Is each layer non-trivial in CNN?

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Abstract
Many convolutional neural network (CNN) models have achieved great success in many fields. The networks get deeper and deeper. However, is each layer non-trivial in networks? To answer these questions, we propose to replace the convolution kernels with zeros. We compare these results with baseline and show that we can reach similar or even same performances. Although convolution kernels are the cores of networks, we demonstrate that some are trivial and that these layers are regular.

Introduction
The structures of neural networks get more and more complex. There are two basic forms: short-connection and no-connection. Long-connection: UNet (Ronneberger, Fischer, and Brox 2015). SegNet (Badrinarayanan, Kendall, and Cipolla 2017). Short-connection: ResNet (He et al. 2015). No-connection: VGG (Simonyan and Zisserman 2014). Long-connection can be seen as a special no-connection in local area. First, we define the non-triviality by the changes of result after convolution kernels replacing by 0. It is obvious that each layer in no-connection form is important. However, we believe many layers in ResNet are trivial.

The main contributions of this paper can be summarized as: (1). We demonstrate some layers are trivial in ResNet. (2). We demonstrate the feature decomposition layers are non-trivial, while the rest are trivial.

Analysis the convolution kernels of ResNet replaced by 0
ResNet residual unit can be formulated as:
\[ x_{l+1} = \sigma(BN(x_l + BN(\sigma(BN(x_l \ast w_{l}^1) \ast w_{l}'))) \]
\[ x_{l+1} = \sigma(BN(x_l \ast w_{l}^{1+1}) + BN(\sigma(BN(x_l \ast w_{l}')) \ast w_{l}'')) \]

Replacing one of the convolution kernels in residual unit with 0 can be written as:
\[ x'_{l+1} = \sigma(x_l + BN(\sigma(BN(x_l \ast 0)) \ast w_{l}''')) \]
\[ x''_{l+1} = \sigma(x_l + BN(\sigma(\beta') \ast w_{l}'')) \]
\[ x'''_{l+1} = \sigma(x_l + BN(\sigma(BN(x_l \ast w_{l}')) \ast 0)) \]
\[ x_l = \sigma(x_l + BN(BN(\sigma(\beta''') \ast w_{l}''')) \]

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Experiment
We choose ResNet34 and PSPNet-ResNet34 (Zhao et al. 2016) conduct classification task and image segmentation task on Cifar-10 (Krizhevsky 2009) and T1 (Fahmy et al. 2019). The baseline are 84% and 87%. We conduct 3 groups of experiments. First, we replace each layer’s convolution kernel with 0. Second, we replace all convolution kernels with 0 in the same layer block (A continuous layer with the same feature maps is a layer block) except for the feature decomposition layers and adjacent layers. Third, we replace feature decomposition layers of short-connection with 0.

Results
The classification results of Cifar-10: Figure 1 and Table 1.2. The segmentation results of T1: Figure 2 and Table 3.4.

Table 1: Cifar-10: Replace all residual layer convolution kernels with 0 except for the first 2 layers in Layer block 1-4

| Layer block | ACC(%) |
|-------------|--------|
| Layer block 1 | 0.51   |
| Layer block 2 | 0.61   |
| Layer block 3 | 0.83   |
| Layer block 4 | 0.84   |

According to the structure of ResNet and the result of Figure 1 and Figure 2, the feature decomposition layers’ convolution kernels are non-trivial, while the rest are trivial.
Figure 1: Cifar-10: Replace the \textit{ith} layer convolution kernel with 0.

Table 2: Cifar-10: Replace feature decomposition layers of short-connection with 0.

| Layer block   | ACC(%) |
|---------------|--------|
| Layer block 2 | 0.28   |
| Layer block 3 | 0.33   |
| Layer block 4 | 0.16   |

Figure 2: T1: Replace the \textit{ith} layer convolution kernel with 0.

Table 3: T1: Replace all residual layer convolution kernels with 0 except for the first 2 layers in Layer block 1-4.

| Layer block   | Dice   |
|---------------|--------|
| Layer block 1 | 0.82   |
| Layer block 2 | 0.86   |
| Layer block 3 | 0.82   |
| Layer block 4 | 0.00   |

Table 4: T1: Replace feature decomposition layers of short-connection with 0.

| Layer block   | Dice   |
|---------------|--------|
| Layer block 2 | 0.00   |
| Layer block 3 | 0.00   |
| Layer block 4 | 0.00   |

1 and Table 3 also prove our conjecture. Table 2 and Table 4 demonstrate the feature decomposition layers of short-connection are non-trivial.

**Discussion**

We argue that ResNet is a continuous process of feature decomposition and information storage. ResNet shows different changes in non-trivialness at the front and back of the network for different tasks. Because the classification task needs to learn enough information about the global abstract feature, if enough information is learned in the front, the back is no longer non-trivial. Segmentation requires information for each pixel, so the back layers are non-trivial.

**Conclusion**

There are redundant parameters in some networks, not all layers of the network are non-trivial, or some layers may not be needed when the network parameters have learned enough information. The feature decomposition layers and identity mapping are important. The feature decomposition layers are responsible for the feature decomposition, the identity mapping is responsible for the information storage, and the residual layers are responsible for the adjustment of the feature to make it fit the final target. According to the above conclusion, we can eliminate unnecessary layers in the ResNet and improve the training efficiency on the premise of ensuring the performance.

**References**

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