

Forecasting Unstable Approaches with Boosting Frameworks and LSTM Networks



9th SESAR Innovation Days

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The problem of Unstable Approaches

- **Approach and landing procedures** are some of the most complex procedures in aircraft operations.
- **Unstable approaches (UAs)** are a major contributing factor in most approach and landing accidents worldwide (ICAO safety report, 2018).
- Airlines and safety agencies have published stabilised approach criteria. If criteria is not met the flight crew must **abort the approach** and perform a **go-around**.

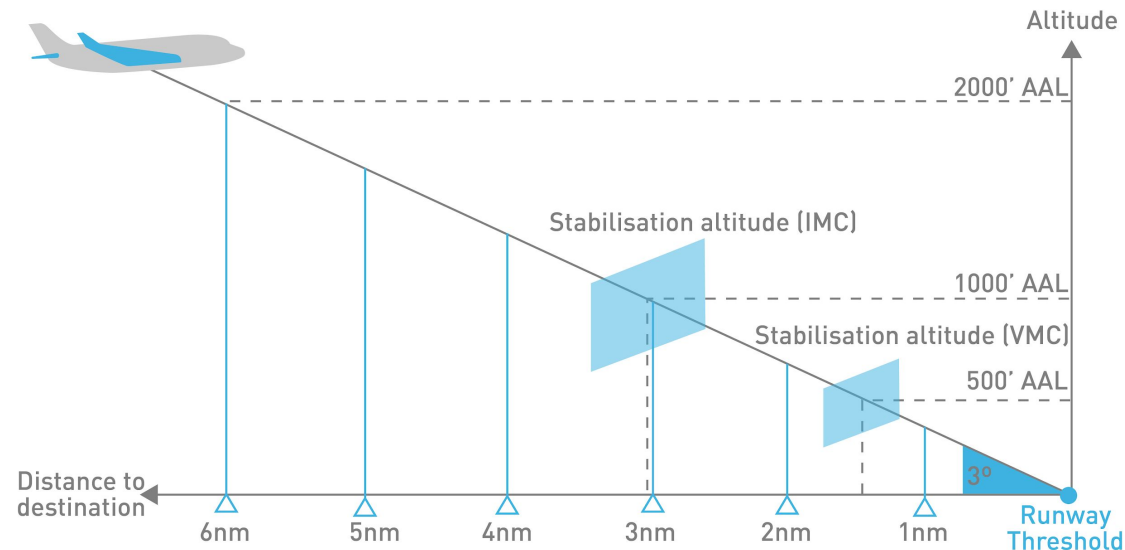


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Stabilised approach criteria

- Landing should be **stabilised** by reaching:
 - **1000 ft AAL (IMC)** or around 3NM from threshold.
 - **500 ft AAL (VMC)** or around 1.5NM from threshold.
- However, definition of aircraft instability is dependent on the **airline**.





Known indicators of an UA

- **High energy** approach: vertical speed and approach speed deviation.
- Exceeding **flap/slat limit speed** during approach.
- **Deviation** from intended path angle, glide slope, localiser.
- Excessive **attitudes**.
- Excessive **tailwind** and **crosswind**.
- **Bad configuration** at time-points (late gear extension, late flaps setting).
- **Excessive fan speed** during approach.



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Predictive modelling using FDM

- Vast amount of **historical Flight Data Monitoring (FDM)** datasets stored in the airlines data silos.
- Indicators in the FDM system are not being used for predictive capabilities. Neither FDM is being merged with external data sources to extract value.
- In the frame of **H2020 SafecLOUDS.eu project**, we aimed to find data-driven prediction models based on contributing factors and collaboration between stakeholders.



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Research questions

- How precisely an UA event can be predicted at a certain point of the approach?
- What are the main precursors, situations and patterns that contribute to the destabilisation on the approach?



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Problem assessment

- The critical point of instability is around 3NM from threshold.
- The pilot needs at least 30 seconds to react.
- Therefore, the **prediction point** needs to be selected at least at **4NM from runway threshold**.



