
Cost-Sensitive Freeze-thaw Bayesian Optimization for Efficient Hyperparameter Tuning

Dong Bok Lee¹ Aoxuan Silvia Zhang^{1*} Byungjoo Kim^{1*} Junhyeon Park^{1*}
Steven Adriaensen² Juho Lee¹ Sung Ju Hwang^{1,3} Hae Beom Lee⁴

¹KAIST ²University of Freiburg ³DeepAuto.ai ⁴Korea University

markhi@kaist.ac.kr haebeomlee@korea.ac.kr

Abstract

In this paper, we address the problem of *cost-sensitive* hyperparameter optimization (HPO) built upon freeze-thaw Bayesian optimization (BO). Specifically, we assume a scenario where users want to early-stop the HPO process when the expected performance improvement is not satisfactory with respect to the additional computational cost. Motivated by this scenario, we introduce *utility* in the freeze-thaw framework, a function describing the trade-off between the cost and performance that can be estimated from the user's preference data. This utility function, combined with our novel acquisition function and stopping criterion, allows us to dynamically continue training the configuration that we expect to maximally improve the utility in the future, and also automatically stop the HPO process around the maximum utility. Further, we improve the sample efficiency of existing freeze-thaw methods with transfer learning to develop a specialized surrogate model for the cost-sensitive HPO problem. We validate our algorithm on established multi-fidelity HPO benchmarks and show that it outperforms all the previous freeze-thaw BO and transfer-BO baselines we consider, while achieving a significantly better trade-off between the cost and performance. Our code is publicly available at <https://github.com/db-Lee/CFBO>.

1 Introduction

Hyperparameter optimization [HPO; 9, 22, 8, 48, 16, 34, 12] stands as a crucial challenge in the domain of deep learning, given its importance in achieving optimal empirical performance. Unfortunately, the field of HPO for deep learning remains relatively underexplored, with many practitioners resorting to simple trial-and-error methods [8, 34]. Moreover, traditional black-box Bayesian optimization (BO) approaches for HPO [9, 48, 12] face limitations when applied to deep neural networks due to the impracticality of evaluating a vast number of hyperparameter configurations until convergence, each of which may take several days.

Recently, multi-fidelity HPO [53, 34, 14, 4, 62, 3, 24, 44] has gained increasing attention to improve the sample efficiency of traditional black-box HPO. It leverages lower-fidelity information (*e.g.*, validation accuracies at fewer training epochs) to predict and optimize performance at higher or full fidelity (*e.g.*, validation accuracies at the last training epoch). Furthermore, unlike black-box HPO, multi-fidelity HPO dynamically selects hyperparameter configurations even before finishing a single training run, demonstrating its ability of finding better configurations sample-efficiently.

*Equal Contribution.

However, one critical limitation of the conventional multi-fidelity HPO frameworks is their lack of awareness of the *trade-off between the cost and performance*. For example, given a limited amount of total credits, customers of cloud computing services (e.g., **GCP**, **AWS**, or **Azure**) can heavily penalize the cost of HPO relative to its performance to conserve credits for other tasks. A similar scenario applies to task manager users such as **Slurm**, who aim to optimize their allocated time within a computing instance. In such cases, users may prefer that the HPO process focuses on exploiting the current belief about good hyperparameter configurations rather than exploring new ones, to efficiently consume their limited resources. However, existing methods [53, 34, 14, 4, 62, 3, 24, 44] generally do not consider this scenario, as they typically assume a sufficiently large budget (e.g., total credits or allocated time) and aim to achieve the best performance on a validation set.

Utility: trade-off between cost and performance.

Therefore, in this paper, we introduce a more sophisticated notion of cost sensitivity for HPO. Specifically, we assume that users have their own preferences regarding the trade-off between the cost and performance of HPO. We formalize this trade-off in a *utility* function that represents user preferences and can be estimated from user preference data. It assigns higher values as costs decrease and performance increases, and vice versa. Some users may strongly penalize the budget spent on HPO, while others may penalize it weakly or not at all, as in the conventional multi-fidelity HPO. We explicitly maximize this utility by dynamically selecting hyperparameter configurations expected to achieve the greatest improvement in the future and by automatically terminating the BO around the maximum utility instead of halting at an arbitrary target budget.

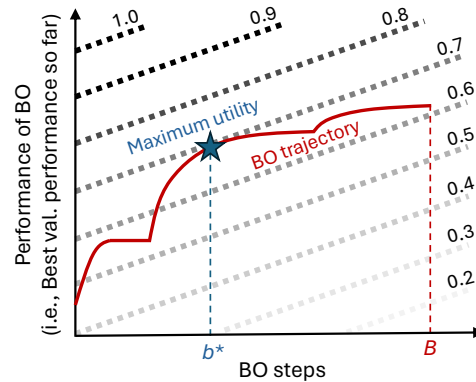


Figure 1: A concept of **user utility**.

Fig. 1 illustrates the concept of utility: the red line shows the BO trajectory, and the blue asterisk marks the maximum utility (around 0.7) achieved at budget b^* . This example heavily penalizes the additional cost, although extending the BO to the full budget B could yield better performance.

Solving this problem requires our method to have the following capabilities. Firstly, it should support **freeze-thaw BO** [53, 44], an advanced form of multi-fidelity BO that dynamically pauses (freezes) and resumes (thaws) hyperparameter configuration trainings based on future performance extrapolated from a set of partially observed learning curves (LCs) with various configurations. Such efficient and fine-grained allocation of computational resources aligns well with the goal of achieving the best trade-off between cost and performance in multi-fidelity HPO. Secondly, freeze-thaw BO requires that its surrogate function be capable of **LC extrapolation** [24, 2, 44]. In our case, this is critical for making probabilistic inferences about future utilities, which guide the selection of the best configuration and enable precise early stopping of the HPO. Lastly, since users are assumed to prefer stopping HPO as early as possible when performance saturates, LC extrapolation must be accurate even in the early stages of HPO. Therefore, it is essential to use **transfer learning** to maximize the sample efficiency of BO [3] and to prevent premature stopping.

Based on these criteria, we introduce our novel **Cost-sensitive Freeze-thaw BO (CFBO)**, which effectively maximizes utility using the three components mentioned above. We first explain the notation and background² on freeze-thaw BO and Prior-Fitted Networks [PFNs; 39, 2, 44] for LC extrapolation (§2). We define the utility function and explain how to estimate it from user preference data³ (§3.1). We describe the acquisition function and the stopping criterion specifically developed for our problem setting, explaining how they achieve a good trade-off between cost and performance (§3.2 and §3.3). We show how to train a PFN using existing real-world LC datasets to create a sample-efficient in-context surrogate function for freeze-thaw BO, which effectively captures correlations between different hyperparameter configurations (§3.4). Finally, we empirically demonstrate the superiority of CFBO on a diverse set of utility functions, three multi-fidelity HPO benchmarks, and a real-world object detection LC dataset we collected, showing that it significantly outperforms relevant baselines, including transfer-BO (§4).

²We defer the discussion of related work, e.g., early-stopping BO methods, to **Appendix A**.

³Some users may already have an exact form of their utility function, but for others, we provide a method to quantify it based on their preference data.

We summarize our contributions and findings as follows:

- We propose a new problem formulation, cost-sensitive multi-fidelity HPO, which focuses on maximizing the trade-off between cost and performance (*i.e.*, utility) as defined by users, rather than optimizing asymptotic validation performance.
- We introduce a novel acquisition function and stopping criterion specifically designed for this problem formulation, incorporating transfer learning to enhance in-context LC extrapolation.
- We extensively validate the effectiveness of our method across diverse cost-sensitive multi-fidelity HPO scenarios using three popular LC benchmarks.

2 Background and Related Work

Notation. Let $\mathcal{X} = \{x_1, \dots, x_N\}$ denote the set of hyperparameter configurations, where $x_n \in \mathbb{R}^{d_x}$ and N is the number of configurations [62, 24, 44]. Let $t \in [T] := \{1, \dots, T\}$ denote the training epochs, with T being the last epoch, and $y_{n,1:T} := (y_{n,1}, \dots, y_{n,T}) \in [0, 1]^T$ the measure of model performance to be maximized, *e.g.*, a learning curve (LC) of validation accuracies with x_n . We now introduce the notation for multi-fidelity BO. $t_n < T$ denotes the last observed epoch of x_n if the model performance of x_n is partially observed ($y_{n,1:t_n}$). Let B denote the total budget spent during BO, and $\tilde{y}_b \in [0, 1]$ the best cumulative performance achieved up to budget $b \in [B]$, respectively. See Tab. 4 in Appendix B for a summary of the notation used throughout this paper.

Freeze-thaw BO. Freeze-thaw BO [53] is an advanced form of multi-fidelity BO, which aims to maximize the best cumulative performance $\tilde{y}_B$ by efficiently allocating the limited total budget B . Assuming that we allocate one budget unit (*i.e.*, one epoch) for each freeze-thaw BO step, it allows us to dynamically select and evaluate the best hyperparameter configuration x_{n^*} , with $n^* \in [N]$ denoting the corresponding index, while pausing the evaluation of the previously selected configuration. Specifically, given the context $\mathcal{C} = \{(x, t, y)\}$, which represents a set of partial (or full) LCs collected up to a specific BO step (*i.e.*, *history*), we select one configuration $x_{n^*} \in \mathcal{X}$ that maximizes a predefined acquisition function (*e.g.*, the expected improvement [38]). We then evaluate the selected configuration x_{n^*} for one additional budget unit (*i.e.*, one epoch) and observe $y_{n^*, t_{n^*}+1}$. Next, we update the history $\mathcal{C}$ with $(x_{n^*}, t_{n^*} + 1, y_{n^*, t_{n^*}+1})$. The cumulative best validation performance $\tilde{y}_b$ is updated accordingly. This process is repeated for B steps. Please see Alg. 1 for the pseudocode (except for the blue parts).

PFNs for LC extrapolation. Freeze-thaw BO usually requires the ability to extrapolate LCs to compute acquisition functions [62, 24, 44]. Among many plausible options, in this paper, we use Prior-data Fitted Networks [PFNs; 39] for the LC extrapolation. PFNs are an in-context Bayesian inference method based on Transformer [54] and show good performance in LC extrapolation [2, 44] without computationally expensive online retraining [62, 24]. Specifically, after training, they allow us to approximate the posterior predictive distribution (PPD) with a single forward pass: $p_\theta(y|x, t, \mathcal{C}) \approx \tilde{p}(y|x, t, \mathcal{C})$, where p_θ is the approximate PPD parameterized by θ . This is achieved by minimizing the cross-entropy for predicting the hold-out example’s label y , given x , t , and $\mathcal{C}$:

$$\mathcal{L}(\theta) = \mathbb{E}_{(x,t,y), \mathcal{C} \sim p(\mathcal{D})} [-\log p_\theta(y|x, t, \mathcal{C})], \quad (1)$$

where $p(\mathcal{D})$ is a prior from which we can sample infinitely many *synthetic* training data. We defer the architectural and training details to Appendix E.

Related work. We defer the discussion of related work on (1) **multi-fidelity HPO**, (2) **freeze-thaw BO**, (3) **LC extrapolation**, (4) **transfer-BO**, (5) **cost-sensitive HPO**, (6) **early stopping BO**, (7) **BO with user preferences**, and (8) **neural processes** to Appendix A.

3 Method: Cost-sensitive Freeze-thaw Bayesian Optimization (CFBO)

We now introduce our method, Cost-sensitive Freeze-Thaw Bayesian Optimization (CFBO), summarized in Alg. 1, where the blue components indicate the parts specific to our approach.

3.1 Utility: Trade-off between Cost and Performance

Utility function. A utility function $U : (b, \tilde{y}_b) \in [B] \times [0, 1] \mapsto [0, 1]$ describes the trade-off between the budget b and the best cumulative performance $\tilde{y}_b$. Its value decreases with increasing

b and increases with increasing $\tilde{y}_b$. We assume that the utility is given by the users. For example, it can be simply defined as $U(b, \tilde{y}_b) = \tilde{y}_b - \alpha \left(\frac{b}{B}\right)^c$, where $0 \leq \alpha \leq 1$ is a penalty coefficient and $c = 1, 2$, or 0.5 for a linear, quadratic, or square-root utility, respectively. Furthermore, the total budget limit can be modeled by setting $U(b, \tilde{y}_b) = -\infty$ if $b > B$ otherwise $\tilde{y}_b$.

Utility estimation. It is often challenging for users to quantify their preference on the trade-off. We therefore propose to use the Bradley-Terry model [10] for utility estimation:

$$p(U(b, \tilde{y}_b) > U(b', \tilde{y}_{b'})) = \frac{\exp(U(b, \tilde{y}_b) / \tau)}{\exp(U(b, \tilde{y}_b) / \tau) + \exp(U(b', \tilde{y}_{b'}) / \tau)}. \quad (2)$$

where U is the user utility we want to estimate, and τ is a temperature hyperparameter. Eq. 2 describes the probability that the user prefers $(b, \tilde{y}_b)$ to $(b', \tilde{y}_{b'})$ in terms of utility U . Following the preference learning literature [6], we can collect *user preference data* by asking users which point they prefer: (1) sampling a pair of points $(b, \tilde{y}_b), (b', \tilde{y}_{b'})$, (2) labeling user preference label $y_{>} \in \{0, 1\}$ as 1 if $U(b, \tilde{y}_b) > U(b', \tilde{y}_{b'})$ otherwise 0, and (3) constructing a dataset $\mathcal{D}_U := \{(b, \tilde{y}_b), (b', \tilde{y}_{b'}), y_{>}\}$. We then optimize the parameter of the utility function (e.g., the penalty coefficient α) by minimizing the binary cross-entropy loss $\ell(x, y) := -y \log x - (1 - y) \log(1 - x)$:

$$\frac{1}{|\mathcal{D}_U|} \sum_{(b, \tilde{y}_b), (b', \tilde{y}_{b'}), y_{>} \in \mathcal{D}_U} \ell(p(U(b, \tilde{y}_b) > U(b', \tilde{y}_{b'})), y_{>}). \quad (3)$$

An example of utility estimation. Fig. 2 illustrates an example of our utility estimation process. Here, we assume a simulated user who consistently favors outcomes that improve upon the baseline freeze-thaw HPO trajectory, e.g., ifBO [44]. We first run ifBO for up to 300 budgets and obtain $\forall b \in [B], \tilde{y}_b$, where $\tilde{y}_b$ denotes the best cumulative performance of BO up to budget b . For each $b \in \{51, \dots, 300\}$, we then sample $\tilde{y}_b^{(\text{up})} \sim \text{Uniform}(\tilde{y}_b, 1)$ and $\tilde{y}_b^{(\text{down})} \sim \text{Uniform}(0, \tilde{y}_b)$, and record the preference $U(b, \tilde{y}_b^{(\text{up})}) > U(b, \tilde{y}_b^{(\text{down})})$. We exclude the initial budgets $b \in \{1, \dots, 50\}$ to prevent the utility model from overfitting to the early steep improvements. This simulates a user who *always prefers* outcomes above the baseline trajectory. The solid black line in Fig. 2 represents the ifBO trajectory ($\tilde{y}_b$), the dotted blue lines indicate the estimated utility, and the yellow asterisk marks the maximum utility. We observe that the utility reaches its maximum when the improvement becomes *saturated*.

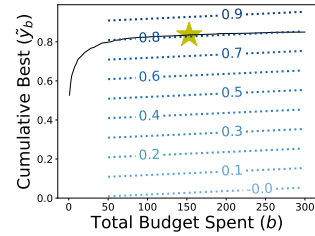


Figure 2: An example of **utility function estimation**.

In practice. We recommend providing a small library of functional forms—e.g., linear ($c = 1$), quadratic ($c = 2$), square-root ($c = 0.5$), or staircase—and fitting the utility via preference learning using Eqs. 2 and 3. Assuming the true utility of users follows one of these forms, Appendix C shows that it can be recovered with only a few pairwise comparisons (e.g., 30 pairs).

3.2 Acquisition

EI-based acquisition function. We define the acquisition function $A(n; U)$ for maximizing utility based on the Expected Improvement (EI) method [38]:

$$A(n; U) := \max_{\Delta t \in [T - t_n]} \mathbb{E}_{y_{n, \cdot} \sim p_\theta} \left[[U(b + \Delta t, \tilde{y}_{b+\Delta t}) - U_p]^+ \right], \quad (4)$$

where $[x]^+ := \max(x, 0)$. In Eq. 4, we first extrapolate $y_{n, \cdot} := \{y_{n, t_n + \Delta t} \mid \Delta t \in [T - t_n]\}$, the remaining part of the learning curve (LC) associated with x_n , using p_θ . Then, we compute the corresponding cumulative best performances $\{\tilde{y}_{b+\Delta t} \mid \Delta t \in [T - t_n]\}$. According to the definition in §2, $\tilde{y}_{b+\Delta t}$ is computed by taking the maximum of the previous best performance $\tilde{y}_b$ and the newly extrapolated validation performances $y_{n, t_n + 1}, \dots, y_{n, t_n + T}$. Based on the updated budget $b + \Delta t$ and the corresponding performance $\tilde{y}_{b+\Delta t}$, we compute the utility and its expected improvement over

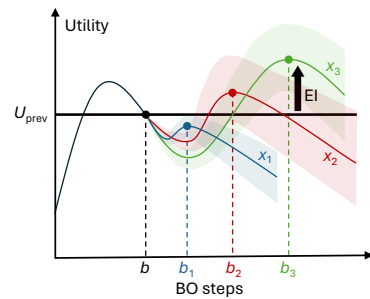


Figure 3: An illustration of **A** in Eq. 4.

the previous utility U_p . The expectation is evaluated over the distribution of LC extrapolations (p_θ), using Monte Carlo estimation (detailed in [Appendix F](#)). Finally, the acquisition $A(n; U)$ for each configuration index n is determined by selecting the best increment $\Delta t \in [T - t_n]$ that maximizes the expected improvement. We then choose the best index over configurations n^* that maximizes $A(n; U)$, i.e., $n^* = \arg \max_n A(n; U)$. Assuming three configurations x_1, x_2 , and x_3 , [Fig. 3](#) illustrates the selection of configuration x_3 .

