report

October 30, 2020

1 Car accident severity predictor

This is the project report by Katharina Egert, submitted October 2020.

1.1 1. Introduction

The objective of this project is to create a way to predict severity of car accidents happening based on road and weather conditions. That is, our algorithm needs to take as input the conditions that may impact severity of accidents:

- road conditions
- weather conditions
- lighting conditions

etc.

and predict the risk profile of potential accidents, i.e. the severity label. A user should then be able to specify the current conditions of their itinerary and should then get back the severity label of accidents happening.

Example: A wet road should potential lead to higher severity accidents than a dry road.

The main stakeholders are:

- **traffic regulators**: They can make policies (e.g. speed limits, higher controls etc) in order to mitigate risks.
- **drivers**: They can recognize risks in advance and adapt their behavior in order to lower their own personal risks, e.g. drive more carefully or even avoid travelling at at risk conditions all together.

1.2 2. Data

In this section we will descibe the underlying data.

1.2.1 2.1 Data Source

The given data set contains all collisions provided by Seattle police departement and recorded by Traffic Records. The level of aggregation is weekly. The timeframe is 2004 to today. (See metadata from the SPD Collision data set.)

1.2.2 2.2 Data Loading

In the next step, we load the data into the notebook and display the first 5 lines of the raw table. Not all columns will be used and some will need to be transformed in order to be exploitable for our later classification.

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

            STATUS      ADDRTYPE   INTKEY  ... ROADCOND                LIGHTCOND  \
        0  Matched  Intersection  37475.0  ...      Wet                 Daylight
        1  Matched         Block      NaN  ...      Wet  Dark - Street Lights On
        2  Matched         Block      NaN  ...      Dry                 Daylight
        3  Matched         Block      NaN  ...      Dry                 Daylight
        4  Matched  Intersection  34387.0  ...      Wet                 Daylight

          PEDROWNOTGRNT  SDOTCOLNUM SPEEDING ST_COLCODE  \
        0           NaN         NaN      NaN         10
        1           NaN   6354039.0      NaN         11
        2           NaN   4323031.0      NaN         32
        3           NaN         NaN      NaN         23
        4           NaN   4028032.0      NaN         10

                                                   ST_COLDESC  SEGLANEKEY  \
        0                                  Entering at angle           0
        1  From same direction - both going straight - bo...           0
        2                              One parked--one moving           0
        3                      From same direction - all others           0
        4                                  Entering at angle           0

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

        [5 rows x 38 columns]
```

1.2.3 2.3 Data Description

The problem consists in predicting accident severity based on outer conditions of accidents recorded. The label to be predicted is 'SEVERITYCODE'. A description of the severity is contained in the column 'SEVERITYDESC' and 'SEVERITYCODE.1' which is therefore redundant.

The following columns are of a technical nature and therefore of no use to us:

- 'OBJECTID',
- 'INCKEY',
- 'COLDETKEY',
- 'REPORTNO',
- 'STATUS'
- 'INTKEY'
- 'EXCEPTRSNCODE',
- 'EXCEPTRSNDESC'

There are several other fields in the data set such as 'UNDER_INF' (influenced by alcohol/drug use) which might be good predictors for severity, however it does not make sense to use these for this problem as traffic planers as well as drivers (apart from their own sobriety) will not be able to input this data when using this analysis. The same goes for pedestrian/cyclist count (which is actually depending on the dependent variable!) as one will not know how many pedestrians/bikes will be on the road on a given day.

The total list of colums concerned is: * 'PERSONCOUNT', * 'PEDCOUNT', * 'PEDCYLCOUNT', * 'VEHCOUNT', * 'INATTENTIONIND', * 'UNDERINFL', * 'HITPARKEDCAR', * 'SPEEDING', * 'HITPARKEDCAR', * 'PEDROWNOTGRNT', * 'SDOTCOLNUM', * 'ST_COLCODE', * 'ST_COLDESC', * 'SEGLANEKEY', * 'CROSSWALKKEY', * 'SDOT_COLCODE' * 'SDOT_COLDESC', * 'COLLISIONTYPE',

The colums that can be explored are * 'ADDRTYPE', 'X', 'Y' * 'LOCATION', * 'INCDATE' and 'INCDTTM', * 'JUNCTIONTYPE', * 'WEATHER' * 'ROADCOND', * 'LIGHTCOND'

2 3. Methodology

This section represents the main component of the report where I will discuss and describe exploratory data analysis and inferential statistical testing performed.

2.0.1 3.1 Label analysis

We need to predict severity of the accident given by the data colum 'SEVERITYCODE'. The following codes are given:

- 3—fatality
- 2b—serious injury
- **2—injury**
- **1—property damage**
- 0—unknown

Only labels of 1 and 2 are present in the dataset.

We will now analyze the frequency of their occurrences. The first static gives the absolute frequency, the second one the relative frequency.

```
Out[3]: 1    136485
        2     58188
        Name: SEVERITYCODE, dtype: int64
```

```
Out[4]: 1    0.701099
        2    0.298901
        Name: SEVERITYCODE, dtype: float64
```

It turns out that property damage appears more than twice as often as injuries. This means that out data set is unbalanced, hence we need to try later on to account for this imbalance.

Secondly, for the algorithm to make sense from the stake holder point of view, it is much more important to detect the risk of potential injury-type accidents than misclassifiying an actual property damage case, since one is rather too careful than take too much risk. This will help us shape the cost function.

2.0.2 3.2 Feature selection

In this section, we will select the features which determine the features to use. For this we will first use business knowledge to select obvious factors and then also check which column seems to have the most impact on the severity outcome.

- 'WEATHER' containing data on the weather such at if it was dry or wet etc.
- 'ROADCOND' containing information whether the road was dry, wet etc.
- 'LIGHTCOND' containing data on lighting, e.g. if it was dark.

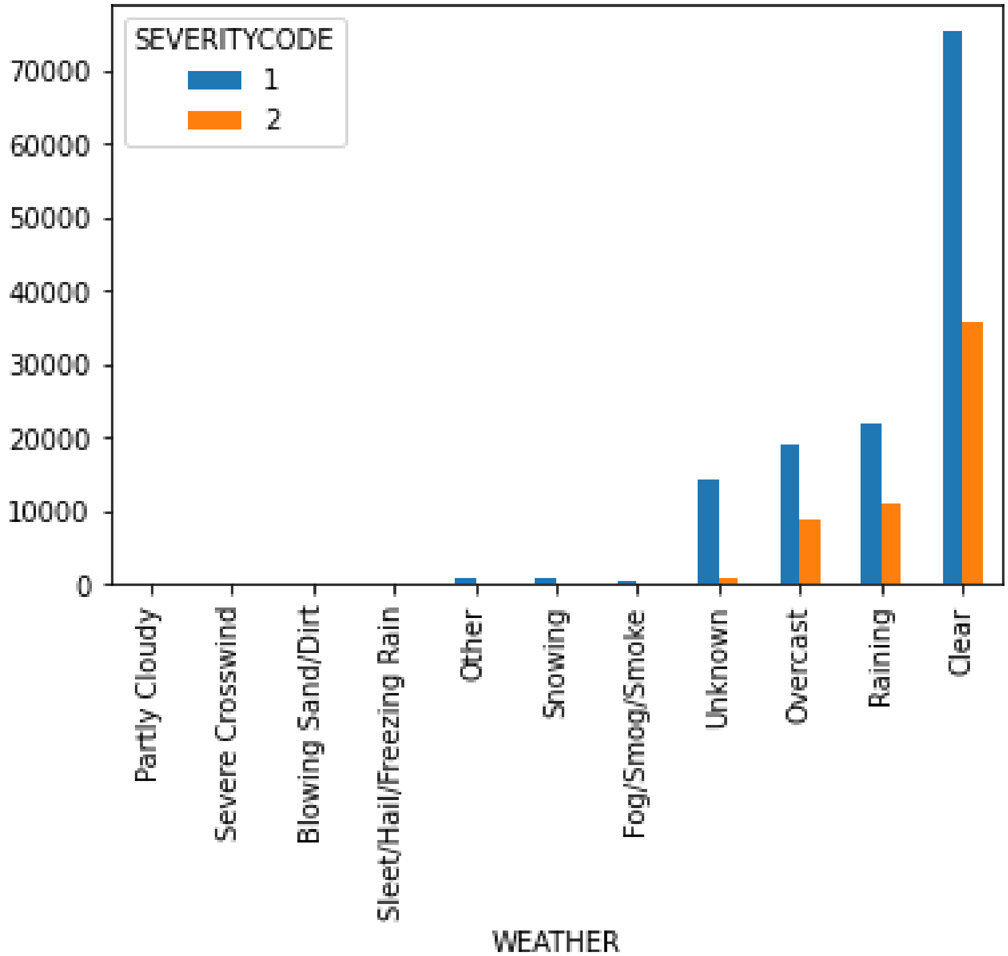
We will check for these three first and eliminate unusable columns.

'WEATHER' We first check for the values.

