DyRep: Bootstrapping Training with Dynamic Re-parameterization

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Abstract

Structural re-parameterization (Rep) methods achieve noticeable improvements on simple VGG-style networks. Despite the prevalence, current Rep methods simply re-parameterize all operations into an augmented network, including those that rarely contribute to the model’s performance. As such, the price to pay is an expensive computational overhead to manipulate these unnecessary behaviors. To eliminate the above caveats, we aim to bootstrap the training with minimal cost by devising a dynamic re-parameterization (DyRep) method, which encodes Rep technique into the training process that dynamically evolves the network structures. Concretely, our proposal adaptively finds the operations which contribute most to the loss in the network, and applies Rep to enhance their representational capacity. Besides, to suppress the noisy and redundant operations introduced by Rep, we devise a de-parameterization technique for a more compact re-parameterization. With this regard, DyRep is more efficient than Rep since it smoothly evolves the given network instead of constructing an over-parameterized network. Experimental results demonstrate our effectiveness, e.g., DyRep improves the accuracy of ResNet-18 by 2.04% on ImageNet and reduces 22% runtime over the baseline. Code is available at: https://github.com/hunto/DyRep.

1. Introduction

The advent of automatic feature engineering fuels deep convolution neural networks (CNNs) to reach the remarkable success in a plethora of computer vision tasks, such as image classification [8,9,29,34], object detection [5,16,19], and semantic segmentation [7,33]. In the path of pursuing better performance than that of early prototypes such as VGG [20] and ResNet [8], current deep learning models [10,15,29] generally are embodied with billions of parameters and paramount well-tailored architectures and operations (e.g., channel-wise attention in SENet [10] and branch-concatenation in Inception [23]). From this perspective, we may encounter a dilemma in the sense that a learning model with good performance should be heavy and computationally intensive, which is extremely hard to deploy and has a high inference time. To this end, a critical question is: how to enhance the ability of neural networks without incurring expensive computational overhead and high inference complexity?

Structural re-parameterization technique (Rep) and its variants [2,3,32], which construct an augmented model in training and transform it back to the original model in inference, have emerged as a leading strategy to address the above issue. Concretely, these methods enhance the representational capacities of models by expanding the original convolution operations with multiple branches in training, then fusing them into one convolution for efficient inference without accuracy drop. Representative examples include RepVGG [3] and DBB [2]. The former enhances VGG-style networks by expanding the $3 \times 3$ Conv to an accumulation of three branches (i.e., $3 \times 3$ Conv, $1 \times 1$ Conv, and residual connection) in the training process and re-parameterizing it back to the original $3 \times 3$ Conv in the inference time. The latter improves CNNs by enriching
the types of expanding branches (i.e., introducing 6 equivalent transformations of re-parameterization) and unifying them into a universal building block which applies to various CNNs such as ResNet [8] and MobileNet [9]. Nevertheless, a common caveat of current Rep and its variants is coarsely re-parameterizing all branches into an augmented network, where a large portion of them may seldom enhance the model’s performance. In other words, directly utilizing the same branches in all layers would lead to suboptimal structures. Furthermore, these redundant operations would result in an expensive or even unaffordable memory and computation cost, since the memory consumption increases linearly with the number of branches.

To conquer the aforementioned issues, we propose a novel re-parameterization method, dubbed as DyRep, to dynamically evolve network structures during training and recover to the original network in inference, as illustrated in Figure 2. In particular, the key concept behind our proposal is adaptively seeking the operations with the biggest contributions to the performance (or loss as its surrogate) instead of pursuing a universal re-parameterization to all of them, which ensures both the efficacy and accuracy to augment the network. In DyRep, the operation with the biggest contribution amounts to the operation with the most significant saliency score. As our first technical contribution, this measure is partially inspired by the gradient-based pruning methods, which utilize the gradients w.r.t. the loss to calculate the saliency scores of filters.

Since the existing Rep methods are designed for transforming the model to a narrow one at the end of the training, there is no plug-and-play technique to expand one convolution to multiple branches while keeping the training stable. To achieve a training-aware Rep, we first extend the Rep technique in such a case, then propose to stabilize the training by initializing the additional branches with small scale factors in batch normalization (BN) layers. By doing so, the additional branches would start with minor importance, making trivial changes on the original weights, and thus obtaining a smooth structure evolution.

