Predictive Maintenance

Wind Turbine Failure Modelling

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Darts

Unit8™

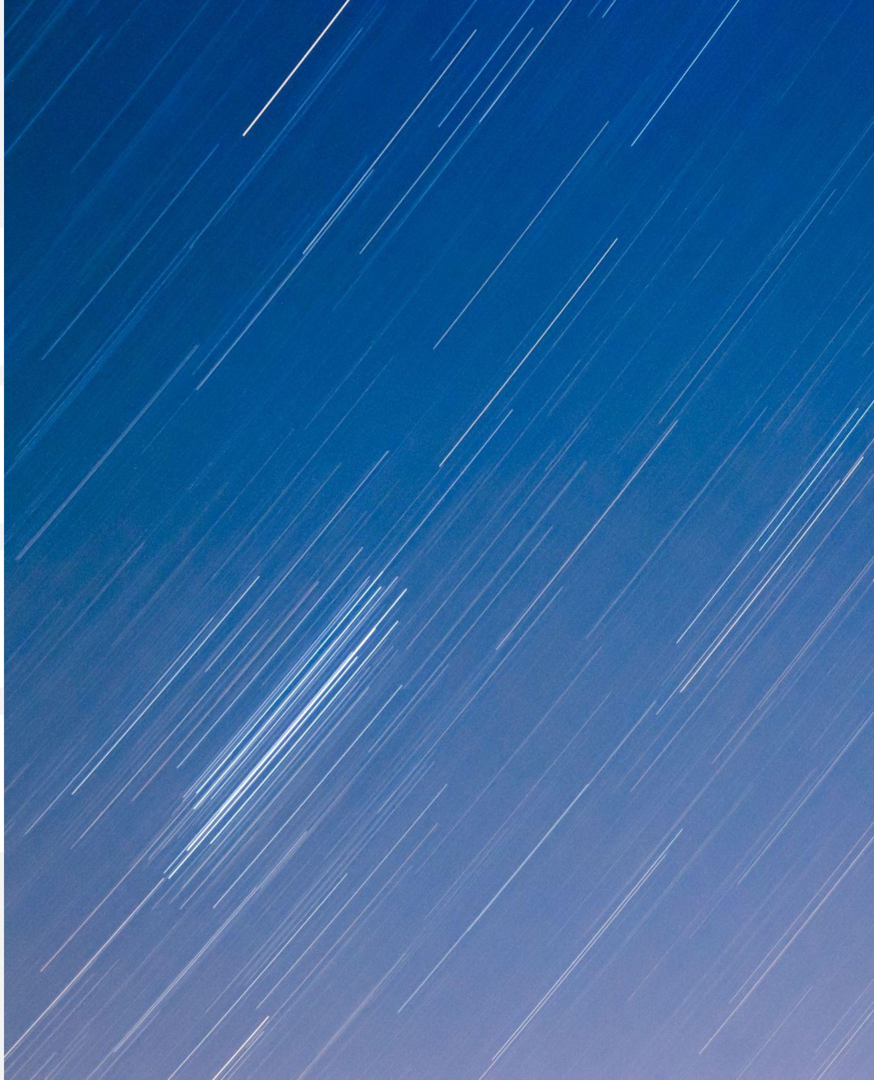
Agenda

1 Why Predictive Maintenance

2 Predictive Maintenance Approaches

3 Real-world example: Wind Turbine Failures

4 Time for the exercise



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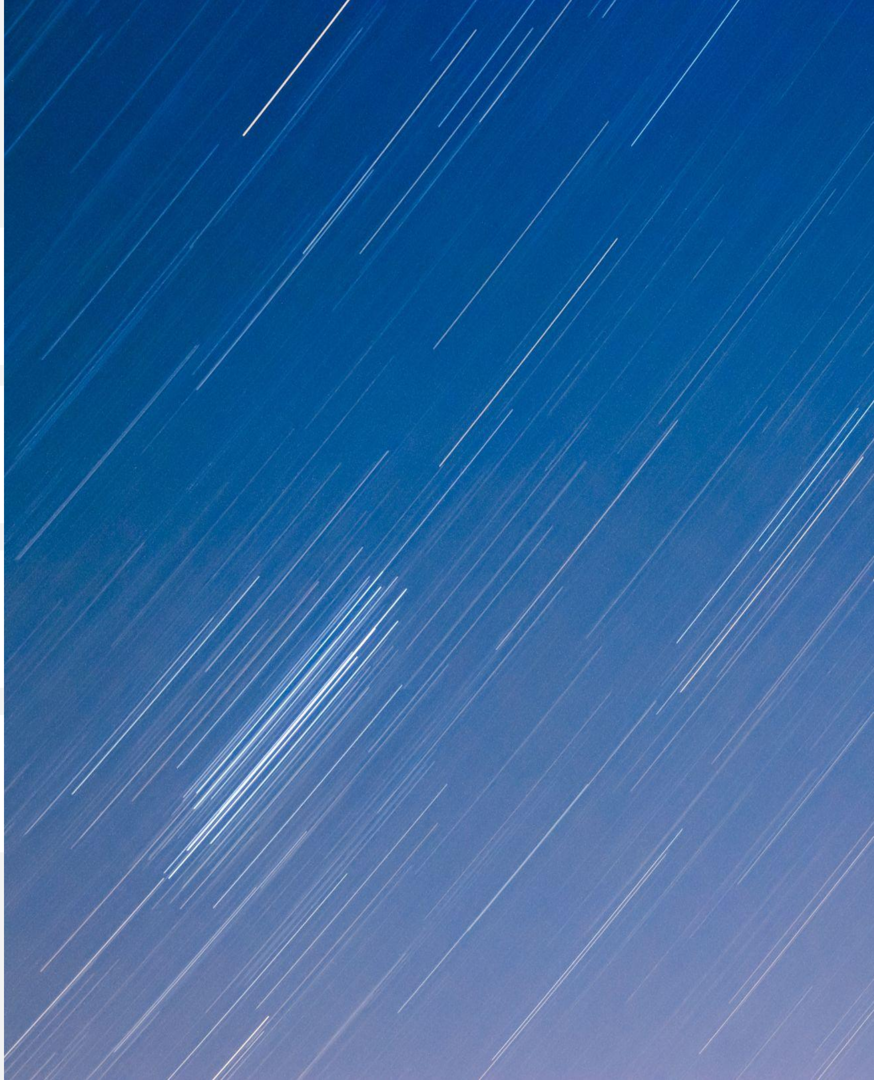
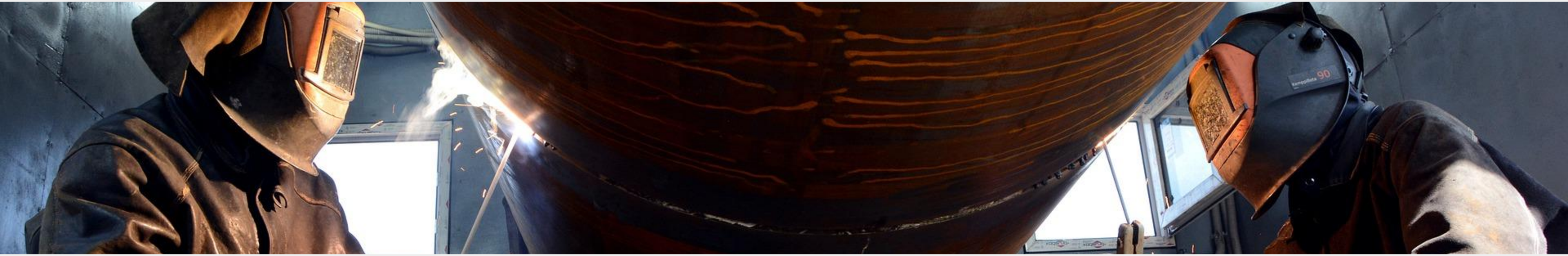


Why Predictive Maintenance?



- **Minimize Downtime**: Reduce unexpected equipment failures by predicting issues before they occur.
- **Cost Efficiency**: Lower maintenance costs by addressing problems proactively rather than reactively.
- **Extend Equipment Life**: Regular monitoring and early intervention help extend the lifespan of machinery.
- **Increase Safety**: Prevents accidents by identifying potential failures in advance.
- **Improve Operational Efficiency**: Ensures continuous and optimal performance of machinery, leading to improved productivity.

