

Fast AutoAugment

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Abstract

Data augmentation is an indispensable technique to improve generalization and also to deal with imbalanced datasets. Recently, AutoAugment (Cubuk et al., 2019) has been proposed to automatically search augmentation policies from a dataset and has significantly improved performances on many image recognition tasks. However, its search method requires thousands of GPU hours to train even in a reduced setting. In this paper, we propose Fast AutoAugment algorithm that learns augmentation policies using a more efficient search strategy based on density matching. In comparison to AutoAugment, the proposed algorithm speeds up the search time by orders of magnitude while maintaining the comparable performances on the image recognition tasks with various models and datasets including CIFAR-10, CIFAR-100, and ImageNet.

1. Introduction

Deep learning has become the state-of-the-art technique for computer vision tasks including object recognition (Yamada et al., 2018; Real et al., 2018; Hu et al., 2018), detection (Ren et al., 2015; Liu et al., 2016), and segmentation (Chen et al., 2018; He et al., 2017). However, deep learning models with large capacity often suffer from an overfitting problem unless significantly large amounts of labeled data are supported. Therefore, data augmentation (DA) has been shown as a beneficial regularization technique not only to increase the quantity of training data but also to make them more diverse. Especially, carefully designed augmentations rather than naive random transformations make it possible to greatly improve the generalization ability of a given network (Krizhevsky et al., 2012; Paschali et al., 2019). However, in most cases, these augmentations have been manually designed by human experts with prior knowledge.

With recent advancement of automated machine learning (AutoML), there exists a number of efforts that deal with automatically finding data augmentation strategies directly from a dataset. Smart Augmentation (Lemley et al., 2017) introduced a network which learns to generate augmented data by merging two or more samples in the same class. Bayesian DA (Tran et al., 2017) combined Monte Carlo expectation maximization algorithm with generative adversarial network (Goodfellow et al., 2014) to generate data by treating augmented data as missing data points on the distribution

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Dataset	AutoAugment	Fast AutoAugment
CIFAR-10	5000	3.5
ImageNet	15000	450

Table 1: GPU hours comparison of AutoAugment with Fast AutoAugment. Ours are estimated with an NVIDIA Tesla V100.

of the training set. AutoAugment (Cubuk et al., 2019) has proposed an automated process of data augmentation policy search using reinforcement learning when a target dataset and model are given. It especially achieves dramatic performance improvements on many benchmark image recognition datasets. However, their search method requires thousands of GPU hours to train even in a reduced proxy task, such as a smaller dataset and network.

In this paper, we propose a fast and efficient search method of augmentation policies, called Fast AutoAugment, motivated from Bayesian DA (Tran et al., 2017). Our strategy is to improve the generalization performance of a given network by learning the augmentation policies which treat augmented data as missing data points of training data. However, different from Bayesian DA, we realize this using efficient density matching algorithm which can be easily implemented by making good use of distributed learning frameworks such as Ray (Moritz et al., 2018) and HyperOpt (Bergstra et al., 2011). In practice, the proposed method can search augmentation policies significantly faster than AutoAugment (see Table 1). Furthermore, it achieves comparable or even better performances on various datasets with the same neural networks.

2. Fast AutoAugment

In this section, we introduce the search space \mathcal{S} of Fast AutoAugment and propose the efficient density matching algorithm to search augmentation policies.

2.1 Search Space

Let \mathbb{O} be a set of augmentation (image transformation) operations $\mathcal{O} : \mathcal{X} \rightarrow \mathcal{X}$ defined on the input image space \mathcal{X} . Each operation \mathcal{O} has two parameters: the probability p and the magnitude λ . Let \mathcal{S} be the set of sub-policies where a sub-policy $\tau \in \mathcal{S}$ consists of N_τ consecutive operations so that $\tau(x) := \left(\bar{\mathcal{O}}_n^{(\tau)}(x; p_n^{(\tau)}, \lambda_n^{(\tau)}) \right)_{n=1}^{N_\tau}$ where each operation is applied with the probability p as:

$$\bar{\mathcal{O}}(x; p, \lambda) := \begin{cases} \mathcal{O}(x; \lambda) & : \text{with probability } p \\ x & : \text{with probability } 1 - p. \end{cases} \quad (1)$$

Hence, the output of sub-policy τ can be described by $\tau(x) = \bar{\mathcal{O}}_{N_\tau}^{(\tau)} \circ \dots \circ \bar{\mathcal{O}}_1^{(\tau)}(x)$ for $x \in \mathcal{X}$. Note that each sub-policy τ is a random sequence of image transformations which depend on p and λ , and this enables to cover a wide range of data augmentations. Our final policy \mathcal{T} is a collection of $N_{\mathcal{T}}$ sub-policies and $\mathcal{T}(D)$ indicates a set of augmented images of dataset D transformed by all sub-policies $\tau \in \mathcal{T}$. Figure 1.(a) shows a specific example of augmented images by $\tau \in \mathcal{T}$.

