Fair Comparison between Efficient Attentions

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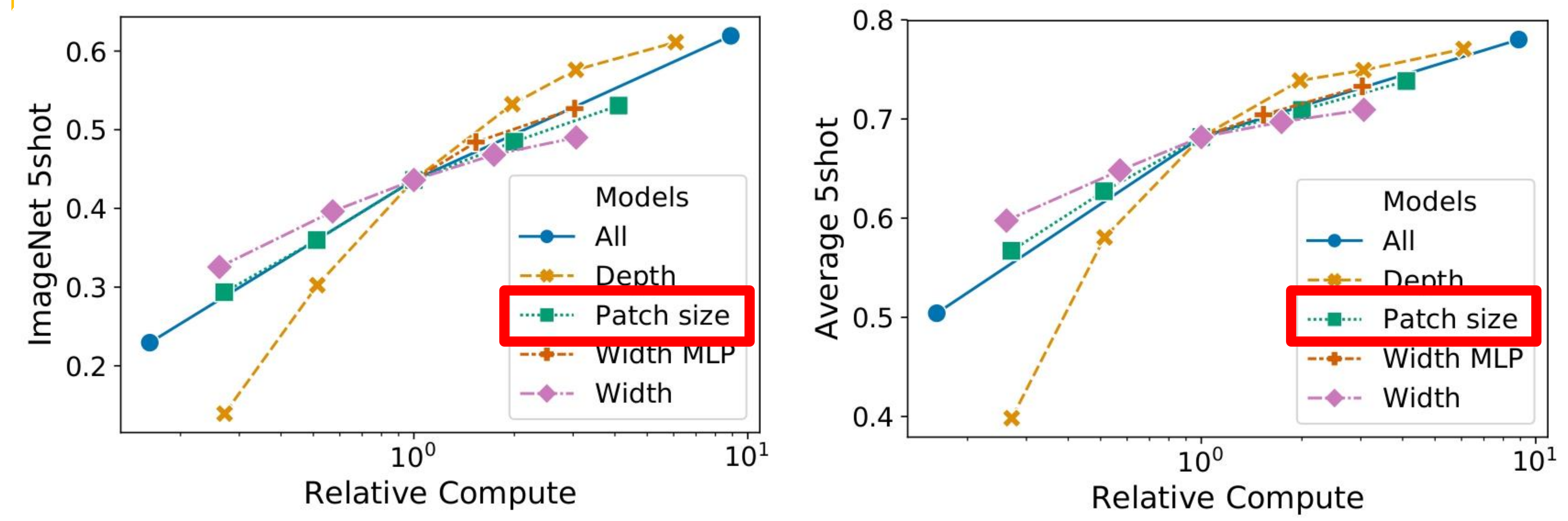
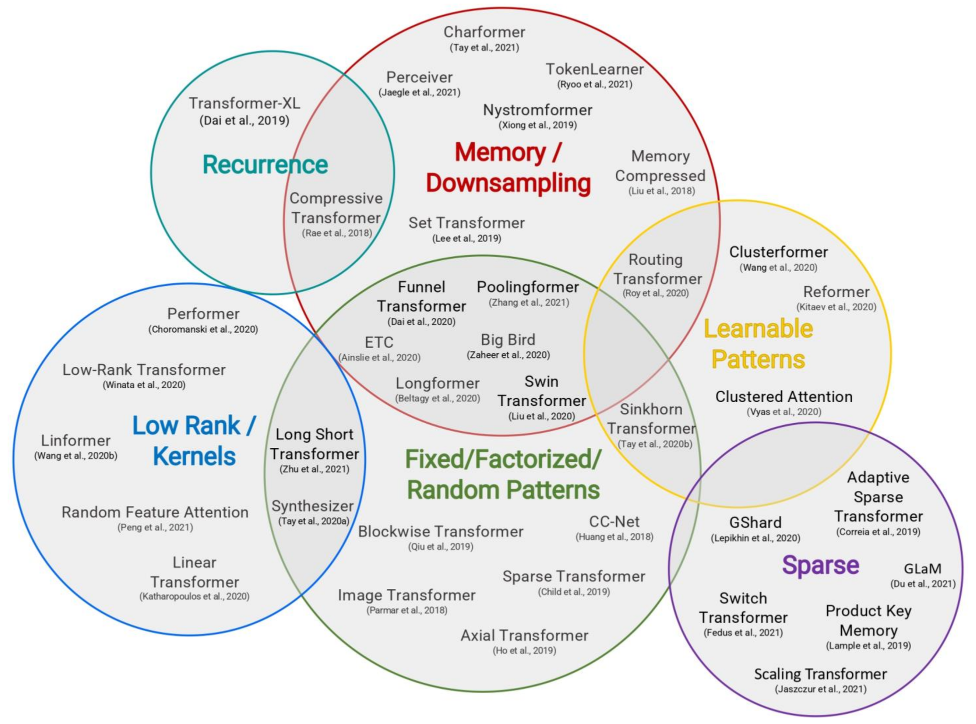
Motivation



✓ In ViT, decreasing the patch size and thus **increasing the effective sequence length shows surprisingly robust improvements** without introducing parameters.

