Swin Transformer: Hierarchical Vision Transformer using Shifted Windows (ICCV 2021)

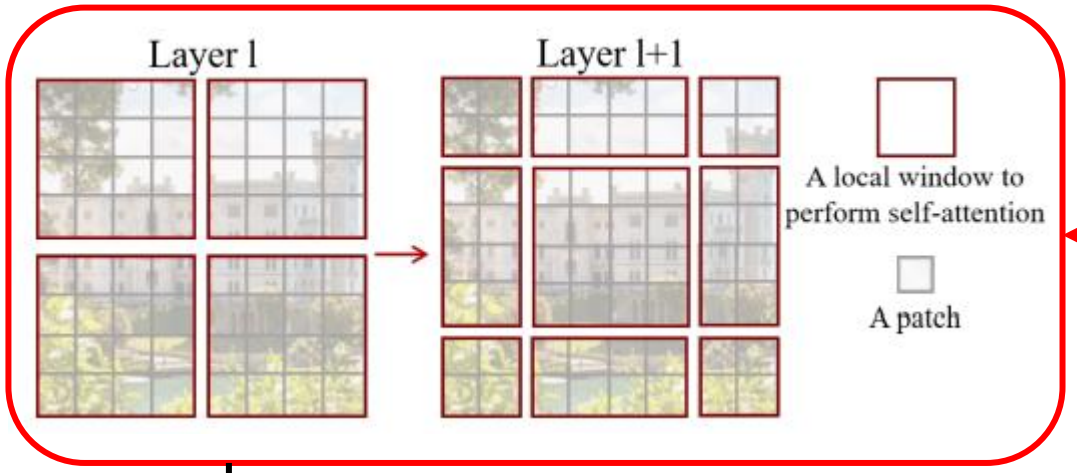
- **연구동기:**

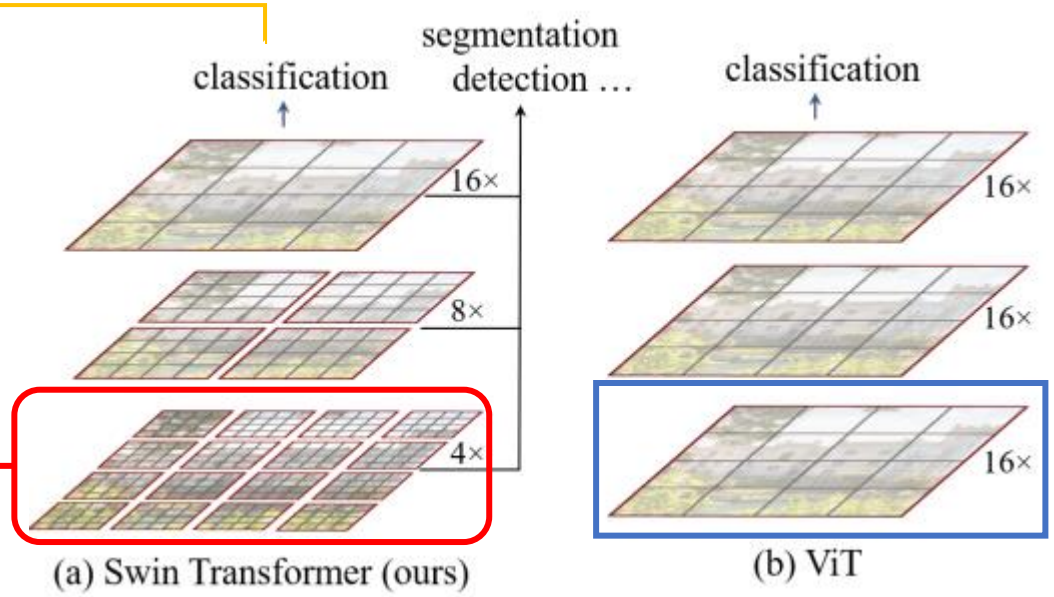
문제 기존의 ViT가 항상 Fixed scale로 접근해 여러 CV의 같은 scale에 민감한 task를 잘 처리하지 못함.
ViT 방식의 경우 고해상도 Image 처리에 있어 Quadratic하게 증가하는 연산량으로 인해 학습에 오랜 시간, 많은 비용이 든다.
+ Semantic segmentation에 Transformer 모델 적용 -> dense prediction을 구하는데 계산량이 많아져 -> Intractable 문제 발생

해결: Transformer 기반의 backbone + CNN vision task 에서 수행하는 역할 일부를 수용해 **Swin Transformer** 제안.

