Gradually Updated Neural Networks for Large-Scale Image Recognition

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Abstract

We present a simple yet effective neural network architecture for image recognition. Unlike the previous state-of-the-art neural networks which usually have very deep architectures, we build networks that are shallower but can achieve better performances on three competitive benchmark datasets, i.e., CIFAR-10/100 and ImageNet. Our architectures are built using Gradually Updated Neural Network (GUNN) layers, which differ from the standard Convolutional Neural Network (CNN) layers in the way their output channels are computed: the CNN layers compute the output channels simultaneously while GUNN layers compute the channels gradually. By adding the computation ordering to the channels of CNNs, our networks are able to achieve better accuracies while using fewer layers and less memory. The architecture design of GUNN is guided by theoretical results and verified by empirical experiments. We set new records on the CIFAR-10 and CIFAR-100 datasets and achieve better accuracy on ImageNet under similar complexity with the previous state-of-the-art methods.

1. Introduction

Deep neural networks have become the state-of-the-art systems for image recognition [6, 9, 14, 23, 31, 35, 37, 42] as well as other vision tasks [1, 4, 19, 24, 26, 30, 39]. The architectures keep going deeper, e.g., from 5 convolutional layers [14] to 1001 layers [7]. The benefit of deep architectures is their strong learning capacities because each new layer can potentially introduce more non-linearities and typically uses larger receptive fields [31]. In addition, adding certain types of layers (e.g. [7]) will not harm the performance theoretically since they can just learn identity mapping. This makes stacking up convolutional layers more appealing in the deep neural network architecture designs.

But we question whether increasing the depth is the right approach. First of all, a network becomes harder to train when it becomes deeper [6]. The Residual Network [6] was proposed to partially address this problem. Secondly, simply adding layers is not computationally efficient because some layers may have only learned identity mapping [10]. Thirdly, experiments [9, 41] show that compared with the depth, increasing the width of the network can be more efficient for getting better performances. These issues motivate us to investigate other design strategies for neural networks.

Let us first revisit the motivations for increasing the depth of neural networks. A deeper network can have more parameters, which usually lead to better learning capacity. But widening networks also increases the number of parameters. What a wide but shallow architecture cannot provide is the increase of the non-linear operations and the receptive fields granted by depth [31]. But if these are what the ultra-deep architectures can provide, we can ask the question: can we also have them within a relatively shallow network?

In this paper, we present a new type of neural networks that enables shallow networks to achieve performances better than the state-of-the-art ultra-deep neural networks. The proposed neural network is based on Convolutional Neural Networks (CNNs), but the channels are computed gradually rather than simultaneously as in CNNs. We call this Gradually Updated Neural Network (GUNN). In essence, for each GUNN layer, we assume that its input and output are of the same size and we synchronize the values of them. Then we add a computation ordering to their channels and compute them sequentially. The added ordering will not change the computation complexity, the number of parameters, nor the runtime memory usage. Instead, it allows thelater computed channels to take the earlier ones as their inputs, so that the demands for large receptive fields and many non-linearities (e.g. ReLU [21]) can be met within one layer. As a result, shallow GUNN networks can achieve comparable performances with ultra-deep architectures, e.g., ResNet [6], ResNeXt [38] and DenseNet [9].

We evaluate GUNN on three highly competitive benchmarks, CIFAR-10, CIFAR-100 [13] and ImageNet [28]. On CIFAR-10/100, we outperform the previous state-of-the-art methods, while using similar numbers of parameters, fewer layers and having better memory efficiency. On ImageNet dataset, GUNN is compared with the previous state-of-the-art methods and achieves better performances.
2. Related Work

The research focuses of image recognition have moved from feature designs [2, 20] to architecture designs [6, 9, 14, 29, 31, 35, 38, 42] due to the recent success of the deep neural networks. A trend in designing neural networks is to increase the depth of the architectures by cascading convolutional layers. But deeper networks are usually harder to train [6]. Highway Networks [34] proposed architectures that can be trained end-to-end with more than 100 layers. The main idea of Highway Networks is to use bypassing paths with gating units to optimize the models. This idea is further investigated in ResNet [6], which simplifies the bypassing paths by using only identity mappings. In fact, this elegant idea helped ResNet outperform the previous state-of-the-arts by a very large margin on various visual tasks including image recognition, localization, and detection tasks [3, 18, 28]. As learning ultra-deep networks became possible, the depths of the models have increased tremendously. ResNet with pre-activation [7] and ResNet with stochastic depth [10] even managed to train neural networks with more than 1000 layers. Despite their state-of-the-art performances, Huang et al. [10] also discover that not all the layers of the ultra-deep models are needed and the layers are redundant as some of them only learn the identity mapping, which wastes computation and parameters. FractalNet [15] argued that in addition to summation, concatenation also helps training ultra-deep architectures. More recently, ResNeXt [38] used group convolutions in ResNet and outperformed the original ResNet. DenseNet [9] proposed an architecture with dense connections by feature concatenation. ResNeXt and DenseNet both achieved the state-of-the-art performances.

