NASTransfer: Analyzing Architecture Transferability in Large Scale Neural Architecture Search

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Abstract

Neural Architecture Search (NAS) is an open and challenging problem in machine learning. While NAS offers great promise, the prohibitive computational demand of most of the existing NAS methods makes it difficult to directly search the architectures on large-scale tasks. The typical way of conducting large scale NAS is to search for an architectural building block on a small dataset (either using a proxy set from the large dataset or a completely different small scale dataset) and then transfer the block to a larger dataset. Despite a number of recent results that show the promise of transfer from proxy datasets, a comprehensive evaluation of different NAS methods studying the impact of different source datasets and training protocols has not yet been addressed. In this work, we propose to analyze the architecture transferability of different NAS methods by performing a series of experiments on large scale benchmarks such as ImageNet1K and ImageNet22K. We find that: (i) On average, transfer performance of architectures searched using completely different small datasets (e.g., CIFAR10) perform similarly to the architectures searched directly on proxy target datasets. However, design of proxy sets has considerable impact on rankings of different NAS methods. (ii) While the different NAS methods show similar performance on a source dataset (e.g., CIFAR10), they significantly differ on the transfer performance to a large dataset (e.g., ImageNet1K). (iii) Even on large datasets, the randomly sampled architecture baseline is very competitive and significantly outperforms many representative NAS methods. (iv) The training protocol has a larger impact on small datasets, but it fails to provide consistent improvements on large datasets. We believe that our NASTransfer benchmark will be key to designing future NAS strategies that consistently show superior transfer performance on large scale datasets.

1 Introduction

Neural Architecture Search (NAS) has been a very active area of research [14], aiming at automatic design of deep learning networks for various applications spanning from image classification [23, 33, 36, 37] to NLP [25, 30, 47], from object detection [7, 16, 34] to semantic segmentation [22] and control tasks [15]. A number of NAS strategies have been proposed, including evolutionary methods [1, 24, 31, 46], reinforcement learning [23, 30, 45, 47], and gradient-based methods [6, 25, 29, 38, 42]. Despite impressive results on commonly used benchmark datasets, the prohibitive computational demand of existing NAS methods makes it difficult to directly search the architectures on large-scale tasks (e.g., ImageNet). Motivated by this, many methods have been proposed to improve the efficiency of NAS by shifting the training and evaluation of candidate architectures from the entire target set to proxy tasks, which could mean learning with only a few blocks, training for a few epochs [13] or use proxy sets [25, 30, 46]. Proxy sets could either be smaller versions of the target dataset obtained through sampling, or datasets with similar distribution to the target, but with reduced number of classes or number of examples per class.
Despite a number of recent work showing promising transfer results, comparison between different NAS methods in terms of architecture transfer remains a novel and rarely addressed problem. Specifically, it is not clear to what extent the architectures depend on the proxy dataset on which the search is conducted and how does the performance on target dataset depend on the NAS method that is used to search the architectures. Moreover, a thorough study on applicability of proxy datasets to large scale contexts such as ImageNet22K is still missing. In fact, even direct training and evaluation of standard human-designed architectures has been relatively limited for ImageNet22K, given not only its sheer scale (~14M images) but also its large imbalance across classes [9, 8, 10, 44].

Motivated by this, in this paper, instead of focusing on beating the latest benchmark numbers on small scale datasets like CIFAR10 [17], we take a step back and aim at filling the above gap with an extensive empirical study on architecture transferability of different NAS methods that explains and suggests best practices for proxy sets design and successful transfer at large scale. We compare five representative NAS methods such as ENAS [30], NSGANet [27], NAO [28] and DARTS [25] using the commonly used DARTS [25] on four datasets (CIFAR [17], CIFAR100 [17], ImageNet1K [11] and ImageNet22K [32]) to analyze their transfer performance under different settings. Our findings suggest that the transfer performance of architectures searched using completely different small datasets perform similarly to the architectures searched directly on proxy target datasets (e.g., CIFAR10 proves to be a valuable dataset for transferring architectures to ImageNet22K). However, design of proxy sets has considerable impact on rankings of different NAS methods. In addition to this, we show that (a) Even on large datasets like ImageNet22K, the randomly sampled architecture baseline is very competitive and significantly outperforms many representative NAS methods confirming that the effect of a search strategy is less influential for final performance of a given architecture compared to accurately designing the search space. (b) The training protocol (i.e., different data augmentation techniques such as Drop path [19], Auxiliary towers [37] and Cutout [12]) has a larger impact on small datasets, but it fails to provide consistent improvements on large datasets. We hope our empirical analysis can bring some insights to the future designs of NAS algorithms. We will make our source code and models publicly available.

