

Program

	Monday 21 Sep	Tuesday 22 Sep	Wednesday 23 Sep	Thursday 24 Sep	Friday 25 Sep
9:00	Lecture N. Boullé	Lecture C.-B. Schönlieb	Lecture H. Gottschalk	Lecture G. Steidl	Lecture F. Filbir
10:00	Break	Break	Break	Break	Break
10:30	Lecture H. Gottschalk	Lecture N. Boullé	Lecture C.-B. Schönlieb	Lecture F. Filbir	Lecture G. Steidl
11:30	Lunch	Lunch	Lunch	Lunch	Lunch
13:00	Session 1 A. Uschmajew	Session 3 C. Duan	Trip ¹	Session 5 R. Joy	End
13:30	M. Hertel	R. Kunsch		F. Bartel	
14:00	M. Poguntke	M. Proell		N. Nagel	
14:30	Break	Break		Break	
15:00	Session 2 J. Castro	Session 4 K. Sadik		Session 6 Posters	
15:30	L. Dehne	S. Zapadlo		Posters	
16:00	M. Moeller	A. Lupoli		Posters	
16:30	End	End	Dinner ²	End	

¹ Travel by regional train (start: 13:30, duration: 47 min) to Stollberg, then short hiking tour and visit of the Hoheneck Memorial Site. The return journey to Chemnitz is again by regional train (start: 17:32).

² 18:30 at the restaurant Moli Modo, Markt 19, 09111 Chemnitz city centre.

Monday, 21 Sep		Wednesday, 23 Sep	
9:00	N. Boullé Operator Learning	9:00	H. Gottschalk Statistical Theory for Generative Learning
10:00	Break	10:00	Break
10:30	H. Gottschalk Statistical Theory for Generative Learning	10:30	C.-B. Schönlieb Inverse Problems Solutions in the Era of AI
11:30	Lunch	11:30	Lunch
13:00	A. Uschmajew On low-rank tensor train approximability for linear nearest neighbor systems	13:00	Trip
13:30	M. Hertel Kolmogorov Widths and Kernel Approximation of Koopman Operators	Thursday, 24 Sep	
14:00	M. Poguntke Certified Posterior Sampling for Bayesian Inverse Problems via Flow Matching and Metropolization	9:00	G. Steidl Generative Flows
14:30	Break	10:00	Break
15:00	J. Castro THINNs: Thermodynamics-Informed Neural Networks	10:30	F. Filbir On Sampling Inequalities and Their Relation to Optics
15:30	L. Dehne Parameter Identification using Physics-informed Neural Networks	11:30	Lunch
16:00	M. Moeller Fourier Gelfand numbers of dominating mixed smoothness spaces	13:00	R. Joy From Oversampling to Optimal Sampling: Constructive Subsampling for Bandlimited Signal Recovery
Tuesday, 22 Sep		13:30	F. Bartel Required number of points in L2-Marcinkiewicz-Zygmund inequalities
9:00	C.-B. Schönlieb Inverse Problems Solutions in the Era of AI	14:00	N. Nagel Infinite sequences with optimal worst-case error decay of QMC-rules for periodic functions
10:00	Break	14:30	Break
10:30	N. Boullé Operator Learning	15:00	Poster Session
11:30	Lunch	Friday, 25 Sep	
13:00	C. Duan Learning-based Approach for Online State Estimation with Error Certification	9:00	F. Filbir On Sampling Inequalities and Their Relation to Optics
13:30	R. Kunsch Randomized approximation based on (non-) adaptive linear measurements	10:00	Break
14:00	M. Proell Order of approximation for orthonormal shift-invariant spaces: a Taylor coefficient characterization, Strang-Fix conditions and polynomial reproduction	10:30	G. Steidl Generative Flows
14:30	Break	11:30	Lunch
15:00	K. Sadik A Nonlinear Second Order Problem Involving Nonlocal Diffusion For Image Processing	13:00	End
15:30	S. Zapadlo Learning Multi-Pool Dynamics in Magnetic Resonance Imaging		
16:00	A. Lupoli Stability of Second-Order Sigma-Delta Quantization via Trajectory Analysis		

