Business Case

Road accidents are extremely common over the world so that AI driven cars is a future topic. Cards drived by humans often leads to a loss of property and even life. Wouldn't it be great to be able to understand what are the most common causes, in order to prevent them from happening? With this analysis, I am attempting to understand these factors and their correlation. This analysis has multiple applications like an app that will prompt the drivers to be more careful depending on the weather and road conditions on any given day or a way for the police to enforce more safety protocols. Also people who really care about the traffic records, especially in the transportation department or mayor als representant of the city. Also, we want to figure out the reason for collisions and help to reduce accidents in the future.

Data

This is an extensive data set from the Seattle Police Department, with over 190,000 observations collected from 2004 till present. We will use SEVERITYCODE as our dependent variable Y, and try different combinations of independent variables X to get the result.

Other important variables include:

- ADDRTYPE: Collision address type: Alley, Block, Intersection
- LOCATION: Description of the general location of the collision
- PERSONCOUNT: The total number of people involved in the collision helps identify severity involved
- PEDCOUNT: The number of pedestrians involved in the collision helps identify severity involved
- PEDCYLCOUNT: The number of bicycles involved in the collision helps identify severity involved
- VEHCOUNT: The number of vehicles involved in the collision identify severity involved
- JUNCTIONTYPE: Category of junction at which collision took place helps identify where most collisions occur
- WEATHER: A description of the weather conditions during the time of the collision
- ROADCOND: The condition of the road during the collision
- LIGHTCOND: The light conditions during the collision
- SPEEDING: Whether or not speeding was a factor in the collision (Y/N)
- SEGLANEKEY: A key for the lane segment in which the collision occurred
- CROSSWALKKEY: A key for the crosswalk at which the collision occurred
- HITPARKEDCAR: Whether or not the collision involved hitting a parked car

Methodology

I used Jupyter Notebooks to conduct that analysis and imported all the necessary Python libraries like Pandas, Numpy, Matplotlib, and Seaborn. The data was mostly categorical so I stuck to graphical representation to see correlation between various variables. I started by importing the csv file and to prepare the data, I dropped the columns we do not need from the dataset, i.e., columns that do not have values or where the values are unknown. Even though this is an important factor, I dropped Speeding entirely because it is missing over 180,000 values and this can hamper the results.

In [40]:

```
import pandas as pd
import numpy as np

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

In [41]:

```
df=pd.read_csv("Data-Collisions.csv",low_memory=False)
df.dtypes
```

Out[41]:
```
SEVERITYCODE        int64
X                 float64
Y                 float64
OBJECTID            int64
INCKEY              int64
COLDETKEY           int64
REPORTNO           object
STATUS             object
ADDRTYPE           object
INTKEY            float64
LOCATION           object
EXCEPTRSNCODE      object
EXCEPTRSNDESC      object
SEVERITYCODE.1      int64
SEVERITYDESC       object
COLLISIONTYPE      object
PERSONCOUNT         int64
PEDCOUNT            int64
PEDCYLCOUNT         int64
VEHCOUNT            int64
INCDATE            object
INCDTTM            object
JUNCTIONTYPE       object
SDOT_COLCODE        int64
SDOT_COLDESC       object
INATTENTIONIND     object
UNDERINFL          object
WEATHER            object
ROADCOND           object
LIGHTCOND          object
PEDROWNOTGRNT      object
SDOTCOLNUM        float64
SPEEDING           object
ST_COLCODE         object
ST_COLDESC         object
SEGLANEKEY          int64
CROSSWALKKEY        int64
HITPARKEDCAR       object
dtype: object
```

In [42]:
```
df.describe()
```

Out[42]:

	SEVERITYCODE	X	Y	OBJECTID	INCKEY	
count	194673.000000	189339.000000	189339.000000	194673.000000	194673.000000	194
mean	1.298901	-122.330518	47.619543	108479.364930	141091.456350	14
std	0.457778	0.029976	0.056157	62649.722558	86634.402737	8
min	1.000000	-122.419091	47.495573	1.000000	1001.000000	
25%	1.000000	-122.348673	47.575956	54267.000000	70383.000000	70
50%	1.000000	-122.330224	47.615369	106912.000000	123363.000000	123
75%	2.000000	-122.311937	47.663664	162272.000000	203319.000000	203
max	2.000000	-122.238949	47.734142	219547.000000	331454.000000	332

In [43]:
```
df.info()
```

```
<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 [44]:
```
df[df.SPEEDING.notna()]
```

Out[44]:

	SEVERITYCODE	X	Y	OBJECTID	INCKEY	COLDETKEY	REPOR
24	2	-122.279658	47.553405	33	1268	1268	367
43	2	-122.337348	47.520472	53	56100	56100	261
62	1	-122.376182	47.499490	74	32000	32000	121
123	1	-122.333924	47.604678	140	29700	29700	148
124	2	-122.322187	47.618733	141	1135	1135	360
...	...	...	...	...	...	...	
194414	1	-122.293204	47.542648	219238	309651	310931	381
194428	2	-122.320008	47.625350	219255	309595	310875	E88
194481	2	-122.307643	47.541919	219317	308340	309620	357
194492	1	NaN	NaN	219329	308810	310090	381
194549	1	-122.346793	47.662069	219399	308693	309973	381

9333 rows × 38 columns

In [45]:

```
df["SEVERITYCODE"].value_counts().to_frame()
```

Out[45]:

	SEVERITYCODE
1	136485
2	58188

Our target variable SEVERITYCODE is only 42% balanced. In fact, severitycode in class 1 is nearly three times the size of class 2.

In [46]:
```
total_cases=df["SEVERITYCODE"].value_counts().sum()
df["SEVERITYCODE"].value_counts()/total_cases*100
```

Out[46]:
```
1    70.109877
2    29.890123
Name: SEVERITYCODE, dtype: float64
```

In [47]:
```
from sklearn import preprocessing

#Converting Severity Code from (1/2) tp (0/1)
severity_code = df['SEVERITYCODE'].values

labels = preprocessing.LabelEncoder()
labels.fit([1, 2])
severity_code = labels.transform (severity_code)

df["SEVERITYCODE"] = severity_code

severity_code
```

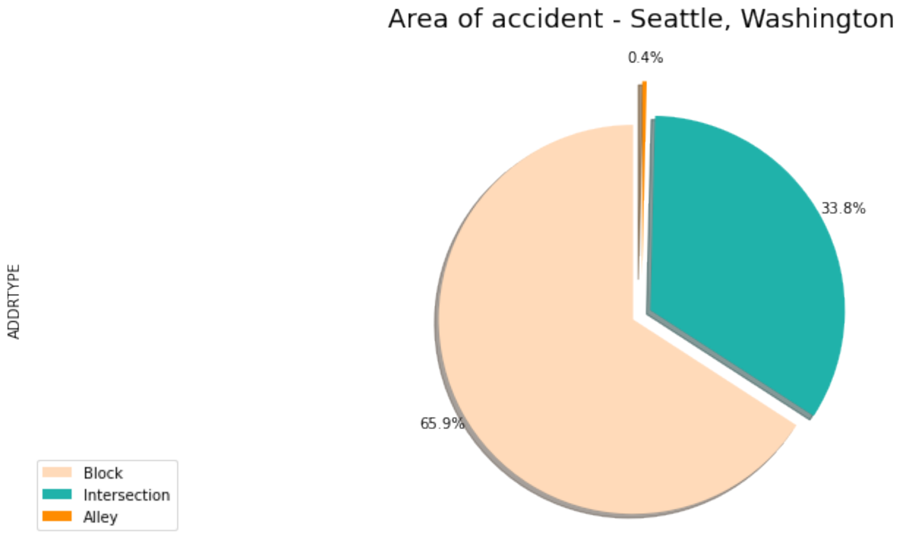
Out[47]:
```
array([1, 0, 0, ..., 1, 1, 0])
```

In [48]:
```
#Area type of each accident
explode_list = [0.05, 0.05, 0.2]
color_list=['peachpuff','lightseagreen','darkorange']
addtype=df['ADDRTYPE'].value_counts()

addtype.plot(kind='pie',
             figsize=(15, 6),
             autopct='%1.1f%%',
             startangle=90,
             shadow=True,
             labels=None,
             pctdistance=1.12,
             colors=color_list,
             explode=explode_list)


plt.title('Area of accident - Seattle, Washington', fontsize=18, y=1.05)
plt.axis('equal')
plt.legend(labels=addtype.index, loc='lower left')

plt.show()
```



In [49]:
```
df["WEATHER"].value_counts().to_frame()
```

Out[49]:

	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

In [50]:
```
df["COLLISIONTYPE"].value_counts().to_frame()
```

Out[50]:

	COLLISIONTYPE
Parked Car	47987
Angles	34674
Rear Ended	34090
Other	23703
Sideswipe	18609
Left Turn	13703
Pedestrian	6608
Cycles	5415
Right Turn	2956
Head On	2024

In [51]:
```
df["ROADCOND"].value_counts().to_frame()
```

Out[51]:

	ROADCOND
Dry	124510
Wet	47474
Unknown	15078
Ice	1209
Snow/Slush	1004
Other	132
Standing Water	115
Sand/Mud/Dirt	75
Oil	64

All kind of wet weather conditions leads to more accidents

In [52]:
```
df["LIGHTCOND"].value_counts().to_frame()
```

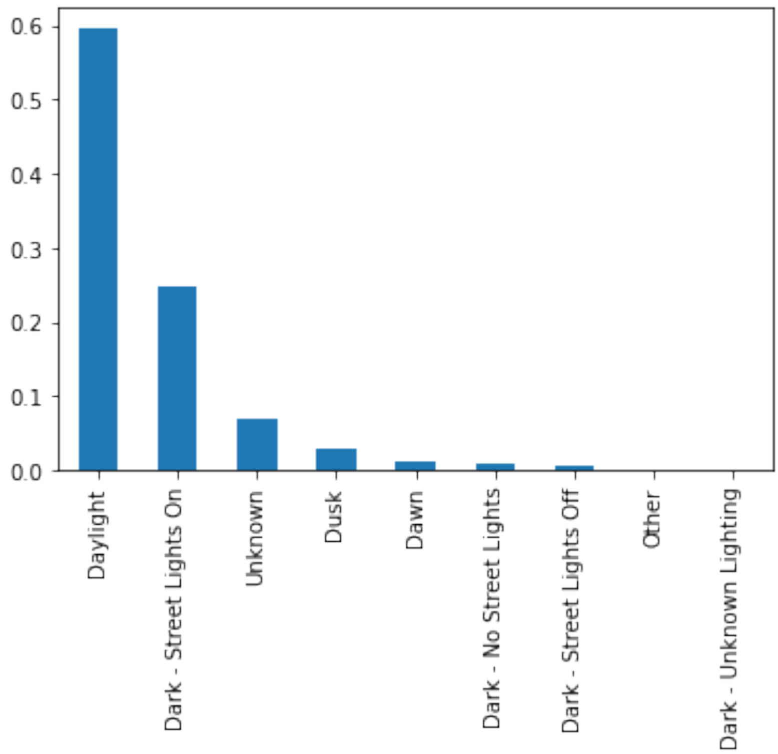
Out[52]:

	LIGHTCOND
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

In [53]:

```
(df["LIGHTCOND"].value_counts()/total_cases).plot(kind="bar")
```

Out[53]: <AxesSubplot:>



In [54]:

```
df["INATTENTIONIND"].value_counts().to_frame()
```

Out[54]:

	INATTENTIONIND
Y	29805

In [55]:

```
df["INATTENTIONIND"].value_counts()/total_cases
```

Out[55]:

```
Y    0.153103
Name: INATTENTIONIND, dtype: float64
```

In [56]:
```
df["UNDERINFL"].value_counts().to_frame()
```

Out[56]:

	UNDERINFL
N	100274
0	80394
Y	5126
1	3995

On the first look it seems that crashes happened in clear, dry, and bright conditions. Most days are clear, dry, and bright, so it’s no surprise that most car crashes occur under these conditions. Further it also seems that crashes with a distracted driver or an impaired driver are statistically more likely to result in injury

Data cleaning

Let's clean our data to generate usable features

In [57]:
```
df["UNDERINFL"].replace(to_replace=['N', 'Y'], value=[0,1], inplace=True)
yes=df["UNDERINFL"].value_counts().to_frame()[0:2].sum()
no=df["UNDERINFL"].value_counts().to_frame()[2:5].sum()

print("Under influence:",yes/total_cases)
print("Not under influence:",no/total_cases)
```

```
Under influence: UNDERINFL    0.928059
dtype: float64
Not under influence: UNDERINFL    0.046853
dtype: float64
```

In [58]:
```
df["UNDERINFL"].replace("N", 0, inplace=True)
df["UNDERINFL"].replace(np.nan, 0, inplace=True)
df["UNDERINFL"].replace("Y", 1, inplace=True)
```

In [59]:
```
df['SPEEDING']
```

Out[59]:
```
0         NaN
1         NaN
2         NaN
3         NaN
4         NaN
         ...
194668    NaN
194669    NaN
194670    NaN
194671    NaN
194672    NaN
Name: SPEEDING, Length: 194673, dtype: object
```

In [60]:
```
# in speed we replace Nan with a negative value N
df["SPEEDING"].replace("Y", 1, inplace=True)
df['SPEEDING'] = df['SPEEDING'].fillna(0)
df['SPEEDING']
```

Out[60]:
```
0         0.0
1         0.0
2         0.0
3         0.0
4         0.0
         ...
194668    0.0
194669    0.0
194670    0.0
194671    0.0
194672    0.0
Name: SPEEDING, Length: 194673, dtype: float64
```

