AutoML for hyperparameter optimization

AutoML for hyperparameter optimization is a research project aimed at developing an automated system that efficiently explores the hyperparameter space of neural networks. Hyperparameters are crucial settings that govern the behavior and performance of neural networks, and finding optimal values for these hyperparameters is often a challenging and time-consuming task. This project aims to alleviate the burden of manual hyperparameter tuning by leveraging techniques such as Bayesian optimization, genetic algorithms, or meta-learning.

One approach to address this problem is through Bayesian optimization. Bayesian optimization treats the hyperparameter optimization as a sequential decision-making process. It builds a probabilistic model, typically a Gaussian process, to model the performance of the neural network as a function of the hyperparameters. Initially, a small set of hyperparameter configurations is evaluated, and the model is updated based on the observed performance. Using an acquisition function, such as Expected Improvement or Upper Confidence Bound, the algorithm selects the next set of hyperparameters to evaluate. This iterative process continues until an optimal set of hyperparameters is found or a predefined stopping criterion is met. Bayesian optimization is known for efficiently exploring the hyperparameter space with relatively few evaluations, making it suitable for resource-constrained scenarios.

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