Hui-Ling Zhen | Curriculum Vitae

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Undergraduate Applied Mathematics and Nonlinear Dynamics during the first doctoral time in Department of Mathematics, Beijing University of Posts and Telecommunications. After I got my first Ph.D in 2016, I started the theoretical researches on inverse problems and multi-objective optimization with the help of statistical inference, deep learning and mathematical means, such as learning algorithms, portfolio decision making and surrogate modeling. This year, my co-workers in City University of Hong Kong and I propose a new framework "learning to guide", in which we firstly obtain the nonlinear generalization of homotopy algorithm, for non-convex optimization and multi-task learning, and such framework is also proved to work well for "learning from small ". Passionate about science, curious about the connection among mathematics, collaboration, risk and neural networks, with strong computational technical, solid theoretically mathematical foundation and interpersonal skills for working in a team or completing a project. I'm open to any interesting questions with respect to modeling, equations, networks and optimization under uncertainty, and I always love high-efficient brainstorm and overworking. I want to apply for a second Ph.D on Quantitative Risk, including but not limited on risk and criticality as well as optimization under uncertainty, not only for the systematic studies, but also for a much longer and more dedicated time to do the researches via mathematics, physics and neural networks.

Recent Employment

- **Visiting Postdoctoral Fellow** — **City University of Hong Kong**
  September 2017 – October 2017

  Qing-Fu Zhang (IEEE Fellow) and I focus on how nonlinear collaboration work for the portfolio decision making, surrogate modeling and deep learning. With the help of statistical inference and multi-objective optimization, we propose a nonlinear homotopy algorithm, where the framework "Learning To Guide" can be used for the non-convex optimization problem and multi-task learning on attacking saddle points. Introducing the knowledge on the smaller/easier dataset, we give a new algorithm for transfer learning, and a lower bound from Fisher metric is firstly given to show when transfer doesn't work. Our distance collabortion and discussion started at March 2017.

- **Postdoctoral Fellow** — **Chinese Academy of Science**
  July 2016– August 2017

  I concentrate upon the inverse problem and multi-objective optimization problems during the postdoctoral time. On inverse problems, I mainly work on the theoretical researches on better learning algorithms and critical structure via statistical inference and mathematical means. Meanwhile, I also work on "learning to optimize" via neural networks, leading to the finding that the natural spatial structure can help to find the critical phenomena like phase transitions, symmetry breaking and chaos during optimization, with the help of distance discussion with Qing-Fu Zhang's Research Group in Hong Kong.

- **Scientist (Deep Learning)** — **Swarm Agents Club**
  April 2016–Now

  I focus on the critical problems, stochastic modeling and optimization under uncertainty here. Based on statistical inference and mathematical means as well as neural networks, I hope to make the bridge among collaboration, risk and criticality clear during optimization and network learning especially for the uncertain cases. My co-workers and I hope to open the black box of nonlinear collaboration and global optimization, sequential decision making and risk in the view of critical information and networks.

Education

Academic Qualifications

- **Beijing University of Posts and Telecommunications** — **Ph.D**
  Physical Electronics , School of Science, Department of Mathematics — *2011–2016*
- **Harbin Normal University** — **BA**
  Computational Mathematics, School of Science, Department of Mathematics — *2007–2011*

Awards and Fundings

- RIKEN Brain Science Institute Foundation, June 2017, and an oral presentation named "Combinational Learning and Surrogate Modeling For Sequential Networks".
- China Postdoctoral Science Foundation under Grant No.2017M610116, 2017, "Learning and Memory For Bayesian Optimization"
- Beijing University of Posts and Telecommunications Excellent Ph.D. Students Foundation under Grant No.CX201422, 2014-2015. "Criticality and Phase Transitions in Stochastic Nonlinear Partical Differential Equations".
- "Academic Star" in 9th and 10th in Beijing University of Posts and Telecommunications, 2013 and 2014.
- Second Prize, China Undergraduate Mathematical Contest in Modeling, 2010. "Tracking Moving Boundary Under Gaussian White Noise "

Technical and Personal skills

- **Programming Languages:** Proficient in: MATLAB and Python, Familiar with some deep learning frameworks, such as Tensorflow, Theano and Keras.
- **Language:** Fluent English, Native Chinese, Learning German.