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Datasets

FDM:

- Main data source
- 64.461 approaches
- 89 european airports

METAR:

- Compliments FDM with more information on weather conditions.
- Reports every 30 minutes -> Closest time-point to approach start.

ADS-B:

- Aircraft position not very accurate in FDM data.
- Also used for calculating traffic congestion at the airport TMA.



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Predictive problems

Machine Learning problem:

- Binary classification
- Labelling of each approach: 1 if UA was presented, 0 if flight was stabilised. Following airline criteria.
- The predictive model needs to maximise the true positives and minimize the false negatives -> go-arounds disrupt the ATM.

Data Imbalance problem

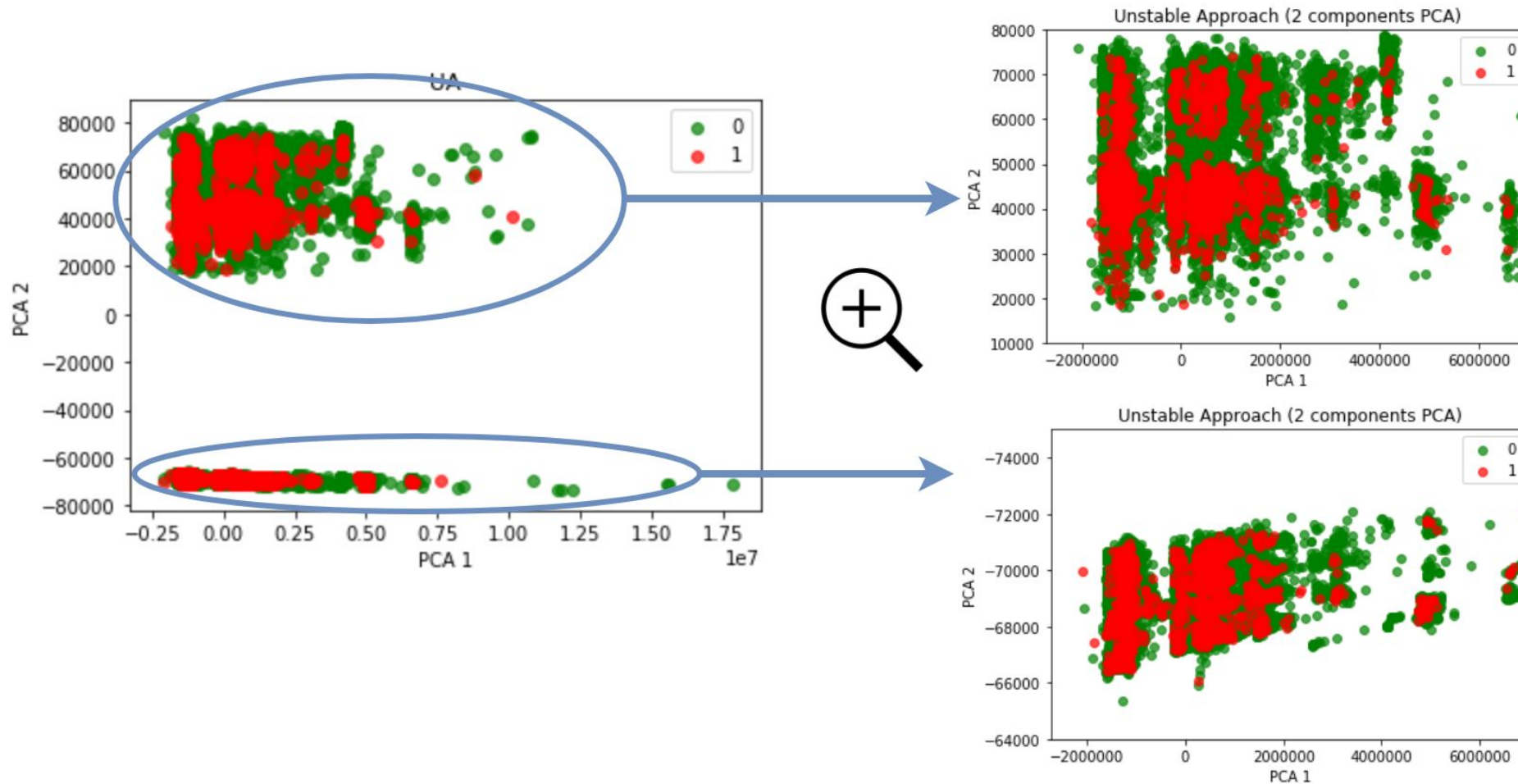
- Low count of positive samples -> only 5% in the best cases.
- Prevents the model from learning the patterns in positive labelled data.



