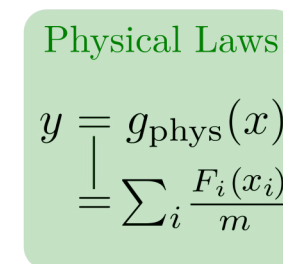
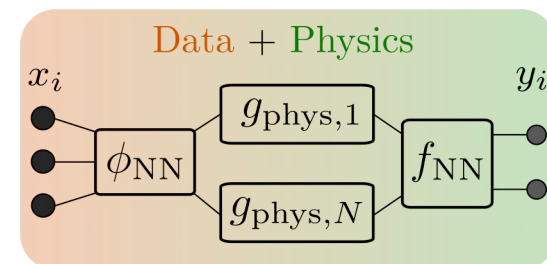
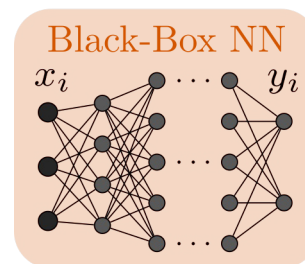
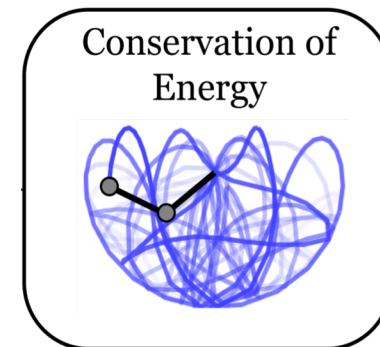
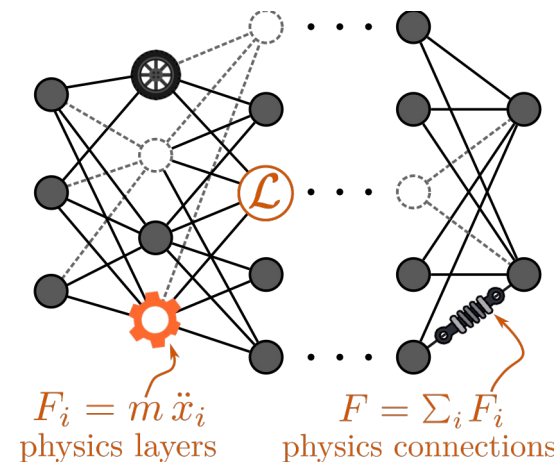


Physics-informed Machine Learning for Modeling, Planning, Control, and Estimation of Physical Systems

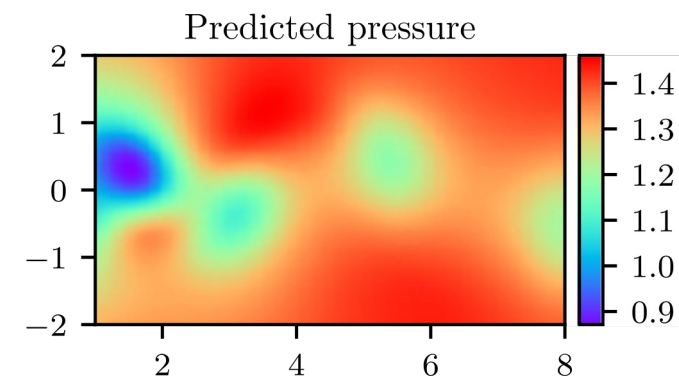
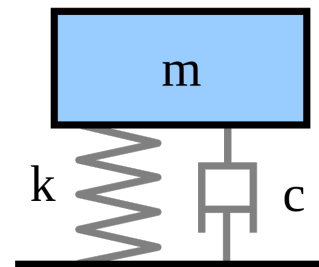
Dr. Mattia Piccinini &
Prof. Gastone Pietro Rosati Papini

University of Trento &
Technical University of Munich,
Autonomous Vehicle Systems Lab