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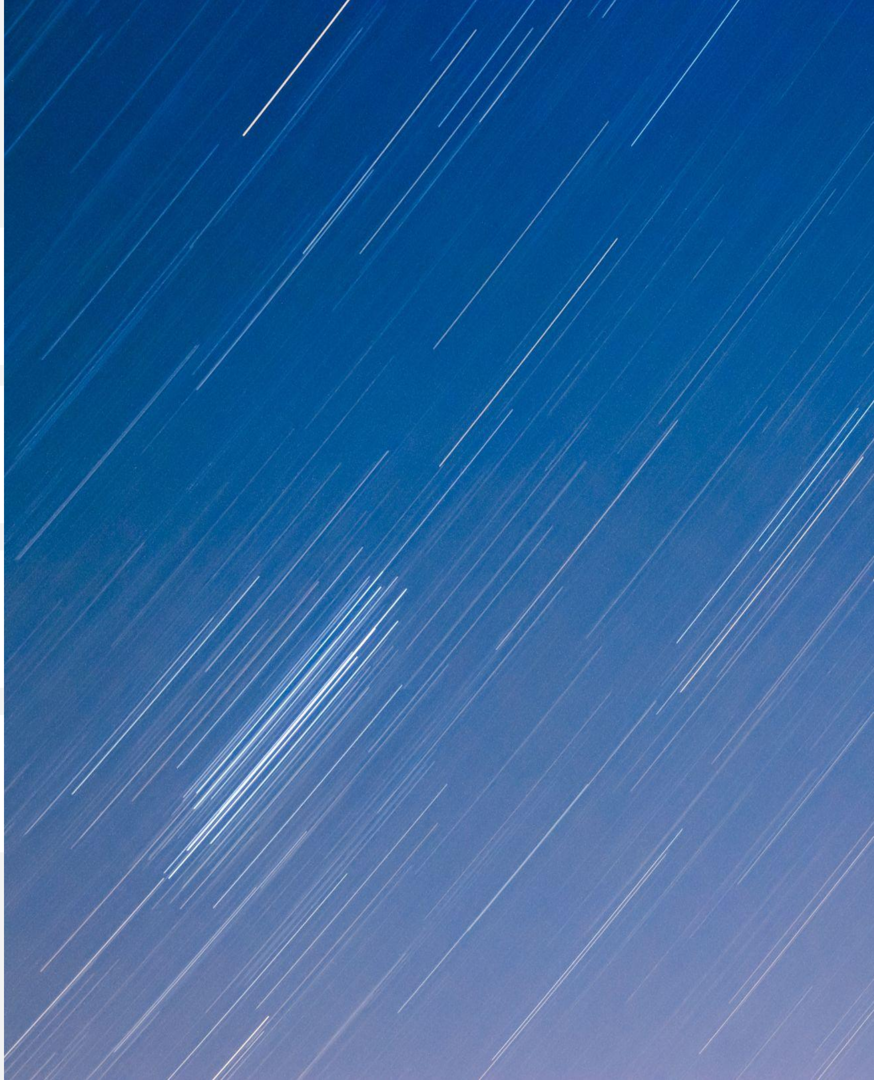


Which Approaches Exist?

- **Outlier Detection**: Identify deviations from a known distribution of normal operating data
    - **Statistical Methods**: use techniques like Z-scores or IQR analysis
    - **Rule-Based Systems**: use predefined thresholds / rules derived from historical data

- **ML Modeling**: Predict future equipment failures based on historical data
    - **Supervised Learning**: Train models n labeled data to predict specific failure types.
    - **Unsupervised Learning**: Detects anomalies without predefined labels, often used for clustering

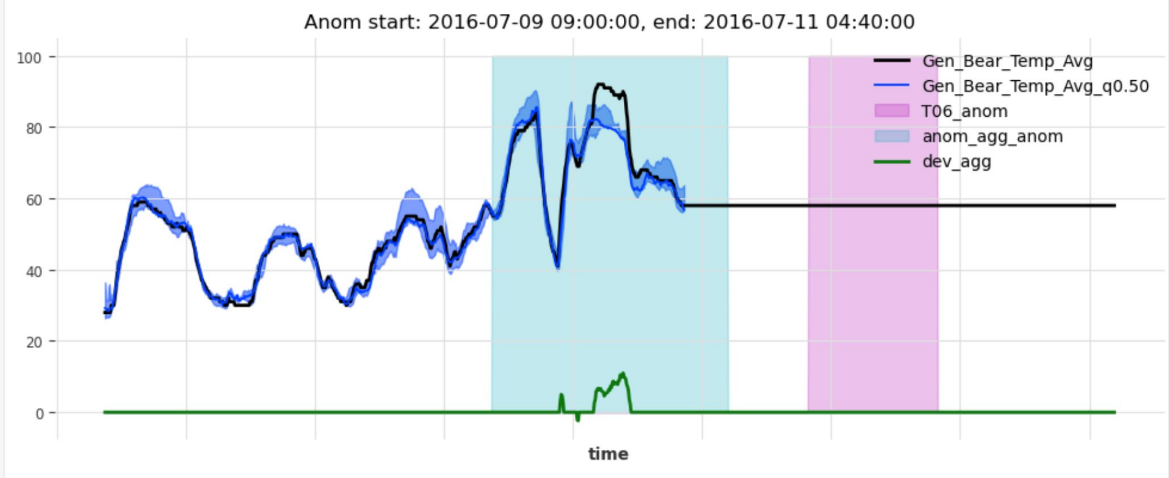
- **Time Series Analysis**: Forecast future conditions and detect deviation trends indicating potential failures

- **Hybrid Approaches**: Combine multiple methodologies to enhance predictive accuracy and robustness

Our Approach

- ML modeling to estimate the normal operating range (NOR) of some signal:
  - Use only **unidirectional causal input features**
  - Train a **probabilistic model** to predict **quantile interval** (proxy for NOR)
  - **Train on anomaly-free** (or cleaned) **historic data**

- On a scheduled basis (e.g. every couple of hours, ...):
  - **Estimate the NOR** over most recent past using the trained model
  - Determine when / how much **actual signal deviated from NOR**
  - **Detect anomalies** looking at **windowed statistics** (minimum dev. threshold, minimum number of points, ...)



