A Probabilistic Graphical Model Foundation for Enabling Predictive Digital Twins at Scale

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AIAA SciTech Forum | January 13, 2021

MIT AEROASTRO

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Outline

1 **Motivation**

Enabling predictive digital twins at scale

2 **Contribution**

From abstraction to
probabilistic graphical model

3 **Demonstration**

Experimental calibration of a structural
digital twin for a fixed-wing UAV

Motivation

Enabling predictive digital twins at scale

A *digital twin* is a computational model that evolves over time to persistently represent the structure, behavior, and context of a unique physical asset

Applications have been proposed and/or demonstrated throughout the aerospace sector and beyond

- manufacturing, structural health monitoring, predictive maintenance, fleet management, …
- healthcare, education, urban planning, …

However, state-of-the-art digital twins are largely the result of custom, application-dependent implementations, requiring considerable expertise and resources

How do we move from the one-off digital twin to accessible and robust digital twin implementations at scale?

Approach

Establishing a mathematical foundation for digital twins

A rigorous, general, and unified mathematical foundation for digital twins is needed.

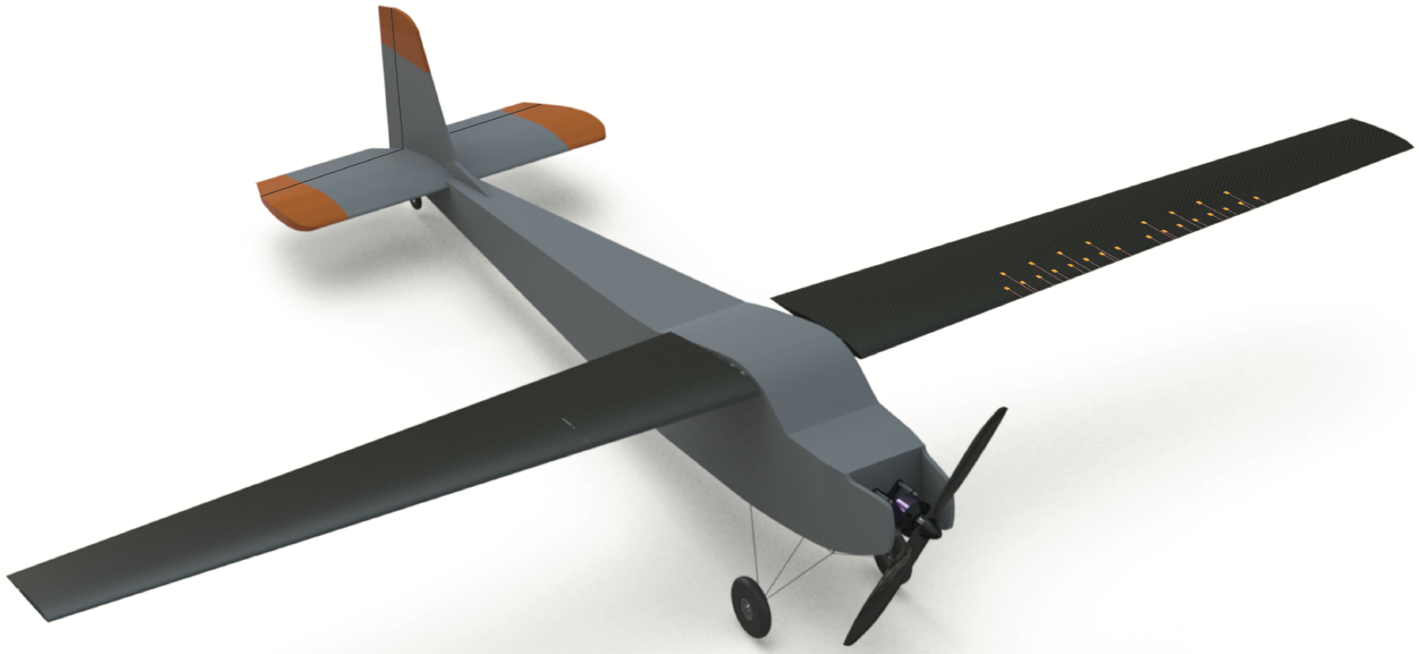
Focus on a common thread central to the digital twin concept:

The infusion of dynamically updated asset-specific computational models into the data-driven analysis and decision-making feedback loop

Our approach:

1. Formulate an abstraction of a combined asset-twin system comprised of six key quantities
2. Formalize the interaction between these quantities
3. Develop a probabilistic graphical model that represents the operation and evolution of an asset-twin system

Our abstraction of an asset-twin system



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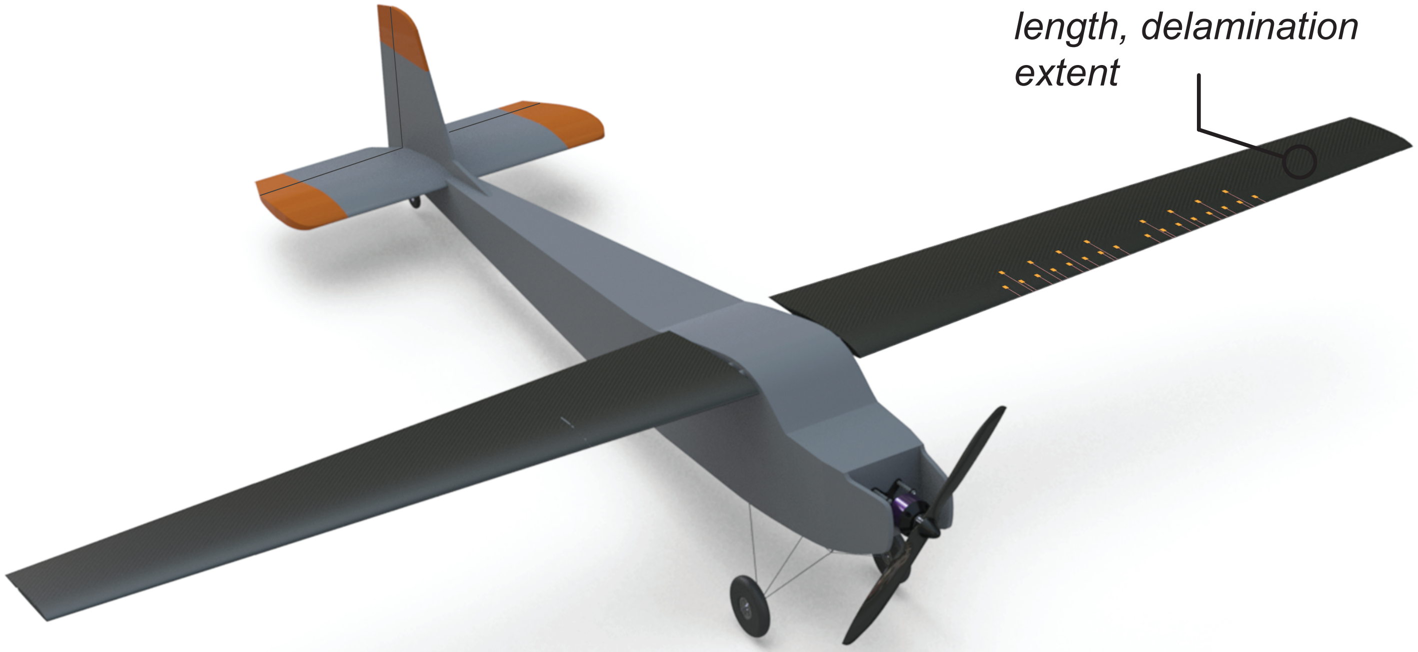

Physical State, S:
Parametrized state of the physical asset

Skin thickness, crack length, delamination extent

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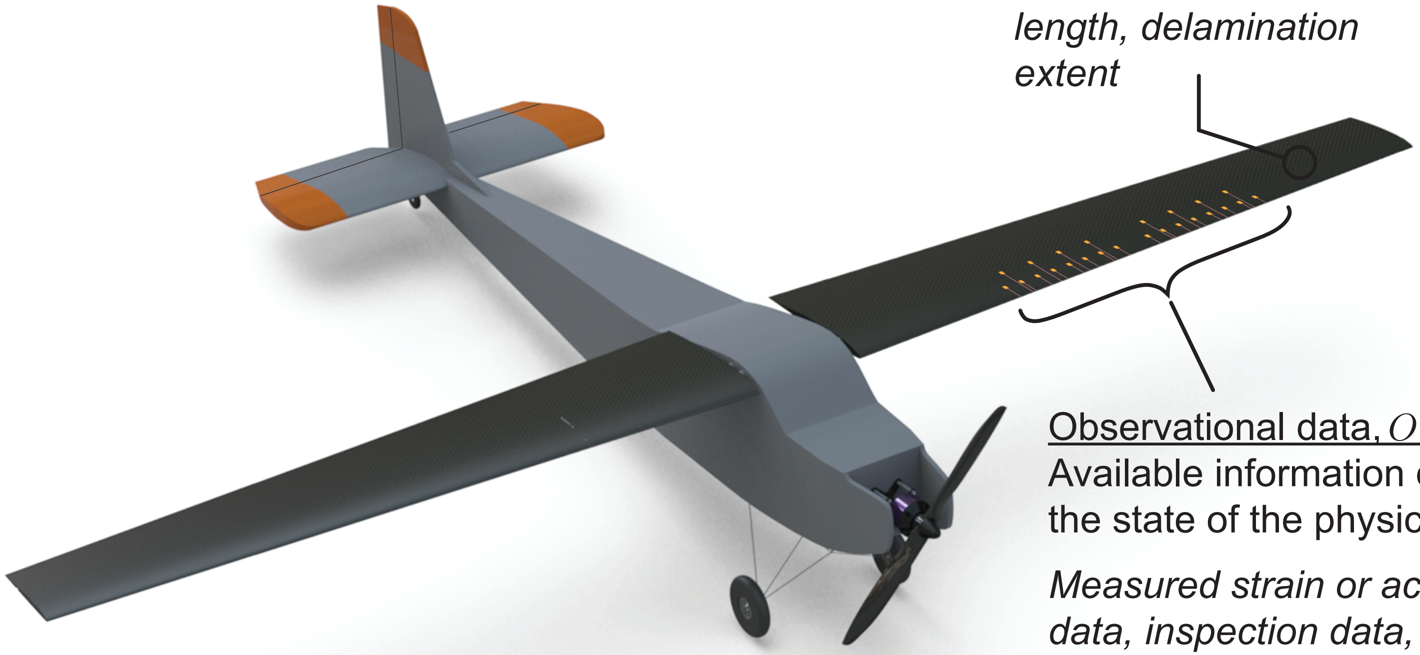


Physical State, S:
Parametrized state of the physical asset

Skin thickness, crack length, delamination extent

Observational data, O:
Available information describing the state of the physical asset

