From Physics-based Models to Predictive Digital Twins via Interpretable Machine Learning

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Outline

1 Motivation

Predictive digital twins to inform critical decision-making

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2 Methodology

Interpretable data-driven adaptation of physics-based models

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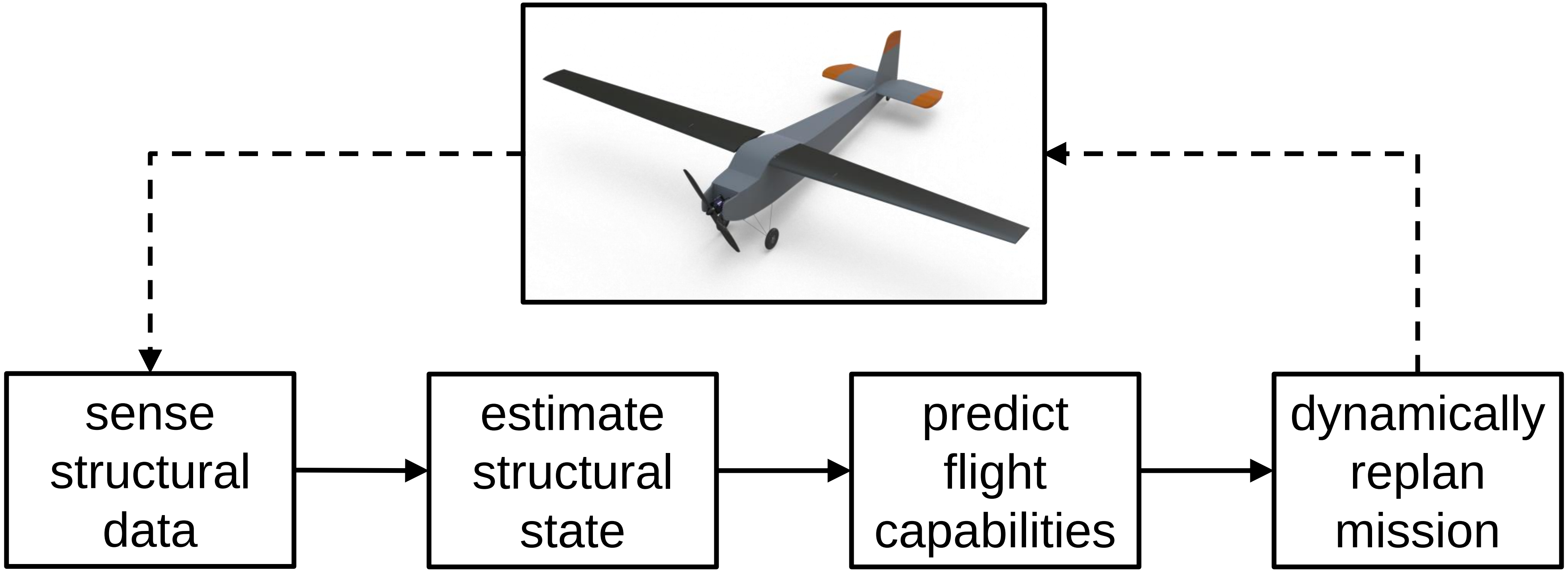
3 Results

Enabling a self-aware UAV: progress and outlook

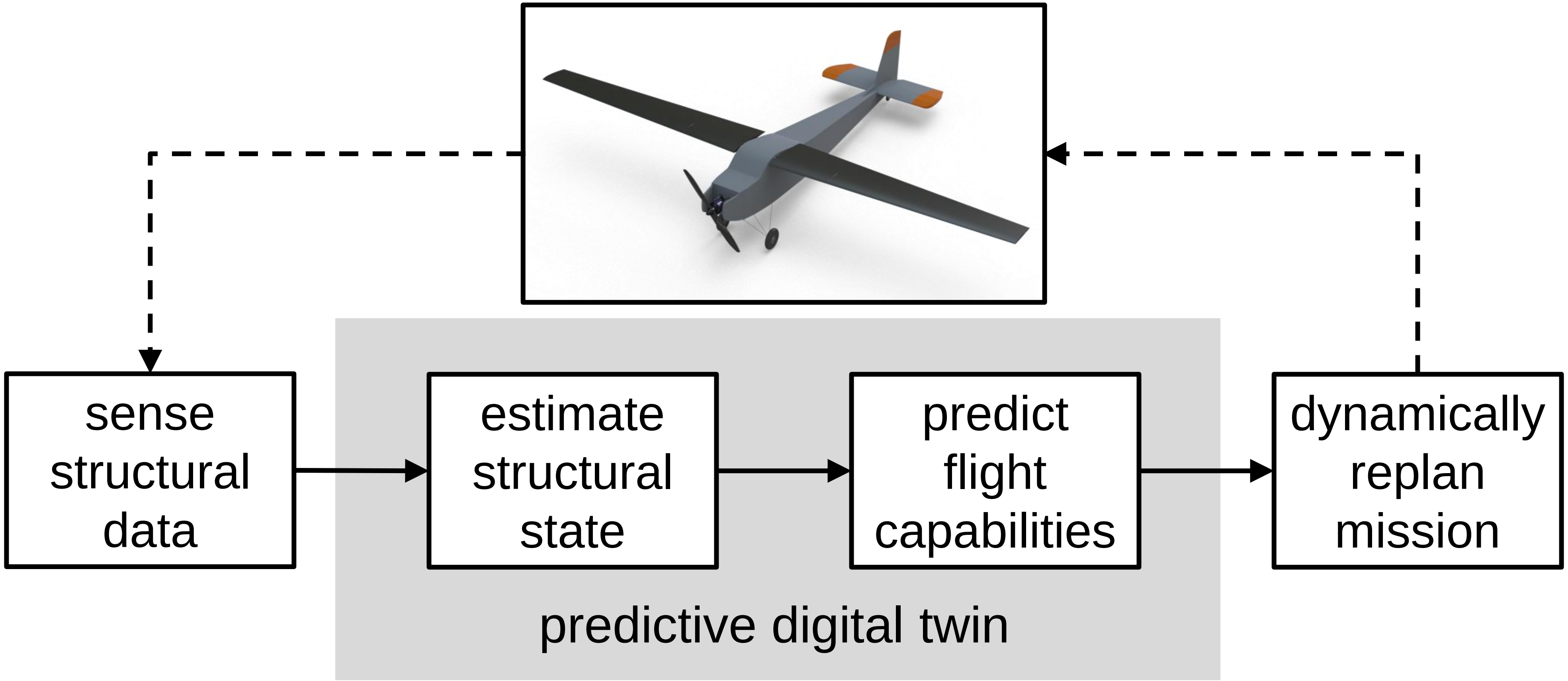
Motivation: Enabling a **self-aware aircraft**



An aircraft that can **sense changes** in its own internal state, **and adapt accordingly**

Prior work has shown that this provides [Kordonowy 2011, Singh 2017]
- Increased survivability
- Increased utilization

Motivation: Enabling a **self-aware aircraft**



We create a **digital twin** that **adapts to the evolving structural health** of the UAV, providing **near real-time capability predictions** to enable **dynamic decision-making**.

