2023 INTERNATIONAL CONGRESS OF ACTUARIES

BRIDGE TO TOMORROW

28 MAY – 1 JUNE 2023 · SYDNEY

Actuaries Institute Australia

IAA AAI International Actuarial Association Association Actuarielle Internationale

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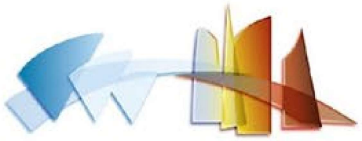

A Bayesian Approach for Prioritising Driving Behaviour Investigations in Telematic Auto-Insurance Policies

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Introduction

Presenters

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UK CUO at AND-E

Mind Foundry is an Oxford University Company. Operating at the intersection of innovation, research, and usability, Mind Foundry empower teams with AI products that are built for the most demanding needs.

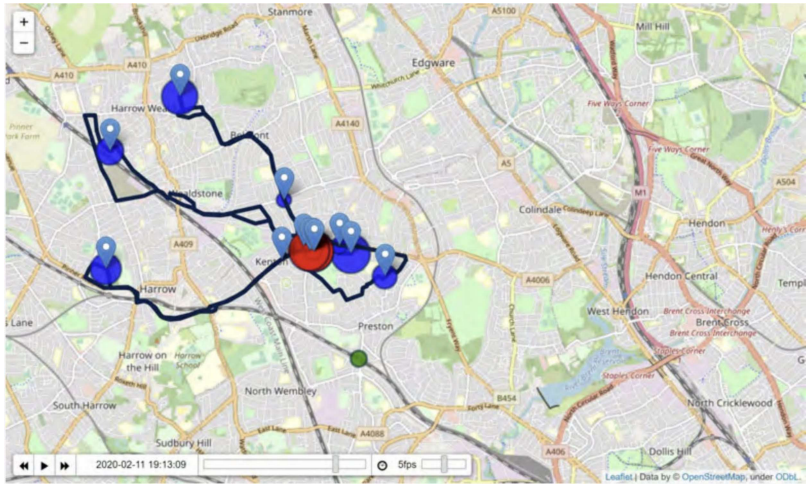
Aioi Nissay Dowa Europe (AND-E) is the European subsidiary of Asia's largest non-life insurer, MS&AD Group. As a market leader in telematics insurance in Europe, AND-E harness the power of artificial intelligence and machine learning to support our purpose to make tomorrow's journeys simpler, safer and smarter.

Aioi R&D Lab Oxford, a joint venture between Mind Foundry and Aioi Nissay Dowa Insurance. The lab aims to solve global-scale societal issues through the creation of products and services powered by AI technologies.

Problem Statement

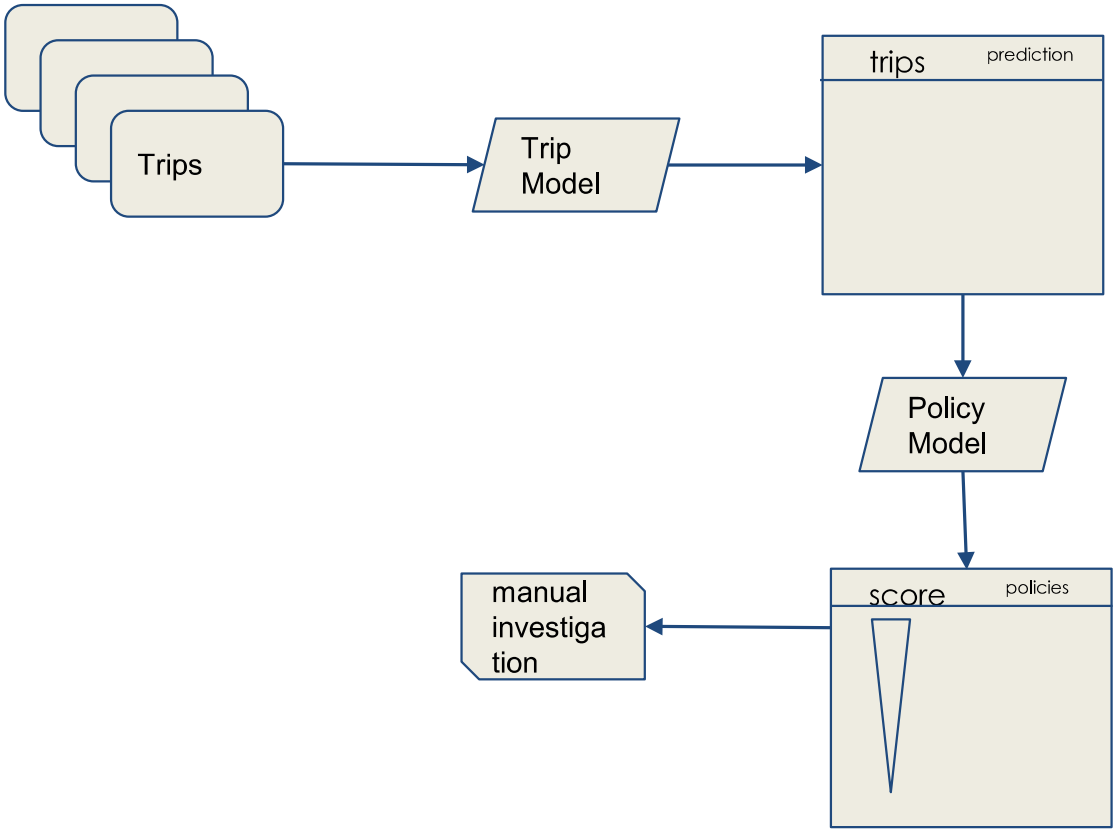
- **Can we identify delivery trips using telematics data to ensure drivers have adequate protection?**

