ML requirements for the Airworthiness of SHM Systems in Aircraft

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Outline

- Predictive maintenance
- Structural health Monitoring Systems and Aircraft Maintenance
- Challenges in SHM

- The usage of ML in SHM

- ML in SHM on Aircraft and regulatory requirements

Considerations

Growing production of and accessibility to data has allowed for PdM to flourish

Emerging SHM techniques have potential for structural integrity insights on aircraft.

Integrating ML approaches with SHM improves with several aspects of the latter. Detecting, localising, and classifying damage in aircraft components

Advantages of using ML, limitations w.r.t to EASA and SAE guidelines.

Focus is centred on damage progression applications

How will PdM and SHM be transformed with ML

What will their roles be, how will they change

Will the operational efficiency of the aviation industry be boosted? How critical are their roles in doing this?

The Emergence of PdM in the Commercial Air Transport Sector

PdM: CBM + Prognostics

Condition-based maintenance (CBM): diagnostics focused.

Condition monitoring: exceedance monitoring from sensors

Predictive maintenance (PdM): synonymous with PHM in asset management.

Benefits of PdM Adoption

LHT AVIATAR helps avoid up to **30%** of unscheduled removals

AFI KLM E&M PROGNOS for CFM56 prognostics enables proactive maintenance planning

45% of operational aircraft fleets to be enabled by 2025

$3 billion in maintenance savings when implementing data-driven PdM

Avert unplanned ground-time for enabled fleets

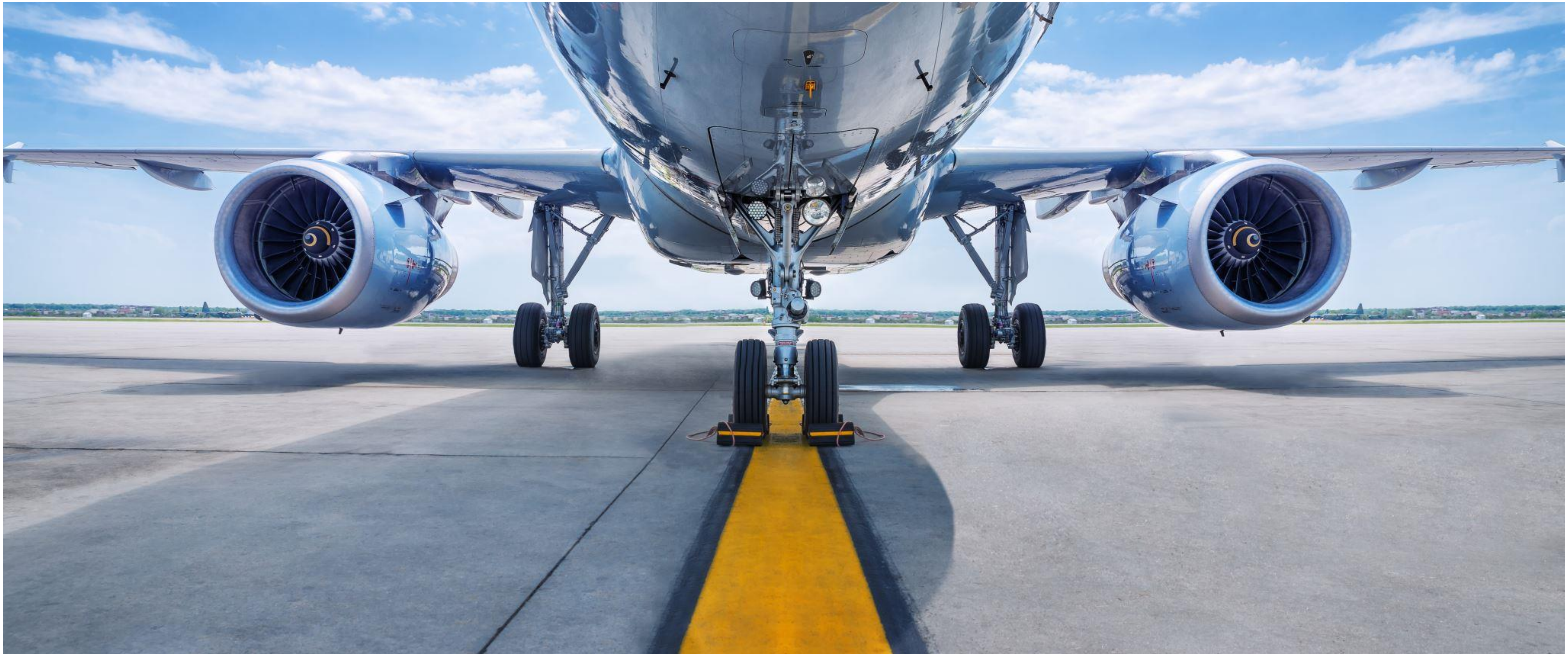
Challenges in PdM Adoption

- Predictive algorithms require a plethora of data.

