

Research Highlight: Determinantal Point Processes Based on Orthogonal Polynomials for Sampling Minibatches in SGD

Work of R. Bardenet, S. Ghosh, M. Lin (authors listed in alphabetical order)

Stochastic gradient descent (SGD) is a cornerstone of machine learning. When the number N of data items is large, SGD relies on constructing an unbiased estimator of the gradient of the empirical risk using a small subset of the original dataset, called a minibatch. Default minibatch construction involves uniformly sampling a subset of the desired size. Dr Subhro Ghosh, jointly with co-authors Remi Bardenet (Lille) and Meixia Lin (NUS Math and IORA) contributed a novel orthogonal polynomial-based determinantal point process paradigm for performing minibatch sampling in SGD. The approach leverages the specific data distribution at hand, which endows it with greater sensitivity and power over existing data-agnostic methods. In particular, they demonstrated an improved exponent of convergence for their gradient estimator compared to the state of the art, leading to more efficient and accurate optimization. Moreover, the proposed estimator is amenable to a recent algorithm of theirs that can directly sample the gradient estimator without sampling the minibatch, thereby further reducing computational overhead.

Reference:

Determinantal point processes based on orthogonal polynomials for sampling minibatches in SGD, by R. Bardenet, S. Ghosh, M. Lin (authors listed in alphabetical order) Advances in Neural Information Processing Systems 34 (2021) **Spotlight paper** (< 3% of all submissions) at **NeurIPS 2021**