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Convolution Kernel Design and Gated Attention for Modern Convolutional Neural Networks

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Timeline of Modern CNNs

InceptionNeXt arXiv’2023

DCN.V4 arXiv’2024

ConvNeXt CVPR’2022

RepLKNet CVPR’2022

SLaK ICLR’2023

ConvNeXt.V2 CVPR’2023

DCN.V3 CVPR’2023

UniRepLKNet CVPR’2024

Convolution Kernel Designs

Large Kernels + Gated Attentions

VAN (2022) CVMJ’2023

HorNet NeurIPS’2022

FocalNet NeurIPS’2022

MogaNet (2022) ICLR’2024

Content

1. **Modern CNNs: Macro Design and Pre-training**

   MetaFormer, ConvNeXt, ConvNeXt.V2 (SparK, A2MIM)

2. **Design of Convolution Kernels**

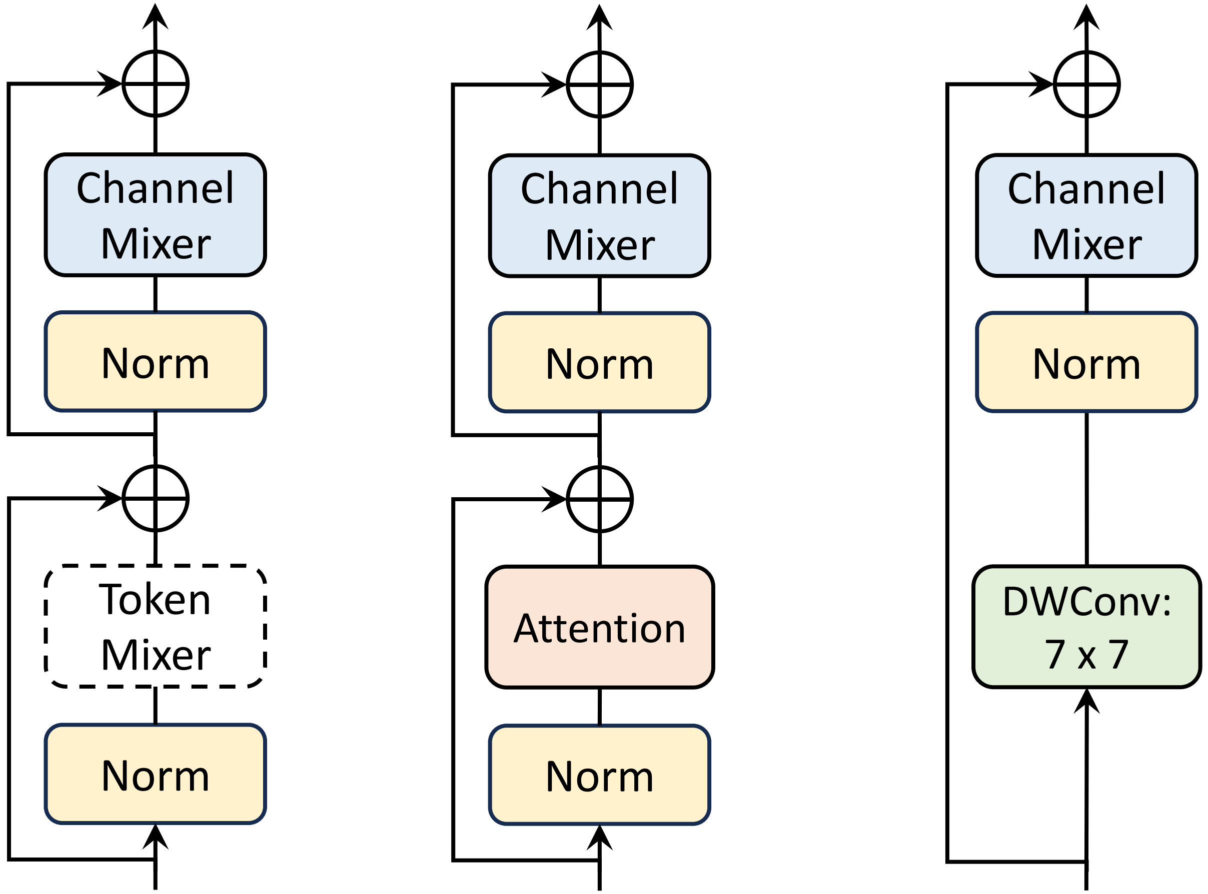
   RepLKNet, SLaK, InceptionNext, DCNv3, UniRepLKNet

3. **Combining Large Kernel with Gated Attention**

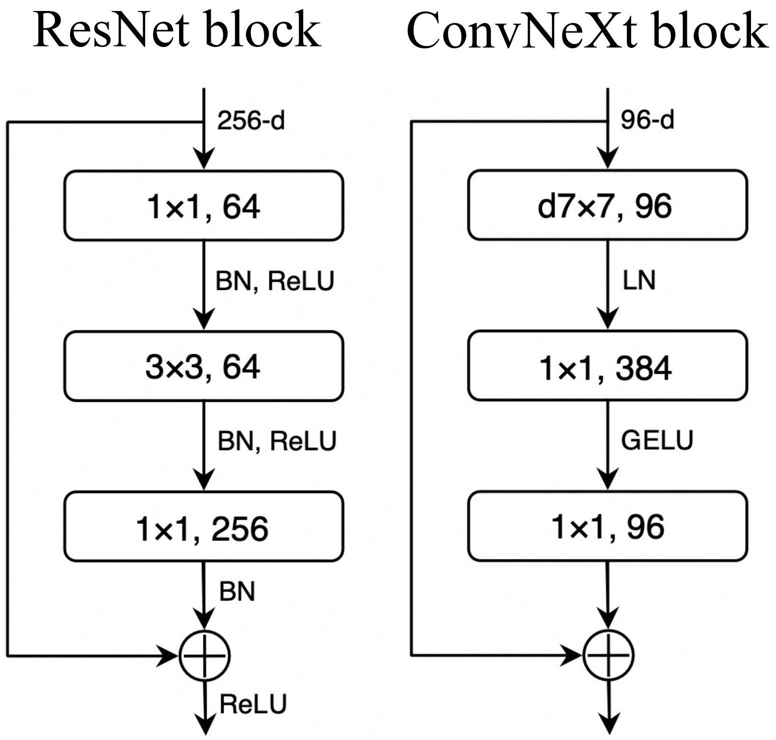
   VAN, HorNet, FocalNet, MogaNet

Modern CNNs: Macro Design

- Macro Design: Token Mixer + Channel Mixer + Pre-Norm & Short-cut).

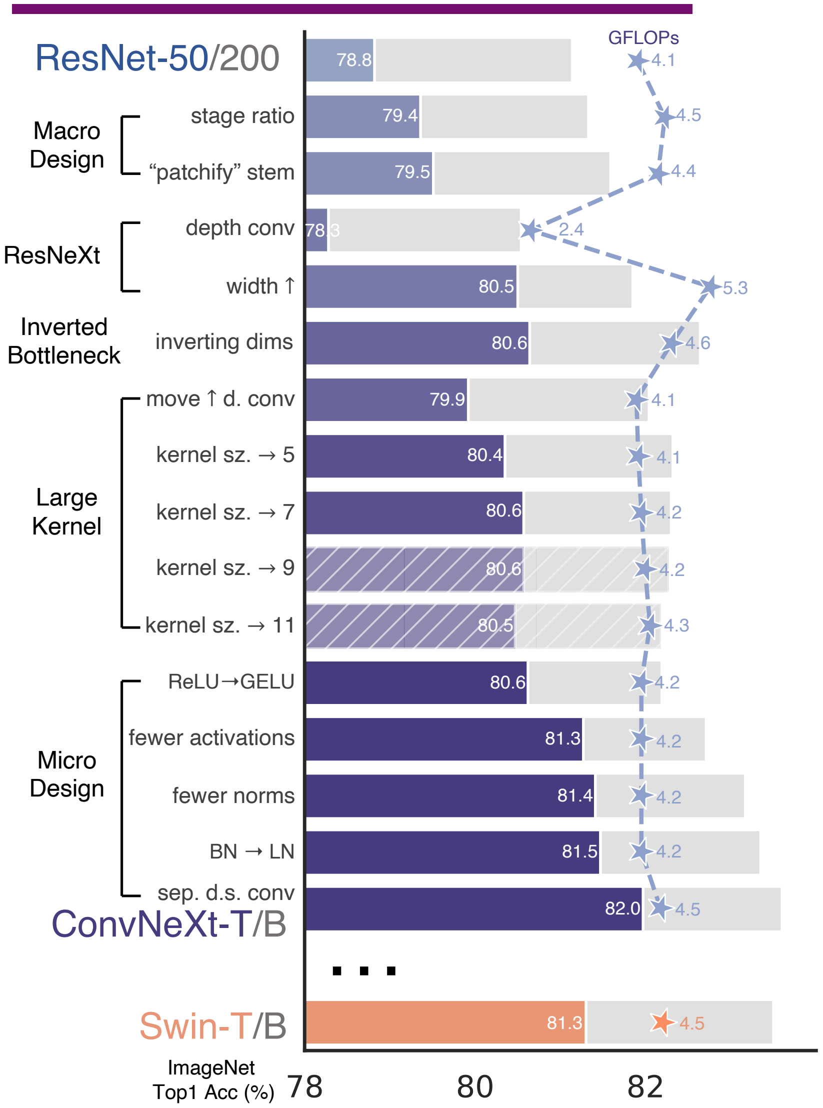


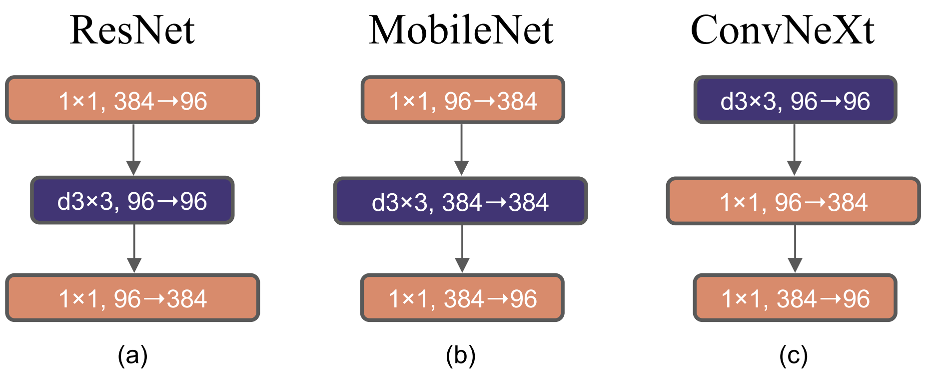
MetaFormer TransFormer ConvNeXt

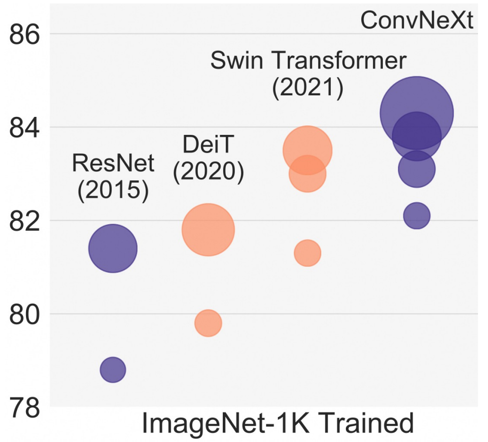


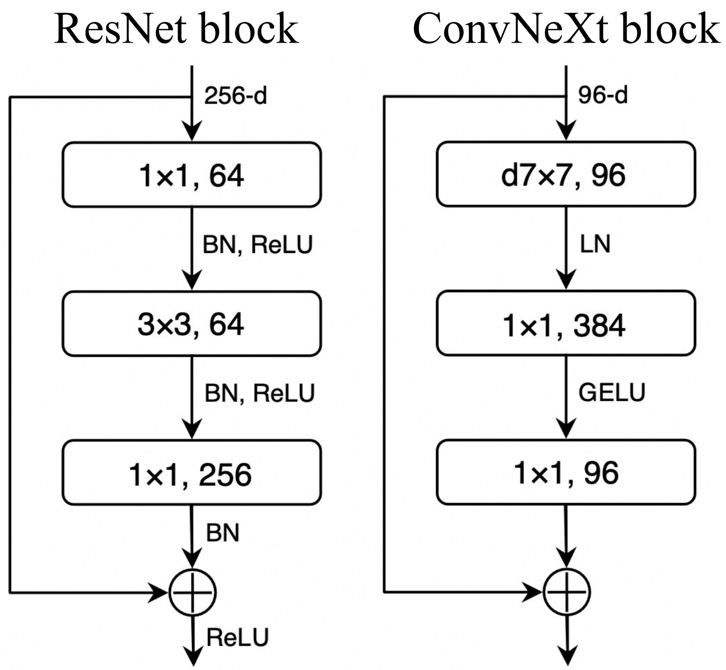
[1] PoolFormer: MetaFormer Is Actually What You Need for Vision. CVPR, 2022.
[2] A ConvNet for the 2020s. CVPR, 2022.

