My previous research aimed to combine a data driven method with model based ones for signal processing and inverse problem. Traditionally people first design a mathematical model to describe the physic laws behind the problem before computation. With the emerging machine learning techniques people tend to use a black-box neural network learned from data without understanding the underlying physics. My dream is to converge these two methodologies and to build data-driven model with both great predictive performance and theoretical guarantee to address inverse problems in signal processing, graphics and other related areas. I hope to combine methods in different areas, like (stochastic)differential equation, optimization and machine learning, and use methodology in one area to promote the research in another. My undergraduate research is my initial attempt under this motivation and can be summarized in the following aspects

Combine Traditional Computational Methods and Deep Learning. My research starts from the idea that considering the neural network as a continuous dynamic system via turning the layer index into time.[1] We show that many effective networks can be interpreted as different numerical discretization of differential equations and using stochastic differential equation to characterize dropout like training method in deep learning . This finding brings us a new perspective on the design of effective deep architectures. From this perspective, we utilize the linear multistep scheme to design a new network and explain the performance boost via a second order modified equation. We also apply this idea to image processing via learning an terminal time for different noise level input[3].

Deep Learning Based Physic Based Simulation. We aim to combine deep learning and traditional numerical scheme to have the most flexibility by learning both differential operators and the nonlinear response function of the underlying PDE model, while preserving the transparency.[2] We also want to apply this method to graphics turbulent simulating and real physic related data. I firmly believe that other learning techniques can be applied in this area to help combine physic laws and observed big data.

Geometry View Of Sparse Representation And PDEs For Manifold Learning. [4] Previous works have point out a Gamma convergence relationship between wavelet-based image processing model and total variation models as an image's resolution increases. I proposed a Gamma convergence result for a modified ell_0 wavelet analysis model to the Mumford-Shah model, which reveals a geometry view of the sparsity – a measure of the non-Lebesgue points. I'm also working on pushing this framework to semi-supervised learning, which aims to perform an extension by solving a PDE or a wavelet sparsity based method.

Appendix

[1] Yiping Lu, AoxiaoZhong, Quanzheng Li, Bin Dong. "Beyond Finite Layer Neural Network:Bridging Deep Architects and Numerical Differential Equations" Thirty-fifth International Conference on Machine Learning (ICML), 2018

[2] Zichao long*, Yiping Lu*, Xianzhong Ma*, Bin Dong. "PDE-Net:Learning PDEs From Data",Thirty-fifth International Conference on Machine Learning (ICML), 2018(equal contribution)

[3] Xiaoshuai Zhang*, Yiping Lu*, Jiaying Liu, Bin Dong. "Dynamically Unfolding Recurrent Restorer: A Moving Endpoint Control Method for Image Restoration" preprint(*equal contribution) arXiv: 1805.07709

[4] Bin Dong, Ting Lin, Yiping Lu, Zuowei Shen. " A New Edge Driven Wavelet Frame Image Restoration Model: The Mumford–Shah functional, Unnatural Zero Norm Minimization And Beyond" In Preparation(*equal contribution)(Alphabetical Order.)