Bag of Baselines for Multi-objective Joint Neural Architecture Search and Hyperparameter Optimization

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Introduction

- Neural architecture search (NAS) methods typically consider fixed hyperparameters, and hyperparameter optimization (HPO) methods typically consider a fixed neural architecture
- NAS has recently often been framed as a multi-objective optimization problem for finding not just well-performing but also efficient architectures (e.g., in terms of latency or energy consumption), which is often necessary for real-world deployment scenarios
- We propose a set of simple baseline methods for multi-objective joint NAS and HPO
- Our baselines extend methods from, e.g., Bayesian optimization (BO), or evolutionary multi-objective algorithms (EMOA)

SH-EMOA

Use successive halving to speed up evolutionary multi-objective algorithms (EMOA)

- Iterate EMOA doubling the training budgets while halving the number of candidates
- Perform many evaluations to cover a wide range of solutions

X = X / 2

Initialization
- Initialize population with minimum budget *b*

EMOA
- Run *X* steps of evolutionary multi-objective algorithm

SH
- Evaluate remaining population with budget *b = 2b*

MO-BOHB

- Generalize BOHB to any number of objectives
  - Replace TPE by MOTPE
  - Extend hyperband (HB) to multiple objectives

Multi-Objective BO
- Greedy splitting of observations with non-dominated sorting (NDS) & result of hypervolume subset selection problem (HSSP) for tie-breaking
- Modelling densities over the input space by means of KDEs

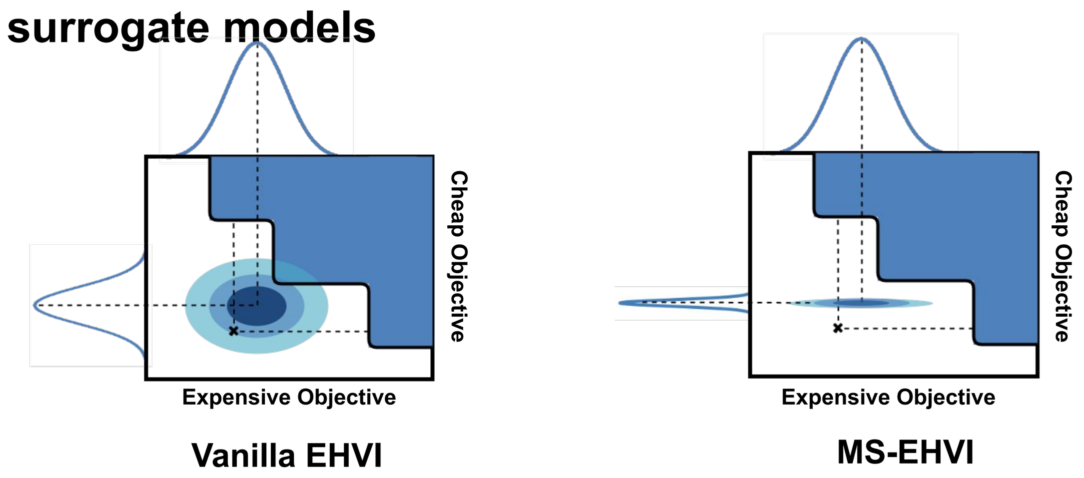
configurations →

← evaluations

Extended HB
- Allocate more resources to best performing configurations on lower budgets
- Advance configurations based on NDS & result of HSSP for tie-breaking

MS-EHVI

- Improve EHVI for cheap-to-evaluate objectives
- Some objectives are expensive to evaluate (e.g., accuracy)
  - We maintain surrogate models for them
- Others are cheap to compute (e.g., network size)
  - We directly evaluate cheap objectives rather than using surrogate models



MO-BANANAS

- Generalize BANANAS to multiple objective
- Additionally, can use multi-fidelity optimization

Selection
- Predict multi-objective performance using ensemble of NN
- Use ITS to choose architectures to evaluate