Modern CNNs: ConvNeXt







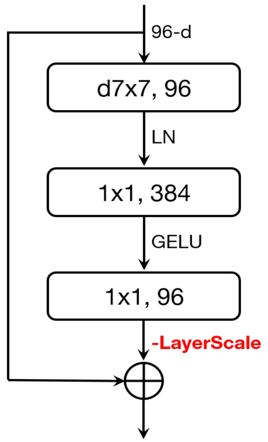


model	image size	#param.	FLOPs	throughput (image / s)	IN-1K top-1 acc.
		ImageNet-1K trained models			
• RegNetY-16G [54]	224^2	84M	16.0G	334.7	82.9
• EffNet-B7 [71]	600^2	66M	37.0G	55.1	84.3
• EffNetV2-L [72]	480^2	120M	53.0G	83.7	85.7
○ DeiT-S [73]	224^2	22M	4.6G	978.5	79.8
○ DeiT-B [73]	224^2	87M	17.6G	302.1	81.8
○ Swin-T	224^2	28M	4.5G	757.9	81.3
• ConvNeXt-T	224^2	29M	4.5G	774.7	**82.1**
○ Swin-S	224^2	50M	8.7G	436.7	83.0
• ConvNeXt-S	224^2	50M	8.7G	447.1	**83.1**
○ Swin-B	224^2	88M	15.4G	286.6	83.5
• ConvNeXt-B	224^2	89M	15.4G	292.1	**83.8**
○ Swin-B	384^2	88M	47.1G	85.1	84.5
• ConvNeXt-B	384^2	89M	45.0G	95.7	**85.1**
• ConvNeXt-L	224^2	198M	34.4G	146.8	**84.3**
• ConvNeXt-L	384^2	198M	101.0G	50.4	**85.5**

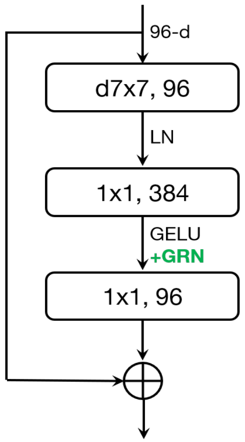
[1] A ConvNet for the 2020s. CVPR, 2022.

Modern CNNs: ConvNeXt.V2

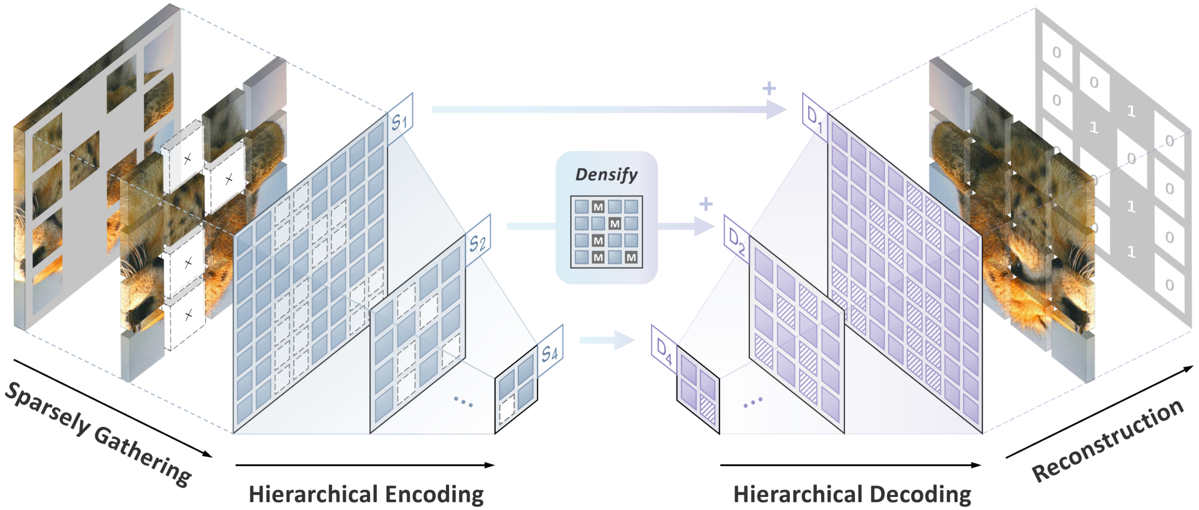
- **CNNs benefit from Masked Image Modeling (MIM) Pre-training.**



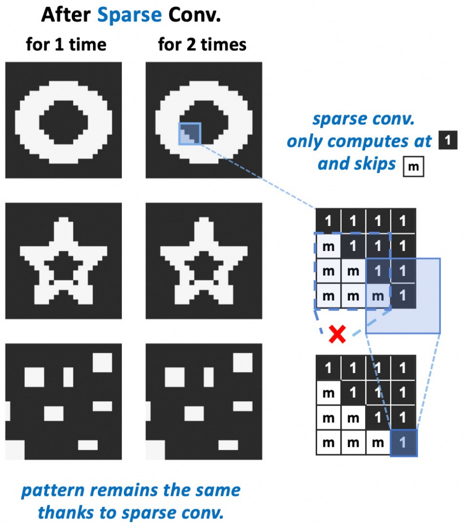
ConvNeXt.V1



ConvNeXt.V2



MIM pre-training with SparK (or FCMAE in ConvNeXt.V2)



Sparse Conv for Masking

Global Response Normalization (GRN)

```
# gamma, beta: learnable affine transform parameters
# X: input of shape (N,H,W,C)

gx = torch.norm(X, p=2, dim=(1,2), keepdim=True)
nx = gx / (gx.mean(dim=-1, keepdim=True)+1e-6)
return gamma * (X * nx) + beta + X
```

$$\mathcal{G}(X) := X \in \mathcal{R}^{H\times W\times C} \rightarrow gx \in \mathcal{R}^{C}$$

$$\mathcal{N}(||X_i||) := ||X_i|| \in \mathcal{R} \rightarrow \frac{||X_i||}{\sum_{j=1,\dots,C} ||X_j||} \in \mathcal{R}$$

Backbone	Method	#param	FLOPs	Val acc.
ConvNeXt V1-B	Supervised	89M	15.4G	83.8
ConvNeXt V1-B	FCMAE	89M	15.4G	83.7
ConvNeXt V2-B	Supervised	89M	15.4G	84.3 (+0.5)
ConvNeXt V2-B	FCMAE	89M	15.4G	**84.6** (+0.8)
ConvNeXt V1-L	Supervised	198M	34.4G	84.3
ConvNeXt V1-L	FCMAE	198M	34.4G	84.4
ConvNeXt V2-L	Supervised	198M	34.4G	84.5 (+0.2)
ConvNeXt V2-L	FCMAE	198M	34.4G	**85.6** (+1.3)

Methods Target	#Para. (M)	Sup. Label	MoCoV3‡ CL	SimMIM‡ RGB	SparK RGB	A^2MIM RGB
ResNet-50	25.6	79.8	80.1	79.9	80.6	**80.4**
ResNet-101	44.5	81.3	81.6	81.3	82.2	**81.9**
ResNet-152	60.2	81.8	82.0	81.9	82.7	**82.5**
ResNet-200	64.7	82.1	82.5	82.2	83.1	**83.0**
ConvNeXt-T	28.6	82.1	82.3	82.1	82.7	**82.5**
ConvNeXt-S	50.2	83.1	83.3	83.2	84.1	**83.7**
ConvNeXt-B	88.6	83.5	83.7	83.6	84.8	**84.1**

[1] ConvNeXt V2: Co-designing and Scaling ConvNets with Masked Autoencoders. CVPR, 2023. [2] Designing BERT for Convolutional Networks: Sparse and Hierarchical Masked Modeling. ICLR, 2023. [3] Architecture-Agnostic Masked Image Modeling - From ViT back to CNN. ICML, 2023.

Content

1. Modern CNNs: Macro Design and Pre-training

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2. <u>Design of Convolution Kernels</u>

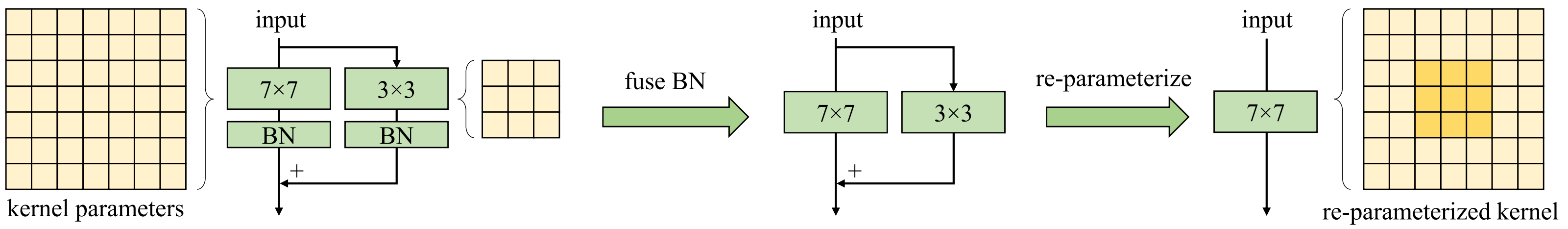
   RepLKNet, SLaK, InceptionNext, DCNv3, UniRepLKNet

3. Combining Large Kernel with Gated Attention

   VAN, HorNet, FocalNet, MogaNet

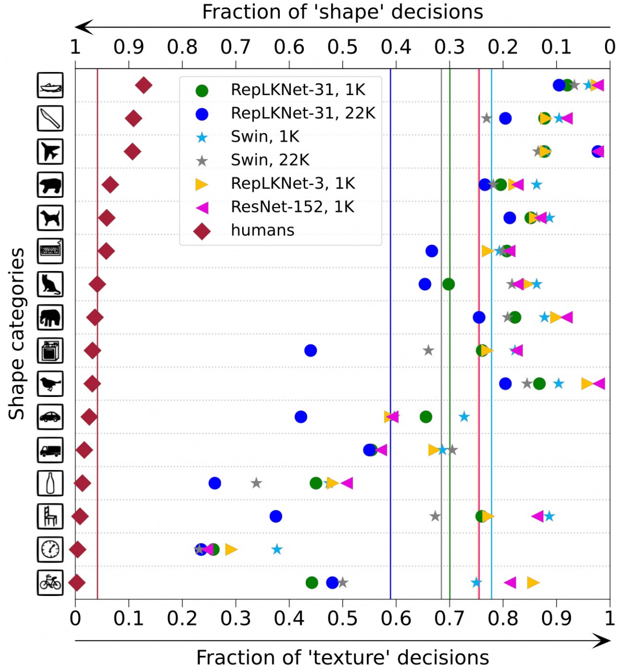
Large Kernels: RepLKNet

- Large-Kernel (LK) Convolutions are efficient and competitive as Self-attention.
- Training extremely large convolutions with Structural Re-parameterization.



DW7×7 = DW3×3 (BN) +DW7×7 (BN)+Short-cut.

Large kernels are **shape biased** as ViTs.

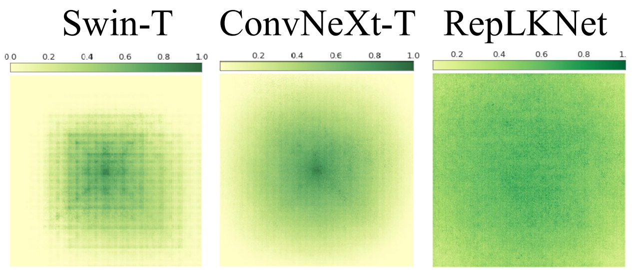


Resolution R	Impl	Latency (ms) @ Kernel size 3	5	7	9	13	17	21	27	29	31
16 × 16	Pytorch	5.6	11.0	14.4	17.6	36.0	57.2	83.4	133.5	150.7	171.4
	Ours	5.6	6.5	6.4	6.9	7.5	8.4	8.4	8.4	8.3	8.4
32 × 32	Pytorch	21.9	34.1	54.8	76.1	141.2	230.5	342.3	557.8	638.6	734.8
	Ours	21.9	28.7	34.6	40.6	52.5	64.5	73.9	87.9	92.7	96.7
64 × 64	Pytorch	69.6	141.2	228.6	319.8	600.0	977.7	1454.4	2371.1	2698.4	3090.4
	Ours	69.6	112.6	130.7	152.6	199.7	251.5	301.0	378.2	406.0	431.7

Large kernels are **memory bound** instead of compute bound.

