

Workshop on Physics-informed Machine Learning for Modeling, Control, and Optimization

At the 2024 American Control Conference (ACC 2024)

July 10-12, 2024 | Vancouver, Canada

The Organizers



Thomas Beckers
Vanderbilt University



Ján Drgoňa
Pacific Northwest National Laboratory



Madelyn Shapiro
Pacific Northwest National Laboratory



Draguna Vrabie
Pacific Northwest National Laboratory



Rolf Findeisen
Technical University of Darmstadt

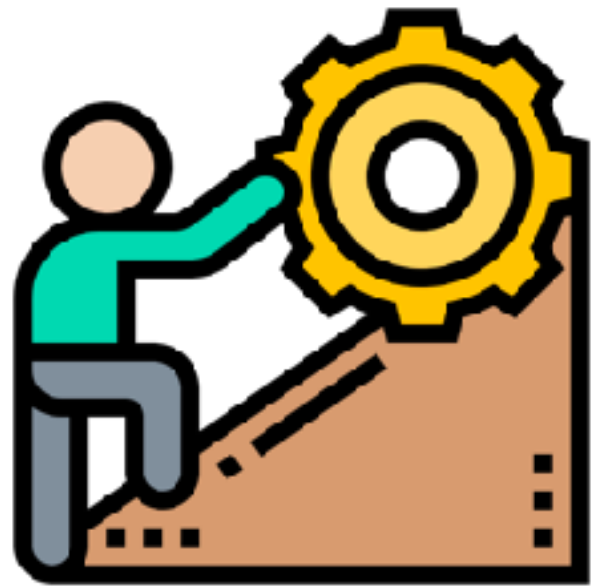


Sandra Hirche
Technical University of Munich

Goals



To provide insight into recent advances in the field of physics-informed machine learning for control and optimization with hands-on tutorials



To sketch some of the open challenges and opportunities in physics-informed machine learning

Speakers are encouraged to share slides on
piml4control.github.io/PIML-ACC2024

Schedule morning

All times are in **EST (UTC-5)**

- **[08:30-08:45]: Workshop Opening**
- **[08:45-09:30]: Invited Talk 1 Thomas Beckers (Vanderbilt University)**
- **[9:30-10:15]: Invited Talk 2 Giulio Evangelisti / Sandra Hirche (Technical University of Munich)**
- **[10:15-10:45]: Coffee Break**
- **[10:45-11:30]: Invited Talk 3 Sivaranjani Seetharaman (Purdue University)**
- **[11:30-12:15]: Invited Talk 4 Rolf Findeisen (TU Darmstadt)**
- **[12:15-13:45]: Lunch (on your own; no sponsored lunch provided)**

Schedule afternoon

- [13:45-15:15]: Open-source Code Tutorial Session I
- [15:15-15:45]: Coffee Break
- [15:45-17:15]: Open-source Code Tutorial Session II
- [17:15-17:30]: Closing Remarks and Discussion