Alternative to increasing the depth of the neural networks, another trend in the neural network design is to increase the width of the networks. GoogleNet [35, 36] proposed an Inception module to concatenate feature maps produced by different filters. Following ResNet [6], the WideResNet [41] argues that compared with increasing the depth, increasing the width of the networks can be more effective in improving the performances. By training a shallower but wider ResNet, WideResNet outperformed ResNet with thousands of layers. FractalNet [15] and DenseNet [9] are at the intersection of deeper networks and wider networks, which increase the depth by concatenating features.

Besides varying the width and the depth, there are also other design strategies for deep neural networks [5, 12, 22, 25, 40]. Deeply-Supervised Nets [16] used auxiliary classifiers to provide direct supervisions for the internal layers. Network in Network [17] proposed micro perceptrons to add to the convolutional layers for better learning capacity. In a recent work Snapshot Ensemble [8], Huang et al. managed to train multiple models using the same training time, and outperformed the single model by a large margin.

3. Model

3.1. Convolutional Neural Networks

Before discussing the models proposed in this paper, we first review the state-of-the-art convolutional networks. In the most recent convolutional neural networks that achieve the best performances, there are usually several stages, each of which is composed of several convolutional blocks cascaded one after another. Notably, within each stage, the numbers of channels are the same [6, 31, 38]. In VGGNet [31], although the numbers of filters are the same within one stage, the first channel of the input does not have any special relationships with the first channel of the output. However, since the introduction of residual connections [5], the first channel of the input is distinguished from the others when computing the first channel of the output because the convolutional output will be added to the input in a channel-wise way. In essence, the output of the convolutional layers updates the input features in the same feature space \( \mathbb{R}^{m \times n} \) where \( m \) denotes the location on the 2-D feature map and \( n \) denotes the channel. The updates are done by replacement in VGGNet [31], and by addition in ResNet and other networks that use residual connections [6, 38]. In the following, without loss of generality, we will study the convolutional layers with a focus on the feature transformation of the same feature space from a feature update perspective, since the transformation with different dimensions of input and output can be achieved by padding channels with 0.

3.2. Feature Update

We consider a feature transformation \( \mathcal{F} : \mathbb{R}^{m \times n} \rightarrow \mathbb{R}^{m \times n} \), where \( m \) denotes the channel of the features and \( n \) denotes the feature location on the 2-D feature map. Let \( x \in \mathbb{R}^{m \times n} \) be the input and \( y \in \mathbb{R}^{m \times n} \) be the output, we have

\[
y = \mathcal{F}(x)
\]

Suppose that \( \mathcal{F} \) is a one-layer CNN, then for any location \( k \) and channel \( c \) we have

\[
y^c_k = \mathcal{F}^c_k(x^r(k))
\]

where \( x^r(k) \) denotes the receptive field of the location \( k \) and \( \mathcal{F}^c \) denotes the transformation on channel \( c \).

Let \( U_C \) denote a feature update on channel set \( C \), i.e.,

\[
U_C(x) : \quad y^c_k = \mathcal{F}^c_k(x^r(k)), \forall c \in C, k
\]

\[
y^c_k = x^c_k, \forall c \in \overline{C}, k
\]

Then, \( U_C = \mathcal{F} \) when \( C = \{1, ..., n\} \).

3.3. Gradually Updated Neural Networks

By defining the feature update \( U_C \) on channel set \( C \), the commonly used one-layer CNN is a special case of
feature updates where every channel is updated simultaneously. However, we can also update the channels gradually. For example, the proposed GUNN can be formulated by
\[
\text{GUNN}(\mathbf{x}) = (U_{c_l} \circ U_{c_{l-1}} \circ \ldots \circ U_{c_2} \circ U_{c_1})(\mathbf{x})
\]
where \( \bigcup_{i=1}^{l} c_i = \{1, 2, \ldots, n\} \) and \( c_i \cap c_j = \emptyset, \forall i \neq j \) \((4)\).

