Quantitative convergence rates for Poisson learning

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Graph-based learning is a field within machine learning that uses similarities between datapoints to create efficient representations of high-dimensional data for tasks like semi-supervised classification, clustering and dimension reduction. Poisson learning was recently proposed for graph-based semi-supervised learning problems with very few labeled examples, where the widely used Laplacian regularization performs poorly. In contrast to Laplacian regularized learning, where labels are represented as Dirichlet boundary conditions, Poisson learning encodes the labels as point sources and sinks in a graph Poisson equation. In this work, we prove quantitative convergence rates for discrete to continuum convergence for Poisson learning. The problem is challenging since the source term is measure-valued in the continuum, and the continuum Poisson equation does not admit a variational interpretation. This work gives a rigorous mathematical justification for using Poisson learning for semi-supervised learning at low label rates.

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