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Data Imbalance: PCA





Methodology

- **Approach A: Machine Learning using a Gradient Boosting machine (GBM)**
 - Classical ML approach.
 - Boosting frameworks are ideal for dealing with imbalanced data.
 - A correct approach for the features engineering is crucial.
 - Precursors analysis using the ML features importance.
- **Approach B: Deep Learning using Neural Networks with LSTM**
 - Learning based on the time-series evolution + context information.
 - No features engineering, but less interpretability.



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Approach A: Machine Learning with GBMs



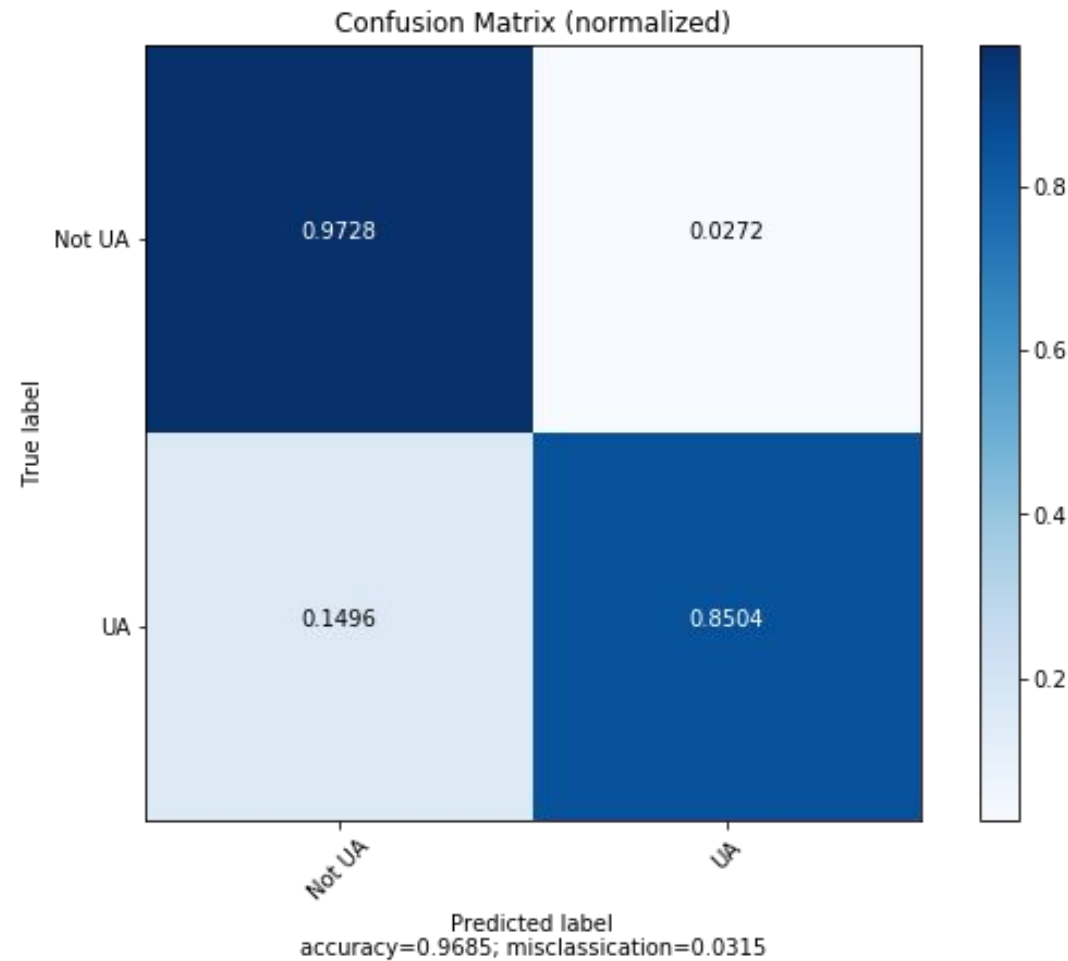
- GBMs is an ensemble of many weak learners, typically decision trees, to minimise the loss.
- The model is iteratively trained. For each new round, the model uses data samples that were “difficult” to learn in previous iterations.
- Time-Point features engineering and static target variable
 - **Sampling** of time-series every 0.5NM (around 30 seconds) from **4NM to 9NM**.
 - Is the aircraft unstable at exactly 2.5NM from threshold?



