Using Machine Learning to Predict Aircraft Braking Performance in Inclement Weather

Presented to: Friends and Partners of Aviation Weather

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Federal Aviation Administration

Outline

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2. **Research Questions**
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4. **Machine Learning Efforts**
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Background and Motivation

- **Build-up of environmental contaminants decreases friction** and braking capability of an aircraft after landing, increasing risk of runway overruns
- **Understanding the contributing factors** and being able to predict when there's an increased risk of reduced braking capability in poor weather is vital to maintain safe operations

What's the problem?

- Recent landing overruns on contaminated runways have **raised questions** regarding current models and other information found in Federal regulations
- **Existing models make assumptions which may not be fully validated** in modern operating conditions
  - **Aircraft now landing faster and in more marginal airports**, elevating the risk of runway overruns

Example: United Express Flight 8050, June 16, 2010

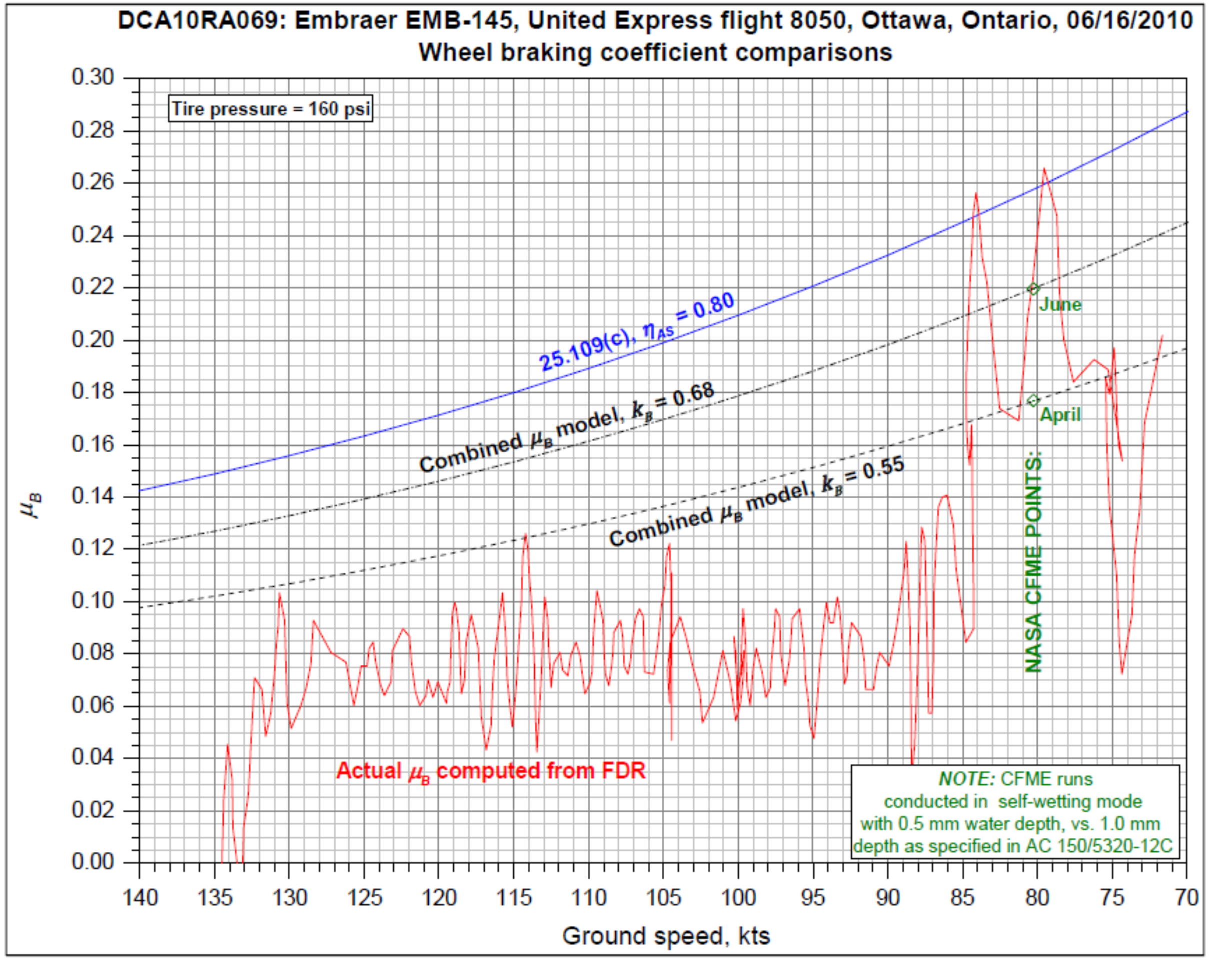


Figure 15. μ_B comparisons for the United Express flight 8050 accident in Ottawa, Ontario, 06/16/2010.