Measured strain or accelerometer data, inspection data, flight logs

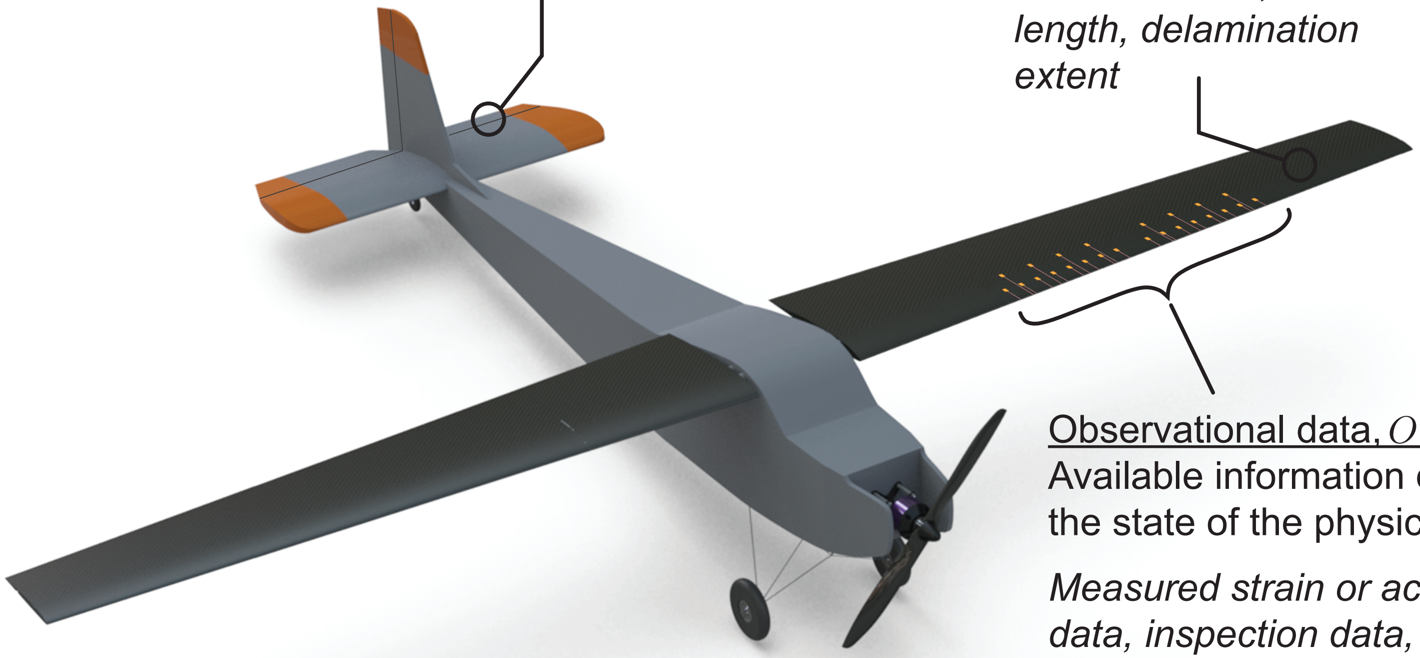
Our abstraction of an asset-twin system

<u>Control inputs, U:</u>
Actions or decisions that influence the physical asset

In-flight maneuvers, maintenance or inspection decisions, sensor installation

<u>Physical State, S:</u>
Parametrized state of the physical asset

Skin thickness, crack length, delamination extent



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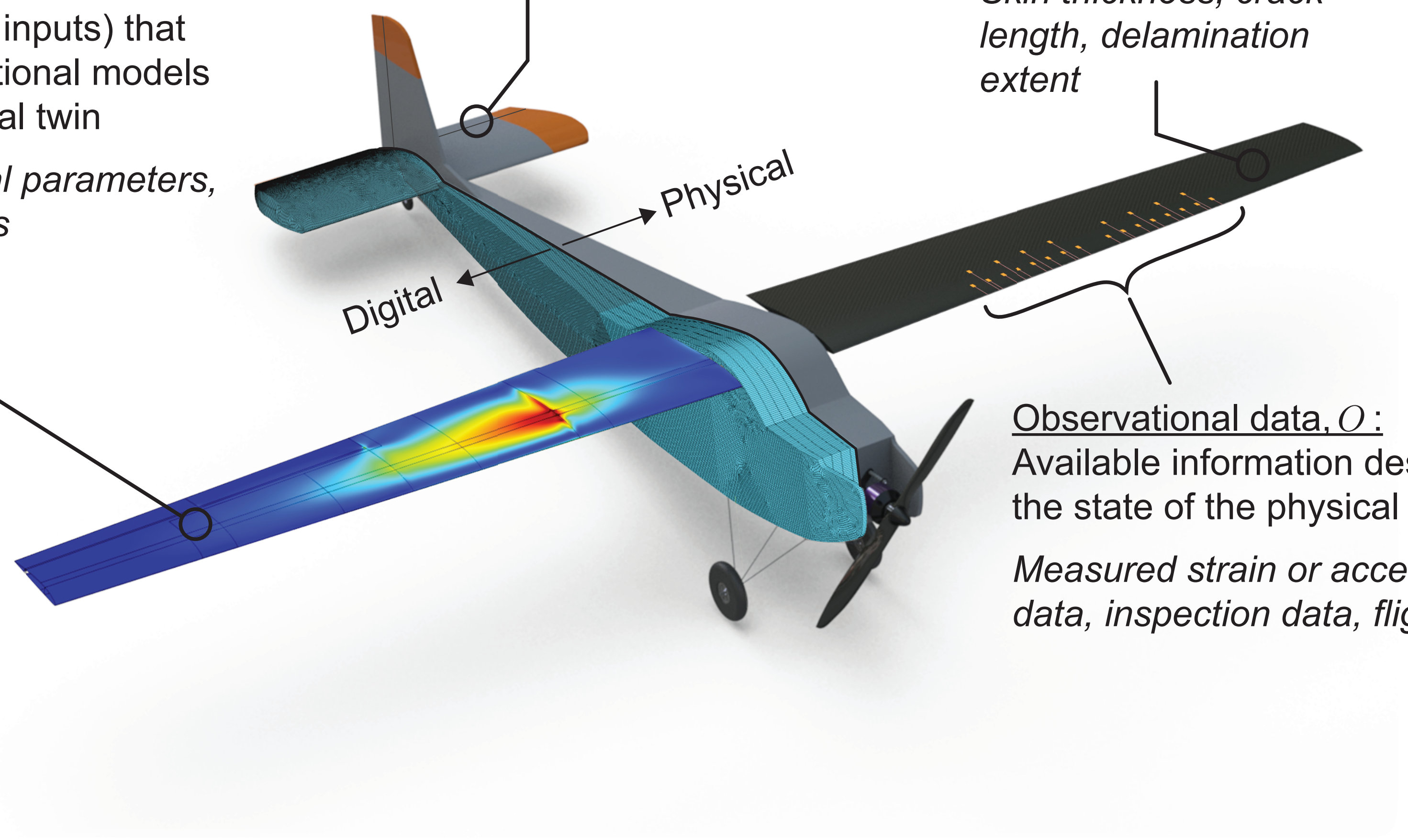
<u>Digital State, D:</u>
Parameters (model inputs) that define the computational models comprising the digital twin

Geometry, structural parameters, boundary conditions



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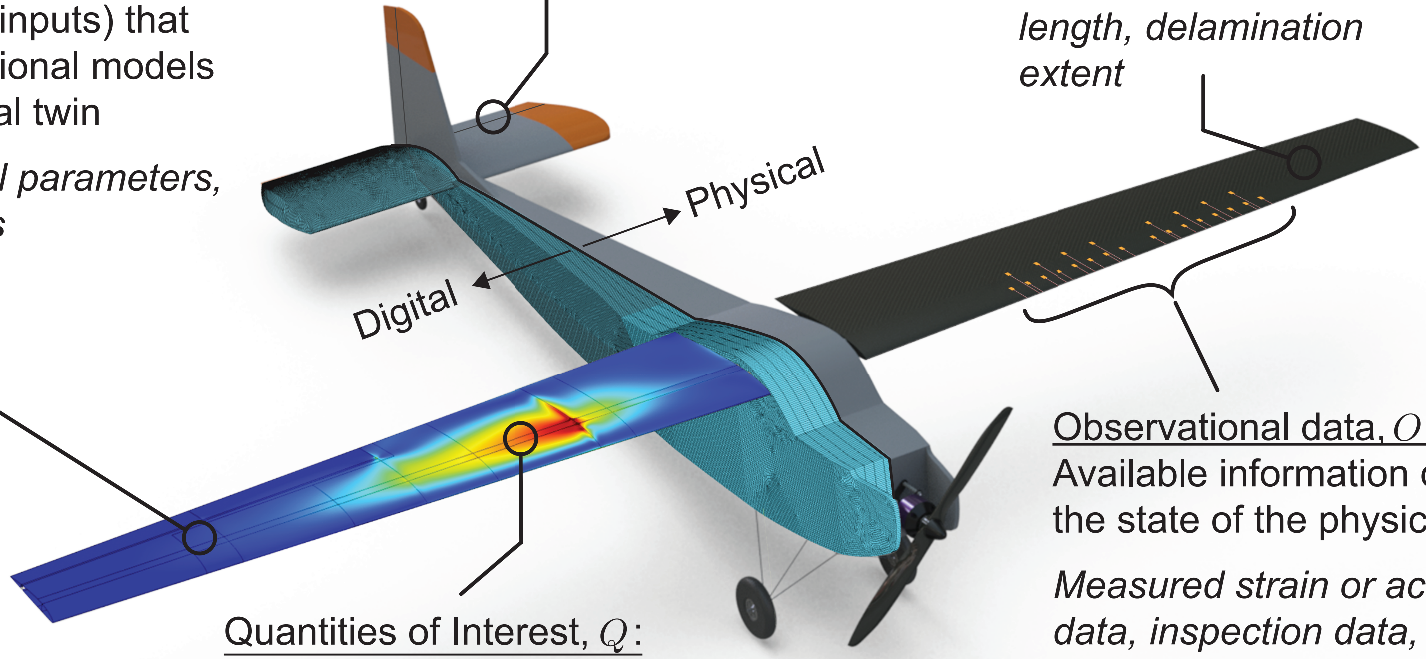

Observational data, O:
Available information describing the state of the physical asset

Measured strain or accelerometer data, inspection data, flight logs

Quantities of Interest, Q:
Quantities describing the asset, estimated via model outputs

Stress, strain, displacement fields, failure stress, remaining useful life

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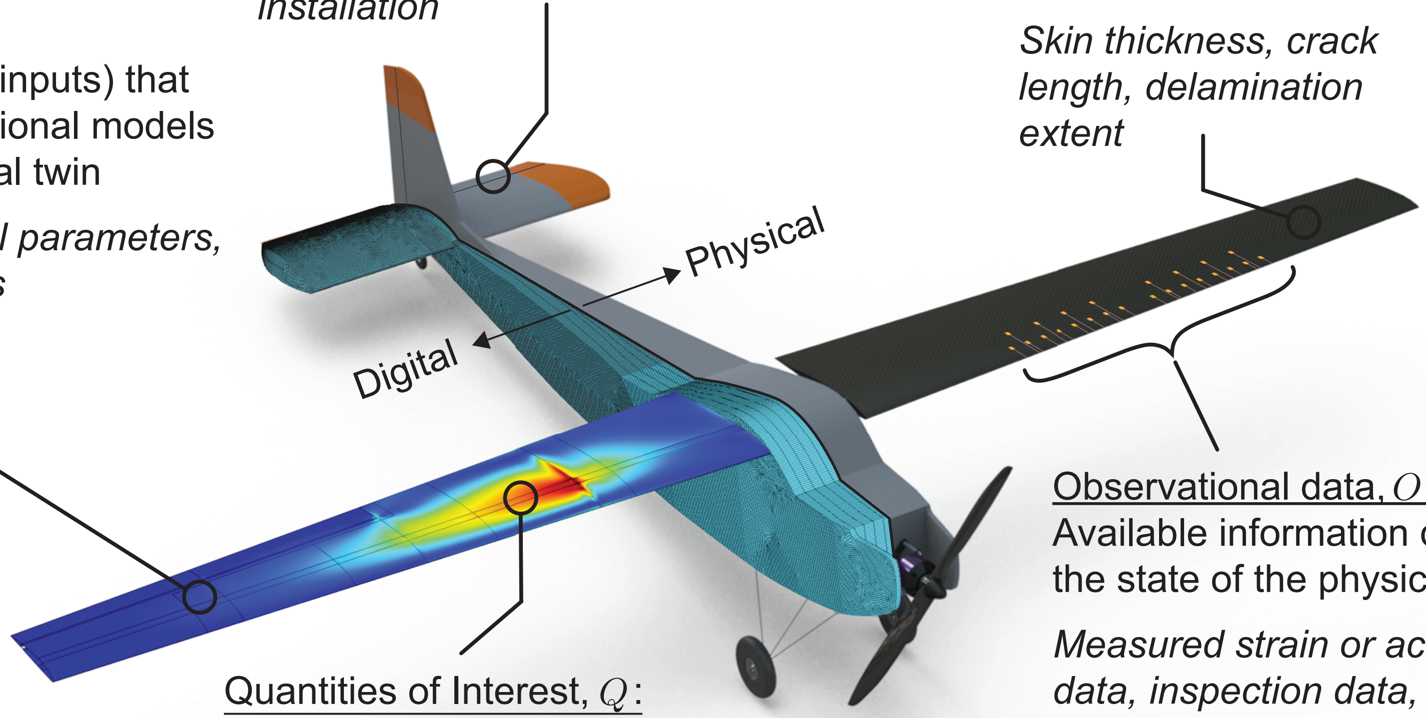

