Hypernetwork-Based Augmentation

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Abstract

Data augmentation is an effective technique to improve the generalization of deep neural networks. Recently, AutoAugment [5] proposed a well-designed search space and a search algorithm that automatically finds augmentation policies in a data-driven manner. However, AutoAugment is computationally intensive. In this paper, we propose an efficient gradient-based search algorithm, called Hypernetwork-Based Augmentation (HBA), which simultaneously learns model parameters and augmentation hyperparameters in a single training. Our HBA uses a hypernetwork to approximate a population-based training algorithm, which enables us to tune augmentation hyperparameters by gradient descent. Besides, we introduce a weight sharing strategy that simplifies our hypernetwork architecture and speeds up our search algorithm. We conduct experiments on CIFAR-10, CIFAR-100, SVHN, and ImageNet. Our results show that HBA is competitive to the state-of-the-art methods in terms of both search speed and accuracy.

1. Introduction

Data augmentation techniques, such as cropping, horizontal flipping, and color jittering, are widely used in training deep neural networks for image classification. Data augmentation acts as a regularizer that reduces overfitting by transforming images to increase the quantity and diversity of training data. Recently, data augmentation has shown to be an effective technique not only for supervised learning [5, 12, 20], but also for semi-supervised learning [29, 2], self-supervised learning [4], and reinforcement learning (RL) [16]. However, given a new task or dataset, it is non-trivial to either manually or automatically design its data augmentation policy: determine a set of augmentation functions and adequately specify their configurations, such as the range of rotation, the size of cropping, the degree of color jittering. A weak augmentation policy may not help much, while a strong one could hinder performance by making an augmented image looks inconsistent to its label.

AutoAugment [5], a representative pioneering work proposed by Cubuk et al., proposed a search space (consisting of 16 image operations) and an RL-based search algorithm to automate the process of finding an effective augmentation policy over the search space. AutoAugment made remarkable improvements in image classification. However, its search algorithm requires 5000 GPU hours for one augmentation policy learning, which is extremely computationally intensive.

To address the computational issue, we formulate the augmentation policy search problem as a hyperparameter optimization problem and propose an efficient algorithm for tuning data augmentation hyperparameters. The central idea of our method is a novel combination of a population-based training algorithm and a hypernetwork, which is a function that outputs the weights of a neural network. In particular, we introduce a population-based training procedure and four modifications to derive our algorithm. First, we employ a hypernetwork to represent the set of models. By doing so, training a hypernetwork can be treated as training a continuous population of models. Second, we propose a new hyper-layer for batch normalization [13] to facilitate the construction of hypernetworks. Third, inspired by one-shot neural architecture search [26, 3, 1], we adopt a weight sharing strategy to the models. We show that such a strategy corresponds to a simplified hypernetwork architecture that effectively reduces the search time. Fourth, instead of evaluating the performance on the discrete set of models, thanks to the use of a hypernetwork, we perform gradient descent to efficiently find the approximate best model. Our method, dubbed as Hypernetwork-Based Augmenta-
tion (HBA), is a gradient-based method that jointly trains the network model and tunes the augmentation hyperparameters. HBA yields hyperparameter schedules that can be used to train on different datasets or to train different network architectures. Experimental results show that HBA achieves significantly faster search speed while maintaining competitive accuracy. Table 1 summarizes our main results.

Our contributions can be summarized as follows. (1) We propose Hypernetwork-Based Augmentation (HBA), an efficient gradient-based method for automated data augmentation. (2) The derivation of HBA reveals the underlying relationship between population-based and gradient-based methods. (3) We propose a weight-sharing strategy that simplifies our hypernetwork architecture and reduces the search time considerably without performance drop.

2. Related work

Data Augmentation. We review previous work relevant to the development of our method. We refer readers to a comprehensive survey paper [31] on data augmentation. Hand-designed data augmentation techniques, such as horizontal flipping, random cropping, and color transformations, are commonly used in training deep neural networks for image classification [18, 11]. In recent years, several effective data augmentation techniques are proposed. Cutout [8] randomly erases contents by sampling a patch from the input image and replace it with a constant value. Mixup [34] performs data interpolation that combines pairs of images and their labels in a convex manner to generate virtual training data. CutMix [32] generates new samples by cutting and pasting image patches within mini-batches. These data augmentation techniques are hand-designed, and their hyperparameters are usually manually-tuned.

Automated Data Augmentation. Inspired by recent advances in neural architecture search [36, 26, 22], one of the recent trends in data augmentation is automatically finding augmentation policies within a pre-defined search space. AutoAugment [5] introduced a well-designed search space and proposed an RL-based search algorithm that trains a recurrent neural network (RNN) controller to search effective augmentation policies within the search space. Although AutoAugment achieves promising results, its search process is computationally expensive (5000 GPU hours on CIFAR-10). Our algorithm treats the data augmentation hyperparameters as continuous variables, and efficiently optimizes them by gradient descent in a single round of training.