DATA-DRIVEN

PHYSICS-BASED

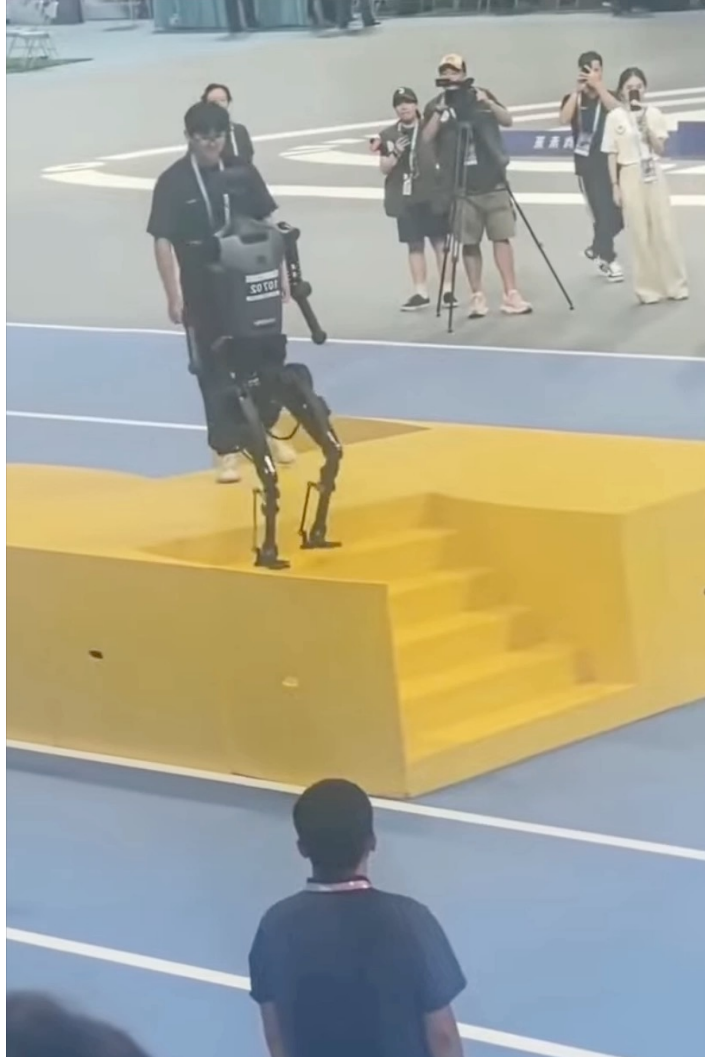


Embodied AI in Physical Systems



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

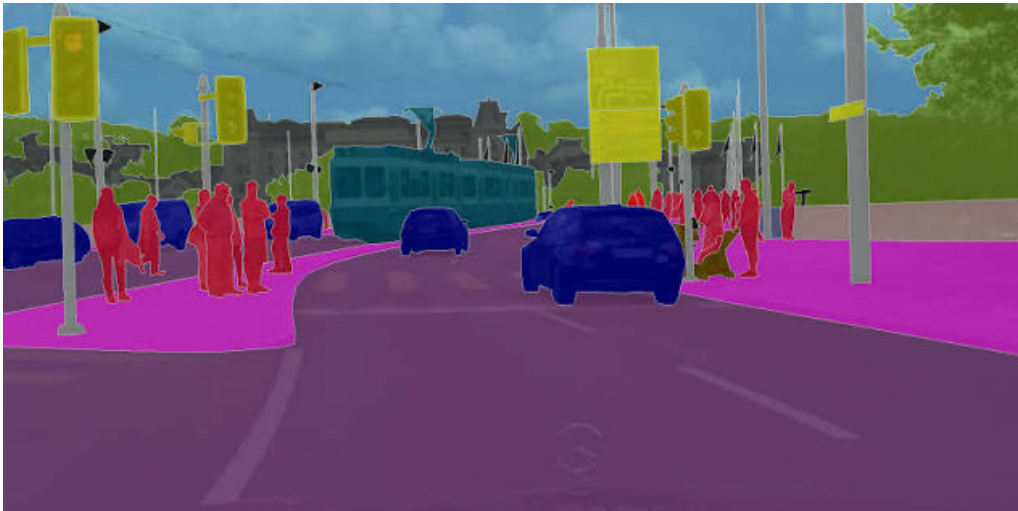
Embodied AI in Physical Systems



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

Is AI Ready to Solve Physical Problems?

- Deep learning + big data “solved” vision



Can AI Solve Physical Problems?

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



ChatGPT



Claude



Gemini



deepseek



Qwen

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

Can AI Solve Physical Problems?

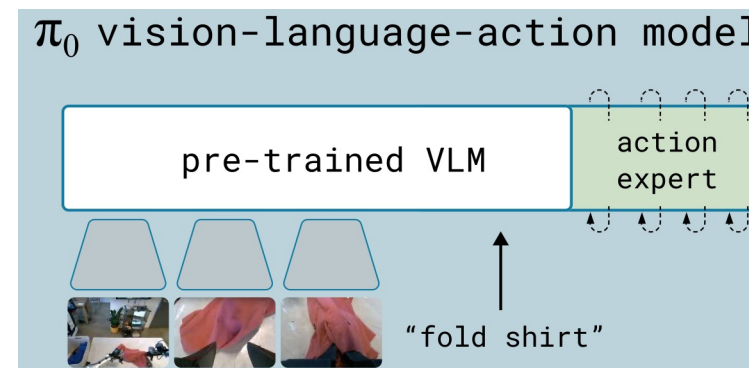
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Can AI Solve Physical Problems?

- 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
 - 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

Physical Autonomous Systems: **Gaps and Challenges**

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

The infographic features a dark blue background. On the left, a globe is composed of many small, identical images of a humanoid robot. To the right of the globe, the text '1. LACK OF INTERNET-SCALE OPEN DATA' is displayed in white, accompanied by a white cloud icon with a diagonal slash. Below this, a red dashed box labeled 'REAL-WORLD ROBOTICS DATA' contains a 3x3 grid of images showing various robots in different environments. The bottom right cell of the grid contains three red dots. At the bottom left, a red 'X' icon is next to the text: 'Data is scarce, fragmented, proprietary and collected in small scale. No internet-scale open datasets.'

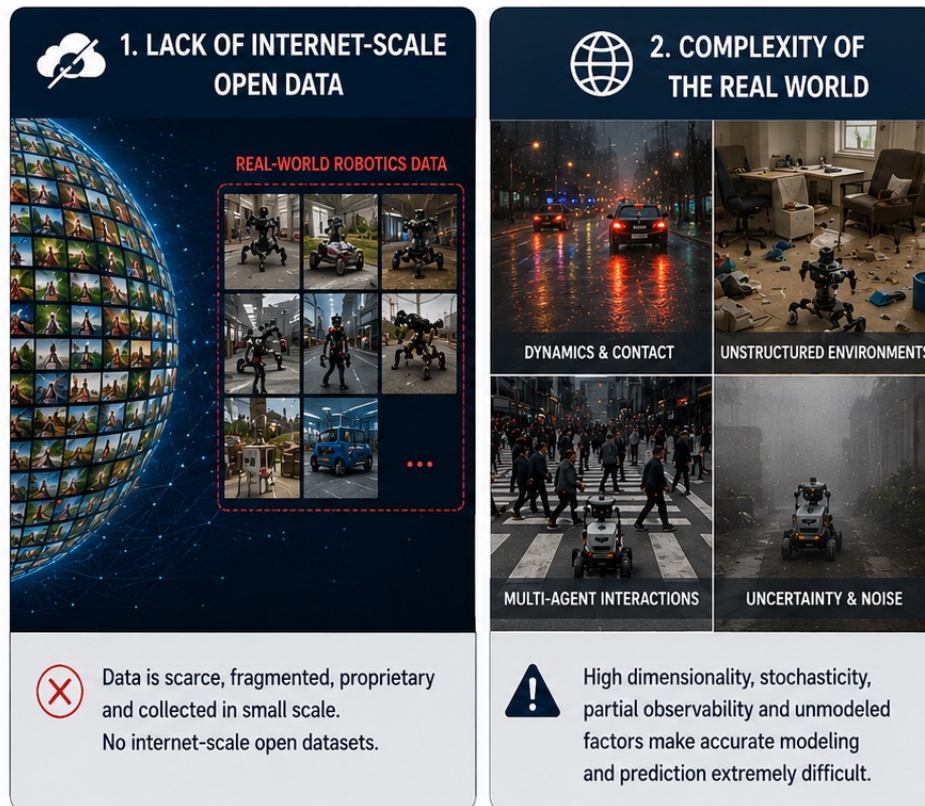
1. LACK OF INTERNET-SCALE OPEN DATA

REAL-WORLD ROBOTICS DATA

✗ Data is scarce, fragmented, proprietary and collected in small scale.
No internet-scale open datasets.