Reward, R :
Quantifies overall performance of the asset-twin system

Mission success, fuel burn, maintenance or inspection costs

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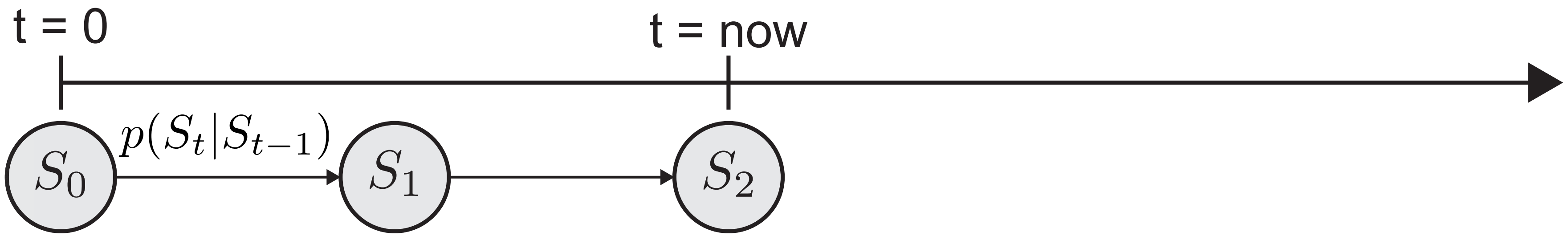
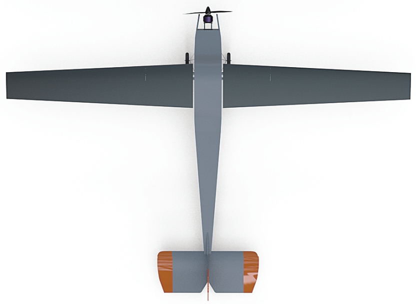
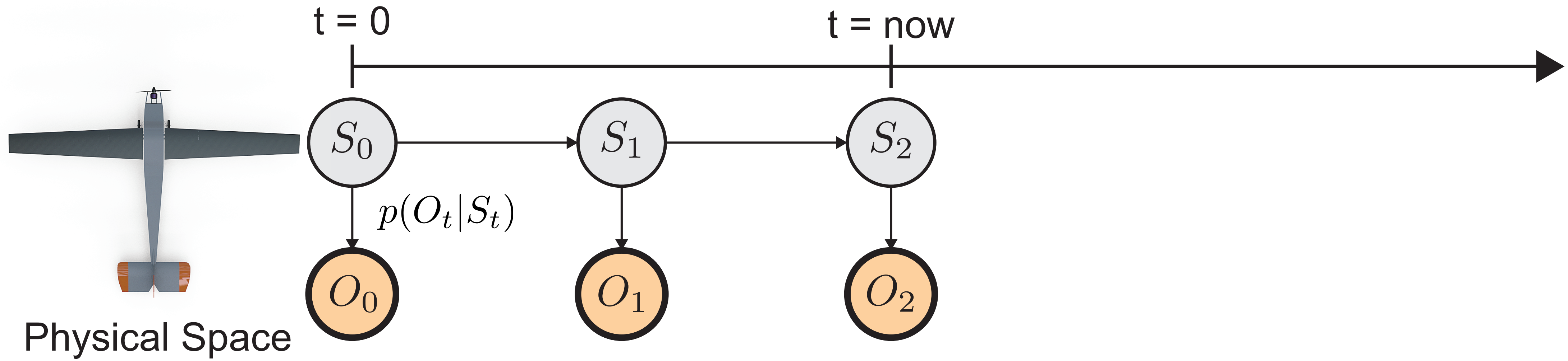
A probabilistic graphical model for digital twins





Physical Space

A probabilistic graphical model for digital twins



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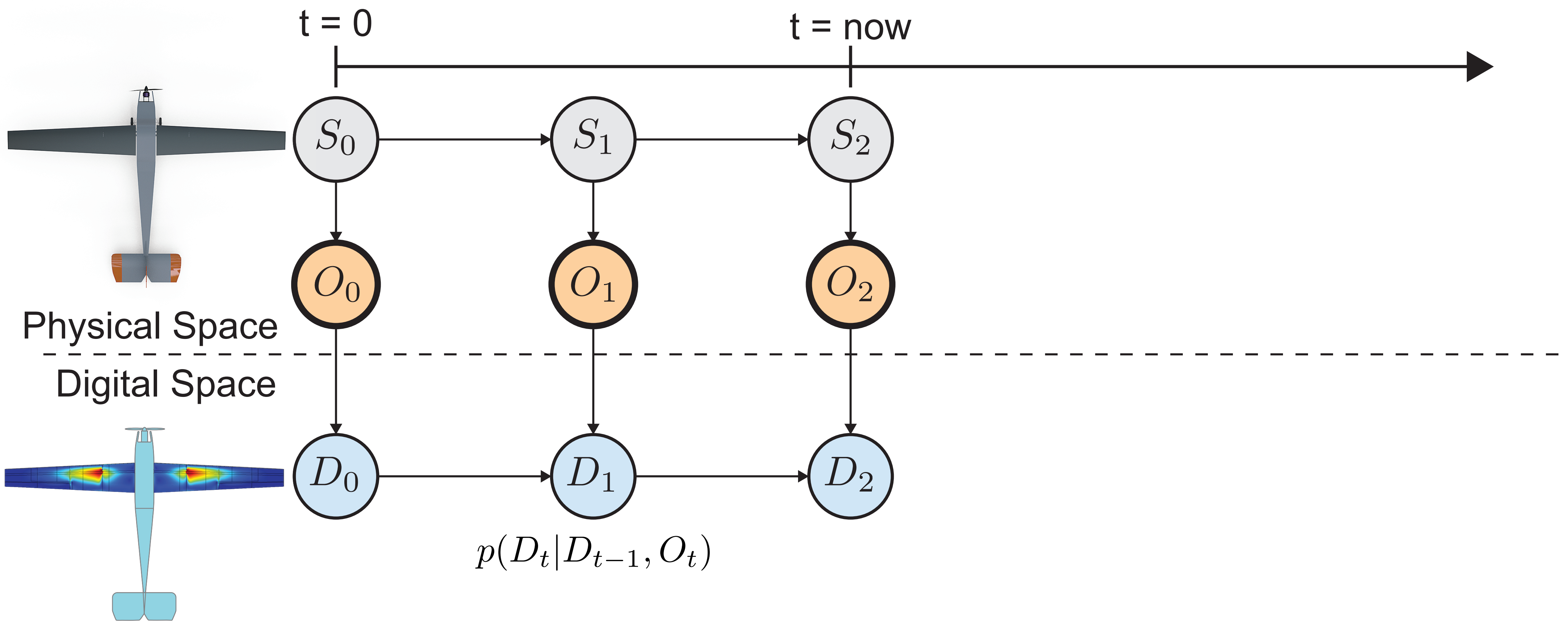

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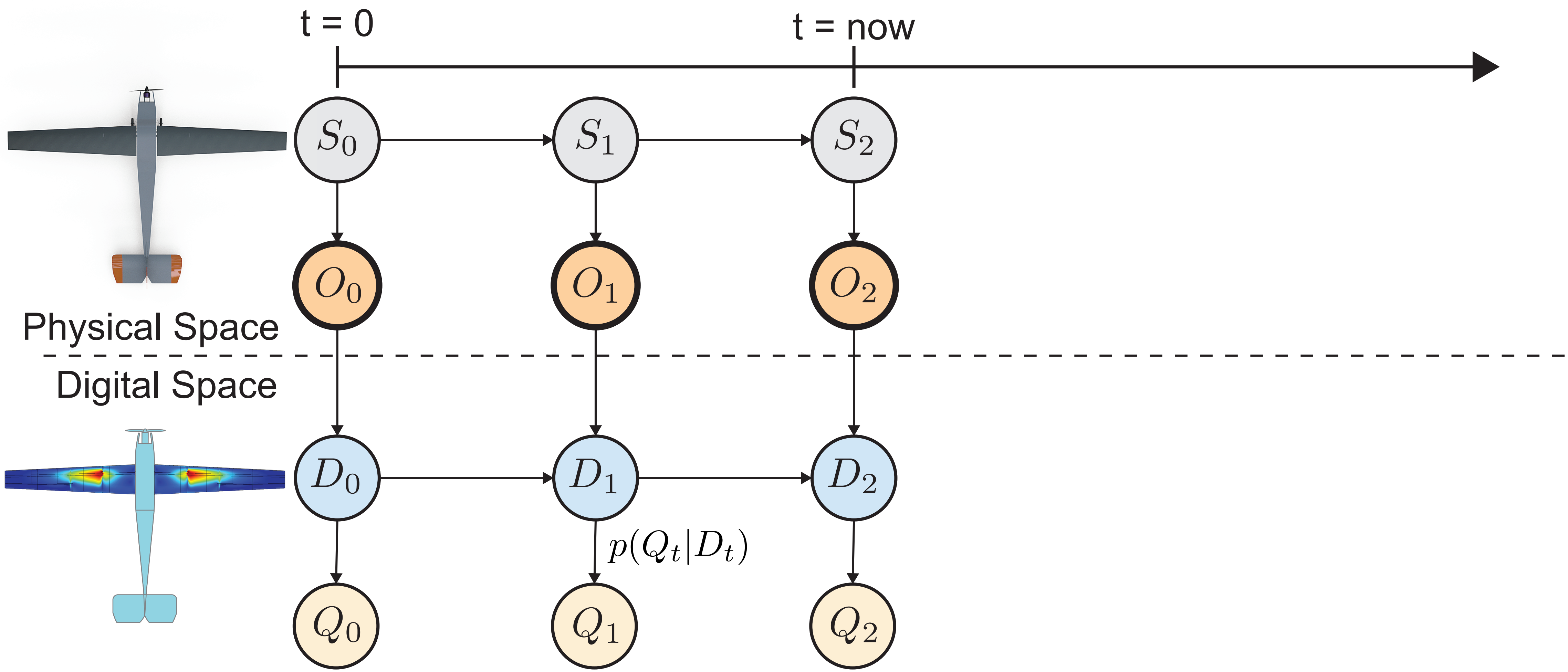