- Data sharing between operators and third-party MROs is not a common occurrence.

- ML offers a solution through a federated learning environment:
  - Control over access and revocation throughout the ML process
  - Privacy and data governance issued addressed
  - Large-scale, cross party validation
  - Research on rare events where individual parties have insufficient data
  - Algorithm viability requirements:
    - Model performance should surpass local training architectures

SHM Systems and their Relevance to Aircraft Maintenance



Basics and Challenges in SHM

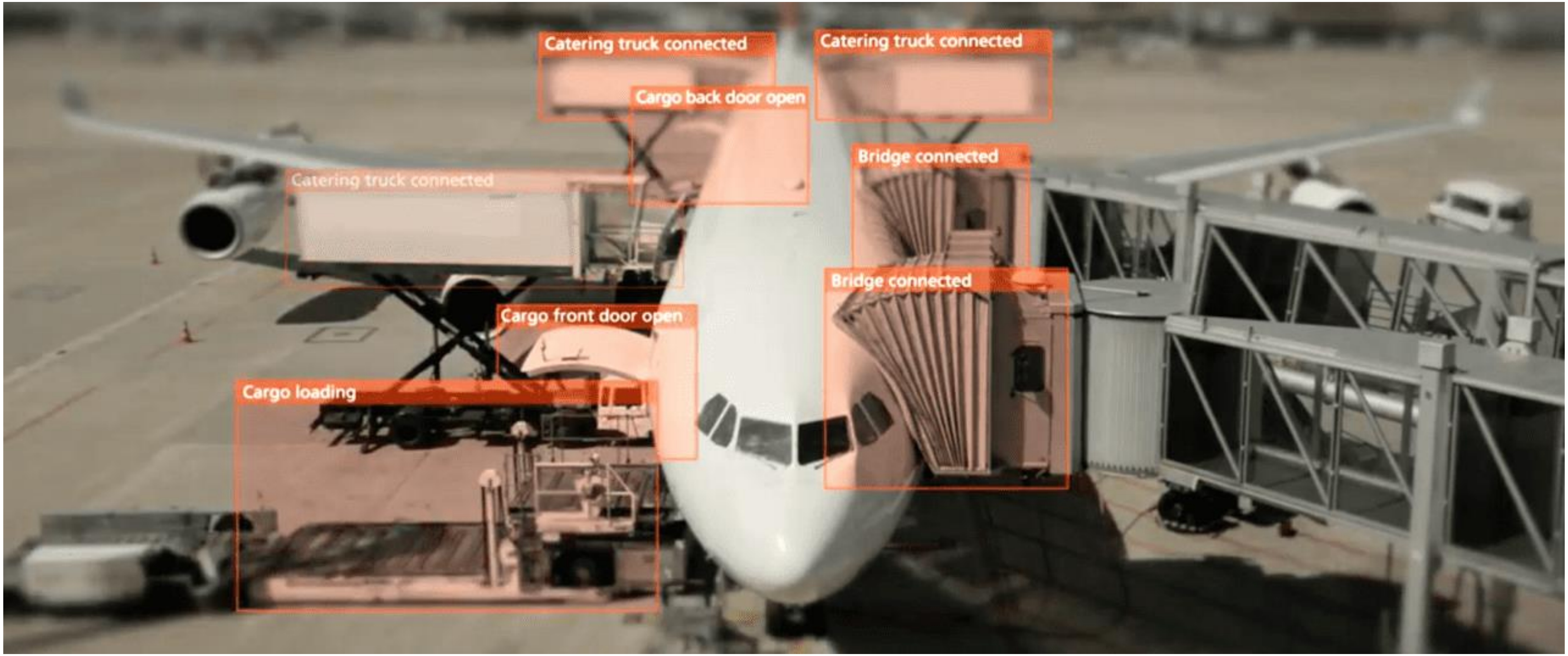
- Optimised selection and placement of SHM sensors still not economically viable to this date.
- Large-scale SHM system validation on real-life aircraft structures is missing.
- Optimisation of sensor configurations, reduction of sensors via data-driven approaches.
- Diagnostics involves answering:

Is there damage? → Where is it located? → To what extent has the damage propagated? → What is the type of damage? → How severe is it w.r.t the defined safe operating limits?