Differences from existing EI. The main differences between our acquisition function in [Eq. 4](#) and the usual EI-based acquisition are twofold. First, instead of maximizing the expected improvement of the validation performance y , we maximize the *EI of utility*. Second, rather than fixing the target epoch for evaluating the acquisition to the last epoch T [24] or using a random increment [44], we dynamically select the *best target epoch* that is expected to yield the highest improvement in utility.

These aspects enable our BO framework to carefully select configurations at each suggestion step, aiming to achieve the best trade-off between the cost and performance of the HPO process. Specifically, the acquisition function initially favors configurations that are expected to yield strong asymptotic validation performances y . However, as the BO progresses, the acquisition function gradually becomes greedier as the performance saturates and the associated cost begins to dominate the utility function (empirically illustrated in [Figs. 8a to 8c](#) of [§4.3](#)). Consequently, the acquisition function shifts from exploration to exploitation—prioritizing the current configurations over selecting new ones to maximize short-term performance.

Utility is irreversible. Note that U_p in [Eq. 4](#), the reference value for EI, is *not* the greatest utility achieved so far (corresponds to f^* in the typical EI $A(x) := \mathbb{E}_f[f - f^*]^+$). Instead, it is set to the utility value achieved most recently (i.e., U_p in line 18 of [Alg. 1](#)), as the computational budgets spent are *irreversible*. This also contrasts with typical EI-based BO settings, where all previous evaluations remain meaningful, allowing the reference value can be set to the maximum among them. Consequently, U_p can either increase or decrease during the BO process.

3.3 Stopping Criterion

Regret-based criterion. The next question is how to properly stop the HPO around the maximum utility. We propose stopping when the following criterion is satisfied:

$$\hat{R}_b := \frac{\hat{U}_{\max} - U_p}{\hat{U}_{\max} - \hat{U}_{\min}} > \delta. \quad (5)$$

In [Eq. 5](#), U_p is the utility value at the previous step $b-1$, $\hat{U}_{\max}$ is defined as the maximum utility value seen up to the previous $(b-1)$ step, and $\hat{U}_{\min} = U(B, \hat{y}_1)$. The role of $\hat{U}_{\max}$ and $\hat{U}_{\min}$ is to *roughly estimate* the maximum and minimum utility achievable over the course of BO, respectively. $\hat{R}_b \in [0, 1]$ can be seen as roughly estimated *normalized regret* at the current step b . This regret-based criterion terminates the BO process once the estimated regret exceeds a predefined threshold $\delta \in [0, 1]$. The intuition is *pessimistic*: if the current utility regret is already high, it is unlikely that further optimization will yield a significant improvement, and thus the BO process is terminated.

Adaptive threshold. We can fix the threshold δ as a hyperparameter in [Eq. 5](#) (e.g., baselines); however, this approach does not account for *possibility* of potential improvement in the future. To

Algorithm 1 Cost-Sensitive Freeze-thaw BO.

Blue parts correspond to specifics of our method.

```

1: Input:  $\mathcal{X}$  : hyperparameter configuration space
2:    $p_\theta$  : LC extrapolator with transfer learning
3:    $A$  : acquisition function
4:    $B$  : total HPO budget
5:    $U$  : utility function
6:    $\delta$  or  $\beta, \gamma$  : threshold hyperparameters
7:  $\tilde{y}_0 \leftarrow -\infty, \mathcal{C} \leftarrow \emptyset, t_1, \dots, t_N \leftarrow 0, U_p \leftarrow 0, \hat{R}_b \leftarrow 0$ 
8: for  $b = 1, \dots, B$  do
9:    $n^* \leftarrow \arg \max_n A(n; U)$  ▷ Acquisition in Eq. 7
10:   $\delta_b \leftarrow \text{BetaCDF}(p_b; \beta, \beta)^\gamma$  ▷  $p_b$  in Eq. 4
11:  if  $\hat{R}_b > \delta$  or  $\delta_b$  then
12:    break ▷ Stopping criterion
13:  end if
14:  Evaluate  $y_{n^*, t_{n^*}+1}$  with  $x_{n^*}$ 
15:   $\mathcal{C} \leftarrow \mathcal{C} \cup \{(x_{n^*}, t_{n^*} + 1, y_{n^*, t_{n^*}+1})\}$ 
16:   $\tilde{y}_b \leftarrow \max(\tilde{y}_{b-1}, y_{n^*, t_{n^*}+1})$ 
17:   $t_{n^*} \leftarrow t_{n^*} + 1$ 
18:   $U_p \leftarrow U(b, \tilde{y}_b)$ 
19:   $\hat{R}_b \leftarrow \frac{\hat{U}_{\max} - U_p}{\hat{U}_{\max} - \hat{U}_{\min}}$  ▷ Estimated regret in Eq. 5
20: end for
21: Output: The model trained with  $x^*$  up to the  $t^*$ -th epoch
    s.t.  $(x^*, t^*, y^*) := \arg \max_{(x, t, y) \in \mathcal{C}} y$ 

```

address this, we propose an *adaptive threshold* based on the probability of improvement [PI; 38]:

$$\delta_b = \text{BetaCDF}(p_b; \beta, \beta)^\gamma, \quad \beta, \gamma > 0, \quad (6)$$

$$p_b = \max_{\Delta t \in [T-t_n]} \mathbb{E}_{y_{n^*}, \cdot \sim p_\theta} [\mathbb{1}(U(b + \Delta t, \tilde{y}_{b+\Delta t}) > U_p)]. \quad (7)$$

Here, BetaCDF is the cumulative distribution function (CDF) of the Beta distribution, and $\mathbb{1}$ is the indicator function. The PI p_b in Eq. 7 represents the probability that the selected configuration x_{n^*} using Eq. 4 improves U_p in some future BO step. Intuitively, we aim to defer termination as p_b increases and vice versa. This behavior is incorporated into Eq. 6—as p_b increases, the adaptive threshold δ_b also increases because $\text{BetaCDF}(\cdot; \beta, \beta)^\gamma$ is a monotonically increasing function in $[0, 1]$. Consequently, according to Eq. 5, there is less motivation to terminate the BO process when p_b is high. For our CFBO, we use the adaptive threshold δ_b instead of the fixed threshold δ in Eq. 5.

Role of γ and β . Fig. 4a shows that γ controls δ_b at $p_b = 0.5$. For example, if we set $\gamma = \log_{0.5} 0.2$, δ_b becomes 0.2 when $p_b = 0.5$ regardless of β . By controlling γ , we can set the threshold to a proper value when the PI is uncertain ($p_b = 0.5$). Fig. 4b illustrates the effect of β . As $\beta \rightarrow 0$, δ_b becomes horizontal, fixing δ_b at 0.2 regardless of p_b . This results in **ignoring the PI** p_b . In contrast, as $\beta \rightarrow \infty$, δ_b becomes vertical, causing δ_b to take binary values, either 0 or 1, depending on whether $p_b > 0.5$ or not. This corresponds to a **purely PI-based criterion**. Thus, β provides a smooth interpolation that controls the degree to which the PI p_b in Eq. 7 is incorporated into the adaptive threshold δ_b in Eq. 6 and the stopping criterion in Eq. 5.

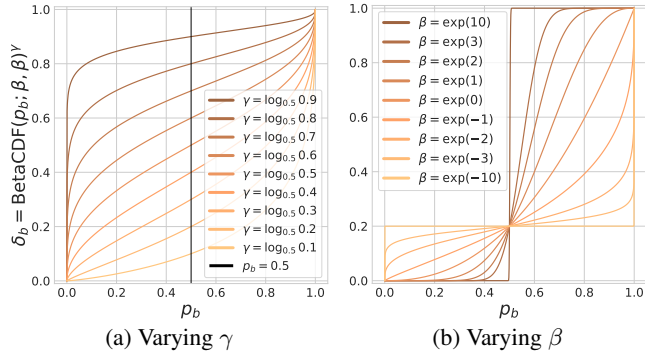


Figure 4: (a) δ_b vs. p_b for **varying γ** with $\beta = \exp(-1)$.
(b) δ_b vs. p_b for **varying β** with $\gamma = \log_{0.5} 0.2$.

3.4 Transfer Learning with LC mixup

Motivation. Since users may want to early-stop the BO process, it is crucial to ensure an *accurate* LC extrapolation to prevent premature stopping during the early stages of BO. To address this, we propose the use of **transfer learning** to maximize the sample efficiency of LC extrapolators.

As discussed in §2, among various plausible options, we employ PFNs [39] for LC extrapolation. Regarding the network architecture and training objective, we primarily follow ifBO [44], with more details deferred to Appendix E. A significant challenge in using PFNs for our purpose is that PFNs require relatively large Transformer architectures and massive amounts of training examples for strong generalization [2], making it *risky* to train them on a limited data.

LC Mixup. To overcome these challenges, we propose a novel transfer learning approach using the mixup strategy [66]. Assume that we have M different training LC datasets and the corresponding M sets of LCs collected from N hyperparameter configurations. Let $l_n^{(m)} = [y_{n,1}^{(m)}, \dots, y_{n,T}^{(m)}]$ be a T -dimensional vector representing the validation performances of the m -th dataset and the n -th configuration, forming a complete LC of length T . Define the matrix $L^{(m)} = [l_1^{(m)}; \dots; l_N^{(m)}]^\top \in \mathbb{R}^{N \times T}$ as the stack of these LCs. To augment LCs, we propose two consecutive mixup strategies across datasets and configurations:

- **Dataset:** Sample a new LC dataset as $L' = \lambda_1 L^{(m)} + (1 - \lambda_1) L^{(m')}$, where $\lambda_1 \sim \text{Uniform}(0, 1)$ and $m, m' \in [M]$.
- **Configuration:** Sample a new configuration $x' = \lambda_2 x_n + (1 - \lambda_2) x_{n'}$ and its corresponding LC $l' = \lambda_2 l_n + (1 - \lambda_2) l_{n'}$, where l_n and $l_{n'}$ denote the n -th and n' -th rows of L' , respectively, $\lambda_2 \sim \text{Uniform}(0, 1)$, and $n, n' \in [N]$.

Using this approach, we can sample infinitely many training examples $\{(x', l')\}$ by interpolating between LCs, resulting in a robust LC extrapolator with reduced overfitting.

4 Experiments

We next empirically validate the proposed method on various cost-sensitive multi-fidelity HPO settings. Our code is publicly available at <https://github.com/db-Lee/CFBO>.

4.1 Experimental Setups

Datasets. We evaluate CFBO on three standard LC benchmarks. **LCBench** [67]: contains learning curves of MLPs trained on multiple tabular datasets, **TaskSet** [37]: provides diverse optimization tasks across domains; we focus on 30 NLP tasks (text classification and language modeling), and **PD1** [56]: includes learning curves of modern neural architectures, such as Transformers, trained on large-scale datasets (CIFAR-10/100 [31], ImageNet [45], and bioinformatics corpora). We split each benchmark into disjoint training and test tasks for transfer learning of LC extrapolators p_θ . Detailed dataset statistics are summarized in **Tab. 1**, and additional descriptions are provided in **Appendix D**.

Table 1: **Dataset overview.**

Dataset	d_x	$ \mathcal{X} $	T	Train	Test
LCBench [67]	7	2,000	51	20 datasets	15 datasets
TaskSet [37]	8	1,000	50	21 tasks	9 tasks
PD1 [56]	4	240	50	16 tasks	7 tasks

Baselines without transfer learning. We compare CFBO with a wide range of multi-fidelity HPO methods. **Random Search** [8] sequentially samples configurations at random. We also evaluate two Hyperband [34] variants: **BOHB** [14], which replaces random sampling with BO, and **DEHB** [4], which integrates evolutionary strategies for knowledge transfer. Among recent multi-fidelity BO methods, we include **DyHPO** [62], which combines a deep kernel Gaussian Process [GP; 58] with greedy short-horizon LC extrapolation; **DPL** [24], which fits power-law functions with ensemble modeling; and **ifBO** [44], a PFN-based [39] freeze-thaw BO method using PI acquisition at random future epochs. For a *fair comparison*, we use a **non-transfer (NT)** variant, **CFBO-NT**, with the LC extrapolator of ifBO: **excludes transfer-learning with LC mixup** in §3.4, but **retains** $A(\cdot; U)$ (cf. Eq. 4 in §3.2) and **stopping criterion with the adaptive threshold** δ_b (cf. Eqs. 5–7 in §3.3).

Baselines with transfer learning. **Quick-Tune**[†] [3] corresponds to the transfer-learning version of DyHPO, trained on the same LC datasets as our extrapolator. **FSBO** [60] is a black-box transfer-BO method that uses the same LC datasets to train a deep kernel GP surrogate. The both do not use the LC mixup in §3.4. The key difference from Quick-Tune[†] lies in the prediction target: FSBO predicts the final-epoch performance, whereas Quick-Tune[†] extrapolates the next-epoch performance.

Implementation details for CFBO and the baselines are provided in **Appendix F**.

Utility function. It is possible to manually collect user preference data and estimate the corresponding utility function (§3.1). In our experiments, however, we simplify this process by using a linear, quadratic or square root function, *i.e.*, $U(b, \tilde{y}_b) = \tilde{y}_b - \alpha \left(\frac{b}{B}\right)^c$, where $c \in \{1, 2, 0.5\}$, with $\alpha \in \{0, 2^{-6}, 2^{-5}, 2^{-4}, 2^{-3}, 2^{-2}\}$. Notably, setting $\alpha = 0$ removes any penalty associated with the budget b spent during HPO, causing the HPO process to continue until the final step B , as in the conventional multi-fidelity HPO setup.

Threshold hyperparameters δ , γ , and β . For the baselines, we set the threshold $\delta = 0.2$ in Eq. 5, as it performs well on the training split. For CFBO, we also use $\gamma = \log_{0.5} 0.2$, which corresponds to the adaptive threshold $\delta_b = 0.2$ when $p_b = 0.5$, to ensure a *fair comparison* with the baselines. We use $\beta = \exp(-1)$ for all experiments in this paper, except for the ablation study in Fig. 8d.

Evaluation protocol. We set the maximum budget⁴ as $B = 300$ and report:

$$R := \frac{U_{\max} - U_p}{U_{\max} - U_{\min}} \in [0, 1], \text{ where } U_{\max} := \max_{n,t} U(t, y_{n,t}) \text{ and } U_{\min} \approx \min_n U(B, y_{n,1}), \quad (8)$$

which is similar to Eq. 5, but uses the *true* $U_{\max}$ and $U_{\min}$. Here, U_p is the utility at termination (*e.g.*, after **break** in line 12 of Alg. 1). $U_{\max} := \max_{n,t} U(t, y_{n,t})$ denotes the maximum utility achievable by a single optimal configuration. Since exact computation of $U_{\min}$ is intractable, we approximate it as $\min_n U(B, y_{n,1})$, where $y_{n,1}$ is the first epoch performance. We report mean $\pm$ std of normalized regrets over 5 runs (30 for Random, BOHB, and DEHB) and the average rank across all tasks.

[†]Modified version without pretrained model selection or wall-time balancing.

⁴While prior work [62, 44] uses $B = 1,000$, we set $B = 300$ to better show the benefit of transfer learning.

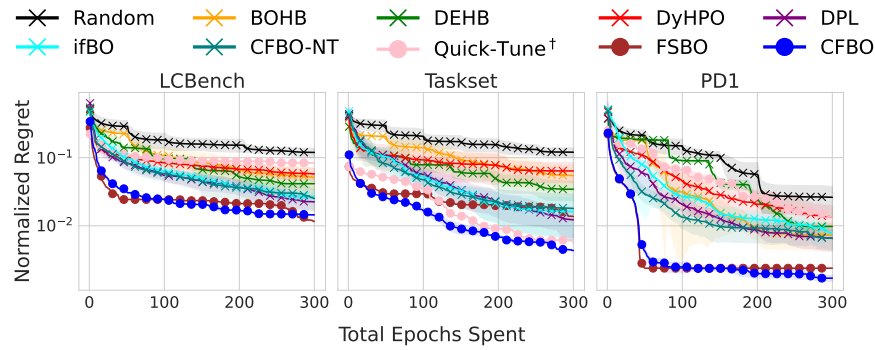


Figure 5: **Results on conventional multi-fidelity HPO ($\alpha = 0$).** **X** and **O** markers denote **non-transfer** and **transfer** learning methods, respectively.

