null  object 
 2   RD_NO                     1009777 non-null  object 
 3   CRASH_DATE                1017922 non-null  object 
 4   UNIT_NO                   1017922 non-null  int64  
 5   UNIT_TYPE                 1016407 non-null  object 
 6   NUM_PASSENGERS            152271 non-null   float64
 7   VEHICLE_ID                994586 non-null   float64
 8   CMRC_VEH_I                18975 non-null    object 
 9   MAKE                      994581 non-null   object 
 10  MODEL                     994438 non-null   object 
 11  LIC_PLATE_STATE           909371 non-null   object 
 12  VEHICLE_YEAR              833120 non-null   float64
 13  VEHICLE_DEFECT            994586 non-null   object 
 14  VEHICLE_TYPE              994586 non-null   object 
 15  VEHICLE_USE               994586 non-null   object 
 16  TRAVEL_DIRECTION          994586 non-null   object 
 17  MANEUVER                  994586 non-null   object 
 18  TOWED_I                   115963 non-null   object 
 19  FIRE_I                    743 non-null      object 
 20  OCCUPANT_CNT              994586 non-null   float64
 21  EXCEED_SPEED_LIMIT_I      2390 non-null     object 
 22  TOWED_BY                  84811 non-null    object 
 23  TOWED_TO                  52961 non-null    object 
 24  AREA_00_I                 39365 non-null    object 
 25  AREA_01_I                 264168 non-null   object 
 26  AREA_02_I                 172979 non-null   object 
 27  AREA_03_I                 96340 non-null    object 
 28  AREA_04_I                 101194 non-null   object 
 29  AREA_05_I                 154181 non-null   object 
 30  AREA_06_I                 153261 non-null   object 
 31  AREA_07_I                 132140 non-null   object 
 32  AREA_08_I                 169626 non-null   object 
 33  AREA_09_I                 43331 non-null    object 
 34  AREA_10_I                 62602 non-null    object 
 35  AREA_11_I                 124791 non-null   object 
 36  AREA_12_I                 122842 non-null   object 
 37  AREA_99_I                 107567 non-null   object 
 38  FIRST_CONTACT_POINT       987736 non-null   object 
 39  CMV_ID                    10794 non-null    float64
 40  USDOT_NO                  6293 non-null     object 
 41  CCMC_NO                   1398 non-null     object 
 42  ILCC_NO                   1018 non-null     object 
 43  COMMERCIAL_SRC            7686 non-null     object 
 44  GVWR                      6264 non-null     object 
 45  CARRIER_NAME              10348 non-null    object 
 46  CARRIER_STATE             9783 non-null     object 
 47  CARRIER_CITY              9609 non-null     object 
 48  HAZMAT_PLACARDS_I         220 non-null      object 
```

```
 49  HAZMAT_NAME               40 non-null      object
 50  UN_NO                     396 non-null     object
 51  HAZMAT_PRESENT_I          7975 non-null    object
 52  HAZMAT_REPORT_I           7726 non-null    object
 53  HAZMAT_REPORT_NO          1 non-null       object
 54  MCS_REPORT_I              7778 non-null    object
 55  MCS_REPORT_NO             5 non-null       object
 56  HAZMAT_VIO_CAUSE_CRASH_I  7853 non-null    object
 57  MCS_VIO_CAUSE_CRASH_I     7718 non-null    object
 58  IDOT_PERMIT_NO            641 non-null     object
 59  WIDE_LOAD_I               91 non-null      object
 60  TRAILER1_WIDTH            2200 non-null    object
 61  TRAILER2_WIDTH            247 non-null     object
 62  TRAILER1_LENGTH           1802 non-null    float64
 63  TRAILER2_LENGTH           47 non-null      float64
 64  TOTAL_VEHICLE_LENGTH      2165 non-null    float64
 65  AXLE_CNT                  3131 non-null    float64
 66  VEHICLE_CONFIG            8992 non-null    object
 67  CARGO_BODY_TYPE           8604 non-null    object
 68  LOAD_TYPE                 8239 non-null    object
 69  HAZMAT_OUT_OF_SERVICE_I   7508 non-null    object
 70  MCS_OUT_OF_SERVICE_I      7708 non-null    object
 71  HAZMAT_CLASS              739 non-null     object
dtypes: float64(9), int64(2), object(61)
memory usage: 559.2+ MB
```

In [7]:
```
len(vehicles)
```

Out[7]: 1017922

In [8]:
```
vehicles['CRASH_DATE'] = vehicles['CRASH_DATE'].astype(str)

vehicles = vehicles[vehicles['CRASH_DATE'].str.contains("2021")]

len(vehicles)
```

Out[8]: 65354

Passengers

In [9]:
```
len(passengers)
```

Out[9]: 1100733

In [10]:
```
passengers['CRASH_DATE'] = passengers['CRASH_DATE'].astype(str)

passengers = passengers[passengers['CRASH_DATE'].str.contains("2021")]

len(passengers)
```

Out[10]: 66772

In [11]:
```
passengers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 66772 entries, 1026587 to 1100732
Data columns (total 30 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   PERSON_ID              66772 non-null  object
 1   PERSON_TYPE            66772 non-null  object
 2   CRASH_RECORD_ID        66772 non-null  object
 3   RD_NO                  58342 non-null  object
 4   VEHICLE_ID             65782 non-null  float64
 5   CRASH_DATE             66772 non-null  object
 6   SEAT_NO                12618 non-null  float64
 7   CITY                   46888 non-null  object
 8   STATE                  47519 non-null  object
 9   ZIPCODE                42455 non-null  object
 10  SEX                    65760 non-null  object
 11  AGE                    45901 non-null  float64
 12  DRIVERS_LICENSE_STATE  38447 non-null  object
 13  DRIVERS_LICENSE_CLASS  31059 non-null  object
 14  SAFETY_EQUIPMENT       66604 non-null  object
 15  AIRBAG_DEPLOYED        65844 non-null  object
 16  EJECTION               66074 non-null  object
 17  INJURY_CLASSIFICATION  66749 non-null  object
 18  HOSPITAL               10571 non-null  object
 19  EMS_AGENCY             6244 non-null   object
 20  EMS_RUN_NO             995 non-null    object
 21  DRIVER_ACTION          54043 non-null  object
 22  DRIVER_VISION          54026 non-null  object
 23  PHYSICAL_CONDITION     54081 non-null  object
 24  PEDPEDAL_ACTION        905 non-null    object
 25  PEDPEDAL_VISIBILITY    905 non-null    object
 26  PEDPEDAL_LOCATION      905 non-null    object
 27  BAC_RESULT             54057 non-null  object
 28  BAC_RESULT VALUE       81 non-null     float64
 29  CELL_PHONE_USE         1 non-null      object
dtypes: float64(4), object(26)
memory usage: 15.8+ MB
```

Merging

In [12]:
```
#Merging and observing
merged = pd.merge(left=crashes, right = vehicles, left_on='CRASH_RECORD_ID',
df = pd.merge(left=merged, right=passengers, left_on = 'VEHICLE_ID', right_on
print(df.shape)
df.head()
```

```
(1147852, 149)
```

Out[12]:

E_CLASS	SAFETY_EQUIPMENT	AIRBAG_DEPLOYED	EJECTION	INJURY_CLASSIFICATION	
D	SAFETY BELT USED	NOT APPLICABLE	NONE	NONINCAPACITATING INJURY	ST.E
NaN	SAFETY BELT USED	NOT APPLICABLE	NONE	NO INDICATION OF INJURY	
D	SAFETY BELT USED	NOT APPLICABLE	NONE	NONINCAPACITATING INJURY	
NaN	SAFETY BELT USED	DEPLOYED, SIDE	NONE	REPORTED, NOT EVIDENT	
C	SAFETY BELT USED	NOT APPLICABLE	NONE	NO INDICATION OF INJURY	

Scrub

In [13]:
```
#I begin by converting the column names to lowercase for ease:
df= df.rename(columns=str.lower)
```

Checking NaN values

In [14]:
```
null_values = df.isna().sum()
null_percentage = null_values[null_values>0] / len(df)
null_percentage.to_frame('% Null')
```

Out[14]:

	% Null
rd_no_x	0.127116
crash_date_est_i	0.930863
lane_cnt	0.999129
report_type	0.102606
intersection_related_i	0.628868
...	...
pedpedal_visibility	0.139198
pedpedal_location	0.139198
bac_result	0.100503
bac_result value	0.999929
cell_phone_use	0.999999

109 rows × 1 columns

In [15]:
```
#Filtering out columns who have more than 95% of null values:
nulls = null_percentage[null_percentage > .95].index.tolist()
nulls
```

Out[15]:
```
['lane_cnt',
 'photos_taken_i',
 'statements_taken_i',
 'dooring_i',
 'work_zone_i',
 'work_zone_type',
 'workers_present_i',
 'num_passengers',
 'cmrc_veh_i',
 'vehicle_year',
 'towed_i',
 'fire_i',
 'exceed_speed_limit_i',
 'towed_by',
 'towed_to',
 'area_00_i',
 'area_01_i',
 'area_02_i',
 'area_03_i',
 'area_04_i',
 'area_05_i',
 'area_06_i',
 'area_07_i',
 'area_08_i',
 'area_09_i',
 'area_10_i',
 'area_11_i',
 'area_12_i',
 'area_99_i',
 'cmv_id',
 'usdot_no',
 'ccmc_no',
 'ilcc_no',
 'commercial_src',
 'gvwr',
 'carrier_name',
 'carrier_state',
 'carrier_city',
 'hazmat_placards_i',
 'hazmat_name',
 'un_no',
 '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',
 'idot_permit_no',
 'wide_load_i',
 'trailer1_width',
 'trailer2_width',
```

```
'trailer1_length',
'trailer2_length',
'total_vehicle_length',
'axle_cnt',
'vehicle_config',
'cargo_body_type',
'load_type',
'hazmat_out_of_service_i',
'mcs_out_of_service_i',
'hazmat_class',
'seat_no',
'ems_run_no',
'bac_result value',
'cell_phone_use']
```

In [16]:

```
#Since the majority of the values in these columns are missing, I will remove

df = df.drop(columns = nulls)
#Then examine:
print(df.shape)
df.info()
```

```
(1147852, 83)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1147852 entries, 0 to 1147851
Data columns (total 83 columns):
 #   Column                          Non-Null Count    Dtype
---  ------                          --------------    -----
 0   crash_record_id_x               1147852 non-null  object
 1   rd_no_x                         1001942 non-null  object
 2   crash_date_est_i                79359 non-null    object
 3   crash_date_x                    1147852 non-null  object
 4   posted_speed_limit              1147852 non-null  int64
 5   traffic_control_device          1147852 non-null  object
 6   device_condition                1147852 non-null  object
 7   weather_condition               1147852 non-null  object
 8   lighting_condition              1147852 non-null  object
 9   first_crash_type                1147852 non-null  object
 10  trafficway_type                 1147852 non-null  object
 11  alignment                       1147852 non-null  object
 12  roadway_surface_cond            1147852 non-null  object
 13  road_defect                     1147852 non-null  object
 14  report_type                     1030075 non-null  object
 15  crash_type                      1147852 non-null  object
 16  intersection_related_i          426005 non-null   object
 17  not_right_of_way_i              61091 non-null    object
 18  hit_and_run_i                   461862 non-null   object
 19  damage                          1147852 non-null  object
 20  date_police_notified            1147852 non-null  object
 21  prim_contributory_cause         1147852 non-null  object
 22  sec_contributory_cause          1147852 non-null  object
 23  street_no                       1147852 non-null  int64
 24  street_direction                1147852 non-null  object
 25  street_name                     1147852 non-null  object
 26  beat_of_occurrence              1147852 non-null  float64
 27  num_units                       1147852 non-null  int64
 28  most_severe_injury              1147852 non-null  object
 29  injuries_total                  1147852 non-null  float64
 30  injuries_fatal                  1147852 non-null  float64
 31  injuries_incapacitating         1147852 non-null  float64
 32  injuries_non_incapacitating     1147852 non-null  float64
 33  injuries_reported_not_evident   1147852 non-null  float64
 34  injuries_no_indication          1147852 non-null  float64
 35  injuries_unknown                1147852 non-null  float64
 36  crash_hour                      1147852 non-null  int64
 37  crash_day_of_week               1147852 non-null  int64
 38  crash_month                     1147852 non-null  int64
 39  latitude                        1137480 non-null  float64
 40  longitude                       1137480 non-null  float64
 41  location                        1137480 non-null  object
 42  crash_unit_id                   1147852 non-null  int64
```

```
 43  rd_no_y                       1001942 non-null  object
 44  crash_date_y                  1147852 non-null  object
 45  unit_no                       1147852 non-null  int64
 46  unit_type                     1061722 non-null  object
 47  vehicle_id                    65782 non-null    float64
 48  make                          65782 non-null    object
 49  model                         65782 non-null    object
 50  lic_plate_state               58680 non-null    object
 51  vehicle_defect                65782 non-null    object
 52  vehicle_type                  65782 non-null    object
 53  vehicle_use                   65782 non-null    object
 54  travel_direction              65782 non-null    object
 55  maneuver                      65782 non-null    object
 56  occupant_cnt                  65782 non-null    float64
 57  first_contact_point           64747 non-null    object
 58  person_id                     1147852 non-null  object
 59  person_type                   1147852 non-null  object
 60  crash_record_id_y             1147852 non-null  object
 61  rd_no                         997462 non-null   object
 62  crash_date                    1147852 non-null  object
 63  city                          998020 non-null   object
 64  state                         989915 non-null   object
 65  zipcode                       769727 non-null   object
 66  sex                           1126092 non-null  object
 67  age                           1000309 non-null  float64
 68  drivers_license_state         74483 non-null    object
 69  drivers_license_class         61635 non-null    object
 70  safety_equipment              983884 non-null   object
 71  airbag_deployed               151020 non-null   object
 72  ejection                      402410 non-null   object
 73  injury_classification         1144553 non-null  object
 74  hospital                      638471 non-null   object
 75  ems_agency                    545692 non-null   object
 76  driver_action                 1016095 non-null  object
 77  driver_vision                 997514 non-null   object
 78  physical_condition            1057629 non-null  object
 79  pedpedal_action               988073 non-null   object
 80  pedpedal_visibility           988073 non-null   object
 81  pedpedal_location             988073 non-null   object
 82  bac_result                    1032489 non-null  object
dtypes: float64(13), int64(8), object(62)
memory usage: 735.6+ MB
```

Removing Irrelevant Columns

After a quick examination, I've determined these columns do not provide valuable information about determining the cause of these car accidents, and have decided to remove them.

In [17]:
```
drop = ['rd_no_x', 'rd_no_y','rd_no','report_type', 'crash_type', 'damage', '
        'sec_contributory_cause','injuries_incapacitating', 'most_severe_inju
        'injuries_reported_not_evident', 'injuries_no_indication', 'injuries_
        'ejection','injury_classification', 'hospital', 'crash_record_id_x',
        'intersection_related_i','num_units','crash_unit_id', 'ems_agency', '
        'pedpedal_location','person_id', "crash_record_id_y", 'street_no', 's
        'zipcode', 'crash_month', 'latitude', 'longitude', 'crash_date_y', 'u
        'not_right_of_way_i', 'vehicle_id', 'model', 'lic_plate_state', 'vehi
        'occupant_cnt', 'first_contact_point']

df = df.drop(columns = drop, axis = 1)
print(df.shape)
df.head()
```

```
(1147852, 33)
```

Out[17]:

	posted_speed_limit	traffic_control_device	device_condition	weather_condition	lighting_cond
0	30	STOP SIGN/FLASHER	FUNCTIONING PROPERLY	CLEAR	DAYL
1	30	STOP SIGN/FLASHER	FUNCTIONING PROPERLY	CLEAR	DAYL
2	30	STOP SIGN/FLASHER	FUNCTIONING PROPERLY	CLEAR	DAYL
3	30	STOP SIGN/FLASHER	FUNCTIONING PROPERLY	CLEAR	DAYL
4	30	STOP SIGN/FLASHER	FUNCTIONING PROPERLY	CLEAR	DARKI

In [18]:
```
df.shape
```

Out[18]: (1147852, 33)

In [19]:
```
#Now that I've cleaned the data a bit, I will first remove any duplicate cras
df.drop_duplicates(subset=['location', 'crash_date'], keep='last', inplace=Tr
```

In [20]:
```
#And drop the Location and Crash Date columns since I've determined they prov
drop2 = ['location', 'crash_date']
df = df.drop(columns = drop2, axis = 1)
df.head()
print(df.shape)
```

```
(920827, 31)
```

Checking the Values of Each Column:

In [21]:

```
for col in df.columns:
    try:
        print(col, df[col].value_counts(dropna=False)[:10]) #<--Display the f
    except:
        print(col, df[col].value_counts())
        #The first print statement will throw an error for an invalid index s
        #values in a column
    print('\n')
```

```
posted_speed_limit 30    687490
25     65134
35     50459
15     48819
20     30732
10     24675
5       4689
40      3046
0       1902
45      1085
Name: posted_speed_limit, dtype: int64


traffic_control_device NO CONTROLS                438694
TRAFFIC SIGNAL              319778
STOP SIGN/FLASHER           103501
UNKNOWN                      37472
PEDESTRIAN CROSSING SIGN      9157
OTHER                         4743
YIELD                         2774
FLASHING CONTROL SIGNAL       1846
OTHER REG. SIGN                955
RAILROAD CROSSING GATE         927
Name: traffic_control_device, dtype: int64


device_condition NO CONTROLS                441669
FUNCTIONING PROPERLY        392087
UNKNOWN                      70177
OTHER                         8467
FUNCTIONING IMPROPERLY        6508
NOT FUNCTIONING               1908
WORN REFLECTIVE MATERIAL         9
MISSING                          2
Name: device_condition, dtype: int64


weather_condition CLEAR                    701568
SNOW                        89915
RAIN                        66082
UNKNOWN                     25325
CLOUDY/OVERCAST             22870
BLOWING SNOW                 4656
OTHER                        3813
FREEZING RAIN/DRIZZLE        3775
FOG/SMOKE/HAZE               1853
SEVERE CROSS WIND GATE        918
```

