Predictive Modeling of Turbofan Engines

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BACKGROUND

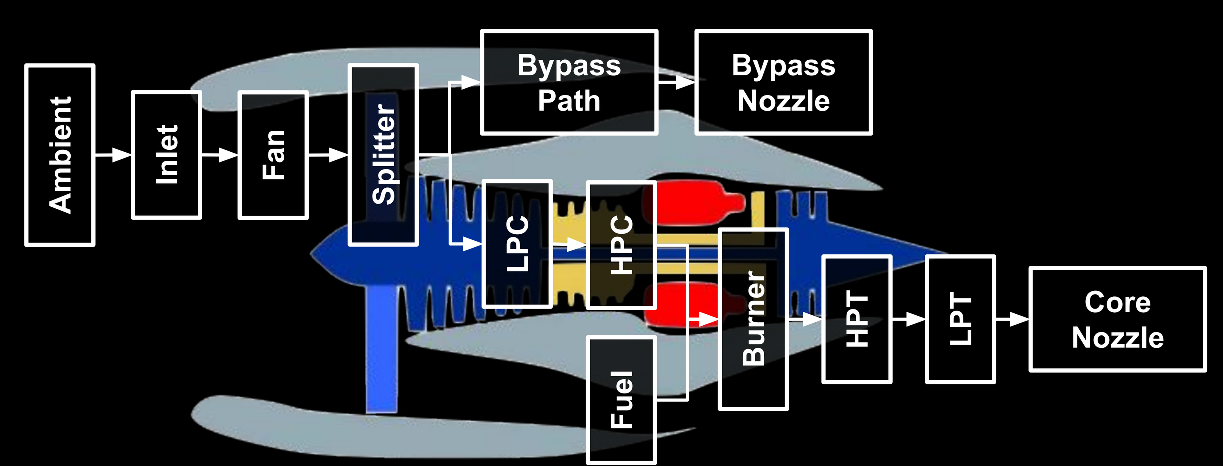
GOAL

- Predict remaining useful life (RUL) of engines
  - RUL indicates when a component requires repair or replacement and measures time until failure
- By accurately predicting RUL, Raytheon can proactively schedule maintenance and reduce any costs associated with repairs and unnecessary servicing

DATA

Dataset	Train	Test	Condition	Fault Mode
1	100	100	Sea Level	HPC Degradation
2	260	259	Above Sea Level	HPC Degradation
3	100	100	Sea Level	HPC and Fan Degradation
4	248	249	Above Sea Level	HPC and Fan Degradation

- Four simulated NASA datasets of engine sensors over time
  - Multiple multivariate time series
    - 3 operational settings and 21 sensors
      - Include temperature, rotation speed, pressure, etc.
  - Calculated RUL using cycle



METHODOLOGY

Preparing Data
- Calculated RUL using Cycle
- Standardized

Variable importance
- Identifies key predictors

Dimension reduction (PCA)
- Simplifies modeling
  - Last 5 and 120 data points

Predictive Model Types
1) Survival Analysis (SV)
   a) good for time-to-failure data
2) Decision Trees (TR)
   a) captures non-linear relationships
   b) easily interpretable
3) Neural Network (NN)
   a) LSTM uses both current and historical data

Final Results
- Interactive GUI
- Model recommendations

- Model success measured by using the validation data and comparing the actual RUL scores to the predicted.

