Large-scale Vibration Monitoring of Aircraft Engines from Operational Data using Self-organized Models

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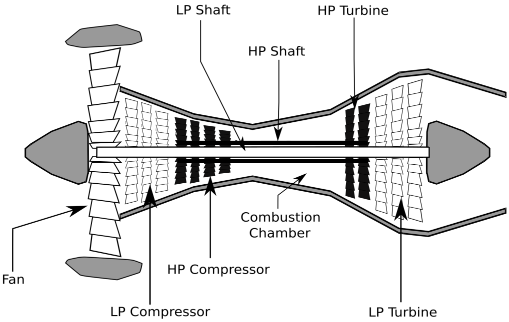
Introduction

Turbofan aircraft engines



- Produces thrust by accelerating air (Newton's third law).
- Most civil aircraft use 2-spool, high-bypass turbofan jet engines.
- In this work: mid-range aircraft.

Use case introduction

Vibration monitoring for aircraft engines condition monitoring (CM)

- Crucial part of CM for rotating industrial equipment. [Randall, 2011, Bastard et al., 2016]
- $\Uparrow$ Availability and safety, $\Downarrow$ Costs
- Engine manufacturers are now responsible for maintenance (leasing).
- Detection of unbalance, misalignment due to wear (blades [Kharyton, 2009, Hazan et al., 2010], bearings [Orsagh et al., 2003], gears [Wang et al., 2001]), rotor/stator contact [Peng et al., 2005]

Overview

Proposition

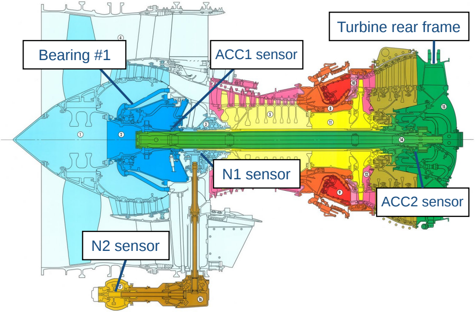
Methodology for large-scale vibration monitoring of a fleet of aircraft engines using historical flight recorder data.

1. Massive extraction of time-domain vibration signatures using distributed processing on a cluster.
2. Unsupervised learning (self-organized maps) for clustering and visualization.

✓ Monitoring, alerting, forecasting.
✗ Diagnosis and prognosis is left to experts.

Large-scale vibration signature extraction

Vibration sensors



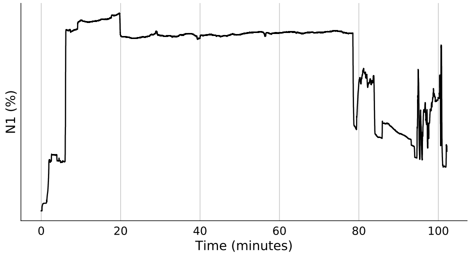
Sensors measure rotation speeds and vibration peak amplitude (displacement, speed or acceleration). Raw signals are processed and downsampled onboard.

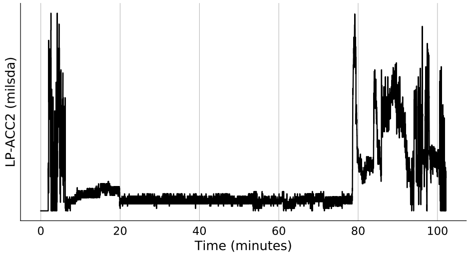
Variables:

- N1: LP shaft rotation speed @66Hz
- N2: HP shaft rotation speed @66Hz
- LP-ACC1, LP-ACC2: vibration amplitude at N1 speed @4Hz
- HP-ACC1, HP-ACC2: vibration amplitude at N2 speed @4Hz

Example signals

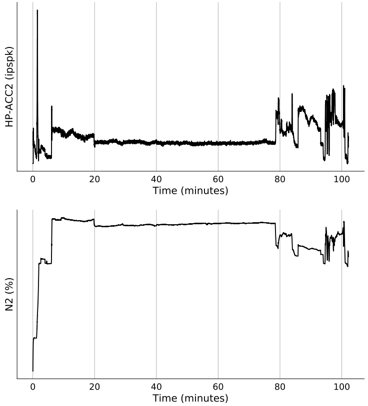
N1 and LP-ACC2 signals during one flight:





Vibration signatures

Vibratory response of the engine: vibration amplitude as a function of regime.



