USTRANSCOM Flight Data Analysis

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Problem Statement

Our capstone project was in collaboration with MIT Lincoln Laboratory (MIT LL) whose mission is to develop technology in support of national security. Our project was part of the Laboratory's program sponsored by the United States Transportation Command (USTRANSCOM) – an organization responsible for providing global transportation to Department of Defense (DoD) missions. In particular, we focused on analytics to support air refueling operations. We sought to answer the following question:

How can USTRANSCOM use their flight data to promote mission effectiveness?

Air Refueling and Maintenance Issues

Air refueling refers to the in-flight transfer of fuel from one aircraft to another aircraft. The Air Force uses air refueling to extend the range of aircraft, such as fighters and bombers, so that they can accomplish their missions. For our capstone project, we had access to flight and maintenance data for the KC-135. The KC-135 is one of the Air Force's oldest operationally active aircraft being first used in the summer of 1957. Most of these KC-135 aircraft have over 20,000 flying hours (see Figure 2). Improving the ability to foresee aircraft maintenance issues would help prevent unscheduled maintenance and thereby increase availability and readiness of the KC-135 fleet.

Figure 1. KC-135 Aerial Refueling

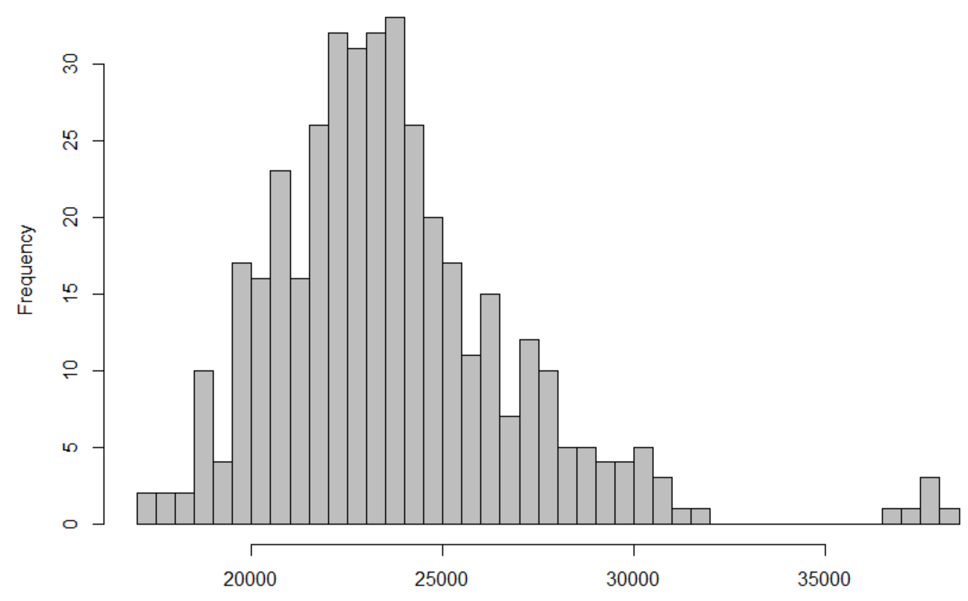


Figure 2. Distribution of KC-135 Cumulative Aircraft Hours.

Analytics Capstone Timeline

The timeline below represents an outline of the capstone process over the past year.

- Jan: Begin work with capstone partner company
- Feb: Introduction to problem and dataset
- Mar: Data exploration and initial modeling
- May: Start of summer capstone experience
- Jun: Model implementation and detailed data analysis
- Jul: Refine and test models, feature engineering and selection
- Aug: Complete modeling and present final results

KC-135 Flight and Maintenance Data

There were two primary datasets that we used in our analysis – maintenance data and flight data.

Maintenance Dataset

Tail Number	CalendarDate	Training	HoursFlown	SortiesFlown	CumulativeAirframeHours
34	1/7/2018	0	2.5	1	22000
67	3/5/2018	0	0	0	23000

We had access to a maintenance dataset for the KC-135 fleet covering a time frame from January 2017 through April 2018. The maintenance data provides, among other features, a daily accounting of the mission capability status for each tail: mission capable (MC), not mission capable (NMC), in depot, or unknown.

Flight Record File

Flight Record	Date-Time at Liftoff	Tail Number	Ground Track Distance during Entire Flight (nm)	Total Fuel Burned during Entire Flight including Ground Ops (lbs)
1	1/7/2018 6:46	34	900	26000
2	3/5/2018 8:33	67	1700	54000

All aircraft have a flight data recorder that tracks multiple parameters over the course of a flight, for instance, time, location, fuel, distance, etc. Our flight dataset included data for 26,169 KC-135 missions across 396 unique tails that occurred between November 2017 and November 2018.

Individual tail numbers and dates were matched to the correct corresponding flights to merge the datasets.

