The underlying dynamical system can also be used to better control the training and prediction phases. Introducing physiological priors in learning systems through biophysical modelling can be done by driving approaches in collaboration with experts in numerical simulations and machine learning. This will enable to benefit from the complementary advantages of these two areas. The main activities will be to propose new methods at the interface between physics-based and data-driven approaches in order to solve complex problems. The vast amount of knowledge in numerical analysis and data assimilation will be leveraged to guide the machine learning formulation.

### Contexte et atouts du poste

Cardiac Arrhythmias are a major healthcare issue. For instance, atrial fibrillation (AF) is the most common cardiac arrhythmia, characterised 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 recur. 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 recur in this patient, to maximize 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.

### Mission confiée

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, 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.

The scientific objective of this project is to combine the advantages of biophysics and deep learning methods, and to develop hybrid models exploiting the complementarity of the two approaches. The objective is to exploit optimally the large amounts of available data 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 numerical analysis and data assimilation will be leveraged to guide the machine learning formulation.

### Informations générales

- **Thème/Domaine :** Neurosciences et médecine numériques
- **Ville :** Sophia Antipolis
- **Centre Inria :** CRI Sophia Antipolis - Méditerranée
- **Date de prise de fonction souhaitée :** 2022-10-01
- **Durée de contrat :** 3 ans
- **Date limite pour postuler :** 2022-09-29

### Contacts

- **Équipe Inria :** EPIONE
- **Directeur de thèse :** Sermesant Maxime / Maxime.Sermesant@inria.fr

### Principal activités

The main activities will be to propose new methods at the interface between physics-based and data-driven approaches in collaboration with experts in numerical simulations and machine learning. This will enable to benefit from the complementary advantages of these two areas.

Introducing physiological priors in learning systems through biophysical modelling can be done by learning spatiotemporal dynamics from simulations or by introducing physically motivated constraints relative to these dynamics in the mathematical formulation. Knowledge of the underlying dynamical system can also be used to better control the training and predicting phases.
These methods will be developed in the particular case of cardiac electromechanical modelling, in order to help diagnosis, prognosis and therapy planning.

Interactions with cardiologists will enable to evaluate the relevance of the clinical results.

The Inria Epione team gathers experts in biophysical modelling and application of AI in healthcare.

**Compétences**
- MSc in Applied Mathematics or Computer Science
- Good knowledge of machine learning
- Good knowledge of mathematical modelling
- Good coding skills in Python

**Avantages**
- Subsidized meals
- Partial reimbursement of public transport costs
- Leave: 7 weeks of annual leave + 10 extra days off due to RTT (statutory reduction in working hours) + possibility of exceptional leave (sick children, moving home, etc.)
- Possibility of teleworking (after 6 months of employment) and flexible organization of working hours
- Professional equipment available (videoconferencing, loan of computer equipment, etc.)
- Social, cultural and sports events and activities
- Access to vocational training
- Social security coverage
- Supplementary social protection

**Rémunération**
Duration: 36 months
Location: Sophia Antipolis, France
Gross Salary per month: 2051€ per month (year 1 & 2) and 2158€ per month (year 3)