Collision in Seattle

Table of Contents

Introduction

There are many accidents occur in Seattle. Each incident has different severity level, such as prop damage, injury, serious injury, or even fatality. Since we have raw data for each accident, one way to reduce it is to learn from the accident that was occurred. To see what behavioral reflects the severity of an accident. This can help us understand the nature of the accident and we can precede preventive action to change on the properties that lead to high severity accident.

Data Preparation

Data Cleaning

There are 37 attribute and 194,673 rows in the raw data that we can use to learn. However, some data is not useful for the analysis which is:

1. no meaning and duplicated data from the data set (a key data, description data)
    a. 'X', 'Y', 'OBJECTID', 'INCKEY', 'COLDETKEY', 'REPORTNO', 'STATUS', 'LOCATION', 'EXCEPTRSNDESC', 'SEVERITYDESC', 'SDOTCOLNUM', 'ST_COLDESC', 'SEGLANEKEY', 'CROSSWALKKEY', 'INTKEY', 'SEVERITYCODE.1', 'INCDTTM', 'INCDATE', 'SDOT_COLDESC', 'INCDTTM'
2. data contain too many null value which is easily lead to incorrect prediction (more than 50% of the data)
    a. 'EXCEPTRSNCODE', 'INATTENTIONIND', 'PEDROWNOTGRNT', 'SPEEDING'

Data that is interesting to be a feature to solve the problem is listed as the following.

1. ADDRTYPE - Collision address type
    a. Sample data = {Alley, Block, Intersection}
2. COLLISIONTYPE - Collision type
    a. Sample data = {Parked car, Angles, Rear Ended, Sidewipe, Left Turn, RightTurn, Pedestrian, Cycles, Head On, Other}
3. PERSONCOUNT - The total number of people involved in the collision
4. PEDCOUNT - The number of pedestrians involved in the collision
5. PEDCYLCOUNT - The number of bicycles involved in the collision
6. VEHCOUNT - The number of vehicles involved in the collision
7. JUNCTIONTYPE - Category of junction at which collision took place
    a. Sample data = {'At Intersection (intersection related)', 'Mid-Block (not related to intersection)', 'Driveway Junction', 'Mid-Block (but intersection related)', 'At Intersection (but not related to intersection)', 'Unknown', 'Ramp Junction'}
8. SDOT_COLCODE - A code given to the collision by SDOT
    a. Sample data = 11 means MOTOR VEHICLE STRUCK MOTOR VEHICLE, FRONT END AT ANGLE, 16 means MOTOR VEHICLE STRUCK MOTOR VEHICLE, LEFT SIDE SIDESWIPE
9. UNDERINFL - Whether or not a driver involved was under the influence of drugs or alcohol.
10. WEATHER - A description of the weather conditions during the time of the collision
    a. Sample data = {Clear, Raining, Overcast, Snowing, Fog/Smog/Smoke, Sleet/Hail/Freezing Rain, Blowing Sand/Dirt, Severe Crosswind, Partly Cloudy, Other, Unknown}
11. ROADCOND - The condition of the road during the collision
    a. Sample data = {Dry, Wet, Unknown, Ice, Snow/Slush, Standing Water, Sand/Mud/Dirt, Oil, Other}
12. LIGHTCOND - The light conditions during the collision
    a. Sample data = {Daylight, Dark - Street Lights On, Dark - No Street Lights, Unknown, Dusk, Dawn, Dark - Street Lights Off, Other, Dark - Unknown Lighting}
13. ST_COLCODE - A code provided by the state that describes the collision

a. Sample data = 0 means 'Vehicle Going Straight Hits Pedestrian', 11 means 'From Same Direction -Both Going Straight-Both Moving- Sideswipe'

14. HITPARKEDCAR - Whether or not the collision involved hitting a parked car. (Y/N)

These columns have below data type.

```
SEVERITYCODE      int64
ADDRTYPE         object
COLLISIONTYPE    object
PERSONCOUNT       int64
PEDCOUNT          int64
PEDCYLCOUNT       int64
VEHCOUNT          int64
JUNCTIONTYPE     object
SDOT_COLCODE      int64
UNDERINFL        object
WEATHER          object
ROADCOND         object
LIGHTCOND        object
ST_COLCODE       object
HITPARKEDCAR     object
```

Data after removal

There are 15 columns of data and 194,673 rows

Handle Null Value

The data has null value as below.

```
SEVERITYCODE        0
ADDRTYPE         1926
COLLISIONTYPE    4904
PERSONCOUNT         0
PEDCOUNT            0
PEDCYLCOUNT         0
VEHCOUNT            0
JUNCTIONTYPE     6329
SDOT_COLCODE        0
UNDERINFL        4884
WEATHER          5081
ROADCOND         5012
LIGHTCOND        5170
ST_COLCODE         18
HITPARKEDCAR        0
```

Methodology

Data field	Method
ST_COLCODE	Replace blank value (‘ ‘) as NaN and replace NaN with maximum frequency data
JUNCTIONTYPE	Replace ‘Unknown’ value as NaN and replace NaN with maximum frequency data
UNDERINFL	Replace ‘Y’ as 1 and ‘N’ as 0 and replace NaN with maximum frequency data
HITPARKEDCAR	Replace ‘Y’ as 1 and ‘N’ as 0

ADDRTYPE	Replace NaN with maximum frequency data
COLLISIONTYPE	Replace NaN with maximum frequency data
WEATHER	Replace NaN with maximum frequency data
ROADCOND	Replace NaN with maximum frequency data
LIGHTCOND	Replace NaN with maximum frequency data

Correct Data Types

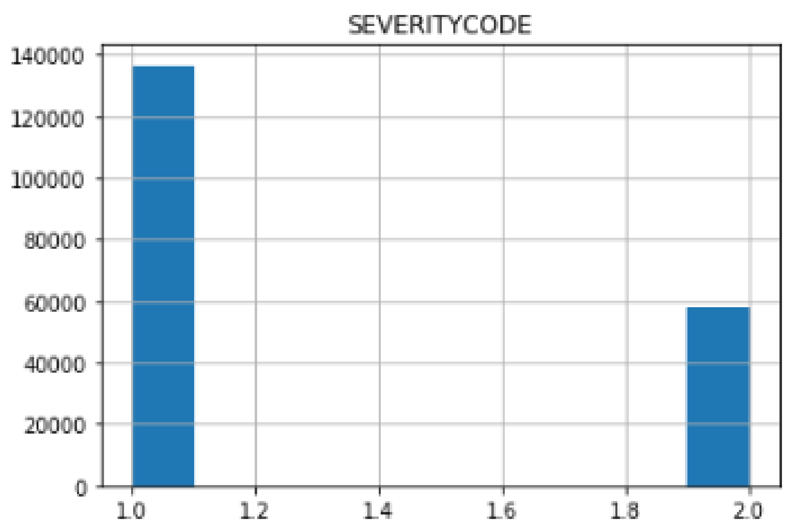
Change ST_COLCODE, UNDERINFL, and HITPARKEDCAR to integer. After changing, the data types is as below.

```
SEVERITYCODE       int64
ADDRTYPE          object
COLLISIONTYPE     object
PERSONCOUNT        int64
PEDCOUNT           int64
PEDCYLCOUNT        int64
VEHCOUNT           int64
JUNCTIONTYPE      object
SDOT_COLCODE       int64
UNDERINFL          int64
WEATHER           object
ROADCOND          object
LIGHTCOND         object
ST_COLCODE         int64
HITPARKEDCAR       int64
```

Data to Predict

Data to predict is SEVERITYCODE. The data in this data set contain only 2 values as below.