```
Name: weather_condition, dtype: int64


lighting_condition DAYLIGHT                  572648
DARKNESS, LIGHTED ROAD    252641
DARKNESS                   39893
DUSK                       25521
UNKNOWN                    15916
DAWN                       14208
Name: lighting_condition, dtype: int64


first_crash_type PEDESTRIAN                  503616
PEDALCYCLIST                210219
FIXED OBJECT                 57571
PARKED MOTOR VEHICLE         43457
OTHER OBJECT                 26812
TURNING                      19680
REAR END                     19189
ANGLE                        17099
SIDESWIPE SAME DIRECTION     11351
ANIMAL                        2754
Name: first_crash_type, dtype: int64


trafficway_type NOT DIVIDED                        354504
FOUR WAY                           148750
DIVIDED - W/MEDIAN (NOT RAISED)    130698
ONE-WAY                             97488
PARKING LOT                         45954
DIVIDED - W/MEDIAN BARRIER          39978
ALLEY                               32520
T-INTERSECTION                      20680
OTHER                               19111
DRIVEWAY                             7400
Name: trafficway_type, dtype: int64


roadway_surface_cond DRY                596697
WET                 146297
SNOW OR SLUSH       108205
UNKNOWN              52622
OTHER                 9242
ICE                   7757
SAND, MUD, DIRT          7
Name: roadway_surface_cond, dtype: int64


road_defect NO DEFECTS           733480
UNKNOWN              166714
OTHER                  6578
RUT, HOLES             6535
WORN SURFACE           4706
DEBRIS ON ROADWAY      1850
SHOULDER DEFECT         964
Name: road_defect, dtype: int64
```

```
hit_and_run_i NaN    557745
Y      344354
N       18728
Name: hit_and_run_i, dtype: int64


prim_contributory_cause UNABLE TO DETERMINE
355502
FAILING TO YIELD RIGHT-OF-WAY
202895
NOT APPLICABLE
65528
FAILING TO REDUCE SPEED TO AVOID CRASH
34295
WEATHER
25839
OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRESSIVE M
ANNER     25101
DRIVING SKILLS/KNOWLEDGE/EXPERIENCE
24834
DISREGARDING TRAFFIC SIGNALS
22553
IMPROPER OVERTAKING/PASSING
16906
VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)
16620
Name: prim_contributory_cause, dtype: int64


beat_of_occurrence 1834.0    11176
1934.0    10156
1935.0     9252
1912.0     9216
623.0      8449
          ...
2023.0       36
2431.0       24
1653.0       11
1655.0        6
1652.0        1
Name: beat_of_occurrence, Length: 274, dtype: int64


injuries_total 1.0    616734
0.0    258282
2.0     37281
3.0      6588
4.0      1900
5.0        28
6.0        10
7.0         3
8.0         1
Name: injuries_total, dtype: int64


crash_hour 17    81614
```

```
16    74532
15    69979
18    62177
14    61614
13    59625
19    55357
11    54804
12    50382
20    44178
Name: crash_hour, dtype: int64


crash_day_of_week 7    166776
6    151277
3    142165
5    136668
4    119249
2    109402
1     95290
Name: crash_day_of_week, dtype: int64


unit_type PEDESTRIAN             535911
BICYCLE                 211826
NaN                      65794
DRIVER                   61930
NON-MOTOR VEHICLE        32869
PARKED                    7907
NON-CONTACT VEHICLE       3657
DRIVERLESS                 931
DISABLED VEHICLE             2
Name: unit_type, dtype: int64


make NaN          889318
UNKNOWN         4522
CHEVROLET       3511
FORD            3232
TOYOTA          2969
NISSAN          2384
HONDA           2107
DODGE           1271
HYUNDAI         1268
JEEP            1228
Name: make, dtype: int64


vehicle_defect NaN             889318
NONE              16574
UNKNOWN           14629
OTHER               150
BRAKES               63
TIRES                29
STEERING             22
SUSPENSION           16
WHEELS               14
ENGINE/MOTOR          6
```

```
Name: vehicle_defect, dtype: int64


vehicle_type NaN                             889318
PASSENGER                         18484
UNKNOWN/NA                         4249
SPORT UTILITY VEHICLE (SUV)        3953
VAN/MINI-VAN                       1283
PICKUP                             1043
TRUCK - SINGLE UNIT                 744
OTHER                               584
BUS OVER 15 PASS.                   427
TRACTOR W/ SEMI-TRAILER             349
Name: vehicle_type, dtype: int64


person_type PEDESTRIAN              583784
BICYCLE                  224769
DRIVER                    64330
NON-MOTOR VEHICLE         36977
NON-CONTACT VEHICLE        5843
PASSENGER                  5124
Name: person_type, dtype: int64


state IL     771621
NaN    125741
CA       3928
IN       3252
MI       2991
XX       2115
WI       2028
FL       1987
TX       1012
OH       1010
Name: state, dtype: int64


sex M      554799
F      318910
X       28286
NaN     18832
Name: sex, dtype: int64


age NaN     114622
25.0     21088
32.0     20948
26.0     20086
28.0     20071
         ...
13.0      5882
68.0      5004
75.0      4903
80.0      4892
10.0      4891
Name: age, Length: 66, dtype: int64
```

```
drivers_license_state NaN    875189
IL      40260
XX       2447
IN       1292
MO        995
WI         81
MI         61
FL         53
CA         44
OH         41
Name: drivers_license_state, dtype: int64


drivers_license_class NaN    884612
D       31838
B        1548
DM       1214
A         753
C         457
AM         95
BM         51
CD         39
DL         26
Name: drivers_license_class, dtype: int64


safety_equipment NONE PRESENT                                 398739
HELMET NOT USED                                135284
NaN                                            133307
USAGE UNKNOWN                                  112055
BICYCLE HELMET (PEDACYCLIST INVOLVED ONLY)      91466
SAFETY BELT USED                                35936
SAFETY BELT NOT USED                             7942
WHEELCHAIR                                       1948
BOOSTER SEAT                                      999
STRETCHER                                         974
Name: safety_equipment, dtype: int64


airbag_deployed NaN                                     825101
NOT APPLICABLE                             35713
DID NOT DEPLOY                             30229
DEPLOYMENT UNKNOWN                         22659
DEPLOYED, COMBINATION                       2764
DEPLOYED, SIDE                              2244
DEPLOYED, FRONT                             2102
DEPLOYED OTHER (KNEE, AIR, BELT, ETC.)        15
Name: airbag_deployed, dtype: int64


driver_action NONE                          479203
UNKNOWN                        147648
OTHER                          120342
NaN                             98533
FAILED TO YIELD                 27944
```

```
DISREGARDED CONTROL DEVICES     22460
WRONG WAY/SIDE                   5905
IMPROPER PASSING                 4185
IMPROPER TURN                    4112
IMPROPER LANE CHANGE             4032
Name: driver_action, dtype: int64


driver_vision NOT OBSCURED              402552
UNKNOWN                   333636
NaN                       114101
OTHER                      55666
MOVING VEHICLES             4948
PARKED VEHICLES             4941
WINDSHIELD (WATER/ICE)      2017
TREES, PLANTS                983
BUILDINGS                    978
BLINDED - HEADLIGHTS         974
Name: driver_vision, dtype: int64



physical_condition NORMAL                           591328
UNKNOWN                           186711
NaN                                66424
REMOVED BY EMS                     30255
OTHER                              15634
IMPAIRED - ALCOHOL                 11785
HAD BEEN DRINKING                   8769
EMOTIONAL                           3950
IMPAIRED - DRUGS                    3901
IMPAIRED - ALCOHOL AND DRUGS         984
Name: physical_condition, dtype: int64


bac_result TEST NOT OFFERED                   815041
NaN                                89775
TEST PERFORMED, RESULTS UNKNOWN     7842
TEST REFUSED                        7142
TEST TAKEN                          1027
Name: bac_result, dtype: int64
```

Removing more columns after careful review

I've determined the following columns are either irrelevant, most values are unknown, or are not applicable (i.e. bac_result; most tests were not offered) and therefore have decided to remove them:

In [22]:

```
drop = ['vehicle_defect', 'make', 'person_type', 'state', 'driver_action', 'p
        'bac_result']
df = df.drop(columns=drop)
print(df.shape)
display(df.head())
df.info()
```

```
(920827, 24)
```

way_surface_cond	road_defect	hit_and_run_i	prim_contributory_cause	beat_of_occurrence	inju
WET	NO DEFECTS	NaN	FAILING TO YIELD RIGHT-OF-WAY	612.0	
DRY	NO DEFECTS	NaN	FAILING TO YIELD RIGHT-OF-WAY	2212.0	
DRY	NO DEFECTS	NaN	UNABLE TO DETERMINE	1925.0	
WET	NO DEFECTS	NaN	FAILING TO YIELD RIGHT-OF-WAY	815.0	
DRY	NO DEFECTS	Y	FAILING TO REDUCE SPEED TO AVOID CRASH	822.0	

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 920827 entries, 3 to 1147851
Data columns (total 24 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   posted_speed_limit      920827 non-null  int64
 1   traffic_control_device  920827 non-null  object
 2   device_condition        920827 non-null  object
 3   weather_condition       920827 non-null  object
 4   lighting_condition      920827 non-null  object
 5   first_crash_type        920827 non-null  object
 6   trafficway_type         920827 non-null  object
 7   roadway_surface_cond    920827 non-null  object
 8   road_defect             920827 non-null  object
 9   hit_and_run_i           363082 non-null  object
 10  prim_contributory_cause 920827 non-null  object
 11  beat_of_occurrence      920827 non-null  float64
 12  injuries_total          920827 non-null  float64
 13  crash_hour              920827 non-null  int64
 14  crash_day_of_week       920827 non-null  int64
 15  unit_type               855033 non-null  object
 16  vehicle_type            31509 non-null   object
 17  sex                     901995 non-null  object
 18  age                     806205 non-null  float64
 19  drivers_license_state   45638 non-null   object
 20  drivers_license_class   36215 non-null   object
 21  safety_equipment        787520 non-null  object
 22  airbag_deployed         95726 non-null   object
 23  driver_vision           806726 non-null  object
```

```
dtypes: float64(3), int64(3), object(18)
memory usage: 175.6+ MB
```

In [23]:
```
len(df)
```

Out[23]:
```
920827
```

Binning and Cleaning Categorical Data

crash_hour:

In [24]:
```
#I'll first observe the values to determine how I'll bin based on the hours:
df.crash_hour.value_counts()
```

Out[24]:
```
17    81614
16    74532
15    69979
18    62177
14    61614
13    59625
19    55357
11    54804
12    50382
20    44178
9     42520
8     39621
10    37126
21    36683
22    23736
23    21842
7     20164
1     18012
0     13543
6     12454
4     11304
2     10491
5     10441
3      8628
Name: crash_hour, dtype: int64
```

Creating time bins for crash_hour

These bins will correspond with the following times:

0-6 = Midnight/Early Morning (12 A.M. to 6 A.M.)

6-12 = Morning (6 A.M. to 12 P.M.)

12-18 = Afternoon/Rush Hour (12 P.M. to 6 P.M.)

18-23 = Evening/Night (6 P.M. to 11 P.M.)

In [25]:
```
df['time_bins'] = pd.cut(x=df['crash_hour'], bins = [0,6,12,18,23],
                         labels = ['Midnight/Early Morning', 'Morning', 'Afte
df.head()
```

Out[25]:

	posted_speed_limit	traffic_control_device	device_condition	weather_condition	lighting_co
3	30	STOP SIGN/FLASHER	FUNCTIONING PROPERLY	CLEAR	DAY
5	30	STOP SIGN/FLASHER	FUNCTIONING PROPERLY	CLEAR	DARK
7	30	TRAFFIC SIGNAL	FUNCTIONING PROPERLY	CLEAR	DAY
11	30	TRAFFIC SIGNAL	FUNCTIONING PROPERLY	SNOW	DARK LIGHTED
13	30	NO CONTROLS	FUNCTIONING PROPERLY	CLEAR	DARK LIGHTED

I will then repeat similar processing for the remaining categorical columns.

posted_speed_limit:

In [26]:
```
df.posted_speed_limit.value_counts()
```

Out[26]:
```
30    687490
25     65134
35     50459
15     48819
20     30732
10     24675
5       4689
40      3046
0       1902
45      1085
55       939
24       917
2        914
50         7
3          7
34         3
39         3
60         2
32         1
14         1
9          1
1          1
Name: posted_speed_limit, dtype: int64
```

In [27]:
```
#Binning and previewing:
df['speed_limit'] = pd.cut(x=df['posted_speed_limit'], bins = [0,15,25,40,75]
                           labels = ['0-15', '16-25', '26-40', 'Over 40'])
df.head()
```

Out[27]:

	posted_speed_limit	traffic_control_device	device_condition	weather_condition	lighting_co
3	30	STOP SIGN/FLASHER	FUNCTIONING PROPERLY	CLEAR	DAY
5	30	STOP SIGN/FLASHER	FUNCTIONING PROPERLY	CLEAR	DARK
7	30	TRAFFIC SIGNAL	FUNCTIONING PROPERLY	CLEAR	DAY
11	30	TRAFFIC SIGNAL	FUNCTIONING PROPERLY	SNOW	DARK LIGHTED
13	30	NO CONTROLS	FUNCTIONING PROPERLY	CLEAR	DARK LIGHTED

age:

In [28]:
```
#Previewing:
df.age.value_counts()
```

Out[28]:
```
25.0     21088
32.0     20948
26.0     20086
28.0     20071
55.0     18813
         ...
93.0         2
96.0         1
95.0         1
98.0         1
101.0        1
Name: age, Length: 99, dtype: int64
```

In [29]:
```
df['age_groups'] = pd.cut(x=df['age'], bins = [0,15,24,35,55,100],
                          labels = ['15 & Under', '16-24',
                         '25-35', '36-55','56&Up'])
df.head()
```

Out[29]:

	posted_speed_limit	traffic_control_device	device_condition	weather_condition	lighting_co
3	30	STOP SIGN/FLASHER	FUNCTIONING PROPERLY	CLEAR	DAY
5	30	STOP SIGN/FLASHER	FUNCTIONING PROPERLY	CLEAR	DARK
7	30	TRAFFIC SIGNAL	FUNCTIONING PROPERLY	CLEAR	DAY
11	30	TRAFFIC SIGNAL	FUNCTIONING PROPERLY	SNOW	DARK LIGHTED
13	30	NO CONTROLS	FUNCTIONING PROPERLY	CLEAR	DARK LIGHTED

traffic_control_device:

In [30]:
```
df.traffic_control_device.value_counts()
```

Out[30]:
```
NO CONTROLS                438694
TRAFFIC SIGNAL             319778
STOP SIGN/FLASHER          103501
UNKNOWN                     37472
PEDESTRIAN CROSSING SIGN     9157
OTHER                        4743
YIELD                        2774
FLASHING CONTROL SIGNAL      1846
OTHER REG. SIGN               955
RAILROAD CROSSING GATE        927
BICYCLE CROSSING SIGN         914
OTHER WARNING SIGN             27
DELINEATORS                    18
RR CROSSING SIGN                7
POLICE/FLAGMAN                  6
SCHOOL ZONE                     5
OTHER RAILROAD CROSSING         2
NO PASSING                      1
Name: traffic_control_device, dtype: int64
```

In [31]:
```
#Mapping out:
traffic_control_mapping = {'NO CONTROLS': 'NO CONTROLS',
                     'TRAFFIC SIGNAL': 'SIGNAL/SIGN',
                     'STOP SIGN/FLASHER': 'SIGNAL/SIGN',
                     'UNKNOWN': 'OTHER-UNKNOWN',
                     'OTHER': 'OTHER-UNKNOWN',
                     'YIELD': 'OTHER-UNKNOWN',
                     'SCHOOL ZONE' : 'OTHER-UNKNOWN',
                     'PEDESTRIAN CROSSING SIGN' : 'SIGNAL/SIGN',
                     'FLASHING CONTROL SIGNAL' : 'SIGNAL/SIGN',
                     'OTHER REG. SIGN' :'OTHER-UNKNOWN',
                     'RAILROAD CROSSING GATE' : 'OTHER-UNKNOWN',
                     'BICYCLE CROSSING SIGN'  : 'OTHER-UNKNOWN',
                     'OTHER WARNING SIGN' : 'OTHER-UNKNOWN',
                     'DELINEATORS' : 'OTHER-UNKNOWN',
                     'RR CROSSING SIGN' : 'SIGNAL/SIGN',
                     'POLICE/FLAGMAN' : 'OTHER-UNKNOWN',
                     'OTHER RAILROAD CROSSING' : 'OTHER-UNKNOWN',
                     'NO PASSING' : 'SIGNAL/SIGN'}

df.traffic_control_device = df.traffic_control_device.map(traffic_control_map
df.traffic_control_device.value_counts()
```

Out[31]:
```
NO CONTROLS      438694
SIGNAL/SIGN      434290
OTHER-UNKNOWN     47843
Name: traffic_control_device, dtype: int64
```

device_condition:

In [32]:
```
df.device_condition.value_counts()
```

Out[32]:
```
NO CONTROLS                 441669
FUNCTIONING PROPERLY        392087
UNKNOWN                      70177
OTHER                         8467
FUNCTIONING IMPROPERLY        6508
NOT FUNCTIONING               1908
WORN REFLECTIVE MATERIAL         9
MISSING                          2
Name: device_condition, dtype: int64
```

In [33]:
```
#Mapping
devices_mapping = {'NO CONTROLS': 'NO CONTROLS',
                'FUNCTIONING PROPERLY': 'FUNCTIONING PROPERLY',
                'UNKNOWN': 'UNKNOWN-NOT FUNCTIONING',
                'OTHER': 'UNKNOWN-NOT FUNCTIONING',
                'FUNCTIONING IMPROPERLY': 'UNKNOWN-NOT FUNCTIONING',
                'NOT FUNCTIONING ': 'UNKNOWN-NOT FUNCTIONING',
                'WORN REFLECTIVE MATERIAL' : 'UNKNOWN-NOT FUNCTIONING' ,
                'MISSING' : 'UNKNOWN-NOT FUNCTIONING'}

df.device_condition = df.device_condition.map(devices_mapping)
df.device_condition.value_counts()
```

