# Physics-informed Machine Learning for Modeling, Planning, Control, and Estimation of Physical Systems


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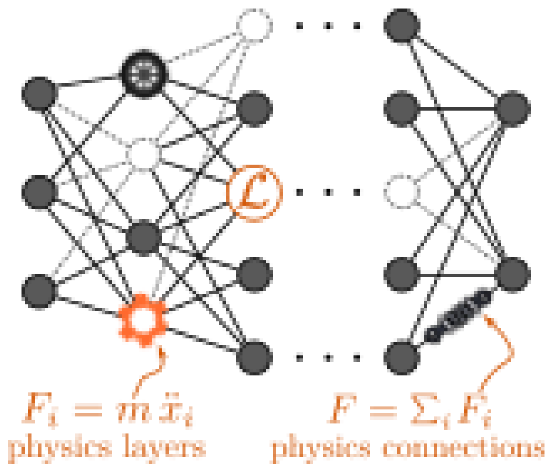
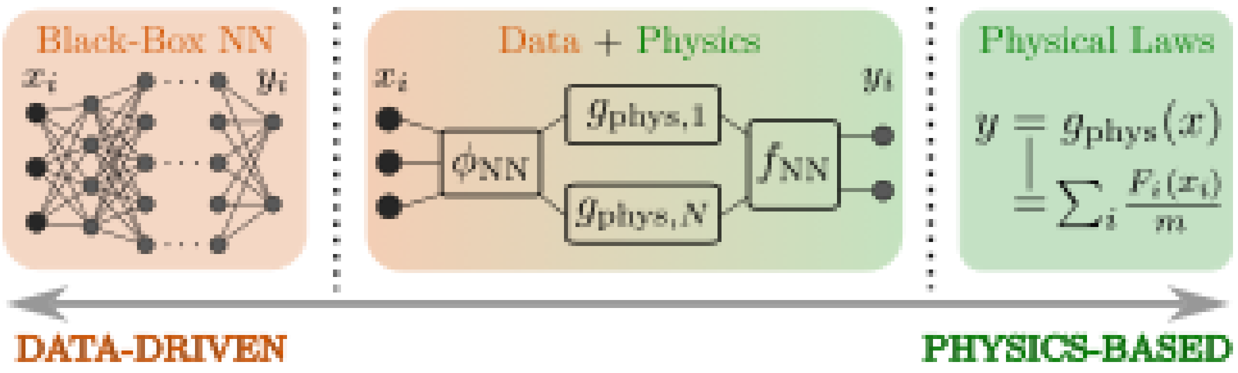
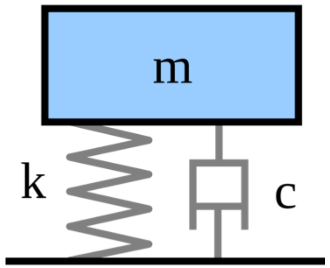
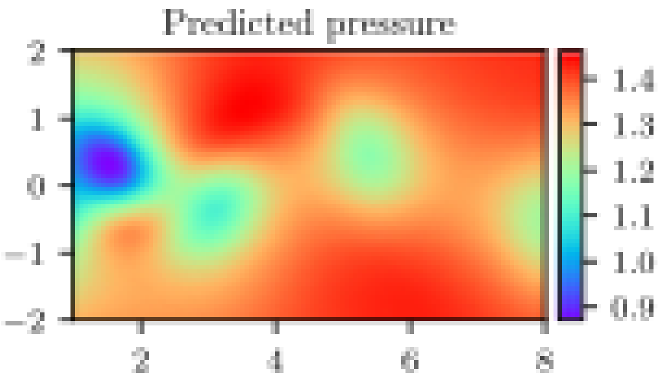


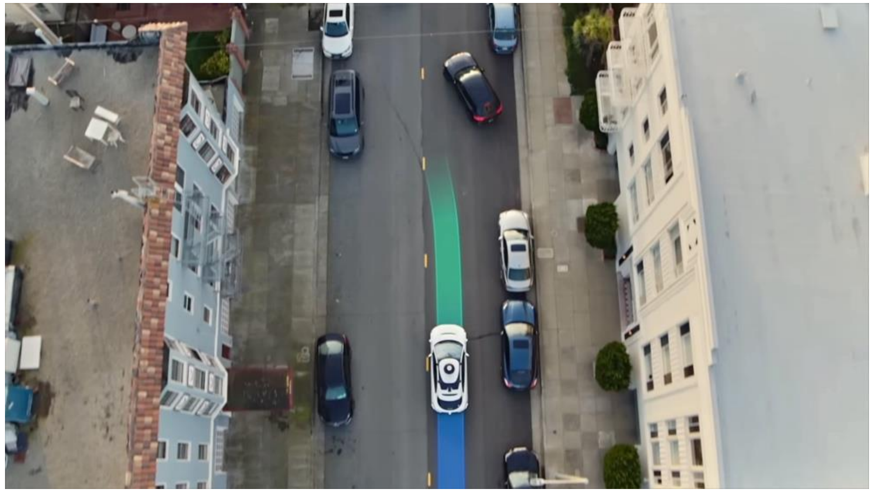




# Embodied AI in Physical Systems



**Are we in the *ChatGPT moment* for physical autonomous systems?**

# Embodied AI in Physical Systems


Will **AI** solve everything
in the **physical world**?

# Is AI Ready to Solve Physical Problems?

- Deep learning + big data "solved" **vision**


Inspired by K. Goldberg, "A Tale of Two Cultures: Can Agentic Coding Close the Gap?", *Plenary Talk at IEEE ICRA* 2026

# Can AI Solve Physical Problems?

- Deep learning + big data “solved” **vision**
- LLMs + big data “solved” **language**

ChatGPT

Claude

Gemini

deepseek

Qwen

Inspired by K. Goldberg, “A Tale of Two Cultures: Can Agentic Coding Close the Gap?”, *Plenary Talk at IEEE ICRA* 2026

# Can AI Solve Physical Problems?

- Deep learning + big data “solved” **vision**
- LLMs + big data “solved” **language**
- Will LLMs / foundation models “solve” **physical systems** (e.g., robotics)?