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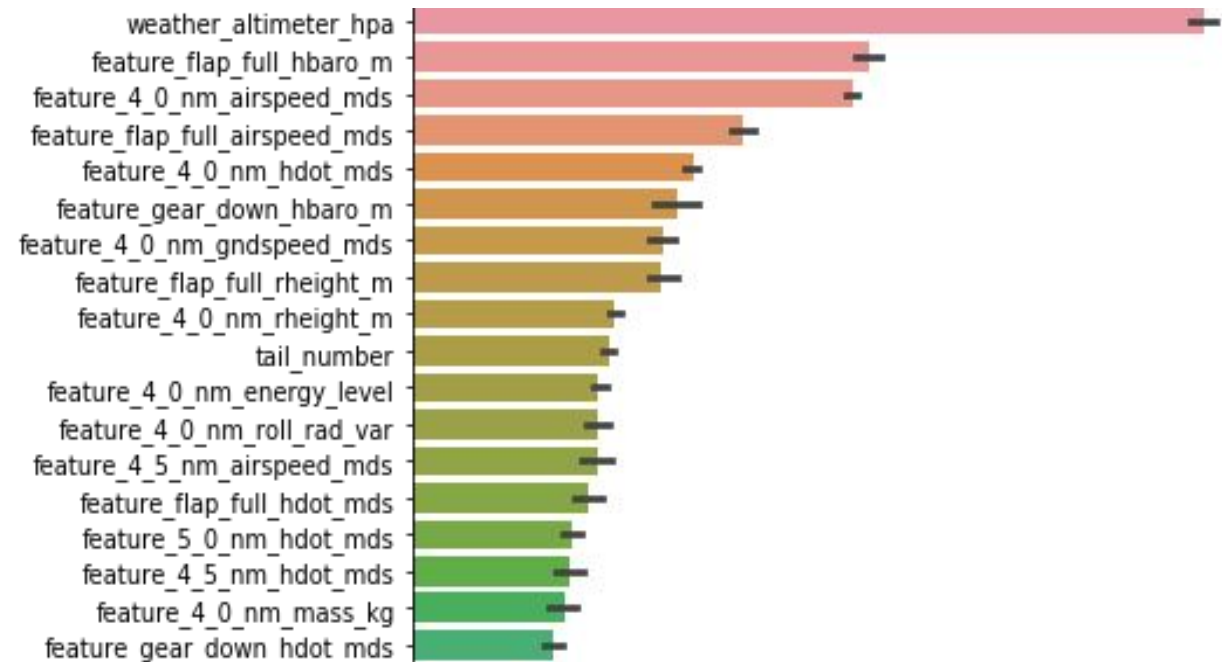


Approach A: Results



Approach A: Precursors analysis

1. QNH
 - a. Meteorological events
 - b. Altitude and position of the destination airport.
2. Altitude and speed
 - a. Rate of descent
3. Configuration
 - a. Flaps full deployed
 - b. Gear down
4. Static flight information
 - a. Tail Number (aircraft type)
 - b. Callsign (route + crew)





Approach A: Limitations and problems

- Sampling data every 0,5 NM (every 30 seconds) is translated in losing large amounts of FDM information.
- High dimensionality of the sampled features matrix might cause to lose important precursors in the analysis (e.g. meteorological factors...).
- Due to the loss of the complete time series you might be missing a precursor.
- Prediction point is fixed at 4 NM, UA being present always at 3NM is a wrong simplification.
- The UA might be happening too soon, the pilot won't have reaction time.



