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RUL ML

POWERING PREDICTIVE MAINTENANCE

- Dinush De Alwis
- GitHub: ddealwis09
- Repo: Remaining_Useful_life

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MEET THE TEAM

Dinush De Alwis

President and CEO
Lead MLE

Dinush De Alwis, President and CEO of RUL ML™ has background in machine learning (0-1 years) and has led start up RUL ML™ for about 4 months.

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SOME DEFINITIONS…

- Predictive Maintenance:
  - Predictive maintenance works by collecting and analyzing data from sensors and other sources, such as historical maintenance records, to identify patterns and trends in equipment performance.
    - develop predictive models that can forecast when a failure is likely to occur.
    - schedule maintenance activities at the most opportune times or replacing components before failure
    - reduce maintenance costs and improve equipment reliability
    - minimize the risk of unplanned downtime and the associated costs of lost productivity

- Remaining Useful Life (RUL):
  - RUL is the estimated time that a machine or component can continue to operate reliably and without interruption.
  - in the current context, the DOD has defined it to be the number of remaining flights an aircraft can take before requiring maintenance.

WHY

IMPORTANCE

So important is predictive maintenance, the U.S Department of Defense's joint artificial intelligence center has designated predictive maintenance as one its two founding national mission initiatives (NMIS).

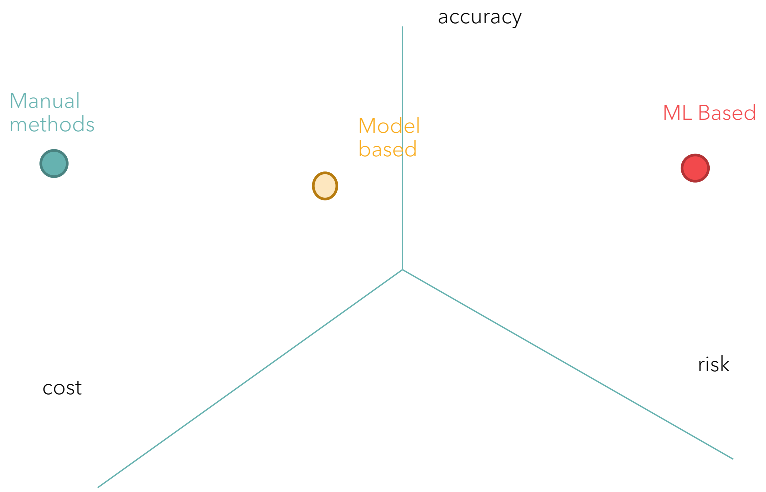
CURRENT STATE

The current methodologies can be labor intensive, highly expensive and don't scale well.

- Manual evaluation by engineering and maintenance teams
- Model based methods require high levels of domain knowledge and significant simplifying assumptions that may not fit reality

MACHINE LEARNING

An ML approach can resolve each of these pain-points or provide a great supplementary tool. The extent of using ML models for predictive maintenance will come down to risk tolerance, asymmetric downside evaluation and even political traction.



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WHY AN ML APPROACH

Scale

One turbo fan engine health evaluation requires 2-3 maintenance engineers

Speed

One turbo fan engine health evaluation can take 3-21 days

Cost

Costs for engine evaluation on one engine can range from 300k – 20M USD

DOWNSTREAM EFFECTS

MANUAL PROCESS

Requires labor intensive involvement by engineering and maintenance teams to evaluate engine health, as well as significant domain knowledge.

COSTS

Higher labor costs, inventory costs, and most importantly, possibly even loss of life associated with field operations.

FIELD OPERATIONS

Critical missions cannot be put at risk, delayed or interrupted by engine failures.

