UNSTABLE APPROACHES AND FDM ANOMALY DETECTION

DataBeacon

MONDAIS
AI Case Studies in Aviation

CONTEXT

Safety is prioritary in aviation industry

During the data period 2011-2015, approximately **65% of all recorded accidents occurred in the approach and landing phases** of flight

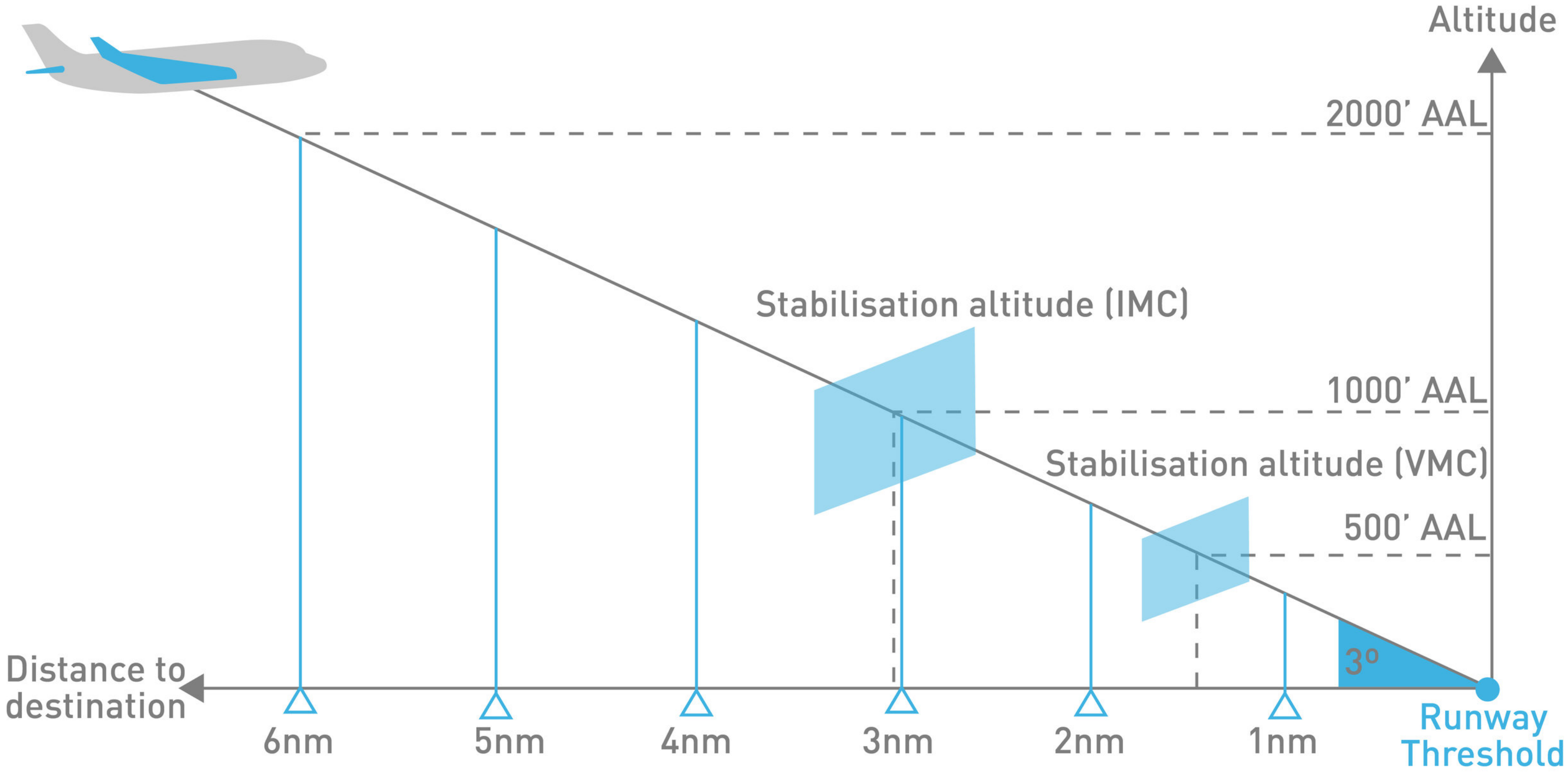
Unstabilized approaches were identified as a factor in **14% of those approach and landing accidents**.

IATA 2016 2nd ed. Unstable approaches

WHAT IS AN STABILIZED APPROACH?

Landing should be **stabilized** by reaching:

- 1000ft AAL (IMC) - around 3NM from THR
- 500ft AAL (VMC) - around 1.5NM from THR



WHAT IS AN UNSTABLE APPROACH?