Recently, several efficient search algorithms based on AutoAugment’s search space have been proposed. Population Based Augmentation (PBA) [12] employed Population Based Training (PBT) [14], an evolution-based hyperparameter optimization algorithm, to search data augmentation schedules. Fast AutoAugment [20] treats the problem as a density matching problem and used Bayesian optimization to find augmentation policies. OHL-Auto-Aug [21] proposed an online hyperparameter learning algorithm that jointly learns network parameters and augmentation policy. Our algorithm also tunes augmentation hyperparameters in an online manner while achieving better search efficiency. RandAugment [6] simplified the search space of AutoAugment and used the grid search method to find the optimal augmentation policy. Differentiable Automatic Data Augmentation (DADA) [19], inspired by Differentiable Architecture Search (DARTS) [22], proposed a gradient-based method that relaxes the discrete policy selection to be differentiable and optimize the augmentation policy by stochastic gradient descent. Our algorithm is also gradient-based but is fundamentally different from DADA. DADA realizes relaxation by the Gumbel-softmax trick, while ours is based on combining population-based training and hypernetworks.

Hypernetworks. Ha et al. [10] used hypernetworks to generate weights for recurrent networks. SMASH [3] presented a gradient-based neural architecture search method that employs a hypernetwork to learn a mapping from a binary-encoded architecture space to the weight space. Self-Tuning Network (STN) [23] used a hypernetwork as an approximation to the best response function in bilevel optimization. Our method uses a hypernetwork to represent a set of models trained with different hyperparameters.

Hyperparameter Optimization. Searching augmentation policies can be formulated as a hyperparameter optimization problem. We refer readers to a recent survey paper [31] on hyperparameter optimization. Population Based Training (PBT) [12] presented a hyperparameter optimization algorithm that trains a population of models in parallel, and periodically evaluates their performance to perform exploitation and exploration. MacKay et al. proposed the Self-Tuning Network (STN) [23], a gradient-based method for tuning regularization hyperparameters, including data augmentation and dropout [28].

HBA is closely related to PBT [14] and STN [23]. In our method, we start from a population-based training algorithm and apply a series of modifications to derive our algorithm, which can be viewed as an efficient approximation of the PBT algorithm. Compared with STN, HBA distinguishes from STN in three aspects. First, the underlying formulations are different. STN is based on the best response approximation to bilevel optimization, while HBA is derived entirely from the perspective of population-based training. Second, HBA adopts a weight sharing strategy, which is intuitive yet novel since it cannot be analogously defined in STN. Third, to facilitate the construction of hypernetworks, we propose a new hyper-layer for batch normalization.
3. Method

We start from a population-based training (Section 3.1) and then present a series of modifications to derive HBA: hypernetworks (Section 3.2 and 3.3), weight sharing strategy (Section 3.4), and gradient-based exploitation (Section 3.5).

3.1. Training a Population of Models by Stochastic Gradient Descent

We formulate tuning data augmentation hyperparameters as training a population of $n$ models. Each model $i$ has the same network architecture but a different initialization of both model parameters $\theta_i$ and augmentation hyperparameters $\lambda_i$. During training, we periodically exploit the best performing model and explore both its augmentation hyperparameters and model parameters. Specifically, our population-based training procedure iterates among three steps: update, exploit, and explore. In the following, we detail each of them.

**Update.** For each model $i$, we update its parameters $\theta_i$ by $T_{\text{train}}$ stochastic gradient descent (SGD) steps. The formula of an SGD step can be expressed as

$$\theta_i = \theta_i - \alpha \nabla_{\theta} \mathcal{L}(\mathcal{F}(\mathcal{A}(x; \lambda_i); \theta_i), y),$$  \hspace{1cm} (1)

where $(x, y)$ is a training example, $\mathcal{F}(\cdot; \theta_i)$ is the $i$-th model, $\mathcal{A}(\cdot; \lambda_i)$ is the augmentation policy used for model $i$, $\mathcal{L}$ is the loss function, and $\alpha$ is the learning rate.

**Exploit.** Our exploitation strategy evaluates each model $i$ on the validation set $D_V$, identifies the best performing model $k$, and copies its parameters and hyperparameters to replace the ones of all the other models. Specifically,

$$\lambda_i = \lambda_k \text{ and } \theta_i = \theta_k,$$  \hspace{1cm} (2)

$$\text{where } k = \arg \min_{i \in \{1, \ldots, n\}} \sum_{(x^v, y^v) \in D_V} \mathcal{L}(\mathcal{F}(x^v; \theta_i), y^v).$$  \hspace{1cm} (3)

**Explore.** We perform exploration by perturbing the value of each model’s parameters and hyperparameters as

$$\lambda_i = \lambda_i + \epsilon_i \text{ and } \theta_i = \theta_i + \epsilon_i',$$  \hspace{1cm} (5)

$$\text{where } \epsilon_i \sim N(0, \sigma) \text{ and } \epsilon_i' \sim N(0, \sigma'),$$  \hspace{1cm} (6)

where $\epsilon_i, \epsilon_i'$ are Gaussian noise.

Figure 1 (a) shows the schematic diagram of our population-based training. Until now, we have presented a population-based training procedure, which serves as the foundation of HBA. In the next two subsections, we introduce hypernetworks, which is the key component to convert the population-based training into a gradient-based training.

