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PHM2024 Data Challenge

Estimating the health of turbine engine based on the relationship between torque margin and density altitude

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Team: goldriver

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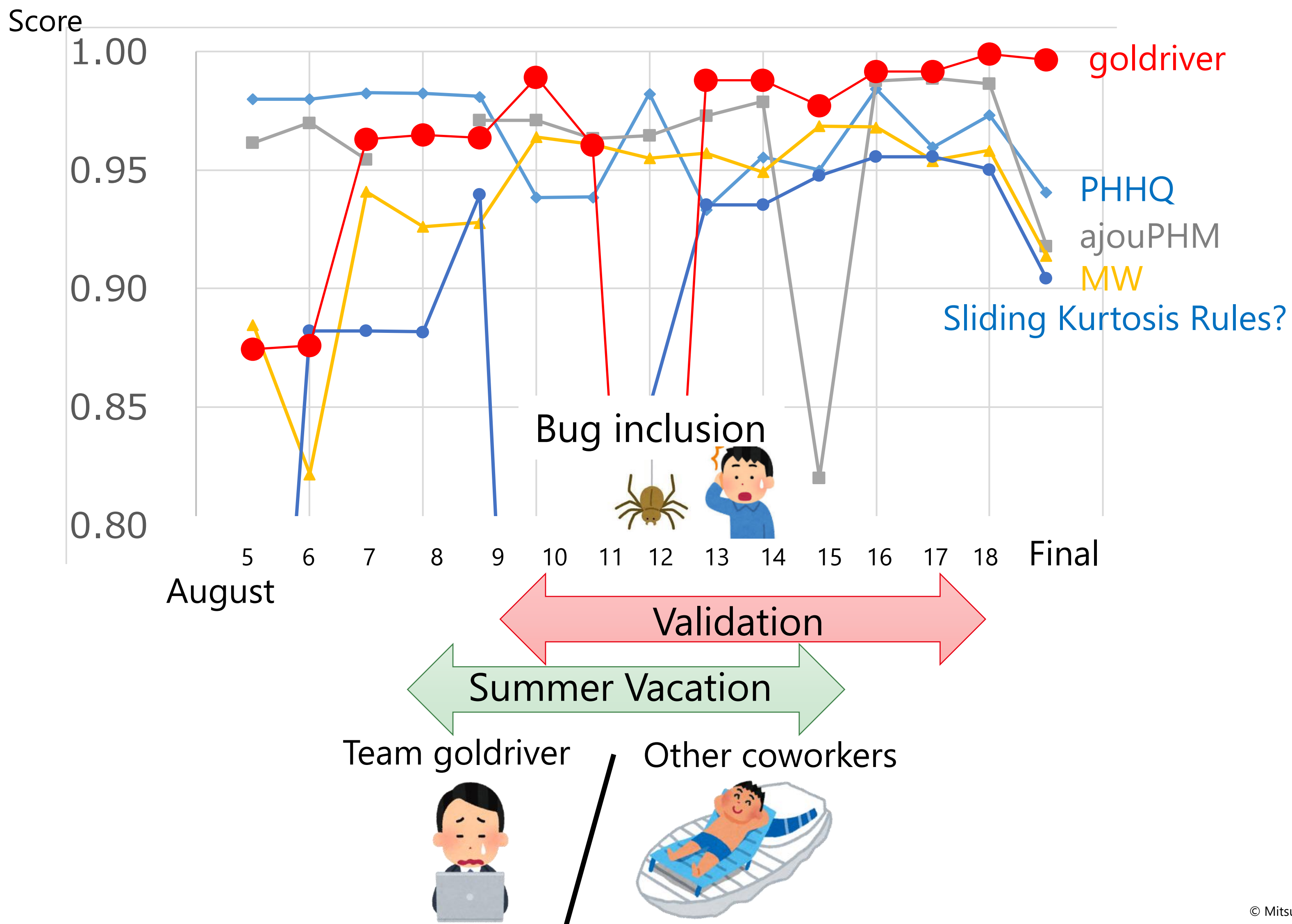
Why the team goldriver managed to score high?

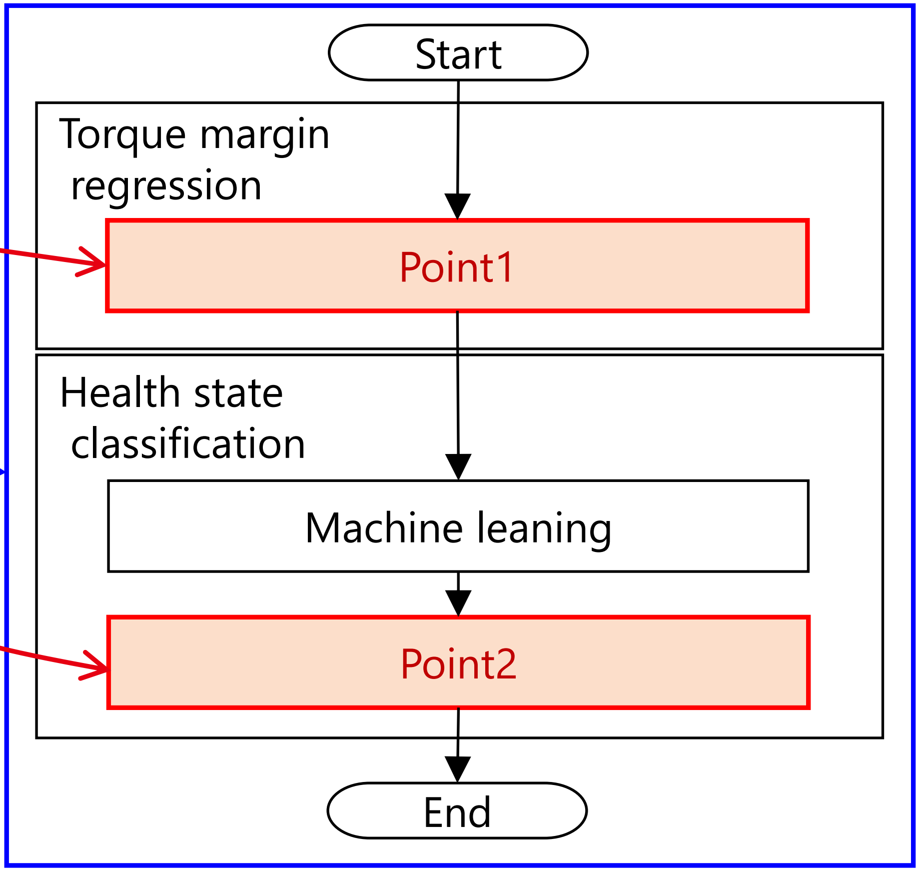
- The validation period was during our summer vacation, but we tackled this data challenge very hard.
- We would be very very happy if the validation period did not include mid-August in next time :-P)



