How to Train Your Super-Net: 
An Analysis of Training Heuristics in Weight-Sharing NAS

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Abstract

Weight sharing promises to make neural architecture search (NAS) tractable even on commodity hardware. Existing methods in this space rely on a diverse set of heuristics to design and train the shared-weight backbone network, a.k.a. the super-net. Since heuristics and hyperparameters substantially vary across different methods, a fair comparison between them can only be achieved by systematically analyzing the influence of these factors. In this paper, we therefore provide a systematic evaluation of the heuristics and hyperparameters that are frequently employed by weight-sharing NAS algorithms. Our analysis uncovers that some commonly-used heuristics for super-net training negatively impact the correlation between super-net and stand-alone performance, and evidences the strong influence of certain hyperparameters and architectural choices. Our code and experiments set a strong and reproducible baseline that future works can build on.

1. Introduction

Neural architecture search (NAS) has received growing attention in the past few years, yielding state-of-the-art performance on several machine learning tasks (Liu et al., 2019a; Wu et al., 2018; Chen et al., 2019b; Ryoo et al., 2020). One of the milestones that led to the popularity of NAS is weight sharing (Pham et al., 2018; Liu et al., 2019b), which, by allowing all possible network architectures to share the same parameters, has reduced the computational requirements from thousands of GPU hours to just a few.

Figure 1 shows the two phases that are common to weight-sharing NAS (WS-NAS) algorithms: the search phase including the design of the search space and the search algorithm; and the evaluation phase which contains the final training protocol on the proxy task. While most of the existing works focus on developing a good sampling algorithm (Cai et al., 2018; Xie et al., 2018) or improving existing ones (Zela et al., 2020a; Nayman et al., 2019; Li et al., 2019), the resulting methods differ in many other factors when it comes to designing and training the shared-weight backbone network, i.e., the super-net. For example, the literature reports diverse hyper-parameter settings for learning, variations of how batch normalization and dropout are used, different capacities for the initial layers of the network, and variations in the total depth of the super-net. All these factors increase the difficulty to perform a fair comparison of NAS algorithms, and thus hinder our understanding of the reasons for success and failure of different strategies in different contexts.

In this paper, we close this gap by performing a systematic evaluation of the effectiveness of commonly-used super-net design and training heuristics. To this end, we leverage

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three benchmark search spaces, NASBench-101 (Ying et al., 2019), NASBench-201 (Dong & Yang, 2020), and DARTS-NDS (Radosavovic et al., 2019), for which the ground-truth stand-alone performance of a large number of architectures is available. We report the results of our extensive experiments according to four metrics, including the super-net accuracy, the probability of the final architecture to surpass a random architecture, a modified Kendall-Tau correlation between the searched architectures and their ground-truth performance, and the stand-alone accuracy of the model found by WS-NAS algorithm.

Our analysis reveals (i) the factors that have a strong influence on the final performance, and thus strongly reduce the discrepancies between different sampling algorithms; (ii) that some commonly-used training heuristics negatively affect performance; (iii) that some factors believed to have a strong impact on performance in fact only have a marginal effect. Furthermore, our evaluation shows that some search spaces are more amenable to weight sharing than others, and that the commonly used metric of super-net accuracy to judge the quality of an architecture has a low correlation with the final stand-alone performance of a searched model. Specifically, on NASBench-101 and DARTS-NDS, the correlation is close to zero. We show that our proposed sparse Kendall-Tau metric shows a significantly higher correlation to stand-alone performance, and is thus a better metric to evaluate the training of the super-net.

Altogether, our work is the first to systematically analyze the impact of the diverse factors of super-net design and training. We uncover the factors that are crucial to design a super-net, as well as the non-important ones. Our analysis allows us to construct a new baseline that achieves state-of-the-art search results with weight-sharing random search on the three studied search spaces. We will release our code and trained models so as to provide a unified WS-NAS framework.

