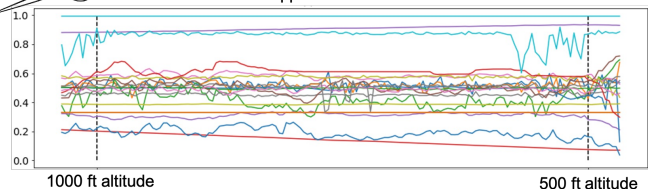




Approach to land

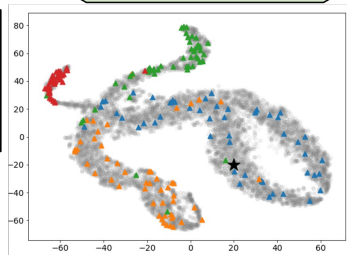


1000 ft altitude

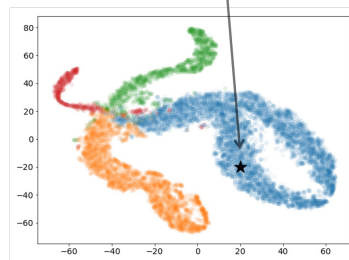
500 ft altitude

Feature Encoder

- Unlabeled
- ▲ Nominal
- ▲ Speed High
- ▲ Path High
- ▲ Flaps Late



Classifier



This sample will be
classified as *Nominal*

AVIATION FESTIVAL

Americas

Miami Florida
May 14th – 16th

Exploring Deep-Rooted Networks: Decision Support for Vulnerability Discovery

Presented by: **Bryan Matthews (KBR Inc.)**

Milad Memarzadeh, Bryan Matthews, and Daniel Weckler
Data Sciences Group, NASA Ames Research Center



System Wide Safety

In this presentation



Learn about the literature in anomaly detection in flight operational data

Dive deep into two developed deep learning models:

- **Convolutional Variational Auto-Encoder (CVAE)**: an **unsupervised** encoder-decoder model for anomaly detection in multivariate time-series
 - Demonstration of CVAE: Fuser Streaming Data Prototype.

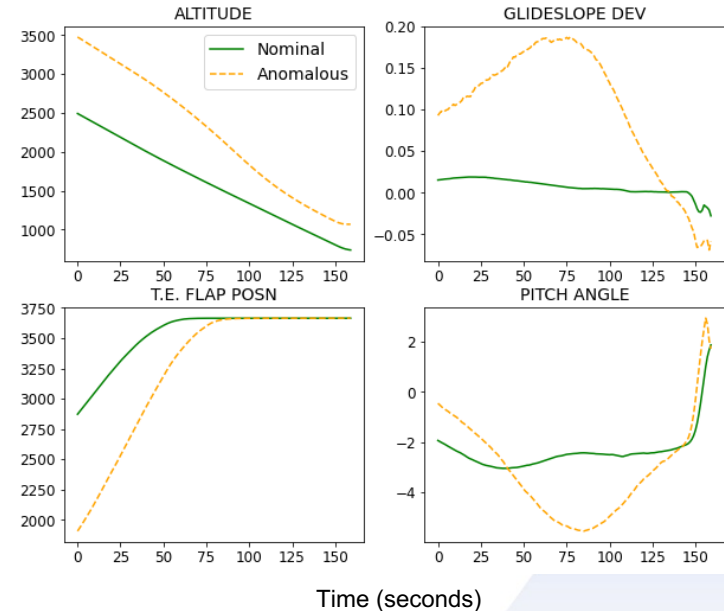
Aviation anomaly detection literature



Exceedance detection:

Comparing against the **pre-defined thresholds**, which are identified by subject-matter experts.

