EdgeViTs: Competing Light-weight CNNs on Mobile Devices with Vision Transformers

Supplementary Materials

Junting Pan\textsuperscript{1*}, Adrian Bulat\textsuperscript{2}, Fuwen Tan\textsuperscript{2}, Xiatian Zhu\textsuperscript{2}, Lukasz Dudziak\textsuperscript{2}, Hongsheng Li\textsuperscript{1}, Georgios Tzimiropoulos\textsuperscript{2,3} and Brais Martinez\textsuperscript{2}

\textsuperscript{1} The Chinese University of Hong Kong
\textsuperscript{2} Samsung AI Cambridge
\textsuperscript{3} Queen Mary University of London

A Computing Complexity

We calculate the computational cost of spatial context modeling involved in our proposed LGL bottleneck. We omit point-wise operations for simplicity as the key difference is on the spatial modeling part. Let us assume an input $X \in \mathbb{R}^{h \times w \times c}$ where $h$, $w$, and $c$ denotes the height, the width, and the channel dimension, respectively. The cost of the local aggregation is $O(k^2hwc)$, where $k^2$ is the local group size. By selecting one delegate out of $r^2$ tokens with $r$ the sub-sampling rate, the complexity of our Sparse Global Self-Attention is then $O(\frac{h^2w^2}{r^4}c)$. Finally, the local propagation step takes a cost of $O(r^2hwc)$. Putting all these together we have a total cost of LGL is $O(k^2hwc + \frac{h^2w^2}{r^4}c + r^2hwc)$. When comparing with the cost of a standard multi-head self-attention $O(h^2w^2c)$, we can see that our LGL significantly reduces the computation overhead when $k \ll h, w$; and $r > 1$. In our experiments, for simplicity we set $k = 3$, and $r$ to $(4,2,2,1)$ for the four stages.

B Implementation Details

In Algorithm 1, we provide Pytorch Style pseudo-code for all the build blocks of our EdgeViTs. All variants of EdgeViTs can be built upon these components according to the schematic overview (Fig. 2a of the main paper), and the model configuration parameters (Table 1a. of the main paper). For more details with the ablation studies in the main paper, we have replaced or removed one of these blocks with the details given below.

(1) In Table 4a, for the case of w/o LA, we aim to test the importance of separate local and global context modeling. Thus we remove both LocalAgg and GlobalSparseAttn, and instead use the Spatial-Reduced Self-Attention\textsuperscript{4} introduced in PVT [7], resulting in a single Self-Attention Block for both local and global context modeling.

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\textsuperscript{4} https://github.com/whai362/PVT/blob/v2/classification/pvt_v2.py#L54-L126
global context modeling. For the case of LA(LSA) we simply replace LocalAgg with Local-grouped Self-Attention\(^5\) introduced in [1].

(2) In Table 4b, we replace the default sampler (Center) with \textbf{Avg} and \textbf{Max} functions which can be implemented with \texttt{AvgPool2d()} and \texttt{MaxPool2d()} in Pytorch \cite{4}, respectively. Note, for both cases the kernel size is set to \texttt{sample_rate}.

(3) In Table 4c, in the case of w/o LP, we replace our GlobalSparseAttn with Spatial-Reduce Self-Attention from PVT \cite{7}, but different from w/o LA, we keep the LocalAgg. For the case of LP(Bilinear), the LocalProp is instantiated as a bilinear interpolation function (\texttt{Upsample(mode='bilinear')} in Pytorch).

Note, the number of layers for each of these variants is down-scaled to have 0.5GFLOPs for fair comparison.

C Accuracy-Speed Pareto-Optimal Models

In order to facilitate the Accuracy vs. Speed interpretation. We identify pareto optimal models when comparing trade-off between accuracy and latency \cite{2}. In our context, the accuracy-latency pareto-optimal models are defined as those upon which no other models can improve in either accuracy or latency without degrading other metrics. As shown in Fig. ??, our EdgeViTs are well comparable with best efficient CNNs \cite{5,3,6}, whilst significantly dominating over all prior ViT counterparts. Specifically, EdgeViTs are all pareto-optimal in both trade-offs.

