PhD thesis
Statistical learning theory
and hybrid dynamical system identification

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Keywords

Artificial Intelligence, Machine Learning, Learning theory, System identification

Sujet

Automatic control deals with the analysis and control of dynamical systems, such as the evolution of a chemical reaction over time, the behavior of an electrical system or the trajectory of a plane, etc. To conduct this analysis or control, the first step consists in modeling the systems, i.e., in building a mathematical model describing the system behavior. In most cases, and as soon as physical principles at play are not perfectly known or too complex, this modeling step is performed from experimental observations of the system behavior.

System identification is the subfield of automatic control that focuses on the estimation of models from such data. In this framework, it is of particular importance to obtain guarantees on the model accuracy. System identification theory, which is mostly based on parametric statistics, provides asymptotic guarantees under rather restrictive assumptions (such as a precise specification of the noise, the model and the estimation method). These guarantees are often not suitable to precisely quantify the error of a model estimated from a finite number of data.

In the field of *artificial intelligence*, building predictive models from experimental data is studied in the framework of *machine learning*. In the “big data" era, this data science became ubiquitous in many computer science applications, but also in many other domains such as biology, medical imaging or robotics. Here also, guaranteeing the performance of the estimated models is of primary importance; and this is the focus of *statistical learning theory*. Contrary to classical parametric statistics, this theory provides guarantees in a much less restrictive and agnostic framework (with nonparametric models, without assumptions of the noise or the shape of the optimal model) and in particular nonasymptotic bounds on the prediction error of the models estimated from a finite number of data. However, most of the results of this type are established under an assumption on the independence of the observations, rather standard in many contexts, but not adapted to the case of dynamical system identification.

This project aims at bridging the gap between these two disciplines: extend learning theory to the nonindependent data in order to obtain the most accurate guarantees for the identification of dynamical systems. The project will in particular consider *hybrid dynamical systems*. These hybrid systems mix continuous and discrete behaviors, and are call for the use of models switching between multiple operating modes. They are found in many applications, such as in communication networks, transport systems, industrial processes, engine control, biological systems, and so on. For such systems, system identification faces an additional difficulty for the practical estimation of the models. Indeed, it is in this case rarely possible to guarantee the accuracy of the optimization algorithms used in practice to fit the model to the data and thus to precisely characterized the estimated model. Statistical learning theory provides an interesting solution to this issue by deriving uniform error bounds, i.e., bounds that hold for all possible models within a predefined class.

Results of this project are expected to have an impact in system identification, but also more downstream, at the level of robust control. Contributions related to the prediction of time-series are also expected.

Candidate profile

- Student holding a master degree in Computer science, Control or Applied mathematics
- Good knowledge in probability and statistics appreciated.

Details

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