Swin Transformer: Hierarchical Vision Transformer using Shifted Windows

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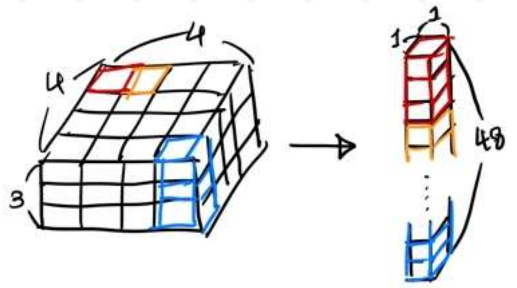
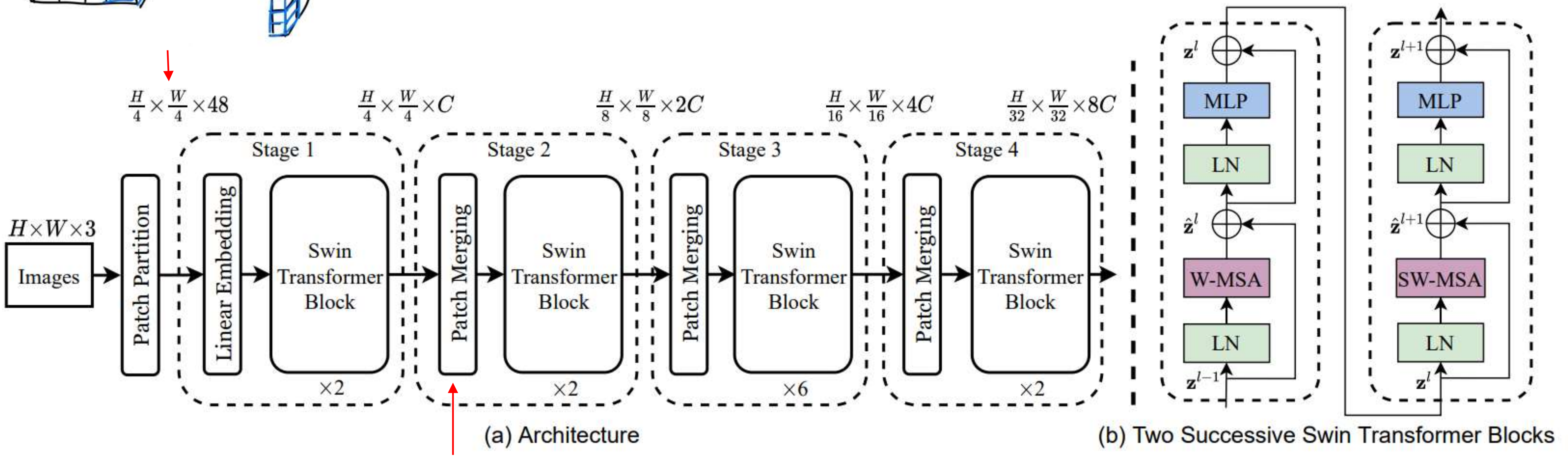
Swin Transformer

- General-purpose backbone for computer vision.
- Hierachical Transformer whose representation is computed with shifted windows.