2 Related Work

Neural Architecture Search. Neural Architecture Search (NAS), has attracted intense attention in recent years. Typically a NAS algorithm first defines a search space and then employs a search strategy within that space. During the search phase, some evaluation criteria are chosen in order to rank the relative performance of possible architecture candidates [14, 41]. Recent studies [13, 20, 39, 40] have shown that performance is highly dependent on the elaborately designed search space, within which the difference between different search strategies results less significant that initially thought, especially when compared to random search [20, 39]. On the other hand, the search strategy and evaluation protocol for any candidate architecture within the search space highly influence the efficiency if a NAS algorithm. The original reinforcement learning based method [47], for example, required hundreds of GPUs in order to evaluate and rank each proposed architecture. Different methods have been proposed to reduce the search and evaluation costs, including micro-search of primary building cells [45, 48], prediction of candidate architectures performance based on learning curves [11] or surrogate models [25], and parameter sharing between child models [2, 4, 25, 30, 43].

Architecture Transferability. Most NAS approaches usually perform well when searching an architecture for a specific dataset and/or task, but have a hard time generalizing. In order to overcome the computational burden of running NAS searches for every new target domain, methods have been developed for joint training and efficient transfer of prior knowledge between multiple search spaces and tasks [8, 35, 20]. Some methods obtain transferability based on meta-learning [21] or learning general supernets from which specialized subnets can be sampled without any additional training [26]. Other approaches search for the best convolutional cell on a small proxy dataset and then apply the searched cell to the target dataset by stacking together more copies of this cell, each with their own parameters to design a convolutional architecture [48]. In this work, we focus on the latter type of approaches and investigate their applicability at large scale.

NAS Proxies. Although recent NAS methods [23, 25, 30] improve the search efficiency from earlier works, the search progress is still time-consuming and requires vast computation overhead when searching in a large search space since all network candidates need to be trained and evaluated. Differentiable approaches such as DARTS [25] require high GPU memory consumption, which still
makes direct search on large dataset prohibitive. A widely used approach to address efficiency in NAS methods is to search for an architectural building block on a small dataset (either using a proxy set from the large dataset or a completely different small scale dataset) and then transfer the block to the larger dataset by replicating and stacking it multiple times in order to increase network capacity (augmenting its depth and/or width) according to the scale of the dataset. While proxy sets have been largely used to expand search results from small (CIFAR10, CIFAR100) to mid-size (ImageNet1K) datasets, and some works have been able to perform search on mid size datasets [5], a study of their applicability to large scale datasets is still missing. In this work, we offer a detailed and exhaustive study of the effects of proxy sets on network transferability to large scale targets. We hope this will contribute to an established protocol of reproducibility when studying NAS algorithms going from small-to-medium proxies to large scale target datasets.

### 3 NASTransfer Benchmark

**Objective.** Our goal is to provide diagnostic information on the architecture transfer performance of different NAS methods and proxy sets for large scale NAS, which can be potentially used for better designs of future NAS algorithms. We adopt a common search space and training protocol to avoid the effect of the manually engineered tricks and search space widely used in different NAS methods.

**Datasets and Proxy Sets.** We select four diverse and challenging datasets within image classification, namely CIFAR10 and CIFAR100 [17], ImageNet1K [11] and ImageNet22K [32] to evaluate the performance of different methods. While most of the existing analysis on NAS [39, 43, 40, 13] focus on small scale datasets such as CIFAR10, and CIFAR100, we show large-scale experiments on ImageNet22K [32] dataset that contains over 14 million labeled high-resolution images belonging to around 22,000 different categories. ImageNet22K dataset skew is reflective of real world situations and provides a natural testbed for our method when comparing training sets of different sizes.

