Learning Causality

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Context In the last decade, Machine Learning, and more specifically deep neural networks, have thoroughly renewed the research perspectives in many fields. Despite indisputable successes however, the introduction of ML approaches in physical systems remains a challenge to overcome the lack of confidence, acceptability, guarantees and explainability. This project aims at developing new Machine Learning techniques tailored to

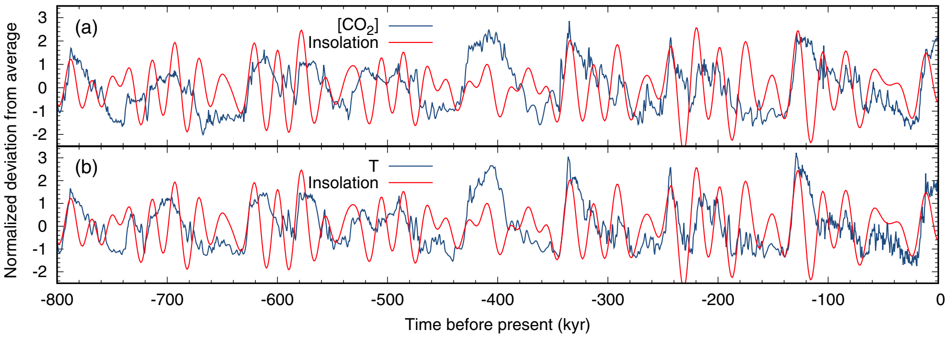

Figure 1: Analysis of the mutual influence between temperatureT and CO2 concentration in paleoclimate data. (From Nature Sci. Rep.)

the modelling and inference of physical complex systems.

Project A recurrent problem in Physics and Engineering Sciences is to try to predict the future **evolution of a physical system according to the partial information** known at the current time, and possibly during a **recent past**. In the absence of a model, this evolution must be learned from the available data and usually takes the form of an optimization problem, possibly under constraints, informed by the potentially large number of observables. This optimization problem can then be of large size and thus present all the associated problems (many local minima of the cost function, need for a lot of data, etc.). To improve the quality (e.g., generalizability) and the efficiency of the learning process (e.g., amount of data needed, dimension of the optimization space, computational load, etc.), it is often essential to **identify only those observations that have a causal link with the quantity to be predicted**. As an example, the modeling of closure terms in Large Scale Simulation (LSS) in fluid mechanics is often based on a fixed support (stencil) chosen a priori whereas the cone of information conditioning the temporal evolution of a variable varies in space and as a function of the flow regime, or even time. In order to avoid conservative choices that have a strong impact on quality and efficiency, it is essential to determine this cone and to restrict the learning problem to it.

More generally, to understand the causality relation between different phenomena is one of the most important, and difficult, issue in physics as well as in philosophy. An example is given in figure concerning climate time-series. Recent results in statistical physics suggest that in some cases the causality link could be understood. It would be very interesting to develop learning strategy capable to recognise this link, and this is the ultimate goal of the project.

The project is strongly interdisciplinary with an interplay of applied mathematics, statistical physics, fluid mechanics and informatics. Depending on the skills of the candidate, different tracks can be explored, for instance learning a representation space aimed at highlighting mutual information between variables from different times.

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