Architecture



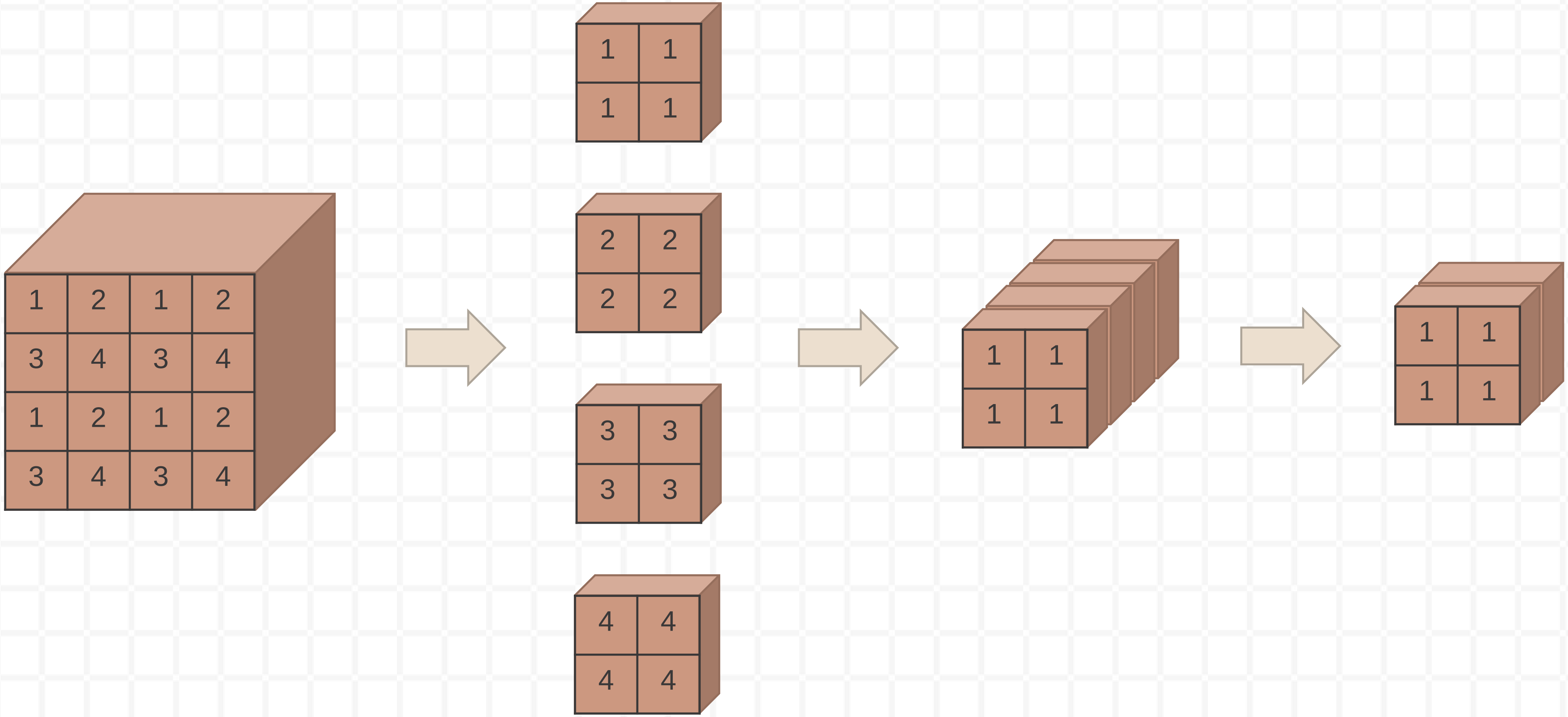


(a) Architecture

(b) Two Successive Swin Transformer Blocks

https://hangjo-o.tistory.com/69

Patch Merging

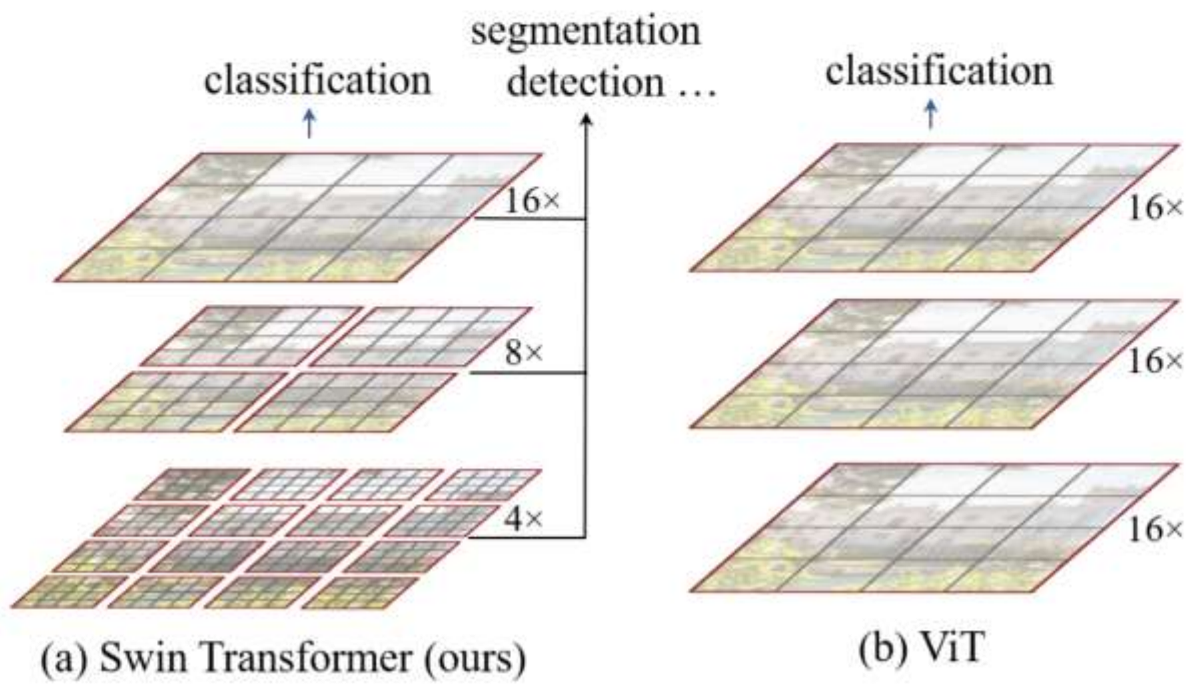


Self-attention in non-overlapped windows

- $M \times M$ (7 x 7)

- Propose to compute self-attention within local windows.

