Exploratory Study on Vehicle Crash Trends in San Jose, CA

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1 Exploratory Study on Vehicle Crash Trends in San Jose, CA (2011-2023)

Author: Austin Kim

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1.1 Introduction

This research aims to analyze vehicle crash incidents in San Jose, CA, from 2011 to June 18, 2023, using data from the San Jose CA Open Data Portal. The study addresses the rising concerns about traffic safety and the increase in vehicular accidents in the area.

1.2 Background

The data for this research comes from two primary sources provided by the San Jose CA Open Data Portal: - vehiclecrashdata2011-2020.csv - vehiclecrashdata2021-present.csv

The study investigates several key questions:

1. Which vehicle type (PartyType) experiences the most severe vehicle damage?
2. Does sobriety impact the severity of vehicle damage?
3. Is there a correlation between the driver's sex and the severity of vehicle damage?
4. Which movements preceding collisions cause the most damage?
5. Which age group experiences the most severe vehicle damage?

An objective will also be in creating a model predicting vehicle damage based on the collected data.

1.3 Analysis

The analysis begins by importing the necessary libraries and loading the CSV files into dataframes. After verifying that the columns are consistent across the files, the dataframes are concatenated into a single dataframe. Missing values are identified and addressed, with columns containing excessive missing data being dropped.

Importing Libraries

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

import matplotlib
```

```
import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns

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

Now let's import the csv file of the vehicle crash data provided by the San Jose CA Open Data portal. One file is from 2011 to 2020 while the other vehicle crash data is from 2021 to the present (as of June 18th 2023). I will verify that the columns are the same for both files and then combine them into one dataframe.

Data Preparation The initial data prepartion includes:

Dropping Columns with excessive values or irrelevant data

Dropping rows with missin gvalues

Converting categorical variables into numerical values

[ ]:
```
dfs = [  # load all csv files into a list of dataframes
    pd.read_csv('vehiclecrashdata2011-2020.csv'),
    pd.read_csv('vehiclecrashdata2021-present.csv')
]

shapeY = dfs[0].shape[1]

for df in dfs:
    if shapeY != df.shape[1]:        # check if columns are the same for each df
        print('Columns are not the same')
    print('Shape of data below', df.shape)
    display(df.head())  # display each df head
```

```
Shape of data below (115302, 15)

      CrashName            Name  Sex  Age  Speed VehicleDamage PartyCategory  \
0  CR-0000063652  ACV-0000000030    M    0    NaN         Minor        Driver
1  CR-0000068628  ACV-0000000031  NaN    0    NaN       Unknown        Driver
2  CR-0000064498  ACV-0000000032    F   50    NaN         Minor        Driver
3  CR-0000068721  ACV-0000000033    M   19    NaN         Minor        Driver
4  CR-0000064227  ACV-0000000034    M   16    NaN       Unknown        Driver

                Sobriety VehicleDirection MovementPrecedingCollision  \
0   Impairment Not Known             East         Proceeding Straight
1   Impairment Not Known          Unknown                     Backing
2  Had Not Been Drinking            South            Parking Maneuver
3  Had Not Been Drinking            North         Proceeding Straight
4  Had Not Been Drinking             East            Making Left Turn
```

```
  PartyType OtherAssociatedFactor  VehicleCount ViolationCode  \
0       Car               Unknown             1         00001
1   Unknown           Inattention             1         00001
2       Car               Unknown             1         00001
3       Car           Inattention             1         00001
4       Car         None Apparent             1         00001

  ViolationCodeDescription
0   Other Improper Driving
1   Other Improper Driving
2   Other Improper Driving
3   Other Improper Driving
4   Other Improper Driving
```

```
Shape of data below (20240, 15)
```

```
       CrashName             Name  Sex  Age  Speed VehicleDamage PartyCategory  \
0  CR-0000085197  ACV-0000174389    M   33    NaN       Unknown        Driver
1  CR-0000085197  ACV-0000174390  NaN    0    NaN       Unknown        Driver
2  CR-0000085218  ACV-0000174429    M   19    NaN         Major        Driver
3  CR-0000085218  ACV-0000174430  NaN    0    NaN      Moderate        Parked
4  CR-0000085218  ACV-0000174431  NaN    0    NaN      Moderate        Parked

                Sobriety VehicleDirection MovementPrecedingCollision  \
0   Impairment Not Known             West                    Stopped
1   Impairment Not Known             West          Making Right Turn
2  Had Not Been Drinking             East         Proceeding Straight
3         Not Applicable   Not Applicable                     Parked
4         Not Applicable   Not Applicable                     Parked

  PartyType OtherAssociatedFactor  VehicleCount   ViolationCode  \
0       Car               Unknown             1         Unknown
1       Car               Unknown             1         Unknown
2       Car              Speeding             1           23103
3       Car               Unknown             1  Not Applicable
4       Car               Unknown             1  Not Applicable

  ViolationCodeDescription
0                  Unknown
1                  Unknown
2       Reckless Driving 2
3           Not Applicable
4           Not Applicable
```

Concatenate the two dataframes into one dataframe called “df”. Here, I am verifying that the individual shape add up to the total shape to make sure I concatenated the dataframes correctly. The columns are checked in the last cell so I will only check the rows here.

[ ]:
```python
df = pd.concat(dfs, axis=0, ignore_index=True)

print('Shape of combined data:', df.shape)
```

```
Shape of combined data: (135542, 15)
```

I want to check the null or empty values for each column. If too much data is missing from a columns I will remove it.