Our second key technical contribution is devising a de-parameterization method to unearth and discard the redundant operations that appeared in Rep. Since we initialize the BN layer in the newly-added branch with small scale factor, which can be treated as a relaxed gate to turn on or cut off one branch. That is, if a branch has a significant small scale value compared to other branches, it will make a minor contribution to the outputs. Therefore, we could discard it and absorb its weights to other branches for better efficiency. Specifically, if a branch has a zero scale factor, its operations would not affect the output.

Our main contributions are summarized as follows.

- We propose DyRep, a dynamic re-parameterization method that applies to training, aiming to enhance the Rep performance with minimal overhead. By identifying the important operations dynamically during training, our proposal achieves significant efficiency and performance improvement.

- Our DyRep is more friendly to downstream tasks such as object detection. Different from previous Rep and NAS methods that need to first train a network on image classification task, followed by transferring it to downstream tasks, DyRep can directly adapt the structures in downstream tasks. This property dramatically reduces the computational cost.

- Extensive experiments on image classification and its downstream tasks demonstrate that DyRep outperforms other Rep methods in the measure of both the accuracy and the runtime cost.
Concretely, these transformations do not only enhance the training steps, and the morphed network can be transformed generations could be randomly initialized without additional ligible reconstruction error using Rep; hence the added op- ing. In this paper, we achieve network morphism with neg- dom initialization [28], and initialization with partial train- initializations, e.g., identity initialization [27], ran- t between the new and original networks. As a result, various should be involved to minimize the reconstruction error be- re-parameterization (Rep) method [2,3]. The core ingredi- in different training stages, meanwhile preserving the function of the original network. The growth of the network would change its outputs, additional training strategies (e.g., mimic learning) should be involved to minimize the reconstruction error bet- ween the new and original networks. As a result, various initialization methods, e.g., identity initialization [27], random initialization [28], and initialization with partial training [13], have been proposed to warrant an effective training. In this paper, we achieve network morphism with neg- ligible reconstruction error using Rep; hence the added op- erations could be randomly initialized without additional training steps, and the morphed network can be transformed back to the original network for efficient inference.

2.2. Neural Architecture Search

Neural architecture search (NAS) methods [17,21,22,31, 35] achieve remarkable performance improvements by automatic architecture designing. However, they are computationally expensive in training intermediate architectures. Although some one-shot NAS methods [17,31] are proposed to reduce the runtime cost by regarding the whole search space as a supernet and training it once, it still suffers from a high memory consumption and an additional cost on supernet training. Recently, RepNAS [32] is proposed to search better Rep architectures by leveraging the different- able NAS method [17]. In this way, RepNAS can directly transform the trained supernet into the final network in in- ference using Rep, without training the searched network again. However, RepNAS still suffers from the expensive computational overhead, as its training interacts with the whole search space (i.e., networks with all the Rep branches equipped). In this work, instead of utilizing NAS to pursue a fixed Rep structure, DyRep assumes that the optimal structures vary at different training phases (epochs) and aims to bootstrap the training with minimal cost. As such, DyRep uses Rep to dynamically evolve the network structures dur- ing training. Since our method starts training with the original networks, it would save much computation cost com- pared to RepNAS.

3. Revisiting Structural Re-parameterization

Let us first recap the mechanism of the vanilla structural re-parameterization (Rep) method [2,3]. The core ingredients of Rep are the equivalent transformations of operations. Concretely, these transformations do not only enhance the representational capacities of neural networks by introducing diverse branches in the training process, but can also be equivalently transformed to simpler operations, which promise a lighten neural networks in inference. These prop- erties are of great importance in model mining, and enable to dramatically reduce the computational cost without losing accuracy. In the rest of this section, we revisit such transformation techniques used in Rep.

