LEVERAGING COORDINATE-BASED NEURAL REPRESENTATIONS WITH MATRIX GROUPS FOR NON-RIGID IMAGE REGISTRATION

JOHANNES BOSTELMANN

Coordinate-based neural representations are powerful tools used in Physics-Informed Neural Networks (PINNs) for solving partial differential equations and in neural fields for vision tasks. This neural architecture can effectively parameterize deformation fields within non-rigid 3-D image registration. Identifying a sufficiently expressive and adaptable parameterization for subsequent optimization is essential to achieve reasonable deformations.We analyze the impact of ensuring diffeomorphic deformations by integrating a stationary velocity flow and evaluate the effect of the parameterization on 3D medical data.

ADDRESSING CLASS UNBALANCE IN TRANSDUCTIVE FEW-SHOT LEARNING

SÉGOLÈNE MARTIN

In this talk, we will explore the challenges and limitations of existing few-shot learning benchmarks and introduce a more flexible and realistic approach. Traditional benchmarks often rely on assumptions that don't always align with real-world scenarios, such as class balance, limiting their effectiveness.
Addressing this, we present a new formulation, the PrimAl Dual Minimum Description LEngth (PADDLE), which offers a composite optimization-based approach to handling data accuracy and model complexity. This method fosters competition among a vast range of possible classes, ensuring only the most relevant are retained for a task. Notably, PADDLE is hyperparameter-free and highly adaptable to various training bases. We will also discuss a developed algorithm for minimizing the loss function, which guarantees convergence and offers computational efficiency. Finally, comprehensive experiments demonstrate the effectiveness of the method.

LEARNING FROM SMALL DATA SETS: PATCH-BASED REGULARIZERS IN INVERSE PROBLEMS FOR IMAGE RECONSTRUCTION

MORITZ PIENING

The solution of inverse problems is of fundamental interest in medical and astronomical imaging, geophysics as well as engineering and life sciences. Recent advances were made by using methods from machine learning, in particular deep neural networks. Most of these methods require a huge amount of (paired) data and computer capacity to train the networks, which often may not be available. Our paper addresses the issue of learning from small data sets by taking patches of very few images into account. We focus on the combination of model-based and data-driven methods by approximating just the image prior, also known as regularizer in the variational model. We review two methodically different approaches, namely optimizing the maximum log-likelihood of the patch distribution, and penalizing Wasserstein-like discrepancies of whole empirical patch distributions. From the point of view of Bayesian inverse problems, we show how we can achieve uncertainty quantification by approximating the posterior using Langevin Monte Carlo methods. We demonstrate the power of the methods in computed tomography, image super-resolution, and inpainting. Indeed, the approach provides also high-quality results in zero-shot super-resolution, where only a low-resolution image is available.

EMPIRICAL BAYESIAN ESTIMATION FOR PLUG & PLAY WITH ACCELERATED DEEP GENERATIVE MODELS AS PRIORS

CHARLESQUIN KEMAJOU

Bayesian Plug & Play (PnP) priors are widely acknowledged as a robust framework that combines Bayesian inference with powerful denoising algorithms to address a variety of inverse problems in imaging. These PnP methods have made tremendous advances in recent years, resulting in state-of-the-art methods. while PnP priors have been distinguished by their ability to regularise Bayesian inverse problems through a denoising algorithm, incorporating a deep generative model as a prior significantly impact the computationally effort of the method. Additionally, setting the amount of regularity enforced by the prior, determined by the noise level parameter of the denoiser, has been a challenge for several reasons. The main novelty of this talk is that we develop an empirical Bayesian PnP approach, using an accelerated deep-generative model as priors. Furthermore, the resulting method directly calibrates the regularisation parameter directly from the observed data through the maximum marginal likelihood estimation (MMLE). Experimental results across three image restoration tasks, including image deblurring, inpainting, and super-resolution, demonstrate that our proposed method achieves state-of-the-art performance.

CONVERGENT BREGMAN PLUG-AND-PLAY IMAGE RESTORATION FOR POISSON INVERSE PROBLEMS

ARTHUR LECLAIRE

Plug-and-Play (PnP) methods are efficient iterative algorithms for solving ill-posed image inverse problems. PnP methods are obtained by using deep Gaussian denoisers instead of the proximal operator or the gradient-descent step within proximal algorithms. Current PnP schemes rely on data-fidelity terms that have either Lipschitz gradients or closed-form proximal operators, which is not applicable to Poisson inverse problems. Based on the observation that the Gaussian noise is not the adequate noise model in this setting, we propose to generalize PnP using the Bregman Proximal Gradient (BPG) method. BPG replaces the Euclidean distance with a Bregman divergence that can better capture the smoothness properties of the problem. We introduce the Bregman Score Denoiser specifically parametrized and trained for the new Bregman geometry and prove that it corresponds to the proximal operator of a nonconvex potential. We propose two PnP algorithms based on the Bregman Score Denoiser for solving Poisson inverse problems. Extending the convergence results of BPG in the nonconvex settings, we show that the proposed methods converge, targeting stationary points of an explicit global functional. Experimental evaluations conducted on various Poisson inverse problems validate the convergence results and showcase effective restoration performance.

TRAINING GRAPH NEURAL NETWORKS SUBJECT TO A TIGHT LIPSCHITZ CONSTRAINT

JUVISA SIMONA

We propose a strategy for training a wide range of graph neural networks (GNNs) under tight Lipschitz bound constraints. Specifically, by leveraging graph spectral theory, we derive computationally tractable expressions of their Lipschitz constant. This allows us to propose a constrained-optimization approach to control the constant, ensuring robustness to adversarial perturbations. Unlike the existing methods for controlling the Lipschitz constant, our approach reduces the size of the handled matrices by a factor equal to the square of the number of nodes in the graph. We employ a stochastic projected subgradient algorithm, which operates in a block-coordinate manner, with the projection step performed via an accelerated iterative proximal algorithm. We focus on defending against attacks that perturb features while keeping the topology of the graph constant. This contrasts with most of the existing defenses, which tackle perturbations of the graph structure. We report experiments on various datasets in the context of node classification tasks, showing the effectiveness of our constrained GNN model.