- Not all damage may be measured by sensors directly

Sensor data → Feature extraction through signal processing + statistical classification → Relevant damage information

Structural Health Monitoring and Machine Learning



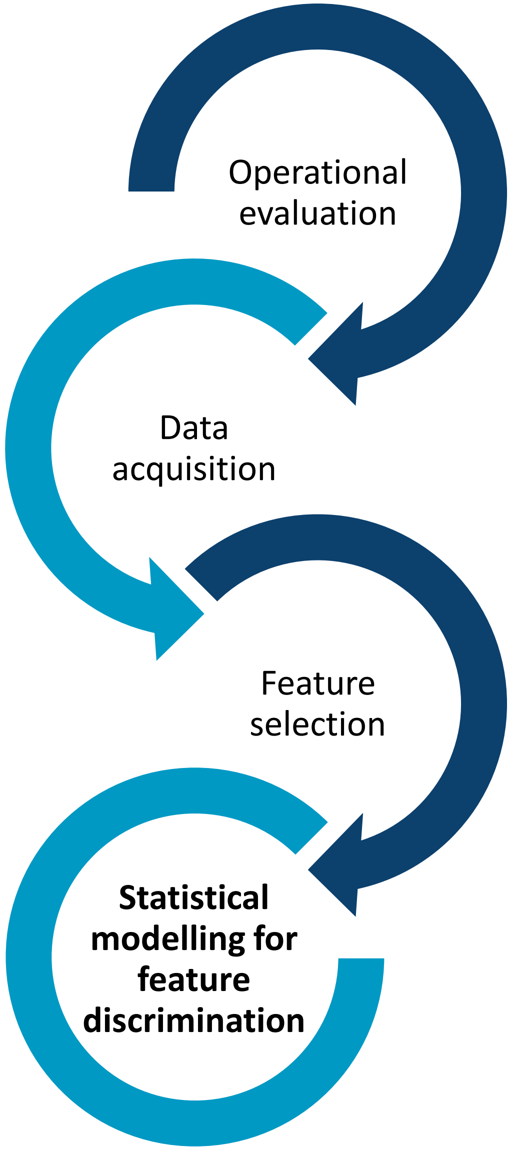
Approaches to SHM – Data-driven Models

Model-based

Knowledge-based

Multi-model based

Data-driven



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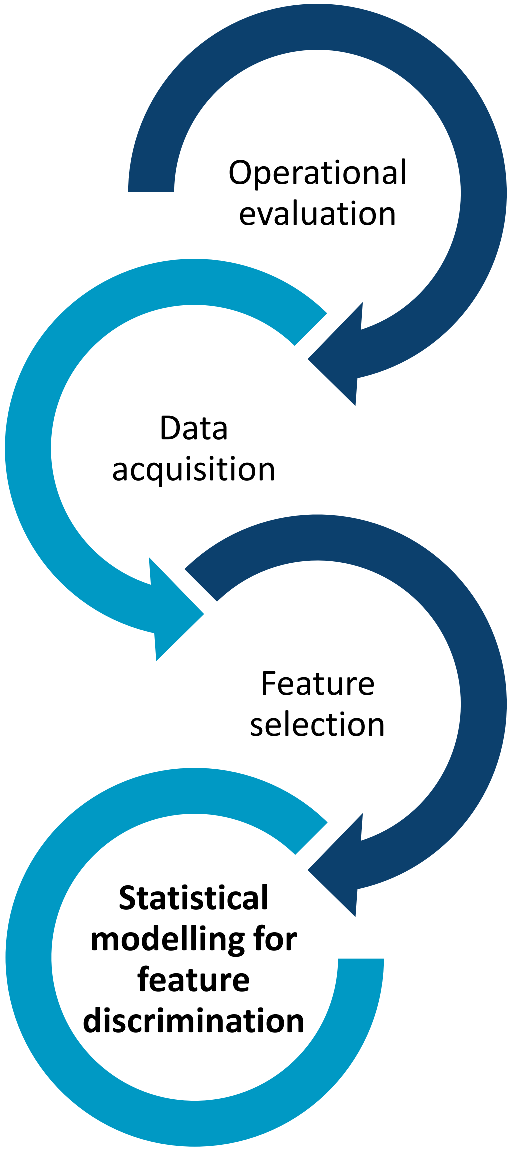

