Compact Global Descriptor for Neural Networks

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Abstract

Long-range dependencies modeling, widely used in capturing spatiotemporal correlation, has shown to be effective in CNN dominated computer vision tasks. Yet neither stacks of convolutional operations to enlarge receptive fields nor recent nonlocal modules is computationally efficient. In this paper, we present a generic family of lightweight global descriptors for modeling the interactions between positions across different dimensions (e.g., channels, frames). This descriptor enables subsequent convolutions to access the informative global features with negligible computational complexity and parameters. Benchmark experiments show that the proposed method can complete state-of-the-art long-range mechanisms with a significant reduction in extra computing cost. Our code is available at https://github.com/HolmesShuan/Compact-Global-Descriptor.

1. Introduction

Modeling long-range correlations, which commonly refers to enlarge receptive fields in deep convolutional neural networks [16, 28], is inherently designed in a stack of multiple convolution operators. This intuitive idea coincides with the empirical success of deeper networks [20, 40, 45]. However, repeating convolutional operations comes with unnecessary computing and the risk of overfitting [4, 43]. Besides that, though the respective fields of many deep CNNs have already covered the input image, the effective receptive field only occupies a fraction of the theoretical receptive field [34]. This insight implies that a series of convolutional layers, which aggregates spatial information within a local respective field (e.g., from a 3 × 3 region), may still lack the mechanism to model the long-range correlations. Capturing long-range dependencies (namely “context”) in CNNs then becomes a hot topic of network designs.

The pioneering work is the Inception family [44, 45] with multi-scale processing. Dilated convolutions [56] shares the similar start-point of aggregating multi-scale contextual information without losing resolution. This idea has been widely discussed in recent semantic segmentation and detection works [29, 9, 11]. A different aspect of network design utilizes the relationship between channels [24, 23] and extend to spatial dimension [36, 51], yet the interactions between positions across channels or within a local respective field might not be fully extracted using a linear combination after global poolings (via fully connected layer or 3 × 3 convolution).

Inspired by the classical non-local algorithm for image denoising [5], nonlocal operations compute the response at a position using a weighted sum of the activations of all positions [49]. There is no doubt that non-local networks utilize the rich global information to greatly improve the performances of baseline methods, however, remains computationally expensive. To partially alleviate the above issue, recent research proposes to reorder the computation between three input feature matrices [12]. [57] further splits the channels dimension into groups and reshape the large matrix into a long vector to avoid heavy matrix multiplications. As illustrated in Figure 1, there is another hidden factor might limit the learning capacity of non-local networks, the depthwise elementwise product without the cross-channel/spatial correlation. Though the depthwise H × W convolution helps to merge the information, it deserves further discussions on the optimal modeling at far less computing cost.

In this paper, we start by capturing the interactions between positions across all channels and the entire respective field. At first glance, this idea requires a significant amount of operations, while as illustrated in Figure 3 and 4, it saves several orders of magnitude in computation complexity. Since positions can be in space and time, our proposed Compact Global Descriptor (CGD) is an efficient module for both static image recognition and video classification.

The main contributions are as follows:

- We present a novel generic network module for long-range dependencies modeling, which considers the correlations among all positions across different di-
Figure 1. The illustration of Non-local module [49]. To show the hidden weighted summation mechanism, we expand the matrix multiplication $\Theta \Phi^T g \in \mathbb{R}^{C \times HW}$ in Non-local networks (illustrated in the upper right dotted box) into product and convolution operations. The “Depthwise Pointwise Product” is applied to the same colored blocks. The time and space complexity of Non-local module is $\mathcal{O}(C(HW)^2)$ and $\mathcal{O}(C^2)$, where $C, H, W$ indicate the channel number, feature map height, and feature map width respectively. In this case, space complexity refers to the extra parameter size, e.g., $1 \times 1$ convolution kernels to produce $\Theta, \Phi$ and $g$.

- The proposed Compact Global Descriptor (CGD) consistently outperforms baseline methods on the benchmark datasets. Compared with state-of-the-art long-range models, CGD gains significant decreases in space and time complexity.

