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Hume Center for National Security and Technology

Bringing Reliability, Prognostics, and Testing to Machine Learning

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Executive Summary

Observation

Machine learning (ML) and engineered systems are **coupled**

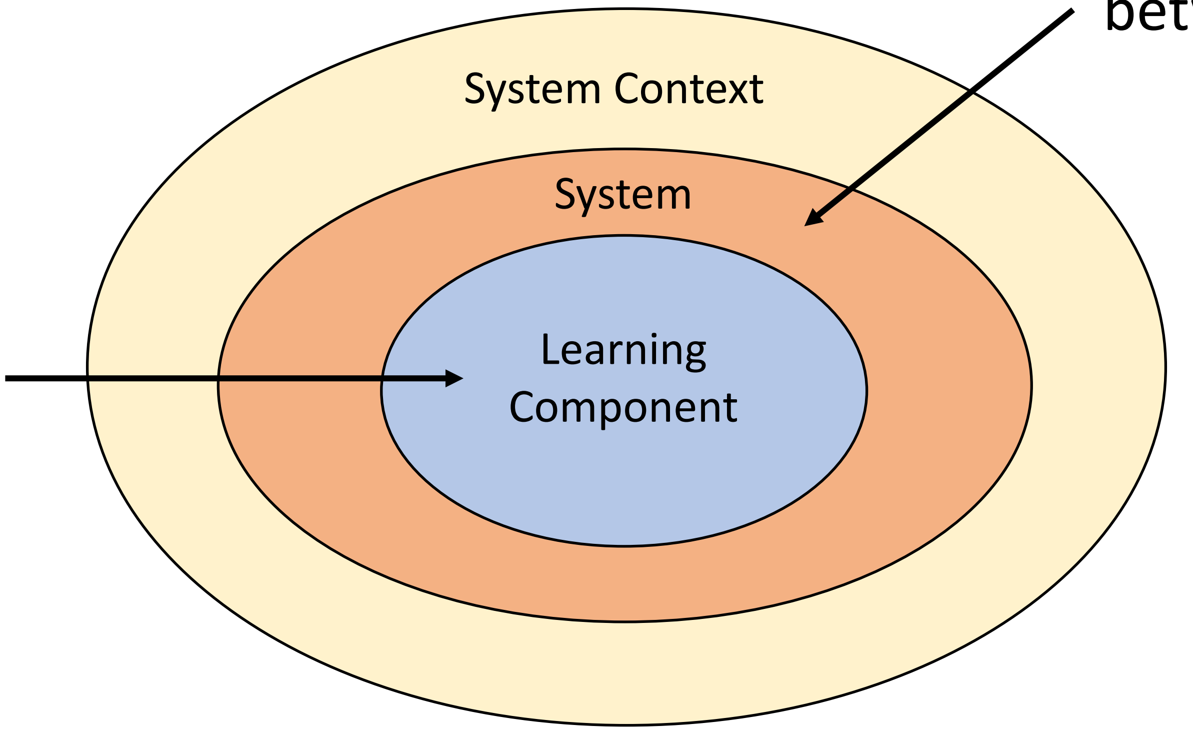
Reliability, V&V, prognostics, etc. for ML
cannot be divorced from system

We propose to use *systems principles* and *systems theory* to:

- Bring ML and learning theory to models of systems (synthesis)
- Integrate ML and systems using an understanding of levels of abstraction

