Jupyter_Notebook

September 27, 2020

1 Car Accident Severity Analysis using Machine Learning Algorithms

1.0.1 Introduction & Business Understanding

Road accidents are one of the major causes of death and disability all over the world. The major reasons for road accidents can be environmental conditions such as weather, traffic on road, type of road, speed and light conditions. This paper addresses the in-depth analysis that identifies as the contributory factors behind the road accidents and the quantification of the factors that affect the frequency and severity of accidents based on the crash data available.The severity of each accident can be predicted quite accurately with various classification machine learning algorithms. This can ultimately help the government, traffic police, medical institutions, individual drivers and the insurance companies by getting useful insights of the accident severity regarding the causes and consequences of the accidents.The Machine Learning model and its results are going to provide some advice for the target audience to make insightful decisions for reducing the number of accidents and injuries for the city. The model will predict the accident severity with various supervised machine learning algorithms i.e. * Algorithm A. Logistic regression * Algorithm B. The K-Nearest Neighbors (KNN) algorithm * Algorithm C. Decision Tree * Algorithm D. Random Forest And finally, the accuracy score for each considered machine learning algorithm will be plotted to check which algorithm performs better.

1.0.2 Data Understanding

The data used for this project was collected by the SDOT traffic management Division and Seattle Traffic Records Group from 2004 to present. It was downloaded from the link shared in the IBM Applied Data Science Capstone course. The data consists of 38 independent variables and 194,673 rows. The dependent variable, “SEVERITYCODE”, contains numbers that correspond to different levels of severity caused by an accident from 1 to 2. Severity codes are as follows:

- Property Damage Only Collision(1)
- Injury Collision(2)

Furthermore, as there are null values in some records, the data needs to be pre-processed before proceeding further.

Importing the libraries

[2]:
```
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

[3]:
```python
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier

# Import DecisionTreeClassifier from sklearn.tree
from sklearn.tree import DecisionTreeClassifier

# Import RandomForestClassifier
from sklearn.ensemble import RandomForestClassifier

# Import LogisticRegression
from sklearn.linear_model import LogisticRegression

from sklearn.model_selection import train_test_split
from sklearn.feature_selection import SelectFromModel
from sklearn.metrics import accuracy_score
```

Reading the CSV Data

[4]:
```python
# Reading the CSV file "Data-Collisions"

df = pd.read_csv (r"C:\Users\salma\Desktop\Data-Collisions.csv")
df.info()
pd.options.display.max_columns=200
df.head()
```

```
c:\users\salma\desktop\projects\venv\new\new\lib\site-
packages\IPython\core\interactiveshell.py:3145: DtypeWarning: Columns (32) have
mixed types.Specify dtype option on import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 194673 entries, 0 to 194672
Data columns (total 37 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   SEVERITYCODE    194673 non-null  int64
 1   longitude       189339 non-null  float64
 2   latitude        189339 non-null  float64
 3   OBJECTID        194673 non-null  int64
 4   INCKEY          194673 non-null  int64
 5   COLDETKEY       194673 non-null  int64
 6   REPORTNO        194673 non-null  object
 7   STATUS          194673 non-null  object
 8   ADDRTYPE        192747 non-null  object
```

```
 9   INTKEY          65070 non-null   float64
 10  LOCATION        191996 non-null  object
 11  EXCEPTRSNCODE   84811 non-null   object
 12  EXCEPTRSNDESC   5638 non-null    object
 13  SEVERITYDESC    194673 non-null  object
 14  COLLISIONTYPE   189769 non-null  object
 15  PERSONCOUNT     194673 non-null  int64
 16  PEDCOUNT        194673 non-null  int64
 17  PEDCYLCOUNT     194673 non-null  int64
 18  VEHCOUNT        194673 non-null  int64
 19  INCDATE         194673 non-null  object
 20  INCDTTM         194673 non-null  object
 21  JUNCTIONTYPE    188344 non-null  object
 22  SDOT_COLCODE    194673 non-null  int64
 23  SDOT_COLDESC    194673 non-null  object
 24  INATTENTIONIND  29805 non-null   object
 25  UNDERINFL       189789 non-null  object
 26  WEATHER         189592 non-null  object
 27  ROADCOND        189661 non-null  object
 28  LIGHTCOND       189503 non-null  object
 29  PEDROWNOTGRNT   4667 non-null    object
 30  SDOTCOLNUM      114936 non-null  float64
 31  SPEEDING        9333 non-null    object
 32  ST_COLCODE      194655 non-null  object
 33  ST_COLDESC      189769 non-null  object
 34  SEGLANEKEY      194673 non-null  int64
 35  CROSSWALKKEY    194673 non-null  int64
 36  HITPARKEDCAR    194673 non-null  object
dtypes: float64(4), int64(11), object(22)
memory usage: 55.0+ MB
```

[4]:

```
   SEVERITYCODE   longitude   latitude  OBJECTID  INCKEY  COLDETKEY REPORTNO  \
0             2 -122.323148  47.703140         1    1307       1307  3502005
1             1 -122.347294  47.647172         2   52200      52200  2607959
2             1 -122.334540  47.607871         3   26700      26700  1482393
3             1 -122.334803  47.604803         4    1144       1144  3503937
4             2 -122.306426  47.545739         5   17700      17700  1807429

    STATUS      ADDRTYPE   INTKEY  \
0  Matched  Intersection  37475.0
1  Matched         Block      NaN
2  Matched         Block      NaN
3  Matched         Block      NaN
4  Matched  Intersection  34387.0

                                     LOCATION EXCEPTRSNCODE EXCEPTRSNDESC  \
0                  5TH AVE NE AND NE 103RD ST                         NaN
```

```
1   AURORA BR BETWEEN RAYE ST AND BRIDGE WAY N          NaN           NaN
2  4TH AVE BETWEEN SENECA ST AND UNIVERSITY ST          NaN           NaN
3     2ND AVE BETWEEN MARION ST AND MADISON ST                        NaN
4              SWIFT AVE S AND SWIFT AV OFF RP          NaN           NaN

                    SEVERITYDESC COLLISIONTYPE  PERSONCOUNT  PEDCOUNT  \
0               Injury Collision        Angles            2         0
1  Property Damage Only Collision     Sideswipe            2         0
2  Property Damage Only Collision    Parked Car            4         0
3  Property Damage Only Collision         Other            3         0
4               Injury Collision        Angles            2         0

   PEDCYLCOUNT  VEHCOUNT                 INCDATE           INCDTTM  \
0            0         2  2013/03/27 00:00:00+00   3/27/2013 14:54
1            0         2  2006/12/20 00:00:00+00  12/20/2006 18:55
2            0         3  2004/11/18 00:00:00+00  11/18/2004 10:20
3            0         3  2013/03/29 00:00:00+00    3/29/2013 9:26
4            0         2  2004/01/28 00:00:00+00    1/28/2004 8:04

                               JUNCTIONTYPE  SDOT_COLCODE  \
0  At Intersection_related to intersection            11
1  Mid-Block (not related to intersection)            16
2  Mid-Block (not related to intersection)            14
3  Mid-Block (not related to intersection)            11
4  At Intersection_related to intersection            11

                                       SDOT_COLDESC INATTENTIONIND UNDERINFL  \
0  MOTOR VEHICLE STRUCK MOTOR VEHICLE, FRONT END …            NaN         N
1  MOTOR VEHICLE STRUCK MOTOR VEHICLE, LEFT SIDE …            NaN         N
2       MOTOR VEHICLE STRUCK MOTOR VEHICLE, REAR END            NaN         N
3  MOTOR VEHICLE STRUCK MOTOR VEHICLE, FRONT END …            NaN         N
4  MOTOR VEHICLE STRUCK MOTOR VEHICLE, FRONT END …            NaN         N

    WEATHER ROADCOND                LIGHTCOND PEDROWNOTGRNT  SDOTCOLNUM  \
0  Overcast      Wet                 Daylight           NaN         NaN
1   Raining      Wet  Dark - Street Lights On           NaN   6354039.0
2  Overcast      Dry                 Daylight           NaN   4323031.0
3     Clear      Dry                 Daylight           NaN         NaN
4   Raining      Wet                 Daylight           NaN   4028032.0

  SPEEDING ST_COLCODE                                        ST_COLDESC  \
0      NaN         10                                  Entering at angle
1      NaN         11  From same direction - both going straight - bo…
2      NaN         32                             One parked--one moving
3      NaN         23                  From same direction - all others
4      NaN         10                                  Entering at angle
```

```
   SEGLANEKEY  CROSSWALKKEY HITPARKEDCAR
0           0             0            N
1           0             0            N
2           0             0            N
3           0             0            N
4           0             0            N
```

Metadata Link https://github.com/Engineer00/Coursera_Capstone/blob/master/Scripts/Metadata.pdf

Checking the percentage (%) of missing values in the columns

Checking the percentage (%) of missing values in the columns

[5]:
```python
df.isna().mean().round(4) * 100
```

[5]:
```
SEVERITYCODE        0.00
longitude           2.74
latitude            2.74
OBJECTID            0.00
INCKEY              0.00
COLDETKEY           0.00
REPORTNO            0.00
STATUS              0.00
ADDRTYPE            0.99
INTKEY             66.57
LOCATION            1.38
EXCEPTRSNCODE      56.43
EXCEPTRSNDESC      97.10
SEVERITYDESC        0.00
COLLISIONTYPE       2.52
PERSONCOUNT         0.00
PEDCOUNT            0.00
PEDCYLCOUNT         0.00
VEHCOUNT            0.00
INCDATE             0.00
INCDTTM             0.00
JUNCTIONTYPE        3.25
SDOT_COLCODE        0.00
SDOT_COLDESC        0.00
INATTENTIONIND     84.69
UNDERINFL           2.51
WEATHER             2.61
ROADCOND            2.57
LIGHTCOND           2.66
PEDROWNOTGRNT      97.60
SDOTCOLNUM         40.96
SPEEDING           95.21
```

```
ST_COLCODE         0.01
ST_COLDESC         2.52
SEGLANEKEY         0.00
CROSSWALKKEY       0.00
HITPARKEDCAR       0.00
dtype: float64
```

[6]:
```
df.shape
```

[6]:
```
(194673, 37)
```

Initial segmentation of the list of features

[7]:
```
numeric_features = df[["PERSONCOUNT","PEDCOUNT","PEDCYLCOUNT", "VEHCOUNT",␣
↪"SEVERITYCODE"]]

categorical_features=df[["ADDRTYPE", "LOCATION", "COLLISIONTYPE",␣
↪"INCDATE","INCDTTM","JUNCTIONTYPE",
                         "SDOT_COLDESC", "UNDERINFL", "WEATHER", "ROADCOND",␣
↪"LIGHTCOND", "ST_COLDESC", "HITPARKEDCAR"]]
```

Checking the Target Variable

[8]:
```
df["SEVERITYCODE"].value_counts()
```

[8]:
```
1    136485
2     58188
Name: SEVERITYCODE, dtype: int64
```

Description of the Numeric Features

[9]:
```
numeric_features.describe()
```

[9]:
```
         PERSONCOUNT       PEDCOUNT    PEDCYLCOUNT       VEHCOUNT  \
count  194673.000000  194673.000000  194673.000000  194673.000000
mean        2.444427       0.037139       0.028391       1.920780
std         1.345929       0.198150       0.167413       0.631047
min         0.000000       0.000000       0.000000       0.000000
25%         2.000000       0.000000       0.000000       2.000000
50%         2.000000       0.000000       0.000000       2.000000
75%         3.000000       0.000000       0.000000       2.000000
max        81.000000       6.000000       2.000000      12.000000