When \( l = 1 \), GUNN is equivalent to a one-layer CNN.

Note that the number of parameters and computation of GUNN are the same as those of the corresponding CNN for any partitions \( c_1, \ldots, c_l \) of \( \{1, \ldots, n\} \). Why do we bother updating the features gradually? The reason is the gradual increase of the non-linearities and the receptive fields along the updating process: each update \( U_C \) on the channel set \( C \) can increase the receptive fields of the channels \( c \in C \). The later updates on other channels \( c' \) will use \( c \in C \) as their inputs, which can further increase the receptive fields of \( c' \). In other words, the later updated channels are illusively deeper than the previous ones as they stand upon their shoulders. To quantitatively evaluate this, we propose an alternative to the depth, the expected depth for each channel.

### 3.4. Expected Depth Maximization

We want to have a quantitative evaluation of the depth of each channel caused by the gradual feature updates. Intuitively, we define the expected depth of each feature channel to be the average depth of its input added by an increment introduced by the update. Formally, we use \( d(c, U) \) to denote the expected depth of channel \( c \) after update \( U \) is applied, which is defined recursively by
\[
d(c, U_C \circ U) = \begin{cases} 
1 + \frac{1}{n} \sum_{c' \in C} d(c', U) & \text{if } c \in C \\
d(c, U) & \text{otherwise}
\end{cases}
\]
\((5)\).

We assume that the image channels have 0 expected depth.

Based on the observation that deeper neural networks usually have better performances \([6, 7, 9]\), we conjecture that \( U \) will also achieve the best performance under a given number of channel updates when it has the maximal average expected depth of the output channels. The relationship between the expected depth and the accuracy will be explored through the experiments in \S 5.5. Here, we first show the optimal architecture that maximizes the expected depth.

#### Theorem 1
Let \( U \) be the feature update that maximizes the average expected depth of the output channels for the given feature space and the number of channel updates, s.t.,
\[
U = U_{c_l} \circ U_{c_{l-1}} \circ \ldots \circ U_{c_2} \circ U_{c_1}
\]
\((6)\).

Then, we have \( \forall i \in \{1, \ldots, l\} \), (1) \( |c_i| = 1 \), and (2) let \( c^* \) be the only element in \( c_i \),
\[
c^* = \arg \min_c d(c, U_{c_{i-1}} \circ \ldots \circ U_{c_1})
\]
\((7)\).

#### Proof Sketch:
We first show that \( |c_i| = 1, \forall i \in \{1, \ldots, l\} \).

Suppose that there exists \( c_k \) such that \( |c_k| > 1 \), then we can construct a new updating function \( U^* \), s.t.
\[
U^* = U_{c_k} \circ \ldots \circ U_{c_{k+1}} \circ \frac{U_{c_k} \circ \ldots \circ U_{c_{i-1}} \circ U_{c_i}}{c^*} \circ U_{c_k} \circ \ldots \circ U_{c_1}
\]
\((8)\), where \( c^* \in c_k \). It can be proved that
\[
\sum_c d(c, U^*) > \sum_c d(c, U)
\]
\((9)\).

Therefore, \( |c_i| = 1, \forall i \in \{1, \ldots, l\} \).

Next, we prove Eq. 7. Let \( U^{i-1} \) denote \( U_{c_{i-1}} \circ \ldots \circ U_{c_1} \).

By Eq. 5, we have
\[
\sum_c d(c, U_{c_{i-1}} \circ U^{i-1}) = \sum_{c \neq c^*} d(c, U^{i-1}) + 1 + \frac{1}{n} \sum_c d(c, U^{i-1})
\]
Therefore, we have that
\[
\arg \max_{c^*} \sum_c d(c, U_{c_{i-1}} \circ U^{i-1}) = \arg \min_c d(c^*, U^{i-1})
\]
\((10)\).

We can show that the greedy solution in Eq. 10 generalizes to any number of channel updates. Hence, Eq. 7 holds. The full proof is in Appendix.

### 3.5. Learning by Back-propagation

In this subsection, we show the back-propagation algorithm for learning the parameters in GUNN using roughly the same amount of computations and memory as in CNN. In Eq. 4, let the feature update \( U_{c_i} \) be parameterized by \( \Theta_{c_i} \). Let BP \((x, \partial L/\partial y, f, \Theta) \) be the back-propagation algorithm for differentiable function \( y = f(x; \Theta) \) with the loss \( L \) and the parameters \( \Theta \). Algorithm 1 presents the back-propagation algorithm for GUNN. When the \( U_{c_i} \) has the residual structures \([6]\), step 5 and 6 can be merged to
\[
(\partial L/\partial x)_c \leftarrow (\partial L/\partial y)_c + (\partial L/\partial y)_c, \forall c
\]
\((11)\)
which further simplifies the implementation.