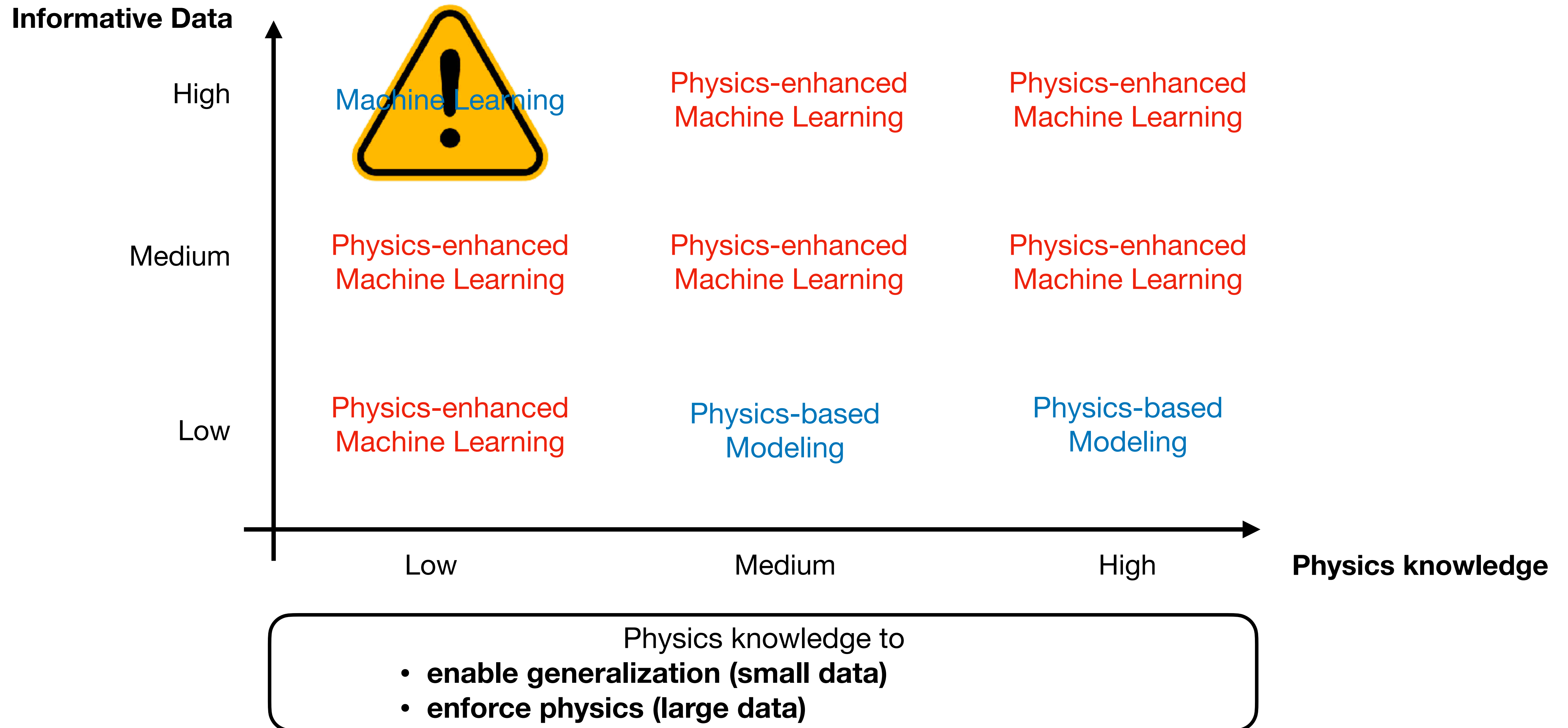
PyEPO - Bo Tang [13:45-15:15]



NeuroMANCER - Jan Drgona [15:45-17:15]

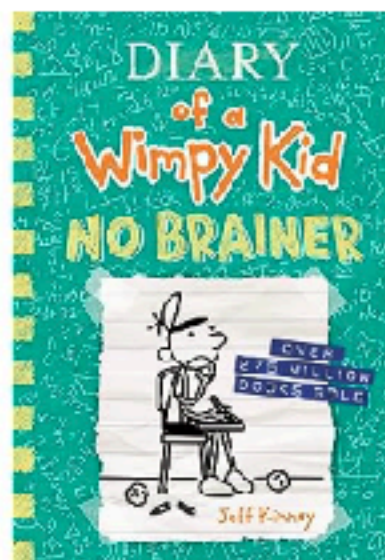


Why do we need to enhance ML?