Invited Lectures

Nicolas Boullé, Imperial College London

Operator Learning

Frank Filbir, Helmholtz Zentrum München / Technische Universität München

On Sampling Inequalities and Their Relation to Optics

Hanno Gottschalk, TU Berlin

Statistical Theory for Generative Learning

Carola-Bibiane Schönlieb, University of Cambridge

Inverse Problems Solutions in the Era of AI

Gabriele Steidl, TU Berlin

Generative Flows

Abstracts of Contributed Talks

Required number of points in L_2 -Marcinkiewicz-Zygmund inequalities

Felix Bartel

Katholische Universität Eichstätt-Ingolstadt, Germany

In recent years, significant progress has been made in the study of L_2 Marcinkiewicz-Zygmund (MZ) inequalities. General constructions achieve either the minimal number of required sampling points or optimal approximation precision/constants, with a trade-off between these extremes. In this paper, we bound the required number of points in terms of the approximation precision of the L_2 MZ inequality for general function spaces. In particular, we construct a hard-to-discretize function space using equiangular tight frames. Our lower bound matches the behavior of existing constructions in the high-approximation-precision regime and captures the correct qualitative trade-off across the full range of approximation precision.

Thermodynamics-informed Neural Networks (THINNs)

Javier Castro and Benjamin Gess

Technische Universität Berlin, Germany

Physics-Informed Neural Networks (PINNs) are a class of deep learning models aiming to approximate solutions of PDEs by training neural networks to minimize the residual of the equation. Focusing on non-equilibrium fluctuating systems, we propose a physically informed choice of penalization that is consistent with the underlying fluctuation structure, as characterized by a large deviations principle. This approach yields a novel formulation of PINNs in which the penalty term is chosen to penalize improbable deviations, rather than being selected heuristically. The resulting thermodynamically consistent extension of PINNs, termed THINNs, is subsequently analyzed by establishing analytical a posteriori estimates, and providing empirical comparisons to established penalization strategies.

Parameter Identification using Physics-Informed Neural Networks

Linéll Dehne

University of Greifswald, Germany

Numerical methods to solve complex Partial Differential Equations (PDEs) often reach their limits, e.g. for higher dimensions, or when the discretization of space and time becomes expensive. Raissi et al. introduce Physics-Informed Neural Networks (PINNs), where the loss function of simple feed-forward neural networks incorporates the PDE as a residual loss, encouraging the solution to satisfy the physics governed by the PDEs. Using PINNs, one can solve PDEs based on initial conditions, boundary conditions and inputs given by spatial and temporal coordinates. This is the forward problem. By slightly adapting these networks, one can feed a discretized solution to the network and recover PDE parameters that otherwise would be guessed or approximated. This is the inverse problem. We define both the forward and inverse problem for the Landau–Lifshitz–Gilbert equation (LLG equation), a nonlinear PDE describing the precession of magnetic moment vectors. The Gilbert damping is a key parameter of the LLG equation. It is often experimentally approximated, which is expensive. We present first results indicating that PINNs can recover this parameter from a discretized solution.

Keywords: PINNs, PDEs, parameter identification, inverse problems, LLG equation, machine learning

Learning-based Approach for Online State Estimation with Error Certification

Markus Bachmayer¹, Wolfgang Dahmen^{1,2}, Chenguang Duan¹, Mathias Oster¹

¹*RWTH Aachen University, Germany*

²*University of South Carolina, Mathematics Department, USA*

We develop a variationally consistent framework for learning the measurement-to-state map arising in inverse problems via deep neural networks. Two families of loss functionals are considered: least-squares losses and residual-based losses, each accommodating data of varying fidelity. For both formulations, we provide explicit characterizations of the optimal recovery map that minimizes the respective loss functional. We further derive a priori error bounds for the learned recovery map that quantify the interplay between the approximation capacity and complexity of the hypothesis class of neural networks and the number of available training samples. The analysis reveals how these competing factors govern the overall reconstruction error and provides guidance for the practical design of network architectures and training regimes. This is joint work with Prof. Dr. Markus Bachmayr, Prof. Dr. Wolfgang Dahmen, and Prof. Dr. Mathias Oster.

Kolmogorov Widths and Kernel Approximation of Koopman Operators

Maximiliano Hertel

Technische Universität Ilmenau, Germany

Kernel Extended Dynamic Mode Decomposition (kernel EDMD) is a popular method for approximating Koopman operators in reproducing kernel Hilbert spaces, where existing convergence analyses typically rely on kernel interpolation arguments. In this talk, we present an approximation-theoretic perspective on kernel EDMD by showing that it realizes a best approximation among all reconstruction operators based on point evaluations. This characterization establishes a direct connection to sampling recovery and makes available a broad range of results from approximation theory, including error bounds in terms of sampling and Kolmogorov widths.

