Turbofan Jet Engine Predictive Maintenance

Hyunyong Lee, 2024/12/6

3. Predictive model

1. Problem statement
Objective

4. Recommandation

2. Data/EDA

Problem statement & Objective

Problem statement: Aircraft engine maintenance

1) Significant engine failure: Passengers' life, Reputation & Cost
   i.e. B777-300ER Max passenger: 392* Cost: $375.5 million**
2) Break-down replacement: $30 million***
3) Maintenance frequency: Normally every 28 flight cycles
   (Assume normal maintenance frequency)****

Objective (Assume B777-300ER GE90 engine)

Develop a predictive model for the engine life time (RUL)

Define engine maintenance criteria

*https://www.boeing.com/commercial/777

**https://simpleflying.com/how-much-does-a-boeing-777-cost/#:~:text=The%20Boeing%20777%2D200ER%20costs,777%2D300ER%20costs%20%24375.5%20million

***https://simpleflying.com/most-expensive-jet-engines/

****https://www.aircraft-commerce.com/wp-content/uploads/aircraft-commerce-docs/Maintenance/2013/ISSUE87_MTCE_A.pdf

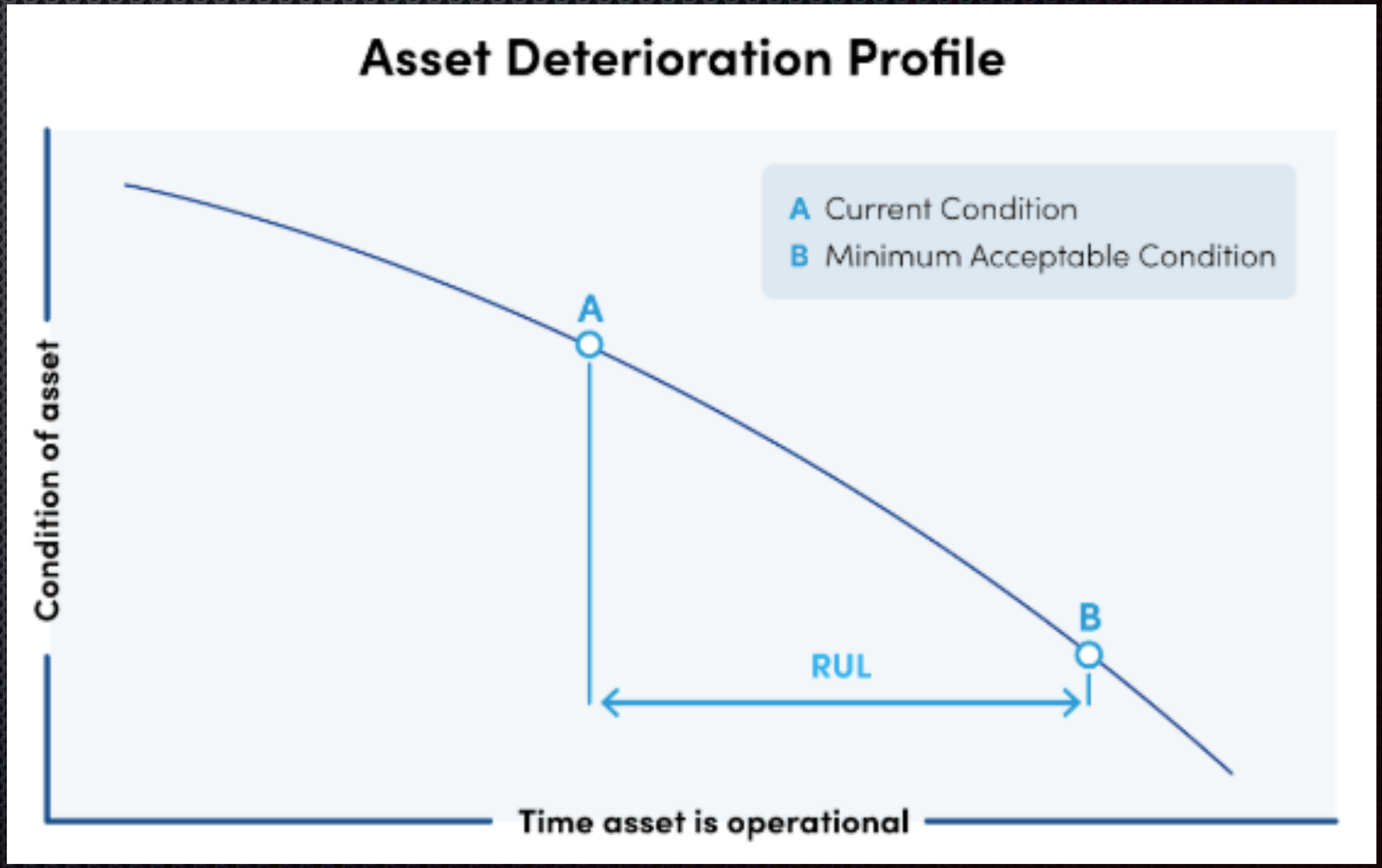
Remaining Useful Life (RUL)*

The estimated amount of time an asset has until it becomes unusable or requires replacement. This is commonly used in predictive maintenance to determine when maintenance need to be performed on equipment.

