

Flight Data Monitoring (FDM) Unknown Hazards detection during Approach Phase using Clustering Techniques and AutoEncoders



9th SESAR Innovation Days

Antonio Fernández Llamas
Innaxis
af@innaxis.org



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Introduction

- Airlines safety departments analyse Flight Data Monitoring (FDM) to inspect safety occurrences
- FDM data is known for presenting a very high variable dimensionality
- Human experts use rule-based systems based on thresholds exceedance
- Rare events or anomalies are the hardest to manually detect
- Anomaly detection using Machine Learning is definitely a challenging concept in aviation field.



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Objectives

- Develop a forensic tool that semi-automatically tags abnormal flights
- Speed up the flight inspection processes, looking at operations that might hide safety implications.
- Focus on outliers detected during **approach** procedures
- Take advantage of the majority of the samples present in most of aviation datasets -> normal flights.
- Detect unknown hazards which might reveal new possible safety concerns



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Problem assessment

- Diagnostic analysis for **flights landing on LEBL 25R**
- Descriptive and predictive analysis.
- Main outcome: predict outlier approaches using an AutoEncoder.

Descriptive analysis	Predictive analysis
• Unsupervised learning • Clustering techniques • Outlier detection	• Semi-supervised learning • AutoEncoders • Binary classification based on reconstruction error



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Data sources

- **FDM, METAR** (in LEBL) and **Flight Plans**.
- The FDM dataset is composed by 35,000 landing attempts in LEBL 25R.
- FDM is known for presenting a very high variable dimensionality.
- We had more than 150 variables with a resolution of up to 8 samples per second.
- **DataBeacon** infrastructure used to process the data, using a 5-node (*m5.4xlarge*) cluster.

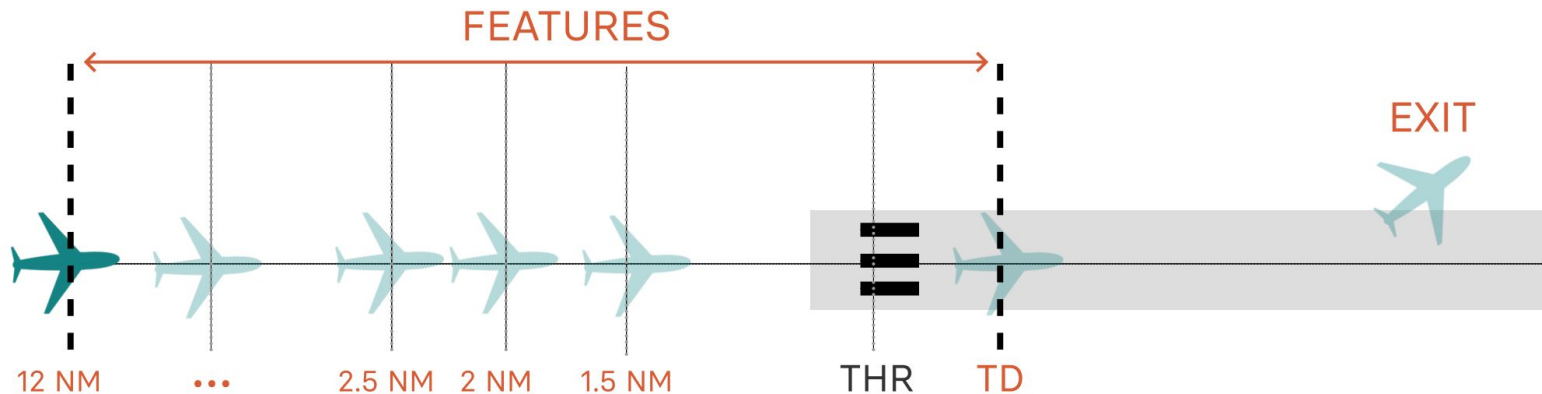


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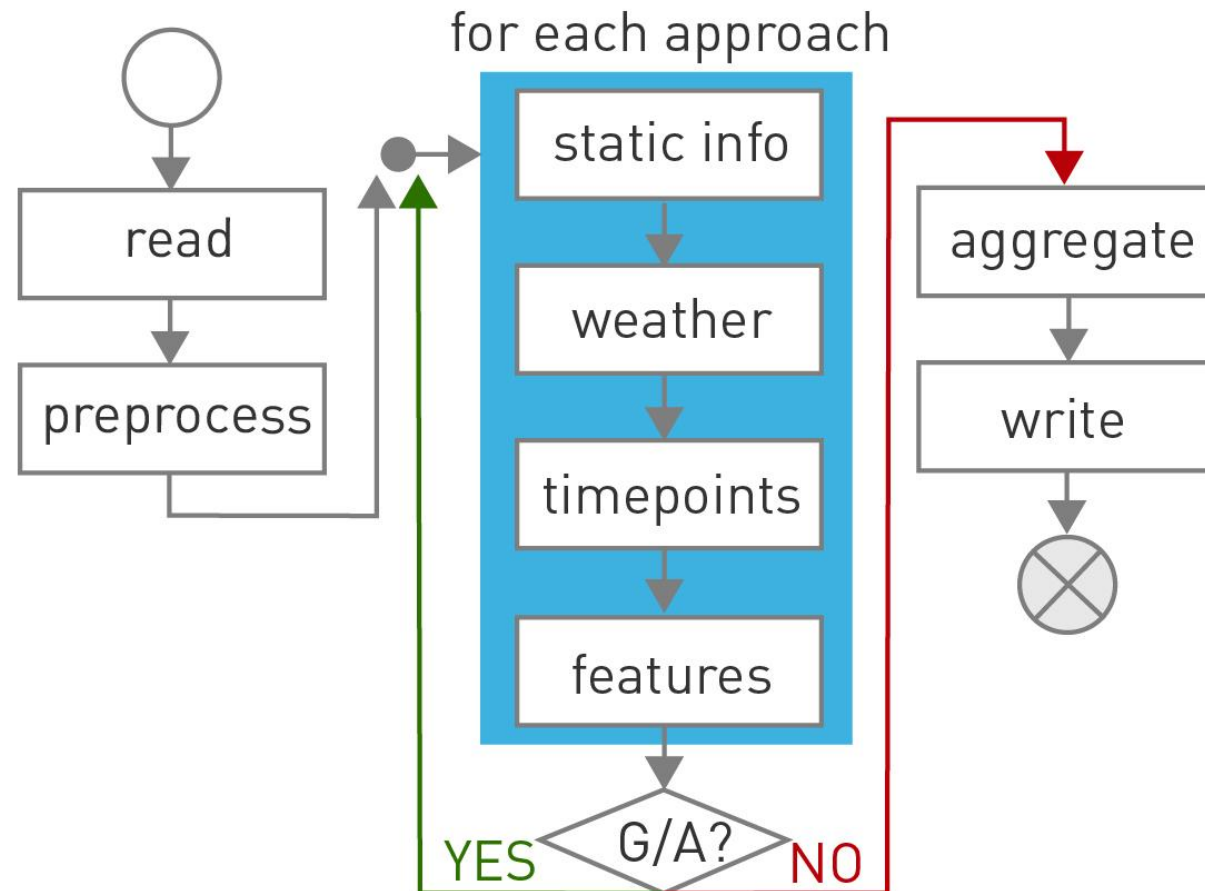


Feature engineering (I)

- Multi-step data preparation pipeline (cleaning, de-identification, merging and sampling)
- We sampled the series from 12 NM to threshold to touchdown (TD) point, with a step of 0.5 NM.