#### Algorithm 1: Back-propagation for GUNN

**Input**: \( U(\cdot) = (U_{c_l} \circ U_{c_{l-1}} \circ \ldots \circ U_{c_1})(\cdot), \) input \( x \), output \( y = U(x) \), gradients \( \partial L/\partial y \), and parameters \( \Theta \) for \( U \).

**Output**: \( \partial L/\partial \Theta, \partial L/\partial x \)

1. \( \partial L/\partial x \leftarrow \partial L/\partial y; \)
2. for \( i \leftarrow l \) to 1 do
3. \( y_c \leftarrow x_c, \forall c \in c_i; \)
4. \( \partial L/\partial y_c, \partial L/\partial \Theta_{c_i} \leftarrow \text{BP}(y, \partial L/\partial x, U_{c_i}, \Theta_{c_i}); \)
5. \( (\partial L/\partial x)_c \leftarrow (\partial L/\partial y)_c, \forall c \in c_i; \)
6. \( (\partial L/\partial x)_c \leftarrow (\partial L/\partial x)_c + (\partial L/\partial y)_c, \forall c \notin c_i; \)
7. end
Figure 1. Overview of the Gradually Updated Neural Network (GUNN). As illustrated, GUNN updates its channels gradually from left to right. The dashed double-headed arrows indicate that the channels are synchronized before and after updating. Here, we use a three-layer residual convolutional block as the update unit for the illustration purpose. GUNN becomes a convolutional layer when the unit is one-layer convolutional network and the updates are done simultaneously.

4. Network Architectures

In this section, we will utilize Theorem 1 to guide our architecture design. We first introduce the update units.

4.1. Update Units

Consider a convolutional layer. Suppose initially, the expected depths of the channels are the same. Now we change it to GUNN and maximize the average expected depth of the output using the same number of updates \( n \), i.e., the number of the channels. The solution to the maximization problem is straightforward. According to Theorem 1, the optimal solution only updates one channel that has the minimal expected depth. Within \( n \) updates, the channel with the minimal expected depth is any channel that has not been updated. Therefore, the solution is to gradually update each channel until all the channels have been updated. We call the operations on each individual channel the update units.

Next, we extend the form of the update units. Note that we only need that any two update units are computationally independent of each other. Therefore, we can also use other neural networks here. For example, Figure 1 illustrates a GUNN with a three-layer convolutional network as the update units. Note that when we compute the expected depth, we will accommodate the incremental value in Eq. 5.

Channel Partition. For GPU implementation reasons, we will not update only one channel each time; instead, we may first partition the channels into several groups, then update them group by group.

4.2. Building Networks with GUNN

Now we are ready to build neural networks using GUNN layers to do image classifications. We will focus on designing relatively shallow networks to prove our point of view, i.e., with the help of GUNN layers, relatively shallow neural networks can achieve comparable performances with the state-of-the-art ultra-deep networks, e.g., ResNet [6], ResNeXt [38] and DenseNet [9].

To prove the general effectiveness of our method, we use a minimal design for the neural network architectures. Table 1 compares WideResNet-28-10 [41] with our proposed network architecture using GUNN. The two architectures both use three major convolution stages for getting visual representations. There are two main differences between the two architectures in comparison: (1) Our GUNN-15 only has 15 layers, which already include the layers within the update units. If we consider each update unit as one block, then essentially we only use three blocks to compute the representations. (2) Three stages in the GUNN-15 are computed using GUNN, which ensures the necessary nonlinearities and the receptive fields. With this example in hand, next we introduce our main design idea.

