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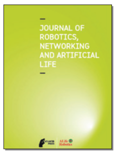

Research Article

Network with Sub-networks: Layer-wise Detachable Neural Network

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ABSTRACT

In this paper, we introduce a network with sub-networks: a neural network whose layers can be detached into sub-neural networks during the inference phase. To develop trainable parameters that can be inserted into both base-model and sub-models, first, the parameters of sub-models are duplicated in the base-model. Each model is separately forward-propagated, and all models are grouped into pairs. Gradients from selected pairs of networks are averaged and used to update both networks. With the Modified National Institute of Standards and Technology (MNIST) and Fashion-MNIST datasets, our base-model achieves identical test-accuracy to that of regularly trained models. However, the sub-models result in lower test-accuracy. Nevertheless, the sub-models serve as alternative approaches with fewer parameters than those of regular models.

1. INTRODUCTION

Deep Neural Networks (DNNs) have gained attraction in recent years owing to their ability to provide state-of-the-art performance in various applications, including image recognition, object detection, and speech recognition. However, deploying DNNs on mobile devices is challenging because the mobile devices have diverse specifications. This raises the question of how to effectively design DNNs given mobile phone specifications. To address this question, two main aspects of DNNs can be optimized.

The first aspect is the performance of DNNs. In general, there is assumption that increasing the number of layers of a DNN leads to better the model performance. One widely used example is the trend observed in the number of layers in the ImageNet Large Scale Visual Recognition Competition (ILSVRC). AlexNet [1], the model that won ILSVRC-2012, consists of eight layers, while ResNet [2], the winner of ILSVRC-2015, contains 152 layers. Compared with AlexNet, ResNet reduces the top-5 test error rate from 15.3 to 3.57.

Although a larger number of layers may reduce the test-error rate of a model, this has a trade-off with the second aspect of DNNs: latency. A larger number of layers in a DNN signifies that there is a larger number of parameters to compute. This increases the memory footprint, which is crucial for a mobile device. A larger number of parameters also leads to an increase in the overall power consumption due to refreshing, moving, and computing data.

To solve this optimization problem, we can select a model that achieves real-time performance given a mobile device specification. However, if the user prefers performance over latency, this method does not satisfy the user demand. Another approach is to allow the user to select the preference and subsequently match this preference to the most suitable model. However, this method has a larger memory footprint due to storing various models on the mobile device. To satisfy user selectivity in both performance and latency without a large memory footprint, we propose a *Network with Sub-networks* (NSN), which is a DNN whose layers can be removed without significantly reducing in the performance.

Generally, if one layer of a DNN is detached during inference, the performance of the model is reduced. To explain our hypothesis, we compare a DNN to a feature extraction model. In the first layer, the model extracts low-level features, while in the last layers, it recombines the low-level features into high-level features. This process creates a dependency relationship between each layer.

In this study, we propose a training method that allows an NSN to dynamically adapt to the removal of weight layers. The two processes in this method are called *copying learn-able parameters* and *sharing gradient*, and both are designed to optimize the learn-able parameters for models, both with and without a layer to be detached.

2. RELATED WORK

In this section, we describe two related studies that are similar to our proposed method.

2.1. Slimmable Neural Network

Slimmable Neural Networks (SNNs) [3] greatly influenced this research. If our proposed method adds or removes weights in the depth-wise or layer-wise direction, SNNs append or detach weights

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in the width-wise direction. The discrete range of possible widths of networks must be predefined as the switch. The main research problem in this study is that mean and variance of activations produced from different-width layers are generally diverse. SNNs propose *switchable batch normalization* for each possible width to correct the mean and variance of SNNs.

2.2. BranchyNet

BranchyNet [4] is a neural network that can reduce the number of floating point operations during inference depending on the complexity of the input data. In BranchyNet, the output activations between immediate layers of neural networks, are connected with a branch, which consists of the layers and a classifier. If the prediction of input data of that branch classifier has higher confidence than a predefined threshold, then the output of the model is produced early from that branch. However, if the confidence is lower than the predefined threshold, then the features are passed to the deeper layers. BranchyNet can thus automatically detect complex data and determine whether to process these data further into the deeper layers or produce an early prediction through the branch.

3. NETWORK WITH SUB-NETWORKS

Network with sub-networks are designed to provide the layer-wise detachability for DNNs. Specifically, NSNs insert a smaller model into a larger model. Therefore, if the layers of the larger model are detached, the larger model becomes the smaller model. To implement this concept for DNNs, NSNs must have the same learning parameters for the smaller and larger models during both forward and backward propagation.