Feature engineering (II) - Pipeline





Feature engineering(III)- Features

- We engineered a total of 825 features per landing attempt

Group	Features	Data Sources
Operation dynamics	Pitch, roll and heading positions and rates. Angle of attack. Vertical descent rate. Barometric altitude. Radio altitude	FDM
Aircraft energy	Air speed. Ground speed. Energy level. Aircraft mass.	FDM
Adverse weather	Static pressure. Static temperature. Relative humidity. Dew point Air density. Wind direction. Wind speed. Wind variation. Ground visibility. 1st Cloud layers height and opacity.	METAR (LEBL) FDM (aircraft sensors)
Aircraft configuration	Flaps orientation	FDM
Crew coordination	Autopilot status. Pilot flying	FDM
Pilot awareness	Current time, Distance travelled, Total Time Flown	FDM
Flight static information	UTC time. Origin Airport. Destination Airport. Call sign. Aircraft type. Tail number. Year. Week. Runway Occupancy Time. Time at threshold. STAR. SID. Time exit. Runway. Runway exit	Flight Plan FDM

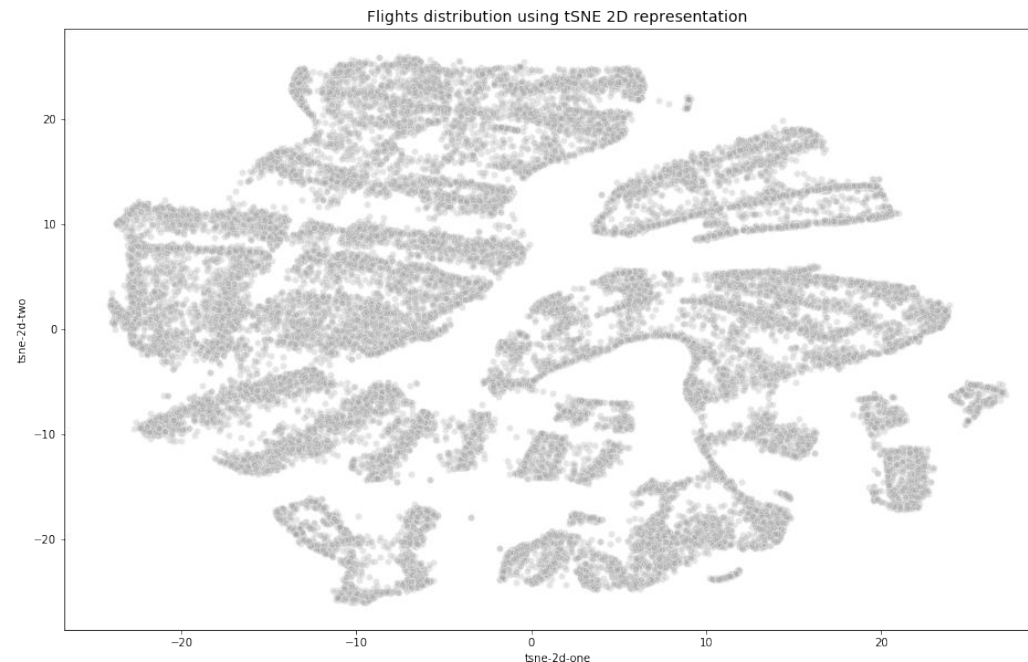


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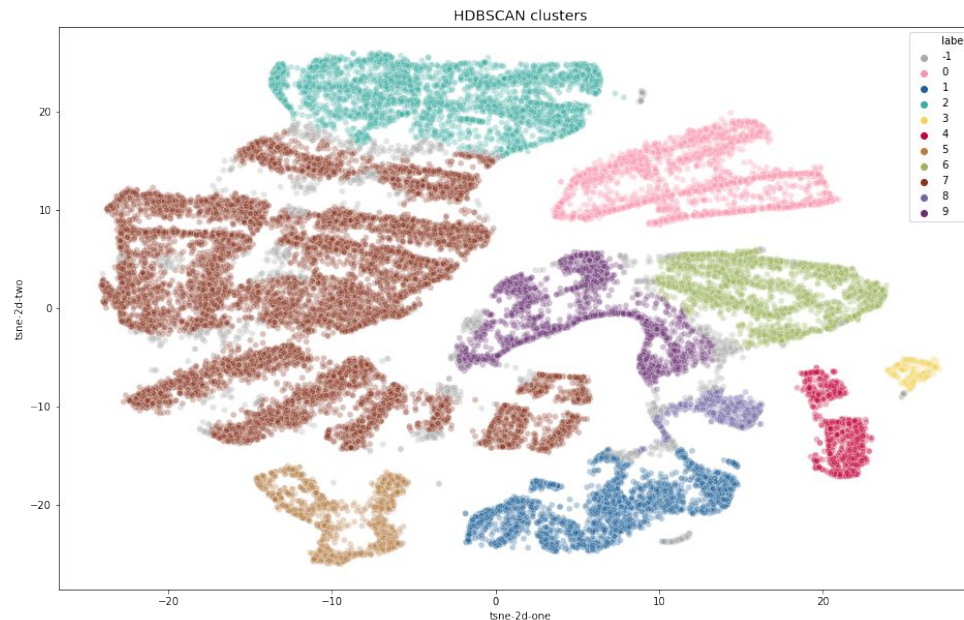
Descriptive analysis(I) - tSNE

- Dimensionality reduction is needed -> tSNE
- It inspects the input statistical properties and manages to represent the same data using less dimensions.