In [61]:
```
#Encoding Light Conditions(0 = Light, 1 = Medium, 2 = Dark, 3 = Unknown)
df["LIGHTCOND"].replace("Daylight", 0, inplace=True)
df["LIGHTCOND"].replace("Dark - Street Lights On", 1, inplace=True)
df["LIGHTCOND"].replace("Dark - No Street Lights", 2, inplace=True)
df["LIGHTCOND"].replace("Dusk", 1, inplace=True)
df["LIGHTCOND"].replace("Dawn", 1, inplace=True)
df["LIGHTCOND"].replace("Dark - Street Lights Off", 2, inplace=True)
df["LIGHTCOND"].replace("Dark - Unknown Lighting", 2, inplace=True)
df["LIGHTCOND"].replace("Other","Unknown", inplace=True)
df["LIGHTCOND"].replace(np.nan,"Unknown", inplace=True)
df["LIGHTCOND"].replace("Unknown", 3, inplace=True)
```

In [62]:
```
#We assign new values to roadcond Road Conditions(0 = Dry, 1 = Mushy, 2 = W
df["ROADCOND"].replace("Dry", 0, inplace=True)
df["ROADCOND"].replace("Wet", 2, inplace=True)
df["ROADCOND"].replace("Ice", 2, inplace=True)
df["ROADCOND"].replace("Snow/Slush", 1, inplace=True)
df["ROADCOND"].replace("Other", "Unknown", inplace=True)
df["ROADCOND"].replace("Standing Water", 2, inplace=True)
df["ROADCOND"].replace("Sand/Mud/Dirt", 1, inplace=True)
df["ROADCOND"].replace("Oil", 2, inplace=True)
df["ROADCOND"].replace("Unknown", 3, inplace=True)
df["ROADCOND"].replace(np.nan, 3, inplace=True)
```

In [63]:
```
#Encoding Weather Conditions(0 = Clear, 1 = Overcast and Cloudy, 2 = Windy,
df["WEATHER"].replace("Clear", 0, inplace=True)
df["WEATHER"].replace("Raining", 3, inplace=True)
df["WEATHER"].replace("Overcast", 1, inplace=True)
df["WEATHER"].replace("Other", "Unknown", inplace=True)
df["WEATHER"].replace("Snowing", 3, inplace=True)
df["WEATHER"].replace("Fog/Smog/Smoke", 2, inplace=True)
df["WEATHER"].replace("Sleet/Hail/Freezing Rain", 3, inplace=True)
df["WEATHER"].replace("Blowing Sand/Dirt", 2, inplace=True)
df["WEATHER"].replace("Severe Crosswind", 2, inplace=True)
df["WEATHER"].replace("Partly Cloudy", 1, inplace=True)

df["WEATHER"].replace(np.nan, 4, inplace=True)
df["WEATHER"].replace("Unknown", 4, inplace=True)
```

In [64]:
```
#Encoding in attention (0 = No, 1 = Yes)
df["INATTENTIONIND"].replace("Y", 1, inplace=True)
df["INATTENTIONIND"].replace(np.nan, 0, inplace=True)
```

In [65]:
```
df.describe()
```

Out[65]:

	SEVERITYCODE	X	Y	OBJECTID	INCKEY
count	194673.000000	189339.000000	189339.000000	194673.000000	194673.000000
mean	0.298901	-122.330518	47.619543	108479.364930	141091.456350
std	0.457778	0.029976	0.056157	62649.722558	86634.402737
min	0.000000	-122.419091	47.495573	1.000000	1001.000000
25%	0.000000	-122.348673	47.575956	54267.000000	70383.000000
50%	0.000000	-122.330224	47.615369	106912.000000	123363.000000
75%	1.000000	-122.311937	47.663664	162272.000000	203319.000000
max	1.000000	-122.238949	47.734142	219547.000000	331454.000000

8 rows × 21 columns

Optimized dataset

In [66]:
```
#Making new dataframe with only variables and unique keys
selected_columns=["X","Y","INCKEY","INATTENTIONIND","UNDERINFL","WEATHER",'
feature_df=df[selected_columns]#.copy()
#feature_df.dropna(axis=0,how='any',inplace=True)
feature_stats=feature_df.describe()
```