For this project

(Train data)
Maximum acceptance cycle - Subsequent cycle

(Test data)
Conditional data for certain time cycle and predict RUL rather than current condition is abnormal or not



*https://fiixsoftware.com/maintenance-metrics/remaining-useful-life/

Data

Data → Predictive Model → Recommandation

Feature selection/engineering

Data extraction → EDA → Select features / Normalized by start value / Maximum RUL limit

Dataset

- Downloaded from Kaggle
  https://www.kaggle.com/datasets/behrad3d/nasa-cmaps/data
  Ref: Reference: A. Saxena, K. Goebel, D. Simon, and N. Eklund, Damage Propagation Modeling for Aircraft Engine Run-to-Failure Simulation, in the Proceedings of the 1st International Conference on Prognostics and Health Management (PHM08), Denver CO, Oct 2008

- Train & Test data already separated (100 engines)
  We will split train data into train & validation set

Symbol	*Description*	*Units*
engine	Engine number	–
cycle_time	Cycle number	–
operational_set_1	Operational set up #1	–
operational_set_2	Operational set up #2	–
operational_set_3	Operational set up #3	–
T2	Total temperature at fan inlet	°R
T24	Total temperature at LPC outlet	°R
T30	Total temperature at HPC outlet	°R
T50	Total temperature at LPT outlet	°R
P2	Pressure at fan inlet	psia
P15	Total pressure in bypass-duct	psia
P30	Total pressure at HPC outlet	psia
Nf	Physical fan speed	rpm
Nc	Physical core speed	rpm
epr	Engine Pressure ratio (P50/P2)	–
Ps30	Static pressure at HPC outlet	psia
phi	Ratio of fuel flow to Ps30	pps/psi
NRf	Corrected fan speed	rpm
NRc	Corrected core speed	rpm
BPR	Bypass Ratio	–
farB	Burner fuel-air ratio	–
htBleed	Bleed Enthalpy	–
Nf_dmd	Demanded fan speed	rpm
PCNfR_dmd	Demanded corrected fan speed	rpm
W31	HPT coolant bleed	lbm/s
W32	LPT coolant bleed	lbm/s

Exploratory Data analysis

No null value

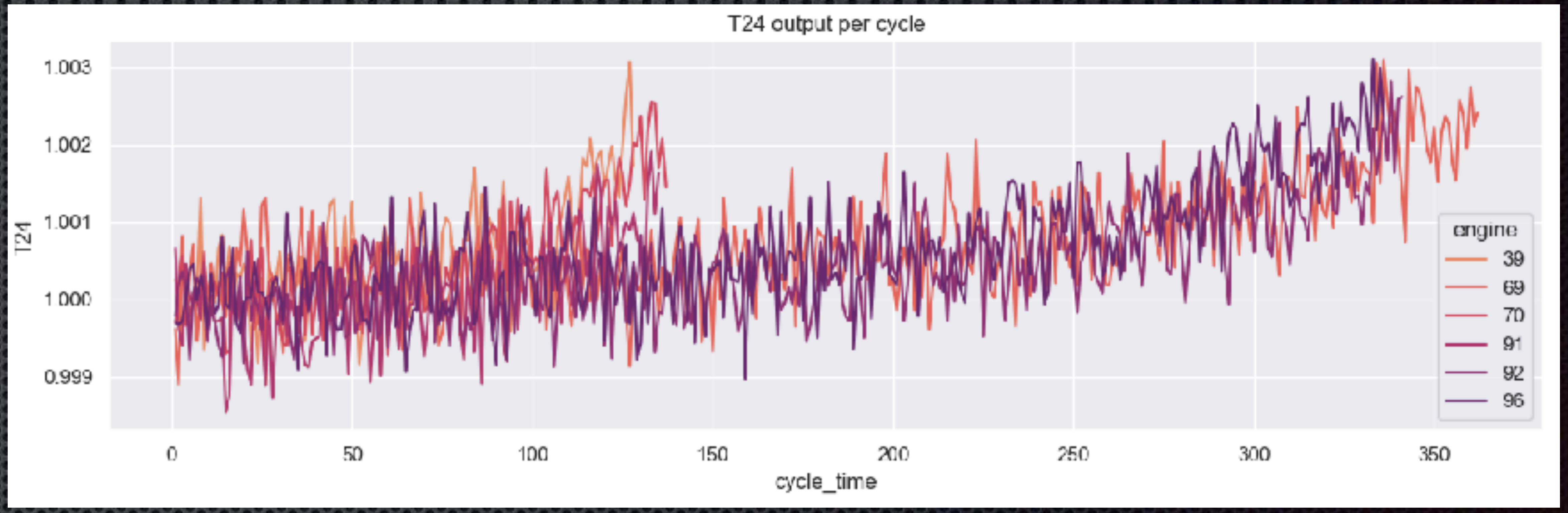
Null value rate	
engine	0.0
cycle_time	0.0
operational_set_1	0.0
operational_set_2	0.0
operational_set_3	0.0
T2	0.0
T24	0.0
T30	0.0
T50	0.0
NRf	0.0
NRc	0.0
BPR	0.0
farB	0.0
htBleed	0.0
Nf_dmd	0.0
PCNfR_dmd	0.0
W31	0.0
W32	0.0
RUL	0.0