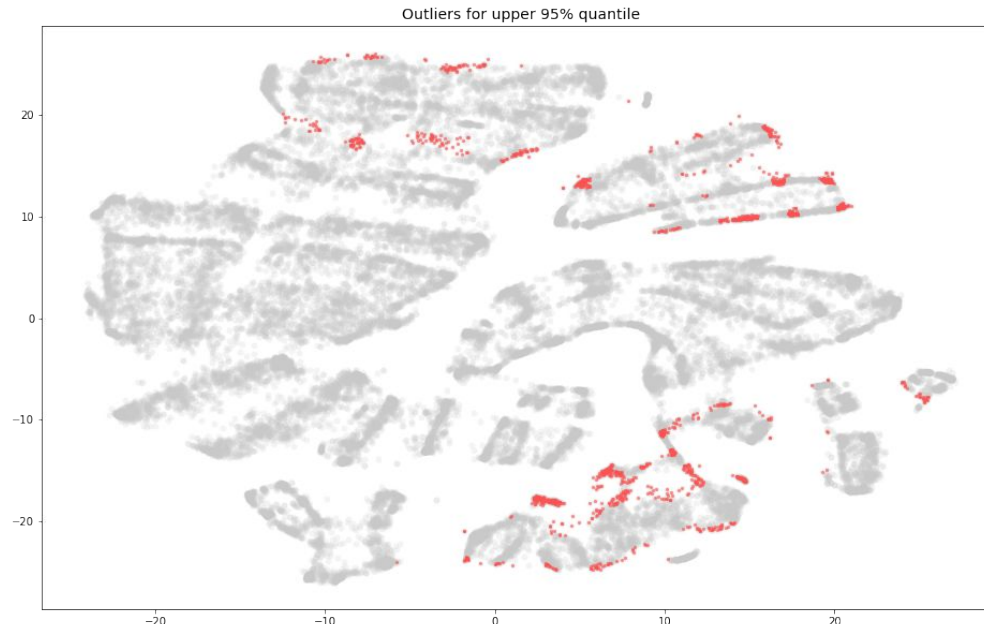
Descriptive analysis(II) - HDBSCAN

- HDBSCAN is a hierarchical clustering algorithm.
- 9 clusters of data identified.
- The algorithm flagged several points as noise, that were not assigned to a cluster

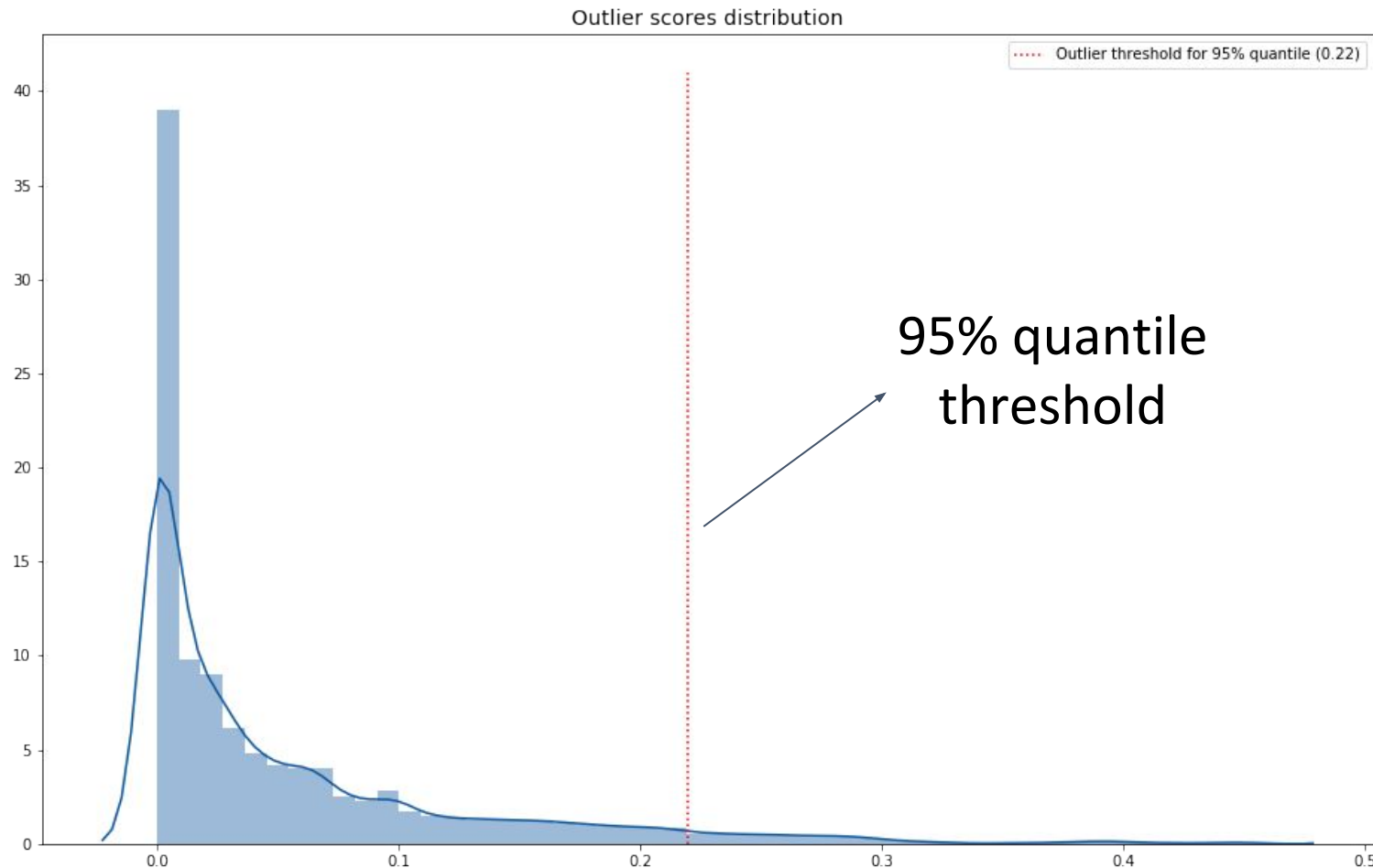


Descriptive analysis(III) - GLOSH outliers

- Anomalies are detected by measuring a local deviation of an observation with respect to its neighbours.
- Outliers can be located within a region or cluster, not only globally.