Merged Flight Maintenance Dataset

Tail Number	CalendarDate	CumulativeAirframeHours	Unscheduled_Maintenance
34	1/7/2018	22000	0
67	3/5/2018	23000	1

Feature Engineered Variables

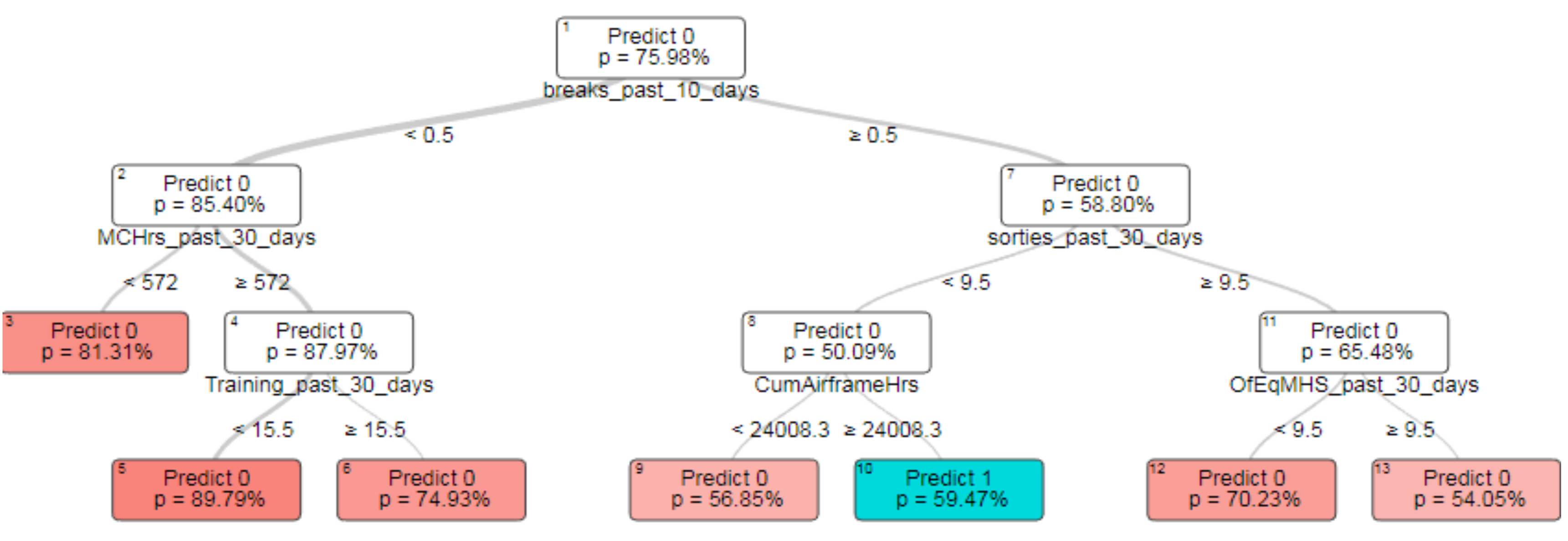
hours_flown_past_30_days	breaks_past_10_days	sorties_past_30_days
15	3	4
32	3	6

After merging and adding additional engineered historical aircraft performance features, the end result was a dataset with 9,517 flight observations and 39 flight performance variables. The final response variable was conditioned as a binary value: 1 if the aircraft received unscheduled maintenance on that particular day, and 0 otherwise.

Machine Learning

Using six machine learning models, we predicted when an aircraft is most likely to experience an unscheduled maintenance event given previously defined flight performance metrics.

Figure 3. Optimal Classification Tree from final model.



The optimal classification tree model shows that an aircraft that has had any breaks in the last 10 days, has flown less than 10 times in the last month, and has more than 24,008 accumulated flying hours has a 60% chance of breaking down on its next flight. Therefore, these results should cause concern for aircraft crew that may be dealing with flight profiles that fit these characteristics.

Results and Impact

A comparison of the six different machine learning methods and their corresponding accuracy metrics are shown in the table below.

Method	AUC	Test Accuracy	True Positive Rate	False Positive Rate
Random Forest	0.7580	79.08%	20.98%	2.54%
Xgboost	0.7480	78.87%	19.76%	2.43%
Logistic Regression	0.7318	77.61%	20.80%	4.48%
SVM	0.7145	78.61%	20.80%	3.10%
OCT	0.7139	76.89%	17.66%	4.26%
CART	0.7064	77.61%	17.31%	3.60%

Table 1. Model performance comparison.

A useful metric for quantifying the impact of our model is the number of total unscheduled maintenance hours converted to scheduled maintenance. For the entire dataset, there were 348,818 total hours of unscheduled maintenance performed on the 398 aircraft. Using the top performing machine learning models, we were able to correctly identify 21% of the unscheduled maintenance occurrences. Therefore, over the course of one year, USTRANSCOM could convert up to **58,253** hours of unscheduled maintenance to scheduled maintenance.

Conclusions and Next Steps

- USTRANSCOM should use this model to anticipate unscheduled maintenance occurrences.
- Unscheduled maintenance events are historically difficult to predict, but the best machine learning models catch 21% of these occurrences. This allows USTRANSCOM to anticipate up to 58,253 hours per year of maintenance events that were previously unscheduled.
- For future work, MIT LL should look at other flight data parameters including information from other maintenance logs, and they can also incorporate individual flight level variables.