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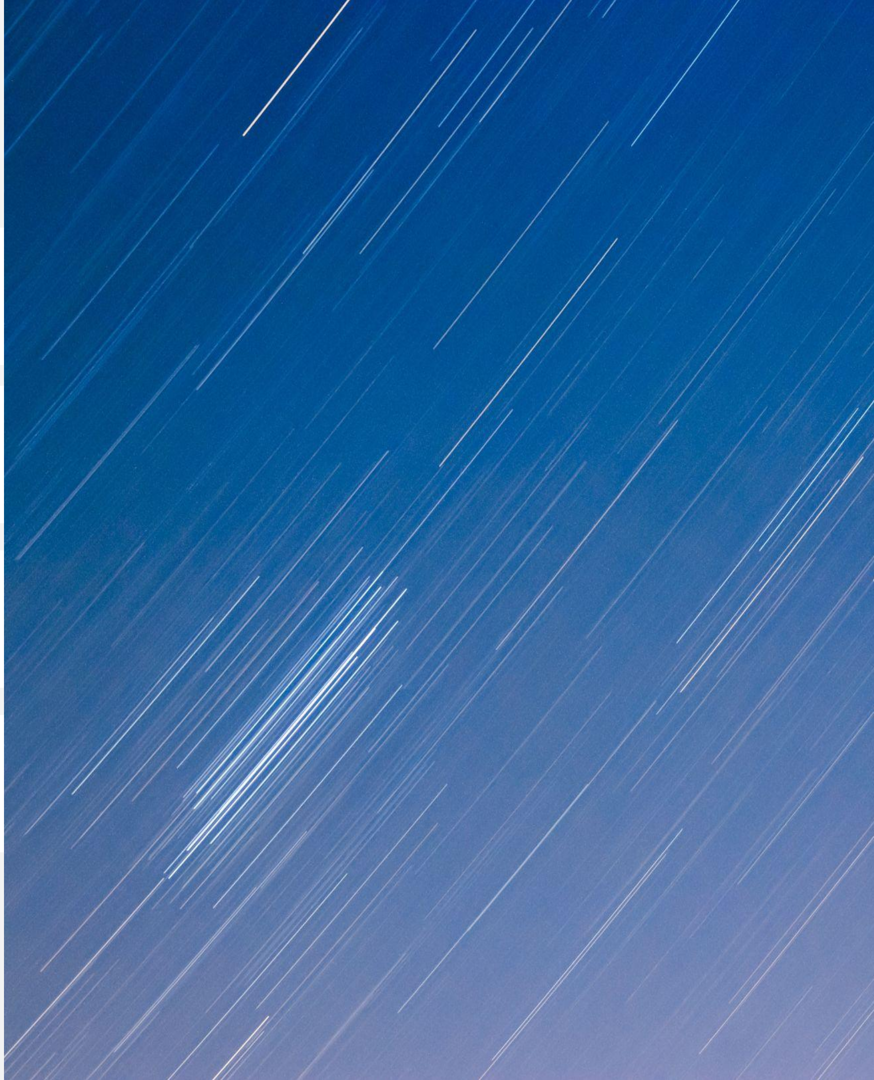
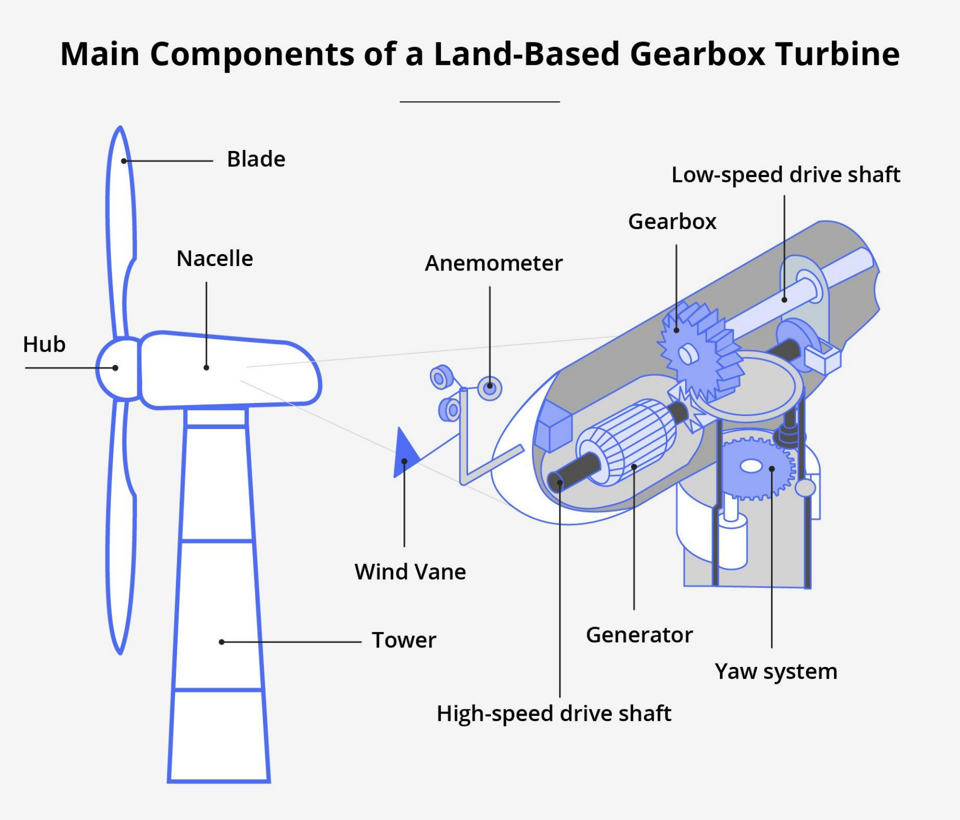
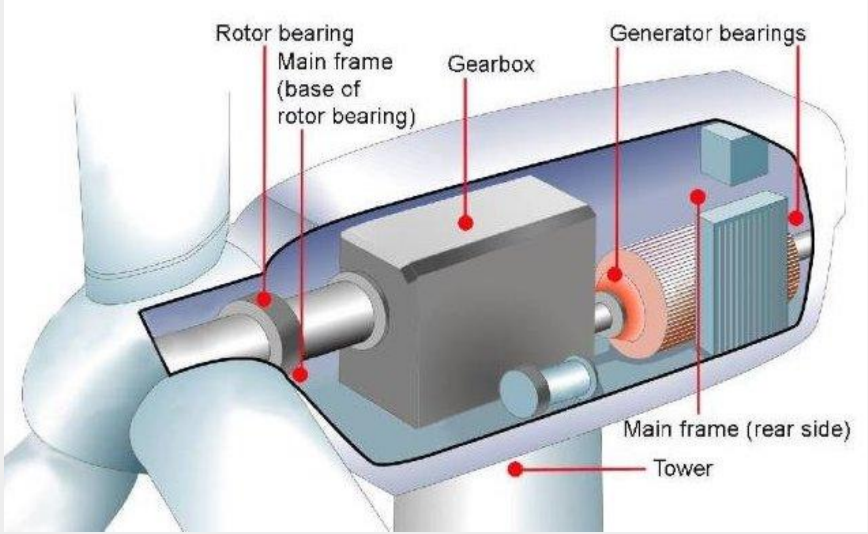