+ Hierarchical feature map, Shifted window (Swin) block 이용

각 계층마다 Representation을 가져 multi-scale entity를 다루는 비전 분야에서 좋은 성능 (Segmentation)





Patch size:16x16
Total Patch:
$224/16^2 = 196$

문제: 단순히 window 기준으로 나누면 self-attention수행 X
해결: **Shifted window partitioning**
Layer l의 분할이 발생한 patch에서 ($[\frac{M}{2}x\frac{M}{2}]$) pixel 단위로 이동시켜 Layer l+1의 window를 분할함으로써 window간의 연결성을 반영한다.

Swin Transformer:
더 작은 단위의 patch로 시작해 점점 patch들을 merge하는 방식
Window내의 patch들끼리 만 self-attention 수행
Linear Computational complexity to image size

Window: M개의 인접한 patch로 구성된 patch set

기존 ViT:
Image를 Fixed Scale patch들로 쪼갬
Resolution ↑ => Self-Attention ↓
Quadratic computational complexity to image size

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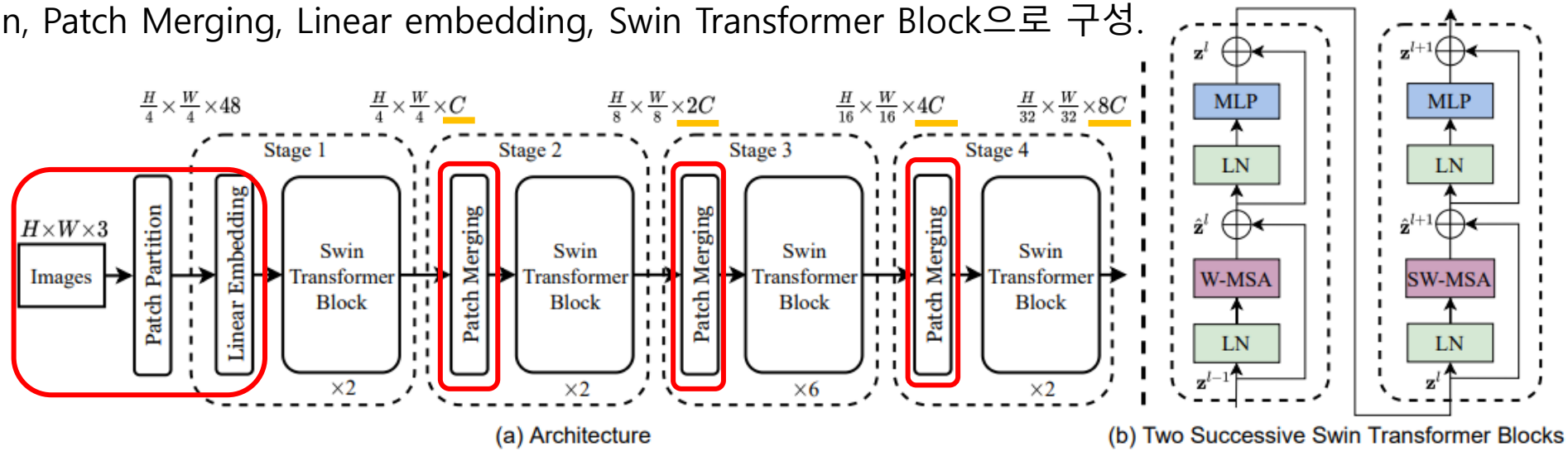
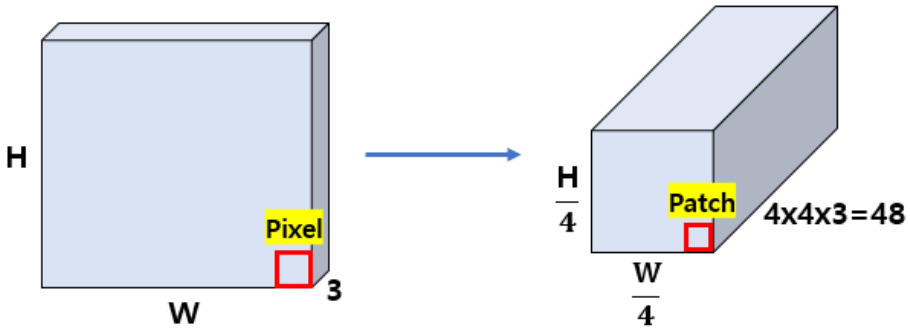
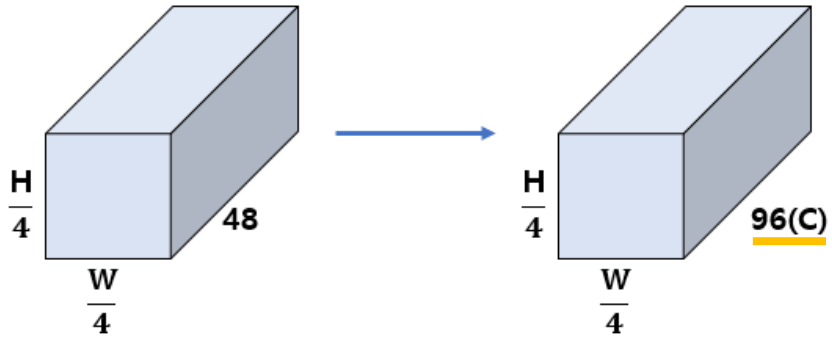
- **Method:**
  Patch partition, Patch Merging, Linear embedding, Swin Transformer Block으로 구성.



