Tied Block Convolution: Leaner and Better CNNs with Shared Thinner Filters

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Motivation

Filters of an optimized CNN become more similar at an increasing depth.

Correlation matrix of 64 randomly selected filters based on their guided back-propagation patterns [1].

Normalized histograms of pairwise filter similarities

Tied Block Convolution (TBC)

Standard Convolution (SC)

Group Convolution (GC)

Tied Block Convolution (TBC)
Tied Block Convolution (TBC) vs Group Convolution (GC)

TBC has several major distinctions from GC in practical consequences (assume that the block number $B$ of TBC is the same as the group number $G$ of GC)

- TBC has $B \times$ fewer parameters than GC.
Tied Block Convolution (TBC) vs Group Convolution (GC)

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- TBC has \( B \times \) fewer parameters than GC.
- TBC only has one fragmentation on GPU utilization, whereas GC has \( G \) fragmentations, greatly reducing the degree of parallelism.

The time cost of processing 1k iterations of each feature map using the RTX 2080Ti GPU. Input feature map size is \( 56 \times 56 \times 2048 \).
Tied Block Convolution (TBC) vs Group Convolution (GC)

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- TBC only has one fragmentation on GPU utilization, where as GC has $G$ fragmentations, greatly reducing the degree of parallelism.
- TBC can better model cross-channel dependencies.
Tied Block Convolution (TBC) vs Group Convolution (GC)

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- TBC only has one fragmentation on GPU utilization, whereas GC has $G$ fragmentations, greatly reducing the degree of parallelism.
- TBC can better model cross-channel dependencies.
- TBC-based TiedResNet greatly surpasses GC-integrated ResNeXt on object detection and instance segmentation tasks.
Tied Block Group Convolution (TGC)

Group Convolution (GC)

$$\tilde{X} = X_1 * W_1 \oplus X_2 * W_2 \oplus \cdots \oplus X_G * W_G$$

Where $\oplus$ is the concatenation operation along the channel dimension, $W_g$ is the convolution filters for group $g$, where $g \in \{1, \ldots, G\}$, $X_g \in \mathbb{R}^\frac{c_i \times h_i \times w_i}{G}$, $W_g \in \mathbb{R}^\frac{c_o \times c_i \times k \times k}{G}$

Tied Block Group Convolution (TGC)

$$\tilde{X} = (X_{11} * W_1' \oplus \cdots \oplus X_{1B} * W_1') \oplus \cdots \oplus (X_{G1} * W_G' \oplus \cdots \oplus X_{GB} * W_G')$$

Where $g \in \{1, \ldots, G\}$, $b \in \{1, \ldots, B\}$, $X_{gb} \in \mathbb{R}^\frac{c_i \times h_i \times w_i}{GB}$, $W_{g}' \in \mathbb{R}^\frac{c_o \times c_i \times k \times k}{GB}$
TBC in ResNet

ResNet Bottleneck

\[ X \]
\[ \text{Conv} \ (1 \times 1) \]
\[ \text{Conv} \ (3 \times 3) \]
\[ \text{Conv} \ (1 \times 1) \]
\[ \bar{X} \]

TiedResNet Bottleneck

\[ X \]
\[ \text{TBC} \ (1 \times 1) \]
\[ \text{Split} \]
\[ \text{TBC} (3 \times 3) \]
\[ \text{TBC} (3 \times 3) \]
\[ \text{TBC} (3 \times 3) \]
\[ \text{TBC} (3 \times 3) \]
\[ \text{mixer} \]
\[ \text{TBC} (3 \times 3) \]
\[ \text{Concatenate} \]
\[ \text{Conv} \ (1 \times 1) \]
\[ \bar{X} \]
TGC/TBC in ResNeXt

ResNeXt Bottleneck

TiedResNeXt Bottleneck
TBC in ResNeSt

Input

Cardinal 1

Split 1

TBC, 1x1, c'/k/r

TBC, 3x3, c'/k

Split Attention

Cardinal k

Split 1

TBC, 1x1, c'/k/r

TBC, 3x3, c'/k

Split Attention

Cardinal 1

Split r

TBC, 1x1, c'/k/r

TBC, 3x3, c'/k

TiedResNeSt Bottleneck

Concatenate

(h, w, c')

Conv, 1x1, c

(h, w, c)

(h, w, c')

(h, w, c)

(h, w, c')

(h, w, c)

(h, w, c')

(h, w, c)
The integration of TBC/TFC/TGC can obtain consistent performance improvements to various backbone networks.