Real World Example - Wind Turbine Failures

Dataset characteristics	Sensors & failure/error logs for 4 offshore Wind Turbines (WT) in the West African Gulf of Guinea
Signals	82 features; wind-turbine components sensors as well as meteorological data
Size	~70’000 measurements per wind turbine
Time resolution	10 minutes
Date	2016-2017
Source	EDP - Energias de Portugal https://www.edp.com/en/innovation/open-data/reuses/hack-the-wind

Wind Turbine Components





Components in Dataset

- Gearbox
- Generator
- Generator Bearing
- Transformer
- Hydraulic Group

Error Log Book Analysis

Observations:

- 12 recorded anomalies
- Turbine 6 had by far the most anomalies (6)
- Majority of anomalies related to generator
- Majority of Generator anomalies are related to temperatures

Takeaways:

- Let’s focus on Turbine 6
- We try to detect anomalous generator behavior
- By monitoring the temperature

	Turbine_ID	Component	Timestamp	Remarks
0	T01	GEARBOX	2016-07-18 02:10:00	Gearbox pump damaged
1	T06	HYDRAULIC_GROUP	2016-04-04 18:50:00	Error in pitch regulation
2	T06	GENERATOR	2016-07-11 19:50:00	Generator replaced
3	T06	GENERATOR	2016-07-24 17:00:00	Generator temperature sensor failure
4	T06	GENERATOR	2016-09-04 08:10:00	High temperature generator error
5	T06	GENERATOR	2016-10-02 17:10:00	Refrigeration system and temperature sensors i...
6	T06	GENERATOR	2016-10-27 16:30:00	Generator replaced
7	T07	GENERATOR_BEARING	2016-04-30 12:40:00	High temperature in generator bearing (replace...
8	T07	TRANSFORMER	2016-07-10 03:50:00	High temperature transformer
9	T07	TRANSFORMER	2016-08-23 02:20:00	High temperature transformer. Transformer refr...
14	T11	GENERATOR	2016-03-03 19:00:00	Electric circuit error in generator
15	T11	HYDRAULIC_GROUP	2016-10-17 17:40:00	Hydraulic group error in the brake circuit

