
A decorative graphic on the left side of the slide consisting of two overlapping parallelograms. The front one is blue and the back one is light green. They are positioned diagonally, with the blue one partially covering the green one.

Predicting traffic
incidents using
historical data



Predicting severity of traffic incidents is useful for

- The General Public
 - We can alert drivers to be more alert in hazardous conditions
- First responders
 - We can provide insight on areas to be present that have a higher likelihood of severe accident



Data Acquisition and Cleaning

- The data we used is provided from coursera and has all collisions in Seattle as provided by SPD and recorded by Traffic Records from 2004 to present.
- Excess data from severity code was reduced to create a more accurate model
- Cleaned data removed excess data and converted written types to numerical data



Using Logistic Regression to create model

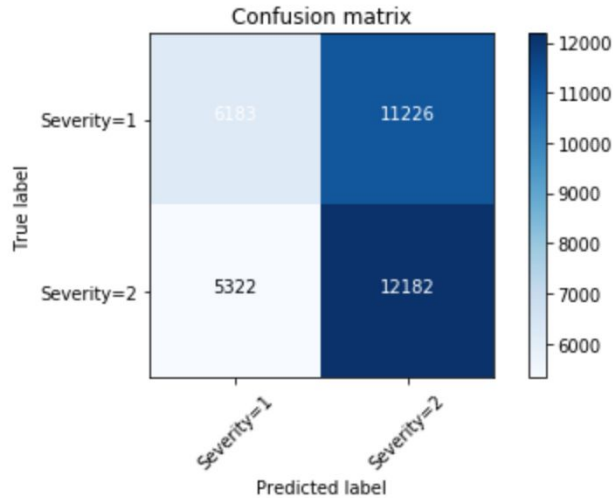
```
In [21]: yhat_prob = LR.predict_proba(X_test)
         yhat_prob
```

```
Out[21]: array([[0.57133499, 0.42866501],
                [0.47089523, 0.52910477],
                [0.67367858, 0.32632142],
                ...,
                [0.47096955, 0.52903045],
                [0.47089523, 0.52910477],
                [0.47096955, 0.52903045]])
```

Confusion Matrix and f1-score

Confusion matrix, without normalization

```
[[ 6183 11226]
 [ 5322 12182]]
```



```
In [27]: print (classification_report(y_test, yhat))
```

	precision	recall	f1-score	support
1	0.54	0.36	0.43	17409
2	0.52	0.70	0.60	17504
micro avg	0.53	0.53	0.53	34913
macro avg	0.53	0.53	0.51	34913
weighted avg	0.53	0.53	0.51	34913

```
In [28]: from sklearn.metrics import log_loss
log_loss(y_test, yhat_prob)
```

```
Out[28]: 0.6849475402881953
```



Conclusion

- Due to lack of severity options we were unable to create an effective predictive model