Publications

So far, there have been 18 first-author papers and 20+ co-author papers published on mainstream SCI journals and 4 forthcoming ones, and the researches involve the nonlinear dynamics, neural networks, surrogate modeling and boundary optimization.

Hui-Ling Zhen's Google Scholar

Website: `https://scholar.google.com.hk/citations?user=gq29DtwAAAAJ&hl=zh-CN`

Selected Publications

- Hui-Ling Zhen, Bo Tian, Wen-Rong Sun, Dynamics of an integrable Kadomtesv-Petviashvili-based system, Appl. Math. Lett., 27, 90 (2014).
- Hui-Ling Zhen, Bo Tian, et.al, Dynamics of Zakharov-Kuznetsov-Burgers equations in dusty plasmas, Phys. Plasmas, 20, 082311 (2013).
- Hui-Ling Zhen, Bo Tian, et.al, Dynamics of the quantum Zakharov-Kuznetsov equations in dense quantum magnetoplasmas, Phys. Plasmas, 21, 012304 (2014).
- Hui-Ling Zhen, Bo Tian, et.al, Soliton solutions and chaotic motion of the extended Zakharov-Kuznetsov equations in a magnetized two-ion-temperature dusty plasma, Phys. Plasmas, 21, 073709 (2014).
- Hui-Ling Zhen, Bo Tian, et.al, Soliton solutions and chaotic motions for the Langmuir wave in the plasma, Phys. Plasmas, 21, 032307 (2015).
- Hui-Ling Zhen, Bo Tian, et.al, Solitons and chaos of the Klein-Gordon- Zakharov in a high-frequency plasma, Phys. Plasmas, 22, 102304(2015).
- Hui-Ling Zhen, Bo Tian, et.al, Dynamics behaviors and soliton solutions of the modified Zakharov-Kuznetsov equation in the electrical transition line, Comput. Math. Appl., 68, 579 (2014).

- Hui-Ling Zhen, Bo Tian, et al., Soliton-like solutions and chaotic motions for a forced and damped Zakharov-Kuznetsov equation in a magnetized electron-positron-ion plasma, J. Plasma Phys., 81, 905810515, (2015).
- Hui-Ling Zhen, Bo Tian, et al.. Soliton solutions and chaotic motions for the (2+1)-dimensional Zakharov equations in a laser-induced plasma. Compt. Math. Appl., 71, 1337 (2016).
- Hui-Ling Zhen, Bo Tian, et al., Soliton solutions and interaction of the generalized (3+1)-dimensional Schrodinger equation in cosmic plasmas, Comput. Math. Math. Phys., 54, 503 (2014).
- Hui-Ling Zhen, Bo Tian, et al., Soliton interaction of the Zakharov-Kuznetsov equation in plasma dynamics, International J. Mod. Phys. B, 27, 1350029 (2013).
- Hui-Ling Zhen, Bo Tian, et al., Optical-soliton and chaotic motions in a nonlocal nonlinear medium, J. Mod. Opt., 63, 902 (2016).
- Hui-Ling Zhen, Bo Tian, et al., Solitonic and chaotic behaviors for the nonlinear dust-acoustic waves in a magnetized dusty plasma. Phys. Plasmas, 23, 052301(2016) 14.Hui-Ling Zhen, Bo Tian, et al., Solitonic and chaotic behaviors of a (3+1)-dimensional Schrodinger equation in a magnetized electron-positron-ion plasma, Astrophys. Space Sci., 357, 1 (2015).
- Hui-Ling Zhen, Bo Tian, et al., Dynamic behavior of the incoherent optical spatial solitons in a nonlocal nonlinear medium, J. Mod. Opt., 62, 793 (2015).
- Hui-Ling Zhen, Bo Tian, et al., Dynamic behavior of the (3+1)-dimensional generalized Johnson model in a dusty plasma, J. Plasma Phys., 81, 905810113 (2015).
- Wen-Rong Sun, Bo Tian and Hui-Ling Zhen, Optical rogue waves associated with the negative coherent coupling in an isotropic medium. Phys. Rev. E, 91, 023205 (2015).
- Wen-Rong Sun, Bo Tian and Hui-Ling Zhen, Breathers and rogue waves of the fifth-order nonlinear Schrodinger equation in the Heisenberg ferromagnetic spin chain. Nonlinear Dynamics, 81, 725 (2015).
- Wen-Rong Sun, Bo Tian, Hui-Ling Zhen, Lax pair, conservation laws and solitons for a (2+1)-dimensional fourth-order nonlinear Schrodinger equation governing an α-helical protein. Ann. Phys., 362, 671 (2015).
- Hui-ling Zhen, Zhen-Yu Tang. Bayesian recovery of compressed images using priors from deep neural networks. Accepted by the workshop of "Neural Information Processing Systems".