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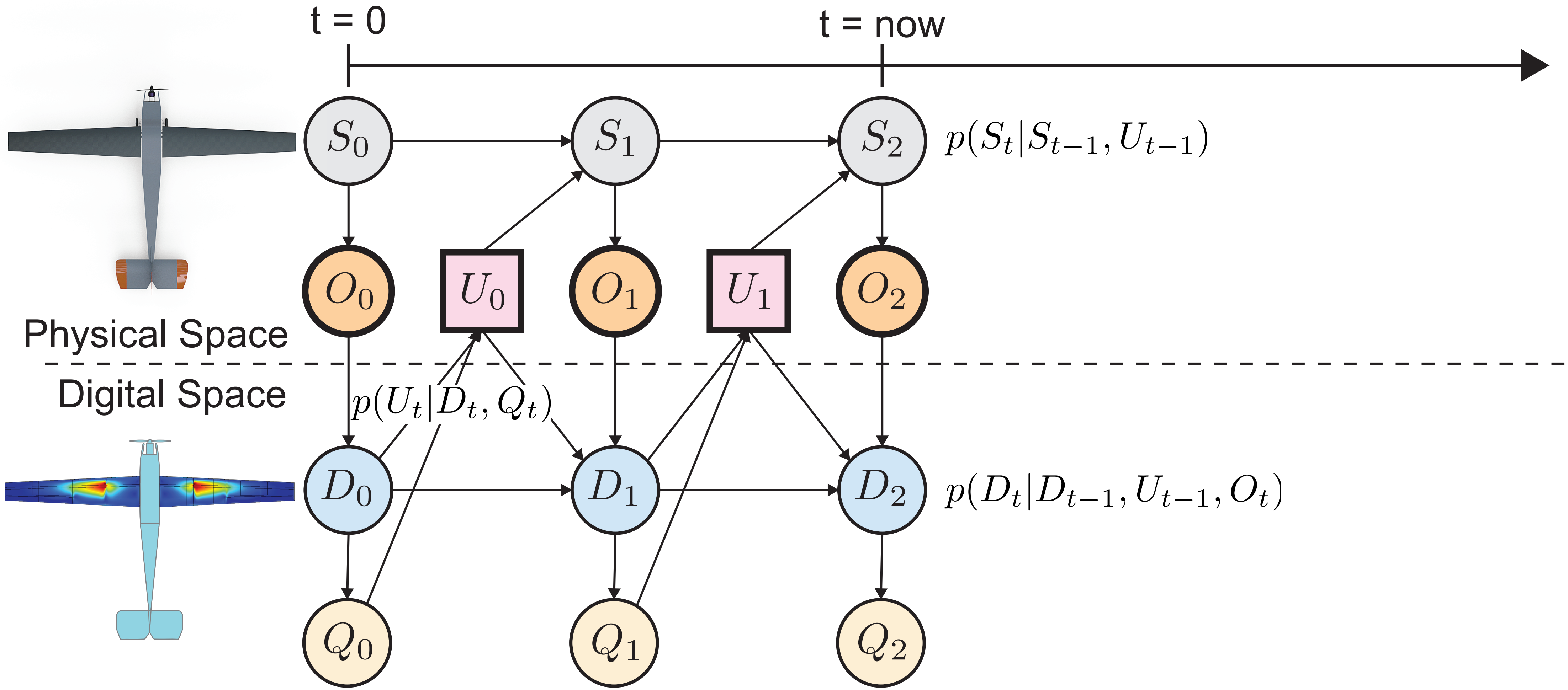

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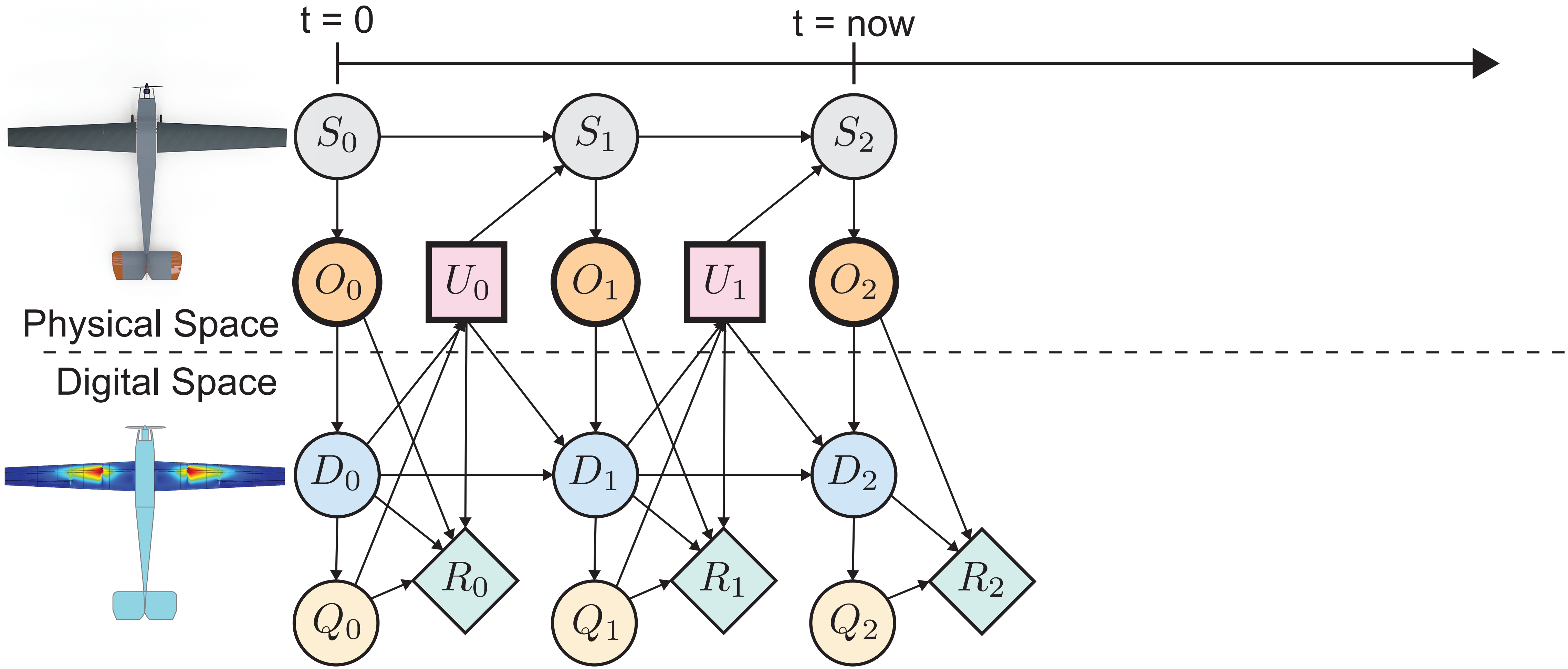
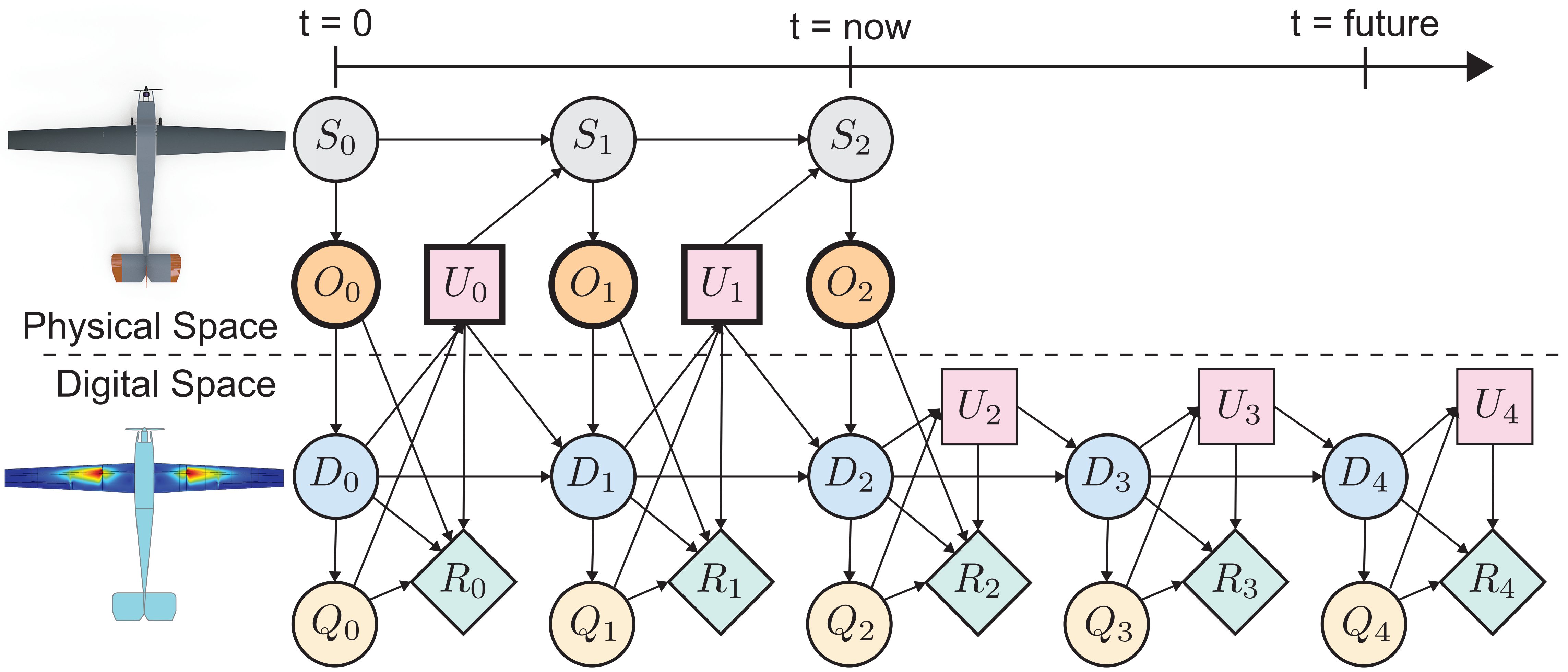


