

A silver sedan is shown from a front-three-quarter view, parked on a paved road. The front of the car is heavily damaged, with the hood crumpled and the front end pushed upwards. The left headlight is shattered and partially missing. The left side mirror is also damaged. The background shows a concrete guardrail and a dense line of green trees under a bright sky. A semi-transparent white box contains the title and subtitle text.

PREDICTING THE SEVERITY OF ROAD VEHICLE ACCIDENTS

How to improve rescue services in road vehicle accidents by implementing a machine learning classifier

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Business Understanding

In the US there are:



280 million vehicles



6 million accidents per year



35.600 fatalities per year (2018)

How to reduce fatality
rate?



ML classifier to predict
severity of accidents



Enable rescue services
to send appropriate
equipment and
number of paramedics

Data Understanding

Data set

- SDOT Traffic Management Division
- Traffic Records Group
- 2004 to present date
- 194.673 data points
- 38 columns
- 2 severity codes (prop damage / injury)

Feature selection

- External/environmental features only
- Must be possible to visually/directly determine feature by anyone
- 5 features selected for modeling:
 - Person count
 - Vehicle count
 - Junction type
 - Weather
 - Road conditions
 - Light conditions

First five rows of resulting data frame

	SEVERITYCODE	PERSONCOUNT	VEHCOUNT	JUNCTIONTYPE	WEATHER	ROADCOND	LIGHTCOND
0	2	2	2	At Intersection (intersection related)	Overcast	Bad_Conditions	Daylight
1	1	2	2	Mid-Block (not related to intersection)	precipitation	Bad_Conditions	Dark - Street Lights On
2	1	4	3	Mid-Block (not related to intersection)	Overcast	Good_Conditions	Daylight
3	1	3	3	Mid-Block (not related to intersection)	Clear	Good_Conditions	Daylight
4	2	2	2	At Intersection (intersection related)	precipitation	Bad_Conditions	Daylight

Methodology

1

Data cleaning

- Delete rows with na
- Delete duplicates
- Drop rows with “other” or “unknown” values
- Summarize attributes
- Balance sample set
- One hot encoding

2

Exploratory Analysis

- Distribution of values
- Correlation weekday and severity
- Detection of outliers

3

Predictive Modeling

- Modeling four different algorithms with changing parameters (iterative)
 1. K-nearest neighbors
 2. Decision Tree
 3. Random Forest
 4. Logistic Regression
- Evaluation based on accuracy, f1 and log loss

Results

Knn

	k	Accuracy_Score	F1_Score
4	5.0	0.61225	0.611384
9	10.0	0.60975	0.606648
6	7.0	0.60875	0.605882
8	9.0	0.60500	0.604183
3	4.0	0.60350	0.594858

Decision Tree

	Max_Depth	Accuracy_Score	F1_Score
6	7.0	0.64850	0.647881
5	6.0	0.64750	0.646833
7	8.0	0.64425	0.644000
4	5.0	0.64375	0.643603
3	4.0	0.64275	0.641532

Highest accuracy with decision tree
with max_depth = 7

	precision	recall	f1-score	support
0	0.66	0.61	0.63	1979
1	0.64	0.69	0.66	2021
micro avg	0.65	0.65	0.65	4000
macro avg	0.65	0.65	0.65	4000
weighted avg	0.65	0.65	0.65	4000

Random Forest

	N_estimators	Accuracy_Score	F1_Score
54	55.0	0.64125	0.641044
4	5.0	0.64075	0.640637
97	98.0	0.64000	0.639960
30	31.0	0.64000	0.639937
66	67.0	0.63950	0.639420

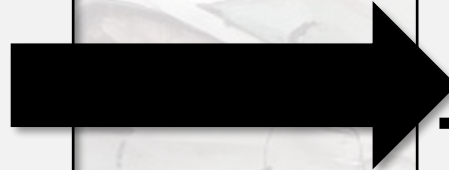
Logistic Regression

	C	Accuracy_Score	F1_Score	Log_loss
2	0.001	0.62300	0.622618	0.656204
0	0.100	0.62125	0.620931	0.654979
1	0.010	0.61950	0.619010	0.654798

Discussion and Conclusion

Discussion

- Max accuracy of 0.6485
- Further data might be needed
- Choice of features must be optimized
- Classifier is not biased towards a certain result
- Future research might include:
 - Possibility to predict probability of accident
 - Include further severity grades



Conclusion

- Machine learning classifier was developed in order to predict the severity of an accident
- Based on data set of accidents in Seattle (2004 to today)
- Best model was found by using Decision Tree with `max_depth = 7`
- Model can be of great help for rescue services