[ ]:
```python
print('\nNull Values for each column:')        # check for null values
print(df.isnull().sum())
```

```

Null Values for each column:
CrashName                        0
Name                             0
Sex                          35804
Age                              0
Speed                        84772
VehicleDamage                 4163
PartyCategory                    0
Sobriety                         0
VehicleDirection                 0
MovementPrecedingCollision       0
PartyType                        0
OtherAssociatedFactor            0
VehicleCount                     0
ViolationCode                    0
ViolationCodeDescription         0
dtype: int64
```

Too many values are missing for "Speed", so I will drop it. "Name" and "CrashName" are not relavent with this study and can be dropped.

[ ]:
```python
df = df.drop(columns=["Speed",
                      "CrashName",
                      "Name"])         # Too many missing values

df = df.dropna()                         # drop rows with missing values
```

Observing the Unique values in each column to see if some columns are irrelevant or can be dropped.

[ ]:
```python
print('Unique Values for each column:')
for col in df.columns:
    print(col, df[col].unique())
```

```
Unique Values for each column:
Sex ['M' 'F']
Age [ 0  50  19  16  23  76  25  48  20  18  38  45  62  36  59  58  28  41
  34  22  57  24  42  37  21  43  40  32  52  80  17  55  31  61  65  74
```

```
  64  35  30  70  47  66  85  56  44  51  39  63  54  77  46  26  67  27
  33  53  71  72  60  29  15  73  90  14  69  49  11  68  82  89  81  13
  10  88  12  93  78   6   8  86  75   9  84  83   1  79  87  92  95   5
   4  98  91  99  96   7   3   2  97  94 100 150 101 140]
VehicleDamage ['Minor' 'Unknown' 'Major' 'Moderate' 'Not Applicable' 'Totaled']
PartyCategory ['Driver' 'Parked' 'Bicycle' 'Pedestrian' 'Other' 'Unknown']
Sobriety ['Impairment Not Known' 'Had Not Been Drinking'
 'Had Been Drinking - Not Under Influence' 'Sleepy/Fatigued'
 'Impairment Physical' 'Had Been Drinking - Under Influence'
 'Under Drug Influence' 'Had Been Drinking - Impairment Unknown'
 'Not Applicable']
VehicleDirection ['East' 'South' 'North' 'Not Applicable' 'West' 'Unknown']
MovementPrecedingCollision ['Proceeding Straight' 'Parking Maneuver' 'Making
Left Turn' 'Parked'
 'Ran Off Road' 'Slowing/Stopping' 'Entering Traffic' 'Making Right Turn'
 'Other' 'Other Unsafe Turning' 'Traveling Wrong Way' 'Stalled'
 'Passing Other Vehicles' 'Other (Bike)' 'Merging' 'Backing' 'Unknown'
 'Stopped' 'Making U-Turn' 'Changing Lanes' 'Crossing Into Opposing Lane'
 'Other (Ped)']
PartyType ['Car' 'Panel Truck' 'Unknown' 'Motorcycle/Moped' 'Car With Trailer'
 'Emergency Vehicle' 'Bus - Other' 'Bicycle' 'Other' 'Scooter Motorized'
 'Construction Equipment' 'Semi Truck' 'Pedestrian' 'Skateboard'
 'Wheelchair' 'Bus - School' 'Scooter Non-Motorized' 'Light Rail Vehicle'
 'Ice Cream Truck' 'Train']
OtherAssociatedFactor ['Unknown' 'Inattention' 'None Apparent' 'Other' 'Other
Violation'
 'Defective Vehicle Equipment' 'Vision Obscurement' 'Speeding'
 'Not Applicable' 'Violation By Bike' 'Stop And Go Traffic'
 'Entering/Leaving Ramp' 'Improper Turn' 'Under Influence'
 'Improper Light' 'Right Of Way' 'Improper Passing'
 'Violation By Pedestrian' 'Unfamiliar With Road' 'Previous Collision'
 'Improper Signal' 'Improper Lane Change' 'Improper Parking'
 'Runaway Vehicle' 'Other Improper Turn' 'DIS R1R/SIG' 'Inva. Brakes'
 'Uninvolved Vehicle' 'Following Too Close' 'Other Defect' 'Dis Control'
 'Lt of Center' 'Other Violation;Inattention' 'Unknown;None Apparent'
 'None Apparent;Stop And Go Traffic'
 'Entering/Leaving Ramp;Vision Obscurement' 'Unknown;Other Violation'
 'Other Violation;Stop And Go Traffic'
 'Other Violation;Unfamiliar With Road' 'None Apparent;Inattention'
 'Entering/Leaving Ramp;Stop And Go Traffic'
 'Inattention;Entering/Leaving Ramp' 'None Apparent;Entering/Leaving Ramp'
 'Other;Stop And Go Traffic' 'None Apparent;Other Violation'
 'None Apparent;Vision Obscurement' 'Other Violation;Previous Collision'
 'Other Violation;Vision Obscurement'
 'Other Violation;Entering/Leaving Ramp' 'Inattention;Other'
 'Other Violation;Under Influence' 'Inattention;Stop And Go Traffic'
 'Other Violation;Other' 'Other Violation;Defective Vehicle Equipment'
 'Inattention;Vision Obscurement' 'Inattention;Under Influence'
```

```
 'Speeding;Under Influence' 'Other Violation;Inattention;Other'
 'Other Violation;Runaway Vehicle' 'Inattention;Previous Collision'
 'Other Violation;Inattention;Entering/Leaving Ramp'
 'Other Violation;Speeding' 'Unknown;Inattention'
 'Other Violation;Entering/Leaving Ramp;Speeding'
 'Entering/Leaving Ramp;Unfamiliar With Road'
 'Inattention;Unfamiliar With Road' 'Other;Previous Collision'
 'Other;Entering/Leaving Ramp;Uninvolved Vehicle' 'Inattention;Speeding'
 'Other;Violation By Pedestrian']
VehicleCount [1]
ViolationCode ['00001' '21235' '21451' '21453' '00002' '12500' '20002' '21200'
'21202'
 '21456' '21803' '21461' '22101' '21209' '22103' '21754' '22114' '22400'
 '22515' '22517' '21951' '21953' '26452' '22108' '21460' '21657' '21712'
 '21755' '21203' '21457' '24002' '22521' '21804' '21658' '21806' '21950'
 '21952' '22100' '22102' '22109' '23109' '23140' '23152' '21650' '21651'
 '21663' '21750' '21751' '21752' '21753' '21949' '21954' '21955' '21956'
 '22350' '21703' '21800' '21801' '21802' '22450' '22451' '22105' '23101'
 '23102' '23103' '26453' '27360' '27456' 'Unknown' '22106' '22107' '22500'
 '23153' '24250' '27465' '29003' '29004' 'Not Applicable' '23123']
ViolationCodeDescription ['Other Improper Driving' 'Laws Apply To Motorized
Scooter'
 'Failure To Go On Green/Arrow' 'Run Red Light' 'Fell Asleep'
 'Unlicensed Driver' 'Leave Accident Scene' 'Laws Applied To Bike'
 'Wrong Way Bike' "Pedestrian Don't Walk" 'Yield Yield Sign'
 'Obey Traffic Control' 'Regulation Of Turns At Intersection'
 'Driving In Bike Lane' 'Unsafe U-Turn' 'Pass' 'Spilling Load'
 'Minimum Speed Law' 'Unattended Vehicle' 'Open Door Traffic'
 'Vehicle Stopped/Pedestrian' 'Overhead Crossing' 'Bad Brakes'
 'Duration/Signal' 'Driving Over Centerline' 'Going Wrong Way'
 'Unlawful Riding' 'Pass On Right' 'Bike Over Centerline'
 'Flashing Signal' 'Vehicle Unsafe' 'Parking On Railroad'
 'Yield From Driveway/Curb' 'Unsafe Lane Change' 'Yield Emergency Vehicle'
 'Yield Pedestrian In Crosswalk' 'Right Of Way/Sidewalk' 'Improper Turn'
 'U-Turn Business District' 'Stop Suddenly' 'Speed Contest'
 'Driving Drunk <21' 'Driving Drunk' 'Driving Wrong Side'
 'Divided Highway' 'Driving On Sidewalk' 'Passing On Left' 'Passing'
 'Driving On Left' 'Yield For Pass' 'Yield Bike-Crosswalk'
 'Pedestrian Yield Car' 'Crossing Controlled Intersection/Jaywalking'
 'Pedestrian On Roadway' 'Speeding' 'Follow Too Closely'
 'Yield Uncontrolled Intersection' 'Yield Left Turn' 'Yield Stop Sign'
 'Fail Stop/Sign' 'Railroad Crossing' 'Obstructed View/U-Turn'
 'Reckless Driving' 'Reckless Driving 1' 'Reckless Driving 2'
 'Condition/Brakes' 'Child Safety/Belt' 'Bald Tires' 'Unknown'
 'Unsafe Backing' 'Unsafe Turn Movement' 'Parking Unlawfully'
 'Driving Drunk With Injury' 'No Head Lights' 'Tire Tread Depth'
 'Unsafe Tow' 'Towed Vehicle' 'Not Applicable' 'Cellphone In Use']
```