- Our methods can be easily combined with the existing network components (e.g., no changes in size) relieving the dilemma of enhancing performance and reducing computation overhead.

We evaluate the generality of CGD on the tasks of ImageNet classification [14], Mini-Kinetics action recognition [52] and COCO object detection [31]. No matter with the strong ResNet-50 backbone or the lightweight MobileNet extractor, our CGD modules can promise a higher accuracy than baselines in all experiments.

2. Related Work

Multi-scale Correlations: Inspired by the primate visual cortex model in neuroscience, the authors of [39] first propose the different size Gabor filters to handle multiple scales. Similarly, GoogLeNet [44] incorporates multi-scales convolutions to cover large patches. Considering the specific dense prediction problems in semantic segmentation, [56] uses dilated convolutions to aggregate multi-scale contextual information without losing resolution. To enlarge the respective field of neural networks, [59, 8, 9] also apply this technique to scene parsing and semantic segmentation.

Channel Correlations: Squeeze-and-Excitation networks [24] shows that reweighting feature channels by explicitly models the interdependencies of its spatial features can improve classification accuracy. Gather-Excite networks further aggregate feature responses across spatial neighborhoods then produce an output with the same dimension as input [23]. Based on previous works, Convolution Block Attention [51] introduces global max pooling to gather another important clue. Our method learns the correlations between any two positions, which enjoys the dense clue to enhance the channel-wise relationships, and can be easily extended to spatiotemporal correlations. Besides that, CGD requires far less extra parameters and computing cost.

Spatial Correlations: The spatial correlations (also known as “attention” or “context”) which coincide with human perception, focus on “where to look”. In the tasks of visual captioning and question answering, spatial attention has been widely applied in structural prediction [53, 54, 7, 55]. Due to the limited channel-spatial modeling, SCA-CNN [10] proposes to first obtain the spatial attention weights, which are then multiplied in each spatial regions. For image classification, CBAM [51] and BAM [36] share a similar idea by using two sequential sub-modules: channel and spatial. Residual Attention Networks [48] presents the separate channel and spatial attention in the form of encoder-decoder. Recently, deformable convolutional networks [13, 61] introduce the spatial sampling with learned offsets to enhance geometric transformations modeling capability of CNNs. Our methods are compatible with these attention mechanisms, and can also be easily applied to the space dimension (detailed in section 3.2).
Spatio-temporal Correlations: Capturing spacetime dependencies is of central importance in video processing. [35, 15] intuitively utilize RNNs for sequences modeling and CNNs for images. Directly applying convolutions to spacetime leads to the 3D filters, known as C3D [26, 47]. Another group of methods focus on high-level feature aggregations using clustering [2, 17] or building graphs [50] to connect space and time. The "relation" networks [38, 60] merge information among frames through multiple MLP and concat/elementwise sum operations. The non-local modules [12, 57, 46, 49] are different from fully-connected and concat/elementwise sum operations. The non-local modules are utilized to connect space and time. The "relation" networks [38, 60] give a further discussion about the specific instantiations.

Table 1. Time complexity comparisons of non-local operations, where "Embedding" refers to $1 \times 1$ convolutions to halve the input channel number and $\Theta \Phi^T g$ is the correlation operation among all positions. $P$ in [57] indicates the order of Taylor expansion for kernel functions.

| Methods     | Embedding | $\Theta \Phi^T g$ |
|-------------|-----------|-------------------|
| Non-local [49] | $O(C^2HW)$ | $O(CHW^2)$ |
| A$^2$ [12] | $O(C^3HW)$ | $O(CHW^2)$ |
| CGNL [57] | $O(C^2HW)$ | $O(CHW(P+1))$ |
| CGD        | –         | $O(C)$            |

3. Compact Global Descriptors

In this section, we review nonlocal networks from the view of extra computing costs and introduce a general formulation of the proposed compact global descriptors. We give a further discussion about the specific instantiations.