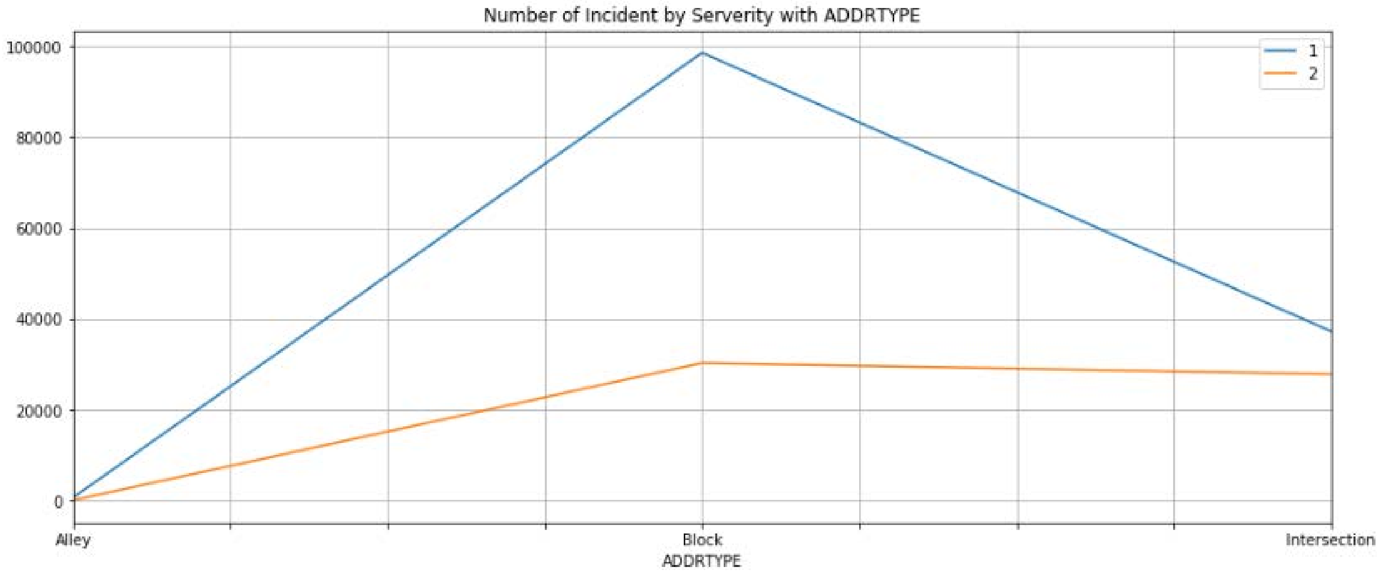
Severity Code	Description	Amount of data
1	Prop damage	136,485
2	Injury	58,188



Data Exploration

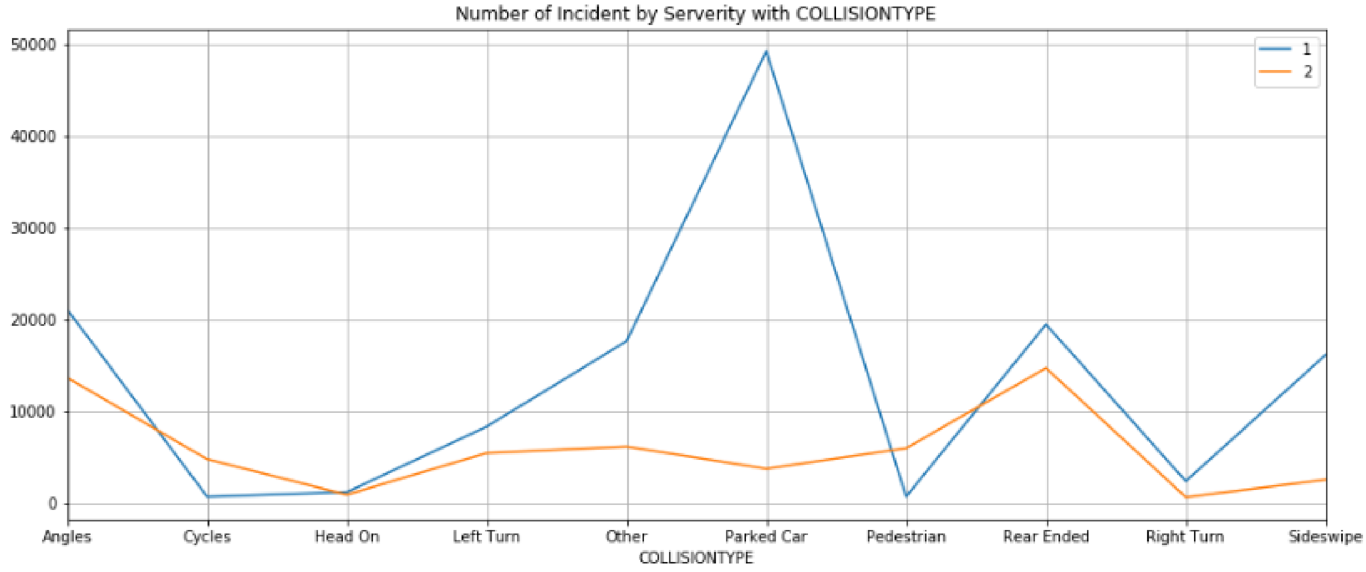
ADDRTYPE data group by severity code

	ADDRTYPE	SEVERITYCODE	COUNT
0	Alley	1	669
1	Alley	2	82
2	Block	1	98565
3	Block	2	30287
4	Intersection	1	37251
5	Intersection	2	27819