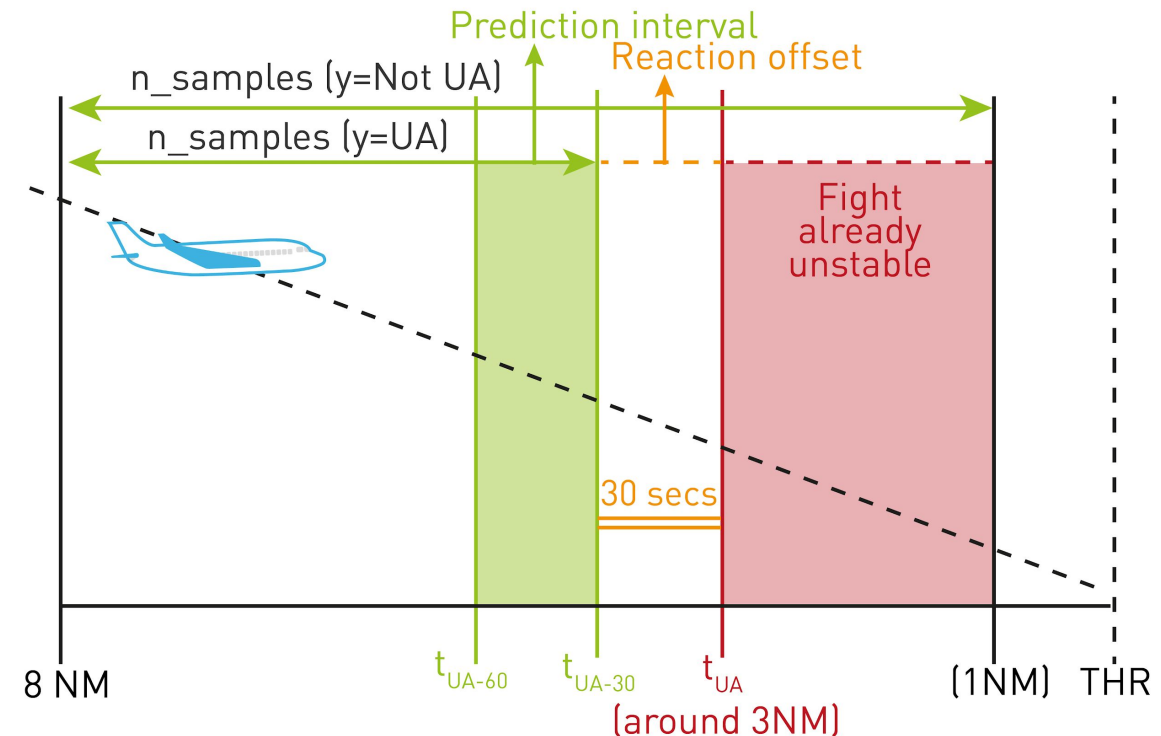
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Approach B: LSTM Deep Learning

The target variable is now dynamic:

- **1**: the aircraft is about to become unstable in the next 30 to 60 seconds.
- **0**: the aircraft will remain stable for the next minute.



