

# Nationwide: Model Risk Management Assessment/Case Study

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# Table of Contents

Exploratory Analysis

Model Building

Model Assessment

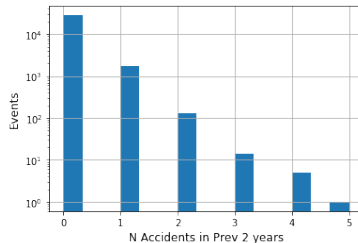
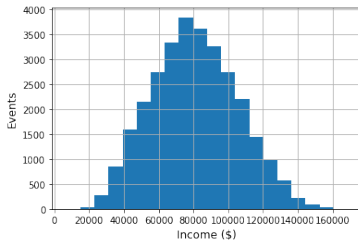
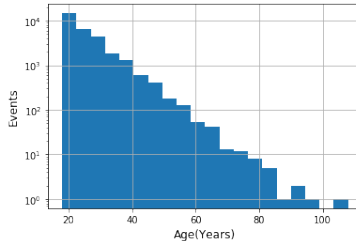
## Code location for further fleshed out examples

All code for these exercises can be found via this hyperlink as ipython/jupyter notebooks located on my github in addition to attachments sent with the presentation:

[https://github.com/JTBarkeloo/JupyterNotebooks/blob/master/MRM Assessment.ipynb](https://github.com/JTBarkeloo/JupyterNotebooks/blob/master/MRM%20Assessment.ipynb)

# Exploratory Data Analysis

- Start by looking at behavior of noncategorical data



# Model Building

Summary of 30,000 vehicles 1Hz telematics datasets

- ▶ Vehicle - Effectively an index on the data
- ▶ Days - Number of days data was collected (365 for all)
- ▶ Distance - Total number of miles vehicle was driven during data collection
- ▶ HardBrakes - Number of hard braking events detected
- ▶ HardAccelerations - Number of hard acceleration events detected
- ▶ NightTime\_Pct - Percentage of total miles driven at night
- ▶ VehicleType - str description of type of vehicle
- ▶ Loss - Indicator if vehicle has been in a collision

Want to build a model that will optimize recognition of Loss events using these values

## Statistical Significance Between Vehicle Types

The conclusions to be drawn depend on how liberal the definition of statistical significance being used is

The use of  $p < 0.05$  is somewhat arbitrary but is what will be used here as it is a standard choice of convention

- ▶ z value for Car and Minivan: 2.48
- ▶ z value for Car and SUV: 4.19
- ▶ z value for Car and Truck: 2.96
- ▶ z value for Minivan and SUV: 4.59
- ▶ z value for Minivan and Truck: 3.92
- ▶ z value for SUV and Truck: 1.62

The null hypothesis cannot be rejected for the combination of Cars and Minivans and the combination of SUVs and Trucks

The implication then is that there are 2 distributions being sampled for these simulated events. This matches intuition as Trucks/SUVs exist in a cargo-loading domain while Cars/Minivans are what parents may gravitate toward

# Model Building

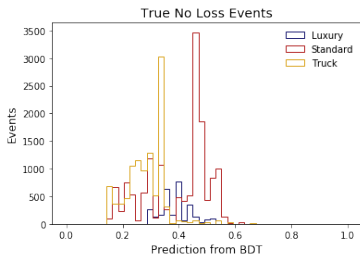
Primarily employing densely connected feed forward neural networks for event classification was chosen as it is the machine learning model I have most experience with for binary classification

- ▶ 1 input layer with all potentially useful features (Distance, HardBrakes, HardAccelerations, NightTime\_Pct, VehicleType)
- ▶ blah

A training (64%)/testing(16%)/validation(16%) random set split was done to help ensure unbiased results

# Naive Approach Neural Network

- ▶ Naively we could train a neural network on the data classes as given
- ▶ With enough separation power i.e., variables distinct enough in each class, this can be used for event classification
- ▶ This is not the case for this dataset, only a few variables inputs with a lot of distribution overlap
- ▶ This would then be expected to fail with a total accuracy that trends toward the class representation of the majority class, which is seen here





# Neural Network with SMOTE Upsampling

- ▶ Another network was created and trained using Synthetic Minority Oversampling Technique (SMOTE) over-sampling with similar results
- ▶ SMOTE generates synthetic data that is similar to, but not exactly like the minority class, using a nearest-neighbors approach and fills in space between neighbors

Loss Events  $P(\text{Loss Event})$ : mean: 0.510, std: 0.096

NoLoss Events  $P(\text{LossEvent})$ : mean: 0.480, std: 0.097

Loss Event Accuracy: 55.7%

# Model Comments

- ▶ Neural networks have been created and trained on a limited set of input variable with success in determination of Loss events
- ▶ The addition of further independent input variables would help the separation of the neural network greatly
- ▶ A bifurcation of the distributions is starting to occur with the ADASYN network, more input variables and events is likely to cause a major splitting of the distribution into likely Loss events and likely NoLoss events
- ▶ Boosted decision tree (BDT) models were also employed in the Jupyter notebook to slightly different ends

# Title

Can Multiple Loss Models be Useful Based on Driver Class i.e., Rural Vs. Urban Drivers?

- ▶ Rural and Urban drivers face different landscapes of challenges on their daily travels
- ▶ Requirement: GPS definition of urban environments
- ▶ Expect longer distance/trip for rural drivers while urban drivers have more stop-and-go traffic
- ▶ Larger Distances and a larger amount of HardAccelerations are both positively correlated with loss this seems to be an interesting intersection of these correlations