Title: DRAFT REPORT – Week 2: Intro/Problem & Data
Topic: Seattle Vehicle Accident Severity Prediction
Project: Applied Data Science Capstone
Author: Mark Snuffin
Created: September 23, 2020

Introduction

The Seattle Department of Transportation (SDOT) Technology Division is preparing their budget for the director and is trying to determine how to allocation funds for the year. The director of SDOT, wants to provide a mobile application to the citizens of Seattle to help improve driver safety but it needs to be more than just general information. Instead it needs to provide some sort of intelligence to really help the public be safer on the roads, better yet indicate when a trip could be risky. The technology division knows how to build a mobile app but is not sure if they can create a capability that would suggest how risky it is to travel to a location given the current driving conditions.

After some research they think they can leverage data sciences to solve the problem and decide on predicting accident severity as a test case. The problem answered by this is test case is given the date, time, weather, light and road conditions, can we predict accident severity within the a geographic area. If they can successfully build and demonstrate to the SDOT director it will satisfy the director's requirement and they can move ahead with confidence. Time is of the essence though. They only have a limited amount of time to work on the test case and present the results otherwise the budget planning process will end and will lose the opportunity to improve the safety and wellbeing for many Seattleites not to mention working on an interesting app.

Data

This project uses accident data from SDOT and is referred to as collisions. The data is hosted (https://data-seattlecitygis.opendata.arcgis.com/datasets/5b5c745e0f1f48e7a53acec63a0022ab_0?geometry=-123.310%2C47.452%2C-121.352%2C47.776) by SDOT GIS Division and curated by the SDOT Traffic Division where collisions are collected from Seattle Police Department after a collision is reported. Instead of using the full data set this project uses a subset (https://s3.us.cloud-object-storage.appdomain.cloud/cf-courses-data/CognitiveClass/DP0701EN/version-2/Data-Collisions.csv) of the data provided by Coursera.

General characteristics of the subset -

- Format: CSV
- Timeframe: January 2004 to May 2020
- Columns: 38, 37 are unique
- Rows: 194,673
- Bounding Coordinates -- West Bounding Coordinate: -122.4754 -- East Bounding Coordinate: -122.2008 -- North Bounding Coordinate: 47.7582 -- South Bounding Coordinate: 47.4814

The subset of the SDOT collision data is used that includes collisions, defined by severity, as property damage, e.g., hitting a parked car, or injury where at least one person involved in the collision was hurt. The complete data set has additional severities however these are not included which might need to be revisited upon further investigation.

Table 1 below represents the attributes to be considered as independent variables for modeling. Definitions and data types are defined in the SDOT Attribute Dictionary (https://www.seattle.gov/Documents/Departments/SDOT/GIS/Collisions_OD.pdf). Samples are extracted from the Coursera Data Set. The dependent variable is accident severity, defined as SEVERITYCODE. There are 37 possible independent variables. Of the 37 possible 17 were selected as independent variables and are specified in the table. While the goal is to use date, time, weather, light and road conditions to predict accident severity other attributes are worth exploring and could be beneficial as features to the model.

A significant omission from the potential features is the type of collision. SDOT uses a state-defined coding scheme that specifies 84 types of collisions including an additional descriptive attribute to further define the code. While the subset includes these codes and is informative the initial iteration does not include these. This might need to be revisited based on further investigation.

Attribute	Data Type	Description	Sample
SEVERITYCODE	Text, 100	A code that corresponds to the severity of the collision: · 3—fatality · 2b—serious injury · 2—injury	1, 2