As proxy sets for the larger datasets, we employed not only the standard CIFAR10 and CIFAR100, but also sampled subsets of ImageNet1K and ImageNet22K directly. Namely, we investigated the proxies listed in Table 1, which are of two types: randomly selected and uniformly selected. For random selection, we simply picked a list on \( N \) classes and used all of their images. In uniform selection we were interested in maintaining the overall distribution of examples for all classes in the dataset, therefore we sorted classes by their number of images and then uniformly sampled in order to obtain the desired number of classes \( N \) in the subset. In order to maintain the order of magnitude consistent across multiple proxies, we then took the same fraction of images from every class, ensuring that the total would meet the requirement and at the same time maintain the overall distribution intact. This is particularly important when designing a proxy set for a non-uniform, imbalanced distribution such as the one of ImageNet22K. For example ImageNet22K Proxy 2 was designed to have the same overall distribution of the full dataset, but the same number of images of ImageNet22K Proxy 1. In order to do so, we sampled 0.97% of images from each class in the dataset, and eliminated classes for which only one image remained for training or validation, thus keeping only approximately 13k classes out the the 22k total. For ImageNet22K Proxy 3 instead we uniformly picked 100 classes whose total number of images would be the same as ImageNet22K Proxy 1. We split each of these datasets into a training, validation and testing subsets with proportions 40/40/20 and use standard data pre-processing and augmentation techniques.
Methods and Search Space. We compare five representative NAS methods: DARTS \cite{cui2019proxylessnas}, ENAS \cite{zoph2018learning}, NSGA-Net \cite{liu2018progressive}, NAO \cite{dong2019neural} including random sampling \cite{chen2017stochastic}. We choose these methods as they have a reasonable search time, specifically under 4 GPU-days on CIFAR10. We perform micro-search at cell level within the search space $O$ introduced in DARTS \cite{cui2019proxylessnas}: $3 \times 3$ and $5 \times 5$ separable convolutions, $3 \times 3$ and $5 \times 5$ dilated separable convolutions, $3 \times 3$ max pooling, $3 \times 3$ average pooling, identity, and zero. All operations are of stride one (if applicable) and the convolved feature maps are padded to preserve their spatial resolution. ReLU-Conv-BN order are used for convolutional operations, and each separable convolution is always applied twice. Note that NASTransfer has a fixed search space and hence provides a unified benchmark for analyzing different NAS algorithms.

Training and Evaluation Protocol. NAS algorithms traditionally work in two phases: first search, in which the best architecture is determined based on the search algorithm employed, and second augmentation, which consists in training from scratch the model selected during the search phase. We choose the search hyperparameters as close as possible to the ones reported in the original papers. Experiments on all datasets use the same hyperparameters except the number of training epochs. For augmentations, we use cross entropy loss, SGD optimizer with learning rate 0.025, momentum 0.9, seed 2, initial number of channels 36, and gradient clipping set at 5. Following \cite{chen2017stochastic}, we compare between BASE Augmentation setting, without any data augmentation strategy or other learning tricks, and a DAC Augmentation setting, which employed three widely used strategies: Drop path \cite{hinton2012improving} (with default probability 0.2), Auxiliary towers \cite{liu2018progressive} (with default loss weight 0.4) and Cutout \cite{devries2017cutout} (with default length 16). The number of cells was fixed to 20 for all experiments and the number of training epochs per dataset was set to 600, 600, 120 and 60 for augment runs on CIFAR10, CIFAR100, ImageNet1K and ImageNet22K, respectively. All searches were performed on single GPU, while augment runs were done on single GPU for CIFAR10 and CIFAR100. We use a minimum of 8 to a maximum of 96 GPUs for ImageNet1K and ImageNet22K augmentation experiments.

Metrics. Following \cite{chen2017stochastic}, we compute not only the Top-1 classification accuracy of augmentation runs on target datasets as a metric of performance for each method, but also the relative improvement (RI) over a random sampling baseline, which is computed as $RI = 100 \times \frac{Acc_m - Acc_r}{Acc_r}$, where $Acc_m$ and $Acc_r$ represent the Top-1 accuracy of the search method and random sampling strategies, respectively. RI provides a measure of the quality of each search strategy alone, since both searched and randomly sampled architectures share the same search space and training protocol. A good, general-purpose NAS method is expected to yield $RI > 0$ consistently over different searches and across different subtasks. Note that this comparison is not against random search, but rather against random sampling, i.e., the average architecture of the search space. In our experiments, we compute $Acc_r$ as the average of augmentation runs over $N$ randomly sampled architectures.