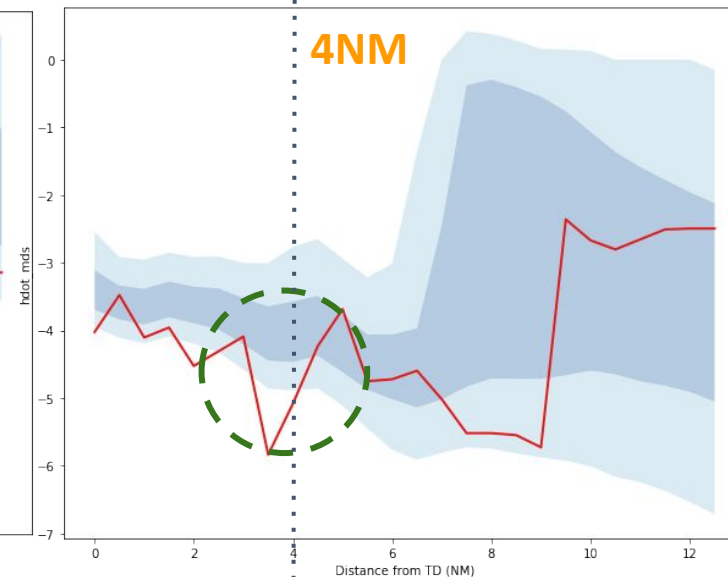
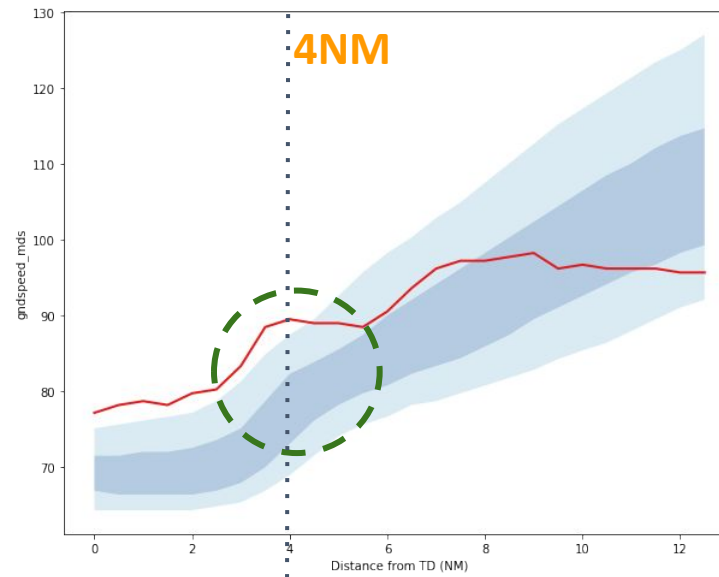
Descriptive analysis(IV) - Outliers histogram



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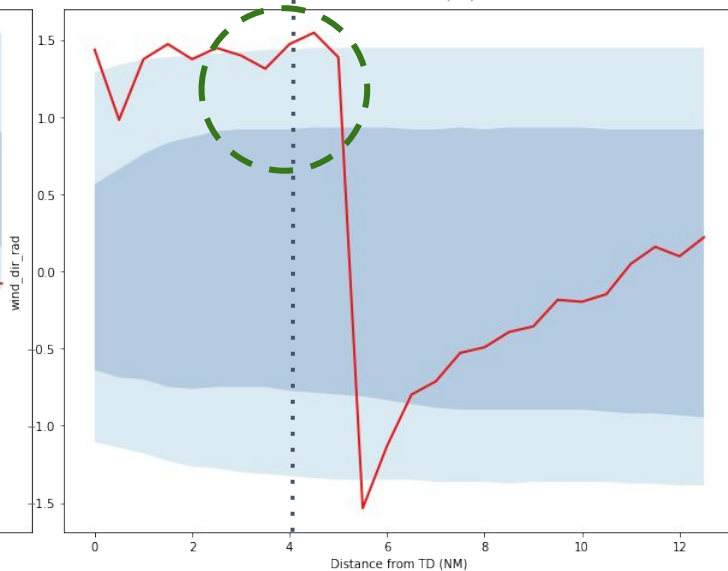
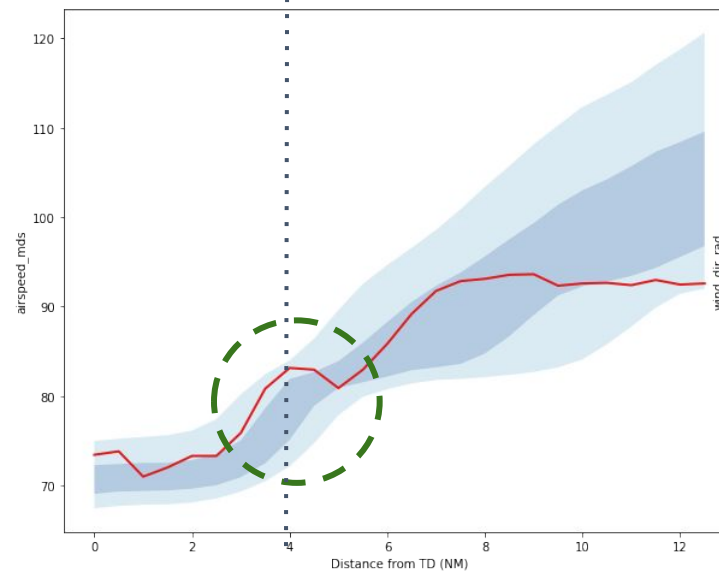
Outlier A

Ground speed



Vertical descent
over time

CAS



Wind direction

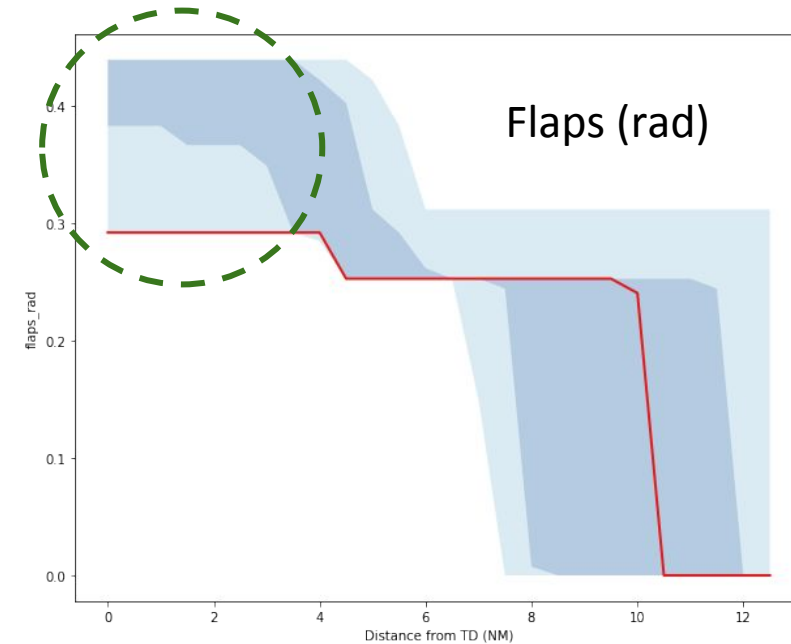
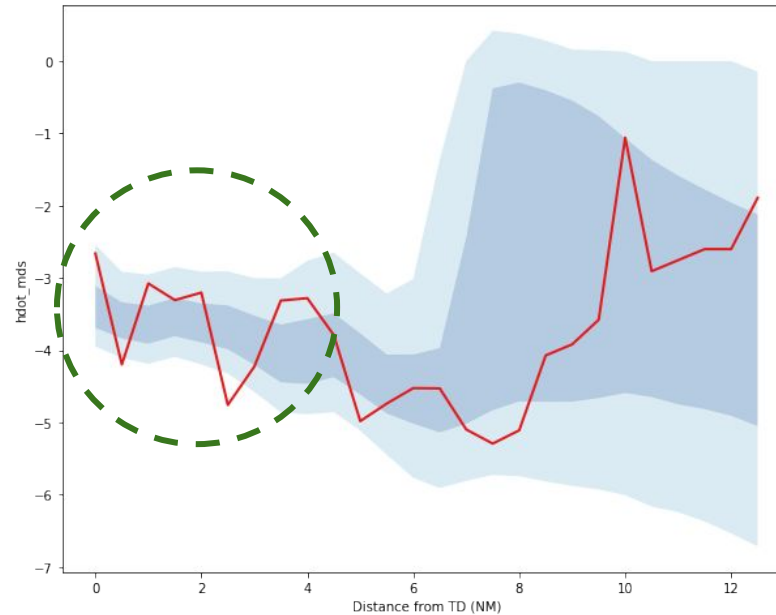


