

Predictive Maintenance

Data modeling

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Challenge overview

Provide recommendations about changing the maintenance plans

The maintenance plan is done with fixed frequency by calendar time

Demonstrate understanding of the problem

Show statistics of the assets

Propose solution

Predict the failure of the company's assets with at least 20 cycles ahead

Work with the available 100 events of failure

Check the viability of the remaining useful life (RUL)

Will the asset fail after 20 cycles ahead?

What is the assets remaining useful life?

KPIs for machine learning algorithms

Simulate scenarios to demonstrate how the model perform against a naive process of changing the asset in a fixed period

Answer how the maintenance team will use your model to reduce costs

Asset id	Complete run of the asset until its failure. "How many operation cycles the asset performed until fail".
Runtime	A measure of time that resets after failure. "Operation cycle".
Setting 1 to 3	Setpoint 1 to 3
Tag 1 to 21	Sensor 1 to 3

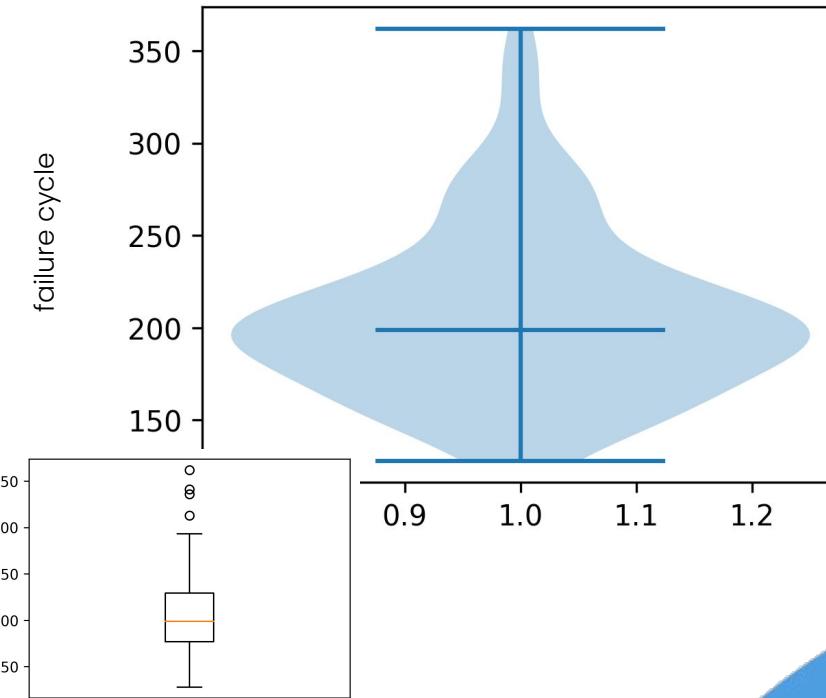
Stats	Failure
min	128
max	362
mean	206
std	46
25%	177
median	199
75%	229

Conservative | Preventive

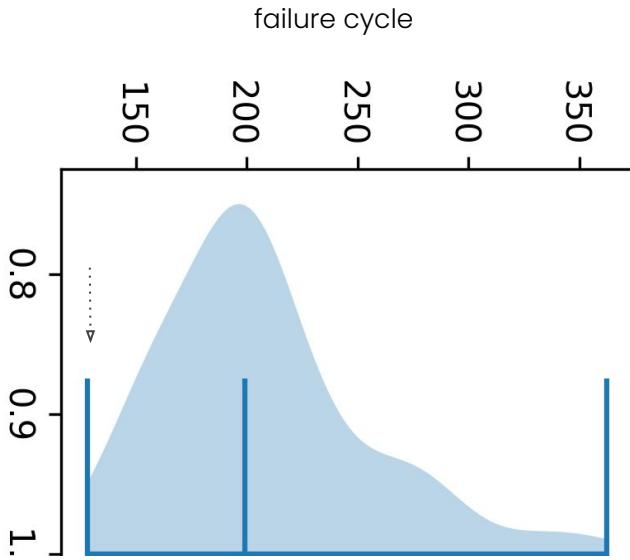
dummy max error @min : 234 (65%)
 dummy mean error @min : 78 (35%)