Purely data-driven methods

Top picks for you



No Brainer (Diary of a Wimpy...
★★★★★ 2,239
\$8.59



Premier Protein Shake 30g Protein
1g Sugar 24 Vitamins Minerals...
★★★★★ 189,480

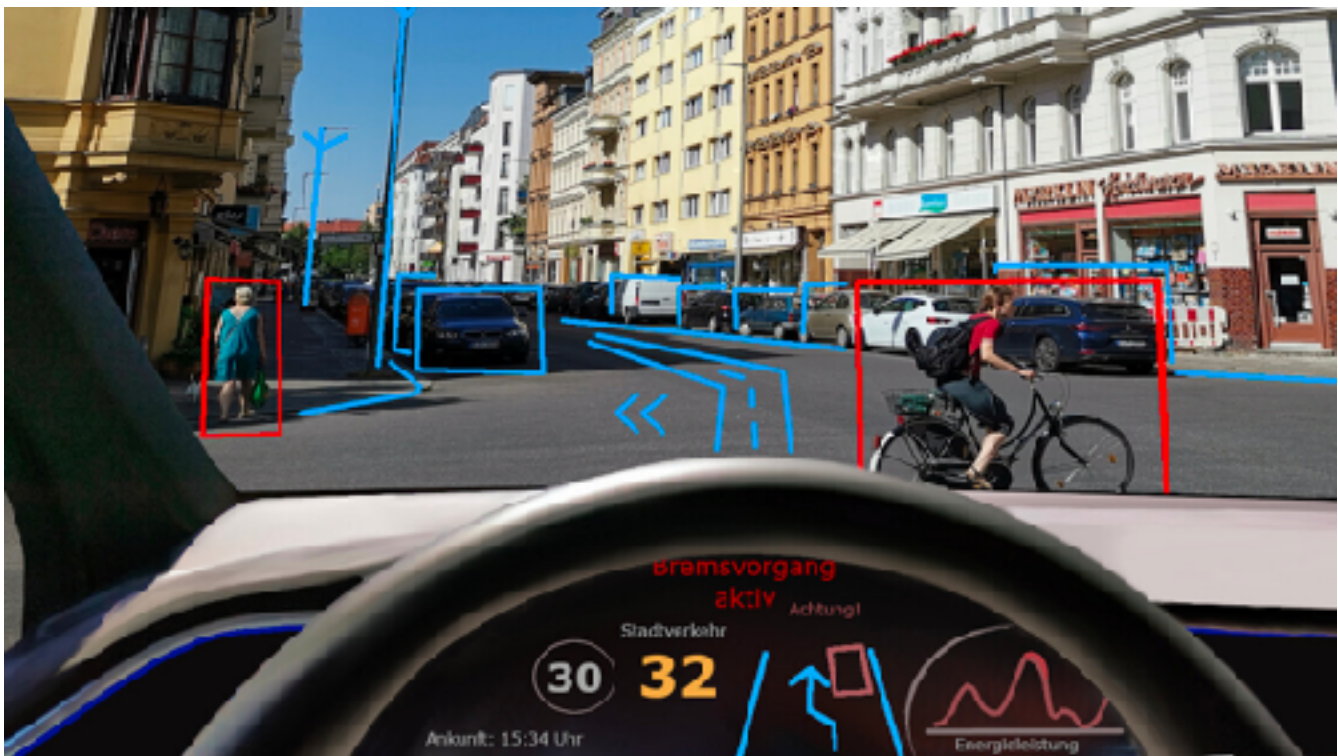


McCafé Premium Keurig
Single Serve K-Cup Pods, Medium
Roast Coffee Pods, 96 Count
★★★★★



Educational Insights Kanoodle 3D
Brain Teaser Puzzle Game...
★★★★★ 24,385

Autonomous driving



[Electric Motor Engineering]

Human-robot collaboration



[Ars Electronica]

Power grids



[Chris Hunkeler]

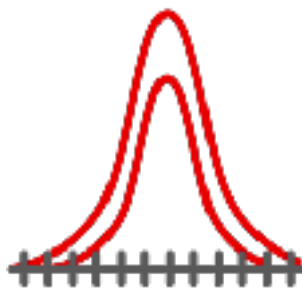
But we need
more for

Goals of PIML



Overcoming poor generalization performance

Removing physically inconsistent or implausible predictions
(Improving control strategies, interaction models,...)