4 Results & Analysis

Transferring Architectures. Despite recent efforts to significantly improve the speed of search algorithms, performing direct search on large scale target datasets remains prohibitive, unless extremely powerful resources are utilized. For example for NSGA-Net, the search times on CIFAR10 and CIFAR100 with single-GPU is 96 GPU-hours on average, while single-GPU direct search on ImageNet1K Proxy 1 would take almost two months (which we estimated based on the progress of a four days long run on CIFAR), over one year and half on the full ImageNet1K and approximately 19 years on ImageNet22K. Even the fastest search method we analyzed, ENAS (0.375 days for CIFAR10), would require over one year on ImageNet22K. Therefore the need for effective, small-scale proxy sets that could provide a ranking of searched architectures which remains consistent when transferring to the target large scale datasets becomes crucial. But, how to properly select a proxy-set? From the results of our extensive experiments, it seems that the number of examples per class is more important than the overall size of the dataset. From Figure 2 we can clearly see that for most search methods transferring to ImageNet1K from CIFAR10 is more effective than transferring from CIFAR100. The overall number of images in CIFAR10 and CIFAR100 is the same, but the number of examples per class is 5, 000 for the former and only 500 for the latter (half of the ImageNet1K distribution). We also notice how the domain of the proxy set does not seem to influence architecture performance on the target dataset. Intuitively, one would think that a proxy set built from a subset of the target dataset (ImageNet1K Proxy 1 in the Figure, on the right) will yield better results than a proxy set coming from a different dataset (CIFAR10). That appears not to be the case for the target dataset ImageNet22K, as shown in Figure 2 on the right. While both CIFAR and ImageNet contain images
While analyzing the search for very large scale datasets with a skewed distribution (ImageNet22K), it would be beneficial, especially when the distribution across classes is significantly skewed as it is for CIFAR10, to work as a proxy for ImageNet22K across all methods. Using CIFAR10 produces the same search space to verify the effectiveness of each method for every augment run. We want to searched with NAO using CIFAR10 as a proxy yields the SOTA published result on ImageNet22K.

Network WRN-50-4-2 [10], project Adam’s network [8] achieved the same accuracy for datasets even at the scale of ImageNet22K: dataset, albeit in the same general field (natural images classification) can lead the search process to be difficult to beat for all methods, and DARTS goes from being the top ranked to the bottom one. This underlines the importance of carefully selecting and designing the proxy set. Random sampling of a subset of classes while maintaining the number of images per class proves to be more beneficial than trying to keep all classes in the target dataset and reducing the number of images per class (Proxy 5).

Direct Search using Proxy Sets. In order to determine the benefit of employing proxy sets directly sampled from the target datasets for search, we compared the performance of the searched architectures versus randomly sampled ones for each of the target datasets. For each method, including random sampling, search was conducted five times, and the resulting mean and standard deviations of the five runs are reported in Figure 4. We observe that for medium scale, uniformly distributed datasets such as ImageNet1K, the rankings of search strategies remains unaffected by proxy set design as DARTS is the best performing method, followed by ENAS and NAO. The number of classes and examples in the proxy set does not bring noticeable improvements, as long as a minimum is guaranteed, as shown by the comparable results using Proxy 1, 2 and 3. Overall, random sampling of a reduced number of classes when building the proxy set seems to provide better performance than keeping all the classes in the target dataset and reducing the number of examples per class (Proxy 5).

While analyzing the search for very large scale datasets with a skewed distribution (ImageNet22K), the design of proxy set has a large impact not only on the overall improvement, but also on the rankings of different NAS methods. ImageNet22K Proxy 1 results are significantly superior to all other proxies sampled from ImageNet22K for DARTS, ENAS and NAO, and better than random sampling. When searching on ImageNet22K proxies 2 and 3, the random sampling baseline becomes difficult to beat for all methods, and DARTS goes from being the top ranked to the bottom one. This underlines the importance of carefully selecting and designing the proxy set. Random sampling of a subset of classes while maintaining the number of images per class proves to be more beneficial, than trying to keep all classes represented in the dataset and eliminating a large portion of examples per class to maintain the search time practically feasible.

Architecture Transfer vs Proxy-based Direct Search. From the results reported in Figure 5, we can see that on average, transfer performance of architectures searched using completely different small datasets (e.g., CIFAR10) can perform similarly or even better than architectures searched directly on proxy target datasets. However, design of proxy sets has considerable impact on rankings of different NAS methods. From the Figure we can see that for NAO, using a small, unrelated small dataset as proxy provides consistently better results than the best possible proxy sampled from the target dataset, both for ImageNet1K and ImageNet22K. It is surprising to observe how well CIFAR10 works as proxy for ImageNet22K across all methods. Using CIFAR10 produces better results not only than proxy sets from ImageNet1K, but also better than proxy sets directly sampled from ImageNet22K. One would assume that using a subset of the target dataset for search would be beneficial, especially when the distribution across classes is significantly skewed as it is for ImageNet22K. The results of our experiments suggest that a small proxy set, different from the target dataset, albeit in the same general field (natural images classification) can lead the search process to find valuable architectures for datasets even at the scale of ImageNet22K: 15 million images. For reference, the SOTA published result on ImageNet22K is 36.9 Top-1 accuracy using a Wide Residual Network WRN-50-4-2 [10], project Adam’s network [8] achieved 29.8%, whereas the architecture searched with NAO using CIFAR10 as a proxy yields 30.91 Top-1 accuracy.