In [67]:
```
feature_df ["LIGHTCOND"].unique()
```

Out[67]:
```
array([0, 1, 2, 3])
```

In [68]:
```
feature_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 194673 entries, 0 to 194672
Data columns (total 10 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   X               189339 non-null  float64
 1   Y               189339 non-null  float64
 2   INCKEY          194673 non-null  int64  
 3   INATTENTIONIND  194673 non-null  float64
 4   UNDERINFL       194673 non-null  object 
 5   WEATHER         194673 non-null  int64  
 6   ROADCOND        194673 non-null  float64
 7   LIGHTCOND       194673 non-null  int64  
 8   SPEEDING        194673 non-null  float64
 9   SEVERITYCODE    194673 non-null  int64  
dtypes: float64(5), int64(4), object(1)
memory usage: 14.9+ MB
```

In [69]:

```
feature_df["SPEEDING"]
```

Out[69]:

```
0         0.0
1         0.0
2         0.0
3         0.0
4         0.0
         ... 
194668    0.0
194669    0.0
194670    0.0
194671    0.0
194672    0.0
Name: SPEEDING, Length: 194673, dtype: float64
```

In [70]:

```
    #Converting remaining to int
feature_df["SPEEDING"]=feature_df["SPEEDING"].astype(int)
feature_df["INATTENTIONIND"]=feature_df["INATTENTIONIND"].astype(int)
feature_df["UNDERINFL"]=feature_df["UNDERINFL"].astype(int)
```

```
<ipython-input-70-2625928d104a>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs
/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  feature_df["SPEEDING"]=feature_df["SPEEDING"].astype(int)
<ipython-input-70-2625928d104a>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs
/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  feature_df["INATTENTIONIND"]=feature_df["INATTENTIONIND"].astype(int)
<ipython-input-70-2625928d104a>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs
/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  feature_df["UNDERINFL"]=feature_df["UNDERINFL"].astype(int)
```

In [75]:

```
#check trough smooth unique values
for col in feature_df.columns:
    print(col,feature_df[col].unique())
```

```
X [-122.3231484 -122.3472943 -122.33454   ... -122.3927543 -122.3042172
 -122.3616722]
Y [47.70314032 47.64717249 47.60787143 ... 47.51527348 47.6695375
 47.55672231]
INCKEY [  1307  52200  26700 ... 311280 309514 308220]
INATTENTIONIND [0 1]
UNDERINFL [0 1]
WEATHER [1 3 0 4 2]
ROADCOND [2. 0. 3. 1.]
LIGHTCOND [0 1 2 3]
SPEEDING [0 1]
SEVERITYCODE [1 0]
```

In [76]:

```
print("With nan Values:",feature_df.size)
feature_df=feature_df.dropna()
print("Without nan Values:",feature_df.size)
```

```
With nan Values: 1893390
Without nan Values: 1893390
```

Now let's have a look to the map on Seatle

In [90]:

```
import folium
from folium import plugins

#Make reduced df from feature_df to get a few random points to make map
limit = 10000 #faster mapping
reduced_df = feature_df.iloc [0:limit:5, 0:]

#Folium Map
# let's start again with a clean copy of the map of San Francisco
seattle_map = folium.Map(location=[47.61536892, -122.3302243], zoom_start=1

# instantiate a mark cluster object for the incidents in the dataframe
incidents = plugins.MarkerCluster().add_to(seattle_map)

# loop through the dataframe and add each data point to the mark cluster
for lat, lng, label, in zip(reduced_df.Y, reduced_df.X, reduced_df.SEVERITY
    folium.Marker(
    location=[lat, lng],
    icon=None,
    popup=label,
    ).add_to(incidents)

seattle_map.add_child(incidents)

# display interactive map
seattle_map
```