Uncertainty Quantification

(Physics, data, learning model, deductible, irreducible)



Providing **explainable** and **interpretable** inference



Informing physics

(Identification of unknown governing physics equations)

Domain knowledge

Prior knowledge: observational,
empirical, physical, mathematical

Small, heterogenous, gappy,
noisy data

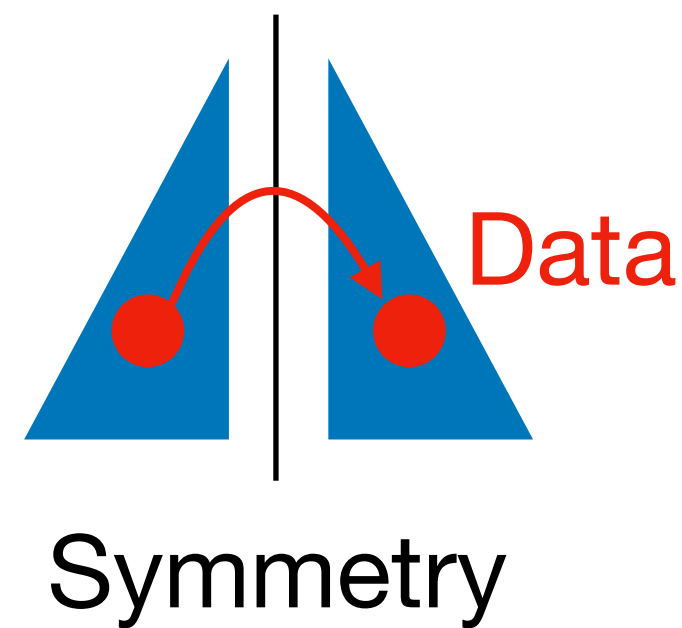
Multi-fidelity data

Dealing with wrong models,
corrupted data, uncertainties and
non-informative data

How to incorporate physics?

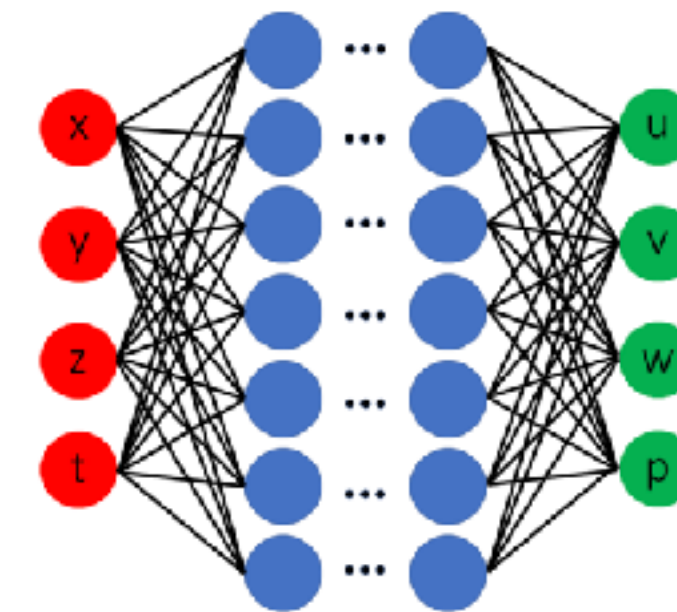
Observational bias

Introducing data that embody underlying physics



Learning bias

Inference/learning algorithm selection, loss function, optimization constraints



$$Loss = \frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial w}{\partial z}$$