For reproducing kernel Hilbert spaces realizing isotropic Sobolev spaces, we show how known estimates for periodic Kolmogorov widths can be transferred to bounded Lipschitz domains, yielding explicit convergence rates under suitable Koopman invariance assumptions. We then discuss extensions to spaces of dominating mixed smoothness, where the multivariate chain rule leads to a quantifiable loss of regularity that determines the resulting approximation rates.

From Oversampling to Optimal Sampling: Constructive Subsampling for Bandlimited Signal Recovery

Rohan Joy

Technical University of Munich, Germany

We discuss the problem of subsampling bandlimited functions that are essentially concentrated on a bounded region. Standard random sampling methods typically require $(r \log r)$ samples, where (r) is the effective prolate dimension associated with the concentration region. The main goal is to reduce this to the optimal order (r) , while still retaining stable reconstruction guarantees.

The talk first explains why an $(O(r))$ -sample result can be obtained using prolate subspaces and Batson–Spielman–Srivastava type sparsification. We then discuss possible ways of making such sampling constructions more explicit and computationally faster, together with the structural properties needed for these methods to work.

Finally, we describe how reconstruction can be performed from the selected samples, for example through least-squares reconstruction in the relevant finite-dimensional prolate space, and discuss the stability and numerical aspects of this approach.

Randomized approximation based on (non-)adaptive linear measurements

Robert J. Kunsch (joint work with Marcin Wnuk)

RWTH Aachen University, Germany

We study the information-based complexity of approximating linear problems based on arbitrary linear measurements. In the deterministic worst case setting it was long known that adaptive information is essentially no better than simpler non-adaptive information. In the randomized setting (Monte Carlo), however, recent results on the approximation of high-dimensional vectors reveal that adaption may significantly reduce the error for some problems. These results rely on new lower bounds for non-adaptive methods in combination with new upper bounds obtained for adaptive approximation. We also found improved non-adaptive randomized approximation methods.

Stability of Second-Order Sigma-Delta Quantization via Trajectory Analysis

Alessandro Lupoli

Technical University of Munich, Germany

Sigma-Delta ($\Sigma\Delta$) quantization is a state-of-the-art technique for digitally representing bandlimited signals. To encode the samples (y_n) of a signal f , $\Sigma\Delta$ schemes sequentially select a bit sequence (q_n) guided by an internal state sequence (v_n) that evolves according to the recurrence relation:

$$v_n = (h * v)_n + y_n - q_n,$$

where h is a causal filter, i.e., $h_j = 0$ for $j \leq 0$, and $q_n = \text{sign}((h * v)_n + y_n)$. Key to the accurate reconstruction of the signals is the stability of the scheme, i.e., the state sequence must be uniformly bounded, which is ensured if $\|h\|_{\ell^1} + \|f\|_{\infty} \leq 2$. While this sufficient criterion mathematically guarantees stability, numerical experiments consistently show that it is overly conservative and that stability holds under much milder conditions.

In this talk, we address this issue for a class of second-order $\Sigma\Delta$ schemes by establishing the first stability guarantees that improve upon the classical criterion. Instead of attempting to characterize complex, high-dimensional invariant sets for this dynamical system—a task that quickly becomes intractable for longer filters—our key insight is to directly analyze the trajectories of the state sequences. We prove that the filter length required for guaranteed stability improves quadratically, reducing the classical requirement of $\mathcal{O}\left(\frac{1}{1-\|f\|_{\infty}}\right)$ down to $\mathcal{O}\left(\frac{1}{\sqrt{1-\|f\|_{\infty}}}\right)$.

This talk is based on joint work with Rohan Joy and Felix Krahmer.

Fourier Gelfand numbers of dominating mixed smoothness spaces

Moritz Moeller

Chemnitz University of Technology, Germany

Fourier Gelfand numbers were first conceived in [1] describe the best possible approximation of a function using only Fourier information. This additional restriction on the Gelfand numbers closely models MRI and CT measurements. They have the additional benefit that, in many cases, they are easier to study than the Gelfand numbers. We show upper bounds for the Fourier Gelfand numbers of dominating mixed smoothness spaces Besov spaces via RIP bounds that allow us to control the L_2 by the L_1 -norm. This enables us to achieve rates that are optimal in the main rates with only small logarithmic gaps compared to the Gelfand numbers.