OUTLINE

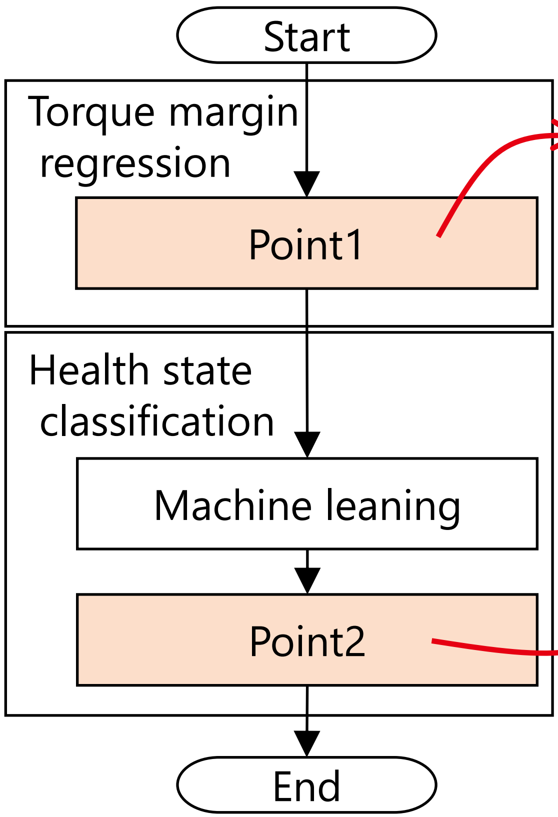
- OUR SOLUTION
  - Overview
  - Torque margin regression
    - Point1
  - Health state classification
    - Point2
- PROPOSED ALGORITHM
  - Probability estimation
- EVALUATION
- RESULTS AND DISCUSSION
- CONCLUSION

Our solution &
Proposed algorithm



OUR SOLUTION Overview

The key points of our proposed method are as follows:



Key point	**Explanation**
Point1: Using "torque target" as regression target	• From the relationship among variables, we realized that the torque target is determined by the physical conditions.
Point2: Focus on data continuity and density altitude (da)	• We estimated the assets of the dataset from the continuous changes in the data in the scatter plot. • We applied rule-based processing based on the relationship between torque margin and density altitude.

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OUR SOLUTION Torque margin regression

Point1: Using torque target as regression target (1/3)

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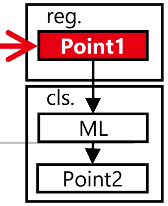
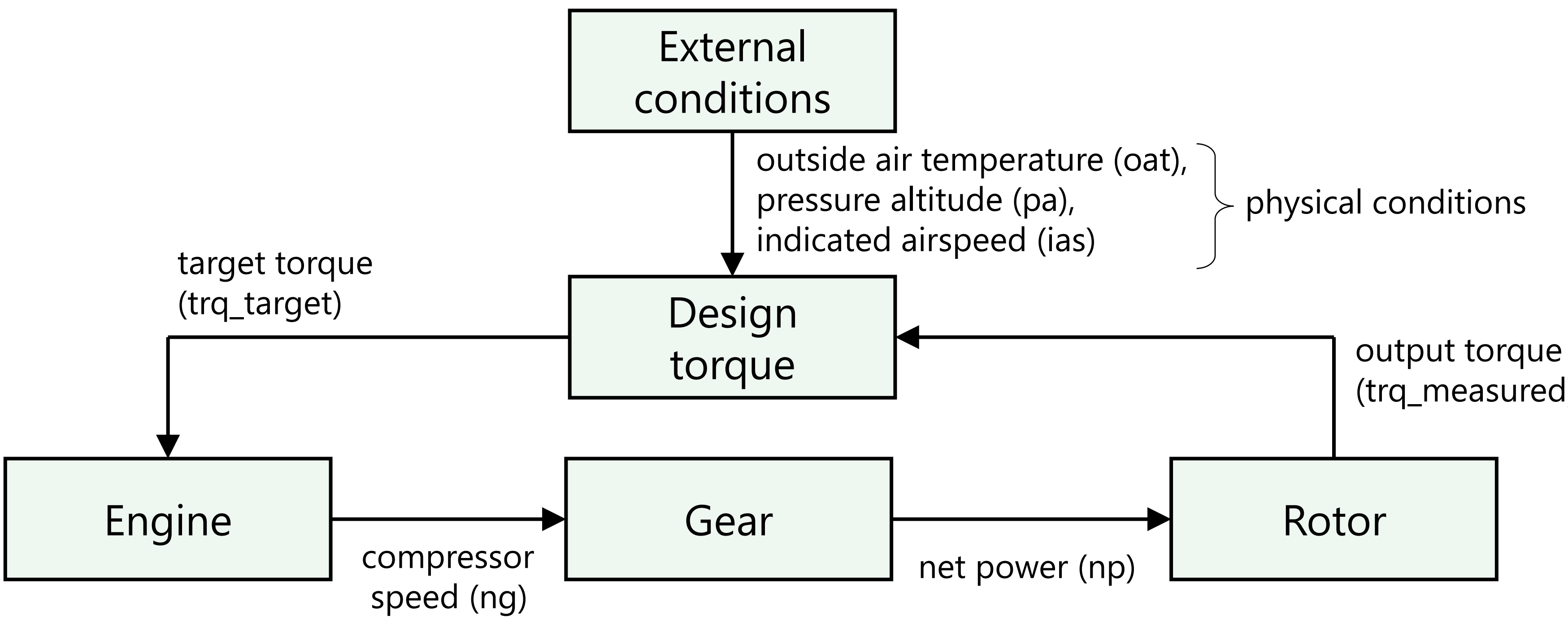


- Based on the literature survey, we assumed that the explanatory variables have the following relationship.
  - Pilots operate helicopters by adjusting the engine output according to external conditions, and by managing the output torque and propeller rotation speed.
  - The target torque is determined by physical conditions such as outside air temperature (oat), pressure altitude (pa) and indicated airspeed (ias).



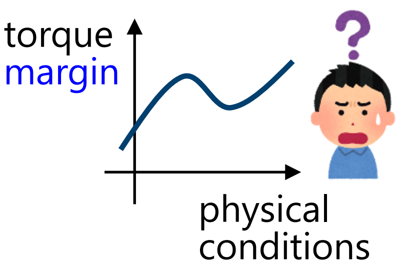
The relationship among explanatory variables