Viewing the unique values for each column, I noticed that there are too many "OtherAssociated-Factor", "ViolationCode" and "ViolationCodeDescription" and these features will not help with the data. The column "VehicleCount" only has one value which won't influence in finding relations.

[ ]:
```
df = df.drop(columns=["OtherAssociatedFactor",
                      "ViolationCode",
                      "ViolationCodeDescription",
                      "VehicleCount"])
```

Removing the Unknown values from all columns.

[ ]:
```
df = df[df.Age != 0]
df = df[df.VehicleDamage != 'Unknown']
df = df[df.VehicleDamage != 'Not Applicable']
df = df[df.PartyCategory != 'Unknown']
df = df[df.Sobriety != 'Impairment Not Known']
df = df[df.Sobriety != 'Not Applicable']
df = df[df.VehicleDirection != 'Not Applicable']
df = df[df.VehicleDirection != 'Unknown']
df = df[df.MovementPrecedingCollision != 'Unknown']
df = df[df.PartyType != 'Unknown']

df = df.rename(columns={'VehicleDamage': 'Damage',  # shorten column name
                        'PartyCategory': 'PartyCat',
                        'VehicleDirection': 'Direction',
                        'MovementPrecedingCollision': 'Movement'})

print('Shape after cleaning', df.shape)                # check new size of␣
 ↪dataset
display(df.head())                             # show first five rows of data
```

```
Shape after cleaning (50733, 8)

   Sex  Age    Damage PartyCat               Sobriety Direction  \
2    F   50     Minor   Driver  Had Not Been Drinking     South
3    M   19     Minor   Driver  Had Not Been Drinking     North
9    M   76     Major   Driver  Had Not Been Drinking      West
13   M   20     Minor   Driver  Had Not Been Drinking      West
14   F   18  Moderate   Driver  Had Not Been Drinking      West

              Movement    PartyType
2     Parking Maneuver          Car
3   Proceeding Straight          Car
9   Proceeding Straight  Panel Truck
13      Making Left Turn          Car
14  Proceeding Straight          Car
```