3.2. Representing a Population of Models by a Hypernetwork

We define a hypernetwork as a function that takes the data augmentation hyperparameters $\lambda$ as inputs and outputs the parameters $\theta$ of the neural network $\mathcal{F}$. The hypernetwork itself is a neural network, and we denote it by $\hat{\theta}_\phi$, where $\phi$ is the hypernetwork parameters. We use a hypernetwork to represent the members of the population by

$$\theta_i = \hat{\theta}_\phi(\lambda_i) \text{ for } i = 1, 2, \ldots, n.$$  \hspace{1cm} (7)

Therefore, the set of model parameters $\{\theta_i\}_{i=1}^n$ now are represented by a single hypernetwork $\hat{\theta}_\phi$. Given model $i$’s hyperparameters $\lambda_i$, its parameters $\theta_i$ can be obtained through $\hat{\theta}_\phi$. Figure 1 (b) illustrates the concept of adopting a hypernetwork to represent a set of models.

Based on Equation 7, training a population of models with parameters $\{\theta_i\}_{i=1}^n$ is changed into training a single hypernetwork with parameters $\phi$. The update step in Equation 1 is accordingly changed as

$$\phi = \phi - \alpha \frac{1}{n} \sum_{i=1}^n \nabla_{\phi} \mathcal{L}(\mathcal{F}(\mathcal{A}(x_i; \lambda_i), \hat{\theta}_\phi(\lambda_i)), y_i).$$  \hspace{1cm} (8)

Comparing with Equation 1 that independently updates each model parameters $\theta_i$ by SGD with a batch size of 1,
3.3. Hypernetwork Architecture

Given the architecture of a neural network $\mathcal{F}$, we define its corresponding hypernetwork architecture as follows. First, we construct a linear hypernetwork in a layer-wise manner: for each trainable layer in $\mathcal{F}$, we associate it with a hyper-layer accordingly, which is a linear layer. Employing hypernetworks could be memory-intensive since even a linear hypernetwork requires a prohibitively large number of parameters, which would be $|\lambda||\theta|$. Therefore, following STN [23], we assume that the weight matrix of each hyper-layer is low-rank to effectively reduce the parameter complexity from $O(|\lambda||\theta|)$ to $O(|\lambda| + |\theta|)$.

In our experiments, there are three types of trainable layers: convolutional (conv) layer, batch normalization (BN) layer, and fully-connected (linear) layer. To associate each trainable layer with a hyper-layer, we employ the hyper-conv and hyper-linear layer proposed by STN and follow its design spirit to propose a hyper-BN layer.

Our hyper-BN layer takes $\lambda$ as input and outputs the affine parameters $\theta_{BN} \in \mathbb{R}^c$ of a BN layer by $\theta_{BN} = \text{HyperBN}(\lambda; \phi_b, \phi_U, \phi_V) = \phi_b + \text{diag}(\phi_V \lambda) \phi_U$, where $\phi_b, \phi_U \in \mathbb{R}^{c}, \phi_V \in \mathbb{R}^{c \times c}, c$ is the number of output channels, and diag($\cdot$) turns a vector into a diagonal matrix.

In Figure 2 (a), we show an example of a population-based training that trains two models, each of which consists of a conv layer and a linear layer. We can convert the set of models into a single hypernetwork by attaching hyper-layers onto each trainable layer, as shown in Figure 2 (b). Up to now, we have introduced hypernetworks and their architecture. Next, we introduce weight sharing as a way to improve population-based training.

3.4. Weight Sharing across Models.

Weight sharing is a commonly-used strategy to promote cooperation in training multiple models. Therefore, it looks natural to consider applying a weight sharing strategy in our population-based training. Recall that the update step (Equation 1) independently updates each model in the population. If some of the layers are shared among the population, the population members can be seen as performing a joint training in the update step. As we can see from the example in Figure 2 (c), if we share the weights of the linear layer, these two models, trained with different hyperparameters, learn different convolutional features while sharing the same linear classifier.

Besides model cooperation, another reason that motivates us to apply weight sharing is based on the following observation: applying a weight sharing strategy to the population is equivalent to adopting a simplified hypernetwork architecture, which can effectively reduce both the search time and memory consumption.

For example, if all the population members share a particular layer’s parameters, then it equivalently means that the corresponding hyper-layer degenerates into a constant function independent of hyperparameters. In other words, if we share a layer’s parameters, there is no need to associate it with a hyper-layer. By doing so, the number of hyper-layers becomes smaller, the memory consumption in the training process is reduced, and the search speed becomes faster. Taking Figure 2 (d) as an example, if we simultaneously employ a hypernetwork and shares the linear layer, then only the conv layer is attached with a hyper-conv layer. The hyper-linear layer degenerates into a constant function and thus is removed, giving us a smaller hypernetwork than the one without weight sharing (Figure 2 (b)). In summary, Figure 2 shows the corresponding model architectures of whether employing a hypernetwork and whether applying a weight sharing strategy.