Comparison with Random Sampling. We compare with randomly sampled architectures within the same search space to verify the effectiveness of each method for every augment run. We want to
Figure 4: Direct search using proxy sets. Comparison of different NAS methods using sampled proxy sets from the same target dataset. Methods lying in the diagonal perform the same as the randomly sampled architecture, while methods above the diagonal outperform it. We use total five proxy sets for ImageNet1K and three proxy sets for ImageNet22K. Best viewed in color.

Figure 5: Architecture transfer vs Proxy-based direct search. Comparison of transfer performance with the best proxy-based direct search on ImageNet1K and ImageNet22K datasets. Methods lying in the diagonal indicate that transfer performance is similar to the direct proxy-based search, while methods above the diagonal outperform it.

emphasize that this comparison is not against random search, but rather against random sampling, i.e., the average architecture of the search space. We sample 5 architectures randomly from the search space and compare with the same number of architectures searched by each method. From the results in Figure 4 and Table 1, the random sampling strategy proves to be a very strong baseline, confirming that the effect of a search strategy is less influential for final performance of a given architecture compared to accurately designing the search space. This effect becomes particularly evident when trying to transfer from a small proxy set to a larger one, especially when the number of examples per class varies significantly between proxy and target sets. This is the case for the transfer experiment between CIFAR100 and ImageNet1K, where the architectures learned by all search methods on CIFAR100, with the exception of NSGA-Net, perform significantly worse than the direct application of randomly sampled ones. Interestingly, CIFAR10 seems instead like a good proxy for transfer to all other target datasets, including ImageNet22K. To further analyze the effect of number of random sampled architectures, we sample 25 more randomly sampled architectures (total 30) on CIFAR10, CIFAR100 and ImageNet1K and use BASE protocol for training. The influence of search space design and the strength of the random sampling baseline becomes less important as the scale of the target dataset increases. The standard deviation around the average performance of 30 randomly sampled architectures expands as the scale of the target dataset increases (Figure 4). This trend signifies a larger opportunity for impact of the search strategy within the space. As direct search on large scale datasets is basically intractable in practice, it shows the importance of finding good proxy sets where search is feasible and performance gains transfer to the target dataset.

Effect of Training Protocol. Techniques such as Drop path [19], Auxiliary towers [37] and Cutout [12] have been developed as general learning tools to improve the accuracy of deep learning models.
Table 2: Relative improvement metric RI for various transfer experiments. S and T indicate the source set and target set respectively. CIFAR10 is a good proxy for all the datasets. Given its much longer search time, we did not perform NSGANet search on ImageNet1K proxies.

| Source Set | Target Set | NSGANet | ENAS | DARTS | NAO | BASE |
|------------|------------|---------|------|-------|----|------|
| S: CIFAR10 | T: CIFAR100 | 1.38    | 1.42 | 1.01  | -0.89 | -0.89 |
| S: CIFAR10 | T: ImageNet1K | -3.39  | -16.26 | 5.93  | 0.99 | -16.26 |
| S: CIFAR100 | T: ImageNet1K | 0.92 | -11.75 | -18.71 | 0.99 | -11.75 |
| S: CIFAR100 | T: ImageNet22K | -0.72 | 3.06 | 6.16 | 6.44 | -0.72 |
| S: ImageNet1K | T: ImageNet22K | 1.62 | 2.03 | 5.44 | 5.44 | 1.62 |

Figure 6: Effect of training protocol on direct experiments. DAC training protocol improves the performance of different NAS methods on CIFAR10 and CIFAR100, but its importance is surprisingly negligible on ImageNet1K direct experiments. Best viewed in color.

