Extensible and Efficient Proxy for Neural Architecture Search

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Abstract

Efficient or near-zero-cost proxies were proposed recently to address the demanding computational issues of Neural Architecture Search (NAS) in designing deep neural networks (DNNs), where each candidate architecture network only requires one iteration of backpropagation. The values obtained from proxies are used as predictions of architecture performance for downstream tasks. However, two significant drawbacks hinder the wide adoption of these efficient proxies: (1) they are not adaptive to various NAS search spaces*; and (2)* they are not extensible to multi-modality downstream tasks*. To address these two issues, we first propose an Extensible proxy (Eproxy) that utilizes self-supervised, few-shot training to achieve near-zero costs. A key component to our Eproxy's efficiency is the introduction of a* barrier layer *with randomly initialized frozen convolution parameters, which adds non-linearities to the optimization spaces so that Eproxy can discriminate the performance of architectures at an early stage. We further propose a Discrete Proxy Search (DPS) method to find the optimized training settings for Eproxy with only a handful of benchmarked architectures on the target tasks. Our extensive experiments confirm the effectiveness of both Eproxy and DPS. On the NDS-ImageNet search spaces, Eproxy+DPS achieves a higher average ranking correlation (Spearman ρ = 0.73) than the previous efficient proxy (Spearman ρ = 0.56). On the NAS-Bench-Trans-Micro search spaces with seven tasks, Eproxy+DPS delivers comparable performance with the early stopping method (146× faster). For the end-to-end task such as DARTS-ImageNet-1k, our method delivers better results than NAS performed on CIFAR-10 while only requiring one GPU hour with a single batch of CIFAR-10 images. Our code is available at https://github.com/leeyeehoo/GenNAS-Zero.*

1. Introduction

As deep neural networks (DNNs) find uses in a wide range of applications, such as computer vision [23, 27, 46, 48] and natural language processing [11,24,47,50,58], Neural Architecture Search (NAS) [4,37,45,49,66] has become an increasingly important technique to automate the design of neural architectures for different tasks [21, 38, 53, 54]. Recent progress in NAS has demonstrated superior results, surpassing those of human designs [49, 56, 66]. However, one major hurdle for NAS is its high computation cost. For example, the seminal work of NAS [66] consumed 2000 GPU hours to obtain a high-quality DNN, a prohibitively high cost for many researchers. The high computation cost of NAS can be attributed to three major factors: (1) the large search space for candidate neural architectures, (2) the training of various candidate neural architectures, and (3) the comparison of the solution quality of candidate neural architectures to guide the NAS search process. Subsequent NAS work has proposed various techniques to address the above issues, such as the constraints on the search space [30], the weight-sharing networks to reduce the training cost [43], and search with synthetic or random labels [35, 65].

Out of the advancement, the latest efficient proxies showed that the quality of a neural architecture could be determined by a proxy metric computed within seconds without full training. Hence they are near zero-cost (ZC). The activations of an untrained network were analyzed as a proxy in NASWOT [41] with promising results. Abdelfattah et al. [1] suggested various proxies for pruning. Zhang et al. [64] proposed a zero-cost pruning method for differentiable NAS at initialization. ZenNAS [34] quantifies network expressivity, which has a positive correlation with model accuracy. ZiCo [31] leverages gradient properties to improve neural network convergence rate. The efficient proxies discussed above have, however, two primary drawbacks:

1. The quality of these efficient proxies is inconsistent across different search spaces. While many proxies show high correlations in the confined search spaces of small NAS Benchmarks, their performance can be vastly different in real-world applications where the search spaces are orders of magnitude larger than those of the tabular benchmarks. For instance, Synflow demonstrates a high ranking correlation on NAS-

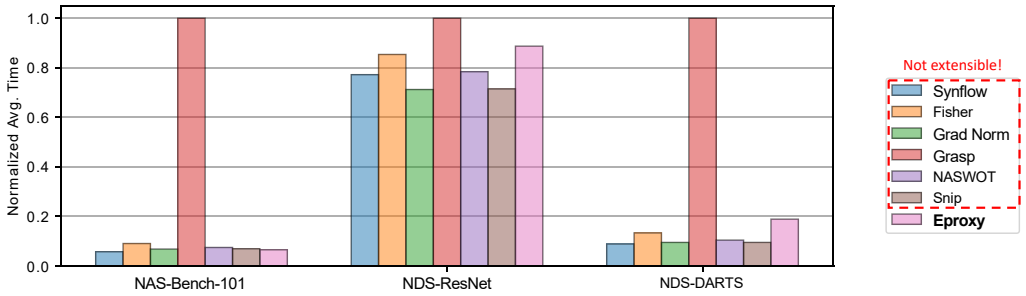


Figure 1. Eproxy is compared to six efficient proxies in terms of evaluation speed on NAS-Bench-101, NDS-ResNet, and NDS-DARTS search spaces, demonstrating that Eproxy falls within the zero-cost category. The plot shows the normalized average time.

Bench-201 [16], but its performance is subpar on NAS-Bench-101 [62], which is 27 times larger than NAS-Bench-201.

2. Efficient proxies don't adapt well to multi-modality downstream tasks. These proxies are typically tailored for CIFAR-10 like classification tasks, resulting in promising prediction results for these specific tasks. However, their performance drops significantly in other scenarios. As an illustration, NASWOT exhibits a dismal average ranking correlation of 0.03 on NAS-Bench-MR [13], which consists of nine real-world tasks. Many efficient proxies employ specific algorithms, like pruning, to convert the weights of architectures into prediction values. This rigid algorithmic approach hinders the proxy's adaptability to tasks beyond classification. Additionally, some zero-cost proxies have been found to favor certain neural architectures [6]. For example, both empirical and theoretical evidence suggest that Synflow has a preference for large models [42].