The Non-local mechanism utilizes the multiplication of three feature embedding matrices $\Theta$, $\Phi$ and $g$, generated by $1 \times 1$ convolutions, to produce the attention tensor with the same size as the original feature map. As shown in Table 1, in the first several layers, $O(CHW^2)$ computing suffers from the unsatisfied time consumption. Recent works make it possible to place non-local modules in the first stage of ResNet, yet the computing cost of linear embeddings have been overlooked. We show that by utilizing the well-designed correlation operations, we can still enjoy the global information with negligible computational complexity and parameters.

3.1. Formulation

Denote the dimension of interest (e.g., channel in Figure 3 and 4) as $d$, with $X = [X_1, X_2, ..., X_N]^T \in \mathbb{R}^{M \times N}$ being the features of an input sample represented along $d$ where $X_n \in \mathbb{R}^M (n = 1, \cdots, N)$. A generic global descriptor is defined as:

$$z_n = \sum_{i \in M} \sum_{j \in [1, N]} \psi(X_{n, j}, X_{i, k}) w_i$$

$$= \mathcal{F}(X_n, X; w).$$  \hspace{1cm} (1)

Here $n, i \in [1, N]$, $j, k \in [1, M]$, scalar $z_n$ is the global description of $X_n$, and $w \in \mathbb{R}^N$ is the learnable weight. A pairwise function $\psi$ produces a scalar between the position $j$ in $X_n$ and all possible position $\forall (i, k)$. It is clear that Eq.(1) considers the long-range dependencies since index $(i, k)$ enumerates the whole feature map.

When incorporating the global descriptor into neural networks, this module can be further formulated as

$$\hat{X}_n := X_n + \phi(\mathcal{F}(X_n, X; w)) X_n$$  \hspace{1cm} (3)

$$= X_n \left(1 + \phi(\mathcal{F}(X_n, X; w))\right),$$  \hspace{1cm} (4)

where $\phi$ is the nonlinear function, such as $tanh(.)$ in this work. Inspired by PreResNet [21], Eq.(3) also leads to nice backward propagation properties. According to the chain rule of backpropagation, we obtain:

$$\frac{\partial \ell}{\partial X_n} = \frac{\partial \ell}{\partial \hat{X}_n} \frac{\partial \hat{X}_n}{\partial X_n}$$  \hspace{1cm} (5)

$$= \frac{\partial \ell}{\partial \hat{X}_n} \left(1 + \phi(\mathcal{F}(X_n, X; w))\right) + \frac{\partial \phi}{\partial \mathcal{F}} \frac{\partial \mathcal{F}}{\partial \hat{X}_n} X_n.$$  \hspace{1cm} (6)

Eq.(6) not only guarantee a term of $\frac{\partial \ell}{\partial X_n}$ that propagates information directly without the influence of residual block, but reweight the gradient tensor based on the global descriptions $\mathcal{F}(X_n, X; w)$. The derivative of $tanh(.)$ also works as the gradient clipping technique to avoid the potential gradient exploding of $\frac{\partial \mathcal{F}}{\partial \hat{X}_n}$.

3.2. Instantiations

Note that the dimension of interest $d$ can be any dimensions in CNNs, not limited to channel dimension in Figure 3. Since it is more intuitive and easy to understand when applying to the channel dimension, we describe several instantiations CGD modules with the following notations: feature map $X \in \mathbb{R}^{W \times H \times T}$, where $W$, $H$, $C$ and $T$ indicate the feature map width, feature map height, channel number, and frame number respectively.
To model the space-time correlations, we concatenate different frames in the channel dimension as illustrated in Figure 2(a). We can also focus on enhancing the “height-wise” or “width-wise” representational power in a similar way (Figure 2(b),(c)). For simplicity, this paper mainly considers the case of $T = 1$ (i.e., single frame) and applying to the channel dimension. The sub-descriptors $f(\cdot)$ and $g(\cdot)$ first map features across spatial dimensions into a response vector. The outer product of $g$ and $f^T$ is then passed to capture the long-distance dependencies among different channels. The learned parameter $w$ further aggregates feature responses containing the correlations between the positions of any two channels.