Physical Autonomous Systems: **Gaps and Challenges**

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



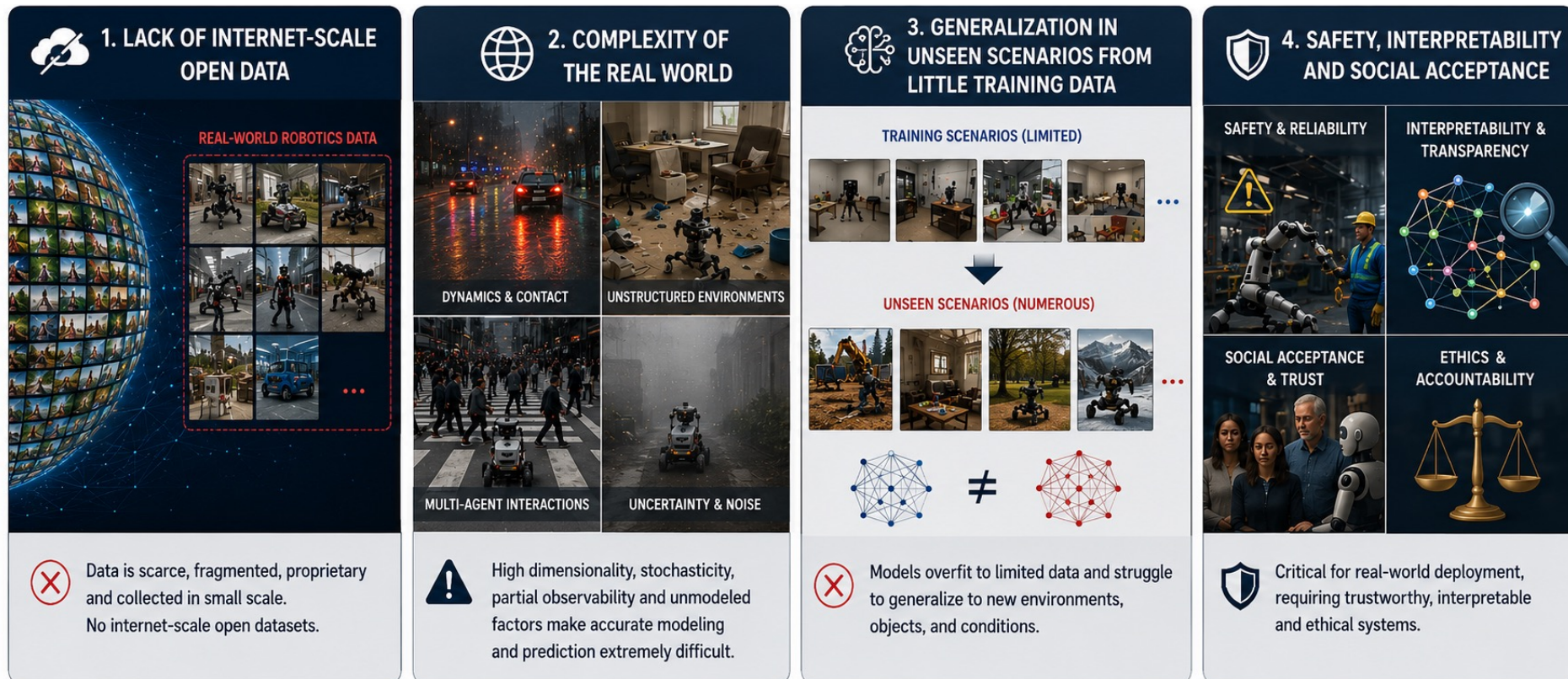
Physical Autonomous Systems: **Gaps and Challenges**

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



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

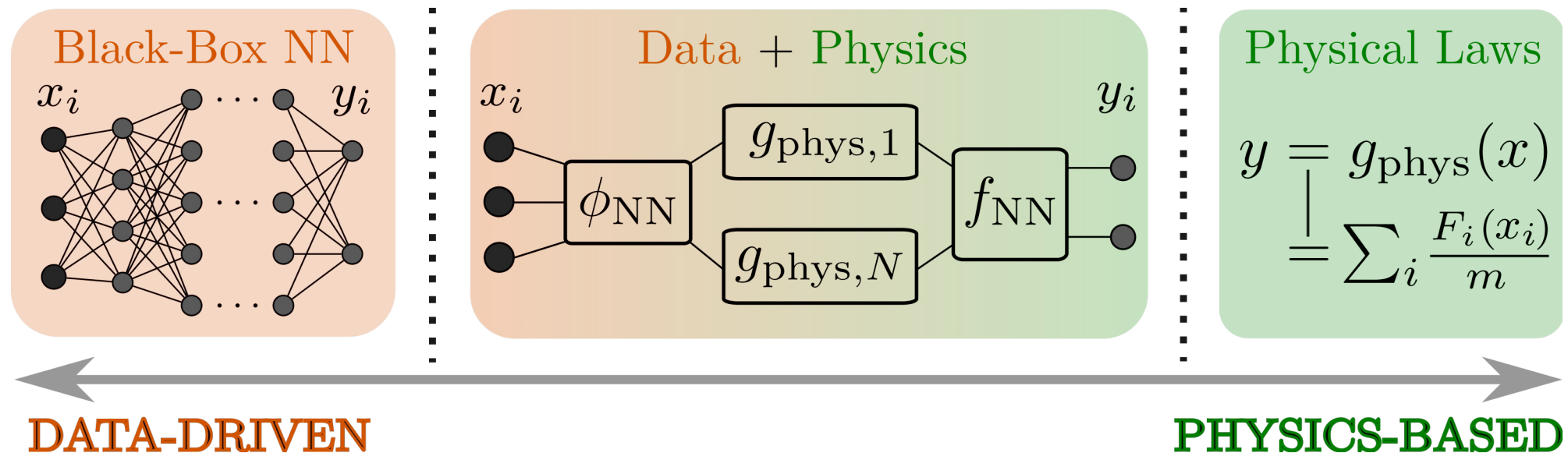


Physical Autonomous Systems: Ways to **Fill the Gaps**

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 Context



Ministero
dell'Università
e della Ricerca



UNIVERSITY
OF TRENTO

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, **mmodely**, 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
- **nnode** 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)