ENGINEERING & MAINTENANCE

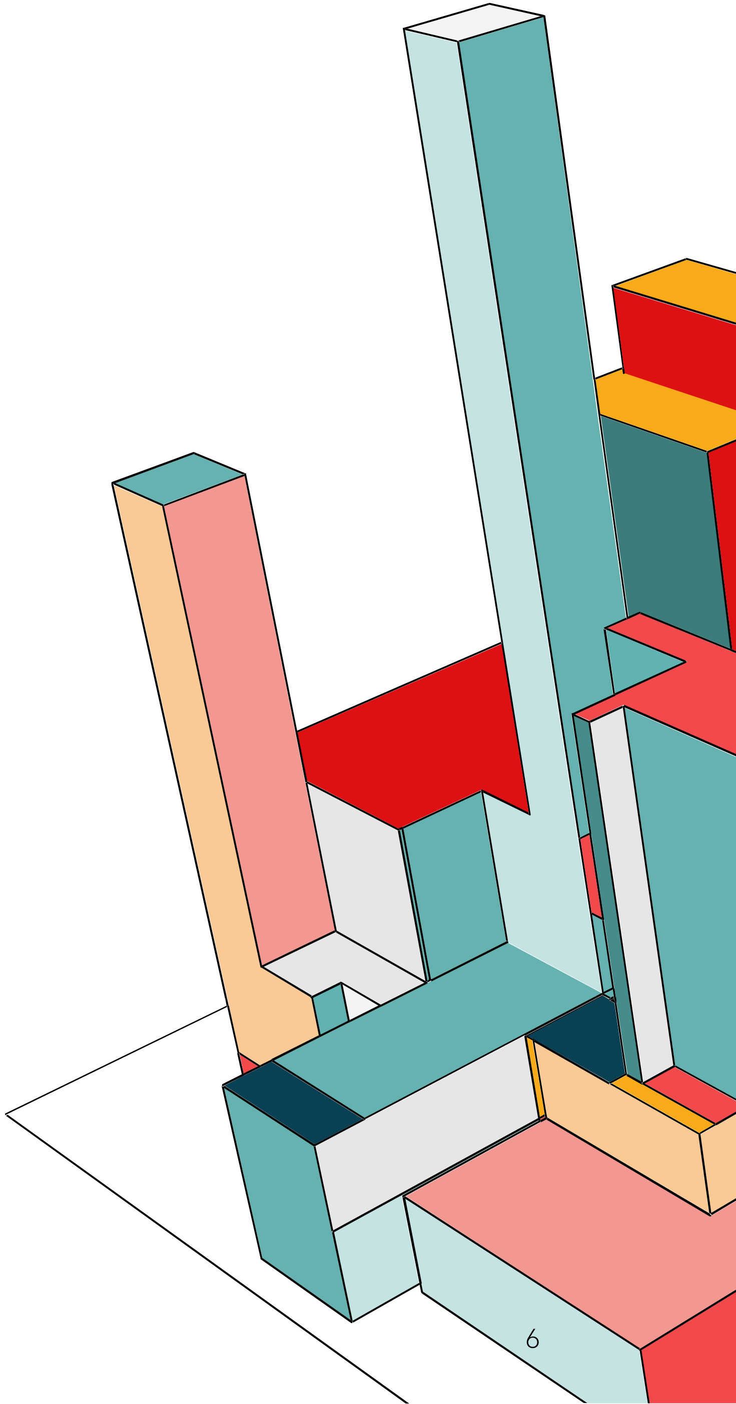
Need better prediction models that can be generated at scale over hundreds or thousands of engines quickly. Edge cases can then be evaluated manually.