Out[33]:
```
NO CONTROLS                441669
FUNCTIONING PROPERLY       392087
UNKNOWN-NOT FUNCTIONING     85163
Name: device_condition, dtype: int64
```

weather_condition:

In [34]:
```
df.weather_condition.value_counts()
```

Out[34]:
```
CLEAR                     701568
SNOW                       89915
RAIN                       66082
UNKNOWN                    25325
CLOUDY/OVERCAST            22870
BLOWING SNOW                4656
OTHER                       3813
FREEZING RAIN/DRIZZLE       3775
FOG/SMOKE/HAZE              1853
SEVERE CROSS WIND GATE       918
SLEET/HAIL                    52
Name: weather_condition, dtype: int64
```

In [35]:
```
#Mapping
weather_mapping = {'CLEAR': 'CLEAR',
                   'RAIN': 'RAIN/CLOUDY/OTHER',
                   'CLOUDY/OVERCAST': 'RAIN/CLOUDY/OTHER',
                   'UNKNOWN': 'RAIN/CLOUDY/OTHER',
                   'BLOWING SNOW' : 'RAIN/CLOUDY/OTHER',
                   'OTHER ': 'RAIN/CLOUDY/OTHER',
                   'FREEZING RAIN/DRIZZLE' : 'RAIN/CLOUDY/OTHER',
                   'FOG/SMOKE/HAZE' : 'RAIN/CLOUDY/OTHER',
                   'SEVERE CROSS WIND GATE' : 'RAIN/CLOUDY/OTHER',
                   'SLEET/HAIL' : 'RAIN/CLOUDY/OTHER',}

df.weather_condition = df.weather_condition.map(weather_mapping)
df.weather_condition.value_counts()
```

Out[35]:
```
CLEAR                701568
RAIN/CLOUDY/OTHER    125531
Name: weather_condition, dtype: int64
```

first_crash_type:

In [36]:
```
df.first_crash_type.value_counts()
```

Out[36]:
```
PEDESTRIAN                       503616
PEDALCYCLIST                     210219
FIXED OBJECT                      57571
PARKED MOTOR VEHICLE              43457
OTHER OBJECT                      26812
TURNING                           19680
REAR END                          19189
ANGLE                             17099
SIDESWIPE SAME DIRECTION          11351
ANIMAL                             2754
SIDESWIPE OPPOSITE DIRECTION       2334
REAR TO FRONT                      2315
OTHER NONCOLLISION                 1883
HEAD ON                            1238
REAR TO SIDE                       1196
REAR TO REAR                         84
OVERTURNED                           28
TRAIN                                 1
Name: first_crash_type, dtype: int64
```

In [37]:
```
first_crash_mapping = {'PEDESTRIAN': 'PED/CYCLIST',
                       'PEDALCYCLIST': 'PED/CYCLIST',
                       'FIXED OBJECT': 'PARKED/FIXED',
                       'PARKED MOTOR VEHICLE': 'PARKED/FIXED',
                       'OTHER OBJECT': 'OTHER',
                       'TURNING': 'TURNING-ANGLE',
                       'REAR END': 'REAR END',
                       'ANGLE': 'TURNING-ANGLE',
                       'SIDESWIPE SAME DIRECTION': 'SIDESWIPE',
                       'ANIMAL' : 'OTHER',
                       'SIDESWIPE OPPOSITE DIRECTION ': 'SIDESWIPE',
                       'REAR TO FRONT' : 'OTHER',
                       'OTHER NONCOLLISION': 'OTHER',
                       'HEAD ON': 'OTHER',
                       'REAR TO SIDE': 'OTHER',
                       'REAR TO REAR': 'OTHER',
                       'OVERTURNED' : 'OTHER',
                       'TRAIN' : 'OTHER'}

df.first_crash_type = df.first_crash_type.map(first_crash_mapping)
df.first_crash_type.value_counts()
```

Out[37]:
```
PED/CYCLIST      713835
PARKED/FIXED     101028
TURNING-ANGLE     36779
OTHER             36311
REAR END          19189
SIDESWIPE         11351
Name: first_crash_type, dtype: int64
```

trafficway_type

In [38]:
```
df.trafficway_type.value_counts()
```

Out[38]:
```
NOT DIVIDED                         354504
FOUR WAY                            148750
DIVIDED - W/MEDIAN (NOT RAISED)     130698
ONE-WAY                              97488
PARKING LOT                          45954
DIVIDED - W/MEDIAN BARRIER           39978
ALLEY                                32520
T-INTERSECTION                       20680
OTHER                                19111
DRIVEWAY                              7400
Y-INTERSECTION                        5538
FIVE POINT, OR MORE                   4621
UNKNOWN                               3959
CENTER TURN LANE                      3844
UNKNOWN INTERSECTION TYPE             1957
RAMP                                  1898
TRAFFIC ROUTE                          960
L-INTERSECTION                         923
ROUNDABOUT                              23
NOT REPORTED                            21
Name: trafficway_type, dtype: int64
```

In [39]:
```
trafficway_mapping = {'NOT DIVIDED': 'NOT DIVIDED',
                      'FOUR WAY': 'FOUR WAY',
                      'DIVIDED - W/MEDIAN (NOT RAISED)': 'DIVIDED',
                      'ONE-WAY': 'ONE-WAY',
                      'PARKING LOT': 'PARKING LOT',
                      'DIVIDED - W/MEDIAN BARRIER': 'DIVIDED',
                      'ALLEY': 'DRIVEWAY-OTHER',
                      'T-INTERSECTION': 'DRIVEWAY-OTHER',
                      'OTHER': 'DRIVEWAY-OTHER',
                      'DRIVEWAY' : 'DRIVEWAY-OTHER',
                      'Y-INTERSECTION': 'DRIVEWAY-OTHER',
                      'FIVE POINT, OR MORE' : 'DRIVEWAY-OTHER',
                      'UNKNOWN': 'UNKNOWN',
                      'CENTER TURN LANE': 'DRIVEWAY-OTHER',
                      'UNKNOWN INTERSECTION TYPE': 'UNKNOWN',
                      'RAMP' : 'DRIVEWAY-OTHER',
                      'TRAFFIC ROUTE' : 'DRIVEWAY-OTHER',
                      'L-INTERSECTION' : 'DRIVEWAY-OTHER',
                      'ROUNDABOUT' : 'FOUR WAY',
                      'NOT REPORTED': 'UNKNOWN'}

df.trafficway_type = df.trafficway_type.map(trafficway_mapping)
df.trafficway_type.value_counts()
```

Out[39]:
```
NOT DIVIDED       354504
DIVIDED           170676
FOUR WAY          148773
DRIVEWAY-OTHER     97495
ONE-WAY            97488
PARKING LOT        45954
UNKNOWN             5937
Name: trafficway_type, dtype: int64
```

road_defect:

In [40]:
```
df.road_defect.value_counts()
```

Out[40]:
```
NO DEFECTS           733480
UNKNOWN              166714
OTHER                  6578
RUT, HOLES             6535
WORN SURFACE           4706
DEBRIS ON ROADWAY      1850
SHOULDER DEFECT         964
Name: road_defect, dtype: int64
```

In [41]:
```
roaddefect_map = {'NO DEFECTS': 'NO DEFECTS',
                  'UNKNOWN': 'UNKNOWN-OTHER',
                  'OTHER': 'UNKNOWN-OTHER',
                  'RUT, HOLES' : 'UNKNOWN-OTHER',
                  'WORN SURFACE' : 'UNKNOWN-OTHER',
                  'DEBRIS ON ROADWAY' : 'UNKNOWN-OTHER',
                  'SHOULDER DEFECT': 'UNKNOWN-OTHER'}

df.road_defect = df.road_defect.map(roaddefect_map)
df.road_defect.value_counts()
```

Out[41]:
```
NO DEFECTS       733480
UNKNOWN-OTHER    187347
Name: road_defect, dtype: int64
```

vehicle_type:

In [42]:
```
df.vehicle_type.value_counts()
```

Out[42]:
```
PASSENGER                                18484
UNKNOWN/NA                                4249
SPORT UTILITY VEHICLE (SUV)               3953
VAN/MINI-VAN                              1283
PICKUP                                    1043
TRUCK - SINGLE UNIT                        744
OTHER                                      584
BUS OVER 15 PASS.                          427
TRACTOR W/ SEMI-TRAILER                    349
BUS UP TO 15 PASS.                         158
SINGLE UNIT TRUCK WITH TRAILER              99
MOTORCYCLE (OVER 150CC)                     42
OTHER VEHICLE WITH TRAILER                  37
TRACTOR W/O SEMI-TRAILER                    34
MOPED OR MOTORIZED BICYCLE                  11
ALL-TERRAIN VEHICLE (ATV)                    7
3-WHEELED MOTORCYCLE (2 REAR WHEELS)         2
FARM EQUIPMENT                               2
RECREATIONAL OFF-HIGHWAY VEHICLE (ROV)       1
Name: vehicle_type, dtype: int64
```

In [43]:
```
vehicletype_map = {'PASSENGER': 'PASSENGER',
                   'UNKNOWN/NA': 'UNKNOWN/NA',
                   'SPORT UTILITY VEHICLE (SUV)': 'SUV/VAN/PICKUP',
                   'VAN/MINI-VAN': 'SUV/VAN/PICKUP',
                   'PICKUP': 'SUV/VAN/PICKUP',
                   'TRUCK - SINGLE UNIT': 'BUS/TRUCK/TRAILER',
                   'OTHER': 'OTHER',
                   'BUS OVER 15 PASS.': 'BUS/TRUCK/TRAILER',
                   'TRACTOR W/ SEMI-TRAILER': 'BUS/TRUCK/TRAILER',
                   'BUS UP TO 15 PASS.': 'BUS/TRUCK/TRAILER',
                   'SINGLE UNIT TRUCK WITH TRAILER': 'BUS/TRUCK/TRAILER',
                   'MOTORCYCLE (OVER 150CC)': 'OTHER',
                   'OTHER VEHICLE WITH TRAILER': 'OTHER',
                   'TRACTOR W/O SEMI-TRAILER' : 'OTHER',
                   'MOPED OR MOTORIZED BICYCLE' : 'OTHER',
                   'ALL-TERRAIN VEHICLE (ATV)' : 'OTHER',
                   'FARM EQUIPMENT' : 'OTHER',
                   '3-WHEELED MOTORCYCLE (2 REAR WHEELS)' : 'OTHER',
                   'RECREATIONAL OFF-HIGHWAY VEHICLE (ROV)' : 'OTHER'}

df.vehicle_type = df.vehicle_type.map(vehicletype_map)
df.vehicle_type.value_counts()
```

Out[43]:
```
PASSENGER            18484
SUV/VAN/PICKUP        6279
UNKNOWN/NA            4249
BUS/TRUCK/TRAILER     1777
OTHER                  720
Name: vehicle_type, dtype: int64
```

safety_equipment:

In [110]:
```
df.safety_equipment.value_counts()
```

Out[110]:
```
NONE PRESENT/UNUSED      541973
SAFETY EQUIPMENT USED    130549
USAGE UNKNOWN            114977
Name: safety_equipment, dtype: int64
```

In [44]:
```
safetyequip_map = {'NONE PRESENT': 'NONE PRESENT/UNUSED',
                   'HELMET NOT USED': 'NONE PRESENT/UNUSED',
                   'USAGE UNKNOWN': 'USAGE UNKNOWN',
                   'BICYCLE HELMET (PEDACYCLIST INVOLVED ONLY)': 'SAFETY EQUI
                   'SAFETY BELT USED': 'SAFETY EQUIPMENT USED',
                   'SAFETY BELT NOT USED': 'NONE PRESENT/UNUSED',
                   'WHEELCHAIR' : 'USAGE UNKNOWN',
                   'BOOSTER SEAT' : 'SAFETY EQUIPMENT USED',
                   'STRETCHER' : 'USAGE UNKNOWN',
                   'HELMET USED' : 'SAFETY EQUIPMENT USED',
                   'CHILD RESTRAINT USED' : 'SAFETY EQUIPMENT USED',
                   'CHILD RESTRAINT - FORWARD FACING': 'SAFETY EQUIPMENT USED
                   'CHILD RESTRAINT - REAR FACING': 'SAFETY EQUIPMENT USED',
                   'CHILD RESTRAINT - TYPE UNKNOWN': 'SAFETY EQUIPMENT USED',
                   'DOT COMPLIANT MOTORCYCLE HELMET ': 'SAFETY EQUIPMENT USED
                   'NOT DOT COMPLIANT MOTORCYCLE HELMET' : 'SAFETY EQUIPMENT
                   'SHOULD/LAP BELT USED IMPROPERLY': 'NONE PRESENT/UNUSED',
                   'CHILD RESTRAINT NOT USED' : 'NONE PRESENT/UNUSED',
                   'CHILD RESTRAINT USED IMPROPERLY' : 'NONE PRESENT/UNUSED'}

df.safety_equipment = df.safety_equipment.map(safetyequip_map)
df.safety_equipment.value_counts()
```

Out[44]:
```
NONE PRESENT/UNUSED      541973
SAFETY EQUIPMENT USED    130549
USAGE UNKNOWN            114977
Name: safety_equipment, dtype: int64
```

airbag_deployed:

In [45]:
```
df.airbag_deployed.value_counts()
```

Out[45]:
```
NOT APPLICABLE                          35713
DID NOT DEPLOY                          30229
DEPLOYMENT UNKNOWN                      22659
DEPLOYED, COMBINATION                    2764
DEPLOYED, SIDE                           2244
DEPLOYED, FRONT                          2102
DEPLOYED OTHER (KNEE, AIR, BELT, ETC.)     15
Name: airbag_deployed, dtype: int64
```

In [46]:
```
airbagdeploy_map = {'NOT APPLICABLE': 'NOT APPLICABLE/UNKNOWN',
                    'DID NOT DEPLOY': 'DID NOT DEPLOY',
                    'DEPLOYMENT UNKNOWN': 'NOT APPLICABLE/UNKNOWN',
                    'DEPLOYED, COMBINATION': 'DEPLOYED',
                    'DEPLOYED, SIDE': 'DEPLOYED',
                    'DEPLOYED, FRONT': 'DEPLOYED',
                    'DEPLOYED OTHER (KNEE, AIR, BELT, ETC.)': 'DEPLOYED'}

df.airbag_deployed = df.airbag_deployed.map(airbagdeploy_map)
df.airbag_deployed.value_counts()
```

Out[46]:
```
NOT APPLICABLE/UNKNOWN    58372
DID NOT DEPLOY            30229
DEPLOYED                   7125
Name: airbag_deployed, dtype: int64
```

driver_vision:

In [47]:
```
df.driver_vision.value_counts()
```

Out[47]:
```
NOT OBSCURED              402552
UNKNOWN                   333636
OTHER                      55666
MOVING VEHICLES             4948
PARKED VEHICLES             4941
WINDSHIELD (WATER/ICE)      2017
TREES, PLANTS                983
BUILDINGS                    978
BLINDED - HEADLIGHTS         974
BLINDED - SUNLIGHT            25
EMBANKMENT                     4
SIGNBOARD                      1
BLOWING MATERIALS              1
Name: driver_vision, dtype: int64
```

In [48]:
```
drivervision_map = {'NOT OBSCURED': 'NOT OBSCURED',
                    'UNKNOWN': 'UNKNOWN',
                    'OTHER': 'OBSCURED',
                    'MOVING VEHICLES': 'OBSCURED',
                    'PARKED VEHICLES': 'OBSCURED',
                    'WINDSHIELD (WATER/ICE)' : 'OBSCURED',
                    'TREES, PLANTS' : 'OBSCURED',
                    'BUILDINGS' : 'OBSCURED',
                    'BLINDED - HEADLIGHTS' : 'OBSCURED',
                    'BLINDED - SUNLIGHT': 'OBSCURED',
                    'EMBANKMENT' : 'OBSCURED',
                    'SIGNBOARD' : 'OBSCURED',
                    'BLOWING MATERIALS' : 'OBSCURED'}

df.driver_vision = df.driver_vision.map(drivervision_map)
df.driver_vision.value_counts()
```

Out[48]:
```
NOT OBSCURED    402552
UNKNOWN         333636
OBSCURED         70538
Name: driver_vision, dtype: int64
```

Choosing and Prepping Our Target

I will begin by creating classes where 0 means no injury and 1 means injury. Next I will rename the column and review before examining and dropping the original columns I've binned.