We question if it is possible for a zero-cost, few-shot proxy task to accurately mimic the true task and result in similar performance ranks for architectures, as shown in Fig. 2. This leads us to introduce a novel and efficient proxy, called the Extensible proxy (Eproxy), approached from a different perspective. Recently, in our prior work, Li et al. [33] introduced a method that employs regression-based training termed GenNAS for the assessment of architectures. Although innovative, their approach is not devoid of costs, both in terms of time and resources. In contrast, our work takes inspiration from the GenNAS framework, achieving nearly zero-cost evaluations. Unlike previous efficient proxies, Eproxy utilizes few-shot spatial-level regression on a set of image-label pairs (see Illustration in Fig. 4). The labels are 2D synthetic features because, as suggested by Li et al. [33], spatial-level regression is more challenging than one-hot classification on a tiny dataset, i.e., a batch of image-label pairs. The key component of Eproxy is the barrier layer. It takes the output of the architecture network into an untrained convolutional layer and performs the regression with the labels. Such a simple mechanism can significantly improve the performance of Eproxy to identify good architectures and bad ones when performing 10 iterations of backpropagation, i.e., near zero-cost. We find that the barrier layer increases the complexity of the optimization space. Hence, poor-performance architectures are more difficult to optimize (see Section 3.1). Since Eproxy is a configurable few-shot trainer, we design a novel search space for Eproxy that includes various hyperparameters, such as feature combinations, output channel numbers, and selection for barrier layers, which makes up Eproxy's multi-modalities. We term such a search method as Discrete Proxy Search (DPS) (the performance of which is shown in Fig. 3). Notably, besides the evaluation of a handful of architectures' performance, DPS does not need to use any task-specific information (e.g., in our experiment, we only use a single batch of CIFAR-10 [26] images throughout all the experiments).

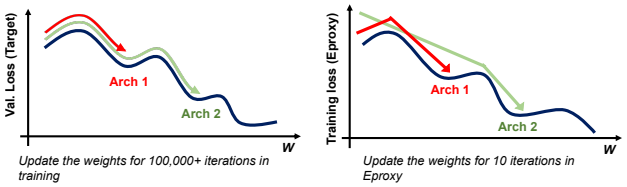
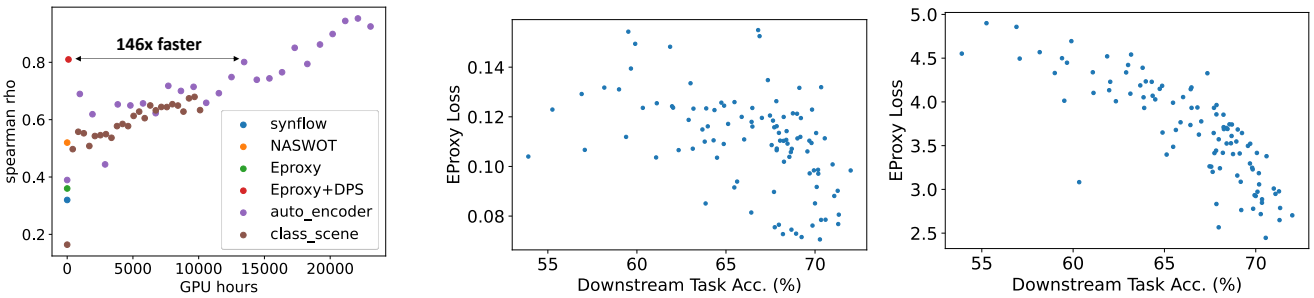


Figure 2. A hypothetical illustration of the validation losses of two architectures on a downstream task is shown on the left. The losses of a sophisticated few-shot proxy, on the right, can reflect the actual performance of the architectures on target tasks. The "W" represents updated weights.

We summarize our contributions as follows:

1. We propose an efficient proxy task with the barrier layer that utilizes a few-shot self-supervised regression. The task adopts one batch of images in the CIFAR-10-level dataset (not necessarily from the target training dataset). It uses synthetic labels to evaluate architectures. Eproxy significantly speeds up the traditional early stopping evaluation process while main-



(a) Autoencoder: Time vs Corr. (b) DARTS-ImgNet: Eproxy (c) DARTS-ImgNet: Eproxy+DPS

Figure 3. **a:** Comparison with efficient proxies and early stopping methods on NAS-Bench-Trans-Micro Autoencoder task. It shows the effectiveness of DPS compared with early stopping methods on either the target task or a classification task when evaluating 4096 architectures. **b, c:** On NDS DARTS-**ImageNet** task, Eproxy and Eproxy+DPS (Searched on DARTS-CIFAR-10, transferred to ImageNet) achieve 0.51, 0.85 ρ respectively. It shows DPS can find a search-space-aware Eproxy.

taining the high-ranking correlation.

2. We propose the downstream-task and search-space aware proxy search algorithm with a proxy search space. We formulate the proxy task search as a discrete optimization problem with only a handful of architectures, such that the performance rankings of the networks on the ground-truth task and the proxy task should be consistent. The searched Eproxy can accurately evaluate the quality of network architectures and make Eproxy search-space and downstream-task aware.