        SEVERITYCODE
count  194673.000000
mean        1.298901
std         0.457778
min         1.000000
```

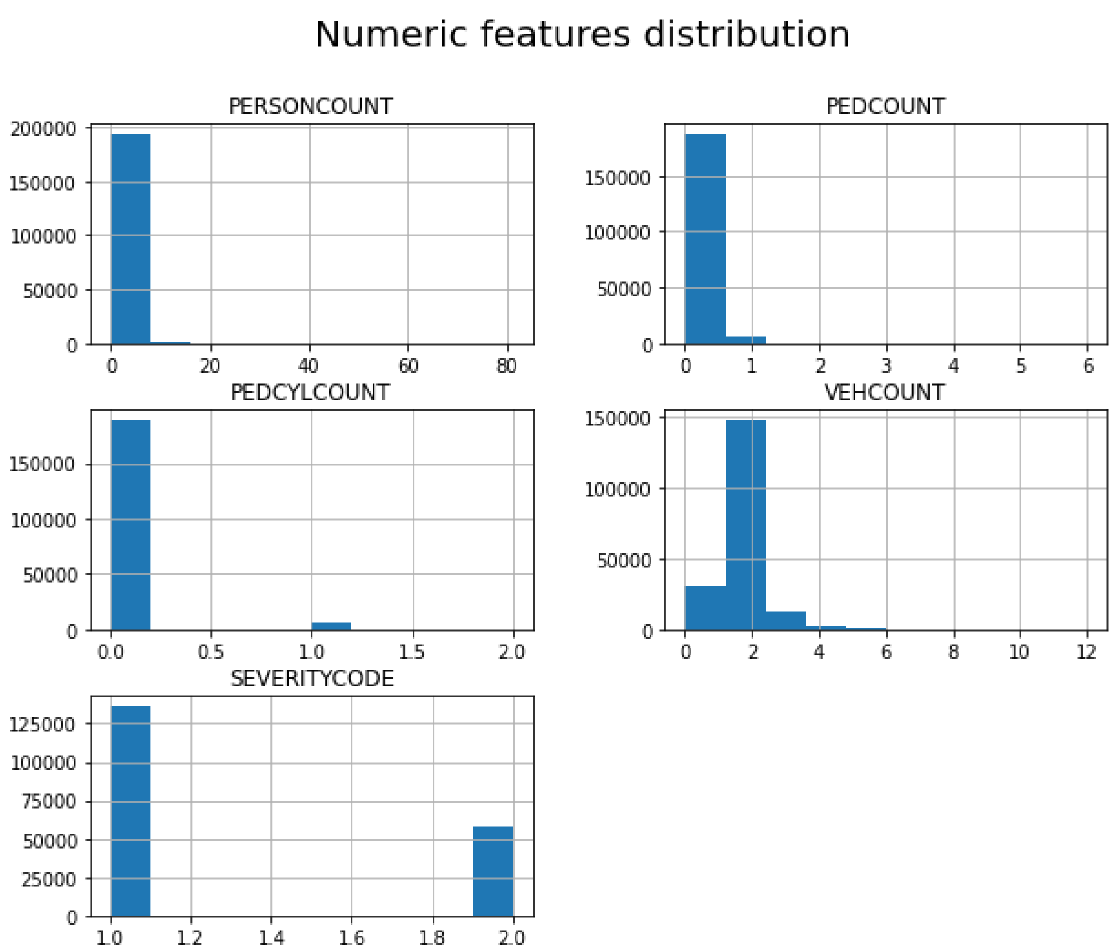
```
25%          1.000000
50%          1.000000
75%          2.000000
max          2.000000
```

Numeric Features Distribution

[10]:
```python
numeric_features.hist(figsize=[10,8])
plt.suptitle("Numeric features distribution", fontsize=20)
plt.show()
```

[10]:
```
array([[<AxesSubplot:title={'center':'PERSONCOUNT'}>,
        <AxesSubplot:title={'center':'PEDCOUNT'}>],
       [<AxesSubplot:title={'center':'PEDCYLCOUNT'}>,
        <AxesSubplot:title={'center':'VEHCOUNT'}>],
       [<AxesSubplot:title={'center':'SEVERITYCODE'}>, <AxesSubplot:>]],
      dtype=object)
```

[10]:
```
Text(0.5, 0.98, 'Numeric features distribution')
```



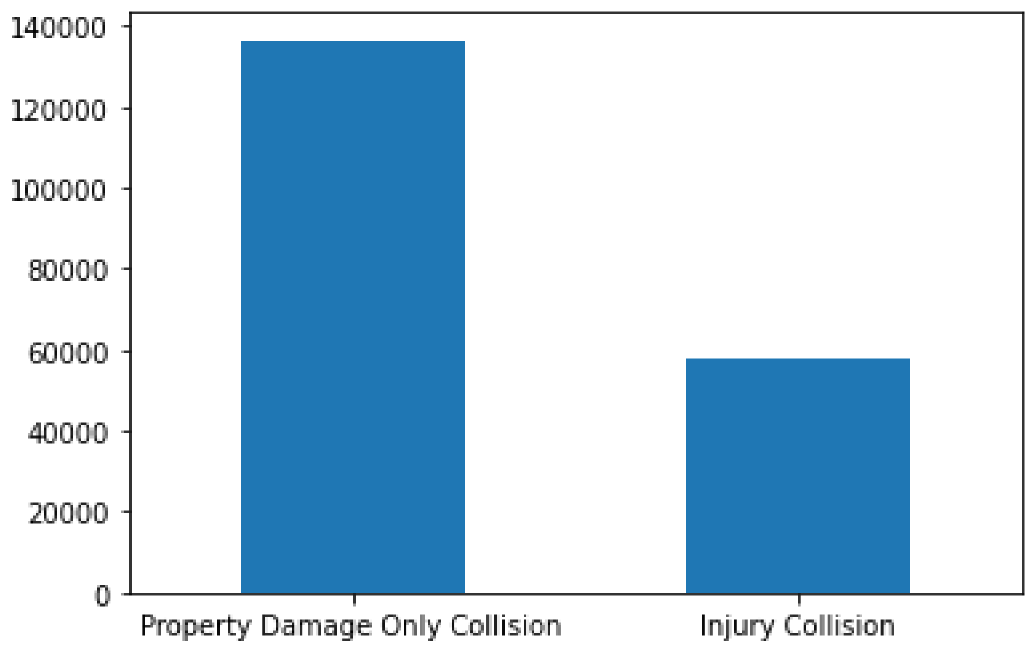
Categorical Features Distribution

"SEVERITYDESC" (Accident Severity Description)

[11]:
```
df['SEVERITYDESC'].value_counts().plot(kind='bar')
plt.xticks(rotation=0)
```

[11]: <AxesSubplot:>

[11]:
```
(array([0, 1]),
 [Text(0, 0, 'Property Damage Only Collision'),
  Text(1, 0, 'Injury Collision')])
```



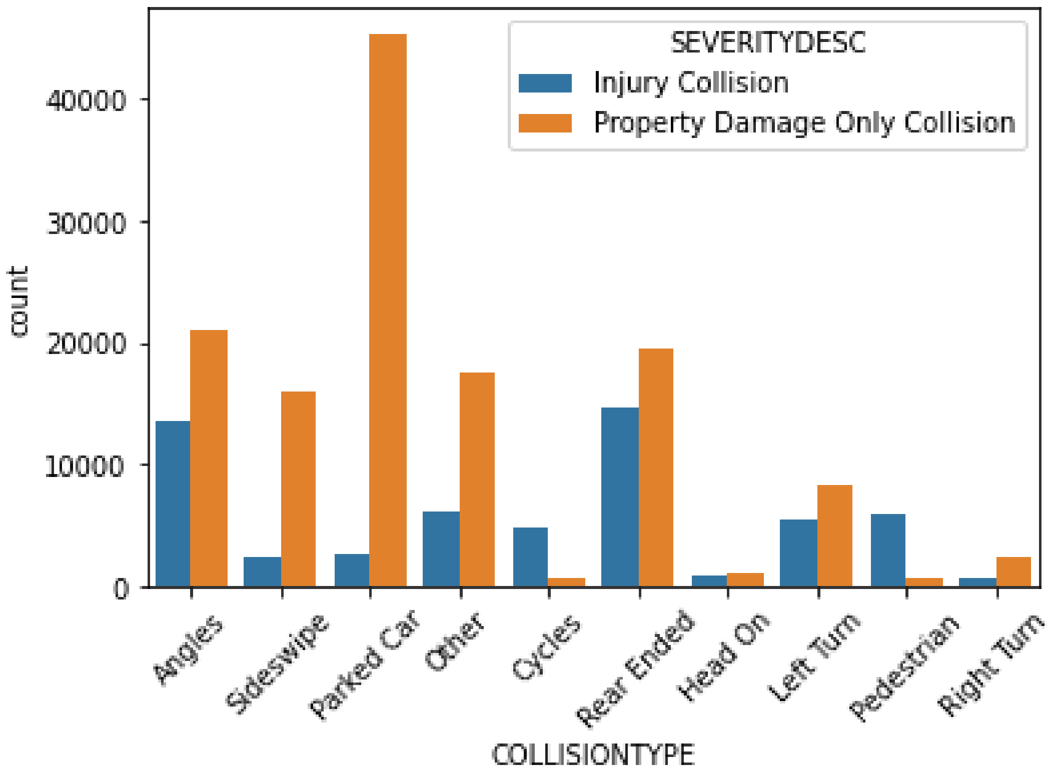
"COLLISIONTYPE"

[12]:
```
# Collision Type
sns.countplot(x="COLLISIONTYPE", hue="SEVERITYDESC", data=df)
plt.xticks(rotation=45)
```

[12]: <AxesSubplot:xlabel='COLLISIONTYPE', ylabel='count'>

[12]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
 [Text(0, 0, 'Angles'),
  Text(1, 0, 'Sideswipe'),
  Text(2, 0, 'Parked Car'),
```

```
 Text(3, 0, 'Other'),
 Text(4, 0, 'Cycles'),
 Text(5, 0, 'Rear Ended'),
 Text(6, 0, 'Head On'),
 Text(7, 0, 'Left Turn'),
 Text(8, 0, 'Pedestrian'),
 Text(9, 0, 'Right Turn')])
```