- The criteria to determine this event is **defined by each airline** safety department
- The definition of this set of indicators is usually **private and unknown among airlines**
- Known indicators of being unstable are:
  - High **energy** (vz and v_app deviations)
  - Exceeding **flap/slat limit speed** during approach
  - Excessive **tailwind** and **crosswind**
  - Excessive changes in **aircraft attitude** (pitch, roll, heading)
  - **Bad configuration** (late gear/flap deployment)
  - Excessive **fan speed** during approach

THE DATA

- FDM
  - Main data source
  - 5 airlines (1-2 years each)
  - We selected around **65.000 approaches** for this case study
  - around **8 measures per second for more than 150 sensors**
- METAR
  - Airport weather conditions
  - Reports every 30 minutes, take the last report released before the prediction point
- ADS-B
  - Surrounding traffic at the airport TMA
  - Second geospatial data source, since FDM isn't very accurate

FLIGHT DATA MONITORING (FDM)

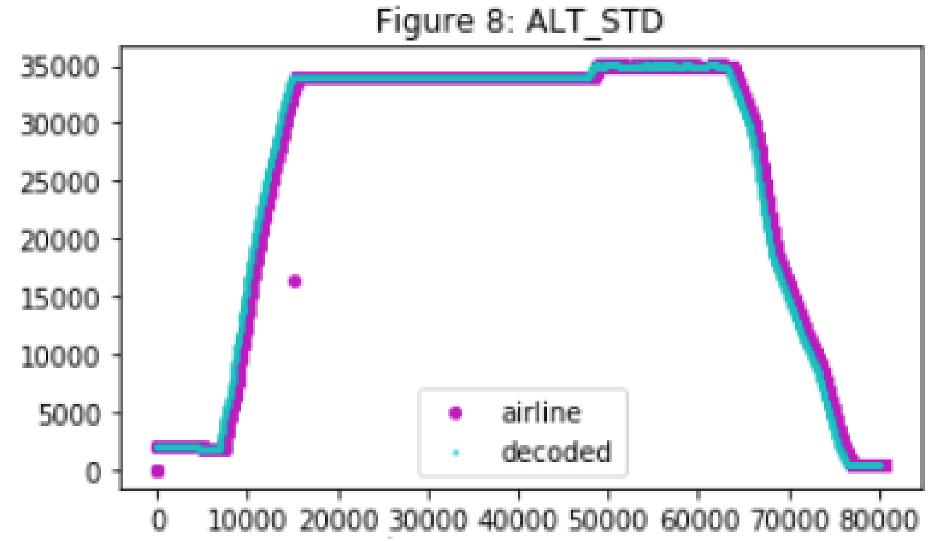
DECODING & VALIDATION

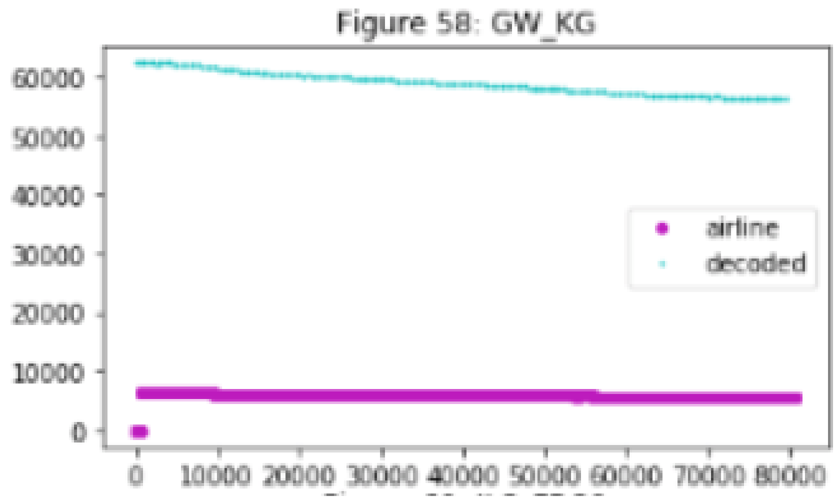
- Decode and validate QAR files is a super slow iterative process
- UA labelling criteria was highly dependent on FDM data quality
- At the end, errors in the decoding and labelling directly impact model accuracy

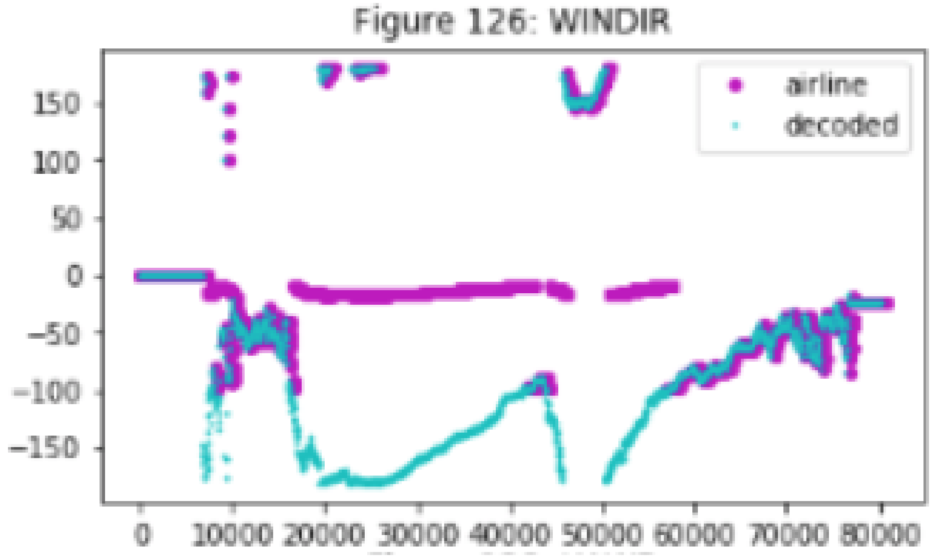
Airline 1		Airline 2		Airline 3		Airline 4		Airline 5	
Dataframe	**Aircraft**	**Dataframe**	**Aircraft**	**Dataframe**	**Aircraft**	**Dataframe**	**Aircraft**	**Dataframe**	**Aircraft**
737-3C	737-800	256	A319	A330GE04	A330	737-3A	B737	10322	A319
		256	A320	A330RR04	A330	737-3B	B737	10325	A320
		256	A321	B737-3C	B737	737-3C	B737	10323	A321
				B737-7	B737	737-7	B737	10534	A330
						A320-CEO	A320	10627	A340
								10628	A340