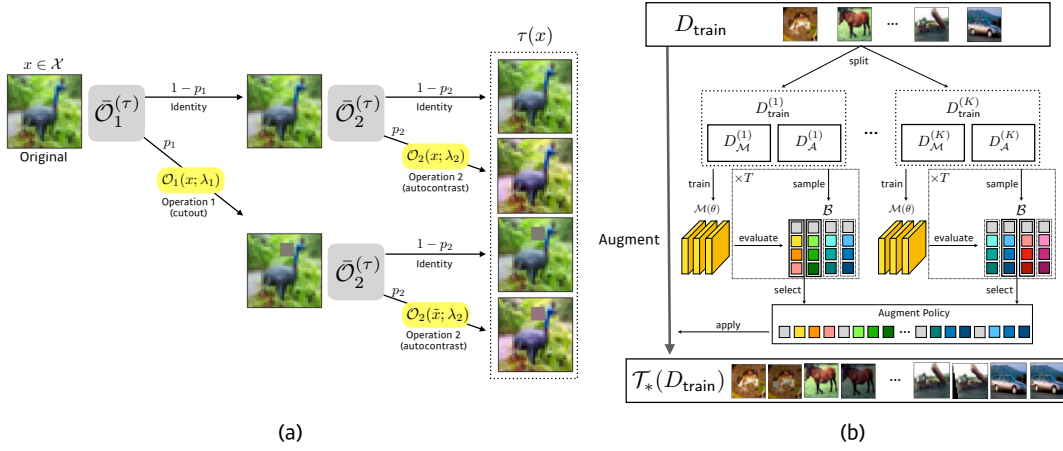


Figure 1: (a) An example of data augmentation in Fast AutoAugment. A sub-policy τ consists of N_τ operations, and each operation \bar{O}_i has two parameters: the probability p_i of calling the operation and the magnitude λ_i of the operation. As a result, τ randomly maps input data x to the one of 2^{N_τ} images. Note that identity map $\tau(x) = x$ is also possible for our search space. (b) An overall procedure of augmentation search by Fast AutoAugment algorithm. At first, model parameter θ is trained on $D_{\mathcal{M}}$ and evaluate B bundles of augmentation policies on $D_{\mathcal{A}}$. The best policies learned from K splits are appended to an obtained augmentation list and applied to D_{train} .

2.2 Search Strategy

Let \mathcal{D} be a probability distribution on $\mathcal{X} \times \mathcal{Y}$ and assume dataset D is sampled from this distribution. For a given classification model $\mathcal{M}(\cdot|\theta) : \mathcal{X} \rightarrow \mathcal{Y}$ that is parameterized by θ , an expected accuracy of $\mathcal{M}(\cdot|\theta)$ on dataset D is denoted by $\mathcal{R}(\theta|D)$.

2.2.1 EFFICIENT DENSITY MATCHING

For any given pair of D_{train} and D_{valid} , our goal is to improve the generalization ability by searching the augmentation policies that match the density of D_{train} with density of augmented D_{valid} . However, it is impractical to compare these two distributions directly for an evaluation of every candidate policy. Therefore, we perform this evaluation by measuring how much one dataset follows the pattern of the other by making use of the model predictions on both datasets. In detail, let us split D_{train} into $D_{\mathcal{M}}$ and $D_{\mathcal{A}}$ that are used for learning the model parameter θ and exploring the augmentation policy \mathcal{T} , respectively. We employ the following objective to find a set of learned augmentation policies

$$\mathcal{T}_* = \underset{\mathcal{T}}{\operatorname{argmax}} \mathcal{R}(\theta^*|\mathcal{T}(D_{\mathcal{A}})) \quad (2)$$

where model parameter θ^* is trained on $D_{\mathcal{M}}$. It is noted that in this objective, \mathcal{T}_* approximately minimizes the distance between density of $D_{\mathcal{M}}$ and density of $\mathcal{T}(D_{\mathcal{A}})$ from the perspective of maximizing the accuracies of both model predictions with the same parameter θ .