Partially Corrective

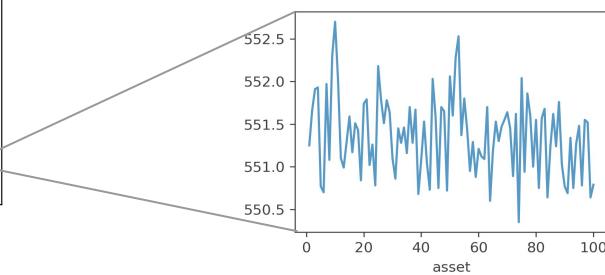
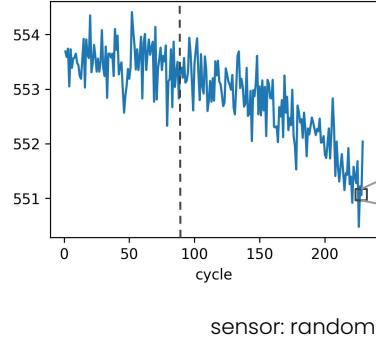
dummy max error @mean : 156 (61%)
 dummy mean error @mean : 34 (17%)



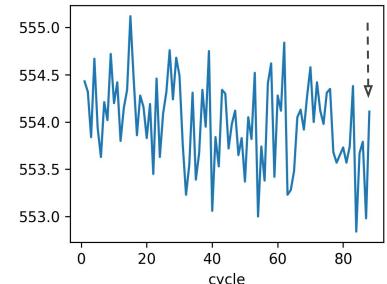
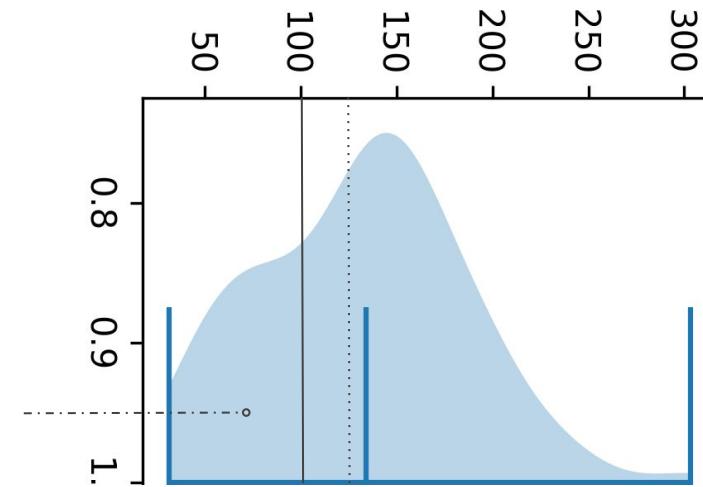
Our system



In practice,
we don't
need to
worry about
this range



The distribution we need to perform well on





Visual Studio Code

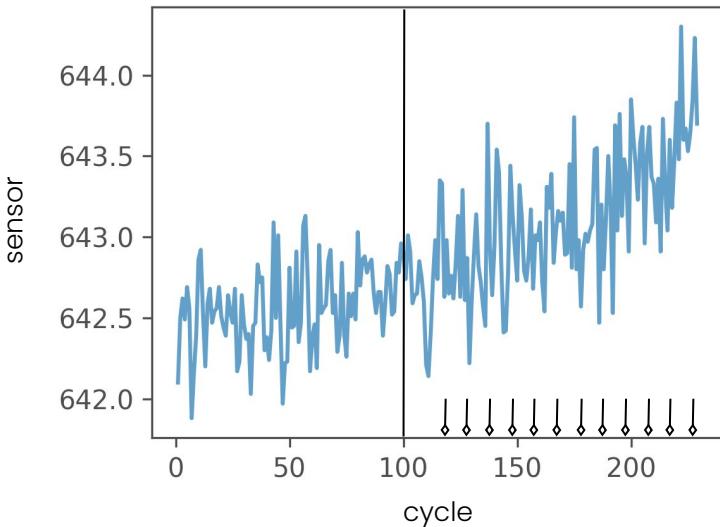


Coding,
analysis
and modeling
framework

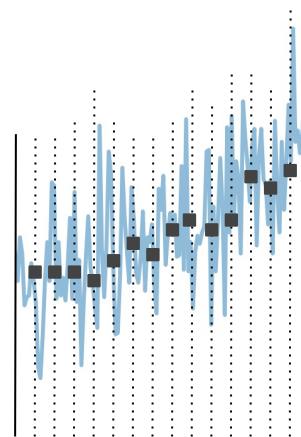
Feature engineering

1. Select the non-constant settings and sensors
2. Treat all features as numeric
3. For the settings, get the value at the failure cycle
4. For the sensors, randomly select monitoring cycle
 - 4.1. Filter signal in a backward windowed fashion
 - 4.2. Calculate the time derivative of the filtered signal
5. Calculate the remaining useful life for each monitoring cycle

4.