2. Preliminaries and Related Work

We first introduce the necessary concepts that will be used throughout the paper. As shown in Fig. 1 (a), weight-sharing NAS algorithms consist of three key components: a search algorithm that samples an architecture from the search space in the form of an encoding, a mapping function $f_{\text{proxy}}$ that maps the encoding into its corresponding neural network, and a training protocol for a proxy task $P_{\text{proxy}}$ for which the network is optimized.

To train the search algorithm, one needs to additionally define the mapping function $f_{\text{ws}}$ that generates the shared-weight network. Note that the mapping $f_{\text{proxy}}$ frequently differs from $f_{\text{ws}}$, since in practice the final model contains many more layers and parameters so as to yield competitive results on the proxy task. After fixing $f_{\text{ws}}$, a training protocol $P_{\text{ws}}$ is required to learn the super-net. In practice, $P_{\text{ws}}$ often hides factors that are crucially important for the final performance of an approach, such as hyper-parameter settings or the use of data augmentation strategies to achieve state-of-the-art performance (Liu et al., 2019b; Chu et al., 2019; Zela et al., 2020a). Again, $P_{\text{ws}}$ can differ from the protocol $P_{\text{proxy}}$ that is used to train the architecture that has been found by the search. For example, our experiments reveal that the learning rate and the total number of epochs frequently differ due to the different training behavior of the super-net and stand-alone architectures.

Many strategies have been proposed to implement the search algorithm, such as reinforcement learning (Zoph & Le, 2017; Zoph et al., 2018), evolutionary algorithms (Real et al., 2017; Miikkulainen et al., 2019; So et al., 2019; Liu et al., 2018; Lu et al., 2018), gradient-based optimization (Liu et al., 2019b; Xu et al., 2020; Li et al., 2019), Bayesian optimization (Kandasamy et al., 2018; Jin et al., 2019; Zhou et al., 2019; Wang et al., 2020), and separate performance predictors (Liu et al., 2018; Luo et al., 2018).

Until very recently, the common trend to evaluate NAS consisted of reporting the searched architecture’s performance on the proxy tasks (Xie et al., 2018; Real et al., 2018; Ryoo et al., 2020). This, however, hardly provides real insights about the NAS algorithms themselves, because of the many different components involved in NAS techniques. Many factors that differ from one algorithm to another can potentially strongly influence the performance. In practice, the literature even commonly compares NAS methods that employ different proxy tasks to train the final model.

Li & Talwalkar (2019) and Yu et al. (2020) were the first to systematically compare different algorithms with the same settings for the proxy task and using several random initializations. Their surprising results revealed that many NAS algorithms produce architectures that do not significantly outperform a randomly-sampled architecture.

In parallel to this line of research, the recent series of “NAS-Bench” works (Ying et al., 2019; Zela et al., 2020b; Dong & Yang, 2020) proposed to benchmark NAS approaches by providing a complete, tabular characterization of the performance of every architecture in a given search space. This was achieved by training every realizable stand-alone architecture using a fixed protocol $P_{\text{proxy}}$. Similarly, other works proposed to provide a partial characterization by sampling and training a sufficient number of architectures in a given search space using a fixed protocol (Radosavovic et al., 2019; Zela et al., 2020a; Wang et al., 2020).

Yang et al. (2020) highlighted the importance of the training protocol $P_{\text{proxy}}$. They showed that optimizing the training protocol can improve the final architecture performance on
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![Diagram of super-net construction](image)

Figure 2. Constructing a super-net. The mapping \( f_{ws} \) maps an encoding to a neural network architecture.

the proxy task by three percent on CIFAR-10 (Krizhevsky et al., 2009). This non-trivial improvement can be achieved regardless of the chosen sampler, which provides clear evidence for the importance of unifying the protocol to build a solid foundation for comparing NAS algorithms.