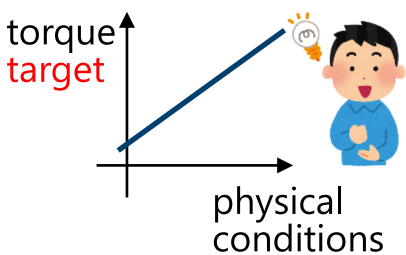
OUR SOLUTION Torque margin regression

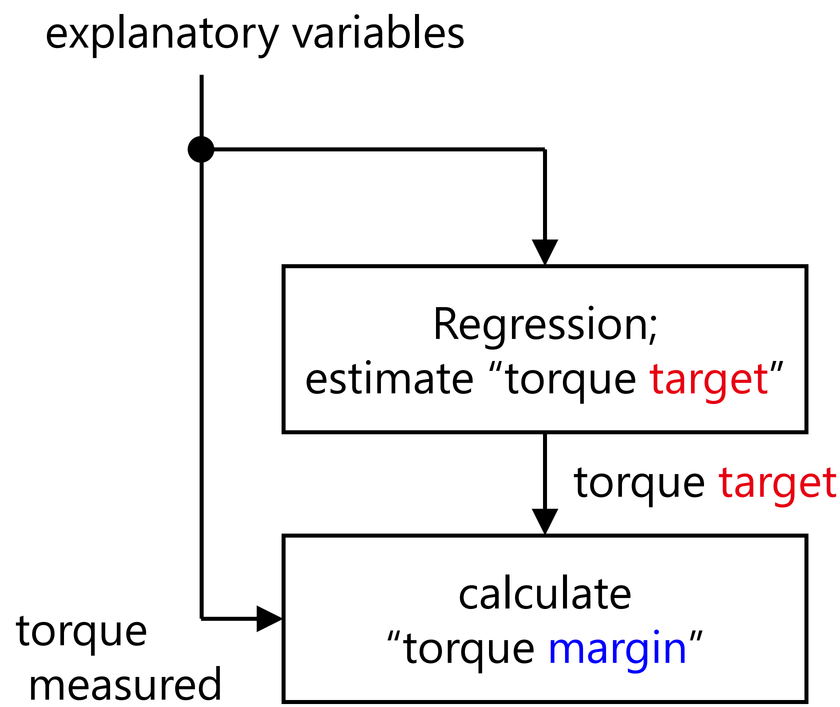
Point1: Using torque target as regression target (2/3)

The “torque target” is determined by physical conditions.

It is more accurate to estimate the “torque target” rather than the “torque margin” from explanatory variables such as physical conditions.







torque margin calculation formula

$$\mathit{trq\_margin} = \frac{\mathit{trq\_measured} - \mathit{trq\_target\_pred}}{\mathit{trq\_target\_pred}} \times 100$$

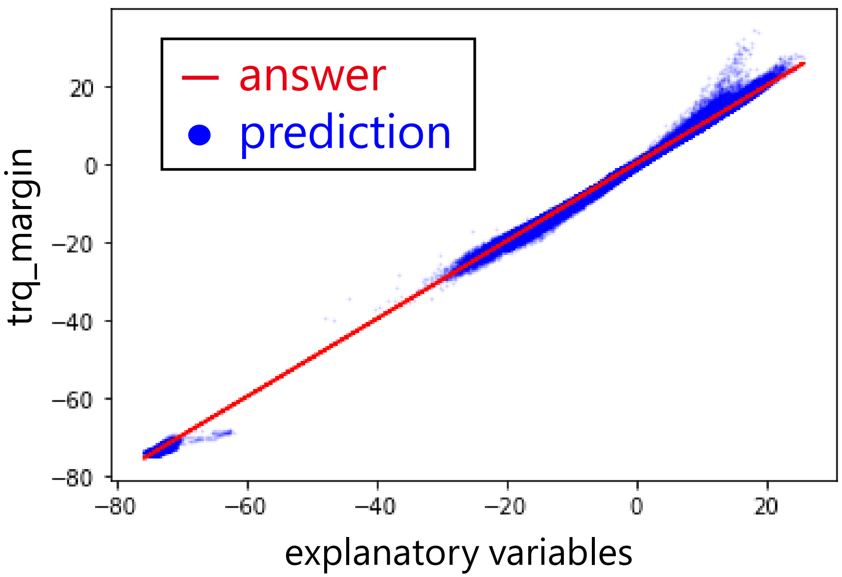
OUR SOLUTION Torque margin regression

Point1: Using torque target as regression target (3/3)

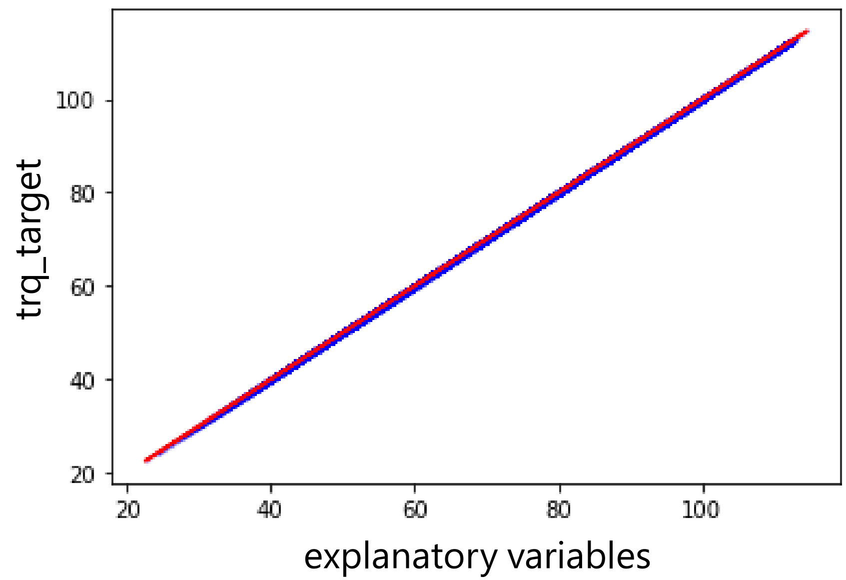
The results for Training dataset.

Conventional method	Proposed method

Estimate “trq_margin” by regression algorithm



Estimate “trq_target” by regression algorithm



Calculate “trq_margin”

MAE(Mean absolute error): 0.296

MAE: 0.034

Point2: Focus on data continuity and density altitude (da) (1/6)

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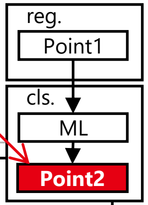
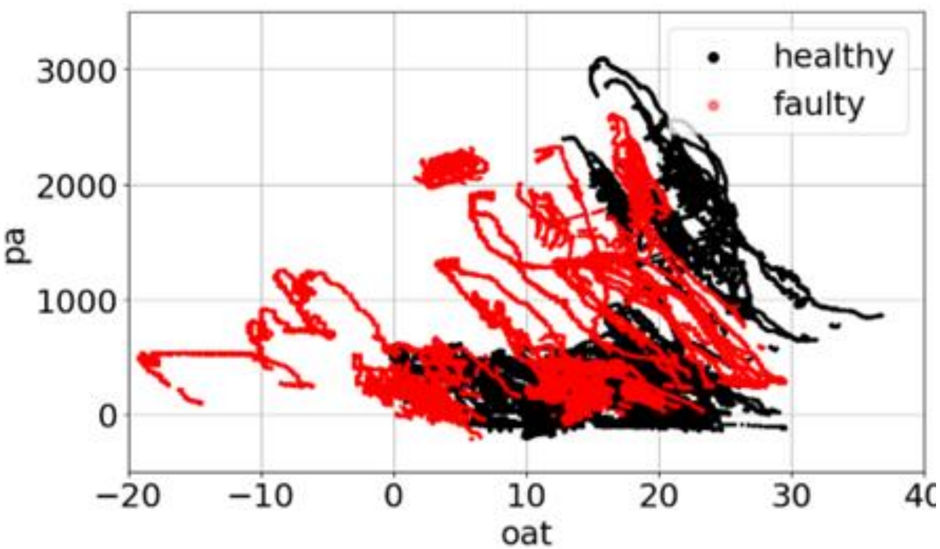
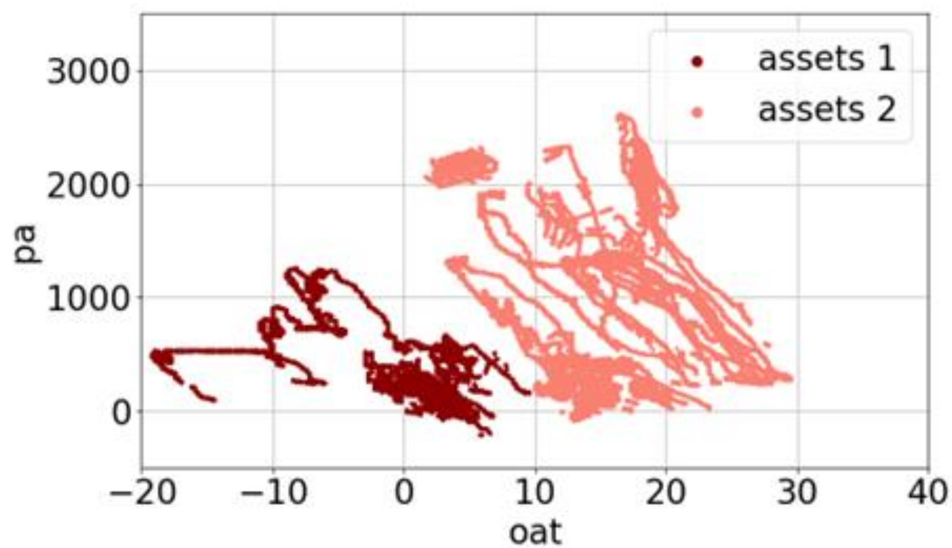