		ImageNet			ADE20K		
Kernel size	Architecture	Top-1	Params	FLOPs	mIoU	Params	FLOPs
7-7-7-7	ConvNeXt-Tiny	81.0	29M	4.5G	44.6	60M	939G
7-7-7-7	ConvNeXt-Small	82.1	50M	8.7G	45.9	82M	1027G
7-7-7-7	ConvNeXt-Base	82.8	89M	15.4G	47.2	122M	1170G
31-29-27-13	ConvNeXt-Tiny	81.6	32M	6.1G	**46.2**	64M	973G
31-29-27-13	ConvNeXt-Small	82.5	58M	11.3G	**48.2**	90M	1081G

Extremely large kernels benefit both classification and downstream tasks and outperforms ViTs.

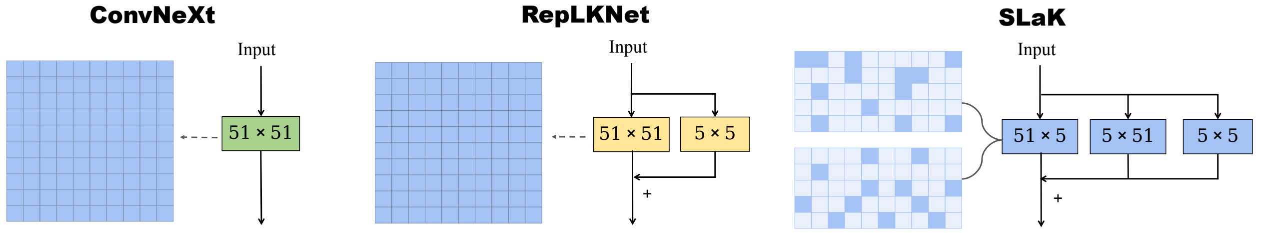


Effective receptive field

[1] Scaling Up Your Kernels to 31x31: Revisiting Large Kernel Design in CNNs. CVPR, 2022.

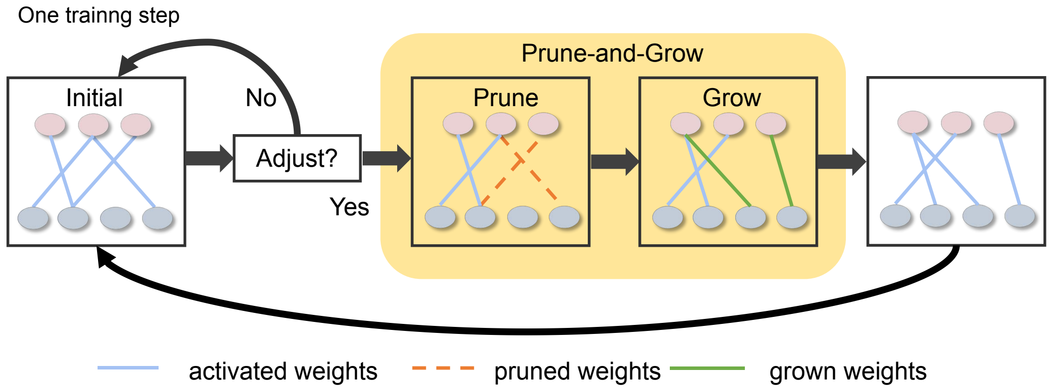
Large Kernels: SLaK

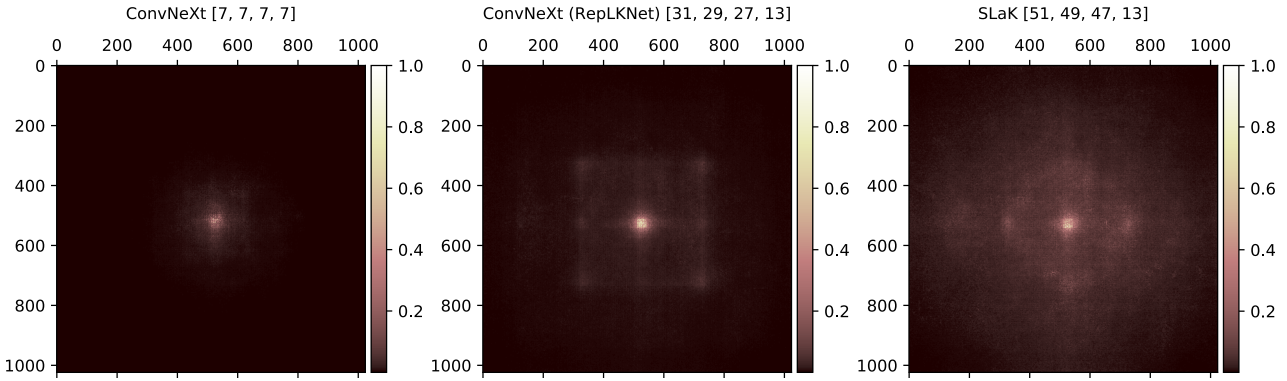
- **Step 1: Decomposing a large kernel (61x61) into two rectangular, parallel kernels.**
- **Step 2: Using sparse groups training (speedup), expanding more width.**



Kernel Size	Top-1 Acc	#Params	FLOPs	Top-1 Acc	#Params	FLOPs	Top-1 Acc	#Params	FLOPs
	Decomposed			Sparse groups			Sparse groups, expand more width		
7-7-7-7	81.0	29M	4.5G	80.0	17M	2.6G	81.1	29M	4.5G
31-29-37-13	81.3	30M	5.0G	80.4	18M	2.9G	81.5	30M	4.8G
51-49-47-13	81.5	31M	5.4G	80.5	18M	3.1G	81.6	30M	5.0G
61-59-57-13	81.4	31M	5.6G	80.4	19M	3.2G	81.5	31M	5.2G

Model	Kernel Size	AP^{box}	AP^{box}_{50}	AP^{box}_{75}	AP^{mask}	AP^{mask}_{50}	AP^{mask}_{75}
pre-trained for 120 epochs, finetuned for 1× (12 epochs)							
ConvNeXt-T (Liu et al., 2022b)	7-7-7-7	47.3	65.9	51.5	41.1	63.2	44.4
ConvNeXt-T (RepLKNET)* (Ding et al., 2022)	31-29-27-13	47.8	66.7	52.0	41.4	63.9	44.7
SLaK-T	51-49-47-13	**48.4**	**67.2**	**52.5**	**41.8**	**64.4**	**45.2**
pre-trained for 300 epochs, finetuned for 3× (36 epochs)							
ConvNeXt-T (Liu et al., 2022b)	7-7-7-7	50.4	69.1	54.8	43.7	66.5	47.3
SLaK-T	51-49-47-13	**51.3**	**70.0**	**55.7**	**44.3**	**67.2**	**48.1**





Effective receptive field (ERF)

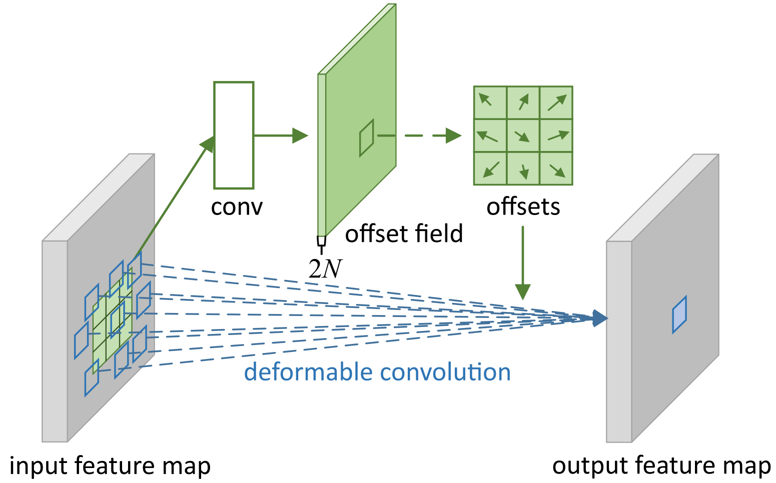
(1) Initialization: Constructing Sparce Convolution based on SNIP[2]

(2) Dynamic sparsity: Pruning (the lowest magnitude) and growing

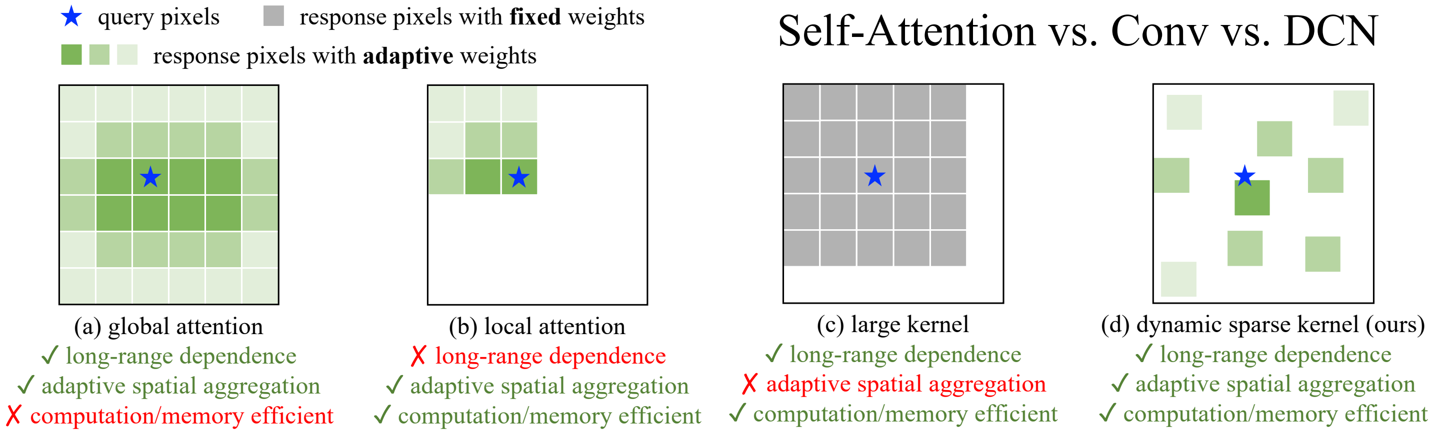
[1] More ConvNets in the 2020s: Scaling up Kernels Beyond 51x51 using Sparsity. ICLR, 2023.
[2] SNIP: Single-shot Network Pruning based on Connection Sensitivity. ICLR, 2019.

Kernel Designs: DCN.V3 (InternImage)

- **DCN.V3: Learnable offsets (V1) + Softmax-normalized modulation (V2) + Grouping.**



Self-Attention vs. Conv vs. DCN



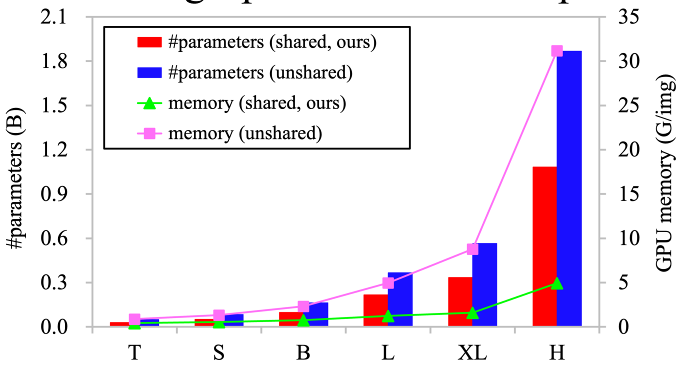
DCN.V1: $\mathbf{y}(\mathbf{p}_0) = \sum_{\mathbf{p}_n \in \mathcal{R}} \mathbf{w}(\mathbf{p}_n) \cdot \mathbf{x}(\mathbf{p}_0 + \mathbf{p}_n + \Delta \mathbf{p}_n)$

DCN.V2: $\mathbf{y}(p_0) = \sum_{k=1}^{K} \mathbf{w}_k \mathbf{m}_k \mathbf{x}(p_0 + p_k + \Delta p_k)$

DCN.V3: $\mathbf{y}(p_0) = \sum_{g=1}^{G} \sum_{k=1}^{K} \mathbf{w}_g \mathbf{m}_{gk} \mathbf{x}_g(p_0 + p_k + \Delta p_{gk})$

Offsets Δp_n, Regular grids p_n, Modulation m_k, weights w

Scaling-up with efficient impl.



method	type	scale	#params	#FLOPs	acc (%)
SwinV2-L/24‡ [16]	T	384^2	197M	115G	87.6
RepLKNet-31L‡ [22]	C	384^2	172M	96G	86.6
HorNet-L‡ [43]	C	384^2	202M	102G	87.7
ConvNeXt-L‡ [21]	C	384^2	198M	101G	87.5
ConvNeXt-XL‡ [21]	C	384^2	350M	179G	87.8
InternImage-L‡ (ours)	C	384^2	223M	108G	87.7
InternImage-XL‡ (ours)	C	384^2	335M	163G	88.0
ViT-G/14# [30]	T	518^2	1.84B	5160G	90.5
CoAtNet-6# [20]	T	512^2	1.47B	1521G	90.5
CoAtNet-7# [20]	T	512^2	2.44B	2586G	90.9
Florence-CoSwin-H# [59]	T	–	893M	–	90.0
SwinV2-G# [16]	T	640^2	3.00B	–	90.2
RepLKNet-XL# [22]	C	384^2	335M	129G	87.8
BiT-L-ResNet152x4# [67]	C	480^2	928M	–	87.5
InternImage-H# (ours)	C	224^2	1.08B	188G	88.9
InternImage-H# (ours)	C	640^2	1.08B	1478G	89.6

[1] Deformable Convolutional Networks. ICCV, 2017. [2] Deformable ConvNets v2: More Deformable, Better Results. CVPR, 2018.
[3] InternImage: Exploring Large-Scale Vision Foundation Models with Deformable Convolutions. CVPR, 2023.