$$\Omega(\mathrm{MSA}) = 4hwC^2 + 2(hw)^2C,$$
$$\Omega(\text{W-MSA}) = 4hwC^2 + 2M^2hwC,$$



Shifted window partitioning in successive blocks

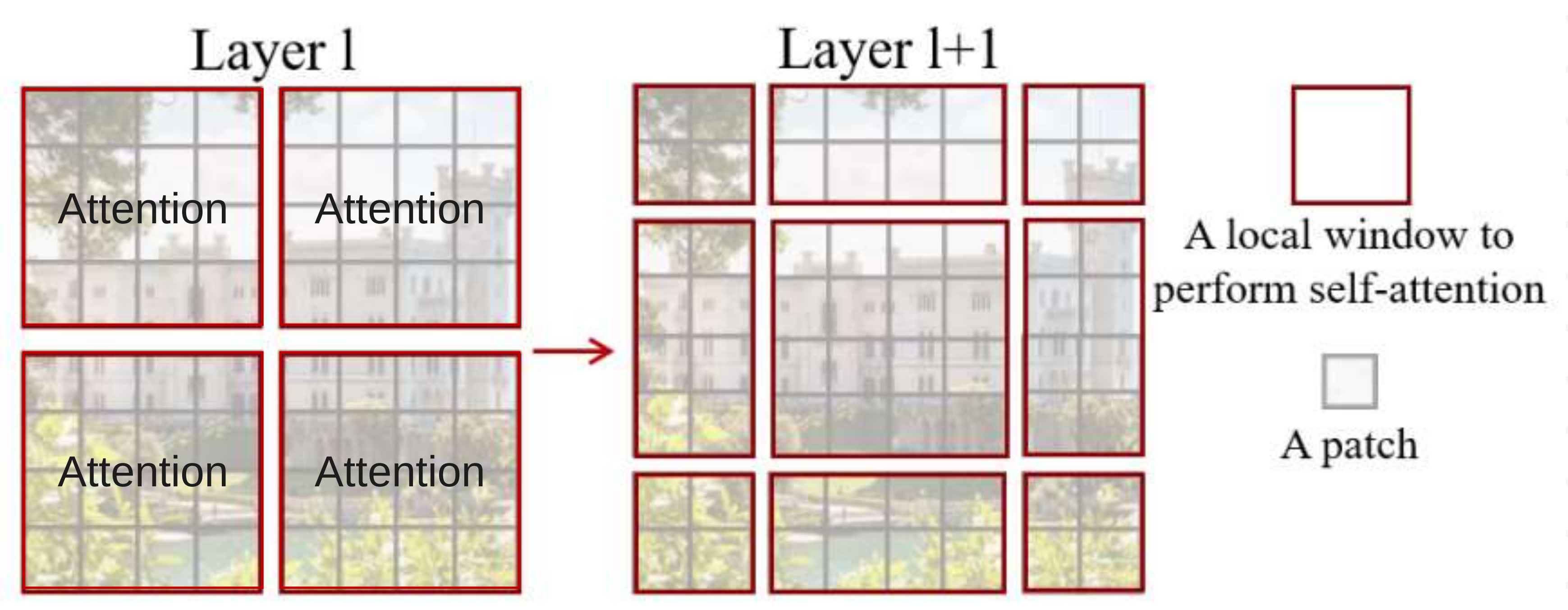
- The window-based self-attention module lacks connections across windows, which limits its modeling power.