Stage 1: Patch partition/Merging

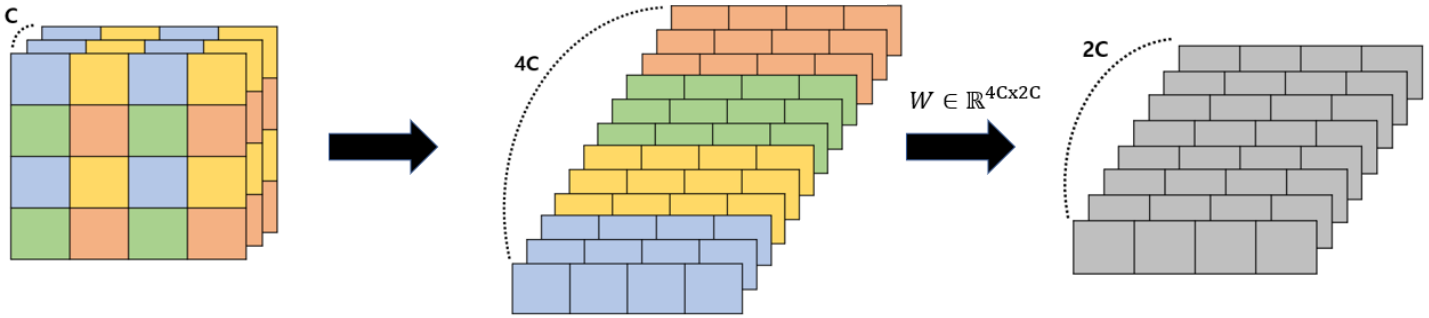


Stage 1: Linear Embedding



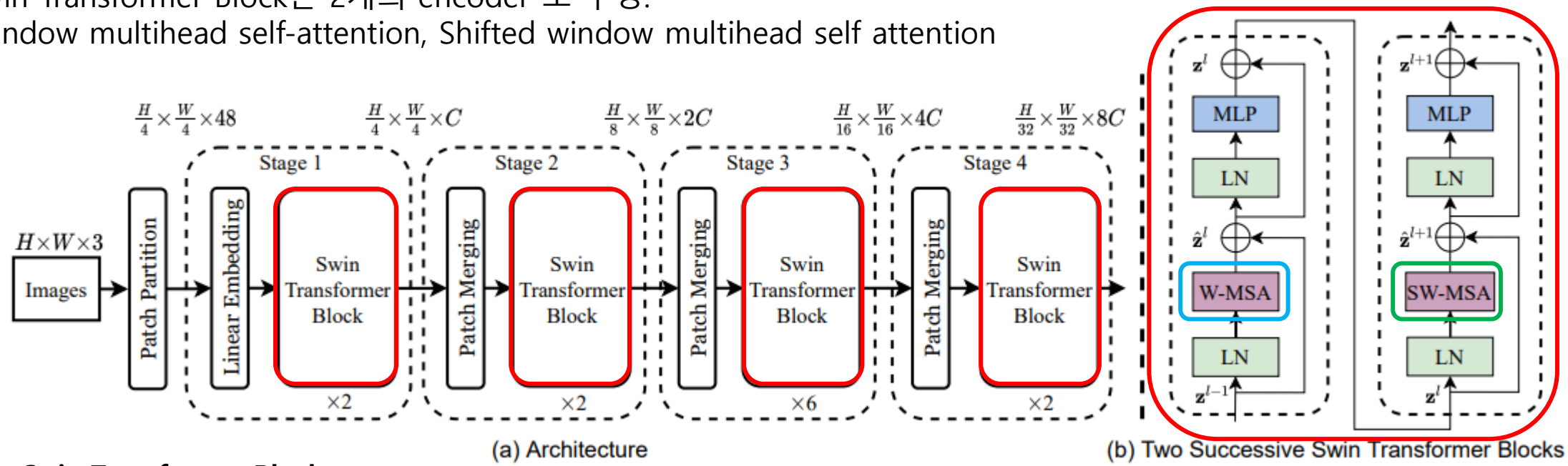
Patch Partition/Merging의 출력이 Linear layer에서 C의 dimension이 됨.
C=(96, 192, 384, 768)

<Tiny model 기준 stage마다>



Swin Transformer: Hierarchical Vision Transformer using Shifted Windows (ICCV 2021)

- **Method:**
  Swin Transformer Block은 2개의 encoder 로 구성:
  Window multihead self-attention, Shifted window multihead self attention



Swin Transformer Block
W-MSA

W-MSA: 현재 window에 있는 패치끼리 만 self-attention 수행
=> computational complexity 해결 (주변 픽셀들끼리 서로 연관성↑)
Quadratic -> Linear!

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

M(Window size) < hw(image size)
=> **W-MSA**의 연산량 < **MSA**의 연산량

단점: Window 고정 ,고정된 부분에서만 self-attention 수행
해결: Window를 이동(Shift)해서 self-attention 수행

SW-MSA !!