Convert all the object datatypes into numerical datatypes so that I can generate a pairplot and correlation matrix.

```
[ ]: print('Data Types:')
     print(df.dtypes)
```

```
Data Types:
Sex            object
Age             int64
Damage         object
PartyCat       object
Sobriety       object
Direction      object
Movement       object
PartyType      object
dtype: object
```

Convert categorical variables into numerical values.

```
[ ]: # prepare data for pairplot
     sex_dict = {'F': 0, 'M': 1}
     df['Sex'] = df['Sex'].map(sex_dict)

     damage_dict = {'None': 0, 'Minor': 1, 'Moderate': 2, 'Major': 3, 'Totaled': 4}
     df['Damage'] = df['Damage'].map(damage_dict)

     partycat_dict = {'Driver': 0, 'Parked': 1, 'Bicycle': 2, 'Pedestrian': 3,␣
      ↪'Other': 4}
     df['PartyCat'] = df['PartyCat'].map(partycat_dict)


     movement = df['Movement'].unique()
     movement_dict = {}
     for i in range(len(movement)):
         movement_dict[movement[i]] = i
     df['Movement'] = df['Movement'].map(movement_dict)

     sobriety = df['Sobriety'].unique()
     sobriety_dict = {}
     for i in range(len(sobriety)):
         sobriety_dict[sobriety[i]] = i
     print('Sobriety Definition Below')
     print(sobriety_dict)
     df['Sobriety'] = df['Sobriety'].map(sobriety_dict)

     direction_dict = {'North': 0, 'West': 1, 'South': 2, 'East': 3}
     df['Direction'] = df['Direction'].map(direction_dict)

     partyType = df['PartyType'].unique()
     partyType_dict = {}
     for i in range(len(partyType)):
```

```
    partyType_dict[partyType[i]] = i
print('PartyType Definition Below')
print(partyType_dict)
df['PartyType'] = df['PartyType'].map(partyType_dict)

print()
display(df.head())

print('Data Types:')
print(df.dtypes)
```

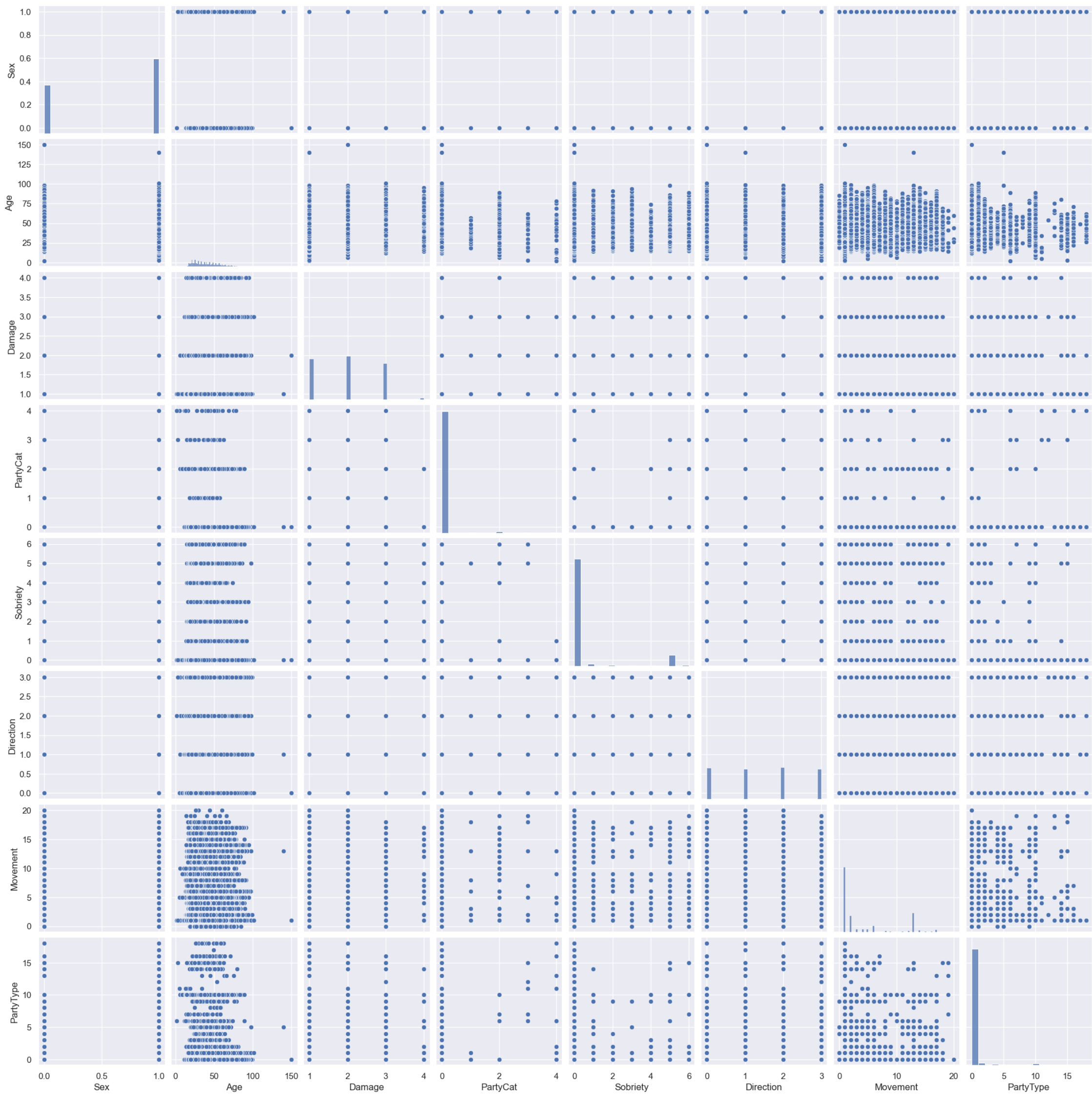
```
Sobriety Definition Below
{'Had Not Been Drinking': 0, 'Had Been Drinking - Not Under Influence': 1,
'Sleepy/Fatigued': 2, 'Impairment Physical': 3, 'Under Drug Influence': 4, 'Had
Been Drinking - Under Influence': 5, 'Had Been Drinking - Impairment Unknown':
6}
PartyType Definition Below
{'Car': 0, 'Panel Truck': 1, 'Motorcycle/Moped': 2, 'Car With Trailer': 3,
'Emergency Vehicle': 4, 'Bus - Other': 5, 'Other': 6, 'Scooter Motorized': 7,
'Construction Equipment': 8, 'Semi Truck': 9, 'Bicycle': 10, 'Skateboard': 11,
'Scooter Non-Motorized': 12, 'Wheelchair': 13, 'Bus - School': 14, 'Pedestrian':
15, 'Light Rail Vehicle': 16, 'Ice Cream Truck': 17, 'Train': 18}
```