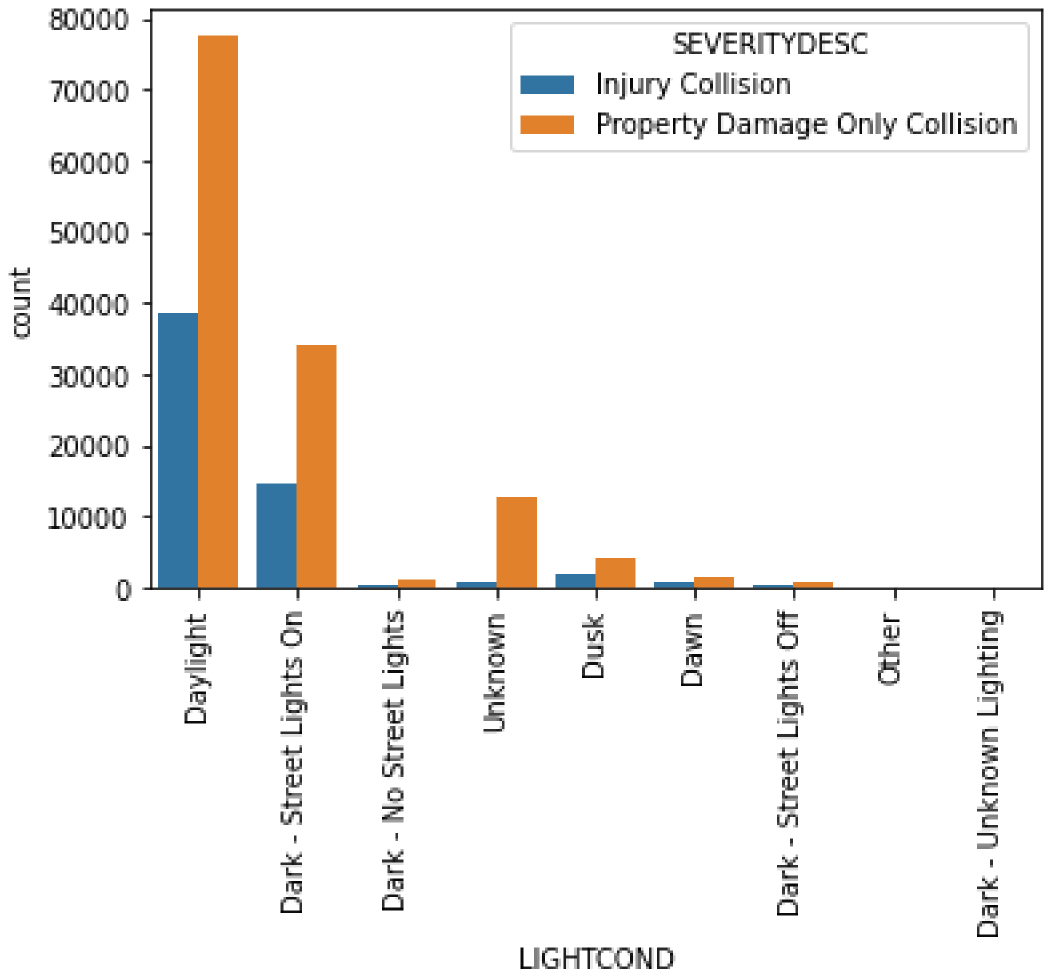
"LIGHTCOND"

[13]:
```python
# LIGHT CONDITIONS
sns.countplot(x="LIGHTCOND", hue="SEVERITYDESC", data=df)
plt.xticks(rotation=90)
```

[13]:
```
<AxesSubplot:xlabel='LIGHTCOND', ylabel='count'>
```

[13]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8]),
 [Text(0, 0, 'Daylight'),
  Text(1, 0, 'Dark - Street Lights On'),
  Text(2, 0, 'Dark - No Street Lights'),
  Text(3, 0, 'Unknown'),
  Text(4, 0, 'Dusk'),
```

```
 Text(5, 0, 'Dawn'),
 Text(6, 0, 'Dark - Street Lights Off'),
 Text(7, 0, 'Other'),
 Text(8, 0, 'Dark - Unknown Lighting')])
```



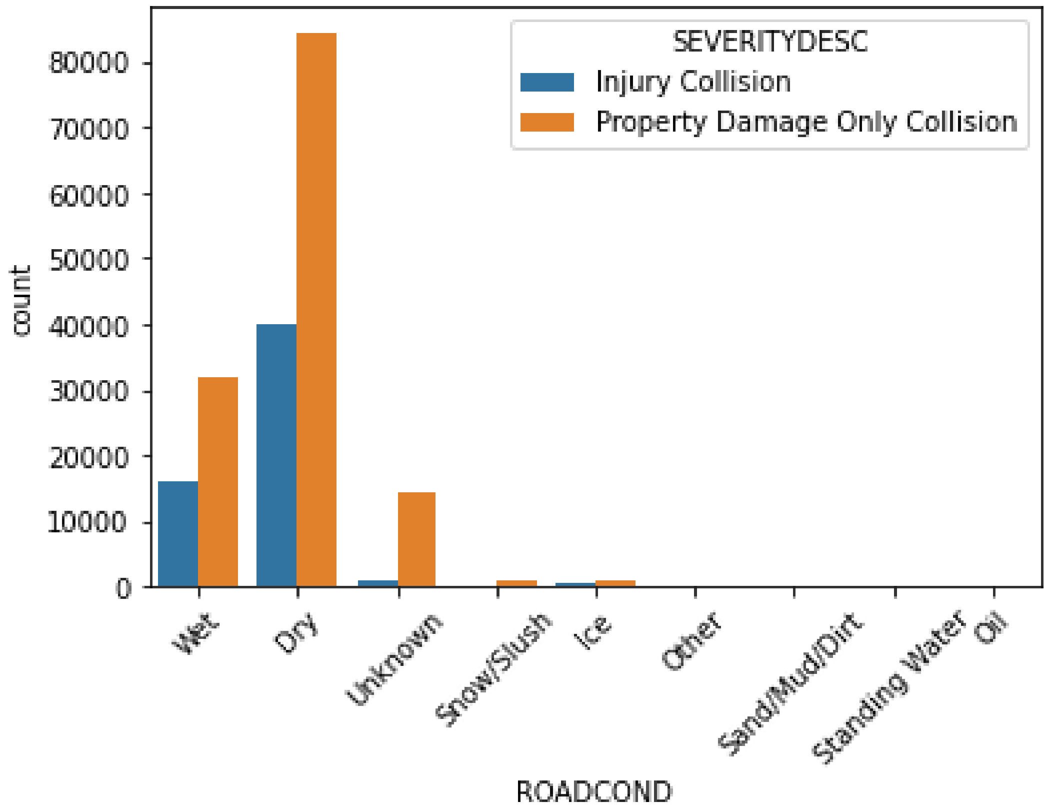
"ROADCOND"

[14]:
```python
# ROAD CONDITIONS
sns.countplot(x="ROADCOND", hue="SEVERITYDESC", data=df)
plt.xticks(rotation=45)
```

[14]:
```
<AxesSubplot:xlabel='ROADCOND', ylabel='count'>
```

[14]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8]),
 [Text(0, 0, 'Wet'),
  Text(1, 0, 'Dry'),
  Text(2, 0, 'Unknown'),
```

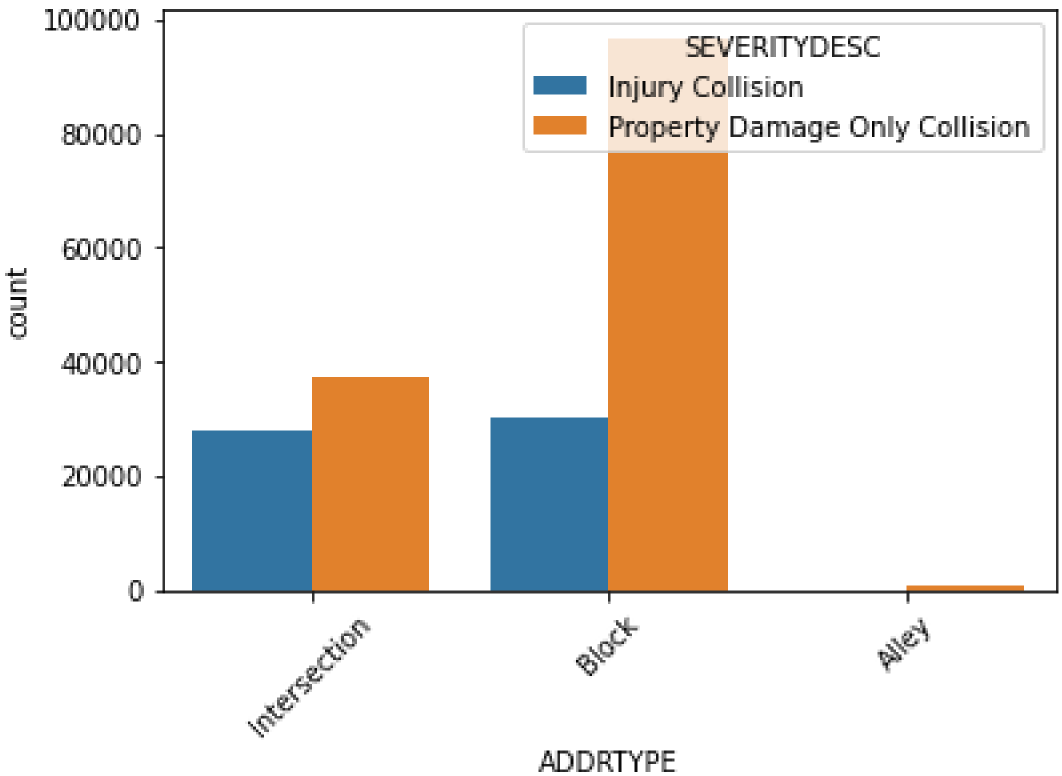
```
 Text(3, 0, 'Snow/Slush'),
 Text(4, 0, 'Ice'),
 Text(5, 0, 'Other'),
 Text(6, 0, 'Sand/Mud/Dirt'),
 Text(7, 0, 'Standing Water'),
 Text(8, 0, 'Oil')])
```



[15]:
```
# ADDRTYPE (Address Type)
sns.countplot(x="ADDRTYPE", hue="SEVERITYDESC", data=df)
plt.xticks(rotation=45)
```

[15]:
```
<AxesSubplot:xlabel='ADDRTYPE', ylabel='count'>
```

[15]:
```
(array([0, 1, 2]),
 [Text(0, 0, 'Intersection'), Text(1, 0, 'Block'), Text(2, 0, 'Alley')])
```



"WEATHER"