Rep engineers with operations that are widely integrated in networks, such as convolution (Conv), average pooling and residual connection. For example, Conv functions by transforming an input feature \( I \in \mathbb{R}^{C \times H \times W} \) to an output \( O \), i.e.,

\[
O := o(I) = I \odot F + b \in \mathbb{R}^{D \times H' \times W'},
\]

where \( C, H, \) and \( W \) refer to channels, height, and width of the input, respectively. \( F \in \mathbb{R}^{D \times C \times K \times K} \) and \( b \in \mathbb{R}^{D} \) are the parameters of the convolution operator \( \odot \). Note that \( H' \) and \( W' \) are determined by several factors such as kernel size, padding, stride, etc.

The linearity of the convolution operator \( \odot \) ensures the additivity. Specifically, for any two convolutions \( o^{(1)} \) and \( o^{(2)} \) with weights \( F^{(1)} \) and \( F^{(2)} \), if they follow the same configurations (e.g., the same \( D, C, \) and \( K \)), we have

\[
I \odot F^{(1)} + I \odot F^{(2)} = I \odot (F^{(1)} + F^{(2)}).
\]

For ease of understanding, the derivation of Eq.(2) omits the term \( b \), but the above results still hold when \( b \) is considered. Supported by the additivity in Eq.(2), an immediate observation is that two compatible Conv operations can thus been merged into a single new Conv operation \( o^{(3)} \) with weights \( F^{(3)} = (F^{(1)} + F^{(2)}) \).

Note that the above additivity can be generalized to other operations once they can be transformed to a convolution operation. This evidences that multi-branch operations, or equivalently a sequence of operations, can be transformed into a single convolution and thus possess the additivity. Without loss of clarity, we follow the convention in [2] to refer a branch as an operation involved in the transformation. Some examples satisfying this rule are listed as follows. See the left panel in Figure 3 for intuition.

- **A conv for sequential convolutions.** A sequence of \( \text{Convs} \ 1 \times 1-K \times K \) can be merged into one \( K \times K \) Conv.
- **A conv for average pooling.** A \( K \times K \) average pool- ing is equivalent to a \( K \times K \) Conv with the same stride.
- **A conv for multi-scale convolutions.** \( K_H \times K_W \) \((K_{H}, K_{W} \leq K)\) convolutions (e.g., \( 1 \times 1 \) Conv and \( 1 \times K \) Conv) can be transformed into a \( K \times K \) Conv via zero-padding on kernel weights.
- **A conv for residual connections.** A residual connec- tion can be viewed as a special \( 1 \times 1 \) Conv with value 1 everywhere, and thus can be transformed into a \( K \times K \) Conv.
Table 1. Operation spaces of RepVGG, DBB, RepNAS, and DyRep. $K \times K$ denotes conv operation with the kernel size $K \times K$, and $1 \times 1-K \times K$ denotes a branch stacking $1 \times 1$ and $K \times K$ Conv sequentially.

| Method      | #Branches | Branches                                                                 |
|-------------|-----------|--------------------------------------------------------------------------|
| RepVGG [3]  | 3         | $K \times K, 1 \times 1$, residual connection                           |
| DBB [2]     | 4         | $K \times K, 1 \times 1-K \times K, 1 \times 1$-AVG, $1 \times 1$       |
| RepNAS [32] | 7         | $K \times K, 1 \times 1-K \times K, 1 \times 1$-AVG, $1 \times 1, 1 \times K, K \times 1$, residual connection |
| DyRep (ours) | 7         | $K \times K, 1 \times 1-K \times K, 1 \times 1$-AVG, $1 \times 1, 1 \times K, K \times 1$, residual connection |

By leveraging the above elementary transformations, one $K \times K$ $Conv$ can be augmented by adding more diverse branches to its output. For example, RepVGG [3] proposes an extended $3 \times 3 Conv$ including $1 \times 1 Conv$ and residual connection; DBB [2] proposes a diverse branch block to replace the original $K \times K Conv$, and each branch in the block can be transformed to a $K \times K Conv$; RepNAS [32] aims to search DBB branches using neural architecture search (NAS). Table 1 summarizes the detailed operation spaces.

We end this section by showing a common caveat of Rep and its variants. Concretely, current methods simply re-parameterize all the candidate branches into an augmented network with the effective operations. However, since re-parameterization techniques in training. Supported by Rep that transforms structures without changing outputs, DyRep can evolve the structures flexibly during training and convert them back to the original network in inference.