Reviewed Papers

There are 2 reviewed first-author paper on the learning algorithm and boundary decision making, combining the statistical physics, deep learning with neural science.

- Hui-Ling Zhen, Zhen-Yu Tang and Yan-Ran Li. Mean-field learning of deep Boltzmann machines. Submitted to " International Conference On Learning Representations" 2018.
- Hui-Ling Zhen and Zhen-Yu Tang. Unsupervised Learning and Boundary Decision Making for An Associated Memory Model. Reviewed by "Physical Review E".

Working Papers

There are 7 working papers on the surrogate modeling, portfolio decision making and nonlinear/stochastic dynamics, combining the learning algorithm,

- Hui-Ling Zhen, Hui-Min Yin and Bo Tian. " Learning Soliton Solutions For Stochastic Burgers-Like Equations Under Gaussian White Noise". In Preparation
- Hui-Ling Zhen, Qian-Yuan Tang and Zhen-Yu Tang. "On the Criticality and Phase Transitions in Compressed Sensing With Noisy Measurements" . In Preparation
- Xi Lin, Hui-Ling Zhen, Qing-Fu Zhang and Zhen-Hua Li. " Escaping From Saddle Points: New Framework Based On Nonlinear Collaboration". Preparing for International Conference on Machine Learning.
- Hui-Ling Zhen, Xi Lin and Qing-Fu Zhang. "MOEA/D For Compressed Sensing Via Network Learning ". In Preparation.
- Hui-Ling Zhen, Xi Lin, Qing-Fu Zhang and Zhen-Hua Li. "Learning To Guide: How Nonlinear Homotopy Work For Optimization". Preparing for IEEE Transactions on Neural Networks and Learning Systems.
- Hui-Ling Zhen, Xi Lin, Qing-Fu Zhang and Zhen-Hua Li. "Nonlinear Homotopy For Transfer Learning: From Optimization To Learning And Phase Transitions". Preparing For Neural Information Processing Systems.
- Xi Lin, Hui-Ling Zhen and Qing-Fu Zhang. "Learning For Surrogate Modeling: A Dynamic Computational

Portfolio Design Procedure For Multi-Objective Optimization". In Preparation.

Research Experience

All of my works can be divided into three parts, including Partial Differential Equations (PDEs) (including nonlinear ones and stochastic ones), neural networks, and multi-objective optimization. Details in contents are listed below:

(i) Nonlinear analysis as well as stochastic partial differential equations:

Series of challenging projects took place on this issue over my first doctoral time. I focused on the analytic and numerical solutions for nonlinear PDEs and stochastic PDEs, leading to more accurate analysis on the solitonic solutions, chaos/bifurcations, criticality and nonlinear Hamiltonian for corresponding models.

- **Nonlinear Dynamics for α-helical protein, plasmas and optics** *(Done)*
  With the help of such analytic approaches as Lax pair and bilinear transformation, solitonic solutions and properties in plasmas, optics and α-helical protein have been discussed. Chaotic motions and nonlinear control have also been obtained with consideration on white noise. Most interesting things happen when I realized that bifurcation and chaos are not always harmful to some special phenomena, leading to that some ill-conditioned equations can bring about the better solutions. Chaotification and bifurcations have been studied on dark solitons and security communication. Characteristics on the criticality in certain dynamical systems have been shown. In this project, I'm responsible for all the analytical and numerical computations. Related papers in this direction can be seen in the publication list.
- **Solving Stochastic Nonlinear Partial Differential Equations (PDEs) Under White Noise** *(Done)*
  This research is initially motivated by the quantitative analysis, rather than the qualitative analysis, on the thermal fluctuations and critical conditions for bifurcations/chaos under noise. My goal is to show the difference between chaos and stochastic motions in certain physical phenomena and extend the non-stochastic analytic approaches to a stochastic equation via Ito integral, martingale and special operator. Here, the white noise is calculated as the derivative of Brownian motion or the Wiener process. Stochastic soliton solutions for corresponding models have been studied, including the characteristics of propagation and robust. Critical conditions for bifurcations and chaos have been obtained, and the changes of chaotic motions under different conditions, e.g., the driven force is the evolutionary functions or white noise with fixed frequency, have also been explored. In this project, I'm responsible for all the analytical and numerical computations. Related papers in this direction can be seen in the publication list.