Hypothesis 1: The outside air temperature (oat) and pressure altitude (pa) change gradually over time. In other words, they do NOT change suddenly or abruptly.

- Estimating assets in training dataset
  - From the data sequence in the oat-pa axis (left figure), we estimated that the faulty data could be classified into two assets (right figure).



The Training Dataset (oat - pa)



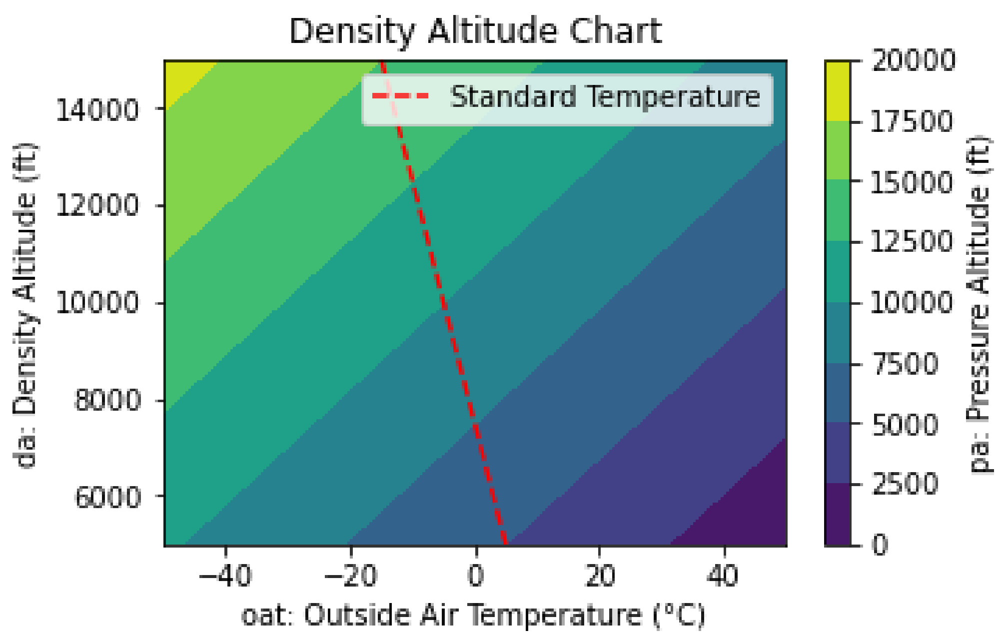
The sequence of faulty assets (oat – pa)

Point2: Focus on data continuity and density altitude (da) (2/6)

Density Altitude(da)* : the pressure altitude corrected by outside air temperature

- Higher density altitudes affect aircraft lift and engine power.
- The density altitude is approximated using the following equation, which incorporates the pressure altitude (pa) and outside air temperature (oat).

$$da = 1.2376 * pa + 118.8 * oat - 1782$$



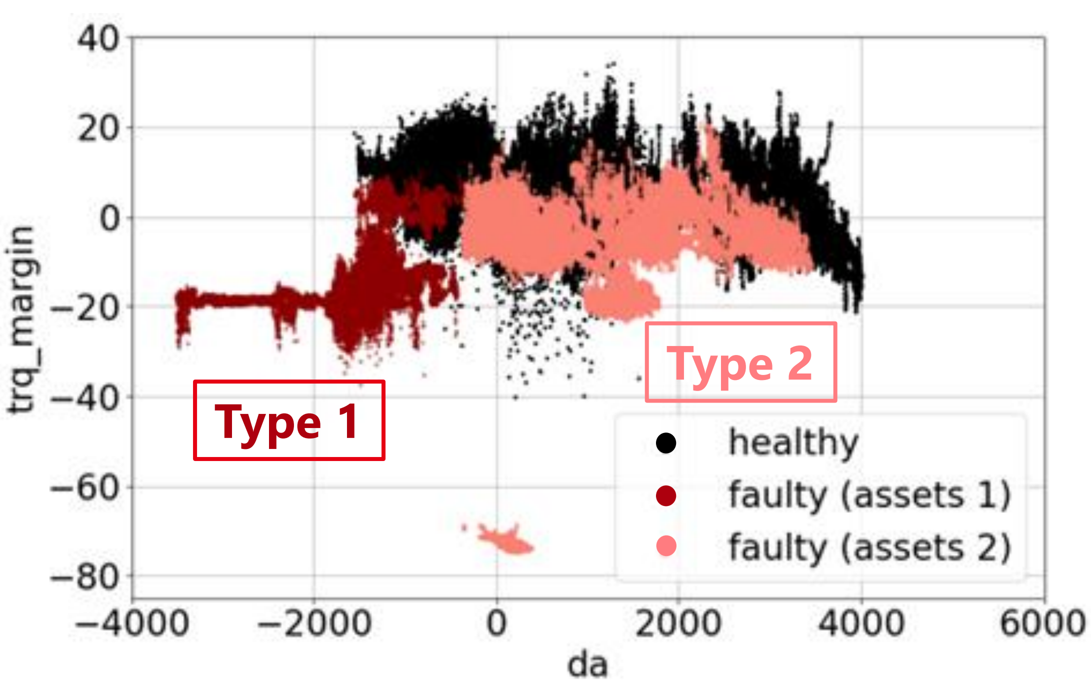
* Density Altitude: https://en.wikipedia.org/wiki/Density_altitude

OUR SOLUTION Health state classification

Point2: Focus on data continuity and density altitude (da) (3/6)

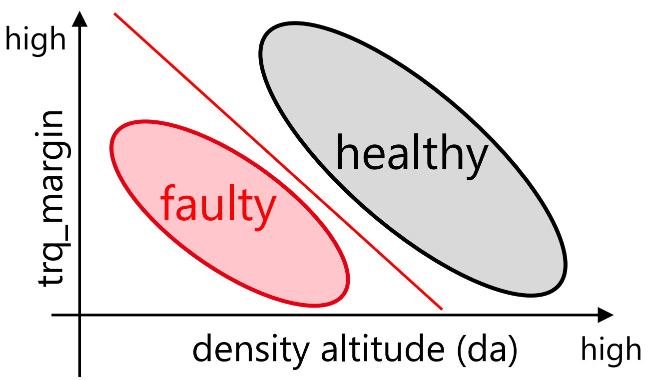
Hypothesis 2: Faulty engines tend to have a small torque margin. On the other hand, healthy engines also have a reduced torque margin under high density altitude conditions.