NTSB Recommendations (Condensed)

- Work with industry to develop technology to outfit aircraft to **routinely calculate, record, and convey the aircraft braking ability** during the landing rollout

- If the above is shown to be feasible, work with airlines and system manufacturers to develop procedures to ensure that braking ability results can be **readily conveyed to, and easily interpreted** by anyone with a safety need for that information

- **Perform flight tests** on representative domestic and international runways to validate the wet-ungrooved and wet-grooved wheel braking coefficient models in Section 25.109(c) and (d)

Research Questions

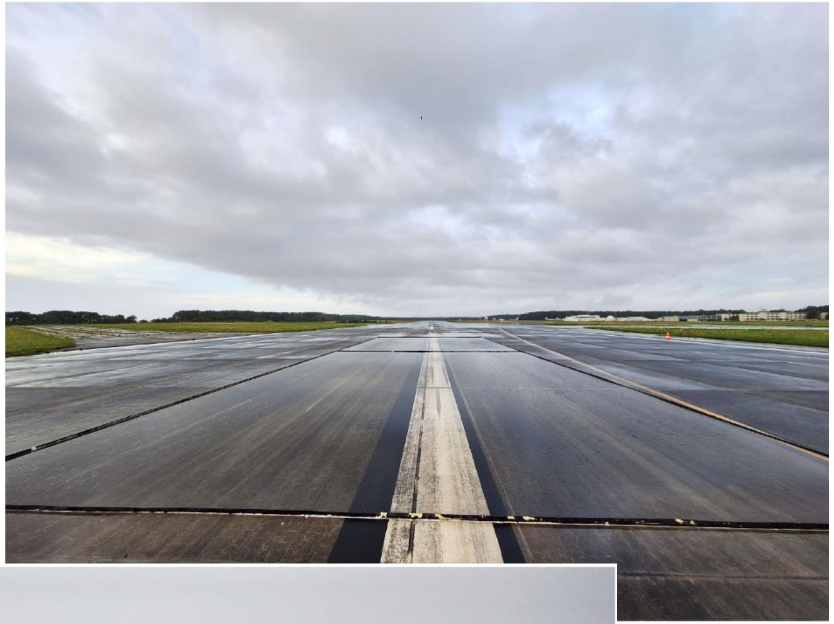
- **Braking availability depends on many different factors** including:
  - Ground speed (indirect relationship)
  - Tire inflation pressure (indirect relationship)
  - Rainfall intensity/water depth (indirect relationship)
  - Pavement texture/grooving (direct relationship)

- **Understanding:** What is the relative effect of different factors on friction and braking availability? Under what conditions does braking availability significantly diminish?

- **Application:** Is it possible to predict braking capability and provide such information to flight crews and airport operators prior to touchdown?

Flight Testing Activities

- Purpose: **acquire high-fidelity data to determine the contributing factors** for significantly reduced braking and understand the underlying physical principles
- **Collaborated with the Netherlands Aerospace Centre (NLR)** to perform flight tests at NASA Wallops using their Cessna Citation test aircraft (Summer 2023)
- Findings: **FAR 25.109 wet runway braking models overestimated friction values** found during flight testing
  - Models only valid for **lower water depths**, which may not hold in heavy rain and/or on un-grooved runways
  - Models only valid for a **sharp, harsh microtexture**



Why machine learning? (Why not flight testing?)

Time: **Flight testing takes a lot of time** to plan, coordinate, and execute, especially in a government setting without access to a readily available aircraft

Effort: **Flight testing involves many moving parts** and collaboration with multiple groups

Money: **The costs of everything involved in a flight test add up**, which can make flight testing very expensive

Risks and safety: The logistics of flight testing can get very complicated, **increasing the risk of something going wrong**

Flight testing is a very beneficial practice, but it may not be the answer for aircraft braking research

Machine Learning for Aircraft Braking Research

- **Explored the use of machine learning techniques** to complement flight testing efforts and gain deeper insights into the issues at hand