```
Out[5]: 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, dtype: int64
```

Now we're interested to see which of these conditions correlate with higher rates of injuries (e.g. higher than 23% – the globale average)

```
Out[6]: SEVERITYCODE                  1      2
        WEATHER
        Unknown                   0.946  0.054
        Other                     0.861  0.139
        Snowing                   0.811  0.189
        Sleet/Hail/Freezing Rain  0.752  0.248
        Blowing Sand/Dirt         0.732  0.268
        Severe Crosswind          0.720  0.280
        Overcast                  0.684  0.316
        Clear                     0.678  0.322
        Fog/Smog/Smoke            0.671  0.329
        Raining                   0.663  0.337
        Partly Cloudy             0.400  0.600
```



Observations:

1. Unknown and other make up for the smalles percentages of injuries.
2. Snowing, while intuitively making up for a big risk, has actually a lower risk than the globale average (19% instead of 23%) Perhaps drivers are already taking this risk into account and drive more carefully.
3. Nice weather, e.g. 'Clear', 'Overcast' or 'Partly Cloudy' still accounts for a more than average amount of injuries. Note that the class 'Partly Cloudy' is very small (n=5), so it's high injury rate is not significant.
4. Raining is the most dangerous condition.

The category 'Unknown' and 'Other' does not lead to any further information, so we will remove these rows as well as missing data rows.

We will use our domain knowledge and group some of the weather conditions together, so that the classes become sufficiently big to be statiscally exploitable.

This leaves us with the following relative frequency.

```
Out[9]: 1    0.676557
```

```
2    0.323443
Name: SEVERITYCODE, dtype: float64
```

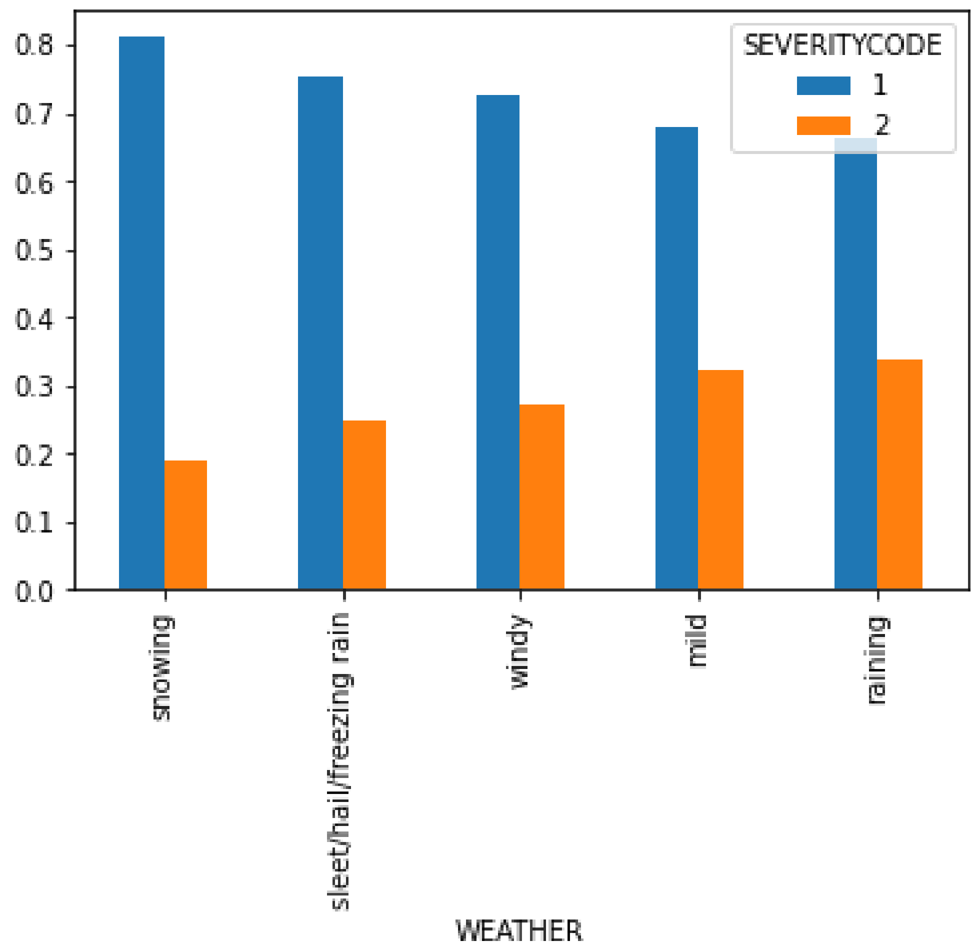
Out[10]:

```
mild                          138854
raining                        33145
snowing                          907
sleet/hail/freezing rain         113
windy                             81
Name: WEATHER, dtype: int64
```

Out[11]:

```
SEVERITYCODE                     1         2
WEATHER
snowing                   0.811466  0.188534
sleet/hail/freezing rain  0.752212  0.247788
windy                     0.728395  0.271605
mild                      0.678886  0.321114
raining                   0.662815  0.337185
```

Out[12]: `<matplotlib.axes._subplots.AxesSubplot at 0x1a1cd7dfd0>`

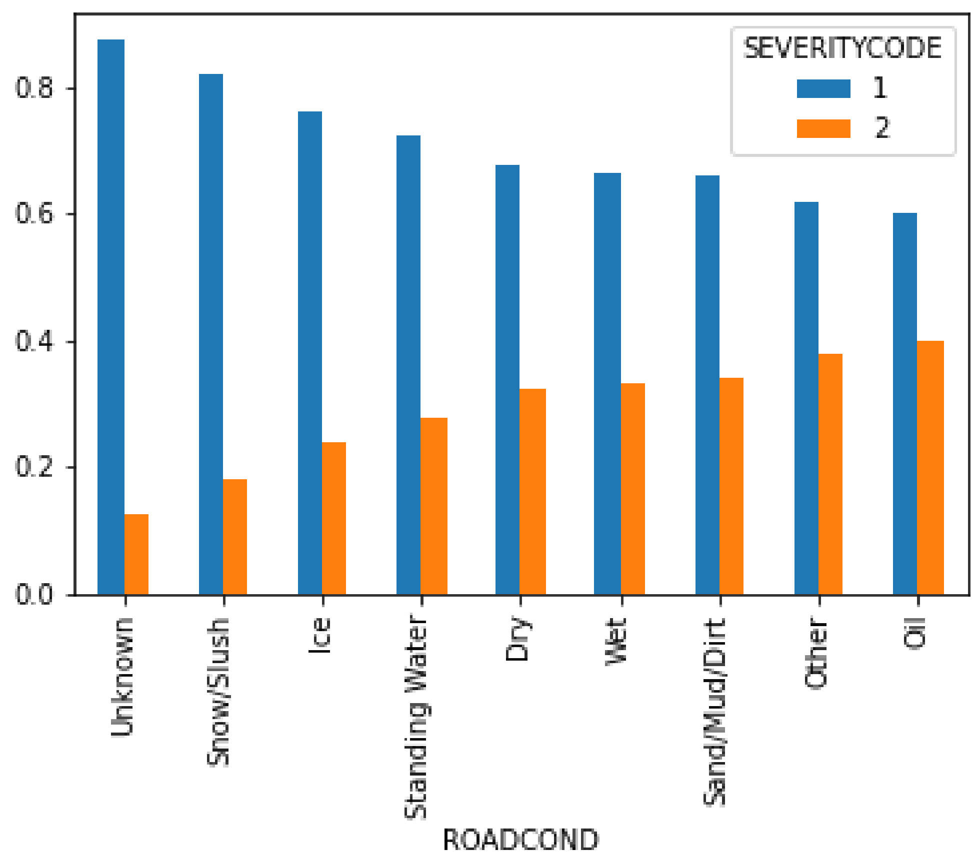


2.0.3 'ROADCOND'

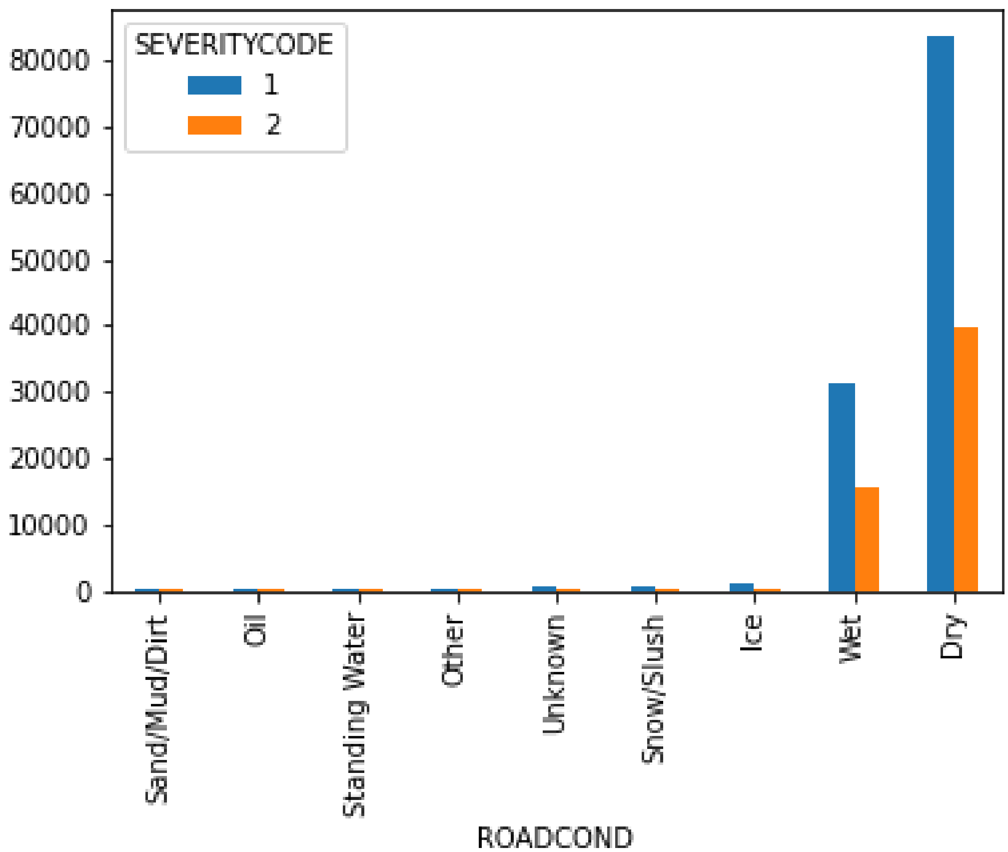
We do the exact same thing for road conditions. We'll start with frequency.

```
Out[13]: Dry                 123402
         Wet                  46956
         Ice                   1113
         Unknown                919
         Snow/Slush             902
         Other                  108
         Standing Water         108
         Sand/Mud/Dirt           65
         Oil                     60
         Name: ROADCOND, dtype: int64
```

```
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1d3f85c0>
```




```
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x10d650e80>
```



Observations

1. Unknown/Other are again categories without information which we can eliminate.
2. Snow/Slush and Ice are again surprisingly, low risk.
3. Oil and Wet yield slippery conditions and are therefore high risk as one would guess.

After elimination of these columns, we have the following average severities.

```
Out[17]: 1    0.675539
         2    0.324461
         Name: SEVERITYCODE, dtype: float64
```

2.0.4 'LIGHTCOND'

We do the exact same thing for light conditions. We'll start with frequency.

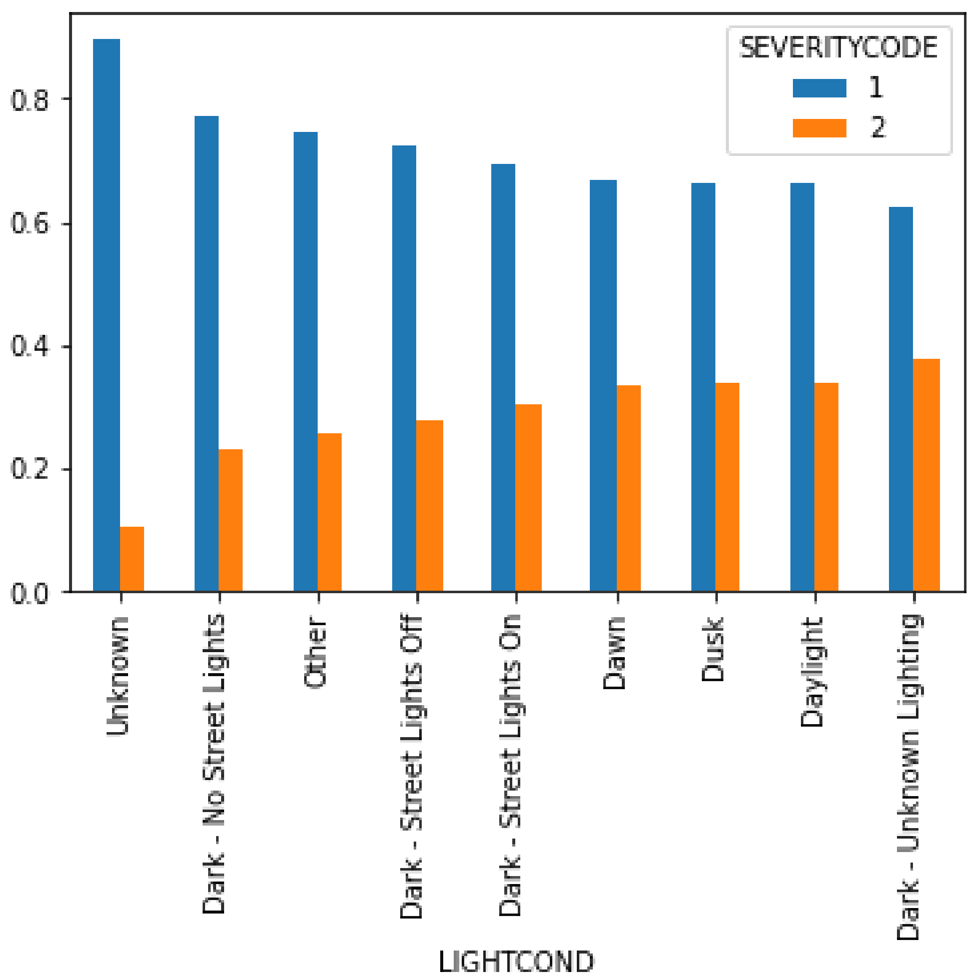
```
Out[18]: Daylight                    112618
         Dark - Street Lights On      46748
         Dusk                          5648
         Dawn                          2413
         Unknown                       2305
```