## Language

- **small** “1-dimensional“ world
- LLM training data: text

## Physical autonomous systems

- **N-dimensional** (robot hand: 22 DoFs)
- LLM / VLM training data: physical action commands + synchronized images + text

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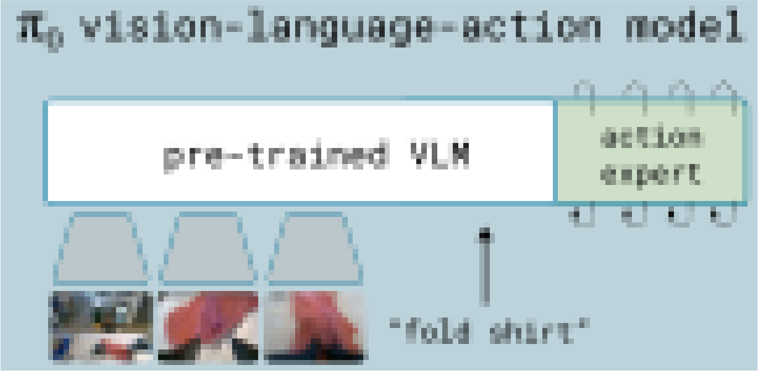


K. Black et al., “π0: A Vision-Language-Action Flow Model for General Robot Control”, *Physical Intelligence Blog, 2025*

# Can AI Solve Physical Problems?

- Deep learning + big data "solved" **vision**
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### Language

- **small** "1-dimensional" world
- LLM training data: text
  - Qwen-2.5: 1.2 **billion** hours of data

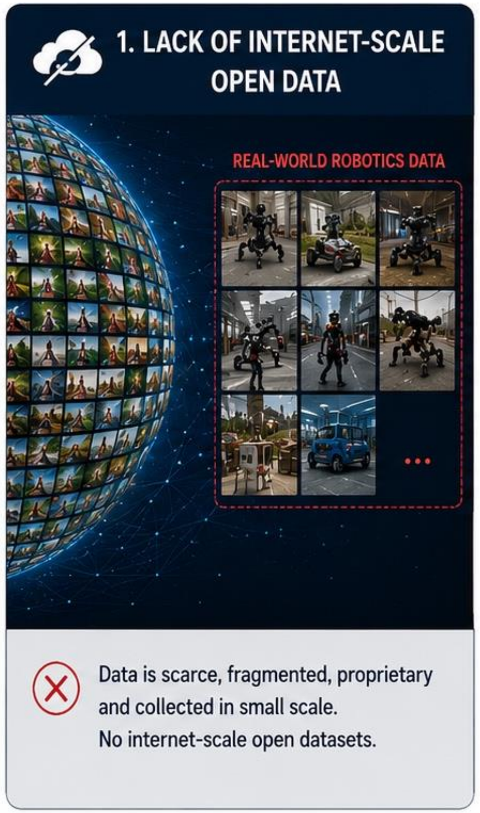
### Physical autonomous systems

- **N-dimensional** (robot hand: 22 DoFs)
- LLM / VLM training data: physical action commands + synchronized images + text
  - **Lack of internet-scale data!**
  - YouTube has 35k hours of videos only, no physical action commands

Inspired by K. Goldberg, "A Tale of Two Cultures: Can Agentic Coding Close the Gap?", *Plenary Talk at IEEE ICRA* 2026

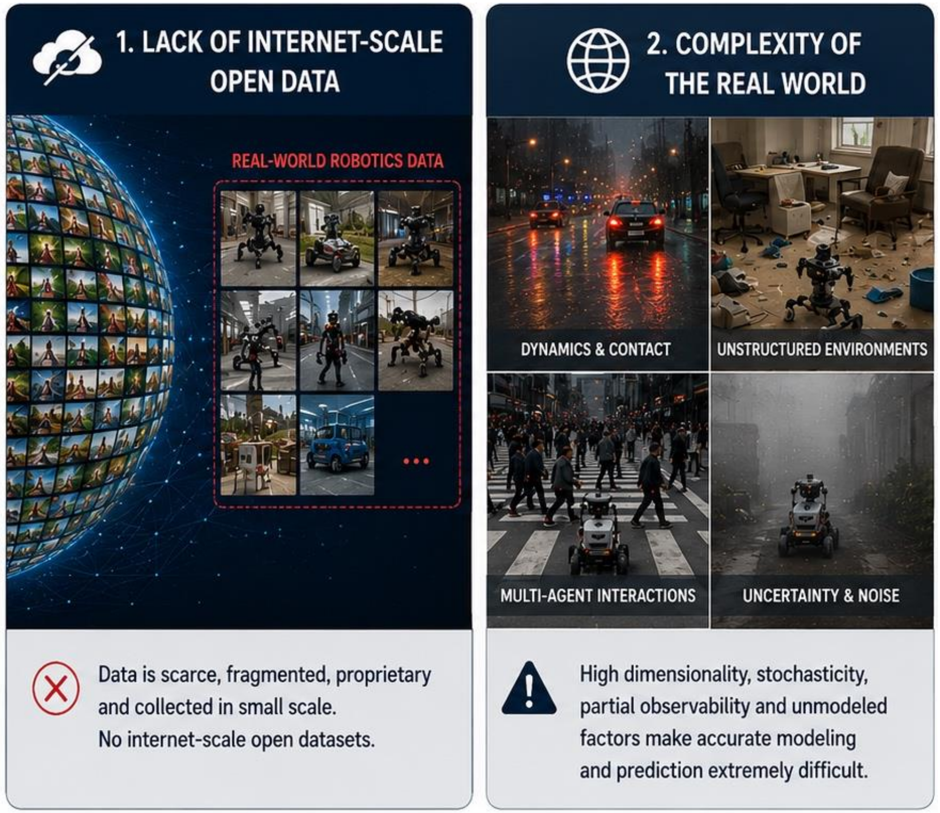
# Physical Autonomous Systems: Gaps and Challenges