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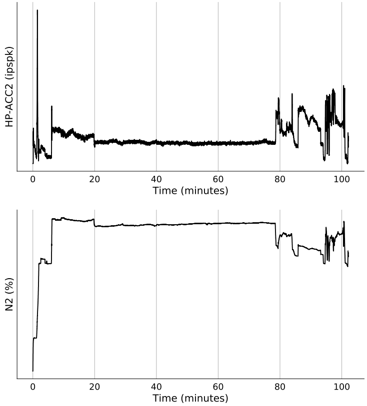

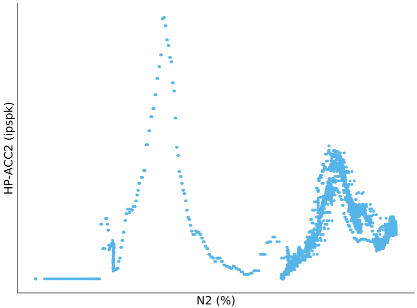

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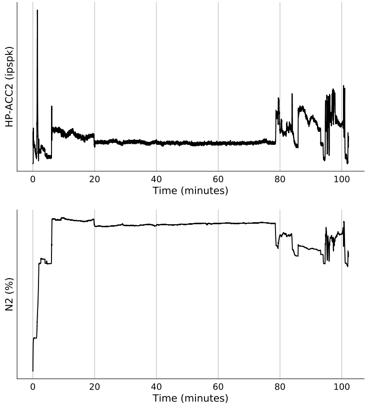

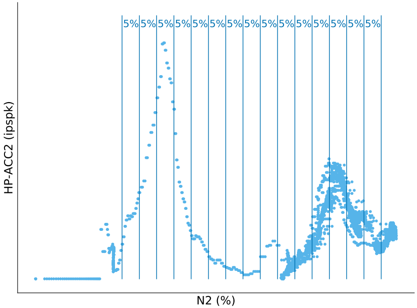

Experts can infer engine behaviors by looking at signatures (modes at different regimes → unbalance at specific locations of the engine).

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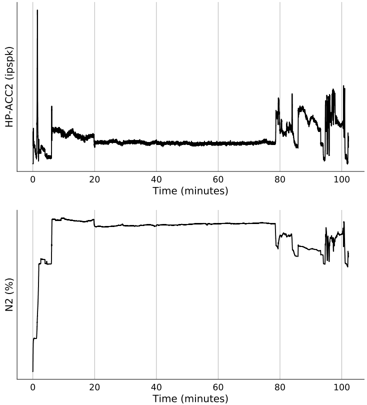

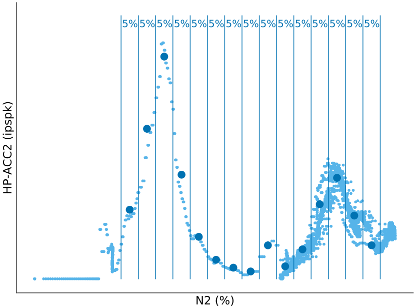

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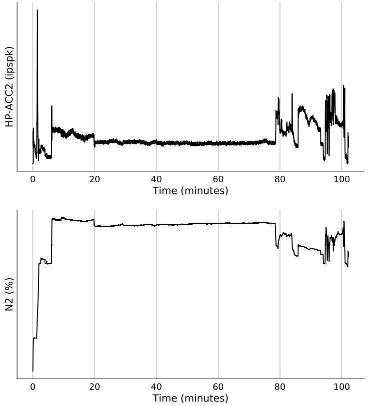

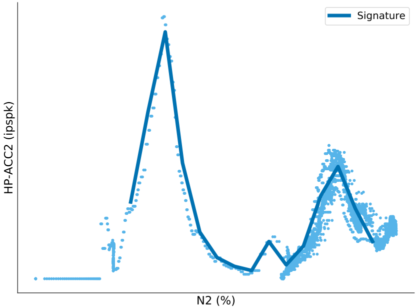

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Vibration signatures

4 vibration signatures are studied in this work:

1. LP-ACC1 vs N1
2. LP-ACC2 vs N1
3. HP-ACC1 vs N2
4. HP-ACC2 vs N2

Data acquisition process & properties

CEOD: Continuous Engine Operational Data

1. Collected during entire flights, stored in the onboard flight recorder (100s of variables @ up to 66Hz).
2. Downloaded on ground between flights, transferred from the airline to the aircraft engine manufacturer.
3. Decoded and ingested into Hadoop cluster (distributed data warehouse).

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Property	Approximate value
Number of engines	1000
Number of flights	1 million
Number of parameters	6
Frequency of parameters	4 Hz or 66 Hz
Total HDFS storage volume	1 TB

The V's of Big Vibration Data

Drivers:

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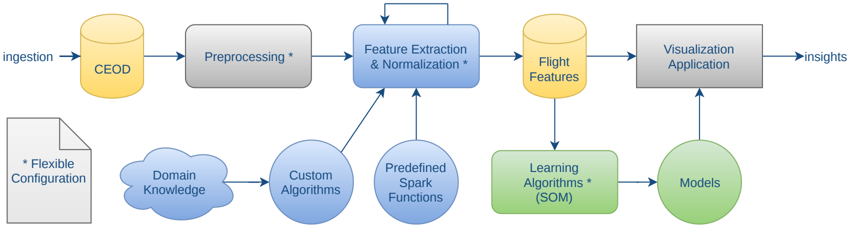
Need for a Big Data stack! (end-to-end scalability)

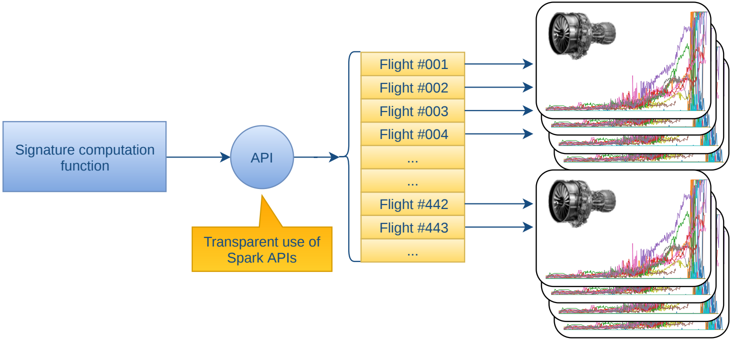
Generic processing pipeline

Based on the generic processing pipeline introduced in [Forest et al., 2018].



Massive signature extraction

- Data-parallel computation of vibration signatures.
- Engineers can easily input their business logic functions.



Clustering and visualization with self-organized models

Self-Organizing Maps

SOM algorithm for clustering and visualization [Kohonen, 1982].

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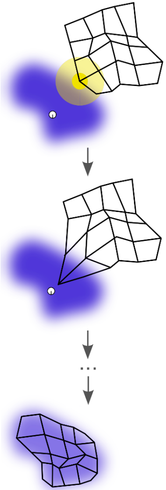

Algorithm (stochastic version):

1. Initialize map prototypes $\{\mathbf{m}_k\}_{1 \leq k \leq K} \in \mathbb{R}^D$.
2. Iterate over data samples $\mathbb{X} = \{\mathbf{x}_i\}_{1 \leq i \leq N}, \mathbf{x}_i \in \mathbb{R}^D$:
   - 2.1 Find best-matching unit $b_i = \text{argmin}_k ||\mathbf{x}_i - \mathbf{m}_k||_2^2$
   - 2.2 Update each prototype vector $\mathbf{m}_k \leftarrow \mathbf{m}_k + \alpha \mathcal{K}^T(\delta(b_i, k))(\mathbf{x}_i - \mathbf{m}_k)$
   - 2.3 Update neighborhood function $\mathcal{K}^T(d) = e^{-d^2/T^2}$

     where $T(t) = T_{max}(T_{min}/T_{max})^{t/\text{iterations}}$

Vibration profiles visualization

- Outputs a **map** of $K \times K$ units associated to prototype vibration signatures (15-d vector), representing **vibration profiles**.
- Self-organization $\rightarrow$ smooth variations, interpretability.
- Each flight is clustered by projecting on the nearest vibration profile (Best-Matching Signature).
- Spark-distributed implementation of batch SOM for scalability (`github.com/FlorentF9/sparkml-som`).