- W-MSA

- SW-MSA

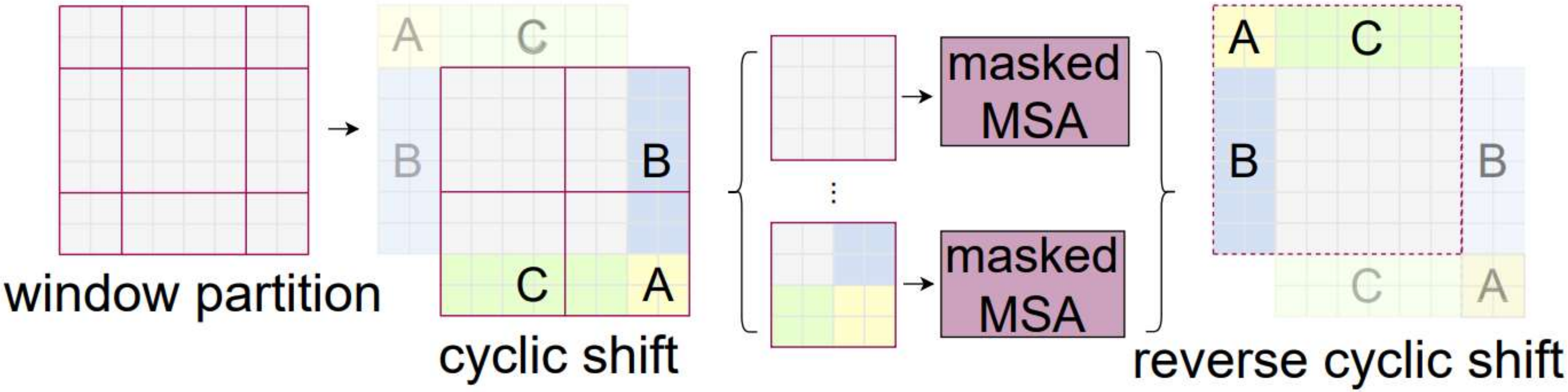
$$
\begin{aligned}
\hat{\mathbf{z}}^{l} &= \text{W-MSA}\left(\text{LN}\left(\mathbf{z}^{l-1}\right)\right) + \mathbf{z}^{l-1}, \\
\mathbf{z}^{l} &= \text{MLP}\left(\text{LN}\left(\hat{\mathbf{z}}^{l}\right)\right) + \hat{\mathbf{z}}^{l}, \\
\hat{\mathbf{z}}^{l+1} &= \text{SW-MSA}\left(\text{LN}\left(\mathbf{z}^{l}\right)\right) + \mathbf{z}^{l}, \\
\mathbf{z}^{l+1} &= \text{MLP}\left(\text{LN}\left(\hat{\mathbf{z}}^{l+1}\right)\right) + \hat{\mathbf{z}}^{l+1},
\end{aligned}
$$