**Elementwise Product:** Following the dot-product in non-local modules [49, 57, 12], a natural choice of $\psi$ is the dot-product. Through a simple reformulation,

$$z_n = \sum_{v_1} \sum_{v_2} \sum_{v_k} X_{n,j} X_{i,k} w_i = \sum_{v_j} X_{n,j} \sum_{v_1} w_i \sum_{v_k} X_{i,k}$$

$$= \frac{1}{WH} \sum_{v_j} X_{n,j} \sum_{v_1} \frac{1}{WH} \sum_{v_k} X_{i,k} w_i'$$

$$= \text{AvePool}(X_n) \sum_{i=1}^{CT} \text{AvePool}(X_i) w_i'$$

where trainable $w_i' = (WH)^2 w_i$, note that there is a compact representation of Eq.(1), formally

$$z = g(X) f(X)^T w'.$$

Here $g$ and $f$ are both global average pooling to produce response vectors ($\in \mathbb{R}^{CT}$) and $w' \in \mathbb{R}^{CT}$ is the trainable weight vector. Specifically, we apply the global average pooling operation to the masked region in Figure 2(a). In the case of single frame ($T = 1$), Figure 4 further shows the correlation between $X$ and $z_n$. Compared with non-local blocks, we make the entire receptive field accessible to any position across all channels through outer-product.

**Nonlinear Embedding:** A simple extension of the outer-product $g(X) f(X)^T$ is to adopt other mappings, $g'$ and $f'$ from $\mathbb{R}^{WH \times CT}$ to $\mathbb{R}^{CT}$. In this paper, we consider max average pooling and softmax wrapped poolings. Since kernel methods are commonly defined on proper inner-product, $\mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$ where $\mathcal{X}$ is the input space, we borrow the insight of measuring the similarity in the kernel space.

**Cascaded:** Inspired by the reproducing kernel [3], in particular $\langle k(\cdot, x), k(\cdot, x') \rangle = k(x, x')$, we consider using the output $z$ of a previous CGD module as an input to replace $g(X)$ and $f(X)$. In this case, we denote $\langle \cdot, \cdot \rangle$ as the outer-product, $x$ and $x'$ refer to different $f$ and $g$. As shown in Table 2, when we directly model $k(g_{\text{ave}}, f_{\text{max}})$ as module v4, the result is unsatisfying. Combining $k(\cdot, f_{\text{ave}}^T)$ (module v3) and $k(\cdot, f_{\text{max}}^T)$ (module v6), the cascaded module v10 outperforms other candidates. It is shown that we still can utilize the relationship between $g_{\text{ave}}(X)$ and $f_{\text{max}}(X)$ implicitly.

**3.3. Block Setting**

A global descriptor in Eq.(3) can be easily added in any residual block without the burden of high computing cost. When incorporated with convolutional layers (directly after the convolutions), it allows us to access a richer hierarchy that combines both local and global information. Based on Eq.(6) and Eq.(10), we define the specific channel-oriented global descriptor as:

$$\tilde{X} = X \left(1 + \text{Tanh}(g(X) f(X)^T w)\right).$$

Compared with Sigmoid($\cdot$), the residual connection with Tanh($\cdot$) is more compatible with pre-trained models, if $w$ is initialized as zero then $\tilde{X} = X$. Also, we make a more aggressive assumption that some channels can be omitted ($1 + \text{Tanh}(-\infty) = 0$), which shares the similar idea with channel prunings [33].

The inner computation of a global descriptor is lightweight when we compute the inner-product $s = f^T w$ first and then calculate $z = gs$ as a scale operation (e.g.,
C.\text{\texttt{blas_sscal}} in OpenBLAS/MKL). We further discuss the following implementations to make it more efficient.

Implementation of CGD blocks: Unless specified, for lightweight networks such as MobileNet [22], SqueezeNet [25] and Cifar-100 networks, we set each CGD module right after the first convolution layer in every block. This benefits from the bottleneck design to reduce the channel number. Besides that, we can further merge the global description \( z \) with the batch-normalization parameters to avoid the axpy operation at inference time. For ResNet-style networks with several stages, we still add a CGD module to the first convolution layer in every residual block, since this setting will enlarge the receptive field of the following two convolution layers at a minimum cost.