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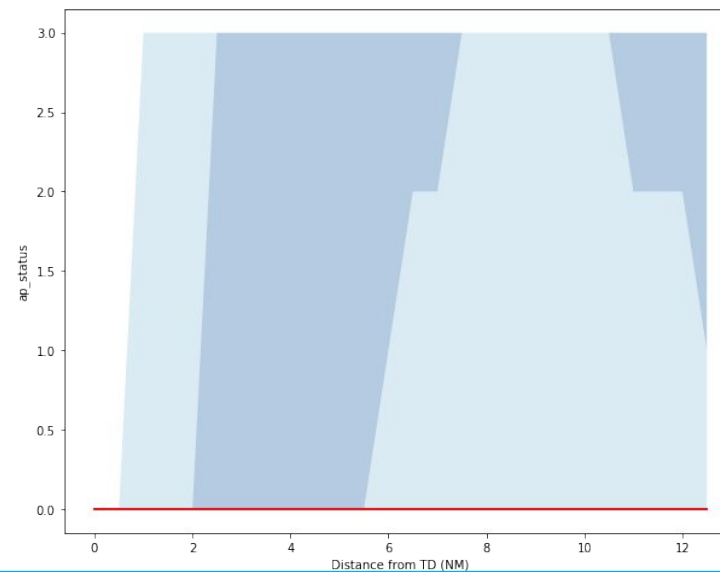
Outlier B