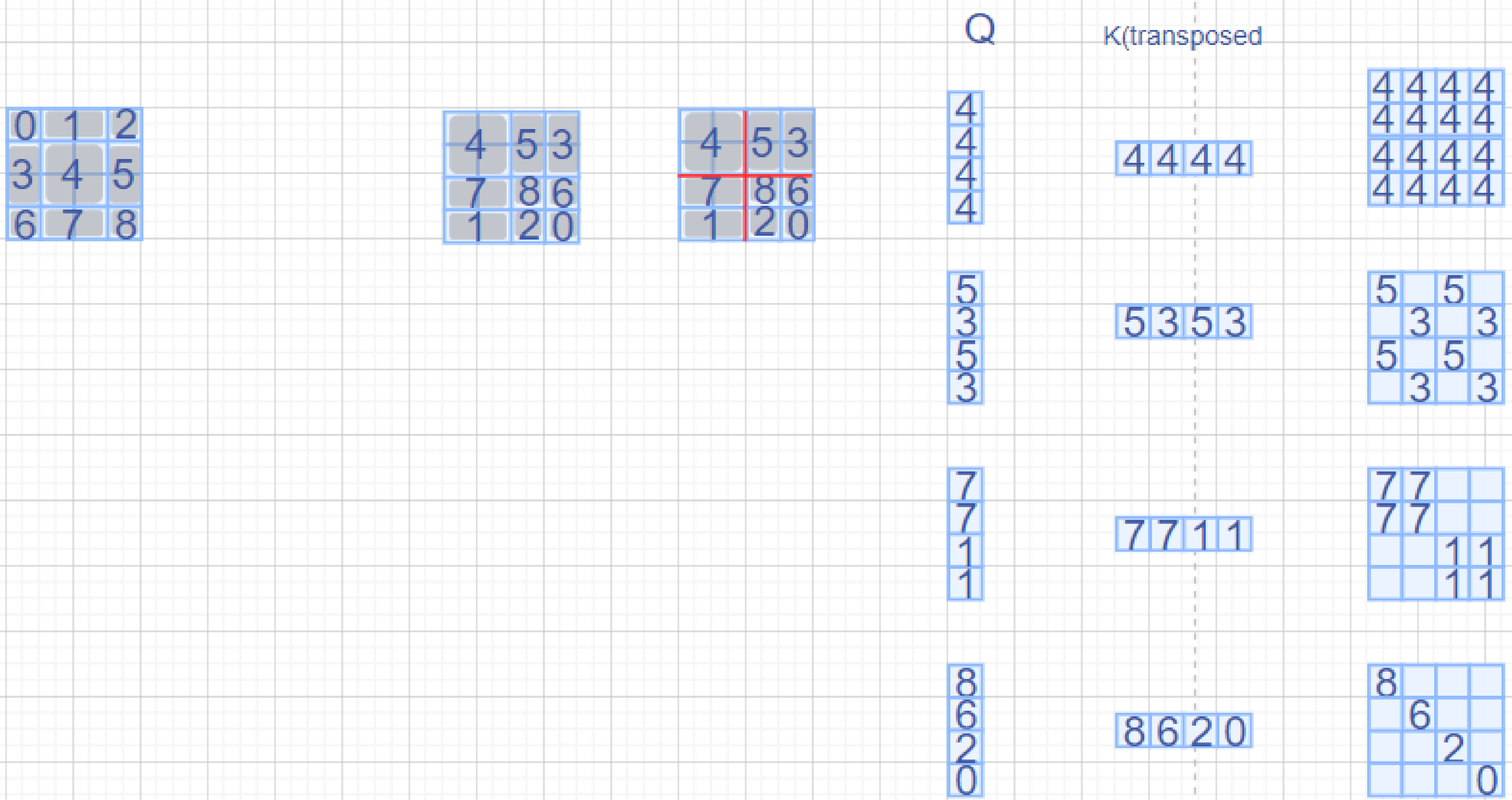
Swin Transformer



Efficient batch computation for shifted configuration

- if.. smaller than M x M ??
  - Add padding -> increased computation
  - Cyclic-Shift




Q
K(transposed

Relative position bias

- Including a relative position bias : $B \in \mathbb{R}^{M^2 \times M^2}$

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d}} + B\right)V$$

Swin Transformer

- We also introduce Swin-T, Swin-S and Swin-L, which are versions of about 0.25×, 0.5× and 2× the model size and computational complexity, respectively.

