SampTA 2019

13th International conference on Sampling Theory and Applications

université de BORDEAUX

July 8-12

Friday July 12, 13.30-15.35

Deep Learning

Chair: Deep Learning

Wegener	13.30-13.55	*Approximation in $L^p(\mu)$ with deep ReLU neural networks* Felix Voigtlaender & Philipp Petersen
Wegener	13.55-14.20	*Modeling Global Dynamics from Local Snapshots with Deep Generative Neural Networks* Scott Gigante, David Van Dijk, Kevin Moon, Alexander Strzalkowski, Guy Wolf & Smita Krishnaswamy
Wegener	14.30-15.30	*Learning from moments - Large-scale learning with the memory of a goldfish* Rémi Gribonval Chair: Ursula Molter
Wegener	15.30-15.35	*Closing*

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Inverse problems
Chair: Inverse problems chair

Edison	13.30-13.55	*Convergence Rates for Hölder-Windows in Filtered Back Projection* Matthias Beckmann & Armin Iske
Edison	13.55-14.20	*Dynamical Sampling with a Burst-like Forcing Term* Akram Aldroubi, Longxiu Huang, Keri Kornelson & Ilya Krishtal
Wegener	14.30-15.30	*Learning from moments - Large-scale learning with the memory of a goldfish* Rémi Gribonval Chair: Ursula Molter
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Deep Learning

Chair: Deep Learning

13.30-13.55: Approximation in $L^p(\mu)$ with deep *ReLU* neural networks

Felix Voigtlaender & Philipp Petersen

Abstract: We discuss the expressive power of neural networks which use the non-smooth *ReLU* activation function $\rho(x) = \max\{0, x\}$ by analyzing the approximation theoretic properties of such networks. The existing results mainly fall into two categories: approximation using *ReLU* networks with a fixed depth, or using *ReLU* networks whose depth increases with the approximation accuracy. After reviewing these findings, we show that the results concerning networks with fixed depth—which up to now only consider approximation in $L^p(\lambda)$ for the Lebesgue measure λ—can be generalized to approximation in $L^p(\mu)$, for any finite Borel measure μ. In particular, the generalized results apply in the usual setting of statistical learning theory, where one is interested in approximation in $L^2(\mathbb{P})$, with the probability measure $\mathbb{P}$ describing the distribution of the data.

13.55-14.20: Modeling Global Dynamics from Local Snapshots with Deep Generative Neural Networks

Scott Gigante, David Van Dijk, Kevin Moon, Alexander Strzalkowski,
Guy Wolf & Smita Krishnaswamy

Abstract: Complex high dimensional stochastic dynamic systems arise in many applications in the natural sciences and especially biology. However, while these systems are difficult to describe analytically, "snapshot" measurements that sample the output of the system are often available. In order to model the dynamics of such systems given snapshot data, or local transitions, we present a deep neural network framework we call Dynamics Modeling Network or DyMoN. DyMoN is a neural network framework trained as a deep generative Markov model whose next state is a probability distribution based on the current state. DyMoN is trained using samples of current and nextstate pairs, and thus does not require longitudinal measurements. We show the advantage of DyMoN over shallow models such as Kalman filters and hidden Markov models, and other deep models such as recurrent neural networks in its ability to embody the dynamics (which can be studied via perturbation of the neural network), generate longitudinal hypothetical trajectories, and denoise measurement artifacts. We perform three case studies in which we apply DyMoN to different types of biological systems and extract features of the dynamics in each case by examining the learned model.

Inverse problems

Chair: Inverse problems chair

13.30-13.55: Convergence Rates for Hölder-Windows in Filtered Back Projection

Matthias Beckmann & Armin Iske

Abstract: In this paper we consider the approximation of bivariate functions by using the well-established filtered back projection (FBP) formula from computerized tomography. We establish error estimates and convergence rates for the FBP reconstruction method for target functions f from a Sobolev space $H^\alpha(\mathbb{R}^2)$ of fractional order $\alpha > 0$, where we bound the FBP reconstruction error with respect to the weaker norms of the Sobolev spaces $H^\sigma(\mathbb{R}^2)$, for $0 \leq \sigma \leq \alpha$. By only assuming Hölder continuity of the low-pass filter's window function, the results of this paper generalize previous of our findings.

13.55-14.20: Dynamical Sampling with a Burst-like Forcing Term

Akram Aldroubi, Longxiu Huang, Keri Kornelson & *Ilya Krishtal*

Abstract: In this paper we consider the problem of recovery of a burst-like forcing term in the framework of dynamical sampling. We introduce the notion of a sensing limit of a collection of samples with respect to a semigroup and indicate its fundamental role in the solvability of the problem.

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Learning from moments - Large-scale learning with the memory of a goldfish

Rémi Gribonval (INRIA Rennes, France)

Abstract: Inspired by compressive sensing, Compressive Statistical Learning allows drastic volume and dimension reduction when learning from large/distributed/streamed data collections. The principle is to exploit random projections to compute a low-dimensional (nonlinear) sketch (a vector of random empirical generalized moments), in essentially one pass on the training collection. Sketches of controlled size have been shown to capture the information relevant to certain learning tasks such as unsupervised clustering, Gaussian mixture modeling or PCA. As a proof of concept, more than a thousand hours of speech recordings can be distilled to a sketch of only a few kilo-bytes that captures enough information to estimate a Gaussian Mixture Model for speaker verification. The talk will highlight the main features of this framework, including statistical learning guarantees —obtained using tools from randomized low-dimensional projections and compressive sensing—, differential privacy guarantees, and open challenges.