Shift-based Primitives for Efficient Convolutional Neural Networks

Huasong Zhong∗2 Xianggen Liu∗2 Yihui He∗1 Yuchun Ma2
1Carnegie Mellon University 2Tsinghua University
he2@andrew.cmu.edu {zhongs16,liuxg16,myc}@mails.tsinghua.edu.cn

Abstract

We propose a collection of three shift-based primitives for building efficient compact CNN-based networks. These three primitives (channel shift, address shift, shortcut shift) can reduce the inference time on GPU while maintains the prediction accuracy. These shift-based primitives only moves the pointer but avoids memory copy, thus very fast. For example, the channel shift operation is 12.7× faster compared to channel shuffle in ShuffleNet but achieves the same accuracy. The address shift and channel shift can be merged into the point-wise group convolution and invokes only a single kernel call, taking little time to perform spatial convolution and channel shift. Shortcut shift requires no time to realize residual connection through allocating space in advance. We blend these shift-based primitives with point-wise group convolution and built two inference-efficient CNN architectures named AddressNet and Enhanced AddressNet. Experiments on CIFAR100 and ImageNet datasets show that our models are faster and achieve comparable or better accuracy.

1. Introduction

Convolutional neural networks (CNNs) have been firmly established as the prevalent methods in image understanding problems such as image classification, image caption, and object detection [18, 9, 4, 25, 21]. The high accuracy is at the cost of increased computation time and memory usage. Real-time processing is vital in some applications such as self-driving cars and speech recognition, where low latency, small storage, and an appropriate accuracy are required [12, 37, 23]. Thus producing fast and energy efficient CNNs are very well motivated.

There are a number of recent efforts aimed at reducing CNN model size and computational requirements while retaining accuracy. For example, MobileNets [12] propose a family of lightweight neural networks based on depthwise separable convolution. ShuffleNet [37] utilizes pointwise group convolution and channel shuffle to reduce parameters and FLOPs. To further decrease parameters, ShiftNet [34] adopts the shift operation on a feature map as an alternative to spatial convolution. Unfortunately, smaller parameter size or number of FLOPs do not always lead to direct reduction of actual inference time, since many core operations introduced by these state-of-the-art compact architectures are not efficiently implemented for GPU-based machines. For instance in MobileNet, depthwise separable convolutions only consume 3% of the total FLOPs and 1% of the parameters, but they constitute 20% of the total inference time. Channel shuffle and shortcut connections in ShuffleNet do not require any FLOPs or parameters; however, these operations still constitute 30% of the total inference time. Similarly, in ShiftNet the feature map shift is parameter-free and FLOP-free, but it occupies 25% of the total inference time. Although MobileNet and ShuffleNet have roughly the same FLOPs, the latter requires two times more inference time. More details are shown in Table 1. Therefore, in practice, neither reducing parameters nor FLOPs ensures a reduction in inference time. Based on the above concerns, we propose a collection of three shift primitives (Fig. 1) for CNN-based compact architectures to reduce parameters, FLOPs and inference time simultaneously for GPU-based machines: 1) the channel shift that acts as a faster alternative to the channel shuffle operation. 2) the address shift that efficiently collects spatial information at no cost of actual inference time. 3) the shortcut shift provides a fast channel concatenation to realize residual connection through allocating continuous memory space in advance, but does not consume inference
time. This collection of primitives mainly involves moving pointers in continuous memory space to minimize actual memory copy and completely avoid floating-point operations, which leads to actual speedup. We combined these collection of shift primitives together with point-wise group convolution to build two compact architectures named AddressNet and Enhanced AddressNet respectively. Experiments on CIFAR100 and ImageNet datasets demonstrate that our models can achieve equal or superior accuracy with less inference time.

2. Related Work

Deep convolutional neural networks provide the best results on many computer vision tasks [33, 21]. However, deep neural networks are not always computationally efficient and there appears to be redundant computation in most models. The desire to deploy accurate deep neural networks in low latency applications motivates the search for methods to decrease model size and operations (parameters, FLOPs), and, more generally, overall inference time. Recently [15] surveyed current approaches to designing small, energy efficient deep neural nets. Here we take another approach and note that these approaches can be categorized into either compressing pre-trained models or training small models directly.