	Sex	Age	Damage	PartyCat	Sobriety	Direction	Movement	PartyType
2	0	50	1	0	0	2	0	0
3	1	19	1	0	0	0	1	0
9	1	76	3	0	0	1	1	1
13	1	20	1	0	0	1	2	0
14	0	18	2	0	0	1	1	0

```
Data Types:
Sex           int64
Age           int64
Damage        int64
PartyCat      int64
Sobriety      int64
Direction     int64
Movement      int64
PartyType     int64
dtype: object
```

Exploratory Data Analysis I will create a pairplot and a correlation matrix to view the relationship between the features.

[ ]:
```
sns.set(rc={'figure.figsize': (10, 10)})  # set figure size
sns.pairplot(df)
plt.show()
```



[ ]:
```python
corr = df.corr()

print('Correlation Matrix:')
display(corr)
```

Correlation Matrix:

	Sex	Age	Damage	PartyCat	Sobriety	Direction	\
Sex	1.000000	-0.019113	0.019291	0.050231	0.109745	0.000649	
Age	-0.019113	1.000000	-0.086239	-0.030016	-0.120345	0.006783	
Damage	0.019291	-0.086239	1.000000	-0.067009	0.165210	-0.003236	
PartyCat	0.050231	-0.030016	-0.067009	1.000000	-0.026878	0.004721	
Sobriety	0.109745	-0.120345	0.165210	-0.026878	1.000000	0.002796	
Direction	0.000649	0.006783	-0.003236	0.004721	0.002796	1.000000	

```
Movement  -0.014118  0.020240 -0.221201 -0.009584 -0.076940   0.006678
PartyType  0.133929  0.000334 -0.124160  0.668826 -0.046169   0.000442

           Movement  PartyType
Sex       -0.014118   0.133929
Age        0.020240   0.000334
Damage    -0.221201  -0.124160
PartyCat  -0.009584   0.668826
Sobriety  -0.076940  -0.046169
Direction  0.006678   0.000442
Movement   1.000000  -0.009605
PartyType -0.009605   1.000000
```

Visually viewing the seaborn pairplot, there are no apprant correlation between any of the features. Viewing the correlation matrix above, "PartyCat" and "PartyType" has a moderate to strong correlation.