Focus on relationship between learning algorithms and their systems

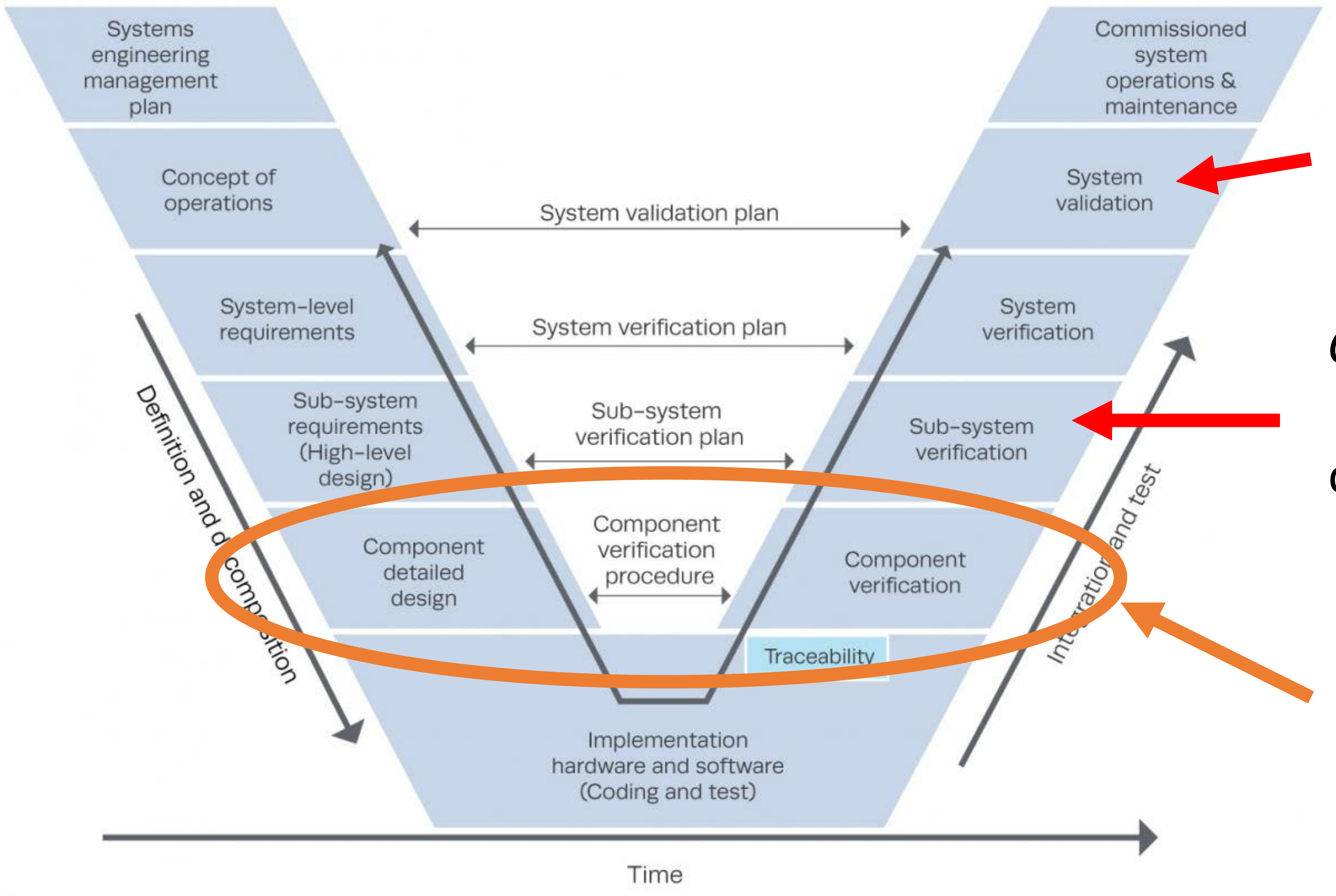
ML/AI focus on learning algorithms (and sometimes data)



Systems $\neq$ Problems

Proposition:
Engineering intelligence requires focusing on **learning systems** not the **problems they solve**

Cody, T. "Mesarovician Abstract Learning Systems". International Conference on Artificial General Intelligence. Springer (2021). *In publishing.*



Courtesy MITRE

(Stronger) Claim

Reliability, V&V, PHM, etc. cannot begin until as least here.

Claim

Reliability, V&V, PHM, etc. cannot begin until as least here.

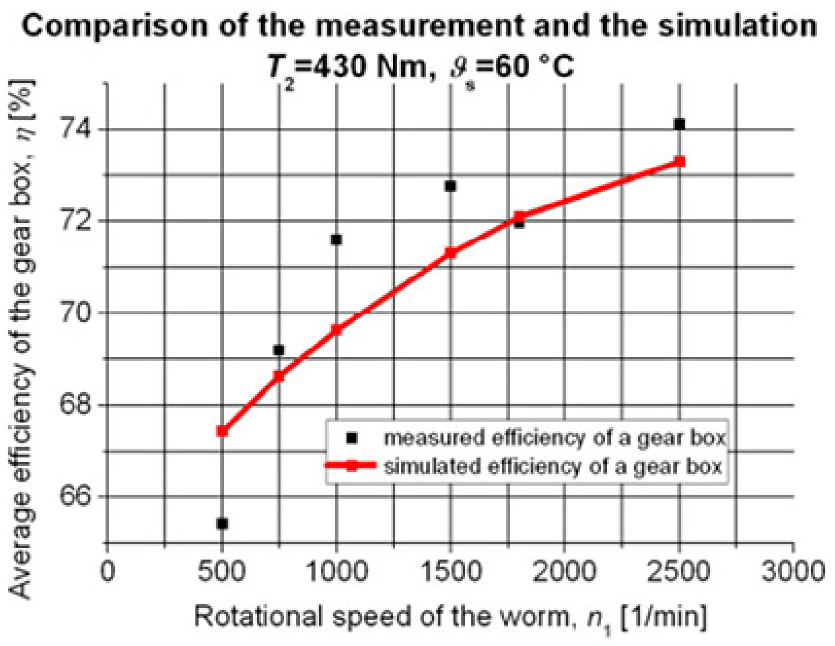
Machine learning is viewed as a component