In [49]:
```
df['injuries_total'] = df['injuries_total'].map(lambda x: 1 if x > 0 else 0)
```

In [50]:
```
#Renaming:
df.rename(columns = {'injuries_total':'injuries'}, inplace = True)

#Reviewing:
df.injuries.value_counts()
```

Out[50]:
```
1    662545
0    258282
Name: injuries, dtype: int64
```

In [51]:
```
#These columns have been binned, so I will drop the originals
drop = ['posted_speed_limit', 'crash_hour', 'age']
df = df.drop(columns=drop)
```

I will now convert a number of columns to strings for easy manipulation:

In [52]:
```
df['beat_of_occurrence'] = df['beat_of_occurrence'].astype('str')
df['crash_day_of_week'] = df['crash_day_of_week'].astype('str')
df['injuries'] = df['injuries'].astype('str')
```

In [53]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 920827 entries, 3 to 1147851
Data columns (total 24 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   traffic_control_device   920827 non-null  object
 1   device_condition         918919 non-null  object
 2   weather_condition        827099 non-null  object
 3   lighting_condition       920827 non-null  object
 4   first_crash_type         918493 non-null  object
 5   trafficway_type          920827 non-null  object
 6   roadway_surface_cond     920827 non-null  object
 7   road_defect              920827 non-null  object
 8   hit_and_run_i            363082 non-null  object
 9   prim_contributory_cause  920827 non-null  object
 10  beat_of_occurrence       920827 non-null  object
 11  injuries                 920827 non-null  object
 12  crash_day_of_week        920827 non-null  object
 13  unit_type                855033 non-null  object
 14  vehicle_type             31509 non-null   object
 15  sex                      901995 non-null  object
 16  drivers_license_state    45638 non-null   object
 17  drivers_license_class    36215 non-null   object
 18  safety_equipment         787499 non-null  object
 19  airbag_deployed          95726 non-null   object
 20  driver_vision            806726 non-null  object
 21  time_bins                907284 non-null  category
 22  speed_limit              918925 non-null  category
 23  age_groups               795305 non-null  category
dtypes: category(3), object(21)
memory usage: 157.2+ MB
```

Re-checking the Values of Each Column:

In [54]:

```
for col in df.columns:
    try:
        print(col, df[col].value_counts()[:10]) #<--Display the first 10 only
    except:
        print(col, df[col].value_counts())

    print('\n')
```

```
traffic_control_device NO CONTROLS      438694
SIGNAL/SIGN      434290
OTHER-UNKNOWN     47843
Name: traffic_control_device, dtype: int64


device_condition NO CONTROLS                441669
FUNCTIONING PROPERLY       392087
UNKNOWN-NOT FUNCTIONING     85163
Name: device_condition, dtype: int64


weather_condition CLEAR                701568
RAIN/CLOUDY/OTHER    125531
Name: weather_condition, dtype: int64


lighting_condition DAYLIGHT                   572648
DARKNESS, LIGHTED ROAD    252641
DARKNESS                   39893
DUSK                       25521
UNKNOWN                    15916
DAWN                       14208
Name: lighting_condition, dtype: int64


first_crash_type PED/CYCLIST      713835
PARKED/FIXED     101028
TURNING-ANGLE     36779
OTHER             36311
REAR END          19189
SIDESWIPE         11351
Name: first_crash_type, dtype: int64


trafficway_type NOT DIVIDED       354504
DIVIDED           170676
FOUR WAY          148773
DRIVEWAY-OTHER     97495
ONE-WAY            97488
PARKING LOT        45954
UNKNOWN             5937
Name: trafficway_type, dtype: int64


roadway_surface_cond DRY                596697
WET                146297
SNOW OR SLUSH      108205
```

```
UNKNOWN             52622
OTHER                9242
ICE                  7757
SAND, MUD, DIRT         7
Name: roadway_surface_cond, dtype: int64


road_defect NO DEFECTS       733480
UNKNOWN-OTHER    187347
Name: road_defect, dtype: int64


hit_and_run_i Y    344354
N     18728
Name: hit_and_run_i, dtype: int64


prim_contributory_cause UNABLE TO DETERMINE
355502
FAILING TO YIELD RIGHT-OF-WAY
202895
NOT APPLICABLE
65528
FAILING TO REDUCE SPEED TO AVOID CRASH
34295
WEATHER
25839
OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRESSIVE M
ANNER     25101
DRIVING SKILLS/KNOWLEDGE/EXPERIENCE
24834
DISREGARDING TRAFFIC SIGNALS
22553
IMPROPER OVERTAKING/PASSING
16906
VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)
16620
Name: prim_contributory_cause, dtype: int64


beat_of_occurrence 1834.0    11176
1934.0    10156
1935.0     9252
1912.0     9216
623.0      8449
2521.0     8413
323.0      8383
1922.0     8330
1832.0     8311
1232.0     7502
Name: beat_of_occurrence, dtype: int64


injuries 1    662545
0    258282
Name: injuries, dtype: int64
```

```
crash_day_of_week 7    166776
6    151277
3    142165
5    136668
4    119249
2    109402
1     95290
Name: crash_day_of_week, dtype: int64


unit_type PEDESTRIAN             535911
BICYCLE                 211826
DRIVER                   61930
NON-MOTOR VEHICLE        32869
PARKED                    7907
NON-CONTACT VEHICLE       3657
DRIVERLESS                 931
DISABLED VEHICLE             2
Name: unit_type, dtype: int64


vehicle_type PASSENGER            18484
SUV/VAN/PICKUP         6279
UNKNOWN/NA             4249
BUS/TRUCK/TRAILER      1777
OTHER                   720
Name: vehicle_type, dtype: int64


sex M    554799
F    318910
X     28286
Name: sex, dtype: int64


drivers_license_state IL    40260
XX     2447
IN     1292
MO      995
WI       81
MI       61
FL       53
CA       44
OH       41
TX       39
Name: drivers_license_state, dtype: int64


drivers_license_class D     31838
B      1548
DM     1214
A       753
C       457
AM       95
BM       51
CD       39
```

```
DL       26
E        25
Name: drivers_license_class, dtype: int64


safety_equipment NONE PRESENT/UNUSED      541973
SAFETY EQUIPMENT USED    130549
USAGE UNKNOWN            114977
Name: safety_equipment, dtype: int64


airbag_deployed NOT APPLICABLE/UNKNOWN    58372
DID NOT DEPLOY            30229
DEPLOYED                   7125
Name: airbag_deployed, dtype: int64


driver_vision NOT OBSCURED    402552
UNKNOWN         333636
OBSCURED         70538
Name: driver_vision, dtype: int64


time_bins Afternoon/Rush Hour       409541
Morning                    244617
Evening/Night              181796
Midnight/Early Morning      71330
Name: time_bins, dtype: int64


speed_limit 26-40      741002
16-25       96783
0-15        79107
Over 40      2033
Name: speed_limit, dtype: int64


age_groups 36-55         245030
56&Up         208407
25-35         187128
16-24         104507
15 & Under     50233
Name: age_groups, dtype: int64
```

Resetting the index and one more look at the data:

In [55]:
```
df.reset_index(inplace=True)
```

In [56]:
```
df.drop('index', axis = 1, inplace =True)
```

In [57]:
```
df.head()
```

Out[57]:

	traffic_control_device	device_condition	weather_condition	lighting_condition	first_crash
0	SIGNAL/SIGN	FUNCTIONING PROPERLY	CLEAR	DAYLIGHT	C
1	SIGNAL/SIGN	FUNCTIONING PROPERLY	CLEAR	DARKNESS	TUR A
2	SIGNAL/SIGN	FUNCTIONING PROPERLY	CLEAR	DAYLIGHT	TUR A
3	SIGNAL/SIGN	FUNCTIONING PROPERLY	NaN	DARKNESS, LIGHTED ROAD	TUR A
4	NO CONTROLS	FUNCTIONING PROPERLY	CLEAR	DARKNESS, LIGHTED ROAD	SIDE

Preparing to Model

Due to the size of this data set (just under 1 million rows), I've decided to run my models on a sample of the data. The sample should give us results as accurate as possible while allowing the models to process in a timely manner.

In [58]:

```
# Generating sample
sample_data = df.sample(frac =.10)

# Checking if sample is 10% of the data or not

if (0.10*(len(df))== len(sample_data)):
    print( "Data Sample")
    print(len(df), len(sample_data))

sample_data
```

Out[58]:

	traffic_control_device	device_condition	weather_condition	lighting_condition	first_
54777	NO CONTROLS	NaN	CLEAR	DARKNESS, LIGHTED ROAD	PE
278142	NO CONTROLS	NO CONTROLS	CLEAR	DAYLIGHT	PE
798628	SIGNAL/SIGN	FUNCTIONING PROPERLY	CLEAR	DAYLIGHT	PE
374010	SIGNAL/SIGN	FUNCTIONING PROPERLY	RAIN/CLOUDY/OTHER	DAYLIGHT	PE
463249	SIGNAL/SIGN	FUNCTIONING PROPERLY	CLEAR	DAYLIGHT	PE
...	...	...	...	...	
647977	NO CONTROLS	NO CONTROLS	CLEAR	DAYLIGHT	PE
435827	SIGNAL/SIGN	FUNCTIONING PROPERLY	CLEAR	DARKNESS, LIGHTED ROAD	
875245	SIGNAL/SIGN	NO CONTROLS	CLEAR	DAYLIGHT	PE
303236	SIGNAL/SIGN	FUNCTIONING PROPERLY	CLEAR	DAYLIGHT	PE
65698	SIGNAL/SIGN	FUNCTIONING PROPERLY	CLEAR	DAYLIGHT	PE

92083 rows × 24 columns

Train Test Split

In [59]:
```
#Setting our X, y
target = 'injuries'
X = sample_data.drop(columns= target)
y = sample_data[target]

#train_test_split, test_size = 25%, random_state = 42
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = .25, ra
```

Preprocessing Numeric Columns:

In [60]:
```
#Creating a list of numerical columns:
num_cols = sample_data.drop(columns=target).select_dtypes('number').columns.t
num_cols
```

Out[60]:
```
[]
```

In [61]:
```
# Creating a Pipeline:  SimpleImputer will use the median to replace any null
#the median to scale
num_transform = Pipeline([('imputer', SimpleImputer(strategy='median')),
                          ('scale', RobustScaler())])
```

Preprocessing Categorical Columns:

In [62]:
```
categorical_cols = sample_data.drop(columns=target).select_dtypes('object').c
categorical_cols
```

Out[62]:
```
['traffic_control_device',
 'device_condition',
 'weather_condition',
 'lighting_condition',
 'first_crash_type',
 'trafficway_type',
 'roadway_surface_cond',
 'road_defect',
 'hit_and_run_i',
 'prim_contributory_cause',
 'beat_of_occurrence',
 'crash_day_of_week',
 'unit_type',
 'vehicle_type',
 'sex',
 'drivers_license_state',
 'drivers_license_class',
 'safety_equipment',
 'airbag_deployed',
 'driver_vision']
```

In [63]:
```
# OneHotEncode to scale the categorical data to a binary column
categoric_transform = Pipeline([('imputer', SimpleImputer(strategy='constant'
                                ('encoder', OneHotEncoder(sparse=False, handle_unknc
```

ColumnTransformer

Next, we use the ColumnTransformer estimator to allow the different columns the input to be transformed separately and the features generated by each transformer to be concatenated to form a single feature space. I will combine the pipelines into one, perfom a train and test, and then convert to a dataframe:

In [64]:
```
# Combining pipelines:
transformed = ColumnTransformer([('num', num_transform, num_cols),
                                 ('cat', categoric_transform, categorical_cc