Approach B: LSTM input

$n_samples$

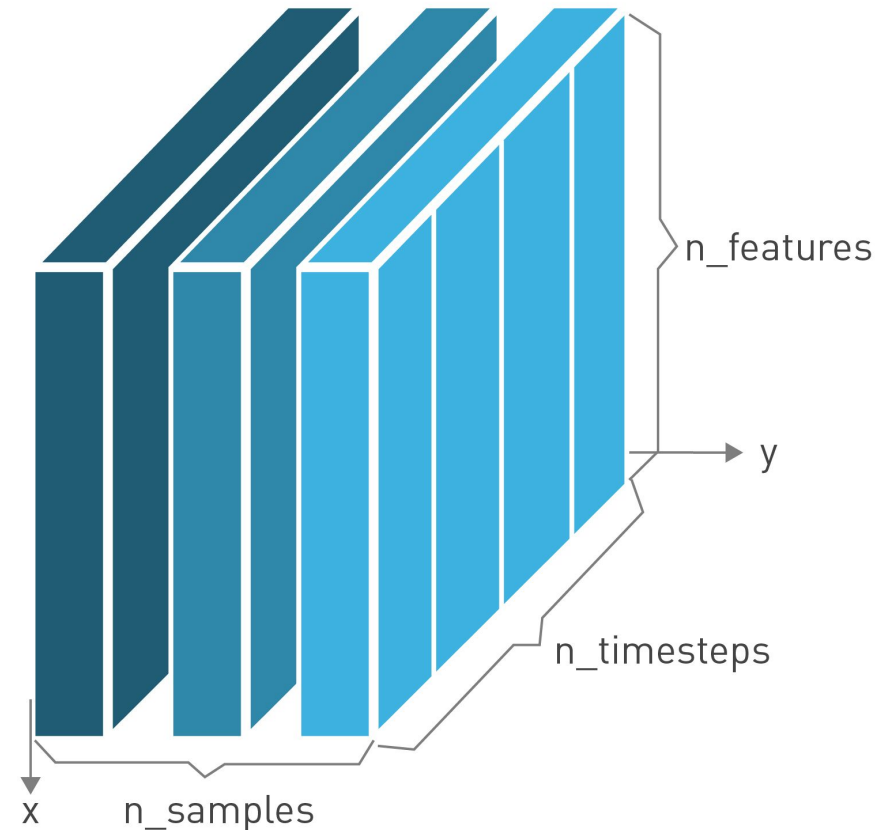
- Training set size.
- Reduced to be able to fit the model.