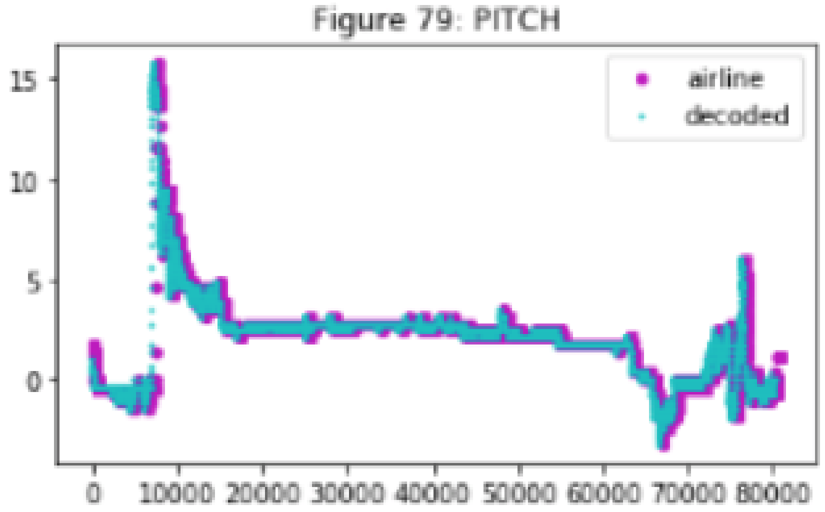
FLIGHT DATA MONITORING (FDM)