# X_train and X_test
X_train_tf = transformed.fit_transform(X_train)
X_test_tf = transformed.transform(X_test)
```

In [65]:
```
# Converting the pipeline categorical columns to dataframe
pipeline_slice = transformed.named_transformers_['cat']
categoric_features = pipeline_slice.named_steps['encoder'].get_feature_names(
X_train_tf = pd.DataFrame(X_train_tf,columns=[*num_cols, *categoric_features]
X_train_tf
```

Out[65]:

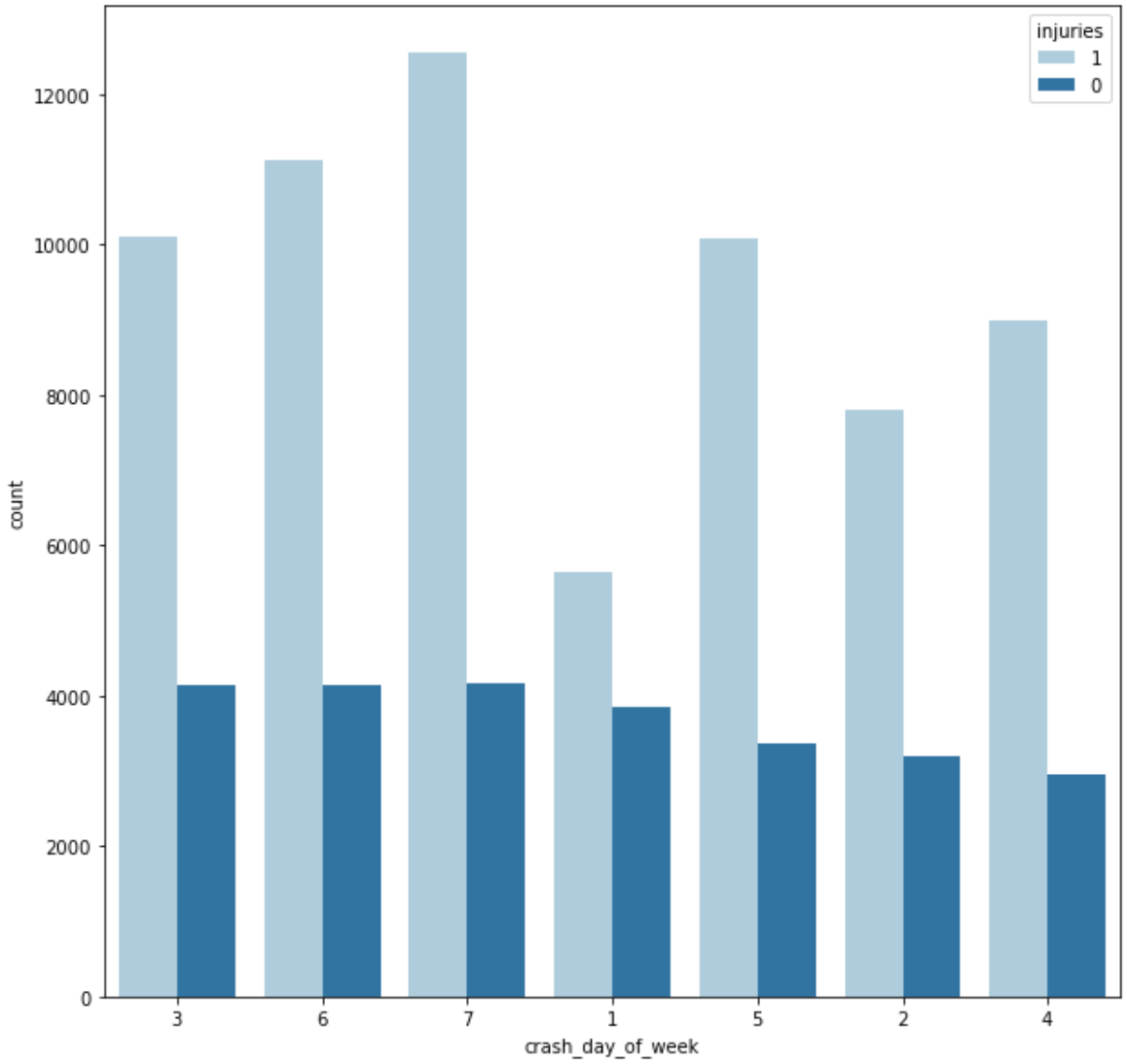
ory_cause_DRIVING .EDGE/EXPERIENCE	prim_contributory_cause_EQUIPMENT - VEHICLE CONDITION	prim_contributory_cause_EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST	pri
0.0	1.0	0.0	
0.0	0.0	0.0	
0.0	0.0	0.0	
0.0	0.0	0.0	
0.0	0.0	0.0	
...	...	...	
0.0	0.0	0.0	
0.0	0.0	0.0	
0.0	0.0	0.0	
0.0	0.0	0.0	
0.0	0.0	0.0	

And now I'll explore each feature through visualizations.

Explore:

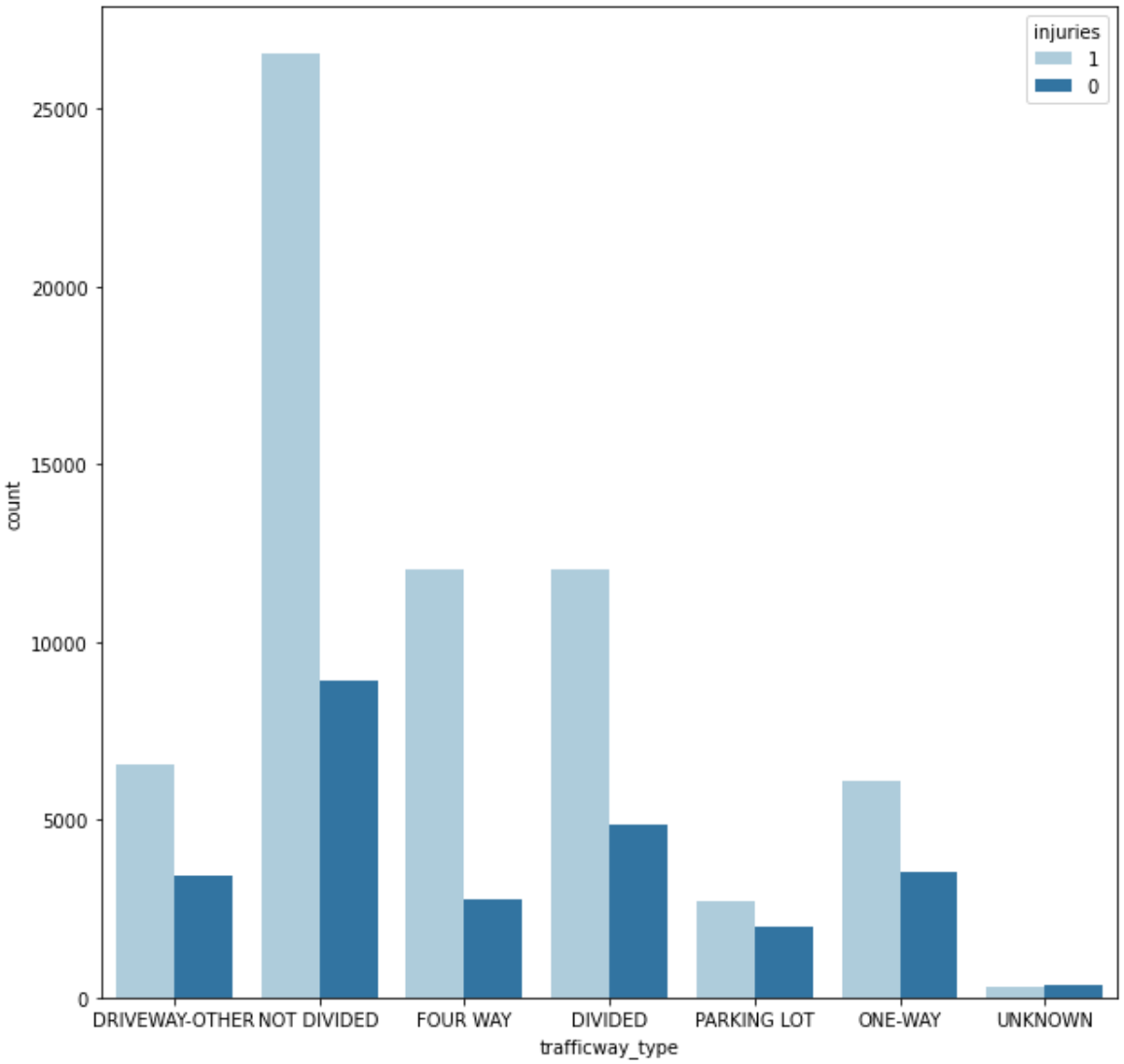
In [68]:
```
plt.figure(figsize=(10,10))
sns.countplot(x = "crash_day_of_week", hue = "injuries", data = sample_data,
```

Out[68]:
```
<AxesSubplot:xlabel='crash_day_of_week', ylabel='count'>
```



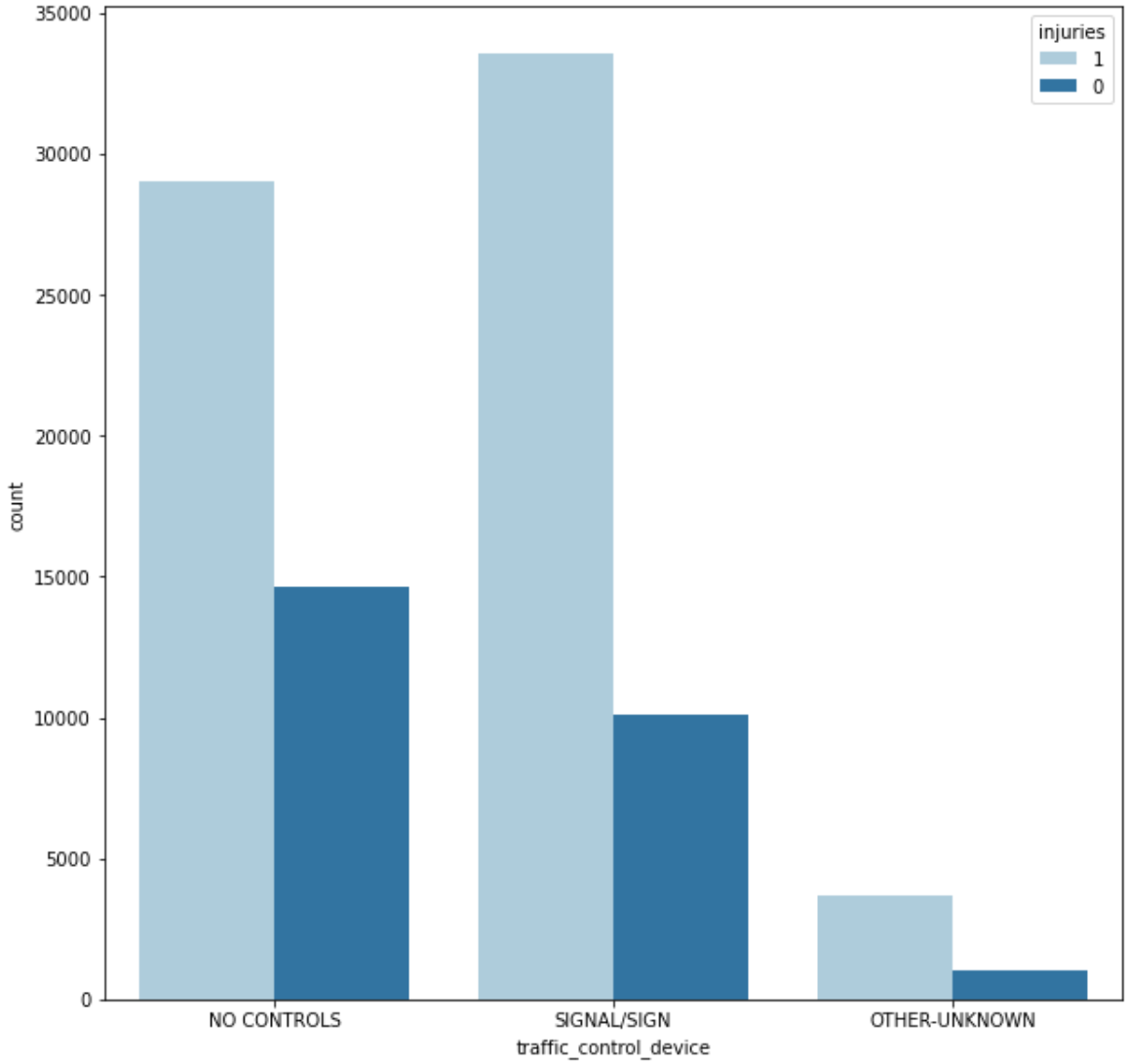
In [111]:
```
plt.figure(figsize=(10,10))
sns.countplot(x = "trafficway_type", hue = "injuries", data = sample_data, pa
```

Out[111]: <AxesSubplot:xlabel='trafficway_type', ylabel='count'>



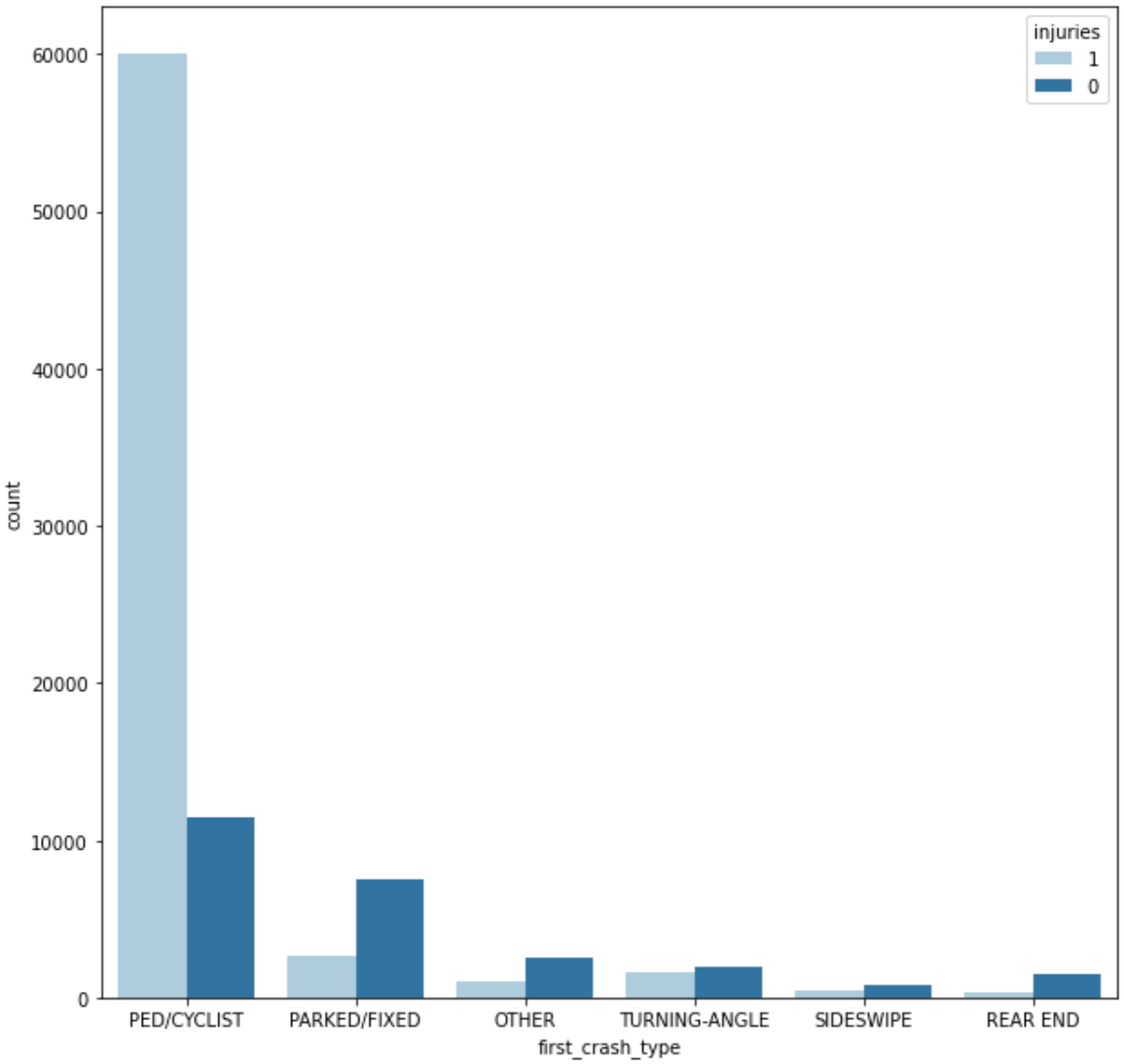
In [69]:
```
plt.figure(figsize=(10,10))
sns.countplot(x = "traffic_control_device", hue = "injuries", data = sample_d
```

Out[69]: <AxesSubplot:xlabel='traffic_control_device', ylabel='count'>



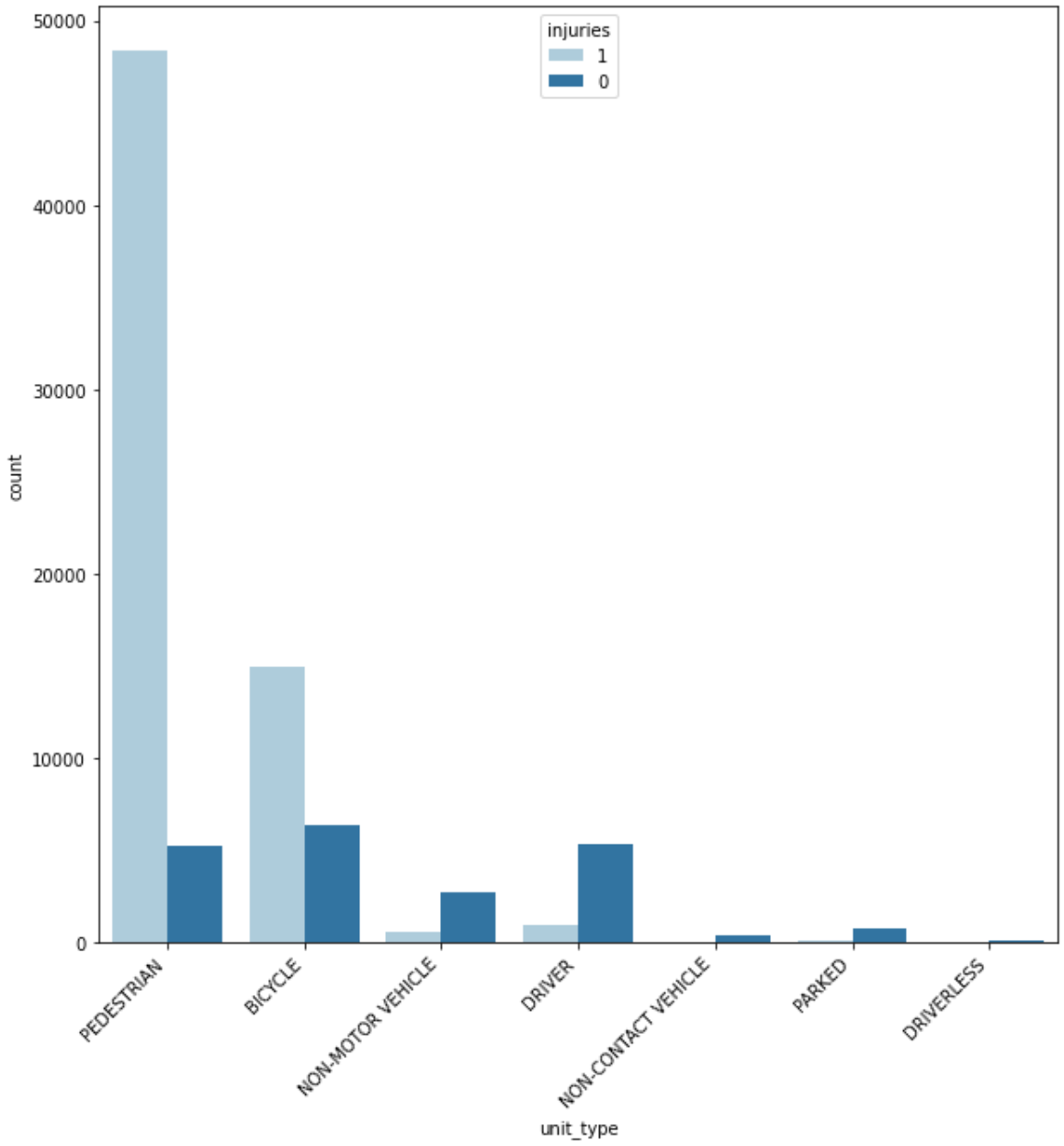
In [70]:
```
plt.figure(figsize=(10,10))
sns.countplot(x = "first_crash_type", hue = "injuries", data = sample_data, p
```

Out[70]: <AxesSubplot:xlabel='first_crash_type', ylabel='count'>



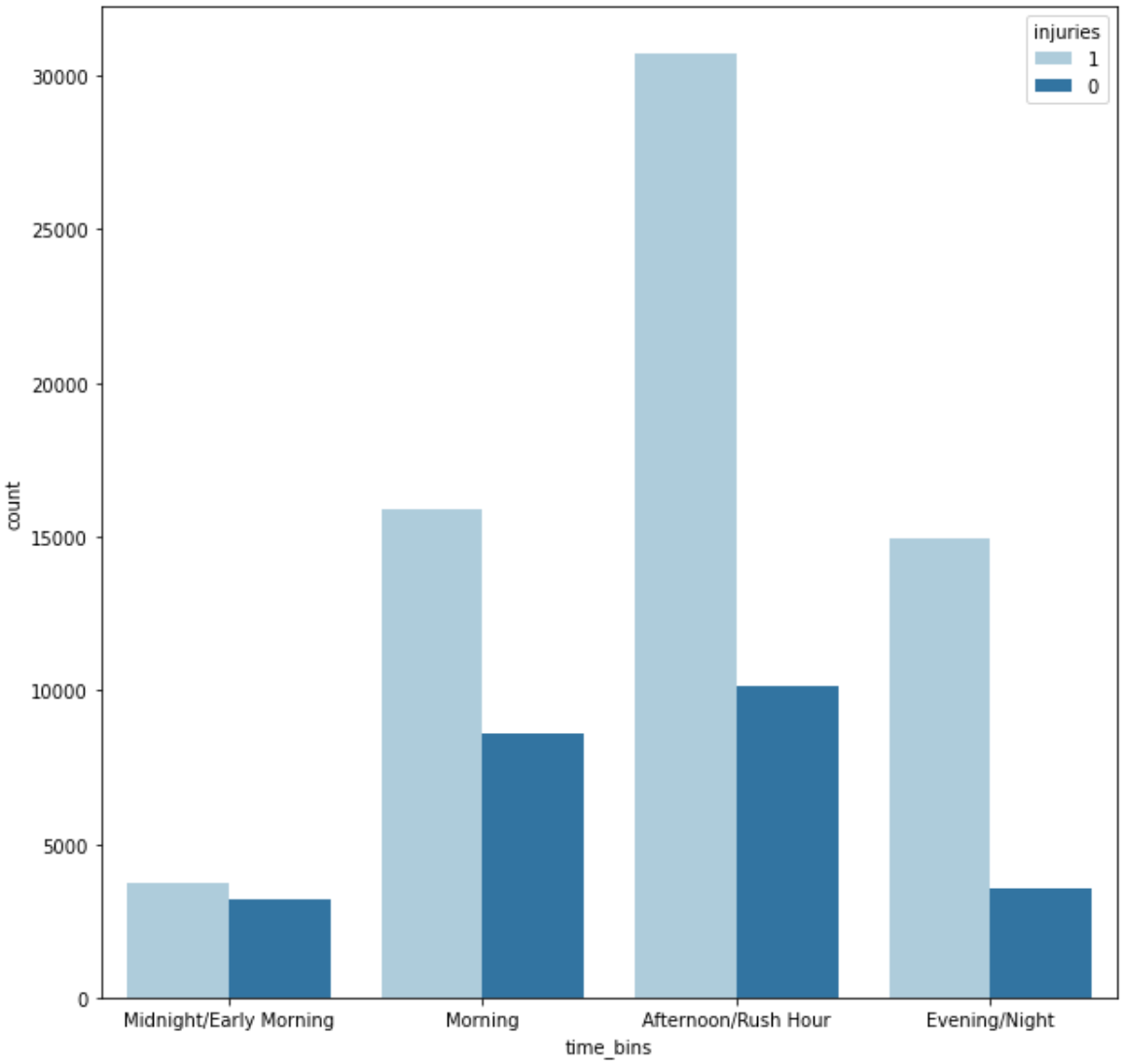
In [71]:

```
plt.figure(figsize=(10,10))
sns.countplot(x = "unit_type", hue = "injuries", data = sample_data, palette
plt.xticks(
    rotation=45,
    horizontalalignment='right')
plt.show()
```



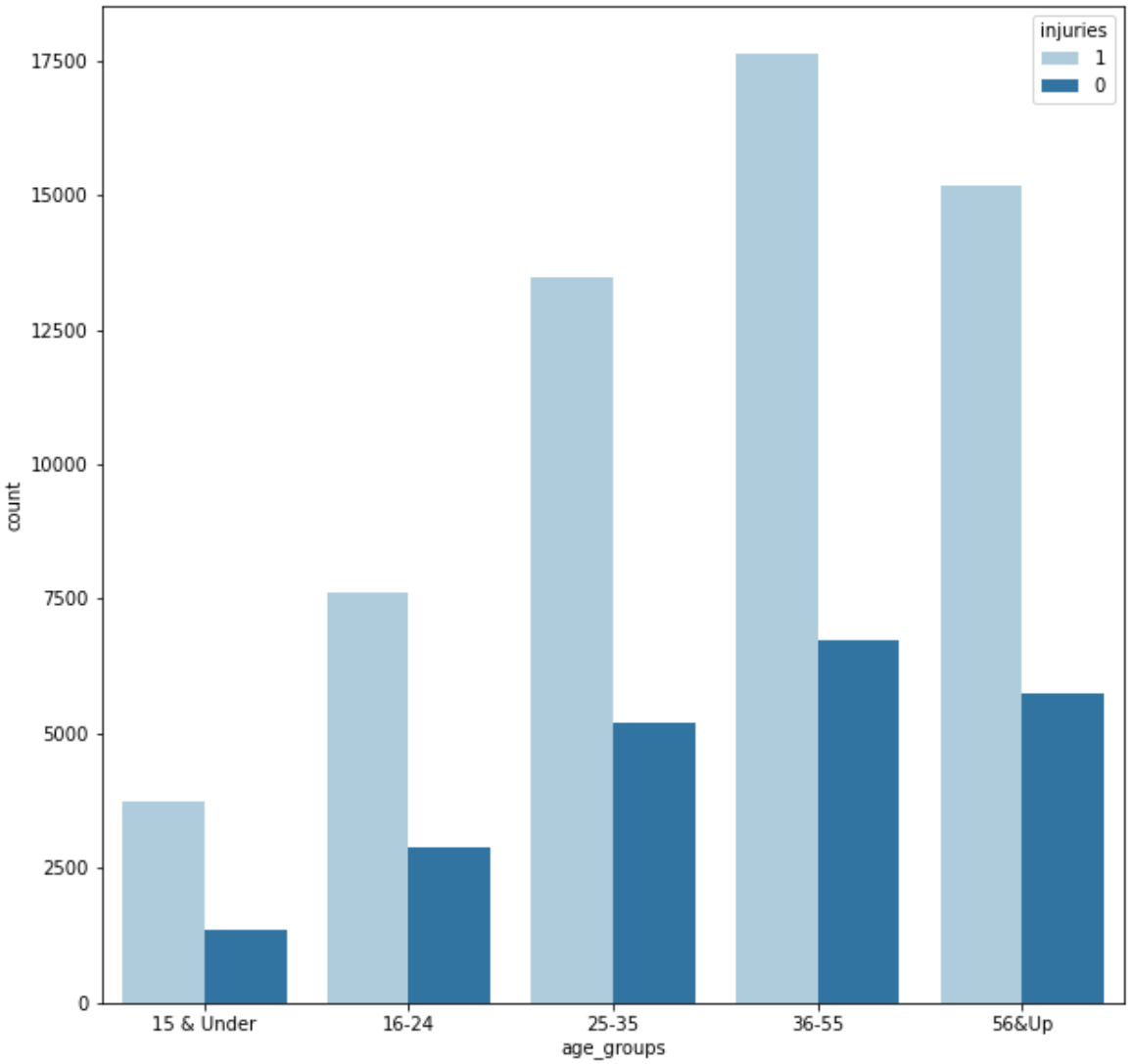
In [72]:
```
plt.figure(figsize=(10,10))
sns.countplot(x = "time_bins", hue = "injuries", data = sample_data, palette
```

Out[72]: <AxesSubplot:xlabel='time_bins', ylabel='count'>



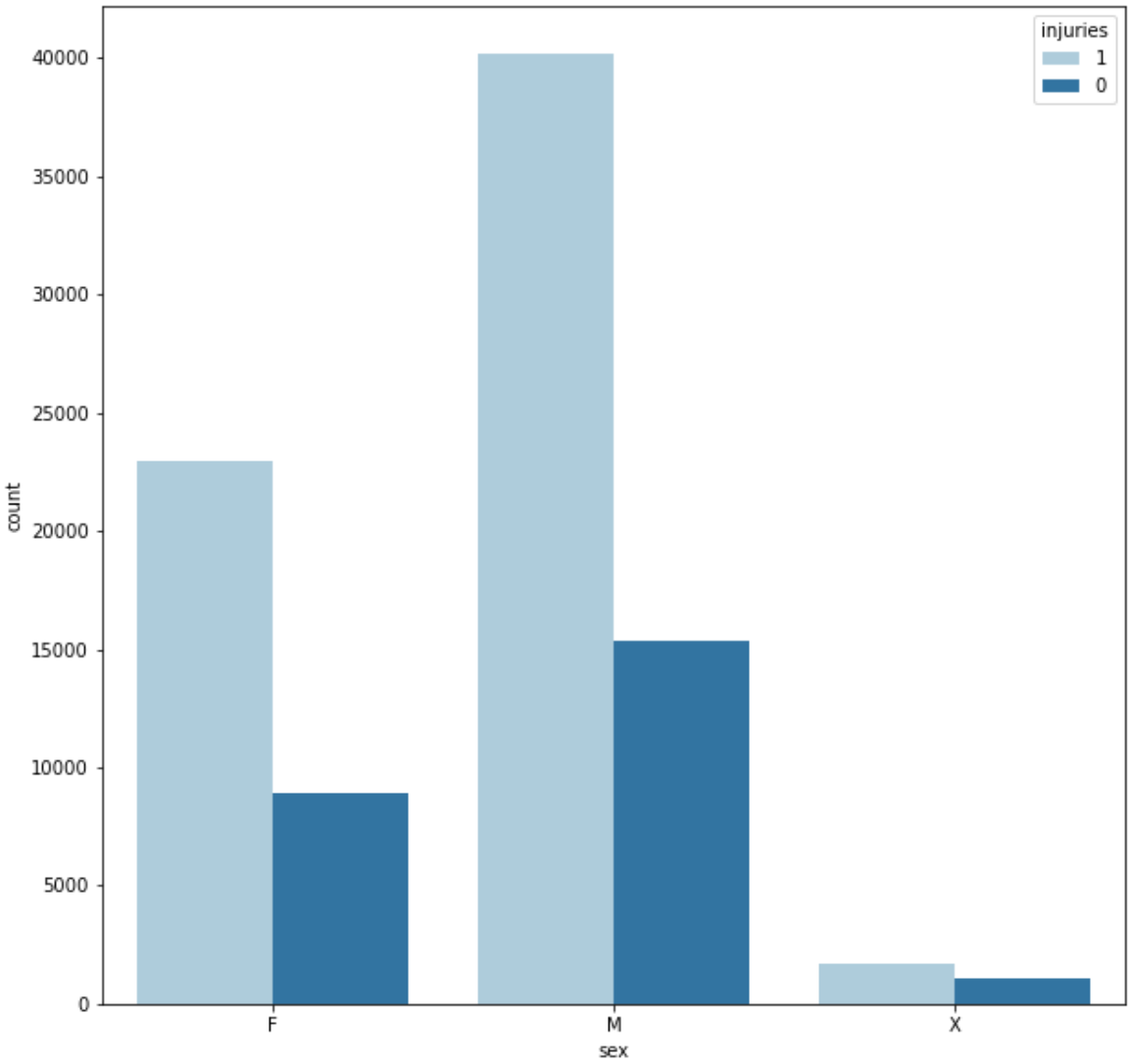
In [73]:
```
plt.figure(figsize=(10,10))
sns.countplot(x = "age_groups", hue = "injuries", data = sample_data, palette
```

Out[73]: <AxesSubplot:xlabel='age_groups', ylabel='count'>



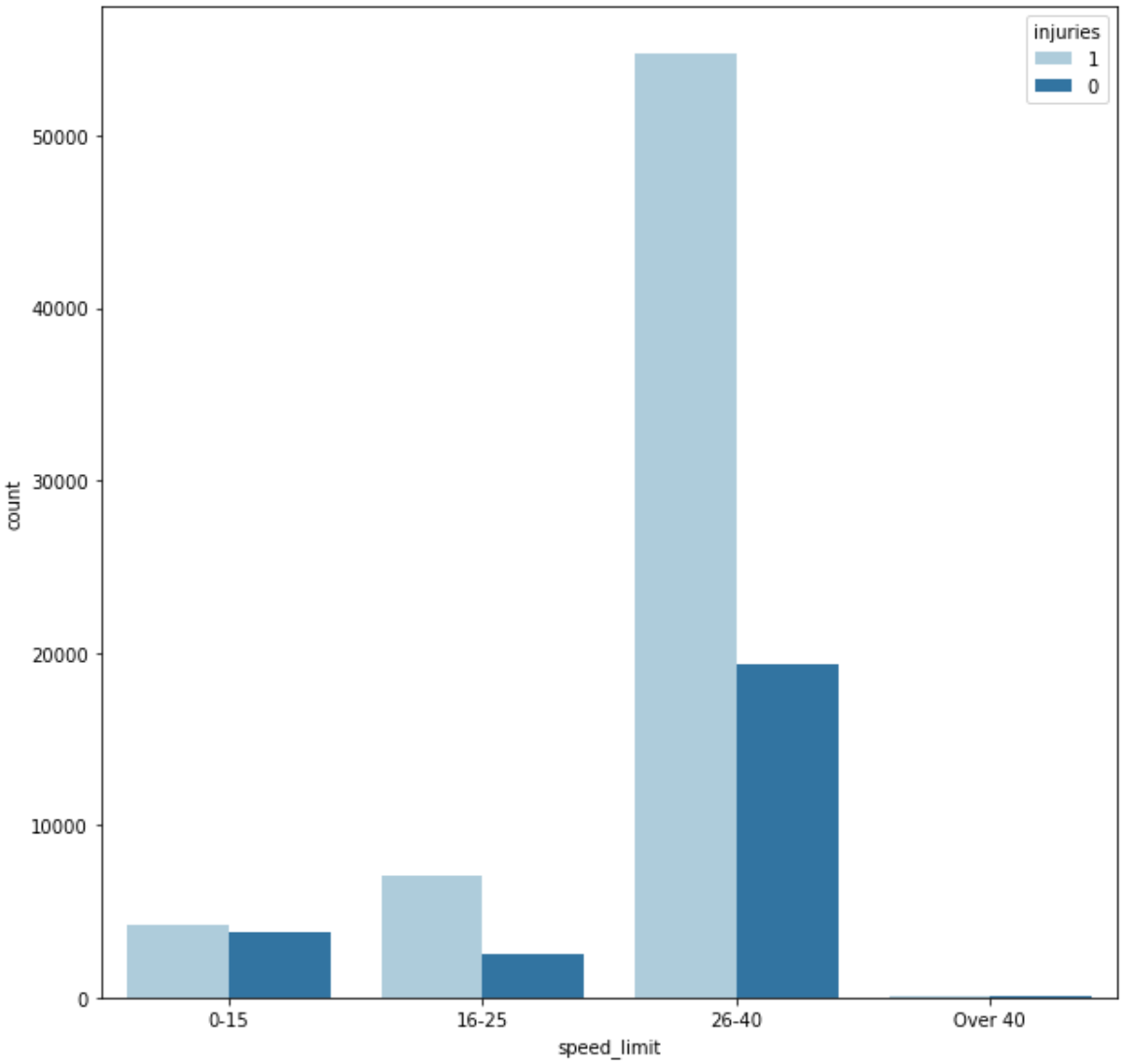
In [74]:
```
plt.figure(figsize=(10,10))
sns.countplot(x = "sex", hue = "injuries", data = sample_data, palette = "Pai
```

Out[74]: <AxesSubplot:xlabel='sex', ylabel='count'>



In [75]:
```
plt.figure(figsize=(10,10))
sns.countplot(x = "speed_limit", hue = "injuries", data = sample_data, palett
```

Out[75]: <AxesSubplot:xlabel='speed_limit', ylabel='count'>



Model

Defining Functions for Modeling:

In [76]:

```
def evaluation(model, X_train_tf, X_test_tf, y_train, y_test, classes = None,
                               normalize = 'true', cmap='Blues_r', label = ''):

    """Input a model, training data and test data to return sklearn metrics
        - Classification Report for training and test
        - Confusion Matrix for training and test
        - ROC Curve for training and test

    """
    # Obtain predictions for train and test:
    y_pred_train = model.predict(X_train_tf)
    y_pred_test = model.predict(X_test_tf)

    #  Display training classification:
    header = label + "Training Classification Report"
    dashes = "---" * 20
    print(dashes, header, dashes, sep='\n')
    print(classification_report(y_train, y_pred_train, target_names = classes

    # Display training figures as visualizations:
    fig, axes = plt.subplots(figsize=(10,4), ncols=2)

    # Planning a confusion matrix:
    plot_confusion_matrix(model, X_train_tf, y_train, labels=classes, normali
                          cmap = 'Blues_r', ax=axes[0])
    axes[0].set(title = "Training Confusion Matrix")

    # Plotting an ROC curve
    plot_roc_curve(model, X_train_tf, y_train, ax=axes[1])
    roc = axes[1]
    roc.legend()
    roc.plot([0,1], [0,1], ls=':')
    roc.grid()
    roc.set_title("ROC Training")
    plt.show()

    # Display classification report
    header_ = label + "Testing Classification Report"
    print(dashes, header_, dashes, sep='\n')
    print(classification_report(y_test, y_pred_test, target_names = classes))

    # Display testing figures as visualizations:
    fig, axes = plt.subplots(figsize=(10,4), ncols=2)

    # Plotting Confusion Matrix
    plot_confusion_matrix(model, X_test_tf, y_test,  labels=classes, normaliz
                          cmap = 'Blues_r', ax=axes[0])


    axes[0].set(title = 'Testing Confusion Matrix')

    # Plotting ROC curve
    plot_roc_curve(model, X_test_tf, y_test, ax=axes[1])
    roc = axes[1]
    roc.legend()
    roc.plot([0,1], [0,1], ls=':')
```

```
    roc.grid()
    roc.set_title('ROC Test')
    plt.show()
```

Model 1: Logistic Regression Model:

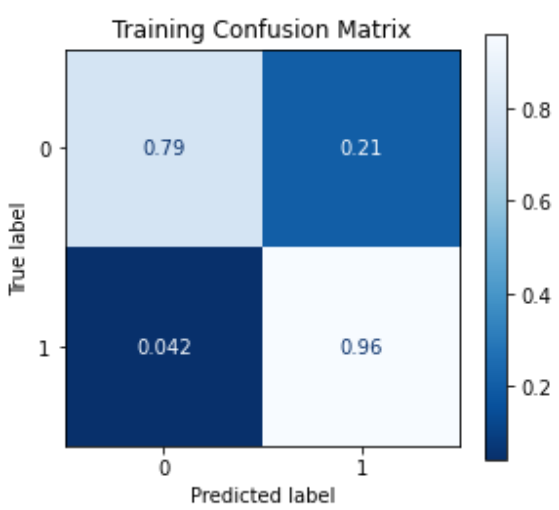
log_reg Vanilla Model

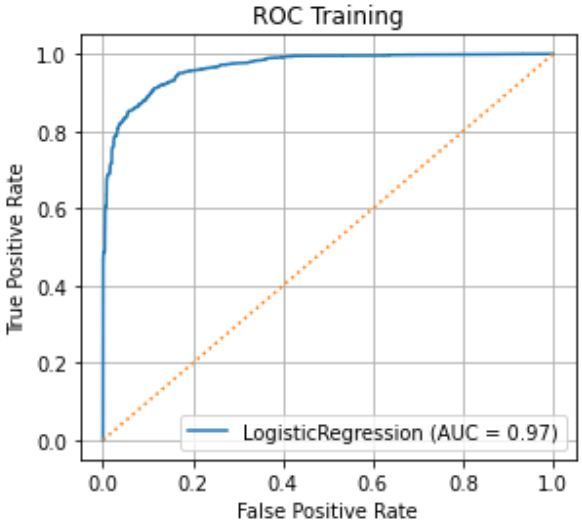
In [77]:

```
# Instantiate LogisticRegression
log_reg = LogisticRegression()

# Fitting the model
log_reg.fit(X_train_tf, y_train)

# Predicting
y_pred = log_reg.predict(X_test_tf)
```

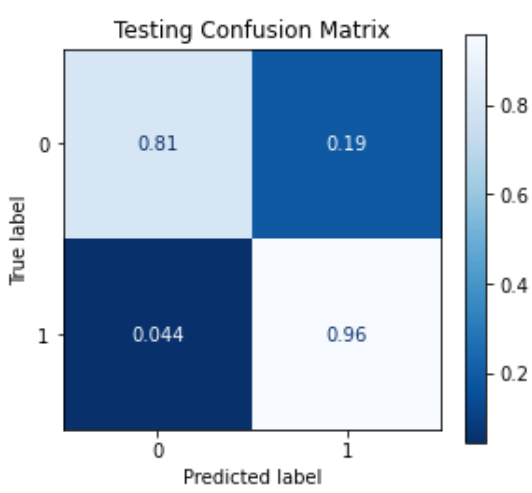
In [78]:
```
# Classification report from above function
evaluation(log_reg,X_train_tf, X_test_tf, y_train, y_test, label = "LOGISTIC
```

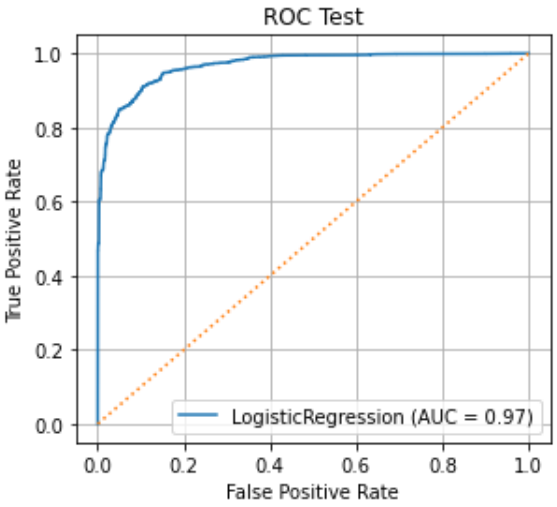
```
------------------------------------------------------------
LOGISTIC REGRESSION Training Classification Report
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.88      0.79      0.84     19407
           1       0.92      0.96      0.94     49655

    accuracy                           0.91     69062
   macro avg       0.90      0.88      0.89     69062
weighted avg       0.91      0.91      0.91     69062
```






```
------------------------------------------------------------
LOGISTIC REGRESSION Testing Classification Report
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.88      0.81      0.84      6413
           1       0.93      0.96      0.94     16608

    accuracy                           0.92     23021
   macro avg       0.90      0.88      0.89     23021
weighted avg       0.91      0.92      0.91     23021
```





log_reg GridsearchCV

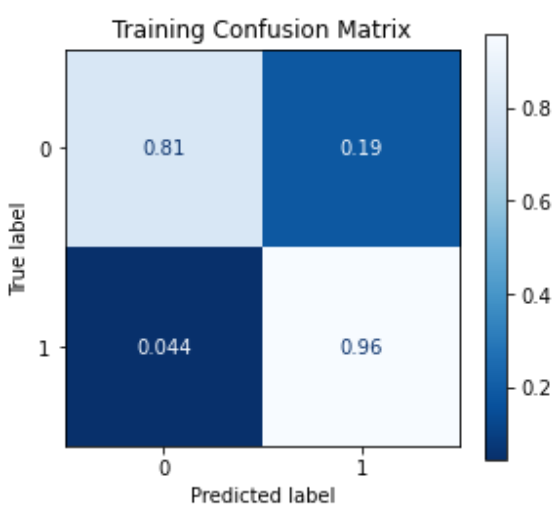
In [79]:
```
# Creating a parameter grid  for Logistic Regression
parameter_grid = {'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'
                  'penalty' : ['l1', 'l2', 'elasticnet', None]}