There are two types of models in NSNs: a base-model and sub-model. The base-model is defined as a DNN with n hidden layers, where n is a positive integer greater than zero. From the base-model, we can create n sub-models. Each sub-model is mapped with $0, \ldots, n-1$ hidden layers. With this concept, the largest sub-model takes all of the layers of the base-model except the input layer. Furthermore, the second largest sub-model takes all of the layers of the largest sub-model except the input layer. This can be performed repeatedly until we obtain the sub-model with no hidden layers.

In the next section, we describe two processes in our purposed method: *copying learn-able parameters* and *sharing gradient*. These processes are designed to be applied repeatedly in every mini-batch training. In addition, they are designed to enforce the similarity of weight values between the base-model and sub-model during forward and backward propagation.

3.1. Copying Learn-able Parameters

The goal of *copying learn-able parameters* is to insert the sub-model into the base-model. To ensure the similarity between the weight and bias parameters for each model, the weights and biases are copied from the smaller sub-model to the larger sub-model. This process is repeated up to the base-model, as express in Equation (1) and Figure 1. Here, $W_{o,m}$ is a weight variable, o is an integer indicating the order of the layer, and m is an integer indicating the model number.

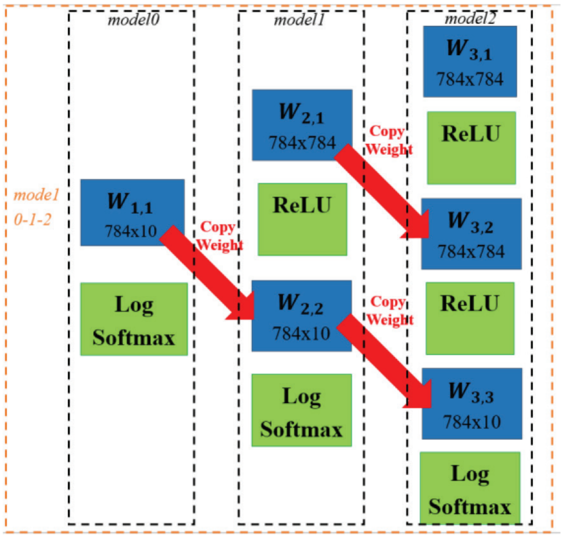

Figure 1 | *Sharing gradient* in *model0-1-2* section. The gradients are shared from the sub-model to the base-model, pair by pair. Only the input layer of $W_{3,1}$ is regularly updated without sharing.

$$W_{o+1,m+1} = W_{o,m} \tag{1}$$

After applying this process, if we remove the input layer of the base-model with the non-linear activation function, the base model becomes the sub-model.

3.2. Sharing Gradient

Sharing gradient is designed to constraint the learnable-variables to able to be perform in two or more networks. First, all of the models are forward propagated. During back propagation, the gradients from each model are collected separately. Each model is paired from the sub-model without any hidden layer to the sub-model with a hidden layer. This process is repeated until the sub-model with $n-1$ hidden layers is paired to the base-model. The gradients from each model's pair are averaged, and the weights and bias are updated. The *sharing gradient* process is expressed in Equation (2) and Figure 2 where l_r is the learning rate and L is the loss function.

$$W_{m,o} = W_{m,o} - \frac{l_r}{2}\left(\frac{\partial L_m}{\partial W_{m,o}} + \frac{\partial L_{m+1}}{\partial W_{m+1,o+1}}\right) \tag{2}$$

The reason for using the *sharing gradient* process for only a pair of models is that when sharing more than a gradient pair, the optimization becomes too complex. In this case, the performance of the NSN does not reach the optimal point. Nonetheless, there is only an input layer of the base-model that does not have a pair. This input layer is updated with regular back propagation without sharing gradient.

4. EXPERIMENTS

Experiments were conducted using a hand-written digit image dataset, MNIST [5], and fashion product image dataset, Fashion-MNIST [6]. The MNIST and Fashion-MNIST datasets both