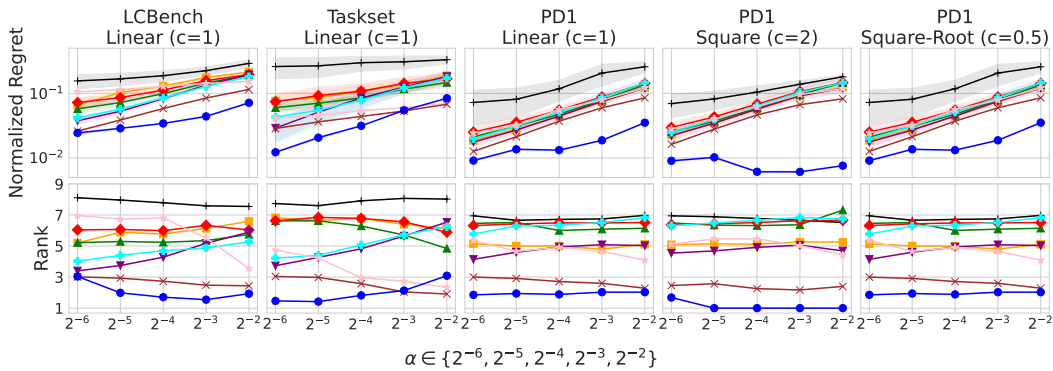


Figure 6: **Results on cost-sensitive multi-fidelity HPO** ($c \in \{1, 2, 0.5\}$ and $\alpha \in \{2^{-6}, 2^{-5}, 2^{-4}, 2^{-3}, 2^{-2}\}$).

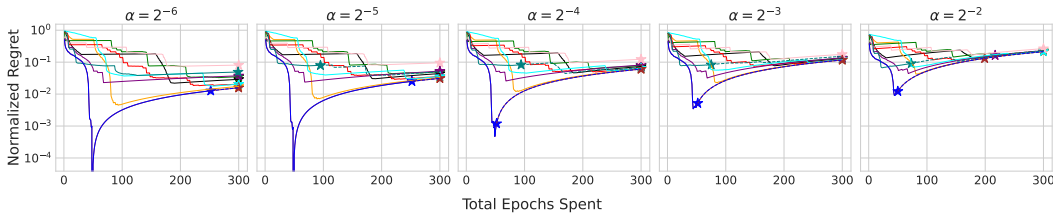


Figure 7: **Visualization of the normalized regrets on PD1 benchmark.** See Appendix G for the others.

4.2 Main Results

Results on conventional multi-fidelity HPO ($\alpha = 0$). We first validate the effectiveness of the proposed CFBO in conventional multi-fidelity HPO setups ($\alpha = 0$). The results are presented in Fig. 5, where **non-transfer** learning and **transfer** learning methods are denoted by **X** and **O** markers, respectively. Notably, although our methods are not specifically designed for conventional setups ($\alpha = 0$), they achieve results **comparable** to the baselines. For example, CFBO-NT, the non-transfer learning variant, performs on par with the best non-transfer baseline, ifBO. Similarly, CFBO achieves comparable performance to transfer-BO baselines, showing better normalized regret on TaskSet and PD1, and slightly higher regret on LCBench compared to FSBO.

Results on cost-sensitive multi-fidelity HPO ($\alpha > 0$). In real-world scenarios, utility functions can take various forms and may be defined differently by different users. To evaluate the effectiveness of CFBO under such realistic cost-sensitive settings, we conduct experiments on *various* utility functions, including linear ($c = 1$), square ($c = 2$), and square-root ($c = 0.5$), with $\alpha \in \{2^{-6}, 2^{-5}, 2^{-4}, 2^{-3}, 2^{-2}\}$. Fig. 6 presents the normalized regret (first row) and rank (second row) for each method. First, CFBO-NT not only **outperforms all non-transfer learning baselines** (denoted with the X markers) but also **surpasses a strong transfer-learning baseline** (i.e., FSBO) in several settings—e.g., most PD1 cases in terms of rank—except for $c = 2$ and $\alpha = 2^{-6}$. CFBO **exceeds all relevant baselines** in most settings, except TaskSet with $c = 1$ and $\alpha = 2^{-2}$, demonstrating the robustness of our method to variations in the utility function.

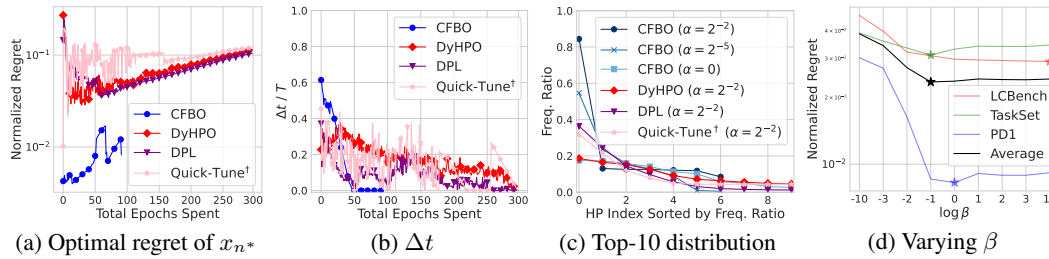


Figure 8: (a) **Optimal regret** of the selected configuration x_{n^*} at a future step $b + \Delta t$. (b) **Future Δt** in (a) at which the optimal regret of x_{n^*} is achieved. (c) **Distribution of the top-10** hyperparameter configurations selected during BO. (d) Normalized regrets with **varying β** of BetaCDF($\cdot, \beta, \beta$) ^{γ} in Eq. 7 ($\gamma = \log_{0.5} 0.2$).

Visualization. We also visualize the normalized regret during the BO process using a task from the PD1 benchmark in Fig. 7. Asterisks indicate stopping points, while dotted lines represent the normalized regret achievable without stopping. Although our CFBO struggles to stop near the maximum utility (minimum regret) during the BO process when the penalty is weak ($\alpha \in \{2^{-6}, 2^{-5}\}$), the regrets obtained at those points are **still lower than the baselines**. In addition, CFBO successfully **stops almost at the optimum** when the penalty is stronger ($\alpha \in \{2^{-4}, 2^{-3}, 2^{-2}\}$).

Algorithm runtime. In Tab. 2, we report the average wall-clock time per BO step over five runs for DPL [24], ifBO [44], and CFBO. All measurements are conducted on a single A100 GPU. While ifBO is the most efficient method, the difference between the wall-clock times of ifBO and CFBO is **negligible**, as neural network training dominates the total wall-clock time in HPO (e.g., 90 seconds for ResNet-50 [20] per training epoch in CIFAR-10/100 [31]).

Table 2: **Wall-clock time (seconds)** per BO step on LCBench, TaskSet, and PD1.

Method	LCBench	TaskSet	PD1
DPL [24]	0.65 ± 0.02	0.64 ± 0.01	0.63 ± 0.01
ifBO [44]	0.58 ± 0.01	0.30 ± 0.00	0.08 ± 0.00
CFBO (ours)	1.52 ± 0.02	0.78 ± 0.01	0.23 ± 0.01

Real-world object detection dataset. We evaluate CFBO on a real-world object detection dataset and observe that it achieves the **best performance** (in terms of both normalized regret and rank) among all baselines. Details and additional experimental results are provided in Appendix G.

4.3 Analysis

Ablation study. To evaluate the effectiveness of each component, we conduct ablation studies on the proposed (1) **stopping criterion** (§3.3), (2) **acquisition function** (§3.2), and (3) **transfer learning with the LC mixup** (§3.4) on the PD1 benchmark. For (1) the stopping criterion, we compare two approaches: the smoothly mixed criterion with our adaptive threshold (δ_b ✓) and the only regret-based criterion with a fixed threshold δ (δ_b ✗), which is used by the baselines. For (2) the acquisition function, we use either our proposed approach (Eq. 4; A ✓) or the acquisition function of ifBO [44, A ✗]. For (3) transfer learning, we compare our surrogate trained with the proposed mixup strategy (T. ✓) against the ifBO [44] which is only trained on synthetic prior data (T. ✗).

In Tab. 3, comparing the first and second rows, we see that transfer learning is relatively more effective in conventional settings ($\alpha = 0$) than in cost-sensitive settings ($\alpha > 0$). Comparing between the second and third rows shows that our acquisition function enhances performance more in cost-sensitive settings. Lastly, comparing between the third and last row shows that our adaptive threshold significantly improves performance in cost-sensitive settings.

Table 3: **Results of ablation studies** using the PD1 benchmark. For better readability, we multiply 100 to normalized regrets.

δ_b	A	T.	α					
			0	2^{-6}	2^{-5}	2^{-4}	2^{-3}	2^{-2}
✗	✗	✗	0.8 ± 0.1	2.3 ± 0.1	3.7 ± 0.3	6.0 ± 0.6	9.8 ± 1.1	15.2 ± 2.0
✗	✗	✓	0.2 ± 0.0	1.7 ± 0.1	3.2 ± 0.1	5.9 ± 0.3	9.4 ± 0.4	11.7 ± 0.4
✗	✓	✓	0.2 ± 0.0	1.5 ± 0.0	2.6 ± 0.0	4.5 ± 0.0	6.9 ± 0.0	8.5 ± 0.0
✓	✓	✓	0.2 ± 0.0	1.0 ± 0.0	1.3 ± 0.0	0.9 ± 0.0	1.1 ± 0.0	1.7 ± 0.0

Analysis on acquisition function (§3.2). To better understand the sources of improvement, we analyze the configurations selected by each method. Specifically, for each BO step b , we run the configuration x_{n^*} currently chosen at step b up to its final epoch T and compute two metrics: the *minimum ground-truth regret* R achievable at some future step $b + \Delta t$ (Fig. 8a) and the *corresponding optimal increment* Δt (Fig. 8b). In Fig. 8a, our method achieves significantly **lower minimum regret** compared to baselines. This indicates that our acquisition function in Eq. 4 performs *as intended*, selecting at each BO step the configuration expected to **maximally improve utility** in the

future. Fig. 8b shows that the configurations selected by our method initially correspond to larger Δt values (*i.e.*, *non-greedy* behavior), but progressively shift to smaller Δt values (*i.e.*, *greedy* behavior). This transition occurs because, as the BO progresses, the performance improvements begin to saturate, causing the cost of BO to dominate the trade-off. Consequently, Δt becomes smaller, eventually approaching zero. These behaviors are **not prominently observed** in the baselines.

Fig. 8c shows the distribution of the top-10 most frequently selected configurations during BO. As expected, our method tends to **focus on a smaller subset** of configurations, optimizing for short-term performance, particularly under stronger penalties (*i.e.*, larger α). The baselines exhibit excessive exploration of configurations, even under the strongest penalty (*i.e.*, $\alpha = 2^{-2}$).

Analysis on stopping criterion (§3.3). Next, we analyze the effectiveness of our stopping criterion with the adaptive threshold δ_b defined in Eqs. 5–7. Fig. 8d presents the normalized regret in various values of β , the mixing coefficient between the two extreme stopping criteria discussed in §3.3. $\log \beta \rightarrow 10$ corresponds to the baseline criterion (the fixed threshold $\delta = 0.2$), which relies solely on the estimated normalized regret in Eq. 5. $\log \beta \rightarrow -10$ corresponds to hard thresholding based exclusively on the PI p_b in Eq. 7. The results show that the optimal criterion is achieved with **a smooth balance** between the two ($\beta = e^{-1}$), demonstrating the importance of incorporating the possibility of further improvement through p_b .

To further assess the significance of the stopping criterion in cost-sensitive multi-fidelity HPO, we quantify the improvement of normalized regrets obtained by an *optimal stopping criterion* for each method. The optimal stopping criterion assumes that the BO process is stopped at the point of *maximum utility* in the BO trajectory for each method. Fig. 9 presents the average improvement on the PD1 benchmark across all $\alpha \in \{2^{-6}, 2^{-5}, 2^{-4}, 2^{-3}, 2^{-2}\}$. The improvement is smaller when using the adaptive threshold δ_b in Eq. 6; *i.e.*, our adaptive stopping criterion **closely approximates** the optimal stopping point, leaving minimal room for improvement and demonstrating its effectiveness.

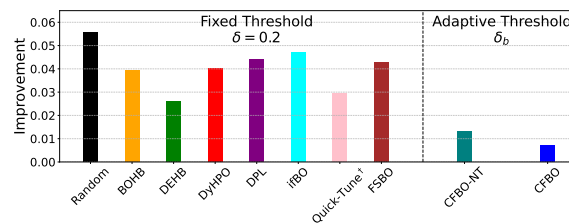


Figure 9: Improvement with the optimal stopping criterion.

5 Conclusion

In this paper, we present cost-sensitive freeze-thaw Bayesian optimization to improve the efficiency of hyperparameter optimization (HPO). Assuming that users aim to early-stop HPO when the utility saturates, we introduced a novel acquisition function and stopping criterion specifically tailored to this problem setup. Additionally, we proposed a novel transfer learning method for training a sample-efficient in-context learning curve (LC) extrapolator. Our empirical evaluation demonstrated the effectiveness of our approach compared to existing multi-fidelity HPO and transfer-BO methods.

Limitations and future work. We identify three main limitations of our study and outline potential directions for future research as follows:

- We focus on **pool-based HPO**, *i.e.*, $|\mathcal{X}| \in \mathbb{N}$, which may not fully reflect real-world applications. To enable continuous optimization over $x_n \in \mathbb{R}^{d_x}$, a common approach [48] is to perform *gradient ascent* on the hyperparameter configuration x_n to maximize the acquisition function A . In this case, A must be differentiable with respect to x_n . Unfortunately, our acquisition function $A(\cdot; U)$ in Eq. 4 does *not satisfy* this property, since the sampling from p_θ (for MC estimation) is not differentiable. Extending CFBO to this continuous setting remains an interesting direction.
- In §3.4, we explore transfer learning by training Prior-Data Fitted Networks [39] on mixed LC datasets. Recently, Tune-Tables [15] have demonstrated strong performance in fine-tuning PFNs on tabular datasets through **context optimization**. Since transfer learning is not only a key component of our work but also widely recognized in the literature [60, 3], integrating the LC mixup with the context optimization approach of Tune-Tables presents a promising direction.
- Our work assumes that users care only about the trade-off within a single task. In real-world scenarios, however, users (*e.g.*, cloud service customers) may also consider **future budgets** or the costs of **multiple tasks** running in parallel. Developing a system that accounts for these more complex and realistic settings would be a valuable direction.

Acknowledgement

We express our sincere gratitude to the anonymous reviewers (**uqhd**, **AJQp**, **Ly5J**, and **Vxb6**) for their valuable feedback and efforts in helping us improve this paper.

Funding. This work was supported by Institute for Information & communications Technology Planning & Evaluation(IITP) grant funded by the Korea government(MSIT) (RS-2019-II190075, Artificial Intelligence Graduate School Program(KAIST), No.RS-2022-II220713, Meta-learning Applicable to Real-world Problems), IITP with a grant funded by the Ministry of Science and ICT (MSIT) of the Republic of Korea in connection with the Global AI Frontier Lab International Collaborative Research (No. RS-2024-00469482 & RS-2024-00509279), National Research Foundation of Korea (NRF) grant funded by MSIT (No. RS-2023-00256259), and Center for Applied Research in Artificial Intelligence (CARAI) grant funded by DAPA and ADD (UD190031RD).