Toward **predictive, reliable, explainable** digital twins

Physics-based models

- ✚ Ubiquitous throughout engineering
- ✚ Simulate new previously unseen scenarios
- ✚ Obey laws of physics with quantifiable uncertainty
- ✚ Parameters represent real-world quantities

physics-based models

interpretable machine learning

predictive digital twin

Toward **predictive, reliable, explainable** digital twins

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Data-driven models

- \+ Leverage the explosion in data availability
- \+ Enable asset-specific decision-making
- − Typically “black-box”
- − Difficult or impossible to understand and explain
- − Generalization requires representative training data

physics-based models

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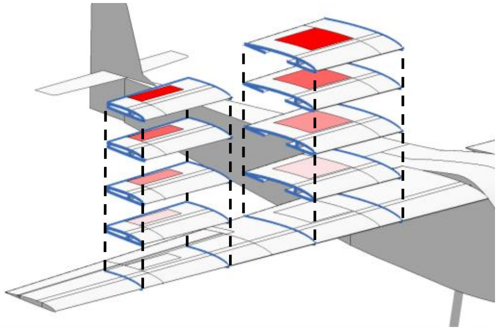
Our approach:

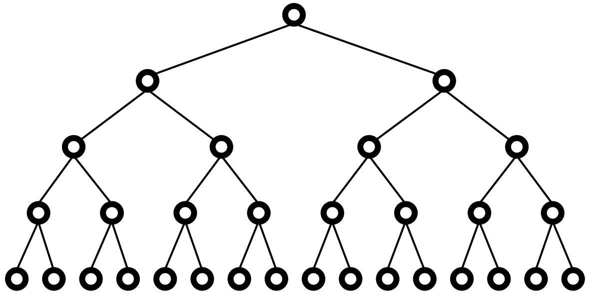
Interpretable machine learning models trained on physics-based models

Predictive Digital Twin:
Physics-based models meet data-driven learning

Offline:



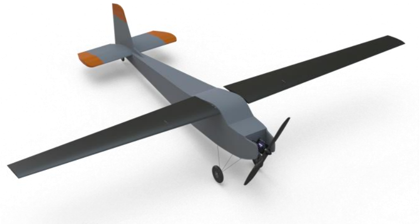
Construct library of physics-based models representing different asset states

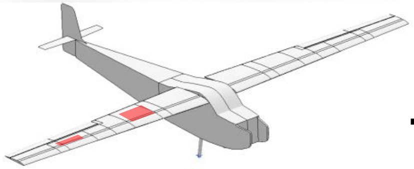


Use model library to train a classifier that predicts asset state based on sensor data

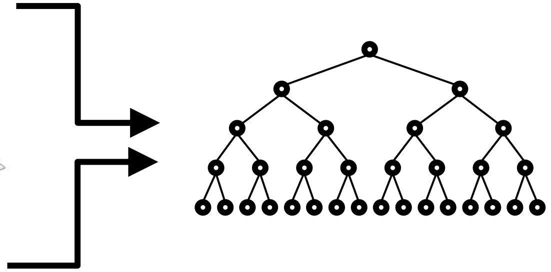
Online:

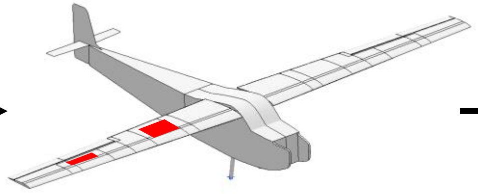
sensor data





current digital twin





updated digital twin

Analysis,
Prediction,
Optimization

Physics-based model library

From physics-based model library to predictive digital twin

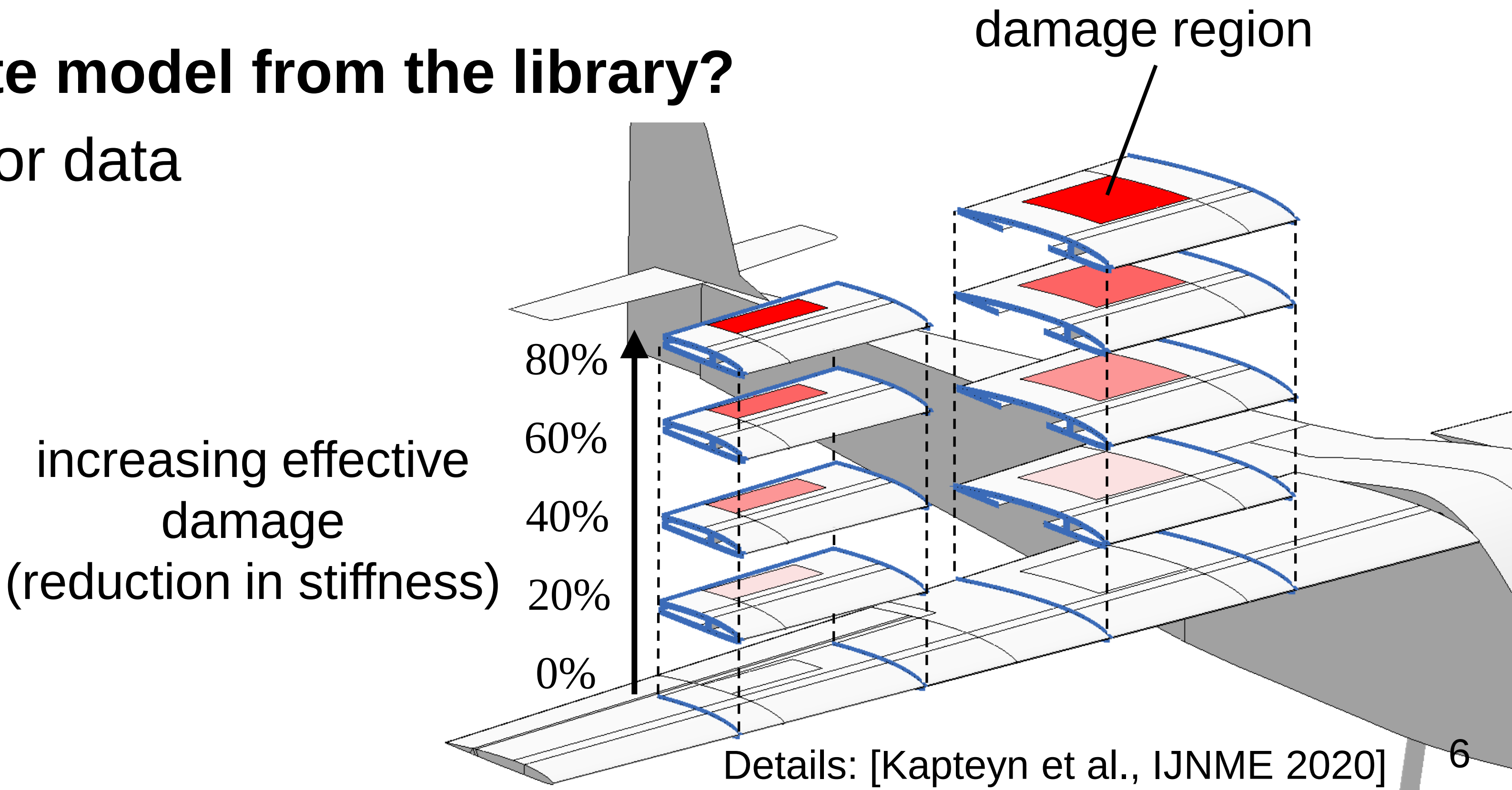
Given: a library of models for various UAV damage states