2.1. Compressing Neural Networks

We outline four types of widely used methods for model compression. First, pruning is an approach that reduces redundant parameters that are insensitive to the accuracy [11, 10, 22, 13, 7]. Second, low-rank factorization, which estimates the informative parameters by matrix decomposition, has been used in [26, 4, 32, 38]. Thirdly, quantization and binarization [5, 35, 24] can reduce the number of bits to represent each weight. Lastly, knowledge distillation [11, 27] is a method that trains a small neural network by distilling knowledge of a large model. We adopt a different approach from these because we design compact network directly instead of compressing a pretrained network.

2.2. Designing compact layers and networks

There has been increasing interest in building efficient and small models, e.g., [17, 35, 24, 20]. In ResNet [9], the bottleneck structure has been proposed to decrease the channel numbers before and after a $3 \times 3$ convolution. ResNeXt [36] introduces a multi-branch and homogeneous architecture to decrease FLOPs and improve accuracy. The fire module is introduced in SqueezeNet [16] where a fraction of $3 \times 3$ convolutions is replaced by $1 \times 1$ convolutions to reduce parameters. GoogLeNet [29] is a well-designed network with a complex structure to reduce computation and increase accuracy. More generally, in order to reduce the amount of parameters and FLOPs, the following operations may be used:

**Depthwise Separable Convolution.** The initial work on depthwise separable convolution is reported in Sires’s thesis which is inspired by prior research from Sifre and Mallat on transformation-invariant scattering [28]. Later, Inception V1 and Inception V2 used it as the first layer. After that, it was adopted by MobileNet to design network architecture for mobile devices. The depthwise separable convolution applies a single filter to each input channel. While this operation can reduce computation in theory, in practice it is hard to implement a depthwise separable convolution layer efficiently because a fragmented set of memory footprints are required. Even though there are few FLOPs in a layer, it is still very expensive for inference time as Table 1 shows, and this drawback is also mentioned in [2, 37].

**Feature Map Shift.** ShiftNet [34] presents a parameter-free, FLOP-free shift operation as an alternative to spatial convolution. It can be viewed as a special case of depthwise separable convolution that results from assigning one of the values in each $n \times n$ kernels to be 1 and the rest to be 0. It can not be implemented efficiently either by depthwise separable convolution. The address shift operation, based on pointer shifting, varies from ShiftNet obviously. To avoid confusion, in this paper, we use the term feature map shift to refer specifically to the method proposed by ShiftNet.

**Pointwise Group Convolution and Channel shuffle.** ShuffleNet [37] adopts pointwise group convolutions to reduce parameters and FLOPs, but it also brings the side effect of blocking information flow between group convolutions. Channel shuffle is proposed to address this problem. This is also difficult to implement efficiently since a channel shuffle will move the entire set of channels into another memory space.

**Residual Connection.** Residual connections are introduced by He et al [9] to enable very smooth forward/backward propagation. There are two categories of shortcut connection operations including identity mapping and channel concatenation. Both of them are used in ResNet and ShuffleNet. DenseNet [14] concatenates all previous output of layers before the activation function.

3. Approach

In this section, we introduce the three shift primitives which we find sufficient for producing fast CNN models. We then fuse these shift primitives together with pointwise group convolution to create two efficient modules and from these we create novel deep neural networks.

3.1. Channel Shift

Group convolution can reduce the computational complexity of ordinary convolution. For example, AlexNet [19] used group convolutions to divide the feature map across
two GPUs. More generally, a group convolution with group number $G$ reduces the FLOPs and parameter size by a factor of $G$. However, stacking group convolution layers together can block the information from flowing among groups and reduce accuracy. To mitigate this, the channel shuffle operation in ShuffleNet [37] is adopted to fuse features among different groups. As illustrated in the left panel of Figure 2, channel shuffle is time-consuming since it requires moving feature maps to another memory space. Note that moving data is much more expensive in terms of latency and energy consumption compared with floating point operations [6]. In contrast, shifting the pointer, or the physical address to load data, is free. Therefore, we propose the channel shift primitive to utilize pointer shift and minimize actual data movement to reduce the time and energy.