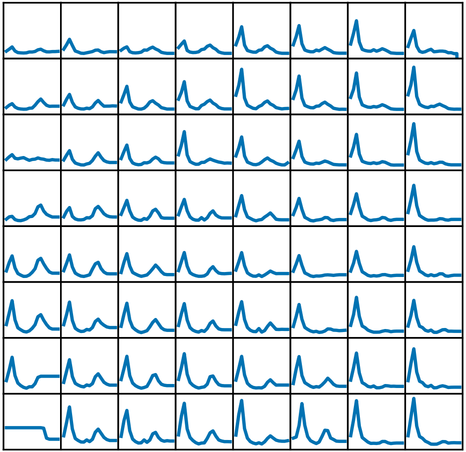

Figure 1: Signature 4 (HP-ACC2 vs N2)

Vibration signatures describe **intrinsic properties** of an engine.

▶ Every engine is different!

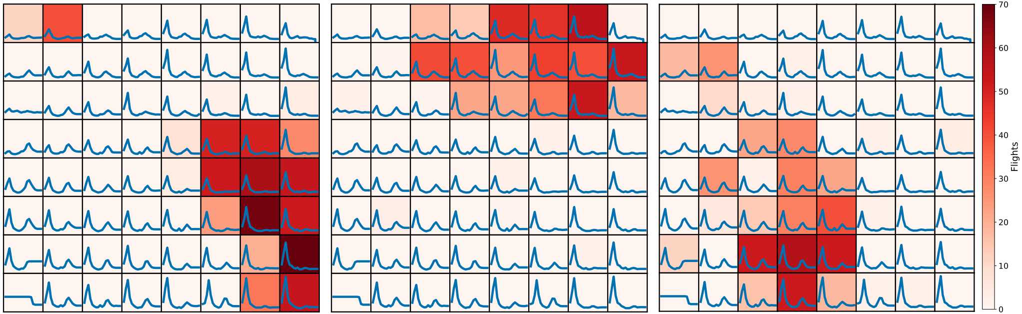

Figure 2: Heatmaps of projection counts for 3 different engines.

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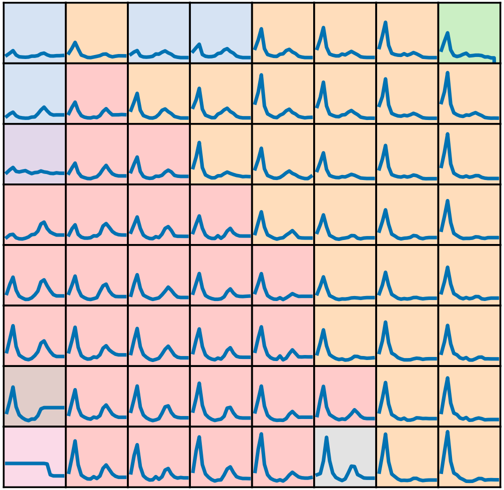
- Periodically re-train models with up-to-date flight data, to account for new trends and the aging of the fleet.

Engine trajectory visualization



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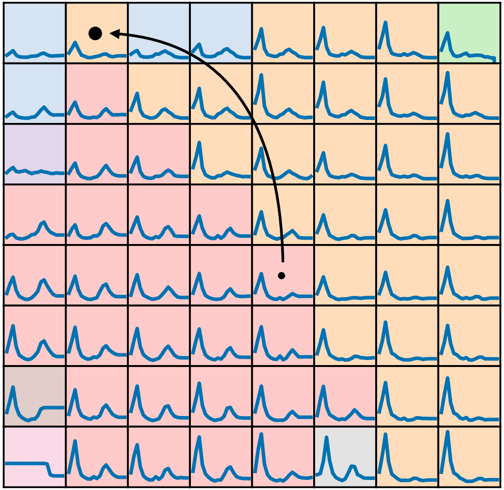