References

- [1] Majid Abdolshah, Alistair Shilton, Santu Rana, Sunil Gupta, and Svetha Venkatesh. Cost-aware multi-objective bayesian optimisation. *arXiv preprint arXiv:1909.03600*, 2019.
- [2] Steven Adriaensen, Herilalaina Rakotoarison, Samuel Müller, and Frank Hutter. Efficient bayesian learning curve extrapolation using prior-data fitted networks. *Advances in Neural Information Processing Systems*, 36, 2023.
- [3] Sebastian Pineda Arango, Fabio Ferreira, Arlind Kadra, Frank Hutter, and Josif Grabocka. Quick-tune: Quickly learning which pretrained model to finetune and how. In *The Twelfth International Conference on Learning Representations*, 2023.
- [4] Noor Awad, Neeratyoy Mallik, and Frank Hutter. Dehb: Evolutionary hyperband for scalable, robust and efficient hyperparameter optimization. In Zhi-Hua Zhou, editor, *Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence, IJCAI-21*, pages 2147–2153. International Joint Conferences on Artificial Intelligence Organization, 8 2021. doi: 10.24963/ijcai.2021/296. URL <https://doi.org/10.24963/ijcai.2021/296>. Main Track.
- [5] Tianyi Bai, Yang Li, Yu Shen, Xinyi Zhang, Wentao Zhang, and Bin Cui. Transfer learning for bayesian optimization: A survey. *arXiv preprint arXiv:2302.05927*, 2023.
- [6] Yuntao Bai, Andy Jones, Kamal Ndousse, Amanda Askell, Anna Chen, Nova DasSarma, Dawn Drain, Stanislav Fort, Deep Ganguli, Tom Henighan, et al. Training a helpful and harmless assistant with reinforcement learning from human feedback. *arXiv preprint arXiv:2204.05862*, 2022.
- [7] Bowen Baker, Otkrist Gupta, Ramesh Raskar, and Nikhil Naik. Accelerating neural architecture search using performance prediction. *arXiv preprint arXiv:1705.10823*, 2017.
- [8] James Bergstra and Yoshua Bengio. Random search for hyper-parameter optimization. *Journal of machine learning research*, 13(2), 2012.
- [9] James Bergstra, Rémi Bardenet, Yoshua Bengio, and Balázs Kégl. Algorithms for hyper-parameter optimization. *Advances in neural information processing systems*, 24, 2011.
- [10] Ralph Allan Bradley and Milton E Terry. Rank analysis of incomplete block designs: I. the method of paired comparisons. *Biometrika*, 39(3/4):324–345, 1952.
- [11] Floriana Ciaglia, Francesco Saverio Zuppichini, Paul Guerrie, Mark McQuade, and Jacob Solawetz. Roboflow 100: A rich, multi-domain object detection benchmark. *arXiv preprint arXiv:2211.13523*, 2022.
- [12] Alexander I Cowen-Rivers, Wenlong Lyu, Rasul Tutunov, Zhi Wang, Antoine Grosnit, Ryan Rhys Griffiths, Alexandre Max Maraval, Hao Jianye, Jun Wang, Jan Peters, et al. Hebo: Pushing the limits of sample-efficient hyper-parameter optimisation. *Journal of Artificial Intelligence Research*, 74:1269–1349, 2022.

- [13] Tobias Domhan, Jost Tobias Springenberg, and Frank Hutter. Speeding up automatic hyperparameter optimization of deep neural networks by extrapolation of learning curves. In *Twenty-fourth international joint conference on artificial intelligence*, 2015.
- [14] Stefan Falkner, Aaron Klein, and Frank Hutter. Bohb: Robust and efficient hyperparameter optimization at scale. In *International conference on machine learning*, pages 1437–1446. PMLR, 2018.
- [15] Benjamin Feuer, Robin T Schirrmeister, Valeriia Cherepanova, Chinmay Hegde, Frank Hutter, Micah Goldblum, Niv Cohen, and Colin White. Tunetables: Context optimization for scalable prior-data fitted networks. *Advances in Neural Information Processing Systems*, 37:83430–83464, 2024.
- [16] Luca Franceschi, Michele Donini, Paolo Frasconi, and Massimiliano Pontil. Forward and reverse gradient-based hyperparameter optimization. In *International Conference on Machine Learning*, pages 1165–1173. PMLR, 2017.
- [17] Matilde Gargiani, Aaron Klein, Stefan Falkner, and Frank Hutter. Probabilistic rollouts for learning curve extrapolation across hyperparameter settings. *arXiv preprint arXiv:1910.04522*, 2019.
- [18] Marta Garnelo, Jonathan Schwarz, Dan Rosenbaum, Fabio Viola, Danilo J Rezende, SM Eslami, and Yee Whye Teh. Neural processes. *arXiv preprint arXiv:1807.01622*, 2018.
- [19] Daniel Golovin, Benjamin Solnik, Subhodeep Moitra, Greg Kochanski, John Karro, and David Sculley. Google vizier: A service for black-box optimization. In *Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining*, pages 1487–1495, 2017.
- [20] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.
- [21] Dan Hendrycks and Kevin Gimpel. Gaussian error linear units (gelus). *arXiv preprint arXiv:1606.08415*, 2016.
- [22] Frank Hutter, Holger H Hoos, and Kevin Leyton-Brown. Sequential model-based optimization for general algorithm configuration. In *Learning and Intelligent Optimization: 5th International Conference, LION 5, Rome, Italy, January 17-21, 2011. Selected Papers 5*, pages 507–523. Springer, 2011.
- [23] Carl Hvarfner, Danny Stoll, Artur Souza, Marius Lindauer, Frank Hutter, and Luigi Nardi. π bo: Augmenting acquisition functions with user beliefs for bayesian optimization. In *International Conference on Learning Representations*, 2021.
- [24] Arlind Kadra, Maciej Janowski, Martin Wistuba, and Josif Grabocka. Scaling laws for hyperparameter optimization. In *Thirty-seventh Conference on Neural Information Processing Systems*, 2023.
- [25] Kirthivasan Kandasamy, Gautam Dasarathy, Barnabas Poczos, and Jeff Schneider. The multi-fidelity multi-armed bandit. *Advances in neural information processing systems*, 29, 2016.
- [26] Kirthivasan Kandasamy, Gautam Dasarathy, Jeff Schneider, and Barnabás Póczos. Multi-fidelity bayesian optimisation with continuous approximations. In *International conference on machine learning*, pages 1799–1808. PMLR, 2017.
- [27] Zohar Karnin, Tomer Koren, and Oren Somekh. Almost optimal exploration in multi-armed bandits. In *International conference on machine learning*, pages 1238–1246. PMLR, 2013.
- [28] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.
- [29] Aaron Klein, Stefan Falkner, Simon Bartels, Philipp Hennig, and Frank Hutter. Fast bayesian optimization of machine learning hyperparameters on large datasets. In *Artificial intelligence and statistics*, pages 528–536. PMLR, 2017.

- [30] Aaron Klein, Stefan Falkner, Jost Tobias Springenberg, and Frank Hutter. Learning curve prediction with bayesian neural networks. In *International conference on learning representations*, 2017.
- [31] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.
- [32] Eric Hans Lee, Valerio Perrone, Cedric Archambeau, and Matthias Seeger. Cost-aware bayesian optimization. *arXiv preprint arXiv:2003.10870*, 2020.
- [33] Liam Li, Kevin Jamieson, Afshin Rostamizadeh, Ekaterina Gonina, Jonathan Ben-Tzur, Moritz Hardt, Benjamin Recht, and Ameet Talwalkar. A system for massively parallel hyperparameter tuning. *Proceedings of Machine Learning and Systems*, 2:230–246, 2020.
- [34] Lisha Li, Kevin Jamieson, Giulia DeSalvo, Afshin Rostamizadeh, and Ameet Talwalkar. Hyperband: A novel bandit-based approach to hyperparameter optimization. *Journal of Machine Learning Research*, 18(185):1–52, 2018.
- [35] Anastasia Makarova, Huibin Shen, Valerio Perrone, Aaron Klein, Jean Baptiste Faddoul, Andreas Krause, Matthias Seeger, and Cedric Archambeau. Automatic termination for hyperparameter optimization. In *International Conference on Automated Machine Learning*, pages 7–1. PMLR, 2022.
- [36] Neeratyoy Mallik, Edward Bergman, Carl Hvarfner, Danny Stoll, Maciej Janowski, Marius Lindauer, Luigi Nardi, and Frank Hutter. Priorband: Practical hyperparameter optimization in the age of deep learning. *Advances in Neural Information Processing Systems*, 36, 2024.
- [37] Luke Metz, Niru Maheswaranathan, Ruoxi Sun, C Daniel Freeman, Ben Poole, and Jascha Sohl-Dickstein. Using a thousand optimization tasks to learn hyperparameter search strategies. *arXiv preprint arXiv:2002.11887*, 2020.
- [38] J Mockus, V Tiesis, and A Zilinskas. The application of bayesian methods for seeking the extremum, vol. 2. *L Dixon and G Szego. Toward Global Optimization*, 2, 1978.
- [39] Samuel Müller, Noah Hollmann, Sebastian Pineda Arango, Josif Grabocka, and Frank Hutter. Transformers can do bayesian inference. In *International Conference on Learning Representations*, 2021.
- [40] Samuel Müller, Matthias Feurer, Noah Hollmann, and Frank Hutter. Pfns4bo: In-context learning for bayesian optimization. In *International Conference on Machine Learning*, pages 25444–25470. PMLR, 2023.
- [41] Tung Nguyen and Aditya Grover. Transformer neural processes: Uncertainty-aware meta learning via sequence modeling. In *International Conference on Machine Learning*, pages 16569–16594. PMLR, 2022.
- [42] Valerio Perrone, Rodolphe Jenatton, Matthias W Seeger, and Cédric Archambeau. Scalable hyperparameter transfer learning. *Advances in neural information processing systems*, 31, 2018.
- [43] Matthias Poloczek, Jialei Wang, and Peter Frazier. Multi-information source optimization. *Advances in neural information processing systems*, 30, 2017.
- [44] Herilalaina Rakotoarison, Steven Adriaensen, Neeratyoy Mallik, Samir Garibov, Edward Bergman, and Frank Hutter. In-context freeze-thaw bayesian optimization for hyperparameter optimization. *arXiv preprint arXiv:2404.16795*, 2024.
- [45] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 115(3):211–252, 2015. doi: 10.1007/s11263-015-0816-y.

- [46] David Salinas, Matthias Seeger, Aaron Klein, Valerio Perrone, Martin Wistuba, and Cedric Archambeau. Syne tune: A library for large scale hyperparameter tuning and reproducible research. In *International Conference on Automated Machine Learning, AutoML 2022*, 2022. URL <https://proceedings.mlr.press/v188/salinas22a.html>.
- [47] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4510–4520, 2018.
- [48] Jasper Snoek, Hugo Larochelle, and Ryan P Adams. Practical bayesian optimization of machine learning algorithms. *Advances in neural information processing systems*, 25, 2012.
- [49] Jasper Snoek, Kevin Swersky, Rich Zemel, and Ryan Adams. Input warping for bayesian optimization of non-stationary functions. In *International conference on machine learning*, pages 1674–1682. PMLR, 2014.
- [50] Jasper Snoek, Oren Rippel, Kevin Swersky, Ryan Kiros, Nadathur Satish, Narayanan Sundaram, Mostofa Patwary, Mr Prabhat, and Ryan Adams. Scalable bayesian optimization using deep neural networks. In *International conference on machine learning*, pages 2171–2180. PMLR, 2015.
- [51] Artur Souza, Luigi Nardi, Leonardo B Oliveira, Kunle Olukotun, Marius Lindauer, and Frank Hutter. Bayesian optimization with a prior for the optimum. In *Machine Learning and Knowledge Discovery in Databases. Research Track: European Conference, ECML PKDD 2021, Bilbao, Spain, September 13–17, 2021, Proceedings, Part III 21*, pages 265–296. Springer, 2021.
- [52] Kevin Swersky, Jasper Snoek, and Ryan P Adams. Multi-task bayesian optimization. *Advances in neural information processing systems*, 26, 2013.
- [53] Kevin Swersky, Jasper Snoek, and Ryan Prescott Adams. Freeze-thaw bayesian optimization. *arXiv preprint arXiv:1406.3896*, 2014.
- [54] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.
- [55] Jingdong Wang, Ke Sun, Tianheng Cheng, Borui Jiang, Chaorui Deng, Yang Zhao, Dong Liu, Yadong Mu, Minghui Tan, Xinggang Wang, et al. Deep high-resolution representation learning for visual recognition. *IEEE transactions on pattern analysis and machine intelligence*, 43(10): 3349–3364, 2020.
- [56] Zi Wang, George E Dahl, Kevin Swersky, Chansoo Lee, Zachary Nado, Justin Gilmer, Jasper Snoek, and Zoubin Ghahramani. Pre-trained gaussian processes for bayesian optimization. *arXiv preprint arXiv:2109.08215*, 2021.
- [57] Ying Wei, Peilin Zhao, and Junzhou Huang. Meta-learning hyperparameter performance prediction with neural processes. In *International Conference on Machine Learning*, pages 11058–11067. PMLR, 2021.
- [58] Andrew Gordon Wilson, Zhiting Hu, Ruslan Salakhutdinov, and Eric P Xing. Deep kernel learning. In *Artificial intelligence and statistics*, pages 370–378. PMLR, 2016.
- [59] James Wilson. Stopping bayesian optimization with probabilistic regret bounds. *Advances in Neural Information Processing Systems*, 37:98264–98296, 2024.
- [60] Martin Wistuba and Josif Grabocka. Few-shot bayesian optimization with deep kernel surrogates. In *International Conference on Learning Representations*, 2020.
- [61] Martin Wistuba and Tejaswini Pedapati. Learning to rank learning curves. In *International Conference on Machine Learning*, pages 10303–10312. PMLR, 2020.
- [62] Martin Wistuba, Arlind Kadra, and Josif Grabocka. Supervising the multi-fidelity race of hyperparameter configurations. *Advances in Neural Information Processing Systems*, 35:13470–13484, 2022.

- [63] Jian Wu and Peter I Frazier. Continuous-fidelity bayesian optimization with knowledge gradient. 2018.
- [64] Jian Wu, Saul Toscano-Palmerin, Peter I Frazier, and Andrew Gordon Wilson. Practical multi-fidelity bayesian optimization for hyperparameter tuning. In *Uncertainty in Artificial Intelligence*, pages 788–798. PMLR, 2020.
- [65] Qian Xie, Raul Astudillo, Peter Frazier, Ziv Scully, and Alexander Terenin. Cost-aware bayesian optimization via the pandora’s box gittins index. *Advances in Neural Information Processing Systems*, 37:115523–115562, 2024.
- [66] Hongyi Zhang, Moustapha Cisse, Yann N. Dauphin, and David Lopez-Paz. mixup: Beyond empirical risk minimization. In *International Conference on Learning Representations*, 2018. URL <https://openreview.net/forum?id=r1Ddp1-Rb>.
- [67] Lucas Zimmer, Marius Lindauer, and Frank Hutter. Auto-pytorch: Multi-fidelity metalearning for efficient and robust autodl. *IEEE transactions on pattern analysis and machine intelligence*, 43(9):3079–3090, 2021.

Appendix Overview

This appendix provides supplementary materials to support the main paper as follows:

- **Related Work** (Appendix A): discusses the relevant literature on (1) multi-fidelity HPO, (2) freeze-thaw BO, (3) LC extrapolation, (4) transfer BO, (5) cost-sensitive HPO, (6) early stopping BO, (7) BO with user preferences, and (8) neural processes.
- **Notation** (Appendix B): summarizes an overview of the notation used throughout this paper.
- **Utility Estimation** (Appendix C): details how we can estimate user utility with Bradley-Terry model [10] and provides several examples.
- **Dataset** (Appendix D): provides details on benchmarks (LCBench [67], TaskSet [37], PD1 [55]) and data preprocessing.
- **Details on LC Extrapolator** (Appendix E): contains the architectural and training details of the LC extrapolator p_θ .
- **Implementation Details** (Appendix F): includes implementation details of CFBO and baselines.
- **Additional Experiments** (Appendix G): presents additional experiments, including results on real-world object detection datasets and visualizations of normalized regrets and LC extrapolations during Bayesian optimization process.

A Related Work

Multi-fidelity HPO. Unlike traditional black-box approaches for HPO [8, 22, 9, 48, 50, 49, 12, 40], multi-fidelity (or gray-box) HPO aims to optimize hyperparameters in a sample-efficient manner by utilizing low-fidelity information (*e.g.*, validation set performances with smaller training datasets) as a proxy for higher or full fidelities [52, 25, 29, 43, 26, 63, 64], dramatically speeding up the HPO process. In this paper, we focus on using performances at fewer training epochs to better predict and optimize performances at longer training epochs. One well-known example is Hyperband [34], a bandit-based method that randomly selects a set of hyperparameter configurations and stops poorly performing ones using successive halving [27] before reaching the last training epoch. While Hyperband shows much better performance than random search [8], its computational or sample efficiency can be further improved by replacing random sampling of configurations with Bayesian optimization [BOHB; 14], adopting an evolution strategy to promote internal knowledge transfer [DEHB; 4], or making it asynchronously parallel [33].

Freeze-thaw BO. Freeze-thaw BO [53] dynamically pauses (freezes) and resumes (thaws) configurations based on the last epoch's performances extrapolated from a set of partially observed learning curves (LCs) obtained from other configurations, leading to an efficient and sensible allocation of computational resources. DyHPO [62] and its transfer version [3] improve the computational efficiency of freeze-thaw BO using deep kernel Gaussian processes [GPs; 58], but their acquisition maximizes one-step forward fidelity (*i.e.*, epoch), producing a myopic strategy. Other recent variants of freeze-thaw BO include DPL [24] and ifBO [44], which are non-myopic, and their acquisitions maximize performance either at the last fidelity or random future steps. On the other hand, we maximize the utility specified by each user.

LC extrapolation. Freeze-thaw BO requires the ability to dynamically update predictions on future performances from partially observed learning curves (LCs), thus heavily relying on LC extrapolation [7, 17, 61]. DyHPO [62] and Quick-Tune [3] propose to extrapolate LCs for only a single step forward. Freeze-thaw BO [53] and DPL [24] use non-greedy extrapolations but limit the shape of the LCs. [13] consider a broader set of basis functions but require computationally expensive Markov Chain Monte Carlo (MCMC), and also do not consider correlations between different configurations. [30] models interactions between configurations with Bayesian neural networks (BNNs) but suffers from the same computational inefficiency of MCMC and online retraining. LC-PFNs [2] are an in-context Bayesian LC extrapolation method without retraining, but they do not consider interactions between configurations. Recently, ifBO [44] further combined LC-PFNs with PFNs4BO [40] to develop an in-context surrogate function for freeze-thaw BO, but they train PFNs only with a prior distribution. On the other hand, we use transfer learning with LC mixup (§3.4), *i.e.*, training PFNs with existing LC datasets, to improve the sample efficiency of freeze-thaw BO while successfully encoding the correlations between configurations at the same time.