$$p(R_t | D_t, U_t, O_t, Q_t)$$

A probabilistic graphical model for digital twins



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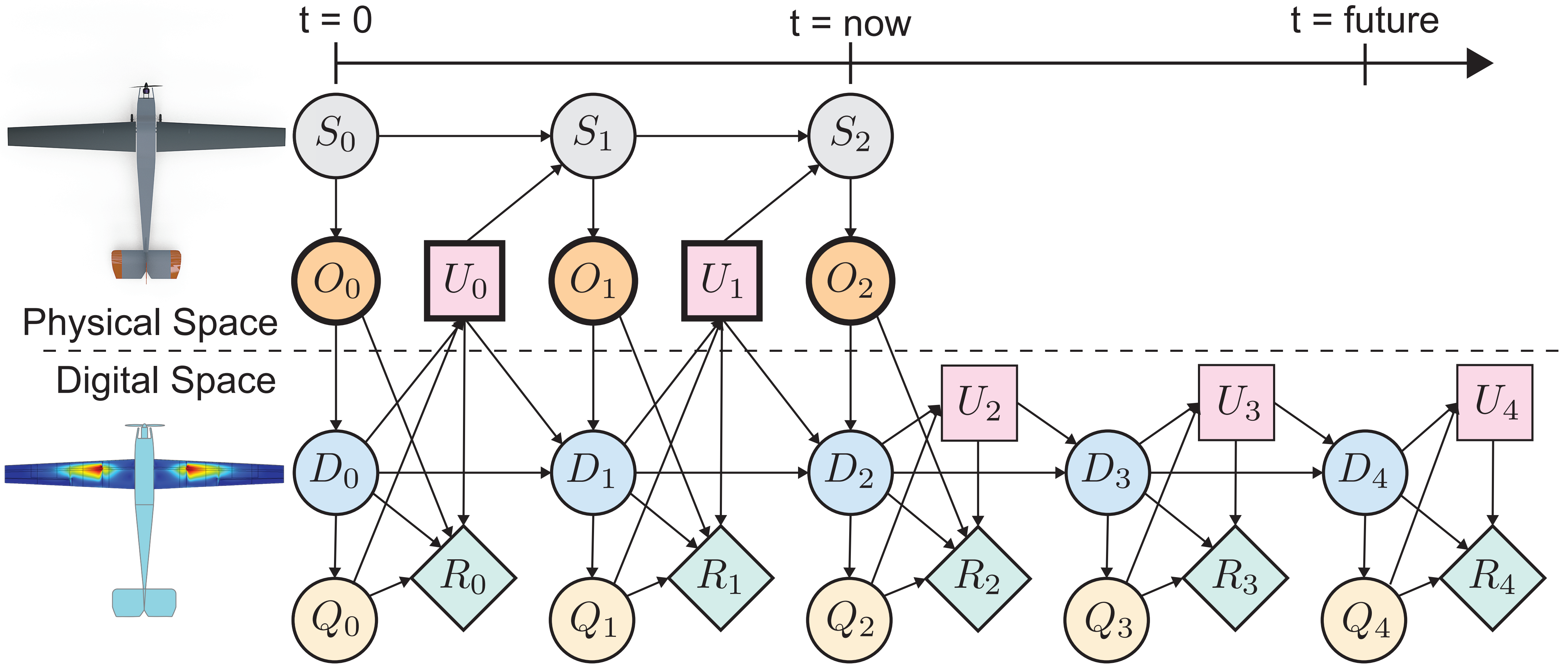
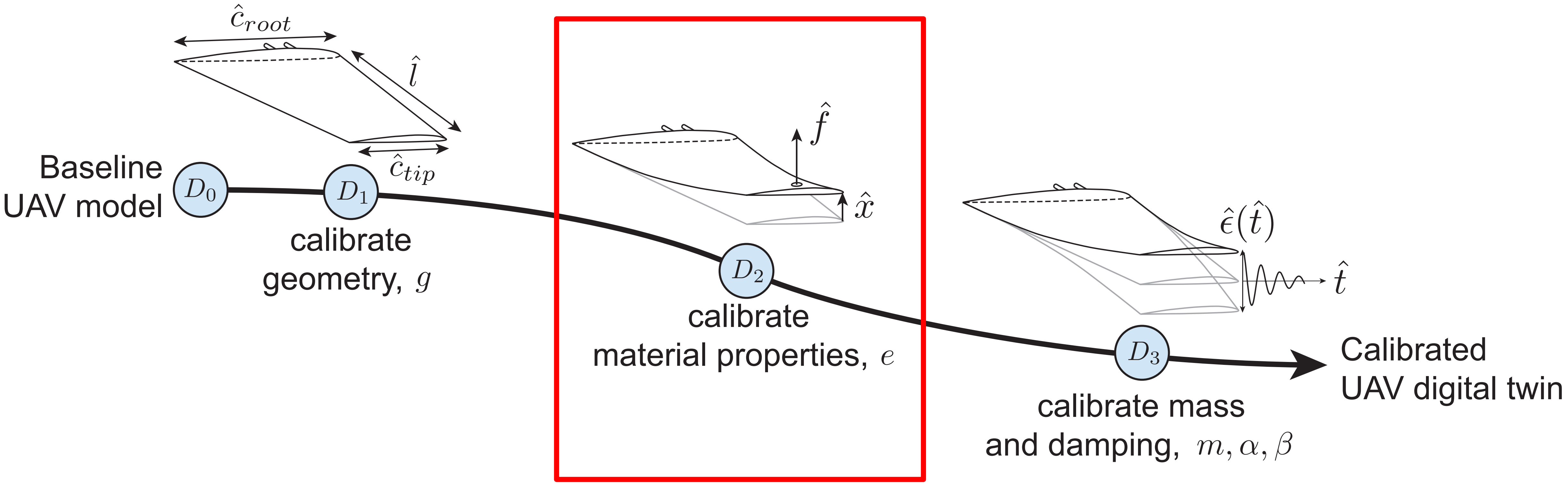


Demonstration: Experimental calibration of a structural digital twin



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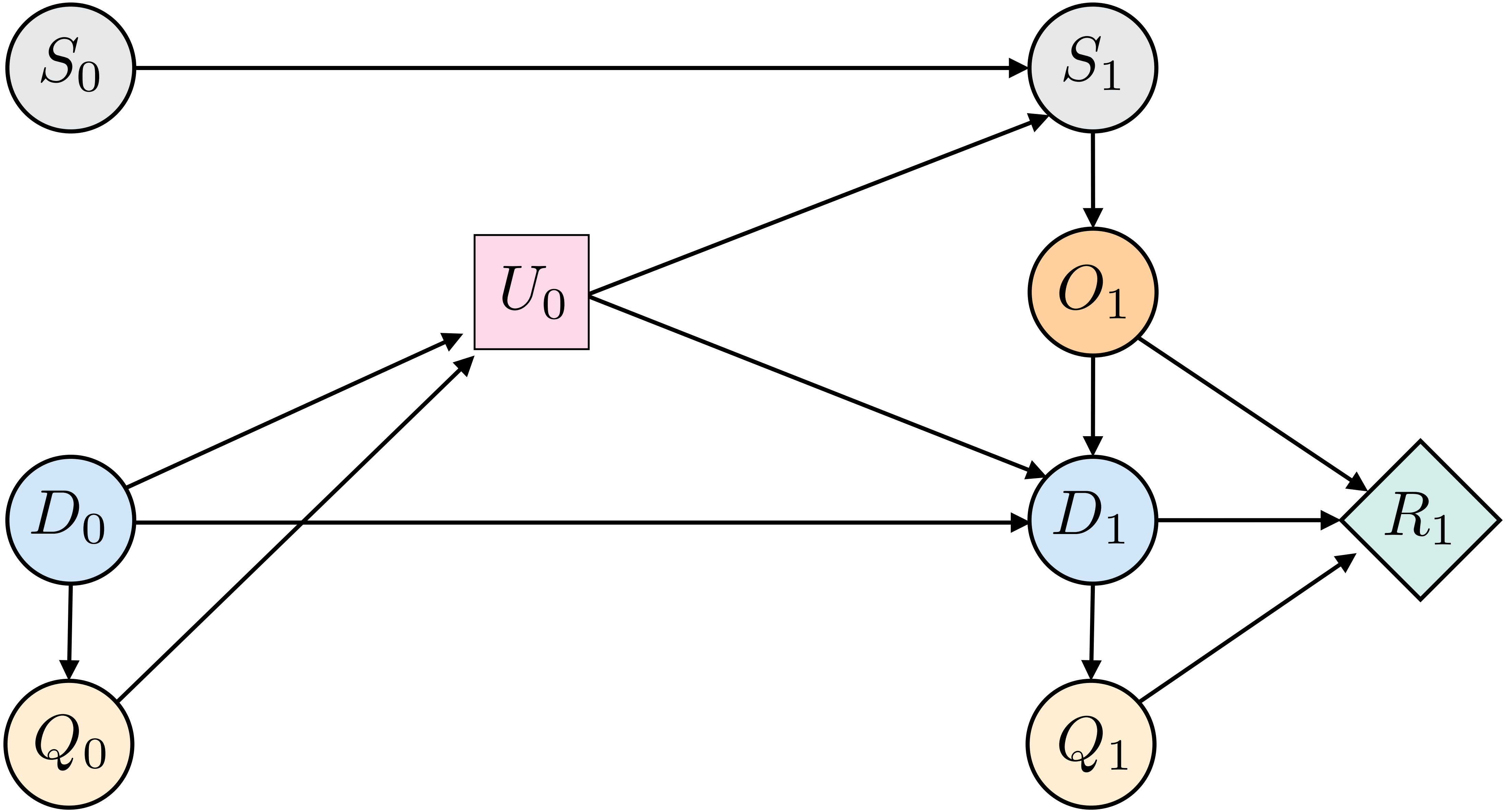

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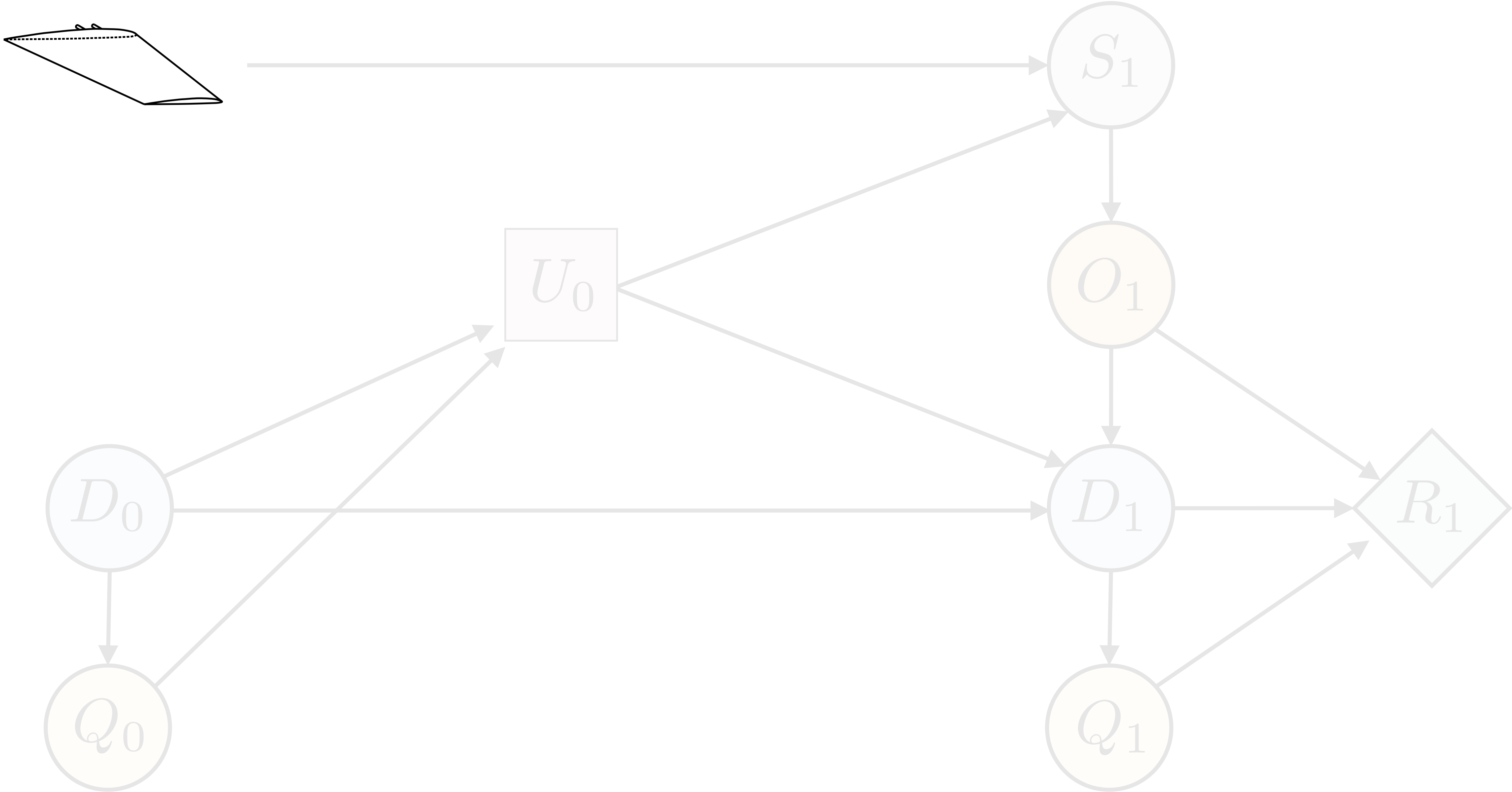

