A Fully Sequential Methodology for Convolutional Neural Networks

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Abstract

Recent work has shown that the performance of convolutional neural networks could be significantly improved by increasing the depth of the representation. We propose a fully sequential methodology to construct and train extremely deep convolutional neural networks.

We first introduce a novel sequential convolutional layer to construct the network. The proposed layer is capable of constructing trainable and highly efficient feedforward networks that consist of thousands of vanilla convolutional layers with rather limited number of parameters. The layer extracts each feature of the produced representation in sequence, allowing feature reuse within the layer. This form of feature reuse introduces in-layer hierarchy to the extracted features which greatly increases the depth of the representation, enabling richer structures to be explored.

Furthermore, we employ the progressive growing training method to optimize each module of the network in sequence. This training manner progressively increases the network capacity allowing later modules to be optimized conditioning on prior knowledge from earlier modules. Thus, it encourages long term dependency to be established among each module of the network, which increases the effective depth of networks with skip connections, as well alleviates multiple optimization difficulties for deep networks.

1. Introduction

Recent work has shown that the depth of representation is of crucial importance to the performance of convolutional neural networks [1, 15, 13, 6, 7, 8]. Eldan et al. conclude that depth is a determinant factor of the expressiveness of neural networks [5]. Previous work has mainly focused on introducing more intermediate representations (more hidden layers) to increase the network depth. The internal depth of each representation was however neglected.

Increasing depth by simply stacking more layers also leads to two major optimization difficulties, the diminishing feature reuse problem [9, 14] during forward propagation and the vanishing gradient problem [4] during backpropagation. These two problems could be summarized in general as the aggregation of information loss during propagation.

The diminishing feature reuse problem arises for deep networks that features calculated by earlier layers get washed out by series of convolution operations with randomly initialized weight matrices, resulting in loss in information during forward propagation. Such information loss hampers meaningful gradient directions for later layers to identify.

A similar optimization difficulty referred as the vanishing gradient problem occurs during the backpropagation of deep networks that the gradient information gets repeatedly multiplied by small weights or tiny derivates of the activation function. The gradient received by earlier layers decays at an exponential rate and is quickly rendered ineffectively small making deep networks untrainable.

Optimization friendly network architectures [6, 7, 8] with skip connections were proposed to ease the information flow for deep networks. These architectures however bring a new problem that these networks optimized in an end-to-end manner lack the long-term dependency that is expected for a genuine deep network. Veit et al. reported that randomly removing building blocks from residual networks did not lead to apparent performance drop [16]. Huang et al. randomly dropped residual blocks during training and actually obtained improved performance [9]. Evidences indicate that network with skip connections behaves like ensembles of shallow networks instead of one extremely deep network.

We propose a fully sequential methodology to further extend the depth of convolutional neural networks as well to ameliorate the aforementioned optimization difficulties of deep networks. Our contributions in this paper could be summarized by two aspects:

- We propose a sequential convolutional layer along with its windowed variant to increase the internal depth of each representation by introducing hierarchical fea-
tures to the representation. Our proposed layer enhances the representational ability of the network as the depth of each produced representation is multiplied by \( n \) where \( n \) is the number of features that each representation has.

- We adopt progressive growing proposed by Karras et al. [10] to optimize each module of the network in a sequential manner. This training method eases the earlier discussed optimization difficulties with the extra advantage of maintaining long-term dependency. Concretely, later modules are enabled to start from an informative representation produced by earlier modules since earlier modules have been optimized in advance. This not only eliminates the diminishing feature reuse problem, but as well allows later modules to be optimized utilizing prior knowledge from earlier modules, which encourages long term dependency to be established for forward propagation. For backpropagation, earlier modules have been optimized with direct supervision before later modules are introduced to the network, which makes them less prone to the vanishing gradient problem.

2. Related Works

2.1. Feature Aggregation

Recent work has demonstrated feature aggregation to be one of the most effective methods to alleviate the optimization difficulties of deep networks [6, 7, 8, 11]. This is mainly due to the shortcut skip connections introduced to the network while collecting features from earlier layers. The skip connections bypass certain layers of the network, allowing to directly pass on information to farther layers during propagation. Such network design eases the information flow during propagation and thus enables deep networks to be effectively trained.

