Predictive Risk Modelling in Aviation Incidents

submitted by the International Air Transport Association (IATA)

The IATA Global Aviation Data Management (GADM) system provides insights for proactive aviation safety management by identifying and assessing hazards and risks through global-scale data-driven analyses. In particular, the Incident Data Exchange (IDX) is the database of incident reports classified into the IATA incident taxonomy to label their safety and security concerns. Currently the IDX provides airlines with a benchmarking tool so that an airline can compare their Safety Performance to global and regional rates and drill down to a specific time period, aircraft type, location, phase of flight, and event descriptor.

IPSW Participation Objectives

By participating in the 2020 IPSW, the IATA aims to discover various perspectives and insights as a proof-of-concept for data-driven risk identifiers and seek future collaboration on data-driven risk identifiers and potential machine learning applications [1].

Challenge

The goal for this challenge is to define the safety risk model, which can detect the potential precursors or anomalies (compared to the previous trends) by drilling down into multiple subsets of attributes.

- First we want to be able to assign risk for a certain attribute or combination of multiple attributes: for example, whether a certain aircraft type or airport has a risk pattern that is significantly different from the others. This is to raise a flag to a human analyst, who will then have a deeper look at the situation. We call this **Anomaly Detection**.

- We also want to be able to predict how many events will occur in a month for a certain descriptor. We are looking not only for a point estimate but for a confidence interval. For example, if the dataset contains a certain number of incidents for February that falls outside of the confidence interval, then this situation should be flagged. We call this **Predictive Analysis**.

Current Progress

As an internal experiment, we focused primarily on GLM models, because the incidence rate ratio and the odds ratio can be extracted from these models and then used for risk modelling. The first GLM we considered was the Poisson regression, but it did not suit our purpose since it failed the Cameron–Trivedi dispersion test. Failure to reject the null hypothesis in the C-T test indicates that an assumption is violated and our model is either underdispersed or overdispersed. The next

model we considered was a Generalized Poisson Model. The previous research [2] highlights the use of Generalized Poisson models in accident data. The problem we faced with the Generalized Poisson Model was that there were convergence issues. The final model that we considered was the Negative Binomial model, which passed the chi squared test as well as the Cameron–Trivedi dispersion test.

Given those experiments we would like to:

1) Find risk metrics for attributes in our data that are not the odds ratio metric;

2) Find better time series prediction models. GLMs can provide time series predictions but in most of the cases will not perform as well as seasonal time series or deep learning models.

[1] F. Bati and L. Withington. 2019. "Application of Machine Learning for Aviation Safety Risk Metric." Paper presented at the *17th IEEE International Conference on Dependable, Automatic and Secure Computing (DASC 2019), Fukuoka, 2019.*

[2] F. Famoye, J. T. Wulu and K. P. Singh. 2004. "On the Generalized Poisson regression model with an application to accident data." *Journal of Data Science* 2: 287-295.