Parallels

Background: Parallels in Reliability (Stateless)

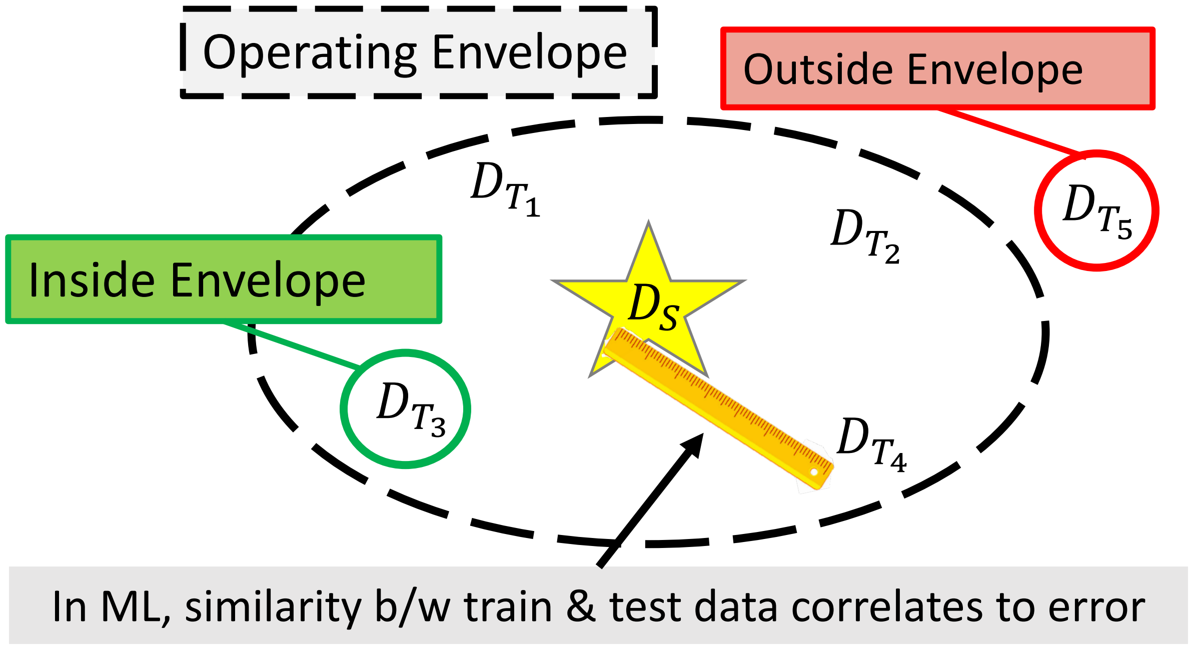
Traditional Components

- Wear curves (exist for all sorts of physical components)



Machine Learning (Cognitive)

- Don't physically degrade
  - Project operating envelopes over a stochastic process



Background: Parallels in PHM (State)

Traditional Components

- Prognostics
  - Physical or data-driven models of health state
- Maintenance
  - Repair,
  - Rebuild,
  - Replace

Machine Learning (Cognitive)

- Prognostics
  - Physical or data-driven *transfer distance*
- Maintenance
  - Fine-tune (calibrate),
  - Transfer learning (from existing model)
  - Retrain (from scratch)

Cody, T., Adams, S., and Beling, P.A. "Empirically Measuring Transfer Distance for System Design and Operation". arXiv preprint. arXiv:2107.01184v1 (2021)

Cody, T., and Beling, P.A. "A Systems Theory of Transfer Learning". arXiv preprint. arXiv:2107.01196v1 (2021)