- By the da-trq_margin scatter plot of training dataset (left figure), we estimated there are two types of assets:

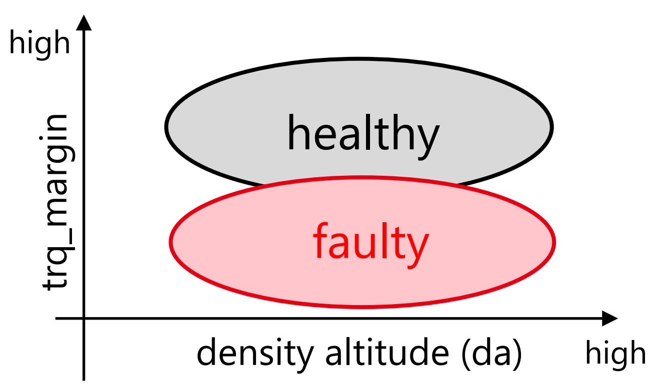


The Training Dataset (da - trq_margin)

Type 1: "Hypothesis 2" is valid.



Type 2: "Hypothesis 2" is NOT valid.



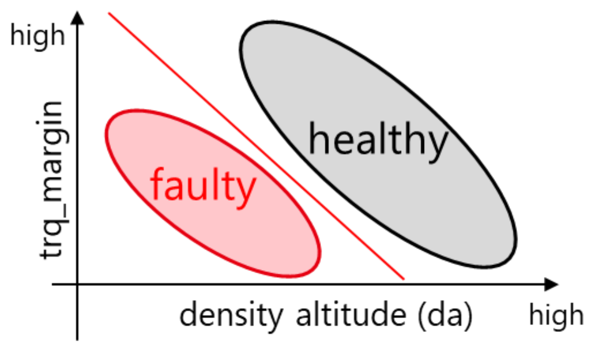
OUR SOLUTION Health state classification

Point2: Focus on data continuity and density altitude (da) (4/6)

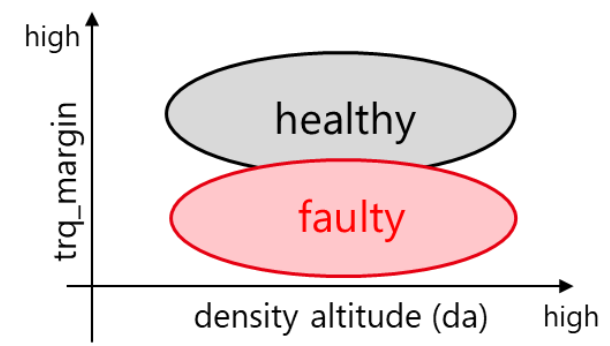
We estimated that assets in testing dataset are Type 1 ("Hypothesis 2" is valid).

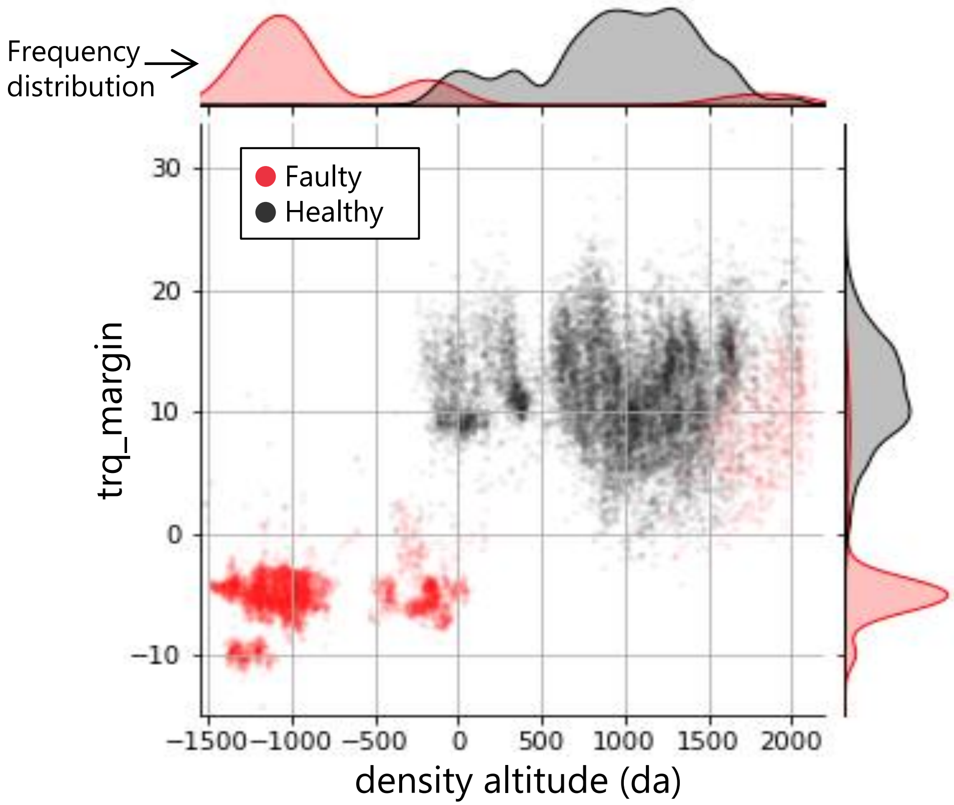
- The result of machine learning on the Testing Dataset is similar to Type 1.

Type 1: "Hypothesis 2" is valid.



Type 2: "Hypothesis 2" is NOT valid.



