Final Report For Capstone Project on Predicting the Severity of accidents for seattle city

IBM Applied Data Science - Capstone Project

Abstract

The purpose of this exploratory data analysis is to assess the possibility and accuracy to predict car accident severity in Seattle, USA by means of supervised machine learning models, exploiting collision track records from past accidents that were recorded by the Seattle Police Department (SPD) and provided as open data by Traffic Records.

Being able to predict car accident severity from extrenal factors like weather, location, road conditions as well as speeding, influence of alcohol/drugs etc. will allow the government to put appropriate meassures in place to reduce accident severity, but above all, allow the police and first response teams to channel their resources and increase efficiency.

Using car accident track records from March 2013, three different machine-learning methods, namely K-Nearest Neighbours (KNN), Decision Trees, and Logistic Regressors, were benchmarked against each other

While the exploratory data analysis suggests, that almost 90% of all accidents, involving pedestrians and 88% of collisions involving cyclists lead to injuries (compare: 28% of accidents without pedestrians/cyclists lead to injuries), the tested machine learning models generally had problems to correctly predict SEVERITYCLASS=2 and therefore exhibited a high number of false negatives for this class which can in real life lead to a wrong allocation of resources of police and first responders and potentially end deadly.

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1) Introduction

Despite the fact that the US population has increased threefold since the beginning of the 20th century and the total number of cars cracking the 280 million mark in 2019 (source), leading to a whopping 3000 billion miles travelled p.a., fatality rates in traffice continously decline. This decrease of deaths in car accidents is related to measures, enforced by the law (e.g. seat belt law, 1968), advanced safety features (mandatory air bags (1998)), but also improved road safety (e.g. signs, traffic lights etc.).

Moreover, thanks to technical advances in computer technology in the last decades, efficient measures can be taken even after an accident happened, e.g. by minimizing the response time of emergency teams and police through the smart analysis of accident records.

This coding exercise demonstrates how collision records can be analysed and provide insight into predicting car accident severity using the example of Seattle, USA.

2) Data Overview

The Data which is used for development of the model is the Collisions data that is provided by the Seattle department of transportation and Seattle police department and recorded in the traffic records. The data consists of all the Accidents taking place from year 2004 to Current year and is updated weekly. The data includes information about various attributes including weather conditions, road conditions, visibility, Accident severity. Since data is updated continuously the model can be trained and tested for continuous improvement and increasing the accuracy. For example:- In case of condtions such as when visiblity is poor or the road condition is not good the model will give a warning to the travellers.

2.1) Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib as mlt
import matplotlib.pyplot as plt
from sklearn import preprocessing
import seaborn as sns
%matplotlib inline
print("The libraries are loaded")
```

```
The libraries are loaded
```

In [2]:
```
import folium
```

2.2) Data Loading

In [3]:
```
accident_df=pd.read_csv("D:\Dataset\Data-Collisions.csv")
accident_df.head()
```

```
D:\Anaconda\lib\site-packages\IPython\core\interactiveshell.py:3071: DtypeWarning: Columns (33) 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,
```

Out[3]:

	SEVERITYCODE	X	Y	OBJECTID	INCKEY	COLDETKEY	REPORTNO	STATUS	ADDRTYPE	INTKEY	...	ROADCON
0	2	-122.323148	47.703140	1	1307	1307	3502005	Matched	Intersection	37475.0	...	W
1	1	-122.347294	47.647172	2	52200	52200	2607959	Matched	Block	NaN	...	W
2	1	-122.334540	47.607871	3	26700	26700	1482393	Matched	Block	NaN	...	D
3	1	-122.334803	47.604803	4	1144	1144	3503937	Matched	Block	NaN	...	D
4	2	-122.306426	47.545739	5	17700	17700	1807429	Matched	Intersection	34387.0	...	W

5 rows × 38 columns

3) Methodology

The workflow for the data analysis is as follows: -

1. Data Loading
   - Involves downloading the data from the repository and storing it as a dataframe using pandas
2. Data Overview
   - Exploring the data in terms of dimensions, format, type of data and volume
3. Data Cleanup
   - Cleaning up the data of non value adding information and making it fit for the model development
4. Exploratory Data Analysis
   - Getting Insights from the data about frequency, distribution and pre-selection of features for Model Building
5. Model Building
   - Normalizing the data
   - Benchmarking Differnet Models

4) Code

4.1) Data Overview

In [4]:
```
print("Dimensions of dataset:",accident_df.shape)
accident_df.info()
```

```
Dimensions of dataset: (194673, 38)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 194673 entries, 0 to 194672
Data columns (total 38 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   SEVERITYCODE    194673 non-null  int64
 1   X               189339 non-null  float64
 2   Y               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  SEVERITYCODE.1  194673 non-null  int64
 14  SEVERITYDESC    194673 non-null  object
 15  COLLISIONTYPE   189769 non-null  object
 16  PERSONCOUNT     194673 non-null  int64
 17  PEDCOUNT        194673 non-null  int64
 18  PEDCYLCOUNT     194673 non-null  int64
 19  VEHCOUNT        194673 non-null  int64
 20  INCDATE         194673 non-null  object
 21  INCDTTM         194673 non-null  object
 22  JUNCTIONTYPE    188344 non-null  object
 23  SDOT_COLCODE    194673 non-null  int64
 24  SDOT_COLDESC    194673 non-null  object
 25  INATTENTIONIND  29805 non-null   object
 26  UNDERINFL       189789 non-null  object
 27  WEATHER         189592 non-null  object
 28  ROADCOND        189661 non-null  object
 29  LIGHTCOND       189503 non-null  object
 30  PEDROWNOTGRNT   4667 non-null    object
 31  SDOTCOLNUM      114936 non-null  float64
 32  SPEEDING        9333 non-null    object
 33  ST_COLCODE      194655 non-null  object
 34  ST_COLDESC      189769 non-null  object
 35  SEGLANEKEY      194673 non-null  int64
 36  CROSSWALKKEY    194673 non-null  int64
 37  HITPARKEDCAR    194673 non-null  object
dtypes: float64(4), int64(12), object(22)
memory usage: 56.4+ MB
```

In [5]:
```
## Frequency Distribution of the predicted variable/Dependent Variable: SeverityCode
print("The Frequency Distribution of Severity of Accidents:")
accident_df["SEVERITYCODE"].value_counts().to_frame()
```