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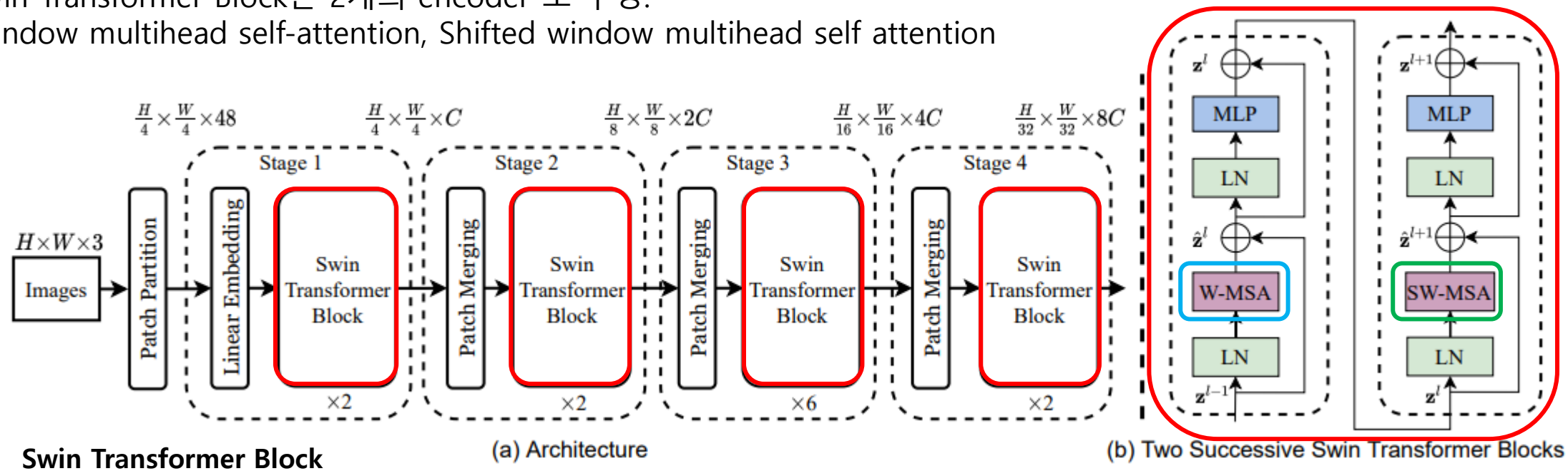
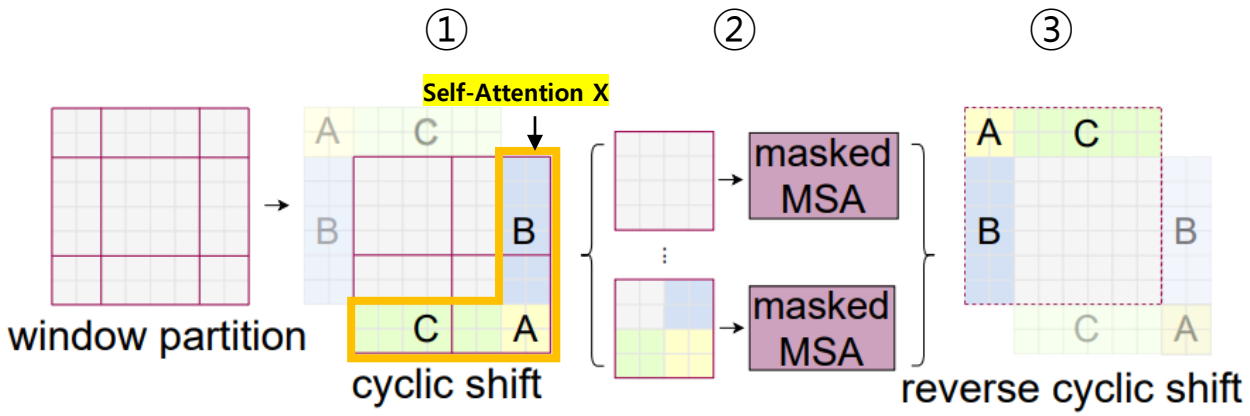


Swin Transformer Block
SW-MSA



1. Window Shift = **Cyclic Shift**
Window size//2 만큼 우측 하단으로 shift

2. A, B, C 구역에 Mask를 씌워 Self-Attention X

3. 원래 값으로 되돌림 (**Reverse cyclic shift**)