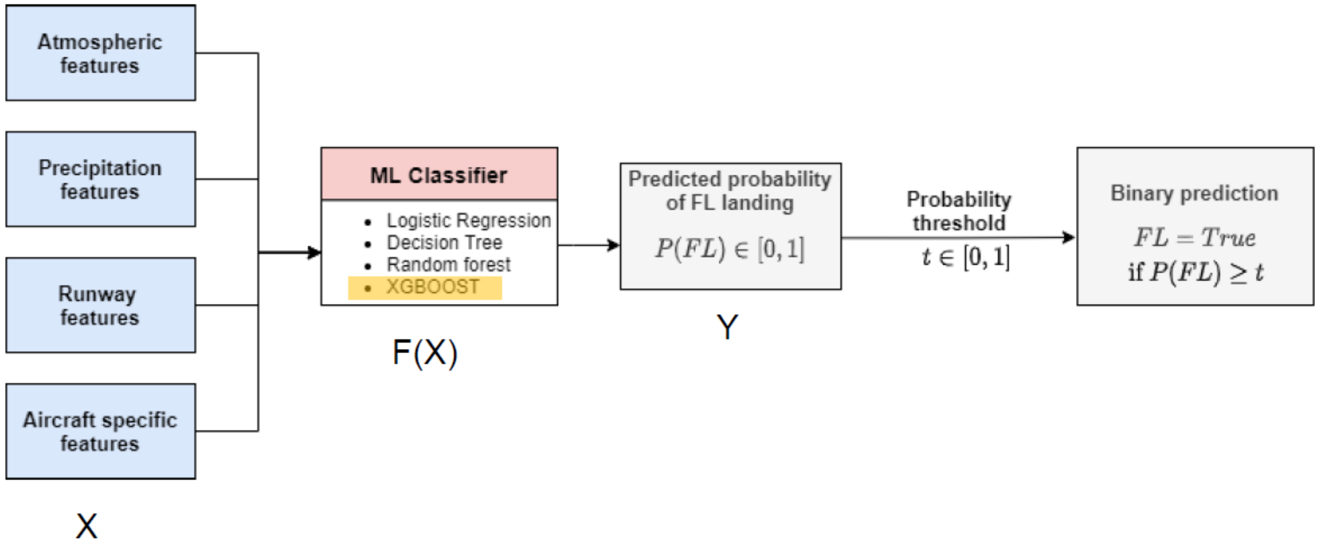
- **Premise:** use readily available data (aircraft, weather, field condition reports, pilot braking action reports, etc.) to identify degraded braking cases, determine contributing factors and conditions, and predict when degraded braking may occur in the future

- **Worked with two academic partners:** MIT (using AST data) and Georgia Tech (using flight data)

Georgia Tech

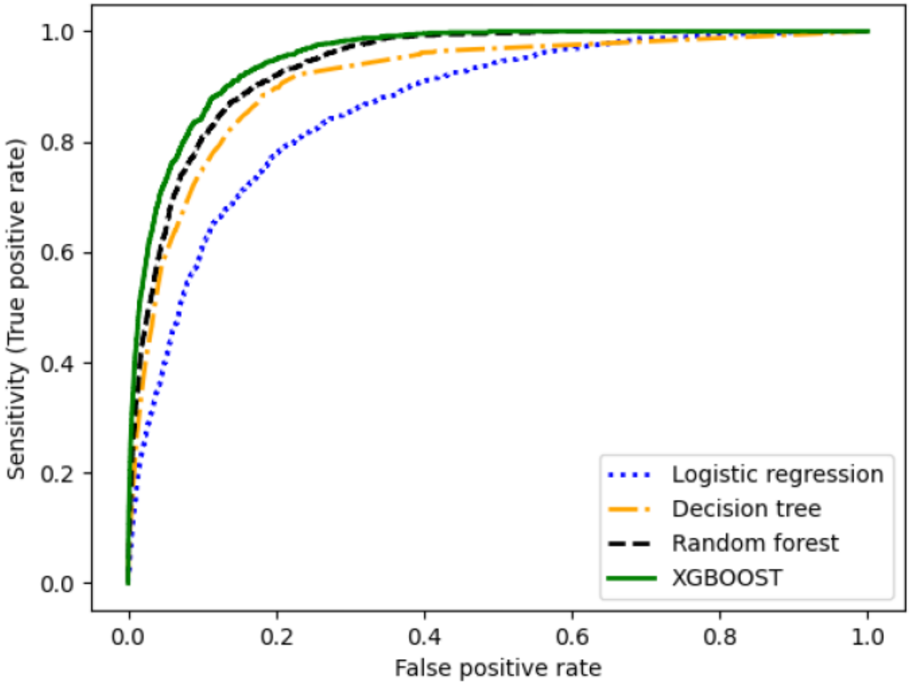
Machine Learning Effort with MIT

- Used data from **Aviation Safety Technologies (AST)**
  - 4.9 million recorded landings, of which 8,693 were “friction-limited” (0.18% of total)
  - **Labeled as either “friction-limited” or “not friction-limited”**
  - Also included weather/precipitation information, aircraft information, airport/runway information, and friction measurements, among other things
- Machine learning models were trained to **map input features to the probability of a given landing being friction-limited**