Transfer-BO. Transfer learning can be used to improve the sample efficiency of BO [5], and here we list a few examples. Some recent work has explored scalable transfer learning with deep neural networks [42, 60]. Additionally, different components of BO can be transferred, such as observations [52], surrogate functions [19, 60], hyperparameter initializations [60], or all of them [57]. However, most of the existing transfer-BO approaches assume traditional black-box BO settings. To the best of our knowledge, Quick-Tune [3] is the only recent work that targets multi-fidelity and transfer-BO simultaneously. However, their multi-fidelity BO formulation is greedy. As described in Figs. 8a and 8b of §4.3, our CFBO can dynamically control the degree of greediness during BO by explicitly taking into account the trade-off between the cost and performance of BO.

Cost-sensitive HPO. Multi-fidelity BO is inherently cost-sensitive since predictions get more accurate as the gap between fidelities becomes smaller. However, the performance metric of such vanilla multi-fidelity BO monotonically increases as we spend more budget. In this paper, we aim to find the *optimal trade-off* between the budget spent and the corresponding intermediate performances of BO, thereby automatically early-stopping the BO around the maximal utility. Quick-Tune [3] also suggests cost-sensitive BO in multi-fidelity settings, but unlike our work, their primary focus is on the trade-off between performance and the cost of BO associated with *pretrained models of various sizes*, which can be seen as a generalization of the traditional notion of cost-sensitive BO [48, 1, 32, 65] from black-box to multi-fidelity settings.

Early stopping BO. Makarova et al. [35] propose a *principled* early stopping BO using:

$$f^* - f_b \leq 2\epsilon + \tilde{y}^* - \tilde{y}_b, \quad (9)$$

where f denotes the true performance of population, $\tilde{y}_b$ the validation performance, $*$ the maximizer, and $\epsilon \in \mathbb{R}_{>0}$ a statistical error term. Eq. 9 leads to stopping condition as follows:

$$\tilde{y}^* - \tilde{y}_b \leq \epsilon. \quad (10)$$

Eq. 10 can be expressed using a utility function:

$$U(b, \tilde{y}_b) = \begin{cases} \tilde{y}_b, & \text{if } \tilde{y}_b \geq \tilde{y}^* - \epsilon, \\ -\infty, & \text{otherwise.} \end{cases} \quad (11)$$

Since $\tilde{y}^*$ and ϵ are unknown, Makarova et al. [35] estimate them using lower confidence bound (LCB), upper confidence bound (UCB), and the coefficient of variation (CV). As these estimators are functions of the budget b , Eq. 11 can be rewritten in a **utility view**:

$$U(b, \tilde{y}_b) = \begin{cases} \tilde{y}_b, & \text{if } \tilde{y}_b \geq c(b), \\ -\infty, & \text{otherwise.} \end{cases} \quad (12)$$

Interpreted this way, the stopping criterion in Makarova et al. [35] *roughly* corresponds to the preference: “*Stop once performance exceeds $c(b)$; additional budget has no value thereafter.*” Therefore, Eq. 12 represents a special case of our utility formulation.

Similarly, Wilson [59] roughly fits into a utility view:

$$U(b, \tilde{y}_b) = \begin{cases} \tilde{y}_b, & \text{if } p(r_b \leq \epsilon|C) < 1 - \delta, \\ -c_b, & \text{otherwise,} \end{cases} \quad (13)$$

where $r_b = f^* - f_b$ and c_b is the cumulative cost. Furthermore, although both Makarova et al. [35] and Wilson [59] provide *principled and general* approaches for early stopping in BO, they primarily target *black-box* BO settings. Due to this fundamental difference, we exclude them from our baselines in §4.

BO with user preference. Several works have tried to encode the user beliefs about hyperparameter configurations into BO frameworks [51, 23, 36]. On the other hand, our paper suggests encoding user preferences regarding the trade-off between cost and performance. Therefore, the notion of user preference in this paper is largely different from the previous literature.

Neural Process Our training method is more similar to Transformer Neural Processes (TNPs) [41], a Transformer variant of Neural Processes [NPs; 18]. Similarly to PFNs [39, 2, 44], TNPs directly maximize the likelihood of target data given context data with a Transformer architecture, which differs from the typical NP variants that summarize the context into a latent variable and perform variational inference on it. Moreover, as with the other NP variants, TNPs meta-learn a model over a distribution of tasks to perform sample-efficient inference. In this vein, the whole training pipeline of our LC extrapolator can be seen as an instance of TNPs—we also meta-learn a sample-efficient LC extrapolator over the distribution of LCs induced by the mixup strategy.

B Notation

In this section, we summarize the notation used throughout the paper in [Tab. 4](#).

Table 4: **Notation summary.**

Notation	Description
$x_n \in \mathbb{R}^{d_x}$	n -th hyperparameter configuration with dimension of $d_x \in \mathbb{N}$
$\mathcal{X} = \{x_1, \dots, x_N\}$	Set of hyperparameter configurations
$T \in \mathbb{N}$	Maximum training epochs for each configuration
$t \in [T] := \{1, \dots, T\}$	Training-epoch index
$y_{n,t} \in [0, 1]$	Validation performance of x_n at epoch t
$B \in \mathbb{N}$	Maximum total training epochs (overall BO budget)
$b \in [B]$	Budget spent so far
$\tilde{y}_b$	(Cumulative) best performance observed up to budget b
$\mathcal{C} = \{(x, t, y)\}$	Collected partial or full learning curves
$p_\theta : \mathbb{R}^{d_x} \times [T] \times \mathcal{C} \rightarrow [0, 1]$	Learning-curve extrapolator
$U : [B] \times [0, 1] \rightarrow [0, 1]$	Utility function
$c \in \mathbb{R}$	Hyperparameter which decides for functional form of $U(b, \tilde{y}_b) = \tilde{y}_b - \alpha(\frac{b}{B})^c$
$\alpha \in [0, 1]$	Penalty coefficient of $U(b, \tilde{y}_b) = \tilde{y}_b - \alpha(\frac{b}{B})^c$
$U_p \in [0, 1]$	Utility immediately before current BO step
$A(\cdot; U) : [N] \rightarrow \mathbb{R}$	Acquisition function in Eq. 4
$\hat{R}_b := \frac{\hat{U}_{\max} - U_p}{\hat{U}_{\max} - \hat{U}_{\min}} \in [0, 1]$	The roughly estimated normalized regret in Eq. 5
$\hat{U}_{\max} \in [0, 1]$	Maximum utility observed so far for computing $\hat{R}_b$ in Eq. 5
$\hat{U}_{\min} := U(B, \tilde{y}_1) \in [0, 1]$	Approximated minimum utility for computing $\hat{R}_b$ in Eq. 5
$R := \frac{U_{\max} - U_p}{U_{\max} - U_{\min}} \in [0, 1]$	the true normalized regret in Eq. 5
$U_{\max} := \max_{n,t} U(t, y_{n,t}) \in [0, 1]$	True maximum utility for computing R in Eq. 8
$U_{\min} \approx \min_n U(B, y_{n,1}) \in [0, 1]$	Approximated true minimum utility for computing R in Eq. 8
$\delta \in [0, 1]$	Fixed stopping threshold for baselines in Eq. 5
$\delta_b := \text{BetaCDF}(p_b, \beta, \beta)^\gamma \in [0, 1]$	Adaptive stopping threshold instead of δ in Eq. 5
$p_b \in [0, 1]$	Probability that current configuration will improve U_p in Eq. 7
$\text{BetaCDF}(\cdot; \beta, \beta) : [0, 1] \rightarrow [0, 1]$	the CDF of Beta distribution with shape β
$\beta \in \mathbb{R}_{>0}$	Hyperparameter controlling interpolation in Eq. 6
$\gamma \in \mathbb{R}_{>0}$	Hyperparameter setting δ_b at $p_b = 0.5$ in Eq. 6

C Utility Estimation

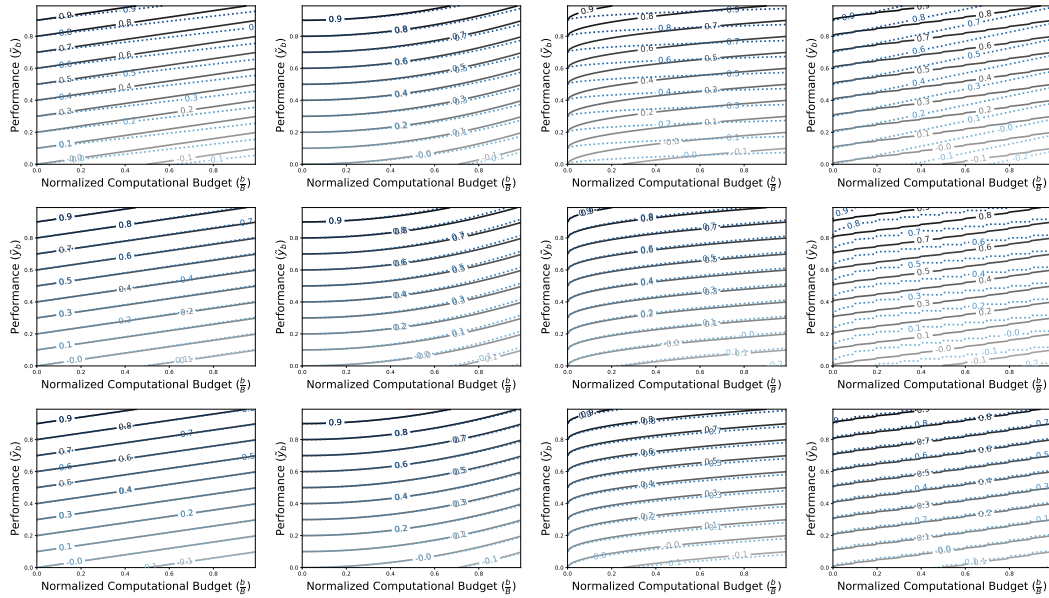


Figure 10: **Contour plots of true utilities and their approximations.** From left to right, the columns show different functional forms of linear ($c = 1$), quadratic ($c = 2$), square root ($c = 0.5$), and a combination of four different functions including a staircase function. From top to bottom, the rows represent 30, 100, and 1000 user preference data pairs.

Functional forms. In real-world scenarios, users can have more complex utility functions. We therefore consider the following functional forms: (1) **Linear**: $\tilde{y}_b - \alpha \frac{b}{B}$, (2) **Quadratic**: $\tilde{y}_b - \alpha (\frac{b}{B})^2$, (3) **Square-Root**: $\tilde{y}_b - \alpha (\frac{b}{B})^{0.5}$, and (4) **Staircase**: $\tilde{y}_b - \sum_i \alpha_i \mathbb{1}(b \in A_i)$ ($\mathbb{1}(\cdot)$ is an indicator function, and A_i is an i -th interval). We further assume that these utility functions can be linearly combined, e.g., $U(\cdot, \cdot) = w^{(\text{linear})}U^{(\text{linear})}(\cdot, \cdot) + \dots + w^{(\text{staircase})}U^{(\text{staircase})}(\cdot, \cdot)$, where $w^{(\text{linear})} + \dots + w^{(\text{staircase})} = 1$.

Data collection. We now describe how we roughly estimate user utility based on the user preference data pairs. First of all, we assume that it is possible for users to decide whether they prefer one point to the other one, instead of quantifying their utility, i.e., we can collect user preference data. For simulation, we assume that we are given these preference data generated by true utility function. True utility function U is randomly defined by sampling penalizing coefficient from $\text{Uniform}(0, 1)$ and linear combination coefficients from Dirichlet distribution. We randomly select *meaningful* data pairs from $b/B \sim \text{Uniform}(0, 1)$ and $\tilde{y}_b \sim \text{Uniform}(0, 1)$. Here, “meaningful data pairs” means that one datapoint of each pair is not trivially preferred by user: for example, one has larger performance $\tilde{y}_b$ with smaller budget b than the other. Users then label their preference on these data pairs; for simulation, we label the pairs by using the true utility functions with sampled α s and linear combination coefficients w s.

Training details. As explained in Eqs. 2 and 3, we use the binary cross-entropy loss $\ell(x, y) := -y \log x - (1 - y) \log(1 - x)$ in Eq. 3 between the probability of preference described by the BT model and the preference label $y_{>} \in \{0, 1\}$. We begin by randomly initializing another utility function to approximate a randomly sampled true utility function, setting the w s and α s to $\frac{1}{4}$ and 0.0001, respectively. We use gradient-based optimization algorithm (e.g., SGD) with 1000 iterations. The temperature term τ in Eq. 2 is set to 0.05.

Estimation results. Fig. 10 demonstrates that not only can single utilities—linear, quadratic, and square root—be well approximated using preference data, but even more complex utilities (e.g., a combination of four different utilities) can also be accurately approximated. Furthermore, we found that the approximation works well even with smaller numbers (e.g., 30, 100) of user preference data pairs for simpler cases (i.e., single utilities).

D Dataset

LCBench. We use the LCBench benchmark [67], which consists of learning curves for MLPs trained on multiple tabular datasets. Each task contains 2,000 learning curves with 51 training epochs. We summarize the hyperparameter settings of LCBench in Tab. 5.

Table 5: The $d_x = 7$ hyperparameters for **LCBench** datasets.

Name	Type	Vaules	Info
batch_size	integer	$[2^4, 2^9]$	log
learning_rate	continuous	$[10^{-4}, 10^{-1}]$	log
max_dropout	continuous	$[0, 1]$	
max_units	integer	$[2^6, 2^{10}]$	log
momentum	continuous	$[0.1, 0.99]$	
max_layers	integer	$[1, 5]$	
weight_decay	continuous	$[10^{-5}, 10^{-1}]$	

The training/test splits are as follows:

- **Training datasets:**

APSFailure, Amazon_employee_access, Australian, Fashion-MNIST, KDDCup09_appetency, MiniBooNE, adult, airlines, albert, bank-marketing, blood-transfusion-service-center, car, christine, cnae-9, connect-4, coverytype, credit-g, dionis, fabert, helena.

- **Test datasets:**

higgs, jannis, jasmine, jungle_chess_2pcs_raw_endgame_complete, kc1, kr-vs-kp, mfeat-factors, nomao, numerai28.6, phoneme, segment, shuttle, sylvine, vehicle, volkert.

TaskSet. We use the TaskSet benchmark [37], which provides learning curves from diverse optimization tasks across multiple domains. Each task contains 1,000 learning curves with 50 training epochs. We summarize the hyperparameter settings of TaskSet in Tab. 6.

Table 6: The $d_x = 8$ hyperparameters for **TaskSet** tasks.

Name	Type	Vaules	Info
learning_rate	continuous	$[10^{-9}, 10^1]$	log
beta1	continuous	$[10^{-4}, 1]$	
beta2	continuous	$[10^{-3}, 1]$	
epsilon	continuous	$[10^{-12}, 10^3]$	log
l1	continuous	$[10^{-9}, 10^1]$	log
l2	continuous	$[10^{-9}, 10^1]$	log
linear_decay	continuous	$[10^{-8}, 10^{-4}]$	log
exponential_decay	continuous	$[10^{-6}, 10^{-3}]$	log

The training/test splits are as follows:

- **Training tasks:**

rnn_text_classification_family_seed{19, 3, 46, 47, 59, 6, 66},
word_rnn_language_model_family_seed{22, 47, 48, 74, 76, 81},
char_rnn_language_model_family_seed{19, 26, 31, 42, 48, 5, 74}.

- **Test tasks:**

rnn_text_classification_family_seed{8, 82, 89},
word_rnn_language_model_family_seed{84, 98, 99},
char_rnn_language_model_family_seed{84, 94, 96}.

PD1. We use the PD1 benchmark [56], where each task contains 240 LCs with 50 training epochs. To facilitate transfer learning, we preprocess the LC data of PD1 by excluding hyperparameter configurations with their training diverging (e.g., LCs with NaN), and linearly interpolate the LCs to match their length across different tasks. We then obtain the LCs of 50 epochs over the 240 configurations. We summarize the hyperparameter of PD1 in Table 7.

Table 7: The $d_x = 8$ hyperparameters for **PD1** tasks.

Name	Type	Vaules	Info
lr_initial_value	continuous	$[10^{-5}, 10^1]$	log
lr_power	continuous	$[10^{-1}, 2]$	
lr_decay_steps_factor	continuous	$[10^{-2}, 0.99]$	
one_minus_momentum	continuous	$[10^{-5}, 1]$	log

The training/test splits are as follows:

- **Training tasks:**

uniref50_transformer_batch_size_128, lm1b_transformer_batch_size_2048,
imagenet_resnet_batch_size_256, mnist_max_pooling_cnn_tanh_batch_size_2048,
mnist_max_pooling_cnn_relu_batch_size_{256, 2048},
mnist_simple_cnn_batch_size_{256, 2048},
fashion_mnist_max_pooling_cnn_tanh_batch_size_2048,
fashion_mnist_max_pooling_cnn_relu_batch_size_{256, 2048},
fashion_mnist_simple_cnn_batch_size_{256, 2048},
svhn_no_extra_wide_resnet_batch_size_1024,
cifar{10,100}_wide_resnet_batch_size_2048.