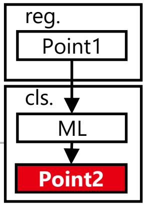


The result of machine learning on the Testing Dataset

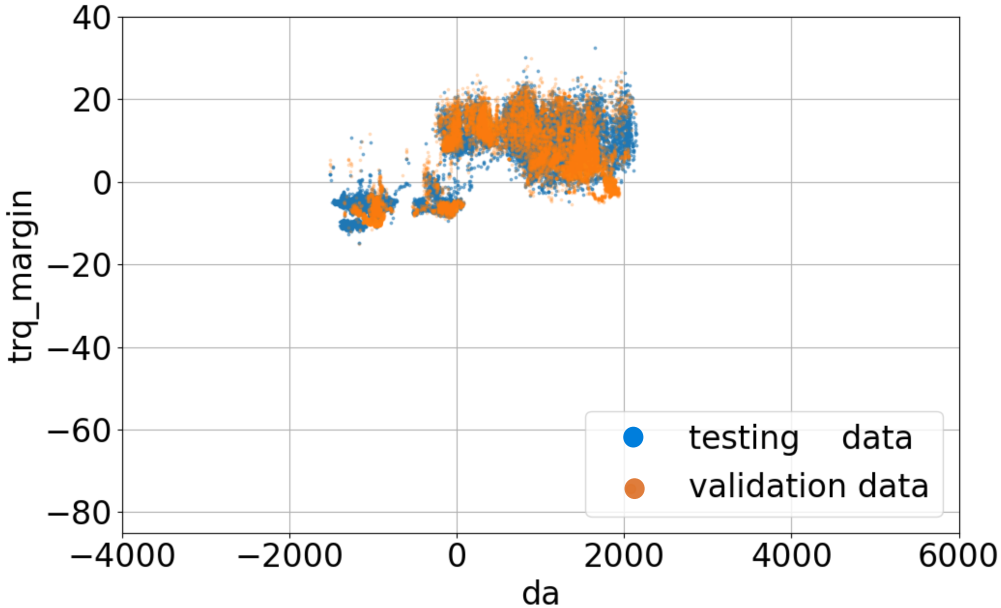
reprint

Hypothesis 2: Faulty engines tend to have a small torque margin. On the other hand, healthy engines also have a reduced torque margin under high density altitude conditions.

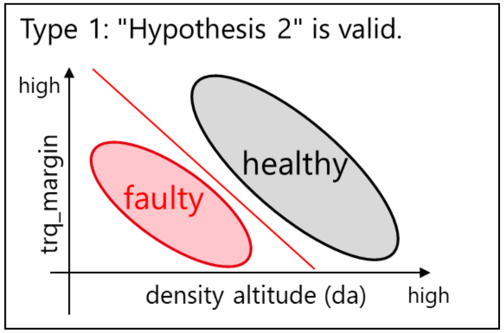
Point2: Focus on data continuity and density altitude (da) (5/6)

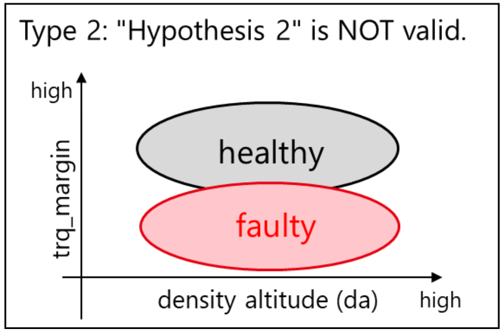


- We estimated that assets in validation dataset are type 1 ("Hypothesis 2" is valid), too.
  - The testing dataset and validation dataset are the same assets.
  - The distribution characteristics are similar (below left figure).



The Testing and Validation Datasets (da - trq_margin)





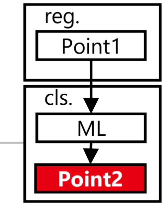
- Between training dataset and testing/validation dataset, the assets characteristics are different.

Dataset	Assets' type
Training dataset	Type 1 and Type 2
Testing/validation datasets	Type 1

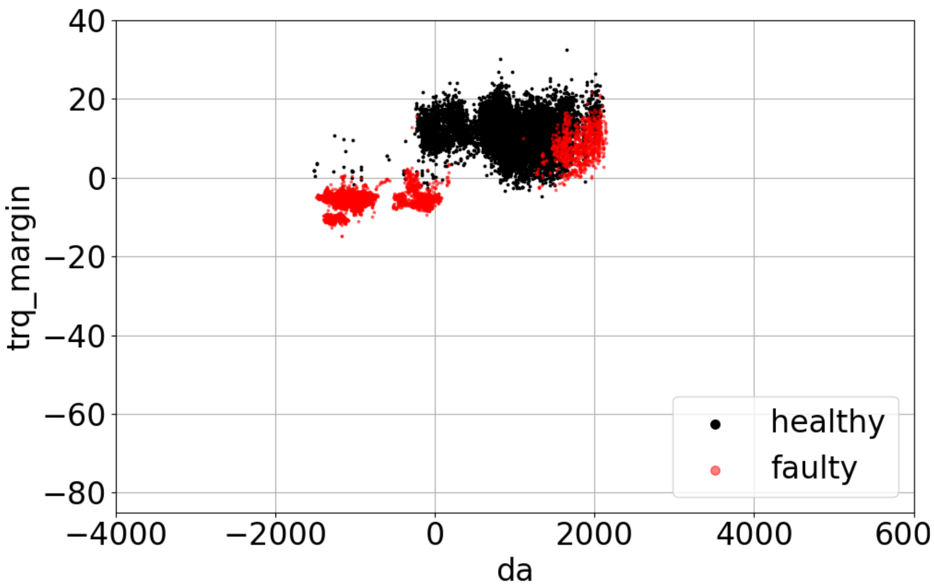
➡ So we used knowledge-based (rule-based) processing.

OUR SOLUTION Health state classification

Point2: Focus on data continuity and density altitude (da) (6/6)

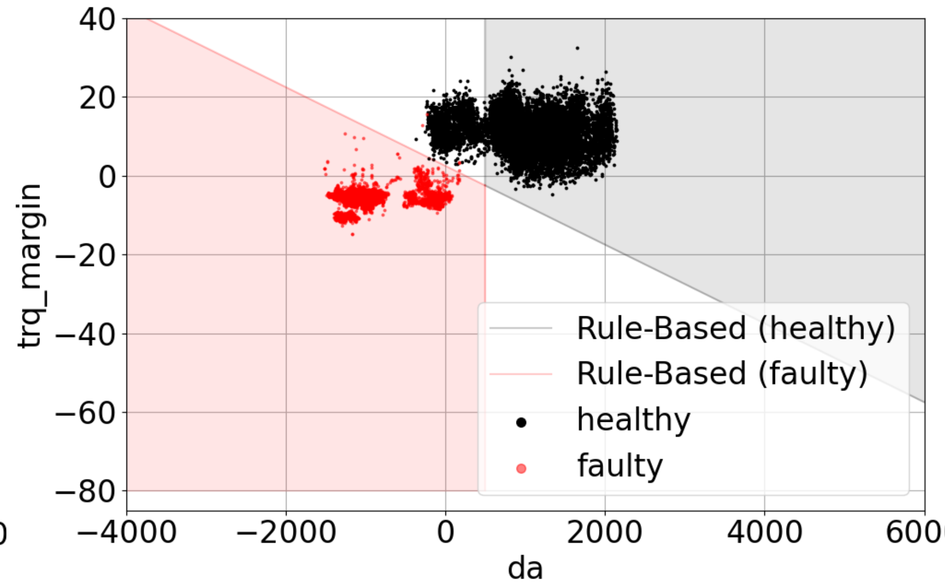


We confirmed that the score could be improved by applying rule-based processing to the testing dataset.