4. Dynamic Re-parameterization (DyRep)

Here we propose Dynamic re-parameterization (DyRep) to seek the optimal structures with minimal cost by conservatively re-parameterizing the original network. We achieve the dynamic structure adaptation by extending the re-parameterization techniques in training. Supported by Rep that transforms structures without changing outputs, DyRep re-parameterizes the operations that contribute the most to the loss.

In DyRep, the contributions of different operations towards decreasing the loss are measured by the gradient information. That is, an operation with small gradients contributes less to the decrease of loss, and is hence more likely to be redundant. Notably, a similar idea has also been broadly used in network pruning [14,24,25], which endows an importance score for weights. Nevertheless, in contrast with network pruning that concentrates on the redundant (unimportant) weights, DyRep is more interested in identifying those operations whose weights correspond to larger gradients.

We next explain the score metric adopted in DyRep to identify the operations with high contributions to decrease the loss. Many gradient-based score metrics [14,24,25] have been proposed to measure the saliency of weights. A recent study [24] proposes a score metric synflow to avoid layer collapse when performing parameter pruning, i.e.,

$$S_p(\theta_i) = \frac{\partial L}{\partial \theta_i} \odot \theta_i,$$

(3)

where $L$ is the loss function of a neural network with parameters $\theta$, $S_p$ is per-parameter saliency and $\theta_i \in \theta$, and $\odot$ denotes Hadamard product. We extend $S_p$ to score an entire operation by summing over all its parameters, i.e,

$$S_o(\theta^{(i)}) = \sum_j S_p(\theta^{(j)}),$$

(4)

where $\theta^{(i)}$ denotes the parameters in operation $o^{(i)}$. By leveraging Eq.(4), we gradually re-parameterize the operation with the largest $S_o w.r.t.$ the accumulated training loss in every $t$ epochs, as described in Algorithm 1. Note that DyRep works on all $K \times K$ convolutions, including the newly-added Rep convolutions. This implies that our method can re-parameterize the operations recursively for even richer forms.

To re-parameterize those identified operations dynamically, we further extend the Rep technique to transform a single learned convolution into a DyRep block with random initialized weights during training. Our DyRep block consists of diverse Rep branches and computes the input feature to accumulate all its branches. The DyRep is equipped with all the candidate operations in Table 1. Its weights are initialized with the proposed training-aware re-parameterization rule detailed below, where its illustration is shown in the left panel of Figure 3.
Training-aware re-parameterization. Suppose we have a set of randomly initialized operations \( \{o^{(1)}, ..., o^{(n)}\} \) to be added to the original operation \( o^{(ori)} \) with weights \( F^{(ori)} \), then the new output of the expanded block becomes
\[
O' = I \otimes F^{(ori)} + I \otimes F^{(1)} + \cdots + I \otimes F^{(n)},
\]
The output of the original operation \( O = I \otimes F^{(ori)} \) would be varied by new additional features. For a consistent output, we adopt Rep to transform the original weights \( F^{(ori)} \) using Eq.(2). The new weights \( F^{(ori')} \) yields
\[
F^{(ori')} \leftarrow F^{(ori)} - (F^{(1)} + \cdots + F^{(n)}),
\]
where \( F^{(n)} \) is the transformed weights of operation \( o^{(n)} \).

Stabilizing training with batch normalization. In Eq.(6), if we initialize the added operations with large weights, the weights of the original operation will change a lot and thus its training would be disturbed. Fortunately, all our branches follow a OP-BN paradigm, in which the last batch normalization (BN) layer \([12]\) computes the input \( x \) as
\[
BN(x; \gamma, \beta) = x - \frac{E(x)}{\sqrt{\text{Var}(x)}} + \beta,
\]
where \( \gamma \) and \( \beta \) are learnable weights for scaling and shifting the normalized value. If we set \( \gamma \) to a small value and make \( \beta = 0 \), the transformed weights \( F \) of this branch will be small and the addition of branches will have a minor impact to the original weights. As a result, the functionality (representational ability) of the original convolution would be retained. We set \( \gamma = 0.01 \) in our experiments.