- Covers representative damage states
- Enables assimilation of sensor measurements (strain)
- Enables estimation of flight capability (stress, failure criteria)

How to choose an appropriate model from the library?

⟶ Informed by online sensor data

- Which sensors to install?
- Which sensors to query?
- Decision boundaries?
- Reliability + robustness



Details: [Kapteyn et al., IJNME 2020]

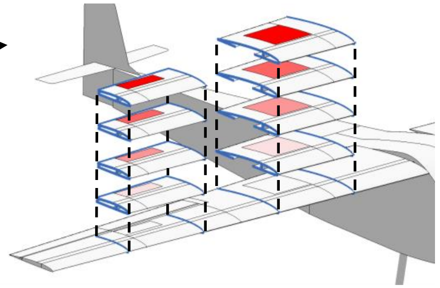
Interpretable machine learning

Onboard sensors inform which model is used in the digital twin

1. Use **predictive models** to **generate training data**

Forward (predictive) model

asset state
$\boldsymbol{y}$



noisy sensor data
$\boldsymbol{X}$

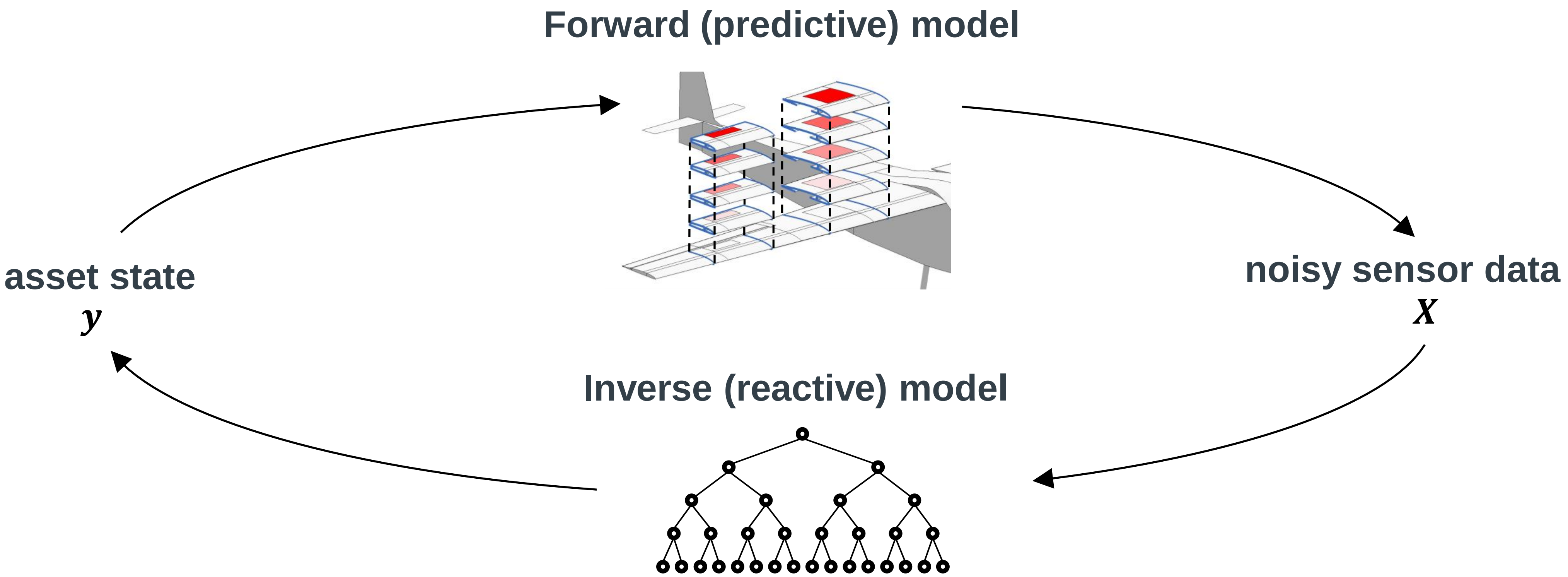
Training data: $(\boldsymbol{X}, \boldsymbol{y})$

Features, $\boldsymbol{X}$: Model predictions of strain at strain gauge locations, corrupted with random noise

Labels, $\boldsymbol{y}$: Location and severity of damage (2 locations, 5 severity levels = 25 possible states)

Onboard sensors inform which model is used in the digital twin

1. Use **predictive models** to **generate training data**
2. Use **machine learning** to train an **interpretable, explainable reactive model**



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Interpretable machine learning via optimal classification trees

Goal: Find a binary tree, T, that partitions the space of possible sensor measurements, and assigns to each partition the model that best explains the measurements

$$T : \boldsymbol{x} \rightarrow \boldsymbol{y}$$

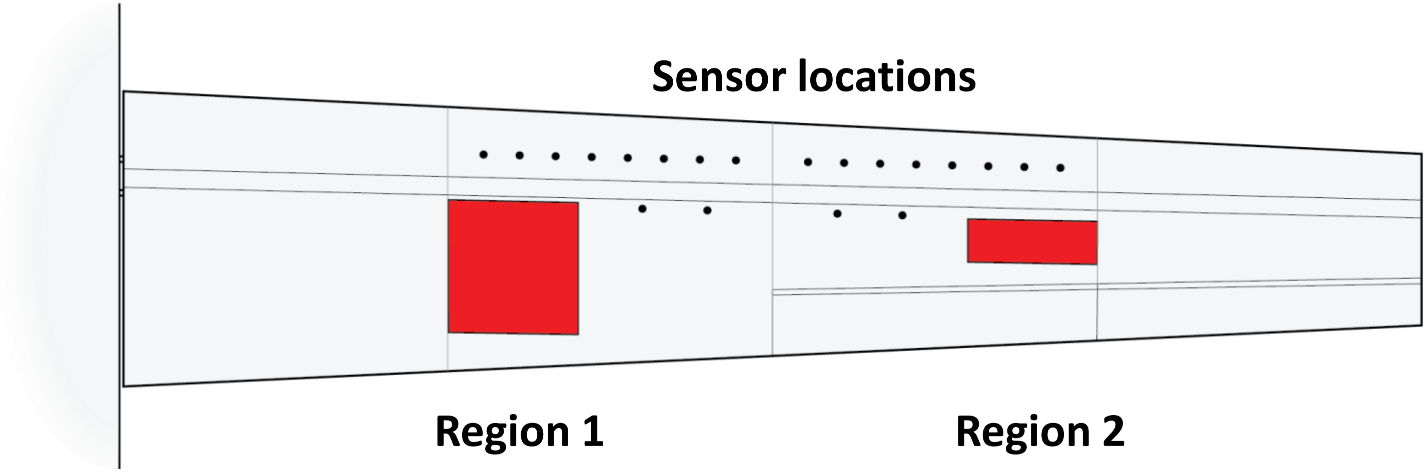
Optimal Classification Trees [Bertsimas, 2019] uses mixed-integer optimization techniques to find a partition in the form of an optimal binary tree, T:

$$\min_{\mathrm{T}} \quad \underbrace{\mathrm{R(T)}}_{\text{error on training data}} + \overbrace{\alpha}^{\text{tradeoff parameter}} \underbrace{|\mathrm{T}|}_{\text{complexity of the tree}}$$

- + Globally optimal
- + Scalable
- + Naturally extends to hyperplane splits

Interpretable AI

Optimal classification trees in practice: damage in region 1



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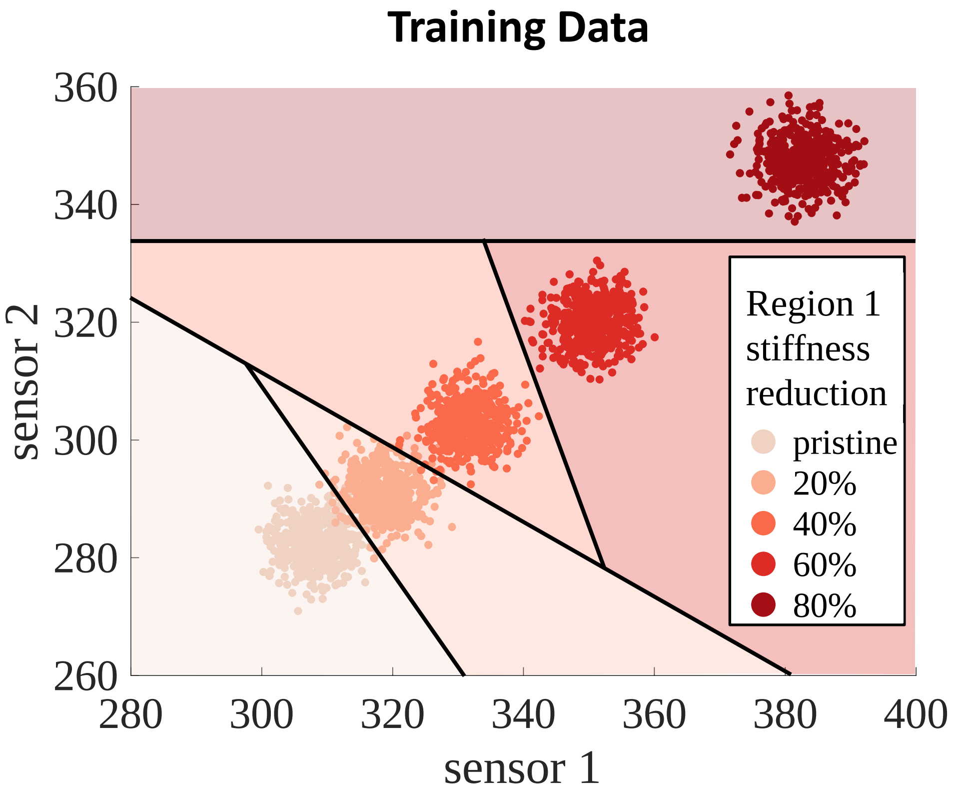
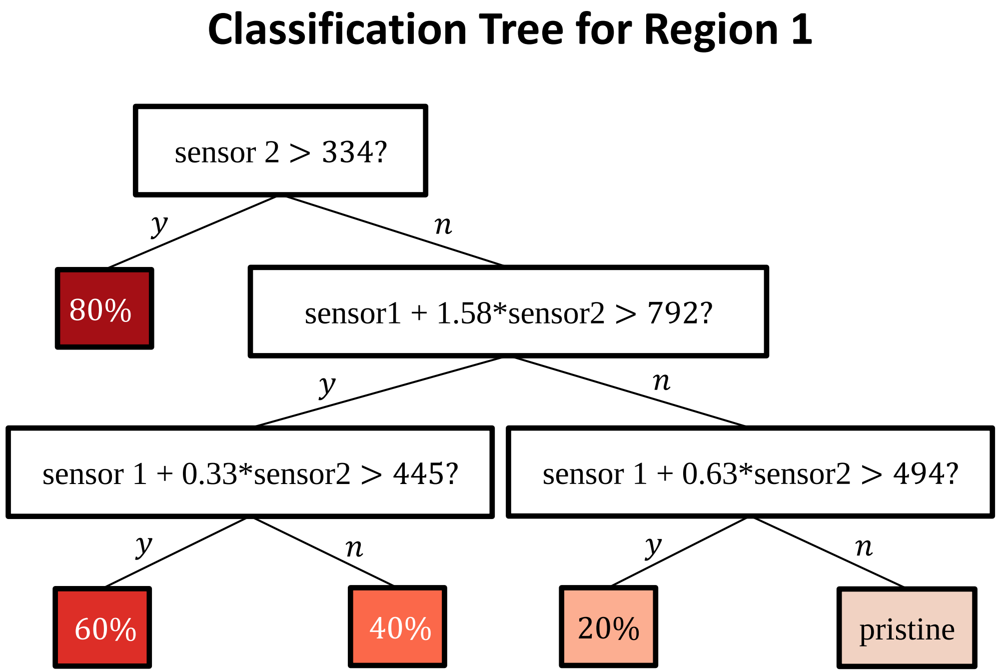
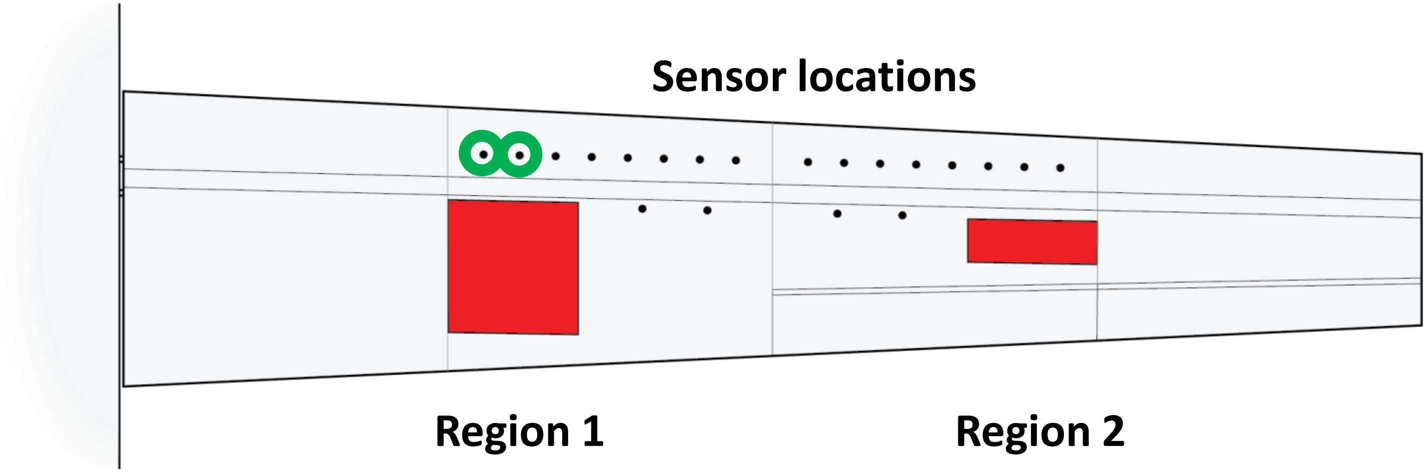
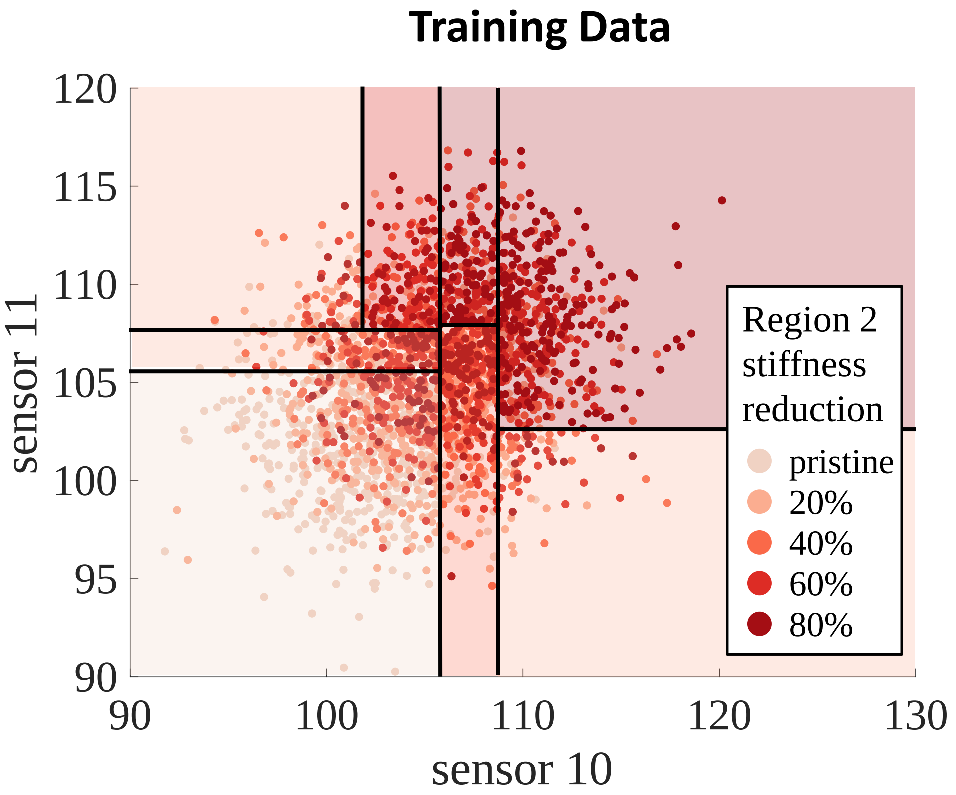
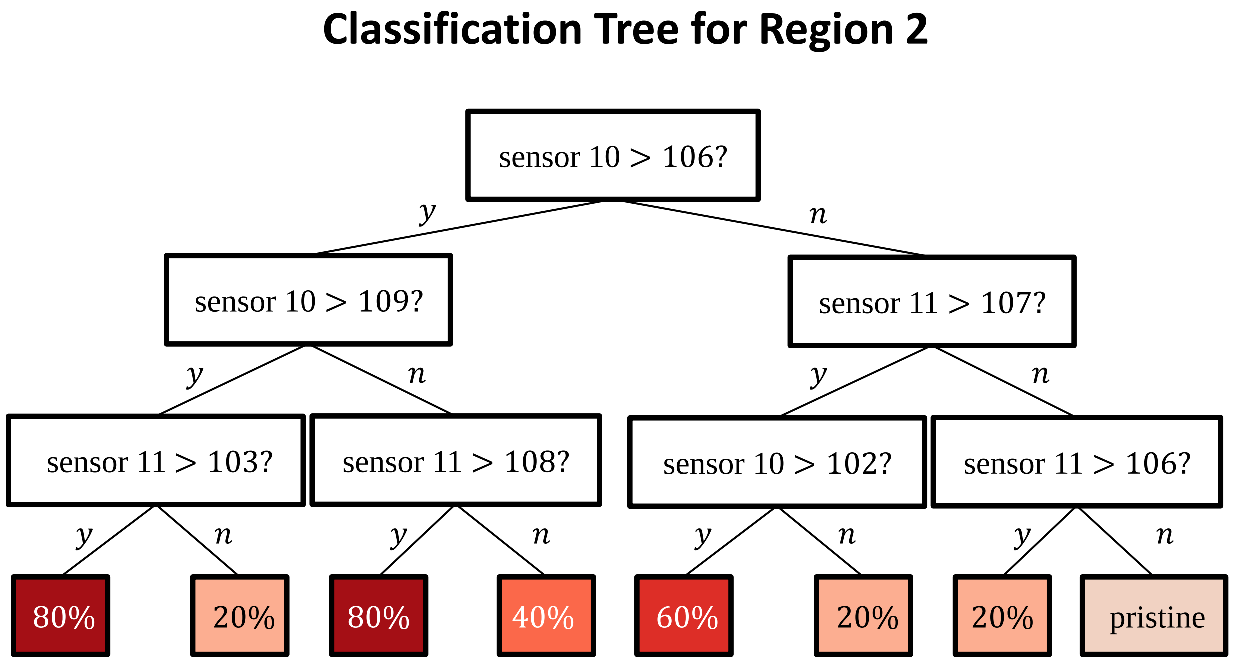