- Lack of **internet-scale** open data



# Physical Autonomous Systems: Gaps and Challenges

- Lack of **internet-scale** open data
- **Complexity** of the real world



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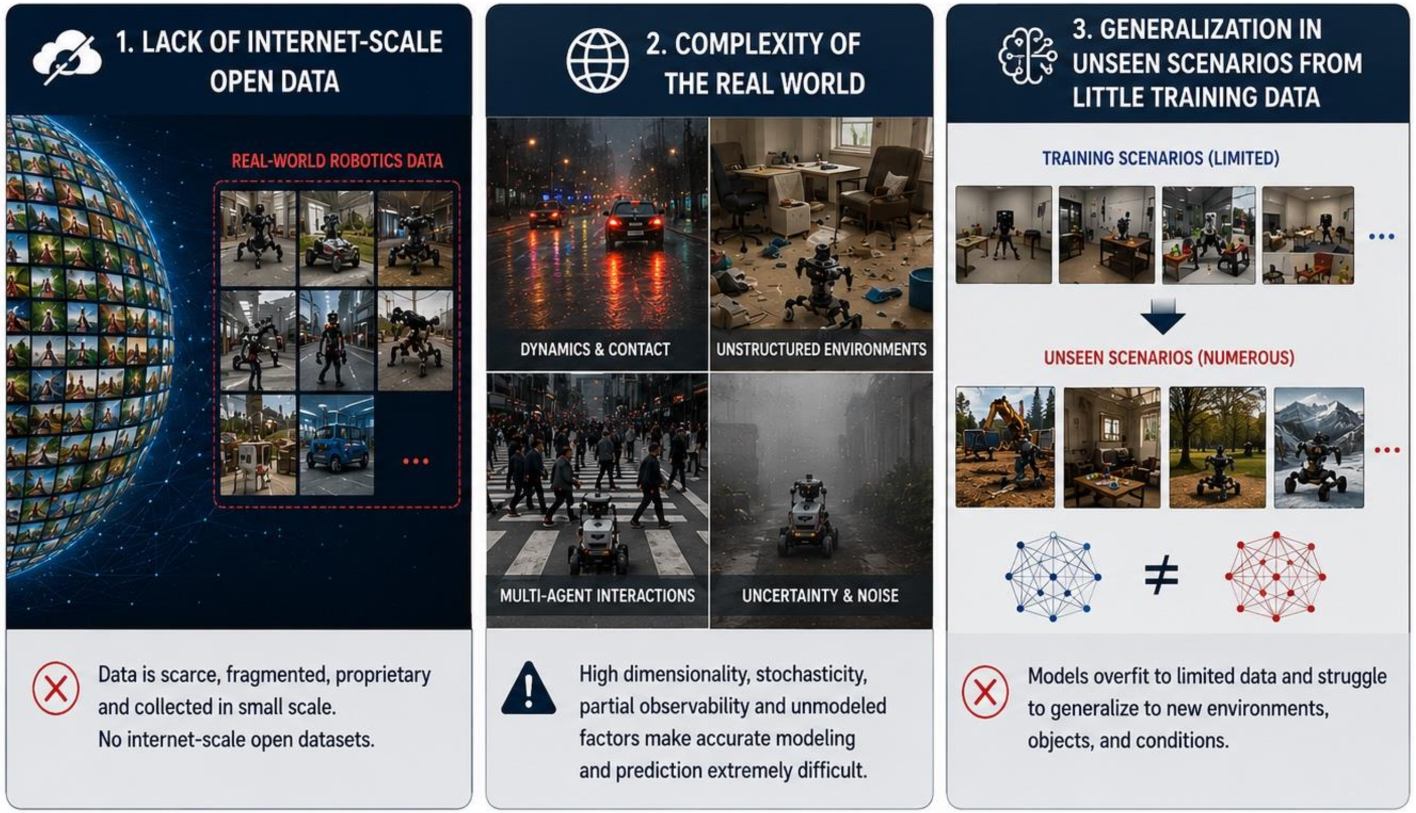
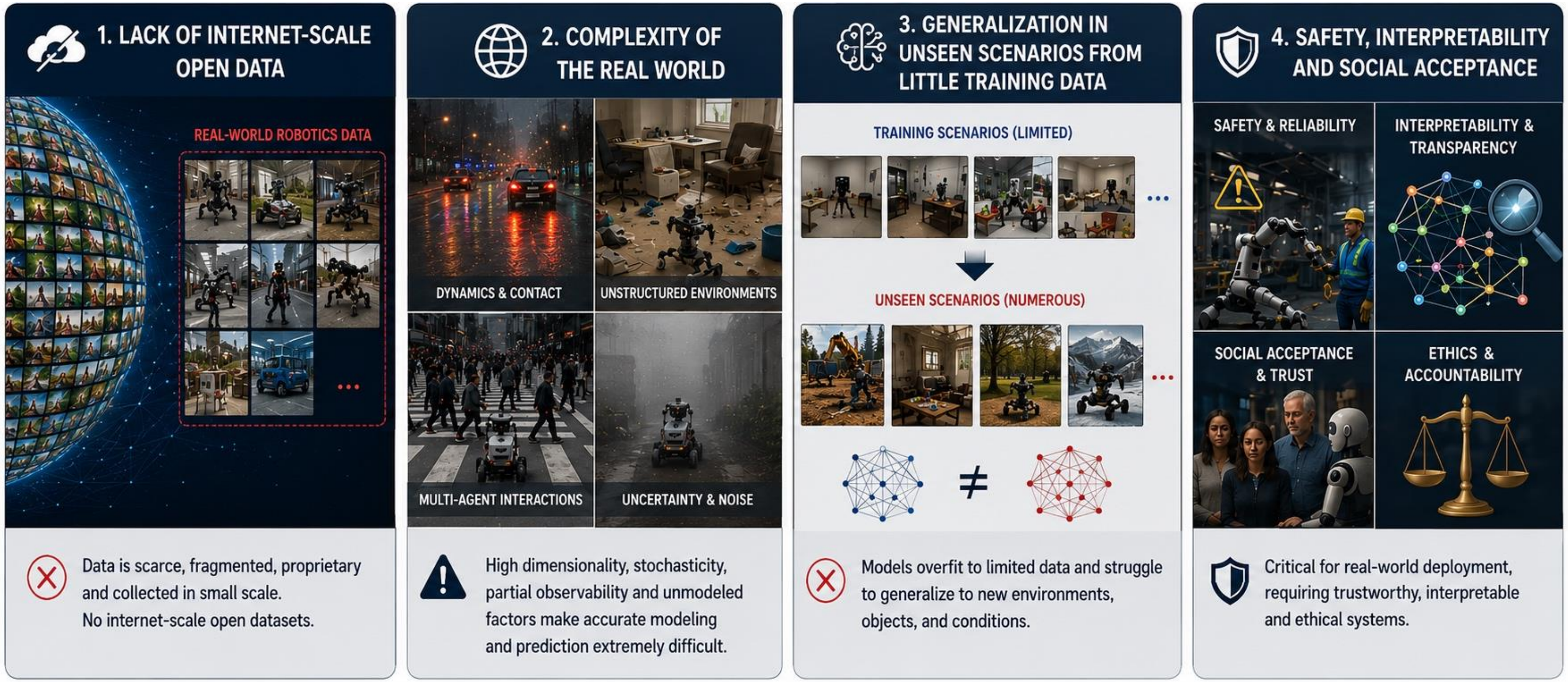
- Lack of **internet-scale** open data
- **Complexity** of the real world
- **Generalization** in unseen scenarios from little training data