One Resolution, One Representation. Since the deep architecture AlexNet [14] was proposed, most of the convolutional neural networks have more than one convolutional layer or block within one resolution. For example, VGGNet [31] has 3 convolutional layers with channel size 512 at the resolution 28 × 28. The ResNet with pre-activation [7] even has hundreds of convolutional blocks within one resolution. Different from the previous state-of-the-art networks, our architectures aim to have one representation at one resolution. Take the architecture in Table 1 as an example. There are two processes for each resolution. The first one is the transition process, which computes the initial features with the dimensions of the next resolution, then down samples it to 1/4 using a 2 × 2 average pooling. The
WideResNet-GUNN—forms the input features to $K \times n_{out}$ using a $1 \times 1$ convolutional layer. The second convolutional layer is of kernel size $3 \times 3$, stride 1, and padding 1, outputting the features of size $K \times n_{out}$. The third layer computes the features of size $n_{out}$ using a $1 \times 1$ convolutional layer. The output is then added back to the input, following the residual architecture proposed in ResNet [6]. We add batch normalization layer [11] and ReLU layer [21] after the first and second convolutional layers, while only adding batch normalization layer after the third layer. Stacking up $M$ update units can also generate a new one. Therefore, we have two hyper-parameters for designing an update unit: the expansion rate $K$ and the number of the $3$-layer update units $M$. For example, the network shown in Table 1 has configuration $\{K = 2, M = 1\}$.

**GUNN Layer with Channel Partition** With the clearly defined update units, we can easily build GUNN layers by using the units to update the representations following Eq. 4. The hyper-parameters for the GUNN layer are the number of the channels $N$ and the partition over those channels. Here, we evenly partition the channels into $P$ segments. Then, we can use $N$ and $P$ to represent the configuration of a GUNN layer. Together with the hyper-parameters in the update units, we have four hyper-parameters to tune for one GUNN layer.

### 4.3. Architectures for CIFAR

We have implemented two neural networks based on GUNN to compete with the previous state-of-the-art methods on CIFAR datasets, i.e., GUNN-15 and GUNN-24. Table 1 shows the big picture of GUNN-15. Here, we present the details of the hyper-parameter settings for GUNN-15 and GUNN-24. For GUNN-15, we have three GUNN layers, Conv2, Conv3 and Conv4. The configuration for Conv2 is $\{N = 240, P = 20, K = 2, M = 1\}$, the configuration for Conv3 is $\{N = 300, P = 25, K = 2, M = 1\}$, and the configuration for Conv4 is $\{N = 360, P = 30, K = 2, M = 1\}$. For GUNN-24, based on GUNN-15, we change the number of output channels of Conv1 to 720, Trans1 to 900, Trans2 to 1080, and Trans3 to 1080. The hyper-parameters are $\{N = 720, P = 20, K = 3, M = 2\}$ for Conv2, $\{N = 900, P = 25, K = 3, M = 2\}$ for Conv3, and $\{N = 1080, P = 30, K = 3, M = 2\}$ for Conv3. The number of parameters of GUNN-15 is 1585746 for CIFAR-10 and 1618236 for CIFAR-100. The number of parameters of GUNN-24 is 29534106 for CIFAR-10 and 29631396 for CIFAR-100. The GUNN-15 is aimed to compete with the methods before ResNeXt [38] and DenseNet [9] using a much smaller model, while GUNN-24 is targeted at comparing with ResNeXt [38] and DenseNet [9] to get the state-of-the-art performance.

| Stage | Output | WideResNet-28-10 | GUNN-15 |
|-------|--------|-------------------|--------|
| Conv1 | $32 \times 32$ | $[3 \times 3, 16]$ | $[3 \times 3, 64]$ |
| Conv2 | $32 \times 32$ | $[3 \times 3, 160] \times 4$ | $[1 \times 1, 2]$ |
| Trans1 | $16 \times 16$ | - | $[1 \times 1, 300]$ |
| Conv3 | $16 \times 16$ | $[3 \times 3, 320] \times 4$ | $[1 \times 1, 2]$ |
| Trans2 | $8 \times 8$ | - | $[1 \times 1, 360]$ |
| Conv4 | $8 \times 8$ | $[3 \times 3, 640] \times 4$ | $[1 \times 1, 2]$ |
| Trans3 | $1 \times 1$ | GAPool | $[1 \times 1, 360]$ |
| GPU Memory | | | |
| # Params | 36.5M | 1.6M |
| Error (C10/C100) | 4.17 / 20.50 | 4.15 / 20.45 |

Table 1. Architecture comparison between WideResNet [41] and GUNN for CIFAR. (Left) WideResNet-28-10. (Right) GUNN-15. GUNN achieves comparable accuracies on CIFAR10/100 while using fewer layers, a smaller number of parameters and consuming less GPU memory during training. The convolution stages with stars are computed using GUNN while others are not.