Entanglement

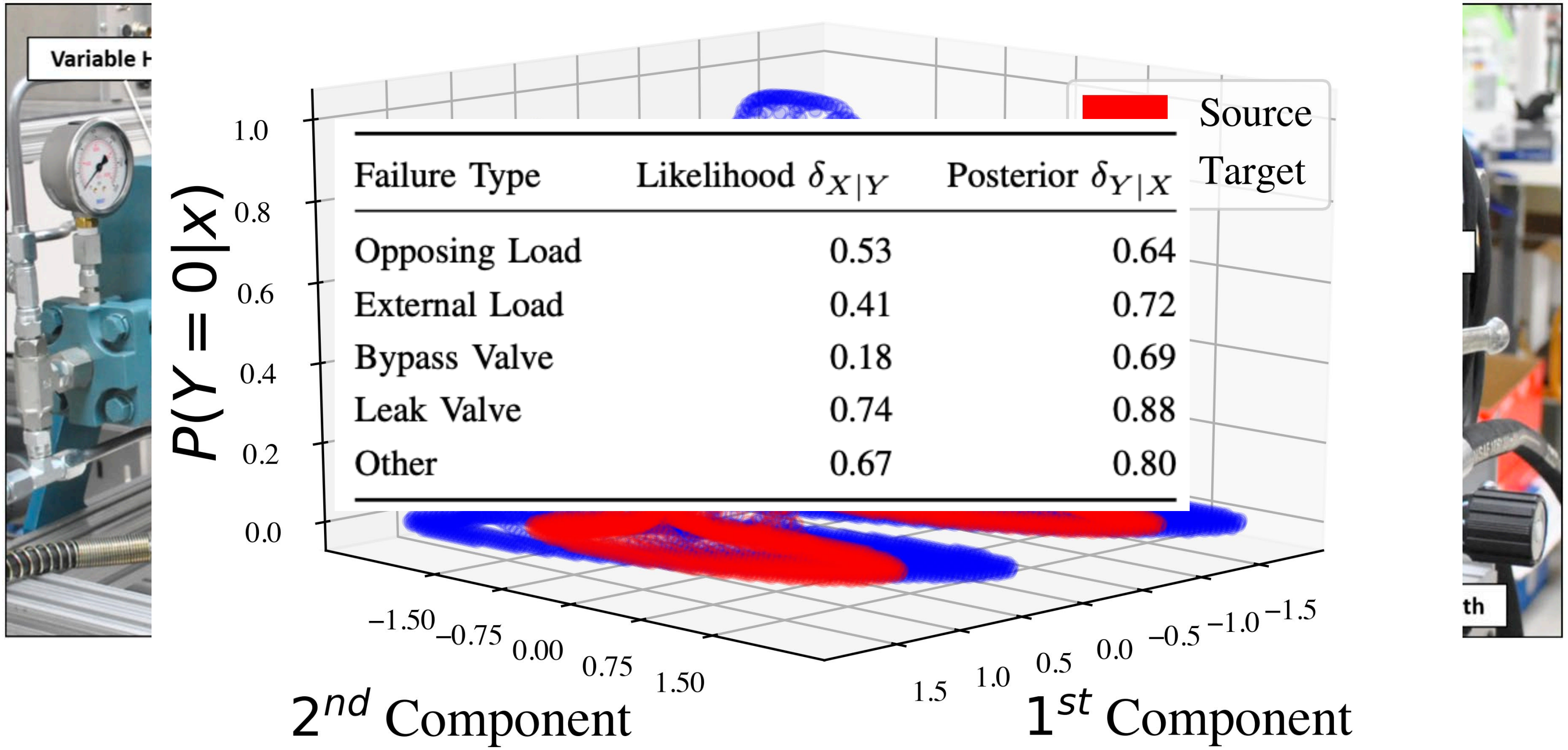
Physical & Cognitive Components Go Hand-in Hand

Thesis

- Any other way makes an **unjustified assumption about the existence of an independent variable**
- Reliability implications
  - (Non-trivial) robustness of ML in a vacuum is meaningless
- PHM implications
  - Maintenance actions change machine behavior (possibly) breaking ML models
- V&V implications
  - ML V&V depends on system state; component-level V&V does not generalize