- M = 7 / d = 32

Swin-T: $C = 96$, layer numbers = $\{2, 2, 6, 2\}$

Swin-S: $C = 96$, layer numbers =$\{2, 2, 18, 2\}$

Swin-B: $C = 128$, layer numbers =$\{2, 2, 18, 2\}$

Swin-L: $C = 192$, layer numbers =$\{2, 2, 18, 2\}$

Experiments - ImageNet

(a) Regular ImageNet-1K trained models

method	image size	#param.	FLOPs	throughput (image / s)	ImageNet top-1 acc.
RegNetY-4G [47]	224^2	21M	4.0G	1156.7	80.0
RegNetY-8G [47]	224^2	39M	8.0G	591.6	81.7
RegNetY-16G [47]	224^2	84M	16.0G	334.7	82.9
EffNet-B3 [57]	300^2	12M	1.8G	732.1	81.6
EffNet-B4 [57]	380^2	19M	4.2G	349.4	82.9
EffNet-B5 [57]	456^2	30M	9.9G	169.1	83.6
EffNet-B6 [57]	528^2	43M	19.0G	96.9	84.0
EffNet-B7 [57]	600^2	66M	37.0G	55.1	84.3
ViT-B/16 [19]	384^2	86M	55.4G	85.9	77.9
ViT-L/16 [19]	384^2	307M	190.7G	27.3	76.5
DeiT-S [60]	224^2	22M	4.6G	940.4	79.8
DeiT-B [60]	224^2	86M	17.5G	292.3	81.8
DeiT-B [60]	384^2	86M	55.4G	85.9	83.1
Swin-T	224^2	29M	4.5G	755.2	81.3
Swin-S	224^2	50M	8.7G	436.9	83.0
Swin-B	224^2	88M	15.4G	278.1	83.3
Swin-B	384^2	88M	47.0G	84.7	84.2

14.2 million images and 22K classes.

(b) ImageNet-22K pre-trained models

method	image size	#param.	FLOPs	throughput (image / s)	ImageNet top-1 acc.
R-101x3 [37]	384^2	388M	204.6G	-	84.4
R-152x4 [37]	480^2	937M	840.5G	-	85.4
ViT-B/16 [19]	384^2	86M	55.4G	85.9	84.0
ViT-L/16 [19]	384^2	307M	190.7G	27.3	85.2
Swin-B	224^2	88M	15.4G	278.1	85.2
Swin-B	384^2	88M	47.0G	84.7	86.0
Swin-L	384^2	197M	103.9G	42.1	86.4

Experiments - Object Detection

(a) Various frameworks

Method	Backbone	AP^{box}	AP^{box}_{50}	AP^{box}_{75}	#param.	FLOPs	FPS
Cascade Mask R-CNN	R-50	46.3	64.3	50.5	82M	739G	18.0
	Swin-T	**50.5**	**69.3**	**54.9**	86M	745G	15.3
ATSS	R-50	43.5	61.9	47.0	32M	205G	28.3
	Swin-T	**47.2**	**66.5**	**51.3**	36M	215G	22.3
RepPointsV2	R-50	46.5	64.6	50.3	42M	274G	13.6
	Swin-T	**50.0**	**68.5**	**54.2**	45M	283G	12.0
Sparse R-CNN	R-50	44.5	63.4	48.2	106M	166G	21.0
	Swin-T	**47.9**	**67.3**	**52.3**	110M	172G	18.4

(b) Various backbones w. Cascade Mask R-CNN

	AP^{box}	AP^{box}_{50}	AP^{box}_{75}	AP^{mask}	AP^{mask}_{50}	AP^{mask}_{75}	param	FLOPs	FPS
DeiT-S†	48.0	67.2	51.7	41.4	64.2	44.3	80M	889G	10.4
R50	46.3	64.3	50.5	40.1	61.7	43.4	82M	739G	18.0
Swin-T	**50.5**	**69.3**	**54.9**	**43.7**	**66.6**	**47.1**	86M	745G	15.3
X101-32	48.1	66.5	52.4	41.6	63.9	45.2	101M	819G	12.8
Swin-S	**51.8**	**70.4**	**56.3**	**44.7**	**67.9**	**48.5**	107M	838G	12.0
X101-64	48.3	66.4	52.3	41.7	64.0	45.1	140M	972G	10.4
Swin-B	**51.9**	**70.9**	**56.5**	**45.0**	**68.4**	**48.7**	145M	982G	11.6