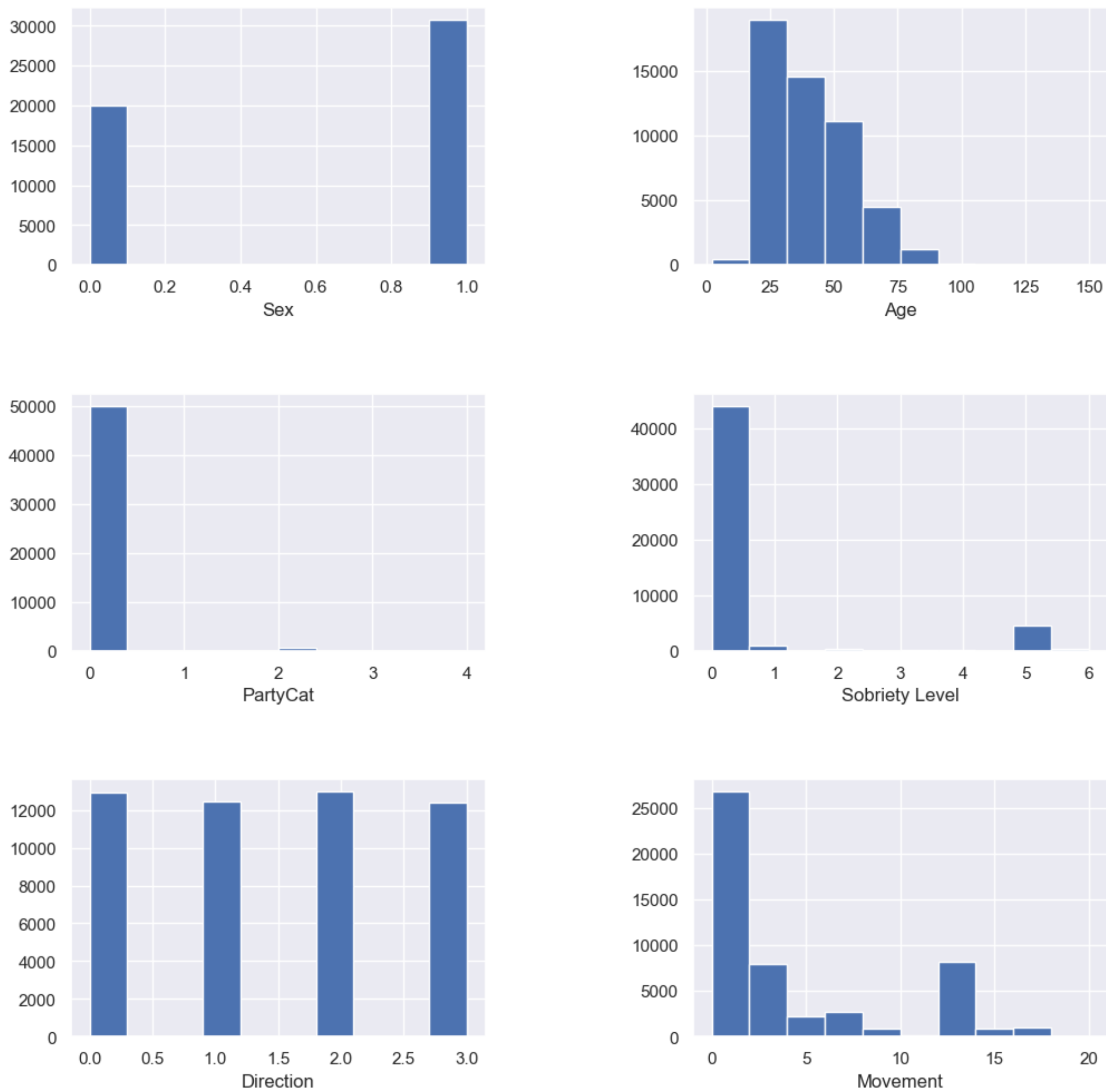
Model Building To start, I will view the distribution of some of the features that might be a good candidate for the model.

I will start by viewing these features in a histogram.

[ ]:
```python
fig = plt.figure(figsize=(12, 12))

plt.subplot(3, 2, 1)       # 2x2 1 subplot
plt.subplots_adjust(hspace=0.5, wspace=0.5)

plt.hist(df['Sex'])
plt.xlabel('Sex')

plt.subplot(3, 2, 2)
plt.hist(df['Age'])
plt.xlabel('Age')

plt.subplot(3, 2, 3)
plt.hist(df['PartyCat'])
plt.xlabel('PartyCat')

plt.subplot(3, 2, 4)
plt.hist(df['Sobriety'])
plt.xlabel('Sobriety Level')

plt.subplot(3, 2, 5)
plt.hist(df['Direction'])
plt.xlabel('Direction')

plt.subplot(3, 2, 6)
plt.hist(df['Movement'])
```

```
plt.xlabel('Movement')
```

[ ]: Text(0.5, 0, 'Movement')

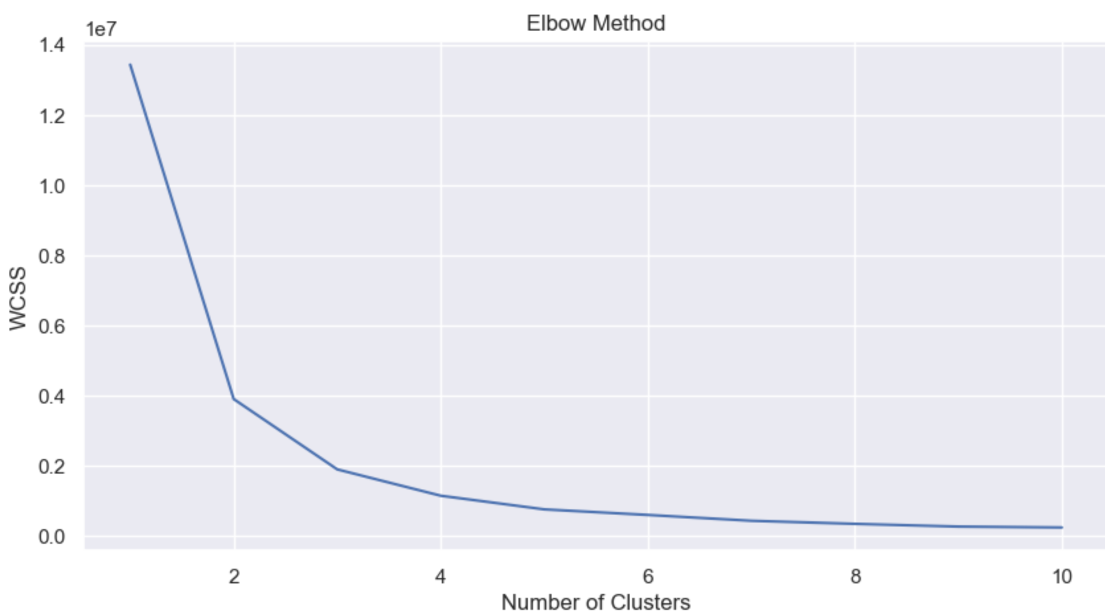


Features “Age” and “Movement” looks like a good candidate to use for the model because it is slightly right skewed. Other features are not good candidates because they are not normally distributed or there are too few parameters to train with therefore the model won’t be near accurate.