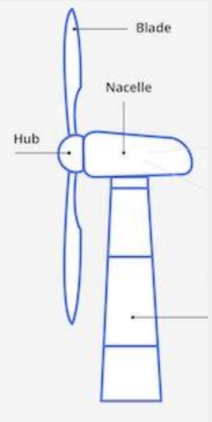
Predictive Maintenance Task Definition

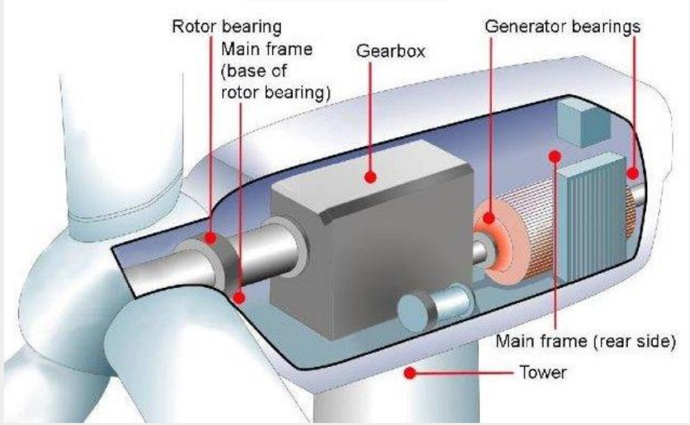
- **Goal**: detect anomalies early in generator by monitoring generator health on a scheduled basis (post hoc)

- **How:** Model the normal operating range (NOR) of the temperature using unidirectional causal signals (UCS)

- **Target signal**: Generator Bearing Temperature Sensor

- **Input features**: We do post hoc monitoring, so we can use measurements of any UCS signal at time T to model the NOR at any time T

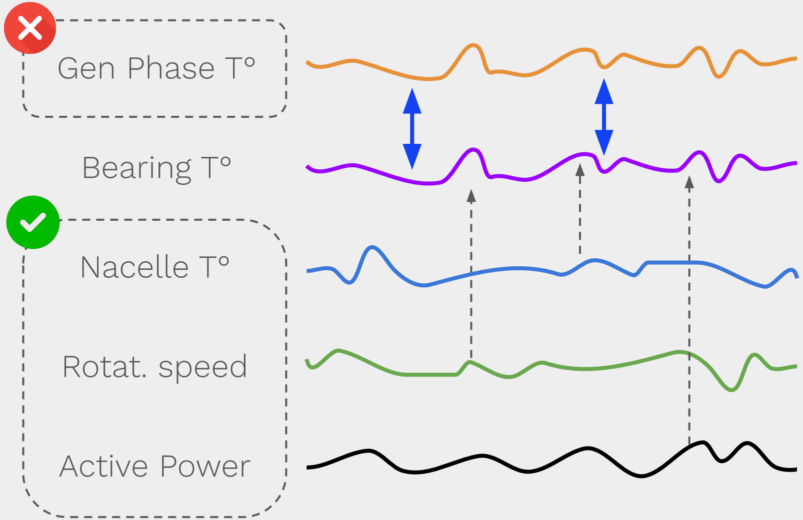




Use only unidirectional causal signals as model input

Unidirectional Causal Signals (UCS): Features that can cause the temperature to change, but which are not themselves affected by a change in temperature (or a temperature anomaly in the generator)

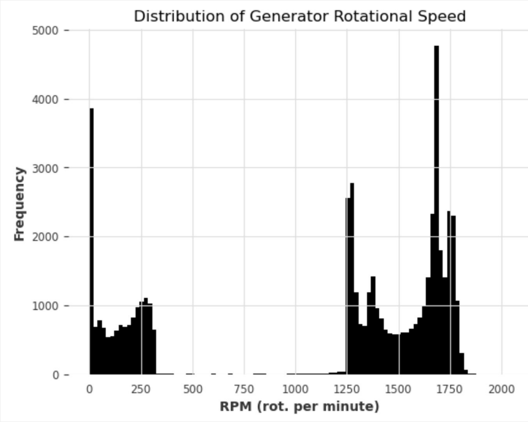
- **Bad features** (available):
  - past values of the bearing temperature
  - another temperature sensor close to it
  - ...
- **Good features** (available):
  - Generator Rotational Speed (heat/energy source)
  - Nacelle (turbine housing) temperature (heat source)
  - Generated Active Power (heat source)
  - ...
- **Good features** (not available):
  - Cooling liquid flow (but not the liquid temperature!)
  - ...