No rule-based

Score: 0.8641

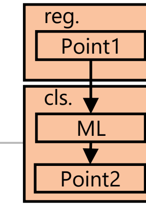


Rule-based

Score: 0.9016

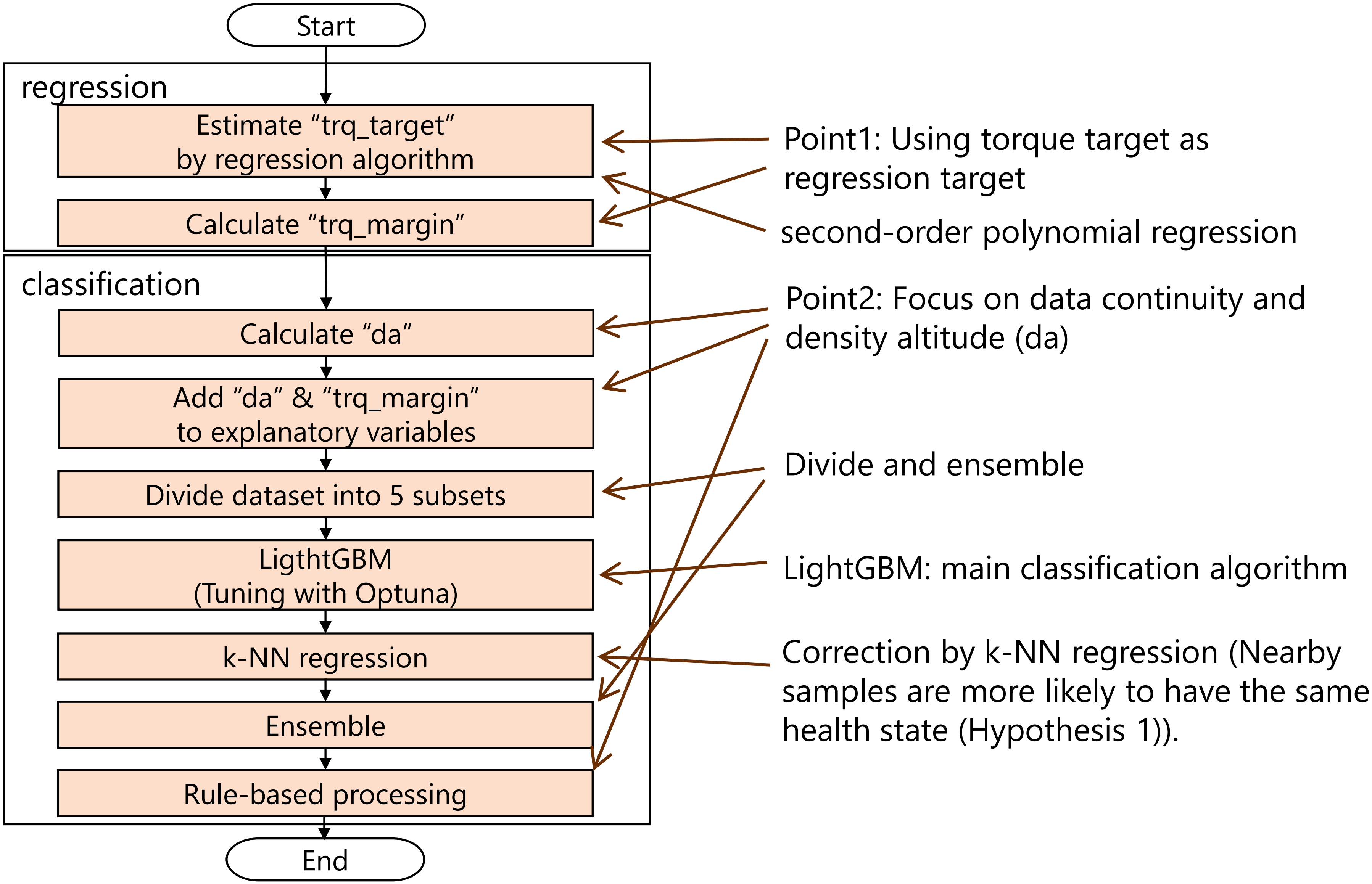
Rule-based processing

No	conditions	consequence
1	(da < 500) and (trq_margin < -0.01 da + 2.5)	faulty
2	(da ≧ 500) and (trq_margin ≧ -0.01 da + 2.5)	healthy

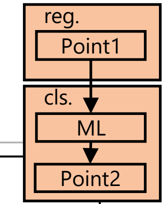


PROPOSED ALGORITHM

Our proposed algorithm is as follows.



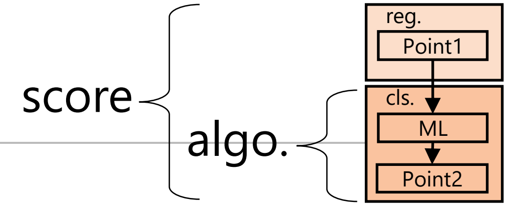
PROPOSED ALGORITHM Probability estimation



For all samples, we used UNIFORM distribution for PDF and 1.0 for class_conf, since we decided the accuracy was sufficient.

Item	Setting		Explanation
PDF for probabilistic regression	UNIFORM distribution (If the error is within 0.5, the score is 1.0)		We assumed the proposed method was accurate enough to allow for a UNIFORM distribution, although the score will be zero if the error is greater than 0.5. (training dataset's MAE (Mean Absolute Error): 0.0343)
Classification confidence	class 1 (faulty)	1.0	When class_conf is 1.0, the expected score is highest.
	class 0 (healthy)	1.0	Initially, we set the class_conf to 0.7, considering the impact of false-negative penalties when the accuracy was low. However, we set class_conf to 1.0 for a trial run and found that it raised the score sufficiently, so we thought it was fine.

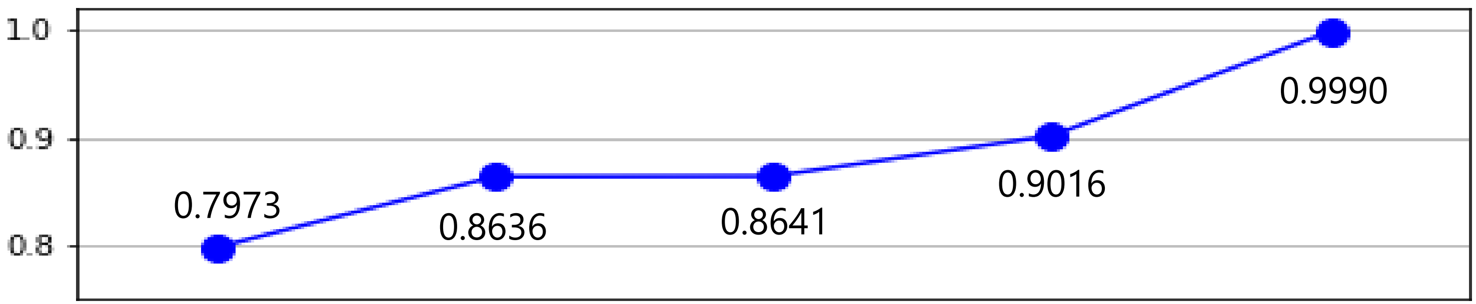
EVALUATION (1)



We confirmed that each processing raised the testing dataset score.