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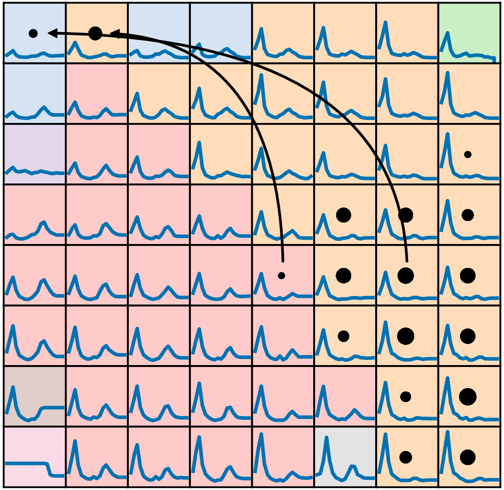

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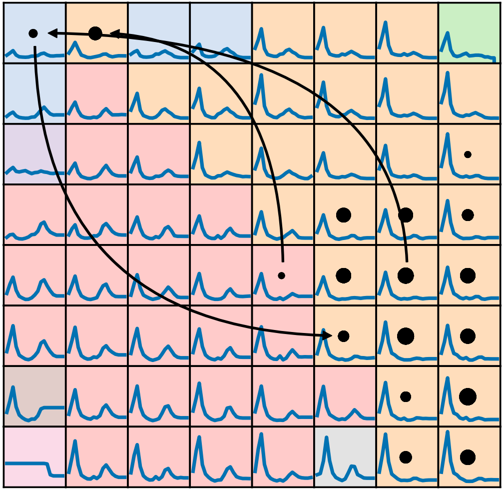

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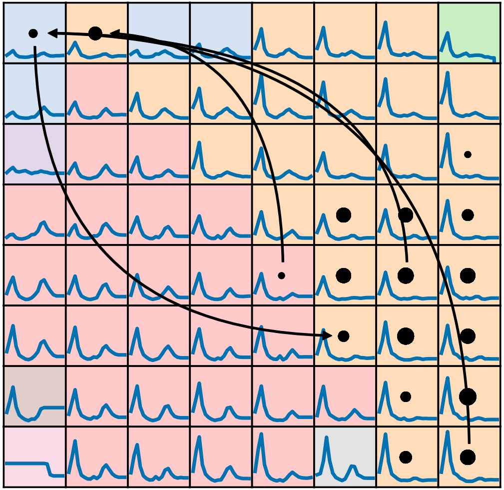

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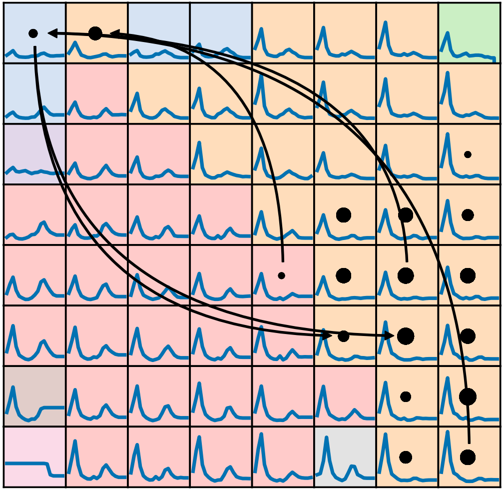

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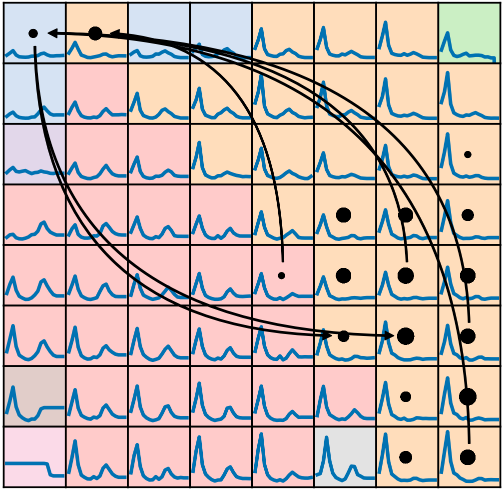

