Remaining Useful Life

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The Remaining Useful Life is a key concept in predictive maintenance

The RUL refers to the time until a component becomes unusable

- If we can estimate the RUL of a component
- ...We can schedule maintenance operations only when they are needed

As a first case study, we will define a RUL-based maintance policy

In particular:

- We wil try to build a data-driven RUL estimator
- ...And we will trigger maintenance only if the estimated RUL becomes too low

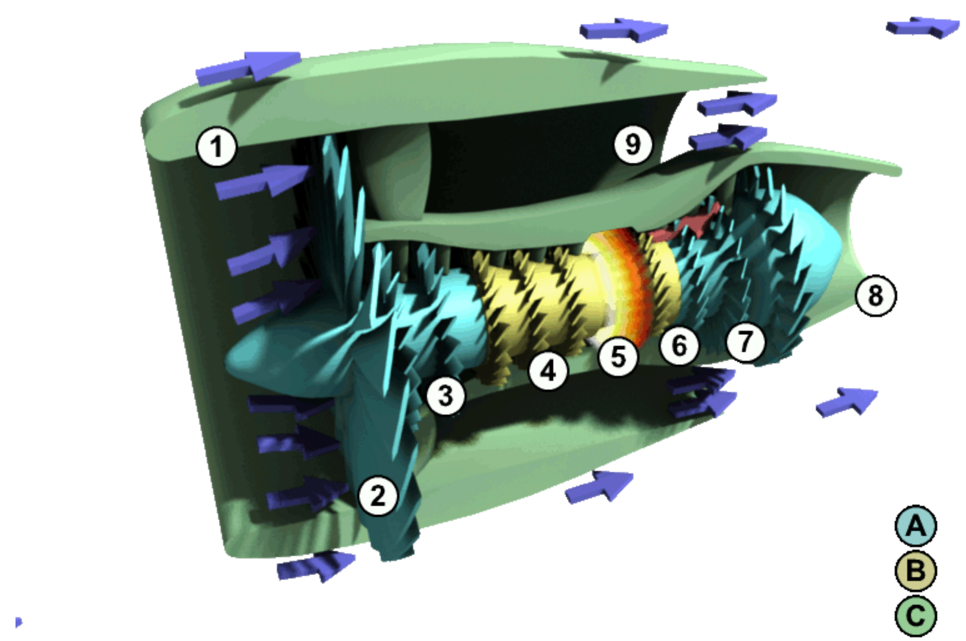
This is sort of the "holy grail" in predictive maintenance

- We will see how to build a successful method
- ...But we will work on a synthetic dataset

The Dataset

We will consider the NASA C-MAPSS dataset

- The Modular Aero-Propulsion System Simulation (MAPSS)
- ...Is a NASA-developed simulator for turbofan engines



- It comes with both a Military (MAPSS) and commercial versionn (C-MAPSS)
- They different in the attributes of the considered engines

The Dataset

The C-MAPSS system can simulate a number of faults and defects

...And it was used to build a high-quality dataset for the PHM08 conference

- Four files contain multiple full run-to-failure experiments
- Other four files contain instead truncated experiments

We will focus on the hardest of the "full" benchmark files

In the dataset, this is referred to as "train_FD004"

```
In [2]: from util import util
        data = util.load_data(data_folder='data', fnames=['train_FD004'])
```

This is the first piece of code that we see:

- You can find the details in the `util/util.py` files
- Or you can disregard them and just focus on the main idea

Inspecting the Data

Let's have a look at the dataset

In [3]:

```
print(f'#Example: {len(data)}, #experiments: {len(data["machine"].unique())}')
data.iloc[:3]
```

```
#Example: 61249, #experiments: 249
```

Out[3]:

	src	machine	cycle	p1	p2	p3	s1	s2	s3	s4	...	s13	s14	s15	s16	s1
0	train_FD004	1	1	42.0049	0.8400	100.0	445.00	549.68	1343.43	1112.93	...	2387.99	8074.83	9.3335	0.02	33
1	train_FD004	1	2	20.0020	0.7002	100.0	491.19	606.07	1477.61	1237.50	...	2387.73	8046.13	9.1913	0.02	36
2	train_FD004	1	3	42.0038	0.8409	100.0	445.00	548.95	1343.12	1117.05	...	2387.97	8066.62	9.4007	0.02	32