Improving the method

Total Score (testing dataset)



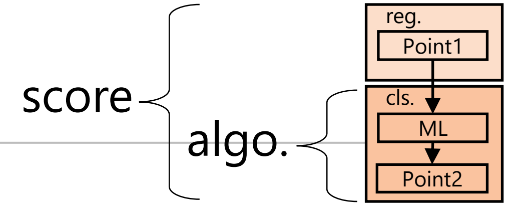
Classification algorithm
- LightGBM (Tuning with Optuna)
- Add correction by k-NN
- Add Rule-based

Input data
- Add “da” & “trq_margin” to explanatory variables

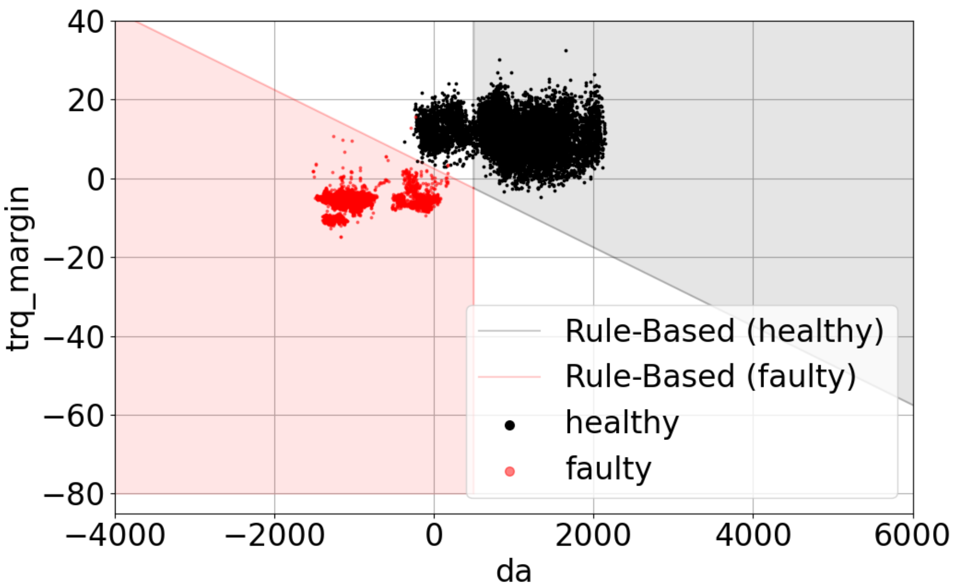
Class0’s class_conf
- 0.7
- 1.0

Since the accuracy was high enough, we could set class0’s class_conf to 1.0

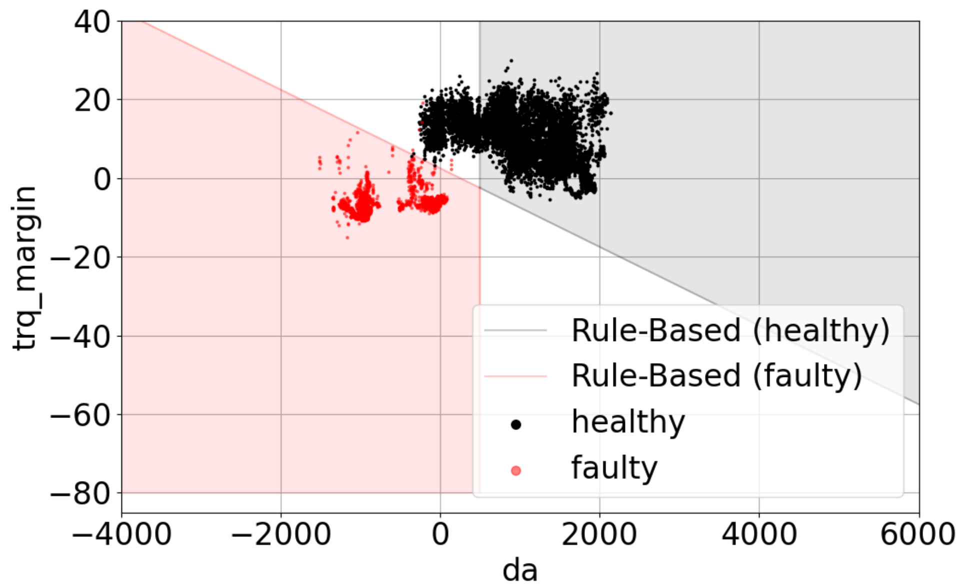
EVALUATION (2)



We applied the same algorithm to the validation dataset as to the testing dataset, and achieved a score of over 0.99.

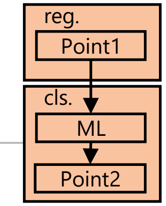


testing dataset



validation dataset

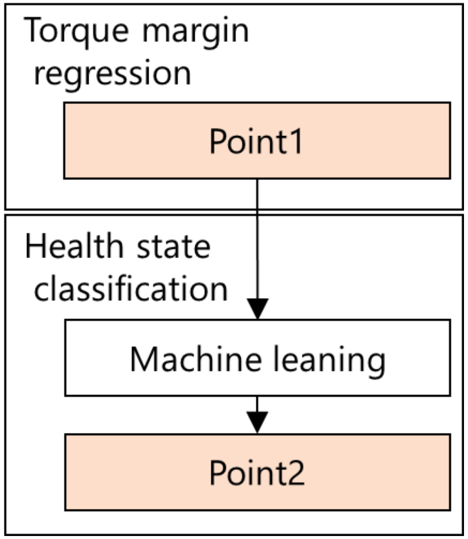
RESULTS AND DISCUSSION

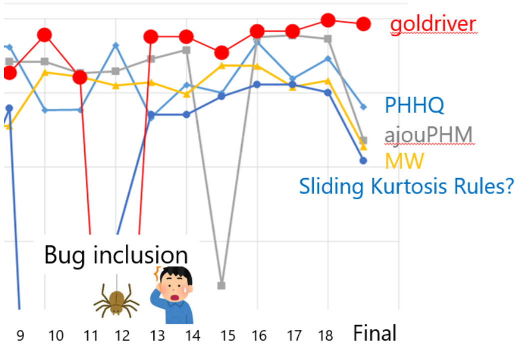


- Results
  - Our proposed method achieved scores over 0.99 for both the testing and validation datasets. These were the highest scores among all teams.
  - The health of the testing and validation datasets were estimated by combining machine learning and the rule-based processing based on domain knowledge.
- Discussion
  - Rule-based processing was necessary in this competition because there were differences in the characteristics of the training and testing/validation datasets.
  - We consider that even when estimating for new assets, it is possible to achieve a highly adaptable estimation of health by using data from past similar assets.

CONCLUSION

- We proposed a hybrid algorithm that combines data-based machine learning and domain knowledge-based processing. This method is based on the following key points:
  - Torque margin regression
    - Point1: Using torque target as regression target
  - Health state classification
    - Point2: Focus on data continuity and density altitude (da)
- Our method achieved scores over 0.99 for both the testing and validation datasets. These results were ranked first among all participating teams.





Any Questions?

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