- Challenges
  - large amount of trip data including GPS and accelerometer data
  - 6 known delivery drivers
  - explainability
  - scalability
  - high level confidence in the classification



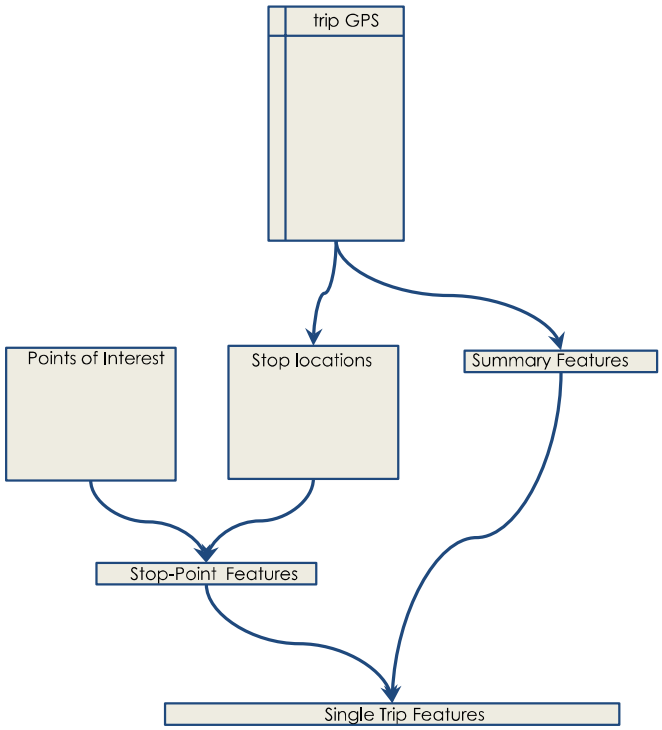
Outline of our Solution

- Trips are individually classified as potential delivery using machine learning
- Policies are ranked based on their associated trip results
- Manual investigation and intervention is focused on the highest-scored policies



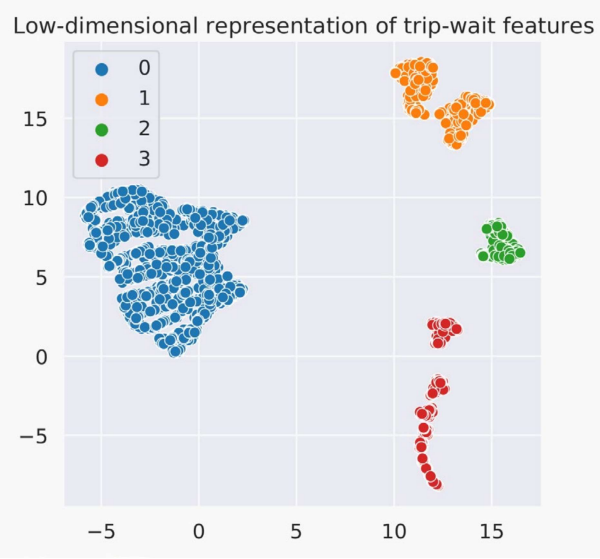
Trip classification

- Trip GPS traces cannot be directly consumed by machine learning models
  - Variable length
  - The actual value does not convey useful information
- Engineered per-trip features provide a tabular representation which is suitable for standard ML models.
- For delivery driving locations where the vehicle has stopped are of particular interest
  - Duration, road class and proximity to locations of interest are valuable