```
The Frequency Distribution of Severity of Accidents:
```

Out[5]:

	SEVERITYCODE
1	136485
2	58188

Checking the Data for Missing Values/Null Values

In [6]:
```
accident_df.isnull().sum().to_frame()
```

Out[6]:

	0
SEVERITYCODE	0
X	5334
Y	5334
OBJECTID	0
INCKEY	0
COLDETKEY	0
REPORTNO	0
STATUS	0
ADDRTYPE	1926
INTKEY	129603
LOCATION	2677
EXCEPTRSNCODE	109862
EXCEPTRSNDESC	189035
SEVERITYCODE.1	0
SEVERITYDESC	0
COLLISIONTYPE	4904
PERSONCOUNT	0
PEDCOUNT	0
PEDCYLCOUNT	0
VEHCOUNT	0
INCDATE	0

[illegible]

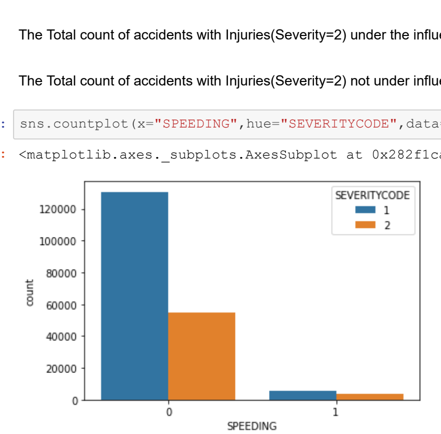
```
print("The Number of NAN values in ROADCOND is:",accident_df["ROADCOND"].isnull().sum())
print("The Number of NAN values in LIGHTCOND is:",accident_df["LIGHTCOND"].isnull().sum())
print("The Number of NAN values in ACCIDENT_MONTH is:",accident_df["ACCIDENT_MONTH"].isnull().sum())
```

```
The Number of NAN values in Severity code is: 0
The Number of NAN values in X is: 0
The Number of NAN values in Y is: 0
The Number of NAN values in ADDRTYPE is: 0
The Number of NAN values in VEHCOUNT is: 0
The Number of NAN values in WEATHER is: 0
The Number of NAN values in ROADCOND is: 0
The Number of NAN values in LIGHTCOND is: 0
The Number of NAN values in ACCIDENT_MONTH is: 0
```

4.3) Exploratory Data Analysis

In [12]:
```
df=accident_df[["INATTENTIONIND","SEVERITYCODE"]]
sns.countplot(x="INATTENTIONIND",hue="SEVERITYCODE",data=df)
```

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x282edf63730>

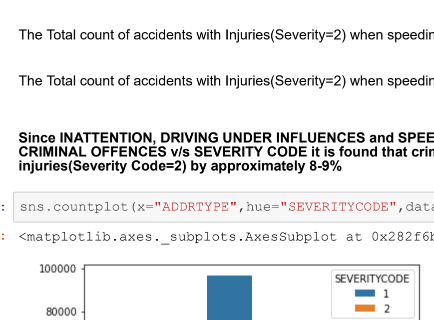


The Total count of accidents with Injury(severity 2) due to inattention are 10397 and percentage is 34.88%

The Total count of accidents with Injury(severity 2) when people were attentive are 47791 and percentage is 28.98%

In [13]:
```
sns.countplot(x="UNDERINFL",hue="SEVERITYCODE",data=accident_df)
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x282f1c39520>

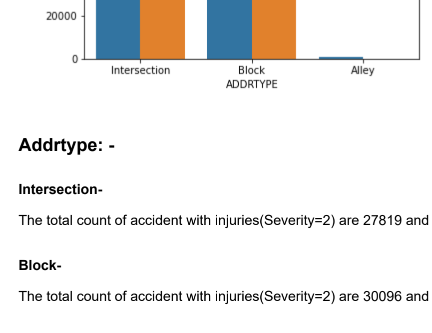


The Total count of accidents with Injuries(Severity=2) under the influence are 3562 and percentage is 39.06%

The Total count of accidents with Injuries(Severity=2) not under influence are 53597 and percentage is 29.67%

In [14]:
```
sns.countplot(x="SPEEDING",hue="SEVERITYCODE",data=accident_df)
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x282f1ca49a0>



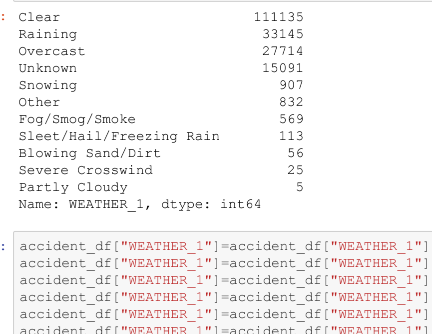
The Total count of accidents with Injuries(Severity=2) when speeding was involved are 3531 and percentage is 37.83%

The Total count of accidents with Injuries(Severity=2) when speeding was not involved are 54657 and percentage is 29.5%

Since INATTENTION, DRIVING UNDER INFLUENCES and SPEEDING are criminal offences we can say that on Analysis of CRIMINAL OFFENCES v/s SEVERITY CODE it is found that criminal offences increases the chances of accidents resulting in injuries(Severity Code=2) by approximately 8-9%

In [15]:
```
sns.countplot(x="ADDRTYPE",hue="SEVERITYCODE",data=accident_df)
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x282f6bd3d30>



Addrtype: -

Intersection-

The total count of accident with injuries(Severity=2) are 27819 and percentage is 42.75%

Block-

The total count of accident with injuries(Severity=2) are 30096 and percentage is 23.71%

Alley-

The total count of accident with injuries(Severity=2) are 82 and percentage is 10.91%

On Analysis of data feature ADDRTYPE, describing the location of accidents shows that majority of accidents that result in injury(SEVERITYCODE=2) are intersection related as compared to any other location.