Algorithm 1: Fast AutoAugment

Input : $(\theta, D_{\text{train}}, K, T, B, N)$

- 1 Split $D_{\text{train}} = \{(D_{\mathcal{M}}^{(k)}, D_{\mathcal{A}}^{(k)})\}_{k=1}^K$
- 2 **for** $k \in \{1, \dots, K\}$ **do**
- 3 $\mathcal{T}_*^{(k)} \leftarrow \emptyset, (D_{\mathcal{M}}, D_{\mathcal{A}}) \leftarrow (D_{\mathcal{M}}^{(k)}, D_{\mathcal{A}}^{(k)})$
- 4 $\theta \leftarrow \text{Train } \theta \text{ on } D_{\mathcal{M}}$
- 5 **for** $t \in \{0, \dots, T-1\}$ **do**
- 6 $\mathcal{B} \leftarrow \text{BayesOptim}(\mathcal{T}, \mathcal{R}(\theta|\mathcal{T}(D_{\mathcal{A}})), B)$
- 7 $\mathcal{T}_t \leftarrow \text{Select top-}N \text{ policies in } \mathcal{B}$
- 8 $\mathcal{T}_*^{(k)} \leftarrow \mathcal{T}_*^{(k)} \cup \mathcal{T}_t$
- 9 **end**
- 10 **end**
- 11 **return** $\mathcal{T}_* = \bigcup_k \mathcal{T}_*^{(k)}$

To achieve (2) efficiently, we propose a new strategy for augmentation policy search (see Figure 1.(b) and Algorithm 1). First, we conduct the K -fold stratified shuffling to split the train dataset into $D_{\text{train}}^{(1)}, \dots, D_{\text{train}}^{(K)}$ where each $D_{\text{train}}^{(k)}$ consists of two datasets $D_{\mathcal{M}}^{(k)}$ and $D_{\mathcal{A}}^{(k)}$. As a matter of convenience, we omit k in the notation of datasets in the remaining parts. Next, we train model parameter θ on $D_{\mathcal{M}}$. At each step $1 \leq t \leq T$, we explore B candidate policies $\mathcal{B} = \{\mathcal{T}_1, \dots, \mathcal{T}_B\}$ via Bayesian optimization to sample \mathcal{T} which maximizes $\mathcal{R}(\theta|\mathcal{T}(D_{\mathcal{A}}))$ (see line 6 in Algorithm 1). The concrete method is explained in the next subsection. After exploration, we select top- N policies over \mathcal{B} and denote them \mathcal{T}_t . Here, we postulate that $\mathcal{R}(\theta|\mathcal{T}_t(D_{\mathcal{A}})) \geq \mathcal{R}(\theta|D_{\mathcal{A}})$ holds statistically since some policies in \mathcal{B} contain identity map in probability when search depth B is large enough. Finally, we merge every \mathcal{T}_t into \mathcal{T}_* . At the end of the process, we augment the whole dataset D_{train} by applying \mathcal{T}_* and retrain the model parameter θ .

2.2.2 POLICY EXPLORATION VIA BAYESIAN OPTIMIZATION

Policy exploration is an essential ingredient in the automatic augmentation process. We apply Bayesian optimization to the exploration of augmentation strategies. Precisely, at the line 6 in Algorithm 1, we employ the following Expected Improvement (EI) criterion (Jones, 2001)

$$\text{EI}(\mathcal{T}) = \mathbb{E}[\max(\mathcal{R}(\theta|\mathcal{T}(D_{\mathcal{A}})) - \mathcal{R}^\dagger, 0)] \quad (3)$$

for acquisition function to sample \mathcal{B} efficiently. Here, \mathcal{R}^\dagger denotes the constant threshold determined by the quantile of observations among previously explored policies. We use variable kernel density estimation (Terrell et al., 1992) on graph-structured search space \mathcal{S} to approximate the criterion (3). Practically, since the optimization method is already proposed in tree-structured Parzen estimator (TPE) algorithm (Bergstra et al., 2011), we apply their HyperOpt library for the implementation.

3. Experiments and Results

In this section, we examine the performance of Fast AutoAugment on the CIFAR-10, CIFAR-100 (Krizhevsky and Hinton, 2009), and ImageNet (Deng et al., 2009) datasets and compare the results

Model	Baseline	Cutout	AutoAugment	Fast AutoAugment (transfer / direct)
Wide-ResNet-40-2	5.3	4.1	3.7	3.6 / 3.7
Wide-ResNet-28-10	3.9	3.1	2.6	2.7 / 2.7
Shake-Shake(26 2×32d)	3.6	3.0	2.5	2.7 / 2.5
Shake-Shake(26 2×96d)	2.9	2.6	2.0	2.0 / 2.0
Shake-Shake(26 2×112d)	2.8	2.6	1.9	2.0 / 1.9
PyramidNet+ShakeDrop	2.7	2.3	1.5	1.8 / 1.7

Table 2: Test set error rate (%) on CIFAR-10.

Model	Baseline	Cutout	AutoAugment	Fast AutoAugment (transfer / direct)
Wide-ResNet-40-2	26.0	25.2	20.7	20.7 / 20.6
Wide-ResNet-28-10	18.8	18.4	17.1	17.8 / 17.5
Shake-Shake(26 2x96d)	17.1	16.0	14.3	14.9 / 14.6
PyramidNet+ShakeDrop	14.0	12.2	10.7	11.9 / 11.7

Table 3: Test set error rate (%) on CIFAR-100.