Out[90]: Make this Notebook Trusted to load map: File -> Trust Notebook 39

\+

−

13

10

4

13

25

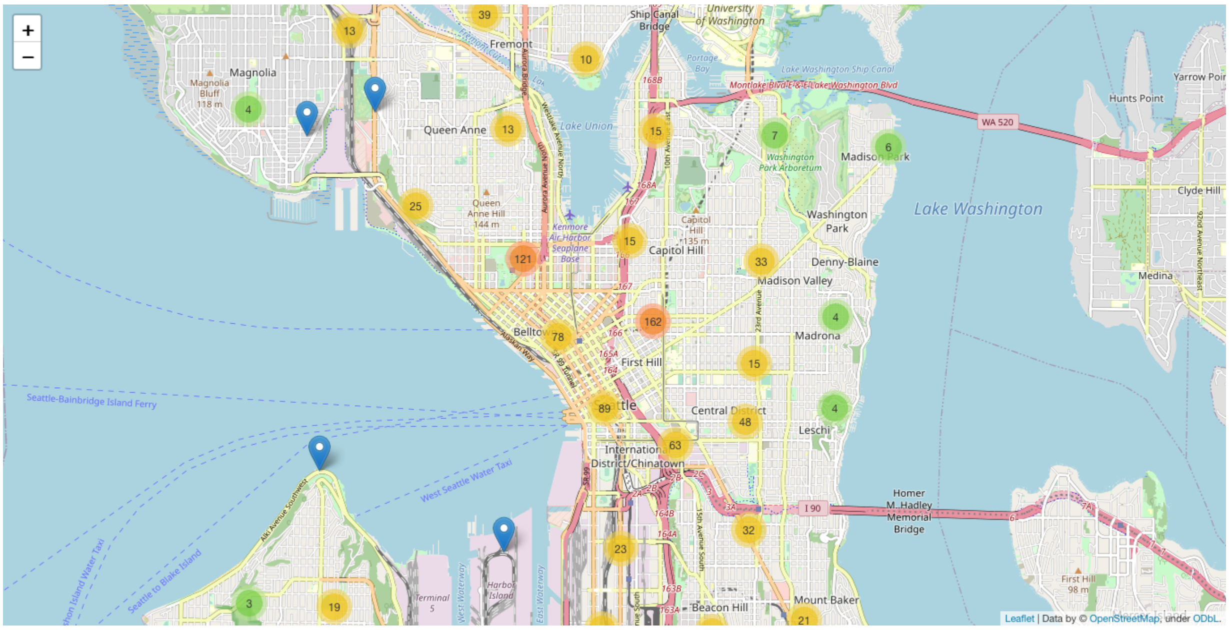
121

Leaflet (https://leafletjs.com) | Data by © OpenStreetMap (http://openstreetmap.org), under ODbL (http://www.openstreetmap.org/copyright).

In [91]:
```
#Workaround for Notebook export with image
import io
from PIL import Image
img_data = seattle_map._to_png(5)
img = Image.open(io.BytesIO(img_data))
img.save('Seattle.png')
```

In [92]:
```
from IPython.display import Image
from IPython.core.display import HTML
Image(url= "Seattle.png")
```

Out[92]:



Here we see that the most accidents are located along the main road. Your first chance to prohibit an accident is to take another way. But that's only a hint :-)

Training the model

In [34]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report
from sklearn.tree import DecisionTreeClassifier
from sklearn import svm
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score
from sklearn import preprocessing
from sklearn.linear_model import LogisticRegression
```

In [35]:
```
#ML Feature Sets
X=feature_df[["SPEEDING","INATTENTIONIND","UNDERINFL","ROADCOND","WEATHER",
y=feature_df[["SEVERITYCODE"]].values

#Test/Train split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ra
print ('Train set:', X_train.shape,  y_train.shape)
print ('Test set:', X_test.shape,  y_test.shape)
```

```
Train set: (132537, 6) (132537, 1)
Test set: (56802, 6) (56802, 1)
```

Selecting model

First let's balanace our data to get a better outcome, because our target variable SEVERITYCODE is only 42% balanced. In fact, severitycode in class 1 is nearly three times the size of class 2. (0 and 1 in our model)

In [37]:
```
from imblearn.over_sampling import SMOTE

# Balance the Data
os = SMOTE (random_state=0)
os_data_X, os_data_y= os.fit_sample(X_train, y_train)
```

In [38]:
```
from sklearn.metrics import accuracy_score,f1_score,log_loss,classificatio
```

Tree model

A decision tree model gives us a layout of all possible outcomes so we can fully analyze the concequences of a decision. It context, the decision tree observes all possible outcomes of different weather conditions.

In [39]:
```
#Decision Tree Clasifier
DT = DecisionTreeClassifier(criterion="entropy", max_depth=6)
DT.fit(os_data_X,os_data_y)

        #Make Prediction:
yhatDT = DT.predict(X_test)

        #Check Accuracy
print('Accuracy score for Decision Tree = ', accuracy_score(yhatDT, y_test)
dt_acc=accuracy_score(yhatDT, y_test)
dt_f1=f1_score(y_test, yhatDT, average='weighted')
print("F1",dt_f1)

        #Visualization
print('Confusion Matrix - Decision Tree')
print(pd.crosstab(y_test.ravel(), yhatDT.ravel(), rownames = ['True'], colr

print(classification_report(yhatDT,y_test))
```

```
Accuracy score for Decision Tree =  0.46005422344283653
F1 0.4468765525831609
Confusion Matrix - Decision Tree
Predicted      0      1    All
True
0          11505  27908  39413
1           2762  14627  17389
All        14267  42535  56802
              precision    recall  f1-score   support