- A well-known concern with self-attention is the quadratic time and memory complexity.
- The quadratic complexity can hinder patch size scalability.

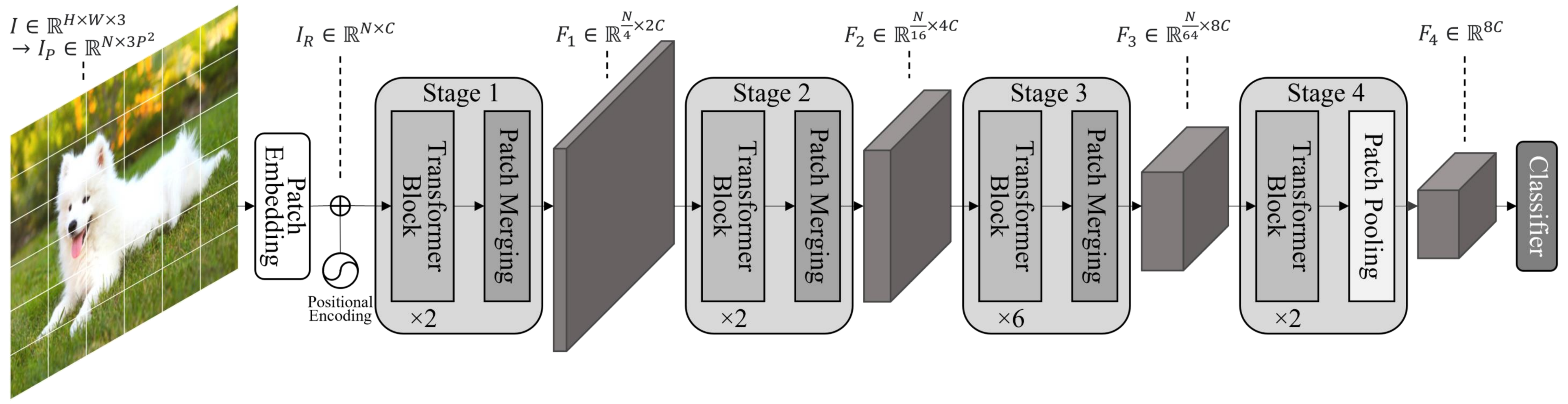


✓ There has been an overwhelming influx of **efficient attentions** proposed recently that address this problem.

- But there are few attempts to compare the works fairly because of model configuration and training schemes.

✓ Then, how about using those works to reduce patch size while decreasing computations?

Experiment Setting



✓ We use the **pyramid architecture** from Pyramid Transformer.

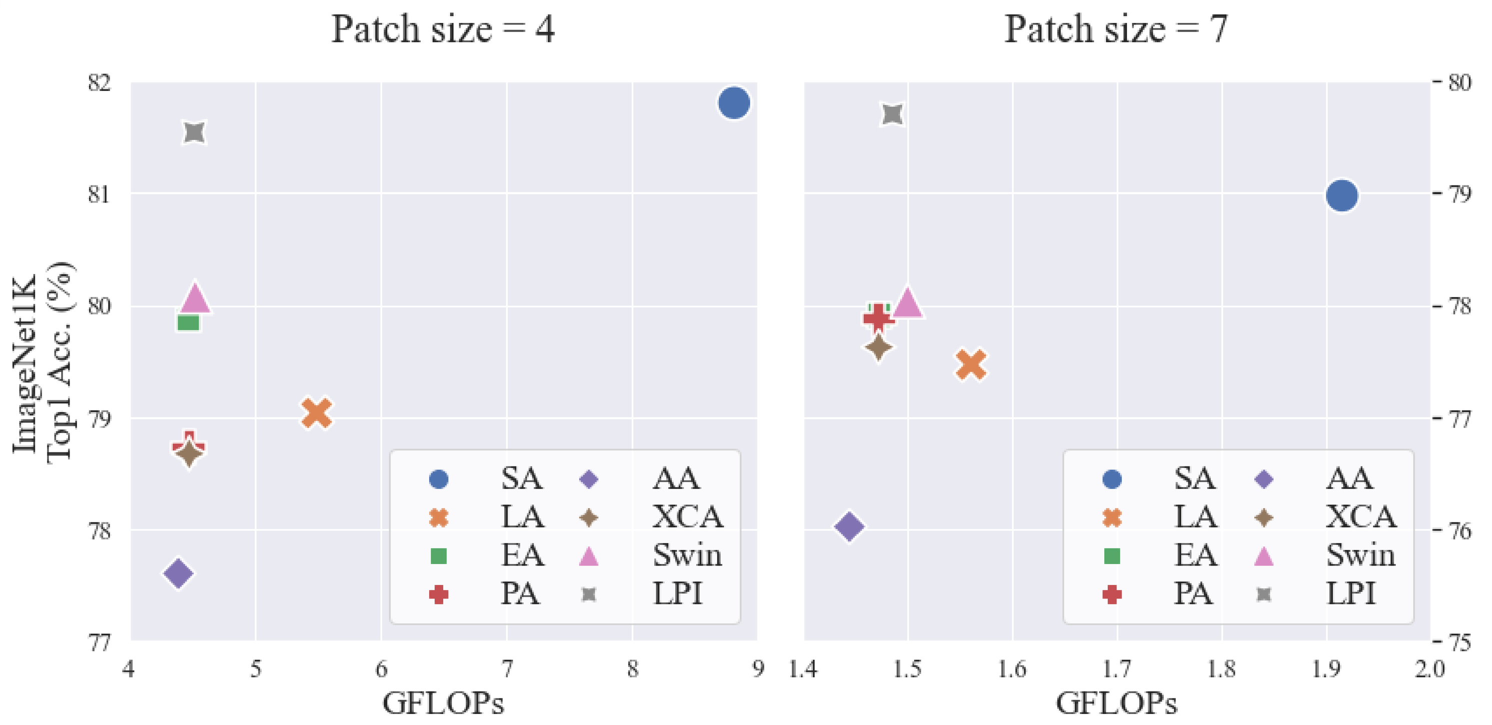
- Like CNN, it reduce spatial dimension and increase feature dimension.
- While we conduct experiment using small size of patch, we cannot afford to handle computation with columnar architecture like ViT.