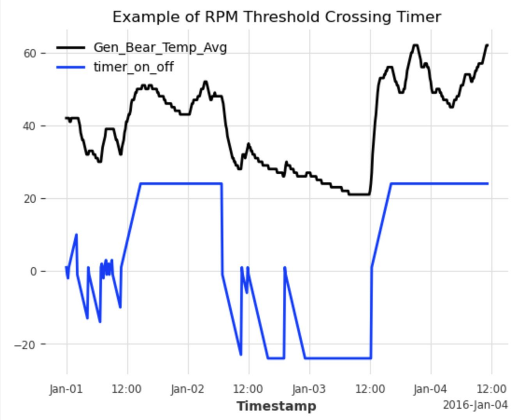


There are other useful features that can be generated

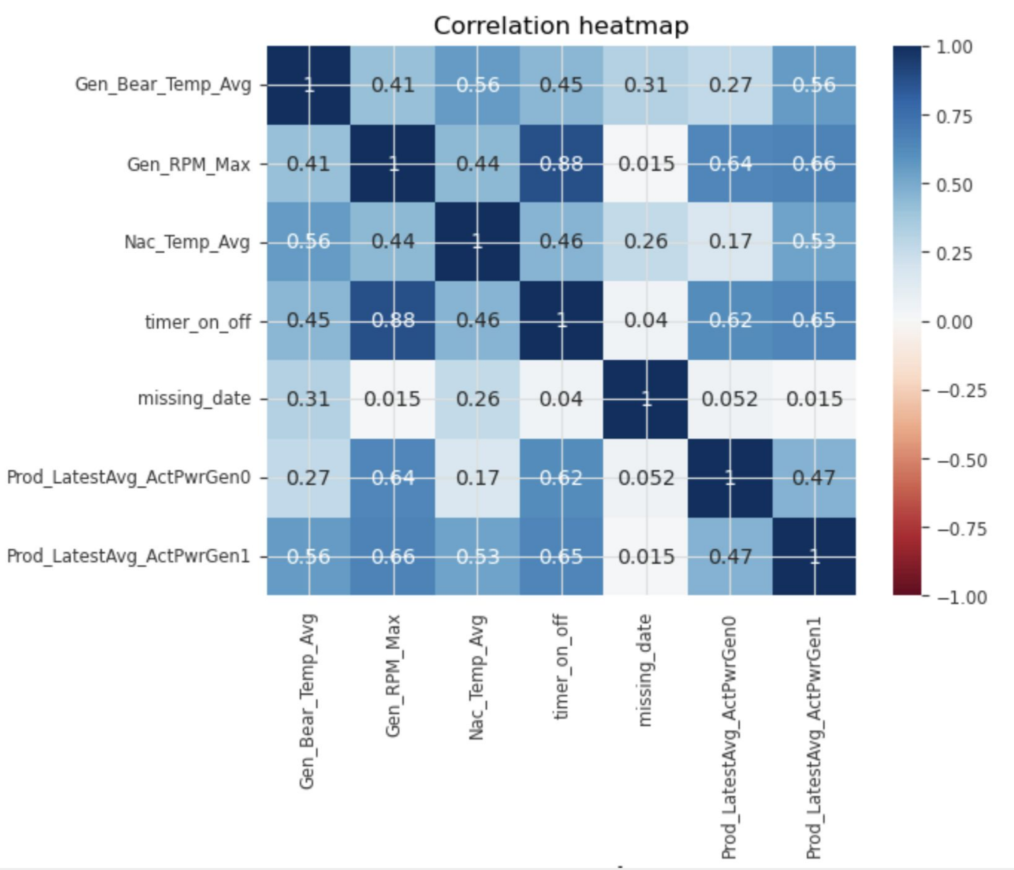
Other UCS features that can be generated

- Timer since Rotational Speed last crossed 1200 RPM mark (linear proxy for heat buildup/cooldown over time)
- Missing date flag
- Timer since last significant change in power generation
- ...