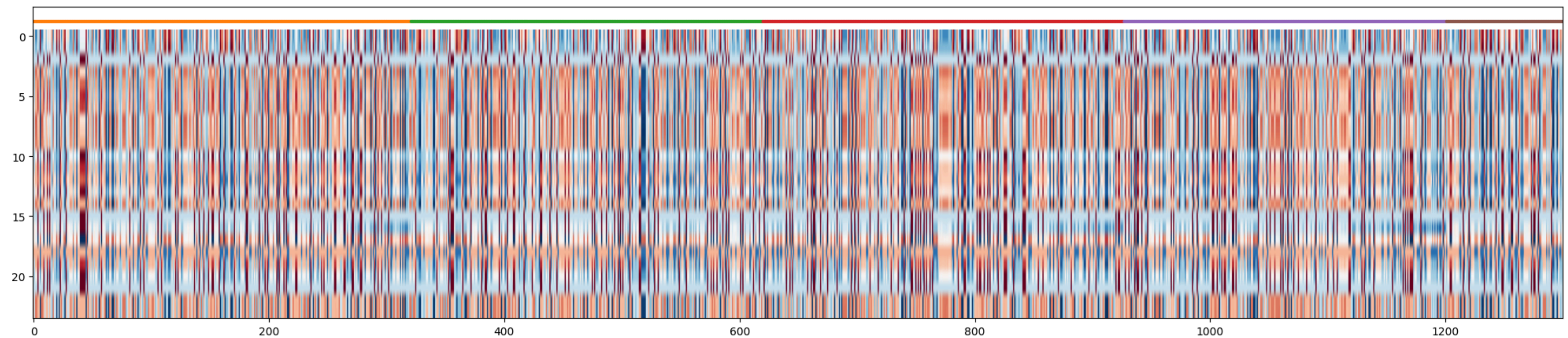
3 rows × 28 columns

- Columns "p1, p2, p3" refer to controlled parameters
- Columns "s1" to "s21" refer to sensor readings
- The "machine" column identifies different experiments
- The "rul" column contains the remaining useful life

Inspecting the Data

Let's have an global look at our dataset

In [4]:
```
dt_in = list(data.columns[3:-1])
tmp = data.iloc[:1300]
util.plot_df_heatmap(tmp[dt_in], labels=tmp['machine'], figsize=figsize)
```

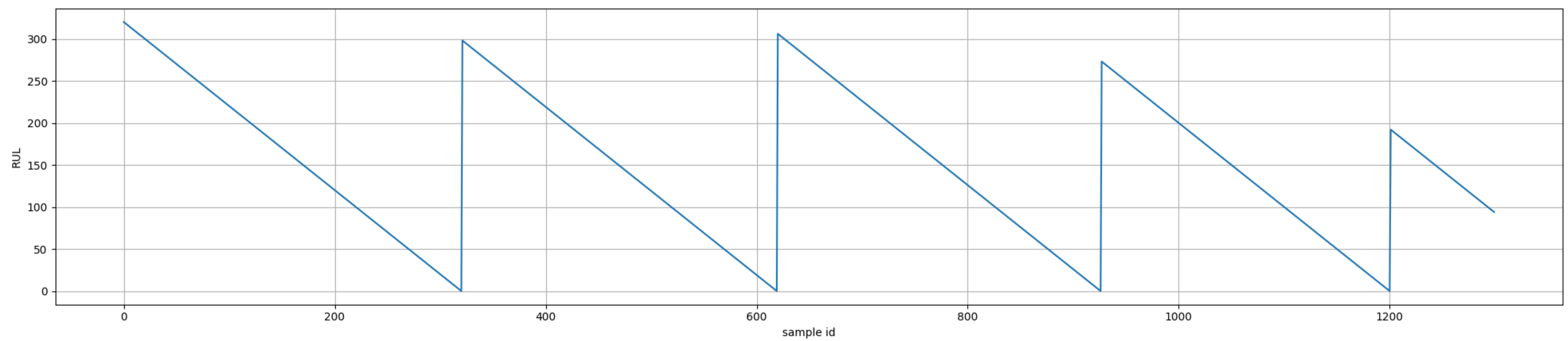


- Each color in the top row identifies a different run-to-failure experiment
- Other rows show (standardized) column values (red = low, blue = high)

Inspecting the Data

Our RUL is literally the time to the experiment end

In [5]:
```
util.plot_series(tmp[['rul']], figsize=figsize, xlabel='sample id', ylabel='RUL')
```



- As a result, in our dataset we will have this "saw-like" patter
- Each "tooth" refers to a full run-to-failure experiment