Using the elbow method, I will determine the optimal number of clusters for the KMeans model.

[ ]:
```
# kmeans clustering
from sklearn.model_selection import train_test_split
from sklearn.cluster import KMeans
from sklearn.metrics import accuracy_score
```

```
X = df[['Age']]
y = df[['Damage']]

wcss = []

for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++')
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)

plt.figure(figsize=(10, 5))
plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()
```



It looks like the optimal number of clusters is 3.

[ ]:
```
kmeans = KMeans(n_clusters=3, init='k-means++')
kmeans.fit(X)
y_pred = kmeans.predict(X)

print('Accuracy Score of KMeans:', accuracy_score(y, y_pred))
```

```
Accuracy Score of KMeans: 0.19027063252715196
```

The accuracy score is not very accurate, as expected. I will try the same feature but use the classification model to see if it will be more accurate.

```
[ ]: # classifcation model Tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

X = df[['Age']]
y = df[['Damage']]

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

model = DecisionTreeClassifier()

model.fit(X_train, y_train)

y_pred = model.predict(X_test)

print('Accuracy Score of DecisionTreeClassifier:', accuracy_score(y_test,␣
 ↪y_pred))
```

```
Accuracy Score of DecisionTreeClassifier: 0.36000788410367596
```

The accuracy score improved but it is still not near accurate.

I will try creating a model for movement. I think it will be a good candidate because it has lots of parameters to train with but it's really right skewed which might effect accuracy.

```
[ ]: # classification model for movement
X = df[['Movement']]
y = df[['Damage']]

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

model = DecisionTreeClassifier()

model.fit(X_train, y_train)

y_pred = model.predict(X_test)

print('Accuracy Score of DecisionTreeClassifier:', accuracy_score(y_test,␣
 ↪y_pred))
```

```
Accuracy Score of DecisionTreeClassifier: 0.42584014979796986
```

As expected, the score is not impressive btu it is better than the previous models.

I will now answer some statistical questions I created from beginning of the project. Answers will be posted in the conclusion section.

1.3.1 Question 1. Which vehicle type (PartyType) has the worst vehicle damage?

[ ]:
```
rev_partyType_dict = {value: key for key, value in partyType_dict.items()}
df['PartyType'] = df['PartyType'].map(rev_partyType_dict)

print('Vehicle Damage by PartyType:')
display(df.groupby('PartyType')['Damage'].mean().sort_values(ascending=False).
  ↪round(3))
```

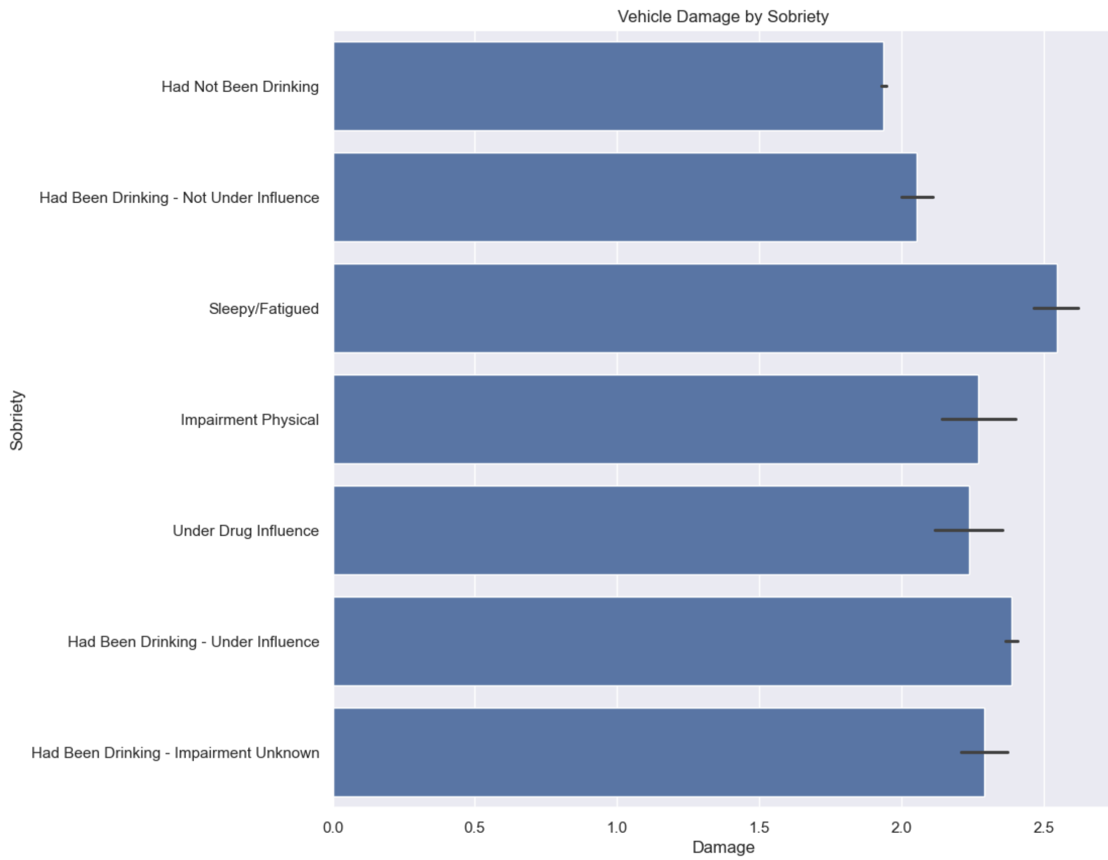
```
Vehicle Damage by PartyType:

PartyType
Scooter Non-Motorized     3.000
Car                       2.022
Motorcycle/Moped          1.964
Panel Truck               1.932
Scooter Motorized         1.733
Construction Equipment    1.714
Car With Trailer          1.658
Bus - School              1.600
Bicycle                   1.533
Other                     1.486
Pedestrian                1.455
Emergency Vehicle         1.401
Semi Truck                1.380
Light Rail Vehicle        1.333
Bus - Other               1.209
Train                     1.200
Skateboard                1.200
Ice Cream Truck           1.000
Wheelchair                1.000
Name: Damage, dtype: float64
```