Example of unstable approach to landing



Aviation anomaly detection literature



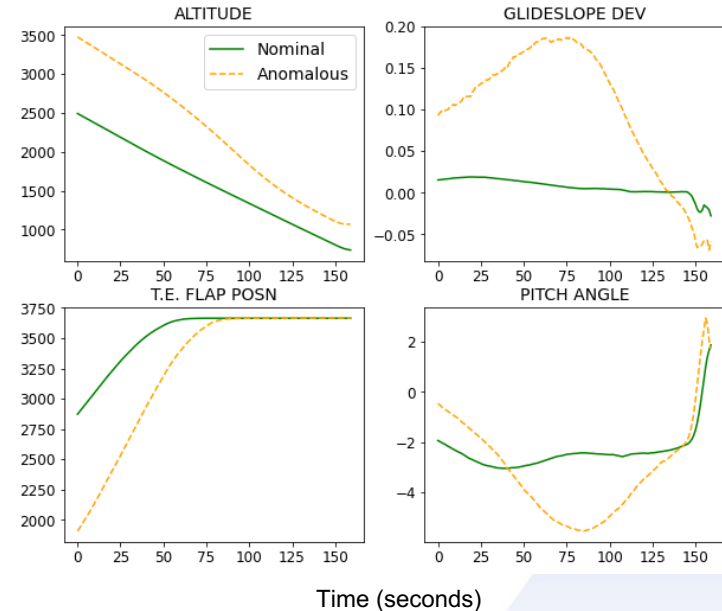
Exceedance detection:

Comparing against the **pre-defined thresholds**, which are identified by subject-matter experts.

Cons:

- Complete reliance on domain knowledge.
- Requires extensive reviews of entire data.
- Can only identify known anomalies.

Example of unstable approach to landing



Aviation anomaly detection literature

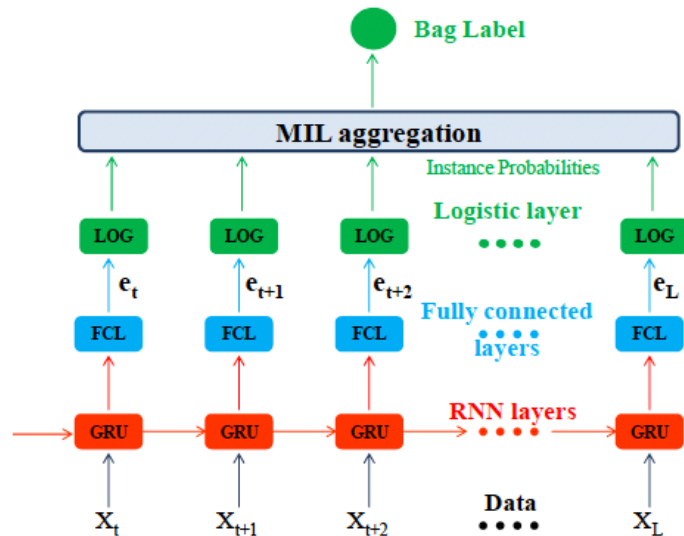


Supervised learning:

Produces inference using only labeled data.

Pros:

- It demonstrates amazing performance when a sufficient number of labeled data is available.



Aviation anomaly detection literature



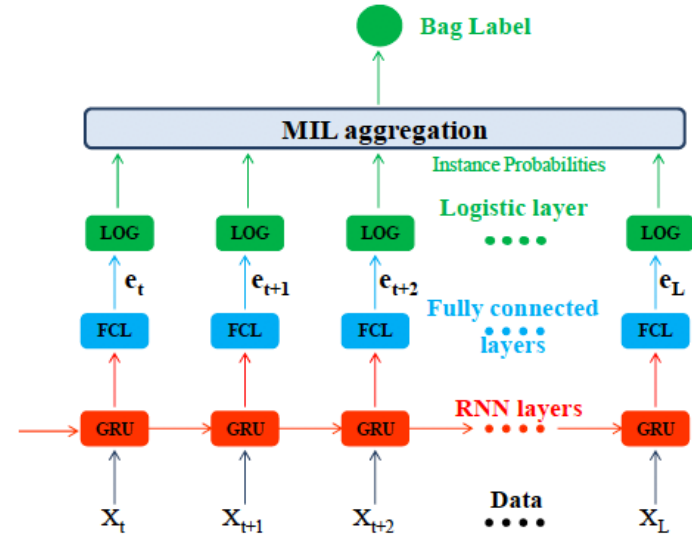
Supervised learning:

Produces inference using only labeled data.

Cons:

- Can only identify **known anomalies**.
- **Creating labels** for data requires huge effort from subject-matter experts and is largely expensive and impractical.

Hence, **unsupervised** learning or **semi-supervised** learning are the only feasible choices.



Convolutional Variational Auto-Encoder - CVAE



Using deep auto-encoders to identify anomalies without the need for labels.