# Physical Autonomous Systems: Gaps and Challenges

- Lack of **internet-scale** open data
- **Complexity** of the real world
- **Generalization** in unseen scenarios from little training data
- **Safety + Interpretability** and social acceptance

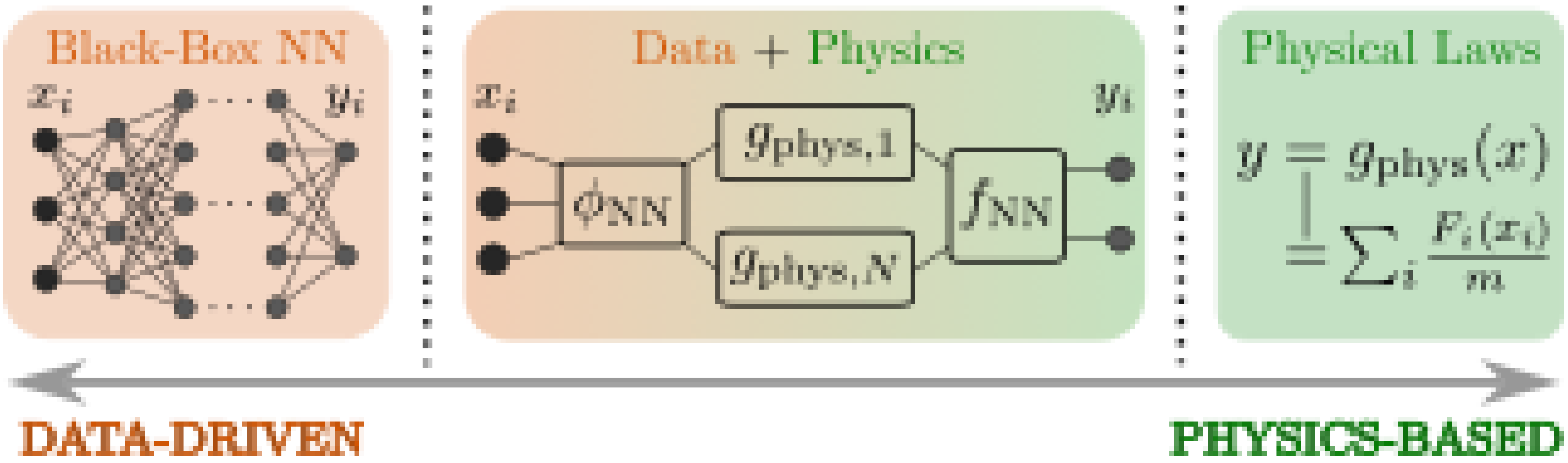


# Physical Autonomous Systems: Ways to Fill the Gaps

**Any ideas?**

# Physical Autonomous Systems: Ways to Fill the Gaps

- **Data "flywheels"**: deploy autonomous systems in the wild to collect data
- Human **teleoperation** (limited by human time)
- **Simulation** (limited by sim-to-real gaps)
- **Embedding physics priors** in **machine learning**
  - Do not forget prior domain expertise & physical laws
  - **Inductive biases** to guide learning while preserving **generality** (trade-off!)



# Questions & Discussion

# Course Information

# Course Context

## The course is part of the Neu4mes Project

- The Neu4mes Project:
  - **Principal Investigator**: Gastone Pietro Rosati Papini, University of Trento
  - **Funded** by the Italian Ministry of University and Research (MUR) under the Science Italian Fund 2023 program, for **1.2 million Euros**
  - **Aim:** New approach to model and control physical systems using *Model-Structured Neural Networks (MS-NNs),* by embedding physics priors
  - **Outcome:** The framework, modely , and **wiki website** to collect *MS-NNs* and not only
  - **Case Study**: Several autonomous systems, including: Drones, Quadrupeds, and Vehicles
- This course encompasses the key skills learned and developed to date in the Neu4mes project
- Obviously, I thank Mattia for the work and for collaborating effectively on the project!