```
Dark - No Street Lights       1408
Dark - Street Lights Off      1114
Other                          185
Dark - Unknown Lighting          8
Name: LIGHTCOND, dtype: int64
```

Out[19]:

```
SEVERITYCODE                     1         2
LIGHTCOND
Unknown                   0.897180  0.102820
Dark - No Street Lights   0.771307  0.228693
Other                     0.745946  0.254054
Dark - Street Lights Off  0.722621  0.277379
Dark - Street Lights On   0.694896  0.305104
Dawn                      0.665976  0.334024
Dusk                      0.663598  0.336402
Daylight                  0.661866  0.338134
Dark - Unknown Lighting   0.625000  0.375000
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x10d65a550>



Observations:

1. Our domain knowledge tells us, the darker the more risky.
2. Most accidents happen at daylight, so lighting does not fully explain higher severity accidents.
3. Domain: Dusk/dawn are similar, also no streetlights when dark, so we can group these together.

We drop again 'Unknown', 'Other', 'Dark - Unknown Lighting' and missing values.

```
Out[22]: 1    0.506446
         2    0.246777
         Name: SEVERITYCODE, dtype: float64
```

```
Out[23]: daylight            112618
         dark with lights     46748
         dusk/dawn             8061
         dark - no lights      2522
         Name: LIGHTCOND, dtype: int64
```

```
Out[24]: SEVERITYCODE             1         2
         LIGHTCOND
         dark - no lights  0.749802  0.250198
         dark with lights  0.694896  0.305104
         dusk/dawn         0.664310  0.335690
         daylight          0.661866  0.338134
```

2.0.5 Time dimension

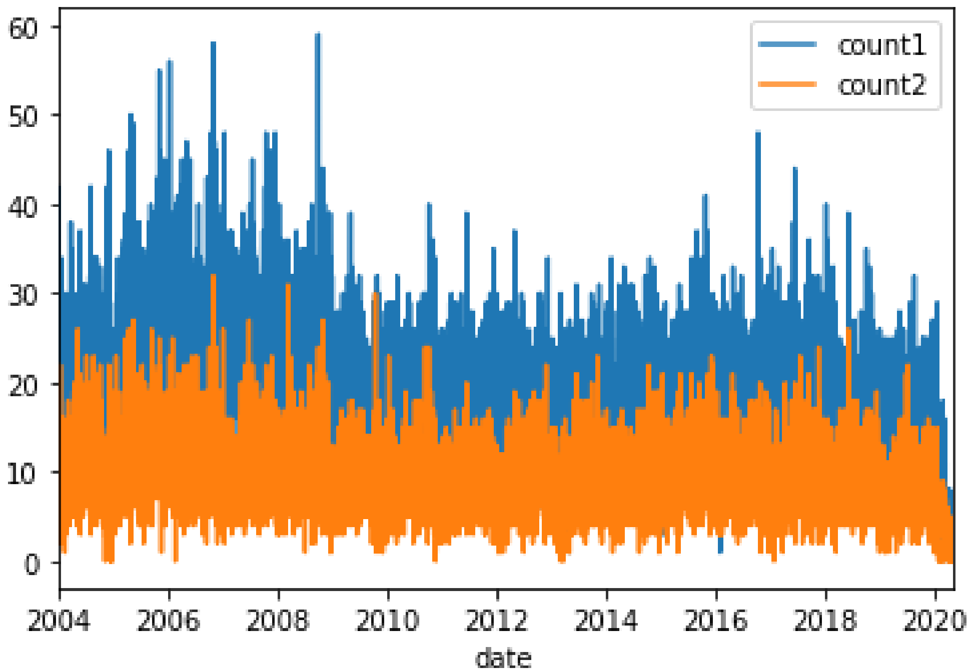
We do get a timing dimension via 'INCDTTM'. First, we need to cast this column as datetime.

```
Out[25]: 0   2013-03-27 14:54:00
         1   2006-12-20 18:55:00
         2   2004-11-18 10:20:00
         3   2013-03-29 09:26:00
         4   2004-01-28 08:04:00
         Name: INCDTTM, dtype: datetime64[ns]
```

Next, we extract dates (for our time series), extract the hour as well as the weekday.

Dates

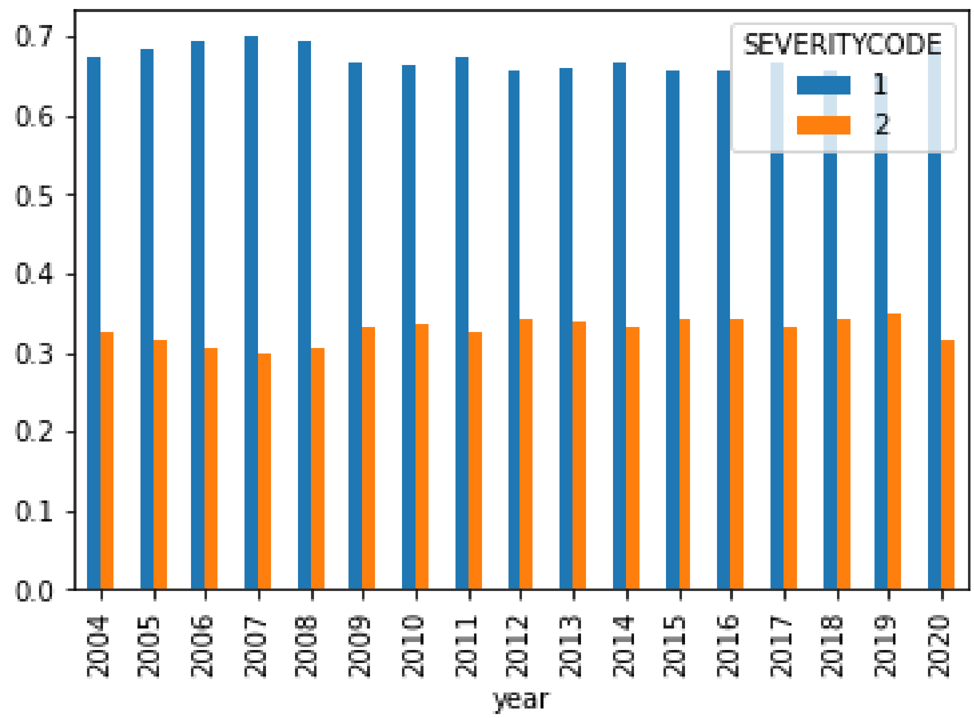
```
Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1c6f6b00>
```



Observations 1. We see a steady decline. Therefore it might make sense to introduce a per year variable.
1. Additionally, there seems to be a by month seasonality.

