

EDUCATION

| | |
|--|---|
| University of Wisconsin-Madison PhD in Statistics | Madison WI, USA 2021/09 – 2026/05 (expected) |
| University of Wisconsin-Madison M.S. in Statistics | Madison WI, USA 2019/09 – 2021/05 |
| Nanjing University B.S. in Mathematics and Statistics – Thesis: “Robust Training of Deep Neural Networks with Noisy Labels” | Nanjing, China 2015/09 – 2019/07 |

RESEARCH INTERESTS

My current research lies in the intersection of applied mathematics and machine learning, with a particular focus on **Interacting Particle System**, **Federated Learning**, and **Score-based Generative Models**.

RESEARCH EXPERIENCE

| | |
|--|--|
| Understanding Score-based Generative Models Advisor: Prof. Qin Li | University of Wisconsin-Madison 2023/08 - 2024/01 |
| Objective: Demonstrate the insufficiency of prevailing theoretical criteria in evaluating the performance of score-based generative models (SGMs). | |
| <ul style="list-style-type: none">– Demonstrate that the SGM with a specific learned score function enjoys nice theoretical convergence property based on current prevailing convergence analysis.– Conduct a comparative study to illustrate that the same SGM, despite its nice theoretical property, resembles Kernel Density Estimation and fails to generate novel, meaningful new samples. | |
| Consensus-based Optimization and Federated Learning Advisor: Prof. Nicolás García Trillos | University of Wisconsin-Madison 2022/01 - 2023/05 |
| Objective: Develop a novel federated training algorithm tailored for clustered federated learning scenarios, and prove its convergence in general non-convex cases. | |
| <ul style="list-style-type: none">– Propose a federated optimization solution by conceptualizing each local agent as a particle in an interacting particle system. This approach facilitates dynamic consensus formation among particle groups with similar objectives, effectively addressing challenges in clustered federated learning.– Conduct a comprehensive mean-field analysis of the interacting particle system. This rigorous approach provides a convergence guarantee for the general clustered federated learning problem. | |

Objective: Propose a unified mathematical framework for neural network (NN) model fusion and make connections to understanding the loss landscapes of neural networks.

- Formulate the NN model fusion problem as a series of Wasserstein (Gromov-Wasserstein) barycenter problems, bridging in this way the NN fusion problem with computational Optimal Transport.
- Empirically demonstrate that our framework is highly effective and robust across various neural networks architectures. (**Python and PyTorch**)
- Visualize the results of our fusion algorithm when aggregating two neural networks in a 2D-plane, casting light over the loss landscape of a variety of NNs. (**Matplotlib**)

PUBLICATIONS

- [1] **S. Li**, S. Chen, and Q. Li, “A Good Score Does not Lead to A Good Generative Model”, 2024.
- [2] J. A. Carrillo, N. G. Trillos, **S. Li**, and Y. Zhu, “FedCBO: Reaching Group Consensus in Clustered Federated Learning through Consensus-based Optimization”, *Journal of Machine Learning Research (accepted with minor revision)*, 2023, <https://arxiv.org/abs/2305.02894>.
- [3] A. K. Akash, **S. Li**, and N. G. Trillos, “Wasserstein Barycenter-based Model Fusion and Linear Mode Connectivity of Neural Networks”, 2022, <https://arxiv.org/abs/2210.06671>.

TEACHING EXPERIENCE

- Spring 2024, 2023, 2022:
STAT 615: Statistical Learning (TA)
- Fall 2023:
STAT 605: Data Science Computing Project (TA)
- Summer 2023, Fall 2022:
STAT 301: Introduction to Statistical Methods (TA)
- Fall 2021:
STAT 312: Introduction to Theory and Methods of Mathematical Statistics II (TA)

COMPUTER SKILLS

- **Programming Languages:** Python, R, Bash