Inductive bias

Incorporate prior assumptions and physical constraints



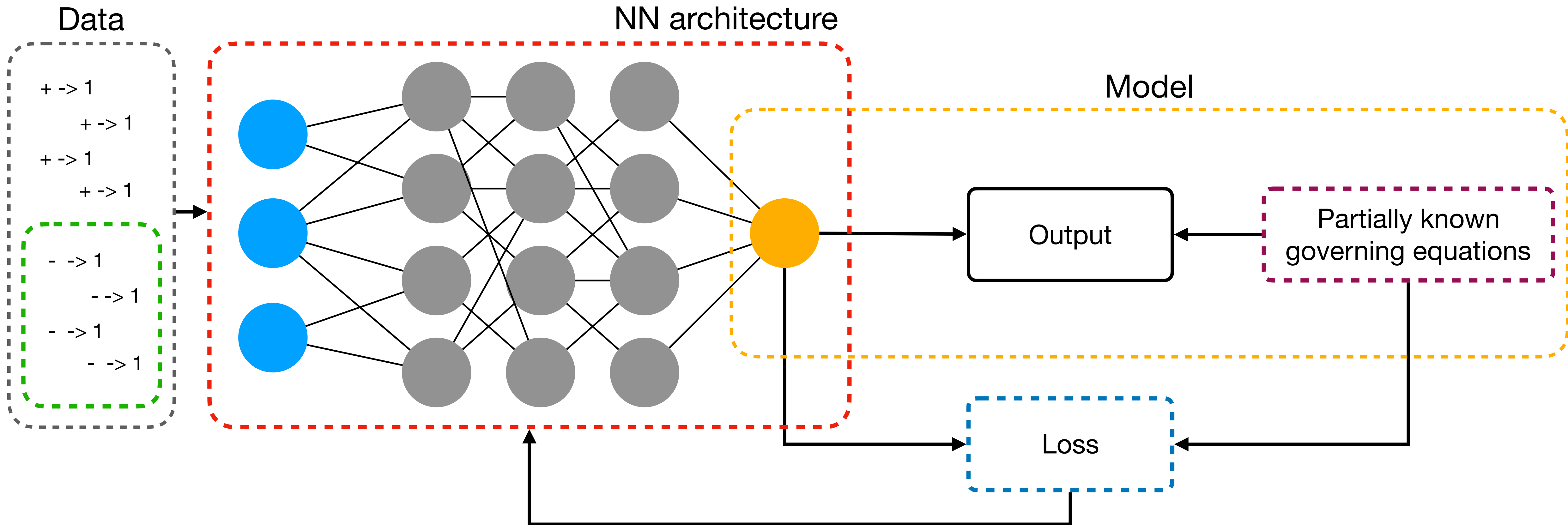
Conservation laws





Discrepancy bias

Including “terms” from partial knowledge of the model

$$\dot{x} = Ax + Bu + f(x, u)$$

Example



-  Observation bias: Introducing data that embodies underlying physics
-  Inductive bias: Prior assumptions and physical constraints
-  Learning bias: Physics based loss function, optimization algorithm
-  Discrepancy bias: Introducing data that embodies underlying physics

Do we need different models?

Complexity

LTI system

Nonlinear, time-varying
system

Multi-scale, multi-physics,
nonlinear, ...

Amount of data

Sparse identification

Bayesian models

Neural networks

Purpose

Identifying unknown physics/
governing equations?