BECOME ONE WITH THE DATA





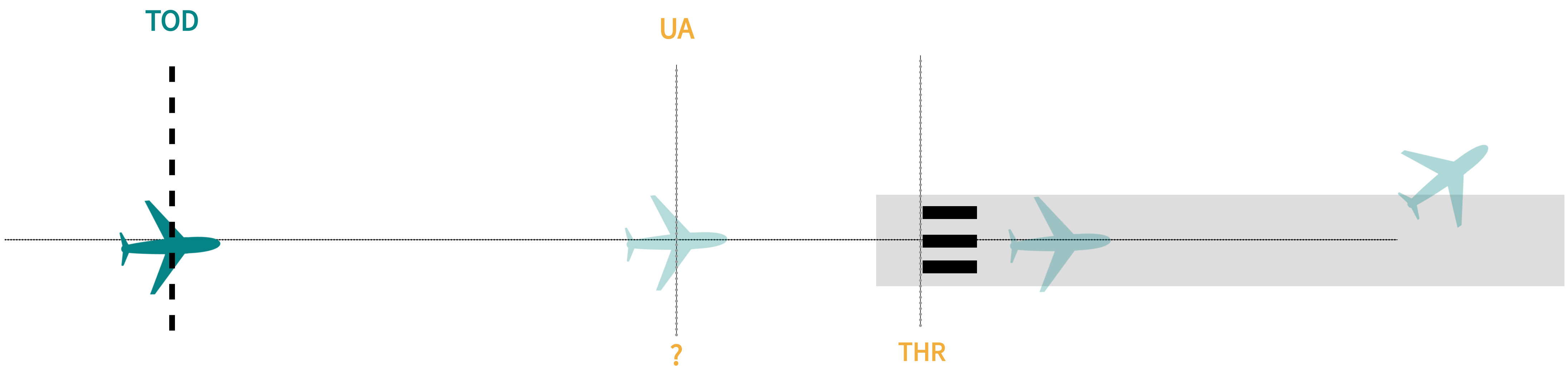




THE MACHINE LEARNING PROBLEM

RESEARCH QUESTIONS

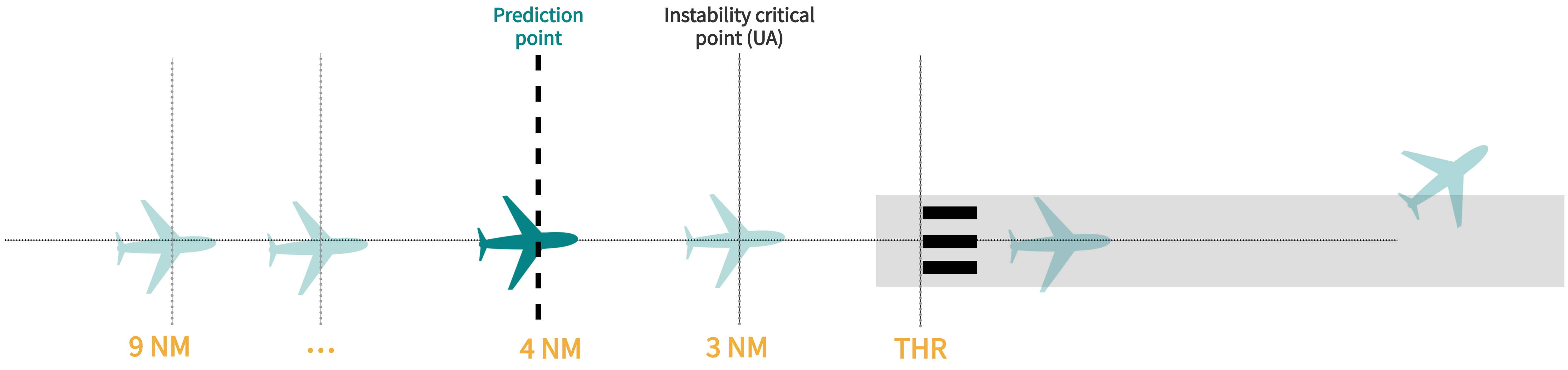
- **RQ1:** How precisely an UA event can be predicted (before occurring) at a certain point of the approach?
- **RQ2:** What are the main **precursors**, situations and patterns that contribute to the occurrence of an UA event?



THE MACHINE LEARNING PROBLEM

PREDICTION POINT (TRIGGER)

- Unstable approaches usually **occur around 3NM** from the runway threshold (THR)
- Let's assume that the **pilot** needs from **90 to 30 seconds to react**
- The prediction point should be **placed between 9NM and 4NM from the THR**
- We decided to set up our **prediction point at 4NM form the THR**



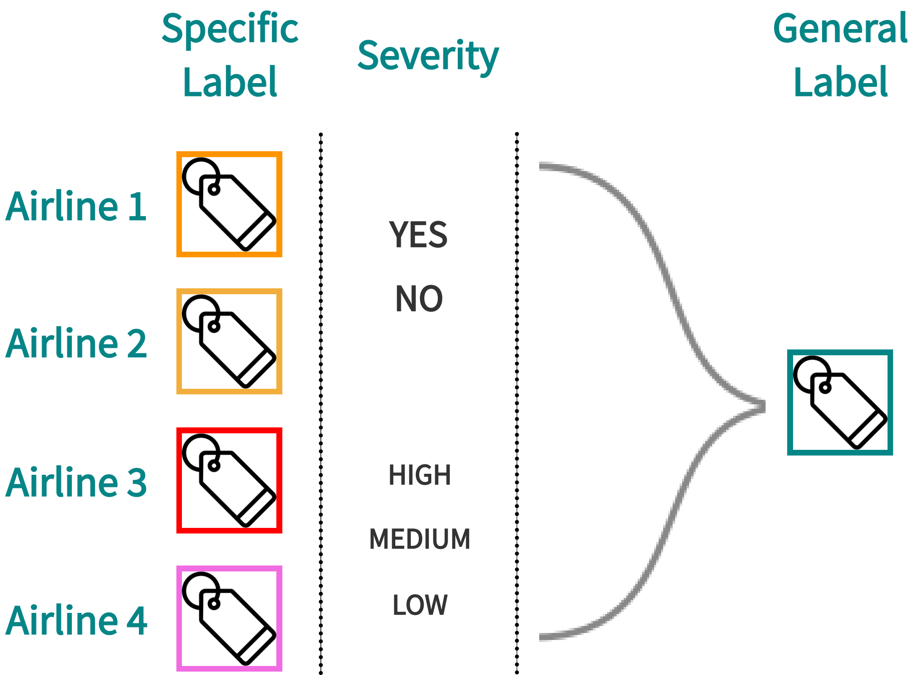
THE MACHINE LEARNING PROBLEM

TARGET VARIABLE (Y)

what do we aim to predict?

Predict **if a flight is about to become unstable (1/0)** at the **prediction point** (**4NM**)

We must **label in historical data if flight became unstable or not** ... however some **challenges** exist:



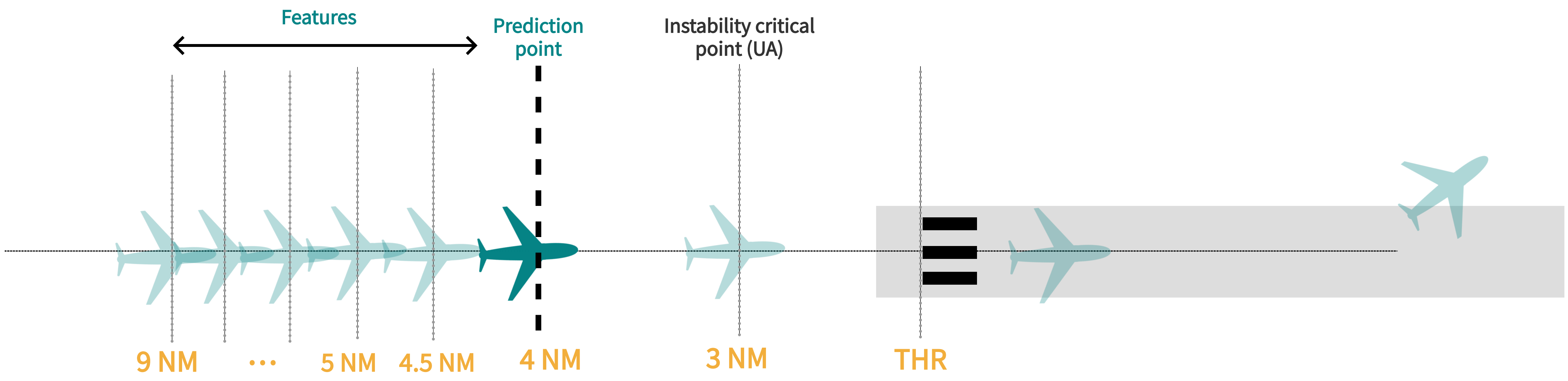
- ***Specific vs General criteria***
- ***What should be learnt?!***
- ***Data imbalance -*** (<5%)