Several implementations of skip connections have been proposed for feature aggregation. He et al. proposed residual networks [6, 7] that sum the outputs of all previous building blocks enabling each block to be optimized for a residual representation. Such network architecture has been shown to be much easier to optimize than a plain network without skip connections [6]. Huang et al. later proposed DenseNet [8] that implemented skip connections via concatenation. Unlike aggregation by summation that provides later layers an entangled view of aggregated features. Such concatenation-based aggregation provides a clean view of features collected from each earlier layer which further benefits the information flow during propagation. Zhu et al. recently investigated the pattern of skip connections and introduced a novel logarithmic aggregation topology [12] that could be applied to both summation-based aggregation and concatenation-based aggregation to address the drawbacks of dense aggregation topology.

We further extend feature aggregation that we allow feature reuse within the layer. The in-layer feature reuse introduces hierarchical features to the produced representation which enhances internal depth of the representation. We discuss in-layer feature reuse in details in sec.3.1 and 3.2.

2.2. Progressive Growing

A progressive manner of training was first proposed for autoencoders [3]. This layer-wise greedy training method however does not always outperform end-to-end training as it freezes the weights of earlier layers when training a later layer. This training manner disables optimization from being globally performed on the network and thus hinders the potential representational power of the network.

Karras et al. recently proposed a progressive growing training method for GANs [10]. Such training method combines the benefits from both layer-wise training and end-to-end training. It allows later layers to be smoothly introduced to the network while training. The progressive growing mechanism can be interpreted as a form of curriculum learning [2] that it enables intermediate representations to be hierarchically explored. The most essential representations required to complete the task would be first captured by earlier layers while later layers are only tasked to refine the representation produced by earlier layers.

In contrast to end-to-end training that tasks the network to find all intermediate representations simultaneously which is often found hard to optimize as we discussed in sec.1, progressive growing allows earlier layers to be optimized ahead which provides informative representations for later layers to begin with. It thus considerably alleviates the information loss problem during propagation for deep networks, as well allows long-term dependency to be established.

In contrast to layer-wise greedy training that terminates the optimization for earlier layers as a later layer is introduced to the network, optimization for earlier layers continues after the introduction of later layers with progressive growing. It thus allows the network to be globally optimized similar to end-to-end training.

3. Proposed Methods

3.1. Sequential Convolutional Layers

For a convolutional layer with \( m \) input features and \( n \) output features, let \( f \) be a set of \( m + n \) feature maps with the first \( m \) maps as the input and the rest \( n \) maps as the produced features. Let \( f^{(i)} \) be the \( i \)-th map in \( f \). The standard convolutional layer with an activation function \( \phi \) can be defined as:
Figure 1. A standard convolutional layer (left), a sequential convolutional layer (middle) and a windowed sequential convolutional layer (right) with \( m = n = 3 \).

\[
f^{(i)}(x) = \phi \left( \sum_{j=1}^{m} w^{(i)}_j * f^{(j)} + \beta^{(i)} \right) \]

where \( * \) denotes the spatial convolution operator, \( w^{(i)}_j \) and \( \beta^{(i)} \) are, respectively, the convolution kernel and the bias for \( f^{(i)} \). It can be observed from eq.1 that the representation produced by the layer consists of \( n \) mutually independent features. Each feature is extracted by a convolution operation with the view of features produced by the previous layer. Thus, the standard convolutional layer does not allow feature reuse within the layer since each convolution operation has no knowledge of features extracted by other convolution operations of the same layer. This parallel manner of convolution operations results in lack of hierarchy and depth of the produced representation.

To address this drawback, we propose sequential convolutional (SeqConv) layers that sequentialize the definition of standard convolutional layers defined as follows to produce representations with hierarchal features:

\[
f^{(i)}(x) = \phi \left( \sum_{j=1}^{m+i-1} w^{(i)}_j * f^{(j)} + \beta^{(i)} \right) \]

Our proposed SeqConv layer with \( n \) output features consists of \( n \) convolution operations in sequence. Each feature is extracted with the view of earlier features not only from the previous layer, but as well from the current layer. This sequential fashion of convolution operations thoroughly encourages in-layer feature reuse that features extracted by earlier convolution operations are shared with subsequent convolution operations of the same layer. Our proposed layer also introduces hierarchy to the extracted features and significantly increases the depth of the produced representation as the layer can be decomposed to \( n \) standard convolutional layers, each with a single output map. Based on this decomposed view of our proposed layer, we find the layer is closely related to DenseNet [8] that the SeqConv layer is an extreme case of DenseNet with growth rate \( k \) set to 1.