In spatio-temporal modeling, \( w \in \mathbb{R}^{CT} \) is still \( T \) times larger than static image recognition models. Therefore, we reformulate \( z \) as:

\[
z = g(\frac{1}{T} \sum_{t} X^{(t)}) f(\frac{1}{T} \sum_{t} X^{(t)}) T_{w}, \quad (12)
\]

where \( X^{(t)} \in \mathbb{R}^{WH \times C} \). The above equation reduces the space complexity from \( \mathcal{O}(CT) \) to \( \mathcal{O}(C) \). This simplification bases on the assumption that the main object remains unchanged for most of neighbor frames, which implies the potential similarity in channels of interest between adjacent frames.

4. Experiments:

In this section, we first conduct extensive ablation studies to obtain the optimal CGD module on ImageNet dataset. Then we evaluate the proposed CGD method using different network architectures on both image recognition and video recognition tasks, and compare it with state-of-the-art approaches. We use PyTorch [1] in all our experiments, specifically, mmdetection [6] on MS COCO and PASCAL VOC objection detection experiments. To fully illustrate the superiority of CGD, we further include extra computing cost (number of multiply-accumulate operations, MAC) and parameter size as the evaluation metrics.

Ablation Studies: For the ablation studies on ImageNet, we replace the basic building block in ResNet-18 with “bottleneck” building block and change the block setting from [2,2,2,2] to [1,2,2,1], which builds a 20 layers residual network, namely ResNet-20. We use 2 GPUs per experiment with a batch size of 256 training from scratch. The ImageNet-1K [14] dataset consists of 1.2 million training images and 50K for validation. We adopt the same data augmentation scheme as described in [51, 36, 57, 12] for training and report the single-crop results with input size 224 \( \times \) 224 at inference time. The learning rate starts from 0.1 which is reduced with a factor of 0.1 at the 30\textsuperscript{th} and 60\textsuperscript{th} epoch. We train the networks for 90 epochs with weight decay of 0.0001 and momentum of 0.9.

Table 2 shows that, in most cases, global average pooling (first row) outperforms other variants. This result indicates that CGD with elementwise product can exploit the second-order information, which is similar to non-local operations [49]. Max pooling may omit the information of most positions, which leads to slightly worse performance. The cascaded scheme further combines the characteristics of max
and average pooling in the hidden space to obtain the optimal long-range dependences modeling.

4.1. Experiments on Video Classification:

In this subsection, we evaluate the proposed method on two benchmark datasets, Mini-Kinetics [52] and UCF-101 [42]. The Mini-Kinetics dataset consists of 200 action categories. Due to some online videos are missing, we download 79551 videos for training and 4784 videos for validation. UCF-101 contains 13320 videos from 101 action categories, we use the official train/test split in our experiments.

Experiments on UCF-101: To make a fair comparison, we keep the same architecture configuration with non-local networks [49] and CGNL [57], i.e., C2D ResNet-50. Following [49], we use ImageNet pre-trained models to initialize the weights, then fine-tune our models using 32-frame input clips. For \( w \) in CGD modules, we adopt the method in [18] to initialize weights and set biases to zeros. We first randomly crop out 64 consecutive frames from the full-length video then drop every other frame. Following [57], the input size is 224 × 224, first randomly cropped between 0.75 and 1 of the original image. Following CGNL [57], the strategy of gradual warmup is used. Then we train our models for 100 epochs in total, starting with a learning rate of 0.01 and reducing it by a factor of 10 at 40\(^{th}\) and 80\(^{th}\) epoch. We use a weight decay of 0.0001 and momentum of 0.9 in default. Specifically, we halve the weight decay of \( w \) in CGD modules since \( g f^2 \) is relatively small, a larger \( w \) is required. A dropout layer with 0.5 dropout rate is adopted after the global pooling layer. BatchNorm (BN) is also enabled to reduce overfitting [49].