THE MACHINE LEARNING PROBLEM

FEATURE ENGINEERING (X)

what data do we provide to the model to obtain a prediction?

We sampled the **features from 9NM** from the THR to the prediction point (**4 NM** from THR), **every 0.5 NM**



THE MACHINE LEARNING PROBLEM

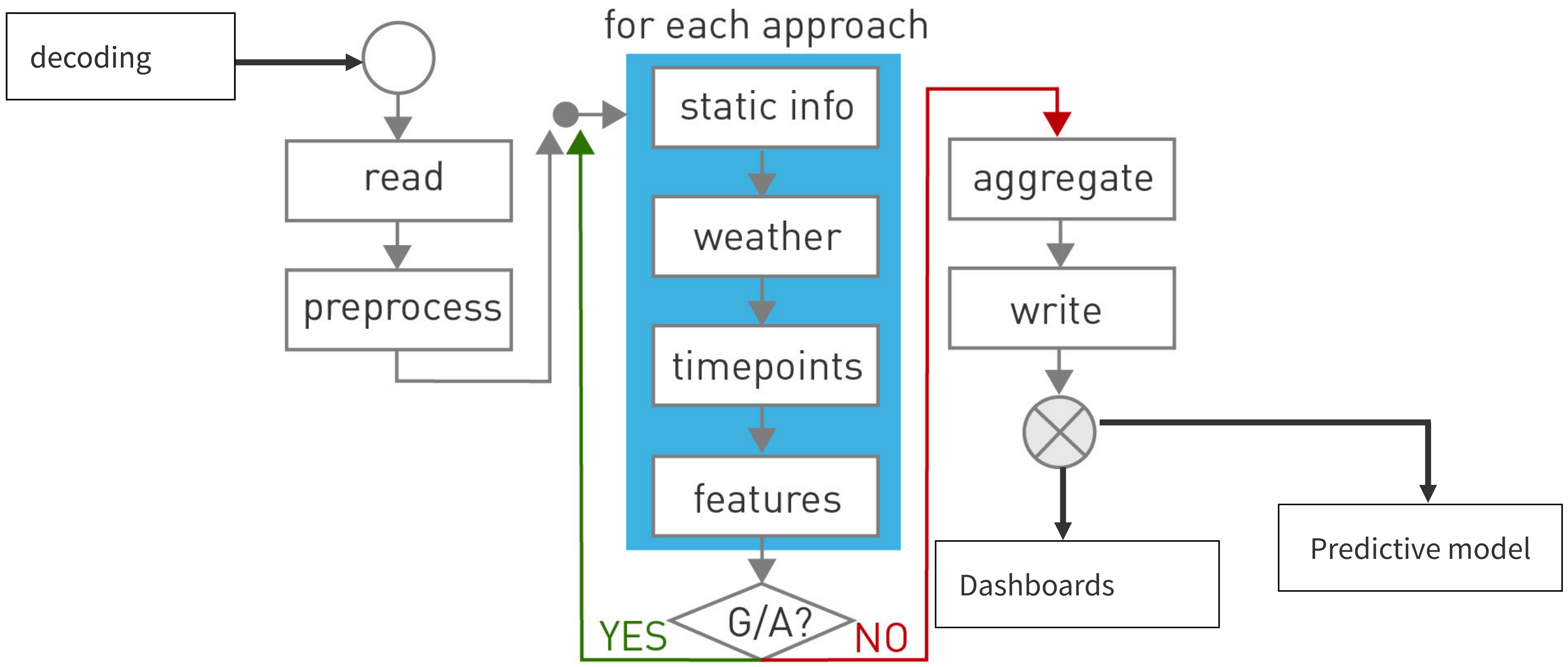
FEATURE ENGINEERING (X)

what data do we provide to the model to obtain a prediction?