Years

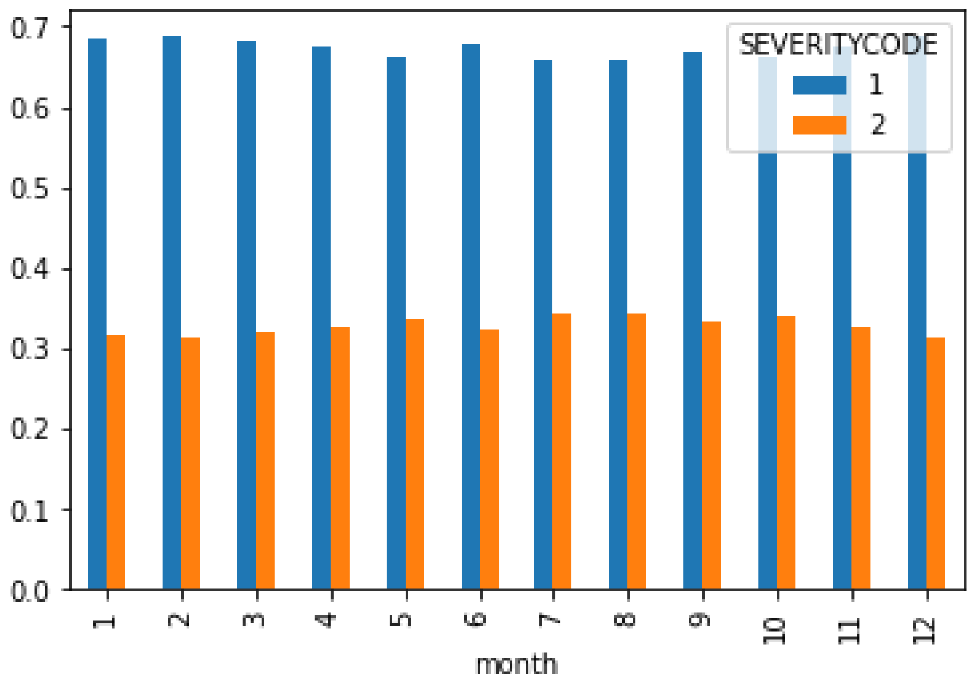
Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1c73e898>




```
Out[30]: SEVERITYCODE         1         2
         year
         2004          0.673354  0.326646
         2005          0.685045  0.314955
         2006          0.694734  0.305266
         2007          0.699609  0.300391
         2008          0.693977  0.306023
         2009          0.666869  0.333131
         2010          0.664574  0.335426
         2011          0.674935  0.325065
         2012          0.657352  0.342648
         2013          0.660225  0.339775
         2014          0.666363  0.333637
         2015          0.656698  0.343302
         2016          0.656442  0.343558
         2017          0.668634  0.331366
         2018          0.655904  0.344096
         2019          0.649699  0.350301
         2020          0.685714  0.314286
```

Month

```
Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1c9e1940>
```



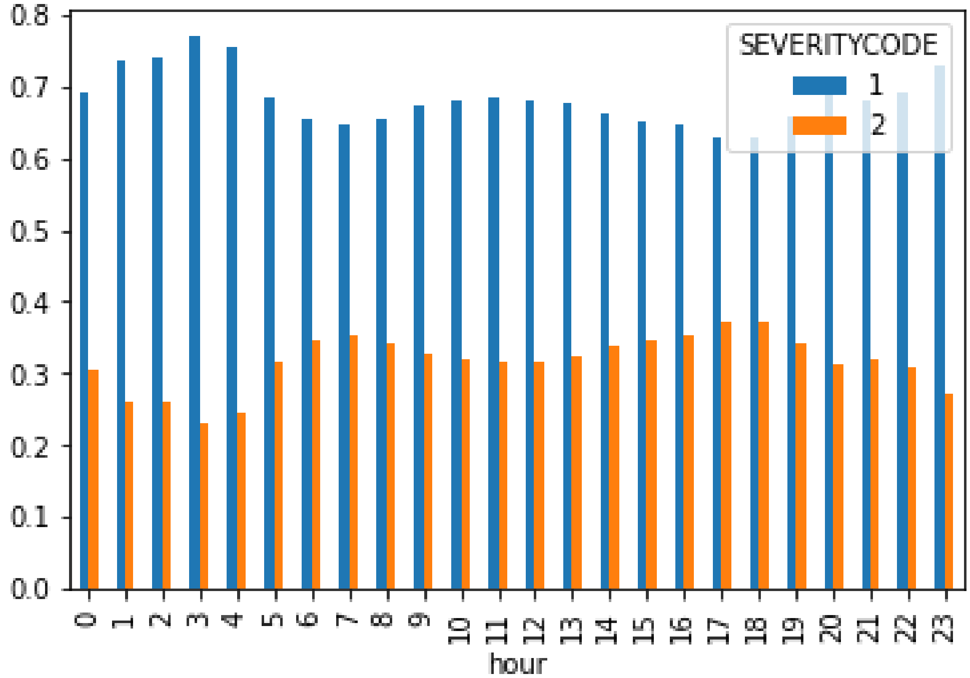
Out[32]:

SEVERITYCODE	1	2
month		
1	0.684810	0.315190
2	0.688054	0.311946
3	0.680452	0.319548
4	0.674265	0.325735
5	0.662940	0.337060
6	0.676699	0.323301
7	0.657716	0.342284
8	0.658525	0.341475
9	0.668089	0.331911
10	0.660083	0.339917
11	0.673975	0.326025
12	0.688254	0.311746

Here we see a seasonality trend for winter and summer. So it suffices to use these as indicator variables.

Hour

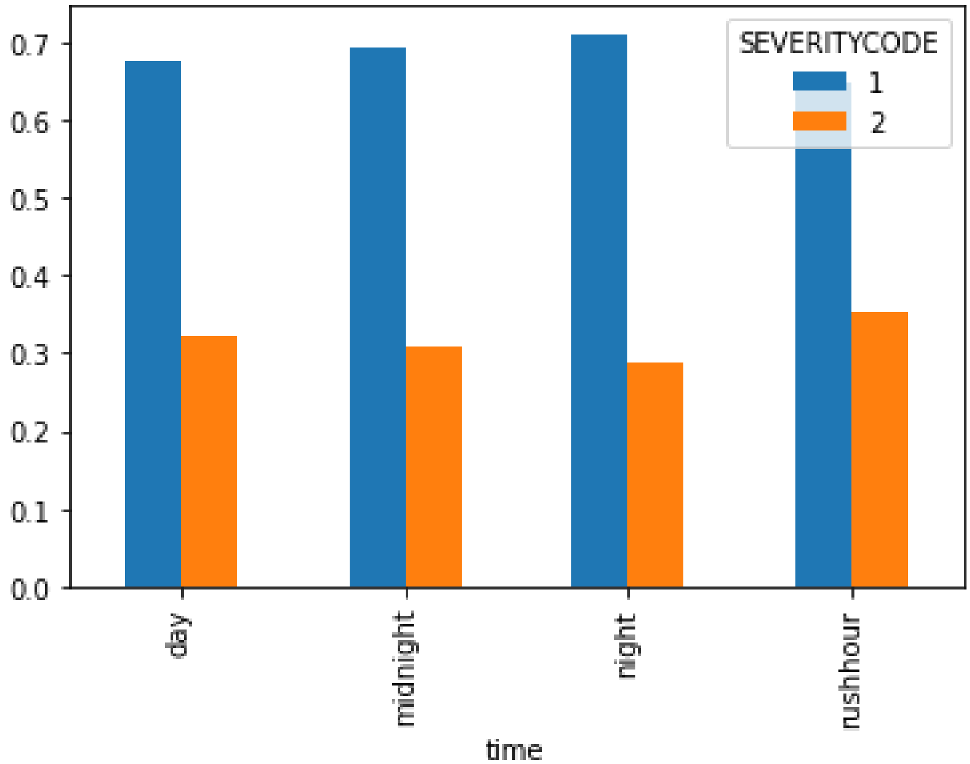
```
Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x1a241f9470>
```



Observations:

1. There is a dip betyeen 1 and 4am.
2. The peak is around 5pm.
3. The relationship is not linear, hence we cannot use it as a standard numerical variable.