While recent advances for systematic evaluation are promising, no work has yet thoroughly studied the influence of the super-net training protocol \( P_{ws} \) and of the mapping function \( f_{ws} \). This is the gap we fill here by benchmarking different choices of \( P_{ws} \) and \( f_{ws} \) that can be found in the existing WS-NAS literature. As will be shown in our experiments, this allows us to evaluate the performance of existing techniques across three benchmark datasets and to provide guidelines on how to train your super-net.

3. Evaluation Methodology

Our goal is to evaluate the influence of the super-net mapping \( f_{ws} \) and weight-sharing training protocol \( P_{ws} \). As shown in Figure 2, \( f_{ws} \) translates an architecture encoding, which typically consists of a discrete number of choices or parameters, into a neural network. Based on a well-defined mapping, the super-net is a network in which every sub-path has a one-to-one mapping with an architecture encoding (Pham et al., 2018). Recent works (Xu et al., 2020; Li et al., 2019; Ying et al., 2019) separate the encoding into cell parameters, which define the basic building block of a network, and macro parameters, which define the way how cells are assembled into a complete architecture.

Weight-Sharing Mapping \( f_{ws} \). To make the search space manageable, all cell and macro parameters are fixed during the search, except for the topology of the cell and its possible operations. However, the exact choices for each of these fixed factors differ between algorithms and search spaces. We evaluate common factors in the left part of Table 1. The factors include various implementation choices, such as the use of convolutions with a dynamic number of channels (Dynamic Conv), super-convolutional layers that support dynamic kernel sizes (OFA Conv) (Cai et al., 2020), weight-sharing batch-normalization (WSBN) that tracks independent running statistics and affine parameters for different incoming edges (Luo et al., 2018), and path and global dropout (Pham et al., 2018; Luo et al., 2018; Liu et al., 2019b). They additionally include heuristics to reduce the computational complexity of super-net training using low fidelity estimates (Elsken et al., 2019), for example by reducing the number of layers (Liu et al., 2019b) and channels (Yang et al., 2020; Chen et al., 2019a), the portion of the training set used for super-net training (Liu et al., 2019b), as well as a reduced batch size.

Weight-Sharing Protocol \( P_{ws} \). Given a mapping \( f_{ws} \), different training protocols \( P_{ws} \) can be employed to train the super-net. Protocols can differ in the training hyper-parameters and the sampling strategies they rely on. We will evaluate the different hyper-parameter choices listed in the right part of Table 1. This includes initial learning rate, hyper-parameters of batch normalization, total number of training epochs, and the amount of weight decay.

We restrict the search algorithm to the uniformly random sampling approach of Cai et al. (2018), which is also known as single path one shot (SPOS) (Guo et al., 2019) or Random-NAS (Li & Talwalkar, 2019). The reason for this choice is that Random-NAS is equivalent to the initial state of many search algorithms (Liu et al., 2019b; Pham et al., 2018; Luo et al., 2018), some of which even freeze the sampler training so to use random sampling to warm-up the super-net (Xu et al., 2020; Dong & Yang, 2020). We additionally include two variants of Random-NAS: 1) As pointed out by Ying et al. (2019), two super-net architectures might be topologically equivalent in the stand-alone network by simply swapping operations. We thus include architecture-aware random sampling that ensures equal probability for unique architectures (Yu et al., 2020). We name this variant Random-A; 2) We evaluate a variant called FairNAS (Chu et al., 2019), which ensures that each operation is selected with equal probability during super-net training. Although FairNAS was designed for a search space where only operations are searched but not the topology, we adapt it to our setting.