*No null cases could differ from actual case; i.e. sensor fault

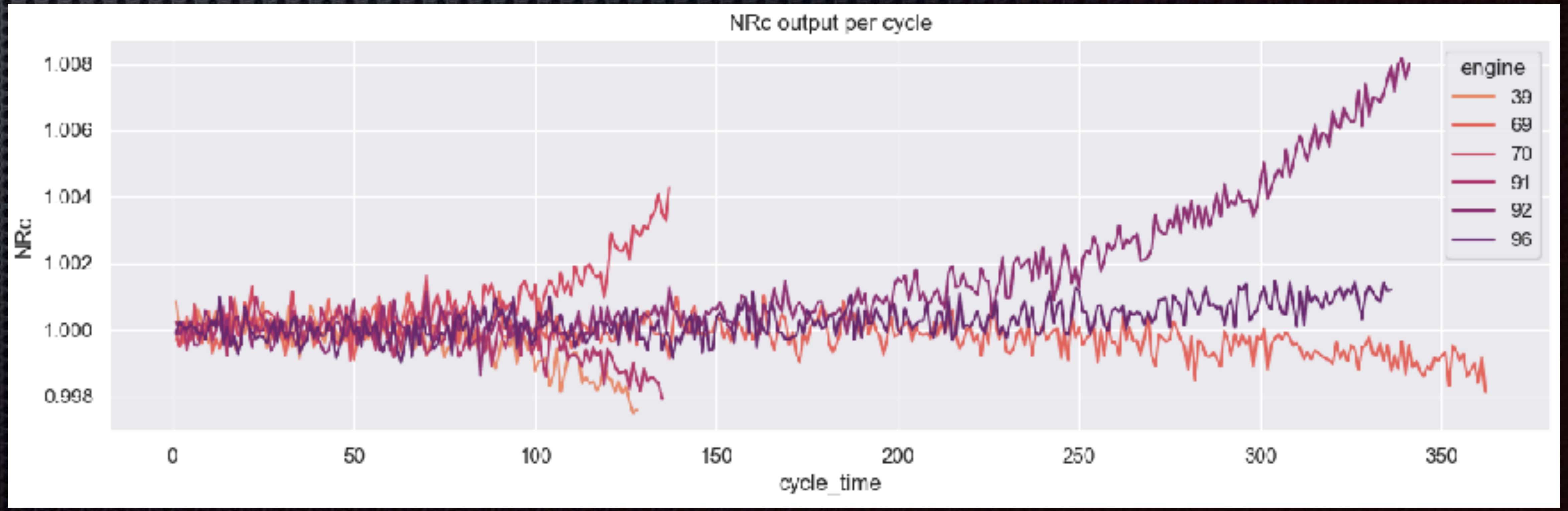
Remove columns

Unique value count	
engine	100
cycle_time	362
operational_set_1	158
operational_set_2	13
operational_set_3	1
T2	1
T24	310
T30	3012
T50	4051
P2	1
P15	2
P30	513
Nf	53
Nc	6403
epr	1
Ps30	159
phi	427
NRf	56
NRc	6078
BPR	1918
farB	1
htBleed	13
Nf_dmd	1
PCNfR_dmd	1
W31	120
W32	4745

Each sensor output per cycle times



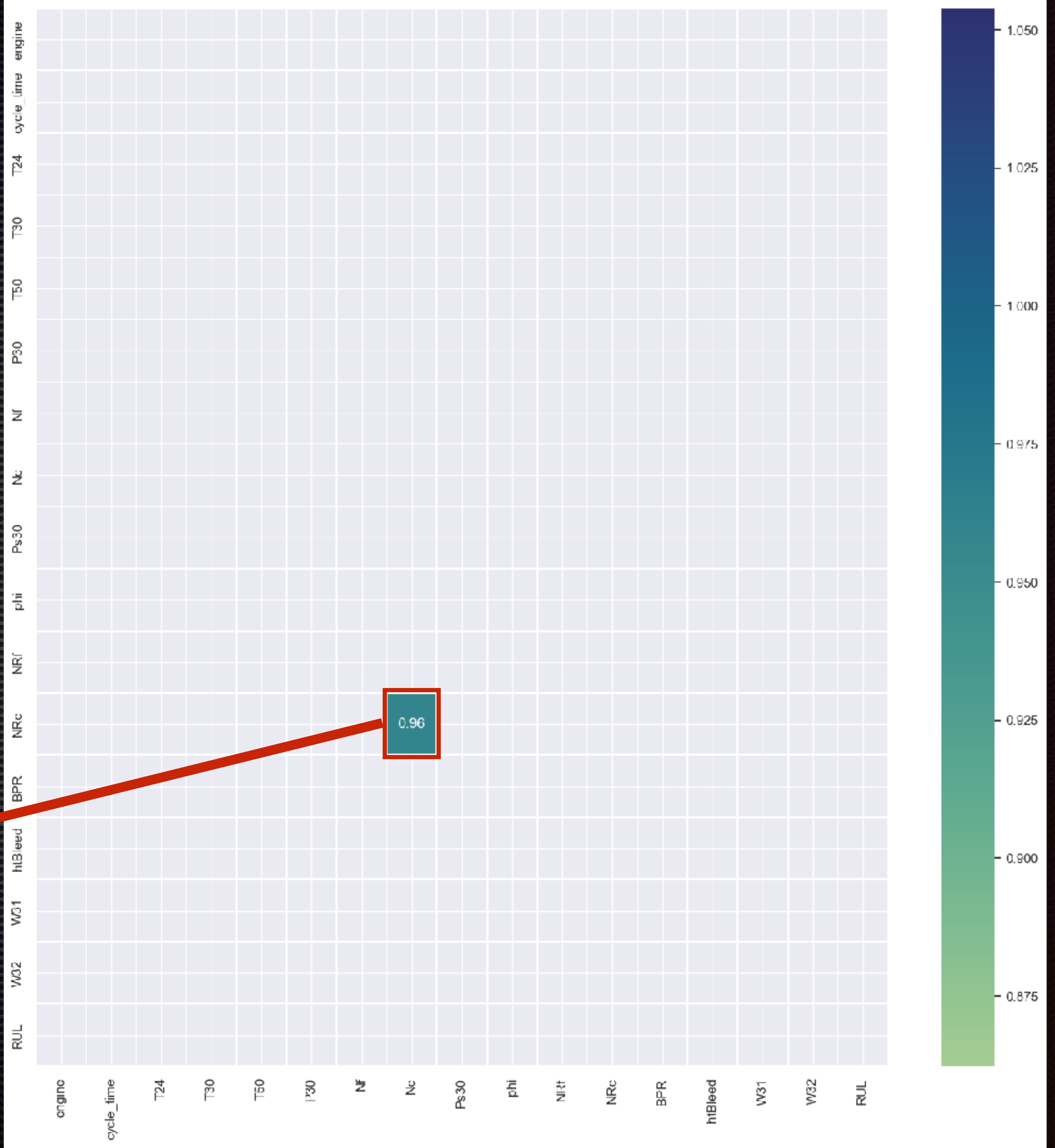
1)Signals have noise;Smoothing..?
→ Not implemented for this time (Assume real situation)
2) Different scale of each sensor: Normalization by start value