The channel shift primitive blends the information in adjacent channels by shifting all the channels along a certain direction. Taking four-group convolution for example, as shown in Fig. 2(b), a predefined storage space (i.e. the two yellow grids) is allocated at the end of the feature map, and half of the first group is moved there. Then, the pointer is shifted backwards by two grids (half of a group). Note that this primitive does not involve any data movement. When the second group convolution ($GConv2$) fetches data from the shifted address, each group in $GConv2$ can get data from two groups of input feature map. Moving data circularly, a single layer of channel shift fuses information between adjacent groups and stacking multilayers can fuse more. This is not equivalent to channel shuffle method, but our experiment show that channel shift lead to similar accuracy. Furthermore, compared to channel shuffle whose mapping is more complex and requires much more actual data movement, channel shift is needs $8 \times$ less data movement in this case because it only needs to copy 2 units of data while channel shuffle needs to copy 16 units, as illustrated in Figure 2.

### 3.2. Address Shift

Modern convolutional neural networks usually consist of convolution layers with different kernel sizes and channels. Nevertheless, as 90% or more time is spent in convolutions, improving the process of convolutions is attractive. Fortunately, feature map shift can provide the equivalent function of spatial convolutions with zero FLOPs and no parameters. Despite all this, feature map shift in ShiftNet [34] still consumes inference time heavily. In order to solve this problem, we propose the address shift primitive and this will be detailed in the following.

Figure 3 presents address shift primitives in four different directions, where A stands for values from adjacent feature map, and the black arrow denotes the address of feature map pointer.

![Figure 2](image1.png)

**Figure 2.** The computation diagrams of channel-shuffle and channel-shift, both with two stacked convolution layers. a): channel shuffle layer with the same number of groups. Input channels are fully mixed when $GConv2$ takes data from different groups after $GConv1$, and each colored arrow denotes copying data one time. b): channel shift layer, where the channels are shifted circularly along a predefined direction and there the process at most spends two units to copy data, thus $8 \times$ less memory movement (in this example) than channel shuffle.

![Figure 3](image2.png)

**Figure 3.** The implementation of address shift in four directions, where A stands for values from adjacent feature map, and the black arrow denotes the address of feature map pointer.
Thus we can just use the boundary, where the feature map shift will lead to 0-padded boundaries, but address shift will have non-zero boundaries. In our experiment however, we found this nuance does not have any noticeable effect to the network’s accuracy.

Based on the four basic address shift operations (up, down, left, right), we can compose arbitrary shift patterns (such as up-left). In practice, the cost of this operation is still expensive in inference, since the number of possible shift directions grows quadratically with respect to kernel size (3x3 kernel: 9 possible directions; 5x5 kernel: 25 possible directions), as explained in [34]. Inspired by convolution decomposition in [30], 3x3 convolution can be divided into 1x3 and 3x1 convolution. Similarly, top-left shift direction can be decomposed into top and left shift. With the increasing of channel number, CNNs equipped with address shift operation can fuse all information from each direction. Thus we can just use four fundamental shift directions to represent other directions to simplify the network architecture.

### 3.3. Shortcut Shift

With the success of ResNet, shortcut connections have become common in deeper network architectures. Both addition and concatenation are effective implementation choices, and concatenation performs better according to the analysis in SparseNet [31]. Shortcut connections integrate the lower and detailed information with the higher representation and offers a shorter path for back propagation and channel concatenation does not require any computation, and can therefore lead to faster inference speed than addition.

We propose a further optimization for channel concatenation: a fixed-size space is allocated in advance which places the output of current layer right after the output of the last layer. In other words, our approach can make the output of two layers located in a pre-allocated continuous storage space so that no copy or computation time is spent on channel concatenation. Considering the starting pointer of current output is shifted to the end of last output, we name it “shortcut shift”, in accordance with our naming style. This optimization can be better leveraged on DenseNet [14] which heavily relies on channel concatenation.