3.5. Gradient-based Exploitation

With hypernetwork $\hat{\theta}_\phi$, the exploit step (Equation 4) can be modified accordingly as

$$k = \arg \min_{\phi_b, \phi_U} \sum_{(x^v, y^v) \in D_u} \mathcal{L}(\mathcal{F}(x^v; \hat{\theta}_\phi(\lambda_i)), y^v).$$

(9)

However, a hypernetwork, as a continuous function, naturally represents not only $n$ models but also a continuous
population of models. Therefore, we propose to find the best performing model \( \hat{\theta}_\phi(\lambda^*) \) in the continuous population by minimizing the validation loss over hyperparameters as

\[
\lambda^* = \arg\min_\lambda \sum_{(x', y') \in D_{val}} \mathcal{L}(\mathcal{F}(x'; \hat{\theta}_\phi(\lambda)), y').
\]  

(10)

We use gradient descent to approximately yet efficiently find \( \lambda^* \). In particular, our exploit step is changed as applying \( T_{val} \) steps of SGD to solve Equation 10, and each step can be written as

\[
\lambda = \lambda - \alpha \frac{1}{n} \sum_{i=1}^n \nabla_\lambda \mathcal{L}(\mathcal{F}(x_i; \hat{\theta}_\phi(\lambda)), y_i).
\]  

(11)

Explore and Update. Based on Equation 11, the explore step of \( \lambda_i \) (Equation 5) can be modified accordingly as

\[
\lambda_i = \lambda + \epsilon_i.
\]  

(12)

Besides, we let the model parameters be implicitly exploited and explored by \( \hat{\theta}_i = \hat{\theta}_\phi(\lambda_i) = \hat{\theta}_\phi(\lambda + \epsilon_i) \), which can be seen as an approximation of \( \hat{\theta}_\phi(\lambda) + \epsilon_i \).

Furthermore, by substituting Equation 12 into Equation 8, we merge the explore and update step together and obtain the formula of updating the hypernetwork as

\[
\phi = \phi - \alpha \frac{1}{n} \sum_{i=1}^n \nabla_\phi \mathcal{L}(\mathcal{A}(x_i; \lambda + \epsilon_i); \hat{\theta}_\phi(\lambda + \epsilon_i)), y_i).
\]  

(13)

where \( \epsilon_i \sim N(0, \sigma) \). Lastly, instead of using the same perturbation noise \( \{\epsilon_i\}_{i=1}^n \) across the \( T_{train} \) SGD steps of Equation 13, we re-sample \( \{\epsilon_i\}_{i=1}^n \) for each iteration to enhance the sample diversity. In other words, at each SGD step, we sample a different discrete set of models from the continuous population to update the hypernetwork.

Summary. Algorithm 1 summarizes our HBA algorithm, which is a gradient-based training algorithm that alternates between updating the hypernetwork (Equation 13) and updating the hyperparameters (Equation 11). HBA builds upon the concept of the population-based training (Equation 1 to 6) while performs a gradient-based training (Equation 11 and 13). In Figure 3, we show the computation graph of the HBA algorithm.

Algorithm 1 The algorithm of HBA.

1: Input: training set \( D_T \), validation set \( D_{val} \), model network \( \mathcal{F}(\cdot; \theta) \), hypernetwork \( \hat{\theta}_\phi \), augmentation policy \( \mathcal{A}(\cdot; \lambda) \), batch size \( n \), number of steps \( T \), \( T_{train} \) and \( T_{val} \), learning rates \( \alpha \) and \( \alpha' \), standard deviation \( \sigma \).
2: Initialize \( \phi \) and \( \lambda \)
3: for \( j = 1 \) to \( T \) do
4: \hspace{1em} for \( t = 1 \) to \( T_{train} \) do
5: \hspace{2em} Sample \( \{(x_i, y_i)\}_{i=1}^n \) from \( D_T \)
6: \hspace{2em} \( \{\epsilon_i\}_{i=1}^n \sim N(0, \sigma) \)
7: \hspace{2em} \( \phi = \phi - \alpha \frac{1}{n} \sum_{i=1}^n \nabla_\phi \mathcal{L}(\mathcal{A}(x_i; \lambda + \epsilon_i); \hat{\theta}_\phi(\lambda + \epsilon_i)), y_i) \) \hspace{1em} Update \( \phi \) (Equation 13)
8: \hspace{1em} end for
9: \hspace{1em} for \( t = 1 \) to \( T_{val} \) do
10: \hspace{2em} Sample \( \{(x_i, y_i)\}_{i=1}^n \) from \( D_{val} \)
11: \hspace{2em} \( \lambda = \lambda - \alpha' \frac{1}{n} \sum_{i=1}^n \nabla_\lambda \mathcal{L}(\mathcal{F}(x_i; \hat{\theta}_\phi(\lambda)), y_i) \) \hspace{1em} Update \( \lambda \) (Equation 11)
12: \hspace{1em} end for
13: end for
14: Output: \( \hat{\theta}_\phi(\lambda) \)

4. Experiments

Implementation Details. Following STN [23], HBA trains the hypernetwork parameters using SGD with \( T_{train} = 2 \) and optimizes the hyperparameters using Adam [15] with \( T_{val} = 1 \). We implemented HBA using the Pytorch [25] framework. We measured the search time of HBA on an NVIDIA Tesla V100 GPU. We reported the last epoch’s performance after training for all of our results using the mean and standard deviation over five runs with different random seeds. For policy evaluation, we scaled the
length of the discovered schedules linearly if necessary.