- **Test tasks:**

imagenet_resnet_batch_size_512, translate_wmt_xformer_translate_batch_size_64,
mnist_max_pooling_cnn_tanh_batch_size_256,
fashion_mnist_max_pooling_cnn_tanh_batch_size_256,
svhn_no_extra_wide_resnet_batch_size_256,
cifar100_wide_resnet_batch_size_256, cifar10_wide_resnet_batch_size_256.

Data Preprocessing We follow the convention of LC-PFN [2] for data preprocessing; we consistently apply a non-linear LC normalization⁵ to the LC data of three benchmarks, which not only maps either accuracy or log-loss LCs into $[0, 1]$ but also simply makes our optimization as a maximization problem. We also use the maximum and minimum values for each task in LCBench and PD1 benchmark for the LC normalization. In TaskSet, we only use the $y_{n,0}$ (*i.e.*, the initial log-loss without taking any gradient steps) for the LC normalization.

E Details on LC Extrapolator

Construction of context and query points. Following ifBO [44], we can simulate each step of BO; predicting the remaining part of LC in all configurations conditioned on the set $\mathcal{C}$ of the collected partial LCs. To do so, we construct a training task by randomly sampling the context and query points from the LC benchmarks after the proposed LC mixup in §3.4 as follows:

1. We choose an LC dataset $L = [l_1, \dots, l_N]^\top \in \mathbb{R}^{N \times T}$ by randomly sampling $m \in [M]$.
2. From $L^{(m)}$, we randomly sample $n_1, \dots, n_C \in [N]$ and $t_1, \dots, t_C \in [T]$ and construct context points of $X^{(c)} = [x_{n_1}, \dots, x_{n_C}]^\top \in \mathbb{R}^{C \times d_x}$, $T^{(c)} = [t_1/T, \dots, t_C/T]^\top \in \mathbb{R}^{C \times 1}$, and $Y^{(c)} = [y_{n_1, t_1}, \dots, y_{n_C, t_C}] \in \mathbb{R}^{C \times 1}$.
3. From the chosen L , we exclude $n_1, \dots, n_C \in [N]$ and $t_1, \dots, t_C \in [T]$ and randomly sample $n'_1, \dots, n'_Q \in [N]$ and $t'_1, \dots, t'_Q \in [T]$ and construct query points of $X^{(q)} = [x_{n'_1}, \dots, x_{n'_Q}]^\top \in \mathbb{R}^{Q \times d_x}$, $T^{(q)} = [t'_1/T, \dots, t'_Q/T]^\top \in \mathbb{R}^{Q \times 1}$, and $Y^{(q)} = [y_{n'_1, t'_1}, \dots, y_{n'_Q, t'_Q}] \in \mathbb{R}^{Q \times 1}$.

Architecture for predicting LCs. From now on, we denote any row vectors of the constructed context and query points in lowercase, *e.g.*, $x^{(q)}$ of $X^{(q)}$, or $y^{(q)}$ of $Y^{(q)}$. We train a Transformer [54] that is a probabilistic model of $f(Y^{(q)} | X^{(c)}, T^{(c)}, Y^{(c)}, X^{(q)}, T^{(q)})$. Conditioned on any subsets of LCs (*i.e.*, $X^{(c)}$, $T^{(c)}$, and $Y^{(c)}$), this model predicts a mini-batch of the remaining part of LCs of existing hyperparameter configurations in a given dataset (*i.e.*, $Y^{(q)}$ of $X^{(q)}$ and $T^{(q)}$). For

⁵The details can be found in Appendix A of PFN [2] and <https://github.com/automl/lcpfn/blob/main/lcpfn/utils.py>.

computational efficiency, we further assume that the query points are independent of each other, as done in PFNs [39, 44]:

$$p_{\theta}(Y^{(q)}|X^{(c)}, T^{(c)}, Y^{(c)}, X^{(q)}, T^{(q)}) = \prod_{x^{(q)}, t^{(q)}, y^{(q)}} p_{\theta}(y^{(q)}|x^{(q)}, t^{(q)}, X^{(c)}, T^{(c)}, Y^{(c)}). \quad (14)$$

Before encoding the input into the Transformer, we first encode the input of $X^{(c)}, T^{(c)}, Y^{(c)}, X^{(q)},$ and $T^{(q)}$ using a simple linear layer as follows:

$$H^{(c)} = X^{(c)}W_x + T^{(c)}W_t + Y^{(c)}W_y \quad (15)$$

$$H^{(q)} = X^{(q)}W_x + T^{(q)}W_t, \quad (16)$$

where $W_x \in \mathbb{R}^{d_x \times d_h}$, $W_t \in \mathbb{R}^{1 \times d_h}$, and $W_y \in \mathbb{R}^{1 \times d_h}$. Here, we abbreviate the bias term.

Then we concatenate the encoded representations of $H^{(c)}$ and $H^{(q)}$, and feedforward it into the Transformer layer by treating each pair of each row vector of $H^{(c)}$ and $H^{(q)}$ as a separate position/token as follows:

$$H = \text{Transformer}([H^{(c)}; H^{(q)}, \text{Mask}]) \in \mathbb{R}^{(M+N) \times d_h} \quad (17)$$

$$\hat{Y} = \text{Head}(H) \in \mathbb{R}^{(M+N) \times d_o}, \quad (18)$$

where $\text{Transformer}(\cdot)$ and $\text{Head}(\cdot)$ denote the Transformer layer and multi-layer perceptron (MLP) for the output prediction, respectively. $\text{Mask} \in \mathbb{R}^{(N_c+N_q) \times (N_c+N_q)}$ is the transformer mask that allows all tokens to attend context tokens only.

In Eq. 18, the output dimension d_o is specified by the output distribution of $y \in [0, 1]$. Following PFNs [39, 2, 44], we discretize the domain of y by $d_o = 1000$ and use the categorical distribution. Finally, we only take the output of the last N_q tokens as the output, i.e., $\hat{Y}^{(q)} = \hat{Y}[:, N_c : (N_c + N_q)] \in \mathbb{R}^{N_q \times d_h}$ (using the indexing operation), since we only need the output of query tokens for modeling $\prod p_{\theta}(y^{(q)}|x^{(q)}, t^{(q)}, X^{(c)}, T^{(c)}, Y^{(c)})$.

Training Objective. Our training objective is then defined as follows:

$$\arg \min_{\theta} \mathbb{E}_p \left[- \sum_{x^{(q)}, t^{(q)}, y^{(q)}} \log p_{\theta}(y^{(q)}|x^{(q)}, t^{(q)}, X^{(c)}, T^{(c)}, Y^{(c)}) \right] + \lambda_{\text{PFN}} \mathcal{L}_{\text{PFN}}, \quad (19)$$

where p is the empirical distribution of LC data with the LC mixup in §3.4. We additionally minimize $\mathcal{L}_{\text{PFN}}$ with coefficient λ_{PFN} , which is the LC extrapolation loss of LC-PFN [2] for each LC. We found $\lambda_{\text{PFN}} = 0.1$ works well for most cases.

Training Details. We sample 4 training tasks for each iteration, i.e., the size of meta mini-batch is set to 4. We uniformly sample the size C of context points from 1 to 300, and the size of query points Q is set to 2,048. Following LC-PFN [2], the hidden size of each Transformer block d_h , the hidden size of feed-forward networks, and the number of layers of Transformer, dropout rate are set 1,024, 2,048, 12, and 0.2, respectively. We use GeLU activation [21]. We train the extrapolator for 100,000 iterations on training split of each benchmark with Adam [28] optimizer. The ℓ_2 norm of the gradient is clipped to 1.0. The learning rate is linearly increased to $2 \cdot 10^{-05}$ for 25,000 iterations (25% of the total iteration), and it is decreased with a cosine scheduling until the end. The whole training process takes roughly 10 hours in a single A100 GPU.

F Implementation Details

0-epoch LC value. We assume access to the 0-epoch LC value ($y_{n,0}$) which is the performance without taking any gradient steps, i.e., *random guessing*. This is also plausible for realistic scenarios, since in most deep-learning models *one evaluation cost* is acceptable in comparison to training costs. The 0-epoch LC values originally are not provided except for LCBench; we use the log-loss of the first epoch as the 0-epoch LC value for TaskSet, as it is already sufficiently large in our chosen tasks. For PD1, we interpolate the LCs to be the length of 51 training epochs, and we take the first performance as the 0-epoch LC value. Furthermore, we take the average over the 0-epoch LC values $\bar{y}_0 := \frac{1}{N} \sum_{n=1}^N y_{n,0}$ for convenience. The average 0-epoch LC value $\bar{y}_0$ is always conditioned on our LC extrapolator p_{θ} for both the training stage in Appendix E and the BO stage in Alg. 1.

Monte-Carlo (MC) sampling for reducing variance of LCs. We estimate the expectation of the proposed acquisition function $A(\cdot; U)$ in Eq. 4 with 1,000 MC samples. We found that each LC $y_{n,t_{n:T}}$ extrapolated from the LC extrapolator $p_\theta(\cdot|x_n, \mathcal{C})$ is *noisy*, due to the assumption that the query points of $y_{n,t_{n:T}}$ are independent of each other in Eq. 14. Since we compute $\tilde{y}_{b+\Delta t}$ by taking the maximum among the last step BO performance (*i.e.*, cumulative max operation), the quality of the estimation degenerates significantly due to the noise. To avoid this, we reduce the variance of the MC samples by taking the *average* of the sampled LCs. For example, we sample 5,000 LC samples from the LC extrapolator p_θ , then divide them into 1,000 groups and take the average among the 5 LC samples in each group. We empirically found that this stabilize the estimation of not only acquisition function $A(\cdot; U)$ and probability of utility improvement p_b in Eq. 7.

Implementation details for baselines. We list the implementation details for baselines as follows:

1. **Random Search** [48]: Instead of randomly selecting a hyperparameter configuration for each BO step, we run the selected configuration until the last epoch T .
2. **BOHB** [14] and **DEHB** [4]: We follow the most recent implementation of these algorithms in [3]. We slightly modify the official code (<https://github.com/releaunifreiburg/QuickTune>), which is based on SyneTune [46] package.
3. **DPL** [24]: We follow the official code (<https://github.com/releaunifreiburg/DPL>), and slightly modify the benchmark implementation to incorporate our experimental setups.
4. **ifBO** [44]: We use the official code (<https://github.com/automl/ifBO>) for the surrogate model (*i.e.*, the LC extrapolator), and incorporate it into our code base to be aligned with our experimental setups.
5. **DyHPO** [62] and **Quick-Tune[†]** [3]: We follow the official code (<https://github.com/releaunifreiburg/DyHPO>), and slightly modify the benchmark implementation to incorporate our experimental setups. For Quick-Tune[†], we pretrain the deep kernel GP for 50,000 iterations with Adam optimizer with batch size of 512. The initial learning rate is set to 10^{-3} and decayed with cosine scheduling. To leverage the transfer learning scenario, we use the best configuration among the LC datasets which is used for training the GP as an initial guess of BO.
6. **FSBO** [60]: We use the official code (<https://github.com/releaunifreiburg/fsbo>), slightly modify it to incorporate our experimental setups, and use the best configuration among the LC datasets as an initial guess.

G Additional Experiments

Table 8: **Results on object detection datasets** ($c = 1$ and $\alpha \in \{0, 2^{-6}, 2^{-4}\}$). We multiply 100 to the normalized regret for better readability.

Method	$\alpha = 0$		$\alpha = 2^{-6}$		$\alpha = 2^{-4}$	
	Regret	Rank	Regret	Rank	Regret	Rank
Random	5.0 $\pm$ 1.3	6.5	7.1 $\pm$ 2.6	6.4	13.1 $\pm$ 2.6	6.5
BOHB	3.2 $\pm$ 1.0	5.2	4.8 $\pm$ 1.0	5.3	10.7 $\pm$ 1.0	5.4
DEHB	5.0 $\pm$ 1.4	6.6	6.6 $\pm$ 1.4	6.5	12.4 $\pm$ 1.3	6.6
DyHPO	16.0 $\pm$ 2.5	5.9	17.5 $\pm$ 2.5	6.0	23.1 $\pm$ 2.7	6.2
DPL	3.9 $\pm$ 1.4	4.6	5.5 $\pm$ 1.4	4.8	11.4 $\pm$ 1.3	5.2
ifBO	2.3 $\pm$ 0.5	4.3	3.9 $\pm$ 0.5	4.3	9.8 $\pm$ 0.5	4.4
Quick-Tune [†]	5.3 $\pm$ 0.0	4.8	6.9 $\pm$ 0.0	4.9	12.6 $\pm$ 0.0	5.0
FSBO	2.1 $\pm$ 0.0	3.9	3.7 $\pm$ 0.0	3.9	9.6 $\pm$ 0.0	4.2
CFBO (ours)	1.3$\pm$0.1	3.3	3.6$\pm$0.3	2.9	5.7$\pm$0.3	1.4

Effectiveness on the real-world HPO. We investigate the effectiveness of CFBO on real-world object-detection dataset. From the 10 different datasets in RoboFlow100 [11], we collect 500 LCs of validation performances by training three different network architectures, such as ResNet-50 [20], HRNet [55], MobileNetv2 [47], with 4 different hyperparameters (batch_size, learning_rate, momentum, and weight_decay_factor). Based on this setting, we construct 30 tasks (=3 network architectures $\times$ 10 datasets) and split them into 20/10 tasks for meta-training/meta-test, respectively. In Tab. 8, we observe that CFBO consistently and significantly outperforms all baselines on this real-world dataset.

Visualization of normalized regret. We provide visualization for the normalized regret of each method on LCBench, TaskSet, and PD1 throughout Figs. 11 to 16.

Visualization of the LC extrapolation over BO steps. We provide visualization for the LC extrapolation over BO steps of CFBO throughout Figs. 17 to 22. Specifically, we plot the LC extrapolation results of *unseen* hyperparameter configurations through BO process. Each row shows the results for a different size of the observation set ($|\mathcal{C}| \in \{0, 10, 50, 300\}$), and each column shows a different size of context points ($y_{n,\leq t}$, where $t \in \{0, 2, 5, 10, 20, 30\}$) in each LC.

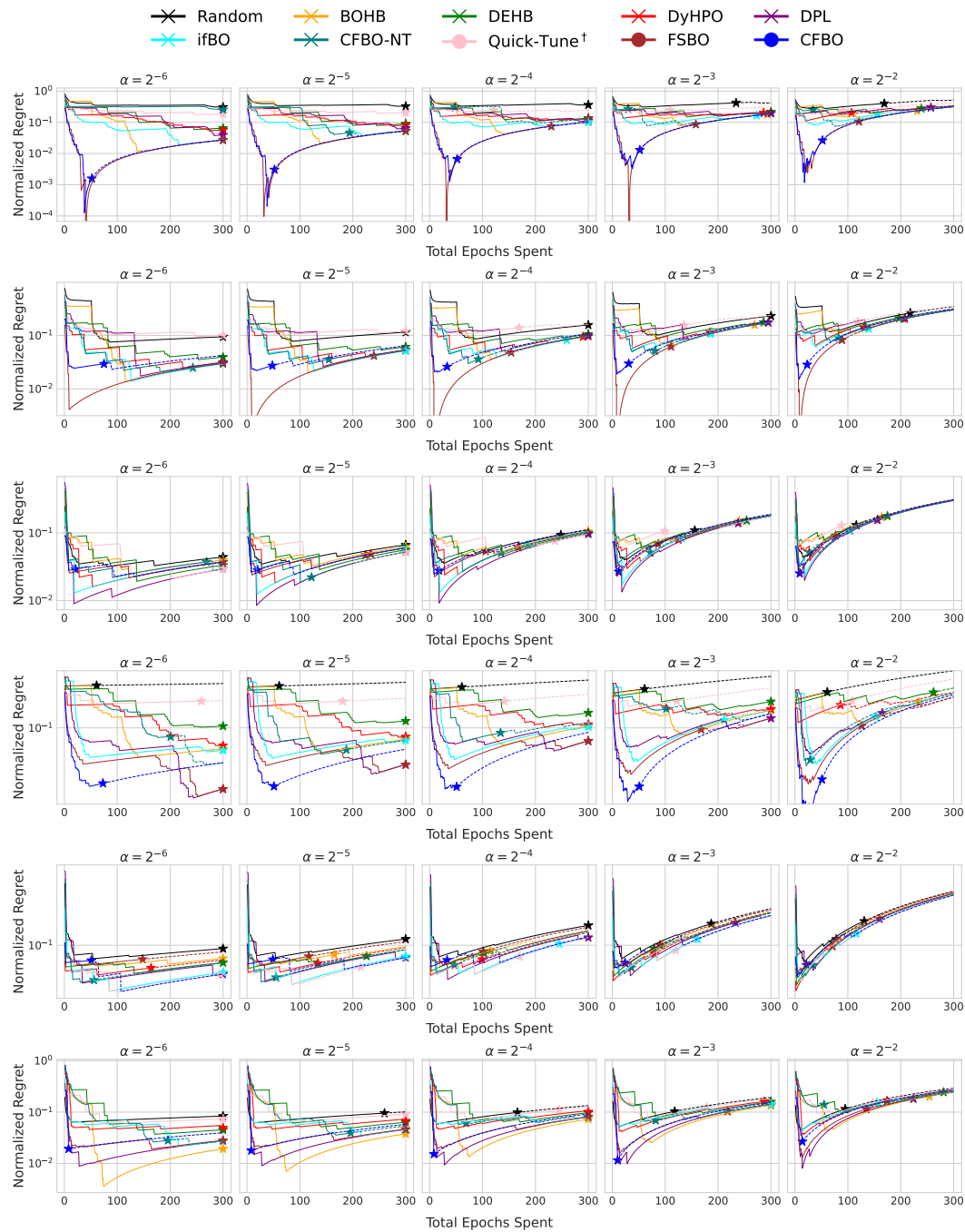


Figure 11: Visualization of the **normalized regret** on LCBench.

