A Boosted Tree framework for runway occupancy and exit prediction

SIDs 2018 - Salzburg
1. Runway utilization problems

Leader misses the procedural runway exit

Follower too close when leader lands

Leader takes too much time in runway

Allocating departures in mixed operations
2. Datasets availability

Scope: Arrivals at R34 of Vienna airport (LOWW)

7 sources (datasets) available:

1. Radar track ➔ Dynamic data
2. Airport information ➔ Static data (flight plan)
3. METAR
4. SNOWTAM
5. Visibility
6. WMA (wind profiles)
7. SODAR

Meteorological data
2.1 Data preparation considerations

- Lack of format coherence
- Data redundancy
- Errors and outliers
- Different time scales and sampling
  - Parsing to tabular format (dataframe)
  - Information as message log

METAR logs example
2.2 Radar track dataset inspection

Dataset Information

- **2 years** of data (2014 - 2016)
- Radar track + Ground radar
- Time series
- Already **preprocessed**:
  - Unknown data wrangling and interpolation methodologies
- Duplicated callsign problem

Potential variables

- Aircraft type
- Flight level
- Latitude
- ICAO category
- On runway
- Longitude
- Speed
2.3 Airport information dataset inspection

**Dataset Information**

- **2 years** of data (2014-2016)
- In message log format
- After message aggregation + filtering:

<table>
<thead>
<tr>
<th>Total Flights</th>
<th>725.187</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total Arrivals</strong></td>
<td>364.583 (50.27%)</td>
</tr>
<tr>
<td><strong>Total Depatures</strong></td>
<td>360.601 (49.73%)</td>
</tr>
</tbody>
</table>

**Potential variables**

- Departure airport
- Arrival airport
- Gate
- ATA
- ETA
- Runway
- ATOT

Runway: AABT/AOBT
2.4 METAR

Dataset Information

- Message log
- Format **not fixed** → Hard to parse
- Message **Filtering** to capture messages.
- **Main** meteo dataset.

Variables extracted

- Ceiling
- Wind direction
- Wind speed
- Temperature
- QNH
- 1º Cloud layer visibility
- Dew point
- Minimum visibility
- Wind variation
- Runway status
- Phenomenas
- 2º Cloud layer visibility
2.5 SNOWTAM

Dataset Information

- Message log
- Only information for R11 and R16.
- But... R11 and R16 are R27 and R34 inverted
- Record *only during the "snow season"*

Potential Variables

- Runway
- Deposits
- Depth
- Apron clearance
- Friction
- Runway clearance
- Taxiway clearance
2.5 Other meteo: WMA, Visibility and SODAR

Datasets Information

- **WMA**: Wind per runway. Higher frequency than METAR.

- **Visibility**: 4 cloud layers, higher frequency, more detailed than METAR.

- **SODAR**: Outliers, **high variance - high bias**. **Discarded** due to bad data quality...

Potential Variables

<table>
<thead>
<tr>
<th>WMA</th>
<th>Visibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind speed</td>
<td>1º Cloud layer visibility</td>
</tr>
<tr>
<td>Wind direction</td>
<td>2º Cloud layer visibility</td>
</tr>
<tr>
<td></td>
<td>3º Cloud layer visibility</td>
</tr>
<tr>
<td></td>
<td>4º Cloud layer visibility</td>
</tr>
<tr>
<td></td>
<td>Minimum visibility</td>
</tr>
</tbody>
</table>
Knowing the Data available and the problem...

- What research questions can you raise?
- How well can your data answer them?
3. Questions and problem definition

RQ1: Can we predict if the aircraft going to take the procedural exit in R34?

- Definition of the expected/procedural exit from AIP.
- Exit taken absent from the data, but can be extracted from the radar.
- Machine learning problem definition:
  - Binary classification
  - Target variable:
    - 1 procedural exit taken
    - 0 procedural exit not taken

<table>
<thead>
<tr>
<th>Total arrivals</th>
<th>59.369</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taking the AIP exit</td>
<td>43.933 (74%)</td>
</tr>
<tr>
<td>Not taking the AIP exit</td>
<td>15.436 (26%)</td>
</tr>
</tbody>
</table>
3. Questions and problem definition

RQ2: Can we predict how much time will certain flight occupy the runway?

- **Runway Occupation Time (ROT):** Time between coordinates of runway threshold and coordinates of exit.

- Ground movements with a second resolution, *bias* is an issue.

- Time error when over-passing threshold is not present in data...

- ML problem definition:
  - Regression
  - Target variable
    - ROT
4. Features engineering

The **most important step** in the data pipeline!!

**Static information**

- **Unique information** per flight.
- Type of aircraft, state of the runway, etc...

**Dynamic information**

- **Time series** per flight: position, velocity, etc...
- More than 100 observations per flight and variable!!
- We need to **abstract** dynamic series **to single variables**!! *e.g. aircraft energy at 2NM*
4. Features engineering

Potential Precursors
(based on ATCOs experience)

Velocity patterns
Weight / Aircraft type
Airlines protocols
Wind direction and speed
Visibility
Succeeding aircraft
distance/speed at threshold
...

Engineered Features

Transversal - parallel wind decomposition
Visibility ranges
Aircraft energy
Velocity at X NM
Velocity slope
Largest break
Wet runway indicator
Delay
...

...
5. ML algorithm: Introduction to Boosting Frameworks

- Also known as **Gradient Boosting Machines (GBMs)**.
- Currently one of the most popular solutions for building predictive models.
- Methodology:

  - Ensemble ML model: Additive model of many weak learners (typically regression trees)
  - The model learns **iteratively**
  - Learns only from data samples that were "difficult to learn" in the previous iteration
  - Huge reduction of bias and variance while maximizing accuracy

Tree-Based boosting framework
5. ML algorithm: LightGBM

- Light Gradient Boosting Machine (LightGBM)

- Gradient boosting framework that uses tree-based learning algorithms.

- Histogram based algorithm - aggregates continuous features into discrete bins - speeds up training and reduces memory usage.

- Grows the trees leaf-wise: can reduce even more the loss than a level-wise algorithm (e.g. XGBoost).

- Can be used for both classification and regression.
6.1 Results: Understanding the classifier

- **78% accuracy** (AUC)
- **92%** when the flights are taking the designated exit.
- **36%** when the flights are not taking the designated exit.
- The classifier is not good at identifying the **abnormal behaviours**...
6.1 Results: Understanding the classifier

- Prediction error **slowly decays with the distance** from threshold.
- **Most of the features** relevant for the prediction are known beforehand.

![Prediction AUCs as a function of distance from threshold]

**Decay of 1.4%**
6.2 Features importance / Precursors analysis

Prediction at 2NM

Prediction at threshold
6.2 Features importance / Precursors analysis

Prediction at 2NM

Prediction at threshold
7. Results: Understanding the regressor

- Mean ROT **49.66 seconds** with a standard deviation of 14.4 seconds.

- **80% of the ROTs** are predicted with < 14 seconds of error.
7. Results: Understanding the regressor

The regressor experiments the same limitations as the classifier:

fails at identifying the flights not behaving correctly.
Thank you!

Darío Martínez
dm@innaxis.org
www.linkedin.com/in/dmartr

SafeClouds.eu