**Search Space.** We define a data augmentation policy as a stochastic transformation function constructed by a set of elementary image operations. Each operation is associated with a probability and a magnitude, which play the role of data augmentation hyperparameters. For a fair comparison in Section 4.1 and 4.2, our transformation function follows PBA [12], which consists of 15 operations and performs three steps: (1) sampling an integer $K$ from a categorical distribution as the number of operations to be applied, where $K \sim \{0: p = 0.2, 1: p = 0.3, 2: p = 0.5\}$. (2) sampling $K$ operations based on the operation probabilities, and (3) sequentially applying these sampled operations to the input image. Figure 4 (b) lists the 15 operations, whose detailed description can be found in the supplementary material.

### 4.1. Ablation Study

**Weight Sharing Strategy.** We first conducted an ablation study on different weight sharing strategies. In general, if we share a subset of the trainable layers’ parameters from the perspective of population-based training, it means that we do not associate them with hyper-layers. We experimented with five weight sharing strategies: Conv+BN, Conv, BN, 1st Conv, and 1st BN. These strategies are named by what layers are added with hyper-layers. For example, the Conv strategy means that we add HyperConv layers to all the convolutional layers and ignore the other layers. The 1st BN strategy means that we only add a HyperBN layer to the lowest BN layer.

The intuition behind our weight sharing strategies is as follows. For the low-level layers, we do not share parameters so that they are enforced to reflect the influence of different augmentation policies. For the mid- and high-level layers, we share parameters to encourage the population to learn a joint feature representation.

In this study, we split the CIFAR training set into three sets (30k/10k/10k) and denoted them as Train30k/Val0/Val. The CIFAR test set was not used in this study. For policy search, we applied HBA to train Wide-ResNet-28-10 (WRN-28-10) [33] on the Train30k/Val0 split to find policies. For policy evaluation, we used the searched policies to train networks on the Train30k+Val0 set and evaluated them on the Val set.

Table 10 shows the comparison results between these five strategies. We can see that adding fewer hyper-layers reduces search time and achieves slightly better performance across different datasets, showing that weight sharing in population-based training is helpful in the manner of model cooperation. We also experimented with WRN-40-2 and obtained similar results, which are included in the supplementary material. Based on the ablation results, we employ the 1st BN strategy in the subsequent experiments unless otherwise mentioned.

**Standard Deviation $\sigma$ for exploration.** Next, we analyzed $\sigma$ in Equation 13, representing the range of exploration. Similar to the previous experiment, we train WRN-28-10 on CIFAR-10. Three values of $\sigma$ are experimented: 0.5, 1.0, and 2.0, which yield Val set errors of 3.43 ± 0.09%, 3.30 ± 0.10%, and 3.38 ± 0.05%, respectively. Based on the results, we used $\sigma = 1.0$ in all of our experiments.

### 4.2. Automated Data Augmentation

We compare HBA with standard augmentation (Baseline), Cutout [8], AutoAugment (AA) [5], Population Based
### Table 3. Comparison of search time in GPU hours. HBA has the least search time and is competitive to DADA.

| Method    | CIFAR-10 | SVHN   | ImageNet |
|-----------|----------|--------|----------|
| AA [5]    | 5000     | 1000   | 15000    |
| PBA [12]  | 5        | 1      | -        |
| FAA [20]  | 3.5      | 1.5    | 450      |
| OHLAA [21]| 83.4     | -      | 625      |
| AdvAA [35]| -        | -      | 1280     |
| DADA [19] | 0.1      | 0.1    | 1.3      |
| HBA       | **0.1**  | **0.1**| **0.9**  |

HBA versus DADA. In terms of search time, HBA is comparable to DADA, which is the current state-of-the-art. Comparing with DADA on the accuracy, HBA achieves 3 wins, 9 ties, and 1 loss, as shown in Table 4.

**Summary.** Table 3 summarizes the comparison of search time. We can see that HBA has the least search time. Besides, we also compare with RandAugment (RA), which does not report its search time in its paper. RA performs a grid search, and its search time (in GPU hours) can be written as $N T$, where $N$ is the number of grid samples, and $T$ is the GPU hours of a single training run. $N$ is 15 in its CIFAR-10 experiment. HBA’s search time is about 1.67, where 1.6 is obtained from measuring the ratio of “HBA’s training time” to “the typical training time,” where both training is conducted on CIFAR-10 with WRN-40-2. Based on the above analysis, we can see that HBA requires much less GPU hours than RA.

#### CIFAR-10 and CIFAR-100.

The CIFAR-10 and CIFAR-100 datasets consist of 60,000 natural images, with a size of 32x32. The training and test sets have 50,000 and 10,000 images, respectively. We applied our augmentation policy, baseline, and Cutout (with 16x16 pixels) in sequence to each training image. The baseline augmentation policy is obtained from measuring the ratio of the typical training time, and Cutout (with 20x20 pixels) in sequence to each training image. The baseline augmentation policy is obtained from measuring the ratio of the typical training time. RA performs a grid search, and its search time (in GPU hours) can be written as $N T$, where $N$ is the number of grid samples, and $T$ is the GPU hours of a single training run. $N$ is 15 in its CIFAR-10 experiment. HBA’s search time is about 1.67, where 1.6 is obtained from measuring the ratio of “HBA’s training time” to “the typical training time,” where both training is conducted on CIFAR-10 with WRN-40-2. Based on the above analysis, we can see that HBA requires much less GPU hours than RA.