#### 3.4. Address-based module

Based on the address shift and channel shift operations described above, we build an Address-based module as a collection of layers in the manner of the bottleneck module in ResNet [9]. As shown in Figure 5(a), we use the pointwise group convolution layer in the beginning. Then the channel shift layer exchanges information among channel groups. Next, the address shift layer mixes spatial information. In the address shift module, we divide the channels into 3 groups, and within each group, the address shift operation moves the data towards four directions of {up, down, left, right}. Finally, we perform another pointwise group convolution to fuse information and match the output channel dimension. Following ShuffleNet [37], we use an additive residual connection if the size of feature map maintains. Otherwise, we use average pooling and concatenation. The first group convolution is followed by batch normalization and non-linear activation function(ReLU) while the second is just followed with batch normalization.

We find that both channel shift and address shift operation can be embedded into the second pointwise group convolution to speed up. Thus we design an enhanced group convolution to realize channel shift, address shift and group convolution together. For simplicity, we set the number of groups to four, each group corresponds to one direction for address shift operation. Also, taking address offset into consideration, as depicted in Figure 5(b), we suggest that shifting left and up (forward offset) are performed in the first two group, and shifting right and down (backward offset) for the last two group. In practice, this design is conducive to implement without memory overflow or extra memory overhead. Thus, we call the Address-based module equipped with the above-sophisticated design as Address-enhanced
Figure 5. Address-based module and Address-enhanced module. a): the unit with pointwise group convolution (GConv), channel shift and address shift, where only the GConv consumes parameters. b): similar to the left one, but different in regard to the second GConv operation in which we embed channel shift and address shift. This is expected to significantly reduce computation.

4. Experiments

As described above, we present a collection of shift operations including channel shift, address shift and shortcut shift, to reduce parameters, FLOPs, and more importantly, actual inference time, while retaining accuracy. In this section, we first build variants of our compact networks, called AddressNet and Enhanced AddressNet, based on the above two basic modules. We then investigate their basic functions by comparing with other primary operations on CI-FAR100 dataset. We then compare the two architectures by comparing with other primary operations on CI-FAR100 dataset. We then compare the two architectures with ShiftResNet [34]. Finally, we use the proposed approaches to modify MobileNet and evaluate it, as well as our own models, on the ImageNet dataset.

In AddressNet and Enhanced AddressNet, a 3x3 convolution is first applied with 36 filters and 16 filters. Then three blocks are stacked with Address-based module and Address-enhanced module on the feature map sizes {32, 16, 8} respectively. The subsampling is performed in the second pointwise group convolution with a stride of 2. An identity map is performed when the adjacent units contain the same feature map size. An average pooling is used to match the shape and double the output channels. The output channel numbers of blocks are {48, 60, 96} and {48, 96, 192} respectively. The network ends with a global average pooling followed by a 100-way fully-connected layer and softmax classifier. Each block contains 3 modules in AddressNet-20 and Enhanced AddressNet-20, 5 modules for AddressNet-32 and Enhanced AddressNet-32, and 7 modules for AddressNet-44 and Enhanced AddressNet-44.

4.1. Implementation details

To improve our experimental results, hyperparameters are fine-tuned with a coarse grid search. Following ShiftResNet, “expansion rate”(ε) is used to scale the number of channels in the intermediate layers. For simplicity, we set the expansion rate to 3 for most experiments on CIFAR100 dataset and the ε for ImageNet is shown in Table 2. On the CIFAR100 dataset, the input image is 32×32. We use a stochastic gradient-descent (SGD) optimizer with mini-batch 128 on 4 GPUs (i.e., 32 per GPU). The weight decay is 0.0005 with momentum 0.9 and training the network for 300 epochs. The learning rate starts with 0.1 and decreases by a factor of 10 after 32k and 48k iterations and a factor of 2 from 64k to 128k in every interval 16k iterations. We adopt the weight initialization of [8]. While on the ImageNet dataset, the input image is randomly cropped from a 256×256 image to 224×224. We start from a learning rate of 0.1 with divided by 10 for every 30 epochs and weight decay of 0.0001. We evaluate the error on the single 224x224 center crop from an image whose shorter side is 256. During testing, we remove all batch normalization (BN) layers because they can be fused into a convolution layer in advance. We implement our network in Caffe framework and test inference time on a single GeForce GTX 1080 GPU for two epochs with a batch size of 1 and report the average performance.