<table>
<thead>
<tr>
<th>Backbone</th>
<th>Group Conv</th>
<th>Tied Block Conv</th>
<th>Params (M)</th>
<th>Top-1 acc (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet101</td>
<td></td>
<td></td>
<td>44.6 vs. 24.0 (54%)</td>
<td>77.4 vs. 77.7</td>
</tr>
<tr>
<td>SENet-101</td>
<td></td>
<td></td>
<td>49.1 vs. 26.4 (54%)</td>
<td>78.3 vs. 79.0</td>
</tr>
<tr>
<td>ResNeXt-101</td>
<td></td>
<td></td>
<td>88.8 vs. 64.0 (65%)</td>
<td>79.3 vs. 79.3</td>
</tr>
<tr>
<td>ResNeSt-50-fast</td>
<td></td>
<td></td>
<td>27.5 vs. 16.5 (60%)</td>
<td>78.6 vs. 78.8</td>
</tr>
</tbody>
</table>
Grad-CAM Visualization

TiedResNet focusing on target objects more properly than ResNet and ResNeXt.
TiedResNet learns less correlated filters than ResNet.
Detection and Segmentation (MS-COCO)

TiedResNet consistently outperforms ResNet, ResNeXt and HRNetV2 with much fewer parameters.
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Object Detection on Pascal VOC

With only 31% parameters, TiedResNet50-S reaches comparable performance with ResNet101.

<table>
<thead>
<tr>
<th>Framework</th>
<th>Backbone</th>
<th>Params (M)</th>
<th>mAP (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSD513 [27]</td>
<td>VGG16 [33]</td>
<td>138.36</td>
<td>80.6</td>
</tr>
<tr>
<td>RefineDet512 [44]</td>
<td>VGG16 [33]</td>
<td>138.36</td>
<td>81.8</td>
</tr>
<tr>
<td>CoupleNet [46]</td>
<td>ResNet101 [17]</td>
<td>44.65</td>
<td>82.7</td>
</tr>
<tr>
<td><strong>Faster R-CNN with FPN [24]</strong></td>
<td>ResNet101 [17]</td>
<td>44.65</td>
<td><strong>82.1</strong></td>
</tr>
<tr>
<td><strong>Faster R-CNN with FPN [24]</strong></td>
<td>TiedResNet50-S</td>
<td><strong>13.91</strong></td>
<td>81.9</td>
</tr>
<tr>
<td>Faster R-CNN with FPN [24]</td>
<td>TiedResNet50</td>
<td>22.03</td>
<td>82.6</td>
</tr>
<tr>
<td>Faster R-CNN with FPN [24]</td>
<td>TiedResNet101-S</td>
<td>23.98</td>
<td>82.9</td>
</tr>
<tr>
<td>Faster R-CNN with FPN [24]</td>
<td>TiedResNet101</td>
<td>39.43</td>
<td><strong>83.8</strong></td>
</tr>
</tbody>
</table>
Instance Segmentation on Cityscapes

TiedResNet50 can reach 2.1% gain for $\text{AP}^{\text{mask}}$

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<tr>
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<th>Backbone</th>
<th>Params (M)</th>
<th>$\text{AP}^{\text{mask}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mask R-CNN [16]</td>
<td>TiedResNet50-S</td>
<td>13.9</td>
<td>32.5</td>
</tr>
<tr>
<td>Mask R-CNN [16]</td>
<td>TiedResNet50</td>
<td>22.0</td>
<td><strong>33.6</strong></td>
</tr>
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</table>
Object Detection Under High Occlusion Ratios

The occlusion ratio \( (r) \) of each image is evaluated by:

\[
 r = \frac{\text{total overlap area}}{\text{total instance area}}
\]

The number of images relative to the instance occlusion ratio \( r \) in MS-COCO val-2017 split.
Object Detection Under High Occlusion Ratios

When \( r = 0.8 \), TiedResNet increases by 8.3% at AP\(^{75}\) and 5.9% at AP, much more effective at handling highly overlapping instances.
Object Detection Under High Occlusion Ratios

Fewer false positive and false negative proposals

ResNet

TiedResNet
Sample Results (Cityscapes, Pascal VOC, MS-COCO)
Attention Modules: SE and TiedSE

Attention Modules: Global Context (GC) and TiedGC

Attention Module (TiedSE and TiedGC)

Significantly reduce attention module parameters with comparable performance

**ImageNet**

<table>
<thead>
<tr>
<th>Model Type</th>
<th>SE + ResNet50</th>
<th>SE + EfficientNet-B0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Params (M)</td>
<td>2.53 vs. 0.04 (1.6%)</td>
<td>0.65 vs. 0.04 (6.4%)</td>
</tr>
</tbody>
</table>

**MS-COCO**

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Global Context + Mask-RCNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Params (M)</td>
<td>10.0 vs. 2.5 (25%)</td>
</tr>
</tbody>
</table>

- SE + ResNet50
  - FC: 2.53
  - Tied FC: 0.04
- SE + EfficientNet-B0
  - FC: 0.65
  - Tied FC: 0.04
- Global Context + Mask-RCNN
  - FC: 10
  - Tied FC: 2.5
Summary

- The proposed Tied Block Convolution (TBC) reduce $B^2 \times$ parameters and $B \times$ computational cost;
- The concept of TBC can be extended to group convolution and fully connected layers;
- TBC/TGC/TFC can be applied to various backbone networks and attention modules;
- Our extensive experimentation on classification, detection, instance segmentation, and attention demonstrates TBC’s significant across-the-board gain over standard convolution and group convolution;
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