In our experiments, for the sake of reproducibility, we ensure that \( f_{ws} \) and \( P_{ws} \), as well as \( f_{ws} \) and \( P_{proxy} \), are as close to each other as possible. For the hyper-parameters of \( P_{ws} \),

![Table 1. Summary of factors](image)

| WS Mapping \( f_{ws} \) | WS Protocol \( P_{ws} \) |
|----------------------|----------------------|
| **Macro Parameters** | **Low fidelity** | **Hyperparam.** | **Sampling** |
| # cells              | layer               | batch-norm       | FairNAS       |
| # channel of first   | train portion       | learning rate    | Random-NAS    |
| dropout rate         |                     | epochs           | Random-A       |
|                      |                      | weight decay     |                |
| **Cell Parameters**  |                      |                  |                |
| # node               |                      |                  |                |
| **Topology**         |                      |                  |                |
| **Operation choices**|                      |                  |                |
| conv-3x3             |                      |                  |                |
| conv-5x5             |                      |                  |                |
| max-3x3              |                      |                  |                |
| **Train Parameters** |                      |                  |                |
| Learning rate        |                      |                  |                |
| Decay                |                      |                  |                |
| Epochs               |                      |                  |                |
| Dropout              |                      |                  |                |
| # channels           |                      |                  |                |

| Op on Node/Edge      |                      |                  |                |
| I                    |                      |                  |                |
| Y                    |                      |                  |                |
| Conv-3x3             |                      |                  |                |
| Conv-5x5             |                      |                  |                |
| Max-3x3              |                      |                  |                |

| Scenario | Description |
|----------|-------------|
| **Dynamic Conv** | Super-convolutional layers that support dynamic kernel sizes. |
| **OFA Conv**     | Architectural flexibility similar to Dynamic Conv. |
| **WSBN**         | Weight-sharing batch-normalization for different incoming edges. |
| **Dropout**      | Global and path dropout for regularization. |
| **Decay**        | Weight decay for each weight parameter. |

| **Sampling Strategies** | |
|-------------------------|---|
| Random-A                | Uniform probability |
| FairNAS                 | Uniform probability with architectural awareness. |
we cross-validate each factor following the order in Table 1, and after each validation, use the value that yields the best performance in $P_{\text{proxy}}$. For all other factors, we change one factor at a time.

**Search spaces.** We use three commonly-used search spaces for which a large number of stand-alone architectures have been trained and evaluated to obtain their ground-truth performance. In particular, we use NASBench-101 (Ying et al., 2019), which consists of 423,624 architectures and is compatible with weight-sharing NAS (Yu et al., 2020; Zela et al., 2020b); NASBench-201 (Dong & Yang, 2020), which contains more operations than NASBench-101 but fewer nodes; and DARTS-NDS (Radosavovic et al., 2019) for which a subset of 5000 models was sampled and trained in a stand-alone fashion. A summary of these search spaces and their properties is shown in Table 2. The search spaces differ in the number of architectures that have known stand-alone accuracy (# Arch.), the number of possible operations (# Op.), how the number of channels are handled in convolution operations (Channel), where dynamic means that the number of super-net channels might change based on the sampled architecture, and the type of optimum that is known for the search space (Optimal). We further provide the maximum number of nodes ($n$), excluding the input and output nodes, in each cell, as well as a bound on the number of shared weights (Param.) and edge connections (Edges). Finally, the search spaces differ in how the nodes aggregate their inputs if they have multiple incoming edges (Merge).

**Metrics.** We define different metrics to evaluate different aspects of a trained super-net. The first metric is the accuracy of the super-net on the proxy task. We will refer to this metric simply as accuracy. Accuracy is frequently used (Guo et al., 2019; Chu et al., 2019) to assess the quality of the trained super-net, but we will show later that it is in fact a poor predictor of the final stand-alone performance.

The second metric is the probability to surpass random search. Given the ground-truth rank $r$ of the best architecture found after $n$ runs and the maximum rank $r_{\text{max}}$, equal to the total number of architectures, the probability that the best architecture found is better than a randomly searched one is computed as $p = 1 - (1 - (r/r_{\text{max}}))^n$.