4.2. Shift-based Primitives vs. baselines

In the following experiments, we will first study the equivalence between our proposed operations and their baselines on CIFAR100 dataset.

4.2.1 Channel shift vs. Channel shuffle

Channel fusion is especially critical to the performance of small networks. Channel shift and channel shuffle promote the information fusion to varying degrees. To compare the performance of channel shift and channel shuffle, we replace all channel shifts in AddressNet-32 with channel shuffle and the results is shown in Table 2. The two models achieved the same accuracy, but AddressNet-32 equipped with channel shift is much faster than channel shuffle, with 1.4 times faster in total time and 12.7 times faster in operation time (operation time denotes the average time that the operation consumes). It is quite interesting that the acceleration is larger than theoretical estimation that is described in Section 3.1. This shows advantages of embedding the shift operations: as introduced in Section 3.4, embedding the channel shuffle into group convolutions saves inference time significantly.

4.2.2 Address Shift vs. Feature map Shift

Based on the analysis in the previous section, we argue that some shift directions are redundant given the four basic directions. To validate this, we first replace nine shift directions (kernel size of 3) on feature map with four fundamental shift directions in ShiftResNet network architecture [34]. Secondly, to compare performance between different shift
Table 2. Comparison between Channel shift and Channel shuffle operations conditioned on the same size of parameters and FLOPs. The following two models conform to the architecture of AddressNet-32 and just differ in channel transformation. The total time (ms) means average runtime of the model and operation time (ms) denotes the average time that the operation consumes.

| Model                    | Params | FLOPs | Top1 Accuracy | Total Time | Operation Time |
|--------------------------|--------|-------|---------------|------------|----------------|
| AddressNet-32-shift      | 0.14M  | 37.3M | 71.96%        | 4.8        | 0.15           |
| AddressNet-32-shuffle    | 0.14M  | 37.3M | 71.97%        | 6.5        | 1.9            |
| Speed Up                 | -      | -     | -             | 1.4×        | 12.7×          |

operations, we replace feature map shift with our address shift in the same network architectures to build Address-ResNet. The result is displayed in Table 3. Firstly, we notice that both two combinations of directions achieve nearly the same performance, which demonstrates the shift operation based on four basic directions is adequate for shifting feature map. Secondly, we find both address shift and feature map shift can achieve nearly the same performance. Thirdly, regarding the inference time, the model that uses address shift achieved nontrivial speedup. Thus, this experiment validates our expectation successfully, and in the following experiments, all the models will use address shift with four directions.

4.2.3 Shortcut shift vs. Identity map

The purpose of the shortcut shift operation is to achieve shortcut connections for free. We replace all the identity map layers in Fast AddressNet-20 with shortcut shift operation to build Enhanced AddressNet-20-concat. To prevent over-accumulation of channels in deep layers, we reduce the output channels of current layer to match the output channel of previous residual function and set the expansion rate to four in all layers. This gives similar FLOPs and parameters. The result is shown in Table 4. We notice that they can achieve almost equivalent performance with the similar parameters and FLOPs. However, our shortcut shift does not need to spend any inference time obviously (so we ignore the comparison of inference time).

4.2.4 Address shift vs. Depthwise separable convolution

When the outputs are used in a spatial aggregation context, there is strong correlation between adjacent units which results in much less loss of information during dimension reduction. Thus, depthwise separable convolutions are critical for extraction of spatial features. Address shift naturally derives spatial features in different views, so we integrate address shift into a CNN-style network to test its utility and expressive ability. To evaluate the performance fairly, we choose depthwise separable convolution to design MobileNet-32 whose number of layers is the same as Enhanced AddressNet-32. We follow most of the hyperparameters in Enhanced AddressNet-32 with one exception: the output channels of first convolution and three blocks are 48 and {56, 112, 224} respectively in MobileNet-32. In Table 5, it shows that Enhanced AddressNet-32 can behave better with similar scales of parameters and FLOPs. It indicates that our address shift is equal or superior to depthwise separable convolutions in its expressive ability and capacity to extract the feature of images.