$n_features$

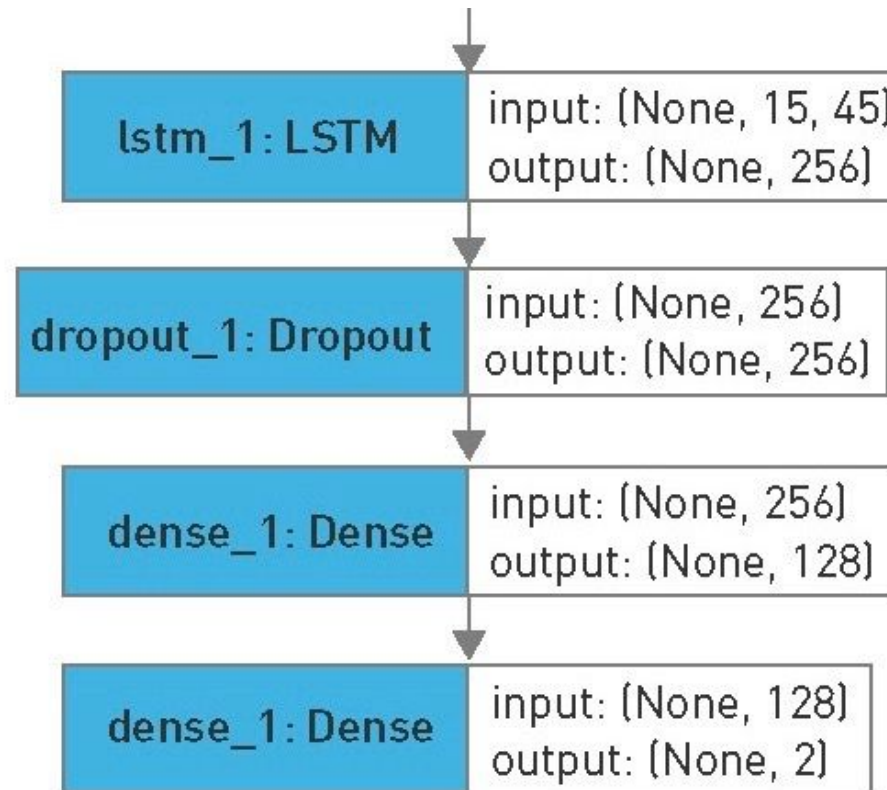
- FDM variables
- 45 time-series

$n_timesteps$

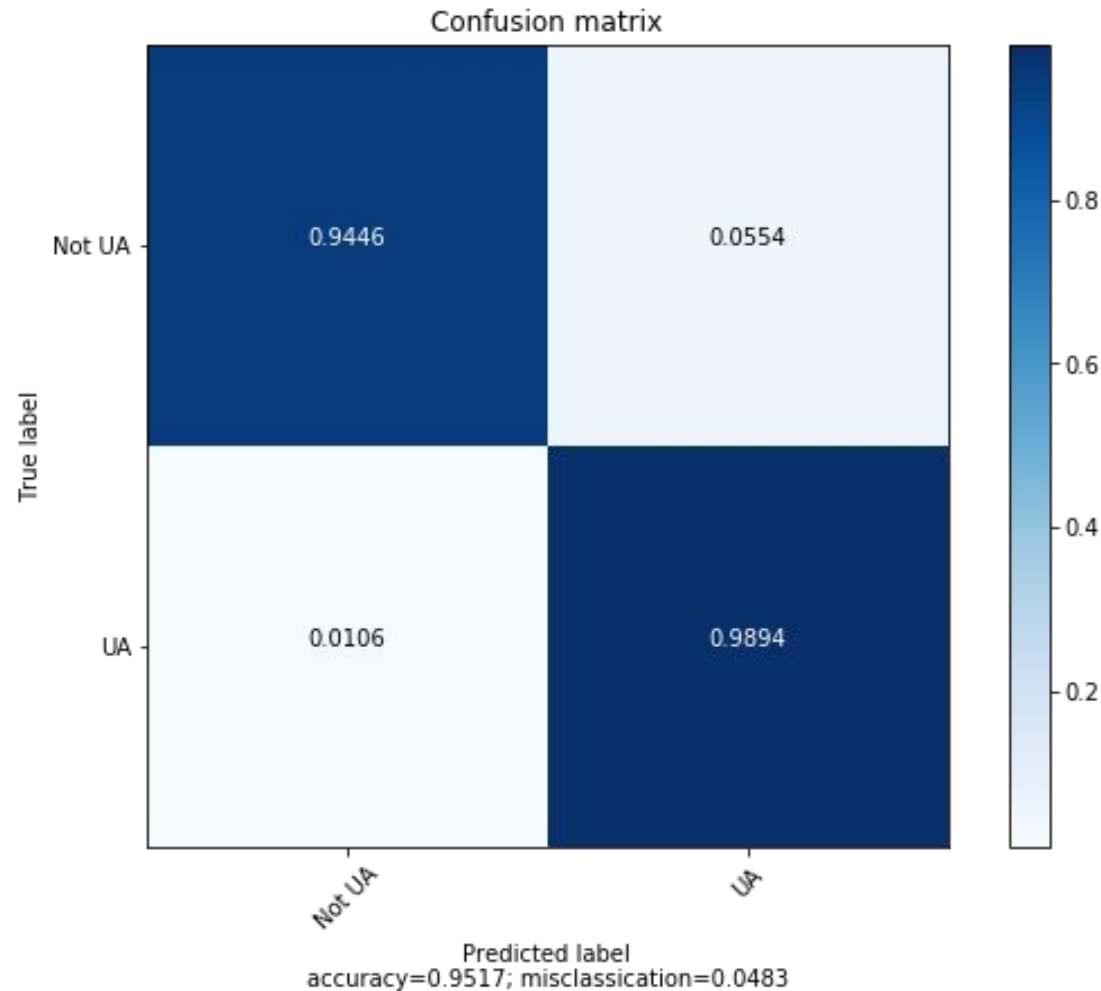
- Time window of past data
- Fixed at 15 seconds