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3. **Combining Large Kernel with Gated Attention**

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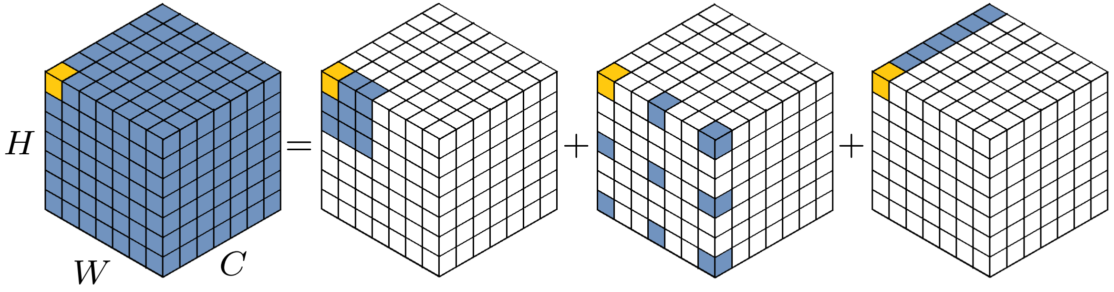
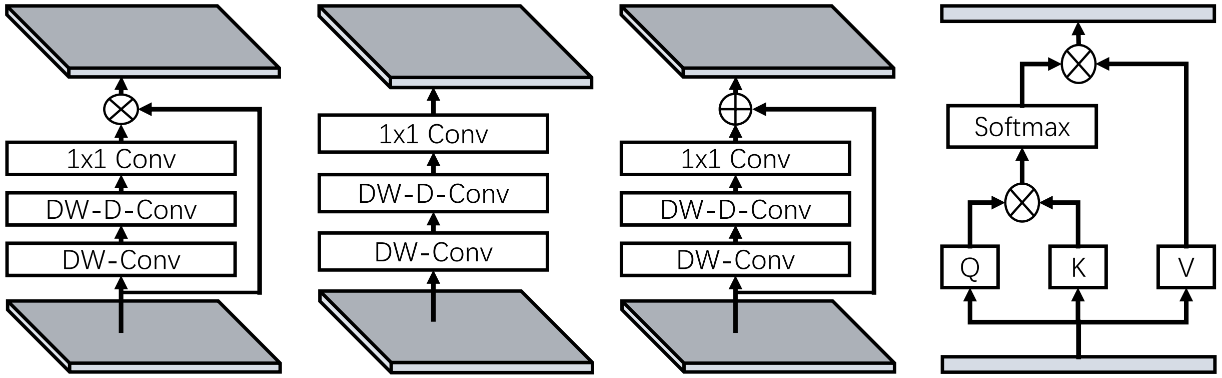
Gating & Large-kernel: VAN

- **Decomposed large kernel + Gating.**

Conv9×9 = DWConv3×3 + DWConv3×3 (Dilation=3) + PWConv1×1





VAN (LKA) | Non-attention | Non-attention (add) | Self-attention

[1] Visual Attention Network. CVMJ, 2023.

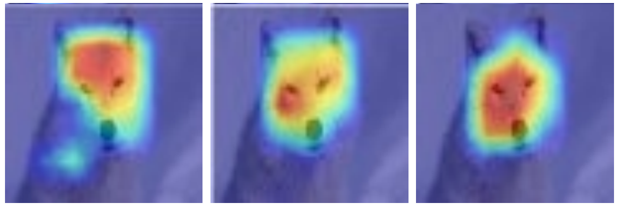
Properties	Convolution	Self-Attention	LKA
Local Receptive Field	✓	✗	✓
Long-range Dependence	✗	✓	✓
Spatial Adaptability	✗	✓	✓
Channel Adaptability	✗	✗	✓
Computational complexity	$\mathcal{O}(n)$	$\mathcal{O}(n^2)$	$\mathcal{O}(n)$

Properties of DWConv vs. MHSA vs. Large-kernel Attention

Method	K	Dilation	Params. (M)	GFLOPs	Acc(%)
VAN-B0	7	2	4.03	0.85	74.8
VAN-B0	14	3	4.07	0.87	75.3
VAN-B0	21	3	4.11	0.88	75.4
VAN-B0	28	4	4.14	0.90	75.4

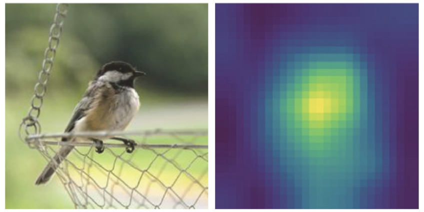
Kernel size vs. Dilation vs. ImageNet Acc (%)

Conv21×21 = DWConv5×5 +DWConv7×7 (Dilation=3) +PWConv1×1



Swin-T | ConvNeXt-T | VAN-B2

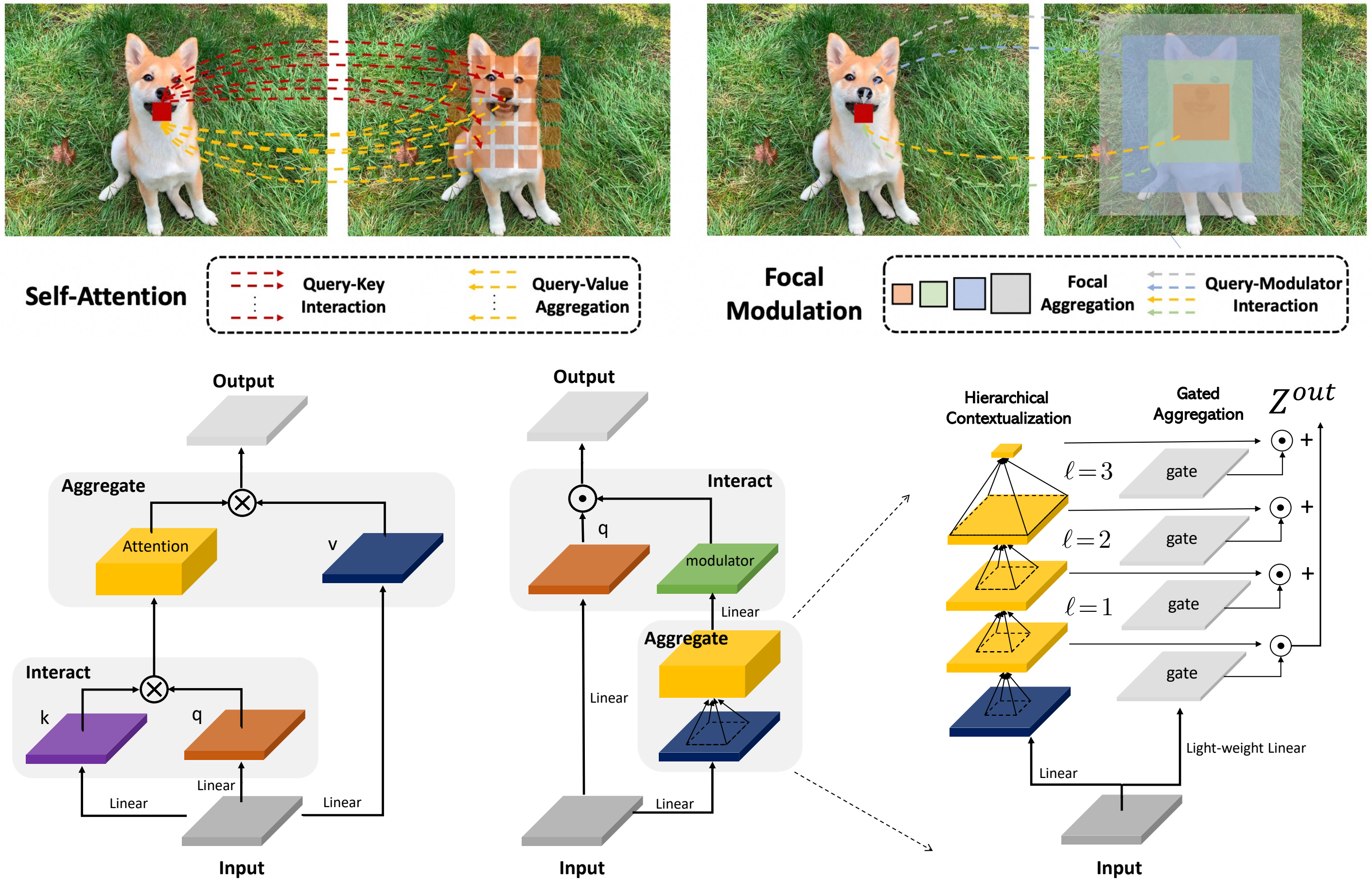
Grad-CAM visualization



Attention map visualization

Gating & Hierarchical Kernel: FocalNet

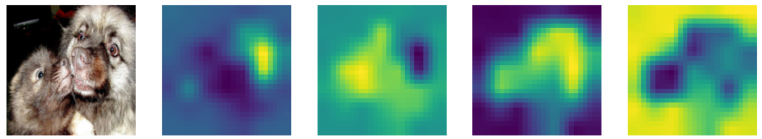
- **Hierarchical Contextualization + Gated Aggregation.**



(a) Self-Attention (b) Focal-Modulation (c) Context Aggregation

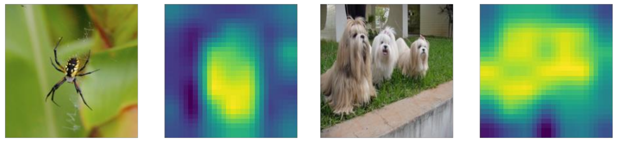
```python
def forward(x, m=0):
    x = pj_in(x).permute(0, 3, 1, 2)
    q, z, gate = split(x, (C, C, L+1), 1)
    for ℓ in range(L):
        z = hc_layers[ℓ](z)              # Eq.(4), hierarchical contextualization
        m = m + z * gate[:, ℓ:ℓ+1]     # Eq.(5), gated aggregation

    m = m + GeLU(z.mean(dim=(2,3))) * gate[:,L:]
    x = q * pj_cxt(m)                   # Eq.(6), Focal Modulation
    return pj_out( x.permute(0, 2, 3, 1) )
```



$$\mathbf{Z}^{\ell} = f_a^{\ell}(\mathbf{Z}^{\ell-1}) \triangleq \mathrm{GeLU}(\mathrm{DWConv}(\mathbf{Z}^{\ell-1})) \in \mathbb{R}^{H\times W\times C} \quad \text{Eq. (4)}$$

$$\mathbf{Z}^{out} = \sum_{\ell=1}^{L+1} \boxed{\mathbf{G}^{\ell}} \odot \mathbf{Z}^{\ell} \in \mathbb{R}^{H\times W\times C} \quad \text{Eq. (5)}$$