We further define a novel metric called sparse Kendall-Tau. Yu et al. (2020) introduced the Kendall-Tau metric to measure the discrepancy between the ordering of stand-alone architectures and the ordering that is implied by the trained super-net. An ideal super-net should yield the same ordering of architectures as the stand-alone one and thus would lead to a high Kendall-Tau. However, the Kendall-Tau is not robust. Architectures might switch places in the ranking due to negligible performance differences and thus yield a ranking with a small Kendall-Tau (c.f. Figure 3). To robustify this metric, we share the rank between two architectures if their stand-alone accuracy difference is within a threshold (set to 0.1% in our case). Since the resulting ranks are sparse, we call this metric sparse Kendall-Tau ($s$-KdT).

Finally, where appropriate, we report the stand-alone accuracy of the model that was found by the complete WS-NAS algorithm. Concretely, we randomly sample 200 architectures, select the 3 best models based on the super-net accuracy and query the ground-truth performance. The mean of these architectures is considered as stand-alone accuracy. Note that the same architectures are used to compute the sparse Kendall-Tau.

**4. Evaluation Results**

In this section, we empirically explore the impact of the factors summarized in Table 1 on WS-NAS across three different search spaces.

**4.1. Weight-Sharing Protocol $P_{ws}$ - Hyper-parameters**

For each search space, we start our experiments based on the original hyper-parameters used in stand-alone training. Because of the large number of hyper-parameters, we do not cross-validate all possible combinations. Doing so might further improve the performance. We will use the parameters validated in this section in later experiments.

**Batch normalization.** A fundamental assumption of batch
normalization is that its input data follows a slowly changing distribution whose statistics can be tracked using a moving average during training. However, in WS-NAS each node can receive wildly different inputs in every training iteration such that tracking the statistics becomes impossible. As shown by Figure 4, using the tracked statistics severely hinders training and leads to many architectures having an accuracy around 10%, i.e., random predictions. This finding corroborates the discussion in (Dong & Yang, 2020). We therefore do not track running statistics in the remaining experiments and only use mini-batch statistics.

**Learning rate.** We observed that the learning rate has a critical impact on the training of the super-net. In the stand-alone protocol $P_{proxy}$, the learning rate is set to 0.2 for NASBench-101, and 0.1 for NASBench-201 and DARTS-NDS. All protocols use cosine learning rate decay. Figure 5 shows that super-net training requires lower learning rates than stand-alone training. This is reasonable as the loss in $P_{ws}$ can be thought of as the sum of millions of architectures’ individual losses. We set the learning rate to 0.025 for the remaining experiments.

**Epochs.** Since the cosine learning rate schedule decays the learning rate to zero towards the end of the training, we evaluate the impact of the number of training epochs. In stand-alone training, the number of epochs was set to 108 for NASBench-101, 200 for NASBench-201, and 100 for DARTS-NDS. Figure 6 shows that increasing the number of epochs significantly improves the accuracy in the beginning, but eventually decreases the accuracy for NASBench-101 and DARTS-NDS. Interestingly, the number of epochs impacts neither the correlation of the ranking nor the final selected model performance after 400 epochs. We thus use 400 epochs for the remaining experiments.

**Weight decay.** Weight decay is used to reduce overfitting. However, for WS-NAS, overfitting does not occur because there are billions of architectures sharing the same set of parameters, which in fact may rather cause underfitting. Based on this observation, Nayman et al. (2019) propose to disable weight decay during super-net training. Figure 7, however, shows that the behavior of weight decay varies across datasets. While on DARTS-NDS weight decay is indeed harmful, it improves results on NASBench 101 and 201. While this may seem to counter the original argument, we conjecture that this is due to the much larger number of architectures in DARTS-NDS (243 billion) than in the NASBench series (less than 500,000).