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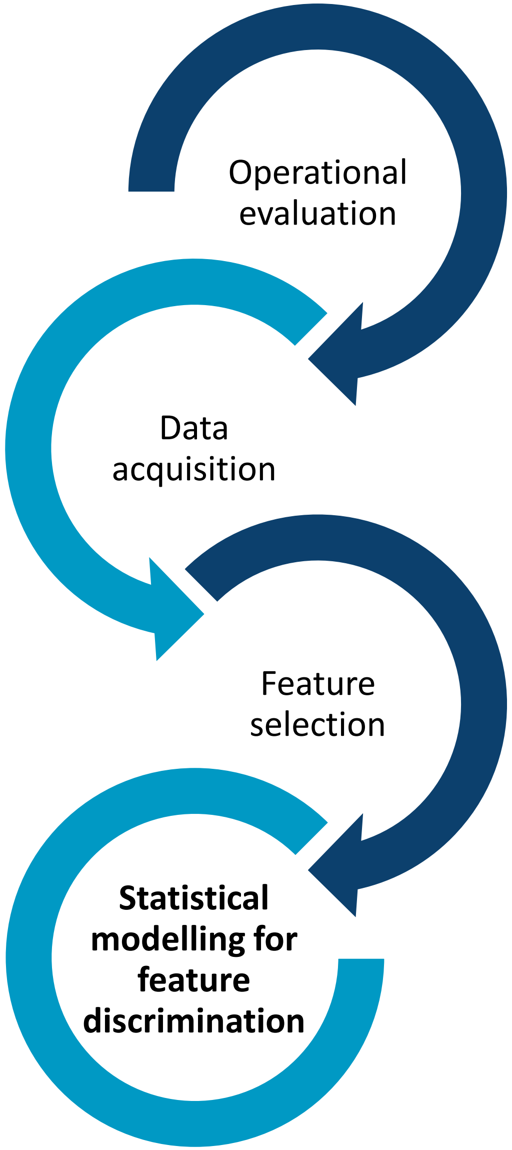

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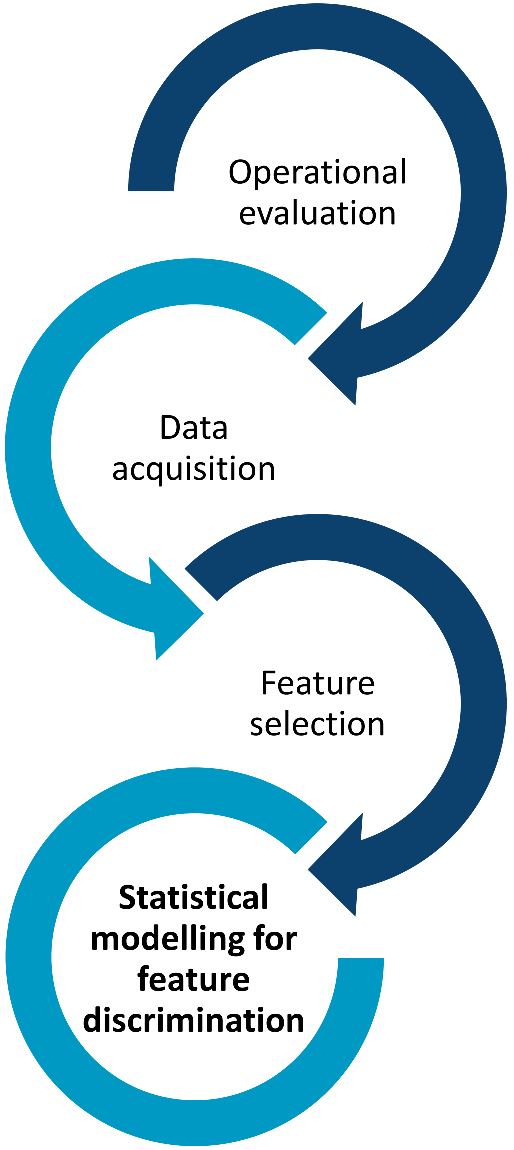