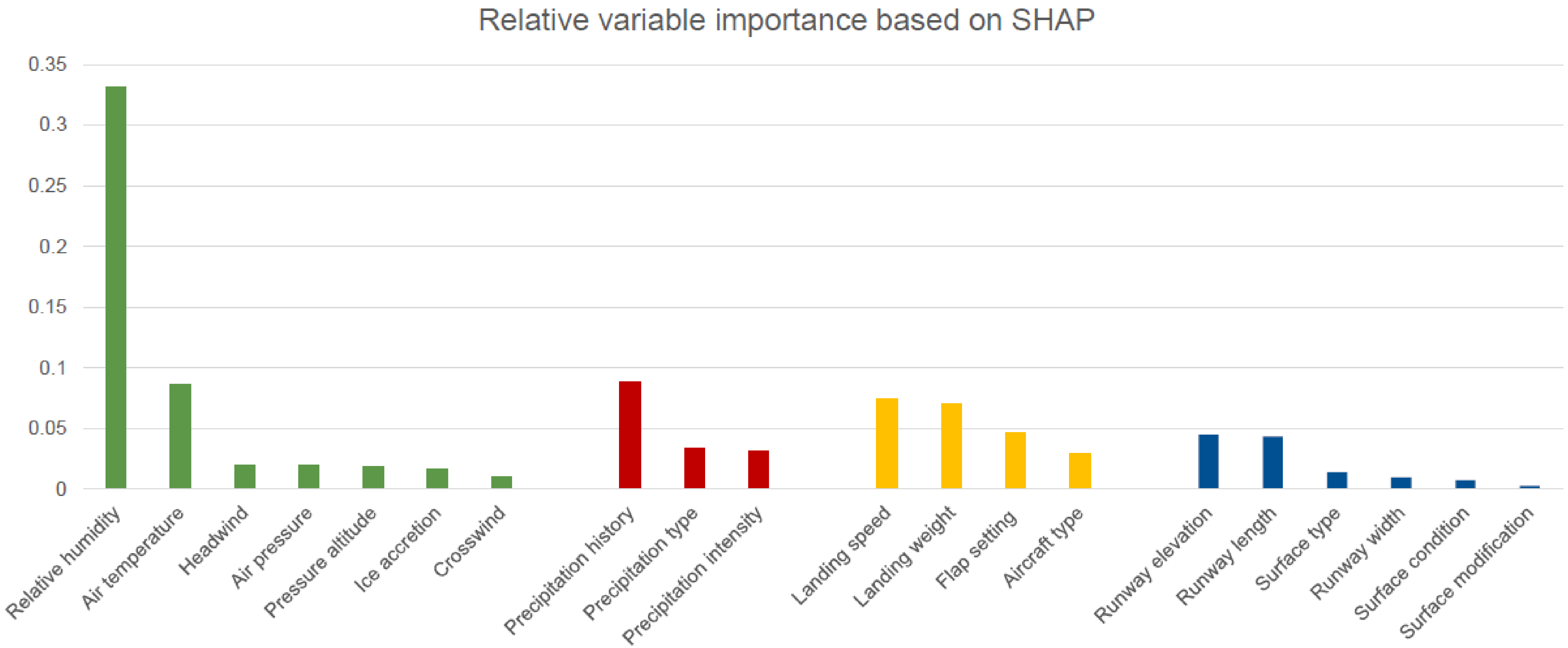
Machine Learning Models

- **Four different models were tested** using the AST data
- The **AUC value** was used as a metric to evaluate the performance of the models
- The **XGBOOST model performed the best** with the highest AUC



MODEL	AUC
Logistic Regression	0.863
Decision tree	0.912
Random forest	0.939
XGBOOST	0.958

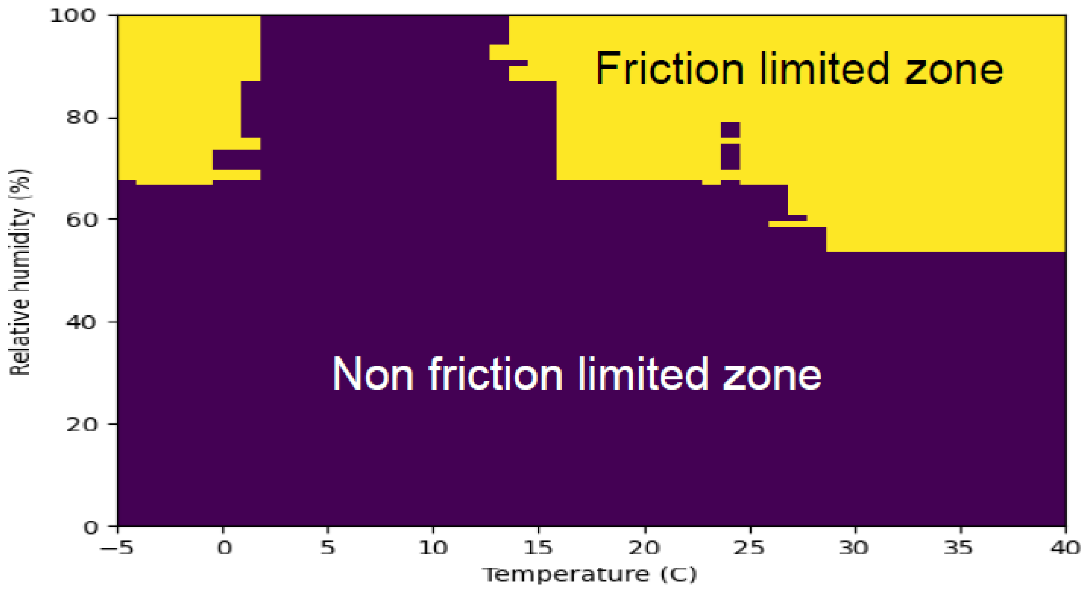
Feature Importance Provided by XGBOOST



Decision Plots

- Visualizations were created of **decision boundaries** for a given runway if certain conditions are held constant
- Example to the right:
  - Constant runway information (surface, length, width)
  - Given weather information (precipitation, wind, pressure)
  - Sampled relative humidity and temperature