SUPPLY CHAIN

Need better stock management, part replacement and speed to operations

FINANCE

Need more reliable predictability associated with cash-flow and future costs

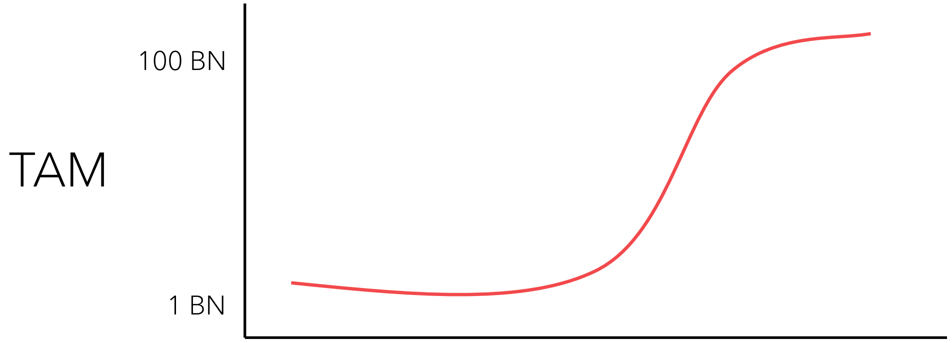


TAM

- Although we do foresee a future whereby large slow moving organizations (such as the DOD's maintenance engineering) slowly creep toward increased risk tolerance as AI and ML gain public and political traction, we are pragmatic about ML based solutions penetrating this sector over the next 5-10 years.

- For these organizations we see our solution as a supplementary tool that may speed up engine health maintenance rather than replacing the status quo, but later accelerating with wider public adoption of AI and ML.

- Therefore we see our TAM taking a classical new product growth profile over the next 10-15 years. We have modelled the market size of ML based solutions for predictive maintenance under a Gompertz curve, whereby the TAM grows from around <u>1BN now to over 100BN in 10-15 years</u>.



OUR SOLUTION

RUL ML

POWERING PREDICTIVE MAINTENANCE

PRODUCT OVERVIEW

EXPLORE

Analyse engine and sensor relationships in simple to to use interface. Evaluate trends and anomalies.

PREDICT

Upload sensor readings across an unlimited number of engines for RUL predictions in seconds.

SIMULATE

Move a particular sensors readings to simulate the impact on RUL for a single engine.

RETRAIN

If the model's performance begins to drift from expectations or underlying conditions change, retrain the model in under 30 minutes to optimize its parameters and features.