Selected Feature Correlation with Bearing Temperature



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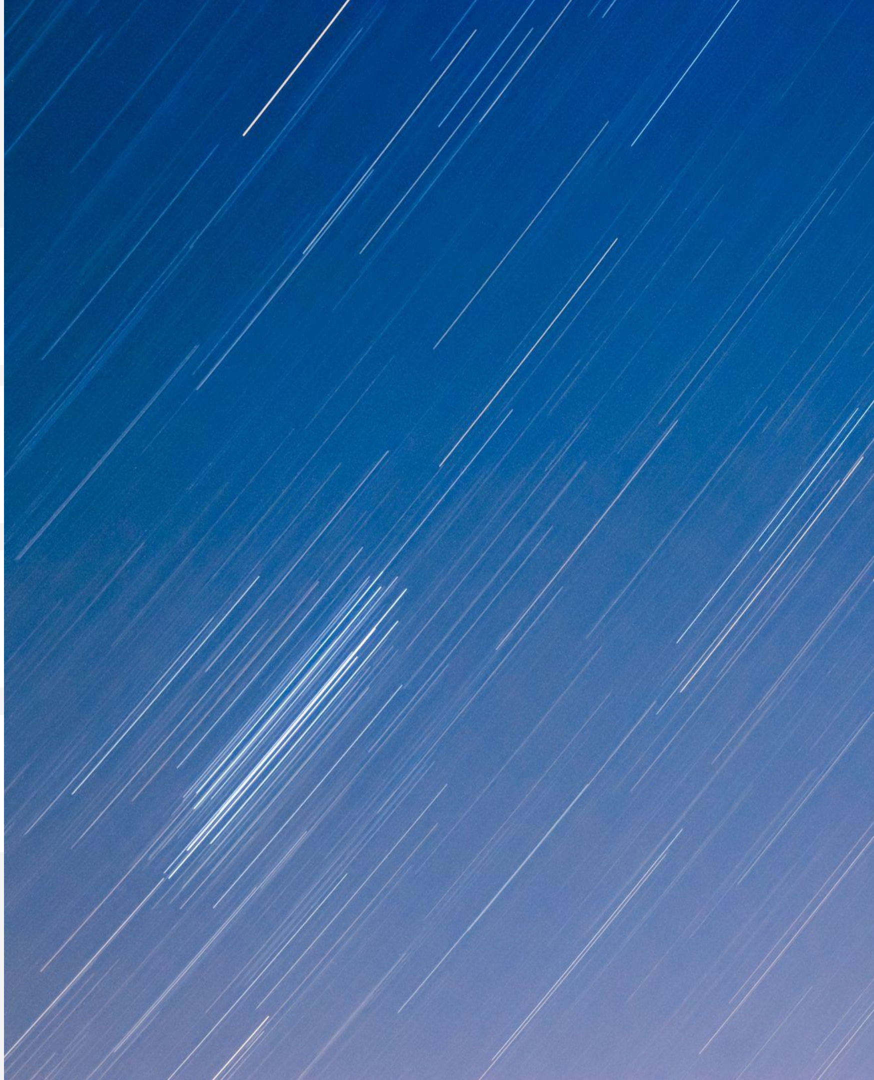
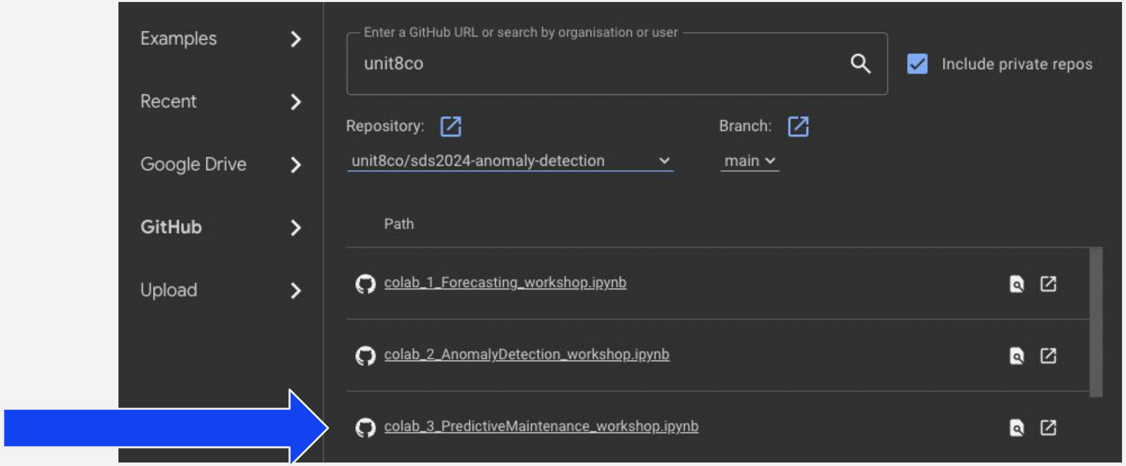


Time To Work

- Open: https://colab.google/
- Click on “Open Colab”
- On the left sidebar click GitHub
  - Enter GitHub URL: “unit8co”
  - Select repository: “unit8co/sds2024-anomaly-detection”
  - Select notebook: “colab_1_Predictive_workshop.ipynb”



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thank you!