More details at https://neu4mes.github.io/

# Course Objectives

- **Methodological principles:**
  - **Where** and **how** can we embed **physics priors** in machine learning models?
  - Map of existing methods and paradigms
- **Pros & cons of embedding physics priors:**
  - Looking at concrete **applications**
  - Comparisons with black-box machine learning based on data only
  - **Trade-offs**: data efficiency vs generality, bias vs variance, …
- **Hands-on understanding:**
  - Existing **software tools** to facilitate the integration of physics priors
  - **Coding** examples
- **Open challenges and future directions:**
  - Towards data-efficient **embodied AI** for physical systems

# Course Contents (Tentative)

## Day 1:

- **Introduction** & **Taxonomy**: Embedding physics priors in machine learning
- **Physics-guided** & **Physics-informed** machine learning: methods + applications

## Day 2:

- **Physics-encoded** machine learning: methods + applications

## Day 3:

- **Model-structured** learning: methods + applications

## Day 4:

- **Software tools** for physics-embedded learning
- **nnodely** software tool and applications (interactive)

## Day 5:

- Open **challenges** & **future directions** (interactive)
- Ideas on **collaborations** and how you can use the methods in **your research** (interactive)

# Course Organization

**Course materials** are openly available in this Google Drive folder:

https://drive.google.com/drive/folders/1CJhFbHEN9IrW7ReRyUZy7jd2wH17h_Ew?usp=share_link

**Lectures** will be **recorded** & will remain online after the course (infos will follow)

**Schedule** (in person & online)

- Day 1: July 6th, 9:00 – 12:00, seminar room @Univ. of Trento
- Day 2: July 7th, 9:00 – 12:00, room A210 @Univ. of Trento
- Day 3: July 8th, 9:00 – 12:00, room A210 @Univ. of Trento
- Day 4: July 9th, 9:00 – 12:00, room A210 @Univ. of Trento
- Day 5: July 10th, 9:00 – 11:00, seminar room @Univ. of Trento

We are happy to **stimulate interaction** & create new **collaborations**!

# How to Get the Final Credits (for PhD Students)?

If you just need the credits for **attending the lectures**:

- Write your presence **at each lecture** in the shared “attendance_sheet” file (Google Drive folder)
- You can attend in person / online (we encourage you to come in person to foster interaction)

If you need the credits for attending the lectures + passing a **final exam (optional)**:

- The “exam” consists of a **final report** in which you explain how you wish to apply any of the presented methods (or conceive new ones) to **your own research**
- A 1-2 page report with a short description of the research idea, possible novelty, and a preliminary diagram is enough
- Send us the report: we will review it, give you feedback, and finally approve it
- Please do it by the **end of August**
- We are happy to **support** you in implementing the research idea, if you like!

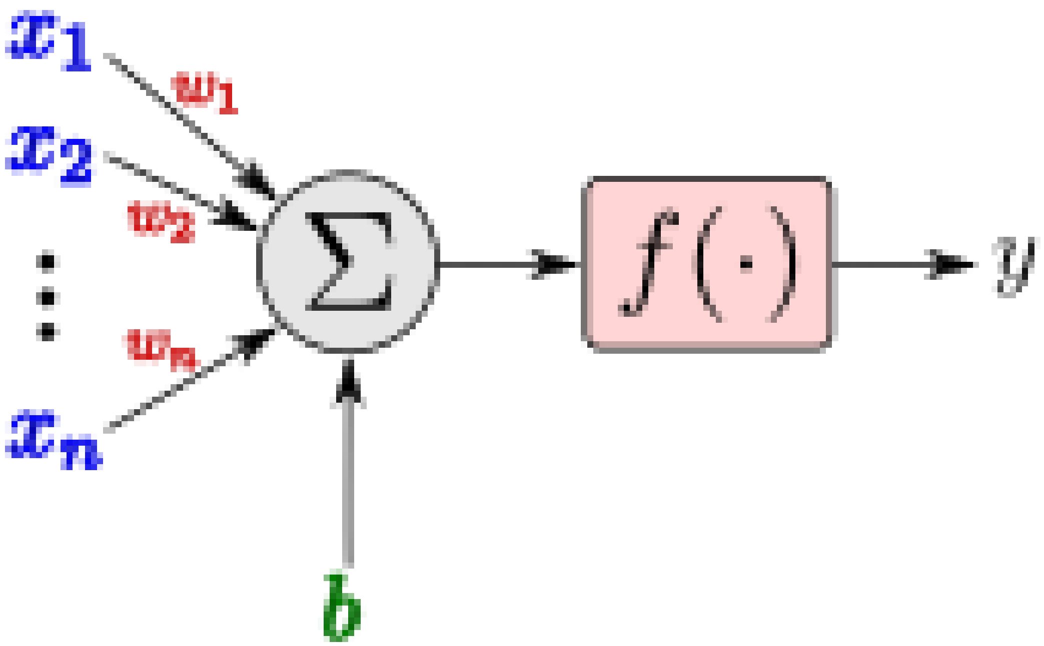
You will finally receive a **certificate of participation** from the University of Trento

# Questions & Discussion

# Neural Networks: Generalistic Black-Boxes?

# The Perceptron

The **basic component** of a Neural Network (**NN**) is the **Perceptron**




$$y = f\left(\sum_{k=1}^{n} x_k \cdot w_k + b\right)$$

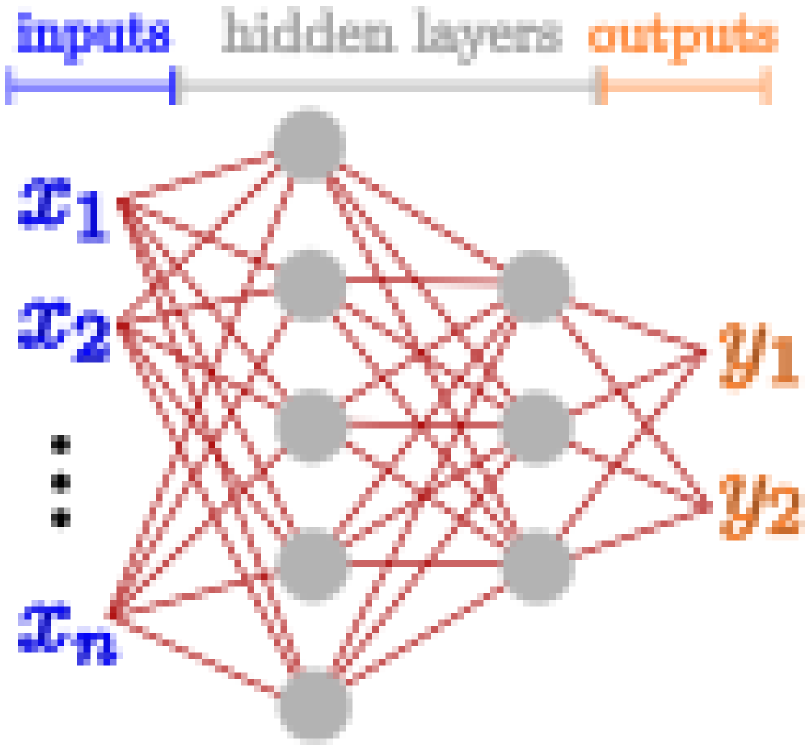
F. Rosenblatt, "The perceptron: a probabilistic model for information storage and organization in the brain", *Psychological review*, 1958