As such, they should be dataset and architecture agnostic. When analyzing our augmentation training results in Figure 10, we observe that the DAC training protocol provides significant benefits in terms of Top-1 accuracy for the smaller datasets (CIFAR10 and CIFAR100), confirming the observations of Yang et al. However, its importance becomes surprisingly negligible on the larger datasets. For example on ImageNet1K (see Figure 10), BASE protocol achieves an accuracy of 72.03 ± 0.2 for DARTS versus 63.64 ± 1.78 for NAO, whereas the DAC protocol achieves an accuracy of only 69.13 ± 0.45 and 61.67 ± 2.11 for DARTS and NAO respectively. The same behavior can also be observed in Figure 11 for the transfer results. Even when transferring, training protocol (DAC methods) are more important for performance gains than search methods or proxy sets adopted for small scale datasets (CIFAR100). When looking at larger datasets such as ImageNet, choices of search methods and proxy sets adopted become more important. For example picking CIFAR10 as proxy set over CIFAR100 for NAO yields an absolute improvement on ImageNet1K of 7.93% (71.3 ± 0.78 versus 63.37 ± 4.99, respectively). The difference between BASE and DAC protocols for almost all search methods on ImageNet1K is instead less than 4% when using either CIFAR10 or CIFAR100 as proxy, with the only exception of NSGA-Net, which exhibits a very wide standard deviation in DAC based runs. Interestingly this result suggests that the choice of an appropriate proxy set and search strategy is more relevant than some of the “tricks” commonly used to improve training performance when analyzing NAS at large scale.

Figure 7: Effect of training protocol on transfer experiments. While DAC training protocol is marginally better than BASE protocol on CIFAR100, BASE training protocol consistently outperforms DAC protocol on ImageNet1K transfer experiments. Best viewed in color.
We have presented the first extensive study on the design and transfer value of proxy sets for NAS while the other two are kept at default values. Default values:

| Parameter | Default Value |
|-----------|---------------|
| Aug. seed | 2             |
| A          | 0.4           |
| C          | 16            |
| D          | 0.2           |

Table 3: *Ablation studies on augmentation seed.* The default value of Aug. seed is set to 2.

Table 4: *Effect of different parameters on DAC protocol.* Results show performance of different NAS methods on ImageNet1K dataset. The value of the parameter controlling one technique is varied while the other two are kept at default values. Default values: \( A = 0.4, C = 16 \) and \( D = 0.2 \)

Table 5: *Effect of number of cells on ImageNet1K.*

Effect of Hyperparameters. We conduct extensive ablation studies over the augmentation training hyperparameters in order to precisely determine the merits of search methods and choice of proxy set versus training protocols. Namely, we investigated augment results varying seed (Table 3), number of cells (Table 5) and DAC techniques parameters (auxiliary towers weight, cut-out length and drop-path probability, Table 4). In general we observe that the parameters of the training protocol have a larger impact on small datasets, but it fails to provide consistent improvements on large datasets. From Table 3 it appears that ENAS is particularly sensitive to choice of augmentation seed, both for the BASE and DAC protocols, especially when transferring from CIFAR10 to ImageNet1K.

5 Conclusions and Best Practices

We have presented the first extensive study on the design and transfer value of proxy sets for NAS at large scale across different search methods. The results of our experiments and ablation studies suggest the following set of best practices when choosing proxy sets. (i) The number of examples per class is more important than the overall size of the proxy set. (ii) The domain of the proxy set does not seem to influence architecture performance on the target dataset. Transfer performance of architectures searched using different small datasets (e.g., CIFAR10) can perform similarly or even better than architectures searched directly on proxies of target datasets (ImageNet1K and ImageNet22K). (iii) For proxy sets directly sampled from the target set, the random sampling of a subset of classes maintaining intact the number of images per class is more beneficial than trying to keep all the classes represented in the proxy. (iv) As the scale of the target dataset increases, the choice of an appropriate proxy set and search strategy matters more on the final augmentation performance on the target dataset than for example towers weight, cut-out length and drop-path probability, Table 4). In general we observe that the parameters of the training protocol have a larger impact on small datasets, but it fails to provide consistent improvements on large datasets. From Table 3 it appears that ENAS is particularly sensitive to choice of augmentation seed, both for the BASE and DAC protocols, especially when transferring from CIFAR10 to ImageNet1K.

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A Datasets

Target Datasets. In this work we use the following four commonly used image datasets, and derive the proxy sets from them to use for our transfer experiments.

CIFAR10 [17]: a collection of 50K training and 10K validation natural images with resolution 32x32, annotated in 10 classes with uniform distribution. Training and validation splits are provided with the dataset which is available to download at https://www.cs.toronto.edu/~kriz/cifar.html.