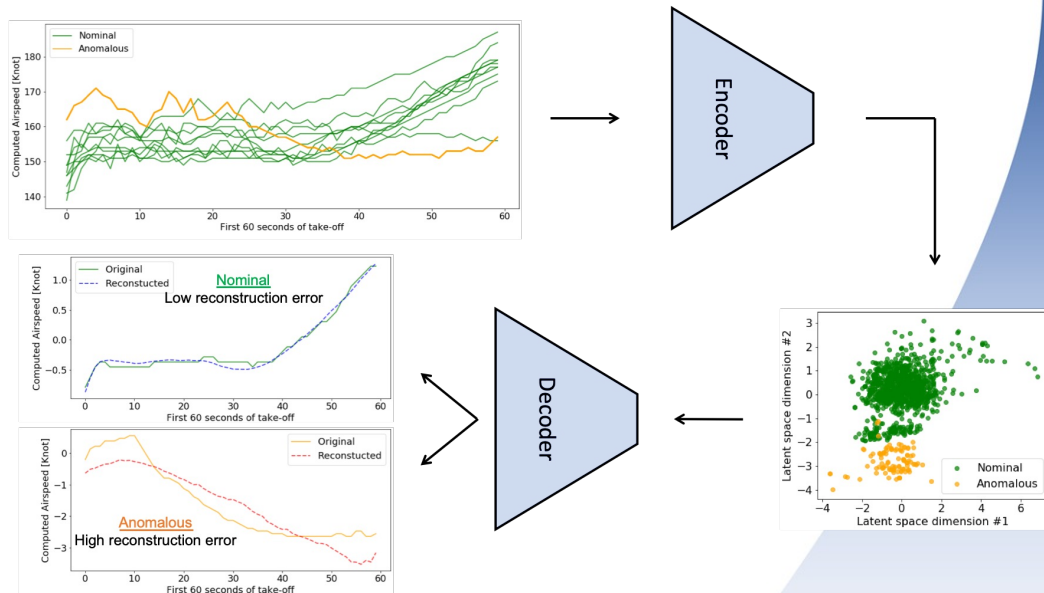
$$\mathcal{J}_{\text{CVAE}} = \mathbb{E}_{q_{\phi}(z|x)} [\log p_{\theta}(x|z)] - \beta \text{KL}(q_{\phi}(z|x) || p_{\theta}(z))$$

reconstruction fidelity
distance between posterior and prior

Identifying anomalies:

$$\zeta_i = \|x_i - \hat{x}_i\|_2^2, i \in \{1, \dots, N\}$$

$$thr = \mathbb{E}[\zeta] + \alpha \sigma(\zeta)$$



Performance comparison



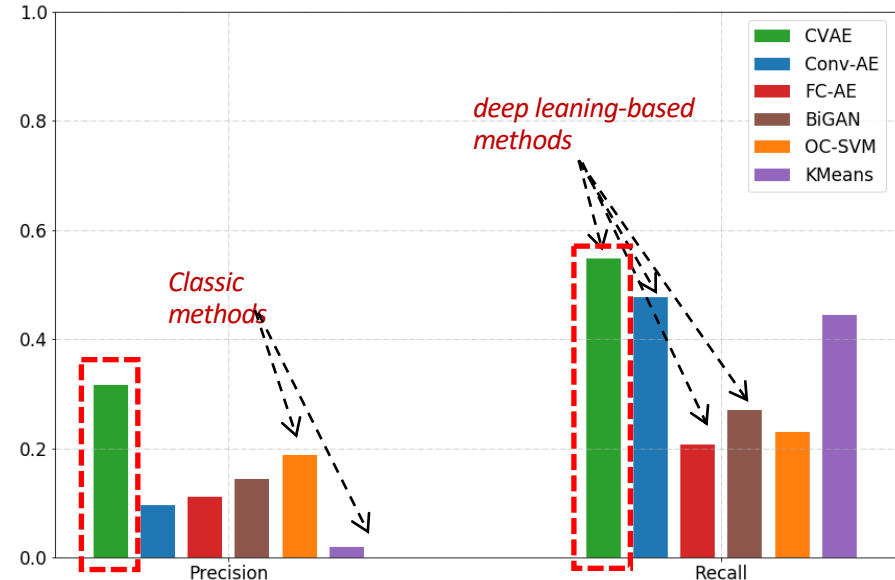
Pros:

- Does not require labels to make inference.