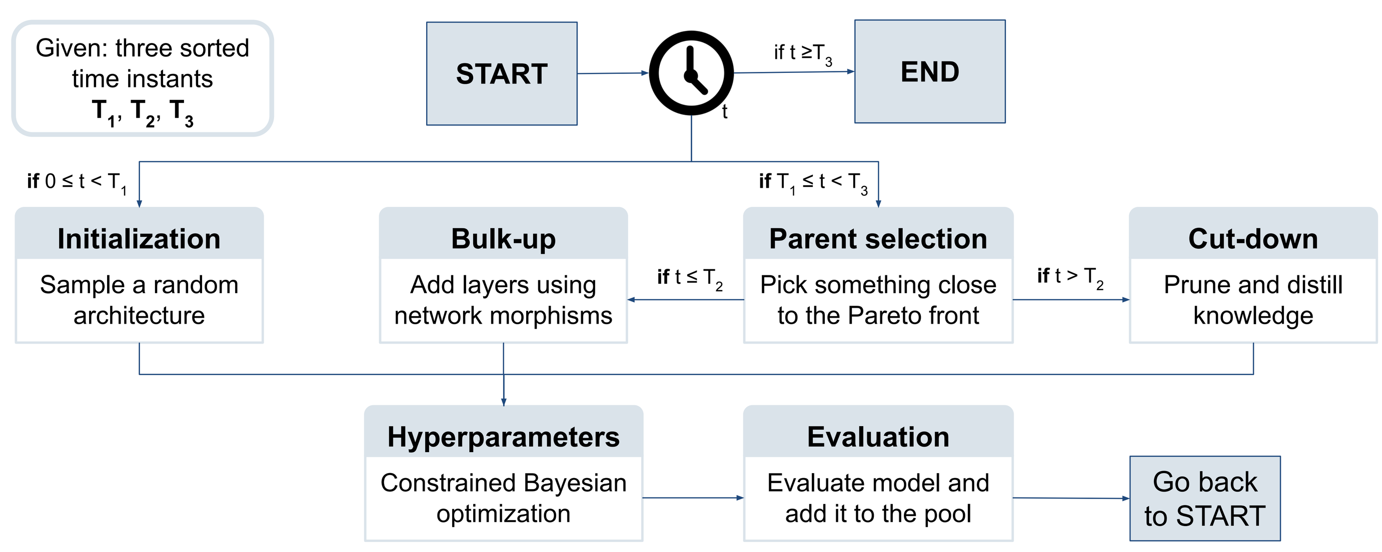
Evaluation
- Evaluate architectures using multi-objective successive halving

Training
- Train ensemble of NN to predict mo performance

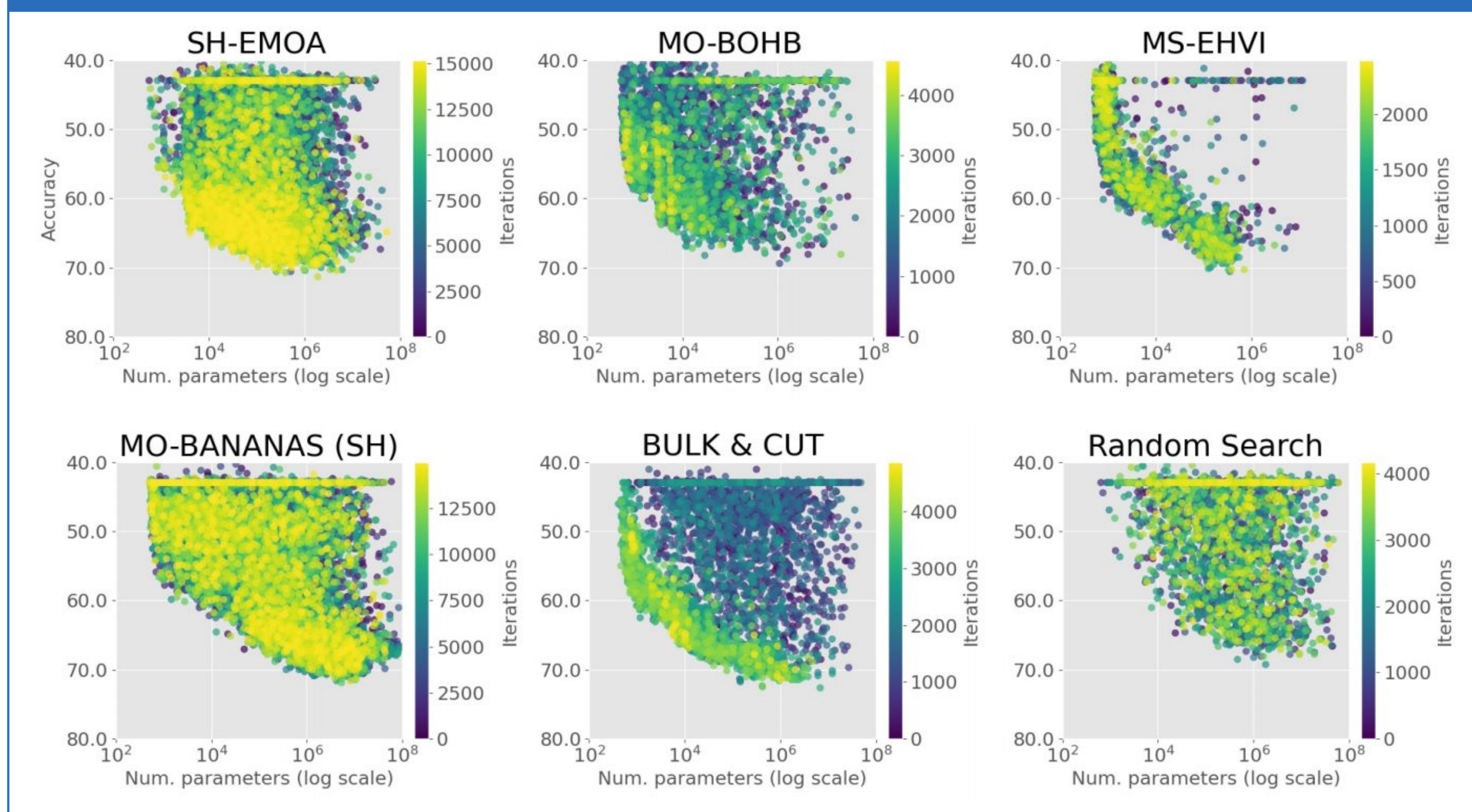
Mutation
- Mutate best previous architectures