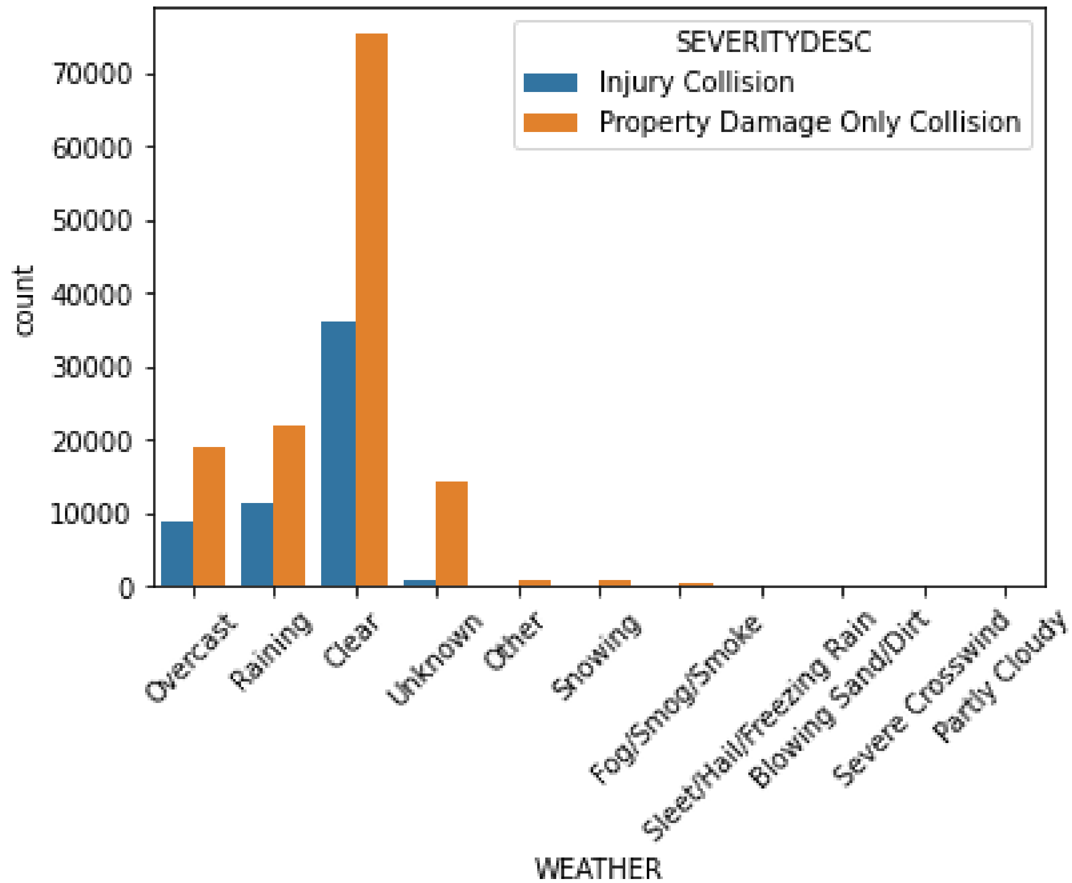
[16]:
```
# WEATHER
df['WEATHER'].value_counts().sort_values(ascending=False).to_frame()
sns.countplot(x="WEATHER", hue="SEVERITYDESC", data=df)
plt.xticks(rotation=45)
```

[16]:

	WEATHER
Clear	111135
Raining	33145
Overcast	27714
Unknown	15091
Snowing	907
Other	832
Fog/Smog/Smoke	569
Sleet/Hail/Freezing Rain	113
Blowing Sand/Dirt	56
Severe Crosswind	25
Partly Cloudy	5

[16]: <AxesSubplot:xlabel='WEATHER', ylabel='count'>

[16]: (array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]),
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10]),
 [Text(0, 0, 'Overcast'),
  Text(1, 0, 'Raining'),
  Text(2, 0, 'Clear'),
  Text(3, 0, 'Unknown'),
  Text(4, 0, 'Other'),
  Text(5, 0, 'Snowing'),
  Text(6, 0, 'Fog/Smog/Smoke'),
  Text(7, 0, 'Sleet/Hail/Freezing Rain'),
  Text(8, 0, 'Blowing Sand/Dirt'),
  Text(9, 0, 'Severe Crosswind'),
  Text(10, 0, 'Partly Cloudy')])
```

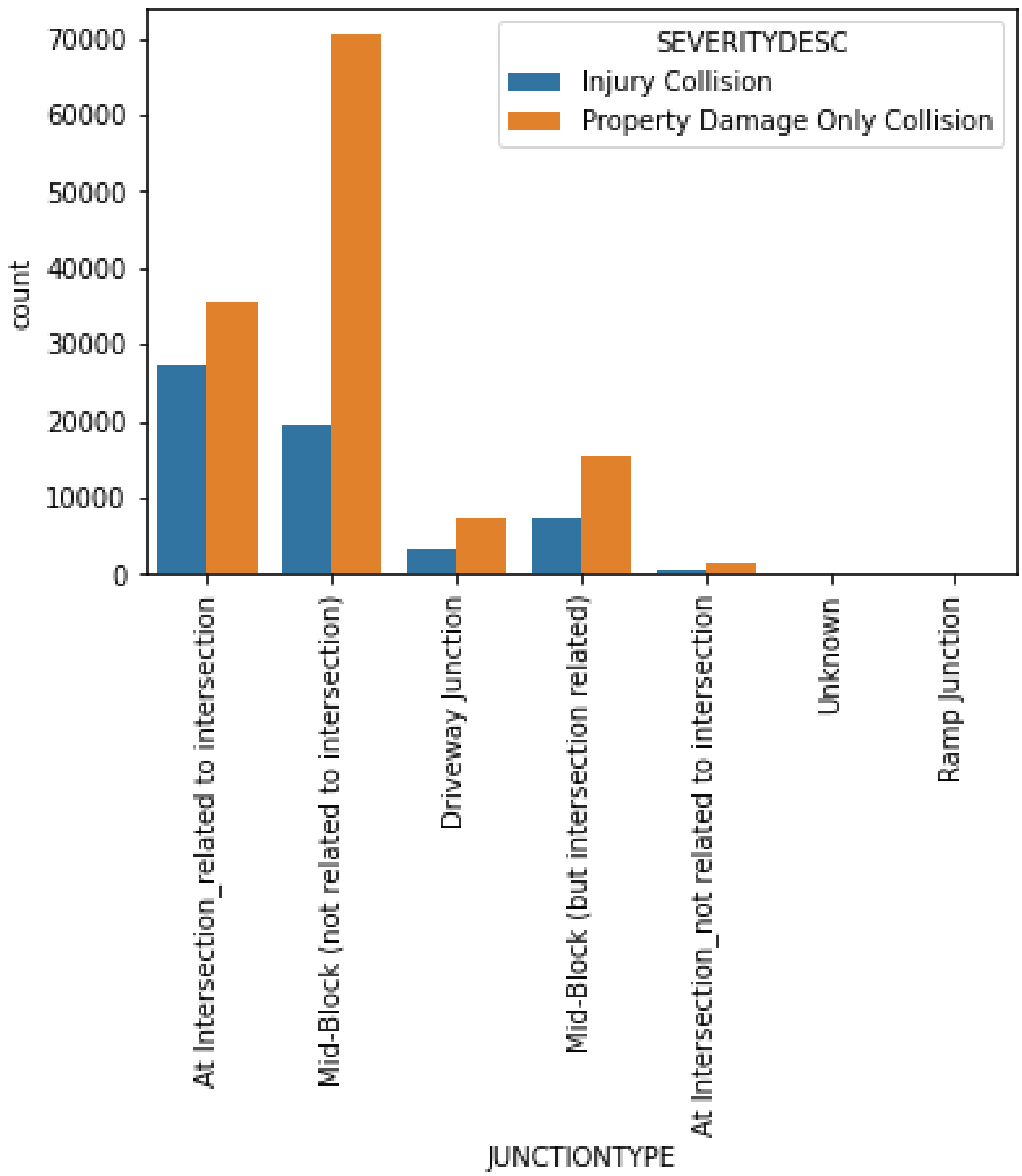


"JUNCTIONTYPE"

[17]:
```
# Junction Type

sns.countplot(x="JUNCTIONTYPE", hue="SEVERITYDESC", data=df)
plt.xticks(rotation=90)
```

[17]: <AxesSubplot:xlabel='JUNCTIONTYPE', ylabel='count'>

```
[17]: (array([0, 1, 2, 3, 4, 5, 6]),
       [Text(0, 0, 'At Intersection_related to intersection'),
        Text(1, 0, 'Mid-Block (not related to intersection)'),
        Text(2, 0, 'Driveway Junction'),
        Text(3, 0, 'Mid-Block (but intersection related)'),
        Text(4, 0, 'At Intersection_not related to intersection'),
        Text(5, 0, 'Unknown'),
        Text(6, 0, 'Ramp Junction')])
```

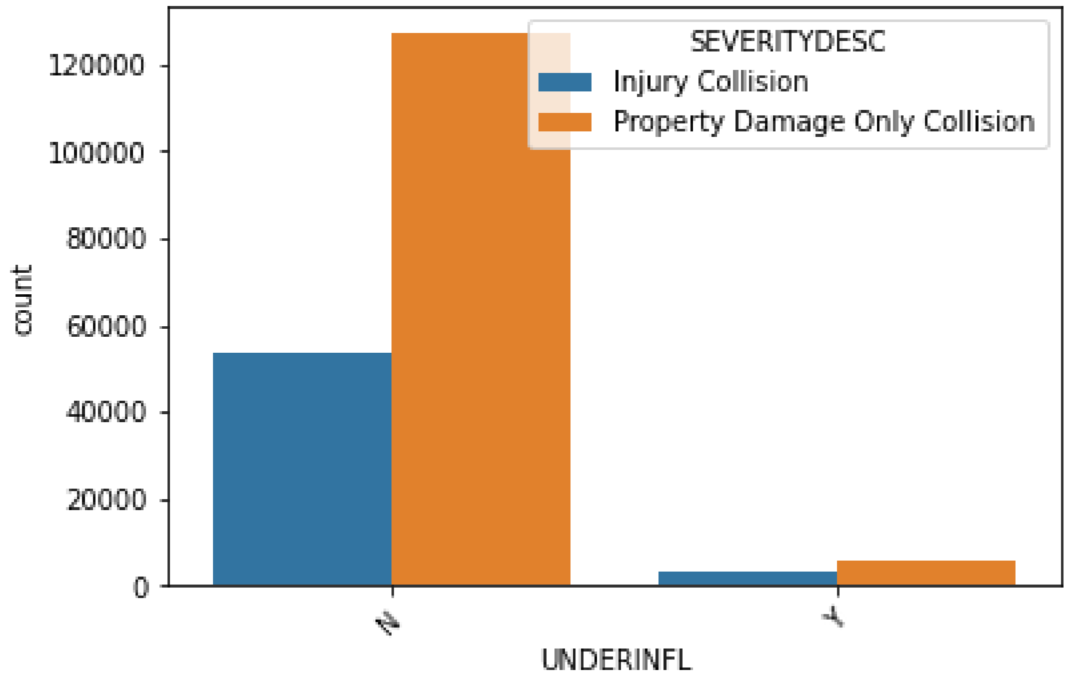


"UNDERINFL" (Under Influence of Alcohol/Drugs)

```
[60]: # UNDER INFLUENCE OF Alcohol/Drugs
sns.countplot(x="UNDERINFL", hue="SEVERITYDESC", data=df)
plt.xticks(rotation=45)
```

