# CASA0006 Assessment: Body Text

Student Number: 22186878

### Background

This notebook presents the development and evaluation of a machine learning model applied to a New Zealand traffic crash dataset, to predict crash injury severity and determine the most influential contributing factors.

### Literature Review

Vehicle crash injuries present a major public health and economic burden on a global scale. In New Zealand, the government has implemented an explicit ‘Road to Zero’ strategy which aims for a road system where nobody is killed or seriously injured (New Zealand Government, 2019). In response to this complex challenge there is an extensive body of research, developed over decades, that has applied statistical and machine learning models to determine contributing factors in crash likelihood and improve prediction of crash severity (Savolainen *et al.*, 2011; Santos, Dias and Amado, 2022). Understanding the association of specific factors with crash outcomes allows for the design of evidence-based countermeasures, whether in the vehicle or in the built environment, whilst predictive capacity has potential implications for directing emergency response, and in the decision making of autonomous vehicles.

In recent years, there has been a broad spectrum of ML methods that have rapidly become the most popular choice for crash severity analysis due to their freedom from prior assumptions, robustness to outliers, and high performance in big data scenarios (Ziakopoulos and Yannis, 2020). Established methods include regression and decision trees (Jeong *et al.*, 2018), support vector machines (Effati, Thill and Shabani, 2015), neural networks (Delen *et al.*, 2017), and ensemble approaches such as Random Forest and Gradient Boosting (Iranitalab and Khattak, 2017; Wang and Kim, 2019). Of these various approaches, a systematic literature review by Santos et al. (2022) found that Random Forest (RF) models proved the highest performing algorithm in the most cases, achieving best performance, comparative to alternatives, in 70% of the studies it was applied.

Irrespective of the approach used, there are certain characteristics of vehicle crash data that need to be accounted for in designing a model. Firstly, these datasets often collect an ordinal categorical outcome – such as crash severity categorised into fatal, serious, minor, or non-injury. These classes are generally heavily imbalanced, with a very high proportion of observations in the low-severity class, and a low proportion classed as severe/fatal. If this imbalance is not addressed, the model may produce overtly promising results with a high overall accuracy, but have very poor predictive performance for the high-severity classes, which are inherently the observations of greatest interest in crash analysis (Jeong *et al.*, 2018). In addition, crash events will have spatial dependence, where crashes occurring geographically close are likely to share effects not otherwise captured in the data, which may introduce bias in model estimates (Savolainen *et al.*, 2011). Therefore, the aim of this study is to develop a reproducible python workflow that evaluates the effectiveness of ensemble ML models in a New Zealand context and quantifies the impact of class imbalance on performance.

### Research Question

1. How effectively can road and environmental factors predict vehicle crash severity?
2. Of these factors, which have the greatest influence on the prediction performance?

### Methodology

Data for this analysis are drawn from the New Zealand Transport Agency’s Crash Analysis System (CAS), which contains a record of all police-reported traffic crashes on New Zealand roadways from 1st January 2000 (Waka Kotahi NZ Transport Agency, 2023). There are over 70 features captured in the dataset, which can be broken down into road factors (such as number of lanes and speed limit), environmental factors (such as location, weather, and conditions), and crash outcomes (such as objects hit, vehicles involved, and injury severity).

Two ensemble classification methods, Random Forest (RF) and Adaptive Boosting (AdaBoost), were fitted to a training subset of the data and performance evaluated against a separate testing set. Numeric features were scaled, and one-hot encoding used to separate categorical features. Default models were compared with balanced estimators which use random undersampling to account for the class imbalance. Moran’s I was used to assess for the presence of spatial autocorrelation in the dataset, and a spatial dependence feature added to the model. Lastly, permutation feature importance was used to identify which input features exhibited the strongest influence on model prediction.

### Results

#### Read data

The CSV file is read in as a pandas data frame, and columns changed to the appropriate data types.

#### Clean missing data

The table below shows the default data type of imported columns, and a count of non-null values for each column. There are 807,933 observations (rows) in the dataset, and 72 features (columns).

Of these, 7 have a very high proportion of missing data (>90% of observations) - they are `advisorySpeed`, `crashRoadSideRoad`, `holiday`, `intersection`, `pedestrian`, `temporarySpeedLimit`, and `weatherB`. These columns contain a mix of true missing data and incorrectly coded real data. For example, `pedestrian` represents a count of how many pedestrians were involved in the crash. However, non-missing values for `pedestrian` range from \[1,6\], meaning that no crash events have a value of '0' recorded. It is reasonable to assume that crashes with a null value for `pedestrian` represent events where no pedestrians were involved. Similarly, `holiday` only records an entry if the event falls into one of the four categories of Christmas/New Year, Easter, Labour Weekend, or Queens Birthday.