# Creating a grid search
grid = GridSearchCV(log_reg, parameter_grid, cv=3, scoring=f1_scorer)

# Fitting X_train and y_train to grid
gridlock = grid.fit(X_train_tf, y_train)

# Display best parameters
gridlock.best_params_
```

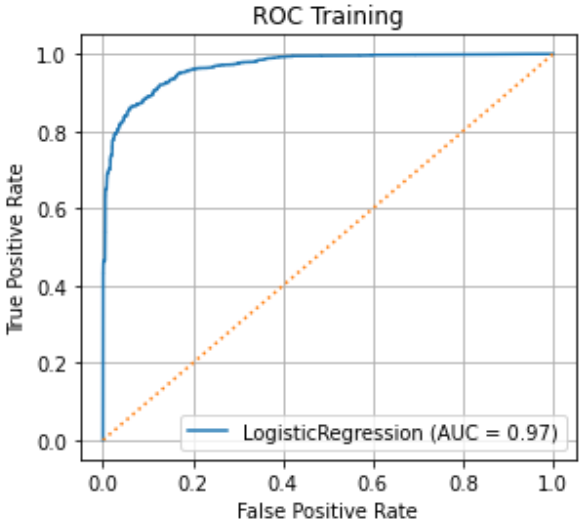
Out[79]:
```
{'penalty': 'l1', 'solver': 'liblinear'}
```

In [80]:

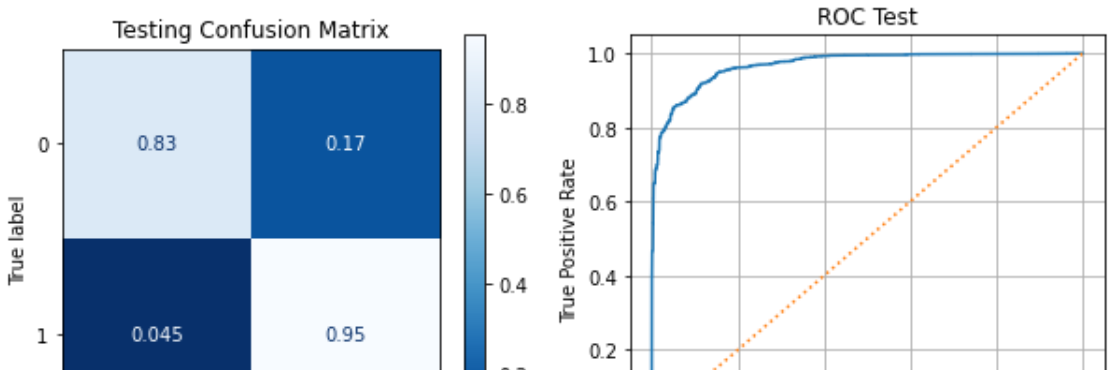
```
# Evaluate
evaluation(grid.best_estimator_, X_train_tf, X_test_tf, y_train, y_test,
                          label ="LOGISTIC REGRESSION ")
```

```
------------------------------------------------------------
LOGISTIC REGRESSION Training Classification Report
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.88      0.81      0.85     19407
           1       0.93      0.96      0.94     49655

    accuracy                           0.92     69062
   macro avg       0.90      0.89      0.89     69062
weighted avg       0.92      0.92      0.92     69062
```






```
------------------------------------------------------------
LOGISTIC REGRESSION Testing Classification Report
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.88      0.83      0.85      6413
           1       0.94      0.95      0.94     16608

    accuracy                           0.92     23021
   macro avg       0.91      0.89      0.90     23021
weighted avg       0.92      0.92      0.92     23021
```



Model 2: Decision Trees:

In [81]:
```
# Due to the large size, I will again take a smaller sample of the data to pl
small_sample = sample_data.sample(frac =.05)

small_sample
```

Out[81]:

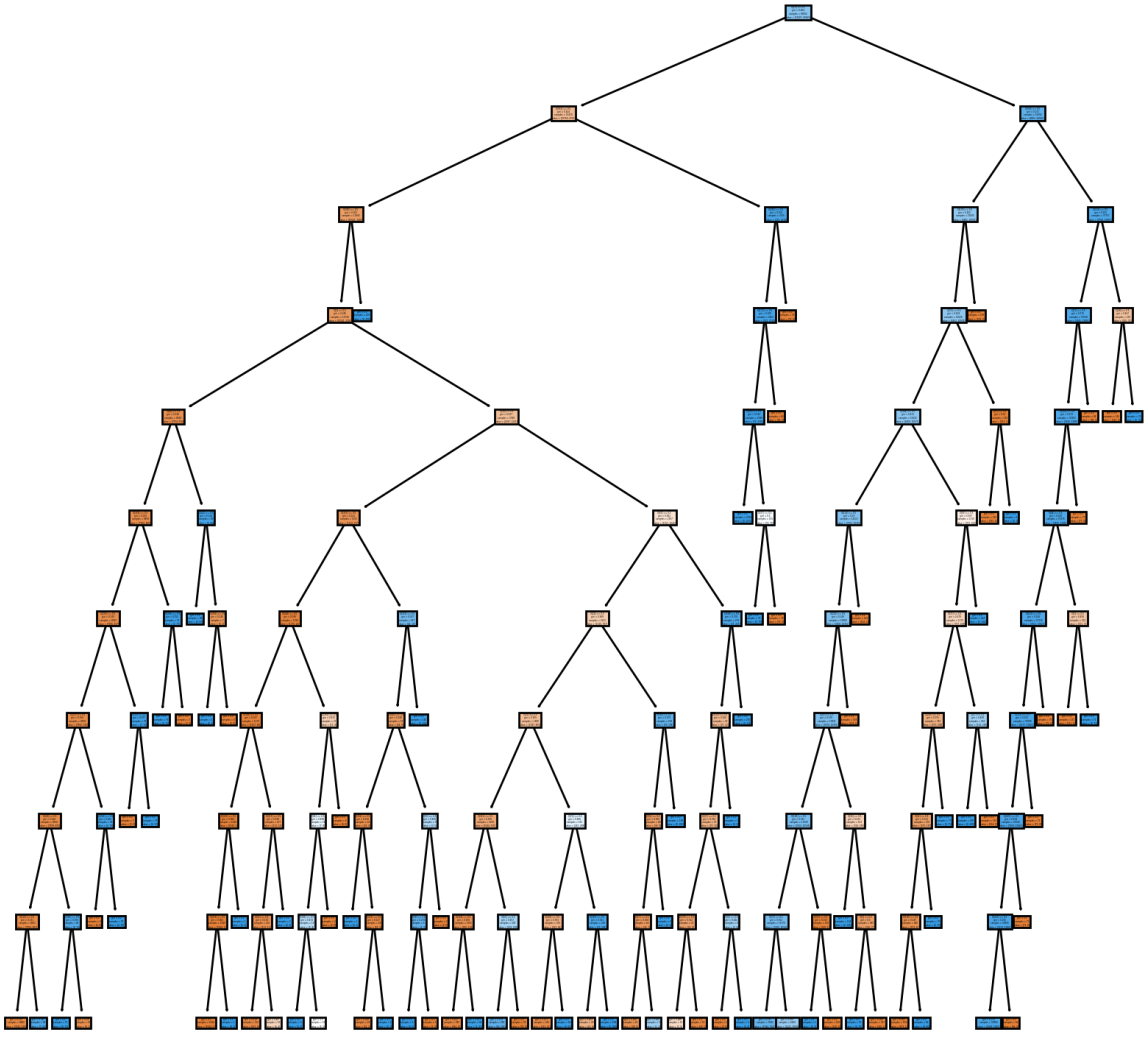
	traffic_control_device	device_condition	weather_condition	lighting_condition	first_
362169	NO CONTROLS	NO CONTROLS	CLEAR	DARKNESS	PE
785988	NO CONTROLS	NO CONTROLS	CLEAR	DAYLIGHT	PE
554556	SIGNAL/SIGN	FUNCTIONING PROPERLY	CLEAR	DAYLIGHT	
203358	NO CONTROLS	NO CONTROLS	CLEAR	DAYLIGHT	PE
185894	NO CONTROLS	NO CONTROLS	CLEAR	DARKNESS, LIGHTED ROAD	PE
...	...	...	...	...	
702225	NO CONTROLS	NO CONTROLS	RAIN/CLOUDY/OTHER	DAYLIGHT	PE
146418	NO CONTROLS	UNKNOWN-NOT FUNCTIONING	NaN	DAYLIGHT	PE
204047	NO CONTROLS	NO CONTROLS	CLEAR	DAYLIGHT	PE
220852	SIGNAL/SIGN	FUNCTIONING PROPERLY	CLEAR	DARKNESS, LIGHTED ROAD	PE
213652	SIGNAL/SIGN	FUNCTIONING PROPERLY	RAIN/CLOUDY/OTHER	DARKNESS, LIGHTED ROAD	PE

4604 rows × 24 columns

In [82]:
```
# Instantiate DecisionTreeClassifier
dt_class = DecisionTreeClassifier(max_depth = 10, random_state=42)
```

In [83]:
```
# Fitting the model
dt_class.fit(X_train_tf, y_train)

# Prediction
y_pred = dt_class.predict(X_test_tf)
```

In [84]:
```
fig, axes = plt.subplots(figsize = (10,10), dpi=200)
tree.plot_tree(dt_class,
               filled = True);
```



dt_class GridSearchCV

In [85]:

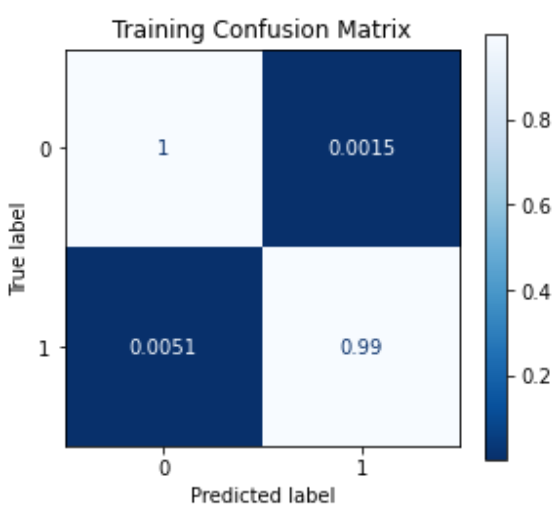
```
# Parameters grid for DecisionTreeClassifier
parameter_grid = {'criterion': ['gini', 'entropy'],
                  'max_depth': [2,4,6,8,10,12,20, None],
                  'min_samples_leaf':[1, 5, 10, 20, 50, 100]}

# Creating a grid search
grid = GridSearchCV(dt_class, parameter_grid, cv=3)

# Fitting to grid
grid.fit(X_train_tf, y_train)

grid.best_params_
```

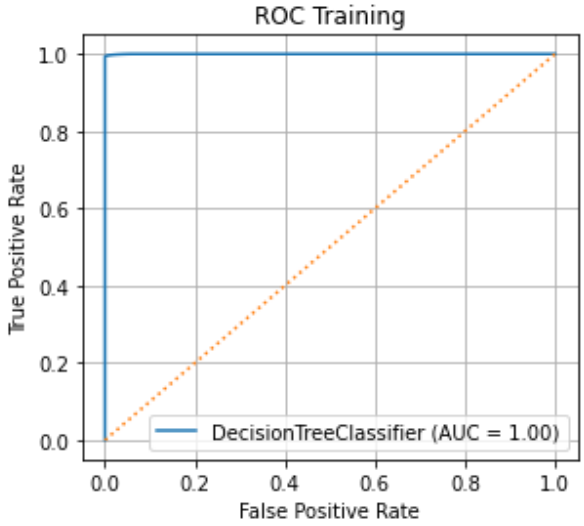
Out[85]:

```
{'criterion': 'entropy', 'max_depth': None, 'min_samples_leaf': 20}
```

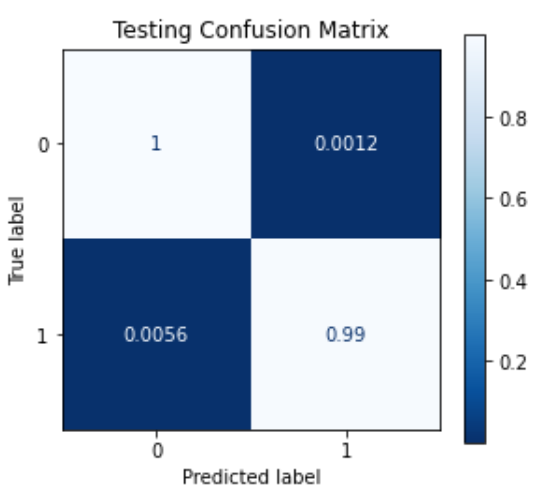
In [86]:
```
evaluation(grid.best_estimator_, X_train_tf, X_test_tf, y_train, y_test,
                        label="DECISION TREE ")
```

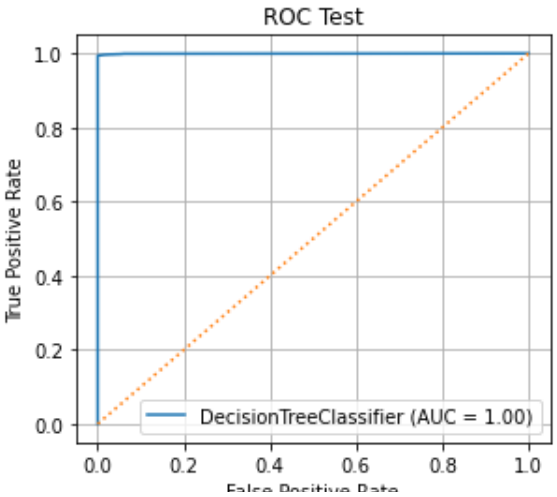
```
------------------------------------------------------------
DECISION TREE Training Classification Report
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.99      1.00      0.99     19407
           1       1.00      0.99      1.00     49655

    accuracy                           1.00     69062
   macro avg       0.99      1.00      0.99     69062
weighted avg       1.00      1.00      1.00     69062
```






```
------------------------------------------------------------
DECISION TREE Testing Classification Report
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      6413
           1       1.00      0.99      1.00     16608

    accuracy                           1.00     23021
   macro avg       0.99      1.00      0.99     23021
weighted avg       1.00      1.00      1.00     23021
```





Model 3: KNN (K-Nearest-Neighbors) Model:

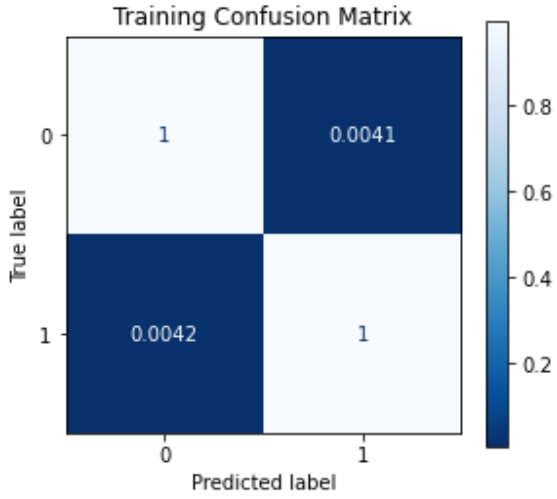
KNN Vanilla Model:

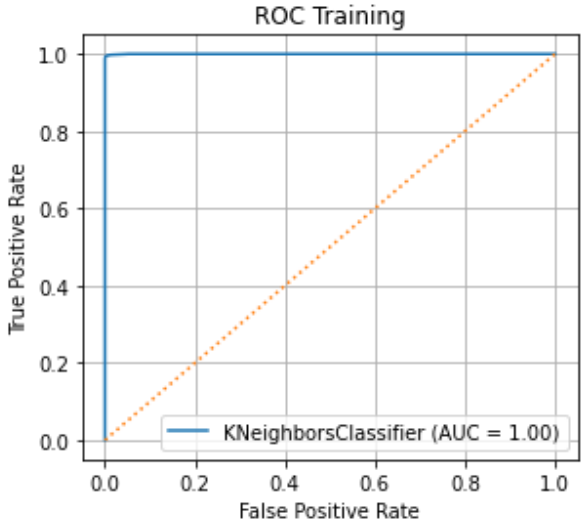
In [87]:

```
# Instantiate KNeighborsClassifier
knn_class = KNeighborsClassifier(n_neighbors= 5)

# Fitting the classifier
knn_class.fit(X_train_tf, y_train)

# Predicting on the test set
y_pred = knn_class.predict(X_test_tf)
```

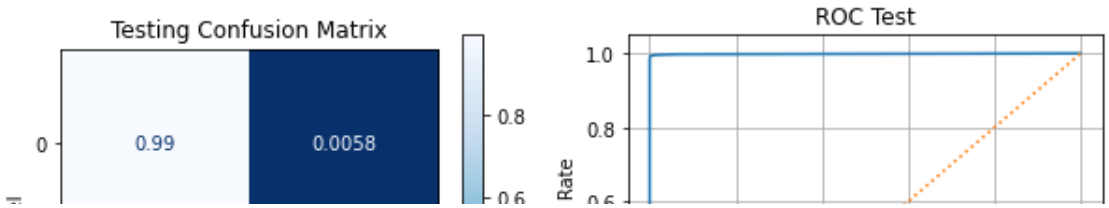
In [88]:
```
evaluation(knn_class, X_train_tf, X_test_tf, y_train, y_test, label = "K-Near
```

```
------------------------------------------------------------
K-Nearest-NeighborsTraining Classification Report
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.99      1.00      0.99     19407
           1       1.00      1.00      1.00     49655

    accuracy                           1.00     69062
   macro avg       0.99      1.00      0.99     69062
weighted avg       1.00      1.00      1.00     69062
```