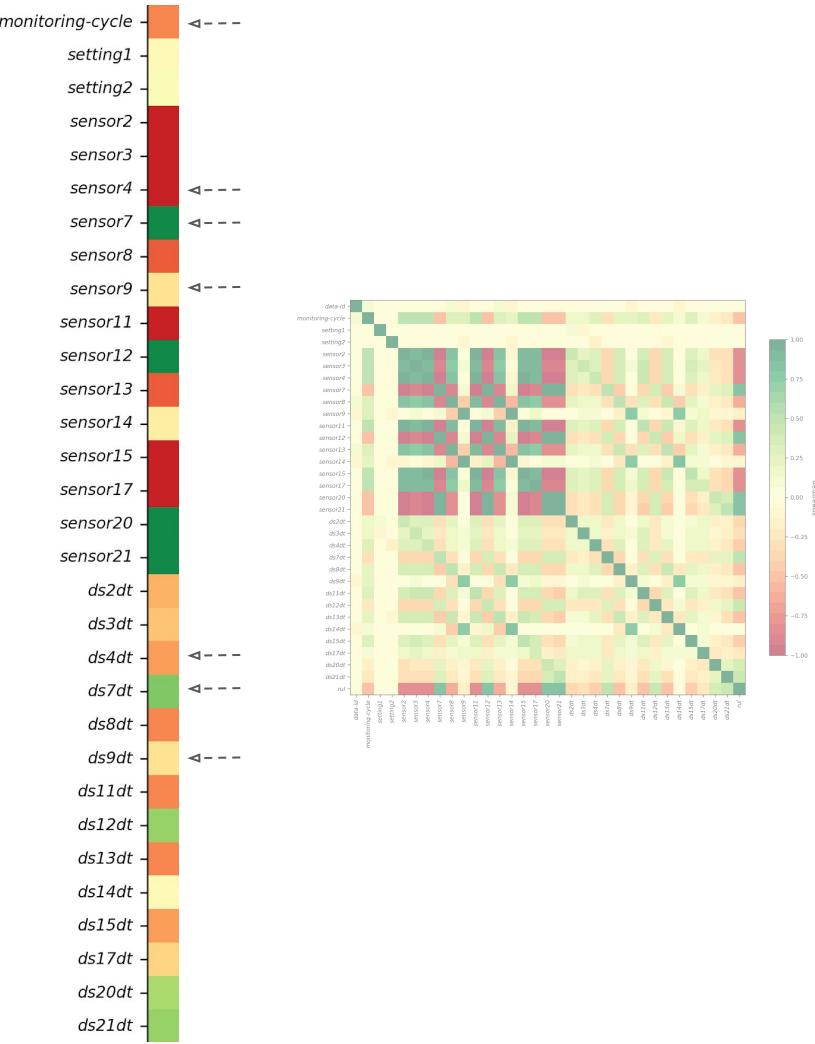


4.1.

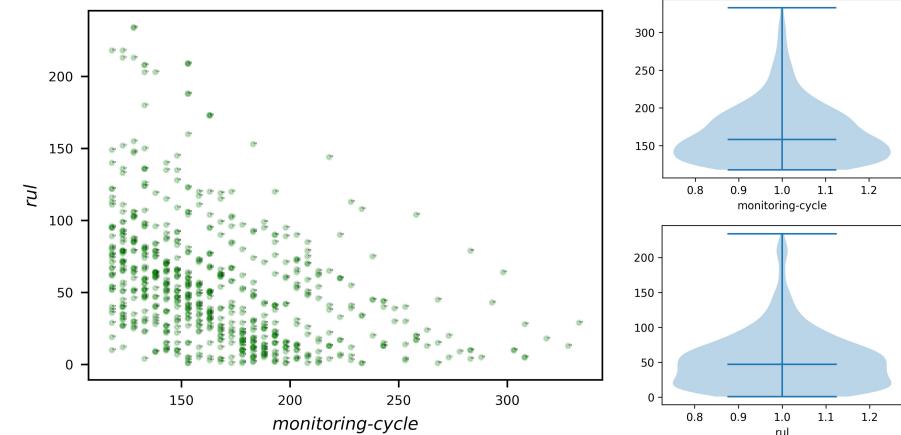


4.2.