Physical Repair → Cognitive Degradation

External Load Failure Posterior Probabilities

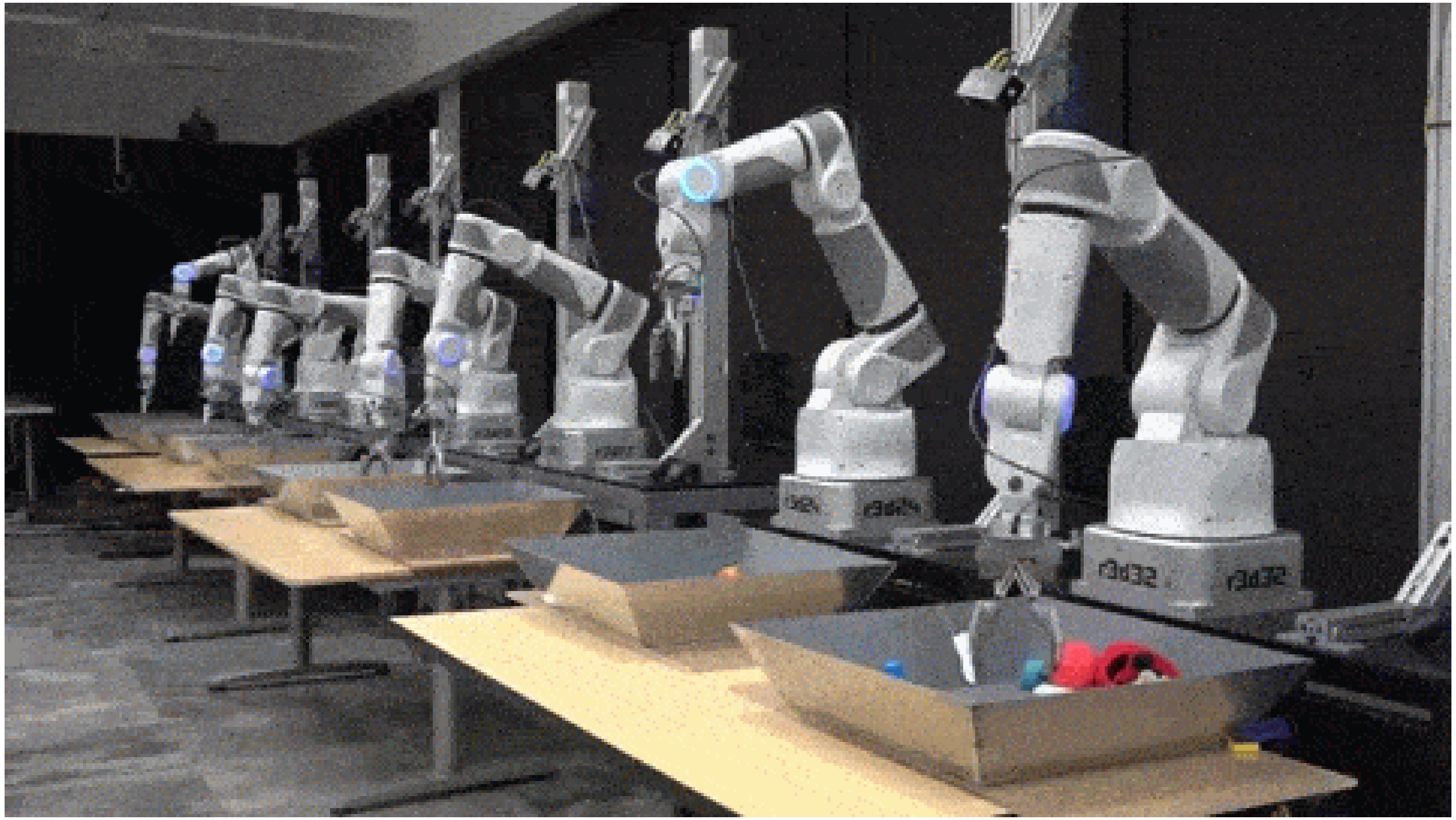


Failure Type	Likelihood $\delta_{X\|Y}$	Posterior $\delta_{Y\|X}$
Opposing Load	0.53	0.64
External Load	0.41	0.72
Bypass Valve	0.18	0.69
Leak Valve	0.74	0.88
Other	0.67	0.80

S. Adams, P.A. Beling, K. Farinholt, N .Brown, S. Polter, and Q. Dong, "Condition based monitoring for a hydraulic actuator," in *Annual Conference of the Prognostics and Health Management Society October 2016*, 2016.