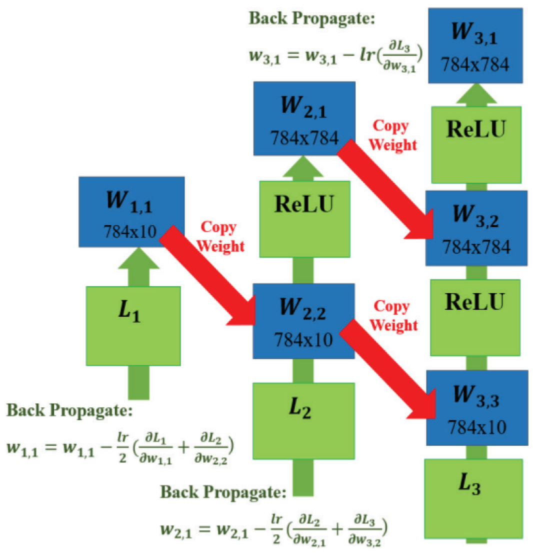
Back Propagate:
$w_{3,1} = w_{3,1} - lr(\frac{\partial L_3}{\partial w_{3,1}})$
$W_{3,1}$ 784x784
$W_{2,1}$ 784x784
Copy Weight
ReLU
$W_{1,1}$ 784x10
Copy Weight
ReLU
$W_{3,2}$ 784x784
L_1
$W_{2,2}$ 784x10
Copy Weight
ReLU
$W_{3,3}$ 784x10
Back Propagate:
$w_{1,1} = w_{1,1} - \frac{lr}{2}(\frac{\partial L_1}{\partial w_{1,1}} + \frac{\partial L_2}{\partial w_{2,2}})$
L_2
L_3
Back Propagate:
$w_{2,1} = w_{2,1} - \frac{lr}{2}(\frac{\partial L_2}{\partial w_{2,1}} + \frac{\partial L_3}{\partial w_{3,2}})$

Figure 2 | Illustration of a *network with sub-networks* and the *copying learn-able parameters* process. Here the base-model is a two hidden layer DNN and the sub-model is a one hidden layer DNN and a softmax-regression model. $\boldsymbol{L}_m$ is the loss function of the m models. In the figure, the weight, $\boldsymbol{W}_{o,m}$ follows with the size of the weight array. *Copying learn-able parameters* leads $\boldsymbol{W}_{1,1}$, $\boldsymbol{W}_{2,2}$ and $\boldsymbol{W}_{3,3}$ to have exactly the same weight.

consisted of 60,000 training images and 10,000 test images. Each image in both datasets was a 28 × 28 pixel grayscale image. Each image pixel was pre-processed into the range [0, 1] by dividing all pixel values by the maximum intensity pixel value, 255.

A Multi-layer Perceptron (MLP) was applied with rectified linear unit as the non-linear activation function. Only the last layer was applied with log-softmax with the cost function as cross-entropy loss. The input layer of the MLP was applied with a dropout [7] rate of p = 0.8. The hidden layers were applied with a dropout rate of p = 0.5. For softmax-regression, we did not apply dropout in the model, as it was already under-fitting. The models were further regulated using the $L2$-weight penalty.

We applied Stochastic Gradient Descent (SGD) with momentum [8] of $\alpha = 0.9$. We applied with slightly different format of SGD with momentum comparing to standard framework. From Tensorflow [9], a neural networks framework, the format of SGD with momentum is defined in Equation (3), where V is the gradient accumulation term, t is the batch iteration step, and G is the gradient at $t + 1$. Our format of SGD with momentum is illustrated in Equation (4). After V is determined, both formats use Equation (5) to update the weight W.

$$V_{t+1} = \alpha V_t + G \tag{3}$$

$$V_{t+1} = \alpha V_t + (1 - \alpha)G \tag{4}$$

$$W_{t+1} = W_{t+1} - l_r(V_{t+1}) \tag{5}$$

Network with sub-networks performed better with our format of SGD with momentum than the regular format or TensorFlow format at $\alpha = 0.9$. We speculate that NSNs required a higher proportion of the gradient accumulation V to converge than with the current gradient G. However, with regularly trained DNNs, our format of SGD with momentum performed slightly worse in term of test accuracy. To perform a fair comparison between both types of models, the regularly-trained models were trained with Equation (3), TensorFlow format SGD with momentum. Our proposed method models were trained with Equation (4), our format of SGD with momentum. We set the training batch to 128. Each model trained for 600 epochs. We reported the best test accuracy that occured during the training. The initial learning rate was $l_r = 0.3$ and was stepped down by one third every 200 epochs.

The experiment consists of two sections. The first section is *model0-1,* or the base-model as an MLP with a hidden layer *(model1)* with a sub-model as the soft-max regression *(model0)*. The second section is *model0-1-2,* or the base-model as a two hidden layers MLP *(model2)*. The sub-models are an MLP with a hidden layer *(model1)*, and the soft-max regression *(model0)*. An illustration of *model0-1-2* is presented in Figure 2. The baseline models, which are trained regularly, are referred to as *ref-model* followed by the number of hidden layers. For example, *ref-model1* is the baseline MLP with one hidden layer. The MNIST results of the baseline models are presented in Table 1, while the Fashion-MNIST results of the baseline model are presented in Table 2.