VARIABLE IMPORTANCE

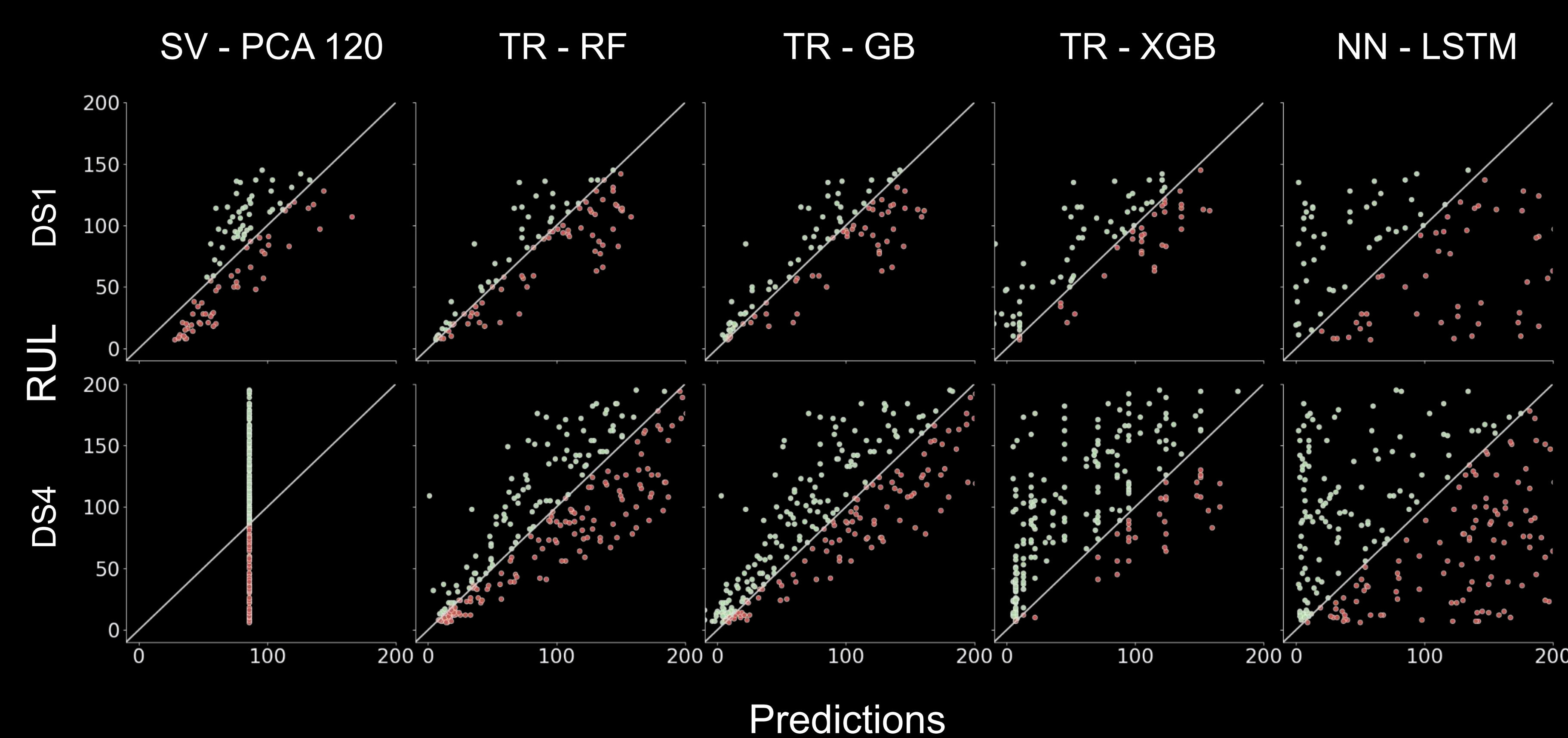
- Methods used to measure variable importance and understand engine component breakdown or failure included:
  - Principal Component Analysis (last 5 cycles and last 120 cycles)
  - Lasso Regression
  - Tree-Based Methods (random forest, gradient boost, and extreme gradient boost)
- The most important engine components across all six techniques were: HPC, LPT, Fuel, and Core Nozzle

Engine Component Importance According to Number of Methods

# of Methods	Dataset 1	Dataset 2	Dataset 3	Dataset 4
6	HPC • Fuel • Core Nozzle	HPC • LPT	HPC • Fuel • Core Nozzle	HPC • LPT
5	LPT	Fuel	LPT	Bypass Path
4	Bypass Nozzle	Fan • Bypass Nozzle	Fan	Inlet • Fan • Fuel
3		Inlet • Bypass Path • LPC • Core Nozzle		Bypass Nozzle • Core Nozzle
2	HPT	HPT	Inlet • Bypass Nozzle • HPT	HPT
1	Fan	Burner	Bypass Path • LPC	LPC • Burner

*HPC: High Pressure Compressor, LPC: Low Pressure Compressor, HPT: High Pressure Turbine, LPT: Low Pressure Turbine