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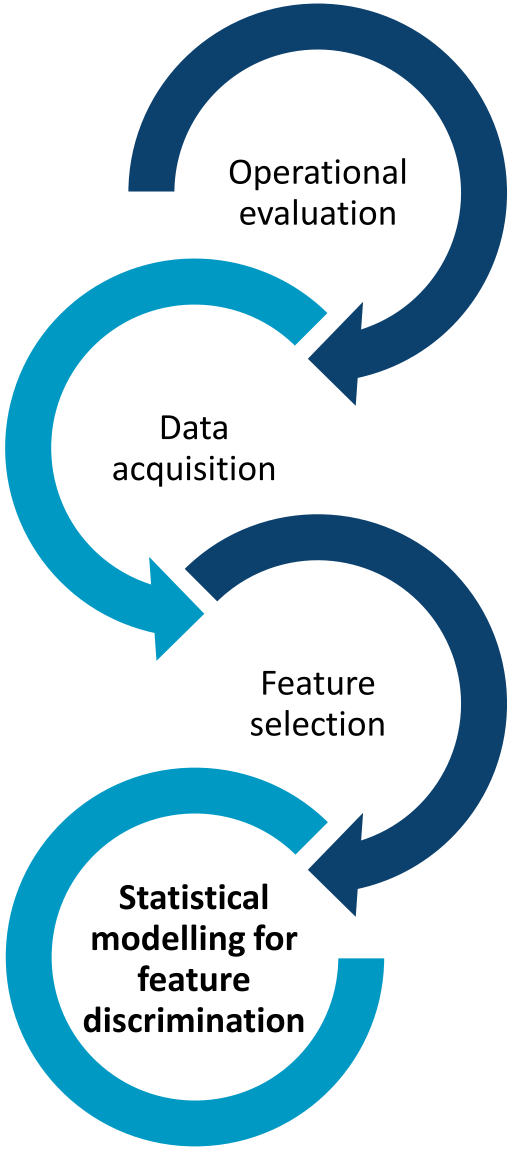
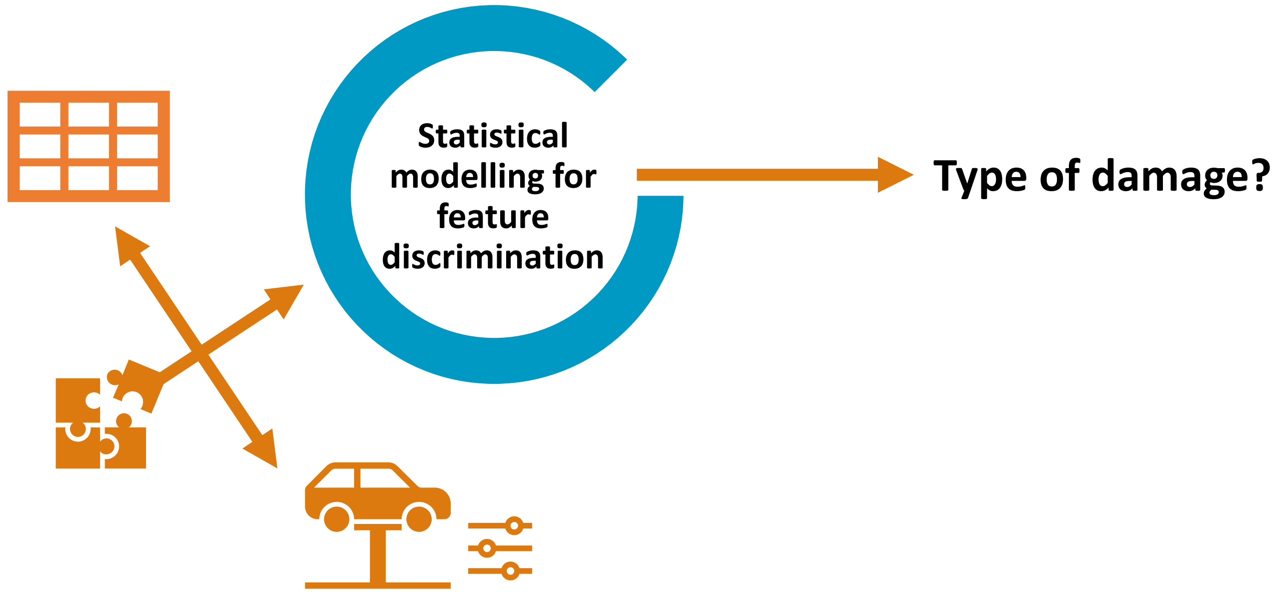


ML in Data-driven SHM

Scenarios in which data-driven models are preferred/necessary:

- Limited knowledge of the component's physics.
- SHM sensor placement.
- Pattern recognition.



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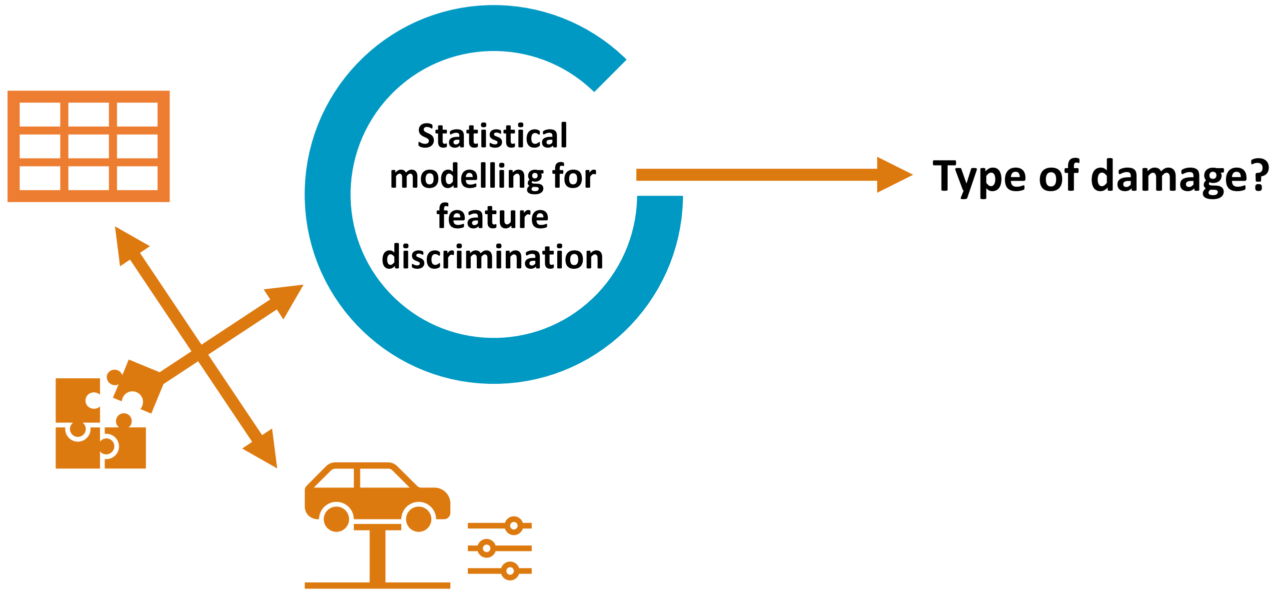