Group	Features	Data Sources
Operation dynamics	Pitch, roll and heading positions and rates. Angle of attack. Vertical descent rate. Barometric altitude. Glideslope. Localiser.	FDM
Aircraft energy	Air speed. Ground speed. Standard altitude. Energy level. Aircraft mass.	FDM
Adverse weather	Static pressure. Static temperature. Relative humidity. Air density. Wind direction. Wind speed. Wind variation. Prevailing visibility. Cloud layers height. Cloud layers opacity. Phenomena (fog, snow, storms, ...).	METAR FDM (aircraft sensors)
Aircraft configuration	Flaps configuration. Slats configuration.	FDM
Crew coordination	Autopilot status.	FDM
Pilot awareness	Current time. Distance from origin. Distance to destination. Total time flown. Number of holdings	FDM
Surrounding traffic	Airport throughput. VHF keying (tower communication indicator).	ADS-B FDM (communication indicators)
Flight static information	De-Identified callsing. Origin Airport. Destination Airport. Aircraft type. Wake vortex category. Tail number. Year and week. ETA. ATOT.	Flight Plan FDM

DATA PREPARATION

PIPELINE



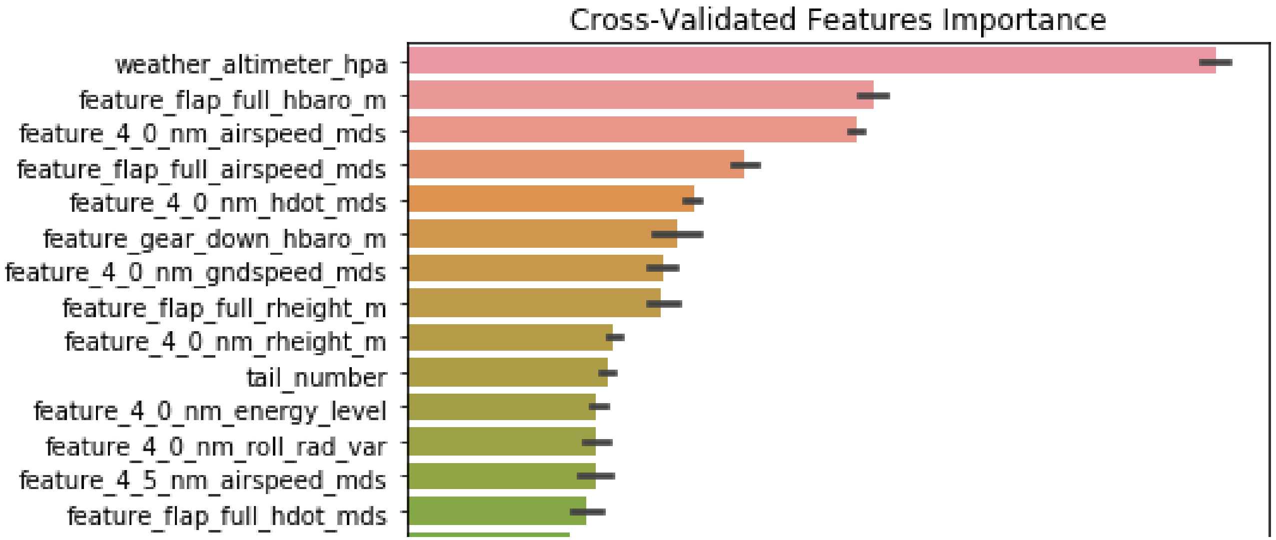
METHODOLOGY

CASE STUDY: UNSTABLE APPROACH - MACHINE LEARNING

- Binary classification
- Labelling of each approach:
  - 1 if UA
  - 0 if flight was stabilized.
- We followed specific **airline criteria**.
- The model needs to maximise the **true positives** (true detected UA) and minimize the **false negatives** (missed safety occurence) and **false positives** (unnecesary go-around impacting ATM).
- ***Goal -*** To better understand the precursors of this safety event
- We used a Gradient Boosting Machine (LightGBM)