**Bottleneck Update Units** As stated in §4.1, the update units can be any computationally independent neural networks. In the architectures proposed in this paper, we adopt bottleneck neural networks as update units. Suppose that the update unit maps the input features of channel size $n_{in}$ to the output features of size $n_{out}$. Each unit contains three convolutional layers. The first convolutional layer transforms the input features to $K \times n_{out}$ using a $1 \times 1$ convolutional layer.
Table 2. Architecture comparison between ResNet [6] and GUNN for ImageNet. (Left) ResNet-152. (Right) GUNN-18. GUNN achieves better accuracies on ImageNet while using much fewer layers, and a smaller number of parameters. The convolution stages with stars are computed using GUNN while others are not.

| Stage | Output | ResNet-152 | GUNN-18 |
|-------|--------|------------|---------|
| Conv1 | 112 × 112 | [7 × 7, 64, 2] | [7 × 7, 64, 2] |
|       |        | 3 × 3 MaxPool, 2 | 3 × 3 MaxPool, 2 |
|       |        | 1 × 1, 1, 400 | 1 × 1, 1, 400 |
| Conv2 | 112 × 112 | [1 × 1, 64] | [1 × 1, ×2] |
|       |        | 3 × 3, 64 | 3 × 3, ×2 |
|       |        | 1 × 1, 256 | 1 × 1, 1, 1 |
| Trans1 | 56 × 56 | – | [1 × 1, 1, 800] |
|       |        | – | [AvgPool] |
| Conv3* | 56 × 56 | [1 × 1, 1, 128] | [1 × 1, ×2] |
|       |        | 3 × 3, 1, 128 | 3 × 3, ×2 |
|       |        | 1 × 1, 1, 512 | 1 × 1, 1, 1 |
| Trans2 | 28 × 28 | – | [1 × 1, 1, 1600] |
|       |        | – | [AvgPool] |
| Conv4* | 28 × 28 | [1 × 1, 1, 256] | [1 × 1, ×2] |
|       |        | 3 × 3, 1, 256 | 3 × 3, ×2 |
|       |        | 1 × 1, 1, 1024 | 1 × 1, 1, 1 |
| Trans3 | 14 × 14 | – | [1 × 1, 1, 2000] |
|       |        | – | [AvgPool] |
| Conv5* | 14 × 14 | [1 × 1, 1, 512] | [1 × 1, ×2] |
|       |        | 3 × 3, 1, 512 | 3 × 3, ×2 |
|       |        | 1 × 1, 1, 2048 | 1 × 1, 1, 1 |
| Trans4×1 | GAPool | fc, softmax | GAPool |
| # Params | 60.2M | 28.9M | 5.1. Benchmark Datasets

CIFAR CIFAR [13] has two color image datasets: CIFAR-10 (C10) and CIFAR-100 (C100). Both datasets consist of natural images with the size of 32 × 32 pixels. The CIFAR-10 dataset has 10 categories, while the CIFAR-100 dataset has 100 categories. For both of the datasets, the training and test set contain 50,000 and 10,000 images, respectively. To fairly compare our method with the state-of-the-arts [6, 9, 10, 15, 16, 17, 27, 32, 34, 38], we use the same training and testing strategies, as well as the data processing methods. Specifically, we adopt a commonly used data augmentation scheme, i.e., mirroring and shifting, for these two datasets. We use channel means and standard derivations to normalize the images for data pre-processing.

ImageNet The ImageNet dataset [28] contains about 1.28 million color images for training and 50,000 for validation. The dataset has 1000 categories. We adopt the same data augmentation methods as in the state-of-the-art architectures [6, 7, 9, 38] for training. For testing, we use single-crop at the size of 224 × 224. Following the state-of-the-arts [6, 7, 9, 38], we report the validation error rates.

5.2. Training Details

We train all of our networks using stochastic gradient descents. On CIFAR-10/100 [13], the initial learning rate is set to 0.1, the weight decay is set to 1e−4, and the momentum is set to 0.9 without dampening. We train the models for 300 epochs. The learning rate is divided by 10 at 150th epoch and 225th epoch. We set the batch size to 64, following [9]. All the results reported for CIFAR, regardless of the detailed configurations, were trained using 4 NVIDIA Titan X GPUs with the data parallelism. On ImageNet [28], the learning rate is also set to 0.1 initially, and decreases following the schedule in DenseNet [9]. The batch size is set to 256. The network parameters are also initialized following [6]. We use 4 NVIDIA Tesla K40M GPUs with the data parallelism to get the reported results. Our results are directly comparable with ResNet [6], WideResNet [41], ResNeXt [38] and DenseNet [9] as we are using the same implementation framework for training and evaluation.