![Fig. 1. Accuracy/Latency and Accuracy/Energy trade off on ImageNet-1K. Note that, all three variants of our EdgeViTs are pareto-optimal, which are highlighted with amber cercle. Testing device: Samsung Galaxy S21 (latency), Snapdragon 888 Hardware Development Kit (energy).](image1)

\(^5\) https://github.com/Meituan-AutoML/Twins/blob/main/gvt.py#L32-L71
Table 1. Detection Efficiency. Input size: 800 × 800

| Model       | AP (%) | CPU (s) | Energy (J) | Efficiency (%/msW) |
|-------------|--------|---------|------------|-------------------|
| PVTv2-B0    | 37.2   | 1.34±0.01 | 3.50±0.77 | 0.011             |
| ResNet18    | 31.8   | 0.58±0.02 | 2.22±0.35 | 0.014             |
| PVTv1-Tiny  | 36.7   | 1.91±0.10 | 4.40±0.44 | 0.008             |
| PVTv2-B1    | 41.2   | 2.81±0.20 | 5.29±1.10 | 0.008             |
| EdgeViT-XXS | 38.7   | 0.59±0.02 | 2.02±0.28 | 0.019             |
| EdgeViT-XS  | 40.6   | 0.90±0.03 | 2.89±0.66 | 0.014             |
| EdgeViT-S   | 43.4   | 1.88±0.10 | 4.36±1.06 | 0.010             |

Table 2. Segmentation Efficiency. Input size: 512 × 512

| Model       | mIoU (%) | CPU (s) | Energy (J) | Efficiency (%/msW) |
|-------------|----------|---------|------------|-------------------|
| PVTv2-B0    | 37.2     | 0.35±0.01 | 1.10±0.30 | 0.034             |
| ResNet18    | 32.9     | 0.23±0.01 | 1.63±0.12 | 0.022             |
| PVTv1-Tiny  | 35.7     | 0.49±0.02 | 2.13±0.82 | 0.020             |
| PVTv2-B1    | 42.5     | 0.75±0.03 | 2.73±1.11 | 0.056             |
| EdgeViT-XXS | 39.7     | 0.19±0.01 | 0.71±0.11 | 0.037             |
| EdgeViT-XS  | 41.4     | 0.31±0.01 | 1.11±0.28 | 0.037             |
| EdgeViT-S   | 45.9     | 0.52±0.02 | 1.73±0.68 | 0.027             |

D Efficiency in detection/segmentation

This work proposes a genetic transformer-based network and demonstrate its efficacy when used as the backbone in detection/segmentation. We provide a evaluation by measuring only the inference time, energy and efficiency of the backbones for detection/segmentation. As shown in Tab. 1 and 2, EdgeViTs demonstrate higher efficiency compared to the baselines.
Algorithm 1 EdgeViTs Building Blocks, PyTorch-like Code

class LocalAgg():
    def __init__(self, dim):
        self.conv1 = Conv2d(dim, dim, 1)
        self.conv2 = Conv2d(dim, dim, 3, padding=1, groups=dim)
        self.conv3 = Conv2d(dim, dim, 1)
        self.norm1 = BatchNorm2d(dim)
        self.norm2 = BatchNorm2d(dim)
    def forward(self, x):
        
        [B, C, H, W] = x.shape
        
        x = self.conv1(self.norm1(x))
        x = self.conv2(x)
        x = self.conv3(self.norm2(x))
        return x

class GlobalSparseAttn():
    def __init__(self, dim, sample_rate, scale):
        self.scale = scale
        self.qkv = Linear(dim, dim * 3)
        self.sampler =AvgPool2d(1, stride=sample_rate)
        self.LocalProp = ConvTranspose2d(dim, dim, kernel_size=sample_rate, stride=sample_rate, groups=dim)
        self.norm = LayerNorm(dim)
        self.proj = Linear(dim, dim)
    def forward(self, x):
        
        [B, C, H, W] = x.shape
        
        x = self.sampler(x)
        q, k, v = self.qkv(x)
        attn = q @ k * self.scale
        attn = attn.softmax(dim=-1)
        x = attn @ v
        x = self.LocalProp(x)
        x = self.proj(self.norm(x))
        return x

class DownSampleLayer():
    def __init__(self, dim_in, dim_out, downsample_rate):
        self.downsample = Conv2d(dim_in, dim_out, kernel_size=downsample_rate, stride=downsample_rate)
        self.norm = LayerNorm(dim_out)
    def forward(self, x):
        x = self.downsample(x)
        x = self.norm(x)
        return x

class PatchEmbed():
    def __init__(self, dim):
        self.embed = Conv2d(dim, dim, 3, padding=1, groups=dim)
    def forward(self, x):
        return x + self.embed(x)

class FFN():
    def __init__(self, dim):
        self.fc1 = nn.Linear(dim, dim*4)
        self.fc2 = nn.Linear(dim*4, dim)
    def forward(self, x):
        x = self.fc1(x)
        x = GELU(x)
        x = self.fc2(x)
        return x
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