Model	Baseline	AutoAugment	Fast AutoAugment
ResNet-50	23.7 / 6.9	22.4 / 6.2	21.4 / 5.9
ResNet-200	21.5 / 5.8	20.00 / 5.0	19.4 / 4.7

Table 4: Validation set Top-1 / Top-5 error rate (%) on ImageNet.

with baseline preprocessing, Cutout (DeVries and Taylor, 2017), and AutoAugment. We follow the experimental setting of AutoAugment for fair comparison, except that an evaluation of the proposed method on AmoebaNet-B model (Real et al., 2018) is omitted. As in AutoAugment, each sub-policy consists of two operations ($N_{\tau} = 2$), each policy consists of five sub-policies ($N_{\mathcal{T}} = 5$), and the search space consists of the same 16 operations (ShearX, ShearY, TranslateX, TranslateY, Rotate, AutoContrast, Invert, Equalize, Solarize, Posterize, Contrast, Color, Brightness, Sharpness, Cutout, Sample Pairing). In Fast AutoAugment algorithm, we utilize 5-folds stratified shuffling ($K = 5$), 2 search width ($T = 2$), 200 search depth ($B = 200$), and the number of selected policies ($N = 10$) for policy evaluation. For scalable implementation, we use Ray (Moritz et al., 2018) library which combines distributed training framework with TPE algorithm. We also increase the batch size and adapt the learning rate accordingly to boost the training. Otherwise, we set other hyperparameters equal to AutoAugment. Our augmentation policies will be open to the public by github¹ of Kakao Brain.

1. <https://github.com/kakaobrain/fast-autoaugment>

3.1 CIFAR-10 and CIFAR-100

For both CIFAR-10 and CIFAR-100, we conduct two experiments using FastAutoAugment: (1) direct search on the full dataset (2) transfer policies found by Wide-ResNet-40-2 on the reduced CIFAR-10 which consists of 4,000 randomly chosen examples. As shown in Table 2 and 3, overall, FastAutoAugment significantly improves the performances of the baseline and Cutout for any network while achieving comparable performances to those of AutoAugment except PyramidNet.

CIFAR-10 Results In Table 2, we present the test set accuracies according to different models. We examine Wide-ResNet-40-2, Wide-ResNet-28-10 (Zagoruyko and Komodakis, 2016), Shake-Shake (Gastaldi, 2017), Shake-Drop (Yamada et al., 2018) models to evaluate the test set accuracy of Fast AutoAugment. It is shown that, Fast AutoAugment achieves comparable results to AutoAugment on both experiments. We emphasize that it only takes 3.5 GPU-hours for the policy search on the reduced CIFAR-10. We also estimate the search time via full direct search. By considering the worst case, Pyramid-Net+ShakeDrop requires 780 GPU-hours which is even less than the computation time of AutoAugment (5000 GPU-hours).

CIFAR-100 Results Results are shown in Table 3. Again, Fast AutoAugment achieves significantly better results than baseline and cutout. However, except Wide-ResNet-40-2, Fast AutoAugment shows worse results than AutoAugment. Nevertheless, the search costs of the proposed method on CIFAR-100 are same as those on CIFAR-10. We conjecture the performance gaps between AutoAugment and Fast AutoAugment are probably caused by the insufficient policy search in the exploration procedure or the over-training of the model parameters in the proposed algorithm.

3.2 ImageNet

Following AutoAugment, we use a reduced subset of the ImageNet train data which is composed of 6,000 samples from randomly selected 120 classes. ResNet-50 on each fold were trained for 90 epochs during policy search phase, and we trained ResNet-50 and ResNet-200 with the searched augmentation policy. In Table 4, we compare the validation accuracies of Fast AutoAugment with those of baseline and of AutoAugment via ResNet-50 and ResNet-200. In this test, we except the AmoebaNet (Real et al., 2018) since its exact implementation is not open to public. As one can see from the table, the proposed method outperforms benchmarks. Furthermore, our search method is 33 times faster than AutoAugment on the same experimental settings (see Table 1). Since extensive data augmentation protects the network from overfitting, we believe the performance will be improved by reducing the weight decay.

4. Conclusion

We propose an automatic process of learning augmentation policies for a given network. Our search method is significantly faster than AutoAugment, and its performances are comparable to those of benchmarks.

One can apply Fast AutoAugment to the advanced architectures. In addition, more augmentation operations can be considered in the proposed algorithm without increasing search costs. Moreover, joint optimization of NAS and Fast AutoAugment is very promising area in AutoML. We leave them for future works. We are also going to deal with the application of Fast AutoAugment to various computer vision tasks beyond image classification in the near future.

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