DESCRIPTIVE/PREDICTIVE ANALYTICS

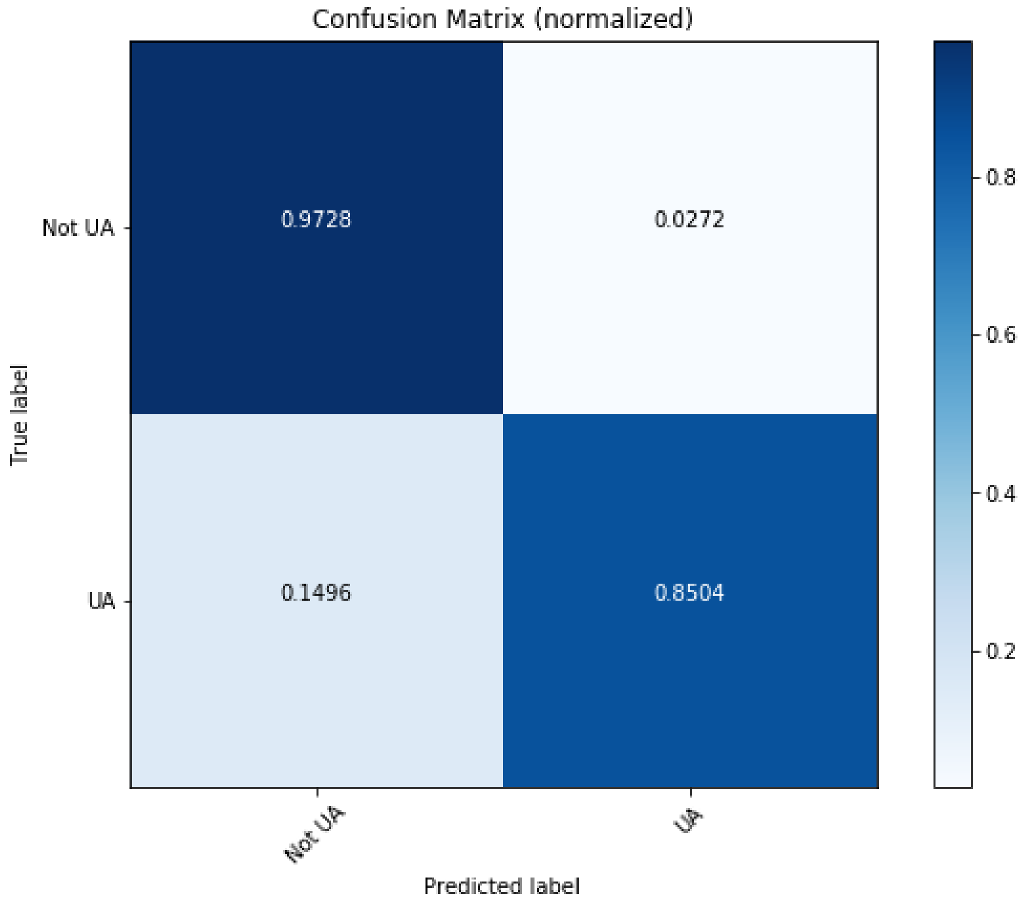
FEATURES IMPORTANCE



- **QNH**
  - Meteorological conditions
  - Altitude and position of the destination airport
- **Altitude and speed**
  - Air speed and rate of descend at 4NM form THR
- **Configuration**
  - Flaps full deployed
  - Gear lever down
- **Static flight information**
  - Tail number (aircraft type)
  - Callsign (route + crew)

DESCRIPTIVE/PREDICTIVE ANALYTICS

CONFUSION MATRIX



POSSIBLE CASE STUDY EXTENSION #1

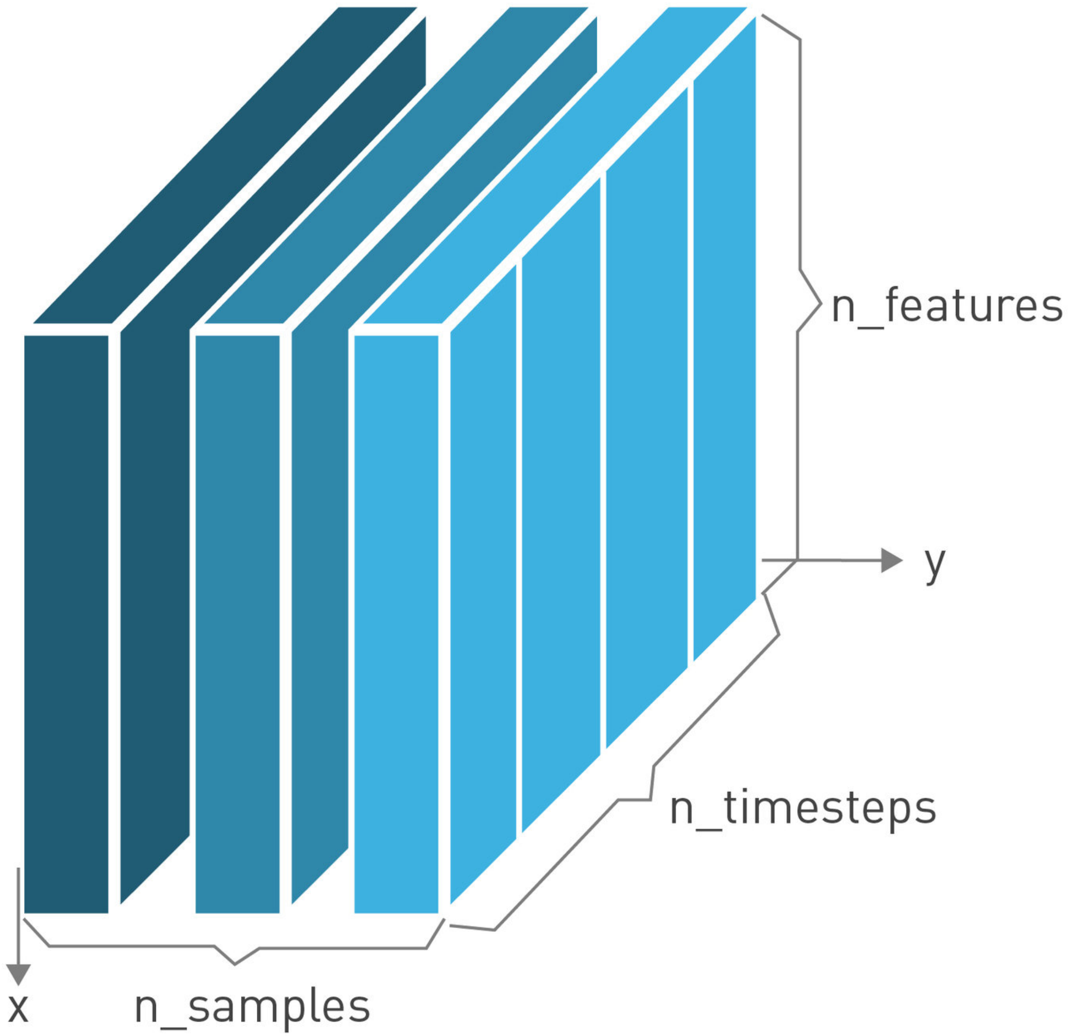
MOVING TO THE COCKPIT? - PREDICTION FOR THE PILOT

- We must **take advantage of FDM time series granularity** rather than sampling.
- Capture input features from aircraft navigation systems to provide a **UA real time prediction**
- Increase model accuracy in exchange of model interpretability → "***black-box***"
- Remove fixed prediction point at 4NM → it must be **dynamic** along the trajectory