5.3. Results on CIFAR

We train two models GUNN-15 and GUNN-24 for the CIFAR-10/100 dataset. Table 3 shows the comparisons between our method and the previous state-of-the-art methods. Our method GUNN achieves the best results in the test
of both the single model and the ensemble test. Here, we use Snapshot Ensemble [8] to ensemble the models.

Baseline Methods Here we present the details of baseline methods that are missing in Table 3. The results of FractalNet [15] are without any dropout [33]/drop-path [15] regularization in order to compare with others. The performances of ResNet [6] are reported in Stochastic Depth [10] for both C10 and C100. The WideResNet [41] in the second group has two configurations WRN-28-10 and WRN-40-10. The performances are reported in their paper and the official code repository on GitHub. The ResNeXt in the third group has two configurations WRN-28-10 [41] and WRN-40-10 [41]. For example, ResNeXt (16 × 64d) [38] uses 8 GPUs to train the network, and DenseNet-190 with k = 40 also requires 4 GPUs, using their official implementation available on GitHub. The hardware requirements limit the study of bigger deep neural networks. The reasons for the memory issues are multifold. First, the models keep going wider and deeper, thus will use more memory. Second, during training, the outputs of every layer are needed to be kept as back-propagation algorithm will use them to compute the gradients. However, since GUNN can achieve comparable performances using relatively shallow architectures, it is expected that the neural networks using GUNN will consume less memory. We compare GUNN with other networks that have similar accuracies on the GPU memory usage, i.e., GUNN-15 with WideResNet-28-10, and GUNN-24 with DenseNet-190. Table 5 shows the results. To get the results, we use 4 NVIDIA Titan X GPUs with 12GB memory each. We set batch size to 64 to make sure they are comparable. All of the methods are implemented by Torch7, thus are directly comparable. We use the original DenseNet implementation to get the memory usage.

5.4. Results on ImageNet

We evaluate the GUNN-18 on the ImageNet classification task, and compare our performance with the state-of-the-art methods. These methods include VGGNet [31],

Table 3. Classification errors (%) on the CIFAR-10/100 test set. All methods are with data augmentation. The third group shows the most recent state-of-the-art methods. The performances of GUNN are presented in the fourth group. A very small model GUNN-15 outperforms all the methods in the second group except WideResNet-40-10. A relatively bigger model GUNN-24 surpasses all the competing methods. GUNN-24 becomes more powerful with ensemble [8].

| Method                        | # layers | # params | C10   | C100  |
|-------------------------------|----------|----------|-------|-------|
| Network in Network [17]       | 110      | 1.7M     | 6.41  | 27.22 |
| All-CNN [32]                  | 1202     | 10.2M    | 4.91  | 24.58 |
| Deeply Supervised Network [16]| 1001     | 10.2M    | 4.62  | 22.71 |
| Highway Network [34]          | 28       | 36.5M    | 4.17  | 20.50 |
| Stochastic Depth [10]          |          |          |       |       |
| ResNet with pre-act [7]       | 28       | 36.5M    | 4.17  | 20.50 |
| WideResNet-28-10 [41]         | 40       | 55.8M    | 3.80  | 18.30 |
| WideResNet-40-10 [41]         |          |          |       |       |
| ResNeXt [38]                  | 29       | 68.1M    | 3.58  | 17.31 |
| DenseNet [9]                  | 190      | 25.6M    | 3.46  | 17.18 |
| Snapshot Ensemble [8]         |          | 163.2M   | 3.44  | 17.41 |
| GUNN-15                       | 15       | 1.6M     | 4.15  | 20.45 |
| GUNN-24                       | 24       | 29.6M    | 3.21  | 16.69 |
| GUNN-24 Ensemble              | 177.6M   | 3.02     | 15.61 |

Table 4. Classification errors (%) on the CIFAR-10/100 test set with GUNN (GUNN-* ) and without GUNN (SUNN-* ).

With and Without GUNN GUNN in fact proposes a way of feedforwarding neural networks. A natural ablation study is to compare GUNN with Simultaneously Updated Neural Network (SUNN), i.e., all the features are updated through one feedforward pass. By changing GUNN to SUNN, the number of parameters, the computation and the memory usage will be the same. Table 4 shows the comparison results, which demonstrate the effectiveness of GUNN.