### 4.2. Weight Sharing Protocol $P_{ws}$ - Path Sampling

With the hyper-parameters fixed, we now compare three path sampling techniques. Since DARTS-NDS does not contain enough samples that were trained in a stand-alone manner, we only report results on NASBench-101 and 201. In Figures 8 (a) and (b), we show the sampling distributions
of different approaches. The impact on the super-net in terms of sparse Kendall-Tau is shown in (c). These experiments reveal that on NASBench-101 uniformly randomly sampling one architecture, as in (Li & Talwalkar, 2019; Yu et al., 2020) is strongly biased in terms of accuracy and ranking. This can be observed from the peaks around rank 0, 100,000, and 400,000. The reason is that a single architecture can have multiple different encodings. Uniform sampling might thus lead to an oversampling of architectures that have equivalent encodings. FairNAS samples architectures more evenly and yields constantly better sparse Kendall-Tau values, albeit by a small margin.

On NASBench-201, the three sampling policies have a similar coverage. This is because in NASBench-201 topologically-equivalent encodings were not pruned. In this case, Random-NAS performs better than in NASBench-101, and FairNAS yields good early performance but quickly saturates. In short, using different sampling strategies might in general be beneficial, but we advocate for FairNAS in the presence of a limited training budget.

4.3. Mapping $f_{ws}$ - Lower Fidelity Estimates

Reducing memory foot-print and training time by proposing smaller super-nets has been an active research direction in WS-NAS, which was dubbed lower fidelity estimates (Elsken et al., 2019). The impact of these strategies on the super-net quality, however, has never been studied. We compare the influence of four commonly-used strategies in Figure 9.

The most commonly-used approach to reduce memory requirement is decreasing the training batch size (Yang et al., 2020). Surprisingly, lowering the batch size from 256 to 64 has very limited impact on the super-net accuracy, but significantly decreases the sparse Kendall-Tau and the final searched model’s performance. Another approach consists of decreasing the number of channels in the first layer (Liu et al., 2019b). This reduces the total number of parameters proportionally, since the number of channels in the consecutive layers directly depend on the first one. As can be seen in the corresponding plots, this strategy decreases the sparse Kendall-Tau value from 0.7 to 0.5. By contrast, reducing the number of repeated cells (Pham et al., 2018; Chu et al., 2019) by 1 has only limited impact. Hence, to train a good super-net, one should avoid changes between $f_{ws}$ and $f_{proxy}$, but one can reduce the batch size by a factor larger 0.5 and reduce only one repeated cell.

The last lower-fidelity factor is the portion of training data that is used (Liu et al., 2019b; Xu et al., 2020). Surprisingly, reducing the training portion only marginally decreases the sparse Kendall-Tau for all three search spaces. On NASBench-201, keeping only 25% of the CIFAR-10 dataset results in a 0.1 drop in sparse Kendall-Tau. This explains why DARTS-based methods typically use only 50% of the data to train the super-net but can still produce reasonable results.
4.4. Mapping $f_{ws}$ - Implementation of the Layers

We further validate the different implementations of the core layers in the mapping function $f_{ws}$.

**Dynamic channels.** In NASBench-101, the output cell concatenates the feature maps from previous nodes. However, the concatenation has a fixed target size, which requires the number of output channels in the intermediate nodes to be dynamically adapted during super-net training. To model this, we initialize the super-net convolution weights so as to accommodate the largest possible number of channels $c_{\text{max}}$, and reduce it dynamically to $c$ output channels using one of the following heuristics: 1) Use a fixed chunk of weights, $[0 : c]$ (Guo et al., 2019); 2) Shuffle the channels before applying 1) (Zhang et al., 2018); 3) Linear interpolation of the $c_{\text{max}}$ channels into $c$ channels via a moving average across the neighboring channels. The strategies are compared in Table 3. Shuffling the channels drastically degrades all metrics. Interpolation yields a lower super-net accuracy than using a fixed chunk, but improves the other metrics. Altogether, interpolation comes out as a more robust solution.

**Weight sharing batch-norm.** Luo et al. (2018) proposed a weight-sharing batch normalization (WSBN), which keeps an independent set of parameters for each incoming edge. Table 4 indicates that WSBN negatively impacts super-net performance and search results.