Decision plot – yellow indicates friction limited
- i.e. with P(FL) > 0.01



Conclusions from MIT Work Using AST Data

- Machine learning classifiers show remarkable performance in detecting friction limited landings **when "truth" data is available**

- XGBOOST flagged **63% of friction limited cases** with only 2.8% false alarms

- Model can also be used to assess **runway maintenance practices** and flag possible issues

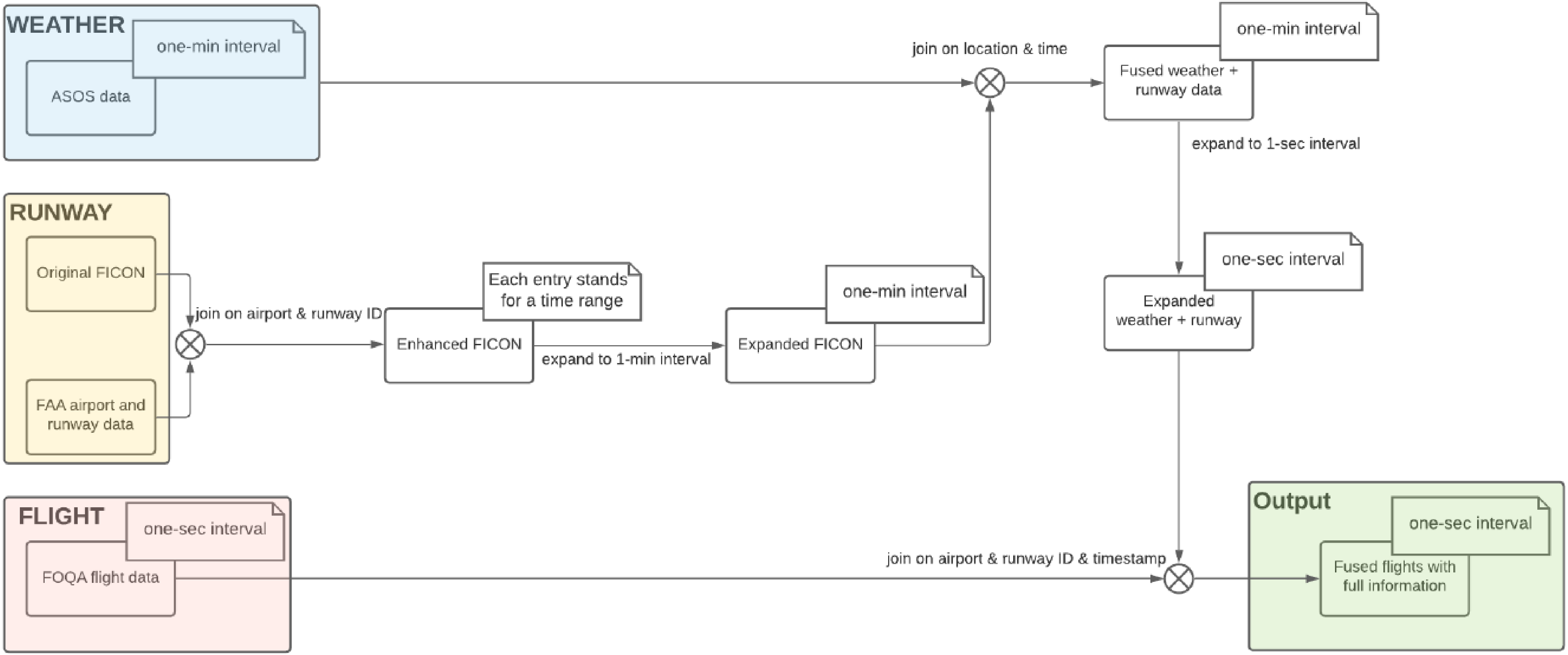
Machine Learning Effort with Georgia Tech

- **Used flight data from partner airlines**, and fused with weather data, runway data, and other relevant data sources

Objectives:

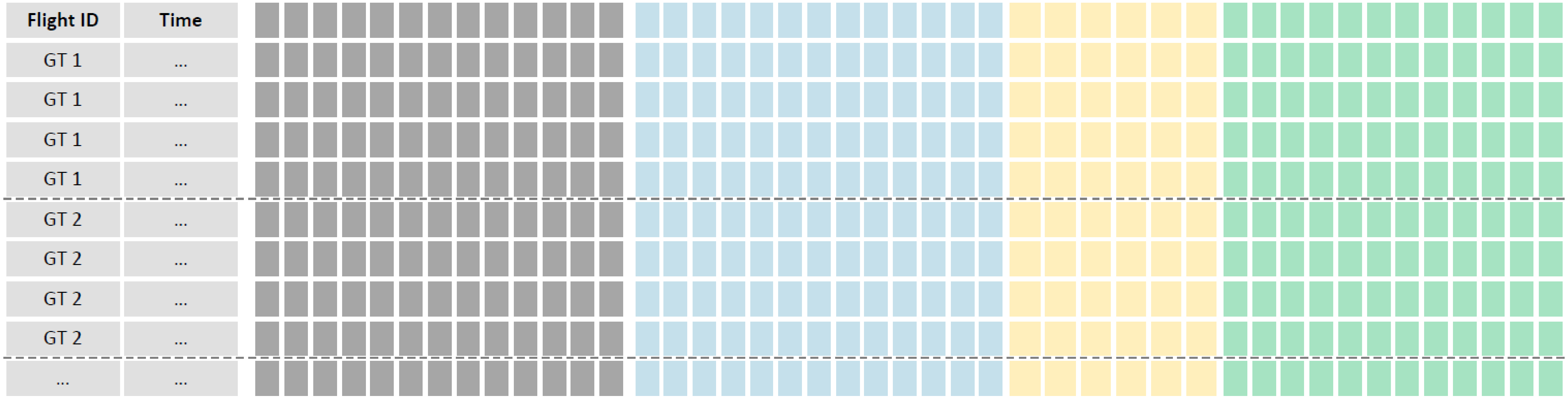
- Use **unsupervised learning to identify degraded braking cases** from normal landings
- Use **supervised learning to build models to predict** when degraded braking may occur given known conditions
- **Identify critical parameters/conditions** in degraded braking circumstances

GT Data Fusion Pipeline



Data Fusion Output

The final output of the data fusion has the following structure:



11,620 flights in total

Flight Data (130 columns)

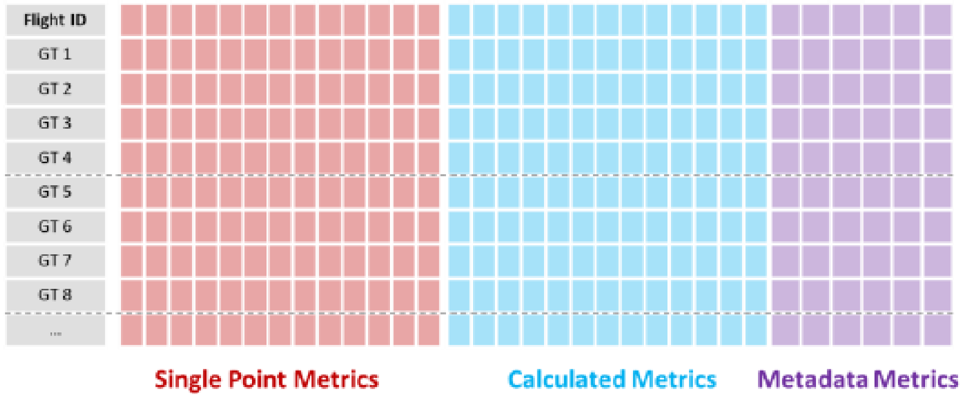
ASOS Weather Data (15 columns)

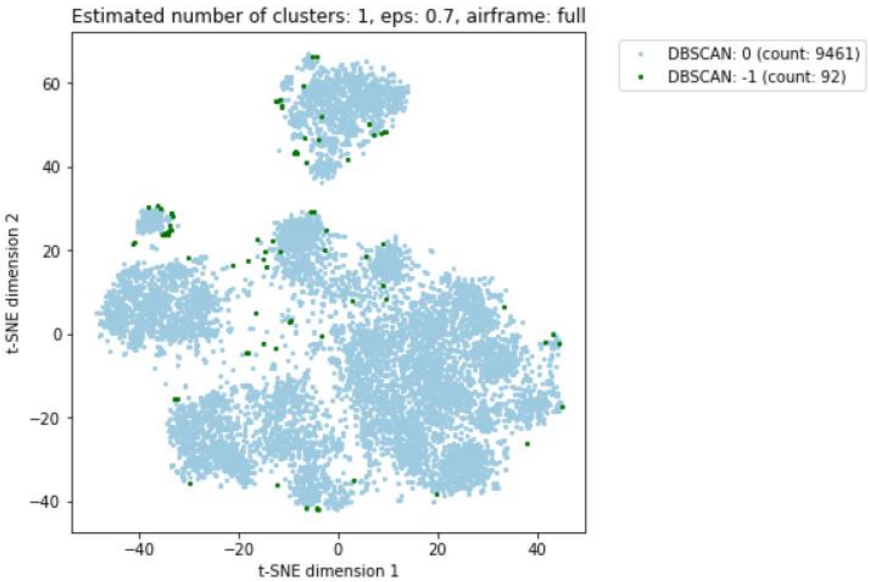
FICON Data (6 columns)