Cons:

- **Low precision**, which means a high number of false positives and low reliability.
- It is not easy to extend to **multi-class** anomaly detection.

CVAE





NASA's Digital Information Platform (DIP)

CVAE USE CASE: STREAMING FUSER DATA

Deploying CVAE on DIP Platform

National Aeronautics and
Space Administration



- Data Source: Fuser
 - Streaming radar track data:
 - TFM/ASDE-X
 - lat/lon, altitude, ground speed
- Focus on the last 20NM before landing at core 30 airports.
- Identify anomalous flight track.
- Generate anomaly report.

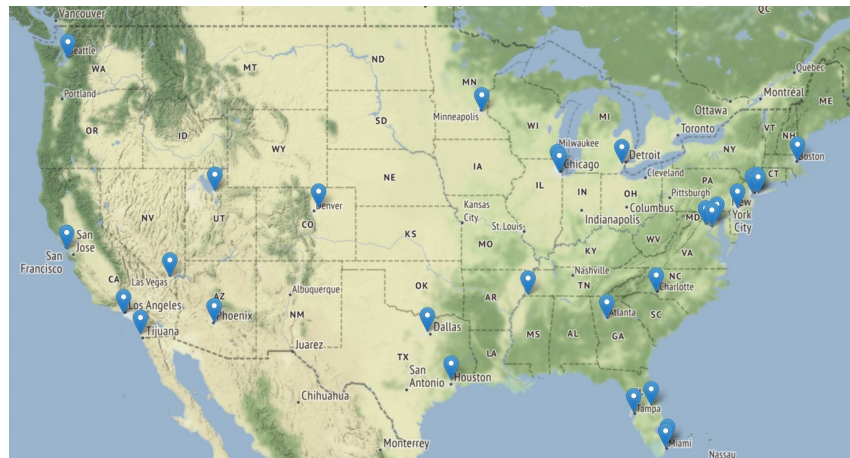
My Subscriptions



NASA
Fuser Public SFTP

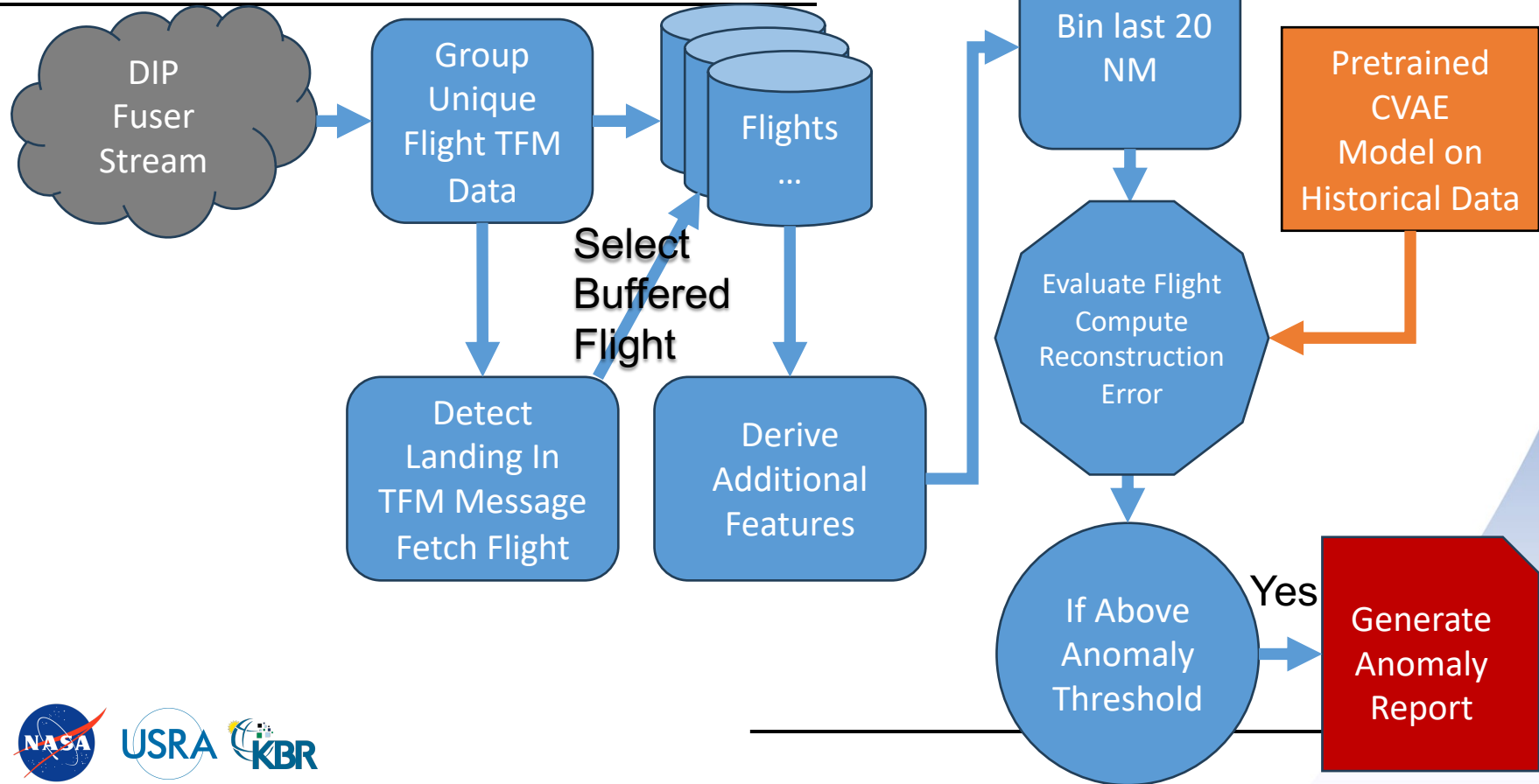


NASA
Fuser Public Stream



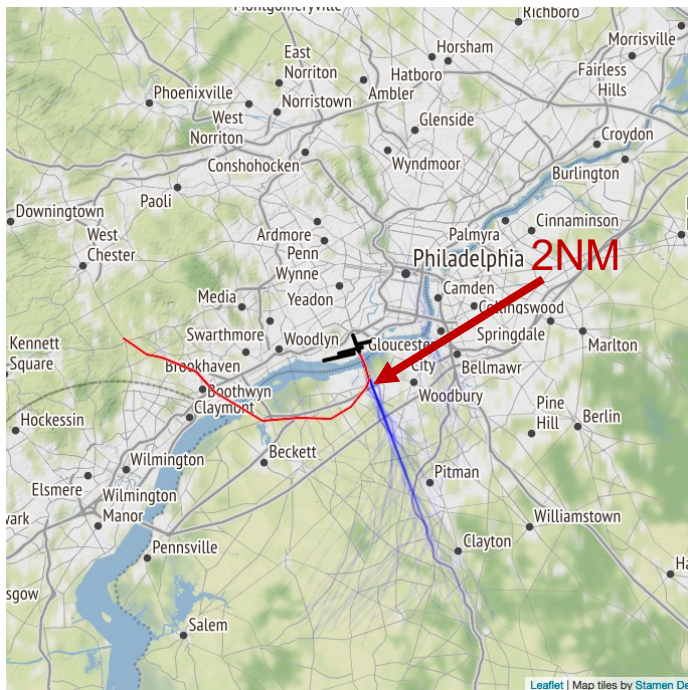
CVAE on Streaming DIP Fuser Data

National Aeronautics and
Space Administration



DIP Fuser TFM Anomalies

- Candidate: Short Turn to Final



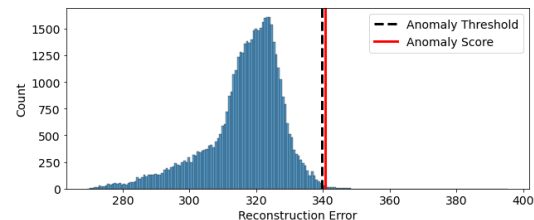
807

National Aeronautics and
Space Administration

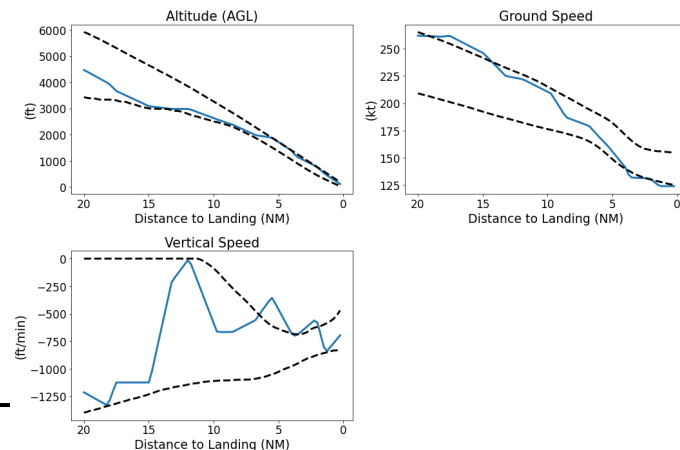


Date: 06/04/23
GUFID: 807.RST.PHL.230604.1540.0091.TMA