COLLISIONTYPE data group by severity code

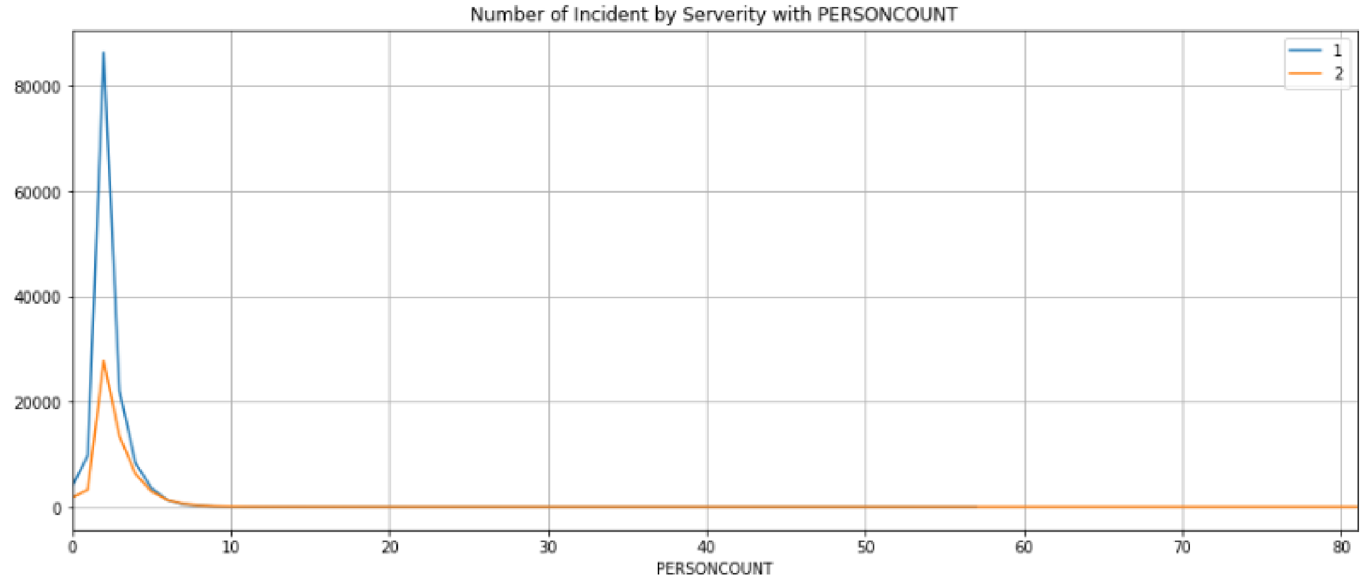
	COLLISIONTYPE	SEVERITYCODE	COUNT
0	Angles	1	21050
1	Angles	2	13624
2	Cycles	1	671
3	Cycles	2	4744
4	Head On	1	1152
5	Head On	2	872
6	Left Turn	1	8292
7	Left Turn	2	5411
8	Other	1	17591
9	Other	2	6112
10	Parked Car	1	49188
11	Parked Car	2	3703
12	Pedestrian	1	672
13	Pedestrian	2	5936
14	Rear Ended	1	19419
15	Rear Ended	2	14671
16	Right Turn	1	2347
17	Right Turn	2	609
18	Sideswipe	1	16103
19	Sideswipe	2	2506



PERSONCOUNT data group by severity code

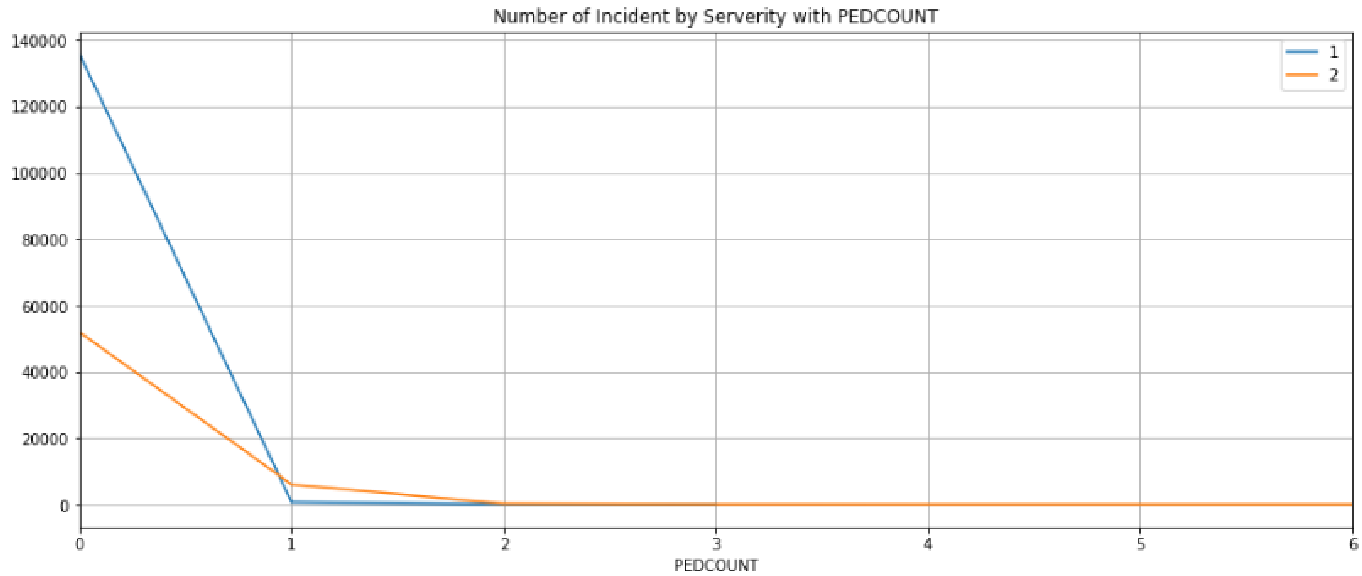
	PERSONCOUNT	SEVERITYCODE	COUNT
0	0	1	3782
1	0	2	1762
2	1	1	9858
3	1	2	3296
4	2	1	86420
5	2	2	27811
6	3	1	22092
7	3	2	13461
8	4	1	8365
9	4	2	6295
10	5	1	3615
11	5	2	2969
12	6	1	1345
13	6	2	1357
14	7	1	494
15	7	2	637
16	8	1	249
17	8	2	284
18	9	1	87
19	9	2	129
20	10	1	54
21	10	2	74
22	11	1	23
23	11	2	33
24	12	1	13
25	12	2	20
26	13	1	9
27	13	2	12
28	14	1	12
29	14	2	7
..	...	...	...
61	32	1	2
62	32	2	1
63	34	1	1
64	34	2	2
65	35	1	1