3. We provide thorough experiments to evaluate the performance of Eproxy and Eproxy boosted by DPS on more than 30 search spaces and tasks. We demonstrate that our methods have overall higher performance than existing efficient proxies in terms of all three factors: architecture ranking correlation score, top-10%-architecture retrieve rate, and end-to-end NAS performance. Our solid experimental results can be further utilized to benefit the NAS community.

2. Our Approaches

In Sec.2.1, we present the Eproxy for efficient network evaluation. Sec.2.2 explains how to find a task and search-space aware Eproxy using Discrete Proxy Search.

2.1. Extensible NAS Proxy

The Eproxy is designed for the architectures to learn the output of an untrained network on a set of image-label pairs (See Fig. 4). We utilize the MSE-based training [33] with a large learning rate and limited backpropagation steps to make it as efficient as the existing near zero-cost proxies. However, directly applying a few-shot regression task with a large learning rate leads to poor correlation based on our observations. To make the Eproxy architecture-performance-aware within a few iterations, we propose an untrained barrier layer to make the task more involved (See Section 3.1). The barrier layer is a randomly initialized convolution layer to the output of the trainable components. Our experiments show that adding such a layer can significantly improve the correlation between the predictions and the performance of neural architectures in the downstream tasks within a few back propagations (Sec 3.1). To be more specific, the Eproxy training loss can be described as:

$$\min_{w_a, w_t} \mathcal{L}_{MSE}(G(w_b, F(w_a, w_t, X)), Y) \tag{1}$$

where the $X \in \mathbb{R}^{b \times c_{in} \times h_{in} \times w_{in}}$ is the a set of input images (b is batch size; c_{in} is number of input channels). F is a fully convolutional neural network (FCN) with a transform layer (a convolutional layer) that transforms the X to $F(\cdot) \in \mathbb{R}^{b \times c_{mid} \times h_{out} \times w_{out}}$. The FCN is obtained using the architecture without a task-specified head in the downstream tasks. For example, the classifier network with the classification (last pooling and linear layer) head was removed. w_a and w_t are the weights of architecture for evaluation and the weights of the transform layer that project the output channels of the architecture to c_{mid} which is the number of the transform layer's output channels. G is the barrier layer, and w_b is the weights. Note in the Eproxy without DPS, $Y \in \mathbb{R}^{b \times c_{out} \times h_{out} \times w_{out}}$ is the output of an untrained 6-layer CNN (Fig. 4, 'Net').

We further provide the pseudo code of Eproxy in Listing 1. The Eproxy utilizes a batch of images and corresponding synthetic features as labels (configurations such as the combination of features and output channel numbers can be searched by DPS). The model is trained for 10 iterations. The model's performance is gauged by the MSE loss (lower values denoting better performance).

```
def Eproxy(arch, barrier, img, features,
    t_iter = 10, **kwargs):
    # img shape: B, C = 3, W_in, H_in
    # features shape: B,  C_out, W_out,
    H_out
```

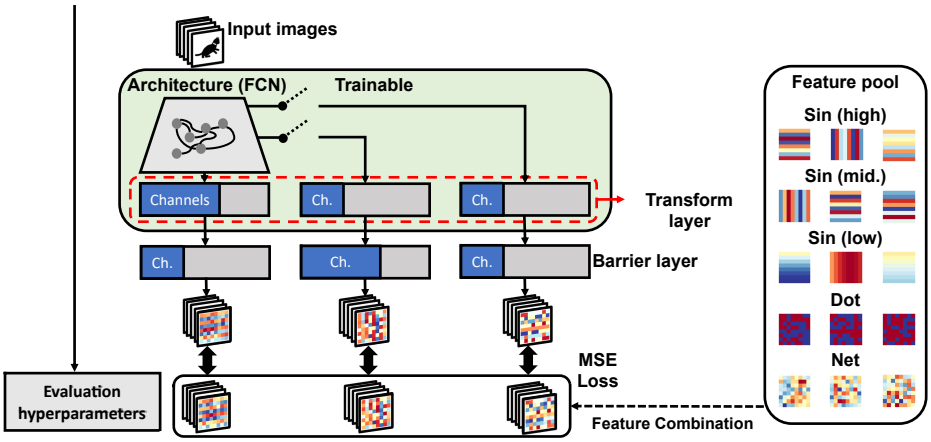


Figure 4. The design of Eproxy and the searchable components. Dotted line: The configurable components for Discrete Proxy Search. Green block: Trainable components. DPS can further utilize the configuration of Eproxy to target search spaces and downstream tasks.

```
    optimizer = SGD(arch.parameters())
    for i in range(t_iter):
        output_mid = model(img) # B, C_mid,
     W_out, H_out
        output = barrier(output_mid) # B,
    C_out, W_out, H_out
        loss = ((output - features)**2).
    mean()
        optimizer.zero_grad()
        loss_m.backward()
        optimizer.step()
    return loss
```

Listing 1. Pseudo PyTorch-style code for Eproxy.

2.2. Discrete Proxy Search

Since Eproxy provides abundant configurable hyperparameters and utilizes data-agnostic spatial labels, different settings can be naturally adjusted for tasks and search spaces. Therefore, we propose a semi-supervised discrete proxy search to find a setting that can be suitable for the specific modality. As shown in Fig. 4, the searchable configurations are provided as follows:

1. Transform and barrier layer: Both layers can have kernel size selected from $\{1, 3, 7\}$, and the channel number c_{mid} can be selected from 16 to 512 geometrically with 2 as a multiplier.

