Bayesian Optimization (BO) is a common solution to search optimal hyperparameters based on sample observations of a machine learning model. Existing BO algorithms could converge slowly even collapse when the potential observation noise misdirects the optimization.

In this paper, we propose a novel BO hyperparameter optimization algorithm called Neighbor Regularized Bayesian Optimization (NRBO):

- We propose a neighbor-based regularization to smooth each sample observation, which could reduce the observation noise efficiently without any extra training cost.
- We further design a density-based acquisition function to adjust the acquisition reward and obtain more stable statistics.
- We design a adjustment mechanism to ensure the framework maintains a reasonable regularization strength and density reward conditioned on remaining computation resources.

Fitting surrogate model on the same dataset with different noise level. From left to right: Gradually increased noise level $\varepsilon$, from 0 to 0.8. Top row: A typical collapse case of Bayesian optimization with Gaussian process. Bottom row: Neighbor regularized Bayesian optimization.

In observation stage, neighbor regularized mechanism is introduced to smooth the observation noise and release the burden of repetitive observation.

In acquisition stage, we propose a density-based acquisition function to accelerate the acquisition process, in which adjacent sample points in the neighbor are considered.

The performance of 9 optimizers on bayesmark benchmark

Experiment results on popular computer vision tasks.

(Left) Proxy task and full-training task results on ImageNet. (Right) Proxy task and full-training task results on COCO.

The hyperparameter searched by NRBO on proxy task still take the lead when transferred to full training tasks.