At inference time, we follow the implementation in [49, 41, 57] to perform inference on videos with shorter side 256. We report the spatial single crop results in Table 3, without temporal domain multiple clips. Since the first and second convolution layer in residual bottleneck blocks has the same channel number which leads to the same extra costs of CGD, we discuss a little bit about where to add a CGD module. The first convolution layer with CGD per-
spatial size along the longer side. For the temporal domain, we evenly sample 10 clips from a full-length video [57, 49]. The bottom section of Table 3 shows that CGD can complete recent long-range mechanisms with far less extra cost.

4.2. Experiments on Image Recognition:

In this subsection, we further report the results of our CGD modules on the large-scale ImageNet dataset and the benchmark Cifar-100 dataset. ImageNet [14] contains 1.2 million training images and 50K images for validation with 1K object classes. Cifar-100 [27] consists of 60,000 color images with 32 × 32 pixels drawn from 100 classes. The training and test sets contain 50,000 and 10,000 images respectively. Experiments on ImageNet:

Unless specified, we keep the same experiment settings as described in ablation studies. For lightweight networks such as MobileNet and SqueezeNet, we set the weight decay to 4 × 10−5 including w in CGDs. For ResNets, we still keep the weight decay as 10−4 except for 5 × 10−5 on w. Since [12] decreases learning rate when training accuracy is saturated, [24, 51] report their performances after 100 epochs and [57] with warmup, we train ResNet-50 for 100 epochs. Note that our approach notably surpass other methods on lightweight architectures (Table 4) with negligible computational complexity and parameters. However, CGD perform poorly on ResNet-50 as shown in Table 6, which may be caused by the overfitting problem using rich global information across different dimensions. To verify the effectiveness of CGD on deep neural networks, we further conduct COCO object detection experiments with ResNet-50 in the next subsection.

Experiments on Cifar-100:

Following [20, 21], we adopt a standard data augmentation method of random cropping with 4-pixel padding and horizontal flipping. We train all models for 300 epochs with initial learning rate 0.1, and is divided by 10 at 150th and 225th epoch [36]. The weight decay is set to 10−4 including w in CGDs. As shown in Table 5, CGD can be easily combined with no matter deeper networks or wider networks to yield higher performance.

Experiments on VOC 2007:

We conduct object detection on the PASCAL VOC 2007 test set. The union set of VOC 2007 trainval and VOC 2012 trainval, namely “07+12”, is used as the training dataset. We evaluate the latest model on the VOC 2007 test after training 240 epochs. The detailed settings are the same as VGG-SSD300 in [6] except that the backbone is replaced by MobileNet. We use

| Methods | #Params | ∆ Params | MACs | ∆ MACs | Top-1 Error (%) | Top-5 Error (%) |
|---------|---------|---------|------|--------|----------------|----------------|
| MobileNet [22] | 4.23M | - | 0.569G | - | 31.39 | 11.51 |
| MobileNet [22] + SE [24] | +0.49M | 16× | +0.480M | 16× | 29.97 | 10.63 |
| MobileNet [22] + BAM [36] | +0.09M | 3× | +20.56M | 685× | 30.58 | 10.90 |
| MobileNet [22] + CBAM [51] | +0.49M | 16× | +3.082M | 103× | 29.01 | 9.99 |
| MobileNet [22] + CGD | +0.03M | 1× | +0.030M | 1× | 27.44 | 9.08 |
| MobileNet α = 0.7 [22] | 2.30M | - | 0.238G | - | 34.86 | 13.69 |
| MobileNet α = 0.7 [22] + SE [23] | +0.24M | 12× | +0.235M | 11× | 32.50 | 12.49 |
| MobileNet α = 0.7 [22] + BAM [36] | +0.04M | 2× | +10.10M | 505× | 33.09 | 12.69 |
| MobileNet α = 0.7 [22] + CBAM [51] | +0.24M | 12× | +2.592M | 130× | 31.51 | 11.48 |
| MobileNet α = 0.7 [22] + CGD | +0.02M | 1× | +0.021M | 1× | 29.89 | 10.56 |
| SqueezeNet [25] | 1.24M | - | 0.716G | - | 43.09 | 20.48 |
| SqueezeNet+BAM [36] | +0.02M | 7× | +14.00M | 7000× | 41.83 | 19.58 |
| SqueezeNet+CGD | +3.2K | 1× | +0.002M | 1× | 39.63 | 17.52 |