66	36	1	2
67	37	1	2
68	37	2	1
69	39	2	1
70	41	1	1
71	43	1	1
72	44	1	6
73	47	1	3
74	48	2	1
75	53	1	1
76	54	2	1
77	57	1	1
78	81	2	1



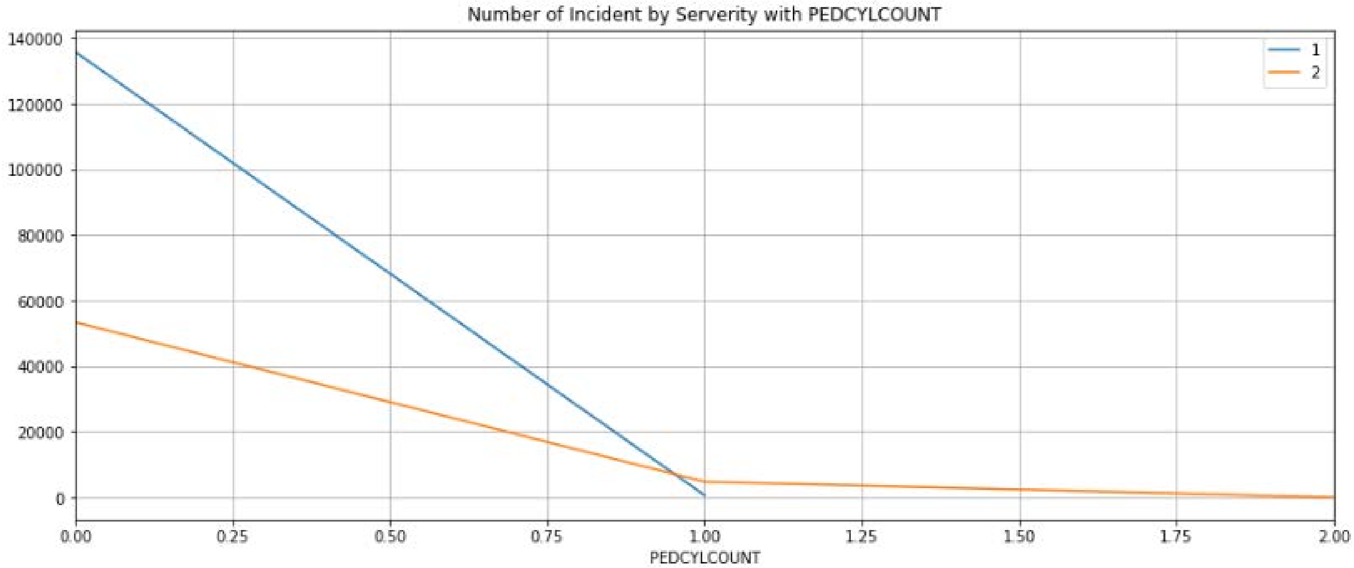
PEDCOUNT data group by severity code

	PEDCOUNT	SEVERITYCODE	COUNT
0	0	1	135787
1	0	2	51947
2	1	1	678
3	1	2	6007
4	2	1	19
5	2	2	207
6	3	1	1
7	3	2	21
8	4	2	4
9	5	2	1
10	6	2	1



PEDCYLCOUNT data group by severity code

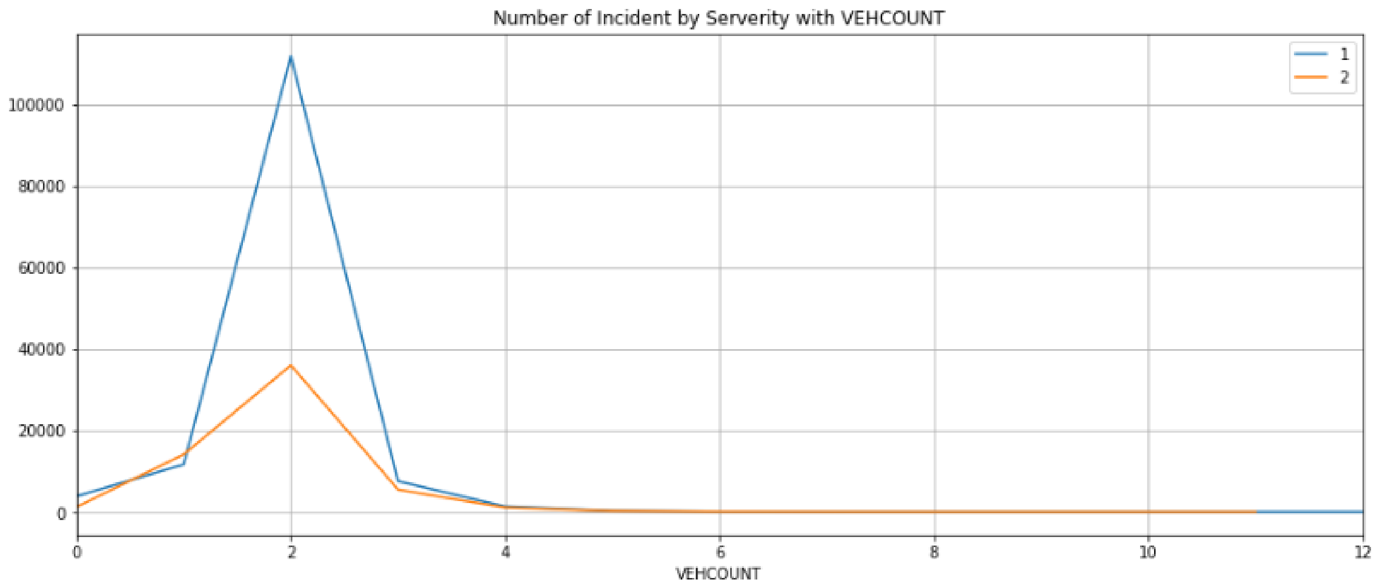
	PEDCYLCOUNT	SEVERITYCODE	COUNT
0	0	1	135806
1	0	2	53383
2	1	1	679
3	1	2	4762
4	2	2	43