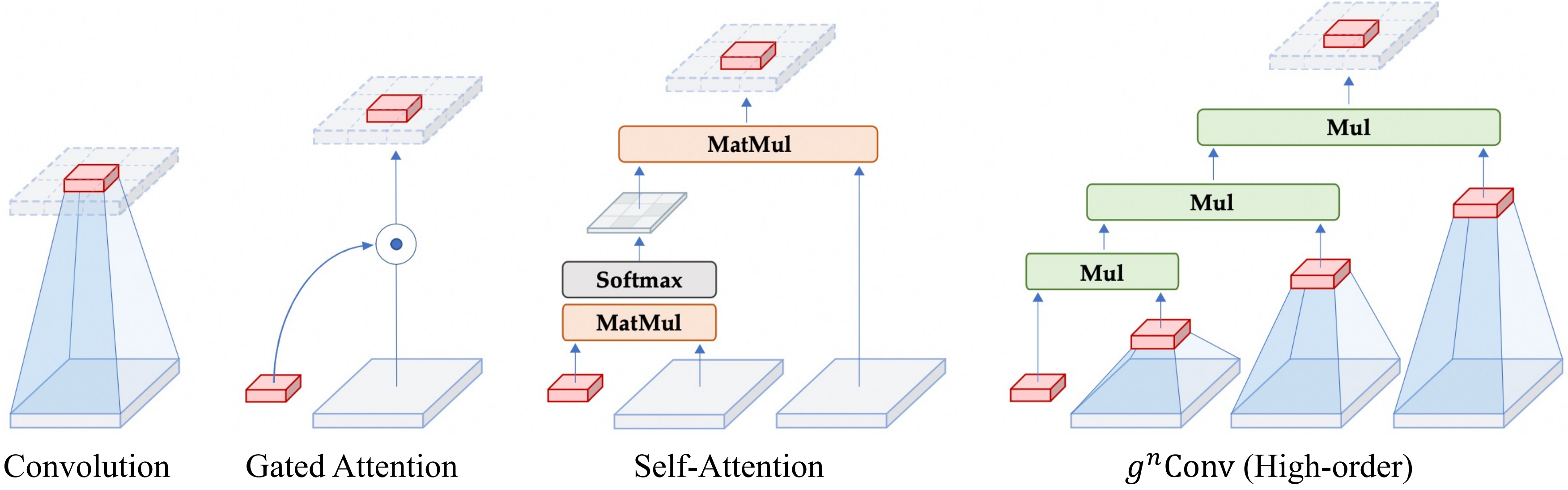


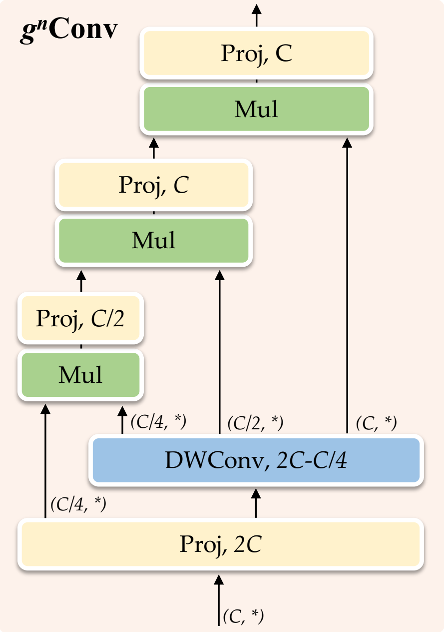
$$\boldsymbol{y}_i = q(\boldsymbol{x}_i) \odot \boxed{h(\sum_{\ell=1}^{L+1} \boldsymbol{g}_i^{\ell} \cdot \boldsymbol{z}_i^{\ell})} \quad \text{Eq. (6)}$$

[1] Focal Modulation Networks. NeurIPS, 2022.

Gating & Hierarchical Kernel: HorNet

- High-order Interactions: Recursive DWConv + Gating.

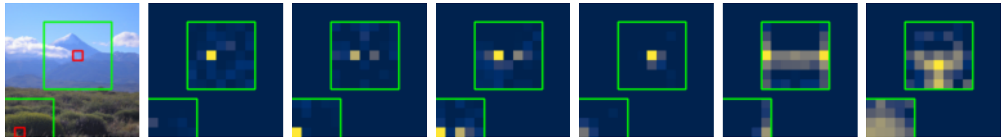




$$x^{(i,c)}_{g^n\mathrm{Conv}} = p_n^{(i,c)} = \sum_{j\in\Omega_i}\sum_{c'=1}^{C} \underline{w^{c}_{n-1,i\to j}\mathbf{g}^{(i,c)}_{n-1}} w^{(c',c)}_{\phi_{\mathrm{in}}} x^{(j,c')} \triangleq \sum_{j\in\Omega_i}\sum_{c'=1}^{C} h^{c}_{ij} w^{(c',c)}_{\phi_{\mathrm{in}}} x^{(j,c')} \quad \text{Eq. (3.8)}$$

```
def forward(self, x):
    x = self.proj_in(x)
    y, x = torch.split(x, (self.dims[0], sum(self.dims)), dim=1)
    x = self.dwconv(x)
    x_list = torch.split(x, self.dims, dim=1)
    x = y * x_list[0]
    for i in range(self.order -1):
        x = self.projs[i](x) * x_list[i+1]
    return self.proj_out(x)
```

```
self.projs = nn.ModuleList(
    [nn.Conv2d(self.dims[i], self.dims[i+1], 1)
    for i in range(order-1)])
self.proj_out = nn.Conv2d(dim, dim, 1)
```



Adaptive weights generated by g^nConv, i.e., $\frac{1}{C}\Sigma_{c=1}^{C} h^{c}_{ij}$ in Eq. (3.8)

[1] HorNet: Efficient High-Order Spatial Interactions with Recursive Gated Convolutions. NeurIPS, 2022.

Multi-order Interaction: MogaNet

- **Representation Bottleneck[1]: Loss in the middle-order interactions.**

Multi-order Interactions

$$I^{(m)}(i,j) = \mathbb{E}_{S \subseteq N \setminus \{i,j\}, |S|=m}[\Delta f(i,j,S)]$$

$$N = \{1, \dots, n\} \quad 0 \leq m \geq n-2$$

$$\Delta f(i,j,S) = f(S \cup \{i,j\}) - f(S \cup \{i\}) - f(S \cup \{j\}) + f(S)$$

Interaction Strengths

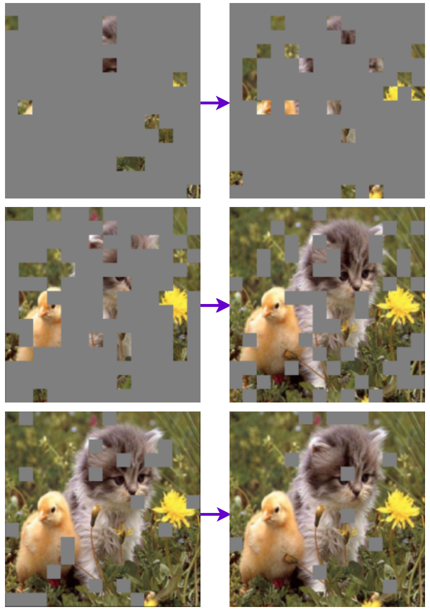
$$J^{(m)} = \frac{\mathbb{E}_{x \in \Omega} \mathbb{E}_{i,j} |I^{(m)}(i,j|x)|}{\mathbb{E}_{m'} \mathbb{E}_{x \in \Omega} \mathbb{E}_{i,j} |I^{(m')}(i,j|x)|}$$

Much new information
Little new infomation

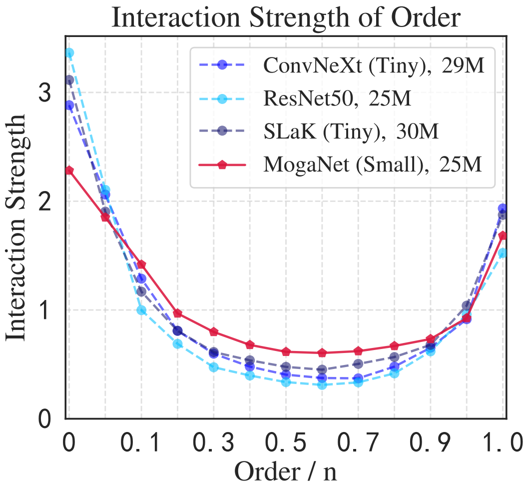
Little new information
Much new infomation

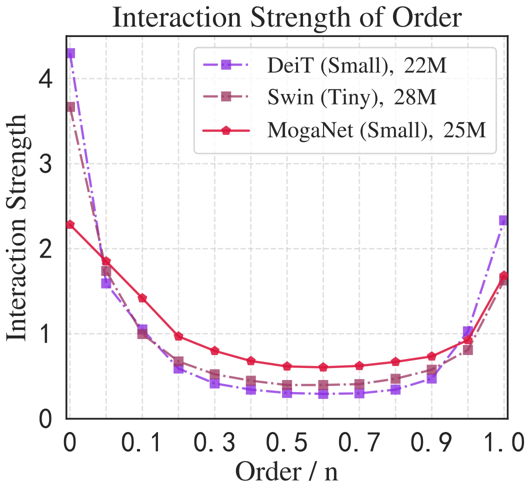
Much new information
Little new infomation

5% 10%
25% 75%
90% 95%



Both ViTs and modern CNN architectures fail to explore middle-order interactions, which are informative to humans.





[1] Discovering and Explaining the Representation Bottleneck of DNNs. ICLR, 2022. [2] MogaNet: Multi-order Gated Aggregation Network. ICLR, 2024.

Multi-order Interaction: MogaNet

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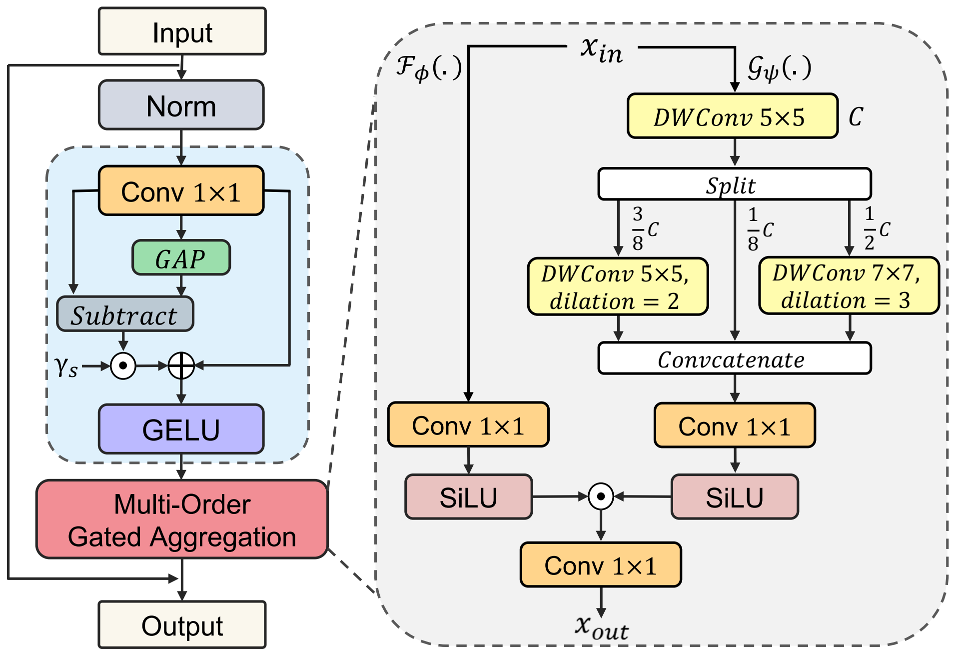
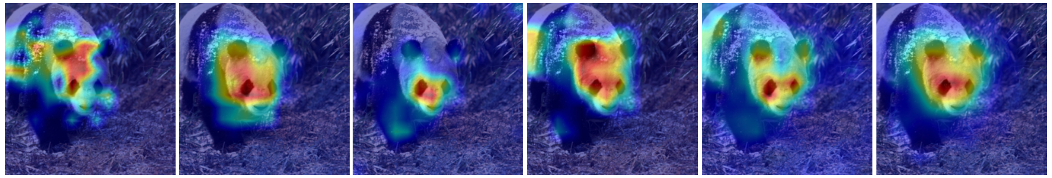
- Spatial Aggregation (SA): Multi-order context extraction + Gated aggregation.



$$Z = X + \mathrm{Moga}\Big(\mathrm{FD}\big(\mathrm{Norm}(X)\big)\Big)$$

\wo Gating | 1: 0: 0 | 0: 0: 1 | \wo FD(.) | \wo CA(.) | MogaNet



Feature decomposition:

$$Y = \mathrm{Conv}_{1\times1}(X),$$
$$Z = \mathrm{GELU}\Big(Y + \gamma_s \odot \big(Y - \mathrm{GAP}(Y)\big)\Big)$$

Gated aggregation branch:

$$Z = \underbrace{\mathrm{SiLU}\big(\mathrm{Conv}_{1\times1}(X)\big)}_{\mathcal{F}_\phi} \odot \underbrace{\mathrm{SiLU}\big(\mathrm{Conv}_{1\times1}(Y_C)\big)}_{\mathcal{G}_\psi}$$