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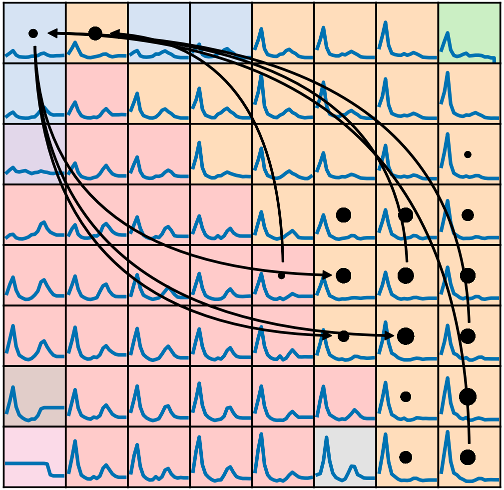

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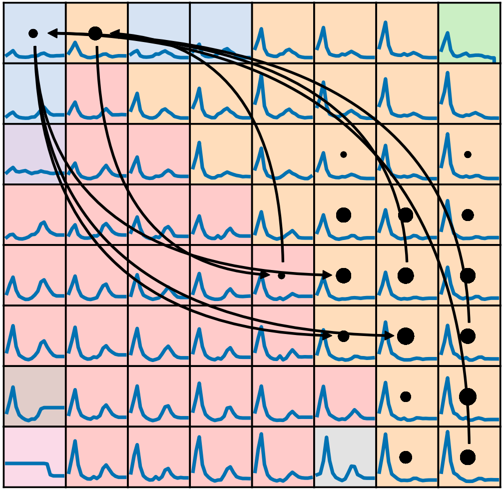

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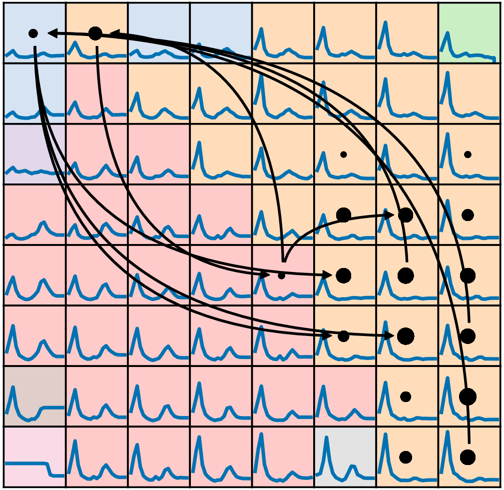

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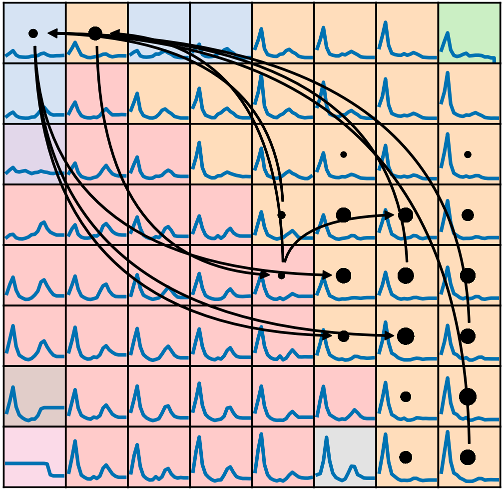

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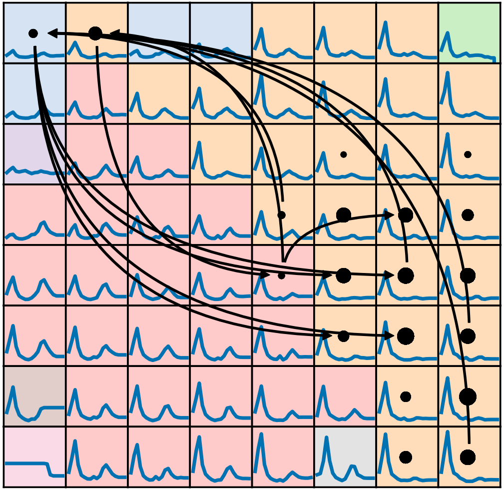