VEHCOUNT data group by severity code

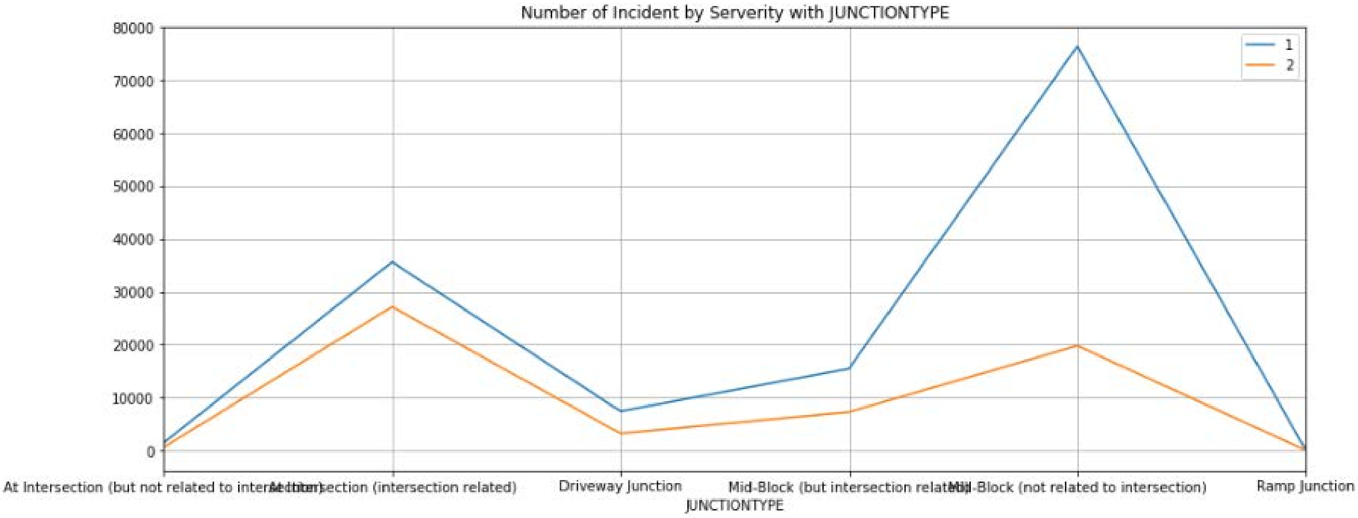
	VEHCOUNT	SEVERITYCODE	COUNT
0	0	1	3858
1	0	2	1227
2	1	1	11643
3	1	2	14105
4	2	1	111701
5	2	2	35949
6	3	1	7540

7	3	2	5470
8	4	1	1348
9	4	2	1078
10	5	1	268
11	5	2	261
12	6	1	86
13	6	2	60
14	7	1	24
15	7	2	22
16	8	1	10
17	8	2	5
18	9	1	3
19	9	2	6
20	10	2	2
21	11	1	3
22	11	2	3
23	12	1	1



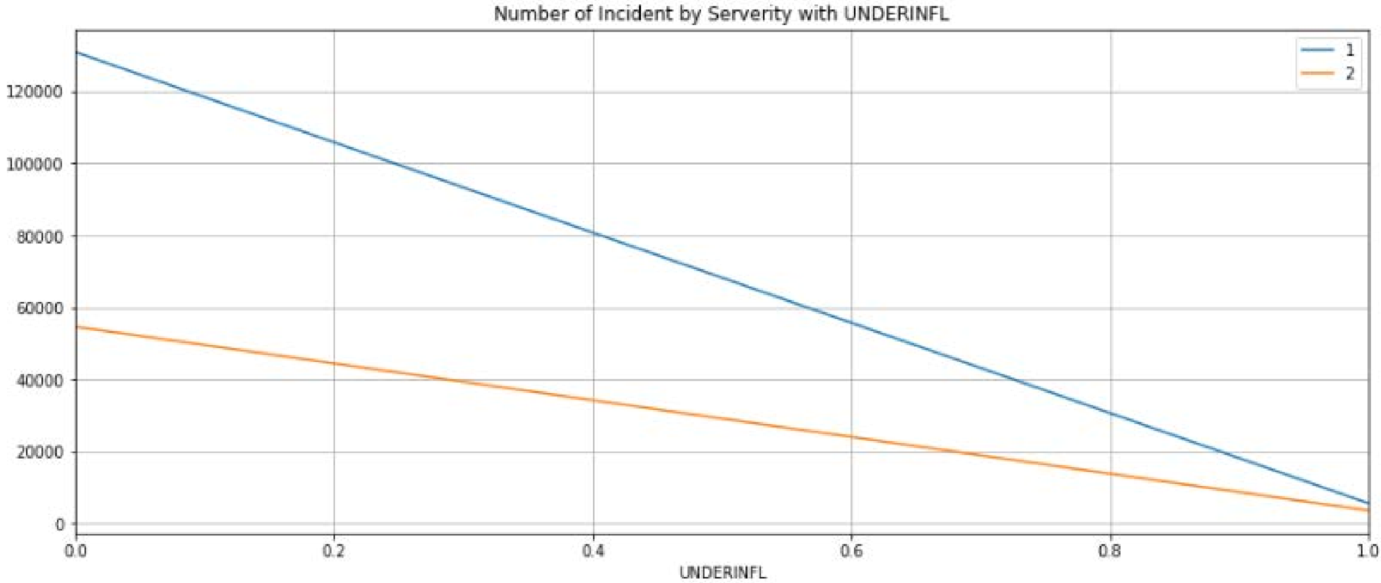
JUNCTIONTYPE data group by severity code

	JUNCTIONTYPE	SEVERITYCODE	COUNT
0	At Intersection (but not related to intersection)	1	1475
1	At Intersection (but not related to intersection)	2	623
2	At Intersection (intersection related)	1	35636
3	At Intersection (intersection related)	2	27174
4	Driveway Junction	1	7437
5	Driveway Junction	2	3234
6	Mid-Block (but intersection related)	1	15493
7	Mid-Block (but intersection related)	2	7297
8	Mid-Block (not related to intersection)	1	76332
9	Mid-Block (not related to intersection)	2	19806
10	Ramp Junction	1	112
11	Ramp Junction	2	54