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RUL ML™ AT A GLANCE

ML BACKGROUND

A little background on our research and production model

SYSTEM DESIGN

Our tech stack and tools

DEPLOYMENT

Our POC easy to use and deploy web app

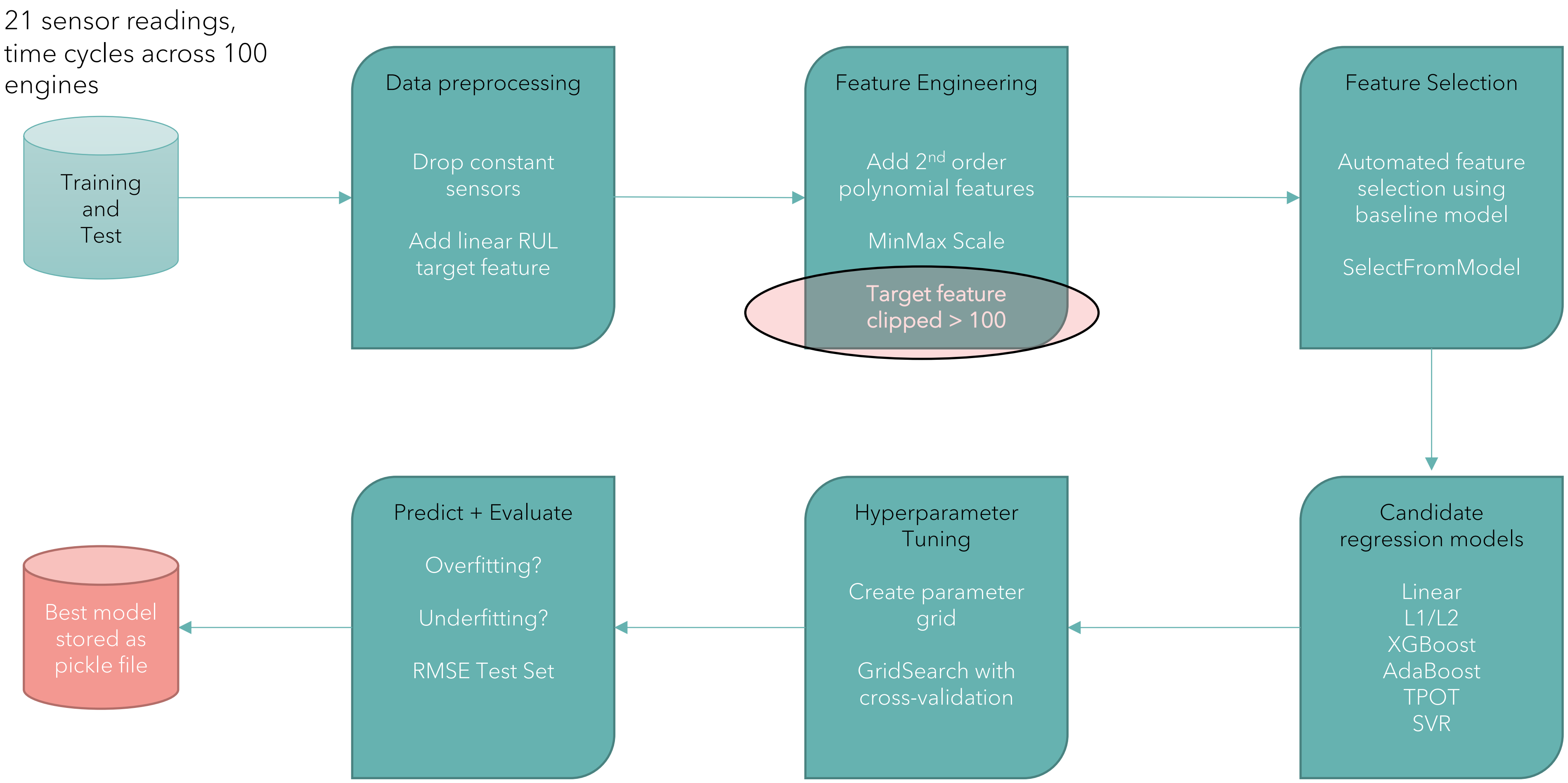
THE TRAINING DATA

Two sources are available for the datasets:
1.Kaggle: https://www.kaggle.com/datasets/behrad3d/nasa-cmaps/code
2.NASA: https://www.nasa.gov/intelligent-systems-division#turbofan

The dataset consists of three separate text files (training, test, RUL) for four different fleets. We consider only the first fleet in our training process (FD001 e.g. F16).

- contains 100 different turbo fan engines and timed cycle readings for 21 sensors for each.
- does not however provide the label (i.e. remaining useful life) at each cycle, therefore a degradation assumption needs to be made.

MODEL PIPELINE



MODELLING RESULTS

Regression Model	Test Set RMSE
Linear	21.33
Ridge (L1)	21.15
Lasso (L2)	21.87
Random Forest	23.73
XGBoost	24.83
TPOT	22.45
SVR 🥉	20.05

MODEL EXPLAINABILITY

One drawback of machine learning models is that they are inherently difficult to explain in terms of causality, i.e. what is the theoretical rationale for their parameter outputs in relation to the target response. Our best approach to help turbofan engineers and maintenance teams understand predictions made by our model is to provide both a 'global' explanation and a 'local' one

GLOBAL

- how a model makes decisions for the overall structure
- the suitability of the model for deployment
- In our case, how does the SVR model work, how were the hyperparameters calculated and what assumptions did we make in training

LOCAL

- how the model makes decisions for a single instance
- explain the individual predictions
- In our case, for a single set of sensor readings, what sensors were the most influential in determining the prediction the SVR model made