In [16]:
```
accident_df["WEATHER_1"]=accident_df["WEATHER"]
accident_df["WEATHER_1"].value_counts()
```

Out[16]:
```
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
Name: WEATHER_1, dtype: int64
```

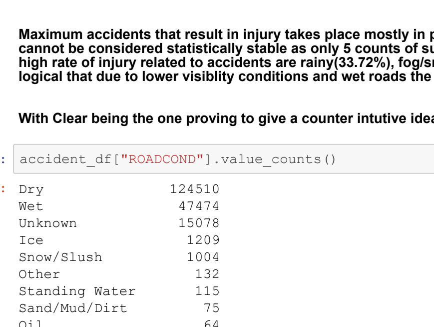
In [17]:
```
accident_df["WEATHER_1"]=accident_df["WEATHER_1"].replace("Clear","1")
accident_df["WEATHER_1"]=accident_df["WEATHER_1"].replace("Raining","2")
accident_df["WEATHER_1"]=accident_df["WEATHER_1"].replace("Overcast","3")
accident_df["WEATHER_1"]=accident_df["WEATHER_1"].replace("Snowing","4")
accident_df["WEATHER_1"]=accident_df["WEATHER_1"].replace("Other","5")
accident_df["WEATHER_1"]=accident_df["WEATHER_1"].replace("Fog/Smog/Smoke","6")
accident_df["WEATHER_1"]=accident_df["WEATHER_1"].replace("Sleet/Hail/Freezing Rain","7")
accident_df["WEATHER_1"]=accident_df["WEATHER_1"].replace("Blowing Sand/Dirt","8")
accident_df["WEATHER_1"]=accident_df["WEATHER_1"].replace("Severe Crosswind","9")
accident_df["WEATHER_1"]=accident_df["WEATHER_1"].replace("Partly Cloudy","10")
accident_df.head()
```

Out[17]:

	SEVERITYCODE	X	Y	ADDRTYPE	PEDCOUNT	PEDCYLCOUNT	VEHCOUNT	INATTENTIONIND	UNDERINFL	WEATH
0	2	-122.323148	47.703140	Intersection	0	0	2	0	0	Overc
1	1	-122.347294	47.647172	Block	0	0	2	0	0	Rai
2	1	-122.334540	47.607871	Block	0	0	3	0	0	Overc
3	1	-122.334803	47.604803	Block	0	0	3	0	0	C
4	2	-122.306426	47.545739	Intersection	0	0	2	0	0	Rai

In [18]:
```
sns.countplot(x="WEATHER_1",hue="SEVERITYCODE",data=accident_df)
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x282f6d29d60>



Weather-

The total count of accident with injuries(Severity=2) when weather was clear(value=1)are 35840 and percentage is 32.25%

The total count of accident with injuries(Severity=2) when weather was rainy(value=2)are 11176 and percentage is 33.72%

The total count of accident with injuries(Severity=2) when weather was overcast(value=3)are 8745 and percentage is 31.55%

The total count of accident with injuries(Severity=2) when weather was snowing(value=4)are 171 and percentage is 18.85%

The total count of accident with injuries(Severity=2) when weather was fog/smog/smoke(value=6) are 187 and percentage is 32.86%

The total count of accident with injuries(Severity=2) when weather was sleet/hail/freezing rain(value=7) are 28 and percentage is 24.78%

The total count of accident with injuries(Severity=2) when weather was blowing sand/dirt(value=8) are 15 and percentage is 21.12%

The total count of accident with injuries(Severity=2) when weather was severe crosswind(value=9) are 7 and percentage is 28%

The total count of accident with injuries(Severity=2) when weather was partly cloudy(value=10) are 3 and percentage is 60%

The total count of accident with injuries(Severity=2) when weather was other than above conditions(value=5) are 116 and percentage is 13.94%

Maximum accidents that result in injury takes place mostly in partly cloudy weather condition that is around 60% but this result cannot be considered statistically stable as only 5 counts of such accidents are recorded. The other weather conditions that have high rate of injury related to accidents are rainy(33.72%), fog/smog/smoke(32.86%), overcast(31.55%) and clear(32.25%). It seems logical that due to lower visiblity conditions and wet roads the chances of accident leading to injuries increases.

With Clear being the one proving to give a counter intutive idea at first glance it can be explained further in the report.

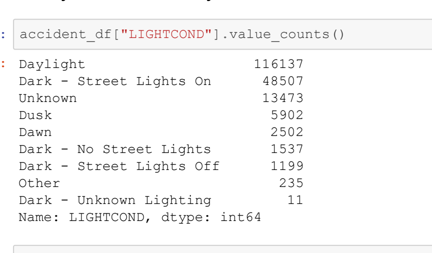
In [19]:
```
accident_df["ROADCOND"].value_counts()
```

Out[19]:
```
Dry               124510
Wet                47474
Unknown            15078
Ice                 1209
Snow/Slush          1004
Other                132
Standing Water       115
Sand/Mud/Dirt         75
Oil                   64
Name: ROADCOND, dtype: int64
```

In [20]:
```
accident_df["ROADCOND_1"]=accident_df["ROADCOND"]
accident_df["ROADCOND_1"]=accident_df["ROADCOND_1"].replace("Dry","1")
accident_df["ROADCOND_1"]=accident_df["ROADCOND_1"].replace("Wet","2")
accident_df["ROADCOND_1"]=accident_df["ROADCOND_1"].replace("Ice","3")
accident_df["ROADCOND_1"]=accident_df["ROADCOND_1"].replace("Snow/Slush","4")
accident_df["ROADCOND_1"]=accident_df["ROADCOND_1"].replace("Other","5")
accident_df["ROADCOND_1"]=accident_df["ROADCOND_1"].replace("Standing Water","6")
accident_df["ROADCOND_1"]=accident_df["ROADCOND_1"].replace("Sand/Mud/Dirt","7")
accident_df["ROADCOND_1"]=accident_df["ROADCOND_1"].replace("Oil","8")
```

In [21]:
```
sns.countplot(x="ROADCOND_1",hue="SEVERITYCODE",data=accident_df)
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x282eedf89a0>