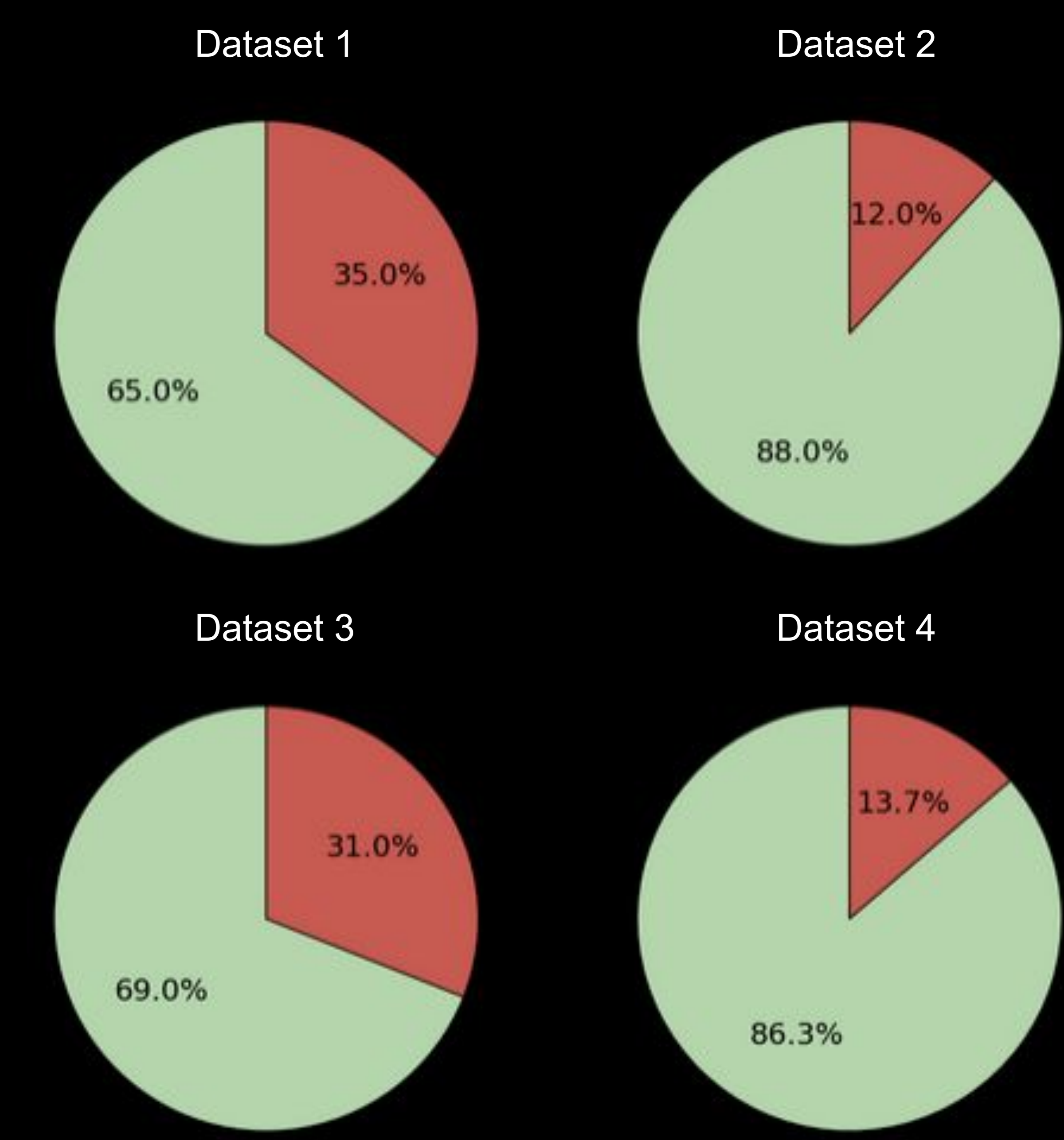
MODEL PERFORMANCE



- Each cell of the grid above shows the predicted RUL versus actual RUL
  - Points above the line were predicted successfully
  - The Survival Analysis model using the PCA120 variables performed the best out of the survival analysis models
  - The XGBoost model performed the best out of the gradient boost models
    - The Gradient Boost model follows the line but overpredicts RUL

CONCLUSION

Prediction Performed for XGBoost Over Datasets



- Results of our exploratory analysis:
  - All engines can be assigned to the correct dataset using predictions from a classification tree
    - This means the best performing model may be selected given an engine with unknown conditions
  - The Tree methods performed the best under all conditions
- Deliverable:
  - A graphical user interface (GUI), allowing users to compare different results across model types and datasets
- Limitations:
  - Simulated data
  - Lack of information surrounding the engine data
  - Time, as our project was confined to Spring 2024

FUTURE GOALS

- Create a regular maintenance schedule based on predictions and actual failure rates
- Optimize batching of engines
  - How many should be kept in reserve based on failure rates?
- Determine which engine components appear to be failing first based on the sensors
- Investigate what makes certain engines more difficult to predict

ACKNOWLEDGEMENTS

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The Data Mine Corporate Partners Symposium 2024