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MODEL EXPLAINABILITY: ELI-5

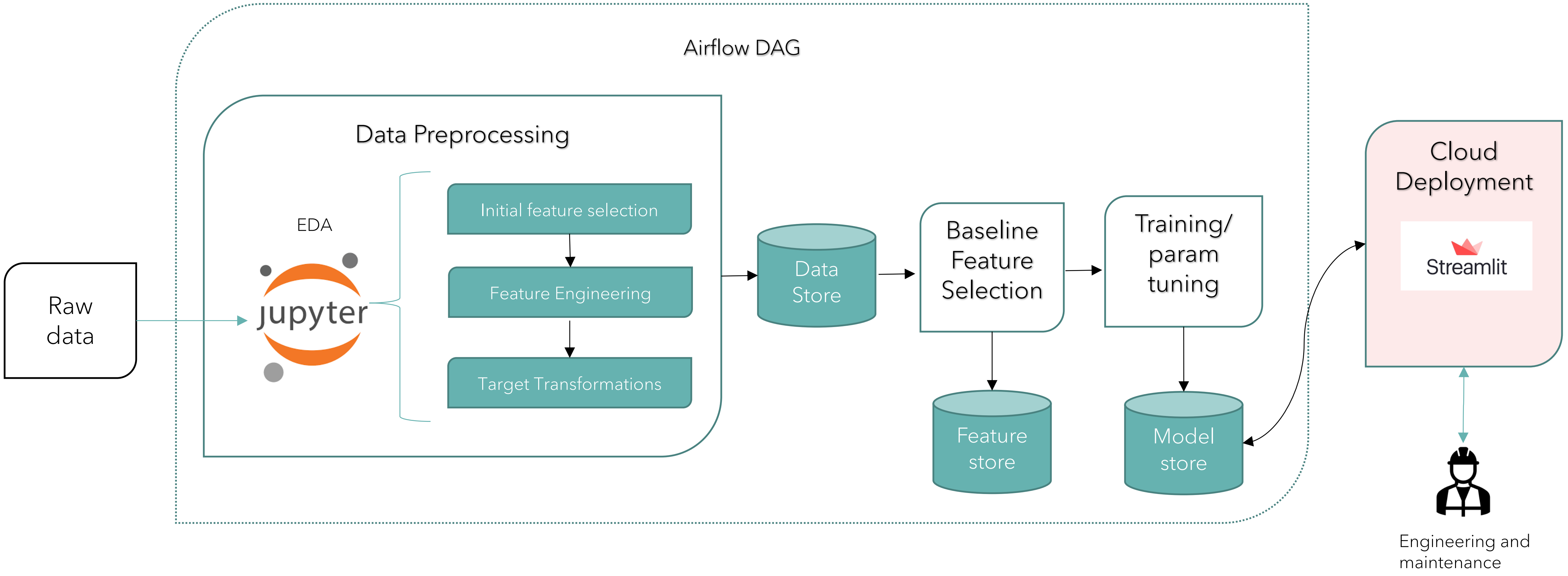
```
perm = PermutationImportance(grid_search.best_estimator_, scoring = 'neg_root_mean_squared_error' ,
                             random_state=101).fit(X_test_final, rul)
show_weights(perm, feature_names = list(X_test_final.columns))
```

Weight	Feature
1.0769 ± 0.4678	s_9
0.9339 ± 0.4084	s_12
0.8909 ± 0.6048	s_7
0.8679 ± 0.3072	s_2 s_4
0.8281 ± 0.7192	s_2 s_11
0.8232 ± 0.5218	s_11 s_17
0.7860 ± 0.3752	s_4 s_15
0.7320 ± 0.4025	s_11 s_15
0.7289 ± 0.3962	s_11
0.6712 ± 0.4483	s_3 s_11
0.6677 ± 0.2597	s_4
0.6228 ± 0.4584	s_14
0.5231 ± 0.2448	s_4 s_11
0.5041 ± 0.4417	s_21
0.4857 ± 0.4049	s_20
0.3831 ± 0.3075	s_4 s_13
0.3648 ± 0.1629	s_4 s_8
0.3406 ± 0.2097	s_13 s_15
0.3250 ± 0.2330	s_8 s_11
0.2917 ± 0.0916	s_11 s_13
… 26 more …	

- A *permutation importance* method, whereby the model's scoring changes with the feature in existence or not.
- High positive Eli-5 scores mean the feature is of importance relative to other features
- Interpretation of the Eli-5 score with respect to sensor reading impacts on RUL will be easier for maintenance and engineering teams.