# Multi-Layer Perceptron (MLP)

**Universal Approximation Theorem** (Cybenko, 1989): MLP with 1 hidden layer approximates any continuous function → **in theory** …

… But is an MLP really the best choice for **every task**?
Maybe yes, if we have enough **data**!

What if we have little data …
… but we have **task-domain priors**?
Can we exploit them in the **NN design**?




G. Cybenko, "Approximation by superpositions of a sigmoidal function", *Math. Control Signal Systems*, 1989

# Do Domain Priors Matter in the NN Design?

**Computer Vision:** Convolutional Neural Networks (**CNNs**) have a tailored architecture to encode spatial translation invariance

- Enables the detection of objects regardless of their position in an image

**Natural Language Processing:**

1. Long Short-Term Memory Networks (**LSTMs**) are designed to capture long-term dependencies in sequential data
   - Via specialized gating mechanisms that selectively retain and discard information
2. **Transformers** encode the concept of attention over structured tokens

➔ These architectures **encode** some form of **domain priors**!

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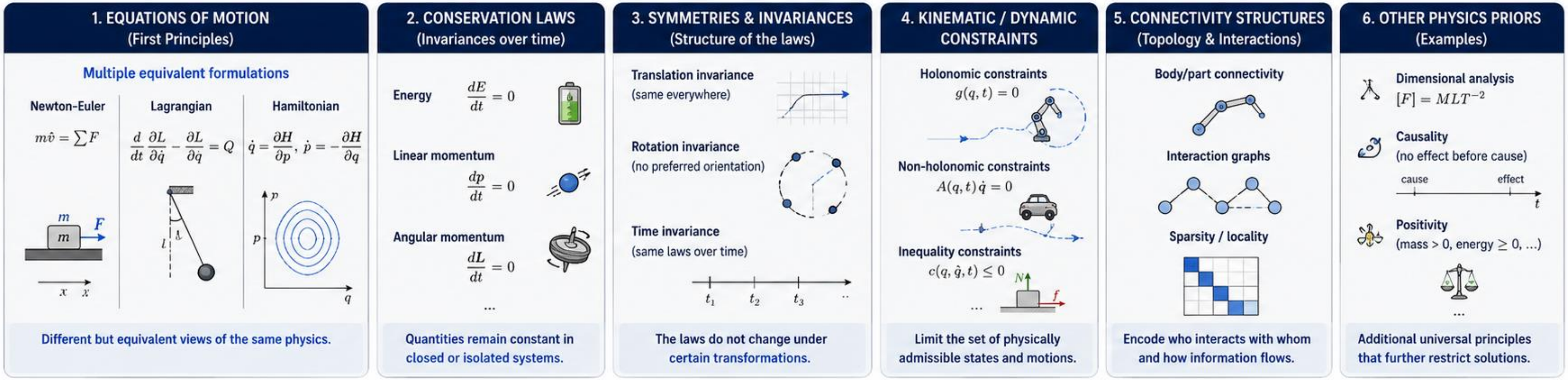
What about **Physical Systems**?

Domain Priors = **Physics Priors**

# What Are Physics Priors?

# What Are Physics Priors?

- Equations of motion:
  - Newton-Euler, Lagrangian, Hamiltonian formulations
- Conservation laws (energy, momentum, …)
- Symmetries and invariances
- Kinematic / Dynamic constraints
- Connectivity structures
- Problem-specific priors: Friction models, actuator dynamics, …



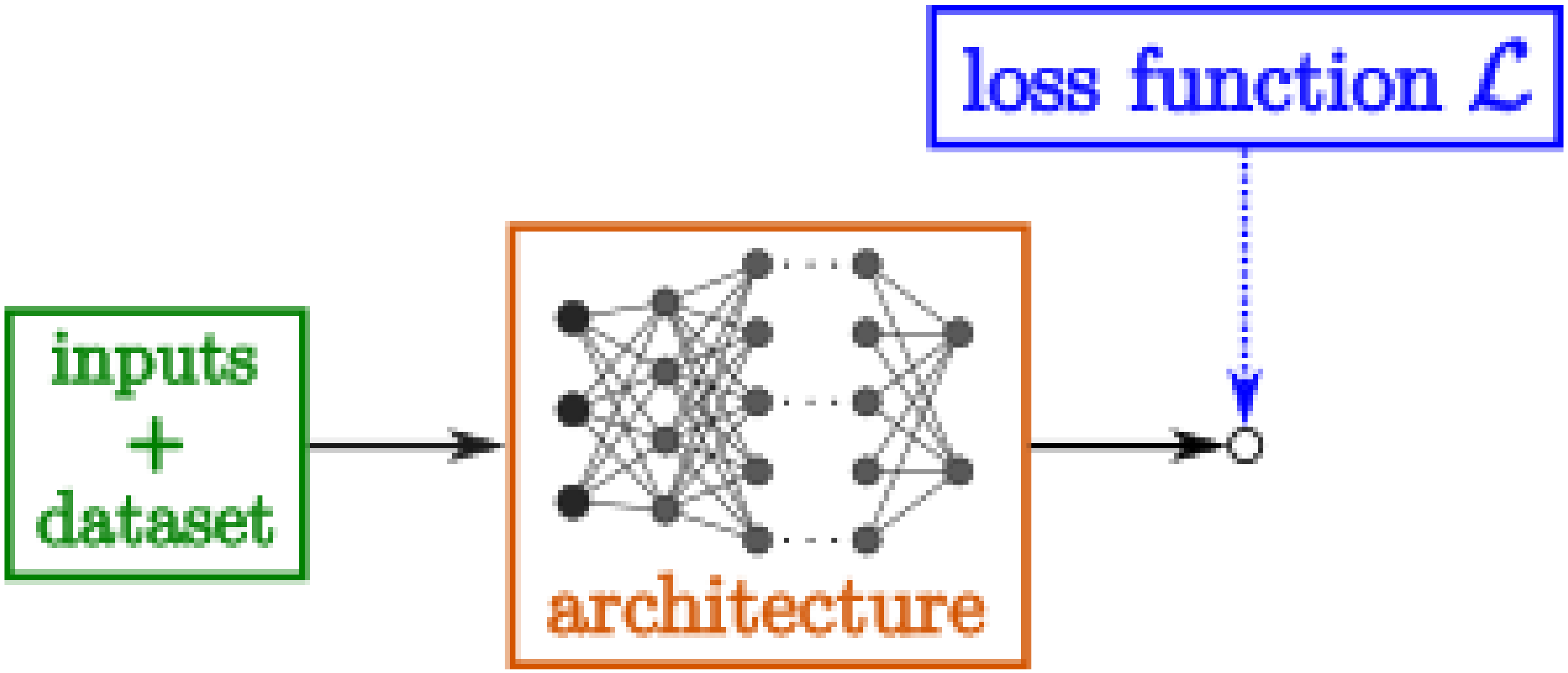
# How to Embed Physics Priors in Machine Learning?