**Policy Search on the Target Tasks.** In the previous experiments (Table 3 and 4), we applied HBA on a reduced task, which trains a smaller network (WRN-40-2) on a reduced dataset. Here, we compared with the performance of policy searched on the target tasks, which trains the target network on the full dataset to find the augmentation policy. We consider training a model $M \in \{\text{WRN-40-2, WRN-28-10}\}$ on a dataset $D \in \{\text{CIFAR-10, CIFAR-100}\}$, giving us four target tasks. Table 5 shows that training on the target tasks requires longer search times while achieving slightly better performances (in three out of four cases), which is similar to the findings in RA [6] and DADA [19]. These results demonstrate that although HBA is designed to pursue efficiency, it can trade off search time for accuracy by searching on the target tasks.

**HBA versus RandAugment.** Although HBA requires fewer GPU hours than RA, HBA does not outperform RA in terms of accuracy. One may still prefer RA over HBA because of the extreme simplicity of grid search. We note...
applied HBA to simultaneously train an AlexNet [18] on CIFAR-10 and tune regularization hyperparameters. Here, the search space consists of 15 regularization hyperparameters: 7 for data augmentation and 8 for dropout. We employed the Conv strategy to construct our hypernetwork for the AlexNet model. As shown in Table 6, both gradient-based methods outperform grid search and random search. Besides, HBA performs better than STN, showing the effectiveness of our weight sharing strategy.

5. Conclusion

We proposed HBA, a gradient-based method for automated data augmentation. HBA employs a hypernetwork to train a continuous population of models and uses gradient descent to tune augmentation hyperparameters. Our weight sharing strategy improved both the search speed and accuracy. Future directions include applying HBA to different domains such as medical images and exploring hybrid algorithms that interpolate between PBT and HBA.

| Dataset      | Model       | Time (GPU hours) |
|--------------|-------------|------------------|
| CIFAR-10     | WRN-40-2    | 0.1              |
| CIFAR-100    | WRN-40-2    | 1.2 ↑            |
| CIFAR-10     | WRN-28-10   | 4.5 ↑            |

Table 5. Comparison between policy search on the proxy task (top half) and the target tasks (bottom half).

| Dataset        | Model       | Test Error (%) |
|----------------|-------------|----------------|
| CIFAR-10       | WRN-40-2    | 3.78 ± 0.15    |
| CIFAR-100      | WRN-40-2    | 20.58 ± 0.37   |
| CIFAR-10       | WRN-28-10   | 2.63 ± 0.10    |
| CIFAR-100      | WRN-28-10   | 17.46 ± 0.48   |

Table 6. Comparison with grid search (GS), random search (RS), and STN on tuning regularization hyperparameters.

| Method | Val. Loss | Test Loss | Test Error (%) |
|--------|-----------|-----------|----------------|
| GS     | 0.794     | 0.809     | -              |
| RS     | 0.921     | 0.752     | -              |
| STN    | 0.579 ± 0.005 | 0.582 ± 0.004 | 19.86 ± 0.21   |
| HBA    | 0.548 ± 0.005 | 0.556 ± 0.005 | 18.76 ± 0.11   |

Table 4. The test set error rates (%) on CIFAR-10, CIFAR-100, SVHN, and ImageNet.

Table 3. Comparison between policy search on the proxy task (top half) and the target tasks (bottom half).

| Dataset       | Model       | Test Error (%) |
|---------------|-------------|----------------|
| CIFAR-10      | WRN-40-2    | 3.80 ± 0.15    |
| CIFAR-100     | WRN-40-2    | 2.63 ± 0.10    |
| CIFAR-10      | WRN-28-10   | 2.63 ± 0.16    |
| CIFAR-100     | WRN-28-10   | 2.03 ± 0.10    |

4.3. Comparison with STN

We followed the experiment settings of STN [23] and applied HBA to simultaneously train an AlexNet [18] on CIFAR-10 and tune regularization hyperparameters. Here, the AutoAugment search space is so well-designed that a reduced grid search could suffice. To address this concern and justify HBA's effectiveness, our next experiment considers a different search space.
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bounded version of the operation magnitudes and probabilities by mapping a range of magnitude $[M_{\text{min}}, M_{\text{max}}]$ to $[-\infty, \infty]$ through a logit function (the inverse of the sigmoid function). The magnitude range of each operation is $[0, 1]$. 

### Appendix B. Population-Based Training Procedure

Our population-based training procedure can be expressed in the format of PBT [14] as follows:

**Step**: each model runs an SGD step with a batch size of 1.

**Eval**: we evaluate each model on a validation set by cross entropy loss.

**Ready**: each model goes through the exploit-and-explore process every $T_{\text{train}}$ steps.

**Exploit**: each model clones the weights and hyperparameters of the best performing model.

**Explore**: for each model, we perturb the value of its parameters and hyperparameters.

#### Algorithm 2 Our population-based training procedure.

1. **Input**: population size $n$, number of steps $T$ and $T_{\text{train}}$, training set $D_T$, augmentation policy $A$, neural network $F$, learning rate $\alpha$, validation set $D_V$, Gaussian sigma $\sigma$ and $\sigma'$.