- Not currently embedded in ML RUL™ app but will be in next release

SYSTEMS DESIGN AND TECH STACK



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DEPLOYMENT AND DEMO

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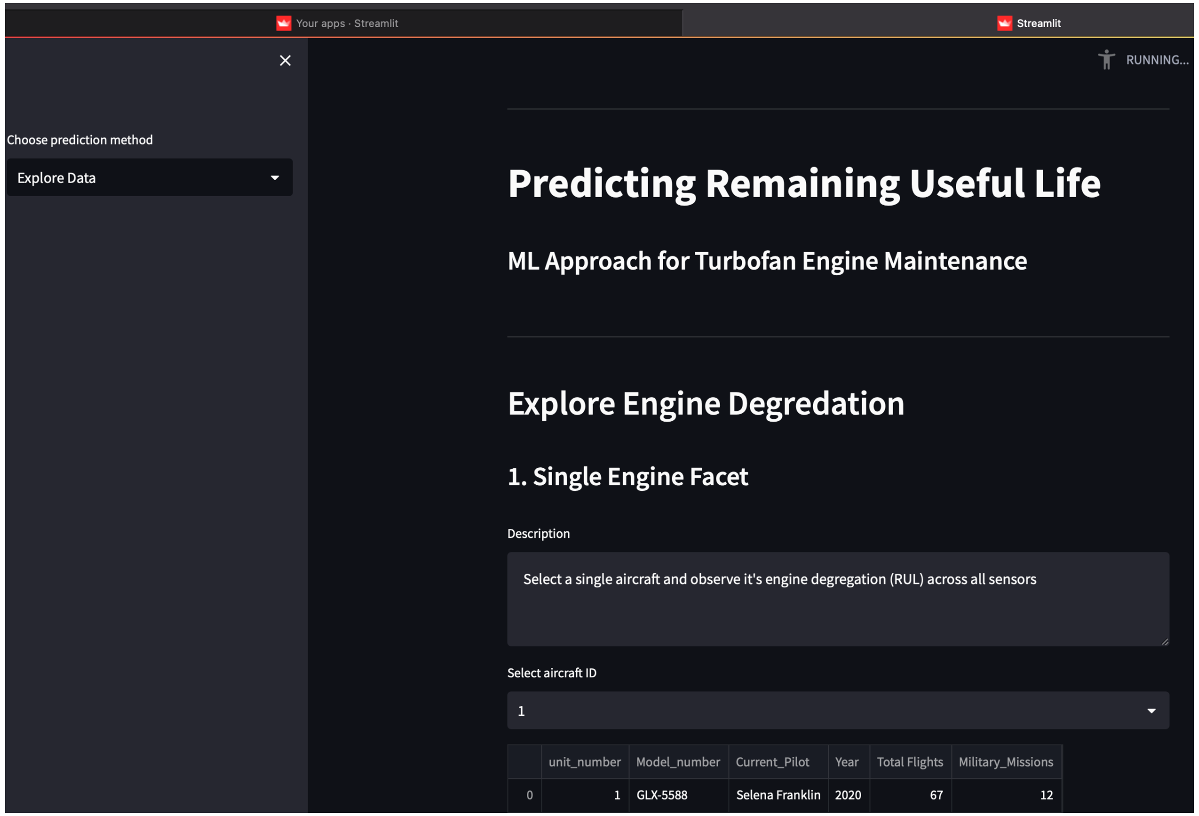