```
[60]: <AxesSubplot:xlabel='UNDERINFL', ylabel='count'>
```

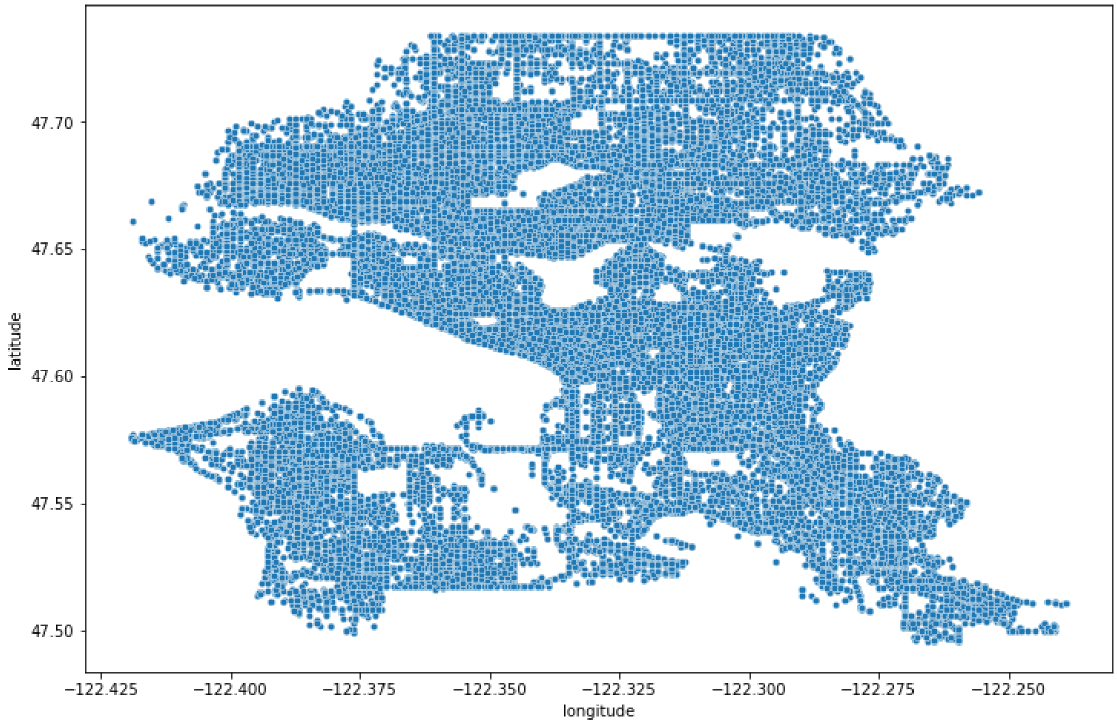
```
[60]: (array([0, 1]), [Text(0, 0, 'N'), Text(1, 0, 'Y')])
```



Scatter plot of the accident coordinates

```
[61]: fig = plt.gcf()
fig.set_size_inches(12, 8)
sns.scatterplot(x='longitude', y='latitude', data=df, legend=False, s=20)
plt.show()
```

```
[61]: <AxesSubplot:xlabel='longitude', ylabel='latitude'>
```



1.0.3 Data Preparation

Formatting the Date & time for the analysis

[19]:
```
df['INCDTTM'] = pd.to_datetime(df['INCDTTM'], errors='coerce')
df['Month']=df['INCDTTM'].dt.strftime('%b')
df['Day']=df['INCDTTM'].dt.day
df['Hour']=df['INCDTTM'].dt.hour
df['Weekday']=df['INCDTTM'].dt.strftime('%a')
```

Yearly Distribution of number of accidents

[20]:
```
fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(20, 6))

df['Year'] = pd.DatetimeIndex(df['INCDATE']).year
df['Year'].value_counts().sort_index()

sns.countplot(x="Year", data=df, ax=ax1)
sns.countplot(x="Year", hue="SEVERITYDESC", data=df, ax=ax2)

plt.xticks(rotation=45)
ax1.set_title('Car accidents in Seattle by Year', fontsize=20)
ax2.set_title('Car accidents in Seattle by Year & type', fontsize=20)
```

[20]:
```
2004    11865
2005    15115
2006    15188
2007    14456
2008    13660
2009    11734
2010    10808
2011    10919
2012    10907
2013    10577
2014    11841
2015    12995
2016    11659
2017    10873
2018    10419
2019     9412
2020     2245
Name: Year, dtype: int64
```

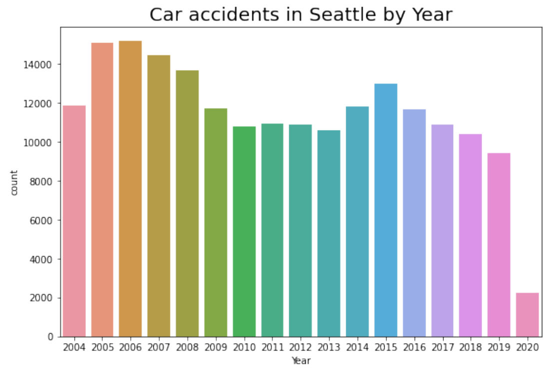
[20]:
```
<AxesSubplot:xlabel='Year', ylabel='count'>
```

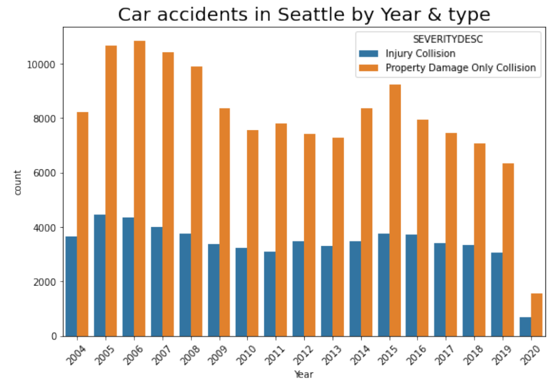
[20]:
```
<AxesSubplot:xlabel='Year', ylabel='count'>
```

[20]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16]),
 [Text(0, 0, '2004'),
  Text(1, 0, '2005'),
  Text(2, 0, '2006'),
  Text(3, 0, '2007'),
  Text(4, 0, '2008'),
  Text(5, 0, '2009'),
  Text(6, 0, '2010'),
  Text(7, 0, '2011'),
  Text(8, 0, '2012'),
  Text(9, 0, '2013'),
  Text(10, 0, '2014'),
  Text(11, 0, '2015'),
  Text(12, 0, '2016'),
  Text(13, 0, '2017'),
  Text(14, 0, '2018'),
  Text(15, 0, '2019'),
  Text(16, 0, '2020')])
```

[20]:
```
Text(0.5, 1.0, 'Car accidents in Seattle by Year')
```

[20]:
```
Text(0.5, 1.0, 'Car accidents in Seattle by Year & type')
```





Checking the Null values in the Dataframe

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

[21]:

	SEVERITYCODE	longitude	latitude	OBJECTID	INCKEY	COLDETKEY	\
0	False	False	False	False	False	False	
1	False	False	False	False	False	False	
2	False	False	False	False	False	False	
3	False	False	False	False	False	False	
4	False	False	False	False	False	False	
…	…	…	…	…	…	…	
194668	False	False	False	False	False	False	
194669	False	False	False	False	False	False	
194670	False	False	False	False	False	False	
194671	False	False	False	False	False	False	
194672	False	False	False	False	False	False	

	REPORTNO	STATUS	ADDRTYPE	INTKEY	LOCATION	EXCEPTRSNCODE	\
0	False	False	False	False	False	False	
1	False	False	False	True	False	True	
2	False	False	False	True	False	True	
3	False	False	False	True	False	False	
4	False	False	False	False	False	True	
…	…	…	…	…	…	…	
194668	False	False	False	True	False	False	
194669	False	False	False	True	False	False	
194670	False	False	False	False	False	False	
194671	False	False	False	False	False	False	
194672	False	False	False	True	False	False	

	EXCEPTRSNDESC	SEVERITYDESC	COLLISIONTYPE	PERSONCOUNT	PEDCOUNT	\
0	True	False	False	False	False	
1	True	False	False	False	False	

```
2                True          False          False          False      False
3                True          False          False          False      False
4                True          False          False          False      False
…               …            …             …          …          …
194668           True          False          False          False      False
194669           True          False          False          False      False
194670           True          False          False          False      False
194671           True          False          False          False      False
194672           True          False          False          False      False

        PEDCYLCOUNT  VEHCOUNT  INCDATE  INCDTTM  JUNCTIONTYPE  SDOT_COLCODE  \
0             False     False    False    False         False         False
1             False     False    False    False         False         False
2             False     False    False    False         False         False
3             False     False    False    False         False         False
4             False     False    False    False         False         False
…             …       …       …       …            …            …
194668        False     False    False    False         False         False
194669        False     False    False    False         False         False
194670        False     False    False    False         False         False
194671        False     False    False    False         False         False
194672        False     False    False    False         False         False

        SDOT_COLDESC  INATTENTIONIND  UNDERINFL  WEATHER  ROADCOND  LIGHTCOND  \
0              False            True      False    False     False      False
1              False            True      False    False     False      False
2              False            True      False    False     False      False
3              False            True      False    False     False      False
4              False            True      False    False     False      False
…              …             …        …       …        …        …
194668         False            True      False    False     False      False
194669         False           False      False    False     False      False
194670         False            True      False    False     False      False
194671         False            True      False    False     False      False
194672         False            True      False    False     False      False

        PEDROWNOTGRNT  SDOTCOLNUM  SPEEDING  ST_COLCODE  ST_COLDESC  \
0                True        True      True       False       False
1                True       False      True       False       False
2                True       False      True       False       False
3                True        True      True       False       False
4                True       False      True       False       False
…               …          …       …         …          …
194668           True        True      True       False       False
194669           True        True      True       False       False
194670           True        True      True       False       False
194671           True        True      True       False       False
```

```
194672          True         True       True        False        False

        SEGLANEKEY  CROSSWALKKEY  HITPARKEDCAR  Month    Day   Hour  Weekday  \
0            False         False         False  False  False  False    False
1            False         False         False  False  False  False    False
2            False         False         False  False  False  False    False
3            False         False         False  False  False  False    False
4            False         False         False  False  False  False    False
…              …            …            …     …     …     …       …
194668       False         False         False  False  False  False    False
194669       False         False         False  False  False  False    False
194670       False         False         False  False  False  False    False
194671       False         False         False  False  False  False    False
194672       False         False         False  False  False  False    False

         Year
0       False
1       False
2       False
3       False
4       False
…         …
194668  False
194669  False
194670  False
194671  False
194672  False

[194673 rows x 42 columns]
```