		· 1—prop damage · 0—unknown	
INCDATE	Date	Date of the incident, from 2004 to 2020	2013/03/27
INCDTTM	Text, 30	Date and time of the incident	3/27/2013 2:54:00 PM
X	Double	Latitude of the collision	-122.32315
Y	Double	Longitude of the collision	47.7031403
ADDRTYPE	Text, 12	Collision address type	Alley, Block, Intersection
LOCATION	Text, 255	Description of the general location of the collision	5TH AVE NE AND NE 103RD ST AURORA BR BETWEEN RAYE ST AND BRIDGE WAY N
WEATHER	Text, 300	Description of the weather conditions during the time of the collision	Blowing Sand/Dirt Clear Fog/Smoke/Smog Other Overcast Partly Cloudy Raining Severe Crosswind Sleet/Hail/Freezing Rain Snowing Unknown
ROADCOND	Text, 300	Condition of the road during the collision	Dry Ice Oil Other Sand/Mud/Dirt Snow/Slush Standing Water Unknown Wet
			Dark – No Street Lights Dark – Street Lights Off Dark – Street Lights On Dark – Unknow Lighting

LIGHTCOND	Text, 300	Light conditions during the collision	Dawn Daylight Dusk Other Unknown
VEHCOUNT	Double	Number of vehicles involved in the collision	0 - 12
PERSONCOUNT	Double	Total number of people involved in the collision	0 - 81
SPEEDING	Text, 1	If speeding was a factor in the collision (Y/N)	Y or blank
HITPARKEDCAR	Text, 1	If the collision involved hitting a parked car	Y, N
JUNCTIONTYPE	Text, 300	Category of junction at which collision took place	- At Intersection (but not related to intersection) - At Intersection (intersection related) - Driveway Junction - Mid-Block (but intersection related) - Mid-Block (not related to intersection) - Ramp Junction
INATTENTIONIND	Text, 1	Whether or not collision was due to inattention. (Y/N)	Y or blank
UNDERINFL	Text, 10	Whether or not a driver involved was under the influence of drugs or alcohol.	0, 1, Y, N

For details covering all attributes visit the following link - https://www.seattle.gov/Documents/Departments/SDOT/GIS/Collisions_OD.pdf (https://www.seattle.gov/Documents/Departments/SDOT/GIS/Collisions_OD.pdf)

Original Data Set - https://data-seattlecitygis.opendata.arcgis.com/datasets/5b5c745e0f1f48e7a53acec63a0022ab_0?geometry=-123.310%2C47.452%2C-121.352%2C47.776 (https://data-seattlecitygis.opendata.arcgis.com/datasets/5b5c745e0f1f48e7a53acec63a0022ab_0?geometry=-123.310%2C47.452%2C-121.352%2C47.776)

Coursera Subset - https://s3.us.cloud-object-storage.appdomain.cloud/cf-courses-data/CognitiveClass/DP0701EN/version-2/Data-Collisions.csv (https://s3.us.cloud-object-storage.appdomain.cloud/cf-courses-data/CognitiveClass/DP0701EN/version-2/Data-Collisions.csv)

ESRI Metadata - https://www.arcgis.com/sharing/rest/content/items/5b5c745e0f1f48e7a53acec63a0022ab/info/metadata/meta format=default&output=html (https://www.arcgis.com/sharing/rest/content/items/5b5c745e0f1f48e7a53acec63a0022ab/info/metadata/met format=default&output=html)

Data Preparation

In [194]:
```
import pandas as pd
import numpy as np
```

In [195]:
```
# Display counts and percentages
def display_count_percent(target_column):
    counts = target_column.value_counts()
    percent = target_column.value_counts(normalize=True)
    print(pd.DataFrame({'Count': counts, 'Percent': percent}))
```

In [228]:
```
# Note - add dtypes to the call to clean this up.  Fine for now
df = pd.read_csv("https://s3.us.cloud-object-storage.appdomain.cloud/c
f-courses-data/CognitiveClass/DP0701EN/version-2/Data-Collisions.csv")
print('File downloaded')
```

```
File downloaded
```

In [197]:
```
df.head()
```

Out[197]:

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

5 rows × 38 columns

In [198]:
```
print(df.dtypes)
df.shape
```

```
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
```