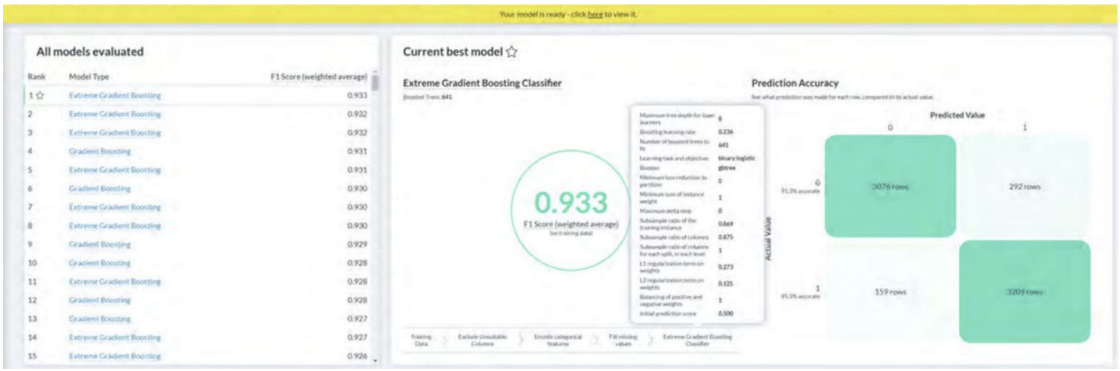
Trip classification

- Unsupervised classification can find more trips that are similar to the few existing labelled example.
  - We used UMAP and HDBSCAN for clustering
- Manual investigation confirmed 58 of 62 candidates in the identified cluster as delivery trips.
- The identified classes can then be used to provide training data for a classification pipeline



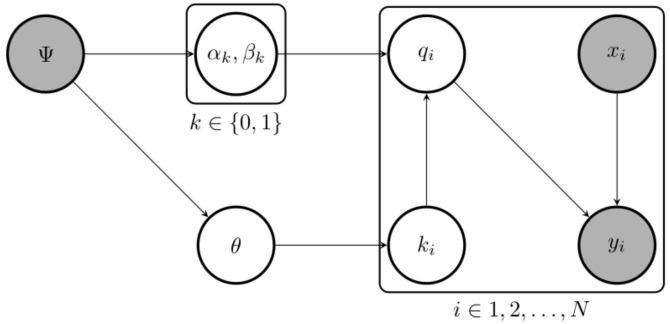
Trip classification

- Training using an automated machine learning pipeline provides promising results
- Further manual investigation confirmed 96 of the 100 highest-confidence positive predictions
- There is still a significant false positive rate and the data is heavily imbalance.



Policy Classification

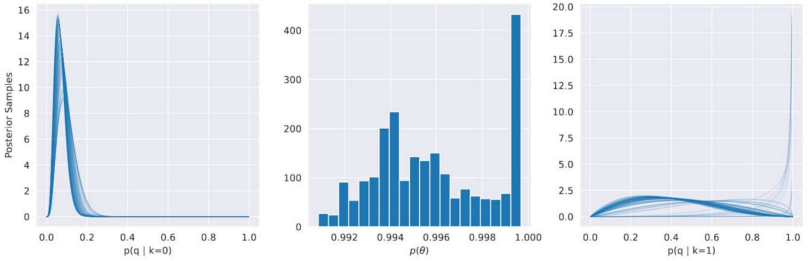
- Manual investigation of delivery-driving is at a policy level, so we want a prioritized ranking
- With a large number of policies entering the portfolio daily there will always be some with 100% false-positive reports on a small number of trips
- We turn to Bayesian methods to infer an underlying propensity of delivery driving in the presence of uncertain observations

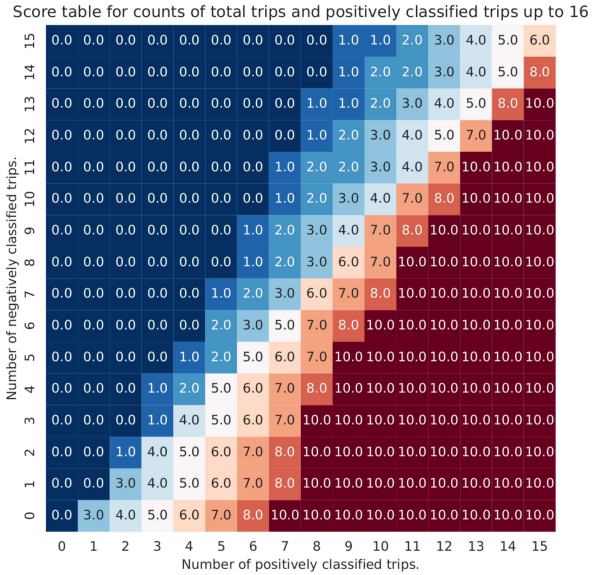


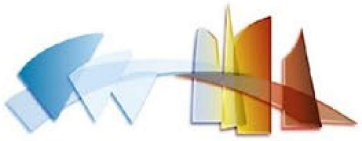
- We observe each trip x_i and the classifier output y_i
- The ith policyholder is a delivery driver if k_i=1
- The ith policyholder has a q_i probability of a trip being identified
- q_i is drawn from a distribution which is dependent on k_i
- We wish to compute a belief over k_i given the observed data

Policy Classification

- We make use of MCMC to find posterior distributions for the model parameters (data was drawn from 1 month of predictions)
- The resulting samples show a split into a majority of policyholders with low trip-classification rates, and a minority with a very high rate
- Given these samples we can plot p(k) (simplified to an [0-10] score) for any individual policyholder as a function of the observations







Results

- The rating system was trialed for 1 year, with investigation prioritized to the highest scoring policies on a rolling month window.
- 0.8% of all unique policies were investigated
  - This represents 2.6% of individually positively classified trips (0.13% of all trips)
- The observed accuracy was **99.6%**

Questions

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