Vertical descent
over time



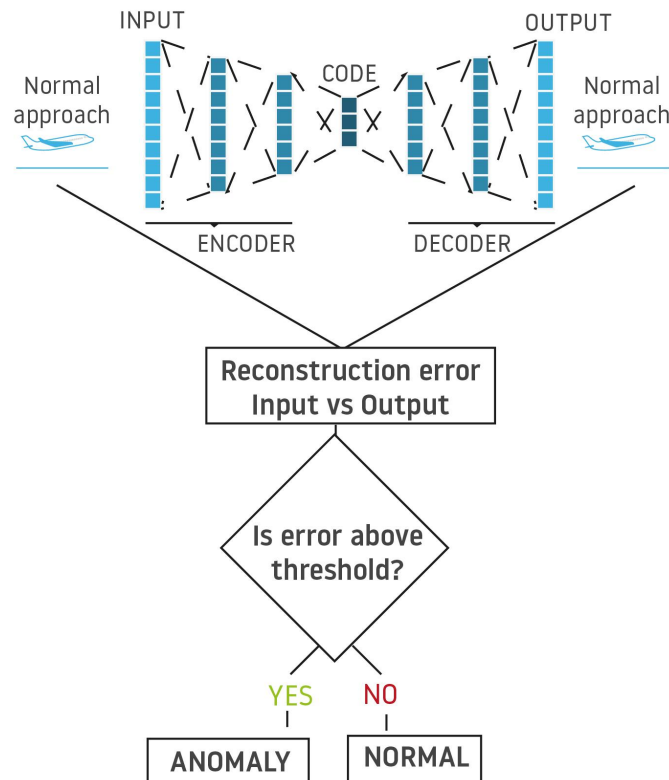
AP status

0 is manual flight
1 is captain's AP
2 is first officer's
3 is dual



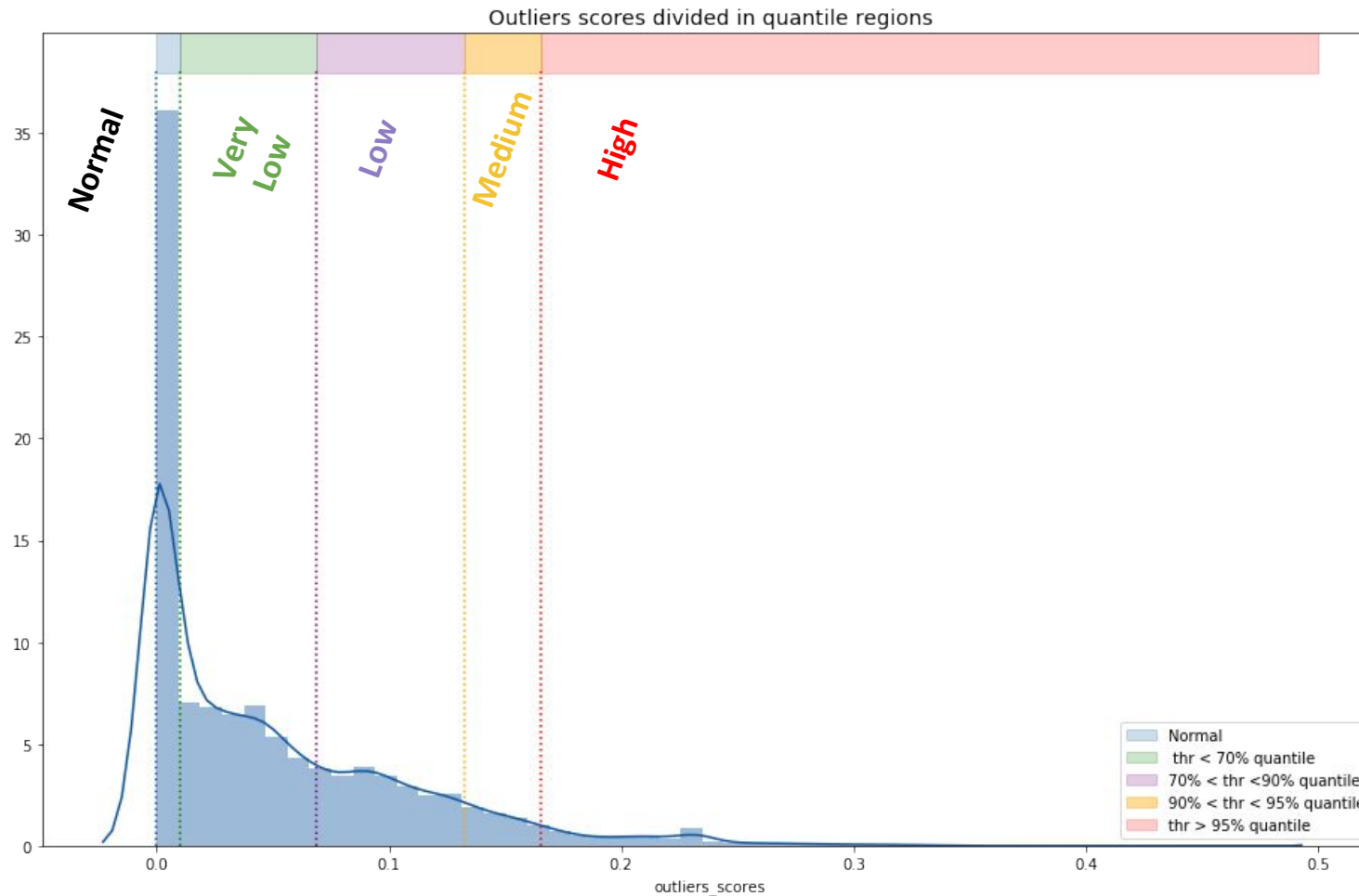


Predictive analysis (I) - AutoEncoder



- **Train only using normal** approaches to learn the behaviour of a non-anomalous procedure
- The AutoEncoder will be tuned to recreate “*normal*” inputs minimizing the loss
- If we test using outliers, the ***reconstruction error*** will be high.
- Set a ***threshold*** to solve a *binary classification* problem.

Predictive analysis (II) - Severity regions



Threshold 1 (THR1) = near zero

Threshold 2 (THR2) = 70% quantile

Threshold 3 (THR3) = 90% quantile

Threshold 4 (THR4) = 95% quantile

Severity regions:

Normal (OS=0) → **12.011 flights**

Very Low (THR1<OS<THR2) → **12.489 flights**

Low (THR2<OS<THR3) → **7.000 flights**

Medium (THR3<OS<THR4) → **1.750 flights**

High (OS>THR4) → **1.750 flights**

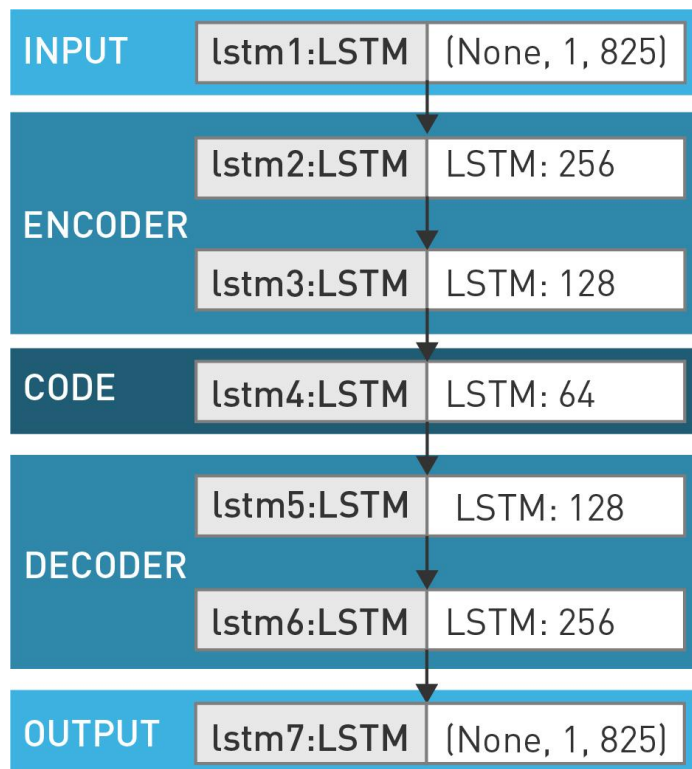
**Note: OS = outlier score*



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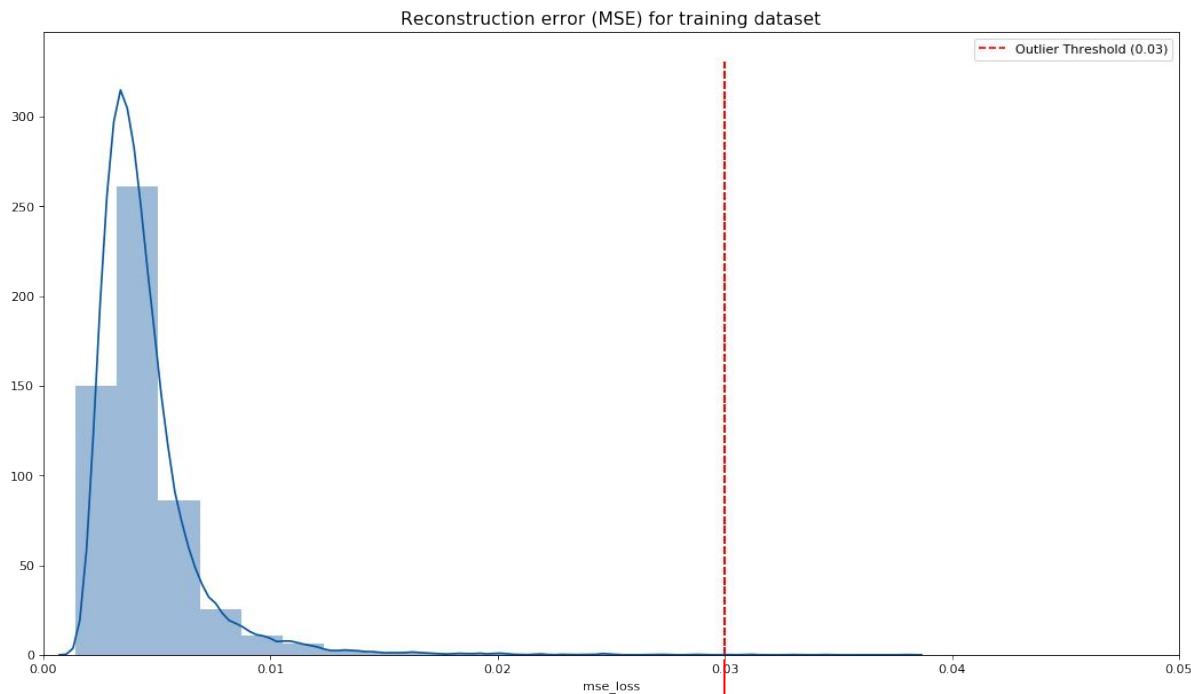