### 3.2. Windowed Variant

It can be inferred from eq.2 that the number of parameters for a SeqConv layer grows at the asymptotic rate of \( O(n^2) \), where \( n \) is the number of output features. The same conclusion has been reported by Zhu et al. [12] for DenseNet, which aligns with our analyses since our proposed layer is an extreme case of DenseNet. It is discussed in [12] that with this asymptotic quadratic growth rate, a significant portion of the network devotes to processing previously seen features and many skip connections have average absolute weights of convolution filters close to zero. To rephrase that for SeqConv layers, although dense connections are adopted within the layer to extensively encourage feature reuse, it is hard to achieve full utilization of aggregated features for later convolution operations. This is mainly because remotely early features and the information they carry have been abundantly exploited by earlier convolution operations.

Hence to balance between parameter efficiency and the representational ability of the layer, as well preserving the hierarchy of the extracted features, we further propose a windowed variant of SeqConv layer to remove redundant skip connections within the layer. It is defined as follows:

\[
f^{(i)}(x) = \phi \left( \sum_{j=i-m}^{i-1} w^{(i)}_j * f^{(j)} + \beta^{(i)} \right) \]

Note that eq.3 is equivalent to applying a rectangular window function \( \Omega \) across the channel dimension on eq.2.
\[ \Omega^i(x) = \begin{cases} 1, & i - m \leq x \leq i - 1 \\ 0, & \text{otherwise} \end{cases} \]  

(4)

\[ \phi \left( \sum_{j=-m}^{i-1} w_j^{(i)} \ast f^{(j)} + \beta^{(i)} \right) \]

(5)

Hence the term windowed sequential convolutional (WSeqConv) layer. Assuming input features \( f^{(1)}, \ldots, f^{(m)} \) are sequentially extracted by a preceding SeqConv or WSeqConv layer, each convolution operation in a WSeqConv layer has the view over a truncated representation consisting of \( m \) most recently extracted features. Remotely early features that fall out of view are discarded as they have been abundantly utilized by earlier convolution operations and are considered of little contribution to the current representation. By erasing skip connections to these redundant features, the number of parameters for a SeqConv layer could be reduced to the same number of that for a standard convolutional layer.

In contrast to a standard convolutional layer that produces a new representation from the previous one at once, a WSeqConv layer allows smooth transition between the previous representation and the produced representation. A progressive updating mechanism is enabled that hierarchal features of the representation are updated in a first-in-first-out manner. Each time the most preceding feature would be removed from the representation and a most recent feature would fill in. The layer goes through multiple intermediate states before it ultimately reaches the produced representation. It thus enhances the representational ability of the layer.

### 3.3. Progressive Growing

We implement progressive growing by introducing a smooth fade-in transition with a real valued gate \( \alpha \) while training. Depending on the nature of the module that is being introduced to the network, it is practiced in two different forms. Let \( F \) denote each module of the current network, the forward propagation is defined as:

\[ F_n(\cdot \cdot \cdot F_2(F_1(x)) \cdot \cdot \cdot) \]  

(6)

where \( x \) denotes the input. For a plain module \( G \) introduced to the network placed after \( F_i \),

\[ F_n(\cdot \cdot \cdot F_{i+1}(G(F_i(\cdot \cdot \cdot F_1(x)) \cdot \cdot \cdot))) \cdot \cdot \cdot \]  

(7)

we apply the gate as follows to smoothly integrate \( G \) to the network.

\[ F_n(\cdot \cdot \cdot F_{i+1}(\alpha \cdot G(\cdot \cdot \cdot F_1(x)) \cdot \cdot \cdot) + (1 - \alpha) \cdot F_i(\cdot \cdot \cdot F_1(x)) \cdot \cdot \cdot)) \]  

(8)

As for a residual module \( H \),

\[ F_n(\cdot \cdot \cdot F_{i+1}(\alpha \cdot H(F_i(\cdot \cdot \cdot F_1(x)) \cdot \cdot \cdot)) + F_i(\cdot \cdot \cdot F_1(x)) \cdot \cdot \cdot)) \]  

(9)

we place the gate on the transformation branch that has module \( H \) on it.

\[ F_n(\cdot \cdot \cdot F_{i+1}(\alpha \cdot H(F_i(\cdot \cdot \cdot F_1(x)) \cdot \cdot \cdot)) + F_i(\cdot \cdot \cdot F_1(x)) \cdot \cdot \cdot)) \]  

(10)

\( \alpha \) is initialized to 0 and grows linearly to 1 until the fade-in transition finishes. The gate is then removed from the current module and the training continues in an end-to-end manner until a new module is introduced to the network. The training starts form a basic network with minimal number of modules and the growing repeats until all modules of the final network are integrated to the current network.

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