Dest. Airport: KPHL
Runway: 35
AC Type: E55P

Anomaly Score: 340.673

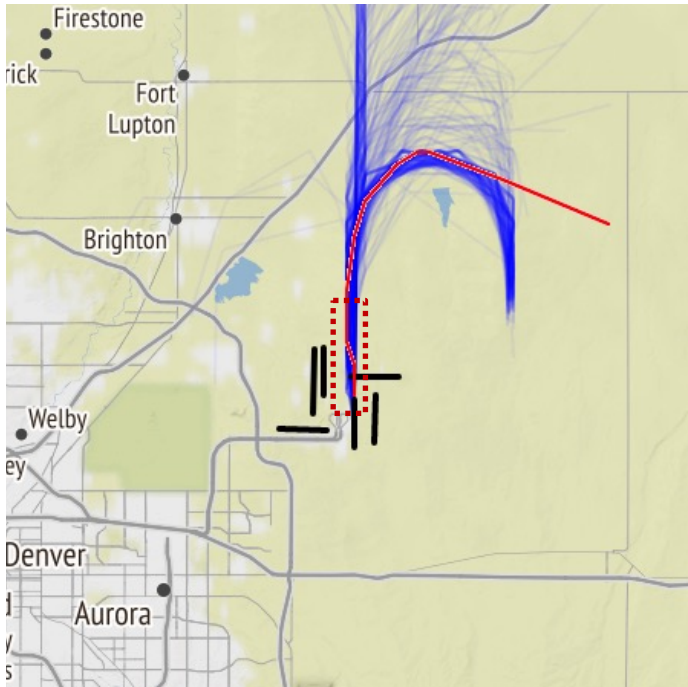


Variables:



DIP Fuser TFM Anomalies

- Candidate: Potential Misalignment



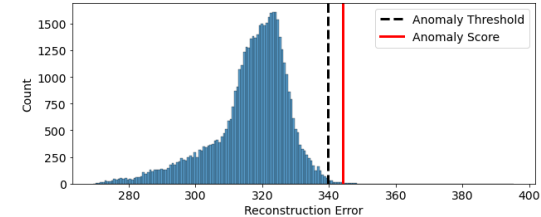
736

National Aeronautics and
Space Administration

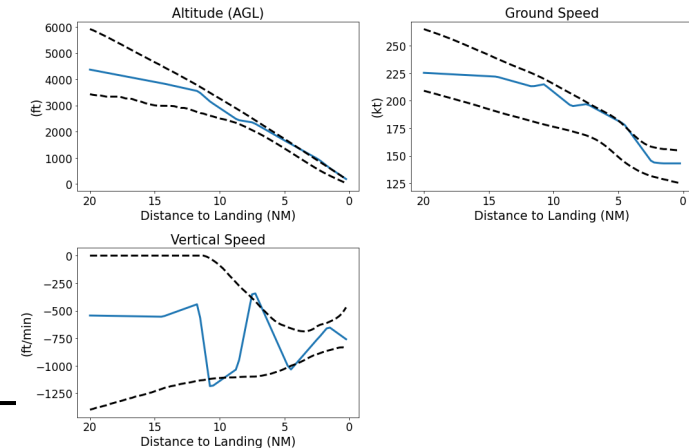


Date: 04/25/23
GUFID: 736.ATL.DEN.230424.1045.0031.TFM
Dest. Airport: KDEN
Runway: 17R
AC Type: A321

Anomaly Score: 344.143



Variables:



Acknowledgement and references



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