References

- [1] Jonathan W. Siegel: Nearly optimal bounds on the Fourier sampling numbers of Besov spaces, arXiv, 2025, 2508.13991.

Infinite sequences with optimal worst-case error decay of QMC-rules for periodic functions

Nicolas Nagel

Johannes Kepler Universität Linz, Austria

We consider the problem of determining infinite sequences $\mathcal{S}_d = \{\mathbf{x}^0, \mathbf{x}^1, \dots\}$ in the d -dimensional torus $\mathbb{T}^d$ for the purpose of quasi-Monte Carlo (QMC) integration algorithms. Concretely, we aim to give asymptotically optimal constructions as to minimize the worst-case error

$$\text{wce}(\mathcal{S}_{d,N}, S_{p,q}^r B(\mathbb{T}^d)) = \sup_{\|f\|_{S_{p,q}^r B(\mathbb{T}^d)} \leq 1} \left| \int_{\mathbb{T}^d} f(\mathbf{x}) \, d\mathbf{x} - \frac{1}{N} \sum_{k=0}^{N-1} f(\mathbf{x}^k) \right|$$

over a Besov space $S_{p,q}^r B(\mathbb{T}^d)$ of dominating mixed smoothness $r > 1/p$. The case of $(r, p, q) = (1, 2, 2)$ corresponds to the notion of periodic L_2 -discrepancy, for which order-5 digital sequences are known to yield the optimal behavior. Using characterizations of the above Besov spaces in the range $1/p < r < 2$ via the Faber basis, we show that order-2 sequences already suffice for this purpose, reducing the complexity and improving the practicality of the constructions. For such sequences we show that

$$\text{wce}(\mathcal{S}_{d,N}, S_{p,q}^r B(\mathbb{T}^d)) \lesssim \begin{cases} (\log N)^{(d-1)(1-1/q)} N^{-\min\{1,r\}}, & r \neq 1 \\ (\log N)^{d(1-1/q)} N^{-1}, & r = 1. \end{cases}$$

Joint work with Peter Kritzer and Friedrich Pillichshammer.

Certified Posterior Sampling for Bayesian Inverse Problems via Flow Matching and Metropolization

Moritz Poguntke (joint work with Jan Blechschmidt, Oliver Ernst, Björn Sprungk)

Chemnitz University of Technology, Germany

Sampling from the posterior distribution is the central computational task of Bayesian inverse problems. Traditionally, this is addressed using Markov chain Monte Carlo (MCMC) methods, which are inherently sequential, produce correlated samples, and require computationally expensive forward model evaluations for every new observation. Recently, Bayesian Flow Matching (FM) has emerged as a promising amortized alternative, utilizing neural ordinary differential equations to encode posteriors for all observations into a single transport map.

While FM can generate independent, parallel samples at negligible online cost, standard implementations lack the computable accuracy guarantees required for rigorous uncertainty quantification. To bridge this gap, particularly for PDE-based problems with function-valued parameters, we equip the method with strict accuracy certificates. By utilizing the tractable density of the flow matching model as a proposal within an Independent Metropolis-Hastings (IMH) scheme, we derive valid bounds on both the Total Variation distance and the Kullback-Leibler divergence between the learned and true posteriors. Furthermore, this IMH framework serves as a hybrid sampler that restores asymptotic exactness, trading approximation error for mixing speed. We systematically validate these certificates against strong MCMC baselines on problems of increasing realism: function-space heat diffusion, electrical impedance tomography (EIT), and a likelihood-free stochastic Lotka-Volterra model.

Order of approximation for orthonormal shift-invariant spaces: a Taylor coefficient characterization, Strang-Fix conditions and polynomial reproduction

Moritz Proell

Universität Passau, Germany

We study the approximation order of orthonormal shift-invariant spaces in $L^2(\mathbb{R})$ generated by a single function φ . In the classical theory, the approximation order is equivalent to Strang-Fix conditions and exact polynomial reproduction, but only under additional assumptions such as stable shifts or compact support. We remove these assumptions entirely. Our main result shows that, for any orthonormal generator φ with $x \mapsto x^k \varphi(x) \in L^1(\mathbb{R})$ and $\hat{\varphi} \in C^{k+1}$ near the origin, approximation order k is equivalent to polynomial reproduction via explicit Taylor coefficient conditions on $\hat{\varphi}$ at 0 combined with Strang-Fix conditions. The proof relies on a polynomial reproduction result under mild assumptions and on a Taylor-coefficient characterization of the approximation order. We also prove that the approximation order is invariant under unitary convolution operators, including the Hilbert transform, yielding examples of generators with high approximation order but without compact support.