FAA Runway Data (12 columns)

Unsupervised Learning

- Prior to beginning unsupervised learning, **metrics of interest were defined** and calculated for assessing the braking performance of aircraft on non-dry runways
  - Single point metrics (e.g., ground speed)
  - Calculated metrics (e.g., speed bleed off during flare)
  - Metadata metrics (e.g., aircraft type)

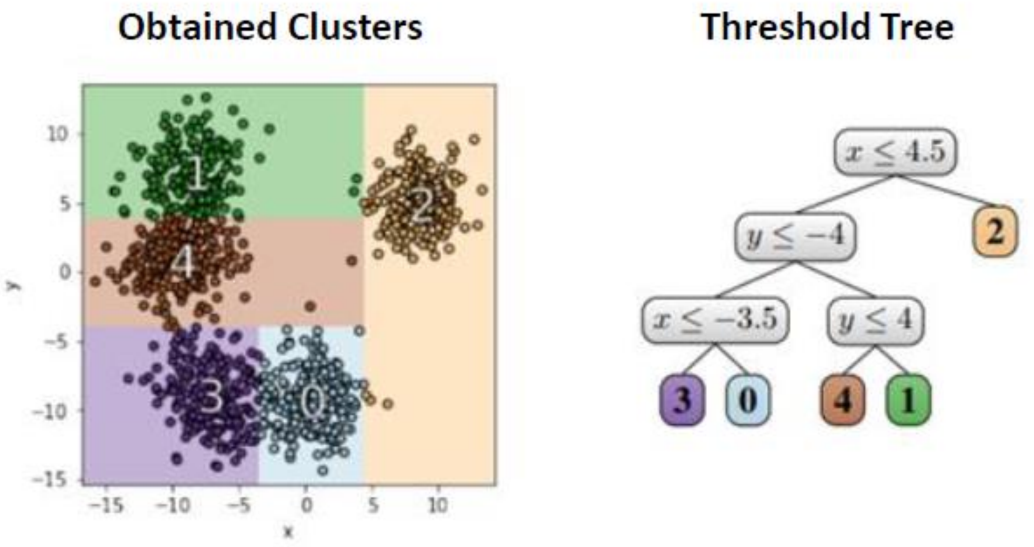




Supervised Learning

- Following the unsupervised learning analysis, **multiple clusters of the data were formed**
  - Each cluster was given an ID, and so the **ID served as the label** for the supervised learning analysis

- **Decision trees were fit to the clustering results** to better understand how the clusters were formed