Road Condtion-

The total count of accident with injuries(Severity=2) when roads were dry(value=1)are 40064 and percentage is 32.18%

The total count of accident with injuries(Severity=2) when roads were wet(value=2)are 15755 and percentage is 33.19%

The total count of accident with injuries(Severity=2) when roads had ice(value=3)are 273 and percentage is 22.58%

The total count of accident with injuries(Severity=2) when roads had snow/slush(value=4)are 167 and percentage is 16.63%

The total count of accident with injuries(Severity=2) when roads had standing water(value=6)are 30 and percentage is 26.09%

The total count of accident with injuries(Severity=2) when roads had sand/mud/dirt(value=7)are 23 and percentage is 30.67%

The total count of accident with injuries(Severity=2) when roads had oil(value=8)are 24 and percentage is 37.5%

The total count of accident with injuries(Severity=2) when roads had condition any other than above(value=5)are 43 and percentage is 32.58%

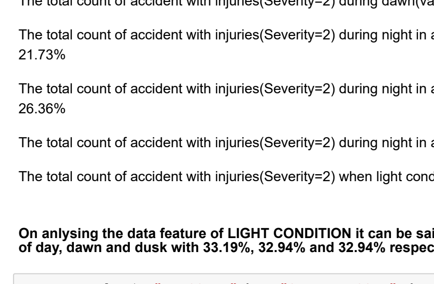
Oily Roads have one of the highest risk causing accidents that lead to injuries at 37.5% but with only 24 counts of such actual accidents being recorded shows that this statement is not stable statistically. The other conditions that impose a high risk are wet and dry which can be directly correlated with weather conditions.

In [22]:
```
accident_df["LIGHTCOND"].value_counts()
```

Out[22]:
```
Daylight                    116137
Dark - Street Lights On      48507
Unknown                      13473
Dusk                          5902
Dawn                          2502
Dark - No Street Lights       1537
Dark - Street Lights Off      1199
Other                          235
Dark - Unknown Lighting         11
Name: LIGHTCOND, dtype: int64
```

In [23]:
```
accident_df["LIGHTCOND_1"]=accident_df["LIGHTCOND"]
accident_df["LIGHTCOND_1"]=accident_df["LIGHTCOND_1"].replace("Daylight","1")
accident_df["LIGHTCOND_1"]=accident_df["LIGHTCOND_1"].replace("Dark - Street Lights On","2")
accident_df["LIGHTCOND_1"]=accident_df["LIGHTCOND_1"].replace("Dusk","3")
accident_df["LIGHTCOND_1"]=accident_df["LIGHTCOND_1"].replace("Dawn","4")
accident_df["LIGHTCOND_1"]=accident_df["LIGHTCOND_1"].replace("Dark - No Street Lights","5")
accident_df["LIGHTCOND_1"]=accident_df["LIGHTCOND_1"].replace("Dark - Street Lights Off","6")
accident_df["LIGHTCOND_1"]=accident_df["LIGHTCOND_1"].replace("Other","7")
accident_df["LIGHTCOND_1"]=accident_df["LIGHTCOND_1"].replace("Dark - Unknown Lighting","8")
sns.countplot(x="LIGHTCOND_1",hue="SEVERITYCODE",data=accident_df)
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x282f10c92b0>



Light Condition-

The total count of accident with injuries(Severity=2) during daylight(value=1)are 38544 and percentage is 33.19%

The total count of accident with injuries(Severity=2) during night in areas where streetlights were on (value=2)are 14475 and percentage is 29.84%

The total count of accident with injuries(Severity=2) during dusk(value=3)are 1944 and percentage is 32.94%

The total count of accident with injuries(Severity=2) during dawn(value=4)are 824 and percentage is 32.94%

The total count of accident with injuries(Severity=2) during night in areas where there are no street lights(value=5)are 334 and percentage is 21.73%

The total count of accident with injuries(Severity=2) during night in areas where street lights were off(value=6)are 316 and percentage is 26.36%

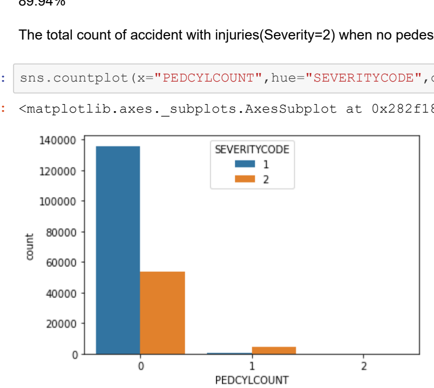
The total count of accident with injuries(Severity=2) during night in an unknown light source(value=8)are 4 and percentage is 36.36%

The total count of accident with injuries(Severity=2) when light conditions were other than above(value=7)are 52 and percentage is 22.13%

On anlysing the data feature of LIGHT CONDITION it can be said that almost majority of injury related accidents take place at time of day, dawn and dusk with 33.19%, 32.94% and 32.94% respectively.

In [24]:
```
sns.countplot(x="PEDCOUNT",hue="SEVERITYCODE",data=accident_df)
```

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x282edf63b50>

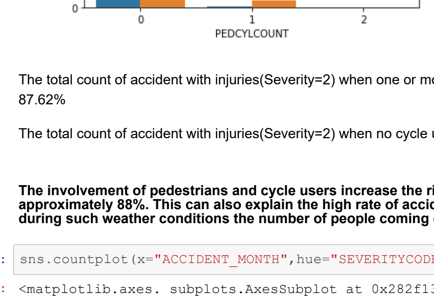


The total count of accident with injuries(Severity=2) when one or more than one pedestrians were involved are 6241 and percentage is 89.94%

The total count of accident with injuries(Severity=2) when no pedestrians were involved are 51947 and percentage is 27.62%

In [25]:
```
sns.countplot(x="PEDCYLCOUNT",hue="SEVERITYCODE",data=accident_df)
```

Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x282f1806460>



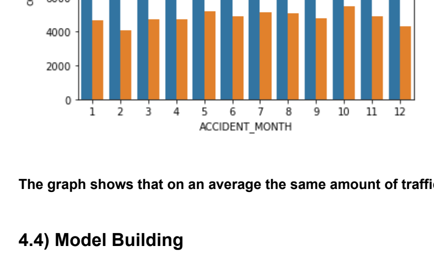
The total count of accident with injuries(Severity=2) when one or more than one cycle users were involved are 4805 and percentage is 87.62%

The total count of accident with injuries(Severity=2) when no cycle users were involved are 53383 and percentage is 28.22%

The involvement of pedestrians and cycle users increase the risk of accidents leading to injury(SEVERITY CODE=2) by approximately 88%. This can also explain the high rate of accidents with injuries during the clear weather, with dry roads as during such weather conditions the number of people coming out of their house increases

In [26]:
```
sns.countplot(x="ACCIDENT_MONTH",hue="SEVERITYCODE",data=accident_df)
```

Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x282f13116d0>



The graph shows that on an average the same amount of traffic accidents take place each month

4.4) Model Building

4.4.1) Data Preprocessing

In [27]:
```
feature=accident_df[["ACCIDENT_MONTH","LIGHTCOND_1","ROADCOND_1","WEATHER_1","X","Y","VEHCOUNT","INATTE
NTIONIND","UNDERINFL","SPEEDING"]]
accident_df.drop(feature,axis=1,inplace=True)
accident_df.head()
```

Out[27]:

	SEVERITYCODE	ADDRTYPE	PEDCOUNT	PEDCYLCOUNT	WEATHER	ROADCOND	LIGHTCOND
0	2	Intersection	0	0	Overcast	Wet	Daylight
1	1	Block	0	0	Raining	Wet	Dark - Street Lights On
2	1	Block	0	0	Overcast	Dry	Daylight
3	1	Block	0	0	Clear	Dry	Daylight
4	2	Intersection	0	0	Raining	Wet	Daylight

In [28]:

```
#Converting Categorical Variables into Numerical Variables to be used for Model
dummy_variable_1=pd.get_dummies(accident_df["ADDRTYPE"])
dummy_variable_1.rename(columns={'ADDRTYPE':'ALLEY','ADDRTYPE':'BLOCK','ADDRTYPE':'INTERSECTION'})
accident_df=pd.concat([accident_df,dummy_variable_1],axis=1)
accident_df.drop("ADDRTYPE",axis=1,inplace=True)
accident_df.head()
```

Out[28]:

	SEVERITYCODE	PEDCOUNT	PEDCYLCOUNT	WEATHER	ROADCOND	LIGHTCOND	Alley	Block	Intersection
0	2	0	0	Overcast	Wet	Daylight	0	0	1
1	1	0	0	Raining	Wet	Dark - Street Lights On	0	1	0
2	1	0	0	Overcast	Dry	Daylight	0	1	0
3	1	0	0	Clear	Dry	Daylight	0	1	0
4	2	0	0	Raining	Wet	Daylight	0	0	1

In [29]:

```
dummy_variable_2=pd.get_dummies(accident_df["WEATHER"])
dummy_variable_2.drop("Unknown",axis=1,inplace=True)
dummy_variable_2.rename(columns={"Other":"Other_W"},inplace=True)
accident_df=pd.concat([accident_df,dummy_variable_2],axis=1)
accident_df.drop("WEATHER",axis=1,inplace=True)
accident_df.head()
```

Out[29]:

	SEVERITYCODE	PEDCOUNT	PEDCYLCOUNT	ROADCOND	LIGHTCOND	Alley	Block	Intersection	Blowing Sand/Dirt	Clear	Fog/Smog/Smoke
0	2	0	0	Wet	Daylight	0	0	1	0	0	
1	1	0	0	Wet	Dark - Street Lights On	0	1	0	0	0	
2	1	0	0	Dry	Daylight	0	1	0	0	0	
3	1	0	0	Dry	Daylight	0	1	0	0	1	
4	2	0	0	Wet	Daylight	0	0	1	0	0	

In [30]:

```
dummy_variable_3=pd.get_dummies(accident_df["ROADCOND"])
dummy_variable_3.drop("Unknown",axis=1,inplace=True)
dummy_variable_3.rename(columns={"Other":"Other_R"},inplace=True)
accident_df=pd.concat([accident_df,dummy_variable_3],axis=1)
accident_df.drop("ROADCOND",axis=1,inplace=True)
accident_df.head()
```

Out[30]:

	SEVERITYCODE	PEDCOUNT	PEDCYLCOUNT	LIGHTCOND	Alley	Block	Intersection	Blowing Sand/Dirt	Clear	Fog/Smog/Smoke	...	Sleet/Ha
0	2	0	0	Daylight	0	0	1	0	0	0	...	
1	1	0	0	Dark - Street Lights On	0	1	0	0	0	0	...	
2	1	0	0	Daylight	0	1	0	0	0	0	...	
3	1	0	0	Daylight	0	1	0	0	1	0	...	
4	2	0	0	Daylight	0	0	1	0	0	0	...	

5 rows × 25 columns

In [31]:

```
dummy_variable_4=pd.get_dummies(accident_df["LIGHTCOND"])
dummy_variable_4.drop("Unknown",axis=1,inplace=True)
dummy_variable_4.rename(columns={"Other":"Other_L"},inplace=True)
accident_df=pd.concat([accident_df,dummy_variable_4],axis=1)
accident_df.drop("LIGHTCOND",axis=1,inplace=True)
accident_df.head()
```

Out[31]:

	SEVERITYCODE	PEDCOUNT	PEDCYLCOUNT	Alley	Block	Intersection	Blowing Sand/Dirt	Clear	Fog/Smog/Smoke	Other_W	...	Standing Water
0	2	0	0	0	0	1	0	0	0	0	...	0
1	1	0	0	0	1	0	0	0	0	0	...	0
2	1	0	0	0	1	0	0	0	0	0	...	0
3	1	0	0	0	1	0	0	1	0	0	...	0
4	2	0	0	0	0	1	0	0	0	0	...	0

5 rows × 32 columns

In [32]:

```
accident_df.shape
```

Out[32]:

```
(194673, 32)
```

4.4.2) Data Resampling

In [33]:

```
accident_df["SEVERITYCODE"].value_counts()
```

Out[33]:

```
1    136485
2     58188
Name: SEVERITYCODE, dtype: int64
```

In [34]:

```
#resampling data to remove thew classification bias from the model
from sklearn.utils import resample
#splitting data into different datasets as per the severity code
accident_df_severitycode1=accident_df[accident_df.SEVERITYCODE==1]
accident_df_severitycode2=accident_df[accident_df.SEVERITYCODE==2]
#downsampling accidents with severity code 1
accident_df_severitycode1_resampled=resample(accident_df_severitycode1,replace=False,n_samples=58188,ra
ndom_state=123)
accident_df_resampled=pd.concat([accident_df_severitycode1_resampled,accident_df_severitycode2])
accident_df_resampled["SEVERITYCODE"].value_counts()
```

Out[34]:

```
2    58188
1    58188
Name: SEVERITYCODE, dtype: int64
```

In [35]:

```
print(accident_df_resampled.isnull().sum()) #Checking for null values one last time before scalingthe d
ata
```

```
SEVERITYCODE                 0
PEDCOUNT                     0
PEDCYLCOUNT                  0
Alley                        0
Block                        0
Intersection                 0
Blowing Sand/Dirt            0
Clear                        0
Fog/Smog/Smoke               0
Other_W                      0
Overcast                     0
Partly Cloudy                0
Raining                      0
Severe Crosswind             0
Sleet/Hail/Freezing Rain     0
Snowing                      0
Dry                          0
Ice                          0
Oil                          0
Other_R                      0
Sand/Mud/Dirt                0
Snow/Slush                   0
Standing Water               0
Wet                          0
Dark - No Street Lights      0
Dark - Street Lights Off     0
Dark - Street Lights On      0
Dark - Unknown Lighting      0
Dawn                         0
Daylight                     0
Dusk                         0
Other_L                      0
dtype: int64
```

4.4.3) Data Normalization

In [36]:

```
from sklearn import preprocessing
feature=accident_df[["PEDCOUNT","PEDCYLCOUNT","Alley","Block","Intersection","Blowing Sand/Dirt","Clea
r","Fog/Smog/Smoke","Other_W","Overcast","Partly Cloudy","Raining","Severe Crosswind","Sleet/Hail/Freez
ing Rain","Snowing","Dry","Ice","Oil","Other_R","Sand/Mud/Dirt","Snow/Slush","Standing Water","Wet","Da
rk - No Street Lights","Dark - Street Lights Off","Dark - Street Lights On","Dark - Unknown Lighting",
"Dawn","Daylight","Dusk","Other_L"]]
x=preprocessing.StandardScaler().fit(feature).transform(feature)
y=accident_df["SEVERITYCODE"]
```

In [37]:

```
feature_1=accident_df_resampled[["PEDCOUNT","PEDCYLCOUNT","Alley","Block","Intersection","Blowing Sand/
Dirt","Clear","Fog/Smog/Smoke","Other_W","Overcast","Partly Cloudy","Raining","Severe Crosswind","Slee
t/Hail/Freezing Rain","Snowing","Dry","Ice","Oil","Other_R","Sand/Mud/Dirt","Snow/Slush","Standing Wate
r","Wet","Dark - No Street Lights","Dark - Street Lights Off","Dark - Street Lights On","Dark - Unknown
 Lighting","Dawn","Daylight","Dusk","Other_L"]]
x_1=preprocessing.StandardScaler().fit(feature_1).transform(feature_1)
y_1=accident_df_resampled["SEVERITYCODE"]
```

4.4.4) Splitting Dataset into Training and Testing Subsets

In [38]:

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=4)
print("The training set is:",x_train.shape,y_train.shape)
print("The test set is:",x_test.shape,y_test.shape)
```

```
The training set is: (155738, 31) (155738,)
The test set is: (38935, 31) (38935,)
```

In [39]:

```
xtrain,xtest,ytrain,ytest=train_test_split(x_1,y_1,test_size=0.2,random_state=4)
print("The training set is:",xtrain.shape,ytrain.shape)
print("The test set is:",xtest.shape,ytest.shape)
```

```
The training set is: (93100, 31) (93100,)
The test set is: (23276, 31) (23276,)
```

Now that we have a clean, balanced and standardised dataset for the city of Seattle. We have converted the categorical variables into numerical variables through the use of standard preprocessing techniques. We are ready to build and test models for predicting the Severity Code from our choosen feature set.

4.4.5) Classification Models

Since the dependent variable is a binary we are going to apply classifcation machine learning techniques to build the model. The followignare the techniques we are going to use: - 1) K-Nearest Neighbors

2) Logistic Regression

3) Support Vector Machine(SVM)

4) Decision Tree Classification

4.4.5.1) Logistic Regression

Model without resampling

In [68]:

```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
```

In [41]:

```
LR=LogisticRegression(C=0.01,solver="liblinear").fit(x_train,y_train)
LR
```

Out[41]:

```
LogisticRegression(C=0.01, solver='liblinear')
```

In [42]:

```
y_hat_LR=LR.predict(x_test)
y_hat_prob=LR.predict_proba(x_test)
print("The accuracy of Logistic Regression is:", metrics.accuracy_score(y_test,y_hat_LR))
```

```
The accuracy of Logistic Regression is: 0.7532040580454604
```

4.4.5.2) Model with resampling

```
In [43]: LR_resampled=LogisticRegression(C=0.01,solver="liblinear").fit(xtrain,ytrain)
         LR

Out[43]: LogisticRegression(C=0.01, solver='liblinear')
```

```
In [44]: y_hat1_LR=LR.predict(xtest)
         y_hat1_prob=LR.predict_proba(xtest)
         print("The accuracy of Logistic Regression is:", metrics.accuracy_score(ytest,y_hat1_LR))

         The accuracy of Logistic Regression is: 0.5897490977831242
```

4.4.5.3) Support Vector Machine(SVM)