CIFAR100 [17]: the same collection as CIFAR10 of 50K training and 10K validation natural images with resolution 32x32, but annotated in 100 classes with uniform distribution. The dataset is publicly available to download at https://www.cs.toronto.edu/~kriz/cifar.html.

ImageNet1K [11]: a collection of 1.2M training and 50K validation natural images with resolution 256x256, annotated in 1,000 classes with uniform distribution. Training and validation splits are provided with the dataset which is available at http://image-net.org/download.

ImageNet22K [32]: a collection of over 14M natural images with resolution 256x256, annotated in 21,841 classes with heavily skewed distribution (as shown in Figure 8 in blue). While the largest class contains 2,469 images, 479 classes have only 1 image. On average, there are 343 images per class. Since there is not an official training/test split for the dataset, in our augment experiments we followed the common practice [8, 9] of randomly splitting the dataset in two halves, one for training and one for testing. We adopted the same split as Cho et al. [9]. This dataset is publicly available to download at http://image-net.org/download.

Proxy Sets. Besides CIFAR10 and CIFAR100, we designed a series of Proxy-Sets by sampling classes and images from ImageNet1K and ImageNet22K, as follows:

ImageNet1K Proxy 1. 100 randomly sampled classes from ImageNet1K.

ImageNet1K Proxy 2. 200 randomly sampled classes from ImageNet1K.

ImageNet1K Proxy 3. 300 randomly sampled classes from ImageNet1K.

ImageNet1K Proxy 4. 200 randomly sampled classes from ImageNet1K, same number of exsamples as Proxy 1.

ImageNet1K Proxy 5. 1,000 classes from ImageNet1K, same number of exsamples as Proxy 1.

ImageNet22K Proxy 1. 100 randomly sampled classes from ImageNet22K, as illustrated in in Figure 8 in green.

ImageNet22K Proxy 2. 13,377 classes, randomly sampled images from each class of ImageNet22K to obtain same cumulative number of examples as Proxy 1 (Figure 8 in yellow).

ImageNet22K Proxy 3. 100 uniformly sampled classes from ImageNet22K, to obtain same cumulative number of examples as Proxy 1 (Figure 8 in red).

We will make all the proxy sets publicly available to enable future comparisons.

B Training Protocol Details

In all our experiments we use the codebase from Yang et al. [39] running Pytorch on NVIDIA Tesla V100 GPUs with 16GB memory. In the following we describe in detail the parameters of the search protocols for each method.

DARTS: Batch size = 64, SGD optimizer, weight decay=3e-4, momentum = 0.9, seed = 2, lr = 0.025;

ENAS: Batch size = 128, SGD optimizer, seed = 2, lr = 0.05, momentum = 0.9, weight decay = 1e-4, controller optimizer = Adam;

NSGA-Net: Batch size = 128, SGD optimizer, seed = 2, lr = 0.025, weight decay = 3e-4, momentum = 0.9, number of offspring is 20, number of generations is 30, population size is 40;

NAO: Batch size = 64, SGD optimizer, seed = 2, learning rate decay = 0.97, momentum = 0.9. For augmentations, batch size was fixed at 128 per GPU across all augment runs, except for models using 40 and 60 cells, where the memory constraints required smaller batch sizes of 96 and 64 per GPU, respectively. For augmentations we followed the default settings as the experiments in [39], using cross entropy loss, SGD optimizer with learning rate 0.025, momentum 0.9, seed 2, initial number of channels 36, and gradient clipping set

http://www.mediafire.com/file/ilqp3nqtr0l269e/NAS-Benchmark-master.zip
Figure 8: **ImageNet22K.** Distribution of training images and visual representation of sampling strategies for the Proxy Sets. While the largest class contains 2,469 images, 479 classes have only 1 image. On average, there are 343 images per class. Best viewed in color.

at 5. Default DAC training protocol values were Auxiliary Towers weight $A = 0.4$, Cutout Length $C = 16$ and Drop-path Probability $D = 0.2$.