# Embedding Physics Priors in Machine Learning

General **structure** of machine learning models

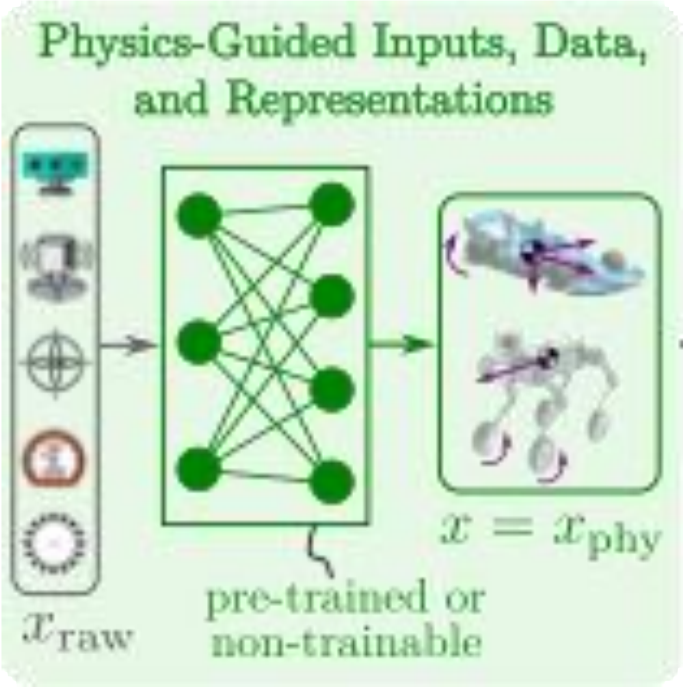
(neural networks, Gaussian Process Regression, foundation models, …)