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x1a30169208>



Weekday

```
Out[37]: SEVERITYCODE         1         2
         weekday
         Sunday        0.694246  0.305754
         Saturday      0.678400  0.321600
         Friday        0.676581  0.323419
         Wednesday     0.667567  0.332433
         Tuesday       0.665932  0.334068
         Monday        0.665849  0.334151
         Thursday      0.662643  0.337357
```

Obervations:

1. Sunday is the safest day.
2. All other weekdays are pretty much equal.

We can therefore create a boolean type (cast as number for later algorithms) to simplify this feature.

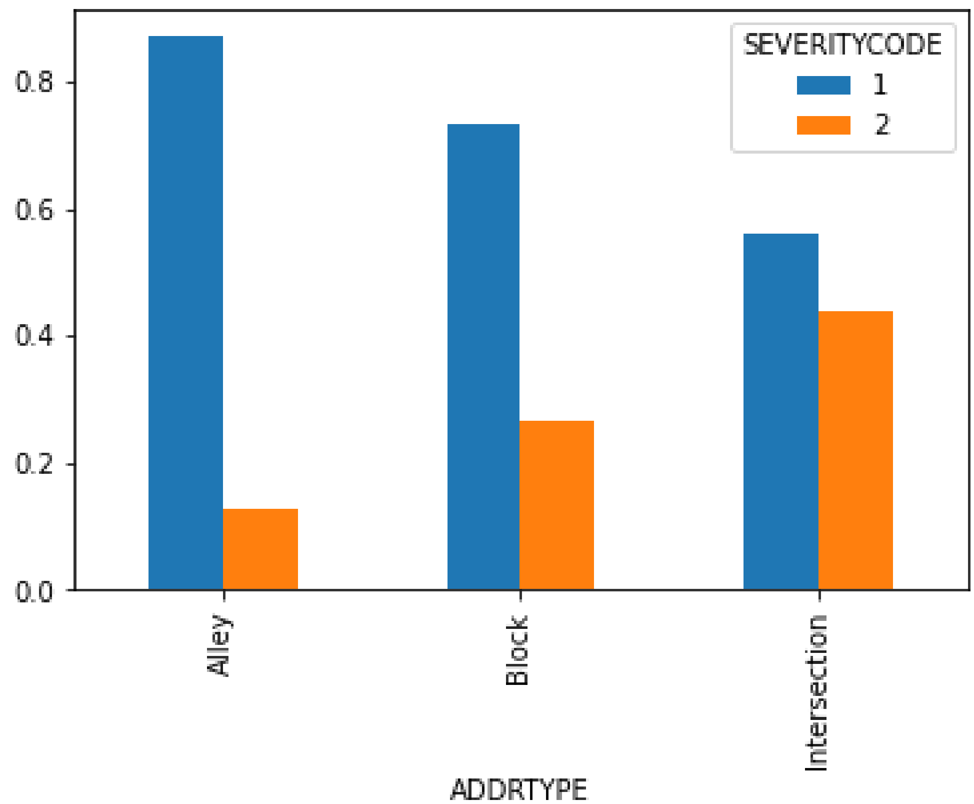
```
Out[39]: SEVERITYCODE         1         2
         is_sunday
         1             0.694246  0.305754
         0             0.669611  0.330389
```

2.0.6 Location type

As a driver, one knows that accidents are more likely at intersections. This information is stored in the variable 'ADDRTYPE'.

```
Out[40]: Block           107379
         Intersection     61267
         Alley              593
         Name: ADDRTYPE, dtype: int64
```

```
Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x1a304dee10>
```



Feature summary We will therefore use

- WEATHER (transformed)
- ROADCOND
- LIGHTCOND (transformed)
- time_of_day (transformed from date)
- is_sunday (transformed from date)
- is_summer and is_winter (transformed from date)
- ADDRTYPE

We therefore reduce the columns as follows:

Out[42]:

	SEVERITYCODE	WEATHER	ROADCOND	LIGHTCOND	time	is_sunday	\
0	2	mild	Wet	daylight	day	0	
1	1	raining	Wet	dark with lights	rushhour	0	
2	1	mild	Dry	daylight	day	0	
3	1	mild	Dry	daylight	rushhour	0	
4	2	raining	Wet	daylight	rushhour	0	

	ADDRTYPE	year	is_summer	is_winter
0	Intersection	2013	0	1
1	Block	2006	0	1
2	Block	2004	0	0
3	Block	2013	0	1
4	Intersection	2004	0	1

First we convert the categorical data into dummy variables encoding our categorical variables.

Out[43]:

	SEVERITYCODE	is_sunday	WEATHER_mild	WEATHER_raining	\
0	2	0	1	0	
1	1	0	0	1	
2	1	0	1	0	
3	1	0	1	0	
4	2	0	0	1	

	WEATHER_sleet/hail/freezing rain	WEATHER_snowing	WEATHER_windy	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	ROADCOND_Dry	ROADCOND_Ice	ROADCOND_Oil	...	year_2015	year_2016	\
0	0	0	0	...	0	0	
1	0	0	0	...	0	0	
2	1	0	0	...	0	0	
3	1	0	0	...	0	0	
4	0	0	0	...	0	0	

	year_2017	year_2018	year_2019	year_2020	is_summer_0	is_summer_1	\
0	0	0	0	0	1	0	
1	0	0	0	0	1	0	
2	0	0	0	0	1	0	
3	0	0	0	0	1	0	
4	0	0	0	0	1	0	

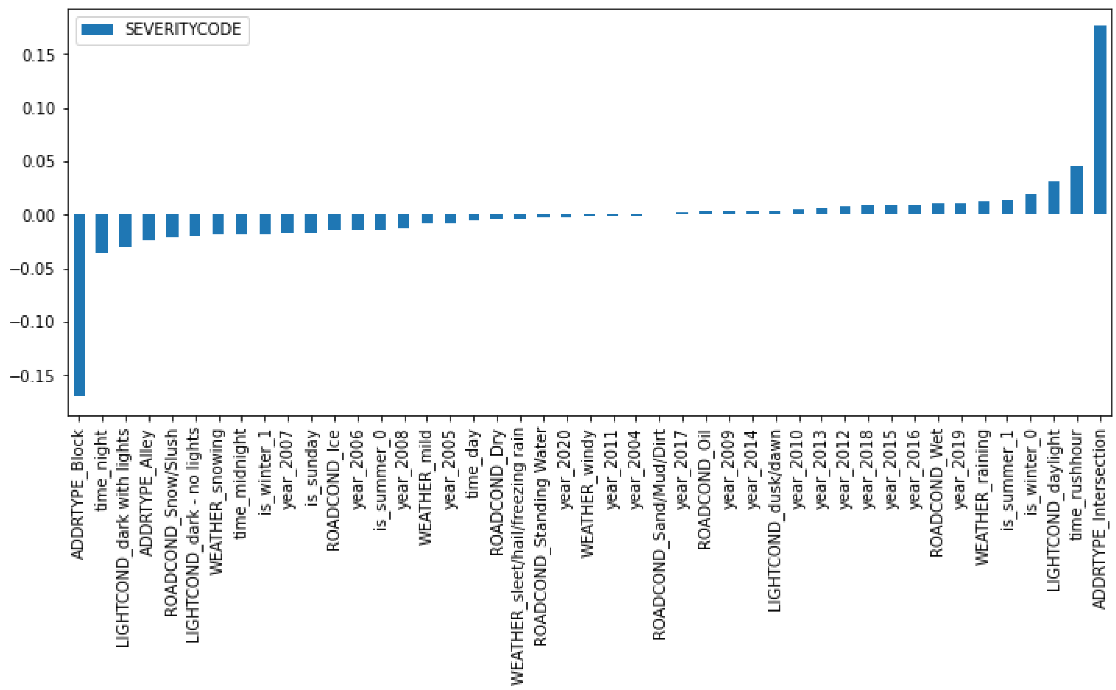
	is_winter_0	is_winter_1
0	0	1

```
1          0          1
2          1          0
3          0          1
4          0          1

[5 rows x 46 columns]
```

2.0.7 Correlation analysis

We will do an analyis of correlations to check which columns have the biggest impact using the Pearson index. Values close to -1 and 1 indicate strong (anti-) correlation.

```
Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x1a234b14a8>
```



2.0.8 3.3 Machine learning models

We will try several variants of machine learning models.