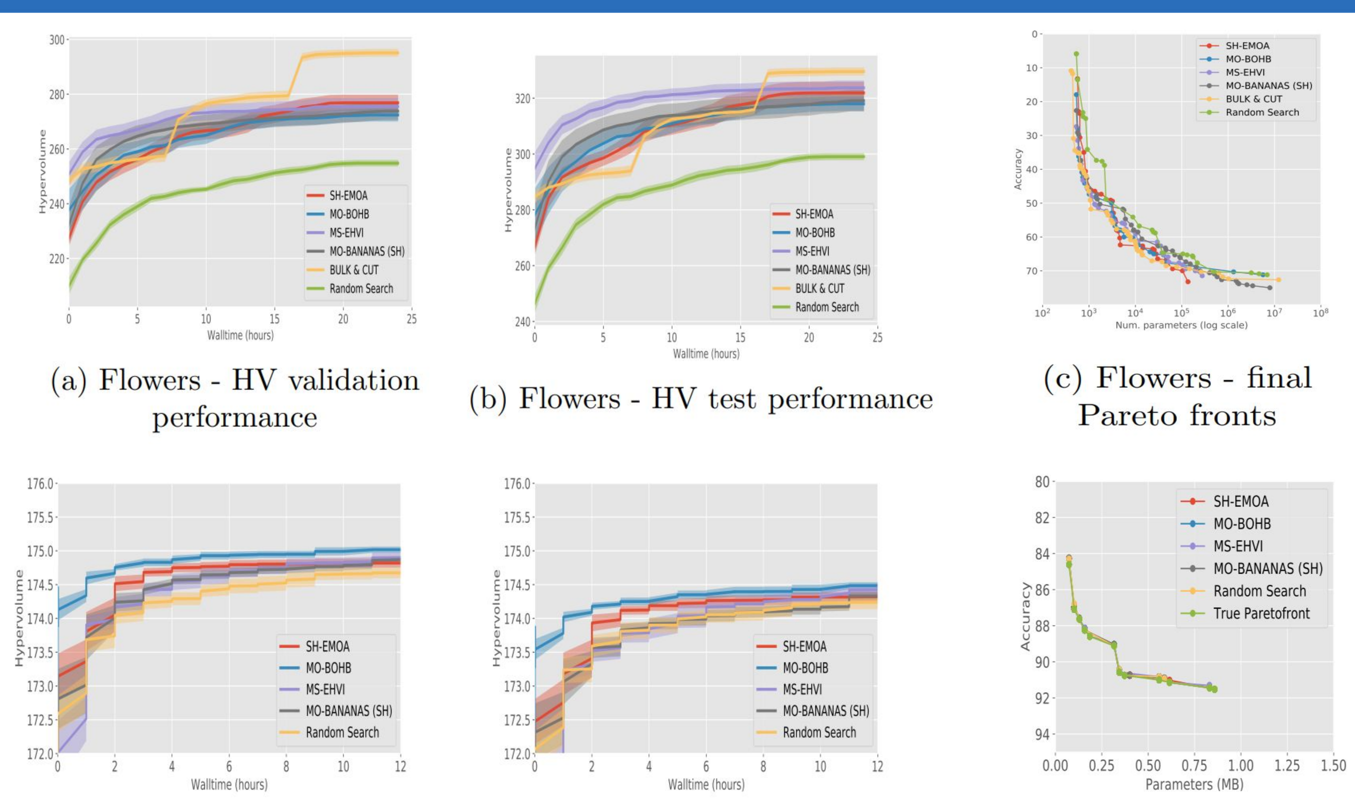
BULK & CUT

- Bulk & Cut combines evolution with Bayesian optimization.
- Child models are either larger (bulked-up) or smaller (cut-down) versions of their parents.
- Hyperparameters are specified by Bayesian optimization.



Experiments





(a) Flowers - HV validation performance

(b) Flowers - HV test performance

(c) Flowers - final Pareto fronts

(d) NAS-Bench-201 - HV validation performance

(e) NAS-Bench-201 - HV test performance

(f) NAS-Bench-201 - final Pareto fronts

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