**Where** can **physics priors** enter? Any ideas?

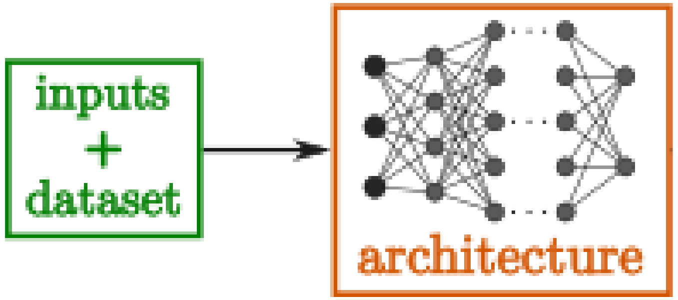


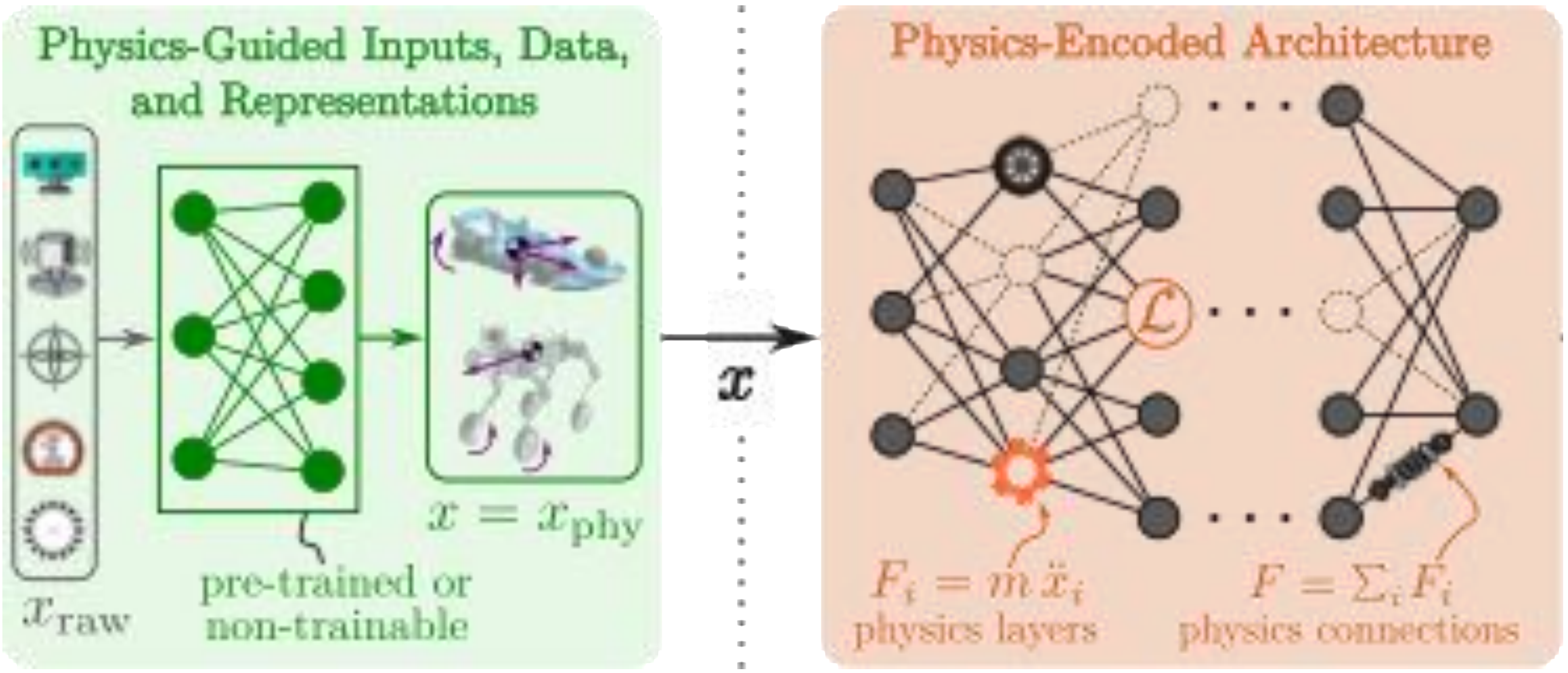
# *Physics-Guided* Machine Learning

inputs
+
dataset

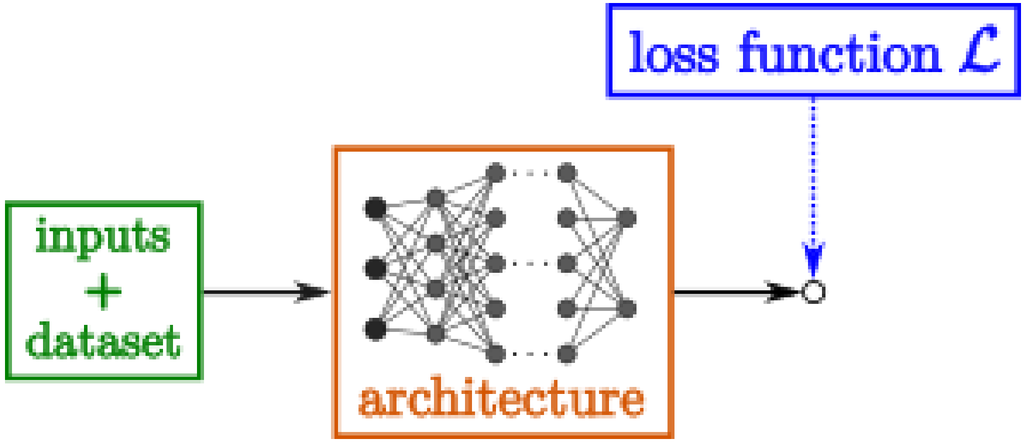


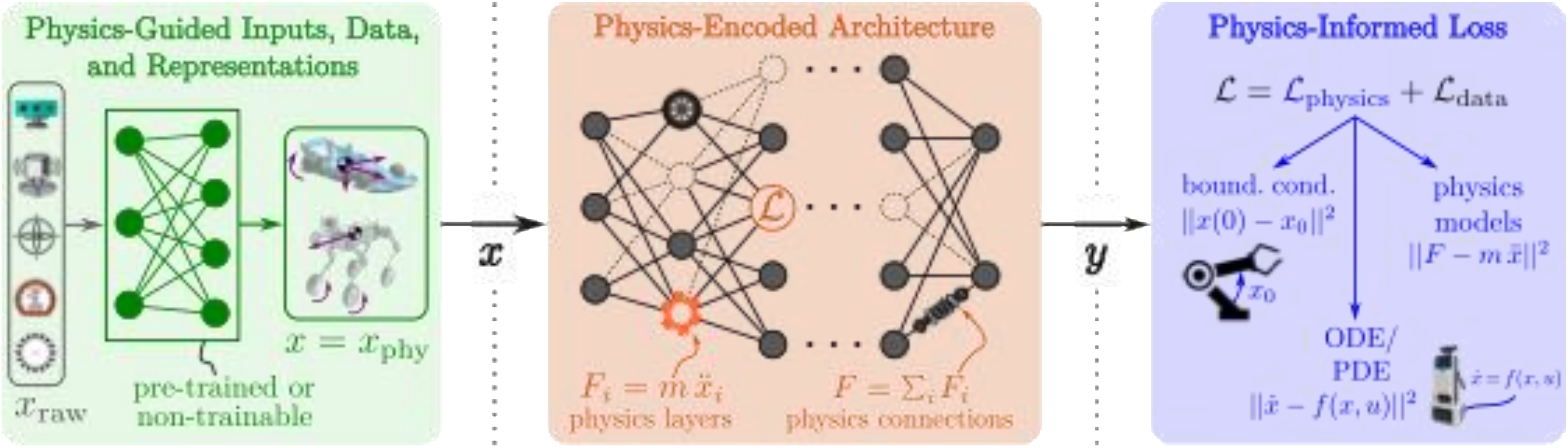
# *Physics-Encoded* Machine Learning



# *Physics-Informed* Machine Learning



# Taxonomy Notes – Confusion in the Community!

- Many people use the term ***physics-informed machine learning*** also when referring to inputs and architectures → we want to make a clear distinction!
- Our taxonomy follows *Faroughi et al., 2024*

ASME Journal of Computing and Information Science in Engineering
Online journal at:
https://asmedigitalcollection.asme.org/computingengineering

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## Physics-Guided, Physics-Informed, and Physics-Encoded Neural Networks and Operators in Scientific Computing: Fluid and Solid Mechanics

# Questions & Discussion




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