2. Initialize $\{\theta_i\}^n_{i=1}$ and $\{\lambda_i\}^n_{i=1}$

3. for $j = 1$ to $T$ do

4. for $i = 1$ to $n$ (synchronously in parallel) do

5. for $t = 1$ to $T_{\text{train}}$ do

6. // Step

7. Sample $(x, y)$ from $D_T$

8. $\theta_i = \theta_i - \alpha \nabla_{\theta_i} \mathcal{L}(F(A(x; \lambda_i); \theta_i), y)$

9. end for

10. end for

11. // Eval

12. $k = \arg\min_{i \in \{1, \ldots, n\}} \sum_{(x', y') \in D_V} \mathcal{L}(F(x'; \theta_i), y')$

13. // Exploit

14. for $i = 1$ to $n$ do

15. $\lambda_i = \lambda_k$

16. $\theta_i = \theta_k$

17. end for

18. // Explore

19. for $i = 1$ to $n$ do

20. $\lambda_i = \lambda_i + \epsilon_i$ where $\epsilon_i \sim N(0, \sigma)$

21. $\theta_i = \theta_i + \epsilon'_i$ where $\epsilon'_i \sim N(0, \sigma')$

22. end for

23. end for

24. Output: $\theta_k$
where $\theta_{\text{conv}1x1} = \hat{\theta}_{\text{conv}1x1}(\lambda; \phi^c_0, \phi^c_U, \phi^c_V)$ and $\phi^c_0 + \text{diag}(\phi^c_U \lambda)\phi^c_U$, respectively.

### C2. Hyper-Conv Layer

A linear layer can be interpreted as a $1 \times 1$ convolutional layer by (1) viewing the input vector $x$ as an image with $c_1$ channels and a spatial size of $1 \times 1$, and (2) viewing the weight matrix $W$ as the set of $1 \times 1$ convolutional filters, where each row of $W$ is a filter. Therefore, we can define the hyper-layer of a $1 \times 1$ convolutional layer in the same way as the hyper-linear layer. We follow the definition of the hyper-linear layer (Equation 20), and define the hyper-conv1x1 layer as

\[
\theta_{\text{conv}1x1} = \hat{\theta}_{\text{conv}1x1}(\lambda; \phi^c_0, \phi^c_U, \phi^c_V) = \phi^c_0 + \text{diag}(\phi^c_U \lambda)\phi^c_U.
\]
where $\theta_{\text{conv}}$, $\phi_{c_0}$, $\phi_{c_U}$, $\phi_{c_V}$ are three sets of $1 \times 1$ filters. $c_1$ and $c_2$ are the number of the input and output channels, respectively. $\text{diag}(\phi_{c_V} \lambda) \phi_{c_U}$ can be interpreted as a filter-wise scaling of $\phi_{c_U}$, in which the j-th filter weights of $\phi_{c_U}$ are scaled by the j-th element of $\phi_{c_V} \lambda$. In general, the hyper-conv layer for a $k \times k$ convolutional layer can be defined with the hyper-conv1x1 layer by changing $\phi_{c_0}$ and $\phi_{c_U}$ from $1 \times 1$ to $k \times k$ filters as follows:

$$\theta_{\text{conv}} = \hat{\theta}_{\text{conv}}(\lambda; \phi_{c_0}, \phi_{c_U}, \phi_{c_V}) = \phi_{c_0} + \text{diag}(\phi_{c_V} \lambda) \phi_{c_U},$$

where each row of $\phi_{c_0}$ and $\phi_{c_U}$ corresponds to the parameters of a $k \times k$ filter. Specifically, $\theta_{\text{conv}}$, $\phi_{c_0}$, $\phi_{c_U}$, $\phi_{c_V}$ are $R^{c_2 \times c_1}$, $R^{c_2 \times 1}$, $R^{c_2 \times n}$, and $c_2$ is the number of the output channels. There is a factor 2 because the affine transformation has $c_2$ scaling parameters and $c_2$ offset parameters.

### C.3. Hyper-BN Layer

A batch normalization layer has a trainable affine transformation. Following the design spirit of the hyper-linear and the hyper-conv layer, we denote the affine parameters by $\theta_{\text{BN}}$ and define the hyper-BN layer as

$$\theta_{\text{BN}} = \text{hyper-BN}(\lambda; \phi_{c_0}^{\text{BN}}, \phi_{c_U}^{\text{BN}}, \phi_{c_V}^{\text{BN}})$$

$$= \phi_{c_0}^{\text{BN}} + \text{diag}(\phi_{c_V}^{\text{BN}} \lambda) \phi_{c_U}^{\text{BN}},$$

where $\phi_{c_0}^{\text{BN}}$ and $\phi_{c_U}^{\text{BN}}$ are $R^{c_2}$, $\phi_{c_V}^{\text{BN}}$ is $R^{c_2 \times n}$, $c_2$ is $R^{c_2 \times c_2}$, and $c_2$ is the number of the output channels. There is a factor 2 because the affine transformation has $c_2$ scaling parameters and $c_2$ offset parameters.