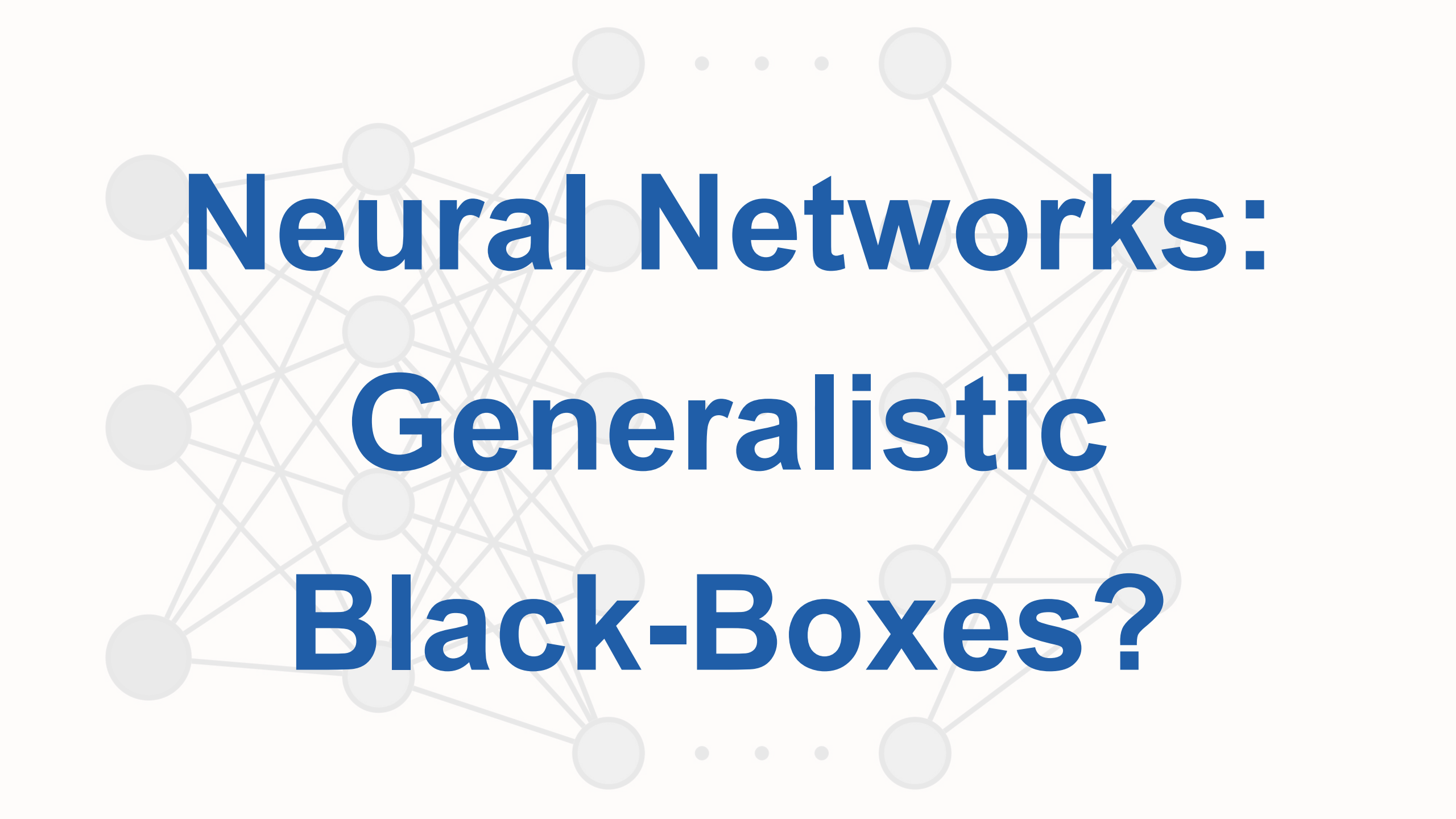
If you need the credits for attending the lectures + passing a **final exam (optional)**:

- 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

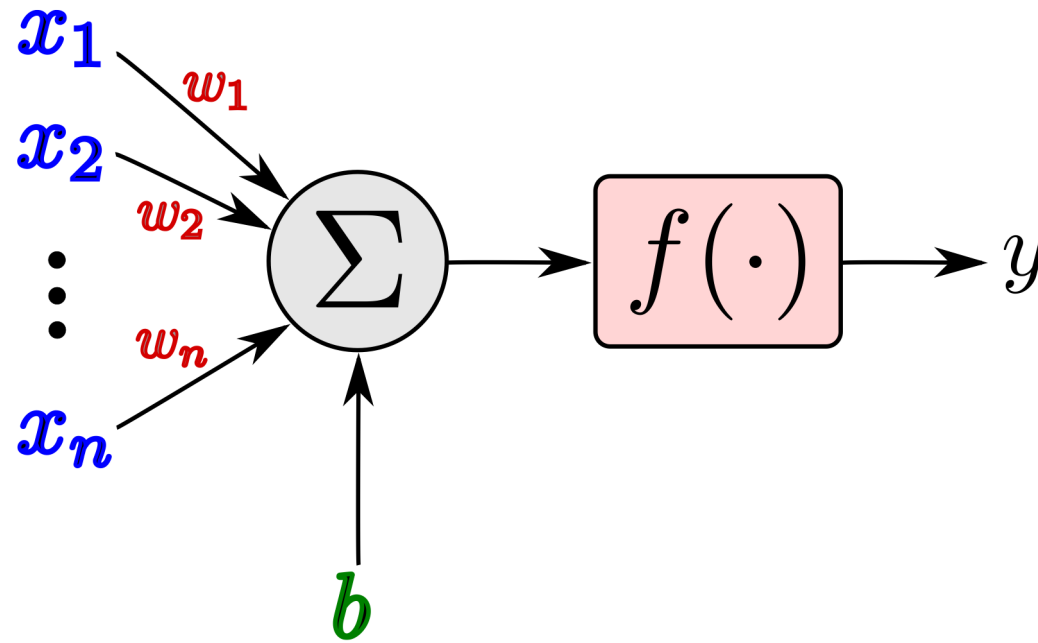




Neural Networks: Generalistic Black-Boxes?