Table 4. Comparisons on the extra computing cost between CGD and other long-range modules on resource constrained architectures, MobileNet-v1 and SqueezeNet-v1.1. We report the single-crop results on ImageNet validation set after 90 epochs.

| Methods | Error (%) |
|---------|-----------|
| WideResNet28 (w=8) [58] | 20.40 |
| WideResNet28 (w=8) [58] + SE [24] | 19.85 |
| WideResNet28 (w=8) [58] + BAM [36] | 19.06 |
| WideResNet28 (w=8) [58] + CGD | 18.72 |
| PreResNet110 [21] | 22.22 |
| PreResNet110 [21] + SE [24] | 21.85 |
| PreResNet110 [21] + BAM [36] | 21.96 |
| PreResNet110 [21] + CGD | 20.96 |
| PreResNet56 [21] | 26.57 |
| PreResNet56 [21] + Nonlocal Modeling [36] | 25.29 |
| PreResNet56 [21] + CGD | 24.30 |

Table 5. Classification error rates (%) on the CIFAR-100 validation set. Top-1 error rates are reported.

| Methods | #Params | MACs | Top-1 (%) | Top-5 (%) |
|---------|---------|------|-----------|-----------|
| ResNet-50 [20] | 25.56M | 3.658G | 23.85 | 7.13 |
| + SE [24] | +2.52M | +2.52M | 23.29 | 6.62 |
| + BAM [36] | +0.36M | +8.2M | 23.14 | 6.53 |
| + CBAM [51] | +2.53M | +6.39M | 22.38 | 6.05 |
| + A^2 [12] | +33.0M | +265G | 23.00 | 6.50 |
| + CGNL [57] | +1.64M | +321M | 22.31 | 6.36 |
| + CGD | +0.02M | +0.023M | 23.10 | 6.49 |

Table 6. Top-1 and Top-5 single crop classification error rates (%) on the ImageNet-1K validation set.
Due to the gap between baseline results, we reach the similar AP setting as in VOC except for training 120 epochs. We further investigate

### Experiments on MS COCO:

When applying CGDs to deep neural networks such as ResNet-50, Table 7 shows a steady improvement (+2.1 points) on both Faster R-CNN and Mask R-CNN. Besides that, the extra computing cost of CGD will not change along with the input size, since the channel dimension remains the same for different input resolutions. This characteristic leads to the several orders of magnitude reduction in computation complexity. Combining Table 7 and Table 10, CGD has shown to be efficient and effective to model the long-range dependencies. It can complete even outperform ageNet pre-training. Table 9 shows that MobileNet-SSD with CGD consistently outperforms baselines (+2.1 points). When applying CGDs to deep neural networks such as ResNet-50, Table 7 shows a steady improvement (+1.5 APbbox) on both Faster R-CNN and Mask R-CNN. Besides that, the extra computing cost of CGD will not change along with the input size, since the channel dimension remains the same for different input resolutions. This characteristic leads to the several orders of magnitude reduction in computation complexity. Combining Table 7 and Table 10, CGD has shown to be efficient and effective to model the long-range dependencies. It can complete even outperform

