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Computational Mathematics • Spring 2026

Helen Barton Lecture Series

Virtual Lecture:
https://teams.microsoft.com/meet/28238004014563?p=7cdyWbqlorlcZOUGv5

April 15 2026 4:00pm-5:00pm

Anna Little

Anna Little is an Assistant Professor of Mathematics at the University of Utah and a core member of the Utah Center for Data Science and AI. She received a PhD in mathematics from Duke University in 2011 and was an Assistant Professor of Mathematics at Jacksonville University from 2012-2017, a primarily undergraduate liberal arts institution.

Motivated by a desire to focus more of her professional energy on research, she left Jacksonville University in 2018 to complete a research postdoc at Michigan State University. After completing her postdoc, she began a tenure-track position at the University of Utah in 2021. She has been the principal investigator on multiple grants from the National Science Foundation, including an NSF CAREER award in 2025. Her research interests include geometric and graph-based methods for high-dimensional data analysis and signal processing with group invariant features.

Constructing Features from Data: Geometry, Dimension Reduction, and Invariants

This talk explores how to construct meaningful features from noisy, high-dimensional data by leveraging geometric and invariant structures. First, we introduce a geometric framework for dimension reduction using a power-weighted path metric, which effectively de-noises high-dimensional data while preserving its intrinsic geometric structure. This framework is particularly useful for analyzing single-cell RNA data and for multi-manifold clustering, and we provide theoretical guarantees for the convergence of the associated graph Laplacian operators.

We then turn to the problem of constructing features invariant to group actions in the multi-reference alignment (MRA) data model. In this setting one has many noisy observation of a hidden signal corrupted by both a group action(s) and additive noise, and one wants to recover the hidden signal from the noisy data. By formulating MRA in function space, we uncover a new connection to deconvolution: the hidden signal can be recovered from second-order Fourier statistics via an approach analogous to Kotlarski's identity. We extend this identity to general dimensions, analyze recovery in the presence of vanishing Fourier transforms, and validate the resulting deconvolution framework with both theoretical guarantees and numerical experiments.