Selecting and finalizing the features for Machine Learning Model

[22]:
```python
selected_features = ["SEVERITYCODE", "longitude", "latitude", "PERSONCOUNT",
                     "PEDCOUNT", "PEDCYLCOUNT", "VEHCOUNT", "ADDRTYPE",␣
 ↪"COLLISIONTYPE", "WEATHER", "ROADCOND",
                     "LIGHTCOND", "SDOT_COLDESC", "HITPARKEDCAR", "Hour"]
df_sel=df[selected_features].copy()
df_sel.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 194673 entries, 0 to 194672
Data columns (total 15 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   SEVERITYCODE    194673 non-null  int64
 1   longitude       189339 non-null  float64
 2   latitude        189339 non-null  float64
 3   PERSONCOUNT     194673 non-null  int64
```

```
 4   PEDCOUNT       194673 non-null  int64
 5   PEDCYLCOUNT    194673 non-null  int64
 6   VEHCOUNT       194673 non-null  int64
 7   ADDRTYPE       192747 non-null  object
 8   COLLISIONTYPE  189769 non-null  object
 9   WEATHER        189592 non-null  object
 10  ROADCOND       189661 non-null  object
 11  LIGHTCOND      189503 non-null  object
 12  SDOT_COLDESC   194673 non-null  object
 13  HITPARKEDCAR   194673 non-null  object
 14  Hour           194673 non-null  int64
dtypes: float64(2), int64(6), object(7)
memory usage: 22.3+ MB
```

[23]:
```
df.isnull().sum()
```

[23]:
```
SEVERITYCODE           0
longitude           5334
latitude            5334
OBJECTID               0
INCKEY                 0
COLDETKEY              0
REPORTNO               0
STATUS                 0
ADDRTYPE            1926
INTKEY            129603
LOCATION            2677
EXCEPTRSNCODE     109862
EXCEPTRSNDESC     189035
SEVERITYDESC           0
COLLISIONTYPE       4904
PERSONCOUNT            0
PEDCOUNT               0
PEDCYLCOUNT            0
VEHCOUNT               0
INCDATE                0
INCDTTM                0
JUNCTIONTYPE        6329
SDOT_COLCODE           0
SDOT_COLDESC           0
INATTENTIONIND    164868
UNDERINFL           4884
WEATHER             5081
ROADCOND            5012
LIGHTCOND           5170
PEDROWNOTGRNT     190006
SDOTCOLNUM         79737
```

```
SPEEDING          185340
ST_COLCODE            18
ST_COLDESC          4904
SEGLANEKEY             0
CROSSWALKKEY           0
HITPARKEDCAR           0
Month                  0
Day                    0
Hour                   0
Weekday                0
Year                   0
dtype: int64
```

[24]:
```
df_sel.shape
```

[24]:
```
(194673, 15)
```

Checking the Null values in the selected dataframe and dropping the rows with the null values

[25]:
```
df_sel.isnull().mean()
```

[25]:
```
SEVERITYCODE     0.000000
longitude        0.027400
latitude         0.027400
PERSONCOUNT      0.000000
PEDCOUNT         0.000000
PEDCYLCOUNT      0.000000
VEHCOUNT         0.000000
ADDRTYPE         0.009894
COLLISIONTYPE    0.025191
WEATHER          0.026100
ROADCOND         0.025746
LIGHTCOND        0.026557
SDOT_COLDESC     0.000000
HITPARKEDCAR     0.000000
Hour             0.000000
dtype: float64
```

[26]:
```
df_sel.dropna(subset=df_sel.columns[df_sel.isnull().mean()!=0], how='any',␣
 ↪axis=0, inplace=True)
df_sel.shape
```

[26]:
```
(184146, 15)
```

[27]:
```
# Export the data with selected features
```

```
df_sel.to_csv('./Data-Collisions_clean_sel.csv',index=False)
```

Generating the dummies for the Categorical Data

[28]:
```
# Generate dummies for categorical data
df_dummy = pd.get_dummies(df_sel, drop_first=True)
# Export data
df_dummy.to_csv("./Data-Collisions_{}_dummy.csv", index=False)
df_dummy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 184146 entries, 0 to 194672
Data columns (total 83 columns):
 #   Column
Non-Null Count   Dtype
---  ------
--------------   -----
 0   SEVERITYCODE
184146 non-null  int64
 1   longitude
184146 non-null  float64
 2   latitude
184146 non-null  float64
 3   PERSONCOUNT
184146 non-null  int64
 4   PEDCOUNT
184146 non-null  int64
 5   PEDCYLCOUNT
184146 non-null  int64
 6   VEHCOUNT
184146 non-null  int64
 7   Hour
184146 non-null  int64
 8   ADDRTYPE_Intersection
184146 non-null  uint8
 9   COLLISIONTYPE_Cycles
184146 non-null  uint8
 10  COLLISIONTYPE_Head On
184146 non-null  uint8
 11  COLLISIONTYPE_Left Turn
184146 non-null  uint8
 12  COLLISIONTYPE_Other
184146 non-null  uint8
 13  COLLISIONTYPE_Parked Car
184146 non-null  uint8
 14  COLLISIONTYPE_Pedestrian
184146 non-null  uint8
 15  COLLISIONTYPE_Rear Ended
```

```
184146 non-null  uint8
 16  COLLISIONTYPE_Right Turn
184146 non-null  uint8
 17  COLLISIONTYPE_Sideswipe
184146 non-null  uint8
 18  WEATHER_Clear
184146 non-null  uint8
 19  WEATHER_Fog/Smog/Smoke
184146 non-null  uint8
 20  WEATHER_Other
184146 non-null  uint8
 21  WEATHER_Overcast
184146 non-null  uint8
 22  WEATHER_Partly Cloudy
184146 non-null  uint8
 23  WEATHER_Raining
184146 non-null  uint8
 24  WEATHER_Severe Crosswind
184146 non-null  uint8
 25  WEATHER_Sleet/Hail/Freezing Rain
184146 non-null  uint8
 26  WEATHER_Snowing
184146 non-null  uint8
 27  WEATHER_Unknown
184146 non-null  uint8
 28  ROADCOND_Ice
184146 non-null  uint8
 29  ROADCOND_Oil
184146 non-null  uint8
 30  ROADCOND_Other
184146 non-null  uint8
 31  ROADCOND_Sand/Mud/Dirt
184146 non-null  uint8
 32  ROADCOND_Snow/Slush
184146 non-null  uint8
 33  ROADCOND_Standing Water
184146 non-null  uint8
 34  ROADCOND_Unknown
184146 non-null  uint8
 35  ROADCOND_Wet
184146 non-null  uint8
 36  LIGHTCOND_Dark - Street Lights Off
184146 non-null  uint8
 37  LIGHTCOND_Dark - Street Lights On
184146 non-null  uint8
 38  LIGHTCOND_Dark - Unknown Lighting
184146 non-null  uint8
 39  LIGHTCOND_Dawn
```

```
184146 non-null  uint8
 40  LIGHTCOND_Daylight
184146 non-null  uint8
 41  LIGHTCOND_Dusk
184146 non-null  uint8
 42  LIGHTCOND_Other
184146 non-null  uint8
 43  LIGHTCOND_Unknown
184146 non-null  uint8
 44  SDOT_COLDESC_DRIVERLESS VEHICLE RAN OFF ROAD - NO COLLISION
184146 non-null  uint8
 45  SDOT_COLDESC_DRIVERLESS VEHICLE STRUCK MOTOR VEHICLE FRONT END AT ANGLE
184146 non-null  uint8
 46  SDOT_COLDESC_DRIVERLESS VEHICLE STRUCK MOTOR VEHICLE LEFT SIDE AT ANGLE
184146 non-null  uint8
 47  SDOT_COLDESC_DRIVERLESS VEHICLE STRUCK MOTOR VEHICLE LEFT SIDE SIDESWIPE
184146 non-null  uint8
 48  SDOT_COLDESC_DRIVERLESS VEHICLE STRUCK MOTOR VEHICLE REAR END
184146 non-null  uint8
 49  SDOT_COLDESC_DRIVERLESS VEHICLE STRUCK MOTOR VEHICLE RIGHT SIDE AT ANGLE
184146 non-null  uint8
 50  SDOT_COLDESC_DRIVERLESS VEHICLE STRUCK MOTOR VEHICLE RIGHT SIDE SIDESWIPE
184146 non-null  uint8
 51  SDOT_COLDESC_DRIVERLESS VEHICLE STRUCK OBJECT IN ROADWAY
184146 non-null  uint8
 52  SDOT_COLDESC_DRIVERLESS VEHICLE STRUCK PEDESTRIAN
184146 non-null  uint8
 53  SDOT_COLDESC_MOTOR VEHCILE STRUCK PEDESTRIAN
184146 non-null  uint8
 54  SDOT_COLDESC_MOTOR VEHICLE OVERTURNED IN ROAD
184146 non-null  uint8
 55  SDOT_COLDESC_MOTOR VEHICLE RAN OFF ROAD - HIT FIXED OBJECT
184146 non-null  uint8
 56  SDOT_COLDESC_MOTOR VEHICLE RAN OFF ROAD - NO COLLISION
184146 non-null  uint8
 57  SDOT_COLDESC_MOTOR VEHICLE STRUCK MOTOR VEHICLE, FRONT END AT ANGLE
184146 non-null  uint8
 58  SDOT_COLDESC_MOTOR VEHICLE STRUCK MOTOR VEHICLE, LEFT SIDE AT ANGLE
184146 non-null  uint8
 59  SDOT_COLDESC_MOTOR VEHICLE STRUCK MOTOR VEHICLE, LEFT SIDE SIDESWIPE
184146 non-null  uint8
 60  SDOT_COLDESC_MOTOR VEHICLE STRUCK MOTOR VEHICLE, REAR END
184146 non-null  uint8
 61  SDOT_COLDESC_MOTOR VEHICLE STRUCK MOTOR VEHICLE, RIGHT SIDE AT ANGLE
184146 non-null  uint8
 62  SDOT_COLDESC_MOTOR VEHICLE STRUCK MOTOR VEHICLE, RIGHT SIDE SIDESWIPE
184146 non-null  uint8
 63  SDOT_COLDESC_MOTOR VEHICLE STRUCK OBJECT IN ROAD
```

```
184146 non-null  uint8
 64  SDOT_COLDESC_MOTOR VEHICLE STRUCK PEDALCYCLIST, FRONT END AT ANGLE
184146 non-null  uint8
 65  SDOT_COLDESC_MOTOR VEHICLE STRUCK PEDALCYCLIST, LEFT SIDE SIDESWIPE
184146 non-null  uint8
 66  SDOT_COLDESC_MOTOR VEHICLE STRUCK PEDALCYCLIST, REAR END
184146 non-null  uint8
 67  SDOT_COLDESC_MOTOR VEHICLE STRUCK PEDALCYCLIST, RIGHT SIDE SIDESWIPE
184146 non-null  uint8
 68  SDOT_COLDESC_MOTOR VEHICLE STRUCK TRAIN
184146 non-null  uint8
 69  SDOT_COLDESC_NOT ENOUGH INFORMATION / NOT APPLICABLE
184146 non-null  uint8
 70  SDOT_COLDESC_PEDALCYCLIST OVERTURNED IN ROAD
184146 non-null  uint8
 71  SDOT_COLDESC_PEDALCYCLIST RAN OFF ROAD - HIT FIXED OBJECT
184146 non-null  uint8
 72  SDOT_COLDESC_PEDALCYCLIST STRUCK MOTOR VEHICLE FRONT END AT ANGLE
184146 non-null  uint8
 73  SDOT_COLDESC_PEDALCYCLIST STRUCK MOTOR VEHICLE LEFT SIDE AT ANGLE
184146 non-null  uint8
 74  SDOT_COLDESC_PEDALCYCLIST STRUCK MOTOR VEHICLE LEFT SIDE SIDESWIPE
184146 non-null  uint8
 75  SDOT_COLDESC_PEDALCYCLIST STRUCK MOTOR VEHICLE REAR END
184146 non-null  uint8
 76  SDOT_COLDESC_PEDALCYCLIST STRUCK MOTOR VEHICLE RIGHT SIDE AT ANGLE
184146 non-null  uint8
 77  SDOT_COLDESC_PEDALCYCLIST STRUCK MOTOR VEHICLE RIGHT SIDE SIDESWIPE
184146 non-null  uint8
 78  SDOT_COLDESC_PEDALCYCLIST STRUCK OBJECT IN ROAD
184146 non-null  uint8
 79  SDOT_COLDESC_PEDALCYCLIST STRUCK PEDALCYCLIST FRONT END AT ANGLE
184146 non-null  uint8
 80  SDOT_COLDESC_PEDALCYCLIST STRUCK PEDALCYCLIST REAR END
184146 non-null  uint8
 81  SDOT_COLDESC_PEDALCYCLIST STRUCK PEDESTRIAN
184146 non-null  uint8
 82  HITPARKEDCAR_Y
184146 non-null  uint8
dtypes: float64(2), int64(6), uint8(75)
memory usage: 25.8 MB
```