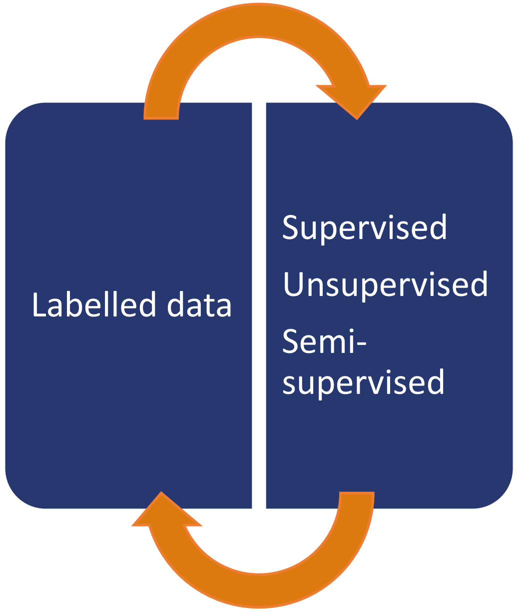

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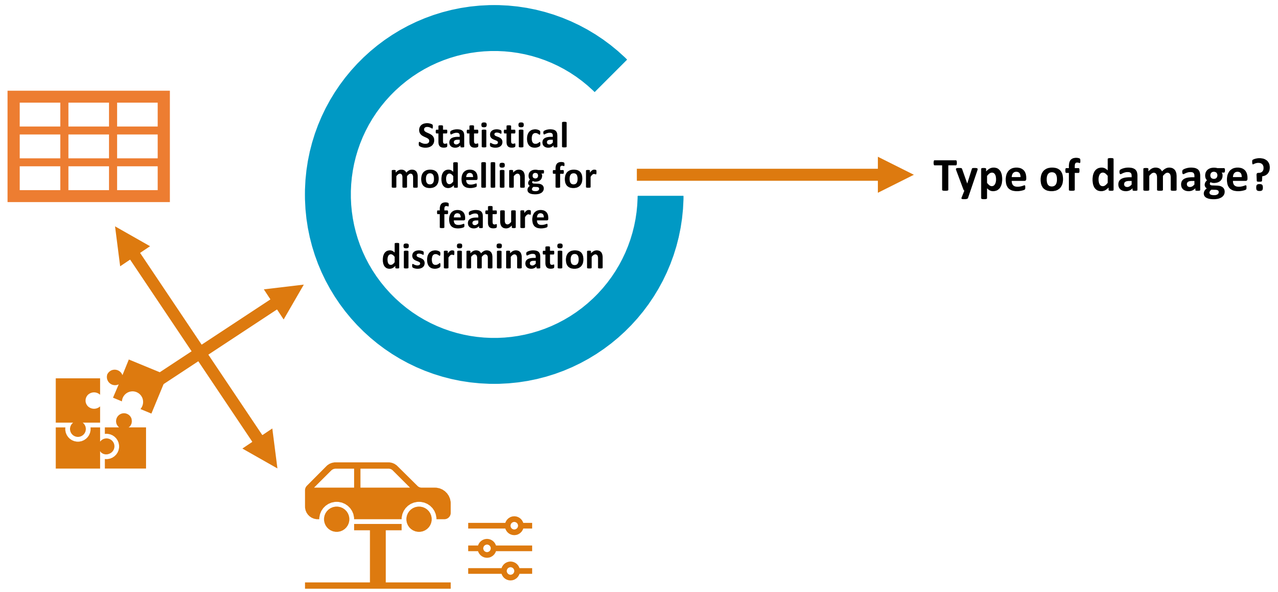
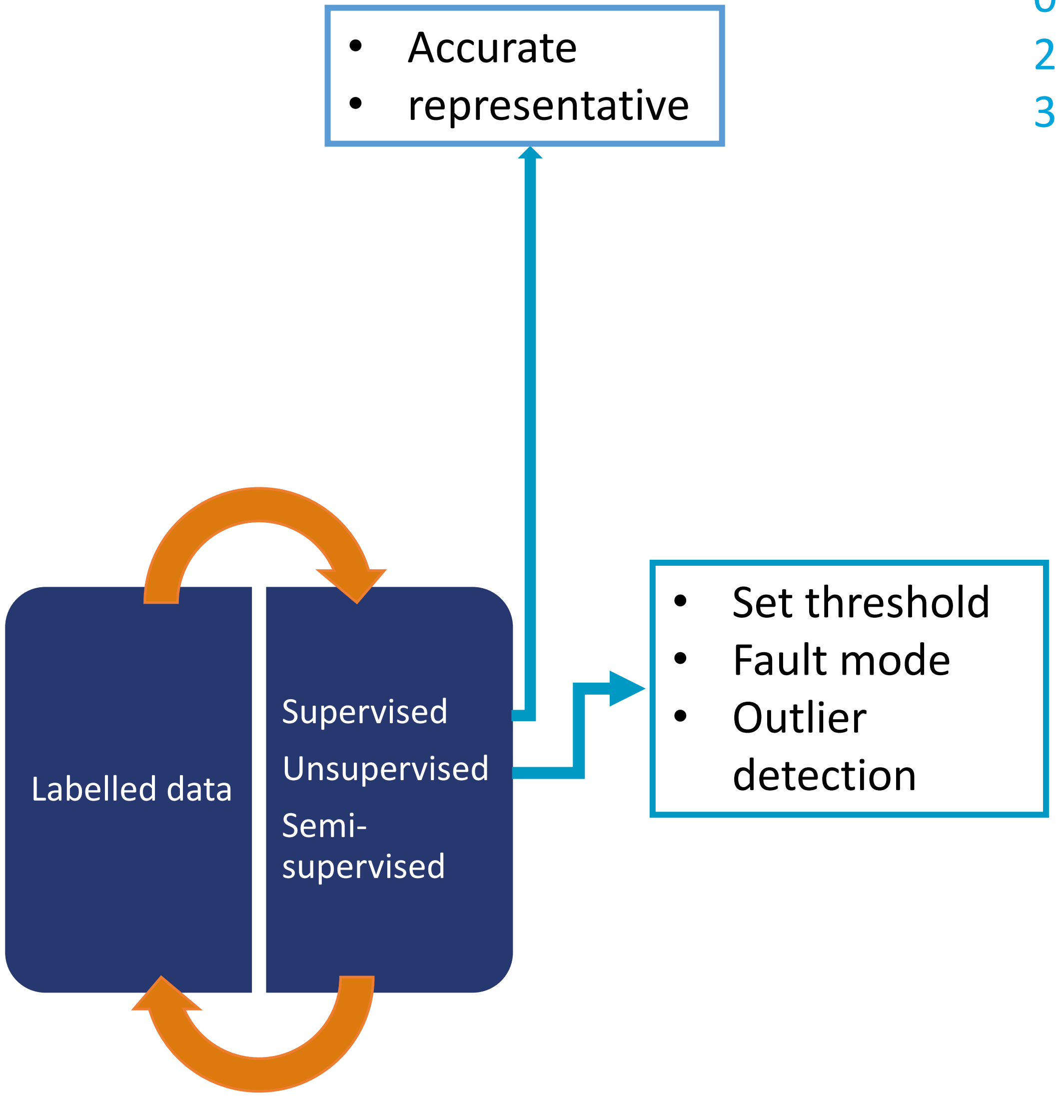




ML in SHM on Aircraft

SHM Application	Data used	ML Type
Aircraft wing CSK rivet hole damage profile [45]	Historical in-service damage readings at set load intervals	Particle Filters
Joint damage localisation on a physics-based composite wing through fasteners [46]	Image-based strain distribution output of a FEM skin-rib joint aircraft wing	CNN
Fatigue Crack Growth prediction in rotorcraft structures [48]	Ultrasonic sensor readings, experimental crack growth data from fatigue tests of rotorcraft structures, Paris–Erdogan physical damage models	Particle Filters

[45] W. B. Yousuf, T. Khan, and T. Ali, 'Prognostic Algorithms for Flaw Growth Prediction in an Aircraft Wing', IEEE Trans. Reliab., vol. 66, no. 2, pp. 478–486, Jun. 2017, doi: 10.1109/TR.2017.2676722.
[46] M. Lin, S. Guo, S. He, W. Li, and D. Yang, 'Structure health monitoring of a composite wing based on flight load and strain data using deep learning method', Compos. Struct., vol. 286, p. 115305, Apr. 2022, doi: 10.1016/j.compstruct.2022.115305.
[48] M. A. Haile, J. C. Riddick, and A. H. Assefa, 'Robust Particle Filters for Fatigue Crack Growth Estimation in Rotorcraft Structures', IEEE Trans. Reliab., vol. 65, no. 3, pp. 1438–1448, Sep. 2016, doi: 10.1109/TR.2016.2590258.