4.3. Performance on CIFAR100

We evaluate AddressNet and Enhanced AddressNet with different depths on the CIFAR100 classification task, and compare it with ShiftResNet architecture. It is reported in [34] that ShiftResNet achieves better accuracy than ResNet with similar architectures, but ShiftResNet requires fewer FLOPs and parameters. We elaborate three variants of AddressNet and Enhanced AddressNet on three different parameter scales and quote the results of ShiftResNet from [34]. The results are shown in Table 6 and visualized in Fig 6. Compared to the best accuracy of ShiftResNet, our model (AddressNet-44) can achieve better performance with 3x fewer FLOPs and 6x fewer parameters. Furthermore, the curves in Fig 6(a) and Fig 6(b) show that our network architectures consistently obtain better accuracy than ShiftResNet in different parameters and FLOPs. In Fig 6(c), it presents that our models can reduce inference time significantly. Also note that the Enhanced AddressNet is always better than AddressNet due to its larger groups and well-designed mechanism for shift operation as described in Section 3.4.

4.4. ImageNet

Based on the above experiments, we have confirmed that our networks outperform ShiftNet [34] on CIFAR100 and the three shift operations can reduce parameters while retaining accuracy. To further assess the scalability and flexibility of our operations, we use our address shift operation to improve MobileNet and show its performance on ImageNet dataset. In our experiments on small models, we modify MobileNet to create Address-MobileNet by doubling the output channel of the first convolution, removing the last 2 ~ 4 layers, and replacing depthwise...
Table 3. Performance of address shift and feature map shift operations following the above comparison method. The four models conform to the architecture of ShiftResNet [34] and just differ in feature map transformation and number of directions.

| Model                  | Params | FLOPs   | Top1 Accuracy | Total time | Operation Time |
|------------------------|--------|---------|---------------|------------|----------------|
| ShiftResNet-four       | 145k   | 22.9M   | 71.80%        | 3.3        | 0.4            |
| ShiftResNet-nine       | 145k   | 22.9M   | 71.86%        | -          | -              |
| AddressResNet-four     | 145k   | 22.9M   | 71.94%        | 3          | 0.3            |
| AddressResNet-nine     | 145k   | 22.9M   | 71.91%        | -          | -              |
| Speed Up               | -      | -       | -             | 1.1×       | 1.3×           |

Figure 6. A more clear comparison between AddressNet and ShiftResNet, summarized from Table 6. These figures show that our network architectures are better than ShiftResNet family members with fewer parameters (a), FLOPs (b) and lower latency (c).

Table 4. Performance of two shortcut connection implementation, following the above comparison method.

| Model                  | Params | FLOPs | Top-1 |
|------------------------|--------|-------|-------|
| Enhanced AddressNet-20 | 0.18M  | 27M   | 69.45%|
| Enhanced AddressNet-20 (concat) | 0.19M  | 29M   | 69.71%|

Table 5. Comparison in expressive ability (accuracy) between address shift and depthwise separable convolution conditioned on the same size of parameters and FLOPs. The following two models conform to the architecture of Enhanced AddressNet-32 and just differ in feature map transformation.

| Model                   | Params | FLOPs | Top-1  |
|-------------------------|--------|-------|--------|
| Enhanced AddressNet-32  | 328k   | 48M   | 73.55% |
| MobileNet-32            | 337k   | 50M   | 71.62% |

Separable convolutions with address shift. Then similarly to MobileNet, we scale the input size to build Address-MobileNet-192 and Address-MobileNet-160. To adapt to ImageNet, we improve the depth and expansion rate $\varepsilon$ of Enhanced AddressNet to form Enhanced AddressNet-A and Enhanced AddressNet-B. The detailed architecture of Enhanced AddressNet-A is listed in Table 7 while Enhanced AddressNet-B is a little shallower to fit the level of low accuracy and we will not show its details for simplicity.