           0       0.29      0.81      0.43     14267
           1       0.84      0.34      0.49     42535

    accuracy                           0.46     56802
   macro avg       0.57      0.58      0.46     56802
weighted avg       0.70      0.46      0.47     56802
```

Tree_model = DecisionTreeClassifier(criterion="entropy", max_depth = 6) Tree_model.fit(x_train, y_train) predicted = Tree_model.predict(x_test) Tree_f1 = f1_score(y_test, predicted, average='weighted') Tree_acc = accuracy_score(y_test, predicted)

Logistic regression

Because our dataset only provides us with two severity code outcomes, our model will only predict one of those two classes. This makes our data binary, which is perfect to use with logistic regression.

In [40]:
```
#Logistic Regression
LR = LogisticRegression(C=0.01, solver='liblinear').fit(os_data_X,os_data_y

yhatLR = LR.predict(X_test)
yhat_prob = LR.predict_proba(X_test)

print("LogLoss",log_loss(y_test, yhat_prob))

print ("Accuracy", accuracy_score(yhatLR,y_test))

lr_acc=accuracy_score(yhatLR,yhatLR)
lr_f1 = f1_score(y_test, yhatLR, average='weighted')
print("F1",lr_f1)

print (classification_report(y_test, yhatLR))

cnf_matrix = confusion_matrix(y_test, yhatLR, labels=[1,0])
np.set_printoptions(precision=2)
```

```
LogLoss 0.6761341512478765
Accuracy 0.4977817682475969
F1 0.5072981549434343
              precision    recall  f1-score   support

           0       0.76      0.40      0.52     39413
           1       0.35      0.72      0.47     17389

    accuracy                           0.50     56802
   macro avg       0.55      0.56      0.50     56802
weighted avg       0.64      0.50      0.51     56802
```

KNN

KNN will help us predict the severity code of an outcome by finding the most similar to data point within k distance.

Find best k

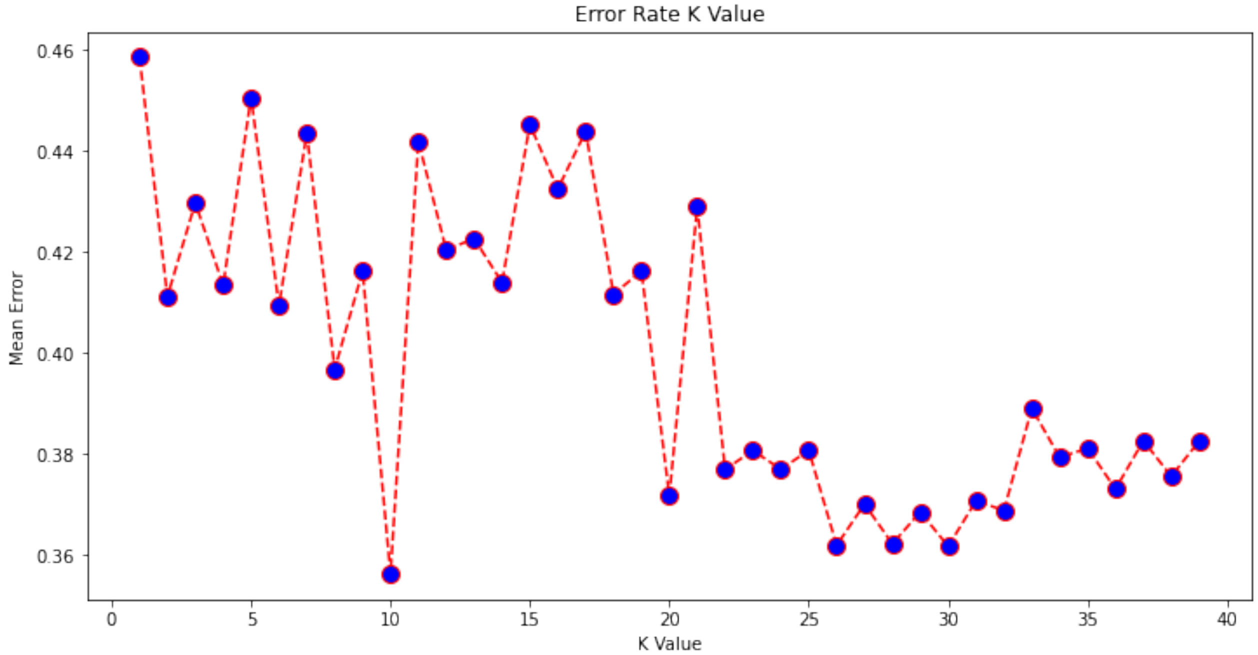
In [41]:
```
error = []
print("Lets go...")
# Calculating error for K values between 1 and 40
for i in range(1, 40):
    knn = KNeighborsClassifier(n_neighbors=i).fit(os_data_X,os_data_y)
    pred_i = knn.predict(X_test)
    print(i,pred_i)
    error.append(np.mean(pred_i != y_test))
```