1.0.4 Modelling

[29]:
```
# Assign the data
df=df_dummy
# Set the target for the prediction
```

```
target="SEVERITYCODE"
# Create arrays for the features and the response variable
# set X and y
y = df[target]
X = df.drop(target, axis=1)

# Split the data set into training and testing data sets
# Split the data set into training and testing data sets
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0,␣
↪test_size=0.33, stratify=y)
```

Selecting the different Algorithms

[30]:
```
algo_lst=['Logistic Regression',' K-Nearest Neighbors','Decision Trees','Random␣
↪Forest']
```

[31]:
```
# Initialize an empty list for the accuracy for each algorithm
accuracy_lst=[]
```

1.0.5 Evaluation

Logistic Regression

[32]:
```
# Logistic regression
lr = LogisticRegression(solver='lbfgs', max_iter=1000, dual=False).fit(X_test,␣
↪y_test)
y_pred=lr.predict(X_test)

# Get the accuracy score
acc=accuracy_score(y_test, y_pred)

# Append to the accuracy list
accuracy_lst.append(acc)

print("[Logistic regression algorithm] accuracy_score: {:.3f}.".format(acc))
```

```
[Logistic regression algorithm] accuracy_score: 0.756.
```

```
c:\users\salma\desktop\projects\venv\new\new\lib\site-
packages\sklearn\linear_model\_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

K-NN Neighbors

[33]:
```
# Create a k-NN classifier with 6 neighbors
knn = KNeighborsClassifier(n_neighbors=6)

# Fit the classifier to the data
knn.fit(X_train,y_train)

# Predict the labels for the training data X
y_pred = knn.predict(X_test)

# Get the accuracy score
acc=accuracy_score(y_test, y_pred)

# Append to the accuracy list
accuracy_lst.append(acc)
print('[K-Nearest Neighbors (KNN)] knn.score: {:.3f}.'.format(knn.score(X_test,␣
 ↪y_test)))
print('[K-Nearest Neighbors (KNN)] accuracy_score: {:.3f}.'.format(acc))
```

[33]:
```
KNeighborsClassifier(n_neighbors=6)
```

```
[K-Nearest Neighbors (KNN)] knn.score: 0.739.
[K-Nearest Neighbors (KNN)] accuracy_score: 0.739.
```

Setting arrays for storing the train and test data accuracies

[34]:
```
# Setup arrays to store train and test accuracies
neighbors = np.arange(1, 9)
train_accuracy = np.empty(len(neighbors))
test_accuracy = np.empty(len(neighbors))

# Loop over different values of k
for i, n_neighbor in enumerate(neighbors):
    # Setup a k-NN Classifier with n_neighbor
    knn = KNeighborsClassifier(n_neighbors=n_neighbor)

    # Fit the classifier to the training data
    knn.fit(X_train,y_train)

    #Compute accuracy on the training set
    train_accuracy[i] = knn.score(X_train, y_train)
    #Compute accuracy on the testing set
    test_accuracy[i] = knn.score(X_test, y_test)
```

[34]:
```
KNeighborsClassifier(n_neighbors=1)
```

[34]:
```
KNeighborsClassifier(n_neighbors=2)
```

```
[34]: KNeighborsClassifier(n_neighbors=3)
```

```
[34]: KNeighborsClassifier(n_neighbors=4)
```

```
[34]: KNeighborsClassifier()
```

```
[34]: KNeighborsClassifier(n_neighbors=6)
```

```
[34]: KNeighborsClassifier(n_neighbors=7)
```

```
[34]: KNeighborsClassifier(n_neighbors=8)
```

Generating a plot for K-NN with varying number of Neighbors

```
[35]: # Generate plot

plt.title('k-NN: Varying Number of Neighbors')
plt.plot(neighbors, test_accuracy, label = 'Testing Accuracy')
plt.plot(neighbors, train_accuracy, label = 'Training Accuracy')
plt.legend()
plt.xlabel('Number of Neighbors')
plt.ylabel('Accuracy')
plt.show()
```

```
[35]: Text(0.5, 1.0, 'k-NN: Varying Number of Neighbors')
```

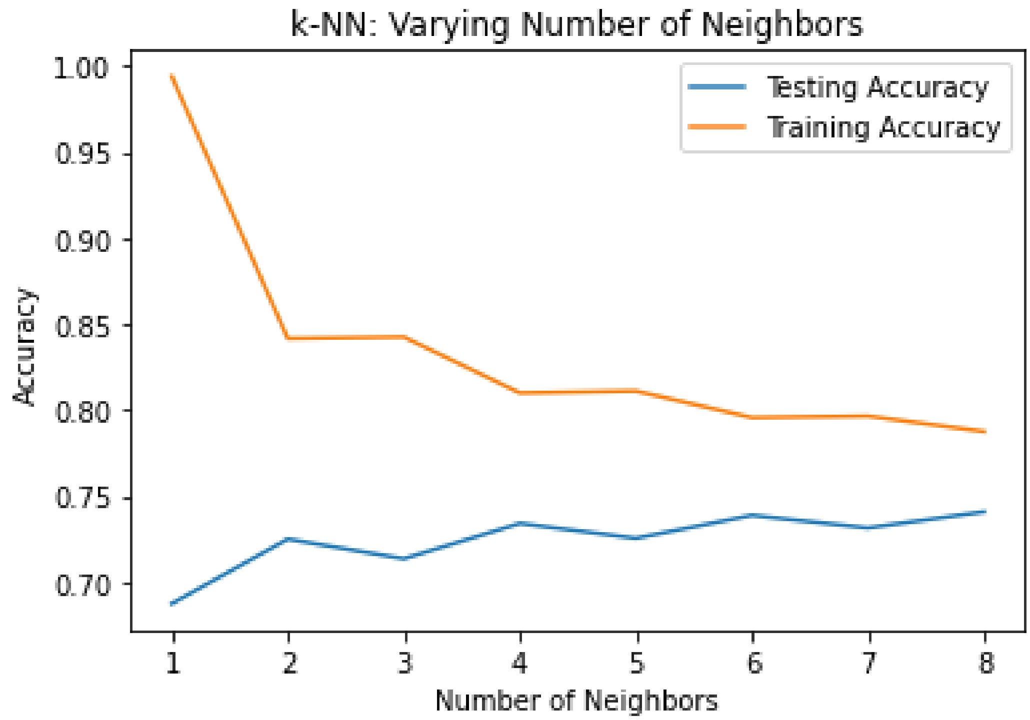
```
[35]: [<matplotlib.lines.Line2D at 0x1e01fd75760>]
```

```
[35]: [<matplotlib.lines.Line2D at 0x1e01fd75970>]
```

```
[35]: <matplotlib.legend.Legend at 0x1e01968b6d0>
```

```
[35]: Text(0.5, 0, 'Number of Neighbors')
```

```
[35]: Text(0, 0.5, 'Accuracy')
```



Decision Tree Algorithm

Instantiate dt_entropy & dt_gini by setting them as the information criterion

[36]:
```
dt_entropy = DecisionTreeClassifier(max_depth=8, criterion='entropy',␣
↪random_state=1)

# Fit dt_entropy to the training set

dt_entropy.fit(X_train, y_train)

# Use dt_entropy to predict test set labels
y_pred= dt_entropy.predict(X_test)

# Evaluate accuracy_entropy
accuracy_entropy = accuracy_score(y_test, y_pred)

# Print accuracy_entropy
print('[Decision Tree -- entropy] accuracy_score: {:.3f}.'.
↪format(accuracy_entropy))

# Instantiate dt_gini, set 'gini' as the information criterion
dt_gini = DecisionTreeClassifier(max_depth=8, criterion='gini', random_state=1)
```

```
# Fit dt_entropy to the training set
dt_gini.fit(X_train, y_train)

# Use dt_entropy to predict test set labels
y_pred= dt_gini.predict(X_test)

# Evaluate accuracy_entropy
accuracy_gini = accuracy_score(y_test, y_pred)

# Append to the accuracy list
acc=accuracy_gini
accuracy_lst.append(acc)

# Print accuracy_gini
print('[Decision Tree -- gini] accuracy_score: {:.3f}.'.format(accuracy_gini))
```

[36]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=8, random_state=1)
```

```
[Decision Tree -- entropy] accuracy_score: 0.754.
```

[36]:
```
DecisionTreeClassifier(max_depth=8, random_state=1)
```

```
[Decision Tree -- gini] accuracy_score: 0.754.
```

Random Forest Algorithm

[37]:
```
# Random Forest algorithm

# Create a Gaussian Classifier

clf=RandomForestClassifier(n_estimators=100)

#Train the model using the training sets y_pred=clf.predict(X_test)

clf.fit(X_train,y_train)
y_pred=clf.predict(X_test)
# Get the accuracy score
acc=accuracy_score(y_test, y_pred)

# Append to the accuracy list
accuracy_lst.append(acc)

# Model Accuracy, how often is the classifier correct?

print("[Random forest algorithm] accuracy_score: {:.3f}.".format(acc))
```

[37]:
```
RandomForestClassifier()
```

```
[Random forest algorithm] accuracy_score: 0.736.
```

Random Forest Classifier

[38]:
```
# Create a selector object that will use the random forest classifier to␣
↪identify

# features that have an importance of more than 0.03
sfm = SelectFromModel(clf, threshold=0.03)

# Train the selector
sfm.fit(X_train, y_train)

feat_labels=X.columns

# Print the names of the most important features
for feature_list_index in sfm.get_support(indices=True):
    print(feat_labels[feature_list_index])
```