4.1. Model0-1

An MLP with a hidden layer was used as the base-model, and the sub-model was softmax-regression. In the following experiments, we prioritized the base-model performance. We reported the test accuracy of all models in the epoch that had the best test accuracy of the base-model. The *model0-1* results are displayed in Tables 3 and 4. We applied the regularization parameter 9×10^{-6} at the base-model.

Compared with *ref-model1* and *model1*, the test accuracy of *model1* was lower on both datasets. This indicates that our purposed method negatively affected the performance of the model due to the ability to detach the layers.

Table 1 | Results of MNIST classification of base-line models

	Test accuracy	Number of parameters	Regularization parameter
ref-model2	0.9886	1.24 M	1×10^{-5}
ref-model1	0.9882	0.62 M	5×10^{-6}
ref-model0	0.9241	7.85 K	9×10^{-5}

Table 2 | Results of Fashion-MNIST classification of base-line models

	Test accuracy	Number of parameters	Regularization parameter
ref-model2	0.9089	1.24 M	1×10^{-5}
ref-model1	0.9085	0.62 M	5×10^{-6}
ref-model0	0.8457	7.85 K	9×10^{-5}

Table 3 | Results of MNIST classification of *model0-1*

	Test accuracy	Number of parameters
model1	0.9857	0.62 M
model0	0.9253	7.85 K

Table 4 | Results of Fashion-MNIST classification of *model0-1*

	Test accuracy	Number of parameters
model1	0.9062	0.62 M
model0	0.8429	7.85 K

Table 5 | Results of MNIST classification of *model0-1-2*

	Test accuracy	Number of parameters
model2	0.989	1.24 M
model1	0.9843	0.62 M
model0	0.926	7.85 K

Table 6 | Results of Fashion-MNIST classification of *model0-1-2*

	Test accuracy	Number of parameters
model2	0.912	1.24 M
model1	0.9047	0.62 M
model0	0.8402	7.85 K

4.2. Model0-1-2

An MLP with two hidden layers was used as the base-model. The sub-models were an MLP with a hidden layer and softmax-regression. The *model0-1-2* results are displayed in Tables 5 and 6. We applied the regularization parameter 9×10^{-5} for the base-model.

The difference in the test accuracy of *model1* and *model2* indicates the bias of our proposed method toward the base-model. We speculate this bias may be a result of the *sharing gradient* process. All of the gradients that the sub-models received were averaged from multi-models. However, our base-model had an input layer that was updated only from the gradient from the model itself as shown in Figure 2. This layer, which the sub-models lack, causes an advantage for the base-model.

On both datasets, compared with the results of *model1* in the *model0-1* section and *ref-model1*, our *model2* in the *model0-1-2* section contrastingly outperformed *ref-model2* by a small margin. We hypothesize that the constraints of our proposed method may cause regularization in the models. In the case of the *model1* in the *model0-1* section, this regularization effect may have been excessively strong, negatively affecting the performance. Nevertheless, in the case of *model2* in the *model0-1-2* section, the regularization positively affected the accuracy.

The experiments on both datasets, indicated that the results on each dataset displayed similar trends. NSNs require a considerable amount of time for training and hyper-parameter tuning due to the number of base-model and sub-models. With our experimental settings, for an MLP with two hidden layers, the time required for training and hyper-parameter tuning is not high. However, the time may increase when NSNs are used with the larger model and dataset.

5. CONCLUSION

In this paper, we propose NSNs, DNNs whose layers can be removed on the fly. NSNs consist of a base-model and sub-models. To assemble sub-models into the base-model, a method consisting of *copying learn-able parameters* and *sharing gradient* is introduced. NSNs were tested in a small-scale experiment with a several hidden layers MLP on the MNIST and Fashion-MNIST datasets. The results from both datasets indicated that our base-model achieved identical test accuracy to that of regularly trained models. However, the sub-models exhibited worse accuracy than that of regularly trained models.

In future work, we plan to explore NSN techniques with a convolutional neural network, which provides better performance than that of MLP, especially in image recognition tasks. To further demonstrate the robustness of our proposed method, the larger dataset will be used in future work. We also plan to address the time problem by detaching, multi-layers per sub-model instead of using layer-wise detachment. This can reduce the number of sub-models to train and reduce the hyper parameter tuning.

CONFLICTS OF INTEREST

The authors declare they have no conflicts of interest.

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