Predictive analysis (III) - Train, valid, test



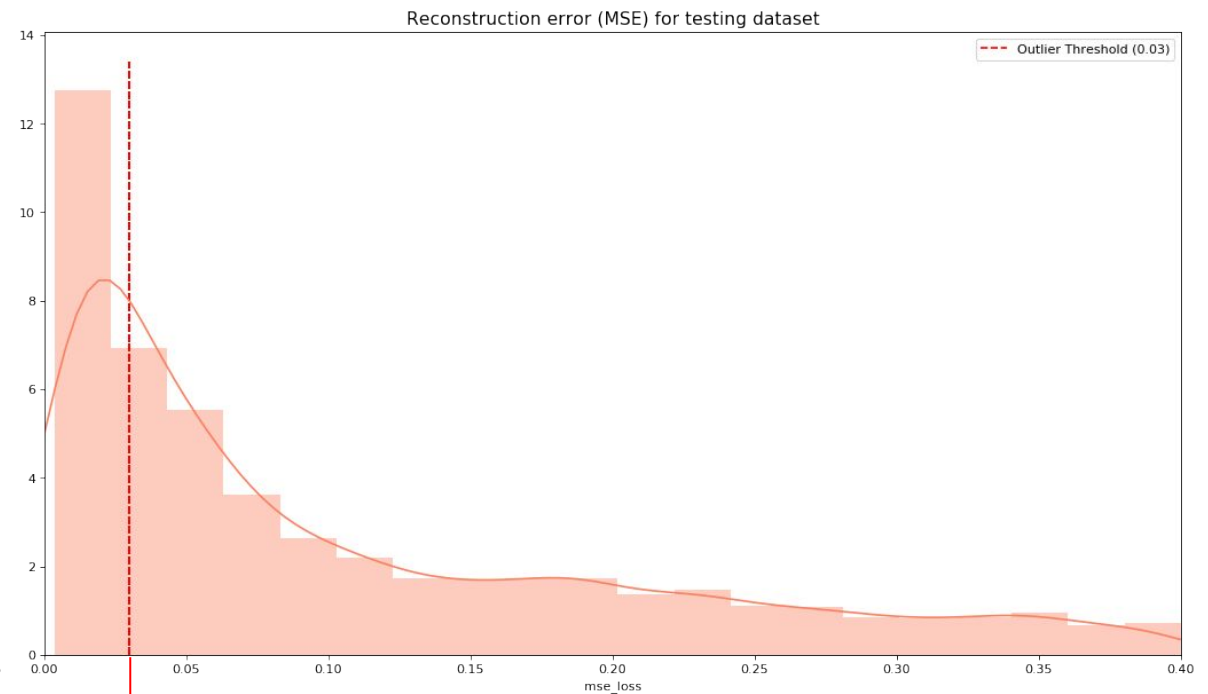
- LSTM layers - useful to extract patterns from sequential data
- LSTM layer input shape is :
(*n_samples*, *n_timesteps*, *n_features*)
- We trained the AutoEncoder with samples having an **OS = 0**
- We used a 10% of these flights as validation dataset
- The rest of the samples with an **OS > 0** will be our testing dataset

Predictive analysis (IV) - MSE Loss



Train loss

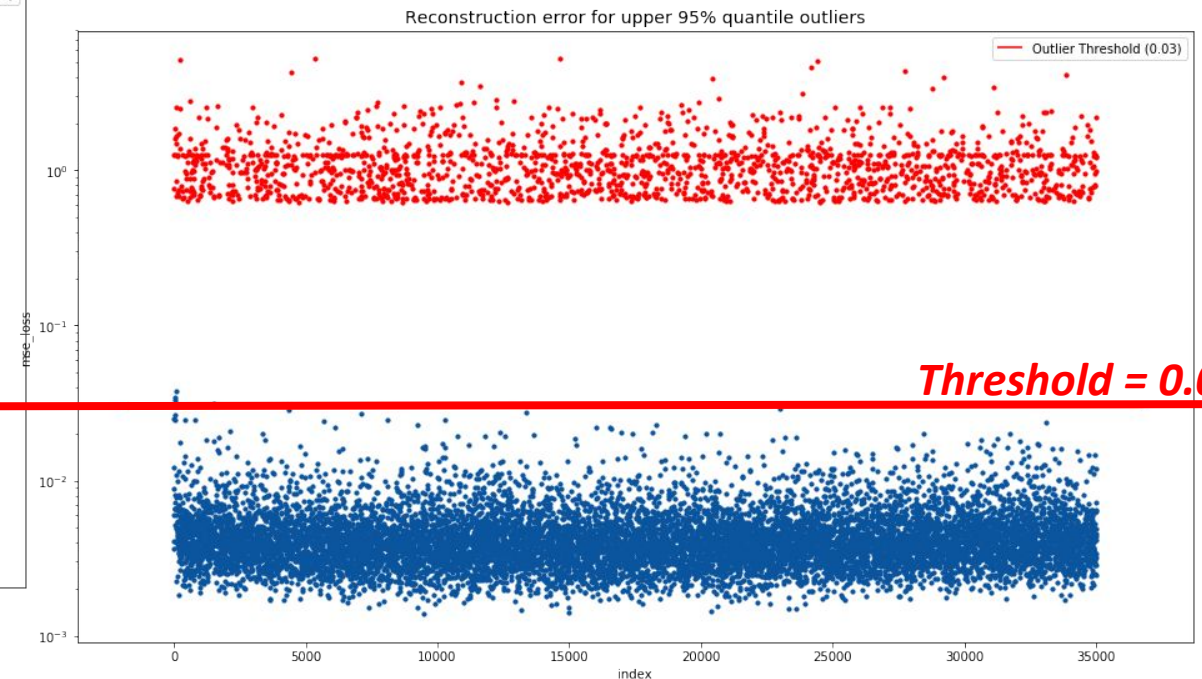
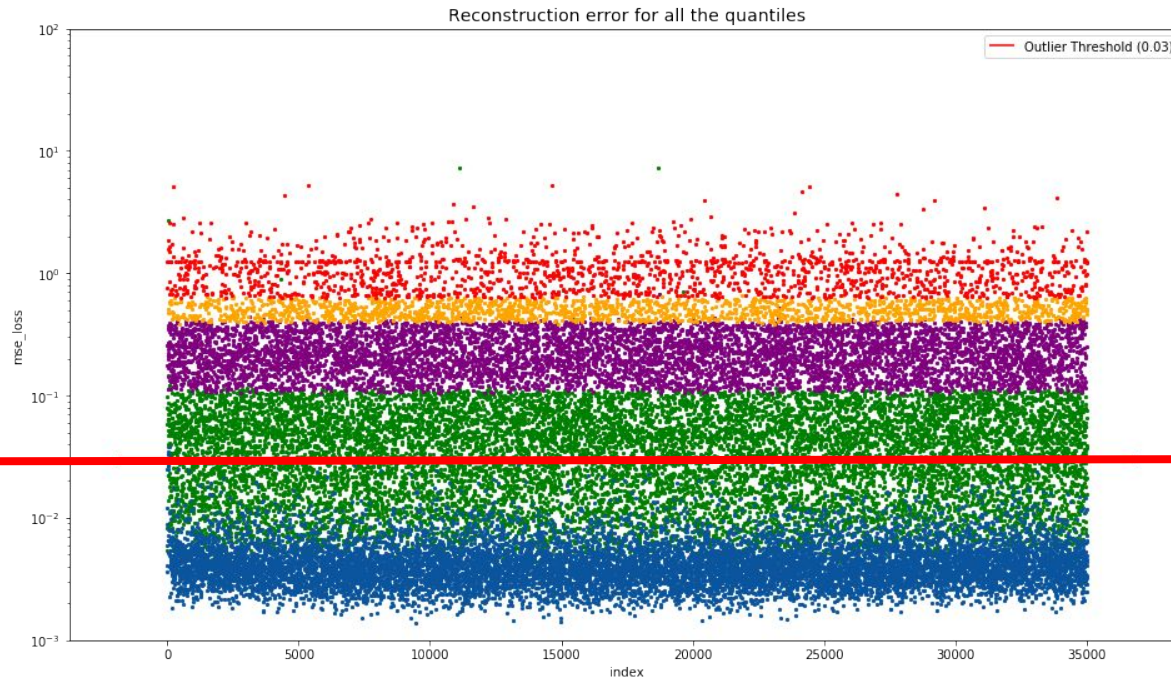
Threshold = 0.03