2. Feature combination: a) Untrained CNN outputs. The experiment results show that an untrained network's output features can be powerful for evaluating architectures on numerous tasks/search spaces. The synthetic features can be interpreted as a tiny knowledge-distillation task from an untrained teacher network. b) Sine wave: we adopt the sine wave features with low/mid/high frequency along width/height. The insight is that good CNNs can learn different frequency signal [33, 61]. The features are generated by $\sin(2\pi fx + \phi)$ or $\sin(2\pi fy + \phi)$ with equal probability to be selected. We set three ranges for frequency f: low (L) $f \in (0, 0.125)$, medium (M) $f \in (0.125, 0.375)$, and high (H) $f \in (0.375, 0.5)$. c) Dot: By utilizing the Rademacher distribution, we generate the synthetic features with only ± 1. The features attempt to simulate the spatial classification that is widely adopted in tasks such as detection [19], segmentation [3], tracking [3, 29]. The combined features can be multiplied by an augment coefficient selected from 0.5 to 2 with 0.5 as a step.

3. Training hyperparameters: a) Learning rate: we adopt the SGD optimizer, and the learning rate can be selected from 0.5 to 1.5 with 0.1 as the step. b) Initialization: we adopt two initialization methods, Kaiming [22] and Xavier [20], with either Gaussian or Uniform initialization, resulting a total of four choices.

4. Intermediate output evaluation: We provide the choices to force the network to learn the intermediate outputs from the layer before the first or second downsample layer. The motivation is that earlier stages of the network have different learning behaviors from the deeper stages [2]. Thus, monitoring the early stages can give more flexibility for adapting Eproxy to different tasks.

5. FLOPS: As works [25, 42, 55, 56] suggested that FLOPS is a good indicator for architecture performance. Hence we incorporate the FLOPS normalized by the largest architecture in the search space with the Eproxy loss as $\mathcal{L} \cdot (1 + \alpha \cdot \text{norm(FLOPS)})$, where α can be selected from -0.5 to 0.5 with 0.1 steps.

The total number of configuration combinations in the proxy search space is 5×10^{15}. We utilize the regularization evolutionary algorithm (REA) [45] to conduct the exploration. First, we randomly sample a small subset of the neural architectures in the NAS search space and obtain their ground truth ranking on the target task or a highly correlated down-scaled task (for example, CIFAR-10 is a good proxy for ImageNet). We then evaluate these networks using Eproxy with different configurations and calculate the performance ranking correlation ρ of the Eproxy and the target task, and the ρ is the fitness function for REA.

We provide the pseudo code of the DPS function in Listing 2. This function utilizes a given set of architectures and their corresponding ground-truth accuracies (`archs_accs`) and iterates over a specified number of cycles (`cycle`). DPS starts with an initial population of configurations, each of which includes parameters like learning rate, channel numbers, feature combinations, among others. The `REAEngine` class is utilized to manage the Regularized Evolutionary Algorithm. It aids in generating random configurations, calculating correlations between Eproxy losses (under the given configuration) and ground-truth accuracies for a set of architectures, and performing evolutionary mutations on the configurations. The function accumulates and returns the history of configurations and their corresponding correlations over the evolutionary cycles in `config_history`.

```
def DPS(archs_accs, cycle, population = 40,
     sample = 10, **kwargs):
    # len(archs_accs): 20 pairs of archs &
    gt accs.
    # config: including lr, channel number,
     feature combination, etc.
    config_history = []
    rea = REAEngine(population, sample,
    mutation_rate)
    # generate the initial pool
    for _ in range(population):
        config = rea.get_random_config()
        corr = rea.get_corr(config,
    archs_accs) # calculate the correlation
    between Eproxy (under the config) losses
     and gt accs based on 20 archs.
        config_history.append({config: corr
    })
    # evolution
    for _ in range(cycle):
        new_config = rea.get_mutate_config
    ()
        corr = rea.get_corr(new_config,
    archs_accs)
        config_history.append({new_config:
    corr})
    return config_history
```

Listing 2. Pseudo PyTorch-sytle code for DPS.

3. Experiments

In this section, we perform the following evaluations for Eproxy and DPS. First, in Sec. 3.1, we conduct the ablation study on NASBench-101 [62], the first and yet the largest tabular NAS benchmark with over 423k CNN models and training statistics on CIFAR-10. We explain the mechanism behind the barrier layer with empirical results. Furthermore, we compared Eproxy and Eproxy boosted by DPS with existing efficient proxies. Second, from Sec. 3.2 to Sec. 3.4, we use metrics including ranking correlation, top-10 architecture retrieve rate [12] to evaluate the proposed method on **NDS** [44] (11 search spaces on CIFAR-10, 8 search spaces on ImageNet), **NAS-Bench-Trans-Micro** [17] (7 tasks), and **NAS-Bench-MR** [13] (9 tasks). Third, in Sec. 3.5, we evaluate the end-to-end NAS on NAS-Bench-101/201. Moreover, we report the end-to-end search on the DARTS-ImageNet search space in Sec. 3.5.

Loss	MSE w/o Barrier			MSE w/ Barrier		
LR	1	1e-1	1e-2	1	1e-1	1e-2
10 iters^{NZC}	0.08	-0.22	-0.19	**0.65**	0.46	0.09
100 iters	0.07	0.67	0.76	0.65	**0.79**	0.79
200 iters	0.22	0.64	0.66	0.61	**0.83**	0.81

Table 1. Ranking correlation (Spearman's ρ) analysis for different losses on NASBench-101. "LR" stands for learning rate; "NZC" stands for near-zero-cost. The results suggest that regression with barrier and large learning rate can achieve a high ranking correlation in 10 iterations near zero cost.