[38]:
```
SelectFromModel(estimator=RandomForestClassifier(), threshold=0.03)
```

```
longitude
latitude
PERSONCOUNT
Hour
COLLISIONTYPE_Parked Car
```

Visualizing the important features

[39]:
```
feature_imp = pd.Series(clf.feature_importances_,index=X.columns).
↪sort_values(ascending=False)

# Creating a bar plot, displaying only the top k features
k=10
sns.barplot(x=feature_imp[:10], y=feature_imp.index[:k])
# Add labels to your graph
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title("Visualizing Important Features")
plt.legend()
plt.show()
```

[39]:
```
<AxesSubplot:>
```

[39]:
```
Text(0.5, 0, 'Feature Importance Score')
```

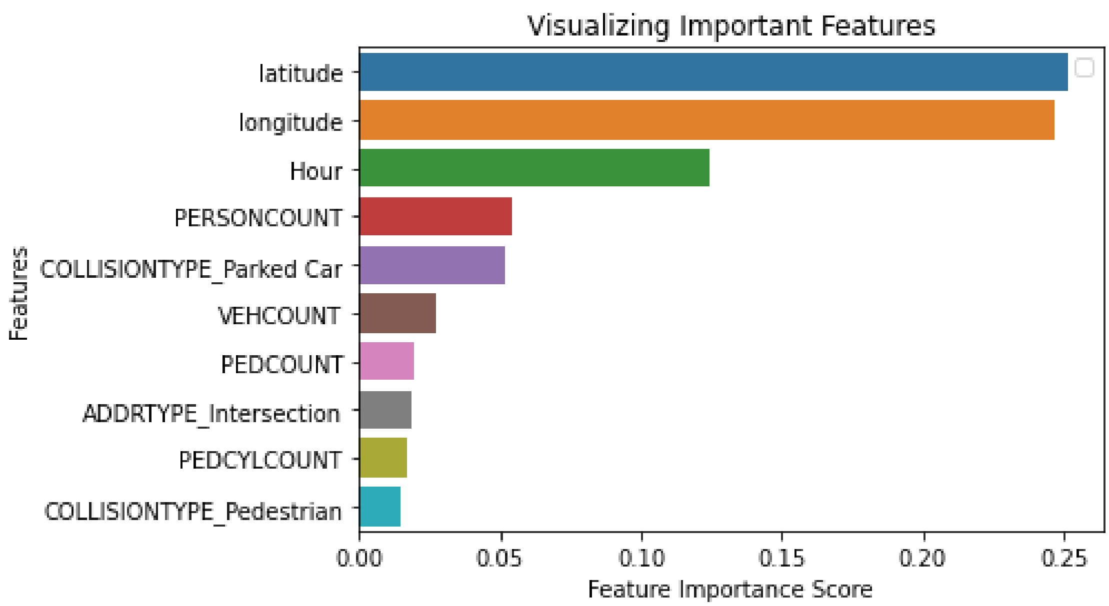
[39]:
```
Text(0, 0.5, 'Features')
```

[39]:
```
Text(0.5, 1.0, 'Visualizing Important Features')
```

```
No handles with labels found to put in legend.
```

[39]:

```
<matplotlib.legend.Legend at 0x1e0194bff40>
```



Creating a new Random Forest Classifier for the most important features

[40]:

```
# Transform the data to create a new dataset containing only the most important␣
↪features

# Note: We have to apply the transform to both the training X and test X data.
X_important_train = sfm.transform(X_train)
X_important_test = sfm.transform(X_test)

# Create a new random forest classifier for the most important features
clf_important = RandomForestClassifier(n_estimators=100, random_state=0,␣
↪n_jobs=-1)

# Train the new classifier on the new dataset containing the most important␣
↪features
clf_important.fit(X_important_train, y_train)
```

[40]:

```
RandomForestClassifier(n_jobs=-1, random_state=0)
```

Checking the Accuracy of Random Forest Algorithm with full and the limited features

[41]:

```
# Apply The Full Featured Classifier To The Test Data
y_pred = clf.predict(X_test)
```

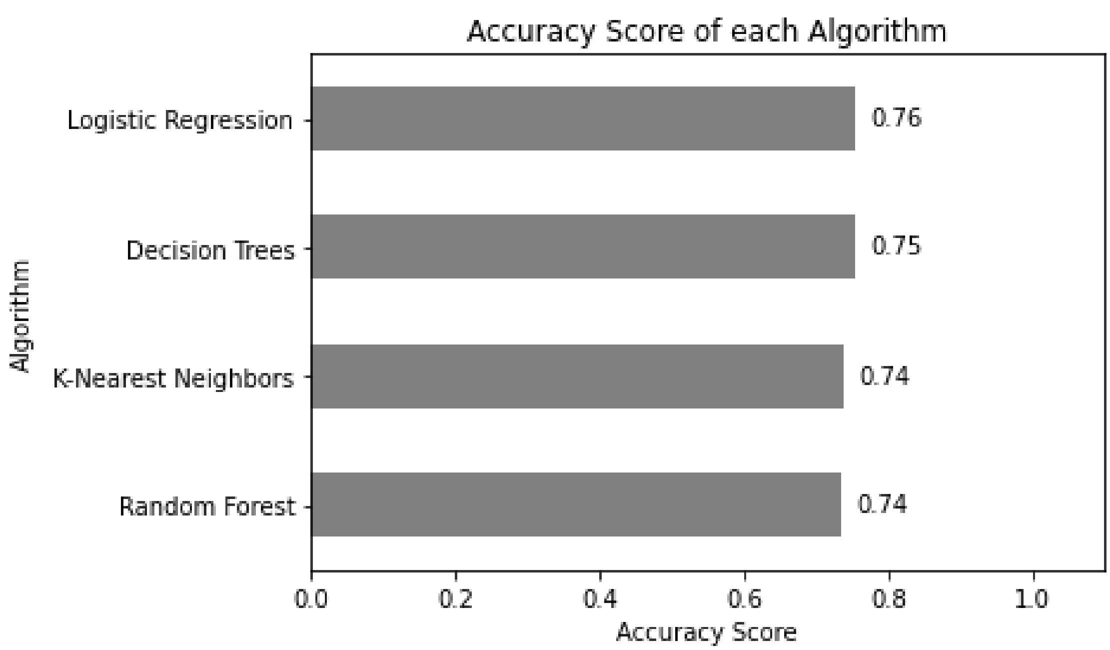
```
# View The Accuracy Of Our Full Feature Model
print('[Random forest algorithm -- Full feature] accuracy_score: {:.3f}.'.
↪format(accuracy_score(y_test, y_pred)))

# Apply The Full Featured Classifier To The Test Data
y_important_pred = clf_important.predict(X_important_test)

# View The Accuracy Of Our Limited Feature Model
print('[Random forest algorithm -- Limited feature] accuracy_score: {:.3f}.'.
↪format(accuracy_score(y_test, y_important_pred)))
```

```
[Random forest algorithm -- Full feature] accuracy_score: 0.736.
[Random forest algorithm -- Limited feature] accuracy_score: 0.661.
```

Making a plot of the accuracy scores for different algorithms

[42]:
```
# Make a plot of the accuracy scores for different algorithms

# Generate a list of ticks for y-axis
y_ticks=np.arange(len(algo_lst))

# Combine the list of algorithms and list of accuracy scores into a dataframe,␣
↪sort the value based on accuracy score
df_acc=pd.DataFrame(list(zip(algo_lst, accuracy_lst)),␣
↪columns=['Algorithm','Accuracy_Score']).
↪sort_values(by=['Accuracy_Score'],ascending = True)

# Export to a file
df_acc.to_csv('./Accuracy_scores_algorithms_{}.csv', index=False)

# Make a plot
ax=df_acc.plot.barh('Algorithm', 'Accuracy_Score',␣
↪align='center',legend=False,color='0.5')

# Add the data label on to the plot
for i in ax.patches:
    # get_width pulls left or right; get_y pushes up or down
    ax.text(i.get_width()+0.02, i.get_y()+0.2, str(round(i.get_width(),2)),␣
↪fontsize=10)

# Set the limit, lables, ticks and title
plt.xlim(0,1.1)
plt.xlabel('Accuracy Score')
plt.yticks(y_ticks, df_acc['Algorithm'], rotation=0)
plt.title('Accuracy Score of each Algorithm')

plt.show()
```

```
[42]: Text(0.755802794187826, -0.04999999999999999, '0.74')

[42]: Text(0.7589458440981421, 0.95, '0.74')

[42]: Text(0.7740686863367836, 1.95, '0.75')

[42]: Text(0.7760269216212213, 2.95, '0.76')

[42]: (0.0, 1.1)

[42]: Text(0.5, 0, 'Accuracy Score')

[42]: ([<matplotlib.axis.YTick at 0x1e0115b3610>,
        <matplotlib.axis.YTick at 0x1e011653b20>,
        <matplotlib.axis.YTick at 0x1e01192a4f0>,
        <matplotlib.axis.YTick at 0x1e0118e1a90>],
       [Text(0, 0, 'Random Forest'),
        Text(0, 1, ' K-Nearest Neighbors'),
        Text(0, 2, 'Decision Trees'),
        Text(0, 3, 'Logistic Regression')])

[42]: Text(0.5, 1.0, 'Accuracy Score of each Algorithm')
```



1.0.6 Deployment

For the deployment phase as it can vary from project to project a simple pdf report has been generated.

1.0.7 Summary

- Seattle road accidents data has been analyzed in order to get useful insights.
- The data contains multiple attributes e.g. accident severity, collision type, coordinates of the incident, date and time of the incident, weather and road conditions, address types, no of persons injured and property damage and many other attributes.
- There are two accident severity types mentioned in the dataset i.e.
  - Property damage only collision(1)
  - Injury collision(2)
- All the mandatory Cross-industry standard process for data mining CRISP-DM phases are covered in this report which contains the following:
  - Business Understanding
  - Data Understanding
  - Data Preparation
  - Modeling
  - Evaluation
  - Deployment
- In the Modeling phase, four algorithms were selected where the target class was "accident severity".
- Based on the predictions, "Logistic Regression" relatively performed better among the others having the accuracy percentage of approx.76%.

1.0.8 Conclusion

Based on the selected dataset(features) for this capstone project which includes mainly, coordinates, hour, person count and the collision type, it can be concluded that these particular classes have a somewhat impact on whether or not travelling along the Seattle roads could result in property damage (class 1) or injury (class 2). In this study, the technique of association rules with a large set of accident data to identify the reasons of road accidents were used.The results show that this model could provide good predictions against traffic accident with approx. 76% correct rate.It should be noted that due to the constraints of data and research condition, there are still some factors, such as engine capacity, traffic flows, gender, age of the driver, attaining the missing data etc. that are not considered in this model and can be taken into account for future study. The results of this study can be used in vehicle safety assistance driving and provide early warnings and proposals for safe driving, hence help in reducing the number of accidents.