Out[198]:
```
(194673, 38)
```

Get rid of the columns not wanted, at least for now

In [199]:
```
df.drop(columns=['OBJECTID','SEVERITYDESC','INCKEY','COLLISIONTYPE','PEDROWNOTGRNT', 'PEDCYLCOUNT','PEDCOUNT', 'REPORTNO',
                 'COLDETKEY', 'INTKEY','STATUS','EXCEPTRSNCODE','EXCEPTRSNDESC','CROSSWALKKEY','ST_COLCODE',
                 'SEGLANEKEY','SDOTCOLNUM','ST_COLDESC','SDOT_COLCODE','SDOT_COLDESC','SEVERITYCODE.1'], inplace=True)
```

In [200]:
```
df = df.dropna(subset=["SEVERITYCODE","ADDRTYPE","UNDERINFL","ROADCOND
", \
                        "LIGHTCOND","WEATHER","LOCATION","X","Y"],axis=
0)
```

In [201]:
```
print(df.dtypes)
df.shape
```

```
SEVERITYCODE        int64
X                 float64
Y                 float64
ADDRTYPE           object
LOCATION           object
PERSONCOUNT         int64
VEHCOUNT            int64
INCDATE            object
INCDTTM            object
JUNCTIONTYPE       object
INATTENTIONIND     object
UNDERINFL          object
WEATHER            object
ROADCOND           object
LIGHTCOND          object
SPEEDING           object
HITPARKEDCAR       object
dtype: object
```

Out[201]:
```
(184167, 17)
```

Fatalities or serious injuries are excluded in the Coursera dump. Would be interesting to see those but these will due for now - I think.

In [202]:
```
display_count_percent(df['SEVERITYCODE'])
```

	Count	Percent
1	128154	0.695858
2	56013	0.304142

Clean-up the dates then breakout the day and hour. The counts and percentages take a while to grind through but yield interesting results. Hours = 0 is when there are no time specified in the data, need to look at that some more. Trying to get home on Friday looks like the the reason, interesting that Sunday AND Monday are lighter accident days. For time of day looks like rush hour is the worst, that's expected.

In [204]:
```
df['INCDATE'] = pd.to_datetime(df['INCDATE'])
df['DAY'] = df['INCDATE'].dt.day_name()
df['INCDTTM'] = pd.to_datetime(df['INCDTTM'])
df['HOUR'] = df['INCDTTM'].dt.hour
display_count_percent(df['DAY'])
display_count_percent(df['HOUR'])
```

```
           Count   Percent
Friday     30518  0.165708
Thursday   27725  0.150543
Wednesday  27170  0.147529
Tuesday    26963  0.146405
Saturday   26057  0.141486
Monday     24869  0.135035
Sunday     20865  0.113294
    Count   Percent
0   28584  0.155207
17  12598  0.068405
16  11814  0.064148
15  11211  0.060874
14  10372  0.056318
12  10065  0.054651
13   9982  0.054201
18   9469  0.051415
8    8275  0.044932
11   7977  0.043314
9    7799  0.042347
10   7225  0.039231
19   7062  0.038346
7    6351  0.034485
20   6041  0.032802
21   5416  0.029408
22   5298  0.028767
23   4434  0.024076
2    3458  0.018776
1    3295  0.017891
6    3085  0.016751
3    1594  0.008655
5    1584  0.008601
4    1178  0.006396
```

In [161]:
```
display_count_percent(df["ADDRTYPE"])
```

```
               Count   Percent
Block         121023  0.657137
Intersection   63144  0.342863
```

Need to investigate furhter, not sure of the difference between mid-block. Might not look at this attribute at all as a feature so todo. Drop anything under ~1%.