In Table 6 we report the single GPU search times for each method, measured in GPU-days for all the small and proxy sets, and estimated for ImageNet1K and ImageNet22K based on those measurements.

| Search Method | CIFAR10 | CIFAR100 | ImageNet1K Proxy 1 | ImageNet1K Proxy 2 | ImageNet1K Proxy 3 | ImageNet22K Proxy 1 | ImageNet1K | ImageNet22K |
|---------------|---------|----------|---------------------|---------------------|---------------------|---------------------|-----------|-----------|
| ENAS          | 0.375   | 0.375    | 1.49                | 2.21                | 3                   | 1                    | 12        | 414       |
| DARTS         | 0.458   | 0.509    | 2.65                | 5.30                | 7.95                | 1.08                | 25        | 447       |
| NANO          | 2.14    | 2.16     | 3.38                | 6.32                | 9.62                | 1.35                | 33        | 560       |
| NSGANET       | 4       | 4        | 60                  | 121                 | 180                 | 16                  | 600       | 6,628     |

Table 6: Search times (in GPU-days) for each method on the proxy sets (measured) and on the direct sets (estimates). NSGANet requires maximum time for search among all the methods.

### C Additional Transfer Results

Figure 9 shows the comparison between architecture transfer and proxy-based direct search on CIFAR100. As can be seen, transfer performance of architectures searched using CIFAR10 can perform similarly or even better than architectures searched directly on proxy target datasets. Figure 10 shows the effect of training protocol on different proxy sets. As discussed in the main paper, the effect of DAC training protocol becomes surprisingly negligible on the larger datasets irrespective of the proxy sets used for searching the architectures. Figure 11 shows the effect of base training protocol on transfer experiments on ImageNet22K.

### D Backward Transfer Results

In the main paper, we presented transfer results for searching on smaller-scale datasets and transferring the architectures to larger-scale datasets, such as ImageNet1K and ImageNet22K. In this section, we present results where the architectures were searched either on proxy sets of large-scale datasets (e.g.: ImageNet1K proxy set1) or on whole datasets (e.g.: CIFAR100) and transferred to smaller datasets such as CIFAR10 or CIFAR100. Our goal is to see if the cells found with higher resolution is
Figure 9: **Architecture transfer vs Proxy-based direct search.** Comparing architectures transferred from CIFAR10 to those obtained directly from CIFAR100. The transferred architectures perform at-par or better than direct searched architectures across NAS methods.

Figure 10: **Effect of training protocol on direct experiments.** BASE and DAC augmentation strategies on various proxy sets of ImageNet1K. NAS methods were only trained with BASE augmentation for ImageNet22K. Best viewed in color.

useful when transferred to lower resolution images. We conducted analysis of backward transferring architectures akin to the experiments conducted in the main paper.

Figure 13 shows the Top-1 test accuracy of transferring architectures searched on large datasets to smaller datasets, such as CIFAR10 and CIFAR100. DARTS transferred from CIFAR100 to CIFAR10
seems to have the largest standard deviation of test accuracy. Figure 14 compares transferring from larger datasets to directly searching on small-scale datasets. For CIFAR10, transferring from larger datasets seems to helpful for ENAS, but for NAO and DARTS performance depends upon the type of large dataset. For CIFAR100, transferring from ImageNet datasets boosts performance of DARTS and NAO, while ENAS performs best with direct search. Overall, searching on data that has larger number of images per class seems to help transfer performance. The effect of training the reverse transferred architectures with BASE and DAC augmentation strategies are illustrated in Figure 15. Using DAC augmentation improved top-1 test accuracy for all NAS methods and search datasets which shows the relevance of augmentation strategy over other design choices.

### E Example Searched Cell Visualizations

We visualize examples of cells obtained from different search strategies for the proxy sets CIFAR10 (Figure 16), CIFAR100 (Figure 17), ImageNet1K Proxy 1 (Figure 18) and ImageNet22K Proxy 1 (Figure 19). As can be seen from the figures, design of proxy sets has considerable impact on the searched cell for different methods.
Broader Impact

Mostly neural network architectures are hand-designed. Which relies on the scientist/engineer’s expertise. Advances in automated Neural Architecture Search democratizes this process. We explore the idea of searching on proxy sets and smaller-datasets and transferring the resultant architectures to larger-dataset. This saves compute and time. So, even entities with limited resources can design good architectures. Bias is inherently built into most existing datasets. As such, NAS models are still subject to learning and perpetrating such bias. One could consider including bias mitigation strategies not only in the augment training phase, but also in the search space and in the proxy set design.

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Figure 16: Visualization of cells searched on CIFAR10.
Figure 17: Visualization of cells searched on CIFAR100.
Figure 18: Visualization of cells searched on ImageNet1K Proxy1.
Figure 19: Visualization of cells searched on ImageNet22K Proxy1.