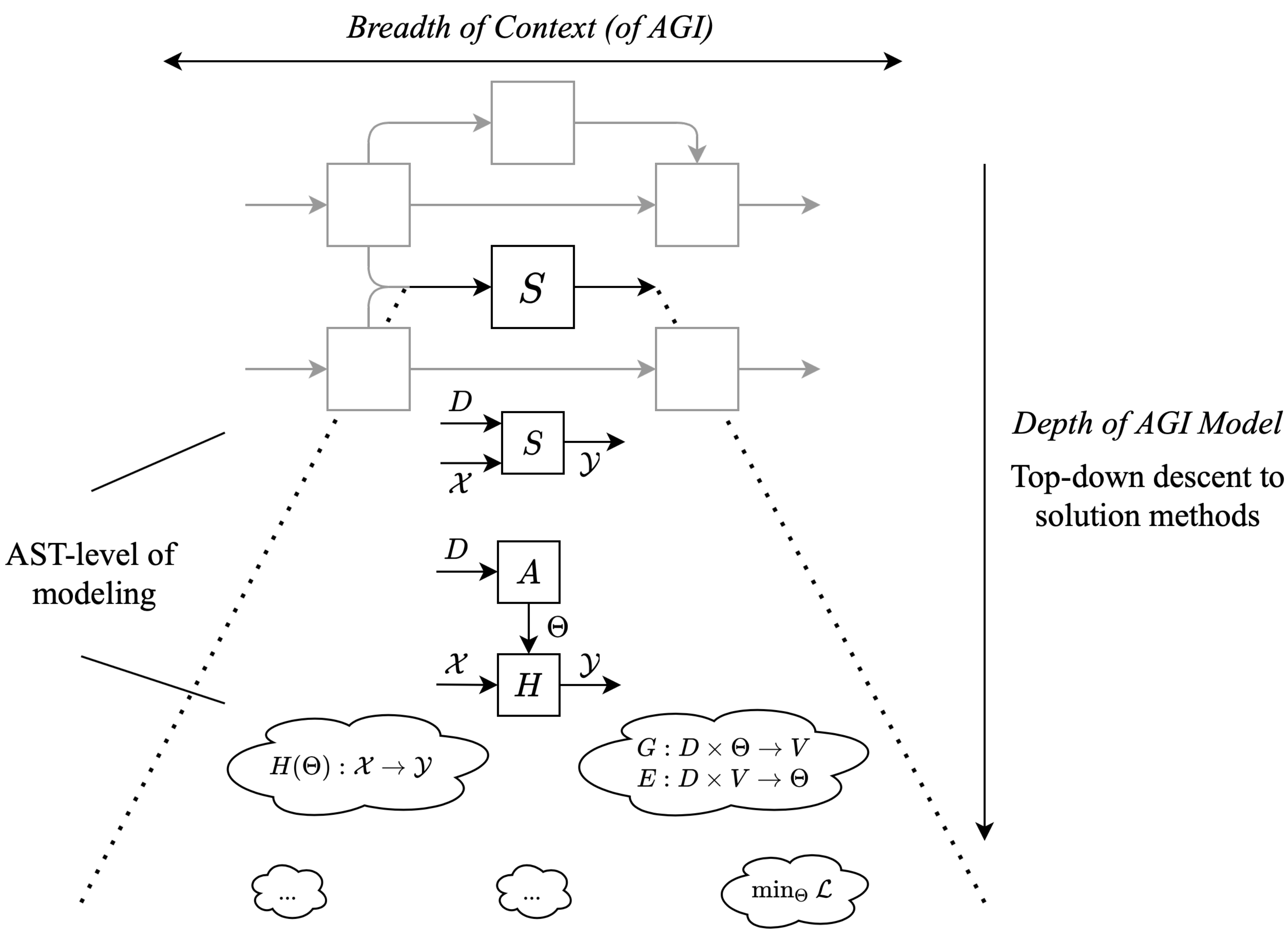
Cody, T., Adams, S., and Beling, P.A. "Empirically Measuring Transfer Distance for System Design and Operation". arXiv preprint. arXiv:2107.01184v1 (2021)

Cognitive Repair → Physical Degradation



Courtesy MITRE

What to do?