The results for four levels of accuracy are shown in the Table 8 and their corresponding scatter diagram is also shown in Figure 7. In the low-accuracy scenario, MobileNet, improved by our address shift operation, excels in both accuracy and inference time significantly (shown in Figure 7(a)). This validates the scalability of the address shift operation on large dataset. In the modest accuracy scenarios, our models achieve comparable performance with other state-of-the-art models with small and compact network architecture.

In the NVIDIA CUDA Deep Neural Network library (cuDNN), there is little optimization for group convolution; therefore, this favors models that are not based on group convolution. That is why our models only achieve comparable results rather than the best results. Generally speaking, our experiments on CIFAR100 and ImageNet demonstrates the value of using address shift to accelerate the inference process and also demonstrates our three shift operations have scalability and flexibility for designing compact architectures.

5. Conclusions

The practical value of using deep neural networks in latency-sensitive power and energy constrained embedded systems naturally motivates the search for techniques to create fast, energy-efficient deep neural-net models. This paper adds a collection of shift based operations, namely, channel shift, shortcut shift and address shift, to the set of useful techniques for designing such models. In particular, these shift-based techniques utilize address offset to realize spatial convolutions and no parameters and no FLOPs, and thereby no inference time. Based on these shift operations,
| Model               | Parameters | FLOPs  | Top1 Accuracy | GPU Time (ms) | CPU Time (ms) |
|---------------------|------------|--------|---------------|---------------|---------------|
| ShiftResNet-20      | 0.19M      | 46.0M  | 68.64%        | 2.5±0.01      | 45.86±0.26    |
| ShiftResNet-56      | 0.58M      | 102M   | 72.13%        | 7.0±0.04      | 115.45±1.50   |
| ShiftResNet-110     | 1.18M      | 187M   | 72.56%        | 14.2±0.02     | 239.83±4.83   |
| AddressNet-20       | 0.08M      | 21.8M  | 68.68%        | 2.9±0.01      | 10.73±0.01    |
| AddressNet-32       | 0.14M      | 37.3M  | 71.96%        | 4.8±0.04      | 17.44±0.00    |
| AddressNet-44       | 0.20M      | 52.8M  | 73.31%        | 6.2±0.08      | 24.08±0.05    |
| Enhanced AddressNet-20 | 0.18M  | 26.7M  | 69.45%        | 2.9±0.03      | 16.86±0.66    |
| Enhanced AddressNet-32 | 0.33M  | 48.0M  | 73.55%        | 4.9±0.01      | 25.90±0.01    |
| Enhanced AddressNet-44 | 0.47M  | 69.2M  | 74.6%         | 6.4±0.01      | 29.14±0.06    |

Table 6. The performance of ShiftResNet and AddressNet in CIFAR100. The results of ShiftResNet are quoted from [34].

Figure 7. The performance of different models in three levels of accuracy, under the reference frame of Inference Time and Accuracy. In this coordinate system, the closer to the left (time) and top (accuracy), the better is the model.

Table 7. Enhanced AddressNet Architecture

we proposed two inference-efficient CNN models named AddressNet and Enhanced AddressNet, which outperform ShiftNet significantly. We have also used our operations to improve state of the art in neural net architecture: on CIFAR and ImageNet datasets we demonstrate that, deep neural nets designed with our shift operations can achieve better accuracy. In the future, we plan to develop a library to optimize group convolution which will make it more adaptable to our shift operations.

Table 8. The performance of different levels of accuracy on ImageNet. We modify MobileNet with address shift operation to build Address-MobileNet family and improve Enhanced AddressNet to build Enhanced AddressNet-A and Enhanced AddressNet-B. Enhanced AddressNet-B is a little shallower to fit the level of low accuracy

References

[1] A. K. Balan, V. Rathod, K. P. Murphy, and M. Welling. Bayesian dark knowledge. In Advances in Neural Informa-
H. Hu, R. Peng, Y.-W. Tai, and C.-K. Tang. Network trimming: Distilling knowledge from noisy teachers. arXiv preprint arXiv:1610.09650, 2016.