During the studies on PDEs, I find that I am interested in the criticality and optimization especially in the uncertain cases, including but not limited to the collaboration with criticality, portfolio with risk, balance between mean and variance, etc. I am curious about how to solve a boundary optimization problem in the view of network, how to learn more and avoid avalanche using collaboration, how to design collaborative algorithm for global optimization, how to measure the risk quantitatively and give the critical condition during decision making under uncertainty, how to find the surrogate modeling or guide function for multi-objective/stochastic optimization, etc. The research experience on nonlinear and stochastic PDEs and criticality for chaos/bifurcations could be quite helpful in the future.

(ii) Neural Networks and Inverse Problems

On this research, I continued to focus on the "criticality" and "optimization" in learning and memory via the approaches in deep learning and statistical inference. For the learning aspect, the research is initially motivated by the observations that the "single-task" learning can be improved by generalizing it to "multi-task" one after introducing a inner loop among all the targets. Based on this, we hope to propose more efficient learning algorithms by the collaboration among different targets and know more about the landscape of deep neural networks. Studies on such inverse problems as compressed sensing or inverse Ising are attractive by the multi-target but conflicted nature. We hope to get the trade-off among the targets in the view of multi-objective optimization by using networks.

- **Structure Of Associated Memory and Decision Making** *(Done)*

  Such research is initially motivated by the observation of phase transition in the memory of a generative model. We firstly find that there exists a “feature to prototype transition" with the nonlinearity of target function increasing, which corresponds to the order-disorder transition and spontaneous magnetization of one- and two-dimensional Ising models under different temperatures. The structure of memory for a generative model then becomes clear through Kronecker product of the memory tensors. We also explain how the flipped probability, numbers of patterns and cluster numbers affect the decision making in the view of generative networks. What is more, such results have been mapped and verified to related issues by research group in University College London in “Sensitivity to Non-Deterministic Pattern Change in Rapid, Stochastic Tone Sequences". Related papers can be seen in publication list.

- **Compressed Sensing Using Networks** *(90% Done)*

  The goal of Compressed Sensing (CS) is to reconstruct a high-resolution image that is sparse in either the ambient domain or some transform basis using few incoherent linear projections. Indeed, performing these incoherent, usually random, projections is a highly non-trivial task, requiring innovative hardware solutions. In this project, generated networks, such as Variational Autoencoder and Convolutional Denoising Autoencoder, had been firstly tried to provide prior for inference, leading to better simulations. It is found that combination between the trained generated networks and approximate message passing works much better than the traditional BM3D on the reconstruction in MNIST, CIFAR-10 and brain/chest MRI images. Related paper is accepted by workshop of NIPS, and I'm responsible for most of the numerical computations. Furthermore, we explore the critical conditions for phase transitions and symmetry breaking in CS, during the reconstruction of dynamics for a weighted network. Based on the multi-objective nature of compressed sensing, we also explore whether the learning can be improved by the collaboration framework like MOEA/D. Related works can be seen in the working papers, and I'm responsible for most numerical simulations and all analytical calculations.

- **Nonlinear Homotopy Algorithm For Saddle Points and Nash Equilibrium** *(90% Done)*

  Training a deep neural network is a high-dimensional non-convex optimization problem, and it is thought that the difficulties come from the existence of saddle points and high-error plateaus, which are common in deep networks. In the practice, we are amazing that the saddle points are observed even in two three-layer shallow networks, like Denoising Auto-encoder and Recurrent Neural Network. What is more, there exists a largest eigenvalue in Hessian matrix while more than half ones are less than 10^{-4}. To tackle the saddle points, we firstly propose a collaborative multi-objective framework, in which two loss functions of a neural network, instead of only one in the traditional setting, are considered. During the optimization process, these two proposed loss functions will be optimized simultaneously in a collaborative manner, rather than a inner loop. From the view of KL divergence, we then prove how such nonlinear collaboration work for saddle points and lead to less reconstruction error. We also design dynamic strategies to let the optimization algorithm efficiently switch between different loss functions. Such framework will also be applied for a zero-sum game theory, where the Nash equilibrium can be seen as saddle points in the view of optimization.