Multi-order DWConvs: DW5×5, DW5×5 (d=2), DW7×7 (d=3)

$$C_l + C_m + C_h = C,\ Y_C = \mathrm{Concat}(Y_{l,1:C_l}, Y_m, Y_h)$$

Modules	Top-1 Acc (%)	Params. (M)	FLOPs (G)
Baseline (+Gating branch)	77.2	5.09	1.070
$\mathrm{DW}_{7\times7}$	77.4	5.14	1.094
$\mathrm{DW}_{5\times5,d=1} + \mathrm{DW}_{7\times7,d=3}$	77.5	5.15	1.112
$\mathrm{DW}_{5\times5,d=1} + \mathrm{DW}_{5\times5,d=2} + \mathrm{DW}_{7\times7,d=3}$	77.5	5.17	1.185
+Multi-order, $C_l : C_m : C_h = 1:0:3$	77.5	5.17	1.099
+Multi-order, $C_l : C_m : C_h = 0:1:1$	77.6	5.17	1.103
+Multi-order, $C_l : C_m : C_h = 1:6:9$	77.7	5.17	1.104
+Multi-order, $C_l : C_m : C_h = 1:3:4$	**77.8**	5.17	1.102

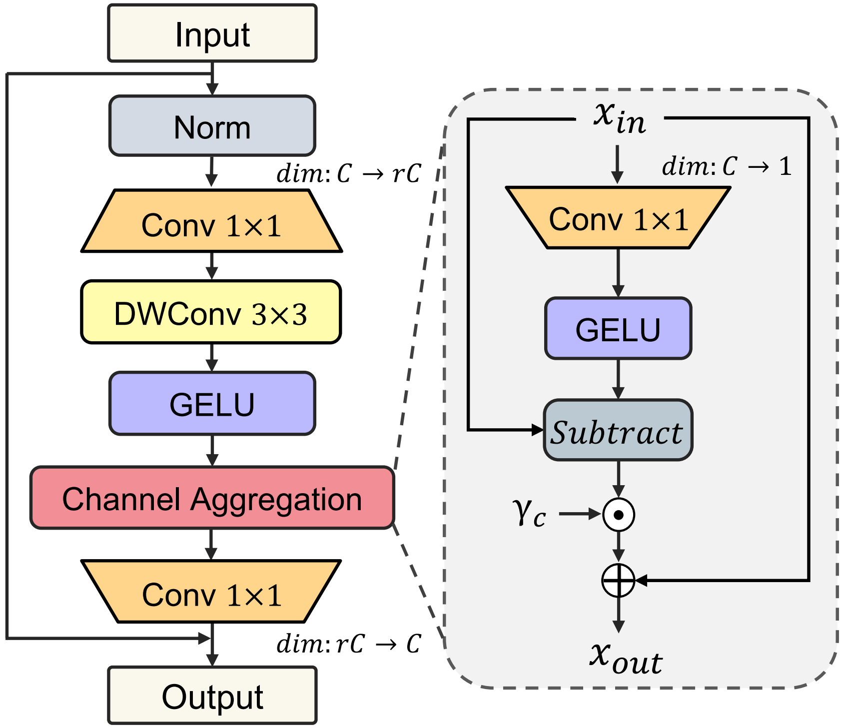
Top-1	Acc (%)	Context branch None	GELU	SiLU
Gating branch	None	76.3	76.7	76.7
	Sigmoid	76.8	77.0	76.9
	GELU	76.7	76.8	77.0
	SiLU	76.9	77.1	**77.2**

Ablation of SA module with MogaNet-T on ImageNet

[1] MogaNet: Multi-order Gated Aggregation Network. ICLR, 2024.

Multi-order Interaction: MogaNet

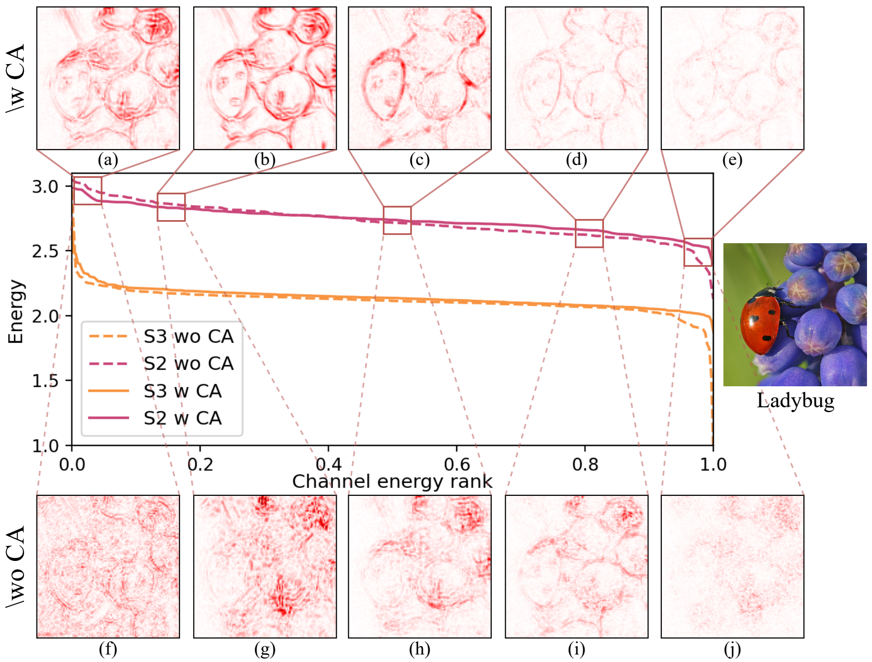
- **Channel Aggregation (CA): Multi-order Channel Reallocation.**



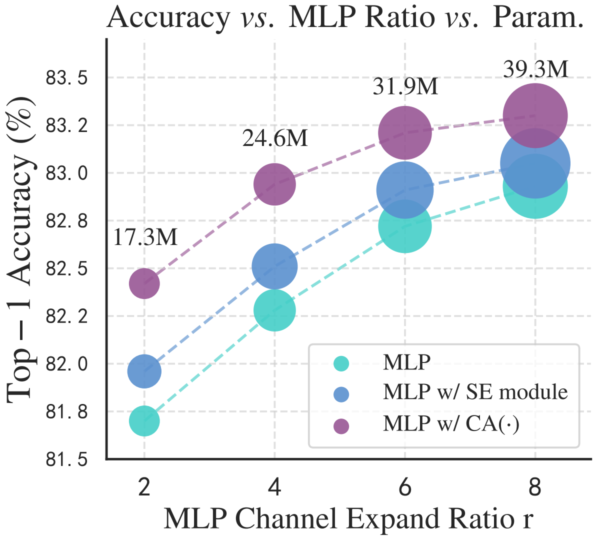
$$Y = \mathrm{GELU}\Big(\mathrm{DW}_{3\times3}\big(\mathrm{Conv}_{1\times1}(\mathrm{Norm}(X))\big)\Big),$$

$$Z = \mathrm{Conv}_{1\times1}(\mathrm{CA}(Y)) + X.$$

$$\mathrm{CA}(X) = X + \gamma_c \odot \big(X - \mathrm{GELU}(XW_r)\big)$$



Channel energy ranks and channel saliency maps (CSM)[1]



Modules		Top-1 Acc (%)	Params. (M)	FLOPs (G)
Baseline		76.6	4.75	1.01
SMixer	+Gating branch	77.3	5.09	1.07
	$+\mathrm{DW}_{7\times7}$	77.5	5.14	1.09
	+Multi-order DW(·)	78.0	5.17	1.10
	+FD(·)	78.3	5.18	1.10
CMixer	+SE module	78.6	5.29	1.14
	+CA(·)	**79.0**	5.20	1.10

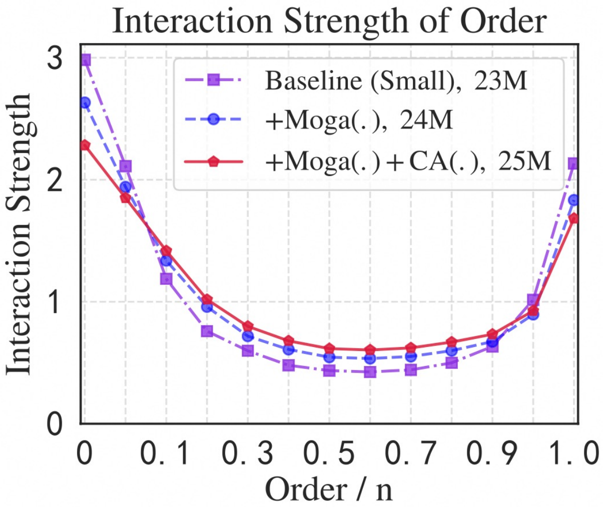
Ablation of MogaNet-S on ImageNet

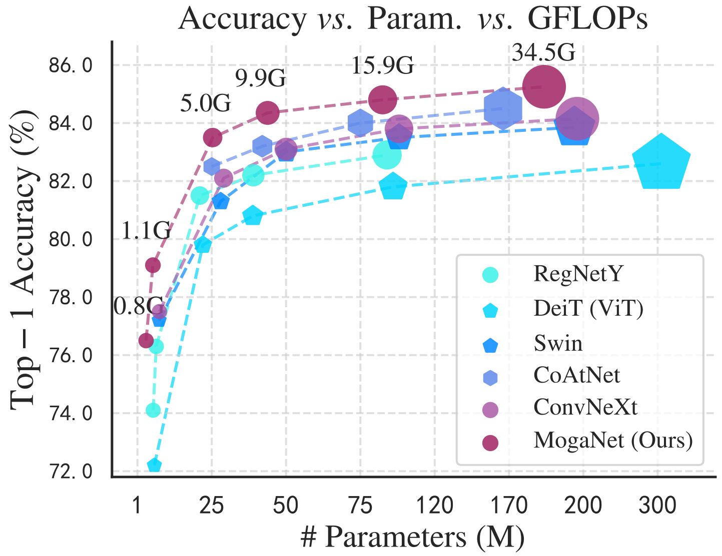
[1] Reflash dropout in image supe-resolution. CVPR, 2022.

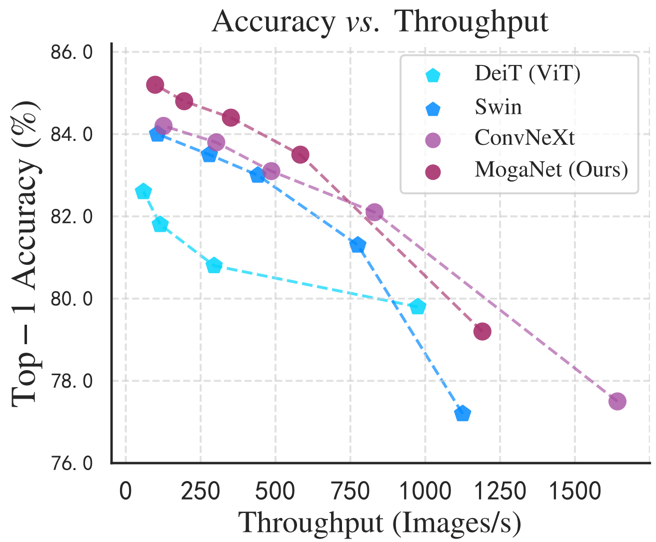
Multi-order Interaction: MogaNet

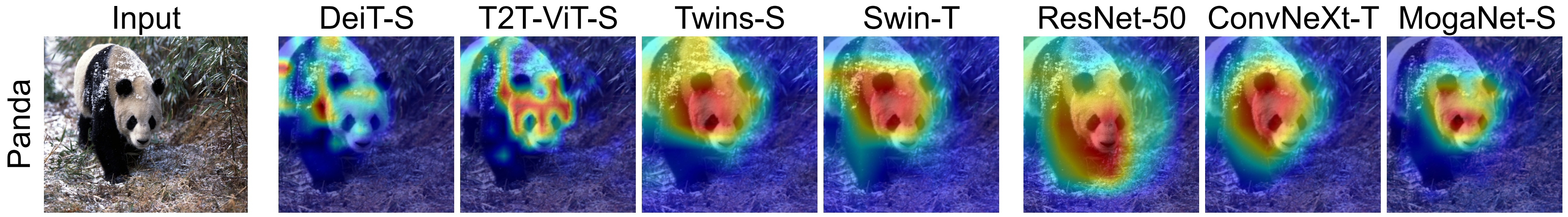
- Great scalability and efficiency of parameters.
- Relieving representation bottleneck.