Test loss

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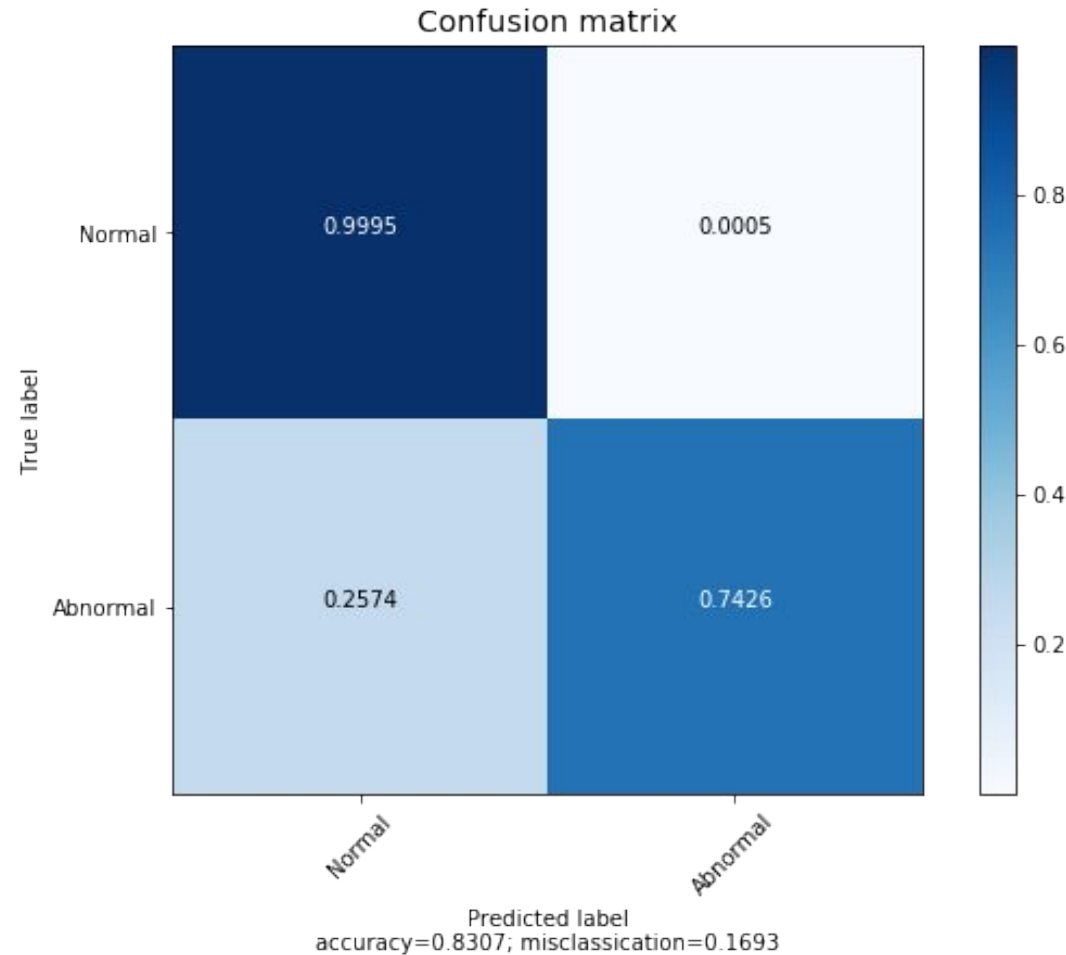
Results (I) - Loss vs Severity



Threshold = 0.03

The model struggles to classify samples with **low** outlier scores because of their similarity with “*normal*” samples
In the other hand, the model perfectly recognizes **high** severity outliers

Results (II) - Confusion matrix





Conclusions and future work

- The results obtained are promising, providing an **extremely useful tool for FDM and safety analysts**.
- Overall, the combination of *clustering* and *AutoEncoders* enabled to solve a **very complex problem** both from the data science and aviation safety perspective
- Benefits are not only to speed up the detection of risk events, but also to **support the recognition of unknown hazards**.
- In future researches, this could enable to develop an application for an airline safety department where **anomalous approaches are tagged at the end of the day**, to be later examined by a safety expert.



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THANKS!

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