- Logistic Regression
- Random Forests

3.3.1 Creating Balance First of all, we need to find a way to deal with the imbalanced-ness of data. This can be handled via weights for logistic regression reflecting the frequency of occurrence.

```
Weight1: 0.7436356317111378
Weight2: 1.526122485632184
```

3.3.2 Train-test-split Secondly, we need to split the data into a train and test set.

```
Train set: (135959, 45) (135959,)
Test set: (33990, 45) (33990,)
```

3.3.3 Logistic Regression Here, we model the probability of a feature set to result in either category. This algorithm is designed for binary decision problems, which is the case for this data set and the posed question.

Model tuning We tune model performance by testing several hyperparameters using RandomizedSearchCV.

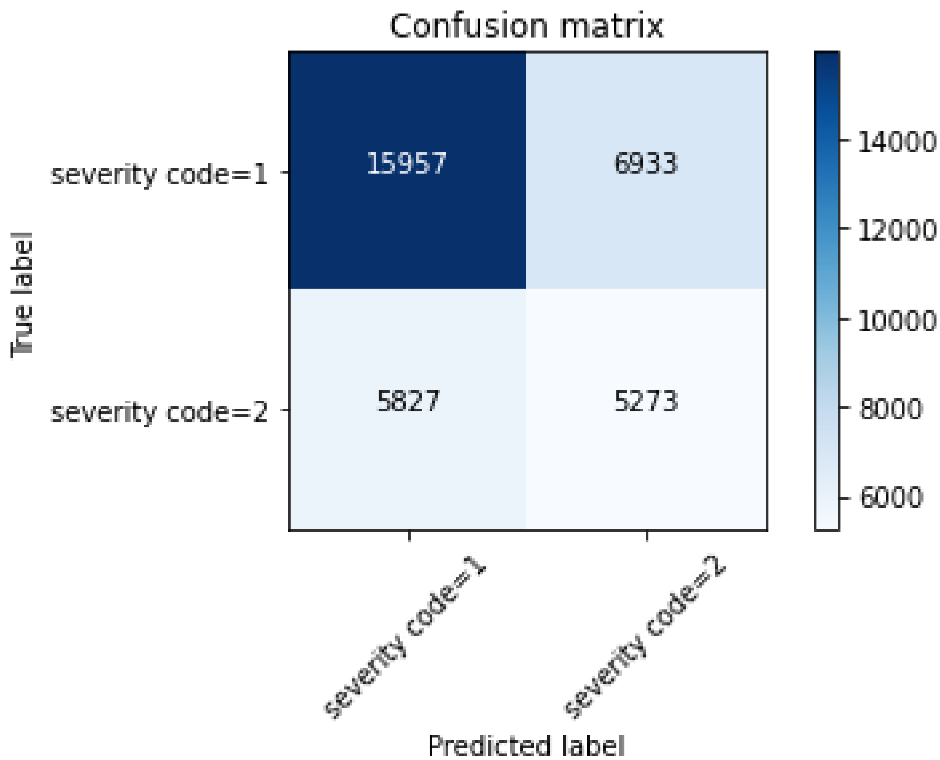
```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:  5.7min
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed: 10.8min remaining:    0.0s
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed: 10.8min finished
```

```
Out[49]: RandomizedSearchCV(cv=3, error_score='raise-deprecating',
                   estimator=LogisticRegression(C=1.0,
                   class_weight={1: 0.7436356317111378, 2: 1.526122485632184},
                   dual=False, fit_intercept=True, intercept_scaling=1,
                   max_iter=100, multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False),
                   fit_params=None, iid='warn', n_iter=10, n_jobs=-1,
                   param_distributions={'penalty': ['l1', 'l2'], 'C': array([1.00000e-04, 2.6366
                1.27427e-02, 3.35982e-02, 8.85867e-02, 2.33572e-01, 6.15848e-01,
                1.62378e+00, 4.28133e+00, 1.12884e+01, 2.97635e+01, 7.84760e+01,
                2.06914e+02, 5.45559e+02, 1.43845e+03, 3.79269e+03, 1.00000e+04]), 'solver': ['l
                   pre_dispatch='2*n_jobs', random_state=0, refit=True,
                   return_train_score='warn', scoring='f1', verbose=5)
```

```
Classification Report: Logistic Regression
              precision    recall  f1-score   support

           1       0.73      0.70      0.71     22890
           2       0.43      0.48      0.45     11100

   micro avg       0.62      0.62      0.62     33990
   macro avg       0.58      0.59      0.58     33990
weighted avg       0.63      0.62      0.63     33990

Accuracy: 62.46% (correctly classified test data)
F1: 0.714375 (weighted average of recall and precision)
```

```
Confusion matrix, without normalization
[[15957  6933]
 [ 5827  5273]]
```



3.3.4 Random Forests Random forests are a good candidate because they are very versatile and will allow us to work with out categorical data.

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:  4.9min
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:  9.7min remaining:    0.0s
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:  9.7min finished
```

```
Out[52]: RandomizedSearchCV(cv=3, error_score='raise-deprecating',
                   estimator=RandomForestClassifier(bootstrap=True,
                     class_weight={1: 0.7436356317111378, 2: 1.526122485632184},
                     criterion='gini', max_depth=None, max_features='auto',
                     max_leaf_nodes=None, min_impurity_decrease=0.0,
                     min_impurity_split=None, min_samples_leaf=1,
```