Modules	Top-1 Acc (%)
ConvNeXt-T	82.1
Baseline	82.2
Moga Block	**83.4**
−FD(·)	83.2
−Multi-DW(·)	83.1
−Moga(·)	82.7
−CA(·)	82.9









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Comparison of CNNs: ImageNet

- **ImageNet-1K Classification: Scaling from 3M (light-weight) to 200M.**

Architecture	Date	Type	Image Size	Param. (M)	FLOPs (G)	Top-1 Acc (%)
ResNet-18	CVPR'2016	C	224^2	11.7	1.80	71.5
ShuffleNetV2 2×	ECCV'2018	C	224^2	5.5	0.60	75.4
EfficientNet-B0	ICML'2019	C	224^2	5.3	0.39	77.1
RegNetY-800MF	CVPR'2020	C	224^2	6.3	0.80	76.3
DeiT-T†	ICML'2021	T	224^2	5.7	1.08	74.1
PVT-T	ICCV'2021	T	224^2	13.2	1.60	75.1
T2T-ViT-7	ICCV'2021	T	224^2	4.3	1.20	71.7
ViT-C	NIPS'2021	T	224^2	4.6	1.10	75.3
SReT-T$_{Distill}$	ECCV'2022	T	224^2	4.8	1.10	77.6
PiT-Ti	ICCV'2021	H	224^2	4.9	0.70	74.6
LeViT-S	ICCV'2021	H	224^2	7.8	0.31	76.6
CoaT-Lite-T	ICCV'2021	H	224^2	5.7	1.60	77.5
Swin-1G	ICCV'2021	H	224^2	7.3	1.00	77.3
MobileViT-S	ICLR'2022	H	256^2	5.6	4.02	78.4
MobileFormer-294M	CVPR'2022	H	224^2	11.4	0.59	77.9
ConvNext-XT	CVPR'2022	C	224^2	7.4	0.60	77.5
VAN-B0	CVMJ'2023	C	224^2	4.1	0.88	75.4
ParC-Net-S	ECCV'2022	C	256^2	5.0	3.48	78.6
MogaNet-XT	Ours	C	256^2	3.0	1.04	77.2
MogaNet-T	Ours	C	224^2	5.2	1.10	79.0
MogaNet-T§	Ours	C	256^2	5.2	1.44	**80.0**

Light-weight (3-10M)

Architecture	Date	Type	Image Size	Param. (M)	FLOPs (G)	Top-1 Acc (%)
Deit-S	ICML'2021	T	224^2	22	4.6	79.8
Swin-T	ICCV'2021	T	224^2	28	4.5	81.3
CSWin-T	CVPR'2022	T	224^2	23	4.3	82.8
LITV2-S	NIPS'2022	T	224^2	28	3.7	82.0
CoaT-S	ICCV'2021	H	224^2	22	12.6	82.1
CoAtNet-0	NIPS'2021	H	224^2	25	4.2	82.7
UniFormer-S	ICLR'2022	H	224^2	22	3.6	82.9
RegNetY-4GF†	CVPR'2020	C	224^2	21	4.0	81.5
ConvNeXt-T	CVPR'2022	C	224^2	29	4.5	82.1
SLaK-T	ICLR'2023	C	224^2	30	5.0	82.5
HorNet-T$_{7\times7}$	NIPS'2022	C	224^2	22	4.0	82.8
MogaNet-S	Ours	C	224^2	25	5.0	**83.4**
Swin-S	ICCV'2021	T	224^2	50	8.7	83.0
Focal-S	NIPS'2021	T	224^2	51	9.1	83.6
CSWin-S	CVPR'2022	T	224^2	35	6.9	83.6
LITV2-M	NIPS'2022	T	224^2	49	7.5	83.3
CoaT-M	ICCV'2021	H	224^2	45	9.8	83.6
CoAtNet-1	NIPS'2021	H	224^2	42	8.4	83.3
UniFormer-B	ICLR'2022	H	224^2	50	8.3	83.9
FAN-B-Hybrid	ICML'2022	H	224^2	50	11.3	83.9
EfficientNet-B6	ICML'2019	C	528^2	43	19.0	84.0
RegNetY-8GF†	CVPR'2020	C	224^2	39	8.1	82.2
ConvNeXt-S	CVPR'2022	C	224^2	50	8.7	83.1
FocalNet-S (LRF)	NIPS'2022	C	224^2	50	8.7	83.5
HorNet-S$_{7\times7}$	NIPS'2022	C	224^2	50	8.8	84.0
SLaK-S	ICLR'2023	C	224^2	55	9.8	83.8
MogaNet-B	Ours	C	224^2	44	9.9	**84.3**

Normal size (25-50M)

Architecture	Date	Type	Image Size	Param. (M)	FLOPs (G)	Top-1 Acc (%)
DeiT-B	ICML'2021	T	224^2	86	17.5	81.8
Swin-B	ICCV'2021	T	224^2	89	15.4	83.5
Focal-B	NIPS'2021	T	224^2	90	16.4	84.0
CSWin-B	CVPR'2022	T	224^2	78	15.0	84.2
DeiT III-B	ECCV'2022	T	224^2	87	18.0	83.8
BoTNet-T7	CVPR'2021	H	256^2	79	19.3	84.2
CoAtNet-2	NIPS'2021	H	224^2	75	15.7	84.1
FAN-B-Hybrid	ICML'2022	H	224^2	77	16.9	84.3
RegNetY-16GF	CVPR'2020	C	224^2	84	16.0	82.9
ConvNeXt-B	CVPR'2022	C	224^2	89	15.4	83.8
RepLKNet-31B	CVPR'2022	C	224^2	79	15.3	83.5
FocalNet-B (LRF)	NIPS'2022	C	224^2	89	15.4	83.9
HorNet-B$_{7\times7}$	NIPS'2022	C	224^2	87	15.6	84.3
SLaK-B	ICLR'2023	C	224^2	95	17.1	84.0
MogaNet-L	Ours	C	224^2	83	15.9	**84.7**
Swin-L‡	ICCV'2021	T	384^2	197	104	87.3
DeiT III-L‡	ECCV'2022	T	384^2	304	191	87.7
CoAtNet-3‡	NIPS'2021	H	384^2	168	107	87.6
RepLKNet-31L‡	CVPR'2022	C	384^2	172	96	86.6
ConvNeXt-L	CVPR'2022	C	224^2	198	34.4	84.3
ConvNeXt-L‡	CVPR'2022	C	384^2	198	101	87.5
ConvNeXt-XL‡	CVPR'2022	C	384^2	350	179	87.8
HorNet-L‡	NIPS'2022	C	384^2	202	102	87.7
MogaNet-XL	Ours	C	224^2	181	34.5	85.1
MogaNet-XL‡	Ours	C	384^2	181	102	**87.8**

Large models (100-300M)

ViT-G/14$^\#$ [30]	T	518^2	1.84B	5160G	90.5
CoAtNet-6$^\#$ [20]	T	512^2	1.47B	1521G	90.5
CoAtNet-7$^\#$ [20]	T	512^2	2.44B	2586G	90.9
Florence-CoSwin-H$^\#$ [59]	T	–	893M	–	90.0
SwinV2-G$^\#$ [16]	T	640^2	3.00B	–	90.2
RepLKNet-XL$^\#$ [22]	C	384^2	335M	129G	87.8
BiT-L-ResNet152x4$^\#$ [67]	C	480^2	928M	–	87.5
InternImage-H$^\#$ (ours)	C	224^2	1.08B	188G	88.9
InternImage-H$^\#$ (ours)	C	640^2	1.08B	1478G	89.6

Scaling-up to 1B

Comparison of CNNs: Det. and Seg.

- COCO Detection and Segmentation: RetinaNet, (Cascade) Mask R-CNN.

Architecture	Type	#P. (M)	FLOPs (G)	RetinaNet 1× AP	AP_{50}	AP_{75}	AP^S	AP_M	AP_L
RegNet-800M	C	17	168	35.6	54.7	37.7	19.7	390	47.8
PVTV2-B0	T	13	160	37.1	57.2	39.2	23.4	40.4	49.2
MogaNet-XT	C	12	167	**39.7**	**60.0**	**42.4**	**23.8**	**43.6**	**51.7**
ResNet-18	C	21	189	31.8	49.6	33.6	16.3	34.3	43.2
RegNet-1.6G	C	20	185	37.4	56.8	39.8	22.4	41.1	49.2
RegNet-3.2G	C	26	218	39.0	58.4	41.9	22.6	43.5	50.8
PVT-T	T	23	183	36.7	56.9	38.9	22.6	38.8	50.0
PoolFormer-S12	T	22	207	36.2	56.2	38.2	20.8	39.1	48.0
PVTV2-B1	T	24	187	41.1	61.4	43.8	26.0	44.6	54.6
MogaNet-T	C	14	173	**41.4**	**61.5**	**44.4**	**25.1**	**45.7**	**53.6**
ResNet-50	C	37	239	36.3	55.3	38.6	19.3	40.0	48.8
Swin-T	T	38	245	41.8	62.6	44.7	25.2	45.8	54.7
PVT-S	T	34	226	40.4	61.3	43.0	25.0	42.9	55.7
Twins-SVT-S	T	34	209	42.3	63.4	45.2	26.0	45.5	56.5
Focal-T	T	39	265	43.7	-	-	-	-	-
PoolFormer-S36	T	41	272	39.5	60.5	41.8	22.5	42.9	52.4
PVTV2-B2	T	35	281	44.6	65.7	47.6	28.6	48.5	59.2
CMT-S	H	45	231	44.3	65.5	47.5	27.1	48.3	59.1
MogaNet-S	C	35	253	**45.8**	**66.6**	**49.0**	**29.1**	**50.1**	**59.8**
ResNet-101	C	57	315	38.5	57.8	41.2	21.4	42.6	51.1
PVT-M	T	54	258	41.9	63.1	44.3	25.0	44.9	57.6
Focal-S	T	62	367	45.6	-	-	-	-	-
PVTV2-B3	T	55	263	46.0	67.0	49.5	28.2	50.0	61.3
PVTV2-B4	T	73	315	46.3	67.0	49.6	29.0	50.1	62.7
MogaNet-B	C	54	355	**47.7**	**68.9**	**51.0**	**30.5**	**52.2**	**61.7**
ResNeXt-101-64	C	95	473	41.0	60.9	44.0	23.9	45.2	54.0
PVTV2-B5	T	92	335	46.1	66.6	49.5	27.8	50.2	62.0
MogaNet-L	C	92	477	**48.7**	**69.5**	**52.6**	**31.5**	**53.4**	**62.7**

Architecture	Type	#P. (M)	FLOPs (G)	Mask R-CNN 1× AP^b	AP^b_{50}	AP^b_{75}	AP^m	AP^m_{50}	AP^m_{75}
RegNet-800M	C	27	187	37.5	57.9	41.1	34.3	56.0	36.8
MogaNet-XT	C	23	185	**40.7**	**62.3**	**44.4**	**37.6**	**59.6**	**40.2**
ResNet-18	C	31	207	34.0	54.0	36.7	31.2	51.0	32.7
RegNet-1.6G	C	29	204	38.9	60.5	43.1	35.7	57.4	38.9
PVT-T	T	33	208	36.7	59.2	39.3	35.1	56.7	37.3
PoolFormer-S12	T	32	207	37.3	59.0	40.1	34.6	55.8	36.9
MogaNet-T	C	25	192	**42.6**	**64.0**	**46.4**	**39.1**	**61.3**	**42.0**
ResNet-50	C	44	260	38.0	58.6	41.4	34.4	55.1	36.7
RegNet-6.4G	C	45	307	41.1	62.3	45.2	37.1	59.2	39.6
PVT-S	T	44	245	40.4	62.9	43.8	37.8	60.1	40.3
Swin-T	T	48	264	42.2	64.6	46.2	39.1	61.6	42.0
MViT-T	T	46	326	45.9	**68.7**	50.5	42.1	**66.0**	45.4
PoolFormer-S36	T	32	207	41.0	63.1	44.8	37.7	60.1	40.0
Focal-T	T	49	291	44.8	67.7	49.2	41.0	64.7	44.2
PVTV2-B2	T	45	309	45.3	67.1	49.6	41.2	64.2	44.4
LITV2-S	T	47	261	44.9	67.0	49.5	40.8	63.8	44.2
CMT-S	H	45	249	44.6	66.8	48.9	40.7	63.9	43.4
Conformer-S/16	H	58	341	43.6	65.6	47.7	39.7	62.6	42.5
Uniformer-S	H	41	269	45.6	68.1	49.7	41.6	64.8	45.0
ConvNeXt-T	C	48	262	44.2	66.6	48.3	40.1	63.3	42.8
FocalNet-T (SRF)	C	49	267	45.9	68.3	50.1	41.3	65.0	44.3
FocalNet-T (LRF)	C	49	268	46.1	68.2	50.6	41.5	65.1	44.5
MogaNet-S	C	45	272	**46.7**	68.0	**51.3**	**42.2**	65.4	**45.5**
ResNet-101	C	63	336	40.4	61.1	44.2	36.4	57.7	38.8
RegNet-12G	C	64	423	42.2	63.7	46.1	38.0	60.5	40.5
PVT-M	T	64	302	42.0	64.4	45.6	39.0	61.6	42.1
Swin-S	T	69	354	44.8	66.6	48.9	40.9	63.4	44.2
Focal-S	T	71	401	47.4	69.8	51.9	42.8	66.6	46.1
PVTV2-B3	T	65	397	47.0	68.1	51.7	42.5	65.7	45.7
LITV2-M	T	68	315	46.5	68.0	50.9	42.0	65.1	45.0
UniFormer-B	H	69	399	47.4	69.7	52.1	43.1	66.0	46.5
ConvNeXt-S	C	70	348	45.4	67.9	50.0	41.8	65.2	45.1
MogaNet-B	C	63	373	**47.9**	**70.0**	**52.7**	**43.2**	**67.0**	**46.6**
Swin-B	T	107	496	46.9	69.6	51.2	42.3	65.9	45.6
PVTV2-B5	T	102	557	47.4	68.6	51.9	42.5	65.7	46.0
ConvNeXt-B	C	108	486	47.0	69.4	51.7	42.7	66.3	46.0
FocalNet-B (SRF)	C	109	496	48.8	70.7	53.5	43.3	67.5	46.5
MogaNet-L	C	102	495	**49.4**	**70.7**	**54.1**	**44.1**	**68.1**	**47.6**