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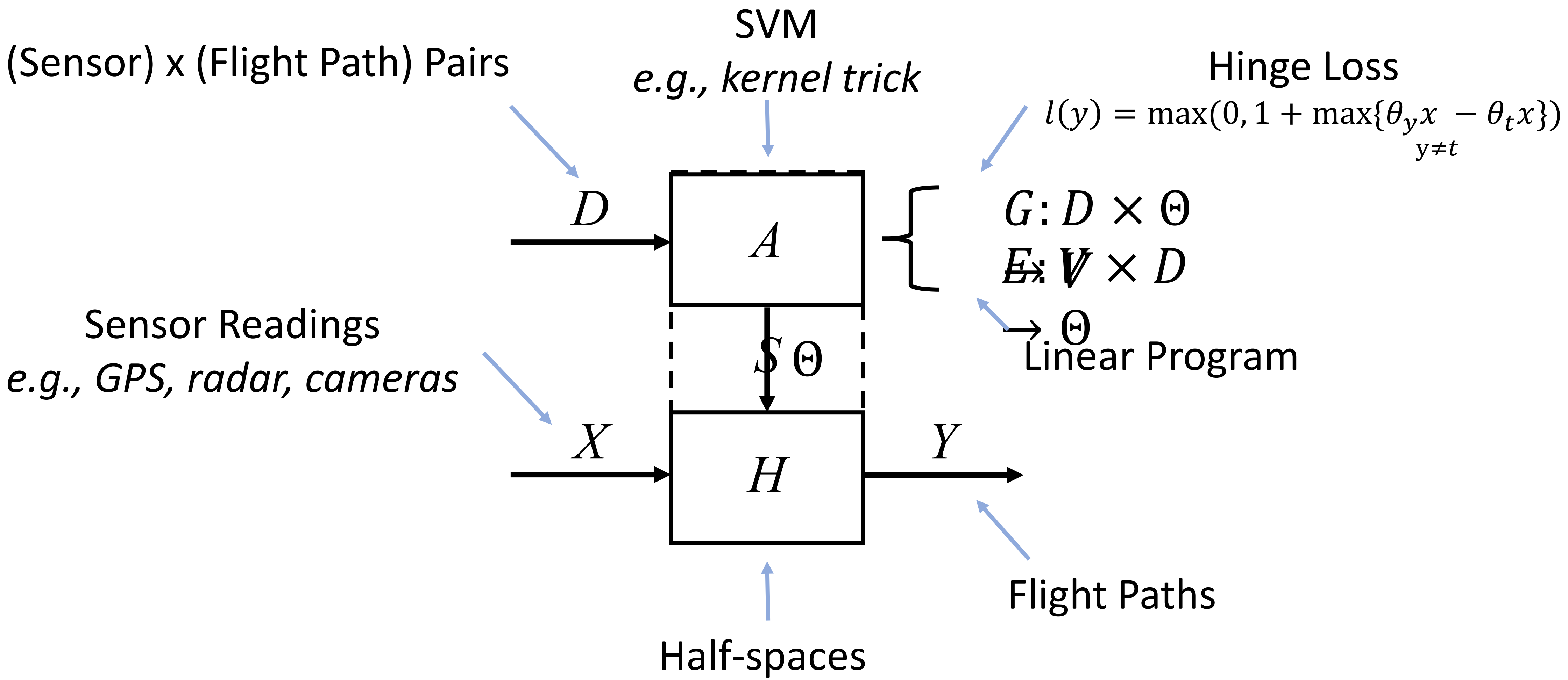
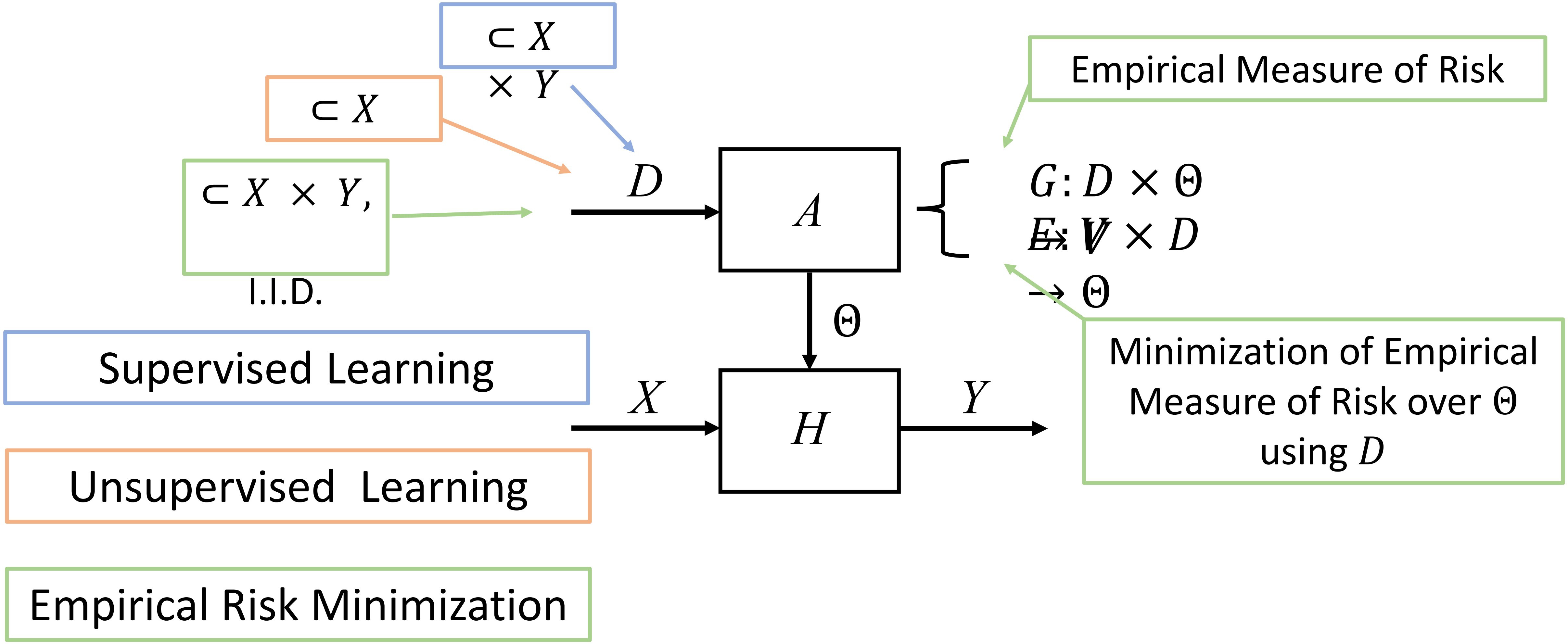
Learning Systems in UAS