✓ For a fair comparison, we use same architecture and training schemes. **Only the patch size and the type of attention change**.

- We compare several attentions, which has global token interaction and linear complexity.
- For reference, we also evaluate Swin, which use local token interaction, and columnar architecture with patch size 14 and 16.
- Below table shows efficient attention used in our paper and its complexity.

Model Architecture	Equation	Complexity per Self-Attention
Transformer (SA)	$\text{softmax}\left[\frac{\mathbf{q}\mathbf{k}^T}{\sqrt{d_k}}\right]\mathbf{v}$	$O(N^2C)$
Linformer (LA)	$\text{softmax}\left(\frac{\mathbf{q}[W_{proj}\mathbf{k}]^T}{\sqrt{d_k}}\right)W_{proj}\mathbf{v}.$	$O(NCm)$
Efficient Attention (EA)	$\text{softmax}(q)\left[\text{softmax}(\mathbf{k}^T)\mathbf{v}\right]$	$O(NC^2)$
Performer (PA)	$\frac{\psi(\mathbf{q})\,[\psi(\mathbf{k})^T\mathbf{v}]}{\text{diag}(\psi(\mathbf{q})[\psi(\mathbf{k})^T\mathbb{I}_N])}$	$O(NCr)$
Fastformer (AA)	q + [k'* v]W	$O(NC)$
XCiT (XCA)	$\left[\text{softmax}\left(\frac{\lVert\mathbf{q}\rVert_2{}^T\lVert\mathbf{k}\rVert_2}{\tau}\right)\mathbf{v}^T\right]^T$	$O(NC^2)$
Swin Transformer (Swin)	same as SA, but using window	$O(NCw^2)$

Result on ImageNet-1K



Type of Attention	#params (M, millions)	FLOPs (G, giga)	FLOPs ratio	Top 1 Acc. (%)
Baseline				
SA-4	28.27	8.821	1	81.80
SA-7	28.28	1.915	1	78.97
Efficient Attentions				
LA-4	30.91	5.496	0.62	79.04(-2.76)
LA-7	28.56	1.561	0.81	77.47(-1.5)
EA-4	28.27	4.480	0.51	79.87**(-1.93)**
EA-7	28.28	1.473	0.77	77.91**(-1.06)**
PA-4	28.27	4.481	0.51	78.73(-3.07)
PA-7	28.28	1.473	0.77	77.87(-1.1)
AA-4	28.27	4.394	0.50	77.60(-3.93)
AA-7	28.28	1.445	0.75	76.02(-2.95)
XCA-4	28.27	4.480	0.51	78.67(-3.13)
XCA-7	28.28	1.473	0.77	77.62(-1.35)
References				
Swin-4	28.27	4.528	0.51	80.08(-1.72)
Swin-7	28.28	1.500	0.78	78.72(-0.25)
LPI-4	28.38	4.520	0.51	81.54(-0.26)
LPI-7	28.39	1.486	0.78	79.7(+0.73)
COL-14	22.00	6.117	0.69	81.30(-0.50)
COL-16	22.00	4.589	0.52	80.97(-0.83)

✓ Efficient attentions has lower performance, but much lower computation.

✓ Additional methods such as two convolution layer before attention (LPI) or shifted window attention (Swin) show comparable result with baseline.

✓ Pyramid architecture with small patches does not show superior performance compared to columnar architecture.

Limitation

✓ More experiments with columnar architecture are needed to show above results are the same in other setting.

✓ Attention with much smaller patches is ineffective due to its unpractical computation.