Model without resampling

```
In [45]: from sklearn import svm
```

```
In [46]: severity=svm.SVC(kernel="rbf")
         severity.fit(x_train,y_train)

Out[46]: SVC()
```

```
In [47]: y_hat_svm=severity.predict(x_test)
         y_hat_svm[0:5]

Out[47]: array([1, 1, 1, 1, 1], dtype=int64)
```

```
In [48]: print("The accuracy of SVM is:", metrics.accuracy_score(y_test,y_hat_svm))

         The accuracy of SVM is: 0.7528701682290998
```

Model with resampling

```
In [49]: severity_1=svm.SVC(kernel="rbf")
         severity_1.fit(xtrain,ytrain)

Out[49]: SVC()
```

```
In [50]: y_hat1_svm=severity_1.predict(xtest)
         y_hat1_svm[0:5]

Out[50]: array([2, 1, 1, 1, 1], dtype=int64)
```

```
In [51]: print("The accuracy of SVM is:", metrics.accuracy_score(ytest,y_hat1_svm))

         The accuracy of SVM is: 0.6397147276164289
```

4.4.5.4) Decision Tree

Model without resampling

```
In [52]: from sklearn.tree import DecisionTreeClassifier
```

```
In [53]: severitytree=DecisionTreeClassifier(criterion='entropy', max_depth=4)
         severitytree.fit(x_train,y_train)

Out[53]: DecisionTreeClassifier(criterion='entropy', max_depth=4)
```

```
In [54]: predtree=severitytree.predict(x_test)
         print("The accuracy of decision tree is:", metrics.accuracy_score(y_test,predtree))

         The accuracy of decision tree is: 0.7532554257095159
```

Model with resampling

```
In [55]: severitytree1=DecisionTreeClassifier(criterion='entropy', max_depth=4)
         severitytree1.fit(xtrain,ytrain)

Out[55]: DecisionTreeClassifier(criterion='entropy', max_depth=4)
```

```
In [56]: predtree1=severitytree1.predict(xtest)
         print("The accuracy of decision tree is:", metrics.accuracy_score(ytest,predtree1))

         The accuracy of decision tree is: 0.6361488228217906
```

4.4.5.5) K-Nearest Neighbors

Model without resampling

```
In [57]: from sklearn.neighbors import KNeighborsClassifier
         neigh=KNeighborsClassifier(n_neighbors=4).fit(x_train,y_train)
         y_hat=neigh.predict(x_test)
         y_hat[0:5]

Out[57]: array([1, 1, 1, 2, 1], dtype=int64)
```

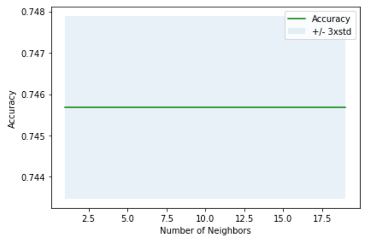
```
In [58]: from sklearn import metrics
         print("Train set accuracy:", metrics.accuracy_score(y_train,neigh.predict(x_train)))
         print("Test set accuracy:", metrics.accuracy_score(y_test,y_hat))

         Train set accuracy: 0.742779539996661
         Test set accuracy: 0.745678695261333
```

```
In [59]: ks=20
         mean_acc=np.zeros((ks-1))
         std_acc=np.zeros((ks-1))
         confusionmx=[];
         for n in range(1,ks):
             neig=KNeighborsClassifier(n_neighbors=n).fit(x_train,y_train)
             y_hat=neigh.predict(x_test)
             mean_acc[n-1]=metrics.accuracy_score(y_test,y_hat)
             std_acc[n-1]=np.std(y_hat==y_test)/np.sqrt(y_hat.shape[0])
         mean_acc

Out[59]: array([0.7456787, 0.7456787, 0.7456787, 0.7456787, 0.7456787, 0.7456787,
                0.7456787, 0.7456787, 0.7456787, 0.7456787, 0.7456787, 0.7456787,
                0.7456787, 0.7456787, 0.7456787, 0.7456787, 0.7456787, 0.7456787,
                0.7456787])
```

```
In [60]: plt.plot(range(1,ks),mean_acc,'g')
         plt.fill_between(range(1,ks),mean_acc - 1*std_acc,mean_acc + 1*std_acc,alpha=0.10)
         plt.legend(('Accuracy','+/- 3xstd'))
         plt.ylabel("Accuracy")
         plt.xlabel("Number of Neighbors")
         plt.tight_layout()
         plt.show()
```

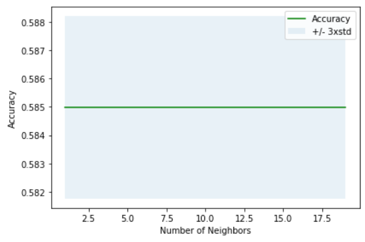


Model with resampling

```
In [62]: neigh_1=KNeighborsClassifier(n_neighbors=4).fit(xtrain,ytrain)
         y_hat1=neigh.predict(xtest)
         print("Train set accuracy:", metrics.accuracy_score(ytrain,neigh.predict(xtrain)))
         print("Test set accuracy:", metrics.accuracy_score(ytest,y_hat1))

         Train set accuracy: 0.584156820622986
         Test set accuracy: 0.5849802371541502
```

```
In [63]: ks=20
         mean_acc=np.zeros((ks-1))
         std_acc=np.zeros((ks-1))
         confusionmx=[];
         for n in range(1,ks):
             neig=KNeighborsClassifier(n_neighbors=n).fit(xtrain,ytrain)
             y_hat1=neigh.predict(xtest)
             mean_acc[n-1]=metrics.accuracy_score(ytest,y_hat1)
             std_acc[n-1]=np.std(y_hat1==ytest)/np.sqrt(y_hat1.shape[0])
         mean_acc
         plt.plot(range(1,ks),mean_acc,'g')
         plt.fill_between(range(1,ks),mean_acc - 1*std_acc,mean_acc + 1*std_acc,alpha=0.10)
         plt.legend(('Accuracy','+/- 3xstd'))
         plt.ylabel("Accuracy")
         plt.xlabel("Number of Neighbors")
         plt.tight_layout()
         plt.show()
```



4.5) Model Evaluation

Model without resampling

```
In [74]: from sklearn.metrics import f1_score
         from sklearn.metrics import log_loss
         from sklearn.metrics import jaccard_score
```