Besides, transforming weights of branch into the weights of a single convolution needs to fuse the BN layer into convolution, which constructs new weight \( F' \) and bias \( b' \) for every channel \( j \) as
\[
F'_j \leftarrow \frac{\gamma_j}{\sigma_j} F_j, \quad b'_j \leftarrow (b_j - \mu_j) \frac{\gamma_j}{\sigma_j} + \beta_j,
\]
where \( \mu \) and \( \sigma \) denote the accumulated running mean and variance in BN, respectively. For a randomly initialized branch, its \( \mu \) and \( \sigma \) in BN are initialized with 0 and 1, thus directly fusing the initialized BN into convolution would result in inaccurate weights. For an exact re-parameterization, we use 20 batches of training data to calibrate the BN statistics before changing the weights in Eq.(6). Note that the cost of BN calibration could be negligible since it does not require gradient computation.

Algorithm 1 Training with DyRep.

Input: Original model \( M \), total training epochs \( E_{tr} \), total iterations \( N_{iter} \) in each epoch, train dataset \( D_{tr} \), model update interval \( t \), de-parameterization threshold \( \lambda \).

1: for \( e = 1, ..., E_{tr} \) do
2: for \( i = 1, ..., N_{iter} \) do
3: train\( (M, D_{tr}) \); \( \triangleright \) train model for one iteration;
4: \( \{ S_0^{(i)} \mid o \in M \} = \text{SCORE}(M) \); \( \triangleright \) scoring operations according to Eq.(4);
5: end for
6: if \( e \% t = 0 \) then
7: \( S_0 = \frac{1}{N_{iter}} \sum_{i=1}^{N_{iter}} S_0^{(i)}, \forall o \in M \) \( \triangleright \) average over all iterations;
8: \( o^* = \arg \max \{ S_0 \mid o \in M \} \); \( \triangleright \) locate the most important operation;
9: \( M = \text{REP}(M, o^*) \); \( \triangleright \) re-parameterize operation to a DyRep block according to Section 4.1;
10: \( M = \text{DEP}(M, \lambda) \); \( \triangleright \) de-parameterize branches according to Section 4.2;
11: end if
12: end for
13: deploy model \( M \) back to the original model;
14: return inference model \( M \).

4.2. De-parameterizing for Better Efficiency

During training, we dynamically locate the most important operation using Eq.(4) and re-parameterize it to a DyRep block; as Rep may introduce redundant operations, we also design a rule to endow the capability of discarding operations, which we call de-parameterization (Dep). In the sequel, we will discuss how the Dep works.

As in Section 4.1, we set the \( \gamma \) of BN to a small value to stabilize training; considering that BN first normalizes
the input $x$ with the same magnitude, then uses $\gamma$ and $\beta$ to scale and shift the values, which means that the $\gamma$ and $\beta$ control the magnitudes of branches’ outputs. If a branch has an obviously smaller output values than other branches, we may think it makes a minor contribution to the final outputs. Note that setting $\gamma = 0$ effectively zeros out the output.

In this way, we now propose an approach to find the redundant operations by comparing the scale factors of BN layers as $[6, 11, 18, 30]$. Concretely, we use the L1 norm $\gamma$ of $\lambda$ where $o_j$, $\mathcal{C}$ of BN for each branch, $\mathcal{C} = 0$ when branches evolve to be sufficiently distinguishable satisfying $\sqrt{\text{Var}(\{s_j\}_{j=1}^n)} > \lambda$, where $\lambda$ is a threshold and $\lambda = 0.02$ would suffice empirically.

**De-parameterization.** Similar to the training-aware Rep technique, for a DyRep block with operations $\{o^{(\text{ori})}, o^{(1)}, ..., o^{(j)}, ..., o^{(n)}\}$, if we want to remove operation $o^{(j)}$, then we can safely cut the operation $o^{(j)}$. Since the redundant operation has a small scale factor $\gamma$, its removal would also have a minor influence on the weights of original convolution, and the training stability would be retained.