Memory Efficiency One important factor affecting the training of deep neural networks is their GPU memory usage. For example, ResNeXt (16 × 64d) [38] uses 8 GPUs to train the network, and DenseNet-190 with k = 40 also requires 4 GPUs, using their official original implementation available on GitHub. The hardware requirements limit the study of bigger deep neural networks. The reasons for the memory issues are multifold. First, the models keep going wider and deeper, thus will use more memory. Second, during training, the outputs of every layer are needed to be kept as back-propagation algorithm will use them to compute the gradients. However, since GUNN can achieve comparable performances using relatively shallow architectures, it is expected that the neural networks using GUNN will consume less memory. We compare GUNN with other networks that have similar accuracies on the GPU memory usage, i.e., GUNN-15 with WideResNet-28-10, and GUNN-24 with DenseNet-190. Table 5 shows the results. To get the results, we use 4 NVIDIA Titan X GPUs with 12GB memory each. We set batch size to 64 to make sure they are comparable. All of the methods are implemented by Torch7, thus are directly comparable. We use the original DenseNet implementation to get the memory usage.
Table 5. Training Memory Efficiency Comparisons.

| Method     | Memory | Method | Memory |
|------------|--------|--------|--------|
| WideResNet-28 | 4.903GB | GUNN-15 | 2.485GB |
| DenseNet-190  | 27.10GB | GUNN-24  | 11.37GB |

Table 6. Single-crop classification errors (%) on the ImageNet validation set. The test size of all the methods is 224 × 224.

ResNet [6], ResNeXt [38], and DenseNet [9]. The comparisons are shown in Table 6. The results of ours, ResNeXt, and DenseNet are directly comparable as these methods use the same framework for training and testing networks. Table 6 groups the methods by their numbers of parameters, except VGGNet which has 1.38 × 10^8 parameters.

The results presented in Table 6 demonstrate that with the similar number of parameters, GUNN-18 can achieve comparable performances with the previous state-of-the-art methods while using fewer layers. The Wide GUNN-18 is of 1.25x width of GUNN-18 for each layer with other settings unchanged. For GUNN-18, we also conduct an ablation experiment by comparing the performance of Simultaneously Updated Neural Network (SUNN) with GUNN using the same configuration. Consistent with the experimental results on the CIFAR-10/100 dataset, the proposed GUNN improves the accuracy on ImageNet dataset.

5.5. Expected Depths and Accuracies

In the model section, we design our model by maximizing the expected depth \( d \). However, it is not necessary that accuracies are positively related to the expected depths. In this subsection, we will focus on discovering the relationships between the expected depths and the accuracies through experiments. In order to do this, we design networks with different expected depths of the final classification layer. These networks are based on GUNN-15. We change the numbers of channels for the stage Conv-2 to Conv-4 all to 32, partition them into 16 groups and remove the residual connections, for the purpose of fast experiments. The resulted networks have 21962 parameters each for training. In order to create networks with different expected depths, we do not update them according to Eq. 4. Instead, we randomly choose a partition to update each time and do not avoid updating one partition more than once. The selections are fixed once determined in the first time. The resulted networks will then have different depths.

We plot the accuracies with expected depths in Figure 2. From Figure 2, we can see that the accuracy is positively related to the expected depth of the classification layer. This observation supports the conjecture proposed in §3.4 that the best accuracy can be achieved by maximizing the expected depth of the output channels, and the design strategy for GUNN layers that is derived from Theorem 1. On the other hand, our proposed architecture can also achieve nearly 90% of accuracy when it has only 21962 parameters.

6. Conclusions

In this paper, we propose Gradually Updated Neural Network (GUNN), a novel, simple yet effective architecture for deep neural networks. GUNN is based on Convolutional Neural Networks (CNNs), but differs from CNNs in the way of computing outputs. The outputs of GUNN are computed gradually rather than simultaneously as in CNNs. Essentially, GUNN assumes the input and the output are of the same size, and synchronizes the values of them. Then, it adds a computation ordering to the channels. The added ordering increases the receptive fields and non-linearities of the later computed channels. As a result, the networks built with GUNN can achieve comparable performances with very deep architectures using only about 20 layers. We test GUNN on the task of image recognition. The evaluations are done in three highly competitive benchmarks, CIFAR-10, CIFAR-100 and ImageNet. The experimental results demonstrate the effectiveness of the proposed GUNN on image recognition. In the future, since the proposed GUNN can be used to replace CNNs in other neural networks, we will study the applications of GUNN in other visual tasks, such as object detection and semantic segmentation.
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