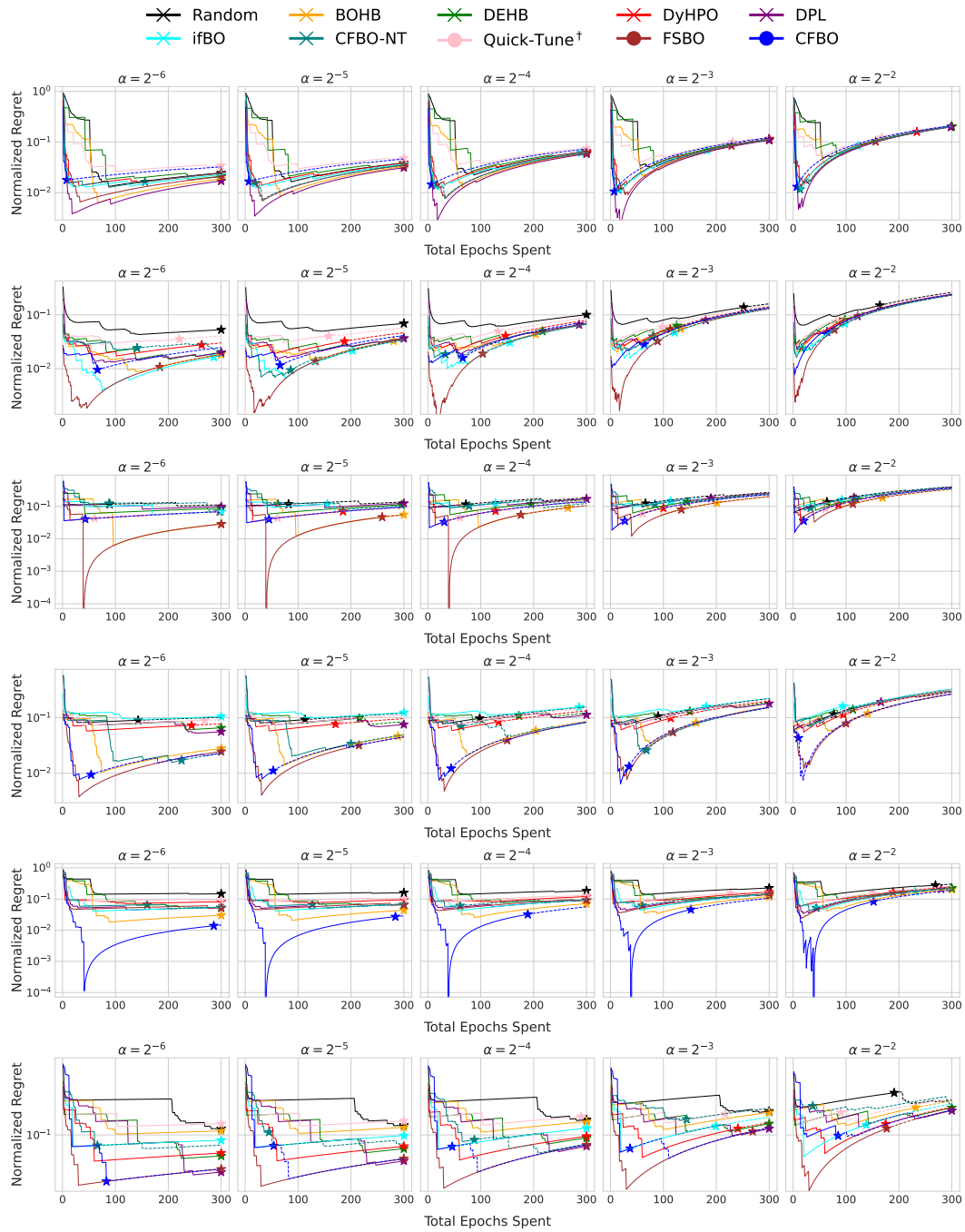


Figure 12: Visualization of the normalized regret on LCBench.

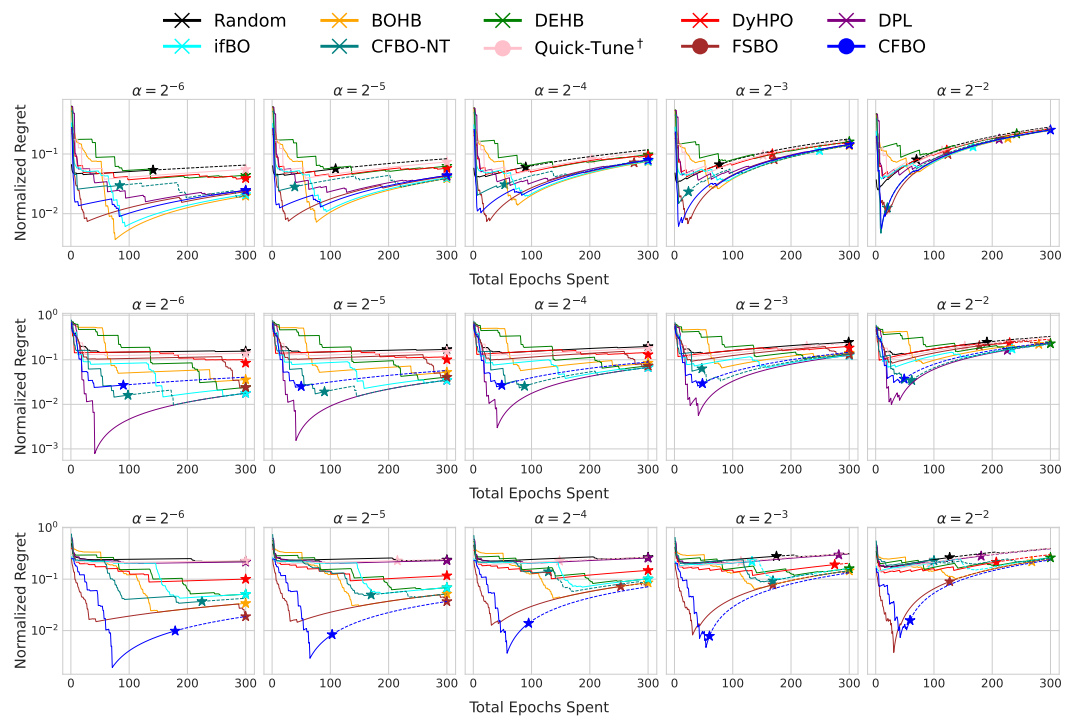


Figure 13: Visualization of the **normalized regret** on LCBench.

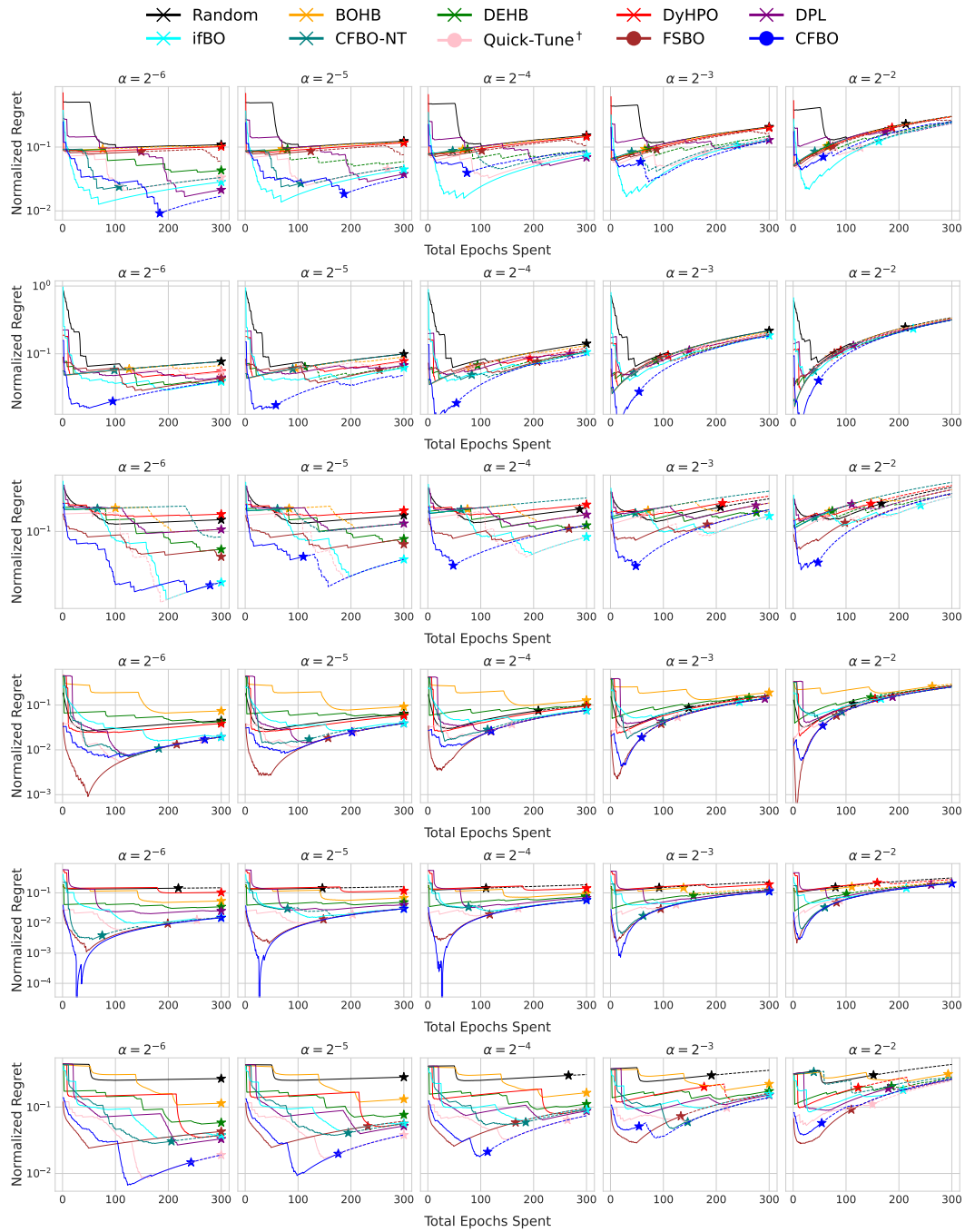


Figure 14: Visualization of the **normalized regret** on TaskSet.

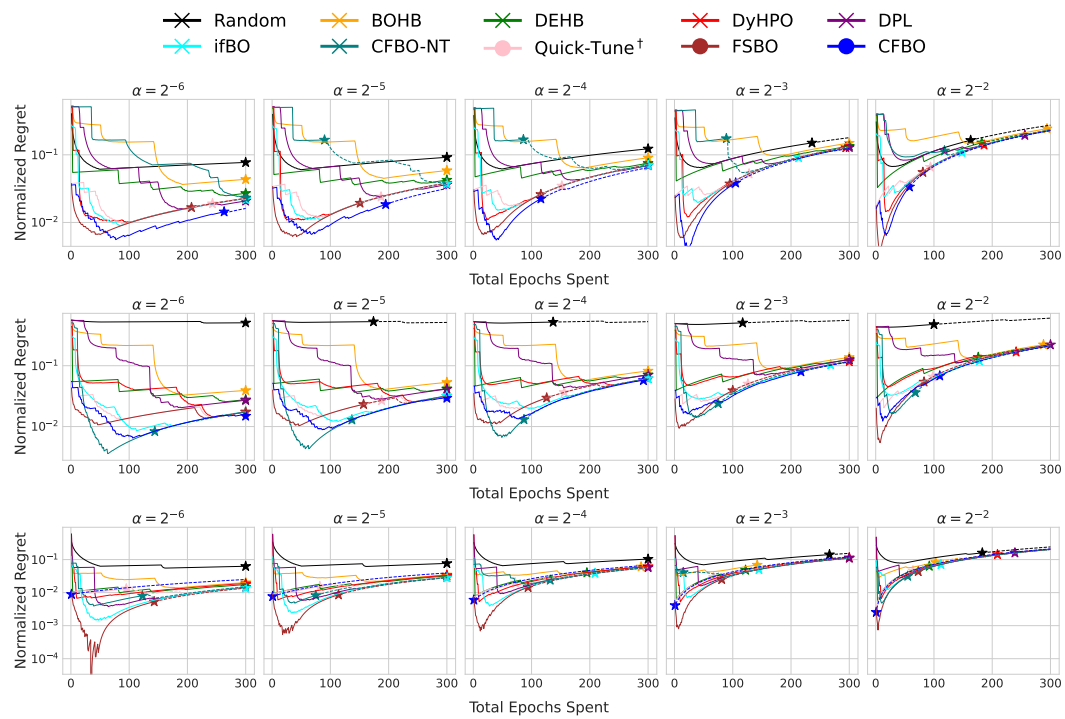


Figure 15: Visualization of the **normalized regret** on TaskSet.

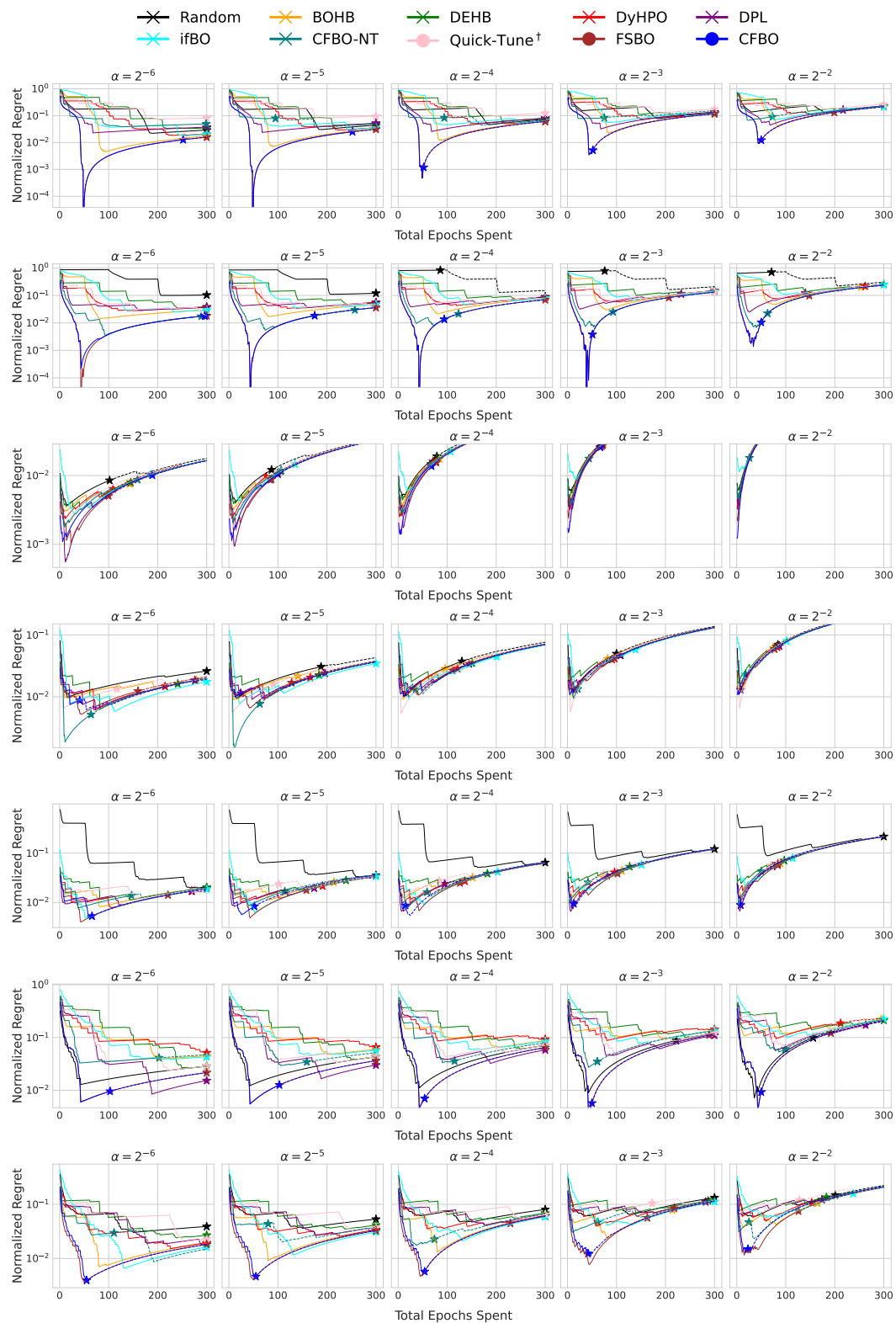


Figure 16: Visualization of the **normalized regret** on PD1.