(c) System-level Comparison

Method	mini-val AP^{box}	mini-val AP^{mask}	test-dev AP^{box}	test-dev AP^{mask}	#param.	FLOPs
RepPointsV2* [11]	-	-	52.1	-	-	-
GCNet* [6]	51.8	44.7	52.3	45.4	-	1041G
RelationNet++* [12]	-	-	52.7	-	-	-
SpineNet-190 [20]	52.6	-	52.8	-	164M	1885G
ResNeSt-200* [75]	52.5	-	53.3	47.1	-	-
EfficientDet-D7 [58]	54.4	-	55.1	-	77M	410G
DetectoRS* [45]	-	-	55.7	48.5	-	-
YOLOv4 P7* [3]	-	-	55.8	-	-	-
Copy-paste [25]	55.9	47.2	56.0	47.4	185M	1440G
X101-64 (HTC++)	52.3	46.0	-	-	155M	1033G
Swin-B (HTC++)	56.4	49.1	-	-	160M	1043G
Swin-L (HTC++)	57.1	49.5	57.7	50.2	284M	1470G
Swin-L (HTC++)*	**58.0**	**50.4**	**58.7**	**51.1**	284M	-

Semantic Segmentation

ADE20K Method	Backbone	val mIoU	test score	#param.	FLOPs	FPS
DANet [22]	ResNet-101	45.2	-	69M	1119G	15.2
DLab.v3+ [10]	ResNet-101	44.1	-	63M	1021G	16.0
ACNet [23]	ResNet-101	45.9	38.5	-		
DNL [68]	ResNet-101	46.0	56.2	69M	1249G	14.8
OCRNet [70]	ResNet-101	45.3	56.0	56M	923G	19.3
UperNet [66]	ResNet-101	44.9	-	86M	1029G	20.1
OCRNet [70]	HRNet-w48	45.7	-	71M	664G	12.5
DLab.v3+ [10]	ResNeSt-101	46.9	55.1	66M	1051G	11.9
DLab.v3+ [10]	ResNeSt-200	48.4	-	88M	1381G	8.1
SETR [78]	T-Large‡	50.3	61.7	308M	-	-
UperNet	DeiT-S†	44.0	-	52M	1099G	16.2
UperNet	Swin-T	46.1	-	60M	945G	18.5
UperNet	Swin-S	49.3	-	81M	1038G	15.2
UperNet	Swin-B‡	51.6	-	121M	1841G	8.7
UperNet	Swin-L‡	**53.5**	**62.8**	234M	3230G	6.2

Ablation Study

	ImageNet top-1	ImageNet top-5	COCO AP^{box}	COCO AP^{mask}	ADE20k mIoU
w/o shifting	80.2	95.1	47.7	41.5	43.3
shifted windows	**81.3**	**95.6**	**50.5**	**43.7**	**46.1**
no pos.	80.1	94.9	49.2	42.6	43.8
abs. pos.	80.5	95.2	49.0	42.4	43.2
abs.+rel. pos.	81.3	95.6	50.2	43.4	44.0
rel. pos. w/o app.	79.3	94.7	48.2	41.9	44.1
rel. pos.	**81.3**	**95.6**	**50.5**	**43.7**	**46.1**

method	MSA in a stage (ms) S1	S2	S3	S4	Arch. (FPS) T	S	B
sliding window (naive)	122.5	38.3	12.1	7.6	183	109	77
sliding window (kernel)	7.6	4.7	2.7	1.8	488	283	187
Performer [13]	4.8	2.8	1.8	1.5	638	370	241
window (w/o shifting)	2.8	1.7	1.2	0.9	770	444	280
shifted window (padding)	3.3	2.3	1.9	2.2	670	371	236
shifted window (cyclic)	3.0	1.9	1.3	1.0	755	437	278

	Backbone	ImageNet top-1	ImageNet top-5	COCO AP^{box}	COCO AP^{mask}	ADE20k mIoU
sliding window	Swin-T	81.4	95.6	50.2	43.5	45.8
Performer [13]	Swin-T	79.0	94.2	-	-	-
shifted window	Swin-T	81.3	95.6	50.5	43.7	46.1

Conclusion

- Proposed Swin Transformer which a new vision Transformer.
- Hierarchical feature representation and has linear computational complexity with respect to input image size.
- Shifted window based self-attention is shown to be effective and efficient on vision problems.