FEATURE SHIPMENT PIPELINE

How we plan to enhance RUL ML™ in the future

DEEPER ANALYTICS

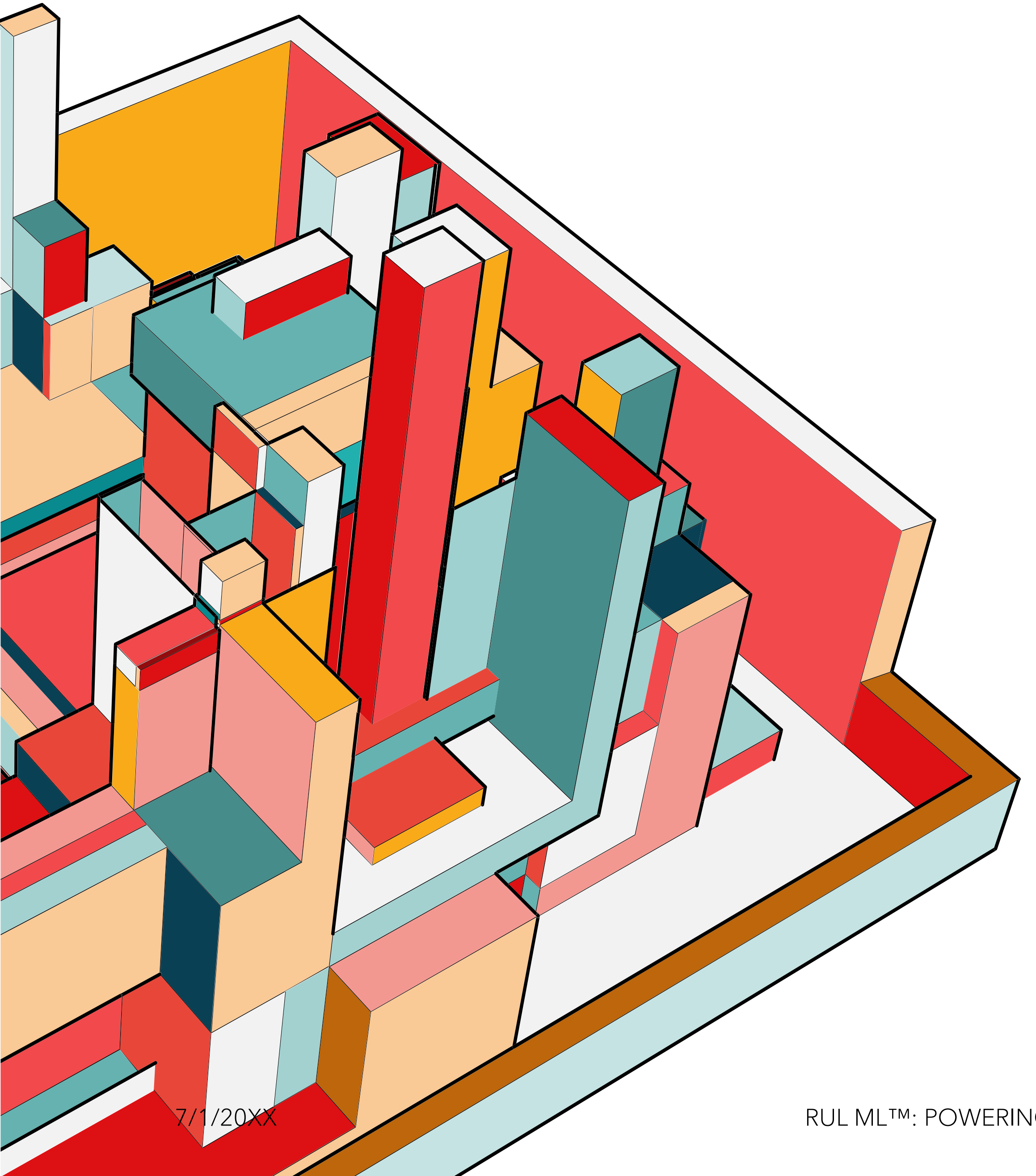
More analytics for users to explore relationships of sensors to RUL; dimensionality reduction visuals

MORE MODELS

We plan to improve our Airflow DAG to run training on multiple models including deep learning models as well as a classification model to assess failure probabilities

BETTER CLOUD + API SOLUTION

The next release will contain a backend FastAPI and be hosted on AWS



SUMMARY

At RUL ML™ we believe in the power of machine intelligence to power real business use cases. Our solution will directly improve the DOD's' ability to improve turbofan engine maintenance, which will have many downstream benefits across multiple departments. We look forward to powering your predictive maintenance needs at scale.

THANK YOU

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