F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and K. Keutzer. SqueezeNet: Alexnet-level accuracy with 50x fewer parameters and ¡0.5 mb model size. arXiv preprint arXiv:1602.07360, 2016.

J. Jin, A. Dundar, and E. Culurciello. Flattened convolutional neural networks for feedforward acceleration. arXiv preprint arXiv:1412.5474, 2014.

A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems, pages 1097–1105, 2012.

A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems, pages 1097–1105, 2012.

Y. He, X. Zhang, Y. He, J. Wang, and N. Zheng. Single image super-resolution via a lightweight residual convolutional neural network. arXiv preprint arXiv:1703.08173, 2017.

J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3431–3440, 2015.

J.-H. Luo, J. Wu, and W. Lin. Thinet: A filter level pruning method for deep neural network compression. arXiv preprint arXiv:1707.06342, 2017.

X. Ma, Y. He, X. Luo, J. Li, M. Zhao, B. An, and X. Guan. Vehicle traffic driven camera placement for better metropolis security surveillance. IEEE Intelligent Systems, 2018.

M. Rastegari, V. Ordonez, J. Redmon, and A. Farhadi. Xnor-net: Imagenet classification using binary convolutional neural networks. In European Conference on Computer Vision, pages 525–542. Springer, 2016.

S. Ren, K. He, R. Girshick, and J. Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In Advances in neural information processing systems, pages 91–99, 2015.

T. N. Sainath, B. Kingsbury, V. Sindhwani, E. Arisoy, and B. Ramabhadran. Low-rank matrix factorization for deep neural network training with high-dimensional output targets. In Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on, pages 6655–6659. IEEE, 2013.

B. B. Sau and V. N. Balasubramanian. Deep model compression: Distilling knowledge from noisy teachers. arXiv preprint arXiv:1610.09650, 2016.

L. Sifre and P. Mallat. Rigid-motion scattering for image classification. PhD thesis, Citeseer, 2014.

C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich, et al. Going deeper with convolutions. Cvpr, 2015.

C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna. Rethinking the inception architecture for computer vision. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2818–2826, 2016.

C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna. Sparsely connected convolutional networks. In arXiv preprint arXiv:1801.05895, pages 2818–2826, 2018.
[32] C. Tai, T. Xiao, Y. Zhang, X. Wang, et al. Convolutional neural networks with low-rank regularization. *arXiv preprint arXiv:1511.06067*, 2015.

[33] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan. Show and tell: A neural image caption generator. In *Computer Vision and Pattern Recognition (CVPR), 2015 IEEE Conference on*, pages 3156–3164. IEEE, 2015.

[34] B. Wu, A. Wan, X. Yue, P. Jin, S. Zhao, N. Golmant, A. Gholaminejad, J. Gonzalez, and K. Keutzer. Shift: A zero flop, zero parameter alternative to spatial convolutions. *arXiv preprint arXiv:1711.08141*, 2017.

[35] J. Wu, C. Leng, Y. Wang, Q. Hu, and J. Cheng. Quantized convolutional neural networks for mobile devices. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 4820–4828, 2016.

[36] S. Xie, R. Girshick, P. Dollár, Z. Tu, and K. He. Aggregated residual transformations for deep neural networks. In *Computer Vision and Pattern Recognition (CVPR), 2017 IEEE Conference on*, pages 5987–5995. IEEE, 2017.

[37] X. Zhang, X. Zhou, M. Lin, and J. Sun. Shufflenet: An extremely efficient convolutional neural network for mobile devices. *arXiv preprint arXiv:1707.01083*, 2017.

[38] X. Zhang, J. Zou, K. He, and J. Sun. Accelerating very deep convolutional networks for classification and detection. *IEEE transactions on pattern analysis and machine intelligence*, 38(10):1943–1955, 2016.