During the researches above, I gradually realize two points: (i) Criticality not only exists in solution space, but also in learning/memory structure even sequential data itself, especially for the uncertain cases. It means that hierarchical learning can not only help for the dynamical behaviors and sequential analysis, it, but also, matters for optimization and modeling. (ii) Learning can be seen as a smooth method for functions, leading to a more easier start for the global/non-convex optimization. It even helps to find a better boundary condition for criticality through the dynamical nonlinear homotopy framework. Thus, during the next doctoral time, I hope to know more about the optimization and stochastic modeling for the risk and uncertainty via the nonlinear/critical computations, combining the neural networks and PDEs.

(iii) Multi-Objective Optimization and Surrogate Modeling Based On Networks

The research is initially motivated by the observations that a “learning-to-learn" framework can be used to speed up the convergence when it is compared to traditional Bayesian optimization. Moreover, according to the study on homotopy algorithm, we argue that the network learning can help to improve the efficiency of non-convex optimization by guided function. In this research, my co-workers and I concentrate upon the multi-objective optimization and surrogate modeling, especially for the cases with noise, in the view of learning.

- **Learning To Guide and Teaching To Learn** *(On-Going)*

  In this research, we firstly propose a nonlinear generalization of homotopy framework for dealing with the training task of neural networks, since it is a non-convex and non-concave optimization problem when the target function is defined as MSE. Supposing that $y(x)$ is the function we want to optimize, we build a strictly decreasing sequence of criterion values from $S_i = \{j \in 1, 2, \cdots, K, g_{\lambda_i}(x_{i,j})\}$. Instead of solving the initial optimization problem which is hard to handle, the principle is to start from a "simple" $H(x)$ (the guided function), and move to the problem of interest, where $\lambda \in [0, 1]$, $g(x)$ is Gaussian noise and $H(x) = [(1-\lambda)f(x)^p + \lambda g(x)^p]^{\frac{1}{p}}$. We prove that such framework can help to escape from some saddle points and reach the better solutions. Generalizing the learning results in a small or easy dataset to a bigger or complex one via introducing the KL divergence as another target, we also propose a "teaching to learn" framework by introducing prior/knowledge more efficiently. Based on this, the bounding of transfer learning or one-shot learning is given. Related works can be seen in the working papers.

- **Learning For Surrogate Modeling Balanced Mean And Variance** *(On-Going)*

  Inspired by the research on the nonlinear homotopy algorithm, we hope to explore the use of Bayesian neural networks as an alternative to Gaussian Processes (GPs) to model distributions over functions. We find that performing adaptive basis function regression with a neural network as the parametric form performs competitively with state-of-the-art GP-based approaches, but scales linearly with the number of data rather than cubically. This allows us to achieve a previously intractable degree of parallelism, which we apply to large scale hyperparameter optimization, rapidly finding competitive models on benchmark object recognition tasks using convolutional networks, and image caption generation using neural language models. Related works can be seen in the working paper.

Although my past research experiences involve the nonlinear dynamics, neural networks, multi-objective optimization as well as surrogate modeling, which are more different than similar, they are the best tools for me to understand optimization and modeling. Most of my completed works concentrate upon criticality and chaos/bifurcations, which provide an analytic view to me to understand some behaviors in finance. My latest works on networks and optimization can give some insights on empirical risk in view of geometry and non-convex optimization. From 2011 to now, PDEs, chaos and neural networks have been changed from the main research objects to main research tools. Owing to the continuous passion on criticality and modeling under uncertainty, and the hope for more systematic and dedicated time on researches, I hope to apply for another Ph.D on quantitative risk, which may include but not limit on the optimization under uncertainty, risk management involving the diversification, concentration and dynamic measures, as well as the dynamic criticality under uncertainty.