| Evaluation | Method | Backbone | AP | AP50 | AP75 | APs | APm | APL |
|------------|--------|----------|----|------|------|------|------|------|
| Bounding Box | Faster R-CNN [19] | ResNet-50-FPN [30] | 36.4 | 58.4 | 39.1 | 21.6 | 40.1 | 46.6 |
| Bounding Box | Faster R-CNN [19] | ResNet-50-FPN [30] + CGD | 37.9 | 60.3 | 40.7 | 23.0 | 42.0 | 48.0 |
| Bounding Box | Mask R-CNN [19] | ResNet-50-FPN [30] | 37.3 | 59.1 | 40.3 | 22.0 | 40.9 | 48.2 |
| Bounding Box | Mask R-CNN [19] | ResNet-50-FPN [30] + CGD | 38.8 | 60.9 | 42.3 | 23.4 | 42.8 | 49.2 |
| Bounding Box | Mask R-CNN [19] | ResNet-50-C4 [19] | 35.6 | - | - | - | - | - |
| Bounding Box | Mask R-CNN [19] | ResNet-50-C4 [19] + CGNL [57] | 36.3 | - | - | - | - | - |
| Segmentation | Mask R-CNN [19] | ResNet-50-FPN [30] | 34.2 | 55.9 | 36.3 | 18.2 | 37.5 | 46.5 |
| Segmentation | Mask R-CNN [19] | ResNet-50-FPN [30] + CGD | 35.4 | 57.6 | 37.6 | 19.4 | 39.2 | 47.4 |
| Segmentation | Mask R-CNN [19] | ResNet-50-C4 [19] | 31.5 | - | - | - | - | - |
| Segmentation | Mask R-CNN [19] | ResNet-50-C4 [19] + CGNL [57] | 32.1 | - | - | - | - | - |
| Segmentation | Mask R-CNN [19] | ResNet-50-FPN [19] + Trainin to-end | 34.6 | 56.4 | 36.5 | - | - | - |
| Segmentation | Mask R-CNN [19] | ResNet-50-FPN [19] + Trainin to-end + Non-local [49] | 35.5 | 58.0 | 37.4 | - | - | - |

Table 7. COCO object detection single-model results on val2017. The detectors are Faster R-CNN with RoIAlign [19] and Mask R-CNN [19]. Due to the gap between baseline results, we reach the similar APmask as Non-local Networks. However, it should be noted that the gain of our method is +1.2AP with +0.2M MACs, compared with Non-local +0.9AP with at least +6.84G MACs. Our method saves over $12^5 \times$ extra computing cost.

| Backbone | Detector | Training Dataset |
|----------|----------|------------------|
| MobileNet [22] | SSD [32] | 68.1 | +07+12 |
| MobileNet [22] + CGD | SSD [32] | 74.8 | +07+12 |
| MobileNet [22] | SSD [32] | 72.7 | +07+12+COCO |

Table 8. Object detection mAP(%) on the VOC 2007 test set.

| Backbone | Detector | mAP | MAC | #Params |
|----------|----------|-----|-----|---------|
| MobileNet [22] | SSD [32] | 19.3 | 1.2G | 6.8M |
| MobileNet [22] + CGD | SSD [32] | 21.4 | 1.2G | 6.8M |
| Deeplab-VGG [22] | SSD [32] | 21.2 | 34.9G | 33.1M |

Table 9. COCO validation set object detection results comparison using different network architectures. mAP (%) is AP (%) at IoU=0.50:0.05:0.95.

| Method | ∆MACs | ∆NMACs | ∆Params | ∆NParams |
|--------|-------|--------|---------|----------|
| +Non-local | +6.84G | +2.10M | 92× |        |
| +CGNL | +4.10G | +1.64M | 72× |        |
| +CGD | +0.02M | +0.02M | 1× |        |

Table 10. Comparisons on the extra computing cost between Non-local, CGNL and CGD on ResNet-50. We assume the input size is $3 \times 800 \times 800$, since images are resized such that their scale (shorter edge) is 800 pixels. $\Delta N$ refers to normalized extra costs.
5. Conclusion

We present a novel network module which models the long-range dependencies between positions across different dimensions (e.g., channels, frames), namely, global descriptors. Our compact global descriptor can be easily combined with lightweight architectures and deeper networks without the burden of high computing costs. On all tasks, the proposed method significantly contribute to the solid improvement over baselines and comes with an impressive reduction in extra computing cost. Benchmark results show that this module is almost free and could be applied in a wide range of applications.

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