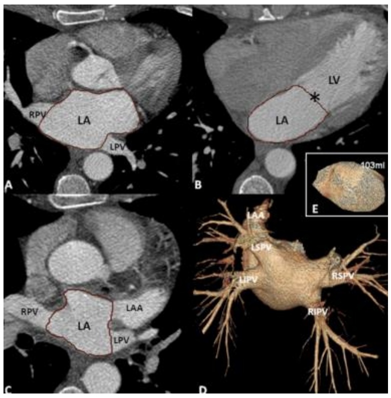
Master / PhD Project: Deep Learning Meets Numerical Modelling

AI and Biophysics for Computational Cardiology
within *3IA Côte d'Azur Interdisciplinary Institute for Artificial Intelligence*
and *DeepNum ANR Collaborative Project*

Clinical Context

Cardiac Arrhythmias are a major healthcare issue. For instance, atrial fibrillation (AF) is the most common cardiac arrhythmia, characterized by chaotic electrical activation of the atria, preventing synchronized contraction. More than 6 million Europeans suffer from it and age is the most powerful predictor of risk. Life-threatening complications and fast progression to persistent or permanent forms call for as early as possible diagnosis and effective treatment.
Arrhythmias are often treated with anti-arrhythmic drugs, with limited efficacy and safety. Catheter ablation, an invasive procedure, is more effective. This procedure is by no means optimized, however, and arrhythmias may reoccur. The efficacy of first-time ablation may range from 30%-75% depending on the individual patient and disease, such that multiple ablation procedures may be recommended.
It is critical to understand whether an ablation procedure is likely to benefit a particular patient, and whether the arrhythmia is likely to reoccur in this patient, to maximize positive patient outcomes and ensure judicious resource allocation in our healthcare systems. Currently, there are no decision support tools enabling clinicians to access integrated patient data together with predictive models to facilitate prognosis and treatment planning.



Scientific Context

Deep Learning has become a major paradigm for data analysis and modelling in the numerical world for semantic data analysis (vision, natural language processing) and games. It is now beginning to play an important role for scientific computing, in domains dealing with the modelling of complex physical processes, such as physics, mechanics or environmental and health sciences, and for industry sectors that exploit intensive simulations, like aeronautics or energy. It is particularly promising for problems involving processes that are not fully understood or when physics-based simulation models are too costly. We focus here on the modelling of complex dynamical systems arising from the observation of natural phenomena with the objective of developing the interplay between two families of approaches, Deep Neural Networks (DNNs) and Differential Equations (DEs). Partial differential equations (PDEs) play a prominent role for modelling complex system dynamics in applied mathematics, physics

and other disciplines. However, in many situations solving PDEs remains complex and challenging for numerical analysis: the governing equations of the underlying system may not be fully known, the state space may be extremely large or the dynamics too complex, the computation cost may be too high or the physical phenomenon may be loosely known. The availability of huge quantities of data, coming from simulations or observations, opens new opportunities for data-driven discovery and modelling of complex natural phenomena dynamics, a new research direction. The benefits could be extremely important: faster model development, reduction of simulation cost, improved modelling quality, targeting problems beyond the reach of traditional approaches.
Pure ML systems have however met limited success for modelling complex spatio-temporal dynamics, due to their inability to produce physically consistent results, their lack of generalizability to out-of-domain (OOD) scenarios and because these problems might be much more complex than current ML achievements. Given that neither physics nor ML methods are sufficient for complex applications, the scientific community has recently started to explore a continuum between mechanistic and ML models where both scientific background and data are integrated in a synergistic manner. Bridging numerical analysis of dynamical systems and ML opens new perspectives for analysing and controlling DNNs, thanks to the rich background of numerical analysis, and for combining the two modelling paradigms in order to solve complex problems.

Position Description

AI and more precisely machine learning have obtained impressive results in several domains like vision, natural language processing, bioinformatics. However, this data intensive paradigm leads to model that often lack interpretability and robustness. Also, it does not allow an easy integration of prior knowledge available in many scientific fields. This can explain its difficult adoption in domains like healthcare. On the other hand, biophysical modelling of the human body is a well-posed mathematical framework to introduce physiology into predictive analysis of clinical data. Moreover, it provides a natural mechanistic framework to interpret results. However, there is often a large computational cost, even more when the quantification of uncertainty has to be performed. And it is sometimes difficult to circumvent model approximations. A major scientific challenge today consists in combining the versatility of data intensive approaches with the physically grounded modelling approaches developed in scientific fields like biophysics.
The scientific objective of this project is to combine the advantages of biophysics and machine learning, more specifically deep learning methods, and to develop hybrid models exploiting the complementarity of the two approaches. We propose to introduce physiological priors in learning systems through biophysical modelling by learning spatiotemporal dynamics from simulations and by introducing physically motivated constraints relative to these dynamics. The objective is to exploit optimally the large amounts of data available in this field together with well-known properties of biophysical cardiac dynamics. Besides, this would also enable us to propose a data-driven correction of biophysical model error. Finally, we will seek a principled integration of uncertainty quantification within this framework. This will encompass both uncertainty on the training data and in the prediction. The vast amount of knowledge in mathematical analysis and data assimilation will be leveraged to optimise the machine learning formulation and understanding.
This project will be done in collaboration with cardiologists and radiologists to access clinical databases in order to evaluate the proposed methods on diagnosis, therapy planning and prognosis for cardiac pathologies.

Preliminary results on this topic were obtained through the collaboration between Inria Epione team specialist of computational physiology and cardiology and Machine Learning and Information Access team LIP6, Sorbonne University, specialist of machine learning and deep learning.

This Master / PhD position will be at Inria, the French Institute for Research in Computer Science and Mathematics, in the Epione research team of the Inria Sophia Antipolis - Méditerranée Research Centre, located on the French Riviera. It will be co-supervised by Pr. Patrick Gallinari from the Machine Learning and Information Access team LIP6, Sorbonne University and done in collaboration with the IHU Liryc, Bordeaux University Hospital, a world leading centre in the treatment of cardiac arrhythmias.

This is part of the recently funded **DeepNum ANR National French project**.

Searched profile

- MSc Level in data science or applied mathematics
- Motivated by machine learning and mathematical modelling
- Eager to work in the medical field
- Good coding skills in Python
- Fluent in English (Reading, Writing, Speaking)

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