The Perceptron

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



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

Multi-Layer Perceptron (MLP)

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

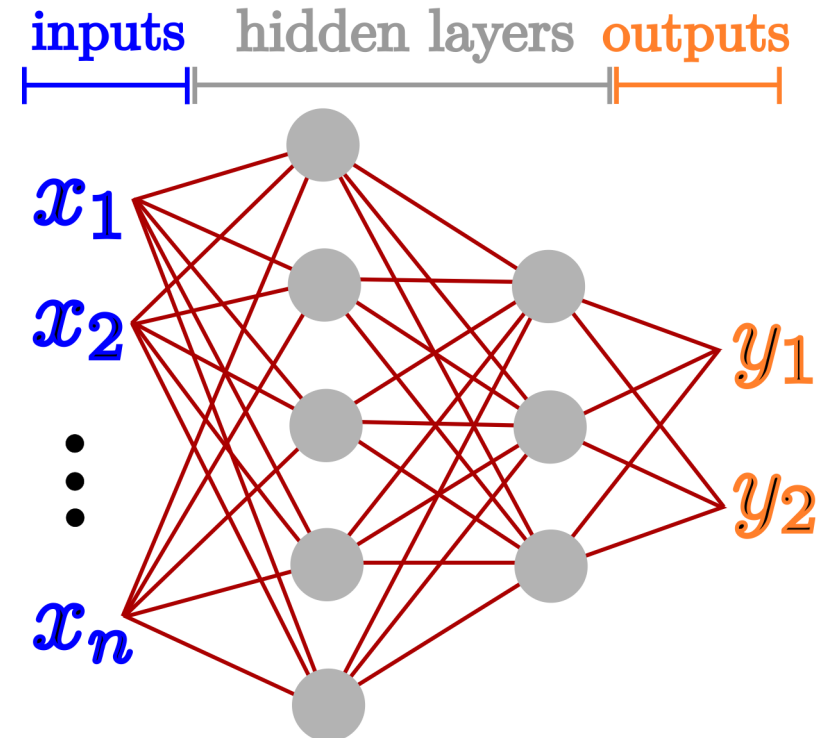
... But is an MLP really the best choice for **every task**?

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**?



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**!

Do Domain Priors Matter in the NN Design?

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

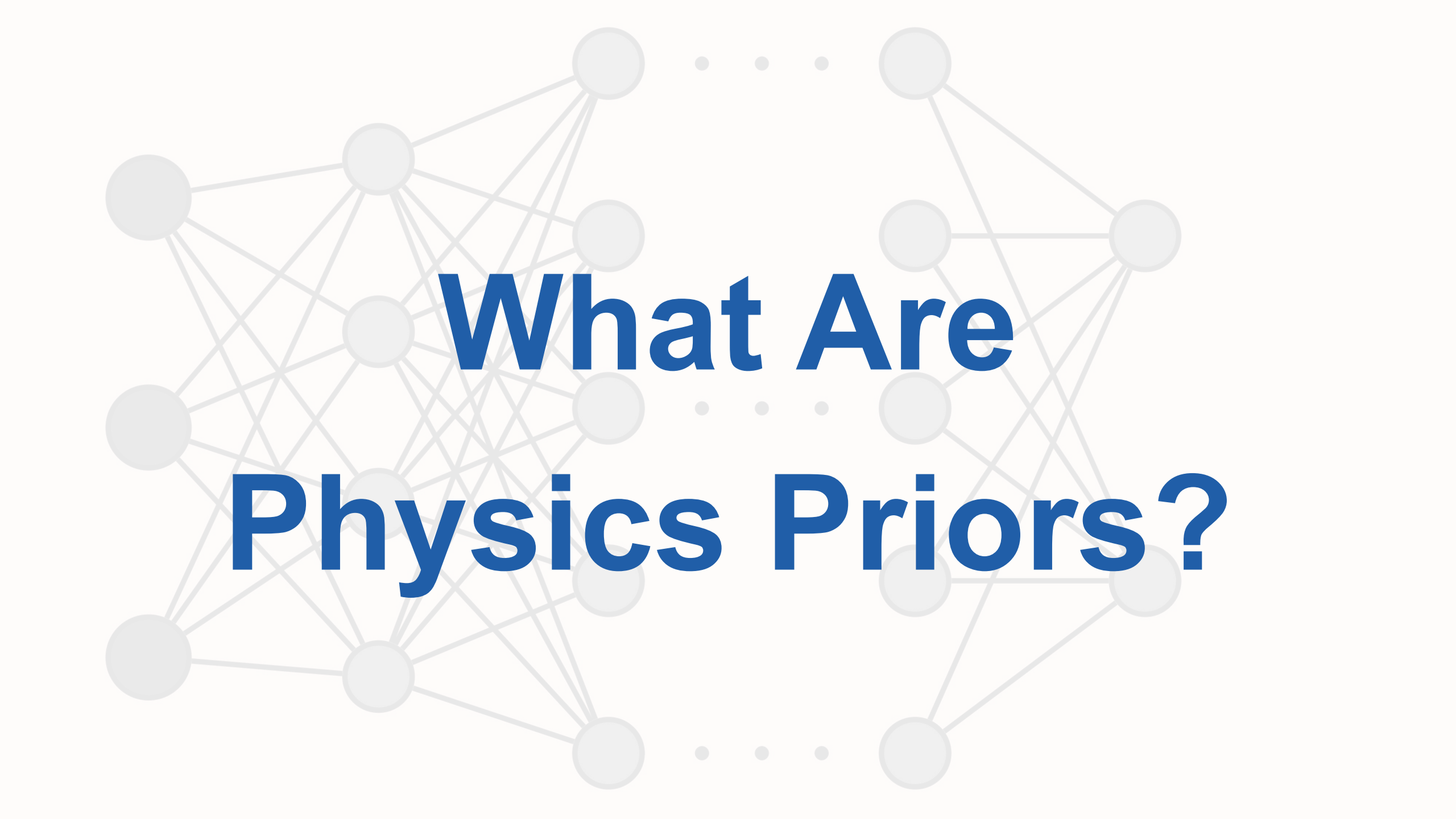
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1. Long Short-Term Memory Networks (**LSTMs**) are designed to capture long-term dependencies in sequential data
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What about **Physical Systems**?