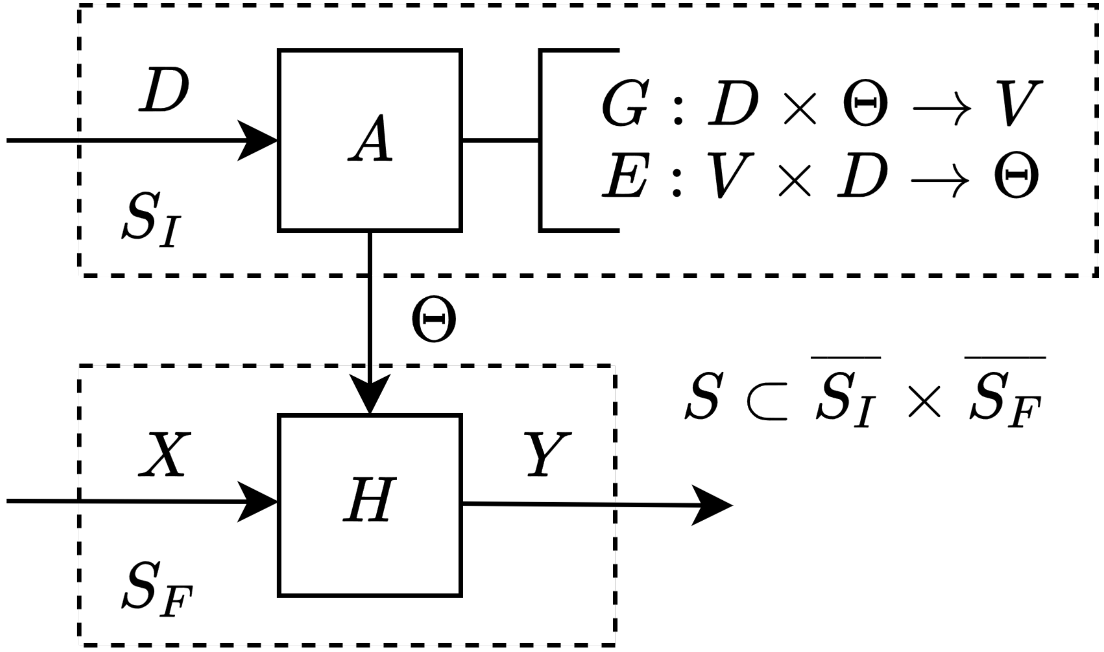
Suppose choice of Support Vector Machines (SVMs)

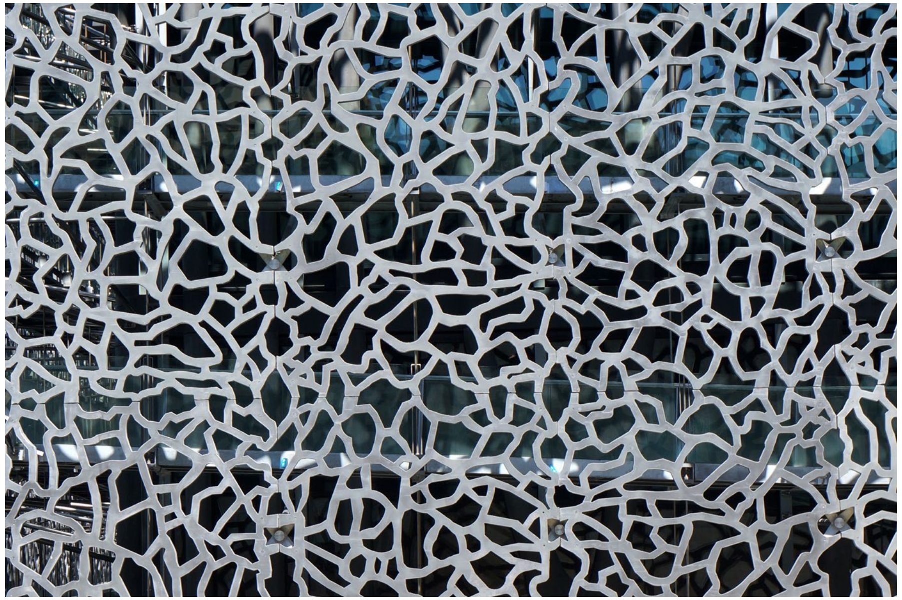


ML and Learning Theory as Learning Systems



Conclusion





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