

Scientific Machine Learning for Inverse Problems in Structured Population Models

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Context

Many biological systems are naturally modeled as structured populations, in which each individual is characterized by one or more physiological variables (*e.g.*, size, age, or developmental stage). The evolution of the corresponding population distribution can be described by transport-reaction partial differential equations (PDEs) of the general form

$$\partial_t u(t, x) + \partial_x (g(x, \theta) u(t, x)) = -\mu(x, \theta) u(t, x) + R(x, \theta),$$

where $u(x, t)$ denotes the density of individuals of state x at time t , while the functions g , μ , and R describe growth, removal, and recruitment processes, respectively. Such models arise in numerous biological applications, including cell populations, developmental biology, tissue remodeling, and microbiology. Recent examples include the modeling of adipocyte size distributions using size-structured PDEs [1,2].

Although these mechanistic models provide a quantitative description of the underlying biological processes, estimating unknown parameters, or even unknown biological functions, from experimental observations remains a challenging inverse problem. In practice, measurements are often sparse, noisy, and available only at a limited number of time points, making classical optimization or Bayesian inference approaches computationally demanding.

Recent advances in Scientific Machine Learning, particularly Physics-Informed Neural Networks (PINNs), provide a promising framework for solving such inverse problems by combining mechanistic models with experimental data. In particular, the recent work [3] demonstrates the potential of PINNs for inverse problems in size-structured population models using repeated cross-sectional biological observations.

Objectives

The objective of this internship is to develop and validate a PINN-based framework for parameter inference in time-dependent structured PDE models.

The work will initially focus on simplified ("toy") models that represent structured population dynamics, enabling methodological development under controlled conditions before their application to experimental data. In particular, the student will:

- develop Physics-Informed Neural Networks for inverse problems governed by structured PDEs;
- generate synthetic datasets under different experimental scenarios;
- investigate the impact of the number and timing of observations on parameter estimation and model discrimination;
- evaluate the robustness of the inference with respect to measurement noise and incomplete observations;

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- perform practical identifiability analyses, global sensitivity analyses, and uncertainty quantification.

The internship will result in a validated computational framework together with quantitative guidelines on the amount and quality of longitudinal data required for reliable parameter inference. These developments will provide the methodological basis for the subsequent application of the framework to biological datasets within the project.

Candidate profile

Applicants should have a strong background in applied mathematics, scientific computing, machine learning, or computational biology. Experience with differential equations, numerical methods, optimization, and Python programming is expected. Knowledge of deep learning frameworks (e.g., PyTorch, TensorFlow, or JAX) is appreciated but not mandatory.

References

- [1] Giacobbi et al. (2024). *Mathematical modeling of adipocyte size distributions: Identifiability and parameter estimation from rat data*. Journal of Theoretical Biology, 581, 111747.
- [2] Fostier et al. (2026). *Rapid cell turnover to model adipocyte size distribution*. Journal of Theoretical Biology, 618, 112311. PubMed
- [3] Fostier et al. (2026). *Physics-Informed Neural Networks for inverse problems in size-structured population models*. HAL preprint, hal-05536280.