UNDERINFL data group by severity code

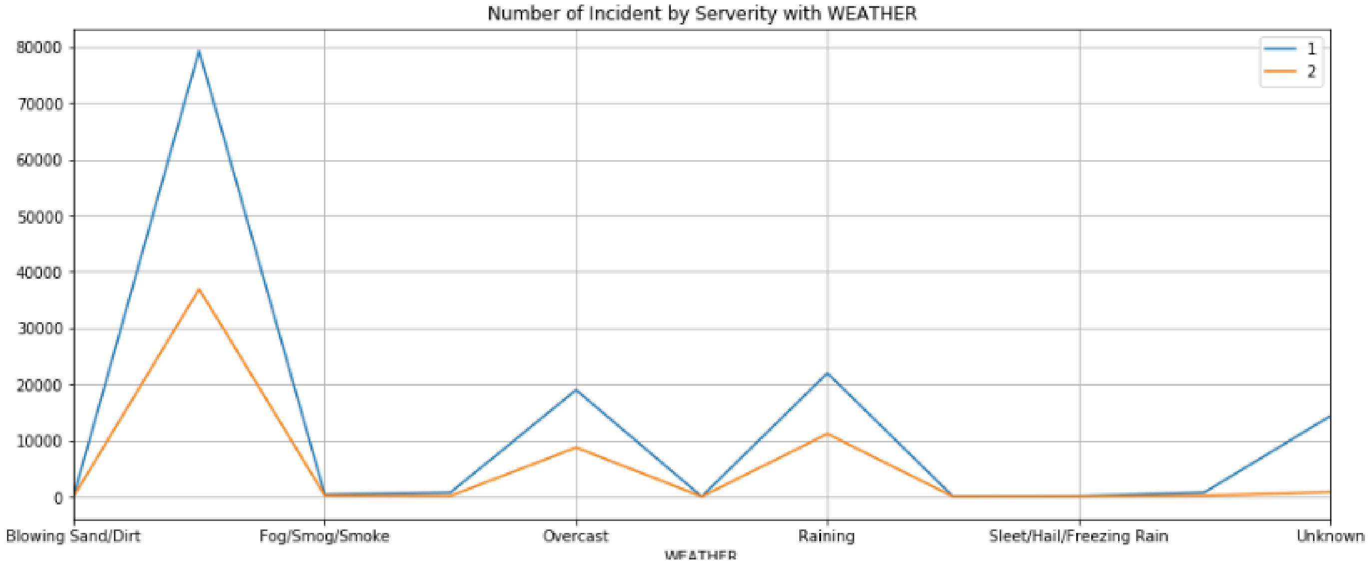
	UNDERINFL	SEVERITYCODE	COUNT
0	0	1	130926
1	0	2	54626
2	1	1	5559
3	1	2	3562



WEATHER data group by severity code

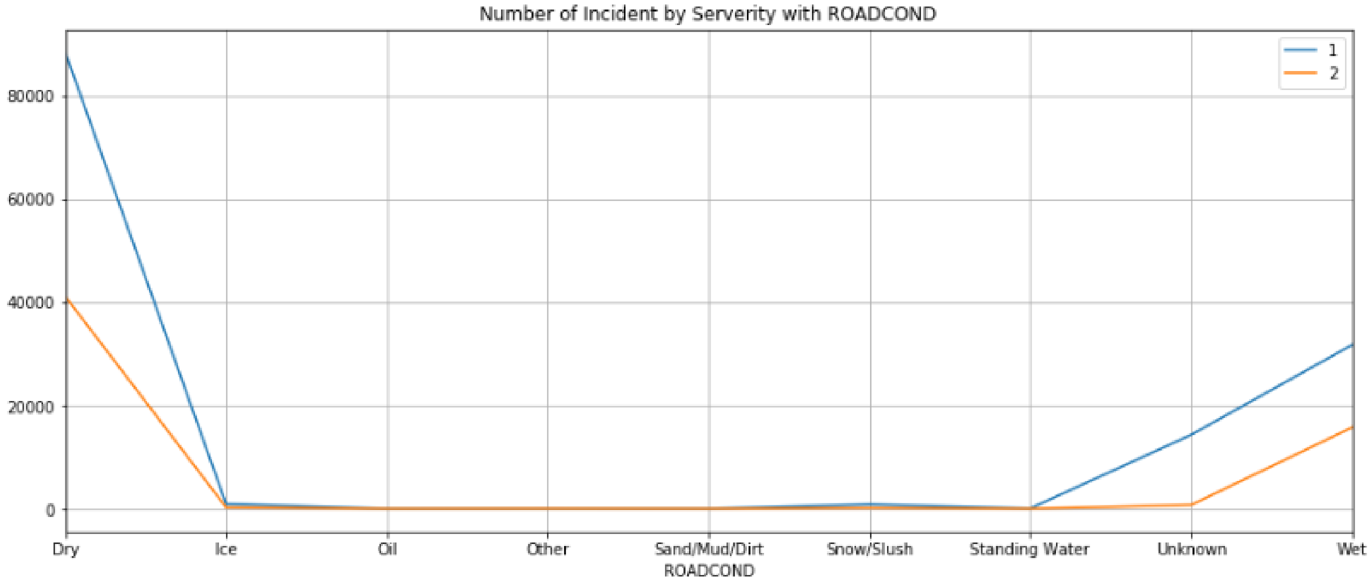
	WEATHER	SEVERITYCODE	COUNT
0	Blowing Sand/Dirt	1	41
1	Blowing Sand/Dirt	2	15
2	Clear	1	79292
3	Clear	2	36924
4	Fog/Smog/Smoke	1	382
5	Fog/Smog/Smoke	2	187
6	Other	1	716
7	Other	2	116
8	Overcast	1	18969

9	Overcast	2	8745
10	Partly Cloudy	1	2
11	Partly Cloudy	2	3
12	Raining	1	21969
13	Raining	2	11176
14	Severe Crosswind	1	18
15	Severe Crosswind	2	7
16	Sleet/Hail/Freezing Rain	1	85
17	Sleet/Hail/Freezing Rain	2	28
18	Snowing	1	736
19	Snowing	2	171
20	Unknown	1	14275
21	Unknown	2	816