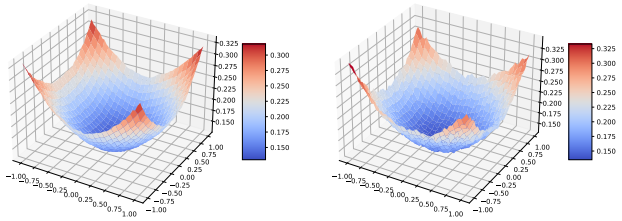
3.1. Ablation Study on NAS-Bench-101

We study the effectiveness of our barrier layer in this section. We use the tool from the work [32] to visualize the loss surface of an architecture selected randomly from NAS-Bench-101 on our few-shot regression task. Figure 5a,5b shows the loss surface without the barrier has a good convexity, which indicates the task is simple, as we use a proxy task that contains very few samples (16 image-label pairs) for a shorter evaluation period. The simplicity of the proxy task gives us two potential problems that can affect the final results. (1) If a task is too simple, every model can perform similarly well. (2) When the optimization is easy, models can have similar performance at the early stage of training. As we observed, loss surfaces from different models have similar shapes without barriers, requiring us to use more training steps to see the difference between good and bad architectures. To mitigate these two problems, Eproxy added a barrier layer which is a random initialized linear/convolution layer with frozen weights. As shown in Figure 4 (b), the loss surface with the barrier has a noticeable non-convexity, which shows the increased complexity of the proxy task, and now it can better reflect the actual performance of ar-

	Grad norm	Snip	Grasp	Fisher	Synflow	NASWOT	ZenNAS	ZiCo	Eproxy	Eproxy+DPS
ρ	0.20	0.16	0.45	0.26	0.37	0.40	0.61	0.61	0.65	**0.69**
Top-10%	2%	3%	26%	3%	23%	29%	39%	**45%**	31%	38%

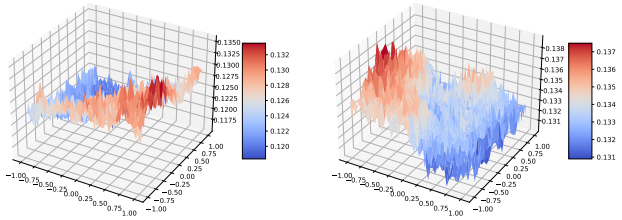
Table 2. Comparison with efficient proxies on NAS-Bench-101 using the Spearman ρ and top-10% retrieve rate. Eproxy outperforms the state-of-the-art zero-shot methods, ZiCo and ZenNAS, in terms of rho when DPS is not utilized.

chitecture (Figure 6a,6b). As the irregular shape of the loss surface varies widely from model to model, it helps us better distinguish the model performance at the early stage of training, allowing us to use fewer training steps to speed up the evaluation further. The results in Table 1 show that with the barrier layer, Eproxy can reach ρ 0.65 in only 10 iterations with a learning rate of 1, and it also significantly improves the ranking correlation score with more training iterations.



(a) Best model without barrier. (b) Worst model without barrier.

Figure 5. The loss surfaces of best and worst model from NAS-Bench-101 regression task without barrier.



(a) Best model with the barrier. (b) Worst model with the barrier.

Figure 6. The loss surfaces of best and worst model from NAS-Bench-101 regression task with barrier.

Next, we sample 20 architectures from NAS-Bench-101 and evaluate DPS. We conduct DPS for 200 epochs, and the total run time is ∼20 mins on a single A6000 GPU. In Table 2, we report the network evaluation results in terms of Spearman's ρ and top-10% network coverage using the proxy task searched by DPS. We evaluated Eproxy against state-of-the-art zero-cost proxies including NASWOT [41], Synflow [1], ZenNAS [34], and ZiCo [31]. Additionally, we considered architecture parameters and FLOPS as important baselines [55]. Eproxy significantly outperforms existing zero-cost proxies by a large margin. For instance, Synflow, scores 0.45, ZiCo scores 0.61, Eproxy scores 0.65 (without DPS), and Eproxy with DPS scores 0.69. In terms of top-10% retrieval rate, Eproxy with DPS retrieves a higher number of architectures than DPS (38% vs 31%). The results support the efficiency and effectiveness of DPS. Meanwhile, Fig. 1 confirms that using Eproxy achieves a comparable evaluation speed with other efficient proxies.

3.2. NDS

The original Network Design Spaces (NDS) work [44] investigates different search spaces. The NDS is perfect for evaluating efficient proxies in more complex search spaces. For example, researchers benchmarked 5,000 architectures on DARTS search space and over 20,000 on ResNet search space. We compared our method with existing zero-cost proxies on **11 search spaces** on **CIFAR-10** and **8 search spaces** on **ImageNet** [10]. We show the results in Table 3. Compared to Synflow, ZenNAS, and ZiCo, Eproxy (without DPS) delivers better results on both CIFAR-10 and ImageNet search spaces. Eproxy (without DPS) performs similarly to NASWOT on both CIFAR-10 and ImageNet search spaces. Boosted by DPS, Eproxy delivers significantly better results on target CIFAR-10 search spaces with 36% and 52% improvement on ranking correlation and top-10% retrieve rate, respectively. Notably, Eproxy+DPS searched on CIFAR-10 with 20 architectures performs significantly better on **ImageNet** search spaces without any prior knowledge of the dataset. Compared to NWT, Eproxy+DPS gains 30% and 57% on ranking correlation and top-10% retrieve rate, respectively. The ImageNet experiment demonstrates the efficiency by utilizing the architectures trained on down-scaled dataset (CIFAR-10) for DPS. It's noteworthy that using FLOPS and Params as evaluation metrics for models may not be suitable in search spaces with limited model size variations, such as DARTS-f, PNAS-f, and ENAS-f.