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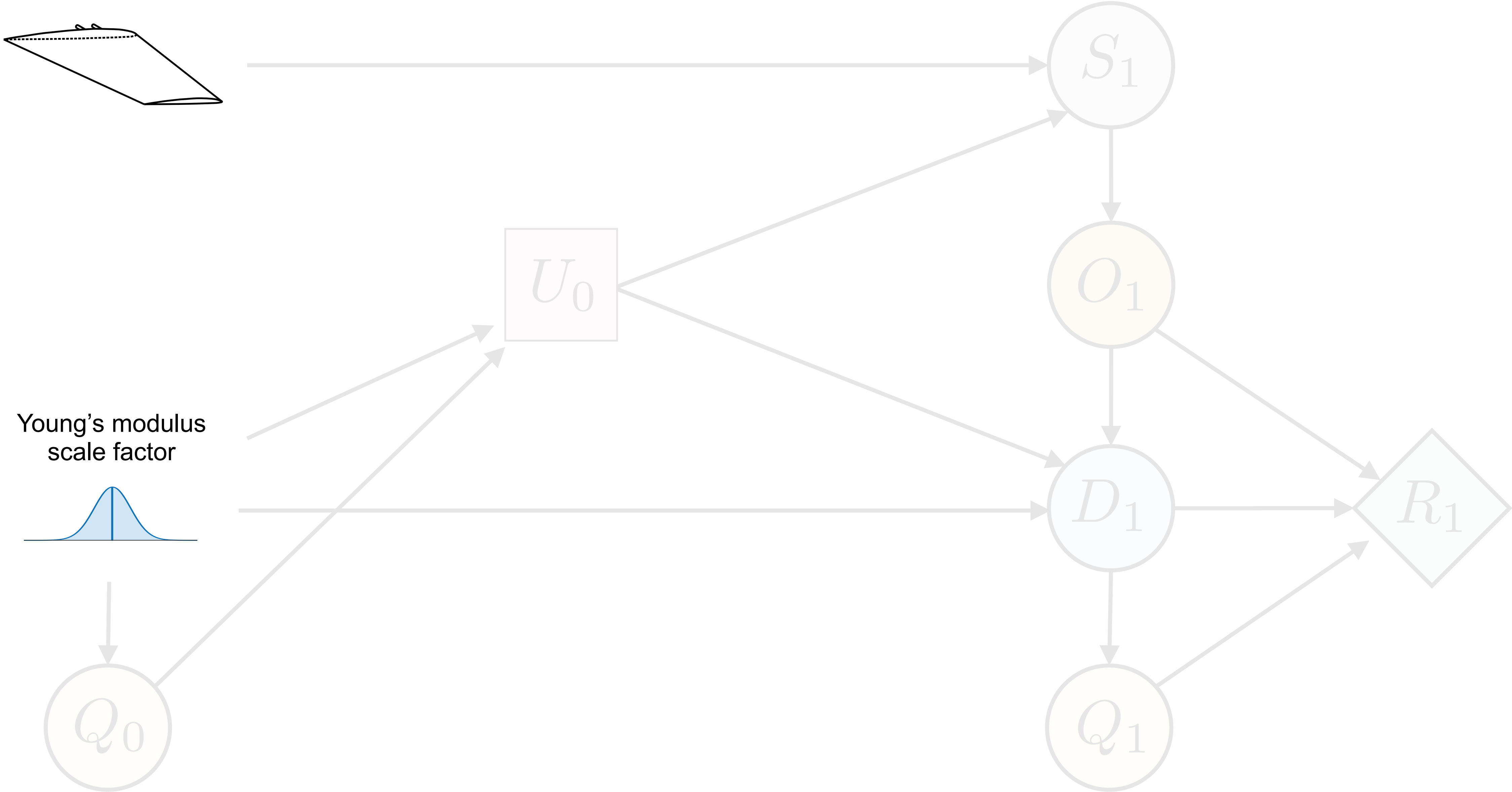

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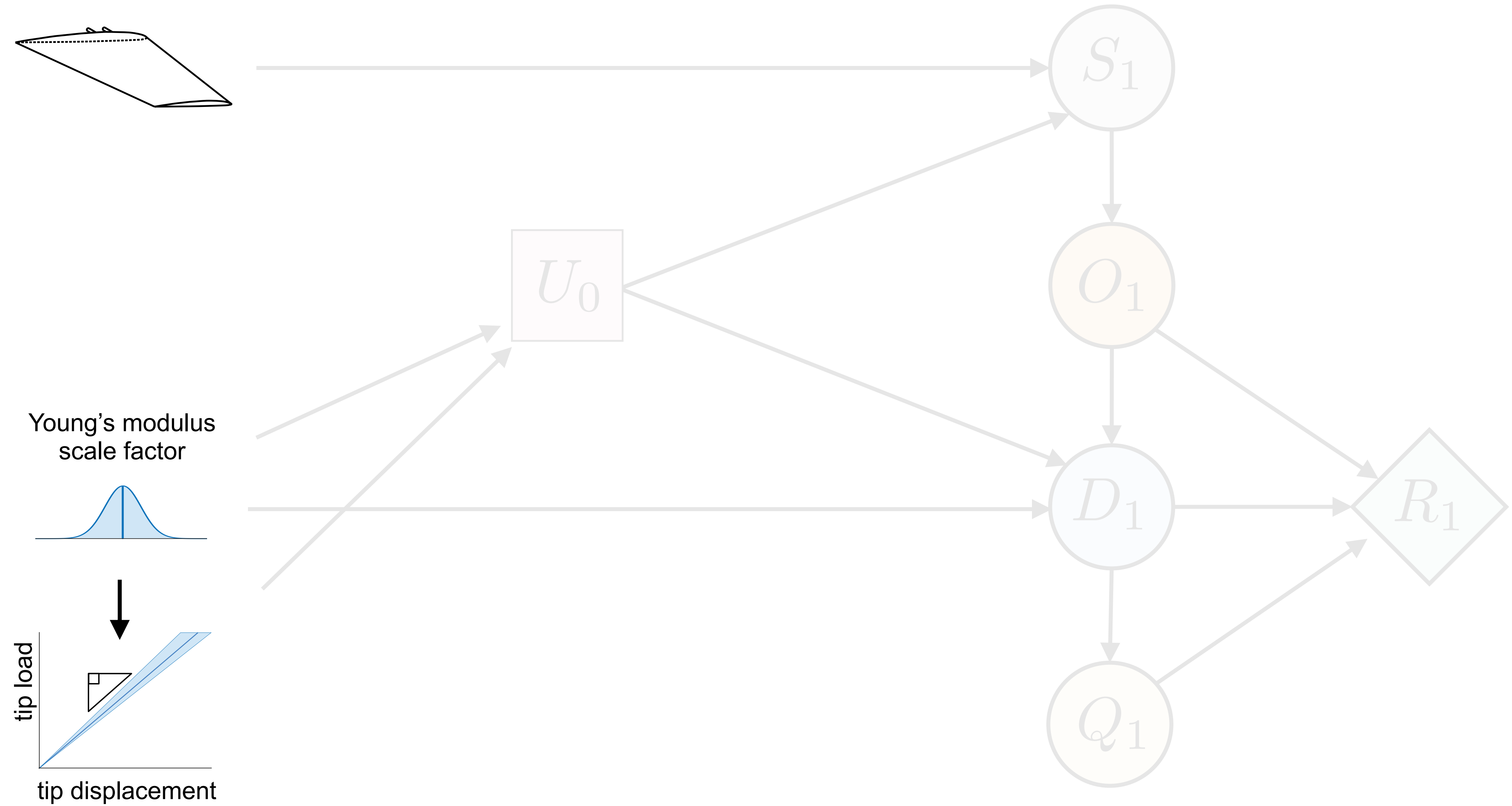

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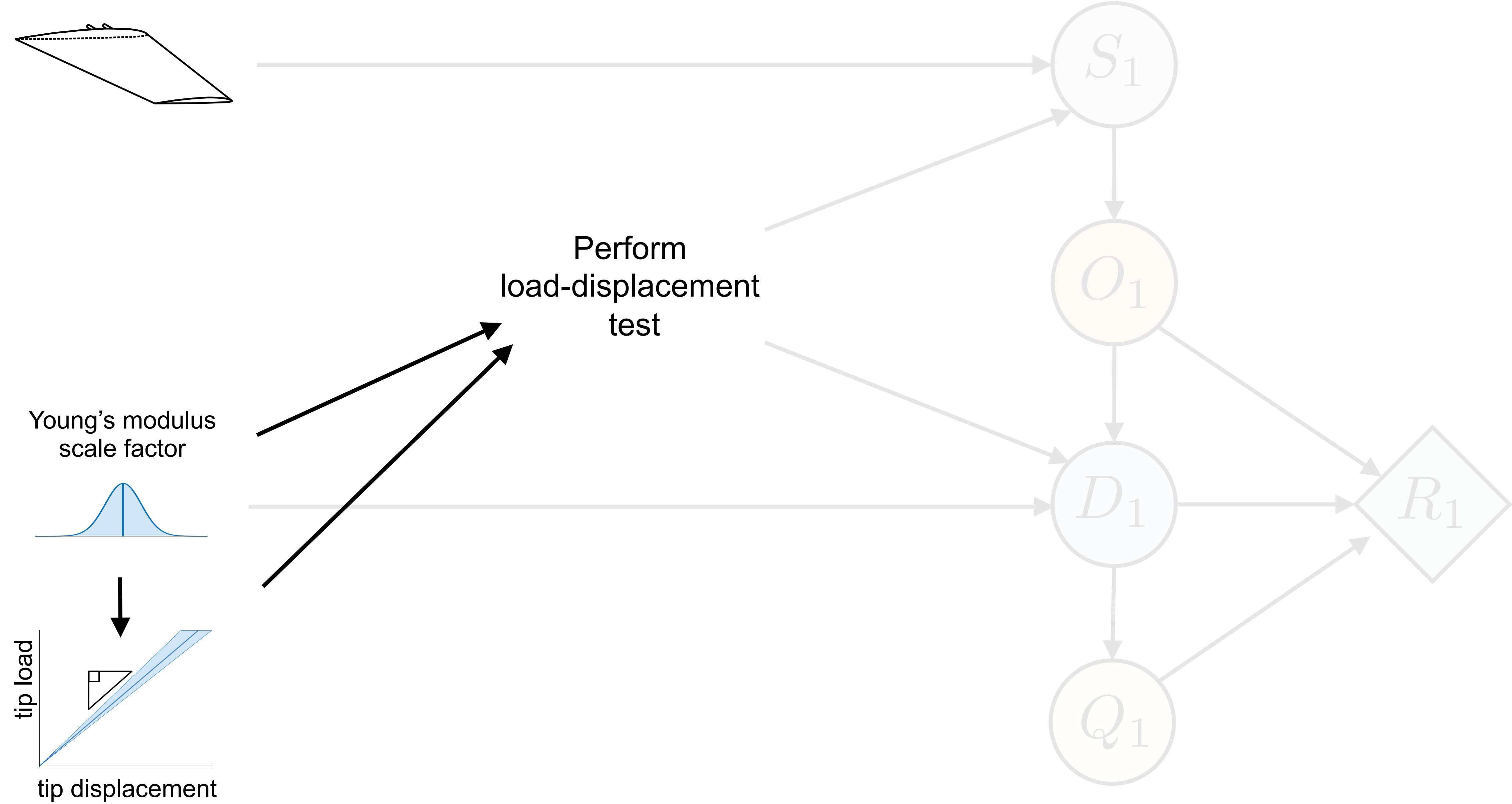