For `temporarySpeedLimit` and `advisorySpeed`, missing data represents a true absence - in these cases, no temporary or advisory speed limit was in effect at the time and location of the crash event. These fields have been converted to boolean - where a present limit is True and no limit classed as False.

The columns `crashRoadSideRoad` and `intersection` are missing all data, and these were removed from the analysis.

Finally, free-text columns have been removed as these will not be useful in the ML model, as well as a series of redundant fields where the information is contained in another variable.

A second subset of 23 columns have a non-null count of 325,939, meaning they are missing data for approximately 60% of observations (Column Set B). These columns all collect data on the number of objects of \*type\* that were struck in the crash, and are systematically either present or missing. Because of the large set of columns in this group, a subset of the dataframe has been created which keeps these columns but removes observations where they have missing data.

After removing unnecessary columns and creating the ColumnSetB subset of the dataframe, the data is checked for any remaining missing values.

The missing values in these columns all represent a very small percentage (<0.05%) of the total observations. Therefore, these observations have been removed.

#### Dependent variable

The outcome variable of interest for this study is the crash severity, which categorises all events as Non-injury, Minor, Serious, or Fatal.

As fatal count and injury count are all heavily skewed towards zero, crash severity category will be used as the main dependent variable for the ML model. Due to the low event counts 'Fatal Crash' and 'Serious Crash' have been combined into a single category for the analysis.

#### Set data types

Categorical features are set as type accordingly, and the levels for each category checked to ensure it matches the metadata provided.

See below for a summary table (Table 1) of each categorical column, broken down proportionally by category. Tables 2 & 3 show the descriptive statistics for numeric variables, for column sets A and B, respectively.

#### Spatial conversion

The pandas dataframe is converted into a geopandas geodataframe, using the X/Y coordinates provided ([NZTM2000](https://www.linz.govt.nz/guidance/geodetic-system/coordinate-systems-used-new-zealand/projections/new-zealand-transverse-mercator-2000-nztm2000" \t "_blank) Easting/Northing values). The geodataframe is then plotted to confirm that the projection has been read as expected.

A spatial weights matrix is then generated using the k-nearest neighbours (KNN) method, where k=8, and the distance band method with a threshold of 100m. Global spatial autocorrelation is then calculated using the KNN weights to ensure no neighbourless points.

The Moran plot below represents a scatter plot of the injury count against its spatial lag. The fitted regression line demonstrates a positive relationship between both variables, which indicates the presence of spatial autocorrelation in the data – for example, crashes with a high injury count are likely to be geographically close to other high-injury crashes. The global Moran’s I statistic of 0.74 (p-value < 0.01) confirms this assumption.

Effati et al. (2015) propose accounting for spatial autocorrelation in a decision tree model by incorporating the coordinates as features in addition to a spatial dependence term. In this case, the standardised injury count spatial lag has been added to the model dataset and the additional columns are dropped.

#### Training Testing Split[¶](http://localhost:8888/lab/tree/work/CASA0006/assessment/final-assessment.ipynb#Training-Testing-Split)

Firstly, the dataset is split into training and testing subsets before any of the preprocessing steps take place. This ensures that there is no data leakage from the testing set, which can lead to inflated performance estimates (Tharwat, 2020).

#### Model Pipeline

To prepare the data for modelling, two pre-processing steps are run: standardisation of numeric variables and one-hot encoding of categorical variables. After defining the pre-processing steps, an estimator is added to the ML pipeline. For this project, a remote forest classifier (Breiman, 2001) has been chosen.

#### Evaluating performance

The classification report below lists a set of performance metrics designed to evaluate imbalanced datasets: precision, recall, specificity, F1 score, geometric mean (G-mean), and index balanced accuracy of the G-mean. The G-mean, calculated as the square root of the product of sensitivity and specificity measures, has been proposed as a more appropriate metric for evaluating models developed from imbalanced datasets (Jeong et al. 2018). Additionally, the balanced\_accuracy\_score function computes the balanced accuracy, which avoids inflated performance estimates on imbalanced datasets.

The results below show that the default random forest model performs poorly for the severe/fatal class.

#### Iterate through multiple models

After testing proof-of-concept with the RF model above, a loop is built to iterate through alternative ensemble models and compare the performance results. In the ML literature, there are two main approaches to dealing with class imbalanced data: under-sampling and over-sampling (Wen et al. 2019). Due to the large size of the cleaned dataset (still over 300,000 observations), an undersampling method has been applied, as this maintains a high performance but at significantly reduced computational load.

Of the four models tested, the balanced RF and balanced adaptive booster (AdaBoost) perform the best in balanced accuracy and G-mean, with roughly equivalent values of **0.49** and **0.48**, respectively. As the RF performs marginally better, this model is chosen for the final analysis.

#### Hyperparameter tuning

The following method finds the optimal values for RF hyperparameters, from the specified set. For this model, the best performing set used a max tree depth of 50 and a minimum leaf sample of 2.