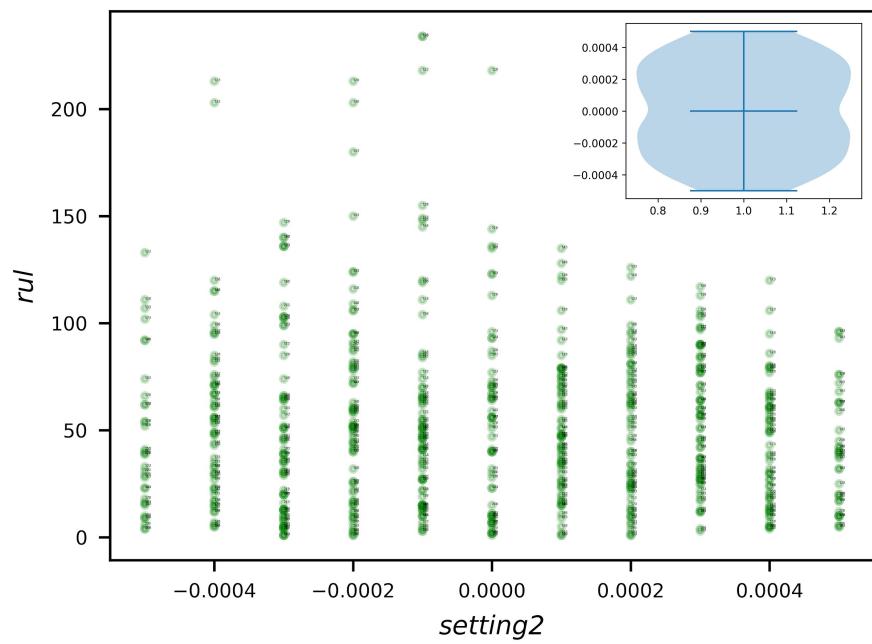
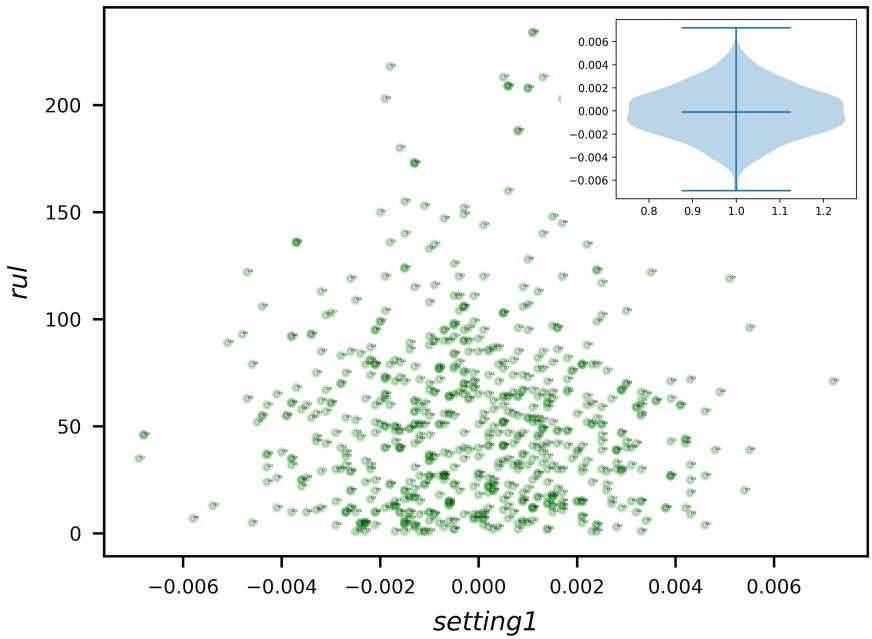