SW-MSA를 통해 Window 사이의 연결성을 나타냄

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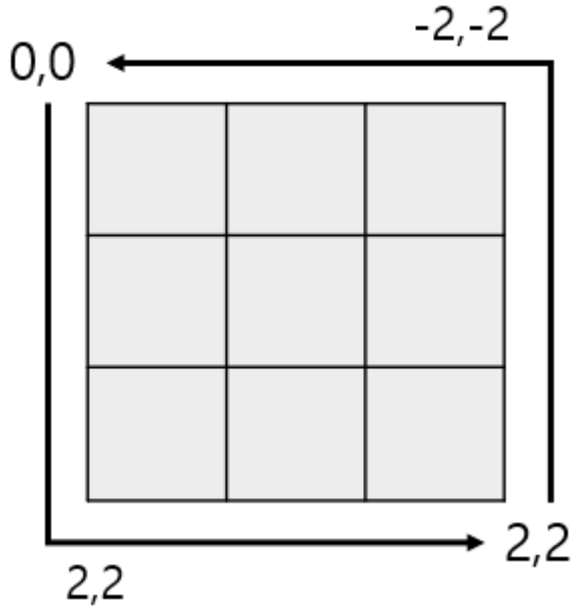
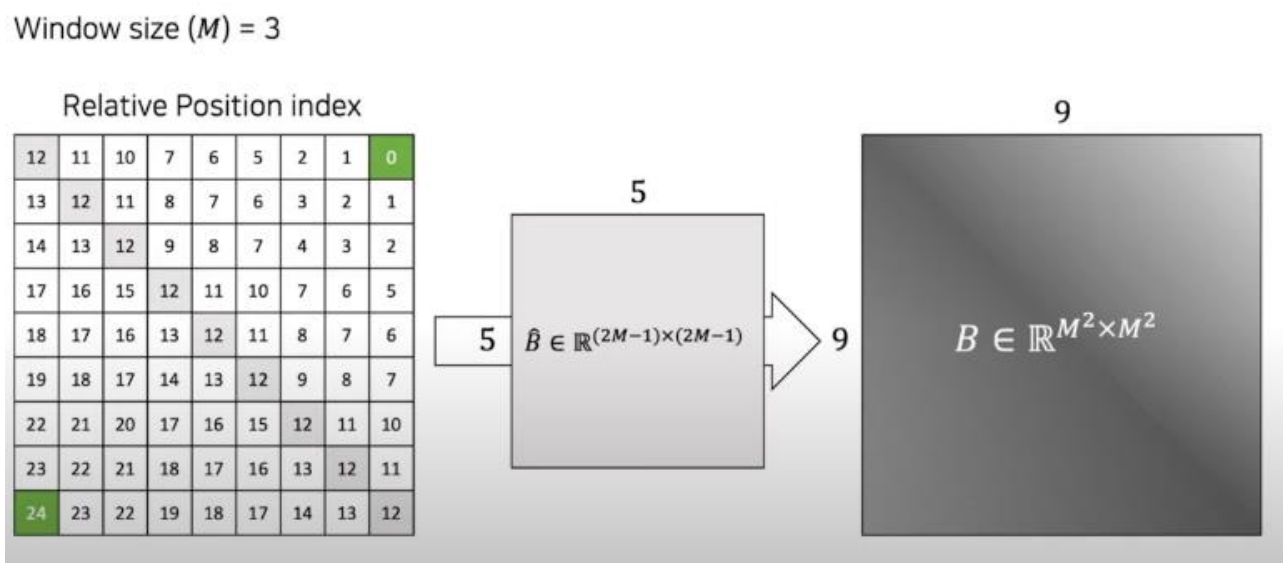
- **Method:**
  ViT 와 다르게 Positional embedding 을 입력 부분에 추가하지 않고, **Relative Position Bias** 활용.

$$\text{Attention}(Q, K, V) = \text{SoftMax}(QK^T/\sqrt{d} + B)V,$$

Relative Position Bias: 기존 ViT에서 softmax를 취하기 전, B를 더함
Author: 기존의 Position Embedding에서의 절대좌표를 더하는 것보다 **상대좌표**를 더해주는 것이 더 좋은 방법





0,0 Pixel에서 2,2 Pixel로 이동하기 위해 2,2 만큼 이동해야 한다. 반대로 2,2 Pixel에서 0,0 Pixel로 이동하기 위해 -2,-2 만큼 이동해야 한다.
=> 어떤 Pixel을 중심으로 하나에 따라 이동 값이 달라짐
=> 단순하게 Sin, Cos의 주기로 구한 절대 좌표를 사용하는 것보다 상대적인 좌표를 embedding해 더하는 것이 더 좋다.