A Nonlinear Second Order Problem Involving Nonlocal Diffusion For Image Processing

Khadija Sadik

EST Essaouira, Cadi Ayyad university, Marrakech, Morocco

The primary objective of image denoising is to remove noise while preserving important image features. Classical PDE-based image restoration methods [2, 4] mainly rely on local information, which may lead to the loss of fine details. To address this limitation, nonlocal diffusion approaches have been developed thanks to their ability to better preserve textures and image structures [3, 5]. The proposed model [1] is derived by interpreting the dynamics of image processing as damped elastic deformation. This approach, which combines a second-order nonlinear equation with a nonlocal mechanism, allowing for a more efficient and faster denoising process. We establish the existence and uniqueness of the proposed model using Schauder's fixed point theorem. Its effectiveness is then demonstrated through image denoising experiments and comparisons with several state-of-the-art methods from the literature.

Joint work with: Fatiha Bendaïda, Fahd Karami, Driss Meskine, Lamia Ziad

References

- [1] F. Bendaïda, F. Karami, D. Meskine, K. Sadik, and L. Ziad, A second-order nonlinear problem involving nonlocal diffusion for image processing. Computational and Applied Mathematics, 45(8):352, 2026. doi: 10.1007/s40314-026-03747-9.
- [2] F. Catté, P.-L. Lions, J.-M. Morel and T. Coll, Image Selective Smoothing and Edge Detection by Nonlinear Diffusion. SIAM Journal on Numerical Analysis, 29(1):182–193, 1992. doi: 10.1137/0729012.
- [3] F. Karami, K. Sadik and L. Ziad, A variable exponent nonlocal $p(x)$ -Laplacian equation for image restoration. Computers & Mathematics with Applications, 75(2):534–546, 2018. doi: 10.1016/j.camwa.2017.09.034.
- [4] P. Perona and J. Malik, Scale-Space and Edge Detection Using Anisotropic Diffusion. IEEE Transactions on Pattern Analysis and Machine Intelligence, 12(7):629–639, 1990. doi: 10.1109/34.56205.
- [5] K. Shi, Image denoising by nonlinear nonlocal diffusion equations. Journal of Computational and Applied Mathematics, Vol. 395, Article 113605, 2021. doi: 10.1016/j.cam.2021.113605.

On low-rank tensor train approximability for linear nearest neighbor systems

André Uschmajew

University of Augsburg, Germany

Low-rank tensor methods are an important tool in the numerical treatment of equations with a high-dimensional state space. Nearest neighbor interaction systems like the Ising model or more general Markov jump processes, as well as 1D finite-state quantum systems are examples of such problems. While low-rank tensor train/matrix product state models have been shown to be highly efficient for the simulation of such systems, providing theoretical justification for this remains a challenging task. One approach for obtaining estimates on required ranks for certain accuracies is to investigate the rank increase in Krylov subspace methods for solving the problem at hand. Nontrivial results of this kind have been obtained in theoretical physics for ground states of 1D spin systems based on the partial commutativity of local operators. In this talk, we explain how this technique can be applied to linear equations and ODEs with nearest neighbor structure in order to derive corresponding low-rank approximability statements. Numerical simulations of high-dimensional nearest neighbor systems illustrate the theoretical findings.

Learning Multi-Pool Dynamics in Magnetic Resonance Imaging

Štěpán Zapadlo

University of Graz, Austria

Magnetic Resonance Imaging (MRI) is a key non-invasive imaging modality offering large versatility in creating high-resolution images. Reconstructing MR images from measurements requires knowledge of the MR physics involved in the measurement process, which are highly complex (e.g., involving quantum-mechanical effects) and are commonly modeled via the Bloch equations. Recent investigations have shown that the consideration of multi-pool models using Bloch-McConnell equations are beneficial, however, the related physics are still not fully understood.

We address the challenge of uncovering hidden physics in MRI through a structured model learning approach. Specifically, we build upon the fundamental Bloch model and propose its extension with a potentially non-linear source term that captures the unknown dynamics associated with the multi-pool structure of the Bloch-McConnell model. The source term is formulated as a recurrent neural network with a highly interpretable architecture, strongly inspired by principles derived from the Bloch-McConnell model. We demonstrate the versatility and generalizability of the proposed framework and evaluate the learning process using artificially generated data in a multi-pool setting.