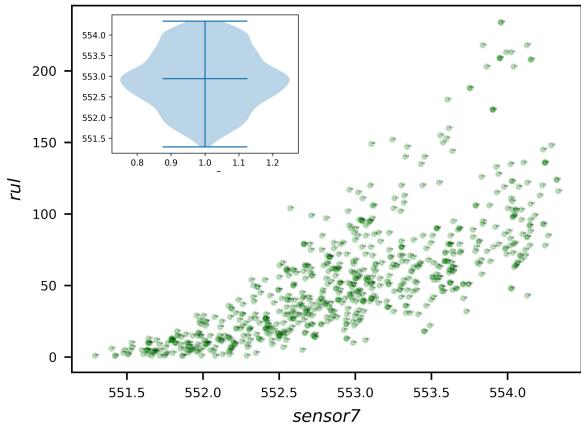
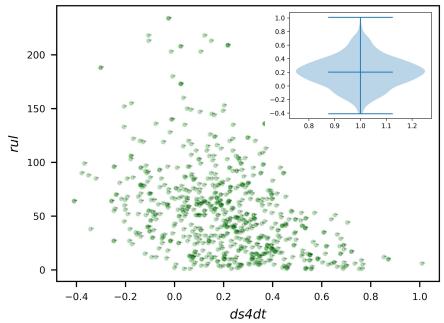
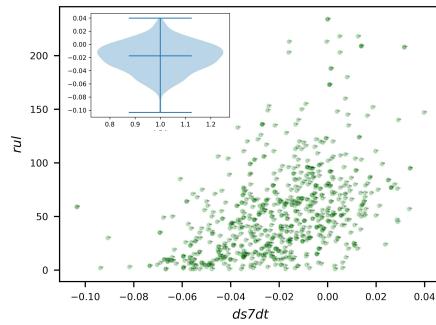
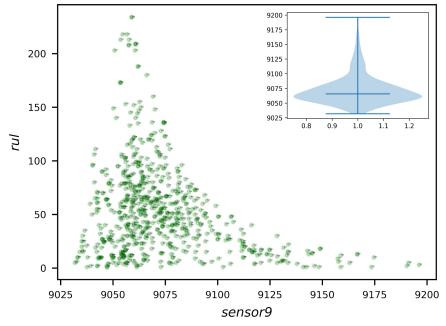
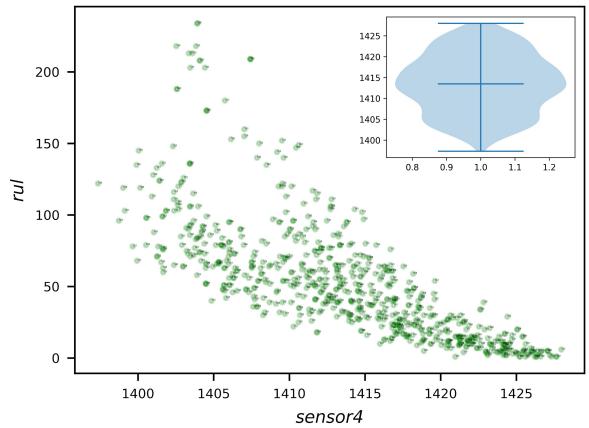


Transformed dataset size: 718



Transformed dataset analysis





Model analysis

Influence of

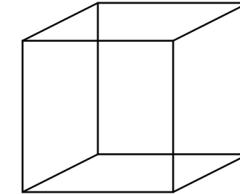
modeling sensor derivatives
11 cycles of improvement on prediction

decreasing minimum cycle
It depends on the distribution difference between val and test dataset

increasing filter size
29 cycles of improvement on prediction

* AdaBoost model | Val-train ratio: 0.3

Model	Derivatives	Minimum cycle	Filter size	train		val	
				ae.max	ae.mean	ae.max	ae.mean
1	True	100	15	38	15	66	18
2	True	100	10	47	21	94	22
3	True	31	15	58	23	142	29
4	True	31	10	57	24	133	28
5	False	100	15	46	17	83	20
6	False	100	10	47	18	136	20
7	False	31	15	65	25	109	27
8	False	31	10	63	25	151	28



Filter window size

10 | 15

Min monitoring cycle

100 | 31

Use sensor derivatives

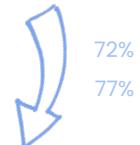
True | False

Chosen scores

Max absolute error | Mean absolute error

Conservative | Preventive

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dummy mean error @min : 78 (35%)

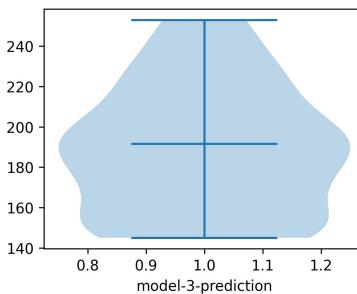
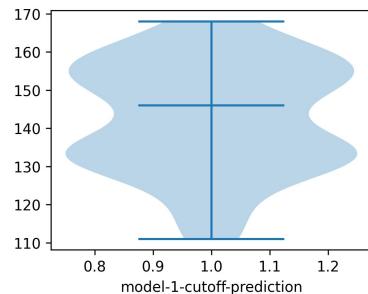
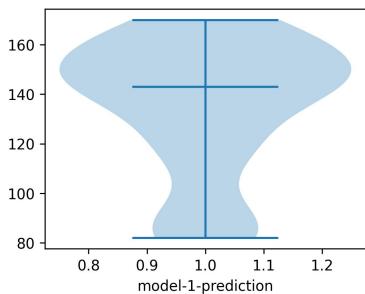


Model	Derivatives	Minimum cycle	Filter size
1	True	100	15

Use this model version if the test dataset could be cut off at the monitoring cycle #100, which is near the minimum failure cycle #124 of the observed data.

Use this model version otherwise. It will try to approximate the train/val distribution into the test one.

Model	Derivatives	Minimum cycle	Filter size
3	True	31	15



RUL
Prediction



How to
improve?

Let's talk about these topics!



Future work