### 4.3. Progressive Training with Rep and Dep

With the proposed re-parameterization (Rep) and de-parameterization (Dep) techniques, we can dynamically enrich the desired operations and discard some redundant operations simultaneously. Combining both Rep and Dep, the networks can be enhanced with great efficiency. The overall training procedure is summarized in Algorithm 1. More precisely, DyRep repeatedly proceeds Rep and Dep in every $t$ epochs, as shown in Lines 3-7. The Rep procedure consists of three components, i.e., selecting the operation with the largest saliency score $S_o$, expanding it with randomly initialized operations, and modifying the weights of the original operation according to Eq.(6) to ensure that the expanded block has the same output as the original operation. The Dep procedure also contains three parts, i.e., finding redundant operations using $\gamma$ of BN for each branch, removing those redundant operations, and modifying the weights of original operation according to Eq.(10).

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**Table 2. Results of base model VGG-16 [20] on CIFAR datasets.** Results are reported based on our implementation with the same training strategies. The FLOPs and parameters in the table are average values in training. Training cost is tested on a NVIDIA Tesla V100 GPU.

| Dataset | Rep method | Cost (GPU hrs.) | Avg. FLOPs (M) | Avg. params (M) | ACC (%) |
|---------|------------|-----------------|----------------|----------------|--------|
| Origin  |            | 2.4             | 313            | 15.0           | 94.68±0.08 |
| CIFAR-10| DBB        | 9.4             | 728            | 34.7           | 94.97±0.06 |
|         | DyRep      | 6.9             | 597            | 26.4           | 95.22±0.13 |
| Origin  |            | 2.4             | 313            | 15.0           | 73.69±0.12 |
| CIFAR-10| DBB        | 9.4             | 728            | 34.7           | 74.04±0.08 |
|         | DyRep      | 6.7             | 582            | 27.1           | 74.37±0.11 |

**Table 3. Results of MobileNet [9] and ResNet [8] models on ImageNet dataset compared to DBB [2].** Training cost is tested on 8 NVIDIA Tesla V100 GPUs. *: Our implementation.

| Model    | Rep method | Cost (GPU days) | Avg. FLOPs (G) | Avg. params (M) | ACC (%) |
|----------|------------|-----------------|----------------|----------------|--------|
| Origin   |            | 2.3             | 0.57           | 4.2            | 71.89  |
| MobileNet| DBB        | 4.2             | 0.61           | 4.3            | 72.88  |
|          | DyRep      | 2.4             | 0.58           | 4.3            | 72.96  |
| Origin   |            | 4.8             | 1.11           | 17.7           | 69.54  |
| ResNet-18| DBB        | 8.1             | 4.13           | 26.3           | 70.99  |
|          | DyRep      | 6.3             | 2.42           | 16.9           | 71.58  |
| Origin   |            | 5.3             | 3.66           | 21.8           | 73.31  |
| ResNet-34| DBB*       | 12.8            | 8.44           | 49.9           | 74.33  |
|          | DyRep      | 7.7             | 4.72           | 33.1           | 74.68  |
| Origin   |            | 7.5             | 4.09           | 25.6           | 76.14  |
| ResNet-50| DBB        | 13.7            | 6.79           | 40.7           | 76.71  |
|          | DyRep      | 8.5             | 5.05           | 31.5           | 77.08  |

### 5. Experiments

#### 5.1. Training Strategies

**CIFAR.** Following DBB [2], we train VGG-16 models with batch size 128, a cosine learning rate which decays 600 epochs is adopted with initial value 0.1, and use SGD optimizer with momentum 0.9 and weight decay $1 \times 10^{-4}$. We set structure update interval $t = 15$ in our method.

**ImageNet.** In Table 3, we train models with the same strategies as DBB [2]. Concretely, we train ResNet-18 and ResNet-50 for 120 epochs with a total batch size 256 and color jitter data augmentation, a cosine learning rate strategy with initial value 0.1 is adopted, and the optimizer is SGD with momentum 0.9 and weight decay $1 \times 10^{-4}$. For MobileNet, we train the model with weight decay $4 \times 10^{-5}$ for 90 epochs. While for VGG-style models, following RepVGG [3], we train the models for 200 epochs with a strong data augmentation (Autoaugment [1] and label smoothing), except for DyRep-A2 we use a simple data augmentation and train it for 120 epochs. In our method, we set structure update interval $t = 5$ for 120-epoch and 200-epoch training; for 300 epoch training, we set $t = 10$. 