Approach B: Net architecture

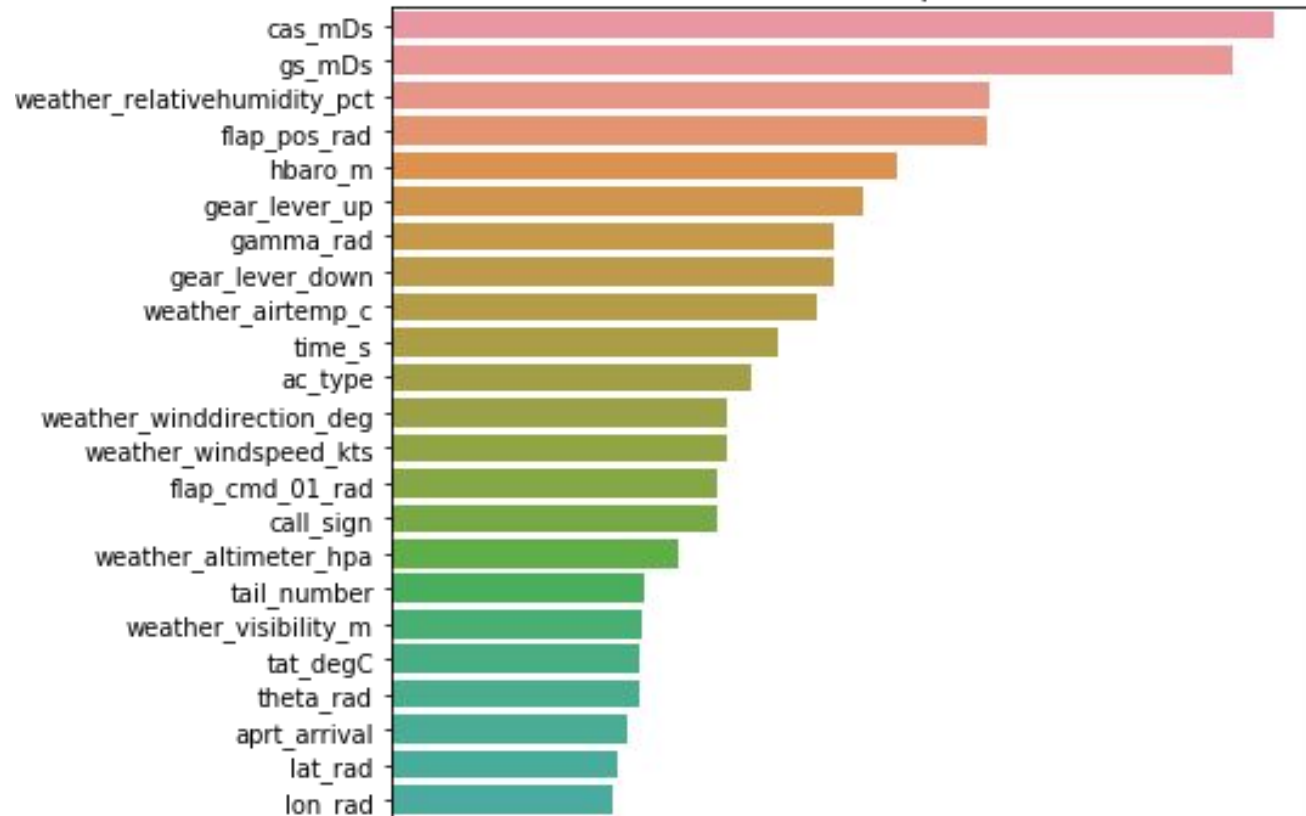


Approach B: Results



Approach B: Precursors analysis

1. Speeds and altitude
2. Configuration
 - Flaps position
 - Gear lever
3. Aircraft dynamics
 - Pitch, yaw, roll
4. Weather
 - Humidity, Wind, Visibility
5. Static information
 - Callsign, aircraft type
 - Arrival airport





Comparison between the two methods

- LSTM approach is more accurate for predicting UAs: **95% vs 82%**
- LSTM is a "black-box" algorithm, you get the order of the variables but don't know the exact time point.
- LGBM gives more detailed information about the precursors and allows to input specific point of the time series to study the influence.
- LGBM misses the prediction of some UAs, because it doesn't consider all the FDM samples.



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Conclusions and future work

- Boosting Frameworks still perform very good with very low tuning.
- Features engineering for Boosting Frameworks are challenging.
- Deep learning LSTMs are a powerful approach for Aviation's sparse datasets.
- High enough accuracy and low rate of false positives, ready for prototyping -> TRL6+
- Next steps: asses data availability and usability in a real operational environment.



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Thanks!

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2 – 6 December 2019, Athens, Greece



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