**Dropout.** We adopt two commonly-used dropout strategies: right before global pooling (global dropout); and at all edge connections between nodes (path dropout). Note that path dropout has been widely used in WS-NAS (Luo et al., 2018; Liu et al., 2019b; Pham et al., 2018). For both dropout strategies, we set the dropout rate to 0.2. The results in Table 4 clearly show that dropout negatively affects the performance.

**Super convolutional kernel.** In CNN search spaces, convolution operations appear as groups, e.g., DARTS-NDS consists of $\text{sep-conv-3} \times 3$ and $\text{sep-conv-5} \times 5$. The recent work of (Cai et al., 2020) uses a super convolution layer that merges the convolutions within the same group, keeping only the largest kernel’s parameters and performing a parametric projection to obtain the other kernels. In Table 4, we can observe a consistent negative impact of this a strategy on the super-net.

**WS on edges or nodes?** Most existing works build $f_{ws}$ to define the shared operations on the graph nodes rather than on the edges. This is because, if $f_{ws}$ maps to the edges, the parameter size increases from $O(n)$ to $O(n^2)$, where $n$ is the number of intermediate nodes. However, the high sparse Kendall-Tau on NASBench-201 in the top part of Table 4, which is obtained by mapping to the edges, may suggest that sharing on the edges is beneficial. Here we investigate if this is truly the case.

On NASBench-101, by design, each node merges the previous nodes’ outputs and then applies parametric operations. This makes it impossible to build an equivalent sharing on the edges. We therefore construct sharing on the edges for DARTS-NDS and sharing on the nodes for NASBench-201. As shown in Table 4, for both spaces, sharing on the edges yields a marginally better super-net than sharing on the nodes. Such small differences might be due to the fact that, in both spaces, the number of nodes is 4, while the number of edges is 6, thus mapping to edges will not drastically affect the number of parameters. Nevertheless, this indicates that one should consider having a larger number of shared weights when the resources are not a bottleneck.

### 5. Discussion and Conclusion

We finally discuss our insights on how to evaluate a trained super-net. We further discuss the importance of different factors and provide a concise set of rules to improve the training of a super-net, and finally compare an algorithm that optimally combines the factors to existing NAS approaches.

**Evaluation of the super-net.** The stand-alone performance of the architecture that is found by a NAS algorithm is clearly the most important metric to judge its merits. However, in practice one cannot access this metric—we wouldn’t need to search if stand-alone performance was easy to query. Consequently, it is important to have appropriate proxy metrics that are well correlated with the final performance, but can be queried efficiently. To this end, we collect all our experiments and plot the pairwise correlation between final performance, sparse Kendall-Tau, and super-net accuracy. As shown in Figure 11, we observe that the super-net accuracy has a very low correlation with final performance on NASBench-101 and DARTS-NDS. Only on NASBench-201 we see a higher correlation of 0.52. We observe that the

### Table 3. Dynamic channels on NASBench-101.

| Type   | Accuracy | S-KdT | $P > R$ | Final searched model |
|--------|----------|-------|---------|----------------------|
| Fixed  | 67.46 ± 6.94 | 0.38  | 0.714   | 92.94 ± 4.89         |
| Shuffle| 31.79 ± 10.90 | 0.17  | 0.391   | 90.58 ± 1.58         |
| Interpolate | 57.53 ± 10.05 | 0.41  | 0.865   | 93.35 ± 3.27         |