3.3. NAS-Bench-Trans-Micro

Previous experiments suggest that DPS can optimize Eproxy across different search spaces. We further evaluate Eproxy and DPS on NAS-Bench-Trans-Micro, a benchmark that contains 4096 architectures across **7 large tasks** from the **Taskonomy** [63] dataset. The tasks include object classification, scene classification, unscrambling the image, and image upscaling. The search space is similar to NAS-Bench-201 but has 4 operator choices per edge instead of

CIFAR-10	DARTS	DARTS-f	AMB	ENAS	ENAS-f	NASNet	PNAS	PNAS-f	Res	ResX-A	ResX-B	Avg.
Synflow	0.42 9%	-0.14 5%	-0.10 3%	0.18 6%	-0.30 2%	0.02 7%	0.25 9%	-0.26 4%	0.21 4%	0.47 25%	0.61 29%	0.12 9%
NASWOT	0.65 29%	0.31 8%	0.29 20%	0.54 31%	0.44 28%	0.42 27%	0.50 24%	0.13 6%	0.29 7%	0.64 28%	0.57 21%	0.43 21%
ZenNAS	0.50 14%	0.01 4%	0.05 7%	0.22 10%	0.07 5%	0.07 11%	0.24 12%	0.20 3%	0.23 2%	0.59 35%	**0.66** 32%	0.26 12%
ZiCo	0.49 13%	0.11 5%	0.09 4%	0.29 12%	0.02 11%	0.16 12%	0.26 9%	0.09 3%	0.23 3%	0.54 32%	0.63 **34%**	0.26 13%
Eproxy	0.38 12%	0.34 17%	0.54 13%	0.59 35%	0.48 31%	0.56 28%	0.22 4%	0.24 4%	0.51 36%	0.47 24%	0.19 10%	0.41 19%
Eproxy+DPS	**0.72** 33%	**0.39** **19%**	**0.56** **29%**	**0.63** **36%**	**0.47** **30%**	**0.54** **32%**	**0.60** **35%**	**0.48** **28%**	**0.56** **36%**	**0.65** **32%**	0.60 19%	**0.56** **29%**

ImageNet	DARTS	DARTS-f	Amoeba	ENAS	NASNet	PNAS	ResX-A	ResX-B	Avg.
Synflow	0.21 0%	-0.36 4%	-0.25 0%	0.17 9%	0.01 0%	0.14 9%	0.42 7%	0.31 13%	0.08 6%
NASWOT	0.66 16%	0.20 8%	0.42 33%	0.69 36%	0.51 33%	**0.61** 10%	0.73 30%	0.63 38%	0.56 26%
ZenNAS	0.21 8%	0.13 4%	0.21 0%	0.22 18%	0.06 17%	0.23 9%	0.60 23%	0.45 25%	0.27 13%
ZiCo	0.24 8%	0.01 4%	0.18 0%	0.26 36%	0.12 17%	0.27 9%	0.52 8%	0.40 19%	0.25 13%
Eproxy	0.51 20%	0.31 17%	0.66 60%	0.58 33%	0.56 30%	0.36 33%	0.73 55%	0.70 **43%**	0.55 36%
Eproxy+DPS$_{\mathrm{T}}$	**0.85** 50%	**0.53** **28%**	**0.66** **60%**	**0.79** 33%	**0.85** 32%	0.60 **35%**	**0.83** **55%**	**0.72** 36%	**0.73** **41%**

Table 3. Comparison with efficient proxies on NDS search spaces. $_{\mathrm{T}}$ denotes the DPS on CIFAR-10 and transferred to ImageNet. Therefore, it does not necessitate knowledge of the ImageNet dataset. When DPS is not employed, Eproxy performs better than ZiCo on 7 out of 11 CIFAR-10 search spaces and all 8 ImageNet search spaces. However, with DPS, Eproxy shows significant superiority over other methods.

	Cls. Scene	Cls Obj	Room Layout	Jigsaw	Seg	Normal	AE	Avg.
Synflow	0.46/16%	0.50/16%	0.45/28%	0.49/19%	0.32/3%	0.52/19%	0.52/34%	0.47/19%
NASWOT	0.57/21%	0.53/21%	0.30/2%	0.41/11%	0.52/30%	0.59/30%	-0.02/2%	0.41/17%
ZenNAS	0.57/**48%**	0.34/32%	0.24/**27%**	0.35/35%	0.37/32%	0.56/47%	0.15/23%	0.37/35%
ZiCo	0.30/31%	0.03/16%	0.04/23%	0.15/26%	0.07/16%	0.29/27%	0.19/9%	0.15/21%
Eproxy	0.15/14%	0.45/34%	0.06/8%	0.17/33%	0.36/46%	0.25/38%	0.61/**80%**	0.29/36%
Eproxy + DPS	0.70/30%	0.56/**44%**	**0.56**/13%	0.64/**45%**	**0.81/53%**	**0.81/63%**	**0.80**/74%	**0.69/46%**
ES$_{\sim 660\text{GPU hrs/task}}$	**0.73**/25%	0.01/7%	0.15/7%	**0.74**/21%	0.39/7%	0.65/27%	0.35/11%	0.43/15%

Table 4. Comparison with efficient proxies and the early stopping method on TransNAS-Bench-Micro. In 5 out of 7 tasks, Eproxy surpasses ZiCo, a recent zero-shot method. Eproxy+DPS outperforms efficient proxies, and the early stopping method which requires 600 GPU hours per task.