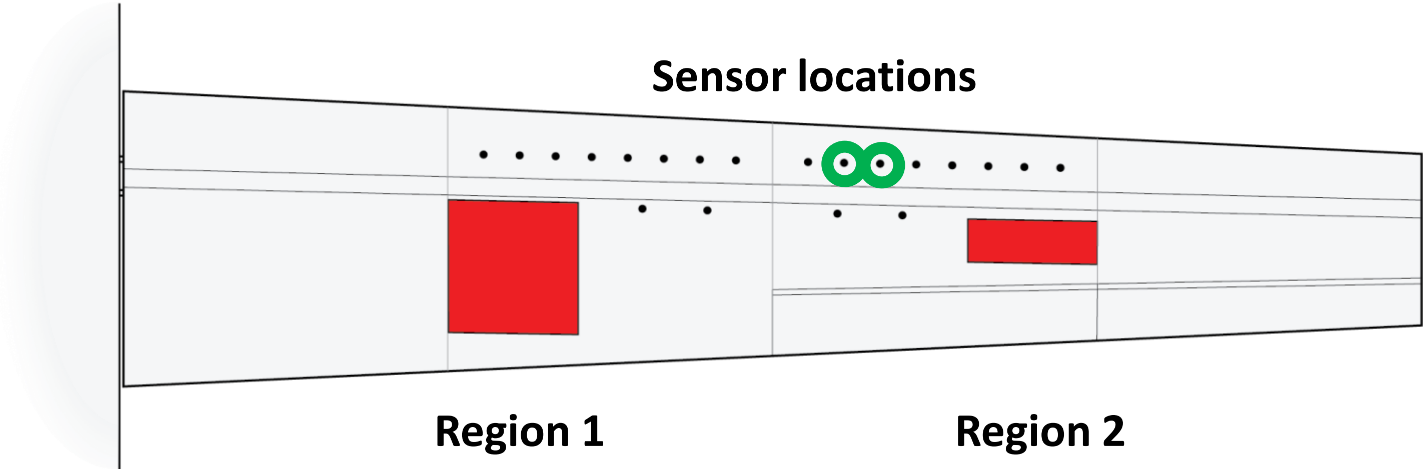




Optimal classification trees in practice: damage in region 2



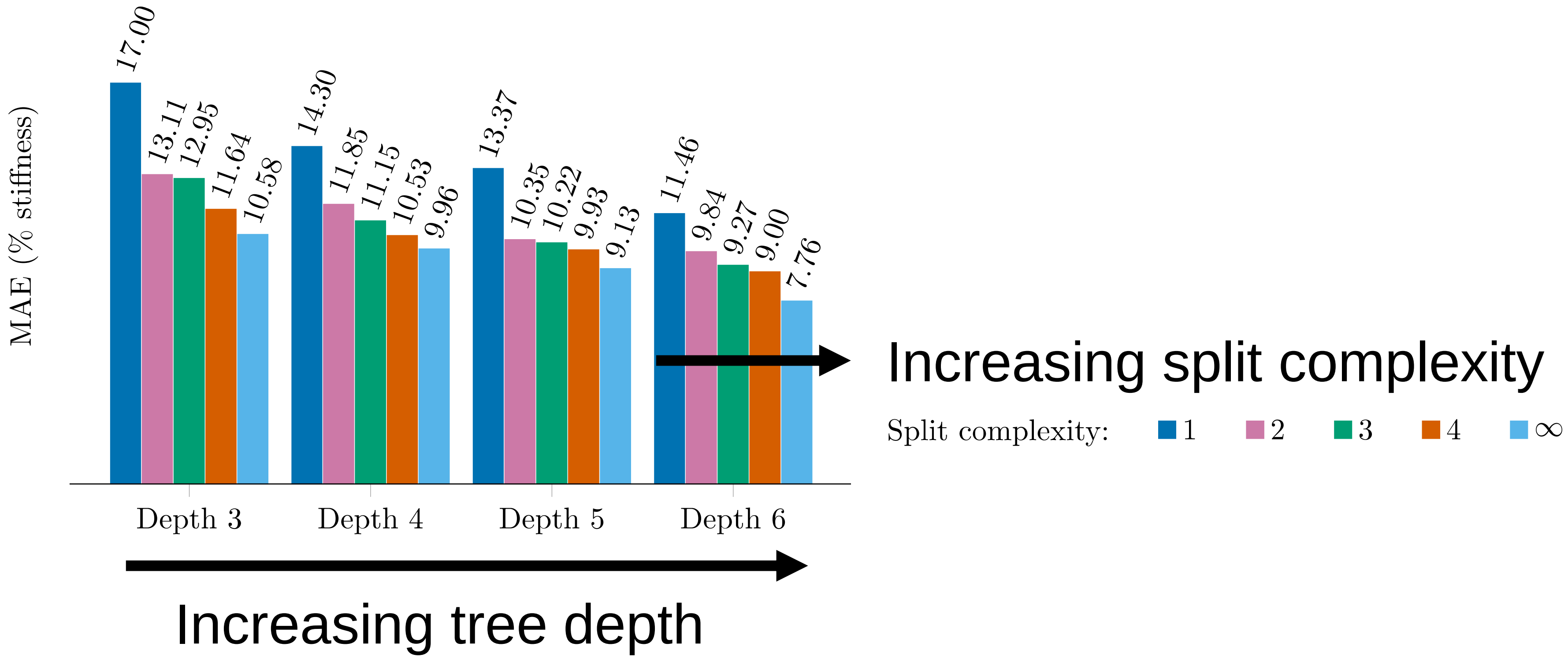




Onboard sensors inform which model is used in the digital twin

Accuracy depends on:

1. Depth of the tree
2. Split complexity (maximum number of sensors in each split)

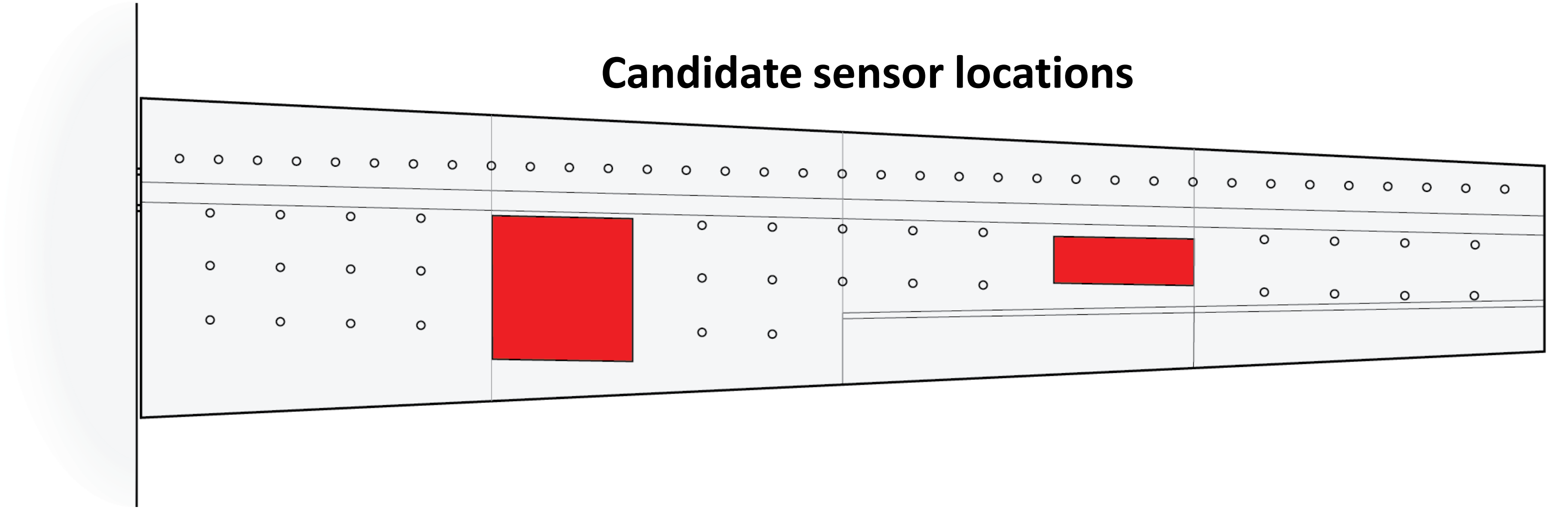


Onboard sensors inform which model is used in the digital twin

Accuracy depends on:

1. Depth of the tree
2. Split complexity (maximum number of sensors in each split)
3. Sensor placement

Physics-based model allows us to **simulate many candidate sensors**
Optimal classification trees **scale to allow many input features**



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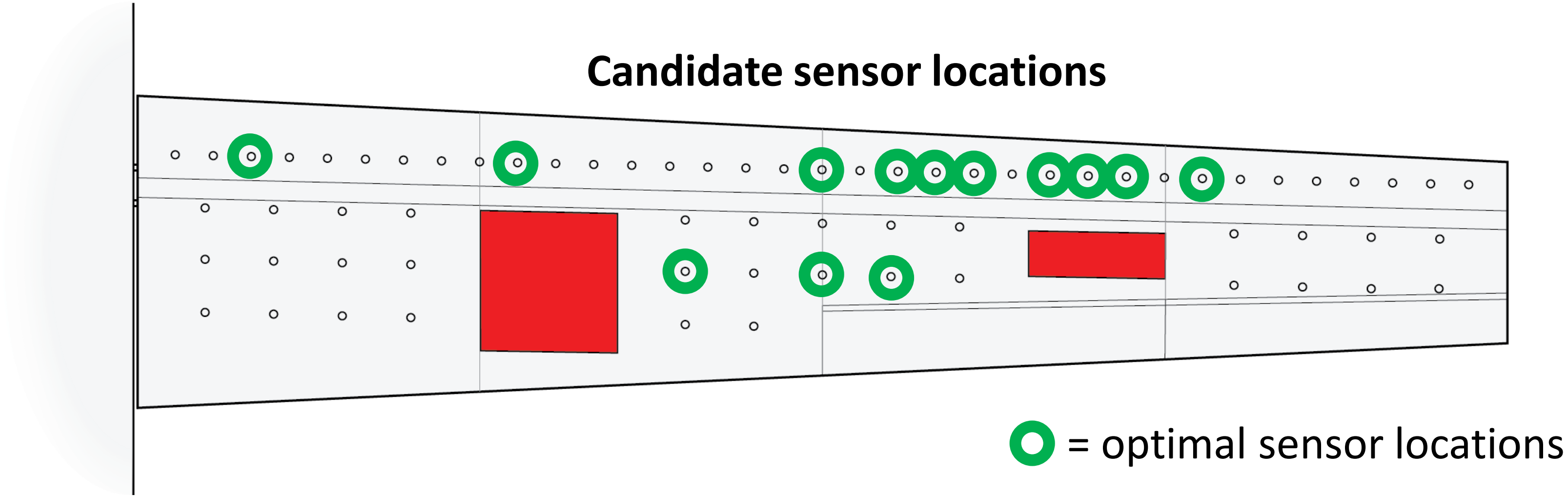
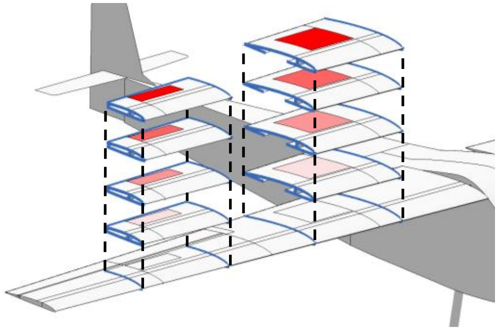
Physics-based model allows us to **simulate many candidate sensors**
Optimal classification trees **scale to allow many input features**
→ **let the optimal classification tree select most informative sensors**



Recall our approach: **data-driven adaptation** of **component-based reduced-order models**

Offline:



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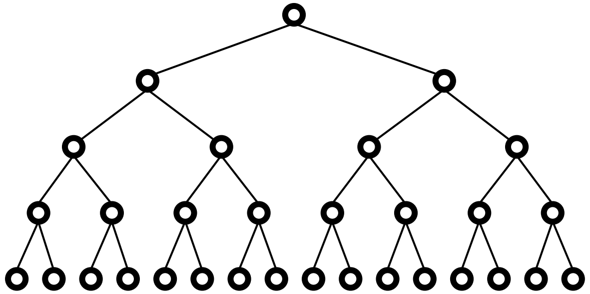

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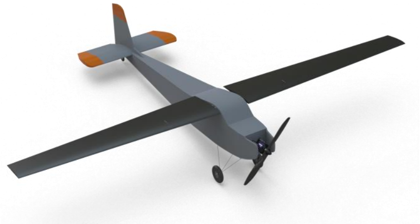
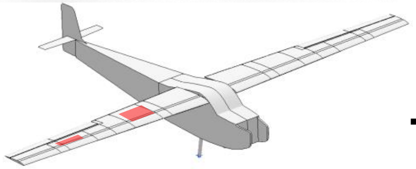
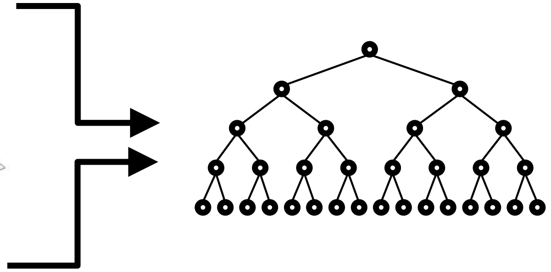
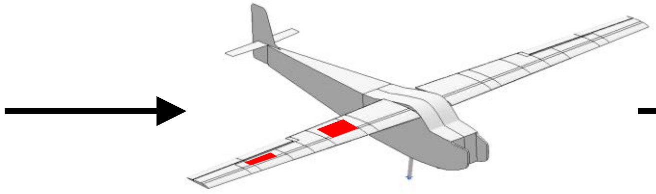