Architecture	Type	#P. (M)	FLOPs (G)	Cascade Mask R-CNN +MS 3× AP^{bb}	AP^b_{50}	AP^b_{75}	AP^m	AP^m_{50}	AP^m_{75}
ResNet-50	C	77	739	46.3	64.3	50.5	40.1	61.7	43.4
Swin-T	T	86	745	50.4	69.2	54.7	43.7	66.6	47.3
Focal-T	T	87	770	51.5	70.6	55.9	-	-	-
ConvNeXt-T	C	86	741	50.4	69.1	54.8	43.7	66.5	47.3
FocalNet-T (SRF)	C	86	746	51.5	70.1	55.8	44.6	67.7	48.4
MogaNet-S	C	78	750	**51.6**	**70.8**	**56.3**	**45.1**	**68.7**	**48.8**
ResNet-101-32	C	96	819	48.1	66.5	52.4	41.6	63.9	45.2
Swin-S	T	107	838	51.9	70.7	56.3	45.0	68.2	48.8
ConvNeXt-S	C	108	827	51.9	70.8	56.5	45.0	68.4	49.1
MogaNet-B	C	101	851	**52.6**	**72.0**	**57.3**	**46.0**	**69.6**	**49.7**
Swin-B	T	145	982	51.9	70.5	56.4	45.0	68.1	48.9
ConvNeXt-B	C	146	964	52.7	71.3	57.2	45.6	68.9	49.5
MogaNet-L	C	140	974	**53.3**	**71.8**	**57.8**	**46.1**	**69.2**	**49.8**
Swin-L‡	T	253	1382	53.9	72.4	58.8	46.7	70.1	50.8
ConvNeXt-L‡	C	255	1354	54.8	73.8	59.8	47.6	71.3	51.7
ConvNeXt-XL‡	C	407	1898	55.2	74.2	59.9	47.7	71.6	52.2
RepLKNet-31L‡	C	229	1321	53.9	72.5	58.6	46.5	70.0	50.6
HorNet-L‡	C	259	1399	56.0	-	-	48.6	-	-
MogaNet-XL‡	C	238	1355	**56.2**	**75.0**	**61.2**	**48.8**	**72.6**	**53.3**

method	detector	#params	AP^b val2017	AP^b test-dev
Swin-L [2]	DyHead [72]	213M	56.2	58.4
Swin-L‡ [2]	HTC++ [2]	284M	58.0	58.7
Swin-L‡ [2]	Soft-Teacher [73]	284M	60.7	61.3
Florence-CoSwin-H# [59]	DyHead [72]	637M	62.0	62.4
ViT-L‡ [9]	ViT-Adapter [69]	401M	62.6	62.6
Swin-L‡ [2]	DINO [74]	218M	63.2	63.3
FocalNet-H‡ [75]	DINO [74]	746M	64.2	64.3
ViT-Huge [76]	Group-DETRv2 [76]	629M	–	64.5
SwinV2-G# [16]	HTC++ [2]	3.00B	62.5	63.1
BEiT-3# [17]	ViTDet [77]	1.90B	–	63.7
FD-SwinV2-G# [26]	HTC++ [2]	3.00B	–	64.2
InternImage-XL‡ (ours)	DINO [74]	602M	64.2	64.3
InternImage-H# (ours)	DINO [74]	2.18B	65.0	65.4

Comparison of CNNs: Seg. and Pose

ADE20K Semantic Segmentation

Architecture	Date	Type	Crop size	Param. (M)	FLOPs (G)	mIoU^{ss} (%)
ResNet-18	CVPR'2016	C	512^2	41	885	39.2
MogaNet-XT	Ours	C	512^2	30	856	**42.2**
ResNet-50	CVPR'2016	C	512^2	67	952	42.1
MogaNet-T	Ours	C	512^2	33	862	**43.7**
DeiT-S	ICML'2021	T	512^2	52	1099	44.0
Swin-T	ICCV'2021	T	512^2	60	945	46.1
TwinsP-S	NIPS'2021	T	512^2	55	919	46.2
Twins-S	NIPS'2021	T	512^2	54	901	46.2
Focal-T	NIPS'2021	T	512^2	62	998	45.8
Uniformer-S_{h32}	ICLR'2022	H	512^2	52	955	47.0
UniFormer-S	ICLR'2022	H	512^2	52	1008	47.6
ConvNeXt-T	CVPR'2022	C	512^2	60	939	46.7
FocalNet-T (SRF)	NIPS'2022	C	512^2	61	944	46.5
HorNet-$T_{7\times7}$	NIPS'2022	C	512^2	52	926	48.1
MogaNet-S	Ours	C	512^2	55	946	**49.2**
Swin-S	ICCV'2021	T	512^2	81	1038	48.1
Twins-B	NIPS'2021	T	512^2	89	1020	47.7
Focal-S	NIPS'2021	T	512^2	85	1130	48.0
Uniformer-B_{h32}	ICLR'2022	H	512^2	80	1106	49.5
ConvNeXt-S	CVPR'2022	C	512^2	82	1027	48.7
FocalNet-S (SRF)	NIPS'2022	C	512^2	83	1035	49.3
SLaK-S	ICLR'2023	C	512^2	91	1028	49.4
MogaNet-B	Ours	C	512^2	74	1050	**50.1**
Swin-B	ICCV'2021	T	512^2	121	1188	49.7
Focal-B	NIPS'2021	T	512^2	126	1354	49.0
ConvNeXt-B	CVPR'2022	C	512^2	122	1170	49.1
RepLKNet-31B	CVPR'2022	C	512^2	112	1170	49.9
FocalNet-B (SRF)	NIPS'2022	C	512^2	124	1180	50.2
SLaK-B	ICLR'2023	C	512^2	135	1185	50.2
MogaNet-L	Ours	C	512^2	113	1176	**50.9**
Swin-L‡	ICCV'2021	T	640^2	234	2468	52.1
ConvNeXt-L‡	CVPR'2022	C	640^2	245	2458	53.7
RepLKNet-31L‡	CVPR'2022	C	640^2	207	2404	52.4
MogaNet-XL‡	Ours	C	640^2	214	2451	**54.0**

method	crop size	#params	#FLOPs	mIoU (SS)	mIoU (MS)
Swin-T [2]	512^2	60M	945G	44.5	45.8
ConvNeXt-T [21]	512^2	60M	939G	46.0	46.7
SLaK-T [29]	512^2	65M	936G	47.6	–
InternImage-T (ours)	512^2	59M	944G	47.9	48.1
Swin-S [2]	512^2	81M	1038G	47.6	49.5
ConvNeXt-S [21]	512^2	82M	1027G	48.7	49.6
SLaK-S [29]	512^2	91M	1028G	49.4	–
InternImage-S (ours)	512^2	80M	1017G	50.1	50.9
Swin-B [2]	512^2	121M	1188G	48.1	49.7
ConvNeXt-B [21]	512^2	122M	1170G	49.1	49.9
RepLKNet-31B [22]	512^2	112M	1170G	49.9	50.6
SLaK-B [29]	512^2	135M	1172G	50.2	–
InternImage-B (ours)	512^2	128M	1185G	50.8	51.3
Swin-L‡ [2]	640^2	234M	2468G	52.1	53.5
RepLKNet-31L‡ [22]	640^2	207M	2404G	52.4	52.7
ConvNeXt-L‡ [21]	640^2	235M	2458G	53.2	53.7
ConvNeXt-XL‡ [21]	640^2	391M	3335G	53.6	54.0
InternImage-L‡ (ours)	640^2	256M	2526G	53.9	54.1
InternImage-XL‡ (ours)	640^2	368M	3142G	55.0	55.3
SwinV2-G$^\#$ [16]	896^2	3.00B	–	–	59.9
InternImage-H$^\#$ (ours)	896^2	1.12B	3566G	59.9	60.3
BEiT-3$^\#$ [17]	896^2	1.90B	–	–	62.8
FD-SwinV2-G$^\#$ [26]	896^2	3.00B	–	–	61.4
InternImage-H$^\#$ (ours) + Mask2Former [80]	896^2	1.31B	4635G	62.5	62.9

DCN.V3 Scaling-up to 1B

COCO 2D Human Pose Estimation

Architecture	Type	Crop size	#P. (M)	FLOPs (G)	AP (%)	AP^{50} (%)	AP^{75} (%)	AR (%)
MobileNetV2	C	256×192	10	1.6	64.6	87.4	72.3	70.7
ShuffleNetV2 2×	C	256×192	8	1.4	59.9	85.4	66.3	66.4
MogaNet-XT	C	256×192	6	1.8	**72.1**	**89.7**	**80.1**	**77.7**
RSN-18	C	256×192	9	2.3	70.4	88.7	77.9	77.1
MogaNet-T	C	256×192	8	2.2	**73.2**	**90.1**	**81.0**	**78.8**
ResNet-50	C	256×192	34	5.5	72.1	89.9	80.2	77.6
HRNet-W32	C	256×192	29	7.1	74.4	90.5	81.9	78.9
Swin-T	T	256×192	33	6.1	72.4	90.1	80.6	78.2
PVT-S	T	256×192	28	4.1	71.4	89.6	79.4	77.3
PVTV2-B2	T	256×192	29	4.3	73.7	90.5	81.2	79.1
Uniformer-S	H	256×192	25	4.7	74.0	90.3	82.2	79.5
ConvNeXt-T	C	256×192	33	5.5	73.2	90.0	80.9	78.8
MogaNet-S	C	256×192	29	6.0	**74.9**	**90.7**	**82.8**	**80.1**
ResNet-101	C	256×192	53	12.4	71.4	89.3	79.3	77.1
ResNet-152	C	256×192	69	15.7	72.0	89.3	79.8	77.8
HRNet-W48	C	256×192	64	14.6	75.1	90.6	82.2	80.4
Swin-B	T	256×192	93	18.6	72.9	89.9	80.8	78.6
Swin-L	T	256×192	203	40.3	74.3	90.6	82.1	79.8
Uniformer-B	H	256×192	54	9.2	75.0	90.6	83.0	80.4
ConvNeXt-S	C	256×192	55	9.7	73.7	90.3	81.9	79.3
ConvNeXt-B	C	256×192	94	16.4	74.0	90.7	82.1	79.5
MogaNet-B	C	256×192	47	10.9	**75.3**	**90.9**	**83.3**	**80.7**
MobileNetV2	C	384×288	10	3.6	67.3	87.9	74.3	72.9
ShuffleNetV2 2×	C	384×288	8	3.1	63.6	86.5	70.5	69.7
MogaNet-XT	C	384×288	6	4.2	**74.7**	**90.1**	**81.3**	**79.9**
RSN-18	C	384×288	9	5.1	72.1	89.5	79.8	78.6
MogaNet-T	C	384×288	8	4.9	**75.7**	**90.6**	**82.6**	**80.9**
HRNet-W32	C	384×288	29	16.0	75.8	90.6	82.7	81.0
Uniformer-S	H	384×288	25	11.1	75.9	90.6	83.4	81.4
ConvNeXt-T	C	384×288	33	33.1	75.3	90.4	82.1	80.5
MogaNet-S	C	384×288	29	13.5	**76.4**	**91.0**	**83.3**	**81.4**
ResNet-152	C	384×288	69	35.6	74.3	89.6	81.1	79.7
HRNet-W48	C	384×288	64	32.9	76.3	90.8	82.0	81.2
Swin-B	T	384×288	93	39.2	74.9	90.5	81.8	80.3
Swin-L	T	384×288	203	86.9	76.3	91.2	83.0	814
HRFormer-B	T	384×288	54	30.7	77.2	91.0	83.6	82.0
ConvNeXt-S	C	384×288	55	21.8	75.8	90.7	83.1	81.0
ConvNeXt-B	C	384×288	94	36.6	75.9	90.6	83.1	81.1
Uniformer-B	C	384×288	54	14.8	76.7	90.8	84.0	81.4
MogaNet-B	C	384×288	47	24.4	**77.3**	**91.4**	**84.0**	**82.2**

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Thank you!

Paper: MogaNet

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