```
Lets go...
1 [1 1 0 ... 1 0 0]
2 [0 0 0 ... 0 0 0]
3 [0 0 0 ... 0 0 0]
4 [0 0 0 ... 0 0 0]
5 [0 0 0 ... 0 0 1]
6 [0 0 0 ... 0 0 0]
7 [0 0 0 ... 0 0 1]
8 [0 0 0 ... 0 0 0]
9 [0 0 0 ... 0 0 0]
10 [0 0 0 ... 0 0 0]
11 [0 0 0 ... 0 0 0]
12 [0 0 0 ... 0 0 0]
13 [0 0 0 ... 0 0 0]
14 [0 0 0 ... 0 0 0]
15 [0 0 0 ... 0 0 0]
16 [0 0 0 ... 0 0 0]
17 [0 0 0 ... 0 0 0]
18 [0 0 0 ... 0 0 0]
19 [0 0 0 ... 0 0 0]
20 [0 0 0 ... 0 0 0]
21 [0 0 0 ... 0 0 0]
22 [0 0 0 ... 0 0 0]
23 [0 0 0 ... 0 0 0]
24 [0 0 0 ... 0 0 0]
25 [0 0 0 ... 0 0 0]
26 [0 0 0 ... 0 0 0]
27 [0 0 0 ... 0 0 0]
28 [0 0 0 ... 0 0 0]
29 [0 0 0 ... 0 0 0]
30 [0 0 0 ... 0 0 0]
31 [0 0 0 ... 0 0 0]
32 [0 0 0 ... 0 0 0]
33 [0 0 0 ... 0 0 0]
34 [0 0 0 ... 0 0 0]
35 [0 0 0 ... 0 0 0]
36 [0 0 0 ... 0 0 0]
37 [0 0 0 ... 0 0 0]
38 [0 0 0 ... 0 0 0]
39 [0 0 0 ... 0 0 0]
```

In [43]:

```
plt.figure(figsize=(12, 6))
plt.plot(range(1, 40), error, color='red', linestyle='dashed', marker='o',
         markerfacecolor='blue', markersize=10)
plt.title('Error Rate K Value')
plt.xlabel('K Value')
plt.ylabel('Mean Error')
```

Out[43]: Text(0, 0.5, 'Mean Error')



We see that with k=10 we will get a good an fast outcome!

In [46]:
```
k =10
```

In [47]:
```
KNN_model = KNeighborsClassifier(n_neighbors = 15).fit(os_data_X,os_data_y)
predicted = KNN_model.predict(X_test)
KNN_f1 = f1_score(y_test, predicted, average='weighted')
KNN_acc = accuracy_score(y_test, predicted)
```

In [48]:
```
print(KNN_f1,KNN_acc)
```

```
0.5739243286095367 0.5652793915707194
```

In [49]:
```
print(classification_report(predicted,y_test))
```

```
              precision    recall  f1-score   support

           0       0.65      0.70      0.67     36420
           1       0.38      0.32      0.35     20382

    accuracy                           0.57     56802
   macro avg       0.51      0.51      0.51     56802
weighted avg       0.55      0.57      0.56     56802
```

Model results

Now we will check the accuracy of our models.

In [50]:
```
df_results=pd.DataFrame({"Model":["Decision Tree","Logistic recession","KNN
df_results
```

Out[50]:

Model	F1	Accuracy
Decision Tree	0.446877	0.460054
Logistic recession	0.507298	1.000000
KNN	0.573924	0.565279

Evaluation metrics used to test the accuracy of our models were jaccard index and f-1 score for logistic regression. Choosing different k, max depth and hyparameter C values helped to improve our accuracy to be the best possible.

Once we analyzed and cleaned the data, it was then fed through three ML models; K-Nearest Neighbor, Decision Tree and Logistic Regression. Although the first two are ideal for this project, logistic regression made most sense because of its binary nature. In our result overview is an accurarcy of 1 maybe a hint for overfitting our model.

Conclusion

For a final solution we have to add Domain knowledge to our results to interpret them in a proper way. With our Logistic regression we built a suitable model which we need to proof with knowledge from our domain part. After this final review we will be able to make a list of the biggest influence for car accidents in Seattle. Maybe this will be more street light, maybe some impossible factors like the weather. In the last case there will be only a solution to adapt the street rules to enhance security for all the people.

In [ ]:

```

```