Reduce features

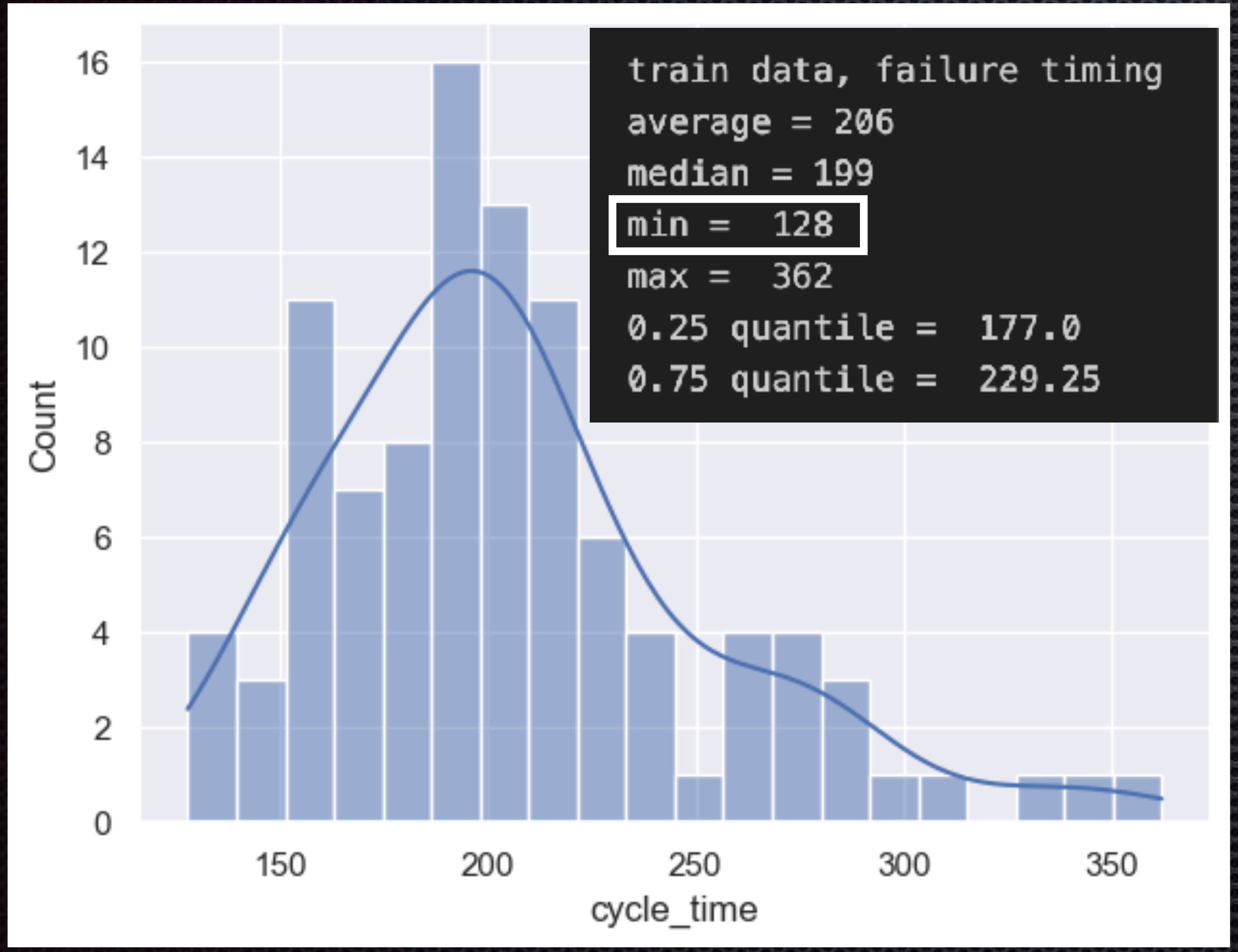
High correlated features are removed

Symbol	Description	Units
~~T2~~	~~Total temperature at fan inlet~~	~~°R~~
T24	Total temperature at LPC outlet	°R
T30	Total temperature at HPC outlet	°R
T50	Total temperature at LPT outlet	°R
~~P2~~	~~Pressure at fan inlet~~	~~psia~~
~~P15~~	~~Total pressure in bypass-duct~~	~~psia~~
P30	Total pressure at HPC outlet	psia
Nf	Physical fan speed	rpm
Nc	Physical core speed	rpm
~~epr~~	~~Engine Pressure ratio (P50/P2)~~	~~—~~
Ps30	Static pressure at HPC outlet	psia
phi	Ratio of fuel flow to Ps30	pps/psi
NRf	Corrected fan speed	rpm
~~NRc~~	~~Corrected core speed~~	~~rpm~~
BPR	Bypass Ratio	—
~~farB~~	~~Burner fuel-air ratio~~	~~—~~
htBleed	Bleed Enthalpy	—
~~Nf_dmd~~	~~Demanded fan speed~~	~~rpm~~
~~PCNfR_dmd~~	~~Demanded corrected fan speed~~	~~rpm~~
W31	HPT coolant bleed	lbm/s
W32	LPT coolant bleed	lbm/s



Maximum RUL limit（Clipping）

- We are interested in RUL which requires maintenance
- No need to have precise prediction higher RUL



	engine	cycle_time	T24	T30	T50	P30	Nf	Nc	Ps30	phi	NRf	BPR	htBleed	W31	W32	RUL
0	1	1	641.82	1589.70	1400.60	554.36	2388.06	9046.19	47.47	521.66	2388.02	8.4195	392	39.06	23.4190	191
1	1	2	642.15	1591.82	1403.14	553.75	2388.04	9044.07	47.49	522.28	2388.07	8.4318	392	39.00	23.4236	190
2	1	3	642.35	1587.99	1404.20	554.26	2388.08	9052.94	47.27	522.42	2388.03	8.4178	390	38.95	23.3442	189
3	1														23.3739	188
4	1														23.4044	187

Set up upper RUL limit based on historical minimum life time * 0.95 (safety net) = 121

	engine	cycle_													W32	RUL
0	1														1.001257	121
1	1	2	0.999921	1.002587	1.001642	0.999376	0.999996	0.999393	1.004612	1.000257	1.000011	1.002784	1.000510	1.000410	1.001454	121
2	1	3	1.000232	1.000175	1.002399	1.000296	1.000013	1.000373	0.999958	1.000525	0.999994	1.001119	0.995406	0.999128	0.998059	121
3	1	4	1.000232	0.996900	1.000735	1.000639	1.000026	0.999991	0.996996	1.001367	1.000015	0.995220	1.000510	0.997332	0.999329	121
4	1	5	1.000263	0.996938	1.003841	0.999827	1.000005	1.000618	1.000169	1.000084	0.999998	1.002499	1.003063	0.997845	1.000633	121

Predictive model

Data → Predictive Model → Recommandation

<u>Regression models</u>
1) Linear
2) ElasticNet
3) SVR
4) Random Forest
5) LightGBM
6) XGBoost