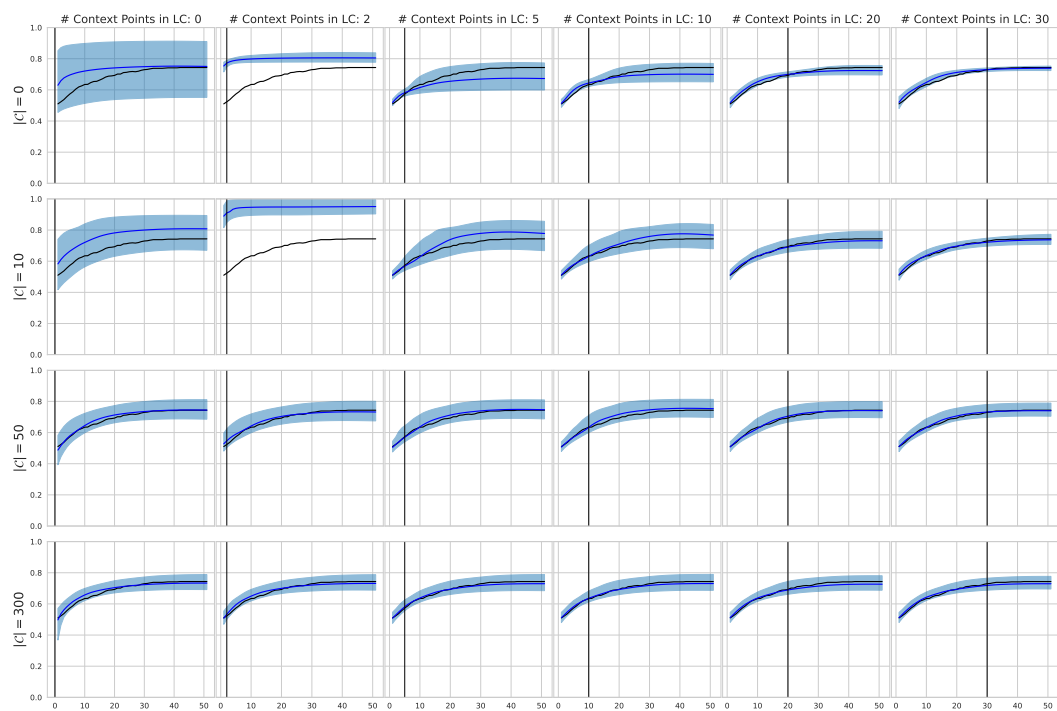


Figure 17: Visualization of LC extrapolation on LCBench.

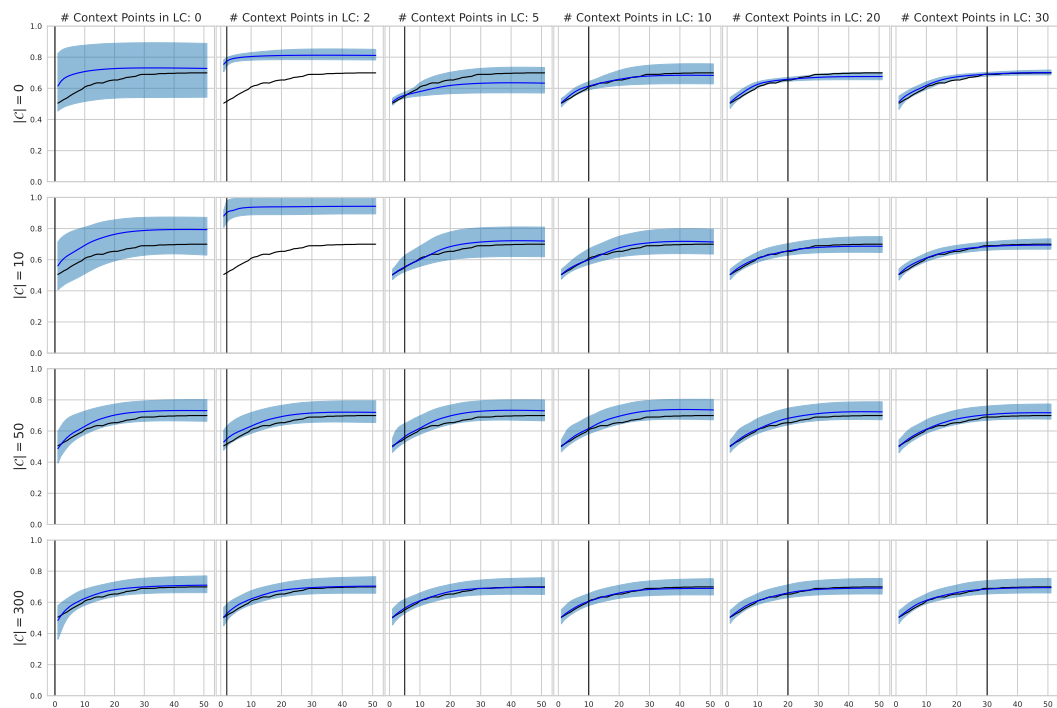


Figure 18: Visualization of LC extrapolation on LCBench.

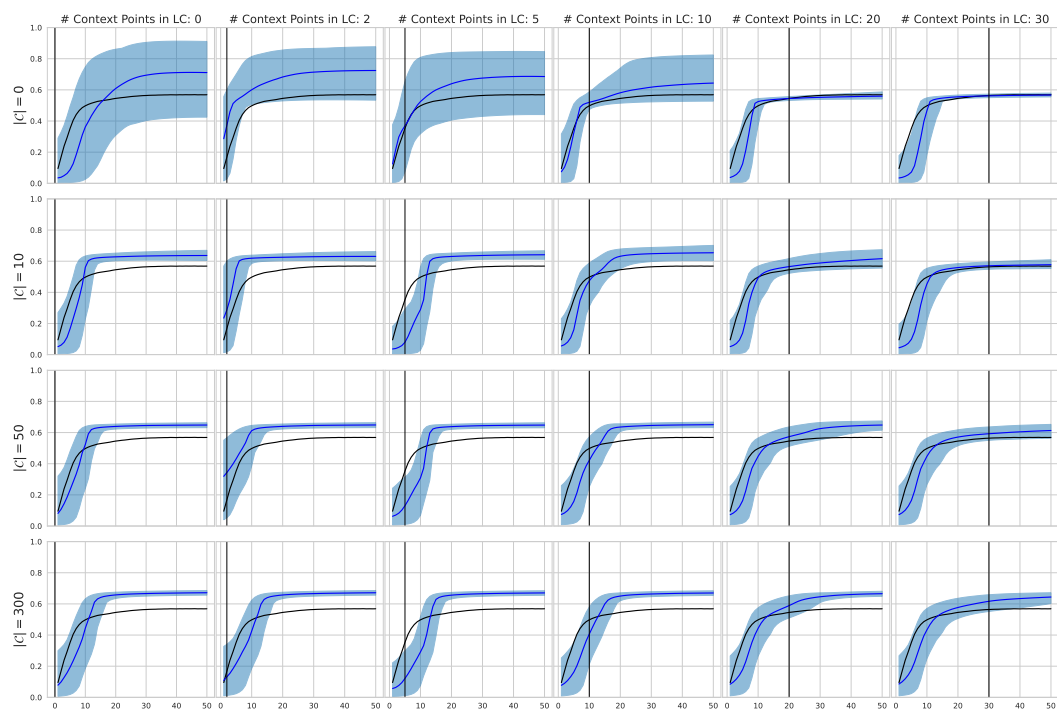


Figure 19: Visualization of LC extrapolation on TaskSet.

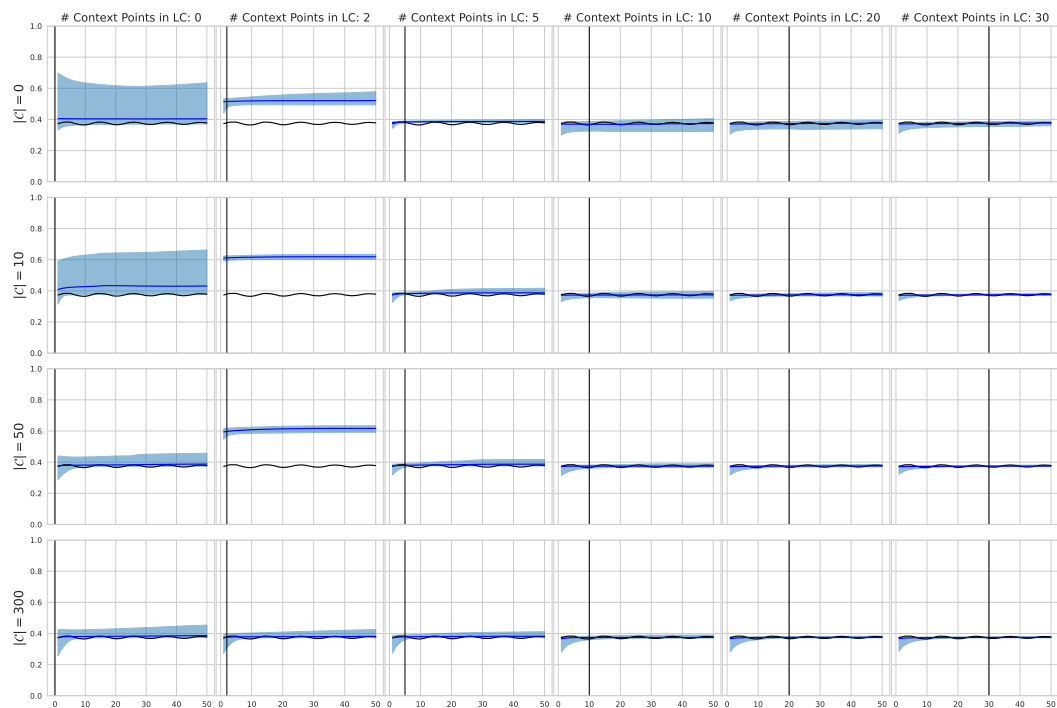


Figure 20: Visualization of LC extrapolation on TaskSet.

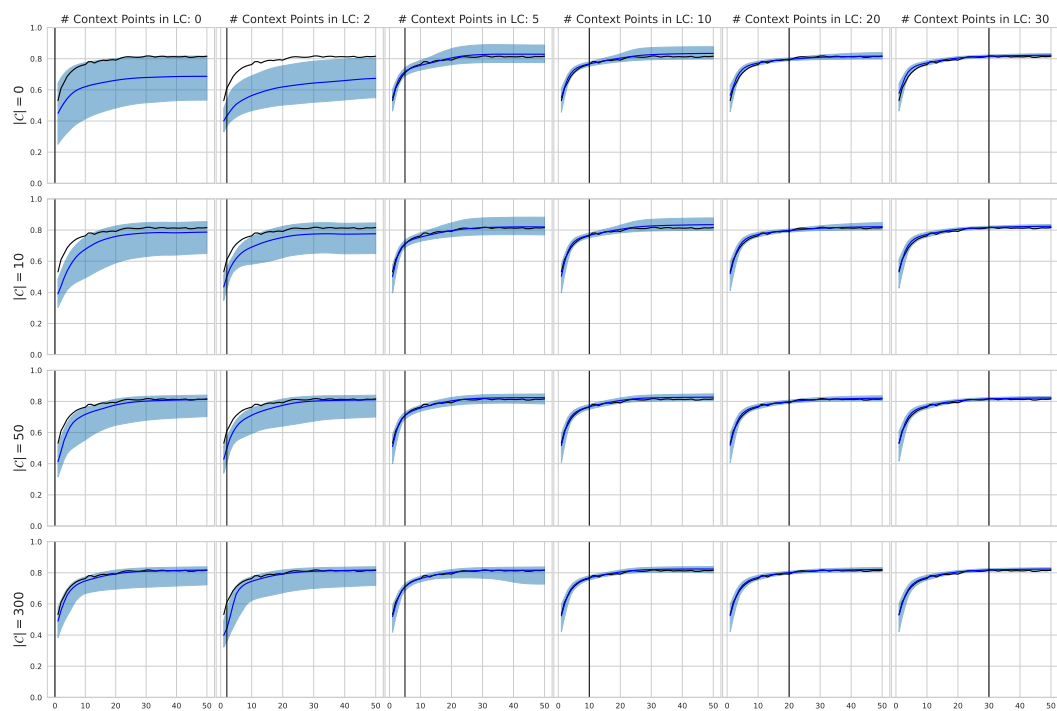


Figure 21: Visualization of LC extrapolation on PD1.

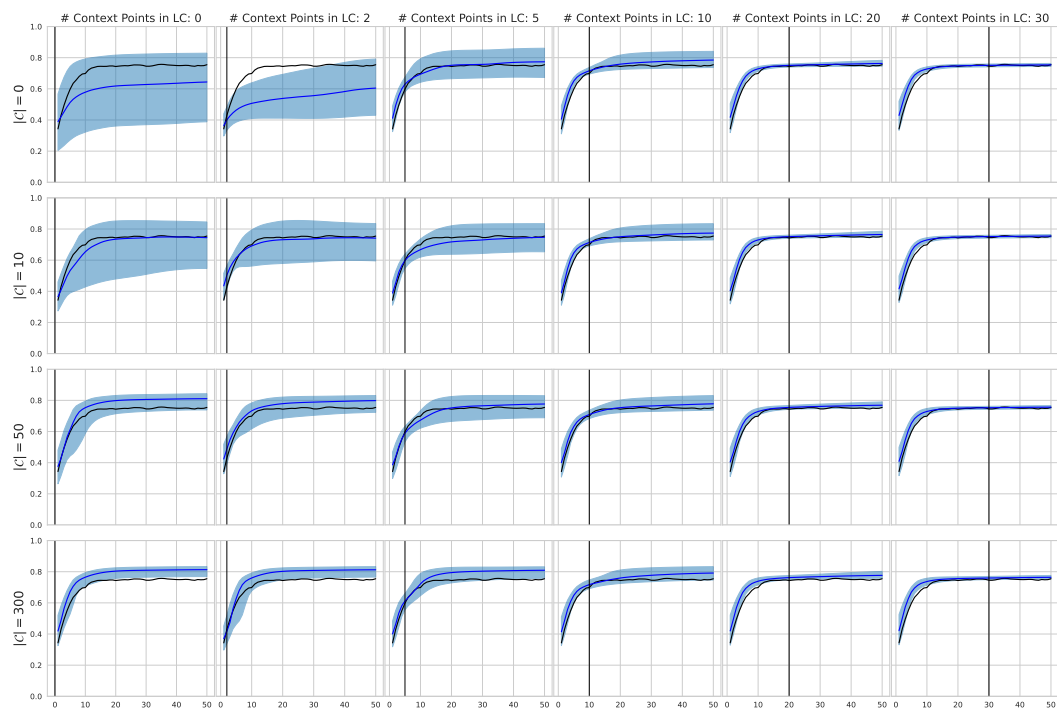


Figure 22: Visualization of LC extrapolation on PD1.

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [Yes]

Justification: In the experimental section, we provided numerous supporting evidences for the claims made in the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: We provide the **Limitations** paragraph in §5.

3. Theory Assumptions and Proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [NA]

Justification: Our paper does not include any theoretical claims.

4. Experimental Result Reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: We provide experimental details including datasets, training details, and baseline implementation throughout **Appendices D** and **F**.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: We use public benchmark datasets and upload anonymous code in the supplemental materials.

6. Experimental Setting/Details

Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: We not only provide experimental setups in main paper but also detail the setups in depth throughout **Appendices D** and **F**.

7. Experiment Statistical Significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [Yes]

Justification: We provide mean and standard deviation over 5 runs (or 30 runs) for all our experiments.

8. Experiments Compute Resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: We provide the detailed information in the Appendix.

9. Code Of Ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: We carefully reviewed the NeurIPS Code of Ethics.

10. Broader Impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [NA] .

Justification: The topic of our paper is about improving the efficiency of hyperparameter optimization, which is irrelevant to societal impacts.

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [Yes]

Justification: Our paper is not relevant to such issues and risks.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes] .

Justification: We properly put citations and URLs for them throughout the paper.

13. New Assets

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [NA]

Justification: Our paper does not release any new assets.

14. Crowdsourcing and Research with Human Subjects

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification: Our paper does not involve any crowdsourcing nor research with human subjects.

15. Institutional Review Board (IRB) Approvals or Equivalent for Research with Human Subjects

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA] .

Justification: Our paper does not involve any crowdsourcing nor research with human subjects.