



Contribution ID: 3

Type: **Talk**

## A Model Falsification Approach to Learning in Non-Stationary Environments for Experimental Design

*Thursday, October 4, 2018 4:50 PM (20 minutes)*

The application of machine learning and advanced statistical tools to complex physics experiments becomes very problematic, when the i.i.d. (independent and identical distribution) hypothesis is not verified, due the varying conditions of the systems to be studied. In particular, new experiments have to be executed in un-explored regions of the operational space. As a consequence, the input quantities used to train and test the performance of the tools are not necessarily sampled by the same probability distribution as in the final applications. In the present study, a new data driven methodology is proposed to guide planning of experiments and to explore the operational space. The approach is based on Symbolic Regression via Genetic Programming to the available data, which allows identifying a set of candidate models. The confidence intervals for the predictions of such models permit to find the best region of the parameter space for their falsification, where the next set of experiments can be more profitably carried out. The procedure is repeated until convergence on a satisfactory model. Extensive numerical tests and applications to the scaling laws in Tokamaks prove the viability of the proposed approach.

**Primary author:** Dr MURARI, Andrea (RFX Consortium and PMU)

**Co-authors:** Dr PELUSO, Emmanuele (Tor Vergata University); Dr GELFUSA, Michela (Tor Vergata University); Dr LUNGARONI, Michele (Tor Vergata University); Dr GAUDIO, Pasquale (Tor Vergata University)

**Presenter:** Dr MURARI, Andrea (RFX Consortium and PMU)

**Session Classification:** Data Mining