→

1) Train data →
Train/Validation data split

2) Hyper parameter tuning:
GridSearchCV with Train data

3)Model selection: MSE
with Train/Validation data

→

Prediction with
test data

→

Maintenance
flag

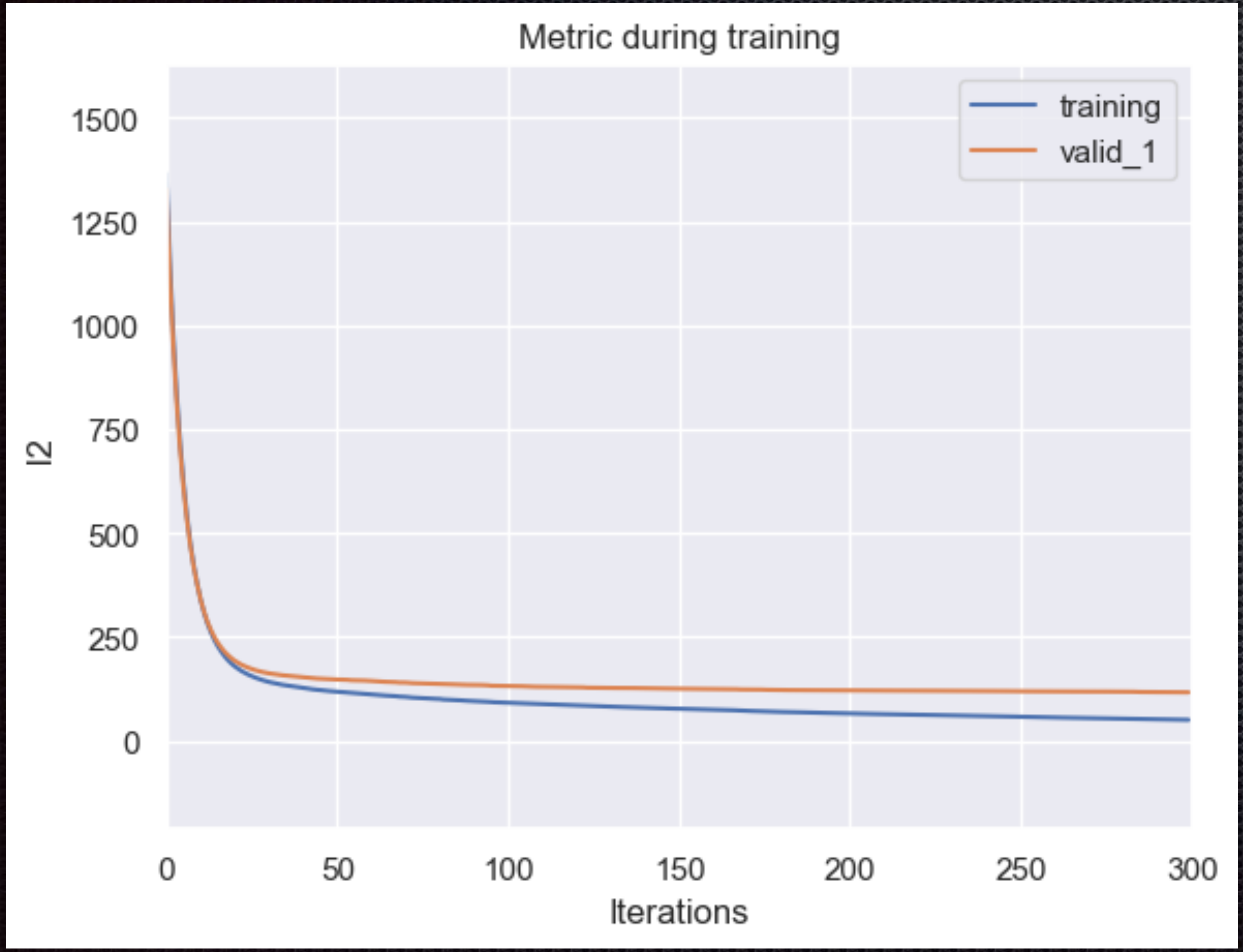
Model selection

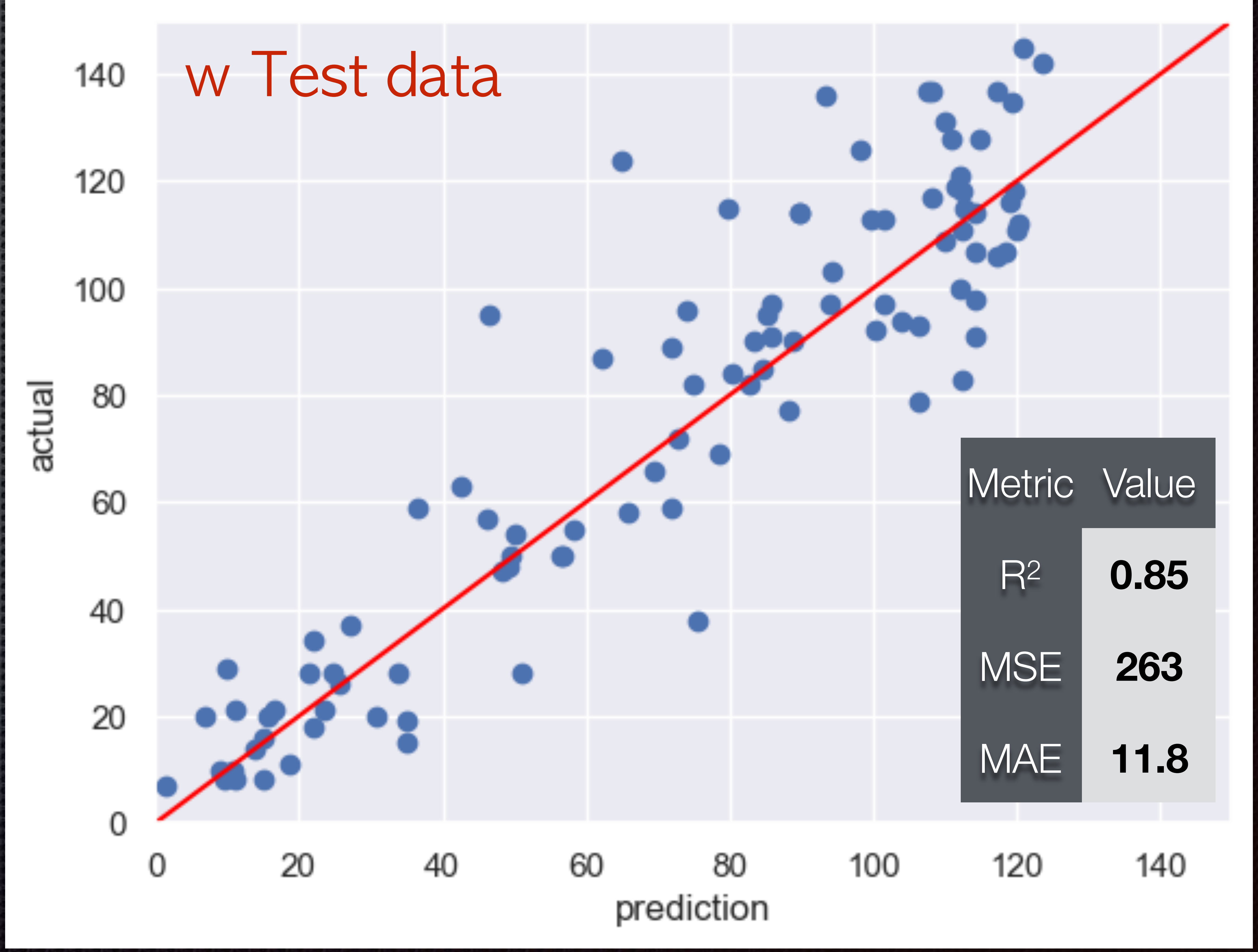
- Hyper parameter tuning done by GridSearchCV