6. We conduct the DPS on each task using only 20 architectures. We do not have any prior knowledge of the tasks besides the 20 architecture's ground truth performance since DPS only utilizes a batch of CIFAR-10 images as input. The results are shown in Table 4. Note that though Eproxy underperforms regarding the ranking correlation, it achieves better top-10% retrieve rate compared to other methods. It also tells that the global ranking correlation is not the golden metric for evaluating the performance of proxies since it merely reflects the difference of top architectures. With the help of DPS, the average ranking correlation and top 10% retrieve rate are significantly improved and substantially better than other methods. Compared to the early stopping method, DPS requires 7.6X less regarding GPU hours (>99% time for obtaining the performance of 20 architectures while the DPS only takes 0.5 GPU hour).

	Cls-A	Cls-B	Cls-C	Cls-10c	Seg	Seg-4x	3dDet	Video	Video-p	Avg.
Synflow	0.25 11%	0.05 14%	0.37 20%	0.21 15%	0.43 17%	0.22 9%	0.22 8%	0.45 18%	0.52 17%	0.30 14.3%
NASWOT	0.37 18%	-0.20 4%	-0.15 2%	-0.39 0%	0.50 10%	0.38 8%	0.48 10%	-0.36 1%	-0.36 0%	0.03 6%
ZenNAS	0.41 4%	0.50 0%	0.30 1%	0.25 0%	0.49 6%	0.22 2%	0.26 10%	0.41 0%	0.39 0%	0.36 3%
ZiCo	0.40 4%	0.52 0%	0.31 1%	0.27 0%	0.48 5%	0.21 1%	0.25 9%	0.42 0%	0.40 0%	0.36 2%
Eproxy	0.52 18%	0.06 10%	0.02 10%	0.29 15%	0.38 17%	0.31 13%	0.34 23%	0.31 11%	0.23 11%	0.27 14%
Eproxy + DPS	**0.57** 16%	**0.53** **35%**	0.30 18%	0.48 32%	**0.60** **24%**	**0.51** **13%**	0.39 **29%**	**0.65** **33%**	**0.59** **27%**	**0.51** **25%**
Cls-C Full training (∼4000GPU hrs)	0.29 **24%**	0.51 26%	**1.0** **100%**	**0.53** **34%**	0.21 16%	0.35 26%	0.17 14%	0.35 22%	0.37 25%	n/a N/A

Table 5. Comparison with efficient proxies, and Cls-C full training which requires 4000 GPU hours on NAS-Bench-MR. In 9 tasks, Eproxy achieves superior top-10% retrieval rates compared to recent zero-cost methods like ZenNAS and ZiCo. Eproxy + DPS demonstrates outstanding performance, even when compared to full training on Cls-C.

	RS	NAO	RE	Semi	WeakNAS			Eproxy+DPS		
Queries	2000	2000	2000	1000	200	150	100	150	60	0
Test Acc.	93.64	93.90	93.96	94.01	94.18	94.10	93.69	**94.23**	**93.92**	**93.07**

Table 6. Comparison with predictor-based methods and efficient proxies on NAS-Bench-101. Eproxy+DPS as the fitness function for Regularization Evolutionary Algorithm can find near-optimal architectures with lower queries.

	Random Search	Regularized Evolution	MCTS	LaNAS	WeakNAS	Eproxy+DPS
C10	7782.1	563.2	528.3	247.1	182.1	**58.0 + 20**
C100	7621.2	438.2	405.4	187.5	78.4	**13.7$_T$**
TinyImg	7726.1	715.1	578.2	292.4	268.4	**74.0$_T$**

Table 7. Comparison with predictor-based methods on NAS-Bench-201 regarding the average queries required for retrieving the global optimal architectures. Eproxy+DPS uses substantially lower queries to find the global optimal architectures.

3.4. NAS-Bench-MR

We applied Eproxy and DPS to a complex search space, NAS-Bench-MR [13], with 9 high-resolution tasks such as 3D detection, ImageNet-level classification, segmentation, and video recognition [9, 10, 18, 28]. Approximately 2,500 architectures were benchmarked. Each architecture underwent full training (over 100 epochs) and followed a multi-resolution paradigm, with each network consisting of four stages. Each stage comprised modularized blocks (parallel and fusion modules). Our work is the first to investigate this benchmark with efficient proxies. The results are displayed in Table 5. The full training consumption on the Cls-C task was calculated based on the source code [14], which took approximately 4000 GPU hours. Note that NASWOT, which performs well on NAS-Bench-Trans-Micro, delivers poor performance on most tasks, implying the inconsistent performance of current efficient proxies. Also, we observed that classification rankings are inconsistent with other tasks, such as segmentation and 3D detection. Our Eproxy+DPS experiments suggest that with a 20-architecture set, the ranking correlation and top-10% retrieve rate are considerably improved (**+89%/+78%**).

3.5. End-to-end NAS with Eproxy

We evaluate Eproxy and DPS on the end-to-end NAS tasks to find efficient architectures in the search space.