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Table 4. Results on ImageNet. The FLOPs and parameters are measured on inference models. Training cost is tested on 8 NVIDIA Tesla V100 GPUs. The baseline ACCs and speeds are reported by RepVGG [3].

| Model       | Speed (examples/second) | FLOPs (G) | params (M) | ACC (%) |
|-------------|-------------------------|-----------|------------|---------|
| ResNet-34   | 1419                    | 21.78     | 74.17      |
| RepVGG-A2   | 1322                    | 5.1       | 25.49      | 76.48   |
| ODBB(A2)    | 1322                    | 5.1       | 25.49      | 76.86   |
| DyRep-A2    | 1322                    | 5.1       | 25.49      | 76.91   |
| ResNet-50   | 719                     | 3.9       | 25.53      | 76.31   |
| RepVGG-B2g4 | 581                     | 11.3      | 55.77      | 79.38   |
| DyRep-B2g4  | 581                     | 11.3      | 55.77      | 80.12   |
| ResNeXt-50  | 484                     | 4.2       | 24.99      | 77.46   |
| ResNet-101  | 430                     | 7.6       | 44.49      | 77.21   |
| RepVGG-B3   | 365                     | 26.2      | 110.96     | 80.52   |
| ODBB(B3)    | 365                     | 26.2      | 110.96     | 80.97   |
| DyRep-B3    | 365                     | 26.2      | 110.96     | 81.12   |
| ResNeXt-101 | 295                     | 8.0       | 44.10      | 78.42   |

5.2. Compare with DBB

We first compare our method with the baseline method DBB [2] on CIFAR and ImageNet datasets. For fair comparisons, we conduct experiments using the same models and training strategies as DBB, and the results are summarized in Table 2 and Table 3. The FLOPs and params in the tables are averaged values in training. The results on both CIFAR and ImageNet datasets show that, our method enjoys significant performance improvements compared to the original and DBB models. Meanwhile, the training cost of our DyRep is obviously lower than DBB. For example, DBB costs 13.7 GPU days to train ResNet-50 on ImageNet, while our DyRep costs 8.5 GPU days (≈ 38% less) and gets 0.37% improvement on accuracy.

5.3. Better Performance with RepVGG

RepVGG [3] proposes a series of VGG-style networks and achieves competitive performance to current state-of-the-art models. We adopt our DyRep on these VGG networks for better performance on ImageNet. Results are summarized in Table 4. Our DyRep obtains higher accuracies with the same transformed models compared to RepVGG since it only adopts two branches \(1 \times 1 Conv\) and residual connection. Meanwhile, compared to the results (ODDB) obtained by RepNAS [32], our method also achieves higher performance. For example, our DyRep-B3 achieves 81.12% accuracy, outperforms RepVGG-B3 and ODBB(B3) by 0.6% and 0.15%, respectively.

5.4. Results on Downstream Tasks

We transfer our ImageNet-pretrained ResNet-50 model to downstream tasks object detection and semantic segmentation to validate our generalization. Concretely, we use the pretrained model as the backbone of the downstream algorithms FPN [16] and PSPNets [33] on COCO and Cityscapes datasets, respectively, then report their evaluation results on validation sets. Moreover, since our DyRep can evolve structures during training, we can directly load the same weights of ResNet-50 and augment its structure in the training of downstream tasks, without training on ImageNet. Therefore, we conduct experiments to adopt DyRep in the training of downstream tasks. The results on Table 5 show that, by directly transferring the trained model to downstream tasks (refers \(C\) in the table), our DyRep can obtain better performance compared to original ResNet-50 and DBB. When we adopt DyRep to update structures in downstream tasks, the performance can be further improved.

5.5. Ablation Studies

Effect of de-parameterization. We propose de-parameterization (Dep) to discard those redundant Rep branches. Now we conduct experiments to validate its effectiveness. As summarized in Table 6, combining Rep and Dep achieves the best performance, while using DyRep without Dep can also boost the performance, but the training efficiency and accuracy will drop.