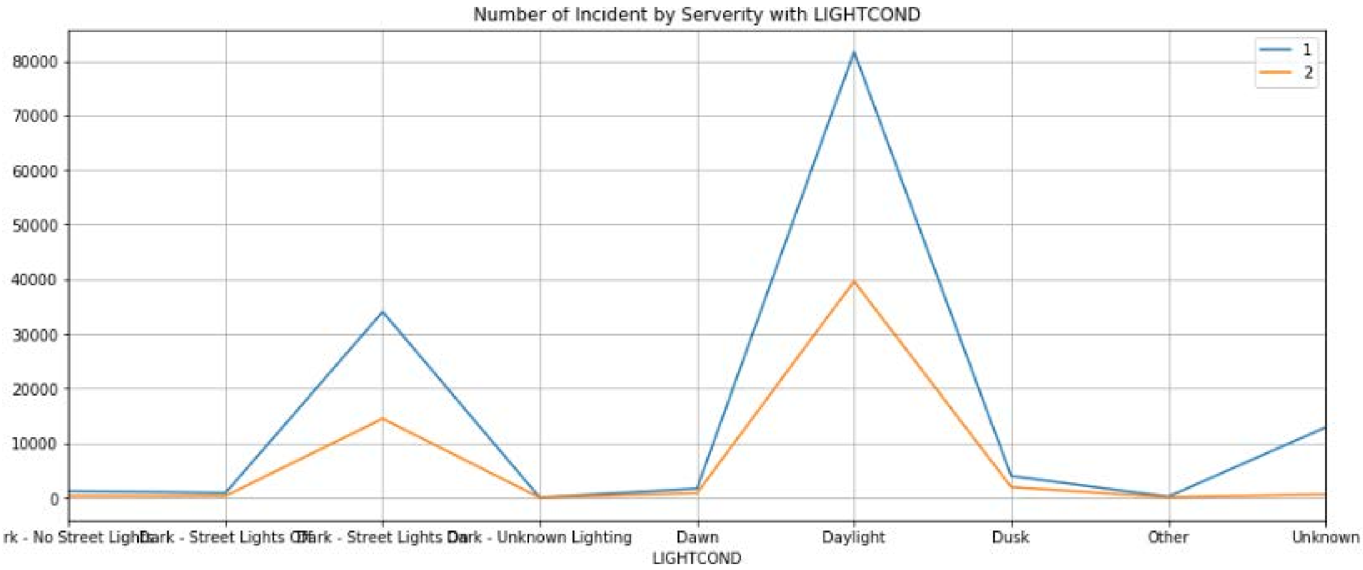
ROADCOND data group by severity code

	ROADCOND	SEVERITYCODE	COUNT
0	Dry	1	88398
1	Dry	2	41124
2	Ice	1	936
3	Ice	2	273
4	Oil	1	40
5	Oil	2	24
6	Other	1	89
7	Other	2	43
8	Sand/Mud/Dirt	1	52
9	Sand/Mud/Dirt	2	23
10	Snow/Slush	1	837
11	Snow/Slush	2	167
12	Standing Water	1	85
13	Standing Water	2	30
14	Unknown	1	14329
15	Unknown	2	749
16	Wet	1	31719
17	Wet	2	15755



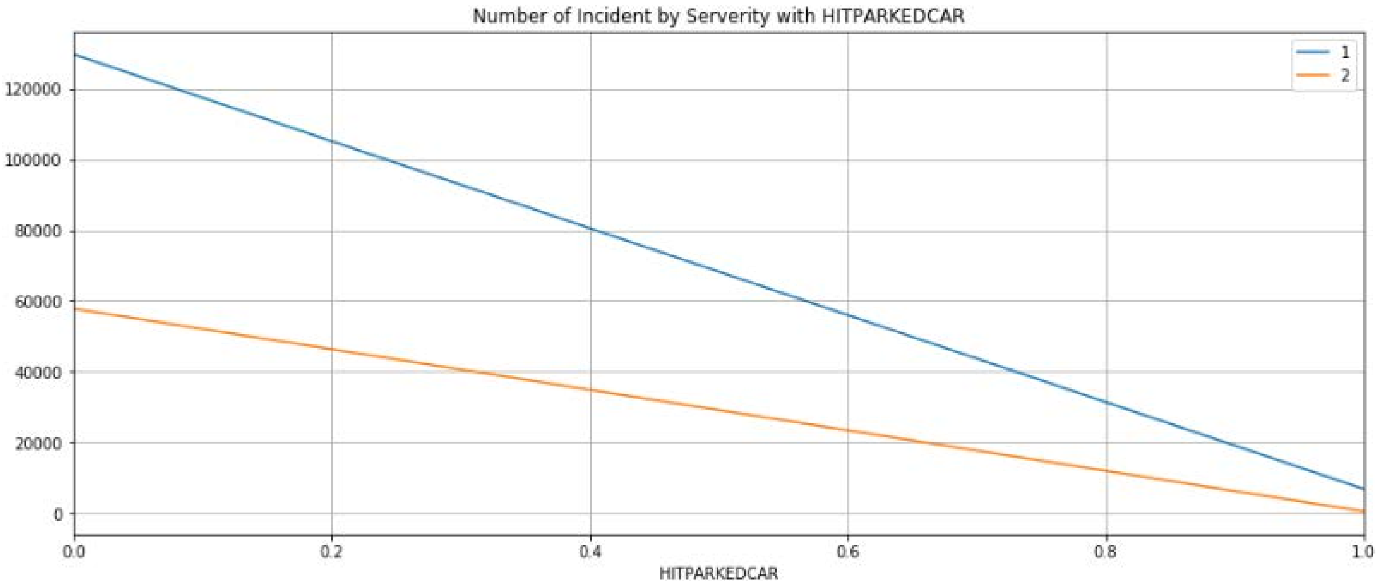
LIGHTCOND data group by severity code

	LIGHTCOND	SEVERITYCODE	COUNT
0	Dark - No Street Lights	1	1203
1	Dark - No Street Lights	2	334
2	Dark - Street Lights Off	1	883
3	Dark - Street Lights Off	2	316
4	Dark - Street Lights On	1	34032
5	Dark - Street Lights On	2	14475
6	Dark - Unknown Lighting	1	7
7	Dark - Unknown Lighting	2	4
8	Dawn	1	1678
9	Dawn	2	824
10	Daylight	1	81673
11	Daylight	2	39634
12	Dusk	1	3958
13	Dusk	2	1944
14	Other	1	183
15	Other	2	52
16	Unknown	1	12868
17	Unknown	2	605



HITPARKEDCAR data group by severity code

	HITPARKEDCAR	SEVERITYCODE	COUNT
0	0	1	129717
1	0	2	57740
2	1	1	6768
3	1	2	448



Convert Categorical Data to Numeric

Since many libraries do not support categorical data, we have to convert them to Numeric value. Then normalize it.

Spit Testing and Training Data

- X = 'ADDRTYPE', 'COLLISIONTYPE', 'PERSONCOUNT', 'PEDCOUNT', 'PEDCYLCOUNT', 'VEHCOUNT', 'JUNCTIONTYPE', 'SDOT_COLCODE', 'UNDERINFL', 'WEATHER', 'ROADCOND', 'LIGHTCOND', 'ST_COLCODE', 'HITPARKEDCAR'
- y = ‘SEVERITYCODE’

Data	Percentage of all data	Amount of data
Training	70%	136,271
Testing	30%	58,402

Data Analysis

Pearson Correlation

The Pearson Correlation measures the linear dependence between two variables X and Y.

The resulting coefficient is a value between -1 and 1 inclusive, where:

- 1: Total positive linear correlation.
- 0: No linear correlation, the two variables most likely do not affect each other.
- -1: Total negative linear correlation.