**NOTE:** The tuning cell takes over an hour to run. Therefore, has been default set to skip, unless explicitly called by setting run\_tuning to True.

#### Interpreting feature importance

After refining the best performing model, permutation feature importance (PFI) has been used to identify which features have the greatest influence on prediction. The 'importance' score for each feature is relative to the other features in the other dataset. The number of cars involved, the year, and the speed limit are found to be the strongest predicting features of crash severity.

### Discussion

1. *How effectively can road and environmental factors predict vehicle crash severity?*
2. *Of these factors, which have the greatest influence on the prediction performance?*

In the final evaluation of models, the balanced random forest performed the best, particularly accounting for prediction of observations in the severe/fatal severity class. However, compared with ML models in other crash severity studies the performance was still relatively low, suggesting that there may be a large amount of unobserved heterogeneity in the New Zealand CAS dataset. As expected, the model was made more complex due to the significant class imbalance and the presence of strong spatial autocorrelation in the crash severity. Model performance may potentially be improved by exploring more computationally intensive methods which were not feasible for the scope of this project – for example, rectifying class imbalance through Synthetic Minority Oversampling Technique (SMOTE), which generates novel observations in the smaller classes through imputation (Fernandez *et al.*, 2018).

The number of cars involved, year, and speed limit had the strongest influence on crash severity. The presence of year indicates there is likely a meaningful time trend in the data – this would be a valuable extension to this study, and provide insight into the long-term success (or failure) of New Zealand’s overarching road safety policy framework.

### References

Breiman, L. (2001) ‘Random Forests’, *Machine Learning*, 45(1), pp. 5–32. Available at: https://doi.org/10.1023/A:1010933404324.

Delen, D. *et al.* (2017) ‘Investigating injury severity risk factors in automobile crashes with predictive analytics and sensitivity analysis methods’, *Journal of Transport & Health*, 4, pp. 118–131. Available at: https://doi.org/10.1016/j.jth.2017.01.009.

Effati, M., Thill, J.-C. and Shabani, S. (2015) ‘Geospatial and machine learning techniques for wicked social science problems: analysis of crash severity on a regional highway corridor’, *Journal of Geographical Systems*, 17(2), pp. 107–135. Available at: https://doi.org/10.1007/s10109-015-0210-x.

Fernandez, A. *et al.* (2018) ‘SMOTE for Learning from Imbalanced Data: Progress and Challenges, Marking the 15-year Anniversary’, *Journal of Artificial Intelligence Research*, 61, pp. 863–905. Available at: https://doi.org/10.1613/jair.1.11192.

Iranitalab, A. and Khattak, A. (2017) ‘Comparison of four statistical and machine learning methods for crash severity prediction’, *Accident Analysis & Prevention*, 108, pp. 27–36. Available at: https://doi.org/10.1016/j.aap.2017.08.008.

Jeong, H. *et al.* (2018) ‘Classification of motor vehicle crash injury severity: A hybrid approach for imbalanced data’, *Accident Analysis & Prevention*, 120, pp. 250–261. Available at: https://doi.org/10.1016/j.aap.2018.08.025.

New Zealand Government (2019) *Road to Zero: New Zealand’s Road Safety Strategy 2020-2030*. Wellington, NZ. Available at: https://www.nzta.govt.nz/safety/what-waka-kotahi-is-doing/nz-road-safety-strategy/.

Santos, K., Dias, J.P. and Amado, C. (2022) ‘A literature review of machine learning algorithms for crash injury severity prediction’, *Journal of Safety Research*, 80, pp. 254–269. Available at: https://doi.org/10.1016/j.jsr.2021.12.007.

Savolainen, P.T. *et al.* (2011) ‘The statistical analysis of highway crash-injury severities: A review and assessment of methodological alternatives’, *Accident Analysis & Prevention*, 43(5), pp. 1666–1676. Available at: https://doi.org/10.1016/j.aap.2011.03.025.

Tharwat, A. (2020) ‘Classification assessment methods’, *Applied Computing and Informatics*, 17(1), pp. 168–192. Available at: https://doi.org/10.1016/j.aci.2018.08.003.

Waka Kotahi NZ Transport Agency (2023) *Crash Analysis System (CAS) Open Data*. Available at: https://opendata-nzta.opendata.arcgis.com/search?tags=CAS (Accessed: 20 April 2023).

Wang, X. and Kim, S.H. (2019) ‘Prediction and Factor Identification for Crash Severity: Comparison of Discrete Choice and Tree-Based Models’, *Transportation Research Record*, 2673(9), pp. 640–653. Available at: https://doi.org/10.1177/0361198119844456.

Ziakopoulos, A. and Yannis, G. (2020) ‘A review of spatial approaches in road safety’, *Accident Analysis & Prevention*, 135, p. 105323. Available at: https://doi.org/10.1016/j.aap.2019.105323.