```
------------------------------------------------------------
K-Nearest-NeighborsTesting Classification Report
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      6413
           1       1.00      0.99      1.00     16608

    accuracy                           0.99     23021
   macro avg       0.99      0.99      0.99     23021
weighted avg       0.99      0.99      0.99     23021
```



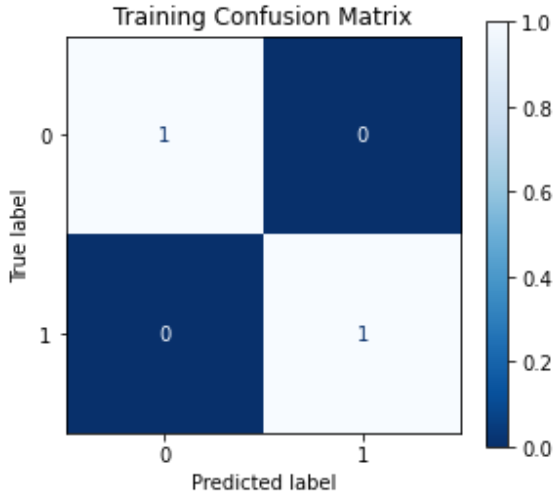
Model 4: Random Forest:

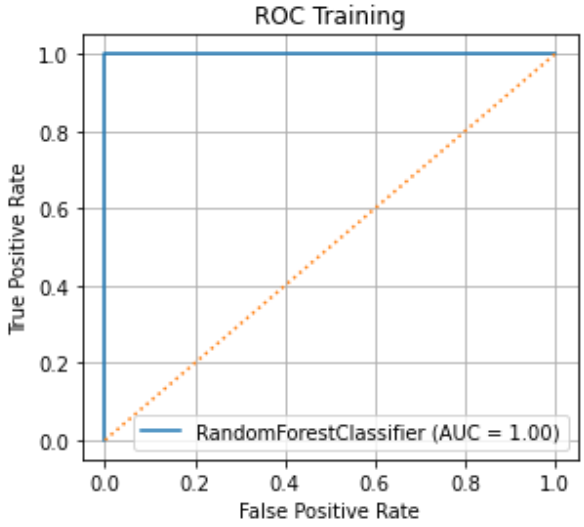
In [89]:

```
forest_class = RandomForestClassifier()

# Fitting
forest_class.fit(X_train_tf, y_train)

#Prediction
y_pred = forest_class.predict(X_test_tf)
```

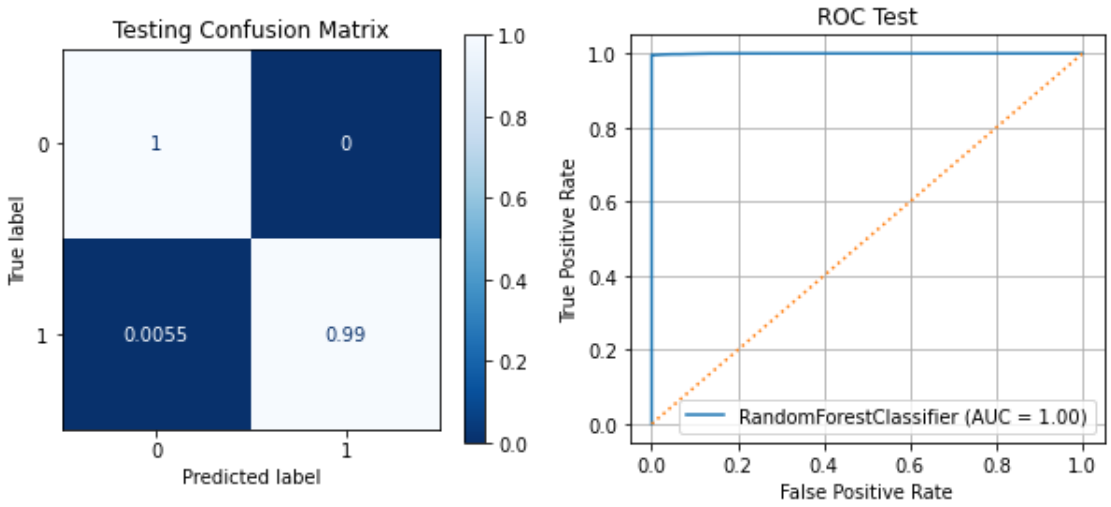
In [90]:
```
evaluation(forest_class, X_train_tf, X_test_tf, y_train, y_test, label = "Ran
```

```
------------------------------------------------------------
Random Forest Training Classification Report
------------------------------------------------------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     19407
           1       1.00      1.00      1.00     49655

    accuracy                           1.00     69062
   macro avg       1.00      1.00      1.00     69062
weighted avg       1.00      1.00      1.00     69062
```






```
------------------------------------------------------------
Random Forest Testing Classification Report
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      6413
           1       1.00      0.99      1.00     16608

    accuracy                           1.00     23021
   macro avg       0.99      1.00      1.00     23021
weighted avg       1.00      1.00      1.00     23021
```



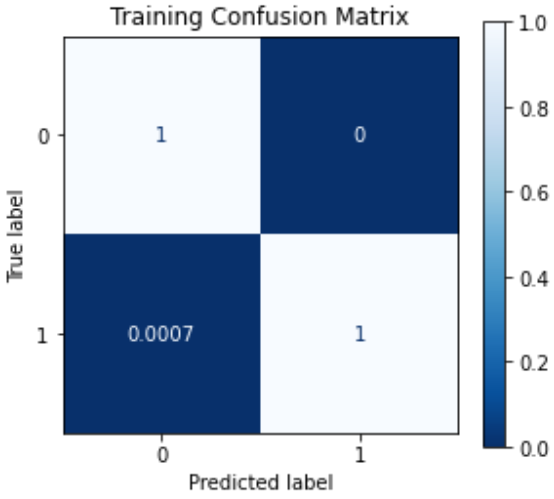
forest_class GridSearchCV:

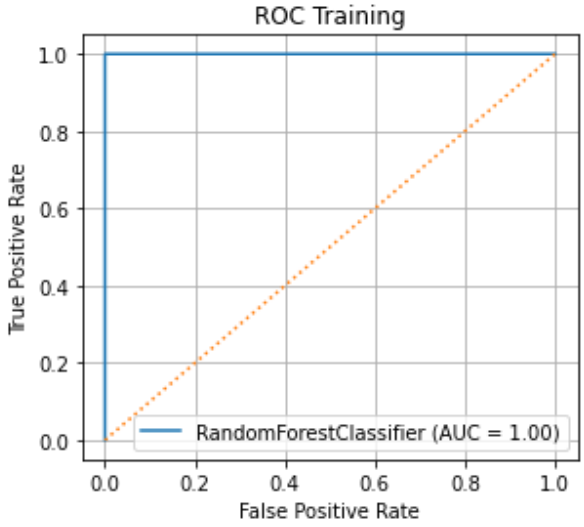
In [91]:
```
parameter_grid = {'criterion': ['gini', 'entropy'],
                  'bootstrap': [True, False],
                  'max_depth': [10, 20, 30, 40, 50, None],
                  'max_features': ['auto', 'sqrt'],
                  'min_samples_leaf': [1, 2, 4],
                  'min_samples_split': [2, 5, 10]}

# Creating grid search
grid = GridSearchCV(forest_class, parameter_grid, cv=3)

# Fitting x_train and y_train to grid
grid.fit(X_train_tf, y_train)

#Display
grid.best_params_
```

Out[91]:
```
{'bootstrap': False,
 'criterion': 'gini',
 'max_depth': None,
 'max_features': 'sqrt',
 'min_samples_leaf': 1,
 'min_samples_split': 10}
```

In [92]:
```
evaluation(grid.best_estimator_, X_train_tf, X_test_tf, y_train, y_test, labe
```

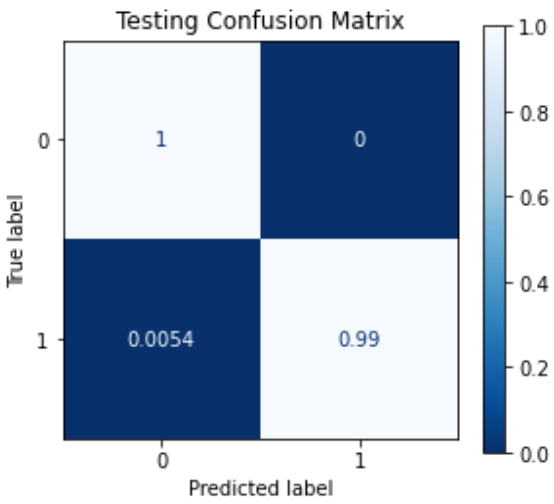
```
------------------------------------------------------------
Random Forest Training Classification Report
------------------------------------------------------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     19407
           1       1.00      1.00      1.00     49655

    accuracy                           1.00     69062
   macro avg       1.00      1.00      1.00     69062
weighted avg       1.00      1.00      1.00     69062
```

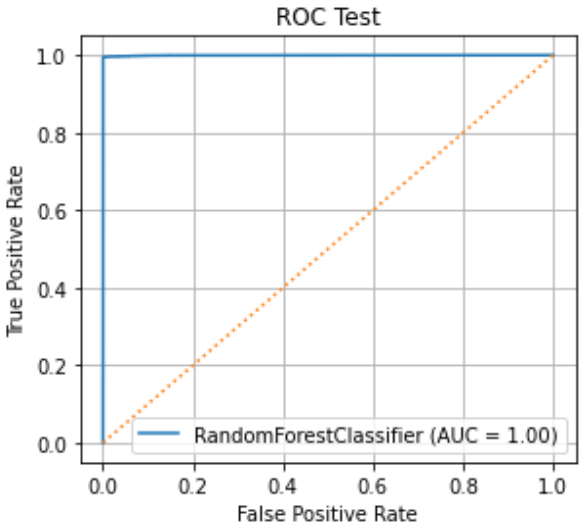





```
------------------------------------------------------------
Random Forest Testing Classification Report
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      6413
           1       1.00      0.99      1.00     16608

    accuracy                           1.00     23021
   macro avg       0.99      1.00      1.00     23021
```

```
weighted avg       1.00      1.00      1.00     23021
```





In [93]:
```
best_class = grid.best_estimator_
```

iNterpretation

Upon examination, I've determined the Logistic Regression Vanilla Model returned an accuracy rate of 92% Our remaining models returned approximately the same rate or higher, however I've chosen this model since the accuracy rate on the training level was not 100%. This means we can somewhat avoid overfitting our model.

In [94]:
```
# Obtaining categorical columns from our pipeline and then converting to a da
sliced_pipe = transformed.named_transformers_['cat']
categoric_features = sliced_pipe.named_steps['encoder'].get_feature_names(cat
X_train_tf = pd.DataFrame(X_train_tf,columns=[*num_cols, *categoric_features]
X_train_tf
```

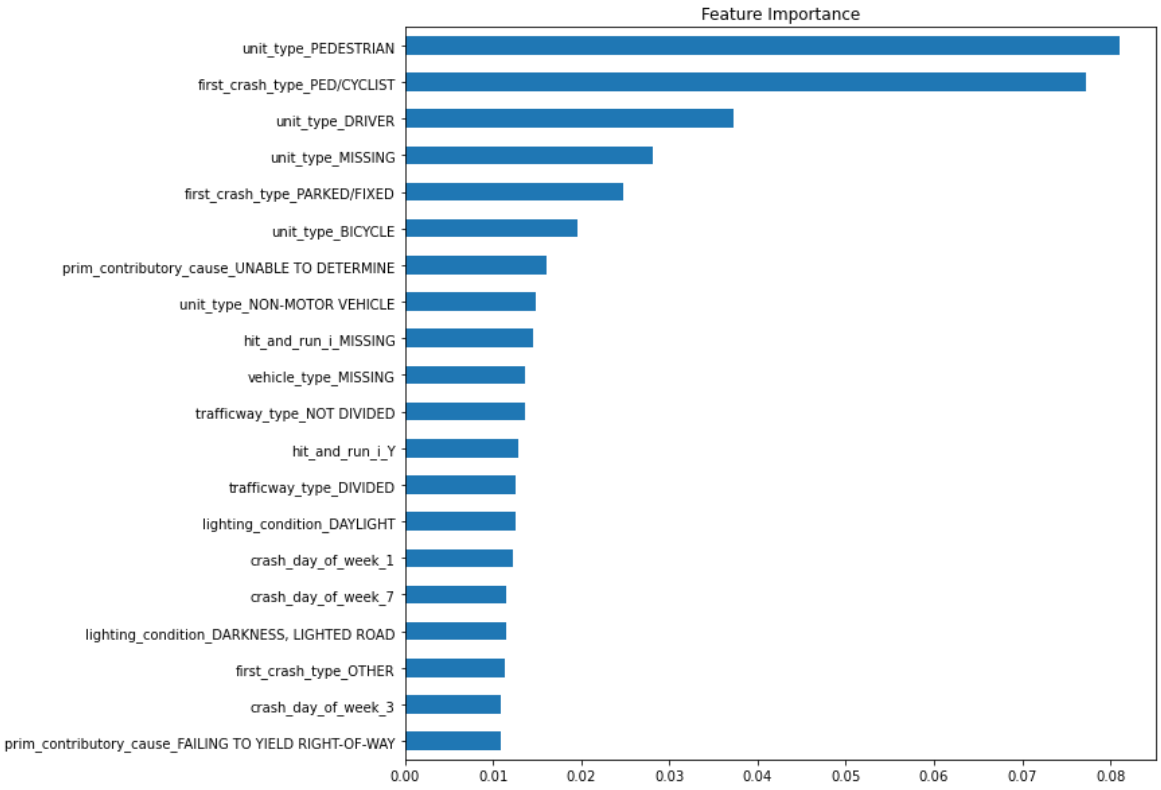
Out[94]:

	traffic_control_device_NO CONTROLS	traffic_control_device_OTHER-UNKNOWN	traffic_control_device_SIGNAL/S
0	0.0	1.0	
1	0.0	0.0	
2	0.0	0.0	
3	1.0	0.0	
4	1.0	0.0	
...	...	...	
69057	0.0	1.0	
69058	1.0	0.0	
69059	1.0	0.0	
69060	1.0	0.0	
69061	0.0	1.0	

69062 rows × 428 columns

In [95]:
```
f_importance = pd.Series(best_class.feature_importances_ ,index=X_train_tf.co
f_importance.sort_values().tail(20).plot(kind='barh', figsize=(10,10), title
```

Out[95]:
```
<AxesSubplot:title={'center':'Feature Importance'}>
```



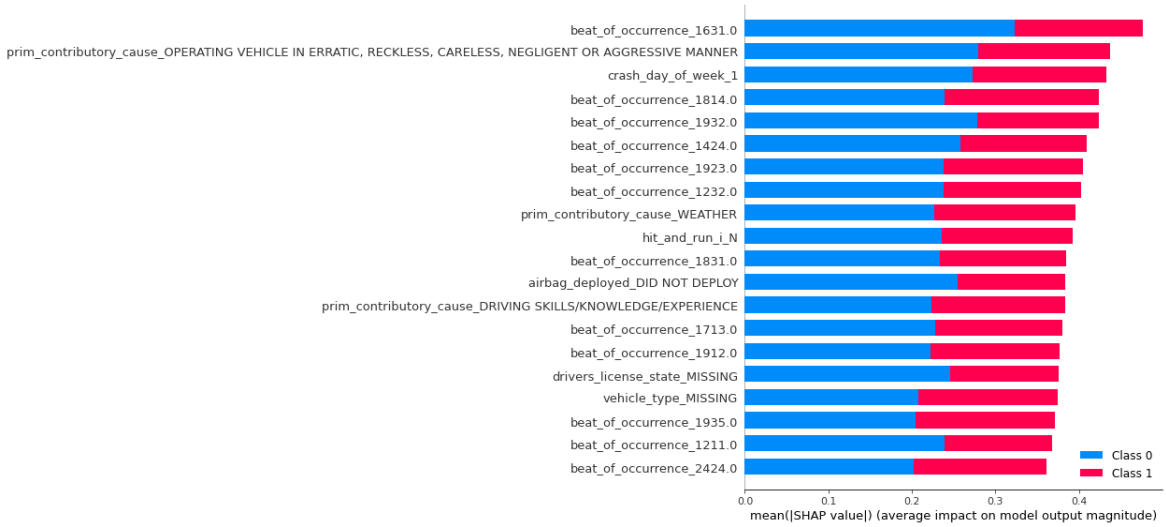
Observations:

Pedestrian, Ped/cyclist, and driver are the most correlated with injuries/accidents

SHAP (SHaplev Additive exPlanations)

A game-theoretic approach to explain the output of any machine learning model.

In [108]:
```
X_shap = shap.sample(X_train_tf)
explainer = shap.TreeExplainer(best_class)
shap_values = explainer.shap_values(X_shap, check_additivity=False)
shap.summary_plot(shap_values, X_shap, plot_type="bar")
```



Observations:

- Most features have a 40/60 split between injuries and no injuries
- While driving recklessly or aggressively causes a lot of accidents, the resulting injuries are less than the lack thereof.
- Less injuries occur when the airbag did not deploy than injuries occurring
- Missing information on type of vehicle involved to determine if the type of vehicle is a cause of injury or not.

Conclusions:

- After examining the data and based on our classification models, the injuries that that seem to result from accidents the most are **collisions between drivers and pedestrians or cyclists.**
- Accidents and injuries occur most often ***in the presence of traffic signals.***
- Additionally most accidents and resulting injuries take place in the **afternoon or during rush hour** as well as on **Saturdays.**
- Most accidents occur in speed limit zones between **30-40 mph.**

My recommendations are as follows:

The city install more cyclist friendly lanes and designated pedestrian walking areas.

Pedestrians and cyclists should be required to wear bright or reflective clothing when traveling at night and in poorly lit areas.

Rush hour speed limit could be lowered.

The city could plan to expand two way roads to include a median/divider to reduce the possibility of wrong way driver collisions

More patrol offered in areas with speed zones that are prone to more accidents.

More classes can be offered in regards to driving safety to teach drivers how to be aware of their surroundings, obey traffic laws, and control road rage.