Table 5. Results on object detection and semantic segmentation tasks. Rep stage \(C+D\) denotes the Rep method is adopted on both ImageNet training and downstream tasks.

| Backbone   | Rep method | Rep stage | ImageNet | COCO  | Cityscapes |
|------------|------------|-----------|----------|-------|------------|
|            |            |           | top-1    | mAP   | mIOU       |
| ResNet-50  | -          | -         | 76.13    | 37.4  | 77.85      |
| ResNet-50  | DBB        | C         | 76.78    | 37.8  | 78.18      |
| ResNet-50  | DyRep      | C         | 77.08    | 38.0  | 78.32      |
| ResNet-50  | DyRep      | D         | 76.13    | 37.7  | 78.09      |
| ResNet-50  | DyRep      | C+D       | 77.08    | 38.1  | 78.49      |

Table 6. Results of DyRep on CIFAR-10 dataset w/ or w/o Dep.

| Method     | FLOPs (M) | Params (M) | ACC (%) |
|------------|-----------|------------|---------|
| Origin     | 313       | 15.0       | 94.68±0.08 |
| DyRep w/ Dep | 597     | 26.4       | 95.22±0.13  |
| DyRep w/o Dep | 658    | 29.3       | 95.03±0.15  |

Effects of different initial scale factors. To stabilize the training, we initialize the last BN layer in each newly-added branch with a small scale factor. Here we conduct experiments to show the effects of different initial values of scale factors. As shown in Figure 4, the performance of different scale factors varies a lot. For a large initial value of 10, the original weights would be changed dramatically; therefore, its accuracy is far below the others. While for a tiny initial value, the performance decreases since the added operations contribute trivially to the outputs. According to the results, we initialize \(\gamma\) with 0.01 in our main experiments.
Retraining obtained structures from scratch. To validate the effect of our dynamic structure adaptation, we retrain the intermediate structures obtained in DyRep training on CIFAR-10. As shown in Table 7, training with DyRep obtains better accuracy compared to training fixed intermediate structures. A possible reason is that the best structures are different at different training phases (epochs). Our DyRep can dynamically adapt the structures to boost the performance in the whole training, thus getting better performance, while the obtained structures at different epochs might not be suitable for other epochs.

Table 7. Retraining results of intermediate structures on CIFAR-10. We fix the structures and retrain them with the same strategy. DyRep denotes training with DyRep, and DyRep-N denotes the structure of DyRep at Nth epoch.

| Model    | FLOPs (M) | Params (M) | ACC (%)  |
|----------|-----------|------------|----------|
| Origin   | 313       | 15.0       | 94.68 ± 0.08 |
| DyRep-200| 466       | 18.2       | 94.83 ± 0.06 |
| DyRep-400| 587       | 20.3       | 95.04 ± 0.07 |
| DyRep-600| 766       | 24.4       | 94.93 ± 0.05 |
| DyRep    | 597       | 26.4       | 95.22 ± 0.13 |

Visualization of convergence curves. We visualize the convergence curves of our method with comparisons of the original ResNet-34 model and DBB. As shown in Figure 5, our DyRep enjoys better convergence during the whole training. It might be because our method efficiently involves effective operations without additional training overhead to the redundant operations.

Visualization of augmented structures. We visualize the first convolution layer in our trained ResNet-18 network in Figure 6. We can see that the original $7 \times 7$ Conv has the largest weight, and all the convolutions with kernel size $K > 1$ are equipped since they help extract information in the previous stages of the network. While on the $1 \times 1$-$7 \times 7$ branch, it expands recursively and leverages average pooling to enrich the features.

5.6. Limitations

DyRep can efficiently enhance the performance of various CNNs, which could be treated as a universal mechanism to boost the training without changing the inference structures. However, its operation space is restricted by the requirements of equivalence in re-parameterization.

6. Conclusion

We propose DyRep, a novel method to bootstrap training with dynamic re-parameterization (Rep). Concretely, to enhance the representational capacity of the operation, which contributes most to the performance, we extend the existing Rep technique to dynamically re-parameterize it and propose an initialization strategy of BN to stabilize the training. Moreover, with the help of the scale factors in BN layers, we propose a mechanism to discard those redundant operations. As a result, the training efficiency and performance can be further improved. Extensive experiments show that our DyRep enjoys significant efficiency and performance improvements compared to existing Rep methods.

Acknowledgements

This work was supported in part by the Australian Research Council under Project DP210101859 and the University of Sydney SOAR Prize.
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