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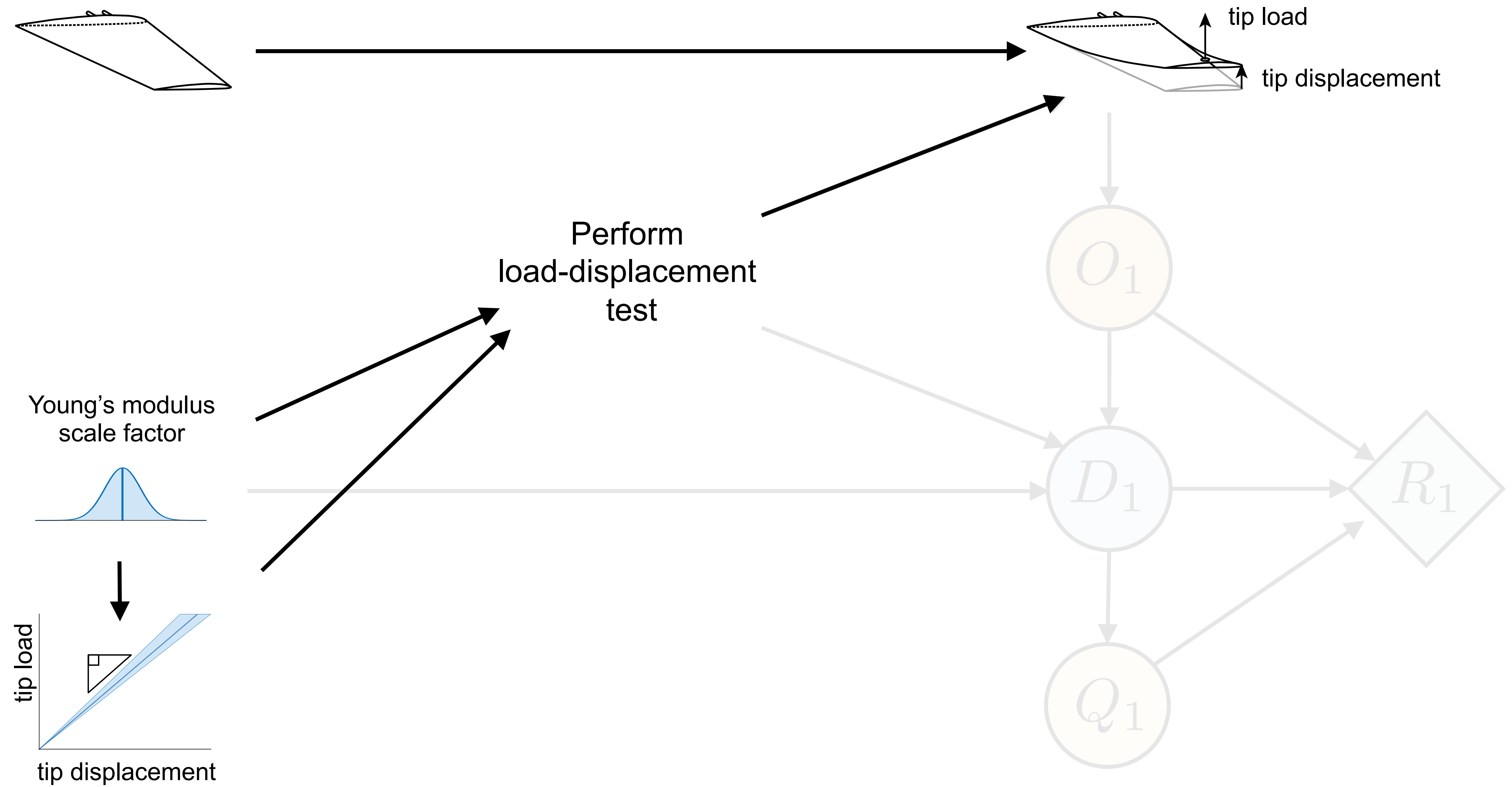

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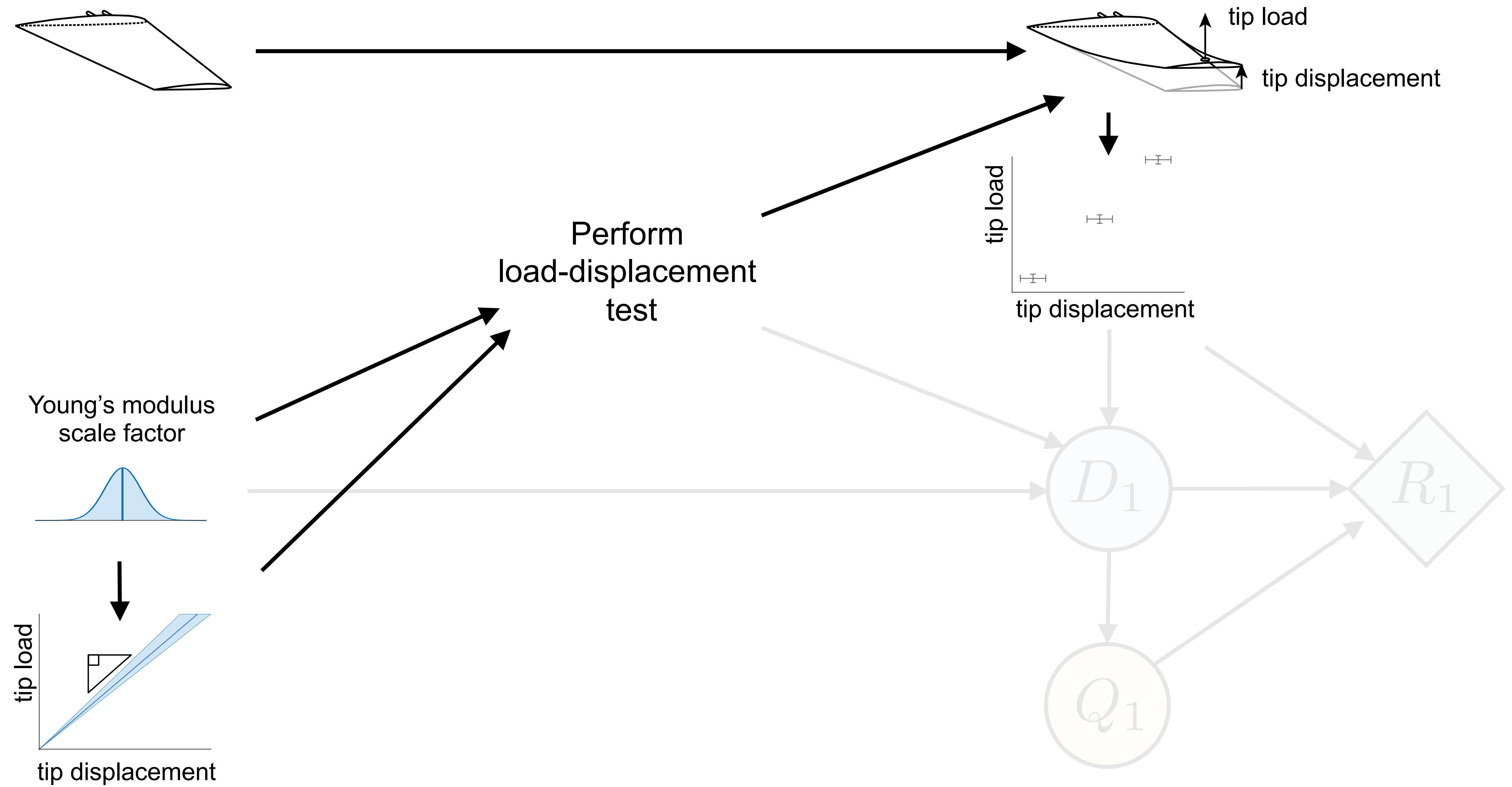

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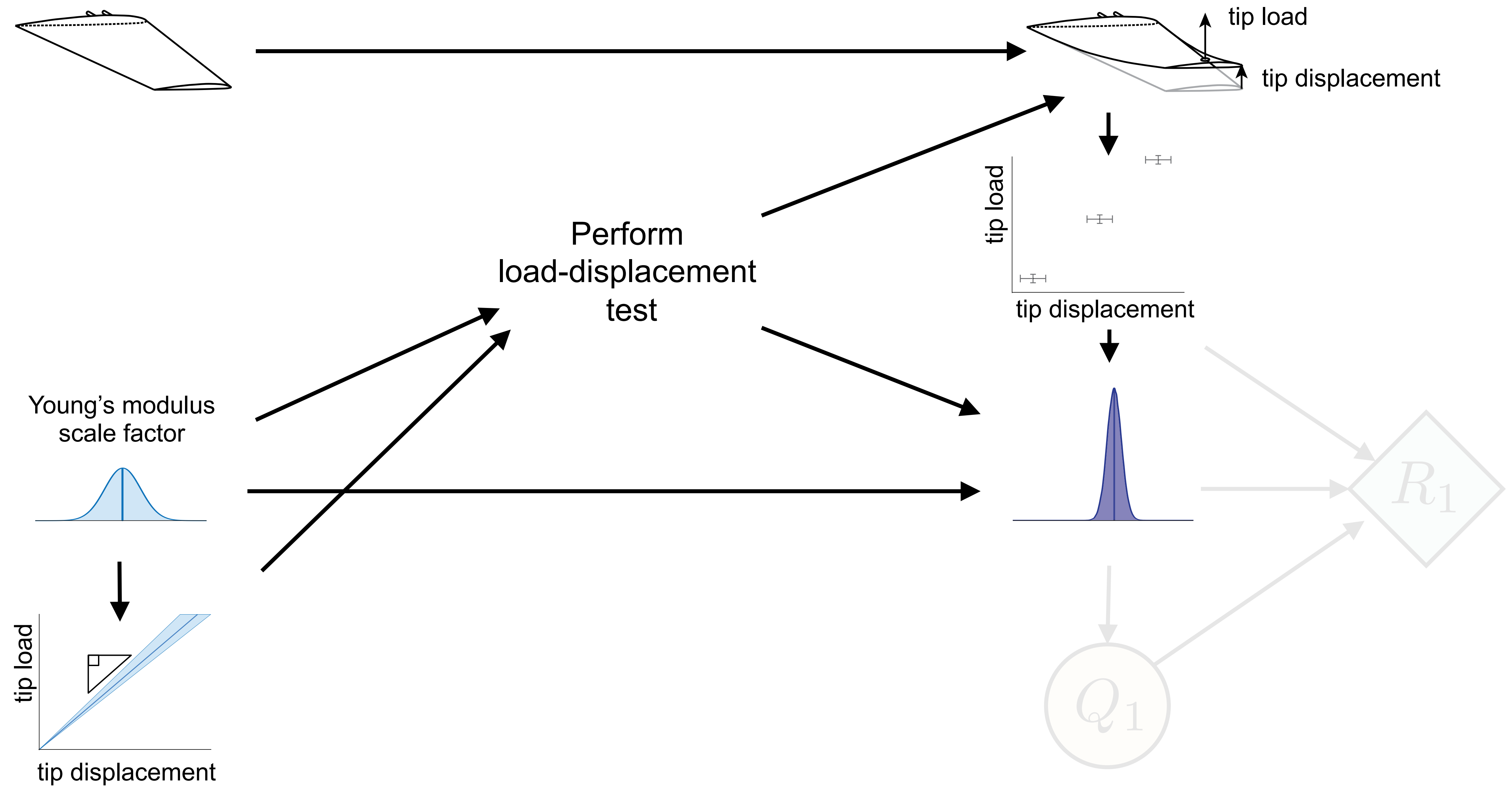