In [205]:
```
display_count_percent(df["JUNCTIONTYPE"])
```

	Count	Percent
Mid-Block (not related to intersection)	84517	0.469315
At Intersection (intersection related)	60930	0.338338
Mid-Block (but intersection related)	22035	0.122358
Driveway Junction	10430	0.057917
At Intersection (but not related to intersection)	2030	0.011272
Ramp Junction	139	0.000772
Unknown	5	0.000028

In [206]:
```
df.drop(df.loc[df['JUNCTIONTYPE']=='Ramp Junction'].index, inplace=Tru
e)
df.drop(df.loc[df['JUNCTIONTYPE']=='Unknown'].index, inplace=True)
display_count_percent(df["JUNCTIONTYPE"])
```

	Count	Percent
Mid-Block (not related to intersection)	84517	0.469690
At Intersection (intersection related)	60930	0.338609
Mid-Block (but intersection related)	22035	0.122456
Driveway Junction	10430	0.057963
At Intersection (but not related to intersection)	2030	0.011281

Driving intoxicated is not a major factor. However probably would be associated to more fatalities. In general looks like not a factor here.

In [207]:
```
df["UNDERINFL"]=df["UNDERINFL"].replace(['N', 'NaN', 'Y', '0', '1'], [
0, 0, 1, 0, 1])
df["UNDERINFL"]=df["UNDERINFL"].replace(np.nan, 0)
df["UNDERINFL"].value_counts().astype(int)
```

Out[207]:
```
0    175172
1      8851
Name: UNDERINFL, dtype: int64
```

Driving and texting here is an issue, not a surprise.

In [208]:
```
df["INATTENTIONIND"] = df["INATTENTIONIND"].replace(['NaN','Y'], [0, 1
])
df["INATTENTIONIND"] = df["INATTENTIONIND"].replace(np.nan, 0)
df["INATTENTIONIND"].value_counts().astype(int)
```

Out[208]:
```
0.0    154963
1.0     29060
Name: INATTENTIONIND, dtype: int64
```

It doesn't snow much in Seattle but it's always raining. Get rid of the unknowns and small % conditions. Really it's about wet or dry.

In [209]:
```
display_count_percent(df["ROADCOND"])
```

	Count	Percent
Dry	121782	0.661776
Wet	45962	0.249762
Unknown	13791	0.074942
Ice	1171	0.006363
Snow/Slush	984	0.005347
Other	115	0.000625
Standing Water	102	0.000554
Sand/Mud/Dirt	63	0.000342
Oil	53	0.000288

In [210]:
```
df.drop(df.loc[df['ROADCOND'] == 'Unknown'].index, inplace=True)
df.drop(df.loc[df['ROADCOND'] == 'Other'].index, inplace=True)
df.drop(df.loc[df['ROADCOND'] == 'Standing Water'].index, inplace=True
)
df.drop(df.loc[df['ROADCOND'] == 'Sand/Mud/Dirt'].index, inplace=True)
df.drop(df.loc[df['ROADCOND'] == 'Oil'].index, inplace=True)
display_count_percent(df["ROADCOND"])
```

	Count	Percent
Dry	121782	0.716791
Wet	45962	0.270525
Ice	1171	0.006892
Snow/Slush	984	0.005792

Results as expected here. Remove the small buckets.

In [211]:
```
display_count_percent(df['LIGHTCOND'])
```

	Count	Percent
Daylight	110695	0.651534
Dark - Street Lights On	45932	0.270349
Dusk	5579	0.032837
Unknown	2715	0.015980
Dawn	2352	0.013844
Dark - No Street Lights	1360	0.008005
Dark - Street Lights Off	1092	0.006427
Other	165	0.000971
Dark - Unknown Lighting	9	0.000053

In [212]:
```
df.drop(df.loc[df['LIGHTCOND'] == 'Unknown'].index, inplace=True)
df.drop(df.loc[df['LIGHTCOND'] == 'Dark - No Street Lights'].index, in
place=True)
df.drop(df.loc[df['LIGHTCOND'] == 'Dark - Street Lights Off'].index, i
nplace=True)
df.drop(df.loc[df['LIGHTCOND'] == 'Other'].index, inplace=True)
df.drop(df.loc[df['LIGHTCOND'] == 'Dark - Unknown Lighting'].index, in
place=True)
display_count_percent(df['LIGHTCOND'])
```

	Count	Percent
Daylight	110695	0.672681
Dark - Street Lights On	45932	0.279123
Dusk	5579	0.033903
Dawn	2352	0.014293

Combining this with road conditions, it's usually raining in Seattle for the most part and much snow. Everything else removed that doesn't account for much.