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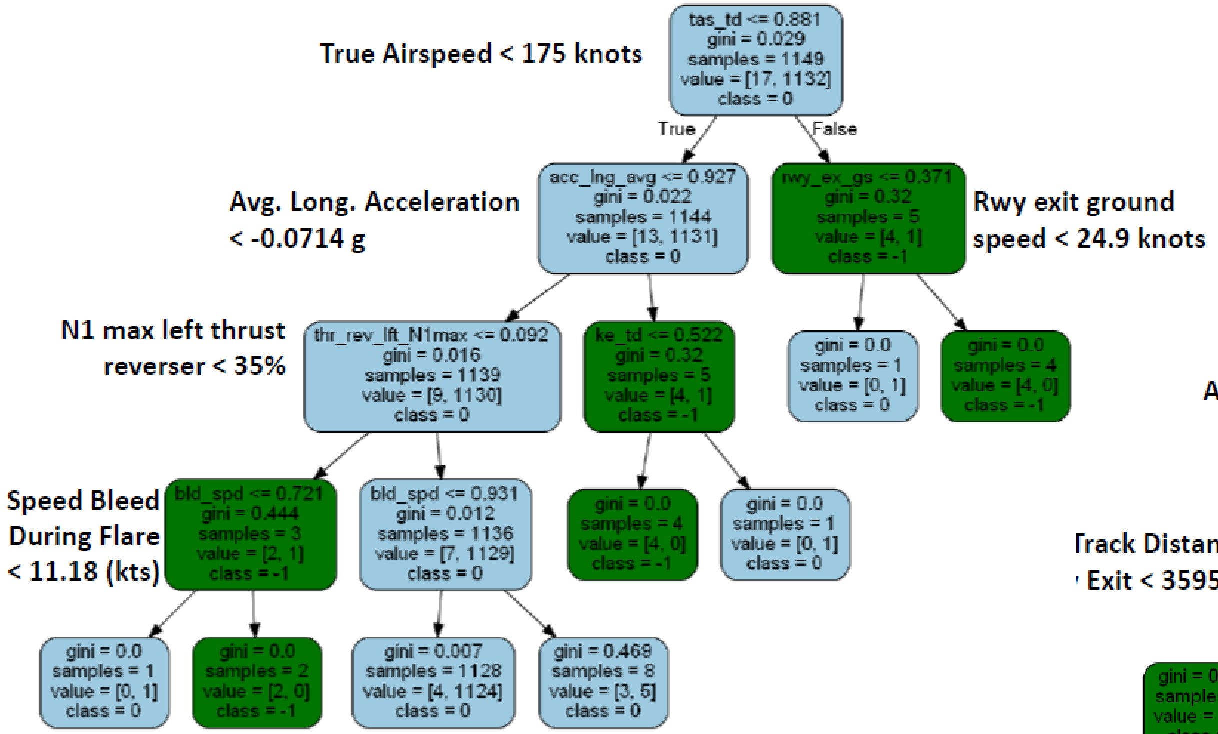
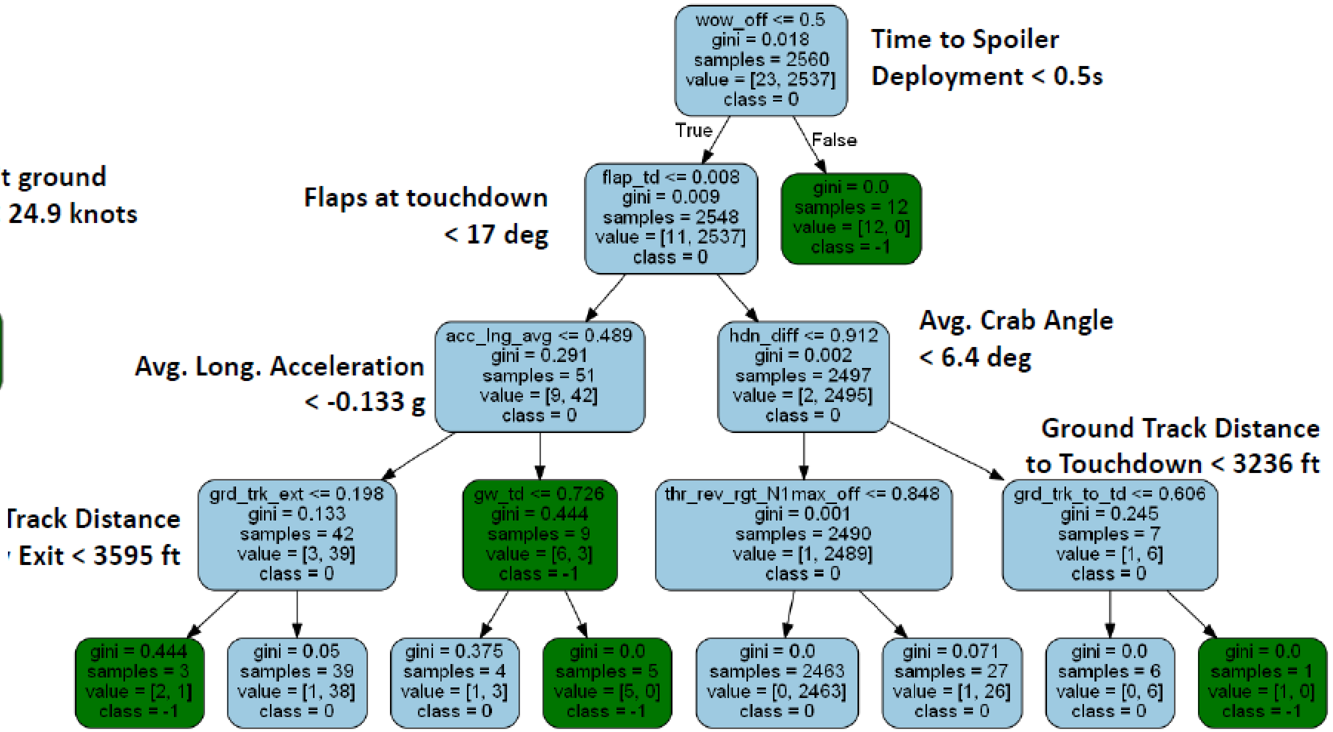
Supervised Learning Results

Decision Tree for Narrow Body Variant 1



Decision Tree for Narrow Body Variant 2



Conclusions from Georgia Tech Work

- Overall, the **decision tree shows high correlation between landing performance and identified outliers**

- Flight conditions before touchdown are shown to have some contribution to landing performance

- Unsupervised and supervised machine learning methods proved to be sufficient in identifying interesting outliers from a landing performance perspective, but **not sufficient to model degraded braking**

- The biggest challenge to the successful use of flight data is the **availability of friction limited data or the ability to apply labels** to the existing datasets

Overall Conclusions

- Contaminated runway braking research is **inherently complex and very multidisciplinary**

- As the limits of air travel are being pushed, **certain assumptions regarding braking performance on non-dry runways may not hold true** in modern operating conditions, motivating the need to reassess and potentially update current models

- Although flight testing is very beneficial overall, it has **proved to be challenging in this domain due to the time, effort, costs, and risks involved**

- **It is possible to gain significant insights using machine learning methods**, however, challenges remain when data is limited and/or not labeled

Thank you for listening!

Questions?

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