Model	Train (MSE)	Validation (MSE)	Execution time (Train, msec)	Execution time (Validation, msec)
Linear	**313.0**	**296.8**	**6**	**2**
ElasticNet	**734.5**	**691.1**	**30**	**1**
SVR	**708.4**	**659.9**	**41629**	**3516**
Random Forest	**37.5**	**152.5**	**98706**	**133**
LightGBM	**51.0**	**117.2**	**3445**	**19**
XGBoost	**69.7**	**125.7**	**12636**	**8**

Model selection

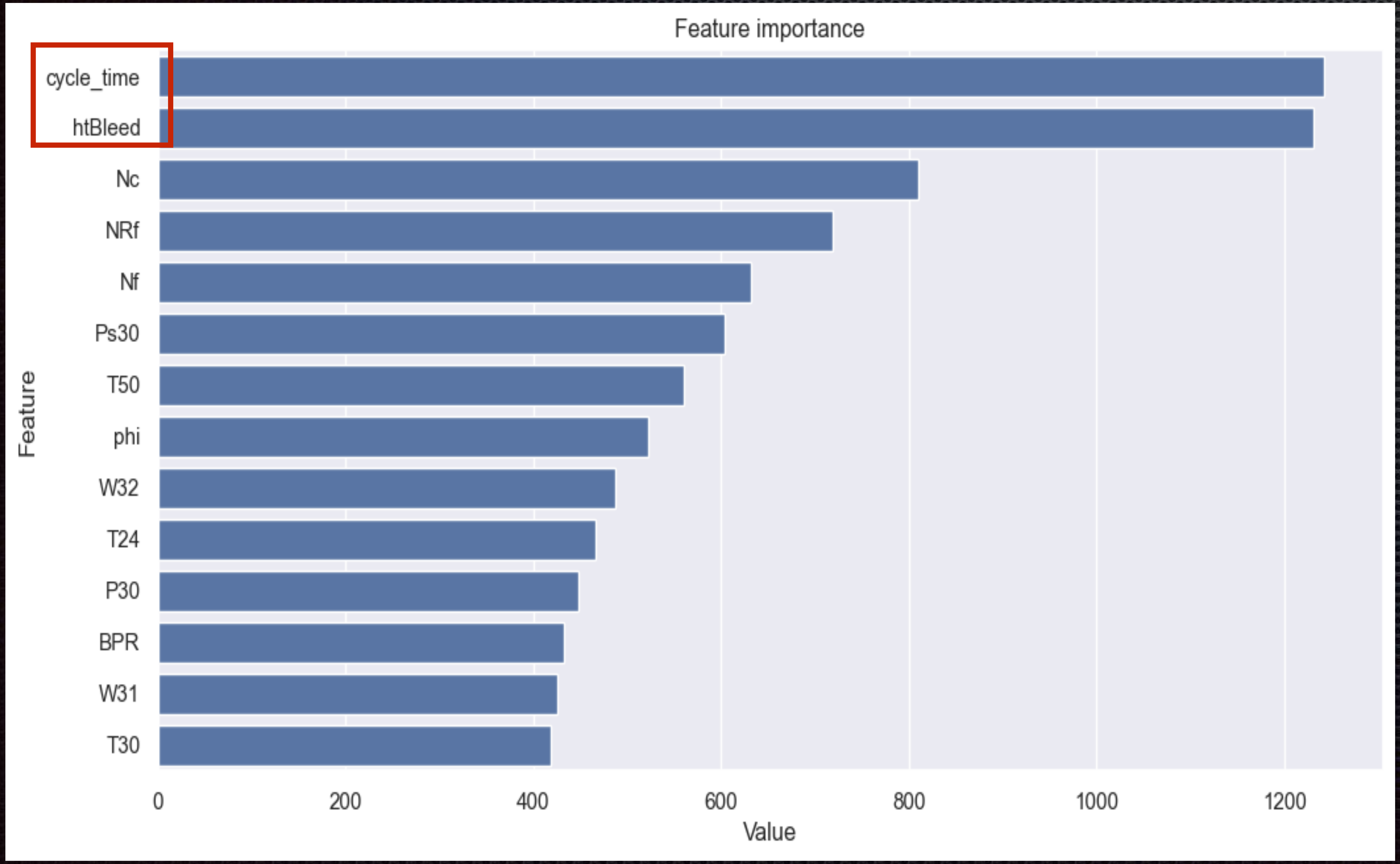
- Hyper parameter tuning done by GridSearchCV