In [213]:
```
display_count_percent(df['WEATHER'])
```

	Count	Percent
Clear	105312	0.639969
Raining	30768	0.186974
Overcast	25932	0.157586
Unknown	863	0.005244
Snowing	790	0.004801
Fog/Smog/Smoke	505	0.003069
Other	222	0.001349
Sleet/Hail/Freezing Rain	100	0.000608
Blowing Sand/Dirt	41	0.000249
Severe Crosswind	21	0.000128
Partly Cloudy	4	0.000024

In [214]:
```
df.drop(df.loc[df['WEATHER'] == 'Unknown'].index, inplace=True)
df.drop(df.loc[df['WEATHER'] == 'Fog/Smog/Smoke'].index,inplace=True)
df.drop(df.loc[df['WEATHER'] == 'Other'].index,inplace=True)
df.drop(df.loc[df['WEATHER'] == 'Sleet/Hail/Freezing Rain'].index,inplace=True)
df.drop(df.loc[df['WEATHER'] == 'Blowing Sand/Dirt'].index,inplace=True)
df.drop(df.loc[df['WEATHER'] == 'Severe Crosswind'].index,inplace=True)
df.drop(df.loc[df['WEATHER'] == 'Partly Cloudy'].index, inplace=True)
display_count_percent(df['WEATHER'])
```

	Count	Percent
Clear	105312	0.646872
Raining	30768	0.188990
Overcast	25932	0.159286
Snowing	790	0.004853

Speeding is not a major factor. Todo fix these format fn

In [217]:
```
display_count_percent(df['SPEEDING'])
```

	Count	Percent
Y	8183	1.0

In [218]:
```
df["SPEEDING"] = df["SPEEDING"].replace(['NaN', 'Y'], [0, 1])
df["SPEEDING"] = df["SPEEDING"].replace(np.nan, 0)
df["SPEEDING"].value_counts().astype(int)
```

Out[218]:
```
0.0    154619
1.0      8183
Name: SPEEDING, dtype: int64
```

Probably won't use vehicle count but interesting to see. As expected the accident is usually with 2 vehicles.

In [230]:
```
display_count_percent(df['VEHCOUNT'])
```

	Count	Percent
2	147650	0.758451
1	25748	0.132263
3	13010	0.066830
0	5085	0.026121
4	2426	0.012462
5	529	0.002717
6	146	0.000750
7	46	0.000236
8	15	0.000077
9	9	0.000046
11	6	0.000031
10	2	0.000010
12	1	0.000005

In [231]:
```
df.drop(df.loc[df['VEHCOUNT'] == 5].index,inplace=True)
df.drop(df.loc[df['VEHCOUNT'] == 0].index,inplace=True)
df.drop(df.loc[df['VEHCOUNT'] == 6].index,inplace=True)
df.drop(df.loc[df['VEHCOUNT'] == 7].index,inplace=True)
df.drop(df.loc[df['VEHCOUNT'] == 8].index,inplace=True)
df.drop(df.loc[df['VEHCOUNT'] == 9].index,inplace=True)
df.drop(df.loc[df['VEHCOUNT'] == 11].index,inplace=True)
df.drop(df.loc[df['VEHCOUNT'] == 10].index,inplace=True)
df.drop(df.loc[df['VEHCOUNT'] == 12].index,inplace=True)
display_count_percent(df['VEHCOUNT'])
```

	Count	Percent
2	147650	0.781904
1	25748	0.136353
3	13010	0.068896
4	2426	0.012847

Interesting here, asking number of people traveling might be helpful. The majority of accidents are with multiple people in the car. This implies distracted driver. The 81 has to be a bus, but that's a lot of people.