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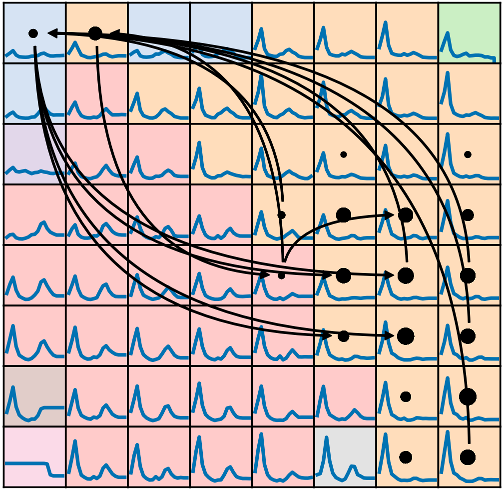

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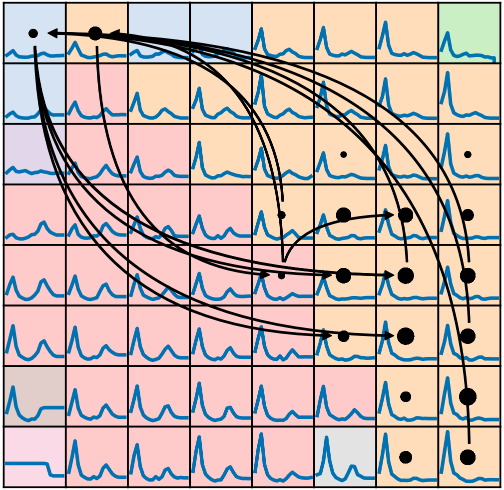

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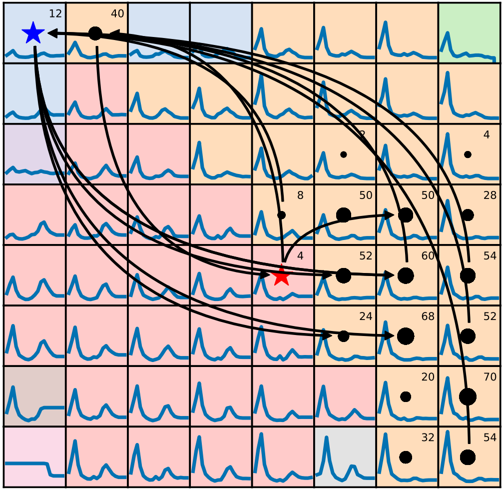

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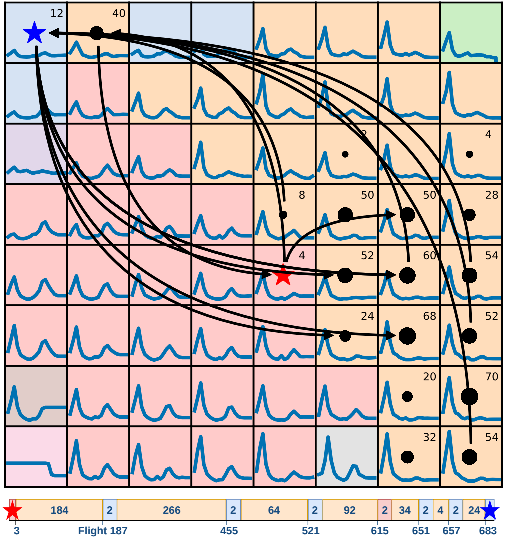

Conclusion & future work

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- As part of CM strategy, allows to quickly detect wear of parts, or abnormal behaviors.
- Large-scale, global approach on entire fleets — running on production cluster.
- Machine learning is able to crunch huge amounts of numbers...
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Future work:

- Study vibration of other engine parts.
- Model and predict future engine trajectories.
- Extract higher-dimensional features from signature point clouds (std, enveloppe, etc.).

Thank you for watching, feel free to read the paper for more details!

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