1.3.2 Question 2: Does sobriety have an impact on vehicle damage?

[ ]:
```
rev_sobreity_dict = {value: key for key, value in sobriety_dict.items()}
df['Sobriety'] = df['Sobriety'].map(rev_sobreity_dict)

print('Vehicle Damage by Sobriety:')
display(df.groupby('Sobriety')['Damage'].mean().sort_values(ascending=False).
  ↪round(3))

# plot bar graph
plt.figure(figsize=(10, 10))
sns.barplot(x='Damage', y='Sobriety', data=df)
plt.title('Vehicle Damage by Sobriety')
plt.show()
```

```
Vehicle Damage by Sobriety:
```

```
Sobriety
Sleepy/Fatigued                              2.545
Had Been Drinking - Under Influence          2.386
Had Been Drinking - Impairment Unknown       2.291
Impairment Physical                          2.270
Under Drug Influence                         2.236
Had Been Drinking - Not Under Influence      2.054
Had Not Been Drinking                        1.937
Name: Damage, dtype: float64
```



1.3.3 Question 3: Does sex and vehicle damage have a correlation?

[ ]:
```
rev_sex_dict = {value: key for key, value in sex_dict.items()}
df["Sex"] = df["Sex"].map(rev_sex_dict)

print("Sex vs Vehicle Damage")
display(df.groupby("Sex")["Damage"].mean().sort_values(ascending=False).
 ↪round(3))
```

```
Sex vs Vehicle Damage
```

```
Sex
M    2.003
F    1.971
Name: Damage, dtype: float64
```

1.3.4 Quetion 4: Which movement preceding collisions causes the most damage?

```
[ ]: rev_movement_dict = {value: key for key, value in movement_dict.items()}
df["Movement"] = df["Movement"].map(rev_movement_dict)

print('Movement vs Vehicle Damage (mean)')
display(df.groupby('Movement')['Damage'].mean().sort_values(ascending=False).
 ↪round(3))
```

```
Movement vs Vehicle Damage (mean)

Movement
Ran Off Road                   2.575
Crossing Into Opposing Lane    2.523
Other Unsafe Turning           2.396
Other                          2.132
Proceeding Straight            2.120
Making Left Turn               2.103
Traveling Wrong Way            2.028
Making U-Turn                  2.013
Entering Traffic               1.886
Parked                         1.829
Passing Other Vehicles         1.818
Changing Lanes                 1.802
Making Right Turn              1.699
Slowing/Stopping               1.636
Other (Ped)                    1.571
Stopped                        1.560
Merging                        1.521
Parking Maneuver               1.505
Backing                        1.437
Other (Bike)                   1.395
Stalled                        1.200
Name: Damage, dtype: float64
```

1.3.5 Question 5: Which age group experiences the most severe vehicle damage?

```
[ ]: bin_list = list(range(0, 101, 5))  # list of bins for age 0-100, inc of 5

print('Age vs Vehicle Damage (mean)')
display(df.groupby(pd.cut(df['Age'], bins=bin_list))['Damage'].mean().
 ↪sort_values(ascending=False).round(3))
```

```python
display(df.head())
```

```
Age vs Vehicle Damage (mean)

Age
(90, 95]     2.222
(15, 20]     2.213
(20, 25]     2.139
(85, 90]     2.080
(80, 85]     2.069
(75, 80]     2.040
(25, 30]     2.025
(70, 75]     1.990
(65, 70]     1.965
(30, 35]     1.963
(95, 100]    1.952
(35, 40]     1.930
(40, 45]     1.904
(55, 60]     1.891
(45, 50]     1.889
(50, 55]     1.884
(60, 65]     1.873
(10, 15]     1.744
(5, 10]      1.333
(0, 5]       1.000
Name: Damage, dtype: float64

   Sex  Age  Damage  PartyCat              Sobriety  Direction  \
2    F   50       1         0  Had Not Been Drinking          2
3    M   19       1         0  Had Not Been Drinking          0
9    M   76       3         0  Had Not Been Drinking          1
13   M   20       1         0  Had Not Been Drinking          1
14   F   18       2         0  Had Not Been Drinking          1

              Movement    PartyType
2     Parking Maneuver          Car
3   Proceeding Straight          Car
9   Proceeding Straight  Panel Truck
13     Making Left Turn          Car
14  Proceeding Straight          Car
```

1.4 Conclusion

The analysis of vehicle crash data in San Jose from 2011 to 2023 reveals several key insights into factors influencing vehicle damage severity. Despite the data limitations and the moderate correlations among features, the findings highlight the significant impact of sobriety, specific movements, and age groups on vehicle damage severity. Future research could benefit from more comprehensive data and advanced modeling techniques to improve prediction accuracy.