Keynotes

Workshop AI4OAC, January 20-23, 2020 Brest

AI and Earth Observation. Prof. Mihai Datcu

Professor, DLR, Germany. Holder of a 2017 Blaise Pascal Chair at CEDRIC, CNAM.

Satellite remote sensing is the only global and continuous Earth Observation (EO) system. In the present context of unprecedented and rapid climate changes EO plays the central role in understanding the planetary scale phenomena. The analysis of the Big EO Data poses many challenges and the solutions are presently mainly based on the advances in Artificial Intelligence (AI). The presentation overviews and analyses specific AI methods for EO data, beginning with the generation of training data sets, data base biases analysis, explainable machine and deep learning paradigms for high complexity phenomena understanding. Selected examples are presented for coastline and polar sea-ice monitoring.

Optimal Transport for Image Assimilation. Dr. Nicolas Papadakis

Scientist CNRS, IMB, Bordeaux, France, webpage

This talk is about the use of optimal transport (OT) tools for the assimilation and the processing of satellite images. In the first part, we introduce basic concepts on OT distances. Then related assimilation strategies are presented. We analyse their limitations and detail how they should be generalized and optimized to be considered in real assimilation pipelines. In the second part, we discuss another potential use of OT, in connection with recent machine learning works. We explain how OT can be used to pre-process automatically large sets of images, which is namely of interest for the denoising of SWOT data.

From symbolic PDEs to trainable neural networks. Dr. Olivier Pannekoucke

Scientist CNRM, CERFACS, Toulouse, France

Bridging physics and deep learning is a topical challenge. While deep learning frameworks open avenues in physical science, the design of physically-consistent deep neural network architectures is an open issue. In the spirit of physics-informed NNs, this talk will present PDE-NetGen framework which provides new means to automatically translate physical equations, given as PDEs, into neural network architectures. PDE-NetGen combines symbolic calculus and a neural network generator. The later exploits NN-based implementations of PDE solvers using Keras. The talk will present different applications of the proposed framework with an emphasis to the data-driven and physics-informed identification of uncertainty dynamics.

Towards Better Understanding Generalization in Deep Learning. Dr. Samy Bengio

Senior Scientist, Google Research, Moutain View, CA, USA, webpage

Abstract: Deep learning has shown incredible successes in the past few years, but there is still a lot of work remaining in order to understand some of these successes. Why such over-parameterized models still generalize so well? In this presentation, I will cover recent work empirically showing interesting relations between learned internal representations and generalization.

Principal Component Analysis for multivariate extremes. Prof. Anne Sabourin

Professor, Telecom Paris, Paris, France, webpage

In the probabilistic framework of multivariate regular variation, the first order behavior of heavy-tailed random vectors above large radial thresholds is ruled by a homogeneous limit measure. For a high dimensional vector, a reasonable assumption is that the support of this measure is concentrated on a lower dimensional subspace, meaning that certain linear combinations of the components are much likelier to be large than others. Identifying this subspace and thus reducing the dimension will facilitate a refined statistical analysis. In this work we apply Principal Component Analysis (PCA) to a re-scaled version of radially thresholded observations. Within the statistical learning framework of empirical risk minimization, our main focus is to analyze the squared reconstruction error for the exceedances over large radial thresholds. We prove that the empirical risk converges to the true risk, uniformly over all projection subspaces. As a consequence, the best projection subspace is shown to converge in probability to the optimal one, in terms of the Hausdorff distance between their intersections with the unit sphere. In addition, if the exceedances are re-scaled to the unit ball, we obtain finite sample uniform guarantees to the reconstruction error pertaining to the estimated projection subspace. Numerical experiments illustrate the relevance of the proposed framework for practical purposes.

Ensemble-based learning of the Koopman operator in a RKHS for predictions of QG flow model. Dr. Gilles Tissot.

Scientist, Flumiance, INRIA Rennes, France, webpage

We propose a method to learn the dynamics of large-scale oceanic systems based on an ensemble. The technique relies on the combination of two concepts: i) the reproducing kernel Hilbert spaces (RKHS), that are smooth functions in the phase space and can be viewed as a basis with interpolatory properties ii) the Koopman operator, that is a linear infinite-dimensional operator able to propagate in time any observable in the phase space. Based on an ensemble embedded in the RKHS, eigenfunctions of the Koopman operator are estimated and used to propagate new ensemble members of the dynamics. This technique is applied on a quasi-geostrophic flow model.