current digital twin





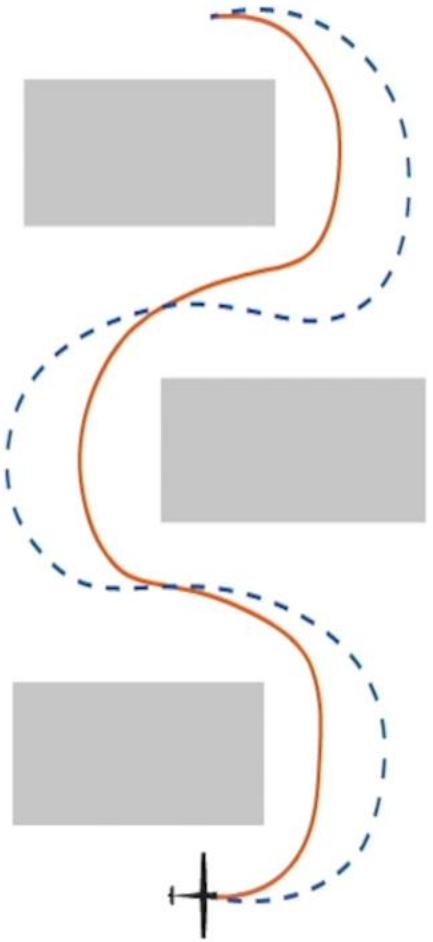
updated digital twin

Analysis,
Prediction,
Optimization

Flight of the UAV

Aggressive flight path

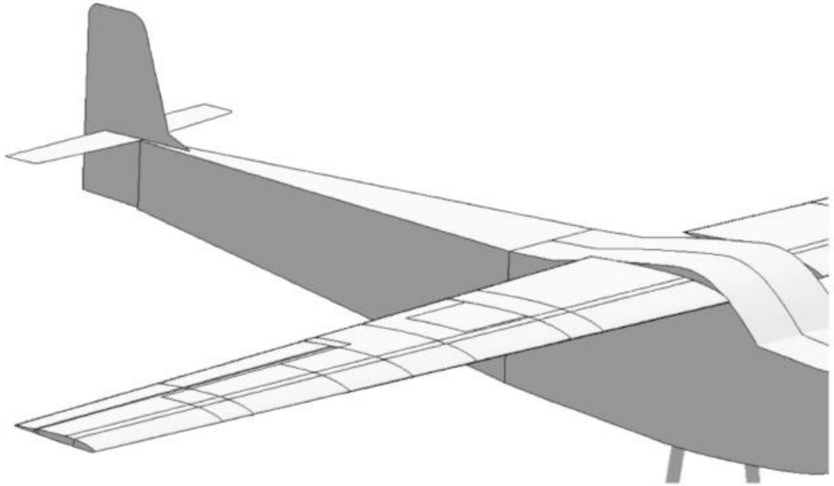
Conservative flight path



Health estimates

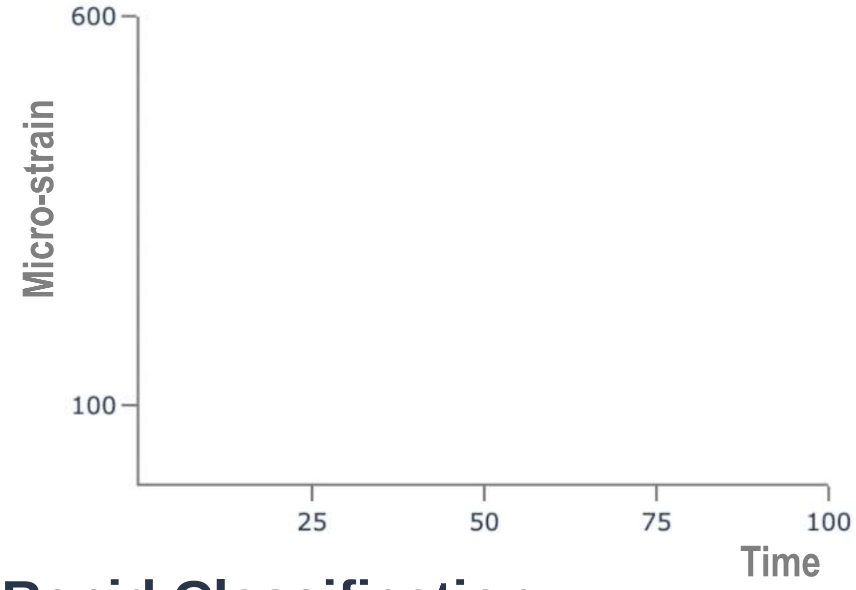
Less damage

More damage

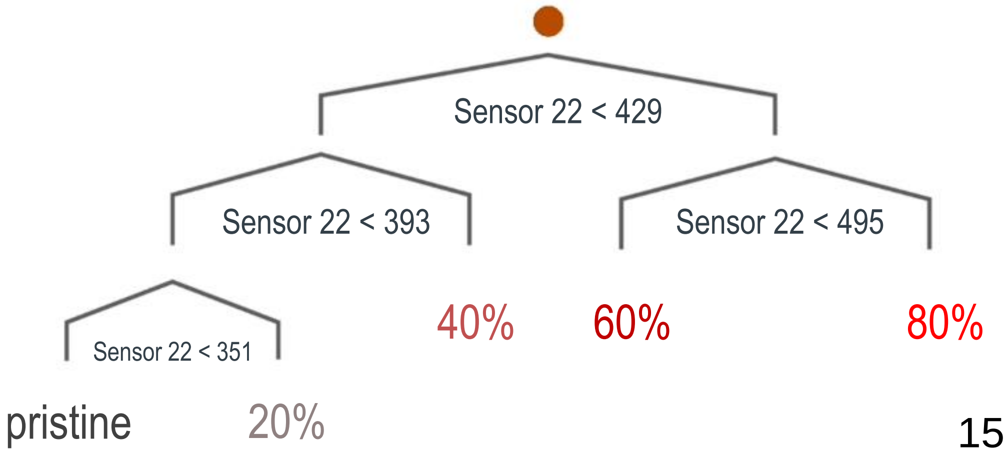


Strain Measurements

Sensor 22 Sensor 12 Sensor 24



Rapid Classification



Combining physics-based models and interpretable machine learning enables predictive digital twins

Optimal Classification Trees

- Highly interpretable
- Natural framework for sensor selection
- Rapid online classification
- As expressive as standard neural networks

Future Work

- Test with **multimodal experimental data**
- Strategies for sensor **fault detection** and **robustness**
- **Flight demonstration**

High-consequence decisions require digital twins that are

predictive • reliable • explainable

physics-based models

interpretable machine learning

predictive digital twin

For a project overview and additional references visit https://kiwi.oden.utexas.edu/research/digital-twin

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