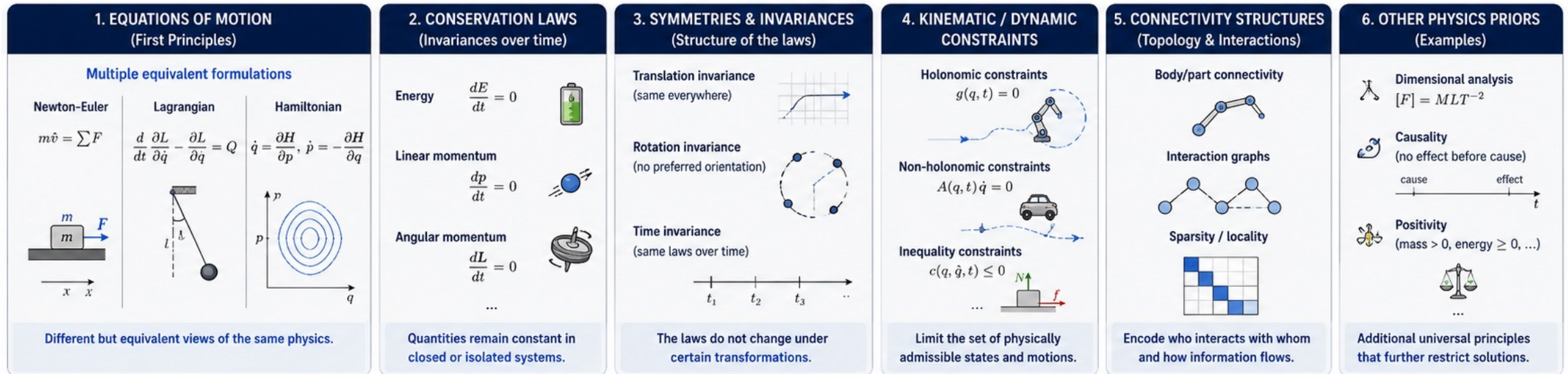
Domain Priors = **Physics Priors**

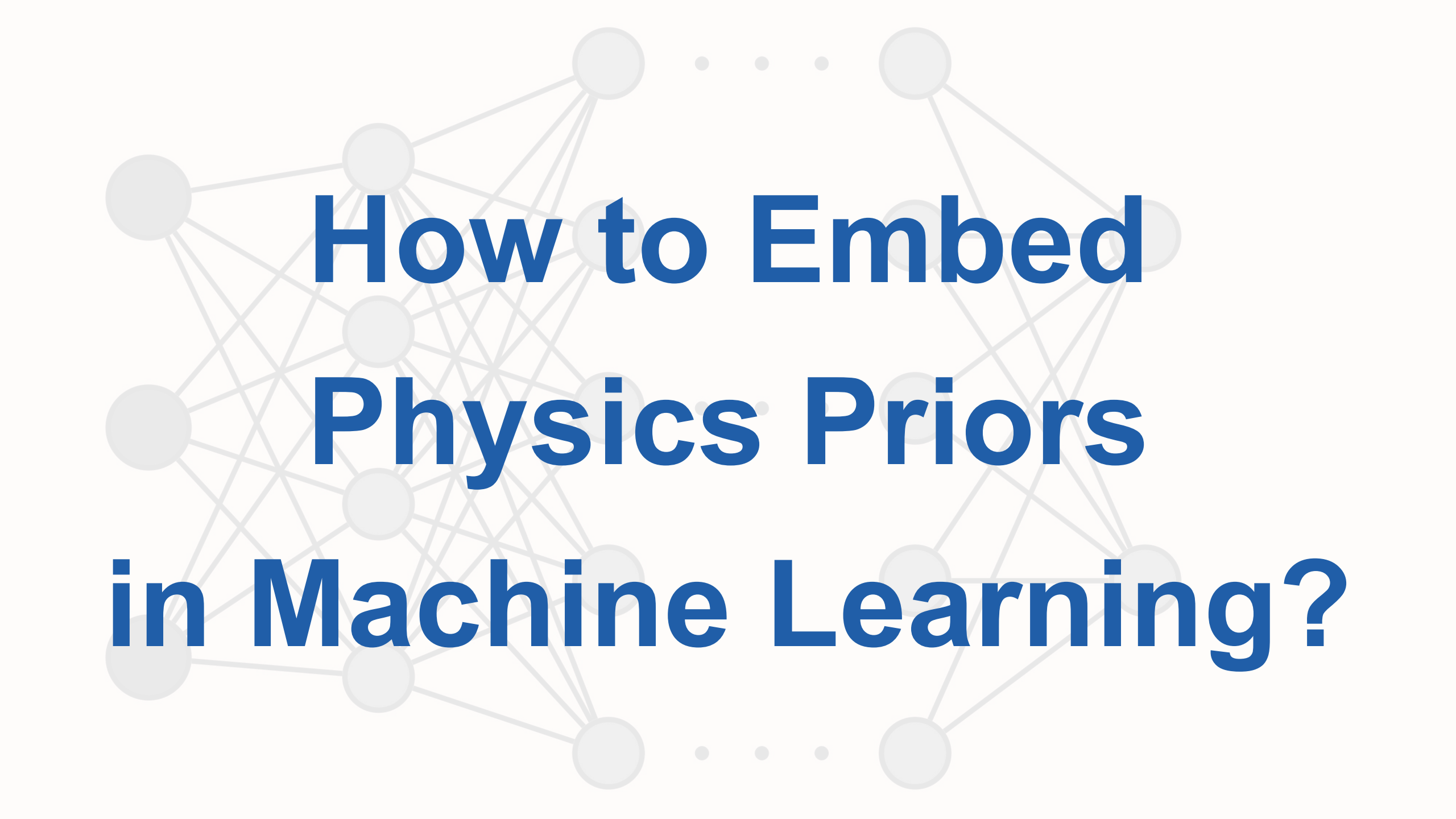


What Are Physics Priors?

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, ...