Evolving regulatory landscape for ML in Aircraft Systems

- ML techniques in SHM show promise for aircraft maintenance and reliability.
- Implementation of ML in aircraft systems must comply with regulatory standards like EASA and SAE G-34.
- SAE G-34 AI in Aviation Committee and EUROCAE are developing standards for safe and accountable AI use in aviation.
- EASA is focusing on guidelines for ML deployment, emphasizing robustness, reliability, explainability, and continuous monitoring.
- Supervised learning in ML should be thoroughly tested and validated as per EASA mandates.
- Acquisition of representative labelled training data for possible failure scenarios is a challenge.
- Unsupervised learning shows potential for damage detection without explicit damage examples.
- The lack of human interpretability in unsupervised learning could be a limitation, as per EASA's stipulations.
- Development of techniques to enhance interpretability of unsupervised learning methods is a challenge.
- EASA and SAE G-34 emphasize the importance of robustness to environmental changes in aviation systems.
- ML techniques in SHM need to account for impacts of external influences on sensor data.
- Regular revalidation and recalibration of ML algorithms are necessary to maintain performance and reliability.
- The standards push for continuous learning strategies within SHM systems.

The status of ML certification in aviation

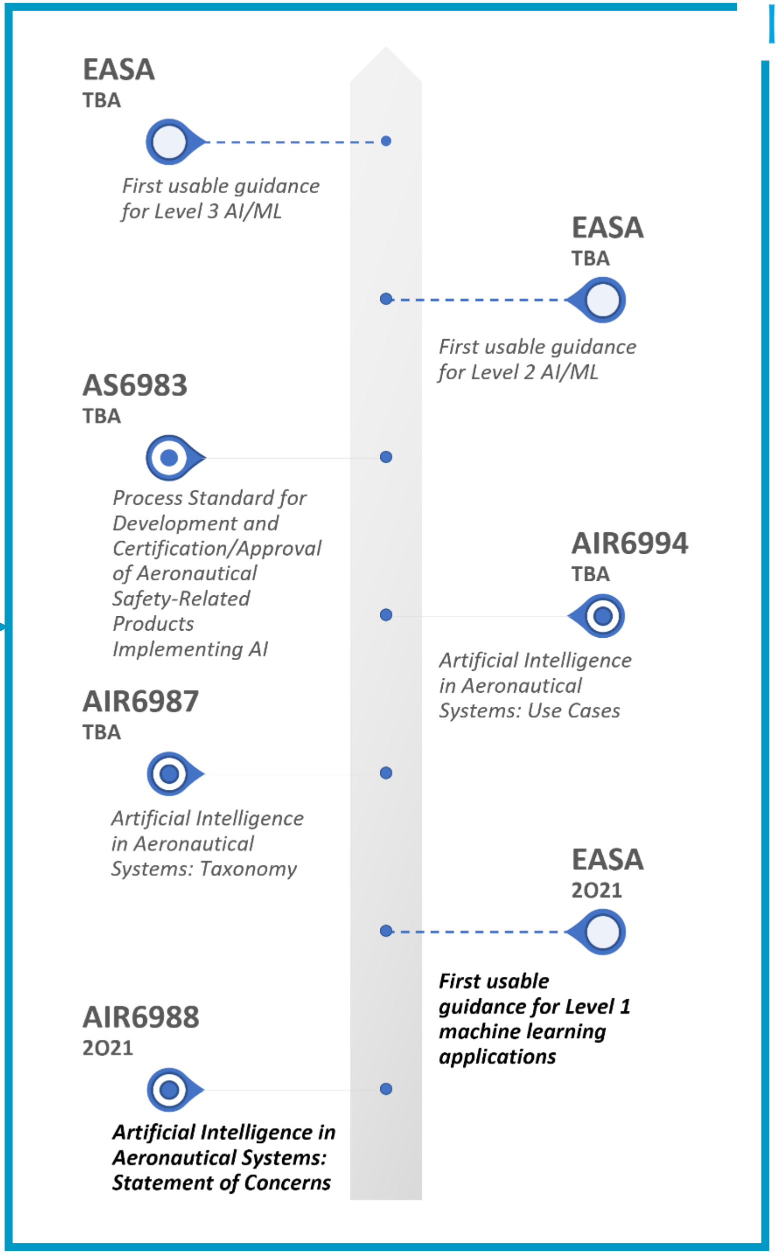
Avionics airworthiness requirements

- ARP4754A
- ARP4761
- DO-178C
- DO-254

AI in aviation certification advisories

- AIR6988
- EASA L1
- AMLAS

SAG G-34/EUROCAE WG-114 & EASA MILESTONE ROADMAP Phase I: exploration and first guidance development 2019-2024



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