Data efficiency

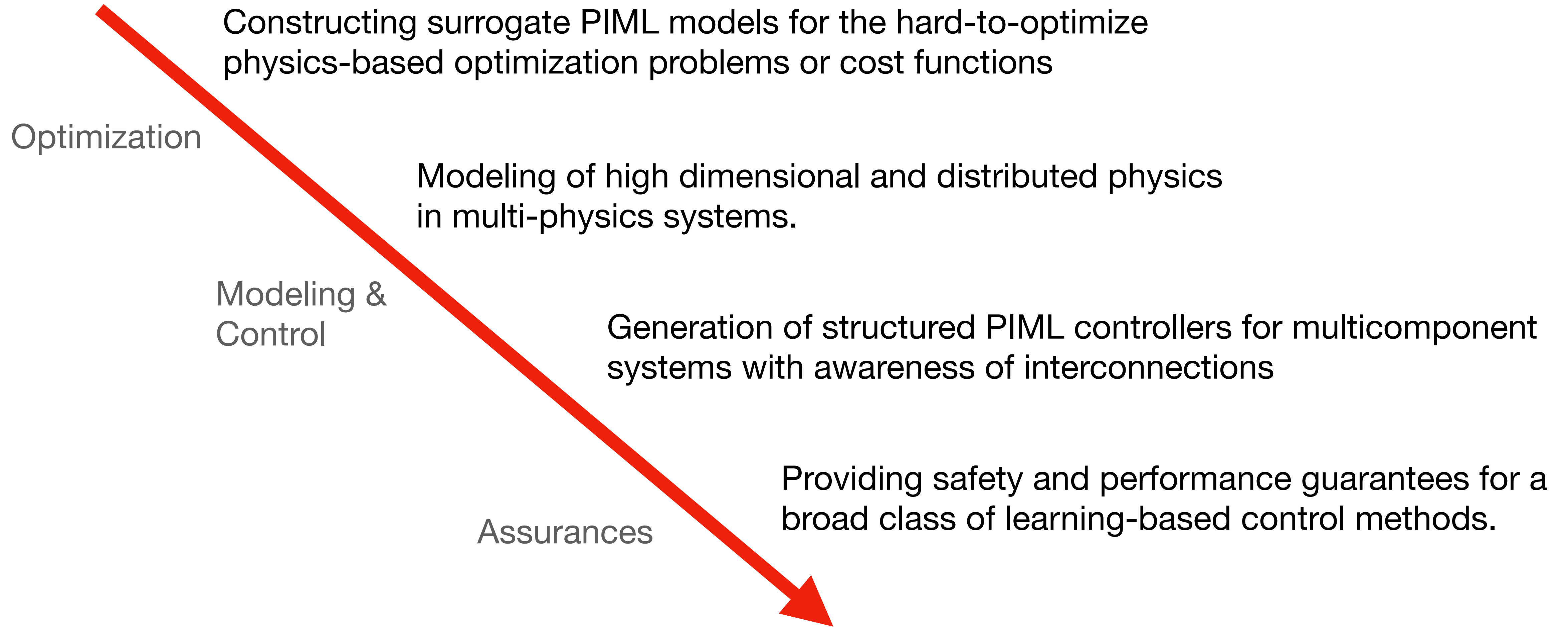
Interpretability

Modeling/Control/Optimization

Development of digital twins

There is not “the one” model

Opportunities in control



Challenges

How to



- unify the terminology of PIML models? (enhanced, informed, constrained, guided, encoded)
 - avoid training failures of PIML models getting stuck in local optima
 - detecting & removing inappropriate physics bias
 - verify methods for PIML to be scaled up for large-scale systems
 - reduce the computational requirements without sacrificing accuracy
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- balance between physics-driven and data-driven based modeling and optimization
 - quantify minimal data requirements for training of PIML models and controllers
 - quantify the uncertainty and modeling errors for PIML-based models
 - effectively select representative training data for sampling-based PIML approaches
 - guarantee stability and safety of a real-world system in closed-loop with PIML-based controllers

More resources



Annual Workshop at NeurIPS
<https://ml4physicalsciences.github.io/2023/>



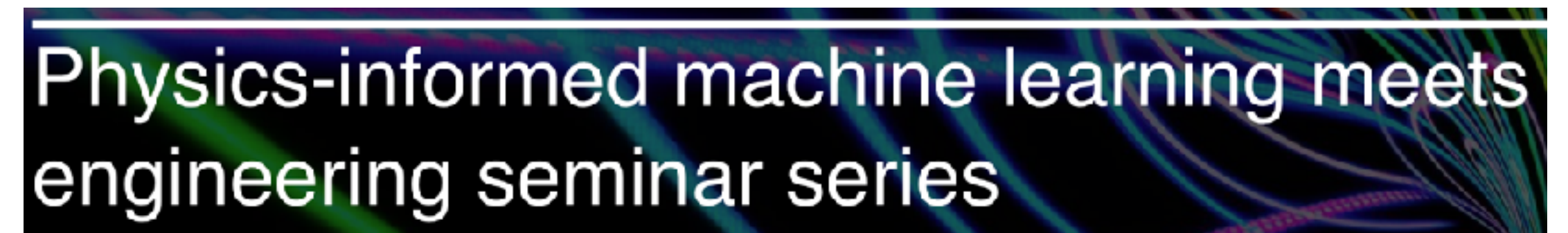
Annual Workshop organized by the IOP
<https://iop.eventsair.com/asm2023/>



Annual Workshop organized by US National Laboratories
<https://aires.ornl.gov/>

DDPS Webinar (*in California time*)

Seminar series
<https://www.librom.net/ddps.html#ddps-webinar-in-california-time>



Seminar series organized by the Alan Turing Institute
<https://www.turing.ac.uk/events/phi-ml-meets-engineering>

CDC 2024

2024 Conference on Decision and Control

December 16–19, 2024

Allianz MiCo, Milan Convention Centre, Italy