```
                          min_samples_split=2, min_weight_fraction_leaf=0.0,
                          n_estimators='warn', n_jobs=None, oob_score=False,
                          random_state=None, verbose=0, warm_start=False),
                        fit_params=None, iid='warn', n_iter=10, n_jobs=-1,
                        param_distributions={'max_depth': [2, 5, 10, 20], 'max_features': [5, 7, 10,
                        pre_dispatch='2*n_jobs', random_state=0, refit=True,
                        return_train_score='warn', scoring='f1', verbose=5)
```

We can then extract the best model and fit the data.

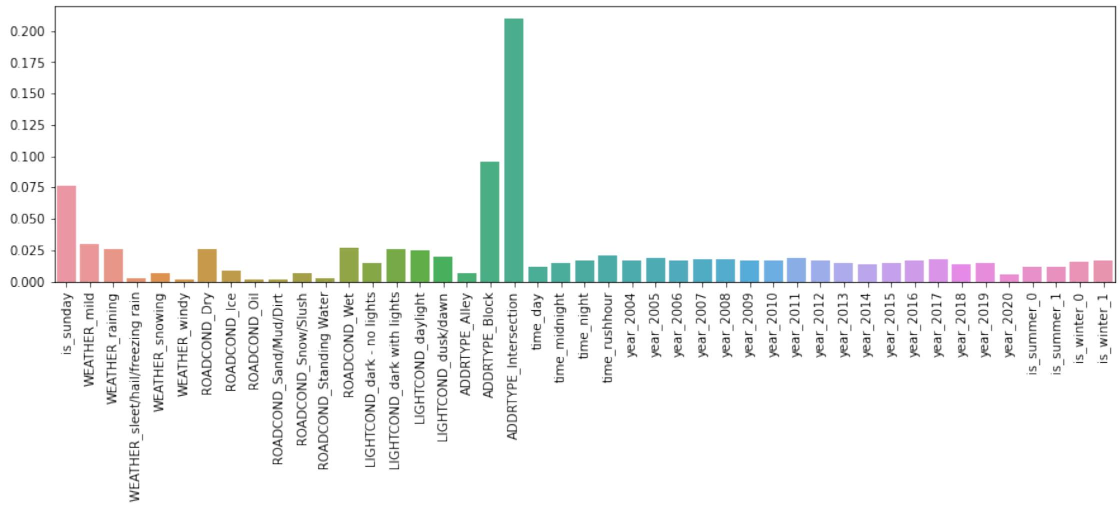
```
/Users/Katie/anaconda3/lib/python3.7/site-packages/sklearn/ensemble/forest.py:246: FutureWarning
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

```
Out[53]: RandomForestClassifier(bootstrap=True,
                          class_weight={1: 0.7436356317111378, 2: 1.526122485632184},
                          criterion='gini', max_depth=None, max_features='auto',
                          max_leaf_nodes=None, min_impurity_decrease=0.0,
                          min_impurity_split=None, min_samples_leaf=1,
                          min_samples_split=2, min_weight_fraction_leaf=0.0,
                          n_estimators=10, n_jobs=None, oob_score=False,
                          random_state=None, verbose=0, warm_start=False)
```

```
Classification Report: Random Forest
              precision    recall  f1-score   support

           1       0.73      0.70      0.71     22890
           2       0.43      0.48      0.45     11100

   micro avg       0.62      0.62      0.62     33990
   macro avg       0.58      0.59      0.58     33990
weighted avg       0.63      0.62      0.63     33990

Accuracy: 62.47% (correctly classified test data)
F1: 0.714462 (weighted average of recall and precision)
```

So, random forests beat logistic regression in the F1-score by a very slight margin.

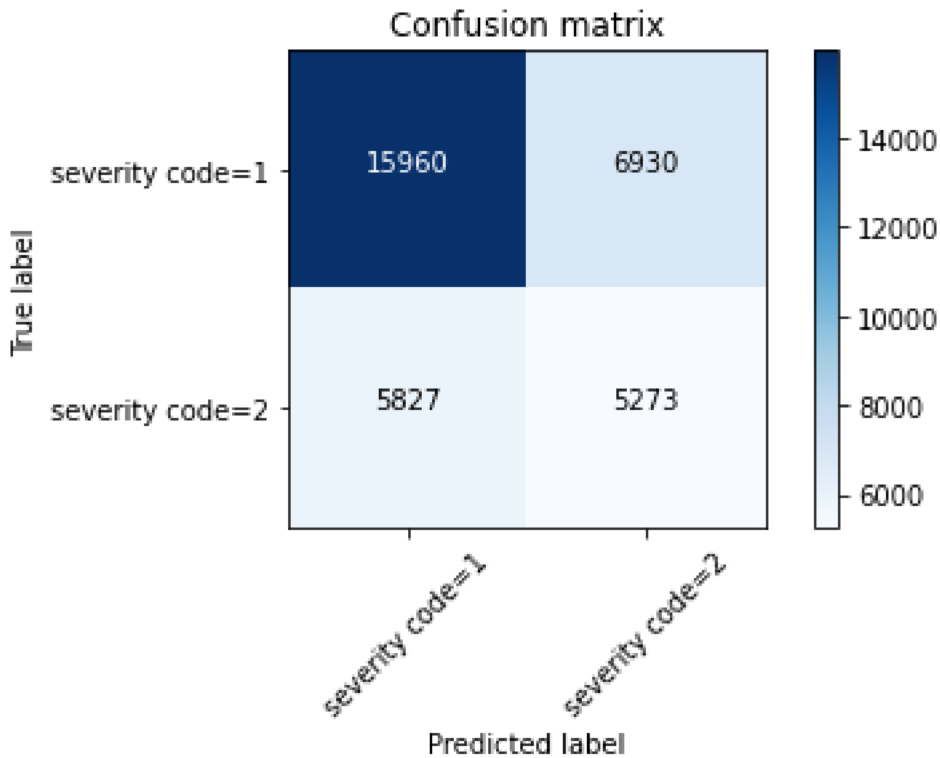
3.3.5 Importances Analysis



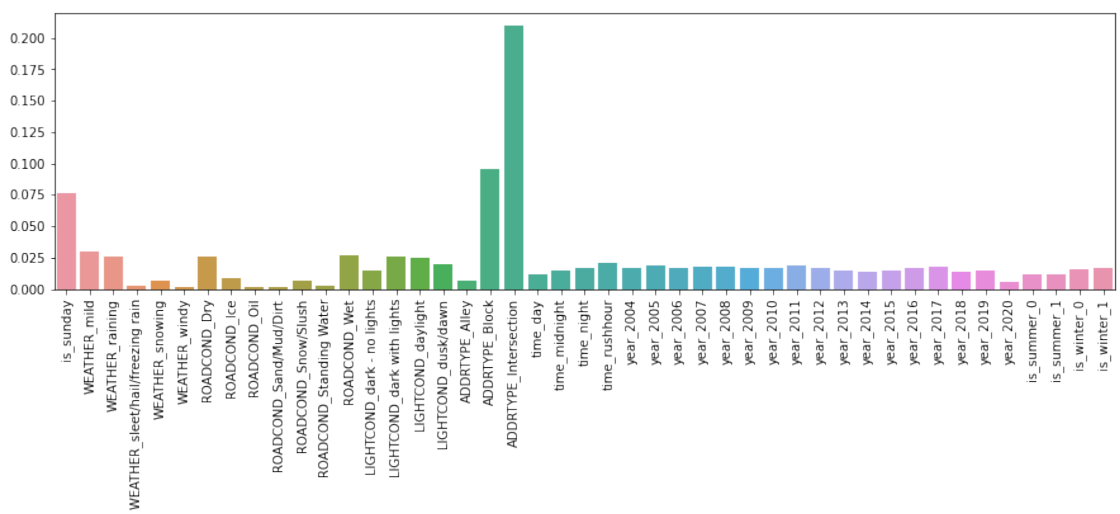
2.1 4. Results

Out of our two approaches, logistic classification and random forests, we pick random foreces because of the better f1 score performance. We summarize it's statisics.

```
Confusion matrix, without normalization
[[15960  6930]
 [ 5827  5273]]
```



Based on our model, we can extract the following importances of the features importances.



We note that **address type: intersection**, **address type: block** and the fact that it is **sunday** play the most dominant roles.

2.2 5. Discussion

Our models work acceptably well to recognize code 1 accidents, however the recall is low for code 2 accidents. One path of improvement could be to increase the weight for code 2 accidents, since misclassifying them (e.g. underestimating an injury-type accident) is more 'costly' for drivers.

The most striking feature we notice in the feature importance analysis is the importance of intersections. They pose a major risk for injuries in accident.

2.3 6. Conclusion

In this analysis, we have analyzed the question of what impacts accident severity based on the overall conditions the driver is facing. We have used as basis the data collected by the Seattle police departement from 2004 to today. We have conducted a data analysis and selected features that had most impact on the accident severity.

As predictive models, we have used logistic regression and random forests, both leading to similar accuracy values with random forests having a small advantage. Both models suffer from lower recall for type 2 classifications. In a future analyis, this may be mitigated by using different weights.

Subsequently, we have analyzed feature importance and concluded that locaton type intersection, block and the fact that it is sunday or not play the most important role.

We have concluded that drivers already drive more carefully under most adverse conditions (e.g. snowing), but underestimate 'medium-type' conditions such as raining.