In [232]:
```
display_count_percent(df['PERSONCOUNT'])
```

	Count	Percent
2	111311	0.589465
3	35141	0.186095
4	14445	0.076496
1	11623	0.061551
5	6270	0.033204
0	5508	0.029168
6	2515	0.013319
7	1028	0.005444
8	485	0.002568
9	188	0.000996
10	111	0.000588
11	45	0.000238
12	27	0.000143
14	17	0.000090
13	17	0.000090
17	10	0.000053
15	9	0.000048
16	7	0.000037
18	6	0.000032
20	6	0.000032
44	6	0.000032
19	5	0.000026
25	5	0.000026
26	4	0.000021
22	4	0.000021
27	3	0.000016
28	3	0.000016
29	3	0.000016
47	3	0.000016
32	3	0.000016
34	3	0.000016
37	3	0.000016
23	2	0.000011
21	2	0.000011
24	2	0.000011
30	2	0.000011
36	2	0.000011
57	1	0.000005
31	1	0.000005
35	1	0.000005
39	1	0.000005
41	1	0.000005
43	1	0.000005
48	1	0.000005
53	1	0.000005
54	1	0.000005
81	1	0.000005

In [233]:
```
df.drop(df.loc[df['PERSONCOUNT'] == 0].index,inplace=True)
index_to_drop = df[(df['PERSONCOUNT'] > 6)].index
df.drop(index_to_drop , inplace=True)
display_count_percent(df['PERSONCOUNT'])
```

	Count	Percent
2	111311	0.613943
3	35141	0.193823
4	14445	0.079672
1	11623	0.064107
5	6270	0.034583
6	2515	0.013872

Not to many instances of hitting a parked car. Probably not valuable to use this.

In [224]:
```
display_count_percent(df['HITPARKEDCAR'])
```

	Count	Percent
N	148357	0.972782
Y	4151	0.027218

Left with 152k of accidents to work with and 19 columns.

In [225]:
```
print(df.shape)
df.head()
```

```
(152508, 19)
```

Out[225]:

	SEVERITYCODE	X	Y	ADDRTYPE	LOCATION	PERSONCOUNT	VEHCO
0	2	-122.323148	47.703140	Intersection	5TH AVE NE AND NE 103RD ST	2	
1	1	-122.347294	47.647172	Block	AURORA BR BETWEEN RAYE ST AND BRIDGE WAY N	2	
2	1	-122.334540	47.607871	Block	4TH AVE BETWEEN SENECA ST AND UNIVERSITY ST	4	
3	1	-122.334803	47.604803	Block	2ND AVE BETWEEN MARION ST AND MADISON ST	3	
4	2	-122.306426	47.545739	Intersection	SWIFT AVE S AND SWIFT AV OFF RP	2	

Reshape the dataframe to see what we have.

In [235]:
```
df_pivot = df[['SEVERITYCODE', 'ROADCOND', 'WEATHER', 'LIGHTCOND']]
df_pivot_2 = (df_pivot.set_index('SEVERITYCODE').stack()
 .groupby(level=[0,1])
 .value_counts()
 .unstack(level=[1,2])
 .fillna(0)
 .sort_index(axis=1))
df_pivot_2.head()
```

Out[235]:

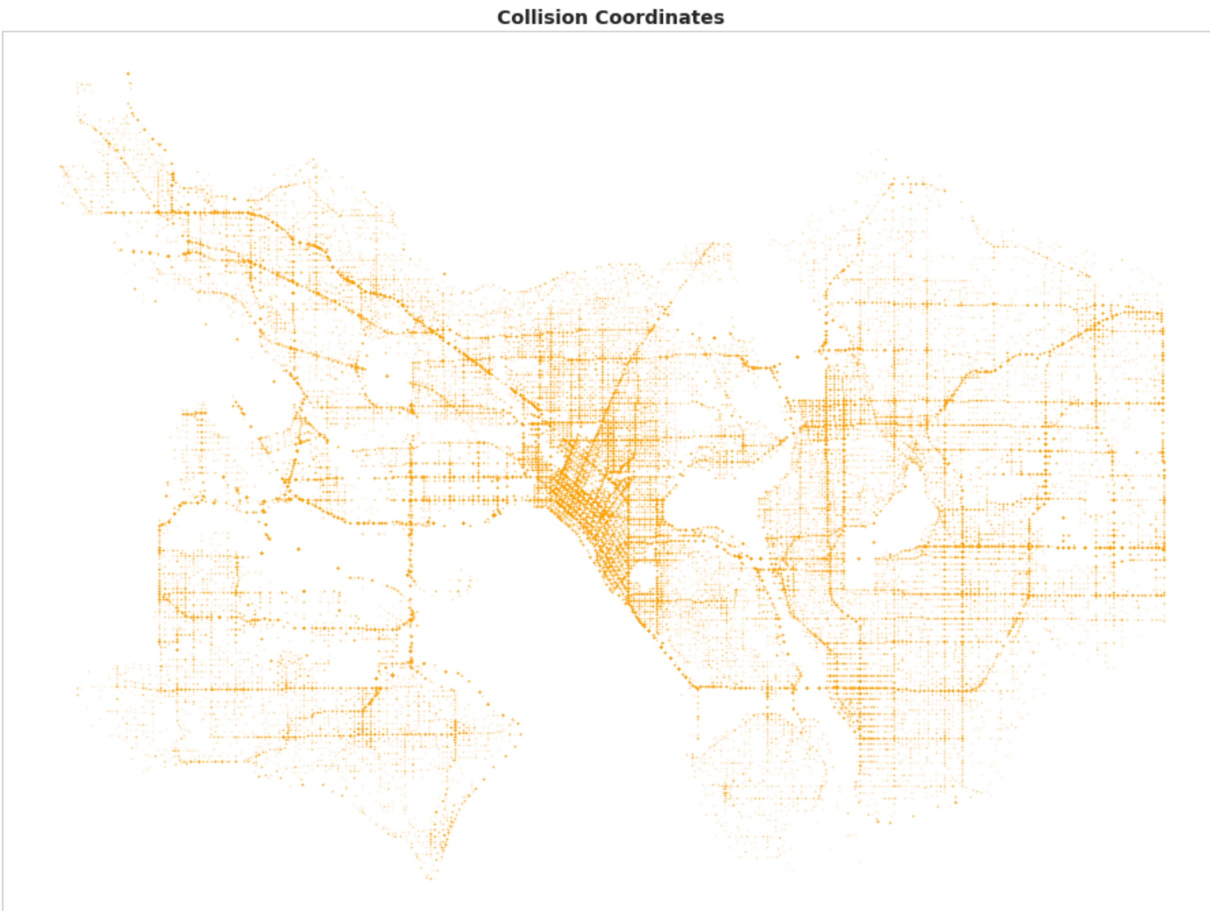
	LIGHTCOND									R
	Dark - No Street Lights	Dark - Street Lights Off	Dark - Street Lights On	Dark - Unknown Lighting	Dawn	Daylight	Dusk	Other	Unknown	D
SEVERITYCODE										
1	1157	857	32788	7	1610	74198	3816	175	12710	
2	310	303	13638	4	784	36197	1838	49	586	

2 rows × 29 columns

Do a sanity check on the coordinates, looks like Seattle to me just skewed. Denisty lines up with roadways and downtown.

In [236]:
```
from matplotlib import pyplot as plt
plt.style.use('seaborn-whitegrid')
```

In [237]:
```
fig, ax1 = plt.subplots(figsize=(16,12))
ax1.scatter(df_new.Y, df_new.X, marker='.', alpha=0.2, s=0.5, c='orang
e')
ax1.set_xticks([])
ax1.set_yticks([])
ax1.axis(aspect='equal')
t=ax1.set_title("Collision Coordinates", fontweight='bold', fontsize=1
4)
```



In [ ]:
```
```