METHODOLOGY

CASE STUDY: UNSTABLE APPROACH - DEEP LEARNING

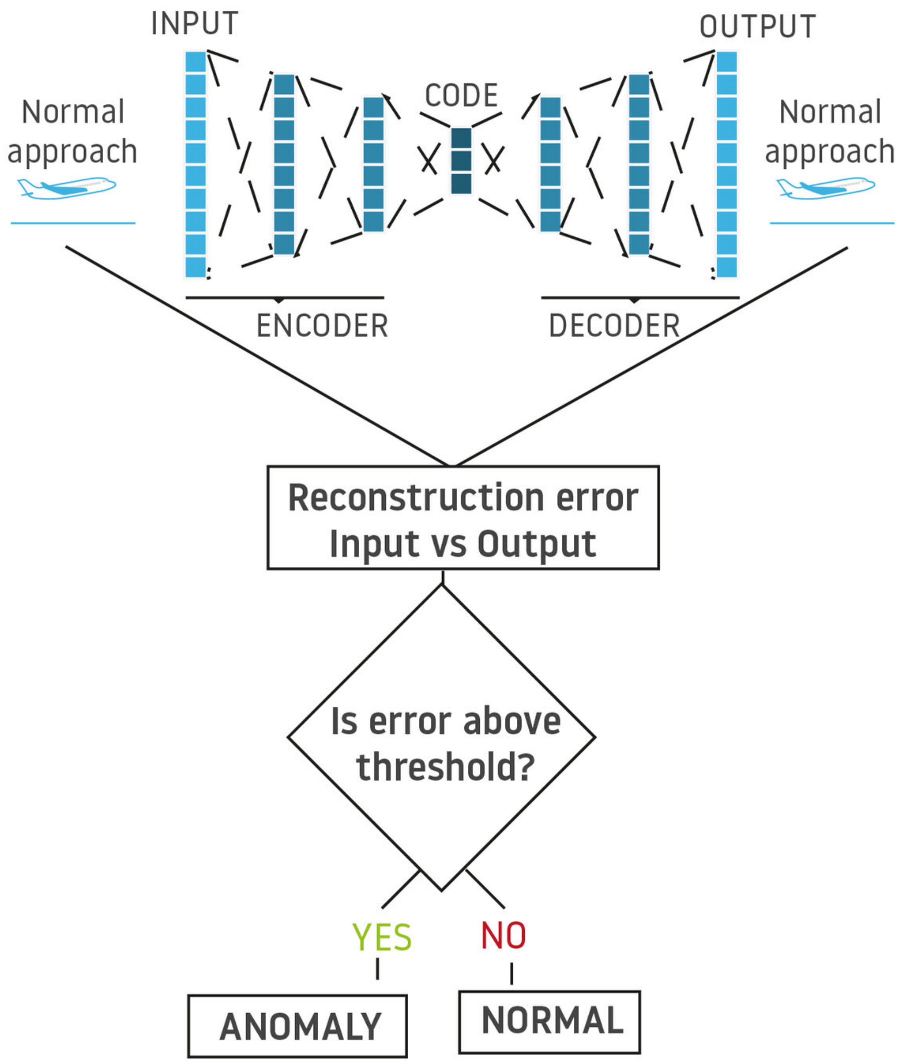
- Dynamic prediction point
- ***Goal -*** to provide a 30" prediction of the likelihood of UA
- Target variable:
  - 1 - The aircraft is about to become unstable in the next 30"
  - 0 - The aircraft will remain stable
- Deep Learning algorithm - LSTM (RNN)



POSSIBLE CASE STUDY EXTENSION #2

FDM ANOMALY DETECTOR - FORENSIC TOOL

- AutoEncoder to identify unknown hazards in FDM data.
- Learn the representation of regular approaches (more presence in data)
- Train a model able to measure the "***normality***" of the inputed approach
- Target variable:
  - 1 - The aircraft is anomalous
  - 0 - The aircraft is normal
- Deep Learning algorithm - AutoEncoders
- Not only detect UAs, also **errors in the decoding** or approaches that might entail **unknown hazards**



CONCLUSIONS & FUTURE WORK

- We presented a **Machine Learning** case study to predict Unstable Approaches and understand the precursors of this event
- We proposed a **Deep Learning** (LSTM) solution to introduce an UA prediction indicator in the cockpit
- We presented a **forensic tool** able to learn how normal flights behave, in order to detect unknown hazards, appart from unstable approaches, that might be present in FDM data.

FUTURE WORK

- Become one with the data and keep curating the training dataset
- Keep improving the cockpit indicator, decreasing the noise in data and considering more FDM samples.

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