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- **Experiment:**
  ImageNet Dataset에서 Swin Transformer는 ViT base model보다 parameter 수, FlOPs는 훨씬 적으면서 높은 성능을 보였다.
  CNN 기반 모델 중 SOTA를 달성한 EfficientNet-B7보다 좋은 성능을 보인다.
  다른 여러 Task(detection, segmentation 등)에서 SOTA를 달성했다.

Comparison of different backbones on ImageNet-1K classification

(a) Regular ImageNet-1K trained models

method	image size	#param.	FLOPs	throughput (image / s)	ImageNet top-1 acc.
RegNetY-4G [48]	224^2	21M	4.0G	1156.7	80.0
RegNetY-8G [48]	224^2	39M	8.0G	591.6	81.7
RegNetY-16G [48]	224^2	84M	16.0G	334.7	82.9
EffNet-B3 [58]	300^2	12M	1.8G	732.1	81.6
EffNet-B4 [58]	380^2	19M	4.2G	349.4	82.9
EffNet-B5 [58]	456^2	30M	9.9G	169.1	83.6
EffNet-B6 [58]	528^2	43M	19.0G	96.9	84.0
EffNet-B7 [58]	600^2	66M	37.0G	55.1	84.3
ViT-B/16 [20]	384^2	86M	55.4G	85.9	77.9
ViT-L/16 [20]	384^2	307M	190.7G	27.3	76.5
DeiT-S [63]	224^2	22M	4.6G	940.4	79.8
DeiT-B [63]	224^2	86M	17.5G	292.3	81.8
DeiT-B [63]	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	83.5
Swin-B	384^2	88M	47.0G	84.7	84.5

(b) ImageNet-22K pre-trained models

method	image size	#param.	FLOPs	throughput (image / s)	ImageNet top-1 acc.
R-101x3 [38]	384^2	388M	204.6G	-	84.4
R-152x4 [38]	480^2	937M	840.5G	-	85.4
ViT-B/16 [20]	384^2	86M	55.4G	85.9	84.0
ViT-L/16 [20]	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	86.4
Swin-L	384^2	197M	103.9G	42.1	87.3

Results on COCO object detection and ADE20K semantic segmentation

(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

ADE20K Method	Backbone	val mIoU	test score	#param.	FLOPs	FPS
DANet [23]	ResNet-101	45.2	-	69M	1119G	15.2
DLab.v3+ [11]	ResNet-101	44.1	-	63M	1021G	16.0
ACNet [24]	ResNet-101	45.9	38.5	-		
DNL [71]	ResNet-101	46.0	56.2	69M	1249G	14.8
OCRNet [73]	ResNet-101	45.3	56.0	56M	923G	19.3
UperNet [69]	ResNet-101	44.9	-	86M	1029G	20.1
OCRNet [73]	HRNet-w48	45.7	-	71M	664G	12.5
DLab.v3+ [11]	ResNeSt-101	46.9	55.1	66M	1051G	11.9
DLab.v3+ [11]	ResNeSt-200	48.4	-	88M	1381G	8.1
SETR [81]	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

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- **Experiment:**
  기존 shifted window, kernel 기반, padding 기반보다 제안한 cyclic shift가 가장 좋은 성능을 입증했다
  또한 relative position bias 를 단독으로 사용할 때 가장 좋은 성능을 달성해 효과를 입증했다.

Shifted windows approach and Different position embedding methods on three benchmarks
(using the Swin-T architecture)

	ImageNet		COCO		ADE20k
	top-1	top-5	AP^{box}	AP^{mask}	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**

Better Performance

Better Performance

성능: Only W-MSA < SW-MSA + W-MSA

성능: 절대좌표(abs.pos), 절대+상대좌표(abs.+rel.pos).. < Only 상대좌표(rel.pos)