# Deep Learning and Physics: Robustness

- **Keywords:** Deep learning, Physical data, Robustness, Dynamical systems
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**Context:** The interaction between machine learning and Physics has transformed the methodology in many research areas [1]. Simulations of complex physical systems provide an illustration of such recent development. While computer simulations are invaluable tools for scientific discovery and forecasting systems, the cost of accurate simulations limits in many cases their applicability and the capacity to explore a wide range of physical parameters or to quantify uncertainty in the prediction. In the last decades, data-driven approaches have offered an efficient workaround. For instance a deep neural network model (DNN) can be learned to emulate the physical model [2]. Then, its computational efficiency makes it a proxy integrated in a forecasting system or a control loop [3].

Another example is the recent link between deep architectures, such as ResNets, and ODEs [4, 5, 6]. This promising research line proposes to analyze and improve DNNs by taking advantage of the long research history in numerical analysis. Another recent trend focuses on the analogy between some neural architectures and dynmical systems to better study the inference and learning steps of DNNs and to improve their stability.

**Research project:** Within this context, the goal of this PhD position is to explore this interaction between Physics and machine learning: how to design DNN models to learn from physical data ? Three axes can be considered to structure this challenge:

- **Noisy, scarce and partial observations.** In modern machine learning, the cornerstone is to let the model learn its own representation of the process from data observation. In the case of complex physical systems, data comes from sensors being partial, noisy and scarce. While these challenging conditions are not completely new in the machine learning domain, we can we can leverage some important properties like symmetries and invariances to address these challenges in the context of Physics. Moreover, recent work on robustness in machine learning (to *adversial noise* for instance) provides a theoretical link between dynamical systems and DNNs that can investigated [7].
- **Training algorithm to enforce physical properties.** The physical phenomena at hand are either simulated from differential equations or observed. However, the underlying physical model is assumed to be governed by differential equations. Therefore, the link between numerical solvers and the architecture of DNNs, along with the training algorithm, can be leveraged to some extent [4]. For instance, it has been recently shown that implicite methods can yield great performance with a reduced number of parameters [8]. This opens nice perspectives to reduce the footprint of large scale models.
- **Applications:** The recent DNN architectures have been applied with great success to different kind of data: from acoustic signal to DNA sequences and from images to simulated data, there

is a wide range of possible applications. Depending on the focus of the PhD, the data will be selected to be consistent with the physical proporties under consideration.

These three axes interact closely and the main focus of the project will depend on the skills of the candidate, but two main approaches are proposed: starting for a problem in Physics, design a model that can efficiently learn its properties; or inspired by physical model improve the robustness of existing models and reduce it footprint.

**Requirements:** The project lies at the intersection of different domains and different kinds of skills are required:

- Outstanding master's degree (or an equivalent university degree) in computer science or another related disciplines (as e.g. mathematics, information sciences, etc.).
- Proficiency in machine learning and numerical methods
- Fluency in spoken and written English is required.
- Background in deep-learning and "fluency" in python.

# References


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