### Table 4. Comparison of different mappings $f_{ws}$. We report s-KdT / final search performance.

|                  | NASBench-101 | NASBench-201 | DARTS-NDS |
|------------------|--------------|--------------|-----------|
| Baseline         | 0.236 / 92.32 | 0.740 / 92.92 | 0.159 / 93.59 |
| WSBN             | 0.056 / 91.33 | 0.675 / 92.04 | 0.331 / 92.95 |
| Global-Dropout   | 0.179 / 90.95 | 0.676 / 91.76 | 0.102 / 92.30 |
| Path-Dropout     | 0.128 / 91.19 | 0.431 / 91.42 | 0.090 / 91.90 |
| Op-Edge          | N/A          | as Baseline  | 0.189 / 93.97 |
| Op-Node          | as Baseline  | 0.738 / 92.36 | as Baseline  |
| OFA              | 0.132 / 92.01 | 0.574 / 91.83 | 0.112 / 92.83 |
sparse Kendall-Tau has constantly higher correlation with the final performance than the super-net accuracy. This is the first concrete evidence that one should not focus too much on improving the super-net accuracy. Note that the sparse Kendall-Tau was computed using the same 200 architectures throughout the experiments. While the metric remains computationally heavy, it serves as a middle ground that is feasible to evaluate in real-world applications.

**So, how should you train your super-net?** Figure 10 summarizes the influence of the individual factors on the final performance with respect to the baseline. It stands out that properly tuned hyper-parameters lead to the biggest improvements by far. Surprisingly, most other factors and techniques either have a hardly measurable effect or in some cases even lead to worse performance. The exceptions are FairNAS, which improves stability of training and leads to a small but consistent improvement, and to some degree the interpolation of dynamic convolutions.

Based on these findings, we formulate the following rules to train your super-net and get competitive performance:

1. **Properly tune your hyper-parameters.** Start from the hyper-parameters from the stand-alone protocol $P_{\text{proxy}}$, and rely on the order provided in Table 1.
2. **Ensure a fair sampling.** This refers to the super-net architecture space, not the stand-alone topologically-equivalent space, i.e., even if some architectures are equivalent when training them separately, we should treat them as two different architectures during super-net training.
3. **Do not use super-net accuracy to judge the quality of your super-net.** The sparse Kendall-Tau has much higher correlation with the final search performance.
4. **Use low fidelity estimates cautiously.** Reducing the size of the training set moderately can be a good idea to reduce training time.

We close with a comparison to the state of the art. Table 5 shows that by carefully controlling the relevant factors, we can push the performance of Random-NAS considerably. The performance of the final model increases from 89.89 to 93.12 on NASBench-101, from 87.66 to 92.90 on NASBench-201, and from 91.33 to 94.26 on DARTS-NDS. In short, thanks to our evaluation, we showed that simple Random-NAS together with an appropriate training protocol $P_{\text{ws}}$ and mapping function $f_{\text{ws}}$ yields results that are competitive to and sometimes even surpass state-of-the-art algorithms. We hope that our work will encourage the community to report detailed hyper-parameter settings to ensure that fair comparisons between NAS algorithms are possible. Our results provide a strong baseline upon which future work can build.

**Table 5. Search results on CIFAR-10 across spaces.** Results on NASBench-101 and NASBench-201 are taken from Yu et al. (2020), and Dong & Yang (2020).

| Method         | NASBench-101 | NASBench-201 | DARTS-NDS | DARTS-NDS* |
|----------------|--------------|--------------|-----------|------------|
| ENAS           | 91.83 ± 0.42 | 54.30 ± 0.00 | 94.45     | 97.11      |
| DARTS-V2       | 92.21 ± 0.61 | 54.30 ± 0.00 | 94.79     | 97.37      |
| NAO            | 92.59 ± 0.59 | -            | -         | 97.10      |
| GDAS           | -            | 93.51 ± 0.13 | -         | 96.23      |

*Result took from Liu & Talwalkar (2019).

**Figure 11. Super-net evaluation.** We collect all experiments across 3 benchmark spaces. (Top) Pairwise plots of super-net accuracy, final performance, and the sparse Kendall-Tau. Each point corresponds to one individual evaluation of the super-net. (Bottom) Spearman correlation coefficients between the metrics.
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