On **NAS-Bench-101**, we utilize the Eproxy as the fitness function for Regularized Evolutionary (RE) algorithm. Our results are shown in Table 6 compared with NAO [40], Semi-NAS [39], WeakNAS [57]. Note that Eproxy, without any query (near-zero-cost) from the benchmark, can find architectures that are significantly better than current SoTA efficient proxies, Synflow (+ 0.87%) and NASWOT (+3.01%). With 20 architectures for DPS and 40

Method	Test Err. (%)		Params	FLOPS	Search Cost	Searched	Searched
	top-1	top-5	(M)	(M)	(GPU days)	Method	dataset
NASNet-A [66]	26.0	8.4	5.3	564	2000	RL	CIFAR-10
AmoebaNet-C [45]	24.3	7.6	6.4	570	3150	evolution	CIFAR-10
PNAS [36]	25.8	8.1	5.1	588	225	SMBO	CIFAR-10
DARTS(2nd order) [37]	26.7	8.7	4.7	574	4.0	gradient-based	CIFAR-10
SNAS [59]	27.3	9.2	4.3	522	1.5	gradient-based	CIFAR-10
GDAS [15]	26.0	8.5	5.3	581	0.21	gradient-based	CIFAR-10
P-DARTS [8]	24.4	7.4	4.9	557	0.3	gradient-based	CIFAR-10
P-DARTS	24.7	7.5	5.1	577	0.3	gradient-based	CIFAR-100
PC-DARTS [60]	25.1	7.8	5.3	586	0.1	gradient-based	CIFAR-10
TE-NAS [7]	26.2	8.3	6.3	-	0.05	training-free	CIFAR-10
PC-DARTS	24.2	7.3	5.3	597	3.8	gradient-based	ImageNet
ProxylessNAS [5]	24.9	7.5	7.1	465	8.3	gradient-based	ImageNet
TE-NAS [7]	24.5	7.5	5.4	599	0.17	training-free	ImageNet
Eproxy	25.7	8.1	4.9	542	0.02	evolution+proxy	CIFAR-10
Eproxy+DPS$_{\text{T}}$	24.4	7.3	5.3	578	0.06	evolution+proxy	CIFAR-10

Table 8. Comparison with state-of-the-art NAS methods on ImageNet. $_{\text{T}}$ stands for DPS is conducted in NDS search space and directly transferred to the target. Note Eproxy+DPS achieves the best results among NAS methods on CIFAR-10.

queries (total of 60) to retrieve the top architectures during RE, Eproxy+DPS achieves better results than existing SoTA predictor-based NAS WeakNAS with 100 queries (+0.23%). Furthermore, we explore the 70 neighbors of the top architectures (a total of 150 queries) and find architectures with an average of 94.23% accuracy. Note that Semi-NAS with 1000 queries can only reach 94.01%. On **NAS-Bench-201**, we perform the DPS on the CIFAR-10 dataset, and the found proxy is directly transferred to CIFAR-100 and Tiny-ImageNet. We compare with MCTS [52], LaNAS [51], WeakNAS [57]. In Table 7, we show that Eproxy+DPS can find optimal global architectures within the RE search history. Compared to RE, which directly queries the benchmark, our approach reduced 7x/32x/9x query times on three datasets. Compared to predictor-based NAS, Eproxy+DPS also requires fewer queries to discover the optimal architectures. Our results offer an exciting yet promising direction besides pure predictor-based NAS.

DARTS-ImageNet search space We conduct end-to-end search on ImageNet-1k dataset within the DARTS search space as defined in [37]. The network depth is 14 blocks. The input channels are 48, and the FLOPS range from 500M to 600M for the searched architectures. We utilize the 20 samples from the NDS-DARTS search space (not the same search space as the target) and conduct DPS on CIFAR-10 for 200 epochs in one GPU hour. Then we perform the NAS by adopting regularized evolutionary algorithm with the loss of the zero-cost proxy as the fitness function in 0.4 GPU hour. We compare our method with (a) existing works on the DARTS search space [7,8,15,37,59,60] and (b) works on the similar search spaces [5, 36, 45, 66]. The results are shown in Table 8. Eproxy achieves a top-1/5 test error of 25.2%/8.1% using Eproxy with only 0.5 GPU hours for NAS. With DPS, Eproxy explores the architecture with 24.4%/7.3% as a top-1/top5 test error. Eproxy+DPS significantly outperforms existing NAS on CIFAR-10, such as PC-DARTS [60], and achieves a comparable result with NAS on ImageNet, demonstrating Eproxy and DPS's efficiency. By utilizing the existing proxy on another search space, DPS shows the transferability between search spaces.

4. Conclusion

We proposed Eproxy that utilizes a self-supervised few-shot regression task within near-zero cost. The Eproxy is benefited from the barrier layer that significantly improves the complexity of the proxy task. To overcome the drawbacks of current efficient proxies that are not adaptive to various tasks/search spaces, we proposed DPS incorporating various settings and hyperparameters in a proxy search space and leveraging REA to conduct efficient exploration. Our experiments on numerous NAS benchmarks demonstrate that Eproxy is a robust, efficient proxy. Moreover, with the help of DPS, Eproxy achieves state-of-the-art results and outperforms existing state-of-the-art efficient proxies, early stopping methods and predictor-based NAS. Our work significantly ameliorates the inconsistency of efficient proxies and sets up a series of solid baselines while pointing out a novel direction for the NAS community.

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