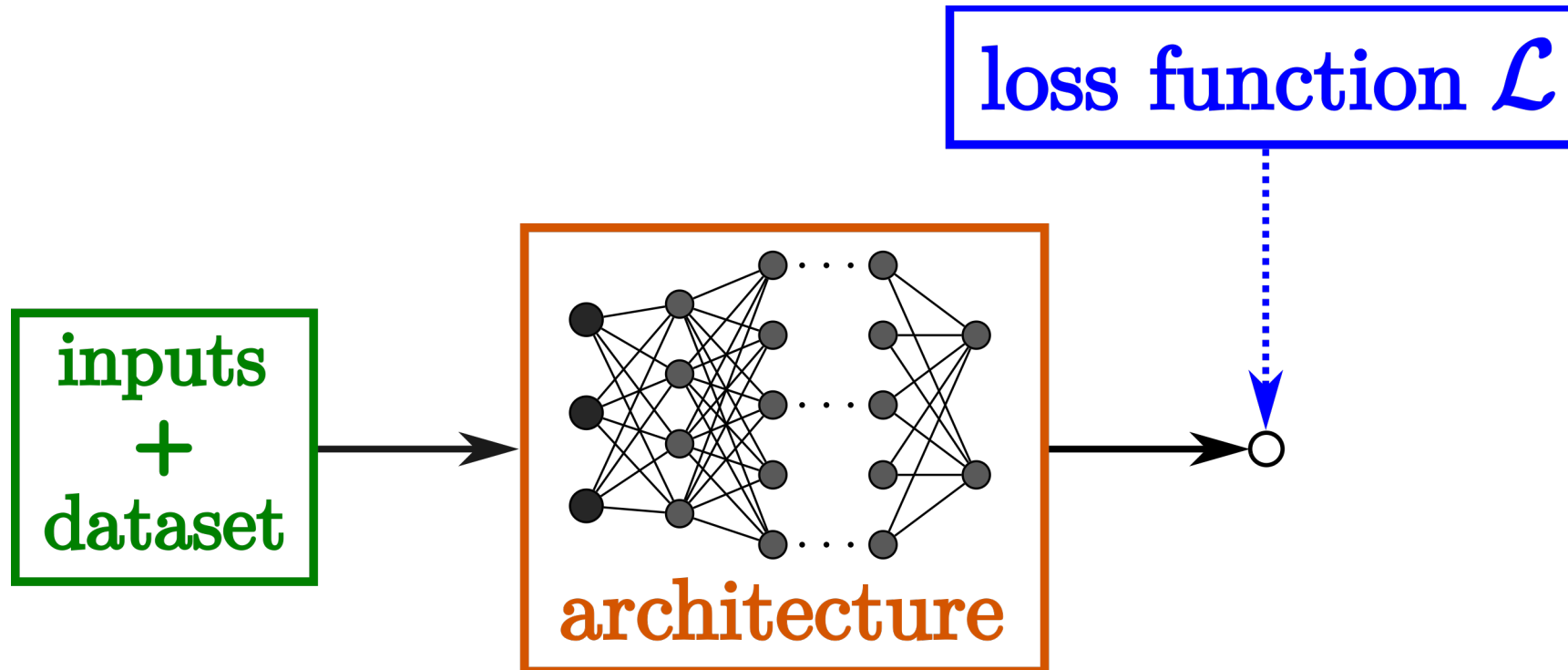


How to Embed Physics Priors in Machine Learning?

Embedding Physics Priors in Machine Learning

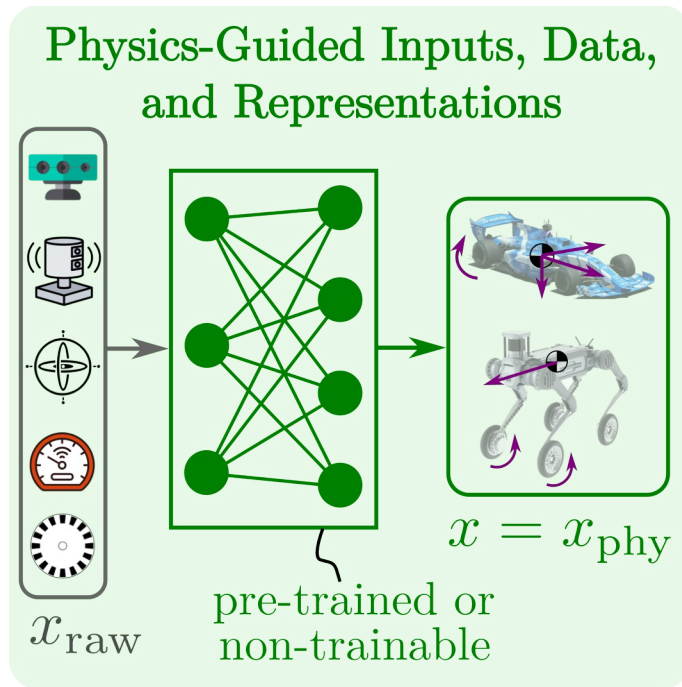
General **structure** of machine learning models
(neural networks, Gaussian Process Regression, foundation models, ...)

Where can physics priors enter? Any ideas?