Result of the correlation with SEVERITYCODE shows as the following

Data	Pearson Correlation with SEVERITYCODE
SEVERITYCODE	1
PERSONCOUNT	0.130949
PEDCOUNT	0.246338
PEDCYLCOUNT	0.214218
VEHCOUNT	-0.054686
SDOT_COLCODE	0.188905
UNDERINFL	0.044377
ST_COLCODE	-0.165233
HITPARKEDCAR	-0.101498

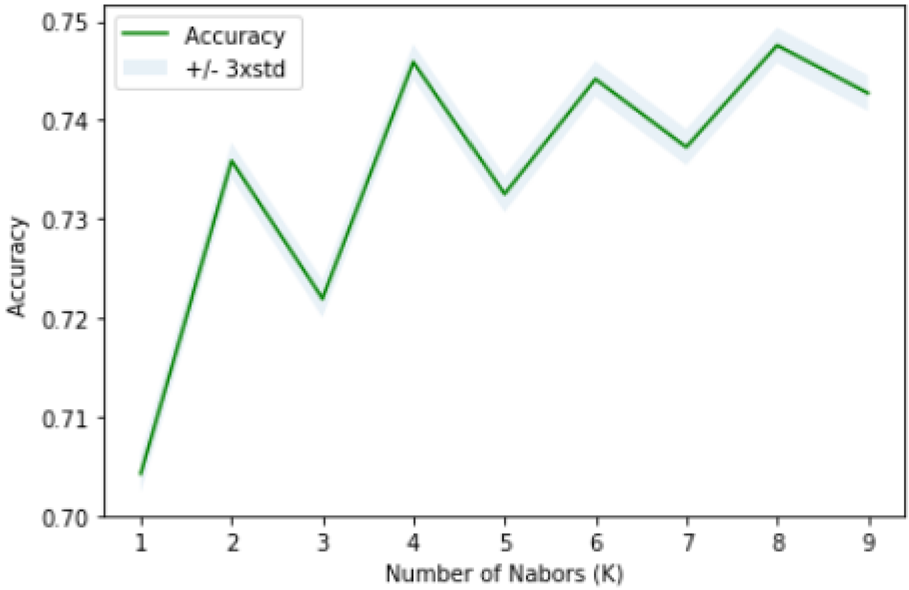
There is no data that nearly -1 or 1 with SEVERITYCODE, all of them nearly to 0. Then there is no linear correlation to SEVERITYCODE. Linear regression should not be a good method to use to predict the severity code.

Decision Tree

- Max depth = 5
- Accuracy (the fraction of correctly classified samples) = 0.7537584329303791

K-Nearest Neighbor (KNN)

- From experiments, K is 1 to 10, the best K is 8.



- Accuracy (the fraction of correctly classified samples) = 0.7475771377692545

Logistic Regression

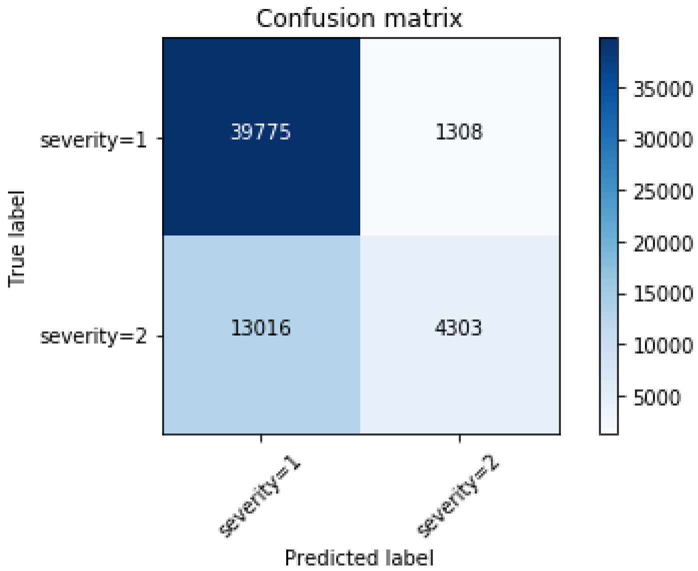
- Use Solver Liblinear
- Accuracy
    - Jaccard similarity score = 0.7547344269031883
      Note that this is equal to the fraction of correctly classified samples.

- Confusion matrix (F1 average) = 0.7173683103496501

```
              precision    recall  f1-score   support

           1       0.75      0.97      0.85     41083
           2       0.77      0.25      0.38     17319

   micro avg       0.75      0.75      0.75     58402
   macro avg       0.76      0.61      0.61     58402
weighted avg       0.76      0.75      0.71     58402
```



Support Vector Machine (SVM)

- Kernel ‘rbf’
- Accuracy
  - The fraction of correctly classified samples = 0.7593404335467964

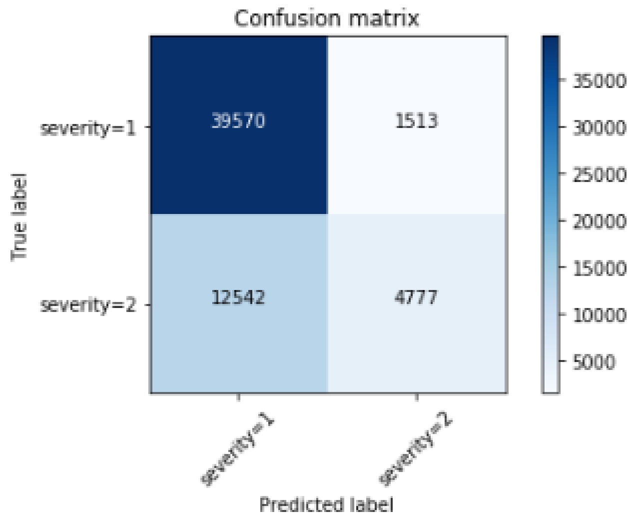
- Confusion matrix (F1 average) = 0.7173683103496501

```
              precision    recall  f1-score   support

           1       0.76      0.96      0.85     41083
           2       0.76      0.28      0.40     17319

   micro avg       0.76      0.76      0.76     58402
   macro avg       0.76      0.62      0.63     58402
weighted avg       0.76      0.76      0.72     58402

Confusion matrix, without normalization
[[39570  1513]
 [12542  4777]]
```



Conclusion

Collision in Seattle happens with many properties. In this study we use properties which are collision address type, collision type, number of people involved in the collision, number of pedestrians, number of bicycles, number of vehicles, category of junction, collision code by SDOT, driver was under influence of drug or alcohol, weather, road condition, light condition, a code that provided by the state, and whether or not the collision involved hitting a parked car, to predict severity level of the collision. The severity level can be prop damage, injury, serious injury, or even fatality.

From the source data, first, the study removed the data which has a duplicated meaning, and data that has null value more than 50%. Second, handle null value with the data that has the highest frequency. Third, change data type to a proper one. Fourth, did the data normalization. Finally, split this data to training set (70% of the data) and testing set (30% of the data).

From the study, Decision tree algorithm, K-Nearest Neighbor algorithm (KNN), Logistic Regression, and Support Vector Machine algorithm (SVM), shows similar ability to predict the severity level. Decision tree and SVM has accuracy score 76%, where KNN and Logistic Regression have accuracy score 75%.