### Appendix D. Hyperparameters

Table 8 and 9 show the hyperparameters used in policy search and policy evaluation, respectively. For the ImageNet dataset, we used a step-decay learning rate schedule that drops by 0.1 at epoch 90, 180, and 240.

### Appendix E. Ablation study of weight sharing strategies.

In Table 10, we show the full results of the ablation study on weight sharing strategies. In particular, we experimented with both Wide-ResNet-40-2 and Wide-ResNet-28-10. Their results are consistent: adding fewer hyper-layers reduces search time and achieves slightly better performance.
| Dataset          | Reduced CIFAR-10 | Reduced SVHN | Reduced ImageNet | CIFAR-10 / CIFAR-100 |
|------------------|------------------|--------------|------------------|----------------------|
| No. classes      | 10               | 10           | 120              | 10                   |
| No. training images | 4,000           | 4,000        | 6,000            | 40,000               |
| No. validation images | 10,000          | 10,000       | 10,000           | 10,000               |
| Model            | WRN-40-2         | WRN-40-2     | WRN-40-2         | WRN-40-2 / WRN-28-10 |
| Input size       | 32x32            | 32x32        | 32x32            | 32x32                |
| No. training epoch | 200              | 160          | 270              | 200                  |
| Learning rate \(\alpha\) | 0.05            | 0.01         | 0.1              | 0.1                  |
| Learning rate schedule (\(\alpha\)) | cosine           | cosine       | step             | cosine               |
| Weight decay     | 0.005            | 0.01         | 0.001            | 0.0005               |
| Batch size       | 128              | 128          | 128              | 128                  |
| Learning rate \(\alpha'\) | 0.03            | 0.02         | 0.007            | 0.003                |
| Learning rate schedule (\(\alpha'\)) | constant         | constant     | constant         | constant             |

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Table 8. Hyperparameters for policy search.

| Dataset          | Model                     | LR  | Schedule | WD     | BS   | Epoch |
|------------------|---------------------------|-----|----------|--------|------|-------|
| CIFAR-10         | WRN-40-2                  | 0.1 | cosine   | 0.0005 | 128  | 200   |
| CIFAR-10         | WRN-28-10                 | 0.1 | cosine   | 0.0005 | 128  | 200   |
| CIFAR-10         | Shake-Shake (26 2x32d)    | 0.01| cosine   | 0.001  | 128  | 1800  |
| CIFAR-10         | Shake-Shake (26 2x96d)    | 0.01| cosine   | 0.001  | 128  | 1800  |
| CIFAR-10         | Shake-Shake (26 2x112d)   | 0.01| cosine   | 0.001  | 128  | 1800  |
| CIFAR-10         | PyramidNet+ShakeDrop      | 0.05| cosine   | 0.00005| 64   | 1800  |
| CIFAR-100        | WRN-28-10                 | 0.1 | cosine   | 0.0005 | 128  | 200   |
| CIFAR-100        | Shake-Shake (26 2x96d)    | 0.01| cosine   | 0.0025 | 128  | 1800  |
| CIFAR-100        | PyramidNet+ShakeDrop      | 0.025| cosine  | 0.0005 | 64   | 1800  |
| SVHN             | WRN-28-10                 | 0.005| cosine  | 0.001  | 128  | 160   |
| SVHN             | Shake-Shake (26 2x96d)    | 0.01| cosine   | 0.00015| 128  | 160   |
| ImageNet         | ResNet-50                 | 0.1 | step     | 0.0001 | 256  | 270   |

Table 9. Hyperparameters for policy evaluation. LR: learning rate. Schedule: learning rate schedule. WD: weight decay. BS: batch size. Epoch: number of training epoch. All the hyperparameters follow the settings in PBA [12] except the ones for the ImageNet dataset. We used 8 NVIDIA Tesla V100 GPUs to train ResNet-50 on the ImageNet dataset.

| Hyper-layers | Wide-ResNet-40-2 | Time (GPU Hours) | WideResNet-28-10 | Time (GPU Hours) |
|--------------|------------------|------------------|------------------|------------------|
| CIFAR-10 Val. Error (%) | 4.01 ± 0.09 | 22.66 ± 0.19 | 2.03 | 2.85 ± 0.13 | 19.15 ± 0.21 | 7.74 |
| CIFAR-100 Val. Error (%) | 3.94 ± 0.08 | 22.71 ± 0.34 | 1.53 | 2.88 ± 0.06 | 19.18 ± 0.26 | 6.85 |
| Conv + BN Val. Error (%) | 3.86 ± 0.07 | 22.86 ± 0.22 | 1.33 | 2.74 ± 0.05 | 19.18 ± 0.34 | 4.23 |
| Conv Val. Error (%) | 3.85 ± 0.06 | 22.66 ± 0.40 | 0.86 | 2.81 ± 0.07 | 19.39 ± 0.25 | 3.36 |
| BN Val. Error (%) | 4.02 ± 0.11 | 22.20 ± 0.10 | 0.87 | 2.72 ± 0.12 | 18.80 ± 0.34 | 3.37 |

Table 10. Ablation study on different weight sharing strategies.