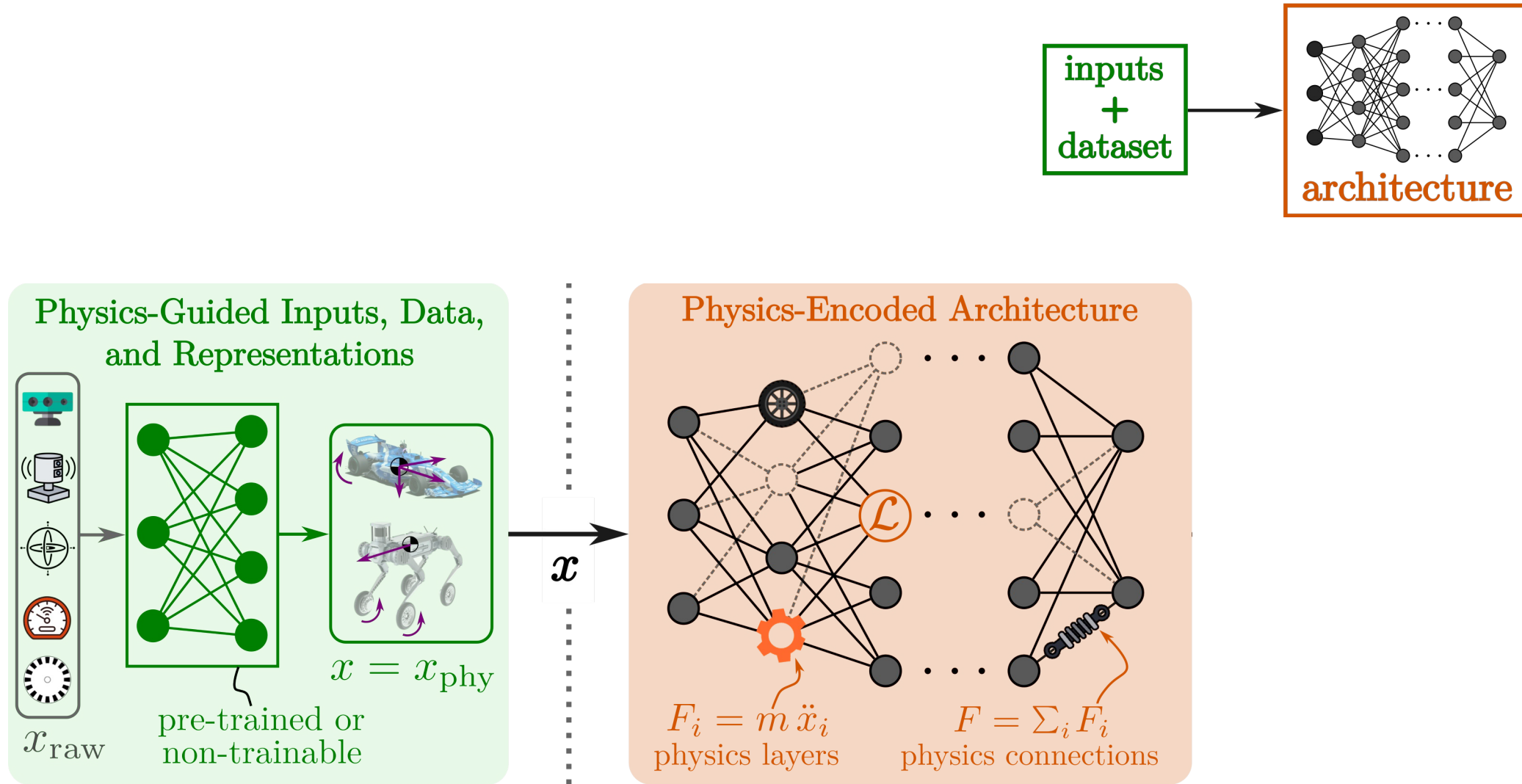


Physics-Guided Machine Learning

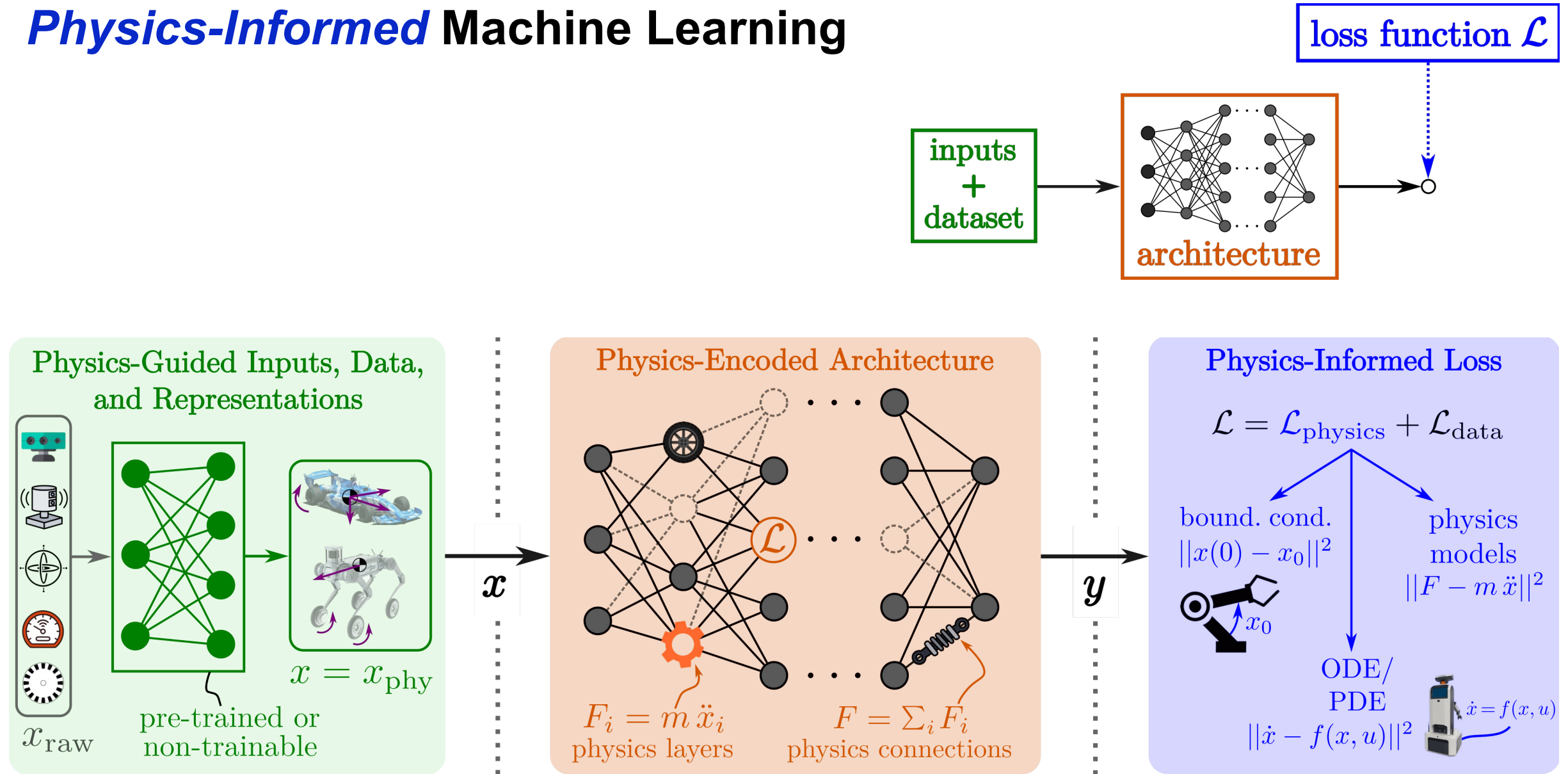
inputs
+
dataset



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
SETTING THE STANDARD

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



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Célio Fernandes
Geo-Intelligence Laboratory,

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

Questions & Discussion