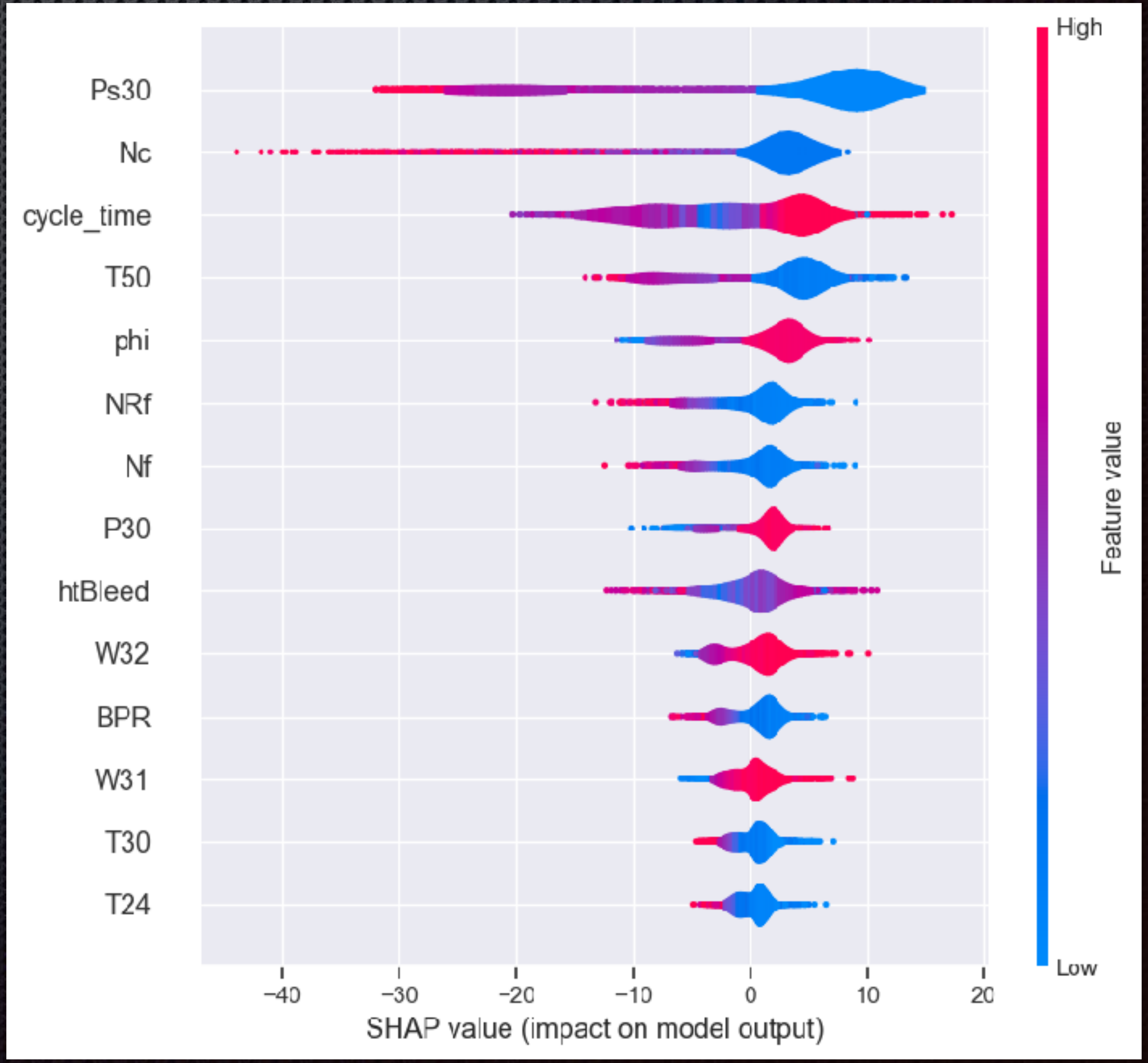




LGBM; feature importance

- htBleed (Bleed Enthalpy) & Cycle time are key features





Maintenance flag

- Lead time of engine maintenance: 3~6weeks*
  - 42 flight cycles (6 weeks) for the maintenance vs. current 28 flight cycles (Assume 1filght/day)

- Mapping maintenance flag if RUL <= 42
  - Accuracy of model: 97%
  - Recall: 92.9%
  - Precision: 96.3%

		Actual	
		Need maintenance	Not yet
Pred	Need maintenance	26	1
	Not yet	2	71

* https://www.avbuyer.com/articles/engine-maintenance-hub#:~:text=How%20long%20does%20aircraft%20engine,costs%20of%20aircraft%20engine%20maintenance.

Recommendation

Data → Predictive Model → Recommandation

- Predictive model: LightGBM for regression of RUL
- Maintenance frequency: 28 flight cycles → 42 flight cycles (30% reduction/year)
  - Max. cost avoidance: ~$700 million/year*

* # of day a year * # of engine x maintenance cost** / maintenance frequency * (Recall / Precision)
** $1.4 million (assume C-checks, https://www.aircraft-commerce.com/wp-content/uploads/aircraft-commerce-docs/Maintenance/2013/ISSUE87_MTCE_A.pdf

Limitation & Further improvement

Limitations

1) Sensor physical faults: Predictive model will not work

2) Maximum cycle time (121 cycles) assumed by historical records: It could vary by engines

Further improvement idea (Recall: 92.9%)

1) Apply smoothing on each sensor signal

2) Feature engineering; Add more features & PCA