Logistic Regression

```
In [75]: print("The Jaccard Score is: %.4f" %jaccard_score(y_test,y_hat_LR))
         print("The F-1 Score is: %.4f" %f1_score(y_test,y_hat_LR,average='weighted'))
         print("The Log loss is: %.4f"%log_loss(y_test,y_hat_prob))

         The Jaccard Score is: 0.7385
         The F-1 Score is: 0.6909
         The Log loss is: 0.5335
```

Support Vector Machine(SVM)

```
In [76]: print("The Jaccard Score is: %.4f" %jaccard_score(y_test,y_hat_svm))
         print("The F-1 Score is: %.4f" %f1_score(y_test,y_hat_svm,average='weighted'))

         The Jaccard Score is: 0.7382
         The F-1 Score is: 0.6904
```

Decision Tree

```
In [77]: print("The Jaccard Score is: %.4f" %jaccard_score(y_test,predtree))
         print("The F-1 Score is: %.4f" %f1_score(y_test,predtree,average='weighted'))
```

```
The Jaccard Score is: 0.7386
The F-1 Score is: 0.6910
```

K-Nearest Neighbors

```
In [78]: print("The Jaccard Score is: %.4f" %jaccard_score(y_test,y_hat))
         print("The F-1 Score is: %.4f" %f1_score(y_test,y_hat,average='weighted'))
```

```
The Jaccard Score is: 0.7290
The F-1 Score is: 0.6905
```

Model with resampling

Logistic Regression

```
In [81]: print("The Jaccard Score is: %.4f" %jaccard_score(ytest,y_hat1_LR))
         print("The F-1 Score is: %.4f" %f1_score(ytest,y_hat1_LR,average='weighted'))
         print("The Log loss is: %.4f"%log_loss(ytest,y_hat1_prob))
```

```
The Jaccard Score is: 0.5466
The F-1 Score is: 0.5115
The Log loss is: 0.7057
```

Support Vector Machine(SVM)

```
In [82]: print("The Jaccard Score is: %.4f" %jaccard_score(ytest,y_hat1_svm))
         print("The F-1 Score is: %.4f" %f1_score(ytest,y_hat1_svm,average='weighted'))
```

```
The Jaccard Score is: 0.5067
The F-1 Score is: 0.6360
```

Decision Tree

```
In [83]: print("The Jaccard Score is: %.4f" %jaccard_score(ytest,predtree1))
         print("The F-1 Score is: %.4f" %f1_score(ytest,predtree1,average='weighted'))
```

```
The Jaccard Score is: 0.4983
The F-1 Score is: 0.6333
```

K-Nearest Neighbors

```
In [84]: print("The Jaccard Score is: %.4f" %jaccard_score(ytest,y_hat1))
         print("The F-1 Score is: %.4f" %f1_score(ytest,y_hat1,average='weighted'))
```

```
The Jaccard Score is: 0.5276
The F-1 Score is: 0.5297
```

	Without Resampling	**With Resampling**				
Algorithm	Jaccard	F1-score	LogLoss	Jaccard	F1-score	LogLoss
------------------	-------	--------	-------	-------	--------	-------
LogisticRegression	0.7385	0.6909	0.5335	0.5466	0.5115	0.7057
SVM	0.7382	0.6904	NA	0.5067	0.6360	NA
Decision Tree	0.7386	0.6910	NA	0.4983	0.6333	NA
KNN	0.7290	0.6905	?	0.5276	0.5297	NA

5) Result

There were two models constructed respectively: - 1) In which the data was not resampled

2) In which data was resampled

Both the models were then trained on the same clasification algorithms to make a fair comparision between the two. It was found that the models which were trained on the dataset that was not resampled had a higher accuracy for the predictions and lower uncertainity as compared to it's counterpart. Though the data without resampling might have a little bias due to a very high value of accidents having SEVERITYCODE 1 in respect to accidents having SEVERITYCODE 2. But due to resampling the accuracy and uncertainity increases and this means that some important information or trend goes missing. Thus, impacting the accuracy and predictive ability of the model.

For Logistic Regression Model the value of log loss for data without resampling is almost 32.27% higher showing a very high level if uncertainity. Similar trend is visible for jaccard score as well as F1 socres for all the other models. This model also gives a large value of false negatives for accidents of severity class 2 and fails to make accurate prediction for them.

6) Conclusion

The aim of this project is to predict the severity of accidents and to reveal the factors affecting the severity. When examining the feature importance after the training step, it seems possible to say that there are several remarkable features. It seems quite effective that a pedestrian or cyclist was involved in the accident.

Going back to the exploratory data analysis step, we were able to get many important following insights such as majority of accidents that take place in wet conditions of road are directly related with the rainy and overcast weather while majority of the accidents that take place in dry conditions involve majority of pedestrians and cyclists. The accidents that result in majority of injuries take place at dawn,daytime and dusk.This proves the logical conditions of lower visibility will result in higher injury accidents to be untrue on majority. The intersection as a place has a large amount of accidents with injuries and property damage as the collision of vehicles take place at an angle. The criminal offences such as inattention, driving under influences and speeding increases the risk of ijury causing accidents and the timings of these offences explains the high accidents during dawn and dusk.

Various points that can make suggestions based on all insights can be listed as follows,

- Drivers should be more careful where pedestrians and/or cyclists are concentrated. (*is_ped* and *is_bike*)
- Drivers should be more careful at intersections. (*addr_type_intersection*)
- Age as a factor should be considered by seattle transportation department which will be very useful in explaining criminal offences.
- Extra measures can be taken to prevent driving under drugs and alcohol. (*under_infl*)

Apart from the features that distinguish the two classes from each other, suggestions for situations where accidents occur frequently can be listed as follows:

- At hours close to office hours drivers should be more careful.
- Special precautions can be taken by the relevant authorities, especially since there are angles type collisions at intersections.
- Authoritites should look at districts with schools, universities and offices where the pedestrians and cyclist are concentrated.
- Authorities should also make rules, take precautions and make arrangements for the safety of pedestrains and cyclist.