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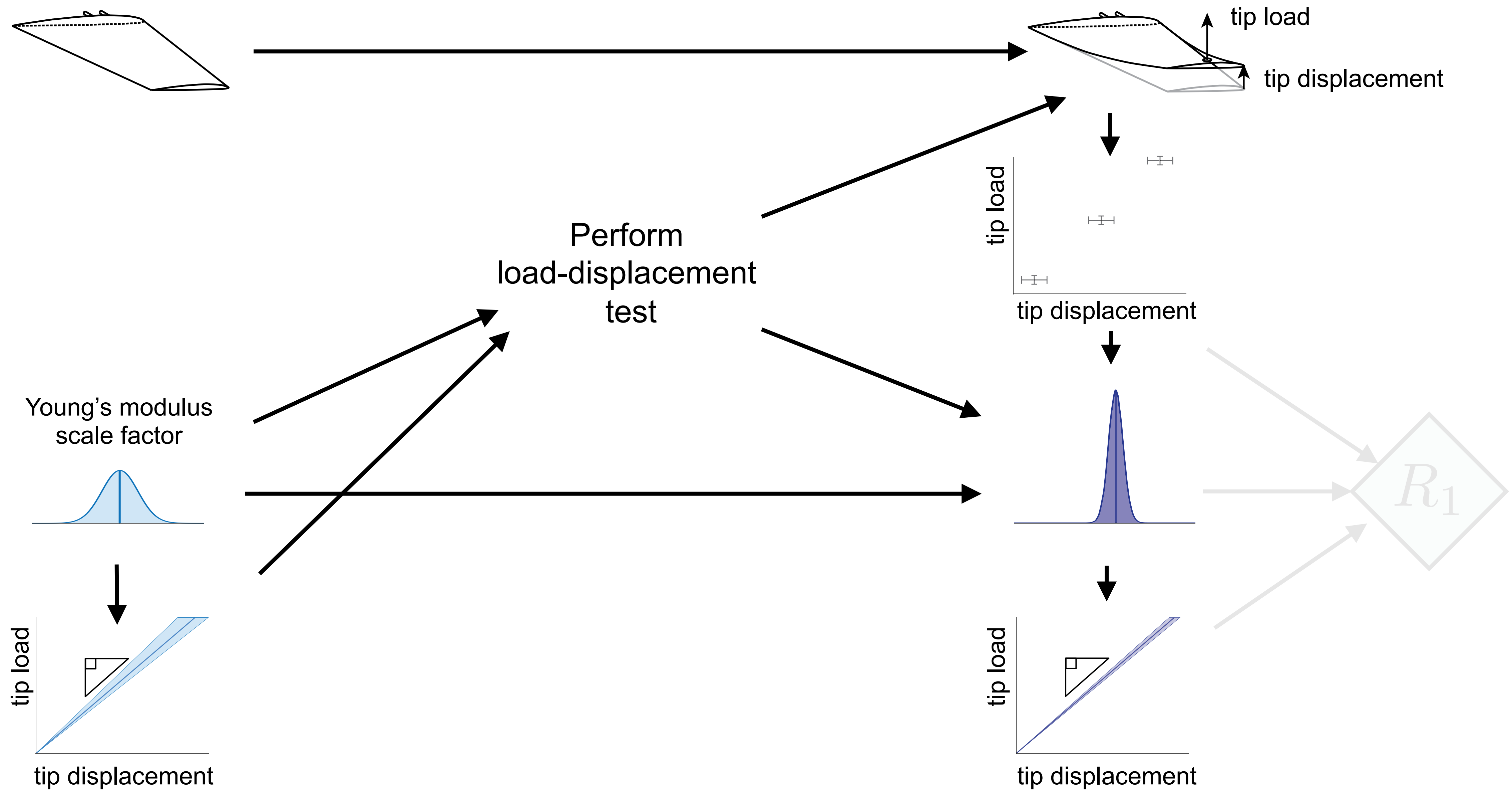

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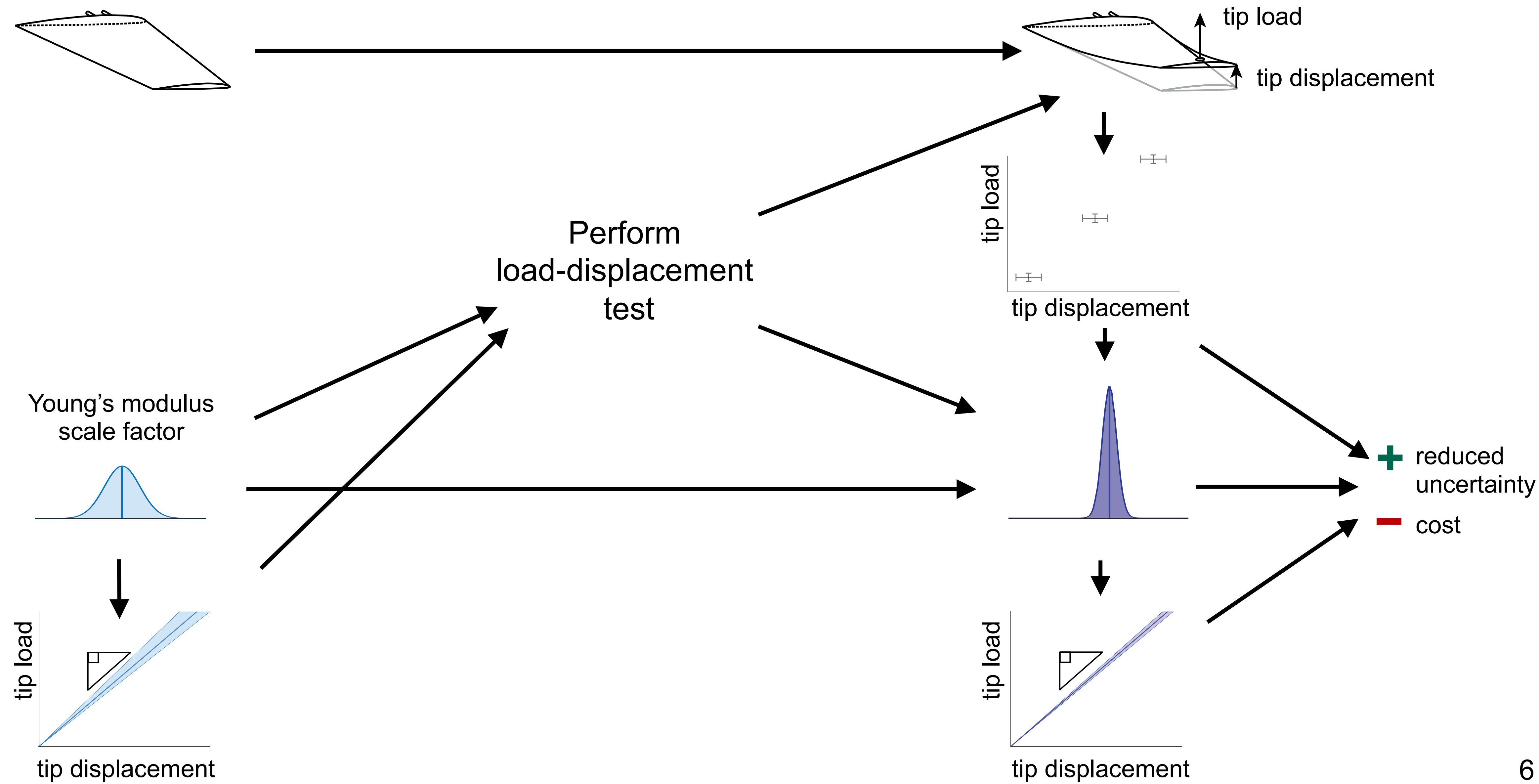


Conclusion

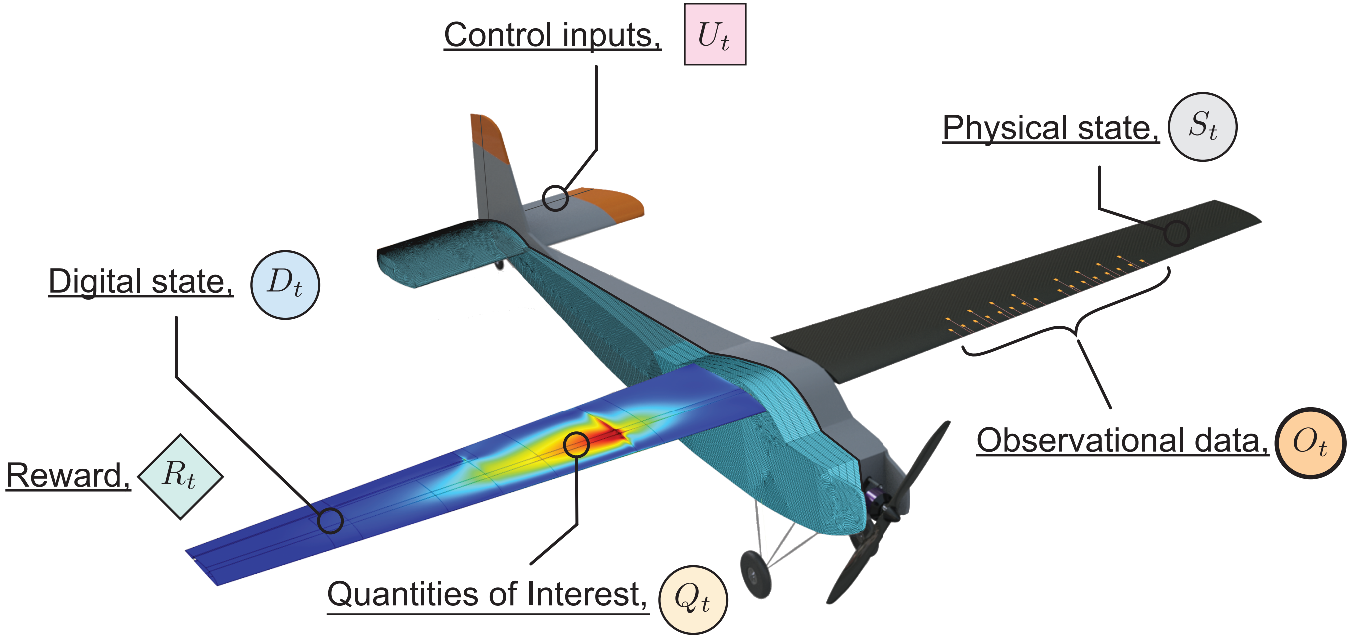
The proposed probabilistic graphical model serves as…

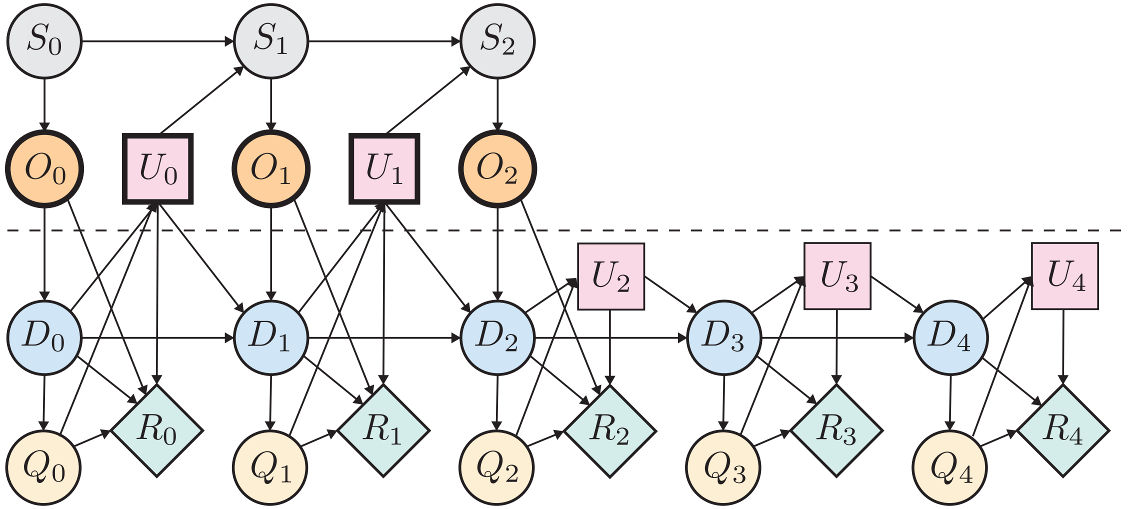
A conceptual model for defining, analyzing, and comparing digital twins

- Across application areas
- Across digital twin use-cases

A mathematical and computational foundation for implementing digital twins at scale

- Rigorous
  - Established algorithms for principled estimation, learning, decision-making, end-to-end uncertainty quantification
- Flexible
  - Models comprising the digital twin can be physics-based, data-driven, or derived from expert knowledge
- Scalable
  - Principled
  - Repeatable





Further information about this ongoing research, including a copy of these slides and the associated paper:
https://kiwi.oden.utexas.edu/research/digital-twin

Funding acknowledgements:

- Air Force Office of Scientific Research (AFOSR) Dynamic Data-Driven Application Systems (DDDAS)
- SUTD-MIT International Design Centre
- AFOSR MURI awards FA9550-15-1-0038 and FA9550-18-1-0023
- AEOLUS center under US Department of Energy Applied Mathematics MMICC award DE-SC0019303.